

Library of ATWL-represented Visual Analytics Workflows

The document contains following examples of ATWL representations of workflows from published visual analytics papers: The diagrammatic representations of the workflow in Section 2 were automatically generated by a different instance of LLM agent (Claude Opus 4.6R) from the ATWL representations. The encoding used in the diagrams is explained in Fig.1.

- 1.1: Cluster-Calendar [14]
- 1.2: Dynamic network analysis [13]
- 1.3: Graph-based analysis of mass mobility flows [15]
- 1.4: EventFlow [10]
- 1.5: EventAction [7]
- 1.6: Extracting significant places from trajectories [1]
- 1.7: Progressive clustering of trajectories [12]
- 1.8: Human-steered topic modelling [6]
- 1.9: Progressive abstraction of multivariate temporal data [4]
- 1.10: Partition-based Regression Modelling [11].
- 1.11: Spatio-temporal analysis and modelling through time series fitting [2].
- 1.12: Data engineering for movement pattern classification [3]
- 1.13: Exploratory Model Analysis [5]
- 1.14: Binary Classifier Diagnostics [9]
- 1.15: Interactive exploration of random forest classifier [8]
- 1.16: Exploring Deep Learning Models in TensorFlow [17]
- 1.17: What-If Probing of ML Models [16]

References

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1 Visual Analytics Workflows Represented in ATWL

1.1 Cluster-calendar workflow

Source: Jarke J. van Wijk and Edward R. van Selow. Cluster and calendar based visualization of time series data. In *Proceedings of the IEEE Symposium on Information Visualization (InfoVis '99)*, pages 4–9, Los Alamitos, CA, USA, 1999. IEEE Computer Society. doi: 10.1109/INFVIS.1999.801851

Concise Workflow Summary

The cluster-calendar workflow combines hierarchical clustering with calendar-based visualization to identify and analyse recurring patterns in time series data measured at regular intervals (e.g., hourly) over extended periods. The workflow partitions continuous time series into daily episodes, characterizes each day by its temporal profile, and

applies hierarchical bottom-up clustering to group days with similar patterns. Users iteratively refine the cluster structure—adjusting the number of clusters, selecting alternative distance measures, or focusing on specific time intervals—until meaningful behavioural patterns emerge. The results are presented through coordinated visualizations: a calendar view where days are colour-coded by cluster membership to reveal weekly and seasonal distributions, and line graphs showing the average temporal profile for each cluster to illustrate characteristic patterns. Through interactive exploration of these coordinated views, analysts identify both standard patterns (e.g., typical weekdays, weekends, seasonal variations) and exceptional days (e.g., holidays, special events), formulating insights about temporal regularities and anomalies that would be difficult to detect through traditional time series analysis methods.

Figure 2 provides a diagrammatic representation of the workflow.

ATWL representation

```

workflow cluster-calendar
  template: define-unit → contextualise → characterise →
            loop(define-unit (similarity-based) →
                 characterise (groups) → visualise →
                 abstract → assess) →
            generate-knowledge
  description: "Identify and analyze recurring daily patterns in time series
              data through interactive clustering and calendar-based visualization;
              detect standard patterns and exceptional days"

artifact D_hour : entities
  origin: given
  internal structure: elementary
  embedment: time
  features:
    - id: f_value
      value structure: atomic
      value type: numeric
      description: "Measured value"
  description: "Time series measurements at regular intervals over extended period
"

artifact D_calendar : entities
  origin: given
  internal structure: elementary
  embedment: time
  features:
    - id: f_temporal_coords
      value structure: vector
      value type: {categorical, numeric}
      description: "Month, day of week, day number"
  description: "Calendar structure providing temporal context with
              month and weekday organization"

```

```

transform T_partition :
  intent: define-unit
  manner: "time-partitioning into daily episodes"
  input: D_hour
  output: D_day
  actor: machine
  description: "Organize time series into daily episodes, each containing
    measurements for one 24-hour period"

artifact D_day : entities
  internal structure: episode
  embedment: time
  features:
    - id: f_day_index
      value structure: atomic
      value type: ordinal
      description: "Sequential position of day in the year"
  description: "Daily episodes consisting of all measurements within each
    24-hour period"

transform T_arrange :
  intent: contextualise
  manner: "calendar-based"
  input: D_day, D_calendar
  output: A_calendar
  actor: machine
  description: "Arrange daily episodes in calendar context
    according to their temporal position"

artifact A_calendar : arrangement(D_day)
  context: D_calendar
  principle: "calendar date mapping to grid position"
  description: "Calendar-based arrangement where each day occupies
    its corresponding calendar cell"

transform T_profile :
  intent: characterise
  manner: "extract temporal profile"
  input: D_day
  output: F_day_profile
  actor: machine
  description: "Represent each day by its measurement sequence"

artifact F_day_profile : feature(D_day)
  value structure: vector
  value type: numeric
  description: "Daily temporal profile: sequence of measurements within each day"

artifact S_clustering : specification
  origin: given
  representation form: "parameter settings"
  description: "Initial parameters for hierarchical clustering:

```

number of clusters (dendrogram cut level), distance measure (geometric, normalized, shift-invariant, max-based), time interval focus"

loop L1:

purpose: "Iteratively explore cluster structure to identify meaningful and interpretable daily patterns"

until: "Clusters provide clear, interpretable decomposition of daily patterns; standard patterns and exceptional days are identified"

body:

transform T_cluster :

intent: *define-unit*

manner: "hierarchical clustering by similarity"

input: D_day, F_day_profile, S_clustering

output: D_cluster, F_cluster_label

actor: *hybrid*

description: "Apply hierarchical clustering to group days with similar profiles; user selects cut through dendrogram to determine clusters"

artifact D_cluster : *entities*

internal structure: group/cluster

embedment: set

features:

- id: cluster_size

value structure: atomic

value type: numeric

description: "Number of days in cluster"

description: "Groups of days with similar daily profiles selected from hierarchical clustering tree"

artifact F_cluster_label : *feature*(D_day)

value structure: atomic

value type: categorical

description: "Cluster membership identifier for each day"

transform T_aggregate :

intent: *characterise*

manner: "aggregate profiles per cluster"

input: D_cluster, F_day_profile

output: F_cluster_profile

actor: *machine*

description: "Compute average daily profile for each cluster to represent typical pattern"

artifact F_cluster_profile : *feature*(D_cluster)

value structure: vector

value type: numeric

description: "Cluster-level average daily profiles representing typical patterns for each group"

transform T_calendar_vis :

intent: *visualise*

```

    manner: "calendar grid with color-coded clusters"
    input: A_calendar, F_cluster_label
    output: V_calendar
    actor: machine
    description: "Display days on calendar grid, colored by cluster
membership"

    artifact V_calendar : visualisation(A_calendar, F_cluster_label)
    layout: "calendar grid (months as rows, weekdays as columns)"
    form: "colored cells"
    encoding: "position from A_calendar; color from F_cluster_label"
    description: "Calendar view showing temporal distribution of cluster
patterns across year and week"

    transform T_profile_vis :
    intent: visualise
    manner: "line graphs of cluster profiles"
    input: F_cluster_profile, D_cluster
    output: V_profiles
    actor: machine
    description: "Display average daily profile for each cluster as line
graph"

    artifact V_profiles : visualisation(F_cluster_profile, D_cluster)
    layout: "time axis (hour of day)"
    form: "line graphs (one per cluster)"
    encoding: "x-position: time within day; y-position: average measurement
value; color: cluster identity matching calendar colors"
    description: "Line graphs showing characteristic temporal patterns for
each cluster"

    transform T_interpret :
    intent: abstract
    manner: "interpret cluster meanings"
    input: V_calendar, V_profiles, D_cluster, F_cluster_profile
    output: P_patterns
    actor: human
    description: "Interpret cluster patterns: identify behavioral meaning
of each cluster type"

    artifact P_patterns : pattern(D_cluster, F_cluster_profile)
    representation form: "textual labels and descriptions"
    description: "Interpreted meanings of daily patterns (e.g., 'typical
weekday', 'weekend', 'holiday', 'summer Friday', 'exceptional event
')"

    transform T_assess_clusters :
    intent: assess
    manner: "evaluate cluster quality and interpretability"
    input: V_calendar, V_profiles, P_patterns, D_cluster
    output: cluster_assessment
    actor: human

```

```

        description: "Assess whether clusters provide meaningful decomposition:
        patterns are interpretable, clusters well-separated, standard vs.
        exceptional days identified"

artifact cluster_assessment : knowledge(D_cluster)
    representation form: "quality judgment"
    description: "Assessment of cluster quality: interpretability,
    separation, coverage of pattern types, and whether refinement
    with adjusted parameters is needed"

if cluster_assessment indicates refinement needed:
    then:
        transform T_adjust :
            intent: generate-knowledge
            manner: "adjust clustering parameters based
            on assessment"
            input: cluster_assessment, V_calendar,
            V_profiles, S_clustering
            output: S_clustering'
            actor: human
            description: "Adjust clustering parameters:
            modify number of clusters, select
            different distance measure, or change
            time interval focus"

            artifact S_clustering' : specification
                representation form: "parameter settings"
                description: "Updated clustering parameters
                after analyst refinement"

            assign:
                S_clustering := S_clustering'
        else:
            exit loop L1
end loop L1

transform T_synthesize :
    intent: generate-knowledge
    manner: "formulate statements about temporal patterns"
    input: P_patterns, V_calendar, V_profiles, cluster_assessment
    output: K1
    actor: human
    description: "Synthesize findings: document discovered patterns, their temporal
    distribution, correlations with external events, and exceptional occurrences
    "

artifact K1 : knowledge(P_patterns)
    representation form: "statements and explanations"
    description: "Understanding of temporal patterns: standard daily patterns
    identified, their distribution over week and year, correlation with
    calendar events, exceptional patterns and their causes"

```

1.2 Dynamic Network Exploration workflow

Source: Stef van den Elzen, Danny Holten, Jorik Blaas, and Jarke J. van Wijk.

Reducing snapshots to points: A visual analytics approach to dynamic network exploration.

IEEE Transactions on Visualization and Computer Graphics, 22(1):1–10, January 2016.

doi: 10.1109/TVCG.2015.2468078

Workflow summary:

The paper presents a visual analytics approach for exploring dynamic networks by treating network snapshots as points in high-dimensional space and projecting them to 2D for visualization. The workflow processes timestamped network activities through four main stages:

1. **Discretisation** creates temporal snapshots using sliding time windows with overlap to smooth temporal transitions and avoid missing patterns.
2. **Vectorisation and normalization** converts each snapshot into a feature vector, with optional normalization to emphasize specific patterns.
3. **Dimensionality reduction** projects high-dimensional vectors to 2D, preserving similarity relationships between snapshots.
4. **Visualisation and interaction** presents two coordinated views: a projection view showing snapshots as coloured points (revealing clusters, outliers, and trajectories) and a network view displaying detailed topology of selected snapshots.

Through interactive exploration, analysts identify stable states (uniform-coloured clusters), recurring states (multi-coloured clusters), outlier topologies (isolated points), and transitions between states. The method is demonstrated on artificial networks and real-world high-school contact patterns, revealing daily rhythms, break periods, and network evolution.

Figure 3 provides a diagrammatic representation of the workflow.

ATWL representation:

```
workflow reducing-snapshots-to-points
  template: define-unit (temporal) → characterise →
            contextualise (projection-based) → visualise → abstract →
            generate-knowledge
  description: "Explore dynamic network evolution by projecting snapshots to
              2D points, revealing stable states, recurring patterns, and transitions"

# =====
# INPUT: Timestamped network activity data
# =====
```

```

artifact event_log : entities
  origin: given
  internal structure: elementary
  embedment: {set, time}
  features:
    - id: activity
      value structure: vector
      value type: reference
      description: "Source-target node pairs with timestamps"
  description: "Timestamped network activities involving node pairs"

# =====
# DISCRETIZATION: Create network snapshots
# =====

transform T_discretize :
  intent: define-unit
  manner: "time-partitioning with sliding windows"
  input: event_log
  output: network_snapshots
  actor: machine
  description: "Discretize activity stream into snapshots using overlapping
    time windows"

artifact network_snapshots : entities
  internal structure: formation
  embedment: time
  features:
    - id: snapshot_time
      value structure: atomic
      value type: temporal
      description: "Timestamp of snapshot"
    - id: network_structure
      value structure: relational configuration
      value type: {reference, numeric}
      description: "Network topology with edge weights"
  description: "Temporal sequence of network snapshots, each aggregating
    activities over a time window"

# =====
# VECTORIZATION: Convert snapshots to feature vectors
# =====

transform T_vectorize :
  intent: characterise
  manner: "encode network structure as vector"
  input: network_snapshots
  output: snapshot_vectors
  actor: machine
  description: "Convert snapshots to high-dimensional vectors representing
    network structure"

```

```

artifact snapshot_vectors : feature(network_snapshots)
  value structure: vector
  value type: numeric
  description: "High-dimensional vectors encoding network topology"

# =====
# NORMALIZATION (optional): Apply scaling
# =====

transform T_normalize :
  intent: characterise
  manner: "scaling"
  input: snapshot_vectors
  output: normalized_vectors
  actor: machine
  description: "Apply normalization to emphasize specific patterns"

artifact normalized_vectors : feature(network_snapshots)
  value structure: vector
  value type: numeric
  description: "Scaled vectors for improved projection"

# =====
# DIMENSIONALITY REDUCTION: Project to 2D
# =====

transform T_project :
  intent: contextualise
  manner: "projection by dimensionality reduction"
  input: network_snapshots, normalized_vectors
  output: projection_space, snapshot_arrangement
  actor: machine
  description: "Reduce to 2D preserving similarity relationships"

artifact projection_space : entities
  internal structure: elementary
  features:
    - id: dimensionality
      value structure: atomic
      value type: numeric
      description: "Number of spatial dimensions (2)"
  description: "Two-dimensional projection space serving as
    reference frame for snapshot arrangement"

artifact snapshot_arrangement : arrangement(network_snapshots)
  context: projection_space
  principle: "dimensionality reduction preserving similarity"
  description: "2D positioning where proximity indicates structural similarity"

# =====
# VISUALIZATION: Create linked views

```

```

# =====
transform T_visualize_projection :
  intent: visualise
  manner: "scatterplot with temporal encoding"
  input: snapshot_arrangement
  output: projection_view
  actor: machine
  description: "Visualize snapshots as colored points with
               connecting lines"

artifact projection_view : visualisation(snapshot_arrangement)
  layout: "2D scatterplot"
  form: "colored points with connecting lines"
  encoding: "position from snapshot_arrangement; color by time;
            lines connect consecutive snapshots"
  description: "Interactive scatterplot revealing clusters, outliers, and
               temporal trajectories"

transform T_visualize_network :
  intent: visualise
  manner: "node-link diagram"
  input: network_snapshots
  output: network_view
  actor: machine
  description: "Visualize detailed network structure for selected snapshot"

artifact network_view : visualisation(network_snapshots)
  layout: "graph layout"
  form: "node-link diagram"
  encoding: "nodes as circles; edges as lines; node color by attributes"
  description: "Detailed topology view linked to projection selection"

# =====
# EXPLORATION: Identify patterns through interaction
# =====

transform T_explore :
  intent: abstract
  manner: "perception-and-interpretation with linked exploration"
  input: projection_view, network_view
  output: identified_patterns
  actor: hybrid
  description: "Identify network states through interactive exploration of
               coordinated views"

artifact identified_patterns : pattern(network_snapshots, snapshot_arrangement)
  representation form: "labeled clusters and trajectories"
  description: "Network states: stable states, recurring states, outliers,
               and transitions"

# =====

```

```

# KNOWLEDGE GENERATION: Synthesize insights
# =====

transform T_generate_knowledge :
  intent: generate-knowledge
  manner: "formulate-statements"
  input: identified_patterns
  output: evolution_insights
  actor: human
  description: "Synthesize understanding of network evolution from identified
    states and transitions"

artifact evolution_insights : knowledge(identified_patterns)
  representation form: "statements and explanations"
  description: "Understanding of network evolution: stable states, recurring
    patterns, outliers, and temporal dynamics"

```

1.3 Visual Analysis of Mass Mobility Dynamics (MobilityGraphs)

Source: Tatiana von Landesberger, Felix Brodkorb, Philipp Roskosch, Natalia Andrienko, Gennady Andrienko, and Andreas Kerren. MobilityGraphs: Visual analysis of mass mobility dynamics via spatio-temporal graphs and clustering. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):11–20, 2016. doi: 10.1109/TVCG.2015.2468111 doi: 10.1109/TVCG.2015.2468111

Workflow summary:

The MobilityGraphs workflow addresses visual analysis of mass mobility dynamics through combined spatial and temporal simplifications. Starting from time-varying flow data showing people’s presence in places and movements between them, the approach employs graph-based clustering to aggregate spatially close places with strong flows into regions. This spatial simplification reduces visual clutter while preserving large-scale movement patterns. Temporal clustering then groups time steps with similar flow patterns, reducing the number of distinct situations requiring analysis. Results are presented through coordinated views: a calendar showing temporal cluster distribution, cluster thumbnails displaying simplified flow graphs, difference views for comparing situations, and geographic maps providing spatial context. Interactive parameter adjustment enables exploration at various abstraction levels. The approach revealed routine mobility patterns in Greater London (mono-centric structure with morning centre-directed flows and evening outward movements) and Abidjan (polycentric structure with three activity centres), showing correspondence between flow topology and transportation networks.

Figure 4 provides a diagrammatic representation of the workflow.

ATWL representation

| workflow mobility-graphs

```

template: loop(define-unit (spatial aggregation) → characterise (quality) →
              visualise → assess) →
              characterise (vectors) →
              loop(define-unit (temporal clustering) → characterise (representatives
) →
              visualise → assess) →
              visualise (additional) → abstract → generate-knowledge
description: "Analyze mass mobility dynamics through combined spatial and
temporal
simplifications, revealing movement patterns occluded in traditional flow
maps"

# =====
# INPUT: Time-varying flow data
# =====

artifact spatial_situations : entities
  origin: given
  internal structure: formation
  embedment: time
  features:
    - id: presence_and_flows
      value structure: vector
      value type: {reference, numeric}
      description: "Presence counts in places and directed flows with magnitudes"
  description: "Spatial situations at successive time steps: distribution of
people
across places and flows between them, represented as directed weighted
graphs"

# =====
# SPECIFICATION: Spatial aggregation parameters
# =====

artifact S_spatial_params : specification
  origin: given
  representation form: "parameter settings"
  description: "Initial spatial aggregation parameters: proximity
threshold, flow strength threshold"

# =====
# SPATIAL SIMPLIFICATION: Aggregate places and flows
# =====

loop L_spatial_refinement:
  purpose: "Iteratively adjust spatial aggregation parameters to find suitable
abstraction level"
  until: "Spatial aggregates balance detail preservation with clutter reduction
and reveal interpretable large-scale patterns"
  body:
    transform T_spatial_aggregate :

```

```

    intent: define-unit
    manner: "graph-based spatial clustering by proximity and flow strength"
    input: spatial_situations, S_spatial_params
    output: aggregated_situations, region_labels
    actor: machine
    description: "Aggregate spatially close places with strong flows into
        regions; aggregate flows between places into flows between regions"

artifact aggregated_situations : entities
    internal structure: formation
    embedment: time
    features:
        - id: aggregated_flow_structure
          value structure: vector
          value type: {reference, numeric}
          description: "Regions with aggregated presence counts and flows"
    description: "Simplified spatial situations where places are grouped
into
        regions and flows are aggregated accordingly"

artifact region_labels : feature(spatial_situations)
    value structure: atomic
    value type: categorical
    description: "Region membership for each place"

transform T_compute_spatial_quality :
    intent: characterise
    manner: "compute clustering quality metrics"
    input: aggregated_situations, region_labels
    output: spatial_quality
    actor: machine
    description: "Compute spatial aggregation quality measures"

artifact spatial_quality : feature(aggregated_situations)
    value structure: list
    value type: numeric
    description: "Quality metrics: within-region flows, number of regions,
        average inter-region distance"

transform T_visualize_quality :
    intent: visualise
    manner: "heatmap of parameter combinations"
    input: spatial_quality
    output: quality_heatmap
    actor: machine
    description: "Display quality metrics for various parameter combinations
"

artifact quality_heatmap : visualisation(spatial_quality)
    layout: "grid with distance and connectivity thresholds as axes"
    form: "colored cells"
    encoding: "position by parameter values; color by quality metrics"

```

```

        description: "Heatmap showing quality of spatial aggregation for
different
        parameter settings"

transform T_assess_spatial :
    intent: assess
    manner: "evaluate aggregation quality and interpretability"
    input: quality_heatmap, aggregated_situations, S_spatial_params
    output: spatial_assessment
    actor: human
    description: "Assess whether spatial aggregation provides
        suitable abstraction level and interpretable patterns;
        determine if parameter adjustment needed"

artifact spatial_assessment : knowledge(aggregated_situations)
    representation form: "quality judgment"
    description: "Assessment of spatial aggregation quality: balance between
        detail and simplicity, interpretability of regions, and whether
        parameter refinement is needed"

if spatial_assessment indicates parameter adjustment needed:
    then:
        transform T_adjust_spatial :
            intent: generate-knowledge
            manner: "select improved spatial parameters from
                quality landscape"
            input: spatial_assessment, quality_heatmap, S_spatial_params
            output: S_spatial_params'
            actor: human
            description: "Adjust proximity and flow strength thresholds
                based on quality heatmap and assessment"

        artifact S_spatial_params' : specification
            representation form: "parameter settings"
            description: "Updated spatial aggregation parameters"

        assign:
            S_spatial_params := S_spatial_params'

    else:
        exit loop L_spatial_refinement
end loop L_spatial_refinement

# =====
# FEATURE EXTRACTION: Prepare for temporal clustering
# =====

transform T_extract_vectors :
    intent: characterise
    manner: "extract flow magnitude vectors"
    input: aggregated_situations
    output: situation_vectors

```

```

actor: machine
description: "Represent each aggregated situation by vector of flow magnitudes
            between regions"

artifact situation_vectors : feature(aggregated_situations)
value structure: vector
value type: numeric
description: "Feature vectors characterizing spatial situations by aggregated
            flow magnitudes"

# =====
# SPECIFICATION: Temporal clustering parameters
# =====

artifact S_temporal_params : specification
origin: given
representation form: "parameter settings"
description: "Initial temporal clustering parameters: number
            of clusters"

# =====
# TEMPORAL SIMPLIFICATION: Cluster time steps
# =====

loop L_temporal_refinement:
purpose: "Iteratively adjust temporal clustering to identify meaningful pattern
        groups"
until: "Temporal clusters reveal interpretable mobility patterns across time
        cycle"
body:
transform T_temporal_cluster :
intent: define-unit
manner: "cluster by similarity of spatial situations"
input: aggregated_situations, situation_vectors, S_temporal_params
output: temporal_clusters, time_labels
actor: hybrid
description: "Group time steps with similar spatial situations into
            temporal clusters"

artifact temporal_clusters : entities
internal structure: group/cluster
embedment: set
features:
- id: cluster_size
value structure: atomic
value type: numeric
description: "Number of time steps in cluster"
description: "Groups of time steps with similar flow patterns"

artifact time_labels : feature(aggregated_situations)
value structure: atomic
value type: categorical

```

```

    description: "Temporal cluster membership for each time step"

transform T_compute_representatives :
  intent: characterise
  manner: "aggregate situations within clusters"
  input: temporal_clusters, aggregated_situations
  output: representative_situations
  actor: machine
  description: "Compute representative spatial situation for each temporal
    cluster by averaging flows"

artifact representative_situations : feature(temporal_clusters)
  value structure: vector
  value type: {reference, numeric}
  description: "Average flow patterns representing each temporal cluster"

transform T_visualize_calendar :
  intent: visualise
  manner: "calendar grid with color-coded clusters"
  input: time_labels, aggregated_situations
  output: calendar_view
  actor: machine
  description: "Display temporal cluster distribution in calendar layout"

artifact calendar_view : visualisation(time_labels)
  layout: "calendar grid (days as rows, hours as columns)"
  form: "colored cells"
  encoding: "position by time coordinates; color by temporal cluster
    membership"
  description: "Calendar view showing temporal distribution of clusters"

transform T_visualize_thumbnails :
  intent: visualise
  manner: "small multiples of flow graphs"
  input: representative_situations, temporal_clusters
  output: thumbnail_view
  actor: machine
  description: "Display representative spatial situation for each temporal
    cluster as flow graph thumbnail"

artifact thumbnail_view : visualisation(representative_situations,
    temporal_clusters)
  layout: "sequential or similarity-based positioning"
  form: "node-link diagrams with geographic positioning"
  encoding: "node position by geography; node size by presence count;
    edge width by flow magnitude; color by temporal cluster"
  description: "Overview of flow patterns for all temporal clusters"

transform T_assess_temporal :
  intent: assess
  manner: "evaluate clustering quality and pattern interpretability"
  input: calendar_view, thumbnail_view, S_temporal_params

```

```

    output: temporal_assessment
    actor: human
    description: "Assess whether temporal clustering reveals
        interpretable mobility patterns and differentiation across
        time cycle; determine if parameter adjustment needed"

    artifact temporal_assessment : knowledge(temporal_clusters)
    representation form: "quality judgment"
    description: "Assessment of temporal clustering quality:
interpretability
        of patterns, temporal differentiation, and whether parameter
        refinement is needed"

    if temporal_assessment indicates refinement needed:
    then:
        transform T_adjust_temporal :
            intent: generate-knowledge
            manner: "adjust number of temporal clusters"
            input: temporal_assessment, calendar_view,
                thumbnail_view, S_temporal_params
            output: S_temporal_params'
            actor: human
            description: "Adjust number of temporal clusters based on
                assessment of pattern quality"

            artifact S_temporal_params' : specification
            representation form: "parameter settings"
            description: "Updated temporal clustering parameters"

            assign:
                S_temporal_params := S_temporal_params'
        else:
            exit loop L_temporal_refinement
    end loop L_temporal_refinement

# =====
# ADDITIONAL VISUALIZATION: Difference and map views
# =====

transform T_visualize_differences :
    intent: visualise
    manner: "difference graphs with change encoding"
    input: representative_situations, temporal_clusters
    output: difference_view
    actor: machine
    description: "Display differences between selected spatial situations with
        color-coded changes"

artifact difference_view : visualisation(representative_situations)
    layout: "graph layout with geographic positioning"
    form: "node-link diagram with change encoding"
    encoding: "color by relative change; node size by initial presence; edge width

```

```

    by initial flow magnitude"
  description: "Detailed comparison showing flow and presence changes between
    two selected situations"

transform T_visualize_maps :
  intent: visualise
  manner: "geographic overlay"
  input: region_labels, aggregated_situations
  output: map_view
  actor: machine
  description: "Display spatial aggregates in geographic context"

artifact map_view : visualisation(aggregated_situations, region_labels)
  layout: "geographic map"
  form: "colored regions"
  encoding: "spatial position by geography; color by region identity"
  description: "Map showing geographic extent of spatial aggregates"

# =====
# EXPLORATION: Identify mobility patterns
# =====

transform T_explore_patterns :
  intent: abstract
  manner: "identify mobility patterns through coordinated views"
  input: calendar_view, thumbnail_view, difference_view, map_view
  output: mobility_patterns
  actor: hybrid
  description: "Identify mobility patterns through interactive exploration:
    daily/weekly cycles, center-directed flows, directional asymmetries,
    correspondence to geography"

artifact mobility_patterns : pattern(temporal_clusters, representative_situations)
  representation form: "labeled patterns with descriptions"
  description: "Identified mobility patterns: morning center-directed flows,
    evening outward flows, weekly cycles, quiet periods, city structure
    (mono/polycentric), correspondence to transportation networks"

# =====
# KNOWLEDGE GENERATION: Synthesize insights
# =====

transform T_generate_insights :
  intent: generate-knowledge
  manner: "formulate-statements"
  input: mobility_patterns, temporal_clusters, representative_situations
  output: mobility_knowledge
  actor: human
  description: "Synthesize understanding of mobility dynamics including routine
    behaviors, city structure, and temporal rhythms"

artifact mobility_knowledge : knowledge(mobility_patterns)

```

```
representation form: "statements and explanations"
description: "Understanding of mass mobility: routine movement patterns, spatial
organization (activity centers and residential areas), temporal cycles,
correspondence between flow topology and geographic features"
```

1.4 EventFlow workflow

Source: Megan Monroe, Rongjian Lan, Hanseung Lee, Catherine Plaisant, and Ben Shneiderman. Temporal event sequence simplification. IEEE Transactions on Visualization and Computer Graphics, 19:2227–2236, 2013 doi: 10.1109/TVCG.2013.200

Workflow summary:

The workflow iteratively simplifies large temporal event sequence datasets (such as EHRs or play-by-play logs) in EventFlow to balance visual comprehensibility with analytic fidelity. Starting from given event records, analysts specify sentinel events and time windows that define a relative-time context; EventFlow then aligns records, aggregates similar sequences into a tree, and visualises an overview plus individual timelines. Visual complexity metrics (e.g., number of visual elements and average aggregation level) together with human judgment are used to assess whether the display remains too cluttered. If further simplification is needed, analysts use interactive filters (by record, category, time, and attributes) and transformation-based operations (interval merging, category merging, marker insertion, and pattern-based Find & Replace) to rewrite the sequences into more compact, semantically meaningful representations. After each simplification, the system realigns and reaggregates the modified records, and this loop continues until the display is both interpretable and sufficient to answer the study questions, at which point analysts interpret domain patterns and formulate explicit findings and recommendations.

Figure 5 provides a diagrammatic representation of the workflow.

ATWL representation:

```
workflow event-sequence-simplification
  template: loop(contextualise (align) → define-unit (aggregate) →
    visualise → characterise (complexity) → assess →
    define-unit (simplify, conditional)) →
    abstract → generate-knowledge
  description: "Iterative simplification of temporal event sequence datasets
  using EventFlow: aligning, aggregating, and repeatedly simplifying
  event sequences until the display is compact yet retains information
  needed to answer study questions"

artifact D_records : entities
  origin: given
  internal structure: sequence
  embedment: set
  features:
```

```
- id: event_data
  value structure: vector
  value type: {categorical, temporal, numeric}
  description: "Event categories, timestamps, and attributes"
description: "Temporal event sequences, one per record, from EHR or
other temporal logs"
```

```
artifact K_questions : knowledge(D_records)
```

```
origin: given
representation form: "study questions and analytic goals"
description: "Analyst questions guiding simplification and determining
adequacy of simplified representation"
```

```
artifact alignment_spec : specification
```

```
origin: given
representation form: "sentinel events and time window parameters"
description: "Analyst-specified sentinel event(s) and relative time
window for alignment"
```

```
loop L_simplify:
```

```
purpose: "Iteratively align, aggregate, visualise, assess complexity, and
simplify event sequences until visualization is interpretable and
adequate for hypothesis generation and testing"
```

```
until: "Aggregated display is compact and interpretable,
and remaining events and records sufficiently support
analytical questions"
```

```
body:
```

```
transform T_align :
```

```
intent: contextualise
manner: "relative-time-alignment with computed context"
input: D_records, alignment_spec
output: D_rel_time_axis, A_aligned
actor: hybrid
description: "Create relative-time context centered at sentinel events
and arrange sequences by transforming absolute to relative times"
```

```
artifact D_rel_time_axis : entities
```

```
internal structure: sequence
embedment: time
features:
- id: relative_time
  value structure: atomic
  value type: temporal
  description: "Time coordinate relative to alignment event"
description: "Computed relative time axis serving as context for
aligned event sequences"
```

```
artifact A_aligned : arrangement(D_records)
```

```
context: D_rel_time_axis
principle: "relative-time alignment at sentinel events"
description: "Arrangement of records and events on relative time axis"
```

centered at key events"

```
transform T_aggregate :
  intent: define-unit
  manner: "hierarchical aggregation by event sequence similarity"
  input: D_records, A_aligned
  output: D_agg_tree
  actor: machine
  description: "Group records with identical or similar aligned
    event sequences into branches of an aggregation tree
    positioned along the relative time axis"

artifact D_agg_tree : entities
  internal structure: formation
  features:
    - id: branch_size
      value structure: atomic
      value type: numeric
      description: "Number of records aggregated at each branch"
    - id: branch_time_span
      value structure: atomic
      value type: temporal
      description: "Temporal extent of each branch on the
        relative time axis, inherited from alignment"
  description: "Tree structure capturing how records share
    event subsequences; branches positioned along the
    relative time axis from alignment"

transform T_visualise_overview :
  intent: visualise
  manner: "aggregated and individual timeline views"
  input: D_agg_tree, A_aligned
  output: V_overview, V_records
  actor: machine
  description: "Render aggregated tree display and synchronized
    individual record display"

artifact V_overview : visualisation(D_agg_tree)
  layout: "branched aggregation tree aligned to relative
    time axis"
  form: "vertical coloured bars"
  encoding: "branch position from D_agg_tree; bar height:
    number of records; color: event categories"
  description: "Population-level overview of event sequence
    patterns and their frequencies"

artifact V_records : visualisation(D_records, A_aligned)
  layout: "stacked aligned timelines"
  form: "horizontal event glyphs and intervals"
  encoding: "horizontal position from A_aligned; shape and color: event
    categories and durations; one row per record"
  description: "Detail view of individual event sequences for
```

```

        intra-record analysis"

transform T_compute_complexity :
    intent: characterise
    manner: "compute structural complexity metrics"
    input: D_agg_tree
    output: F_complexity
    actor: machine
    description: "Compute structural complexity metrics of the
        aggregation tree that determine visual complexity
        of the display"

artifact F_complexity : feature(D_agg_tree)
    value structure: list
    value type: numeric
    description: "Structural complexity metrics: number of
        branches, distinct event categories, average
        aggregation depth"

transform T_assess_simplification :
    intent: assess
    manner: "evaluate display complexity and adequacy"
    input: V_overview, V_records, F_complexity, K_questions
    output: simplification_assessment
    actor: human
    description: "Assess whether complexity is acceptable and display
        contains sufficient information to answer study questions"

artifact simplification_assessment : knowledge(V_overview, F_complexity)
    representation form: "quality judgment"
    description: "Assessment of visualization adequacy: balance between
        clutter and information, sufficiency for analytical goals, need
        for further simplification"

if simplification_assessment indicates further simplification needed:
    then:

        transform T_filter :
            intent: define-unit
            manner: "filter by record selection and event criteria"
            input: D_records, K_questions, V_overview, V_records
            output: D_records_f
            actor: hybrid
            description: "Remove unneeded records and events through
                interactive filters: record selection, category filters,
                time windows, attribute-based queries"

        artifact D_records_f : entities
            internal structure: sequence
            embedment: set
            description: "Subset of records and events after filter-based
                simplification"

```

```

transform T_restructure :
  intent: define-unit
  manner: "transform sequences through merging and substitution"
  input: D_records_f, K_questions
  output: D_records'
  actor: hybrid
  description: "Transform event sequences: merge intervals and
               categories, insert markers, apply pattern-based replacements
"

artifact D_records' : entities
  internal structure: sequence
  embedment: set
  description: "Simplified event sequences after
transformation-based
               simplification"

  assign:
    D_records := D_records'

  else:
    exit loop L_simplify
end loop L_simplify

transform T_identify_patterns :
  intent: abstract
  manner: "interpret domain-specific temporal patterns"
  input: V_overview, V_records, D_records, K_questions
  output: P_domain_patterns
  actor: human
  description: "Interpret patterns in final simplified dataset relevant to
               study questions"

artifact P_domain_patterns : pattern(D_records)
  representation form: "named temporal pattern types and descriptions"
  description: "Named temporal patterns and behaviors identified in simplified
               event sequences"

transform T_generate_knowledge :
  intent: generate-knowledge
  manner: "formulate-statements"
  input: P_domain_patterns, V_overview, V_records, K_questions
  output: K_findings
  actor: human
  description: "Formulate study conclusions, recommendations, and narratives
               based on identified temporal patterns"

artifact K_findings : knowledge(P_domain_patterns)
  representation form: "statements, explanations, illustrative figures"
  description: "Documented insights about temporal behaviors: evidence of
               practices, validation of classifications, factors influencing outcomes"

```

1.5 EventAction: temporal event sequence recommendation

Source:

F. Du, C. Plaisant, N. Spring and B. Shneiderman,
"EventAction: Visual analytics for temporal event sequence recommendation," 2016
IEEE Conference on Visual Analytics Science and Technology (VAST), Baltimore, MD,
USA, 2016, pp. 61-70,
doi: 10.1109/VAST.2016.7883512.

Workflow summary

This paper presents EventAction, a visual analytics system for prescriptive analytics on temporal event sequences. The workflow helps analysts recommend actions to improve outcomes by leveraging historical records.

Review Current Record. The analyst loads the current subject's temporal event sequence and reviews it as a timeline table showing event categories over time periods.

Find Similar Archived Records. The system computes similarity scores between the current record and each archived record based on event sequence feature distances. The analyst examines the similarity distribution and interactively selects a cohort of similar records by adjusting a similarity threshold, guided by indicators including cohort size, proportion with the desired outcome, and average similarity.

Explore Outcomes and Recommendations. The system computes outcome distributions relative to baseline, event-outcome correlations per category, and aggregated temporal activity patterns for the cohort and the desired-outcome subgroup. Coordinated views display outcome probability bars, per-category correlation charts with trend encoding, and an activity summary integrated with the current record's timeline — filterable by overall cohort, desired-outcome subgroup, and distinguishing activities. The analyst identifies which event categories are most associated with the desired outcome and when they typically occur.

Plan Specification and Iterative Tuning. The analyst creates an initial action plan by specifying planned events by category and time period, guided by identified recommendation patterns. The system recomputes similarity with the extended record and updates outcome probability estimates. The analyst assesses whether the plan achieves sufficient probability improvement; if not, they refine the plan based on outcome feedback and recommendation patterns. This cycle continues until the analyst is satisfied with the plan's estimated impact.

Finalize Guidance. The analyst integrates the data-driven action plan with domain expertise to formulate actionable guidance with associated outcome probability estimation.

Figure 6 provides a diagrammatic representation of the workflow.

ATWL representation

| `workflow` EventActionPrescriptiveAnalytics

```

template: visualise →
    characterise → visualise → define-unit →
    characterise → visualise → abstract →
    generate-knowledge (specify) →
    loop(characterise → visualise → assess →
        generate-knowledge (refine)) →
    generate-knowledge

description: "Visual analytics workflow for prescriptive temporal event
sequence recommendation: finding similar archived records, exploring
potential outcomes, reviewing recommended actions, and iteratively
tuning a personalized action plan with outcome feedback"

# =====
# GIVEN ARTIFACTS
# =====

artifact current_record : entities
    origin: given
    internal structure: sequence
    description: "Current subject's temporal event sequence with
events categorized by type and positioned in time periods"

artifact archived_records : entities
    origin: given
    internal structure: elementary
    embedment: set
    description: "Collection of historical records, each containing
a temporal event sequence with known outcome"

artifact desired_outcome : specification
    origin: given
    representation form: "outcome category identifier"
    description: "User's target outcome to optimize for in the
action plan"

# =====
# PHASE 1: REVIEW CURRENT RECORD
# =====

transform T_visualize_current :
    intent: visualise
    manner: "render timeline table with event categories as rows
and time periods as columns, encoding event frequency by
square size"
    input: current_record
    output: current_viz
    actor: machine
    description: "Display the current record's event sequence for
initial review and orientation"

artifact current_viz : visualisation(current_record)

```

```

    layout: "matrix grid (event categories as rows, time periods
           as columns)"
    form: "sized squares"
    encoding: "row: event category; column: time period; square
             size: event frequency per cell"
    description: "Timeline of current record with event categories
                over time periods and square-size encoding for event
                frequency per cell"

# =====
# PHASE 2: FIND SIMILAR ARCHIVED RECORDS
# =====

transform T_compute_similarity :
  intent: characterise
  manner: "extract feature vectors from event sequences within
          the comparison window and compute pairwise distance-based
          similarity scores"
  input: current_record, archived_records
  output: similarity_scores
  actor: machine
  description: "Compute similarity between the current record
              and each archived record based on event sequence patterns"

artifact similarity_scores : feature(archived_records)
  value structure: atomic
  value type: numeric
  description: "Distance-based similarity scores between the
              archived records and current record"

transform T_visualize_similarity :
  intent: visualise
  manner: "show similarity distribution with range selection
          widget and summary indicators including cohort size,
          proportion with desired outcome, and average similarity"
  input: archived_records, similarity_scores, desired_outcome
  output: similarity_viz
  actor: machine
  description: "Display similarity score distribution for
              interactive cohort selection"

artifact similarity_viz : visualisation(archived_records,
                                       similarity_scores)
  layout: "horizontal axis (similarity score)"
  form: "histogram bars with range selector"
  encoding: "x-position: similarity score; bar height: record
            count; interactive range selector for cohort threshold;
            summary indicators for cohort size, outcome proportion,
            average similarity"
  description: "Distribution of similarity scores with
              interactive range selector and cohort summary indicators"

```

```

transform T_select_cohort :
  intent: define-unit
  manner: "interactively set similarity range based on
          distribution shape, cohort size, and desired-outcome
          proportion"
  input: archived_records, similarity_scores, similarity_viz
  output: similar_cohort
  actor: human
  description: "Select the cohort of similar archived records by
               adjusting the similarity threshold"

artifact similar_cohort : entities
  internal structure: elementary
  embedment: set
  description: "Subset of archived records selected as similar
               to the current record based on user-specified similarity
               range"

# =====
# PHASE 3: EXPLORE OUTCOMES AND RECOMMENDATIONS
# =====

transform T_analyze_cohort :
  intent: characterise
  manner: "calculate outcome probabilities relative to baseline;
          compute correlation between event category frequency and
          outcome probability; aggregate event prevalence and
          typical frequency per time period for overall cohort and
          desired-outcome subgroup"
  input: similar_cohort, archived_records, desired_outcome
  output: cohort_analysis
  actor: machine
  description: "Compute outcome distributions, event-outcome
               correlations, and temporal activity patterns for the
               cohort"

artifact cohort_analysis : feature(similar_cohort)
  value structure: list
  value type: numeric
  description: "Outcome probability distributions compared to
               baseline, per-category event-outcome correlations, and
               aggregated temporal activity patterns for the cohort and
               desired-outcome subgroup"

transform T_visualize_recommendations :
  intent: visualise
  manner: "coordinated views showing outcome distributions vs.
          baseline, per-category correlation charts with trend
          encoding, and activity summary integrated with current
          record timeline, filterable by subgroup"
  input: current_record, similar_cohort, cohort_analysis,
         desired_outcome

```

```

output: recommendation_viz
actor: machine
description: "Display outcome estimation, event-outcome
            correlations, and temporal activity patterns for
            recommendation exploration"

artifact recommendation_viz : visualisation(similar_cohort,
            cohort_analysis, current_record)
layout: "coordinated panels: outcome distribution,
        per-category correlation charts, activity timeline"
form: "bars, trend-encoded charts, and timeline cells"
encoding: "outcome bars: height by probability with baseline
          comparison; correlation charts: bar height by strength,
          trend arrows; activity timeline: cell color and size by
          event prevalence; filterable by subgroup"
description: "Outcome distribution comparing cohort to
            baseline; correlation charts showing event-outcome
            relationships with encoded strength; activity summary
            integrated with current record timeline, filterable by
            subgroup and distinguishing activities"

transform T_identify_recommendations :
intent: abstract
manner: "identify positively correlated event categories from
        correlation charts; recognise temporal activity patterns
        from desired-outcome subgroup; identify distinguishing
        activities between desired-outcome subgroup and overall
        cohort"
input: recommendation_viz, cohort_analysis
output: recommendation_patterns
actor: human
description: "Identify which event categories are most
            associated with the desired outcome and their recommended
            timing"

artifact recommendation_patterns : pattern(similar_cohort)
representation form: "identified action recommendations with
                    timing"
description: "Key event categories correlated with the desired
            outcome and their recommended timing based on temporal
            activity patterns of successful archived records"

# =====
# PHASE 4: PLAN SPECIFICATION AND ITERATIVE TUNING
# =====

transform T_specify_initial_plan :
intent: generate-knowledge
manner: "specify planned events by category and time period,
        referencing activity patterns and correlation insights
        from the desired-outcome subgroup"
input: recommendation_patterns, recommendation_viz,

```

```

    current_record
  output: action_plan
  actor: human
  description: "Create initial action plan guided by identified
    recommendation patterns"

artifact action_plan : specification
  representation form: "planned events per category and time
    period"
  description: "User-specified action plan defining planned
    events with their categories and time periods"

loop L_plan_tuning:
  purpose: "Refine the action plan based on immediate feedback
    on estimated outcome probability"
  until: "the user is satisfied with the plan's estimated impact
    on the probability of achieving the desired outcome"
  body:

    transform T_recompute_estimation :
      intent: characterise
      manner: "extend current record with planned events;
        recompute similarity with extended comparison
        window; update outcome probability distribution"
      input: current_record, archived_records, action_plan
      output: plan_estimation
      actor: machine
      description: "Recompute outcome estimation
        incorporating the current action plan"

    artifact plan_estimation : feature(current_record)
      value structure: vector
      value type: numeric
      description: "Revised outcome probability distribution
        reflecting the action plan's impact on similarity
        matching and outcome estimation"

    transform T_visualize_estimation :
      intent: visualise
      manner: "overlay updated outcome probabilities on
        original distribution as distinct markers"
      input: plan_estimation, cohort_analysis
      output: estimation_viz
      actor: machine
      description: "Display updated outcome estimation
        showing the plan's impact"

    artifact estimation_viz :
      visualisation(plan_estimation, cohort_analysis)
      layout: "horizontal axis (outcome categories)"
      form: "bars with overlay markers"
      encoding: "bar height: original outcome probability; overlay

```

```

        markers: plan-adjusted probability"
    description: "Outcome distribution showing original
        and plan-adjusted probabilities side by side"

transform T_assess_plan :
    intent: assess
    manner: "compare estimated likelihood with and without
        plan; judge whether further refinement is needed"
    input: estimation_viz, action_plan, plan_estimation
    output: plan_assessment
    actor: human
    description: "Evaluate whether the plan achieves
        sufficient probability improvement for the
        desired outcome"

artifact plan_assessment : knowledge(action_plan)
    representation form: "quality judgment"
    description: "Assessment of whether the action plan
        provides satisfactory probability improvement
        for the desired outcome"

if plan_assessment indicates further refinement needed:
    then:
        transform T_refine_plan :
            intent: generate-knowledge
            manner: "adjust planned events by adding,
                removing, or retiming events, guided by
                identified recommendation patterns and
                outcome probability feedback"
            input: action_plan, plan_assessment,
                recommendation_patterns, estimation_viz
            output: updated_action_plan
            actor: human
            description: "Refine the action plan based on
                outcome feedback and recommendation
                patterns"

            artifact updated_action_plan : specification
                representation form: "planned events per
                    category and time period"
                description: "Refined action plan with
                    adjusted event timing and composition"

            assign: action_plan := updated_action_plan
        else:
            exit loop L_plan_tuning

    end loop L_plan_tuning

# =====
# PHASE 5: FINALIZE GUIDANCE
# =====

```

```

transform T_finalize :
  intent: generate-knowledge
  manner: "integrate recommended action sequences and timing
          with outcome probability estimation and domain knowledge"
  input: action_plan, plan_assessment, recommendation_patterns
  output: final_guidance
  actor: human
  description: "Finalize action plan and synthesize actionable
               guidance combining data-driven recommendations with
               domain expertise"

artifact final_guidance : knowledge(current_record)
  representation form: "actionable guidance with supporting
                       evidence"
  description: "Finalized action plan with recommended event
               sequences and timing, associated outcome probability
               estimation, and domain-informed rationale"

```

1.6 Extracting significant places from trajectories

Source: Gennady Andrienko, Natalia Andrienko, Christophe Hurter, Salvatore Rinzivillo, and Stefan Wrobel. From movement tracks through events to places: Extracting and characterizing significant places from mobility data. In 2011 IEEE Conference on Visual Analytics Science and Technology (VAST), pages 161–170, 2011 doi: 10.1109/VAST.2011.6102454

Workflow summary

The paper presents a visual analytics procedure for analyzing movement data to determine significant places based on recurring events. The procedure addresses problems where relevant places have arbitrary shapes and sizes and must be delineated by processing movement data rather than selected from predefined areas.

The workflow consists of four main steps applied iteratively:

Step 1: Event extraction - Relevant movement events (m-events) are identified from trajectories using dynamic attributes representing movement characteristics (speed, direction, acceleration) and relations to spatio-temporal context. Interactive visual query tools enable specification of event-defining conditions.

Step 2: Place determination through clustering - Density-based clustering identifies places where events occur repeatedly. Two-stage clustering may be applied: first, spatio-temporal clustering filters occasional events by grouping events concentrated in both space and time; second, spatial clustering unites spatio-temporal clusters sharing spatial positions. A custom distance function accounts for spatial distance, temporal distance, and thematic attributes (particularly movement direction). Interactive parameter adjustment and visual assessment guide refinement until spatially coherent, interpretable clusters emerge. Spatial buffers around clusters define relevant places.

Step 3: Spatio-temporal aggregation - Events and trajectories are aggregated by places and time intervals, producing time series of counts and statistics (visit counts, visitor counts, durations, speeds, directions). For trajectory aggregation, flows between place pairs are also computed.

Step 4: Analysis - Aggregated data are explored through coordinated interactive visualizations to identify temporal patterns of event occurrences and movements between places.

The procedure was demonstrated on traffic congestion analysis (Milan car trajectories) and air traffic analysis (French flight data), revealing temporal patterns and spatial organization of movements.

Figure 7 provides a diagrammatic representation of the workflow.

ATWL representation

```

workflow events-to-places
  template: characterise → define-unit (extract events) →
           loop(define-unit (two-stage clustering) →
                visualise → assess) →
           define-unit (delineate places) →
           characterise (aggregate) → visualise → abstract →
           generate-knowledge
  description: "Extract significant places from movement data by identifying
              recurring events, clustering them spatially and temporally, and analyzing
              spatio-temporal patterns"

# =====
# INPUT: Movement trajectories
# =====

artifact trajectories : entities
  origin: given
  internal structure: sequence
  embedment: {set, time}
  features:
    - id: movement_data
      value structure: vector
      value type: {reference, temporal, spatial}
      description: "Time-stamped positions with object identifiers"
  description: "Movement trajectories of tracked entities recorded over time"

# =====
# STEP 1: Event extraction from trajectories
# =====

transform T_compute_dynamic_attributes :
  intent: characterise
  manner: "compute movement characteristics and context relations"
  input: trajectories
  output: trajectory_attributes

```

```

actor: machine
description: "Compute dynamic attributes: instant and interval movement
characteristics, cumulative measures, and relations to spatio-temporal
context elements"

artifact trajectory_attributes : feature(trajectories)
value structure: vector
value type: numeric
description: "Dynamic attributes including speed, direction, acceleration,
distances to context elements, temporal and spatial neighborhoods"

transform T_extract_events :
intent: define-unit
manner: "interactive visual querying by attribute values"
input: trajectories, trajectory_attributes
output: movement_events
actor: hybrid
description: "Define and extract trajectory points or segments satisfying
user-specified attribute value constraints through interactive visual
query composition"

artifact movement_events : entities
internal structure: elementary
embedment: {set, space, time}
features:
- id: spatial_position
value structure: atomic
value type: spatial
description: "Location in space"
- id: temporal_position
value structure: atomic
value type: temporal
description: "Time instant or interval"
- id: thematic_attributes
value structure: vector
value type: numeric
description: "Duration, extent, speed, direction, and attribute aggregates"
description: "Spatial events extracted from trajectories where specific
movement characteristics or context relations occur"

# =====
# STEP 2: Two-stage clustering to determine places
# =====

artifact S_clustering_params : specification
origin: given
representation form: "parameter settings"
description: "Initial clustering parameters: spatial distance
threshold, temporal distance threshold, density threshold,
direction weight, and minimum cluster size"

loop L_cluster_refinement:

```

```

purpose: "Iteratively apply two-stage clustering with parameter adjustment
to identify spatially coherent, interpretable concentrations"
until: "Clusters represent meaningful places where events occur repeatedly;
occasional events filtered as noise"
body:
  # STAGE 1: Spatio-temporal clustering
  transform T_cluster_spatiotemporal :
    intent: define-unit
    manner: "density-based clustering by spatial, temporal, and
    thematic proximity"
    input: movement_events, S_clustering_params
    output: st_clusters, st_labels
    actor: machine
    description: "Group events concentrated in space, time, and
    thematic attributes using density-based clustering"

  artifact st_clusters : entities
    internal structure: group/cluster
    embedment: set
    description: "Groups of events concentrated in space, time, and
    thematic attributes; filters out occasional scattered events"

  artifact st_labels : feature(movement_events)
    value structure: atomic
    value type: categorical
    description: "Spatio-temporal cluster membership or noise designation"

  transform T_filter_noise :
    intent: define-unit
    manner: "exclude noise events"
    input: movement_events, st_clusters, st_labels
    output: clustered_events
    actor: machine
    description: "Retain only events belonging to spatio-temporal
    clusters, excluding occasional scattered events"

  artifact clustered_events : entities
    internal structure: elementary
    embedment: {set, space, time}
    description: "Events occurring as members of spatio-temporal
    concentrations"

  # STAGE 2: Spatial clustering
  transform T_cluster_spatial :
    intent: define-unit
    manner: "density-based clustering by spatial and thematic proximity"
    input: clustered_events, S_clustering_params
    output: spatial_clusters, s_labels
    actor: machine
    description: "Unite spatio-temporal clusters sharing spatial
    positions by clustering according to location and thematic
    attributes"

```

```

artifact spatial_clusters : entities
  internal structure: group/cluster
  embedment: set
  description: "Groups of events concentrated spatially, potentially
    spanning multiple time periods"

artifact s_labels : feature(clustered_events)
  value structure: atomic
  value type: categorical
  description: "Spatial cluster membership or noise designation"

transform T_visualize_clusters :
  intent: visualise
  manner: "events on map and space-time cube colored by cluster"
  input: clustered_events, s_labels
  output: cluster_views
  actor: machine
  description: "Display events colored by cluster membership on map
    and in space-time cube"

artifact cluster_views : visualisation(clustered_events, s_labels)
  layout: "geographic map and space-time cube"
  form: "colored points"
  encoding: "position from event coordinates; color by cluster membership"
  description: "Spatial and spatio-temporal distribution of event clusters
"

```

```

transform T_assess_clusters :
  intent: assess
  manner: "evaluate cluster quality and coherence"
  input: cluster_views, spatial_clusters, S_clustering_params
  output: cluster_assessment
  actor: human
  description: "Assess whether clusters are spatially coherent,
    interpretable, and appropriately sized; determine if parameter
    adjustment needed"

artifact cluster_assessment : knowledge(spatial_clusters)
  representation form: "quality judgment"
  description: "Assessment of clustering quality: spatial coherence,
    interpretability, appropriate size and extent, and whether
    parameter adjustment is needed"

if cluster_assessment indicates parameter adjustment needed:
  then:
    transform T_adjust_params :
      intent: generate-knowledge
      manner: "adjust clustering parameters based on
        visual assessment"
      input: cluster_assessment, cluster_views,
        S_clustering_params

```

```

        output: S_clustering_params'
        actor: human
        description: "Adjust distance thresholds, density
                    parameters, and direction weights based on
                    cluster quality assessment"

    artifact S_clustering_params' : specification
        representation form: "parameter settings"
        description: "Updated clustering parameters after
                    analyst refinement"

    assign:
        S_clustering_params := S_clustering_params'
    else:
        exit loop L_cluster_refinement
end loop L_cluster_refinement

transform T_delineate_places :
    intent: define-unit
    manner: "build spatial buffers around clusters"
    input: spatial_clusters, clustered_events
    output: places
    actor: machine
    description: "Construct spatial buffers or convex hulls around event
                clusters to delineate place boundaries"

artifact places : entities
    internal structure: region
    embedment: space
    features:
        - id: spatial_extent
          value structure: atomic
          value type: spatial
          description: "Area boundary"
        - id: characteristic_attributes
          value structure: vector
          value type: numeric
          description: "Prevailing movement directions and other characteristics"
    description: "Significant places defined by spatial buffers around event
                clusters, representing areas where events occur repeatedly"

# =====
# STEP 3: Spatio-temporal aggregation
# =====

transform T_aggregate_events :
    intent: characterise
    manner: "spatio-temporal aggregation by places and time intervals"
    input: movement_events, places
    output: place_event_aggregates
    actor: machine
    description: "Group events by places and time intervals; compute counts"

```

```

    and statistics of event attributes"

artifact place_event_aggregates : feature(places)
  value structure: vector
  value type: numeric
  representation form: "time series per place"
  description: "Time series of event counts, object counts, and attribute
    statistics for each place"

transform T_aggregate_trajectories :
  intent: characterise
  manner: "spatio-temporal aggregation by places and time intervals"
  input: trajectories, places
  output: place_visit_aggregates, place_flow_aggregates
  actor: machine
  description: "Group trajectory segments by places and time intervals;
    compute visit statistics and flows between places"

artifact place_visit_aggregates : feature(places)
  value structure: vector
  value type: numeric
  representation form: "time series per place"
  description: "Time series of visit counts, visitor counts, and movement
    statistics for each place"

artifact place_flow_aggregates : feature(places)
  value structure: relational configuration
  value type: {reference, numeric}
  representation form: "directed flows with time series"
  description: "Aggregate movements between pairs of places with time series
    of counts, durations, speeds, and path lengths"

# =====
# STEP 4: Analysis of aggregated data
# =====

transform T_visualize_place_dynamics :
  intent: visualise
  manner: "temporal diagrams on map, time graphs, flow maps"
  input: places, place_event_aggregates, place_visit_aggregates,
    place_flow_aggregates
  output: dynamics_views
  actor: machine
  description: "Display time series as temporal diagrams positioned on map,
    time graphs with interactive selection, and flow maps"

artifact dynamics_views : visualisation(places, place_event_aggregates,
    place_visit_aggregates,
    place_flow_aggregates)
  layout: "geographic map with temporal diagrams, time graphs, flow maps, tables"
  form: "temporal bar diagrams, line graphs, directed arrows, colored cells"
  encoding: "diagram position from place location; bar heights and line

```

```

        positions from time series values; arrow widths from flow magnitudes;
        colors from movement directions or place identities"
    description: "Coordinated views showing spatial distribution of places,
        temporal dynamics of events and movements, and flows between places"

transform T_explore_patterns :
    intent: abstract
    manner: "identify temporal and spatial patterns"
    input: dynamics_views
    output: spatio_temporal_patterns
    actor: hybrid
    description: "Identify temporal patterns of event occurrences and movements
        through interactive exploration: peak times, recurring patterns, spatial
        variations, flow connectivity"

artifact spatio_temporal_patterns : pattern(places, place_event_aggregates,
        place_visit_aggregates,
        place_flow_aggregates)
    representation form: "categorized patterns with descriptions"
    description: "Identified patterns: temporal profiles of place usage,
        recurring patterns across time cycles, directional preferences,
        connectivity structures between places"

# =====
# KNOWLEDGE GENERATION: Synthesize insights
# =====

transform T_generate_knowledge :
    intent: generate-knowledge
    manner: "formulate-statements"
    input: spatio_temporal_patterns, places
    output: movement_knowledge
    actor: human
    description: "Synthesize understanding of movement dynamics and place
        significance from identified patterns"

artifact movement_knowledge : knowledge(spatio_temporal_patterns)
    representation form: "statements and explanations"
    description: "Understanding of movement dynamics: significant place locations
        and characteristics, temporal patterns of event occurrences and movements,
        connectivity patterns between places"

```

1.7 Progressive clustering of trajectories

Source: Salvatore Rinzivillo, Dino Pedreschi, Mirco Nanni, Fosca Giannotti, Natalia Andrienko, and Gennady Andrienko. Visually-driven analysis of movement data by progressive clustering. *Information Visualization*, 7:225–239, 07 2008. doi: 10.1057/PALGRAVE.IVS.9500183

Workflow summary

The paper presents progressive clustering as a method for visually-driven analysis of large trajectory datasets. Progressive clustering proceeds through iterative steps where simple, interpretable distance functions are applied sequentially, with visual assessment guiding refinement decisions. The workflow addresses four successive analytical questions through progressive refinement:

Phase 1: **Destination clustering with density adaptation** - Progressive clustering by trip destinations with iteratively decreasing sensitivity handles uneven spatial data density, identifying major destination regions across varying densities.

Phase 2: **Route analysis of selected subsets** - Examining major destination clusters by route similarity reveals patterns within destinations, such as prevalence of low-displacement trips.

Phase 3: **Pattern verification on complete dataset** - Observations from subset analysis lead to hypothesis testing: clustering ALL trajectories by start-end proximity verifies pattern prevalence across the complete dataset.

Phase 4: **Route analysis of refined subset** - After excluding verified patterns, clustering remaining trajectories by route similarity identifies route types characterized by spatial structure and frequency, revealing route diversity and repetition.

The progressive approach enables sophisticated analysis while maintaining interpretability, showing how the analyst's understanding evolves through exploration. The method was demonstrated on Milan car trajectory data, revealing movement patterns and route organization.

The workflow is schematically represented in Fig. 8.

ATWL representation

```
workflow progressive-trajectory-clustering
  template: loop(define-unit (destinations) → visualise → assess) →
    define-unit (select major) →
    loop(define-unit (routes: subset) → visualise → assess) →
    define-unit (verification) → visualise → assess →
    define-unit (exclude) → define-unit (routes: final) → visualise →
    abstract (route types) → abstract (synthesize) → generate-knowledge
  description: "Iteratively cluster trajectories through sequence of analytical
    questions, progressively refining understanding of movement patterns"

# =====
# INPUT: Complete movement trajectory dataset
# =====

artifact all_trajectories : entities
  origin: given
  internal structure: sequence
  embedment: {set, time}
  features:
    - id: movement_data
```

```

    value structure: vector
    value type: {reference, temporal, spatial}
    description: "Time-stamped positions with object identifiers,
                 speeds and directions"
description: "Movement trajectories of tracked entities over time"

artifact analysed_trajectories : entities
  internal structure: sequence
  embedment: {set, time}
  features:
    - id: movement_data
      value structure: vector
      value type: {reference, temporal, spatial}
      description: "Time-stamped positions with object identifiers,
                   speeds and directions"
    description: "Subset of trajectories currently under analysis, initially
                  equal to all_trajectories"

# =====
# PHASE 1: Destination clustering with density adaptation
# =====

assign:
  analysed_trajectories := all_trajectories

artifact S_dest_sensitivity : specification
  origin: given
  representation form: "parameter settings"
  description: "Initial sensitivity parameter settings for destination
               clustering"

loop L_destination_clustering:
  purpose: "Handle uneven spatial density by progressively clustering with
           same distance function but decreasing sensitivity"
  until: "Major destination regions identified across all density levels;
         remaining trajectories are sparse"
  body:
    transform T_cluster_destinations :
      intent: define-unit
      manner: "density-based clustering by destination similarity"
      input: analysed_trajectories, S_dest_sensitivity
      output: destination_clusters, cluster_labels
      actor: machine
      description: "Group trajectories with similar destinations using
                   current sensitivity parameter"

    artifact destination_clusters : entities
      internal structure: group/cluster
      embedment: set
      features:
        - id: cluster_size
          value structure: atomic

```

```

        value type: numeric
        description: "Number of trajectories in cluster"
description: "Groups of trajectories with similar trip destinations"

artifact cluster_labels : feature(analysed_trajectories)
value structure: atomic
value type: categorical
description: "Cluster membership or noise designation"

transform T_visualize_destinations :
intent: visualise
manner: "trajectories on map colored by cluster"
input: analysed_trajectories, cluster_labels
output: destination_map
actor: machine
description: "Display trajectories colored by cluster membership
with adjustable transparency"

artifact destination_map : visualisation(analysed_trajectories,
cluster_labels)

layout: "geographic map"
form: "colored trajectory lines"
encoding: "position from coordinates; color by cluster;
transparency adjustable"
description: "Map showing spatial distribution and coherence of
destination clusters"

transform T_assess_destinations :
intent: assess
manner: "evaluate cluster quality and coverage"
input: destination_map, destination_clusters
output: destination_assessment
actor: human
description: "Assess whether major destination regions are captured
with spatial coherence and interpretability"

artifact destination_assessment : knowledge(destination_clusters)
representation form: "quality judgment"
description: "Assessment of clustering quality: spatial coherence,
interpretability, coverage of dense regions, and whether
significant clusters identified for exclusion"

if destination_assessment indicates significant clusters identified:
then:
transform T_select_major_destinations :
intent: define-unit
manner: "interactive selection of interpretable clusters"
input: destination_clusters, cluster_labels, destination_map
output: selected_destination_clusters
actor: human
description: "Select sufficiently large spatially coherent
clusters for exclusion from further density analysis"

```

```

artifact selected_destination_clusters : entities
  internal structure: group/cluster
  embedment: set
  description: "Major destination clusters to exclude from
    further density-based analysis"

transform T_exclude_major :
  intent: define-unit
  manner: "filter by excluding selected clusters"
  input: analysed_trajectories, selected_destination_clusters,
    cluster_labels
  output: remaining_trajectories
  actor: machine
  description: "Remove trajectories in identified clusters to
    focus on remaining unanalyzed data"

artifact remaining_trajectories : entities
  internal structure: sequence
  embedment: {set, time}
  description: "Trajectories not yet assigned to interpretable
    destination clusters"

transform T_decrease_sensitivity :
  intent: generate-knowledge
  manner: "decrease clustering sensitivity for next density level"
  input: destination_assessment, S_dest_sensitivity
  output: S_dest_sensitivity'
  actor: human
  description: "Reduce sensitivity to capture clusters
    in sparser density regions"

artifact S_dest_sensitivity' : specification
  representation form: "parameter settings"
  description: "Decreased sensitivity parameter
    for next clustering iteration"

assign:
  analysed_trajectories := remaining_trajectories
  S_dest_sensitivity := S_dest_sensitivity'

else:
  exit loop L_destination_clustering
end loop L_destination_clustering

# =====
# PHASE 2: Route analysis of selected subsets
# =====

transform T_select_for_route_analysis :
  intent: define-unit
  manner: "interactive selection from destination clusters"

```

```
input: selected_destination_clusters
output: major_destination_clusters
actor: human
description: "Select largest destination clusters for in-depth route analysis"
```

```
artifact major_destination_clusters : entities
  internal structure: group/cluster
  embedment: set
  description: "Largest destination clusters selected for detailed route
    similarity analysis"
```

```
loop L_route_analysis_subsets:
  purpose: "Examine routes within major destinations by analyzing each cluster
    separately"
  until: "All major destination clusters of interest have been examined
    for route patterns"
```

```
body:
  transform T_select_one_destination :
    intent: define-unit
    manner: "interactive selection of single cluster"
    input: major_destination_clusters
    output: selected_subset
    actor: human
    description: "Select one destination cluster for route similarity
      analysis"
```

```
artifact selected_subset : entities
  internal structure: sequence
  embedment: {set, time}
  description: "Trajectories from one destination cluster for route
    analysis"
```

```
transform T_cluster_routes_subset :
  intent: define-unit
  manner: "density-based clustering by route similarity"
  input: selected_subset
  output: route_clusters_subset, route_labels_subset
  actor: machine
  description: "Group trajectories with similar spatial routes"
```

```
artifact route_clusters_subset : entities
  internal structure: group/cluster
  embedment: set
  description: "Groups of trajectories following similar paths within
    destination cluster"
```

```
artifact route_labels_subset : feature(selected_subset)
  value structure: atomic
  value type: categorical
  description: "Route cluster membership or noise designation"
```

```
transform T_visualize_routes_subset :
```

```

    intent: visualise
    manner: "trajectories on map colored by route cluster"
    input: selected_subset, route_labels_subset
    output: route_map_subset
    actor: machine
    description: "Display trajectories colored by route cluster"

artifact route_map_subset : visualisation(selected_subset,
                                         route_labels_subset)

    layout: "geographic map"
    form: "colored trajectory lines"
    encoding: "position from coordinates; color by route cluster"
    description: "Map showing route similarity patterns within destination
                 cluster"

transform T_assess_routes_subset :
    intent: assess
    manner: "evaluate route patterns and low-displacement prevalence"
    input: route_map_subset, route_clusters_subset
    output: route_assessment_subset
    actor: human
    description: "Assess route patterns within destination cluster:
                 prevalence of low-displacement trips, route similarity, pattern
                 coherence, and whether more clusters need examination"

artifact route_assessment_subset : knowledge(route_clusters_subset)
    representation form: "quality judgment with observations"
    description: "Assessment of route patterns within destination cluster:
                 prevalence of low-displacement trips, route coherence, and whether
                 additional destination clusters require analysis"

end loop L_route_analysis_subsets

# =====
# PHASE 3: Pattern verification on complete dataset
# =====

transform T_verify_pattern_hypothesis :
    intent: define-unit
    manner: "density-based clustering by source and destination proximity"
    input: all_trajectories
    output: verification_clusters, verification_labels
    actor: machine
    description: "Test hypothesis generated from subset analysis by clustering
                 ALL trajectories to assess pattern prevalence across complete dataset"

artifact verification_clusters : entities
    internal structure: group/cluster
    embedment: set
    description: "Clusters from verification analysis on complete dataset"

artifact verification_labels : feature(all_trajectories)

```

```

value structure: atomic
value type: categorical
description: "Classification of all trajectories according to verified pattern"

transform T_visualize_verification :
  intent: visualise
  manner: "trajectories on map colored by pattern type"
  input: all_trajectories, verification_labels
  output: verification_map
  actor: machine
  description: "Display complete trajectory set colored by pattern classification"

artifact verification_map : visualisation(all_trajectories, verification_labels)
  layout: "geographic map"
  form: "colored trajectory lines"
  encoding: "position from coordinates; color by pattern classification"
  description: "Map showing spatial distribution of verified pattern across
    complete dataset"

transform T_assess_verification :
  intent: assess
  manner: "evaluate pattern prevalence and hypothesis confirmation"
  input: verification_map, verification_clusters
  output: pattern_verification
  actor: human
  description: "Assess pattern prevalence, spatial distribution, and
    confirmation or refutation of hypothesis"

artifact pattern_verification : knowledge(verification_clusters)
  representation form: "quantitative and qualitative assessment"
  description: "Assessment of pattern prevalence and distribution across
    complete dataset, confirming or refuting hypothesis from subset analysis"

# =====
# PHASE 4: Route analysis of refined subset
# =====

transform T_exclude_verified_pattern :
  intent: define-unit
  manner: "filter by excluding clusters"
  input: all_trajectories, verification_clusters, verification_labels
  output: refined_trajectories
  actor: machine
  description: "Exclude trajectories matching verified pattern to focus on
    complementary subset for further analysis"

artifact refined_trajectories : entities
  internal structure: sequence
  embedment: {set, time}
  description: "Trajectories from complementary subset after pattern exclusion"

transform T_cluster_routes_final :

```

```

intent: define-unit
manner: "density-based clustering by route similarity"
input: refined_trajectories
output: route_clusters_final, route_labels_final
actor: machine
description: "Group trajectories with similar spatial routes in refined subset"

artifact route_clusters_final : entities
internal structure: group/cluster
embedment: set
description: "Groups of trajectories following similar paths in refined subset"

artifact route_labels_final : feature(refined_trajectories)
value structure: atomic
value type: categorical
description: "Route cluster membership or noise designation"

transform T_visualize_routes_final :
intent: visualise
manner: "trajectories on map colored by route cluster"
input: refined_trajectories, route_labels_final
output: route_map_final
actor: machine
description: "Display trajectories colored by route cluster"

artifact route_map_final : visualisation(refined_trajectories, route_labels_final)
layout: "geographic map"
form: "colored trajectory lines"
encoding: "position from coordinates; color by route cluster"
description: "Map showing route patterns in refined subset"

transform T_identify_route_types :
intent: abstract
manner: "identify and characterize route types"
input: route_map_final, route_clusters_final
output: route_patterns
actor: human
description: "Identify route types and assess frequency of route repetition"

artifact route_patterns : pattern(route_clusters_final)
representation form: "categorized route types with characteristics"
description: "Identified route types characterized by spatial structure
and frequency; assessment of route diversity vs. repetition"

# =====
# PATTERN SYNTHESIS: Integrate findings across all phases
# =====

transform T_synthesize_findings :
intent: abstract
manner: "synthesize findings across progressive clustering phases"
input: destination_assessment, route_assessment_subset, pattern_verification,

```

```

        route_patterns
    output: movement_patterns
    actor: human
    description: "Integrate patterns identified across four analytical phases"

artifact movement_patterns : pattern(all_trajectories)
    representation form: "comprehensive findings with descriptions"
    description: "Integrated movement patterns: destination distribution and
        popularity, prevalence of low-displacement trips, route diversity and
        repetition, spatial organization of routes"

# =====
# KNOWLEDGE GENERATION: Formulate insights
# =====

transform T_generate_knowledge :
    intent: generate-knowledge
    manner: "formulate-statements"
    input: movement_patterns
    output: mobility_knowledge
    actor: human
    description: "Synthesize comprehensive understanding of movement dynamics
        from progressive clustering results"

artifact mobility_knowledge : knowledge(movement_patterns)
    representation form: "statements and explanations"
    description: "Comprehensive understanding of movement dynamics: spatial
        distribution of destinations, prevalence of different trip types by
        displacement, route diversity and common patterns, spatial organization
        of movement flows"

```

1.8 Human-Steered Topic Modelling

Source: J. Choo, C. Lee, C. K. Reddy and H. Park, "UTOPIAN: User-Driven Topic Modeling Based on Interactive Nonnegative Matrix Factorization," in IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 1992-2001, Dec. 2013, doi: 10.1109/TVCG.2013.212.

Workflow summary

The paper presents UTOPIAN, a visual analytics system for interactive topic modelling using Nonnegative Matrix Factorization (NMF). The workflow begins by applying NMF to decompose a term-document matrix into two representations: topics as weighted combinations of keywords, and documents as weighted combinations of topics. A modified t-SNE algorithm creates a 2D layout visualizing documents as points coloured by their topic assignments, with enhanced cluster separation for clarity.

The core of UTOPIAN is an iterative refinement loop where users assess topic quality and interact with the model through multiple mechanisms: keyword refinement adjusts

weights of terms within topics; topic merging combines similar topics; topic splitting divides topics based on semantic differences; document-induced topic creation builds topics from exemplar documents; and keyword-induced topic creation generates topics from selected terms. Each interaction produces reference specifications (V and G matrices with supervision weights) that guide subsequent topic modelling through semi-supervised NMF, which regularizes the solution toward user specifications while maintaining fit to the data.

Through iterative exploration and refinement, analysts progressively improve topic quality and interpretability, discovering meaningful semantic structures in document collections. The approach was demonstrated on research papers, product reviews, and news-group data, revealing topic relationships and document organization.

A schematic representation of the workflow is provided in Fig. 9.

ATWL representation

```

workflow interactive-topic-modeling
  template: characterise (matrix representation) →
            define-unit (initial topics) →
            characterise (assign topics) →
            contextualise (projection) → visualise →
            loop(assess →
                generate-knowledge (specify refinement) →
                define-unit (semi-supervised) →
                characterise (assign topics) →
                contextualise → visualise) →
            abstract → generate-knowledge
  description: "Iteratively refine topic modeling through user interactions that
              guide semi-supervised matrix decomposition, progressively improving topic
              quality and interpretability"

# =====
# INPUT: Document corpus
# =====

artifact documents : entities
  origin: given
  internal structure: elementary
  embedment: set
  features:
    - id: text_content
      value structure: atomic
      value type: text
      description: "Document text"
  description: "Collection of text documents for topic analysis"

# =====
# PREPROCESSING: Matrix representation
# =====

```

```

transform T_create_matrix :
  intent: characterise
  manner: "bag-of-words encoding with weighting"
  input: documents
  output: term_document_matrix
  actor: machine
  description: "Represent documents as weighted term vectors with tf-idf
    and normalization"

artifact term_document_matrix : feature(documents)
  value structure: matrix
  value type: numeric
  description: "Term frequency representation of documents with weighting
    and normalization"

# =====
# INITIAL TOPIC MODELING: Unsupervised matrix decomposition
# =====

transform T_initial_topic_modeling :
  intent: define-unit
  manner: "matrix decomposition with non-negativity constraints"
  input: term_document_matrix
  output: topics, topic_keyword_weights, document_topic_weights
  actor: machine
  description: "Decompose term-document matrix into topics and their
    relationships to keywords and documents"

artifact topics : entities
  internal structure: elementary
  embedment: set
  features:
    - id: topic_id
      value structure: atomic
      value type: categorical
      description: "Topic identifier"
  description: "Discovered topics representing semantic themes in corpus"

artifact topic_keyword_weights : feature(topics)
  value structure: vector
  value type: numeric
  description: "Representation of each topic as a vector of keyword weights"

artifact document_topic_weights : feature(documents)
  value structure: vector
  value type: numeric
  description: "Representation of each document as a vector of topic weights"

transform T_assign_topics :
  intent: characterise
  manner: "assign primary topic based on maximum weight"
  input: documents, document_topic_weights

```

```

    output: topic_assignments
    actor: machine
    description: "Assign each document to its dominant topic for visualization"

artifact topic_assignments : feature(documents)
    value structure: atomic
    value type: categorical
    description: "Primary topic assignment for each document"

# =====
# VISUALIZATION: Layout and display
# =====

transform T_compute_projection :
    intent: contextualise
    manner: "dimensionality reduction with cluster enhancement"
    input: documents, term_document_matrix, topic_assignments
    output: projection_space, document_layout
    actor: machine
    description: "Project documents to 2D preserving similarities while enhancing
        topic cluster separation"

artifact projection_space : entities
    internal structure: elementary
    features:
        - id: dimensionality
          value structure: atomic
          value type: numeric
          description: "Number of spatial dimensions (2)"
    description: "Two-dimensional projection space serving as
        reference frame for document layout"

artifact document_layout : arrangement(documents)
    context: projection_space
    principle: "dimensionality reduction preserving similarities with cluster
        separation enhancement"
    description: "2D positioning where proximity indicates similarity and topic
        clusters are spatially separated"

transform T_visualize_topics :
    intent: visualise
    manner: "scatterplot with topic coloring and keyword summaries"
    input: document_layout, topic_assignments, topic_keyword_weights
    output: topic_view
    actor: machine
    description: "Display documents as colored points with topic keyword summaries
        and interactive capabilities"

artifact topic_view : visualisation(document_layout, topic_assignments,
                                     topic_keyword_weights)
    layout: "2D scatterplot"
    form: "colored points with topic labels"

```

```

encoding: "position from document_layout; color by topic_assignments;
  annotations show top keywords per topic"
description: "Interactive view showing document distribution and topic structure
  with keyword summaries"

```

```

# =====
# ITERATIVE REFINEMENT: User-guided improvement
# =====

```

```

loop L_refinement:

```

```

  purpose: "Iteratively refine topic model through user interactions that express
    desired topic characteristics or structure"
  until: "Topics are interpretable, semantically coherent, and appropriately
    structured for analytical goals"

```

```

  body:

```

```

    transform T_assess_topics :

```

```

      intent: assess
      manner: "evaluate semantic coherence and interpretability"
      input: topic_view, topic_keyword_weights, document_topic_weights
      output: topic_assessment
      actor: human
      description: "Assess topic quality: semantic coherence, interpretability

```

```

    ,

```

```

      appropriate granularity, and coverage"

```

```

    artifact topic_assessment : knowledge(topics)

```

```

      representation form: "quality judgment"
      description: "Assessment of topic quality identifying needed

```

```

  improvements:

```

```

    unclear topics, overly similar topics, missing themes, inappropriate
    keyword weights"

```

```

  if topic_assessment indicates refinement needed:

```

```

    then:

```

```

      transform T_specify_refinement :

```

```

        intent: generate-knowledge
        manner: "formulate desired topic characteristics"
        input: topics, topic_keyword_weights, document_topic_weights,
          topic_assessment
        output: user_guidance
        actor: human
        description: "Specify desired changes through interactions:
          keyword weight adjustments, topic combinations or divisions,
          creation of new topics from exemplar documents or keywords"

```

```

      artifact user_guidance : specification

```

```

        representation form: "reference matrices (V, G) with
          supervision weights (MW, MH)"
        description: "User-specified constraints defining
          desired topic-keyword relationships (V),
          document-topic relationships (G),
          and supervision strengths (MW, MH) for

```

```

        semi-supervised refinement"

transform T_refine_topics :
  intent: define-unit
  manner: "semi-supervised matrix decomposition guided by user
    specifications"
  input: term_document_matrix, user_guidance
  output: topics', topic_keyword_weights', document_topic_weights'
  actor: machine
  description: "Recompute topic model incorporating user guidance
    as soft constraints while maintaining fit to data"

artifact topics' : entities
  internal structure: elementary
  embedment: set
  description: "Refined topics incorporating user guidance"

artifact topic_keyword_weights' : feature(topics')
  value structure: vector
  value type: numeric
  description: "Updated keyword weights"

artifact document_topic_weights' : feature(documents)
  value structure: vector
  value type: numeric
  description: "Updated topic weights"

transform T_update_assignments :
  intent: characterise
  manner: "assign primary topic based on updated weights"
  input: documents, document_topic_weights'
  output: topic_assignments'
  actor: machine
  description: "Update document topic assignments based on
    refined model"

artifact topic_assignments' : feature(documents)
  value structure: atomic
  value type: categorical
  description: "Updated primary topic assignments"

transform T_update_projection :
  intent: contextualise
  manner: "incremental dimensionality reduction"
  input: documents, term_document_matrix, topic_assignments',
    document_layout
  output: document_layout'
  actor: machine
  description: "Update 2D layout to reflect topic changes while
    preserving spatial stability"

artifact document_layout' : arrangement(documents)

```

```

        context: projection_space
        principle: "updated projection incorporating topic changes with
            smooth transitions"
        description: "Updated 2D positioning reflecting refined topic
structure"

    transform T_update_visualization :
        intent: visualise
        manner: "animated transition showing topic changes"
        input: document_layout', topic_assignments',
topic_keyword_weights'
        output: topic_view'
        actor: machine
        description: "Update visualization with smooth animations
showing
            topic membership changes"

        artifact topic_view' : visualisation(document_layout',
topic_assignments',
            topic_keyword_weights')
            layout: "2D scatterplot with animated transitions"
            form: "colored points with change indicators"
            encoding: "position from updated layout; color by new
assignments;
            split coloring shows changes"
            description: "Updated view showing refined topic structure with
            explicit change indicators"

        assign:
            topics := topics'
            topic_keyword_weights := topic_keyword_weights'
            document_topic_weights := document_topic_weights'
            topic_assignments := topic_assignments'
            document_layout := document_layout'
            topic_view := topic_view'
        else:
            exit loop L_refinement
    end loop L_refinement

# =====
# PATTERN IDENTIFICATION: Characterize final topics
# =====

transform T_characterize_topics :
    intent: abstract
    manner: "identify semantic themes and relationships"
    input: topics, topic_keyword_weights, document_topic_weights, topic_view
    output: topic_patterns
    actor: human
    description: "Identify and characterize semantic themes, topic relationships,
        and document organization"

```

```

artifact topic_patterns : pattern(topics, documents)
  representation form: "categorized themes with descriptions and relationships"
  description: "Identified semantic themes with their characteristics,
    representative keywords, document distributions, and inter-topic
    relationships"

# =====
# KNOWLEDGE GENERATION: Synthesize insights
# =====

transform T_generate_knowledge :
  intent: generate-knowledge
  manner: "formulate-statements"
  input: topic_patterns, topics, topic_keyword_weights
  output: corpus_knowledge
  actor: human
  description: "Synthesize understanding of corpus organization, dominant themes,
    and semantic structure"

artifact corpus_knowledge : knowledge(topic_patterns)
  representation form: "statements and explanations"
  description: "Understanding of document corpus: major themes and their
    characteristics, document organization by topics, semantic relationships
    between themes, coverage of subject matter"

```

1.9 Progressive Abstraction Analysis of Multivariate Temporal Data

Source: Andrienko, N., Andrienko, G. and Shirato, G. (2023), Episodes and Topics in Multivariate Temporal Data. Computer Graphics Forum, 42: e14926. doi: 10.1111/cgf.14926

Workflow summary:

This visual analytics workflow analyses multivariate temporal data partitioned into episodes to understand complex dynamic phenomena through progressive abstraction. The approach has three main analytical phases:

1. **Single-attribute pattern extraction:** Transform temporal sequences of attribute values within episodes into symbolic representations (using methods like SAX encoding) that capture variation patterns. Analysts iteratively refine encoding parameters (segment counts, discretization breaks) to achieve interpretable patterns.
2. **Multi-attribute pattern discovery:** Apply topic modeling to collections of symbolic patterns to discover "topics" - combinations of single-attribute patterns that frequently co-occur across episodes. Analysts experiment with parameters (number of topics), assess topic interpretability, and may merge semantically similar topics.

3. **Distribution pattern analysis:** Visualize and explore how multi-attribute patterns (topics) are distributed across episodes in relevant contexts (time, space, external conditions). Analysts identify higher-level distribution patterns and formulate domain insights.

A schematic representation of the workflow is shown in Fig. 10.

ATWL representation:

```

workflow Episode_Based_Temporal_Analysis
  template: define-unit →
    loop(characterise → visualise → assess → generate-knowledge) →
    loop(abstract → visualise → assess → generate-knowledge) →
    loop(contextualise → visualise → abstract → generate-knowledge →
      assess → define-unit (focused exploration))

  description: "Progressive abstraction workflow for episode-based analysis
    of multivariate temporal data through three main phases:
    single-attribute pattern extraction, multi-attribute pattern
    discovery via topic modeling, and distribution pattern analysis"

# =====
# PHASE 0: Episode Preparation
# =====

artifact raw_timeseries : entities
  origin: given
  internal structure: elementary
  embedment: {set, time}
  features:
    - id: entity_id
      value structure: atomic
      value type: categorical
      description: "Entity identifier (e.g., country)"
    - id: attr_values
      value structure: vector
      value type: numeric
      description: "Multiple attribute values at each time point"
  description: "Multivariate time series from multiple entities; each time point
    contains vector of attribute values describing dynamic phenomena"

transform T_define_episodes :
  intent: define-unit
  manner: "temporal segmentation into episodes"
  input: raw_timeseries
  output: episodes
  actor: hybrid
  description: "Segment continuous time series into meaningful temporal intervals
    based on domain-specific criteria"

artifact episodes : entities

```

```

internal structure: episode
embedment: time
features:
  - id: time_span
    value structure: atomic
    value type: temporal
    description: "Episode temporal extent"
  - id: attribute_series
    value structure: vector
    value type: numeric
    description: "Multivariate time series within episode"
description: "Temporal intervals each containing multivariate
time series representing distinct periods in dynamic
process"

# =====
# PHASE 1: Single-Attribute Pattern Extraction
# =====

artifact encoding_params : specification
  origin: given
  representation form: "parameter set"
  description: "Parameters controlling symbolic encoding: number of temporal
segments, alphabet size, value discretization breaks"

loop L_encoding_refinement:
  purpose: "Iteratively refine encoding parameters until symbolic patterns
are interpretable and align with domain knowledge"
  until: "Symbolic patterns are interpretable and discretization breaks
reflect domain-meaningful thresholds"
  body:
    transform T_encode_patterns :
      intent: characterise
      manner: "symbolic encoding of temporal variation"
      input: episodes, encoding_params
      output: symbolic_patterns
      actor: machine
      description: "Transform each attribute's time series within
episodes into symbolic codes capturing variation patterns"

    artifact symbolic_patterns : feature(episodes)
      value structure: vector
      value type: text
      description: "Symbolic codes representing single-attribute
temporal variation patterns for each episode; one code
per attribute encoding discretized value levels over
temporal segments"

    transform T_visualize_patterns :
      intent: visualise
      manner: "tabular display with color coding"
      input: symbolic_patterns, episodes

```

```

output: pattern_table_vis
actor: machine
description: "Display symbolic patterns for all attributes
            and episodes in a color-coded table"

artifact pattern_table_vis : visualisation(symbolic_patterns, episodes)
layout: "table with episodes as rows, attributes as columns"
form: "color-coded symbols"
encoding: "table position from episodes structure; symbol colors
          represent value levels; symbols show variation patterns"
description: "Table showing symbolic patterns for all attributes and
            episodes with color coding for efficient perception"

transform T_assess_encoding :
intent: assess
manner: "evaluate pattern interpretability"
input: pattern_table_vis, symbolic_patterns
output: encoding_assessment
actor: human
description: "Assess whether symbolic patterns are
            interpretable and whether discretization aligns
            with domain knowledge"

artifact encoding_assessment : knowledge(symbolic_patterns)
representation form: "quality judgment"
description: "Assessment of whether symbolic patterns are interpretable
            and whether discretization aligns with domain knowledge"

if encoding_assessment indicates refinement needed:
then:
transform T_adjust_encoding :
intent: generate-knowledge
manner: "decide parameter adjustments"
input: encoding_assessment
output: encoding_params_updated
actor: human
description: "Decide how to adjust encoding parameters
            based on assessment of pattern interpretability
            and domain alignment"

artifact encoding_params_updated : specification
representation form: "parameter set"
description: "Updated encoding parameters with adjusted segment counts,
            alphabet size, or discretization breaks"

assign:
encoding_params := encoding_params_updated
else:
exit loop L_encoding_refinement

end loop L_encoding_refinement

```

```

# =====
# PHASE 2: Multi-Attribute Pattern Discovery
# =====

artifact topic_params : specification
  origin: given
  representation form: "parameter set"
  description: "Parameters for topic modeling: target number of topics,
               convergence criteria"

loop L_topic_refinement:
  purpose: "Iteratively refine topics until they represent distinct,
           interpretable multi-attribute behaviors"
  until: "Topics are interpretable, distinct, and semantically coherent"
  body:
    transform T_discover_topics :
      intent: abstract
      manner: "topic modeling of pattern co-occurrences"
      input: symbolic_patterns, topic_params
      output: topics
      actor: machine
      description: "Apply topic modeling to discover combinations
                   of single-attribute patterns that frequently co-occur
                   across episodes"

    artifact topics : pattern(episodes)
      representation form: "weighted combinations of patterns"
      description: "Multi-attribute combination patterns
                   representing integrated temporal behaviors; each topic
                   defined by weights of constituent single-attribute
                   patterns"

    transform T_compute_topic_weights :
      intent: characterise
      manner: "compute episode-topic associations"
      input: topics, episodes
      output: topic_weights
      actor: machine
      description: "Compute how strongly each topic relates to
                   each episode"

    artifact topic_weights : feature(episodes)
      value structure: vector
      value type: numeric
      description: "Weights indicating relevance of each topic to each episode"

    transform T_visualize_topics :
      intent: visualise
      manner: "tabular display of topic compositions"
      input: topics
      output: topic_table_vis
      actor: machine

```

```

description: "Display which single-attribute patterns
            contribute to each topic with their weights"

artifact topic_table_vis : visualisation(topics)
  layout: "table with topics as rows, attributes as columns"
  form: "weighted pattern symbols with color coding"
  encoding: "table structure from topics; symbol weights shown by size or
            intensity; colors match pattern encoding"
  description: "Table showing which single-attribute patterns contribute
            to each topic with their weights"

transform T_assess_topics :
  intent: assess
  manner: "evaluate topic quality"
  input: topic_table_vis, topics
  output: topic_assessment
  actor: human
  description: "Assess whether topics represent distinct,
            interpretable behaviors; identify semantically
            similar topics or inconsistent mixtures"

artifact topic_assessment : knowledge(topics)
  representation form: "quality judgment"
  description: "Assessment of whether topics represent distinct,
            interpretable behaviors; identification of semantically
            similar topics or inconsistent mixtures"

if topic_assessment indicates refinement needed:
then:
  transform T_decide_refinement :
    intent: generate-knowledge
    manner: "formulate refinement strategy"
    input: topic_assessment
    output: topic_refinement_strategy
    actor: human
    description: "Decide on merge operations, definition edits,
            or topic count adjustment"

  artifact topic_refinement_strategy : specification
    representation form: "strategic decisions"
    description: "Decisions on merging similar topics, editing definitions,
            or adjusting topic count parameter"

  transform T_merge_topics :
    intent: abstract
    manner: "consolidate semantically similar topics"
    input: topics, topic_weights, topic_refinement_strategy
    output: topics_updated, topic_weights_updated,
            topic_params_updated
    actor: hybrid
    description: "Combine semantically similar topics by
            summing weights; edit individual topic definitions;

```

```

        produce updated effective parameters"

artifact topics_updated : pattern(episodes)
  representation form: "weighted combinations of patterns"
  description: "Consolidated multi-attribute patterns
    after merging semantically similar topics"

artifact topic_weights_updated : feature(episodes)
  value structure: vector
  value type: numeric
  description: "Updated topic weights after refinement"

artifact topic_params_updated : specification
  representation form: "parameter set"
  description: "Updated topic modeling parameters reflecting
    effective number of topics and adjustments after
    merge and editing operations"

assign:
  topics := topics_updated
  topic_weights := topic_weights_updated
  topic_params := topic_params_updated
else:
  exit loop L_topic_refinement

end loop L_topic_refinement

# =====
# Topic Interpretation
# =====

transform T_interpret_topics :
  intent: generate-knowledge
  manner: "formulate semantic interpretations"
  input: topics, topic_table_vis
  output: topic_interpretations
  actor: human
  description: "Formulate human-understandable interpretations using domain
    knowledge"

artifact topic_interpretations : knowledge(topics)
  representation form: "semantic descriptions"
  description: "Human-understandable interpretations of what each topic
    represents in domain terms"

# =====
# PHASE 3: Distribution Pattern Analysis
# =====

transform T_characterise_context :
  intent: characterise
  manner: "extract contextual attributes from episode metadata"

```

```

input: episodes, raw_timeseries
output: context_info
actor: machine
description: "Derive contextual attributes for each episode from
    underlying time series metadata: temporal positions, spatial
    locations, entity identifiers, external conditions"

artifact context_info : feature(episodes)
value structure: vector
value type: {temporal, spatial, reference, categorical}
description: "Contextual attributes: temporal positions, spatial
    locations, involved entities, external conditions"

transform T_create_context :
intent: define-unit
manner: "define context structure from contextual dimensions"
input: context_info
output: context_structure
actor: machine
description: "Create reference structure from contextual
    dimensions for arranging episodes"

artifact context_structure : entities
internal structure: formation
features:
- id: context_dims
value structure: relational configuration
value type: {temporal, spatial, reference, numeric}
description: "Contextual dimensions and their organisation"
description: "Context structure serving as reference frame for
    arranging episodes"

loop L_distribution_analysis:
purpose: "Explore topic distributions in context space to
    identify higher-level patterns and formulate insights
    through iterative focused exploration"
until: "Distribution patterns are sufficiently understood and
    domain insights formulated"
body:
transform T_arrange_in_context :
intent: contextualise
manner: "spatial or temporal positioning"
input: episodes, context_info, context_structure
output: episode_arrangement
actor: machine
description: "Position episodes according to relevant
    contextual dimensions"

artifact episode_arrangement : arrangement(episodes)
context: context_structure
principle: "positioning based on contextual attributes"
description: "Episodes arranged according to relevant contextual

```

```

        dimensions"

transform T_visualize_distribution :
  intent: visualise
  manner: "context-aware spatial display"
  input: topic_weights, episode_arrangement, topics
  output: distribution_vis
  actor: machine
  description: "Display topic weight distributions across
    episodes in context space"

artifact distribution_vis : visualisation(topic_weights, episode_arrangement)
  layout: "spatial layout from episode_arrangement"
  form: "colored marks, pie charts, or proportional symbols"
  encoding: "position from episode_arrangement; colors from topics;
    sizes or proportions from topic_weights"
  description: "Visual representation of topic distributions across
    episodes in relevant context space"

transform T_visualize_aggregated :
  intent: visualise
  manner: "aggregated characteristic displays"
  input: symbolic_patterns, topics, topic_weights
  output: aggregated_pattern_vis
  actor: machine
  description: "Display aggregated pattern characteristics
    grouped by topic for verification"

artifact aggregated_pattern_vis : visualisation(symbolic_patterns, topics)
  layout: "grouped by topic"
  form: "segmented bar charts or distribution plots"
  encoding: "grouping by topic; segments show pattern characteristics;
    sizes show frequencies"
  description: "Aggregated view of pattern characteristics grouped by
    topics for verification"

transform T_identify_distribution_patterns :
  intent: abstract
  manner: "discover distributional regularities"
  input: distribution_vis, aggregated_pattern_vis, context_info
  output: distribution_patterns
  actor: human
  description: "Identify higher-level patterns in topic
    distributions across contexts"

artifact distribution_patterns : pattern(topics, context_info)
  representation form: "described regularities"
  description: "Higher-level patterns in topic distributions: temporal
    sequences, spatial associations, relationships to
    external conditions, complementary distributions"

transform T_formulate_insights :

```

```

    intent: generate-knowledge
    manner: "synthesize understanding"
    input: distribution_patterns, topic_interpretations, context_info
    output: domain_insights
    actor: human
    description: "Synthesize domain understanding from
        distribution patterns"

artifact domain_insights : knowledge(distribution_patterns)
    representation form: "statements and explanations"
    description: "Documented high-level findings about the
        dynamic phenomenon: behavioral phases, response
        patterns to conditions, entity-specific
        characteristics, temporal evolution"

# Assessment of understanding completeness
transform T_assess_understanding :
    intent: assess
    manner: "evaluate completeness of pattern understanding"
    input: distribution_vis, distribution_patterns, domain_insights
    output: understanding_assessment
    actor: human
    description: "Assess whether distribution patterns are sufficiently
        understood or require focused exploration of specific
        episode subsets"

artifact understanding_assessment : knowledge(distribution_patterns)
    representation form: "quality judgment"
    description: "Assessment of whether distribution patterns are
        sufficiently understood; identification of areas
        requiring focused exploration"

# Conditional focused exploration
if understanding_assessment indicates focused exploration needed:
then:
    transform T_formulate_query :
        intent: generate-knowledge
        manner: "formulate selection criteria"
        input: distribution_vis, understanding_assessment
        output: user_query
        actor: human
        description: "Formulate query criteria for examining specific episode
            subsets based on identified gaps in understanding"

artifact user_query : specification
    representation form: "query criteria"
    description: "User-specified selection criteria for episode subsets:
        topic dominance, context properties, pattern characteristics"
"

transform T_filter_episodes :
    intent: define-unit

```

```

    manner: "subset selection by criteria"
    input: episodes, topic_weights, context_info, user_query
    output: filtered_episodes
    actor: machine
    description: "Select episodes satisfying query criteria
        for detailed examination"

artifact filtered_episodes : entities
    internal structure: episode
    embedment: time
    features:
        - id: episode_data
          value structure: vector
          value type: numeric
          description: "Episode characteristics"
    description: "Selected episodes satisfying query criteria for
        detailed examination"

transform T_examine_details :
    intent: visualise
    manner: "detailed episode display"
    input: filtered_episodes, symbolic_patterns, topic_weights
    output: detail_vis
    actor: machine
    description: "Display detailed patterns and topic
        compositions for selected episodes"

artifact detail_vis : visualisation(filtered_episodes, symbolic_patterns)
    layout: "detailed tabular or timeline layout"
    form: "detailed patterns and topic compositions"
    encoding: "episode structure from filtered_episodes; patterns from
        symbolic_patterns; topic weights from topic_weights"
    description: "Detailed view of patterns and topic compositions for
        selected episodes supporting verification and refinement"

else:
    exit loop L_distribution_analysis

end loop L_distribution_analysis

```

1.10 Partition-based Regression Modelling

Source: T. Mühlbacher and H. Piringer "A Partition-Based Framework for Building and Validating Regression Models" IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 1962-1971, Dec. 2013 doi: 10.1109/TVCG.2013.125

Workflow summary

This paper presents a partition-based framework for building and validating regression models through interactive, iterative feature subset selection. The workflow combines quantitative relevance ranking with visual exploration of conditional target distributions.

- **Data Preparation.** The dataset is split into training and validation subsets for model fitting and unbiased evaluation.
- **Initial Model Identification.** Feature domains are partitioned into disjoint regions, and goodness-of-fit relevance measures are computed for individual features and feature pairs. Ranked small-multiple visualisations of conditional target distributions allow the analyst to identify the most relevant features and characterise relationship structures (non-linearity, local patterns, interactions). The analyst then specifies an initial model (choosing features, transformations, and model type) informed by discovered relationships and domain knowledge.
- **Iterative Model Refinement.** The analytical target switches to model residuals. Relevance rankings and conditional-distribution visualisations are recomputed with respect to residuals, exposing effects not yet captured by the model: previously included features rank lower while new relevant features and pair-wise interactions emerge. The analyst discovers additional explanatory variables, transformations, and interactions, and builds a refined model. This cycle of assessment, residual-based exploration, pattern discovery, and model refinement repeats until accuracy is satisfactory.
- **Final Assessment.** Model variants are compared through visualisations of local accuracy differences, and the analyst synthesises domain insights about feature–target relationships, interaction effects, and model adequacy.

Figure 11 represents the workflow in a flow diagram.

ATWL representation

```

workflow PartitionBasedRegressionModeling
  description: "Interactive framework for regression model building through
    iterative feature subset selection, combining partition-based relevance
    ranking with visual exploration of conditional target distributions"

  template: define-unit →
    characterise → visualise → abstract → generate-knowledge (specify) →
    build-model →
    loop(assess → characterise → visualise → abstract →
    generate-knowledge (specify) → build-model) →
    assess → generate-knowledge

  # =====
  # GIVEN ARTIFACTS
  # =====

  artifact measurement_data : entities
    origin: given
    internal structure: elementary
    embedment: set

```

```

        description: "Records containing a quantitative target variable and
            candidate continuous or categorical independent variables"

# =====
# PHASE 1: DATA PREPARATION
# =====

transform T_split_data :
    intent: define-unit
    manner: "partition dataset into disjoint subsets"
    input: measurement_data
    output: training_data, validation_data
    actor: human
    description: "Separate records into training and validation subsets
        for unbiased model fitting and evaluation"

artifact training_data : entities
    internal structure: elementary
    embedment: set
    description: "Subset of records for fitting regression models"

artifact validation_data : entities
    internal structure: elementary
    embedment: set
    description: "Subset of records for evaluating model performance
        and computing feature rankings"

# =====
# PHASE 2: INITIAL MODEL IDENTIFICATION (target = predicted variable Y)
# =====

transform T_rank_features :
    intent: characterise
    manner: "partition feature domains and compute multi-resolution
        relevance measures for conditional target distributions"
    input: validation_data
    output: feature_relevance
    actor: machine
    description: "Rank features by relevance to the target variable
        using partition-based approximation of conditional distributions"

artifact feature_relevance : feature(validation_data)
    value structure: vector
    value type: numeric
    description: "Relevance measures for individual features
        and feature pairs at increasing partition complexities,
        with local distributional statistics per partition
        region"

transform T_visualize_relationships :
    intent: visualise
    manner: "display ranked small-multiple partition-based plots with

```

```

        selectable domain- or frequency-preserving layouts"
input: validation_data, feature_relevance
output: relationship_viz
actor: machine
description: "Present conditional target distributions over ranked
        features and feature pairs for visual relationship exploration"

artifact relationship_viz :
    visualisation(validation_data, feature_relevance)
layout: "ranked small-multiple grid ordered by relevance"
form: "1D percentile plots and 2D colour-coded cells"
encoding: "grid position: relevance rank; 1D plots:
        x-axis from feature partition, y-axis from target
        percentiles; 2D plots: colour from conditional
        statistics; layout toggle: domain- or frequency-
        preserving partitions"
description: "Ranked 1D percentile plots over partitioned
        features and 2D colour-coded conditional statistics
        over feature pairs, with domain- or frequency-
        preserving layout options"

transform T_identify_patterns :
    intent: abstract
manner: "identify dominant features and characterise relationship
        shapes from visual and quantitative evidence"
input: relationship_viz, feature_relevance
output: relationship_patterns
actor: human
description: "Discover which features are most relevant and what
        relationship structures they exhibit with the target"

artifact relationship_patterns : pattern(validation_data)
representation form: "characterised relationship structures"
description: "Discovered feature-target relationships including
        dominant features, relationship shapes, and interaction effects
        between feature pairs"

transform T_specify_model :
    intent: generate-knowledge
manner: "decide model structure integrating observed patterns with
        domain expertise"
input: relationship_patterns
output: model_spec, modeling_rationale
actor: human
description: "Formulate initial model configuration by selecting
        features, transformations, and model type based on discovered
        relationships and domain knowledge"

artifact model_spec : specification
representation form: "model configuration"
description: "Regression model type, selected features, and
        transformations such as polynomial expansions, categorisations,

```

```

    and interaction terms"

artifact modeling_rationale : knowledge(relationship_patterns)
  representation form: "domain-informed reasoning"
  description: "Analyst's rationale for feature selection and model
    structure choices, integrating domain expertise with observed
    relationships"

transform T_build_model :
  intent: build-model
  manner: "fit regression model to training data using specified
    configuration"
  input: training_data, model_spec
  output: regression_model
  actor: machine
  description: "Create initial regression model from specified
    features and transformations"

artifact regression_model : model(training_data, model_spec)
  description: "Fitted regression model predicting the target
    variable from selected features and transformations"

# =====
# PHASE 3: ITERATIVE MODEL REFINEMENT (target = residuals)
# =====

loop L_refinement:
  purpose: "Improve the regression model by incorporating features,
    transformations, and interactions that explain residual variance"
  until: "prediction accuracy is satisfactory and no further relevant
    features are discoverable in residual distributions"
  body:

    transform T_assess_model :
      intent: assess
      manner: "compute prediction accuracy on validation data and
        track error metrics across model variants"
      input: regression_model, validation_data
      output: model_assessment
      actor: hybrid
      description: "Evaluate whether the current model captures
        sufficient variance and whether refinement is warranted"

    artifact model_assessment : knowledge(regression_model)
      representation form: "quality judgment with error metrics"
      description: "Assessment of prediction accuracy on
        validation data with comparison across model variants"

    if model_assessment indicates refinement needed:
      then:
        transform T_rank_on_residuals :
          intent: characterise

```

```

manner: "compute residuals as analytical target
        and re-rank features and feature pairs by
        residual-based relevance"
input: regression_model, validation_data
output: updated_feature_relevance
actor: machine
description: "Re-rank features by relevance to
             model residuals, exposing effects not yet
             captured"

artifact updated_feature_relevance :
    feature(validation_data)
value structure: vector
value type: numeric
description: "Residual-based relevance measures;
            features already captured by the model rank
            lower while new relevant features and
            interactions emerge"

assign: feature_relevance := updated_feature_relevance

transform T_visualize_residuals :
    intent: visualise
manner: "display ranked partition-based plots of
        conditional residual distributions over
        features and feature pairs"
input: validation_data, feature_relevance
output: updated_relationship_viz
actor: machine
description: "Present conditional residual
            distributions for visual exploration of
            unexplained effects"

artifact updated_relationship_viz :
    visualisation(validation_data, feature_relevance)
layout: "ranked small-multiple grid ordered by residual
        relevance"
form: "1D percentile plots and 2D colour-coded cells"
encoding: "grid position: residual relevance rank; 1D
          plots: x-axis from feature partition, y-axis from
          residual percentiles; 2D plots: colour from
          conditional residual statistics"
description: "Ranked partition-based plots showing
            conditional residual distributions, revealing local
            prediction bias and unexplained effects"

assign: relationship_viz := updated_relationship_viz

transform T_discover_refinement :
    intent: abstract
manner: "identify residual-based patterns from
        visual and quantitative evidence"

```

```

    input: relationship_viz, feature_relevance
    output: updated_relationship_patterns
    actor: human
    description: "Discover additional features,
                 interactions, and local bias structures in
                 residual distributions"

artifact updated_relationship_patterns :
    pattern(validation_data)
    representation form: "characterised residual
                        structures"
    description: "Discovered residual-based patterns
                 including additional relevant features,
                 interaction effects, and local bias structures"

assign:
    relationship_patterns := updated_relationship_patterns

transform T_decide_refinement :
    intent: generate-knowledge
    manner: "formulate refinement strategy integrating
            residual analysis with domain expertise"
    input: relationship_patterns, model_assessment
    output: updated_model_spec,
            updated_modeling_rationale
    actor: human
    description: "Decide which additional features,
                 transformations, and interactions to
                 incorporate based on residual patterns and
                 domain knowledge"

artifact updated_model_spec : specification
    representation form: "model configuration"
    description: "Refined model specification
                 incorporating additional features,
                 transformations, and interactions"

artifact updated_modeling_rationale :
    knowledge(relationship_patterns)
    representation form: "domain-informed reasoning"
    description: "Analyst's rationale for refinement
                 choices, integrating residual analysis with
                 domain expertise"

assign: model_spec := updated_model_spec
assign: modeling_rationale := updated_modeling_rationale

transform T_build_refined :
    intent: build-model
    manner: "fit regression model to training data
            using updated configuration"
    input: training_data, model_spec

```

```

        output: updated_regression_model
        actor: machine
        description: "Create refined regression model with
            expanded feature set and transformations"

    artifact updated_regression_model :
        model(training_data, model_spec)
        description: "Refined regression model with expanded
            feature set and transformations"

    assign: regression_model := updated_regression_model

else:
    exit loop L_refinement

end loop L_refinement

# =====
# PHASE 4: FINAL ASSESSMENT AND KNOWLEDGE SYNTHESIS
# =====

transform T_compare_models :
    intent: assess
    manner: "visualise point-wise differences of residual magnitudes
        between model variants across feature subspaces"
    input: regression_model, validation_data
    output: final_assessment
    actor: hybrid
    description: "Compare model variants from the refinement history
        by examining local differences in prediction accuracy"

artifact final_assessment : knowledge(regression_model)
    representation form: "comparative quality judgment"
    description: "Comparative assessment of model variants identifying
        regions of relative superiority and overall prediction adequacy"

transform T_synthesize :
    intent: generate-knowledge
    manner: "synthesise insights from model characteristics, assessment
        results, and accumulated modeling rationale"
    input: regression_model, final_assessment, modeling_rationale
    output: domain_knowledge
    actor: human
    description: "Formulate domain understanding of feature-target
        relationships, interaction effects, and model adequacy"

artifact domain_knowledge : knowledge(regression_model)
    representation form: "comprehensive domain insights"
    description: "Understanding of feature-target relationships,
        interaction effects, and model capabilities for prediction
        and domain decisions"

```

1.11 Spatio-temporal analysis and modelling

Source:

N. Andrienko and G. Andrienko

"A visual analytics framework for spatio-temporal analysis and modelling"

Data Mining and Knowledge Discovery, vol.27, no. 1, 2013, pp. 55-83,

doi: 10.1007/s10618-012-0285-7

Workflow summary

The workflow supports analysis and modelling of spatio-temporal data in the form of spatially referenced numeric time series. Raw data are first transformed into spatial time series through spatio-temporal aggregation. The time series are then clustered by temporal similarity, and the resulting grouping is iteratively refined through visual assessment of within-group homogeneity on time graphs and spatial pattern interpretability on maps.

For each group of similar time series, the analyst visually identifies temporal variation characteristics—such as periodicity, cycle lengths, and trends—from the time graph. A representative time series is derived from the group, and a suitable modelling method is selected and configured. A statistical model is fitted and iteratively refined by adjusting parameters while comparing the model curve against the data until it captures the group's characteristic temporal variation.

Model quality is evaluated by examining distributions of residuals over time and space: randomly distributed residuals indicate that the model captures the essential spatio-temporal variation. If systematic residual patterns emerge, the analyst decides whether to subdivide clusters, adjust the modelling approach, or both, and repeats the analysis cycle. Once all models pass the residual check, their descriptions—including method, parameters, group membership, and distribution statistics—are stored externally for reuse, communication, and prediction.

The same workflow structure applies to modelling dependencies between two spatio-temporal variables, using dependency series and regression models in place of temporal models.

A flow diagram of the workflow is shown in Fig. 12.

ATWL representation:

```
workflow ST_analysis_modelling
template: define-unit (prepare) →
  loop(define-unit (group) → visualise (grouping) → assess (grouping) →
    abstract (temporal) → characterise (representative) →
    generate-knowledge (configure) → build-model →
    visualise (model) → assess (fit) →
    characterise (residuals) → visualise (residuals) → assess (residuals) →
    generate-knowledge (refinement)) →
  generate-knowledge (externalize)
```

```

description: "Visual analytics framework for analysis and modelling of
spatio-temporal data: combines interactive clustering with statistical
time series modelling to build externally storable, reusable
spatio-temporal models"

# =====

# INPUT

# =====

artifact D_raw : entities
  origin: given
  internal structure: elementary
  embedment: {set, time, space}
  features:
    - id: measurements
      value structure: vector
      value type: numeric
      description: "Attribute values (e.g., call duration) with
associated spatial coordinates and time stamps"
  description: "Raw spatio-temporal data records to be aggregated into
spatial time series"

# =====

# STEP 0: DATA PREPARATION

# =====

transform T_prepare :
  intent: define-unit
  manner: "spatio-temporal aggregation"
  input: D_raw
  output: D_locations, F_TS
  actor: hybrid
  description: "Transform raw spatio-temporal data into spatial time
series by dividing territory into spatial compartments and
aggregating attribute values by location and time interval"

artifact D_locations : entities
  internal structure: elementary
  embedment: space
  description: "Spatial locations or objects, each associated with a
numeric time series"

artifact F_TS : feature(D_locations)
  value structure: vector
  value type: numeric
  description: "Numeric time series of attribute values, one per
spatial location"

```

```

# =====
# SPECIFICATIONS AND INITIAL LOOP ARTIFACTS
# =====

artifact S_clustering : specification
  origin: given
  representation form: "parameter settings"
  description: "Initial clustering parameters: number of clusters and
    distance measure"

artifact K_refinement_strategy : knowledge
  origin: given
  representation form: "refinement strategy"
  description: "Refinement guidance from prior residual analysis;
    initially neutral (no prior guidance available)"

# =====
# OUTER LOOP: ANALYSIS CYCLE (Steps 1-3)
# =====

loop L_analysis:
  purpose: "Iteratively group time series, build statistical models,
    and evaluate model quality until residual distributions indicate
    satisfactory spatio-temporal models"
  until: "Model residuals are randomly distributed over time and space
    for all groups"
  body:

    # =====
    # STEP 1: GROUPING (inner loop for cluster refinement)
    # =====

    loop L_grouping:
      purpose: "Iteratively cluster and refine grouping until groups
        are homogeneous and form meaningful spatial patterns"
      until: "Groups exhibit sufficient within-group homogeneity and
        interpretable spatial patterns"
      body:

        transform T_cluster :
          intent: define-unit
          manner: "clustering by temporal similarity"
          input: D_locations, F_TS, S_clustering
          output: D_groups, F_group_label
          actor: hybrid
          description: "Group time series by similarity of temporal
            variation; includes progressive clustering of
            heterogeneous groups"

        artifact D_groups : entities
          internal structure: group/cluster
          embedment: set

```

```

description: "Groups of spatial locations with similar
temporal variation"

artifact F_group_label : feature(D_locations)
value structure: atomic
value type: categorical
description: "Cluster membership identifier for each
location"

transform T_vis_timegraph :
intent: visualise
input: F_TS, F_group_label
output: V_timegraph
actor: machine
description: "Display time series colored by cluster
membership in detailed or summarized form"

artifact V_timegraph : visualisation(F_TS, F_group_label)
layout: "temporal axis"
form: "colored lines and summary bands"
encoding: "color from cluster membership; vertical position
from value; quintile stripes for summarized view"
description: "Time graph showing temporal variation of time
series grouped by cluster"

transform T_vis_map :
intent: visualise
input: D_locations, F_group_label
output: V_map
actor: machine
description: "Display spatial distribution of clusters on a
map with similarity-based coloring"

artifact V_map : visualisation(D_locations, F_group_label)
layout: "geographic map"
form: "colored areas"
encoding: "color from cluster membership; similar colors
reflect similar cluster centres"
description: "Map showing spatial distribution of clusters"

transform T_assess_grouping :
intent: assess
input: V_timegraph, V_map, D_groups
output: K_grouping_quality
actor: human
description: "Assess within-group homogeneity on the time
graph and spatial pattern interpretability on the map"

artifact K_grouping_quality : knowledge(D_groups)
representation form: "quality judgment"
description: "Assessment of grouping quality: homogeneity,
spatial interpretability, and whether refinement is

```

```

needed"

if K_grouping_quality indicates satisfactory grouping:
  then:
    exit loop L_grouping
  else:
    transform T_adjust_clustering :
      intent: generate-knowledge
      manner: "adjust clustering approach"
      input: K_grouping_quality, V_timegraph, V_map,
            S_clustering
      output: S_clustering_g
      actor: human
      description: "Adjust clustering parameters: modify
                    number of clusters, apply progressive clustering
                    to heterogeneous groups, or change distance
                    measure"

    artifact S_clustering_g : specification
      representation form: "parameter settings"
      description: "Updated clustering parameters for
                    grouping refinement"

    assign:
      S_clustering := S_clustering_g

end loop L_grouping

# =====
# STEP 2: ANALYSIS AND MODELLING
# =====

# Step 2a: Identify temporal characteristics

transform T_identify_characteristics :
  intent: abstract
  input: V_timegraph, D_groups
  output: P_temporal_chars
  actor: human
  description: "Identify characteristics of temporal variation by
                visual inspection: periodicity, cycle lengths, and trends"

artifact P_temporal_chars : pattern(D_groups)
  representation form: "identified temporal characteristics"
  description: "Characteristics of temporal variation within each
                group: periodicity, cycle lengths, trends"

# Step 2b: Derive representative time series

transform T_derive_representative :
  intent: characterise
  manner: "aggregate within-group statistics"

```

```

input: D_groups, F_TS
output: F_representative
actor: hybrid
description: "Derive representative time series for each group
  from mean, median, or percentile values at each time step"

artifact F_representative : feature(D_groups)
value structure: vector
value type: numeric
description: "Representative time series capturing typical
  temporal variation for each group, derived from mean,
  median, or percentile values"

# Step 2c: Configure and build model

transform T_configure_model :
intent: generate-knowledge
input: P_temporal_chars, K_refinement_strategy
output: S_model_config
actor: human
description: "For each group, select a suitable modelling method
  and configure initial parameters based on identified
  temporal characteristics and, when available, refinement
  guidance from prior residual analysis"

artifact S_model_config : specification
representation form: "model configuration"
description: "Model type selection, smoothing coefficients,
  cycle length, trend parameters, and initialisation values"

transform T_build_model :
intent: build-model
input: F_representative, S_model_config
output: M_temporal
actor: machine
description: "For each group, fit the selected statistical model
  to the representative time series with automatic parameter
  optimization; may involve per-cycle models when multiple
  temporal cycles are present"

artifact M_temporal : model(F_representative, P_temporal_chars)
model type: "statistical time series model"
representation form: "fitted parametric model"
description: "Statistical model of characteristic temporal
  variation for each group, fitted to representative time
  series; may be a combination of per-cycle models when
  multiple temporal cycles are present"

# Step 2d: Model refinement (inner loop)

loop L_modelling:
purpose: "Iteratively adjust model parameters until the model

```

```

    curve captures the characteristic temporal variation"
until: "Model curve adequately represents the general temporal
    variation pattern"
body:

transform T_predict :
    intent: characterise
    input: M_temporal, D_groups
    output: F_model_curve
    actor: machine
    description: "Generate model-predicted values for original
        and future time steps"

artifact F_model_curve : feature(D_groups)
    value structure: vector
    value type: numeric
    description: "Model-predicted values representing
        characteristic temporal variation for each group"

transform T_vis_model :
    intent: visualise
    input: F_model_curve, F_representative, F_TS
    output: V_model
    actor: machine
    description: "Display model curve on time graph alongside
        representative and individual time series"

artifact V_model : visualisation(F_model_curve,
    F_representative, F_TS)
    layout: "temporal axis"
    form: "lines"
    encoding: "color distinguishing model curve from
        representative and individual series; extended range
        for future predictions"
    description: "Time graph showing model prediction overlaid
        on data for visual comparison"

transform T_assess_fit :
    intent: assess
    input: V_model
    output: K_model_fit
    actor: human
    description: "Assess whether model curve captures the
        general temporal variation pattern"

artifact K_model_fit : knowledge(M_temporal)
    representation form: "quality judgment"
    description: "Assessment of model fit and whether parameter
        refinement is needed"

if K_model_fit indicates satisfactory fit:
    then:

```

```

    exit loop L_modelling
else:
    transform T_adjust_model_config :
        intent: generate-knowledge
        input: K_model_fit, V_model, S_model_config
        output: S_model_config_m
        actor: human
        description: "Adjust model parameters or method
            based on fit assessment and visual inspection
            of the model curve"

    artifact S_model_config_m : specification
        representation form: "model configuration"
        description: "Updated model configuration with
            adjusted parameters"

    transform T_refit_model :
        intent: build-model
        manner: "re-fitting with adjusted parameters"
        input: F_representative, S_model_config_m
        output: M_temporal_r
        actor: machine
        description: "Re-fit model with updated
            configuration"

    artifact M_temporal_r : model(F_representative,
        P_temporal_chars)
        model type: "statistical time series model"
        representation form: "fitted parametric model"
        description: "Refined temporal model with adjusted
            parameters"

    assign:
        S_model_config := S_model_config_m
        M_temporal := M_temporal_r

end loop L_modelling

# =====
# STEP 3: MODEL EVALUATION
# =====

transform T_compute_residuals :
    intent: characterise
    input: D_locations, F_TS, M_temporal, D_groups
    output: F_residuals
    actor: machine
    description: "Compute per-location residuals as differences
        between actual values and individually adjusted model
        predictions"

artifact F_residuals : feature(D_locations)

```

```

value structure: vector
value type: numeric
description: "Model residual time series for each location,
  computed as differences between actual values and
  individually adjusted model predictions"

transform T_vis_residuals_temporal :
  intent: visualise
  input: F_residuals, D_groups
  output: V_residuals_temporal
  actor: machine
  description: "Display temporal distribution of residuals as
    quintile summaries and segmented temporal histograms"

artifact V_residuals_temporal : visualisation(F_residuals, D_groups)
  layout: "temporal axis"
  form: "summary bands and histogram bars"
  encoding: "quintile stripes for distribution shape; color-coded
    segments for residual value intervals"
  description: "Time graph summarizing residual distributions
    over time"

transform T_vis_residuals_spatial :
  intent: visualise
  input: F_residuals, D_locations
  output: V_residuals_spatial
  actor: machine
  description: "Display spatial distribution of residuals on a
    map"

artifact V_residuals_spatial : visualisation(F_residuals,
  D_locations)
  layout: "geographic map"
  form: "colored areas"
  encoding: "color for residual magnitude"
  description: "Map showing spatial distribution of model
    residuals"

transform T_assess_residuals :
  intent: assess
  input: V_residuals_temporal, V_residuals_spatial, D_groups
  output: K_residual_quality
  actor: human
  description: "Assess whether residuals are randomly distributed
    over time and space; may involve clustering residual time
    series to isolate subgroups with systematic non-random
    patterns"

artifact K_residual_quality : knowledge(M_temporal, D_groups)
  representation form: "quality judgment"
  description: "Assessment of residual distributions: presence or
    absence of systematic temporal or spatial patterns"

```

```

if K_residual_quality indicates random residual distribution:
  then:
    exit loop L_analysis
  else:
    transform T_decide_refinement :
      intent: generate-knowledge
      input: K_residual_quality, V_residuals_temporal,
            V_residuals_spatial, S_clustering
      output: S_clustering_a, K_refinement_strategy_a
      actor: human
      description: "Determine refinement approach from residual
                    patterns: subdivide groups by updating clustering
                    parameters, adjust the modelling approach, or both"

    artifact S_clustering_a : specification
      representation form: "parameter settings"
      description: "Potentially updated clustering parameters;
                    unchanged if only modelling adjustments are needed"

    artifact K_refinement_strategy_a : knowledge(M_temporal,
        D_groups)
      representation form: "refinement strategy"
      description: "Decision on whether to subdivide groups,
                    adjust modelling method or parameters, or both"

    assign:
      S_clustering := S_clustering_a
      K_refinement_strategy := K_refinement_strategy_a

end loop L_analysis

# =====

# STEP 4: MODEL EXTERNALIZATION

# =====

transform T_externalize :
  intent: generate-knowledge
  input: M_temporal, D_groups
  output: K_externalized
  actor: machine
  description: "Store model descriptions externally in reusable format
                including modelling method, parameters, group membership, and
                distribution statistics for each location"

artifact K_externalized : knowledge(M_temporal, D_groups)
  representation form: "formal descriptions and data files"
  description: "Externally stored model descriptions enabling
                re-creation, review, communication, prediction, and further
                analysis"

```

1.12 Feature engineering for behaviour pattern recognition

Source: N. Andrienko, G. Andrienko, A. Artikis, P. Mantenoglou and S. Rinzivillo, "Human-in-the-Loop: Visual Analytics for Building Models Recognizing Behavioral Patterns in Time Series," in IEEE Computer Graphics and Applications, vol. 44, no. 3, pp. 14-29, May-June 2024, doi: 10.1109/MCG.2024.3379851

Concise Workflow Summary

The human-in-the-loop workflow for recognizing behavioural patterns in vessel trajectories combines feature engineering with interactive visual analytics to build classification models that are both flexible and tolerant to data noise. The workflow partitions continuous vessel trajectories into overlapping episodes of appropriate duration (3-hour windows with 1-hour shifts), then derives interval-based synoptic features capturing behavioural aspects such as speed levels, movement curvature, and spatial context (e.g., distance to ports) that distinguish trawling activities from other movements.

Through iterative visual exploration, domain experts refine the feature space by evaluating whether episodes clustered by feature similarity exhibit coherent behavioural patterns, adjusting or adding features (such as applying logarithmic transformations to handle skewed distributions) until groups are interpretable and well-separated. A dimensionality reduction projection (UMAP) enables simultaneous visual inspection of feature similarity across all episodes, while coordinated views showing trajectory shapes on geographic maps and feature distributions in histograms allow experts to efficiently examine and label cluster cores as representative examples of different pattern types.

This iterative refinement process—cycling between feature engineering, clustering, visualization, pattern interpretation, and quality assessment—continues until labelled examples enable reliable automated classification, as validated through k-nearest neighbour testing. The approach not only successfully identified expected trawling patterns but also revealed three distinct trawling subtypes (wide curves, tight loops, and straight movements with 180-degree turns) that would have remained hidden without the flexibility and discovery capabilities of the human-in-the-loop methodology.

A flow diagram representing the workflow is shown in Fig. 13.

ATWL representation:

```
workflow behaviour-pattern-recognition-in-time-series
  template: define-unit → characterise →
    loop(define-unit (cluster) → contextualise → visualise →
      abstract (interpret) → assess → characterise (refine features)) →
    define-unit (label) → build-model →
    loop(characterise (predict) → visualise → assess →
      build-model (refine)) →
    generate-knowledge
  description: "Human-in-the-loop visual analytics workflow for building
    classification models that recognize behavioral patterns in movement
    trajectories through iterative feature engineering and example selection"
```

```

artifact D0 : entities
  origin: given
  internal structure: sequence
  embedment: {set, time}
  features:
    - id: movement_data
      value structure: vector
      value type: {numeric, spatial}
      description: "Geographic positions, speeds, headings"
  description: "Multivariate movement trajectories of multiple
    vessels over extended time period"

transform T1 :
  intent: define-unit
  manner: "time-partitioning with overlapping windows"
  input: D0
  output: D1
  actor: hybrid
  description: "Partition continuous trajectories into overlapping episodes of
    appropriate duration to capture behavioral patterns"

artifact D1 : entities
  internal structure: episode
  embedment: {set, time}
  features:
    - id: entity_id
      value structure: atomic
      value type: reference
      description: "Entity identifier"
    - id: temporal_extent
      value structure: atomic
      value type: temporal
      description: "Episode time span"
  description: "Time-bounded trajectory segments potentially
    containing behavioral patterns of interest"

transform T2 :
  intent: characterise
  manner: "compute interval-based synoptic features"
  input: D1
  output: F1
  actor: machine
  description: "Abstract elementary positional data into summary statistics
    representing behavioral aspects such as speed level, trajectory curvature,
    and spatial context"

artifact F1 : feature(D1)
  value structure: vector
  value type: numeric
  description: "Initial set of synoptic features capturing speed
    characteristics, movement curvature, and spatial

```

```

relationships"

loop L1:
  purpose: "Iteratively refine feature space to align with interpretable
  behavioral
  patterns"
  until: "Features adequately distinguish target patterns from other behaviors;
  episode groups show clear behavioral coherence"
  body:
    transform T3 :
      intent: define-unit
      manner: "cluster-by-similarity"
      input: D1, F1
      output: D2, F2
      actor: machine
      description: "Group episodes with similar feature profiles to reveal
      natural behavioral clusters"

    artifact D2 : entities
      internal structure: group/cluster
      embedment: set
      description: "Groups of episodes exhibiting similar behavioral
      characteristics"

    artifact F2 : feature(D1)
      value structure: atomic
      value type: categorical
      description: "Cluster membership indicators"

    transform T4 :
      intent: contextualise
      manner: "projection by dimensionality reduction"
      input: D1, F1
      output: D_proj_space, A1
      actor: machine
      description: "Create low-dimensional projection space from feature
      similarity
      and arrange episodes within it to expose behavioral groupings"

    artifact D_proj_space : entities
      internal structure: elementary
      features:
        - id: dimensions
          value structure: atomic
          value type: numeric
          description: "Number of spatial dimensions (2)"
      description: "Computed 2D projection space where proximity
      reflects feature similarity"

    artifact A1 : arrangement(D1)
      context: D_proj_space
      principle: "similarity-preserving projection from feature space"

```

```

description: "Spatial arrangement where proximity indicates behavioral
similarity"

transform T5 :
intent: visualise
manner: "coordinated multiple views"
input: A1, F2, D1
output: V1
actor: machine
description: "Display episodes in projection space with cluster coloring
,
linked to geographic trajectory views and feature distribution
displays"

artifact V1 : visualisation(A1, F2, D1)
layout: "coordinated views: projection plot, geographic map, feature
distributions"
form: "colored points, trajectory lines, distribution charts"
encoding: "projection position from arrangement; color from cluster
membership; trajectory shape and feature values from episode data"
description: "Interactive visualization enabling assessment of cluster
quality and behavioral coherence"

transform T6 :
intent: abstract
manner: "interpret behavioral patterns from clusters"
input: V1, D2, F1
output: P2
actor: human
description: "Interpret clusters as behavioral patterns; assign
preliminary semantic labels to discovered groupings"

artifact P2 : pattern(D1, D2)
representation form: "tentative behavioral labels with descriptions"
description: "Conceptual interpretations of discovered behavioral
patterns
with preliminary semantic labels"

transform T7 :
intent: assess
manner: "evaluate feature adequacy and cluster coherence"
input: V1, D2, F1, P2
output: feature_assessment
actor: human
description: "Assess whether episodes within clusters exhibit coherent
behavioral patterns and evaluate cluster separation; determine if
feature refinement needed"

artifact feature_assessment : knowledge(D2, F1)
representation form: "quality judgment"
description: "Expert judgment of feature adequacy: whether current
features

```

```

        achieve meaningful behavioral discrimination and cluster coherence,
        and whether refinement is needed"

    if feature_assessment indicates refinement needed:
        then:
            transform T8 :
                intent: characterise
                manner: "feature space engineering"
                input: D1, F1, feature_assessment
                output: F1'
                actor: hybrid
                description: "Refine features based on assessment: add new
features,
                apply transformations, adjust feature selection to better
                capture behavioral distinctions"

            artifact F1' : feature(D1)
                value structure: vector
                value type: numeric
                description: "Updated synoptic features with refined
                or expanded feature set"

            assign:
                F1 := F1'
            else:
                exit loop L1
    end loop L1

transform T9 :
    intent: define-unit
    manner: "interactive selection and labeling of representative exemplars"
    input: D1, D2, A1, V1, P2
    output: D3, F3
    actor: human
    description: "Select cluster cores or high-quality representatives through
visual
    inspection; label episodes as instances of identified behavioral patterns"

artifact D3 : entities
    internal structure: group/cluster
    embedment: set
    features:
        - id: cluster_size
            value structure: atomic
            value type: numeric
            description: "Number of labeled episodes per pattern type"
    description: "Labeled training set of behavioral pattern
    exemplars representing diverse pattern types discovered
    in the data"

artifact F3 : feature(D3)
    value structure: atomic

```

value type: categorical
description: "Expert-assigned behavioral pattern labels for supervised learning"

transform T10 :

intent: build-model
manner: "supervised classification model training"
input: D3, F1, F3
output: M1
actor: hybrid
description: "Train machine learning classifier to map synoptic features to behavioral pattern labels using labeled exemplars"

artifact M1 : model(F1, F3)

model type: "classifier"
representation form: "supervised learning model"
description: "Computational model for automated recognition of behavioral patterns from trajectory episodes"

loop L2:

purpose: "Validate and refine model to ensure reliable pattern recognition"
until: "Model errors are understood and minimized; classification accuracy is acceptable for intended application"

body:

transform T11 :

intent: characterise
manner: "apply model for prediction"
input: D1, F1, M1
output: F4
actor: machine
description: "Apply trained model to classify episodes based on their feature profiles"

artifact F4 : feature(D1)

value structure: atomic
value type: categorical
description: "Model-predicted behavioral pattern labels"

transform T12 :

intent: visualise
manner: "comparative error analysis display"
input: D1, D3, F3, F4, A1
output: V2
actor: machine
description: "Visualize classification results showing agreement/disagreement

between predictions and human labels; highlight uncertain classifications"

artifact V2 : visualisation(D1, F3, F4, A1)

layout: "coordinated views with classification results"

```

    form: "color-coded trajectories and confidence indicators"
    encoding: "position from arrangement; color from predicted class;
opacity
    or highlighting indicates classification confidence or error"
    description: "Visual display of model performance showing accuracy,
    systematic errors, and uncertain classifications"

transform T13 :
    intent: assess
    manner: "evaluate model performance and diagnose errors"
    input: V2, D1, M1, F3, F4
    output: model_assessment
    actor: human
    description: "Analyze classification errors to determine causes:
ambiguous
    features, borderline cases, insufficient training coverage, labeling
    inconsistencies; decide if refinement needed"

artifact model_assessment : knowledge(M1, D1)
    representation form: "quality judgment with diagnostic insights"
    description: "Understanding of model performance: identification of
error
    types, error patterns, and potential causes; assessment of whether
    model refinement is needed"

if model_assessment indicates refinement needed:
    then:
        transform T14 :
            intent: build-model
            manner: "model or training set adjustment"
            input: D3, F1, F3, model_assessment, M1
            output: M1'
            actor: hybrid
            description: "Refine model based on error analysis: adjust
parameters,
                modify training examples, or revise feature selection"

            artifact M1' : model(F1, F3)
                model type: "classifier"
                representation form: "refined supervised learning model"
                description: "Updated behavioral pattern recognition model with
                improved performance"

            assign:
                M1 := M1'
        else:
            exit loop L2
    end loop L2

transform T15 :
    intent: generate-knowledge
    manner: "formulate-statements"

```

```

input: M1, P2, model_assessment, feature_assessment
output: K1
actor: human
description: "Synthesize insights from pattern discovery and model development
            process"

artifact K1 : knowledge(M1, P2)
representation form: "statements and insights"
description: "Discovered behavioral pattern subtypes and their characteristics;
            understanding of pattern manifestations in data; insights into data-driven
            pattern recognition compared to specification-based approaches"

```

1.13 Exploratory Model Analysis

Source:

Cashman, D., Humayoun, S.R., Heimerl, F., Park, K., Das, S., Thompson, J., Saket, B., Mosca, A., Stasko, J., Endert, A., Gleicher, M. and Chang, R. (2019), A User-based Visual Analytics Workflow for Exploratory Model Analysis. Computer Graphics Forum, 38: 185-199. doi:10.1111/cgf.13681

Workflow summary

This paper presents a visual analytics workflow for Exploratory Model Analysis (EMA) — discovering and selecting predictive models on a dataset when neither the modeling task nor the model type is predetermined.

Data Exploration. The analyst examines dataset attributes through interactive, cross-linked visualizations appropriate to the data types present (histograms for tabular data, node-link diagrams for graphs, line charts for time-series), identifying feature distributions, inter-attribute relationships, and potentially predictive variables. From this exploration, the analyst forms initial modelling interests — which variables appear predictive and what types of models might be suitable.

Problem Exploration. The system automatically enumerates valid modelling problems by pairing each variable as a potential prediction target with compatible model types (classification, regression, clustering, forecasting, etc.) and evaluation metrics. The analyst browses these candidate problems in context of their data understanding.

Iterative Model Discovery. The analyst specifies a modelling problem by selecting a target variable, model type, evaluation metric, and predictor features — choosing from system-generated candidates or defining a custom specification, informed by their analytical direction from data exploration and diagnostic reasoning from any prior modelling attempts. An automated system trains a diverse set of candidate models, which are visualized through type-appropriate prediction displays (confusion matrices for classification, residual bar charts for regression) cross-linked with data exploration views. The analyst identifies comparative performance patterns across models and assesses their suitability for deployment. If models are unsatisfactory — exhibiting poor performance or system-

atic bias in certain subgroups — the analyst diagnoses deficiencies and returns to specify a different modelling problem. This cycle continues until suitable models are found.

Model Selection. When satisfactory models have been identified, the analyst selects preferred models based on prediction quality, error distribution, and deployment requirements, and exports them for use on unseen data.

Figure 14 shows the workflow represented as a flow diagram.

ATWL representation

```

workflow ExploratoryModelAnalysis
  description: "Visual analytics workflow for exploratory model analysis:
    discovering and selecting predictive models through iterative
    problem specification, automated model training, and interactive
    model comparison on holdout data"

  template: characterise → visualise → abstract →
    characterise → visualise →
    loop(generate-knowledge (specify) → build-model →
      visualise → abstract → assess →
      generate-knowledge (diagnose)) →
    generate-knowledge (select)

  # =====
  # GIVEN ARTIFACTS
  # =====

  artifact dataset : entities
    origin: given
    internal structure: elementary
    embedment: set
    description: "Multi-type dataset with tabular, graph, temporal,
      text, image, or other data types for model discovery"

  # =====
  # PHASE 1: DATA EXPLORATION (Step 1)
  # =====

  transform T_compute_data_stats :
    intent: characterise
    manner: "calculate per-attribute distributional statistics and
      data type properties"
    input: dataset
    output: data_statistics
    actor: machine
    description: "Compute summary statistics and distributions for
      all dataset attributes"

  artifact data_statistics : feature(dataset)
    value structure: vector
    description: "Summary statistics and distributional
      properties for all dataset attributes"
  
```

```

transform T_visualize_data :
  intent: visualise
  manner: "render cross-linked type-appropriate visualizations:
    histograms for tabular data, node-link diagrams for graphs,
    line charts for time-series, sortable collections for text
    and media"
  input: dataset, data_statistics
  output: data_viz
  actor: machine
  description: "Display interactive data overview for exploration
    of attribute distributions and relationships"

artifact data_viz : visualisation(dataset, data_statistics)
  layout: "cross-linked multi-panel dashboard"
  form: "histograms, node-link diagrams, line charts,
    sortable collections"
  encoding: "view type matched to data type; cross-linking
    by shared instances for coordinated exploration"
  description: "Interactive visualizations of dataset
    attributes with cross-linking between views for
    coordinated exploration"

transform T_explore_data :
  intent: abstract
  manner: "explore feature distributions and inter-attribute
    relationships to assess predictive potential and form
    analytical direction"
  input: data_viz, data_statistics
  output: data_characteristics, analytical_direction
  actor: human
  description: "Identify data characteristics, potentially
    predictive relationships, and initial modelling interests"

artifact data_characteristics : pattern(dataset)
  representation form: "identified data properties"
  description: "Notable data characteristics including feature
    distributions, inter-attribute relationships, and
    potentially predictive variables"

artifact analytical_direction : knowledge(dataset)
  representation form: "recorded modelling interests and goals"
  description: "Analyst's initial assessment of which variables
    and model types appear promising based on data exploration"

# =====
# PHASE 2: PROBLEM EXPLORATION (Step 2)
# =====

transform T_enumerate_problems :
  intent: characterise
  manner: "enumerate each variable as potential prediction target;"

```

```

        determine compatible model types and evaluation metrics per
        target variable type"
    input: dataset
    output: modeling_possibilities
    actor: machine
    description: "Generate the set of valid modeling problems based
        on dataset structure and variable types"

artifact modeling_possibilities : feature(dataset)
    value structure: vector
    description: "Valid modeling problems pairing target
        variables with compatible model types and evaluation
        metrics"

transform T_present_problems :
    intent: visualise
    manner: "show list of auto-generated problem specifications
        organized by target variable, model type, and metric"
    input: modeling_possibilities
    output: problems_viz
    actor: machine
    description: "Display candidate modeling problems for user
        exploration and selection"

artifact problems_viz : visualisation(modeling_possibilities)
    layout: "organized list grouped by target variable"
    form: "interactive list entries"
    encoding: "grouping by target variable; entries show
        model type and evaluation metric"
    description: "Interactive list of candidate modeling
        problems with target variables, model types, and
        metrics"

# =====
# PHASE 3: ITERATIVE MODEL DISCOVERY (Steps 3-7)
# =====

loop L_model_discovery:
    purpose: "Discover suitable predictive models by iteratively
        specifying modeling problems, training candidate models,
        and evaluating their predictions"
    until: "satisfactory models have been found and selected for
        export"
    body:

        transform T_specify_problem :
            intent: generate-knowledge
            manner: "choose target variable, model type, evaluation
                metric, and predictor features informed by
                analytical direction and data characteristics"
            input: modeling_possibilities, data_characteristics,
                problems_viz, analytical_direction

```

```

    output: problem_spec
    actor: human
    description: "Select and refine a modeling problem
                specification defining the prediction task"

artifact problem_spec : specification
    representation form: "modeling problem configuration"
    description: "Target variable, model type, evaluation
                metric, and selected predictor features defining
                the modeling task"

transform T_train_models :
    intent: build-model
    manner: "automated search across compatible algorithms
            and hyperparameter configurations"
    input: dataset, problem_spec
    output: candidate_models
    actor: machine
    description: "Train diverse candidate models for the
                specified modeling problem"

artifact candidate_models :
    model(dataset, problem_spec)
    description: "Diverse set of trained candidate models
                ranked by the specified evaluation metric"

transform T_visualize_models :
    intent: visualise
    manner: "render ranked, problem-type-appropriate
            prediction visualizations with cross-linking
            between models and to data exploration views"
    input: candidate_models, dataset, data_viz
    output: model_viz
    actor: machine
    description: "Display model predictions on holdout data
                for exploration and comparison"

artifact model_viz :
    visualisation(candidate_models, dataset)
    layout: "ranked model comparison grid"
    form: "confusion matrices, residual charts, or other
            type-appropriate prediction displays"
    encoding: "grid position by evaluation rank;
              prediction displays matched to problem type;
              cross-linking to data exploration views"
    description: "Ranked model prediction visualizations on
                holdout data with cross-linking to data views for
                instance-level exploration"

transform T_identify_performance :
    intent: abstract
    manner: "compare prediction patterns, error

```

```

        distributions, and per-class or per-subset
        performance across models"
    input: model_viz, candidate_models
    output: performance_patterns
    actor: human
    description: "Identify performance characteristics and
        differences across candidate models"

artifact performance_patterns : pattern(candidate_models)
    representation form: "identified performance
        characteristics"
    description: "Comparative performance patterns across
        candidate models including error distributions,
        per-class accuracy, and relative strengths"

transform T_assess_models :
    intent: assess
    manner: "judge model quality, robustness, and
        suitability based on performance patterns and
        task requirements"
    input: performance_patterns, model_viz
    output: model_assessment
    actor: human
    description: "Evaluate whether candidate models are
        suitable for the analyst's deployment needs"

artifact model_assessment : knowledge(candidate_models)
    representation form: "quality judgment"
    description: "Assessment of whether candidate models
        meet task requirements, identifying deficiencies
        or confirming suitability"

if model_assessment indicates further problem exploration needed:
    then:
        transform T_revise_approach :
            intent: generate-knowledge
            manner: "diagnose why current models are
                unsatisfactory and decide which
                alternative problem to try"
            input: model_assessment, data_characteristics
            output: updated_analytical_direction
            actor: human
            description: "Determine what alternative
                modeling problem to explore based on
                observed deficiencies"

        artifact updated_analytical_direction :
            knowledge(candidate_models)
            representation form: "diagnostic reasoning"
            description: "Understanding of why current
                models are inadequate and rationale for
                exploring an alternative modeling problem"

```

```

        assign:
            analytical_direction := updated_analytical_direction
    else:
        exit loop L_model_discovery

    end loop L_model_discovery

# =====
# PHASE 4: MODEL SELECTION (Steps 6-7)
# =====

transform T_select_models :
    intent: generate-knowledge
    manner: "choose one or more models based on prediction
            quality, error distribution, and deployment requirements"
    input: model_assessment, performance_patterns, model_viz
    output: selection_decision
    actor: human
    description: "Select preferred models for export based on
                 comparative evaluation"

artifact selection_decision : knowledge(candidate_models)
    representation form: "model preference ranking"
    description: "Selected models with preference ranking and
                 rationale for deployment on unseen data"

```

1.14 Diagnosing binary classifiers

Source:

J. Krause, A. Dasgupta, J. Swartz, Y. Aphinyanaphongs and E. Bertini,
 "A Workflow for Visual Diagnostics of Binary Classifiers using Instance-Level Explanations,"
 2017 IEEE Conference on Visual Analytics Science and Technology (VAST), Phoenix, AZ, USA, 2017, pp. 162-172,
 doi: 10.1109/VAST.2017.8585720.

Workflow summary

This paper presents a visual analytics workflow for diagnosing binary classifiers using instance-level explanations. The workflow enables data scientists and domain experts to understand model decisions, identify weaknesses, and generate actionable improvement hypotheses through a structured multi-level exploration.

Data Preparation and Model Training. The analyst prepares a feature set based on domain requirements, splits data into training and test subsets, and trains a binary classifier.

Explanation Computation and Grouping. Prediction scores are computed for all test instances. Instance-level explanations are then generated for each data item by deter-

mining the minimal set of features whose removal changes the predicted label, treating the classifier as a black box. Instances sharing identical explanation feature sets are grouped into subsets representing distinct model decisions, and per-group statistics (prediction distributions, odds ratios with confidence intervals, discriminative feature rankings) are computed.

Initial Overview. Three linked diagnostic views are rendered: prediction score histograms, confusion matrix, and ROC curve at the outcome level; a sortable explanation list with prediction distributions and statistical significance at the feature level; and an item-feature matrix with discriminative ordering at the instance level. The analyst reads the statistical summary to assess overall accuracy, error distribution, and generalization.

Multi-Level Exploration. The analyst iteratively explores across the three levels — re-sorting explanations by frequency, significance, or uncertainty; filtering by prediction score range or feature search; and drilling down to instance-level feature matrices for specific explanation groups. Each cycle reveals decision patterns, significant or ambiguous predictors, misclassification sources, and feature associations that explain prediction errors. Exploration continues until sufficient patterns and root causes have been identified.

Diagnostic Synthesis and Improvement. The analyst synthesizes diagnostic insights about model behavior, data limitations, and improvement opportunities. If the insights indicate that data engineering changes, additional features, or model adjustments could improve predictions, the analyst specifies those improvements and the cycle repeats with updated data and a retrained model. When the model is adequate or fundamental limitations are understood, the analyst formulates a final assessment of the classifier’s practical utility.

A flow diagram representing this workflow is shown in Fig. 15.

ATWL representation

```

workflow BinaryClassifierDiagnostics
  description: "Visual analytics workflow for diagnosing binary
    classifiers using instance-level explanations: computing
    model-agnostic explanations, grouping instances by shared
    decision logic, and iteratively exploring decisions at
    outcome, explanation, and instance levels to produce
    diagnostic insights for model and data improvement"

  # Outer loop: model improvement cycle
  # Inner exploration loop retained in body only
  template: loop(define-unit → build-model →
    characterise → characterise →
    define-unit → characterise →
    visualise → abstract →
    visualise (explore) → abstract → assess →
    generate-knowledge (diagnose) →
    generate-knowledge (specify) →
    generate-knowledge (finalize)

  # =====

```

```

# GIVEN ARTIFACTS
# =====

artifact raw_data : entities
  origin: given
  internal structure: elementary
  embedment: set
  description: "Records with binary feature vectors and ground
    truth labels for binary classification"

artifact data_model_spec : specification
  origin: given
  representation form: "feature selection and model
    configuration"
  description: "Initial specification of feature selection
    and model type based on domain requirements"

# =====
# OUTER LOOP: MODEL IMPROVEMENT CYCLE
# =====

loop L_model_improvement:
  purpose: "Iteratively build, diagnose, and improve binary
    classifiers to understand model behavior and identify
    data and model improvement opportunities"
  until: "model behavior is understood and either adequate for
    deployment or fundamental limitations are identified"
  body:

    # -----
    # Phase 1: Data Preparation and Model Training
    # -----

    transform T_prepare_data :
      intent: define-unit
      manner: "select and engineer features per
        specification; split into training and test
        subsets"
      input: raw_data, data_model_spec
      output: training_data, test_data
      actor: machine
      description: "Prepare training and test datasets
        according to current data and feature
        specifications"

    artifact training_data : entities
      internal structure: elementary
      embedment: set
      description: "Subset of records for model training"

    artifact test_data : entities
      internal structure: elementary

```

```

    embedment: set
    description: "Subset of records for model evaluation
        and explanation computation"

transform T_train_model :
    intent: build-model
    manner: "evaluate candidate model types and fit
        classifier using best-performing type and
        parameters"
    input: training_data, data_model_spec
    output: trained_classifier
    actor: machine
    description: "Train binary classifier on the
        training data"

artifact trained_classifier : model(training_data, data_model_spec)
    description: "Trained binary classifier predicting
        class labels from feature vectors"

# -----
# Phase 2: Prediction and Explanation Computation
# -----

transform T_compute_predictions :
    intent: characterise
    manner: "apply classifier to compute prediction
        scores and derive labels using optimal threshold"
    input: test_data, trained_classifier
    output: prediction_scores
    actor: machine
    description: "Compute prediction scores for all test
        instances"

artifact prediction_scores : feature(test_data)
    value structure: vector
    description: "Classifier prediction scores and
        threshold-derived labels for all test instances"

transform T_compute_explanations :
    intent: characterise
    manner: "for each instance, determine minimal set of
        features whose removal changes the predicted
        label, treating the model as a black box"
    input: test_data, trained_classifier
    output: instance_explanations
    actor: machine
    description: "Compute instance-level explanations
        describing the classifier's decision logic for
        each data item"

artifact instance_explanations : feature(test_data)
    value structure: vector

```

```

        description: "For each instance, the minimal set of
            features whose removal changes the classifier's
            prediction, describing the local decision logic"

# -----
# Phase 3: Explanation Grouping and Statistics
# -----

transform T_group_explanations :
    intent: define-unit
    manner: "aggregate instances by identical explanation
        feature sets"
    input: test_data, instance_explanations
    output: explanation_groups
    actor: machine
    description: "Group instances sharing the same
        explanation into subsets representing distinct
        model decisions"

artifact explanation_groups : entities
    internal structure: group/cluster
    embedment: set
    description: "Subsets of instances grouped by shared
        explanation, each representing a distinct
        decision pattern of the classifier"

transform T_compute_group_stats :
    intent: characterise
    manner: "calculate prediction score distributions,
        label distributions, odds ratios with confidence
        intervals, and relative feature importance per
        group"
    input: explanation_groups, prediction_scores
    output: group_statistics
    actor: machine
    description: "Compute prediction accuracy and
        statistical significance for each explanation
        group"

artifact group_statistics : feature(explanation_groups)
    value structure: vector
    description: "Prediction distributions, odds ratios
        with confidence intervals, and discriminative
        feature rankings per explanation group"

# -----
# Phase 4: Initial Visualization and Overview
# -----

transform T_visualize_diagnostic :
    intent: visualise
    manner: "display prediction score histograms,

```

```

        confusion matrix, and ROC curve at outcome
        level; sortable explanation list with prediction
        distributions, group sizes, and odds ratios at
        feature level; item-feature matrix with
        discriminative feature ordering at instance
        level"
    input: test_data, prediction_scores,
           explanation_groups, group_statistics,
           instance_explanations
    output: diagnostic_viz
    actor: machine
    description: "Render linked multi-level diagnostic
                 views for exploring classifier decisions"

artifact diagnostic_viz : visualisation(test_data,
                                       explanation_groups, group_statistics)
    layout: "three linked vertical panels: outcome level,
            feature level, instance level"
    form: "histograms and confusion matrix; sortable list
           with embedded distribution bars; item-feature
           binary matrix"
    encoding: "outcome panel: score histograms with
              class coloring, confusion matrix cell counts,
              ROC curve; feature panel: rows sorted by
              frequency, significance, or uncertainty, with
              embedded prediction distribution bars and odds
              ratio indicators; instance panel: binary matrix
              with discriminative feature ordering"
    description: "Outcome-level statistical summary,
                 feature-level explanation explorer with sortable
                 group statistics, and instance-level feature
                 matrix with discriminative ordering"

transform T_read_overview :
    intent: abstract
    manner: "recognise prediction score distribution
            characteristics, confusion matrix balance, ROC
            performance, and training-test generalization
            patterns"
    input: diagnostic_viz, group_statistics
    output: diagnostic_patterns
    actor: human
    description: "Identify overall accuracy
                 characteristics and error distribution from
                 the statistical summary"

artifact diagnostic_patterns :
    pattern(trained_classifier)
    representation form: "identified model behavior
                        characteristics"
    description: "Overall accuracy patterns, error
                 clustering, and generalization characteristics"

```

```

        from the statistical summary"

# -----
# Phase 5: Multi-Level Diagnostic Exploration
# -----

loop L_exploration:
    purpose: "Explore model decisions through outcome,
              explanation, and instance levels to identify
              decision patterns, accuracy issues, and root
              causes"
    until: "sufficient decision patterns, accuracy
            issues, and potential root causes have been
            identified for diagnostic synthesis"
    body:

        transform T_explore_views :
            intent: visualise
            manner: "re-sort explanation list by
                    frequency, odds ratio, or uncertainty;
                    filter by prediction score range or
                    feature search; drill down to
                    instance-level feature matrix for
                    specific explanation groups"
            input: diagnostic_viz, explanation_groups,
                  group_statistics, instance_explanations
            output: updated_diagnostic_viz
            actor: hybrid
            description: "Navigate between diagnostic
                         levels by re-sorting, filtering, or
                         drilling down to explore specific
                         decisions"

        artifact updated_diagnostic_viz :
            visualisation(test_data, explanation_groups,
                          group_statistics)
            layout: "three linked vertical panels: outcome level,
                    feature level, instance level"
            form: "histograms and confusion matrix; sortable list
                  with embedded distribution bars; item-feature
                  binary matrix"
            encoding: "same encoding as diagnostic_viz with
                      updated sorting, filtering, or drill-down state"
            description: "Diagnostic visualization reflecting
                         current sorting, filtering, or drill-down state"

    assign:
        diagnostic_viz := updated_diagnostic_viz

        transform T_identify_patterns :
            intent: abstract
            manner: "recognise significant predictors,

```

```

        uncertain or ambiguous explanations,
        misclassification patterns, and feature
        associations that explain prediction
        errors"
    input: diagnostic_viz, group_statistics
    output: updated_diagnostic_patterns
    actor: human
    description: "Identify decision patterns,
        accuracy issues, and potential root
        causes from the current view"

artifact updated_diagnostic_patterns :
    pattern(trained_classifier)
    representation form: "identified model
        behavior characteristics"
    description: "Accumulated decision patterns
        including significant predictors,
        uncertain explanations,
        misclassification sources, and root
        cause hypotheses"

assign: diagnostic_patterns :=
    updated_diagnostic_patterns

transform T_assess_exploration :
    intent: assess
    manner: "judge completeness of model
        behavior understanding across decision
        types and accuracy levels"
    input: diagnostic_patterns, diagnostic_viz
    output: exploration_assessment
    actor: human
    description: "Evaluate whether sufficient
        patterns and root causes have been
        identified for diagnostic synthesis"

artifact exploration_assessment :
    knowledge(diagnostic_patterns)
    representation form: "quality judgment"
    description: "Assessment of whether model
        behavior is sufficiently understood
        for diagnostic synthesis"

end loop L_exploration

# -----
# Phase 6: Diagnostic Synthesis and Improvement Decision
# -----

transform T_synthesize :
    intent: generate-knowledge
    manner: "synthesise decision patterns, accuracy

```

```

        issues, and root causes into actionable
        diagnostic understanding"
    input: diagnostic_patterns, exploration_assessment
    output: diagnostic_insights
    actor: human
    description: "Formulate diagnostic insights about
        model behavior, data limitations, and
        improvement opportunities"

    artifact diagnostic_insights :
        knowledge(trained_classifier)
    representation form: "diagnostic statements"
    description: "Documented findings about model
        decision patterns, data limitations, and
        whether model or data changes could improve
        prediction quality"

    if diagnostic_insights indicate improvement warranted:
        then:
            transform T_specify_improvements :
                intent: generate-knowledge
                manner: "determine which features to add or
                    remove, what data to capture, and what
                    model changes to make based on
                    diagnostic findings"
                input: diagnostic_insights,
                    diagnostic_patterns
                output: updated_data_model_spec
                actor: human
                description: "Specify data engineering and
                    model changes to address identified
                    limitations"

            artifact updated_data_model_spec : specification
                representation form: "data and model
                    improvement plan"
                description: "Specification of feature
                    engineering changes, additional data
                    sources, and model adjustments to
                    address identified limitations"

            assign:
                data_model_spec := updated_data_model_spec
        else:
            exit loop L_model_improvement

    end loop L_model_improvement

# =====
# PHASE 7: FINAL KNOWLEDGE SYNTHESIS
# =====

```

```

transform T_finalize :
  intent: generate-knowledge
  manner: "integrate diagnostic findings across all modeling
          rounds into comprehensive model assessment"
  input: diagnostic_insights, diagnostic_patterns,
         exploration_assessment
  output: model_understanding
  actor: human
  description: "Synthesize final understanding of model
               capabilities, limitations, and practical utility"

artifact model_understanding : knowledge(trained_classifier)
  representation form: "statements and assessment report"
  description: "Documented assessment of the classifier's
               decision logic, prediction strengths, data
               limitations, and practical deployment
               considerations"

```

1.15 Interactive Exploration of Trained Ensemble Classifier

Source:

Eirich, J., Münch, M., Jäckle, D., Sedlmair, M., Bonart, J. and Schreck, T. (2022), RfX: A Design Study for the Interactive Exploration of a Random Forest to Enhance Testing Procedures for Electrical Engines. Computer Graphics Forum, 41: 302-315. doi: 10.1111/cgf.14452

Workflow summary:

This visual analytics workflow enables domain experts without machine learning expertise to extract interpretable decision rules from complex trained classifiers. The approach addresses a common challenge: making black-box ensemble models (like Random Forests) accessible to practitioners who need actionable insights rather than raw model predictions. The workflow consists of three main phases:

1. **Phase 1:** Automated Model Structuring - The system automatically analyzes the ensemble's internal structure by computing component similarities, grouping similar decision components, and creating spatial overviews. This preprocessing transforms an opaque ensemble into an organized landscape ready for exploration.
2. **Phase 2:** Progressive Component Selection - Through multiple coordinated visualizations, users progressively narrow from the entire model down to individual promising components. This involves iterative cycles of visualization, quality assessment, and selection decisions at multiple granularity levels (groups → representatives → individuals).
3. **Phase 3:** Rule Derivation - Once a suitable component is identified, users explore its detailed structure through interactive visualization, assess interpretability, option-

ally refine decision boundaries using domain knowledge, and extract human-readable rules for operational deployment.

The workflow emphasizes human-in-the-loop refinement, where domain expertise guides the exploration process and validates extracted rules, successfully bridging the gap between complex ML models and practical industrial applications.

Figure 16 provides a simplified flow diagram of the workflow.

ATWL representation:

```
workflow ModelExplorationForRuleExtraction
  template:
    characterise (model structure) →
    define-unit (organize components) →
    contextualise (spatial overview) →
    loop(visualise → assess →
      generate-knowledge (select component)) →
    loop(visualise → assess →
      generate-knowledge (refine)) →
    abstract (extract rules) →
    generate-knowledge (formulate deployable rules)

  description: "Visual analytics workflow enabling domain experts
    without ML expertise to interactively explore trained
    ensemble classifiers, identify interpretable decision
    patterns, and extract actionable rules for operational
    deployment"

  # =====
  # Given Inputs
  # =====

  artifact source_data : entities
    origin: given
    internal structure: elementary
    embedment: set
    features:
      - id: measurements
        value structure: vector
        value type: numeric
        description: "Feature measurements from domain sensors"
      - id: labels
        value structure: atomic
        value type: categorical
        description: "Classification outcomes"
    description: "Domain data with feature measurements and
      classifications used for model training and evaluation"

  artifact trained_model : model(source_data)
    origin: given
    description: "Pre-trained ensemble classifier containing
```

```

        multiple independent decision components; optimized for
        prediction accuracy but lacks inherent interpretability"

# =====
# Phase 1: Automated Model Structure Analysis
# =====

transform T_extract_components :
  intent: define-unit
  manner: "extract individual decision components from ensemble"
  input: trained_model
  output: model_components
  actor: machine
  description: "Decompose ensemble into individual interpretable
    components for separate analysis"

artifact model_components : entities
  internal structure: elementary
  embedment: set
  features:
    - id: component_id
      value structure: atomic
      value type: categorical
      description: "Component identifier"
    - id: decision_logic
      value structure: relational configuration
      description: "Component's decision tree structure"
  description: "Individual decision-making components extracted
    from ensemble; each represents independent classification
    logic"

transform T_characterize_structure :
  intent: characterise
  manner: "compute component similarity and performance metrics"
  input: model_components, source_data
  output: component_similarities, component_metrics
  actor: machine
  description: "Analyze relationships between components through
    similarity measures combining prediction agreement and
    structural properties"

artifact component_similarities : feature(model_components)
  value structure: matrix
  value type: numeric
  description: "Pairwise similarity scores between components
    based on prediction behavior and structural
    characteristics"

artifact component_metrics : feature(model_components)
  value structure: vector
  description: "Performance characteristics: classification
    accuracy, structural complexity, error patterns"

```

```

transform T_organize_components :
  intent: define-unit
  manner: "group similar components into clusters"
  input: model_components, component_similarities
  output: component_groups
  actor: machine
  description: "Organize components into coherent groups based
    on similarity; reduces exploration space from hundreds
    to manageable clusters"

artifact component_groups : entities
  internal structure: group/cluster
  embedment: set
  features:
    - id: group_id
      value structure: atomic
      value type: categorical
      description: "Group identifier"
    - id: members
      value structure: list
      value type: reference
      description: "Component identifiers belonging to this
        group"
  description: "Clusters of similar decision components; each
    group represents components with related prediction
    behavior and structure"

transform T_characterize_groups :
  intent: characterise
  manner: "compute aggregate group properties"
  input: component_groups, component_metrics
  output: group_properties
  actor: machine
  description: "Compute aggregate performance and structural
    statistics for each component group"

artifact group_properties : feature(component_groups)
  value structure: vector
  description: "Group-level characteristics: aggregate accuracy,
    size, statistical properties of member components"

transform T_create_spatial_overview :
  intent: contextualise
  manner: "project components to spatial layout"
  input: model_components, component_similarities,
    component_groups
  output: spatial_reference, component_arrangement
  actor: machine
  description: "Create spatial arrangement where proximity
    reflects similarity; projection establishes 2D coordinate
    space and positions components to enable visual overview
  
```

```

    of model structure"

artifact spatial_reference : entities
  internal structure: elementary
  features:
    - id: axes
      value structure: atomic
      value type: numeric
      description: "Number of spatial dimensions (2)"
  description: "Two-dimensional coordinate space created by
    dimensionality reduction projection for component
    visualization"

artifact component_arrangement : arrangement(model_components)
  context: spatial_reference
  principle: "dimensionality reduction preserving similarity
    relationships"
  description: "Spatial layout of components where proximity
    indicates similarity; provides entry point for
    exploration"

transform T_identify_representatives :
  intent: define-unit
  manner: "select exemplar components for each group"
  input: component_groups, component_arrangement,
    group_properties
  output: representative_components
  actor: machine
  description: "Identify representative component per group
    for efficient browsing"

artifact representative_components : entities
  internal structure: elementary
  embedment: set
  features:
    - id: component_id
      value structure: atomic
      value type: categorical
      description: "Component identifier"
    - id: group_id
      value structure: atomic
      value type: reference
      description: "Parent group identifier"
  description: "Subset of components representing each group;
    selected for typicality within group and quality metrics"

# =====
# Phase 2: Progressive Interactive Selection
# =====

loop L_progressive_selection:
  purpose: "Iteratively explore model structure at multiple

```

```

granularity levels, assess component quality, and
progressively narrow down to promising individual
components through guided navigation"
until: "Suitable component identified for detailed
examination and rule extraction"
body:
transform T_visualize_overview :
intent: visualise
manner: "multi-view display of model structure"
input: component_arrangement, component_groups,
group_properties, representative_components,
component_metrics
output: model_overview_vis
actor: machine
description: "Present multiple coordinated views: spatial
overview showing component relationships, tabular
summaries enabling efficient comparison, structural
previews of representatives"

artifact model_overview_vis :
visualisation(component_arrangement,
component_groups,
representative_components)
layout: "coordinated multiple views with spatial, tabular,
and hierarchical displays"
form: "spatial scatterplot, sortable tables, structural
glyphs"
encoding: "position from component_arrangement; colors by
group membership; sizes by performance; tables sorted
by quality metrics; glyphs show decision structure
compactly"
description: "Multi-view visualization supporting both
exploratory browsing (via spatial overview) and
goal-directed search (via sortable tables)"

transform T_assess_components :
intent: assess
manner: "evaluate component suitability and promise"
input: model_overview_vis, component_metrics,
group_properties
output: component_assessment
actor: human
description: "Assess which groups and individual components
are promising based on performance metrics, structural
characteristics, and domain relevance indicators"

artifact component_assessment :
knowledge(model_components, component_groups)
representation form: "quality judgment with selection
rationale"
description: "Assessment identifying promising components
based on accuracy, interpretability potential, error

```

```

        characteristics, and domain interest"

    if component_assessment indicates suitable component found:
    then:
        transform T_select_component :
            intent: generate-knowledge
            manner: "decide which component to examine in detail"
            input: component_assessment, component_metrics
            output: selected_component
            actor: human
            description: "Select the most promising component for
                detailed examination based on assessment of
                performance, complexity, and interpretability"

        artifact selected_component : specification
            representation form: "component identifier"
            description: "Selected component for detailed
                examination; chosen for balance of good performance,
                low complexity, and interpretability"

        exit loop L_progressive_selection
    else:
        # Continue exploring at different granularity levels

end loop L_progressive_selection

# =====
# Phase 3: Detailed Exploration and Rule
#     Extraction
# =====

transform T_extract_component_detail :
    intent: define-unit
    manner: "retrieve full component structure"
    input: model_components, selected_component
    output: examined_component
    actor: machine
    description: "Retrieve full structural detail for the
        selected component"

artifact examined_component : entities
    internal structure: formation
    features:
        - id: decision_nodes
          value structure: relational configuration
          description: "Decision tree structure with features and
              thresholds at each node"
        - id: node_statistics
          value structure: vector
          value type: {numeric, categorical}
          description: "Classification statistics at each decision
              point"

```

description: "Selected component with complete structural detail including decision logic, features, thresholds, and prediction statistics"

transform T_compute_distributions :

intent: characterise

manner: "compute feature distributions for decision points"

input: examined_component, source_data

output: feature_distributions

actor: machine

description: "Compute data distributions for features used in the component's decision logic"

artifact feature_distributions : feature(examined_component)

value structure: vector

description: "Data distributions for features used in component; enables evaluation of decision boundary quality"

loop L_component_refinement:

purpose: "Explore component structure in detail, assess interpretability, optionally refine decision boundaries using domain knowledge, until component produces domain-sensible decision logic"

until: "Component structure is interpretable and decision logic is satisfactory"

body:

transform T_visualize_detail :

intent: visualise

manner: "detailed hierarchical display with decision paths"

input: examined_component, component_metrics,
feature_distributions

output: component_detail_vis

actor: machine

description: "Display component as detailed hierarchical diagram showing decision paths, feature names, thresholds, classification statistics, and error distributions"

artifact component_detail_vis :

visualisation(examined_component)

layout: "hierarchical tree structure with statistics at nodes"

form: "node-link diagram with confusion matrices and feature distributions"

encoding: "hierarchical layout from component structure; nodes show classification statistics; edges labeled with features and thresholds; colors indicate prediction patterns"

description: "Detailed visualization enabling exploration of decision logic, understanding of feature interactions, and assessment of decision boundary

```

    quality"

transform T_assess_interpretability :
  intent: assess
  manner: "evaluate domain sensibility and interpretability"
  input: component_detail_vis, examined_component,
        feature_distributions
  output: interpretability_assessment
  actor: human
  description: "Assess whether component structure makes
    domain sense: do feature combinations reflect known
    relationships? Are decision boundaries appropriate?
    Are error patterns acceptable?"

artifact interpretability_assessment :
  knowledge(examined_component)
  representation form: "quality judgment with
    interpretability evaluation"
  description: "Assessment of component interpretability:
    domain sensibility of feature logic, appropriateness
    of decision boundaries, acceptability of error
    patterns, identification of refinement needs"

if interpretability_assessment indicates refinement needed:
then:
  transform T_refine_boundaries :
    intent: generate-knowledge
    manner: "adjust decision boundaries based on domain
      knowledge"
    input: interpretability_assessment,
          component_detail_vis, feature_distributions
    output: boundary_adjustments
    actor: human
    description: "Specify boundary adjustments to achieve
      better class separation, reduce critical errors,
      or align with domain-meaningful thresholds"

  artifact boundary_adjustments : specification
    representation form: "modified decision boundary
      parameters"
    description: "User-specified adjustments to decision
      boundaries; optimizes logic based on domain
      expertise to reduce errors, align with physical
      constraints, or improve interpretability"

transform T_update_component :
  intent: define-unit
  manner: "apply boundary modifications"
  input: examined_component, boundary_adjustments
  output: examined_component_updated
  actor: machine
  description: "Update component structure with modified

```

```

        boundaries; recalculate statistics"

artifact examined_component_updated : entities
  internal structure: formation
  features:
    - id: decision_nodes
      value structure: relational configuration
      description: "Updated decision tree structure"
    - id: node_statistics
      value structure: vector
      value type: {numeric, categorical}
      description: "Recalculated statistics"
  description: "Component with user-refined decision
    boundaries reflecting domain expertise"

  assign:
    examined_component := examined_component_updated

  else:
    exit loop L_component_refinement

end loop L_component_refinement

# =====
# Rule Extraction and Formulation
# =====

transform T_extract_decision_rules :
  intent: abstract
  manner: "extract decision paths as structured rules"
  input: examined_component, component_detail_vis
  output: decision_rules
  actor: human
  description: "Extract decision paths from component structure
    as rule patterns: identify paths from root to outcomes,
    capturing feature-threshold conditions defining each
    classification"

artifact decision_rules : pattern(examined_component)
  representation form: "conditional rule structures"
  description: "Structured decision rules extracted from
    component: IF-THEN conditions specifying
    feature-threshold sequences leading to classifications"

transform T_formulate_deployable_rules :
  intent: generate-knowledge
  manner: "synthesize operational rules with domain context"
  input: decision_rules, examined_component,
    interpretability_assessment
  output: deployable_rules
  actor: human
  description: "Translate extracted rules into domain-specific

```

```
operational guidance; add contextual explanation,  
rationale, implementation details, and validation  
criteria"
```

```
artifact deployable_rules : knowledge(decision_rules)  
  representation form: "operational rules with domain  
  interpretation"  
  description: "Human-readable rules for operational deployment:  
  measurement sequences, threshold values, decision logic,  
  domain interpretation, implementation guidance, and  
  validation procedures; ready for testing on new  
  operational data"
```

1.16 Exploring Deep Learning Models in TensorFlow

Source: Kanit Wongsuphasawat, Daniel Smilkov, James Wexler, Jimbo Wilson, Dandelion Mané, Doug Fritz, Dilip Krishnan, Fernanda B. Viégas, and Martin Wattenberg "Visualizing Dataflow Graphs of Deep Learning Models in TensorFlow," IEEE Transactions on Visualization and Computer Graphics, vol. 24, no. 1, pp. 1-12, Jan. 2018, doi: 10.1109/TVCG.2017.2744878.

Workflow summary

This paper presents the TensorFlow Graph Visualizer, a tool for understanding deep learning model architectures through interactive exploration of their dataflow graphs. The analytical workflow proceeds through progressive graph simplification, automated pattern detection, and iterative interactive exploration.

Graph Simplification. A raw dataflow graph containing thousands of heterogeneous operations is progressively simplified through two stages: first, non-critical operations (constants, summaries) are extracted and encoded as embedded icons while remaining operations are grouped into a hierarchical clustered graph using namespace annotations, with edges bundled along the hierarchy. Second, high-degree non-critical nodes (variable declarations, bookkeeping hubs) are extracted using degree-based outlier detection, preserving connectivity information.

Pattern Detection and Feature Computation. Repeated modular structures are automatically detected across group nodes using heuristic subgraph similarity checking, and quantitative properties (tensor sizes, device allocation, compute time, memory usage) are computed for visual encoding.

Layout and Visualization. A hierarchical flow layout is computed recursively per cluster subgraph, and an interactive overview is rendered showing top-level model components with colour-coded repeated modules, an auxiliary node panel, and tensor-size edge encoding.

Initial Reading. From the overview, the analyst immediately recognises high-level architectural features — top-level component organisation, colour-coded repeated module

groups, and main-versus-auxiliary structure — forming an initial understanding before detailed exploration.

Interactive Exploration. The analyst iteratively explores the model by expanding clusters to reveal nested structure, inspecting individual node details, switching between quantitative overlays, and recognising further architectural patterns including layer organisation, modular composition, and data flow paths. This cycle continues until the analyst has sufficient understanding of the model architecture.

Knowledge Synthesis. The analyst formulates a coherent understanding of the model's structure, modular composition, and operational organisation for development, debugging, or communication.

A diagrammatic representation of the process of model exploration in TensorFlow is provided in Fig.17.

ATWL representation:

```
workflow TensorFlowGraphVisualization
  template: define-unit (cluster) → define-unit (simplify) →
           define-unit (detect repeated) → characterise →
           contextualise → visualise → abstract →
           loop(visualise → abstract → assess) →
           generate-knowledge
  description: "Interactive exploration of deep learning model architecture
               through progressive dataflow graph simplification and hierarchical
               visualization"

# =====
# GIVEN ARTIFACTS
# =====

artifact dataflow_graph : entities
  origin: given
  internal structure: formation
  description: "Directed dataflow graph of a deep learning model
               containing operations connected by data dependency, reference,
               and control dependency edges, with hierarchical namespace
               annotations"

# =====
# PHASE 1: GRAPH SIMPLIFICATION
# =====

transform T_simplify_and_cluster :
  intent: define-unit
  manner: "extract degree-one operations (constants, summaries) as
           embedded icons; group operations by hierarchical namespace;
           bundle edges along the hierarchy"
  input: dataflow_graph
  output: clustered_graph
  actor: machine
```

```

description: "Reduce graph complexity by extracting non-critical
operations and grouping remaining operations into a
hierarchical clustered graph"

artifact clustered_graph : entities
internal structure: formation
description: "Hierarchically clustered dataflow graph with
non-critical operations extracted as embedded icons on
neighbouring nodes and edges bundled along the hierarchy"

transform T_extract_auxiliary :
intent: define-unit
manner: "identify auxiliary nodes by degree-based outlier detection
and domain-specific subgraph patterns; separate from core
computational structure while preserving connectivity
information"
input: clustered_graph
output: simplified_graph
actor: machine
description: "Separate high-degree non-critical nodes from the
core computational structure to declutter the clustered graph"

artifact simplified_graph : entities
internal structure: formation
description: "Decluttered hierarchical graph with auxiliary nodes
extracted from the main layout, retaining proxy connections"

# =====
# PHASE 2: REPEATED STRUCTURE DETECTION
# =====

transform T_detect_repeated :
intent: define-unit
manner: "partition group nodes by structural equivalence"
input: simplified_graph
output: structural_templates
actor: machine
description: "Identify sets of structurally identical group
nodes by metadata-based candidate selection and
heuristic subgraph similarity comparison"

artifact structural_templates : entities
internal structure: group/cluster
embedment: set
features:
- id: template_size
value structure: atomic
value type: numeric
description: "Number of group nodes sharing the
structure"
description: "Sets of group nodes with identical nested
subgraph structure, representing repeated module

```

```

        types in the model"

# =====
# PHASE 3: FEATURE COMPUTATION
# =====

transform T_compute_features :
  intent: characterise
  manner: "derive tensor sizes from edge dimensions; aggregate
         device allocation, compute time, and memory usage per
         operation and group"
  input: simplified_graph
  output: graph_features
  actor: machine
  description: "Compute quantitative properties of operations and
              edges for visual encoding"

artifact graph_features : feature(simplified_graph)
  value structure: vector
  value type: numeric
  description: "Tensor sizes, device allocation, compute
              time, and memory usage for operations and groups"

# =====
# PHASE 4: LAYOUT AND INITIAL VISUALIZATION
# =====

transform T_layout :
  intent: contextualise
  manner: "recursively compute flow layout per cluster subgraph
         with edges routed along the hierarchy"
  input: simplified_graph
  output: layout_space, graph_arrangement
  actor: machine
  description: "Position graph elements in a hierarchical flow
              layout conveying dataflow direction"

artifact layout_space : entities
  internal structure: elementary
  features:
    - id: dimensions
      value structure: atomic
      value type: numeric
      description: "Number of spatial dimensions (2)"
  description: "Two-dimensional display space with vertical
              flow direction for conveying dataflow relationships"

artifact graph_arrangement : arrangement(simplified_graph)
  context: layout_space
  principle: "hierarchical flow layout with edges bundled along
            the cluster hierarchy"
  description: "Operations and clusters positioned in a

```

bottom-to-top flow layout supporting stable and responsive cluster expansion"

```
transform T_visualize_overview :
  intent: visualise
  manner: "display clustered flow layout with colour-coded repeated
    structures, auxiliary node side panel, embedded icons for
    extracted operations, and tensor size encoded on edges"
  input: graph_arrangement, structural_templates, graph_features
  output: graph_viz
  actor: machine
  description: "Render interactive overview showing top-level model
    components and their dataflow relationships"

artifact graph_viz : visualisation(graph_arrangement,
  structural_templates, graph_features)
  layout: "hierarchical flow layout with auxiliary side panel"
  form: "rounded rectangles for groups, ovals for operations,
    curved edges, embedded icons for extracted operations"
  encoding: "vertical position: dataflow direction; nesting:
    cluster hierarchy; colour: repeated module groups;
    edge thickness: tensor size; side panel: auxiliary
    nodes with proxy connections"
  description: "Overview of model architecture with
    expandable clusters, colour-coded repeated modules,
    auxiliary node panel, embedded icons, tensor-size edge
    encoding, and information card for node detail
    inspection"

# =====
# PHASE 5: INITIAL READING
# =====

transform T_initial_reading :
  intent: abstract
  manner: "recognise top-level model components, repeated module
    groups, and main-versus-auxiliary organisation from the
    overview"
  input: graph_viz
  output: architecture_patterns
  actor: human
  description: "Identify high-level architectural structure from
    the initial overview"

artifact architecture_patterns : pattern(simplified_graph)
  representation form: "recognised architectural features"
  description: "Identified architectural elements including
    top-level component organisation, repeated module groups,
    and main-versus-auxiliary structure"

# =====
# PHASE 6: INTERACTIVE EXPLORATION
```

```

# =====

loop L_exploration:
  purpose: "Progressively explore the model's hierarchical
    structure, modular composition, and operational details"
  until: "the analyst has sufficient understanding of the model
    architecture for their current task"
  body:

    transform T_explore :
      intent: visualise
      manner: "expand group nodes to reveal nested subgraphs;
        select nodes for attribute and connection detail;
        switch colour encoding among structural similarity,
        device distribution, compute time, or memory"
      input: graph_viz, graph_arrangement, graph_features,
        structural_templates
      output: updated_graph_viz
      actor: hybrid
      description: "Adjust the visualization by expanding or
        collapsing clusters, inspecting node details, or
        switching quantitative overlay"

    artifact updated_graph_viz : visualisation(graph_arrangement,
      structural_templates, graph_features)
      layout: "hierarchical flow layout with expanded clusters"
      form: "rounded rectangles for groups, ovals for operations,
        curved edges, embedded icons"
      encoding: "same as graph_viz with expanded cluster detail;
        colour overlay switchable among structural similarity,
        device distribution, compute time, or memory"
      description: "Updated visualization reflecting expanded
        clusters, selected node details, or alternative
        quantitative overlay"

    assign: graph_viz := updated_graph_viz

    transform T_identify_structure :
      intent: abstract
      manner: "identify layer organisation, repeated modules,
        data flow paths, and nesting relationships"
      input: graph_viz
      output: updated_architecture_patterns
      actor: human
      description: "Recognise architectural patterns and modular
        composition from the current view"

    artifact updated_architecture_patterns :
      pattern(simplified_graph)
      representation form: "recognised architectural features"
      description: "Identified architectural elements including
        layer types, repeated modules, data flow paths, and

```

```

        nesting relationships"

assign: architecture_patterns := updated_architecture_patterns

transform T_assess_understanding :
  intent: assess
  manner: "judge completeness of structural understanding
         and identify unexplored areas"
  input: architecture_patterns, graph_viz
  output: understanding_assessment
  actor: human
  description: "Evaluate whether the model structure is
              sufficiently understood for the analyst's task"

artifact understanding_assessment :
  knowledge(architecture_patterns)
  representation form: "quality judgment"
  description: "Assessment of whether model architecture
              is sufficiently understood, identifying areas
              requiring further exploration"

end loop L_exploration

# =====
# PHASE 7: KNOWLEDGE SYNTHESIS
# =====

transform T_synthesize :
  intent: generate-knowledge
  manner: "synthesise architectural patterns, modular composition,
         and quantitative characteristics into coherent structural
         understanding"
  input: architecture_patterns, understanding_assessment
  output: model_understanding
  actor: human
  description: "Formulate understanding of the model architecture
              for development, debugging, or communication"

artifact model_understanding : knowledge(simplified_graph)
  representation form: "statements and diagrams"
  description: "Documented description of the model's
              high-level structure, modular composition, layer
              organisation, and data flow paths, supporting
              development, debugging, and communication"

```

1.17 What-If Probing of ML Models

Source:

Wexler, James, Mahima Pushkarna, Tolga Bolukbasi, Martin Wattenberg, Fernanda B. Viégas and Jimbo Wilson.

“The What-If Tool: Interactive Probing of Machine Learning Models.”

Workflow Summary

Although this paper describes a tool rather than a single analytical methodology, it is possible to extract an assumed composite workflow by synthesising the tool’s three core workflows (Section 6: sense-making, hypothetical probing, fairness evaluation) with the analytical progressions demonstrated in the three case studies (Sections 5.1–5.3). Each case study follows a different path through the tool’s capabilities, and together they describe a coherent analytical pattern for black-box ML model understanding.

This assumed workflow captures the typical analytical process enabled by the What-If Tool for black-box ML model understanding, synthesised from the tool’s three core workflows and three case studies.

Data Understanding. The analyst examines feature distributions in the test dataset, identifying imbalances, anomalous distributions, and data quality issues that may influence model behaviour.

Model Performance Overview. Model predictions are computed on the test dataset and visualised through customisable multi-view displays — confusion matrices, score comparison scatterplots, feature-based histograms, and small multiples. The analyst identifies global performance patterns, regions of model agreement and disagreement, and areas warranting deeper investigation, forming initial observations of model behaviour.

Hypothetical Investigation. The analyst selects data points, features, and sub-groups to probe, then iteratively investigates model behaviour through feature editing with re-inference, nearest counterfactual identification, and partial dependence analysis. Each cycle reveals feature sensitivities, unexpected responses, and decision boundary characteristics. The analyst assesses whether behavioural understanding is sufficient and refines the investigation focus until key questions are answered.

Fairness Evaluation. The analyst slices the dataset by individual features and feature intersections, computing per-slice performance and fairness metrics. Initial visualisations reveal performance disparities across demographic subgroups. The analyst then iteratively explores threshold optimisation strategies (demographic parity, equal opportunity, equal accuracy), each time visualising the resulting performance changes and identifying how disparities shift under the new configuration, continuing until a satisfactory fairness–performance trade-off is found.

Knowledge Synthesis. The analyst integrates data characteristics, performance patterns, behavioural findings, and fairness assessments into a comprehensive understanding of model behaviour, feature effects, and fairness properties, supporting model improvement and deployment decisions.

A diagrammatic representation of the workflow can be seen in Fig. 18.

ATWL representation

| `workflow` WhatIfToolModelProbing

```

description: "Assumed composite workflow for black-box ML model
  understanding through interactive data exploration, hypothetical
  probing, and fairness evaluation, synthesised from the tool's
  core workflows and case studies"

# Three-phase structure:
# Phases 1-2: Data and performance understanding
# Phases 3-4: Hypothetical probing
# Phases 5-6: Fairness evaluation and synthesis

template: characterise → visualise → abstract →
  characterise → visualise → abstract →
  generate-knowledge (specify) →
  loop(characterise → visualise → abstract → assess →
    generate-knowledge (specify)) →
  characterise → visualise → abstract →
  generate-knowledge (specify) →
  loop(assess → visualise → abstract →
    generate-knowledge (select strategy)) →
  generate-knowledge

# =====
# GIVEN ARTIFACTS
# =====

artifact trained_models : model
  origin: given
  description: "One or two trained ML models (classification or
    regression) to be probed as black boxes"

artifact test_data : entities
  origin: given
  internal structure: elementary
  embedment: set
  description: "Sample dataset with ground truth labels for
    model evaluation"

# =====
# PHASE 1: DATA UNDERSTANDING
# =====

transform T_compute_statistics :
  intent: characterise
  manner: "calculate distributional statistics for numeric and
    categorical features; assess non-uniformity and missing
    values"
  input: test_data
  output: feature_statistics
  actor: machine
  description: "Compute summary statistics and distributions for
    all features in the test dataset"

```

```

artifact feature_statistics : feature(test_data)
  value structure: vector
  value type: numeric
  description: "Summary statistics and distributional properties
    for all features"

transform T_visualize_distributions :
  intent: visualise
  manner: "render histograms and cumulative distribution plots
    for all features, sortable by non-uniformity or missing
    value count"
  input: test_data, feature_statistics
  output: distribution_viz
  actor: machine
  description: "Display feature distributions for data quality
    assessment and understanding"

artifact distribution_viz : visualisation(test_data,
  feature_statistics)
  layout: "scrollable feature list sorted by non-uniformity
    or missing value count"
  form: "histograms and cumulative distribution plots"
  encoding: "x-axis: feature values; y-axis: frequency or
    cumulative proportion; sorting by distributional
    properties"
  description: "Distribution charts for all features with
    summary statistics, highlighting imbalances and
    anomalies"

transform T_identify_data_characteristics :
  intent: abstract
  manner: "recognise feature imbalances, skewed distributions,
    and potential quality issues"
  input: distribution_viz, feature_statistics
  output: data_characteristics
  actor: human
  description: "Identify notable data properties that may affect
    model behaviour"

artifact data_characteristics : pattern(test_data)
  representation form: "identified distributional characteristics"
  description: "Notable data properties including feature
    imbalances, anomalous distributions, and quality issues
    relevant to model evaluation"

# =====
# PHASE 2: MODEL PERFORMANCE OVERVIEW
# =====

transform T_compute_performance :
  intent: characterise
  manner: "run inference for all data points; compute accuracy,

```

```

        error rates, confusion matrices, score distributions, and
        model comparison metrics"
    input: trained_models, test_data
    output: performance_metrics
    actor: machine
    description: "Compute model predictions and derive performance
        metrics on the test dataset"

artifact performance_metrics : feature(test_data)
    value structure: vector
    value type: {numeric, categorical}
    description: "Model prediction scores and derived labels for
        all data points with aggregate performance metrics
        including accuracy, error rates, and confusion counts"

transform T_visualize_performance :
    intent: visualise
    manner: "display data points positioned, binned, and coloured
        by configurable combinations of features, predictions,
        and performance metrics; support confusion matrices, score
        distributions, histograms, scatterplots, and small
        multiples"
    input: test_data, performance_metrics
    output: performance_viz
    actor: hybrid
    description: "Create customisable visualisations of model
        predictions and performance"

artifact performance_viz : visualisation(test_data,
    performance_metrics)
    layout: "configurable multi-panel display"
    form: "confusion matrices, scatterplots, histograms, and
        small multiples"
    encoding: "position, binning, and colour configurable by
        combinations of features, predictions, and performance
        metrics"
    description: "Customisable visualisations of model predictions
        and performance including confusion matrices, score
        comparison scatterplots, and feature-based histograms"

transform T_identify_behavior :
    intent: abstract
    manner: "recognise regions of model agreement and disagreement,
        performance variations across subgroups, and areas
        warranting deeper investigation"
    input: performance_viz, data_characteristics
    output: performance_patterns, behavior_patterns
    actor: human
    description: "Identify global performance patterns and initial
        model behaviour characteristics"

artifact performance_patterns : pattern(test_data)

```

```

    representation form: "identified performance characteristics"
    description: "Global performance patterns including model
        agreement and disagreement regions, performance variations,
        and areas of interest"

artifact behavior_patterns : pattern(trained_models)
    representation form: "model behaviour observations"
    description: "Initial observations of model behaviour including
        feature sensitivity, prediction patterns, and areas
        requiring hypothetical investigation"

# =====
# PHASE 3: INVESTIGATION FOCUS
# =====

transform T_specify_focus :
    intent: generate-knowledge
    manner: "select investigation targets based on observed
        performance patterns and behavioural observations"
    input: performance_patterns, behavior_patterns
    output: investigation_focus
    actor: human
    description: "Determine which data points, features, and
        subgroups to investigate through hypothetical probing"

artifact investigation_focus : specification
    representation form: "investigation targets"
    description: "Selected data points, features, and subgroups
        to probe through hypothetical analysis"

# =====
# PHASE 4: HYPOTHETICAL INVESTIGATION (loop)
# =====

loop L_hypothetical:
    purpose: "Probe model behaviour through counterfactual
        reasoning, feature editing, and partial dependence analysis
        to understand feature effects and decision boundaries"
    until: "analyst has sufficient understanding of model behaviour
        for the current investigation questions"
    body:

        transform T_compute_hypotheticals :
            intent: characterise
            manner: "edit feature values and re-infer; find nearest
                counterfactual examples via distance-based search;
                compute partial dependence across feature ranges"
            input: trained_models, test_data, investigation_focus
            output: hypothetical_results
            actor: hybrid
            description: "Compute model responses to hypothetical
                inputs based on current investigation focus"

```

```

artifact hypothetical_results : feature(test_data)
  value structure: vector
  value type: numeric
  description: "Model predictions for edited data points,
    counterfactual distances and examples, and partial
    dependence values across feature ranges"

transform T_visualize_hypotheticals :
  intent: visualise
  manner: "render edited data point predictions with
    deltas, counterfactual comparisons with highlighted
    feature differences, and partial dependence plots
    for numeric and categorical features"
  input: test_data, hypothetical_results,
    performance_metrics
  output: hypothetical_viz
  actor: machine
  description: "Display hypothetical analysis results for
    feature effect and decision boundary exploration"

artifact hypothetical_viz : visualisation(test_data,
  hypothetical_results, performance_metrics)
  layout: "side-by-side original and edited data point panels
    with partial dependence plots below"
  form: "data point cards with prediction deltas,
    counterfactual comparison tables, and line/bar charts"
  encoding: "prediction deltas highlighted by magnitude;
    counterfactual feature differences highlighted;
    partial dependence: x-axis feature value, y-axis
    predicted score"
  description: "Visualisations of prediction changes from
    feature edits, counterfactual comparisons, and
    partial dependence plots showing feature effects
    across value ranges"

transform T_discover_patterns :
  intent: abstract
  manner: "identify feature sensitivities, unexpected
    responses, decision boundary characteristics, and
    salient features from counterfactual and partial
    dependence evidence"
  input: hypothetical_viz, hypothetical_results
  output: updated_behavior_patterns
  actor: human
  description: "Discover model behaviour patterns from
    hypothetical analysis results"

artifact updated_behavior_patterns : pattern(trained_models)
  representation form: "model behaviour observations"
  description: "Accumulated understanding of feature
    effects, decision boundaries, and unexpected model

```

```

        responses discovered through hypothetical probing"

assign: behavior_patterns := updated_behavior_patterns

transform T_assess_understanding :
  intent: assess
  manner: "judge completeness of behavioural understanding
         and identify remaining questions"
  input: behavior_patterns, hypothetical_viz
  output: understanding_assessment
  actor: human
  description: "Evaluate whether model behaviour is
              sufficiently understood for current questions"

artifact understanding_assessment :
  knowledge(behavior_patterns)
  representation form: "quality judgment"
  description: "Assessment of whether model behaviour is
              sufficiently understood, identifying remaining
              questions"

if understanding_assessment indicates further investigation needed:
  then:
    transform T_refine_focus :
      intent: generate-knowledge
      manner: "select new data points, features, or
             subgroups to probe based on discovered
             patterns and outstanding questions"
      input: behavior_patterns,
            understanding_assessment
      output: updated_investigation_focus
      actor: human
      description: "Refine investigation focus based
                  on findings and remaining questions"

    artifact updated_investigation_focus : specification
      representation form: "investigation targets"
      description: "Refined selection of data points,
                  features, and subgroups for continued
                  hypothetical probing"

    assign:
      investigation_focus := updated_investigation_focus
  else:
    exit loop L_hypothetical

end loop L_hypothetical

# =====
# PHASE 5: FAIRNESS EVALUATION
# =====

```

```

transform T_compute_fairness :
  intent: characterise
  manner: "slice data by individual features and feature
    intersections; compute per-slice accuracy, error rates,
    confusion matrices, and fairness measures"
  input: test_data, performance_metrics
  output: fairness_metrics
  actor: machine
  description: "Compute intersectional performance and fairness
    metrics across demographic subgroups"

artifact fairness_metrics : feature(test_data)
  value structure: vector
  value type: numeric
  description: "Performance metrics and fairness measures for
    intersectional subgroups including accuracy, false
    positive and negative rates, and confusion matrices
    per slice"

transform T_visualize_fairness :
  intent: visualise
  manner: "render per-slice confusion matrices, ROC curves, and
    performance tables with sortable fairness measures and
    interactive threshold controls"
  input: test_data, fairness_metrics
  output: fairness_viz
  actor: machine
  description: "Display fairness metrics and performance
    comparisons across demographic subgroups"

artifact fairness_viz : visualisation(test_data,
  fairness_metrics)
  layout: "tabular slice comparison with ROC curves and
    threshold controls"
  form: "per-slice confusion matrices, ROC curves, and
    sortable performance tables"
  encoding: "rows: demographic slices; cells: confusion
    counts and rates; ROC curves per slice; interactive
    threshold slider"
  description: "Per-slice performance tables, confusion
    matrices, and ROC curves with interactive threshold
    controls"

transform T_identify_disparities :
  intent: abstract
  manner: "recognise differential performance across slices,
    identify advantaged and disadvantaged groups, and
    characterise disparity structures"
  input: fairness_viz, fairness_metrics
  output: fairness_patterns
  actor: human
  description: "Identify performance disparities and fairness

```

```

patterns across demographic subgroups"

artifact fairness_patterns : pattern(test_data)
  representation form: "identified fairness disparities"
  description: "Performance disparities across demographic
    subgroups including differentially advantaged and
    disadvantaged groups and disparity structures"

transform T_select_initial_strategy :
  intent: generate-knowledge
  manner: "choose threshold optimisation approach informed by
    observed disparity patterns"
  input: fairness_patterns
  output: strategy_direction
  actor: human
  description: "Select initial fairness optimisation strategy
    based on identified disparities"

artifact strategy_direction : specification
  representation form: "strategy selection"
  description: "Choice of fairness optimisation strategy to
    apply and rationale"

loop L_fairness_strategy:
  purpose: "Explore threshold optimisation strategies to find
    acceptable fairness-performance trade-offs across
    demographic subgroups"
  until: "analyst has identified a satisfactory fairness strategy
    or concluded that threshold adjustment alone is
    insufficient"
  body:

    transform T_explore_thresholds :
      intent: assess
      manner: "adjust classification thresholds per
        demographic slice according to chosen fairness
        strategy and evaluate resulting trade-offs"
      input: fairness_viz, fairness_patterns,
        fairness_metrics, strategy_direction
      output: fairness_assessment, threshold_config
      actor: hybrid
      description: "Apply chosen fairness optimisation
        strategy and evaluate its impact on per-slice
        performance"

    artifact fairness_assessment : knowledge(trained_models)
      representation form: "fairness evaluation"
      description: "Assessment of trade-offs between fairness
        constraints and overall performance under the
        current threshold strategy"

    artifact threshold_config : specification

```

```

representation form: "per-slice classification
  thresholds"
description: "Optimised classification thresholds per
  demographic slice under chosen fairness strategy"

transform T_visualize_strategy :
  intent: visualise
  manner: "render updated confusion matrices, ROC curves,
    and performance tables reflecting per-slice
    threshold adjustments"
  input: test_data, fairness_metrics, threshold_config
  output: updated_fairness_viz
  actor: machine
  description: "Display updated performance metrics under
    the current threshold configuration"

artifact updated_fairness_viz :
  visualisation(test_data, fairness_metrics)
  layout: "tabular slice comparison with ROC curves
    and threshold controls"
  form: "per-slice confusion matrices, ROC curves,
    and sortable performance tables"
  encoding: "same as fairness_viz with thresholds
    adjusted per strategy"
  description: "Performance tables, confusion
    matrices, and ROC curves reflecting threshold
    adjustments under the current fairness
    strategy"

assign: fairness_viz := updated_fairness_viz

transform T_evaluate_strategy_impact :
  intent: abstract
  manner: "recognise shifts in per-slice performance,
    identify remaining disparities, and compare with
    prior strategy results"
  input: fairness_viz, fairness_metrics
  output: updated_fairness_patterns
  actor: human
  description: "Identify how disparities changed under
    the current fairness strategy"

artifact updated_fairness_patterns : pattern(test_data)
  representation form: "identified fairness disparities"
  description: "Updated performance disparities across
    demographic subgroups reflecting threshold
    adjustments and remaining inequities"

assign: fairness_patterns := updated_fairness_patterns

if fairness_assessment indicates further strategy exploration needed:
  then:

```

```

transform T_select_next_strategy :
  intent: generate-knowledge
  manner: "select alternative optimisation
          strategy informed by comparison of
          results across previously explored
          strategies"
  input: fairness_assessment, fairness_patterns
  output: updated_strategy_direction
  actor: human
  description: "Decide which fairness strategy
               to explore next based on observed
               trade-offs and remaining disparities"

artifact updated_strategy_direction : specification
  representation form: "strategy selection"
  description: "Choice of next fairness
               optimisation strategy to explore and
               rationale"

  assign:
    strategy_direction := updated_strategy_direction
else:
  exit loop L_fairness_strategy

end loop L_fairness_strategy

# =====
# PHASE 6: KNOWLEDGE SYNTHESIS
# =====

transform T_synthesize :
  intent: generate-knowledge
  manner: "integrate data characteristics, performance patterns,
          behavioural findings, and fairness assessments into
          comprehensive model understanding"
  input: behavior_patterns, performance_patterns,
        fairness_assessment, fairness_patterns,
        data_characteristics, understanding_assessment
  output: model_understanding
  actor: human
  description: "Synthesise understanding of model behaviour,
               performance, and fairness for model improvement decisions"

artifact model_understanding : knowledge(trained_models)
  representation form: "statements and recommendations"
  description: "Documented assessment of model behaviour,
               feature effects, decision boundaries, performance
               characteristics, and fairness properties, supporting
               model improvement and deployment decisions"

```

2 Diagrammatic Representations of Visual Analytics Workflows

Diagram Legend

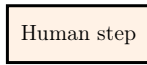
Node types



Data artifact: dataset, feature, arrangement, visualisation, pattern, or knowledge



Machine-driven processing or computation step



Human-driven or hybrid step: assessment, interpretation, parameter adjustment



Parameter settings or configuration guiding a transform



Loop exit condition: determines whether to iterate (refine) or proceed

Edge types



Primary data or control flow
Secondary or cross-boundary data flow



(e.g., loop-internal artifact, post-loop step)



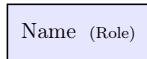
dated artifact replaces original for next iteration

Grouping

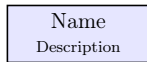


Iterative refinement loop: enclosed steps repeat-until exit-condition is satisfied

Node labels



Single-line format: artifact or transform name followed by ATWL role in parentheses



Two-line format: used when horizontal space is constrained



Decision branch labels: *yes* continues the loop; *no* exits to subsequent steps

Figure 1: Legend of visual encodings used in the ATWL workflow diagrams.

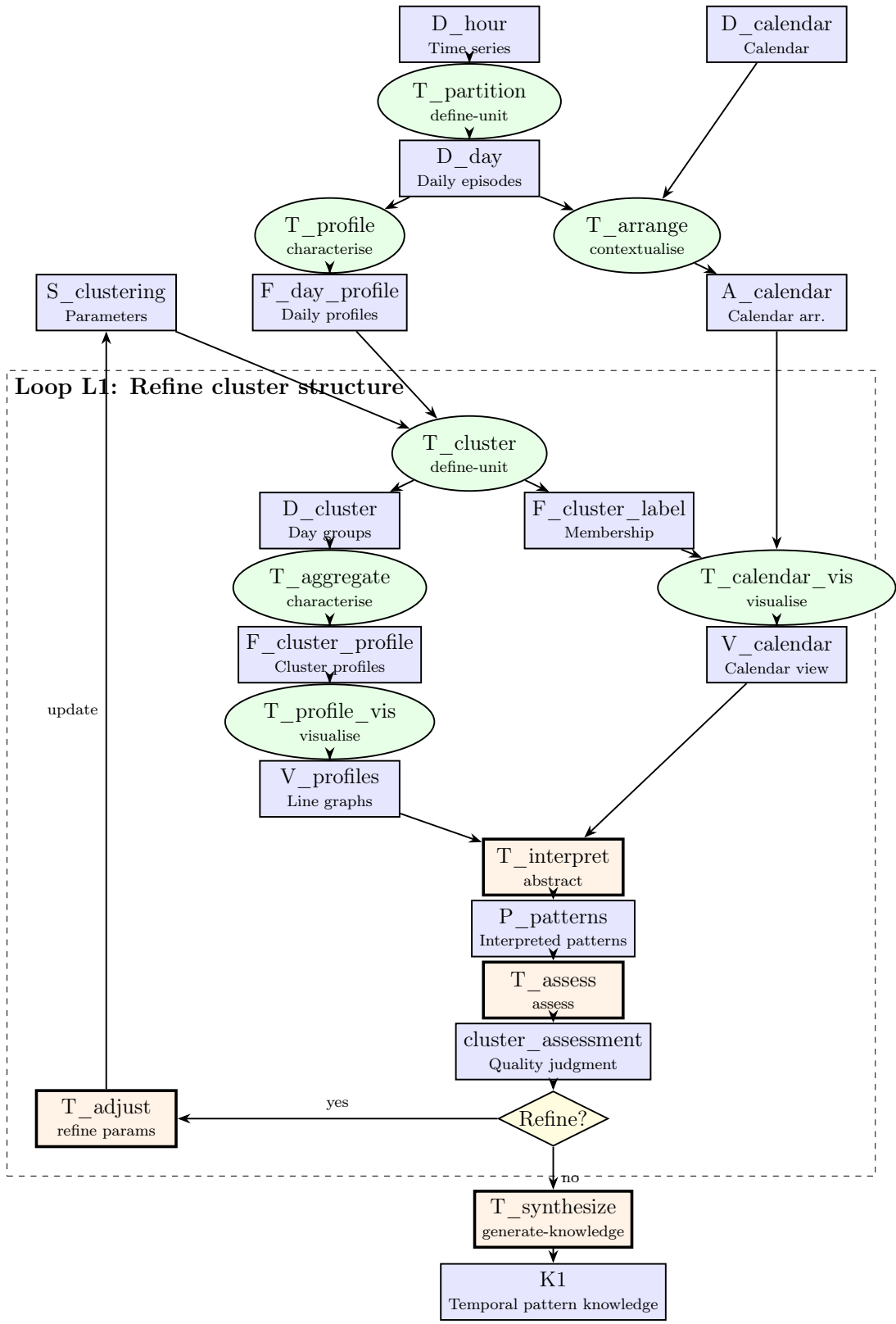


Figure 2: Diagrammatic representation of the Cluster-Calendar workflow

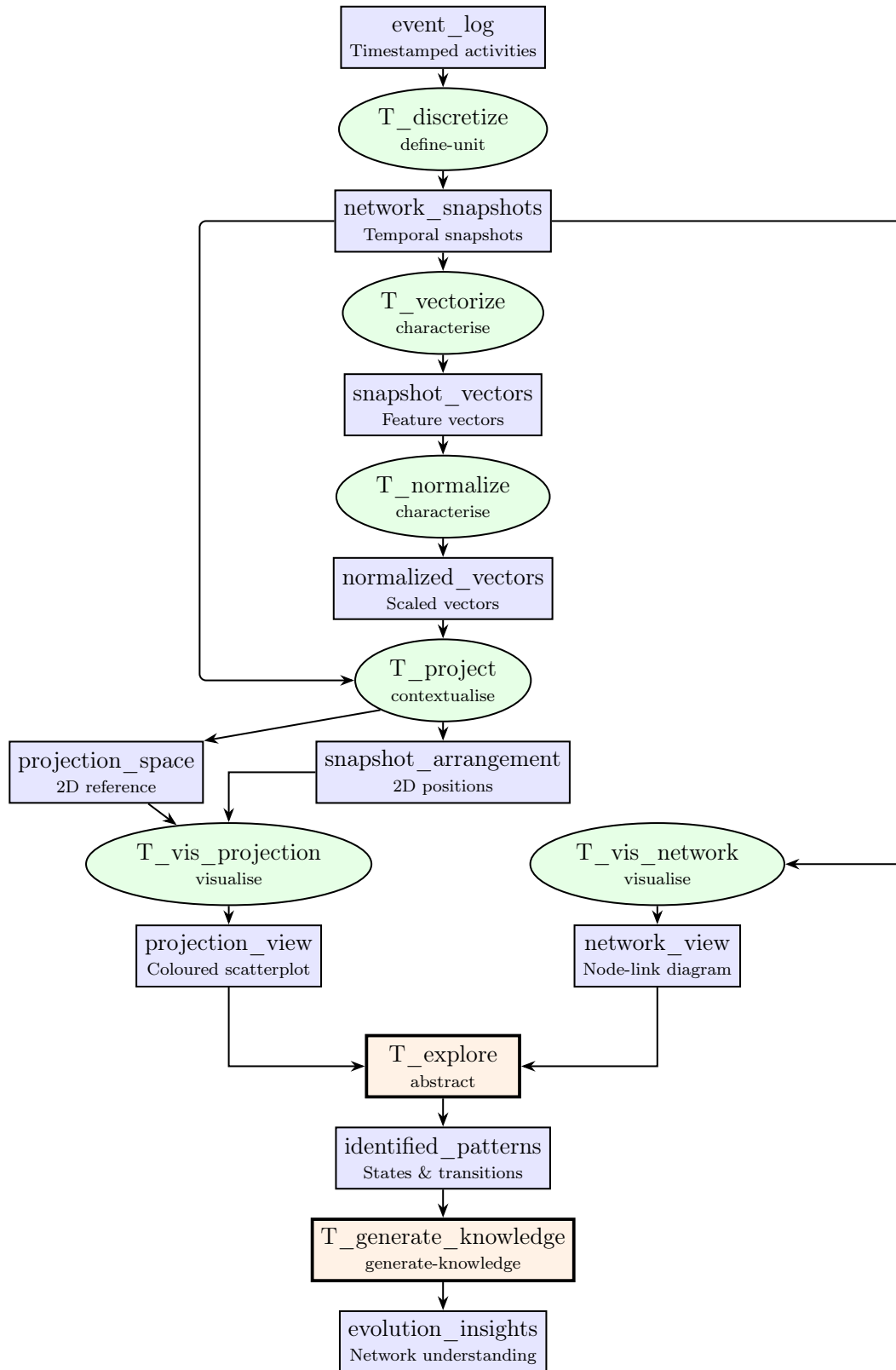


Figure 3: Diagrammatic representation of the Dynamic Network Exploration workflow

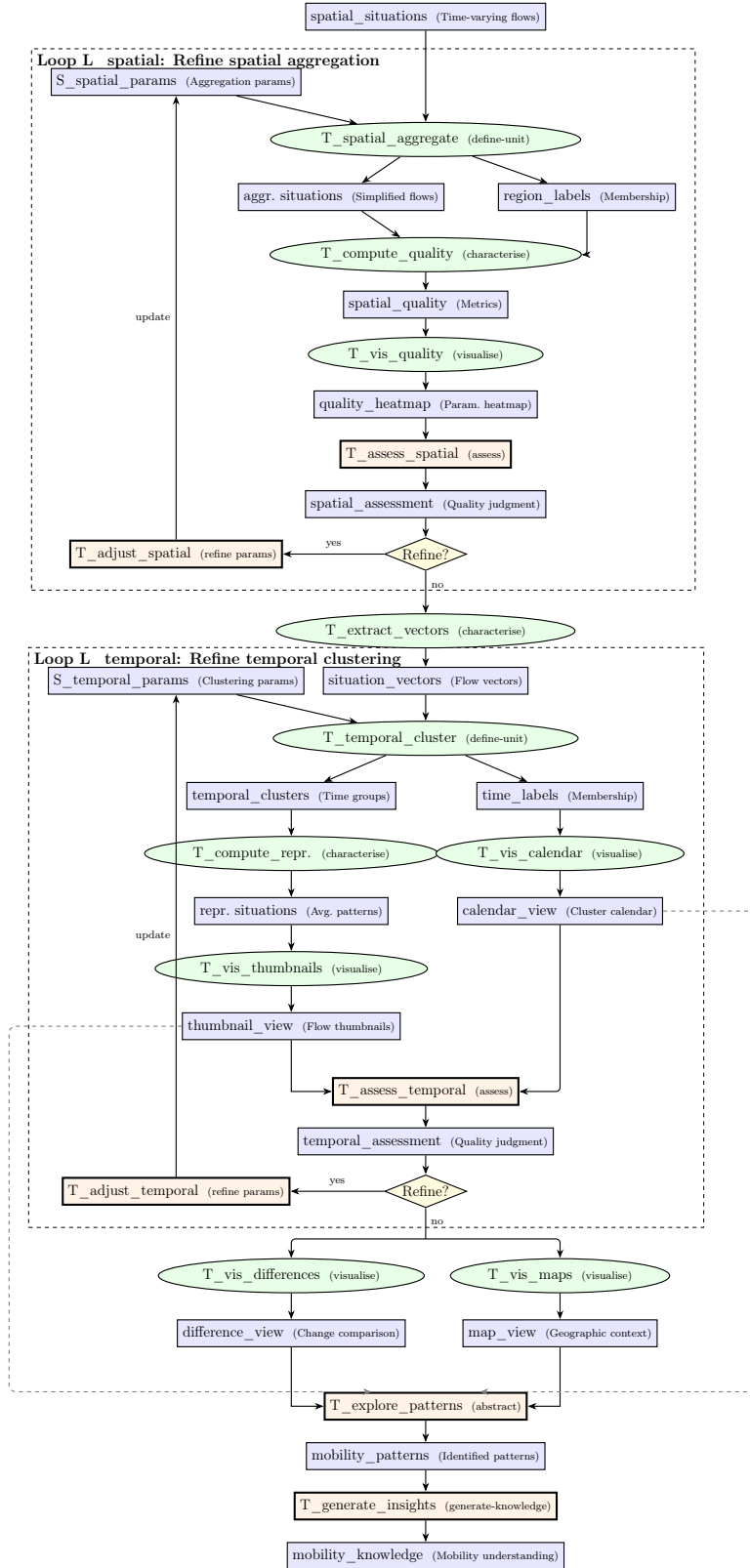


Figure 4: Diagrammatic representation of the MobilityGraphs workflow

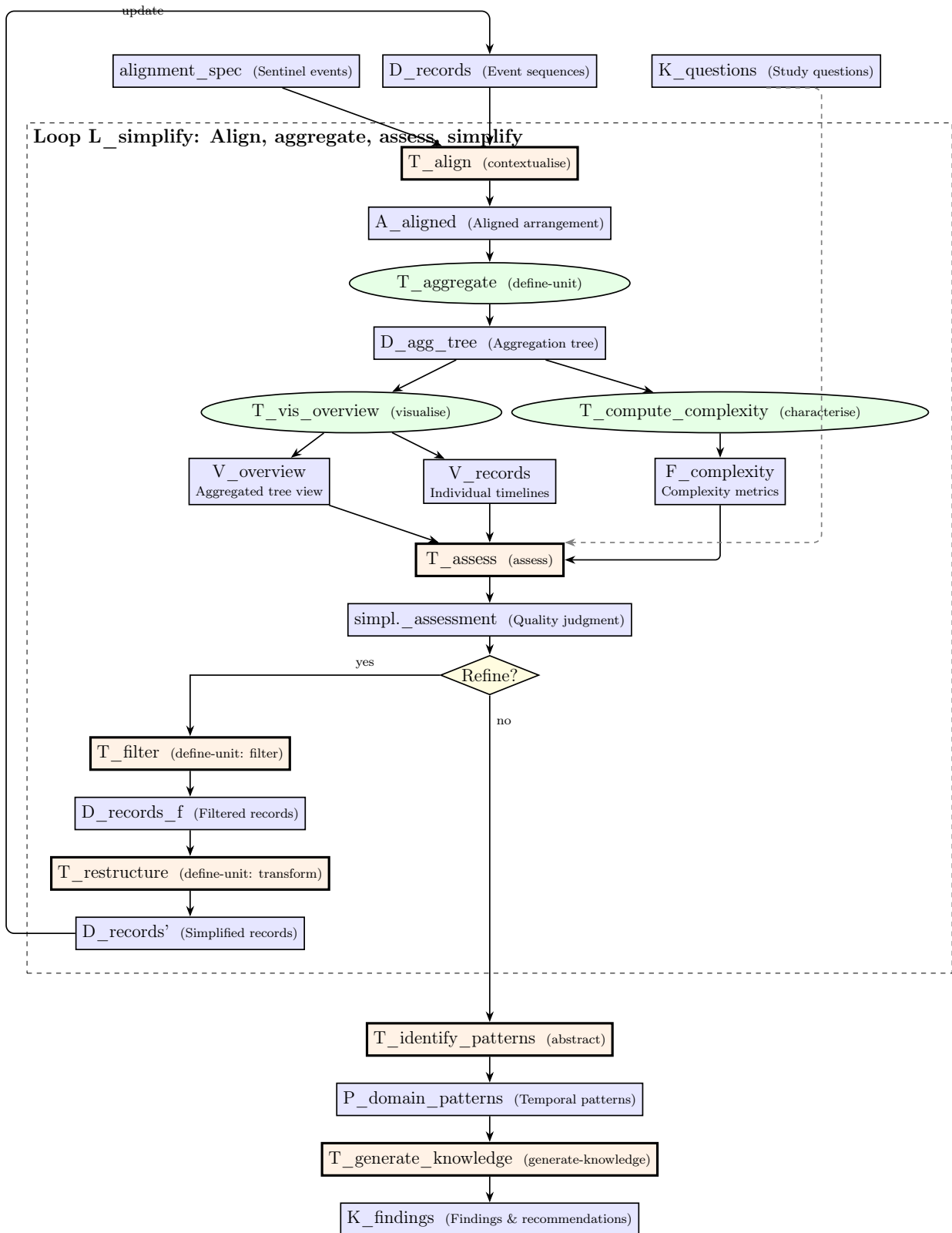


Figure 5: Diagrammatic representation of the EventFlow workflow

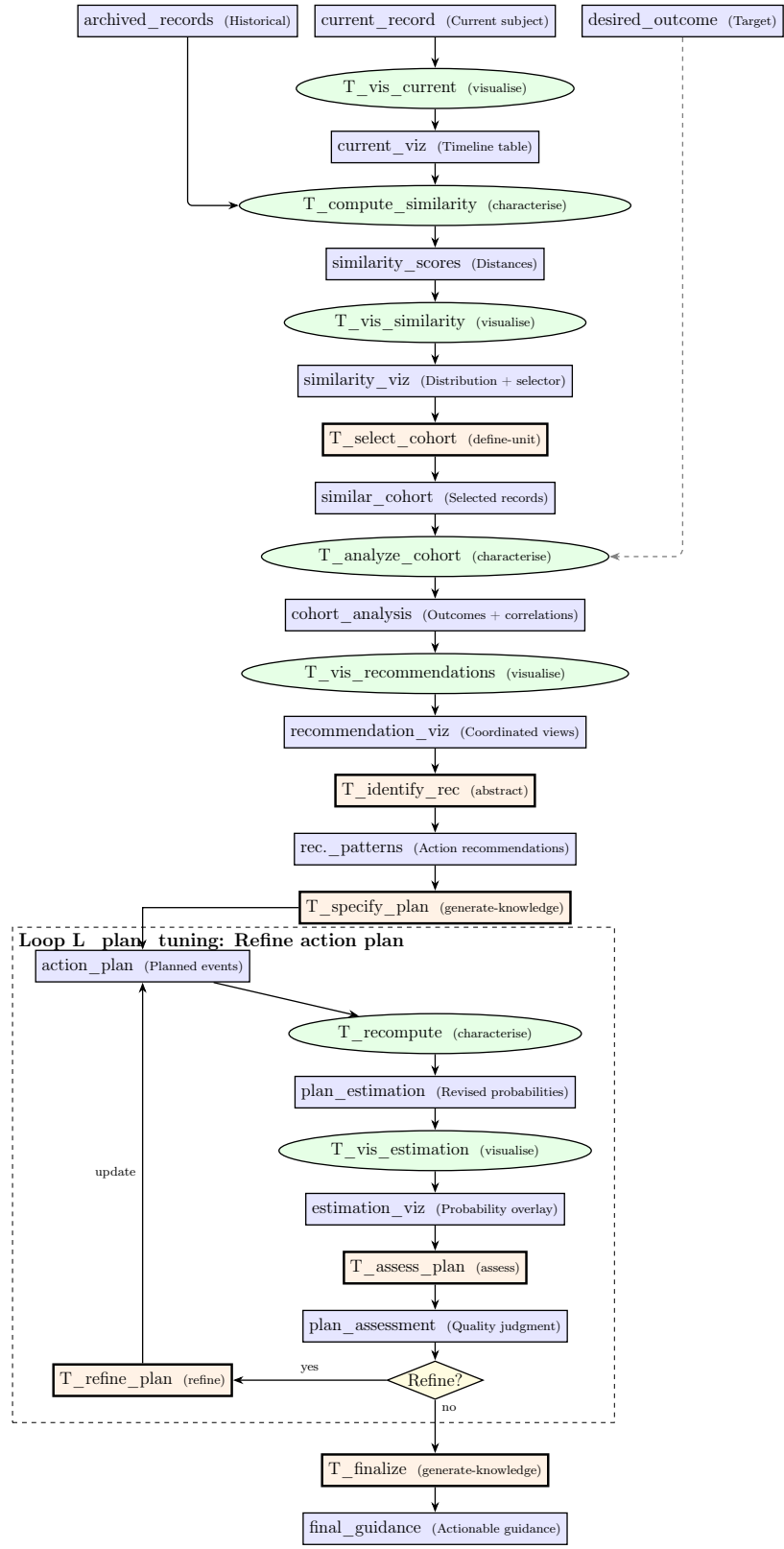


Figure 6: Diagrammatic representation of the EventAction workflow

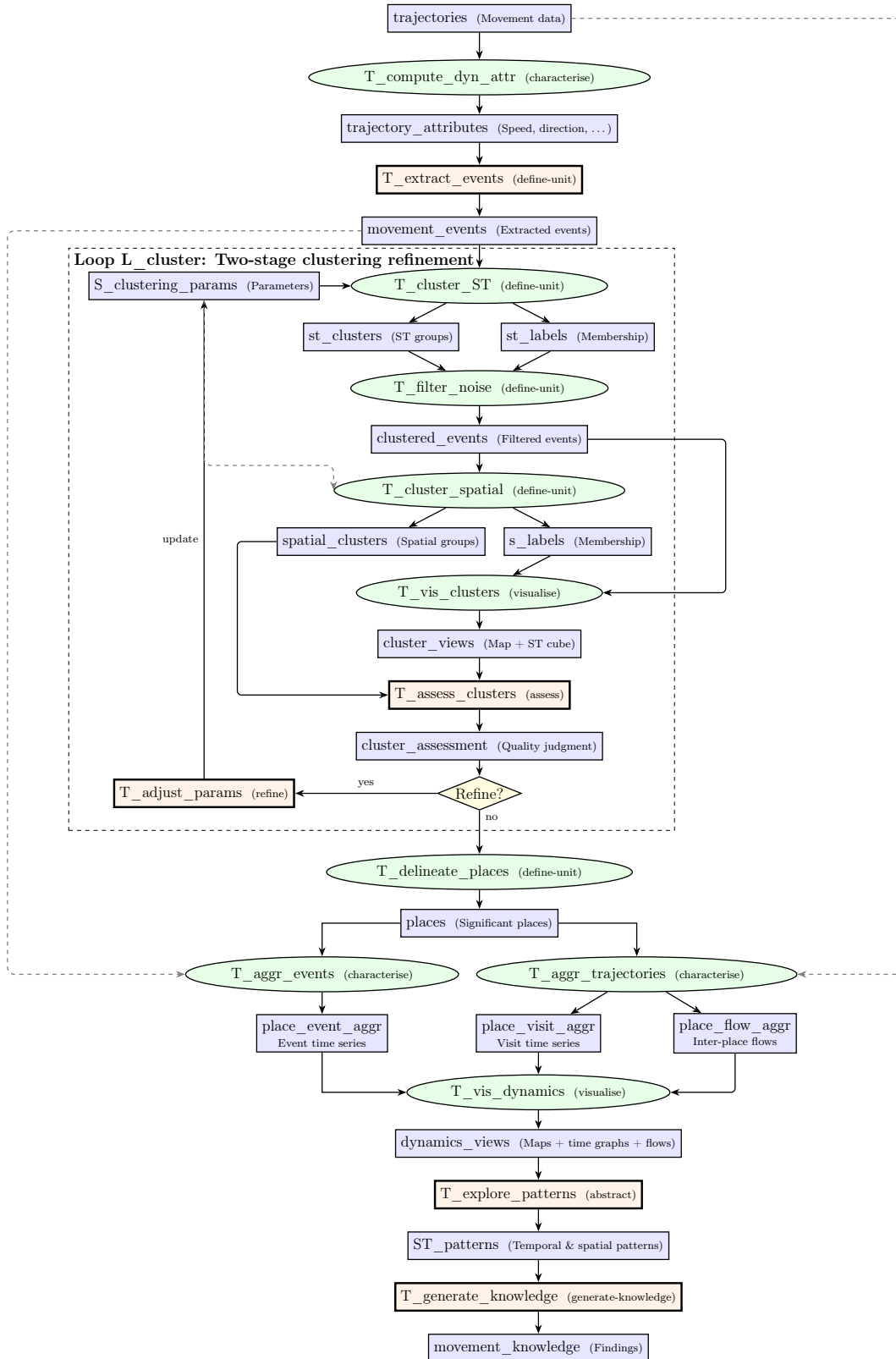


Figure 7: Diagrammatic representation of the Events-to-Places workflow

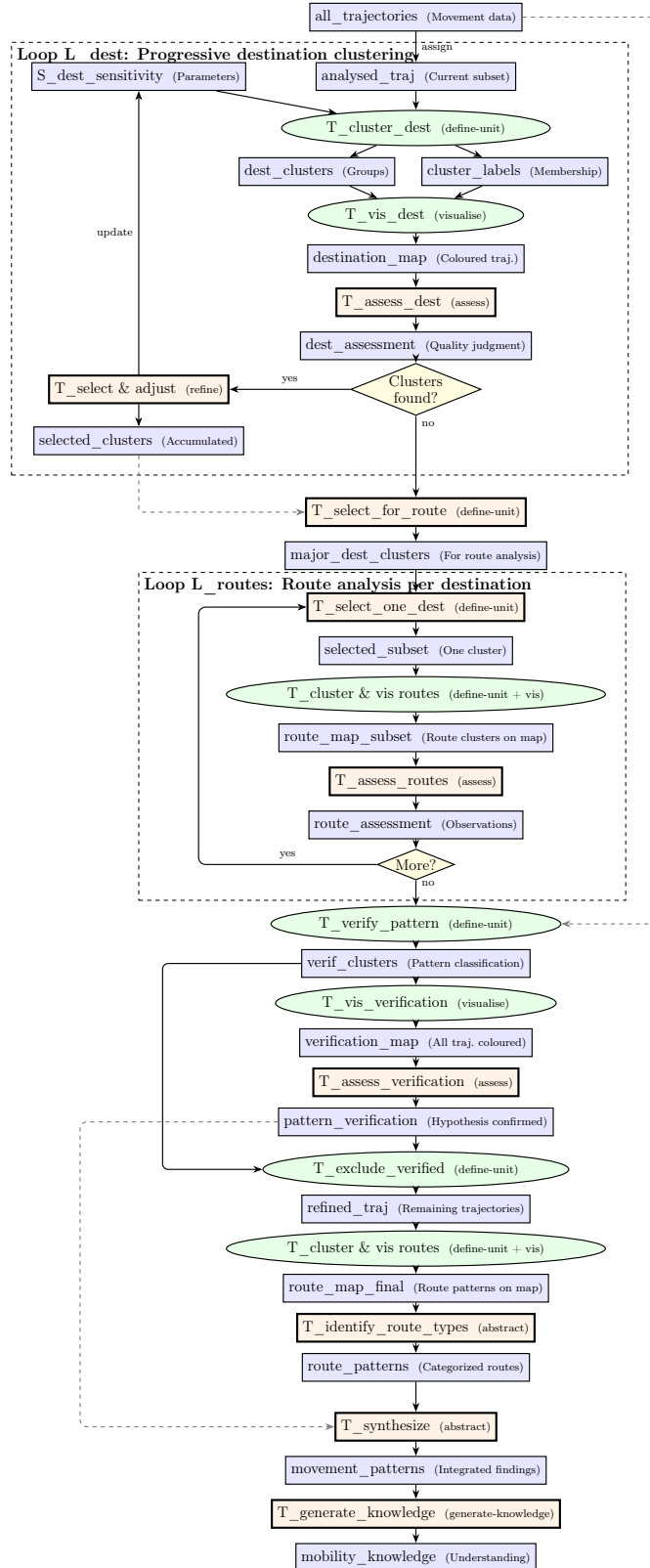


Figure 8: Diagrammatic representation of the Progressive Clustering workflow

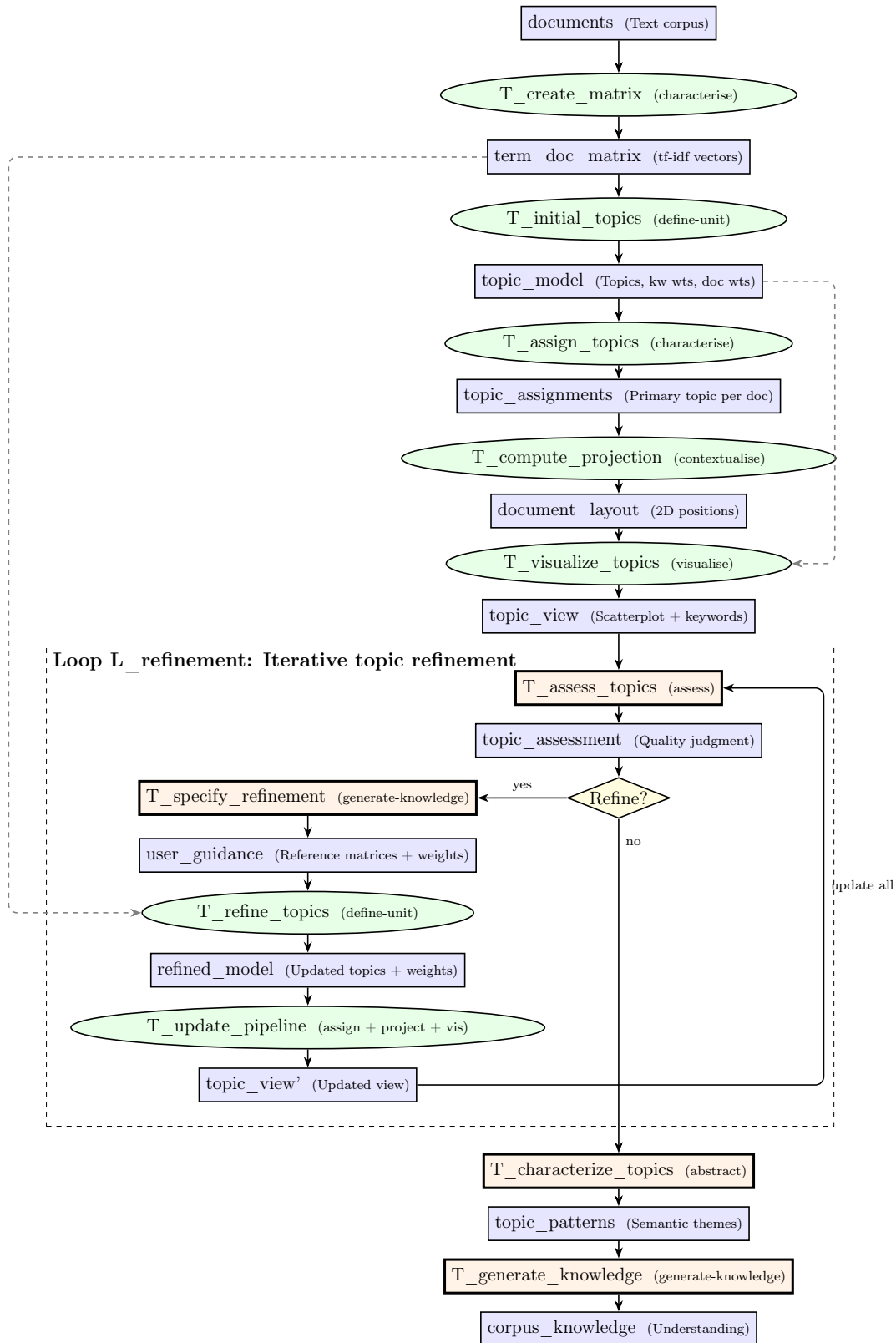


Figure 9: Diagrammatic representation of the Human-Steered Topic Modelling workflow

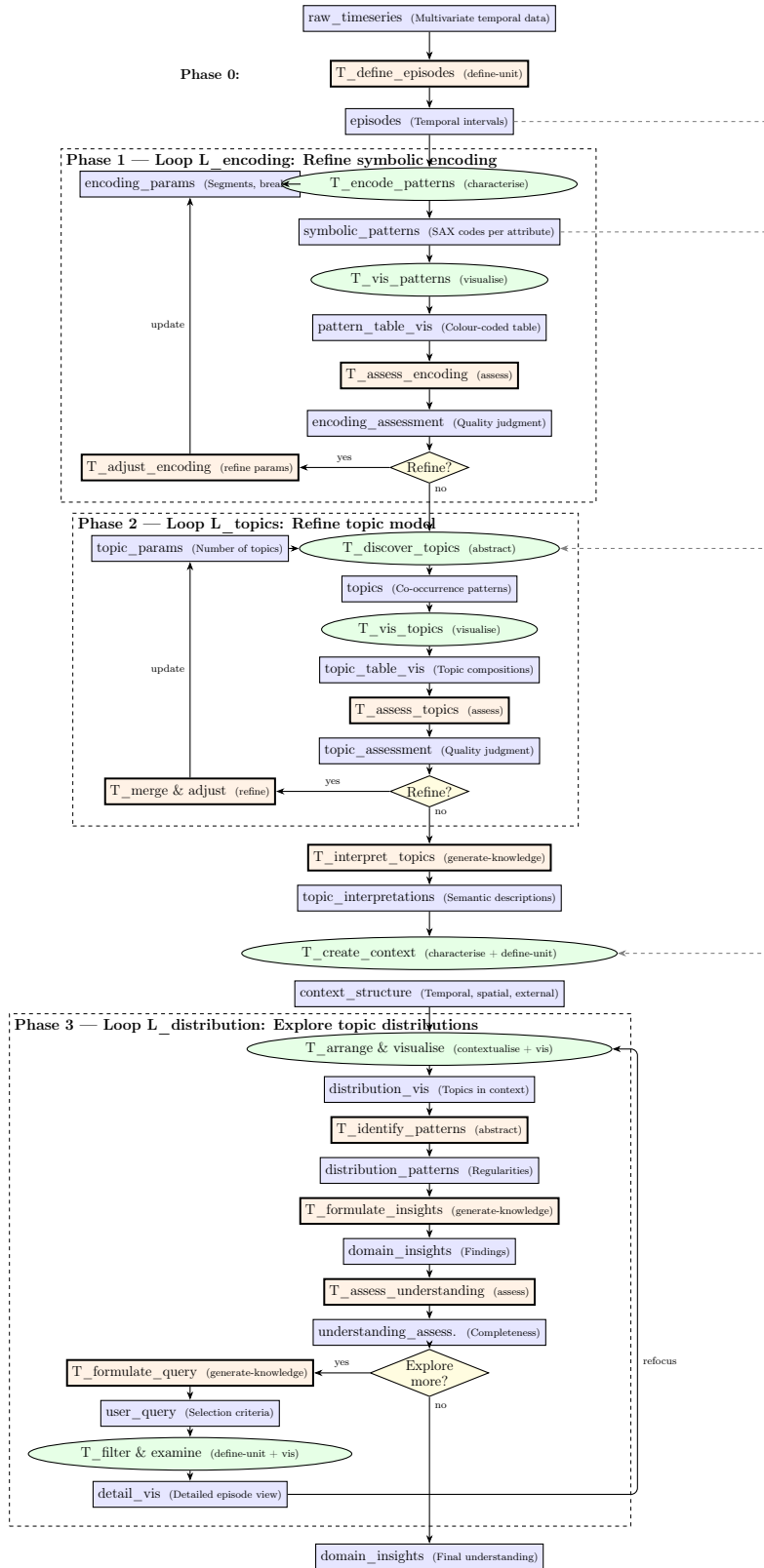


Figure 10: Diagrammatic representation of the Multivariate Time Series Abstraction workflow

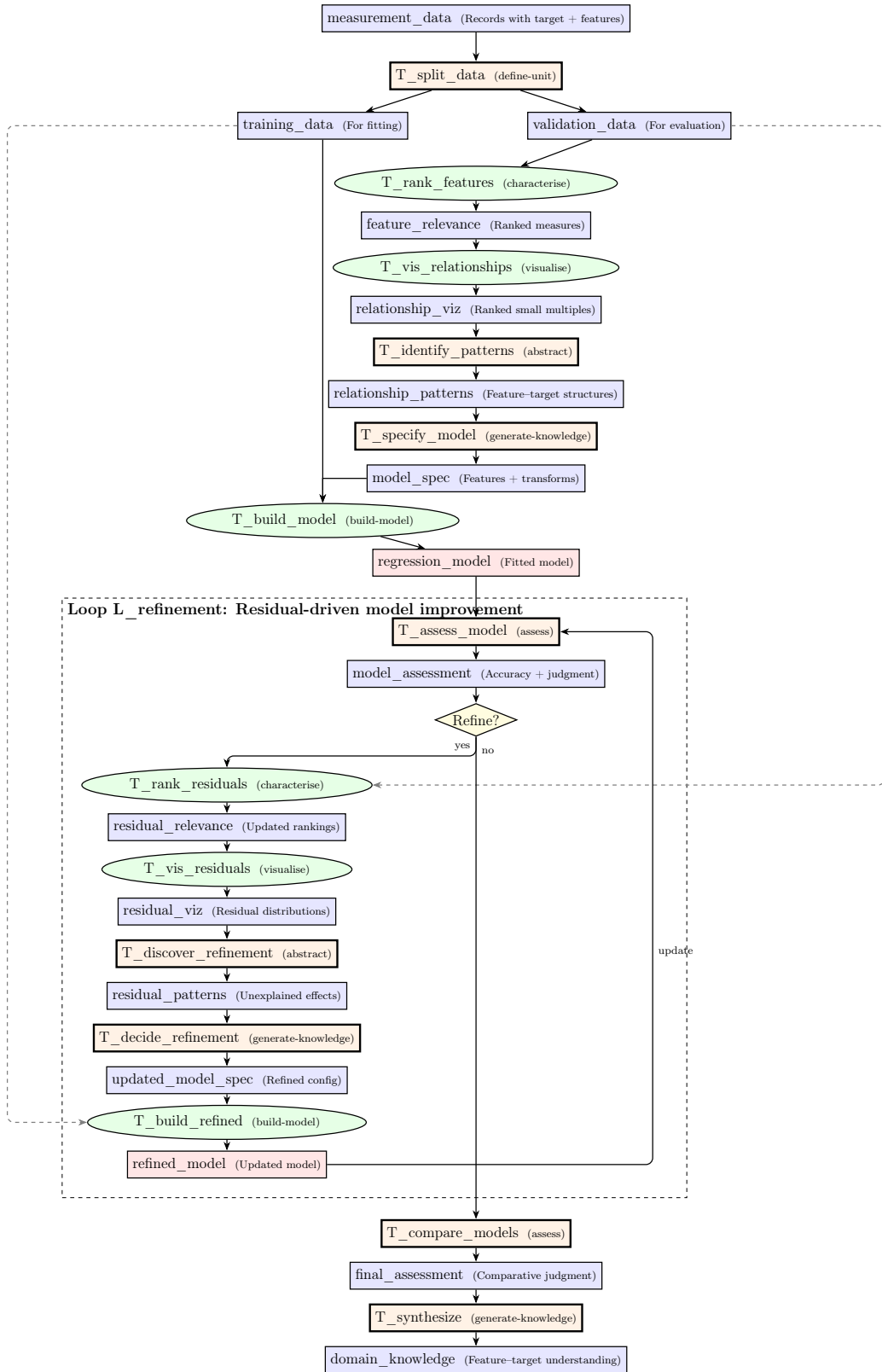


Figure 11: Diagrammatic representation of the Partition-Based Regression Modelling workflow

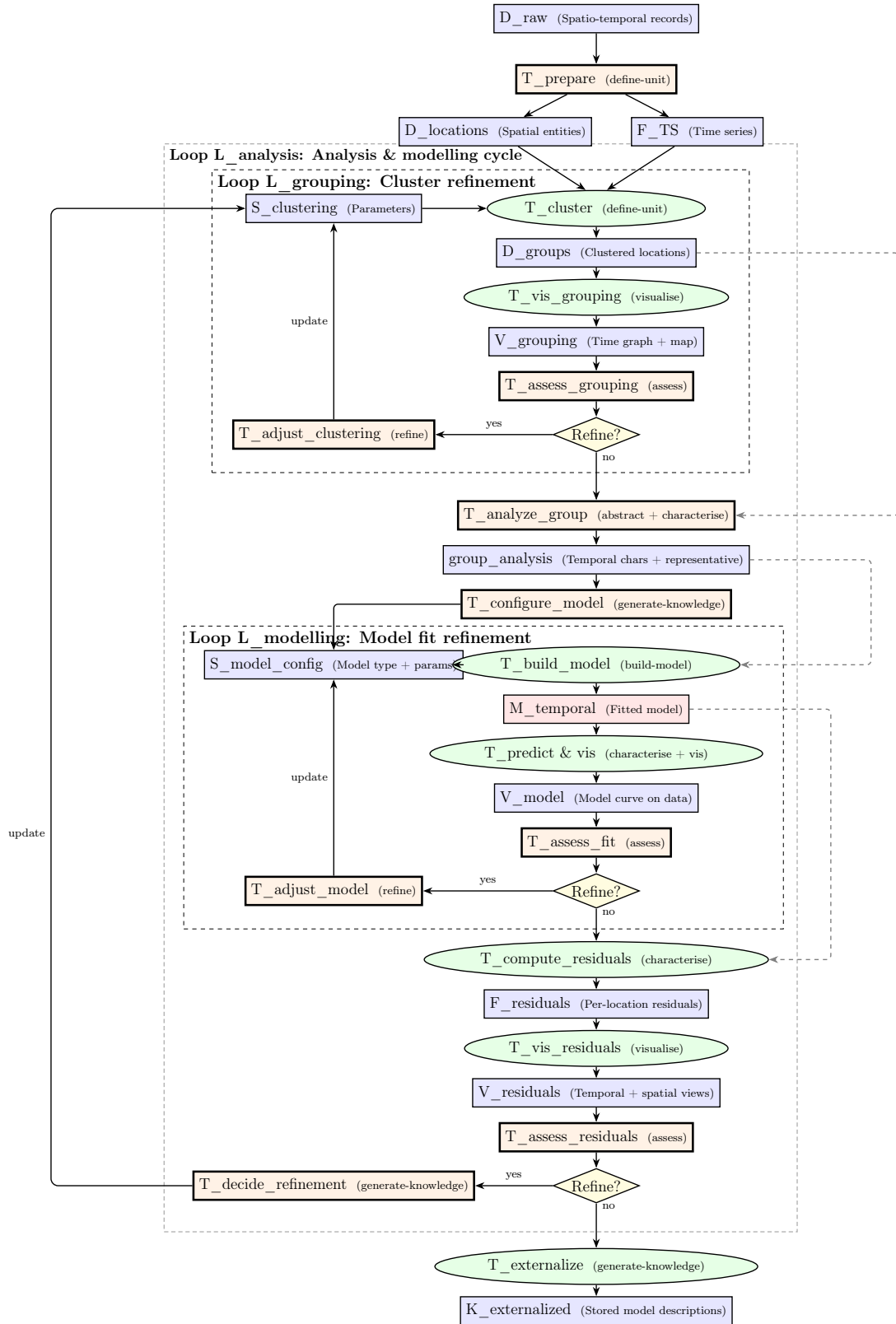


Figure 12: Diagrammatic representation of the Spatio-Temporal Modelling workflow

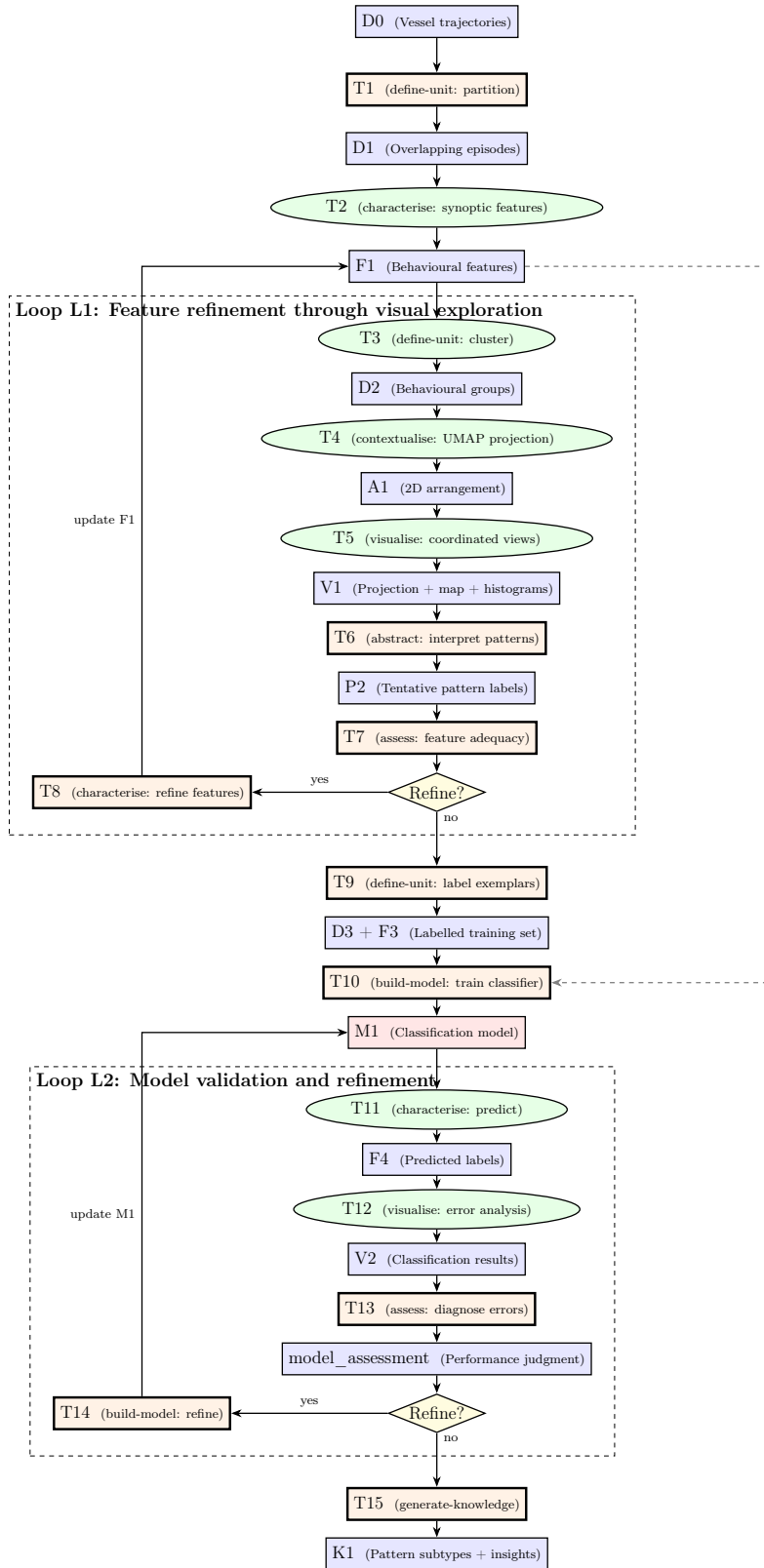


Figure 13: Diagrammatic representation of the Data Engineering for Movement Pattern Classification

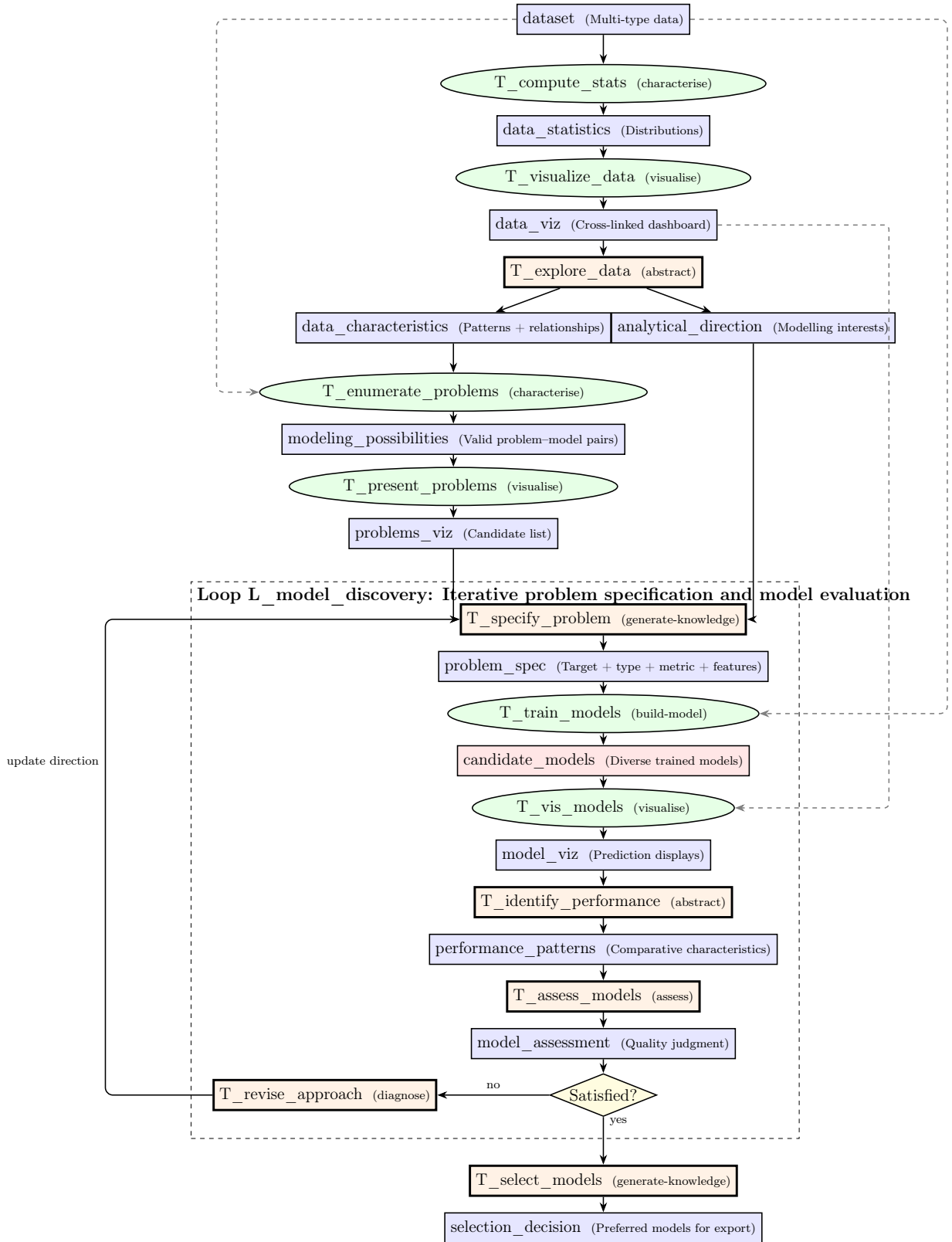


Figure 14: Diagrammatic representation of the Exploratory Model Analysis workflow

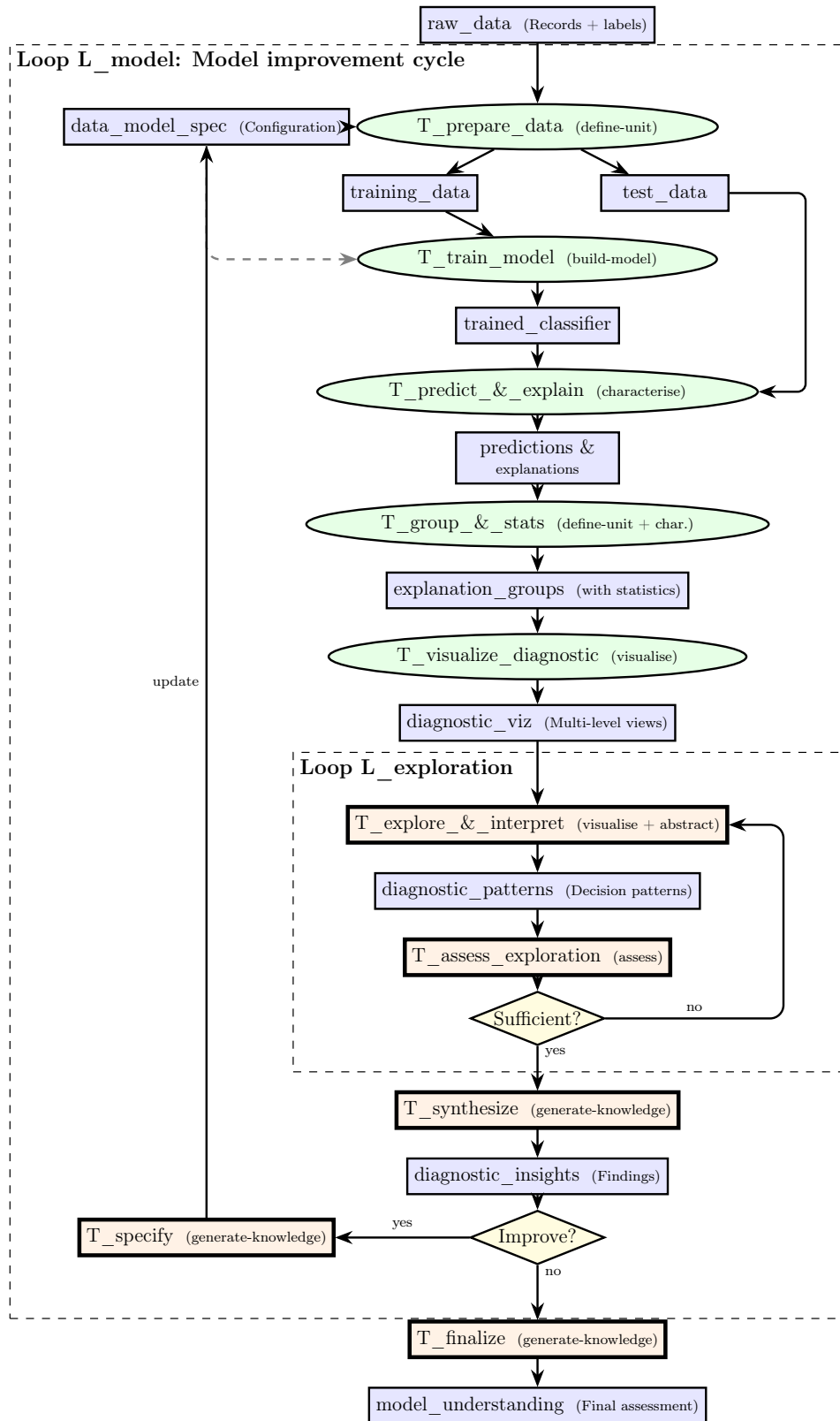


Figure 15: Diagrammatic representation of the Binary Classifier Diagnostics workflow

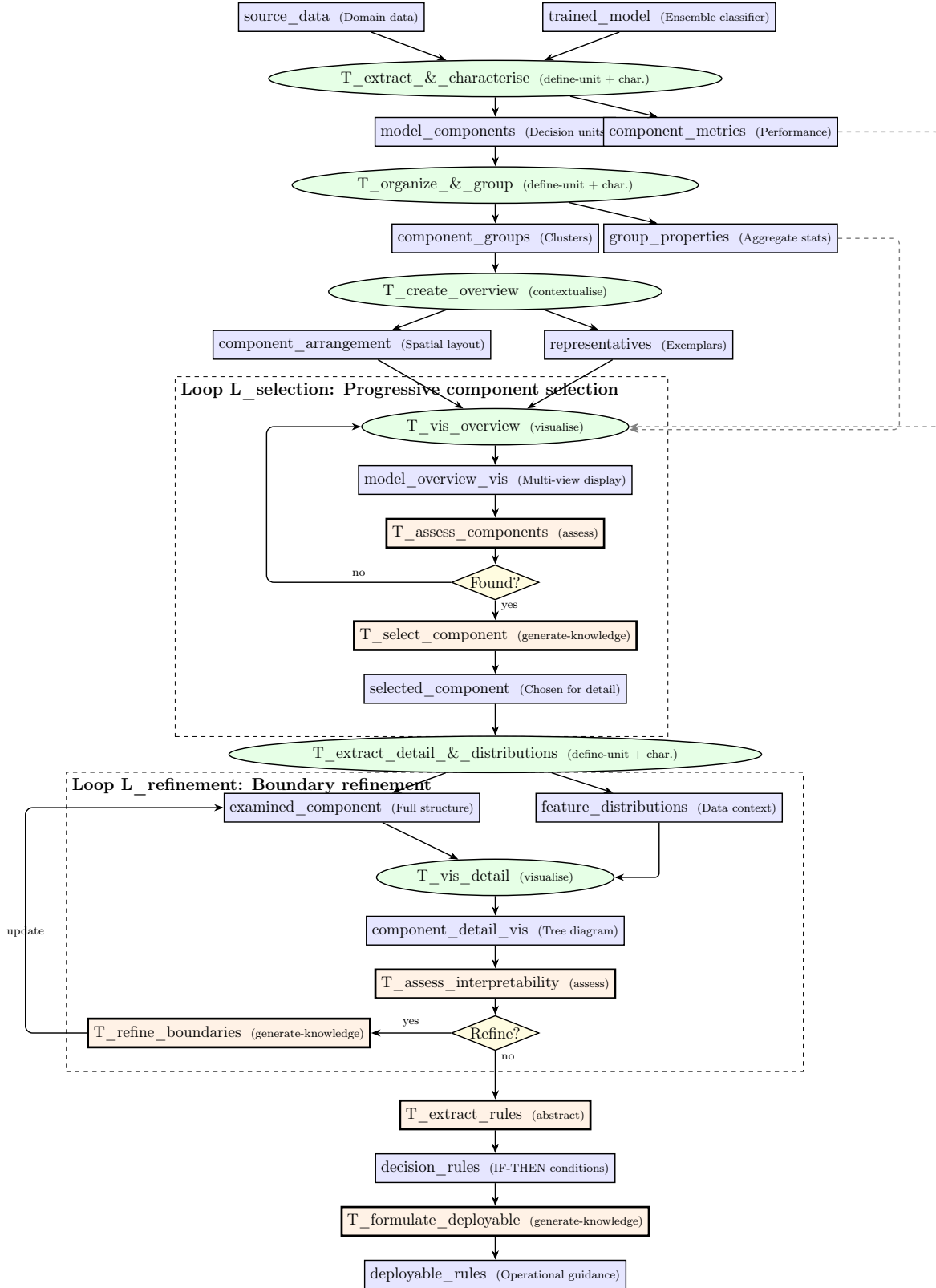


Figure 16: Diagrammatic representation of the Ensemble Classifier Exploration workflow

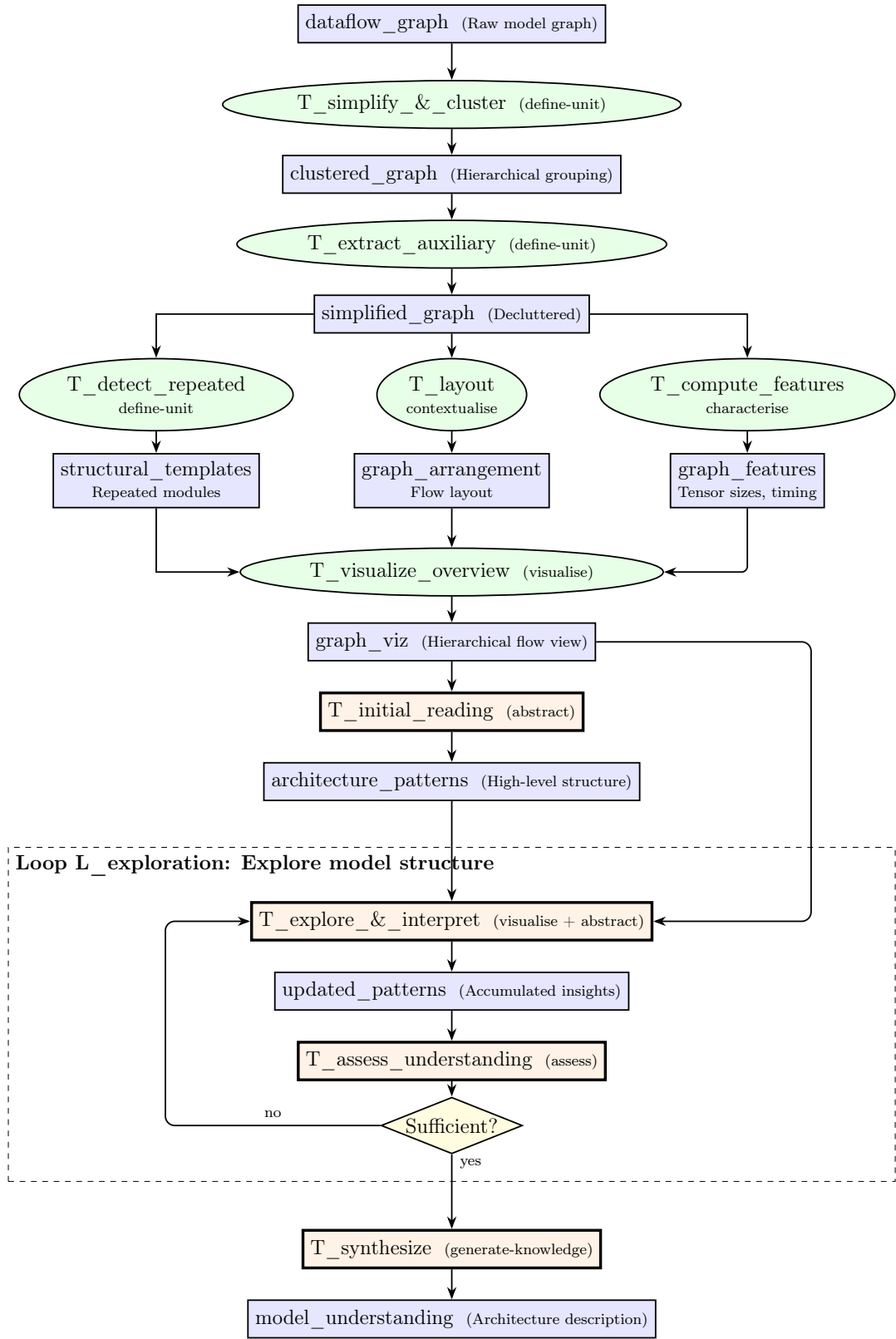


Figure 17: Diagrammatic representation of the Deep Learning Models Exploration in TensorFlow

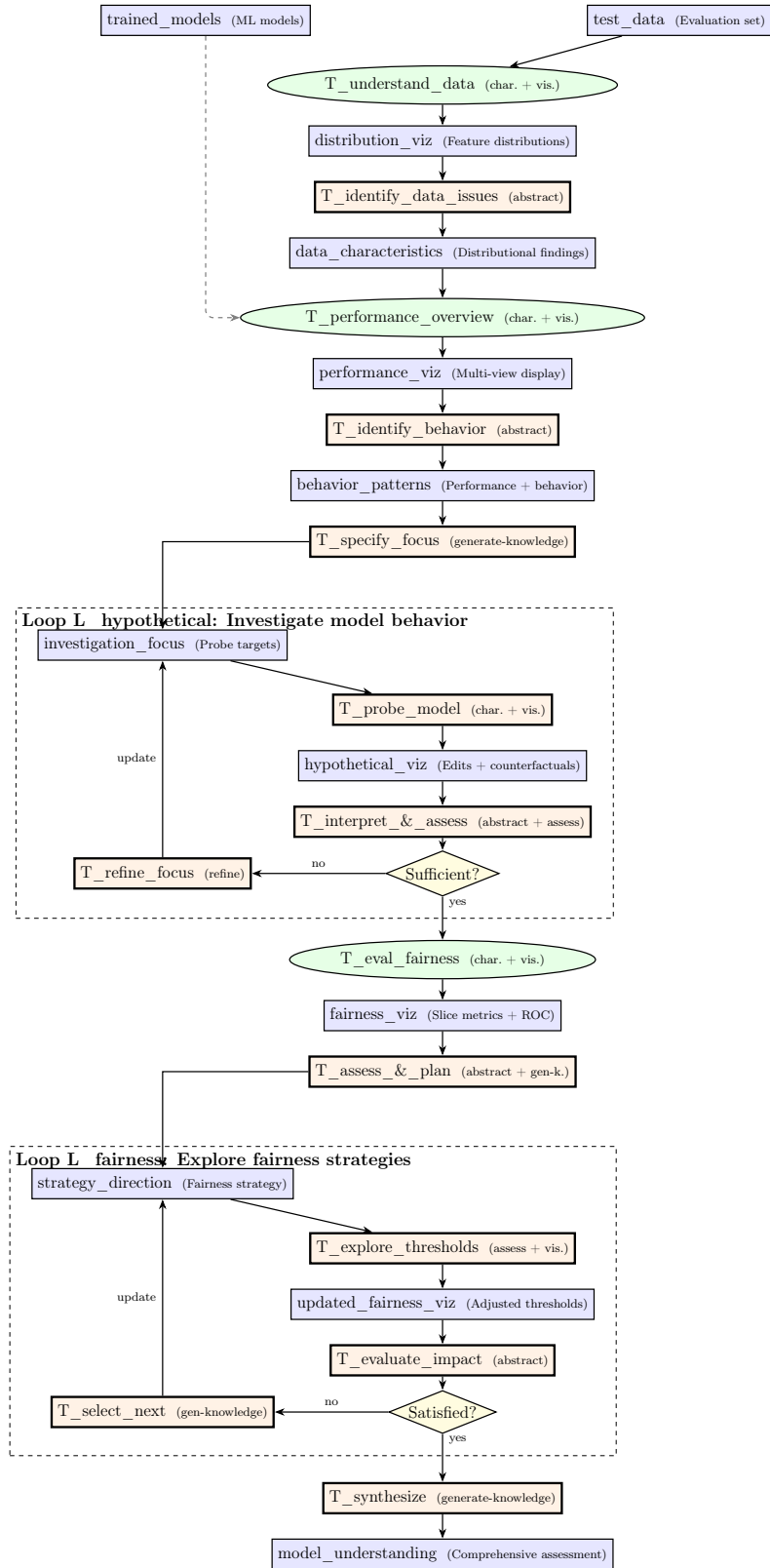


Figure 18: Diagrammatic representation of the process of What-If Probing of ML Models