Visual Analysis of **High-Dimensional Event Sequence Data** via **Dynamic Hierarchical Aggregation**

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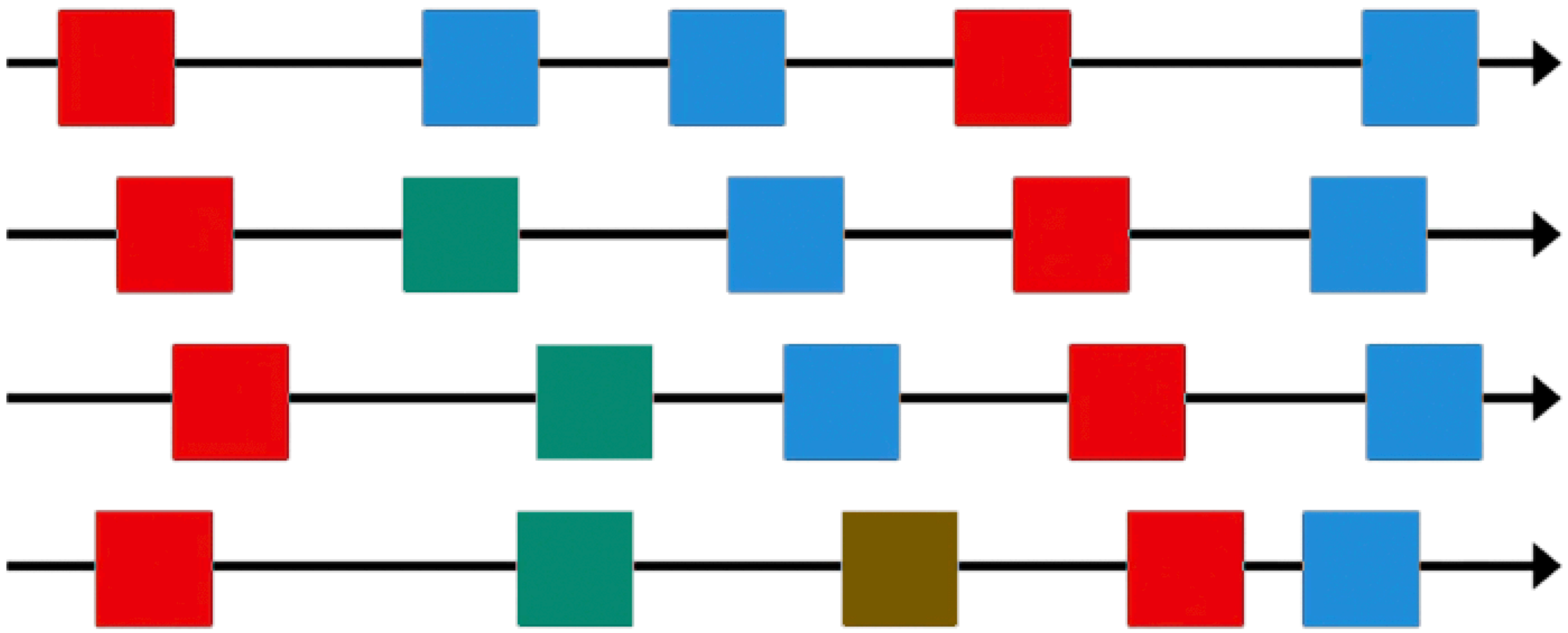
CPSC 547 | Kevin Chow

Event Sequences

- Time-ordered lists of discrete events
- Analyze to discover **patterns** or **rare event paths**
- But… real-world datasets are large and complex:
  - Volume and length of event sequences
  - High-dimensional event data



Volume and length of event sequences

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Aggregate sequences

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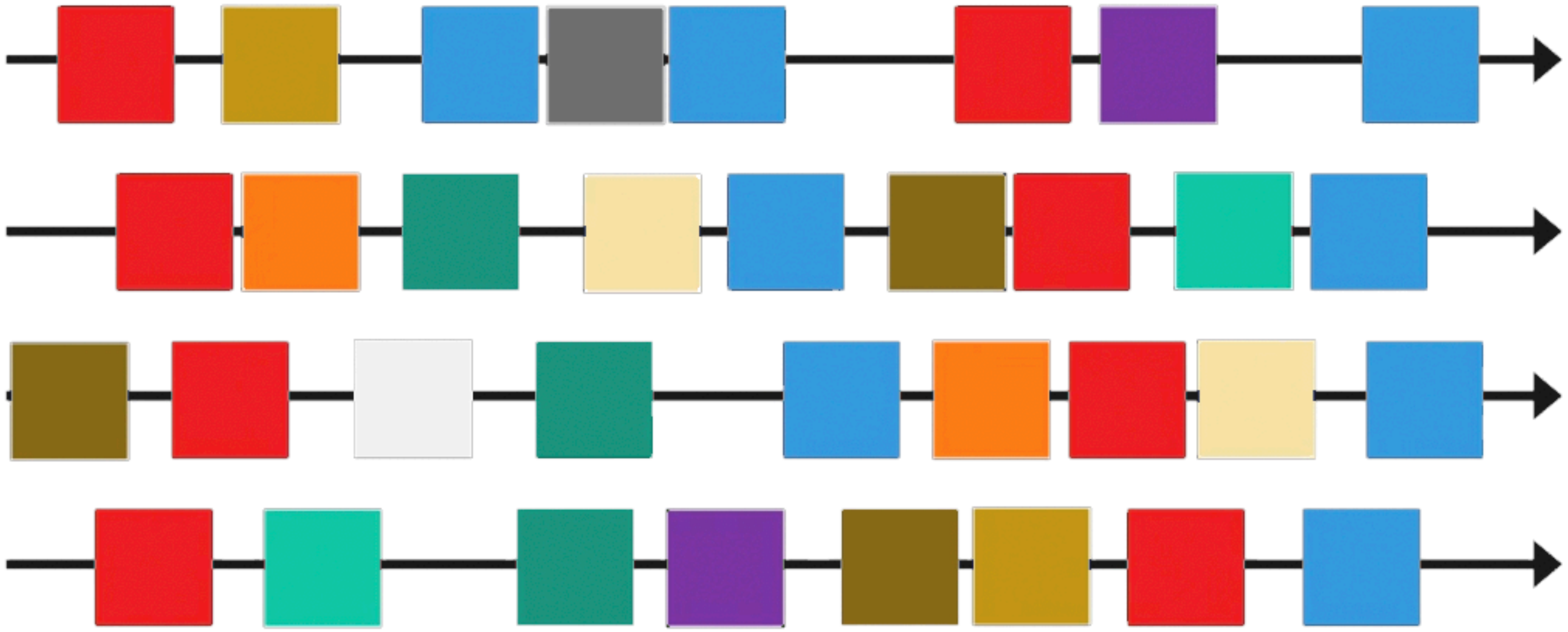
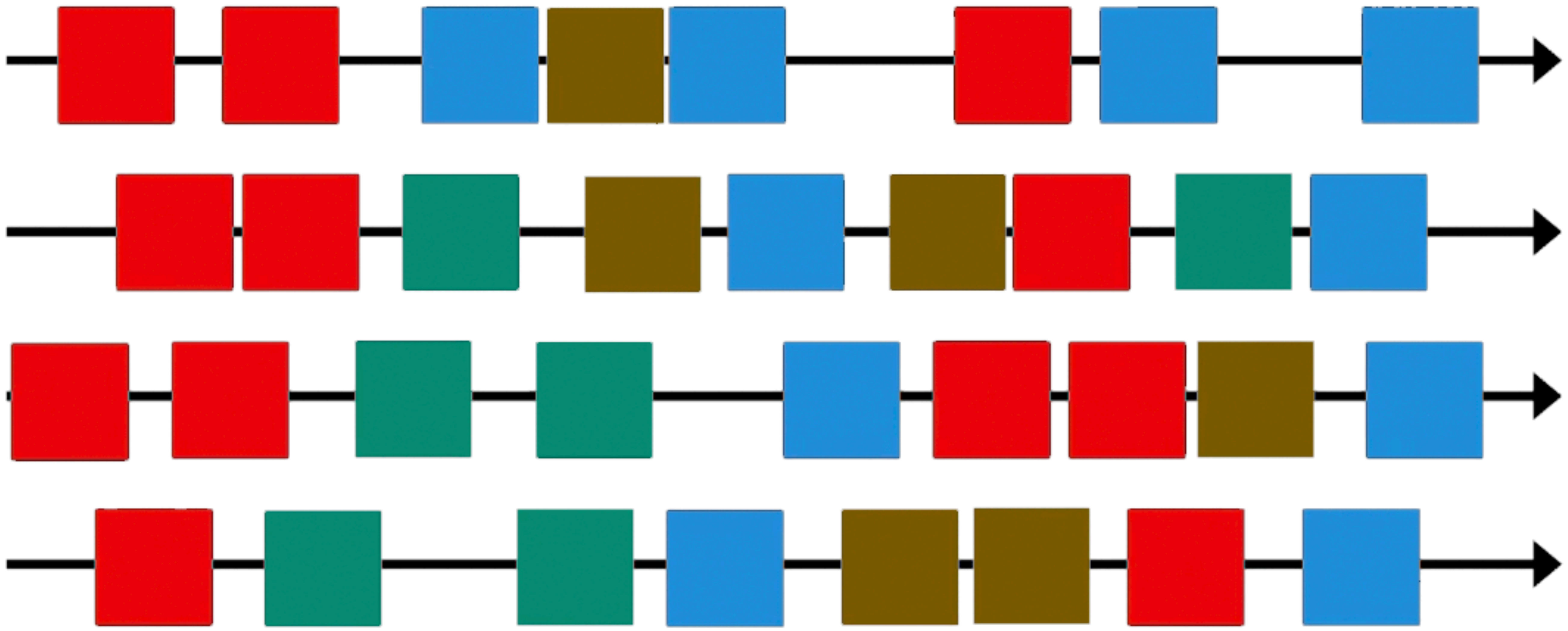


High-dimensional event data

Volume and length of event sequences

Aggregate sequences

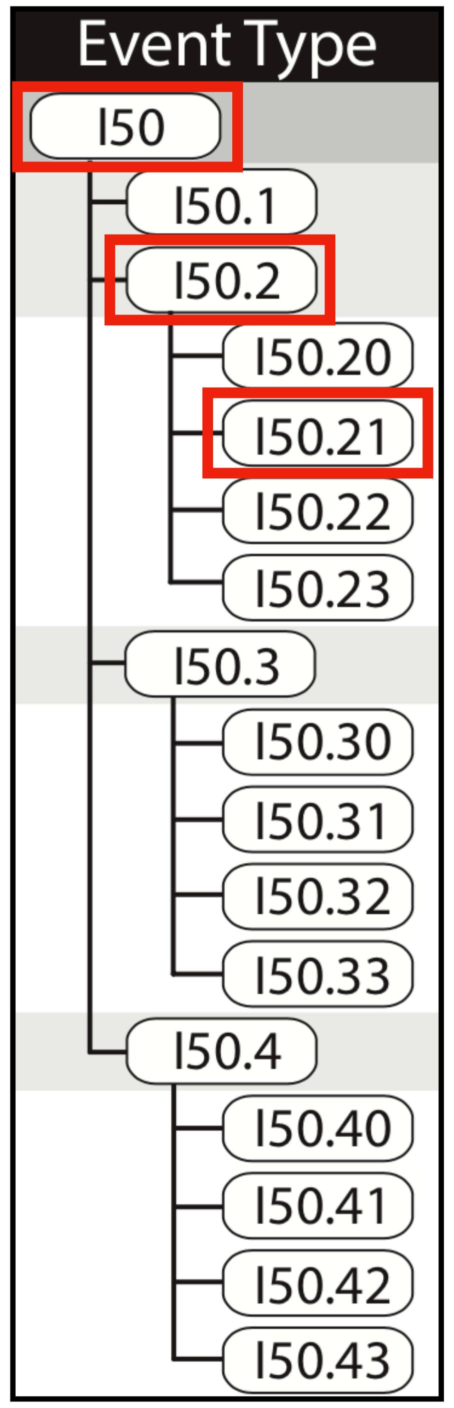


High-dimensional event data

Group events

Grouping Events

- Typically, events are grouped in a **pre-processing** step
- Requires **foreknowledge** and **expertise** about events



Event type hierarchy

ICD-10 Coding System

I50: Heart Failure

I50.2: Systolic Heart Failure

I50.21: Acute Systolic Heart Failure

……

Grouping Events

- Can't change event groups interactively
  - May want multiple groupings — **different levels of detail**
  - An ideal grouping may not exist — **data- and task-dependent**

Cadence

Visual Analysis for Medical Event Sequences

Cadence

Visual Analysis for Medical Event Sequences

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Visual Analysis for Medical Event Sequences

Dynamic Hierarchical Aggregation

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Dynamic Hierarchical Aggregation

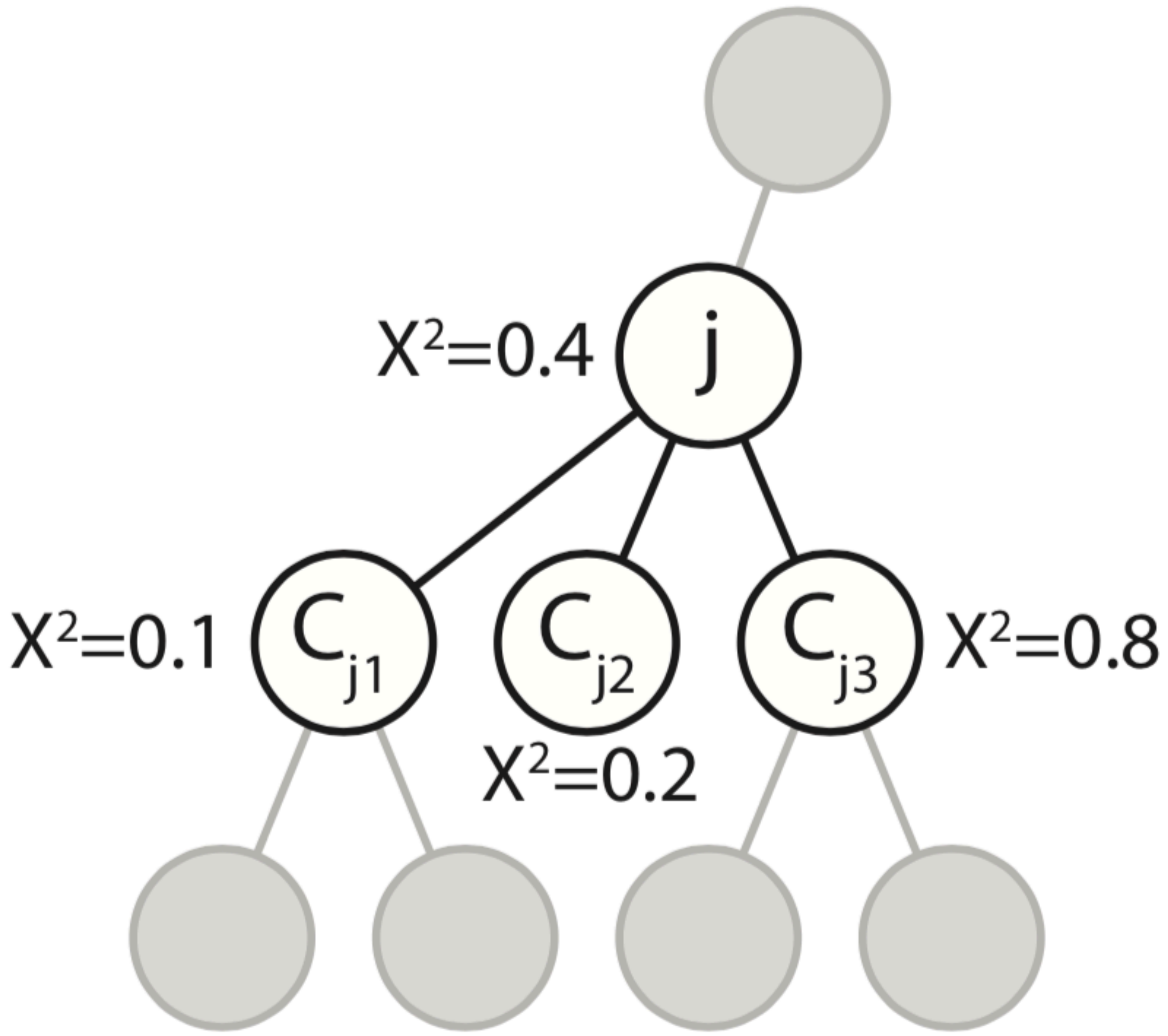
1. Determining an **optimal** and **adjustable** level of grouping events based on an **informativeness score**
2. Supporting navigation of the **event type hierarchy** with a **scatter-plus-focus** visualization
3. **Scenting** to enable discovery of interesting event types

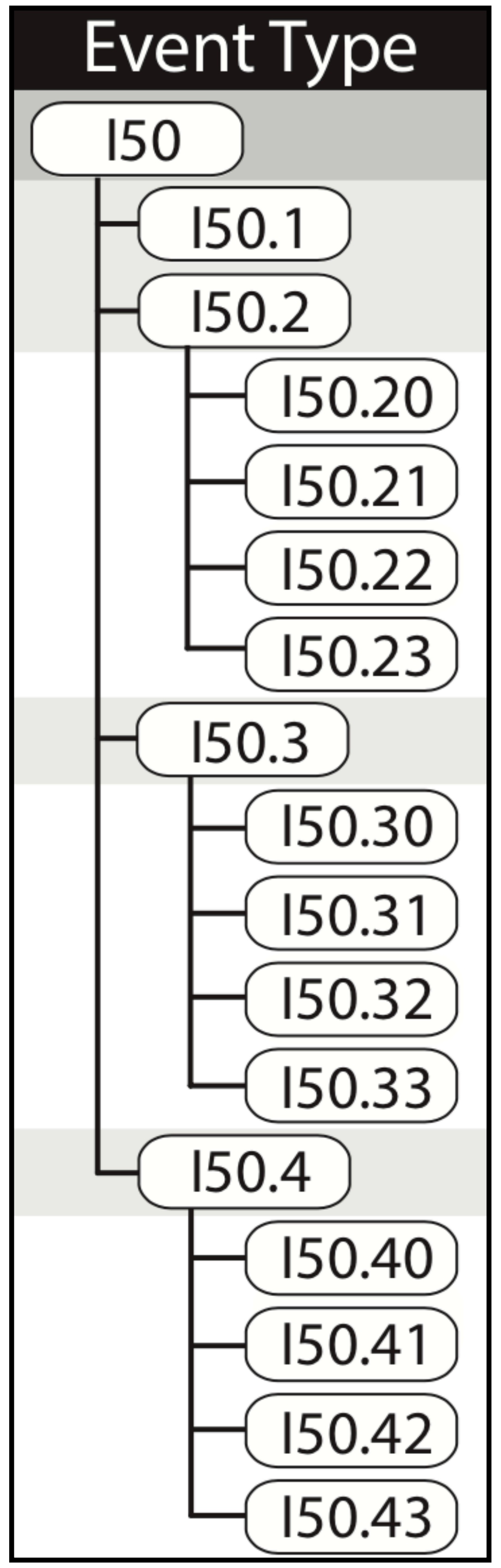
Informativeness Score

- Computed for each event type j in the event type hierarchy
- Measures the **strength of the association** between an **event type** and the **outcome**
    - If this patient had outcome v, did they also experience event type j?
- Based on the **chi-square test statistic** X_j^2

Algorithm: **Optimal Grouping Level**

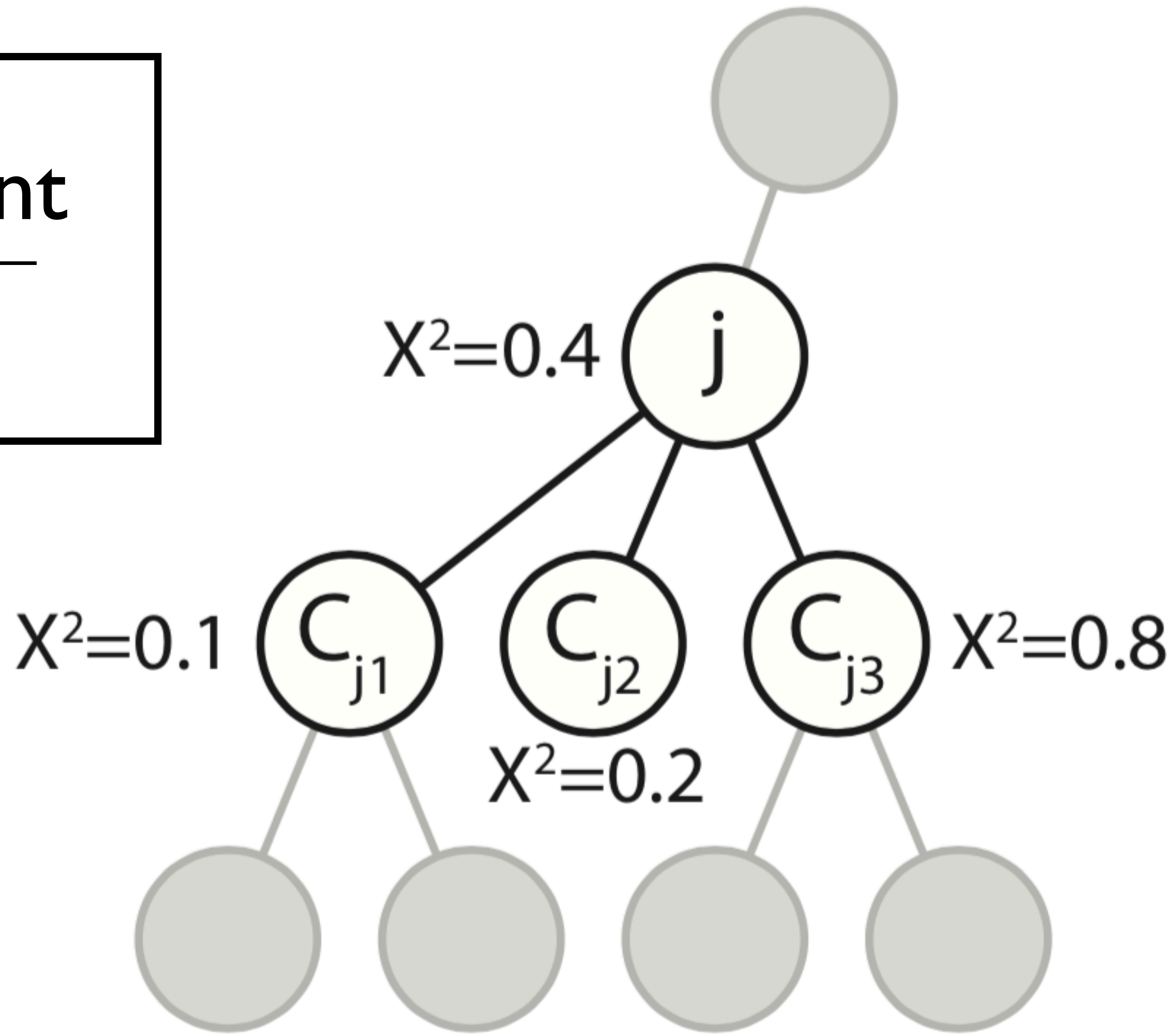
- <u>Goal</u>: Determine the **most informative cut** through the event type hierarchy
- Recursively traverse event type hierarchy
- **Compare informativeness score of parent with each child**





Algorithm: **Optimal Grouping Level**

$$R_j = \frac{\text{\# of children more informative than parent}}{\text{total \# of children}}$$

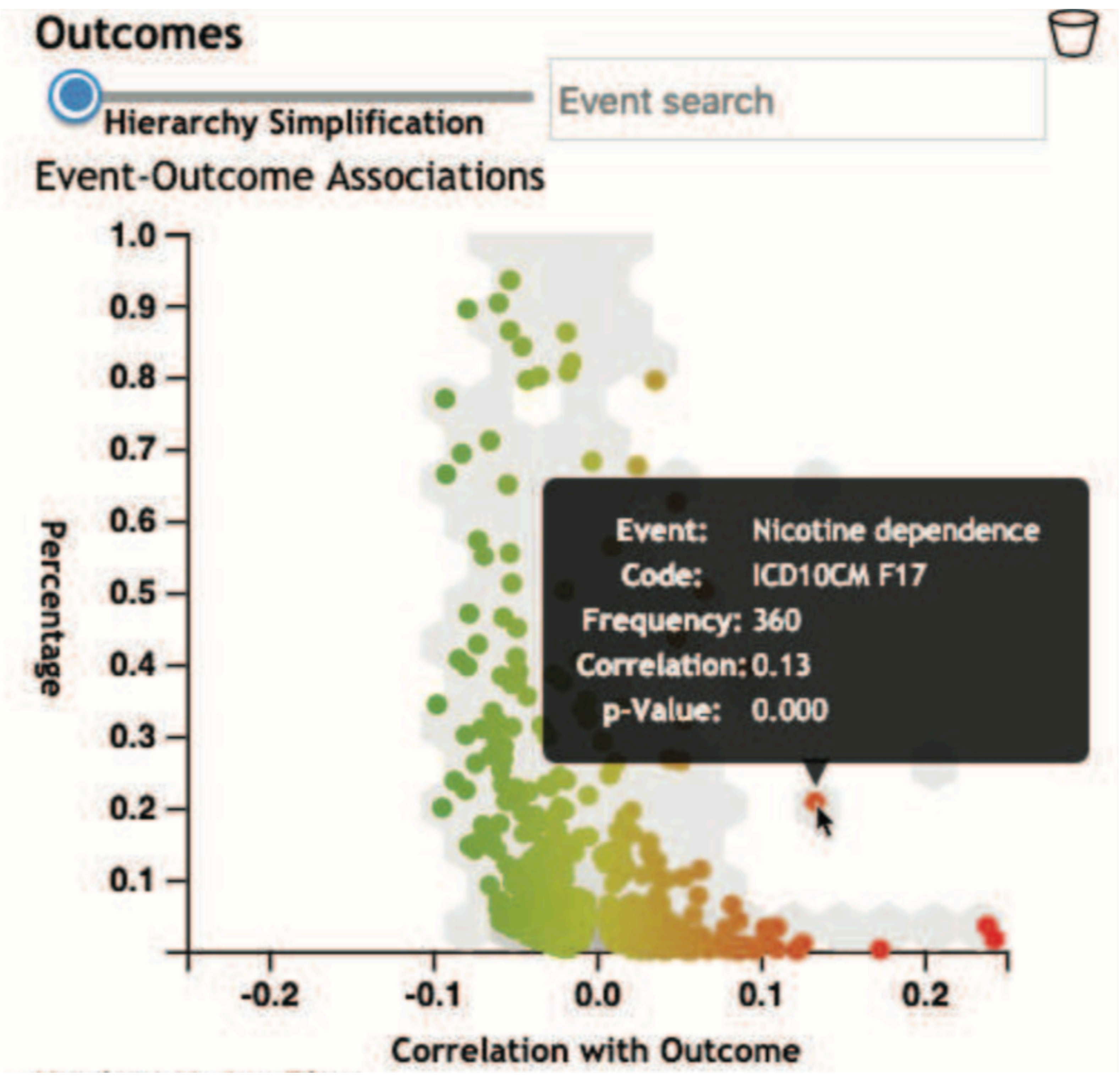


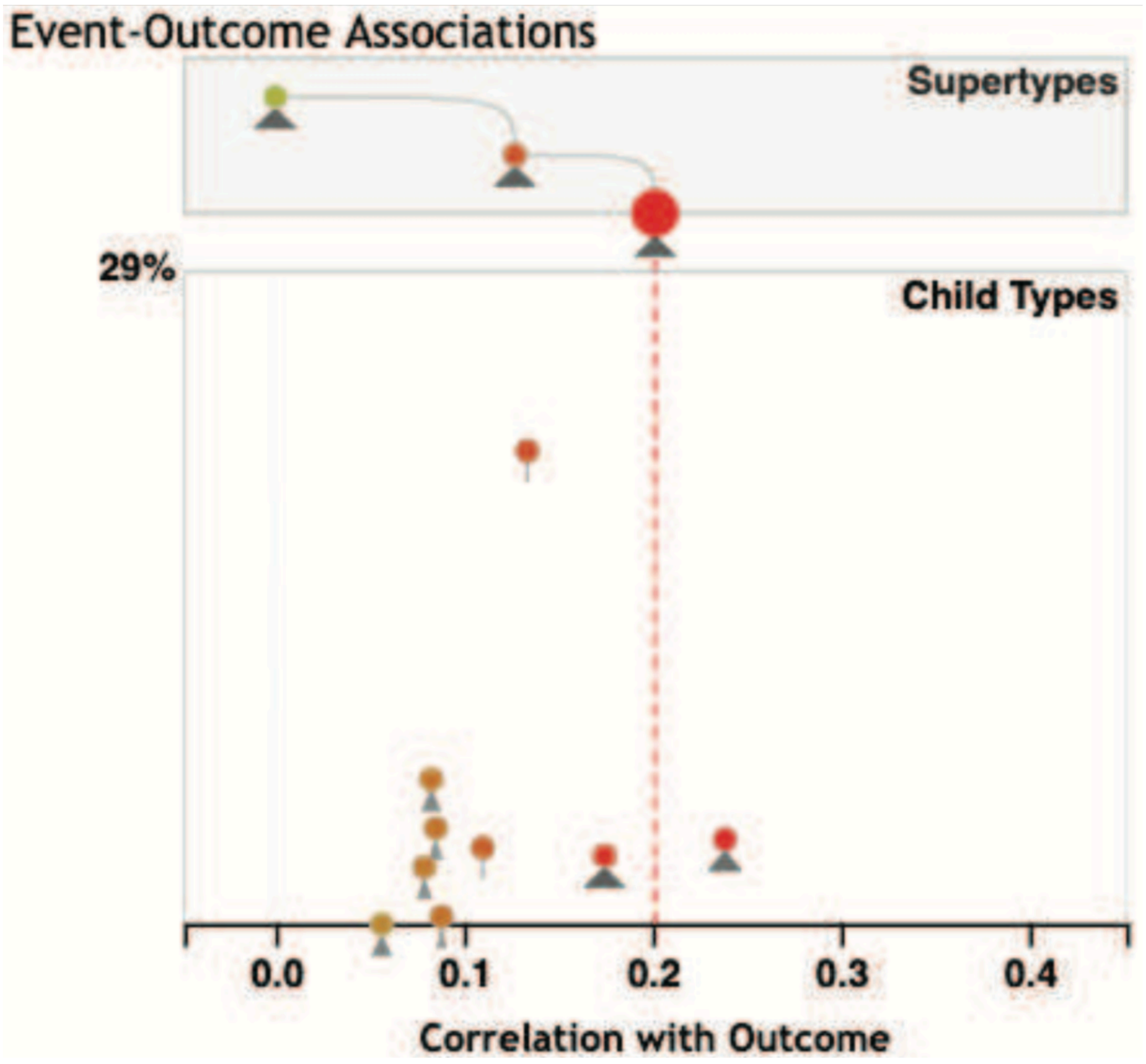
Add j to cut if: (else, recurse)

1. No more children (leaf)
2. $R_j \leq R$ where $0 \leq R \leq 1$

R controls level of aggregation (larger = more aggregation)

Scatter-plus-Focus



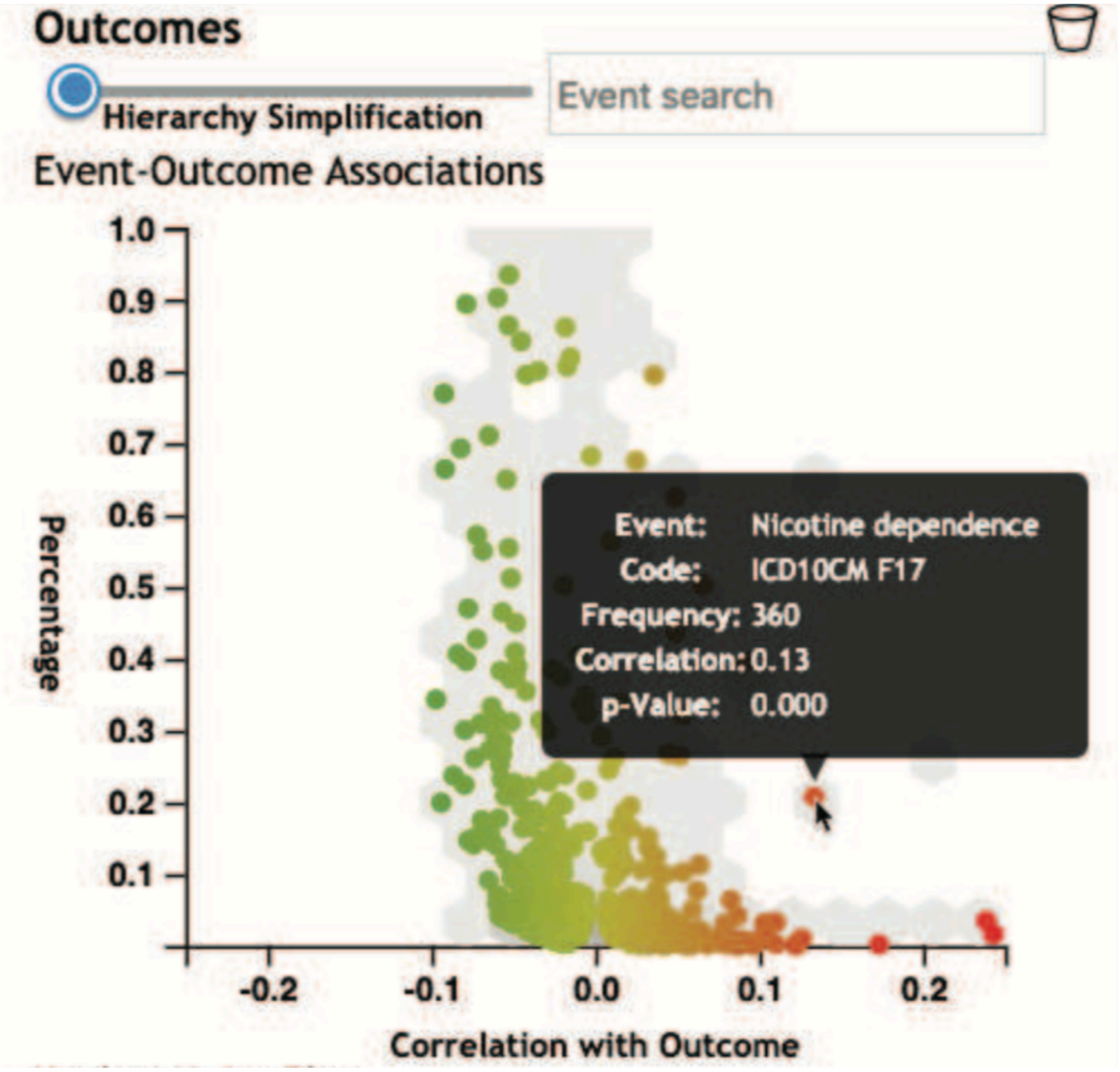


Scatter plot

Focused dual-view

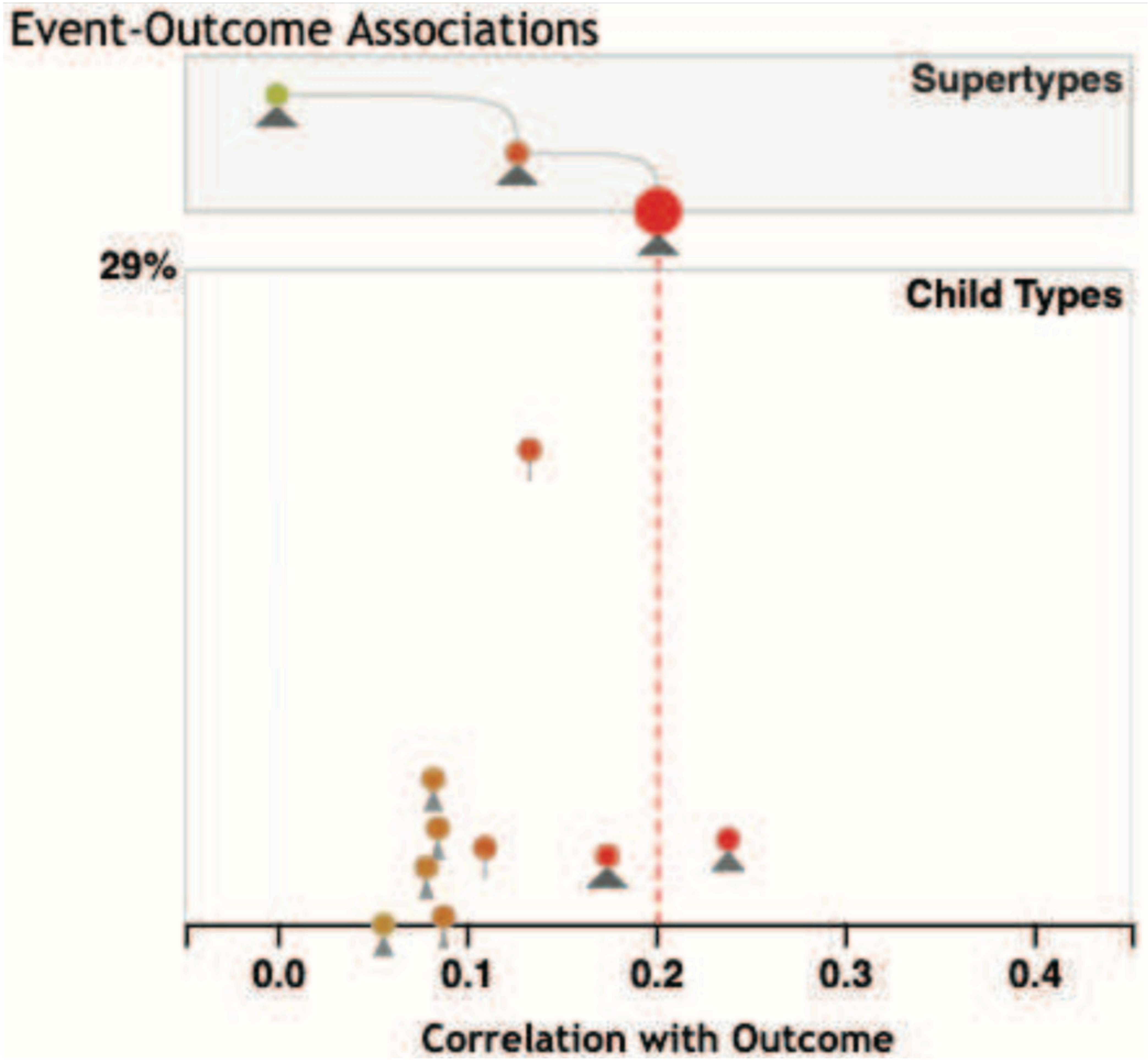
Scatter-plus-Focus

- Challenges of **overplotting!**
- Grey hexes hint at **density** of all possible event types
- Marks are only event types part of **informative cut**
  - Control R with slider



Scatter-plus-Focus

- Focuses on **hierarchy of selected event type**
- X-axis is centred on correlation
- Y-axis: determined by **optimization-based layout algorithm**



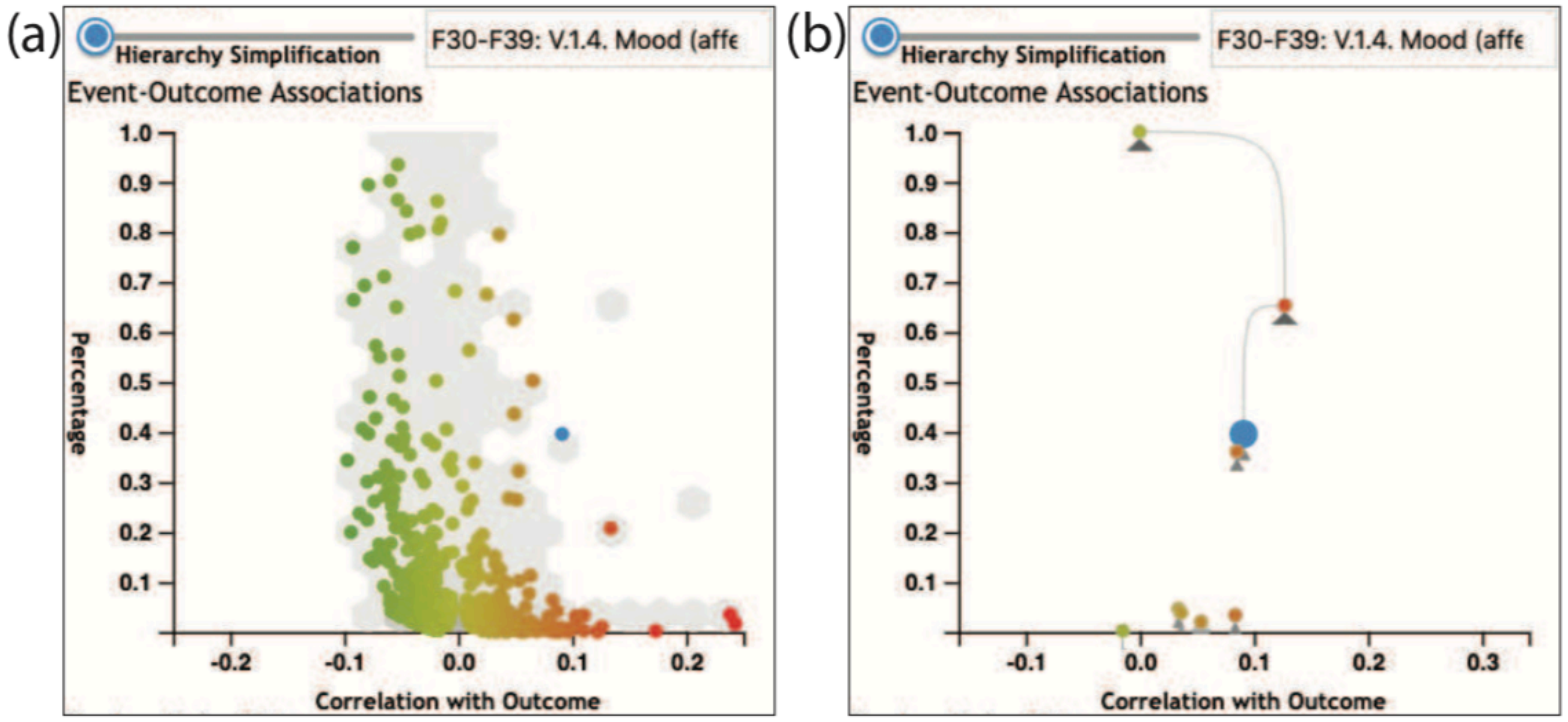
Algorithm: **Optimize Layout**

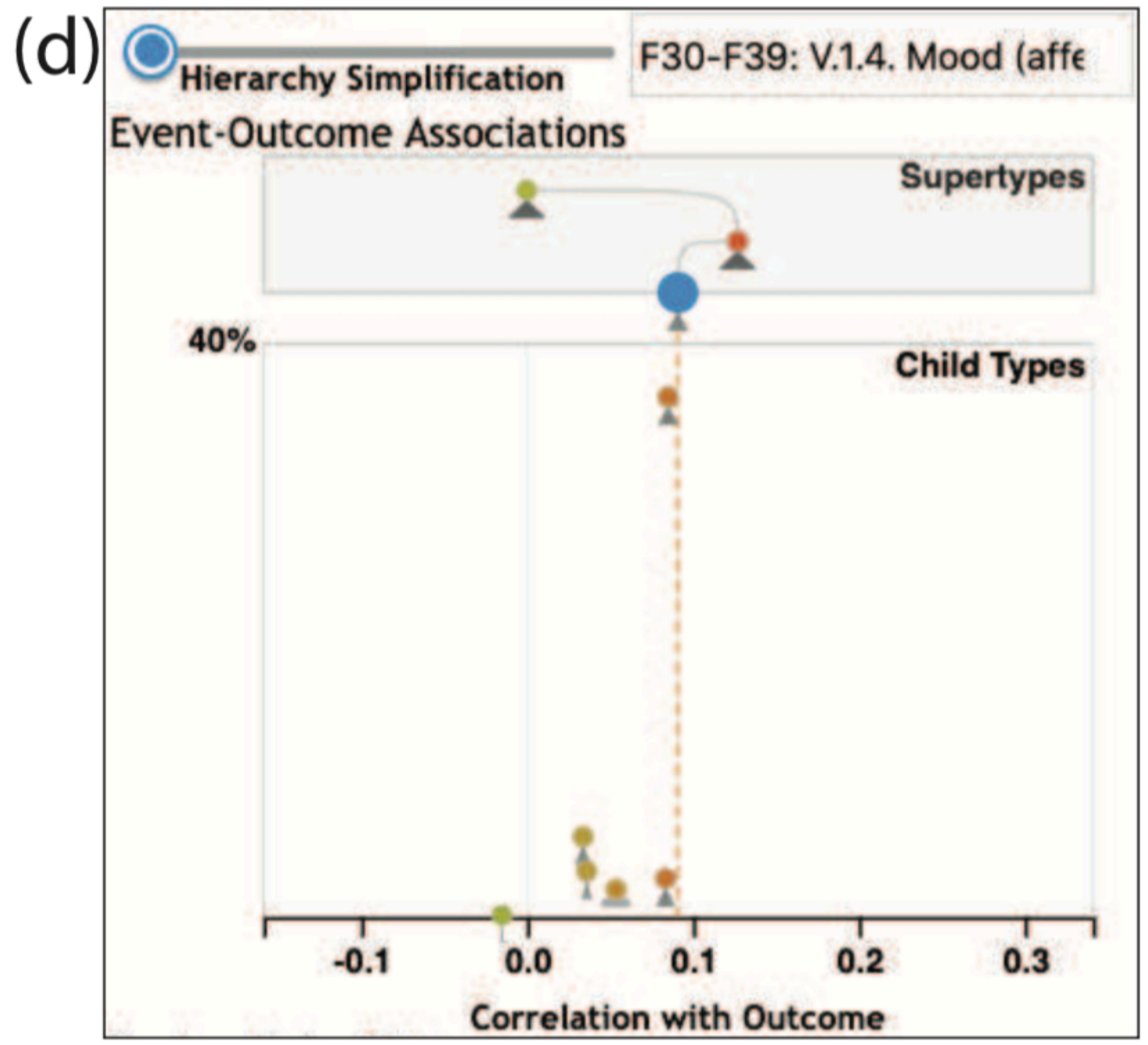
- Cost function that balances **two layout priorities:**
  - Y-positions should be **close to original in scatter view**
  - Marks should **not** overlap
- Two constraints:
  - Optimized y-positions must be within y-axis scale
  - Original y-position **order of marks** must be preserved

Algorithm: **Optimize Layout**

No changes to y-positions

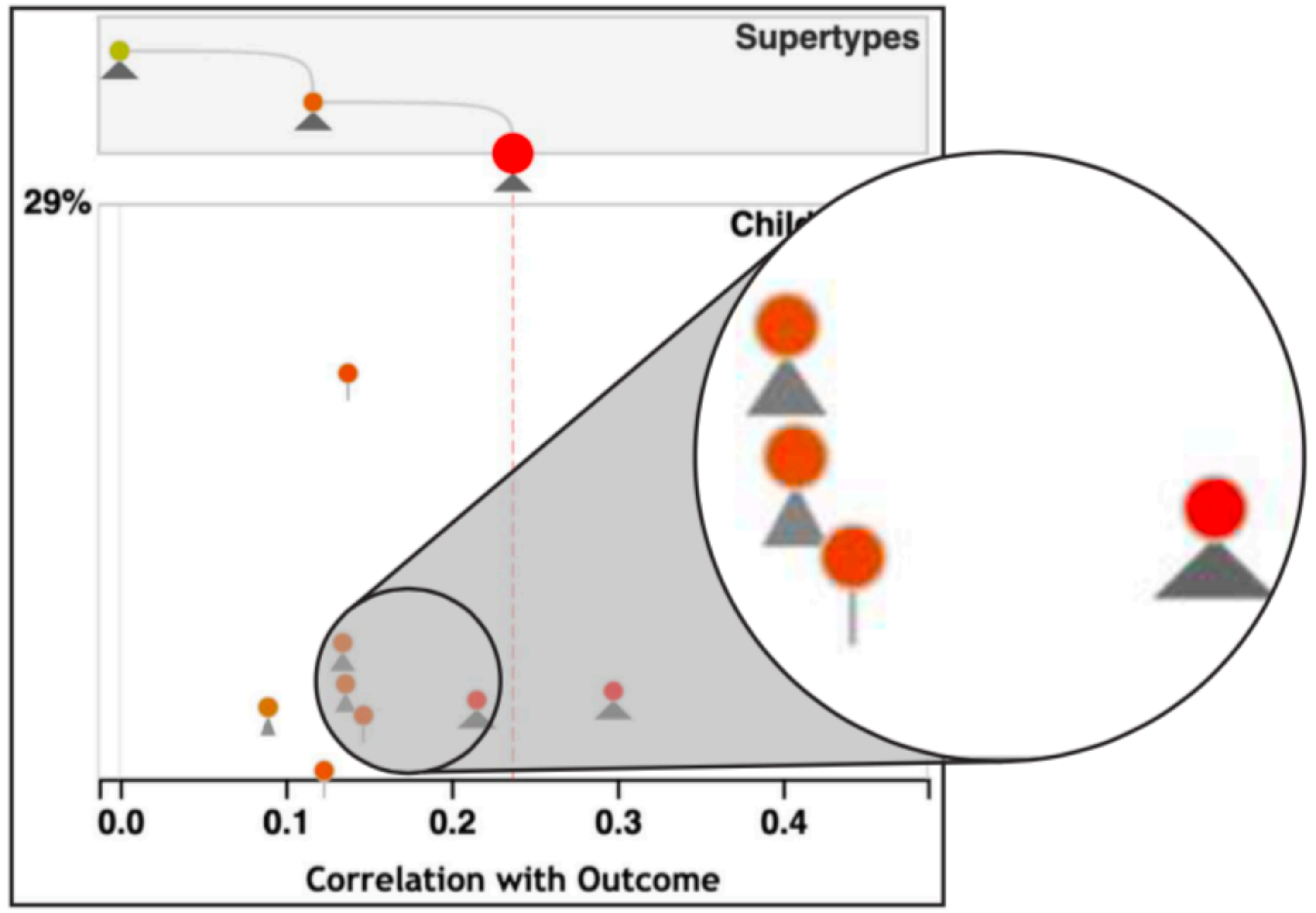
With algorithm

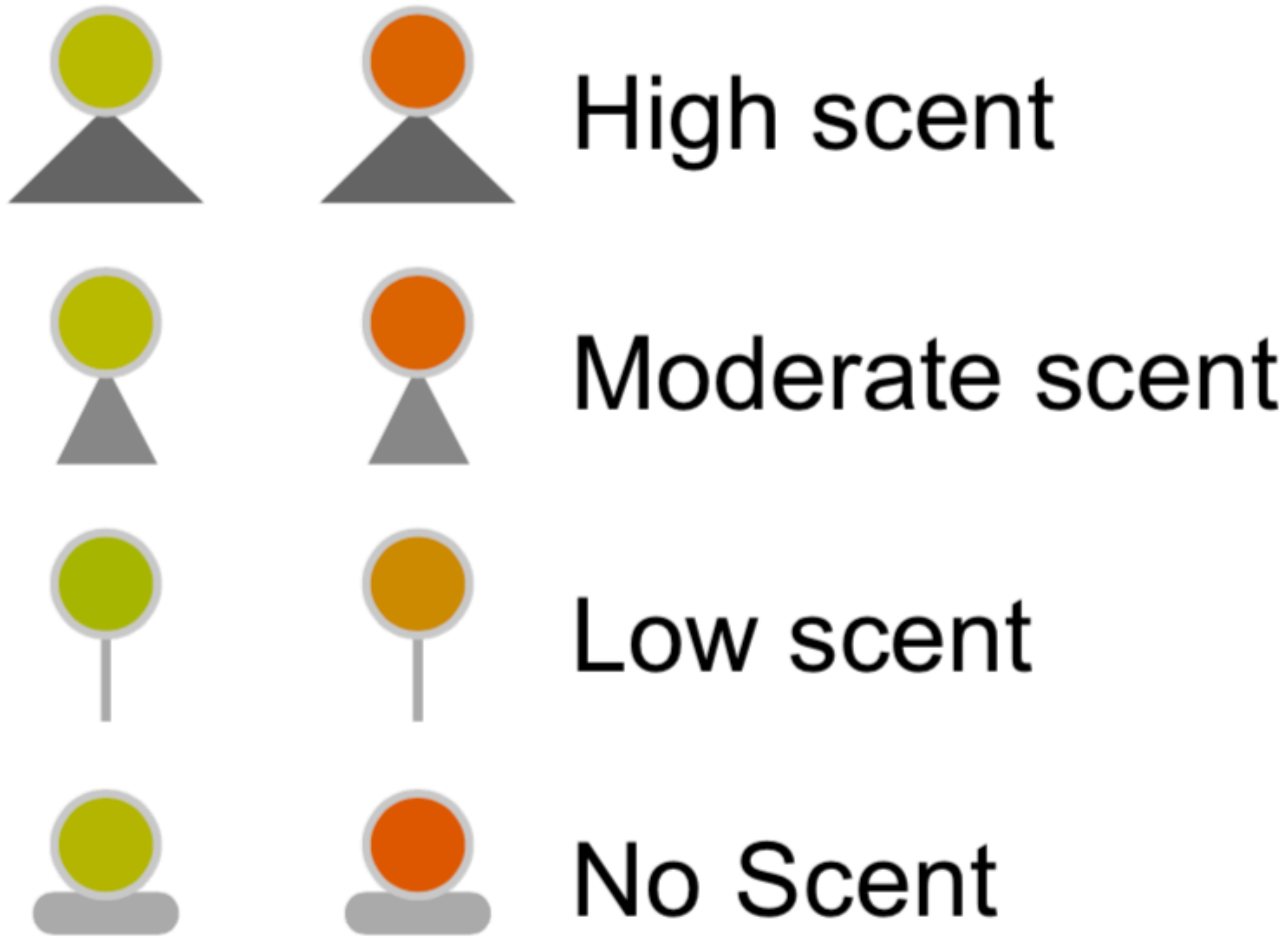




Scenting

- Shows up when exploring type hierarchy in focused view
- Scent value: **range of correlations to outcome** in children
- Size of glyph indicates magnitude of scent value





Evaluation

- **3 medical experts:** health researchers with data analysis experience
- Hands-on demonstration and semi-structured interviews
- Results from **thematic analysis:**
  - Training is required
  - Automated selection of aggregation level useful
  - Navigating through event type hierarchy was intuitive

What-Why-How Analysis

What: Data

- Tree (event type hierarchy)
- Table (patient data)

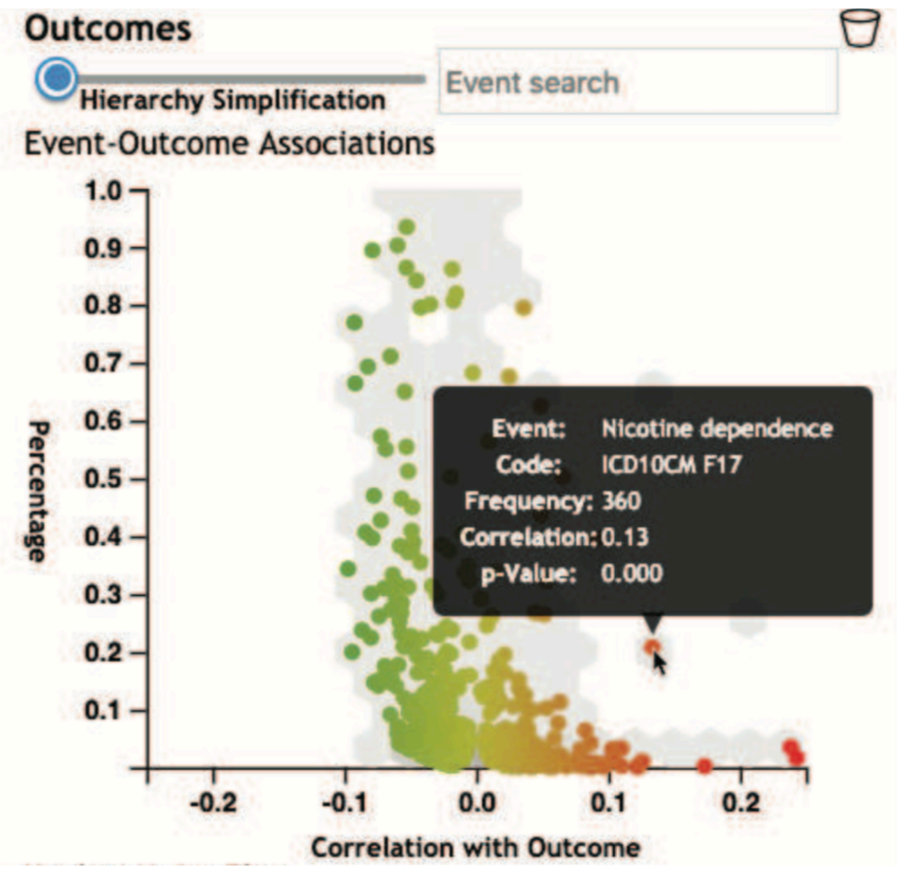
What: Derived

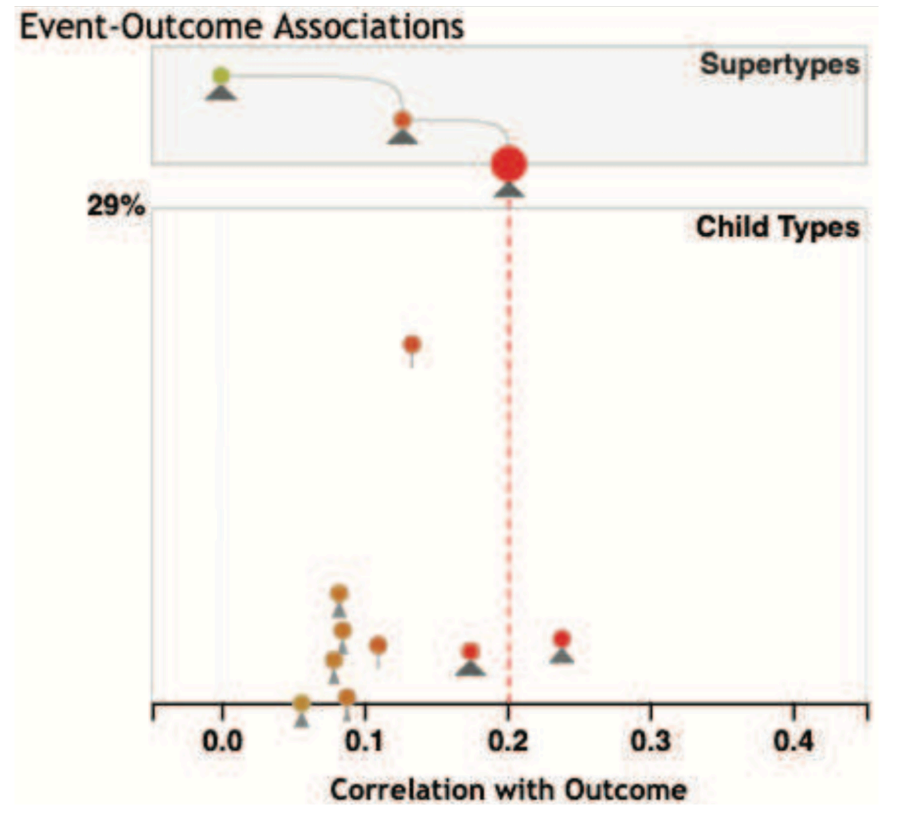
- Optimal event grouping
- Informativeness score, scent value, optimized y-positions

Why

- Discover and produce (event type groupings)

Scale: 5,000 patients, 700,000 events, 10,000 unique event types





What-Why-How Analysis

How: Encode

- Scatterplots
- Color (outcome correlation)

How: Reduce

- Item aggregation (grouping event types)
- Scenting (picking event type)

How: Change

- Select (mark in scatter)

How: Facet

- Overview+detail view (scatter-plus-focus)
- Layering (grey hexes in background)

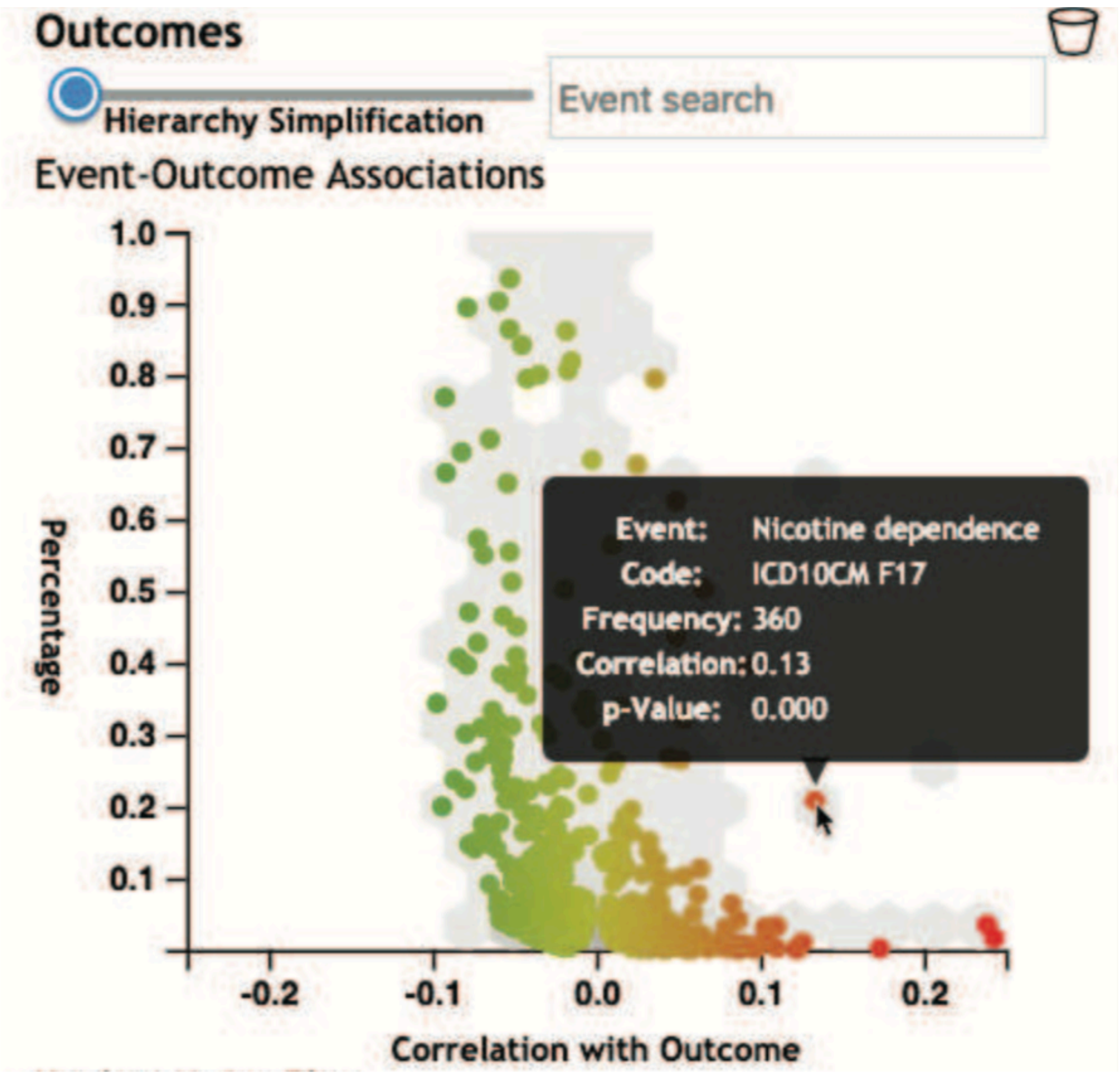
Critique

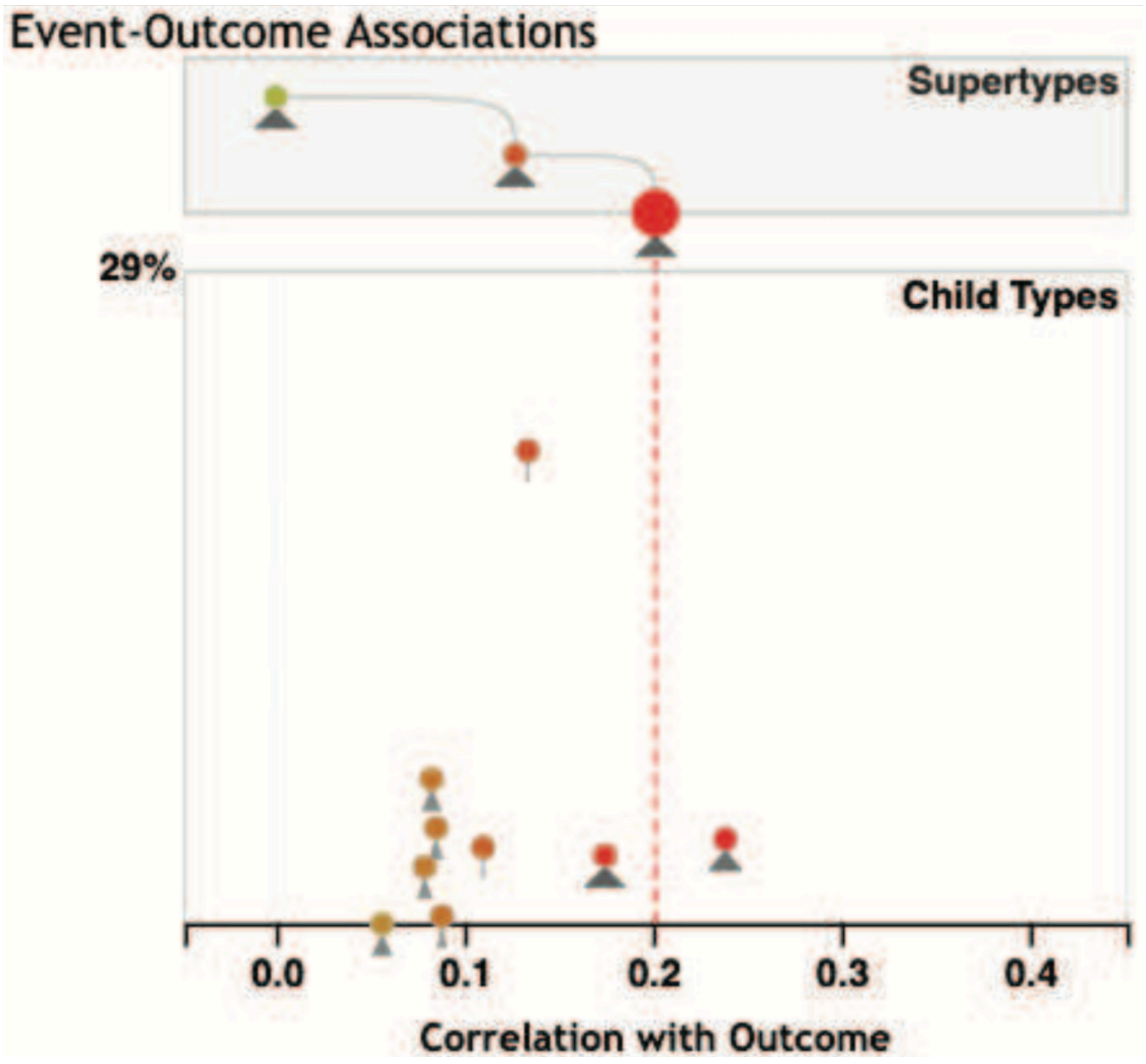
- Strengths
  - Intuitive, simple algorithms
  - Dealt with challenges of occlusion and distortion
  - Switching between views and parameter control reduces load
  - Generalizable to contexts other than health

Critique

- Weaknesses/Limitations
  - Automated approach to aggregation may hide better custom groupings
  - Adding event type groups can be tedious
  - Reliance on tree-based event type hierarchy

Thank You!





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