Sequence Synopsis: Optimize Visual Summary of Temporal Event Data

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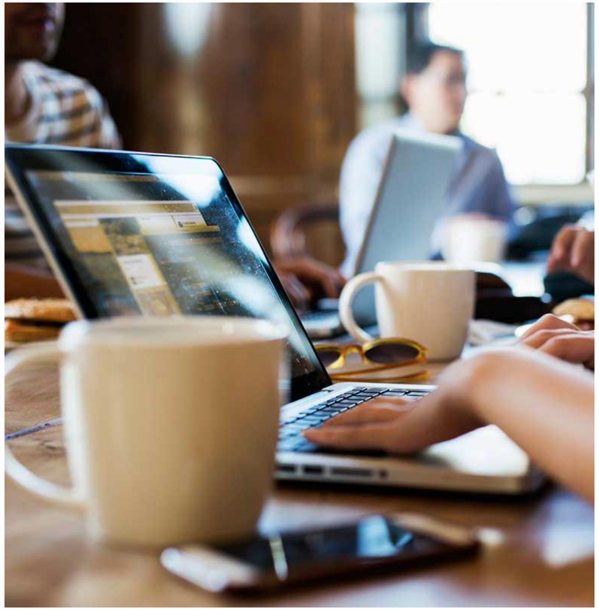
MOTIVATION

Event Sequences
Use Case: Human Activities Analysis



wake up → breakfast → start work

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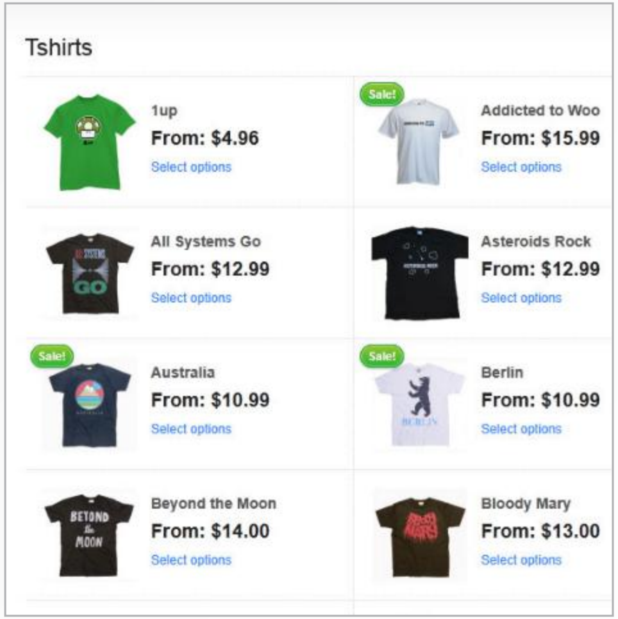
Event Sequences

Use Case: Website Click Streams Analysis



log in → browse products → checkout

Understand customer behavior

Adjust UI design & improve customer experience

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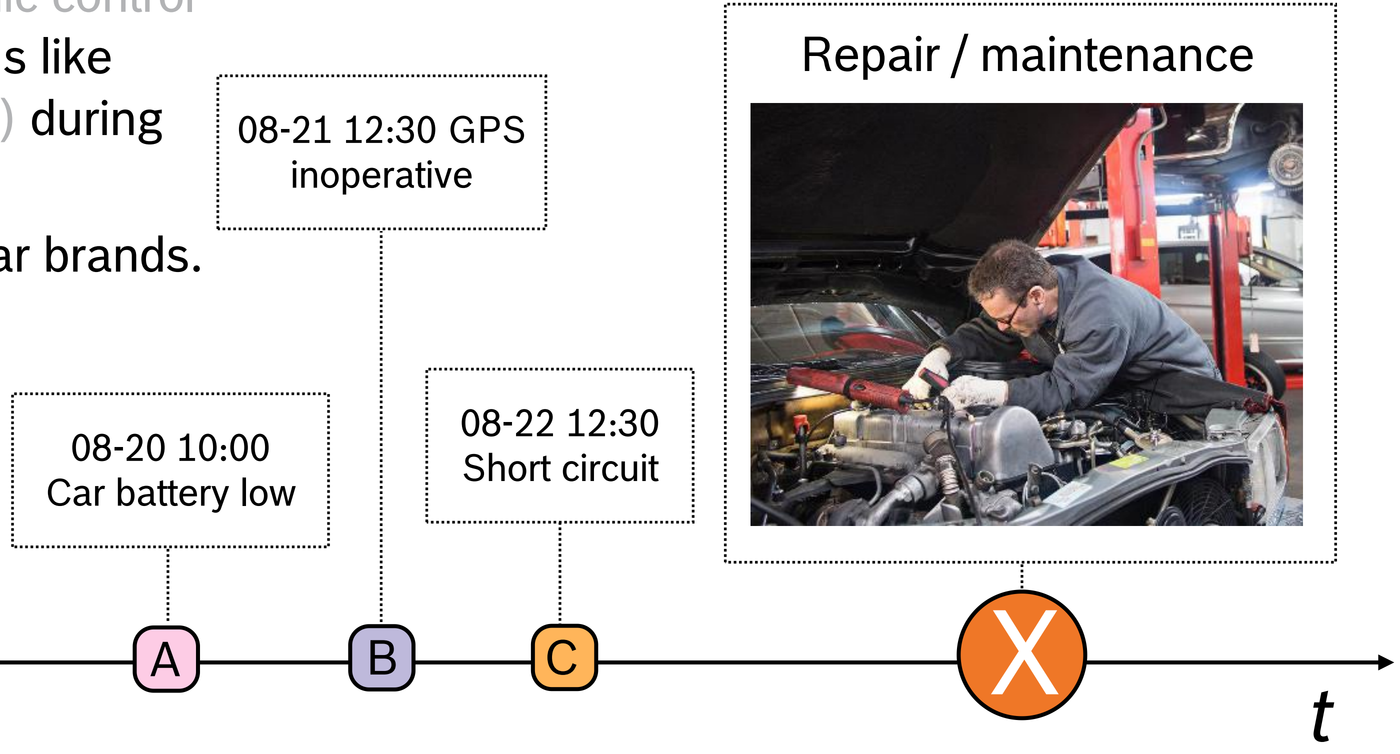
Event Sequences
Use Case: Car Faults Analysis

- Car modules like ECUs (electronic control units) / sensors emits fault signals like DTCs (diagnostics trouble codes) during operation.
- Fault data is archived for most car brands.



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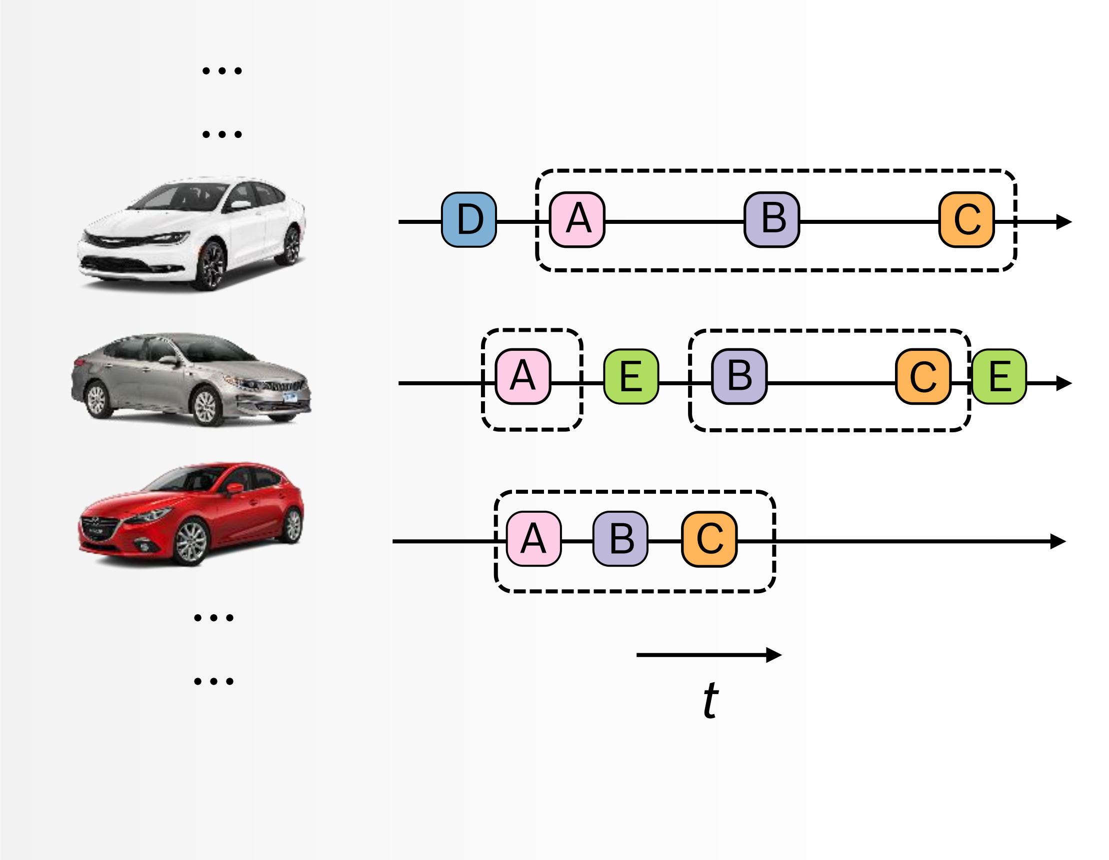
Event Sequences
Use Case: Car Faults Analysis

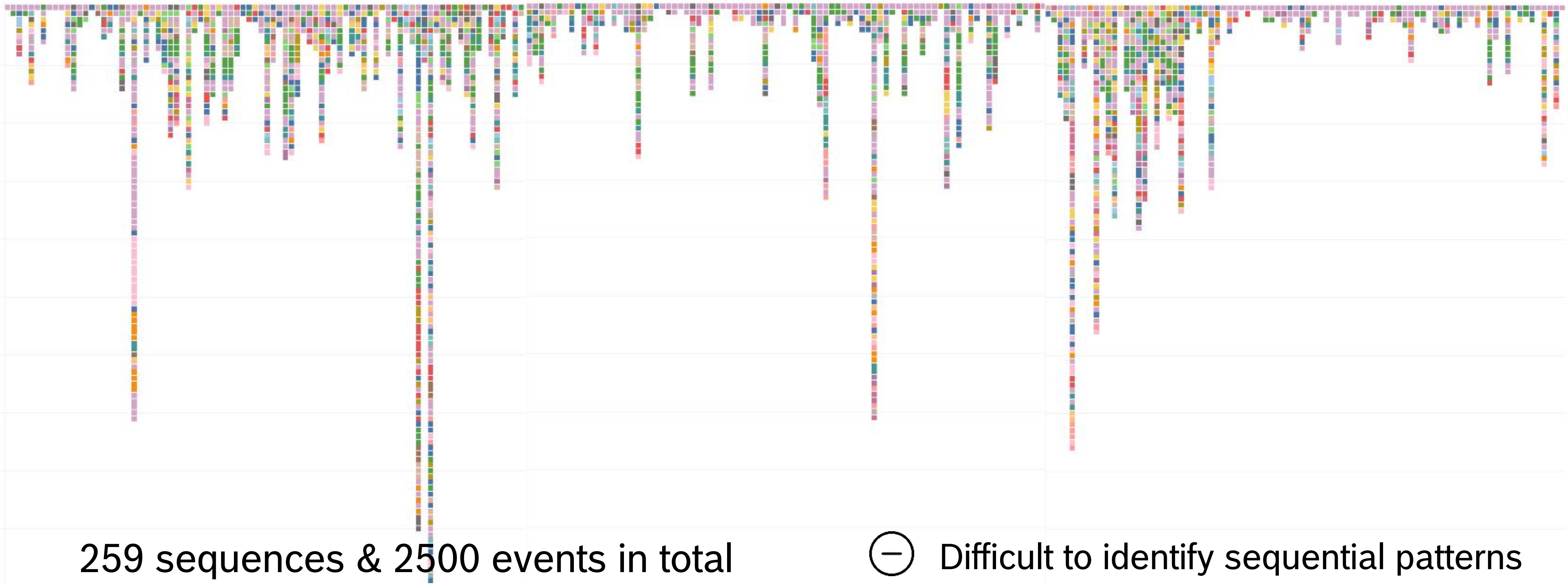


- What are the **typical development paths of faults**? (Identify sequential patterns)
- Do cars matched to the same pattern come from the same country? (correlation analysis)

Insights support predictive diagnostics (i.e. identify faults likely to happen in the future).

Better driving experience & warranty cost saving.

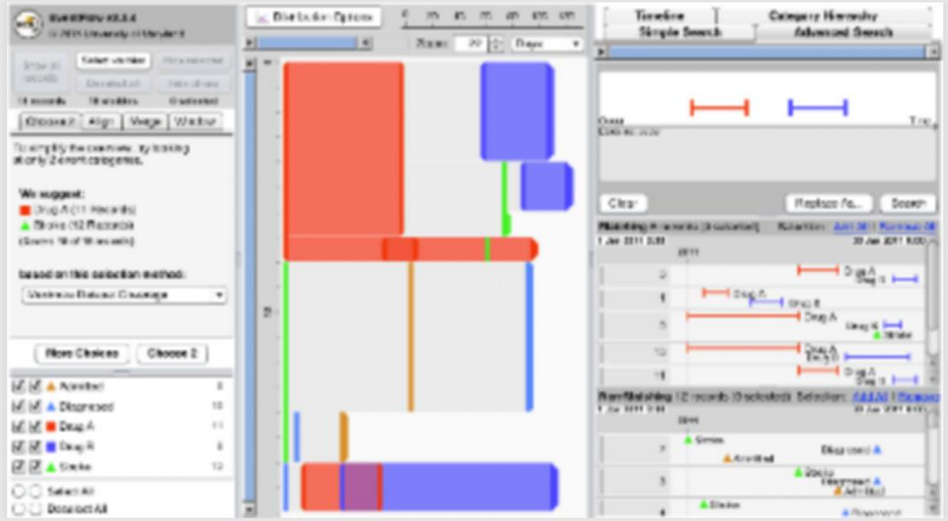
Visualize Event Sequences
Plotting Raw Data



259 sequences & 2500 events in total

⊖ Difficult to identify sequential patterns

Visualizing Event Sequences
Aggregation and Interaction



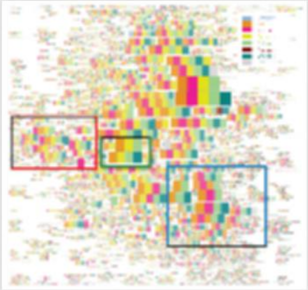
EventFlow
Monroe et. al. 2013

Outflow
Wongsuphasawat and Gotz, 2015

⊕ Provide succinct overview of sequences

⊖ Not robust to noisy data

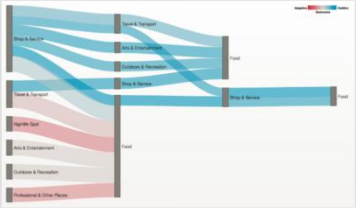
Visualizing Event Sequences
Visual Summary through Sequential Pattern Mining / Clustering



Unsupervised clickstream clustering, *Wang et. al. 2016*

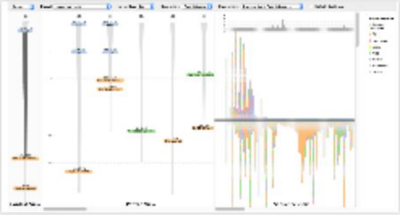
Visual cluster exploration, *Wei et. al. 2012*

- Sequence Clustering
  - ⊕ Robust to noisy data
  - ⊖ Interpretation of clusters: How to characterize each sequence cluster



Frequence, *Perer and Wang, 2014*

Peekquence, Kwon *et. al. 2016*



Patterns&Sequences,

- Sequential Pattern Mining
  - ⊕ Interpretable algorithmic parameters and results
  - ⊖ Large number of patterns: Need to be pruned based on heuristics

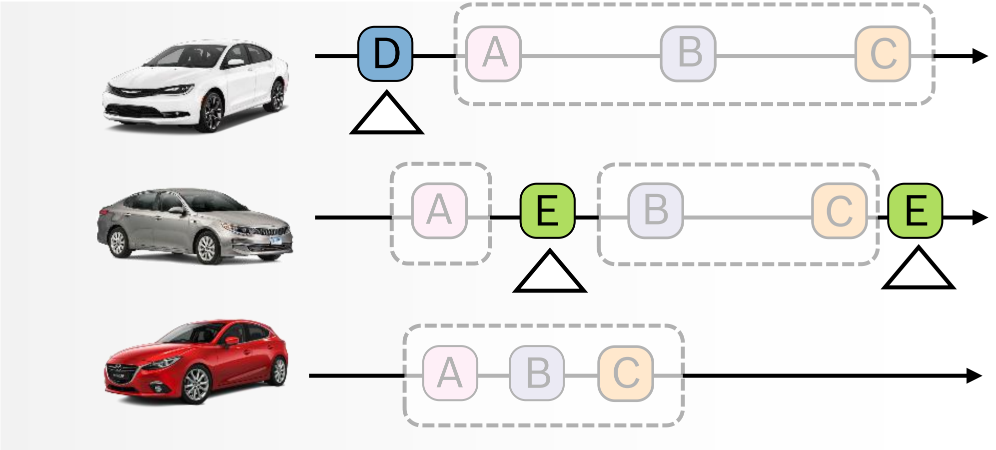
ents

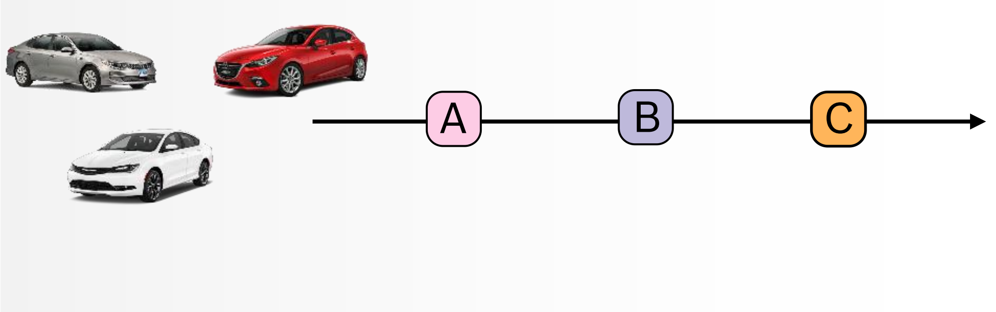
We need to have an **interpretable**, **noise tolerant**, **principled** approach for event sequence summarization.

OUR APPROACH

Our Approach – Sequence Synopsis
Overview

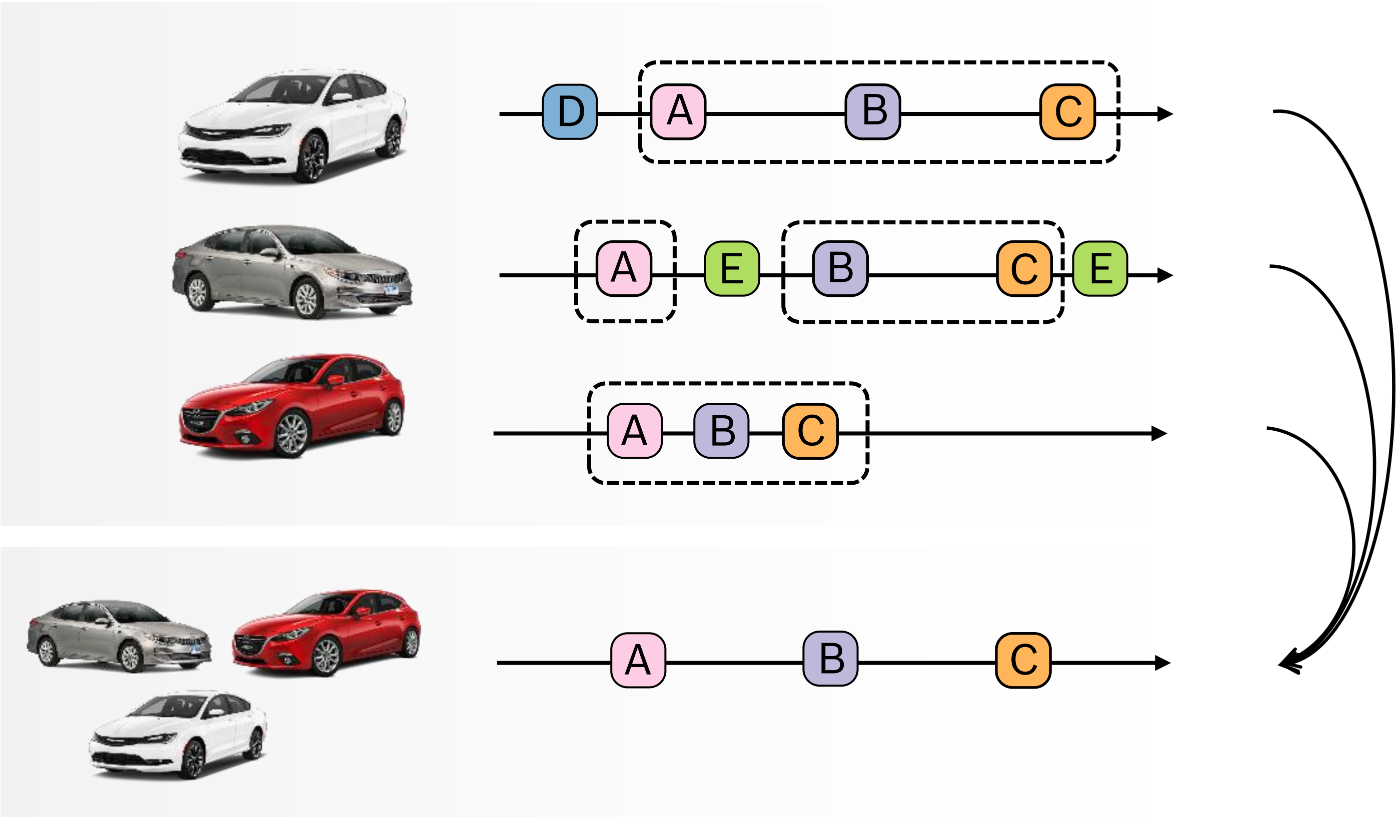
- Two-part representation of event sequences as lossless compression of the data
- Optimal pattern set selection for visual summary based on the Minimum Description Length (MDL) principle
  - Optimization algorithm
  - Speedup with locality sensitive hashing





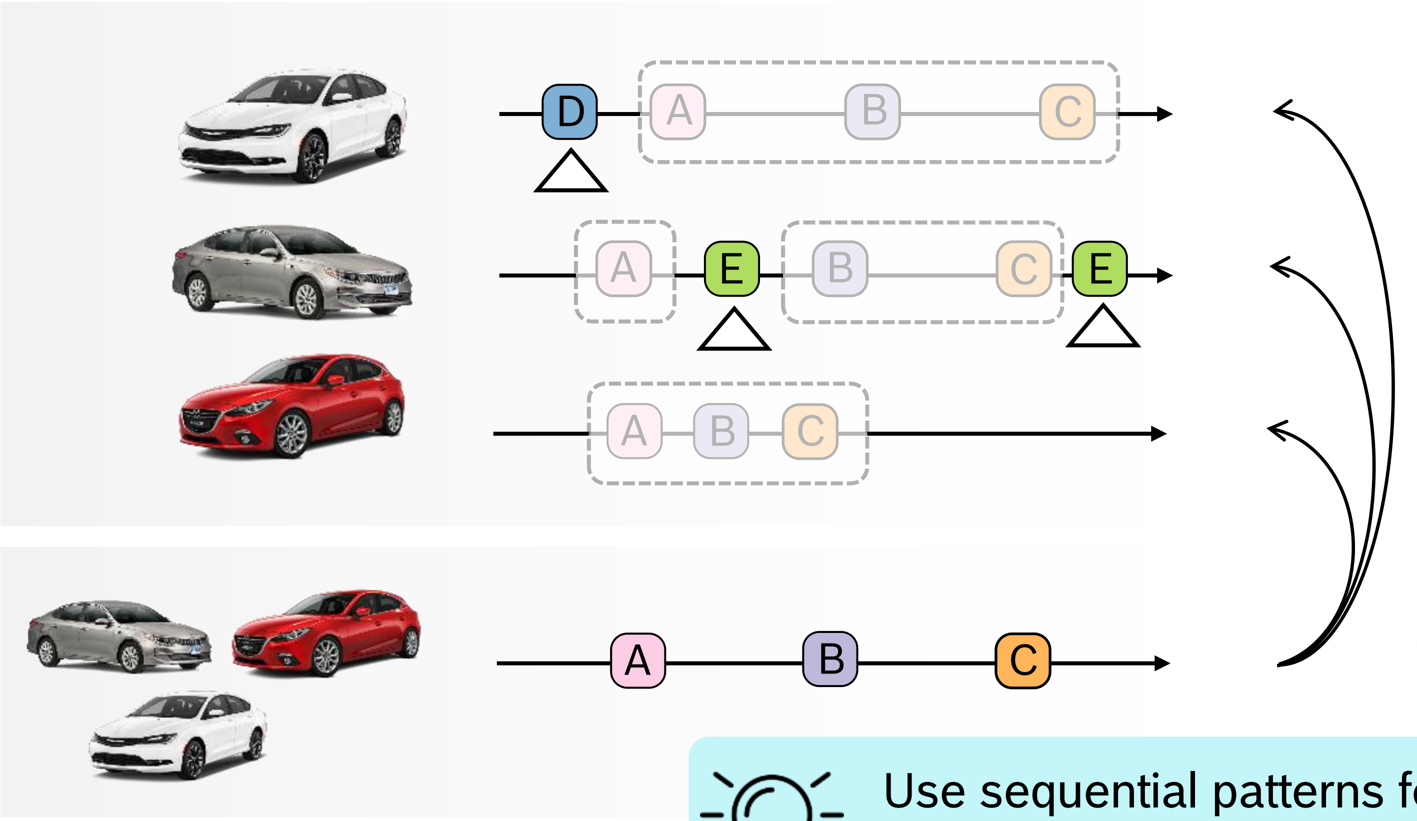
Our Approach – Sequence Synopsis

Two-Part Representation of Event Sequences



*Representative **pattern** summarizes multiple sequences.*

Our Approach – Sequence Synopsis
Two-Part Representation of Event Sequences



Corrections *- event* ***insertions*** *(edits) recover the original sequences from the pattern.*

Representative ***pattern*** *summarizes multiple sequences.*

Use sequential patterns for **visual summary**.

Model **information loss** with the required edits (corrections).

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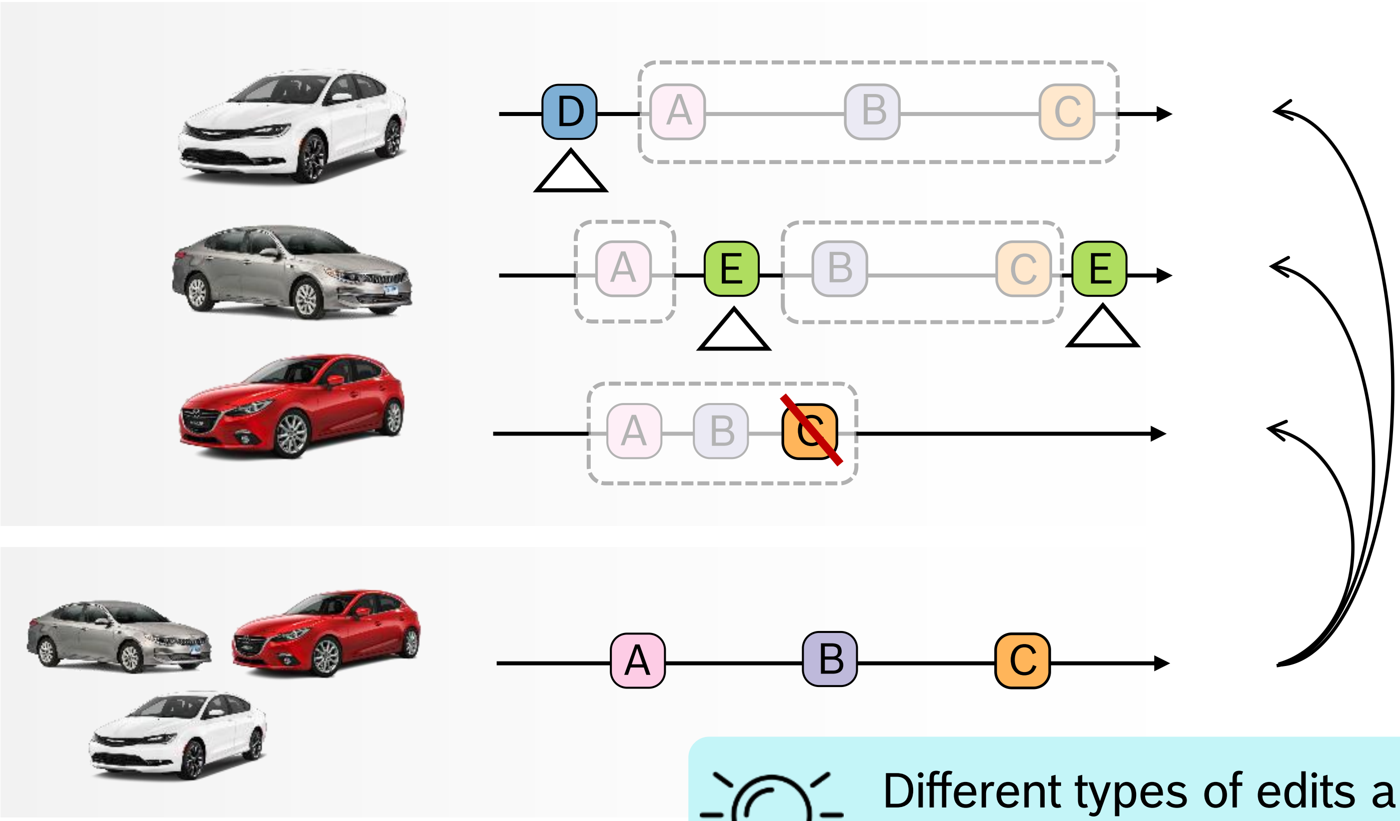
Our Approach – Sequence Synopsis

Two-Part Representation of Event Sequences



*Event **deletion** is another possible type of edit.*

*Representative **pattern** summarizes multiple sequences.*

Different types of edits allow different variations from the pattern. Enable **noise tolerant & robust** pattern matching.

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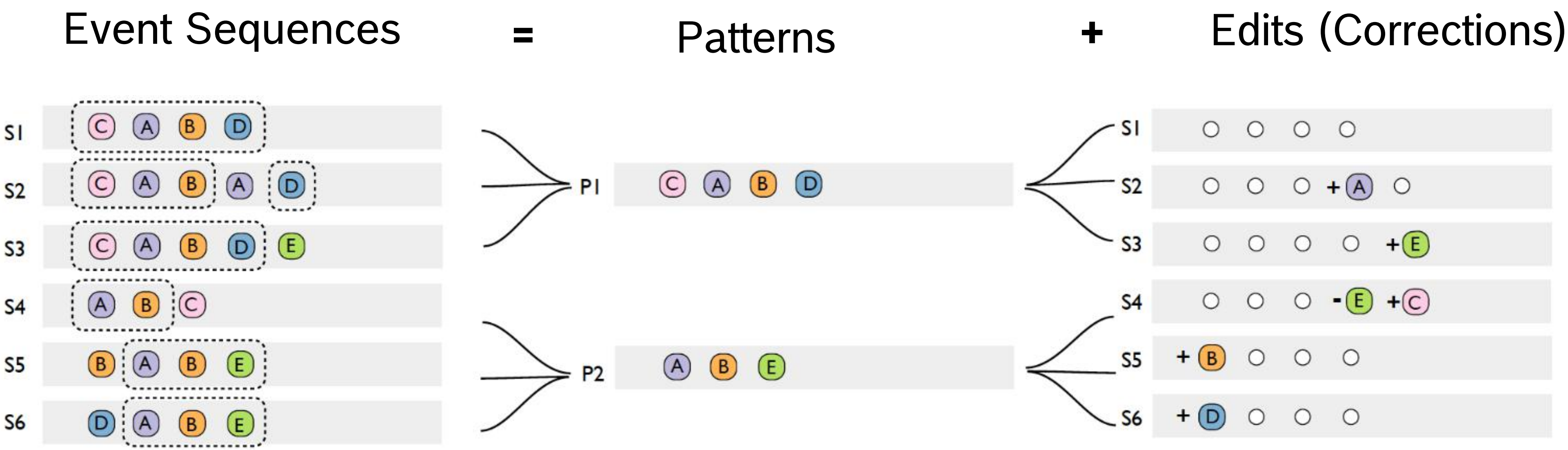
Our Approach – Sequence Synopsis
Two-Part Representation of Event Sequences



What can be considered as a good set of patterns to summarize a collection of event sequences?

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Our Approach – Sequence Synopsis
The Minimum Description Length (MDL) Principle

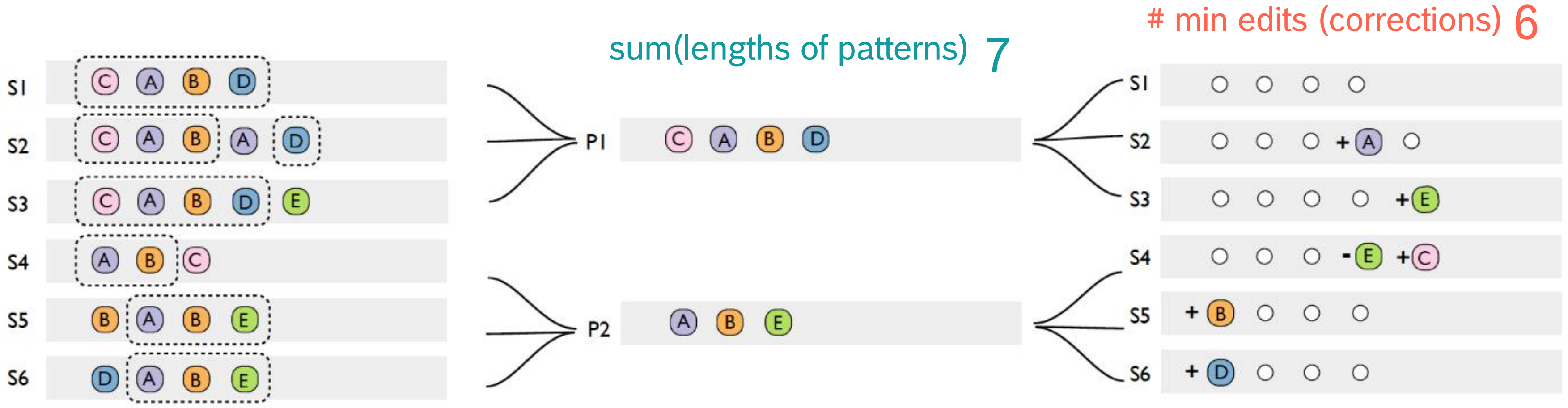
- The best model (or hypothesis) of a data set should minimize its **total description length**:

$$L = \underbrace{L(M)}_{\text{Model description length}} + \underbrace{L(D|M)}_{\text{Data description length with the help of the model}}$$

- Widely used **information-theoretic** criteria for model selection
- Introduced by Jorma Rissanen in 1978
- Formalizes "**Occam's Razor**"

Our Approach – Sequence Synopsis
Description Length of Event Sequences

$$\underbrace{L = L(M)}_{} + \underbrace{L(D|M)}_{} \longrightarrow L(\mathcal{P}, f) = \underbrace{\Sigma_{P\in\mathcal{P}}\, len(P)}_{} + \alpha\, \underbrace{\Sigma_{S\in\mathcal{S}} \|edits(S, f(S))\|}_{} + \lambda\|\mathcal{P}\|$$



Trade-off between **reducing visual complexity** & **minimizing information loss.**

Our Approach – Sequence Synopsis
Optimize Description Length for the Best Set of Patterns

- Basic Idea: **iteratively find & merge** two groups of sequences with maximum description length reduction
- How to calculate description length reduction?
  - Find **representative sequence** for the merged group
  - Calculate the **minimum number of edits** (insertion, deletion, swapping event positions) needed to transform the representative sequence to the individual sequence in the merged group
    - Assuming insertion & deletion are allowed. Longest common subsequence (LCS) algorithm can be applied to calculate min #edits
  - **Sum up** the description length

Our Approach – Sequence Synopsis
Optimize Description Length for Best Set of Patterns

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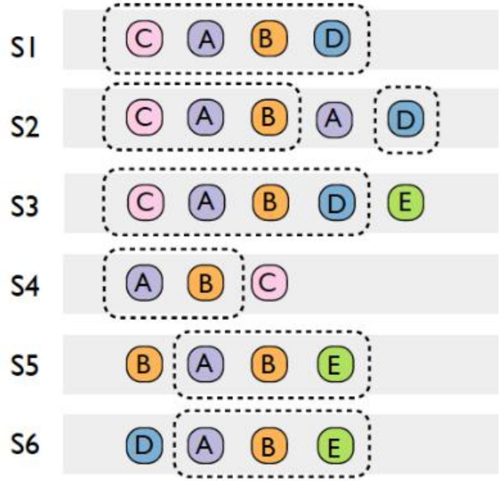

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Optimize Description Length for Best Set of Patterns

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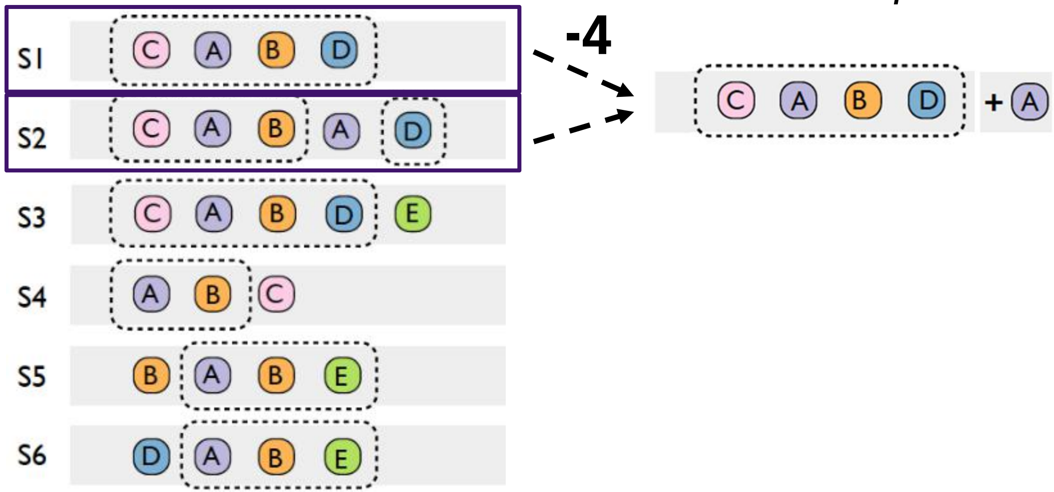
Calculate description length reduction



Try to merge each pair of sequences/patterns

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Optimize Description Length for Best Set of Patterns

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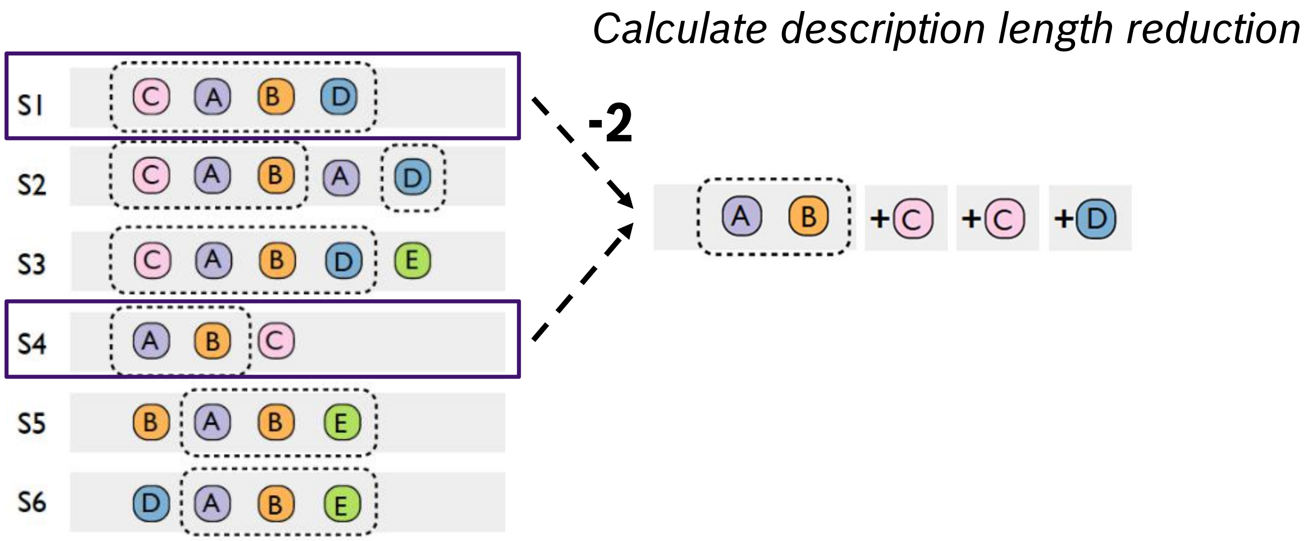

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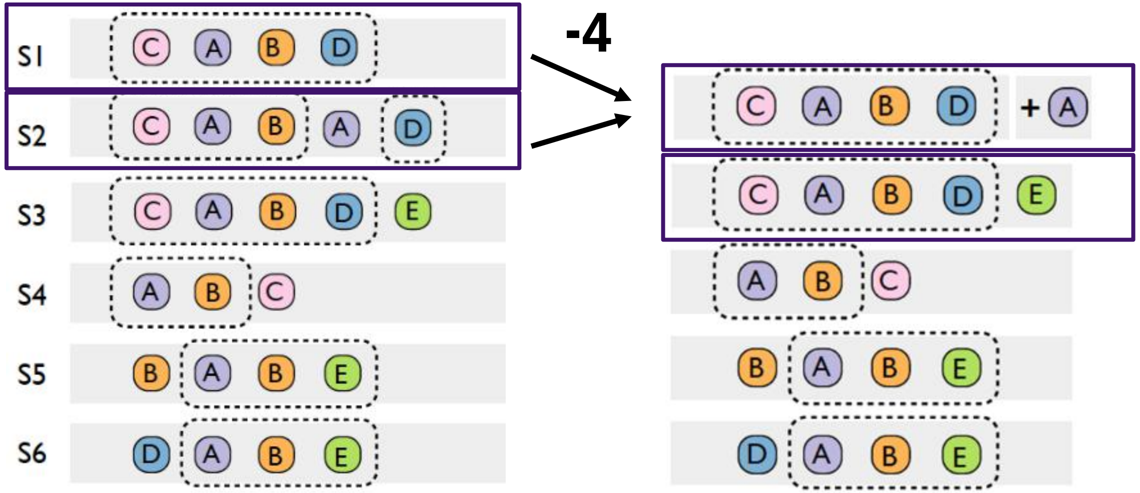

Merge the pair with maximum description length reduction

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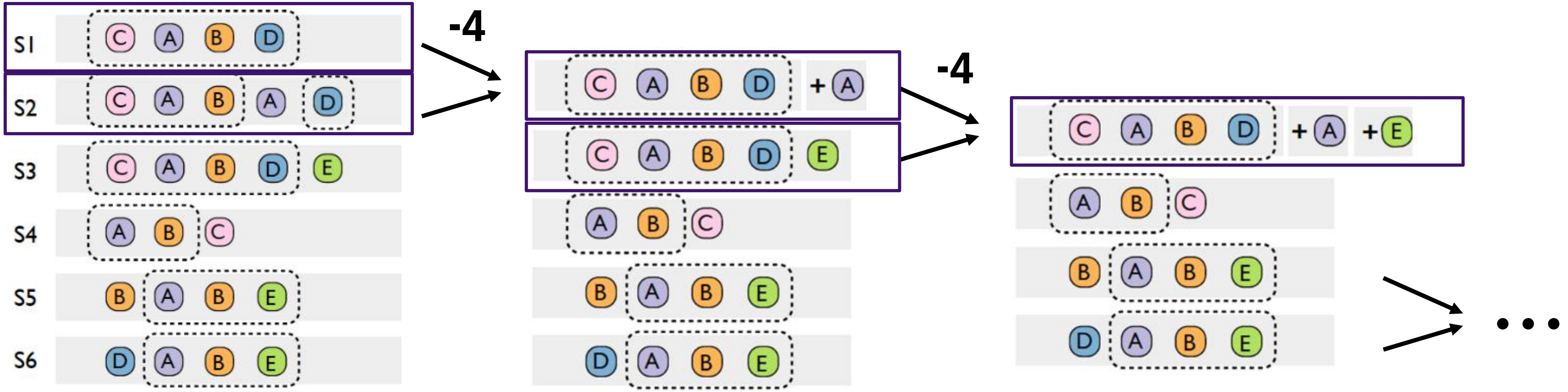
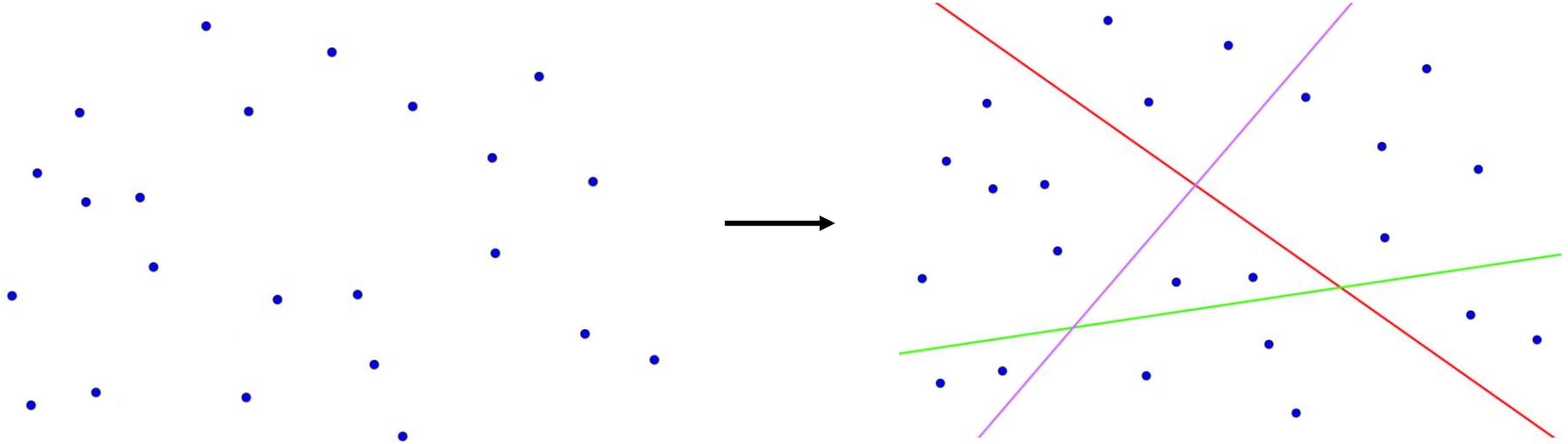


Need to perform pairwise comparison at each iteration

Our Approach – Sequence Synopsis
Algorithm Speedup through Locality Sensitive Hashing (LSH)

- **Bottleneck of the approach:** find best pair of event sequence groups to merge
- **Locality sensitive hashing**: algorithm for fast approximate neighbor search



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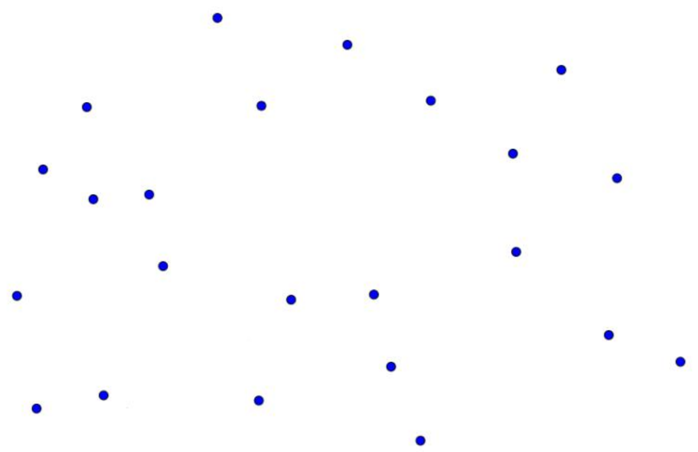

Simplified similarity measure with set relation

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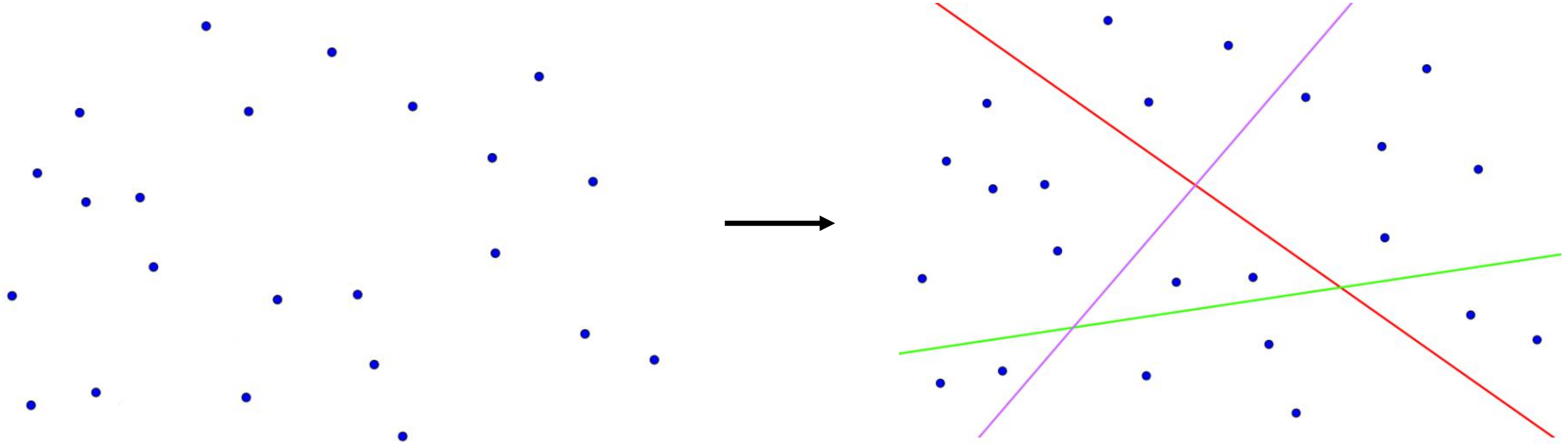

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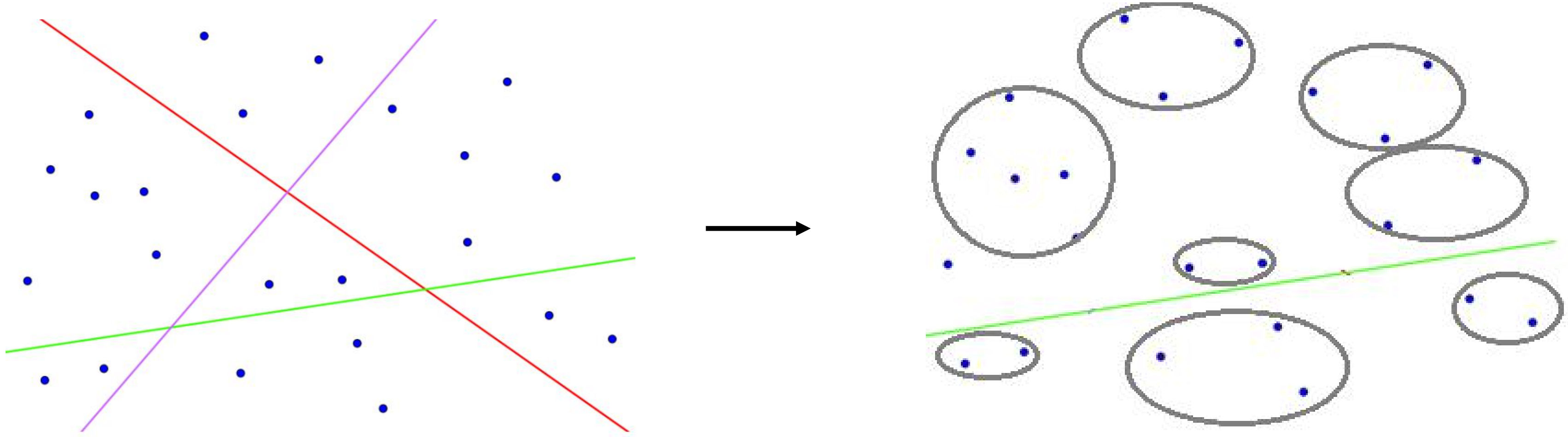

20x ~ 50x speed gain

Our Approach – Sequence Synopsis
Algorithm Speedup through Locality Sensitive Hashing (LSH)

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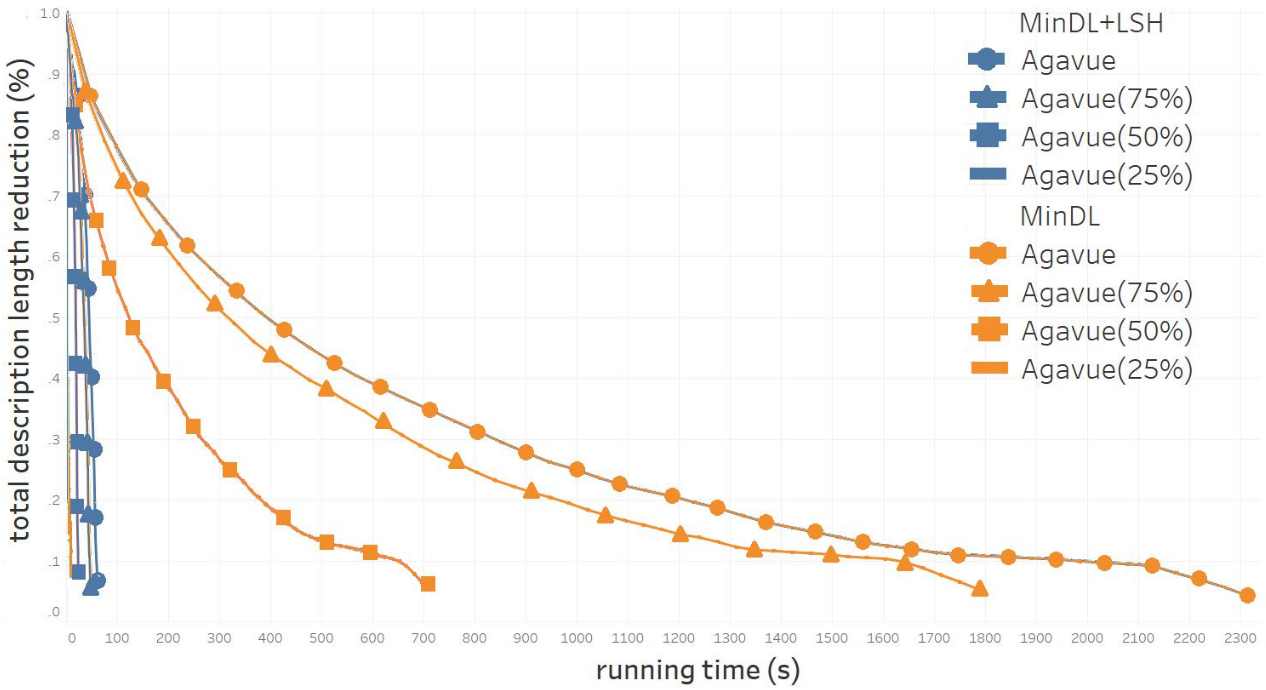
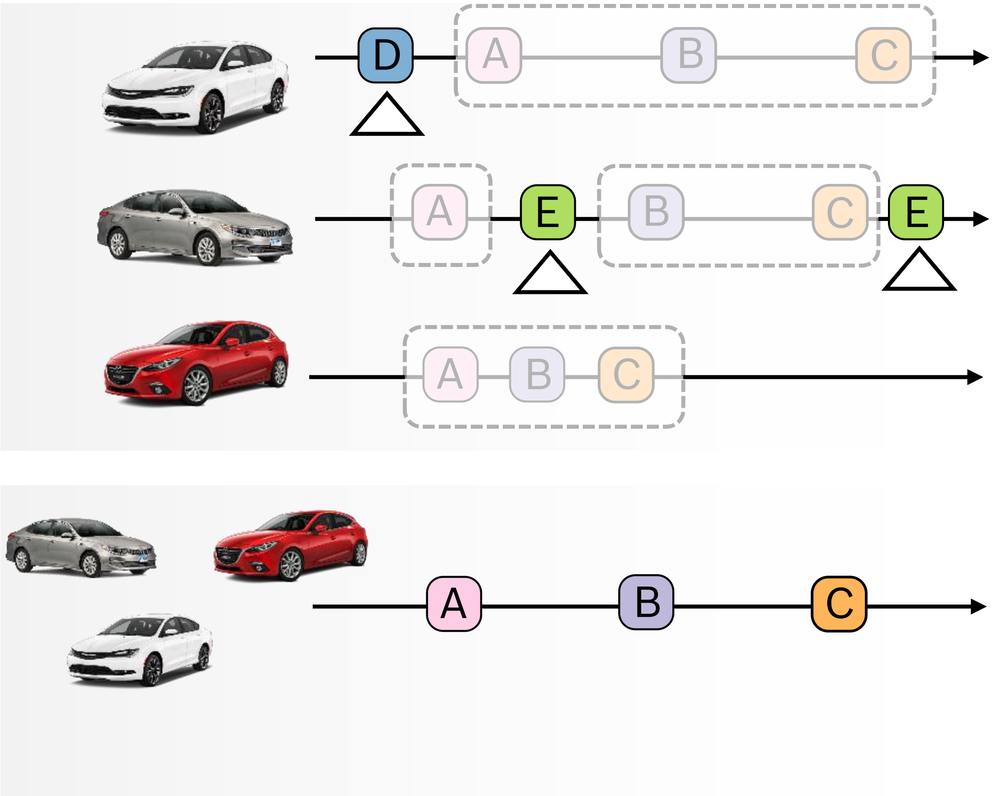


Our Approach – Sequence Synopsis
Advantages

- **Simultaneous** event sequence clustering and pattern extraction
- **Soft constraints** on pattern matching, therefore robust to noisy data
- **Generalizability**: possibility to include different sequence editing operations (e.g. event insertion, deletion, swapping positions)



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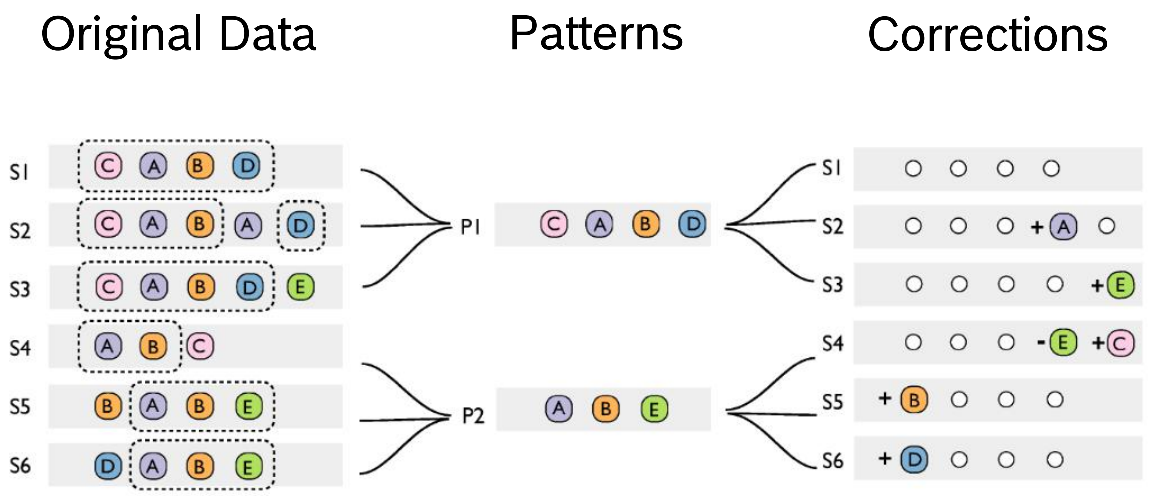
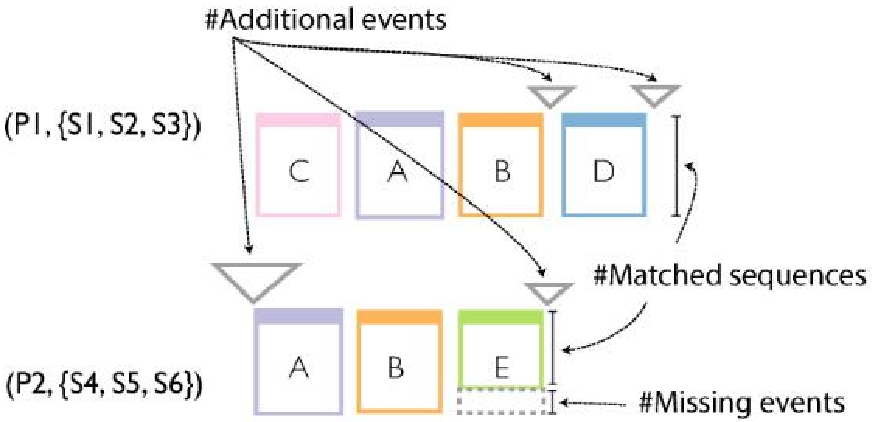
SYSTEM

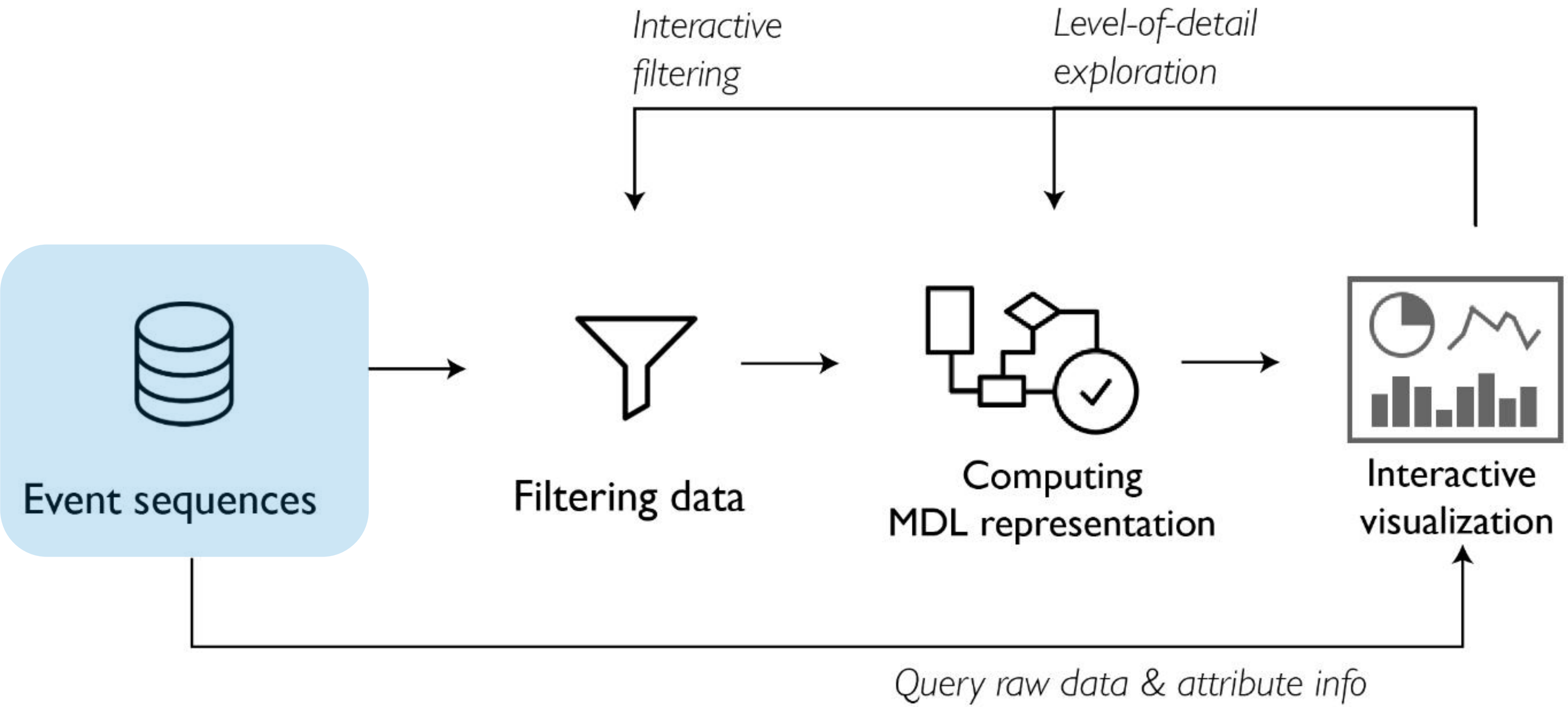
System
Visual Design



Visual Design

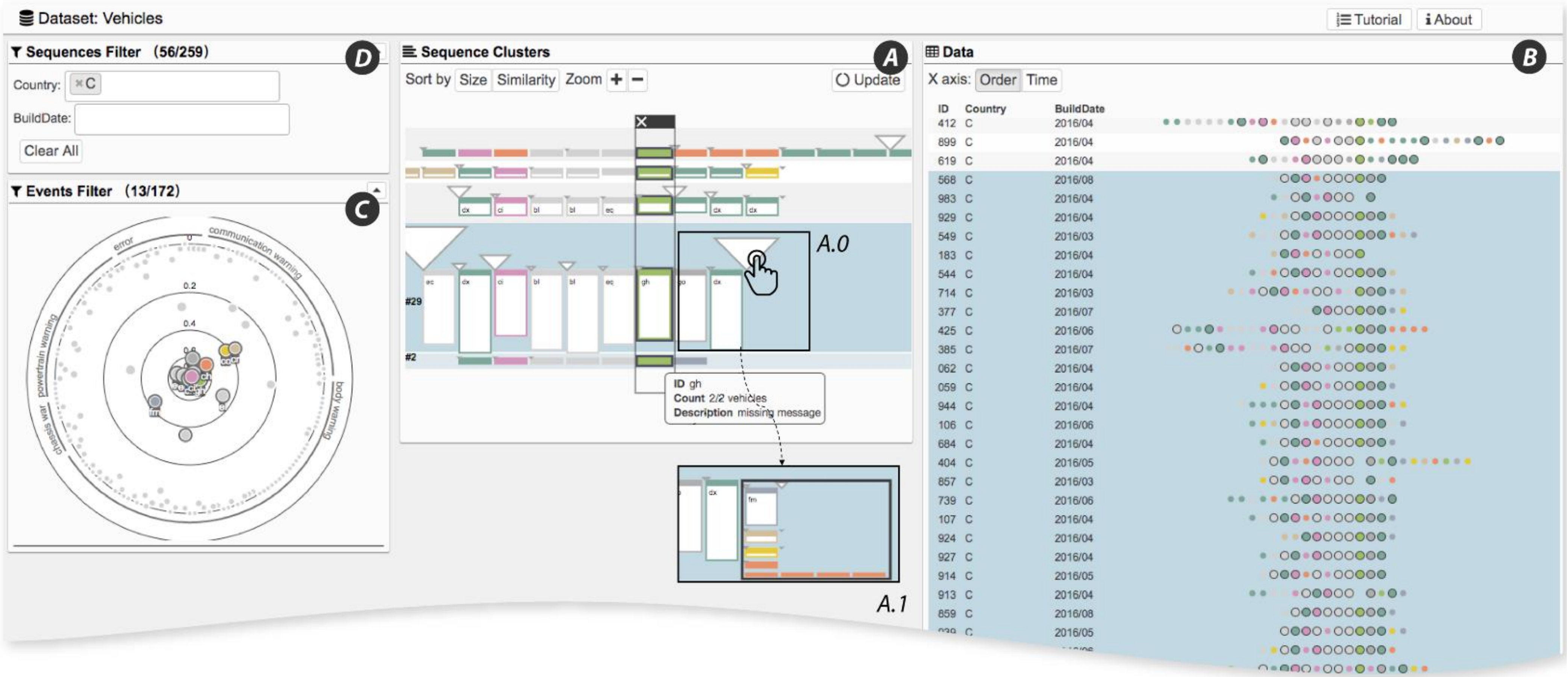


System
Architecture



System

Supportive Views, UI, Case Study – Vehicle Fault Analysis



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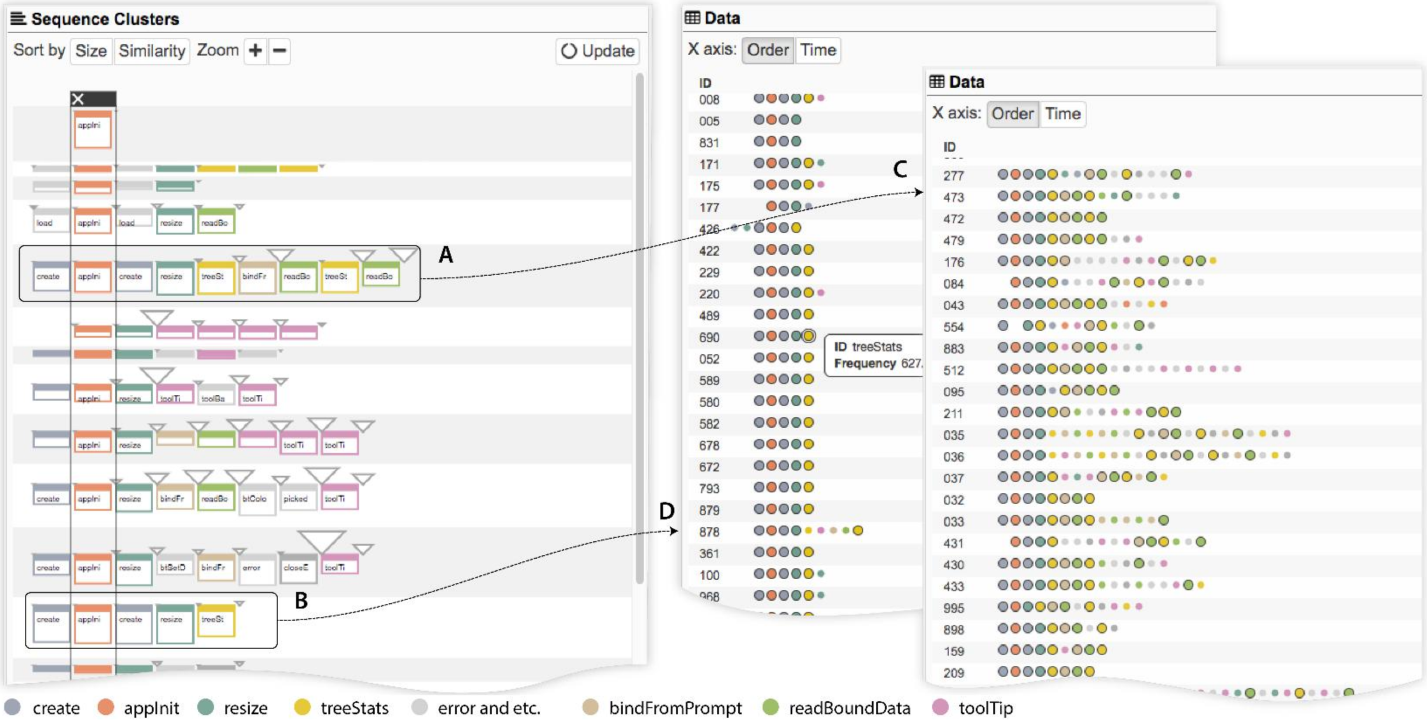
System
Case Study – Application Log Analysis

- D. Fisher. Agavue event data sample
- ~2000 user sessions
- Interaction log of using a data visualization application



System
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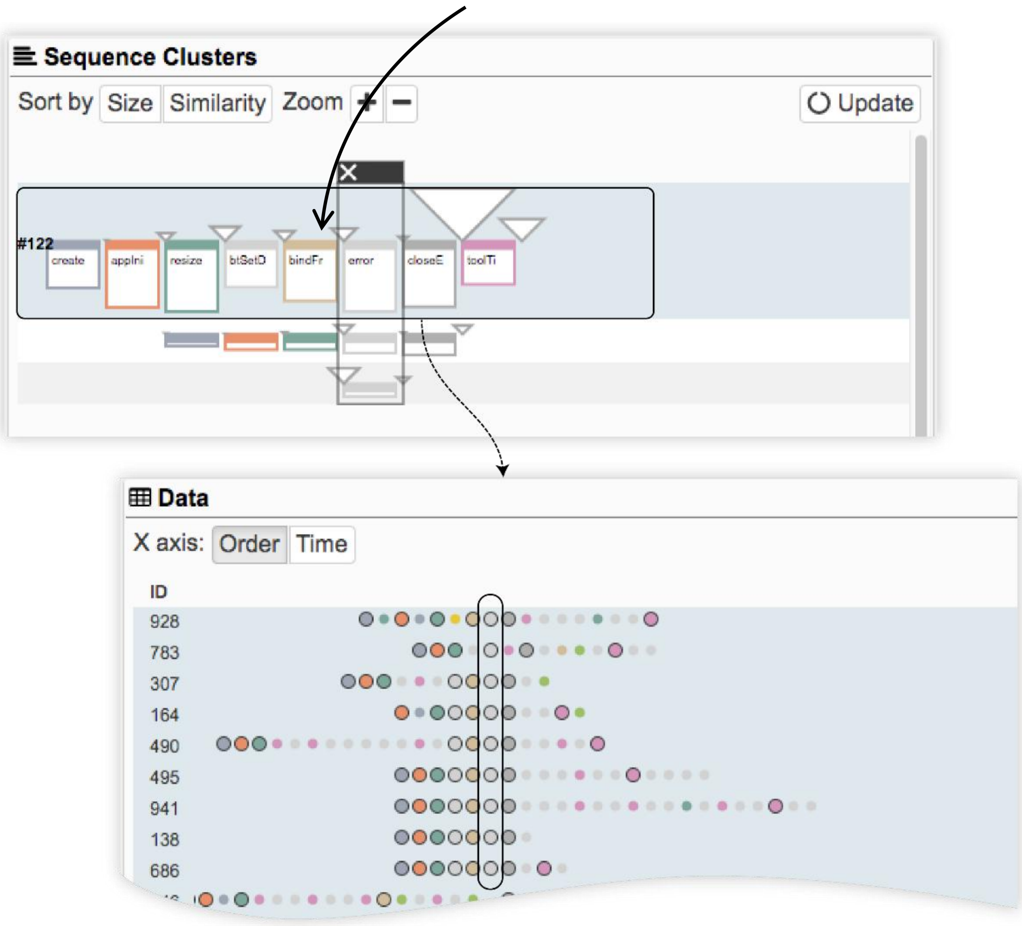
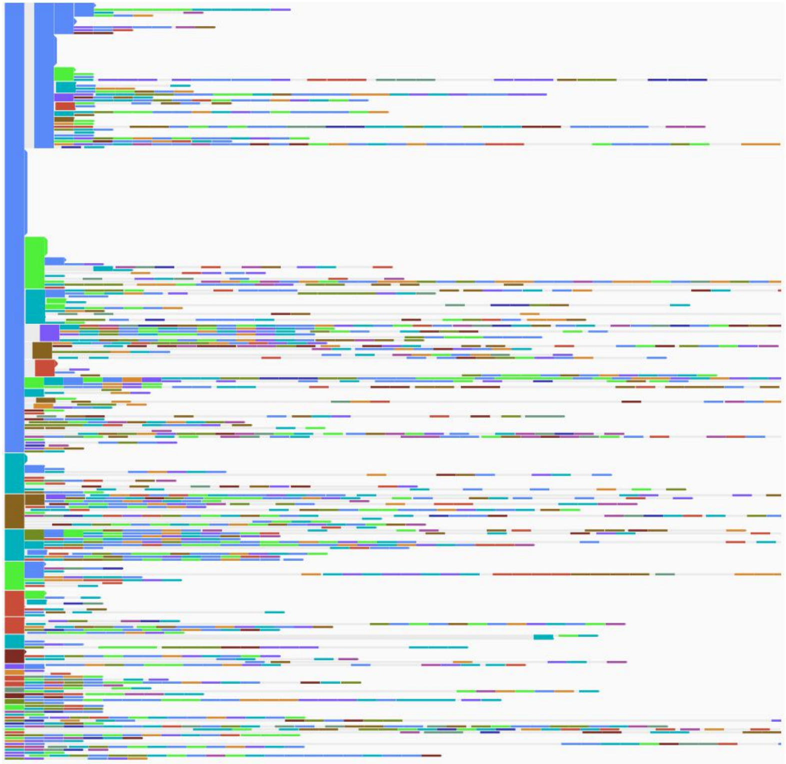
Binding data



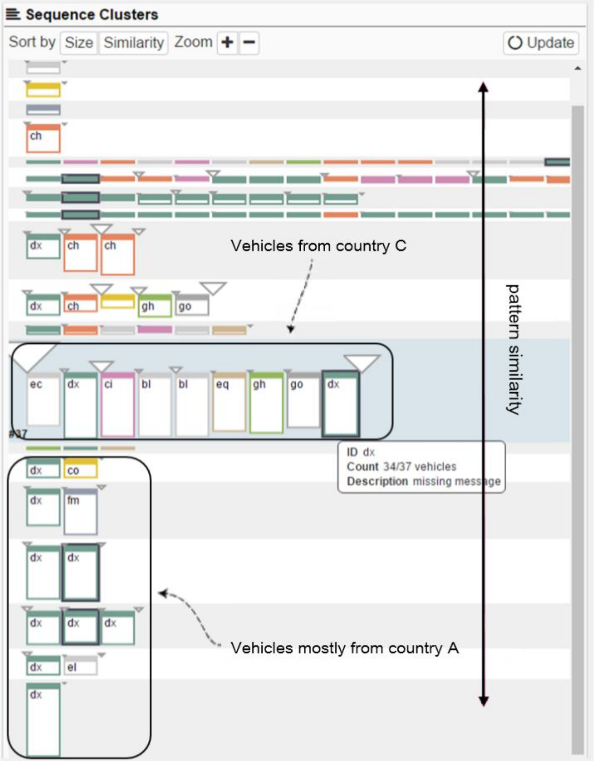
EVALUATION & SUMMARY

Evaluation & Summary
Comparative Experiment

- Vehicle Fault Sequence
- 259 cars & 2500 events



EventFlow
Monroe et. al. 2013



Our method

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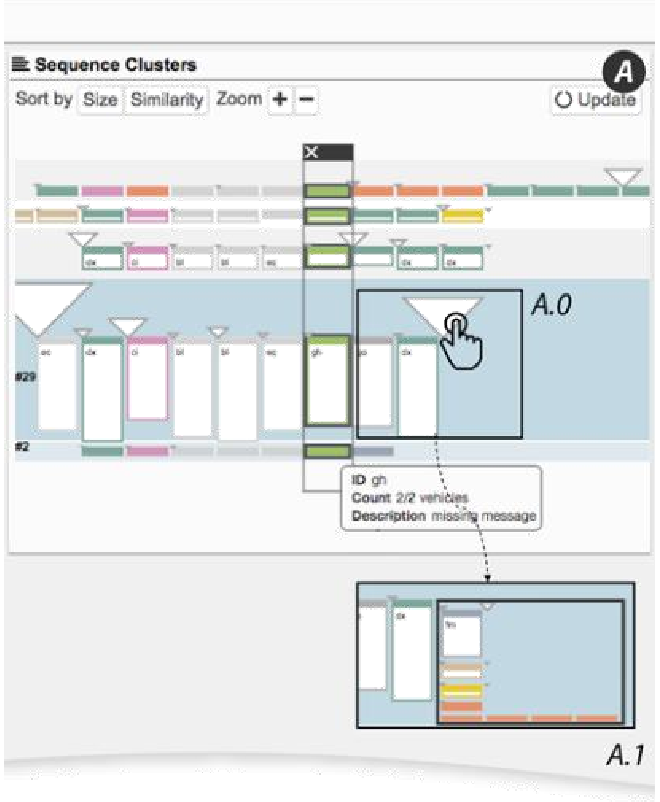
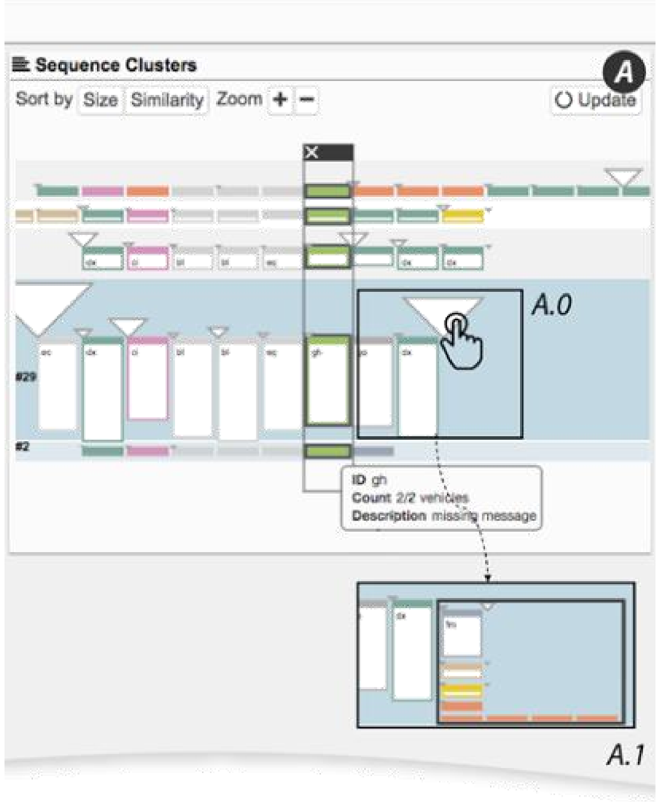
Evaluation & Summary
Contributions

- A new application domain of event sequence visualization
- A generic **two-part representation** of event sequences that:
  - **Quantifies visual complexity & information loss** in visual summaries
  - Combined with the **MDL principle**, defines an optimal set of patterns for summary
- An efficient algorithm to optimize visual summary using LSH
- A visual analytics system that supports interactive analysis of **real-world** event sequences from **different application domains**



Evaluation & Summary
Future Work

- Revise model representation to discover multiple patterns in a single sequence
- Towards **quantifiable visual designs** by applying the MDL principle to different types of data: graph/networks, time series …



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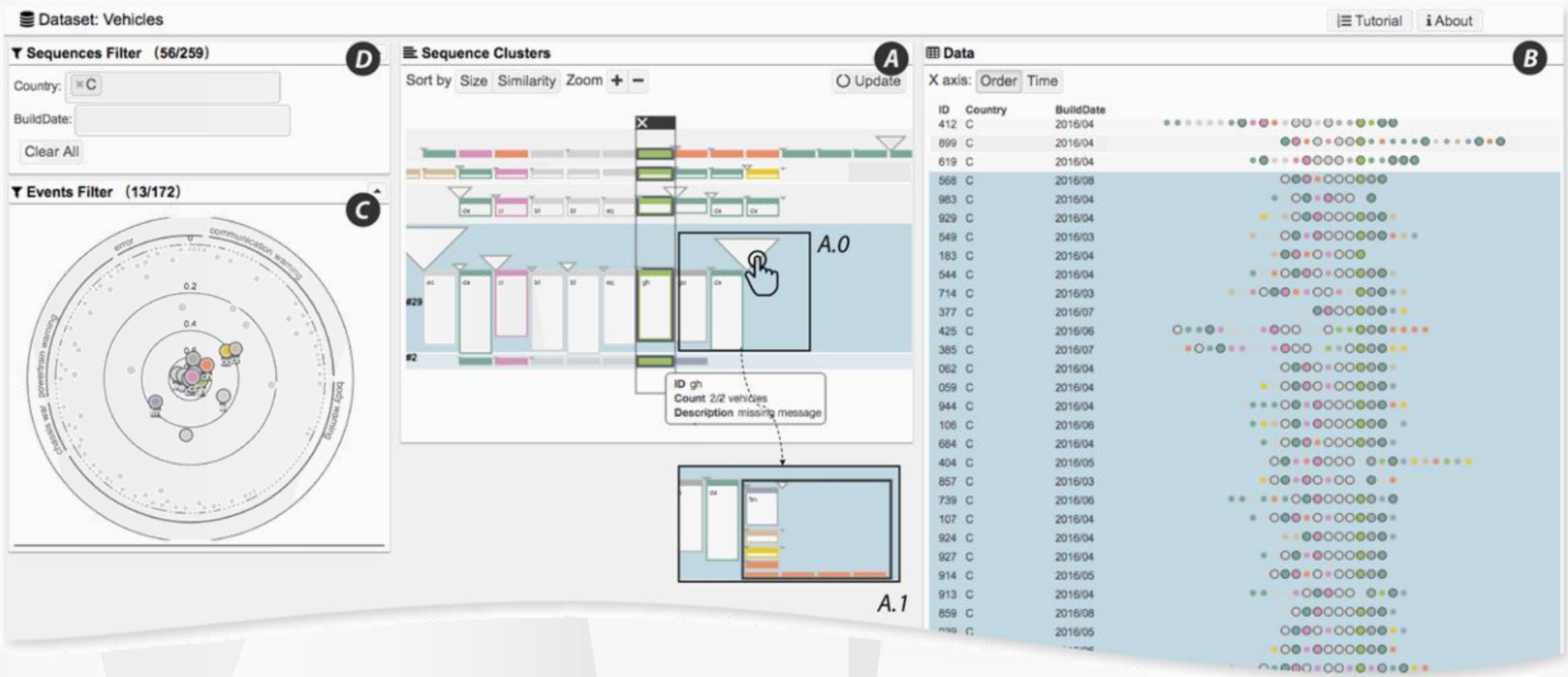
THANK YOU!
Q&A



Dataset: Vehicles
Tutorial
About
Sequences Filter (56/259)
D
Country:
C
BuildDate:
Clear All
Events Filter (13/172)
C
Sequence Clusters
A
Sort by Size Similarity Zoom
Update
A.0
A.1
ID gh
Count 2/2 vehicles
Description missing message
Data
B
X axis: Order Time
ID Country BuildDate