THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

HKUST VIS

# Visualization in Smart Manufacturing

Dong SUN

The Hong Kong University of Science and Technology

## Introduction

## Visualization in Smart Manufacturing

## Sequence Synopsis: Optimize Visual Summary of Temporal Event Data

## ViDX: Visual Diagnostics of Assembly Line Performance in Smart Factories

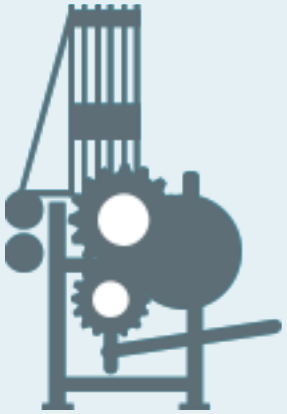
## Introduction

- Industrial Revolution
- The Rise of Industrial Big Data
- What is “Smart”?
- Potential Application Scenarios

# Introduction

## Industrial Revolution

**1st industrial revolution**



In 1784, the first loom was created.

**2nd industrial revolution**

In 1870, the first conveyor belt was created at the Cincinnati Slaughterhouse.

**3rd industrial revolution**

In 1969, the first programmable logic controller (PLC) , Modicon 084, was created.

**4th industrial revolution**


The implementation of the physical information system.

1800 1900 2000 now

### Industry 4.0

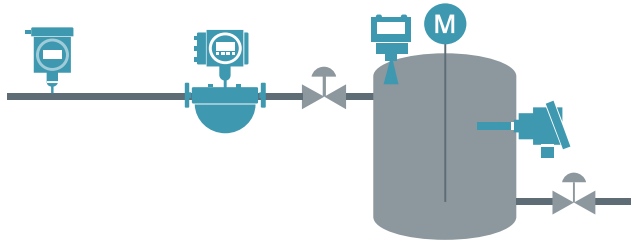
- The people, devices and systems in the value chain are connected.
- All the related information is accessible in real time.
- The components in the value chain are continuous optimized to meet personalized requirements.

# Introduction

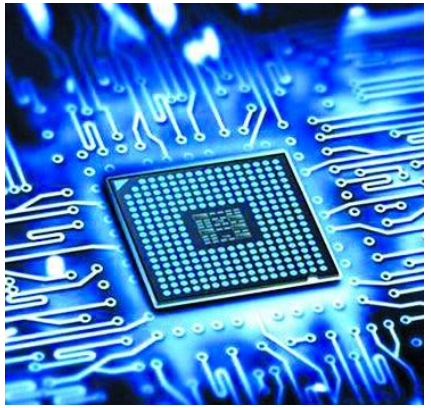
## The Rise of Industrial Big Data

- Industry 4.0 (Germany), Industrial Internet (America), and Made in China 2025 (China): Emphasize the use of big data. Big data is an important feature in future.
- The main factors for the rise of big data in the industrial field:

- Human experience and analysis cannot satisfy the requirement of the complex management.




- The vast amount of data generated in the manufacturing process are not fully dug.



- The development of sensing and communication equipment makes it cheap to access real-time data.


- Cloud computing provides computing power for big data processing.

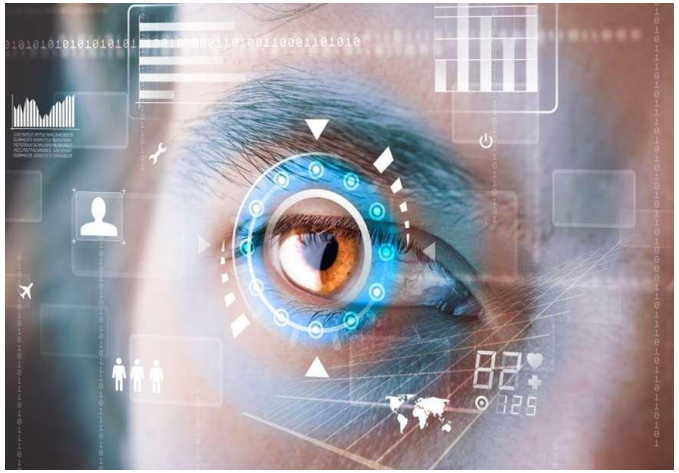
# Introduction

## What is “Smart”?

**Artificial intelligence**: Simulate and extend human intelligence through computer programs. It summarizes patterns from phenomena and provides tools for people.


Super doctors


Go master

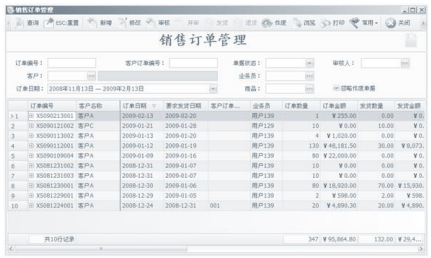


Smart eyes

# Introduction

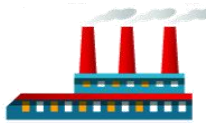
## Potential Application Scenarios

### Reporting tools




### Analysis decision tools

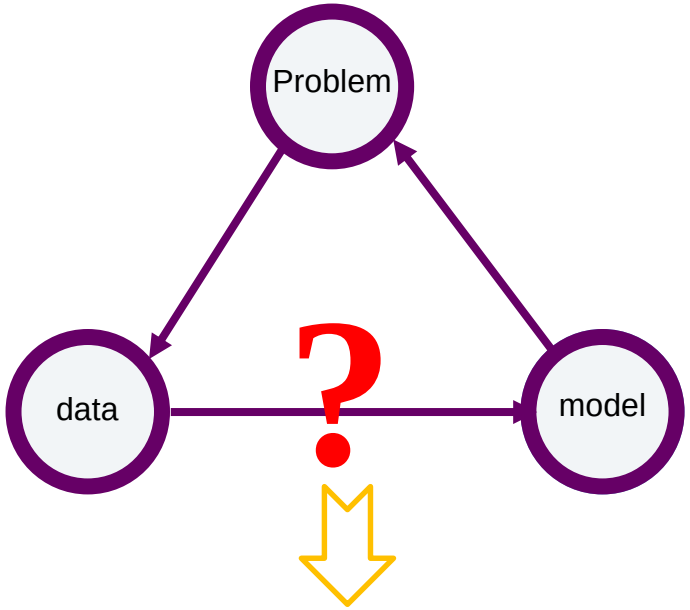
devices



manufacturing

management

### Enterprise-level central database




Interactive and intelligent data analysis tools


Data scientist

Domain expert

## Visualization in Smart Manufacturing

- Opportunities and Challenges
- Research Taxonomy
- Planning and Scheduling Visualization
- Manufacturing Simulation Visualization
- Manufacturing Process Visualization
- Supply Chain Visualization
- Conclusion and Future work

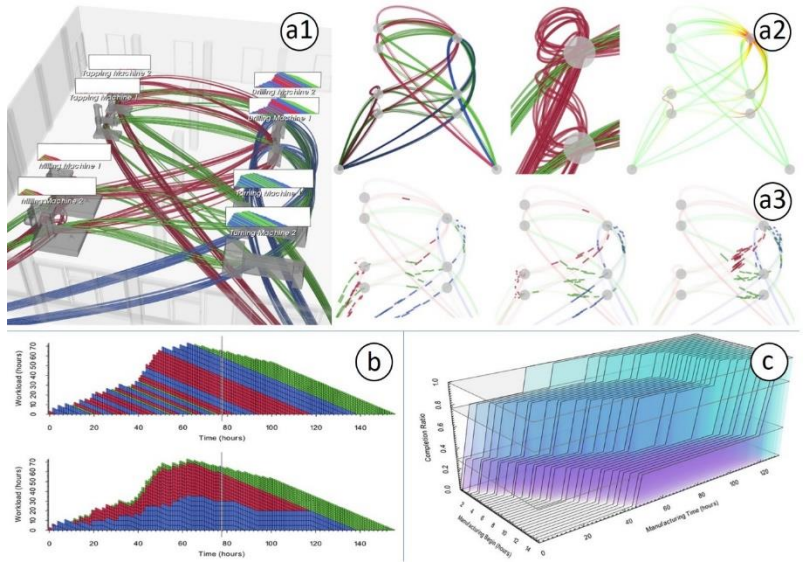
# Visualization in Smart Manufacturing

## Opportunities and Challenges

Manufacturing data are collected and network-accessible.

Visualization helps analyze manufacturing data.

| Item | Item_type | Material_cost | LT_days | Product_category | Holding_cost |
|---|---|---|---|---|---|
| 21 | Raw Material | 6.91 | 0 | W-MPT | 0 |
| 8 | Forecast Component | 2978.89 | 0 | GUC | 0.993 |
| 24 | Raw Material | 0.05 | 0 | Adapter | 0 |
| 11 | Order Only | 5215.97 | 0 | FDD LTE | 1.7387 |
| 9 | Order Only | 3054.54 | 0 | GUC | 1.0182 |
| 15 | Normal | 835.55 | 0 | GUC | 0.2785 |
| 16 | Order Only | 3150.44 | 0 | FDD LTE | 1.0501 |
| 36 | Raw Material | 19.31 | 0 | FDD | 0 |
| 13 | Type4 Component | 874.42 | 0 | GUC | 0.2915 |
| 33 | Raw Material | 575.05 | 0 | FDD LTE | 0 |
| 34 | Raw Material | 1074.3 | 0 | FDD LTE | 0 |
| 28 | Raw Material | 0.13 | 0 | FDD | 0 |
| 5 | Normal | 2972.07 | 0 | FDD | 0.9907 |
| 29 | Raw Material | 0.13 | 0 | OLT | 0 |
| 27 | Raw Material | 8.82 | 0 | FDD LTE | 0 |
| 7 | Normal | 3100.95 | 0 | GUC | 1.0336 |
| 3 | Normal | 2943.14 | 0 | GUC | 0.981 |
| 25 | Raw Material | 0.01 | 0 | Adapter | 0 |
| 22 | Raw Material | 0.08 | 0 | FDD LTE | 0 |
| 23 | Raw Material | 0.51 | 0 | TDD&e-LTE | 0 |
| 4 | Normal | 2942.11 | 0 | GUC | 0.9807 |
| 14 | Normal | 187.34 | 0 | Secondary power supply module | 0.0624 |
| 10 | Normal | 3050.61 | 0 | GUC | 1.0169 |
| 32 | Raw Material | 10.84 | 0 | FDD | 0 |
| 30 | Raw Material | 13.75 | 0 | FDD LTE | 0 |
| 12 | Type4 Component | 1077.37 | 0 | GUC | 0.3591 |
| 35 | Raw Material | 4.58 | 0 | Secondary power supply module | 0 |
| 26 | Raw Material | 0.42 | 0 | Power supply of the boards | 0 |
| 6 | Order Only | 3336.93 | 0 | GUC | 1.1123 |
| 17 | Normal | 1368.68 | 0 | Microwave | 0.4562 |
| 18 | Normal | 1357.4 | 0 | Microwave | 0.4525 |
| 19 | Normal | 968.3 | 0 | Microwave | 0.3228 |
| 20 | Normal | 963.87 | 0 | Microwave | 0.3213 |
| 31 | Raw Material | 11.8443 | 0 | Microwave | 0 |




(Post et al., 2017)
Journal of Computing and Information Science in Engineering

Traditional: table data, tedious, inefficient.

Visualization: intuitive, easy, effective.

# Visualization in Smart Manufacturing

## Opportunities and Challenges

Difficulty in understanding, analyzing, and optimizing product manufacturing.

| | |
|---|---|
| 1. complex systems | decode the complex system |
| 2. sheer number of data | bridge the gap between humans and data |
| 3. professional knowledge required | do not require expertise |
| 4. advanced algorithms | explain the algorithm result |

**Visualization**

# Visualization in Smart Manufacturing

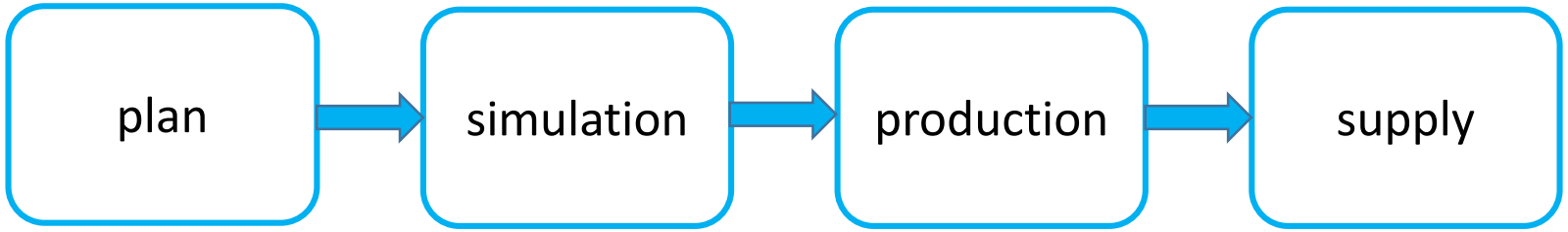
## Research Taxonomy

The taxonomy is based on:

**1. The challenges and opportunities brought about by Industry 4.0**

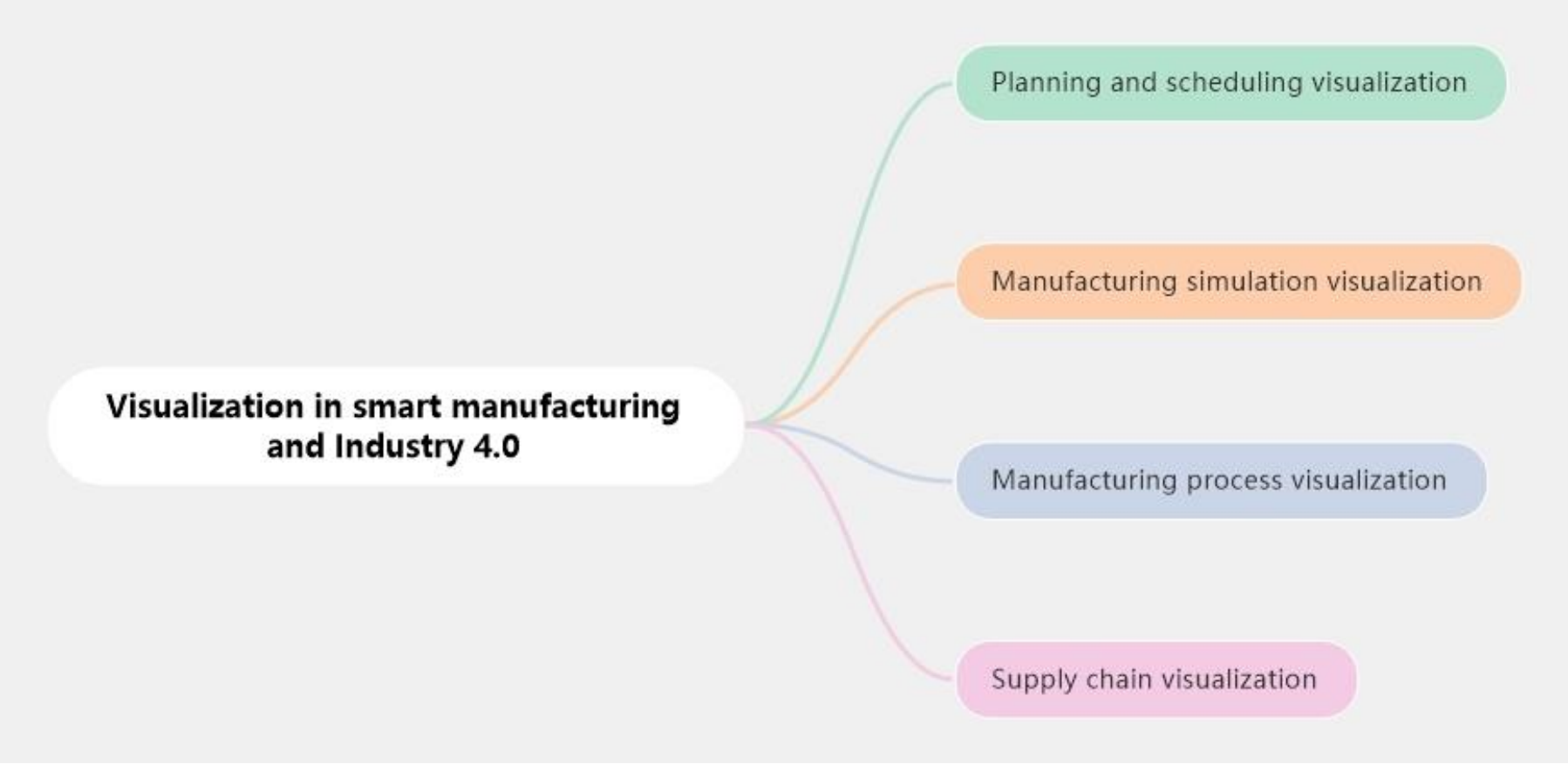
- The changeability and various constraints of planning and scheduling.
- Vast simulation runs and complex manufacturing systems.
- Complicated state info and unpredicted risks in production processes.
- The globalization, hierarchy, and uncertainty of supply chains.

**2. The lifecycle of product manufacturing**



# Visualization in Smart Manufacturing

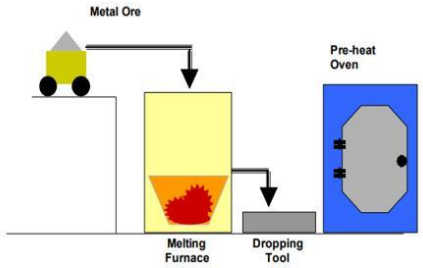
## Research Taxonomy



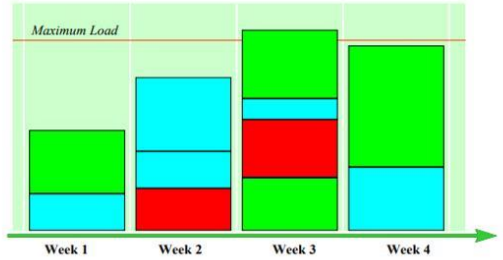
# Visualization in Smart Manufacturing

## Planning and Scheduling Visualization

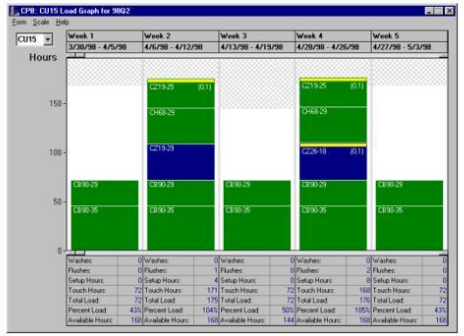
How to explore and optimize product planning under certain constraints?



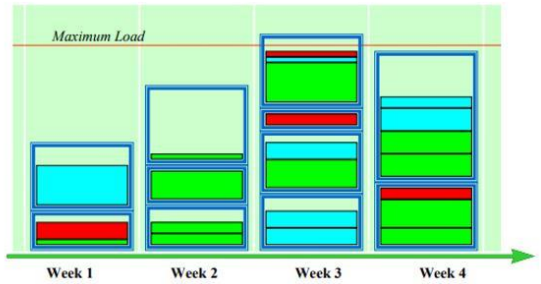

(a)




(b)




(c)




(d)

**Constraints**

- Machine load
- Equipment capacity

**Bar chart-based visualization**

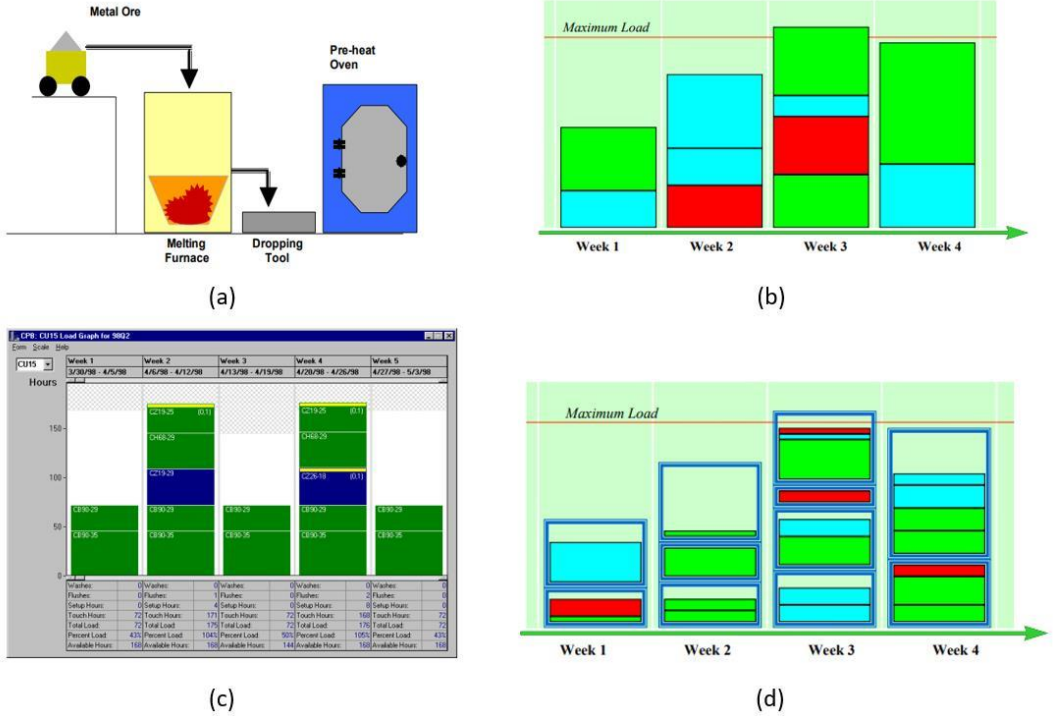
**Visually adjust the plan**

(Wu, 2001) Information Visualization

# Visualization in Smart Manufacturing

## Planning and Scheduling Visualization

How to explore and optimize product planning under certain constraints?




**Pros:**

- Intuitive and effective
- User friendly
- Reveals bottlenecks

**Cons:**

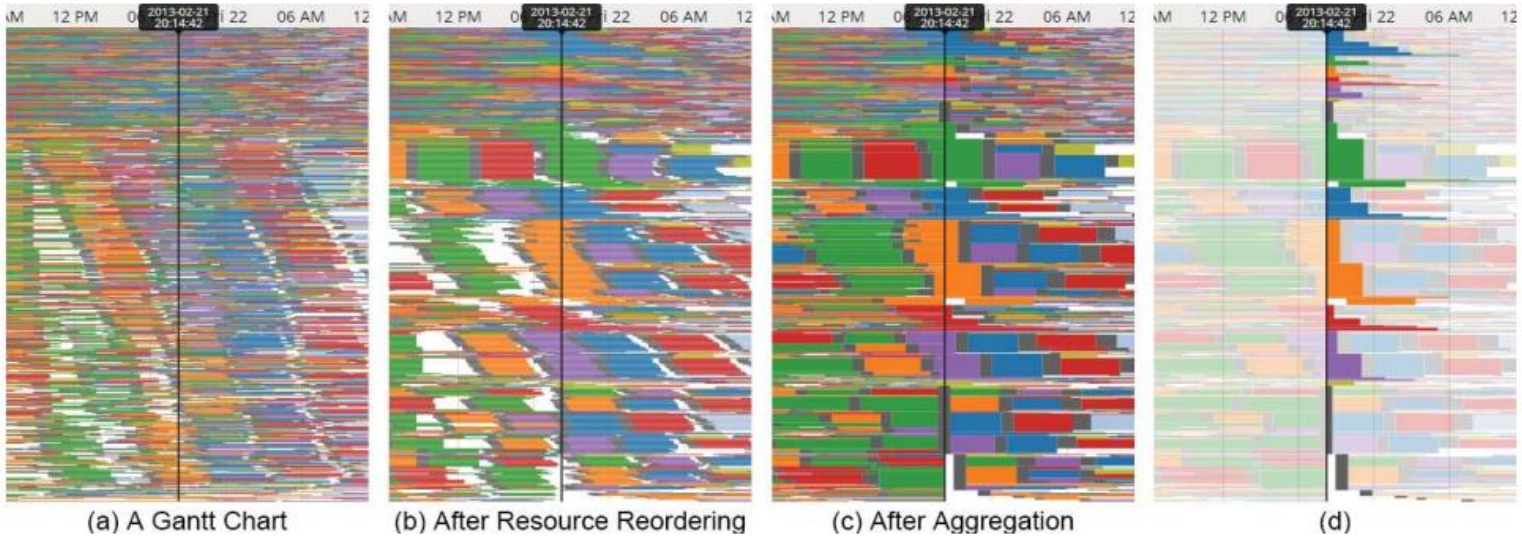
- Other constraints?
- Coarse-grained

(Wu, 2001) Information Visualization

# Visualization in Smart Manufacturing

## Planning and Scheduling Visualization

How to alleviate visual clutter and reveal frequent sequences in scheduling?




LiveGantt (Jo et al., 2014) TVCG

Visualization: the extended Gantt chart.

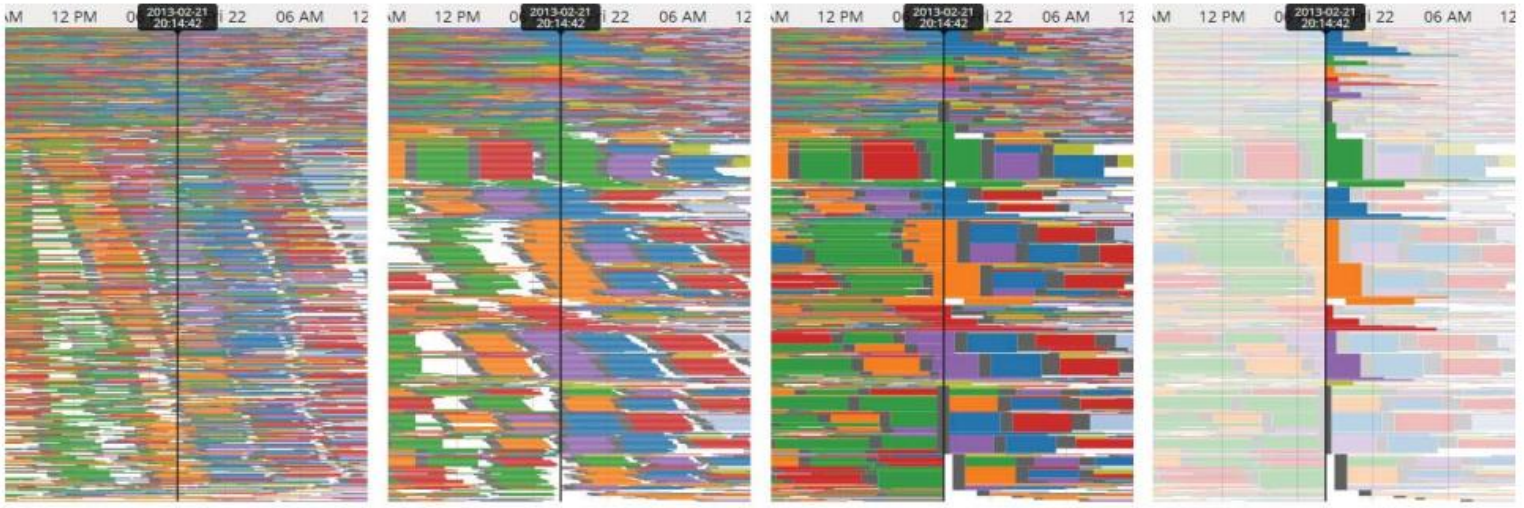
Severe visual clutter in the Gantt chart.

Adopt reordering and aggregation algorithms to reveal highly concurrent scheduling.

# Visualization in Smart Manufacturing

## Planning and Scheduling Visualization

How to alleviate visual clutter and reveal frequent sequences in scheduling?




LiveGantt (Jo et al., 2014) TVCG

**Pros:**

- Reduce visual cluster
- Disclose highly concurrent sequences

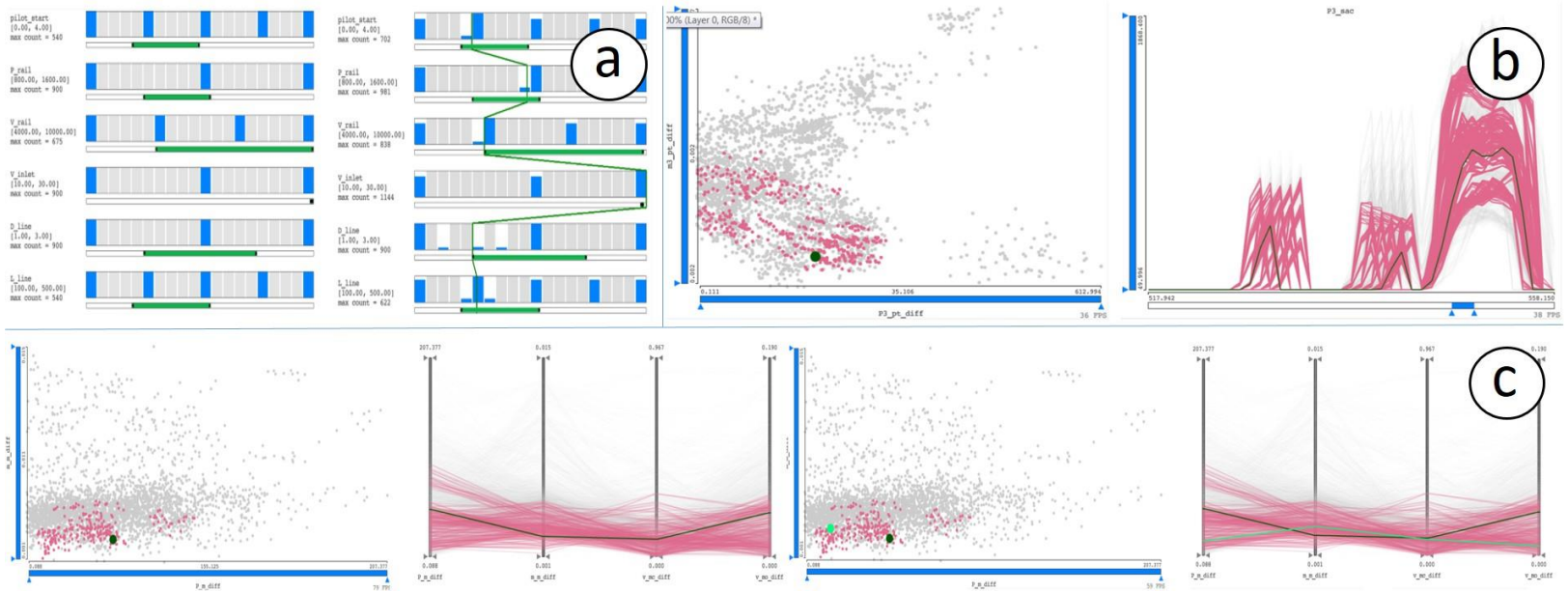
**Cons:**

- Only reveal sequences following the timeline
- Difficult to compare different sequences

# Visualization in Smart Manufacturing

## Manufacturing Simulation Visualization

How to decrease required simulation ensembles for exploration?




(Matkovic et al., 2014) TVCG

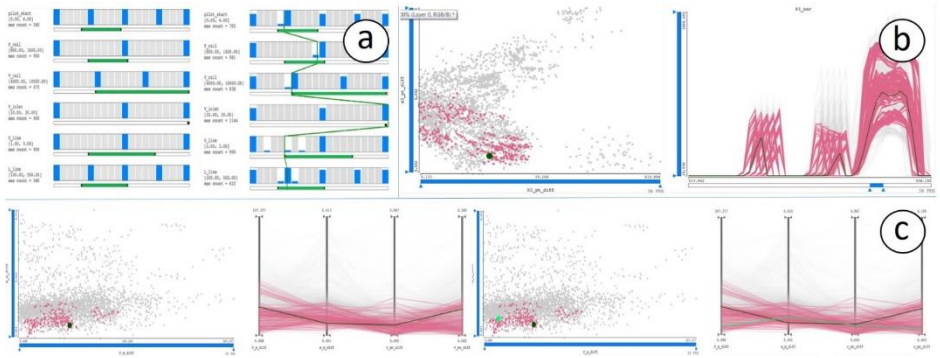
Combine optimization algorithms with visual exploration.

Decrease required simulation runs and guide parameter selection

# Visualization in Smart Manufacturing

## Manufacturing Simulation Visualization

How to decrease required simulation ensembles for exploration?




(Matkovic et al., 2014) TVCG

**Pros:**

- Reduce the number of data for exploration.
- Combine the advantages of both optimization algorithms and human judgment.

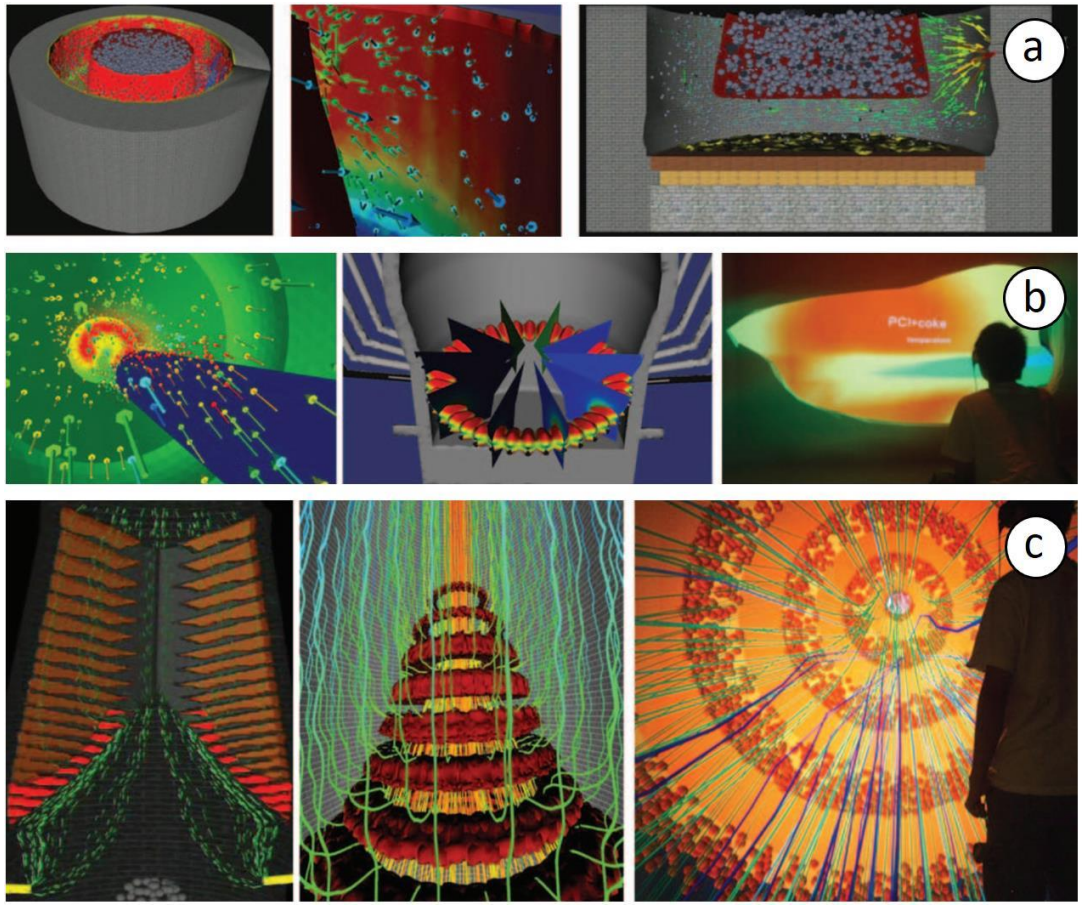
**Cons:**

- Does not explain why the result is optimal.
- Difficult to compare different parameter configurations for different purposes.

# Visualization in Smart Manufacturing

## Manufacturing Simulation Visualization

How does the complex production process work?




(Zhou, 2011) Iron & Steel Technology

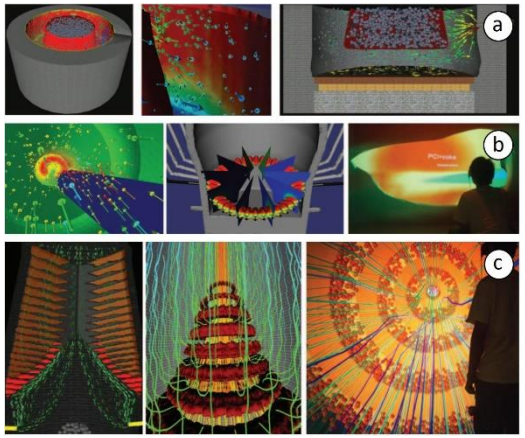
Visualize the steel manufacturing process.

Volume Rendering + Augmented Reality (AR)

# Visualization in Smart Manufacturing

## Manufacturing Simulation Visualization

How does the complex production process work?




(Zhou, 2011) Iron & Steel Technology

**Pros:**

- Immersive environment.
- Explain the complex process in a simple and intuitive way.

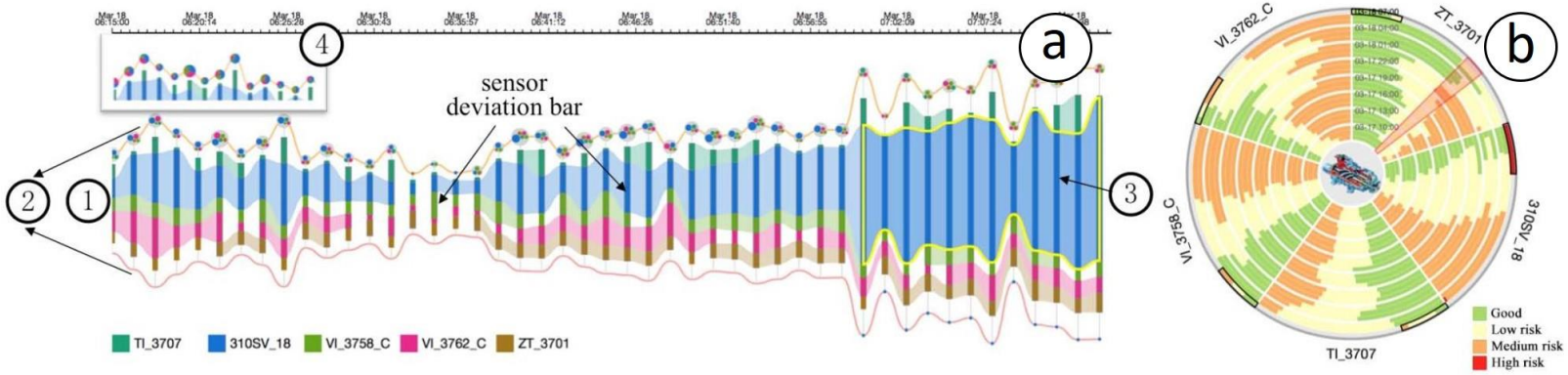
**Cons:**

- Visual clutter and occlusion.
- No visual summary.

# Visualization in Smart Manufacturing

## Manufacturing Process Visualization

How to detect risks? when does the system need maintenance?




(Wu et al., 2018) PacificVis

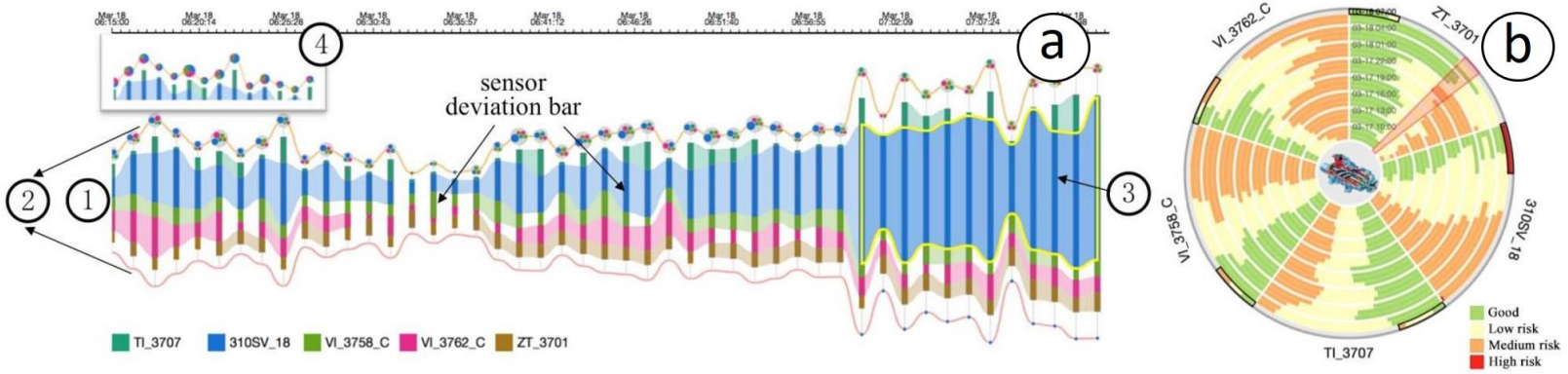
Employ advanced algorithms to reveal the risk level of time series data.

Visualization: the stacked bar chart, the pack layout, and the ring map.

# Visualization in Smart Manufacturing

## Manufacturing Process Visualization

How to detect risks? when does the system need maintenance?




(Wu et al., 2018) PacificVis

**Pros:**

- Easy to identify sensors in the high risk level.
- Guide predictive maintenance.

**Cons:**

- Do not consider the topology of sensors.
- Do not verify the correctness of the algorithm.

# Visualization in Smart Manufacturing

## Manufacturing Process Visualization

How to detect risks? when does the system need maintenance?


Heatmap, multi-scale exploration

(Zhou et al., 2018) Journal of Visual Languages & Computing

Adopt a situation awareness model to monitor facilities in a factory producing lithium battery cathode materials.

# Visualization in Smart Manufacturing

## Manufacturing Process Visualization

How to detect risks? when does the system need maintenance?


(Zhou et al., 2018) Journal of Visual Languages & Computing

**Pros:**

- Intuitive, easy to use
- Help non-experts understand and locate problems.

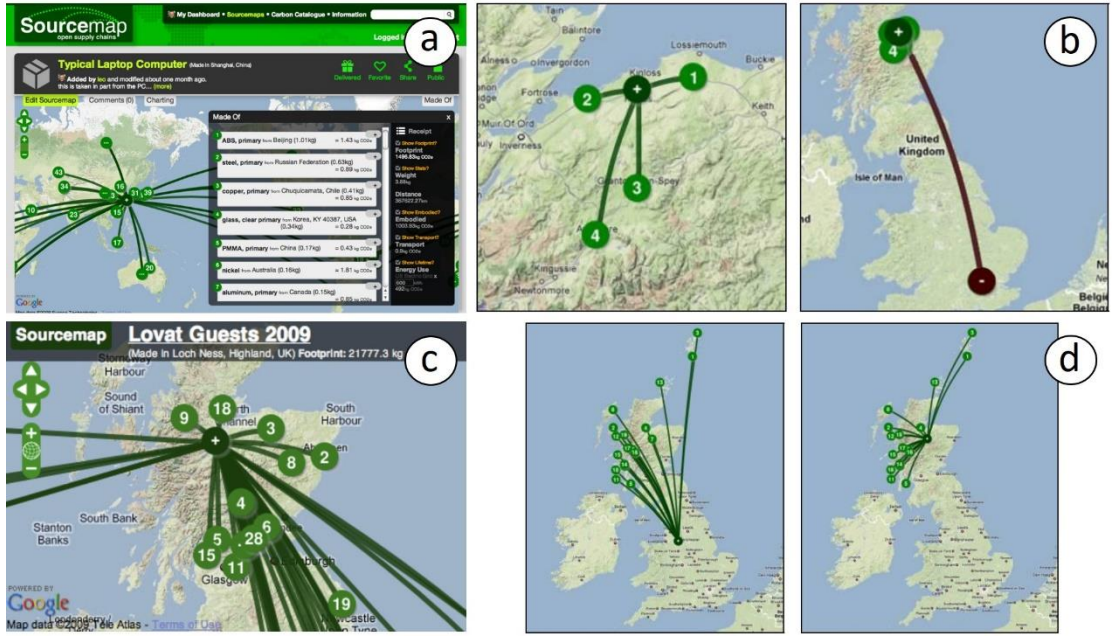
**Cons:**

- Cannot display equipment condition in a long time span.
- Scalability: not suitable for a larger system.

# Visualization in Smart Manufacturing

## Supply Chain Visualization

How to optimize the design of supply chains?




Sourcemap (Bonanni et al., 2010) CHI

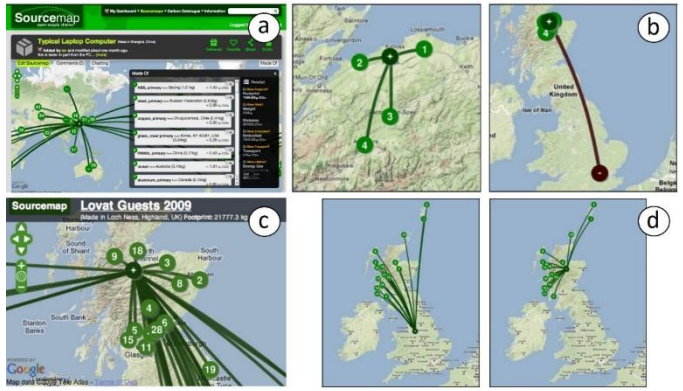
Graph-based visualization, incorporate geographic information.

Reveal the transportation path and the carbon footprint.

# Visualization in Smart Manufacturing

## Supply Chain Visualization

How to optimize the design of supply chains?




Sourcemap (Bonanni et al., 2010) CHI

**Pros:**

- Supporting visually designing the supply chain network.
- Intuitive and easy.

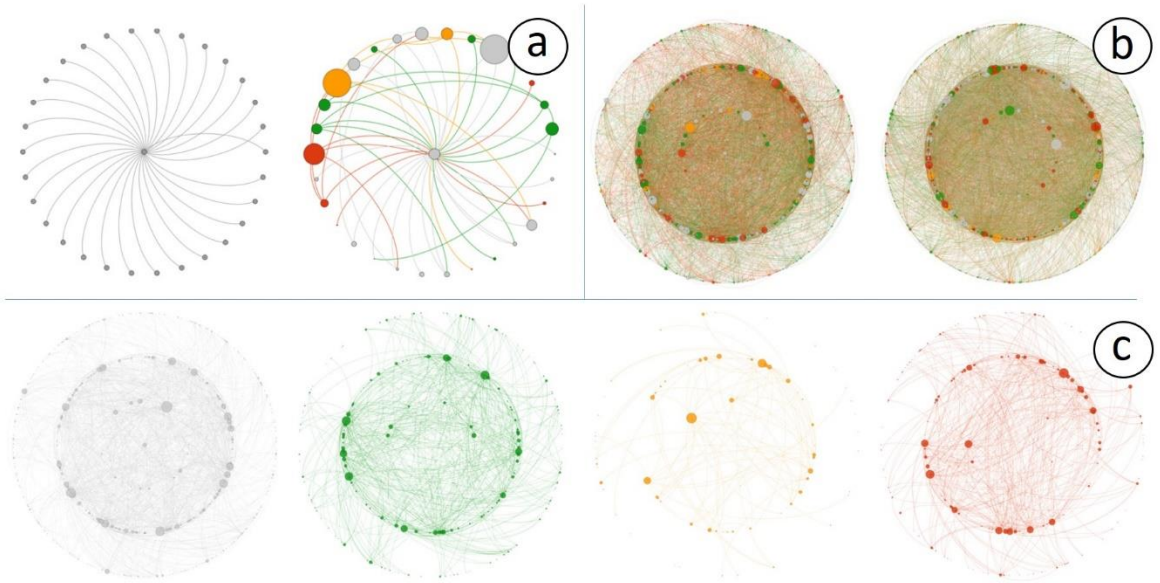
**Cons:**

- Do not consider the uncertainty in demands.
- Do not support what-if analysis.

# Visualization in Smart Manufacturing

## Supply Chain Visualization

How to reveal the risk interrelationships between different companies?




(Basole et al., 2014) Decision Support Systems

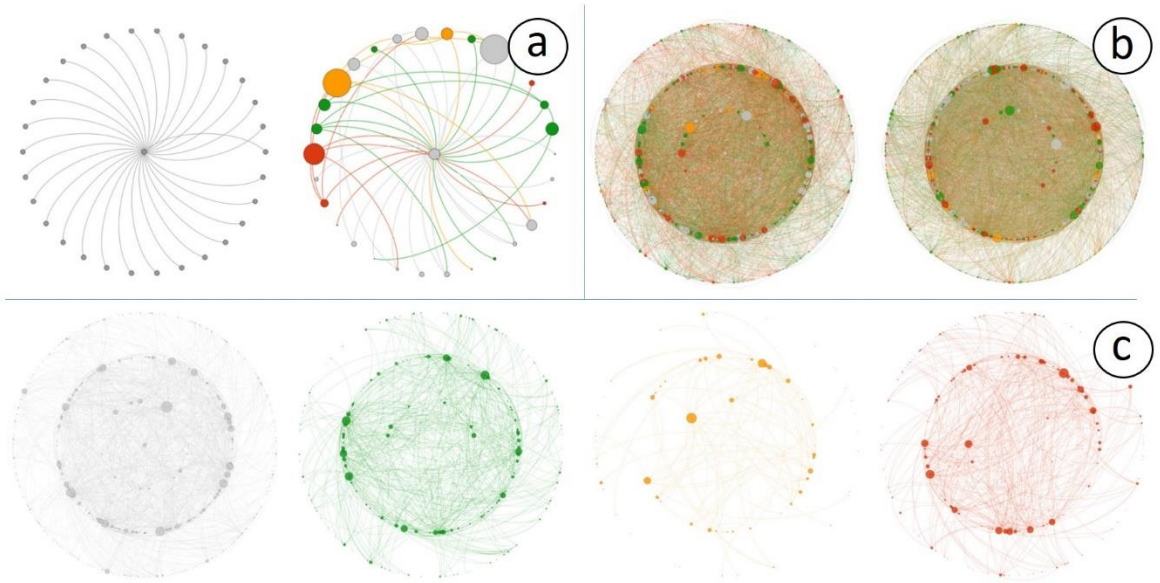
Visualization: the node-link diagram, the ego-centric network

Interrelationships and risk levels of companies in a three-tier supply chain network.

# Visualization in Smart Manufacturing

## Supply Chain Visualization

How to reveal the risk interrelationships between different companies?




(Basole et al., 2014) Decision Support Systems

**Pros:**

- Support subtier network analysis.
- Reveal patterns of different risk levels.

**Cons:**

- Only local views.
- No geographical information.

# Visualization in Smart Manufacturing

## Conclusion

**Visualization in planning and Scheduling**

- Interactively optimize the planning, the scheduling, and process layouts.

**Visualization in manufacturing simulation**

- Configure parameters, diagnose problems, and understand manufacturing.

**Visualization in manufacturing processes**

- Reveal inefficiencies, anomalies, and bottlenecks; predictive maintenance.

**Visualization in supply chain**

- Visually design the supply chain network; reveal patterns in risks.

# Visualization in Smart Manufacturing

## Future Work

**The uncertainty and multiple constraints of planning are still unresolved.**

- Reflect uncertainty in demands.
- Combine various constraints together.

**Predictive maintenance is not fully explored.**

- Self-monitoring.
- Maintenance on demand.

**What-if analysis is needed.**

- What if there is unpredictable fault?
- What if there is a increase / decrease in demands / supplies?

**The algorithm result is not explained and convincing.**

- Leverage domain knowledge to understand and build the model.

# Sequence Synopsis: Optimize Visual Summary of Temporal Event Data

- Our Approach
- System
- Evaluation & Summary

# Sequence Synopsis: Optimize Visual Summary of Temporal Event Data

IEEE Transactions on Visualization and Computer Graphics (TVCG), 2018

**Yuanzhe Chen[1], Panpan Xu[2], Liu Ren[2]**

[1]Hong Kong University of Science and Technology
[2]Bosch Research North America

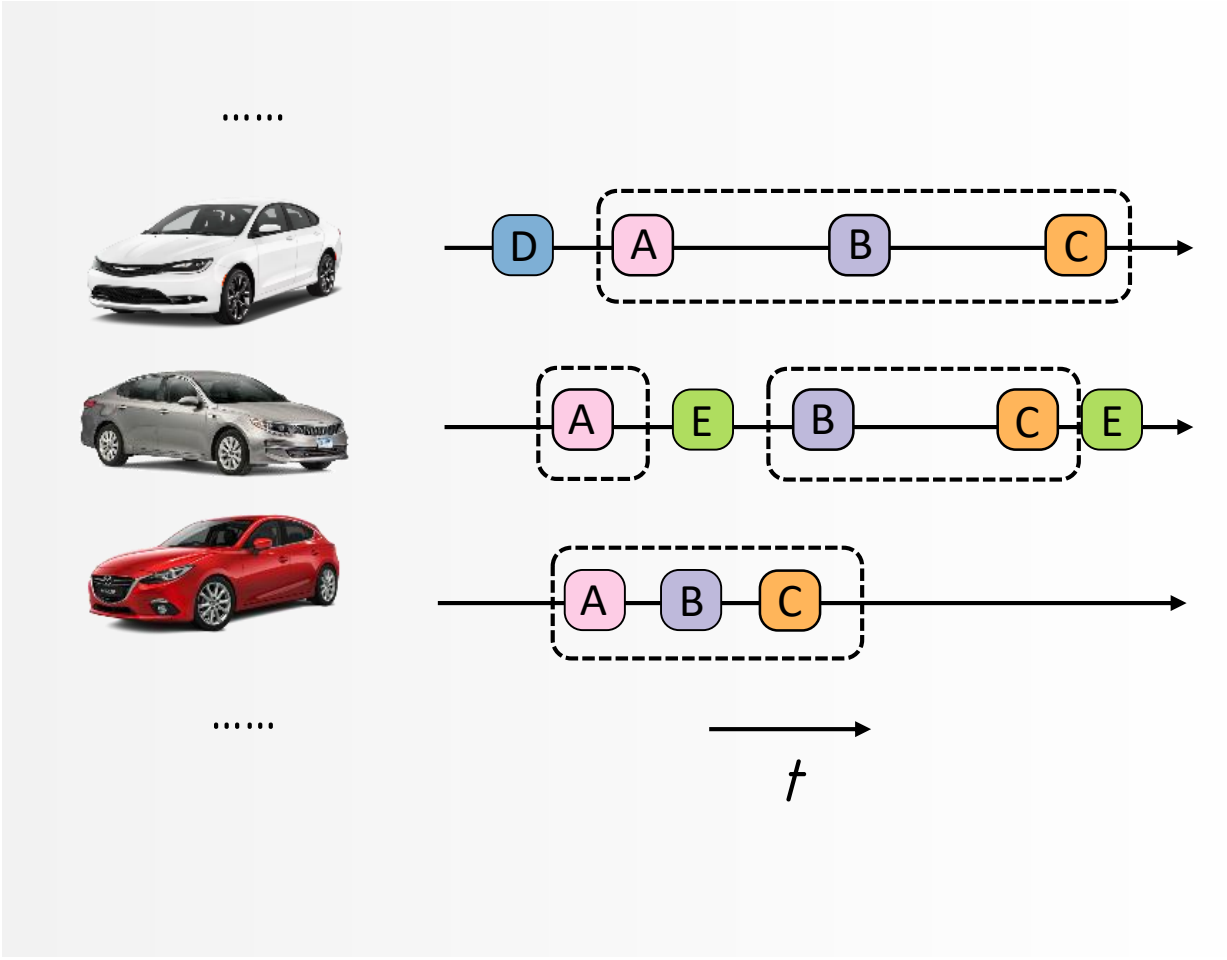
# Event Sequences

## 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.

# Event Sequences

## Use Case: Car Faults Analysis



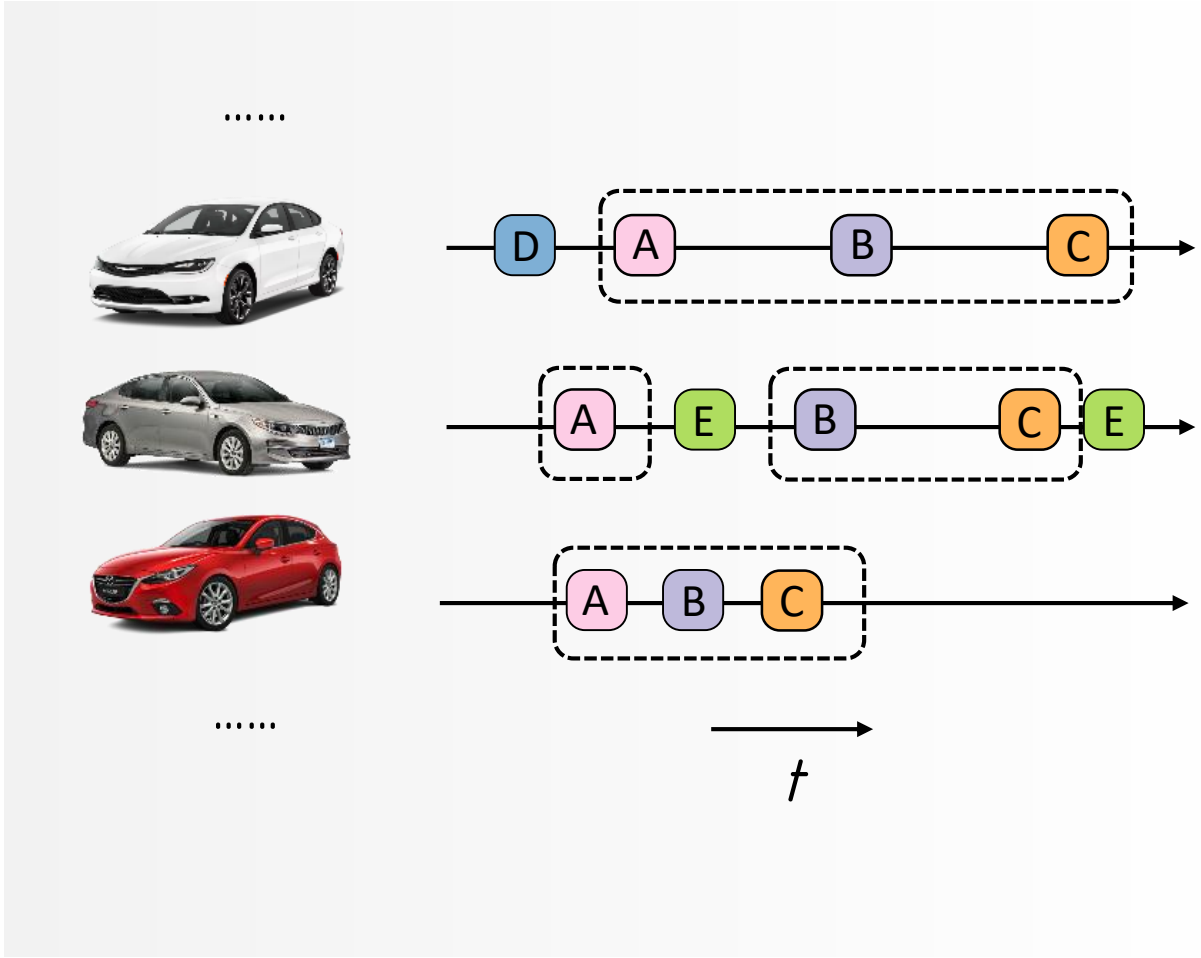

- What are the **typical development paths of faults**? (Identify sequential patterns )
- Do cars matched to the same pattern come from the same country? (correlation analysis)

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

Better driving experience & warranty cost saving.

# 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)

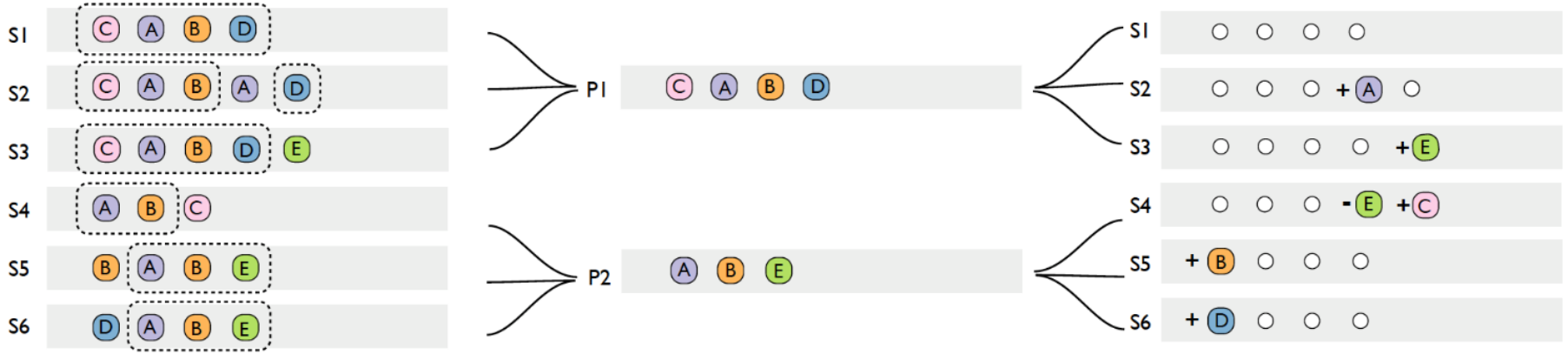
- Robust to noisy data
- Interpretable results
- Succinct visual overview

# Our approach

# Our Approach – Sequence Synopsis

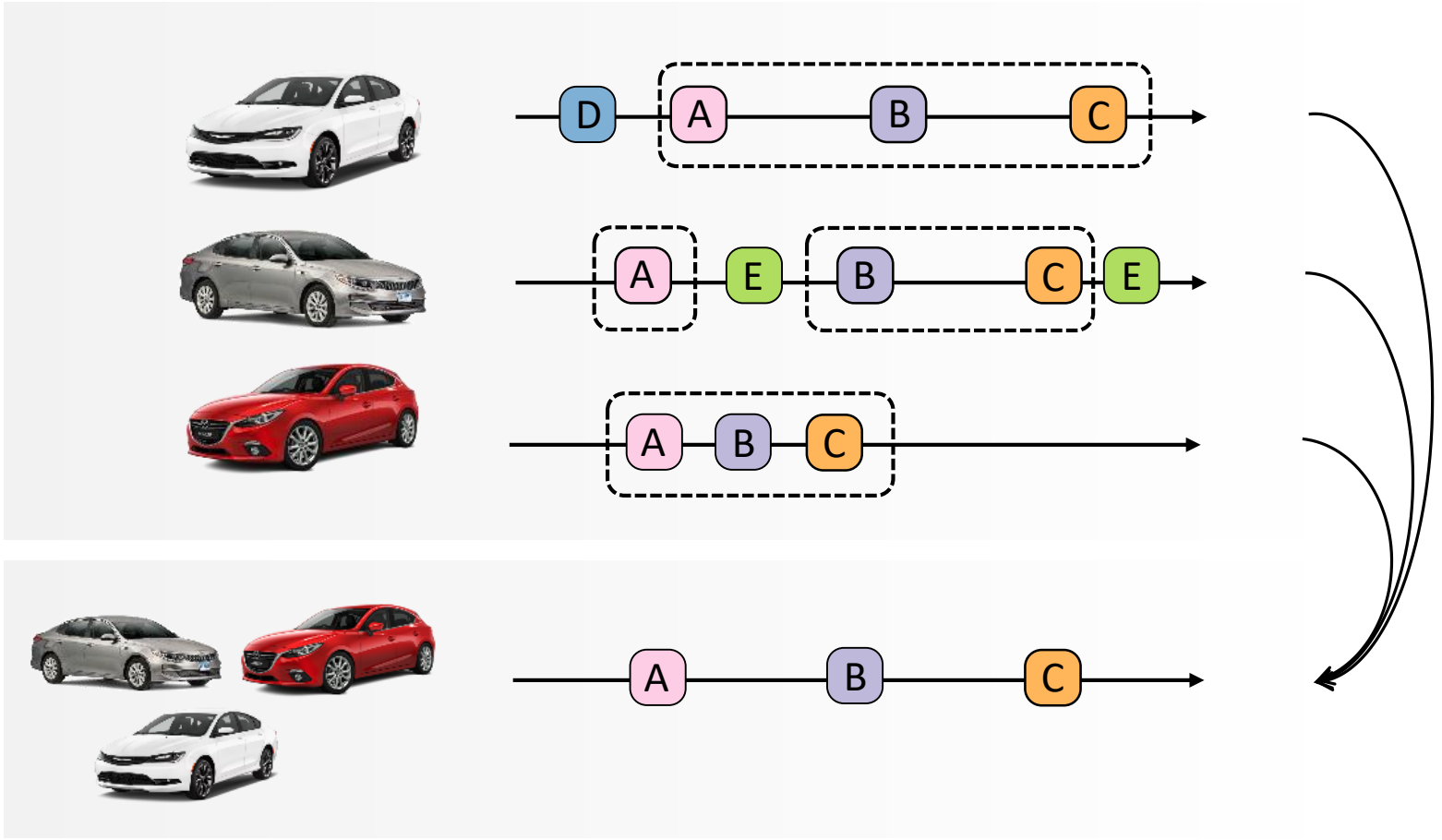
## Overview

- 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

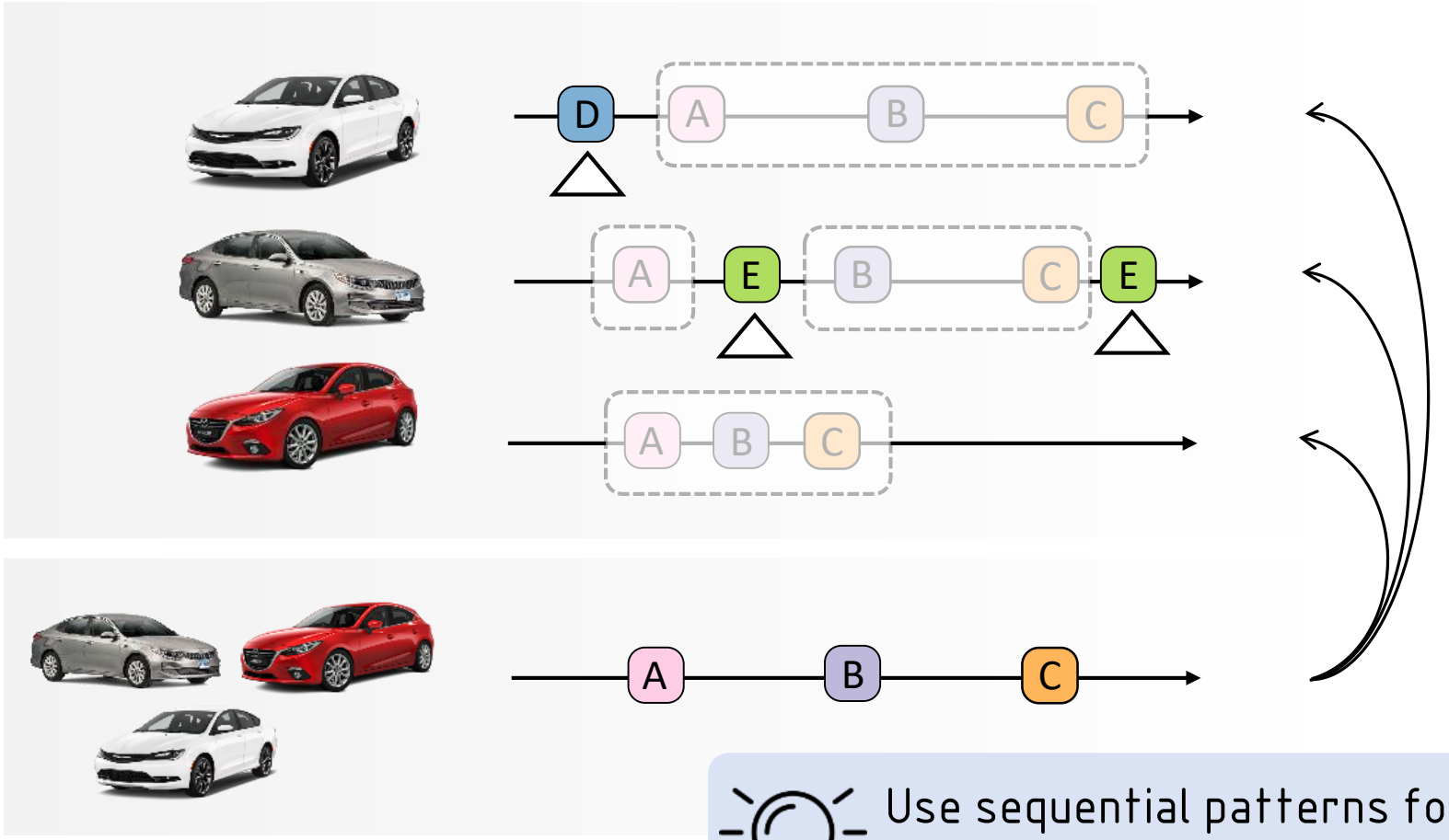
## Two-Part Representation of Event Sequences




*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.*

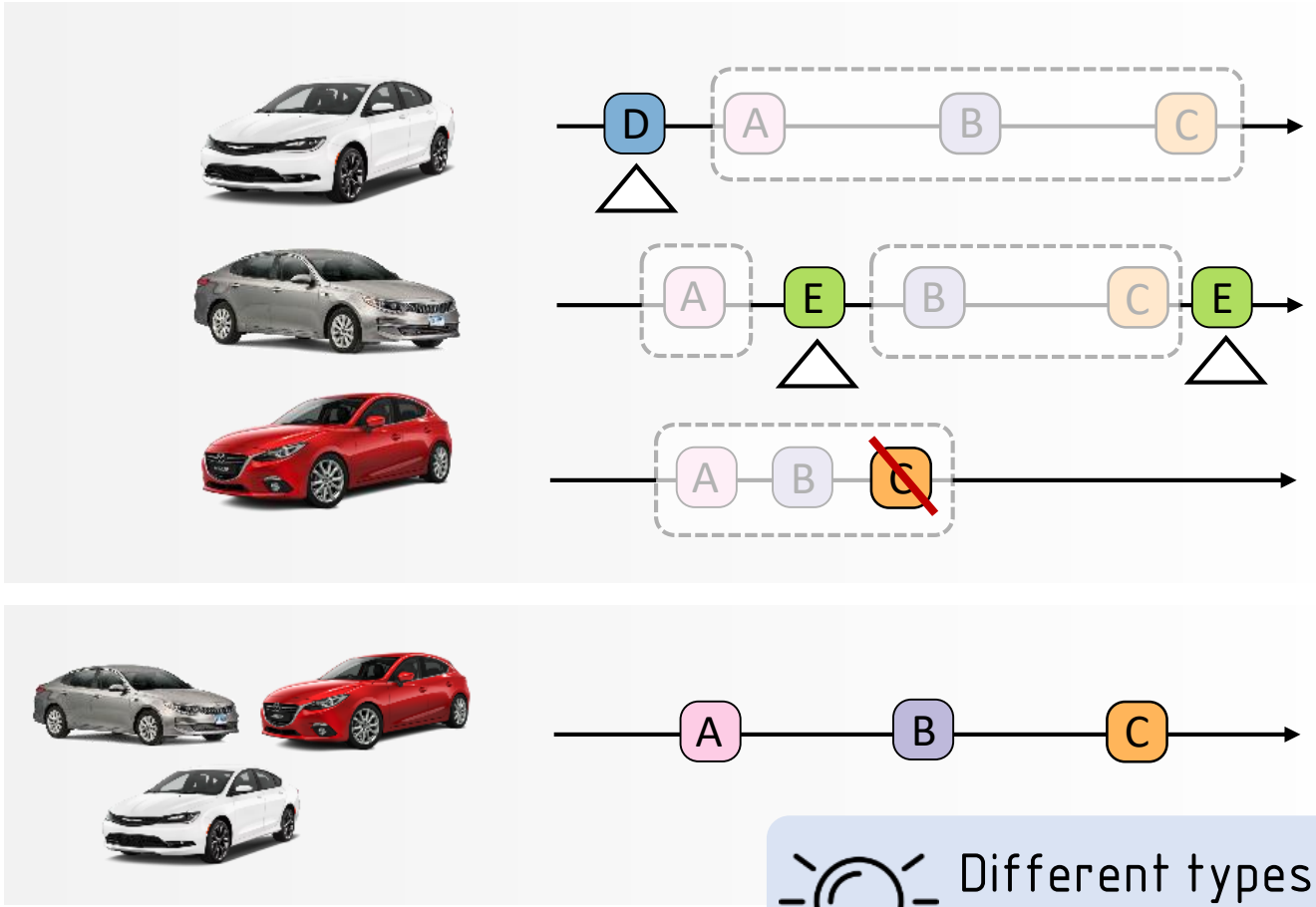
*Representative* ***pattern*** *summarizes multiple sequences.*

Use sequential patterns for **visual summary**.

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

# Our Approach – Sequence Synopsis

## Two-Part Representation of Event Sequences



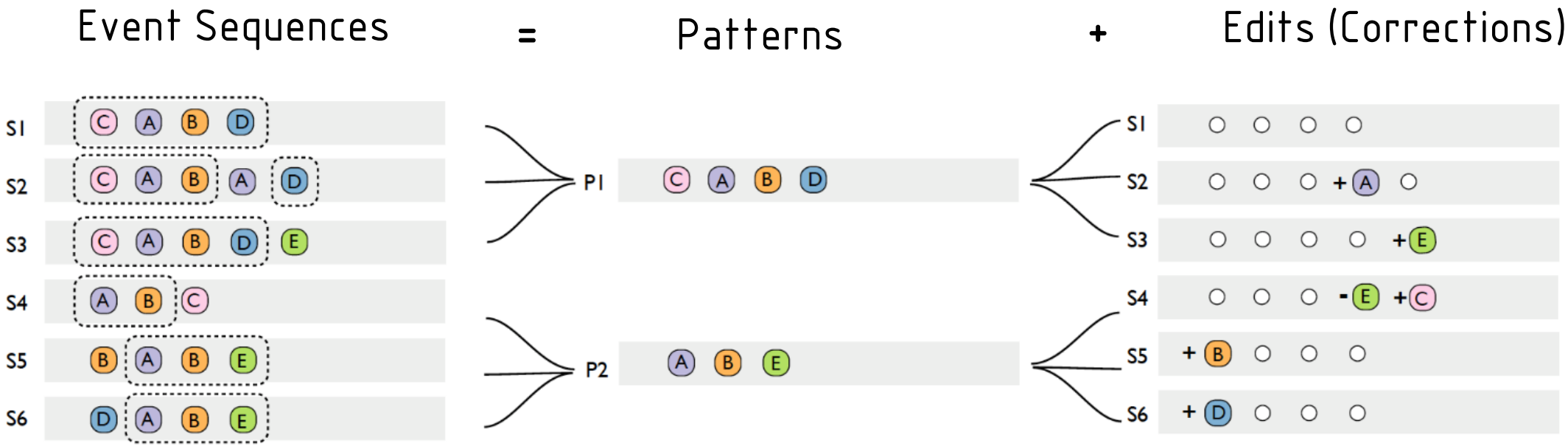

*Event **deletion** is another possible type of edit.*

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

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

# 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?

# 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**:

$$L = L(M) + L(D|M)$$

Model description length

Data description length with the help of the model

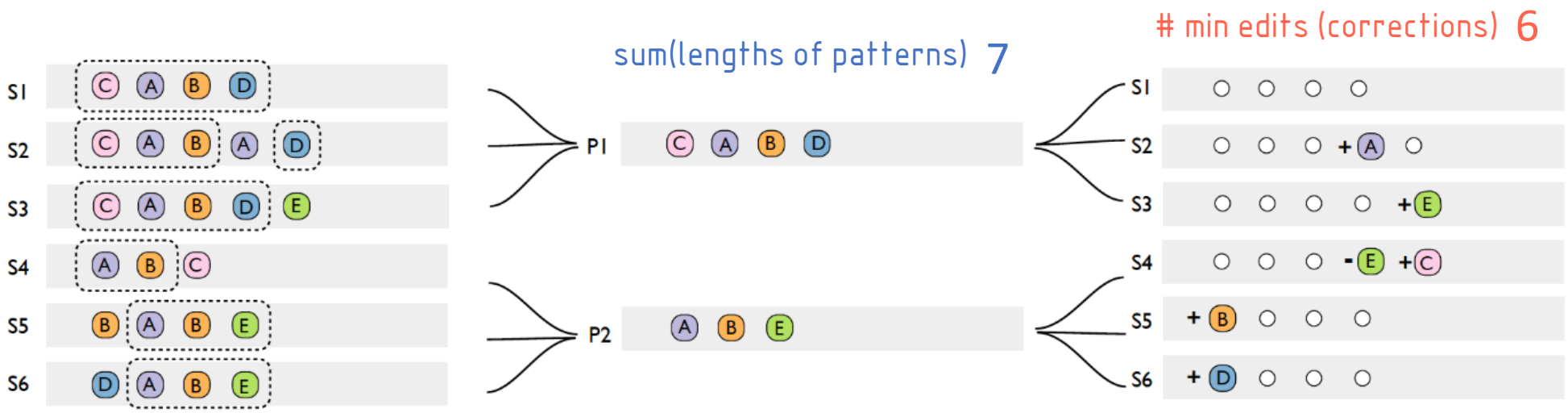
- Widely used **information-theoretic** criteria for model selection
- Introduced by Jorma Rissanen in 1978
- Formalizes "**Occam's Razor**"

> *"We consider it a good principle to explain the phenomena by the simplest hypothesis [model] possible."* *(but not simpler)*
> *- Ptolemy (c. AD 90 – c. AD 168)*

# Our Approach – Sequence Synopsis

## Description Length of Event Sequences

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




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

# Our Approach – Sequence Synopsis

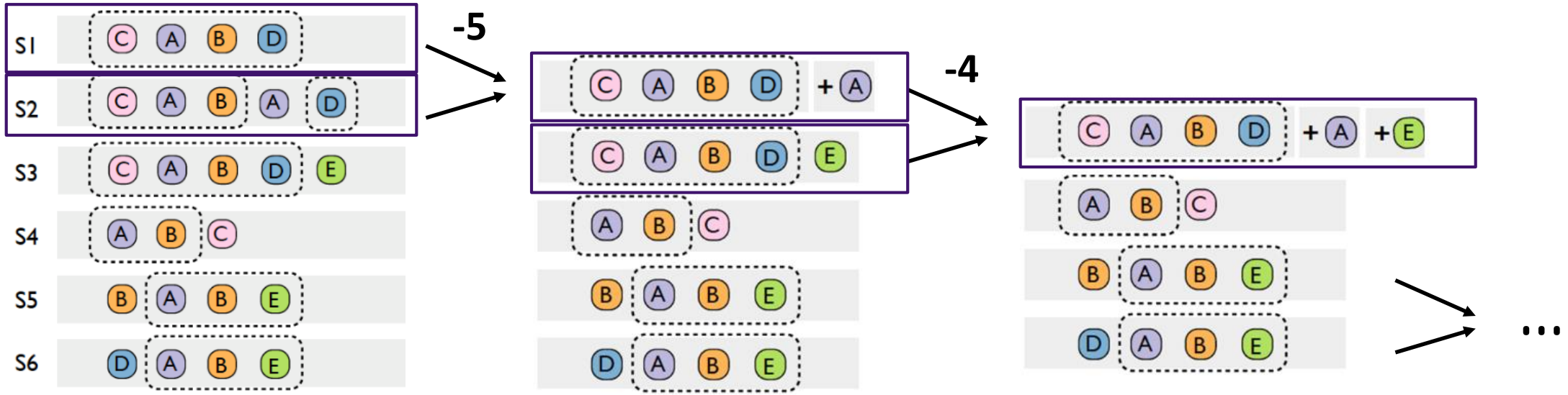
## Optimize Description Length for the Best Set of Patterns

- 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

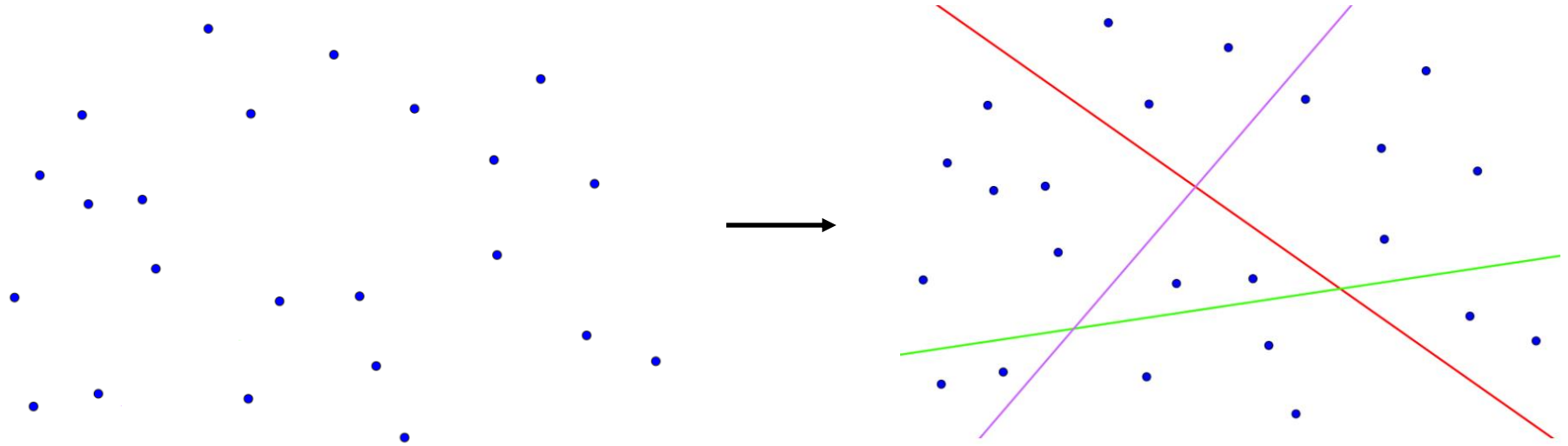
- Basic Idea: **iteratively find & merge** two groups of sequences with maximum description length reduction



# Our Approach – Sequence Synopsis

## Algorithm Speedup through Locality Sensitive Hashing (LSH)

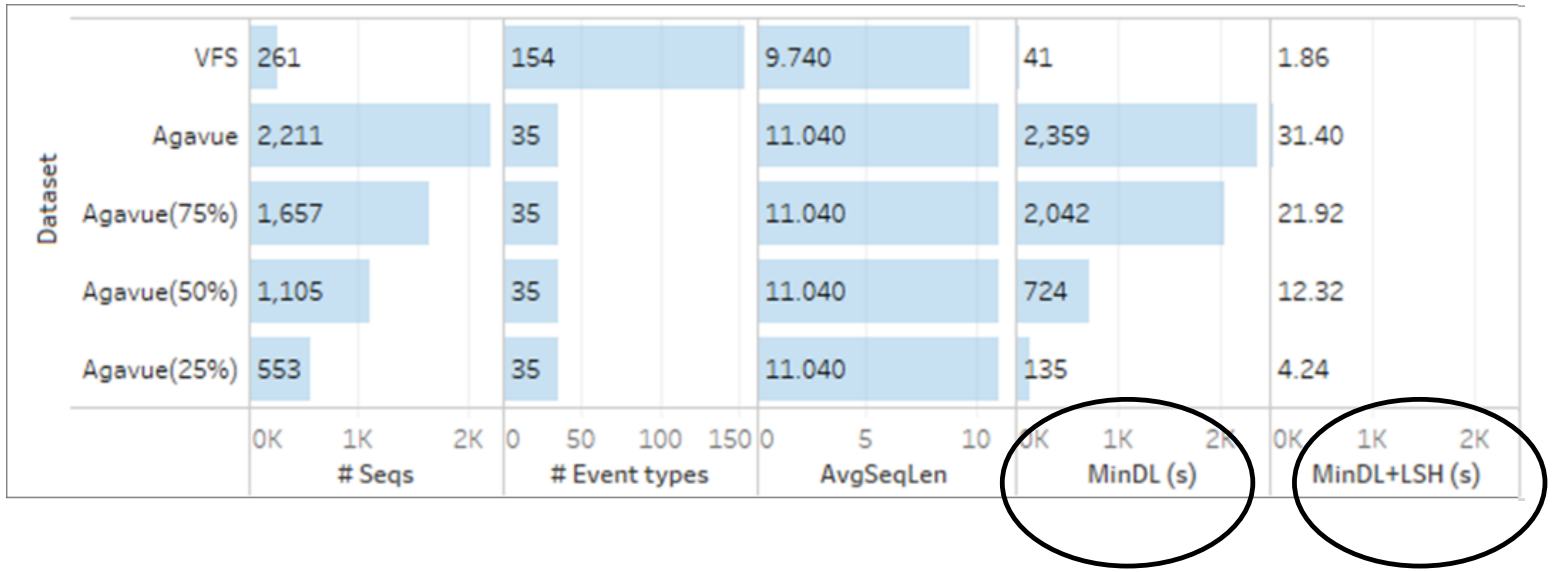
- **Bottleneck of the approach:** find best pair of event sequence groups to merge
- **Locality sensitive hashing**: algorithm for fast approximate neighbor search



# Our Approach – Sequence Synopsis

## Algorithm Speedup through Locality Sensitive Hashing (LSH)

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




**20x ~ 50x** speed gain with LSH
compared with "vanilla" approach

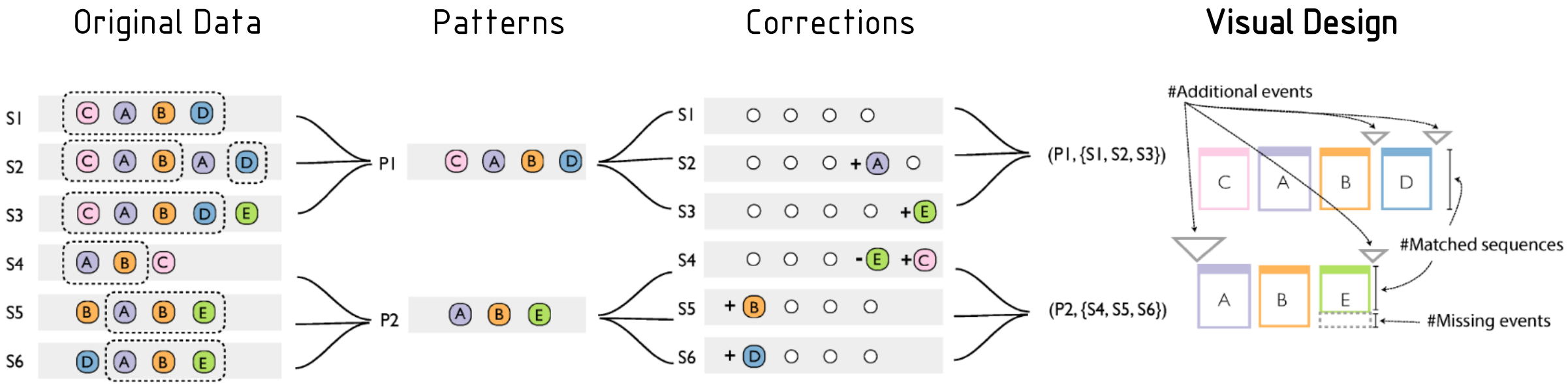
# Our Approach – Sequence Synopsis

## Advantages

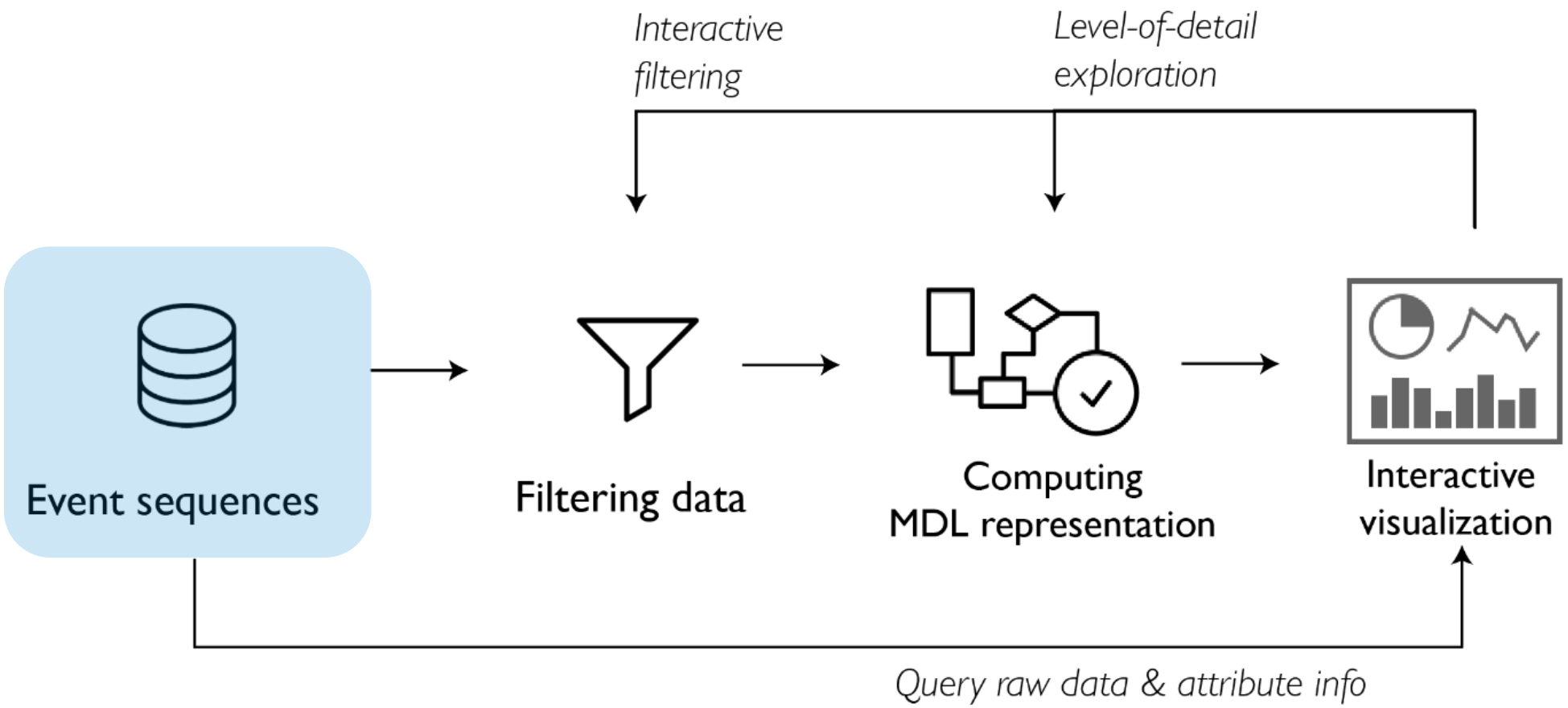
- **Simultaneous** event sequence clustering and pattern extraction
- **Soft constraints** on pattern matching, therefore robust to noisy data
- **Generalizability**: possibility to include different sequence editing operations (e.g. event insertion, deletion, swapping positions)

# System

# System
## Visual Design

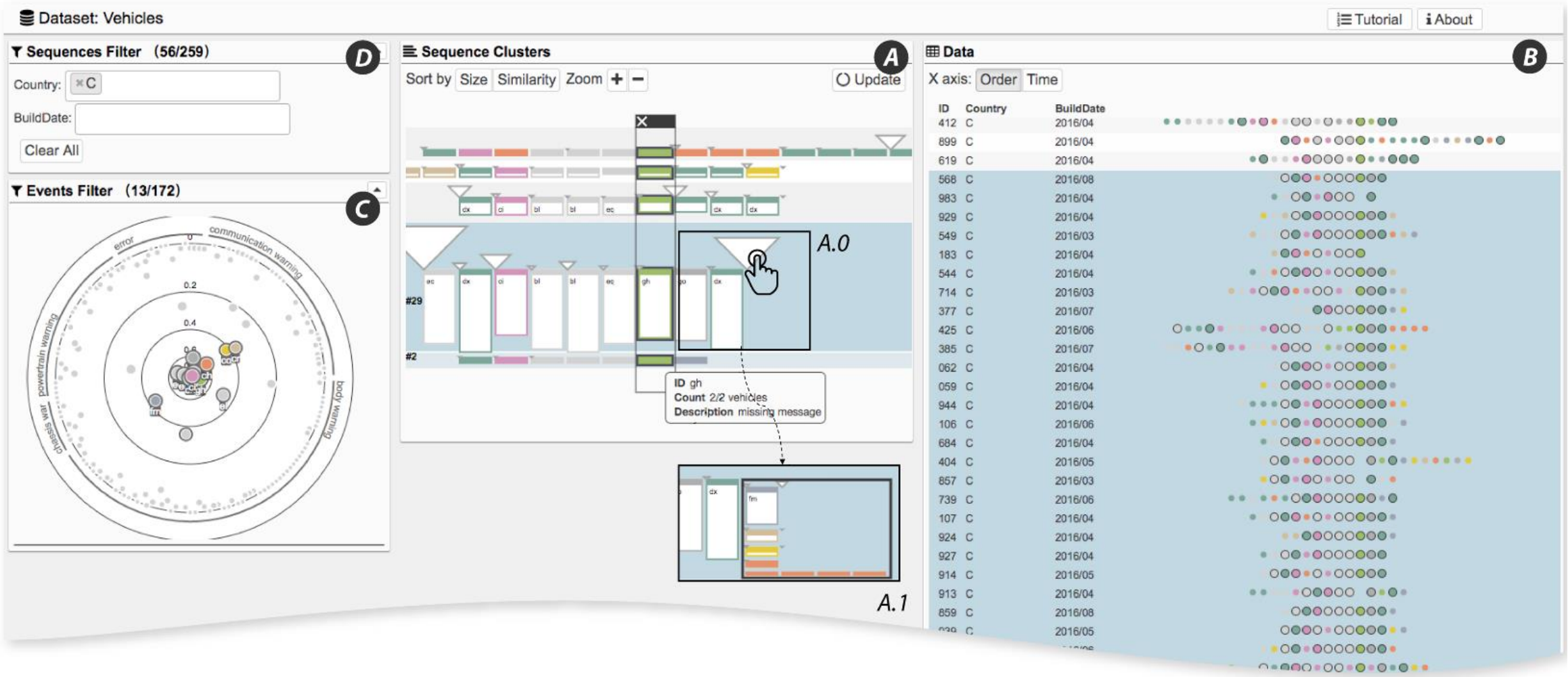


# System
## Architecture



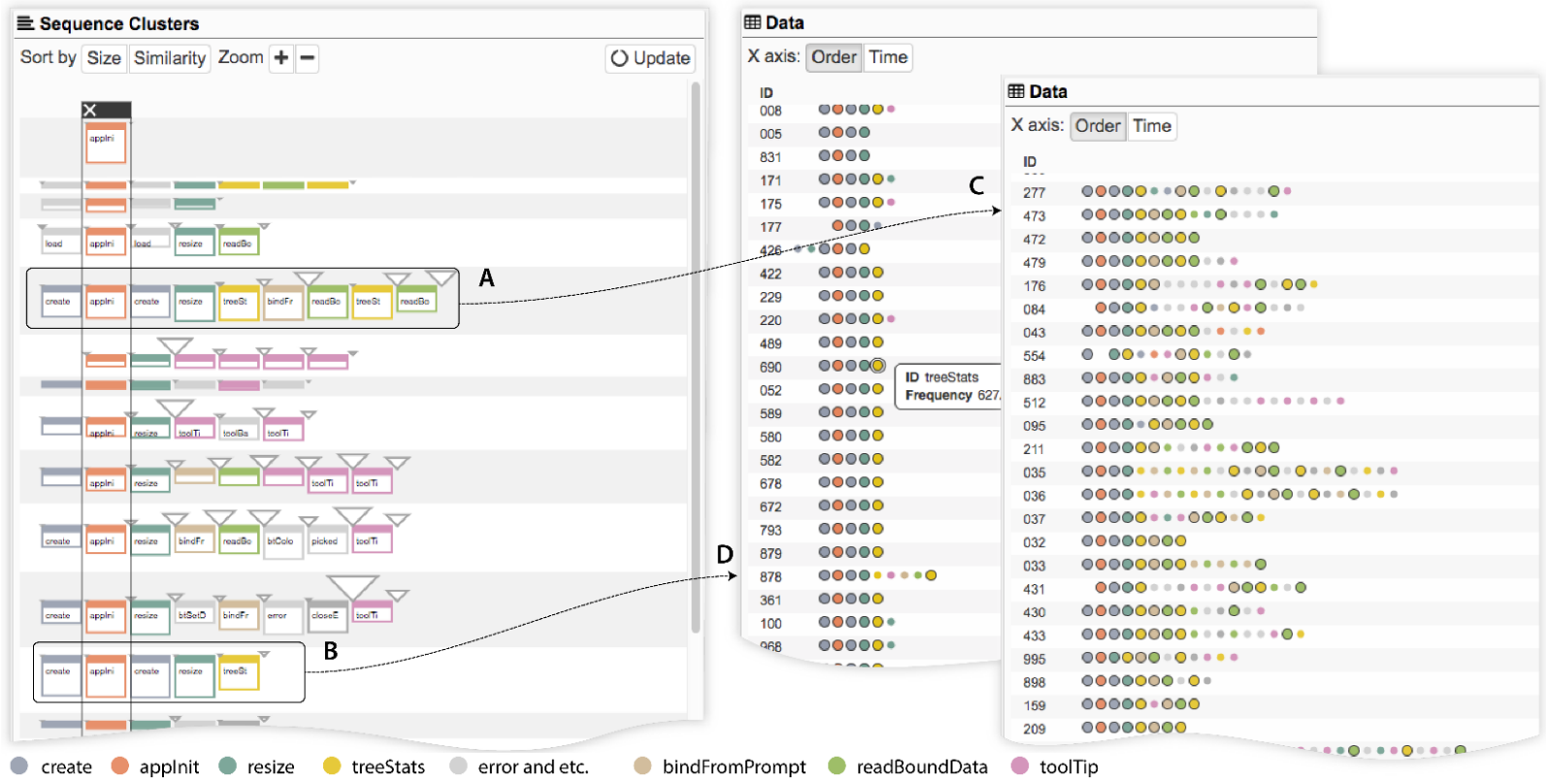
# System

## Supportive Views, UI, Case Study – Vehicle Fault Analysis



# System
## Case Study – Application Log Analysis

- **Dataset**:
  - D. Fisher. Agavue event data sample
- **Size**:
  - ~2000 user sessions
- **Description**:
  - Interaction log of using a data visualization application

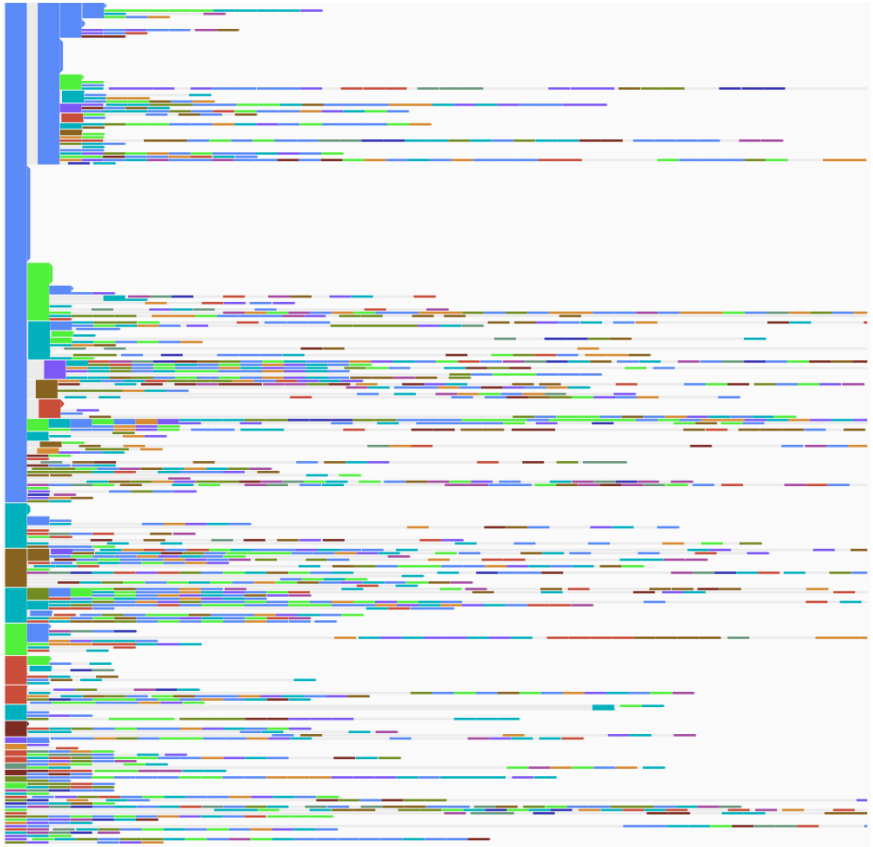


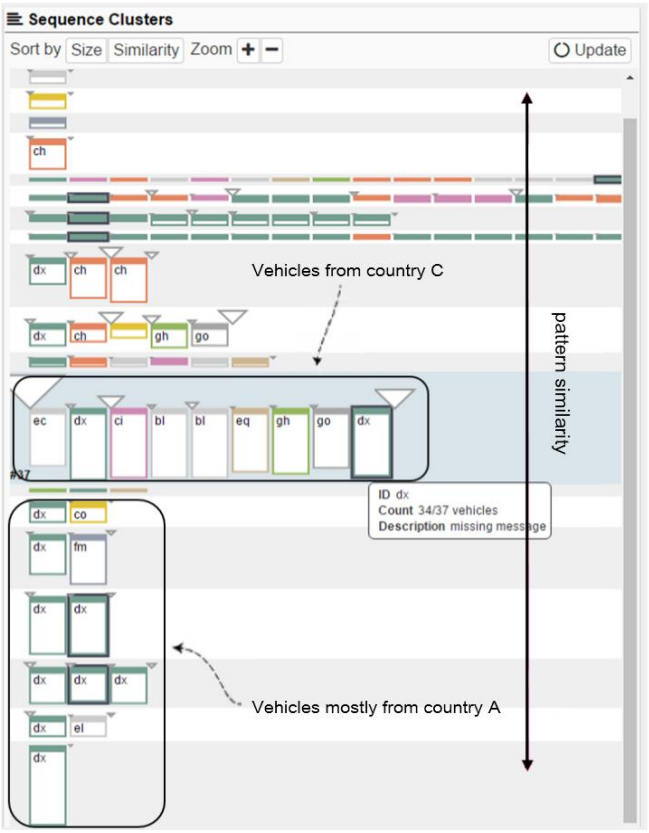
# Evaluation & Summary

# Evaluation & Summary

## Comparative Experiment

- **Dataset**: Vehicle Faults
- **Left**: EventFlow
- **Right**: Sequence Synopsis





# 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 …

# ViDX: Visual Diagnostics of Assembly Line Performance in Smart Factories

Introduction

The ViDX System

Summary

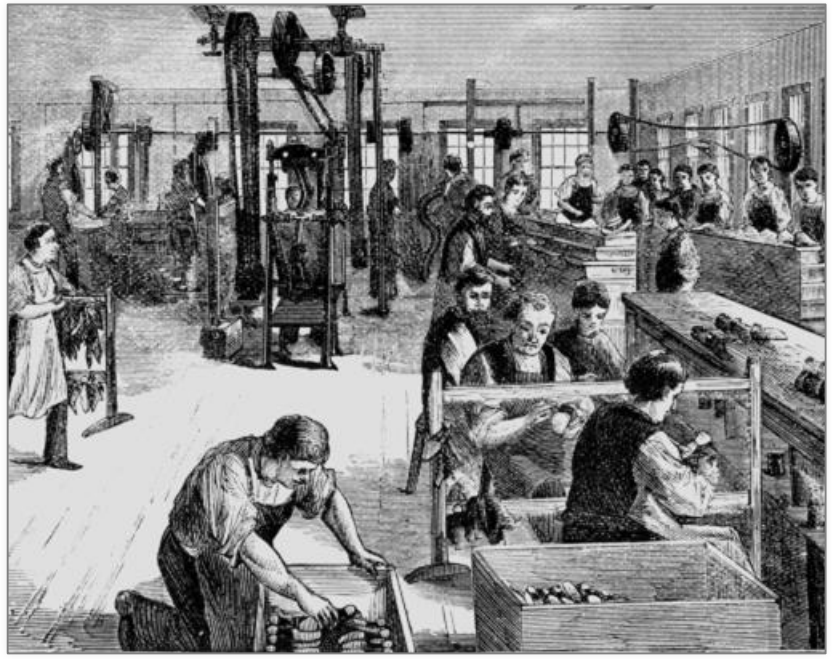
# **ViDX**: Visual Diagnostics of Assembly Line Performance in Smart Factories

Best Paper Honorable Mention
IEEE VAST, Oct 2016

Panpan Xu et al.

BOSCH

# Introduction
## Smart factories in Industry 4.0



Factories in the 19th century*.

Manufacturing today.

Towards Industry 4.0 (a.k.a. connected industry, industrial internet)

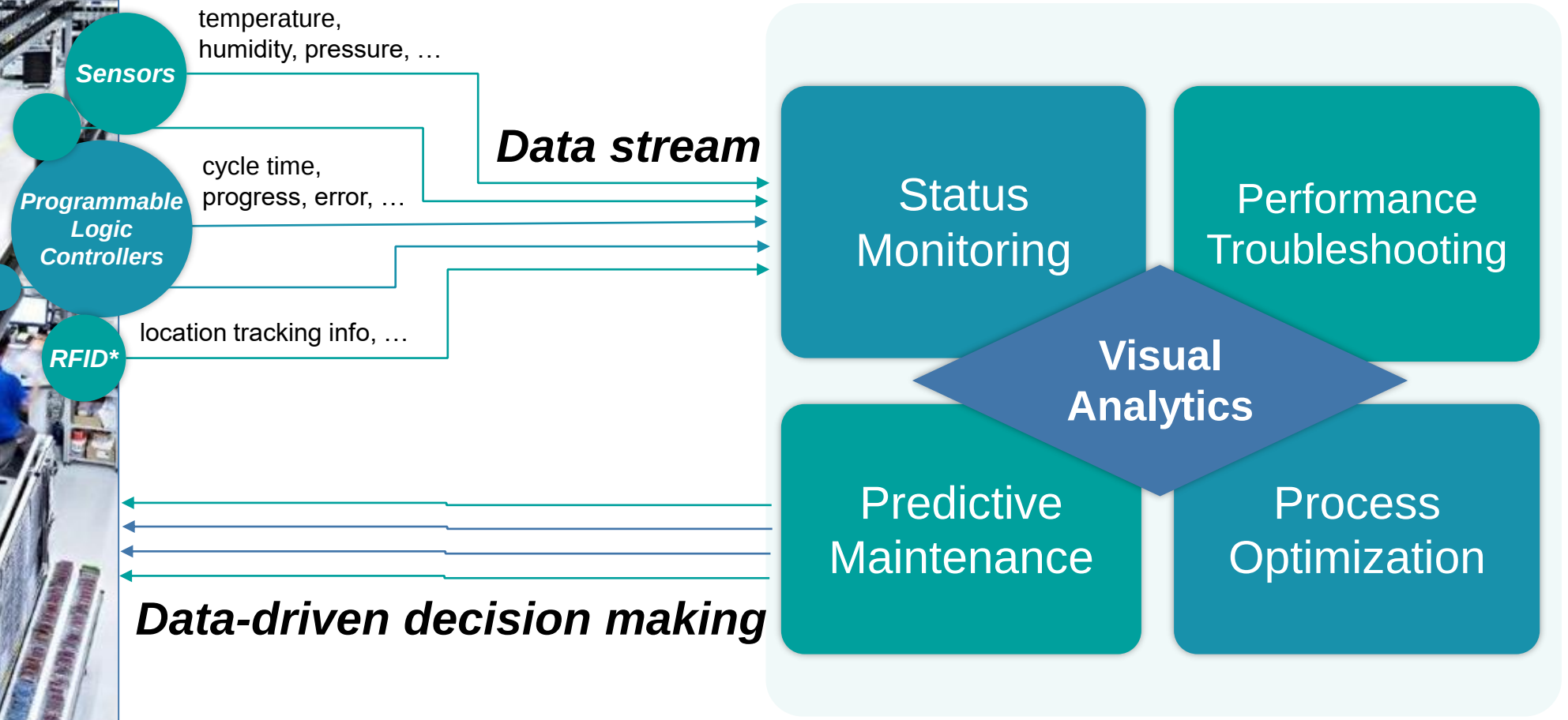
Digitalized


Automated


Connected

*Image source: http://www.alamy.com/stock-photo/19th-century-factory.html

# Introduction
## Big data in smart factories




* RFID: Radio frequency identification

# Introduction

## Challenges of real manufacturing data

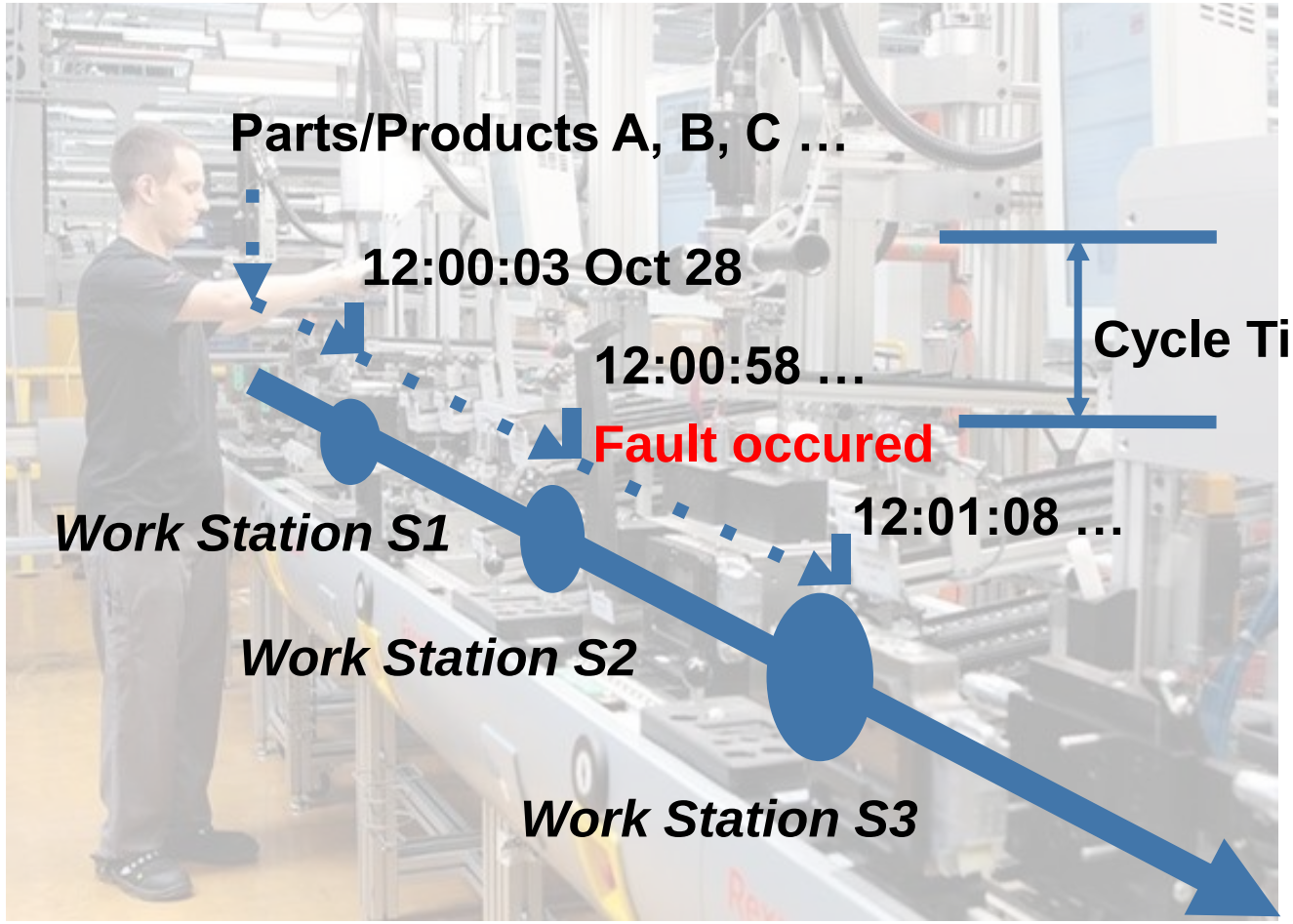
- High volume & speed
  - **Short cycle time** (time to finish one step)
  - **High throughput**
- High complexity
  - **Tens to hundreds of measurements** along a **single** manufacturing line

# Introduction
## Our work

- Raise the awareness of this **new, important and exciting research area** for visual analytics
- ViDX: The **first** visual analytics system for **real manufacturing data** in **industry 4.0** applications.
  - Data provided by Bosch Anderson plant at South Carolina producing hydraulic modules, electronic modules and sensor elements in cars (deployment in progress)
- Addressing challenges with novel visualization & interaction
  - **Target user:** shop floor technicians/operators and managers
  - **Application**: intuitive status monitoring & easy performance troubleshooting on assembly lines
  - **Data**: complex, large scale manufacturing process data**.**

# The ViDX System

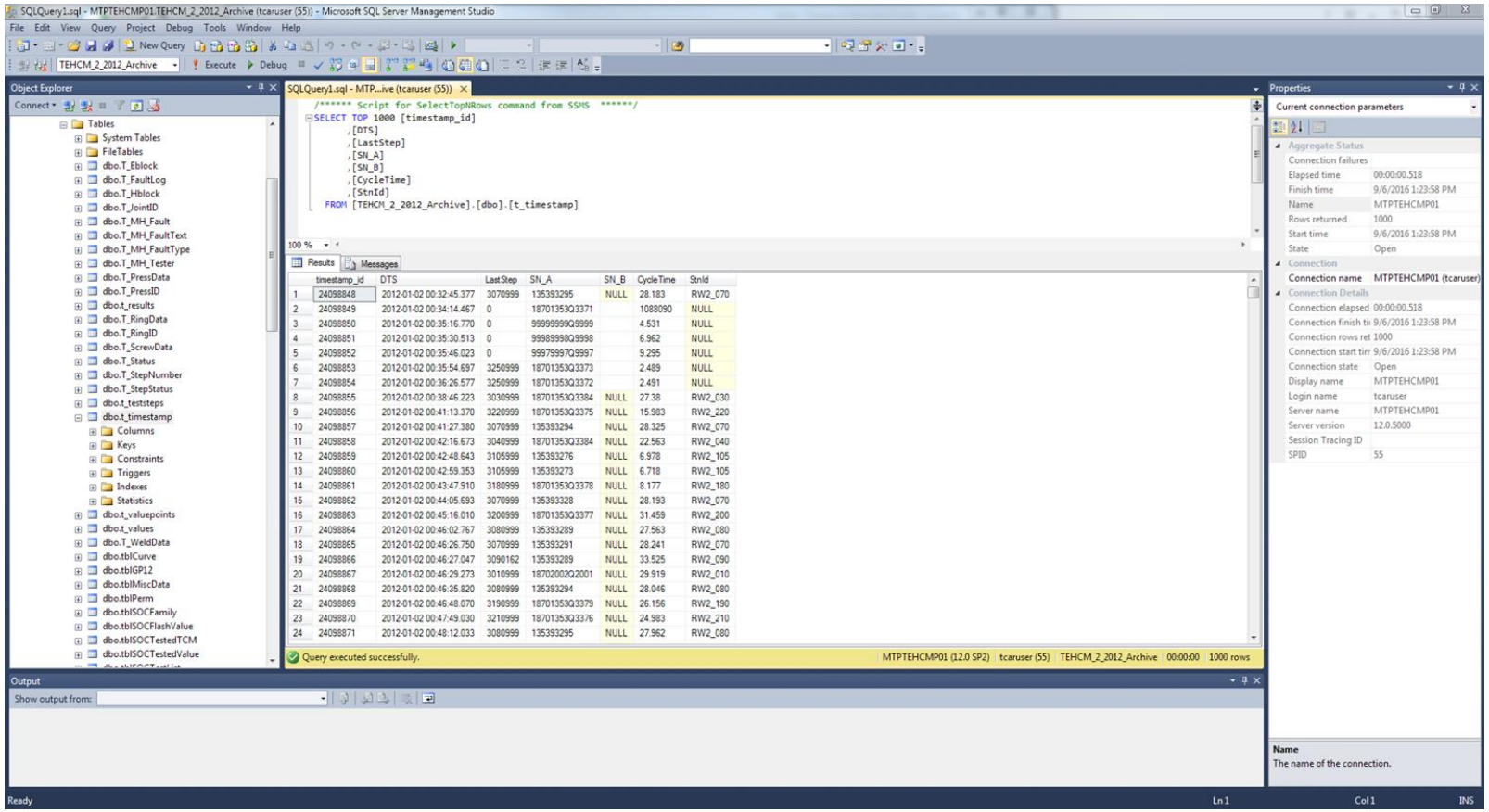
## Data




- **Data**:
  - When a part/product arrives at which station (with the derived cycle time)
  - Which fault occurred

# The ViDX System

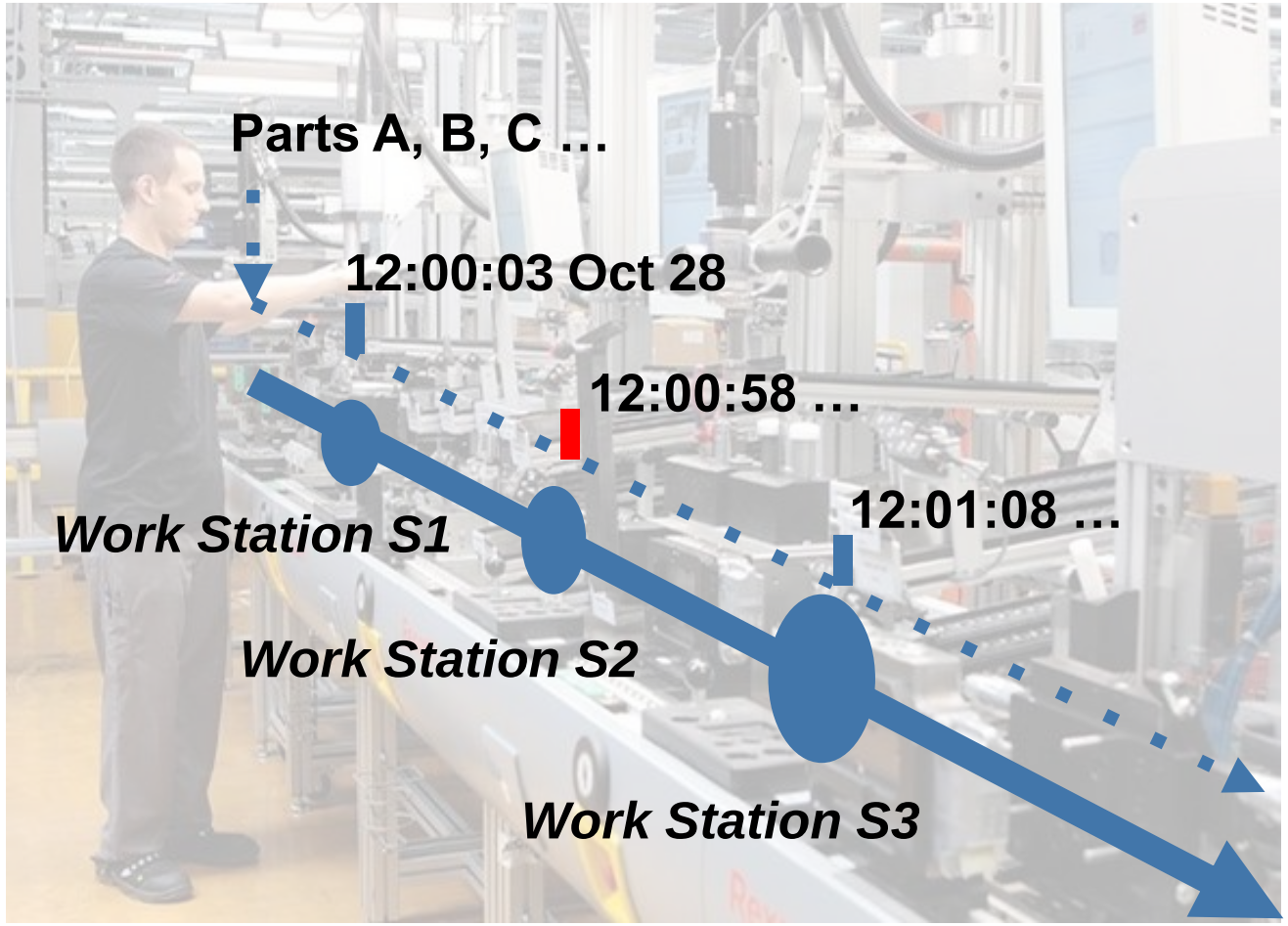
## Data




Database for historical records
(millions per year for a single production line).

# The ViDX System

## Tasks & system requirements

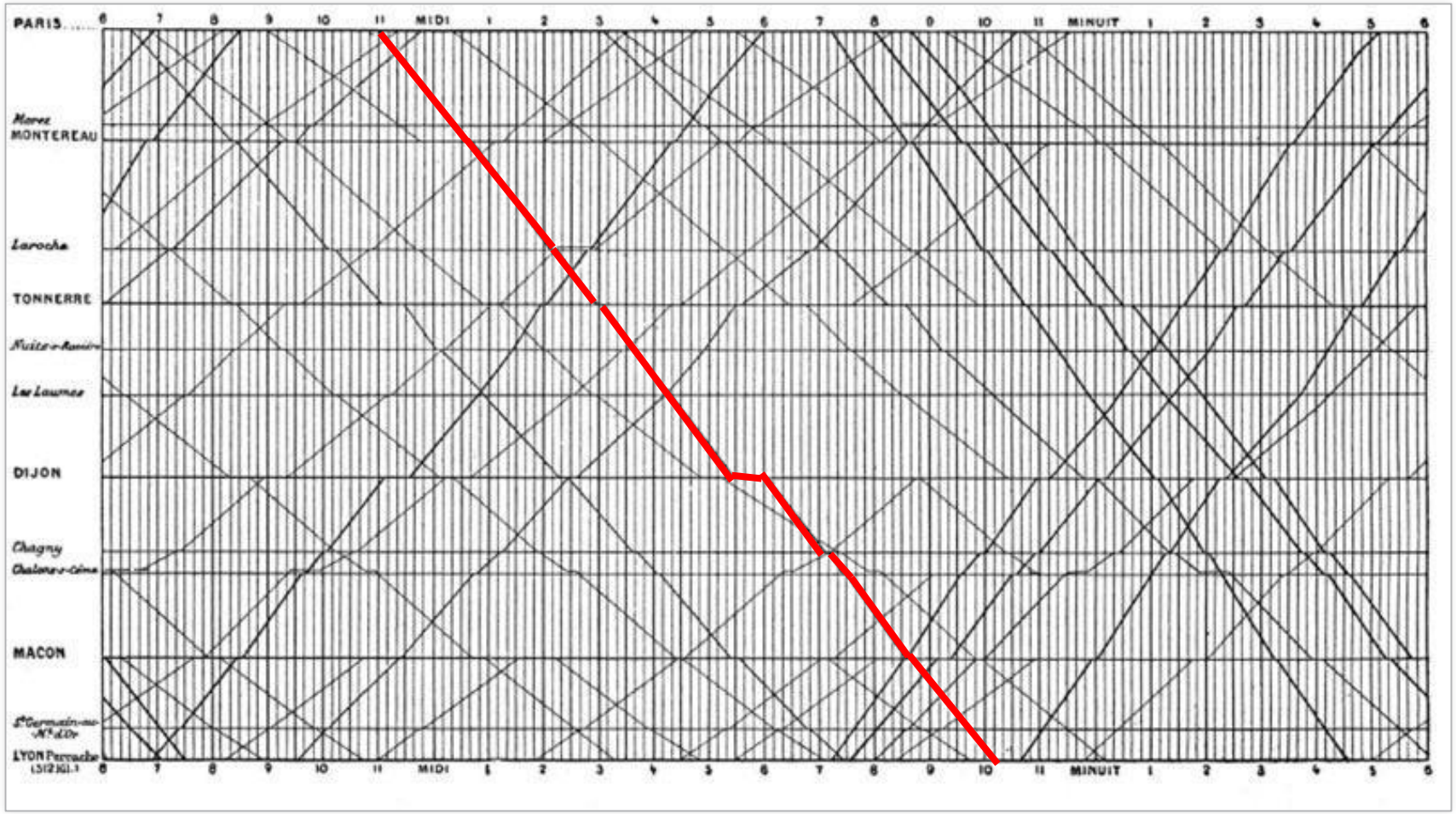



- Task: performance troubleshooting
  - Identify **when** (during which minute/hour/day…), **where** (on which work station), **how** production efficiency decreases.
  - Determine **the effect of faults** on production efficiency.
- System requirements
  - **Scalable** to handle year long records.
  - Support both **historical data analysis** & **real-time monitoring**.

# The ViDX System

## Inspiration: E.J. Marey's graphical train schedule from 1880's

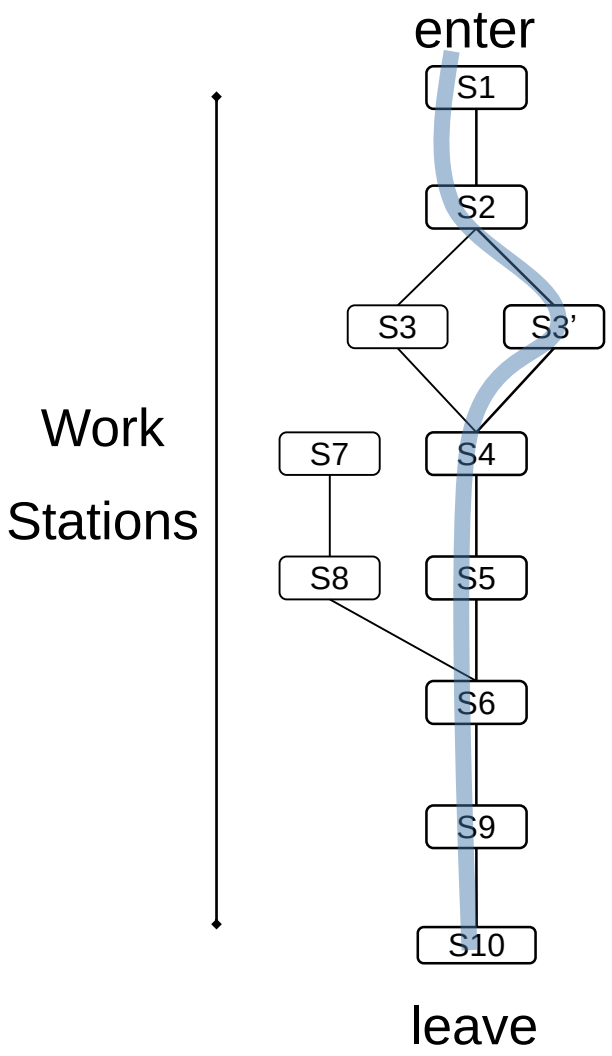
Train Stations

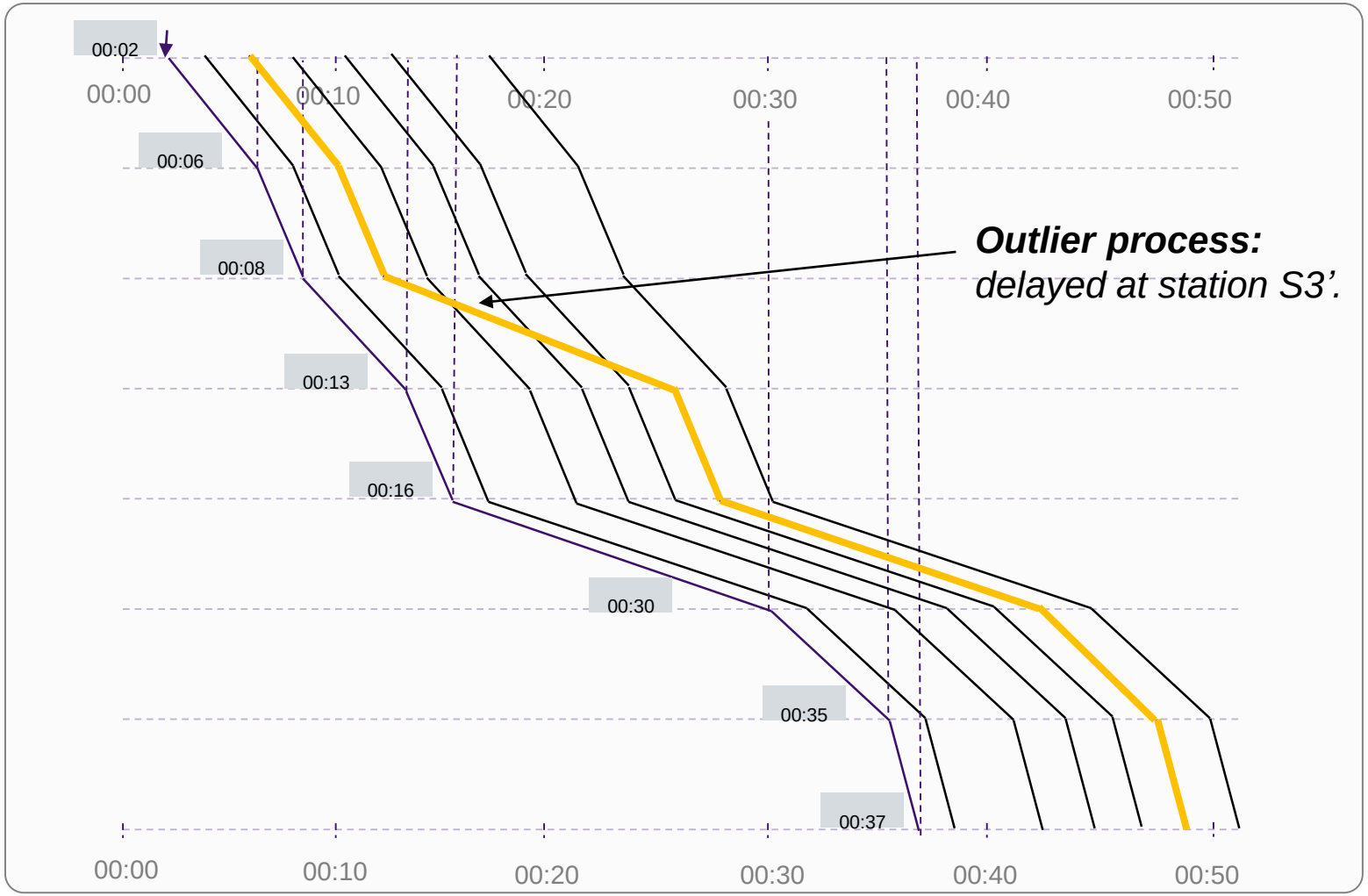



Timeline

# The ViDX System

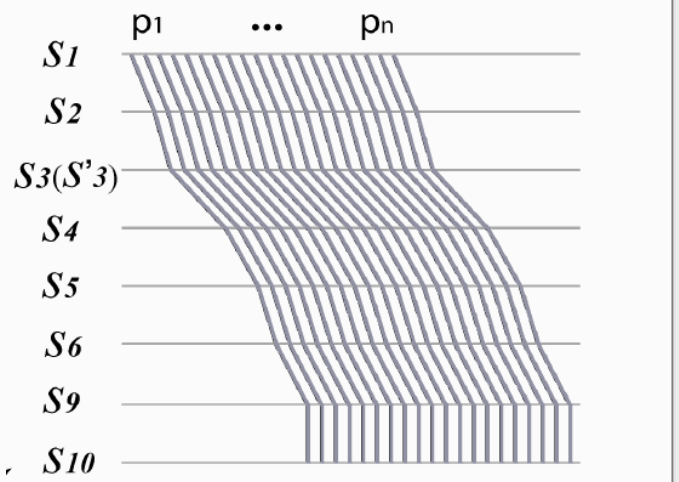
## Idea 1: Visualize manufacturing processes as Marey's Graph



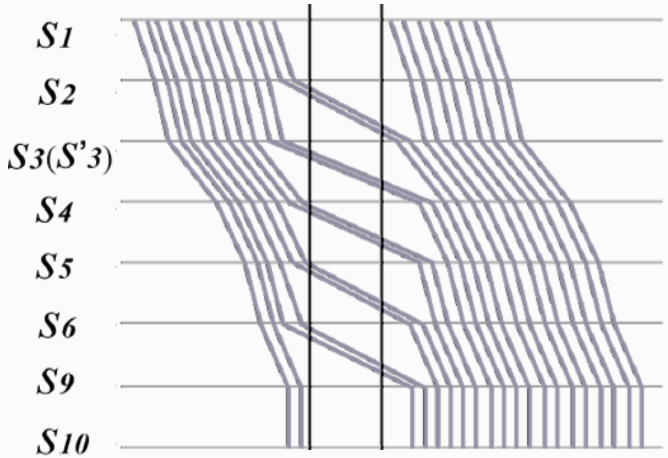



# The ViDX System

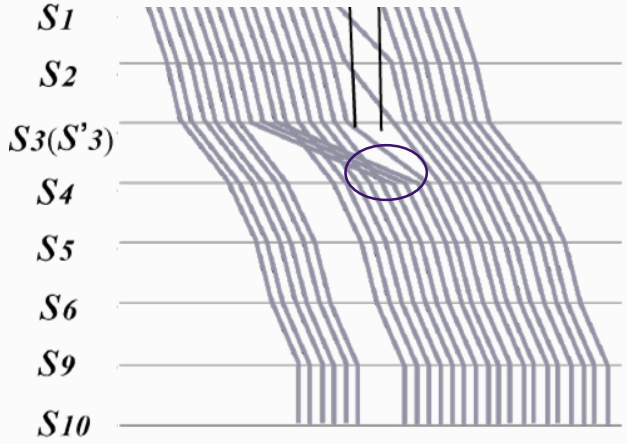
## Intuitive visual patterns for performance troubleshooting




☑Normal, efficient operation




☒The assembly line stopped

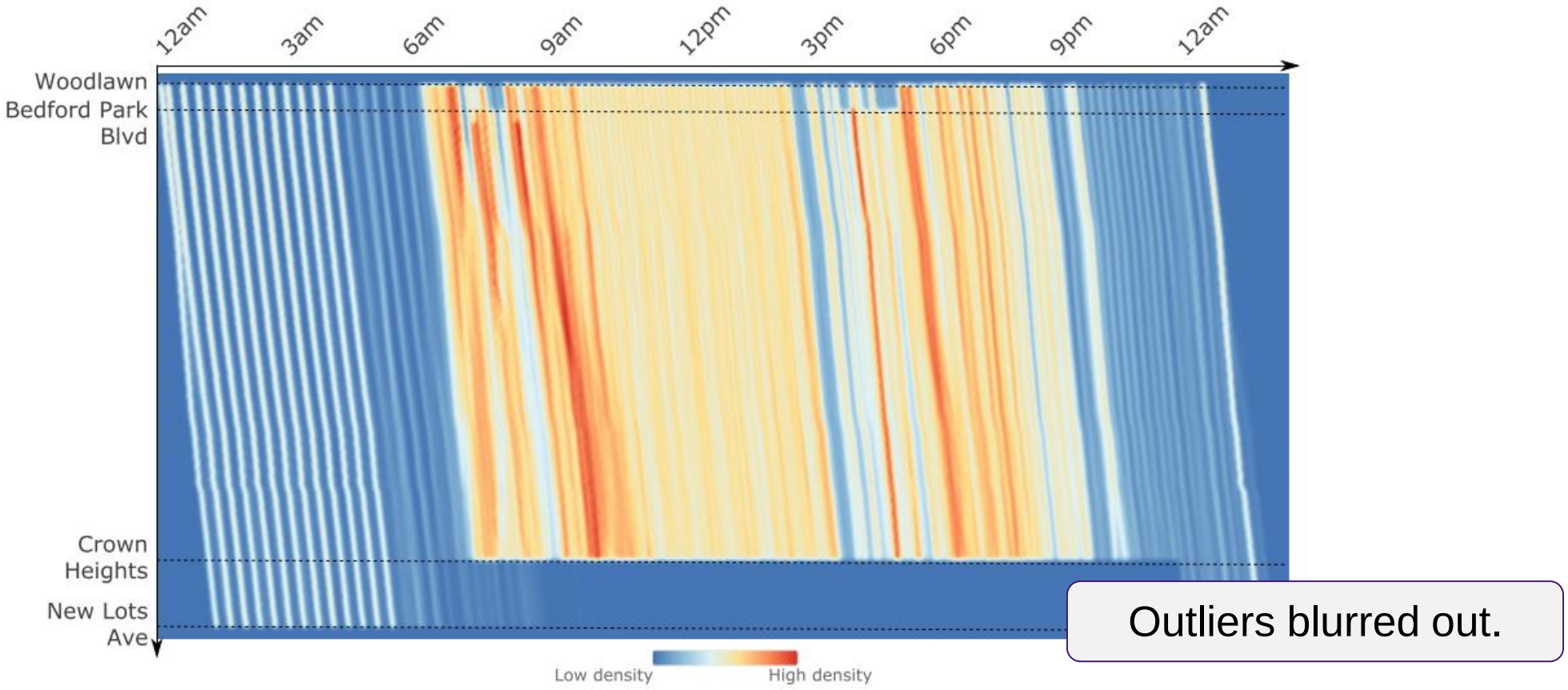



☒Processes stuck at some station

# The ViDX System

## How to scale-up? (related work)

Kernel density estimation (KDE)

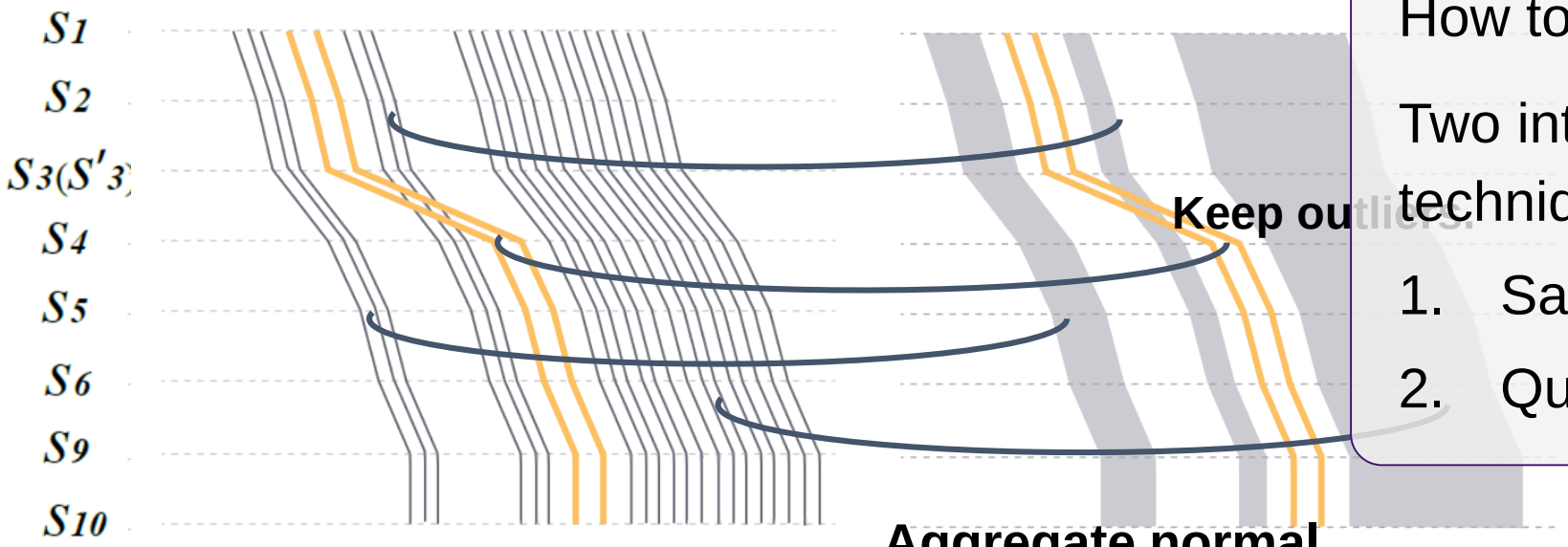



Outliers blurred out.

Visualize public transportation schedules [Palomo et al. 2015]

# The ViDX System

## Idea 2: Interactive outlier detection and visualization.




How to define the outliers?

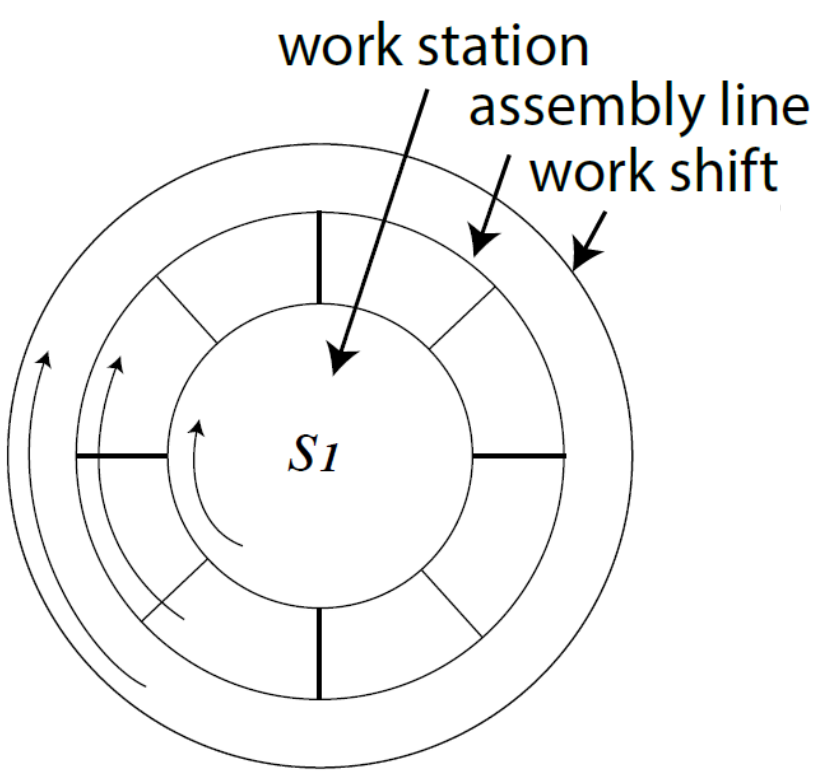
Two interactive outlier detection techniques:

1. Samples brush
2. Quantiles brush

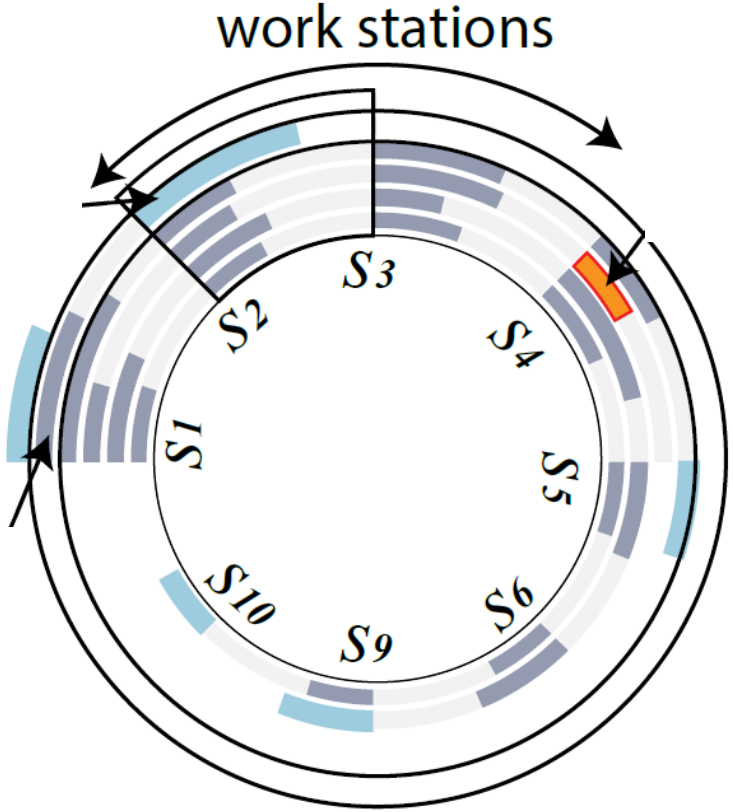
Outlier-preserving visual aggregation.

# The ViDX System

## Animated radial graph for real-time production progress monitoring




Original design proposed by the target user.




Redesigned graph.

# The ViDX System
## User interview

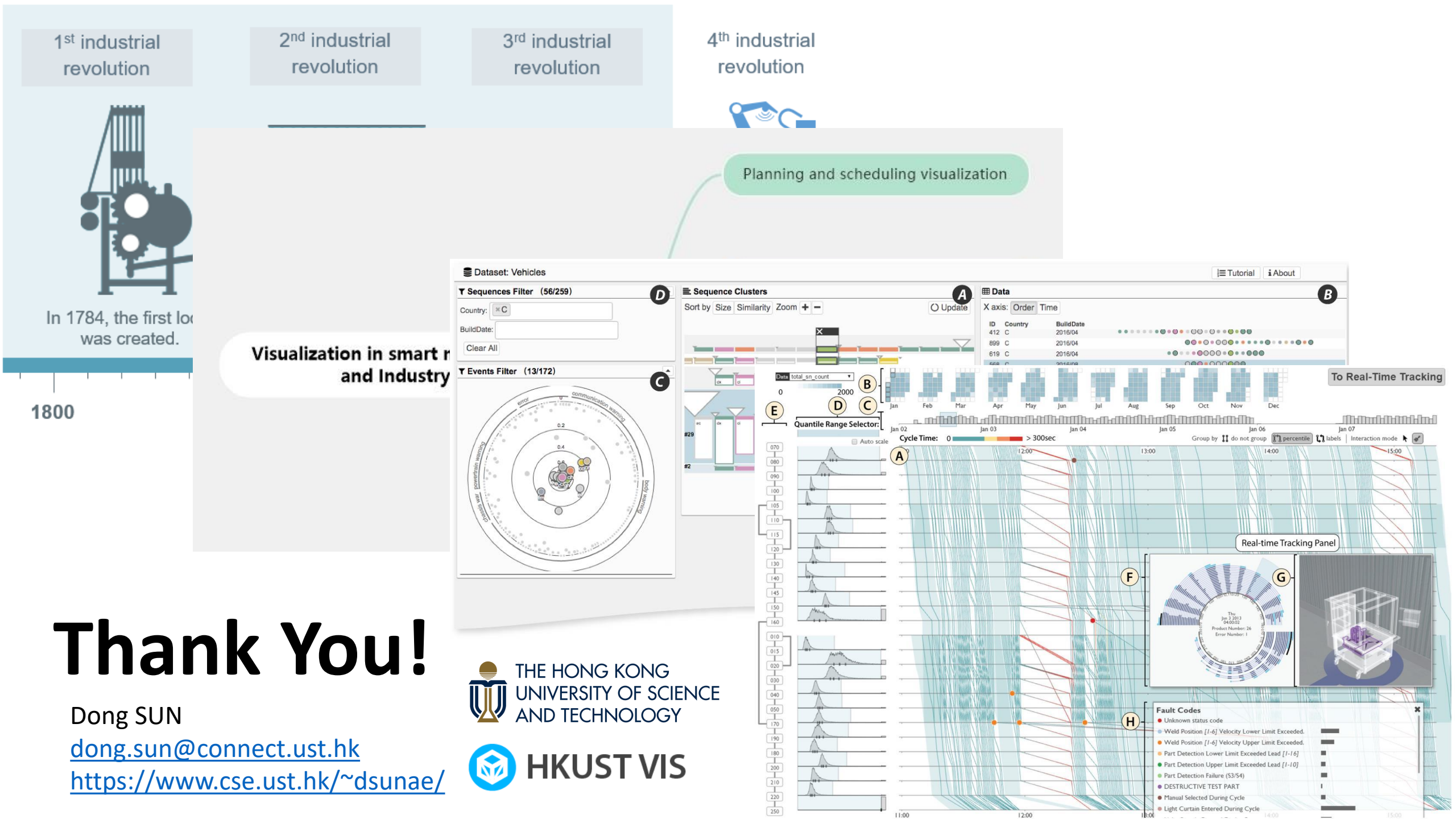
- Participants
  - 11 users, all have experience with basic visualization techniques (e.g., barcharts)
- Summary of feedback
  - Samples brush is preferred over quantiles brush for its intuitiveness.
  - Extensions suggested to apply the current system for analyzing other process related parameters.
  - **Deployment of the system in progress**

"This is a good interface for gaining an **intuitive** picture of how the line is running. These same methods could applied to process parameters during the manufacture of parts giving engineers the intuitive picture of process stability".

"it's very **effective** in the system's ability to show real-time data [in the radial graph] and highlight abnormalities"

# Summary
## Contributions

- The **first** visual analytics system for real data in **Industry 4.0** applications.
- Application & extension of the **Marey's graph** to visualize large amount of manufacturing processes with **outlier-preserving visual aggregation** techniques.
- Two novel **interactive outlier detection** techniques:
  - Samples brush based on label propagation algorithms
  - Quantiles brush based on statistical summaries




# Thank You!

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THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

HKUST VIS