

ICDM 2019

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Multi-Aspect Mining of Complex Sensor Sequences

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Motivation

Analysis of IoT sensor data, e.g., car - Advanced driving assistance service

Risk



Fuel

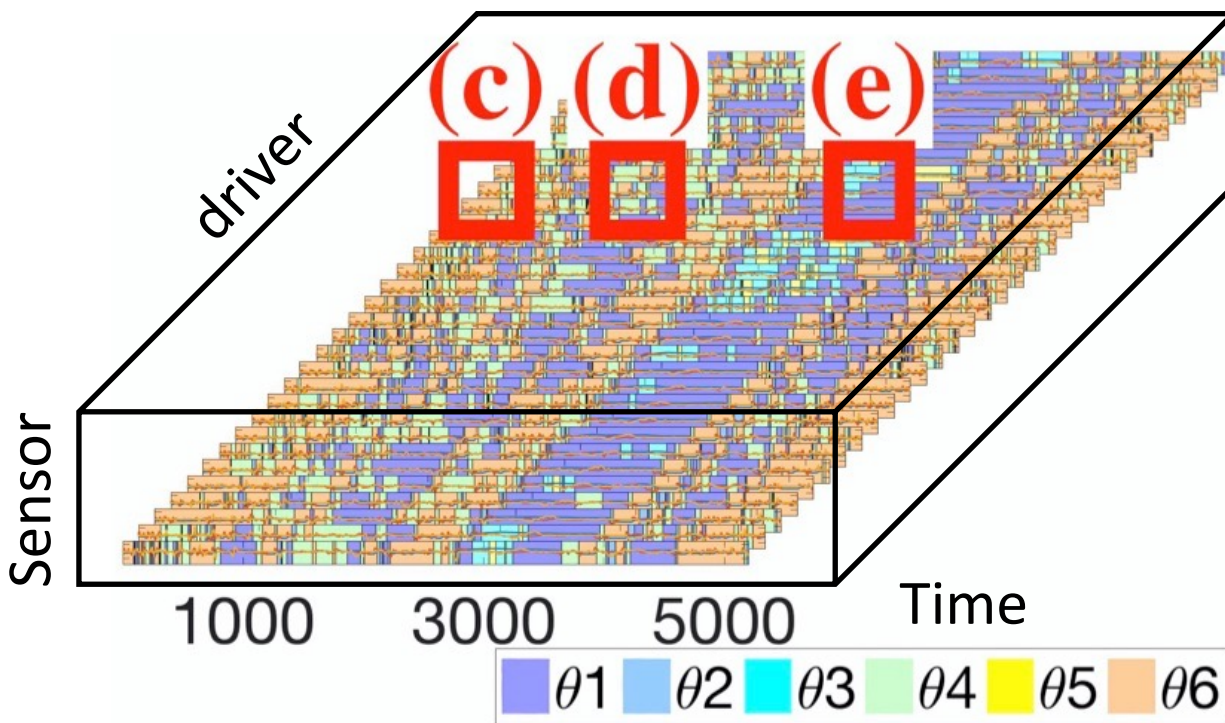


Congestion

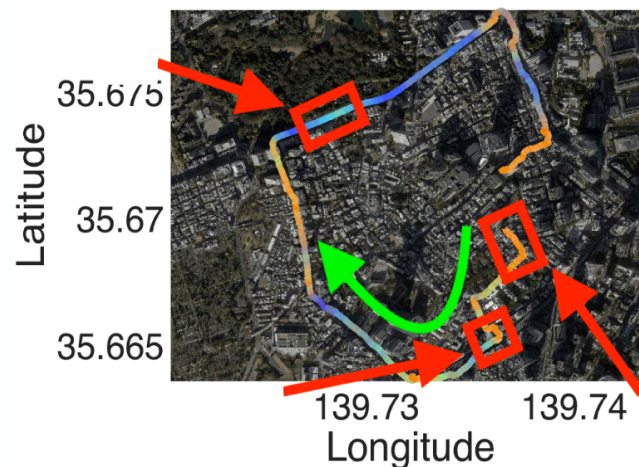


Motivation

IoT sensor data is a tensor
(sensor \times driver \times time)



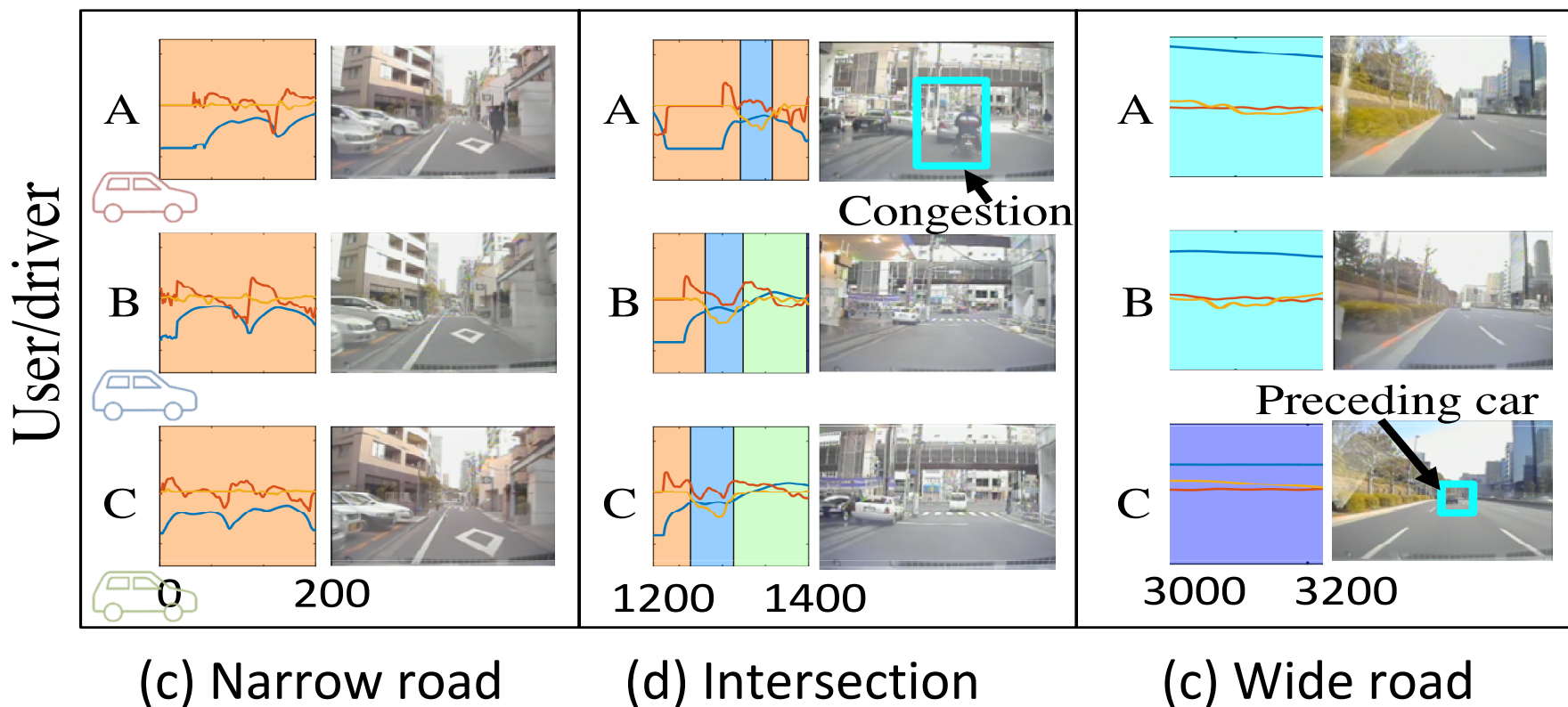
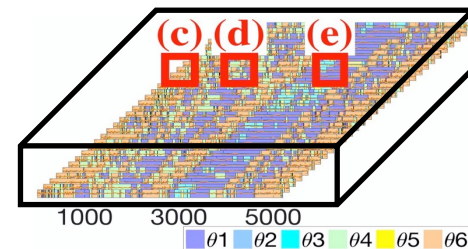
(a) Time series tensor of automobile dataset



(b) On a map

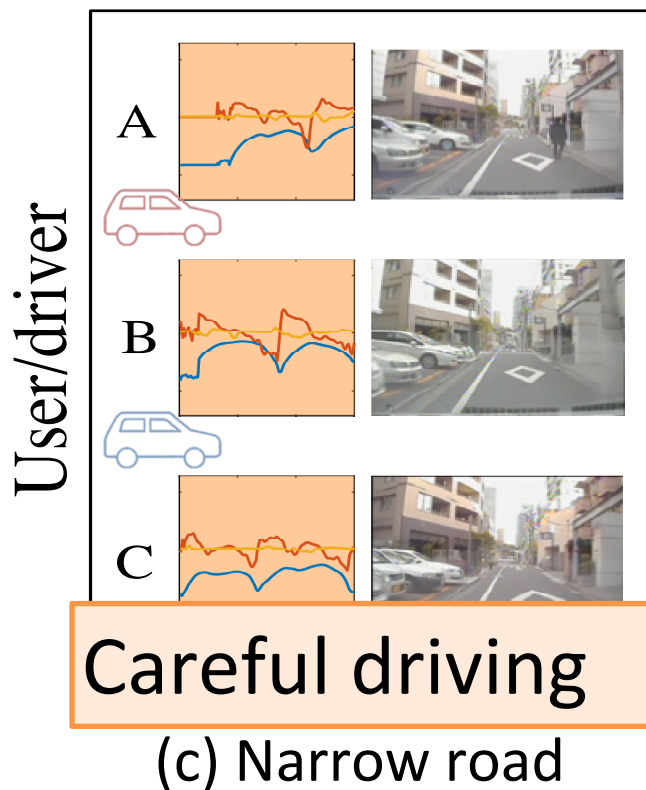
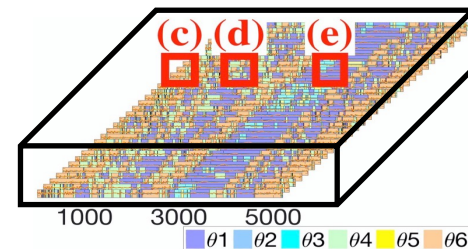
Motivation

Tensor has multi-aspect patterns:
time-aspect and **user-aspect**



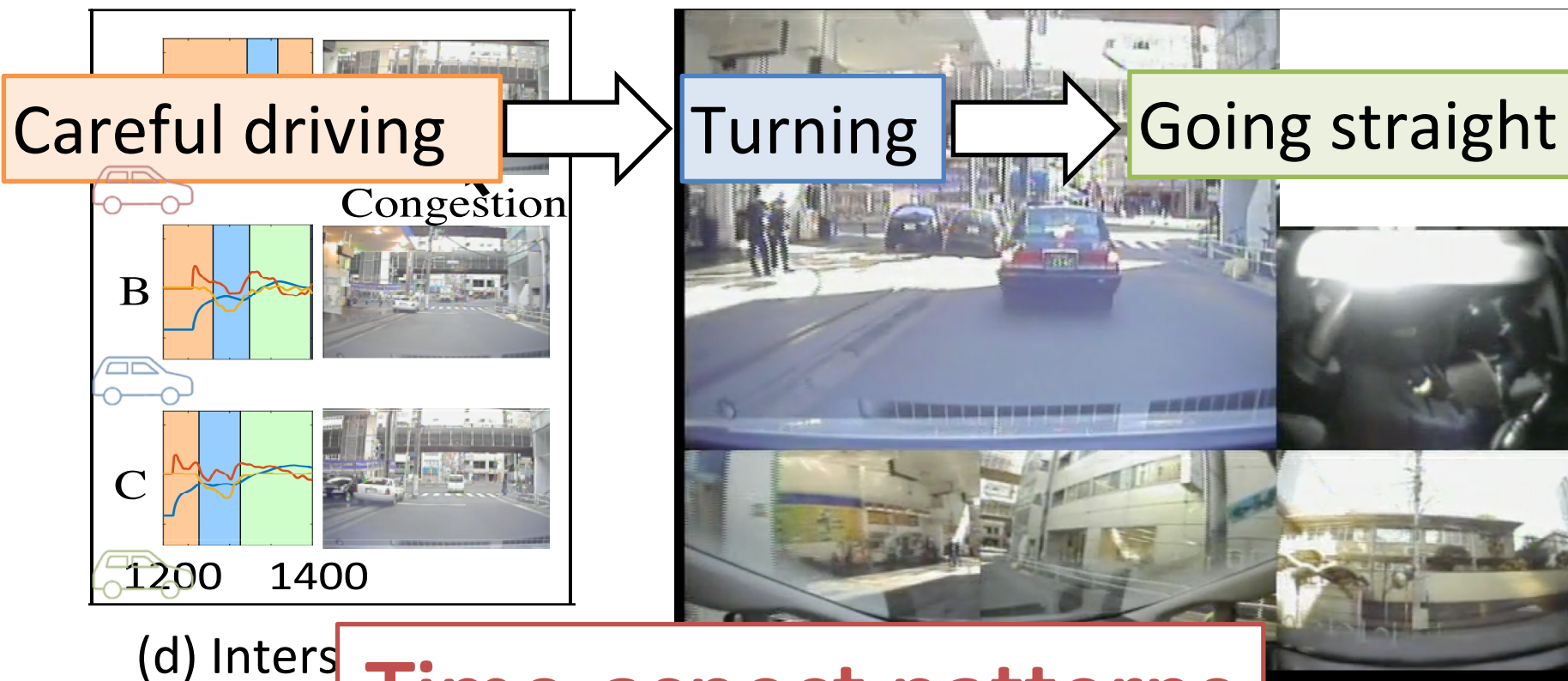
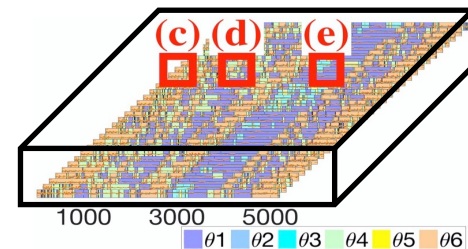
Motivation

Tensor has multi-aspect patterns:
time-aspect and **user-aspect**



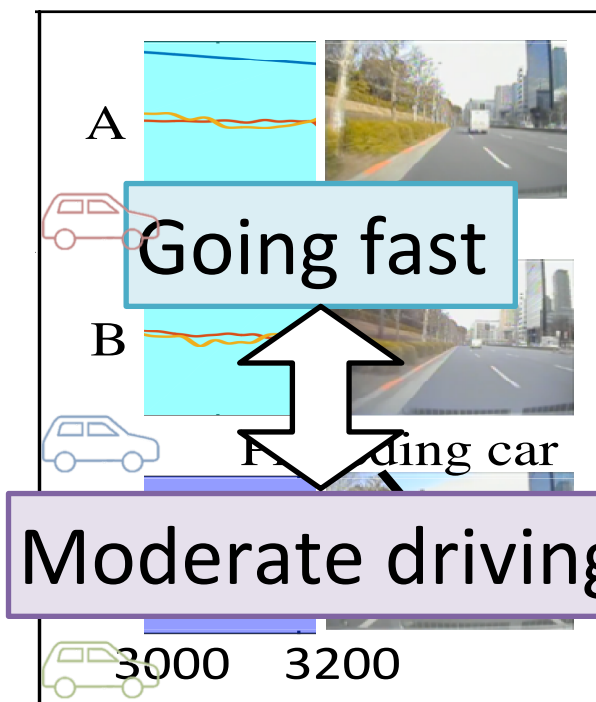
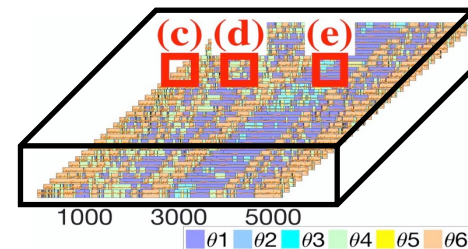
Motivation

Tensor has multi-aspect patterns:
time-aspect and **user-aspect**



Motivation

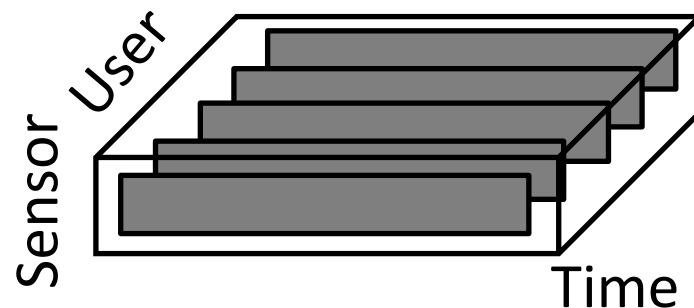
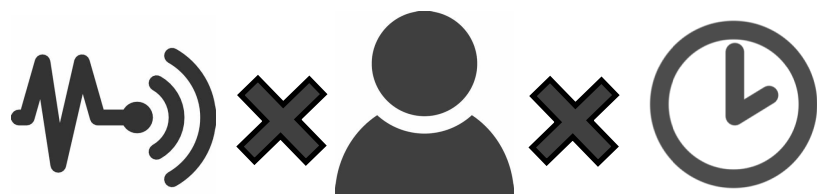
Tensor has multi-aspect patterns:
time-aspect and **user-aspect**



User-aspect patterns

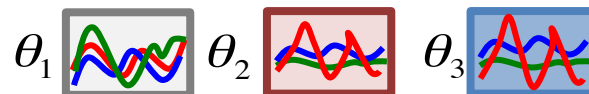
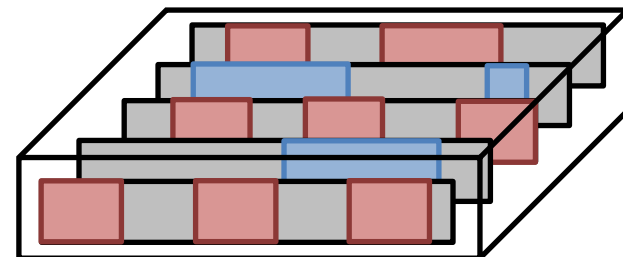
Motivation

Given: **Time-series tensor**
(sensor \times user \times time)



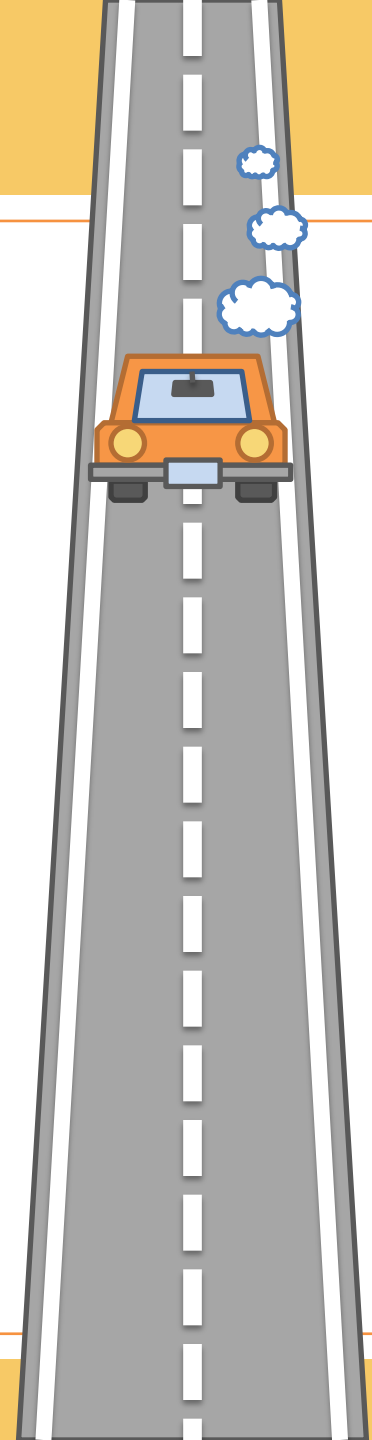
Find: **Multi-aspect patterns**
(**time** and **user**-aspect)

Automatically & quickly



Outline

- Motivation
- Problem definition
- Main ideas
- Algorithms
- Experiments
- Conclusions



Problem definition

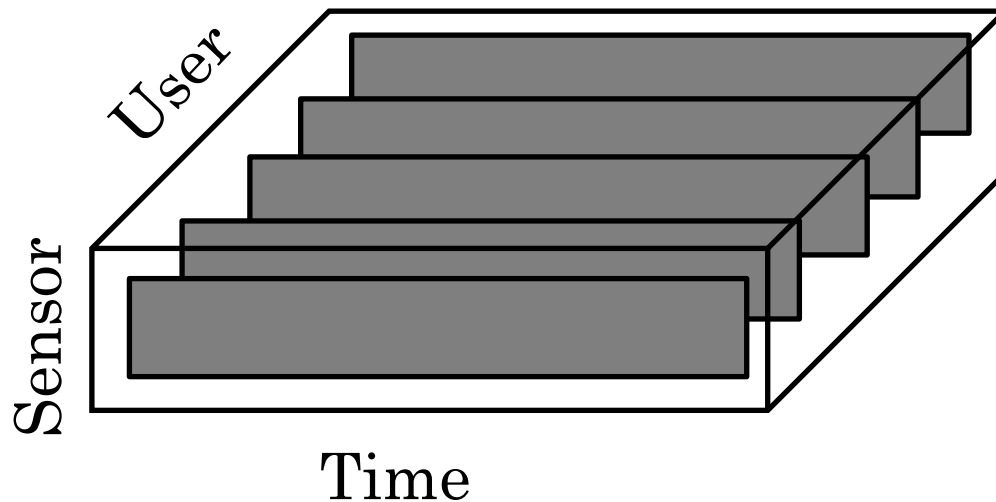
Key concepts

- **Tensor:** \mathcal{X} given
- **Segment:** S hidden
- **Regime:** Θ hidden
- **Segment-membership:** F hidden

Problem definition

Tensor : $\mathcal{X} \in \mathbb{R}^{d \times w \times n} = \{X_1, \dots, X_w\}$

given



Problem definition

Segment : $\mathcal{S} = \{s_1, \dots, s_m\}$

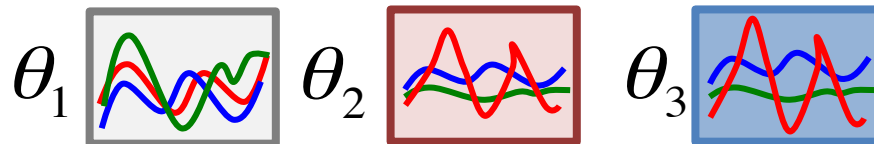
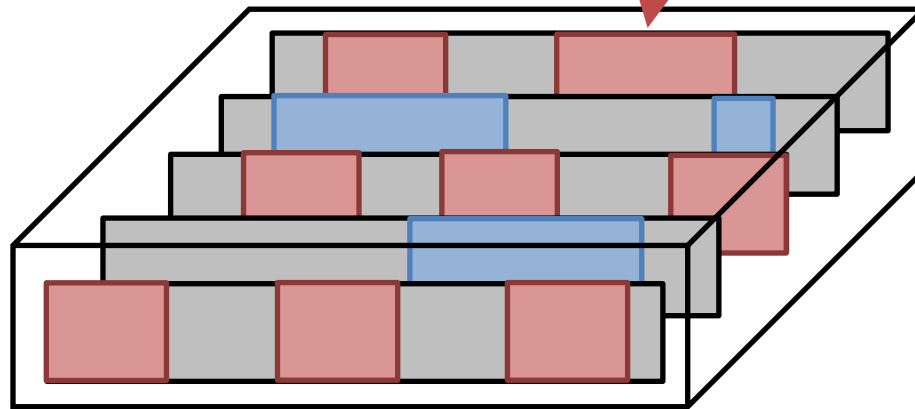
hidden

$$s_i = \{t_s, t_e, userID\}$$

start
position

end
position

$m = 25$ segments



Problem definition

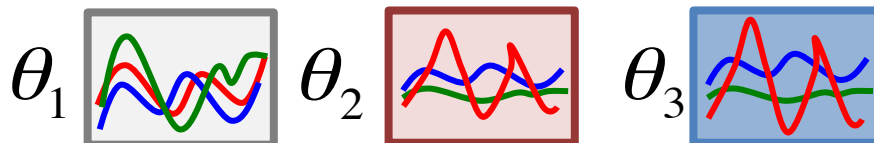
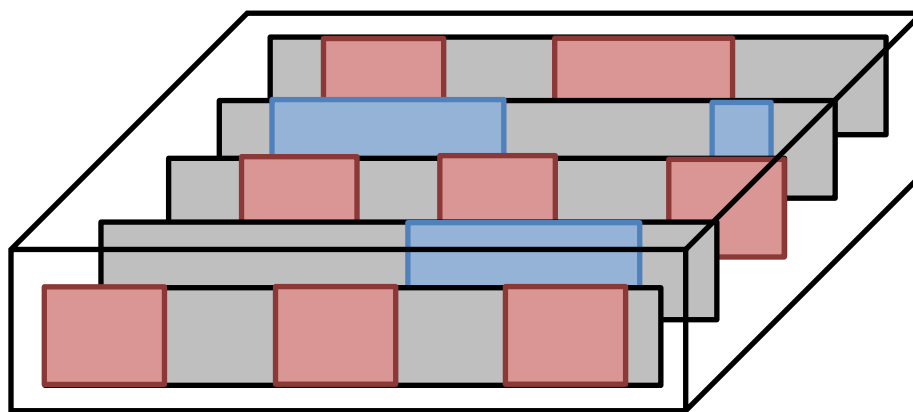
Regime: $\Theta = \{\theta_1, \theta_2, \dots, \theta_r, \Delta_{r \times r}\}$

hidden

$\theta_i = \{\pi, A, B\}$ (hidden Markov model)

Initial prob. transition prob. output prob.

$r = 3$ regimes



Problem definition

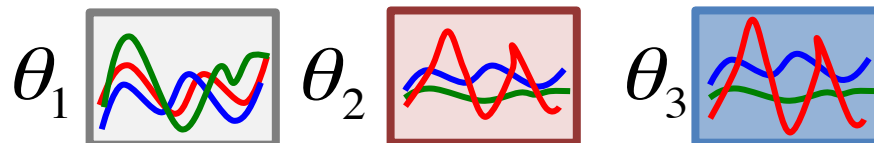
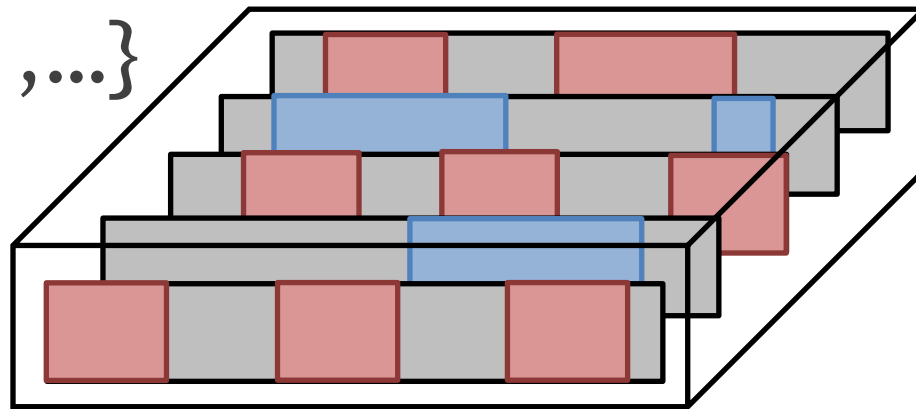
Membership: $F = \{f_1, f_2, \dots, f_m\}$

hidden

$$1 \leq f_i \leq r$$

Example:

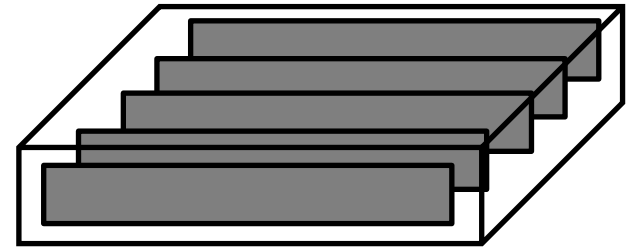
$$F = \{1, 2, 1, 2, 1, \dots\}$$



Problem definition

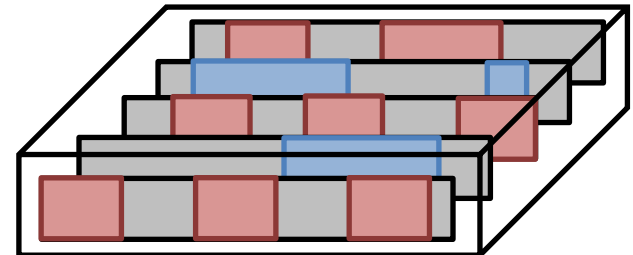
Given: tensor \mathcal{X}

$$\mathcal{X} = \{X_1, \dots, X_w\}$$

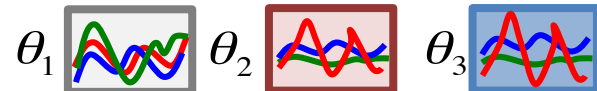


Find: compact description \mathcal{C} of \mathcal{X}

$$\mathcal{C} = \{m, r, S, \Theta, F\}$$

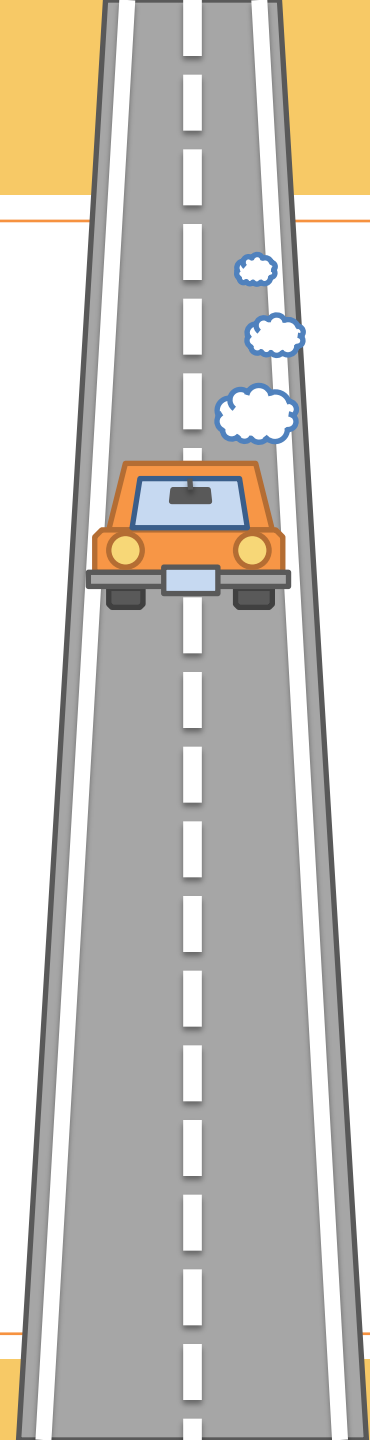


Automatically & quickly



Outline

- Motivation
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- **Main ideas**
- Algorithms
- Experiments
- Conclusions



Main ideas

Goal: compact description of

$$C = \{m, r, S, \Theta, F\}$$

without user intervention

Challenges:

Q1. How to decide m and r **automatically**

Q2. How to find **multi-aspect** regimes

Main ideas

Goal: compact description of

$$C = \{m, r, S, \Theta, F\}$$

without user intervention

Challenges:

Q1. How to decide m and r **automatically**

Idea 1: Model description cost

Q2. How to find **multi-aspect** regimes

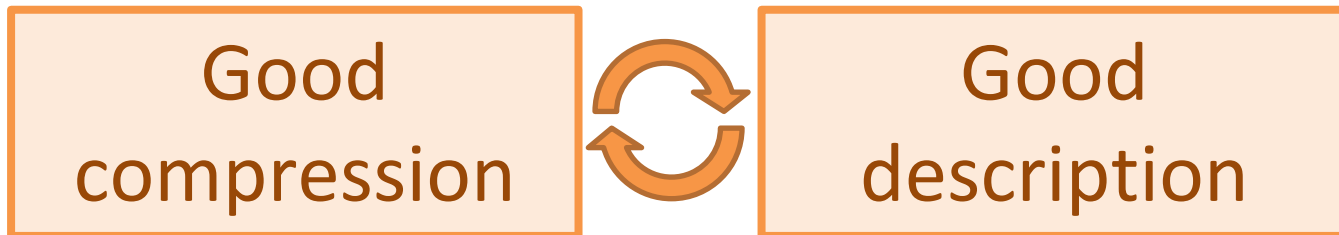
Idea 2: Multi-splitting algorithm

(1): model description cost

Q1. How to decide # of regimes/segments?

Idea 1: Model description cost

- Minimize coding cost
- Optimal # of segments/regimes

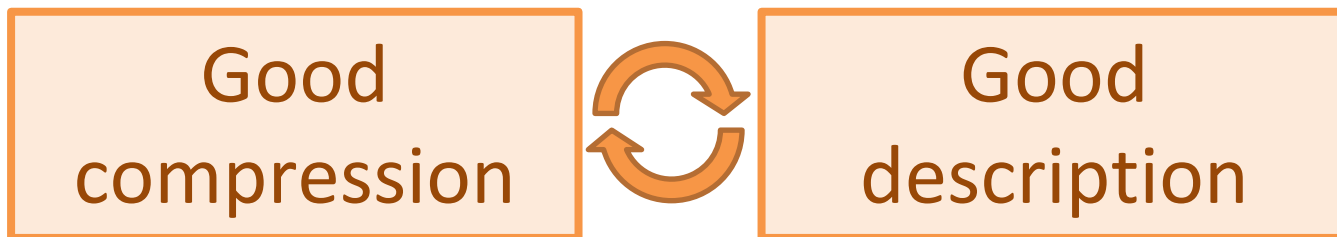
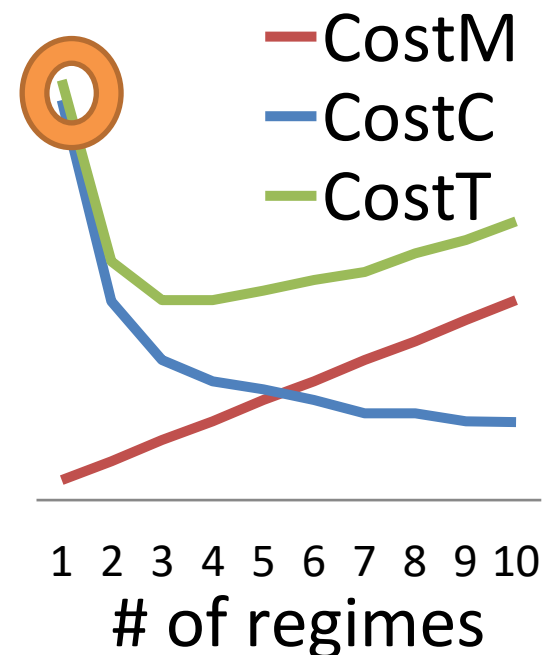


(1): model description cost

Idea: Minimize total cost

$$\min \left(\boxed{\text{Cost}_M(M)} + \boxed{\text{Cost}_c(X|M)} \right)$$

Model cost Coding cost

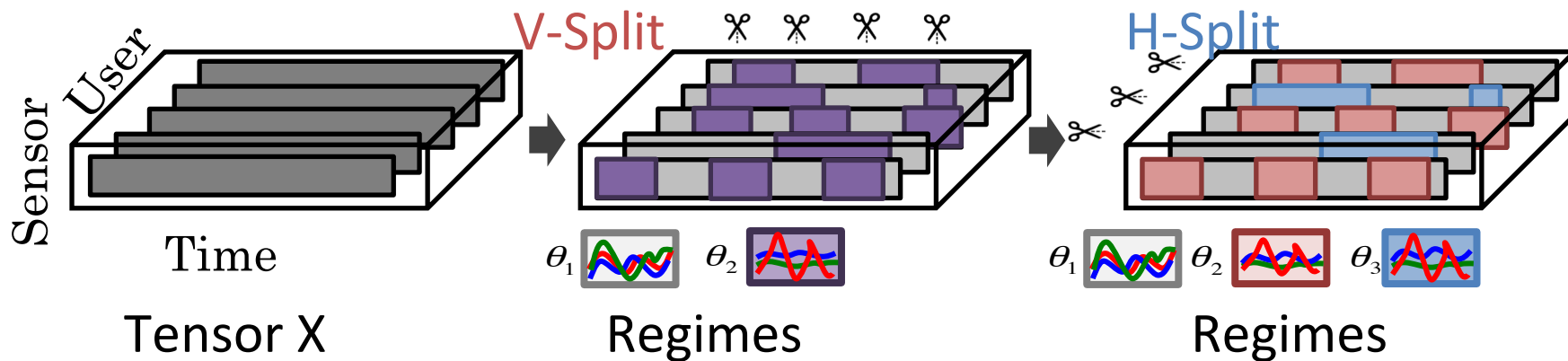


(2): Multi-aspect mining

Q2. How to find multi-aspect regimes?

Idea 2: Multi-aspect splitting algorithm

- Find **time**-aspect transitions
- And their differences between **users**



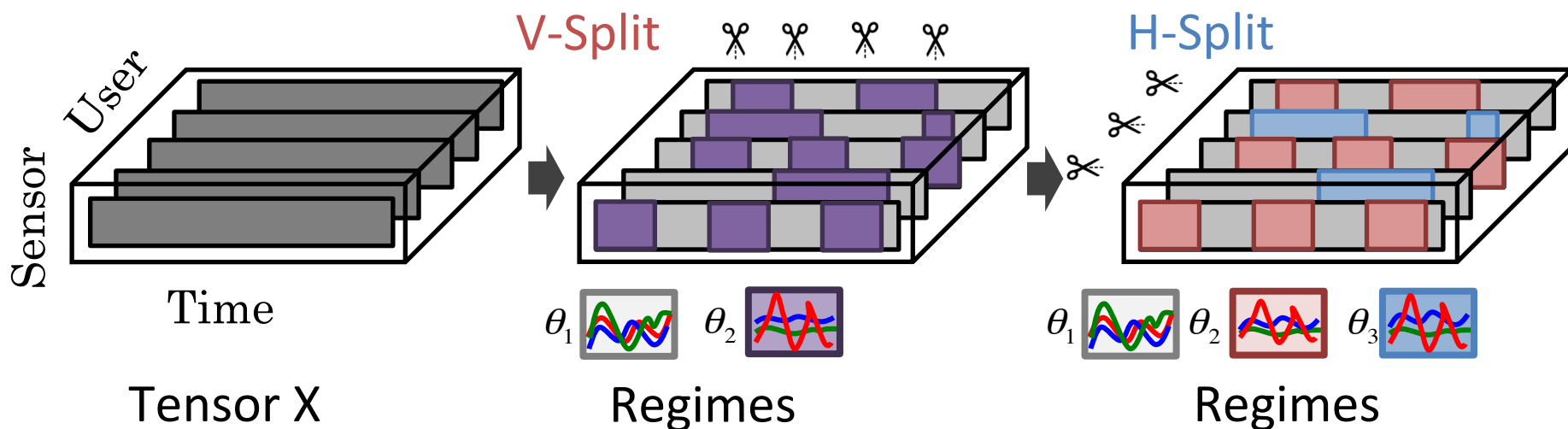
(2): Multi-aspect mining

V-Split (vertical):

split \mathcal{X} into **time**-aspect

H-Split (horizontal):

split \mathcal{X} into **user**-aspect



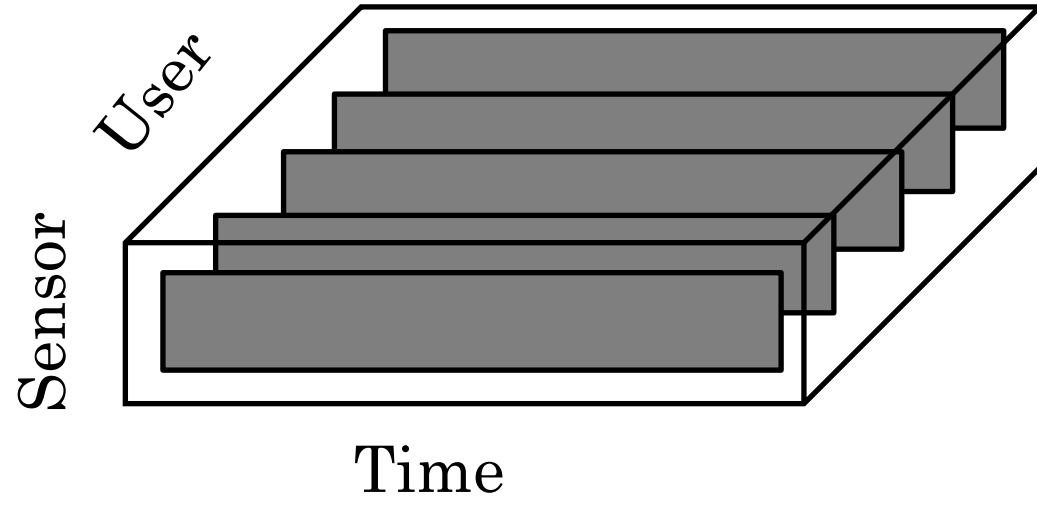
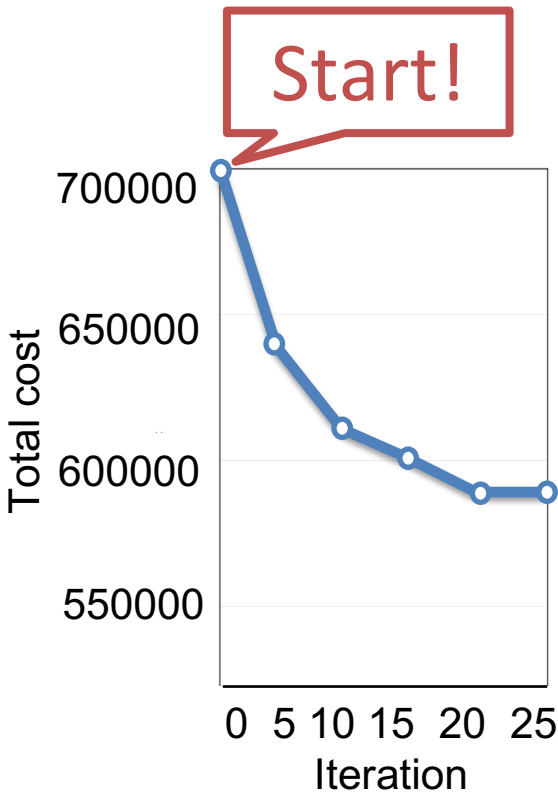
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Proposed algorithm

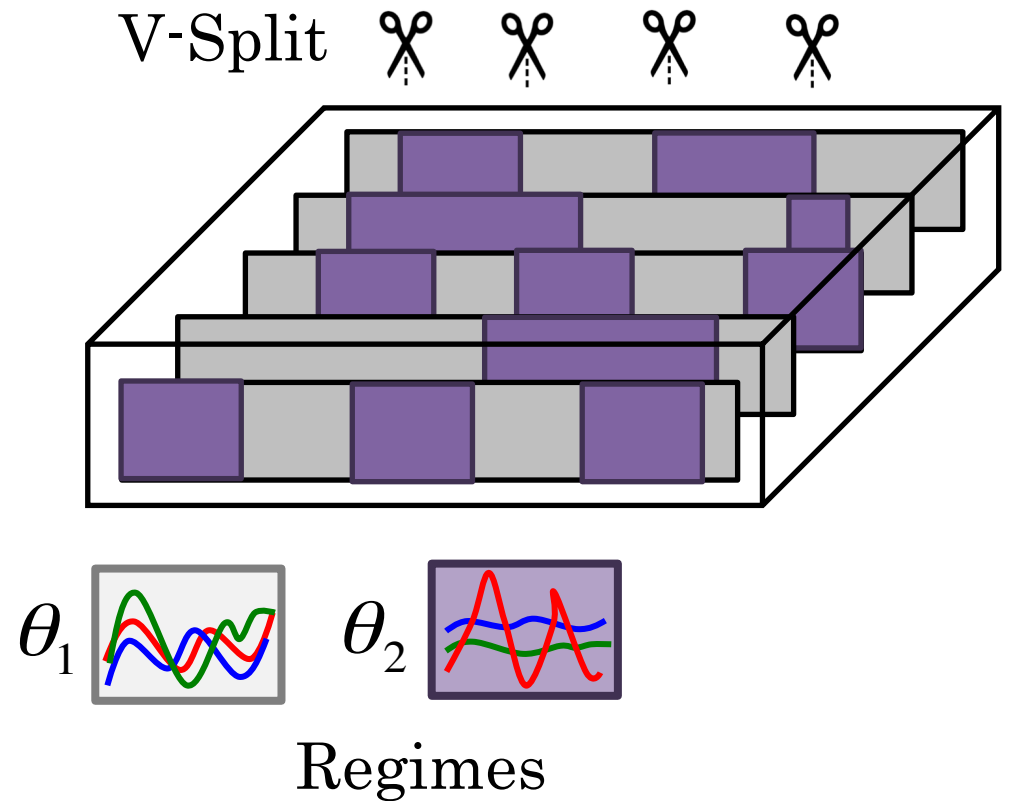
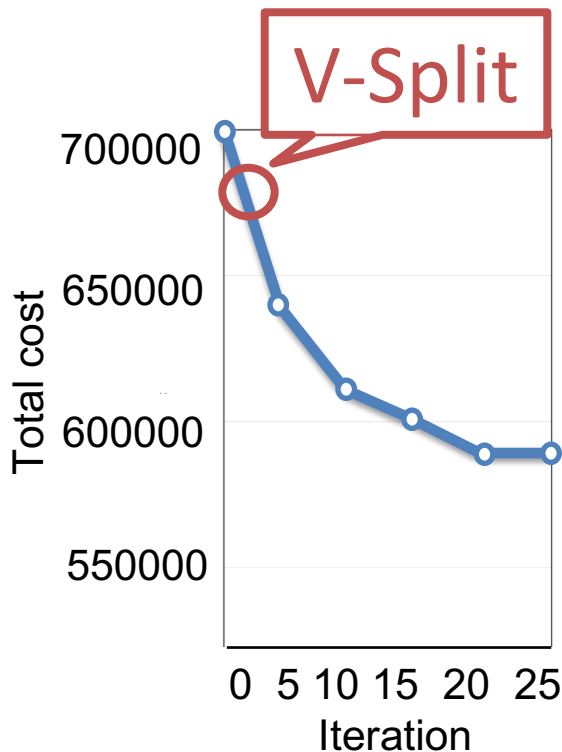
Overview



Iteration 0 (r=1)

Proposed algorithm

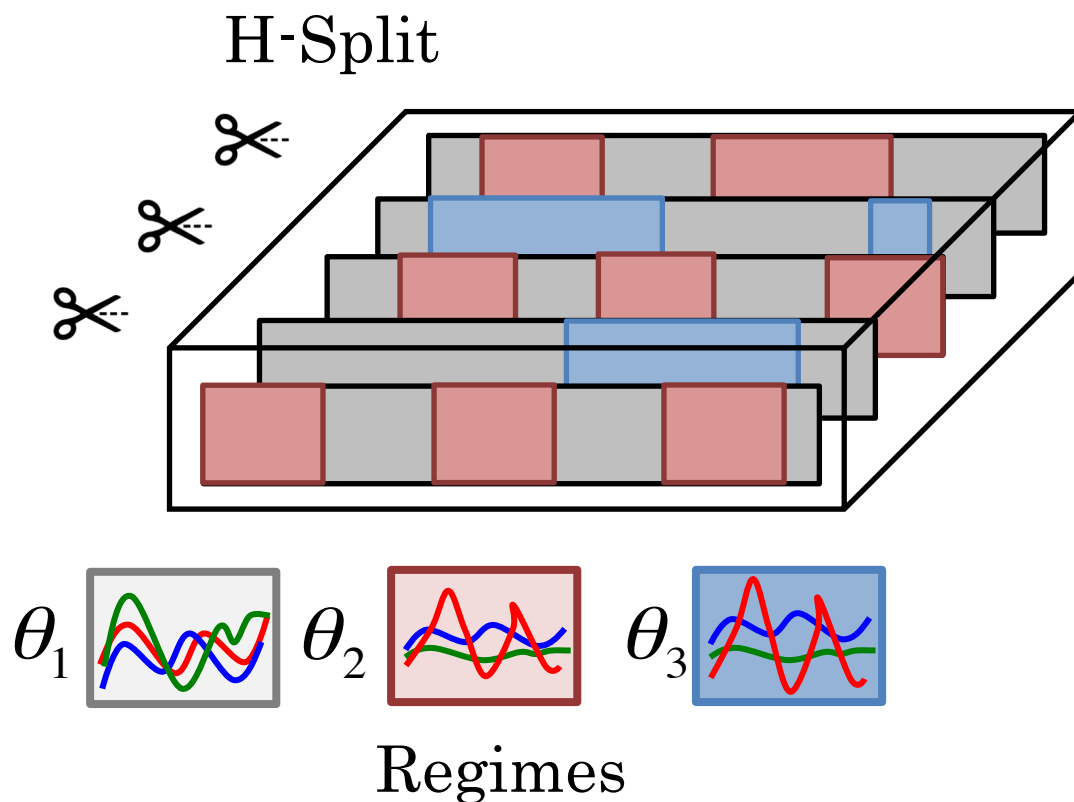
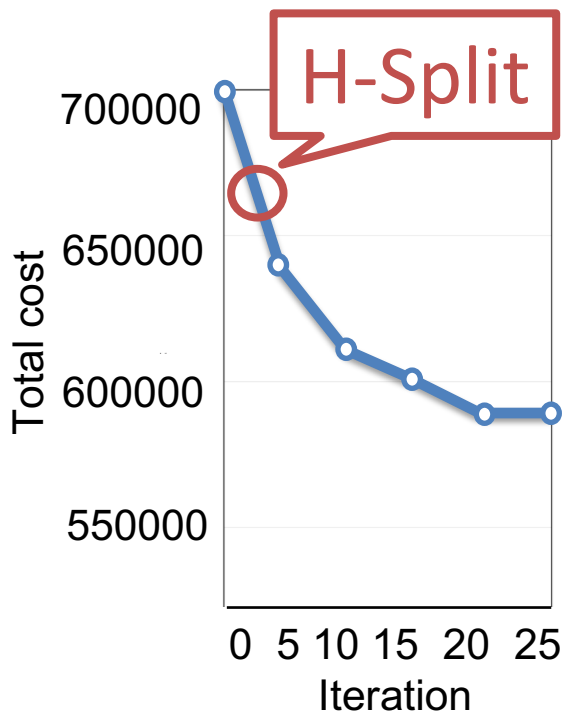
Overview



Iteration 1 (r=2)

Proposed algorithm

Overview



Iteration 2 ($r=3$)

Algorithms

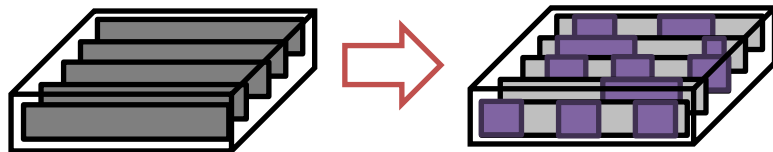
Algorithms of our method

CubeMarker

V-Split

Inner loop

- V-Assignment
- ModelEstimation

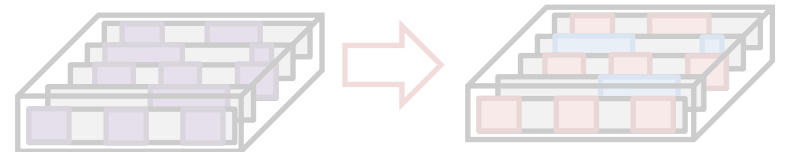


Find time-aspect regime

H-Split

Inner loop

- H-Assignment
- ModelEstimation



Find user-aspect regime

Outer loop

Decide splitting algorithm

V-Split

Inner loop

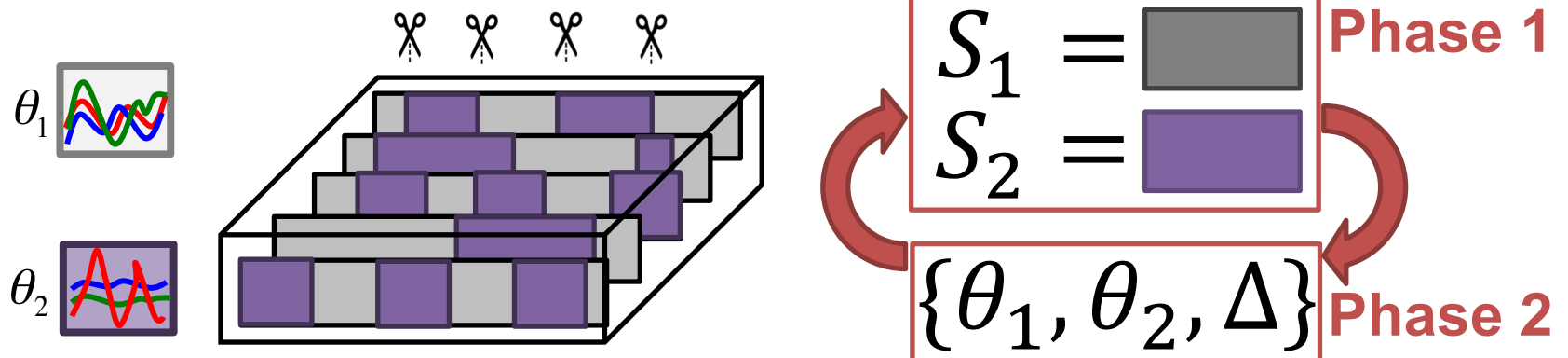
Two phase iterative approach

- Phase 1: (V-Assignment)

- Split segments into two groups: S_1, S_2

- Phase 2: (ModelEstimation)

- Update model parameters: $\Theta = \{\theta_1, \theta_2, \Delta\}$



Algorithms

Algorithms of our method

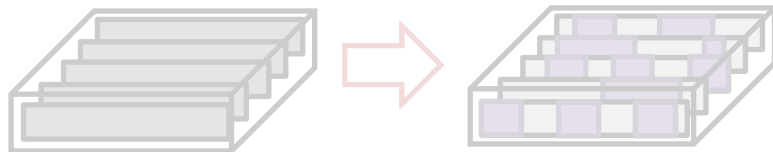
CubeMarker

Outer loop

V-Split

Inner loop

- V-Assignment
- ModelEstimation

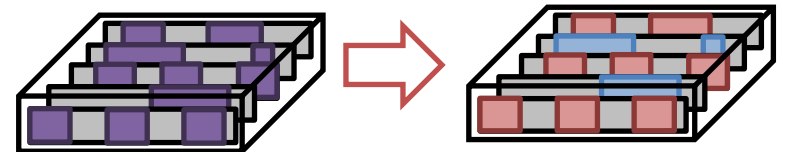


Find time-aspect regime

H-Split

Inner loop

- H-Assignment
- ModelEstimation



Find user-aspect regime

Decide splitting algorithm

H-Split

Inner loop

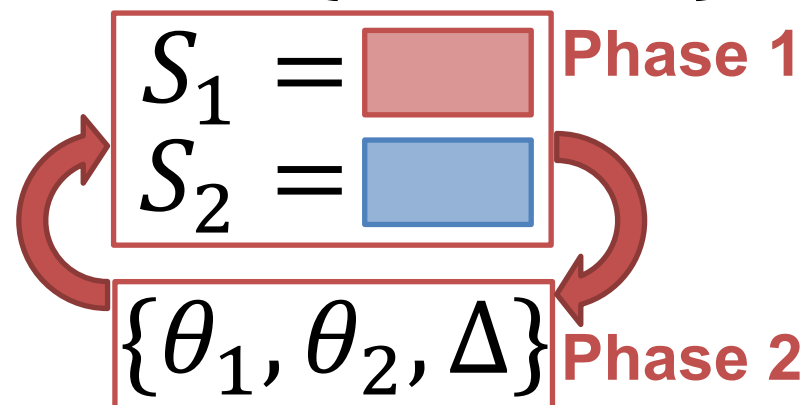
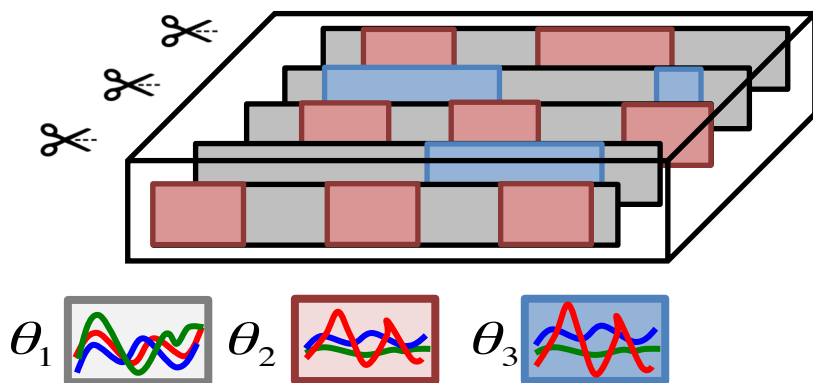
Two phase iterative approach

- Phase 1: (H-Assignment)

- Split segments into two groups: S_1, S_2

- Phase 2: (ModelEstimation)

- Update model parameters: $\Theta = \{\theta_1, \theta_2, \Delta\}$



H-Split

Inner loop

Given:

- tensor \mathcal{X}

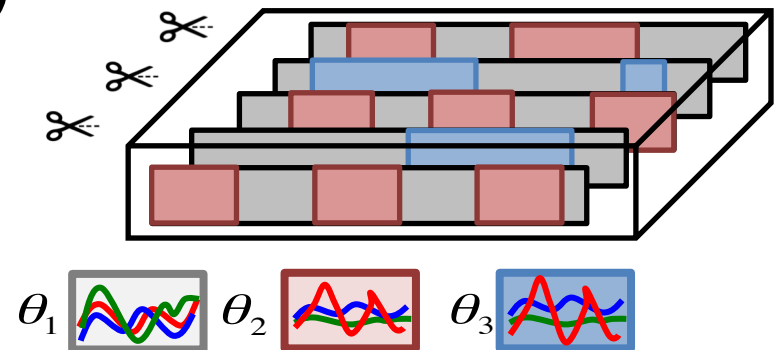
- model parameter set $\Theta = \{\theta_1, \theta_2, \Delta\}$

Find: two user-aspect regimes based on the

similarity: $Cost_C(X_i | \theta_j)$

\mathcal{X}

$\{\theta_1, \theta_2, \Delta\}$



Algorithms

Algorithms of our method

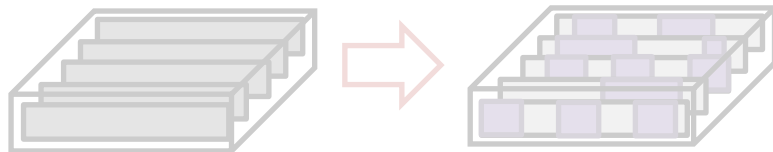
CubeMarker

Outer loop

V-Split

Inner loop

- V-Assignment
- ModelEstimation

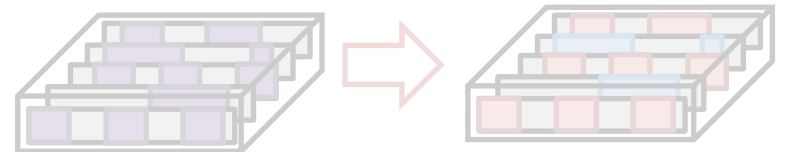


Find time-aspect regime

H-Split

Inner loop

- H-Assignment
- ModelEstimation

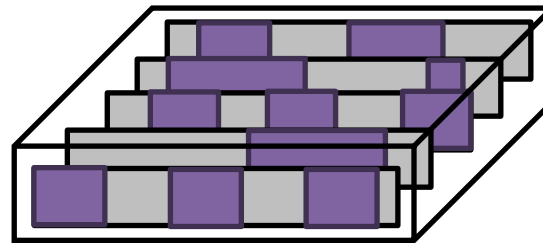


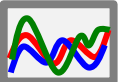
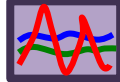
Find user-aspect regime

Decide splitting algorithm

CubeMarker

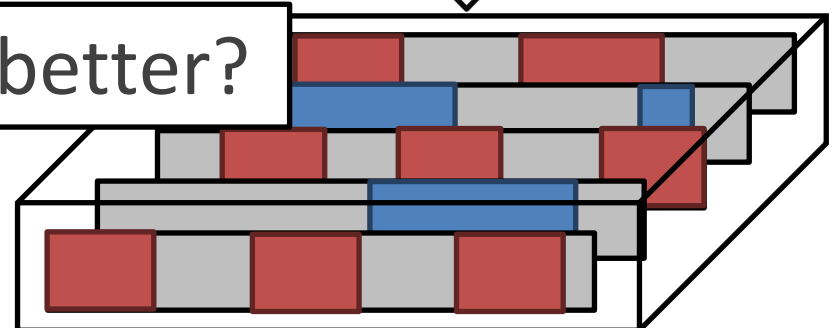
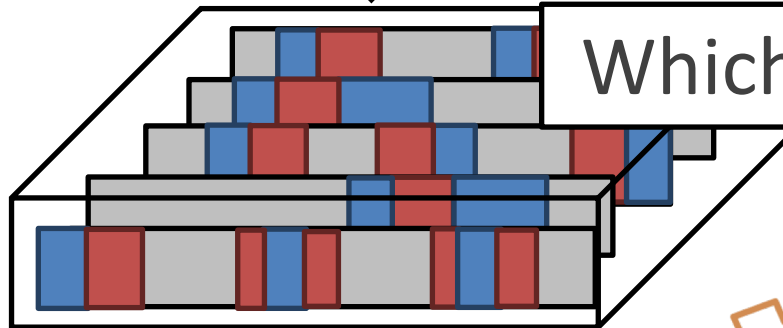
Outer loop

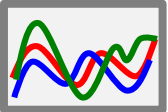
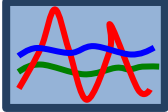
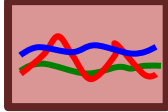



θ_1  θ_2  Regimes

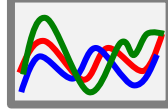
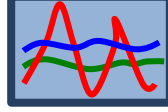
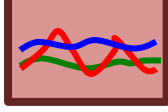

Tensor (cost: 687,395)

Which is better?



θ_1  θ_2  θ_3  

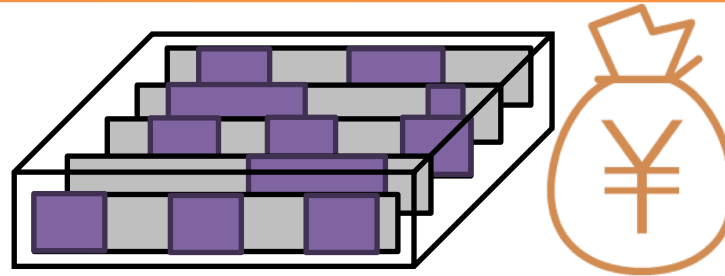
V-Split result (cost: 673,255) vs.

θ_1  θ_2   

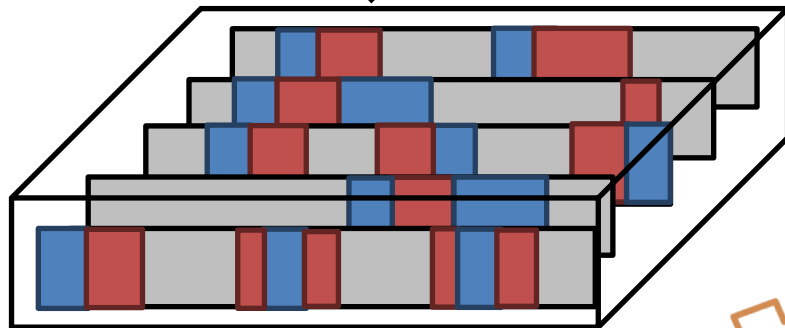
H-Split result (cost: 642,441)

CubeMarker

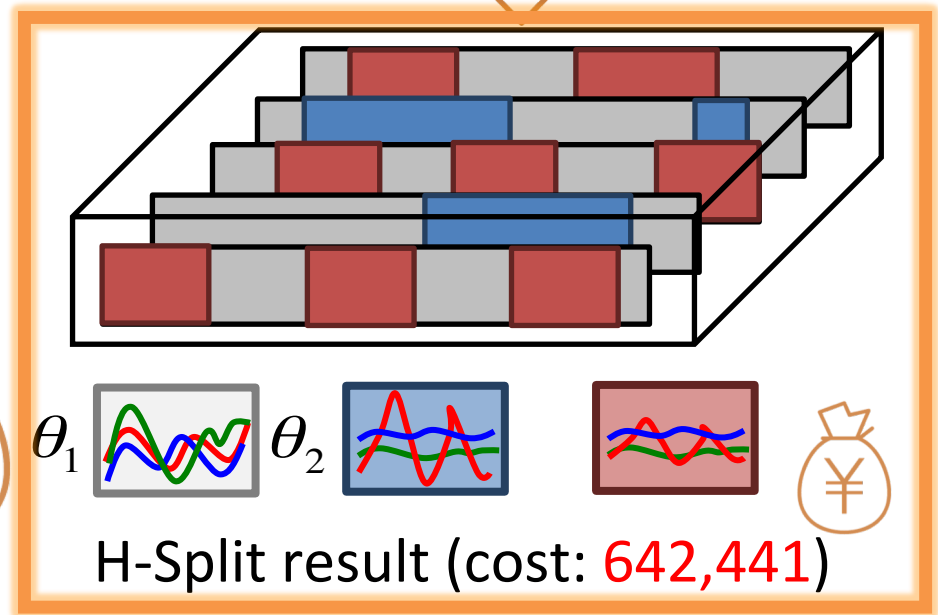
Outer loop



θ_1 θ_2 Regimes
Tensor (cost: 687,395)



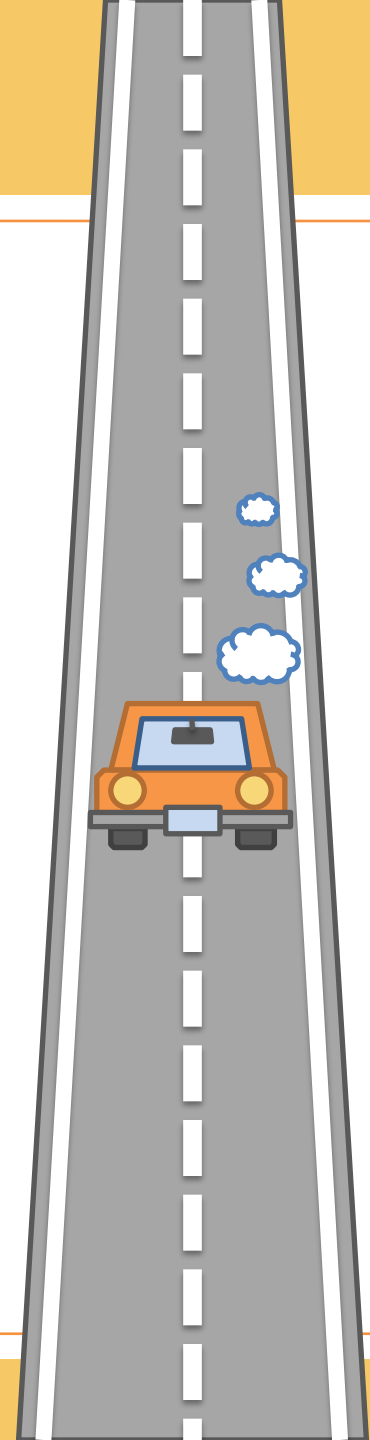
θ_1 θ_2 θ_3
V-Split result (cost: 673,255) vs.



θ_1 θ_2
H-Split result (cost: 642,441)

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Experiments

Q1. Effectiveness

Can it help us understand the given tensor?

Q2. Scalability

How does it scale in terms of computational cost?

Q3. Accuracy

How well does it find segments and regimes?

Competitors:

pHMM (SIGMOD'11)

AutoPlait (SIGMOD'14)

TICC (KDD'17)

CubeMarker-V (naïve ver. of our method)

Datasets

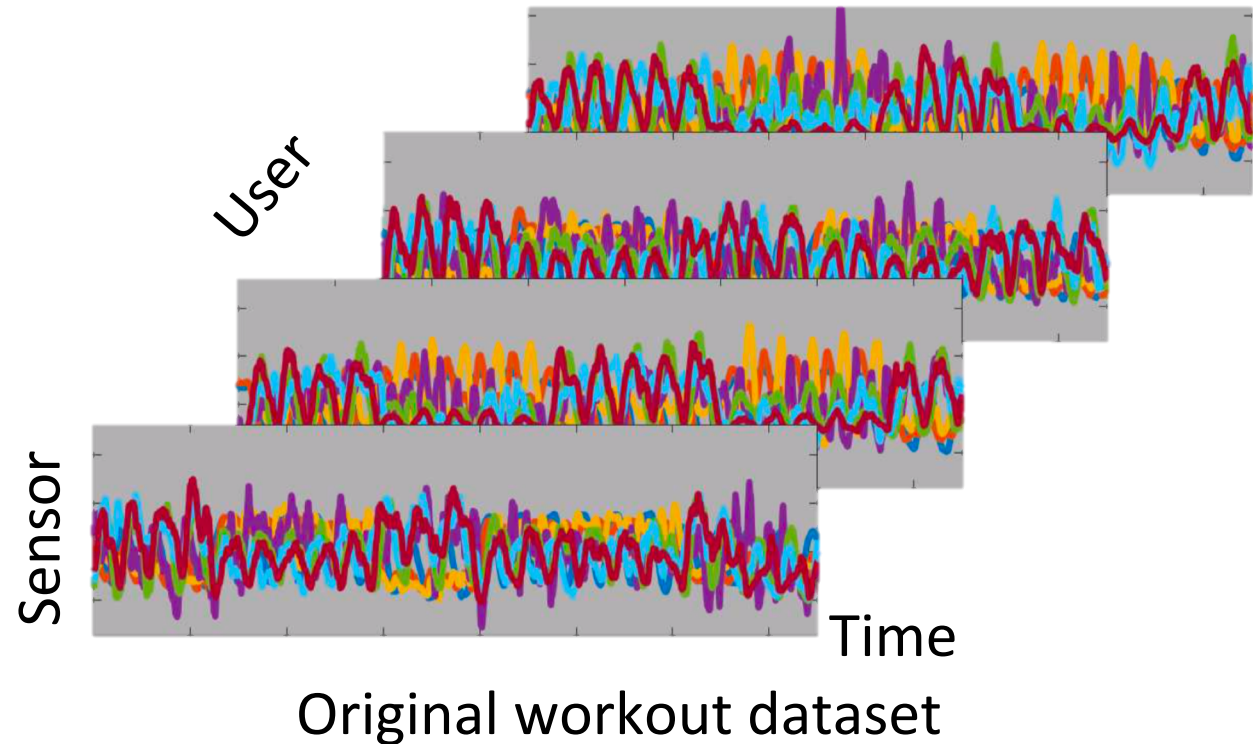
Experiments on the 8 real-world datasets:

Dataset	Data size ($w \times n \times d$)
(#1) <i>Workout</i>	$182 \times 4000 \times 7$
(#2) <i>Tennis</i>	$100 \times 4500 \times 7$
(#3) <i>Factory</i>	$60 \times 3000 \times 7$
(#4) <i>Reading</i>	$71 \times 10000 \times 5$
(#5) <i>Free throw</i>	$170 \times 2000 \times 7$
(#6) <i>Automobile-Tokyo</i>	$171 \times 2400 \times 3$
(#7) <i>Automobile-Expressway</i>	$13 \times 9100 \times 3$
(#8) <i>Automobile-Togu</i>	$32 \times 5200 \times 3$

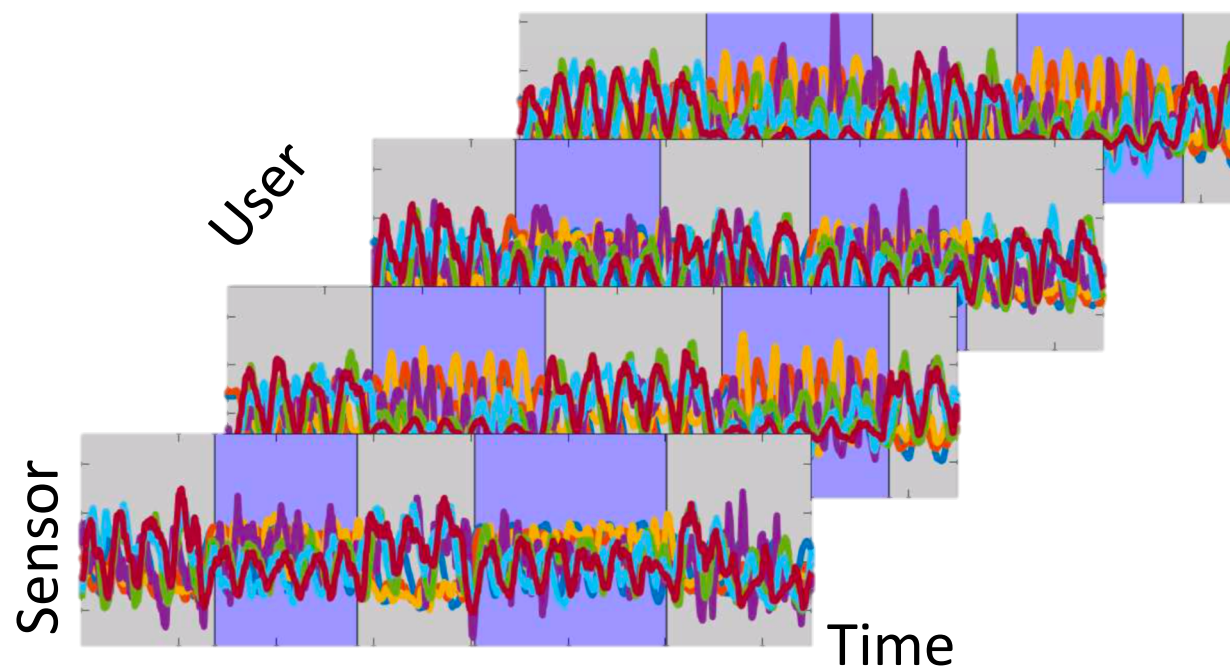
Summary of the datasets

Q1. Effectiveness - Workout

How many and what kind of patterns does it include?

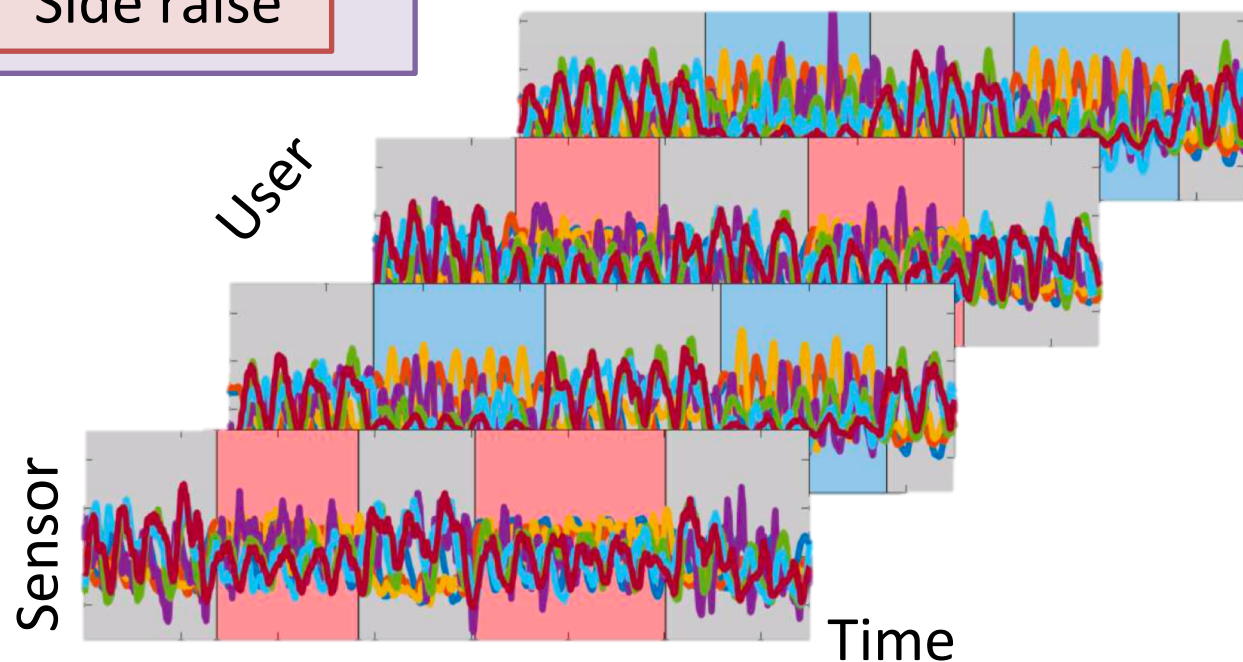
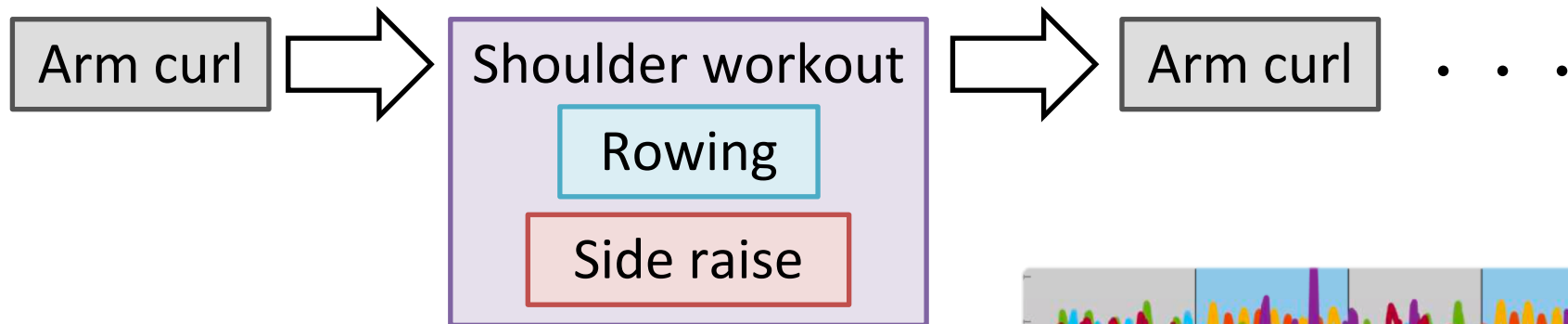


Q1. Effectiveness - Workout



Time-aspect patterns for a workout dataset

Q1. Effectiveness - Workout

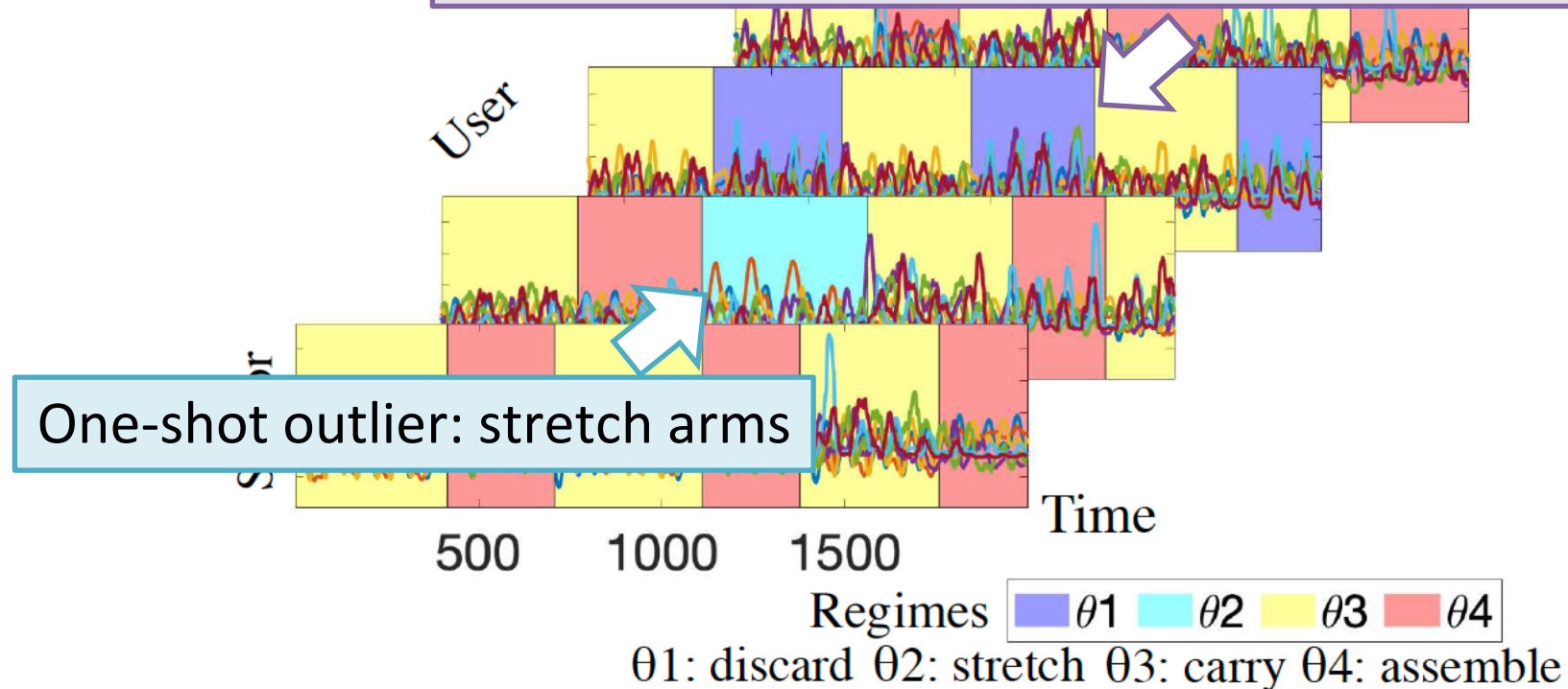


Multi-aspect patterns for a workout dataset

Q1. Effectiveness - Factory worker

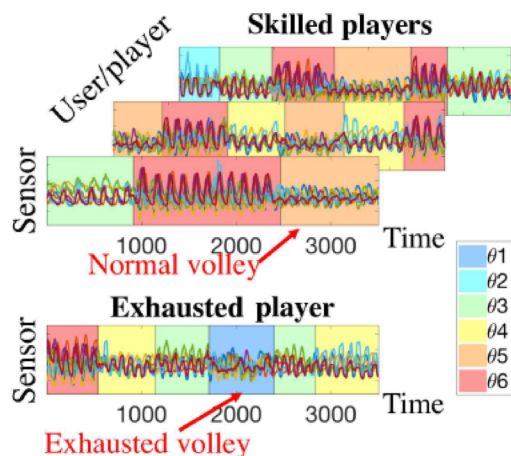
Basic pattern transitions: carrying \Rightarrow assembling \Rightarrow . . .

User-aspect pattern: Discarding defective products

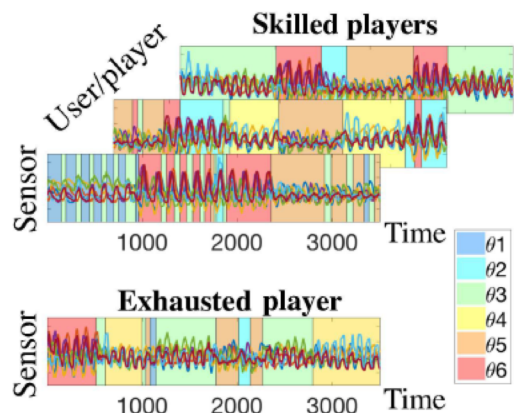


Multi-aspect patterns for a factory workers

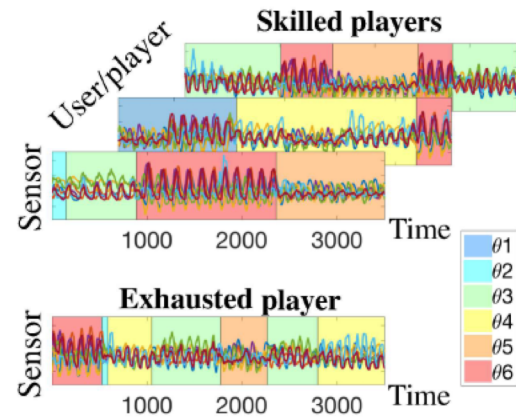
Q1. Effectiveness - Tennis



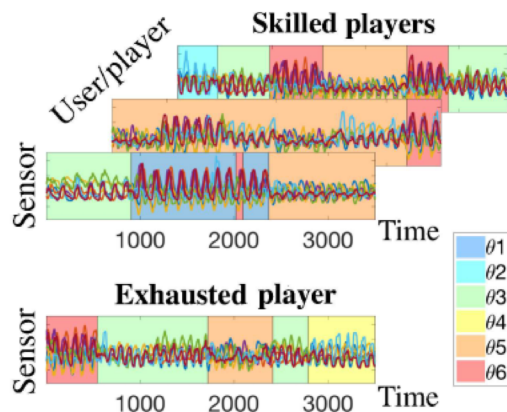
(a) CUBEMARKER
(no parameter setting)



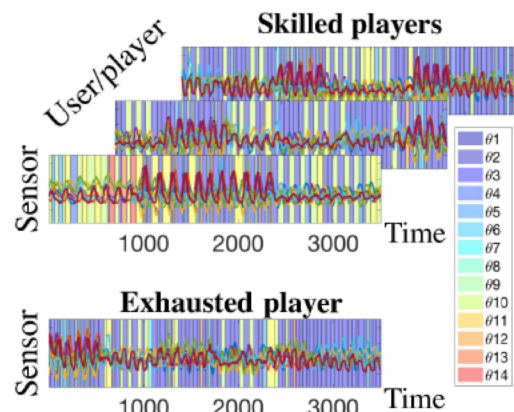
(b-1) TICC ($\beta = 100, \lambda = 1000$)
(need parameter setting)



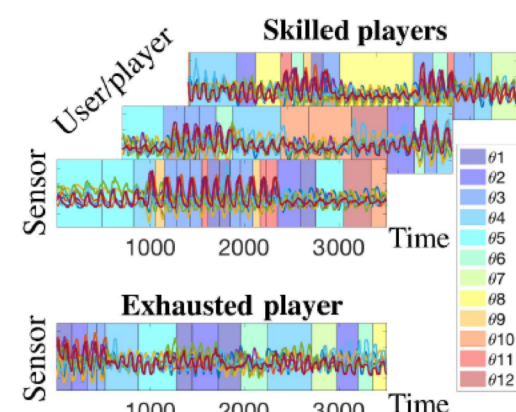
(b-2) TICC ($\beta = 600, \lambda = 1000$)
(need parameter setting)



(c) AutoPlait
(no parameter setting)

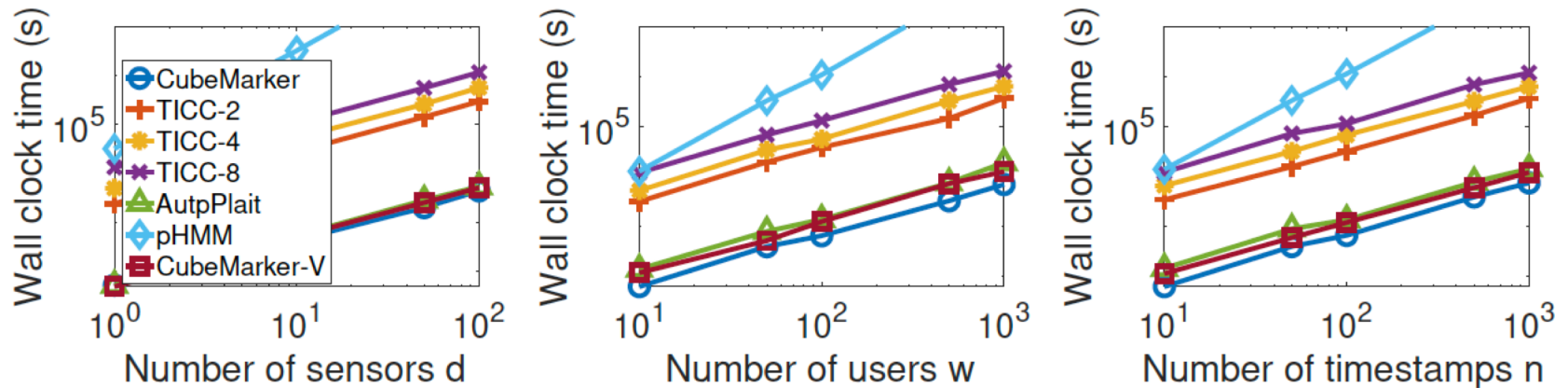


(d-1) pHMM ($\epsilon_r = 0.1, \epsilon_c = 0.8$)
(need parameter setting)

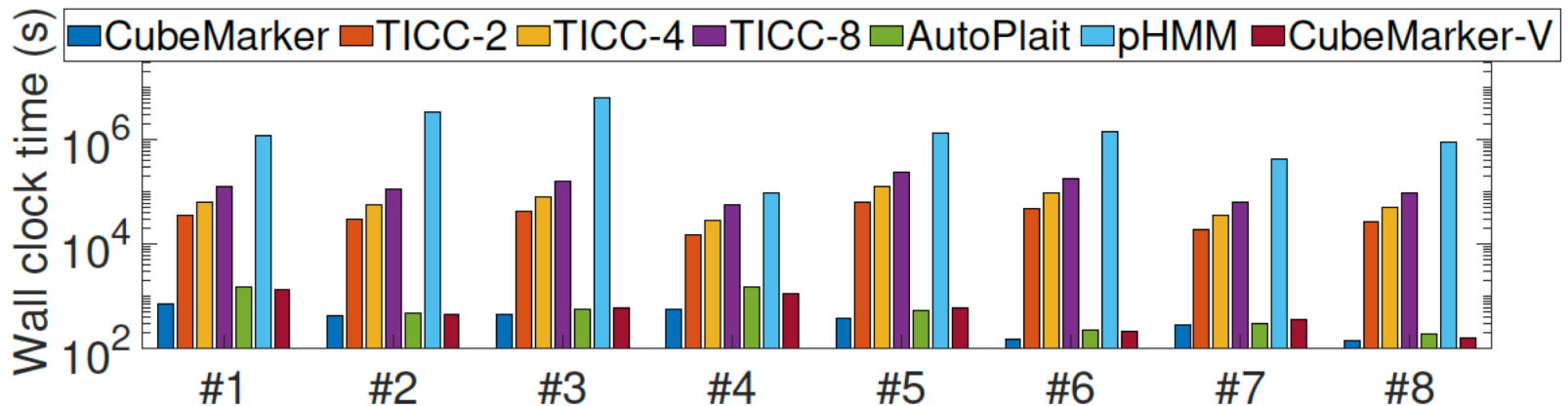


(d-2) pHMM ($\epsilon_r = 10, \epsilon_c = 0.8$)
(need parameter setting)

Q2. Scalability

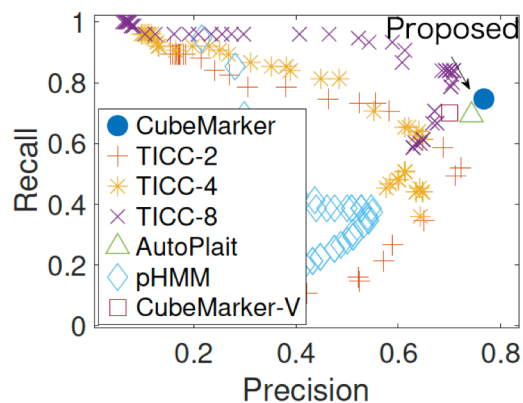


Wall clock time v.s. dataset size for (#1) Workout ($O(dwn)$)

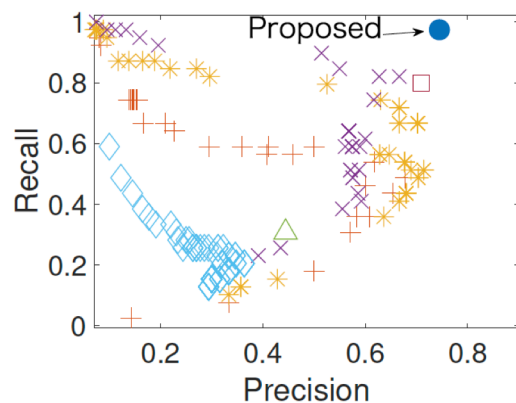


Wall clock time for each dataset (1700x faster than pHMM)

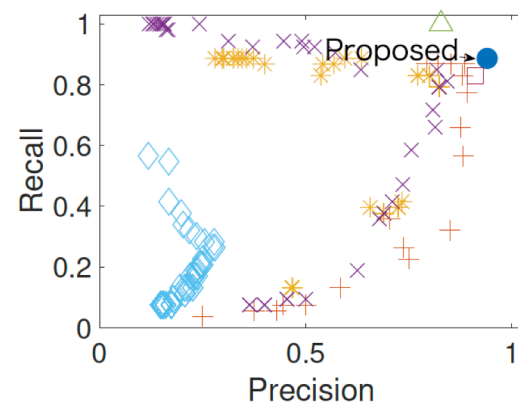
Q3. Accuracy (segment/regime)



(a) (#1) *Workout*

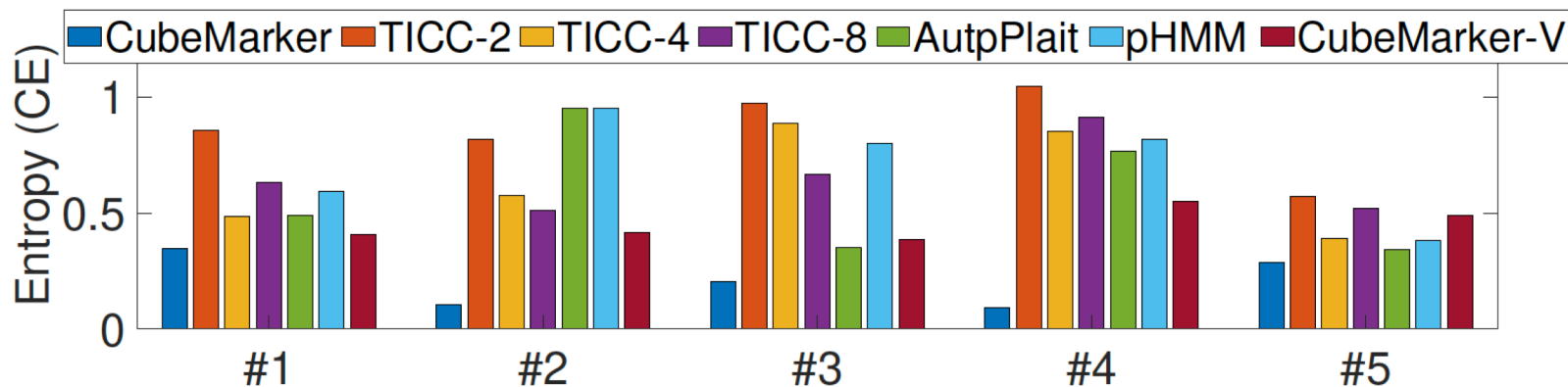


(b) (#2) *Tennis*



(c) (#3) *Factory*

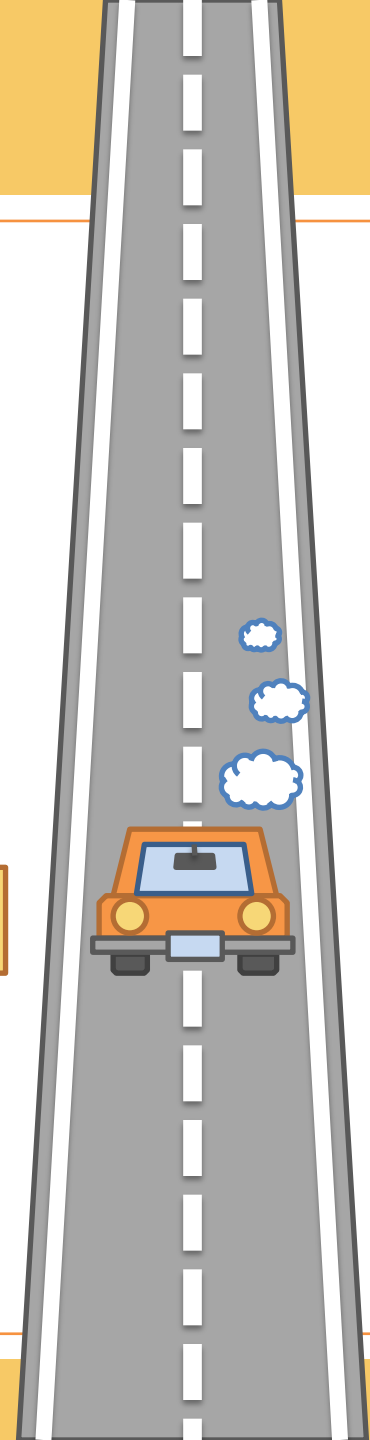
Segmentation accuracy (top right is better)



Regime clustering accuracy (lower is better)

Outline

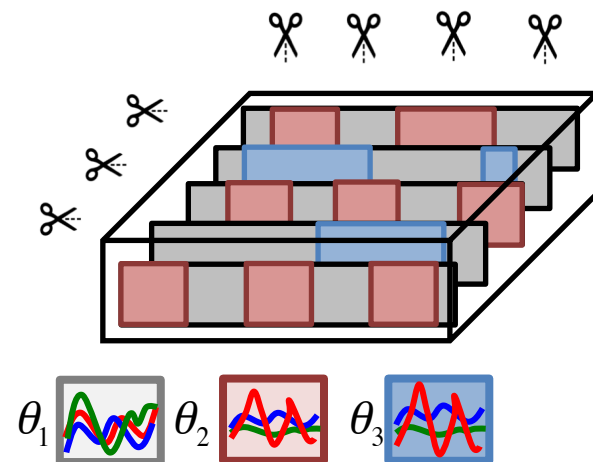
- Motivation
- Problem definition
- Main ideas
- Algorithms
- Experiments
- Conclusions



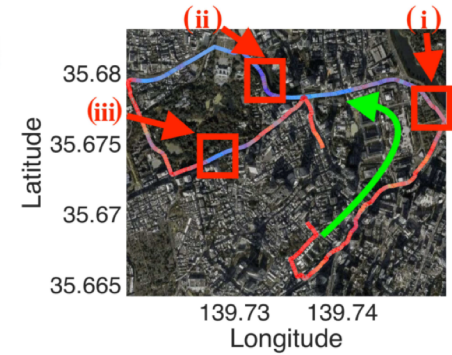
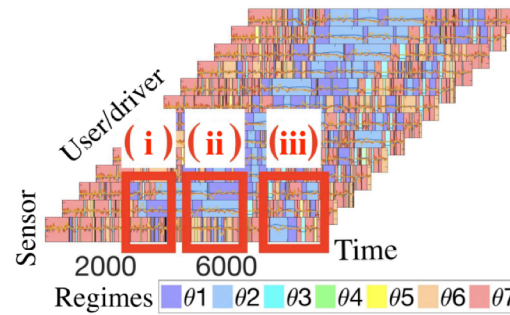
Conclusions

Our method has the following properties:

- **Effective**
Find multi-aspect segments/regimes
- **Automatic**
No magic numbers
- **Scalable**
It scales linearly to the data size

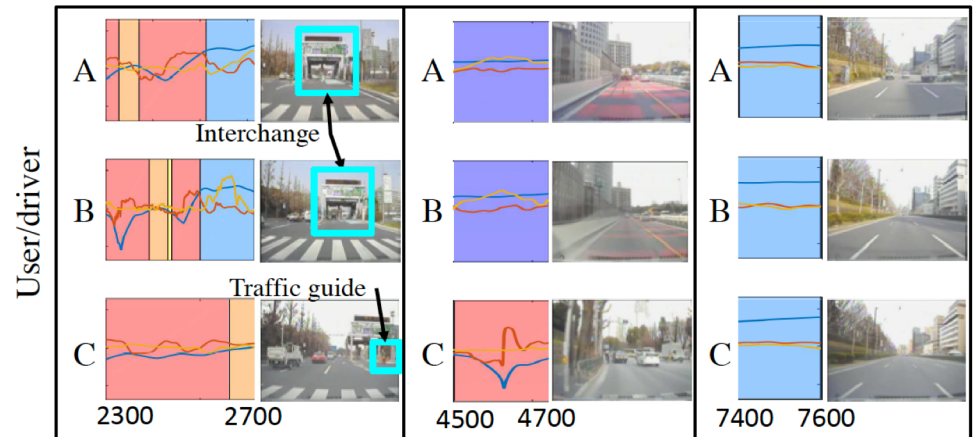


Thank you!



(a) Multi-aspect segmentation and summarization

(b) Representative driving behavior on a map



(c-i) Interchange (c-ii) Expressway (c-iii) Wide road
(c) User/driver-specific behavior at three different locations