Fast Mining and Forecasting of Complex Time-Stamped Events

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Motivation

Complex time-stamped events

consists of {timestamp + multiple attributes}

e.g., web click events:

{timestamp, URL, user ID, access devices, http referrer,…}

Timestamp	URL	User	Device
2012-08-01-12:00	CNN.com	Smith	iphone
2012-08-02-15:00	YouTube.com	Brown	iphone
2012-08-02-19:00	CNET.com	Smith	mac
2012-08-03-11:00	CNN.com	Johnson	ipad
…	…	…	…

Motivation

Q1. Are there any topics ?

- news, tech, media, sports, etc…

Timestamp	URL	User	Device
2012-08-01-12:00	CNN.com	Smith	iphone
2012-08-02-15:00	YouTube.com	Brown	iphone
2012-08-02-19:00	CNET.com	Smith	mac
2012-08-03-11:00	CNN.com	Johnson	ipad
…	…	…	…

e.g., CNN.com, CNET.com -> news topic
YouTube.com -> media topic

Motivation

Q2. Can we group URLs/users accordingly?

Timestamp	URL	User	Device
2012-08-01-12:00	CNN.com	Smith	iphone
2012-08-02-15:00	YouTube.com	Brown	iphone
2012-08-02-19:00	CNET.com	Smith	mac
2012-08-03-11:00	CNN.com	Johnson	ipad
…	…	…	…

e.g., CNN.com & CNET.com (related to news topic)
Smith & Johnson (related to news topic)

Motivation

Q3. Can we forecast future events?

- How many clicks from ‘Smith’ tomorrow?
- How many clicks to ‘CNN.com’ over next 7 days?

Timestamp	URL	User	Device
2012-08-01-12:00	CNN.com	Smith	iphone
2012-08-02-15:00	YouTube.com	Brown	iphone
2012-08-02-19:00	CNET.com	Smith	mac
2012-08-03-11:00	CNN.com	Johnson	ipad
2012-08-05-12:00	CNN.com	Smith	iphone
2012-08-05-19:00	CNET.com	Smith	iphone

future clicks?

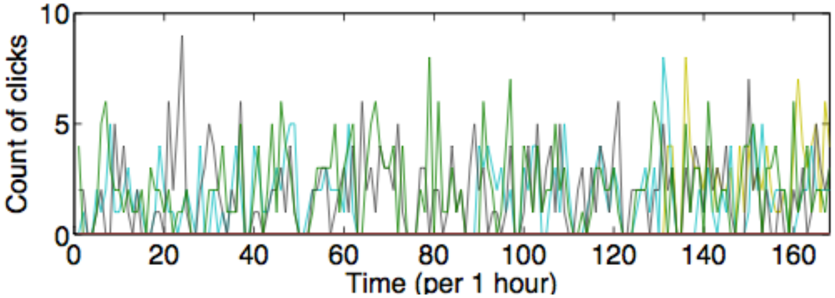
Motivation

Web click events – can we see any trends?

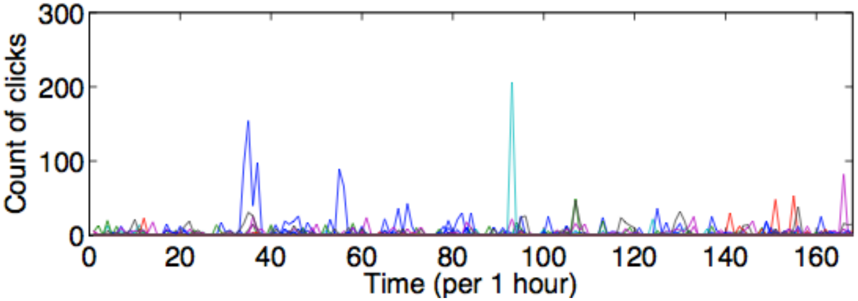
Original access counts of each URL

- 100 random users
- 1 week (window size = 1 hour)

URL: money site



URL: blog site



Motivation

Web click events – can we see any trends?

Original access counts of each URL

- 100 random users

(windov

ır)

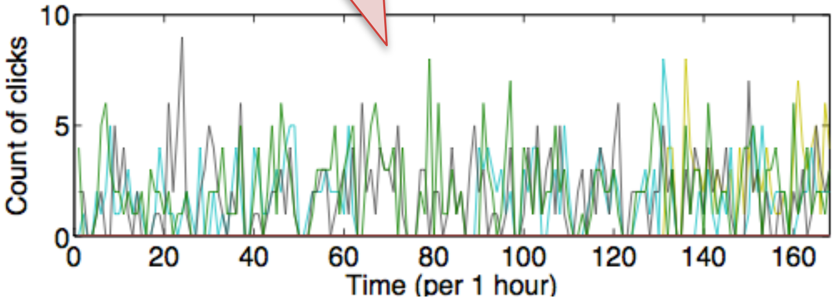
Noisy ☹

Sparse ☹

Bursty ☹

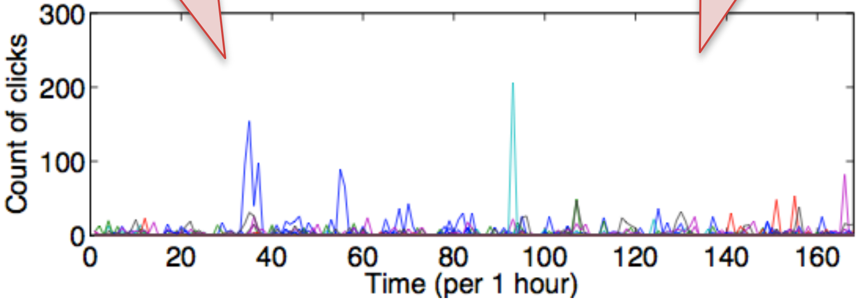
URL: mo

y site



UR

blog site



☹ <u>We cannot see any trends !!</u>

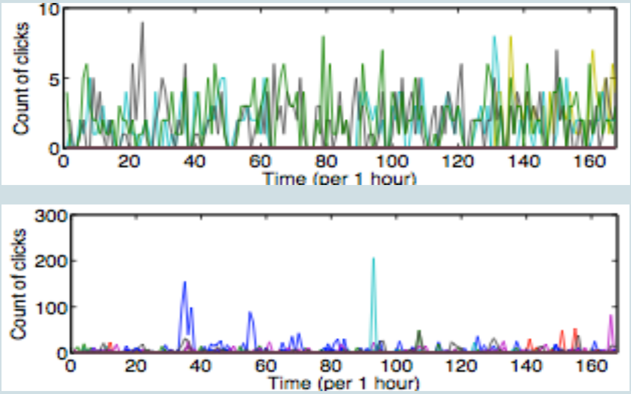
Outline

- Motivation
- Problem definition
- Proposed method: TriMine
- TriMine-F forecasting
- Experiments
- Conclusions

Problem definition

Given: a set of complex time-stamped events

Original web-click events

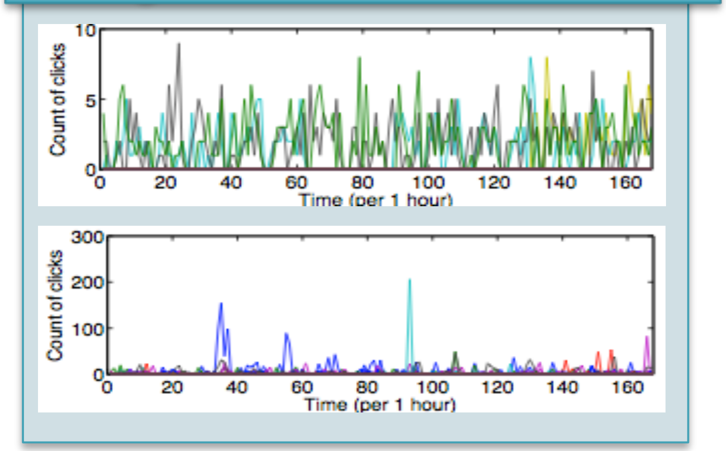


Problem definition

Given: a set of complex time-stamped events

1. Find major topics/trends
2. Forecast future events

Original web-click events



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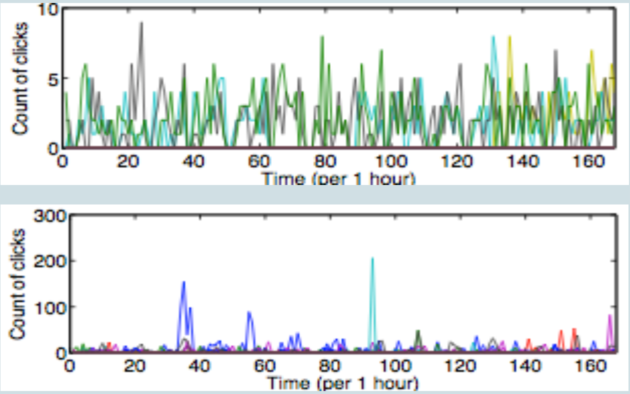
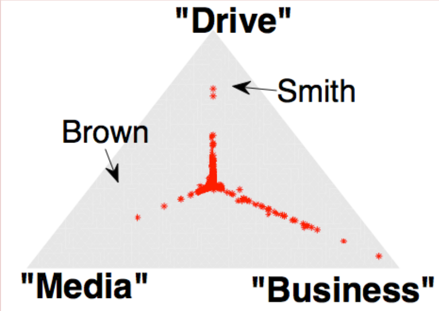
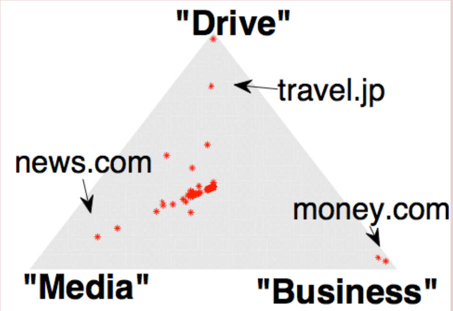
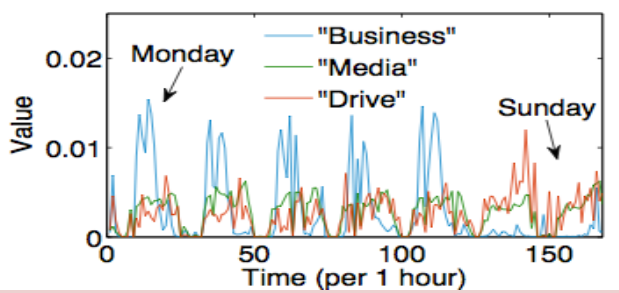


URL in topic space



User in topic space





Time evolution

"Hidden topics" wrt each aspect *(URL, user, time)*

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Main idea (1) : M-way analysis

Complex time-stamped events

e.g., web clicks

Time	URL	User
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Main idea (1) : M-way analysis

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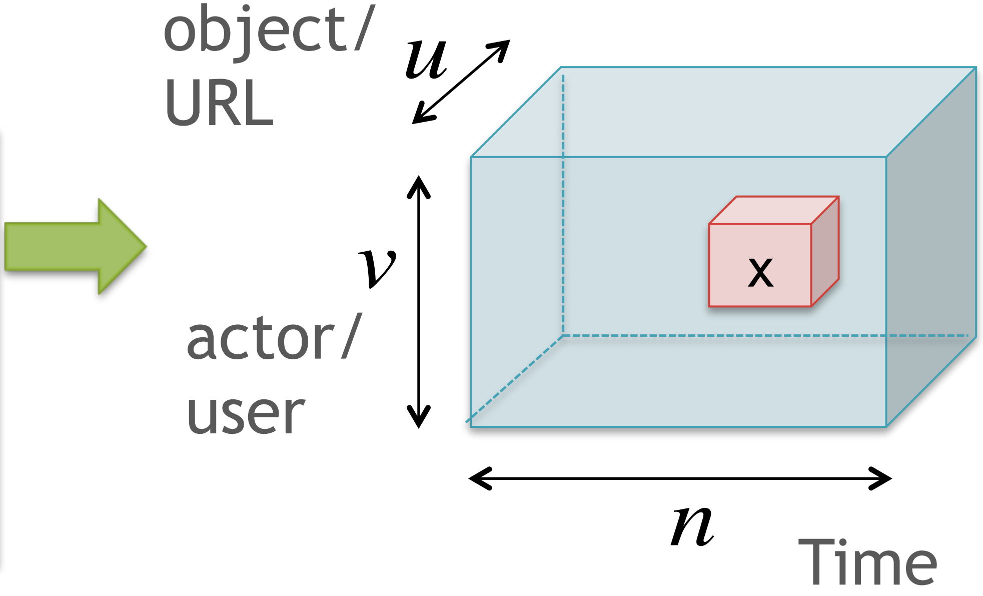

Represent as
M^th order tensor (M=3)

$$\mathcal{X} \in \mathbb{N}^{u \times v \times n}$$

Main idea (1) : M-way analysis

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e.g., web clicks

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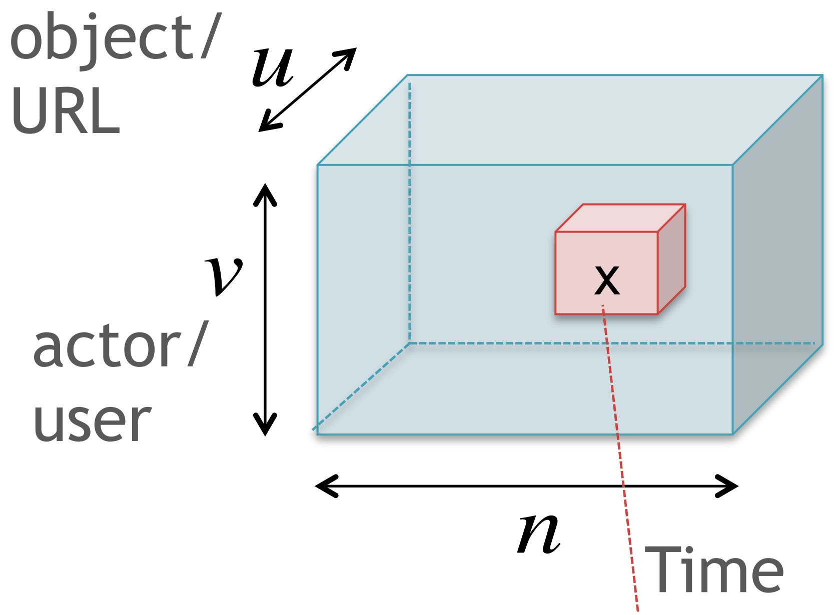


Represent as
M^th^ order tensor (M=3)

$$\mathcal{X} \in \mathbb{N}^{u \times v \times n}$$

Element x: # of events

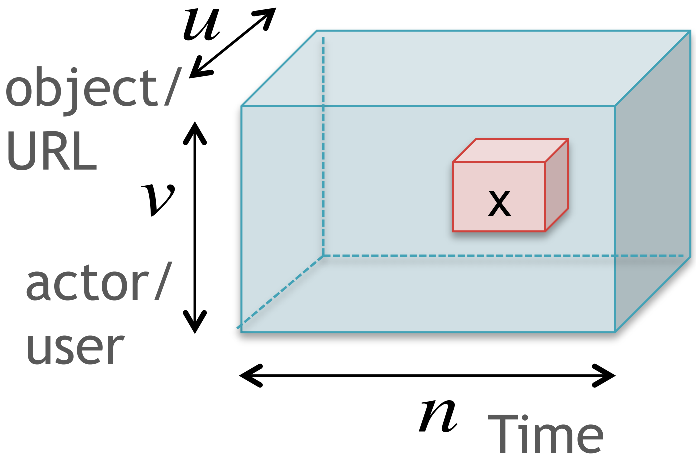
e.g., ‘Smith’, ‘CNN.com’, ‘Aug 1, 10pm’; 21 times

Main idea (1) : M-way analysis

Undesirable properties

- High dimension ☹
- Categorical data 😐
- Sparse tensor 😐
- Look like noise ☹

e.g., x={0, 1, 0, 2, 0, 0, 0, …}



Event tensor

$$\mathcal{X} \in \mathbb{N}^{u \times v \times n}$$

Main idea (1) : M-way analysis

Undesirable properties

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- Categorical data 😐
- Sparse tensor 😐
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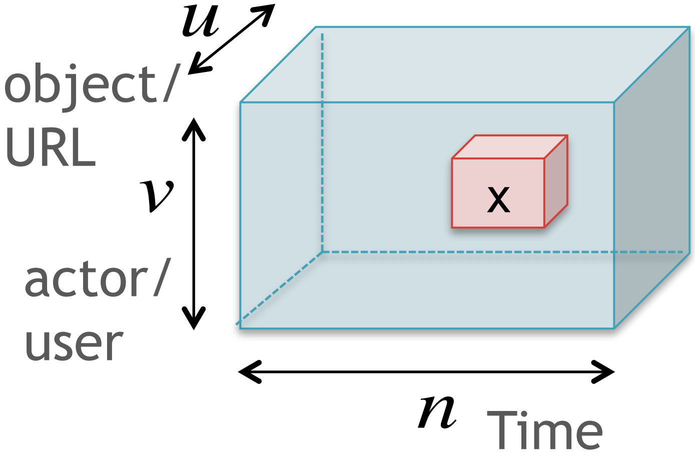


Event tensor

$\mathcal{X} \in \mathbb{N}^{u \times v \times n}$

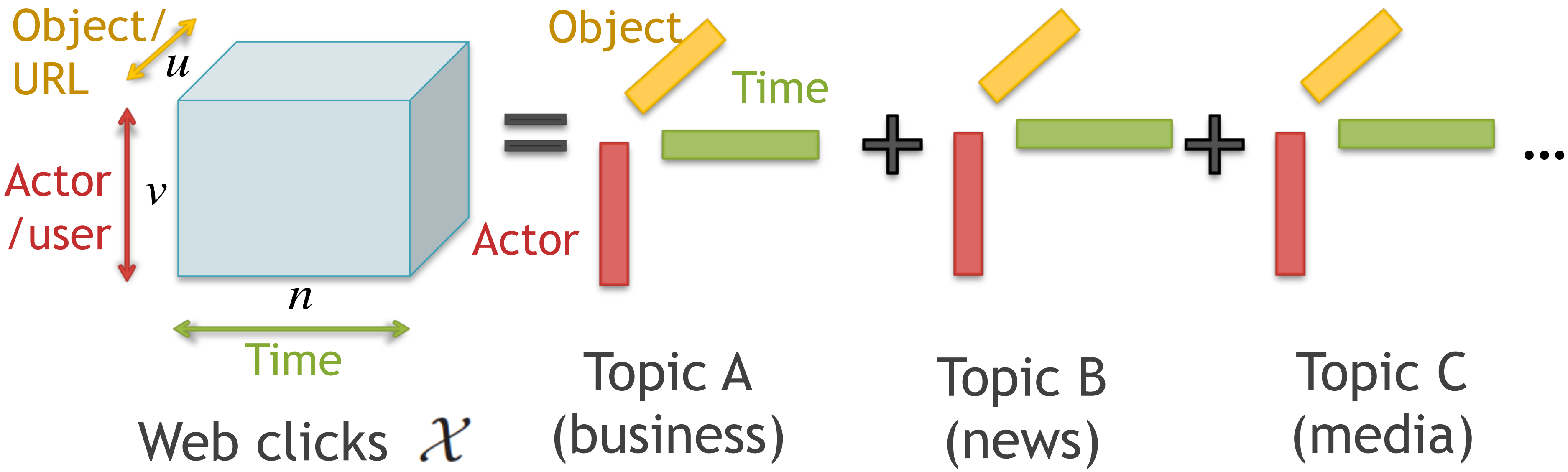
Questions:

How to find **meaningful patterns?**

Main idea (1) : M-way analysis

A. decompose to a set of **3 topic vectors:**

Object vector **Actor vector** **Time vector**



Main idea (1) : M-way analysis

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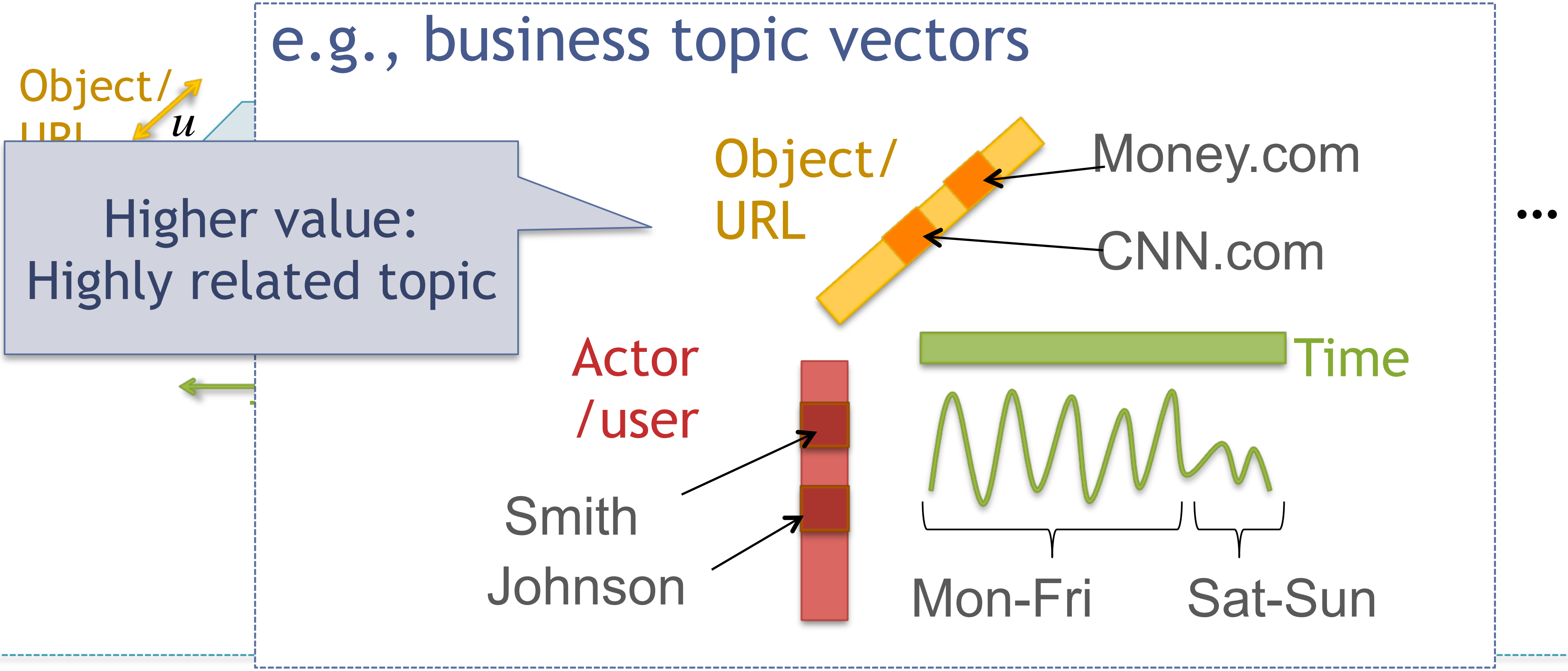


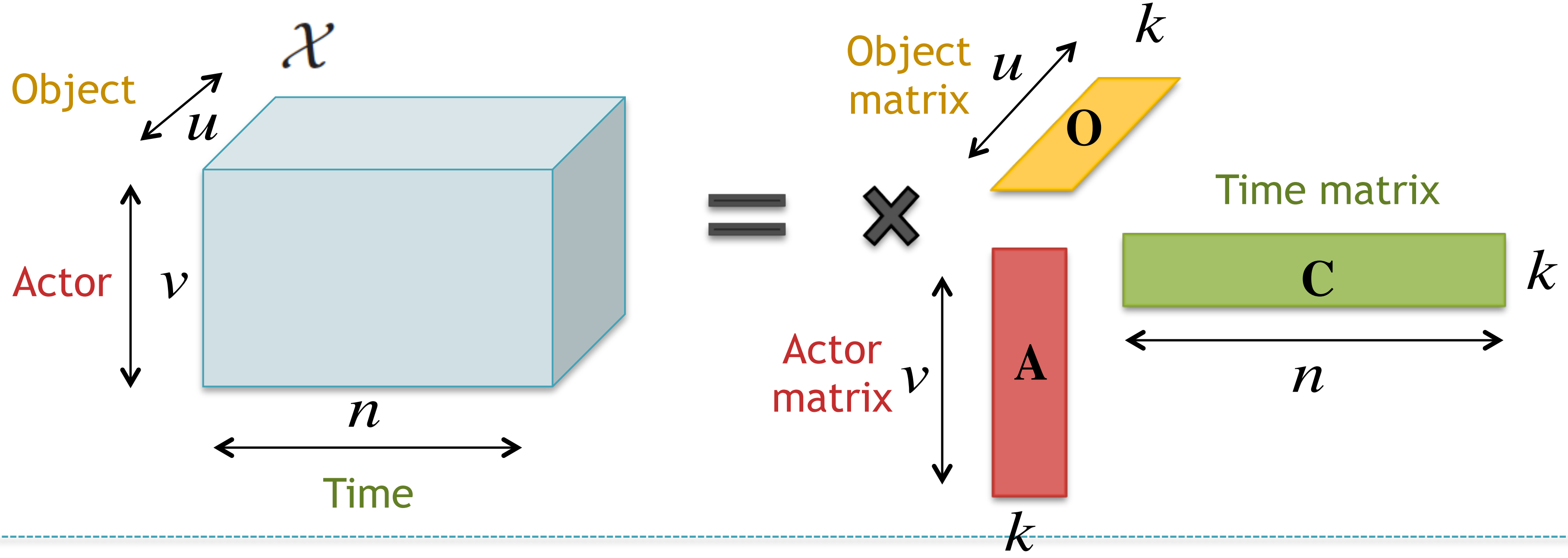
e.g., business topic vectors

Higher value:
Highly related topic

Main idea (1) : M-way analysis

A set of 3 topic vectors = 3 topic matrices

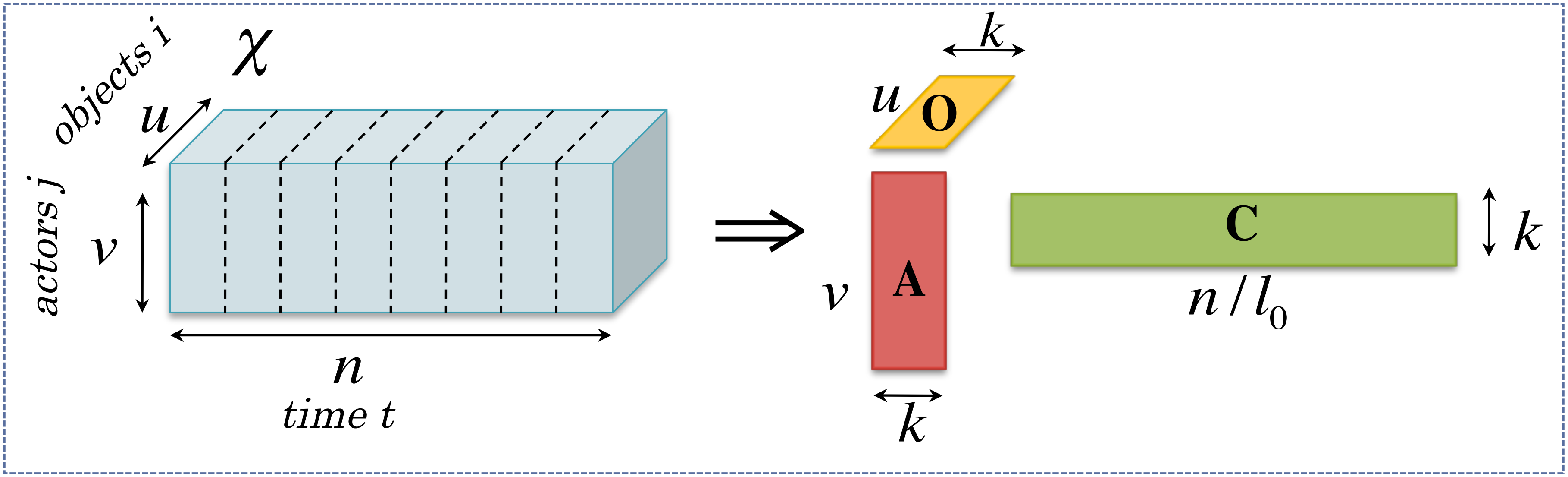
- [O] Object-topic matrix (u x k)
- [A] Actor-topic matrix (k x v)
- [C] Time-topic matrix (k x n)



Main idea (1) : M-way analysis (details)

M-way decomposition (M=3)

[Gibbs sampling] infer k hidden topics for each non-zero element of X, according to probability p



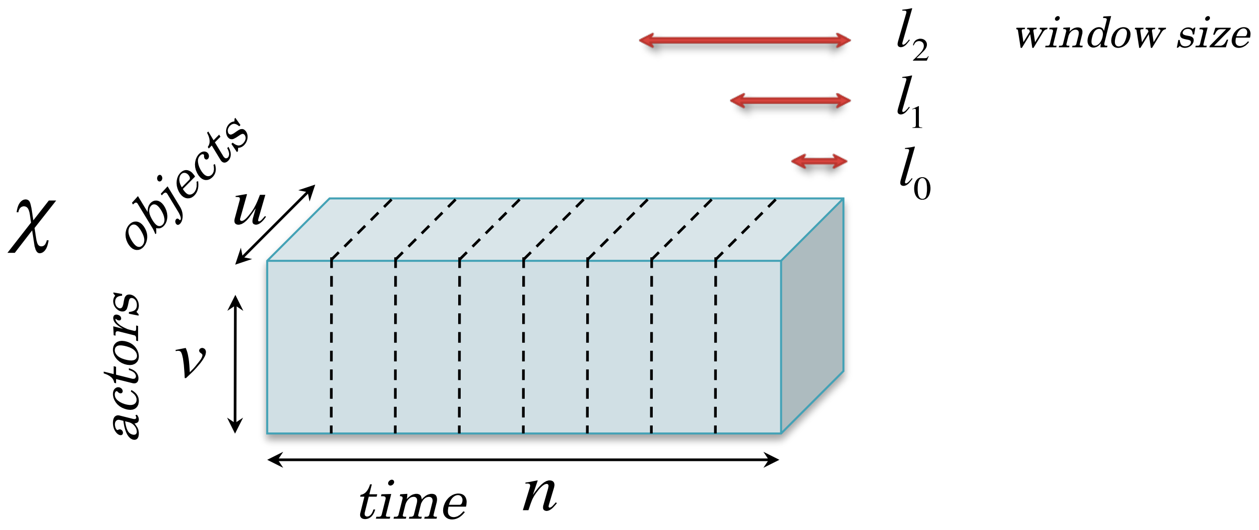
$$
\begin{aligned}
p(z_{i,j,t} &= r \mid \mathcal{X}, \mathbf{O}', \mathbf{A}', \mathbf{C}', \alpha, \beta, \gamma) \qquad (1)\\
&\propto \frac{o'_{i,r} + \alpha}{\sum_r o'_{i,r} + \alpha k} \cdot \frac{a'_{r,j} + \beta}{\sum_j a'_{r,j} + \beta v} \cdot \frac{c'_{r,t} + \gamma}{\sum_t c'_{r,t} + \gamma n}
\end{aligned}
$$

Main idea (2) : Multi-scale analysis

Q: What is the right window size
to capture meaningful patterns?

… minute? hourly?

… daily?

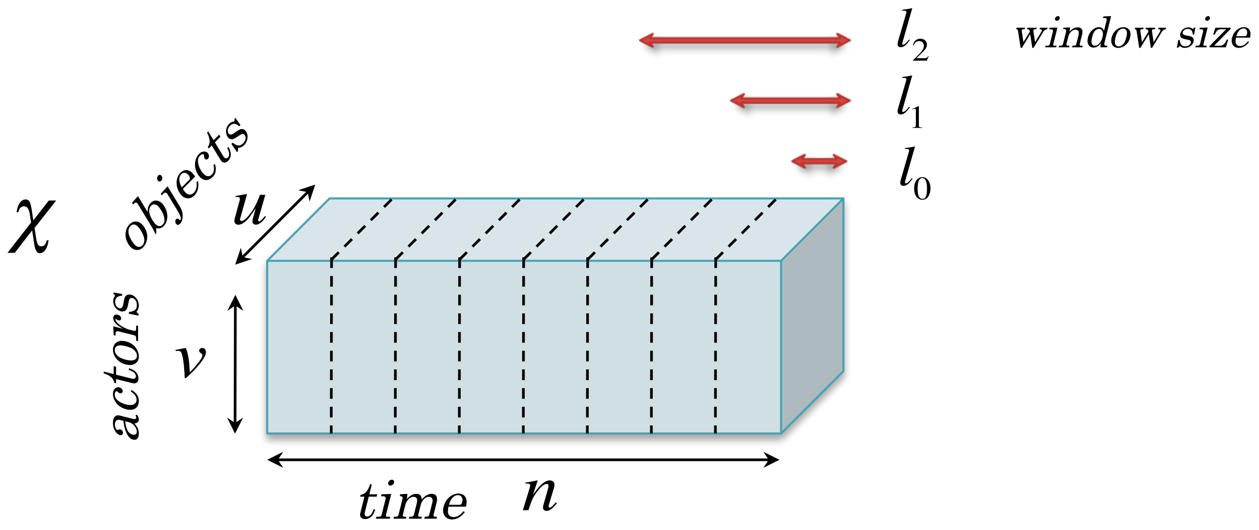


Main idea (2) : Multi-scale analysis

Q: What is the right window size

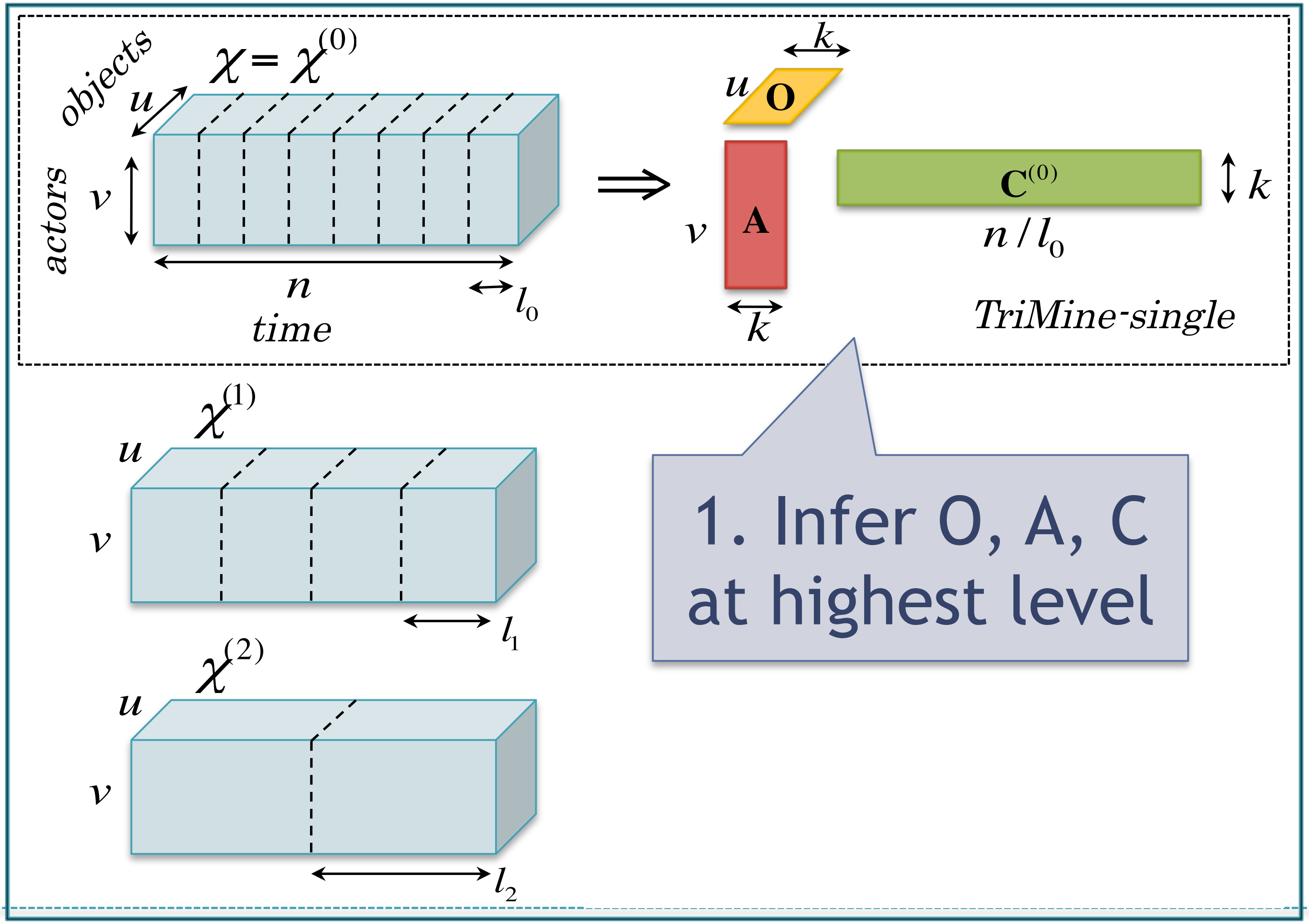
to capture meaningful patterns?

A. Our solution: Multiple window sizes



Main idea (2) : Multi-scale analysis (details)

Tensors with multiple window sizes



1. Infer O, A, C at highest level

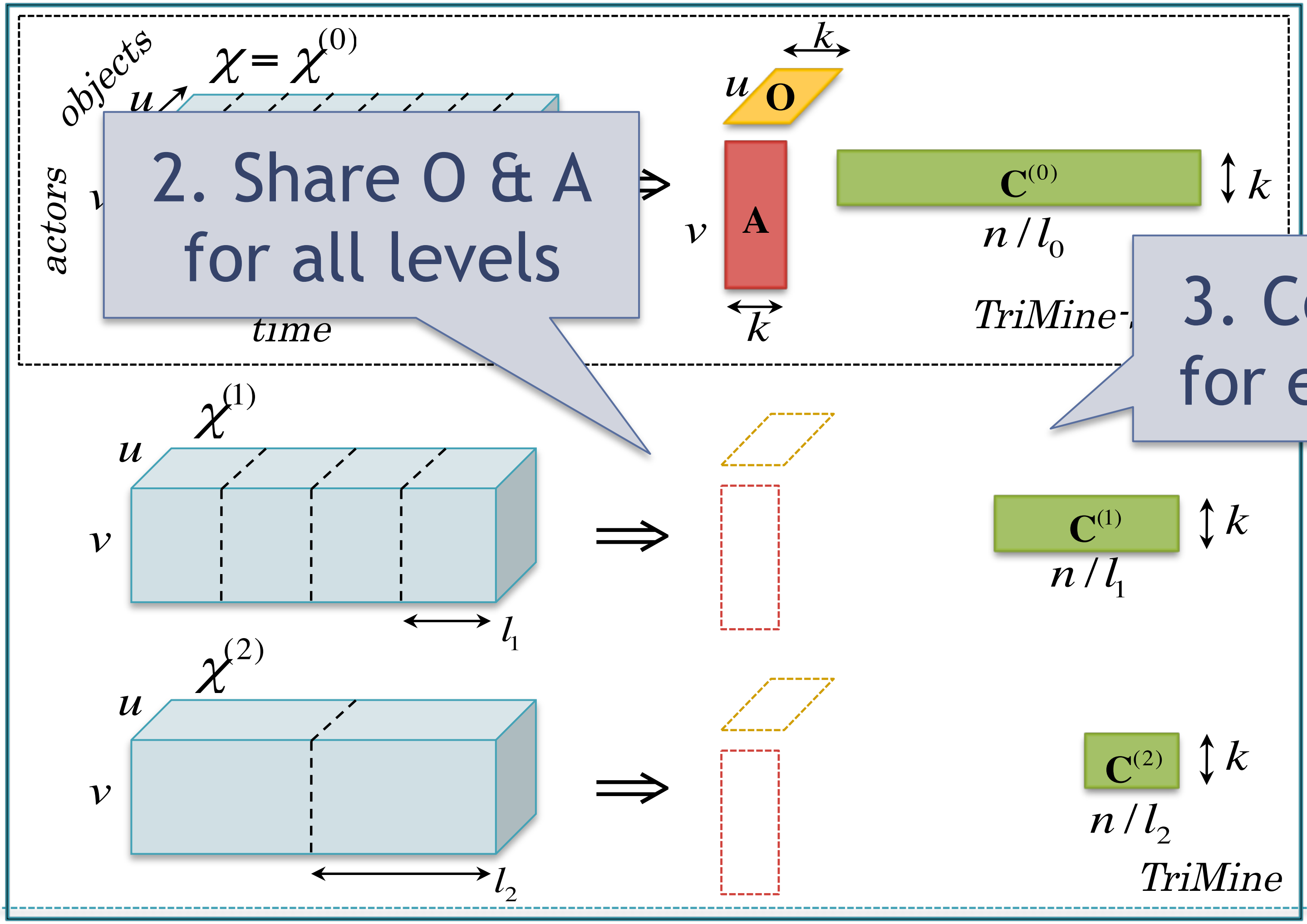
Hourly pattern

Daily pattern

Weekly pattern

Main idea (2) : Multi-scale analysis (details)

Tensors with multiple window sizes



2. Share O & A for all levels

3. Compute C for each level

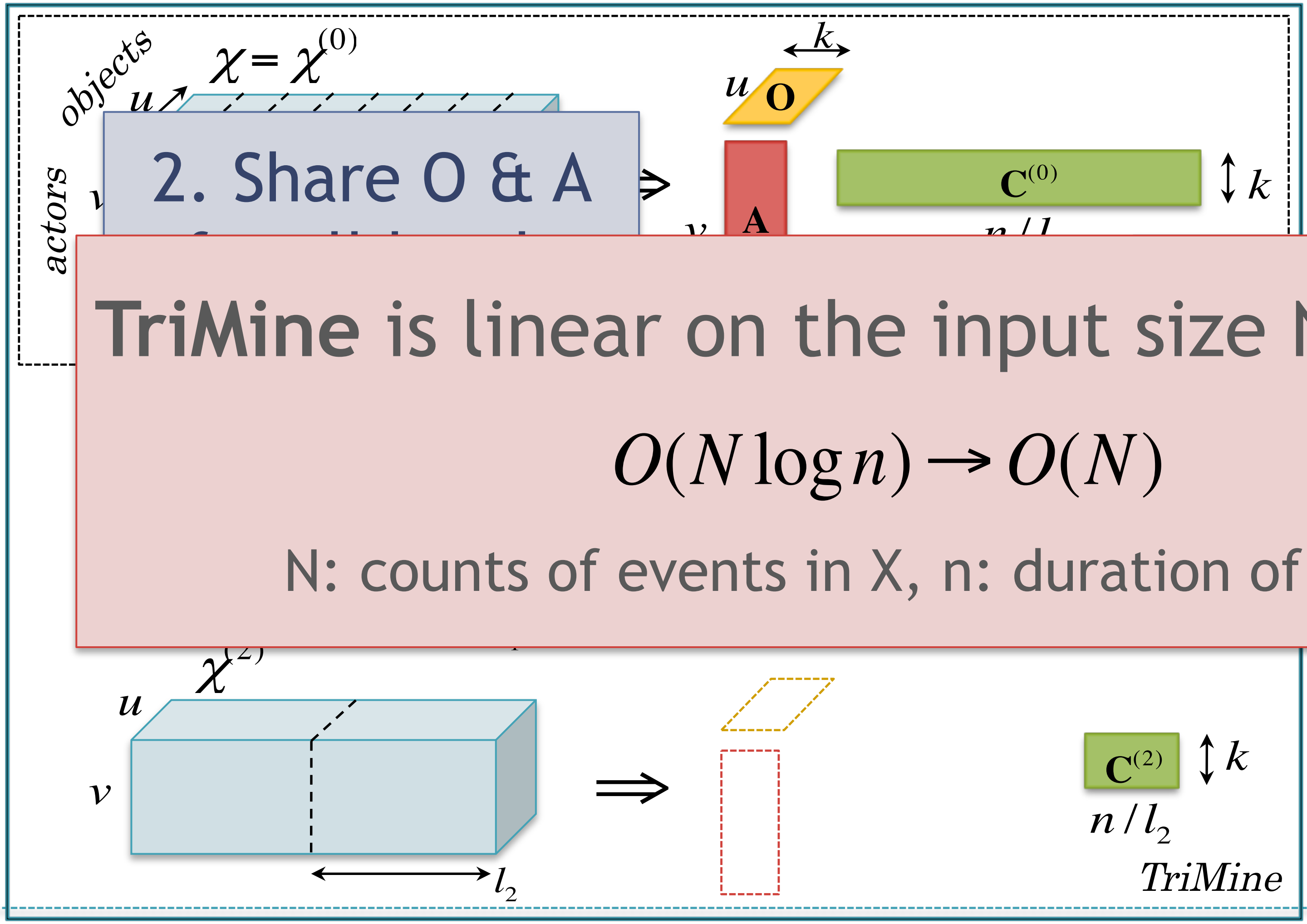
Hourly pattern

Daily pattern

Weekly pattern

Main idea (2) : Multi-scale analysis (details)

Tensors with multiple window sizes



2. Share O & A

TriMine is linear on the input size N, i.e.,

$$O(N \log n) \rightarrow O(N)$$

N: counts of events in X, n: duration of X

Hourly pattern

Weekly pattern

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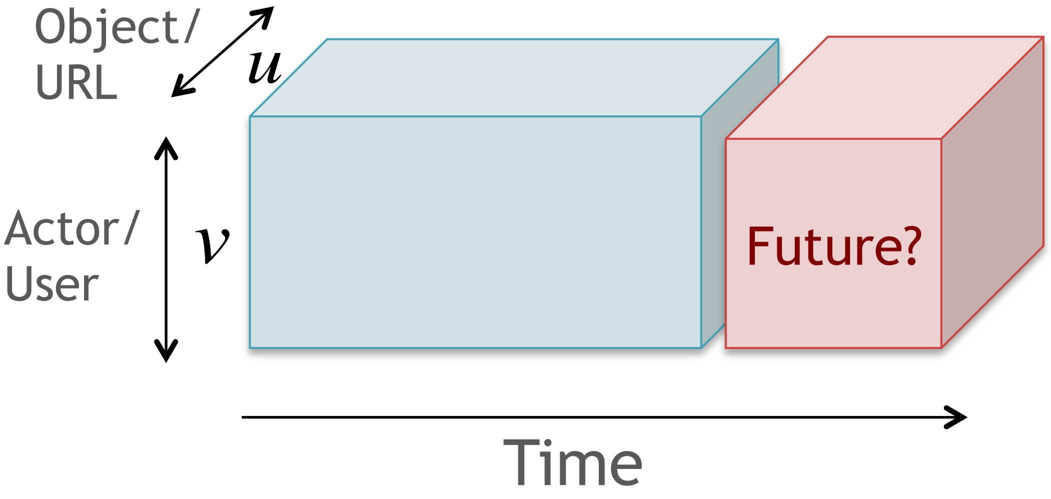
TriMine-Forecasts

Final goal: “forecast future events”!

Q. How can we generate a realistic events?

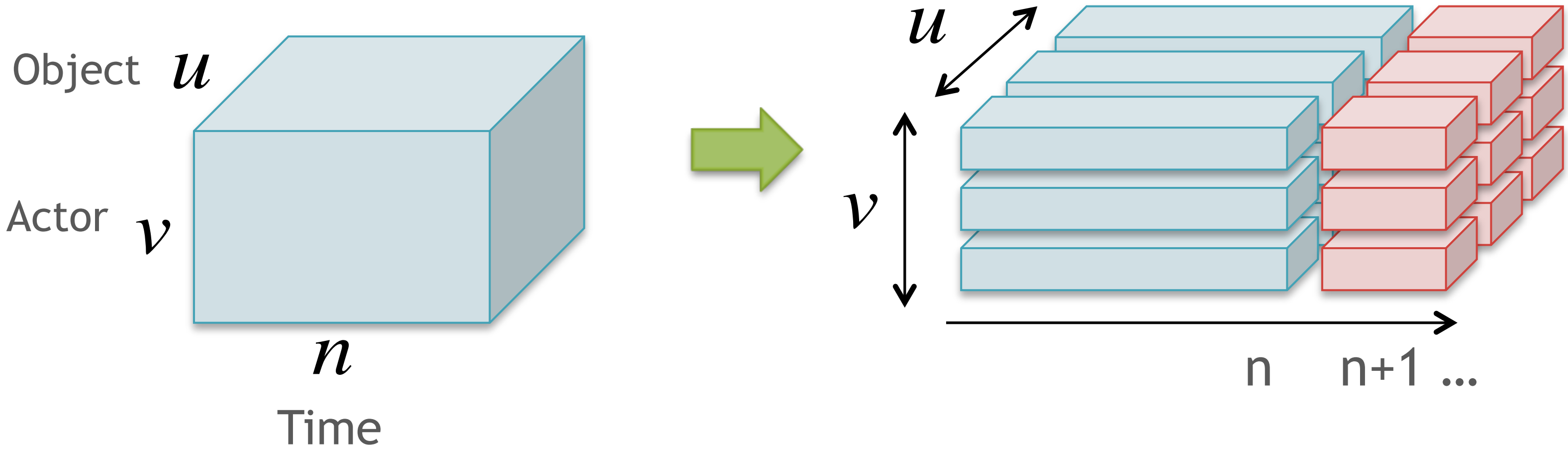


e.g., estimate the number of clicks for user “smith”, to URL “CNN.com”, for next 10 days

Why not naïve?

Individual-sequence forecasting

- Create a set of (u * v) sequences of length(n)
- apply the forecasting algorithm for each sequence



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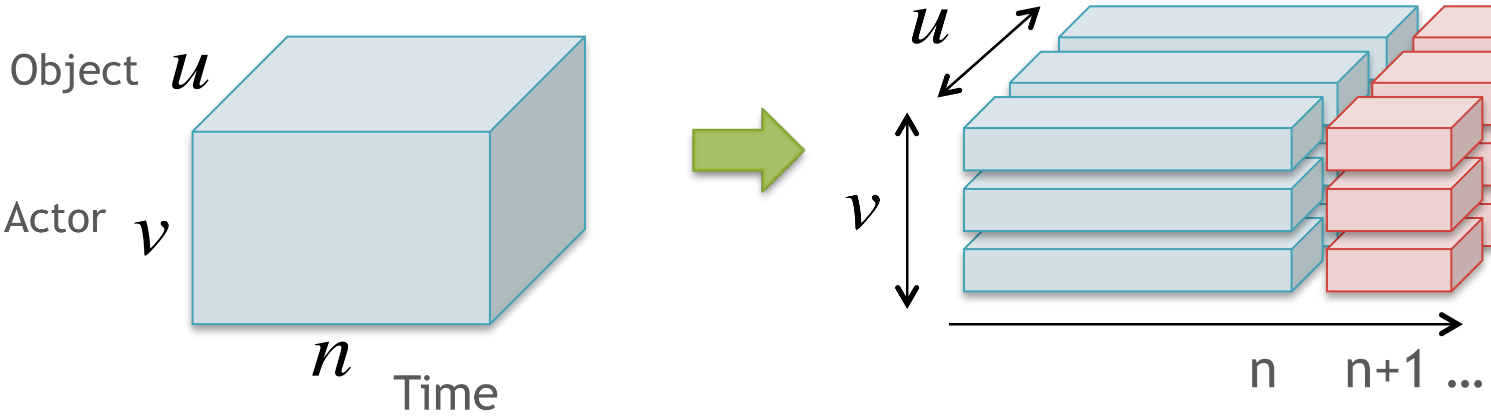


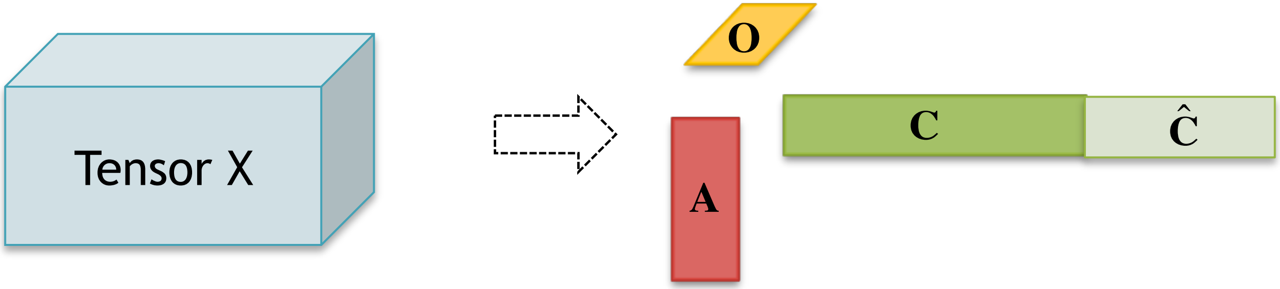
- ☹ Scalability : time complexity is at least $O(uvn)$
- ☹ Accuracy : each sequence "looks" like noise,

  (e.g., {0, 0, 0, 1, 0, 0, 2, 0, 0, ….}) -> hard to forecast

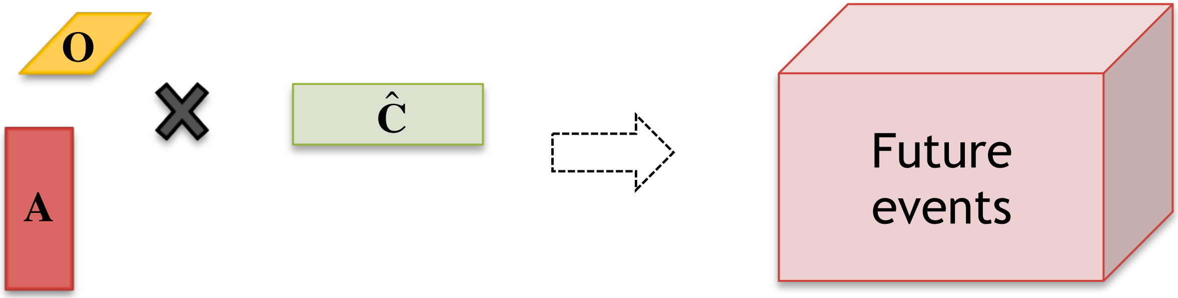
TriMine-F

Our approach:

- [Step 1] Forecast time-topic matrix: $\hat{C}$



- [Step 2] Generate events using 3 matrices



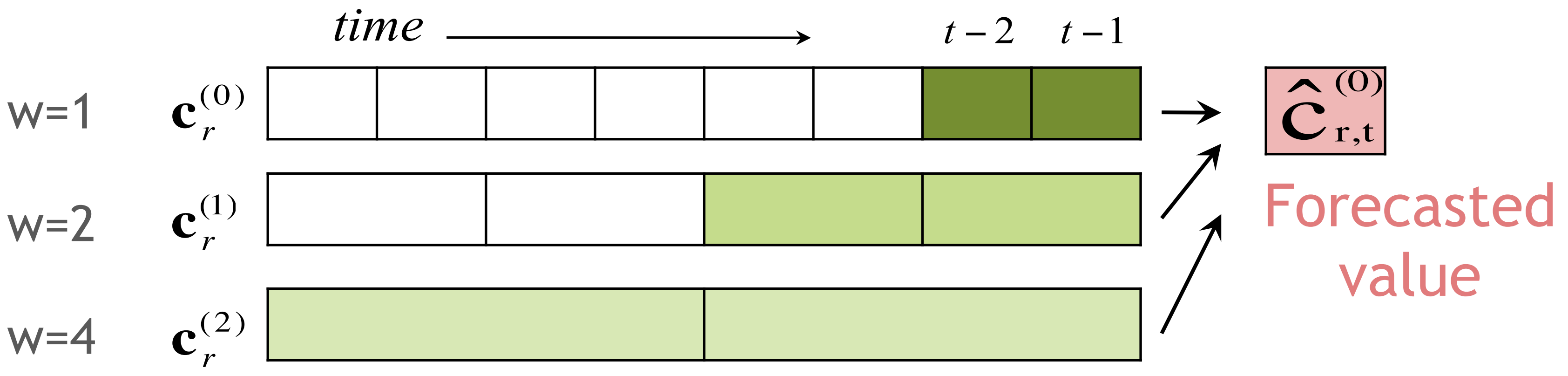
[Step 1] Forecast 'time-topic matrix' (details)

Q. How to capture multi-scale dynamics ?

e.g., bursty pattern, noise, multi-scale period

A. Multi-scale forecasting

Forecast $\hat{\mathbf{c}}^{(0)}_{\mathrm{r,t}}$ using multiple levels of matrices



$$c_{r,t}^{(0)} = \sum_{h=0}^{\lceil \log n \rceil} \sum_{i=1}^{w} \lambda_{i,r}^{(h)} c_{r,t-i}^{(h)} + \epsilon_t .$$

(Details in paper)

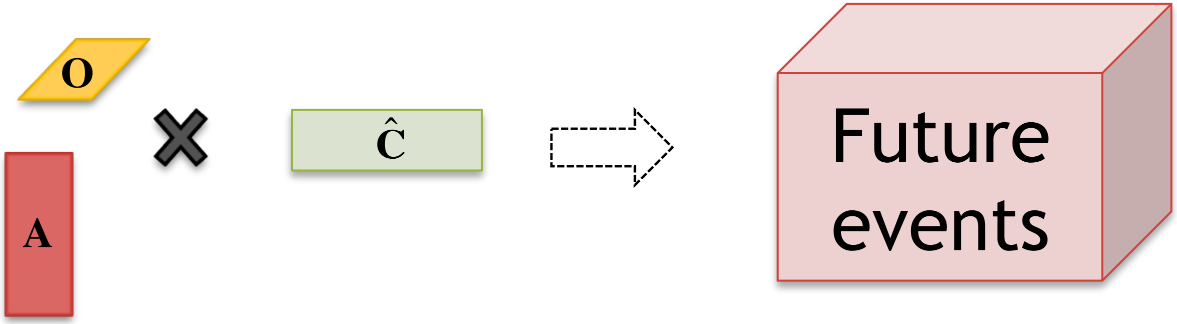
[Step 2] Generate events using O A Ĉ (details)

We propose 2 solutions:

A1. Count estimation

Use O A Ĉ matrices

$$\hat{x}_{i,j,t} = n\bar{x}_i \sum_{r=1}^{k} o_{i,r} \cdot a_{r,j} \cdot \hat{c}_{r,t},$$



A2. Complex event generation

Use sampling-based approach (Details in paper)

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Experimental evaluation

The experiments were designed to answer:

- Effectiveness

  Q1. How successful is TriMine in spotting patterns?

- Forecasting accuracy

  Q2. How well does TriMine forecast events?

- Scalability

  Q3. How does TriMine scale with the dataset size?

Experimental evaluation

Datasets

- *WebClick* data

  Click: {URL, user ID, time}

  - 1,797 URLs, 10,000 heavy users, one month

- *Ondemand TV* data

  View: {channel ID, viewer ID, time}

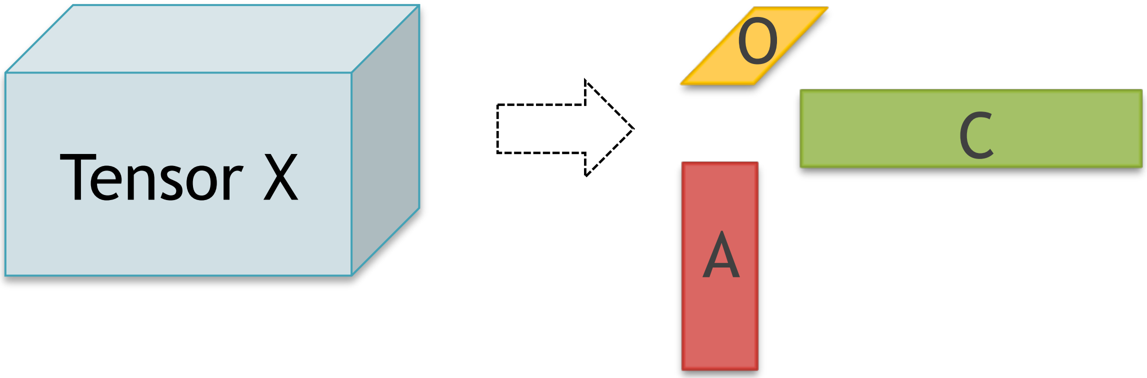
  - 13,231 TV program, 100,000 users, 6 month

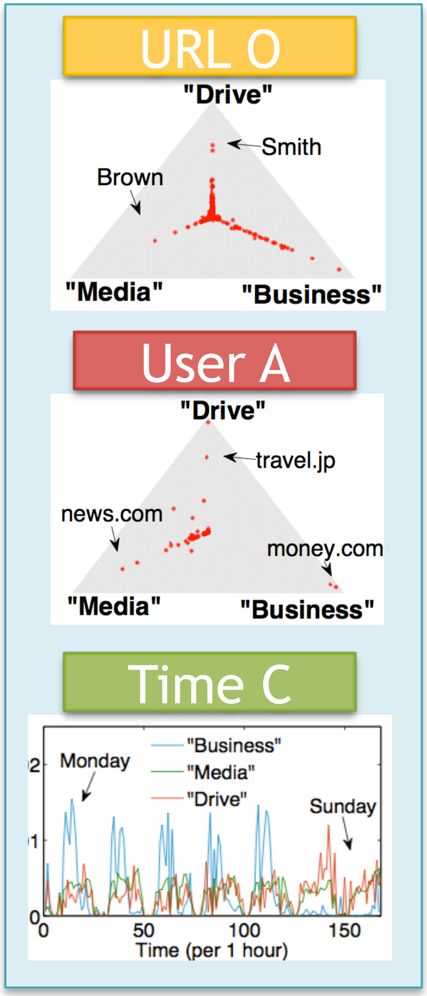
Q1. Effectiveness

Result of three matrices O, A, C

Visualization: “TriMine-plots”

- URL-topic matrix O
- User-topic matrix A
- Time-topic matrix C



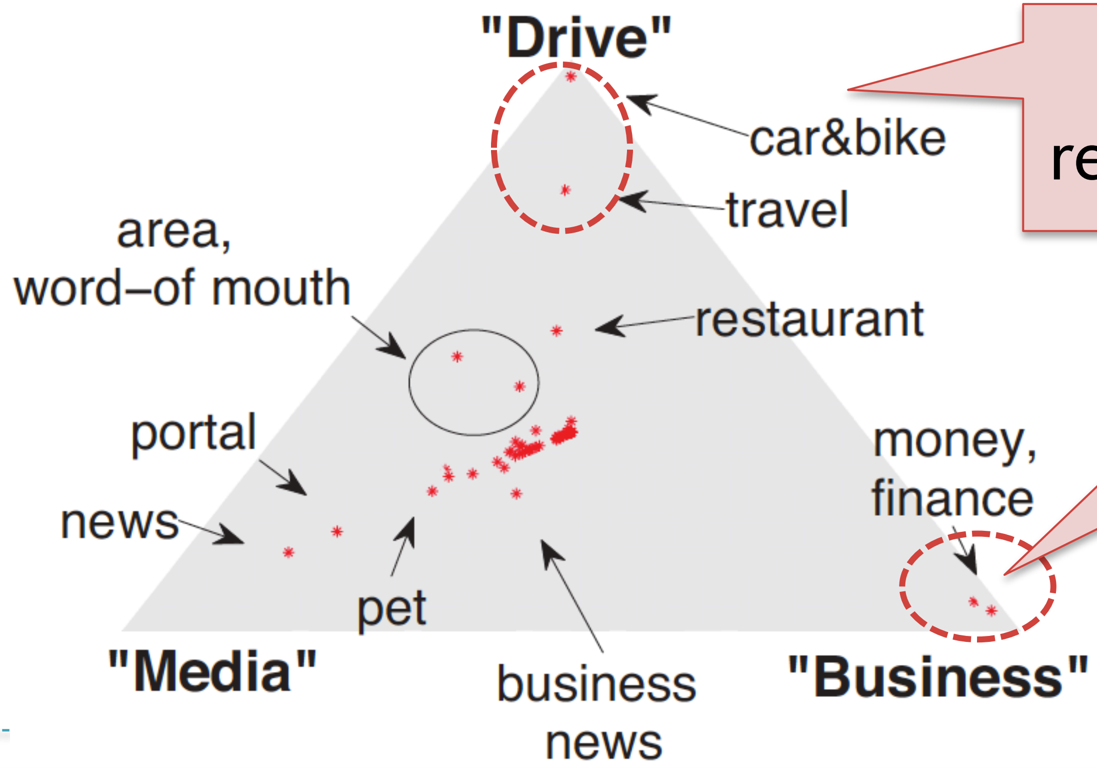


Q1-1. WebClick data

URL-topic matrix (O)

Three hidden topics: “drive”, “business”, “media”

* Red point : each web site



Car & bike site is related to travel site

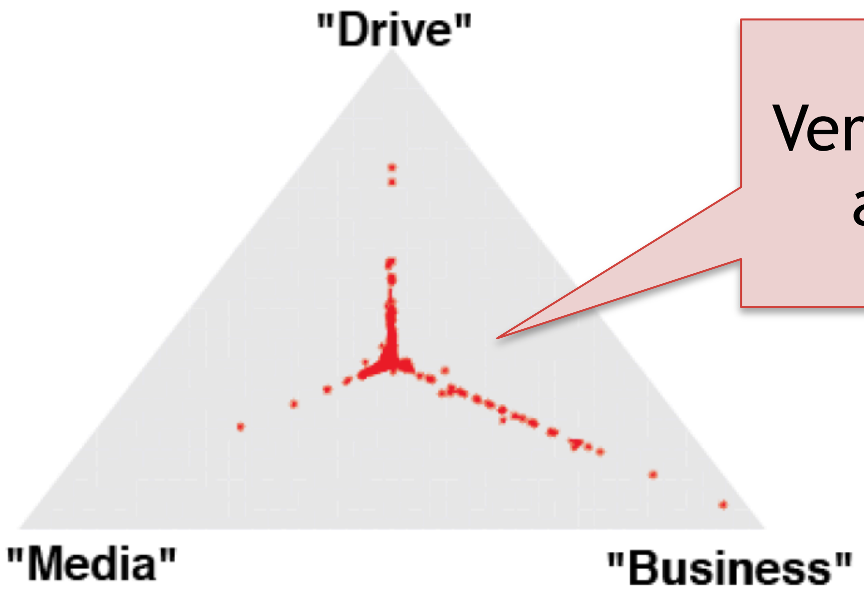
Money site& Finance site have similar trends

Q1-1. WebClick data

User-topic matrix (A)

Three hidden topics: “drive”, “business”, “media”

* Red point : each user



Very clear user groups along the spokes

Q1-1. WebClick data

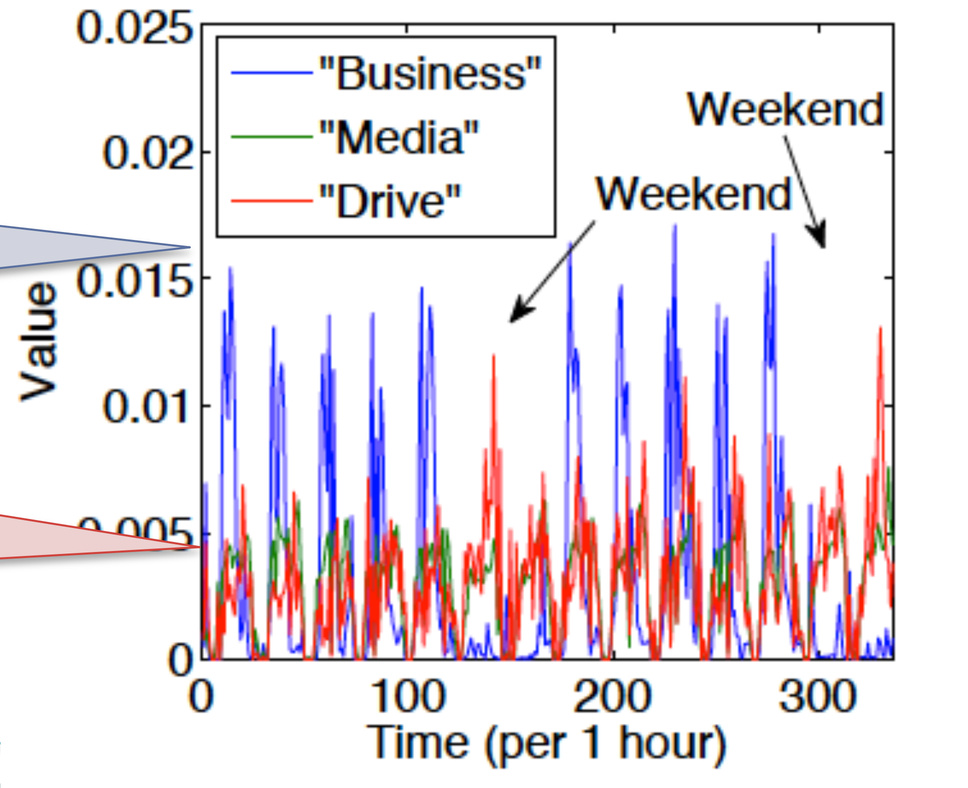
Time-topic matrix (C)

Three hidden topics: “drive”, “business”, “media”

* Each sequence: each topic over time

“Business” topic: Less access during weekend

“Drive” topic: Spikes during weekend



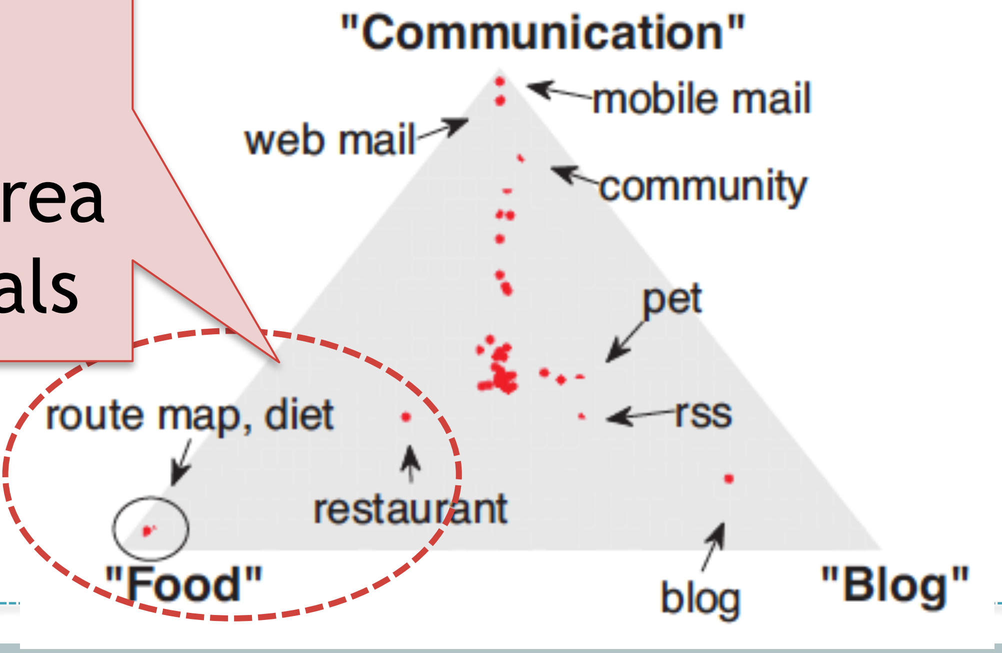
Q1-1. WebClick data

Other topics

Three topics: “Communication”, “food”, “blog”

Three related sites:
route-map, diet, restaurant
i.e., users check out
1. Restaurants
2. route map in their area
3. Calories of their meals

URL-topic matrix O



Q1-1. WebClick data

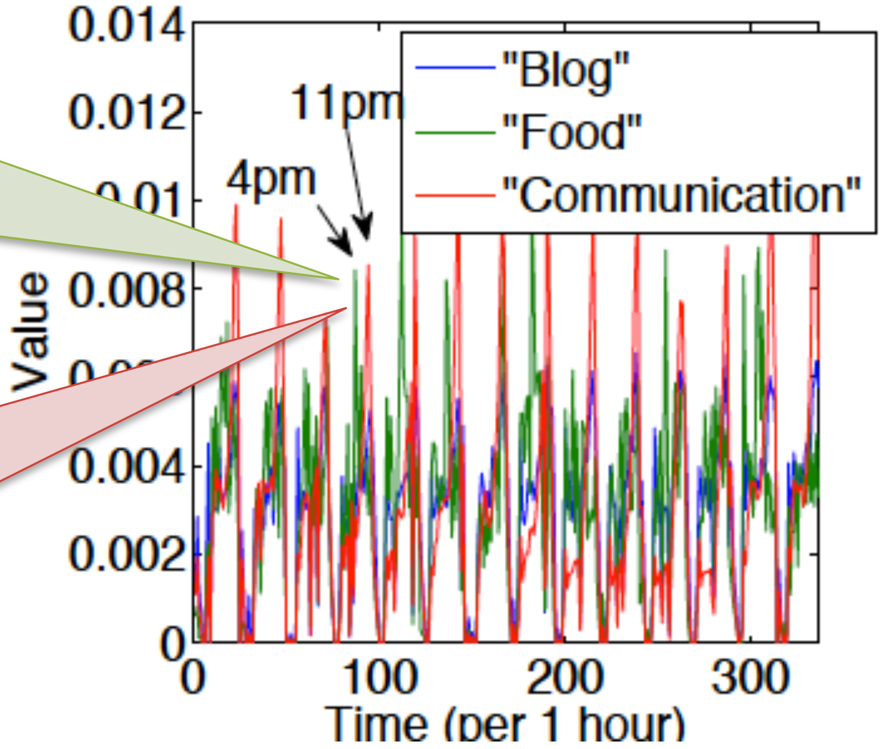
Other topics

Three topics: “Communication”, “food”, “blog”

4pm: Food related sites:
visited in the early evening before users go out

11pm: Communication sites:
Used in the late evening for private purposes

Time-topic matrix C

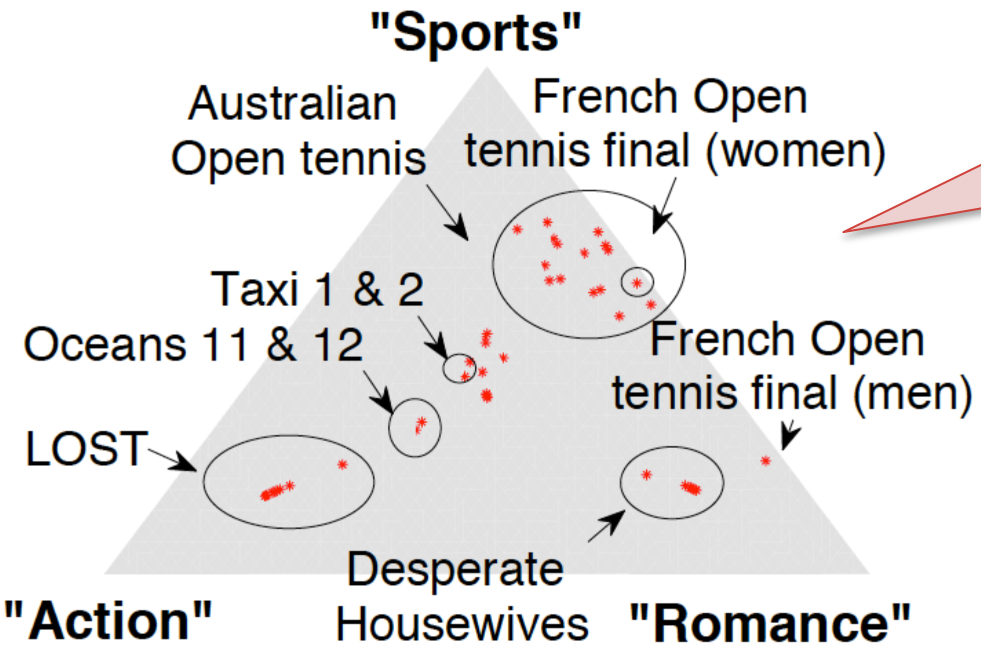


Q1-2. Ondemand TV data

TV program-topic matrix (O)

Three topics: “sports ”, “action”, “romance”

* Red point : each TV program



Several clusters (LOST, tennis etc.)

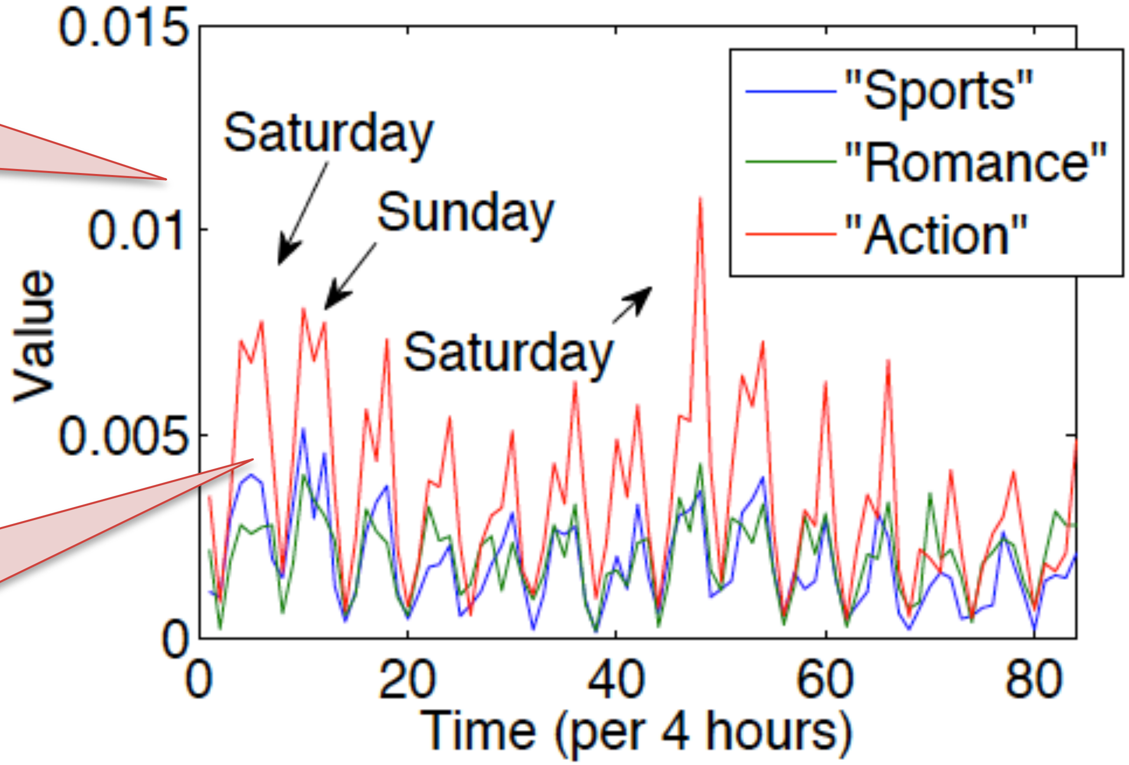
Q1-2. Ondemand TV data

Time-topic matrix (C)

Three hidden topics: “sports ”, “action”, “romance”

* Each sequence: each topic over time

Daily & weekly periodicities

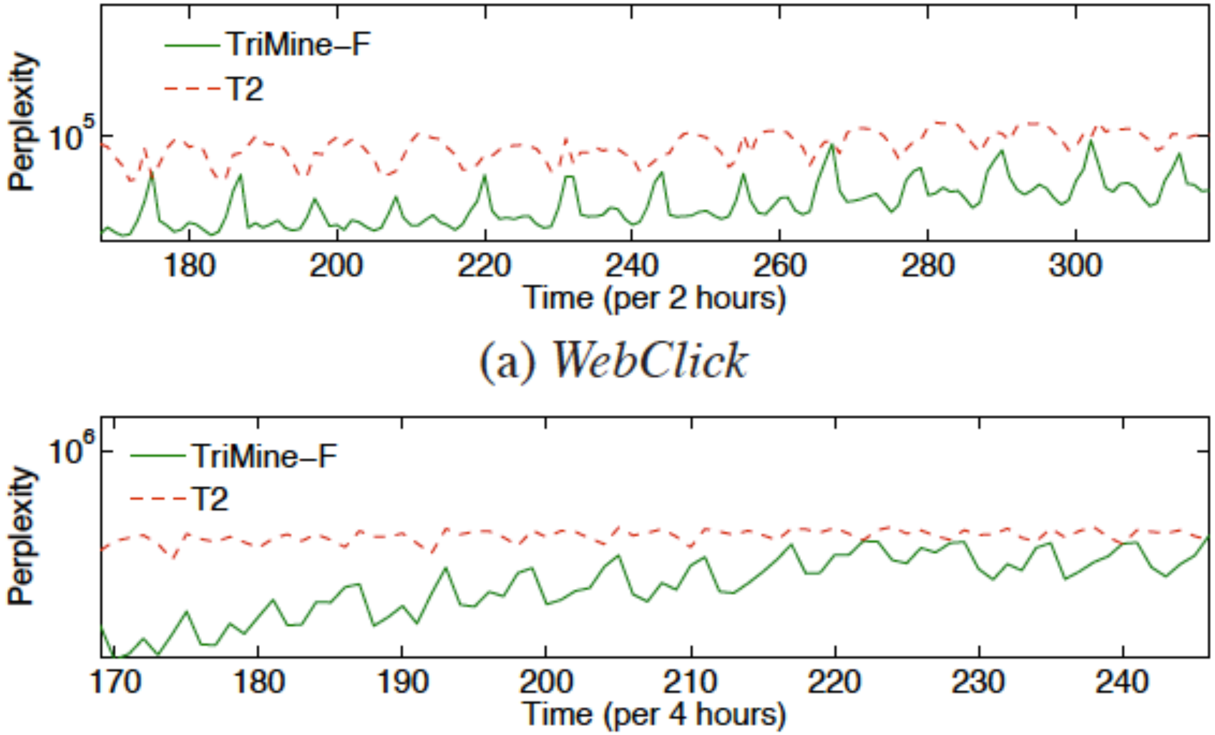


“Action”: High peeks on weekends

Q2-1. Forecasting accuracy

Temporal perplexity (entropy for each time-tick)

Lower perplexity: higher predictive accuracy



(a) *WebClick*

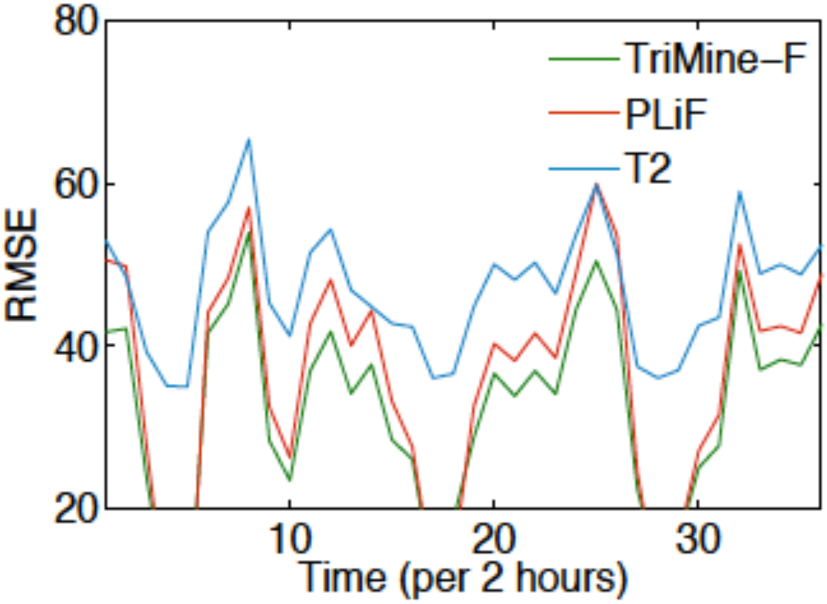
(b) *Ondemand TV*

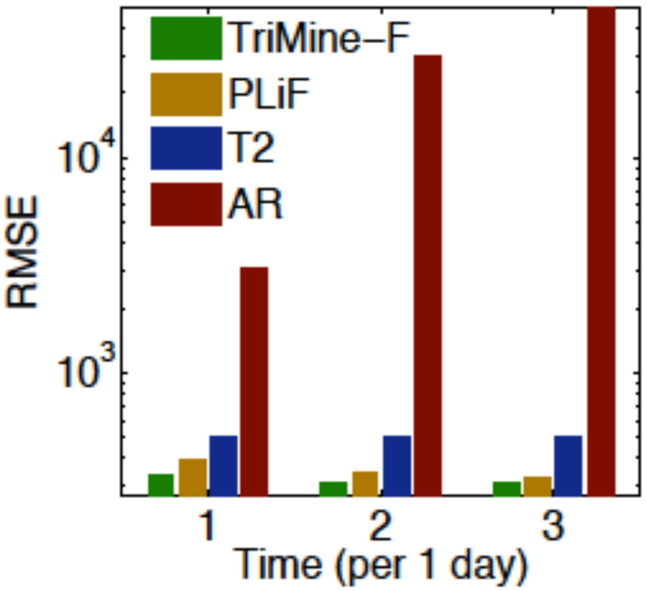
T2: [Hong et al. KDD’11]

Q2-2. Forecasting accuracy

Accuracy of event forecasting

RMSE between original and forecasted events (lower is better)

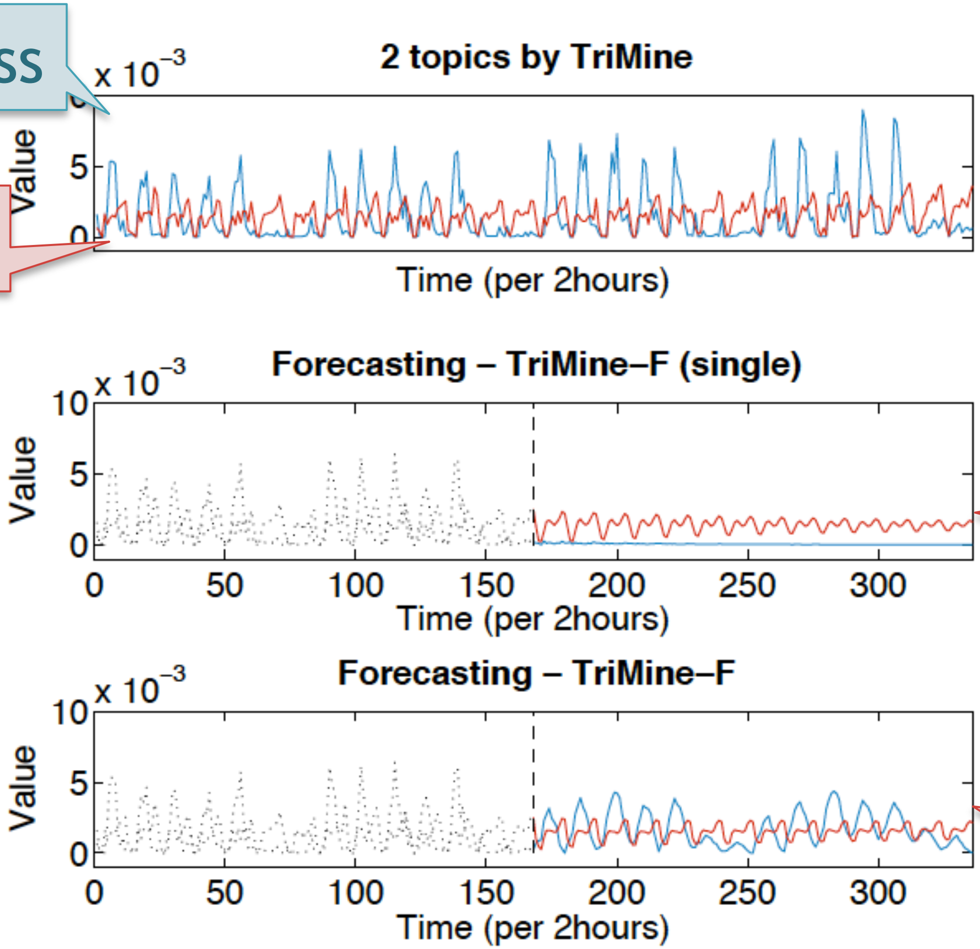




PLiF [Li et al.VLDB’10] , T2: [Hong et al.KDD’11]

Q2-3. Forecasting accuracy

Benefit of multiple time-scale forecasting



business

drive

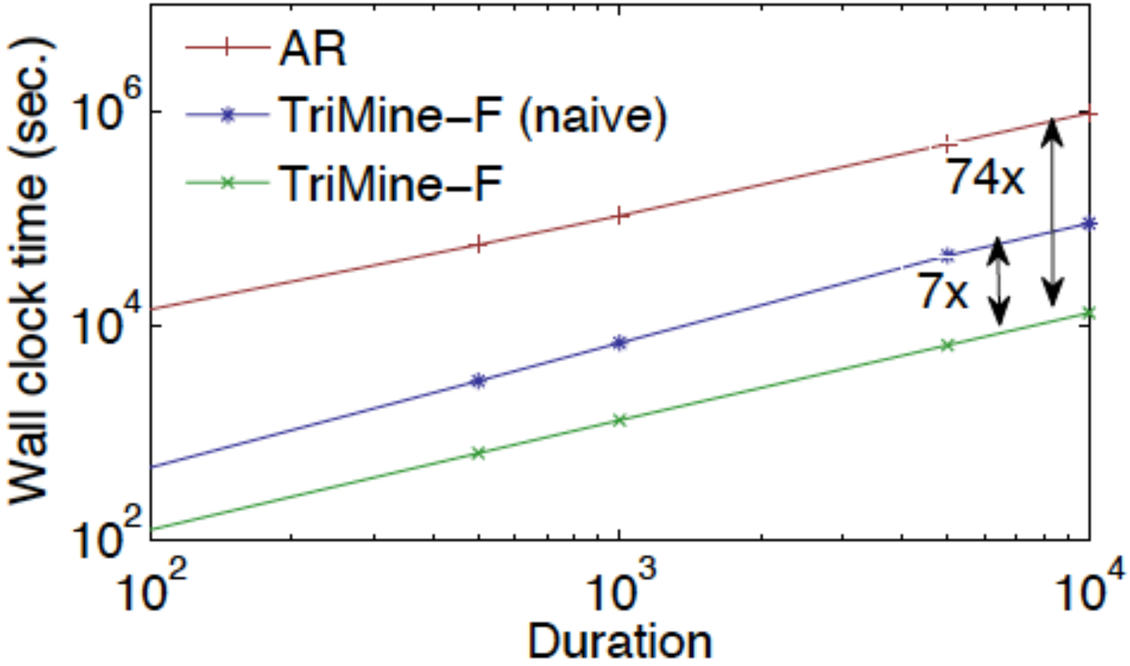
Original sequence of matrix (C)

Forecast C' using single level -> failed

Multi-scale forecast -> captured cyclic patterns

Q3. Scalability

Computation cost (vs. AR)



TriMine provides a reduction in computation time (up to 74x)

Outline

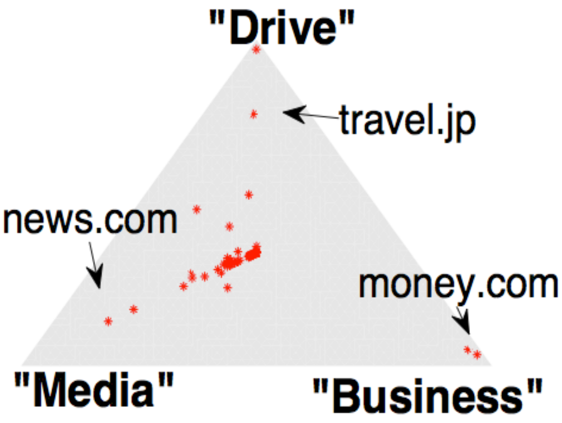
- Motivation
- Problem definition
- Proposed method: TriMine
- TriMine-F forecasting
- Experiments
- Conclusions

Conclusions

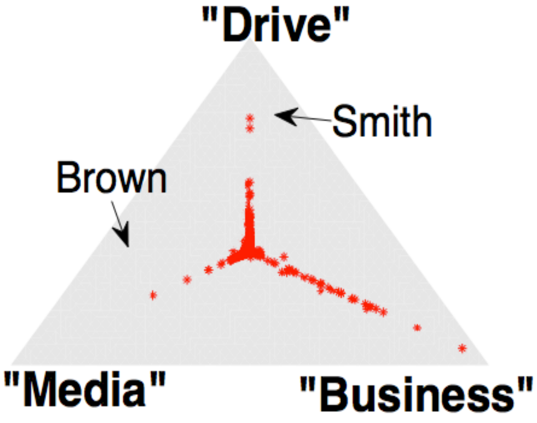
- TriMine has following properties:
  - Effective
    - –It finds meaningful patterns in real datasets
  - Accurate
    - –It enables forecasting
  - Scalable
    - –It is linear on the database size

Thank you

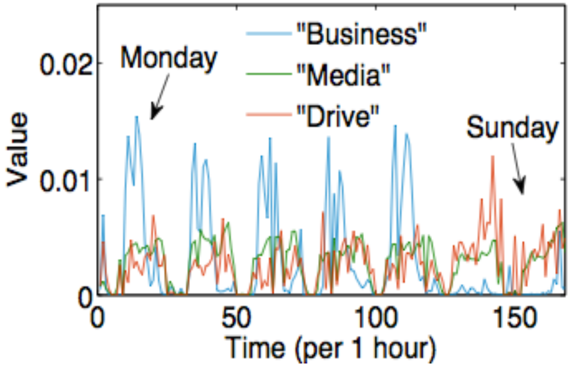
URL matrix



User matrix



Time matrix



Code: http://www.kecl.ntt.co.jp/csl/sirg/people/yasuko/software.html

Email: matsubara.yasuko @ lab.ntt.co.jp