Event Analytics for Strengthening Community Resilience in a Cyber-Physical Society

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Thank you!

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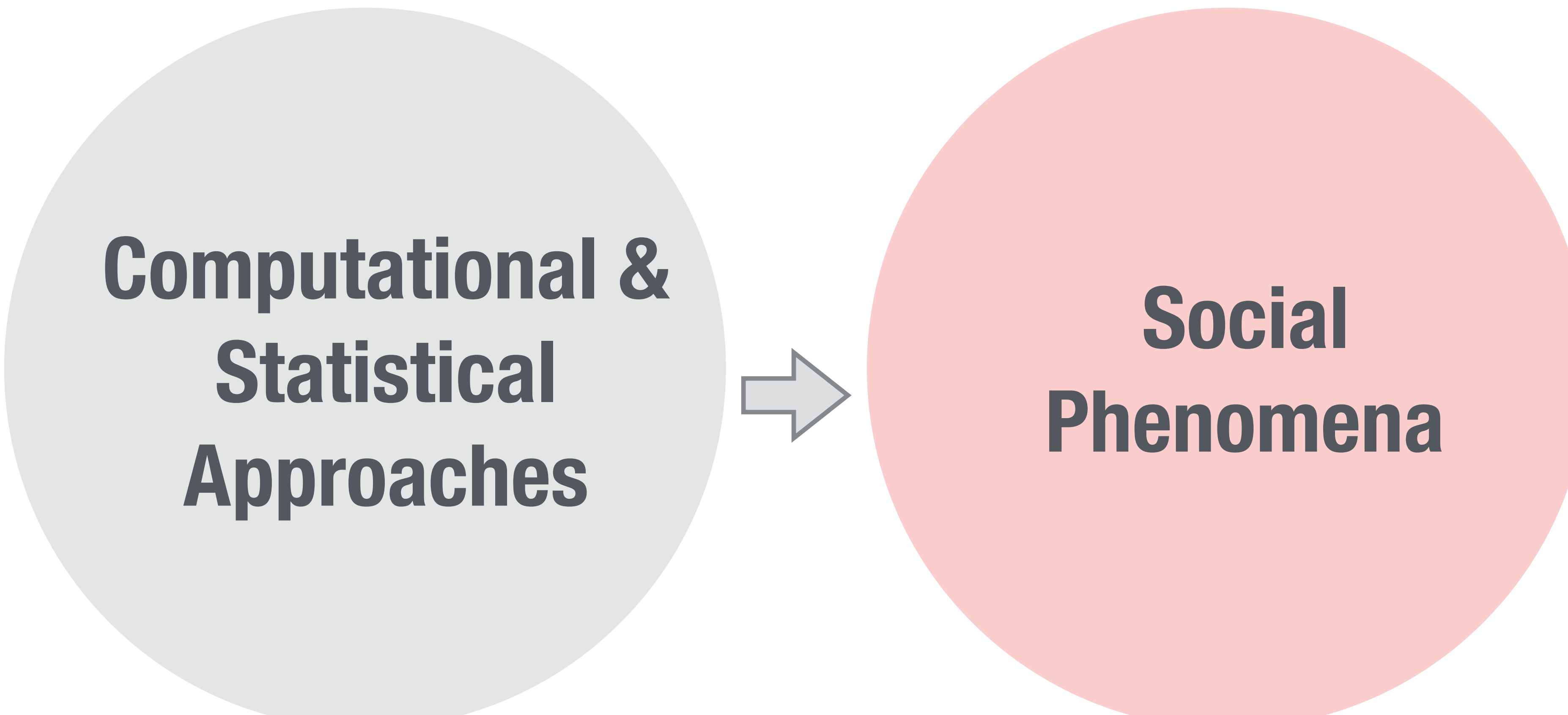
Research interest



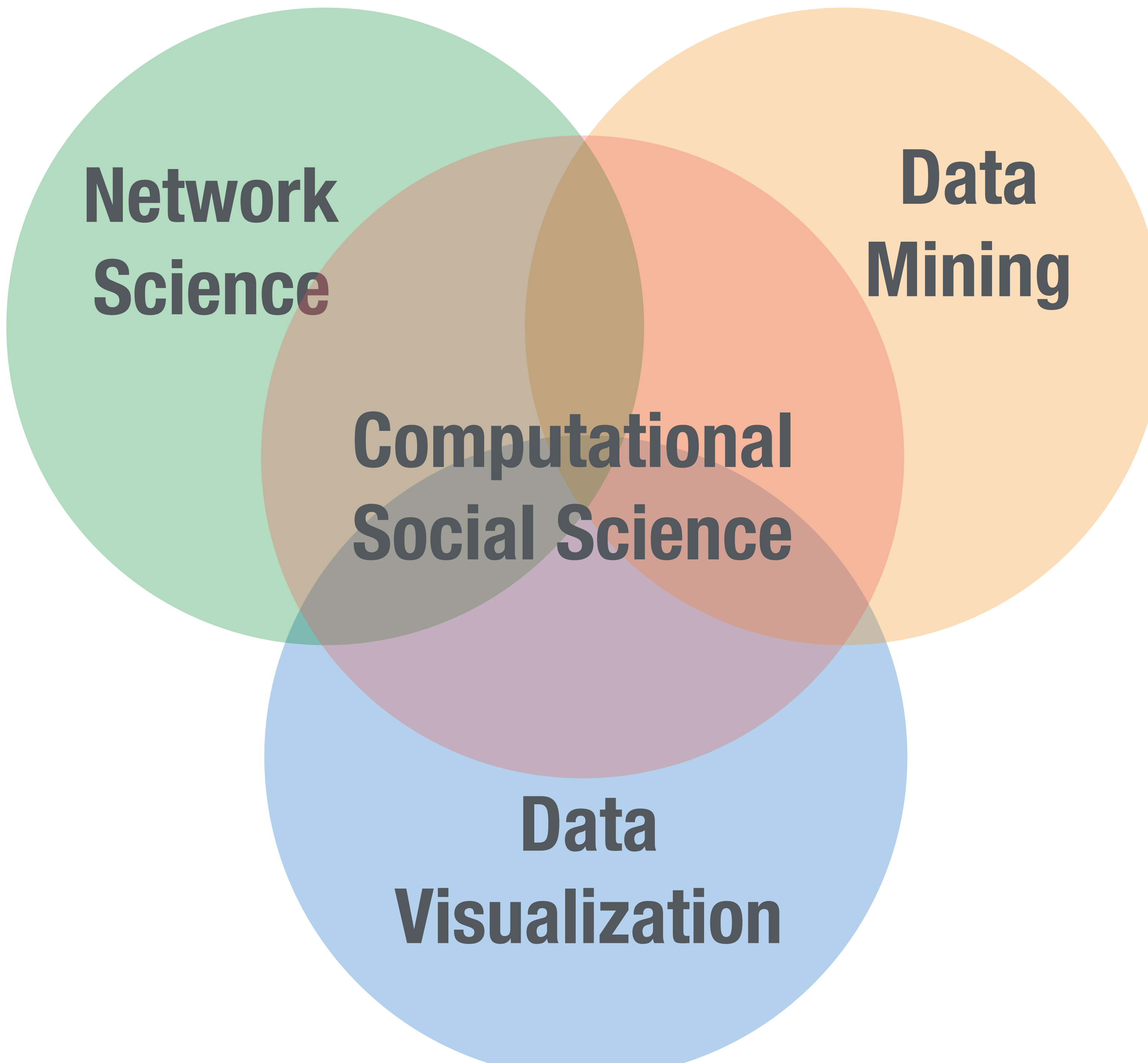
Motivation

How might we ***empirically*** *study the social world?*

(given that almost all ***social systems*** are inherently ***multifarious***, ***complex*** and ***evolving*** over time and space)

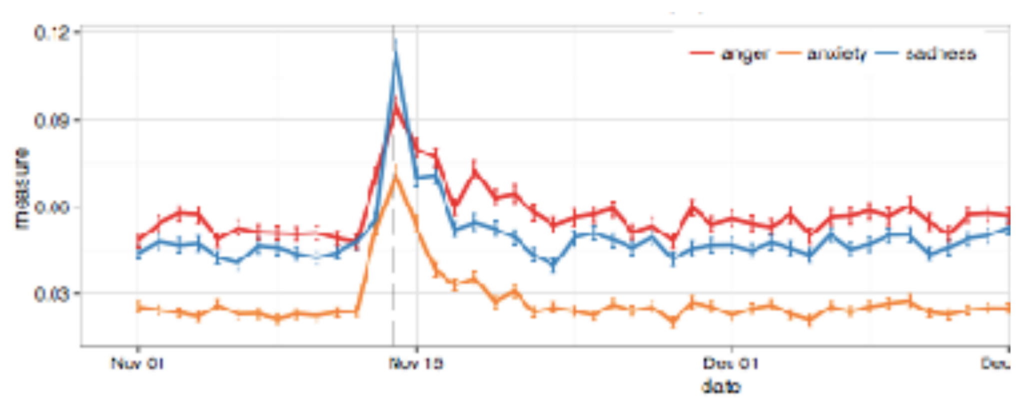
To help characterize the processes that reflect the social **structure**, **content**, and **dynamics** over time and space

Research areas



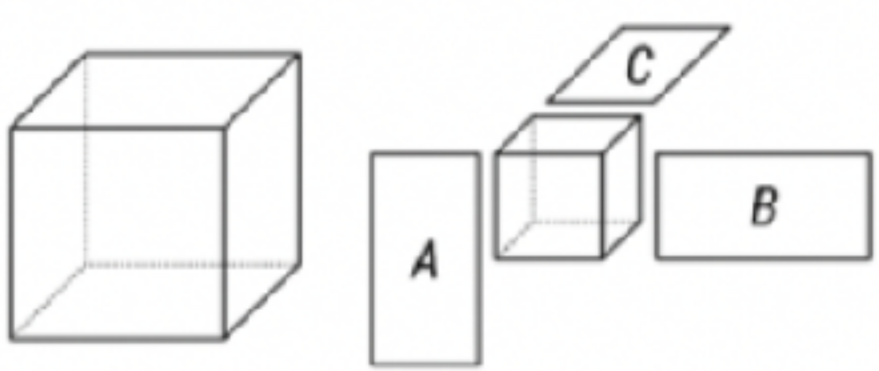
Computational Social Dynamics Lab

Analysis

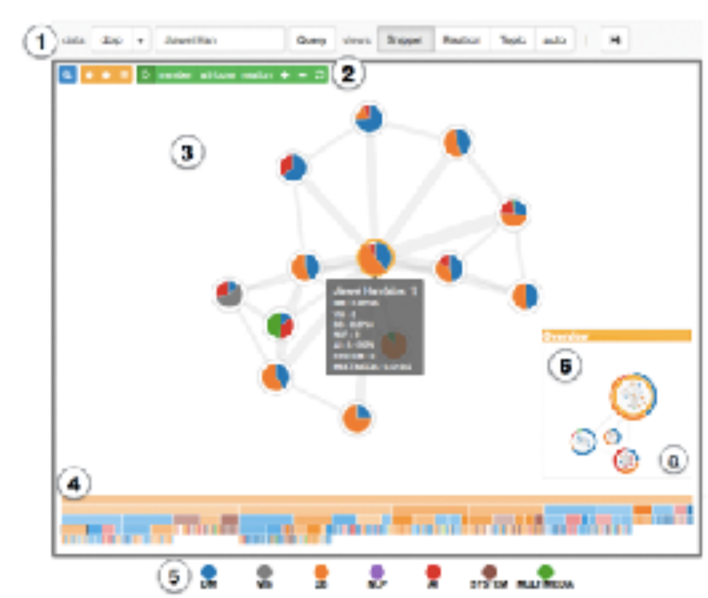


Analyses of
Social Systems

Mining



Visualization



Community Resilience & Data-Driven Crisis Response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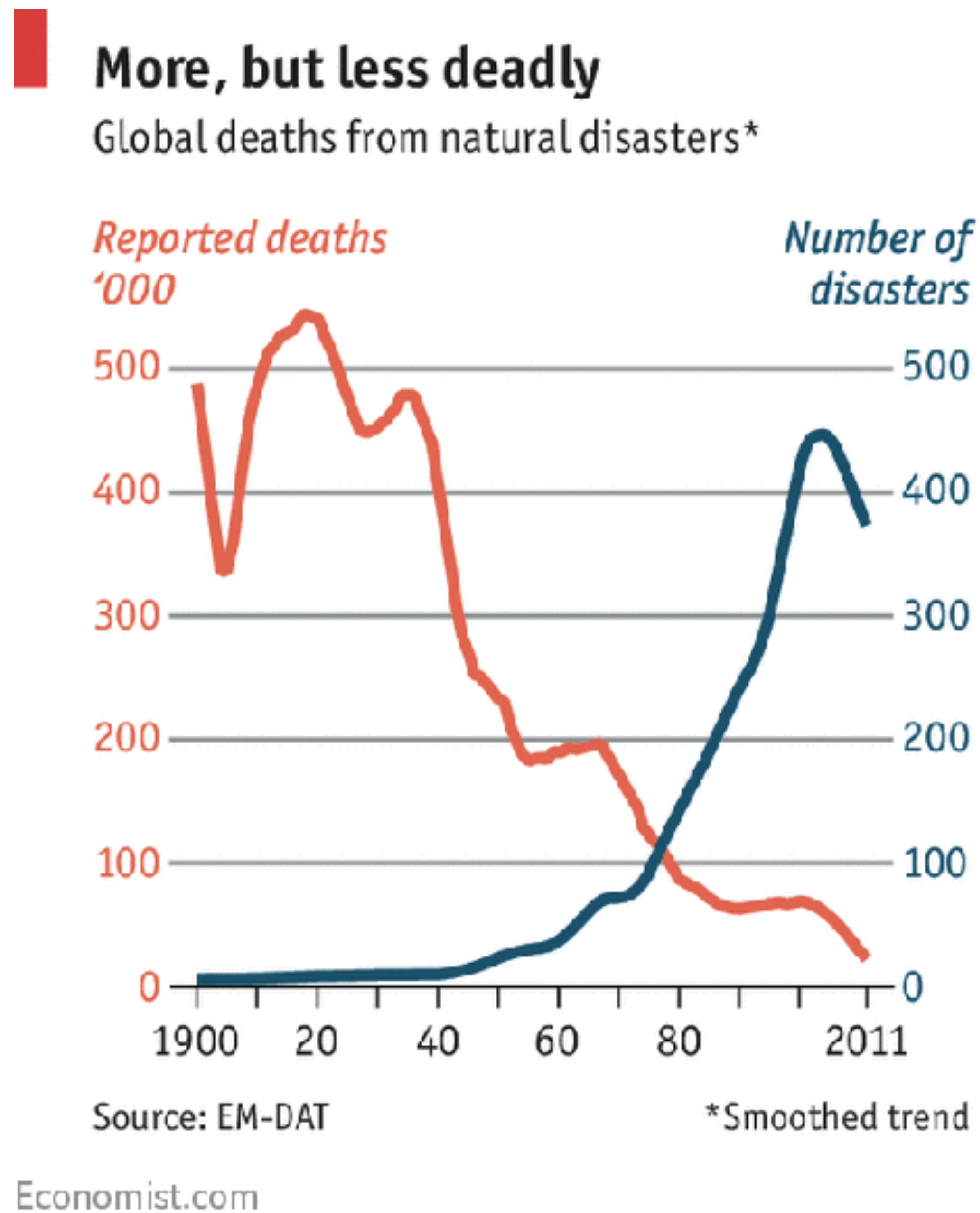
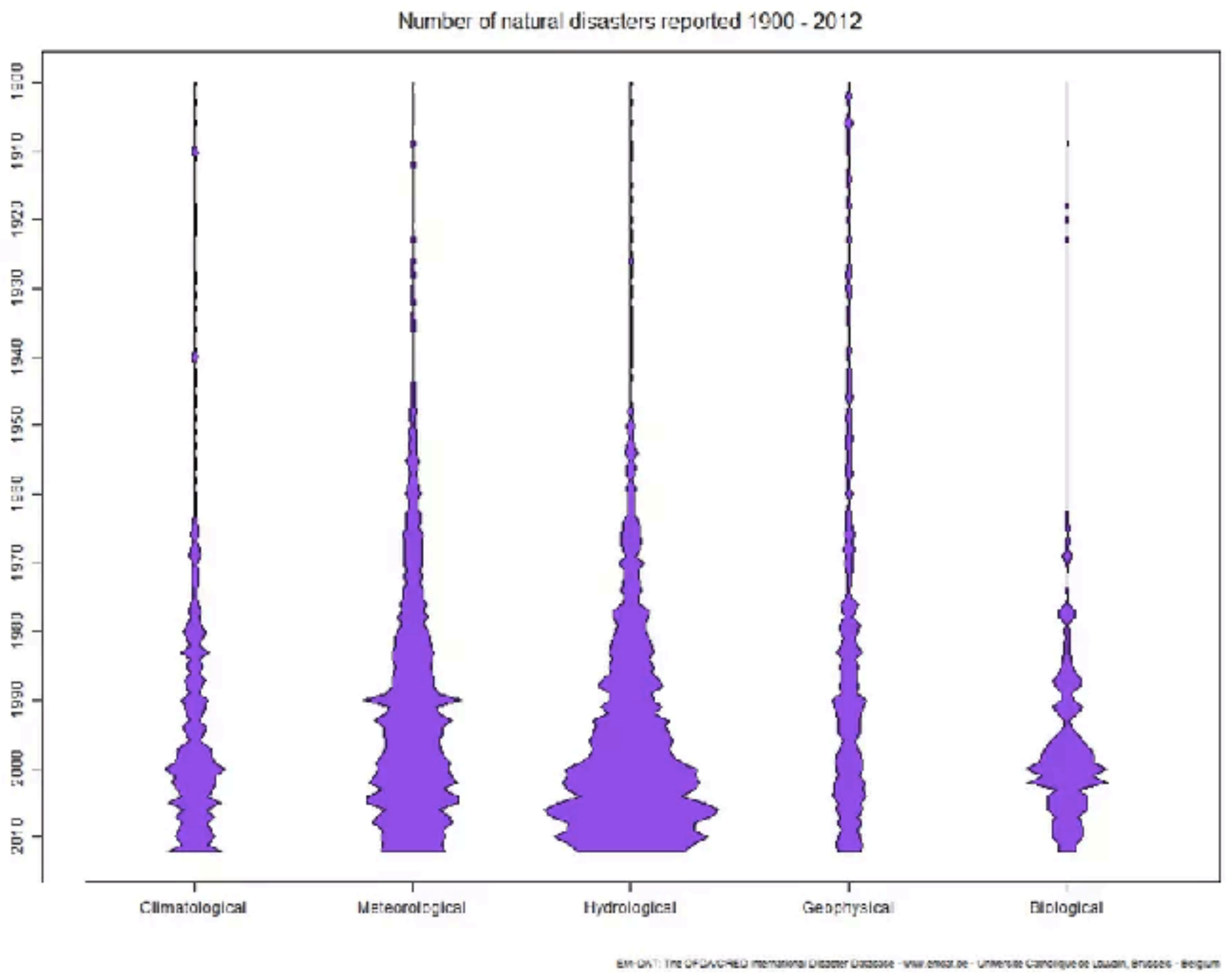
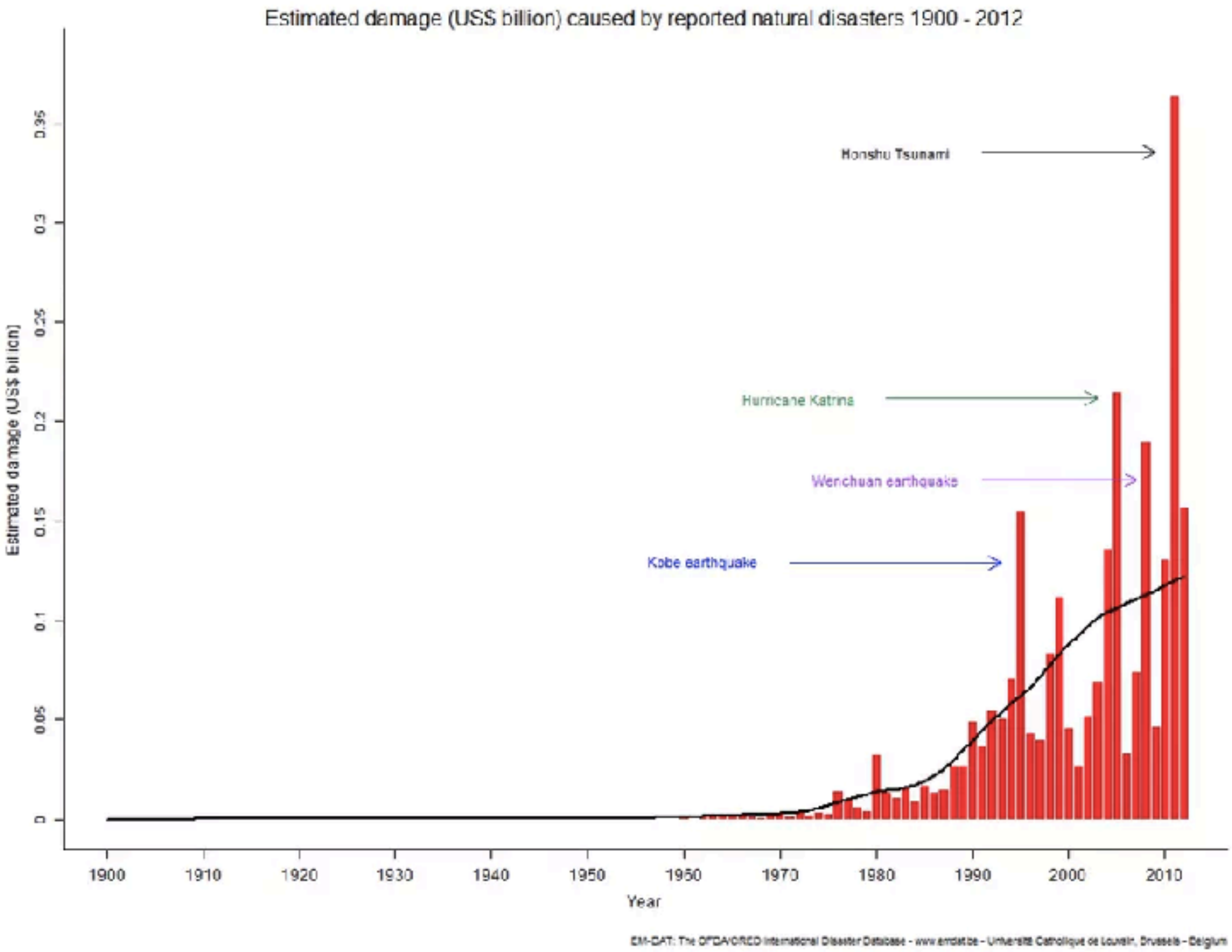
Disaster on the Rise?



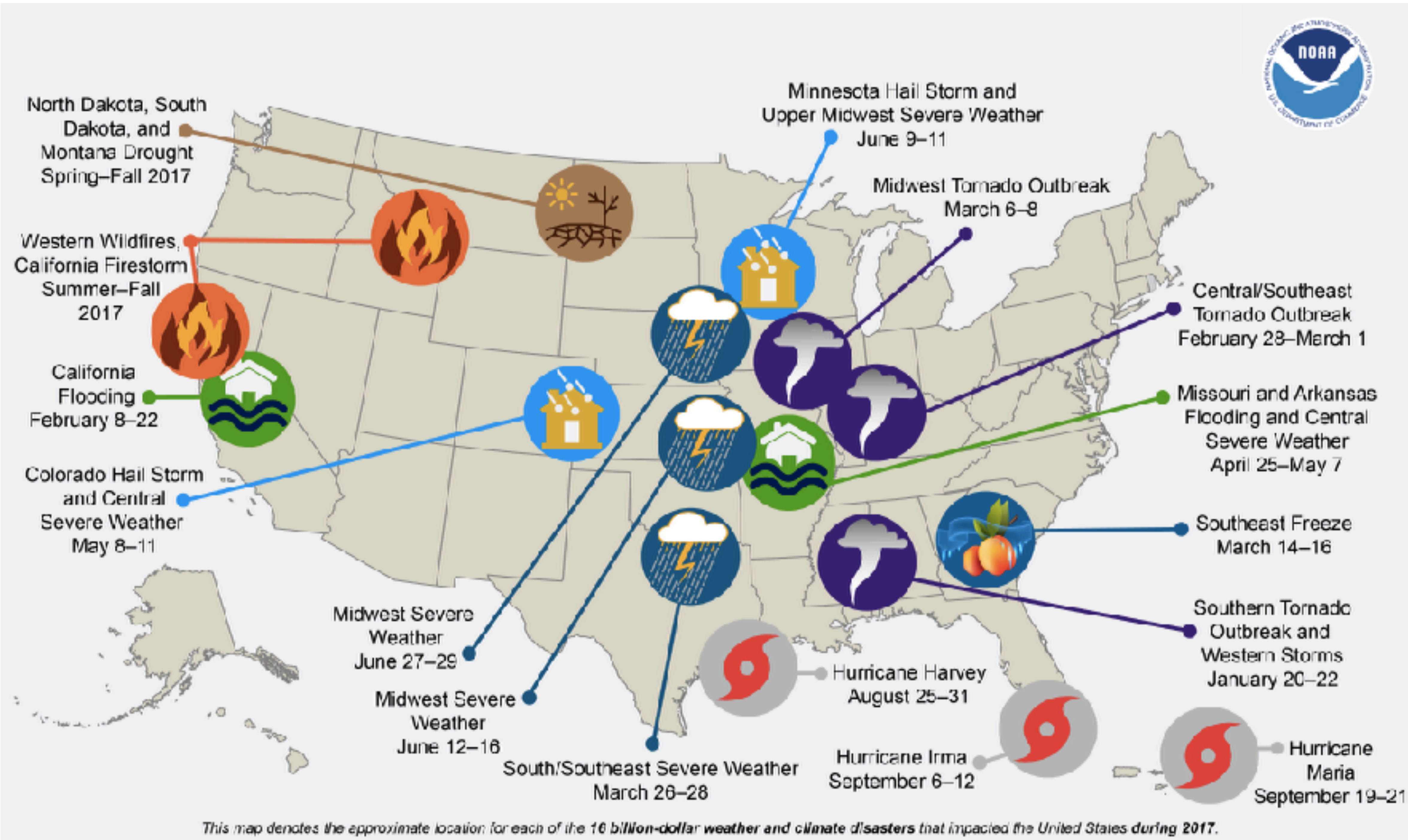
Disaster on the Rise?



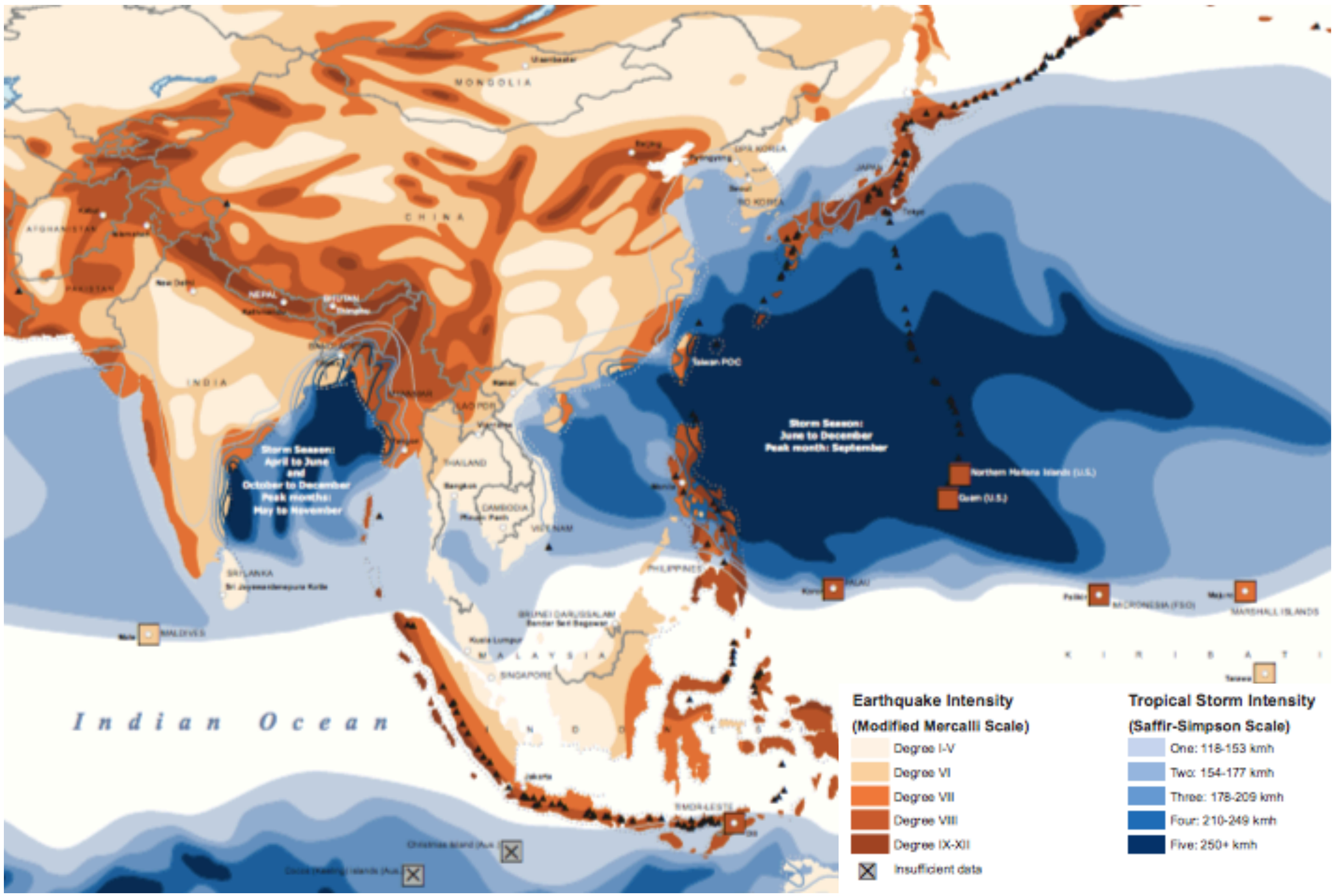
Disaster on the Rise?



Greatest threats to national security



Major natural hazards in Asia and the Pacific



UN OCHA 2017

~~Are we doomed?~~

What can we do?

- Make sense of the complex challenges society now faces
- Build **community resilience**

Richard Heinberg "Think Resilience"

Community Resilience

Society's adaptive capability

- to draw upon its individual, collective and institutional resources & competencies
- to adapt to, & develop from the demands, challenges and changes encountered ***before***, ***during*** and ***after*** a disaster

Becker et al., GNS Science Report 2011

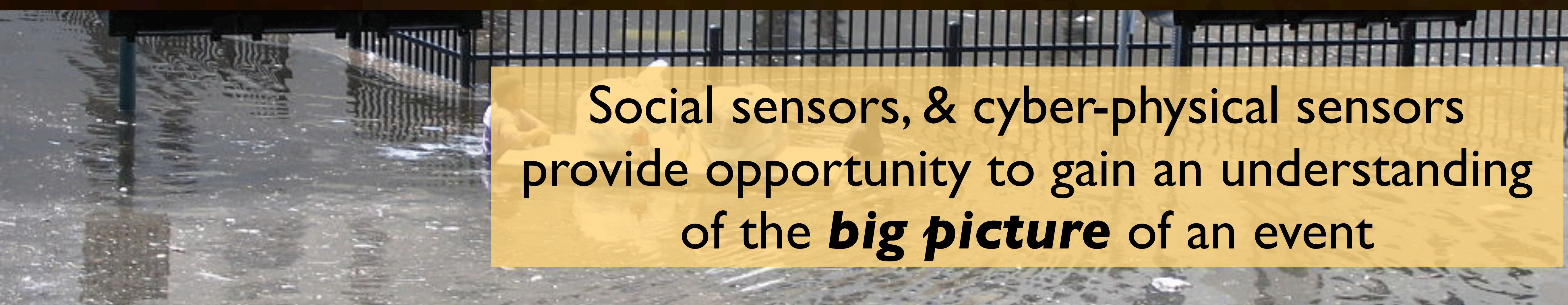
Emergencies and disasters become ***global***...

We are all ***connected***

natural, transportation, economic, political systems

social and information systems

We may be affected, or can affect others



Social sensors, & cyber-physical sensors provide opportunity to gain an understanding of the ***big picture*** of an event

Data-Driven Crisis Response

- harness big data to facilitate disaster and risk management
- engage citizen participation in disaster response
- design socio-technical systems
- build trust in global and local communities
- build resilience to disasters via ***ubiquitous intelligence***

human x machine intelligence

Data-Driven Crisis Response

Before

Anomalous event detection

catch early signs of anomalous events in dynamic, complex systems

During

Collective Sensemaking

how individuals perceive and communicate risk during the event

After

Impact Discovery

evaluate the impact of a disastrous or hazardous event in an efficient manner

Automatic Impact Discovery

after

Courtesy of Dan Lampariello/Reuters

Disaster Impact

Assessment of a disaster's impact
primarily through manual collections and analysis of surveys, questionnaires, and authoritative documents

Social media and other mobile technologies
allow for the collection of urban behavior data with rich, multi-dimensional behavioral contexts (*when*, *where*, *what*, etc.)

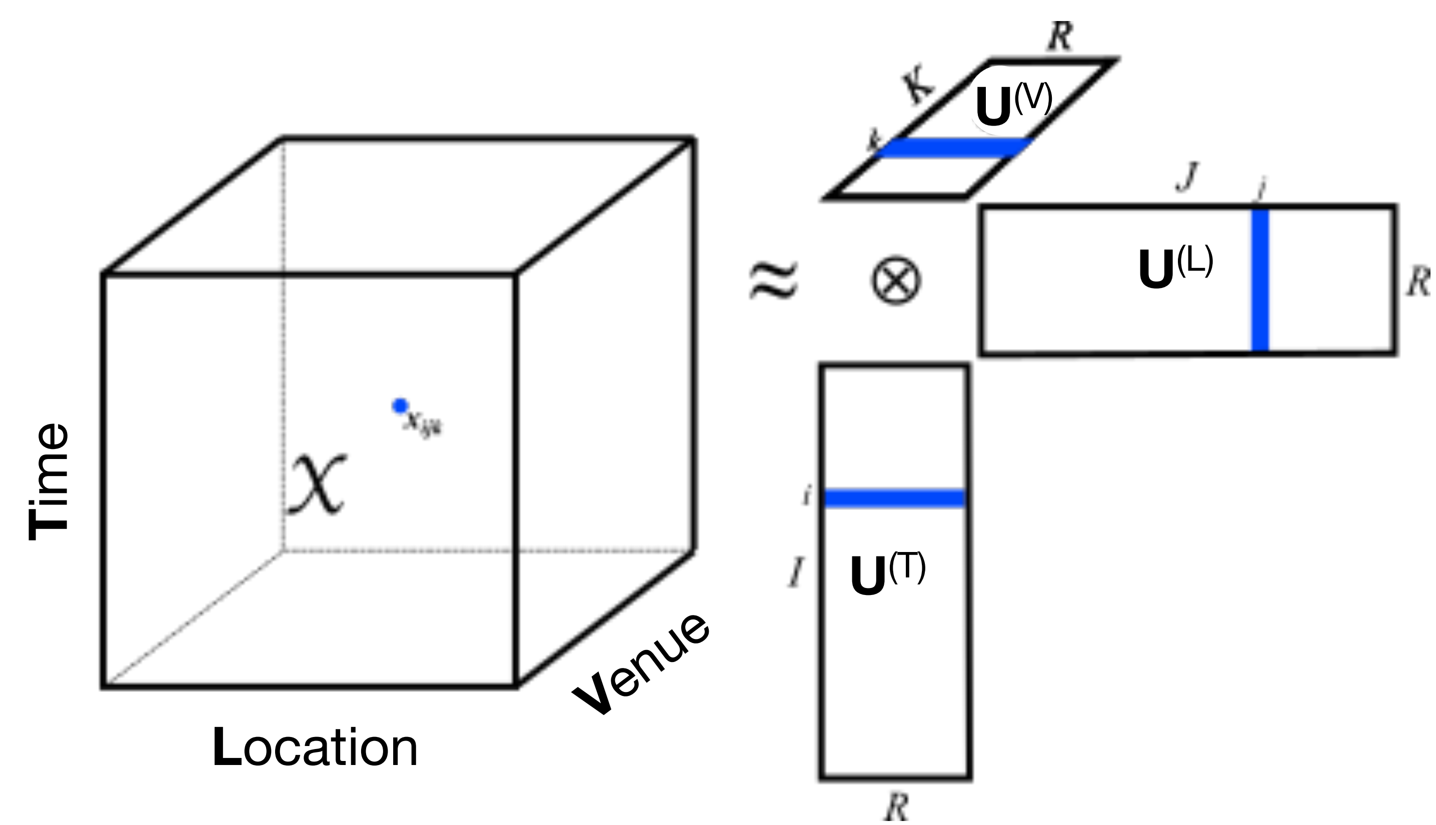
How can we evaluate the impact of a disastrous or hazardous event in an efficient manner?

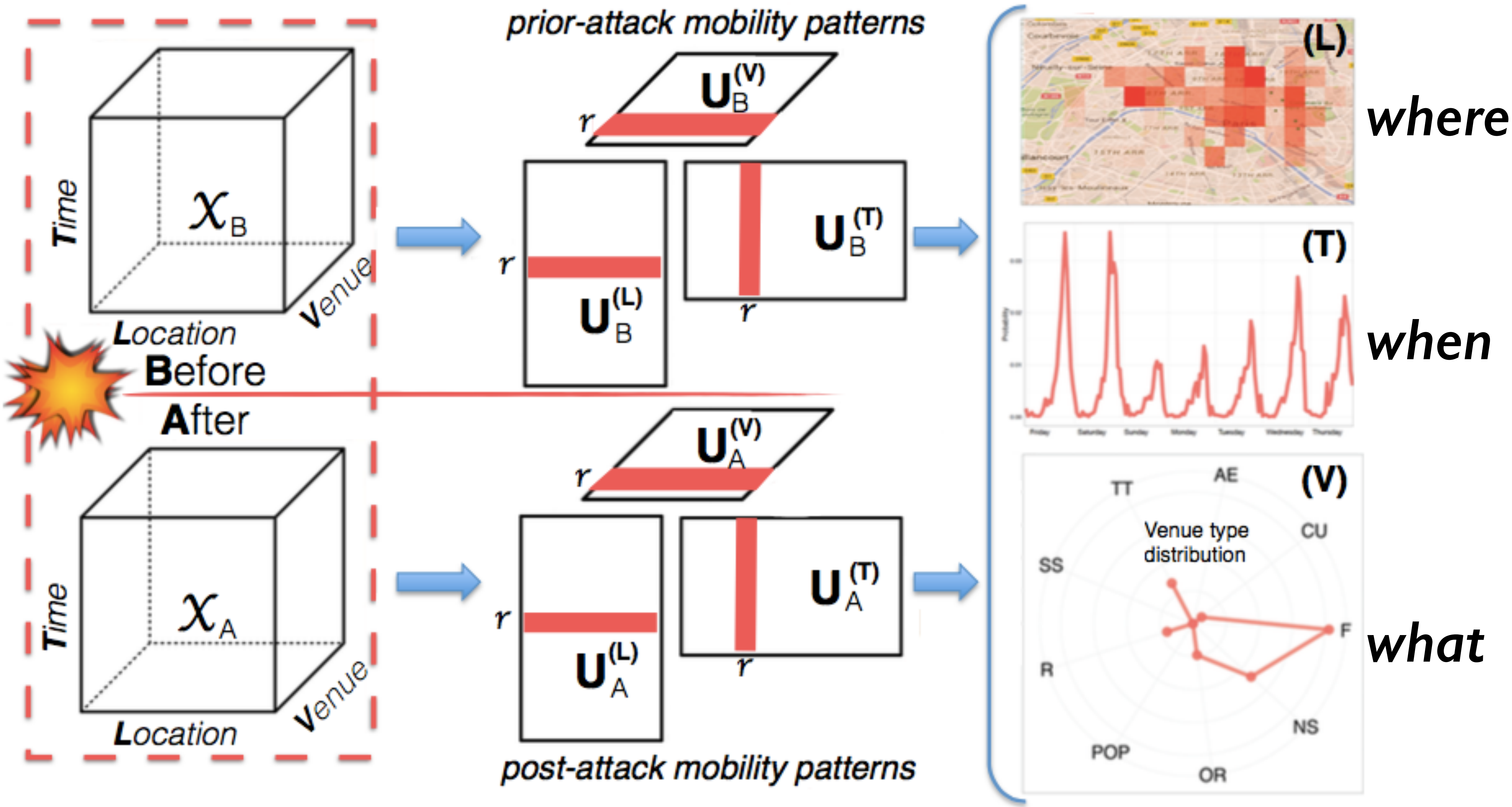
Can we capture how an event change ***when***, ***where*** and ***what*** citizens normally do in a city?

Modeling Challenges

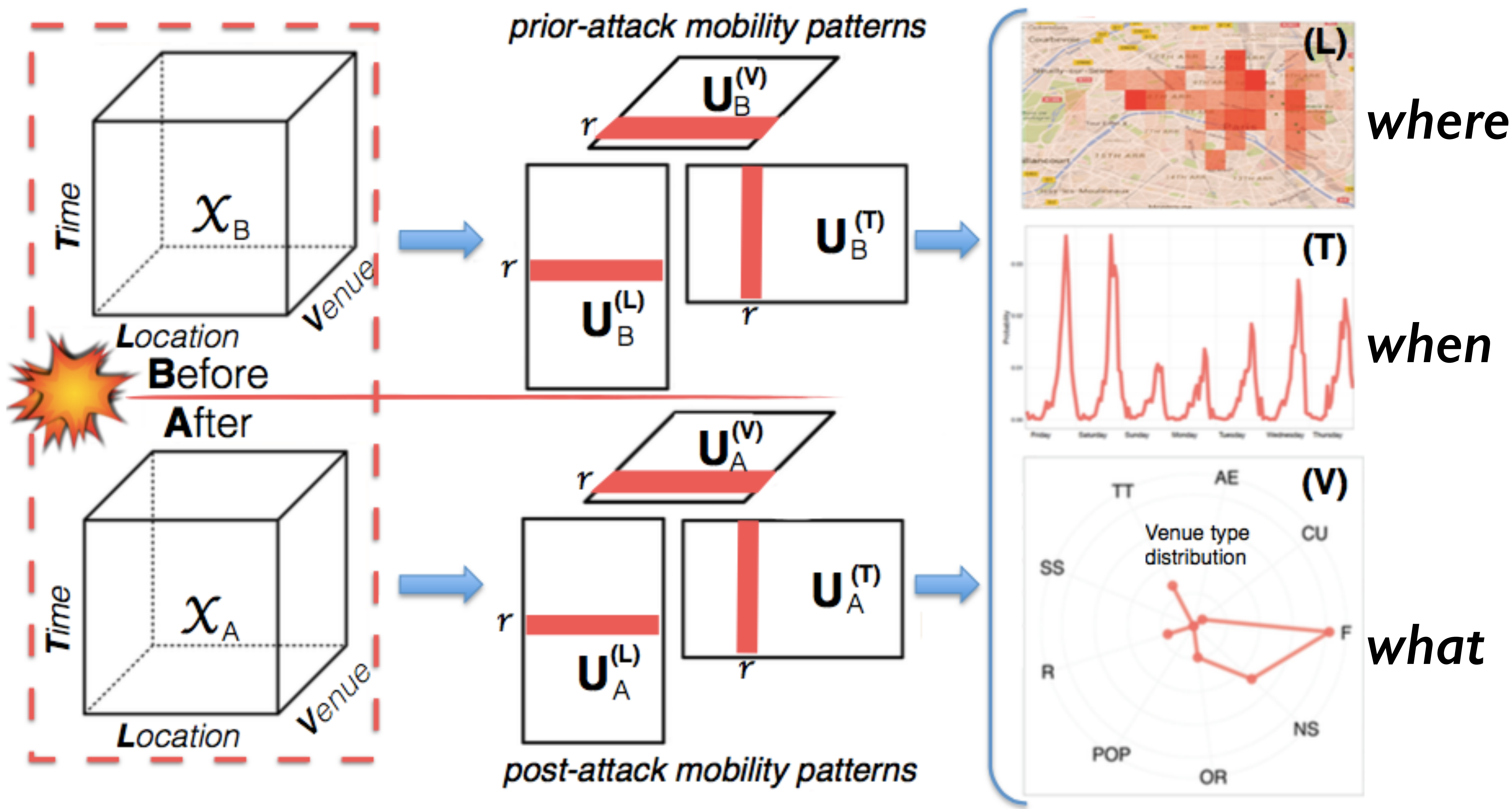
How to mine multifaceted patterns (*when*, *where*, *what*)?
How to extract changes in multifaceted patterns?

Tensor factorization
  discover patterns (associations) among multiple dimensions



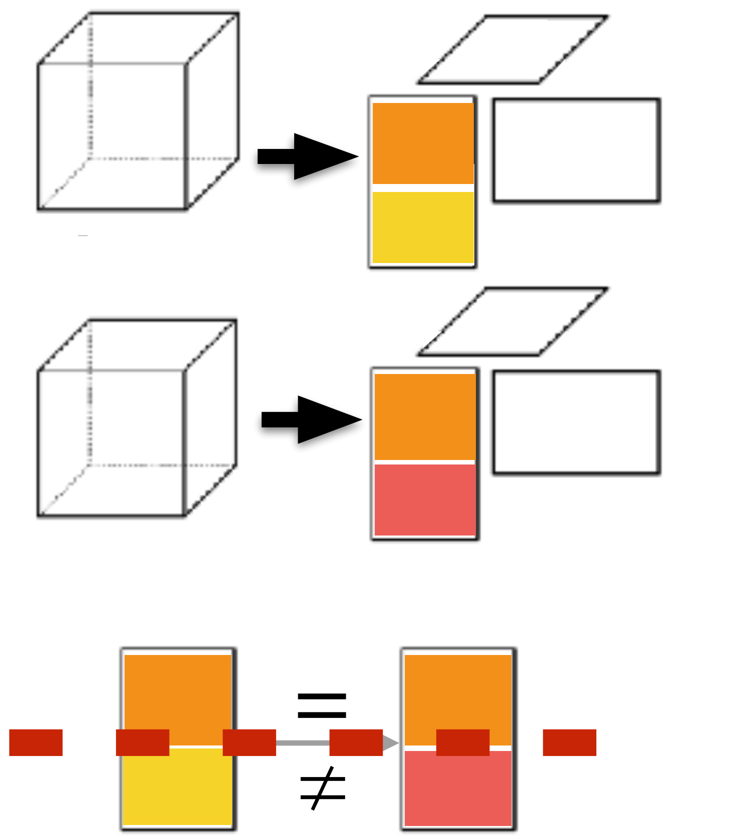


PairFac: joint factorization of a pair of data tensors that capture activity data ***before*** and ***after*** an impactful event

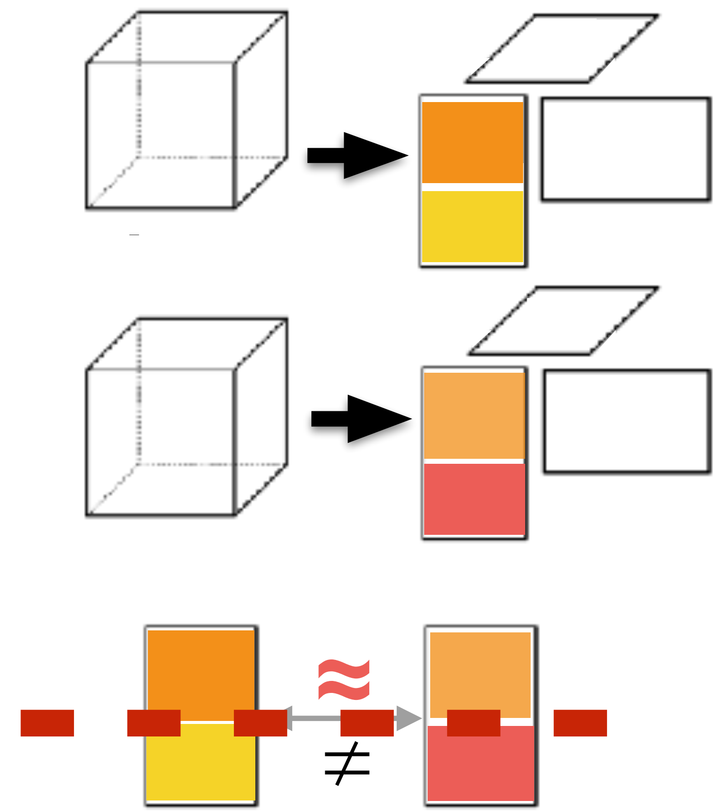


Common Patterns? Vanished Patterns? Emerging Patterns?

Existing solutions for discriminative subspace learning



?



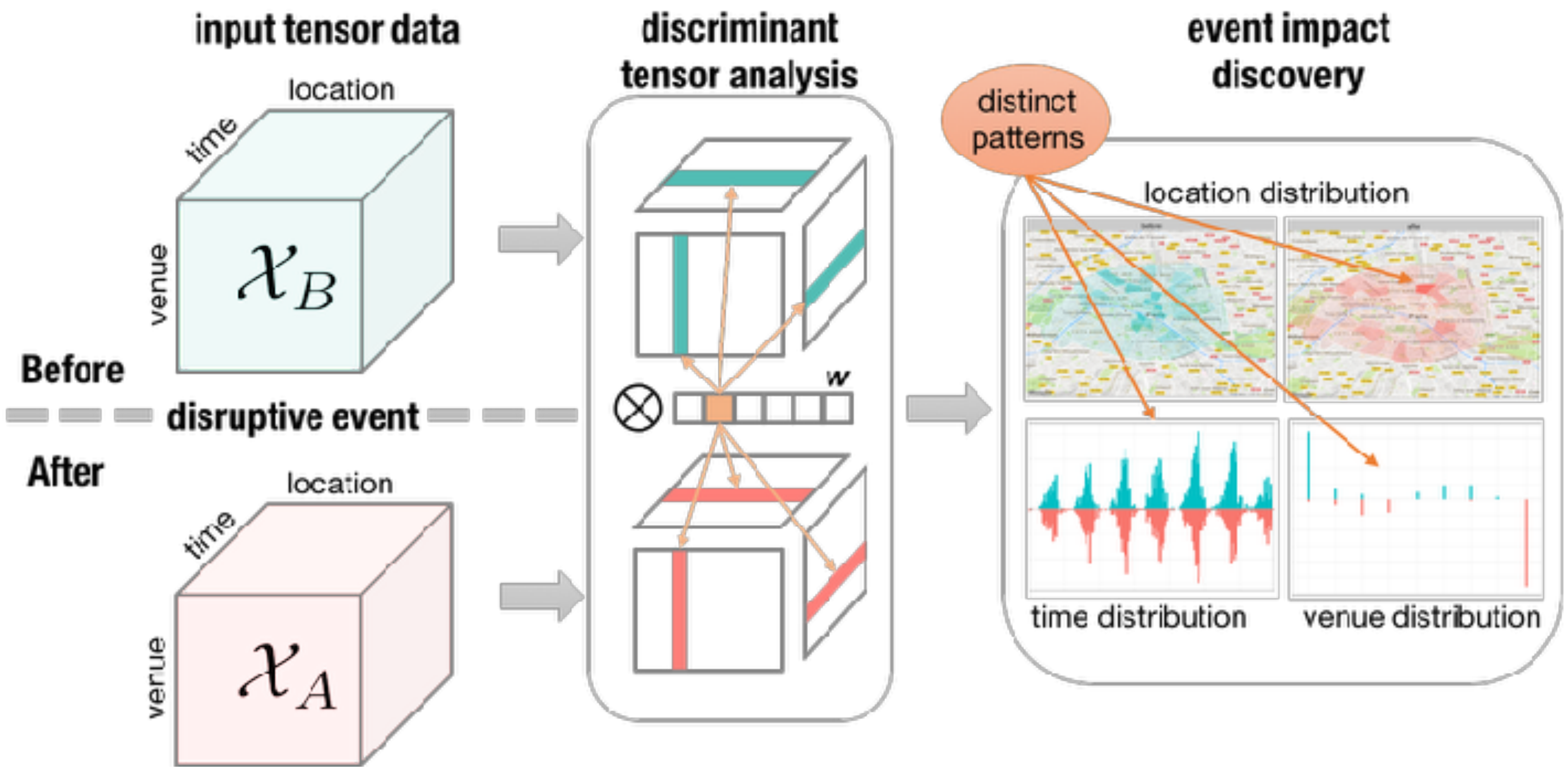
Solution I
CDNTF (Liu et al. 2013)
RJSNTF (Gupta et al. 2013)

Solution II
SDCDNTF (Kim et al., 2015)

Requires to know discriminative components ***beforehand***!

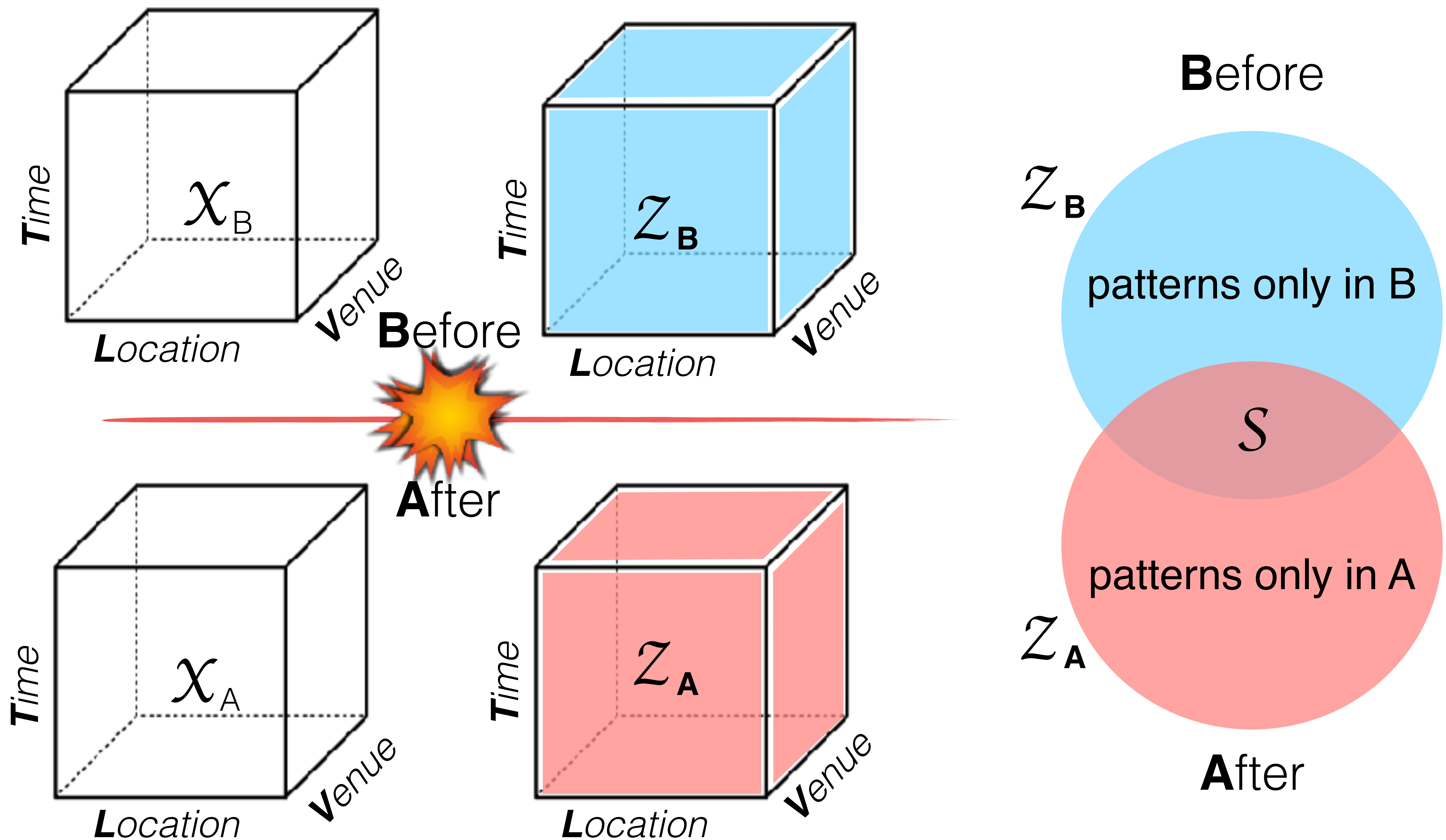
Solution

PairFac: Automatic Discovery of Discriminative Components

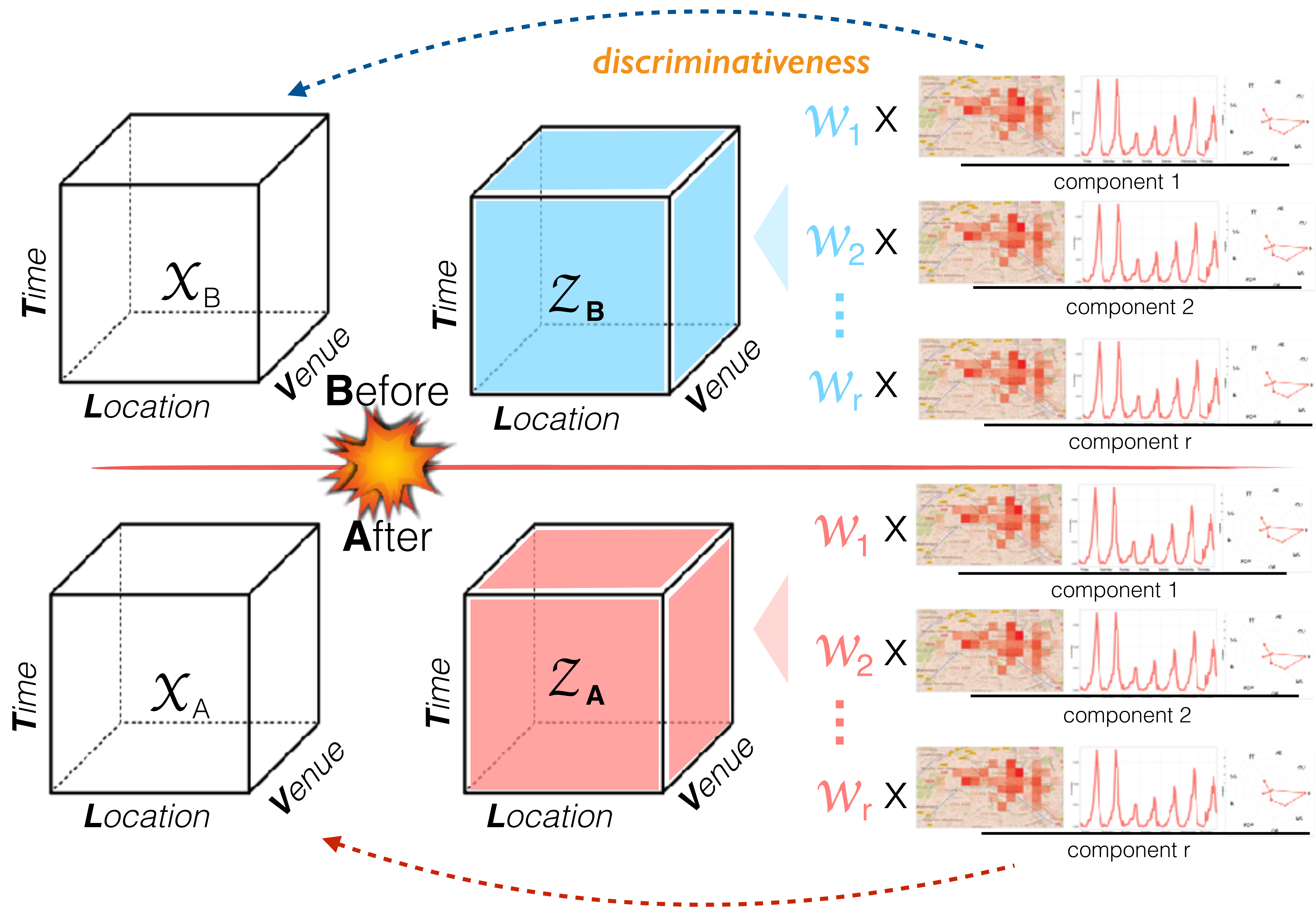


Automatic: ***no pre-defined*** components to separate common and discriminative parts

- automatically learn weights (coefficients) for each component indicating the **discriminativeness** of the component
- create ***auxiliary tensors*** to encode the discriminative information



Time
$\mathcal{X}_B$
Venue
Location
Time
$\mathcal{Z}_\mathbf{B}$
Venue
Location
Before
After
Time
$\mathcal{X}_A$
Venue
Location
Time
$\mathcal{Z}_\mathbf{A}$
Venue
Location
Before
$\mathcal{Z}_\mathbf{B}$
patterns only in B
S
patterns only in A
$\mathcal{Z}_\mathbf{A}$
After



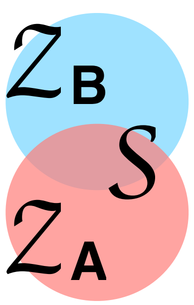
discriminativeness
Time
Location
Venue
$\mathcal{X}_B$
Time
Location
Venue
$\mathcal{Z}_B$
w_1 X
component 1
w_2 X
component 2
w_r X
component r
Before
After
Time
Location
Venue
$\mathcal{X}_A$
Time
Location
Venue
$\mathcal{Z}_A$
w_1 X
component 1
w_2 X
component 2
w_r X
component r

PairFac Formulation

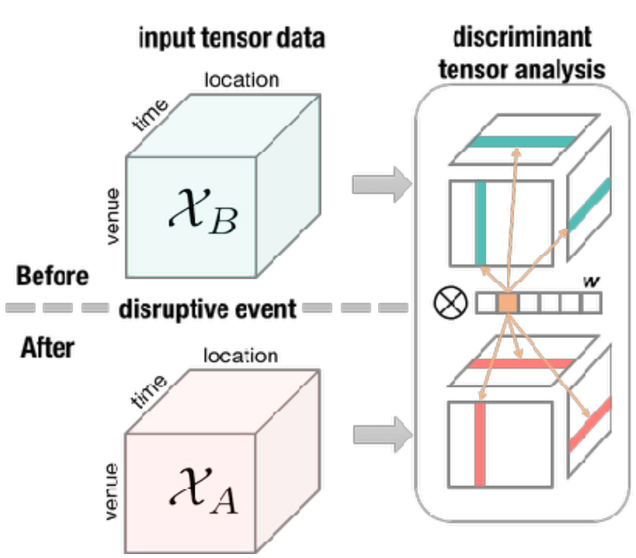
Objective function

$$\mathcal{J} = \mathcal{J}_{\text{reconstruct}} + \mathcal{J}_{\text{discriminative}} + \mathcal{J}_{\text{align}}$$

$$\sum_{q\in\{A,B\}} (\frac{1}{n_q}\left\|\mathbf{X}_{q(m)} - \mathbf{U}_q^{(m)}(\mathbf{U}_q^{(m'')}\odot\mathbf{U}_q^{(m')})^T\right\|^2$$

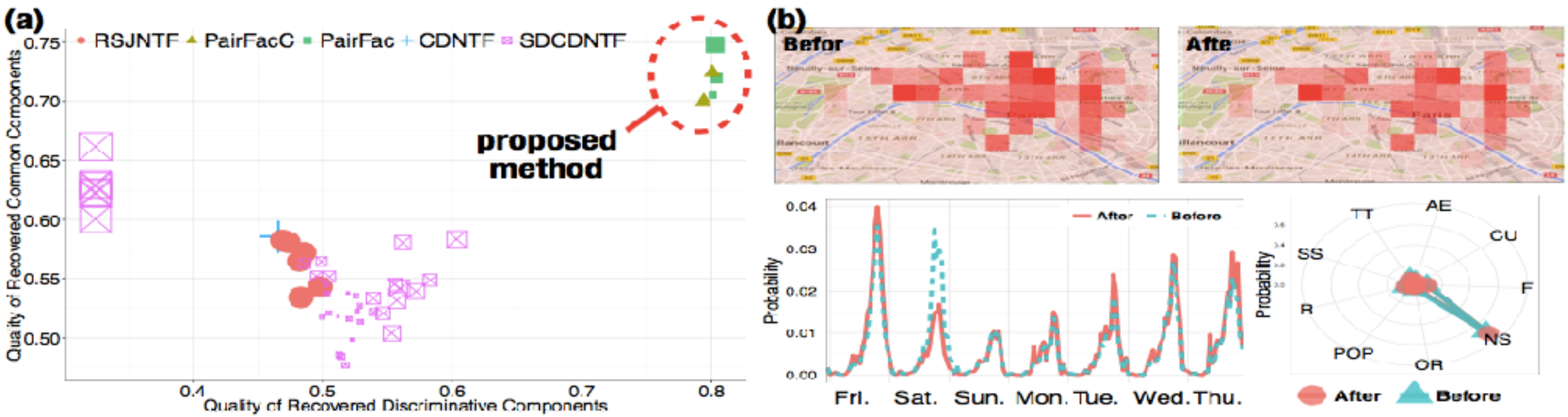


$$\alpha \sum_{q\in\{A,B\}} \|\boldsymbol{\mathcal{Z}}_q - [\![\mathbf{w}_q;[\mathbf{U}_q]]\!]\|^2 + \beta \sum_{q\in\{A,B\}} \|\boldsymbol{\mathcal{S}}_q - [\![(1-\mathbf{w}_q);[\mathbf{U}_q]]\!]\|^2$$



$$\gamma \sum_{m\in\{L,V,T\}} \sum_{j}^{R} \left\|(1-\mathbf{w}_{q_j})\mathbf{U}_{qj}^{(m)} - (1-\mathbf{w}_{q'_j})\mathbf{U}_{q'j}^{(m)}\right\|^2$$

PairFac Results



PairFac clearly outperforms the state-of-the-art methods

Real-world case: Paris attacks (social media and traffic sensor data)

- Results suggested after the attacks, a shift in citizens' activities at the city's night-life spots

CIKM 2016; TKDD (to appear)

Anomaly Detection in Dynamic Context

before

Anomaly in Context

Anomaly detection is hard!

- no clear or static boundary between normal and abnormal patterns
- few or no labeled data for training and verifying models

What if…

Learn anomalies in dynamic, complex systems without relying on labeled data

Learn anomalies as users give feedbacks

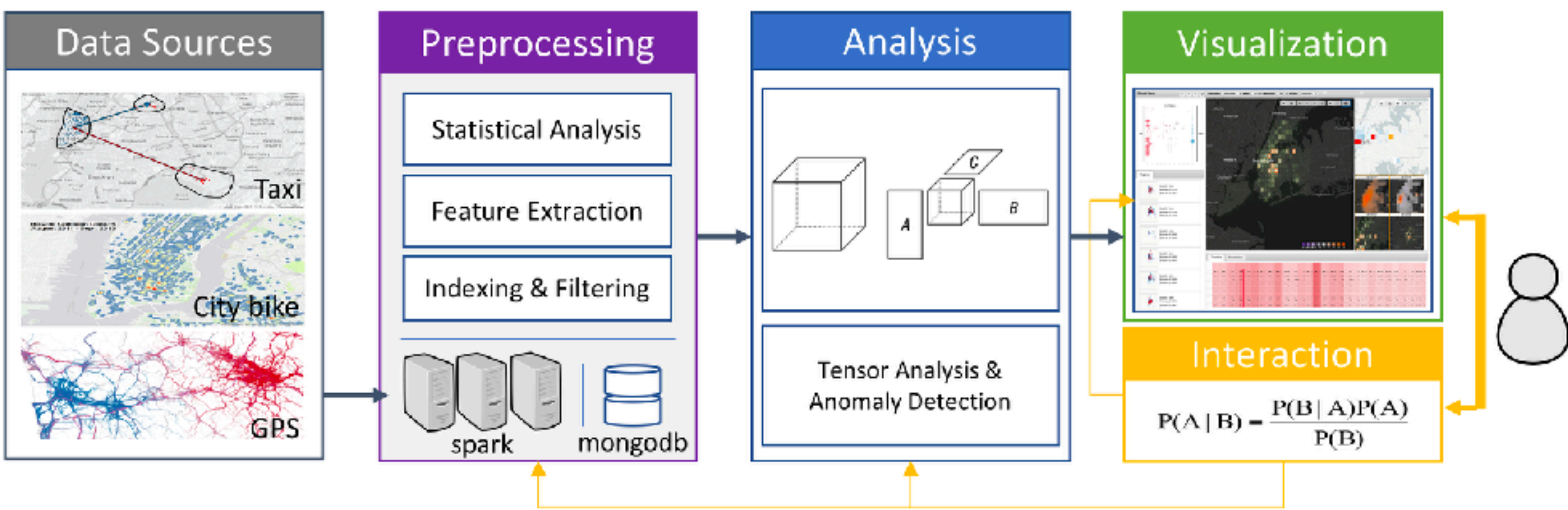
1

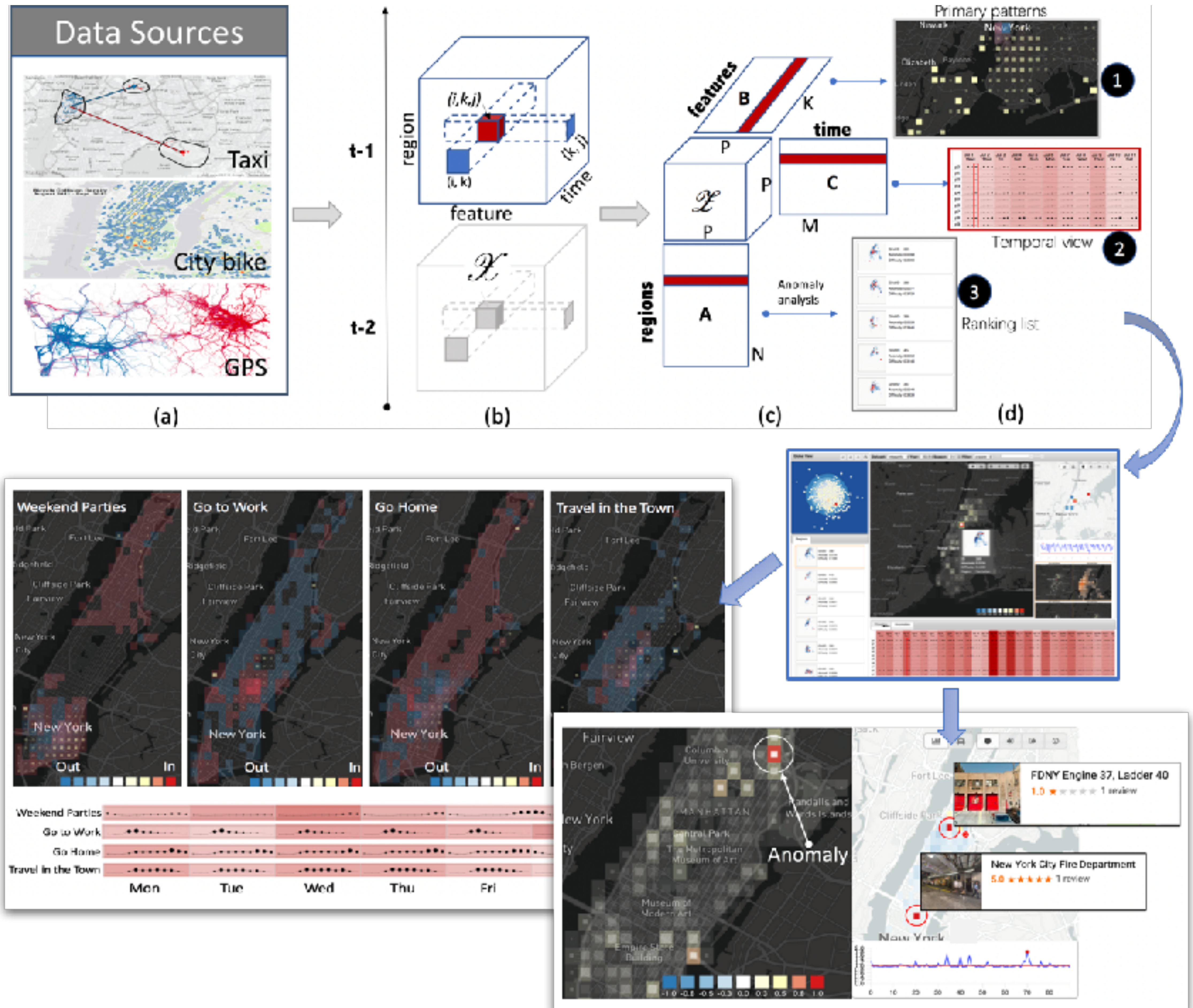
Visual Anomaly Detection & Monitoring

Adaptivity: toward dynamic, rich context data

Interpretability: show anomalous patterns in their spatiotemporal context

Interactivity: online anomaly investigation and incorporating human judgment

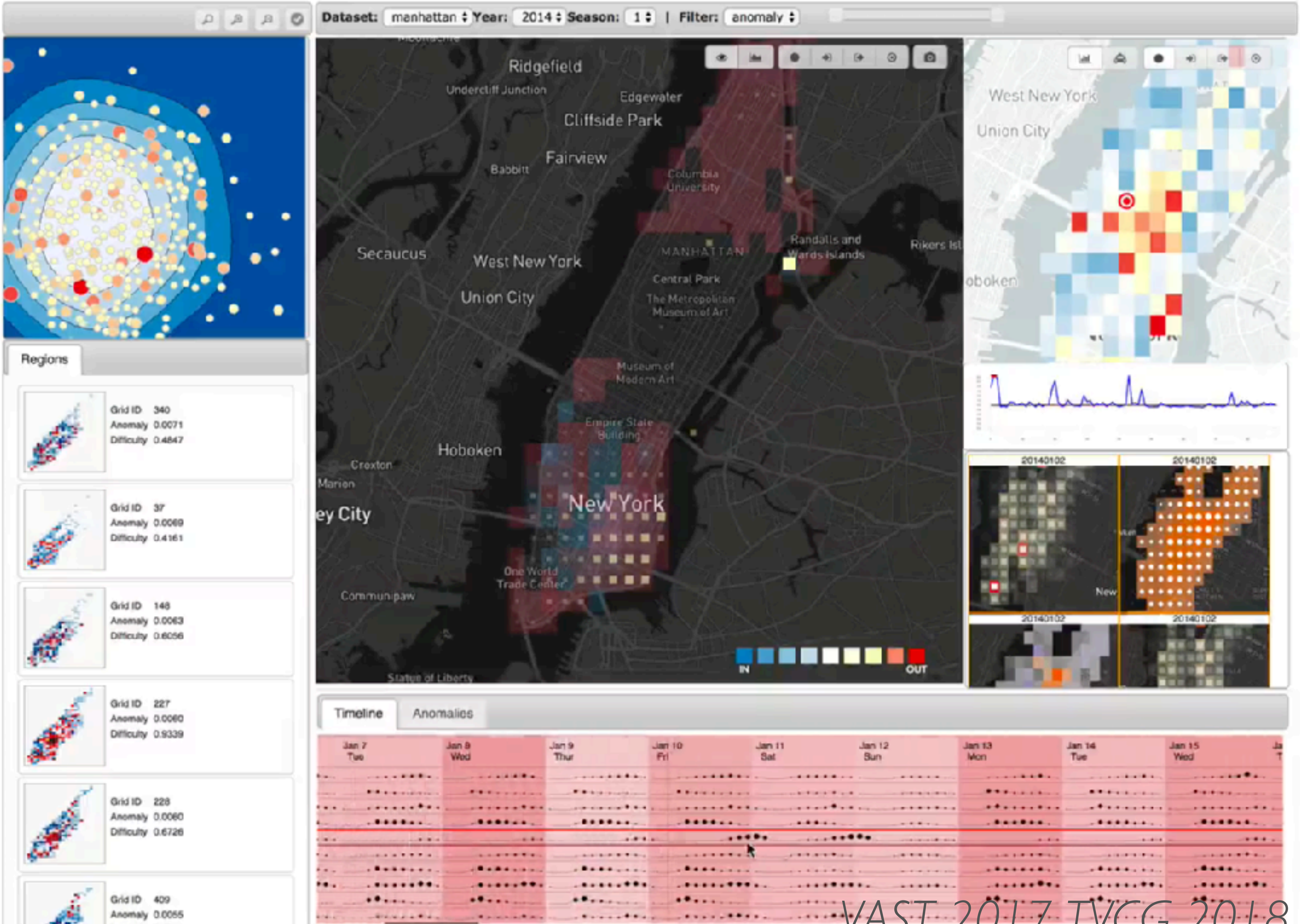




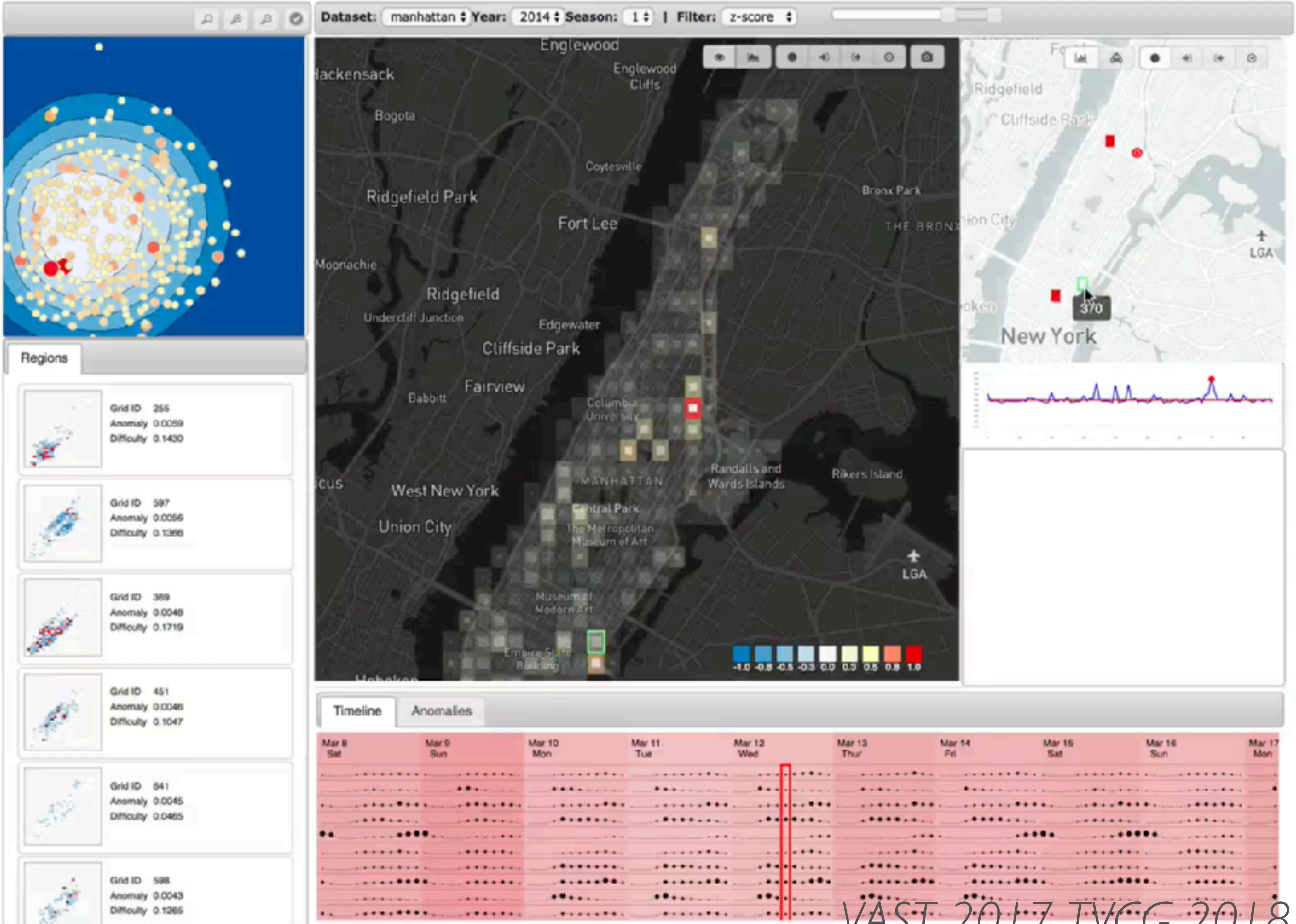
Data Sources
Taxi
City bike
GPS
(a)
t-1
t-2
region
feature
time
(i,k,j)
(i, k)
(k, j)
(b)
features
B
K
P
time
C
M
regions
A
N
Anomaly analysis
(c)
Primary patterns
Temporal view
Ranking list
1
2
3
(d)
Weekend Parties
Go to Work
Go Home
Travel in the Town
New York
Out
In
Weekend Parties
Go to Work
Go Home
Travel in the Town
Mon
Tue
Wed
Thu
Fri
Anomaly
FDNY Engine 37, Ladder 40
New York City Fire Department

Visual Anomaly Detection & Monitoring with Streaming Spatiotemporal Data

VAST 2017, TVCG 2018



VAST 2017, TVCG 2018



VAST 2017, TVCG 2018

Anomaly in Dynamic Networks

Multi-View Time-Series Learning

What is anomaly?

do not conform to normal patterns

to capture normal & abnormal patterns (over time)

Why dynamic networks?

to capture time-varying systems

consist of interdependent components

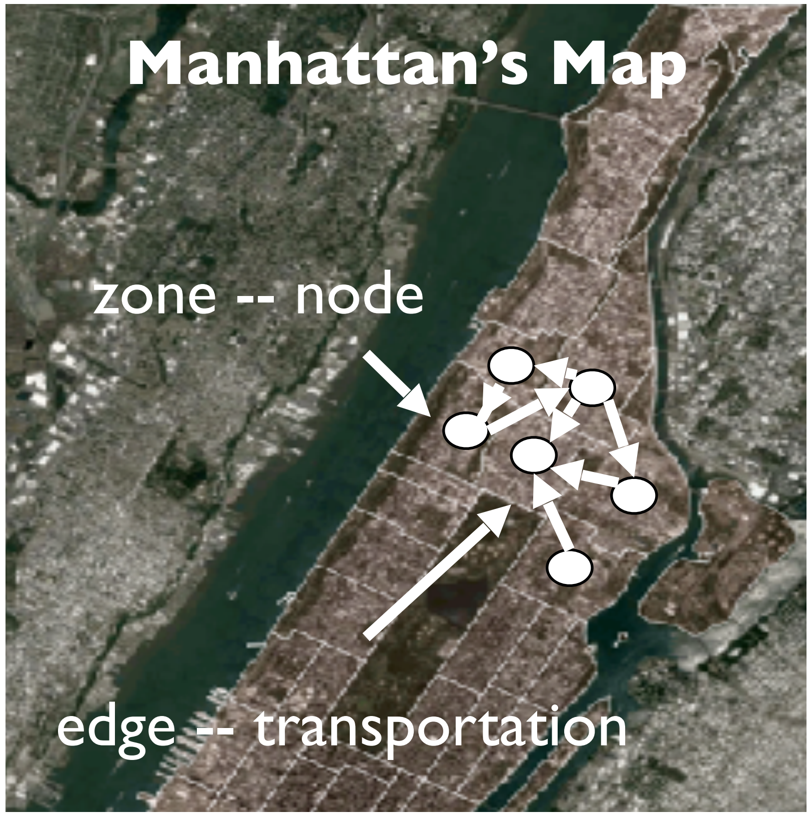
Multi-view time-series?

multiple data sources

E.g.,

node attribute - activity from social media

edge attribute - traffics from sensors

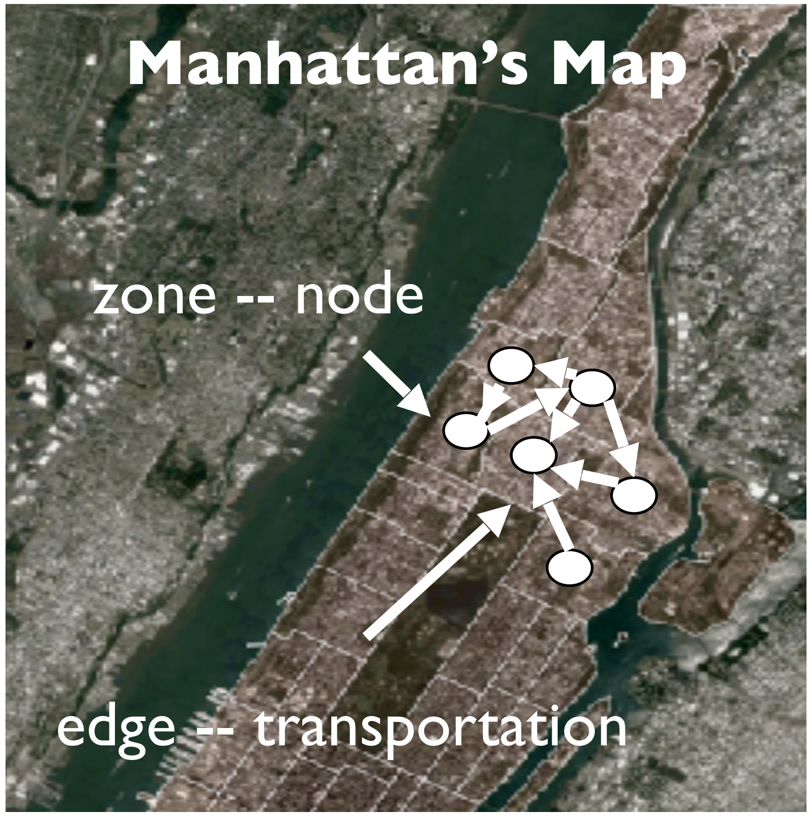


Modeling Challenges

How to capture temporal patterns?

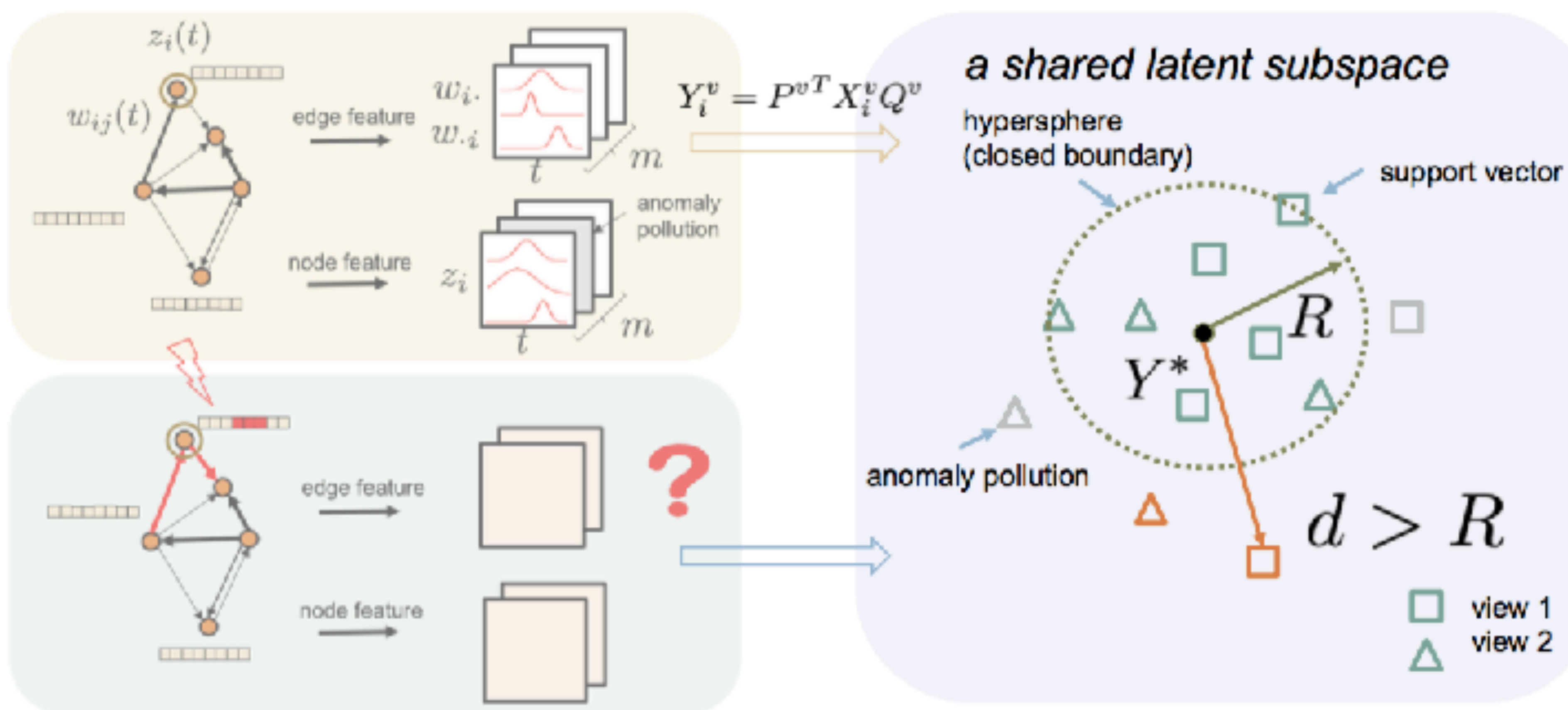
How to combine multi-view time-series data?

How to learn outliers in unlabeled training data?



Solution

Multi-View Time-Series Hypersphere Learning

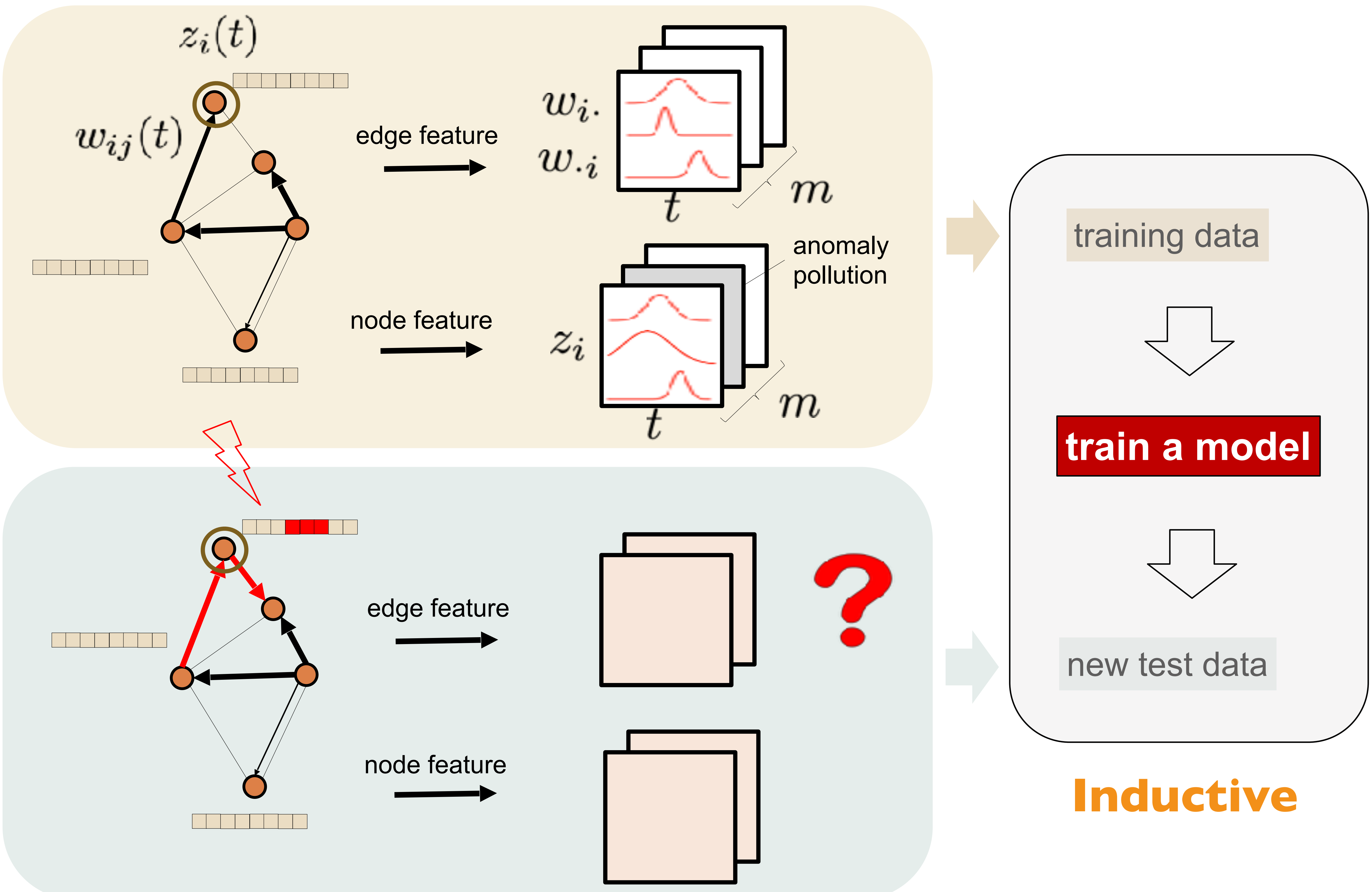


Map multi-view time-dependent network to a shared latent space

learn support vectors to form hypersphere that enables ***inductive anomaly detection***

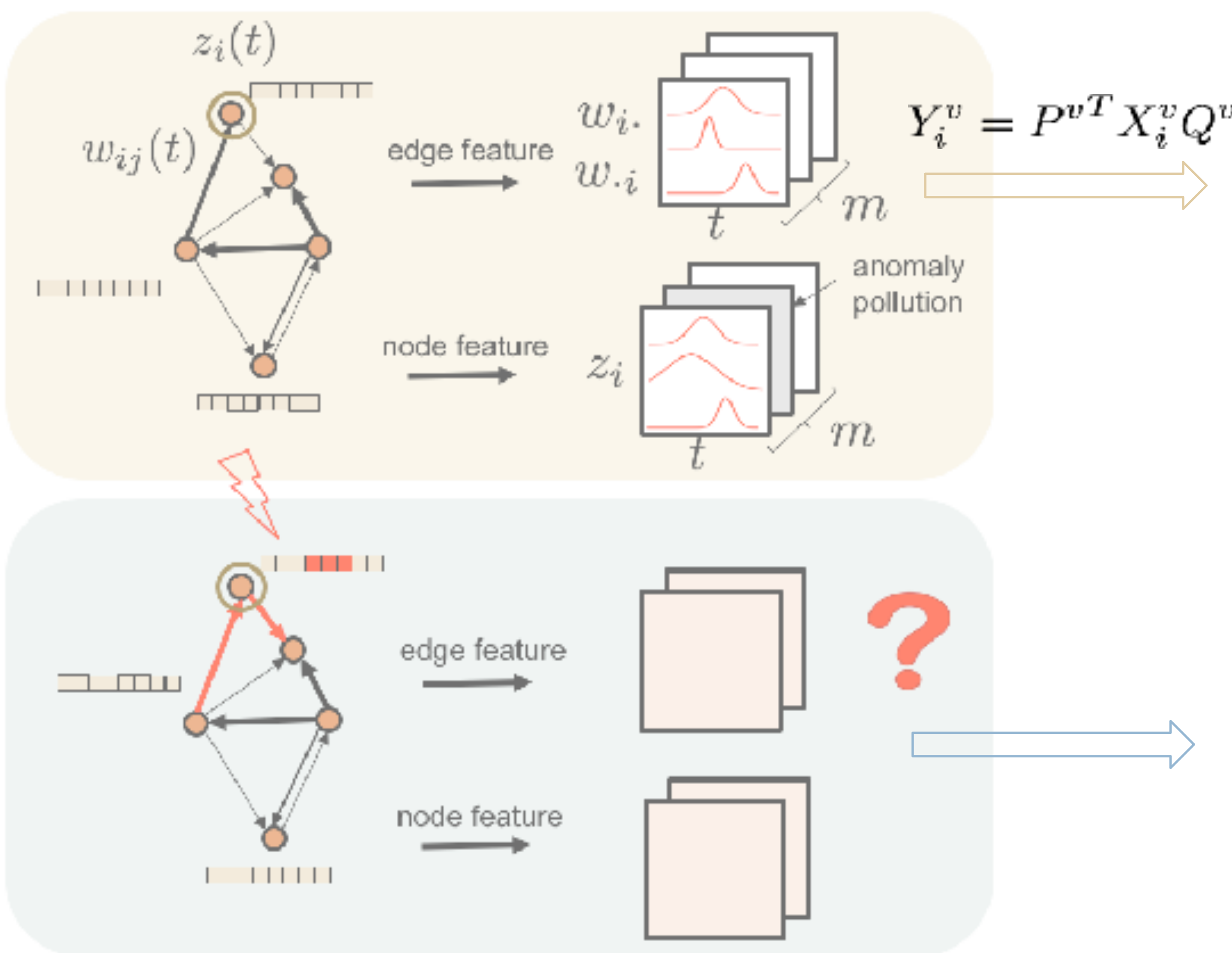
CIKM 2017

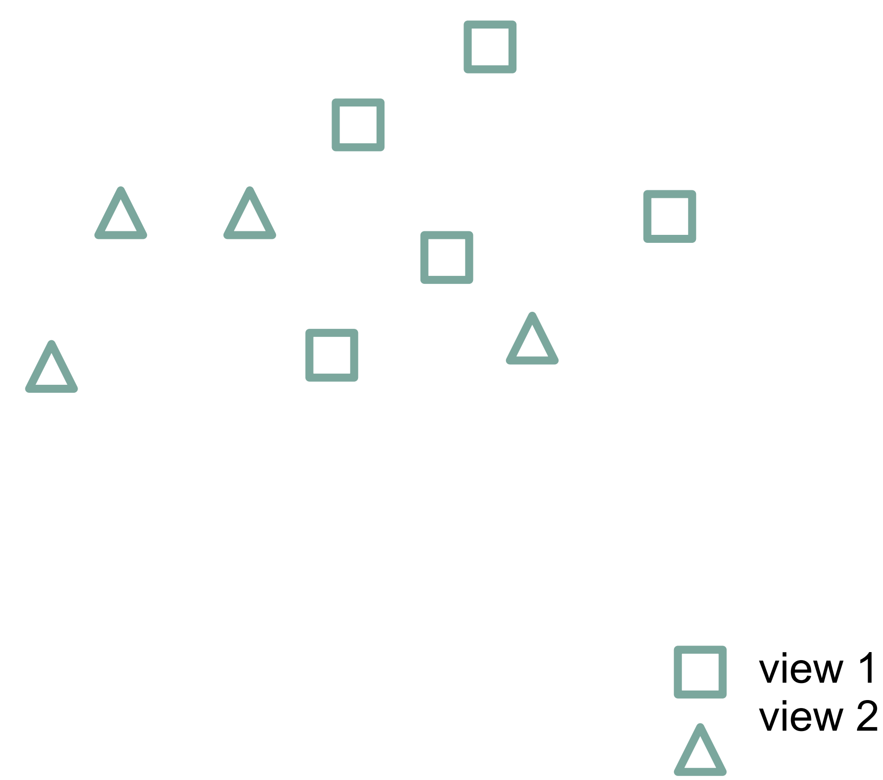
Inductive Anomaly Detection



MTHL: Multi-View Time-Series Hypersphere Learning

- **bilinear dimension reduction** – *C1. temporal pattern?*
- **share a common space** – *C2. multi-view time-series data?*
- **hypersphere learning** – *C3. unlabeled outliers (anomaly pollution)?*





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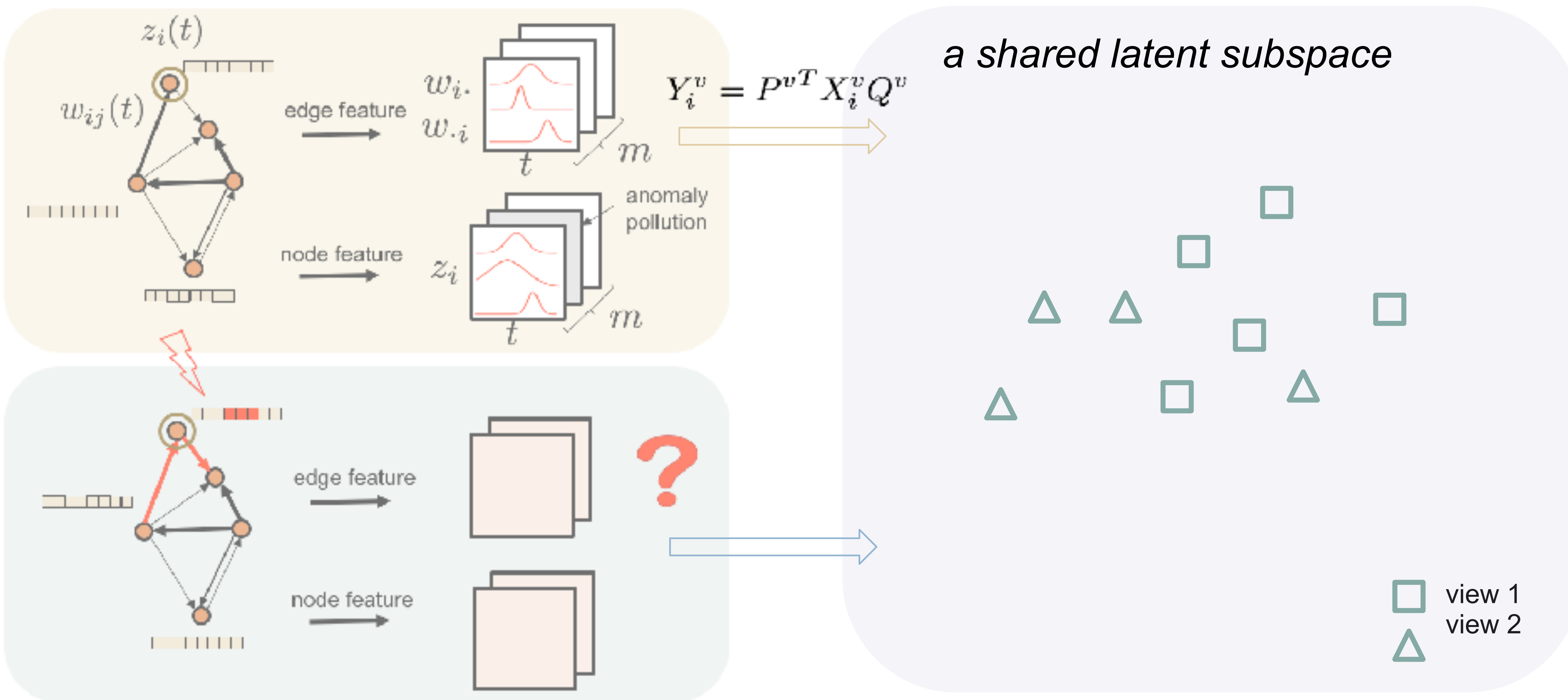

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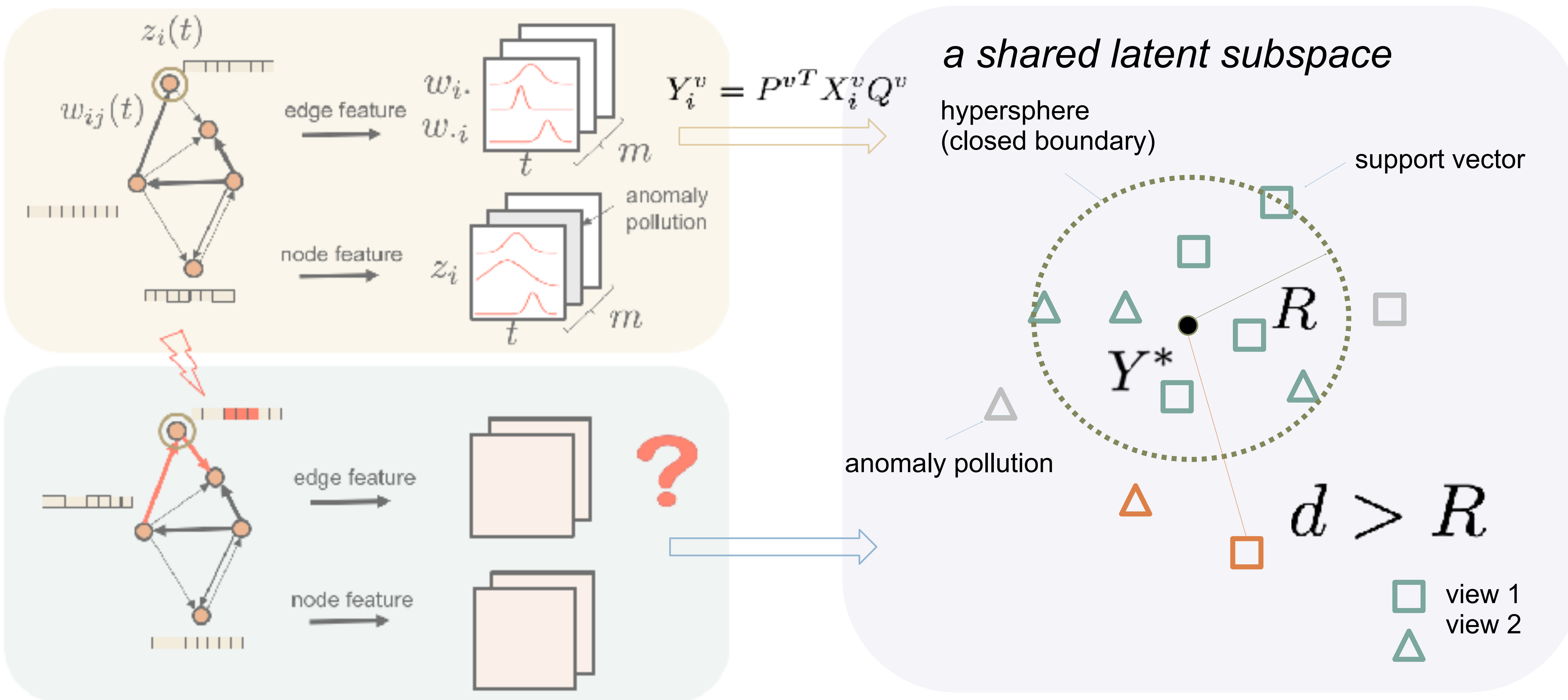


Formulation

Objective function

$$\min_{\mathcal{P}} f(\mathcal{P}) = \min_{\mathcal{P}} \{\boxed{\Theta} + \boxed{\Phi} + \boxed{\Psi}\}$$

Bilinear Projection

$$\Theta = \tau \sum_v \sum_i \| P^{v^T} X_i^v Q^v - Y^* \|_F^2$$

Hypersphere Learning

$$\Phi = R^2 + \lambda_1 \sum_v \sum_i \xi_i^v$$

Temporal Smoothing

$$\Psi = \frac{1}{2} \lambda_2 \sum_v \sum_i Tr(P^{v^T} X_i^v L_p X_i^{v^T} P^v)$$

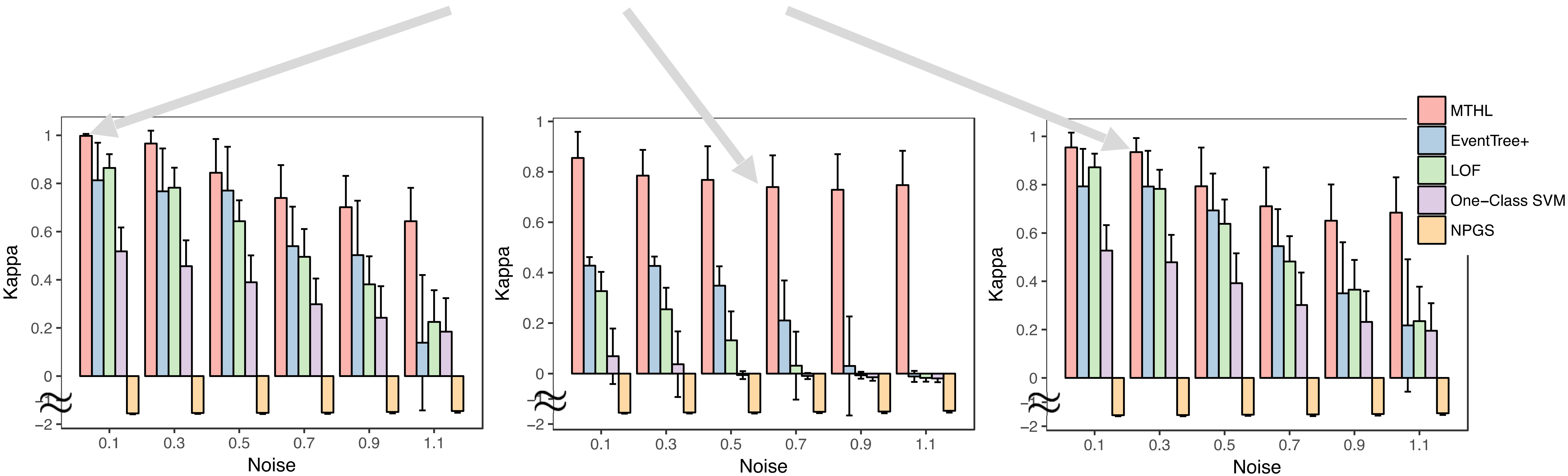
Parameter set $\mathcal{P} = \{\boxed{P^v, Q^v}, \boxed{Y^*, R}\}$

bilinear matrices

hypersphere centroid & radius

MTHL Results

Our proposed method - MTHL



(a) Aggregated Anomaly (b) Temporal Anomaly (c) Both Types of Anomaly

MTHL outperforms all state-of-the-art methods

MTHL Results

detect specific regions – Trump tower, Trump hotel

MTHL detects anomalous activities from multiple data sources (NYC Taxi Trip & Twitter Data)

3

Transparency in Anomaly Discovery

Complex autonomous systems

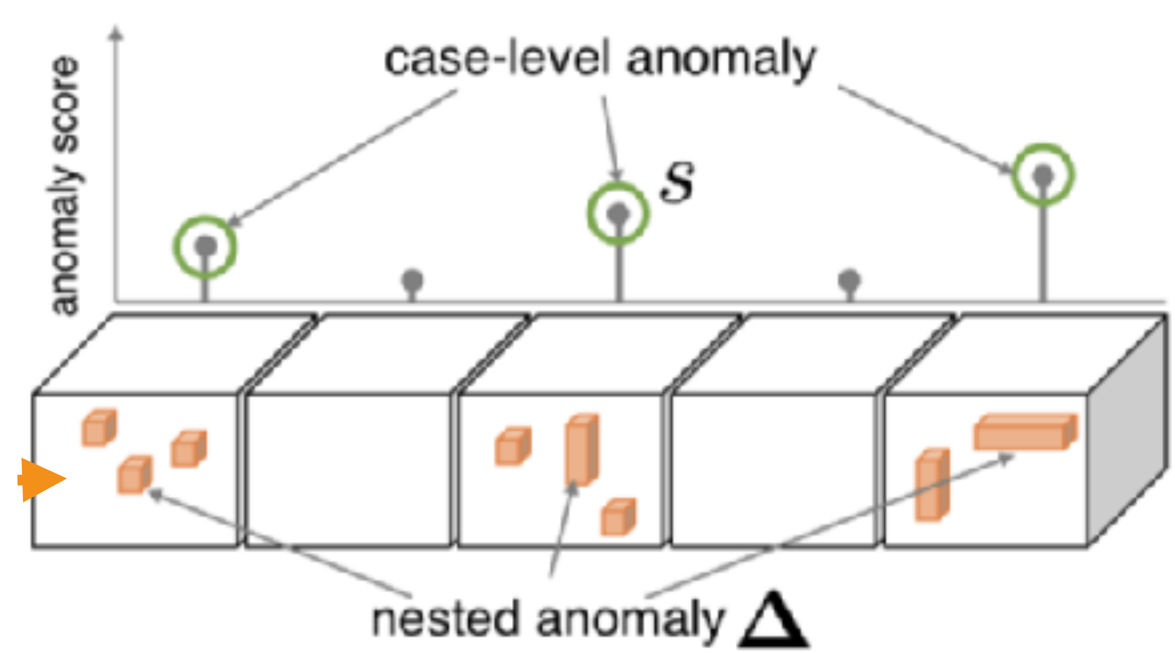
common theme in Smart-X applications

consist of internal states and relationships among sub-systems

require:

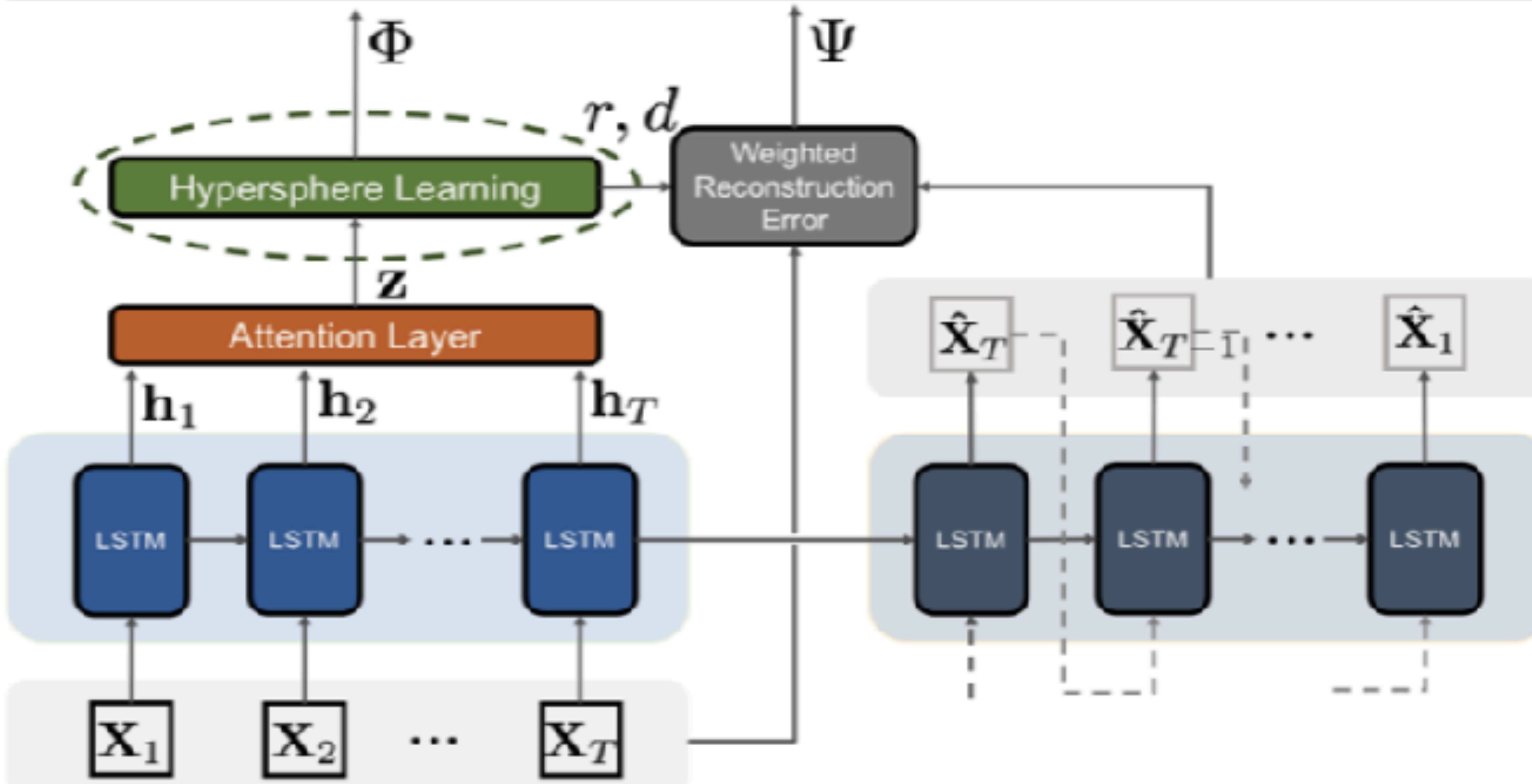
early warning: signal anomalous situations

transparency: how the anomalies deviate from normalcy for more appropriate intervention



Solution

DeepSphere: Robust and Unsupervised Anomaly Discovery in Dynamic Networks



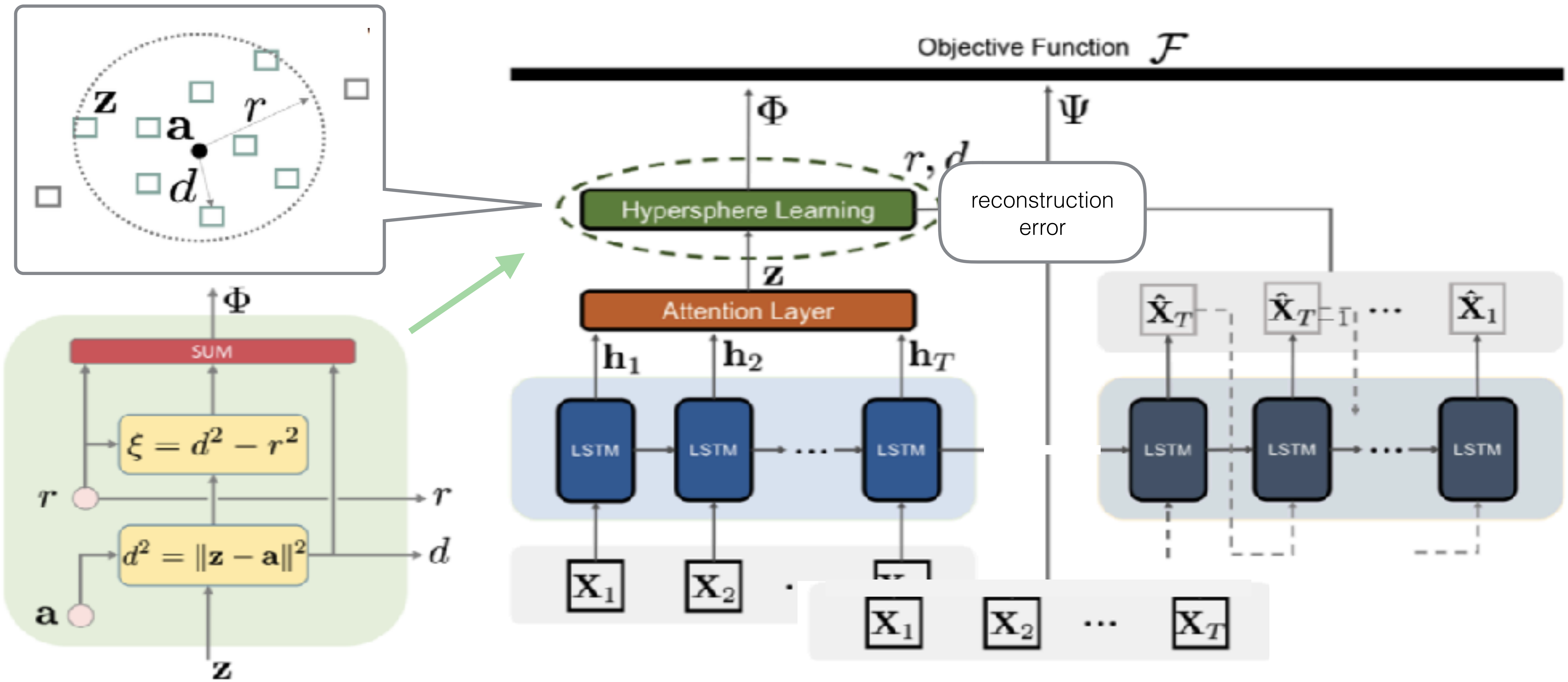
leverages deep auto-encoders and hypersphere learning

unified, ***end-to-end*** and ***unsupervised learning*** method that does not require outlier-free or labeled training data

Interpretable AI: transparent nested information

IJCAI 2018

DeepSphere Formulation

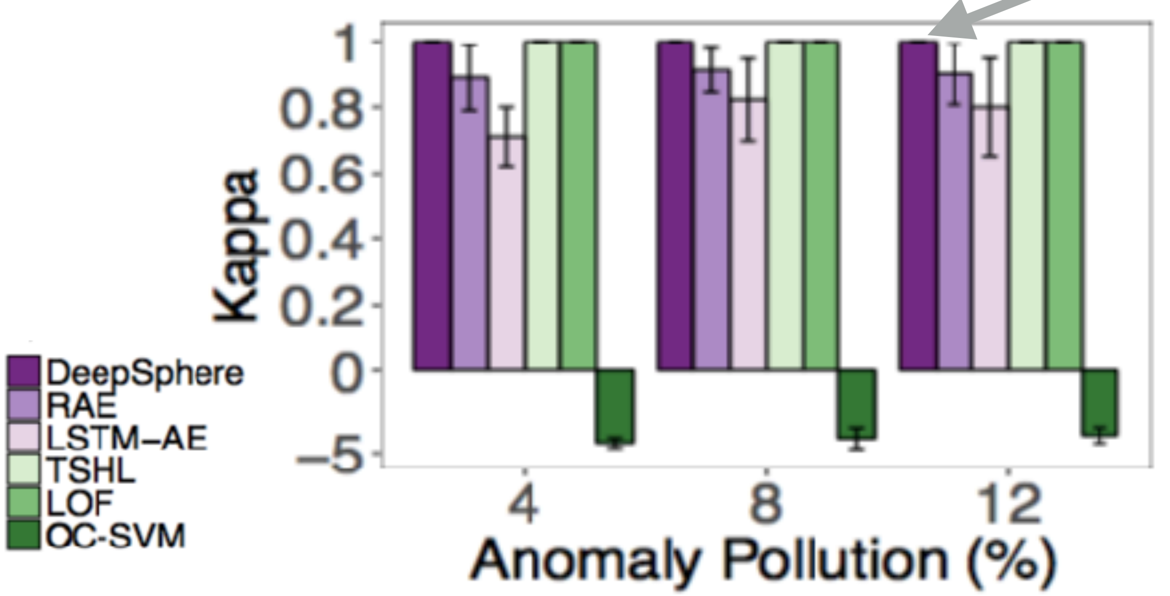


- no training labels: use auto-encoder to minimize reconstruction error
- potential outliners (anomaly pollution): weighted reconstruction error; weights given by hypersphere learning
- inductive, two-level anomaly discovery: *case-level* anomaly detection & *nested* anomaly discovery

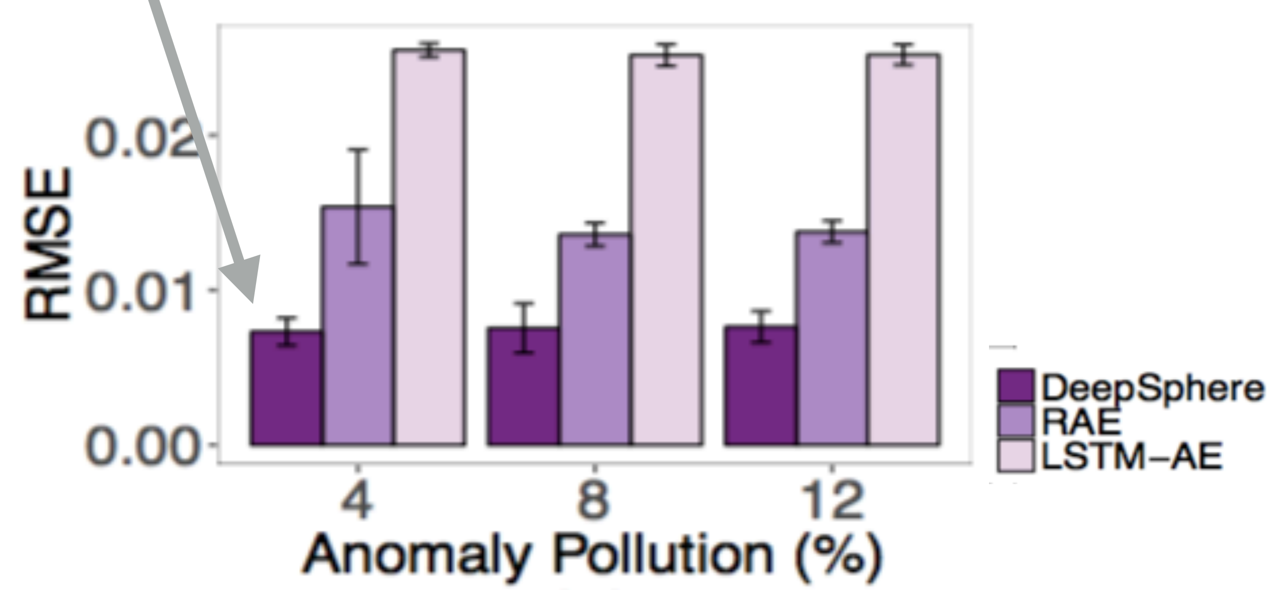
DeepSphere Results

DeepSphere

case-level

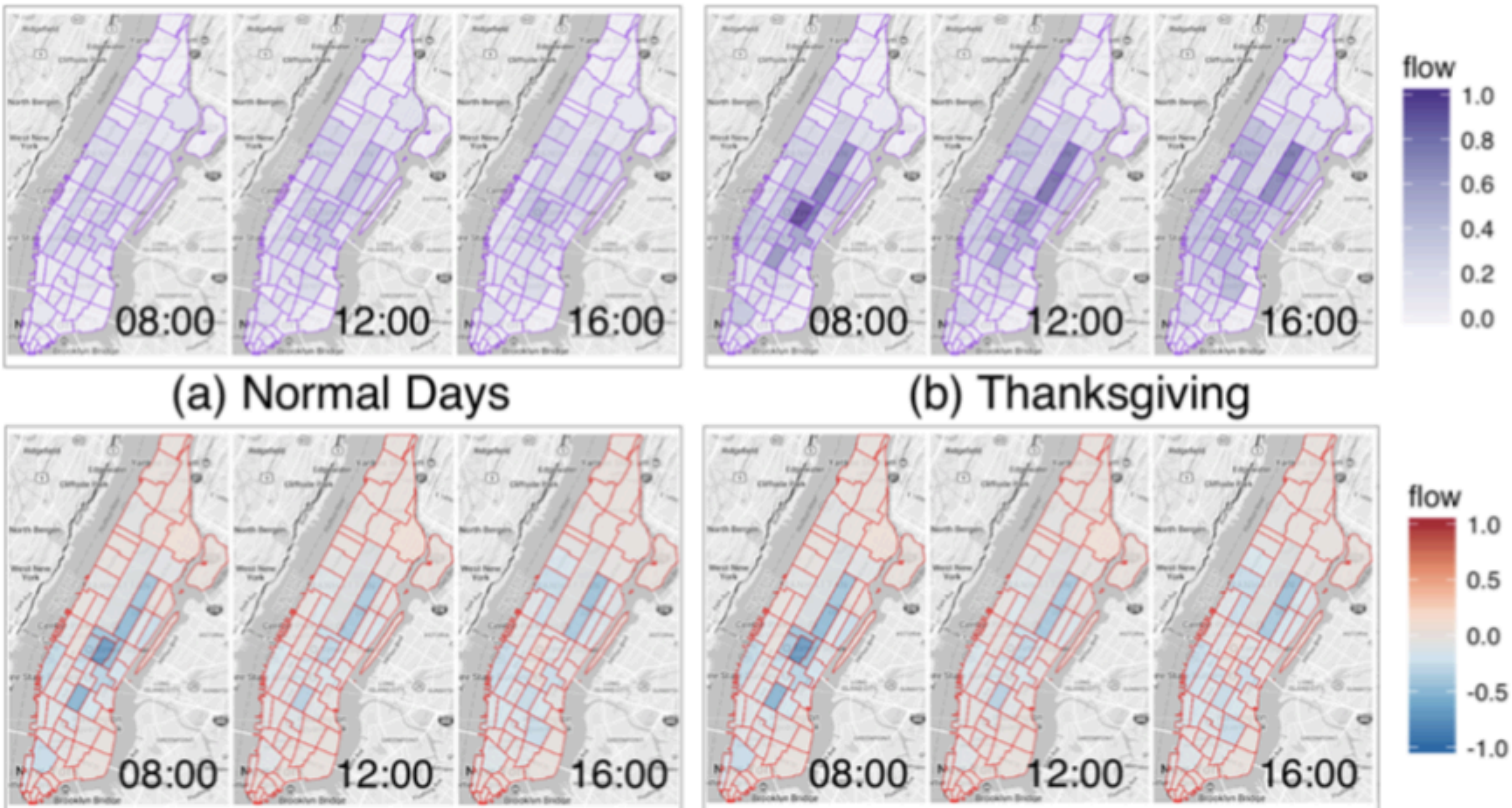


nested-level



DeepSphere outperforms state-of-the-art methods in both case and nested levels

Detecting distinctive local traffic patterns



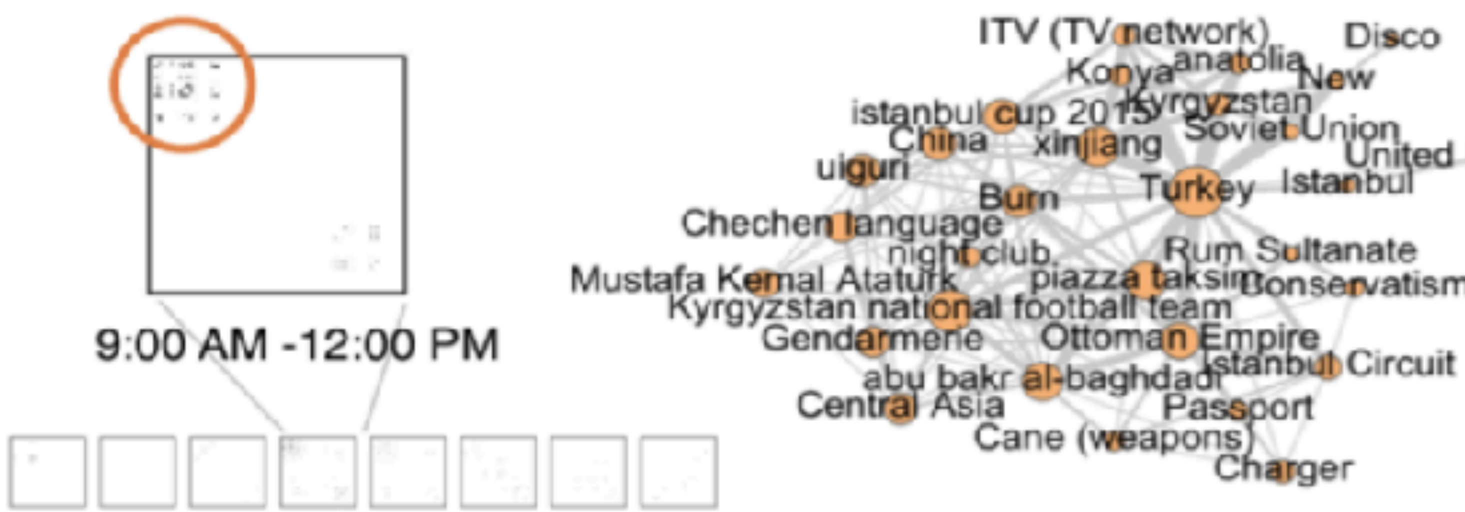
(a) Normal Days

(b) Thanksgiving

(c) Ground Truth Change

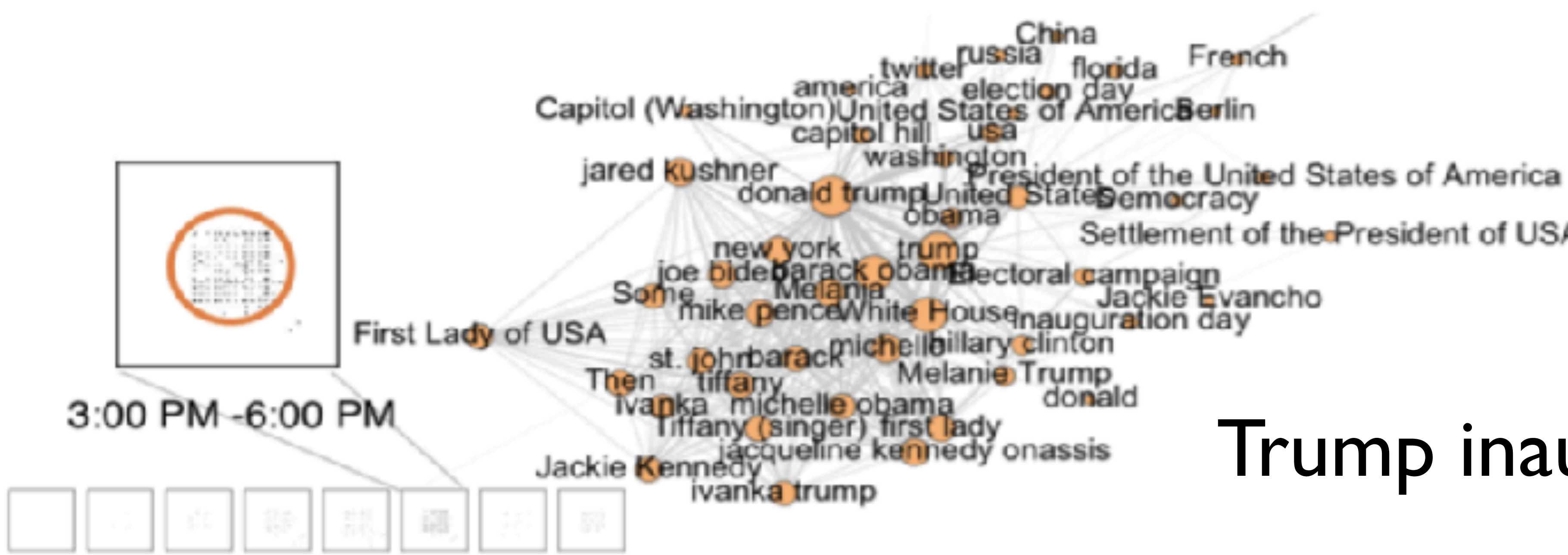
(d) Detected Change

Detecting significant events from dynamic phrase nets



(a) 01-03-2017

Istanbul shooting



(b) 01-20-2017

Trump inauguration

Detecting foreground activity from videos without image labeling/processing

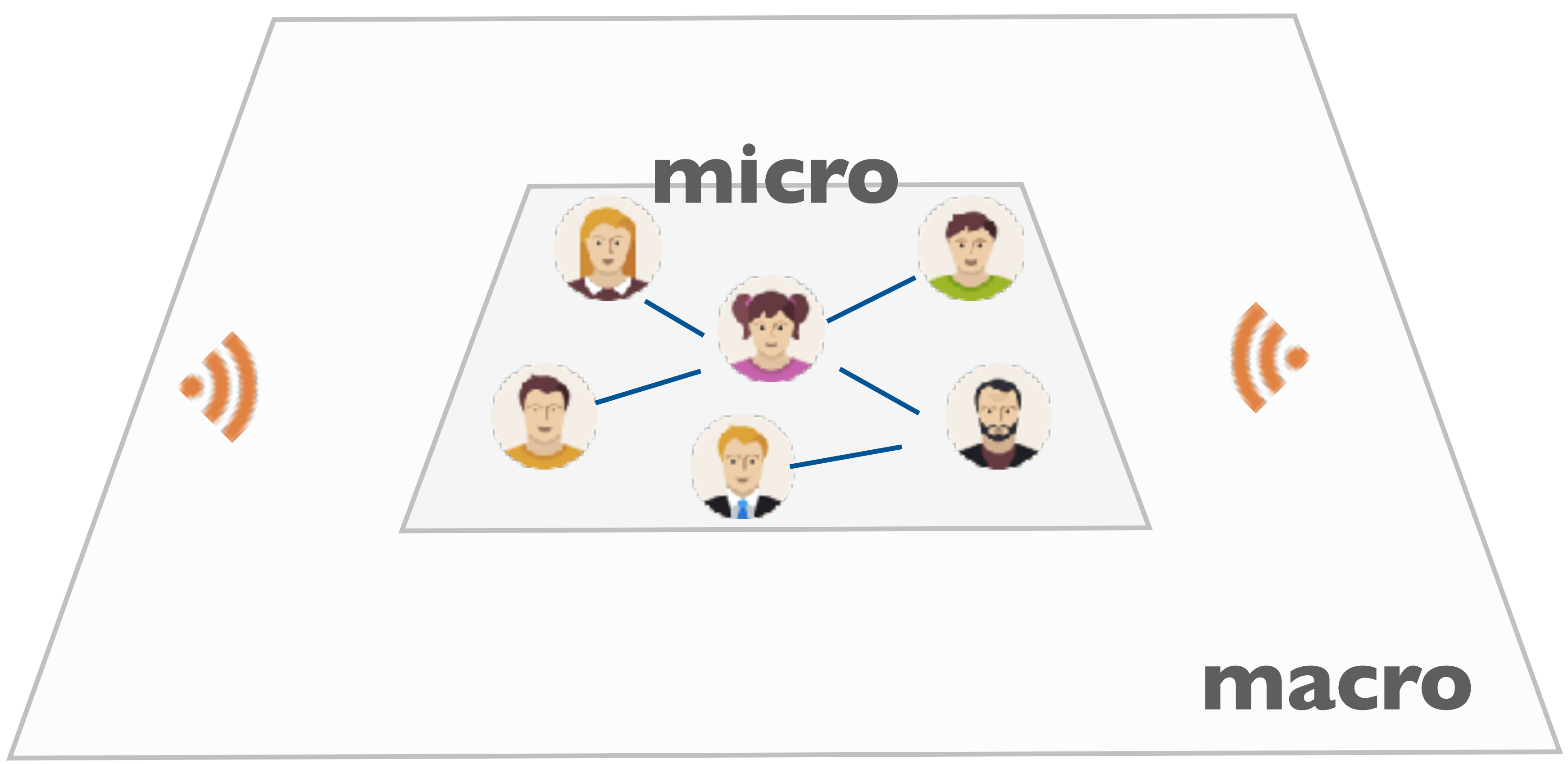
Measuring Social & Emotional Response

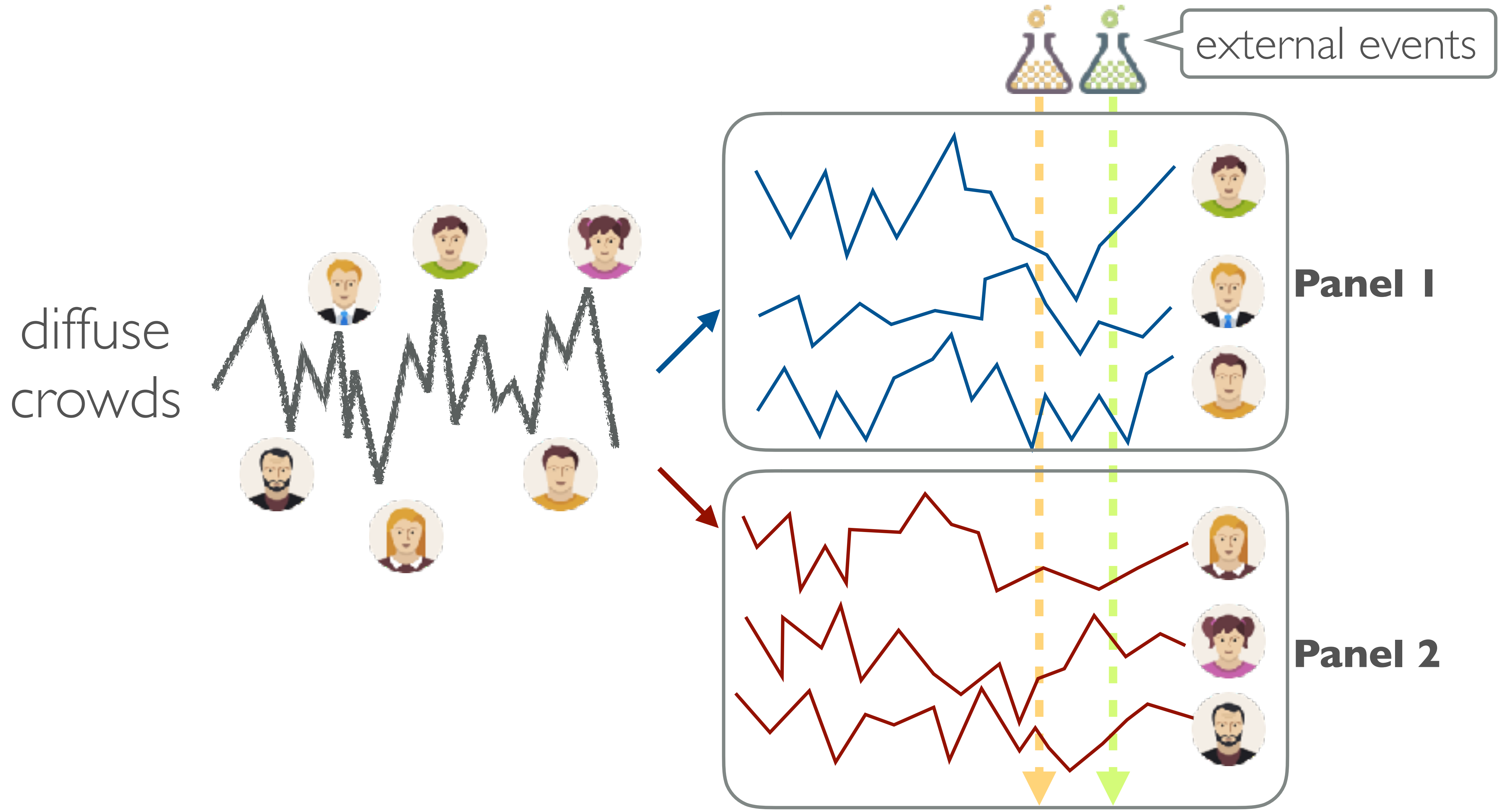
during

Analysis Challenge

Emotional reactions to shocking, threatening events have complex causes operating at multiple levels

Compare to *baseline*, how different do crisis patterns look from usual?





Computational focus groups:

external shock for various level of exposures

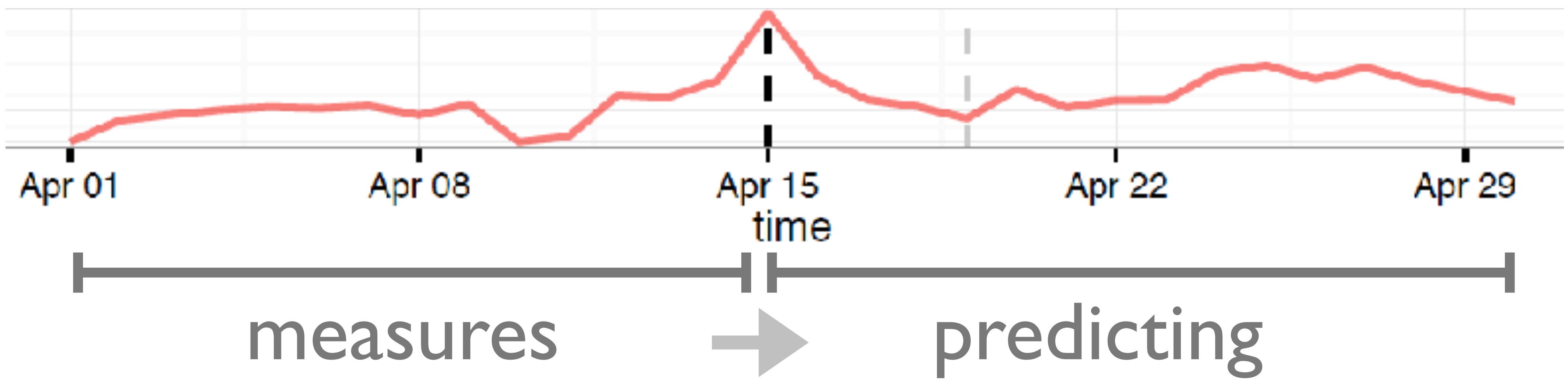
geographic, social, or media exposure relevant to the event

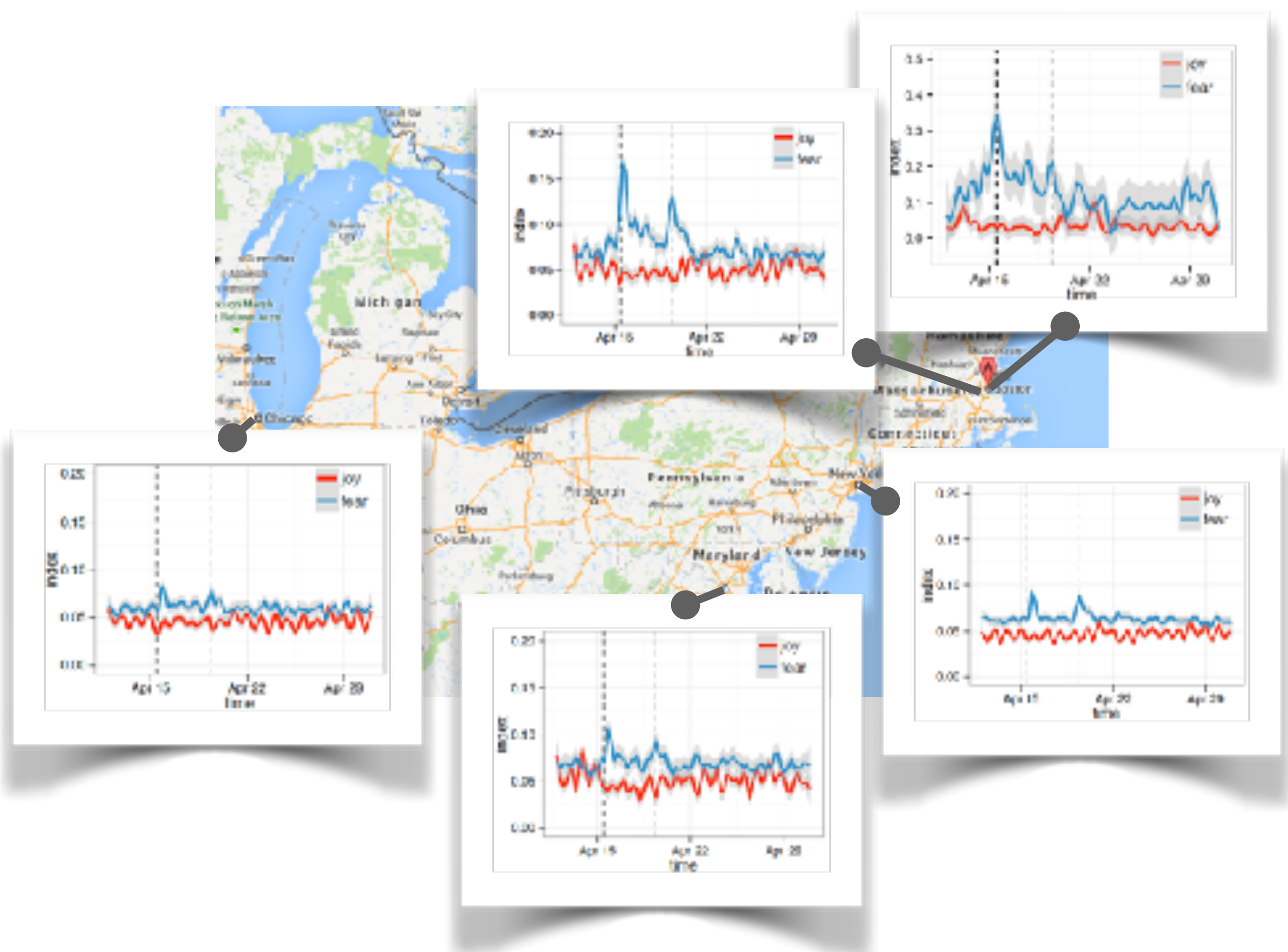
Fear

How does fear spread across communities?

What is the relationship between the expression of fear and social support?

Use prediction framework to examine factors





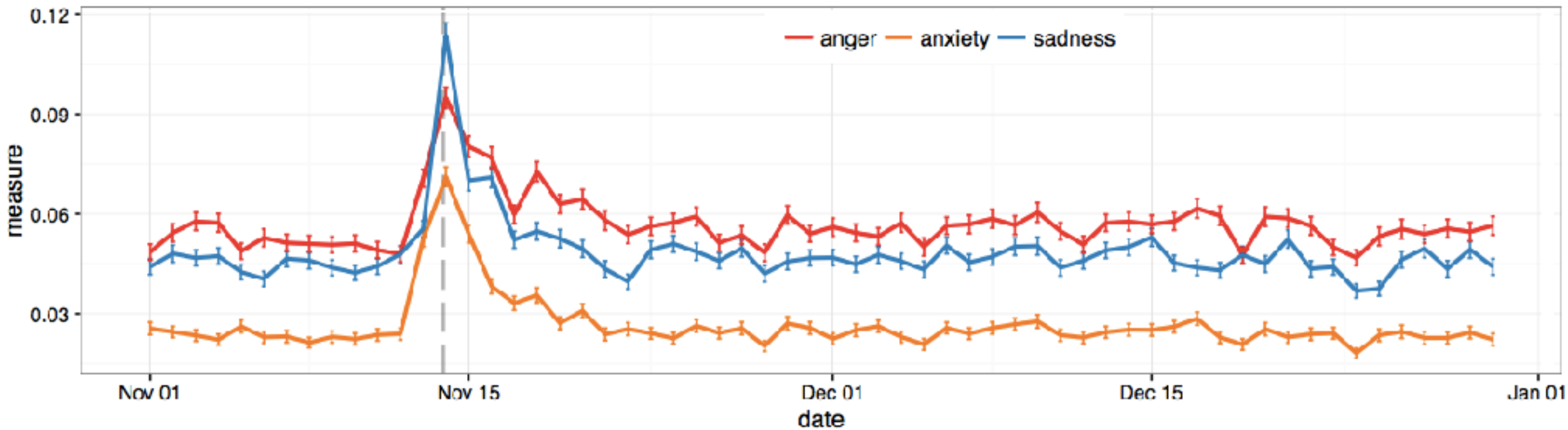
[Results] Synchronous expressions of fear are associated with geo proximity, social ties, and personal visit; fear has **productive role** in social support

EPJ Data Science, 2014

Distress

How did a terrorist event provoke **adverse psychological outcomes** (**distress**), such as ***anxiety***, ***anger***, and ***depression*** from targeted communities?

How **long** did such stress linger?



First empirical evidence for *fine-grained time-varying* emotional response to terrorist attacks

[Results] Novel ***dynamic*** relationships

News media exposure had competing, time-dependent effects on *anxiety*, as it was associated with heightened initial anxiety but also a more rapid return to normal anxiety levels

Risk Analysis, 2017

Summary

Model and analyze ***patterns of change*** within complex social systems

Crisis response: build community resilience to disasters via ***coupling human and machine intelligence***

before: **Anomaly detection**

during: **Collective sensemaking**

after: **Impact discovery**

AI/ML can help make sense of data in an efficient manner

For dynamic & complex situations, we want models ***not only good, but interpretable***

Team & Collaborators





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Questions? Feedback?

Code & Data available:
http://picsolab.github.io

Thanks!

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