

Smart Analytics for Big Time-series Data

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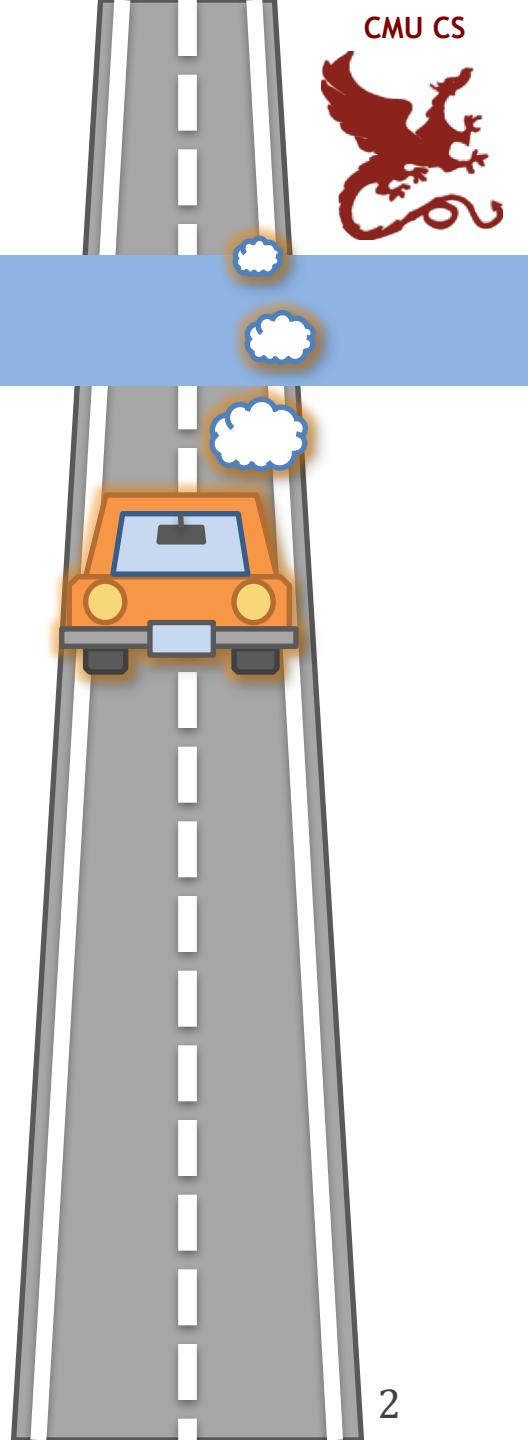
Roadmap

- Motivation
- Similarity search, pattern discovery and summarization
- Non-linear modeling and forecasting
- Extension of time-series data: tensor analysis

Part 1

Part 2

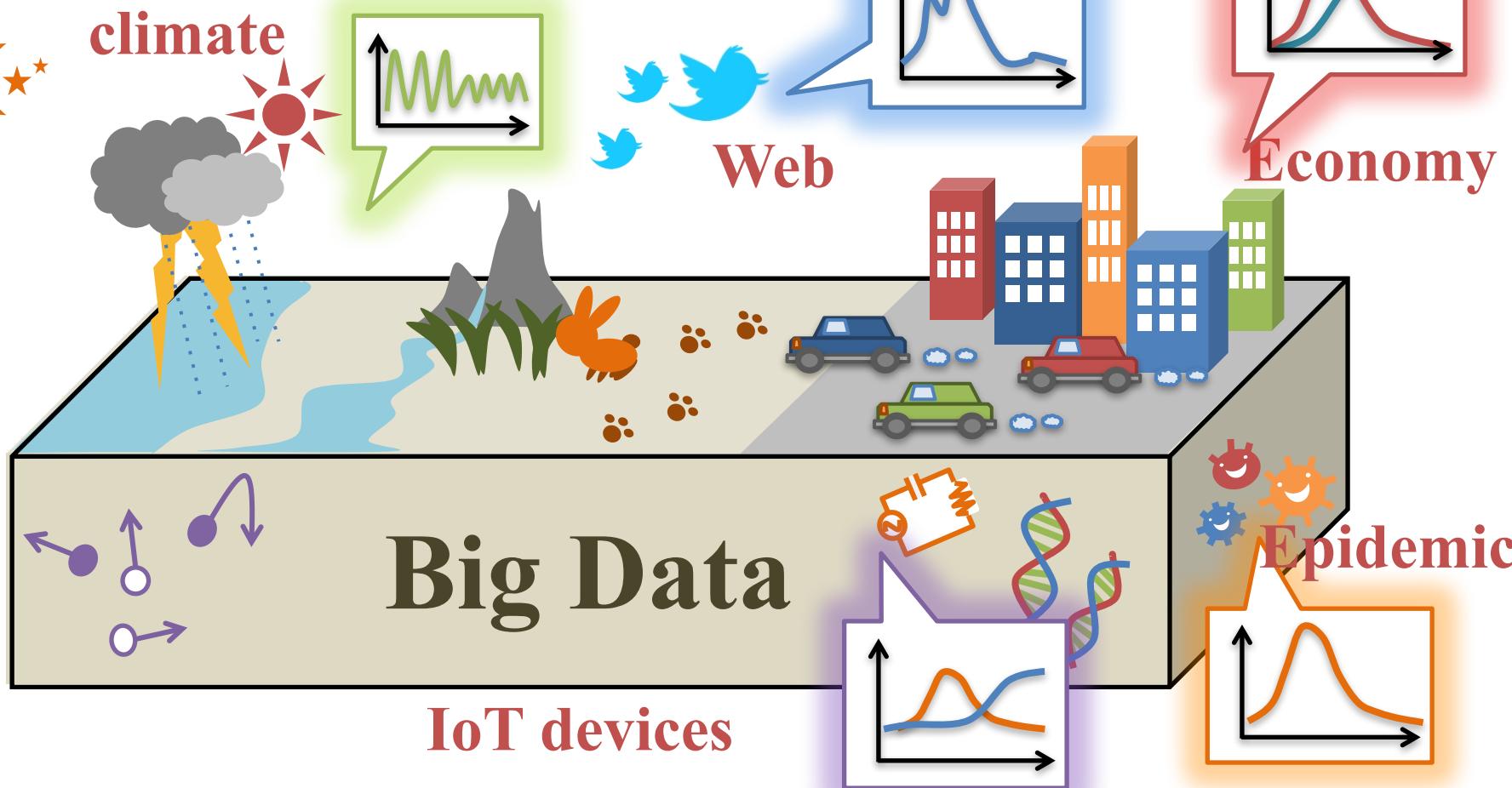
Part 3





Big time-series data

Social/natural phenomena





Big time-series data

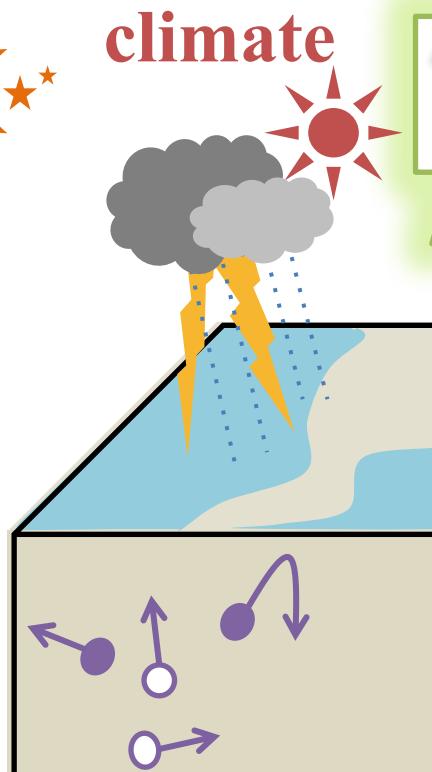
Social/natural phenomena





Big time-series data

Social/natural phenomena



climate



IoT data streams

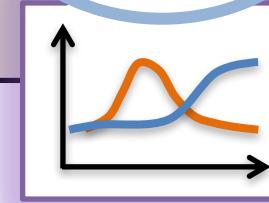
- Vibration sensors, acceleration, temperature, etc.

Application

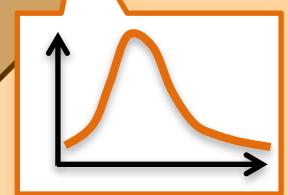
- Self-driving car
- Structural health monitoring
- Manufacturing



IoT devices



Epidemic





Motivation

- **Given:** Big time-series data
- **Goal:**

Find important patterns

Forecast future social activities

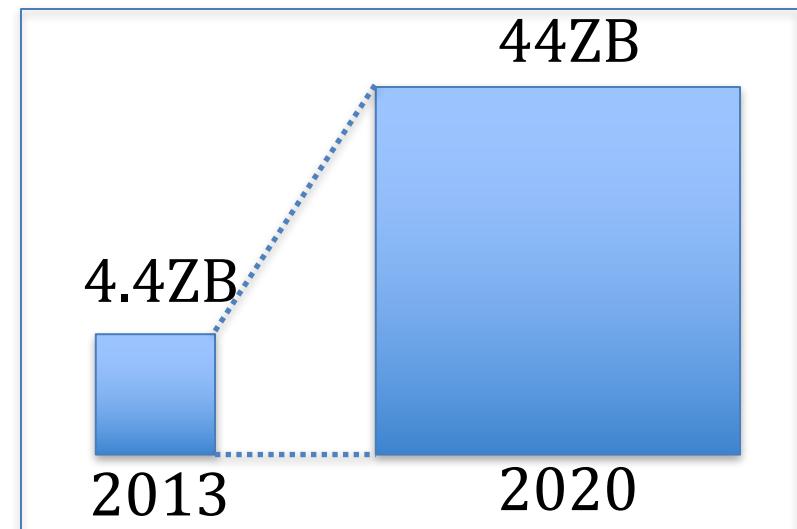
- **At-work:**
 - Online marketing
 - Sensor monitoring, anomaly detection
 - Forecasting future events





Motivation

- Time-series analysis for big data
 - Web and social networks
 - IoT data streams
 - Medical and healthcare records
- Digital universe growth
 - 4.4 zettabytes
 - (4.4 trillion gigabytes)
 - 44 zettabytes in 2020

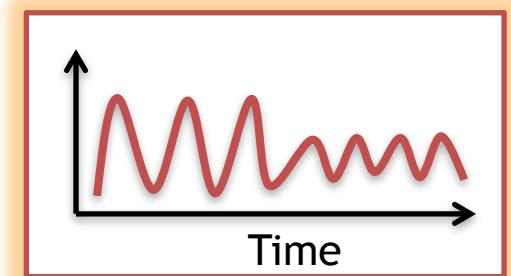


The DIGITAL UNIVERSE of
OPPORTUNITIES (IDC 2014)



Big Time-series analysis

- Volume and Velocity
 - High-speed processing for large-scale data
 - Low memory consumption
 - Online processing for real-time data management
- Variety of data types
 - Multi-dimensional time-series data (e.g., IoT device data)
 - Complex time-stamped events (e.g., web-click logs)
 - Time-evolving graph (e.g., social networks)
- Advanced techniques for big data
 - Model estimation, summarization
 - Anomaly detection, forecasting



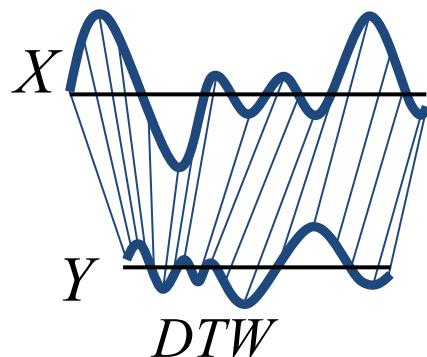


Big Time-series analysis

- Time-series data mining

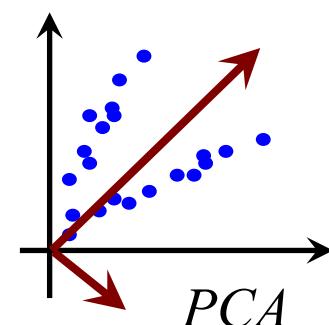
**Indexing,
similarity
search**

**ED, DTW
Correlation**



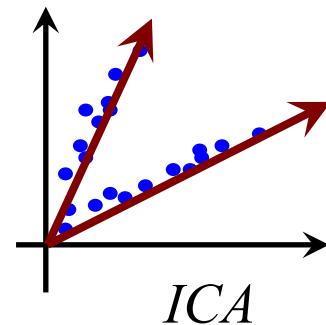
**Feature
extraction**

**DFT, DWT,
SVD, ICA**



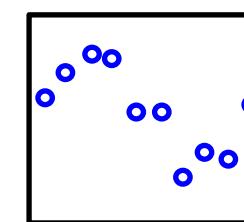
**Linear
modeling**

**AR,
ARIMA,
LDS**

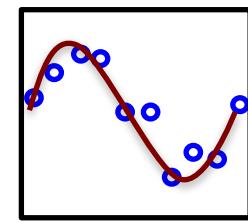


**Stream
mining**

**StatStream
etc...**



Data (X)



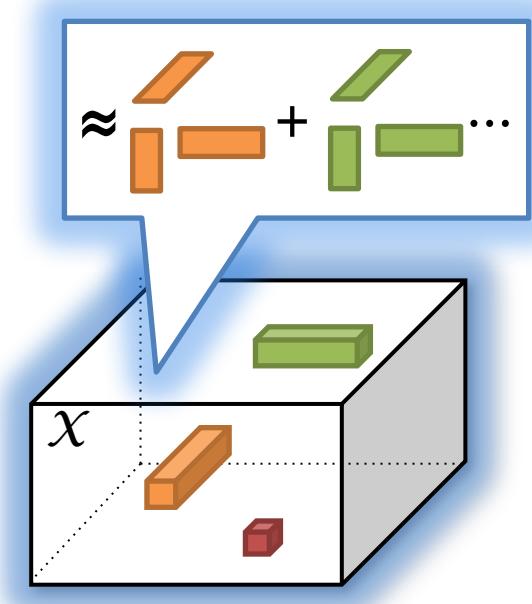
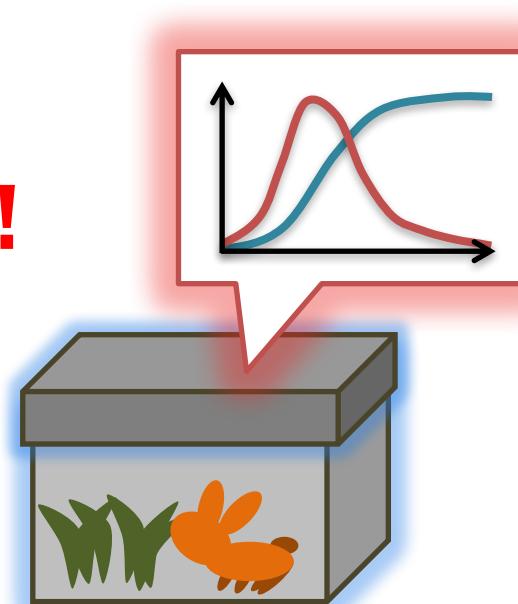
Model (M)



New research directions

- R1. Automatic mining (no magic numbers!)
- R2. Non-linear (gray-box) modeling
- R3. Tensor analysis

**NO magic
numbers !**





(R1) Automatic mining

No magic numbers! ... because,

Manual

- sensitive to the parameter tuning
- long tuning steps (hours, days, ...)



Automatic (no magic numbers)

- no expert tuning required

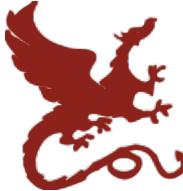


Big data mining:

-> we cannot afford human intervention!!



(R2) Non-linear (gray-box) modeling



- Gray-box mining
 - If we know the equations
- Non-linear (differential) equations
 - Epidemic
 - Biology
 - Physics, Economics, etc.,
- Modeling non-linear phenomena
 - Non-linear analysis for big time-series data

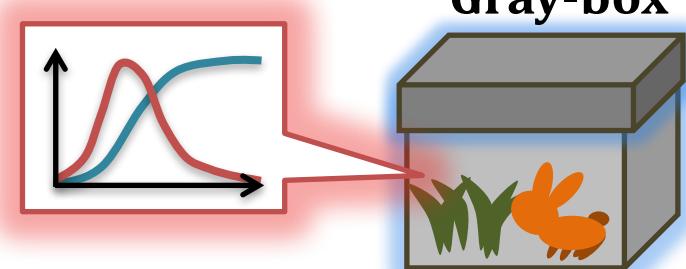


Image courtesy of Tina Phillips and amenic181 at FreeDigitalPhotos.net.

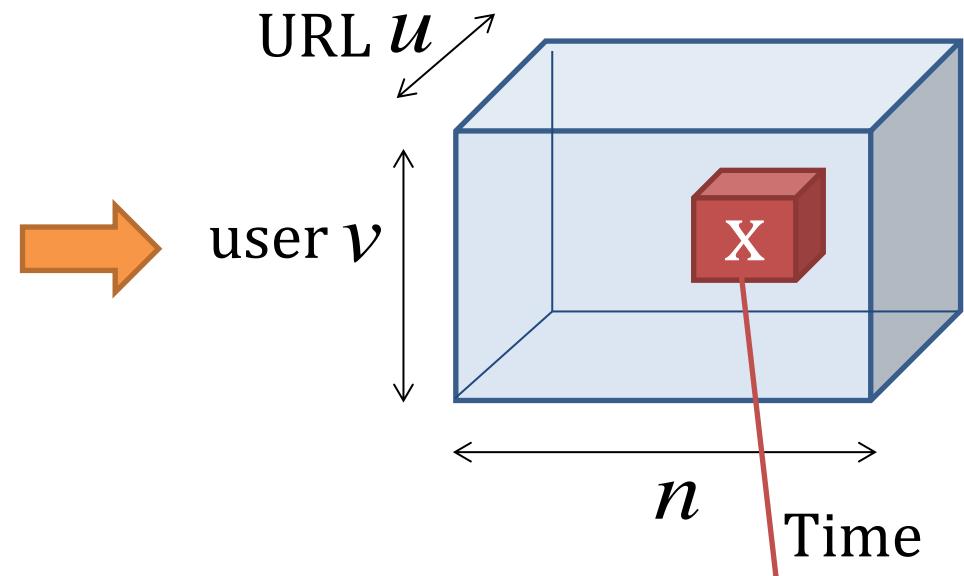


(R3) Large-scale tensor analysis



- Time-stamped events
 - e.g., *web clicks*

Time	URL	User
08-01-12:00	CNN.com	Smith
08-02-15:00	YouTube.com	Brown
08-02-19:00	CNET.com	Smith
08-03-11:00	CNN.com	Johnson
...



Represent as
Mth order tensor (M=3)

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

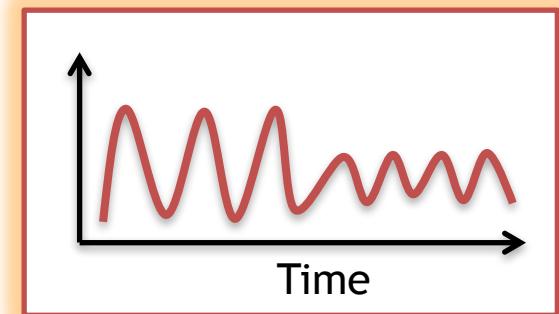
Element x: # of events

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

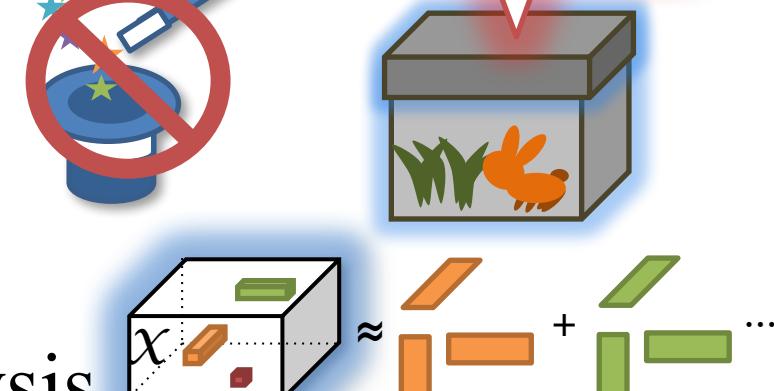


New research directions

- Time-series data analysis
 - Indexing and fast searching
 - Sequence matching
 - Clustering
 - etc.



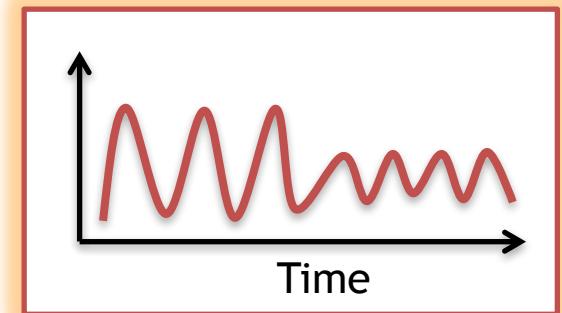
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 - R1. Automatic mining
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- New research directions
 - R1. Automatic mining
 - R2. Non-linear modeling
 - R3. Large-scale tensor analysis

