Smart Analytics for Big Time-series Data

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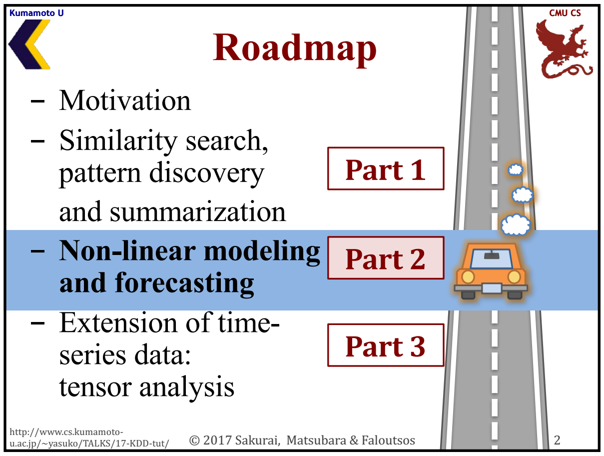

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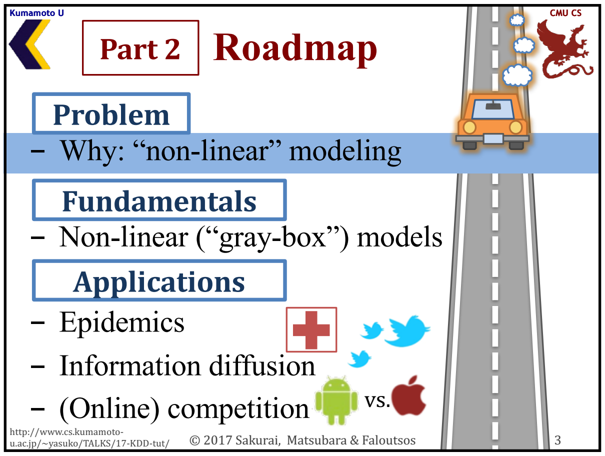
Roadmap

- Motivation
- Similarity search, pattern discovery and summarization **Part 1**
- **Non-linear modeling and forecasting** **Part 2**
- Extension of time-series data: tensor analysis **Part 3**



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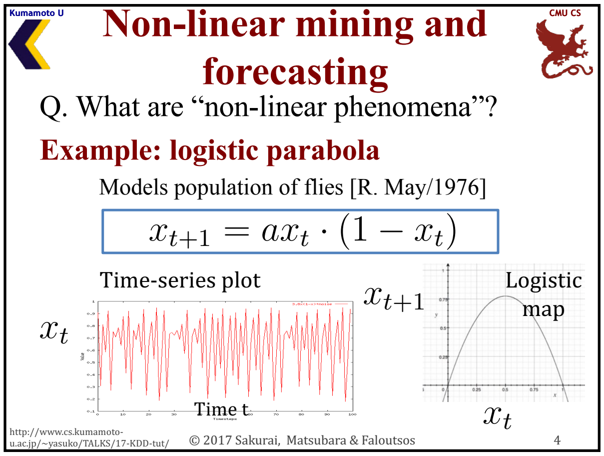
Part 2 Roadmap

Problem
- Why: "non-linear" modeling

Fundamentals
- Non-linear ("gray-box") models

Applications
- Epidemics
- Information diffusion
- (Online) competition



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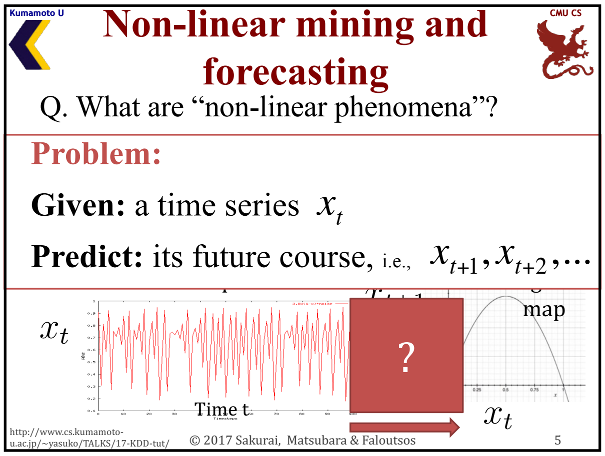
Non-linear mining and forecasting

Q. What are "non-linear phenomena"?

Example: logistic parabola

Models population of flies [R. May/1976]

$$x_{t+1} = a x_t \cdot (1 - x_t)$$



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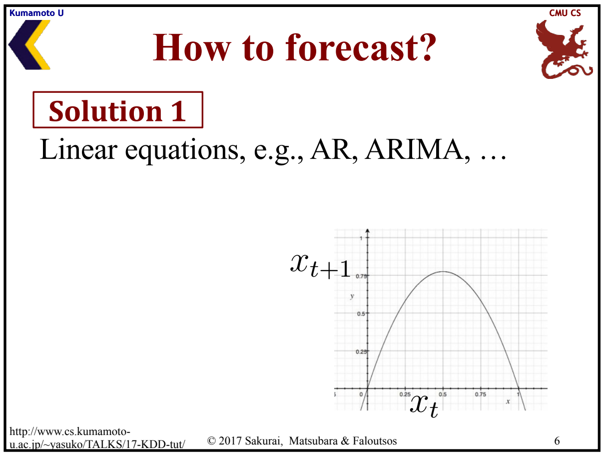
Non-linear mining and forecasting

Q. What are "non-linear phenomena"?

Problem:

Given: a time series x_t

Predict: its future course, i.e., $x_{t+1}, x_{t+2}, \ldots$



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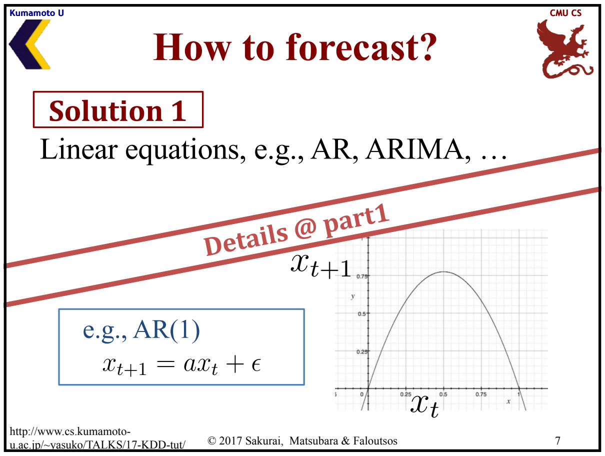
How to forecast?

Solution 1

Linear equations, e.g., AR, ARIMA, …



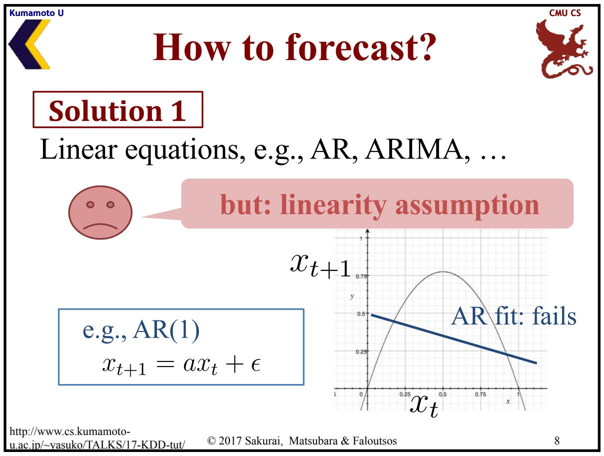
How to forecast?

Solution 1

Linear equations, e.g., AR, ARIMA, …

Details @ part1

e.g., AR(1)
$x_{t+1} = a x_t + \epsilon$



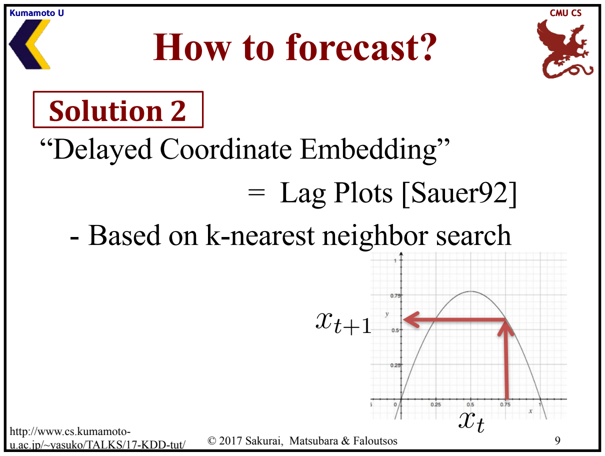
How to forecast?

Solution 1

Linear equations, e.g., AR, ARIMA, …

but: linearity assumption

e.g., AR(1)
$x_{t+1} = a x_t + \epsilon$



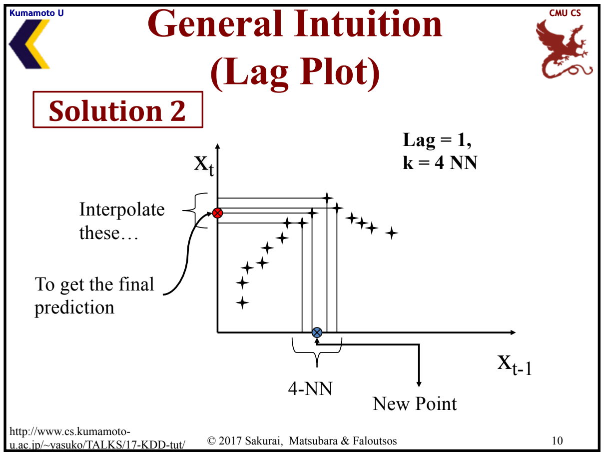
How to forecast?

Solution 2

"Delayed Coordinate Embedding"

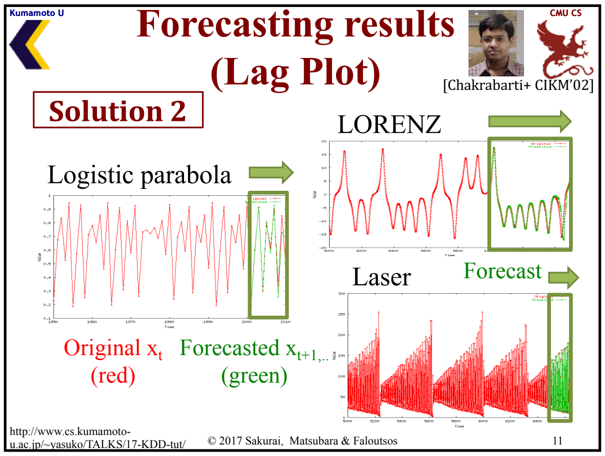
= Lag Plots [Sauer92]

- Based on k-nearest neighbor search



General Intuition (Lag Plot)

Solution 2



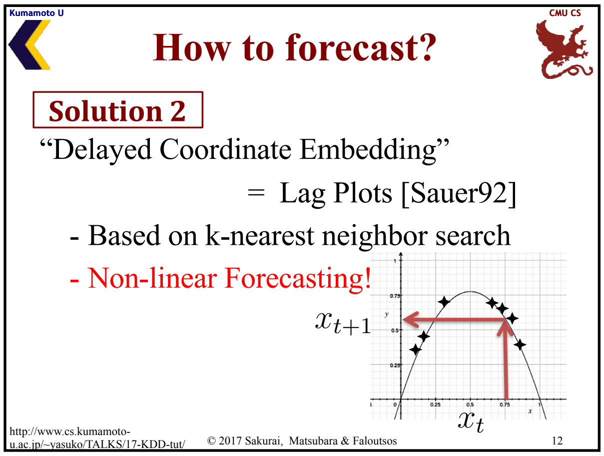
Forecasting results (Lag Plot)

[Chakrabarti+ CIKM'02]

Solution 2

Original x_t (red)

Forecasted x_{t+1},… (green)



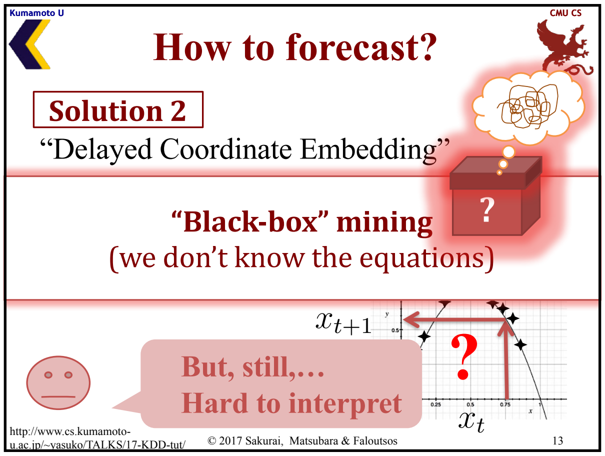
How to forecast?

Solution 2

"Delayed Coordinate Embedding"

= Lag Plots [Sauer92]

- Based on k-nearest neighbor search
- Non-linear Forecasting!



How to forecast?

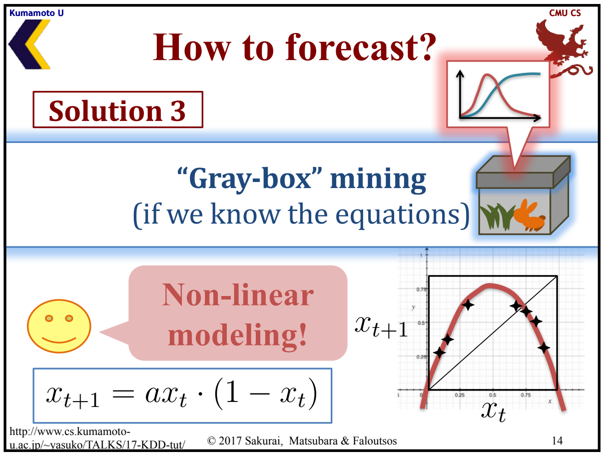
Solution 2

"Delayed Coordinate Embedding"

"Black-box" mining

(we don't know the equations)

But, still,…
Hard to interpret



How to forecast?

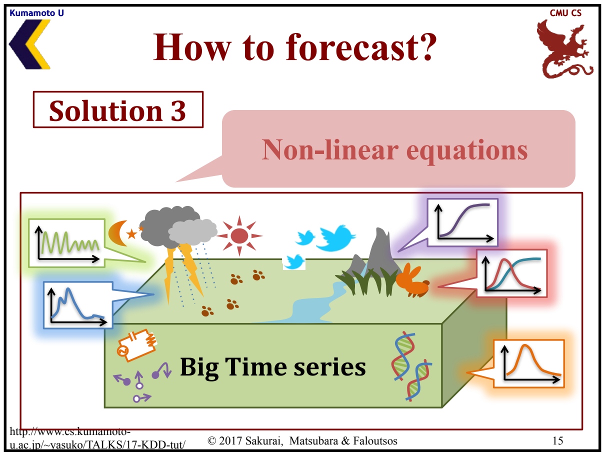
Solution 3

"Gray-box" mining

(if we know the equations)

Non-linear modeling!

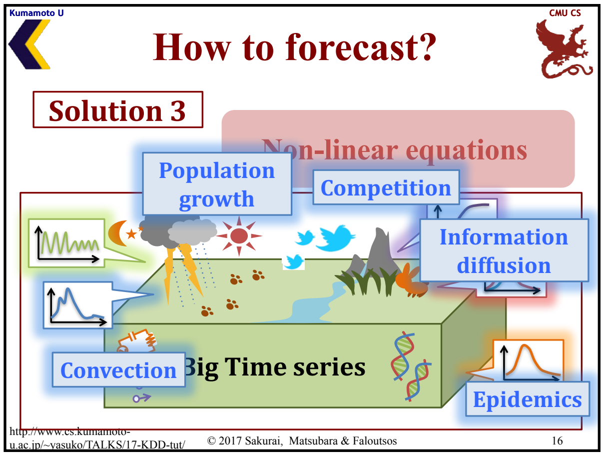
$$x_{t+1} = a x_t \cdot (1 - x_t)$$



How to forecast?

Solution 3

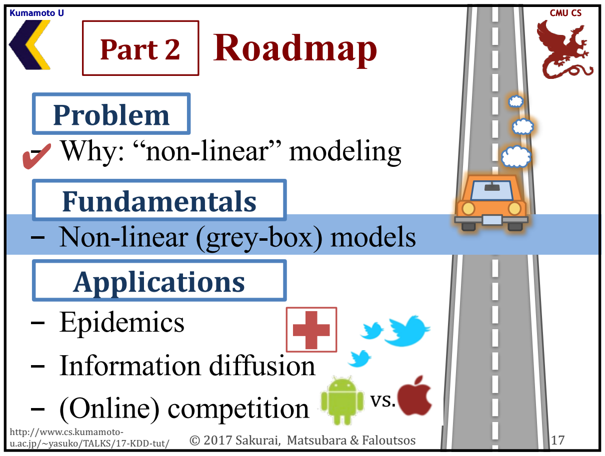
Non-linear equations



How to forecast?

Solution 3

Non-linear equations



Part 2 Roadmap

Problem

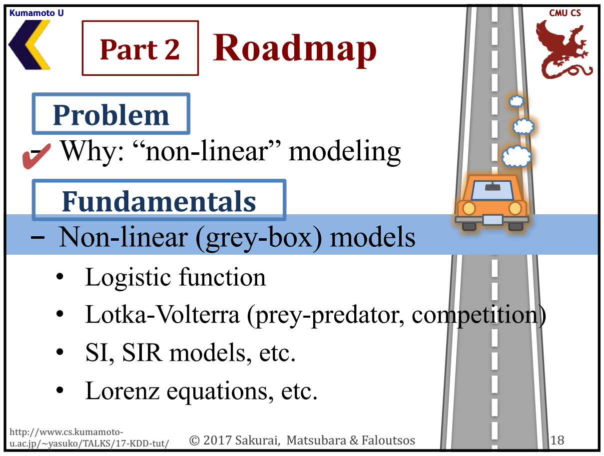
✓ Why: "non-linear" modeling

Fundamentals

- Non-linear (grey-box) models

Applications

- Epidemics
- Information diffusion
- (Online) competition



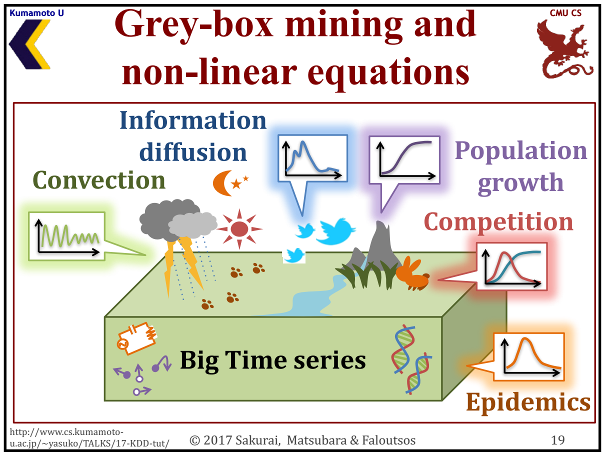
Part 2 Roadmap

Problem

✓ Why: "non-linear" modeling

Fundamentals

- Non-linear (grey-box) models
  - Logistic function
  - Lotka-Volterra (prey-predator, competition)
  - SI, SIR models, etc.
  - Lorenz equations, etc.



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Grey-box mining and non-linear equations

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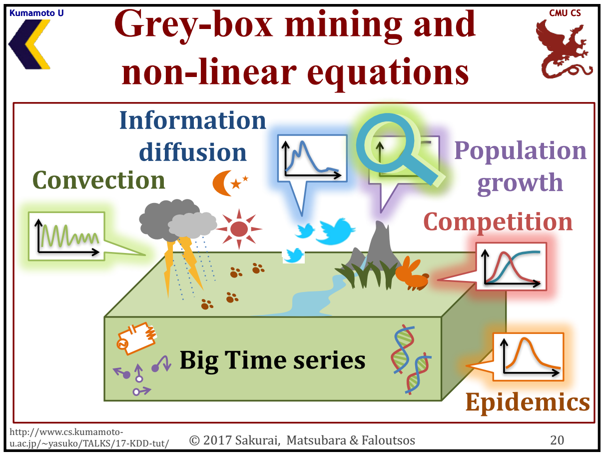

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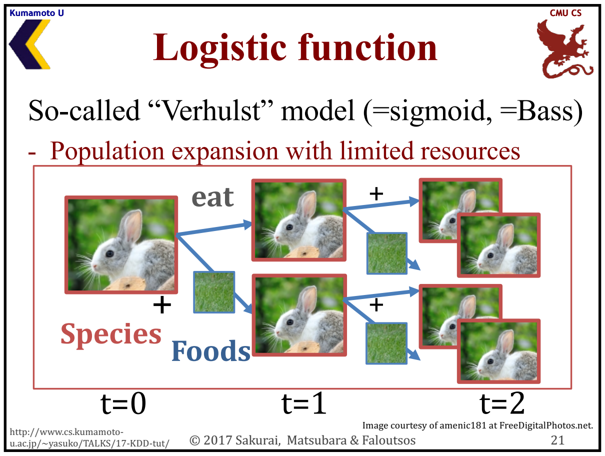

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Logistic function

So-called "Verhulst" model (=sigmoid, =Bass)

- Population expansion with limited resources

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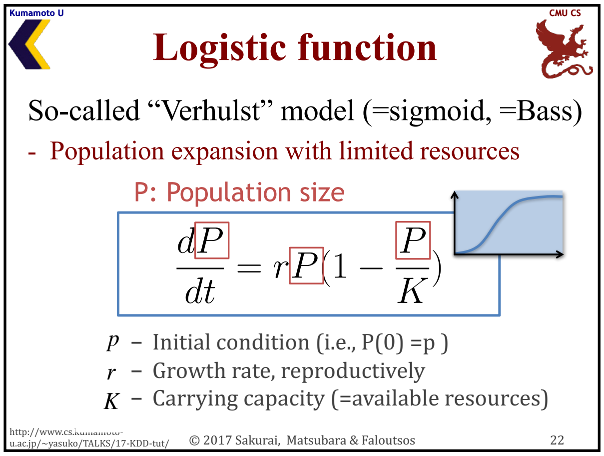

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Logistic function

So-called "Verhulst" model (=sigmoid, =Bass)

- Population expansion with limited resources

P: Population size

$$\frac{d\boxed{P}}{dt} = r\boxed{P}(1 - \frac{\boxed{P}}{K})$$

p – Initial condition (i.e., P(0) =p)
r – Growth rate, reproductively
K – Carrying capacity (=available resources)

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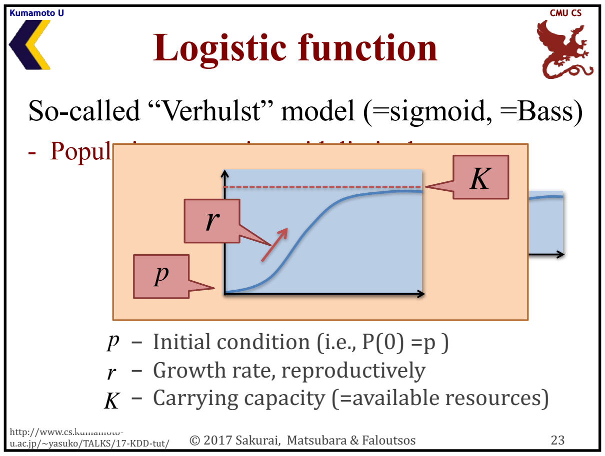

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- Popul

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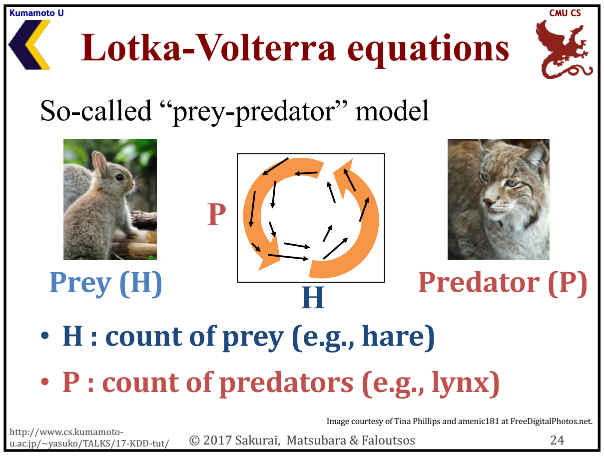

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Lotka-Volterra equations

So-called "prey-predator" model

- **H : count of prey (e.g., hare)**
- **P : count of predators (e.g., lynx)**

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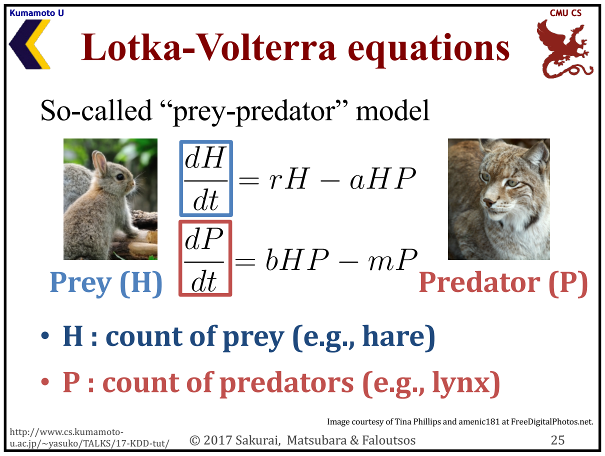

Lotka-Volterra equations

So-called “prey-predator” model

$$\boxed{\frac{dH}{dt}} = rH - aHP$$

$$\boxed{\frac{dP}{dt}} = bHP - mP$$

Prey (H) **Predator (P)**

- **H : count of prey (e.g., hare)**
- **P : count of predators (e.g., lynx)**

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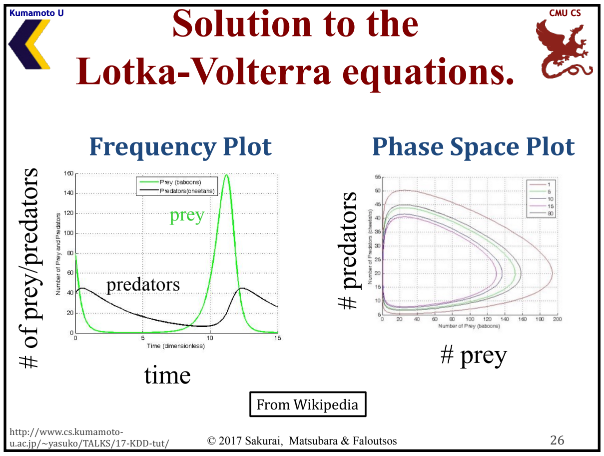

Solution to the Lotka-Volterra equations.

Frequency Plot **Phase Space Plot**

From Wikipedia

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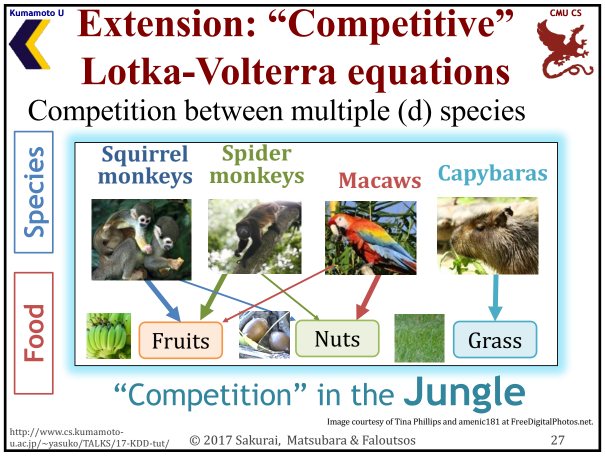

Extension: “Competitive” Lotka-Volterra equations

Competition between multiple (d) species

“Competition” in the **Jungle**

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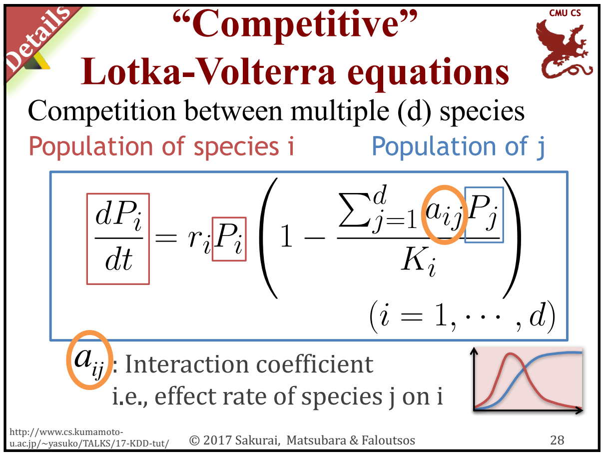

“Competitive” Lotka-Volterra equations

Competition between multiple (d) species

Population of species i   Population of j

$$\boxed{\frac{dP_i}{dt}} = r_i \boxed{P_i} \left(1 - \frac{\sum_{j=1}^{d} a_{ij} \boxed{P_j}}{K_i} \right) \quad (i = 1, \cdots, d)$$

a_{ij}: Interaction coefficient
i.e., effect rate of species j on i

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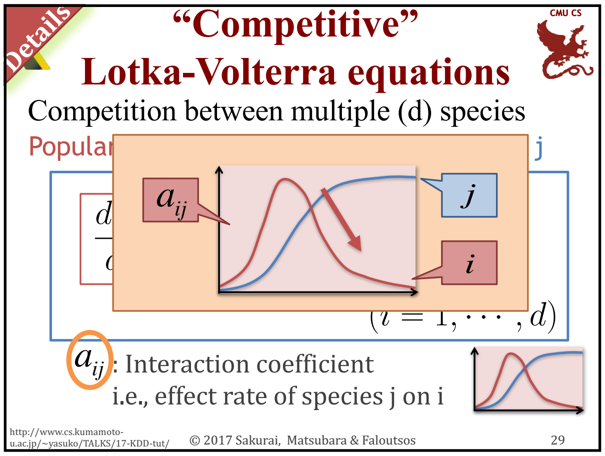

“Competitive” Lotka-Volterra equations

Competition between multiple (d) species

Popular ... j

$(i = 1, \cdots, d)$

a_{ij}: Interaction coefficient
i.e., effect rate of species j on i

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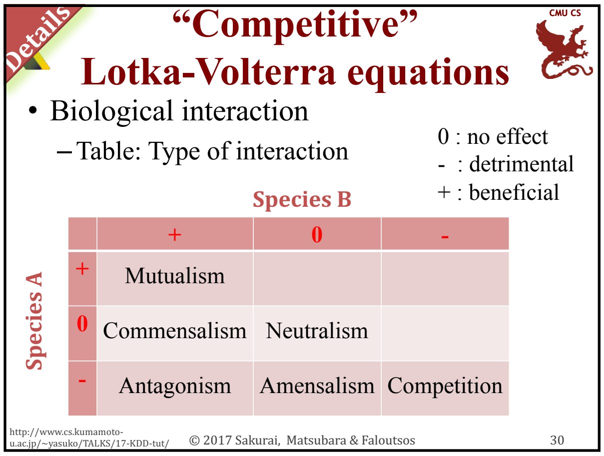

“Competitive” Lotka-Volterra equations

- Biological interaction
  - Table: Type of interaction

0 : no effect
- : detrimental
+ : beneficial

Species A \ Species B	+	0	-
+	Mutualism		
0	Commensalism	Neutralism	
-	Antagonism	Amensalism	Competition

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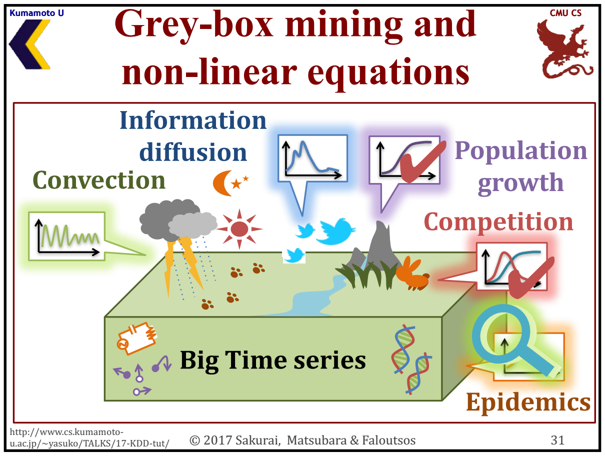

Grey-box mining and non-linear equations

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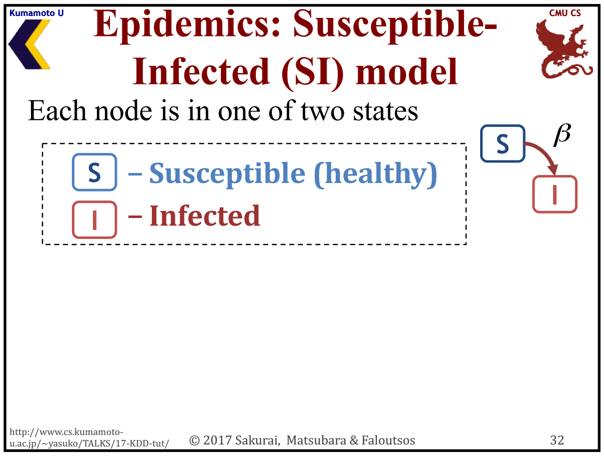

Epidemics: Susceptible-Infected (SI) model

Each node is in one of two states

S – Susceptible (healthy)
I – Infected

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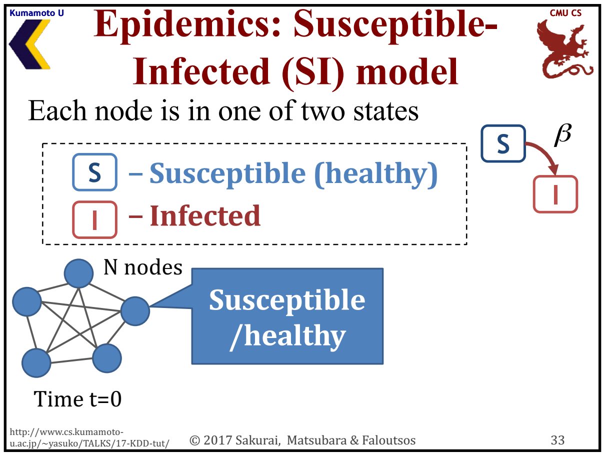

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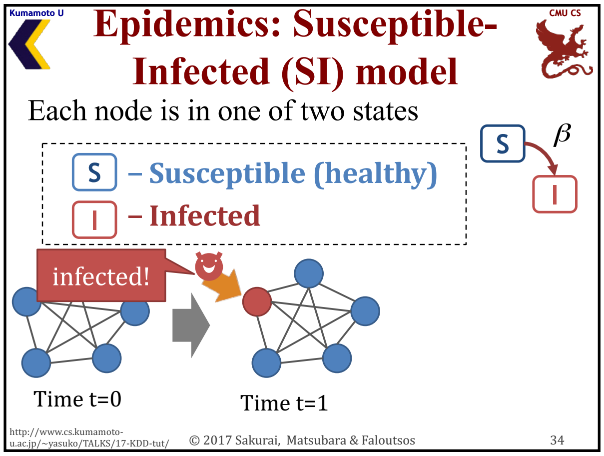

Epidemics: Susceptible-Infected (SI) model

Each node is in one of two states

S – Susceptible (healthy)
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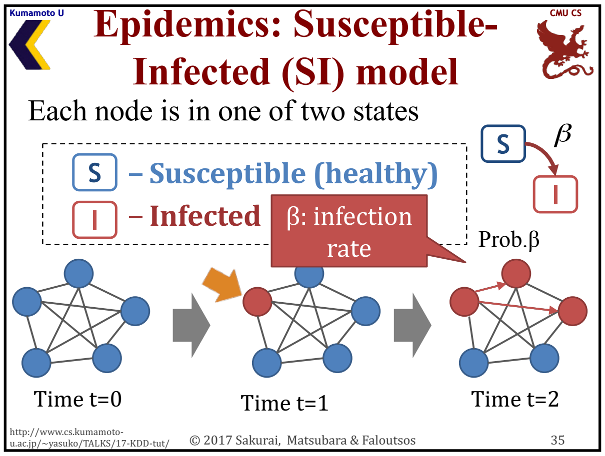

Epidemics: Susceptible-Infected (SI) model

Each node is in one of two states

S – Susceptible (healthy)
I – Infected

β: infection rate

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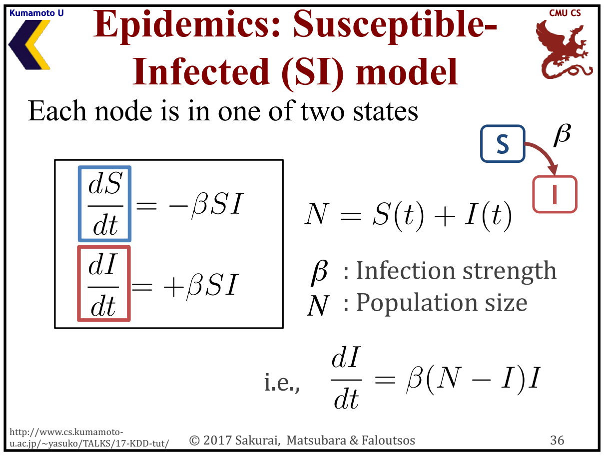

Epidemics: Susceptible-Infected (SI) model

Each node is in one of two states

$$\boxed{\begin{aligned}\frac{dS}{dt} &= -\beta S I \\ \frac{dI}{dt} &= +\beta S I\end{aligned}}$$

$$N = S(t) + I(t)$$

β : Infection strength
N : Population size

i.e., $$\frac{dI}{dt} = \beta(N - I)I$$

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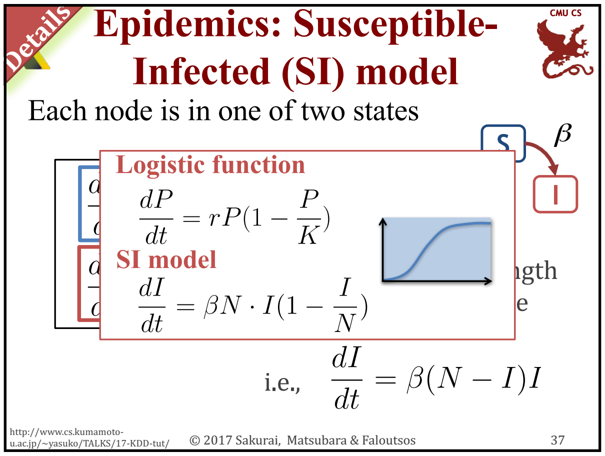

Epidemics: Susceptible-Infected (SI) model

Each node is in one of two states

Logistic function

$$\frac{dP}{dt} = rP(1 - \frac{P}{K})$$

SI model

$$\frac{dI}{dt} = \beta N \cdot I(1 - \frac{I}{N})$$

i.e., $$\frac{dI}{dt} = \beta(N - I)I$$

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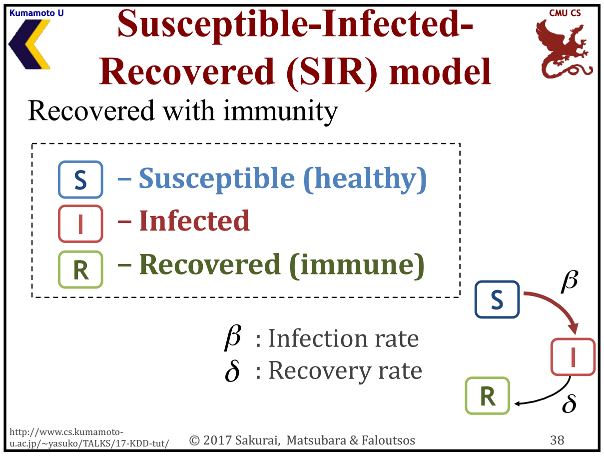

Susceptible-Infected-Recovered (SIR) model

Recovered with immunity

- S – Susceptible (healthy)
- I – Infected
- R – Recovered (immune)

β : Infection rate
δ : Recovery rate

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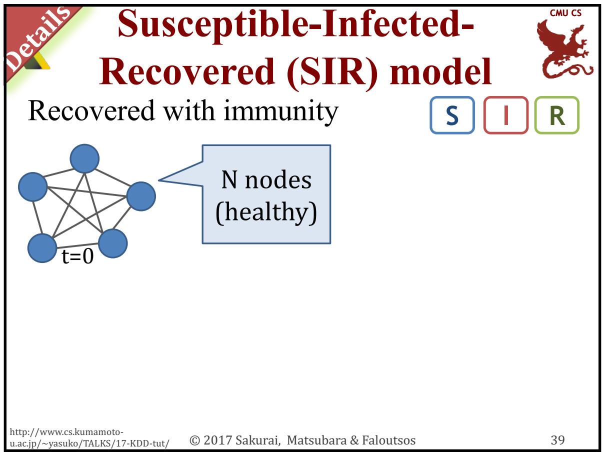

Susceptible-Infected-Recovered (SIR) model

Recovered with immunity

N nodes
(healthy)

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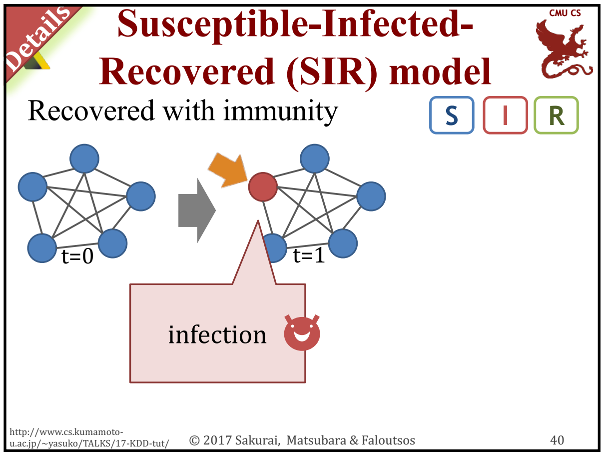

Susceptible-Infected-Recovered (SIR) model

Recovered with immunity

infection

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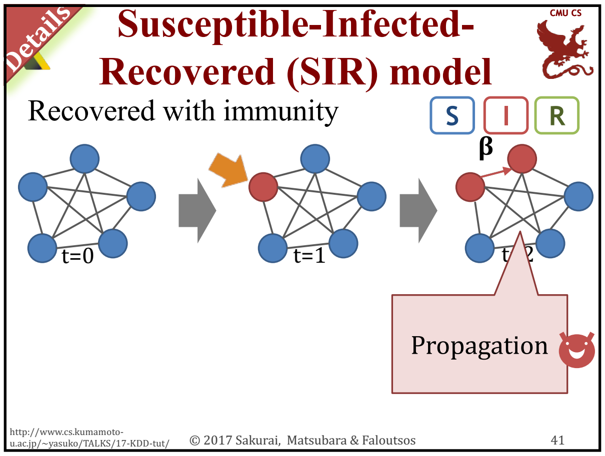

Susceptible-Infected-Recovered (SIR) model

Recovered with immunity

Propagation

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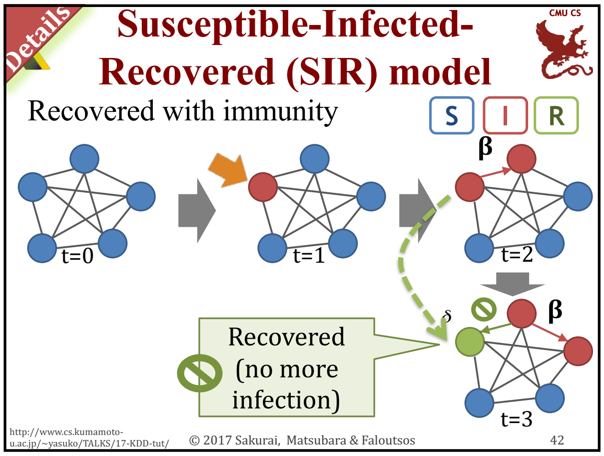

Susceptible-Infected-Recovered (SIR) model

Recovered with immunity

Recovered
(no more
infection)

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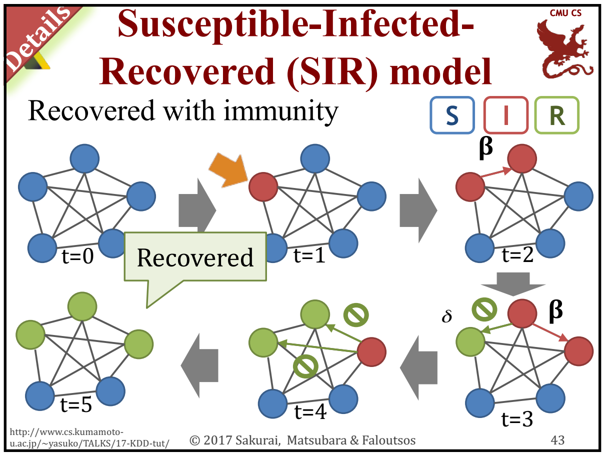
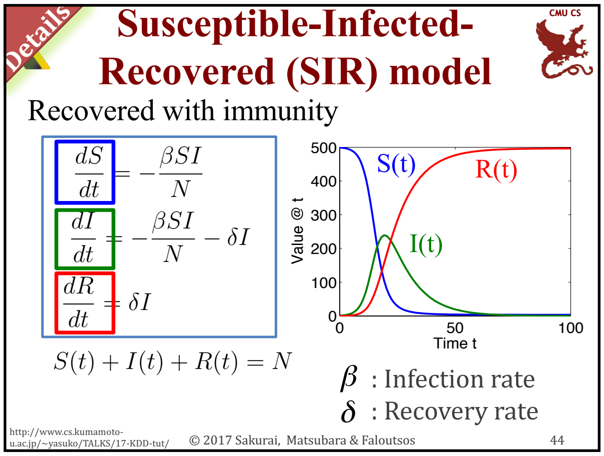


Susceptible-Infected-Recovered (SIR) model

Recovered with immunity



Susceptible-Infected-Recovered (SIR) model

Recovered with immunity

$$\frac{dS}{dt} = -\frac{\beta SI}{N}$$

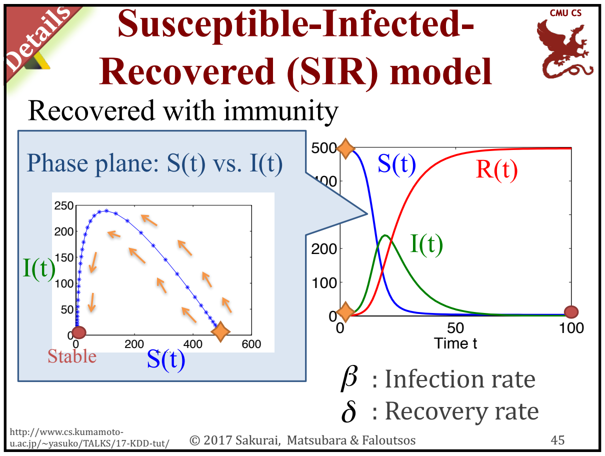
$$\frac{dI}{dt} = \frac{\beta SI}{N} - \delta I$$

$$\frac{dR}{dt} = \delta I$$

$$S(t) + I(t) + R(t) = N$$

β : Infection rate

δ : Recovery rate



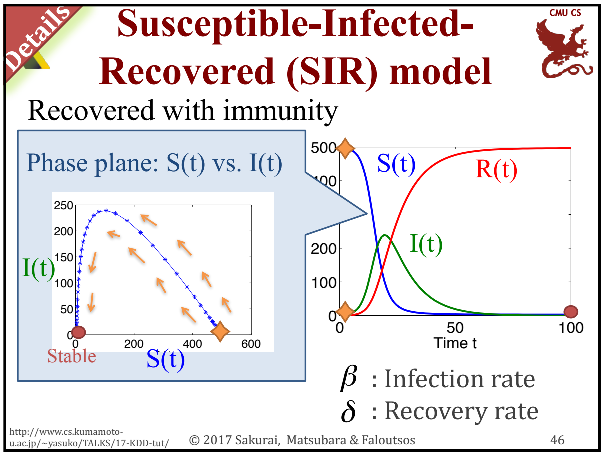
Susceptible-Infected-Recovered (SIR) model

Recovered with immunity

Phase plane: S(t) vs. I(t)

β : Infection rate

δ : Recovery rate



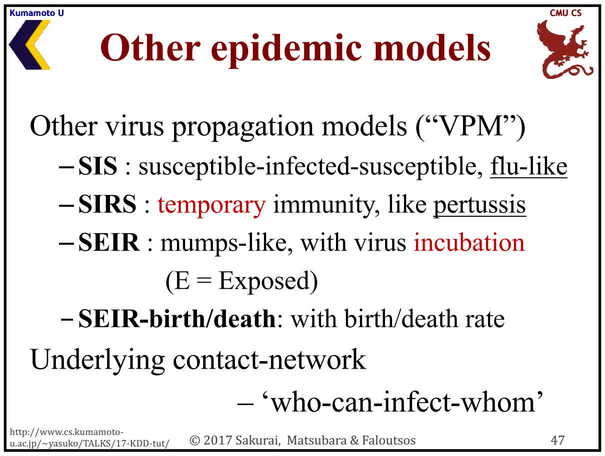
Susceptible-Infected-Recovered (SIR) model

Recovered with immunity

Phase plane: S(t) vs. I(t)

β : Infection rate

δ : Recovery rate



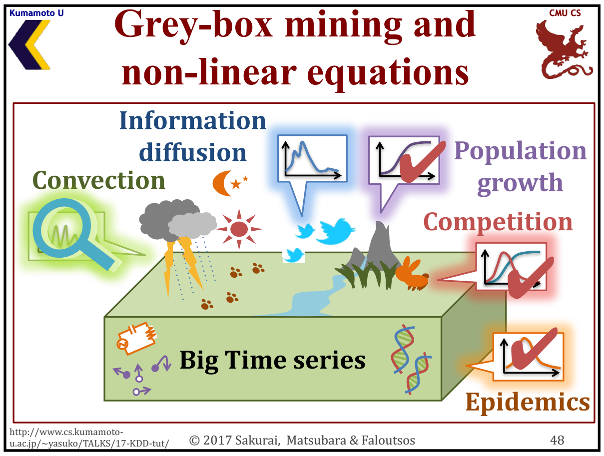
Other epidemic models

Other virus propagation models ("VPM")

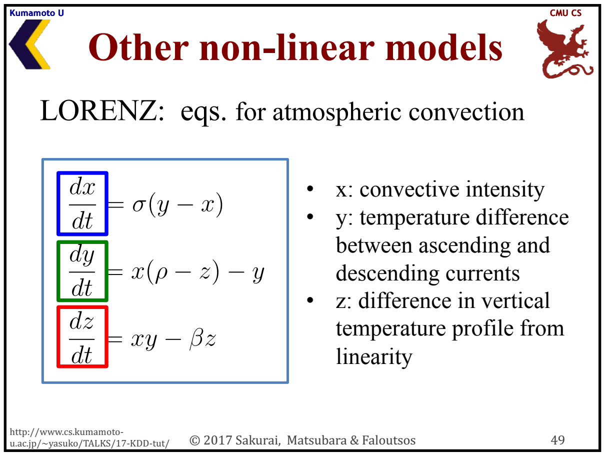
- **SIS** : susceptible-infected-susceptible, flu-like
- **SIRS** : temporary immunity, like pertussis
- **SEIR** : mumps-like, with virus incubation
  (E = Exposed)
- **SEIR-birth/death**: with birth/death rate

Underlying contact-network

– 'who-can-infect-whom'



Grey-box mining and non-linear equations

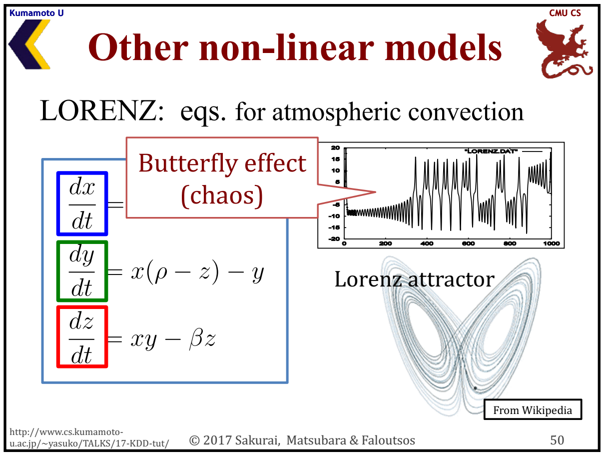


Other non-linear models

LORENZ: eqs. for atmospheric convection

$$\boxed{\frac{dx}{dt}} = \sigma(y-x)$$
$$\boxed{\frac{dy}{dt}} = x(\rho-z)-y$$
$$\boxed{\frac{dz}{dt}} = xy-\beta z$$

- x: convective intensity
- y: temperature difference between ascending and descending currents
- z: difference in vertical temperature profile from linearity



Other non-linear models

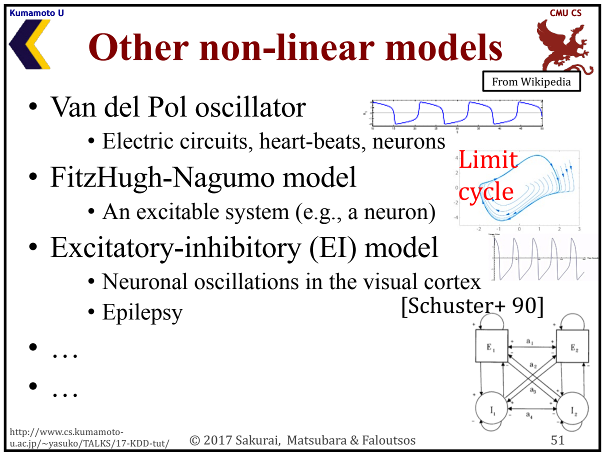
LORENZ: eqs. for atmospheric convection

$$\boxed{\frac{dx}{dt}} =$$
$$\boxed{\frac{dy}{dt}} = x(\rho-z)-y$$
$$\boxed{\frac{dz}{dt}} = xy-\beta z$$

Butterfly effect (chaos)

Lorenz attractor

From Wikipedia

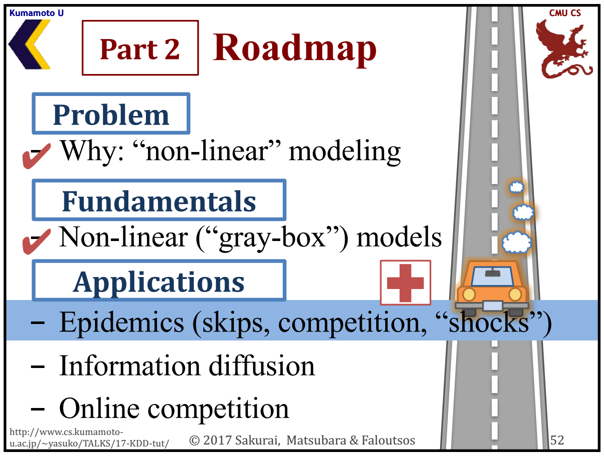


Other non-linear models

From Wikipedia

- Van del Pol oscillator
  - Electric circuits, heart-beats, neurons
- FitzHugh-Nagumo model
  - An excitable system (e.g., a neuron)
- Excitatory-inhibitory (EI) model
  - Neuronal oscillations in the visual cortex
  - Epilepsy [Schuster+ 90]
- …
- …

Limit cycle



Part 2 Roadmap

Problem

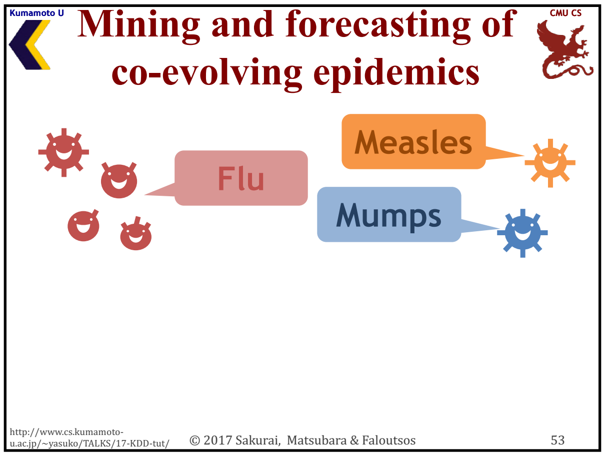
✓ Why: "non-linear" modeling

Fundamentals

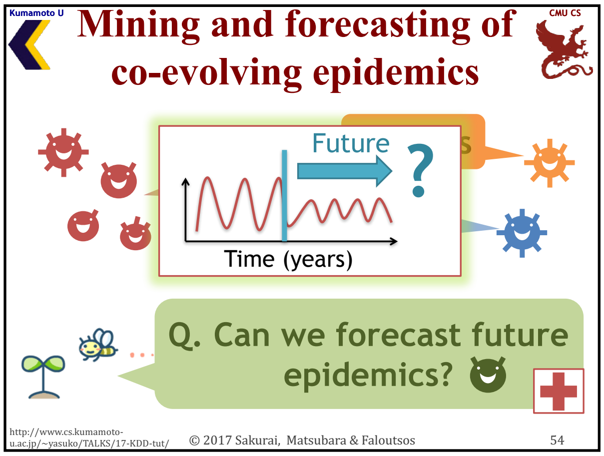
✓ Non-linear ("gray-box") models

Applications

- Epidemics (skips, competition, "shocks")
- Information diffusion
- Online competition

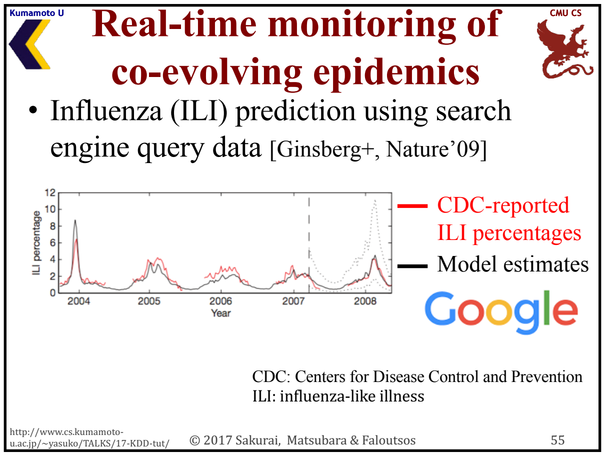


Mining and forecasting of co-evolving epidemics



Mining and forecasting of co-evolving epidemics

Q. Can we forecast future epidemics?

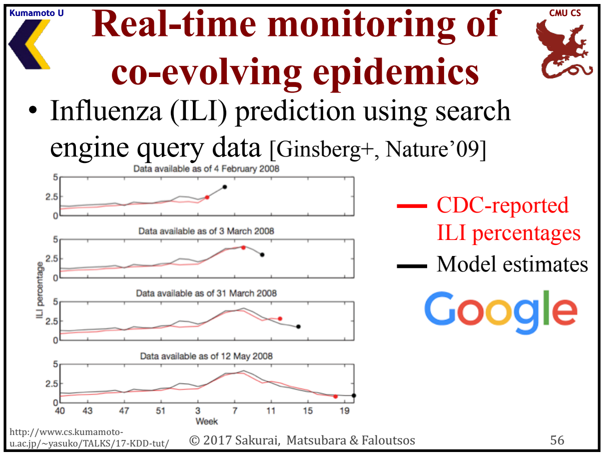


Real-time monitoring of co-evolving epidemics

- Influenza (ILI) prediction using search engine query data [Ginsberg+, Nature'09]

— CDC-reported ILI percentages
— Model estimates

CDC: Centers for Disease Control and Prevention
ILI: influenza-like illness



Real-time monitoring of co-evolving epidemics

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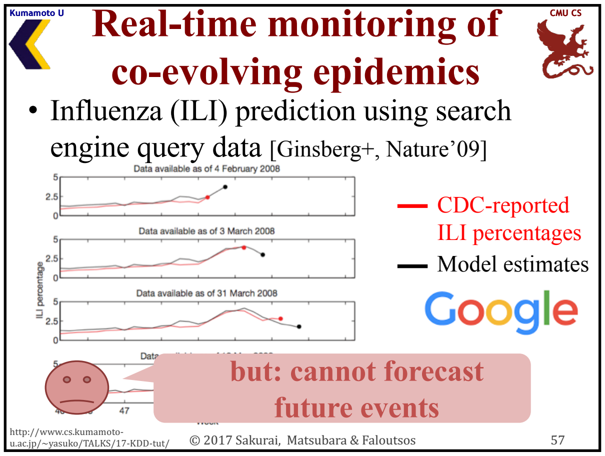
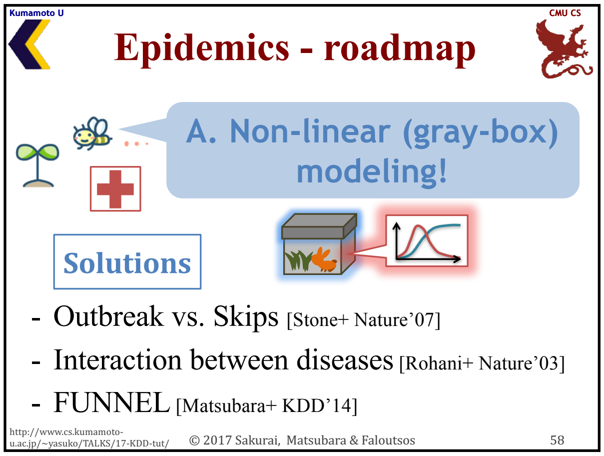


Real-time monitoring of co-evolving epidemics

- Influenza (ILI) prediction using search engine query data [Ginsberg+, Nature'09]

— CDC-reported ILI percentages
— Model estimates

but: cannot forecast future events

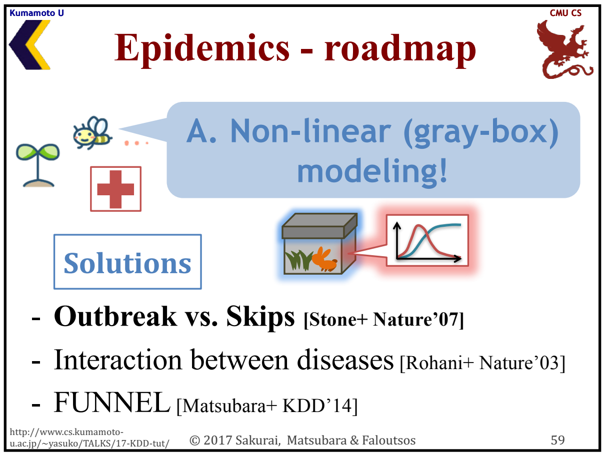


Epidemics - roadmap

A. Non-linear (gray-box) modeling!

Solutions

- Outbreak vs. Skips [Stone+ Nature'07]
- Interaction between diseases [Rohani+ Nature'03]
- FUNNEL [Matsubara+ KDD'14]



Epidemics - roadmap

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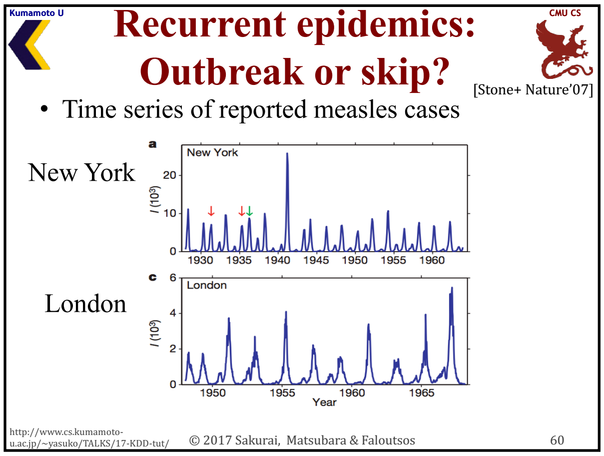


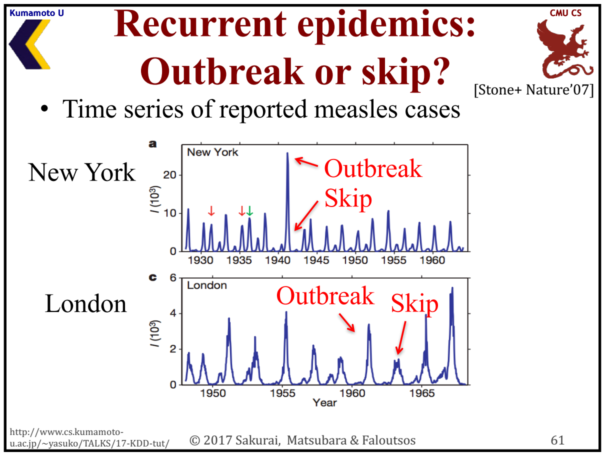
Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Time series of reported measles cases

New York

London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Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Time series of reported measles cases

New York

London

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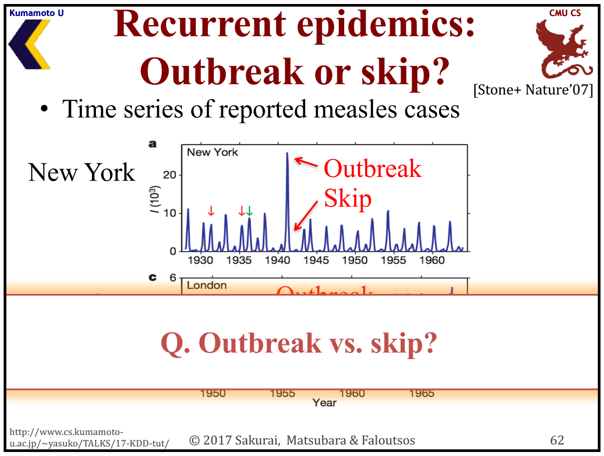
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Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Time series of reported measles cases

New York

Q. Outbreak vs. skip?

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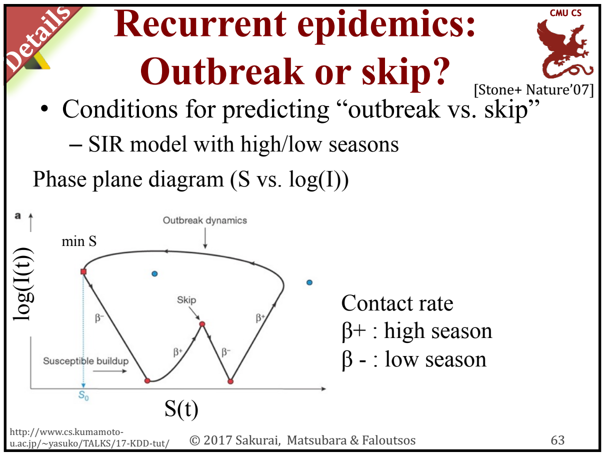
Details

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Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Conditions for predicting "outbreak vs. skip"
  - SIR model with high/low seasons

Phase plane diagram (S vs. log(I))

Contact rate

β+ : high season

β - : low season

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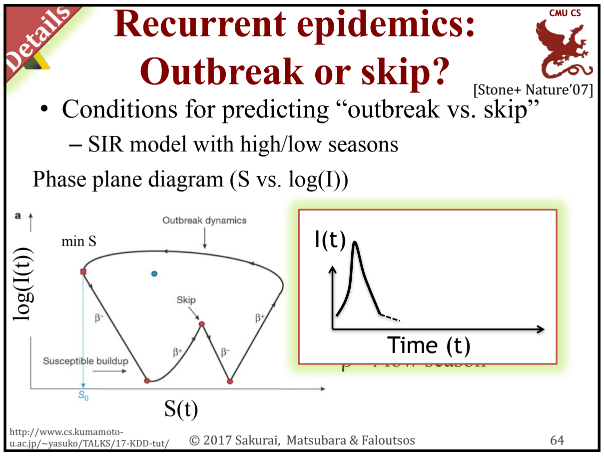
Details

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Recurrent epidemics: Outbreak or skip?

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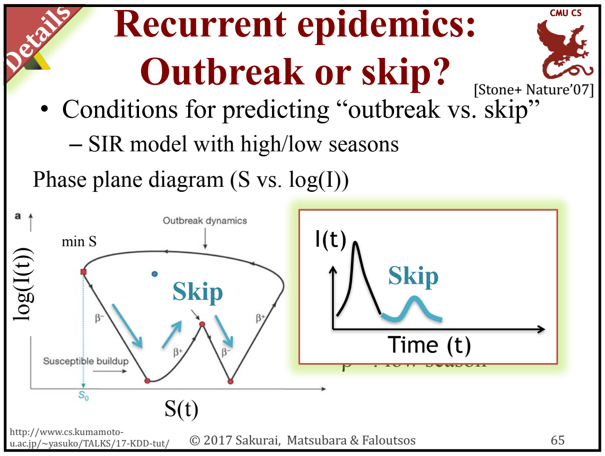
Details

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Recurrent epidemics: Outbreak or skip?

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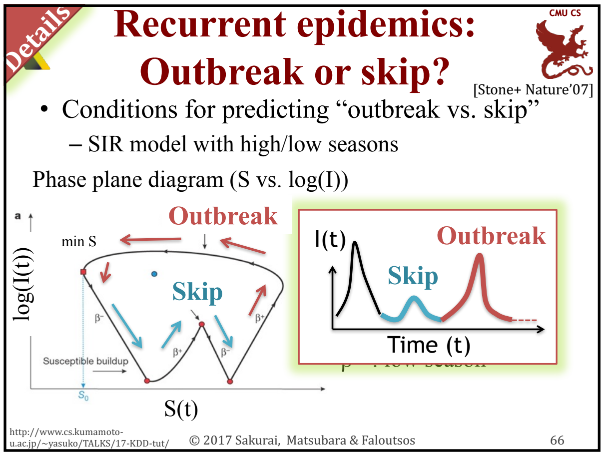
Details

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Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Conditions for predicting "outbreak vs. skip"
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Phase plane diagram (S vs. log(I))

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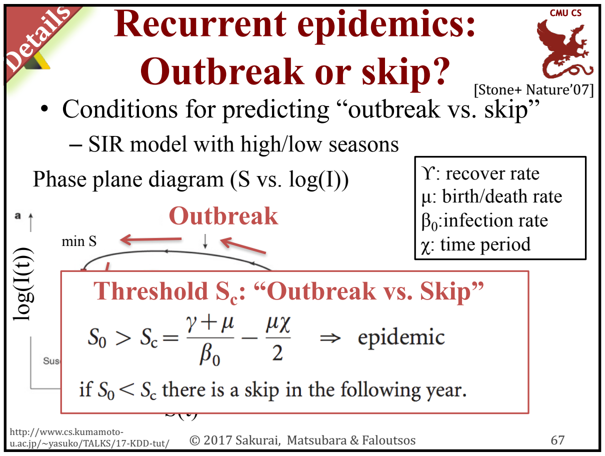


Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Conditions for predicting "outbreak vs. skip"
  - SIR model with high/low seasons

Phase plane diagram (S vs. log(I))

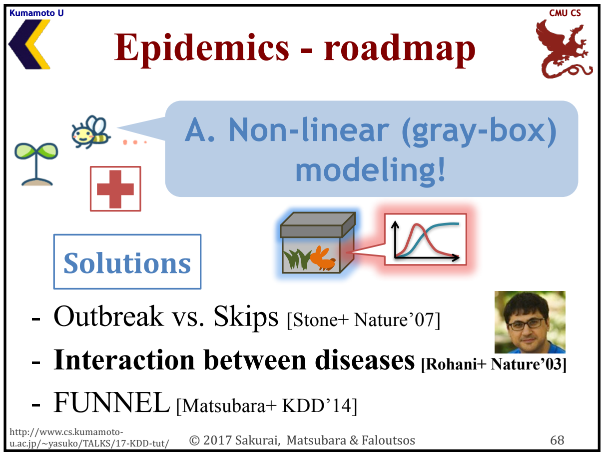
ϒ: recover rate
μ: birth/death rate
β_0:infection rate
χ: time period

Outbreak

Threshold S_c: "Outbreak vs. Skip"

$$S_0 > S_c = \frac{\gamma+\mu}{\beta_0} - \frac{\mu\chi}{2} \Rightarrow \text{epidemic}$$

if $S_0 < S_c$ there is a skip in the following year.



Epidemics - roadmap

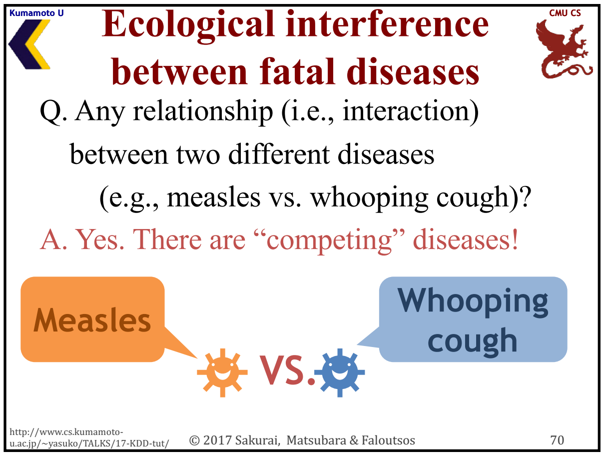
A. Non-linear (gray-box) modeling!

Solutions

- Outbreak vs. Skips [Stone+ Nature'07]
- **Interaction between diseases [Rohani+ Nature'03]**
- FUNNEL [Matsubara+ KDD'14]

Ecological interference between fatal diseases

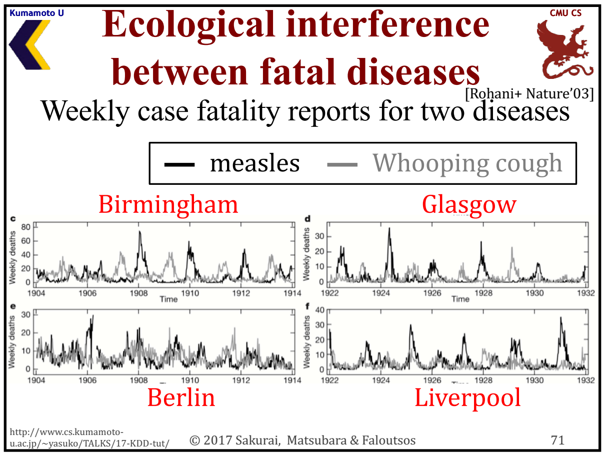
Q. Any relationship (i.e., interaction) between two different diseases (e.g., measles vs. whooping cough)?



Ecological interference between fatal diseases

Q. Any relationship (i.e., interaction) between two different diseases (e.g., measles vs. whooping cough)?

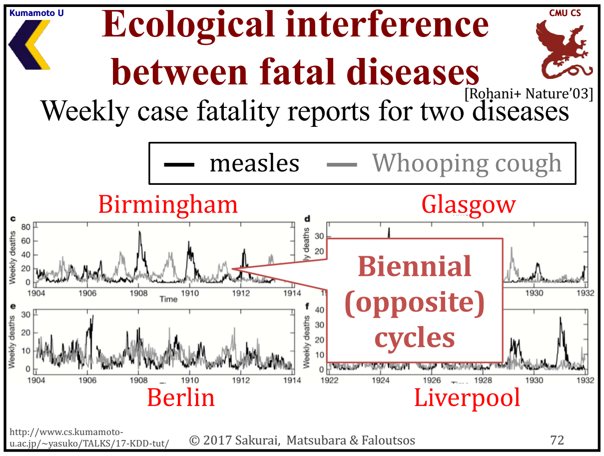
A. Yes. There are "competing" diseases!



Ecological interference between fatal diseases

[Rohani+ Nature'03]

Weekly case fatality reports for two diseases

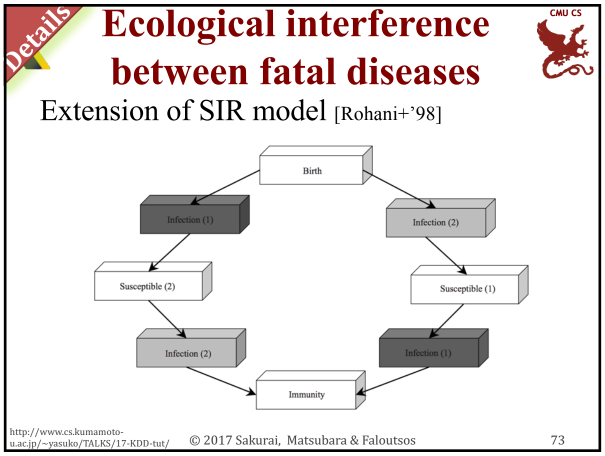


Ecological interference between fatal diseases

[Rohani+ Nature'03]

Weekly case fatality reports for two diseases

Biennial (opposite) cycles



Ecological interference between fatal diseases

Extension of SIR model [Rohani+'98]

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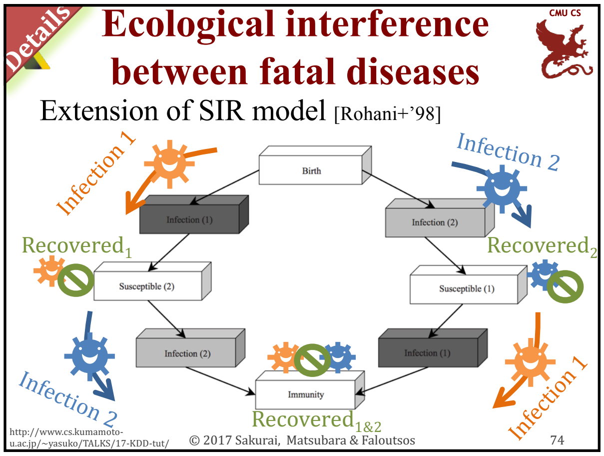

Ecological interference between fatal diseases

Extension of SIR model [Rohani+'98]

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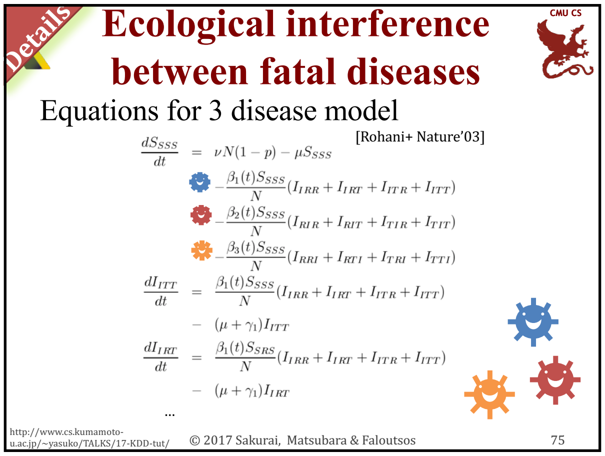

Ecological interference between fatal diseases

Equations for 3 disease model

[Rohani+ Nature'03]

$$\begin{aligned}\frac{dS_{SSS}}{dt} &= \nu N(1-p) - \mu S_{SSS}\\ &\quad -\frac{\beta_1(t)S_{SSS}}{N}(I_{IRR}+I_{IRT}+I_{ITR}+I_{ITT})\\ &\quad -\frac{\beta_2(t)S_{SSS}}{N}(I_{RIR}+I_{RIT}+I_{TIR}+I_{TIT})\\ &\quad -\frac{\beta_3(t)S_{SSS}}{N}(I_{RRI}+I_{RTI}+I_{TRI}+I_{TTI})\\ \frac{dI_{ITT}}{dt} &= \frac{\beta_1(t)S_{SSS}}{N}(I_{IRR}+I_{IRT}+I_{ITR}+I_{ITT})\\ &- (\mu+\gamma_1)I_{ITT}\\ \frac{dI_{IRT}}{dt} &= \frac{\beta_1(t)S_{SRS}}{N}(I_{IRR}+I_{IRT}+I_{ITR}+I_{ITT})\\ &- (\mu+\gamma_1)I_{IRT}\end{aligned}$$

...

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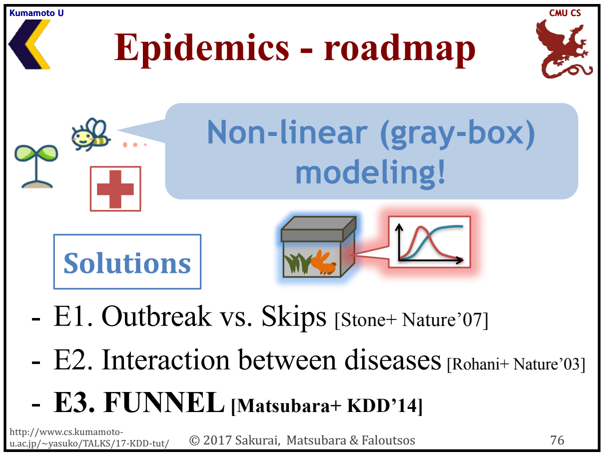

Epidemics - roadmap

Non-linear (gray-box) modeling!

Solutions

- E1. Outbreak vs. Skips [Stone+ Nature'07]
- E2. Interaction between diseases [Rohani+ Nature'03]
- **E3. FUNNEL [Matsubara+ KDD'14]**

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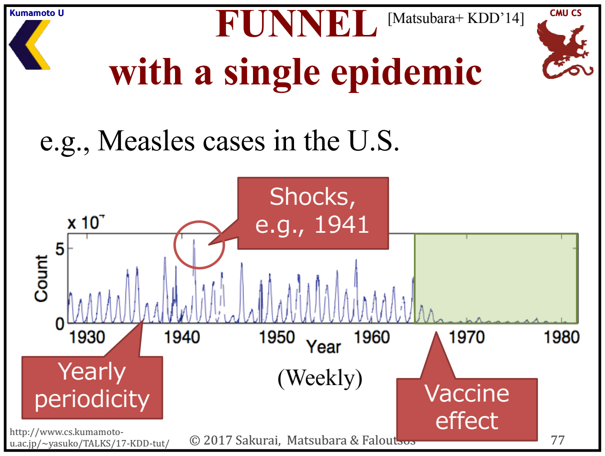

FUNNEL [Matsubara+ KDD'14] with a single epidemic

e.g., Measles cases in the U.S.

(Weekly)

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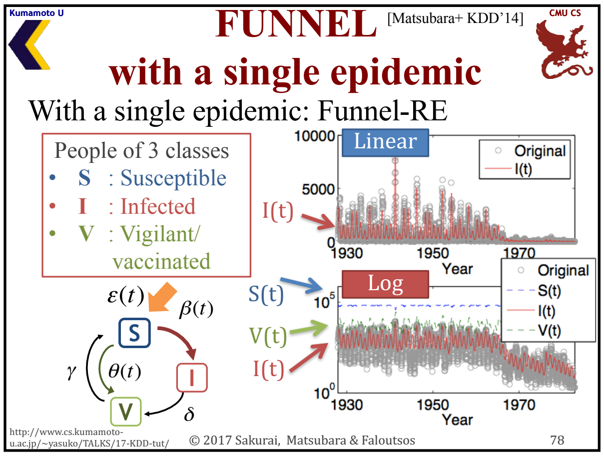

FUNNEL [Matsubara+ KDD'14] with a single epidemic

With a single epidemic: Funnel-RE

People of 3 classes
- **S** : Susceptible
- **I** : Infected
- **V** : Vigilant/ vaccinated

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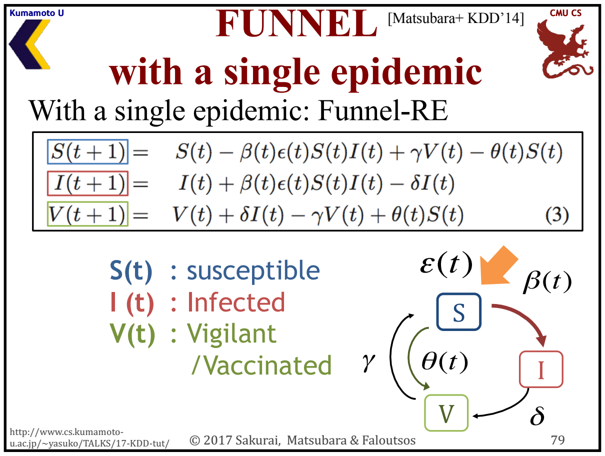

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FUNNEL [Matsubara+ KDD'14]
with a single epidemic

With a single epidemic: Funnel-RE

$$\boxed{S(t+1)} = S(t) - \beta(t)\epsilon(t)S(t)I(t) + \gamma V(t) - \theta(t)S(t)$$
$$\boxed{I(t+1)} = I(t) + \beta(t)\epsilon(t)S(t)I(t) - \delta I(t)$$
$$\boxed{V(t+1)} = V(t) + \delta I(t) - \gamma V(t) + \theta(t)S(t) \quad (3)$$

S(t) : susceptible
I (t) : Infected
V(t) : Vigilant /Vaccinated

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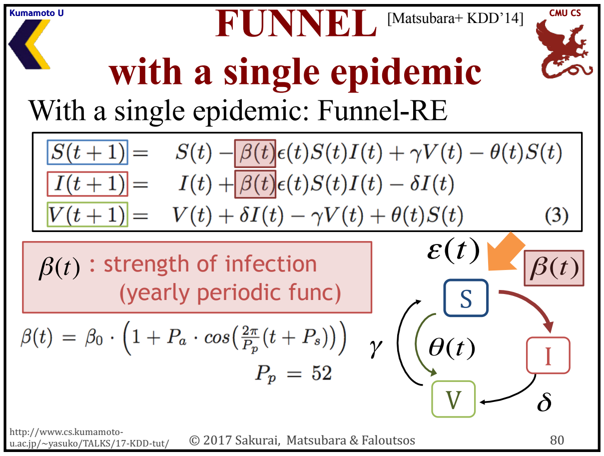

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with a single epidemic

With a single epidemic: Funnel-RE

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$$\boxed{I(t+1)} = I(t) + \boxed{\beta(t)}\epsilon(t)S(t)I(t) - \delta I(t)$$
$$\boxed{V(t+1)} = V(t) + \delta I(t) - \gamma V(t) + \theta(t)S(t) \quad (3)$$

$\beta(t)$: strength of infection (yearly periodic func)

$$\beta(t) = \beta_0 \cdot \left(1 + P_a \cdot cos\left(\frac{2\pi}{P_p}(t + P_s)\right)\right)$$
$$P_p = 52$$

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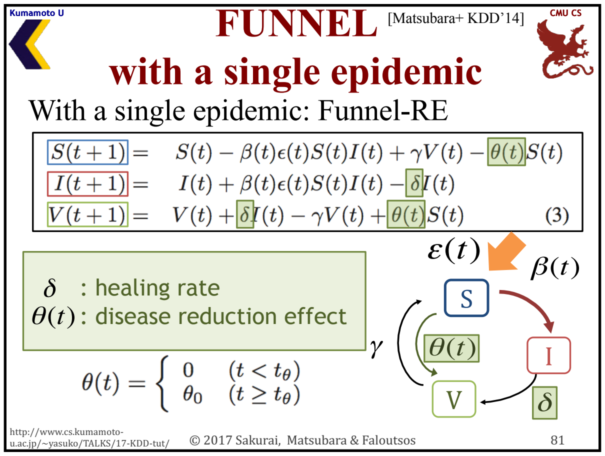

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FUNNEL [Matsubara+ KDD'14]
with a single epidemic

With a single epidemic: Funnel-RE

$$\boxed{S(t+1)} = S(t) - \beta(t)\epsilon(t)S(t)I(t) + \gamma V(t) - \boxed{\theta(t)}S(t)$$
$$\boxed{I(t+1)} = I(t) + \beta(t)\epsilon(t)S(t)I(t) - \boxed{\delta}I(t)$$
$$\boxed{V(t+1)} = V(t) + \boxed{\delta}I(t) - \gamma V(t) + \boxed{\theta(t)}S(t) \quad (3)$$

δ : healing rate
$\theta(t)$: disease reduction effect

$$\theta(t) = \begin{cases} 0 & (t < t_\theta) \\ \theta_0 & (t \geq t_\theta) \end{cases}$$

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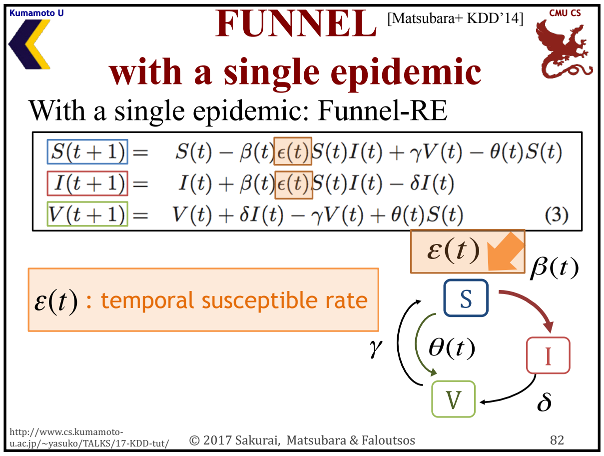

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FUNNEL [Matsubara+ KDD'14]
with a single epidemic

With a single epidemic: Funnel-RE

$$\boxed{S(t+1)} = S(t) - \beta(t)\boxed{\epsilon(t)}S(t)I(t) + \gamma V(t) - \theta(t)S(t)$$
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$$\boxed{V(t+1)} = V(t) + \delta I(t) - \gamma V(t) + \theta(t)S(t) \quad (3)$$

$\varepsilon(t)$: temporal susceptible rate

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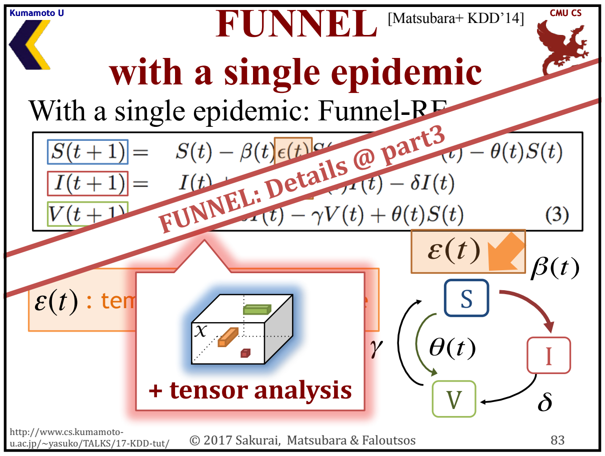

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FUNNEL [Matsubara+ KDD'14]
with a single epidemic

With a single epidemic: Funnel-RE

$$\boxed{S(t+1)} = S(t) - \beta(t)\boxed{\epsilon(t)}S \quad \theta(t)S(t)$$
$$\boxed{I(t+1)} = I(t \quad I(t) - \delta I(t)$$
$$\boxed{V(t+1} \quad I(t) - \gamma V(t) + \theta(t)S(t) \quad (3)$$

FUNNEL: Details @ part3

$\varepsilon(t)$: tem

+ tensor analysis

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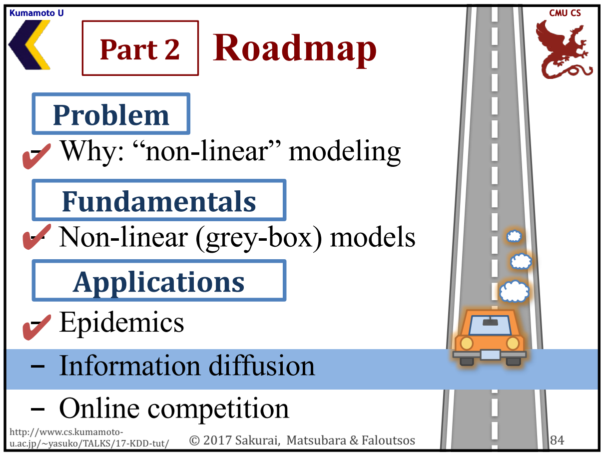

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Part 2 Roadmap

Problem
✓ Why: "non-linear" modeling

Fundamentals
✓ Non-linear (grey-box) models

Applications
✓ Epidemics
– Information diffusion
– Online competition

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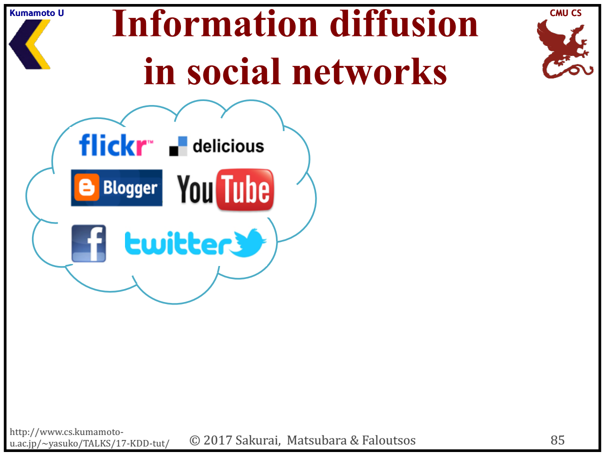

Information diffusion in social networks

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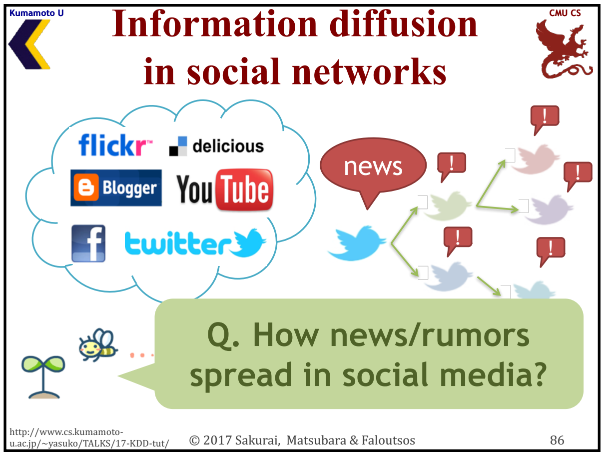

Information diffusion in social networks

Q. How news/rumors spread in social media?

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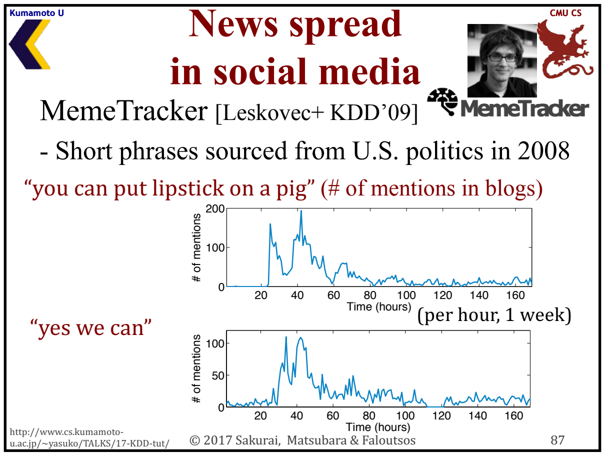

News spread in social media

MemeTracker [Leskovec+ KDD'09]

- Short phrases sourced from U.S. politics in 2008

"you can put lipstick on a pig" (# of mentions in blogs)

(per hour, 1 week)

"yes we can"

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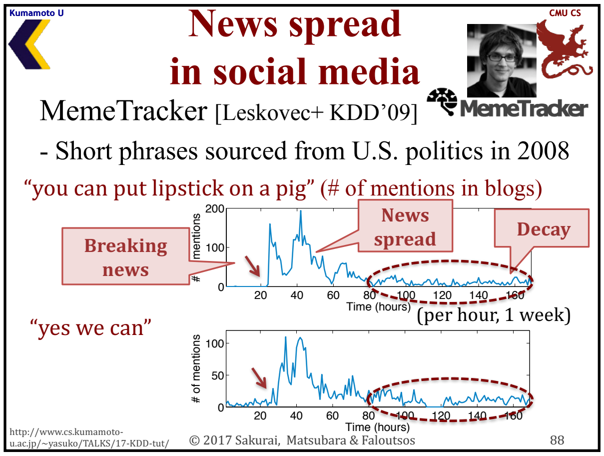

News spread in social media

MemeTracker [Leskovec+ KDD'09]

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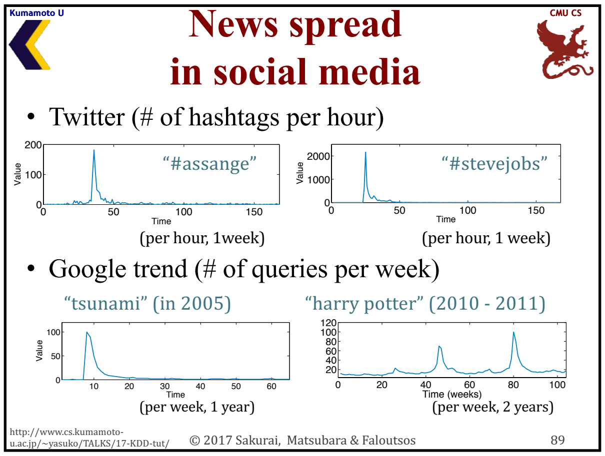

News spread in social media

- Twitter (# of hashtags per hour)

(per hour, 1week) (per hour, 1 week)

- Google trend (# of queries per week)

"tsunami" (in 2005) "harry potter" (2010 - 2011)

(per week, 1 year) (per week, 2 years)

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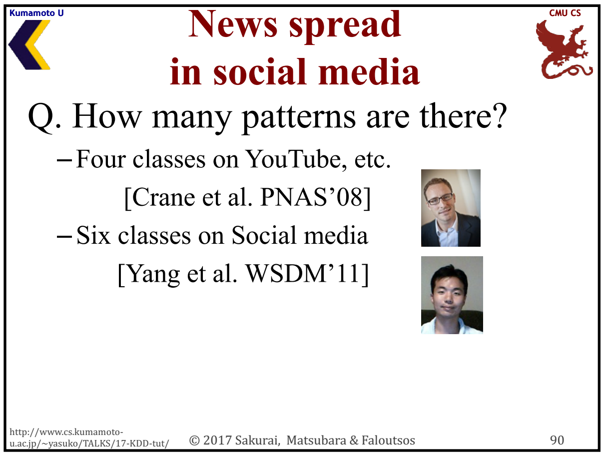

News spread in social media

Q. How many patterns are there?

- Four classes on YouTube, etc. [Crane et al. PNAS'08]
- Six classes on Social media [Yang et al. WSDM'11]

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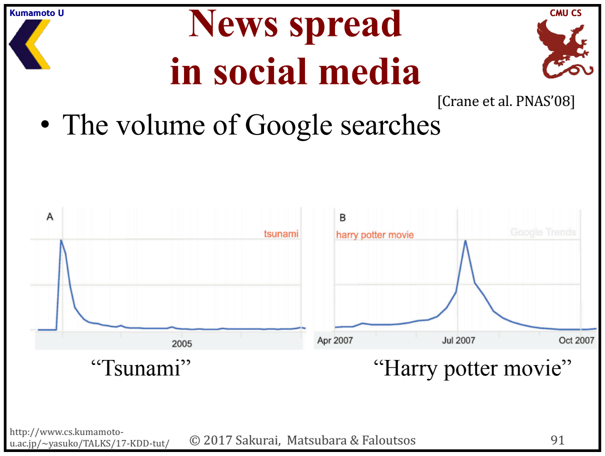
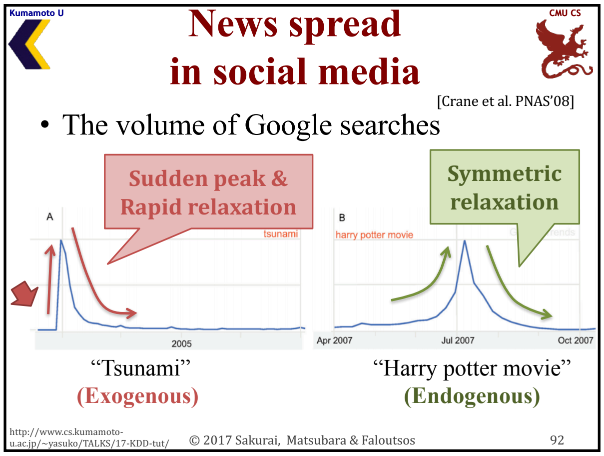


News spread in social media

[Crane et al. PNAS'08]

- The volume of Google searches

"Tsunami" "Harry potter movie"



News spread in social media

[Crane et al. PNAS'08]

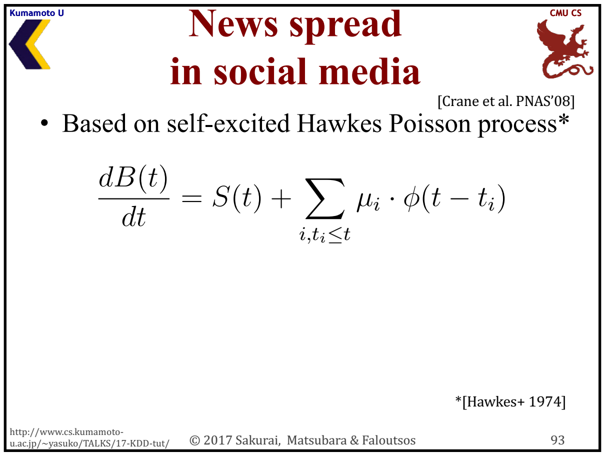
- The volume of Google searches

Sudden peak & Rapid relaxation

Symmetric relaxation

"Tsunami" (Exogenous)

"Harry potter movie" (Endogenous)



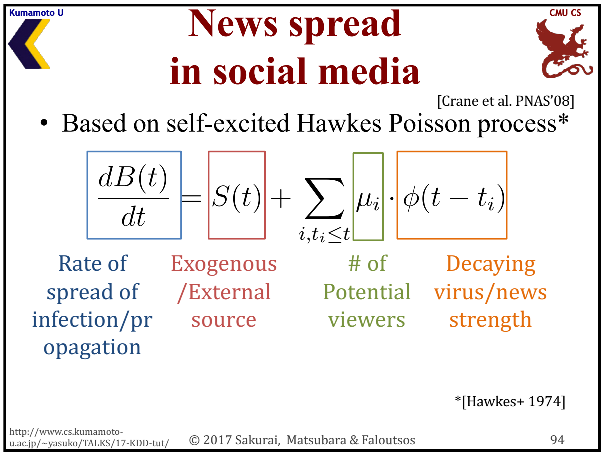
News spread in social media

[Crane et al. PNAS'08]

- Based on self-excited Hawkes Poisson process*

$$\frac{dB(t)}{dt} = S(t) + \sum_{i,t_i \le t} \mu_i \cdot \phi(t - t_i)$$

*[Hawkes+ 1974]



News spread in social media

[Crane et al. PNAS'08]

- Based on self-excited Hawkes Poisson process*

$$\boxed{\frac{dB(t)}{dt}} = \boxed{S(t)} + \sum_{i,t_i \le t} \boxed{\mu_i} \cdot \boxed{\phi(t - t_i)}$$

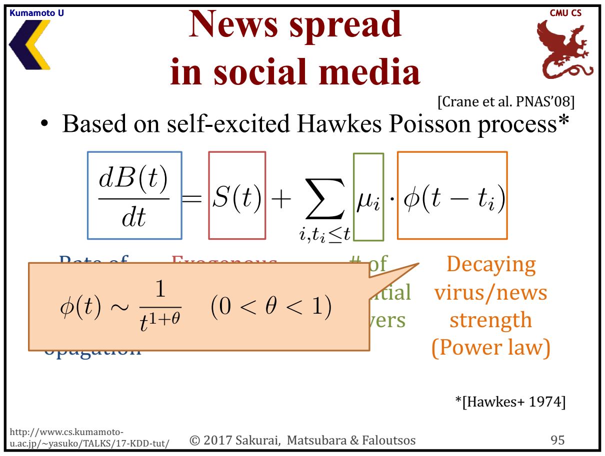
Rate of spread of infection/propagation

Exogenous /External source

# of Potential viewers

Decaying virus/news strength

*[Hawkes+ 1974]



News spread in social media

[Crane et al. PNAS'08]

- Based on self-excited Hawkes Poisson process*

$$\boxed{\frac{dB(t)}{dt}} = \boxed{S(t)} + \sum_{i,t_i \le t} \boxed{\mu_i} \cdot \boxed{\phi(t - t_i)}$$

Rate of Exogenous # of

tial

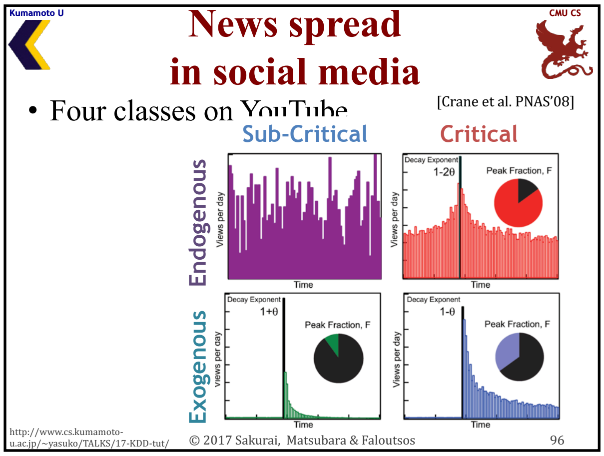
vers

opagation

$$\phi(t) \sim \frac{1}{t^{1+\theta}} \quad (0 < \theta < 1)$$

Decaying virus/news strength (Power law)

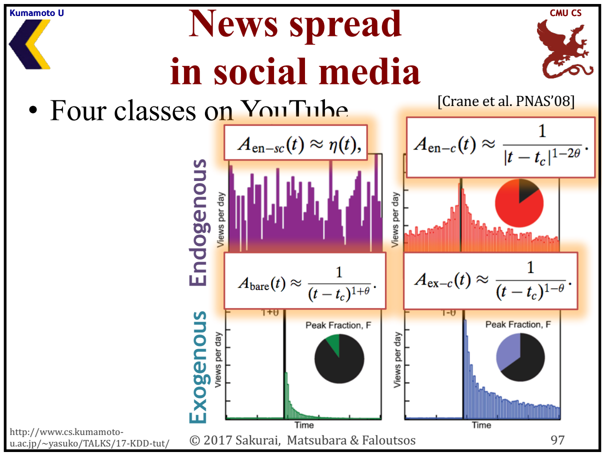
*[Hawkes+ 1974]



News spread in social media

[Crane et al. PNAS'08]

- Four classes on YouTube



News spread in social media

- Four classes on YouTube

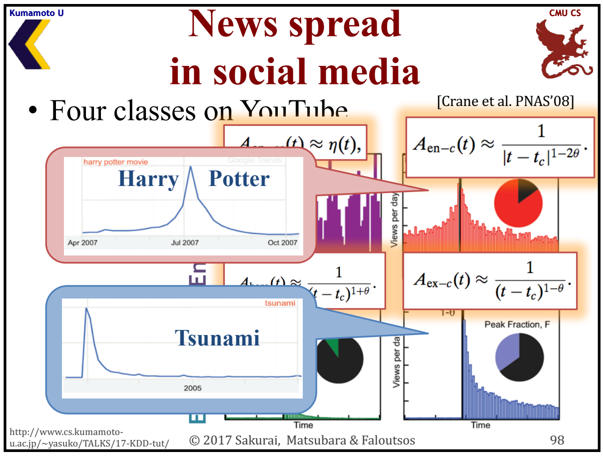
[Crane et al. PNAS'08]

$A_{en-sc}(t) \approx \eta(t),$

$A_{en-c}(t) \approx \frac{1}{|t-t_c|^{1-2\theta}}.$

$A_{bare}(t) \approx \frac{1}{(t-t_c)^{1+\theta}}.$

$A_{ex-c}(t) \approx \frac{1}{(t-t_c)^{1-\theta}}.$



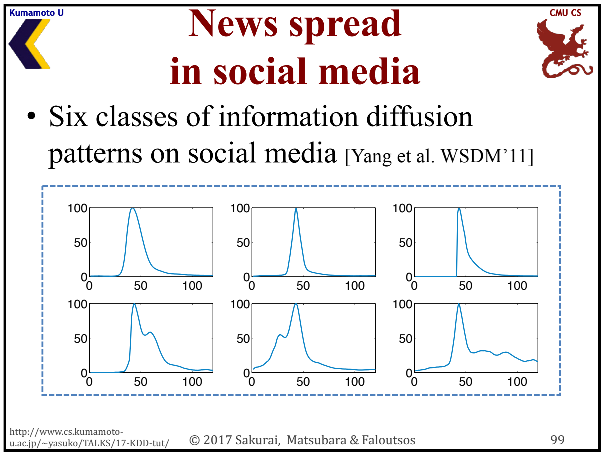
News spread in social media

- Four classes on YouTube

[Crane et al. PNAS'08]

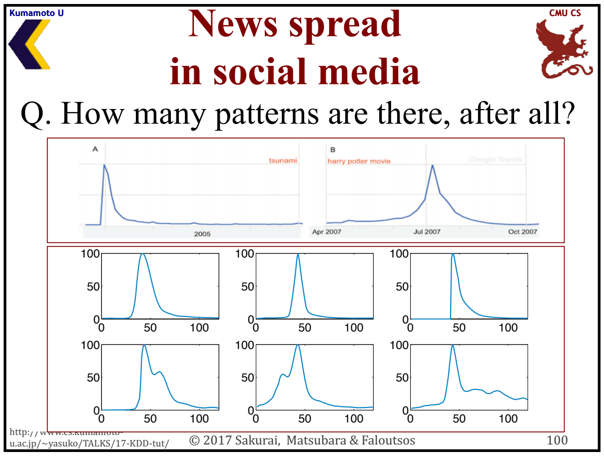
$A_{en-c}(t) \approx \frac{1}{|t-t_c|^{1-2\theta}}.$

$A_{ex-c}(t) \approx \frac{1}{(t-t_c)^{1-\theta}}.$



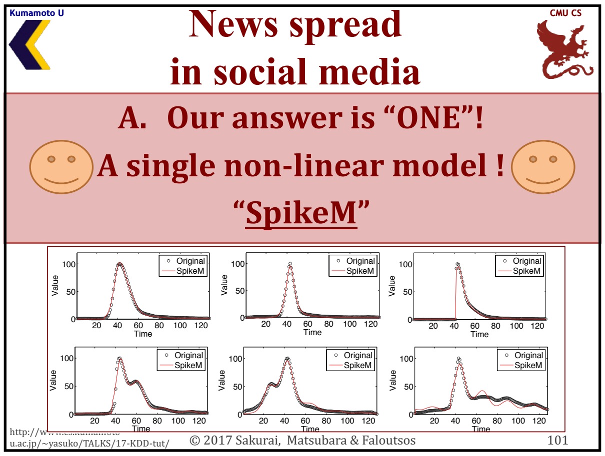
News spread in social media

- Six classes of information diffusion patterns on social media [Yang et al. WSDM'11]



News spread in social media

Q. How many patterns are there, after all?

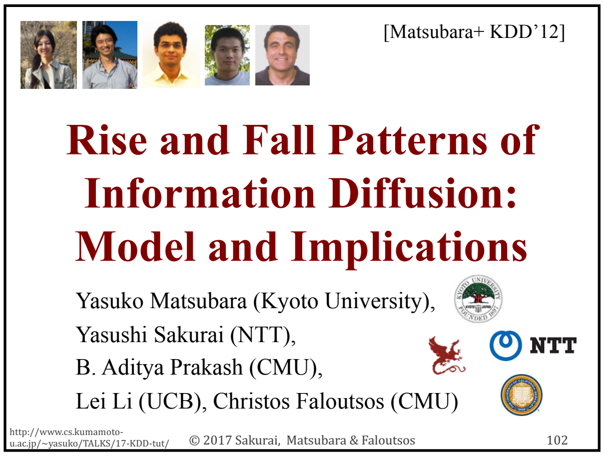


News spread in social media

A. Our answer is "ONE"!

A single non-linear model !

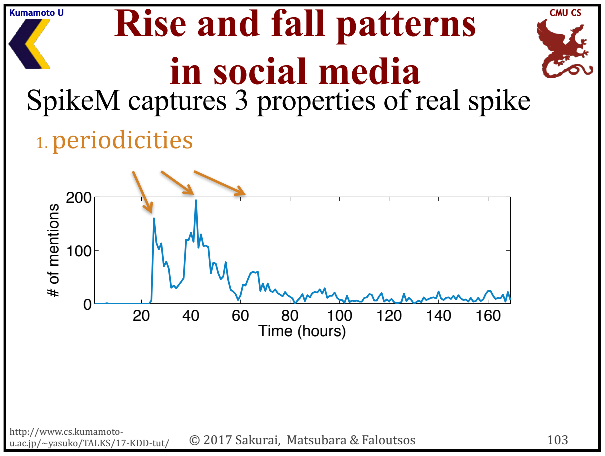
"SpikeM"



[Matsubara+ KDD'12]

Rise and Fall Patterns of Information Diffusion: Model and Implications

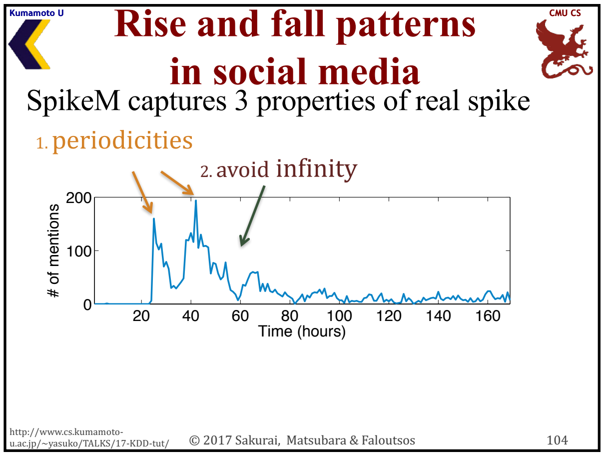
Yasuko Matsubara (Kyoto University),
Yasushi Sakurai (NTT),
B. Aditya Prakash (CMU),
Lei Li (UCB), Christos Faloutsos (CMU)



Rise and fall patterns in social media

SpikeM captures 3 properties of real spike

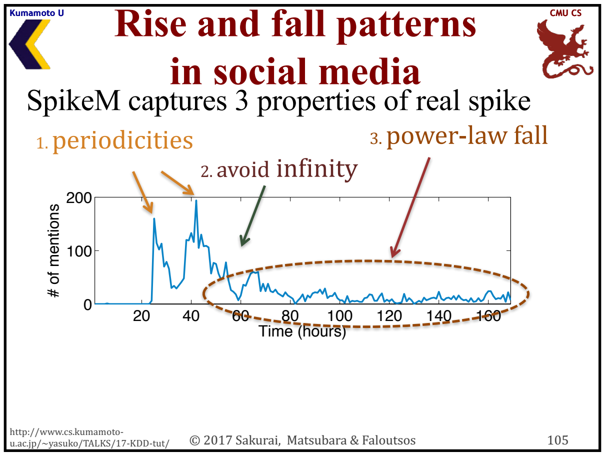
1. periodicities



Rise and fall patterns in social media

SpikeM captures 3 properties of real spike

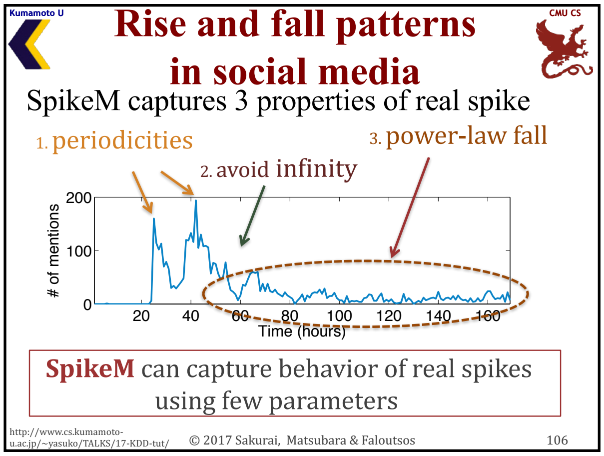
1. periodicities
2. avoid infinity



Rise and fall patterns in social media

SpikeM captures 3 properties of real spike

1. periodicities
2. avoid infinity
3. power-law fall

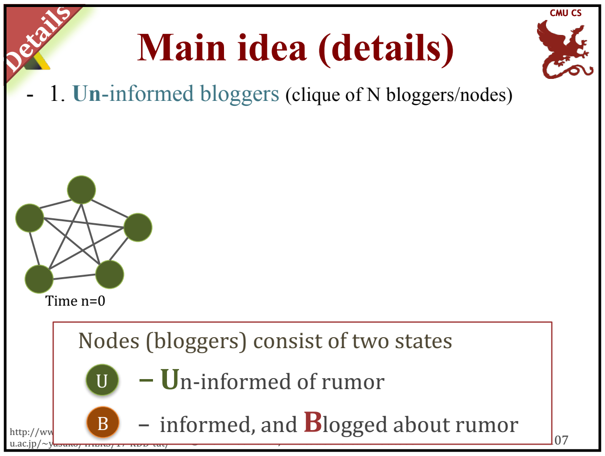


Rise and fall patterns in social media

SpikeM captures 3 properties of real spike

1. periodicities
2. avoid infinity
3. power-law fall

SpikeM can capture behavior of real spikes using few parameters



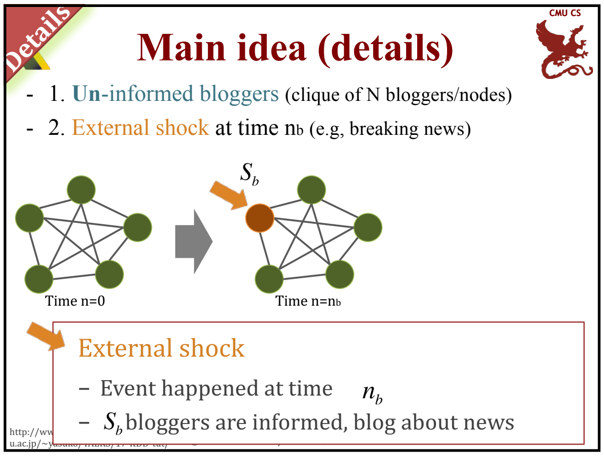
Main idea (details)

- 1. **Un**-informed bloggers (clique of N bloggers/nodes)

Nodes (bloggers) consist of two states

U – **U**n-informed of rumor

B – informed, and **B**logged about rumor

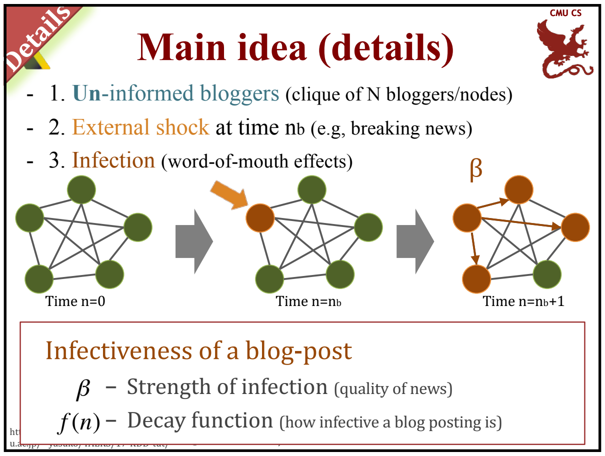


Main idea (details)

- 1. **Un**-informed bloggers (clique of N bloggers/nodes)
- 2. External shock at time n_b (e.g, breaking news)

External shock

- Event happened at time n_b
- S_b bloggers are informed, blog about news



Details

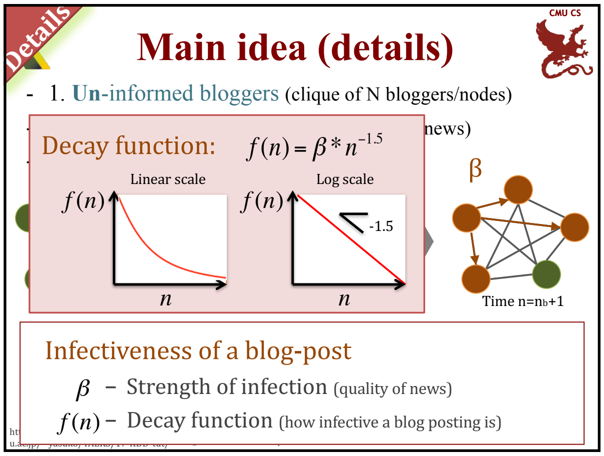
Main idea (details)

- 1. Un-informed bloggers (clique of N bloggers/nodes)
- 2. External shock at time nb (e.g, breaking news)
- 3. Infection (word-of-mouth effects)

Infectiveness of a blog-post

β – Strength of infection (quality of news)

$f(n)$ – Decay function (how infective a blog posting is)



Details

Main idea (details)

- 1. Un-informed bloggers (clique of N bloggers/nodes)

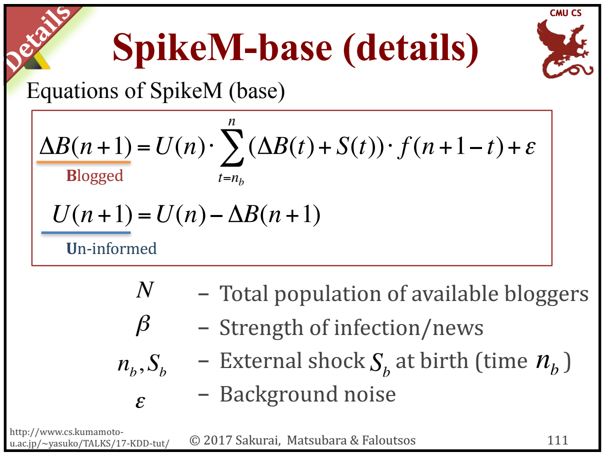
news)

Decay function: $f(n) = \beta * n^{-1.5}$

Infectiveness of a blog-post

β – Strength of infection (quality of news)

$f(n)$ – Decay function (how infective a blog posting is)



Details

SpikeM-base (details)

Equations of SpikeM (base)

$$\underbrace{\Delta B(n+1)}_{\text{Blogged}} = U(n)\cdot\sum_{t=n_b}^{n}(\Delta B(t)+S(t))\cdot f(n+1-t)+\varepsilon$$

$$\underbrace{U(n+1)}_{\text{Un-informed}} = U(n)-\Delta B(n+1)$$

N – Total population of available bloggers

β – Strength of infection/news

n_b, S_b – External shock S_b at birth (time n_b)

ε – Background noise

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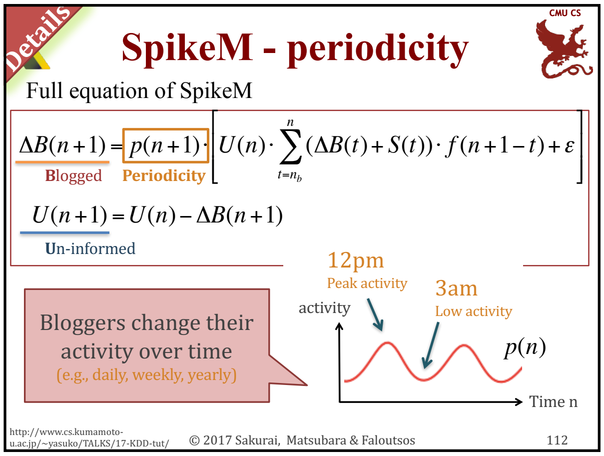

Details

SpikeM - periodicity

Full equation of SpikeM

$$\underbrace{\Delta B(n+1)}_{\text{Blogged}} = \underbrace{\boxed{p(n+1)}}_{\text{Periodicity}}\cdot\left[U(n)\cdot\sum_{t=n_b}^{n}(\Delta B(t)+S(t))\cdot f(n+1-t)+\varepsilon\right]$$

$$\underbrace{U(n+1)}_{\text{Un-informed}} = U(n)-\Delta B(n+1)$$

Bloggers change their activity over time (e.g., daily, weekly, yearly)

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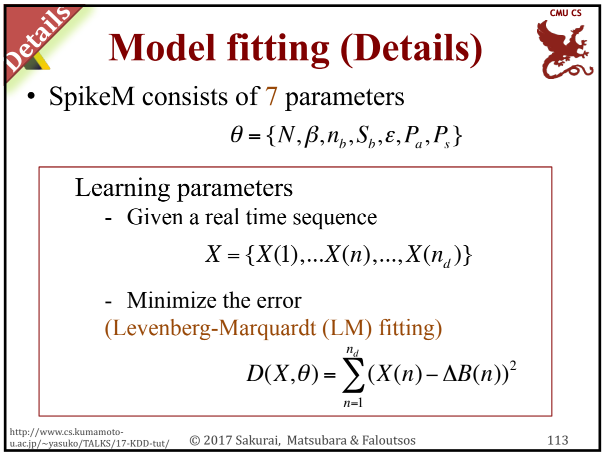

Details

Model fitting (Details)

- SpikeM consists of 7 parameters

$$\theta = \{N, \beta, n_b, S_b, \varepsilon, P_a, P_s\}$$

Learning parameters

- Given a real time sequence

$$X = \{X(1), \ldots X(n), \ldots, X(n_d)\}$$

- Minimize the error (Levenberg-Marquardt (LM) fitting)

$$D(X,\theta) = \sum_{n=1}^{n_d}(X(n)-\Delta B(n))^2$$

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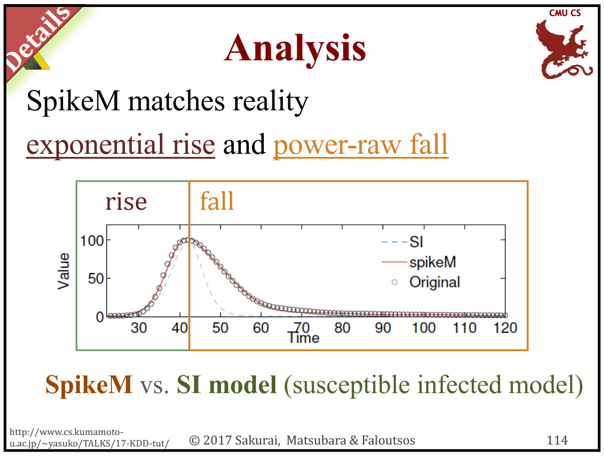

Details

Analysis

SpikeM matches reality

exponential rise and power-raw fall

SpikeM vs. SI model (susceptible infected model)

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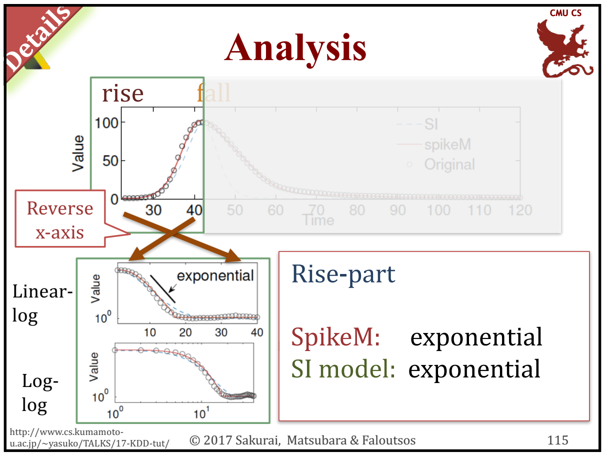


Analysis

Reverse x-axis

Linear-log

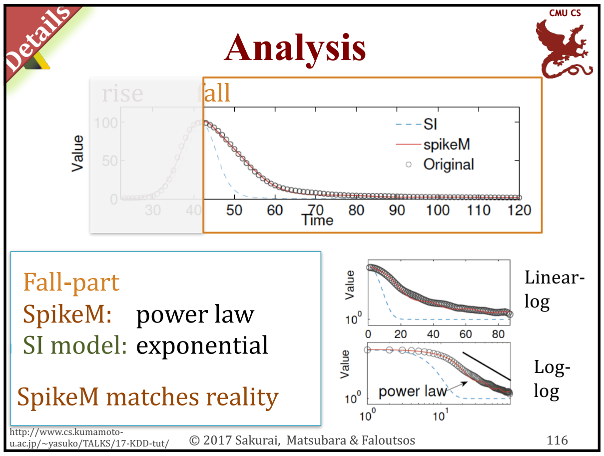
Log-log

exponential

Rise-part

SpikeM: exponential

SI model: exponential



Analysis

Fall-part

SpikeM: power law

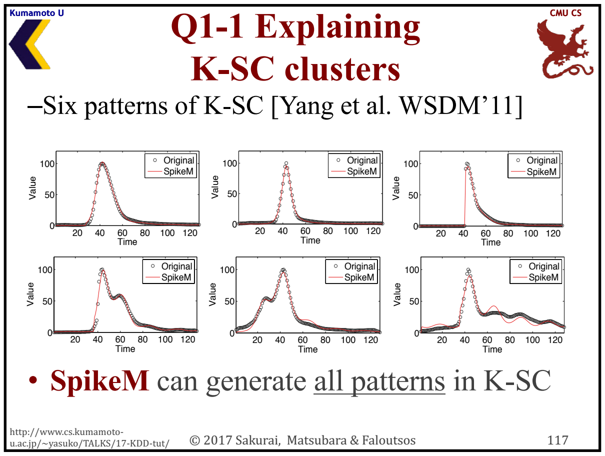
SI model: exponential

SpikeM matches reality

Linear-log

Log-log

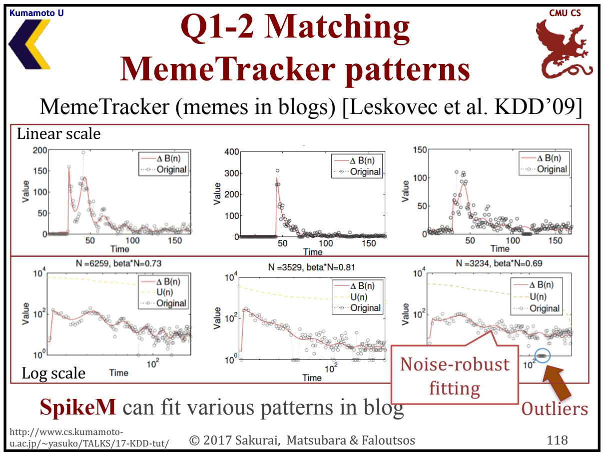
power law



Q1-1 Explaining K-SC clusters

–Six patterns of K-SC [Yang et al. WSDM'11]

- **SpikeM** can generate all patterns in K-SC



Q1-2 Matching MemeTracker patterns

MemeTracker (memes in blogs) [Leskovec et al. KDD'09]

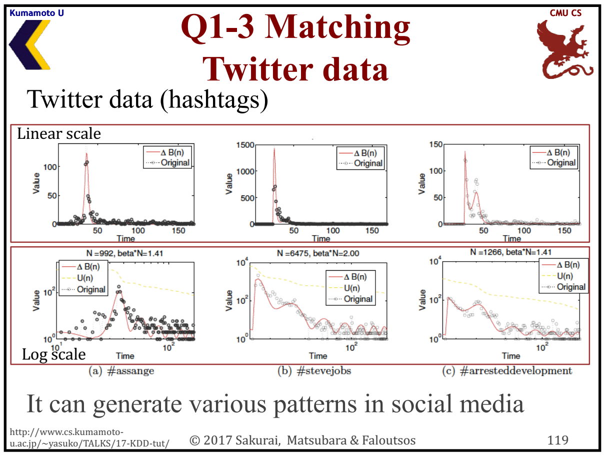
Linear scale

Log scale

Noise-robust fitting

Outliers

SpikeM can fit various patterns in blog



Q1-3 Matching Twitter data

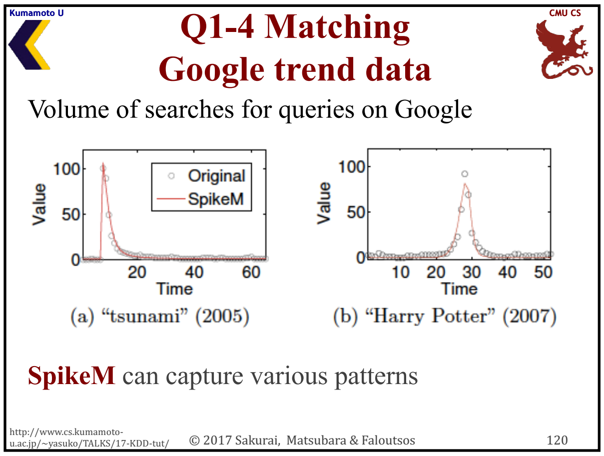
Twitter data (hashtags)

Linear scale

Log scale

(a) #assange (b) #stevejobs (c) #arresteddevelopment

It can generate various patterns in social media

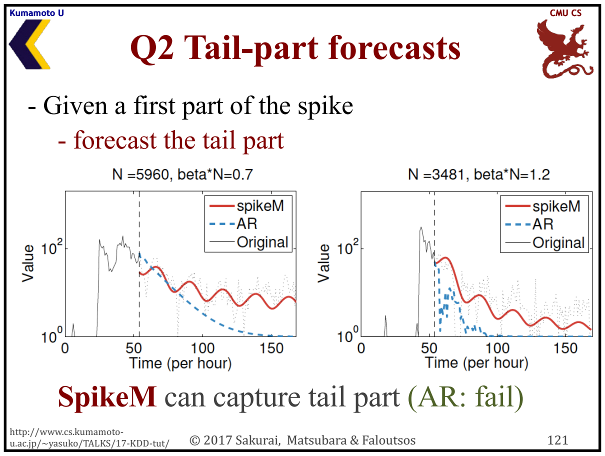


Q1-4 Matching Google trend data

Volume of searches for queries on Google

(a) "tsunami" (2005) (b) "Harry Potter" (2007)

SpikeM can capture various patterns



Q2 Tail-part forecasts

- Given a first part of the spike
  - forecast the tail part

SpikeM can capture tail part (AR: fail)

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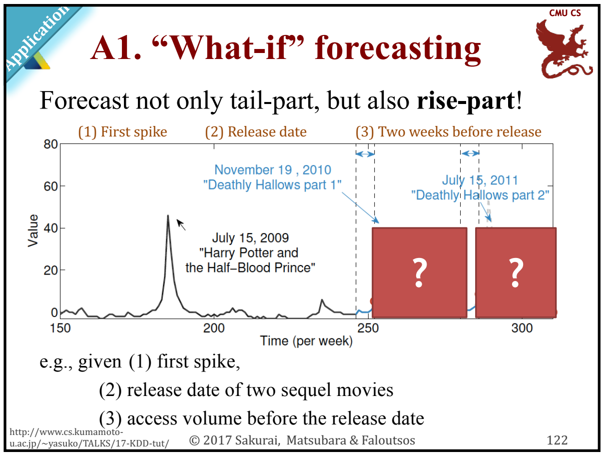

A1. “What-if” forecasting

Forecast not only tail-part, but also **rise-part**!

e.g., given (1) first spike,

(2) release date of two sequel movies

(3) access volume before the release date

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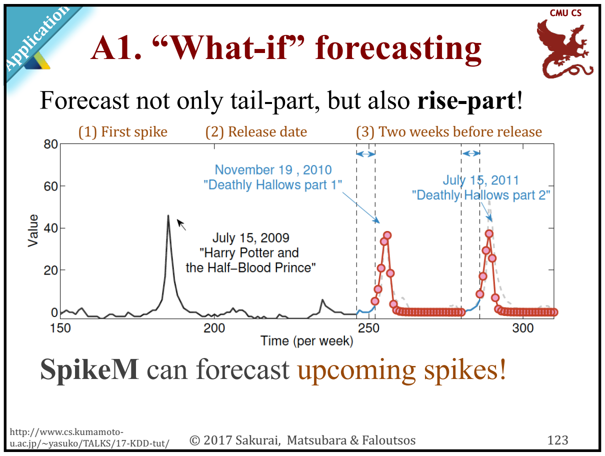

A1. “What-if” forecasting

Forecast not only tail-part, but also **rise-part**!

SpikeM can forecast upcoming spikes!

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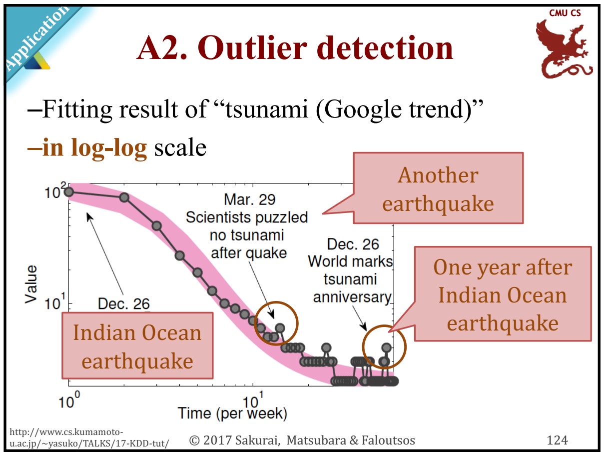

A2. Outlier detection

–Fitting result of “tsunami (Google trend)”

–**in log-log** scale

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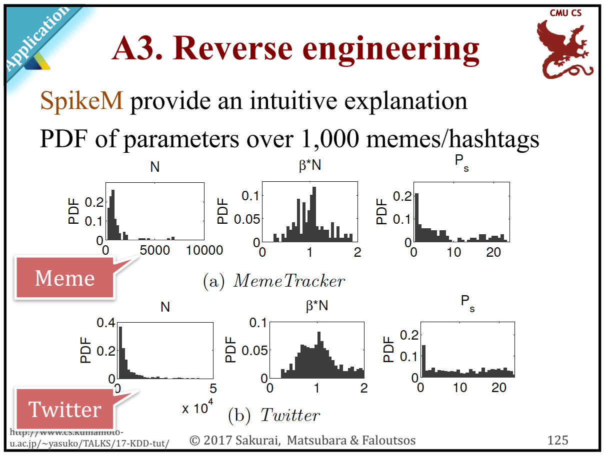
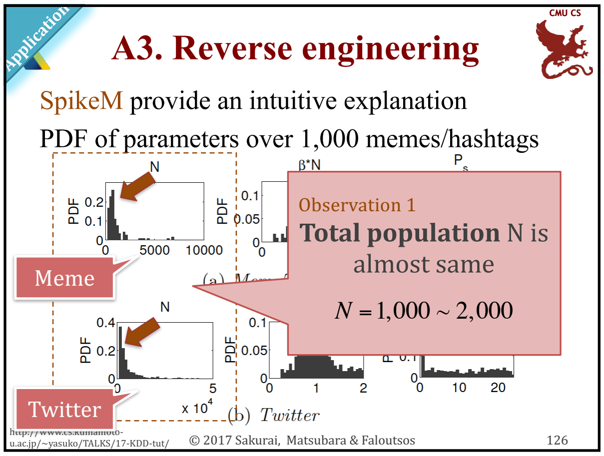


A3. Reverse engineering

SpikeM provide an intuitive explanation

PDF of parameters over 1,000 memes/hashtags

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 125



A3. Reverse engineering

SpikeM provide an intuitive explanation

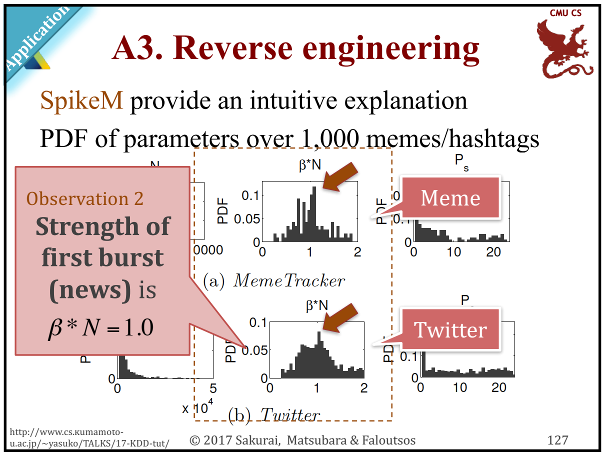
PDF of parameters over 1,000 memes/hashtags

Observation 1

Total population N is almost same

$N = 1{,}000 \sim 2{,}000$

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 126



A3. Reverse engineering

SpikeM provide an intuitive explanation

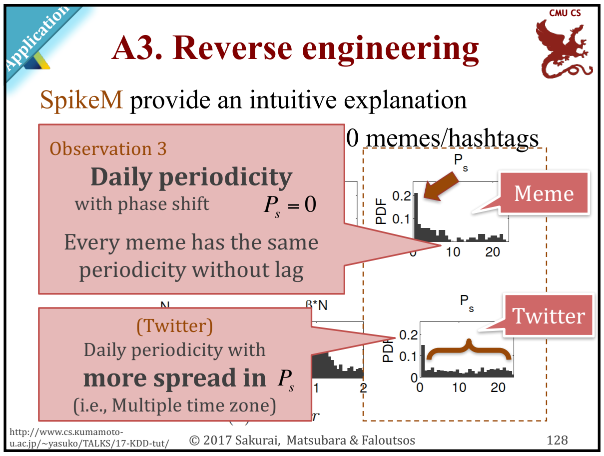
PDF of parameters over 1,000 memes/hashtags

Observation 2

Strength of first burst (news) is $\beta * N = 1.0$

(a) *MemeTracker*

(b) *Twitter*



A3. Reverse engineering

SpikeM provide an intuitive explanation

0 memes/hashtags

Observation 3

Daily periodicity

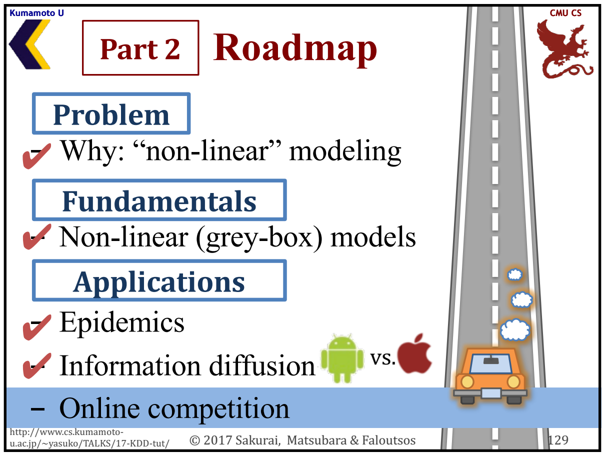
with phase shift $P_s = 0$

Every meme has the same periodicity without lag

(Twitter)

Daily periodicity with **more spread in** P_s

(i.e., Multiple time zone)



Part 2 Roadmap

Problem

✓ Why: “non-linear” modeling

Fundamentals

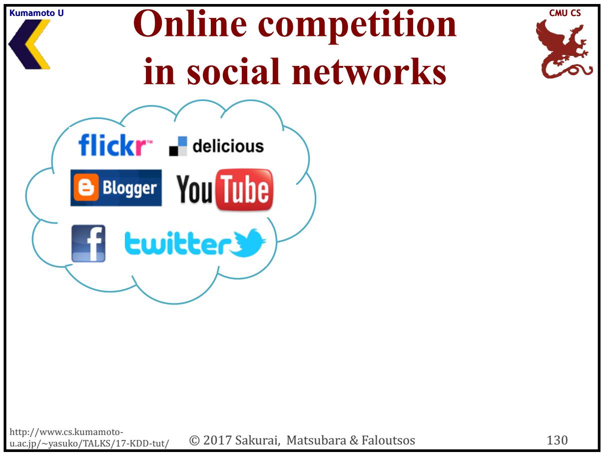
✓ Non-linear (grey-box) models

Applications

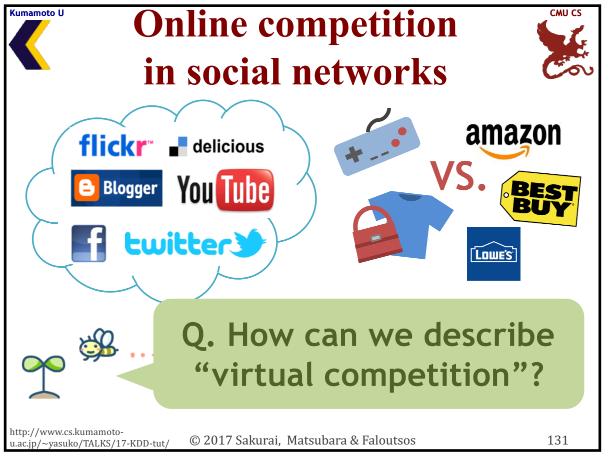
✓ Epidemics

✓ Information diffusion vs.

– Online competition

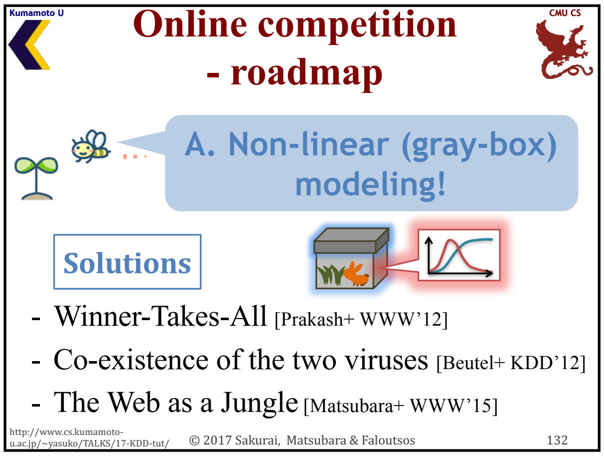


Online competition in social networks



Online competition in social networks

Q. How can we describe “virtual competition”?

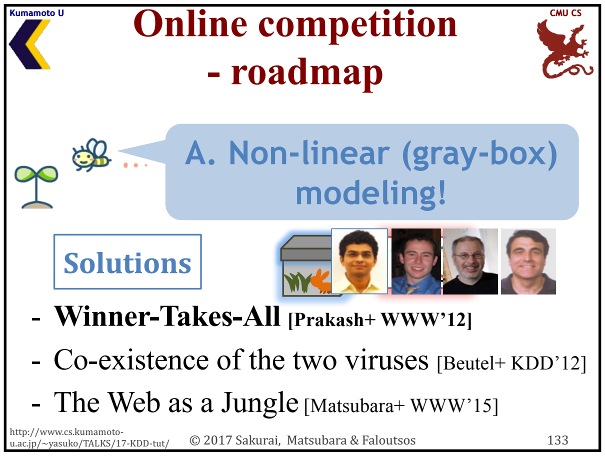


Online competition - roadmap

A. Non-linear (gray-box) modeling!

Solutions

- Winner-Takes-All [Prakash+ WWW’12]
- Co-existence of the two viruses [Beutel+ KDD’12]
- The Web as a Jungle [Matsubara+ WWW’15]



Online competition - roadmap

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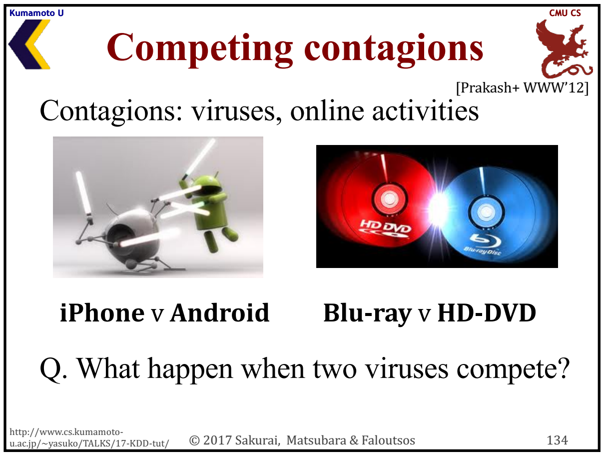

Competing contagions

[Prakash+ WWW'12]

Contagions: viruses, online activities

iPhone v **Android**

Blu-ray v **HD-DVD**

Q. What happen when two viruses compete?

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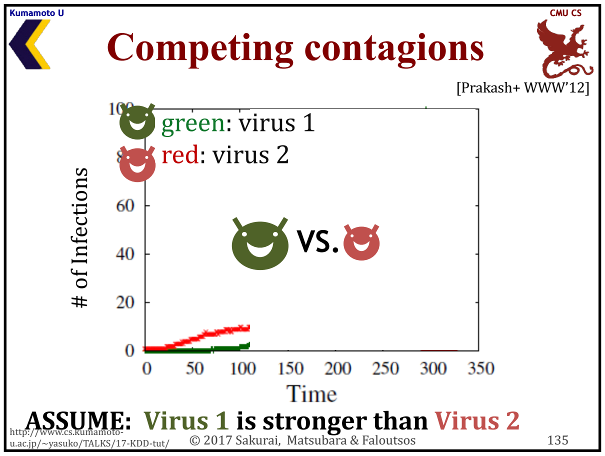
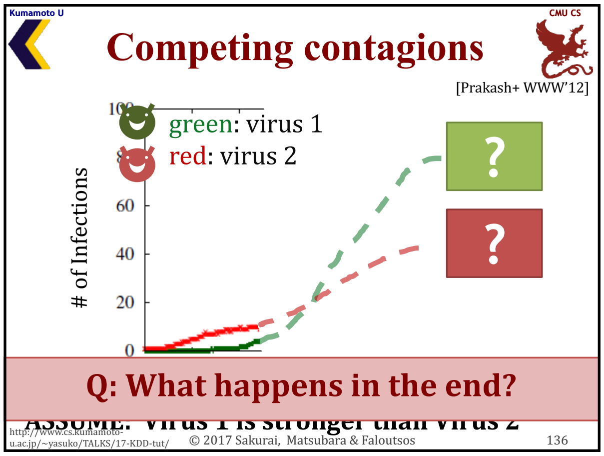


Competing contagions

[Prakash+ WWW'12]

ASSUME: Virus 1 is stronger than Virus 2

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 135



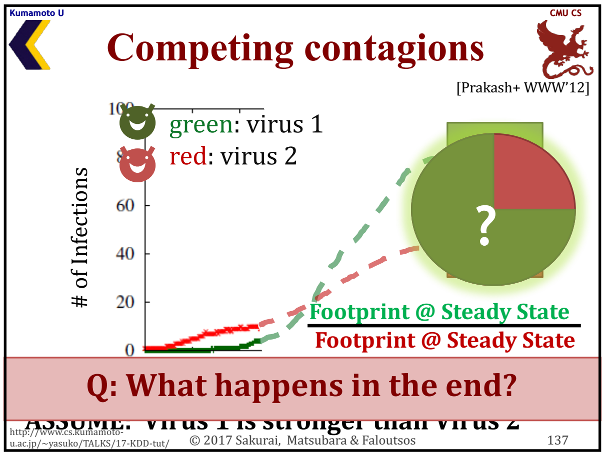
Competing contagions

[Prakash+ WWW'12]

Q: What happens in the end?

ASSUME: Virus 1 is stronger than Virus 2

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 136



Competing contagions

[Prakash+ WWW'12]

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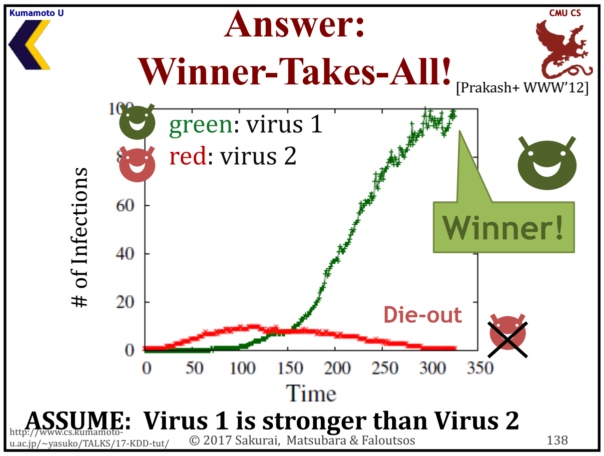
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 137



Answer: Winner-Takes-All!

[Prakash+ WWW'12]

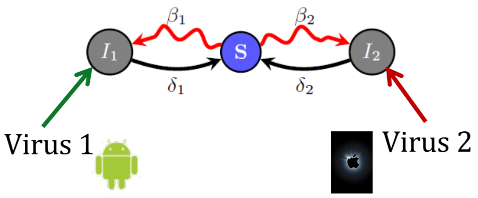
ASSUME: Virus 1 is stronger than Virus 2

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 138

A simple model

[Prakash+ WWW'12]

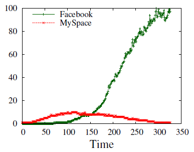
- Modified flu-like (SIS) model
- Mutual Immunity ("pick one of the two")
- Susceptible-Infected1-Infected2-Susceptible



Result: Winner-Takes-All

[Prakash+ WWW'12]

Given this model,
and ***any graph***,
the weaker virus always
dies-out, *completely*

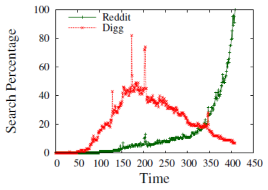


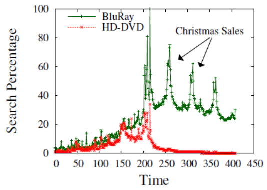
1. The stronger survives only if it is above threshold
2. Virus 1 is stronger than Virus 2, if:
   strength(Virus 1) > strength(Virus 2)
3. Strength(Virus) = λ β / δ → same as before!

Real Examples of "WTA"

[Prakash+ WWW'12]

[Google Search Trends data]



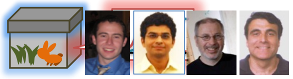


Reddit v **Digg**

Blu-Ray v **HD-DVD**

Online competition in social networks

A. Non-linear (gray-box) modeling!



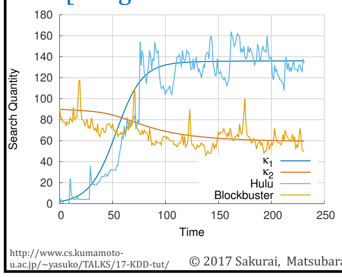
Solutions

- Winner-Takes-All [Prakash+ WWW'12]
- **Co-existence of the two viruses [Beutel+ KDD'12]**
- The Web as a Jungle [Matsubara+ WWW'15]

Interacting Viruses: Can Both Survive?

Real example of "co-existence"

[Google Search Trends data]

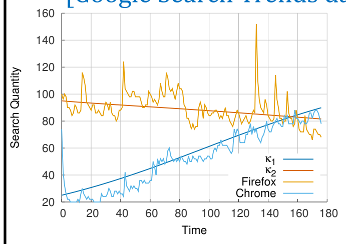


Hulu v **Blockbuster**

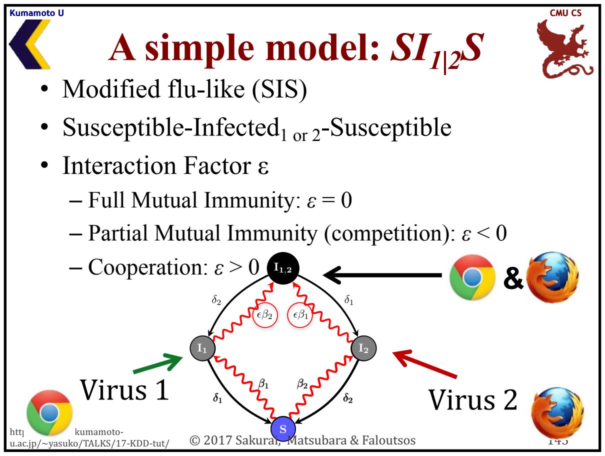
Interacting Viruses: Can Both Survive?

Real example of "co-existence"

[Google Search Trends data]



Chrome v **Firefox**



A simple model: $SI_{1|2}S$

- Modified flu-like (SIS)
- Susceptible-Infected$_{1\text{ or }2}$-Susceptible
- Interaction Factor ε
  - Full Mutual Immunity: $\varepsilon = 0$
  - Partial Mutual Immunity (competition): $\varepsilon < 0$
  - Cooperation: $\varepsilon > 0$

Virus 1

Virus 2

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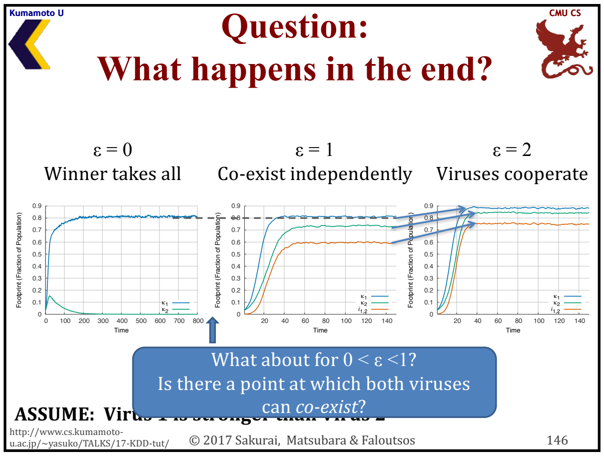

Question: What happens in the end?

ε = 0
Winner takes all

ε = 1
Co-exist independently

ε = 2
Viruses cooperate

What about for 0 < ε <1?
Is there a point at which both viruses can *co-exist*?

ASSUME: Virus 1 is stronger than Virus 2

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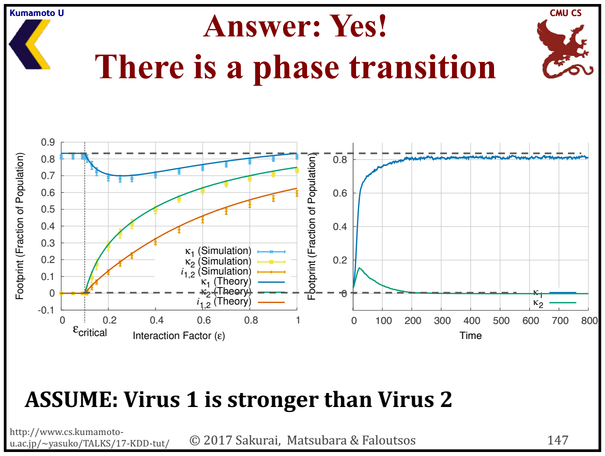
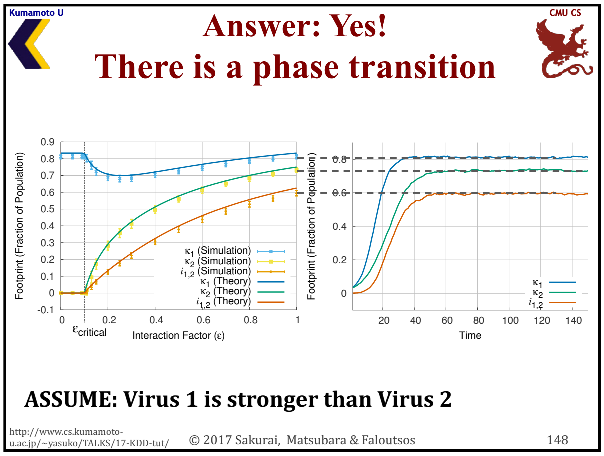


Answer: Yes! There is a phase transition

ASSUME: Virus 1 is stronger than Virus 2

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 147



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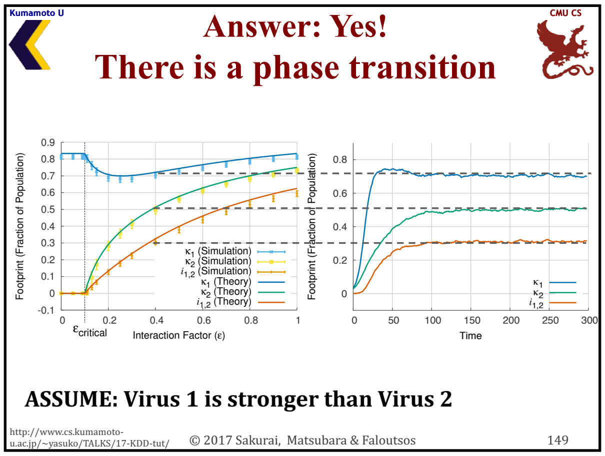

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ASSUME: Virus 1 is stronger than Virus 2

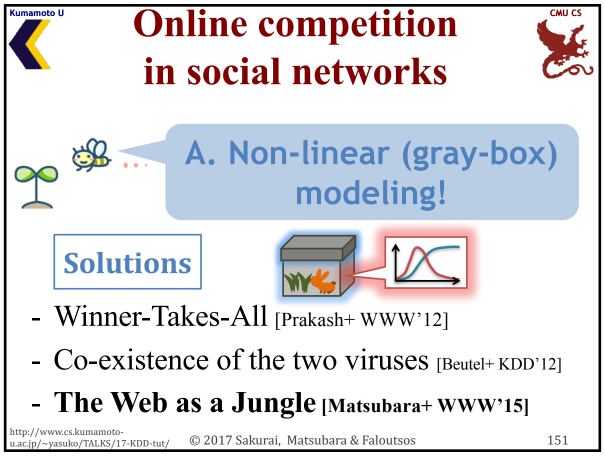
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 149

Result: Viruses can Co-exist

> Given this model and a fully connected graph, there exists an $\varepsilon_{critical}$ such that for $\varepsilon \geq \varepsilon_{critical}$, there is a fixed point where both viruses survive.

1. The stronger survives only if it is above threshold
2. Virus 1 is stronger than Virus 2, if:
   strength(Virus 1) > strength(Virus 2)
3. Strength(Virus) $\sigma = N \beta / \delta$

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 150



Kumamoto U

CMU CS

Online competition in social networks

A. Non-linear (gray-box) modeling!

Solutions

- Winner-Takes-All [Prakash+ WWW'12]
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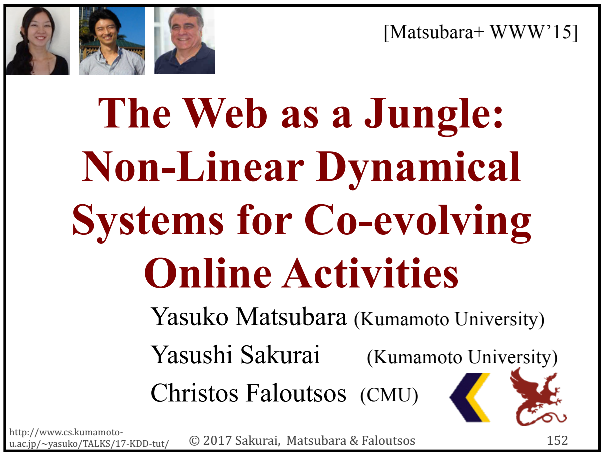
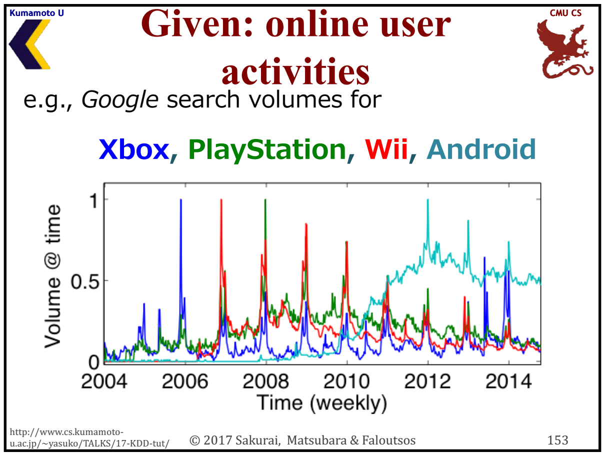
- **The Web as a Jungle [Matsubara+ WWW'15]**



[Matsubara+ WWW'15]

The Web as a Jungle: Non-Linear Dynamical Systems for Co-evolving Online Activities

Yasuko Matsubara (Kumamoto University)
Yasushi Sakurai (Kumamoto University)
Christos Faloutsos (CMU)



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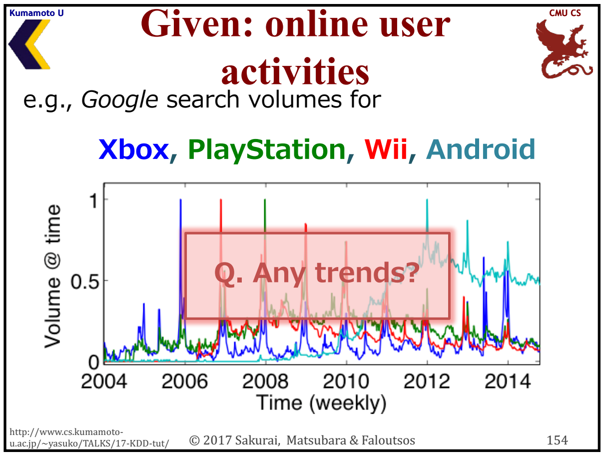
CMU CS

Given: online user activities

e.g., *Google* search volumes for

Xbox, PlayStation, Wii, Android



Kumamoto U

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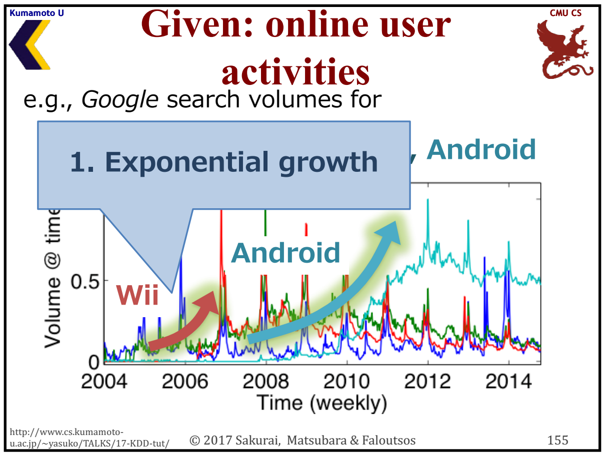
Given: online user activities

e.g., *Google* search volumes for

Xbox, PlayStation, Wii, Android

Q. Any trends?



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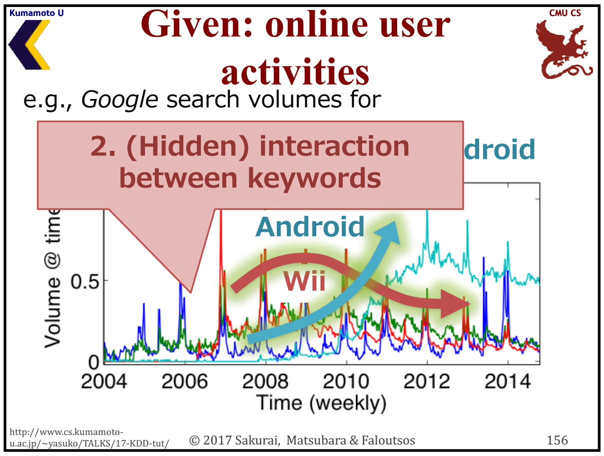
Given: online user activities

e.g., *Google* search volumes for

, Android

1. Exponential growth



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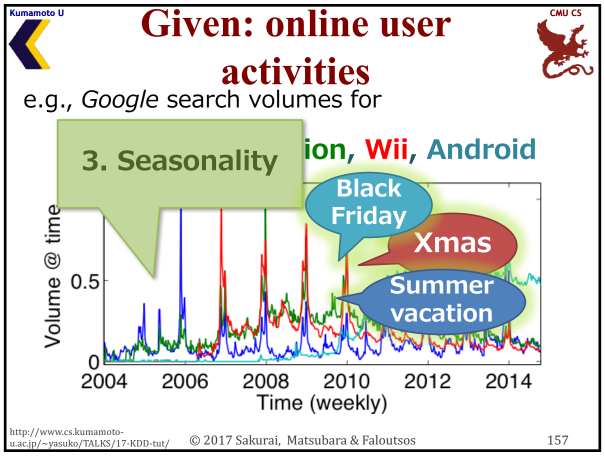
Given: online user activities

e.g., *Google* search volumes for

droid

2. (Hidden) interaction between keywords



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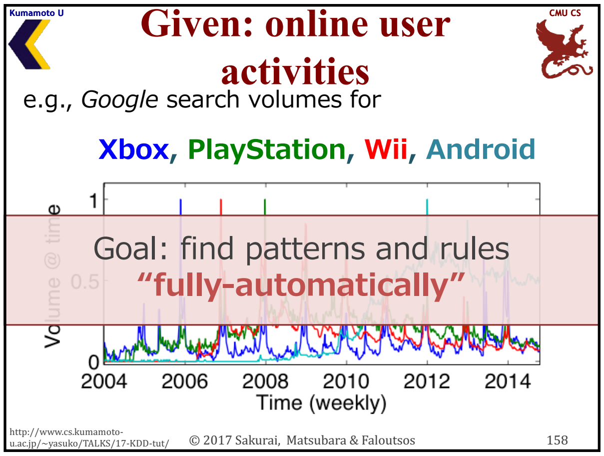
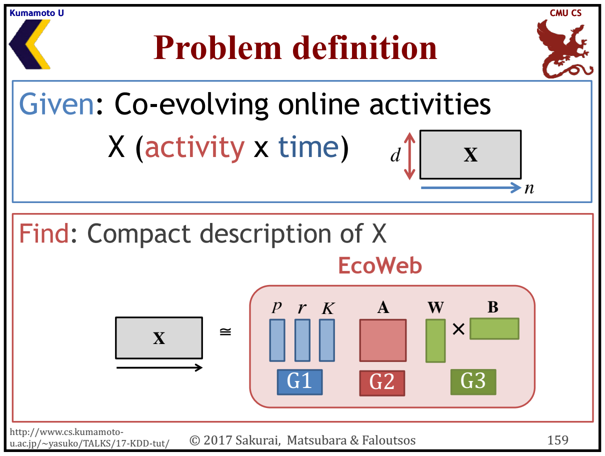


Given: online user activities

e.g., *Google* search volumes for

Xbox, PlayStation, Wii, Android

Goal: find patterns and rules
"fully-automatically"

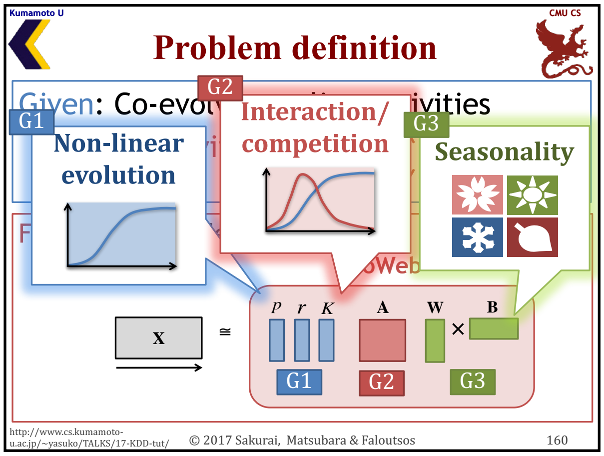


Problem definition

Given: Co-evolving online activities
X (activity x time)

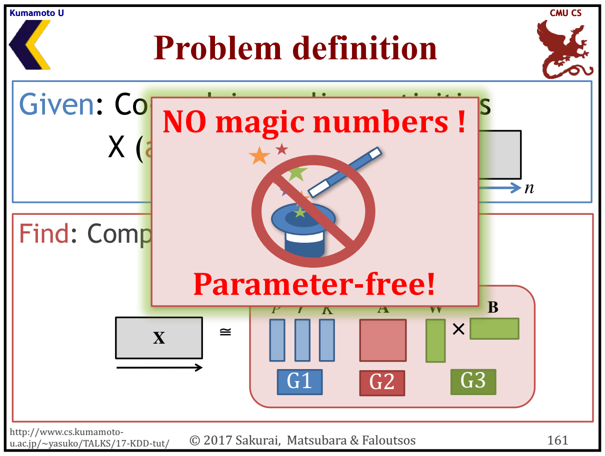
Find: Compact description of X

EcoWeb



Problem definition

Given: Co-evol ivities



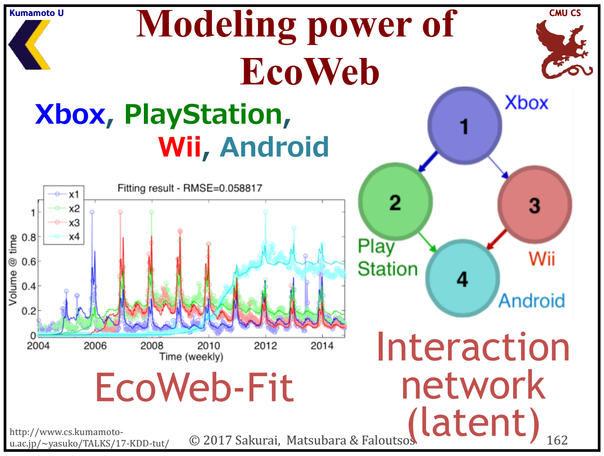
Problem definition

Given: Co s
X (

Find: Comp

NO magic numbers !

Parameter-free!

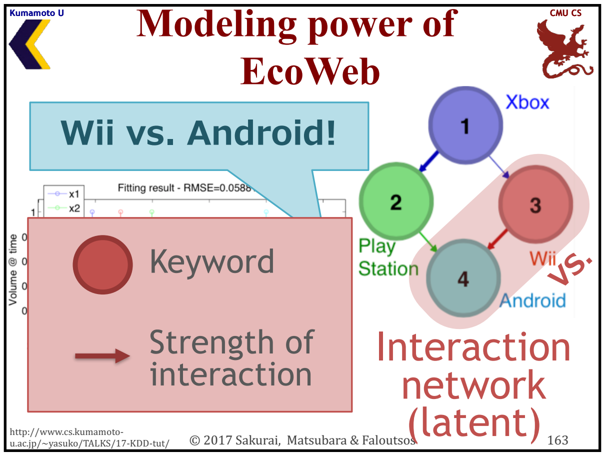


Modeling power of EcoWeb

Xbox, PlayStation, Wii, Android

EcoWeb-Fit

Interaction network (latent)



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Modeling power of EcoWeb

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Wii vs. Android!

Keyword

Strength of interaction

Interaction network (latent)

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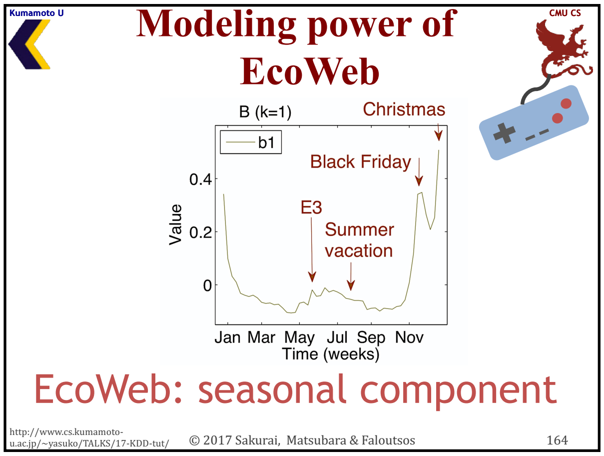

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Modeling power of EcoWeb

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EcoWeb: seasonal component

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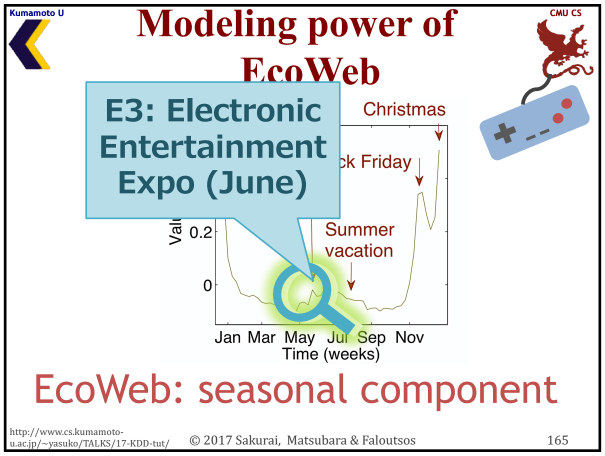

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Modeling power of EcoWeb

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E3: Electronic Entertainment Expo (June)

EcoWeb: seasonal component

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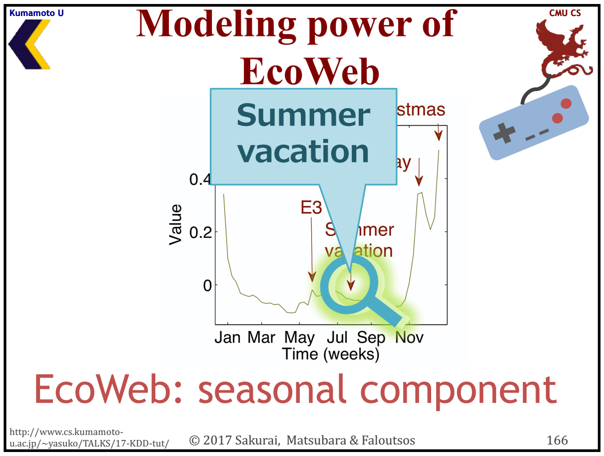

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Modeling power of EcoWeb

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Summer vacation

EcoWeb: seasonal component

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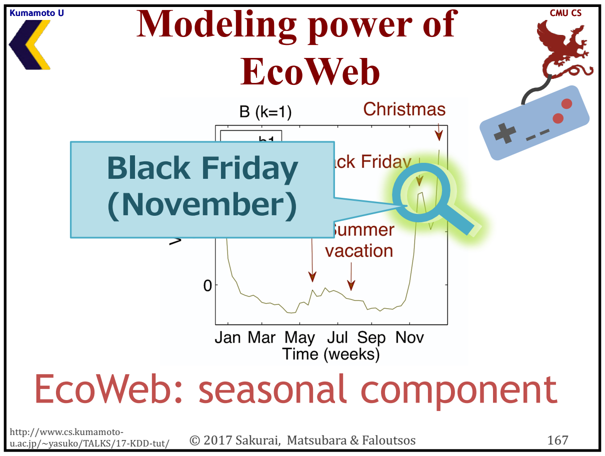

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Modeling power of EcoWeb

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Black Friday (November)

EcoWeb: seasonal component

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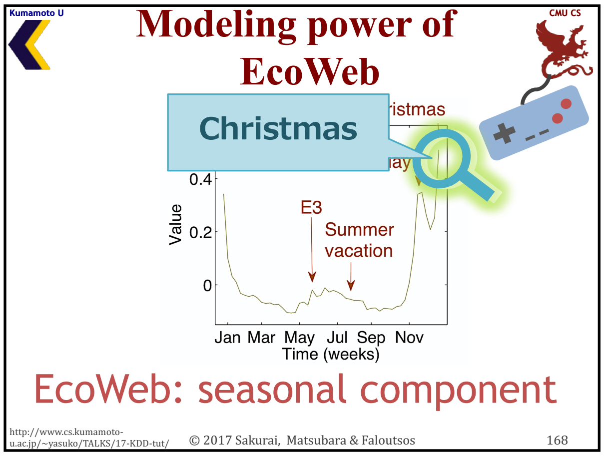

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Modeling power of EcoWeb

CMU CS

Christmas

EcoWeb: seasonal component

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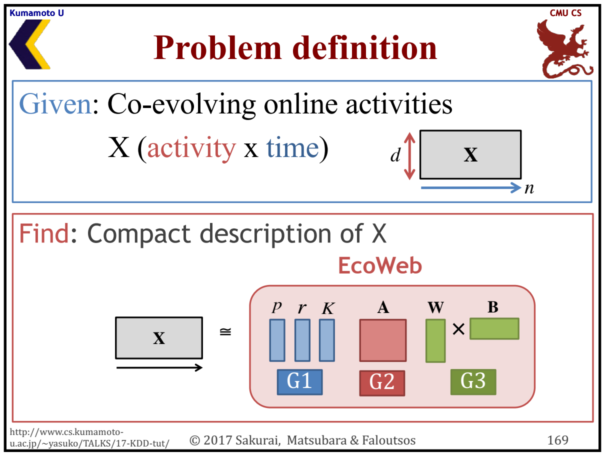

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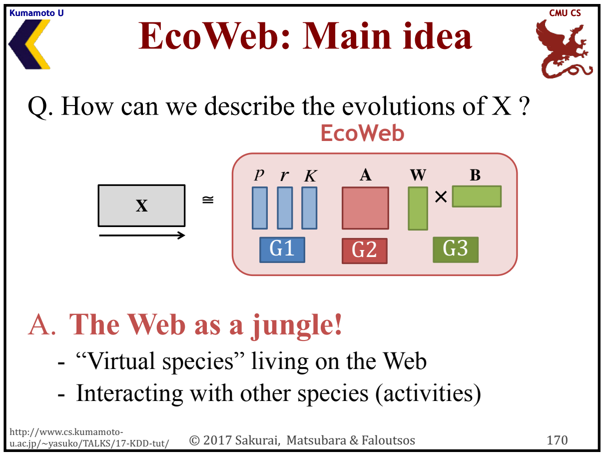
Given: Co-evolving online activities

X (activity x time)

Find: Compact description of X

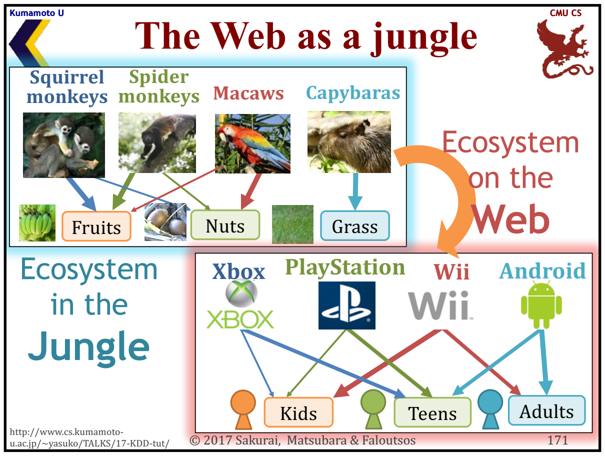


EcoWeb: Main idea

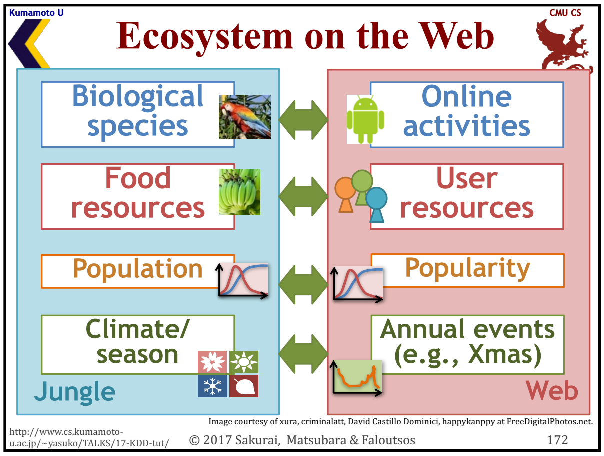
Q. How can we describe the evolutions of X ?

A. **The Web as a jungle!**

- "Virtual species" living on the Web
- Interacting with other species (activities)

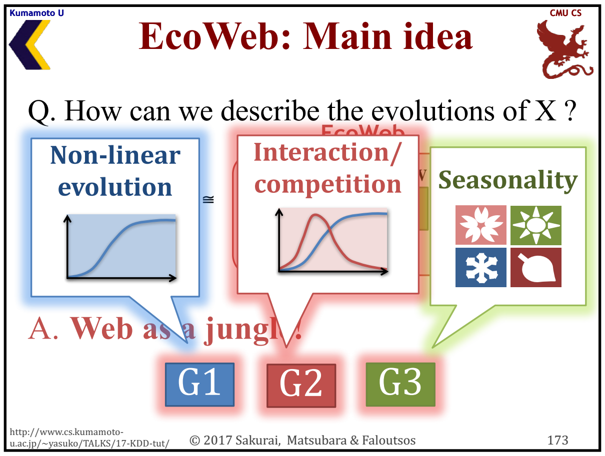


The Web as a jungle



Ecosystem on the Web

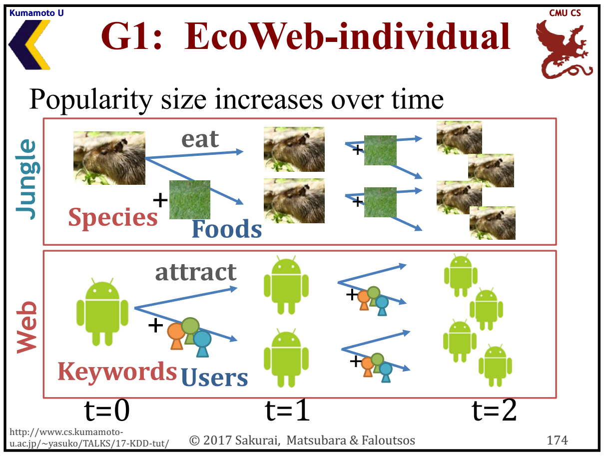
Image courtesy of xura, criminalatt, David Castillo Dominici, happykanppy at FreeDigitalPhotos.net.



EcoWeb: Main idea

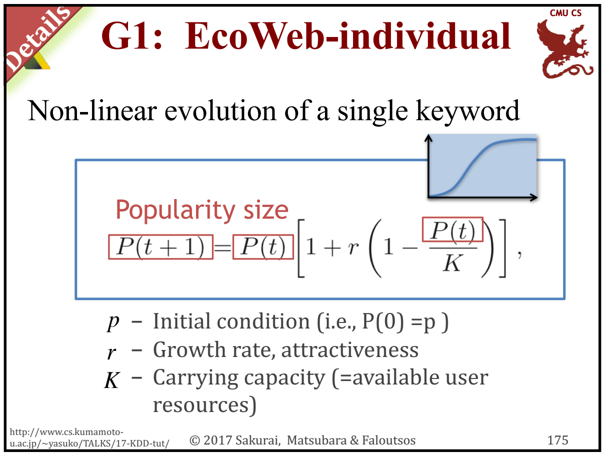
Q. How can we describe the evolutions of X ?

A. Web as a jungle!



G1: EcoWeb-individual

Popularity size increases over time



Details

G1: EcoWeb-individual

CMU CS

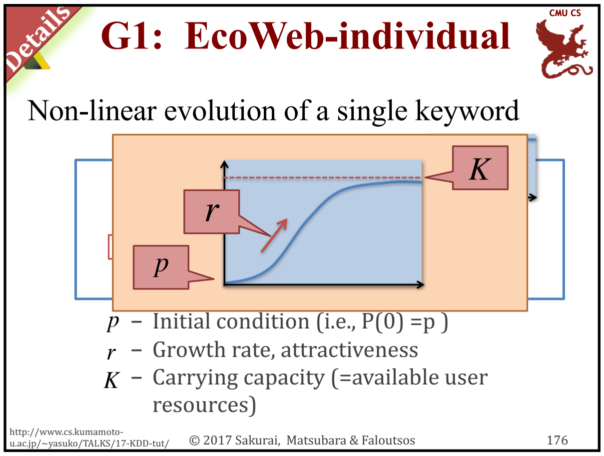
Non-linear evolution of a single keyword

Popularity size

$$P(t+1) = P(t)\left[1 + r\left(1 - \frac{P(t)}{K}\right)\right],$$

- p – Initial condition (i.e., P(0) =p)
- r – Growth rate, attractiveness
- K – Carrying capacity (=available user resources)

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 175



Details

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CMU CS

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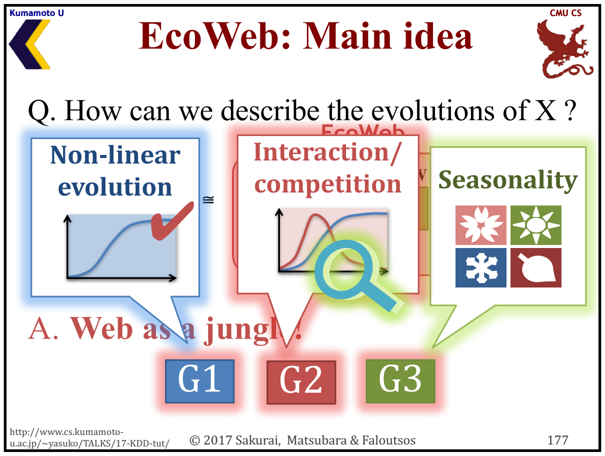

Kumamoto U

EcoWeb: Main idea

CMU CS

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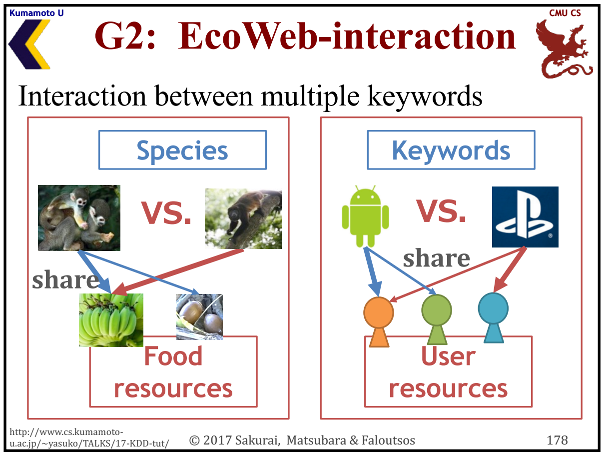

Kumamoto U

G2: EcoWeb-interaction

CMU CS

Interaction between multiple keywords

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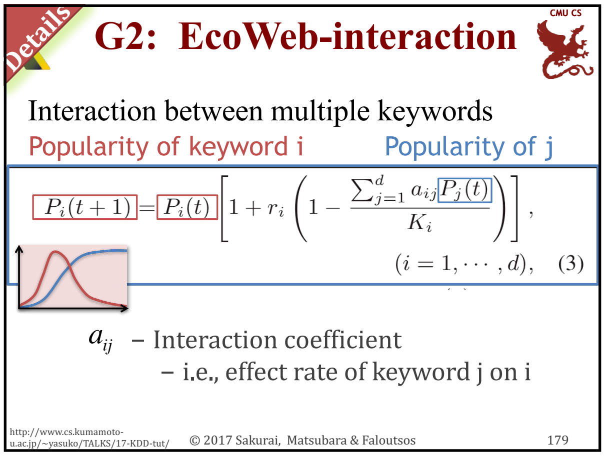

Details

G2: EcoWeb-interaction

CMU CS

Interaction between multiple keywords

Popularity of keyword i Popularity of j

$$P_i(t+1) = P_i(t)\left[1 + r_i\left(1 - \frac{\sum_{j=1}^{d} a_{ij} P_j(t)}{K_i}\right)\right], \quad (i = 1, \cdots, d), \quad (3)$$

a_{ij} – Interaction coefficient
– i.e., effect rate of keyword j on i

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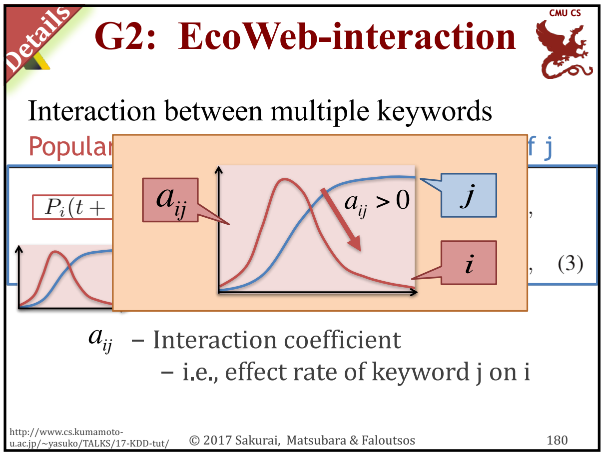


Details

G2: EcoWeb-interaction

CMU CS

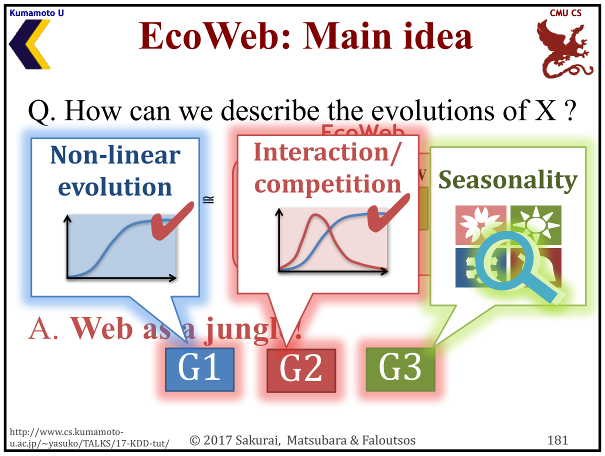
Interaction between multiple keywords

Popular f j

$P_i(t+$, (3)

a_{ij} – Interaction coefficient
– i.e., effect rate of keyword j on i

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 180



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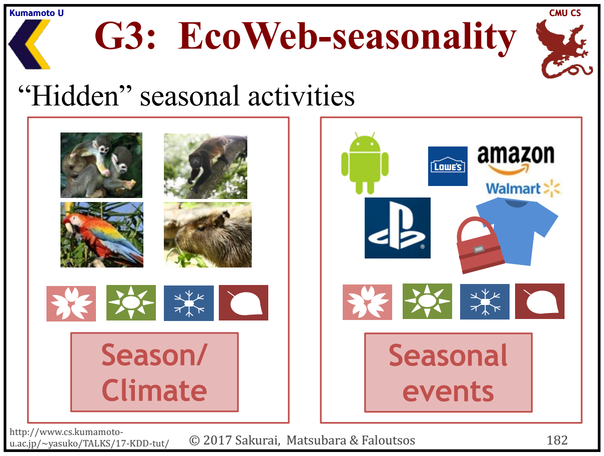
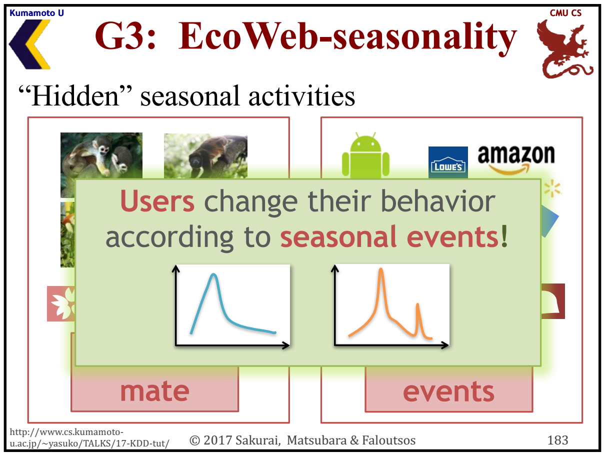


G3: EcoWeb-seasonality

"Hidden" seasonal activities

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 182

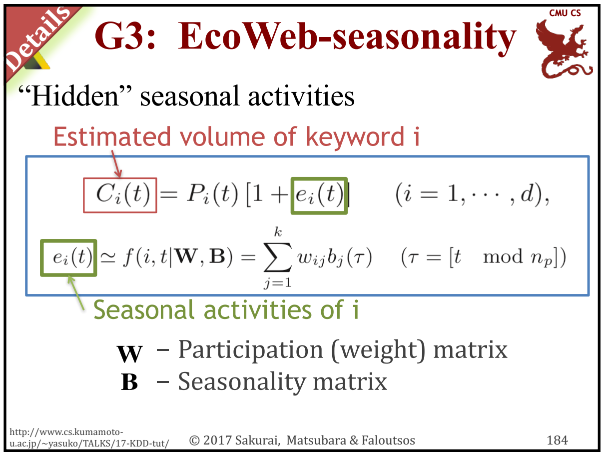


G3: EcoWeb-seasonality

"Hidden" seasonal activities

Users change their behavior according to **seasonal events!**

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 183



G3: EcoWeb-seasonality

Details

"Hidden" seasonal activities

Estimated volume of keyword i

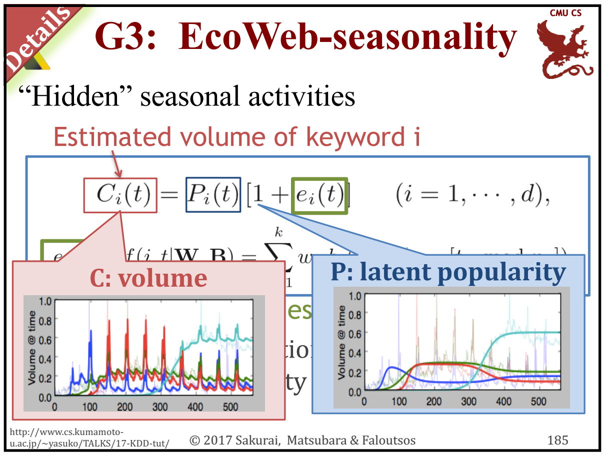
$$\boxed{C_i(t)} = P_i(t)\,[1 + \boxed{e_i(t)}] \qquad (i = 1, \cdots, d),$$

$$\boxed{e_i(t)} \simeq f(i, t|\mathbf{W}, \mathbf{B}) = \sum_{j=1}^{k} w_{ij} b_j(\tau) \qquad (\tau = [t \mod n_p])$$

Seasonal activities of i

W – Participation (weight) matrix
B – Seasonality matrix

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 184



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Details

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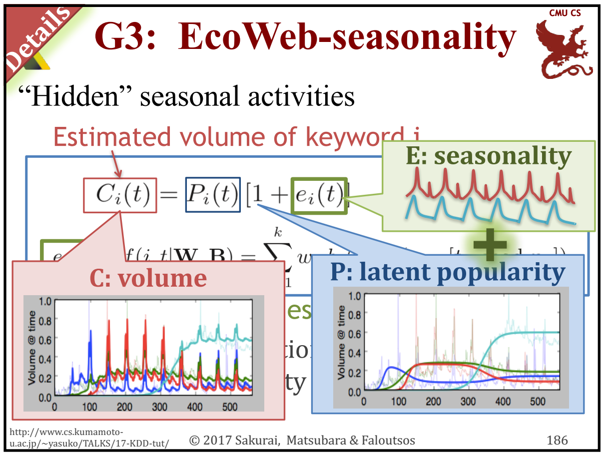

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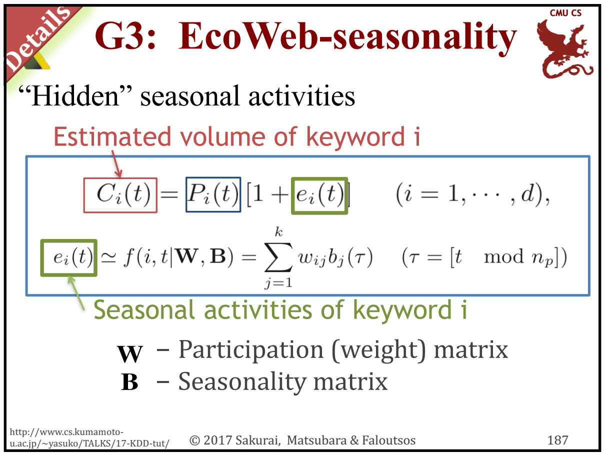

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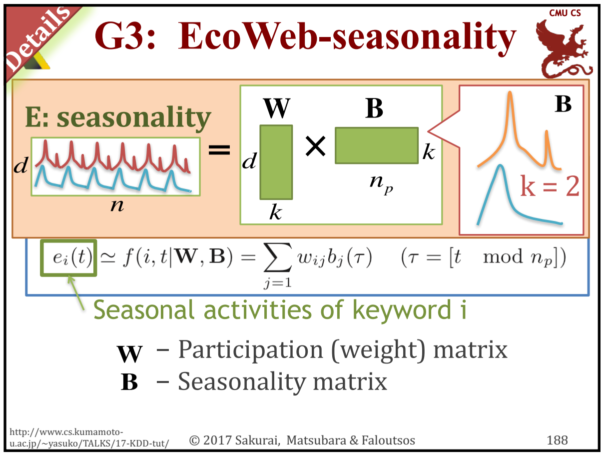

G3: EcoWeb-seasonality

E: seasonality =

$$\boxed{e_i(t)} \simeq f(i, t|\mathbf{W}, \mathbf{B}) = \sum_{j=1}^{k} w_{ij} b_j(\tau) \quad (\tau = [t \mod n_p])$$

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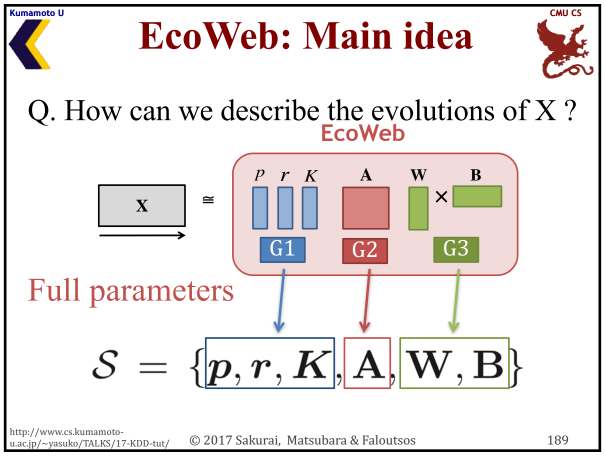

EcoWeb: Main idea

Q. How can we describe the evolutions of X ?

Full parameters

$$\mathcal{S} = \{\boxed{\boldsymbol{p}, \boldsymbol{r}, \boldsymbol{K}}, \boxed{\mathbf{A}}, \boxed{\mathbf{W}, \mathbf{B}}\}$$

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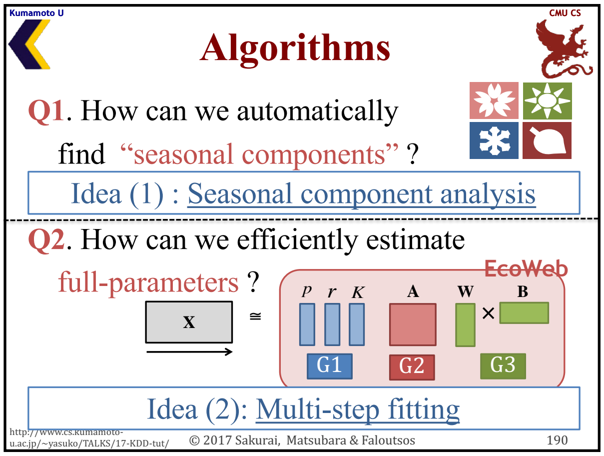


Algorithms

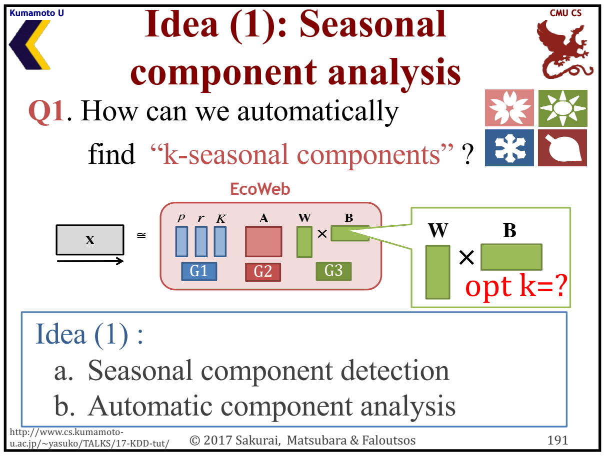
Q1. How can we automatically find "seasonal components" ?

Idea (1) : Seasonal component analysis

Q2. How can we efficiently estimate full-parameters ?

Idea (2): Multi-step fitting

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/ © 2017 Sakurai, Matsubara & Faloutsos 190



Idea (1): Seasonal component analysis

Q1. How can we automatically find "k-seasonal components" ?

Idea (1) :
a. Seasonal component detection
b. Automatic component analysis

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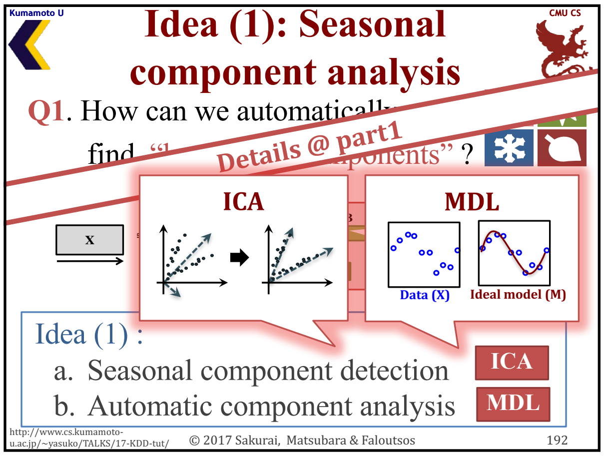

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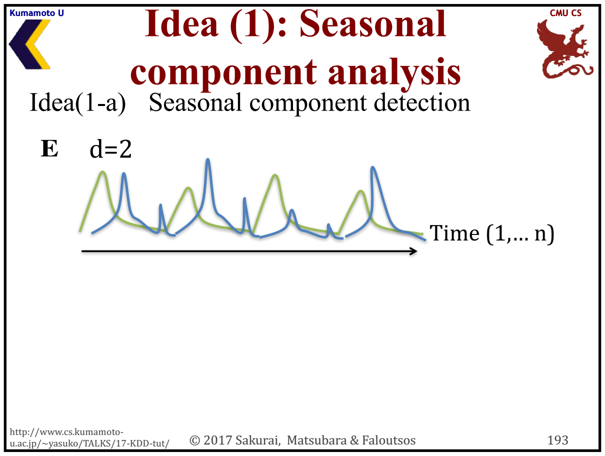
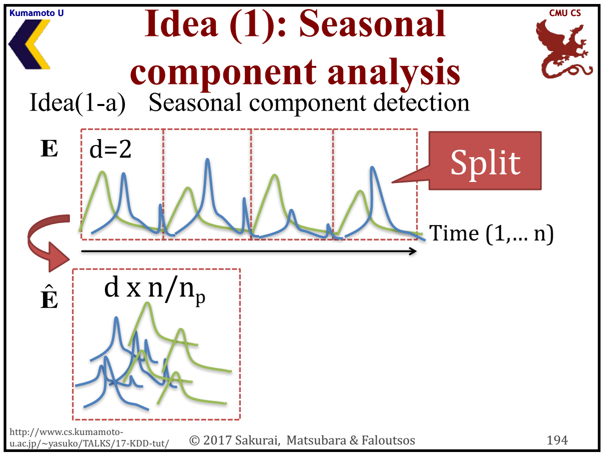


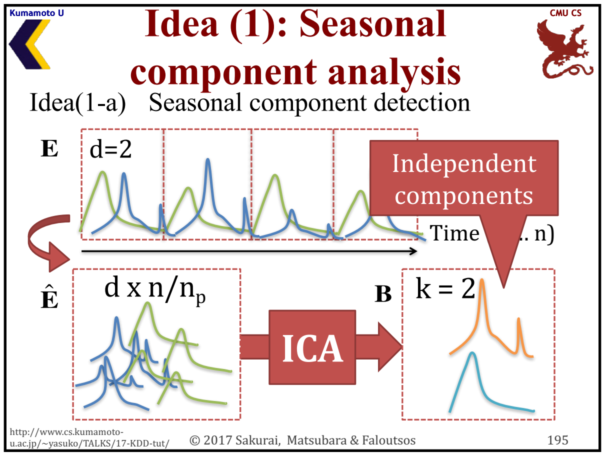
Idea (1): Seasonal component analysis

Idea(1-a) Seasonal component detection



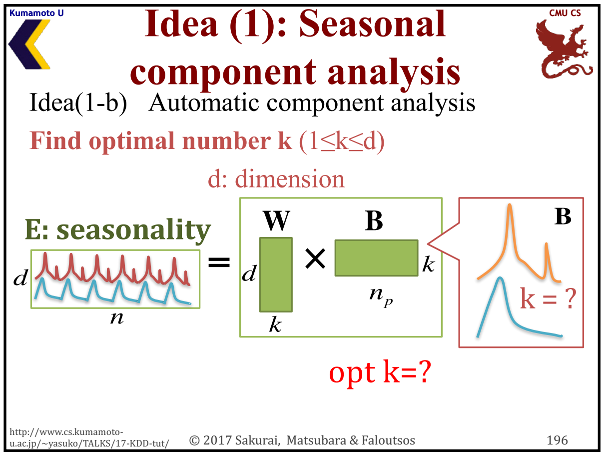
Idea (1): Seasonal component analysis

Idea(1-a) Seasonal component detection



Idea (1): Seasonal component analysis

Idea(1-a) Seasonal component detection

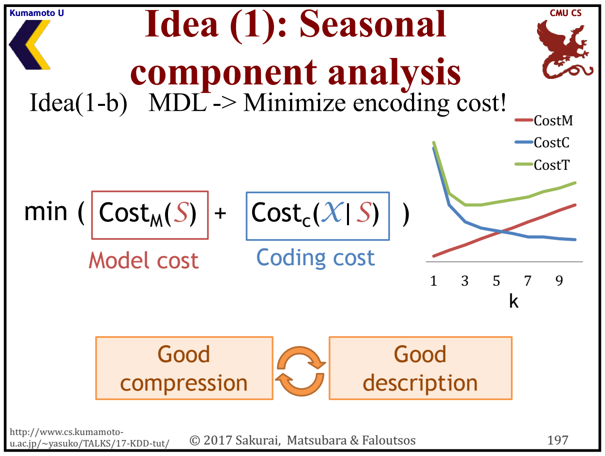


Idea (1): Seasonal component analysis

Idea(1-b) Automatic component analysis

Find optimal number k (1≤k≤d)

d: dimension



Idea (1): Seasonal component analysis

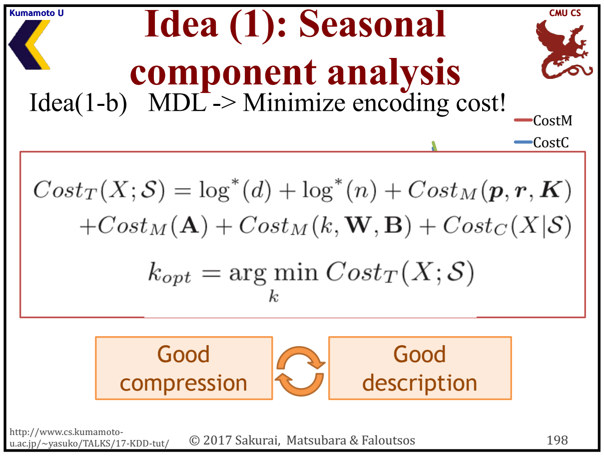
Idea(1-b) MDL -> Minimize encoding cost!

min ($\boxed{\mathrm{Cost}_M(\mathcal{S})}$ + $\boxed{\mathrm{Cost}_c(\mathcal{X} | \mathcal{S})}$)

Model cost

Coding cost

Good compression ⟳ Good description



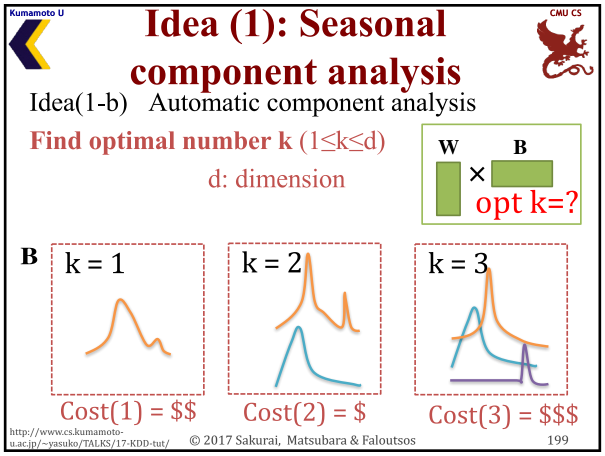
Idea (1): Seasonal component analysis

Idea(1-b) MDL -> Minimize encoding cost!

$$Cost_T(X;\mathcal{S}) = \log^*(d) + \log^*(n) + Cost_M(\boldsymbol{p}, \boldsymbol{r}, \boldsymbol{K})$$
$$+Cost_M(\mathbf{A}) + Cost_M(k, \mathbf{W}, \mathbf{B}) + Cost_C(X|\mathcal{S})$$

$$k_{opt} = \arg\min_k Cost_T(X;\mathcal{S})$$

Good compression ⟳ Good description



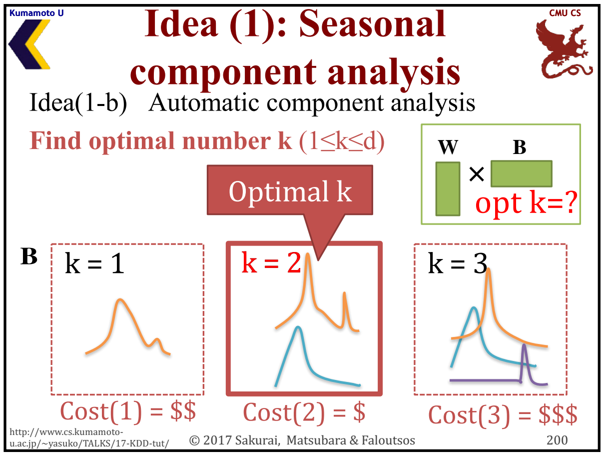
Idea (1): Seasonal component analysis

Idea(1-b) Automatic component analysis

Find optimal number k (1≤k≤d)

d: dimension

Cost(1) = $$ Cost(2) = $ Cost(3) = $$$

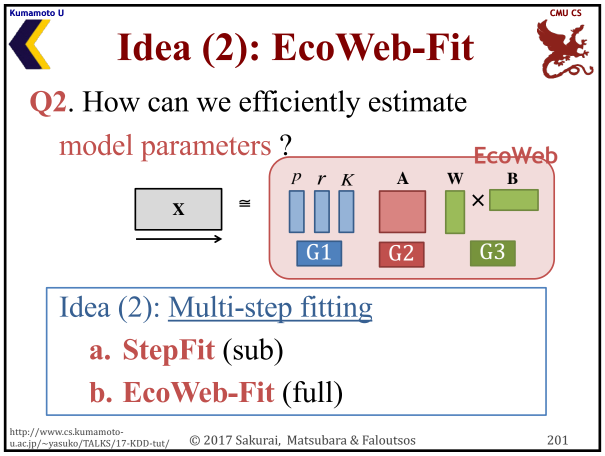


Idea (1): Seasonal component analysis

Idea(1-b) Automatic component analysis

Find optimal number k (1≤k≤d)

Cost(1) = $$ Cost(2) = $ Cost(3) = $$$

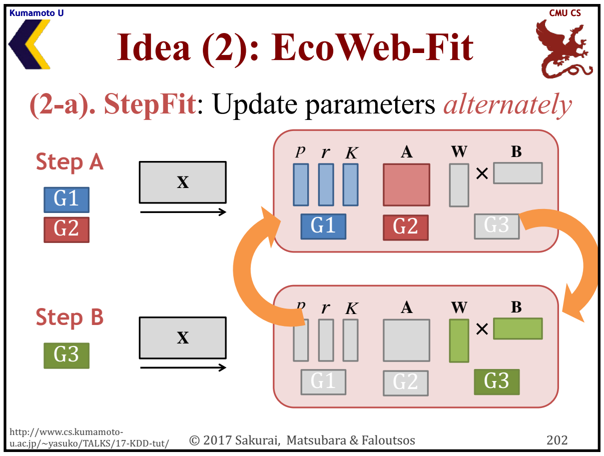


Idea (2): EcoWeb-Fit

Q2. How can we efficiently estimate model parameters ?

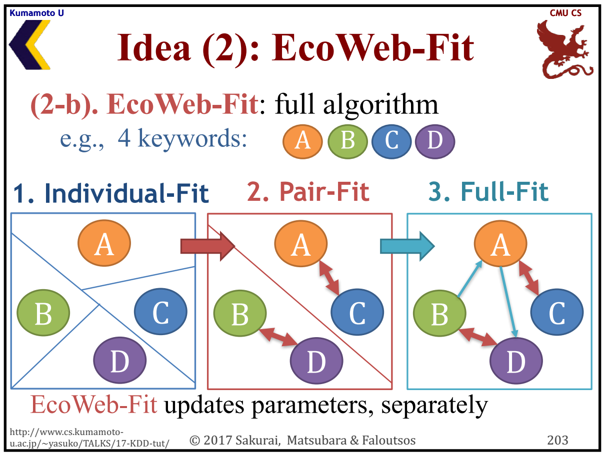
Idea (2): Multi-step fitting

a. **StepFit** (sub)
b. **EcoWeb-Fit** (full)



Idea (2): EcoWeb-Fit

(2-a). StepFit: Update parameters *alternately*



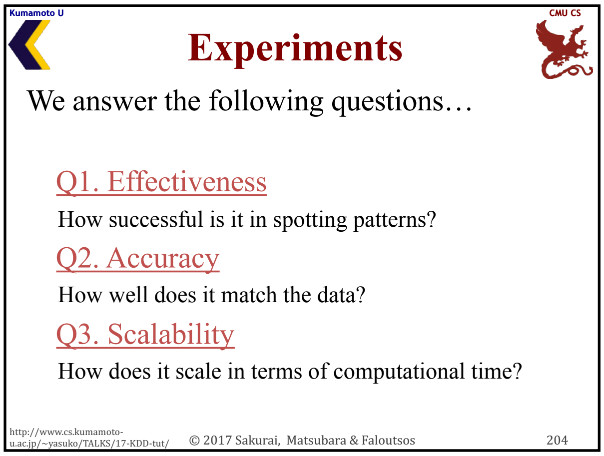
Idea (2): EcoWeb-Fit

(2-b). EcoWeb-Fit: full algorithm

e.g., 4 keywords: A B C D

1. Individual-Fit **2. Pair-Fit** **3. Full-Fit**

EcoWeb-Fit updates parameters, separately



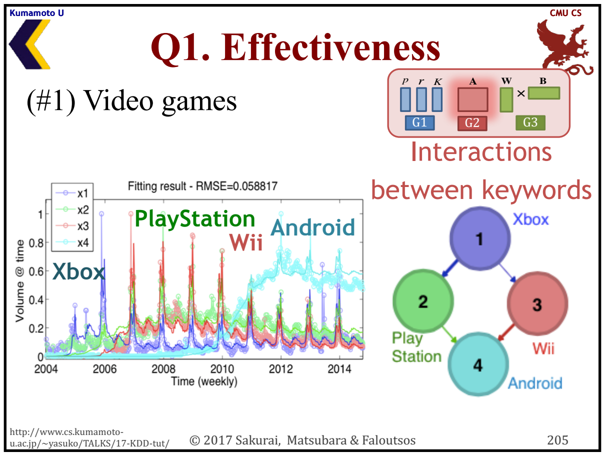
Experiments

We answer the following questions…

Q1. Effectiveness
How successful is it in spotting patterns?

Q2. Accuracy
How well does it match the data?

Q3. Scalability
How does it scale in terms of computational time?



Kumamoto U

CMU CS

Q1. Effectiveness

(#1) Video games

Interactions between keywords

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/

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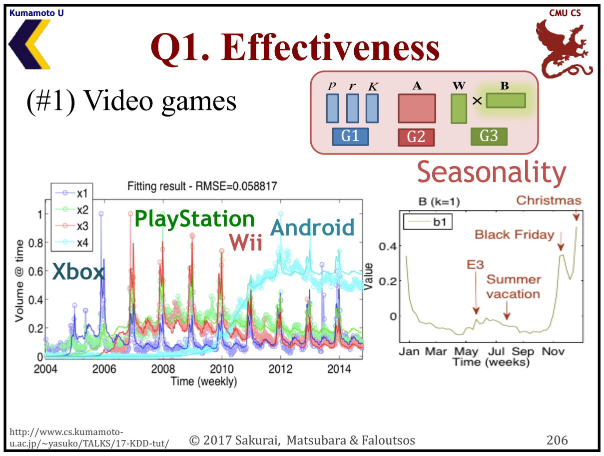

Kumamoto U

CMU CS

Q1. Effectiveness

(#1) Video games

Seasonality

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/

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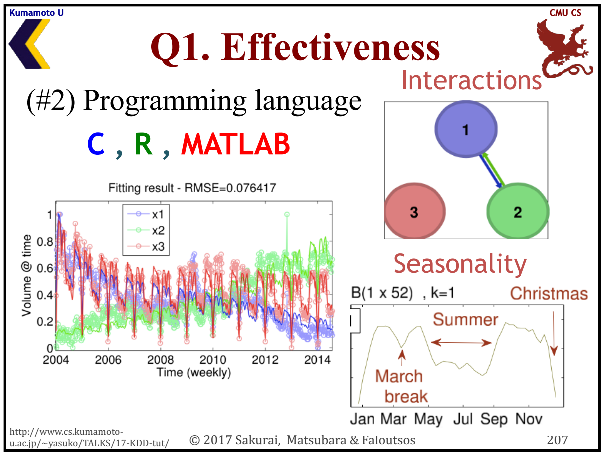

Kumamoto U

CMU CS

Q1. Effectiveness

(#2) Programming language

C , R , MATLAB

Interactions

Seasonality

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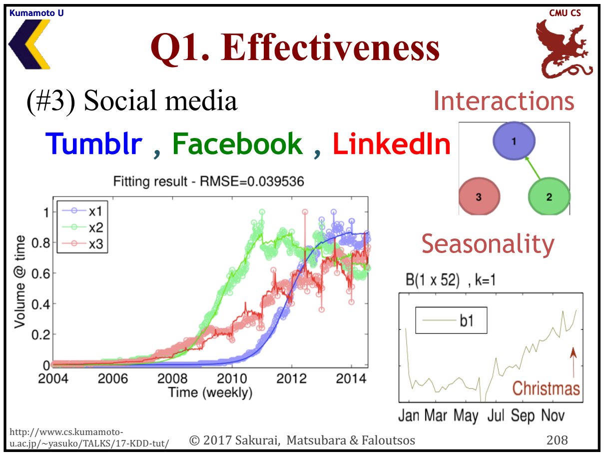

Kumamoto U

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Q1. Effectiveness

(#3) Social media

Tumblr , Facebook , LinkedIn

Interactions

Seasonality

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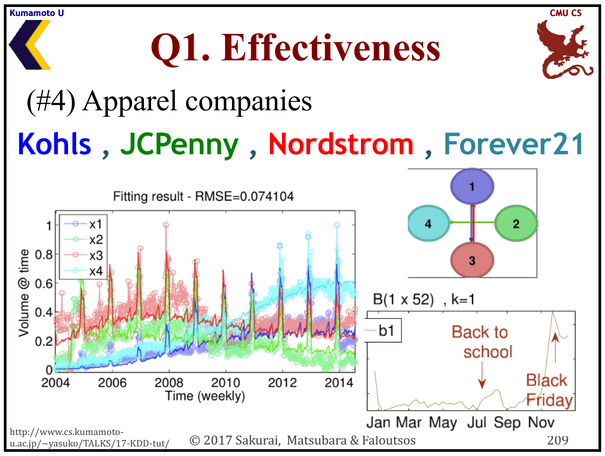

Kumamoto U

CMU CS

Q1. Effectiveness

(#4) Apparel companies

Kohls , JCPenny , Nordstrom , Forever21

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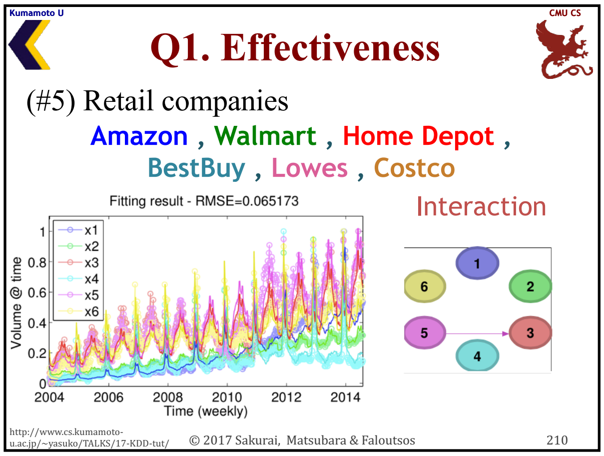

Kumamoto U

CMU CS

Q1. Effectiveness

(#5) Retail companies

Amazon , Walmart , Home Depot , BestBuy , Lowes , Costco

Interaction

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/17-KDD-tut/

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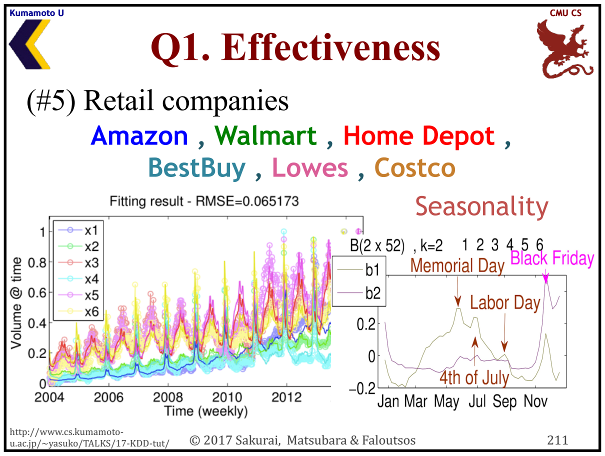
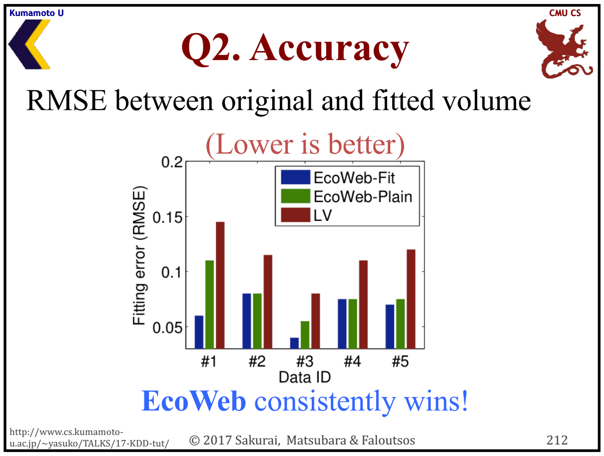


Q1. Effectiveness

(#5) Retail companies

Amazon , Walmart , Home Depot , BestBuy , Lowes , Costco

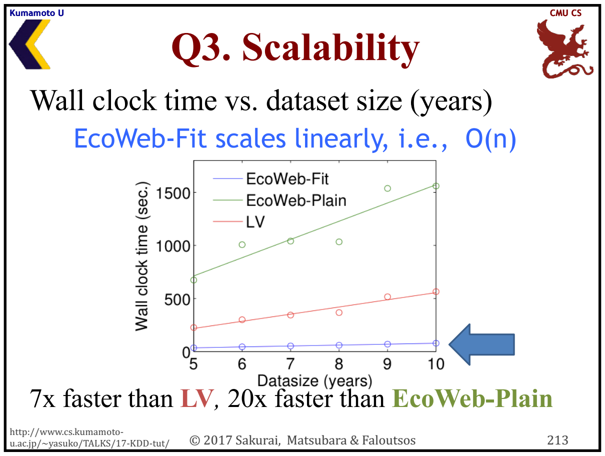


Q2. Accuracy

RMSE between original and fitted volume

(Lower is better)

EcoWeb consistently wins!

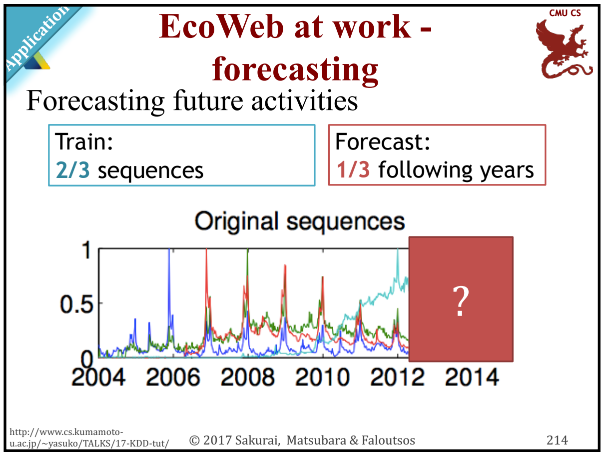


Q3. Scalability

Wall clock time vs. dataset size (years)

EcoWeb-Fit scales linearly, i.e., O(n)

7x faster than **LV**, 20x faster than **EcoWeb-Plain**

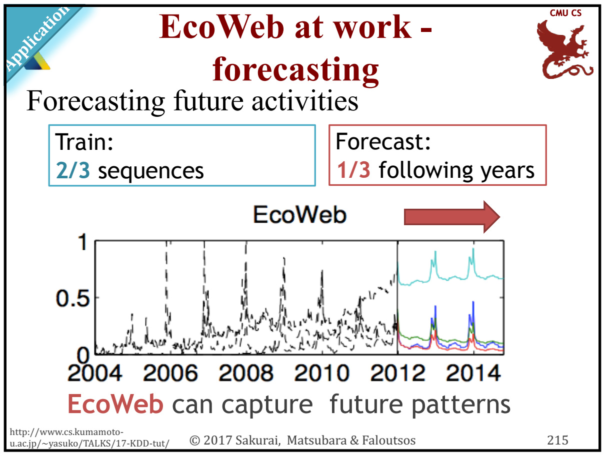


EcoWeb at work - forecasting

Forecasting future activities

Train:
2/3 sequences

Forecast:
1/3 following years



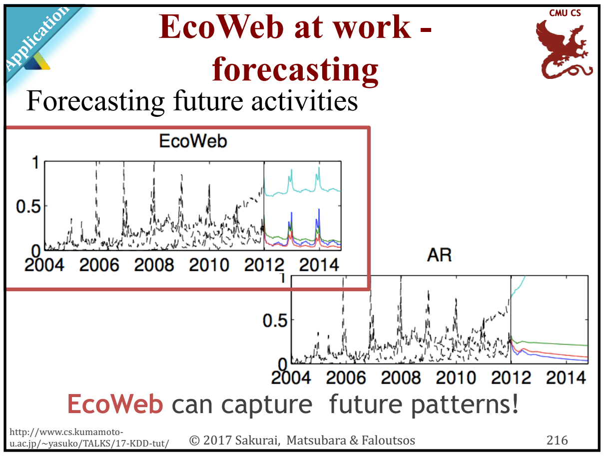
EcoWeb at work - forecasting

Forecasting future activities

Train:
2/3 sequences

Forecast:
1/3 following years

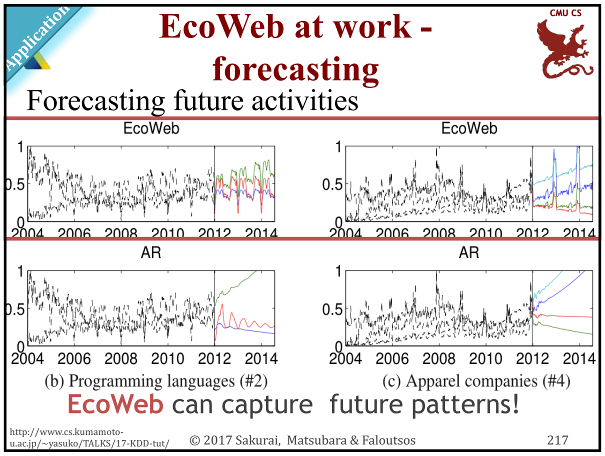
EcoWeb can capture future patterns



EcoWeb at work - forecasting

Forecasting future activities

EcoWeb can capture future patterns!



EcoWeb at work - forecasting

Forecasting future activities

(b) Programming languages (#2)

(c) Apparel companies (#4)

EcoWeb can capture future patterns!

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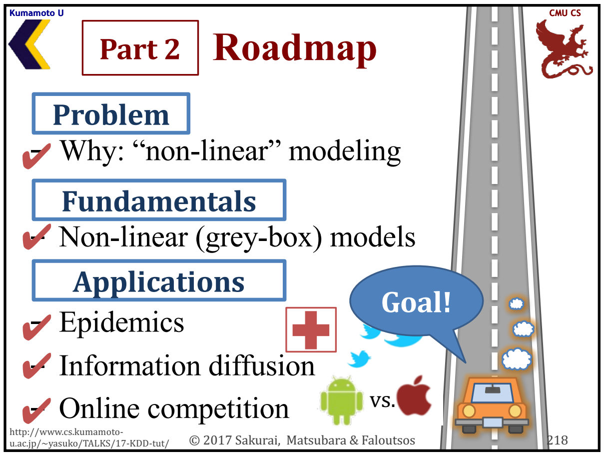

Part 2 Roadmap

Problem

- ✓ Why: "non-linear" modeling

Fundamentals

- ✓ Non-linear (grey-box) models

Applications

- ✓ Epidemics
- ✓ Information diffusion
- ✓ Online competition

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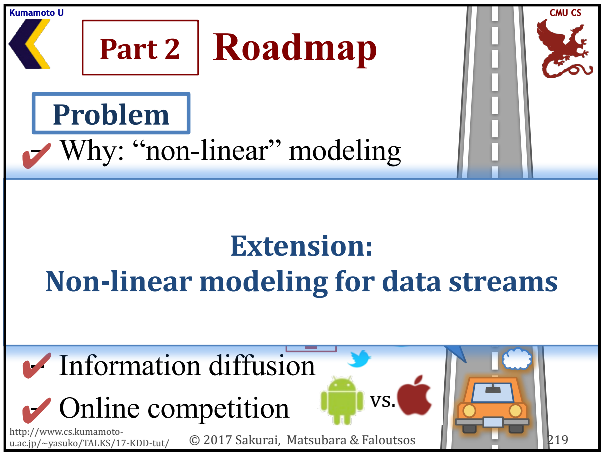

Part 2 Roadmap

Problem

- ✓ Why: "non-linear" modeling

Extension:
Non-linear modeling for data streams

- ✓ Information diffusion
- ✓ Online competition

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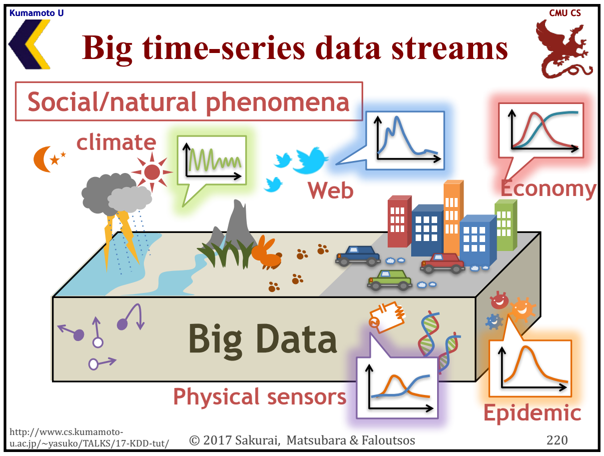

Big time-series data streams

Social/natural phenomena

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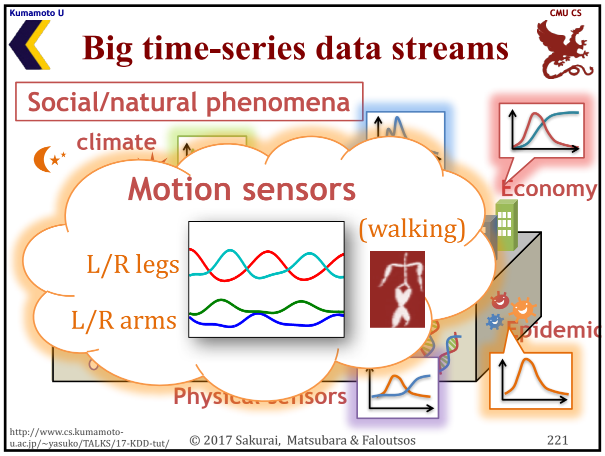

Big time-series data streams

Social/natural phenomena

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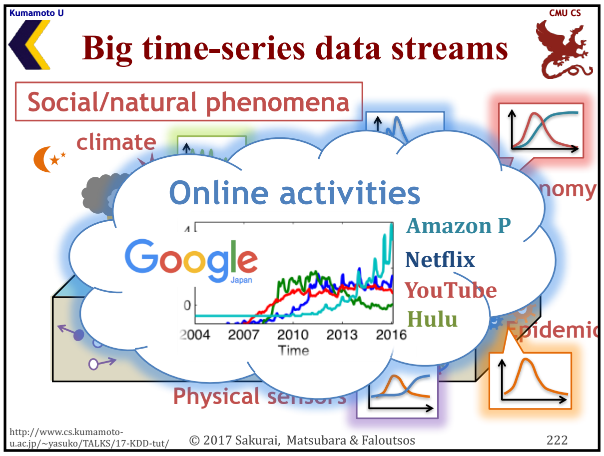

Big time-series data streams

Social/natural phenomena

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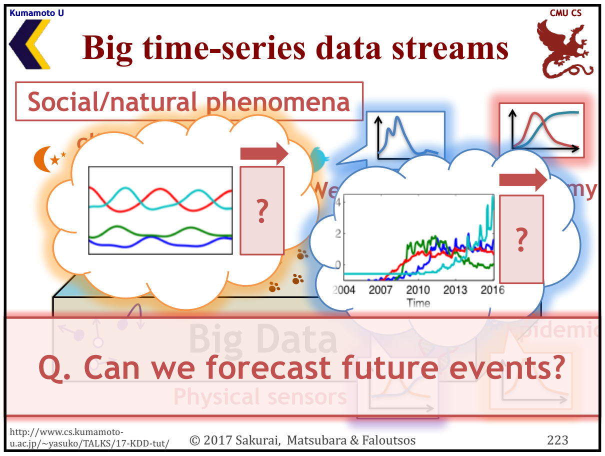


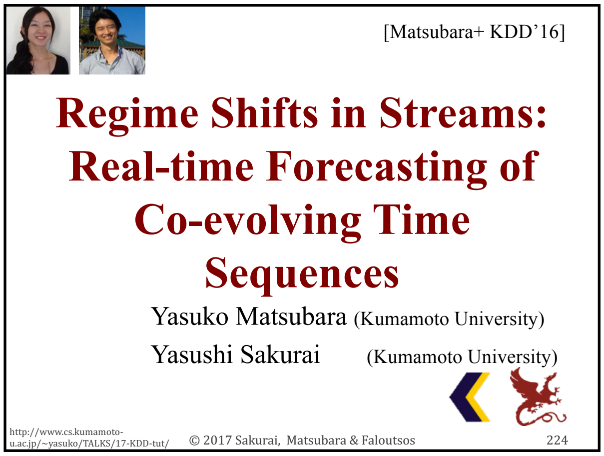
Big time-series data streams

Social/natural phenomena

Big Data

Physical sensors

Q. Can we forecast future events?

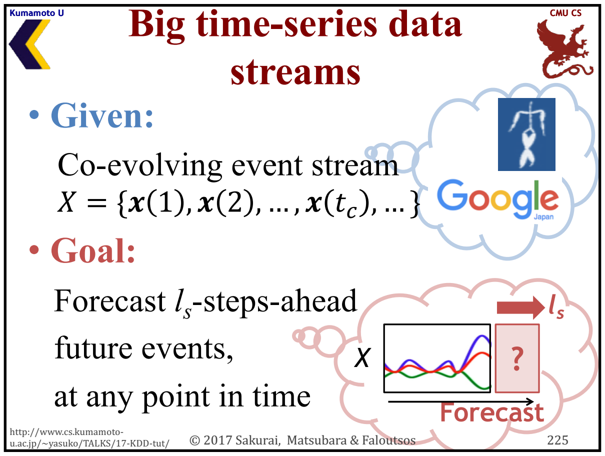


[Matsubara+ KDD'16]

Regime Shifts in Streams: Real-time Forecasting of Co-evolving Time Sequences

Yasuko Matsubara (Kumamoto University)

Yasushi Sakurai (Kumamoto University)



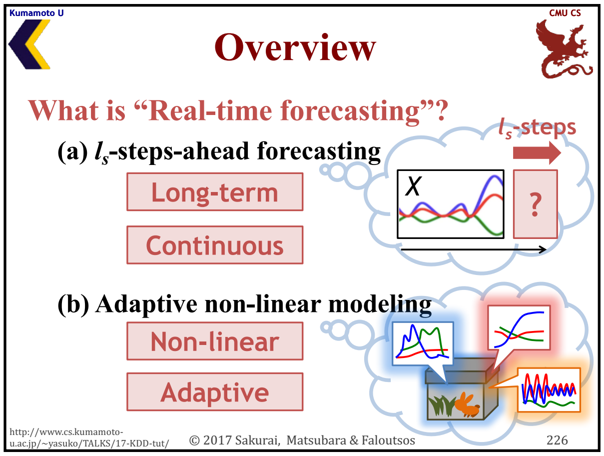
Big time-series data streams

- **Given:**

  Co-evolving event stream
  $X = \{\boldsymbol{x}(1), \boldsymbol{x}(2), \dots, \boldsymbol{x}(t_c), \dots\}$

- **Goal:**

  Forecast l_s-steps-ahead
  future events,
  at any point in time



Overview

What is "Real-time forecasting"?

(a) l_s-steps-ahead forecasting

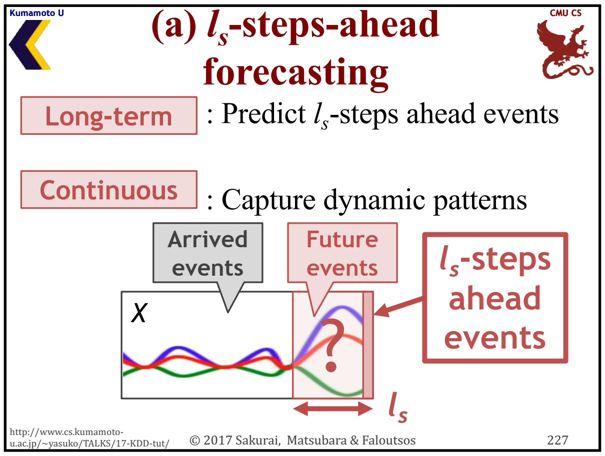
Long-term

Continuous

(b) Adaptive non-linear modeling

Non-linear

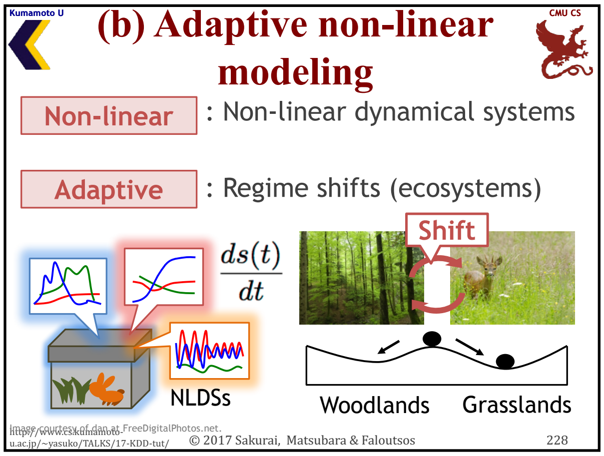
Adaptive



(a) l_s-steps-ahead forecasting

Long-term : Predict l_s-steps ahead events

Continuous : Capture dynamic patterns

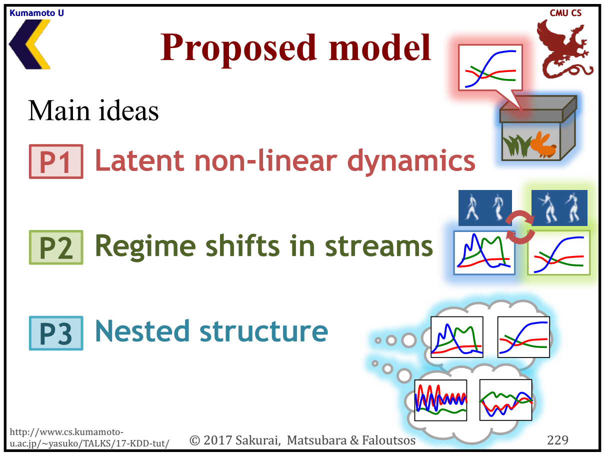


(b) Adaptive non-linear modeling

Non-linear : Non-linear dynamical systems

Adaptive : Regime shifts (ecosystems)

image courtesy of dan at FreeDigitalPhotos.net.



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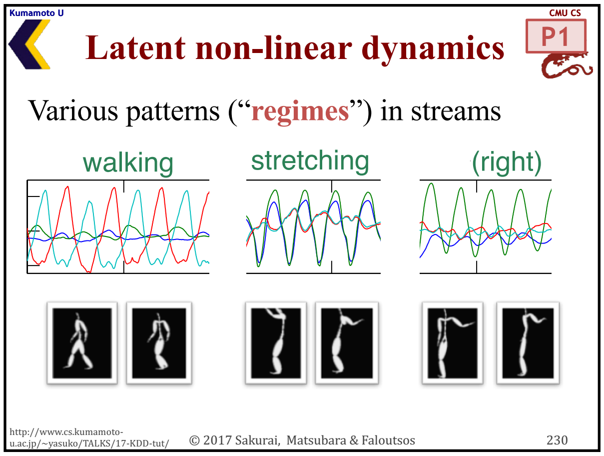
Proposed model

Main ideas

P1 Latent non-linear dynamics

P2 Regime shifts in streams

P3 Nested structure



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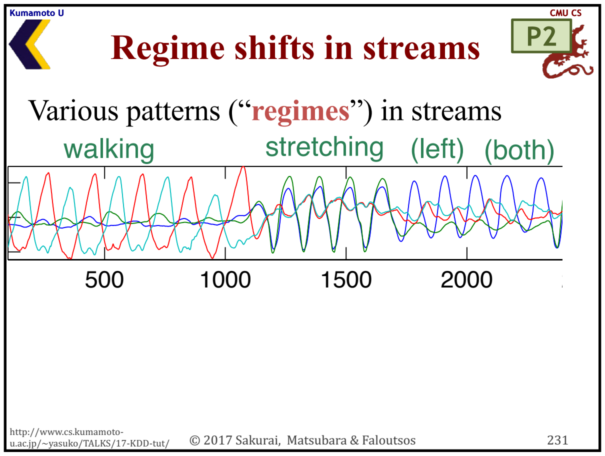
Latent non-linear dynamics

P1

Various patterns ("**regimes**") in streams



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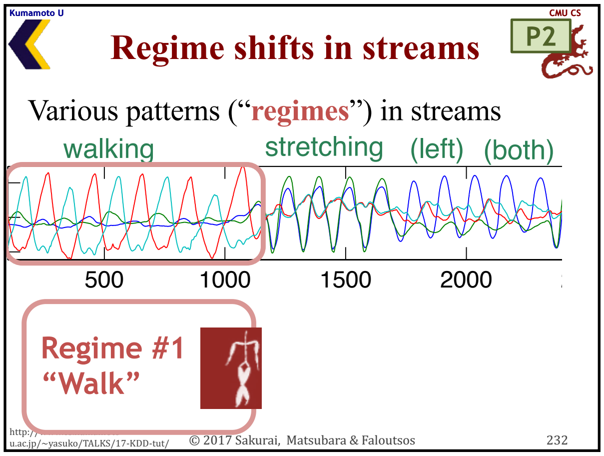
Regime shifts in streams

P2

Various patterns ("**regimes**") in streams



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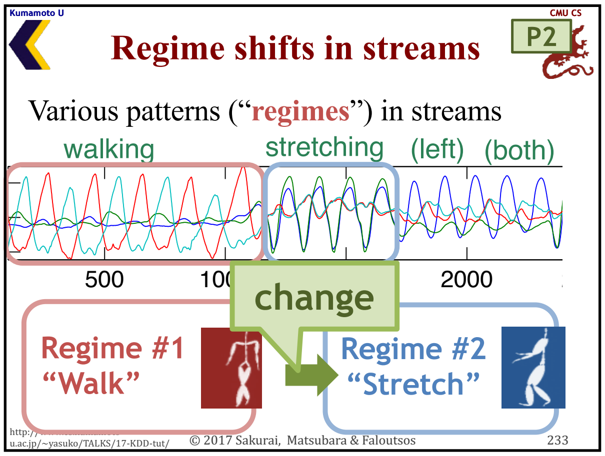
Regime shifts in streams

P2

Various patterns ("**regimes**") in streams

Regime #1
"Walk"



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Regime shifts in streams

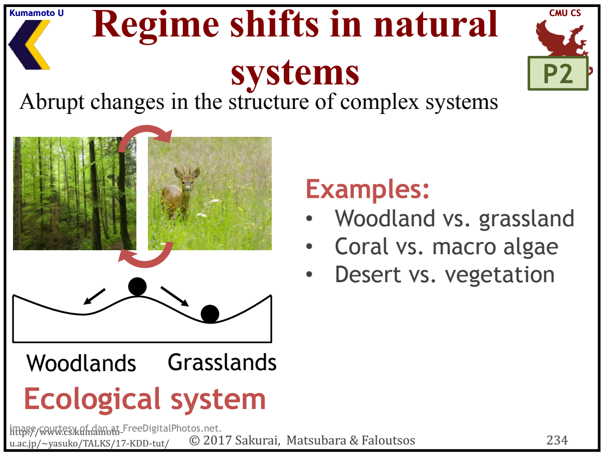
P2

Various patterns ("**regimes**") in streams

change

Regime #1
"Walk"

Regime #2
"Stretch"



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Regime shifts in natural systems

P2

Abrupt changes in the structure of complex systems

Ecological system

Examples:

- Woodland vs. grassland
- Coral vs. macro algae
- Desert vs. vegetation

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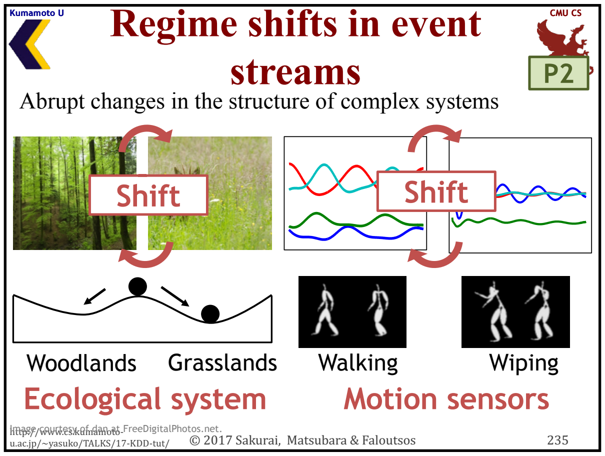

Regime shifts in event streams

Abrupt changes in the structure of complex systems

Ecological system

Motion sensors

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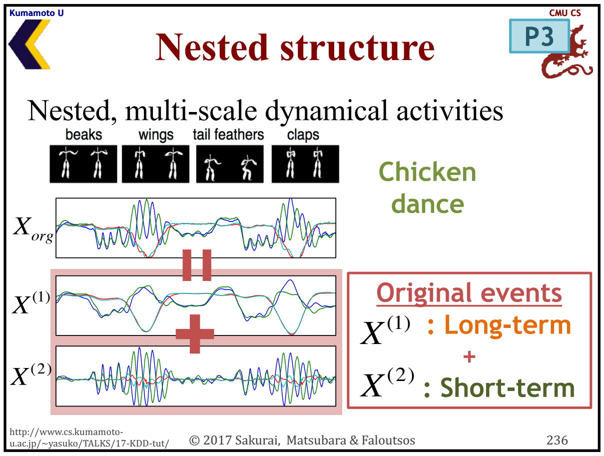

Nested structure

Nested, multi-scale dynamical activities

Chicken dance

Original events

$X^{(1)}$: Long-term

+

$X^{(2)}$: Short-term

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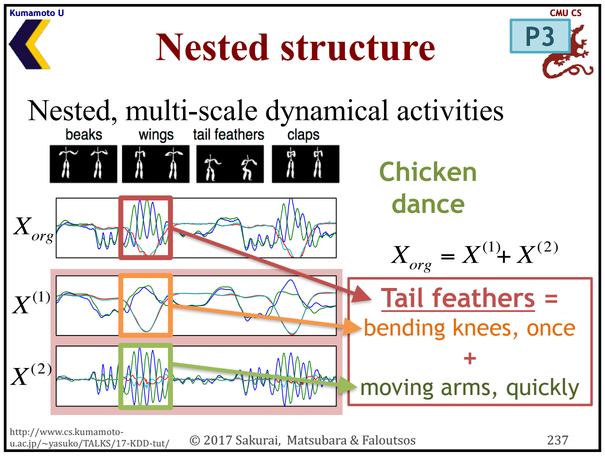

Nested structure

Nested, multi-scale dynamical activities

Chicken dance

$X_{org} = X^{(1)} + X^{(2)}$

Tail feathers = bending knees, once + moving arms, quickly

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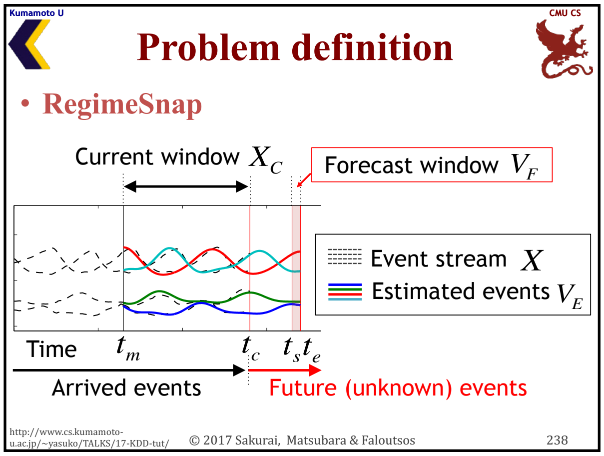

Problem definition

- RegimeSnap

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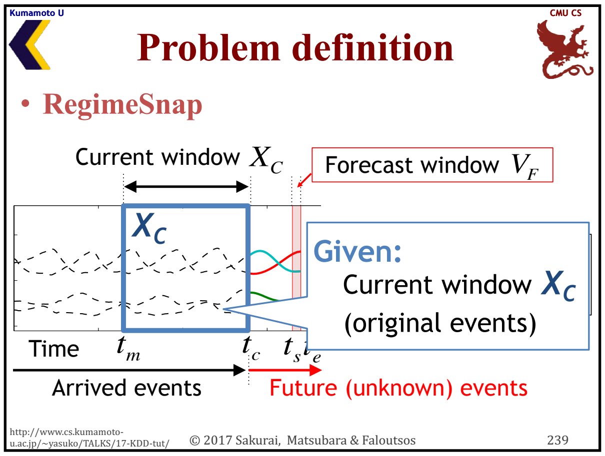

Problem definition

- RegimeSnap

Given: Current window X_C (original events)

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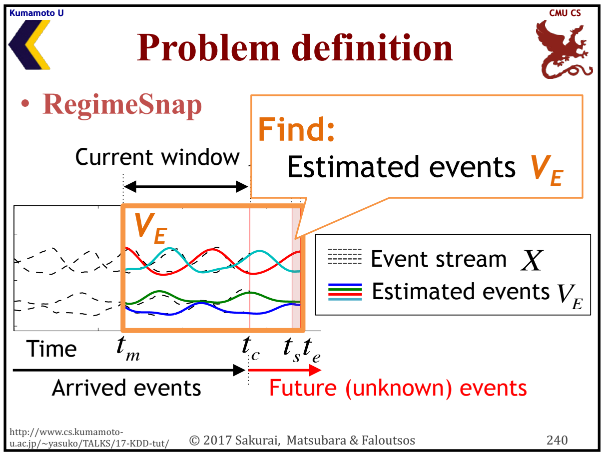

Problem definition

- RegimeSnap

Find: Estimated events V_E

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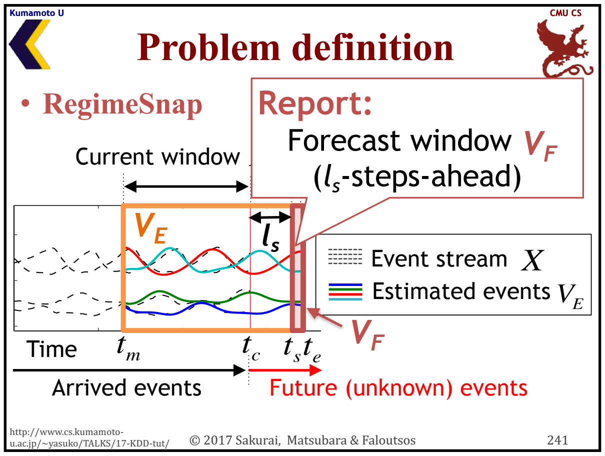

Problem definition

- **RegimeSnap**

Report:
Forecast window V_F
(l_s-steps-ahead)

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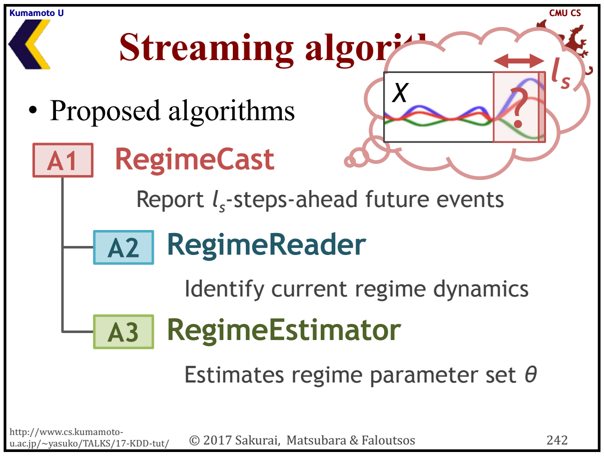

Streaming algori

- Proposed algorithms

A1 RegimeCast
Report l_s-steps-ahead future events

A2 RegimeReader
Identify current regime dynamics

A3 RegimeEstimator
Estimates regime parameter set θ

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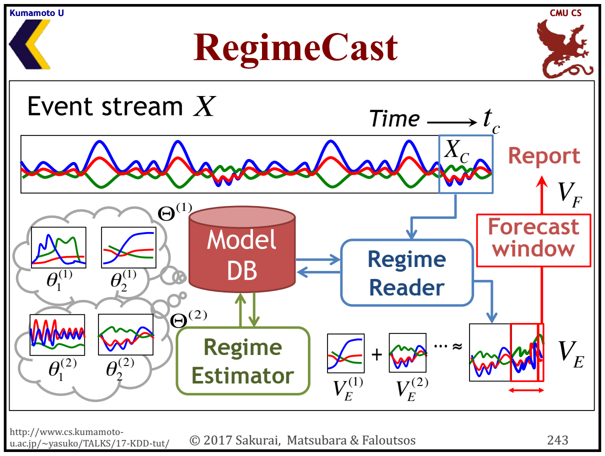

RegimeCast

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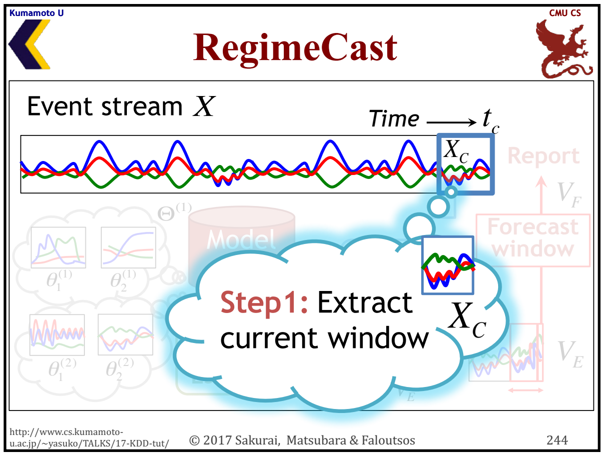

RegimeCast

Step1: Extract current window X_C

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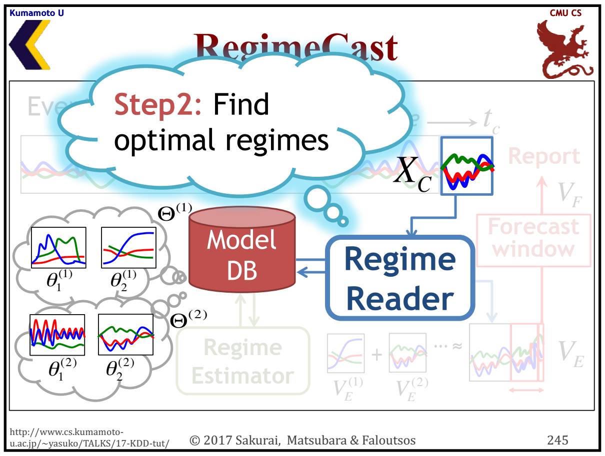

RegimeCast

Step2: Find optimal regimes

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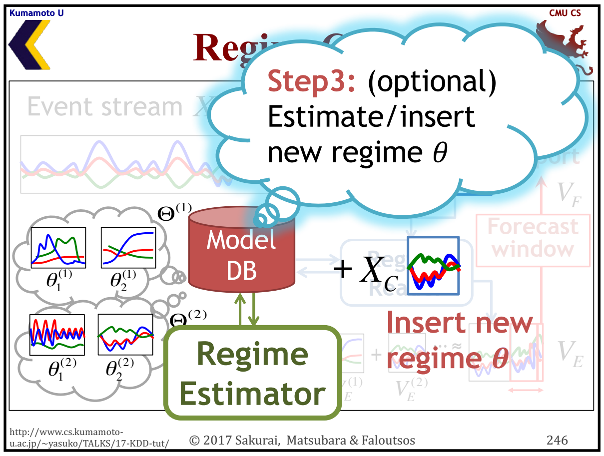

Regi

Step3: (optional) Estimate/insert new regime θ

Insert new regime θ

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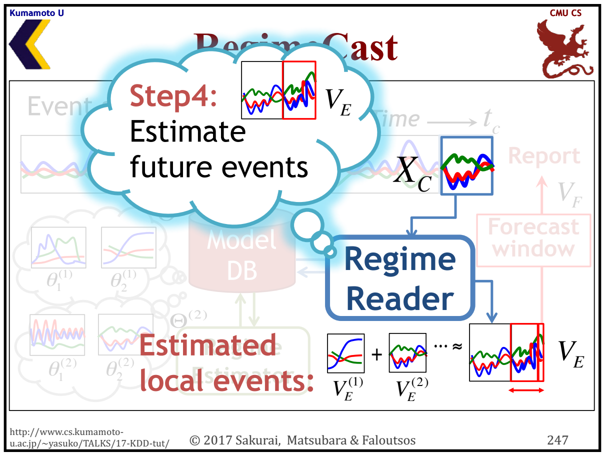
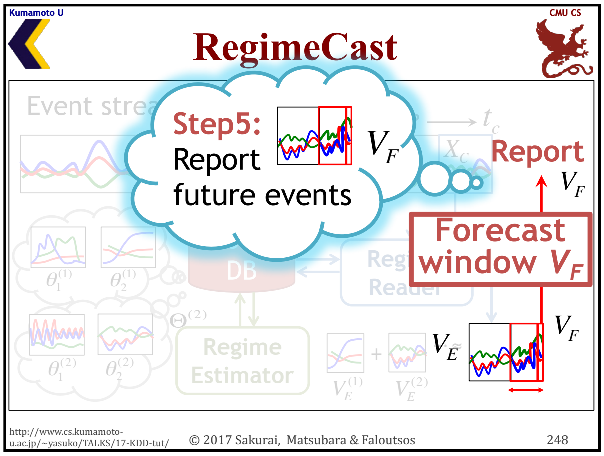


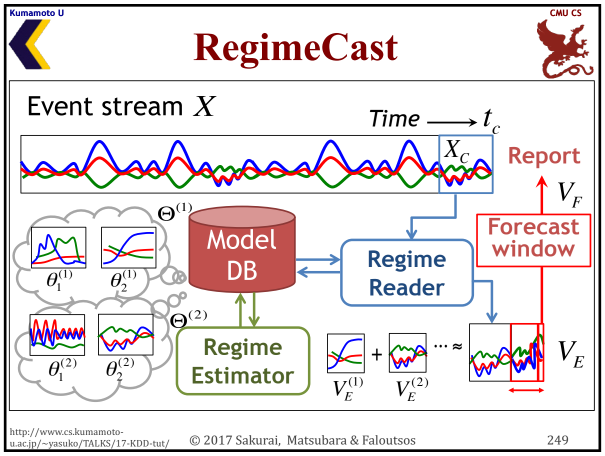
RegimeCast

Step4: Estimate future events V_E

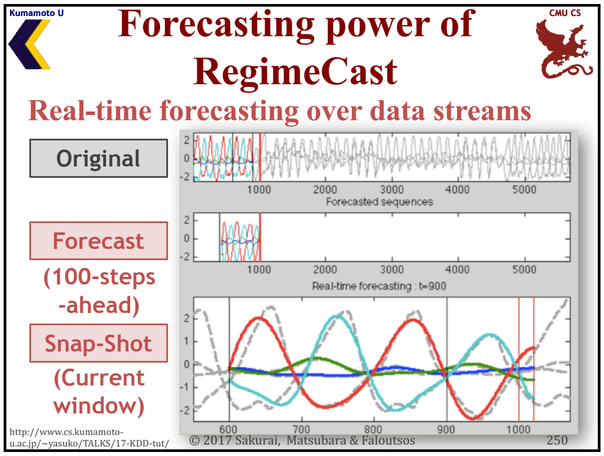


RegimeCast

Step5: Report V_F future events



RegimeCast



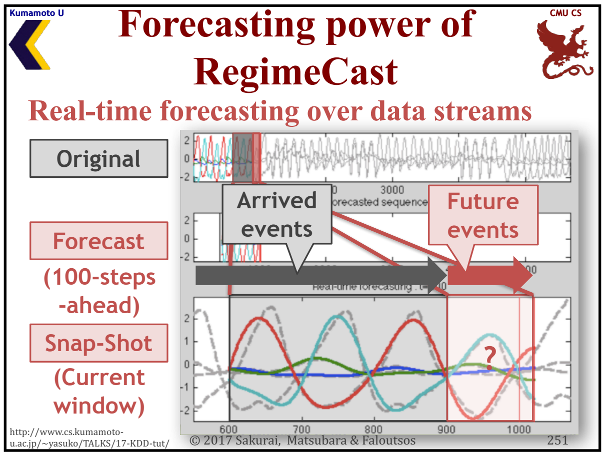
Forecasting power of RegimeCast

Real-time forecasting over data streams

Original

Forecast (100-steps -ahead)

Snap-Shot (Current window)



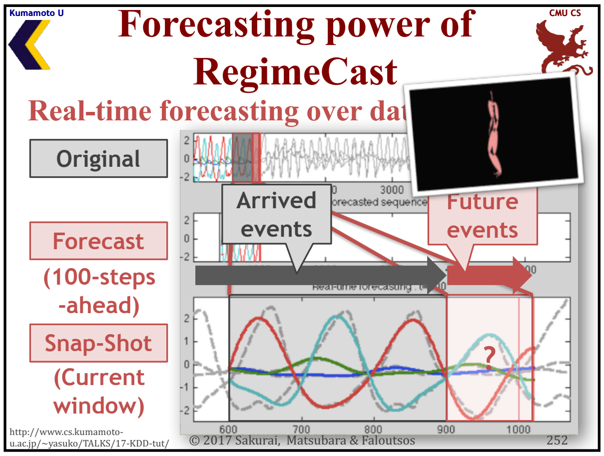
Forecasting power of RegimeCast

Real-time forecasting over data streams

Original

Forecast (100-steps -ahead)

Snap-Shot (Current window)



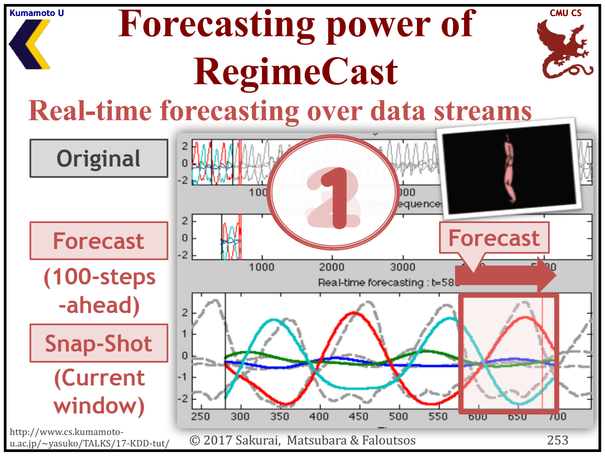
Forecasting power of RegimeCast

Real-time forecasting over dat

Original

Forecast (100-steps -ahead)

Snap-Shot (Current window)



Forecasting power of RegimeCast

Real-time forecasting over data streams

Original

Forecast (100-steps -ahead)

Snap-Shot (Current window)

Forecast

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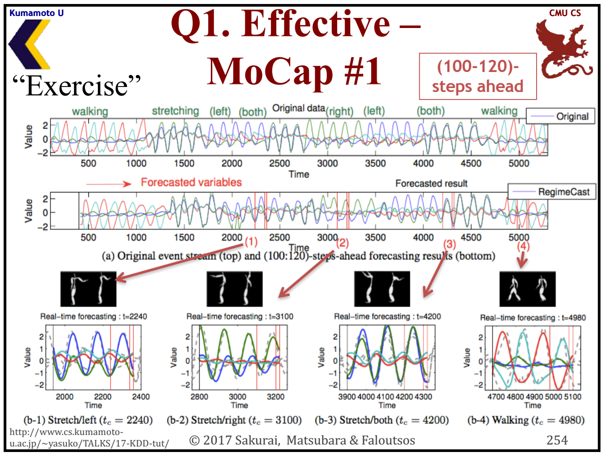

Q1. Effective – MoCap #1

"Exercise"

(100-120)-steps ahead

(a) Original event stream (top) and (100:120)-steps-ahead forecasting results (bottom)

(b-1) Stretch/left ($t_c = 2240$) (b-2) Stretch/right ($t_c = 3100$) (b-3) Stretch/both ($t_c = 4200$) (b-4) Walking ($t_c = 4980$)

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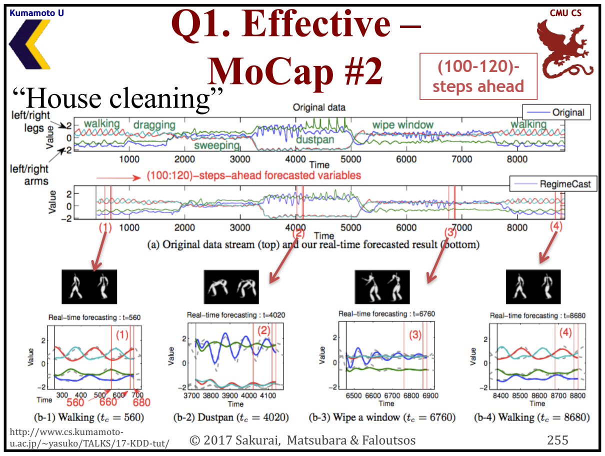

Q1. Effective – MoCap #2

"House cleaning"

(100-120)-steps ahead

(a) Original data stream (top) and our real-time forecasted result (bottom)

(b-1) Walking ($t_c = 560$) (b-2) Dustpan ($t_c = 4020$) (b-3) Wipe a window ($t_c = 6760$) (b-4) Walking ($t_c = 8680$)

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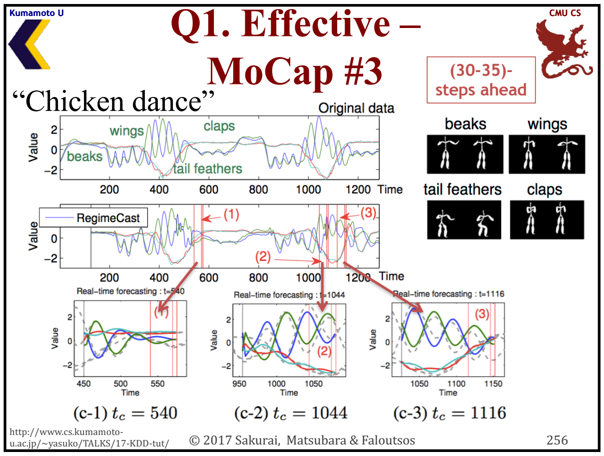

Q1. Effective – MoCap #3

"Chicken dance"

(30-35)-steps ahead

(c-1) $t_c = 540$ (c-2) $t_c = 1044$ (c-3) $t_c = 1116$

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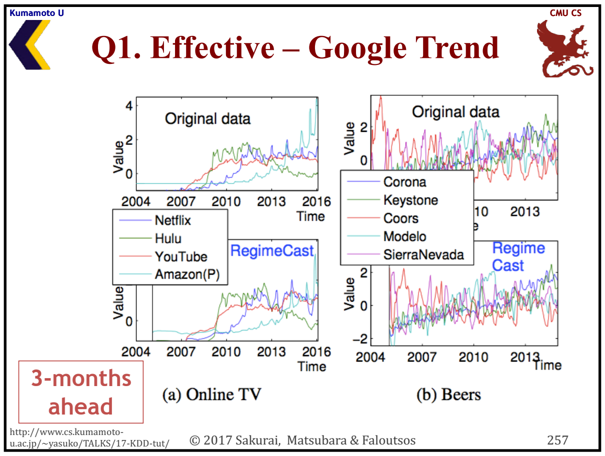

Q1. Effective – Google Trend

3-months ahead

(a) Online TV (b) Beers

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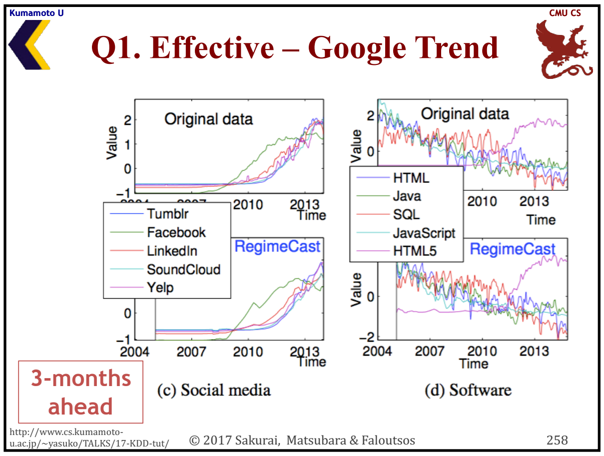

Q1. Effective – Google Trend

3-months ahead

(c) Social media (d) Software

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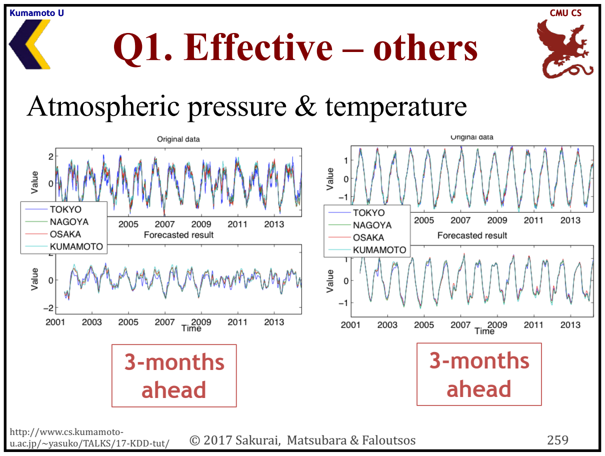

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Q1. Effective – others

Atmospheric pressure & temperature

3-months ahead

3-months ahead

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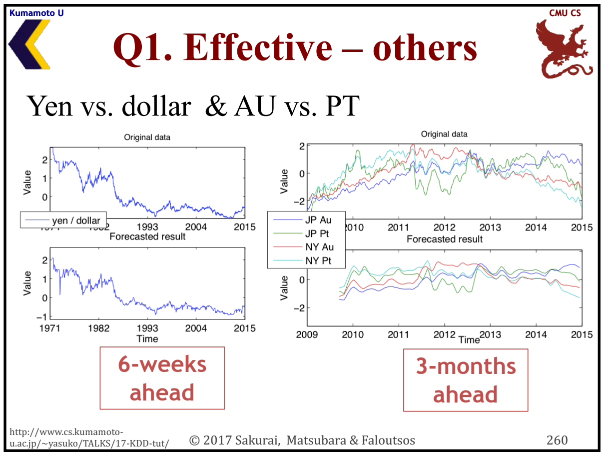

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Q1. Effective – others

Yen vs. dollar & AU vs. PT

6-weeks ahead

3-months ahead

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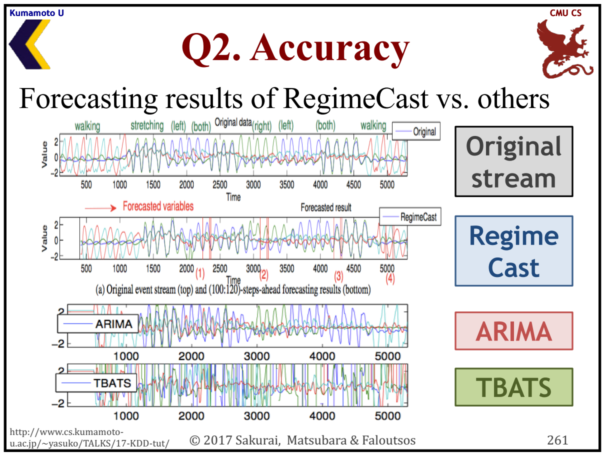

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Q2. Accuracy

Forecasting results of RegimeCast vs. others

(a) Original event stream (top) and (100:120)-steps-ahead forecasting results (bottom)

Original stream

Regime Cast

ARIMA

TBATS

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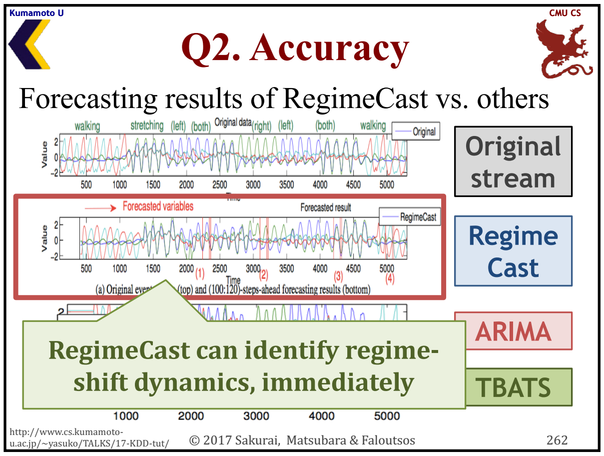

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Q2. Accuracy

Forecasting results of RegimeCast vs. others

(a) Original event stream (top) and (100:120)-steps-ahead forecasting results (bottom)

Original stream

Regime Cast

ARIMA

TBATS

RegimeCast can identify regime-shift dynamics, immediately

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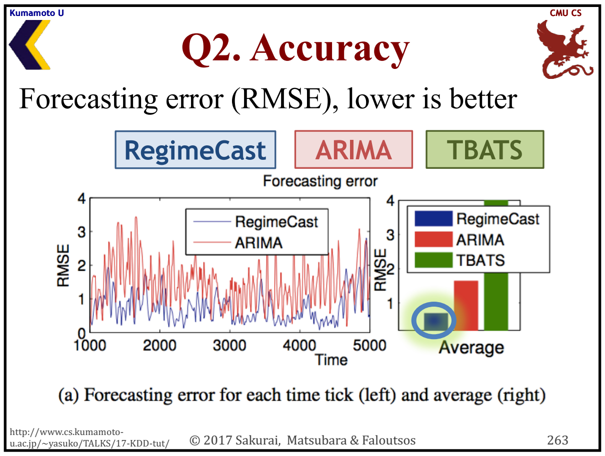

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Q2. Accuracy

Forecasting error (RMSE), lower is better

RegimeCast ARIMA TBATS

(a) Forecasting error for each time tick (left) and average (right)

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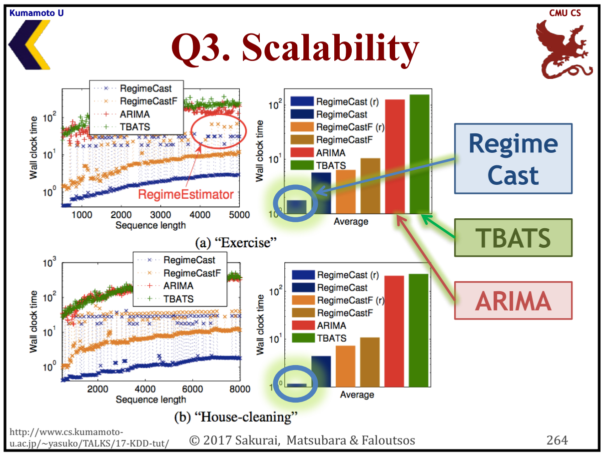

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Q3. Scalability

(a) "Exercise"

(b) "House-cleaning"

Regime Cast

TBATS

ARIMA

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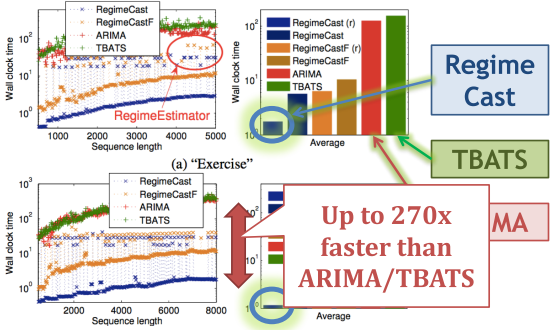
Q3. Scalability



(a) "Exercise"

(b) "House-cleaning"

Regime Cast

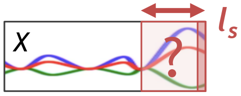
TBATS

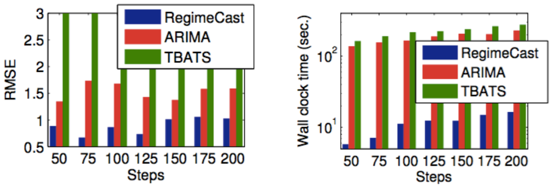
ARIMA

Up to 270x faster than ARIMA/TBATS

Q. Discussion

Q. How long ahead can it forecast?





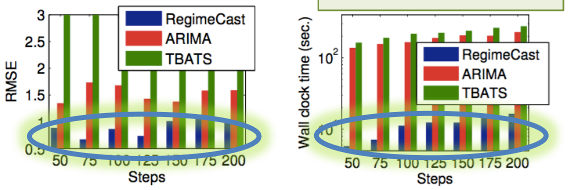
l_s-steps vs. error

l_s-steps vs. speed

Q. Discussion

Q. How long ahead can it forecast?

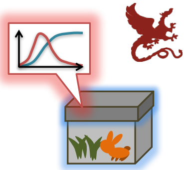
A. It can forecast future events for every step l_s



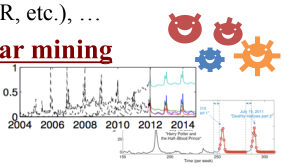
l_s-steps vs. error

l_s-steps vs. speed

Part 2 Conclusions



- ✓ **Why: "non-linear" modeling**
  - Black box: lag plots (k-NN search)
  - Grey-box: given a model
- ✓ **Fundamentals: popular non-linear models**
  - Logistic function, Lotka-Volterra, Competition, ...
  - Epidemics (SI, SIR, SEIR, etc.), …
- ✓ **Applications: non-linear mining**
  - Epidemics
  - Information diffusion
  - Online competition



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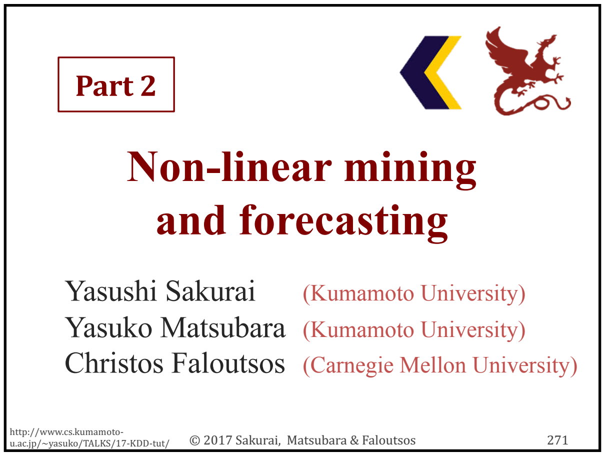

Part 2

Non-linear mining and forecasting

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