Mining Big Time-series Data on the Web

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Yasuko Matsubara (Kumamoto University)
Christos Faloutsos (Carnegie Mellon University)

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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 vs.

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Non-linear mining and forecasting

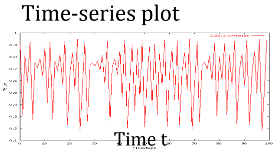
Q. What are "non-linear phenomena"?

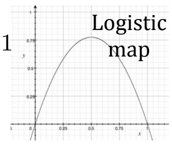
Example: logistic parabola

Models population of flies [R. May/1976]

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

Time-series plot





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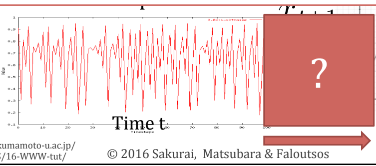
Non-linear mining and forecasting

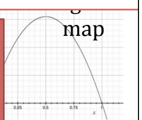
Q. What are "non-linear phenomena"?

Problem:

Given: a time series x_t

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





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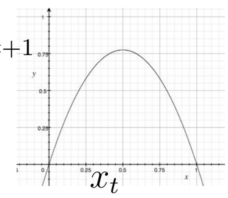
How to forecast?

Solution 1

Linear equations, e.g., AR, ARIMA, …



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How to forecast?

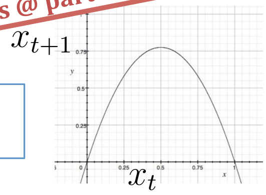
Solution 1

Linear equations, e.g., AR, ARIMA, …

Details @ part1

e.g., AR(1)

$x_{t+1} = ax_t + \epsilon$



How to forecast?

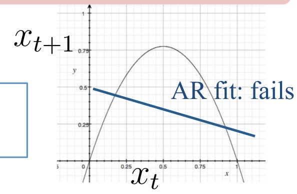
Solution 1

Linear equations, e.g., AR, ARIMA, …

but: linearity assumption

e.g., AR(1)

$x_{t+1} = ax_t + \epsilon$



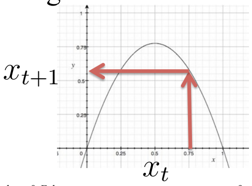
How to forecast?

Solution 2

"Delayed Coordinate Embedding"

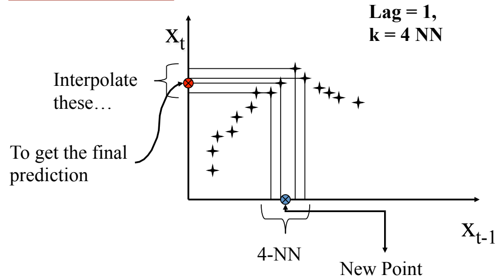
= Lag Plots [Sauer92]

- Based on k-nearest neighbor search



General Intuition (Lag Plot)

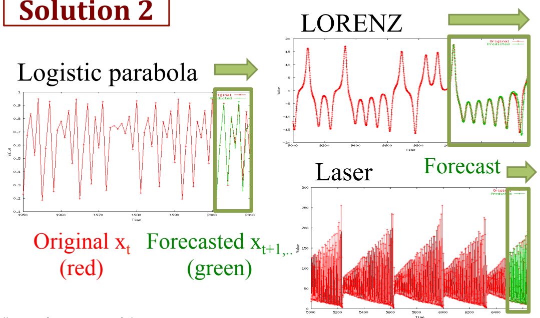
Solution 2



Forecasting results (Lag Plot)

[Chakrabarti+ CIKM'02]

Solution 2



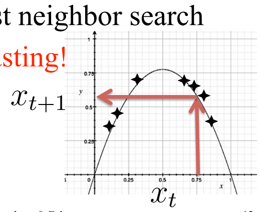
How to forecast?

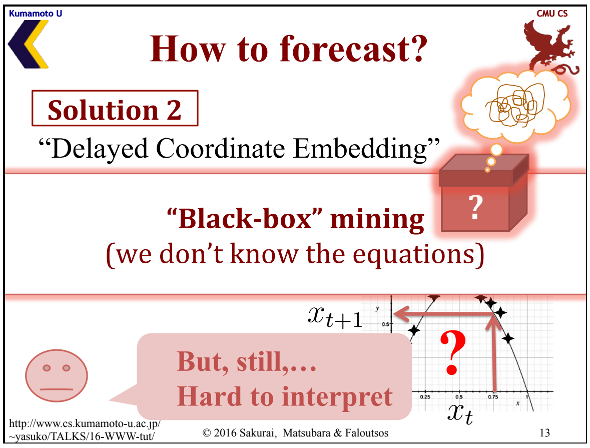
Solution 2

"Delayed Coordinate Embedding"

= Lag Plots [Sauer92]

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

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How to forecast?
Solution 2
"Delayed Coordinate Embedding"
"Black-box" mining
(we don't know the equations)
?
x_{t+1}
?
But, still,…
Hard to interpret
x_t
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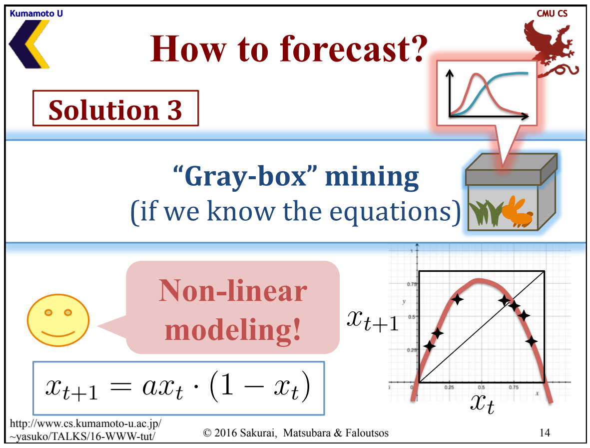
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How to forecast?
Solution 3
"Gray-box" mining
(if we know the equations)
Non-linear modeling!
x_{t+1}
$x_{t+1} = ax_t \cdot (1 - x_t)$
x_t
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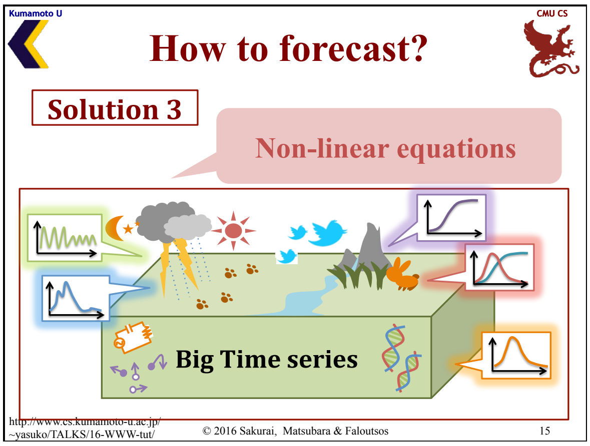
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Solution 3
Non-linear equations
Big Time series
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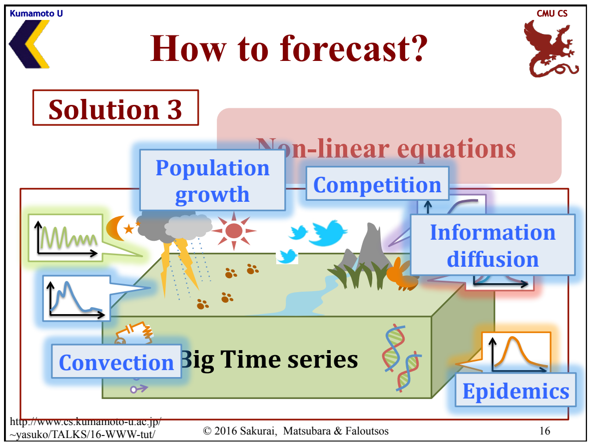
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Solution 3
Non-linear equations
Population growth
Competition
Information diffusion
Convection
Big Time series
Epidemics
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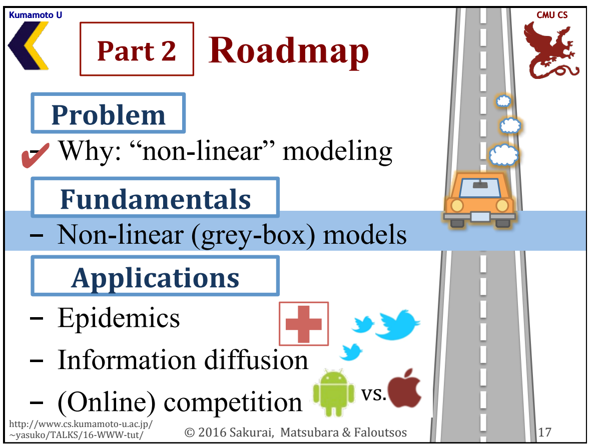
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Part 2 Roadmap
Problem
Why: "non-linear" modeling
Fundamentals
– Non-linear (grey-box) models
Applications
– Epidemics
– Information diffusion
– (Online) competition
vs.
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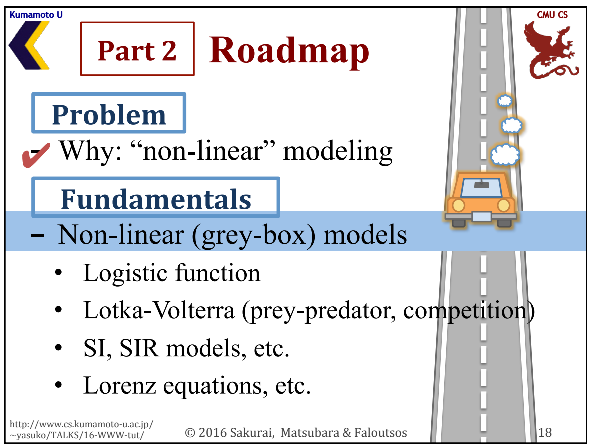
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Part 2 Roadmap
Problem
Why: "non-linear" modeling
Fundamentals
– Non-linear (grey-box) models
• Logistic function
• Lotka-Volterra (prey-predator, competition)
• SI, SIR models, etc.
• Lorenz equations, etc.
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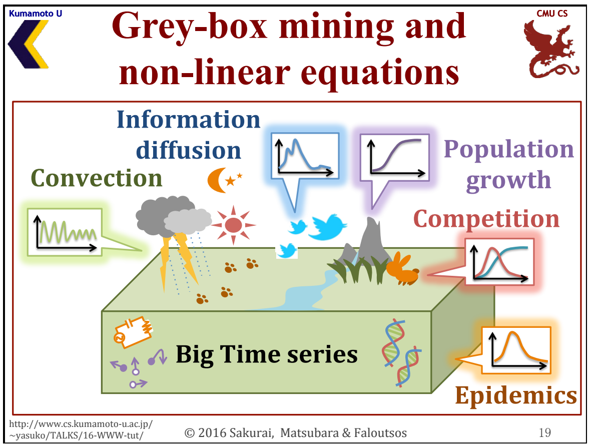
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Information diffusion
Convection
Population growth
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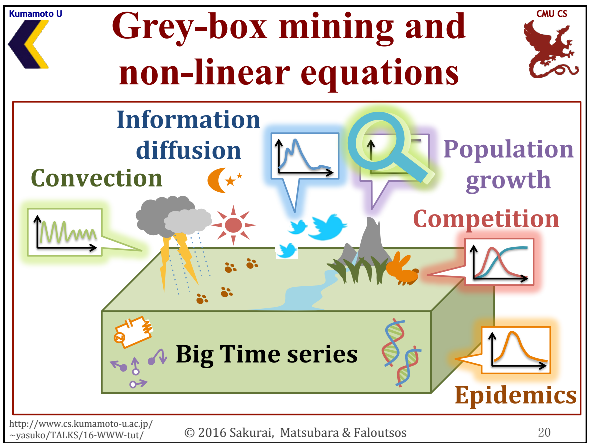
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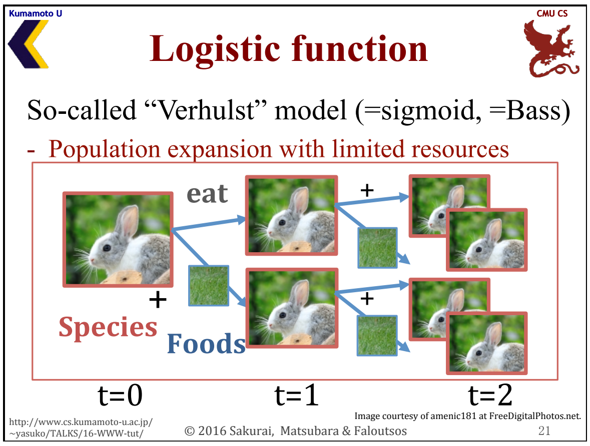
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Logistic function
So-called "Verhulst" model (=sigmoid, =Bass)
- Population expansion with limited resources
eat
+
Species
Foods
t=0
t=1
t=2
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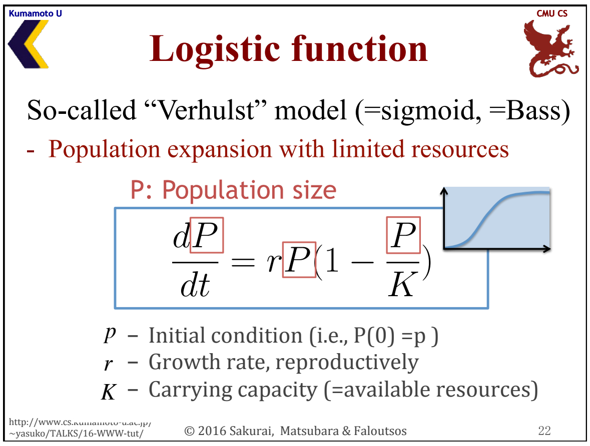
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Logistic function
So-called "Verhulst" model (=sigmoid, =Bass)
- Population expansion with limited resources
P: Population size
$\frac{dP}{dt} = rP(1 - \frac{P}{K})$
p – Initial condition (i.e., P(0) =p)
r – Growth rate, reproductively
K – Carrying capacity (=available resources)
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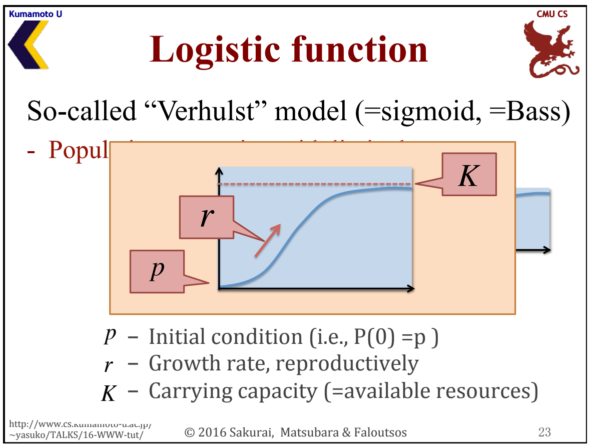
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Logistic function
So-called "Verhulst" model (=sigmoid, =Bass)
K
r
p
p – Initial condition (i.e., P(0) =p)
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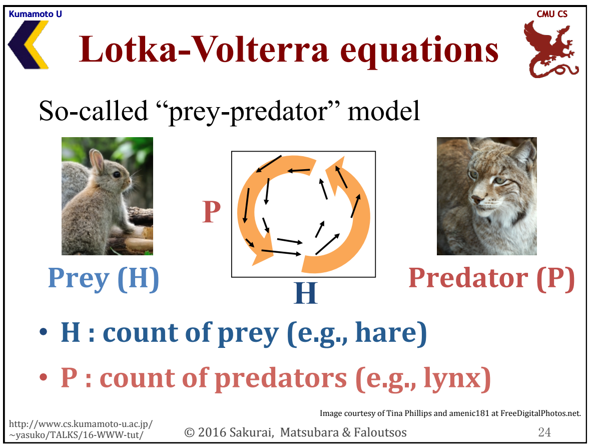
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Lotka-Volterra equations
So-called "prey-predator" model
P
H
Prey (H)
Predator (P)
• H : count of prey (e.g., hare)
• P : count of predators (e.g., lynx)
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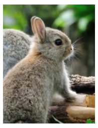
Lotka-Volterra equations

So-called "prey-predator" model



Prey (H)

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

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

Predator (P)

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

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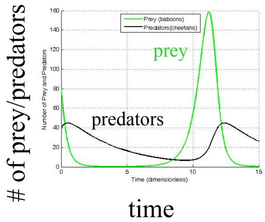
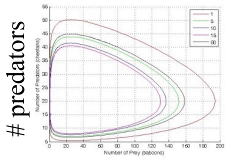
Solution to the Lotka-Volterra equations.

Frequency Plot



Phase Space Plot



From Wikipedia

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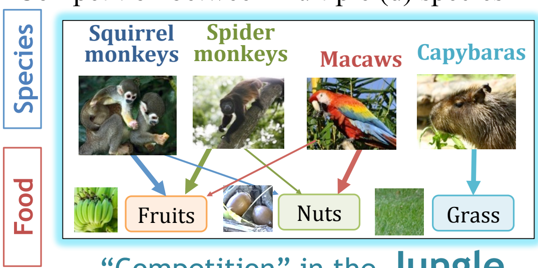
Extension: "Competitive" Lotka-Volterra equations

Competition between multiple (d) species



"Competition" in the **Jungle**

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"Competitive" Lotka-Volterra equations

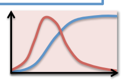
Competition between multiple (d) species

Population of species i — Population of j

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

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

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



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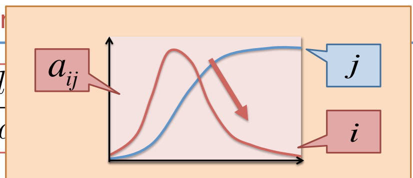
"Competitive" Lotka-Volterra equations

Competition between multiple (d) species

Popular... j



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

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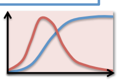

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"Competitive" Lotka-Volterra equations

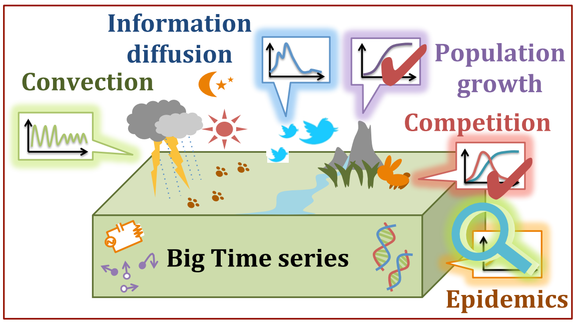
- Biological interaction
  - Table: Type of interaction

0 : no effect
\- : detrimental
\+ : beneficial

Species B

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

Grey-box mining and non-linear equations



Epidemics: Susceptible-Infected (SI) model

Each node is in one of two states

- S – Susceptible (healthy)
- I – Infected

$S \xrightarrow{\beta} I$

Epidemics: Susceptible-Infected (SI) model

Each node is in one of two states

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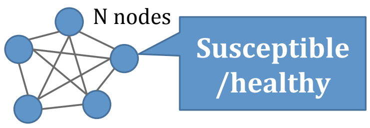
$S \xrightarrow{\beta} I$



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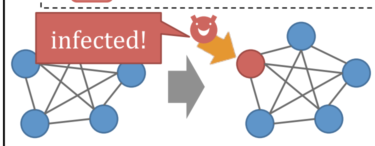

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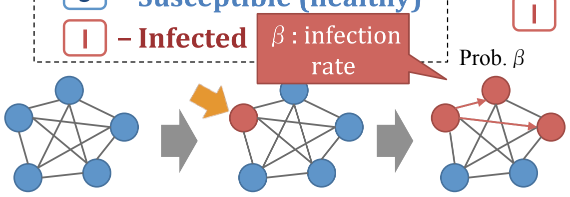


Epidemics: Susceptible-Infected (SI) model

Each node is in one of two states

$S \xrightarrow{\beta} I$

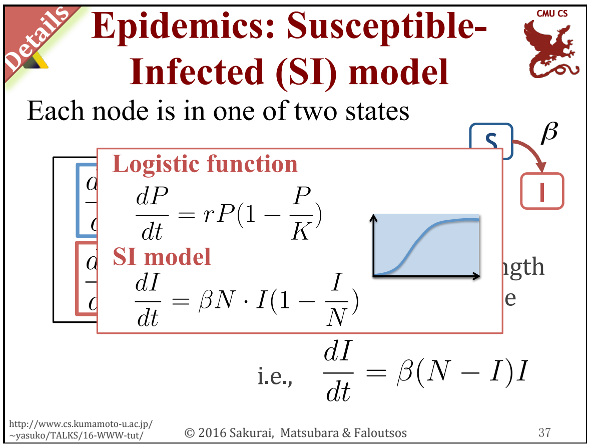
$$\frac{dS}{dt} = -\beta S I$$

$$\frac{dI}{dt} = +\beta S I$$

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

β : Infection strength
N : Population size

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


Details
Epidemics: Susceptible-Infected (SI) model
Each node is in one of two states
S
I
β
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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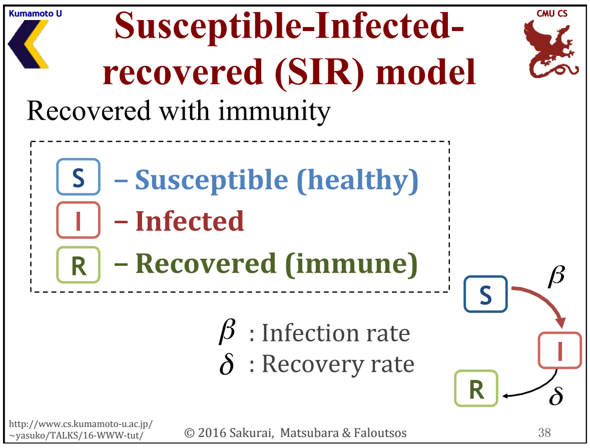
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Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S – Susceptible (healthy)
I – Infected
R – Recovered (immune)
β : Infection rate
δ : Recovery rate
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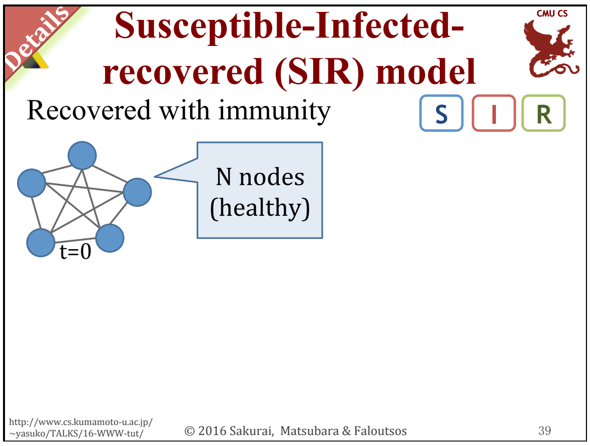
Details
Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S I R
N nodes (healthy)
t=0
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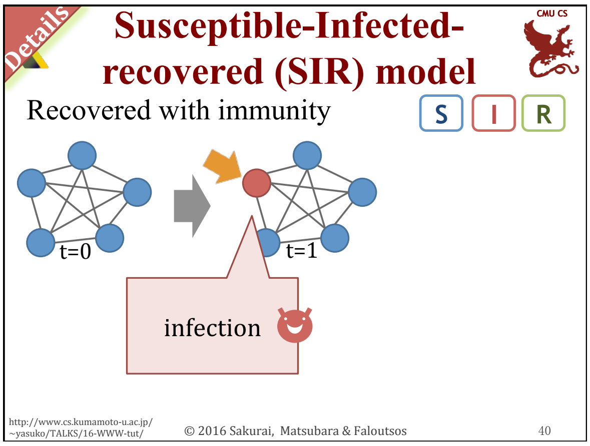
Details
Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S I R
t=0
t=1
infection
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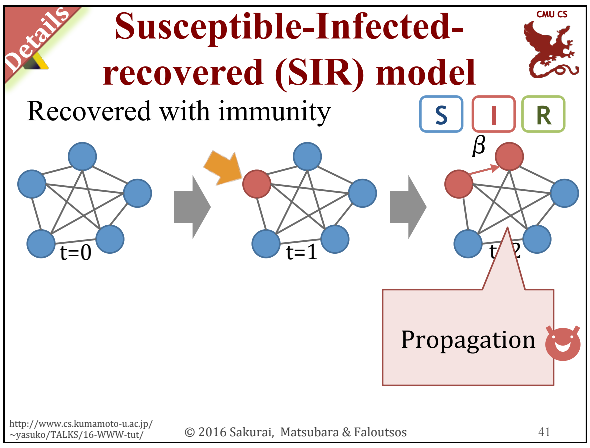
Details
Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S I R
β
t=0
t=1
t=2
Propagation
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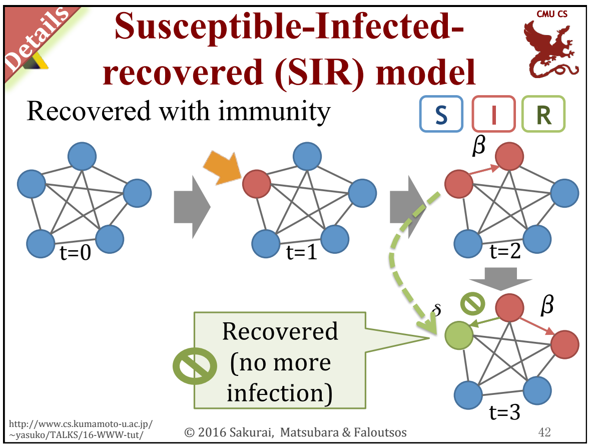
Details
Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S I R
β
t=0
t=1
t=2
δ
β
Recovered (no more infection)
t=3
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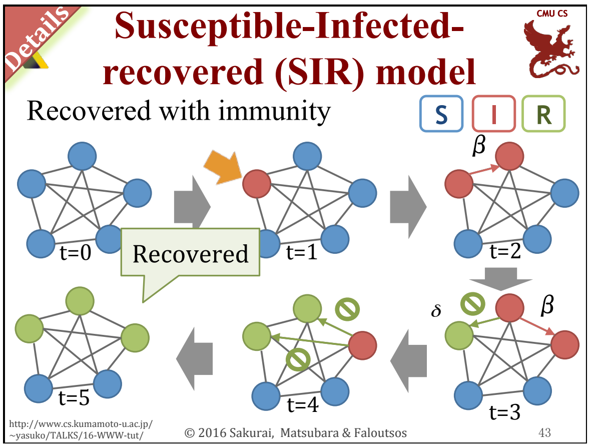
Details
Susceptible-Infected-recovered (SIR) model
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Recovered with immunity
S
I
R
β
t=0
Recovered
t=1
t=2
δ
β
t=5
t=4
t=3
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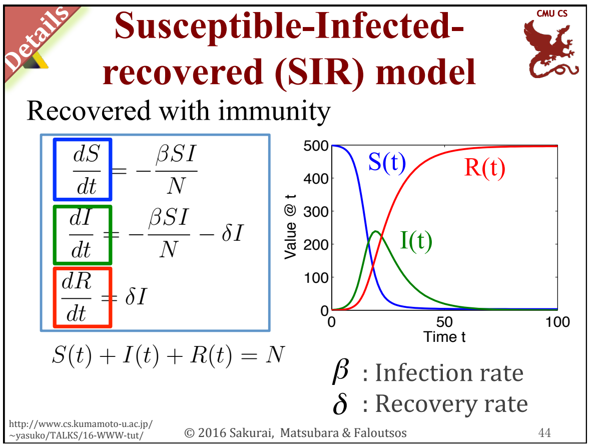
Details
Susceptible-Infected-recovered (SIR) model
CMU CS
Recovered with immunity
$\frac{dS}{dt} = -\frac{\beta SI}{N}$
$\frac{dI}{dt} = -\frac{\beta SI}{N} - \delta I$
$\frac{dR}{dt} = \delta I$
$S(t) + I(t) + R(t) = N$
S(t)
R(t)
I(t)
Value @ t
Time t
β : Infection rate
δ : Recovery rate
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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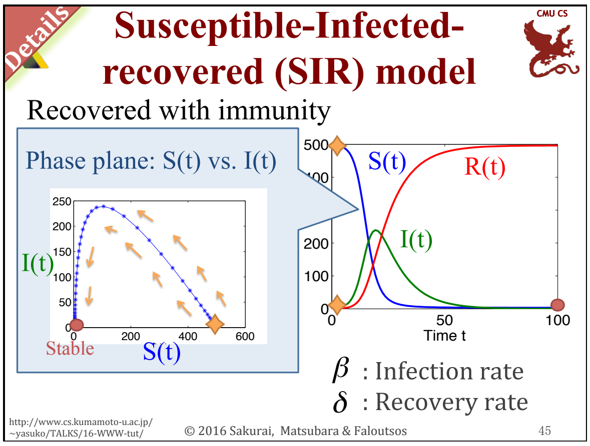
Details
Susceptible-Infected-recovered (SIR) model
CMU CS
Recovered with immunity
Phase plane: S(t) vs. I(t)
I(t)
Stable
S(t)
S(t)
R(t)
I(t)
Time t
β : Infection rate
δ : Recovery rate
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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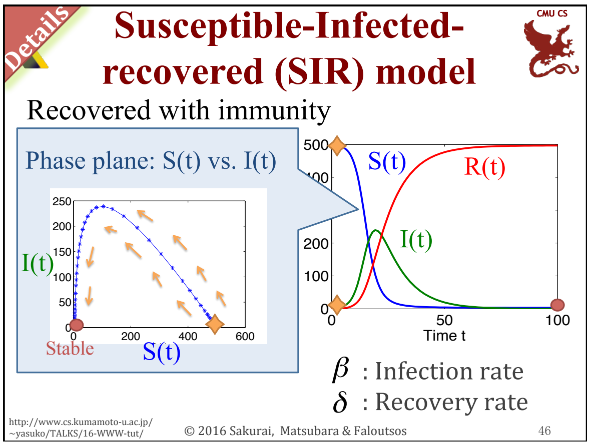
Details
Susceptible-Infected-recovered (SIR) model
CMU CS
Recovered with immunity
Phase plane: S(t) vs. I(t)
I(t)
Stable
S(t)
S(t)
R(t)
I(t)
Time t
β : Infection rate
δ : Recovery rate
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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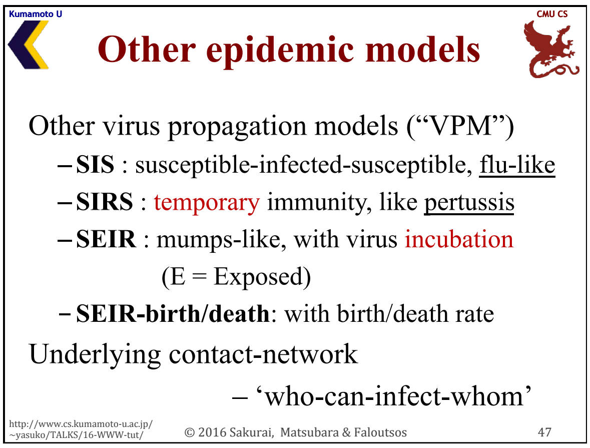
Kumamoto U
Other epidemic models
CMU CS
Other virus propagation models (“VPM”)
– SIS : susceptible-infected-susceptible, flu-like
– SIRS : temporary immunity, like pertussis
– SEIR : mumps-like, with virus incubation
(E = Exposed)
– SEIR-birth/death: with birth/death rate
Underlying contact-network
– ‘who-can-infect-whom’
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
© 2016 Sakurai, Matsubara & Faloutsos
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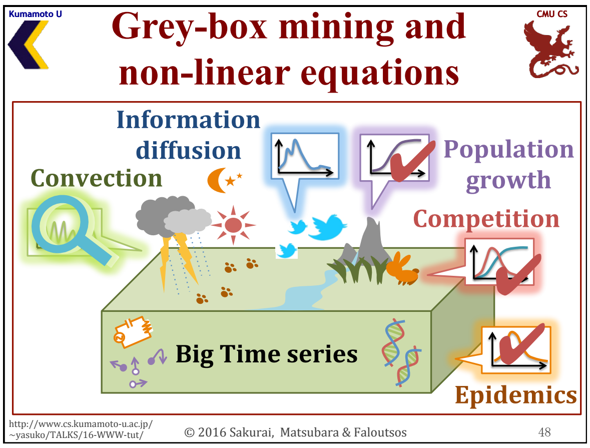
Kumamoto U
Grey-box mining and non-linear equations
CMU CS
Information diffusion
Convection
Population growth
Competition
Big Time series
Epidemics
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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Other non-linear models

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

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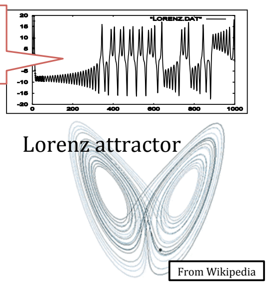
Other non-linear models

LORENZ: eqs. for atmospheric convection

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

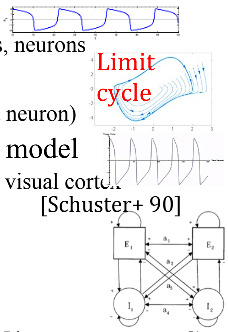
Butterfly effect (chaos)



http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/ © 2016 Sakurai, Matsubara & Faloutsos 50

Other non-linear models

- 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
- …
- …



http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/ © 2016 Sakurai, Matsubara & Faloutsos 51

Part 2 Roadmap

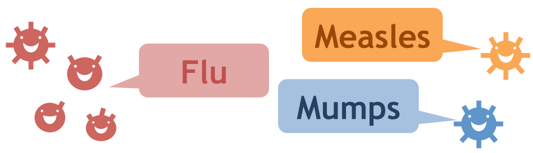
Problem
✔ Why: "non-linear" modeling

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

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

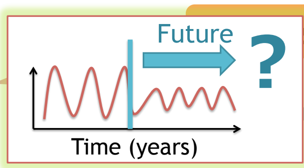
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/ © 2016 Sakurai, Matsubara & Faloutsos 52

Mining and forecasting of co-evolving epidemics



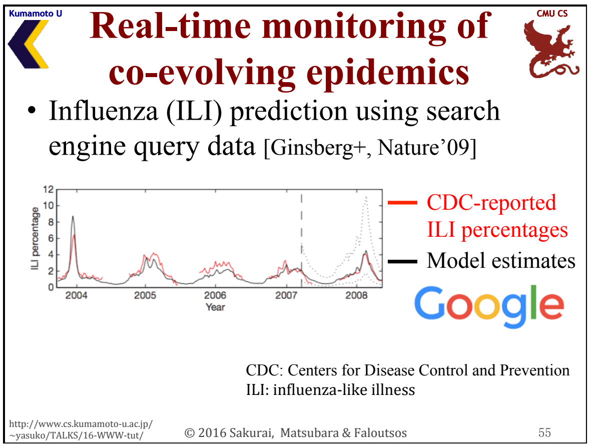
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/ © 2016 Sakurai, Matsubara & Faloutsos 53

Mining and forecasting of co-evolving epidemics



Q. Can we forecast future epidemics?

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/ © 2016 Sakurai, Matsubara & Faloutsos 54


Kumamoto U
CMU CS
Real-time monitoring of co-evolving epidemics
• Influenza (ILI) prediction using search engine query data [Ginsberg+, Nature'09]
CDC-reported ILI percentages
Model estimates
Google
ILI percentage
Year
CDC: Centers for Disease Control and Prevention
ILI: influenza-like illness
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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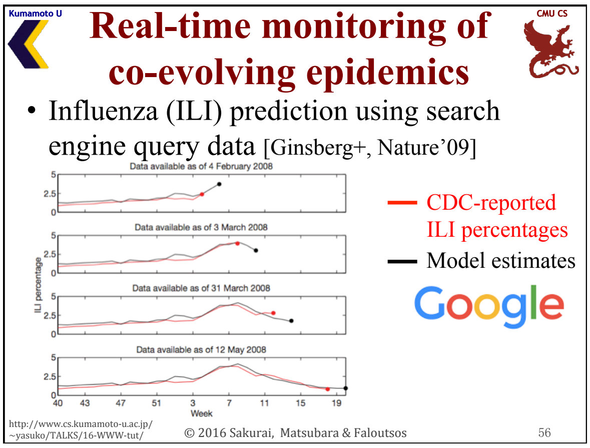
Kumamoto U
CMU CS
Real-time monitoring of co-evolving epidemics
• Influenza (ILI) prediction using search engine query data [Ginsberg+, Nature'09]
Data available as of 4 February 2008
Data available as of 3 March 2008
Data available as of 31 March 2008
Data available as of 12 May 2008
ILI percentage
Week
CDC-reported ILI percentages
Model estimates
Google
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
© 2016 Sakurai, Matsubara & Faloutsos
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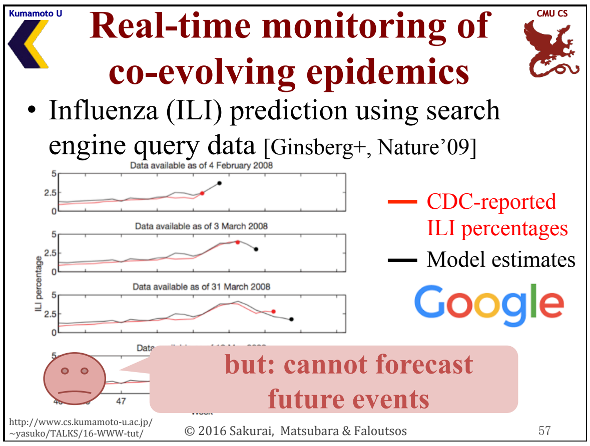
Kumamoto U
CMU CS
Real-time monitoring of co-evolving epidemics
• Influenza (ILI) prediction using search engine query data [Ginsberg+, Nature'09]
Data available as of 4 February 2008
Data available as of 3 March 2008
Data available as of 31 March 2008
CDC-reported ILI percentages
Model estimates
Google
but: cannot forecast future events
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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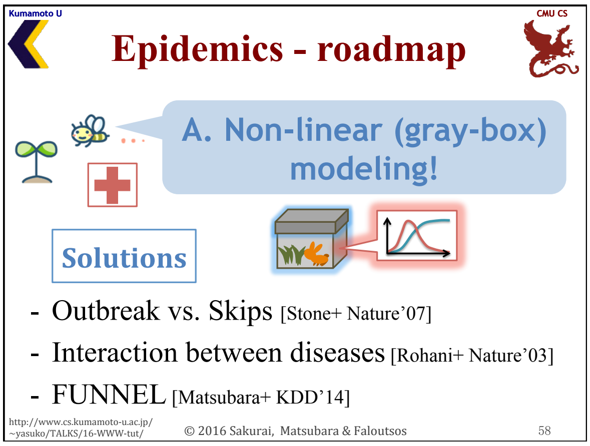
Kumamoto U
CMU CS
Epidemics - roadmap
A. Non-linear (gray-box) modeling!
Solutions
- Outbreak vs. Skips [Stone+ Nature'07]
- Interaction between diseases [Rohani+ Nature'03]
- FUNNEL [Matsubara+ KDD'14]
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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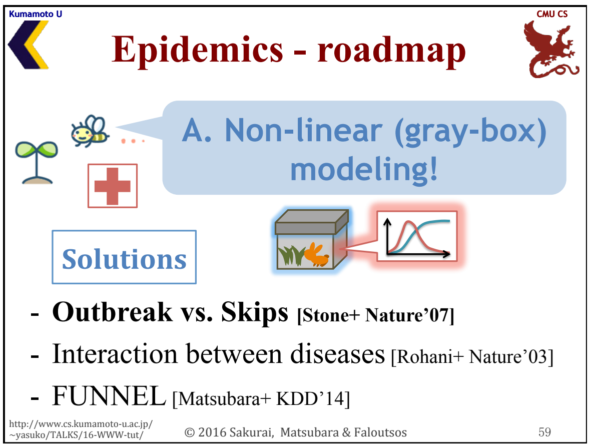
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http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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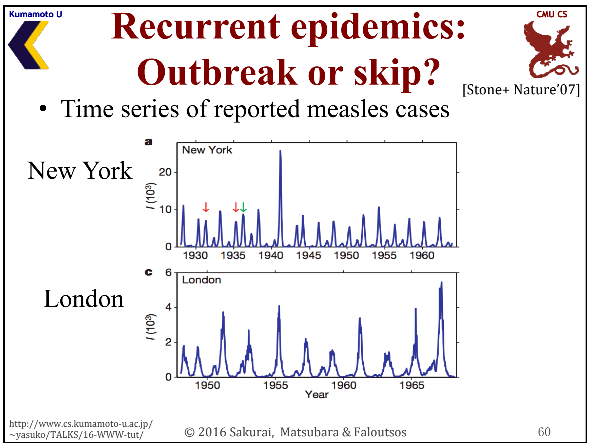
Kumamoto U
CMU CS
Recurrent epidemics: Outbreak or skip?
[Stone+ Nature'07]
• Time series of reported measles cases
New York
London
Year
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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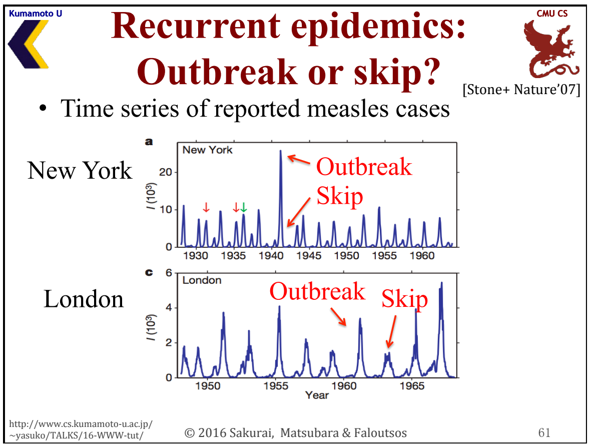
Kumamoto U
CMU CS
Recurrent epidemics: Outbreak or skip?
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• Time series of reported measles cases
New York
London
Outbreak
Skip
Year
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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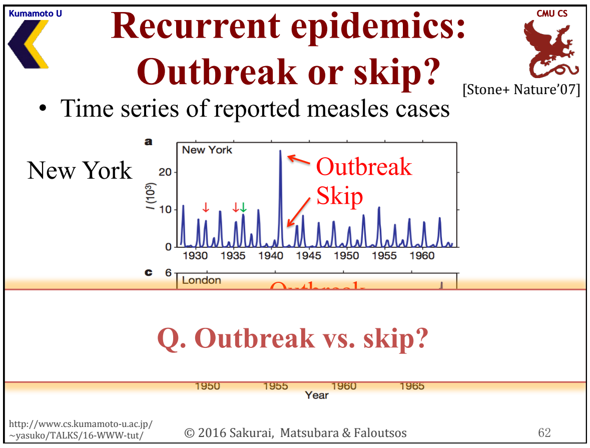
Kumamoto U
CMU CS
Recurrent epidemics: Outbreak or skip?
[Stone+ Nature'07]
• Time series of reported measles cases
New York
Outbreak
Skip
Q. Outbreak vs. skip?
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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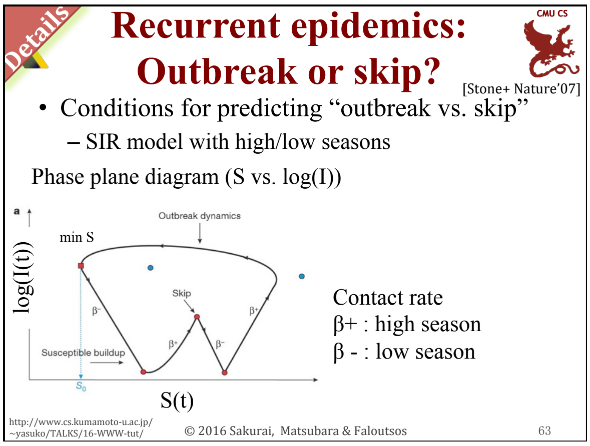
Details
CMU CS
Recurrent epidemics: Outbreak or skip?
[Stone+ Nature'07]
• Conditions for predicting "outbreak vs. skip"
– SIR model with high/low seasons
Phase plane diagram (S vs. log(I))
log(I(t))
min S
Outbreak dynamics
Skip
Susceptible buildup
S(t)
Contact rate
β+ : high season
β - : low season
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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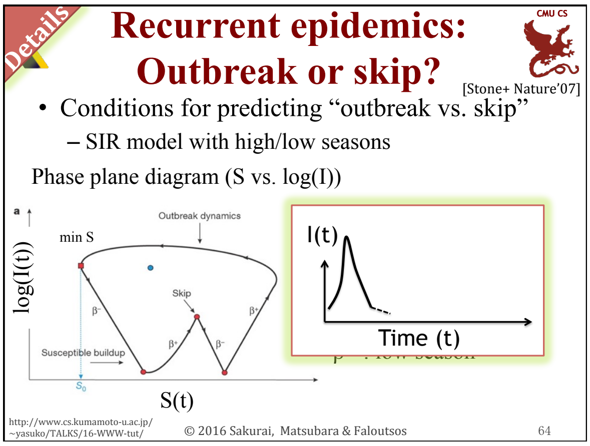
Details
CMU CS
Recurrent epidemics: Outbreak or skip?
[Stone+ Nature'07]
• Conditions for predicting "outbreak vs. skip"
– SIR model with high/low seasons
Phase plane diagram (S vs. log(I))
log(I(t))
min S
Outbreak dynamics
Skip
Susceptible buildup
S(t)
I(t)
Time (t)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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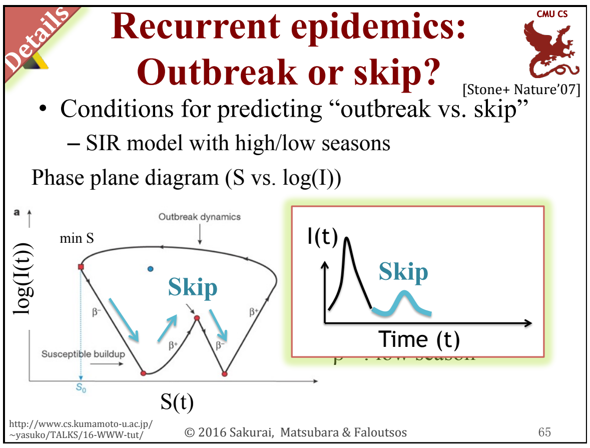
Details
CMU CS
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[Stone+ Nature'07]
• Conditions for predicting "outbreak vs. skip"
– SIR model with high/low seasons
Phase plane diagram (S vs. log(I))
log(I(t))
min S
Outbreak dynamics
Skip
Susceptible buildup
S(t)
I(t)
Skip
Time (t)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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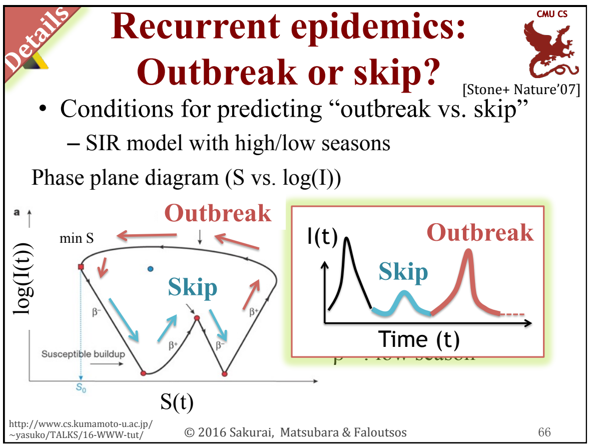
Details
CMU CS
Recurrent epidemics: Outbreak or skip?
[Stone+ Nature'07]
• Conditions for predicting "outbreak vs. skip"
– SIR model with high/low seasons
Phase plane diagram (S vs. log(I))
log(I(t))
Outbreak
min S
Skip
Susceptible buildup
S(t)
I(t)
Outbreak
Skip
Time (t)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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Details

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

min S

log(I(t))

S(t)

Threshold S_c: "Outbreak vs. Skip"

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

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

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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]

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Ecological interference between fatal diseases

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

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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!

Measles VS. Whooping cough

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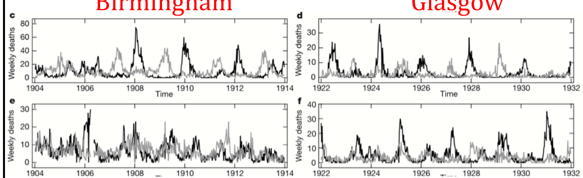
Ecological interference between fatal diseases

[Rohani+ Nature'03]

Weekly case fatality reports for two diseases

— measles — Whooping cough



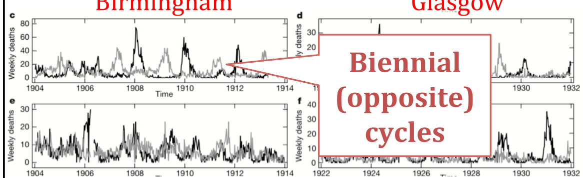
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/ © 2016 Sakurai, Matsubara & Faloutsos 71

Ecological interference between fatal diseases

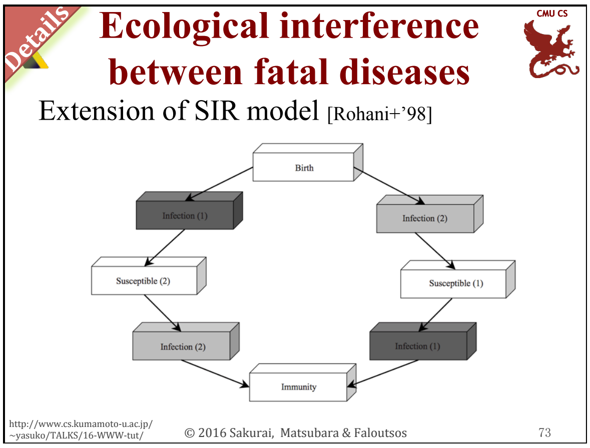
[Rohani+ Nature'03]

Weekly case fatality reports for two diseases

— measles — Whooping cough



http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/ © 2016 Sakurai, Matsubara & Faloutsos 72


Details
Ecological interference between fatal diseases
Extension of SIR model [Rohani+'98]
Birth
Infection (1)
Infection (2)
Susceptible (2)
Susceptible (1)
Infection (2)
Infection (1)
Immunity
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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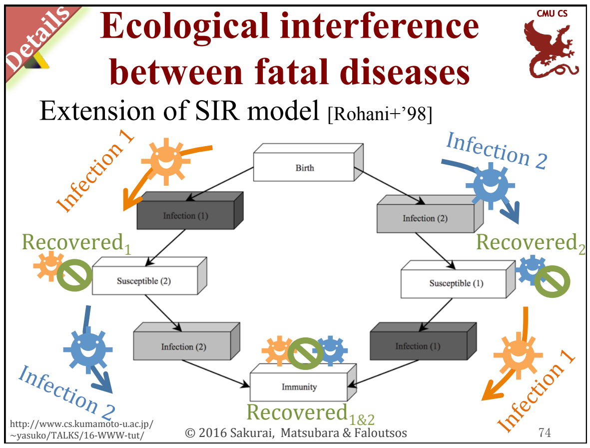
Details
Ecological interference between fatal diseases
Extension of SIR model [Rohani+'98]
Infection 1
Infection 2
Recovered1
Recovered2
Infection 2
Recovered1&2
Infection 1
Birth
Infection (1)
Infection (2)
Susceptible (2)
Susceptible (1)
Infection (2)
Infection (1)
Immunity
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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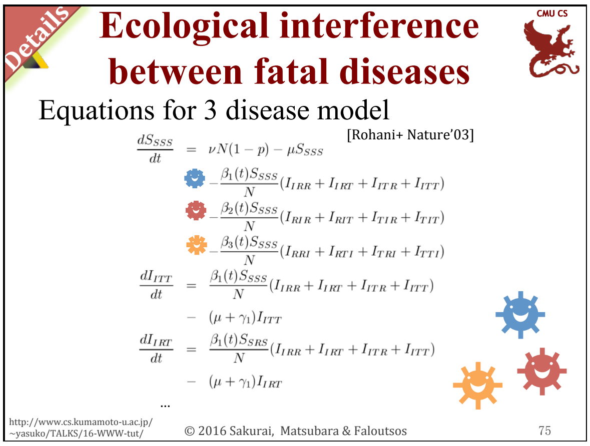
Details
Ecological interference between fatal diseases
Equations for 3 disease model
[Rohani+ Nature'03]
$\frac{dS_{SSS}}{dt} = \nu N(1-p) - \mu S_{SSS}$
$- \frac{\beta_1(t)S_{SSS}}{N}(I_{IRR} + I_{IRT} + I_{ITR} + I_{ITT})$
$- \frac{\beta_2(t)S_{SSS}}{N}(I_{RIR} + I_{RIT} + I_{TIR} + I_{TIT})$
$- \frac{\beta_3(t)S_{SSS}}{N}(I_{RRI} + I_{RTI} + I_{TRI} + I_{TTI})$
$\frac{dI_{ITT}}{dt} = \frac{\beta_1(t)S_{SSS}}{N}(I_{IRR} + I_{IRT} + I_{ITR} + I_{ITT})$
$- (\mu + \gamma_1)I_{ITT}$
$\frac{dI_{IRT}}{dt} = \frac{\beta_1(t)S_{SRS}}{N}(I_{IRR} + I_{IRT} + I_{ITR} + I_{ITT})$
$- (\mu + \gamma_1)I_{IRT}$
...
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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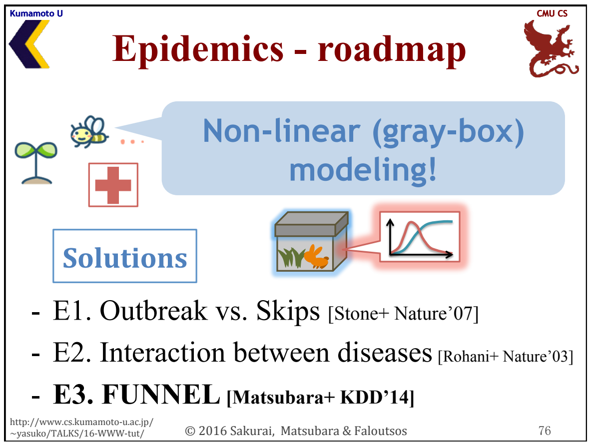
Kumamoto U
CMU CS
Epidemics - roadmap
Non-linear (gray-box) modeling!
Solutions
- E1. Outbreak vs. Skips [Stone+ Nature'07]
- E2. Interaction between diseases [Rohani+ Nature'03]
- E3. FUNNEL [Matsubara+ KDD'14]
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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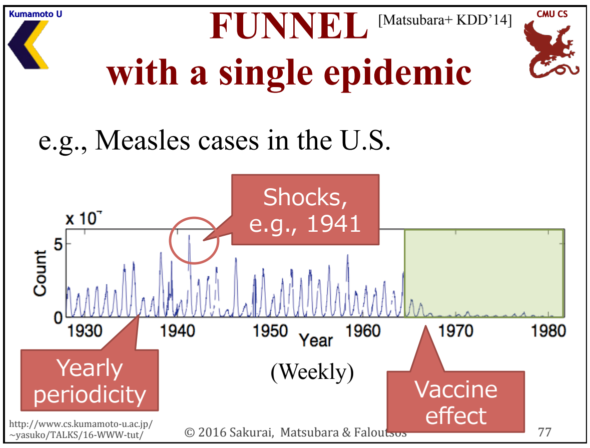
Kumamoto U
CMU CS
FUNNEL [Matsubara+ KDD'14]
with a single epidemic
e.g., Measles cases in the U.S.
Shocks, e.g., 1941
x 10
Count
5
0
1930
1940
1950
1960
1970
1980
Year
(Weekly)
Yearly periodicity
Vaccine effect
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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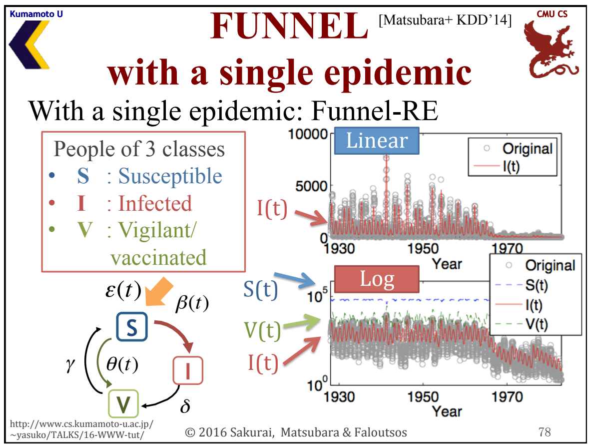
Kumamoto U
CMU CS
FUNNEL [Matsubara+ KDD'14]
with a single epidemic
With a single epidemic: Funnel-RE
People of 3 classes
• S : Susceptible
• I : Infected
• V : Vigilant/ vaccinated
ε(t)
β(t)
S
γ
θ(t)
I
V
δ
Linear
10000
5000
0
1930
1950
1970
Year
Original
I(t)
I(t)
S(t)
V(t)
I(t)
Log
Original
S(t)
I(t)
V(t)
1930
1950
1970
Year
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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Kumamoto U

FUNNEL with a single epidemic

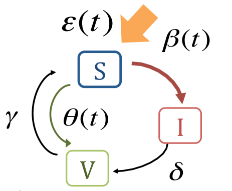
[Matsubara+ KDD'14]

CMU CS

With a single epidemic: Funnel-RE

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

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



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Kumamoto U

FUNNEL with a single epidemic

[Matsubara+ KDD'14]

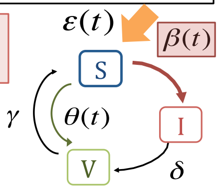
CMU CS

With a single epidemic: Funnel-RE

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

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

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



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FUNNEL with a single epidemic

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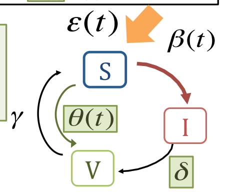
CMU CS

With a single epidemic: Funnel-RE

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

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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FUNNEL with a single epidemic

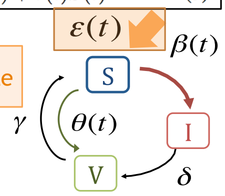
[Matsubara+ KDD'14]

CMU CS

With a single epidemic: Funnel-RE

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

$\varepsilon(t)$: temporal susceptible rate



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FUNNEL with a single epidemic

[Matsubara+ KDD'14]

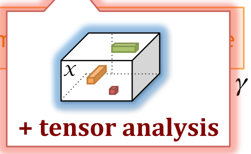
CMU CS

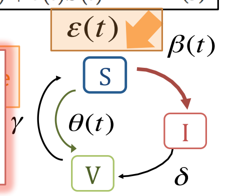
With a single epidemic: Funnel-RE

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

FUNNEL: Details @ part3

$\varepsilon(t)$: tem...





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Part 2 Roadmap

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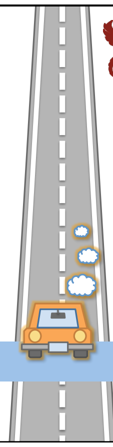
Problem
- ✔ Why: "non-linear" modeling

Fundamentals
- ✔ Non-linear (grey-box) models

Applications
- ✔ Epidemics
- – Information diffusion
- – Online competition



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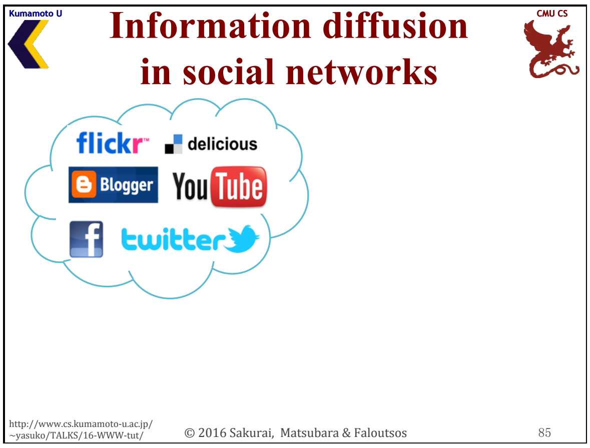
Kumamoto U
CMU CS
Information diffusion
in social networks
flickr
delicious
Blogger
YouTube
twitter
http://www.cs.kumamoto-u.ac.jp/
~yasuko/TALKS/16-WWW-tut/
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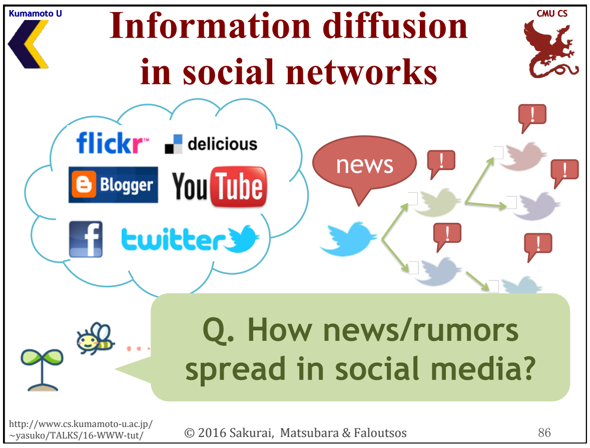
Kumamoto U
CMU CS
Information diffusion
in social networks
flickr
delicious
Blogger
YouTube
twitter
news
Q. How news/rumors
spread in social media?
http://www.cs.kumamoto-u.ac.jp/
~yasuko/TALKS/16-WWW-tut/
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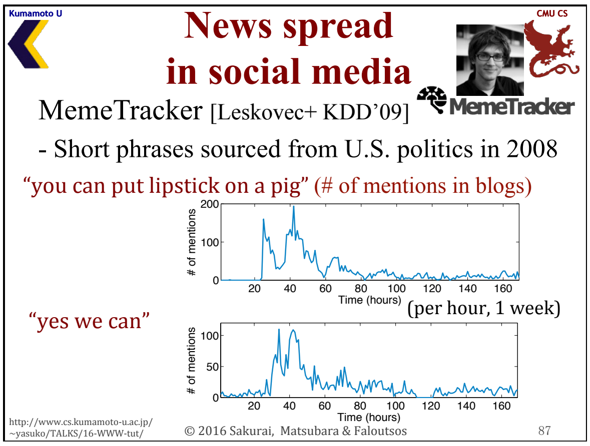
Kumamoto U
CMU CS
News spread
in social media
MemeTracker [Leskovec+ KDD'09]
MemeTracker
- Short phrases sourced from U.S. politics in 2008
"you can put lipstick on a pig" (# of mentions in blogs)
# of mentions
Time (hours)
(per hour, 1 week)
"yes we can"
# of mentions
Time (hours)
http://www.cs.kumamoto-u.ac.jp/
~yasuko/TALKS/16-WWW-tut/
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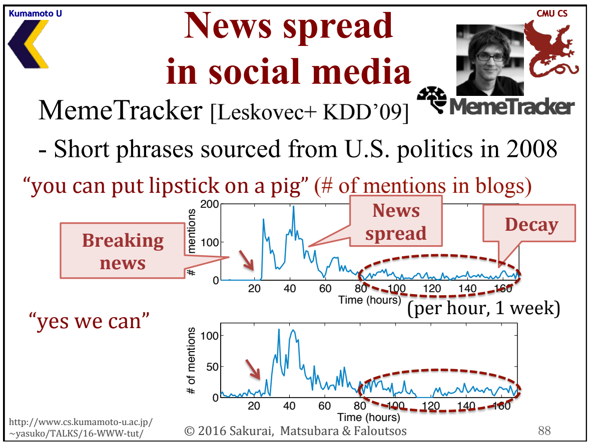
Kumamoto U
CMU CS
News spread
in social media
MemeTracker [Leskovec+ KDD'09]
MemeTracker
- Short phrases sourced from U.S. politics in 2008
"you can put lipstick on a pig" (# of mentions in blogs)
Breaking
news
News
spread
Decay
Time (hours)
(per hour, 1 week)
"yes we can"
# of mentions
Time (hours)
http://www.cs.kumamoto-u.ac.jp/
~yasuko/TALKS/16-WWW-tut/
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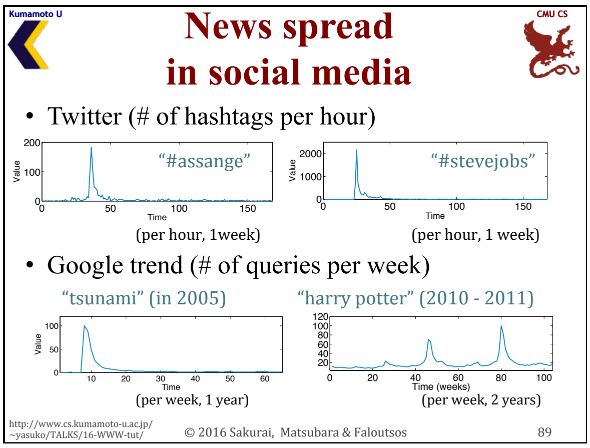
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CMU CS
News spread
in social media
• Twitter (# of hashtags per hour)
"#assange"
"#stevejobs"
Value
Time
(per hour, 1week)
(per hour, 1 week)
• Google trend (# of queries per week)
"tsunami" (in 2005)
"harry potter" (2010 - 2011)
Time
Time (weeks)
(per week, 1 year)
(per week, 2 years)
http://www.cs.kumamoto-u.ac.jp/
~yasuko/TALKS/16-WWW-tut/
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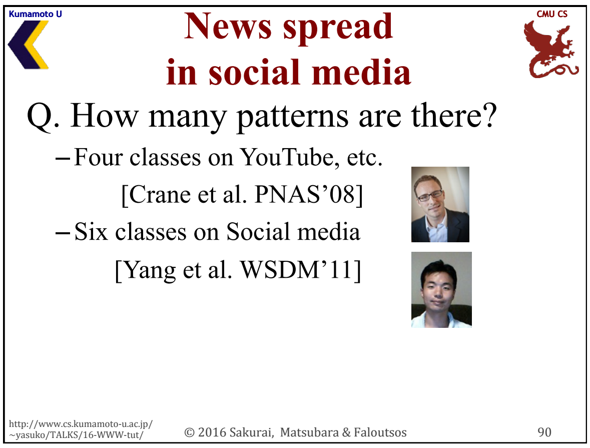
Kumamoto U
CMU CS
News spread
in social media
Q. How many patterns are there?
– Four classes on YouTube, etc.
[Crane et al. PNAS'08]
– Six classes on Social media
[Yang et al. WSDM'11]
http://www.cs.kumamoto-u.ac.jp/
~yasuko/TALKS/16-WWW-tut/
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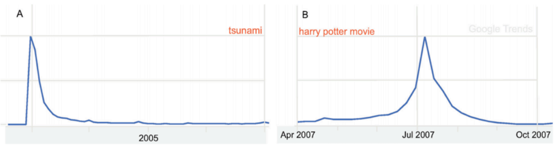
News spread in social media

[Crane et al. PNAS'08]

- The volume of Google searches

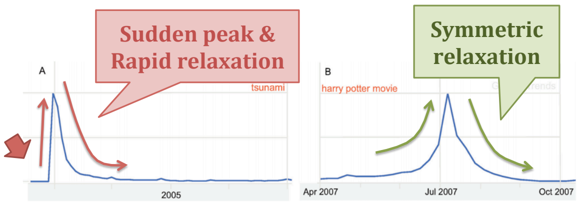


"Tsunami" "Harry potter movie"

News spread in social media

[Crane et al. PNAS'08]

- The volume of Google searches



"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*

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

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

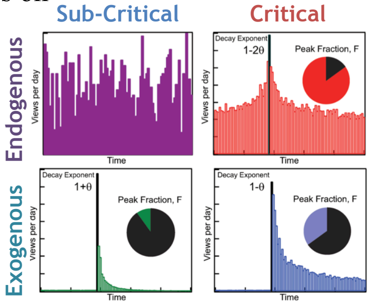
Decaying virus/news strength (Power law)

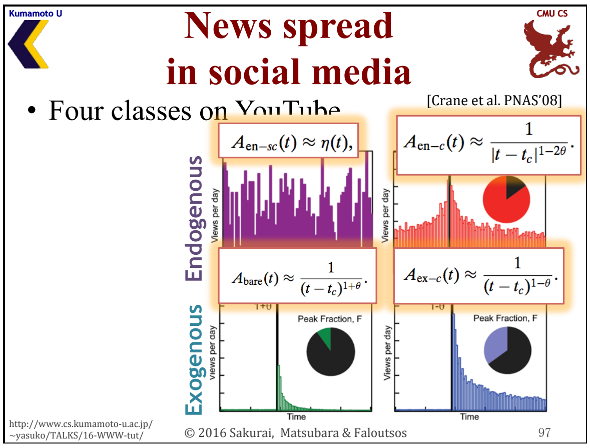
*[Hawkes+ 1974]

News spread in social media

[Crane et al. PNAS'08]

- Four classes on YouTube




Kumamoto U
CMU CS
News spread
in social media
• Four classes on YouTube
[Crane et al. PNAS'08]
$A_{\text{en-sc}}(t) \approx \eta(t),$
$A_{\text{en-c}}(t) \approx \frac{1}{|t-t_c|^{1-2\theta}}.$
$A_{\text{bare}}(t) \approx \frac{1}{(t-t_c)^{1+\theta}}.$
$A_{\text{ex-c}}(t) \approx \frac{1}{(t-t_c)^{1-\theta}}.$
Endogenous
Exogenous
Views per day
Peak Fraction, F
Time
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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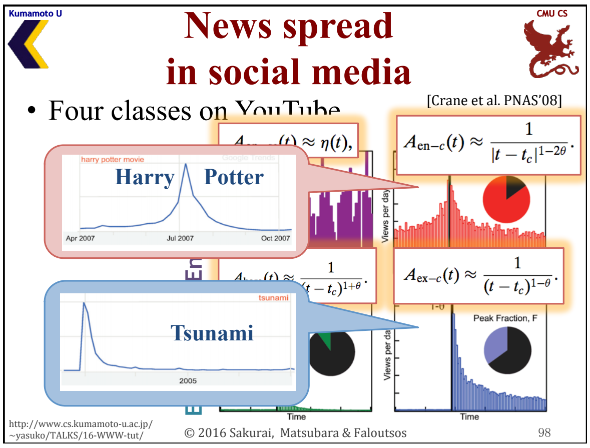
97


Kumamoto U
CMU CS
News spread
in social media
• Four classes on YouTube
[Crane et al. PNAS'08]
harry potter movie
Harry Potter
Apr 2007
Jul 2007
Oct 2007
tsunami
Tsunami
2005
$A_{\text{en-c}}(t) \approx \frac{1}{|t-t_c|^{1-2\theta}}.$
$A_{\text{ex-c}}(t) \approx \frac{1}{(t-t_c)^{1-\theta}}.$
Peak Fraction, F
Time
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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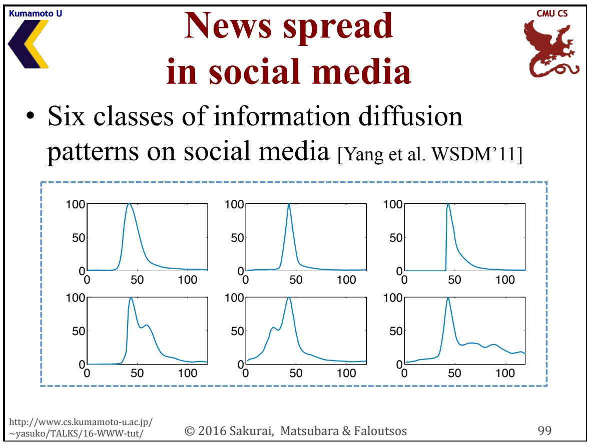
Kumamoto U
CMU CS
News spread
in social media
• Six classes of information diffusion patterns on social media [Yang et al. WSDM'11]
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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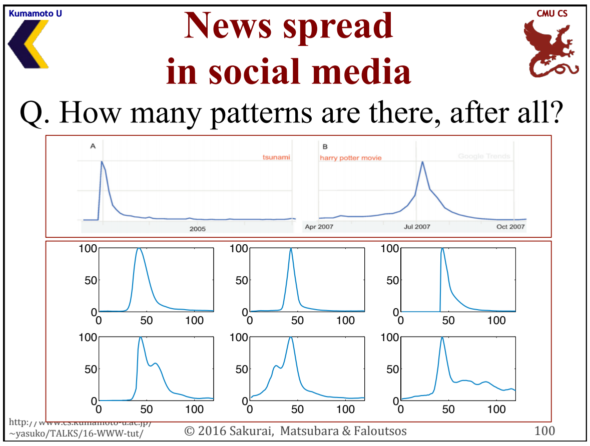
Kumamoto U
CMU CS
News spread
in social media
Q. How many patterns are there, after all?
tsunami
harry potter movie
2005
Apr 2007
Jul 2007
Oct 2007
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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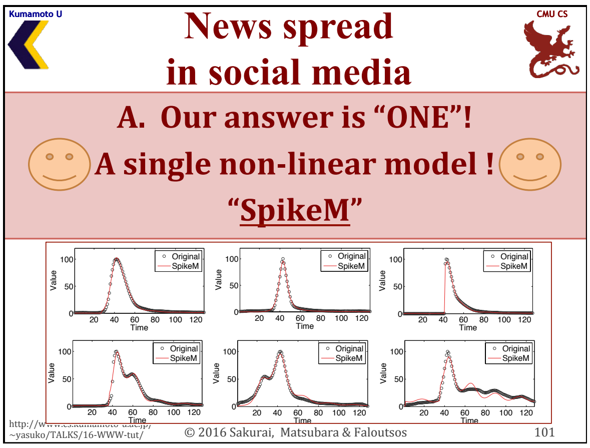
Kumamoto U
CMU CS
News spread
in social media
A. Our answer is "ONE"!
A single non-linear model !
"SpikeM"
Original
SpikeM
Value
Time
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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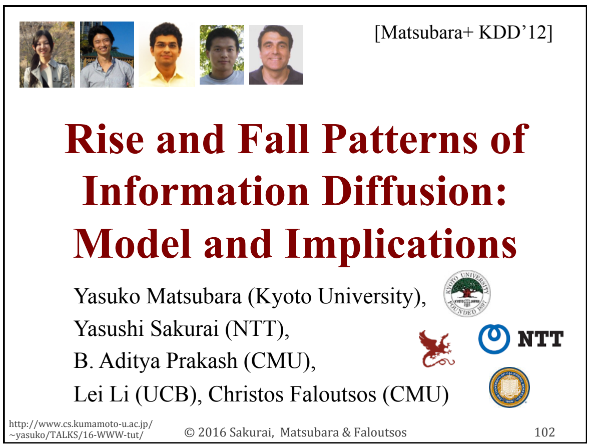
[Matsubara+ KDD'12]
Rise and Fall Patterns of Information Diffusion: Model and Implications
Yasuko Matsubara (Kyoto University),
Yasushi Sakurai (NTT),
B. Aditya Prakash (CMU),
Lei Li (UCB), Christos Faloutsos (CMU)
NTT
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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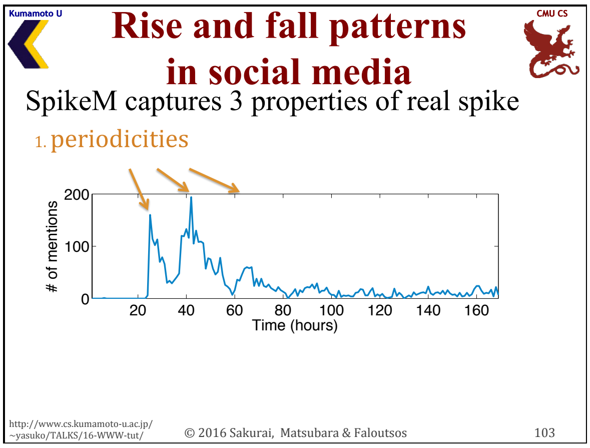
Kumamoto U
Rise and fall patterns in social media
CMU CS
SpikeM captures 3 properties of real spike
1. periodicities
# of mentions
200
100
0
20 40 60 80 100 120 140 160
Time (hours)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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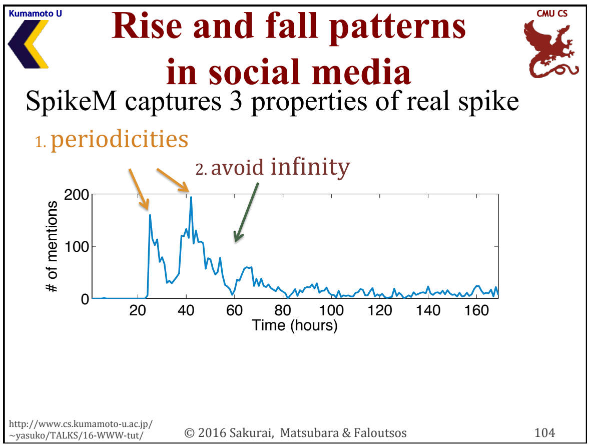
Kumamoto U
Rise and fall patterns in social media
CMU CS
SpikeM captures 3 properties of real spike
1. periodicities
2. avoid infinity
# of mentions
200
100
0
20 40 60 80 100 120 140 160
Time (hours)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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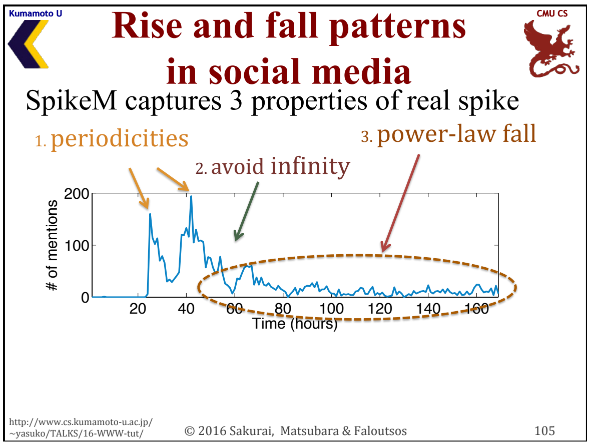
Kumamoto U
Rise and fall patterns in social media
CMU CS
SpikeM captures 3 properties of real spike
1. periodicities
3. power-law fall
2. avoid infinity
# of mentions
200
100
0
20 40 60 80 100 120 140 160
Time (hours)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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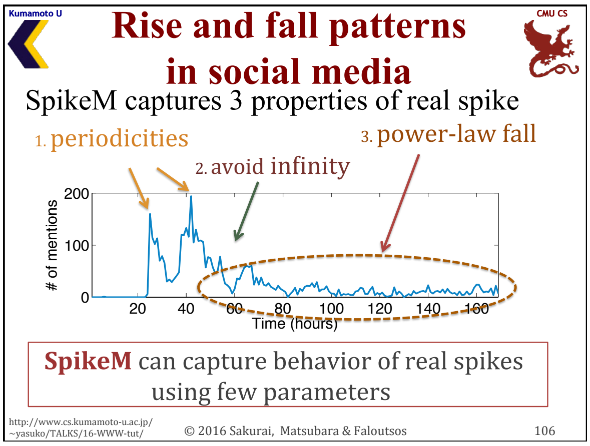
Kumamoto U
Rise and fall patterns in social media
CMU CS
SpikeM captures 3 properties of real spike
1. periodicities
3. power-law fall
2. avoid infinity
# of mentions
200
100
0
20 40 60 80 100 120 140 160
Time (hours)
SpikeM can capture behavior of real spikes using few parameters
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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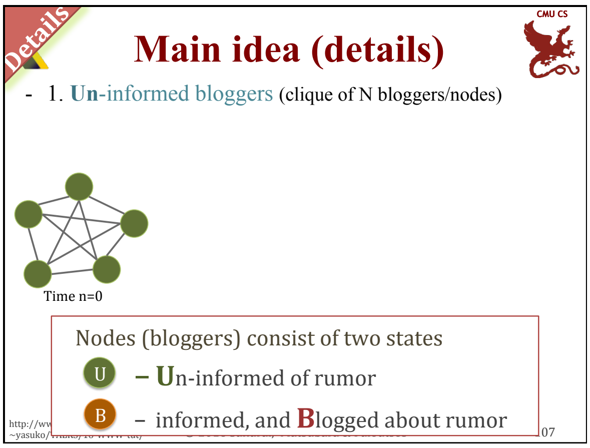
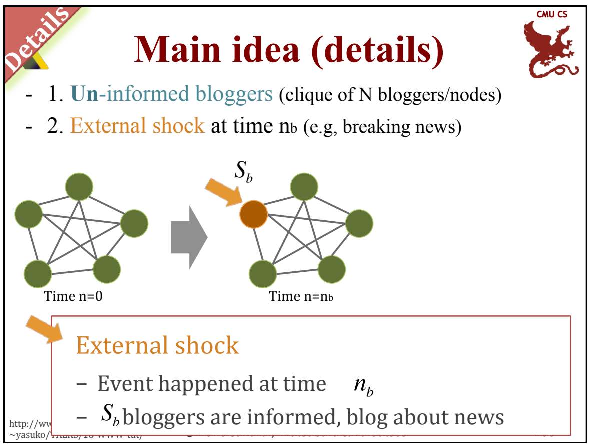
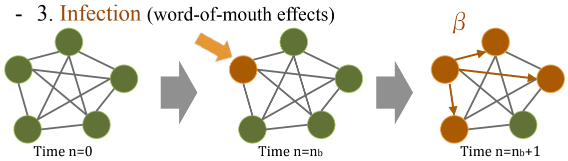

Details
Main idea (details)
CMU CS
- 1. Un-informed bloggers (clique of N bloggers/nodes)
Time n=0
Nodes (bloggers) consist of two states
U – Un-informed of rumor
B – informed, and Blogged about rumor


Details
Main idea (details)
CMU CS
- 1. Un-informed bloggers (clique of N bloggers/nodes)
- 2. External shock at time nb (e.g, breaking news)
S_b
Time n=0
Time n=nb
External shock
– Event happened at time n_b
– S_b bloggers are informed, blog about news

Main idea (details)

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)

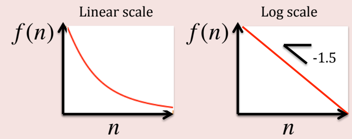
Main idea (details)

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)

SpikeM-base (details)

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

SpikeM - periodicity

Details

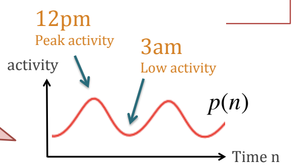
Full equation of SpikeM

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

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

Bloggers change their activity over time

(e.g., daily, weekly, yearly)



Model fitting (Details)

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)

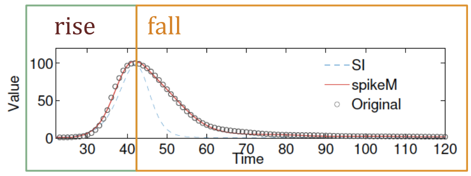
$$D(X, \theta) = \sum_{n=1}^{n_d} (X(n) - \Delta B(n))^2$$

Analysis

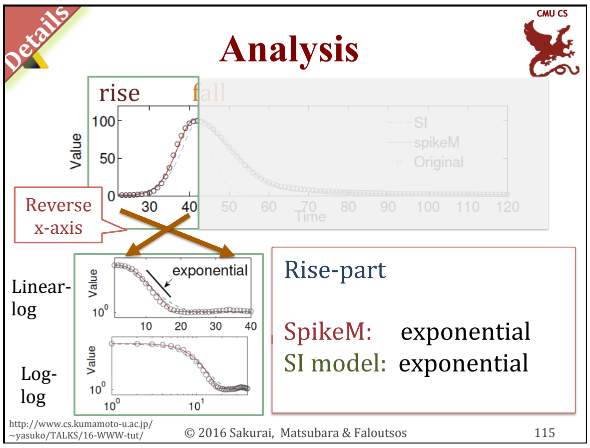
Details

SpikeM matches reality

exponential rise and power-raw fall



SpikeM vs. **SI model** (susceptible infected model)


Details
Analysis
CMU CS
rise
fall
SI
spikeM
Original
Value
Time
Reverse x-axis
Linear-log
Log-log
exponential
Rise-part
SpikeM: exponential
SI model: exponential
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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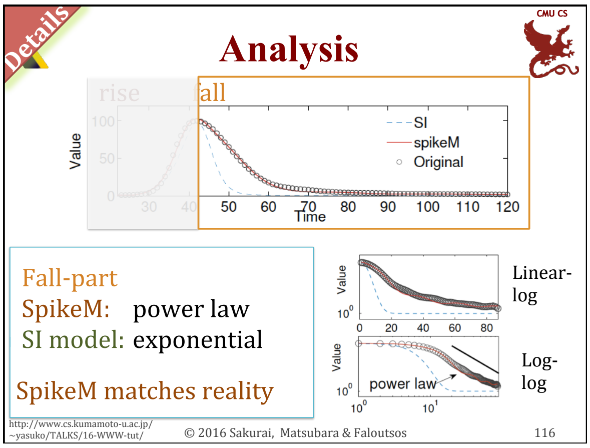
Details
Analysis
CMU CS
rise
fall
SI
spikeM
Original
Value
Time
Fall-part
SpikeM: power law
SI model: exponential
SpikeM matches reality
Linear-log
Log-log
power law
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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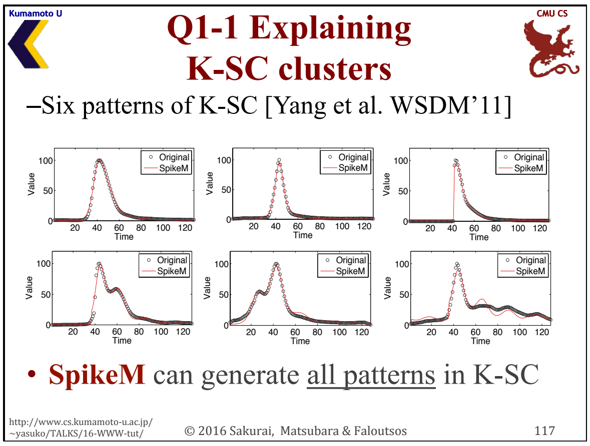
Kumamoto U
CMU CS
Q1-1 Explaining K-SC clusters
–Six patterns of K-SC [Yang et al. WSDM'11]
Original
SpikeM
Value
Time
• SpikeM can generate all patterns in K-SC
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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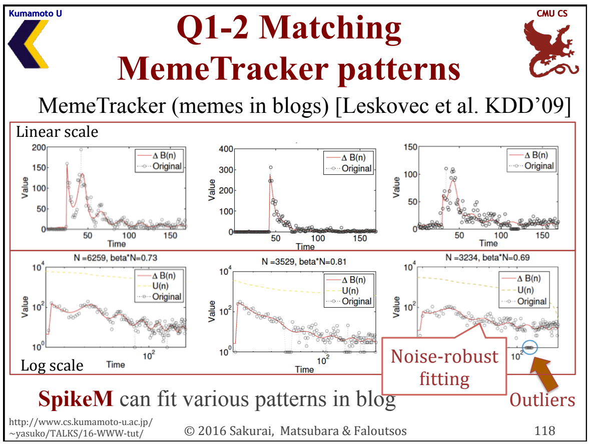
Kumamoto U
CMU CS
Q1-2 Matching MemeTracker patterns
MemeTracker (memes in blogs) [Leskovec et al. KDD'09]
Linear scale
Log scale
Noise-robust fitting
Outliers
SpikeM can fit various patterns in blog
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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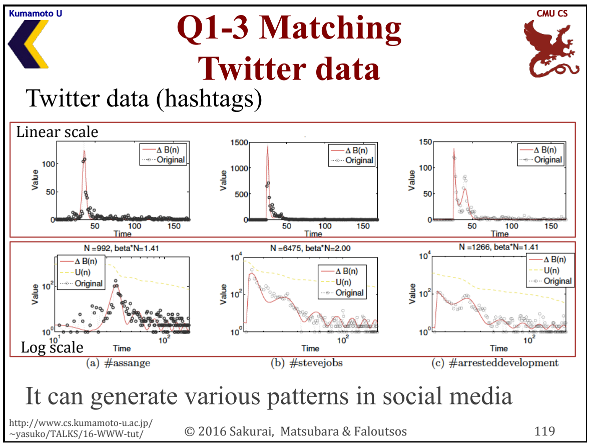
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CMU CS
Q1-3 Matching Twitter data
Twitter data (hashtags)
Linear scale
Log scale
(a) #assange
(b) #stevejobs
(c) #arresteddevelopment
It can generate various patterns in social media
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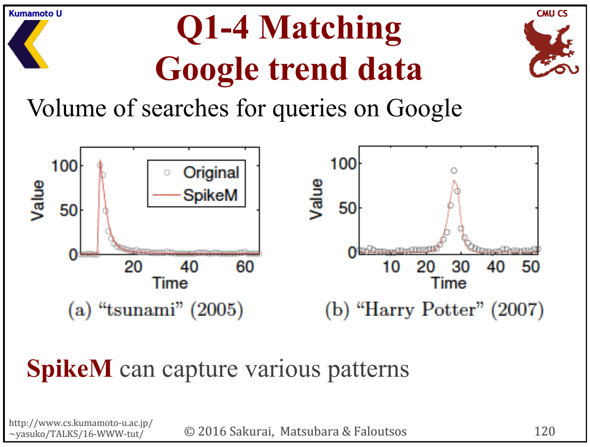
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Q1-4 Matching Google trend data
Volume of searches for queries on Google
Original
SpikeM
Value
Time
(a) "tsunami" (2005)
(b) "Harry Potter" (2007)
SpikeM can capture various patterns
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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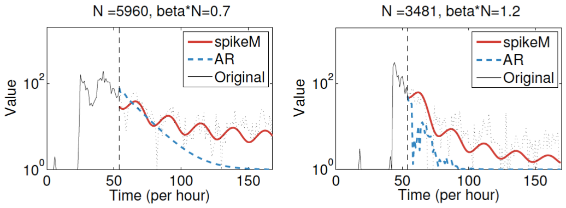
Q2 Tail-part forecasts

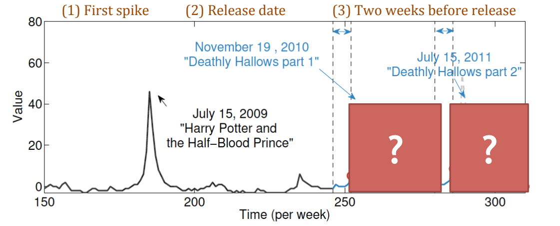
- Given a first part of the spike
  - forecast the tail part



SpikeM can capture tail part (AR: fail)

A1. "What-if" forecasting

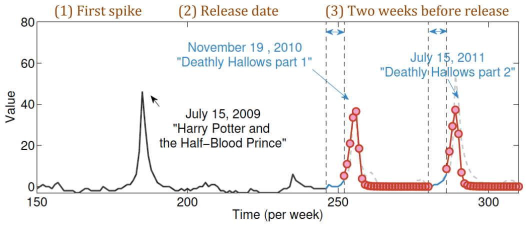
Forecast not only tail-part, but also **rise-part**!



e.g., given (1) first spike,
(2) release date of two sequel movies
(3) access volume before the release date

A1. "What-if" forecasting

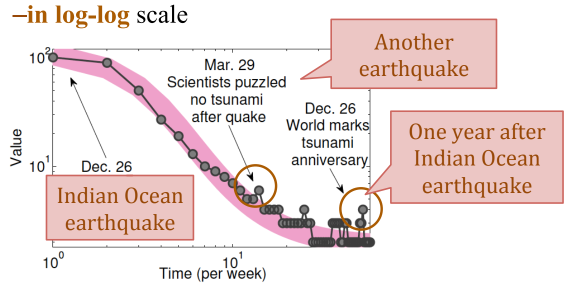
Forecast not only tail-part, but also **rise-part**!



SpikeM can forecast upcoming spikes!

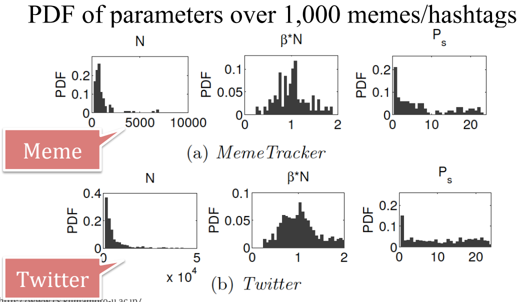
A2. Outlier detection

–Fitting result of "tsunami (Google trend)"
–in log-log scale



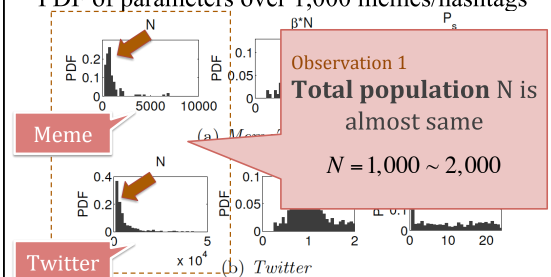
A3. Reverse engineering

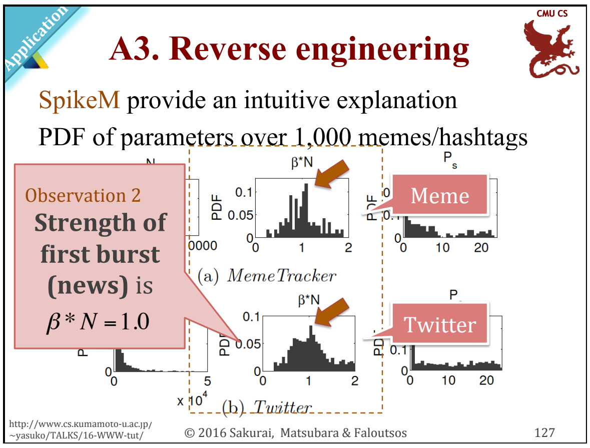
SpikeM provide an intuitive explanation
PDF of parameters over 1,000 memes/hashtags



A3. Reverse engineering

SpikeM provide an intuitive explanation
PDF of parameters over 1,000 memes/hashtags




Application
A3. Reverse engineering
SpikeM provide an intuitive explanation
PDF of parameters over 1,000 memes/hashtags
Observation 2
Strength of first burst (news) is
β*N = 1.0
Meme
Twitter
(a) MemeTracker
(b) Twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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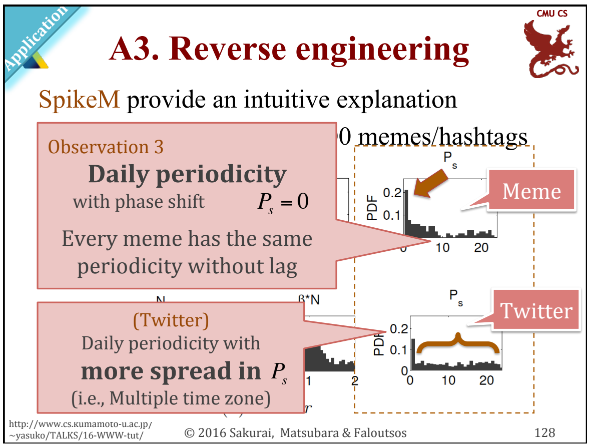
Application
A3. Reverse engineering
SpikeM provide an intuitive explanation
Observation 3
Daily periodicity
with phase shift $P_s = 0$
Every meme has the same periodicity without lag
(Twitter)
Daily periodicity with
more spread in P_s
(i.e., Multiple time zone)
Meme
Twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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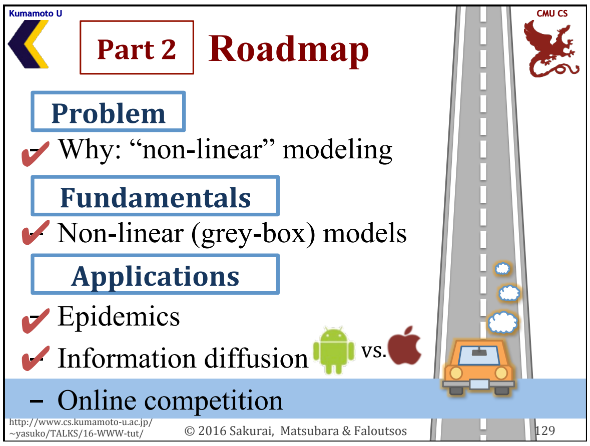
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Part 2 Roadmap
Problem
Why: "non-linear" modeling
Fundamentals
Non-linear (grey-box) models
Applications
Epidemics
Information diffusion vs.
– Online competition
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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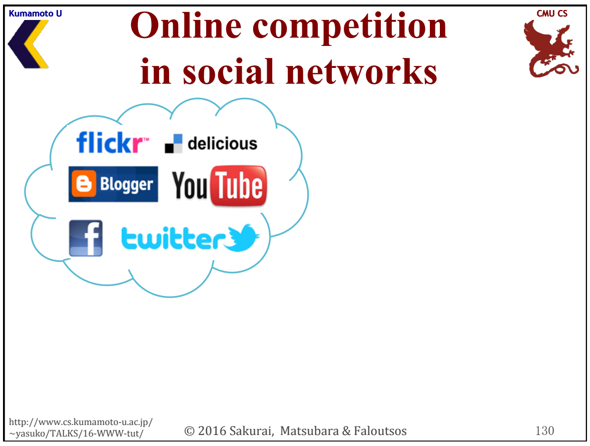
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Online competition
in social networks
flickr
delicious
Blogger
YouTube
twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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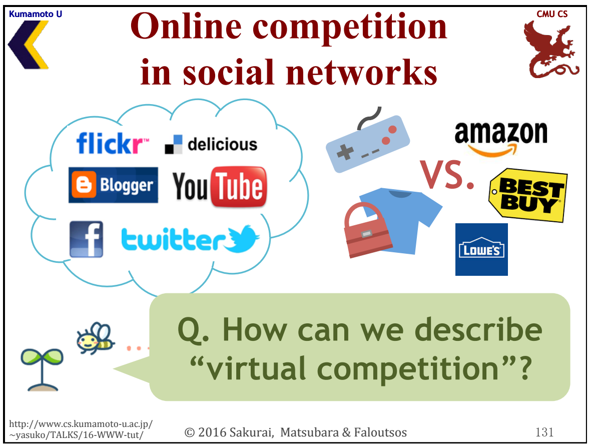
Kumamoto U
Online competition
in social networks
flickr
delicious
Blogger
YouTube
twitter
amazon
VS.
BEST BUY
LOWE'S
Q. How can we describe "virtual competition"?
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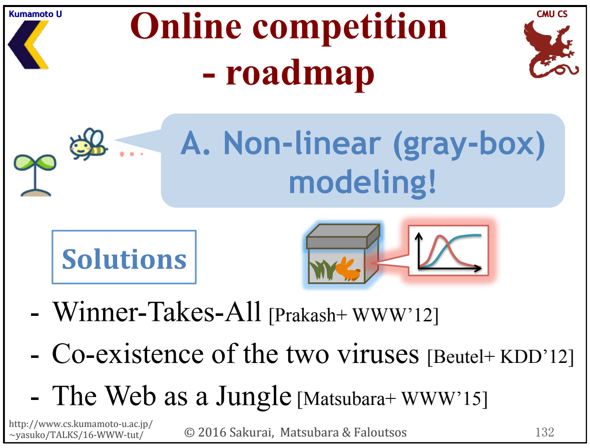
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Online competition
- roadmap
A. Non-linear (gray-box) modeling!
Solutions
- Winner-Takes-All [Prakash+ WWW'12]
- Co-existence of the two viruses [Beutel+ KDD'12]
- The Web as a Jungle [Matsubara+ WWW'15]
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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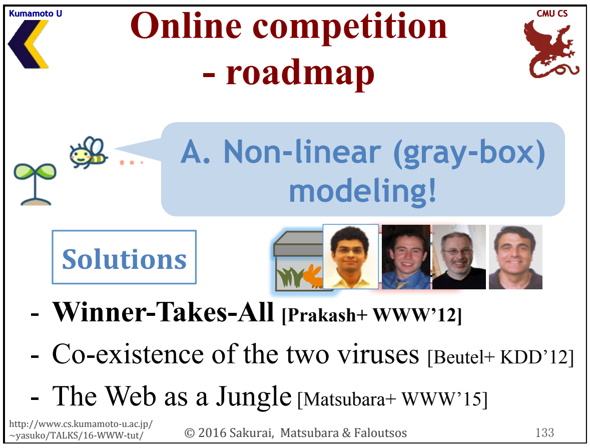

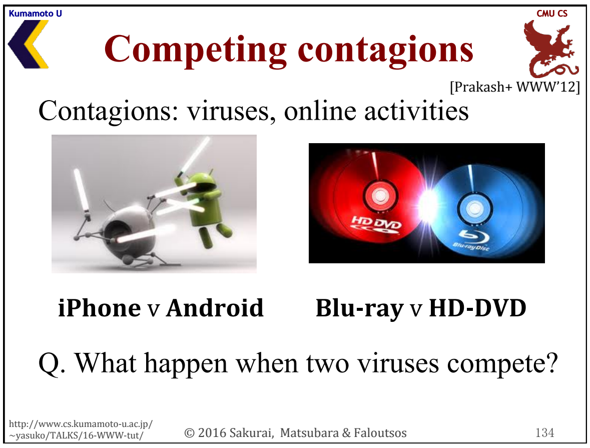

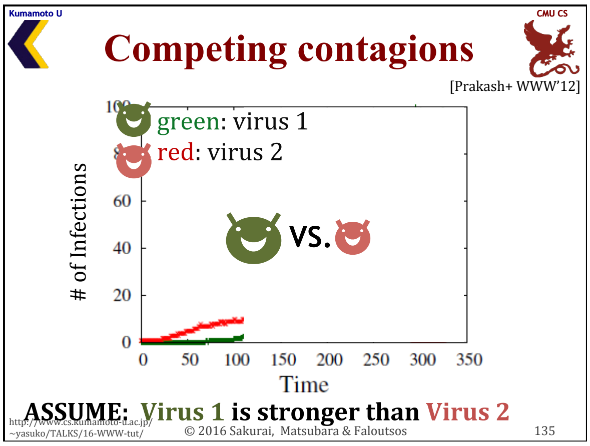

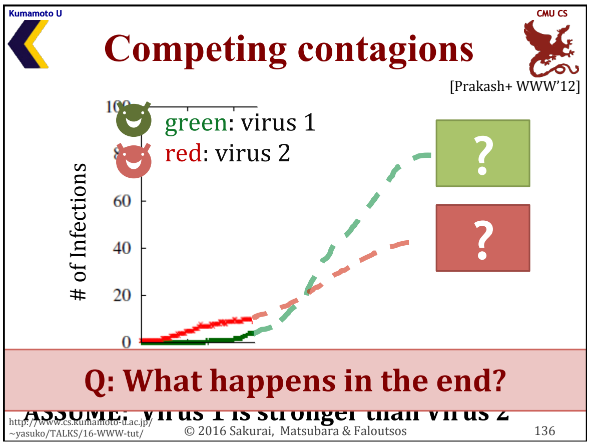

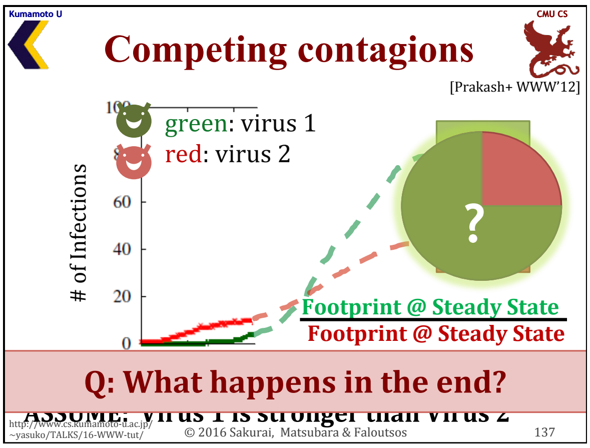

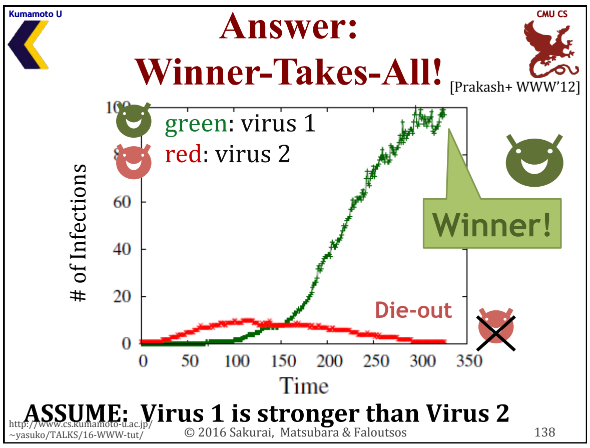

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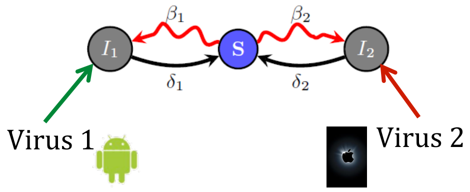
A simple model

[Prakash+ WWW'12]

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



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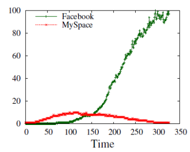
Result: Winner-Takes-All

[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!

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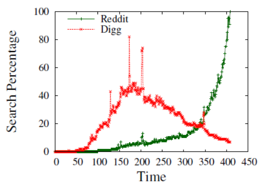
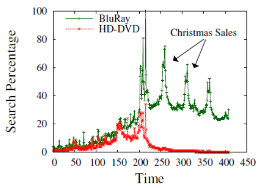
Real Examples of "WTA"

[Prakash+ WWW'12]

[Google Search Trends data]





Reddit v **Digg** **Blu-Ray** v **HD-DVD**

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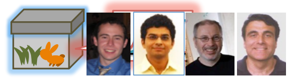
Online competition in social networks

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]

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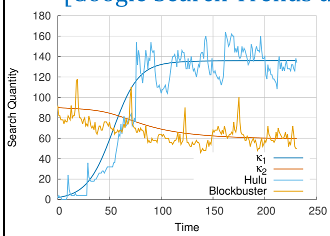
Interacting Viruses: Can Both Survive?

Real example of "co-existence"

[Google Search Trends data]



Hulu v **Blockbuster**

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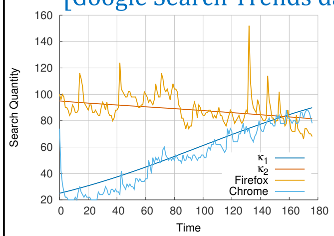
Interacting Viruses: Can Both Survive?

Real example of "co-existence"

[Google Search Trends data]



Chrome v **Firefox**

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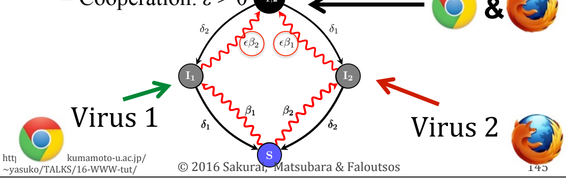
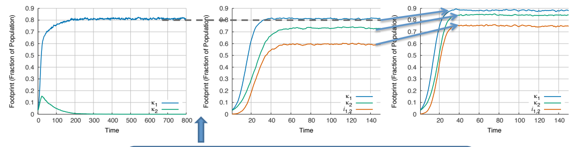
A simple model: $SI_{1|2}S$

- 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: $\varepsilon > 0$



Question: What happens in the end?

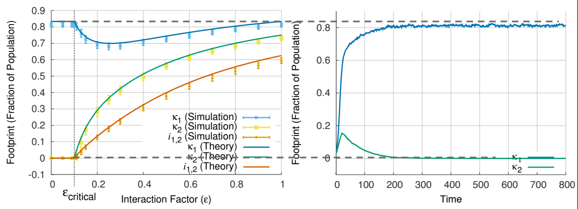
ε = 0	ε = 1	ε = 2
Winner takes all	Co-exist independently	Viruses cooperate



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

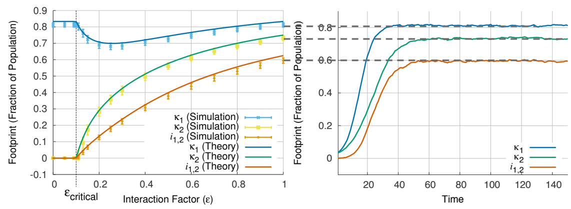
ASSUME: Virus 1 is stronger than Virus 2

Answer: Yes! There is a phase transition



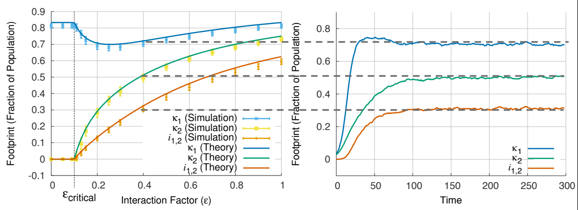
ASSUME: Virus 1 is stronger than Virus 2

Answer: Yes! There is a phase transition



ASSUME: Virus 1 is stronger than Virus 2

Answer: Yes! There is a phase transition

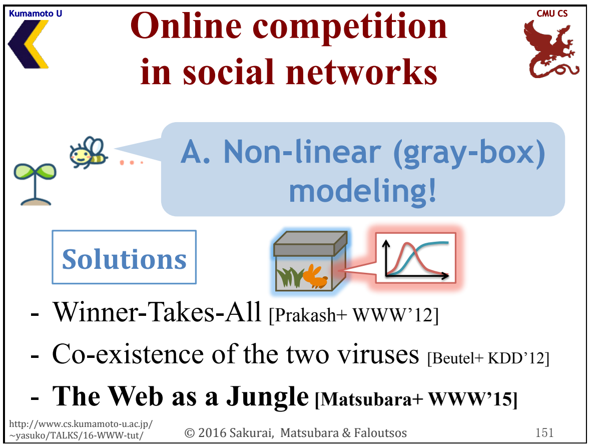


ASSUME: Virus 1 is stronger than Virus 2

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) $\sigma = N \beta / \delta$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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]
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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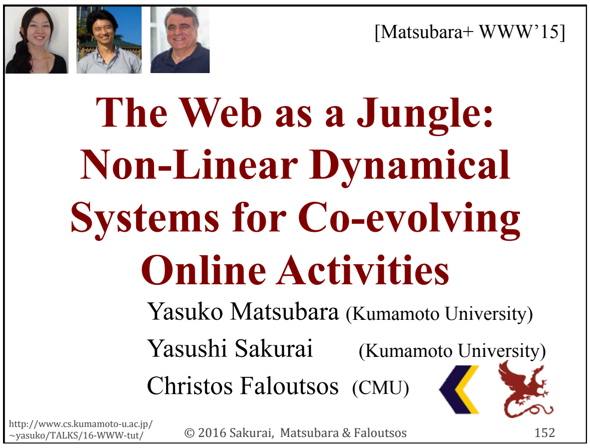
[Matsubara+ WWW'15]
The Web as a Jungle: Non-Linear Dynamical Systems for Co-evolving Online Activities
Yasuko Matsubara (Kumamoto University)
Yasushi Sakurai (Kumamoto University)
Christos Faloutsos (CMU)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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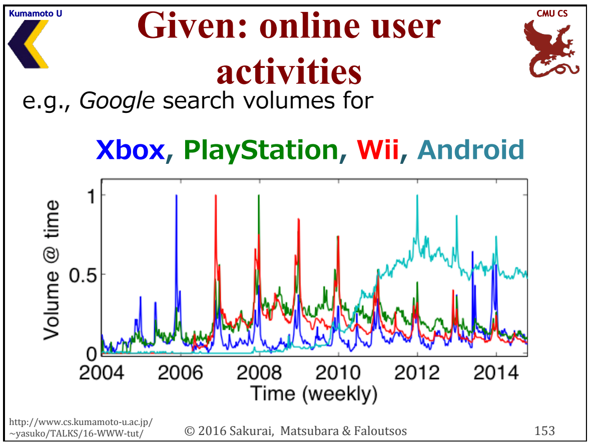
Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
Xbox, PlayStation, Wii, Android
Volume @ time
1
0.5
0
2004 2006 2008 2010 2012 2014
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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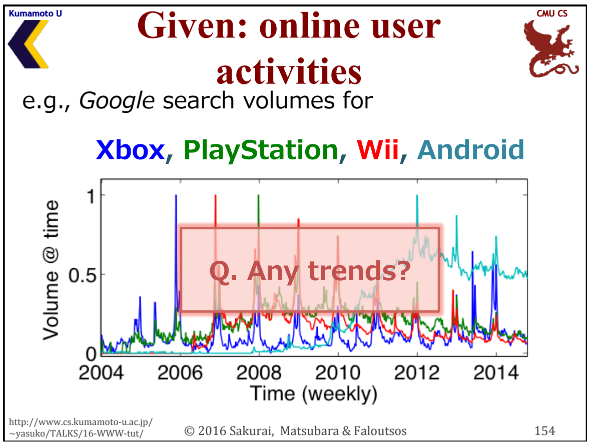
Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
Xbox, PlayStation, Wii, Android
Q. Any trends?
Volume @ time
1
0.5
0
2004 2006 2008 2010 2012 2014
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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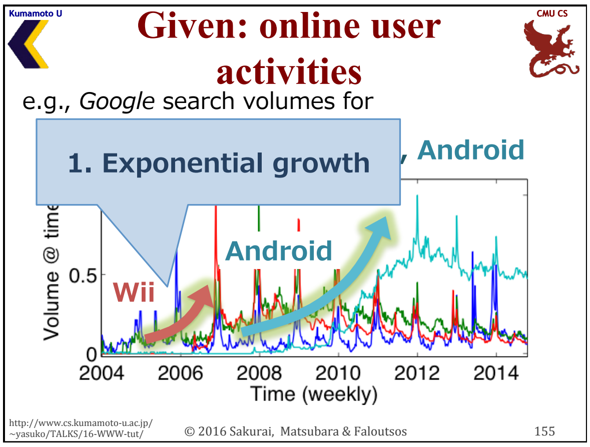
Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
1. Exponential growth
, Android
Wii
Android
Volume @ time
0.5
0
2004 2006 2008 2010 2012 2014
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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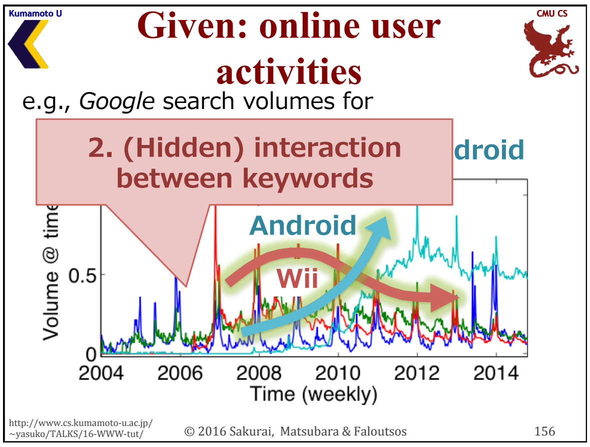
Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
2. (Hidden) interaction between keywords
droid
Android
Wii
Volume @ time
0.5
0
2004 2006 2008 2010 2012 2014
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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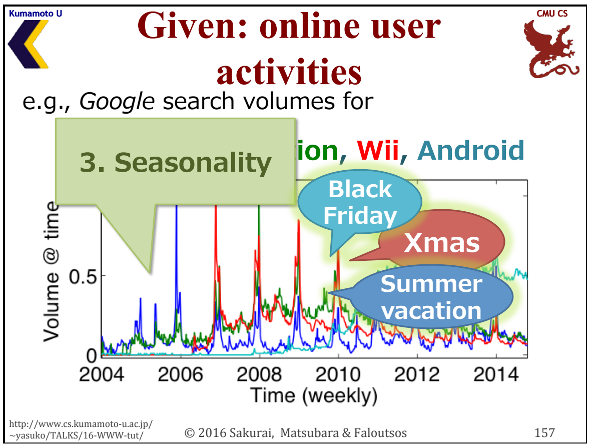
Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
3. Seasonality
ion, Wii, Android
Black Friday
Xmas
Summer vacation
Volume @ time
0.5
0
2004
2006
2008
2010
2012
2014
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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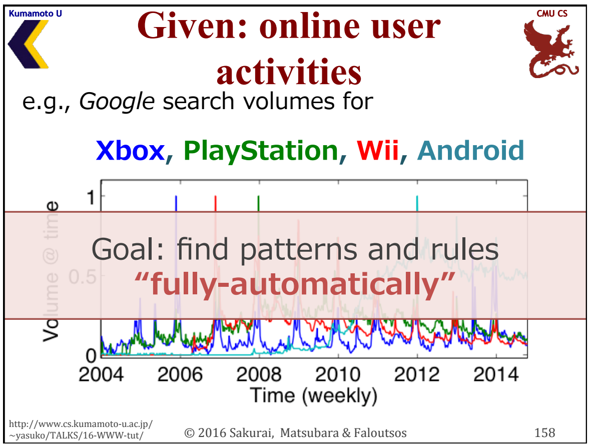
Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
Xbox, PlayStation, Wii, Android
Goal: find patterns and rules
"fully-automatically"
1
0
2004
2006
2008
2010
2012
2014
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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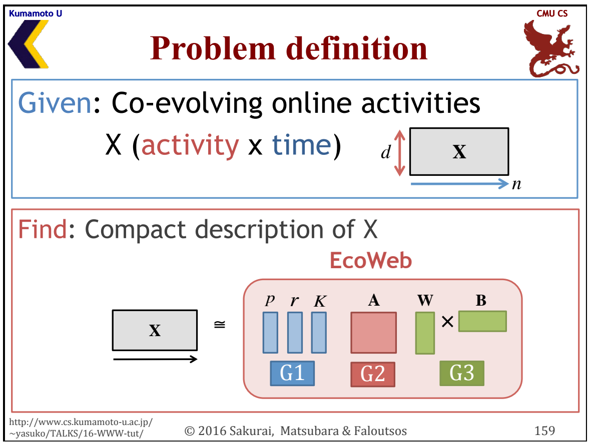
Kumamoto U
CMU CS
Problem definition
Given: Co-evolving online activities
X (activity x time)
d
X
n
Find: Compact description of X
EcoWeb
X
≅
p r K
A
W
B
×
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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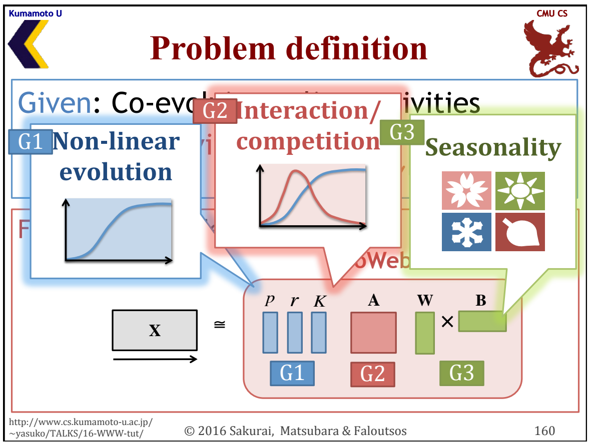
Kumamoto U
CMU CS
Problem definition
Given: Co-evo
ivities
G1 Non-linear evolution
G2 Interaction/ competition
G3 Seasonality
oWeb
X
≅
p r K
A
W
B
×
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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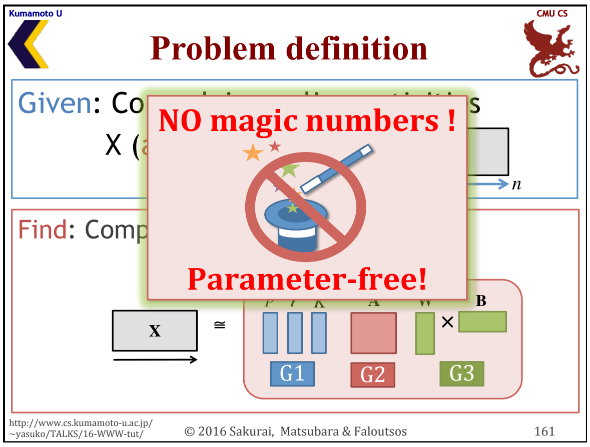
Kumamoto U
CMU CS
Problem definition
Given: Co
X (
Find: Comp
NO magic numbers !
Parameter-free!
X
≅
B
×
G1
G2
G3
n
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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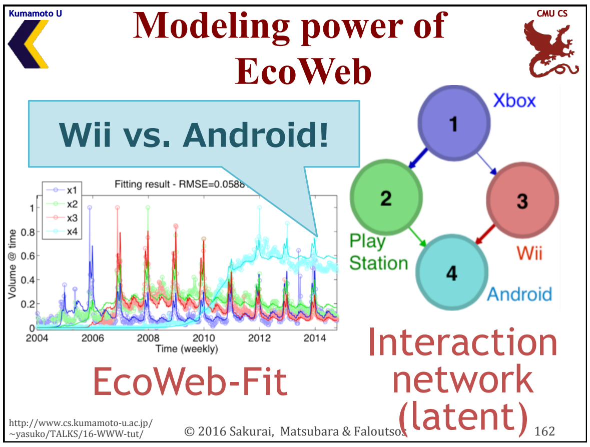
Kumamoto U
CMU CS
Modeling power of EcoWeb
Wii vs. Android!
Fitting result - RMSE=0.0588
Volume @ time
Time (weekly)
2004
2006
2008
2010
2012
2014
EcoWeb-Fit
1 Xbox
2 Play Station
3 Wii
4 Android
Interaction network (latent)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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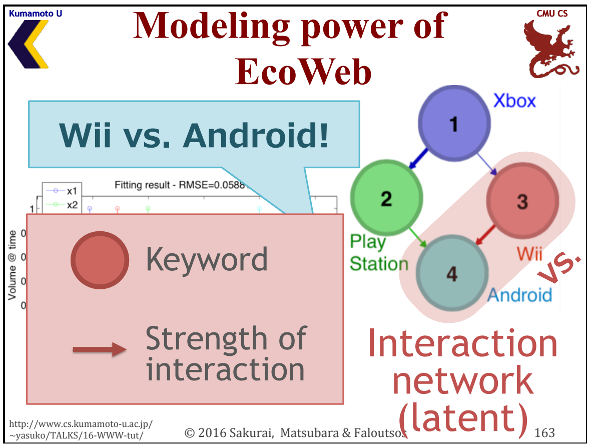
Kumamoto U
CMU CS
Modeling power of EcoWeb
Wii vs. Android!
Fitting result - RMSE=0.0588
Keyword
Strength of interaction
Xbox
Play Station
Wii
Android
vs.
Interaction network (latent)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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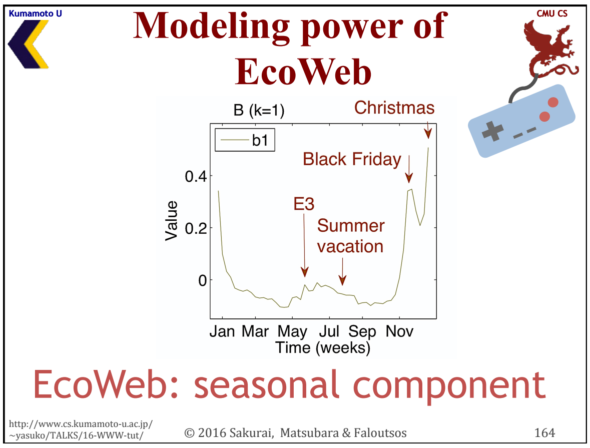
Kumamoto U
CMU CS
Modeling power of EcoWeb
B (k=1)
b1
Christmas
Black Friday
E3
Summer vacation
Value
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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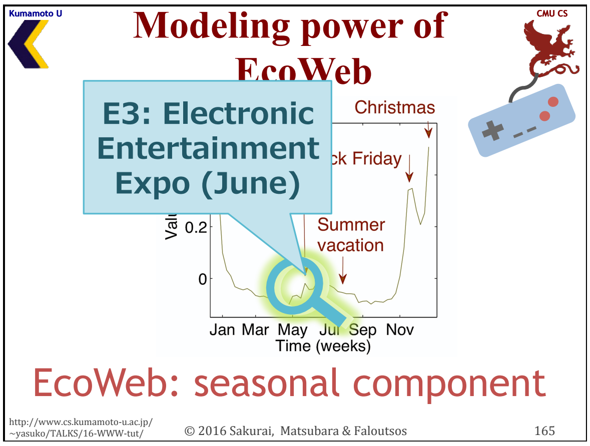
Kumamoto U
CMU CS
Modeling power of EcoWeb
E3: Electronic Entertainment Expo (June)
Christmas
Summer vacation
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
© 2016 Sakurai, Matsubara & Faloutsos
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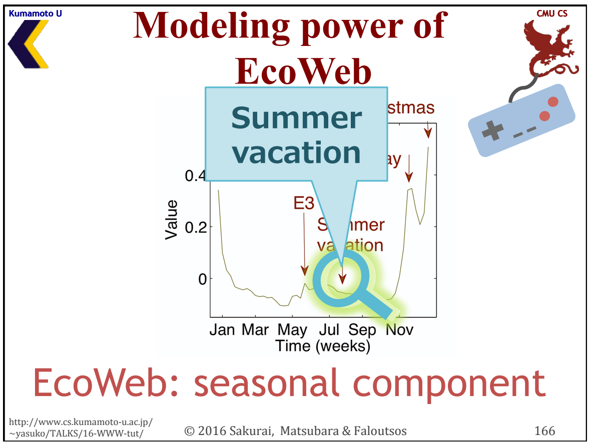
Kumamoto U
CMU CS
Modeling power of EcoWeb
Summer vacation
E3
Value
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
© 2016 Sakurai, Matsubara & Faloutsos
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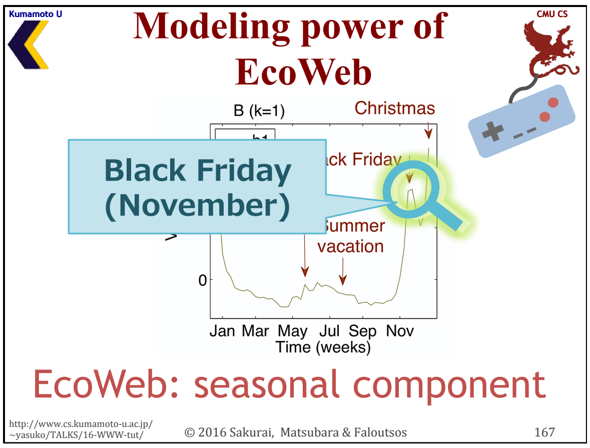
Kumamoto U
CMU CS
Modeling power of EcoWeb
B (k=1)
Christmas
Black Friday (November)
vacation
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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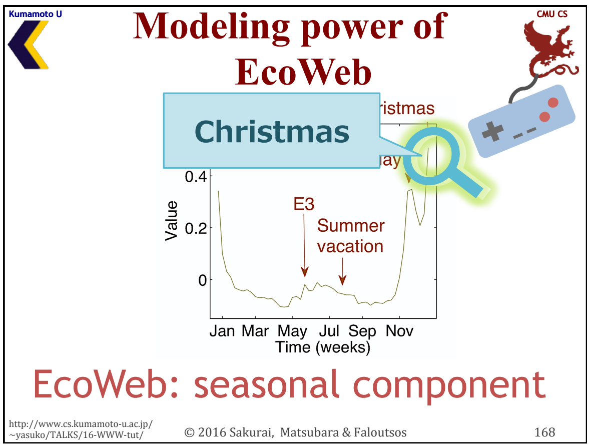
Kumamoto U
CMU CS
Modeling power of EcoWeb
Christmas
E3
Summer vacation
Value
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
© 2016 Sakurai, Matsubara & Faloutsos
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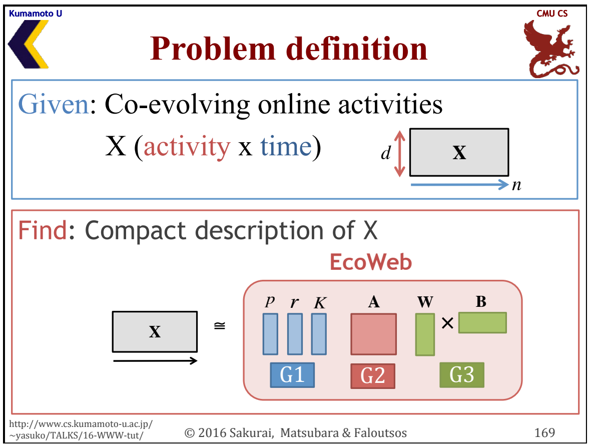

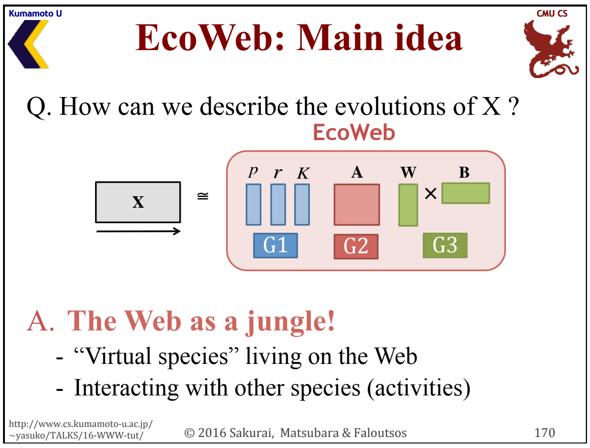

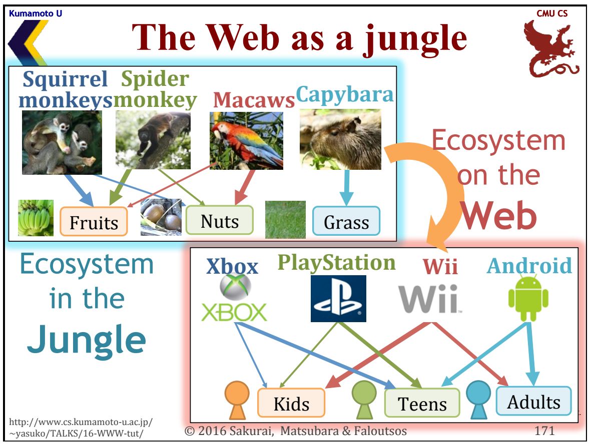

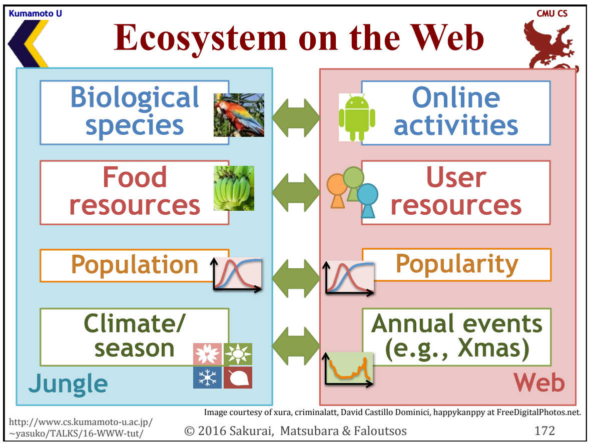

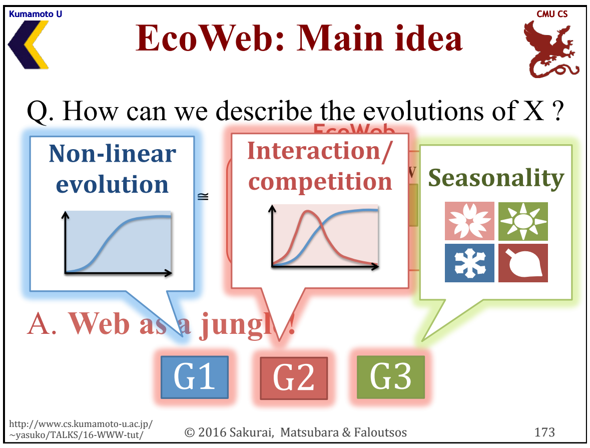

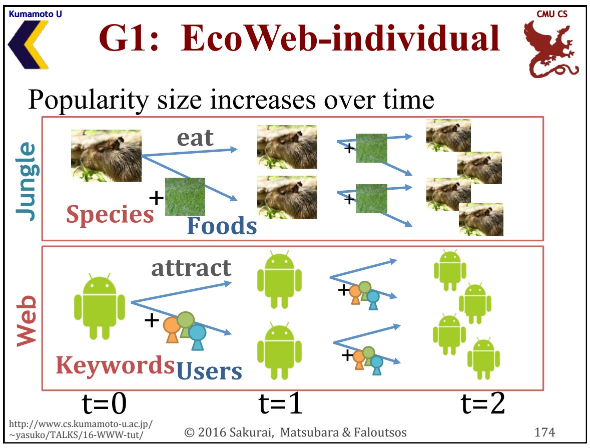

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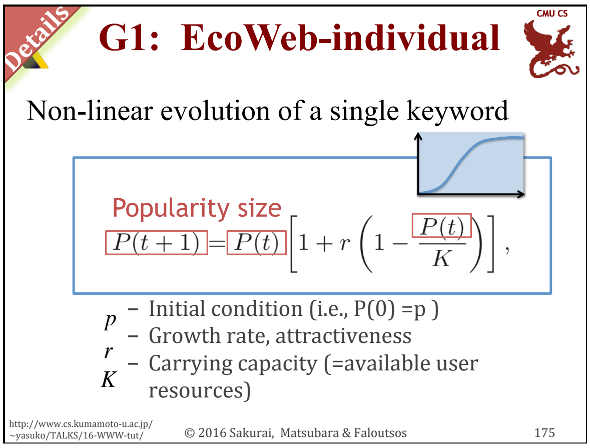

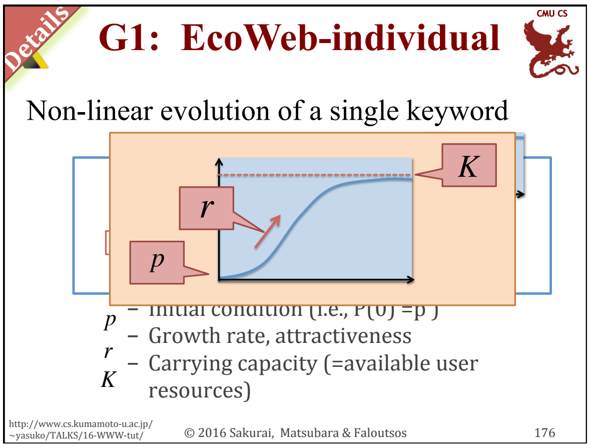

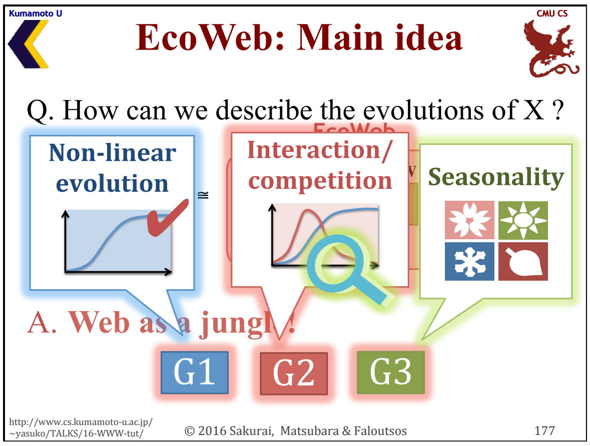

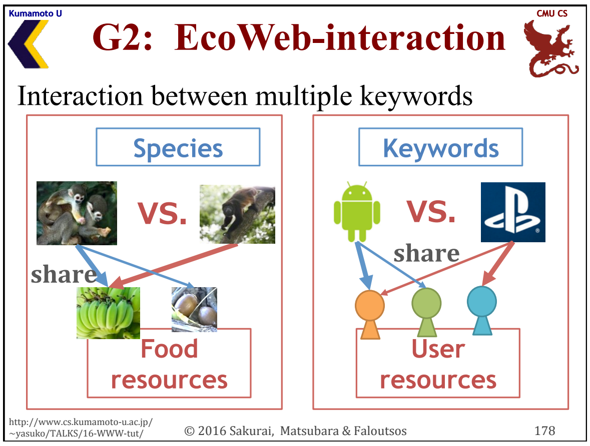

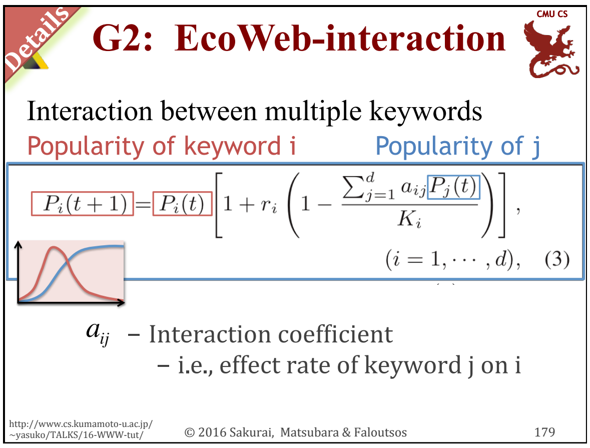

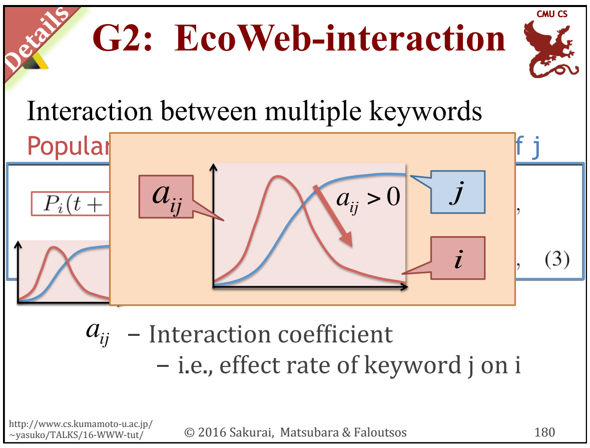

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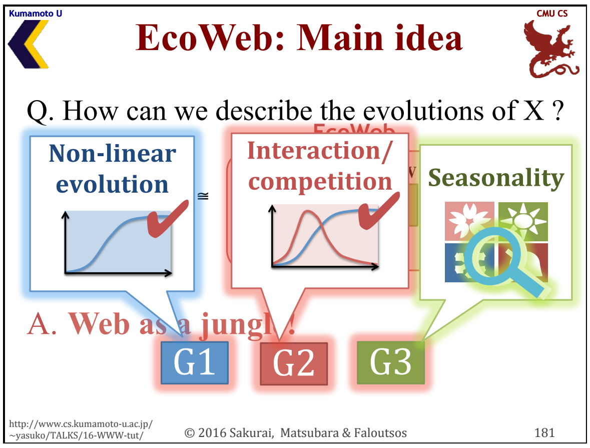
EcoWeb: Main idea
Q. How can we describe the evolutions of X ?
Non-linear evolution
Interaction/ competition
Seasonality
A. Web as a jungle!
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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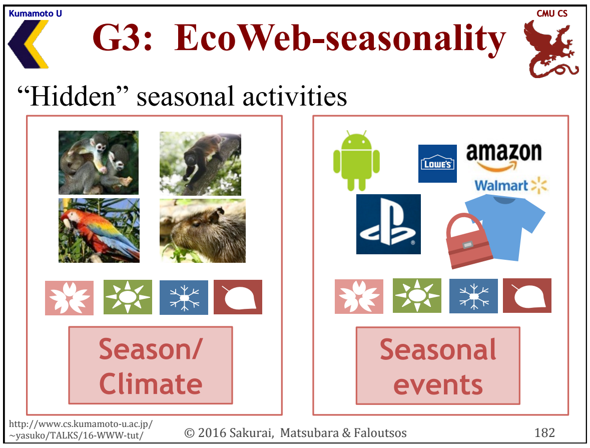
G3: EcoWeb-seasonality
"Hidden" seasonal activities
amazon
Walmart
Season/ Climate
Seasonal events
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
© 2016 Sakurai, Matsubara & Faloutsos
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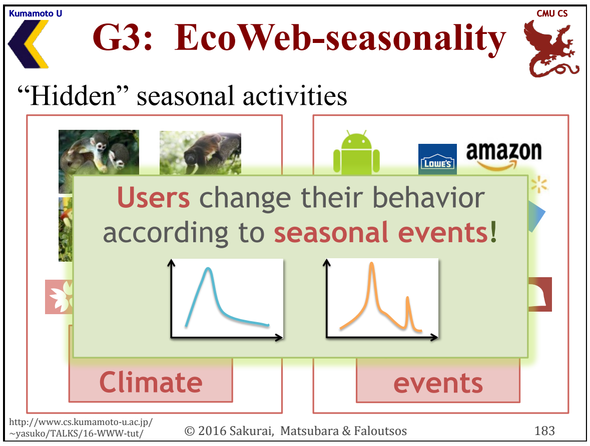
G3: EcoWeb-seasonality
"Hidden" seasonal activities
Users change their behavior according to seasonal events!
Climate
events
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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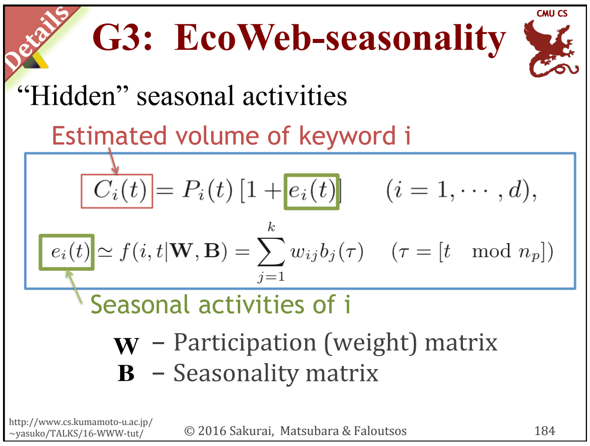
Details
G3: EcoWeb-seasonality
"Hidden" seasonal activities
Estimated volume of keyword i
$C_i(t) = P_i(t)\,[1 + e_i(t)] \quad (i = 1, \cdots, d),$
$e_i(t) \simeq f(i, t|\mathbf{W}, \mathbf{B}) = \sum_{j=1}^{k} w_{ij} b_j(\tau) \quad (\tau = [t \mod n_p])$
Seasonal activities of i
W – Participation (weight) matrix
B – Seasonality matrix
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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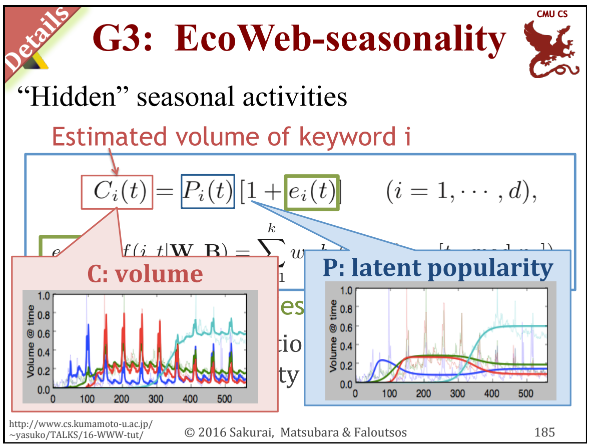
Details
G3: EcoWeb-seasonality
"Hidden" seasonal activities
Estimated volume of keyword i
$C_i(t) = P_i(t)\,[1 + e_i(t)] \quad (i = 1, \cdots, d),$
C: volume
P: latent popularity
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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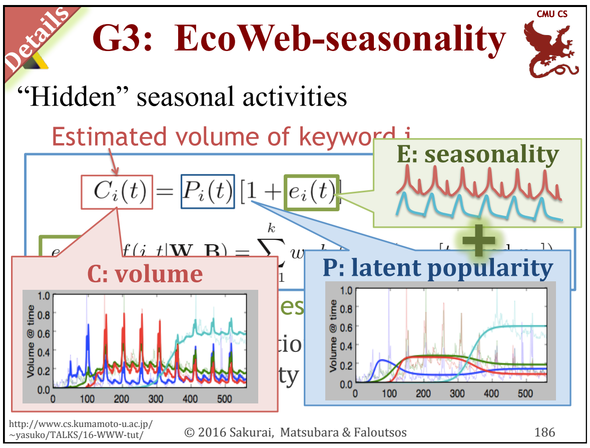
Details
G3: EcoWeb-seasonality
"Hidden" seasonal activities
Estimated volume of keyword i
$C_i(t) = P_i(t)\,[1 + e_i(t)]$
E: seasonality
C: volume
P: latent popularity
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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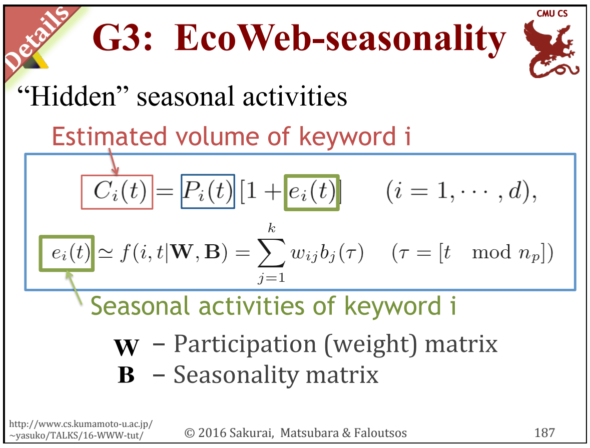
Details
G3: EcoWeb-seasonality
CMU CS
"Hidden" seasonal activities
Estimated volume of keyword i
$C_i(t) = P_i(t)[1 + e_i(t)] \quad (i = 1, \cdots, d),$
$e_i(t) \simeq f(i, t|\mathbf{W}, \mathbf{B}) = \sum_{j=1}^{k} w_{ij} b_j(\tau) \quad (\tau = [t \mod n_p])$
Seasonal activities of keyword i
W – Participation (weight) matrix
B – Seasonality matrix
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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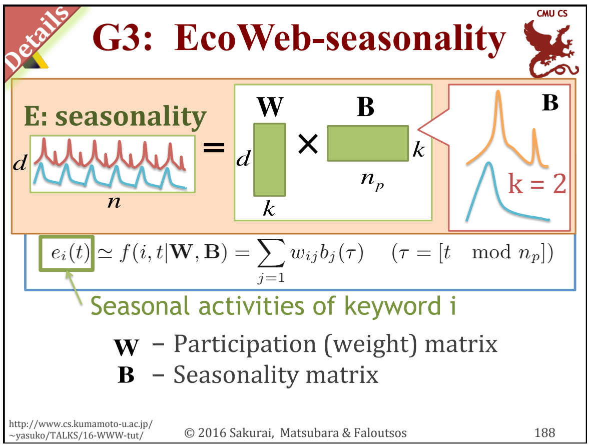
Details
G3: EcoWeb-seasonality
CMU CS
E: seasonality
d
n
=
W
B
d
k
×
k
n_p
B
k = 2
$e_i(t) \simeq f(i, t|\mathbf{W}, \mathbf{B}) = \sum_{j=1} w_{ij} b_j(\tau) \quad (\tau = [t \mod n_p])$
Seasonal activities of keyword i
W – Participation (weight) matrix
B – Seasonality matrix
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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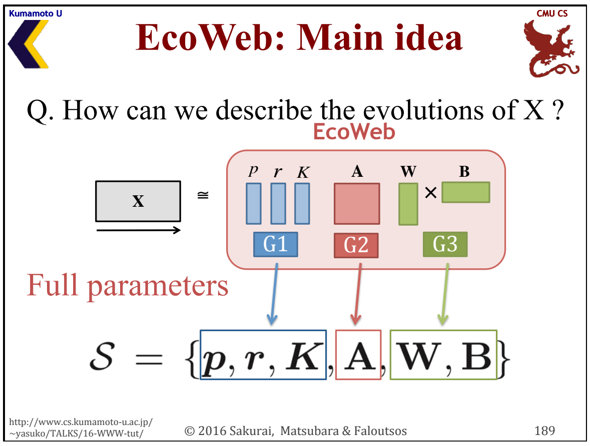
Kumamoto U
EcoWeb: Main idea
CMU CS
Q. How can we describe the evolutions of X ?
EcoWeb
X
≅
p r K
A
W
B
×
G1
G2
G3
Full parameters
$\mathcal{S} = \{\boldsymbol{p}, \boldsymbol{r}, \boldsymbol{K}, \mathbf{A}, \mathbf{W}, \mathbf{B}\}$
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
© 2016 Sakurai, Matsubara & Faloutsos
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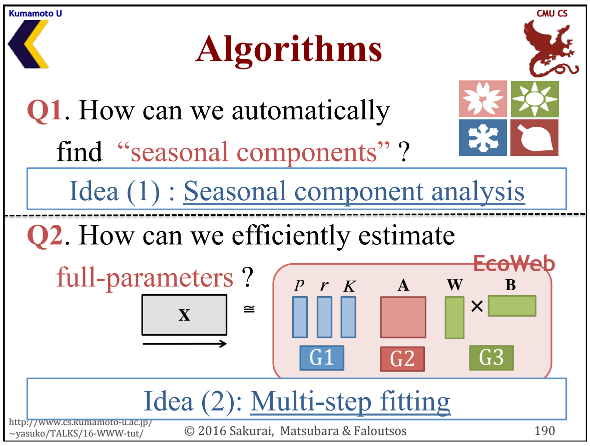
Kumamoto U
Algorithms
CMU CS
Q1. How can we automatically
find "seasonal components" ?
Idea (1) : Seasonal component analysis
Q2. How can we efficiently estimate
full-parameters ?
EcoWeb
X
≅
p r K
A
W
B
×
G1
G2
G3
Idea (2): Multi-step fitting
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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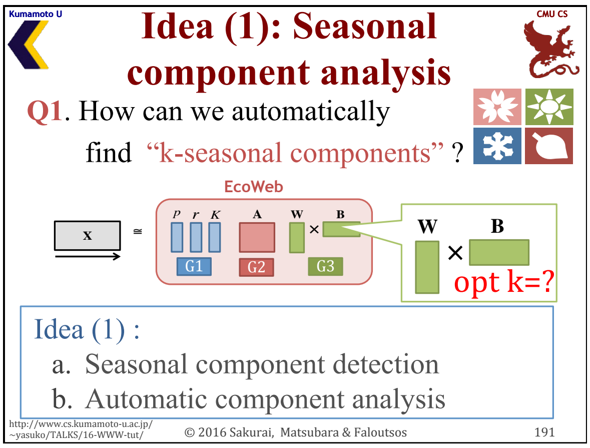
Kumamoto U
Idea (1): Seasonal component analysis
CMU CS
Q1. How can we automatically
find "k-seasonal components" ?
EcoWeb
X
≅
p r K
A
W
B
×
G1
G2
G3
W
B
×
opt k=?
Idea (1) :
a. Seasonal component detection
b. Automatic component analysis
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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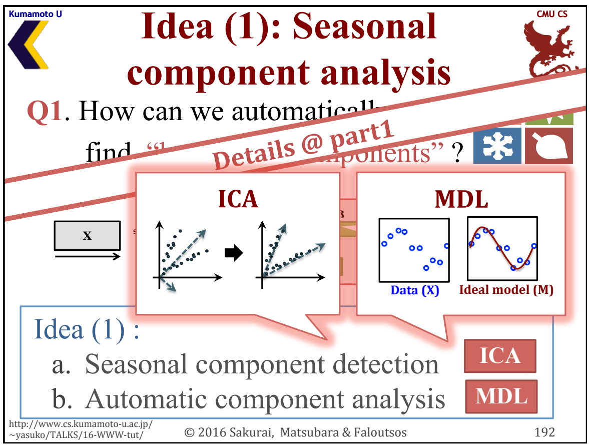
Kumamoto U
Idea (1): Seasonal component analysis
CMU CS
Q1. How can we automatically
Details @ part1
ICA
MDL
Data (X)
Ideal model (M)
Idea (1) :
a. Seasonal component detection
b. Automatic component analysis
ICA
MDL
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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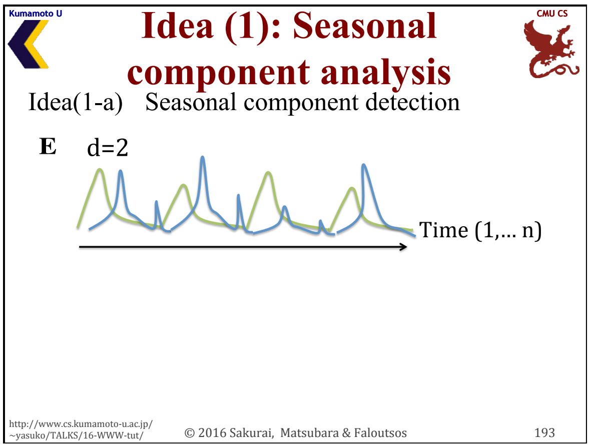
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-a) Seasonal component detection
E
d=2
Time (1,... n)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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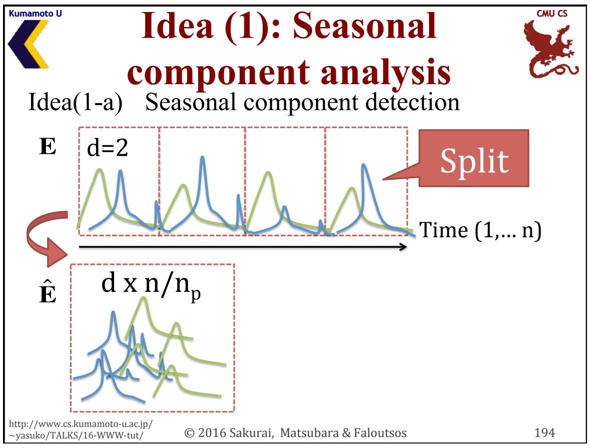
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-a) Seasonal component detection
E
d=2
Split
Time (1,... n)
Ê
d x n/n_p
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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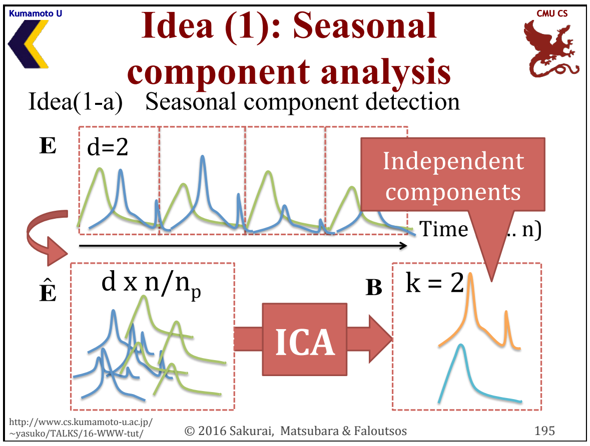
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-a) Seasonal component detection
E
d=2
Independent components
Time ... n)
Ê
d x n/n_p
ICA
B
k = 2
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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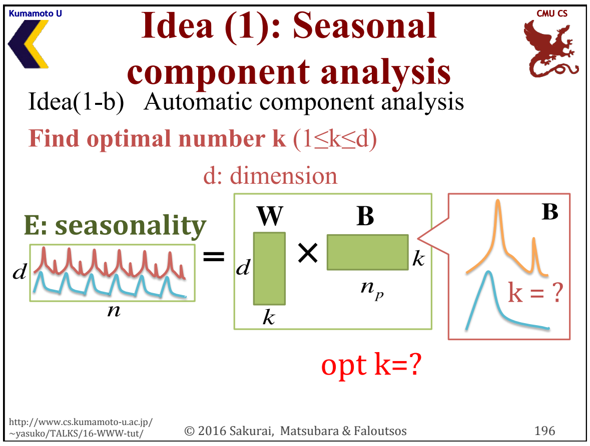
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-b) Automatic component analysis
Find optimal number k (1≤k≤d)
d: dimension
E: seasonality
d
n
=
W
d
k
×
B
k
n_p
B
k = ?
opt k=?
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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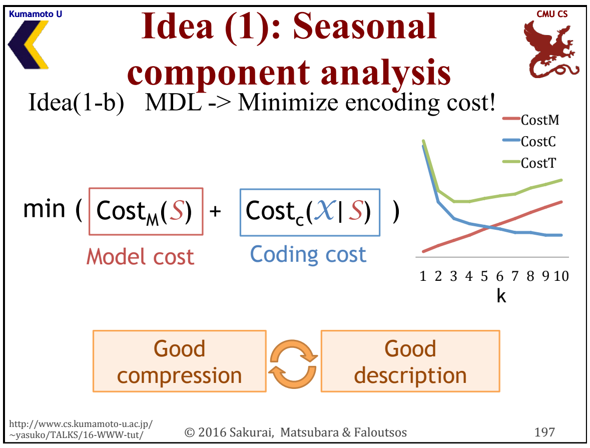
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-b) MDL -> Minimize encoding cost!
CostM
CostC
CostT
min (Cost_M(S) + Cost_c(X| S))
Model cost
Coding cost
1 2 3 4 5 6 7 8 9 10
k
Good compression
Good description
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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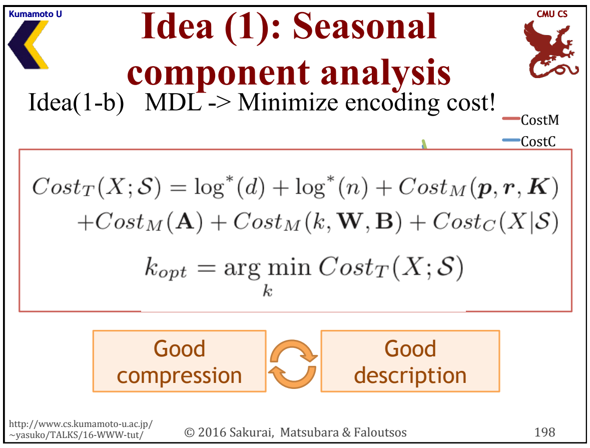
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-b) MDL -> Minimize encoding cost!
CostM
CostC
$Cost_T(X;\mathcal{S}) = \log^*(d) + \log^*(n) + Cost_M(\boldsymbol{p}, \boldsymbol{r}, \boldsymbol{K})$
$+Cost_M(\mathbf{A}) + Cost_M(k, \mathbf{W}, \mathbf{B}) + Cost_C(X|\mathcal{S})$
$k_{opt} = \arg\min_k Cost_T(X;\mathcal{S})$
Good compression
Good description
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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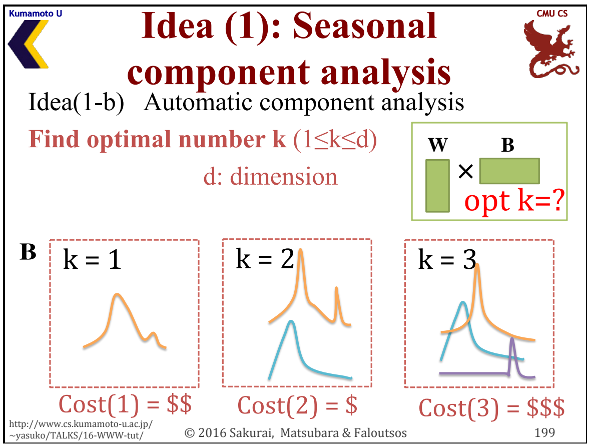
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-b) Automatic component analysis
Find optimal number k (1≤k≤d)
d: dimension
W
B
×
opt k=?
B
k = 1
k = 2
k = 3
Cost(1) = $$
Cost(2) = $
Cost(3) = $$$
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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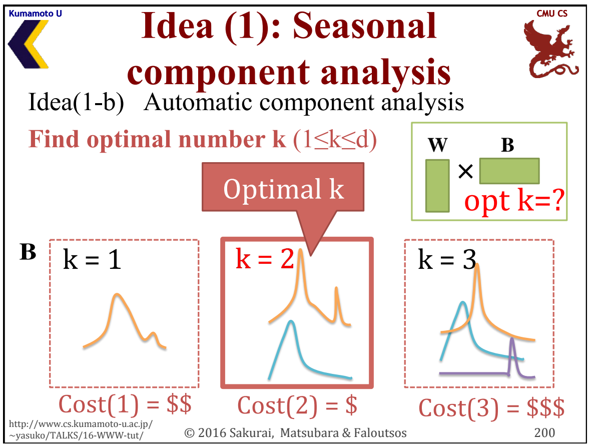
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-b) Automatic component analysis
Find optimal number k (1≤k≤d)
Optimal k
W
B
×
opt k=?
B
k = 1
k = 2
k = 3
Cost(1) = $$
Cost(2) = $
Cost(3) = $$$
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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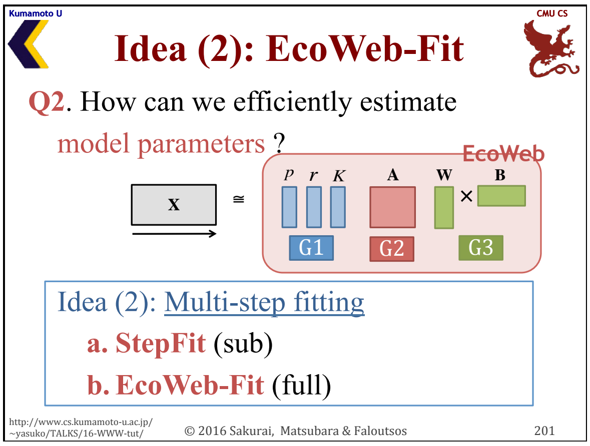
Kumamoto U
CMU CS
Idea (2): EcoWeb-Fit
Q2. How can we efficiently estimate model parameters ?
EcoWeb
X
≅
P r K
A
W
B
×
G1
G2
G3
Idea (2): Multi-step fitting
a. StepFit (sub)
b. EcoWeb-Fit (full)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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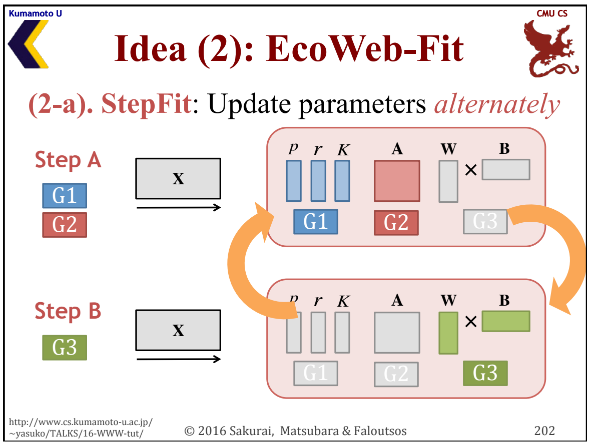
Kumamoto U
CMU CS
Idea (2): EcoWeb-Fit
(2-a). StepFit: Update parameters alternately
Step A
G1
G2
X
P r K
A
W
B
G1
G2
G3
Step B
G3
X
P r K
A
W
B
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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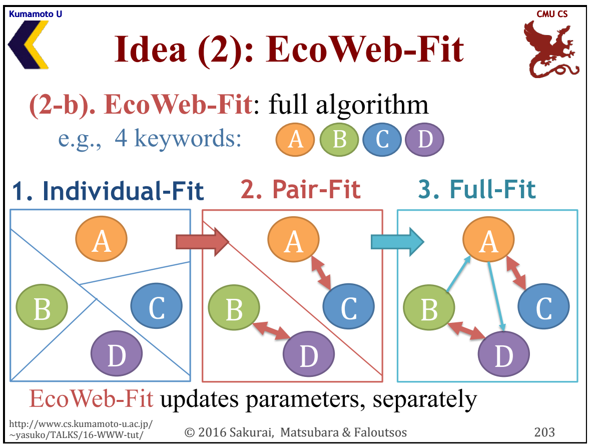
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Idea (2): EcoWeb-Fit
(2-b). EcoWeb-Fit: full algorithm
e.g., 4 keywords: A B C D
1. Individual-Fit
2. Pair-Fit
3. Full-Fit
A B C D
A B C D
A B C D
EcoWeb-Fit updates parameters, separately
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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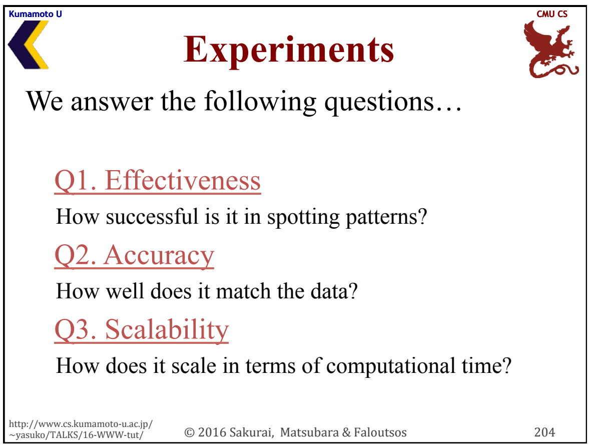
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Experiments
We answer the following questions…
Q1. Effectiveness
How successful is it in spotting patterns?
Q2. Accuracy
How well does it match the data?
Q3. Scalability
How does it scale in terms of computational time?
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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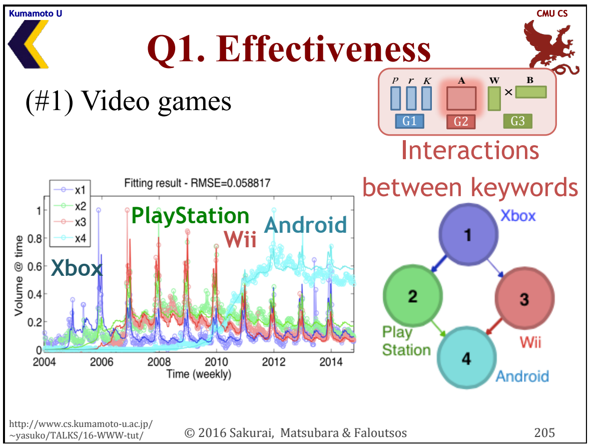
Kumamoto U
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Q1. Effectiveness
(#1) Video games
Interactions
between keywords
Fitting result - RMSE=0.058817
PlayStation
Wii
Android
Xbox
Volume @ time
Time (weekly)
Xbox
Play Station
Wii
Android
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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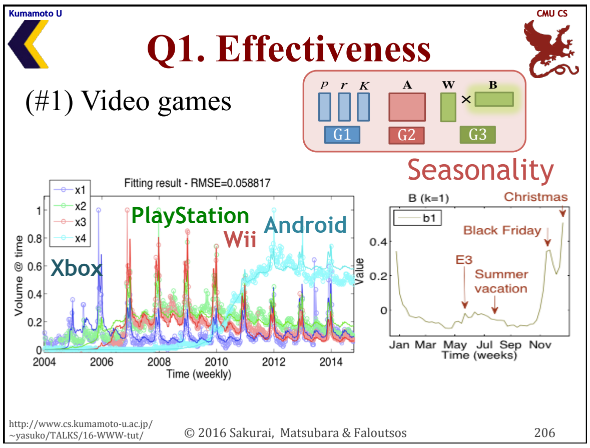
Kumamoto U
CMU CS
Q1. Effectiveness
(#1) Video games
Seasonality
Fitting result - RMSE=0.058817
PlayStation
Wii
Android
Xbox
Volume @ time
Time (weekly)
B (k=1)
Christmas
Black Friday
E3
Summer vacation
Jan Mar May Jul Sep Nov
Time (weeks)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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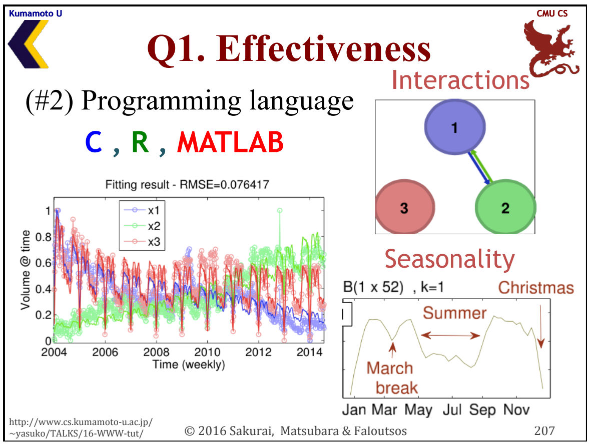
Kumamoto U
CMU CS
Q1. Effectiveness
(#2) Programming language
C , R , MATLAB
Interactions
Fitting result - RMSE=0.076417
Volume @ time
Time (weekly)
Seasonality
B(1 x 52) , k=1
Christmas
Summer
March break
Jan Mar May Jul Sep Nov
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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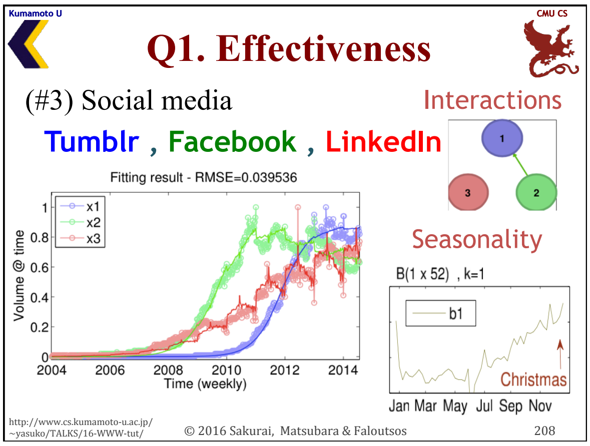
Kumamoto U
CMU CS
Q1. Effectiveness
(#3) Social media
Tumblr , Facebook , LinkedIn
Interactions
Fitting result - RMSE=0.039536
Volume @ time
Time (weekly)
Seasonality
B(1 x 52) , k=1
Christmas
Jan Mar May Jul Sep Nov
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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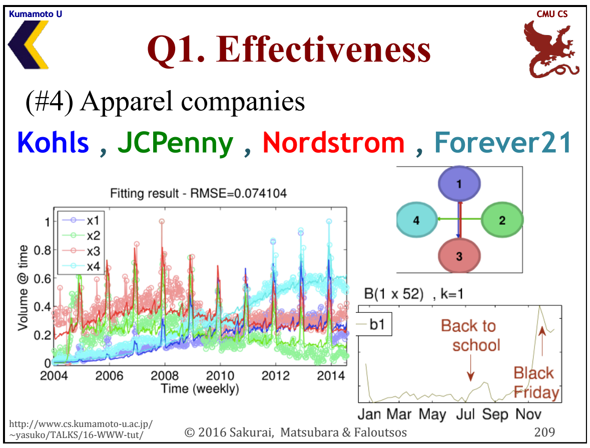
Kumamoto U
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Q1. Effectiveness
(#4) Apparel companies
Kohls , JCPenny , Nordstrom , Forever21
Fitting result - RMSE=0.074104
Volume @ time
Time (weekly)
B(1 x 52) , k=1
Back to school
Black Friday
Jan Mar May Jul Sep Nov
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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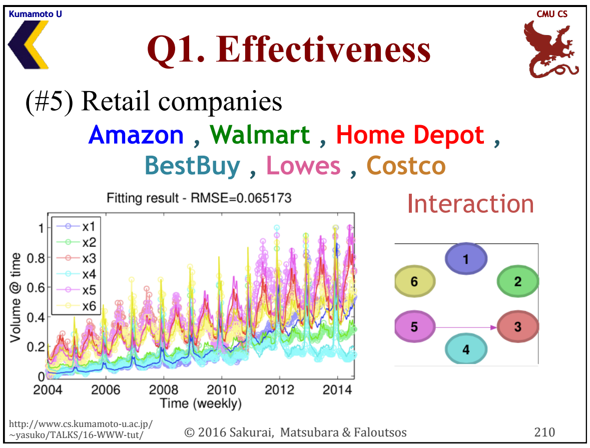
Kumamoto U
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Q1. Effectiveness
(#5) Retail companies
Amazon , Walmart , Home Depot ,
BestBuy , Lowes , Costco
Fitting result - RMSE=0.065173
Interaction
Volume @ time
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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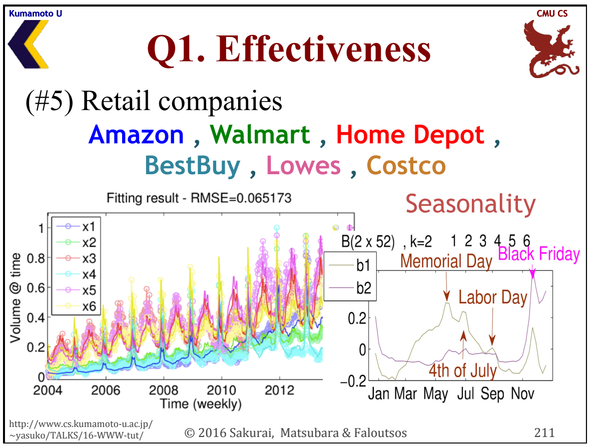
Kumamoto U
CMU CS
Q1. Effectiveness
(#5) Retail companies
Amazon , Walmart , Home Depot ,
BestBuy , Lowes , Costco
Fitting result - RMSE=0.065173
Seasonality
x1
x2
x3
x4
x5
x6
Volume @ time
Time (weekly)
2004 2006 2008 2010 2012
B(2 x 52) , k=2 1 2 3 4 5 6
b1
b2
Memorial Day
Black Friday
Labor Day
4th of July
Jan Mar May Jul Sep Nov
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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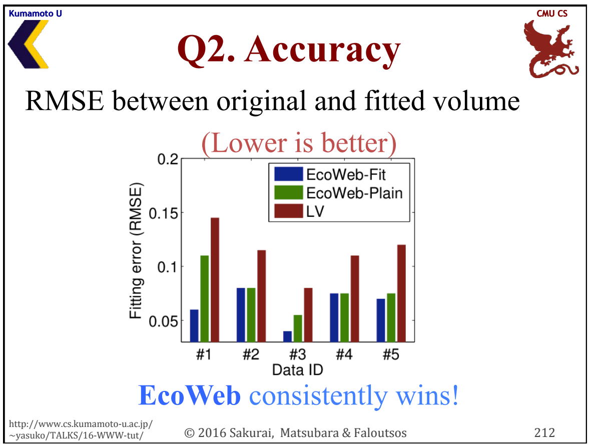
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CMU CS
Q2. Accuracy
RMSE between original and fitted volume
(Lower is better)
EcoWeb-Fit
EcoWeb-Plain
LV
Fitting error (RMSE)
#1 #2 #3 #4 #5
Data ID
EcoWeb consistently wins!
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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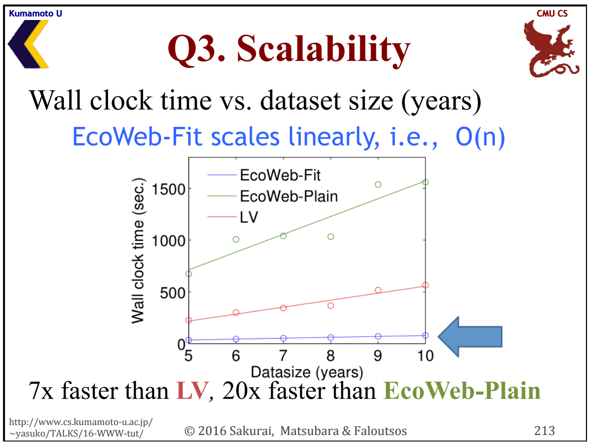
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CMU CS
Q3. Scalability
Wall clock time vs. dataset size (years)
EcoWeb-Fit scales linearly, i.e., O(n)
EcoWeb-Fit
EcoWeb-Plain
LV
Wall clock time (sec.)
Datasize (years)
7x faster than LV, 20x faster than EcoWeb-Plain
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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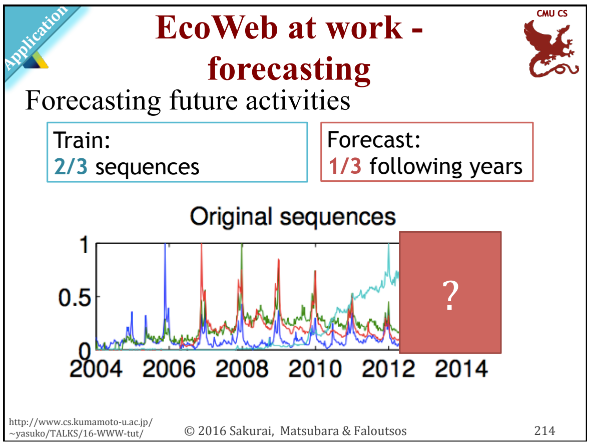
Application
CMU CS
EcoWeb at work - forecasting
Forecasting future activities
Train:
2/3 sequences
Forecast:
1/3 following years
Original sequences
?
2004 2006 2008 2010 2012 2014
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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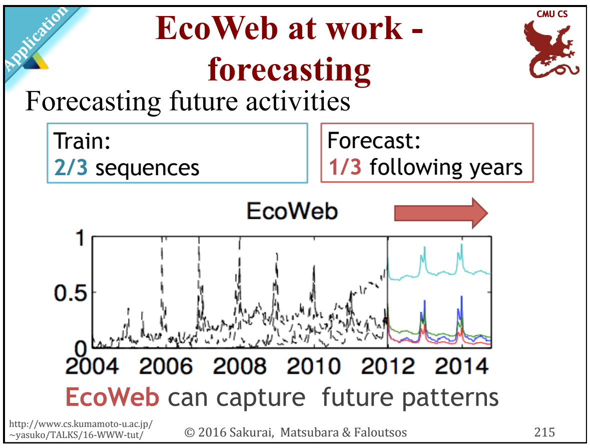
Application
CMU CS
EcoWeb at work - forecasting
Forecasting future activities
Train:
2/3 sequences
Forecast:
1/3 following years
EcoWeb
2004 2006 2008 2010 2012 2014
EcoWeb can capture future patterns
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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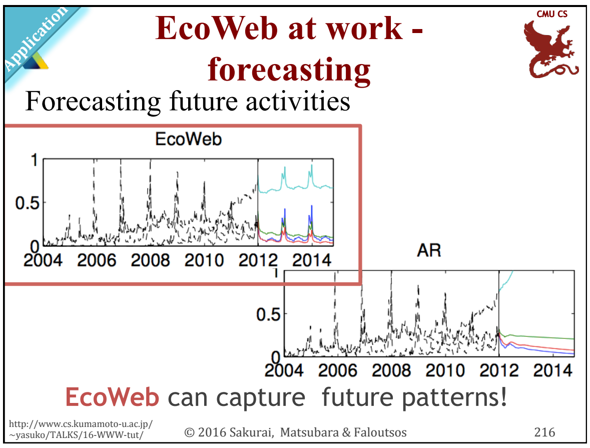
Application
CMU CS
EcoWeb at work - forecasting
Forecasting future activities
EcoWeb
AR
2004 2006 2008 2010 2012 2014
EcoWeb can capture future patterns!
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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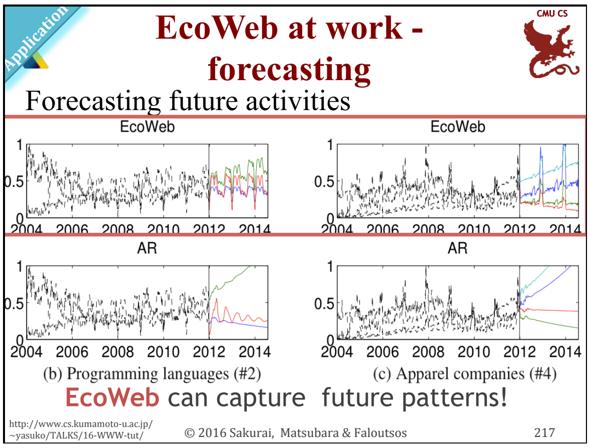

Application
EcoWeb at work - forecasting
CMU CS
Forecasting future activities
EcoWeb
EcoWeb
AR
AR
2004 2006 2008 2010 2012 2014
(b) Programming languages (#2)
(c) Apparel companies (#4)
EcoWeb can capture future patterns!
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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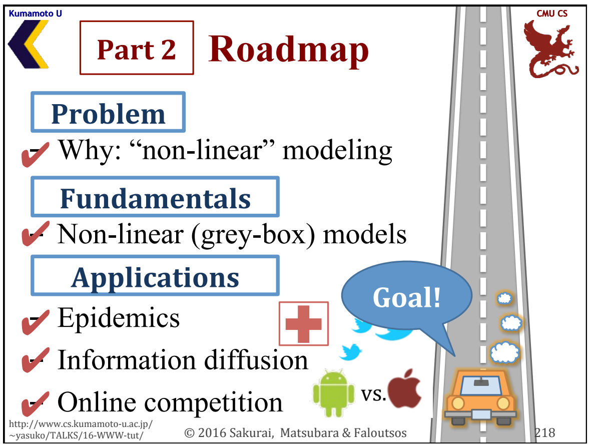

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CMU CS
Part 2
Roadmap
Problem
Why: "non-linear" modeling
Fundamentals
Non-linear (grey-box) models
Applications
Epidemics
Information diffusion
Online competition
Goal!
vs.
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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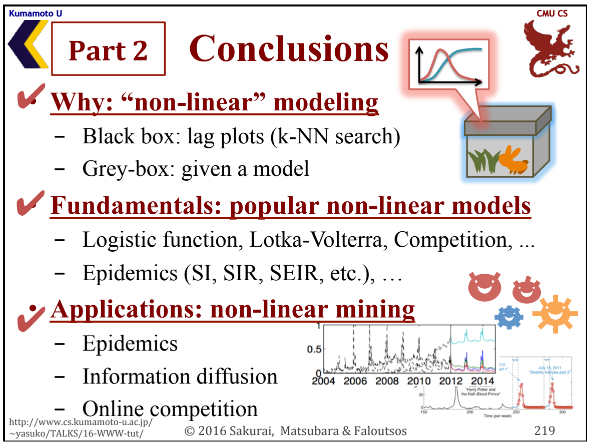

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Part 2
Conclusions
Why: "non-linear" modeling
– Black box: lag plots (k-NN search)
– Grey-box: given a model
Fundamentals: popular non-linear models
– Logistic function, Lotka-Volterra, Competition, ...
– Epidemics (SI, SIR, SEIR, etc.), …
Applications: non-linear mining
– Epidemics
– Information diffusion
– Online competition
2004 2006 2008 2010 2012 2014
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/16-WWW-tut/
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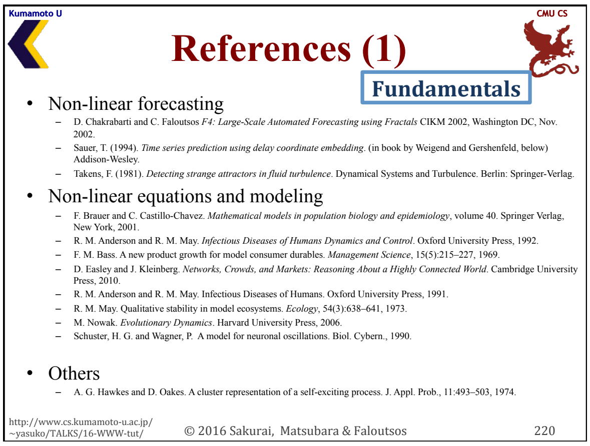

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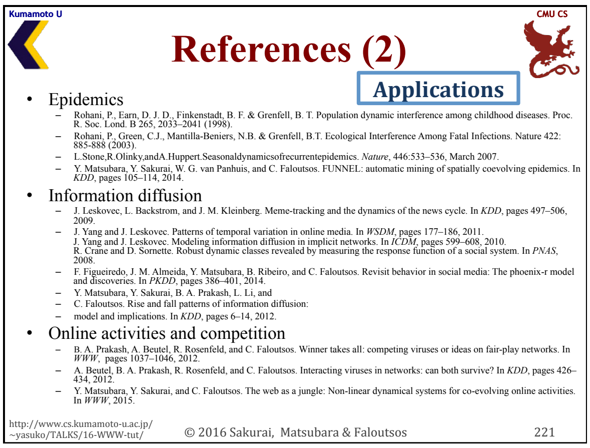

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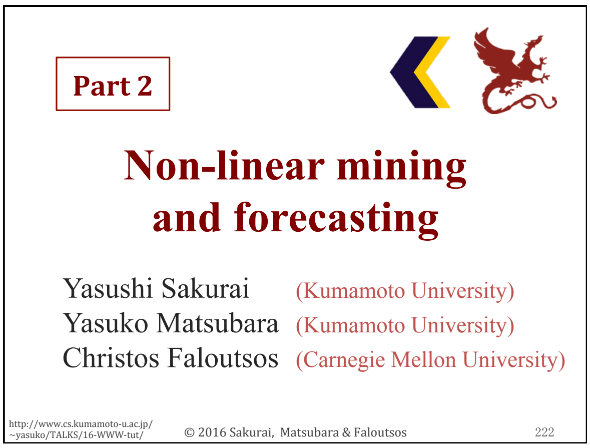

Part 2
Non-linear mining and forecasting
Yasushi Sakurai (Kumamoto University)
Yasuko Matsubara (Kumamoto University)
Christos Faloutsos (Carnegie Mellon University)
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