Mining and Forecasting of Big Time-series Data

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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

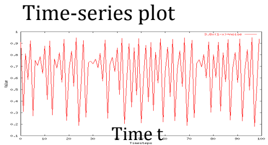
Q. What are "non-linear phenomena"?

Example: logistic parabola

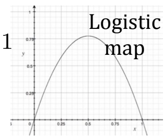
Models population of flies [R. May/1976]

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

Time-series plot



Logistic map



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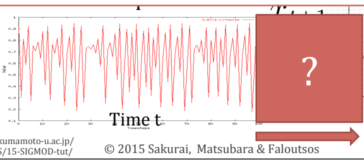
Non-linear mining and forecasting

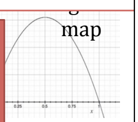
Q. What are "non-linear phenomena"?

Problem:

Given: a time series x_t

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





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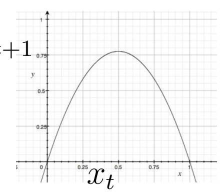
How to forecast?

Solution 1

Linear equations, e.g., AR, ARIMA, …



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How to forecast?

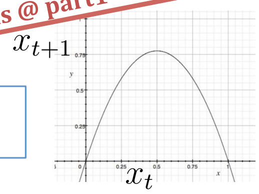
Solution 1

Linear equations, e.g., AR, ARIMA, …

Details @ part1

e.g., AR(1)

$x_{t+1} = a x_t + \epsilon$



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How to forecast?

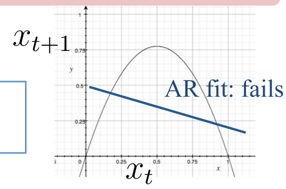
Solution 1

Linear equations, e.g., AR, ARIMA, …

but: linearity assumption

e.g., AR(1)

$x_{t+1} = a x_t + \epsilon$



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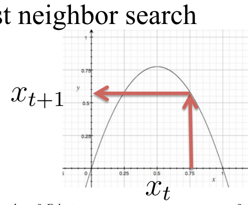
How to forecast?

Solution 2

“Delayed Coordinate Embedding”

= Lag Plots [Sauer92]

- Based on k-nearest neighbor search



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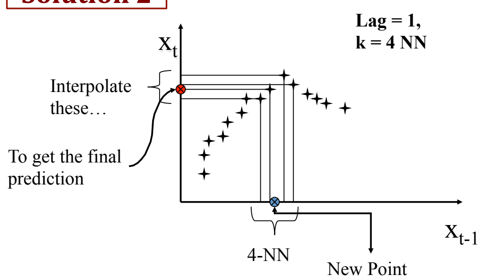
General Intuition (Lag Plot)

Solution 2



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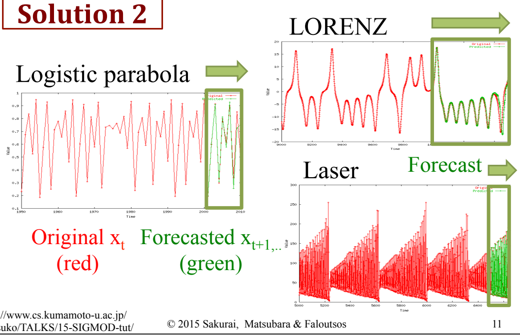
Forecasting results (Lag Plot)

[Chakrabarti+ CIKM'02]

Solution 2



Original x_t (red) Forecasted $x_{t+1,\ldots}$ (green)

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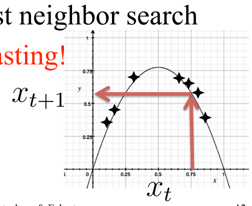
How to forecast?

Solution 2

“Delayed Coordinate Embedding”

= Lag Plots [Sauer92]

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



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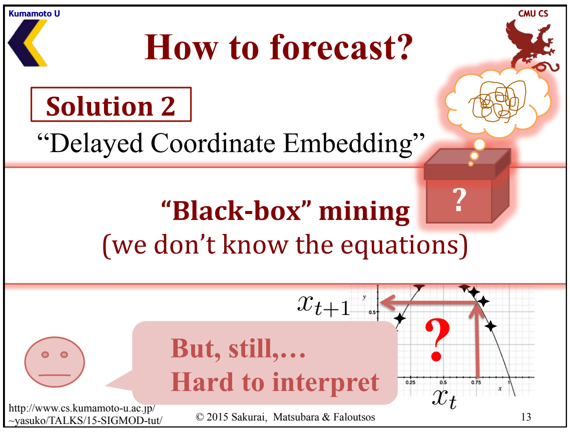
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How to forecast?
Solution 2
"Delayed Coordinate Embedding"
"Black-box" mining
(we don't know the equations)
?
x_{t+1}
x_t
But, still,…
Hard to interpret
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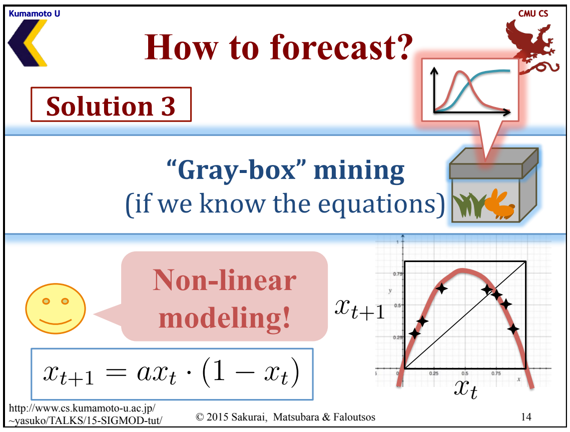
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How to forecast?
Solution 3
"Gray-box" mining
(if we know the equations)
Non-linear modeling!
$x_{t+1} = a x_t \cdot (1 - x_t)$
x_{t+1}
x_t
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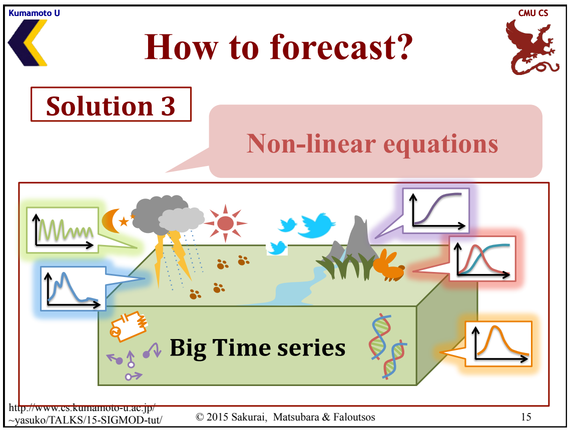
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How to forecast?
Solution 3
Non-linear equations
Big Time series
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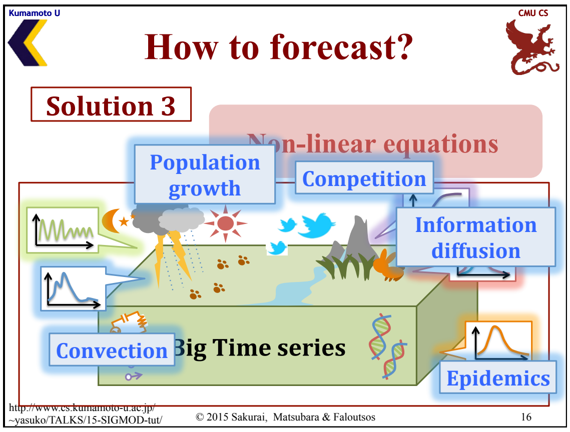
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Solution 3
Non-linear equations
Population growth
Competition
Information diffusion
Convection
Big Time series
Epidemics
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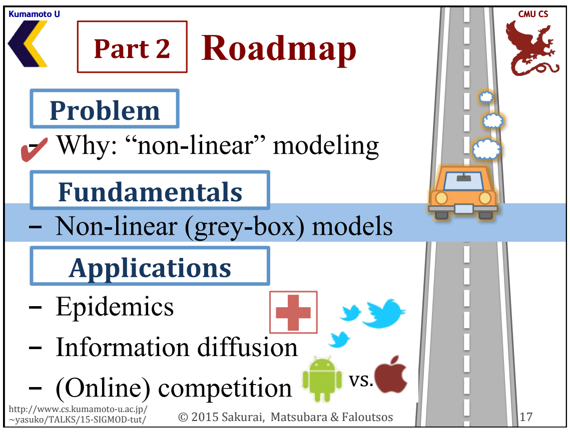
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Part 2 Roadmap
Problem
Why: "non-linear" modeling
Fundamentals
– Non-linear (grey-box) models
Applications
– Epidemics
– Information diffusion
– (Online) competition
vs.
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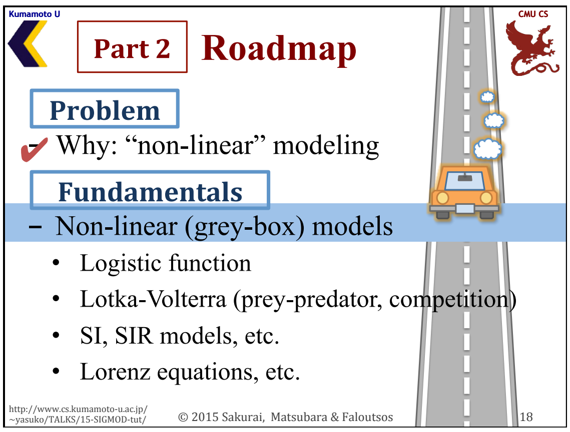
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Part 2 Roadmap
Problem
Why: "non-linear" modeling
Fundamentals
– Non-linear (grey-box) models
• Logistic function
• Lotka-Volterra (prey-predator, competition)
• SI, SIR models, etc.
• Lorenz equations, etc.
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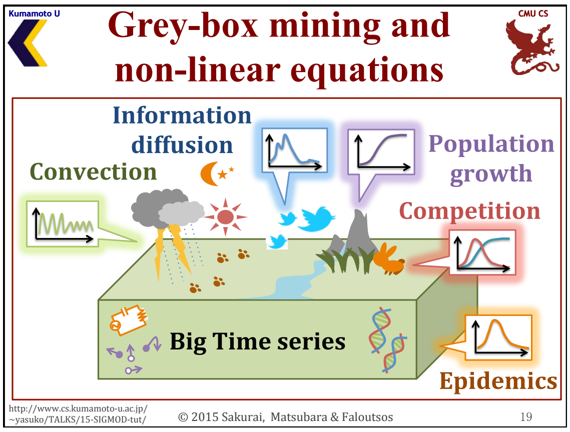
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Convection
Population growth
Competition
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Epidemics
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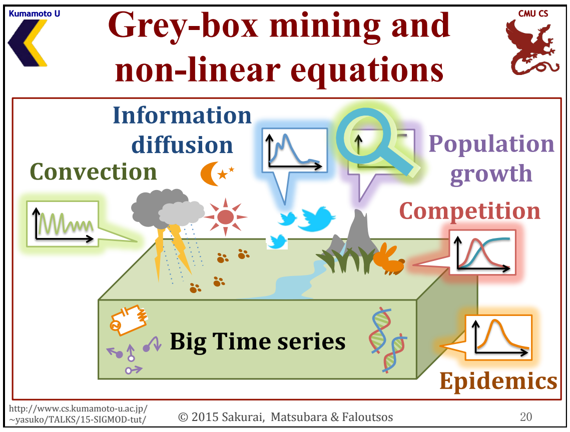
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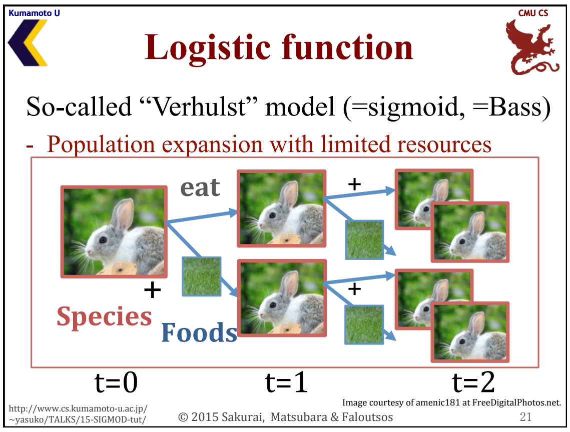
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Logistic function
So-called "Verhulst" model (=sigmoid, =Bass)
- Population expansion with limited resources
eat
+
Species
Foods
t=0
t=1
t=2
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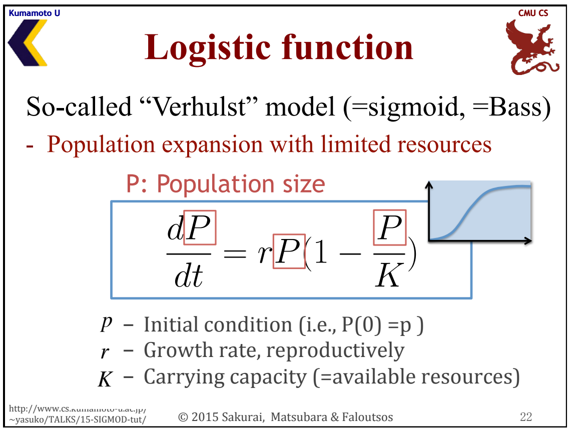
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Logistic function
So-called "Verhulst" model (=sigmoid, =Bass)
- Population expansion with limited resources
P: Population size
$\frac{dP}{dt} = rP(1 - \frac{P}{K})$
p – Initial condition (i.e., P(0) =p)
r – Growth rate, reproductively
K – Carrying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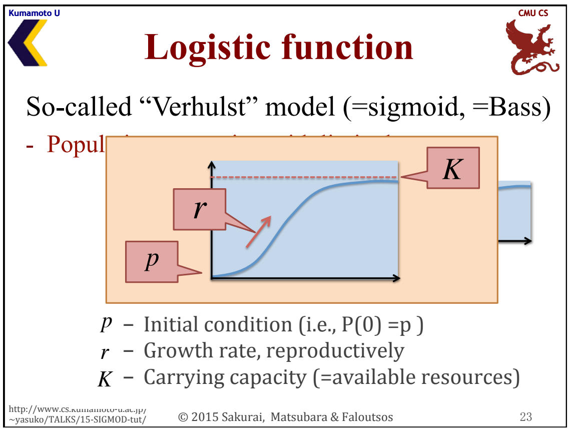
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Logistic function
So-called "Verhulst" model (=sigmoid, =Bass)
K
r
p
p – Initial condition (i.e., P(0) =p)
r – Growth rate, reproductively
K – Carrying capacity (=available resources)
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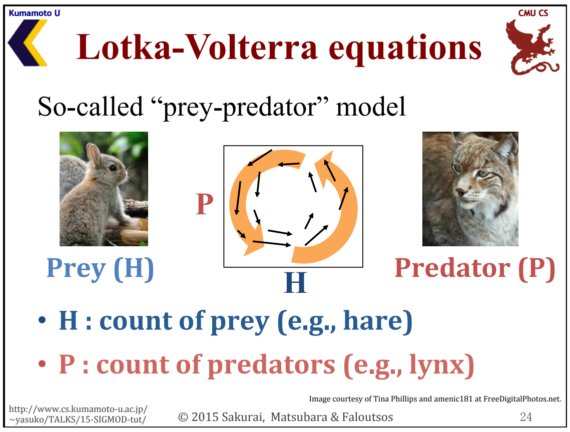
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Lotka-Volterra equations
So-called "prey-predator" model
P
H
Prey (H)
Predator (P)
• H : count of prey (e.g., hare)
• P : count of predators (e.g., lynx)
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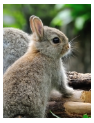
Lotka-Volterra equations

So-called "prey-predator" model



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

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

Prey (H) Predator (P)

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

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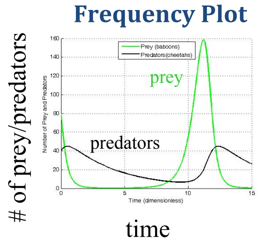
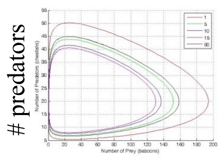
Solution to the Lotka-Volterra equations.

Frequency Plot



Phase Space Plot



From Wikipedia

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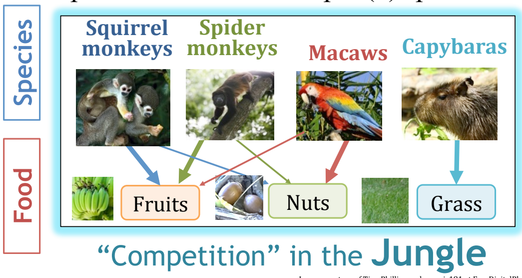
Extension: "Competitive" Lotka-Volterra equations

Competition between multiple (d) species



"Competition" in the Jungle

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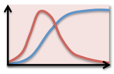
"Competitive" Lotka-Volterra equations

Competition between multiple (d) species

Population of species i Population of j

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

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



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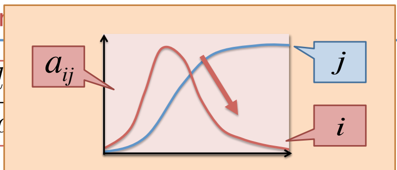
"Competitive" Lotka-Volterra equations

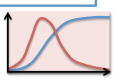
Competition between multiple (d) species

Popular j



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

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



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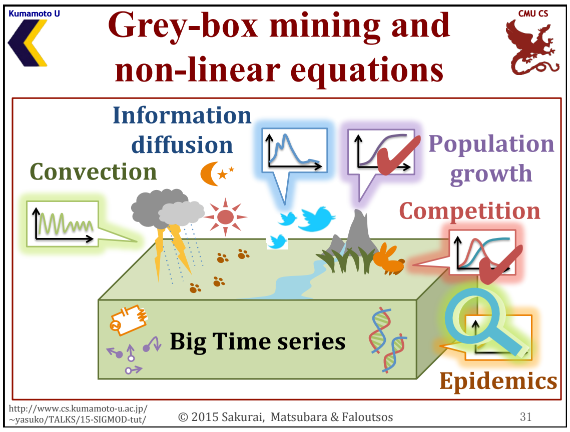
"Competitive" Lotka-Volterra equations

- Biological interaction
  - Table: Type of interaction

0 : no effect
- : detrimental
+ : beneficial

Species B

Species A	+	0	-
+	Mutualism		
0	Commensalism	Neutralism	
-	Antagonism	Amensalism	Competition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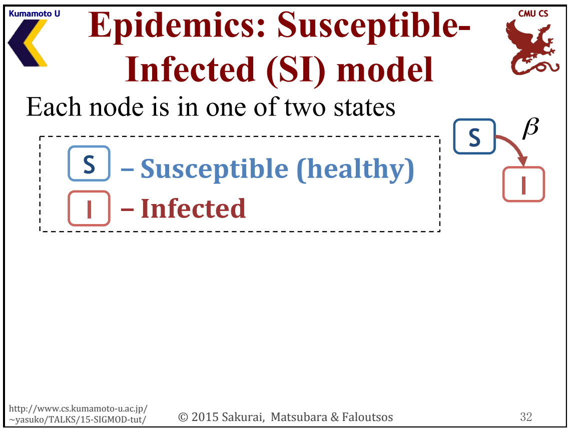
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Epidemics: Susceptible-Infected (SI) model
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Each node is in one of two states
S – Susceptible (healthy)
I – Infected
S
β
I
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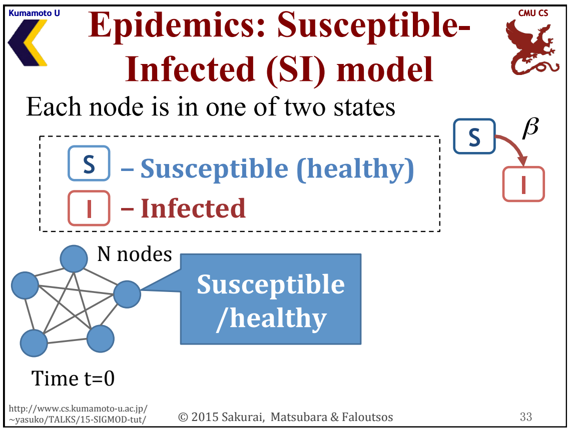
Kumamoto U
Epidemics: Susceptible-Infected (SI) model
CMU CS
Each node is in one of two states
S – Susceptible (healthy)
I – Infected
S
β
I
N nodes
Susceptible /healthy
Time t=0
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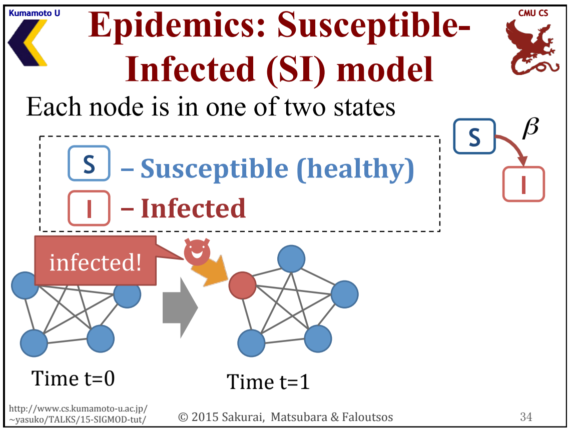
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Epidemics: Susceptible-Infected (SI) model
CMU CS
Each node is in one of two states
S – Susceptible (healthy)
I – Infected
S
β
I
infected!
Time t=0
Time t=1
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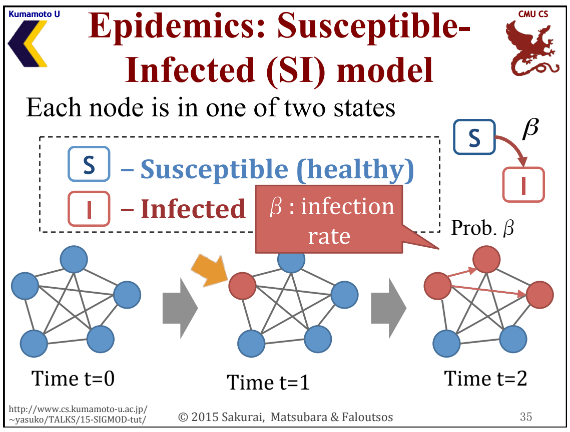
Kumamoto U
Epidemics: Susceptible-Infected (SI) model
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Each node is in one of two states
S – Susceptible (healthy)
I – Infected
β : infection rate
S
β
I
Prob. β
Time t=0
Time t=1
Time t=2
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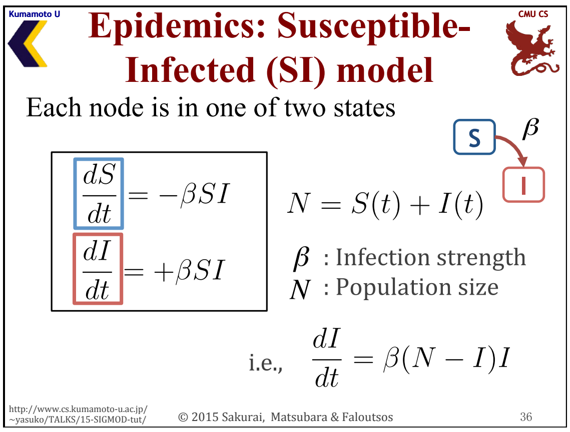
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Epidemics: Susceptible-Infected (SI) model
CMU CS
Each node is in one of two states
S
β
I
$\frac{dS}{dt} = -\beta SI$
$\frac{dI}{dt} = +\beta SI$
$N = S(t) + I(t)$
β : Infection strength
N : Population size
i.e., $\frac{dI}{dt} = \beta(N - I)I$
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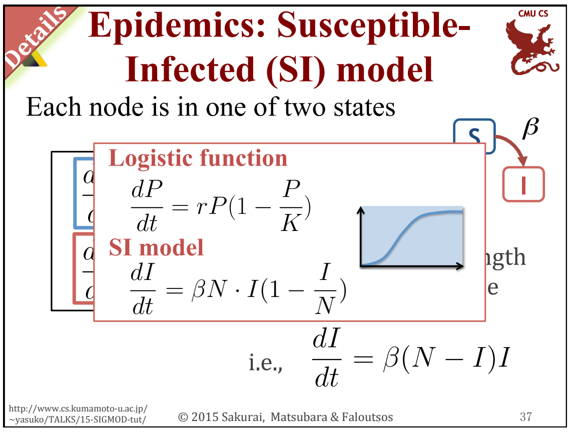
Details
Epidemics: Susceptible-Infected (SI) model
Each node is in one of two states
S
I
β
Logistic function
$\frac{dP}{dt} = rP(1 - \frac{P}{K})$
SI model
$\frac{dI}{dt} = \beta N \cdot I(1 - \frac{I}{N})$
i.e., $\frac{dI}{dt} = \beta(N - I)I$
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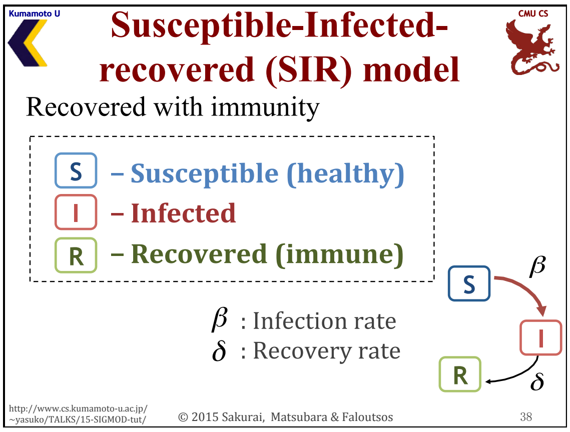
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Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S – Susceptible (healthy)
I – Infected
R – Recovered (immune)
β : Infection rate
δ : Recovery rate
S
I
R
β
δ
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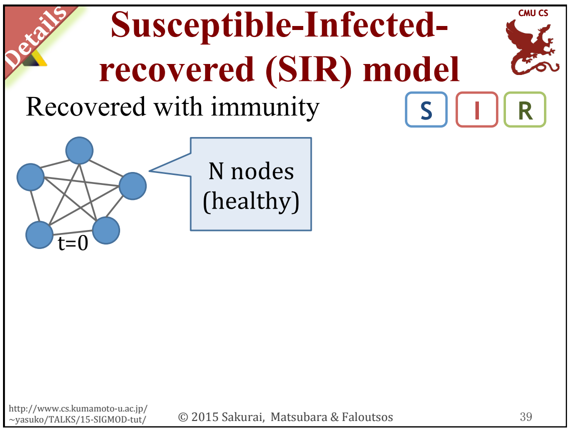
Details
Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S I R
N nodes
(healthy)
t=0
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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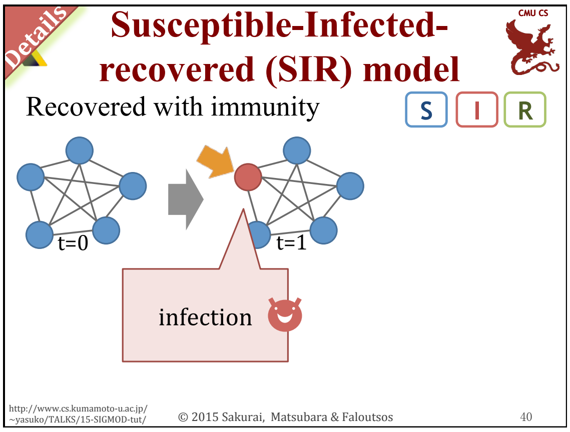
39


Details
Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S I R
t=0
t=1
infection
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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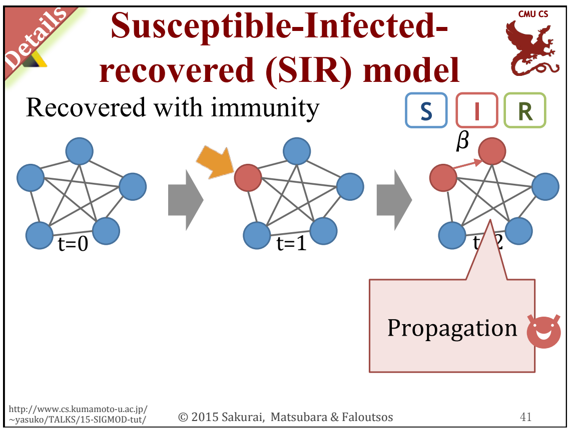
Details
Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S I R
β
t=0
t=1
Propagation
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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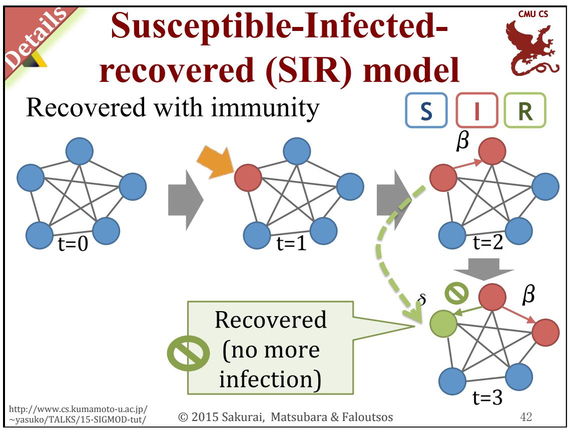
Details
Susceptible-Infected-recovered (SIR) model
Recovered with immunity
S I R
β
t=0
t=1
t=2
β
t=3
Recovered
(no more
infection)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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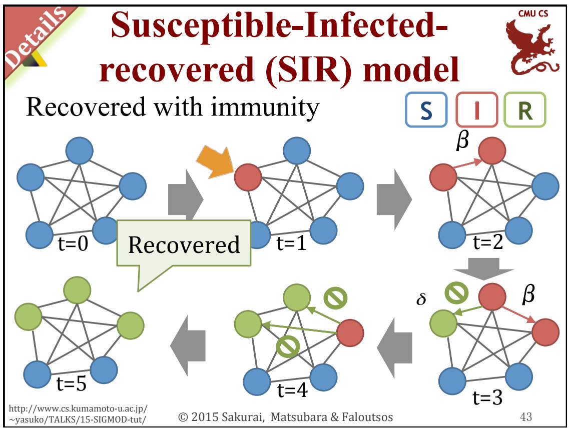
Details
Susceptible-Infected-recovered (SIR) model
CMU CS
Recovered with immunity
S
I
R
β
t=0
Recovered
t=1
t=2
δ
β
t=5
t=4
t=3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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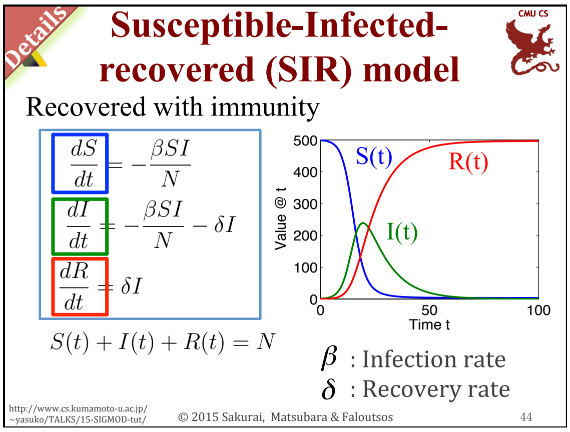
Details
Susceptible-Infected-recovered (SIR) model
CMU CS
Recovered with immunity
$\frac{dS}{dt} = -\frac{\beta SI}{N}$
$\frac{dI}{dt} = \frac{\beta SI}{N} - \delta I$
$\frac{dR}{dt} = \delta I$
$S(t) + I(t) + R(t) = N$
S(t)
R(t)
I(t)
Value @ t
Time t
β : Infection rate
δ : Recovery rate
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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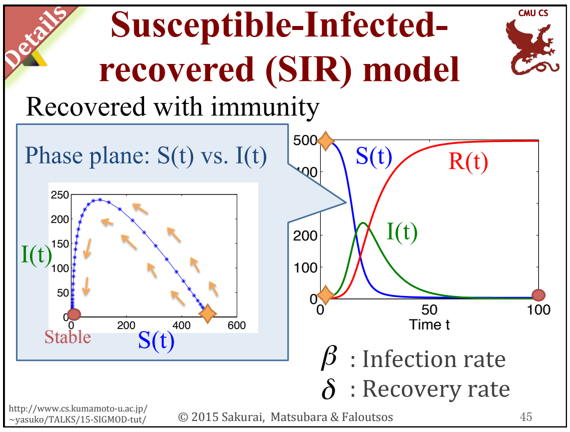
Details
Susceptible-Infected-recovered (SIR) model
CMU CS
Recovered with immunity
Phase plane: S(t) vs. I(t)
I(t)
Stable
S(t)
S(t)
R(t)
I(t)
Time t
β : Infection rate
δ : Recovery rate
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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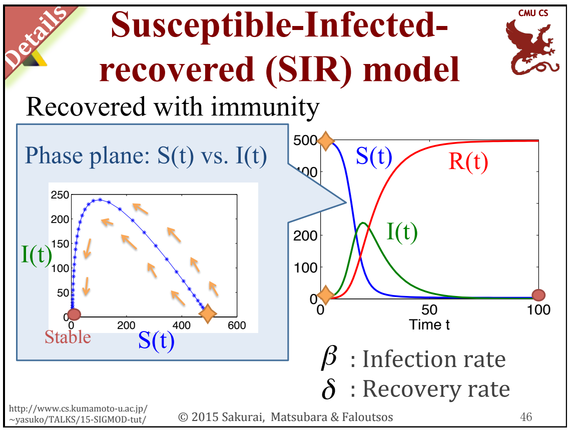
Details
Susceptible-Infected-recovered (SIR) model
CMU CS
Recovered with immunity
Phase plane: S(t) vs. I(t)
I(t)
Stable
S(t)
S(t)
R(t)
I(t)
Time t
β : Infection rate
δ : Recovery rate
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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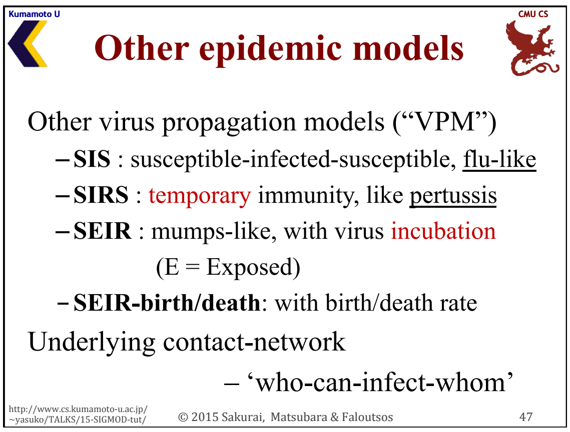
Kumamoto U
Other epidemic models
CMU CS
Other virus propagation models ("VPM")
– SIS : susceptible-infected-susceptible, flu-like
– SIRS : temporary immunity, like pertussis
– SEIR : mumps-like, with virus incubation
(E = Exposed)
– SEIR-birth/death: with birth/death rate
Underlying contact-network
– 'who-can-infect-whom'
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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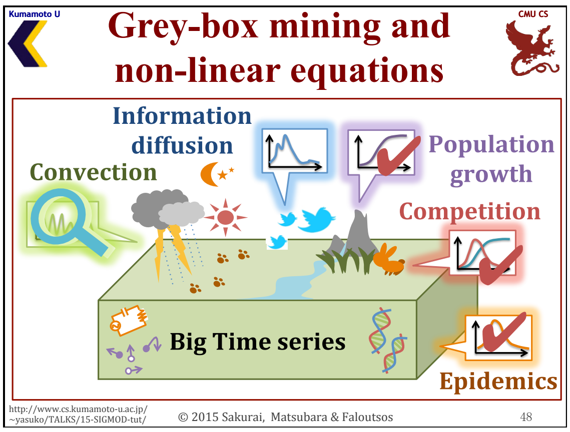
Kumamoto U
Grey-box mining and non-linear equations
CMU CS
Information diffusion
Population growth
Convection
Competition
Big Time series
Epidemics
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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Other non-linear models

LORENZ: eqs. for atmospheric convection

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

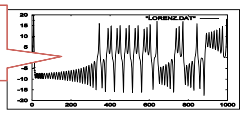
- x: convective intensity
- y: temperature difference between ascending and descending currents
- z: difference in vertical temperature profile from linearity

Other non-linear models

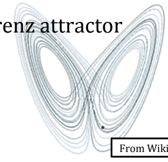
LORENZ: eqs. for atmospheric convection

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

Butterfly effect (chaos)



Lorenz attractor

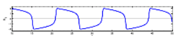


From Wikipedia

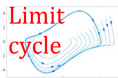
Other non-linear models

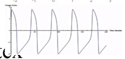
From Wikipedia

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

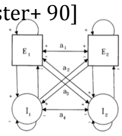


Limit cycle





[Schuster+ 90]



Part 2 Roadmap

Problem

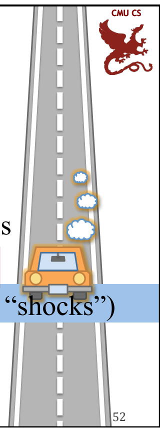
✔ Why: "non-linear" modeling

Fundamentals

✔ Non-linear ("gray-box") models

Applications

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



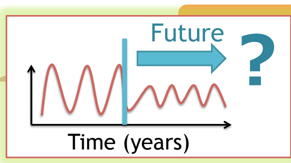
Mining and forecasting of co-evolving epidemics

Flu

Measles

Mumps

Mining and forecasting of co-evolving epidemics



Q. Can we forecast future epidemics?

Epidemics - roadmap

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

Solutions

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

Epidemics - roadmap

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

Solutions

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

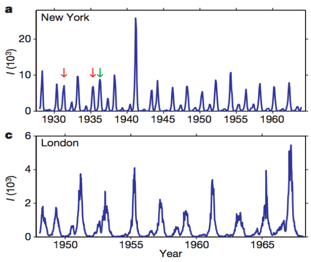
Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Time series of reported measles cases

New York

London



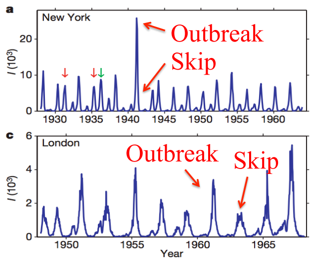
Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Time series of reported measles cases

New York

London

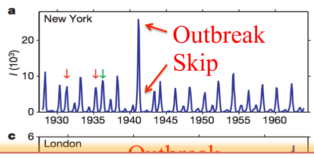


Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

- Time series of reported measles cases

New York



Q. Outbreak vs. skip?

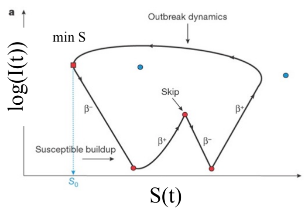
Details

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))



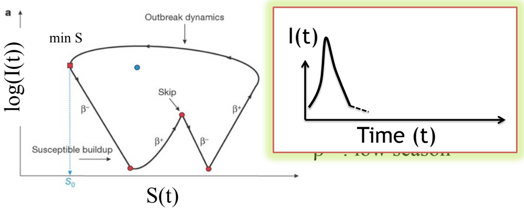
Contact rate
β+ : high season
β - : low season

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))

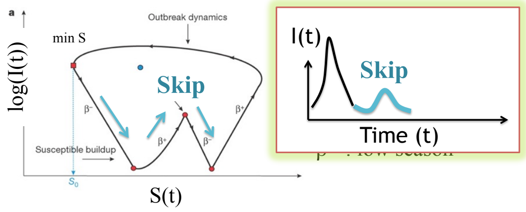


Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

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

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

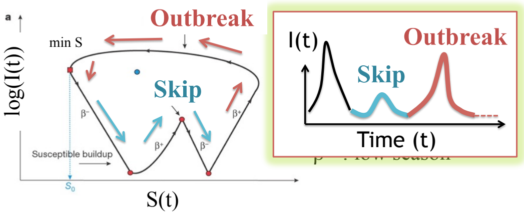


Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

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

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



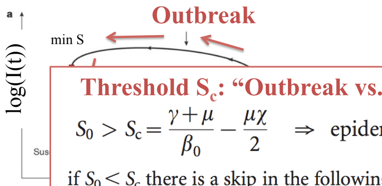
Recurrent epidemics: Outbreak or skip?

[Stone+ Nature'07]

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

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

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

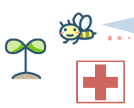


Threshold S_c: "Outbreak vs. Skip"

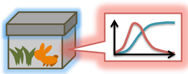
$$S_0 > S_c = \frac{\gamma+\mu}{\beta_0} - \frac{\mu\chi}{2} \quad \Rightarrow \quad \text{epidemic}$$

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

Epidemics - roadmap



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

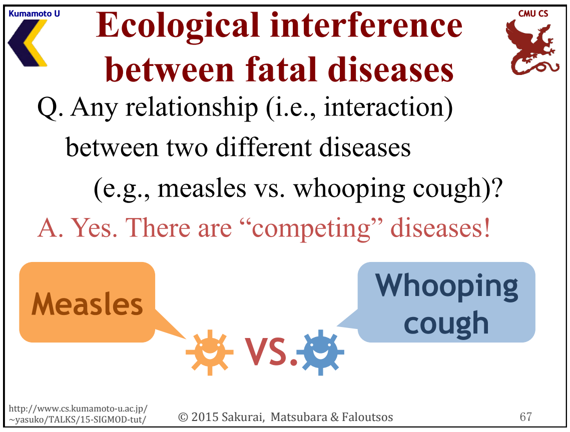


Solutions

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

Ecological interference between fatal diseases

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


Kumamoto U
CMU CS
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
Whooping cough
VS.
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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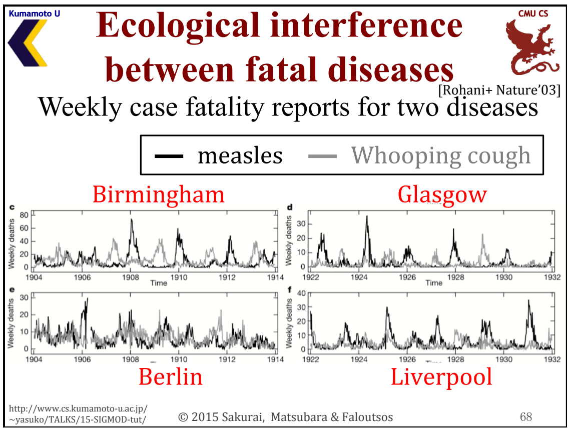
Kumamoto U
CMU CS
Ecological interference between fatal diseases
[Rohani+ Nature'03]
Weekly case fatality reports for two diseases
measles
Whooping cough
Birmingham
Glasgow
Berlin
Liverpool
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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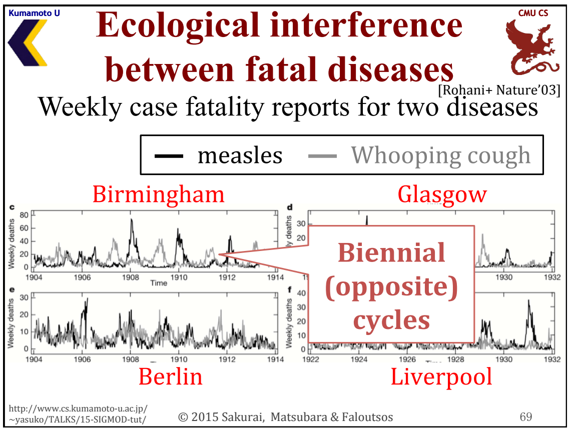
Kumamoto U
CMU CS
Ecological interference between fatal diseases
[Rohani+ Nature'03]
Weekly case fatality reports for two diseases
measles
Whooping cough
Birmingham
Glasgow
Biennial (opposite) cycles
Berlin
Liverpool
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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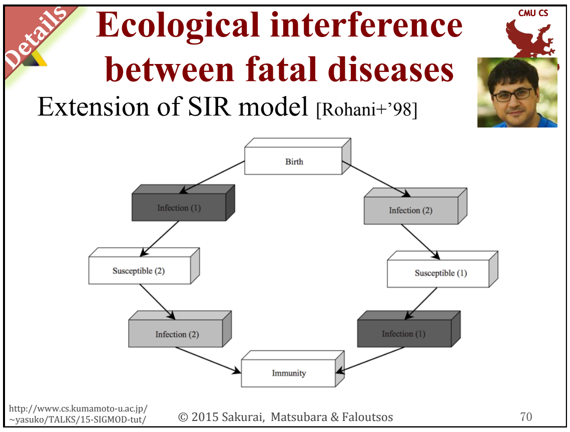
Details
CMU CS
Ecological interference between fatal diseases
Extension of SIR model [Rohani+'98]
Birth
Infection (1)
Infection (2)
Susceptible (2)
Susceptible (1)
Infection (2)
Infection (1)
Immunity
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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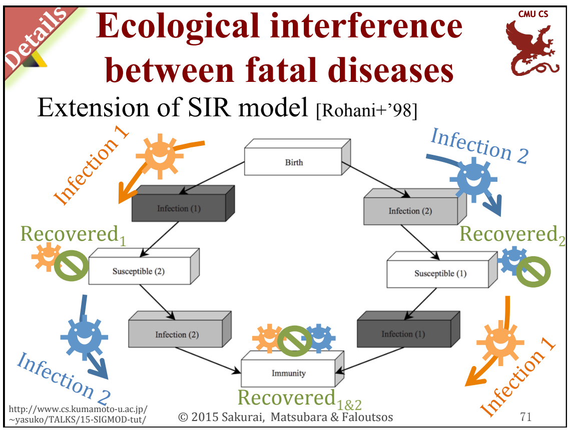
Details
CMU CS
Ecological interference between fatal diseases
Extension of SIR model [Rohani+'98]
Infection 1
Infection 2
Birth
Recovered1
Recovered2
Infection (1)
Infection (2)
Susceptible (2)
Susceptible (1)
Infection (2)
Infection (1)
Immunity
Infection 2
Recovered1&2
Infection 1
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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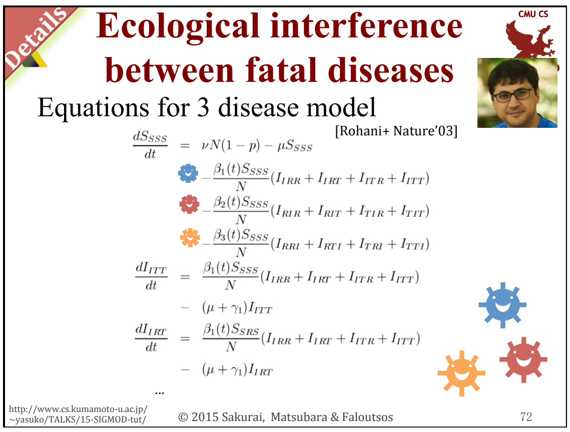
Details
CMU CS
Ecological interference between fatal diseases
Equations for 3 disease model
[Rohani+ Nature'03]
$\frac{dS_{SSS}}{dt} = \nu N(1-p) - \mu S_{SSS}$
$- \frac{\beta_1(t)S_{SSS}}{N}(I_{IRR} + I_{IRT} + I_{ITR} + I_{ITT})$
$- \frac{\beta_2(t)S_{SSS}}{N}(I_{RIR} + I_{RIT} + I_{TIR} + I_{TIT})$
$- \frac{\beta_3(t)S_{SSS}}{N}(I_{RRI} + I_{RTI} + I_{TRI} + I_{TTI})$
$\frac{dI_{ITT}}{dt} = \frac{\beta_1(t)S_{SSS}}{N}(I_{IRR} + I_{IRT} + I_{ITR} + I_{ITT})$
$- (\mu + \gamma_1)I_{ITT}$
$\frac{dI_{IRT}}{dt} = \frac{\beta_1(t)S_{SRS}}{N}(I_{IRR} + I_{IRT} + I_{ITR} + I_{ITT})$
$- (\mu + \gamma_1)I_{IRT}$
...
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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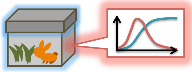
Epidemics - roadmap

Non-linear (gray-box) modeling!



Solutions

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

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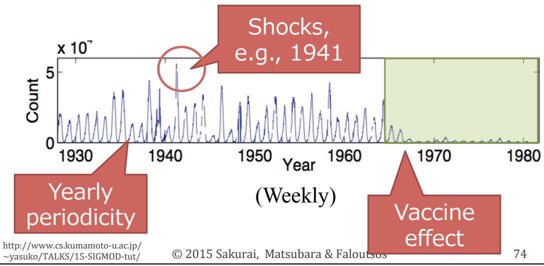
FUNNEL [Matsubara+ KDD'14] with a single epidemic

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



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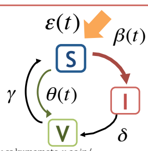
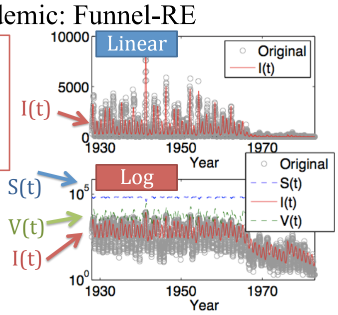
FUNNEL [Matsubara+ KDD'14] with a single epidemic

With a single epidemic: Funnel-RE

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





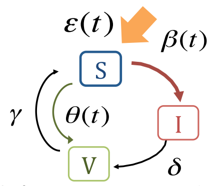
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/ © 2015 Sakurai, Matsubara & Faloutsos 75

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

With a single epidemic: Funnel-RE

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

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



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

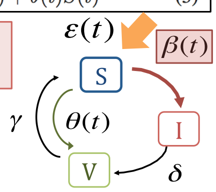
With a single epidemic: Funnel-RE

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

$\beta(t)$: 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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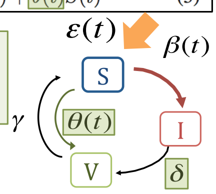
FUNNEL [Matsubara+ KDD'14] with a single epidemic

With a single epidemic: Funnel-RE

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

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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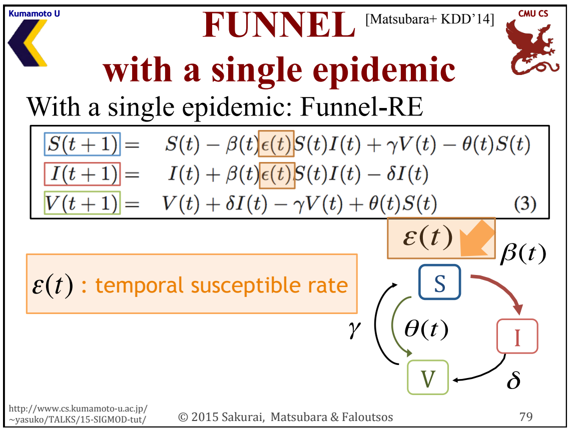
Kumamoto U
FUNNEL [Matsubara+ KDD'14]
with a single epidemic
CMU CS
With a single epidemic: Funnel-RE
$S(t+1) = S(t) - \beta(t)\epsilon(t)S(t)I(t) + \gamma V(t) - \theta(t)S(t)$
$I(t+1) = I(t) + \beta(t)\epsilon(t)S(t)I(t) - \delta I(t)$
$V(t+1) = V(t) + \delta I(t) - \gamma V(t) + \theta(t)S(t)$ (3)
$\varepsilon(t)$
$\varepsilon(t)$: temporal susceptible rate
$\beta(t)$
S
I
V
$\theta(t)$
γ
δ
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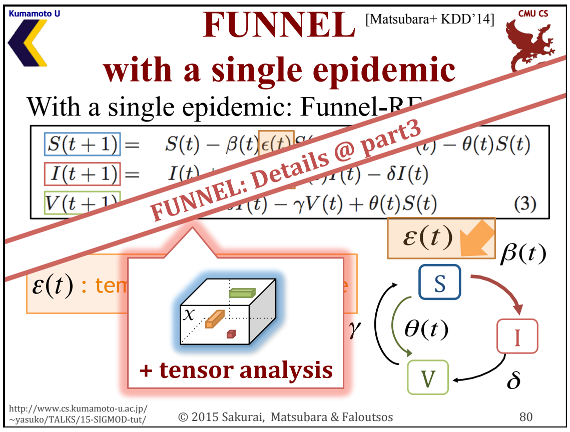
Kumamoto U
FUNNEL [Matsubara+ KDD'14]
with a single epidemic
CMU CS
With a single epidemic: Funnel-RE
FUNNEL: Details @ part3
+ tensor analysis
$\varepsilon(t)$
$\beta(t)$
S
I
V
$\theta(t)$
γ
δ
(3)
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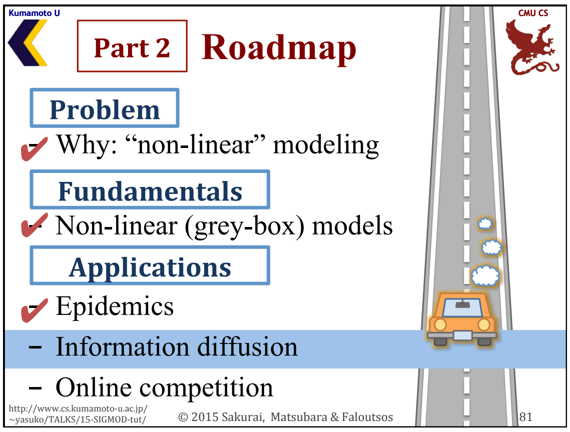
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Part 2 Roadmap
CMU CS
Problem
Why: "non-linear" modeling
Fundamentals
Non-linear (grey-box) models
Applications
Epidemics
– Information diffusion
– Online competition
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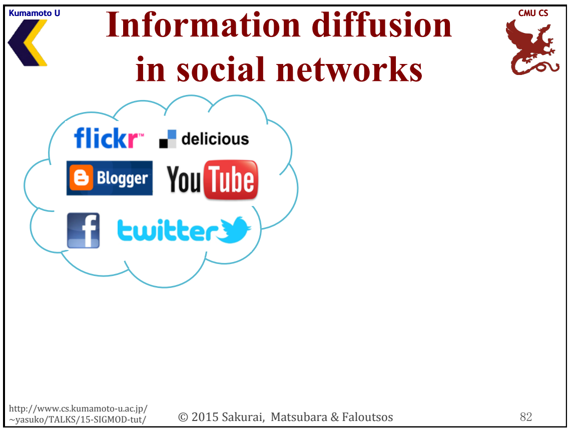
Kumamoto U
Information diffusion
in social networks
CMU CS
flickr
delicious
Blogger
YouTube
twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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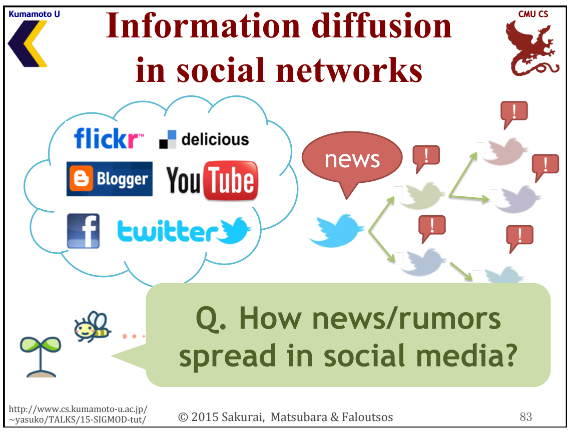
Kumamoto U
Information diffusion
in social networks
CMU CS
flickr
delicious
Blogger
YouTube
twitter
news
Q. How news/rumors
spread in social media?
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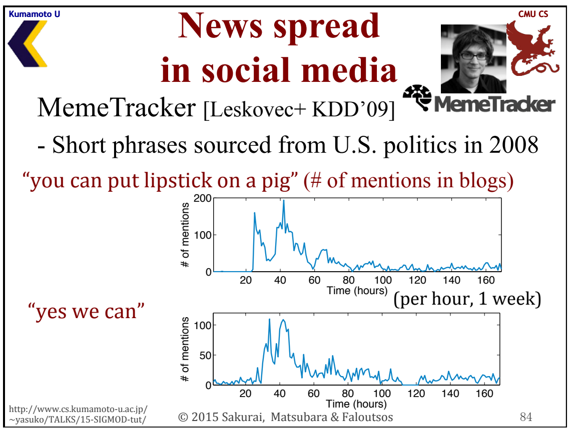
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News spread
in social media
CMU CS
MemeTracker [Leskovec+ KDD'09]
MemeTracker
- Short phrases sourced from U.S. politics in 2008
"you can put lipstick on a pig" (# of mentions in blogs)
# of mentions
200
100
0
20 40 60 80 100 120 140 160
Time (hours)
(per hour, 1 week)
"yes we can"
# of mentions
100
50
0
20 40 60 80 100 120 140 160
Time (hours)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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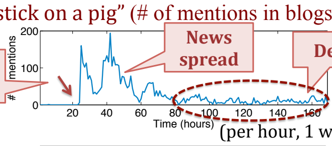
News spread in social media

MemeTracker [Leskovec+ KDD'09]

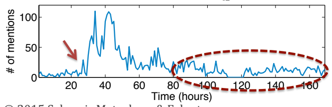
- Short phrases sourced from U.S. politics in 2008

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



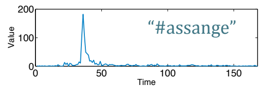
(per hour, 1 week)

"yes we can"

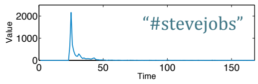


News spread in social media

- Twitter (# of hashtags per hour)



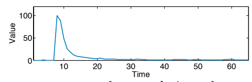
(per hour, 1week)



(per hour, 1 week)

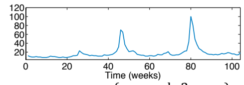
- Google trend (# of queries per week)

"tsunami" (in 2005)



(per week, 1 year)

"harry potter" (2010 - 2011)

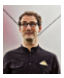


(per week, 2 years)

News spread in social media

Q. How many patterns are there?

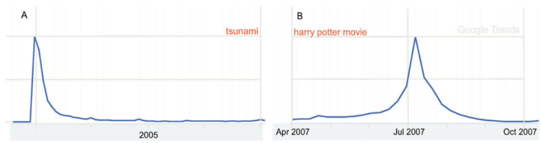
- Four classes on YouTube, etc. [Crane et al. PNAS'08]
- Six classes on Social media [Yang et al. WSDM'11]



News spread in social media

[Crane et al. PNAS'08]

- The volume of Google searches

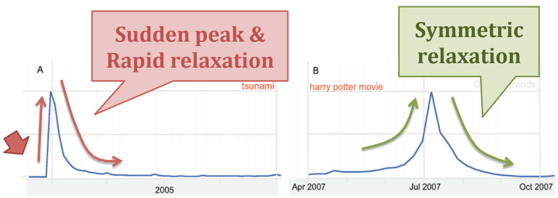


"Tsunami" "Harry potter movie"

News spread in social media

[Crane et al. PNAS'08]

- The volume of Google searches



"Tsunami" (Exogenous)

"Harry potter movie" (Endogenous)

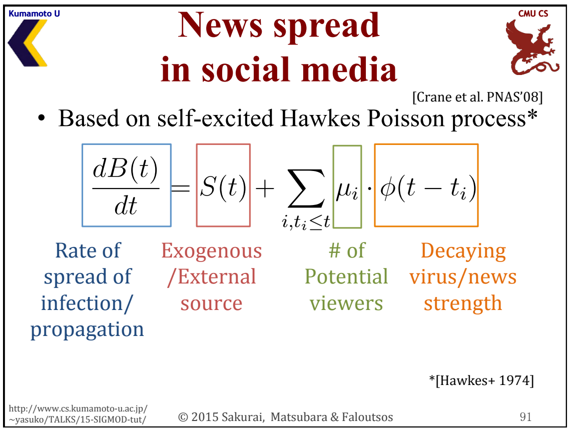
News spread in social media

[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]


Kumamoto U
CMU CS
News spread in social media
[Crane et al. PNAS'08]
• Based on self-excited Hawkes Poisson process*
$\frac{dB(t)}{dt} = S(t) + \sum_{i,t_i \le t} \mu_i \cdot \phi(t - t_i)$
Rate of spread of infection/ propagation
Exogenous /External source
# of Potential viewers
Decaying virus/news strength
*[Hawkes+ 1974]
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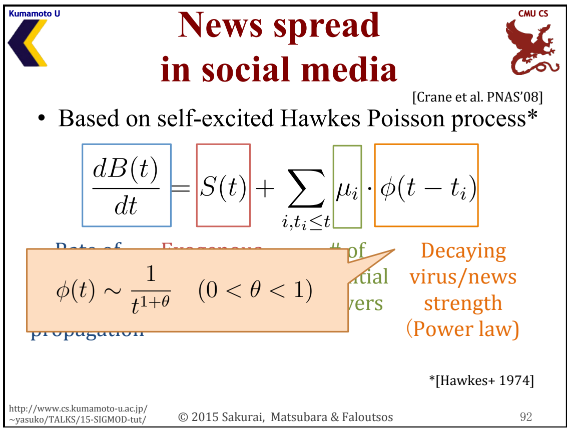
Kumamoto U
CMU CS
News spread in social media
[Crane et al. PNAS'08]
• Based on self-excited Hawkes Poisson process*
$\frac{dB(t)}{dt} = S(t) + \sum_{i,t_i \le t} \mu_i \cdot \phi(t - t_i)$
$\phi(t) \sim \frac{1}{t^{1+\theta}} \quad (0 < \theta < 1)$
Decaying virus/news strength (Power law)
*[Hawkes+ 1974]
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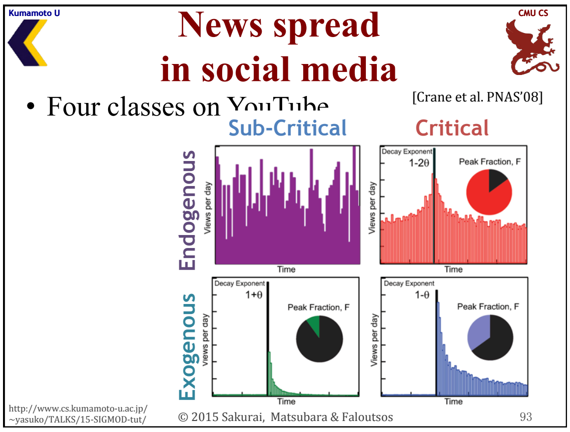
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CMU CS
News spread in social media
[Crane et al. PNAS'08]
• Four classes on YouTube
Sub-Critical
Critical
Endogenous
Exogenous
Decay Exponent 1-2θ
Decay Exponent 1+θ
Decay Exponent 1-θ
Peak Fraction, F
Views per day
Time
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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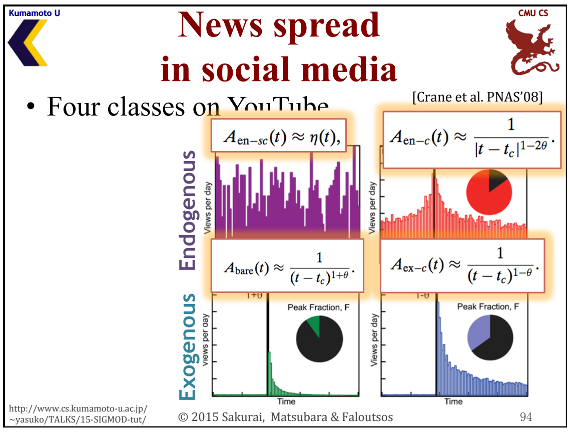
Kumamoto U
CMU CS
News spread in social media
[Crane et al. PNAS'08]
• Four classes on YouTube
$A_{en-sc}(t) \approx \eta(t),$
$A_{en-c}(t) \approx \frac{1}{|t-t_c|^{1-2\theta}}.$
$A_{bare}(t) \approx \frac{1}{(t-t_c)^{1+\theta}}.$
$A_{ex-c}(t) \approx \frac{1}{(t-t_c)^{1-\theta}}.$
Endogenous
Exogenous
Peak Fraction, F
Views per day
Time
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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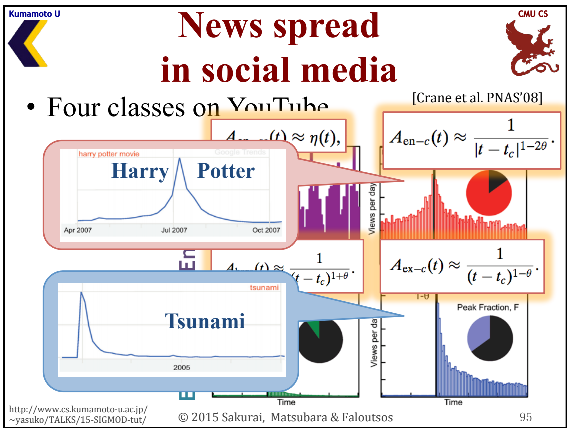
Kumamoto U
CMU CS
News spread in social media
[Crane et al. PNAS'08]
• Four classes on YouTube
$A_{en-c}(t) \approx \frac{1}{|t-t_c|^{1-2\theta}}.$
$A_{ex-c}(t) \approx \frac{1}{(t-t_c)^{1-\theta}}.$
Harry Potter
Apr 2007
Jul 2007
Oct 2007
Tsunami
2005
Peak Fraction, F
Time
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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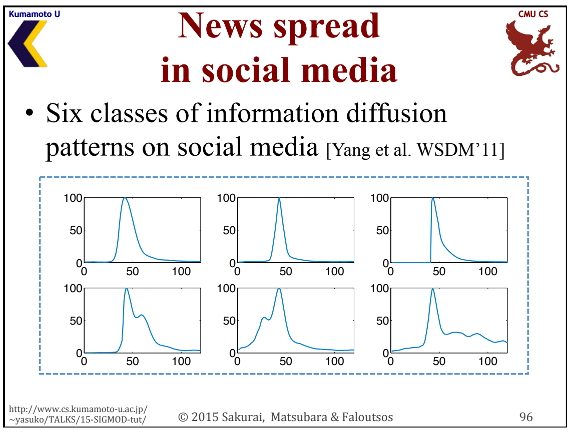
Kumamoto U
CMU CS
News spread in social media
• Six classes of information diffusion patterns on social media [Yang et al. WSDM'11]
100
50
0
50
100
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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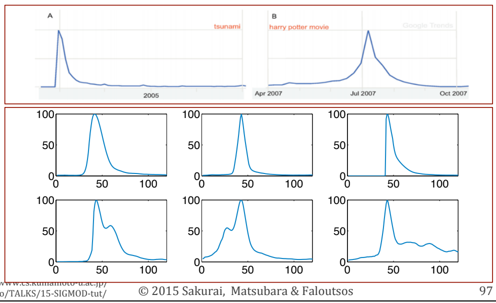
News spread in social media

Q. How many patterns are there, after all?



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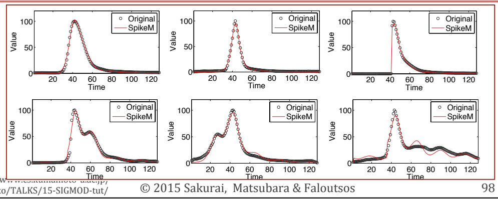
News spread in social media

A. Our answer is “ONE”!

A single non-linear model !

“SpikeM”



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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)

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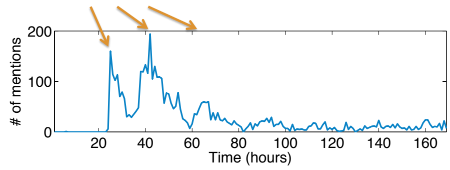
Rise and fall patterns in social media

SpikeM captures 3 properties of real spike

1. periodicities



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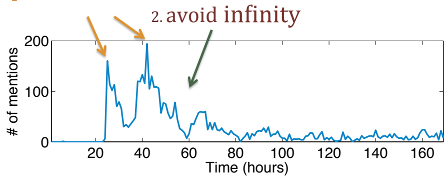
Rise and fall patterns in social media

SpikeM captures 3 properties of real spike

1. periodicities
2. avoid infinity



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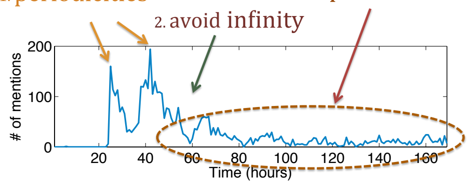
Rise and fall patterns in social media

SpikeM captures 3 properties of real spike

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



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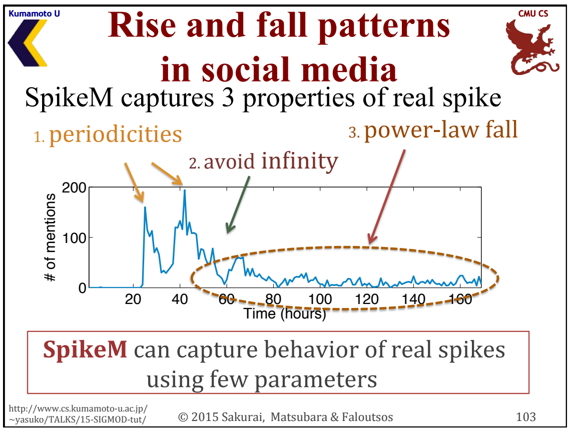
Kumamoto U
CMU CS
Rise and fall patterns in social media
SpikeM captures 3 properties of real spike
1. periodicities
2. avoid infinity
3. power-law fall
# of mentions
200
100
0
20 40 60 80 100 120 140 160
Time (hours)
SpikeM can capture behavior of real spikes using few parameters
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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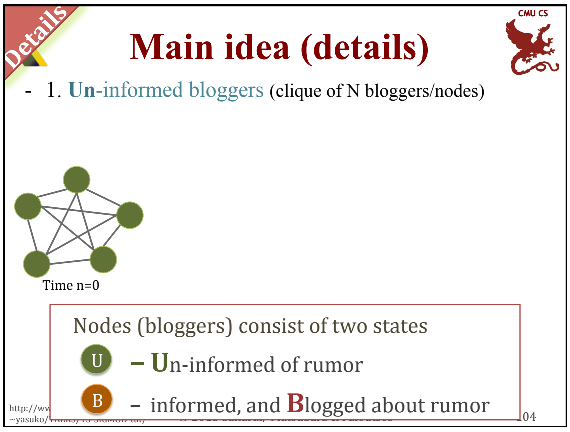
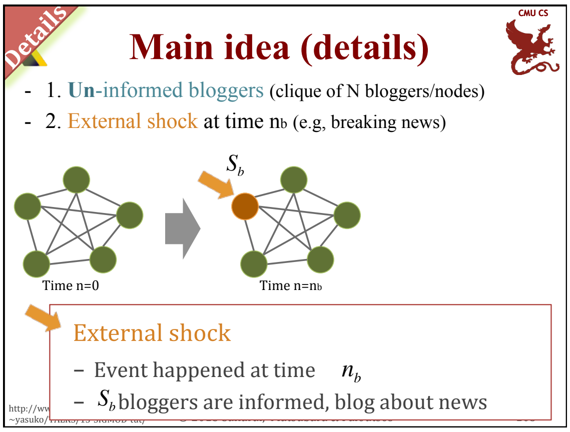
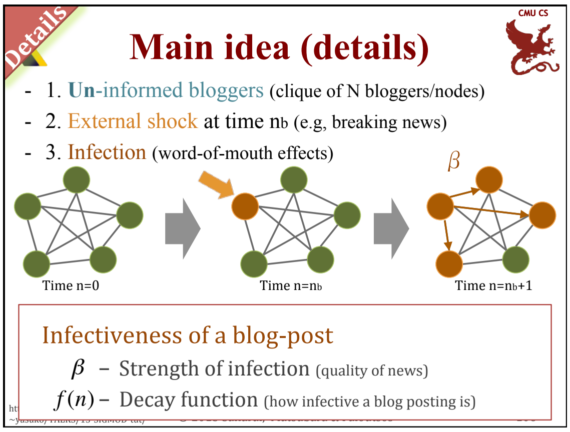
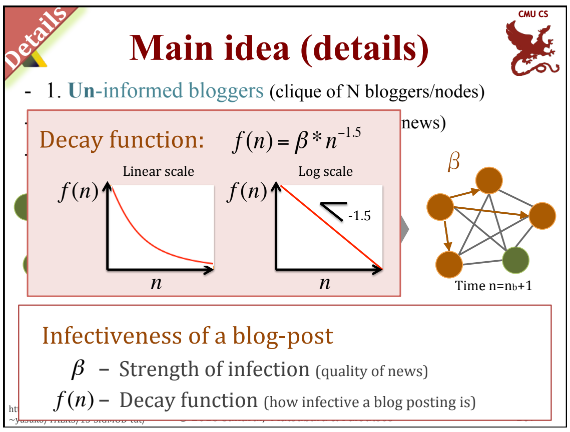
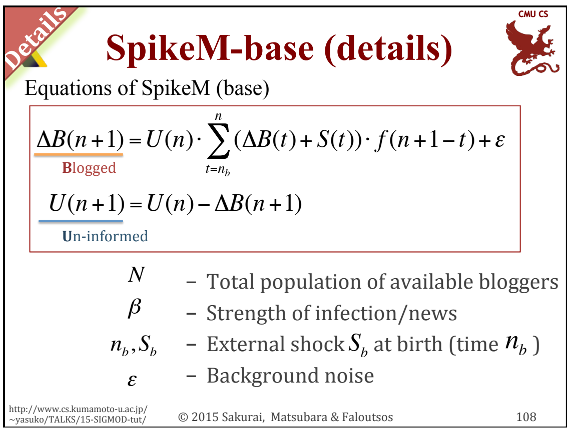

Details
CMU CS
Main idea (details)
- 1. Un-informed bloggers (clique of N bloggers/nodes)
Time n=0
Nodes (bloggers) consist of two states
U – Un-informed of rumor
B – informed, and Blogged about rumor
104


Details
CMU CS
Main idea (details)
- 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


Details
CMU CS
Main idea (details)
- 1. Un-informed bloggers (clique of N bloggers/nodes)
- 2. External shock at time nb (e.g, breaking news)
- 3. Infection (word-of-mouth effects)
β
Time n=0
Time n=nb
Time n=nb+1
Infectiveness of a blog-post
β – Strength of infection (quality of news)
$f(n)$ – Decay function (how infective a blog posting is)


Details
CMU CS
Main idea (details)
- 1. Un-informed bloggers (clique of N bloggers/nodes)
news)
Decay function: $f(n) = \beta * n^{-1.5}$
Linear scale
Log scale
$f(n)$
n
-1.5
β
Time n=nb+1
Infectiveness of a blog-post
β – Strength of infection (quality of news)
$f(n)$ – Decay function (how infective a blog posting is)


Details
CMU CS
SpikeM-base (details)
Equations of SpikeM (base)
$\Delta B(n+1) = U(n) \cdot \sum_{t=n_b}^{n} (\Delta B(t) + S(t)) \cdot f(n+1-t) + \varepsilon$
Blogged
$U(n+1) = U(n) - \Delta B(n+1)$
Un-informed
N – Total population of available bloggers
β – Strength of infection/news
n_b, S_b – External shock S_b at birth (time n_b)
ε – Background noise
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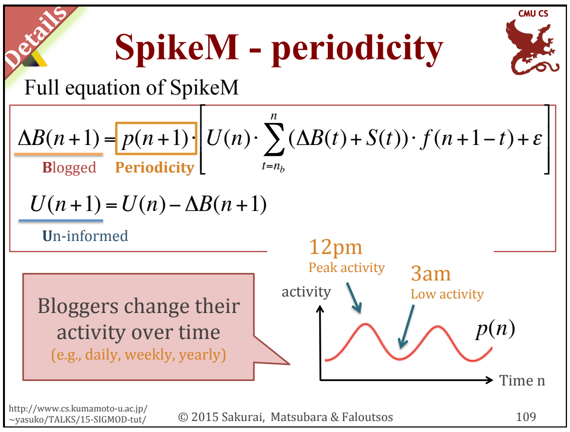
Details
SpikeM - periodicity
Full equation of SpikeM
$\Delta B(n+1) = p(n+1) \cdot \left[U(n) \cdot \sum_{t=n_b}^{n} (\Delta B(t) + S(t)) \cdot f(n+1-t) + \varepsilon \right]$
Blogged
Periodicity
$U(n+1) = U(n) - \Delta B(n+1)$
Un-informed
12pm
Peak activity
3am
Low activity
activity
$p(n)$
Time n
Bloggers change their activity over time
(e.g., daily, weekly, yearly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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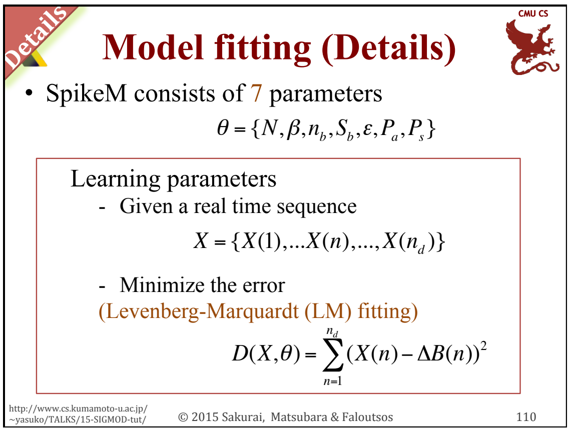
Details
Model fitting (Details)
• SpikeM consists of 7 parameters
$\theta = \{N, \beta, n_b, S_b, \varepsilon, P_a, P_s\}$
Learning parameters
- Given a real time sequence
$X = \{X(1), \ldots X(n), \ldots, X(n_d)\}$
- Minimize the error
(Levenberg-Marquardt (LM) fitting)
$D(X,\theta) = \sum_{n=1}^{n_d} (X(n) - \Delta B(n))^2$
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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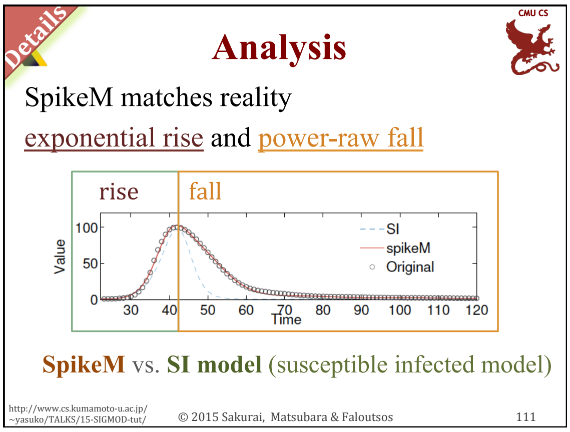
Details
Analysis
SpikeM matches reality
exponential rise and power-raw fall
rise
fall
SI
spikeM
Original
Value
Time
SpikeM vs. SI model (susceptible infected model)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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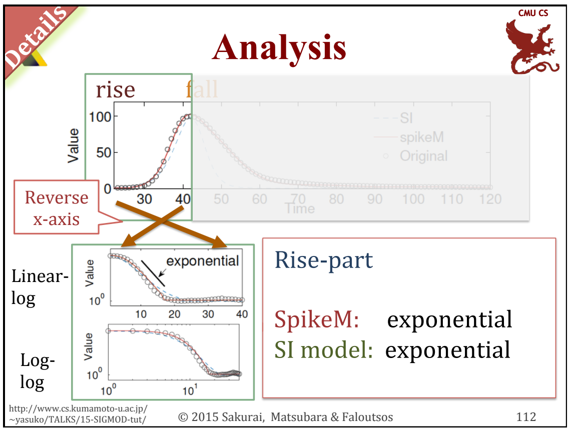
Details
Analysis
rise
fall
Value
Time
Reverse x-axis
Linear-log
Log-log
exponential
Rise-part
SpikeM: exponential
SI model: exponential
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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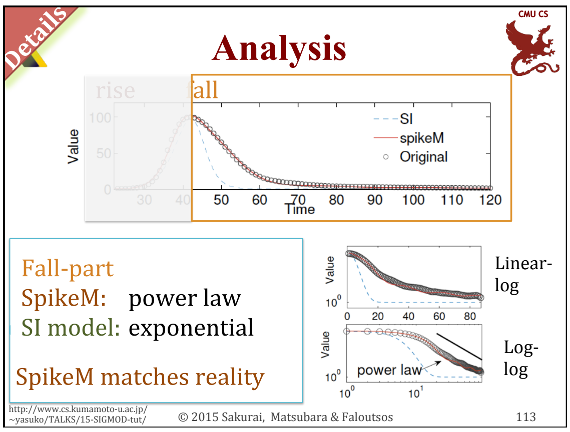
Details
Analysis
rise
fall
SI
spikeM
Original
Value
Time
Fall-part
SpikeM: power law
SI model: exponential
SpikeM matches reality
Linear-log
Log-log
power law
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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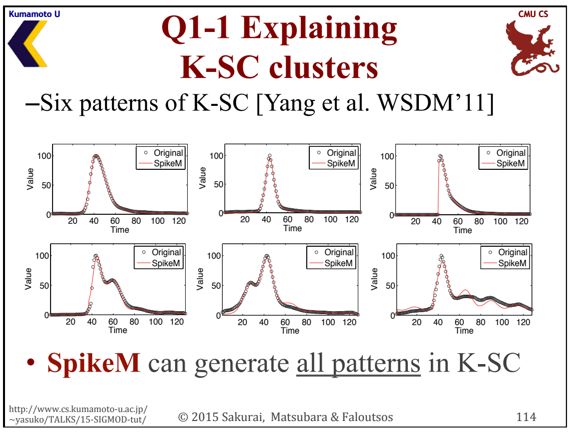
Kumamoto U
Q1-1 Explaining K-SC clusters
–Six patterns of K-SC [Yang et al. WSDM'11]
Original
SpikeM
Value
Time
• SpikeM can generate all patterns in K-SC
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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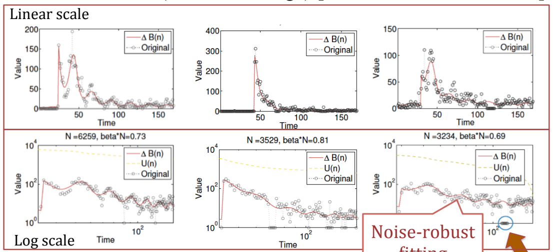
Q1-2 Matching MemeTracker patterns

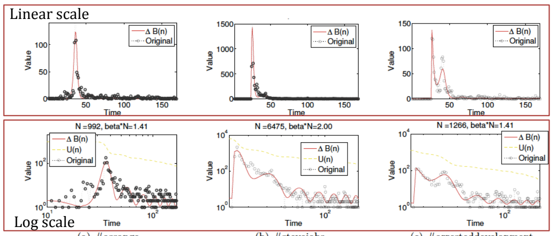
MemeTracker (memes in blogs) [Leskovec et al. KDD'09]



SpikeM can fit various patterns in blog

Q1-3 Matching Twitter data

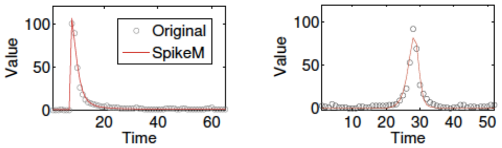
Twitter data (hashtags)



It can generate various patterns in social media

Q1-4 Matching Google trend data

Volume of searches for queries on Google

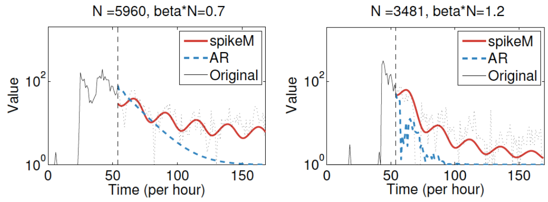


(a) "tsunami" (2005) (b) "Harry Potter" (2007)

SpikeM can capture various patterns

Q2 Tail-part forecasts

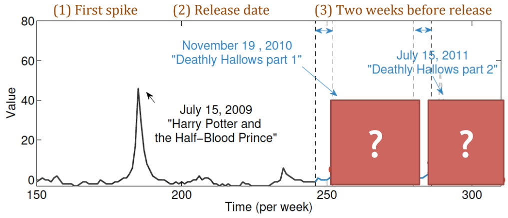
- Given a first part of the spike
  - forecast the tail part



SpikeM can capture tail part (AR: fail)

A1. "What-if" forecasting

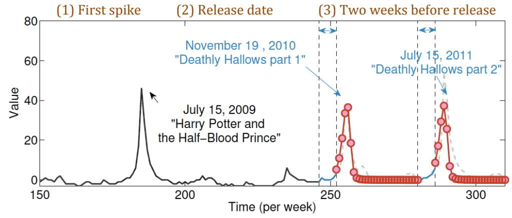
Forecast not only tail-part, but also **rise-part**!



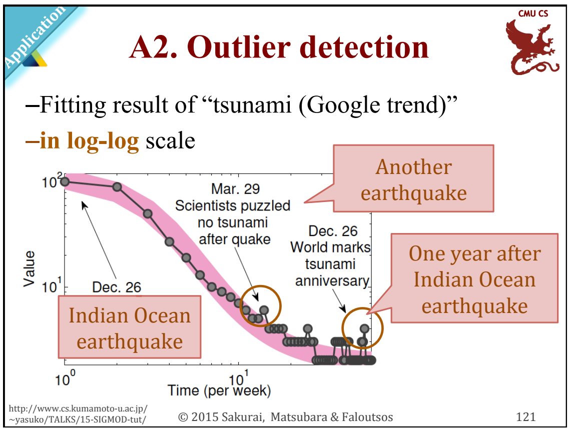
e.g., given (1) first spike,
(2) release date of two sequel movies
(3) access volume before the release date

A1. "What-if" forecasting

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



SpikeM can forecast upcoming spikes!



Application
A2. Outlier detection
–Fitting result of "tsunami (Google trend)"
–in log-log scale
Another earthquake
Mar. 29 Scientists puzzled no tsunami after quake
Dec. 26 World marks tsunami anniversary
One year after Indian Ocean earthquake
Dec. 26
Indian Ocean earthquake
Value
Time (per week)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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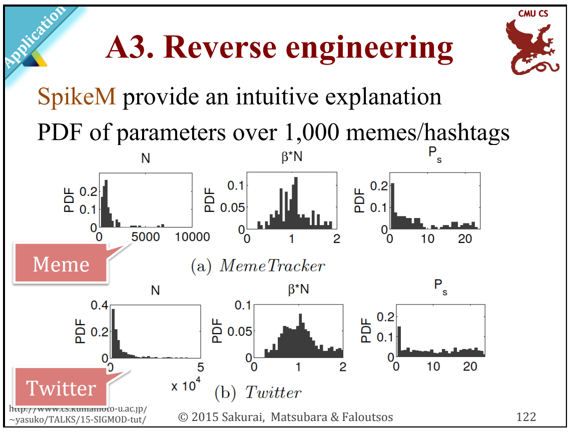

Application
A3. Reverse engineering
SpikeM provide an intuitive explanation
PDF of parameters over 1,000 memes/hashtags
N
β*N
Ps
Meme
(a) MemeTracker
Twitter
(b) Twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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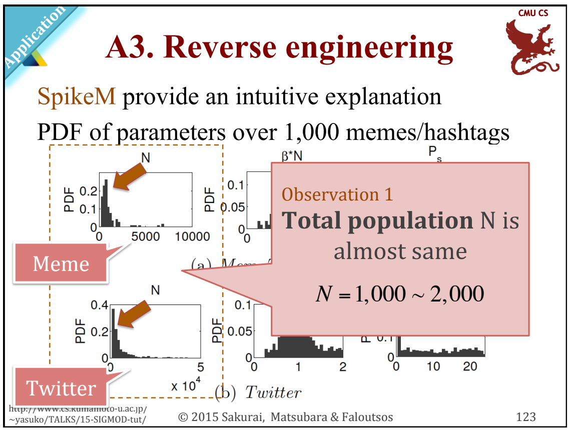

Application
A3. Reverse engineering
SpikeM provide an intuitive explanation
PDF of parameters over 1,000 memes/hashtags
Observation 1
Total population N is almost same
N = 1,000 ~ 2,000
Meme
Twitter
(b) Twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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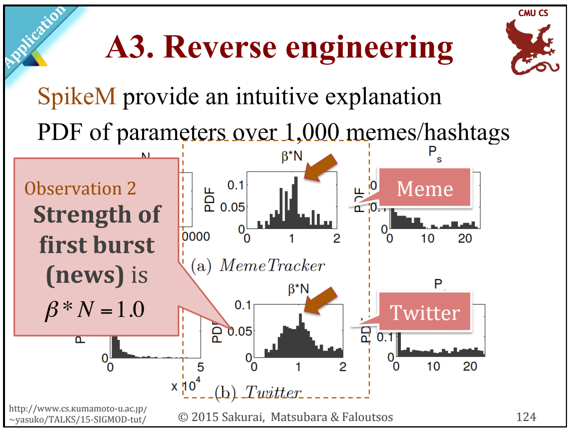

Application
A3. Reverse engineering
SpikeM provide an intuitive explanation
PDF of parameters over 1,000 memes/hashtags
Observation 2
Strength of first burst (news) is
β * N = 1.0
Meme
Twitter
(a) MemeTracker
(b) Twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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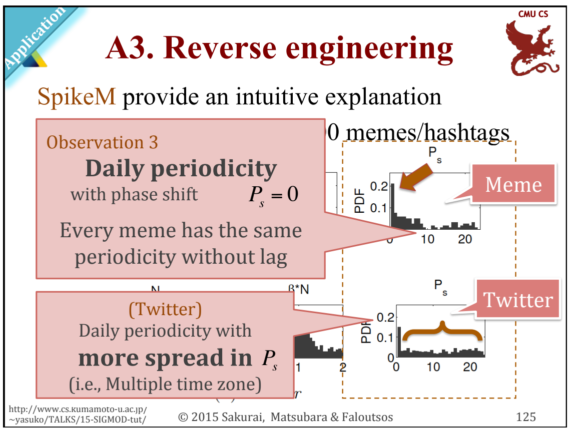

Application
A3. Reverse engineering
SpikeM provide an intuitive explanation
Observation 3
Daily periodicity
with phase shift Ps = 0
Every meme has the same periodicity without lag
Meme
(Twitter)
Daily periodicity with more spread in Ps
(i.e., Multiple time zone)
Twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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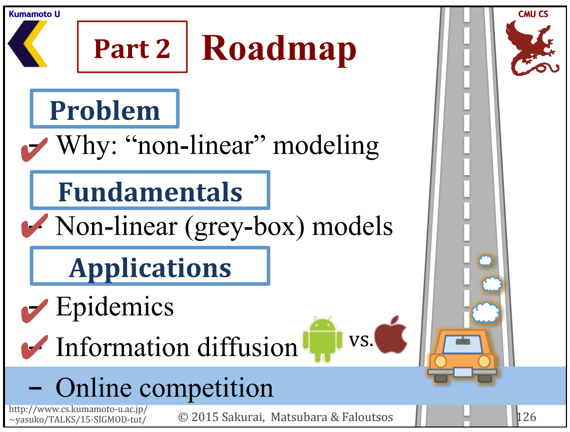

Kumamoto U
Part 2
Roadmap
Problem
Why: "non-linear" modeling
Fundamentals
Non-linear (grey-box) models
Applications
Epidemics
Information diffusion vs.
– Online competition
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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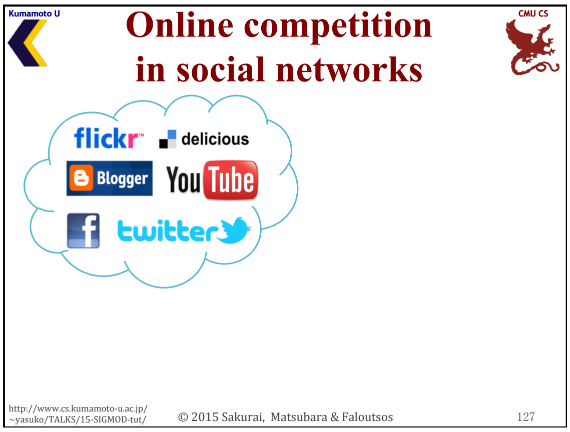
Kumamoto U
CMU CS
Online competition in social networks
flickr
delicious
Blogger
YouTube
twitter
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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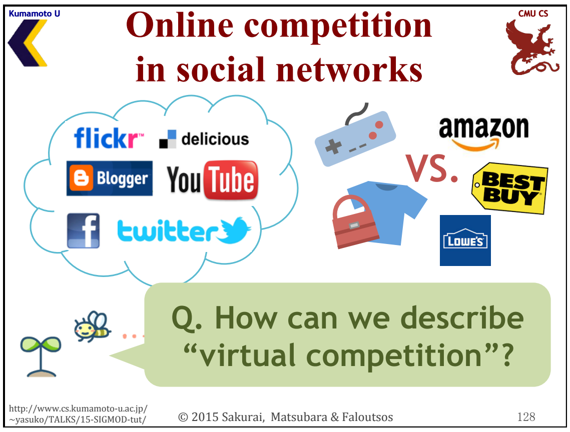
Kumamoto U
CMU CS
Online competition in social networks
flickr
delicious
Blogger
YouTube
twitter
amazon
VS.
BEST BUY
LOWE'S
Q. How can we describe "virtual competition"?
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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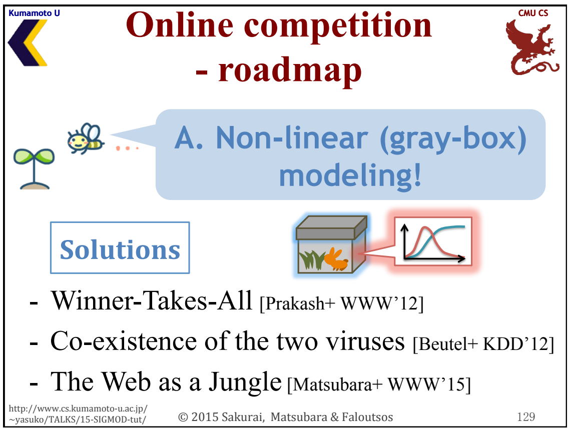
Kumamoto U
CMU CS
Online competition - roadmap
A. Non-linear (gray-box) modeling!
Solutions
- Winner-Takes-All [Prakash+ WWW'12]
- Co-existence of the two viruses [Beutel+ KDD'12]
- The Web as a Jungle [Matsubara+ WWW'15]
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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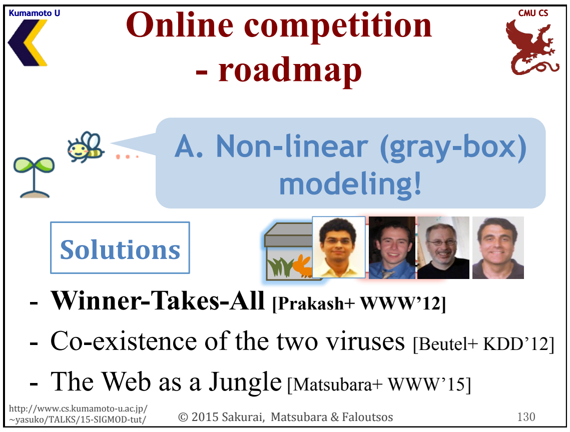
Kumamoto U
CMU CS
Online competition - roadmap
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http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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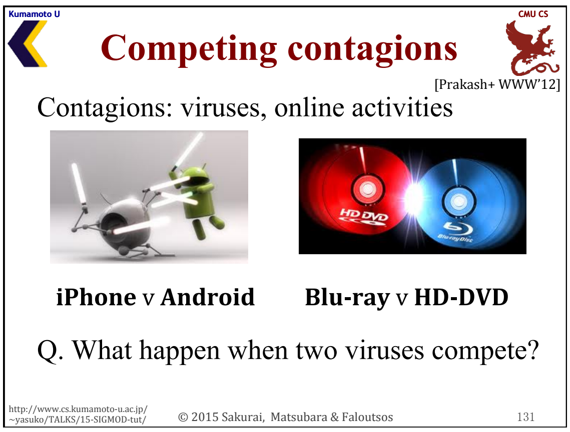
Kumamoto U
CMU CS
Competing contagions
[Prakash+ WWW'12]
Contagions: viruses, online activities
HD DVD
iPhone v Android
Blu-ray v HD-DVD
Q. What happen when two viruses compete?
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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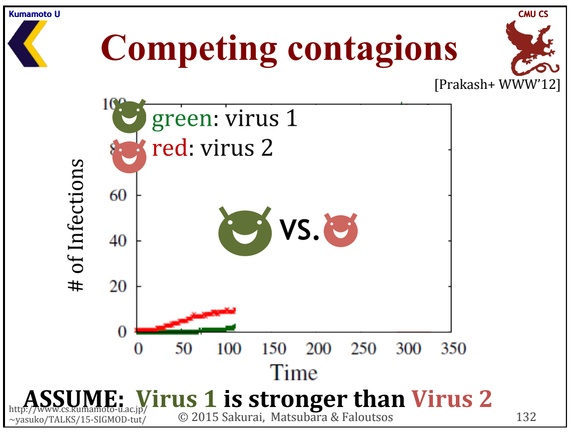
Kumamoto U
CMU CS
Competing contagions
[Prakash+ WWW'12]
green: virus 1
red: virus 2
VS.
# of Infections
0
20
40
60
0
50
100
150
200
250
300
350
Time
ASSUME: Virus 1 is stronger than Virus 2
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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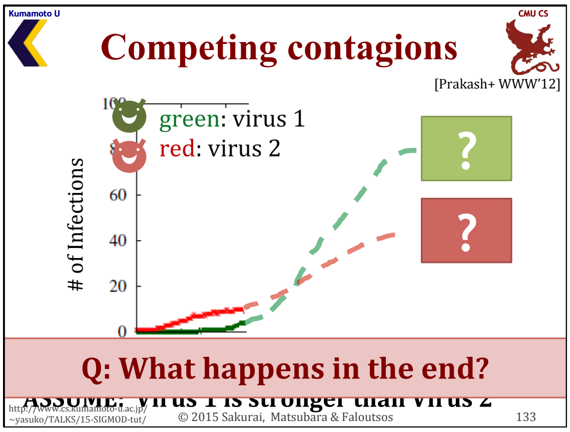
Competing contagions
[Prakash+ WWW'12]
green: virus 1
red: virus 2
# of Infections
?
?
Q: What happens in the end?
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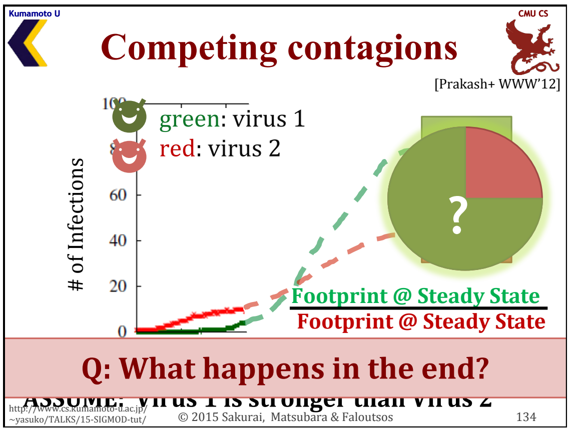
Competing contagions
[Prakash+ WWW'12]
green: virus 1
red: virus 2
# of Infections
?
Footprint @ Steady State
Footprint @ Steady State
Q: What happens in the end?
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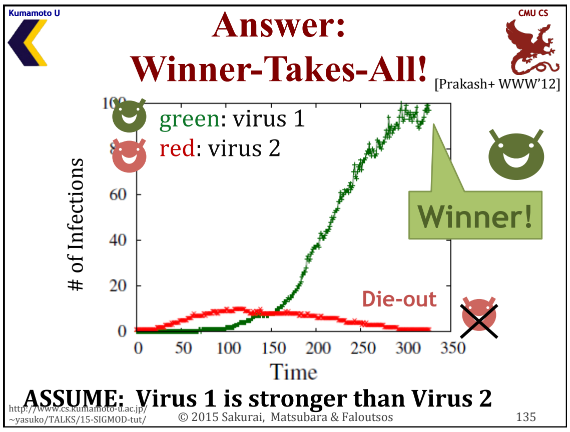
Answer:
Winner-Takes-All!
[Prakash+ WWW'12]
green: virus 1
red: virus 2
# of Infections
Winner!
Die-out
Time
ASSUME: Virus 1 is stronger than Virus 2
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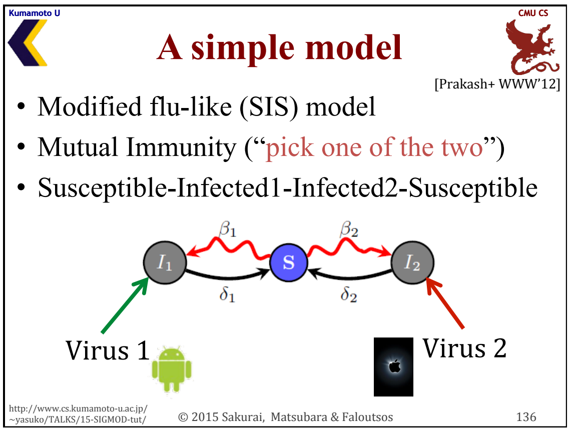
A simple model
[Prakash+ WWW'12]
• Modified flu-like (SIS) model
• Mutual Immunity ("pick one of the two")
• Susceptible-Infected1-Infected2-Susceptible
Virus 1
Virus 2
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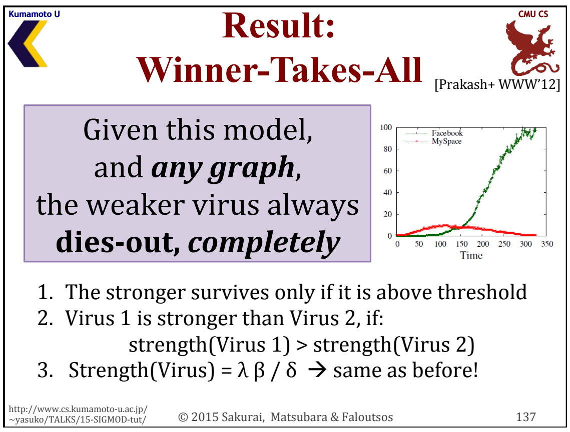
Result:
Winner-Takes-All
[Prakash+ WWW'12]
Given this model, and any graph, the weaker virus always dies-out, completely
1. The stronger survives only if it is above threshold
2. Virus 1 is stronger than Virus 2, if: strength(Virus 1) > strength(Virus 2)
3. Strength(Virus) = λ β / δ → same as before!
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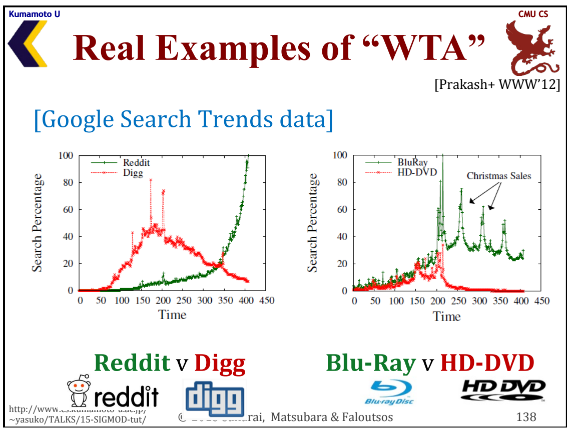
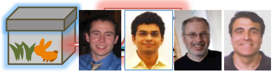

Real Examples of "WTA"
[Prakash+ WWW'12]
[Google Search Trends data]
Search Percentage
Time
Christmas Sales
Reddit v Digg
Blu-Ray v HD-DVD
138

Online competition in social networks

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

Solutions

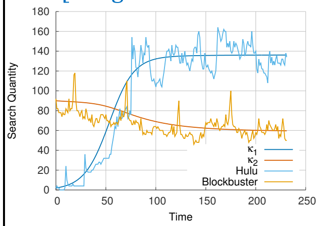


- Winner-Takes-All [Prakash+ WWW'12]
- **Co-existence of the two viruses [Beutel+ KDD'12]**
- The Web as a Jungle [Matsubara+ WWW'15]

Interacting Viruses: Can Both Survive?

Real example of "co-existence"

[Google Search Trends data]

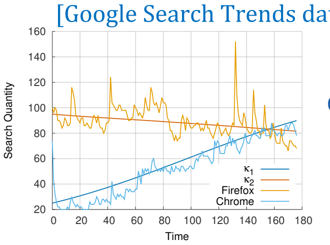


Hulu v Blockbuster

Interacting Viruses: Can Both Survive?

Real example of "co-existence"

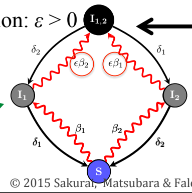
[Google Search Trends data]



Chrome v Firefox

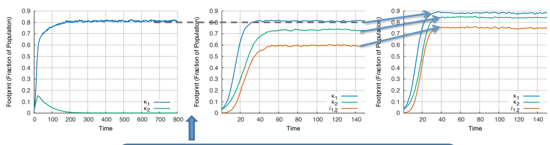
A simple model: $SI_{1|2}S$

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



Question: What happens in the end?

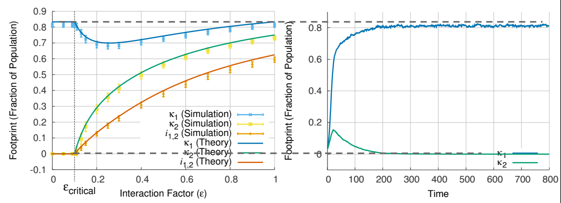
ε = 0	ε = 1	ε = 2
Winner takes all	Co-exist independently	Viruses cooperate



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

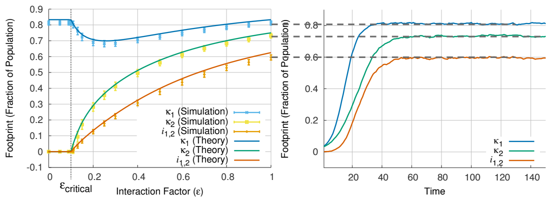
ASSUME: Virus 1 is stronger than Virus 2

Answer: Yes! There is a phase transition



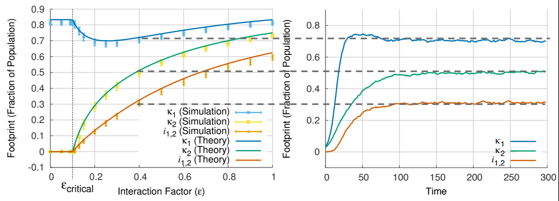
ASSUME: Virus 1 is stronger than Virus 2

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

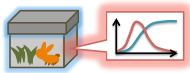
Given this model and a fully connected graph, there exists an $\varepsilon_{critical}$ such that for $\varepsilon \geq \varepsilon_{critical}$, there is a fixed point where both viruses survive.

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) $\sigma = N\beta / \delta$

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]**

[Matsubara+ WWW'15]

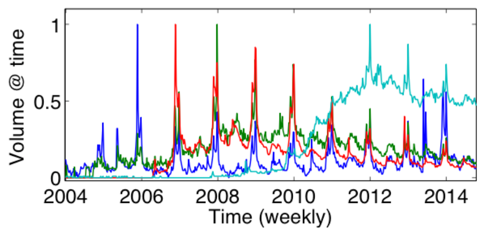
The Web as a Jungle: Non-Linear Dynamical Systems for Co-evolving Online Activities

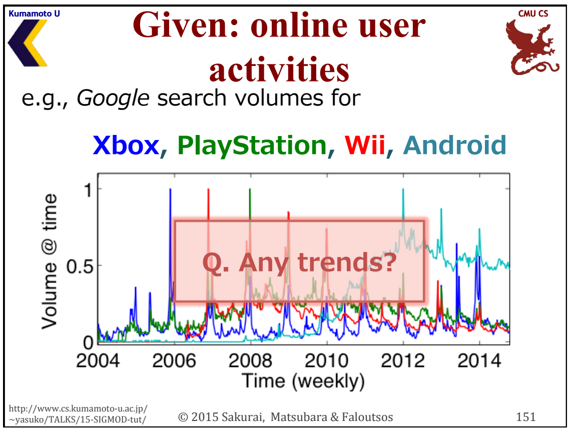
Yasuko Matsubara (Kumamoto University)
Yasushi Sakurai (Kumamoto University)
Christos Faloutsos (CMU)

Given: online user activities

e.g., *Google* search volumes for

Xbox, PlayStation, Wii, Android




Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
Xbox, PlayStation, Wii, Android
Q. Any trends?
Volume @ time
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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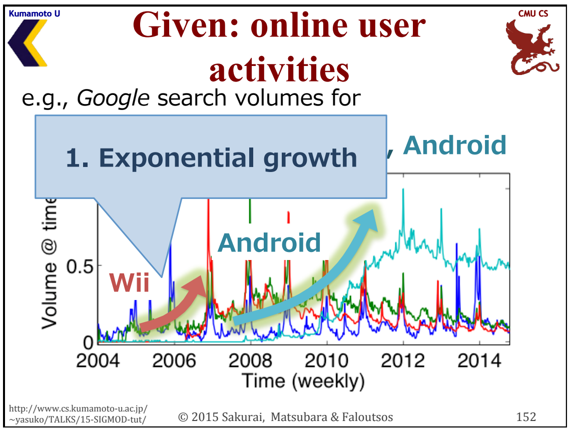
151


Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
1. Exponential growth
, Android
Android
Wii
Volume @ time
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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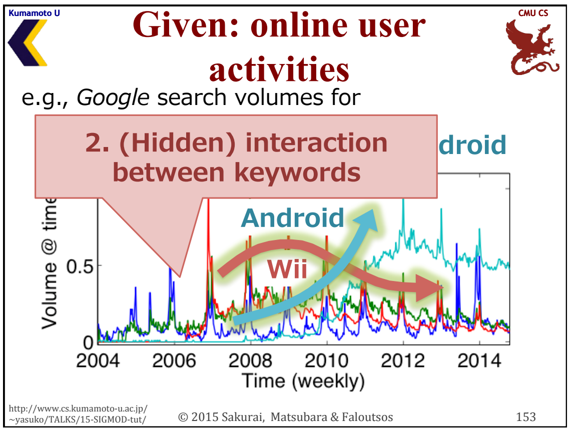
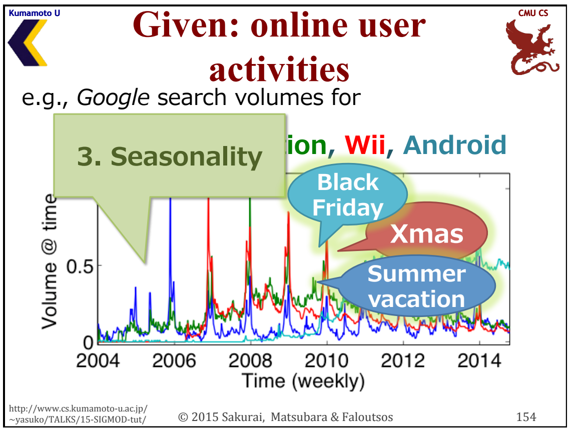
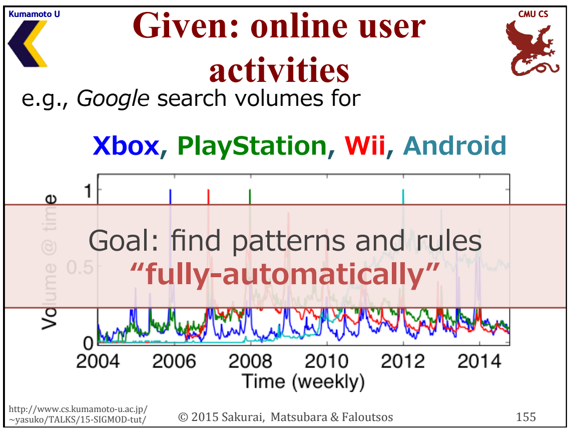
152


Kumamoto U
CMU CS
Given: online user activities
e.g., Google search volumes for
2. (Hidden) interaction between keywords
droid
Android
Wii
Volume @ time
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
153


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
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
154


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"
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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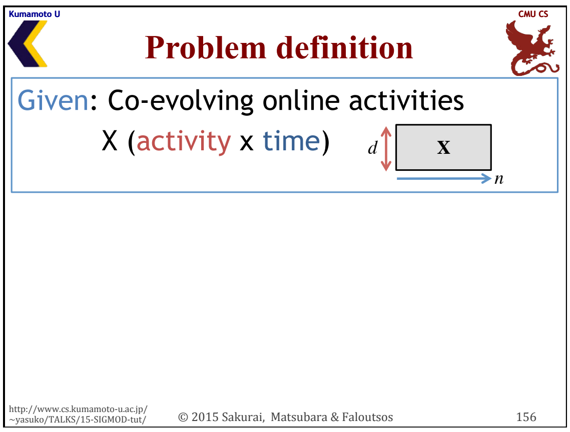
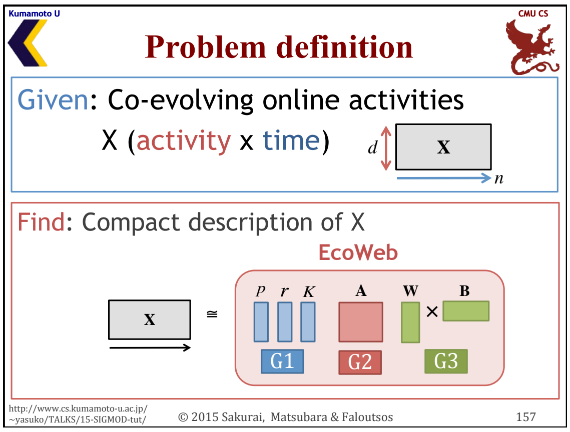
155


Kumamoto U
CMU CS
Problem definition
Given: Co-evolving online activities
X (activity x time)
d
X
n
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
156


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/15-SIGMOD-tut/
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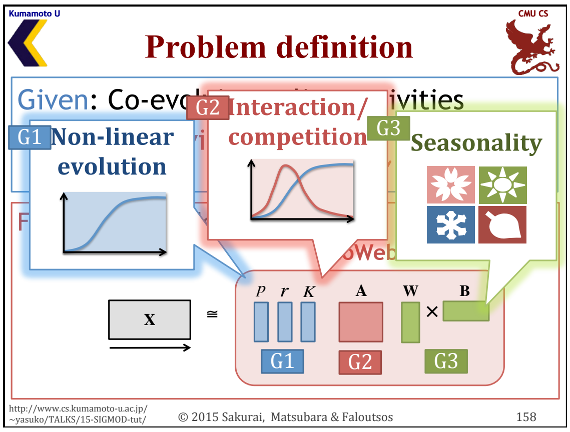
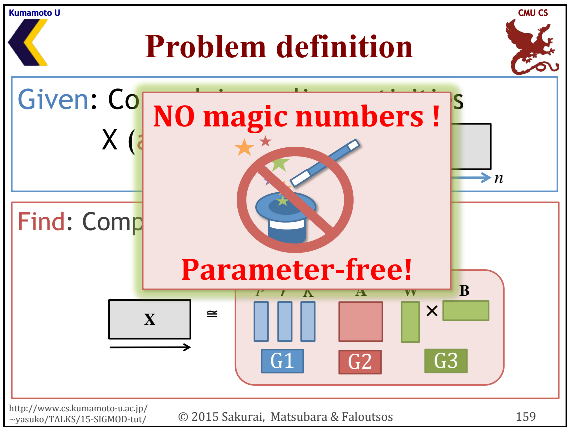
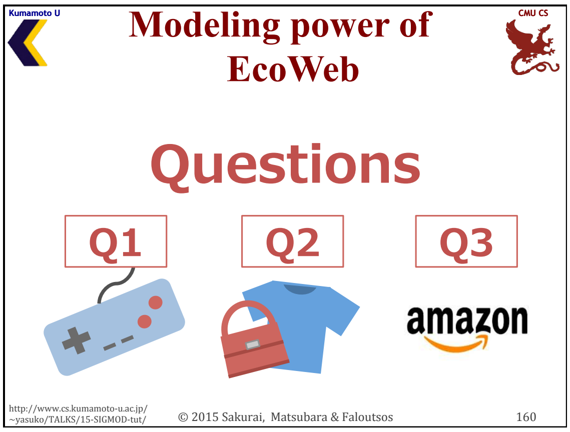
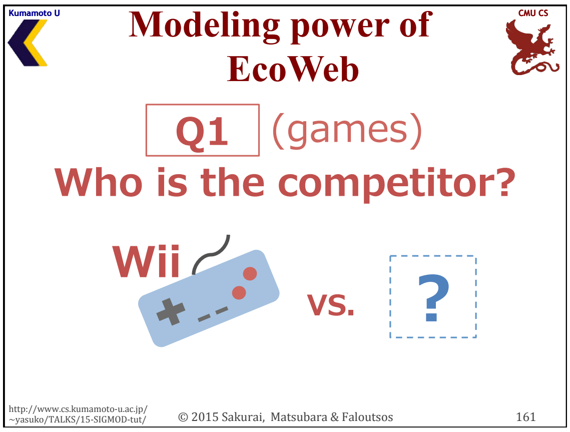
157


Kumamoto U
CMU CS
Problem definition
Given: Co-evo
ivities
G1 Non-linear evolution
G2 Interaction/ competition
G3 Seasonality
Web
X
≅
p r K
A
W
B
×
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
158


Kumamoto U
CMU CS
Problem definition
Given: Co
X (a
n
Find: Comp
NO magic numbers !
Parameter-free!
X
≅
B
×
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
159


Kumamoto U
CMU CS
Modeling power of EcoWeb
Questions
Q1
Q2
Q3
amazon
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
160


Kumamoto U
CMU CS
Modeling power of EcoWeb
Q1 (games)
Who is the competitor?
Wii
vs.
?
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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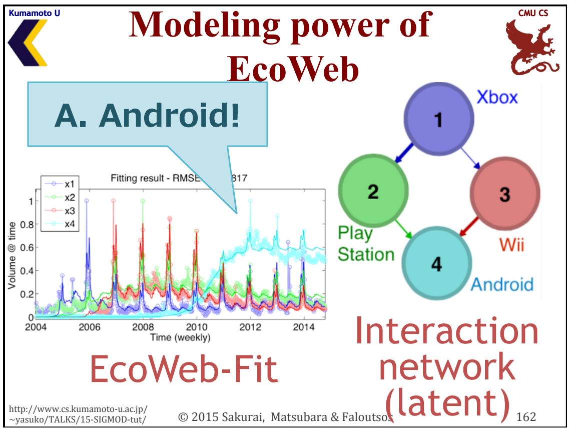
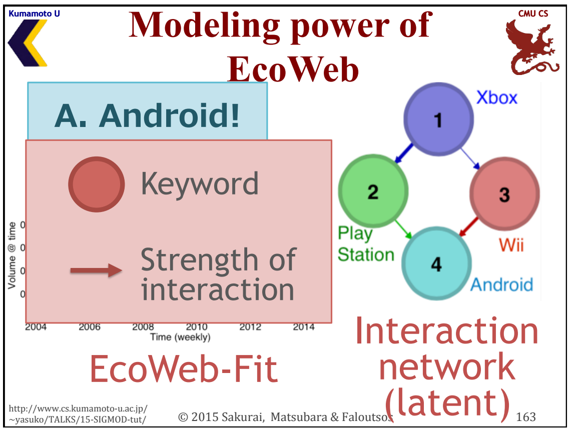
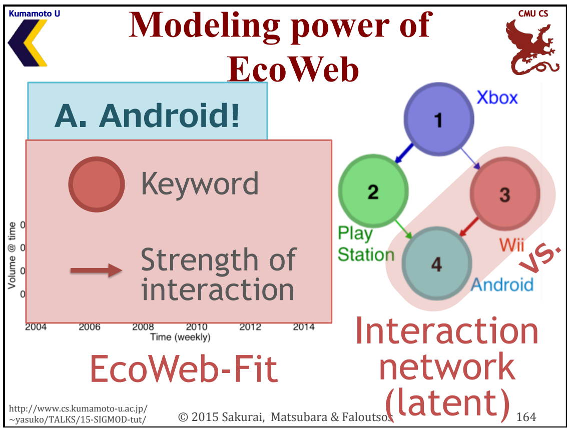
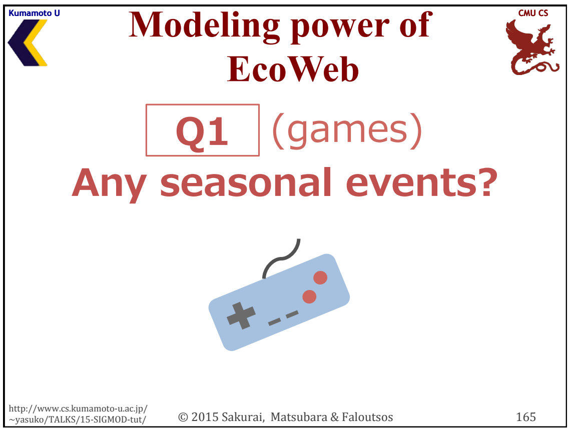
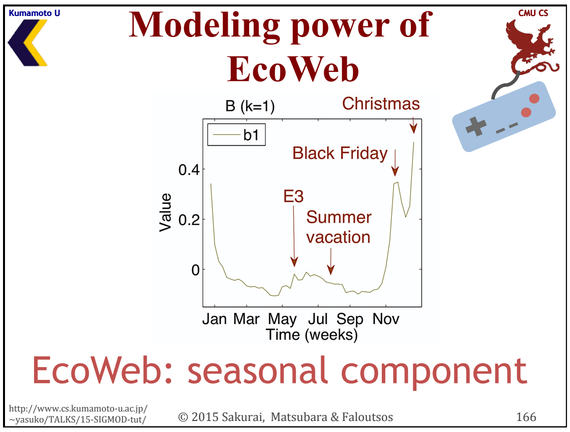
161

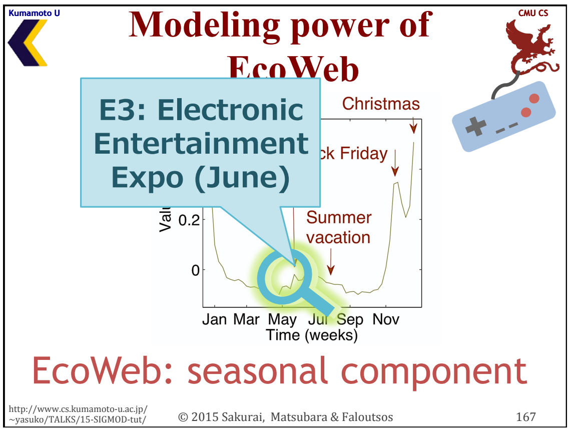

Kumamoto U
CMU CS
Modeling power of EcoWeb
A. Android!
Fitting result - RMSE
x1
x2
x3
x4
Volume @ time
Time (weekly)
EcoWeb-Fit
1 Xbox
2 Play Station
3 Wii
4 Android
Interaction network (latent)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
162

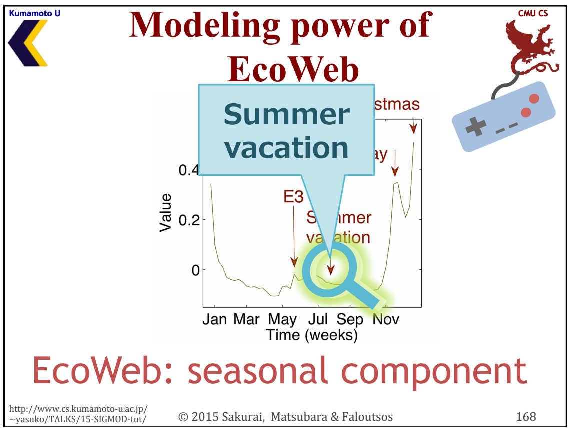

Kumamoto U
Modeling power of EcoWeb
CMU CS
A. Android!
Keyword
Strength of interaction
Xbox
Play Station
Wii
Android
EcoWeb-Fit
Interaction network (latent)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
163

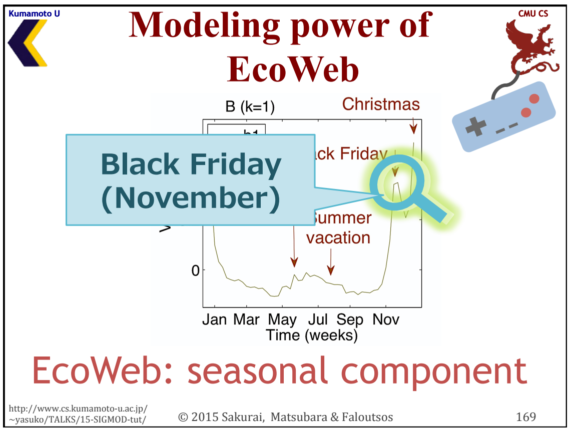

Kumamoto U
Modeling power of EcoWeb
CMU CS
A. Android!
Keyword
Strength of interaction
Xbox
Play Station
Wii
Android
VS.
EcoWeb-Fit
Interaction network (latent)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
164

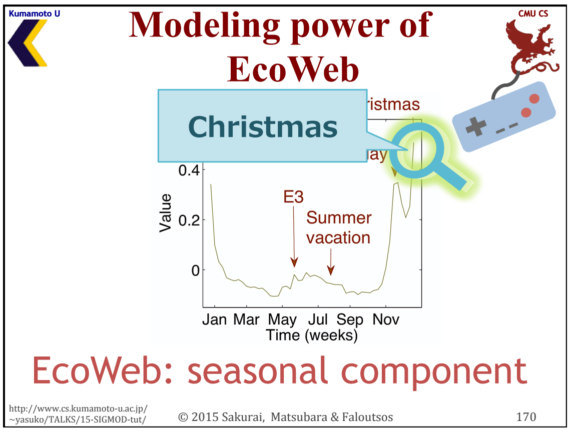

Kumamoto U
Modeling power of EcoWeb
CMU CS
Q1 (games)
Any seasonal events?
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
165

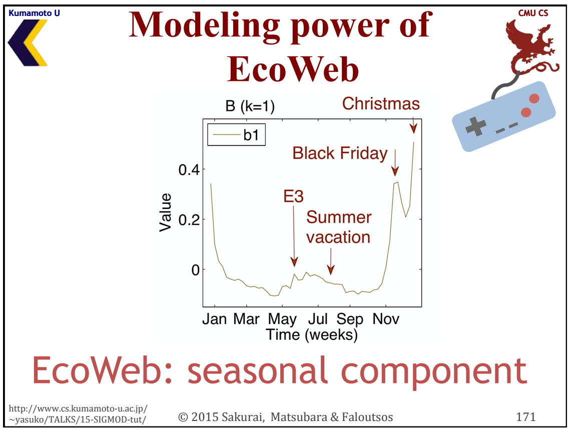

Kumamoto U
Modeling power of EcoWeb
CMU CS
B (k=1)
b1
Christmas
Black Friday
E3
Summer vacation
Value
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
166

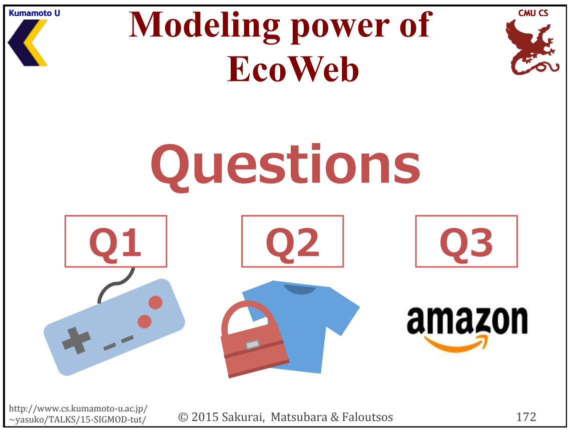

Kumamoto U
Modeling power of EcoWeb
CMU CS
E3: Electronic Entertainment Expo (June)
Christmas
Summer vacation
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
167

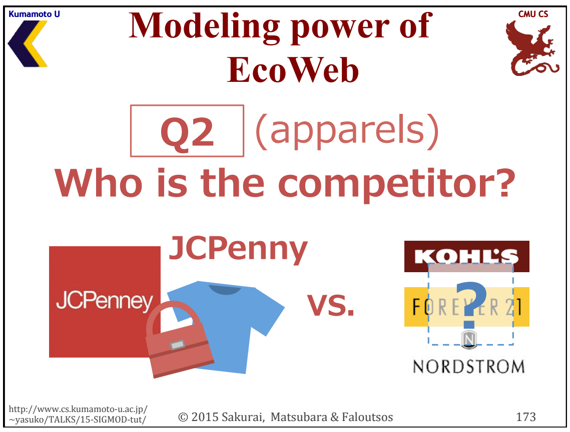

Kumamoto U
Modeling power of EcoWeb
CMU CS
Summer vacation
E3
Value
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
168

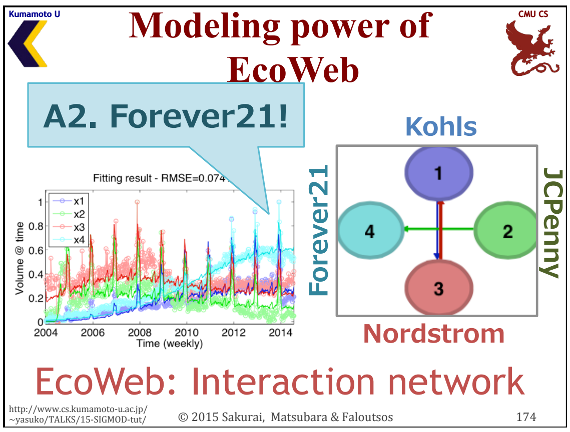

Modeling power of EcoWeb
Black Friday (November)
B (k=1)
Christmas
Summer vacation
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
© 2015 Sakurai, Matsubara & Faloutsos
169


Modeling power of EcoWeb
Christmas
E3
Summer vacation
Value
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
© 2015 Sakurai, Matsubara & Faloutsos
170


Modeling power of EcoWeb
B (k=1)
Christmas
b1
Black Friday
E3
Summer vacation
Value
Jan Mar May Jul Sep Nov
Time (weeks)
EcoWeb: seasonal component
© 2015 Sakurai, Matsubara & Faloutsos
171


Modeling power of EcoWeb
Questions
Q1
Q2
Q3
amazon
© 2015 Sakurai, Matsubara & Faloutsos
172


Modeling power of EcoWeb
Q2 (apparels)
Who is the competitor?
JCPenny
JCPenney
vs.
KOHL'S
NORDSTROM
© 2015 Sakurai, Matsubara & Faloutsos
173


Modeling power of EcoWeb
A2. Forever21!
Fitting result - RMSE=0.074
Volume @ time
Time (weekly)
Kohls
Forever21
JCPenny
Nordstrom
EcoWeb: Interaction network
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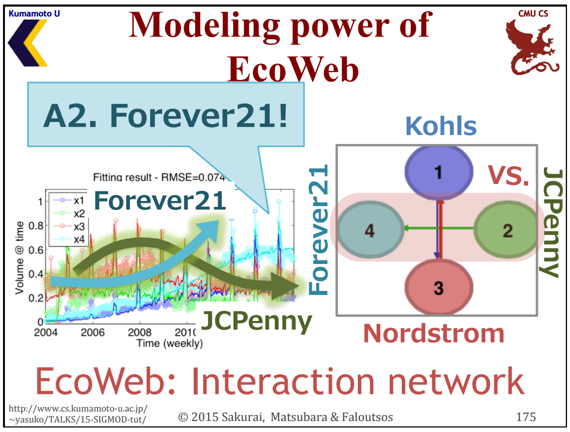
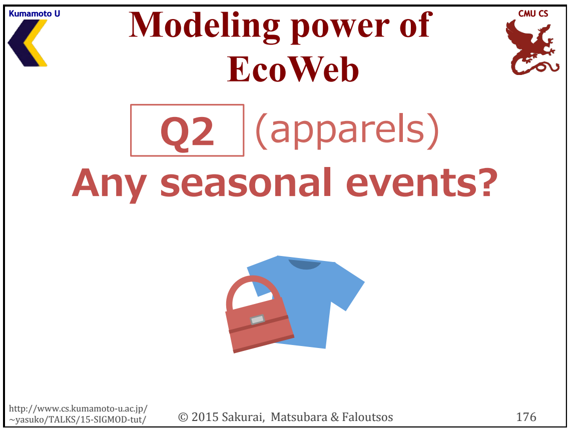
174


Kumamoto U
CMU CS
Modeling power of EcoWeb
A2. Forever21!
Fitting result - RMSE=0.074
Forever21
Kohls
vs.
Forever21
JCPenny
JCPenny
Nordstrom
Volume @ time
Time (weekly)
EcoWeb: Interaction network
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
175


Kumamoto U
CMU CS
Modeling power of EcoWeb
Q2 (apparels)
Any seasonal events?
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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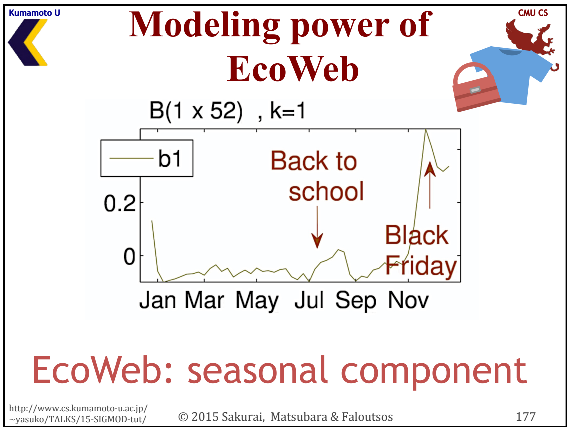
176


Kumamoto U
CMU CS
Modeling power of EcoWeb
B(1 x 52) , k=1
b1
Back to school
Black Friday
Jan Mar May Jul Sep Nov
EcoWeb: seasonal component
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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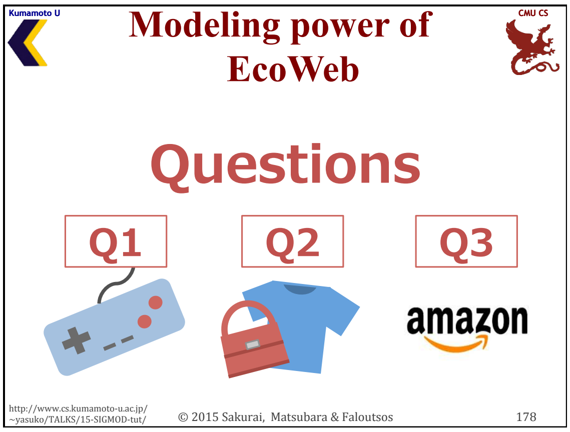
177


Kumamoto U
CMU CS
Modeling power of EcoWeb
Questions
Q1
Q2
Q3
amazon
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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178


Kumamoto U
CMU CS
Modeling power of EcoWeb
Q3 (retails)
Any patterns/trends?
amazon
LOWE'S
COSTCO WHOLESALE
BEST BUY
Walmart
THE HOME DEPOT
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
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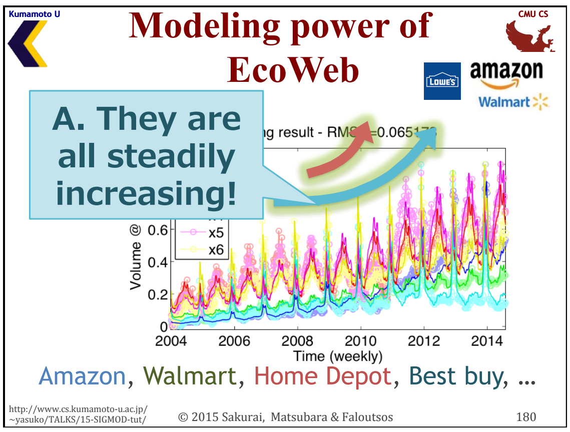
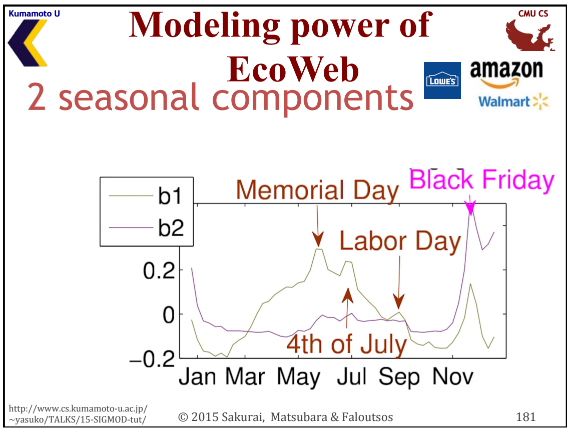
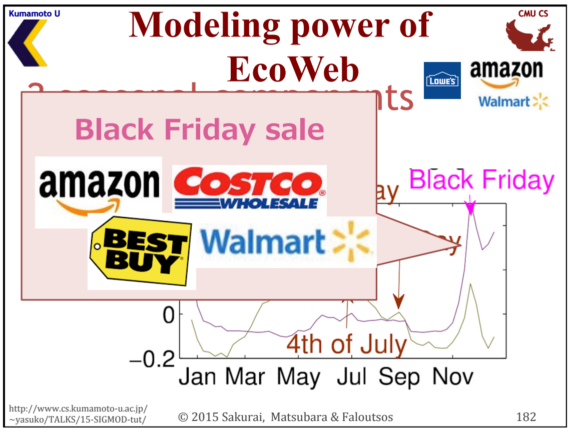
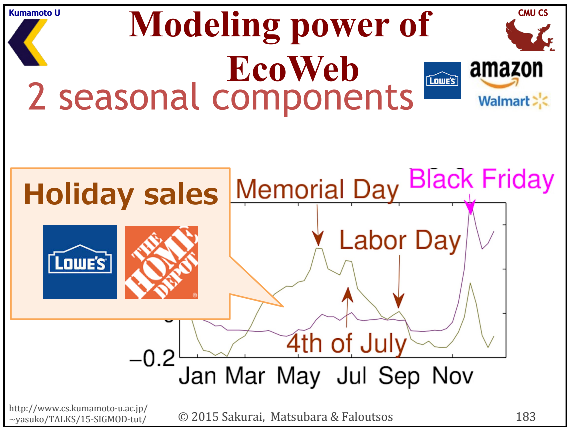
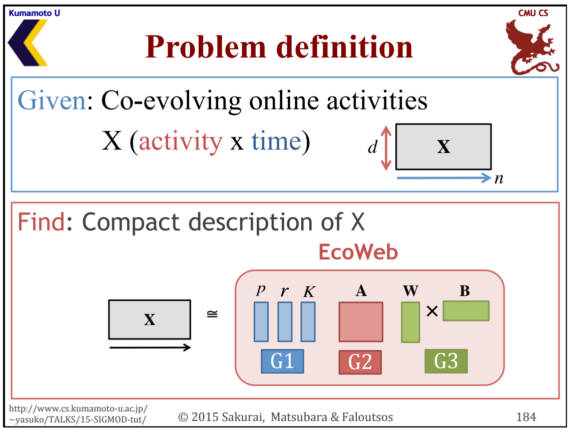

Kumamoto U
CMU CS
Modeling power of EcoWeb
LOWE'S
amazon
Walmart
A. They are all steadily increasing!
Volume @
Time (weekly)
Amazon, Walmart, Home Depot, Best buy, ...
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
180


Kumamoto U
CMU CS
Modeling power of EcoWeb
2 seasonal components
amazon
Walmart
b1
b2
Memorial Day
Black Friday
Labor Day
4th of July
0.2
0
−0.2
Jan Mar May Jul Sep Nov
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
181


Kumamoto U
CMU CS
Modeling power of EcoWeb
amazon
Walmart
Black Friday sale
amazon
COSTCO WHOLESALE
BEST BUY
Walmart
Black Friday
0
−0.2
4th of July
Jan Mar May Jul Sep Nov
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
182


Kumamoto U
CMU CS
Modeling power of EcoWeb
2 seasonal components
amazon
Walmart
Holiday sales
LOWE'S
THE HOME DEPOT
Memorial Day
Black Friday
Labor Day
4th of July
−0.2
Jan Mar May Jul Sep Nov
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
183


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/15-SIGMOD-tut/
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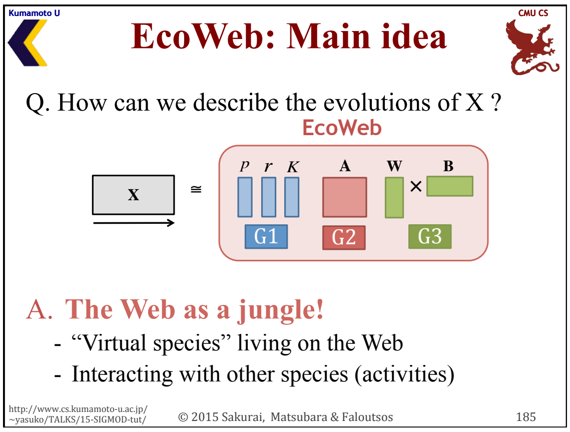
Kumamoto U
CMU CS
EcoWeb: Main idea
Q. How can we describe the evolutions of X ?
EcoWeb
X
≅
P r K
A
W
B
×
G1
G2
G3
A. The Web as a jungle!
- "Virtual species" living on the Web
- Interacting with other species (activities)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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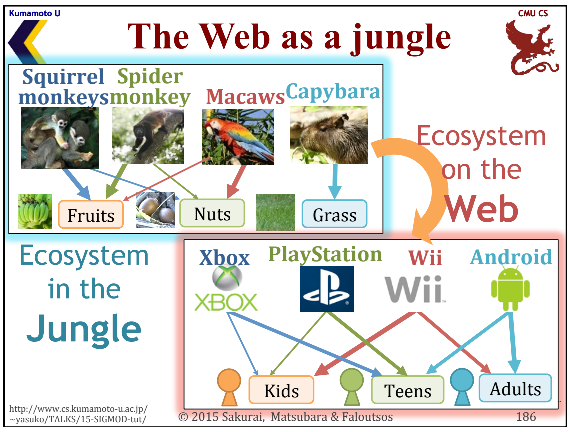
185


Kumamoto U
CMU CS
The Web as a jungle
Squirrel monkeys
Spider monkey
Macaws
Capybara
Fruits
Nuts
Grass
Ecosystem on the Web
Ecosystem in the Jungle
Xbox
XBOX
PlayStation
Wii
Android
Kids
Teens
Adults
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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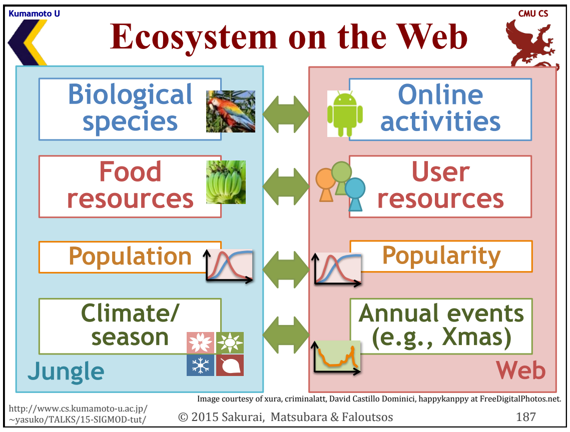
186



Kumamoto U
CMU CS
Ecosystem on the Web
Biological species
Online activities
Food resources
User resources
Population
Popularity
Climate/ season
Annual events (e.g., Xmas)
Jungle
Web
Image courtesy of xura, criminalatt, David Castillo Dominici, happykanppy at FreeDigitalPhotos.net.
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
© 2015 Sakurai, Matsubara & Faloutsos
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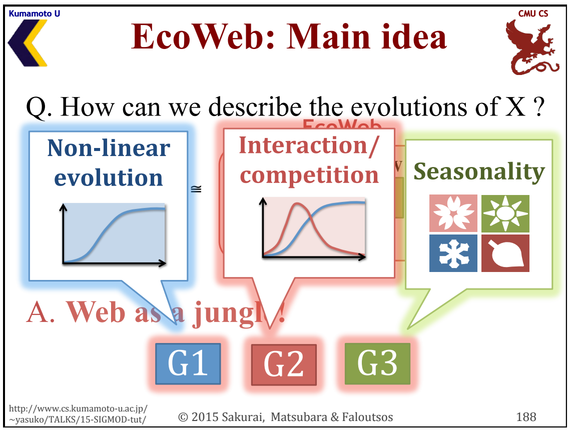

Kumamoto U
CMU CS
EcoWeb: Main idea
Q. How can we describe the evolutions of X ?
Non-linear evolution
Interaction/ competition
Seasonality
A. Web as a jungle!
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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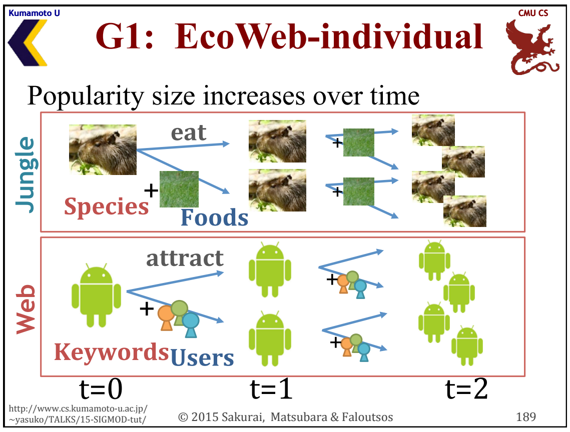
188



Kumamoto U
CMU CS
G1: EcoWeb-individual
Popularity size increases over time
Jungle
eat
Species
Foods
Web
attract
Keywords
Users
t=0
t=1
t=2
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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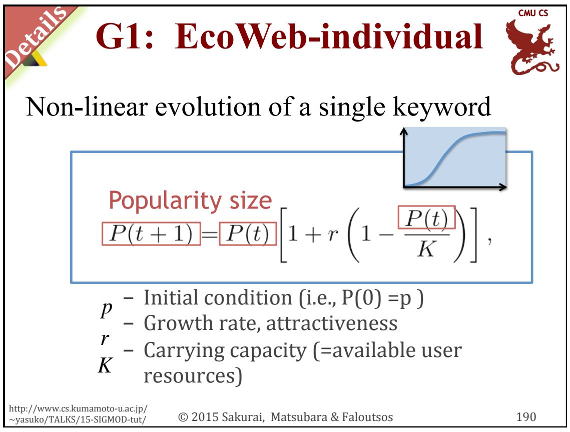
189



Details
CMU CS
G1: EcoWeb-individual
Non-linear evolution of a single keyword
Popularity size
$P(t+1) = P(t)\left[1 + r\left(1 - \frac{P(t)}{K}\right)\right],$
p – Initial condition (i.e., P(0) =p)
r – Growth rate, attractiveness
K – Carrying capacity (=available user resources)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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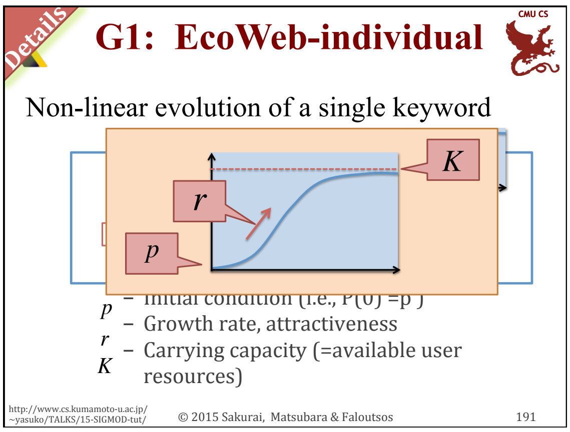

Details
CMU CS
G1: EcoWeb-individual
Non-linear evolution of a single keyword
K
r
p
p – Initial condition (i.e., P(0) =p)
r – Growth rate, attractiveness
K – Carrying capacity (=available user resources)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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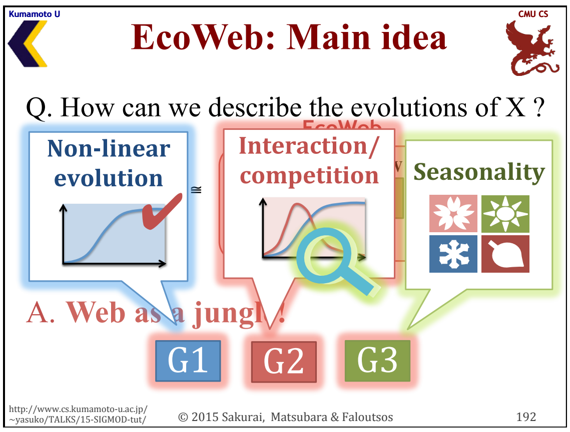

Kumamoto U
CMU CS
EcoWeb: Main idea
Q. How can we describe the evolutions of X ?
Non-linear evolution
Interaction/ competition
Seasonality
A. Web as a jungle!
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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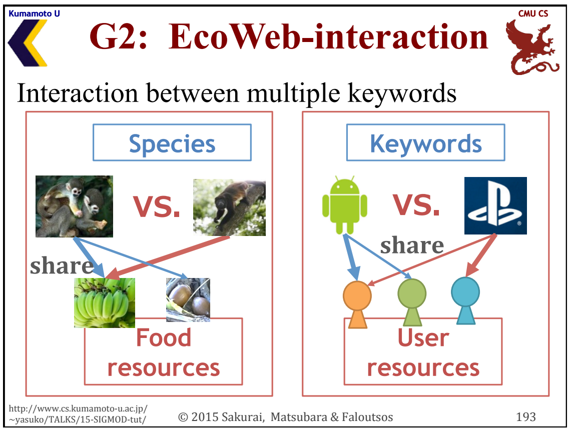
Kumamoto U
CMU CS
G2: EcoWeb-interaction
Interaction between multiple keywords
Species
vs.
share
Food resources
Keywords
vs.
share
User resources
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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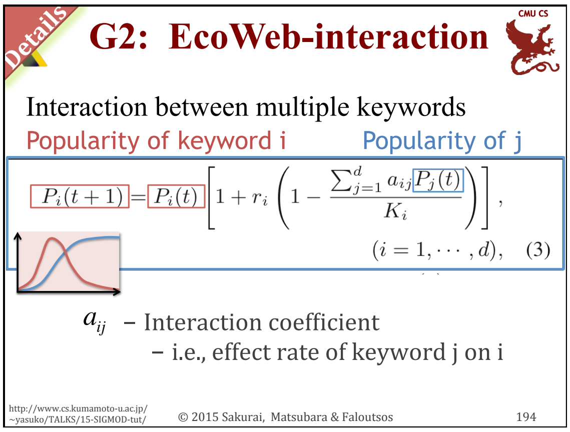
Details
CMU CS
G2: EcoWeb-interaction
Interaction between multiple keywords
Popularity of keyword i
Popularity of j
$P_i(t+1) = P_i(t)\left[1 + r_i\left(1 - \frac{\sum_{j=1}^{d} a_{ij} P_j(t)}{K_i}\right)\right],$
$(i = 1, \cdots, d),$ (3)
a_{ij} – Interaction coefficient
– i.e., effect rate of keyword j on i
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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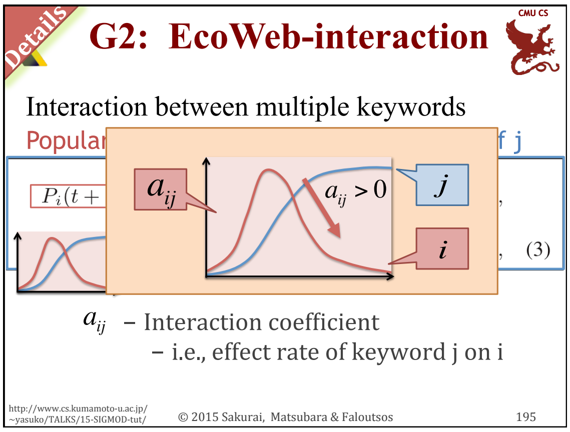
Details
CMU CS
G2: EcoWeb-interaction
Interaction between multiple keywords
Popular
f j
$P_i(t+$
a_{ij}
$a_{ij} > 0$
j
i
(3)
a_{ij} – Interaction coefficient
– i.e., effect rate of keyword j on i
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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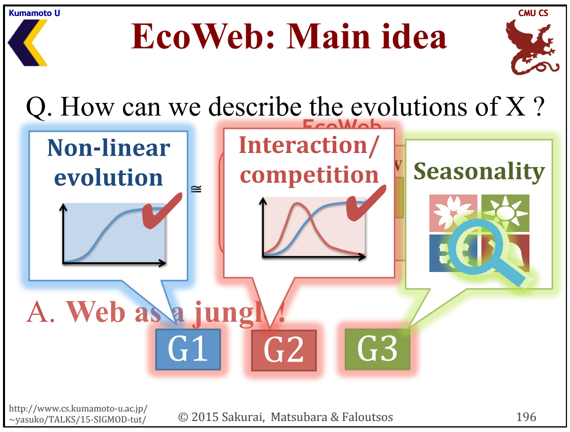
Kumamoto U
CMU CS
EcoWeb: Main idea
Q. How can we describe the evolutions of X ?
Non-linear evolution
Interaction/ competition
Seasonality
A. Web as a jungle!
G1
G2
G3
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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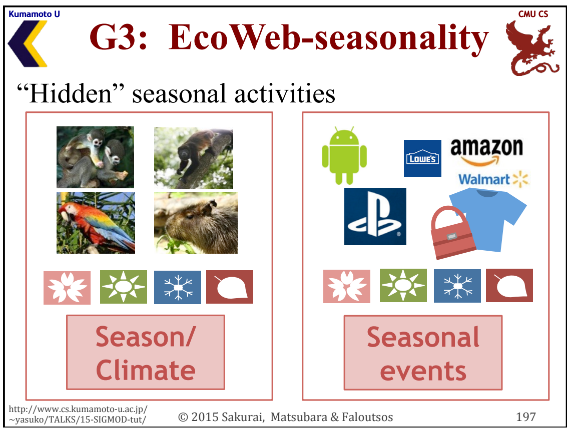
Kumamoto U
CMU CS
G3: EcoWeb-seasonality
"Hidden" seasonal activities
amazon
Walmart
Season/ Climate
Seasonal events
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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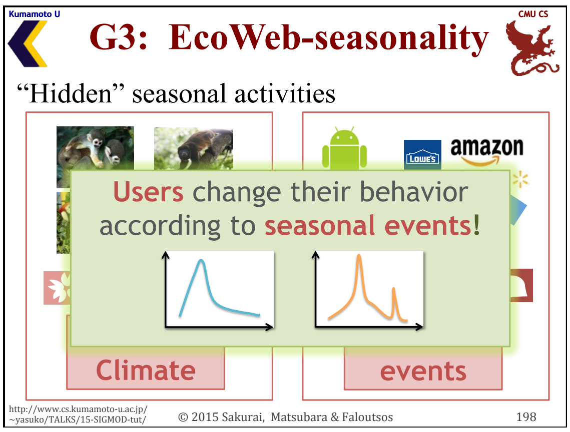
Kumamoto U
CMU CS
G3: EcoWeb-seasonality
"Hidden" seasonal activities
amazon
Users change their behavior according to seasonal events!
Climate
events
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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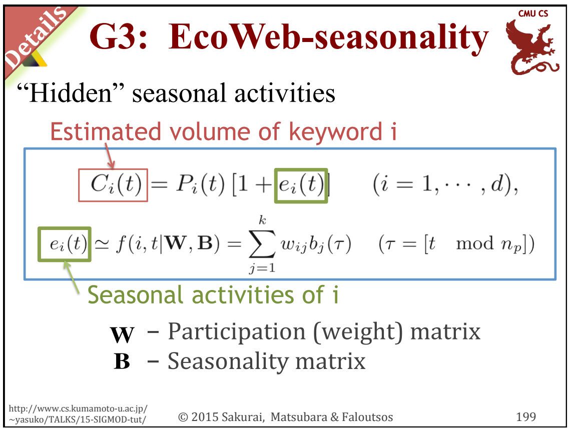
Details
G3: EcoWeb-seasonality
CMU CS
"Hidden" seasonal activities
Estimated volume of keyword i
$C_i(t) = P_i(t)\,[1 + e_i(t)]$ $(i = 1, \cdots, d)$,
$e_i(t) \simeq f(i, t|\mathbf{W}, \mathbf{B}) = \sum_{j=1}^{k} w_{ij} b_j(\tau)$ $(\tau = [t \mod n_p])$
Seasonal activities of i
W – Participation (weight) matrix
B – Seasonality matrix
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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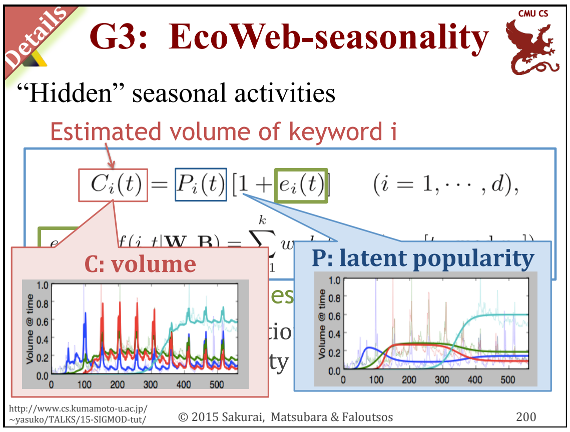
Details
G3: EcoWeb-seasonality
CMU CS
"Hidden" seasonal activities
Estimated volume of keyword i
$C_i(t) = P_i(t)\,[1 + e_i(t)]$ $(i = 1, \cdots, d)$,
C: volume
P: latent popularity
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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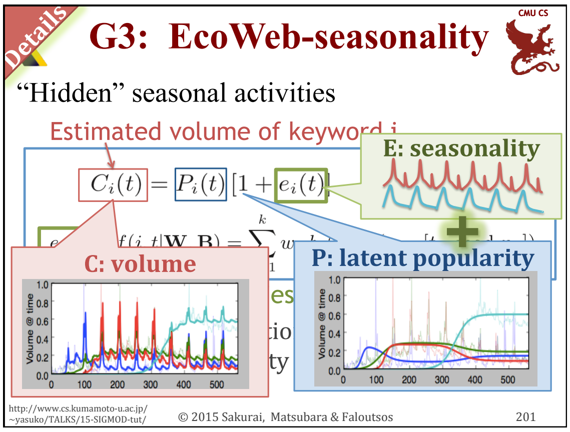
Details
G3: EcoWeb-seasonality
CMU CS
"Hidden" seasonal activities
Estimated volume of keyword i
$C_i(t) = P_i(t)\,[1 + e_i(t)]$
E: seasonality
C: volume
P: latent popularity
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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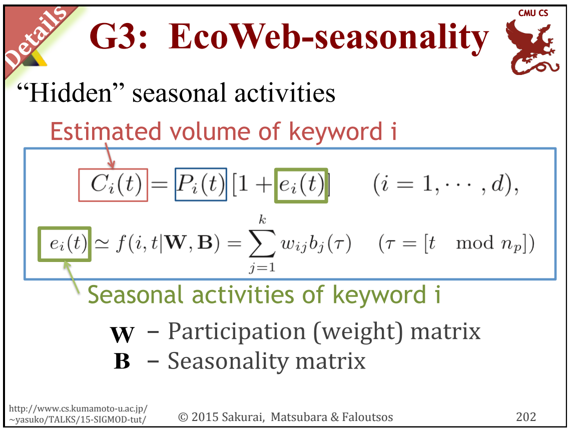
Details
G3: EcoWeb-seasonality
CMU CS
"Hidden" seasonal activities
Estimated volume of keyword i
$C_i(t) = P_i(t)\,[1 + e_i(t)]$ $(i = 1, \cdots, d)$,
$e_i(t) \simeq f(i, t|\mathbf{W}, \mathbf{B}) = \sum_{j=1}^{k} w_{ij} b_j(\tau)$ $(\tau = [t \mod n_p])$
Seasonal activities of keyword i
W – Participation (weight) matrix
B – Seasonality matrix
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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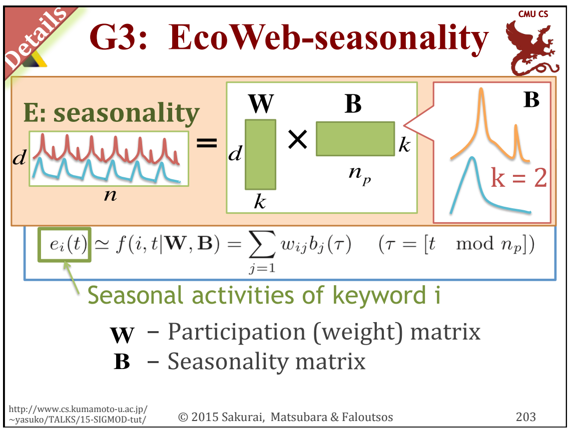
Details
G3: EcoWeb-seasonality
CMU CS
E: seasonality
d
n
=
W
d
k
×
B
k
n_p
B
k = 2
$e_i(t) \simeq f(i, t|\mathbf{W}, \mathbf{B}) = \sum_{j=1}^{k} w_{ij} b_j(\tau)$ $(\tau = [t \mod n_p])$
Seasonal activities of keyword i
W – Participation (weight) matrix
B – Seasonality matrix
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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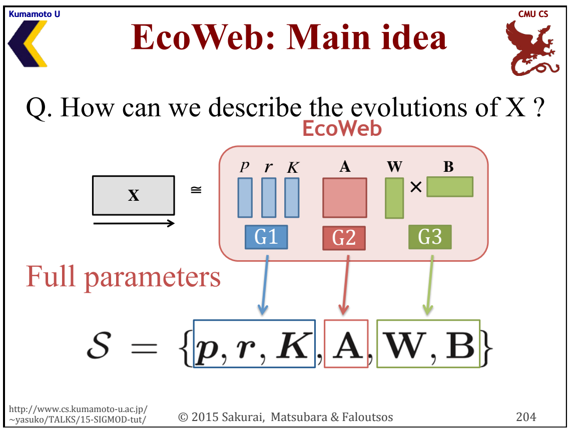
Kumamoto U
EcoWeb: Main idea
CMU CS
Q. How can we describe the evolutions of X ?
EcoWeb
X
≅
p r K
A
W
×
B
G1
G2
G3
Full parameters
$\mathcal{S} = \{\mathbf{p}, \mathbf{r}, \mathbf{K}, \mathbf{A}, \mathbf{W}, \mathbf{B}\}$
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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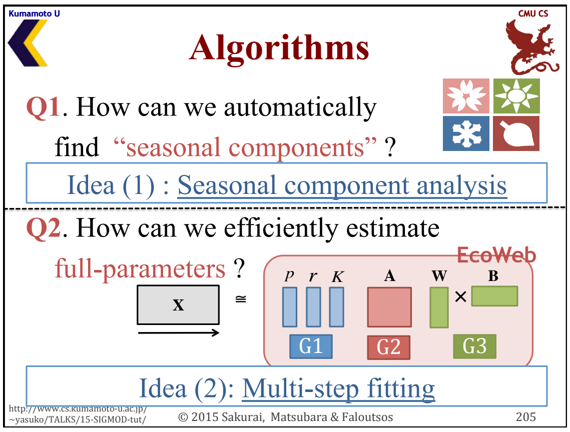
Kumamoto U
CMU CS
Algorithms
Q1. How can we automatically find "seasonal components" ?
Idea (1) : Seasonal component analysis
Q2. How can we efficiently estimate full-parameters ?
EcoWeb
X
p r K
A
W
B
G1
G2
G3
Idea (2): Multi-step fitting
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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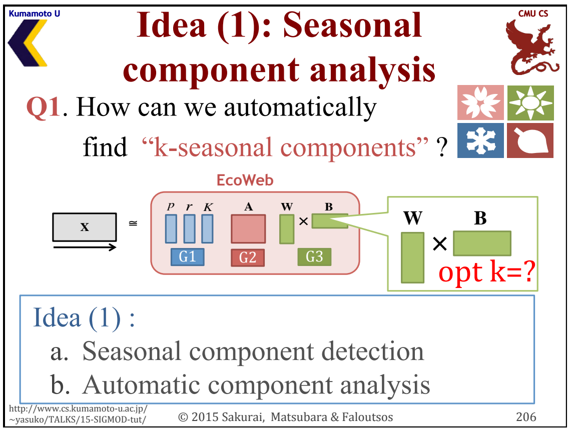
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Q1. How can we automatically find "k-seasonal components" ?
EcoWeb
X
p r K
A
W
B
G1
G2
G3
W
B
opt k=?
Idea (1) :
a. Seasonal component detection
b. Automatic component analysis
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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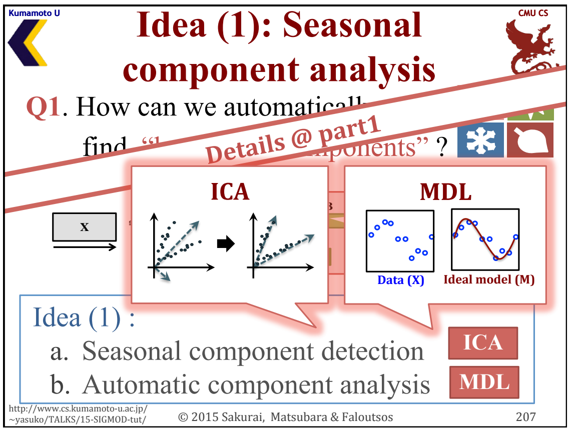
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Q1. How can we automaticall
Details @ part1
ICA
MDL
Data (X)
Ideal model (M)
Idea (1) :
a. Seasonal component detection
b. Automatic component analysis
ICA
MDL
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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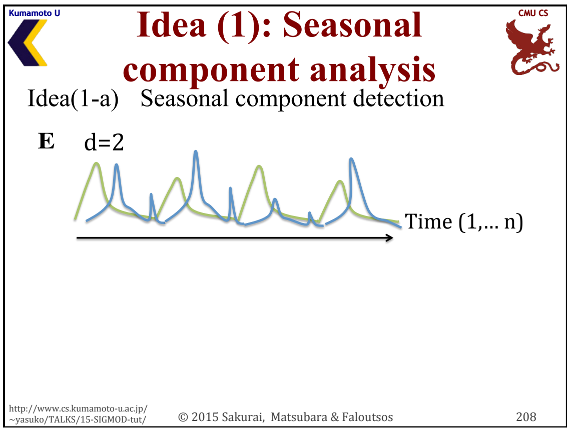
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-a) Seasonal component detection
E
d=2
Time (1,... n)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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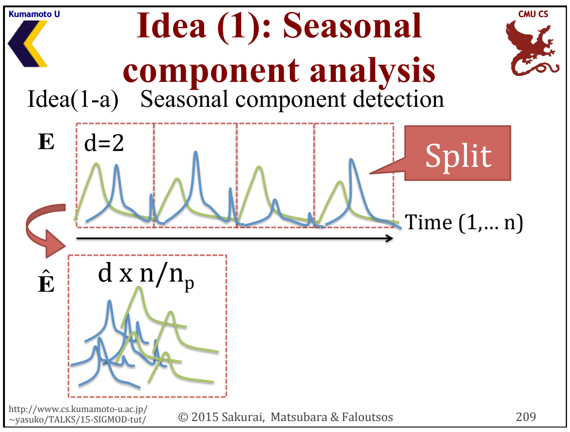
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-a) Seasonal component detection
E
d=2
Split
Time (1,... n)
Ê
d x n/n_p
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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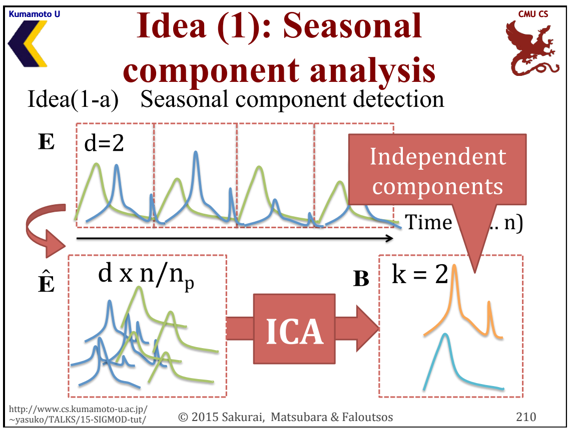
Kumamoto U
CMU CS
Idea (1): Seasonal component analysis
Idea(1-a) Seasonal component detection
E
d=2
Independent components
Time
. n)
Ê
d x n/n_p
ICA
B
k = 2
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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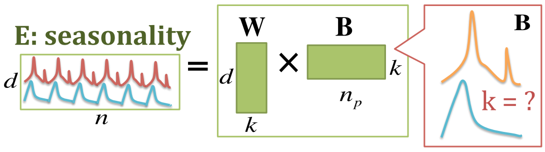
Idea (1): Seasonal component analysis

Idea(1-b) Automatic component analysis

Find optimal number k (1≤k≤d)

d: dimension



opt k=?

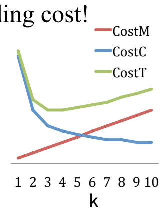
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/ © 2015 Sakurai, Matsubara & Faloutsos 211

Idea (1): Seasonal component analysis

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

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

Model cost   Coding cost



Good compression ⟲ Good description

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/ © 2015 Sakurai, Matsubara & Faloutsos 212

Idea (1): Seasonal component analysis

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

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

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

Good compression ⟲ Good description

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/ © 2015 Sakurai, Matsubara & Faloutsos 213

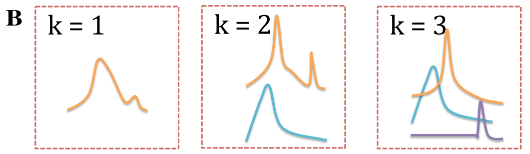
Idea (1): Seasonal component analysis

Idea(1-b) Automatic component analysis

Find optimal number k (1≤k≤d)

d: dimension

W × B opt k=?



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

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/ © 2015 Sakurai, Matsubara & Faloutsos 214

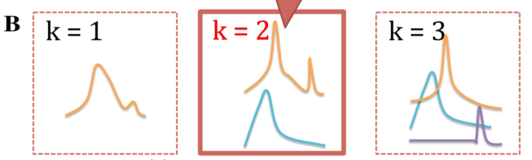
Idea (1): Seasonal component analysis

Idea(1-b) Automatic component analysis

Find optimal number k (1≤k≤d)

W × B opt k=?

Optimal k

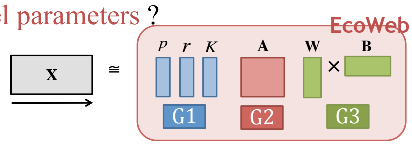


Cost(1) = $$ Cost(2) = $ Cost(3) = $$$

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/ © 2015 Sakurai, Matsubara & Faloutsos 215

Idea (2): EcoWeb-Fit

Q2. How can we efficiently estimate model parameters ?



Idea (2): Multi-step fitting

a. **StepFit** (sub)

b. **EcoWeb-Fit** (full)

http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/ © 2015 Sakurai, Matsubara & Faloutsos 216

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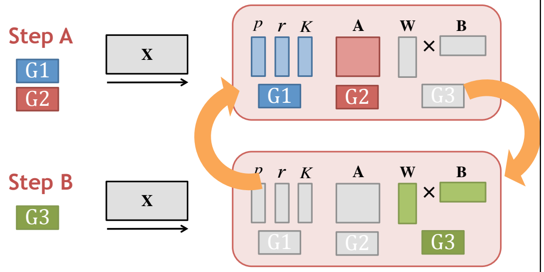
Idea (2): EcoWeb-Fit

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



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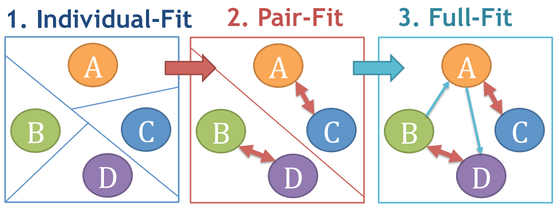
Idea (2): EcoWeb-Fit

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

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



EcoWeb-Fit updates parameters, separately

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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?

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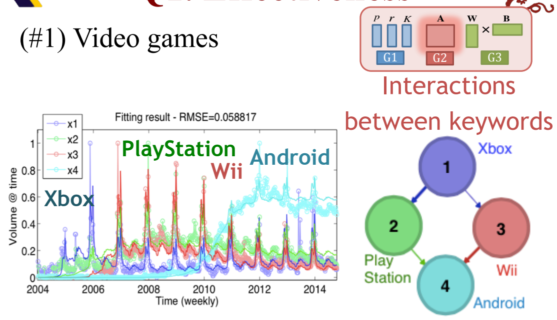
Q1. Effectiveness

(#1) Video games



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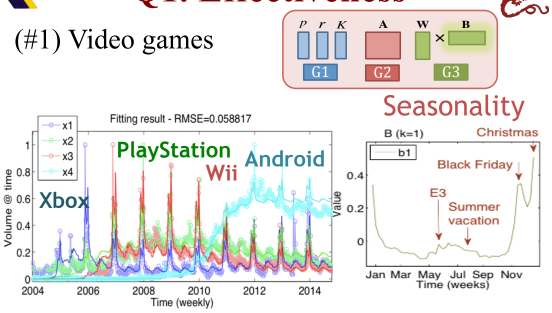
Q1. Effectiveness

(#1) Video games



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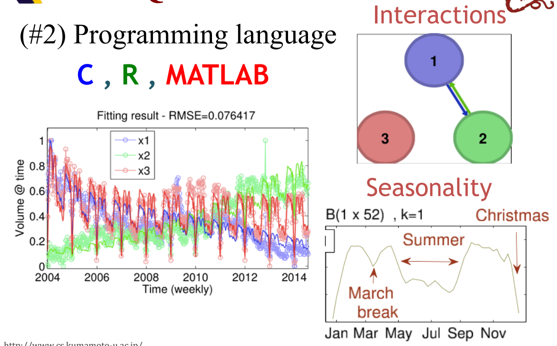
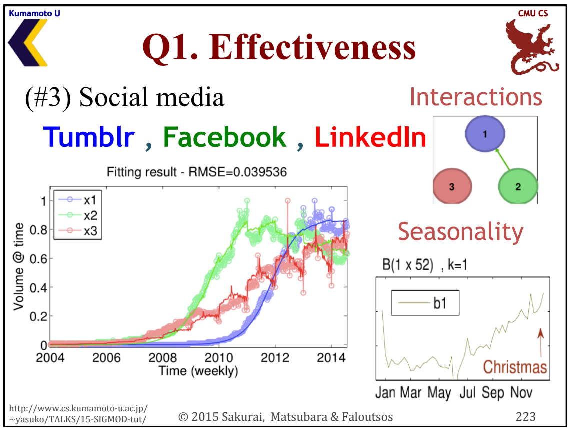
Q1. Effectiveness

(#2) Programming language

C , R , MATLAB




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/15-SIGMOD-tut/
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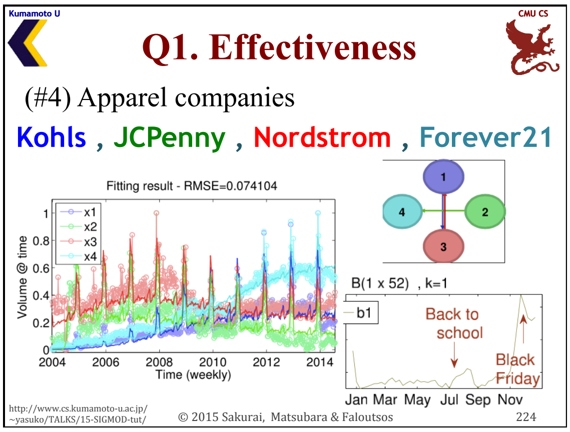
Kumamoto U
CMU CS
Q1. Effectiveness
(#4) Apparel companies
Kohls , JCPenny , Nordstrom , Forever21
Fitting result - RMSE=0.074104
Volume @ time
Time (weekly)
B(1 x 52) , k=1
Back to school
Black Friday
Jan Mar May Jul Sep Nov
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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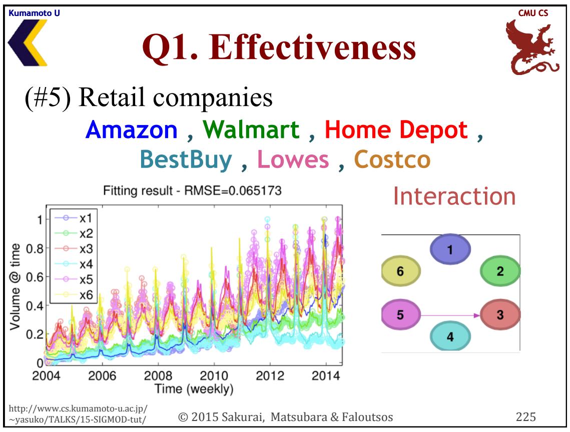
Kumamoto U
CMU CS
Q1. Effectiveness
(#5) Retail companies
Amazon , Walmart , Home Depot ,
BestBuy , Lowes , Costco
Fitting result - RMSE=0.065173
Interaction
Volume @ time
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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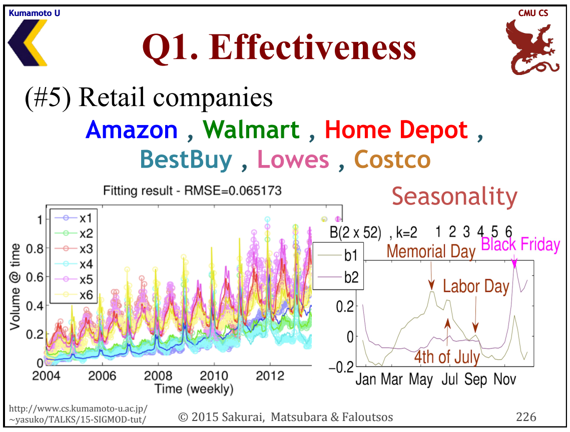
Kumamoto U
CMU CS
Q1. Effectiveness
(#5) Retail companies
Amazon , Walmart , Home Depot ,
BestBuy , Lowes , Costco
Fitting result - RMSE=0.065173
Seasonality
B(2 x 52) , k=2
Memorial Day
Black Friday
Labor Day
4th of July
Jan Mar May Jul Sep Nov
Volume @ time
Time (weekly)
http://www.cs.kumamoto-u.ac.jp/~yasuko/TALKS/15-SIGMOD-tut/
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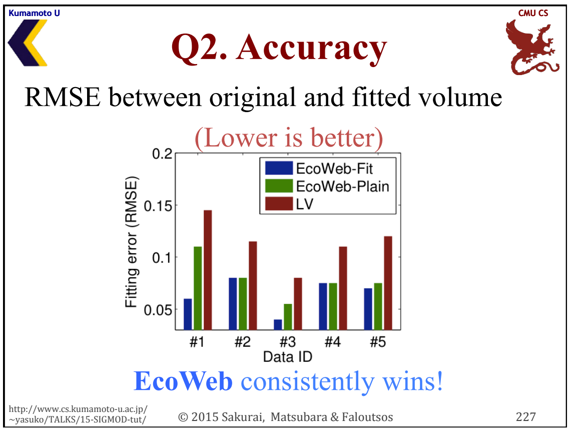
226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Q2. Accuracy
RMSE between original and fitted volume
(Lower is better)
EcoWeb-Fit
EcoWeb-Plain
LV
Fitting error (RMSE)
Data ID
EcoWeb consistently wins!
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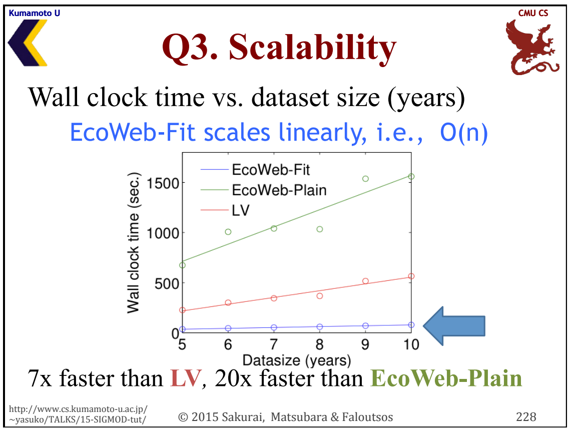
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Q3. Scalability
Wall clock time vs. dataset size (years)
EcoWeb-Fit scales linearly, i.e., O(n)
EcoWeb-Fit
EcoWeb-Plain
LV
Wall clock time (sec.)
Datasize (years)
7x faster than LV, 20x faster than EcoWeb-Plain
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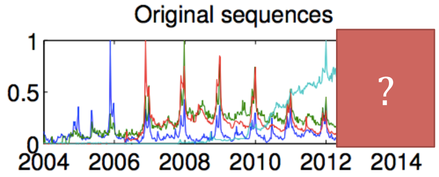
228

EcoWeb at work - forecasting

Forecasting future activities

Train: 2/3 sequences

Forecast: 1/3 following years

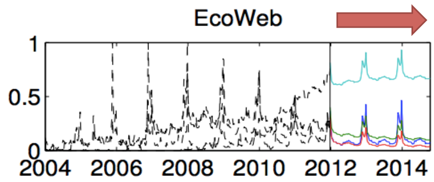


EcoWeb at work - forecasting

Forecasting future activities

Train: 2/3 sequences

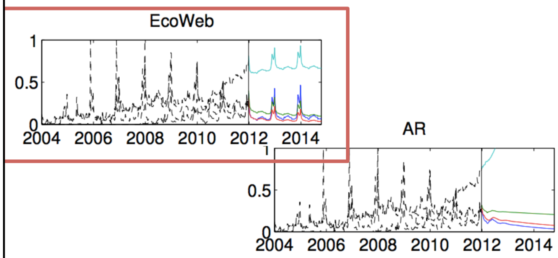
Forecast: 1/3 following years



EcoWeb can capture future patterns

EcoWeb at work - forecasting

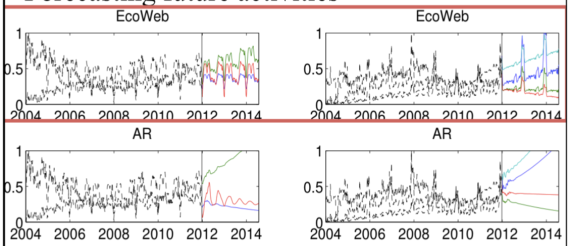
Forecasting future activities



EcoWeb can capture future patterns!

EcoWeb at work - forecasting

Forecasting future activities



(b) Programming languages (#2) (c) Apparel companies (#4)

EcoWeb can capture future patterns!

Part 2 Roadmap

Problem

✔ Why: "non-linear" modeling

Fundamentals

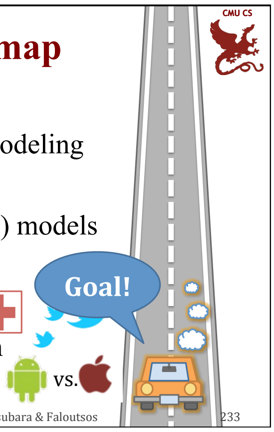
✔ Non-linear (grey-box) models

Applications

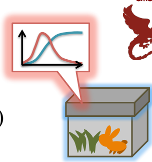
✔ Epidemics

✔ Information diffusion

✔ Online competition



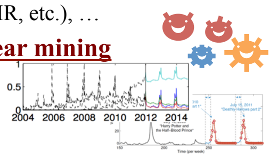
Part 2 Conclusions



✔ **Why: "non-linear" modeling**
- Black box: lag plots (k-NN search)
- Grey-box: given a model

✔ **Fundamentals: popular non-linear models**
- Logistic function, Lotka-Volterra, Competition, ...
- Epidemics (SI, SIR, SEIR, etc.), …

✔ **Applications: non-linear mining**
- Epidemics
- Information diffusion
- Online competition



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Part 2

Non-linear mining and forecasting

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