

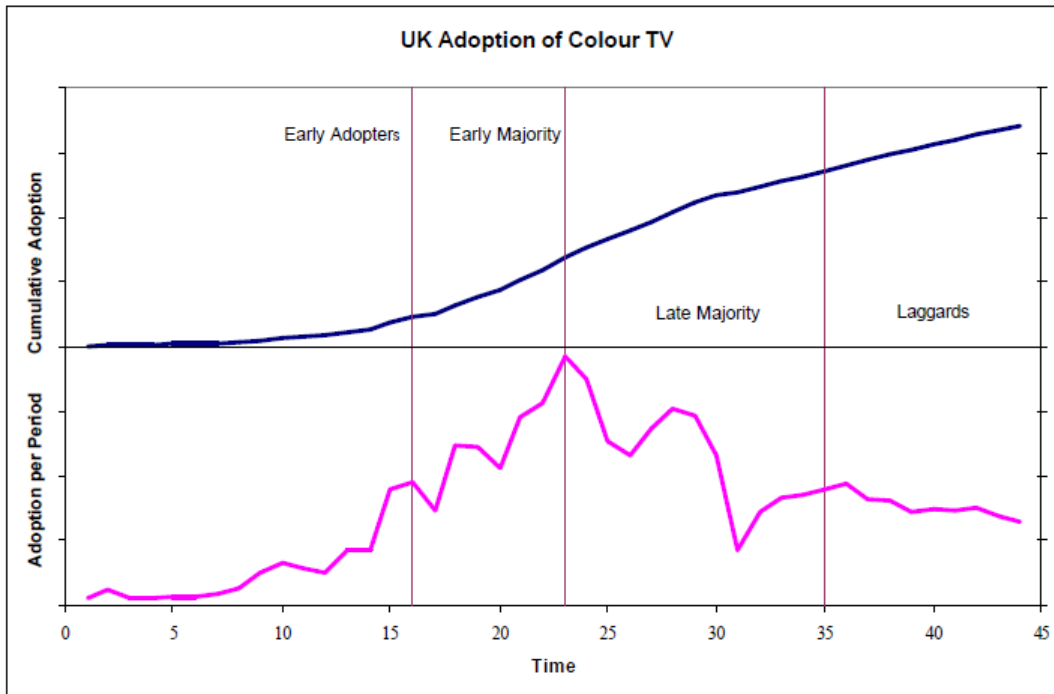


Modeling Diffusion in Social Networks using Network Properties

Minh-Duc LUU*, Ee-Peng LIM,
Tuan-Anh HOANG, Freddy Chong Tat CHUA

Why Diffusion in Social Networks?

Diffusion of items (videos, news, photos, etc) is **important** and **ubiquitous** in social networks



Proper models of diffusion can predict:

- **Rate of adoption** at a particular time
- The time of **peak demand**
- The magnitude of peak demand

Applications of Diffusion Models in Telecommunications, Nigel Meade

<http://www.itu.int/ITU-D/finance/work-cost-tariffs/events/expert-dialogues/forecasting/meade-presentation.pdf>

Why Modeling Diffusion using Network Properties?

For item diffusion we have micro and macro models.

	Micro models	Macro models
Work at	Individual level	Network level
Representatives	Independent Cascade (IC) ^[1] , Linear Threshold (LT) ^[2]	Bass Model ^[3] and its extensions
Parameters	Local , each user has his own parameters	Global , for the whole network
Network properties	Exploit (+)	Do NOT exploit (-)
No. of parameters	So many (-)	Just a few (+)

[1] Goldenberg et al. (2001) *Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth*

[2] Granovetter, M. (1978) *Threshold Models of Collective Behavior*

[3] Bass, F. M. (1969) *A new Product Growth Model for Consumer Durables*

Research Questions

How can macro models exploit network properties (e.g. **degree distribution**)?

In this work:

Q1) How to model diffusion in a network given its **degree distribution**?

Q2) How to **combine parameters** of diffusion and of degree distribution to give a better model?

Concepts & Notations

- N : network size.
- $f(t)$: **instantaneous** fraction of adopters at time t
- $F(t)$: **cumulative** fraction of adopters at time t

$$f(t) = F'(t)$$

- a_t : adoption at t , A_t : adoption before t .

Observe that:

$$\underbrace{f(t)}_{\text{fract of new adopters}} = \underbrace{(1 - F(t))}_{\text{nonadopters at } t} \cdot \underbrace{\mathbb{E}[P(a_t | \bar{A}_t)]}_{\text{avg. adopting prob}}$$

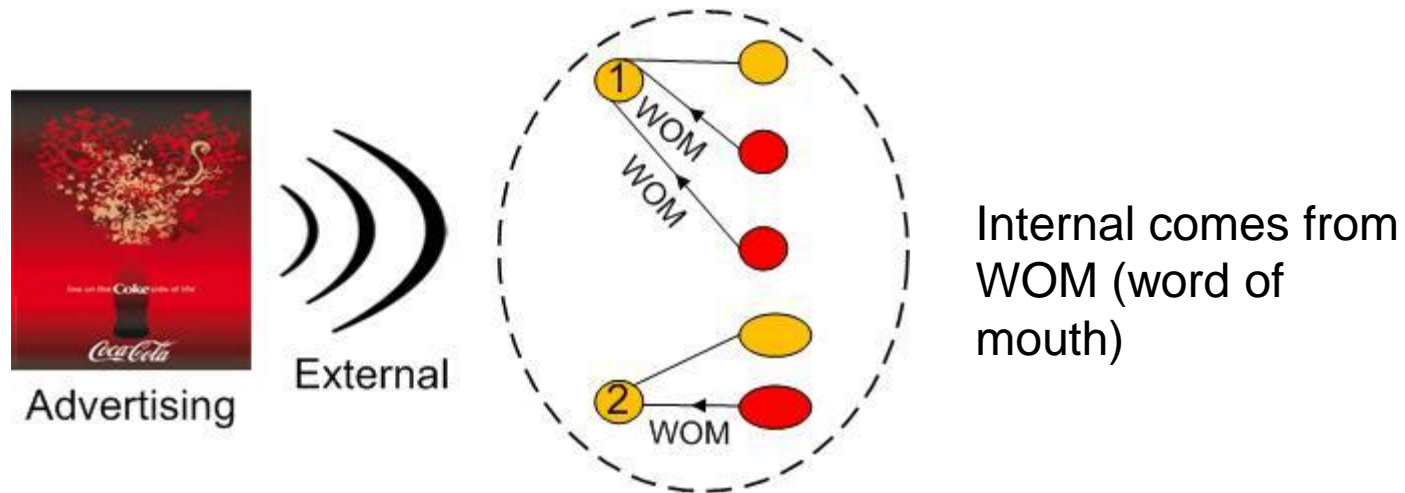
Ordinary differential equation (ODE) linking $F(\cdot)$, $P(\cdot)$:

$$F'(t) = (1 - F(t)) \cdot P(a_t | \bar{A}_t)$$

Goal: **estimate the adoption probability $P(\cdot)$ as a function of $F(\cdot)$**

Estimation of Adoption Probability

General Case



Contributions from **external** & **internal** influences are weighted with w_e and $1-w_e$ respectively.

$$P(a_t | \bar{A}_t) = w_e \cdot P_{ext}(a_t | \bar{A}_t) + (1 - w_e) \cdot P_{int}(a_t | \bar{A}_t)$$
$$= w_e \cdot p_e + (1 - w_e) \cdot P_{int}(a_t | \bar{A}_t)$$

Bass Model (BM)

Assumptions of BM:

B1) Each user can influence **every other** user.

$$|u\text{'s adopted neighbors}| = N \cdot F(t), \quad \forall u, \forall t$$

B2) Internal influence is **proportional to No. of adopted neighbors**:

$$P_{int}(a_t | \bar{A}_t) = q_1 \cdot N \cdot F(t)$$

$$\Rightarrow P(a_t | \bar{A}_t) = p + q \cdot F(t) \quad (*)$$

$$\text{where } p = w_e \cdot p_e \text{ and } q = (1 - w_e) \cdot q_1 \cdot N$$

(*) combines with the **ODE**

→ Bass Model (1969)

$$F(t) = \frac{e^{[(p+q)t]} - 1}{e^{[(p+q)t]} + q/p}$$
$$f(t) = F'(t) = \frac{(p+q)^2}{p} \cdot \frac{e^{[(p+q)t]}}{\{e^{[(p+q)t]} + q/p\}^2}$$

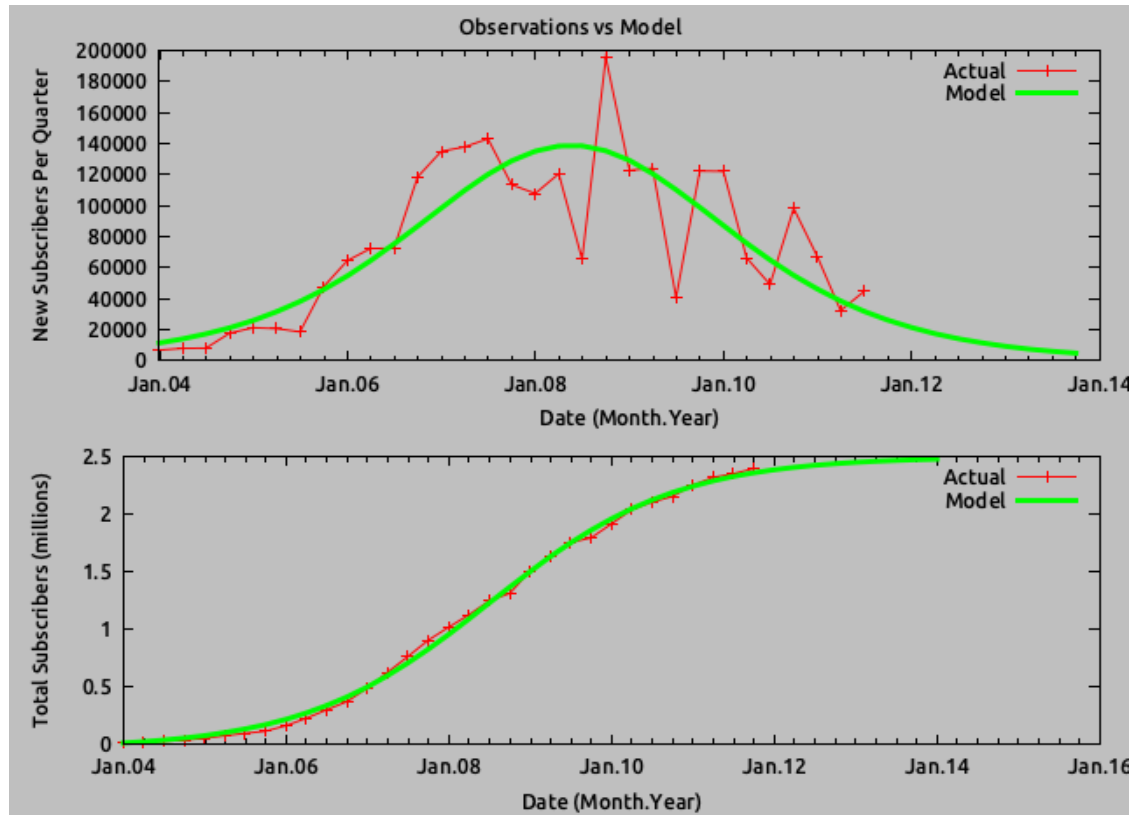
Bass Model (cont.)

“...Bass model **ignores** the **network structure**...”
[Xiaodan S. et al, WWW 07]

B1) Each user can influence/influenced **every other** user

Each user can influence/influenced only **his friends**
→his adoption prob. depends on his **degree**

Bass Model (cont.)



<http://serial.innovatiasystems.eu/cms/>

Adoption Probability for Specific Degree Distributions

- Given any degree distribution $P(k)$, we obtained the formula:

(**Internal** adoption probability)

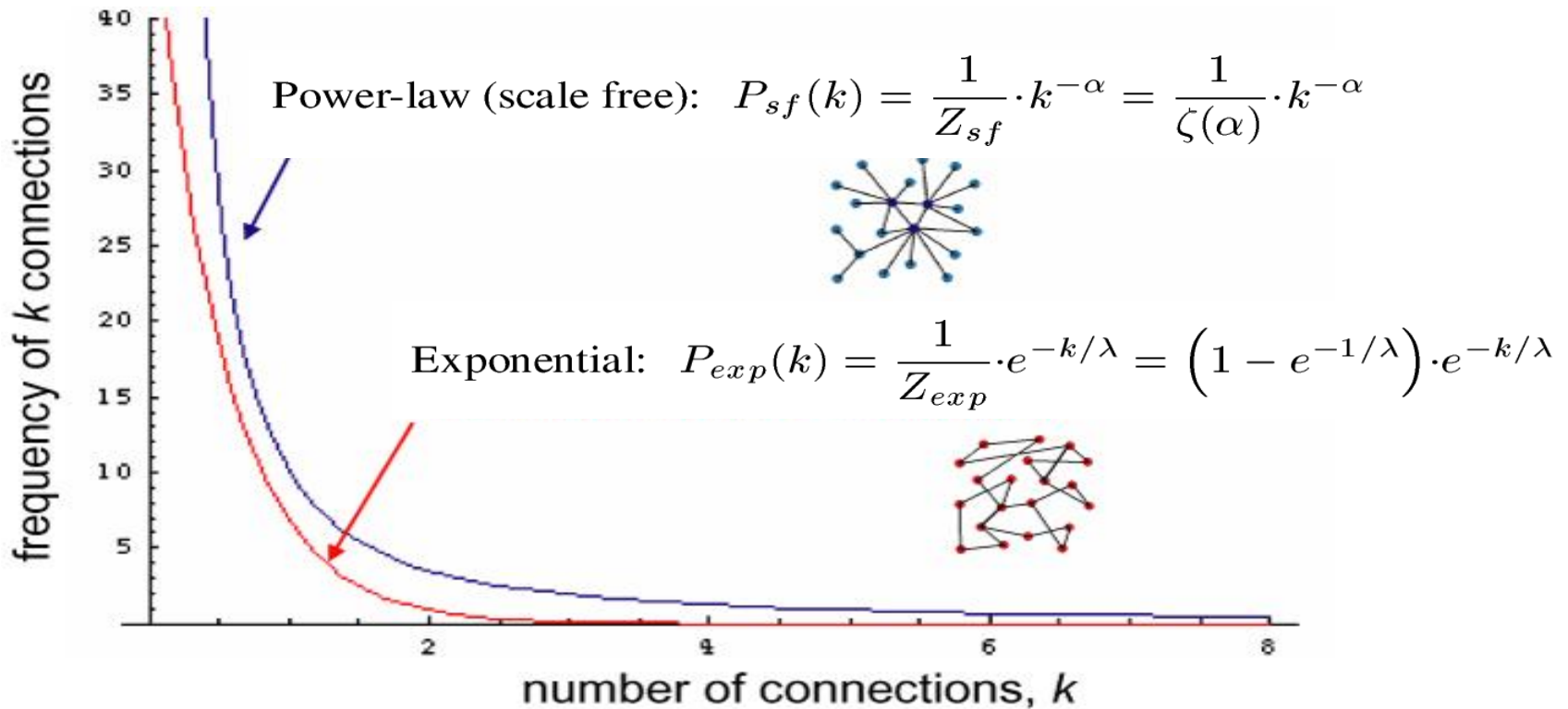
$$P_{\text{int}}(a_t | \bar{A}_t) = \sum_{k=1}^{N-1} P(k) \sum_{j=0}^k \left[\binom{k}{j} F_t^j (1 - F_t)^{k-j} P(a_t | \bar{A}_t, j) \right]$$

where $F_t \equiv F(t)$ and $P(a_t | \bar{A}_t, j)$ is the prob of adopting given that a user has j adopted neighbors

- Still keep B2), **linear influence**: $P(a_t | \bar{A}_t, j) = c \cdot j$
where c is a constant

To complete estimation, needs **specific** degree distributions!

Specific Degree Distributions



Pagel *et al.* *BMC Evolutionary Biology*
2007 7(Suppl 1):S16

Parameter of degree distribution: α (power law) or λ (exponential)

Estimation of Internal Adoption Probability

Linear assumption & specific degree distribution provide estimations:

1) Scale free network:

$$P_{int}^{sf}(a_t | \overline{A}_t) = \frac{\zeta(\alpha - 1)}{\zeta(\alpha)} \cdot c \cdot F_t$$

where $\zeta(\alpha) = \sum_{k=1}^{\infty} k^{-\alpha}$ is the Riemann Zeta function

2) Exponential network:

$$P_{int}^{exp}(a_t | \overline{A}_t) = \frac{e^{-1/\lambda}}{1 - e^{-1/\lambda}} \cdot c \cdot F_t$$

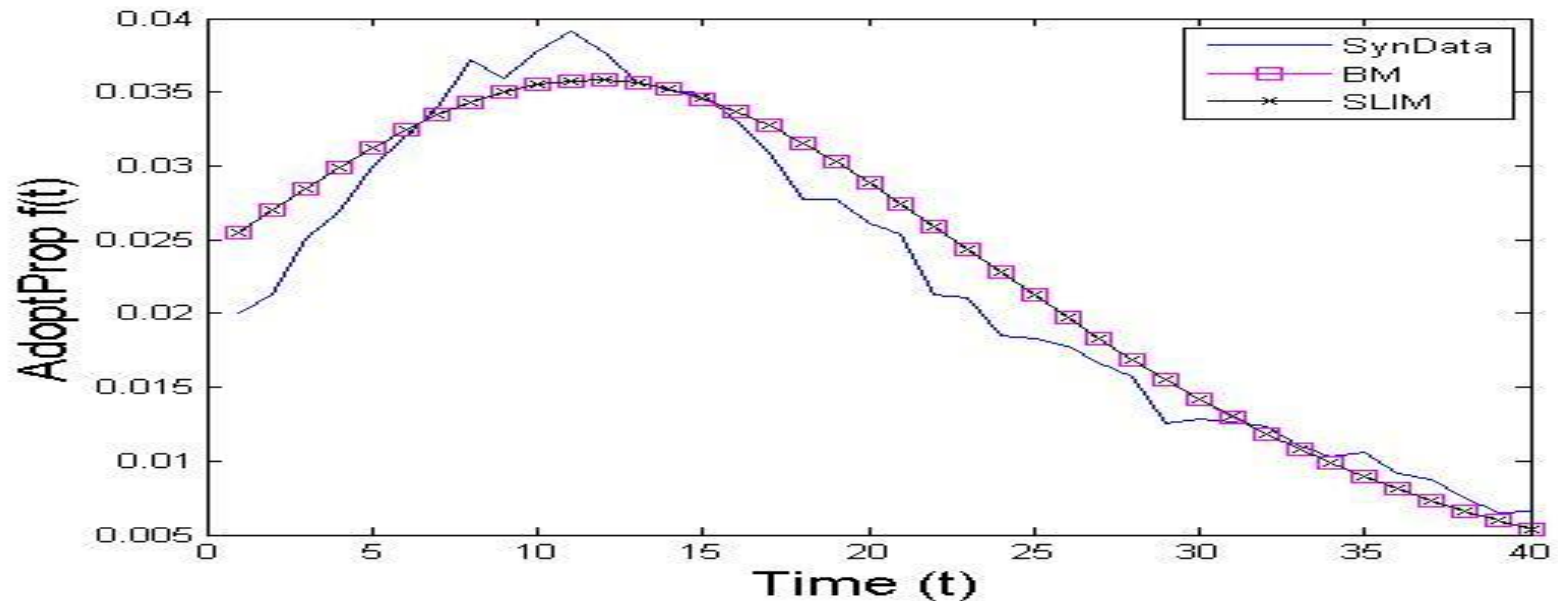
These estimations → **two models** in our work.

Proposed Models

1. **SLIM** (Scale-free Linear Influence Model): **Scale-free** network.
2. **ELIM** (Exponential Linear Influence Model): **Exponential** network

Remarks:

- Give **more rigorous** estimation of adoption probability by **combining parameters** of diffusion and of degree distribution.
- Give the **same** fitting error as BM though!



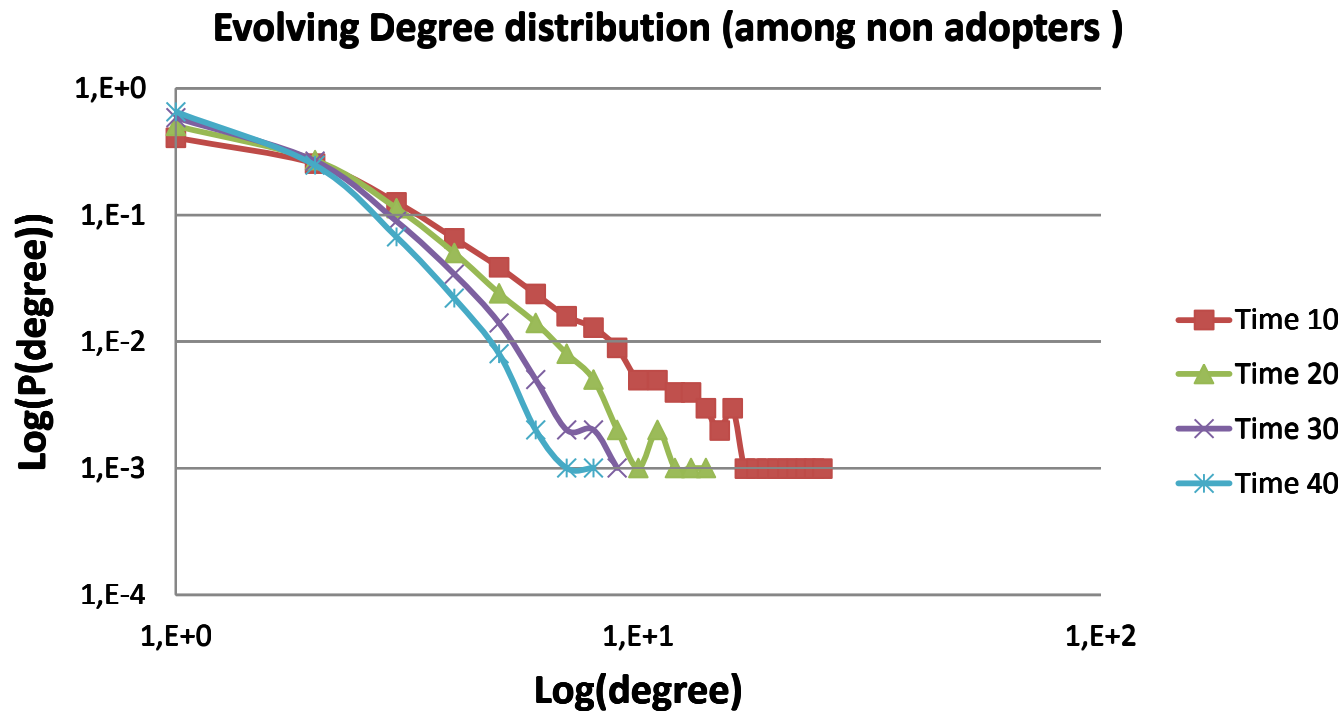
What is the problem?

$$\underbrace{f(t)}_{\text{fract of new adopters}} = \underbrace{(1 - F(t))}_{\text{nonadopters at } t} \cdot \underbrace{E[P(a_t | \bar{A}_t)]}_{\text{avg. adopting prob}}$$

- Is it correct to use degree distribution of the whole network for $P(k)$?
NO. Should use degree distribution over the set of **non-adopters** (NA).
- **NA** changes over time \rightarrow its degree distribution also changes?

YES.

Degree Distribution is **Dynamic** !!



Synthetic scale-free network; 27,289 nodes and 27,031 edges ($\alpha_0=3$).

As time proceed, users with **high/low** degs are more/less likely to adopt and leave/stay **NA** set. Thus later distributions are **more biased** to low degrees.

Multi-Stage Model (MLIM)

For different time pts, need to employ different models.

How to decide the proper model?

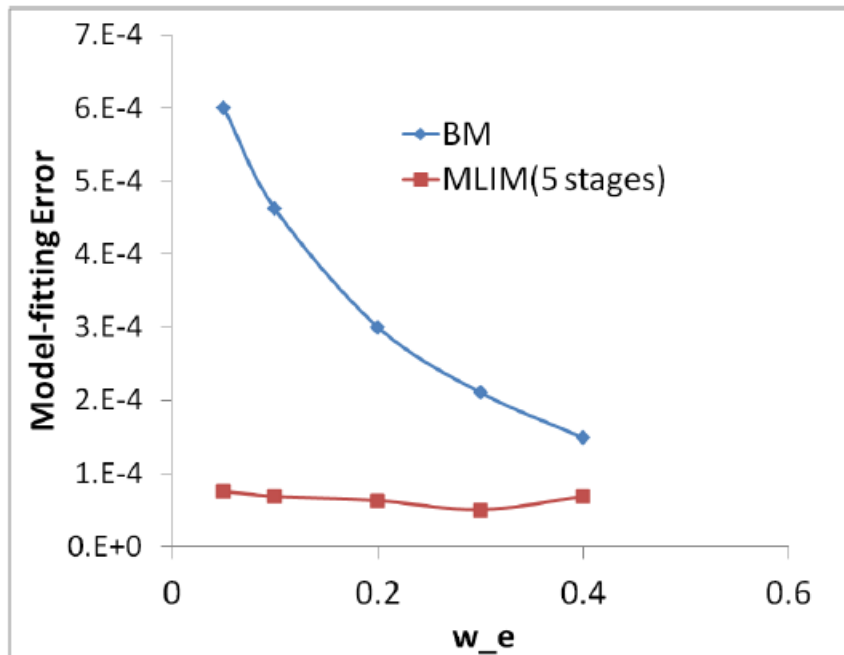
Heuristic approach: in a **short** duration, degree distribution does **NOT** significantly change.

- Divide diffusion process into n stages. Each has short duration (< 10 time steps).
- For each stage, choose between SLIM and ELIM the one that gives **smaller fitting error**.

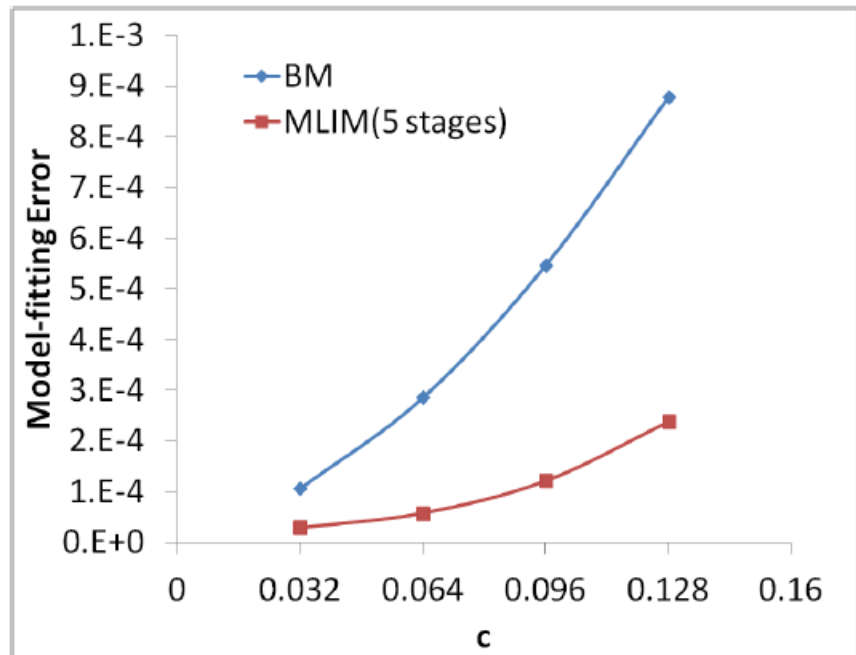
→ Multi-Stage Model

Experiments on Synthetic Data

- Network: 28,172 nodes; 34,578 edges ($\alpha=2.5$).
- Evaluation metrics: **model-fitting** error (LSE) & **parameter-learning** error

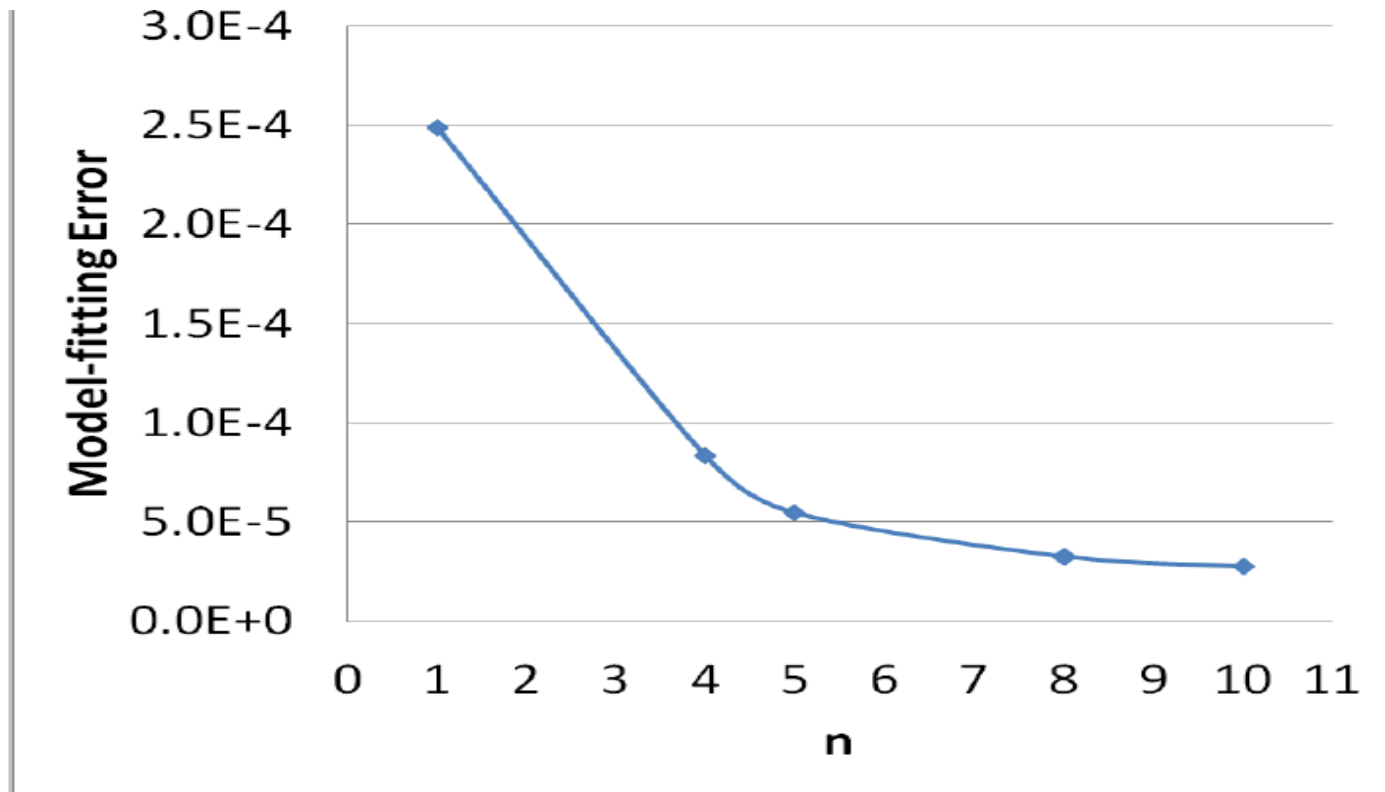


(a) w_e in $\{0.05, 0.1, 0.2, 0.3, 0.4\}$



(b) c in $\{0.032, 0.064, 0.096, 0.12\}$

Experiments on Synthetic Data



(c) $n \in \{1, 4, 5, 8, 10\}$

$n=1$ corresponds to BM

Real-world Dataset

From Goodreads network (www.goodreads.com), \cong 87K users;
159,442 follow links

goodreads Title / Author / ISBN Home My Books Friends Recommendations

showing: friends and people I'm following ▼

You have no updates from **your friends** yet.

Recent Updates From the Community

updates discussions

05/15
Alice gave ★★★★★ to:
Pudd'nhead Wilson and Other Tales (World's Classics)
by **Mark Twain**

My rating:
★★★★★
add to my books

Alice said: "I really didn't think I would enjoy this book....why did I ever think that?!
AMAZING!!!! loved it. "

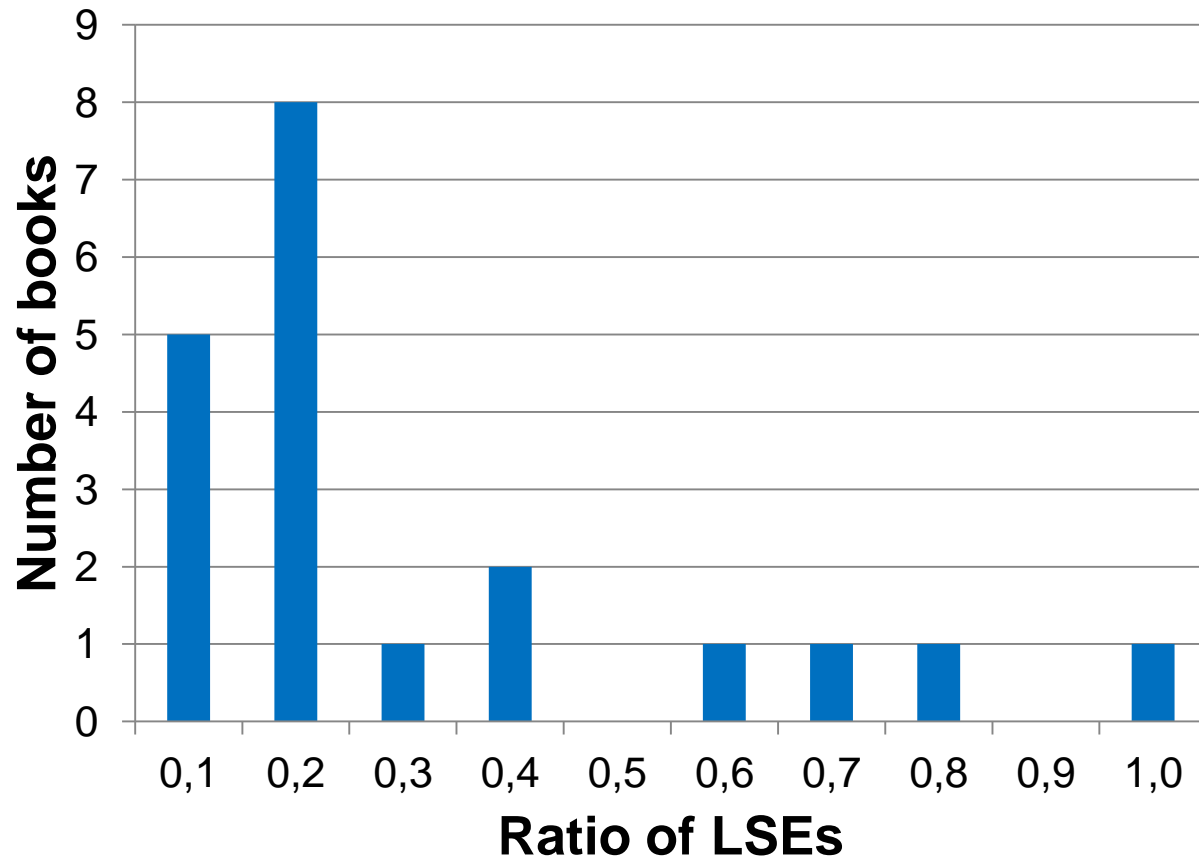
5 minutes ago · comment · see review

Experiment Design

- Adopting a book \cong **writing review** on it.
- Review data was collected for 73 popular books.
- Period: 05/2007 to 02/2011 (45 months).
- Filter out books with review data spans < 30 months
→ **20** books remain (Harry Potter 7, Breaking Dawn, ...).
- Evaluation metric: ratio of **model-fitting errors** (LSE of **MLIM** over LSE of **BM**)
→ less than 1 shows improvement of our model.

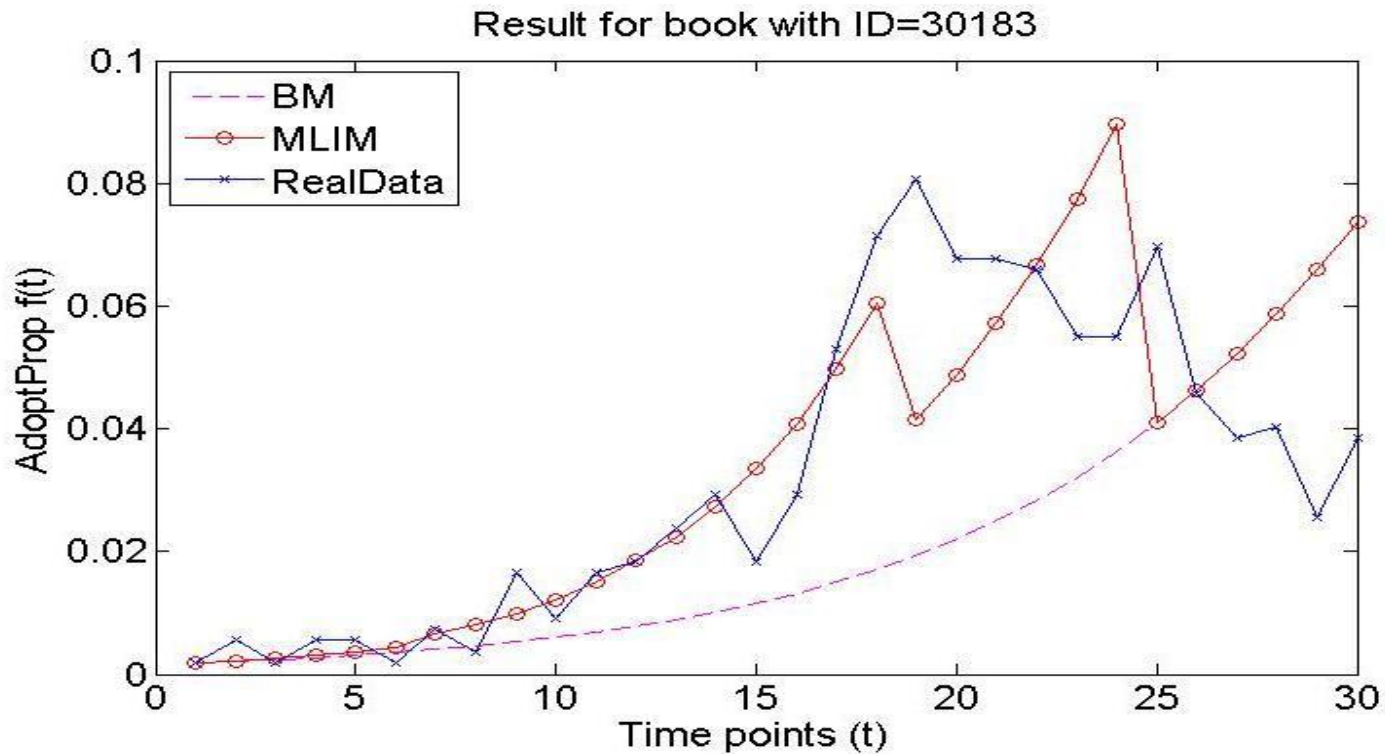
Special thanks to Agus and Anh.T.H

Results for Top-20 Popular Books



- MLIM outperforms BM for **all** top-20 popular books.
- **75%** of books have error ratios less than $\frac{1}{2}$.

Zoom-in for One Book



Fitting result for *City of Ashes* by Cassandra Clare

MLIM provides **significant** improvement over BM in terms of fitting data.

Conclusion

- This work:
 - Proposed two models **SLIM**, **ELIM** for diffusion in **scale-free** and **exponential** networks respectively.
 - Proposed multi-stage model (**MLIM**) to deal with **dynamic** degree distribution.
- Future works:
 - Derive a more rigorous way to deal with dynamic degree distribution.
 - Replace linear influence by other (e.g. **quadratic**, **exponential**) influence?
 - Examine the effect of **other network quantities** on diffusion.



Thank You!

More Formulae

Adoption prob. for scale free and exponential network

$$P_{sf}(a_t | \bar{A}_t) = w_e \cdot p_e + (1 - w_e) \cdot \frac{\zeta(\alpha - 1)}{\zeta(\alpha)} \cdot c \cdot F_t$$

$$P_{exp}(a_t | \bar{A}_t) = w_e \cdot p_e + (1 - w_e) \cdot \frac{e^{-1/\lambda}}{1 - e^{-1/\lambda}} \cdot c \cdot F_t$$

Formulae of SLIM, ELIM

$$F_{SLIM}(t) = \frac{\exp[(p + q_{SLIM}) \cdot t] - 1}{\exp[(p + q_{SLIM}) \cdot t] + (q_{SLIM} / p)}$$

where $p = p_e \cdot w_e$ and $q_{SLIM} = (1 - w_e) \cdot \frac{\zeta(\alpha - 1)}{\zeta(\alpha)} \cdot c$

$$F_{ELIM}(t) = \frac{\exp[(p + q_{ELIM}) \cdot t] - 1}{\exp[(p + q_{ELIM}) \cdot t] + (q_{ELIM} / p)}$$

where $p = p_e \cdot w_e$ and $q_{ELIM} = (1 - w_e) \cdot \frac{e^{-1/\lambda}}{1 - e^{-1/\lambda}} \cdot c$