Competition over Timeline in Social Networks

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Overview

Outline

Social Networks to Content Networks

- Popular Online Social Networks (OSN): Facebook, Twitter, Google+
- Massive userbase: Facebook (1 billion), Google+ (500million), Twitter (300million)

[1] Source: The New York Times

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  - Content could be news articles, photos, videos, etc.
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  - Content could be news articles, photos, videos, etc.
  - Users need not own the content
- Services like Reddit, Digg, Twitter serve as the *Pulse of the Internet*[1]

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Timelines on Social Networks

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  - Reverse chronological - latest entries pushing out older entries
  - Much akin to an email inbox
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- Google+, So.cl(Microsoft) employ parallel timelines
- Recently, OSNs also sort the entries according to user preference
  - Priority Inbox, Facebook's EdgeRank, etc.

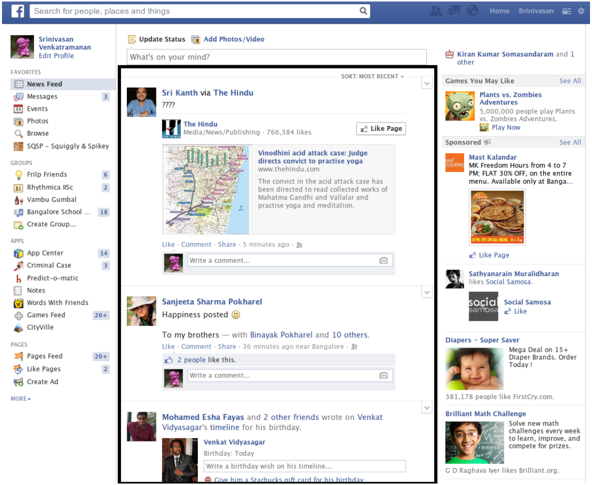

Figure: Facebook NewsFeed

Source: images.google.com

Traditional Online Advertising

- Advertising: the backbone of Internet economy
- Traditional online ads: Sponsored search slots, Featured links, Banner ads
  - Consumers are becoming more immune to traditional advertising
  - Ads cannot be shared to our social circle

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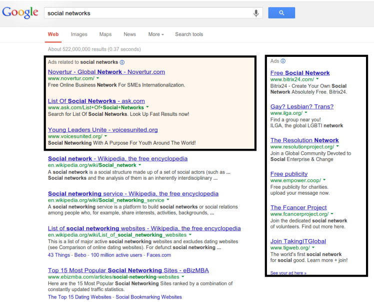

Figure: Sponsored search results

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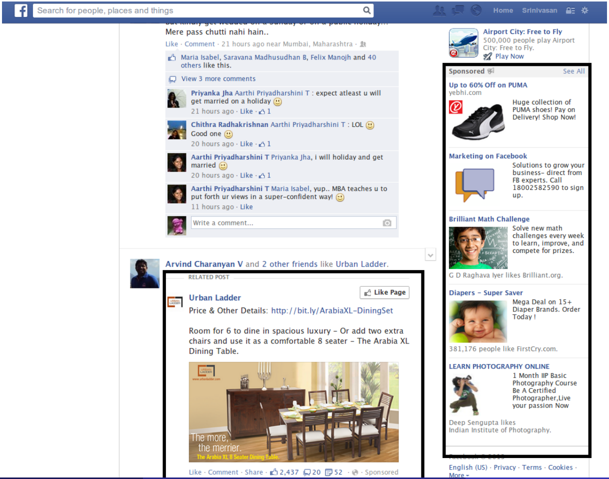

Limited User Attention

- User attention is scarce
- Most precious resource in the Internet
- Justifies assumption of moderate sized timelines ($\sim 10 - 100$)

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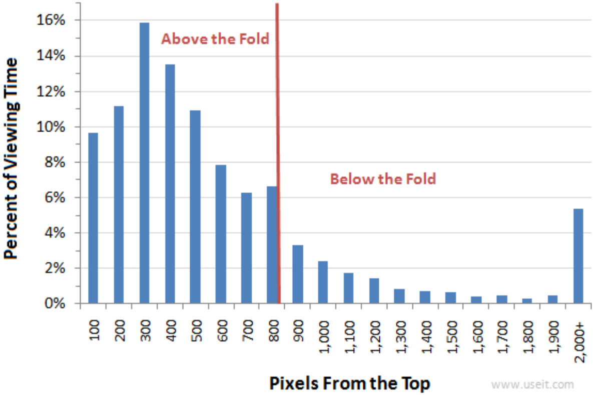

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Literature Survey

- Economy of user attention
  - Models on dynamic collection attention to novel items[6]
  - Interaction between multiple contagions [7]

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- Competition between content creators for timeline space needs to be analytically modeled

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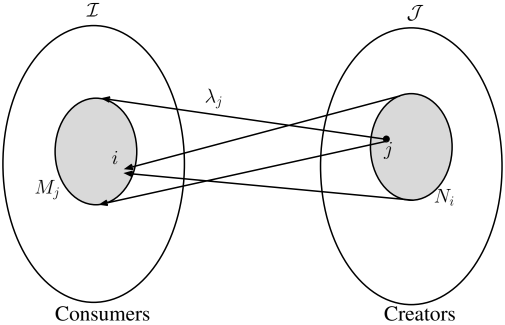
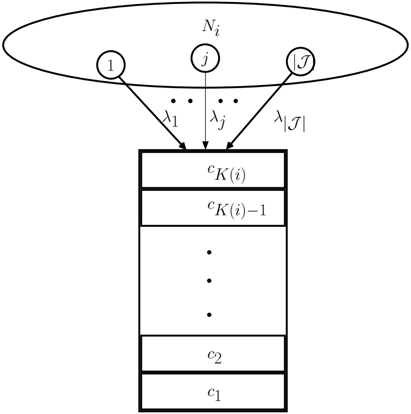
Network Model Description

- Bipartite graph between $\mathcal{J}$ content creators and $\mathcal{I}$ users
  - Content creators don't consume or share competing content
- Simplifying assumptions
  - All users follow all content creators
  - Absence of content sharing among users



Timeline Model

- Reverse chronological timeline of size $K(i)$
- Content j generated at points of a Poisson process of rate λ_j
- $\Lambda := \sum_j \lambda_j$, $\Lambda_{[-j]} := \sum_{l \neq j} \lambda_l$



User i's timeline

Outline

Timeline Evolution

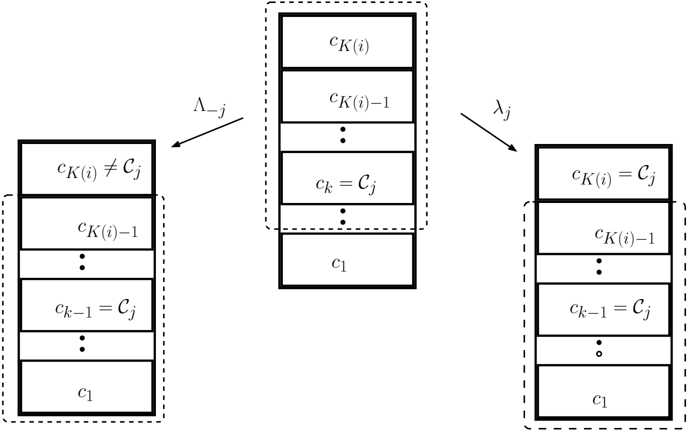


Figure: Evolution of a single user's timeline

Occupancy distribution

We model the timeline as a continuous time Markov chain (CTMC) $\mathbf{C}(t)$, the vector of contents that occupy the K(i) locations in the timeline of i at time t.

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Theorem

The stationary probability distribution for the CTMC $\mathbf{C}(t)$ is given by,

$$\pi_{\mathbf{c}} = \Pi_{k=1}^{K(i)} \frac{\lambda_{c_k}}{\Lambda} \tag{1}$$

where c_k is the content at the kth position on the timeline.

Expected ij-busy period

Define the *ij-busy period*, as the duration for which *j*'s content is present in user *i*'s timeline. Let $\alpha_j = \frac{\Lambda_{[-j]}}{\Lambda}$

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$$E[T_{ij}(K(i))] = \frac{1}{\Lambda_{[-j]}} \left(\frac{1 - \alpha_j^{-K(i)}}{1 - \alpha_j^{-1}} \right) \tag{2}$$

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Recursive Equation:

$$E[T_{ij}(0)] = 0,$$

$$E[T_{ij}(k+1)] = \frac{1}{\Lambda} + \frac{\lambda_j}{\Lambda} E[T_{ij}(K(i))] + \frac{\Lambda_{[-j]}}{\Lambda} E[T_{ij}(k)]$$

Probability of finding content j

Define p_{ij} to be the probability of finding content j in user i's timeline at any time t

$$p_{ij} = \frac{E[T_{ij}(K(i))]}{E[T_{ij}(K(i))] + 1/\lambda_j} = 1 - \alpha_j^{K(i)} \tag{3}$$

Recall: $\alpha_j = \frac{\Lambda_{[-j]}}{\Lambda}$
Note that for $K(i) = 1$, $p_{ij} = \lambda_j/\Lambda$.

Outline

Game description

- **Players**: Content creators $j \in \mathcal{J}$, $|\mathcal{J}| = N_i$
- **Strategies**: $\lambda_j \in [\phi, \infty)$, $\forall j \in \mathcal{J}$
- **Utility of player** j: $W_j^i := p_{ij} - \gamma_j \left(\lambda_j - \phi\right)$

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Optimization problem

$$\begin{array}{rl} \textbf{max} & 1 - \alpha_j^{K(i)} - \gamma_j \left(\lambda_j - \phi\right) \\ \textbf{s.t.} & \lambda_j \geq \phi \end{array}$$

Best response solution

We seek the Nash equilibrium rates $(\lambda_j, j \in \mathcal{J})$ of this game.

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Lagrangian relaxation

$$L_j^i = 1 - \alpha_j^{K(i)} - \gamma_j \left(\lambda_j - \phi\right) + \beta_j \left(\lambda_j - \phi\right)$$

The *Best response* rate for content creator j is given by

$$\lambda_j = \Lambda \left[1 - \left(\frac{\gamma_j \Lambda}{K(i)}\right)^{\frac{1}{K(i)}}\right] \tag{4}$$

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Theorem

In a symmetric game ($\gamma_j = \gamma, \forall j \in \mathcal{J}$), at equilibrium each player sends either

$$\lambda_j = \frac{K(i)}{\gamma} \frac{(N_i - 1)^{K(i)}}{N_i^{(K(i)+1)}} \tag{5}$$

or ϕ, whichever is larger.

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  - Can be extended to model user-generated content

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Best Response, $\forall j \in \mathcal{J}_1$,

$$\begin{aligned} \lambda_j &= (N_i(1)\lambda_j + (N_i - N_i(1))\phi_2) \cdot \\ & \left[1 - \left(\frac{\gamma_j (N_i(1)\lambda_j + (N_i - N_i(1))\phi_2)}{K(i)} \right)^{\frac{1}{K(i)}} \right] \end{aligned} \tag{6}$$

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Numerical Study

- We study the behavior of equilibrium rate λ_j for various values of N_i (number of content creators) and $K(i)$ (timeline size)

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  - Critical value of K for which equilibrium rate is maximized
  - For the symmetric game, $K^* = N$, i.e., competition is maximum when $N_i = K(i)$

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- A similar behavior is observed for fixed K and varying N
- Equilibrium rate increases linearly with fraction of competing players

Effect of K

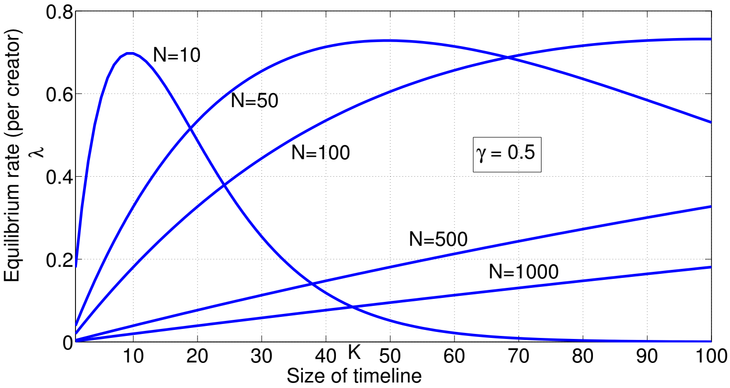

Figure: Variation of equilibrium rate λ against $K(i)$ for $N_i = 10$, 50, 100, 500, 1000.

Effect of N

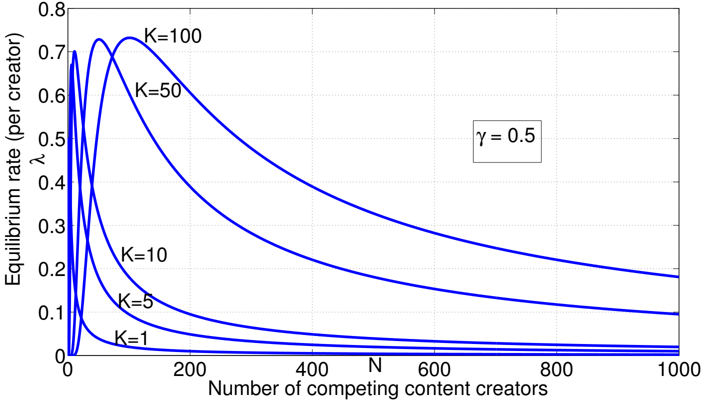

Figure: Variation of equilibrium rate λ against N_i for $K(i) = 1, 5, 10, 50, 100$.

Effect of Partial Competition

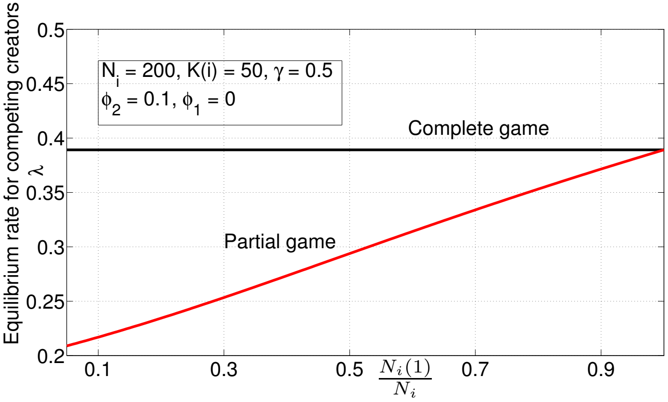

Figure: Variation of equilibrium rate λ for the partial control game setting for various values of $\frac{N_i(1)}{N_i}$, the fraction of competing players.

Outline

Summary

- Importance of **characterizing competition on timeline** based social networks
- Modeled occupancy of a single user's timeline using **queueing** techniques
- Characterized competition using a **non-cooperative game** among content creators
- Studied effect of system parameters in cases of complete and partial competition

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- More general social graph
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  - Social network characterized by degree distribution
- Incorporating datasets from Digg, Twitter

Future Work

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- User-generated content: can be treated as noise
- Varying levels of user activity (timeline size, login frequency)
- Role of social network: Revenue maximization
- Social utility for each user: how useful is the information I receive?
- Are timelines the best way to show contents to users?

Funding Organizations

- Project GANESH (funded by INRIA, France)
- Department of Science and Technology, Govt. of India

Thank you