Holistic Influence Maximization: Combining Scalability and Efficiency with Opinion-Aware Models

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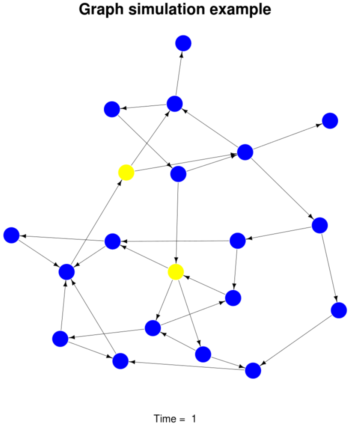
[1]The first two authors have contributed equally to this work.

Information Propagation[2]: Need for Modelling??

- Many real-world processes can be interpreted using concepts from information propagation
- For example: Spread of Diseases



[2]Propagation/Flow/Spread/Diffusion, would be used interchangeably

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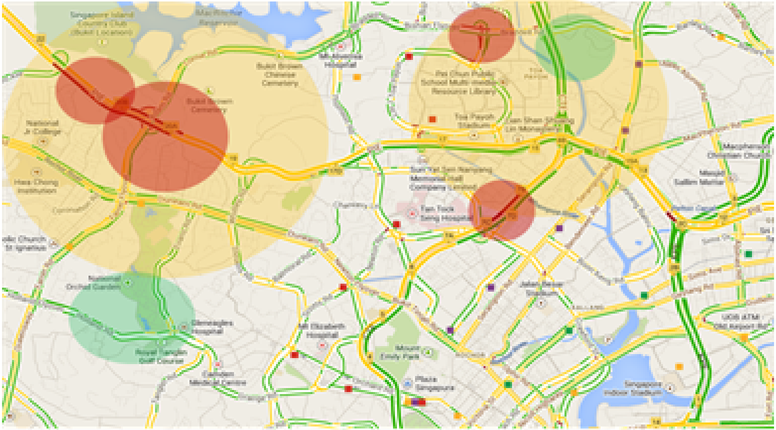

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- Independent Cascade (IC) and Weighted Cascade (WC) Models
- Linear Threshold (LT) Model
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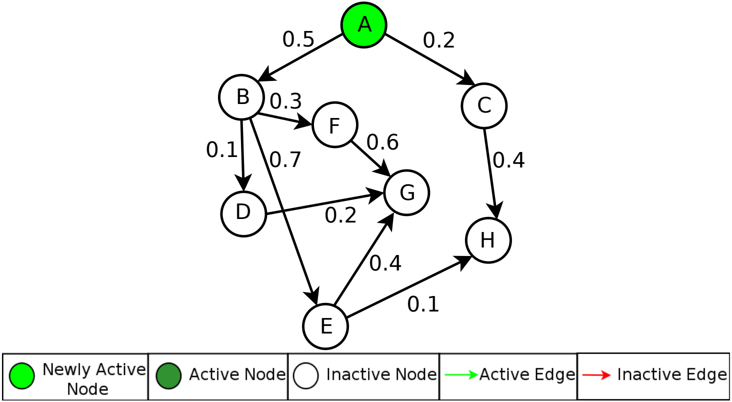

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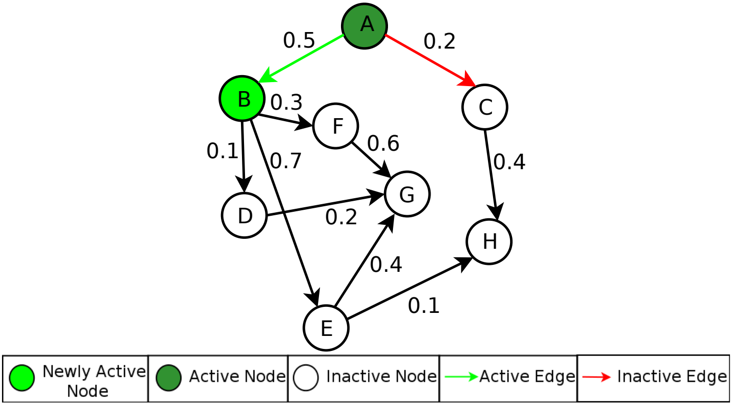

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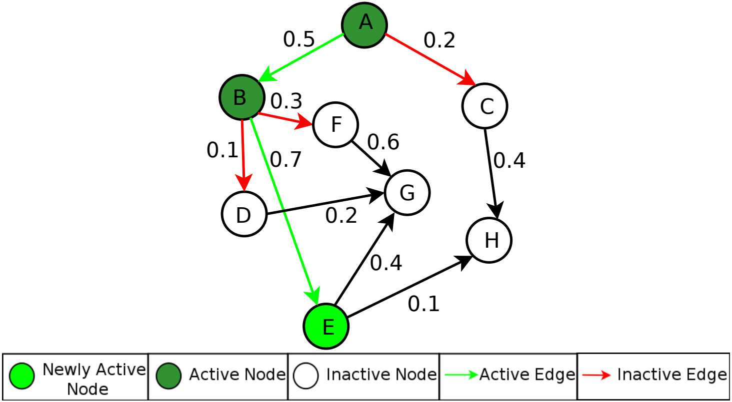

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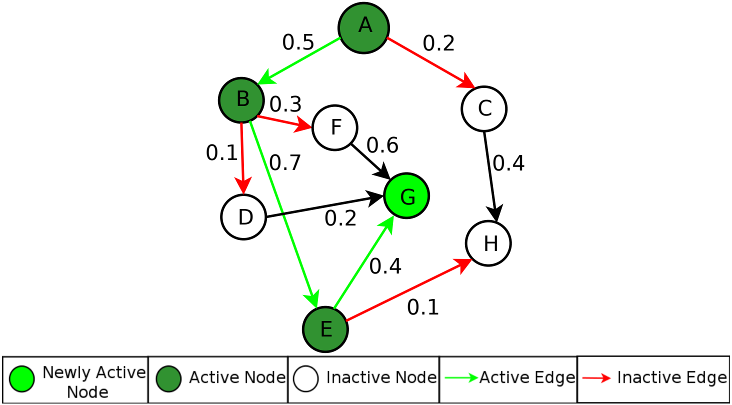
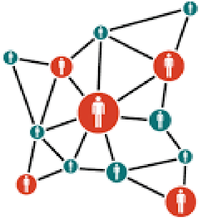


The Influence Maximization (IM) Problem



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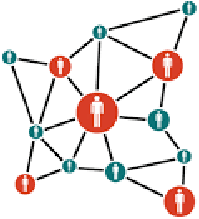

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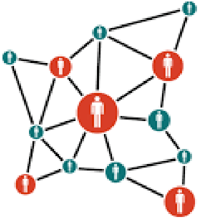

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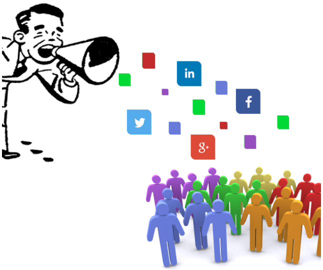
- Tractability: The IM problem is NP-hard. Need for Approximate Solutions!
- The spread function σ is Monotone and Submodular, thus, a simple GREEDY algorithm provides the best possible $(1 - 1/e)$ approximation

Real-world Applications[3]



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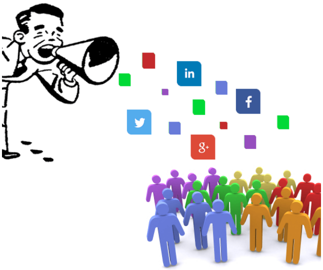

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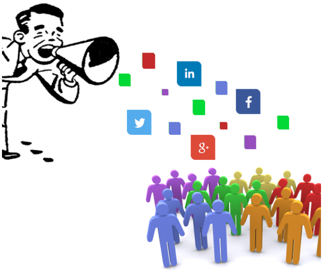

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  - Viral Marketing: Product/Topic/Event promotion
  - Managing Celebrity/Political campaigns
- Detect and Prevent Outbreaks/Epidemics/Rumours
- Many more . . .

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Contributions!

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- Seed Selection Algorithm:
  - Run-time efficiency and efficacy attributes have been extensively studied [KKT03, LKG+07, GLL11, BBCL14, TXS14, CDPW14]
  - However, scalable solutions (catering to both running-time and memory-consumption) are non-existent

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Contribution 2: Scalable algorithms – EaSyIM and OSIM

W14]

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Need for Opinion-Aware IM

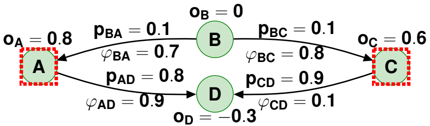

Figure: ***A sample representation of the Twitter network.***

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Need for Opinion-Aware IM

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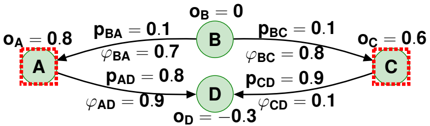

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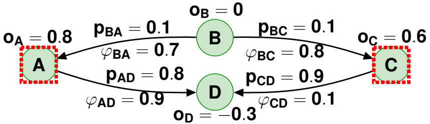

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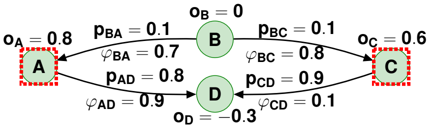

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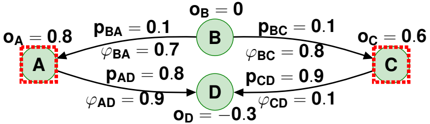

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Opinion-cum-Interaction (OI) Model

- Second layer on the top of IC/WC and LT to model the propagation and change of opinion
- Models Opinion Spread – The contribution of a newly activated node can be signed
- Two components – opinion ($o_v \in [-1, 1]$) and interaction ($\varphi_{(u,v)} \in [0, 1]$)

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- Interaction probabilities (directed), between two nodes, can be estimated by accounting for all of their possible interactions in the past
- Effective opinion (o'_v) of an activated node v is dependent upon both, its personal opinion o_v and the effective opinion (o'_u) of all the nodes $u \in V_{(a)}$ (set of nodes activated at previous steps)

The Opinion Maximization (MEO) Problem

Opinion Spread

Sum of opinions of the users in the activated set, when S is the chosen seed set

Effective Opinion Spread

Weighted difference between the opinion spread of the users with positive polarity and the opinion spread of negatively polarised users, in the set of activated nodes.

- Task: Identify the set of most-influential nodes
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- Result: The opinion spread function σ^o is neither monotonous nor submodular, thus, approximating MEO within any constant ratio is not possible (Proof in the paper)

Outline of our approach

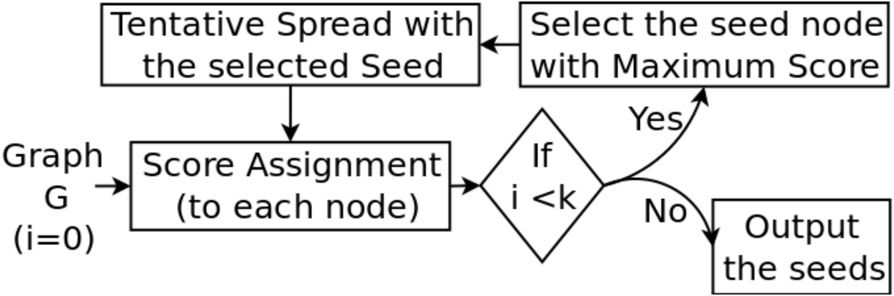

Figure: *Overview of our algorithm*

Seed Selection Algorithms: Intuition

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- Paths of length l from a node u can be calculated as the sum of all paths of length $l-1$ from its neighbors
- $\Delta^l(u)$ ($\forall u \in V$) is defined as the weighted sum of the number of simple paths of length at most (l) starting from u
- Path length $l \leq \mathcal{D}$ (diameter) of the graph is a parameter to control accuracy
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This algorithm can easily be extended to opinion-aware settings (OSIM)

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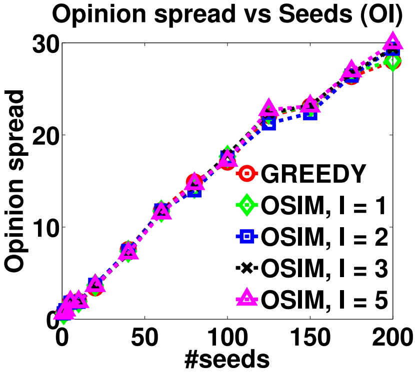
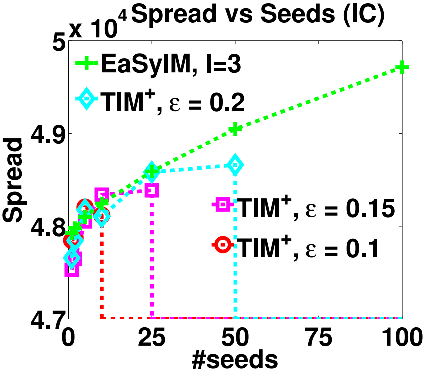
Analysis

- Time Complexity for score assignment – $O((m+n)l)$
- Time taken by EaSyIM/OSIM for selecting k seeds – $O(k(m+n)l)$
- Memory Complexity – $O(n)$
- Approximation Guarantee same as [KKT03] for trees under the IC/WC model and DAGs under the LT model

Quality

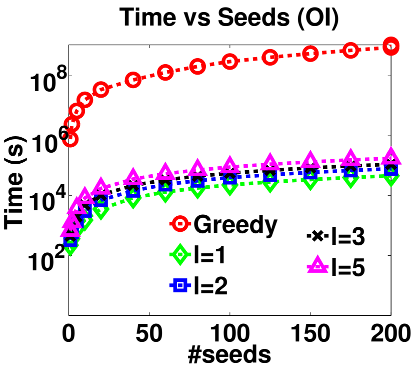


(a) NetHept

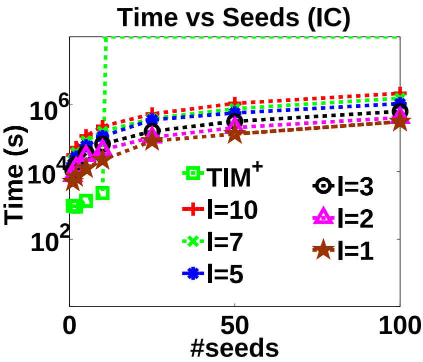


(b) DBLP

Efficiency: Running Time

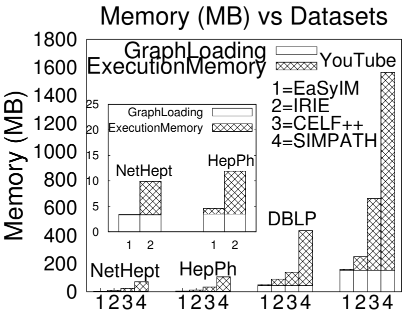


(c) NetHept OI

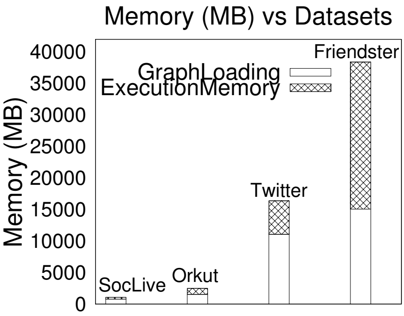


(d) DBLP IC

Scalability: Memory Consumption



(e) EaSyIM: Medium Data



(f) EaSyIM: Large Data

Scalability: SNAP Datasets – Challenges

Dataset	n	m	Type	Avg. Degree	Diameter
NetHEPT	15K	62K	Undirected	4.13	10
HepPh	12K	118K	Undirected	9.87	5.8
DBLP	317K	1M	Undirected	3.3	8
YouTube	1M	3M	Undirected	2.63	6.5
SocLiveJournal	5M	65M	Directed	14.23	6.5

Dataset	**Running Time (min)**			**Memory (MB)**		
	CELF++	**EaSyIM**	**Gain**	**CELF++**	**EaSyIM**	**Gain**
NetHEPT	5352.25	118	**45.35x**	23.26	3.39	6.86x
HepPh	9746.74	230	**41x**	24.60	3.47	7.08x
DBLP	NA	5071.67	**∞**	NA	44.73	∞

Dataset	**Running Time (min)**			**Memory (MB)**		
	TIM$^+$	**EaSyIM**	**Gain**	**TIM$^+$**	**EaSyIM**	**Gain**
DBLP	783.1	2183	0.36x	35234.75	46.5	**758x**
YouTube	NA	5089.5	∞	NA	158.3	∞
socLive	NA	15433.33	**∞**	NA	974.94	∞

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- First work to propose a holistic solution
  - Realistic and generic information propagation models and optimization objectives
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Questions?
Answers!

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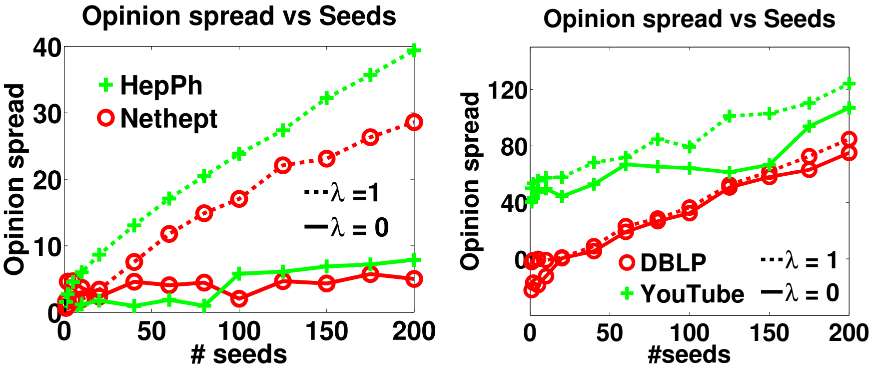
- Election/Celebrity campaigns can get affected
- Why not maximize the difference?
- More specifically, Maximize $|\mathbb{F}^{+}(S) - \lambda \times \mathbb{F}^{-}(S)|$, $\lambda \in [-1, 1]$

Optimization Objectives



(g) NetHept and HepPh

(h) DBLP and YouTube

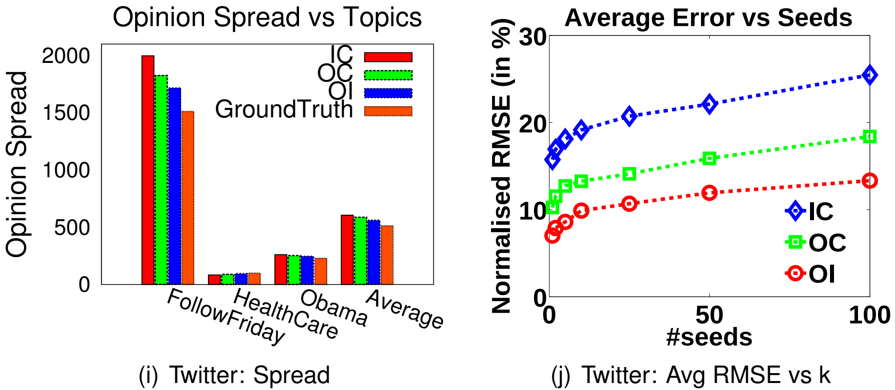
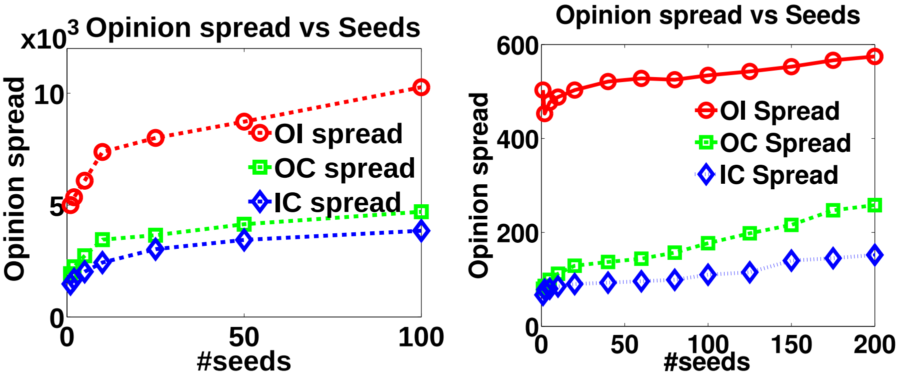


Figure: ***Comparing opinion-spreads under OI, OC and IC with the real-world opinion-spread.***



(a) Twitter (b) PAKDD

Figure: ***Comparing OI with OC and IC: Opinion spread vs k.***

References I

Christian Borgs, Michael Brautbar, Jennifer Chayes, and Brendan Lucier.
Maximizing social influence in nearly optimal time.
In *SODA*, pages 946–957, 2014.

Edith Cohen, Daniel Delling, Thomas Pajor, and Renato F. Werneck.
Sketch-based influence maximization and computation: Scaling up with guarantees.
In *CIKM*, pages 629–638, 2014.

Amit Goyal, Wei Lu, and Laks V.S. Lakshmanan.
Celf++: Optimizing the greedy algorithm for influence maximization in social networks.
In *WWW (Companion Volume)*, pages 47–48, 2011.

David Kempe, Jon Kleinberg, and Éva Tardos.
Maximizing the spread of influence through a social network.
In *KDD*, pages 137–146, 2003.

Jure Leskovec, Andreas Krause, Carlos Guestrin, Christos Faloutsos, Jeanne VanBriesen, and Natalie Glance.
Cost-effective outbreak detection in networks.
In *KDD*, pages 420–429, 2007.

Youze Tang, Xiaokui Xiao, and Yanchen Shi.
Influence maximization: Near-optimal time complexity meets practical efficiency.
In *SIGMOD*, pages 75–86, 2014.