香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Efficient Influence Maximization in Social Networks

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Wei Chen, et al, “Efficient Influence Maximization in Social Networks”, KDD09’

OUTLINE

- Problem
- Previous Work
- Degree Discount Heuristics
- Summary
- References

Problem Statement

- Find a small subset of nodes in a social network that could maximize the spread of influences.
- Known as *Influence Maximization*
- A.k.a *Viral Marketing* which makes use of "word-of-mouth marketing" properties of social network

Problem Statement

- Optimization problem first introduced by Domingos and Rechardson, KDD01'/02', *NP-hard to solve*

- Elegant graph formulation introduced by Kempe, et al, KDD03'

Given:

- ✓ A graph G(V, E):
  - --Vertices: individuals in social network
  - --Edges: connection or relationship
- ✓ k, size of output seeds
- ✓ A cascade model: LTM, ICM

Output:

S, a set of seeds (nodes) that maximize the expected number of nodes active in the end

Problem Statement: Cascade Model

- Models how influences propagate
- Linear Threshold Model *(LTM)*
- Independent Cascade Model *(ICM)*
- … …
- Analogous to Epidemic Models like SIS, SIR

Linear Threshold Model

- A node *u* has random threshold $\theta_u \sim U[0,1]$

- A node *u* is influenced by each neighbor *v* according to a *weight* b_{uv} witch satisfies:

$$\sum_{\text{v neighbor of u}} b_{u,v} = 1$$

- A node *u* becomes active when at least θ_u fraction of its neighbors are active

$$\sum_{\text{v active neighbor of u}} b_{u,v} \geq \theta_u$$

Independent Cascade Model

- When node *u* becomes active, it has a *single* chance of activating each currently inactive neighbor *v.*

- The activation attempt succeeds with probability p_{uv} .

- In both LTM and ICM, active nodes never deactivate.

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Previous Work: “Maximizing the Spread of Influence Through a Social Network”,KDD03’

- Proposed by D.Kempe, J.Kleinberg and E.Tardos

- Greedy hill-climbing algorithm:

  In each round add a vertex v^* into S such that v^* and S maximize the influence spread f:

$$v^* = arg \max_{v} f(S+v) - f(S)$$

- Monte Carlo:

  Influence spread is estimated with R repeated simulations

- Effectiveness:

  Can guarantees a solution with (1 – 1/e) of the optimal

- Drawback:

  poor efficiency, 15,000 nodes takes a few days to compete

Previous Work:
"Cost-effective Outbreak Detection in Networks", KDD07'

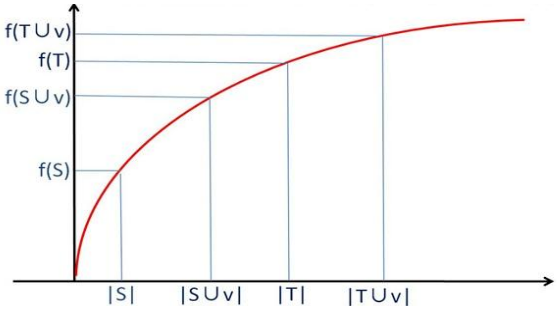
- Proposed by J. Leskovec, A. Krause, et al

- Cost-effective Lazy Forward algorithm:

The CELF optimization utilizes submodularity of influence spread function to greatly reduce the number of evaluations of vertices, and get the same performance as the original greedy algorithm.

- Submodularity:

$$\forall S \subset T \subset N, \forall v \in N \setminus T,$$
$$f(S+v) - f(S) \geq f(T+v) - f(T)$$



- Efficiency:

approximately 700 times fast than original greedy algorithm, but still hours to finish.

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Degree Discount Heuristics

- Proposed by W.Chen, Y.Wang , S.Yang from MSRA and Tsinghua

- High Efficiency:

  Amazingly reduces the running time by over *six orders* of magnitude with *less than 3.5%* degradation in performance.

- Motivation:

  Conventional degree/centrality based heuristics perform poorly in practical scenarios because they *ignore the network effect*.

  Important Fact: Since many of the most central nodes may be clustered, targeting all of them is not at all necessary.

Degree Discount Heuristics

- **Basic Idea**

Consider edge $\overline{uv}$, with *u* in the seed set S and *v* being considered. Since *u* is in the seed set, by taking network effect into consideration, we should not count edge $\overline{uv}$ towards v's degree. i.e. Degree Discount

- **Assumption**

In ICM, when propagation probability *p* is small, we may ignore indirect influence of *v* to multi-hop neighbors and focus on the *direct influence* of *v* to its immediate neighbors.

Remarks : Is this assumption still reasonable when k is small ? Or when neighbor overlapping is prominent?

Degree Discount Heuristics

- ## Degree Discount Model:

  t_v -- number of *v*'s neighbors that in seed set *S*

  d_v-- degree of node *v*

✓ Probability that v is influenced by its immediate neighbors: $1 - (1 - p)^{t_v}$
in such case, selecting v dose not contribute additional influence.

✓ Probability that v is not influenced by its immediate neighbors: $(1 - p)^{t_v}$
in such case, selecting v will in expectation influence $1 + (d_v - t_v) * p$ vertices.

So that the *expected number of additional vertices influenced by selecting v as seed* is:

$$[1 - (1 - p)^{t_v}] * 0 + [(1 - p)^{t_v}] * [1 + (d_v - t_v) * p]$$
$$= \left(1 - t_v * p + o(p)\right) * (1 + (d_v - t_v) * p)$$
$$\cong 1 + (d_v - 2t_v - (d_v - t_v) * t_v * p) * p \triangleq A$$

If no neighbor of *v* is selected as seed, the answer above is $1 + d_v * p \triangleq B$

Let γ be the degree discount caused by each neighbor in seed set, then

$$\gamma * t_v * \mathrm{p} = \mathrm{B} - \mathrm{A}$$
$$\gamma = 2 + (d_v - t_v) * p$$

Degree Discount Heuristics

- Algorithm:

Algorithm 4 DegreeDiscountIC(G, k)

initialize $S = \emptyset$
for each vertex v **do**
  compute its degree d_v
  $dd_v = d_v$
  initialize t_v to 0
end for
for $i = 1$ to k **do**
  select $u = \arg\max_v \{dd_v \mid v \in V \setminus S\}$
  $S = S \cup \{u\}$
  for each neighbor v of u and $v \in V \setminus S$ **do**
    $t_v = t_v + 1$
    $dd_v = d_v - 2t_v - (d_v - t_v)t_v p$
  end for
end for
output S

Degree Discount Heuristics

- Evaluations on NetHEPT:

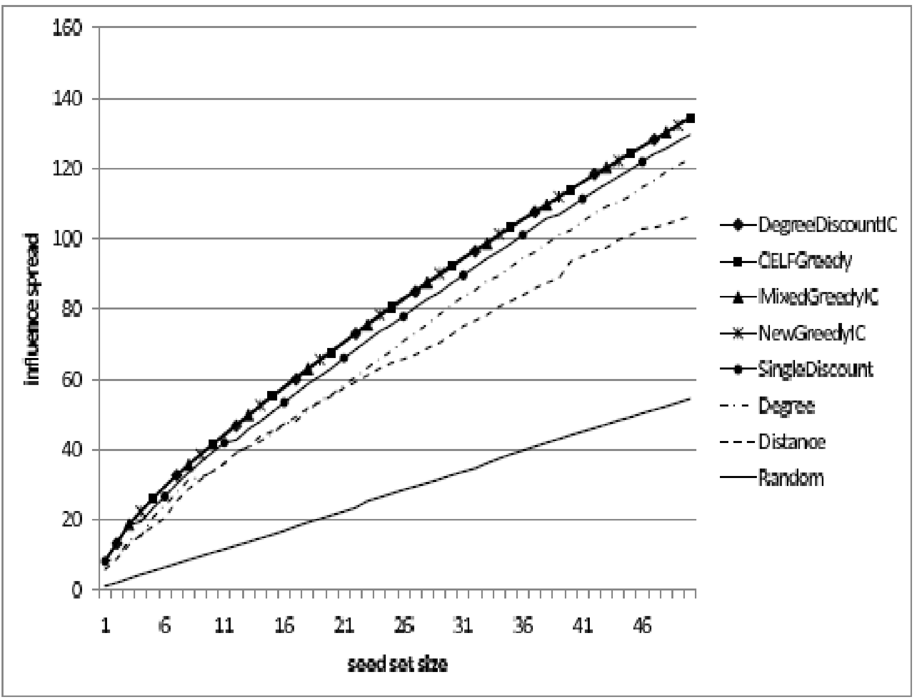

Figure 1: Influence spreads of different algorithms on the collaboration graph NetHEPT under the independent cascade model ($n = 15,233$, $m = 58,891$, and $p = 0.01$).

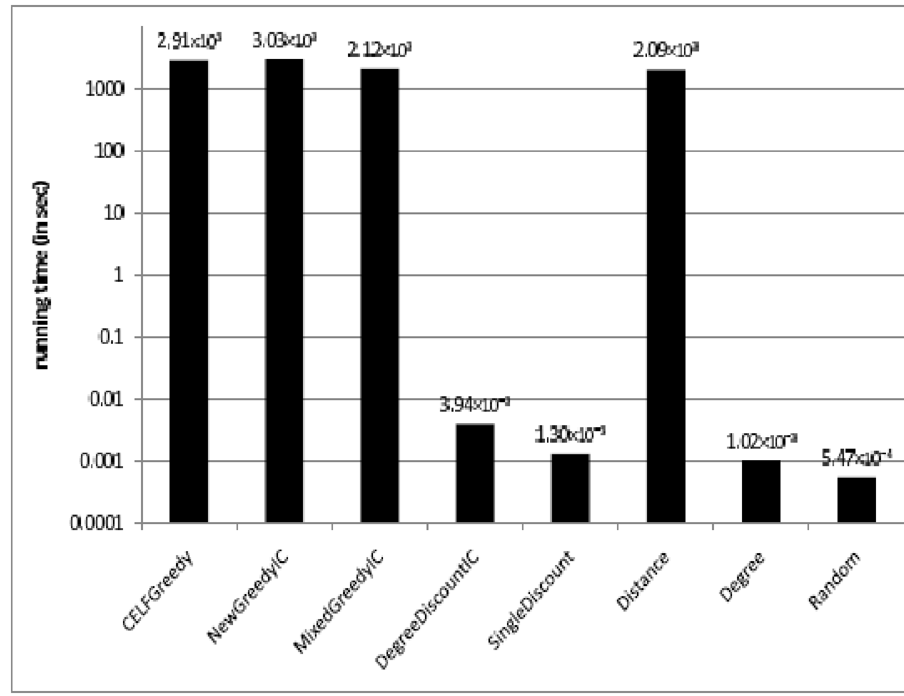

Figure 3: Running times of different algorithms on the collaboration graph NetHEPT under the independent cascade model ($n = 15,233$, $m = 58,891$, $p = 0.01$, and $k = 50$).

Degree Discount Heuristics

- Evaluations on NetPHY:

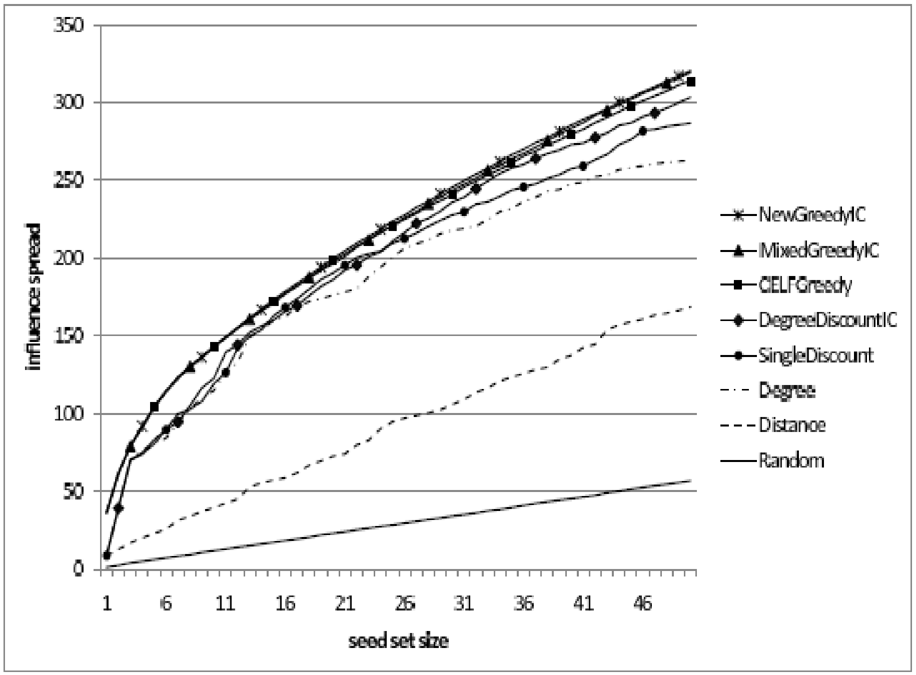

Figure 2: Influence spreads of different algorithms on the collaboration graph NetPHY under the independent cascade model ($n = 37,154$, $m = 231,584$, and $p = 0.01$).

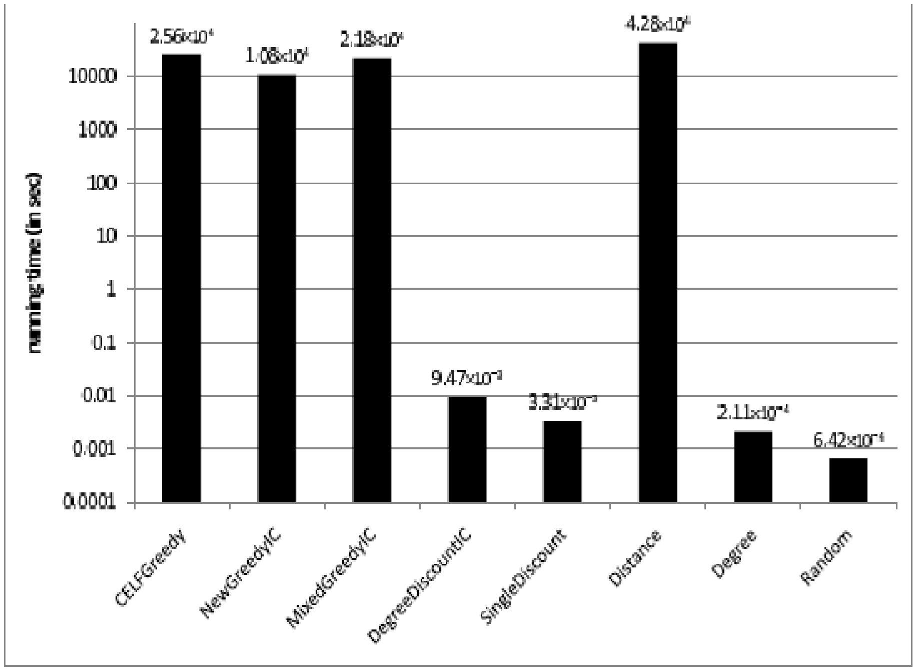

Figure 4: Running times of different algorithms on the collaboration graph NetPHY under the independent cascade model ($n = 37,154$, $m = 231,584$, $p = 0.01$, and $k = 50$).

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Summary

- The current influence maximization problem is simplified, without considering other features in social networks, such as community structures and small-world phenomenon.

- The author suggests that we should focus our research efforts on searching for more effective heuristics for different influence cascade model in real life influence maximization anpplications

- More sophisticated heuristics are promising, such as taking into consideration multiple links between nodes, higher-order influences, cross-neighborhood structure…

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- *D. Kempe, J. Kleinberg and E. Tardos, “Maximizing the Spread of Influence through a Social Network”, KDD 2003*

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Thank you !