INFLUENCE IN NETWORKS

M. Vazirgiannis
École Polytechnique
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Outline

- Introduction
- Identifying Influential Spreaders
- Simulating Information Diffusion
- Influence Maximization

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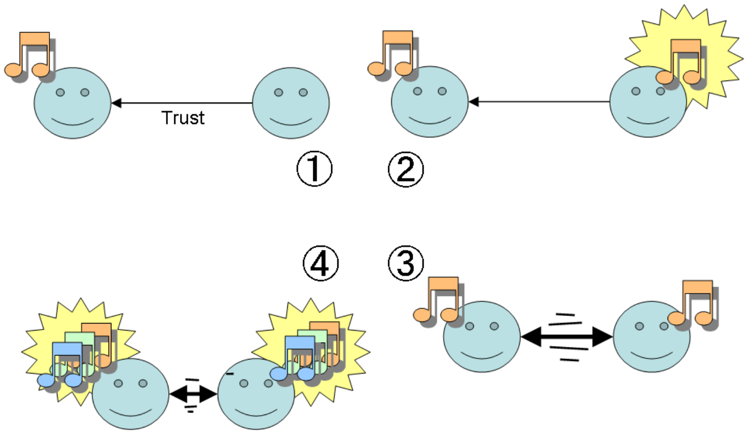
Influence and Information Diffusion

Social Influence



[Matsuo et al. WWW'09]

Example: Large Scale Behavioral Change

- Can someone use online social networks to shape a massive behavioral change?
- 61M users on Facebook [RM. Bond et al, 2012]

- Users split in three randomized groups
- A simple post was used to motivate voting
- Users could claim they voted by pressing “I voted” and access further information about the elections

Example: Large Scale Behavioral Change

- Simple message :the message included the count of FB users who reported they voted.

- Social message : The message included a list of the users’ friends that have also voted.

- Control group : no message.

Example: Large Scale Behavioral Change

- Validated real world impact using public voting records
- Users who received the social message were more likely to click “I voted” then users with the simple message
- The “closer” the friend, the higher the difference in voting
- Friends of users who received the social message were more likely to vote then friends of users with no message

Influence and Information Diffusion

Applications:

- Viral Marketing
- Political Campaigns
- News and rumor spreading
- Opinion shaping
- Epidemiology and virus propagation
- “Friends” recommendation

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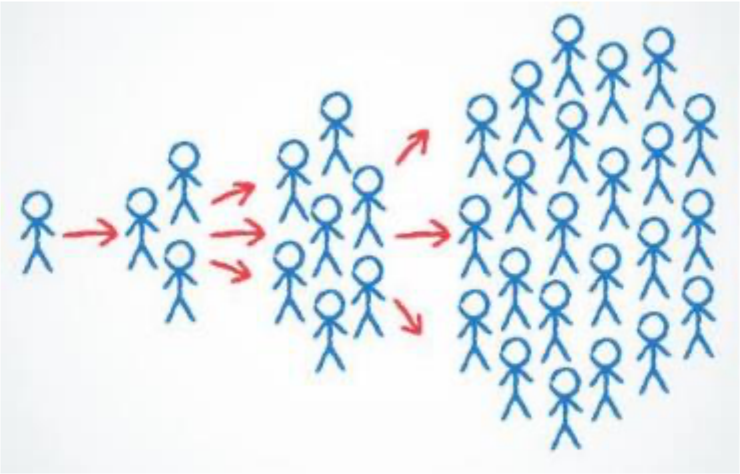
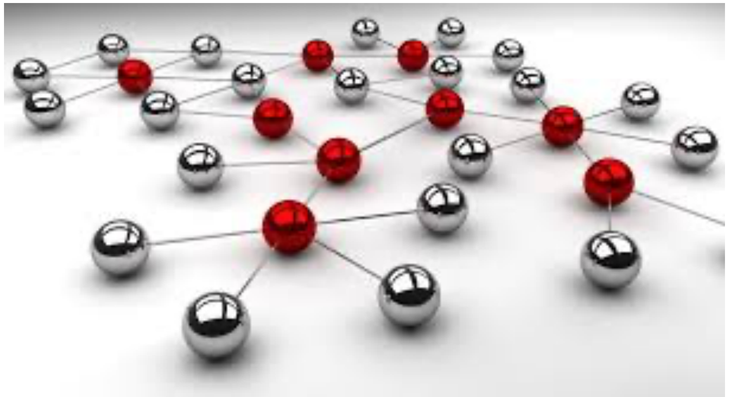
Identifying Influential Spreaders

- Locate “influencers” that broadcast information in a network
- Each of them can effect a substantial amount of other nodes
  - The effect can extend far from the immediate neighbors
  - We need methods that take into account higher order connectivity

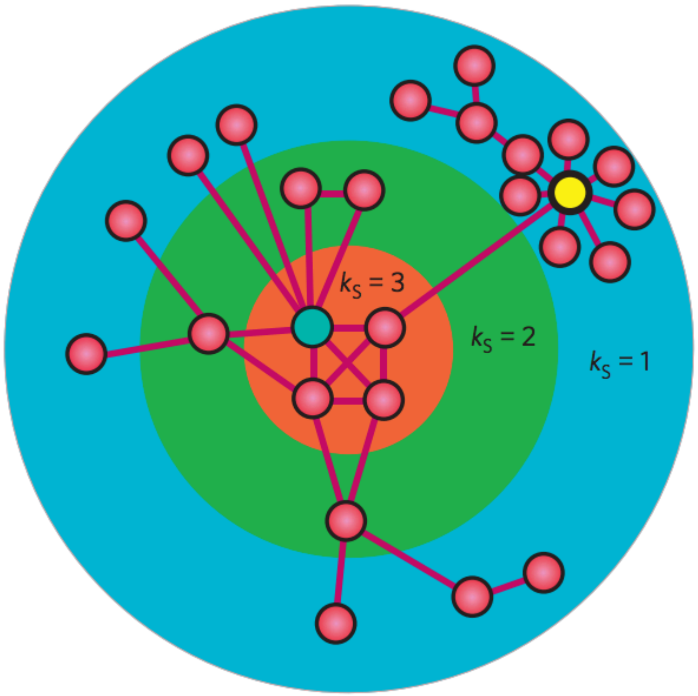




Identifying Influential Spreaders

- Degree
- Indegree
- Pagerank
- Closeness

- What if the node is well connected but in the periphery of the network?
  - Use K-core decomposition



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Diffusion Models

- Stochastic processes run over a directed graph where each node can be activated or not
- Once activated, a node cannot deactivate (does not apply to the epidemiological models)
- The diffusion proceeds iteratively in a synchronous way along a discrete time axis starting from a set of initially activated nodes

Linear Threshold

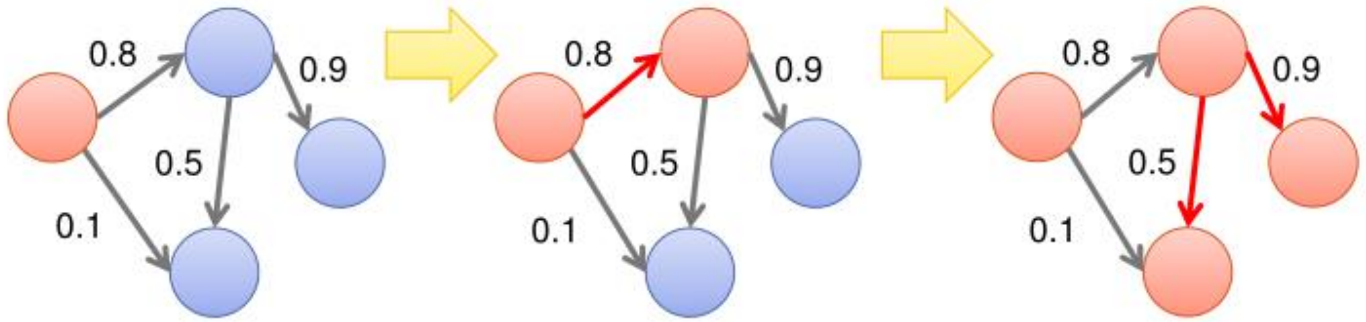
- Every edge $e=(u,v)$ has a weight $w_{u,v}$
- $\Sigma_u w_{u,v} \leq 1$
- Each node v has a threshold $\Theta_v \in [0,1]$
- At each step, for each node v we check

$$\sum_{u \in N(v)} w_u > \theta_v$$

and if so, it is activated

Independent Cascade

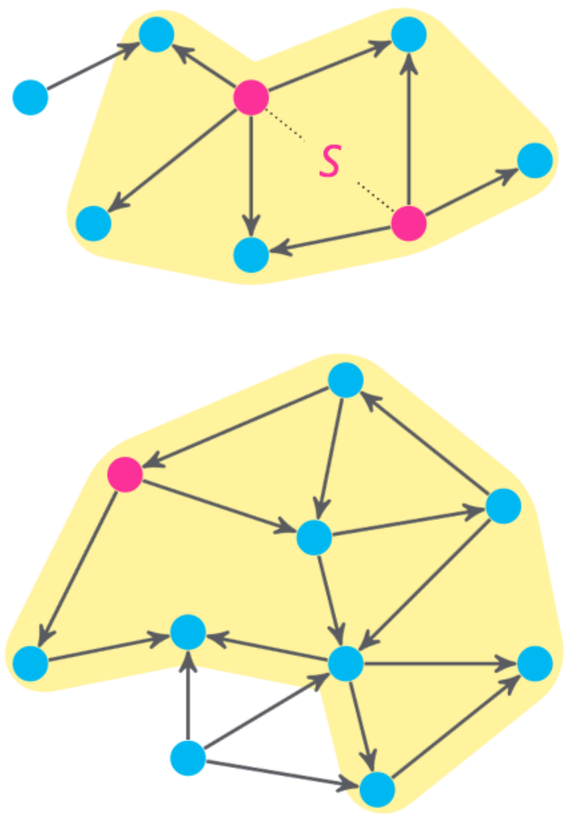
- Every edge $e=(u,v)$ has a propagation probability $p_{u,v}$
- At each step t, all the nodes u activated at $t\text{-}1$ activate their neighbor v with a probability $p_{u,v}$
- Each node has only <u>one chance</u> to activate its neighbor



David Kempe, Jon Kleinberg, and Éva Tardos. "Maximizing the spread of influence through a social network.” ACM SIGKDD,2003.

Influence Spread

- Influence Spread of a seed set: σ(S) = The expected number of nodes activated at the end of a diffusion process started from the nodes in S



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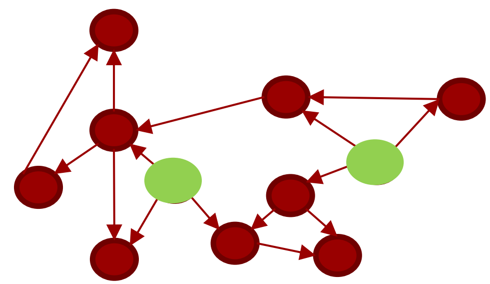
Influence Maximization

- Given
  - A directed network G(V,E)
  - A diffusion model (IC/LT)



- Find
  - S: A set of *K* nodes that would maximize spreading if diffusion started from them : $S^* = argmax_{|S| \leq k}\ \sigma(S)$
  - σ(S): Estimated total spreading

- The diffusion models have randomly assigned parameters

NP-Complete ☹

Monotonicity and Submodularity

Definition (Monotonicity)

The set function f is **monotone** if adding an element to a set cannot cause f to decrease :

$$\forall v \in V,\ \forall A \subseteq V,\ f(A \cup \{v\}) \geq f(A)$$

Definition (Submodularity)

The set function f is **submodular** if, for any $A \subseteq B \subseteq V$ and for any $v \in V \setminus B$, we have :

$$f(A \cup \{v\}) - f(A) \geq f(B \cup \{v\}) - f(B)$$

Greedy

- Iteratively, add in the seed set the node with the best marginal gain [Kempe D., ,2003]

Algorithm 1 Greedy

Input: G, k, σ_m

Output: seed set S

1: $S \leftarrow \emptyset$
2: **while** $|S| < k$ **do**
3: select $u = \arg\max_{w \in V \setminus S}(\sigma_m(S \cup \{w\}) - \sigma_m(S))$
4: $S \leftarrow S \cup \{u\}$

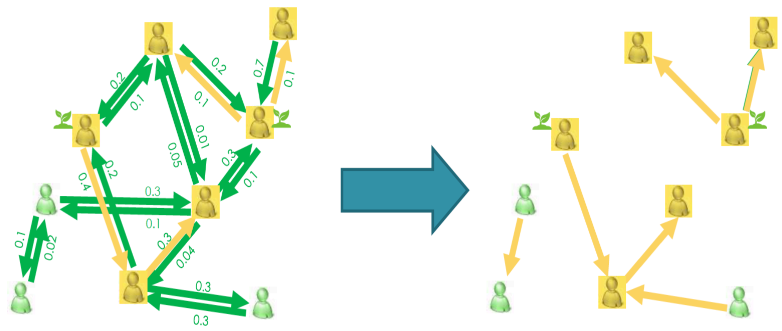
- $\left(1 - \frac{1}{e}\right)$ theoretical guarantee
- Estimating the expected influence spread in each round is #P-hard
  - Because you simulate a diffusion process for each candidate seed
  - Use the live-edge model and Monte Carlo estimation

Live Edge Model

- The influence spread under the live edge model can be computed as:

$$\sigma(S) = \sum_{g} P(g)\sigma_g(S)$$

- During each simulation, a random realization of the network g is sampled and the influence spread is defined as the nodes that lie in a path that is connected to one of the seeds



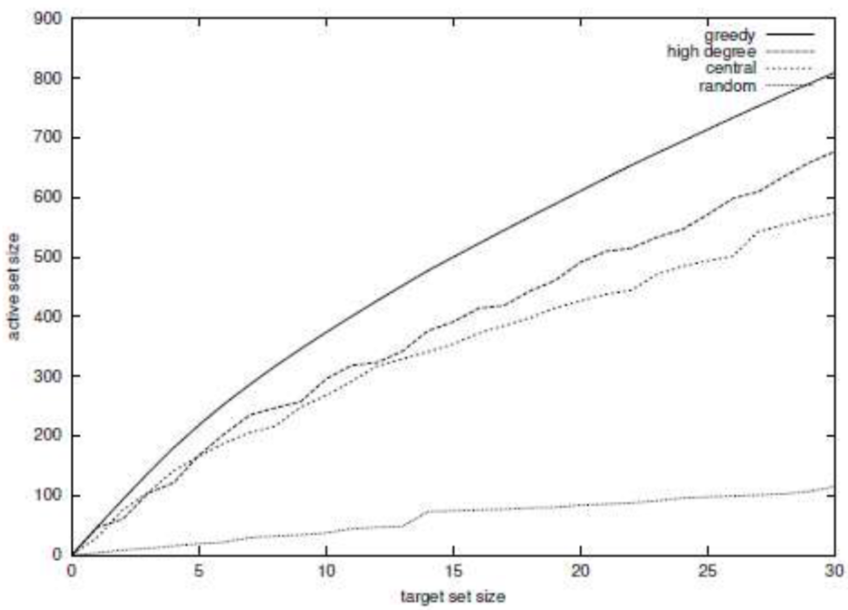
- The probability weighs the influence spread to indicate the possibility of this type of spread happening for this realization and this seed set, and is

$$P(g) = \prod_{e \in g} P_e \prod_{e\prime \in G/g} (1 - P_{e'})$$

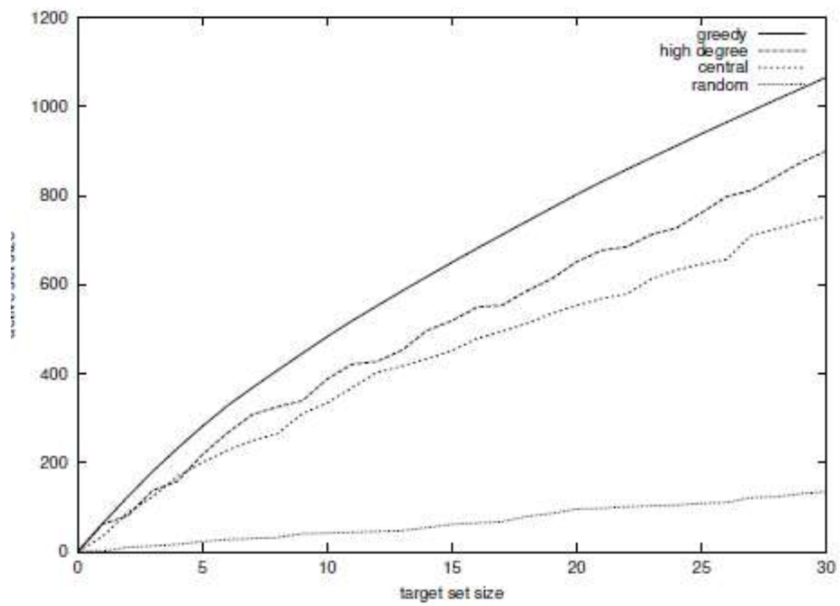
Performance of Greedy Algorithm

- Compare greedy with top nodes based on centralities
- Evaluate centralities seeds by taking the average influence spread from 10000 simulations of LT and IC

weighted cascade model



linear threshold model



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