
Spread of Influence through a Social Network

Adapted from :

<http://www.cs.washington.edu/affiliates/meetings/talks04/kempe.pdf>

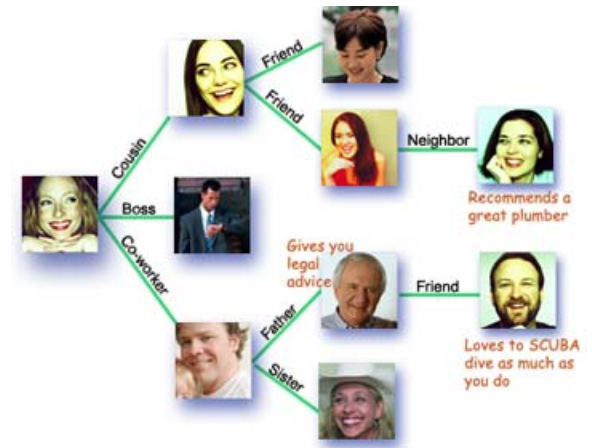
Influence Spread

- We live in communities and interact with our friends, family and even strangers.
- In the process, we influence each other.

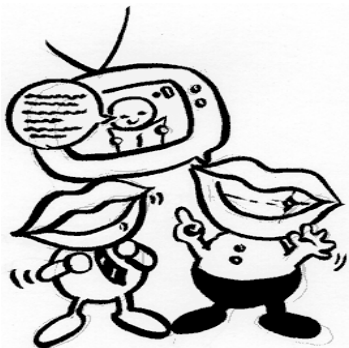


Social Network and Spread of Influence

- Social network plays a fundamental role as a medium for the spread of INFLUENCE among its members
 - Opinions, ideas, information, innovation...



- Direct Marketing takes the “word-of-mouth” effects to significantly increase profits (Gmail, Tupperware popularization, Microsoft Origami ...)



Social Network and Spread of Influence

■ Examples:

- ❑ Hotmail grew from zero users to 12 million users in 18 months on a small advertising budget.
- ❑ A company selects a small number of customers and ask them to try a new product. The company wants to choose a small group with largest influence.
- ❑ Obesity grows as fat people stay with fat people (homofily relations)
- ❑ Viral Marketing..

Viral Marketing

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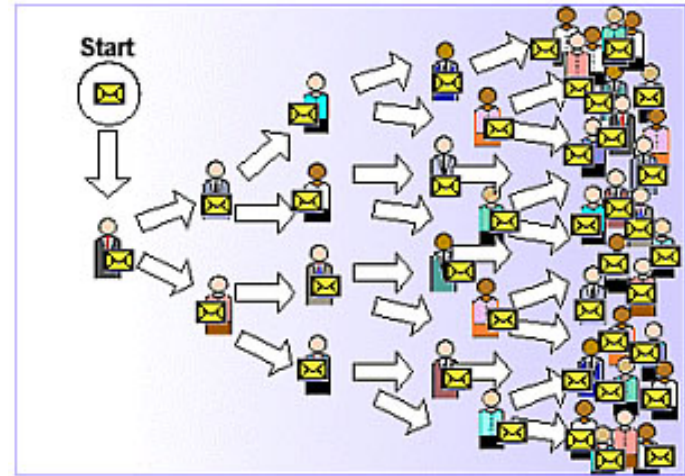
Identify
influential
customers



Convince them to
adopt the product –
Offer discount/free
samples



These customers
endorse the product
among their friends



Problem Setting

- Given
 - a limited budget B for initial advertising (e.g. give away free samples of product)
 - estimates for influence between individuals
- Goal
 - trigger a large cascade of influence (e.g. further adoptions of a product)
- Question
 - Which set of individuals should B target at?
- Application besides product marketing
 - spread an innovation
 - detect stories in blogs (gossips)
 - Epidemiological analysis

What we need

- Models of influence in social networks.
 - Obtain data about particular network (to estimate inter-personal influence).
 - Devise algorithms to maximize spread of influence.
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Outline

- Stochastic Models of influence diffusion
 - Linear Threshold
 - Independent Cascade
 - Influence maximization problem
 - Algorithm
-

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- **Models of influence**
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Models of Influence

- Two basic classes of diffusion models: **threshold** and **cascade**
 - General operational view:
 - A social network is represented as a directed graph, with each person (customer) as a node
 - Nodes start either **active** or **inactive**
 - An active node may trigger activation of neighboring nodes
 - **Monotonicity assumption**: active nodes never deactivate (not always true, e.g. epidemics (e.g. flu, covid), here more complex models are used)
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Linear Threshold Model

- A node v has (random) threshold $\theta_v \sim U[0, 1]$
- A node v is influenced by each neighbor w according to a *weight* b_{vw} such that

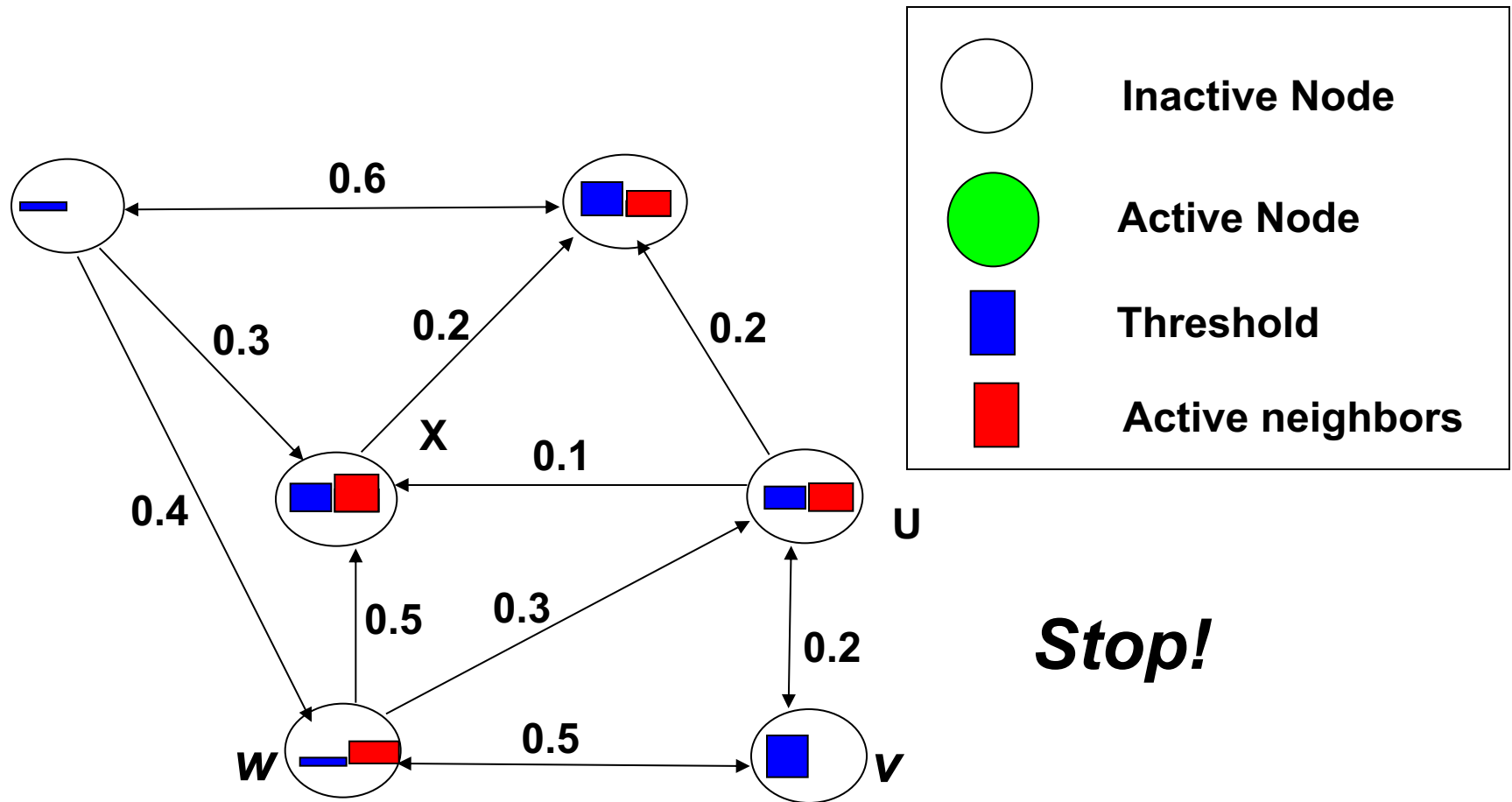
$$\sum_{w \text{ neighbor of } v} b_{v,w} \leq 1$$

- A node v becomes **active** when at least (weighted) θ_v fraction of its neighbors are active

$$\sum_{w \text{ active neighbor of } v} b_{v,w} \geq \theta_v$$

Similar to perceptron model..

Example (weights on edges are the $b_{u,v}$)



Outline

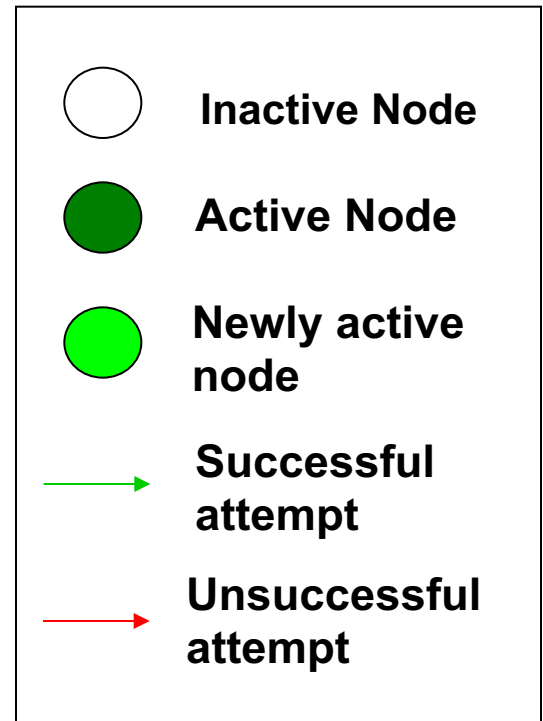
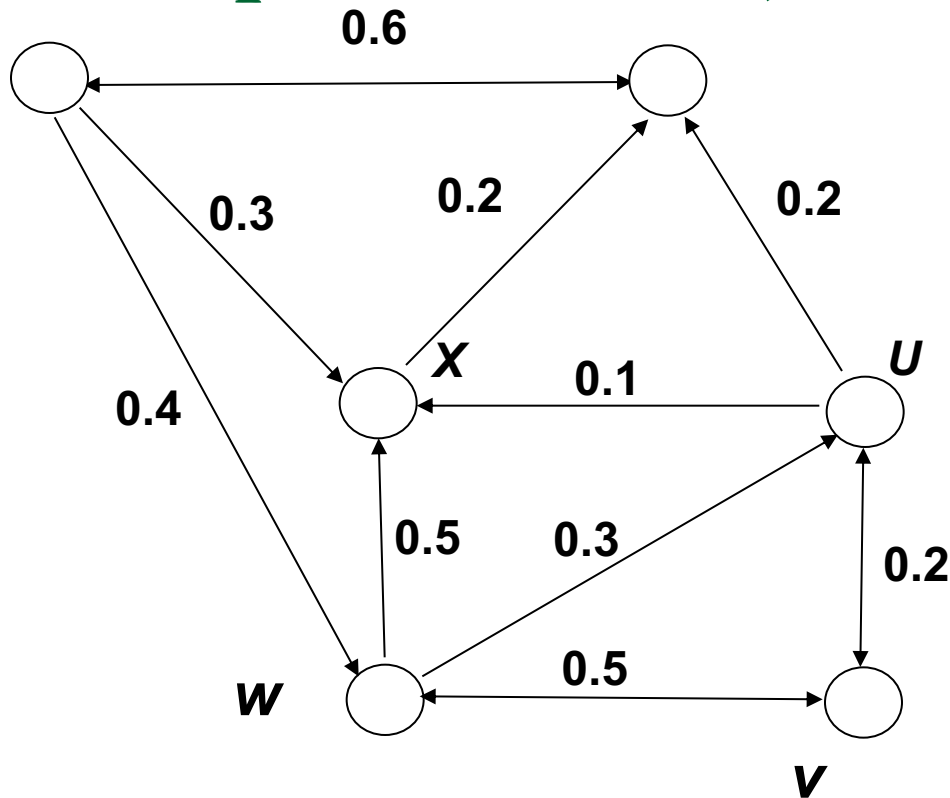
- Models of influence
 - Linear Threshold
 - **Independent Cascade**
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-

Independent Cascade Model

- When node v becomes active, it has a **single** chance of activating **each** currently inactive neighbor w .
- The activation attempt succeeds with probability p_{vw} .



Example (edges are now weighted with probabilities)



Stop!

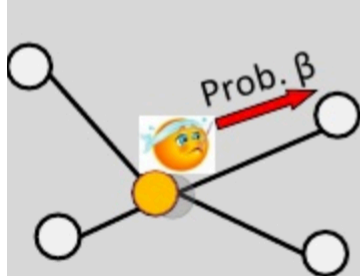
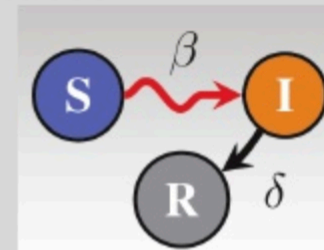
Virus Diffusion model (simple SIR model)

- Each node in the graph is in one of three states

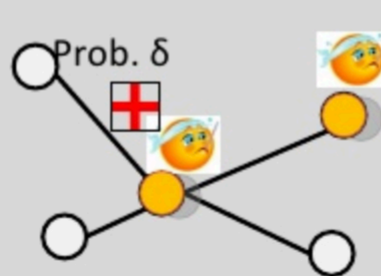
- **S**usceptible (i.e. healthy) ○

- **I**nfected ●

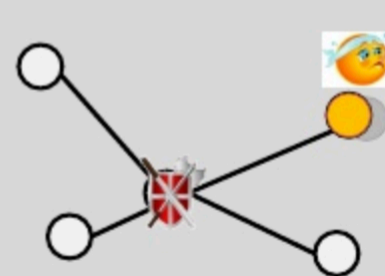
- **R**emoved (i.e. can't get infected again) 🏠



$t = 1$



$t = 2$



$t = 3$

Outline

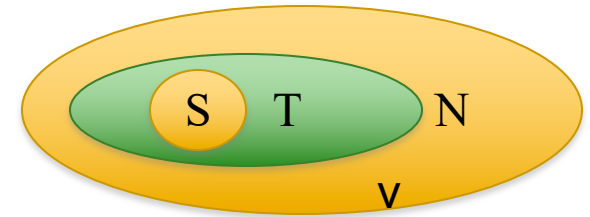
- Models of influence
 - Linear Threshold
 - Independent Cascade
 - SIR
 - Influence maximization problem
 - Algorithm
-

Influence Maximization Problem

- Influence of node set S : $f(S)$
 - **expected** number of active nodes at **steady state**, if set S is the initial **active set** in t_0
- Problem:
 - Given a parameter k (**budget**), find a **k -node set S** to maximize $f(S)$
 - This can be casted as a constrained optimization problem with $f(S)$ as the objective function
 - Of course for disease epidemics the problem is to **minimize**

$f(S)$: properties (to be demonstrated)

- Non-negative (obviously)
- Monotone: $f(S + v) \geq f(S)$
- Submodular:



- Let N be a finite set
- A set function $f : 2^N \mapsto \mathfrak{R}$ is submodular *iff*

$$\forall S \subset T \subset N, \forall v \in N \setminus T,$$

$$f(S + v) - f(S) \geq f(T + v) - f(T)$$

$$N \setminus T = N - T$$

Intuitive explanation: The **difference** in the value of the function that a **single element** (v) makes when added to an input set decreases as the size of the input set increases.
(Also called *diminishing returns*)

Bad News

- For a submodular function f , if f only takes non-negative value, and is monotone, finding a k -element set S for which $f(S)$ is maximized is an **NP-hard** optimization problem.
- **It is NP-hard to determine** the optimum for influence maximization for both independent cascade model and linear threshold model.



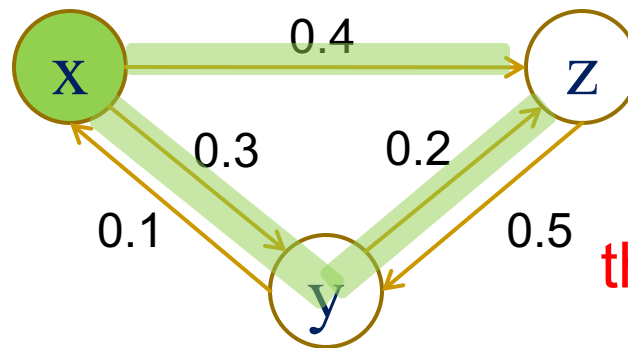
Good News

- We can use Greedy Algorithm!
 - Start with an empty set S
 - For k iterations:
 - Add node v to S that maximizes $f(S + v) - f(S)$.
 - How good (bad) it is?
 - Theorem: The greedy algorithm is a $(1 - 1/e)$ approximation.
 - The resulting set S activates at least $(1 - 1/e) > 63\%$ of the number of nodes that any size- k set S could activate (so at **worst 63% of the optimum**).
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Estimating Spread $S(v)$ (Linear Threshold Model)

- We observe that the influence of a node x on node z can be computed by enumerating all simple paths starting from x and ending in z .

A simple path is a path that doesn't contain any cycle

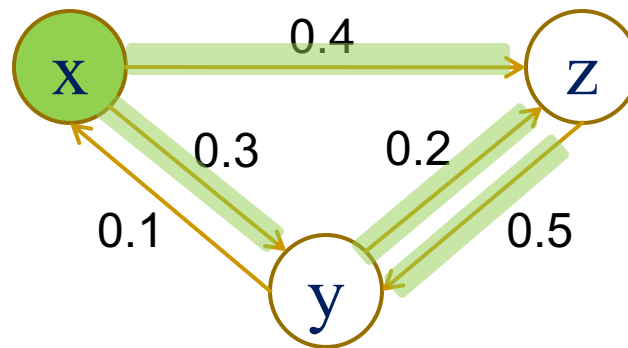


Total influence of x on z is 0.46
Influence of x on z through path $x \rightarrow z$ is 0.4
Influence of x on z through path $x \rightarrow y \rightarrow z$ is $0.3 \cdot 0.2 = 0.06$

$$\Upsilon_{x,z} = 0.3 \cdot 0.2 + 0.4 = 0.46$$

Estimating Spread (Linear Threshold Model)

- Thus, the spread of a node can be computed by enumerating simple paths starting from the node.



Influence of x on x itself
 Influence of x on y
 Influence of x on z
 node x is 1.96

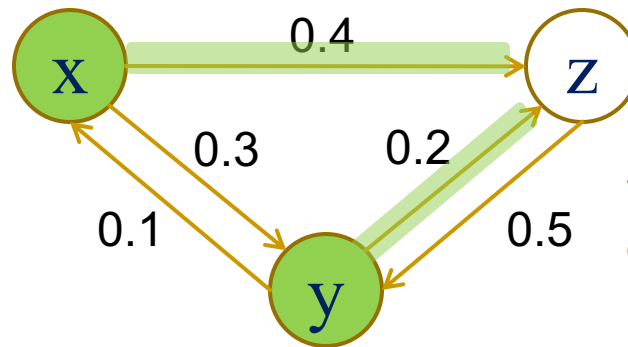
Influence Spread of node x is $\Upsilon_{x,x} + \Upsilon_{x,y} + \Upsilon_{x,z}$

$$= 1 + (0.3 + 0.4 * 0.5) + (0.4 + 0.3 * 0.2) = 1.96$$

Estimating Spread (Linear Threshold Model)

Theorem 1. *In the LT model, the spread of a set S is the sum of the spread of each node $u \in S$ on subgraphs induced by $V - S + u$. That is,*

$$\sigma(S) = \sum_{u \in S} \sigma^{V-S+u}(u)$$



Total influence of node x in a subgraph that does not contain y is 2.6

Let the seed set $S = \{x, y\}$, then influence spread of S is

$$\sigma(S) = \sigma^{V-y}(x) + \sigma^{V-x}(y) = 1 + 0.4 + 1 + 0.2 = 2.6$$

Performance

- Spread of influence algorithms have been demonstrated to obtain much better performance wrt simpler methods such as:
 - **Page Rank** – Top-k nodes with highest page rank.
 - **High Degree** – Top-k nodes with highest degree.
 - Temporal complexity is an issue (several algorithms recently improved over “base” algorithm described here)
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