Ranking Mechanisms in Interaction Networks

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Ranking

- Ranking is the process of ordering a set of candidates in the decreasing order (or increasing order) of their merit/status/utility/…

- Broad concept that serves as a key concept in many diverse disciplines
  - Social Choice Theory
  - Information Retrieval and Search
  - Game Theory
  - Social Network Analysis

- Popular Applications
    - Voting and evaluation methods
    - Ranking sportspersons, teams, etc.
    - Ranking web-pages based on search keywords

- Our Focus: Recent advances in Ranking methods for Interaction Networks

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Age-long, folklore ranking technique

- **Step 1: Somehow collect "scores" for each candidate that is reflective of the candidate's merit**
  - **Conduct Exams, Cumulative Statistics of performance, Surveys,**
- **Step 2: Rank the candidates in the sorted order of their scores**

- **Pros: easy to implement if the scoring function is treated as a black-box…**
- **Cons: Difficult to come up with scoring functions that can be deemed fair by all the candidates**

- **Success Story: Widely accepted as the technique for evaluation large number of candidates in examination (or situations of very limited range)**

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Need for different Ranking Mechanisms

- Arises due to unacceptable scoring functions
  - Is examination score truly reflective of merit?
  - Can sportsmen be ranked based merely on statistical aggregates?
  - Solution Concept: Rank Aggregation

- Ranking is a post-facto analysis of a set of artifacts of a social/scientific/technical process.
  - Often we come across networks that are abstractions of a process of interaction of entities. Ex: friendship network, web-page links, etc.
  - Ranking of the entities/relationships is an after-thought and is intended to understand a specific aspect of the underlying process and hence the ranking method should explicitly take that into account.
  - Ranking in friendship networks to identify nodes that are important for its sustenance, ranking web-pages that reflect their relative importance to a keyword based on the link structure, etc.
  - Solution Concept: Social Network Ranking

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Rank Aggregation

- Rank aggregation is the process of arriving at a final ordering of a set of candidates based on multiple rank-orders on the candidates
  - Rank-orders could be obtained from experts (more reliable)
  - Could be obtained based on surveys
  - Sometimes just pairwise preferences collected from a population is used.
  - Applications: Voting (fundamental concept in social choice theory), Scientific applications such as chronologically ordering archeological sites, etc.
- Typically, the final rank order is required to minimize its discrepancy with respect to the input rank orders.
  - Most aggregation problems are NP-Complete.
  - Typically involves breaking ties or cycles that are arise due to contradictions in the ranking of different experts.
  - Combinatorial and LP based algorithms exist. But, the most popular algorithm is due to Charikar et al, called the PIVOT algorithm.

- This is a deep and exciting area by itself. But, we will not focus on rank aggregation in this tutorial.

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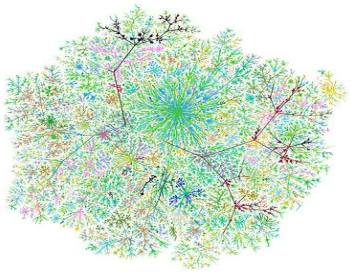
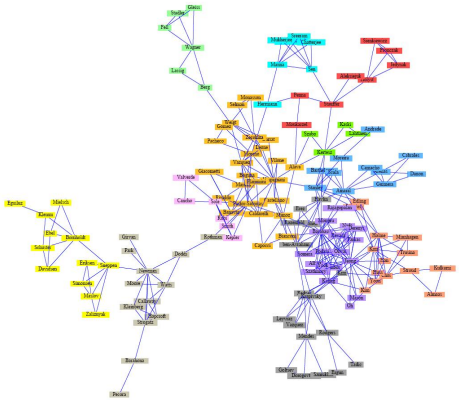
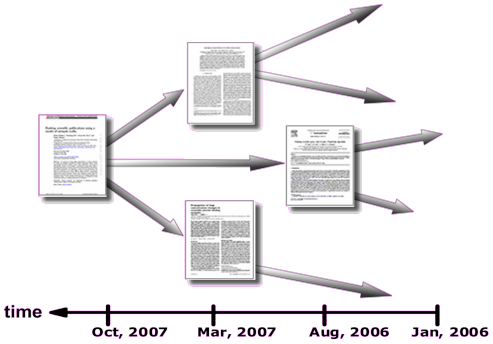
Social Networks: A Brief Introduction

- With this brief introduction to general ranking mechanisms, we now get into ranking over social networks and study the unique challenges posed by social networks
- ***Social Network*:** A system made up of individuals/entities and interactions among individuals/entities. A few examples are web graph, co-authorship networks, citation networks, email networks, friendship networks, etc.







- Represented using **graphs**
  - **Nodes:** Web pages, Authors, Publications, Emails, Individuals, etc.
  - **Edges:** Hyperlinks, Co-authorship, Citations, Email Exchanges, Friendships, etc.

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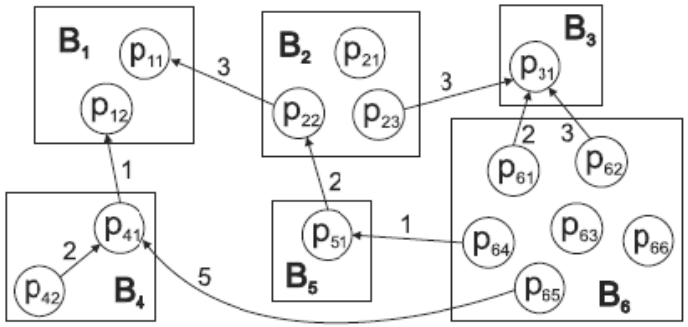
Ranking in Social Networks: Motivation

- **Viral Marketing in Social Networks**
  - It leverages the social contacts among individuals for the spread of information
  - To design a successful viral marketing campaign, it is important to identify influential trend setters (or initial seeds)
  - For economic reasons, we would like to limit the number of these initial seeds
  - In a social network consisting of thousands of nodes, how to identify a small set of initial seeds?
- **Vaccination Strategies for Virus Out-breaks**
  - Consider virus dissemination through email networks
  - It is not possible to vaccinate every individual during the virus out-break due to economic constraints
  - How to identify individuals whose vaccination would result in a lower number of infected people
- **Determining Authoritative Blogs**
  - Edges indicate the temporal flow of information: the cascade starts at some post and then the information propagates recursively by other posts linking to it
  - Our goal is to select a small set of blogs which "catch" as many cascades (stories) as possible
  - A more more cost-effective solution can be obtained, by reading smaller, but higher quality blogs



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Ranking in Social Networks – Trivial Mechanisms

- We first investigate a few trivial techniques that reduce social ranking into a score based ranking

- **Degree Centrality** of a node in the network is the number of nodes in its immediate neighborhood
  - Here we rank nodes in the network based on the degree of the nodes in the network
  - Freeman, L. C. (1979). *Centrality in social networks: Conceptual clarification*. Social Networks, 1(3), 215-239.

- **Closeness Centrality:** The *farness* of a node **s** is defined as the sum of its distances to all other nodes, and its *closeness* is defined as the inverse of the farness
  - The more central a node is in the network, the lower its total distance to all other nodes

- **Local Clustering Coefficient** of a vertex is the proportion of links between the vertices within its neighbourhood divided by the number of links that could possibly exist between them.
  - D. J. Watts and S. Strogatz. *Collective dynamics of 'small-world' networks*. Nature 393 (6684): 440–442 , 1998.

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Ranking in Social Networks – Non-Trivial Mechanisms

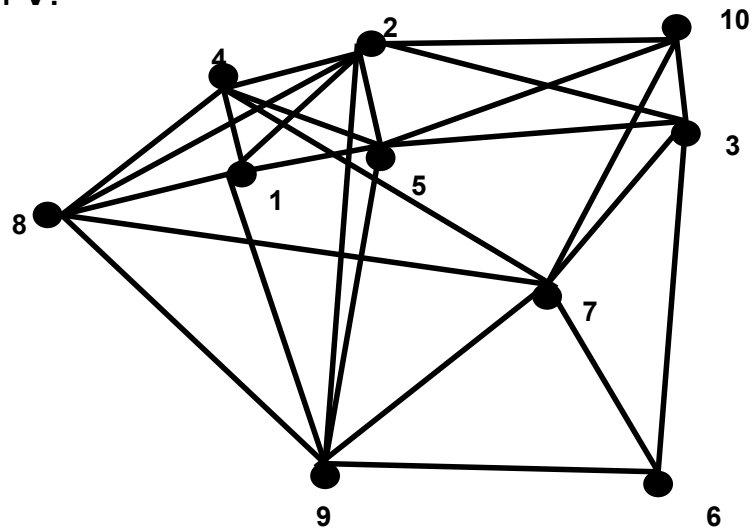
- **Betweenness Centrality**

  • L. Freeman. *A set of measures of centrality based upon betweenness*. Sociometry, 1977. Vertices that have a high probability to occur on a randomly chosen shortest path between two randomly chosen nodes have a high betweenness.

  • More precisely, betweenness centrality of a vertex **v** is given by $c(v) = \sum_{s,t} \frac{\sigma_{s,t}(v)}{\sigma_{s,t}}$

  where the denominator is the number of shortest paths from **s** to **t** and the numerator is the number of shortest paths from **s** to **t** that pass through **v**.

Node	FlowBet
1	3.8
2	20
3	16.954
4	4.22
5	25.876
6	1.5
7	8.4
8	2.954
9	4.054
10	4.092



  • Betweenness centrality is extensively used to determine communities in social netwoks

  • M. Girvan and MEJ Newman. *Community structure in social and biological networks*. PNAS, USA, 99, 8271-8276, 2002.

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Ranking in Social Networks – Non-Trivial Mechanisms (Cont.)

- **Eigen-Vector Centrality**
  - P. Bonacich and P. Lloyd. *Eigenvector-like measures of centrality for asymmetric relations*. Social Networks, 23(3):191-201, 2001.
  - P. Bonacich. *Some unique properties of eigenvector centrality*. Social Networks, 2007.

  - For node **i**, let the centrality score be proportional to the sum of the scores of all nodes which are connected to it. Hence

$$x_i - \frac{1}{\lambda} \sum_{j \in M(i)} x_j - \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} x_j$$

  where **M(i)** is the set of nodes connected to node **i**, **N** is the number of nodes, and λ is a constant.
  - In vector notation, the above can be rewritten as $x = \frac{1}{\lambda} Ax$
  - It assigns relative scores to all nodes in the network based on the principle that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes.
  - Google Page-Rank and Kats measure are variants of the Eigenvector centrality.

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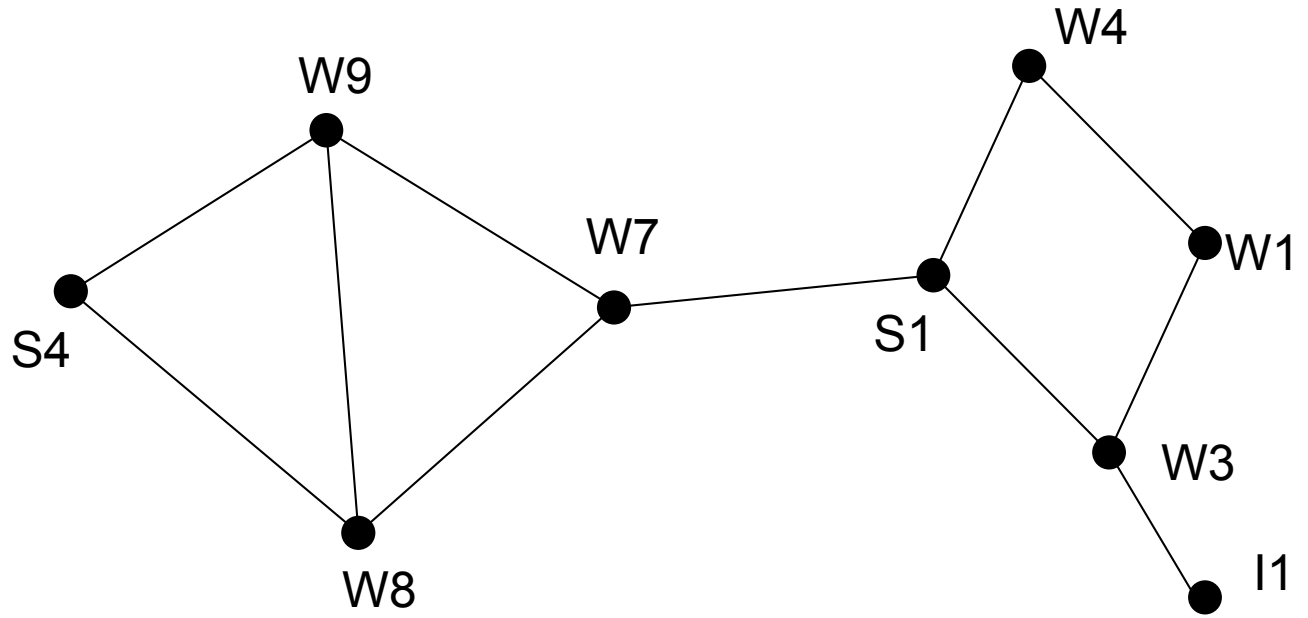
Ranking in Social Networks – Non-Trivial Mechanisms (Cont.)



Eigen-Vector Ranking	Degree Centrality	Closeness Centrality	Betweenness Centrality
S1 (0.498)	W3, S1	S1	S1
W3 (0.472)	W9, W8, W7, W1, W4	W7	W7
W1,W4 (0.438)	S4	W3	W3
W7 (0.254)	I1	W1, W4	W8, W9
W8, W9 (0.159)		W8, W9	W1, W4, I1, S4
I1 (0.147)		I1	
S4 (0.098)		S4	

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Inadequacies of the Traditional Ranking Mechanisms for Social Networks

- The traditional ranking mechanisms are solely dependent on the structure of the underlying network
- Emergence of several applications wherein the ranking mechanisms should take into account not only the structure of the network but also other important aspects of the networks such as the value created by the nodes in the network and the marginal contribution of the nodes in the network
- Several empirical evidences reveal that the traditional ranking mechanisms are not scalable to deal with large scale network data
- Often it is required to rank the nodes/edges not only based on the link structure of the underlying network but also based on auxiliary information or data
- The traditional ranking mechanisms are not tailored to take into account the strategic behaviour of the nodes

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Recent Trends in Ranking Mechanisms Over Social Networks

- **Viral Marketing in Social Networks**
  - Design of efficient and scalable algorithms/heuristics
  - Captures various relationships among the products
  - Captures the spread of both the positive opinions and the negative opinions about the products over the social networks
  - Design of reward mechanisms for recommending products in viral marketing
  - Kempe et al. *Maximizing the spread of influence in social networks*. In SIGKDD 2003.
  - Leskovec et al. *Cost-effective outbreak detection in Networks*. In SIGKDD 2007
  - Chen et al. *Efficient influence maximisation in social networks*. In SIGKDD 2009.
  - Chen et al. *Influence maximization in social networks when negative opinions may emerge and propagate*. In SIAM SDM 2011.
  - Datta et al. *Viral marketing for multiple products*. In ICDM 2010.
  - Borodin et al. *Threshold models for competitive influence in social networks*. In WINE 2010.
  - Emek et al. *Mechanisms for multi-level marketing*. In ACM EC 2011.

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Recent Trends in Ranking Mechanisms Over Social Networks (Cont.)

- **Vaccination Strategies for Virus Out-breaks**
  - Social network data can be exploited for attacks such as email virus spreading using users' address books, warm spreading on mobile phone networks
  - In such settings, we want to minimize the propagation of undesirable things by blocking either nodes or links in the network
  - Probabilistic models of virus spread have been proposed recently

- **The following are a few important references of this kind**
  - Abbassi et al. *Toward optimal vaccination strategies for probabilistic models*. In WWW 2011.
  - Kimura et al. *Blocking links to minimize contamination spread in a social network*. In TKDD 2009.

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Recent Trends in Ranking Mechanisms Over Social Networks (Cont.)

- **Ranking based on Link Structure + Auxiliary Information (Data)**
  - Given that the link structure and data about traces of information propagation over the networks (or data about actions/activities performed by the individuals)
  - This auxiliary information is used to remove noise in the network or to delete the unnecessary nodes/ edges in the network
  - With the available advanced technologies for WWW and Internet, it is not difficult to collect data about the activities of the individuals/traces of information propagation over the network

- **A Few Important References of This Category**
  - Goyal et al. *A Data-based Approach to Social Influence Maximization*. In VLDB 2011.
  - Mathioudakis et al. *Sparsification of influence networks*. In SIGKDD 2011.
  - Sarma et al. *Ranking mechanisms in Twitter-like Forums*. In WSDM 2010.

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Recent Trends in Ranking Mechanisms Over Social Networks (Cont.)

- **Ranking based on Game Theoretic Techniques**
  - Game theoretic models (such as *Banzhaf power index*) are employed to rank nodes/edges with respect to their positional power towards performing an activity over the network
  - Game theoretic models (such as *Shapley value*) are employed (i) for influence attribution in networks and (ii) for determining top-**k** initial trend setters in social networks
  - Strategic aspects of product adoption are studied to reveal the social behaviour
  - Incentive mechanisms are designed to reward the individuals for recommending products or spreading information over the network
- **A Few Important References of This Category**
  - Y. Bachrach and J.S. Rosenschein. *Computing the Banzhaf power index in network flow games.* In AAMAS 2007.
  - Bachrach et al. *Power and stability in connectivity games.* In AAMAS 2008.
  - Y. Singer. *How to Win Friends and Influence People, Truthfully: Influence Maximization Mechanisms for Social Networks*. In WSDM 2012.
  - Emek et al. *Mechanisms for multi-level marketing*. In ACM EC, 2011.
  - Meier et al. On the windfall of friendship: Inoculation strategies on social networks. In ACM EC, 2008
  - Papapetrou et al. *A Shapley value approach for influence attribution*. In ECML/PKDD 2011.

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Value Creation Networks by Sampath-Mehta-Pandit (SDM09, CIKM10, AAAI11)

- **Typically, the SNA literature is mainly interested in the structure of social interactions**
  - Structure of WWW, Degree Centrality of nodes, Degree distributions, etc.

- **Overlooks the fact that most of these interaction networks are aimed at creating value**
  - Academic Collaborations for knowledge creation and dissemination
  - Artistic collaboration for popularity, awards, etc.
  - Orchestrated networks such as service delivery networks: software services, supply chains, etc.

- **Key Question: How should we rank the nodes so as to reflect their importance in the network as well as their ability to create value?**

- **Applications: Viral Marketing, Team based Rankings, Influence Maximization, etc.**

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Interactions and Outcomes

Collaborations

- *Undirected, complete graph*
- Authors collaborate on an article
- Team members of projects

Hierarchical

- *Directed/undirected tree*
- Task distribution in organization

Hybrid

- *Directed graph*
- Supply chains

Categorical

- Success, Failure
- High, Medium, Low

Continuous

- Revenue generated
- Ratings

Discrete

- Number of publications
- Number of awards
- Intervals

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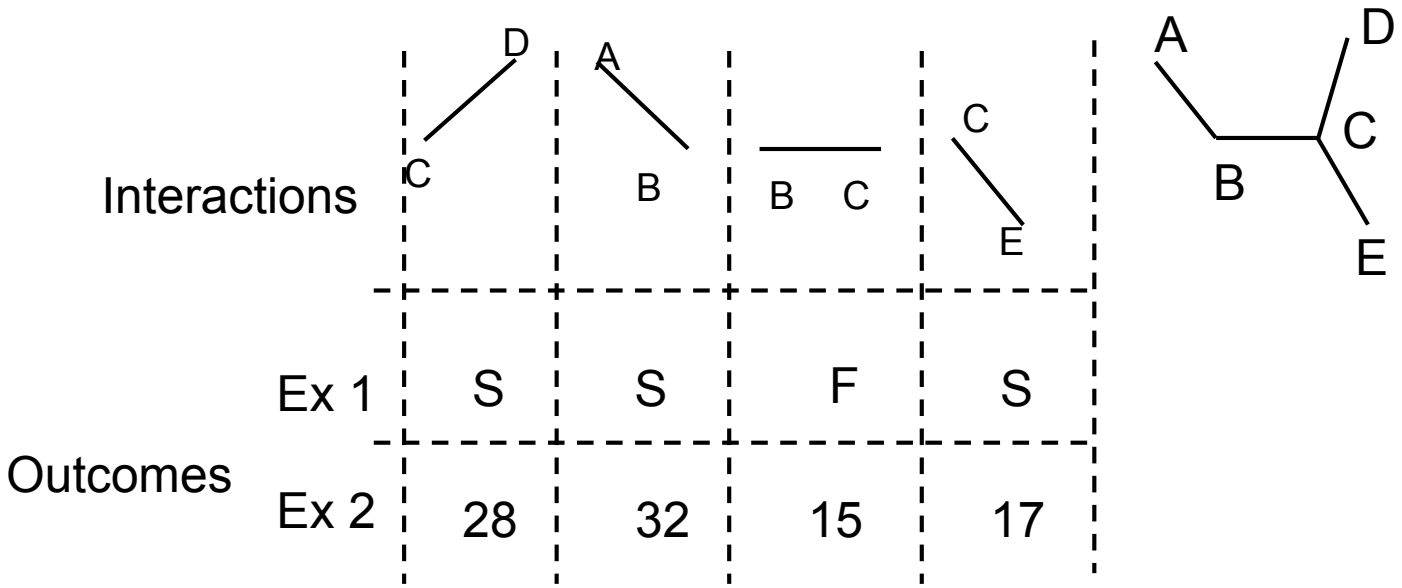
Problem Formulation



- Degree Based Ranking: C, B, {A, D, E}; Fails distinguish between majority of the nodes.
- Eigen-vector based Ranking: C, B, {D, E}, A; A is much more effective, but ranked below E!
- Outcome based Ranking: C, B, A, D, E; Scores of A and D are very close, but D is connected to the central node C and this is not taken into account.

- **Ideal Ranking: C, B, D, A, E …how to achieve this?**

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Ranking based on past interactions and outcomes

Capture the outcomes generated as part of the interaction networks

- *Representation of Value Creation Networks*

Algorithm for ranking the nodes

- *Outcome Aware Ranking Algorithm*

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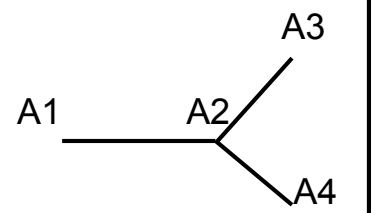
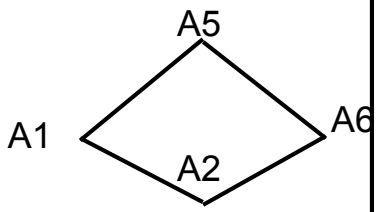
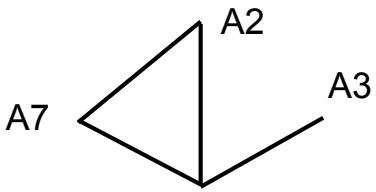
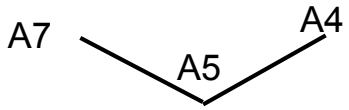
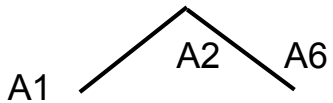
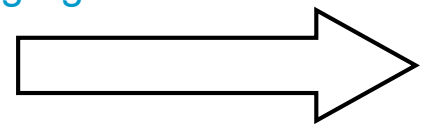
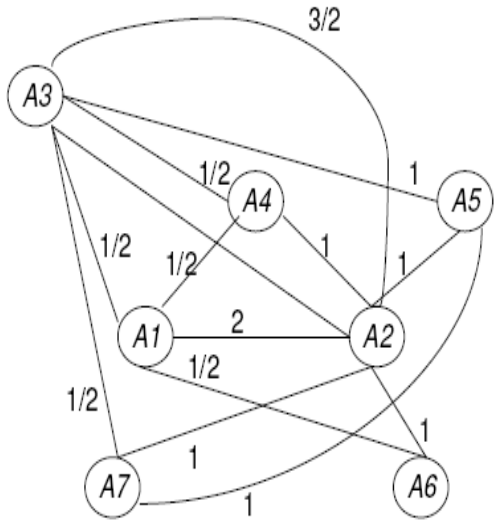
Traditional Interaction Network

Interactions	Outcomes
	S
	F
	S
	F
	S

Collapse the individual interactions to create an aggregate – a network





Typical Social Network

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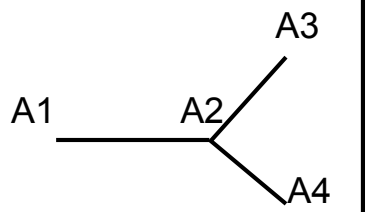
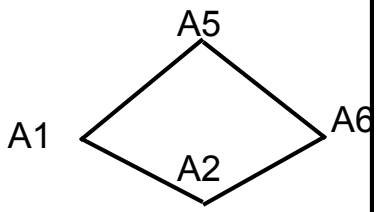
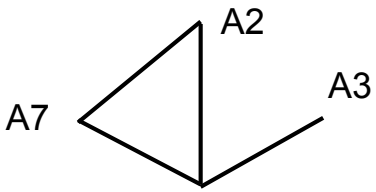
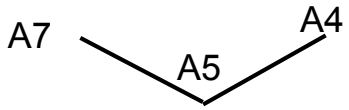
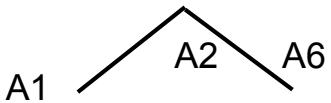
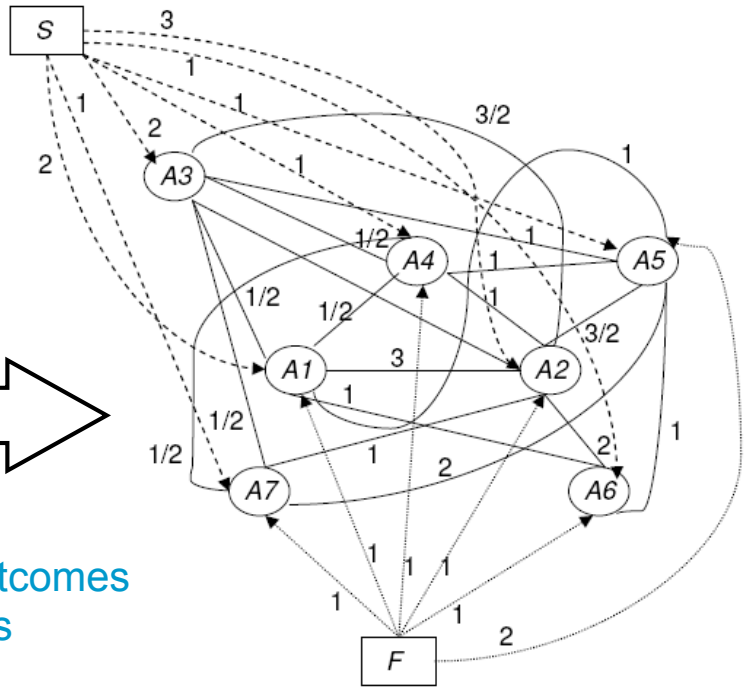
Interaction Network with Outcomes

Interactions	Outcomes
	S
	F
	S
	F
	S

Augment the outcomes as special nodes



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An augmentation that works well

Special Nodes corresponding to outcomes

- Intuition: to retain the status of outcomes

Directed Edges from outcomes to agents

- The outcomes influence the relative ranking/prestige of agents.

No Directed Edges from agents to outcome

- The agents do not influence the ranking/importance of outcomes – we are dealing with past interactions where the outcomes are already observed.

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Value Creation Networks

N+*M* nodes in the network

- *N* agents (1, …, *n*, …, *N*)
- *M* outcomes (*N*+1, …, *N*+*m*, …, *N*+*M*)

Adjacency matrix

- *N* x *N* adjacency submatrix is symmetric
- *N*+*M* x *N*+*M* adjacency matrix is asymmetric (the *M* outcome nodes are only source nodes/unchosen nodes with zero indegree)

Ranking

- We need to rank only the *N* agent nodes
- We need to capture the value generated or utilities associated with the outcomes

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Outcome Aware Ranking: Intuition

Note that the nodes have exogenous status

- *Outcome nodes have a status which reflects their utility*
- *Let e denote the vector of exogenous utilities.*

Let us now consider an iterative process (similar to Eigen-Vector Ranking) in which the status of a node is a scaled linear combination of the status of its neighbors.

- $x_t = \alpha \Delta^T x_{t-1}$
- Let x be the converged vector of final status.
- The iterative process needs to explain

the difference $(x - e)$

- This suggests solving for : $(x - e) = \alpha \Delta^T x$

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Comparison of Eigen-vector Ranking and Outcome Aware Ranking

- **The interaction matrix: Δ (non-negative, symmetric)**
- **Largest Eigen-value of Δ: λ**
- **Centrality vector: *x***
- **Computation: Eigen-value**

Eigen Centrality
Status depends on the status of your connections

$$\Delta x = \lambda x$$

- **Non-negative, asymmetric: Δ**
- **Endogenous status vector: e**
- **Parameter $\alpha \in [0, 1/\lambda)$**
- **By judiciously choosing e we rank the augmented network**
- **Computation: Inverse of a matrix**

Outcome Aware Ranking
Status depends on the status of your connections and endogenous status

$$x = \alpha \Delta^T x + e$$

$$x = (1 - \alpha \Delta^T)^{-1} e$$

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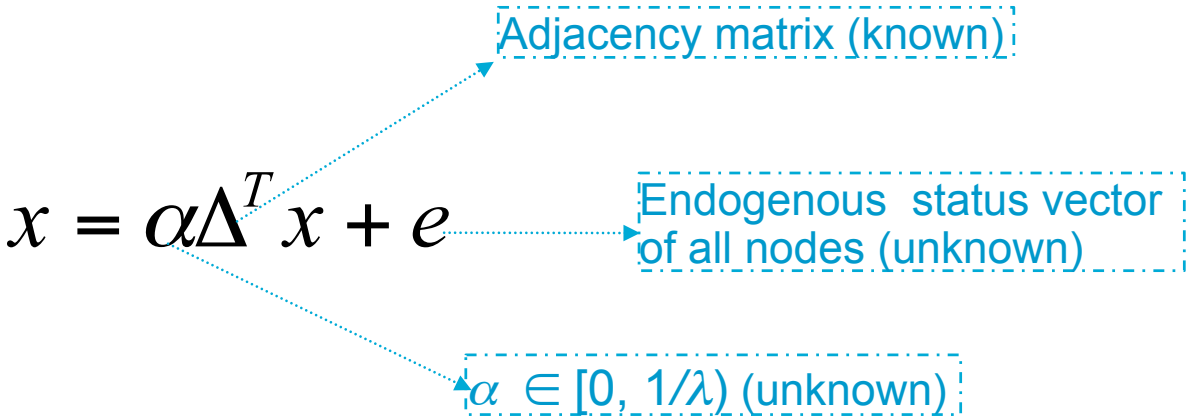
Outcome Aware Ranking Algorithm: Main Computational Aspect



- We capture the value of the outcomes using the endogenous status vector
- Easy to show that, for outcome nodes, their status in x is same as their status in e
- Use *α* as a parameter to trade-off of the influence of *interactions* versus *outcome values* on the final ranks

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Vector of Outcome Values e

- Let $\alpha \in (0, 1/\lambda)$
- Utility of outcome *m:* ρ_m

- We need to find: $(e_1, e_2, \ldots, e_N, e_{N+1}, \ldots, e_{N+M})$
- Assign as follows:

$$e_i = 1, \ \forall i$$
$$e_{N+m} = \theta \rho_m, \ \forall m, \ \theta > 0$$

- All agents receive equal status
- $\{\theta \rho_m\}$ preserves the cardinal structure of the outcomes
- What is the optimal θ?

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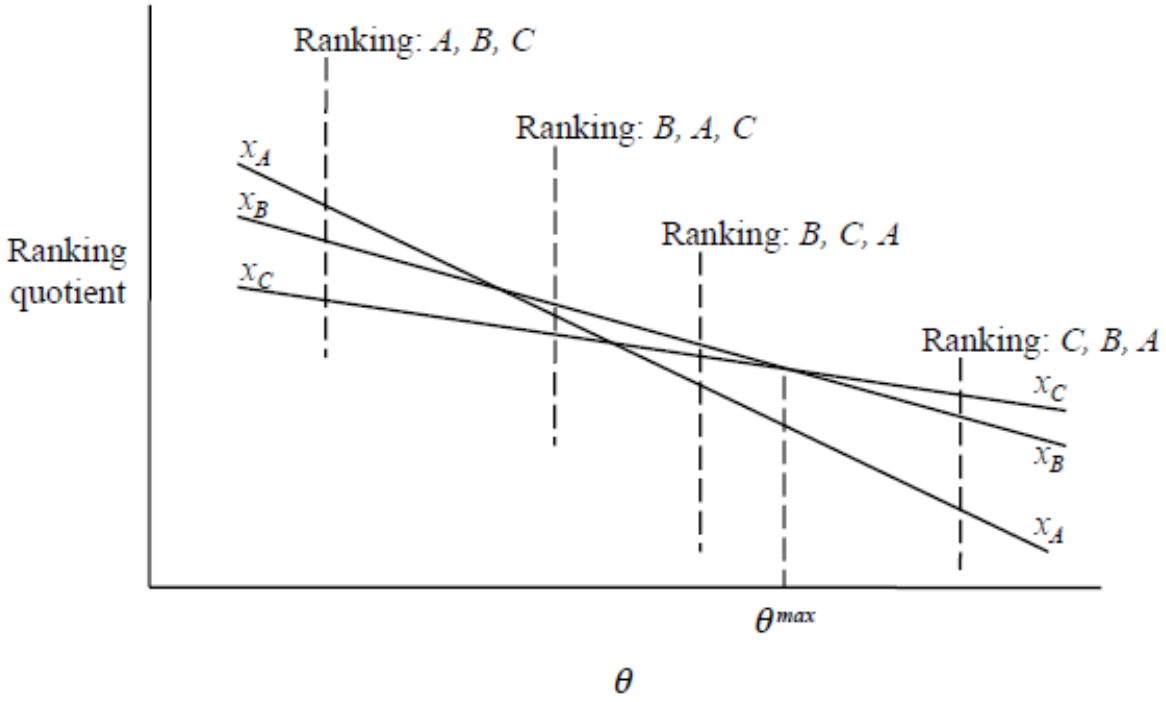
Optimal θ

- The inter-status of outcomes nodes are not changed:

$$x_{N+m} = \theta \rho_m, \ \forall m$$

- Ranking of the agent nodes varies with θ as follows:



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The α Value

$$x = \alpha \Delta^T x + e$$

- $\alpha \in [0, 1/\lambda)$
- $\alpha = 0 \rightarrow x = e$, ranking is purely based on external status
- $\alpha \rightarrow 1/\lambda$, ranking is eigen-vector like, however the unchosen nodes (outcomes) have less influence and hence interactions dominate
- Is it possible to characterize the above the trade-off?
- How can one choose an optimal α ?

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The α Value

α - Values	Ranks
α_1	R_1
α_2	R_2
α_3	R_3
α_4	R_4

Now reverse the utilities of the outcome nodes and calculate the ranks

Ranks of Reversed Utilities
S_1
S_2
S_2
S_4

Kendall correlation of R and S
τ_1
τ_2
τ_3
τ_4

- If the Kendall correlation is → 1, then Utilities have less influence
- If the Kendall correlation is → -1, then Utilities have more influence
- If the Kendall correlation is ~ 0, then Utilities and Interactions have equal influence

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Application 1: Movie Collaboration Network (CIKM 10)

- Experiment conducted on dataset from IMDB (http://www.imdb.com/interfaces).
- Lists of movies, actors in the movies, ratings for the movies, were extracted.
- Each movie is an interaction among the actors in the movie.
- Its user rating is the outcome of the interaction.
- Example: A rating of 8 indicates success; A rating of 7 and below is a failure.
- In this case, outcomes is graded instead of categorical.

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Empirical Study

- Experiment conducted on following datasets
  - A list of 28 connected actors across all times.
  - A list of 30 connected actors from old times (prior to 1980)
  - Larger networks containing 200 and 400 actors.
- Lists in both the small networks contained familiar names so that manual verification is possible.
- For larger networks, the Kendall *tau* (τ) distance was used to check the sensitivity of the method to structural and outcome changes.

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List 1	List 2
Brando, Marlon; Pacino, Al	Brando, Marlon; Mason, James (I)
De Niro, Robert; Bean, Sean	Calhern, Louis; Ford, Glenn (I)
Reno, Jean (I); Cheadle, Don	Malden, Karl; Johnson, Ben (I)
Travolta, John; Jackman, Hugh	Carey, Timothy; Harris, Richard (I)
Clooney, George; Pitt, Brad	Clift, Montgomery; Martin, Dean (I)
Affleck, Casey; Damon, Matt	Overton, Frank; Atterbury, Malcolm
Fredenburgh, Dan; Nighy, Bill	Ryan, Robert (I); Lancaster, Burt
Depp, Johnny; Bloom, Orlando	Sinatra, Frank; Borgnine, Ernest
Davenport, Jack; Arenberg, Lee	Marvin, Lee; Williams, Rhys (I)
Hollander, Tom; Law, Jude	Kelley, DeForest; Wayne, John (I)
Hopkins, Anthony; Penn, Sean (I)	Brennan, Walter; Wynn, Ed
Jackson, Samuel L.; Bacon, Kevin	Boyd, Stephen (I); Berle, Milton
Hanks, Tom; Buscemi, Steve	Bennett, Tony (I); Pacino, Al
Owen, Clive; Cage, Nicolas	De Niro, Robert; Crawford, Broderick
	Nelson, Ricky (I); Ebsen, Buddy

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Experiment 1

- Let Ranking R1 be the ranking obtained from the original data.
- Let A1, A2 be the top ranked actors; and, let A3 and A4 be two median ranked actors.
  - A1 = George Clooney; A2=Samuel Jackson; A3 = Nicolas Cage; A4 = Orlando Bloom
- Now change the ratings of the movies in which A1 and A2 appear by two points and increase the ratings the movies of A3 and A4 by two points.
- Let Ranking R2 be the ranking obtained after the modification.

- Result: The modified rankings not only reflect changes in outcomes, but also the characteristics of the connections.
  - Tom Hanks moves to the top as he is not connected to the affected actors.
  - Don Cheadle goes down, thanks to his frequent interactions with Clooney.

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Experiment 2

- Let Ranking R1 be the ranking obtained from the original data for list 1 of all-time actors.
- Let Ranking R2 be the ranking obtained for the actors in list 2 of only old actors.
- Let C be the set of common actors in the two list, say Al Pacino and Robert De Niro.
- Result: The actors in C are ranked high in the global data and at the bottom in the data upto 1980. Their “connections” status grew from their work post-1980.
    - De Niro is 9th in the global list (even though many of his frequent co-stars are missing from the experiment) and
    - And ranked last in the second list (which includes his prominent co-star Marlon Brando in the old actors list).

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Experiment 3: on exogenous vector

- Every outcome is viewed as having some positive value. Example: research papers in conferences and journals.
- The outcomes could have both positive and negative value. Example: A movie with a rating of 9 is a success whereas a movie with a rating 5 is essentially of negative value.
- The outcomes could be linearly related or they could have quantum jumps
  - Revenue of $18 has a value roughly 0.9 times the value of revenue $20.
  - A paper with 1000 citations has a value more than 100 times a paper with 10 citations!
- How do these settings affect the experimental results?

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Experiment 3: on exogenous vector

- When every outcome has some positive value
  - Make the value of a movie equal to its user rating
  - In this case, the rankings do not always match intuition. This is because, the “structure” dominates the “outcomes” as a great outcome like 9 is only 1.5 times better than an outcome of 6.
- When the outcomes have positive and negative value
  - Use a threshold (say rating of 6) to define success and failure. Reward success and failure proportionately in +ve and –ve range.
  - Rankings match the intuition very well; The reflection of rankings after the modification in Experiment1 reflects nearly perfect results.
- When outcomes are not linearly dependent
  - In this case, the rankings matched intuition very well even though a threshold for success and failure was not used.
- How to choose the exogenous vector?
  - Depends on the application (whether outcomes are categorical, graded categorical, non-linear valuations and so on)
  - Relative importance of structure and outcome
  - If any special status needs to be endowed on a subset of actors.

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Application 2: Academic Collaboration Networks

- Set of all publications in 8 leading conferences in DB/DM/KDD conferences between the years 1999 and 2004 were considered.
- A total of 2509 papers and 2914 authors were considered.
- The utility of the venues were determined by the impact ratings provided by Citeseer
- Citations of the papers were obtained by google.scholar.com
- The citations are as on Feb 2011

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Venues and their Utility

Venue Utility in the decreasing order	Number of Papers under Consideration
SIGMOD Conference	481
PODS Conference	152
VLDB	550
ICDE	468
KDD	314
CIKM	293
EDBT	128
SDM	78

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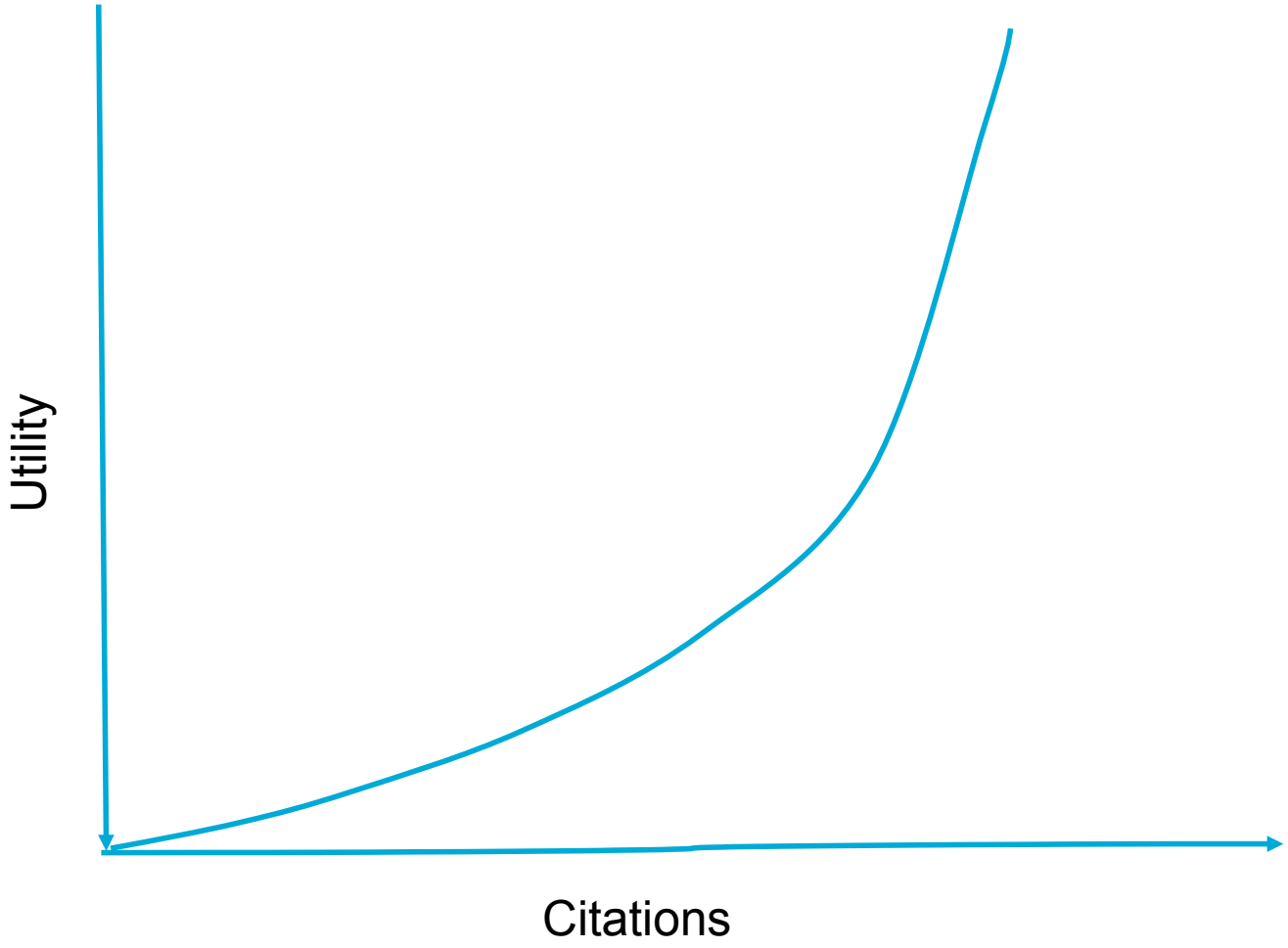
Utility of the Citations



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Comparison of rankings by different methods

Name	Citation Augmented OARA	Venue Augmented OARA	Eigen Ranking	Sorted by Citation Outcome	Sorted by Venue Outcome
Divesh Srivastava	1	1	1	13	2
Jiawei Han	2	3	21	7	6
Phillip Yu	3	4	50	23	10
Nick Koudas	4	5	2	18	11
H V Jagadish	5	7	3	30	19
Surajit Chowdhury	6	2	54	29	1
Beng Chin Ooi	7	16	13	69	29
Divyakant Aggarwal	8	18	919	97	30
Christos Faloutsos	9	6	58	31	5
T V Lakshmanan	10	11	4	82	18

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Summary

- Rank of a node depends on the following:
  - number of interactions (experience)
  - structure of interactions (connections)
  - outcome of interactions (contribution)

- Rank of a node depends on the rank of the nodes to which it is connected (transfer of status)

- Ranking is scale invariant of the outcome utilities

- Allows for trade-offs between varying degrees of influence of contribution (outcomes) and connections (structure of interactions)

- Can handle negative utilities

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