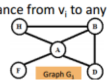
Eccentricity: The eccentricity of a node v_i is the maximum distance from v_i to any other nodes in the graph



- $e(v_i) = \max_j \{d(v_i, v_j)\}$
- E.g., $e(A) = 1$, $e(F) = e(B) = e(D) = e(H) = 2$

Radius of a connected graph G: the min eccentricity of any node in G

- $r(G) = \min_i \{e(v_i)\} = \min_i \{\max_j \{d(v_i, v_j)\}\}$
- E.g., $r(G_1) = 1$

Diameter of a connected graph G: the max eccentricity of any node in G

- $d(G) = \max_i \{e(v_i)\} = \max_{i,j} \{d(v_i, v_j)\}$
- E.g., $d(G_1) = 2$

Diameter is sensitive to outliers. Effective diameter: min # of hops for which a large fraction, typically 90%, of all connected pairs of nodes can reach each other

Generalizing to path of arbitrary length, we have: $N_{ij}^{(r)} = [A^r]_{ij}$

When starting and ending at the same vertex i, we have: $L_r = \sum_{i=1}^{n} [A^r]_{ii} = Tr\, A^r$

Matrix A written in the form of $A = UKU^T$, where U is the orthogonal matrix of eigenvalue and K is the diagonal matrix of eigenvalue

$$L_r = Tr\,(UKU^T)^r = Tr\,(UK^rU^T) = Tr\,(UU^TK^r) = Tr\,(K^r) = \sum_i k_i^r$$

- where k_i is the i-th eigenvalue of the adjacency matrix

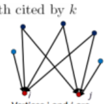
- The clustering coefficient of a node v_i is a measure of the density of edges in the neighborhood of v_i
- Let $G_i = (V_i, E_i)$ be the subgraph induced by the neighbors of vertex v_i, $|V_i| = n_i$ (# of neighbors of v_i), and $|E_i| = m_i$ (# of edges among the neighbors of v_i)
- **Clustering coefficient** of v_i for **undirected network** is

$$C(v_i) = \frac{\#\ edges\ in\ G_i}{max\ \#\ edges\ in\ G_i} = \frac{m_i}{\binom{n_i}{2}} = \frac{2 \times m_i}{n_i(n_i - 1)}$$

(corresp. to when G_i is a complete graph)

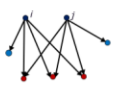
- For directed network, $C(v_i) = \frac{\#\ edges\ in\ G_i}{max\ \#\ edges\ in\ G_i} = \frac{m_i}{n_i(n_i - 1)}$
- Clustering coefficient of a graph G: Averaging the local clustering coefficient of all the vertices (Watts & Strogatz): $C(G) = \frac{1}{n} \sum_i C(v_i)$

- Co-citation of vertices i and j: $A_{ik}A_{jk} = 1$ if i and j are both cited by k
  - # of vertices having outgoing edges pointing to both i and j $C_{ij} = \sum_{k=1}^{n} A_{ik}A_{jk} = \sum_{k=1}^{n} A_{ik}A_{kj}^T$
  - Co-citation matrix: It is a symmetric matrix $\mathbf{C} = \mathbf{A}\mathbf{A}^T$
  - Diagonal matrix (C_{ii}): total # papers citing i



Vertices i and j are co-cited by 3 papers

- Bibliographic coupling of vertices i and j: $A_{ki}A_{kj} = 1$ if i and j both cite k
  - Bibliographic coupling of i and j: $B_{ij} = \sum_{k=1}^{n} A_{ki}A_{kj} = \sum_{k=1}^{n} A_{ik}^T A_{kj}$
  - Bibliographic coupling matrix: $\mathbf{B} = \mathbf{A}^T\mathbf{A}$
  - Diagonal matrix (B_{ii}): total # papers cited by i



Vertices i and j cite 3 same papers

- The projection to one-mode can be written in terms of the incidence matrix B as follows

$$P_{ij} = \sum_{k=1}^{g} B_{ki} B_{kj} = \sum_{k=1}^{g} B_{ik}^T B_{kj}$$

- Centrality: How "central" a node is in the network
- **Degree centrality**: degree of a node (the higher degree, more important the node)
- **Eccentricity centrality**: the less eccentric, the more central
  - $c(v_i) = 1/e(v_i)$
  - Central node: $e(v_i) = r(G)$ (if it equals the radius of G)
  - Periphery node: $e(v_i) = d(G)$ (if it equals the diameter of G)
  - Often used in facility location, e.g., emergency center
- **Closeness centrality**: the average of the shortest path length from the node to every other node in the network, indicating how close a node is to all other nodes in the network
  - $c(v_i) = 1/\sum_j d(v_i, v_j)$
  - median node v_m if v_m has the smallest total distance $\sum_j d(v_m, v_j)$
  - Facility location, e.g., shopping center, minimize total distance
- **Eigenvector centrality**: Measure the influence of a node in a network, i.e., connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes

- **Eigenvector centrality**, or prestige, importance, or rank of a node v
  - The more nodes point to v, the higher v's prestige
  - The more prestige of a node pointing to v, the higher v's prestige
- Let p(u) be prestige score for node u. Then

$$p(v) = \sum_u A(u, v) \cdot p(u) = \sum_u A^T(v, u) \cdot p(u)$$

- Written in vector form: $\mathbf{p}' = \mathbf{A}^T\mathbf{p}$
- At k-th iteration, we have $\mathbf{p}_k = (\mathbf{A}^T)^k \mathbf{p}_0$
  - Vetor $\mathbf{p}_k$ converges to the dominant eigenvector of $\mathbf{A}^T$ with increasing k
- Pagerank score computation: $\mathbf{p}' = (1-\alpha)\mathbf{N}^T\mathbf{p} + \alpha\mathbf{N}_r^T\mathbf{p} = ((1-\alpha)\mathbf{N}^T + \alpha\mathbf{N}_r^T)\mathbf{p} = \mathbf{M}^T\mathbf{p}$

- For a specific query, a page of high Pagerank score may not be that relevant
- HITS (Hyperlink Induced Topic Search) computes two values for a page
  - Authority score: analogous to pagerank/prestige scores
  - Hub score: based on how many "good" pages it points to
- How is HITS query-based?
  - first uses standard search engines to retrieve the set of relevant pages
  - then expands the set to include any page that point to or is pointed to by) some pages in the set
  - Any pages originating from the same host are eliminated
  - HITS is only applied on this expanded query-specific graph G
- Computation: $a(v) = \sum_u \mathbf{A}^T(v,u) \cdot h(u)$ $\quad h(v) = \sum_u \mathbf{A}(v,u) \cdot a(u)$
- In matrix computation (essentially two eigenvector computation):

$$\mathbf{a}_k = \mathbf{A}^T\mathbf{h}_{k-1} = \mathbf{A}^T(\mathbf{A}\mathbf{a}_{k-2}) = (\mathbf{A}^T\mathbf{A})\mathbf{a}_{k-2} \qquad \mathbf{h}_k = \mathbf{A}\mathbf{a}_{k-1} = \mathbf{A}(\mathbf{A}^T\mathbf{h}_{k-2}) = (\mathbf{A}\mathbf{A}^T)\mathbf{h}_{k-2}$$

- $\mathbf{AA}^T$ is the co-citation matrix and $\mathbf{A}^T\mathbf{A}$ is the bibliographic coupling matrix. Authority centrality is eigenvector centrality for the co-citation network

PathSim: favor peers objects with strong connectivity and similar visibility under the given meta-path. s(x,y)=2*|{px~>y: px~>y in P}|/|{px~>x: px~>x in P}|+|{py~>y: py~>y in P}|
co-clustering-based pruning: top k as threshold.

- A typical network has the following common properties:
  - *Few* connected components:
    - often only 1 or a small number, independent of network size
  - *Small* diameter:
    - often a constant independent of network size (like 6)
    - growing only logarithmically with network size or even shrink?
    - typically exclude infinite distances
  - A *high* degree of clustering:
    - considerably more so than for a random network
  - A *heavy-tailed* degree distribution:
    - a small but reliable number of high-degree vertices
    - often of *power law* form
- Real network: **large, sparse** (# of edges |E| = O(n), n: # of nodes)
- **Small-world property**: Avg. path length μ_L scales logarithmically with n (# of nodes in the graph): $\mu_L \propto \log n$
  - Ultra-small-world property: $\mu_L \ll \log n$
- **Scale-free property (power law distribution)**: most nodes have very small degree, but a few hub nodes have high degrees
  - The probability that a node has degree k: $f(k) \propto k^{-\gamma}$
  - log-log plot shows a straight line: $\log f(k) = \log(\alpha k^{-\gamma}) = -\gamma \log k + \log \alpha$
- **Clustering effect**:
  - Two nodes are more likely to be connected if they share a common neighbor
  - Clustering effect: a high clustering coefficient for graph G
  - C(k): avg clustering coefficient for nodes with degree k
  - Power law relationship between C(k) and k: $C(k) \propto k^{-\gamma}$

- ***Erdös-Rényi Random graph model:***
  - Gives few components and small diameter
  - does not give high clustering and heavy-tailed degree distributions
  - is the mathematically most well-studied and understood model
- ***Watts-Strogatz small world graph model:***
  - gives few components, small diameter and high clustering
  - does not give heavy-tailed degree distributions
- ***Barabási-Albert Scale-free model:***
  - gives few components, small diameter and heavy-tailed distribution
  - does not give high clustering

- The ER graphs fail to explain two important properties observed in real-world networks:
  - By assuming a constant and independent probability of two nodes being connected, they do not account for local clustering, i.e., having a low *clustering coefficient*
  - Do not account for the formation of hubs. Formally, the degree distribution of ER graphs converges to a Poisson distribution, rather than a *power law* observed in most real-world, *scale-free networks*

- Simple Ranking
  - Proportional to # of publications of an author and a venue
  - Considers only **immediate neighborhood** in the network

$$\begin{cases} \vec{r}_X(x) = \dfrac{\sum_{j=1}^{n} W_{XY}(x,j)}{\sum_{i=1}^{m}\sum_{j=1}^{n} W_{XY}(i,j)} \\ \vec{r}_Y(y) = \dfrac{\sum_{i=1}^{n} W_{XY}(i,y)}{\sum_{i=1}^{m}\sum_{j=1}^{n} W_{XY}(i,j)} \end{cases}$$

- Clustering and ranking are mutually enhanced
  - Better clustering: Rank distributions for clusters are more distinguishing from each other
  - Better ranking: Better metric for objects is learned from the ranking

Authority Ranking

- Methodology: **Propagate** the ranking scores in the network over different types
- Rule 1: Highly ranked authors publish *many* papers in highly ranked venues

$$\vec{r}_Y(j) = \sum_{i=1}^{m} W_{YX}(j,i)\vec{r}_X(i)$$

- Rule 2: Highly ranked venues attract *many* papers from *many* highly ranked authors

$$\vec{r}_X(i) = \sum_{j=1}^{n} W_{XY}(i,j)\vec{r}_Y(j)$$

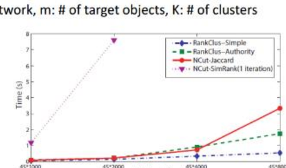
- Rule 3: The rank of an author is enhanced if he or she co-authors with *many* highly ranked authors

$$\vec{r}_Y(i) = \alpha \sum_{j=1}^{m} W_{YX}(i,j)\vec{r}_X(j) + (1-\alpha)\sum_{j=1}^{n} W_{YY}(i,j)\vec{r}_Y(j)$$

- **E-step** assigns objects to clusters according to the current probabilistic clustering or parameters of probabilistic clusters
- **M-step** finds the new clustering or parameters that minimize the sum of squared error (SSE) or maximize the expected likelihood

- Conditional rank distribution as cluster feature
  - For each cluster C_k, *the conditional rank scores,* $r_X|C_k$ *and* $r_Y|C_k$*, can be viewed as conditional rank distributions of X and Y, which are the features for cluster* C_k
- Cluster membership as object feature
  - From $p(k|o_i) \propto p(o_i|k)p(k)$, *the higher its conditional rank in a cluster (*$p(o_i|k)$*), the higher possibility an object will belong to that cluster (*$p(k|o_i)$*)*
  - Highly ranked attribute object has more impact on determining the cluster membership of a target object
- Parameter estimation using the Expectation-Maximization algorithm
  - E-step: Calculate the distribution $p(z = k|y_j, x_i, \Theta)$ *based on the current value of* Θ
  - M-Step: Update Θ according to the current *distribution*

- At each iteration, |E|: edges in network, m: # of target objects, K: # of clusters
  - Ranking for sparse network
    - ~O(|E|)
  - Mixture model estimation
    - ~O(K|E|+mK)
  - Cluster adjustment
    - ~O(mK^2)
- In all, linear to |E|
  - ~O(K|E|)



Comparison of algorithms on execution time

- Note: SimRank will be at least quadratic at each iteration since it evaluates distance between every pair in the network

- Random walk (RW):
  - The probability of random walk starting at x and ending at y, with meta-path P

$$s(x,y) = \sum_{p \in P} prob(p)$$

  - Used in Personalized PageRank (P-Pagerank) (Jeh and Widom 2003)
  - Favors **highly visible** objects (i.e., objects with large degrees)
- Pairwise random walk (PRW):
  - The probability of pairwise random walk starting at (x, y) and ending at a common object (say z), following a meta-path (P_1, P_2)

$$s(x,y) = \sum_{(p_1,p_2)\in(P_1,P_2)} prob(p_1)prob(p_2)$$

  - Used in SimRank (Jeh and Widom 2002)
  - Favors ***pure*** objects (i.e., objects with highly skewed distribution in

- SimRank (Jeh and Widom 2002)
  - Base: objects are maximally similar to themselves, i.e., $s_0(a,b) = \begin{cases} 1, & \text{if } a = b, \\ 0, & \text{if } a \neq b. \end{cases}$
  - Induction: Two objects are considered to be similar if they are referenced by similar objects $s(a,b) = \frac{C}{|I(a)||I(b)|}\sum_{i=1}^{|I(a)|}\sum_{j=1}^{|I(b)|} s(I_i(a), I_j(b))$
  - The computation is quite costly: Many efficient computation methods proposed

Glen Jeh and Jennifer Widom. SimRank: A Measure of Structural-Context Similarity. In KDD'02

- Personalized PageRank (P-Pagerank) (Jeh and Widom 2003)
  - P-PageRank score x is defined as: $x = \alpha Px + (1-\alpha)b$, where P is a transition matrix of the network G, b is a stochastic vector, called *personalized vector*, and $\alpha \in (0, 1)$ is the *teleportation constant*
  - Efficient computation methods are also studied (e.g., Maehara, et al., VLDB'14)

Glen Jeh and Jennifer Widom. Scaling Personalized Web Search, In *WWW* 2003

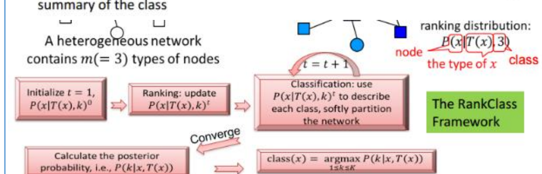
Why User Guidance in Clustering?

- Different users may like to get different clusters for different clustering goals
  - Ex. Clustering authors based on their connections in the network
- **Problem: User-guided clustering with meta-path selection**
- Input:
  - The target type for clustering T
  - # of clusters k
  - Seeds in some clusters: L_1, …, L_k
  - Candidate meta-paths: P_1, …, P_M
- Output:
  - Weight of each meta-path: w_1, …, w_m
  - Clustering results that are consistent with the user guidance

- Two levels of personalization
  - Data level
    - Most recommendation methods use one model for all users and rely on personal feedback to achieve personalization
  - Model level
    - With different entity relationships, we can learn personalized models for different users to further distinguish their differences

- **Classification in heterogeneous networks**
  - **Knowledge propagation:** Class label knowledge propagated across multi-typed objects through a heterogeneous network
- **GNetMine [Ji et al., PKDD'10]:** Objects are treated equally
- **RankClass [Ji et al., KDD'11]:** Ranking-based classification
  - Highly ranked objects will play more role in classification
  - An object can only be ranked high in some focused classes
  - Class membership and ranking are stat. distributions
  - Let ranking and classification mutually enhance each other!
  - Output: Classification results + ranking list of objects within each class

- Different objects within one class have different importance/visibility!
- The ranking of objects within one class serves as an informative understanding and summary of the class



Graph-Based Ranking

- Intuitive idea: authority propagation
  - Objects linked together are likely to share similar ranking scores within class k
- Update the ranking score of each object by looking t the ranking of its neighbors

The initial ranking score

$$P(x_{ip}|\chi_i,k)^{t+1} \propto \frac{\boxed{\sum_{j=1}^{m}\sum_{q=1}^{n_j} \lambda_{ij} S_{ij,pq} P(x_{jq}|\chi_j,k)^t} + \alpha_i \boxed{P(x_{ip}|\chi_i,k)^0}}{\sum_{j=1}^{m} \lambda_{ij} + \alpha_i}$$

Weighted average of the neighbors' ranking scores

The NetClus Algorithm

- Generate initial partitions for target objects and induce initial net-clusters from the original network
- Repeat // An E-M Framework
  - Build ranking-based probabilistic generative model for each net-cluster
  - Calculate the posterior probabilities for each target object
  - Adjust their cluster assignment according to the new measure defined by the posterior probabilities to each cluster
- Until the clusters do not change significantly
- Calculate the posterior probabilities for each attribute object in each net-cluster

$A - P \rightarrow P - A$	a_i cites a_j
$A - P \leftarrow P - A$	a_i is cited by a_j
$A - P - V - P - A$	a_i and a_j publish in the same venues
$A - P - A - P - A$	a_i and a_j are co-authors of the same authors
$A - P - T - P - A$	a_i and a_j write the same topics
$A - P \rightarrow P \rightarrow P - A$	a_i cites papers that cite a_j
$A - P \leftarrow P \leftarrow P - A$	a_i is cited by papers that are cited by a_j
$A - P \rightarrow P \leftarrow P - A$	a_i and a_j cite the same papers
$A - P \leftarrow P \rightarrow P - A$	a_i and a_j are cited by the same papers

- Training and test pair: <$\mathbf{x}_i$, y_i> = <history feature list, future relationship label>

	A—P—A—P—A	A—P—V—P—A	A—P—T—P—A	A—P→P—A	A—P—A
<Mike, Ann>	4	5	100	3	**Yes = 1**
<Mike, Jim>	0	1	20	2	**No = 0**

- Logistic Regression Model
  - Model the probability for each relationship as

$$p_i = \frac{e^{\mathbf{x}_i \beta}}{e^{\mathbf{x}_i \beta} + 1}$$

  - β is the coefficients for each feature (including a constant 1)
  - MLE (Maximum Likelihood Estimation)
  - Maximize the likelihood of observing all the relationships in the training data

$$L = \prod_i p_i^{y_i} (1 - p_i)^{(1-y_i)}$$

We study four measures that defines a relationship *R* encoded by a meta path

- Path Count: Number of path instances between authors following *R*

$$PC_R(a_i, a_j)$$

- Normalized Path Count: Normalize path count following *R* by the "degree" of authors

$$NPC_R(a_i, a_j) = \frac{PC_R(a_i,a_j) + PC_{R^{-1}}(a_j,a_i)}{PC_R(a_i,\cdot) + PC_R(\cdot,a_j)}$$

- Random Walk: Consider one way random walk following *R*

$$RW_R(a_i, a_j) = \frac{PC_R(a_i,a_j)}{PC_R(a_i,\cdot)}$$

- Symmetric Random Walk: Consider random walk in both directions

$$SRW_R(a_i, a_j) = RW_R(a_i, a_j) + RW_{R^{-1}}(a_j, a_i)$$

Generate *L* different **meta-path** (path types) connecting users and items → Propagate user implicit feedback along each meta-path → Calculate latent-features for users and items for each meta-path with **NMF** related method

Recommendation Models

Observation 1: Different meta-paths may have different importance

Global Recommendation Model

$$\underbrace{\hat{r}(u_i, e_j)}_{\text{ranking score}} = \sum_{q=1}^{L} \underbrace{\theta_q}_{\text{the q-th meta-path}} \cdot \underbrace{\hat{U}_i^{(q)} \hat{V}_j^{(q)T}}_{\text{features for user } i \text{ and item } j} \quad (1)$$

Observation 2: Different users may require different models

Personalized Recommendation Model

$$\hat{r}_p(u_i, e_j) = \sum_{k=1}^{c} \underbrace{sim(C_k, u_i)}_{\text{user-cluster similarity}} \sum_{q=1}^{L} \theta_q^{\{k\}} \cdot \hat{U}_i^{(q)} \hat{V}_j^{(q)T} \quad (2)$$

c total soft user clusters

- Bayesian personalized ranking (Rendle UAI'09)
- Objective function

sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$

$$\min_{\Theta} \; -\sum_{u_i \in \mathcal{U}} \sum_{(e_a > e_b) \in R_i} \ln \sigma(\hat{r}(u_i, e_a) - \hat{r}(u_i, e_b)) + \frac{\lambda}{2} \|\Theta\|_2^2 \quad (3)$$

for each correctly ranked item pair i.e., u_i gave feedback to e_a but not e_b

Soft cluster users with NMF + k-means → For each user cluster, learn one model with Eq. (3) → Generate personalized model for each user on the fly with Eq. (2)

Learning Personalized Recommendation Model

How likely a query manuscript ***q*** will cite a candidate paper ***p*** (suppose **K** interest groups):

$$s(q,p) = \sum_{k=1}^{K} \theta_q^{(k)} \cdot \left\{ r^{(k)}(q,p) + f_{\mathcal{P}}^{(k)}(p) \right\}$$

query's group membership

relative citation score (how likely ***q*** will cite ***p***) within each group

paper relative relevance (query-candidate paper)

paper relative authority (candidate paper)

It is desirable to suggest papers that have *high* relative citation scores across *multiple* related interest groups of the query manuscript

- **Learn each query's group membership: scalability & generalizability**
- **Leverage the group memberships of related attribute objects to *approximate* query's group membership**

$$\theta_q^{(k)} = \sum_{\mathcal{X} \in \{\mathcal{A}, \mathcal{V}, \mathcal{T}\}} \sum_{x \in N_{\mathcal{X}}(q)} \frac{\theta_x^{(k)}}{|N_{\mathcal{X}}(q)|}$$

Different types of attribute objects (***X*** = authors/venues/terms)

Query's related (linked) objects of type-***X***

Attribute object's group membership (*to learn*)

$$r^{(k)}(q,p) = \sum_{l=1}^{L} w_k^{(l)} \phi^{(l)}(q,p)$$

$$s(q,p) = \sum_{k=1}^{K} \theta_q^{(k)} \cdot \left\{ r^{(k)}(q,p) + f_{\mathcal{P}}^{(k)}(p) \right\}$$

Paper relative authority: A paper may have quite different visibility/authority among different groups, even it is overall highly cited

- Propagation of simple, commonly accepted constraints in Time-Constrained Probabilistic Factor Graph (TPFG)
  - *"Advisor has more publications and longer history than advisee at the time of advising"*
  - *"Once an advisee becomes advisor, s/he will not become advisee again"*

model	small diameter	few components	high clustering	heavy-tailed
Random Graph	Yes	Yes	No	No
Small World	Yes	Yes	Yes	No
Scale-free Network	Yes	Yes	No	Yes

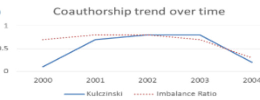
- Right heuristics: Advisee (B) tends to coauthor with advisor (A) during the advising period
- Kulczinski measure :

$$kulc(A,B) = \frac{|A \cap B|}{2}\left(\frac{1}{|A|} + \frac{1}{|B|}\right)$$

  - high overlap between their publications – Kulczinski measure
  - It is more often to see advisor in a publication but not advisee: Imbalance Ratio measure:

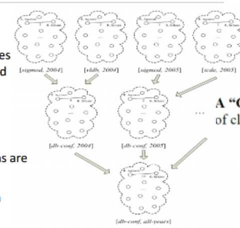
$$IR(A,B) = \frac{|A| - |B|}{|A \cup B|}$$

  - start time ≈ the year they start to collaborate
  - end time ≈ the year Kulczinski measure dropped significantly



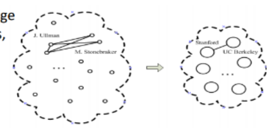
Informational OLAP

- In the DBLP network, study the collaboration patterns among researchers
- Dimensions come from informational attributes attached at the whole snapshot level, so-called *Info-Dims*
- I-OLAP Characteristics:
  - Overlay multiple pieces of information
  - No change on the objects whose interactions are being examined
    - In the underlying snapshots, each node is a researcher
    - In the summarized view, each node is still a researcher



Topological OLAP

- Dimensions come from the node/edge attributes inside individual networks, so-called *Topo-Dims*
- T-OLAP Characteristics
  - Zoom in/Zoom out
  - Network topology changed: "generalized" nodes and "generalized" edges
    - In the underlying network, each node is a researcher
    - In the summarized view, each node becomes an institute that comprises multiple researchers



The DISTINCT Methodology

- Measure similarity between references
  - Link-based similarity: Linkages between references
    - References to the same object are more likely to be connected (Using random walk probability)
  - Neighborhood similarity
    - Neighbor tuples of each reference can indicate similarity between their contexts
- Self-boosting: Training using the "same" bulky data set
- Reference-based clustering
  - Group references according to their similarities

- Build a training set automatically
  - Select distinct names, e.g., Johannes Gehrke
  - The collaboration behavior within the same community share some similarity
  - Training parameters using a typical and large set of "unambiguous" examples
- Use SVM to learn a model for combining different join paths
  - Each join path is used as two attributes (with link-based similarity and neighborhood similarity)
  - The model is a weighted sum of all attributes
- Single-link (highest similarity between points in two clusters) ?
  - No, because references to different objects can be connected.
- Complete-link (minimum similarity between them)?
  - No, because references to the same object may be weakly connected.
- Average-link (average similarity between points in two clusters)?
  - A better measure
  - *Refinement: Average neighborhood similarity* and *collective random walk probability*

	InfoNet I-OLAP	InfoNet T-OLAP
Roll-up	Overlay multiple snapshots to form a higher-level summary via I-aggregated network	Shrink the topology & obtain a T-aggregated network that represents a compressed view, with topological elements (i.e., nodes and/or edges) merged and replaced by corresp. higher-level ones
Drill-down	Return to the set of lower-level snapshots from the higher-level overlaid (aggregated) network	A reverse operation of roll-up
Slice/dice	Select a subset of qualifying snapshots based on Info-Dims	Select a subnetwork based on Topo-Dims

<u>evolution and dynamic of info-net</u>: EvoNetClus, dirichlet process mixture model-based generative model, along with time find underneath generative model changes based on observable things. At each timestamp, a community is dependent on historical communities and background community distribution. To generate a new paper, decide whether to join an existing community or a new one. 1. generating prior groups, 2. iterative hidden community label assignment with EM, 3 community distribution estimation.

Measures in SN analysis- Centrality: This measure gives a rough indication of the social power of a node based on how well they "connect" the network. "Betweenness", "Closeness", and "Degree" are all measures of centrality.- **Centralization**: The difference between the number of links for each node divided by maximum possible sum of differences. A centralized network will have many of its links dispersed around one or a few nodes, while a decentralized network is one in which there is little variation between the number of links each node possesses. - **Clustering coefficient**: A measure of the likelihood that two associates of a node are associates themselves. A higher clustering coefficient indicates a greater 'cliquishness'. - **Cohesion**: The degree to which actors are connected directly to each other by *cohesive* bonds. Groups are identified as '*cliques*' if every individual is directly tied to every other individual, '*social circles*' if there is less stringency of direct contact, which is imprecise, or as *structurally cohesive* blocks if precision is wanted. - **(Individual-level) Density:** The degree a respondent's ties know one another/ proportion of ties among an individual's nominees. Network or global-level density is the proportion of ties in a network relative to the total number possible (sparse versus dense networks). - **Flow betweenness centrality**: The degree that a node contributes to sum of maximum flow between all pairs of nodes (not that node). - **Eigenvector centrality**: A measure of the importance of a node in a network. It assigns relative scores to all nodes in the network based on the principle that connections to nodes having a high score contribute more to the score of the node in question. - **Local Bridge**: An edge is a local bridge if its endpoints share no common neighbors. Unlike a bridge, a local bridge is contained in a cycle. - **Path Length**: The distances between pairs of nodes in the network. Average path-length is the average of these distances between all pairs of nodes -**Structural cohesion**: The minimum number of members who, if removed from a group, would disconnect the group - **Structural hole**: Static holes that can be strategically filled by connecting one or more links to link together other points. Linked to ideas of *social capital*: if you link to two people who are not linked you can control their communication

A "Canonical" Natural Network: *1) Few* connected components; 2) *Small* diameter; 3)*high* degree of clustering 4) *heavy-tailed* degree distribution

PathSim is designed to find peer objects Random walk favors objects with large degrees, and the pairwise random walk favors concentrated objects that the majority of the links goes to a small portion of objects

Given a heterogeneous information network, different users may want to cluster the network in different ways, which can be captured by different semantics in different meta-path. The user can give guidance by providing some seeds in some of the clusters that the user wants to obtain, which could then be used to learn the weight for each candidate meta-path in the clustering process. The clustering results generated in this way should be as consistent as possible with the user guidance. Technically, we can employ user guidance to help select appropriate meta-paths for rank-based clustering by constructing a probabilistic model that contains the following steps:
(i) Modeling the Relationship Generation. A good clustering result should lead to high likelihood in observing existing relationships.
(ii) Modeling the Guidance from Users. The more consistent with the user guidance, the higher probability of the clustering result.
(iii) Modeling the Quality Weights for Meta-Paths. The more consistent with the clustering result, the higher quality weight.