Mining Web Data

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Outline

- **Introduction**
- Web Crawling and Resource Discovery
- Search Engine Indexing and Query Processing
- Ranking Algorithms
- Recommender Systems
- Web Usage Mining
- Summary

Introduction

- Web is an unique phenomenon
  - The scale, the distributed and uncoordinated nature of its creation, the openness of the underlying platform, and the diversity of applications
- Two Primary Types of Data
  - Web content information
    - ✓ Document data, Linkage data (Graph)
  - Web usage data
    - ✓ Web transactions, ratings, and user feedback, Web logs

Applications on the Web

- Content-Centric Applications
  - Data mining applications
    - ✓ Cluster or classify web documents
  - Web crawling and resource discovery
  - Web search
    - ✓ Linkage and content
  - Web linkage mining
- Usage-Centric Applications
  - Recommender systems
  - Web log analysis
    - ✓ Anomalous patterns, and Web site design

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Web Crawling

- Web Crawlers or Spiders or Robots
- Motivations
  - Resources on the Web are dispensed widely across globally distributed sites
  - Sometimes, it is necessary to download all the relevant pages at a central location
- Universal Crawlers
  - Crawl all pages on the Web (Google, Bing)
- Preferential Crawlers
  - Crawl pages related to a particular subject or belong to a particular site

Crawler Algorithms

- A real crawler algorithm is complex
  - A selection Algorithm, Parsing, Distributed, multi-threads
- A Basic Crawler Algorithm

Algorithm *BasicCrawler*(Seed URLs: S, Selection Algorithm: $\mathcal{A}$)
begin
  $FrontierList = S$;
  repeat
    Use algorithm $\mathcal{A}$ to select URL $X \in FrontierSet$;
    $FrontierList = FrontierList - \{X\}$;
    Fetch URL X and add to repository;
    Add all relevant URLs in fetched document X to
      end of $FrontierList$;
  until termination criterion;
end

Selection Algorithms

- Breadth-first
- Depth-first

- Frequency-Based
  - Most universal crawlers are incremental crawlers that are intended to refresh previous crawls
- PageRank-Based
  - Choose Web pages with high PageRank

Preferential Crawlers

- User-defined Criteria
  - Keyword presence in the page
  - A topical criterion defined by a machine learning algorithm
  - A geographical criterion about page location
  - A combination of the different criteria
- Modify the approach for updating the frontier list
  - The web page or pages that it points to need to satisfy the criteria
- Modify the selection algorithm

Multiple Threads

- Network is slow
  - The system is idle when a crawler issues a request for a URL and waits for it
- Concurrency
  - Use multiple threads to update a shared data structure for visited URLs and the page repository (locking or unlocking)
  - The crawler may also distributed geographically with each “sub-crawler” collecting pages in its geographical proximity

Combatting Spider Traps

- The crawling algorithm maintains a list of previously visited URLs for comparison purposes
  - So, it always visits distinct Web pages
- However, many sites create dynamic URLs
  - http://www.examplesite.com/page1
  - http://www.examplesite.com/page1/page2
  - Limit the maximum size of the URL
  - Limit the number of URLs from a site

Near Duplicate Detection

- Many duplicates of the same page may be crawled
- A k-shingle (k-gram)
  - A string of k consecutively occurring words

    Mary had a little lamb, its fleece was white as snow.

  - "Mary had", "had a", "a little", ...
- The Shingle-Based Similarity

  Jaccard coefficient $J(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}$

  - S_1 and S_2 be the k-shingles extracted from two documents D_1 and D_2

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The Process of Search

- Offline Stage
  - The search engine preprocesses the crawled documents to extract the tokens and constructs an index
  - A quality-based ranking score is also computed for each page

- Online Query Processing
  - The relevant documents are accessed and then ranked using both their relevance to the query and their quality

Offline Stage

- The Preprocessing Steps
  - The relevant tokens are extracted and stemmed
  - Stop words are removed
- Construct the Inverted Index
  - Maps each word identifier to a list of document identifiers containing it
    - ✓ Document ID, Frequency, Position
- Construct the Vocabulary Index
  - Access the storage location of the inverted word

Ranking (1)

- Content-Based Score
  - A word is given different weights, depending upon whether it occurs in the title, body, URL token, or the anchor text
  - The number of occurrences of a keyword in a document will be used in the score
  - The prominence of a term in font size and color may be leveraged for scoring
  - When multiple keywords are specified, their relative positions in the documents are used as well

Ranking (2)

- Limitations of Content-Based Score
  - It does not account for the reputation, or the quality, of the page
    - ✓ A user may publish incorrect material
  - Web Spam
    - ✓ Content-spamming: The Web host owner fills up repeated keywords in the hosted Web page
    - ✓ Cloaking: The Web site serves different content to crawlers than it does to users
  - Search Engine Optimization (SEO)
    - ✓ The Web set owners attempt to optimize search results by using their knowledge

Ranking (3)

- Reputation-Based Score
  - Page citation mechanisms: When a page is of high quality, many other Web pages point to it
  - User feedback or behavioral analysis mechanisms: When a user chooses a Web page, this is clear evidence of the relevance of that page to the user
- The Final Ranking Score

$$RankScore = f(IRScore, RepScore).$$

  - Spams always exist

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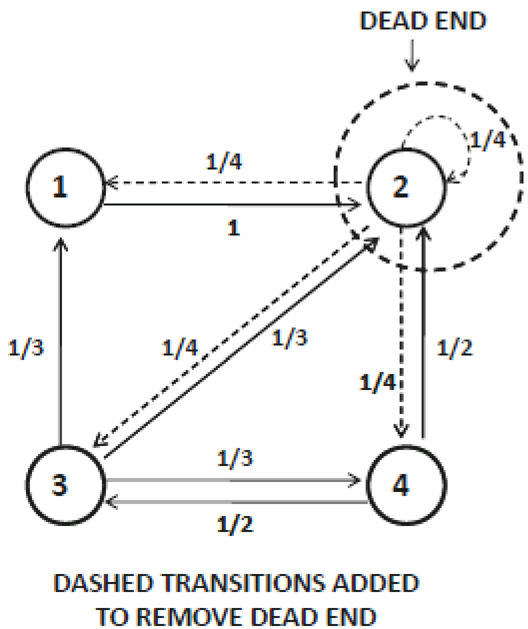
Google's PageRank (1)

- Random Walk Model
  - A random surfer who visits random pages on the Web by selecting random links on a page

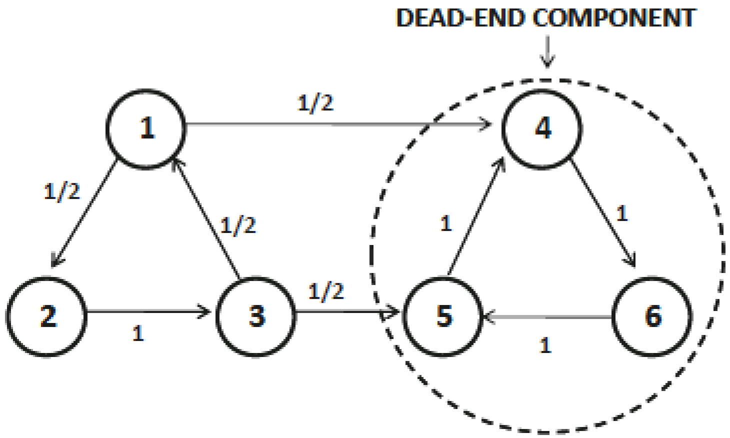
1. The long-term relative frequency of visits to any particular page is clearly influenced by the number of in-linking pages to it
2. The long-term frequency of visits to any page will be higher if it is linked to by other frequently visited pages

Google's PageRank (2)

- Random Walk Model
  - Dead ends: pages with no outgoing links
  - Dead-end component



(a) Dead-end node



(b) Dead-end component

Google's PageRank (3)

□ Random Walk Model

- Dead ends: pages with no outgoing links
  - ✓ Add links from the dead-end node (Web page) to all nodes (Web pages), including a self-loop to itself

- Dead-end component
  - ✓ A teleportation (restart) step: The random surfer may either jump to an arbitrary page with probability α, or it may follow one of the links on the page with probability $1 - \alpha$

Steady-state Probabilities (1)

- $G = (N, A)$ be the directed Web graph
  - Nodes correspond to pages
  - Edges correspond to hyperlinks
    - ✓ Include added edges for dead-end nodes
  - $\pi(i)$: the steady-state probability at i
  - $In(i)$: set of nodes incident on i
  - $Out(i)$: the set of end points of the outgoing links of node i
  - Transition matrix P of the Markov chain

$$p_{ij} = \frac{1}{|Out(i)|} \quad \text{if there is an edge form } i \text{ to } j$$

Steady-state Probabilities (2)

- The probability of a teleportation into i

$$\frac{\alpha}{n}$$

- The probability of a transition into i

$$(1-\alpha)\sum_{j\in In(i)}\pi(j)\cdot p_{ji}$$

- Then, we have

$$\pi(i) = \alpha/n + (1-\alpha)\cdot\sum_{j\in In(i)}\pi(j)\cdot p_{ji}$$

Steady-state Probabilities (3)

- Let $\bar{\pi} = [\pi(1), \dots, \pi(n)]^\top$

$$\overline{\pi} = \alpha \overline{e}/n + (1-\alpha) P^T \overline{\pi}$$

  - With the constraint $\sum_{i=1}^{n} \pi(i) = 1$

- Optimization
  - $\bar{\pi}^{(0)} = \frac{\bar{e}}{n}$
  - $\bar{\pi}^{(t+1)} = \frac{\alpha \bar{e}}{n} + (1-\alpha) P^\top \bar{\pi}^{(t)}$
  - $\bar{\pi}^{(t+1)} \leftarrow \frac{\bar{\pi}^{(t+1)}}{|\bar{\pi}^{(t+1)}|_1}$

Topic-Sensitive PageRank

- The Motivation
  - Provide greater importance to some topics than others
- The Procedure
  - Fix a list of topics, and determine a high-quality sample of pages from each topic
  - Teleportation is only performed on this sample set of Web documents belonging to a specific topic

$$\overline{\pi} = \alpha \overline{e_p}/n_p + (1-\alpha)P^T\overline{\pi}$$

    - ✓ $\overline{e_p}$ is an indicator vector for the specific topic

SimRank (1)

- An Asymmetric Ranking Problem
  - Given a target node i_q and a subset of nodes $S \subseteq N$ from graph $G = (N, A)$, rank the nodes in S in their order of similarity to i_q
    - ✓ Very popular in bipartite graph
  - A limiting case of topic-sensitive PageRank
    - ✓ The teleportation is performed to the single node i_q

$$\overline{\pi} = \alpha \overline{e_q} + (1-\alpha) P^T \overline{\pi}.$$

    - ✓ $\overline{e_q}$ is a vector of all 0s, except for a single 1, corresponding to the node i_q

SimRank (2)

The Goal

- Compute the structural/symmetric similarity between nodes

The Definition

$$SimRank(i,j) = \frac{C}{|In(i)| \cdot |In(j)|} \sum_{p \in In(i)} \sum_{q \in In(j)} SimRank(p,q)$$

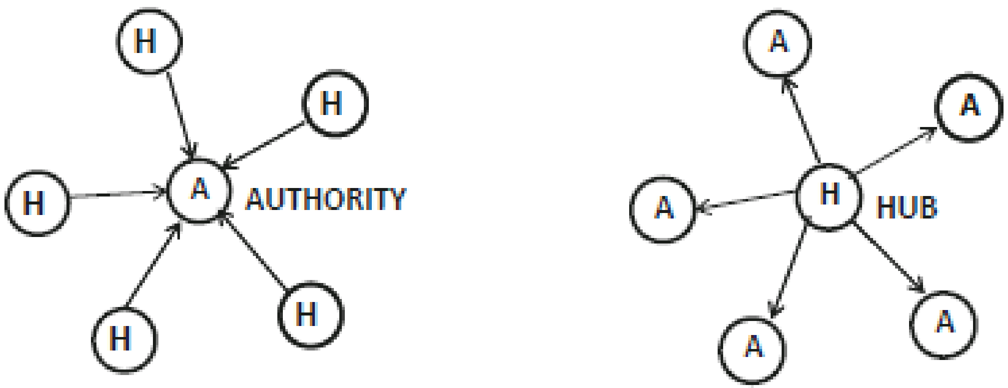
- $In(i)$: in-linking nodes of i
- $C \in (0,1)$ is a constant

Optimization

- $SimRank(i,j) = 1$ if $i = j$
- Apply the above equation iteratively

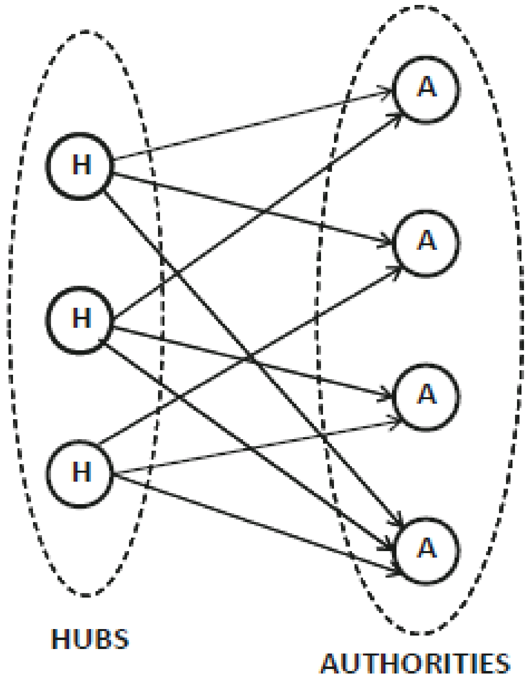
Hypertext Induced Topic Search (HITS)

- Authority
  - A page with many in-links
  - It contains authoritative content on a particular subject
- Hub
  - A page with many out-links to authorities



The Insight of HITS

- Good hubs point to many good authorities
- Good authority pages are pointed to by many hubs



The Procedure of HITS (1)

- Collect the top-r most relevant results to the search query at hand
  - This defines the root set R
  - $r = 50$
- Determine all nodes immediately connected (either in-linking or out-linking) to R
  - This provides a larger base set S
  - The number of in-linking nodes is restricted to k
  - $k = 50$

The Procedure of HITS (2)

- $G = (S, A)$ be the subgraph of the Web graph defined on the base set S, where A is the set of edges between nodes in the root set S
- Each page i is assigned both a hub score $h(i)$ and authority score $a(i)$

$$h(i) = \sum_{j:(i,j)\in A} a(j) \quad \forall i \in S$$

$$a(i) = \sum_{j:(j,i)\in A} h(j) \quad \forall i \in S.$$

  - Reward hubs for pointing to good authorities and reward authorities for being pointed to by good hubs

The Procedure of HITS (3)

- An Iterative Algorithm
  - $h^0(i) = a^0(i) = 1/\sqrt{|S|}$

    for each $i \in S$ set $a^{t+1}(i) \Leftarrow \sum_{j:(j,i)\in A} h^t(j)$;
    for each $i \in S$ set $h^{t+1}(i) \Leftarrow \sum_{j:(i,j)\in A} a^{t+1}(j)$;
    Normalize L_2-norm of each of hub and authority vectors to 1;

- $\bar{h} = [h(1), \dots, h(n)]^\top$ and $\bar{a} = [a(1), \dots, a(n)]^\top$

$$\bar{a} = A^\top \bar{h} \qquad \bar{h} = A\bar{a}$$

$$\bar{a} = A^\top A\bar{a} \qquad \bar{h} = AA^\top \bar{h}$$

  - Eigenvectors or singular vectors

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Recommender Systems

- Data About User Buying Behaviors
  - User profiles, interests, browsing behavior, buying behavior, and ratings about various items

- The Goal
  - Leverage such data to make recommendations to customers about possible buying interests

Utility Matrix (1)

- For n users and d items, there is an $n \times d$ matrix D of utility values
  - The utility value for a user-item pair could correspond to either the buying behavior or the ratings of the user for the item
  - Typically, a small subset of the utility values are specified

Utility Matrix (2)

- For n users and d items, there is an $n \times d$ matrix D of utility values
  - Positive preferences only
    - ✓ A specification of a "like" option on a social networking site, the browsing of an item at an online site, the buying of a specified quantity of an item, or the raw quantities of the item bought by each user
  - Positive and negative preferences (ratings)
    - ✓ The user specifies the ratings that represent their like or dislike for the item

Utility Matrix (3)

- For n users and d items, there is an $n \times d$ matrix D of utility values

	GLADIATOR	GODFATHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
U_1	1			5		2
U_2		5			4	
U_3	5	3		1		
U_4			3			4
U_5				3	5	
U_6	5		4			

(a) Ratings-based utility

	GLADIATOR	GODFATHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
U_1	1			1		1
U_2		1			1	
U_3	1	1		1		
U_4			1			1
U_5				1	1	
U_6	1		1			

(b) Positive-preference utility

Types of Recommendation

- Content-Based Recommendations
  - The users and items are both associated with feature-based descriptions
    - ✓ The text of the item description
    - ✓ The interests of user in a profile
- Collaborative Filtering
  - Leverage the user preferences in the form of ratings or buying behavior in a "collaborative" way
  - The utility matrix is used to determine either relevant users for specific items, or relevant items for specific users

Content-Based Recommendations (1)

- User is associated with some documents that describe his/her interests
  - Specified demographic profile
  - Specified interests at registration time
  - Descriptions of the items bought
- The items are also associated with textual descriptions

1. If no utility matrix is available
   - k-nearest neighbor approach: find the top-k items that are closest to the user
     - ✓ The cosine similarity with tf-idf can be used

Content-Based Recommendations (1)

- User is associated with some documents that describe his/her interests
  - Specified demographic profile
  - Specified interests at
  - Descriptions of the i
- The items are also as
  textual descriptions

Donot need the utility matrix

1. If no utility matrix is available
   - k-nearest neighbor approach: find the top-k items that are closest to the user
     - ✓ The cosine similarity with tf-idf can be used

Content-Based Recommendations (2)

2. If a utility matrix is available

- Classification-Based Approach
  - ✓ Training documents representing the descriptions of the items for which that user has specified utilities
  - ✓ The labels represent the utility values.
  - ✓ The descriptions of the remaining items for that user can be viewed as the test documents
- Regression-Based Approach

Limitations

- Depends on the quality of features

Collaborative Filtering

- Missing-value Estimation or Matrix Completion

$$M = \begin{bmatrix} \blacksquare & & \blacksquare & & & \blacksquare & \\ & \blacksquare & & \blacksquare & \blacksquare & & \blacksquare \\ \blacksquare & & & \blacksquare & & \blacksquare & \\ & & \blacksquare & & \blacksquare & & \\ & \blacksquare & & \blacksquare & & & \blacksquare \end{bmatrix} \in \mathbb{R}^{n \times d}$$

  - The Matrix is extremely large
  - The Matrix is extremely sparse

Algorithms for Collaborative Filtering

- Neighborhood-Based Methods for Collaborative Filtering
  - User-Based Similarity with Ratings
  - Item-Based Similarity with Ratings
- Graph-Based Methods
- Clustering Methods
  - Adapting k-Means Clustering
  - Adapting Co-Clustering
- Latent Factor Models
  - Singular Value Decomposition
  - Matrix Factorization
  - Matrix Completion

User-Based Similarity with Ratings

- A Similarity Function between Users
  - $\bar{X} = (x_1, \ldots, x_s)$ and $\bar{Y} = (y_1, \ldots, y_s)$ be the common ratings between a pair of users
  - The Pearson correlation coefficient

$$\text{Pearson}(\overline{X}, \overline{Y}) = \frac{\sum_{i=1}^{s} (x_i - \hat{x}) \cdot (y_i - \hat{y})}{\sqrt{\sum_{i=1}^{s} (x_i - \hat{x})^2} \cdot \sqrt{\sum_{i=1}^{s} (y_i - \hat{y})^2}}$$

    - ✓ $\hat{x} = \sum_{i=1}^{s} x_i / s$ and $\hat{y} = \sum_{i=1}^{s} y_i / s$

1. Identify the peer group of the target user
   - Top-k users with the highest Pearson coefficient
2. Return the weighted average ratings of each of the items of this peer group
   - Normalization is needed

Item-Based Similarity with Ratings

- A Similarity Function between Items
  - The average of each row in the ratings matrix is subtracted from that row
  - $\bar{U} = (u_1, \ldots, u_s)$ and $\bar{V} = (v_1, \ldots, v_s)$ are two columns of the matrix

$$\mathrm{Cosine}(\overline{U}, \overline{V}) = \frac{\sum_{i=1}^{s} u_i \cdot v_i}{\sqrt{\sum_{i=1}^{s} u_i^2} \cdot \sqrt{\sum_{i=1}^{s} v_i^2}}$$

1. Determine the top-k most similar items to item j
2. Among those items, identify the ones for which user i provides ratings
3. Return the weighed average value of those ratings

Graph-Based Methods (1)

- A Bipartite User-Item Graph $G = (N_u \cup N_i)$
  - N_u is the set of nodes representing users
  - N_i is the set of nodes representing items
  - Each nonzero entry in the utility matrix corresponds an edge in A

	GLADIATOR	GODFATHER	BEN-HUR	GOODFELLAS	SCARFACE	SPARTACUS
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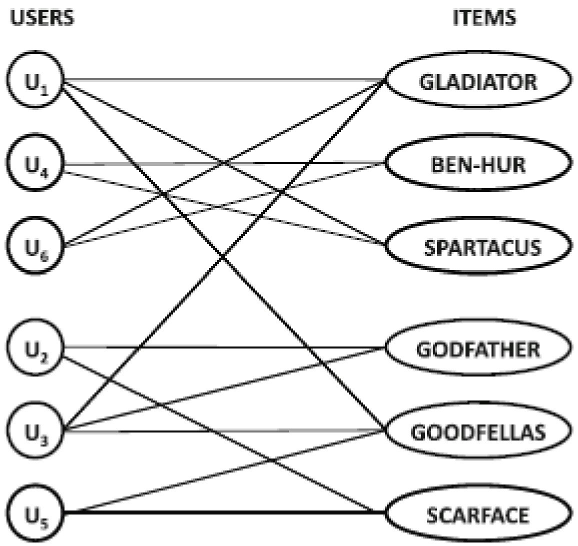

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- Combine with Previous Methods
  - Similarity Between Users/Items
    - ✓ Topic-Sensitive PageRank
    - ✓ SimRank
  - Return the weighted average

Graph-Based Methods (2)

- A Positive and Negative Link Prediction Problem
  - The normalized rating of a user for an item, after subtracting the user-mean, can be viewed as either a positive or negative weight on the edge
- A Positive Link Prediction Problem
  - Random Walk Model

1. The top ranking items for the user i can be determined by returning the item nodes with the largest *PageRank* in a random walk with restart at node i.
2. The top ranking users for the item j can be determined by returning the user nodes with the largest *PageRank* in a random walk with restart at node j.

Clustering Methods (1)

- Motivations
  - Reduce the computational cost
  - Address the issue of data sparsity to some extent

- The Result of Clustering
  - Clusters of users
    - ✓ User-user similarity recommendations
  - Clusters of items
    - ✓ Item-item similarity recommendations

Clustering Methods (2)

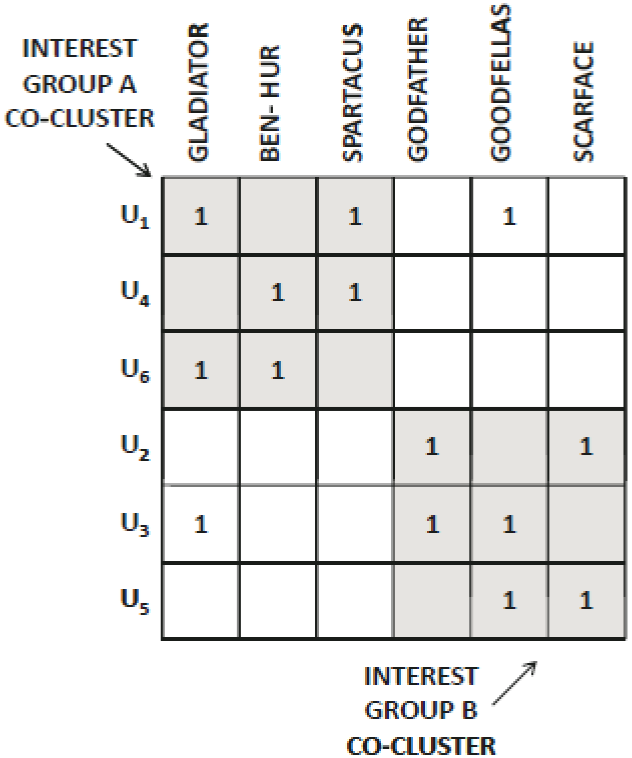
- User-User Recommendation Approach
  1. Cluster all the users into n_g groups of users using any clustering algorithm
  2. For any user i, compute the average (normalized) rating of the specified items in its cluster
  3. Report these ratings for user i
- Item–Item Recommendation Approach
  1. Cluster all the items into n_g groups of items
  2. The rest is the same as “Item-Based Similarity with Ratings”

Adapting k-Means Clustering

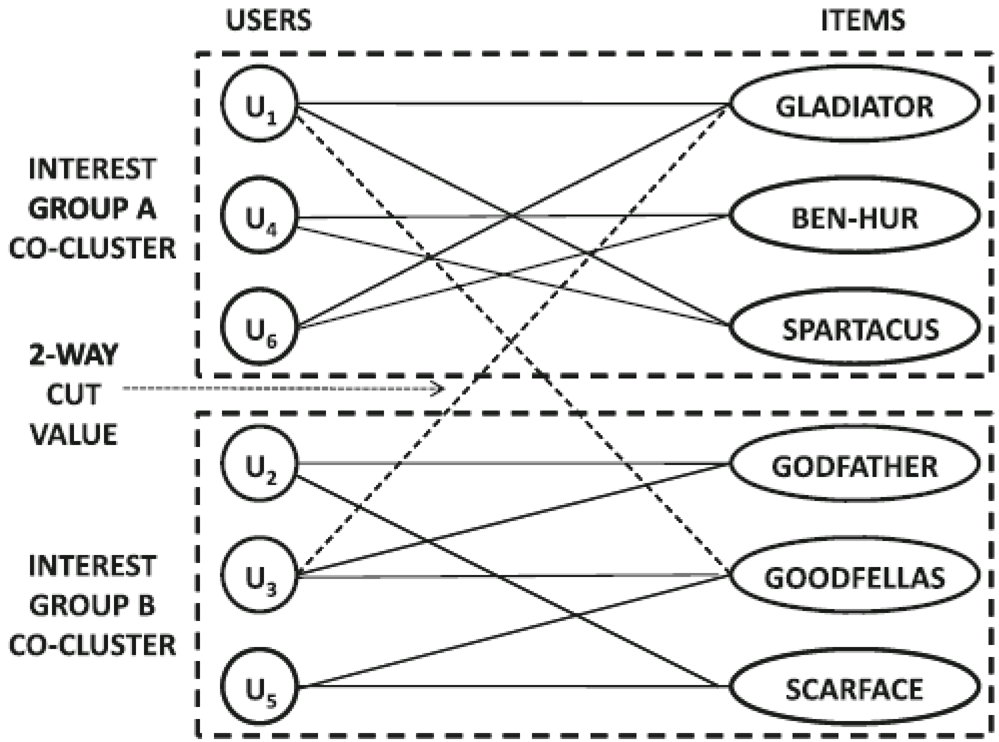
1. In an iteration of k-means, centroids are computed by averaging each dimension over the number of specified values in the cluster members
   - Furthermore, the centroid itself may not be fully specified
2. The distance between a data point and a centroid is computed only over the specified dimensions in both
   - Furthermore, the distance is divided by the number of such dimensions in order to fairly compare different data points

Adapting Co-Clustering

- User-neighborhoods and item-neighborhoods are discovered simultaneously



(a) Co-cluster



(b) User-item graph

Latent Factor Models

The Key Idea

- Summarize the correlations across rows and columns in the form of lower dimensional vectors, or latent factors
- These latent factors become hidden variables that encode the correlations in the data matrix in a concise way and can be used to make predictions
- Estimation of the k-dimensional dominant latent factors is often possible even from incompletely specified data

Modeling

- The n users are represented by n factors: $\overline{U_1}, \ldots, \overline{U_n} \in \mathbb{R}^k$
- The d items are represented by d factors: $\overline{I_1}, \ldots, \overline{I_d} \in \mathbb{R}^k$
- The rating r_{ij} for user i and item j

$$r_{ij} \approx \langle \overline{U_i}, \overline{I_j} \rangle = \overline{U_i}^\top \overline{I_j} = \overline{I_j}^\top \overline{U_i}$$

- The rating matrix $D = [r_{ij}]_{n \times d}$

$$D \approx F_{user} F_{item}^T$$

  - $F_{user} \in \mathbb{R}^{n \times k}$ and $F_{item} \in \mathbb{R}^{d \times k}$

Singular Value Decomposition

- SVD of $D \in \mathbb{R}^{n\times d}$

$$D = Q\Sigma P^\top$$

  - $Q^\top Q = I,\ P^\top P = I$
  - $\Sigma = \mathrm{diag}(\sigma_1, \sigma_2, \dots, \sigma_d) \in \mathbb{R}^{d\times d},\ \sigma_1 \geq \cdots \geq \sigma_d$
- Truncated SVD

$$D \approx Q_k \Sigma_k P_k^\top$$

  - $\Sigma_k = \mathrm{diag}(\sigma_1, \sigma_2, \dots, \sigma_k) \in \mathbb{R}^{k\times k},\ \sigma_1 \geq \cdots \geq \sigma_k$
- Discussions
  - SVD is undefined for incomplete matrices
  - PLSA may be used for nonnegative matrices

Matrix Factorization (MF)

- SVD is a special form of MF

$$D \approx UV^\top$$

- The objective when D is fully observed

$$J = \|D - UV^\top\|_F^2$$

- The objective when D is partially observed

$$J = \sum_{(i,j)\in\Omega} \left(D_{ij} - \overline{U_i}^\top \overline{V_j}\right)^2$$

  - Ω is the set of observed indices
  - Constrains can be added: $U \geq 0$ and $V \geq 0$

Matrix Factorization (MF)

- SVD is a special form of MF

$$D \approx UV^\top$$

- The objective when D is fully observed

$$J = \|D - UV^\top\|_F^2$$

- The objective when D is partially observed

$$J = \sum_{(i,j)\in\Omega} \left(D_{ij} - \overline{U_i}^\top \overline{V_j}\right)^2 + \lambda(\|U\|_F^2 + \|V\|_F^2)$$

  - Ω is the set of observed indices
  - Constrains can be added: $U \geq 0$ and $V \geq 0$
  - Regularization can also be introduced

Matrix Completion

- Assuming the Utility matrix is low-rank

$$M = \begin{bmatrix} \blacksquare & & \blacksquare & & & \blacksquare & \\ & \blacksquare & & \blacksquare & \blacksquare & & \blacksquare \\ \blacksquare & & & \blacksquare & & \blacksquare & \\ & & \blacksquare & & \blacksquare & & \\ & \blacksquare & & \blacksquare & & & \blacksquare \end{bmatrix} \in \mathbb{R}^{n\times d}$$

- The Optimization Problem

$$\min_{X\in\mathbb{R}^{n\times d}} \quad \operatorname{rank}(X) \qquad \text{s.t.} \quad X_{ij} = M_{ij}, \forall (i,j) \in \Omega$$

$$\min_{X\in\mathbb{R}^{n\times d}} \quad \|X\|_* \qquad \text{s.t.} \quad X_{ij} = M_{ij}, \forall (i,j) \in \Omega$$

  - Ω is the set of observed indices

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Types of Logs

- Web Server Logs
  - User activity on Web servers
  - Stored in *NCSA common log format* or its variants

```
98.206.207.157 - - [31/Jul/2013:18:09:38 -0700] "GET /productA.pdf
HTTP/1.1" 200 328177 "-" "Mozilla/5.0 (Mac OS X) AppleWebKit/536.26
(KHTML, like Gecko) Version/6.0 Mobile/10B329 Safari/8536.25"
"retailer.net"
```

- Query Logs
  - Queries posed by a user during search

Data Preprocessing

- Data in the Log File
  - A continuous sequence of entries that corresponds to the user accesses
  - The entries for different users are typically interleaved with one another randomly
- Distinguish between different user sessions
  - Client-side cookies, IP address, user agents
- A subset of users can be identified
  - A set of sequences in the form of page views (click streams), or search tokens

Applications

- Recommendations
  - Recommend Web pages based on browsing patterns
- Frequent Traversal Patterns
  - Web site reorganization
- Forecasting and Anomaly Detection
  - Forecast future clicks of the user
  - Identify unusual clicks or patterns
- Classification
  - Label (shopping, intrusion) the sequence

Outline

- Introduction
- Web Crawling and Resource Discovery
- Search Engine Indexing and Query Processing
- Ranking Algorithms
- Recommender Systems
- Web Usage Mining
- **Summary**

Summary

- Web Crawling and Resource Discovery
  - Universal, Preferential, Multiple Threads, Spider Traps, Near Duplicate Detection
- Search Engine Indexing and Query Processing
  - Content-based score, reputation-based scores
- Ranking Algorithms
  - PageRank and its variants, HITS
- Recommender Systems
  - Content-Based, Collaborative Filtering (Neighborhood-Based, Graph-Based, Clustering, Latent Factor Models)
- Web Usage Mining
  - Data Preprocessing, Applications