Special Topics in Social Media Services
社會媒體服務專題

Social Network Analysis, Link Mining, Text Mining, Web Mining, and Opinion Mining in Social Media

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Sat. 6,7,8 (13:10-16:00) D502

Min-Yuh Day
戴敏育
Assistant Professor
專任助理教授
Dept. of Information Management, Tamkang University
淡江大學 資訊管理學系

http://mail.im.tku.edu.tw/~myday/

2011-06-04

Syllabus

週次	月／日	內容（Subject/Topics）
1	100/02/19	Course Orientation for Social Media Services
2	100/02/26	Web 2.0, Social Network and Social Media
3	100/03/05	Theories of Media and Information
4	100/03/12	Theories of Social Media Services and Information Systems
5	100/03/19	Paper Reading and Discussion
6	100/03/26	Behavior Research on Social Media Services
7	100/04/02	Research Methods in Social Media Services *
8	100/04/09	教學行政觀摩日
9	100/04/16	Business Models and Issues of Social Medial Service * (Invited Speaker)
10	100/04/23	期中考試週 (期中報告)

Syllabus

週次 月／日 內容（Subject/Topics）

11 100/04/30 Paper Reading and Discussion

12 100/05/07 Strategy of Social Media Service

13 100/05/14 Paper Reading and Discussion

14 100/05/21 Social Media Marketing

15 100/05/28 Paper Reading and Discussion [*2011/05/21]

16 100/06/04 Social Network Analysis, Link Mining,
Text Mining, Web Mining,
and Opinion Mining in Social Media

17 100/06/11 Project Presentation and Discussion [*2011/06/04]

18 100/06/18 期末考試週 (期末報告) [*2011/06/18]

Learning Objective

- Social Network Analysis
- Link Mining
- Text Mining
- Web Mining
- Opinion Mining in Social Media

Social Network Analysis

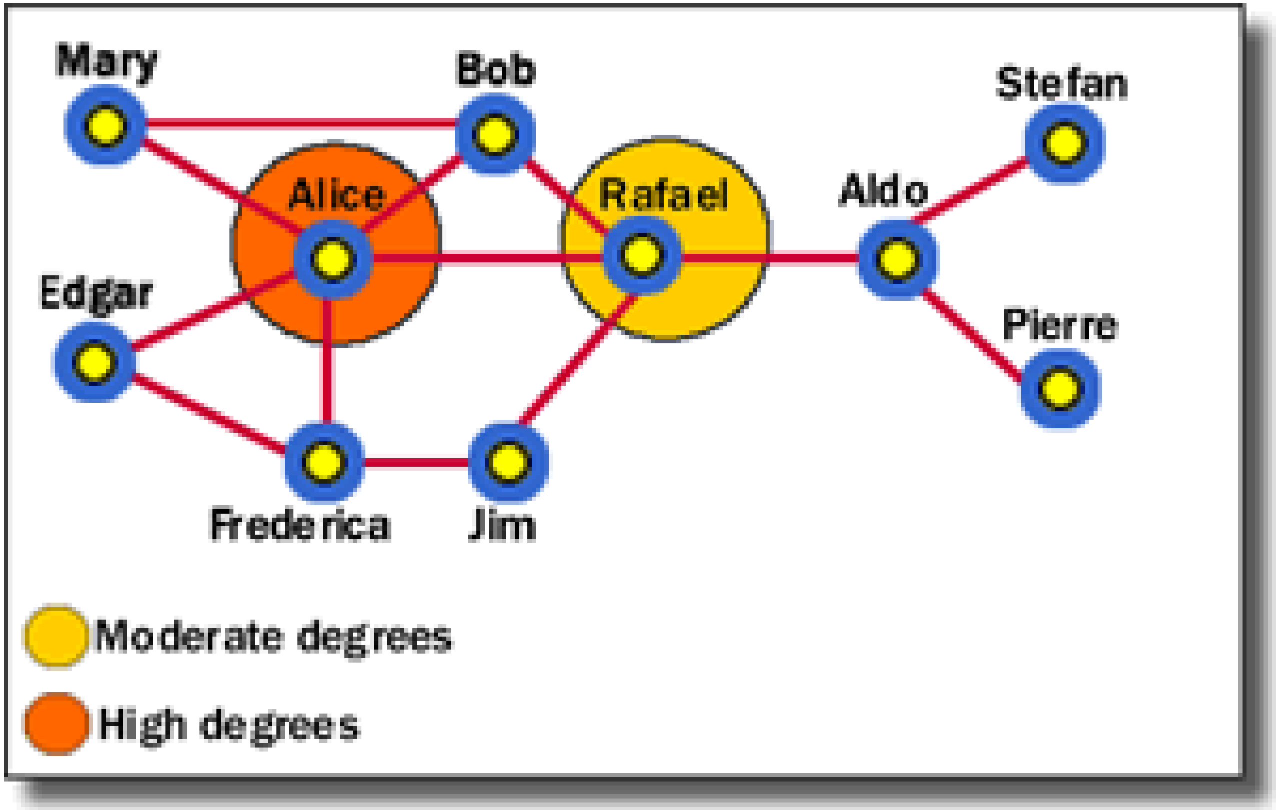
- A **social network** is a social structure of people, related (directly or indirectly) to each other through a common relation or interest
- **Social network analysis (SNA)** is the study of social networks to understand their structure and behavior

Social Network Analysis

- Using Social Network Analysis, you can get answers to questions like:
  - How highly connected is an entity within a network?
  - What is an entity's overall importance in a network?
  - How central is an entity within a network?
  - How does information flow within a network?

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

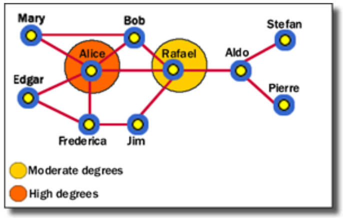
Social Network Analysis: Degree Centrality



Alice has the highest degree centrality, which means that she is quite active in the network. However, she is not necessarily the most powerful person because she is only directly connected within one degree to people in her clique—she has to go through Rafael to get to other cliques.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

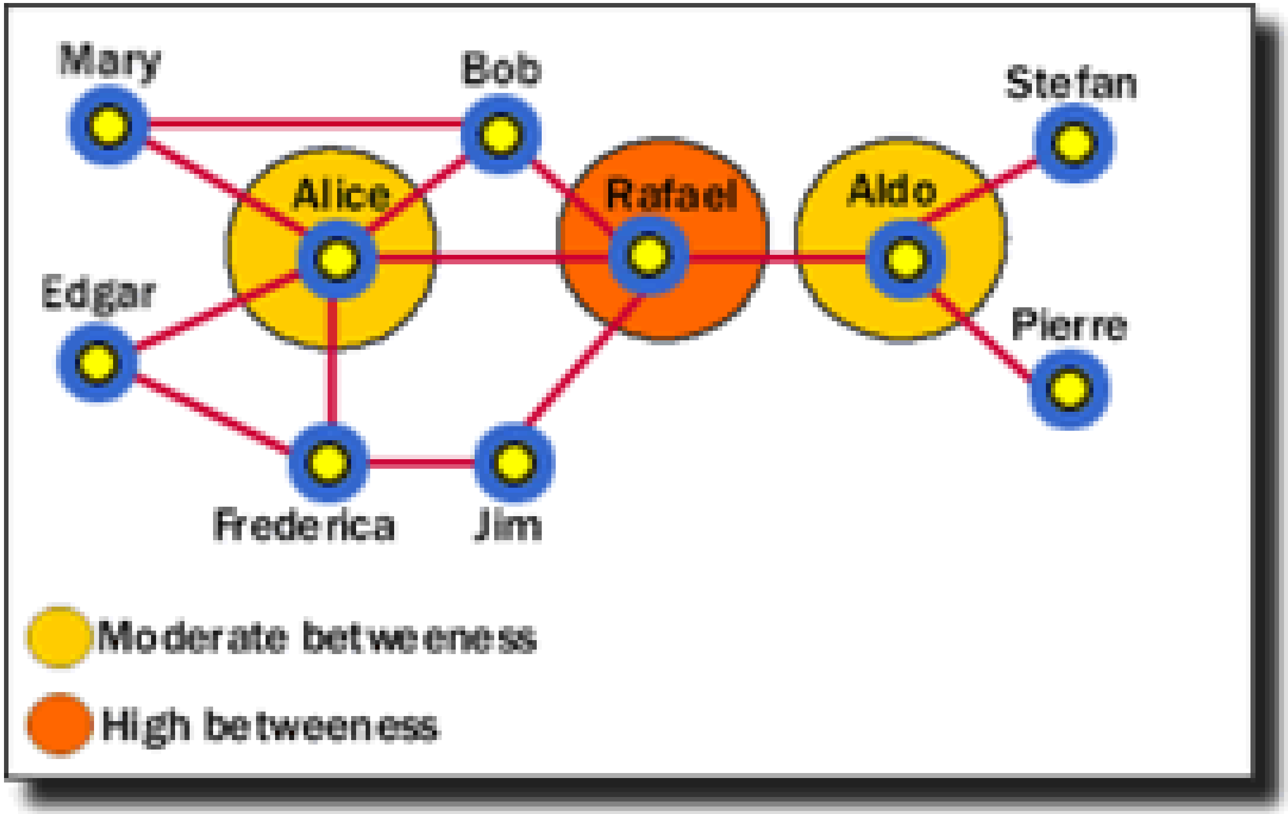
Social Network Analysis: Degree Centrality



- Degree centrality is simply the number of direct relationships that an entity has.
- An entity with high degree centrality:
  - Is generally an active player in the network.
  - Is often a connector or hub in the network.
  - s not necessarily the most connected entity in the network (an entity may have a large number of relationships, the majority of which point to low-level entities).
  - May be in an advantaged position in the network.
  - May have alternative avenues to satisfy organizational needs, and consequently may be less dependent on other individuals.
  - Can often be identified as third parties or deal makers.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

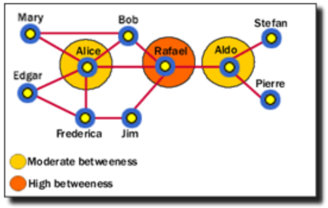
Social Network Analysis: Betweenness Centrality



Rafael has the highest betweenness because he is between Alice and Aldo, who are between other entities. Alice and Aldo have a slightly lower betweenness because they are essentially only between their own cliques. Therefore, although Alice has a higher degree centrality, Rafael has more importance in the network in certain respects.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

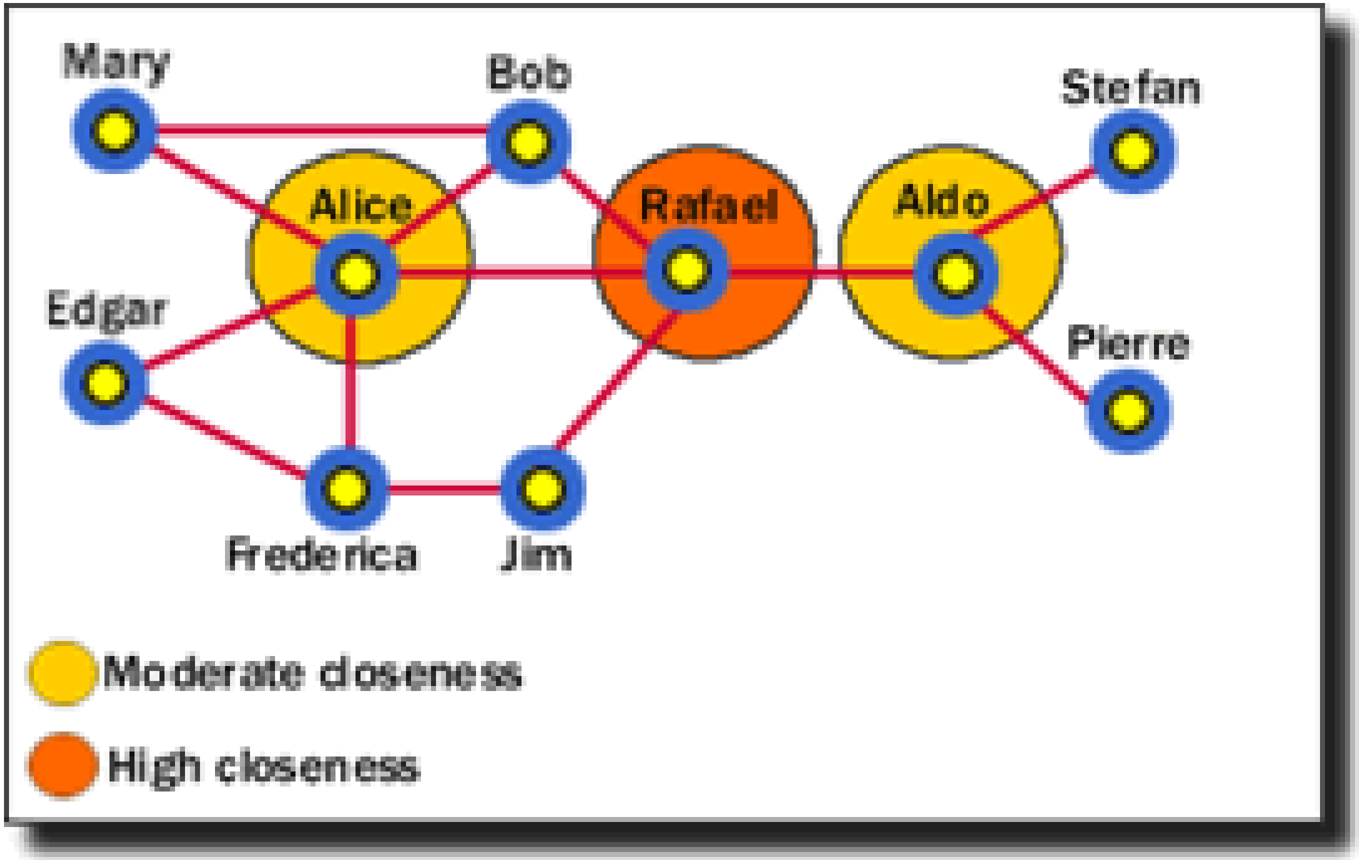
Social Network Analysis: Betweenness Centrality



- Betweenness centrality identifies an entity's position within a network in terms of its ability to make connections to other pairs or groups in a network.
- An entity with a high betweenness centrality generally:
  – Holds a favored or powerful position in the network.
  – Represents a single point of failure—take the single betweenness spanner out of a network and you sever ties between cliques.
  – Has a greater amount of influence over what happens in a network.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

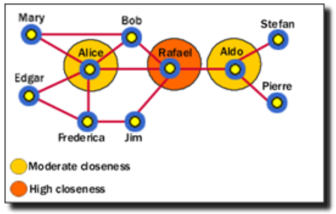
Social Network Analysis: Closeness Centrality



Rafael has the highest closeness centrality because he can reach more entities through shorter paths. As such, Rafael's placement allows him to connect to entities in his own clique, and to entities that span cliques.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

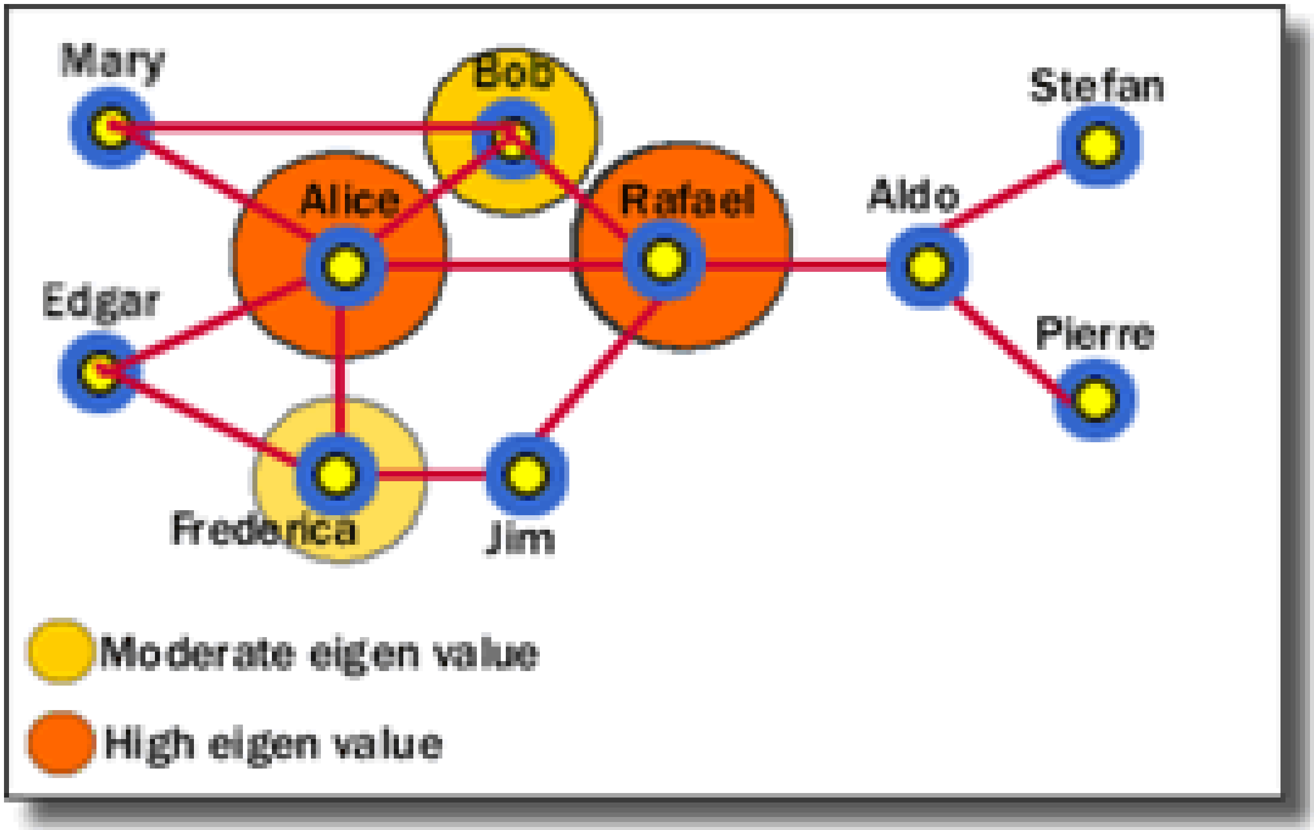
Social Network Analysis: Closeness Centrality



- Closeness centrality measures how quickly an entity can access more entities in a network.
- An entity with a high closeness centrality generally:
  - Has quick access to other entities in a network.
  - Has a short path to other entities.
  - Is close to other entities.
  - Has high visibility as to what is happening in the network.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

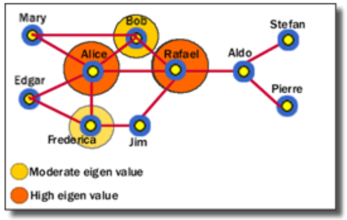
Social Network Analysis: Eigenvalue



Alice and Rafael are closer to other highly close entities in the network. Bob and Frederica are also highly close, but to a lesser value.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

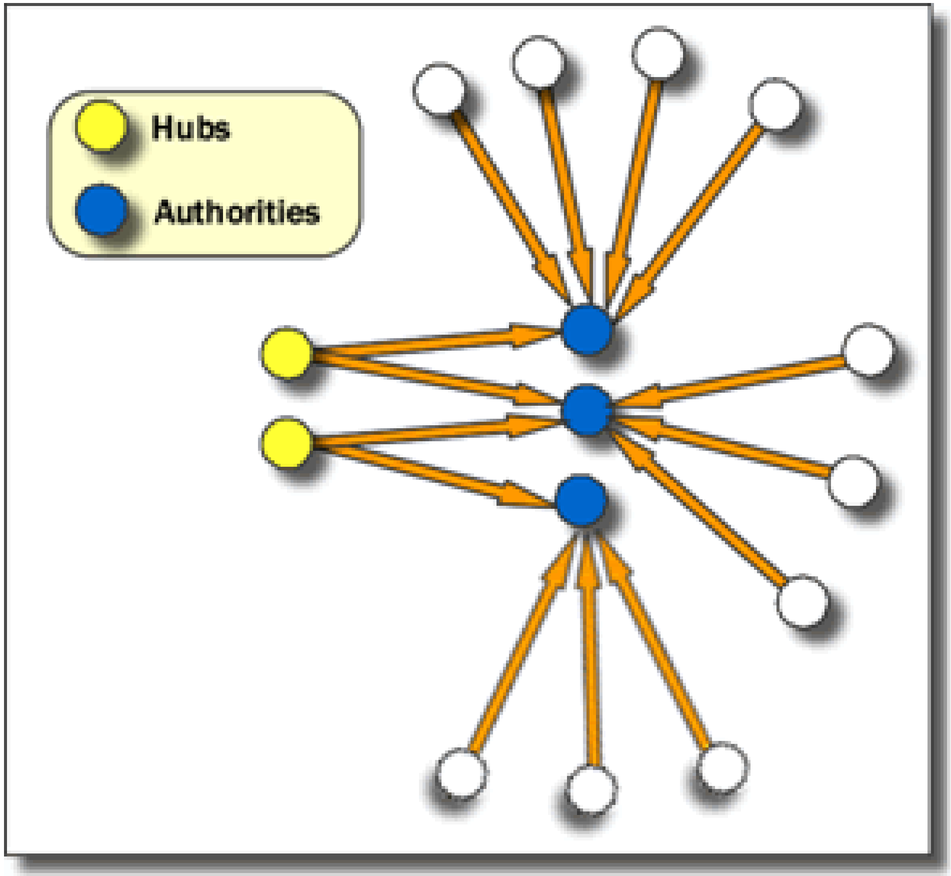
Social Network Analysis: Eigenvalue



- Eigenvalue measures how close an entity is to other highly close entities within a network. In other words, Eigenvalue identifies the most central entities in terms of the global or overall makeup of the network.
- A high Eigenvalue generally:
  - Indicates an actor that is more central to the main pattern of distances among all entities.
  - Is a reasonable measure of one aspect of centrality in terms of positional advantage.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

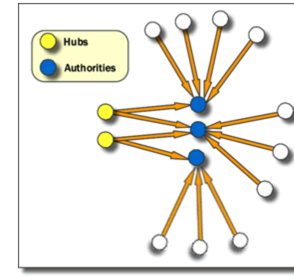
Social Network Analysis: Hub and Authority



Hubs are entities that point to a relatively large number of authorities. They are essentially the mutually reinforcing analogues to authorities. Authorities point to high hubs. Hubs point to high authorities. You cannot have one without the other.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

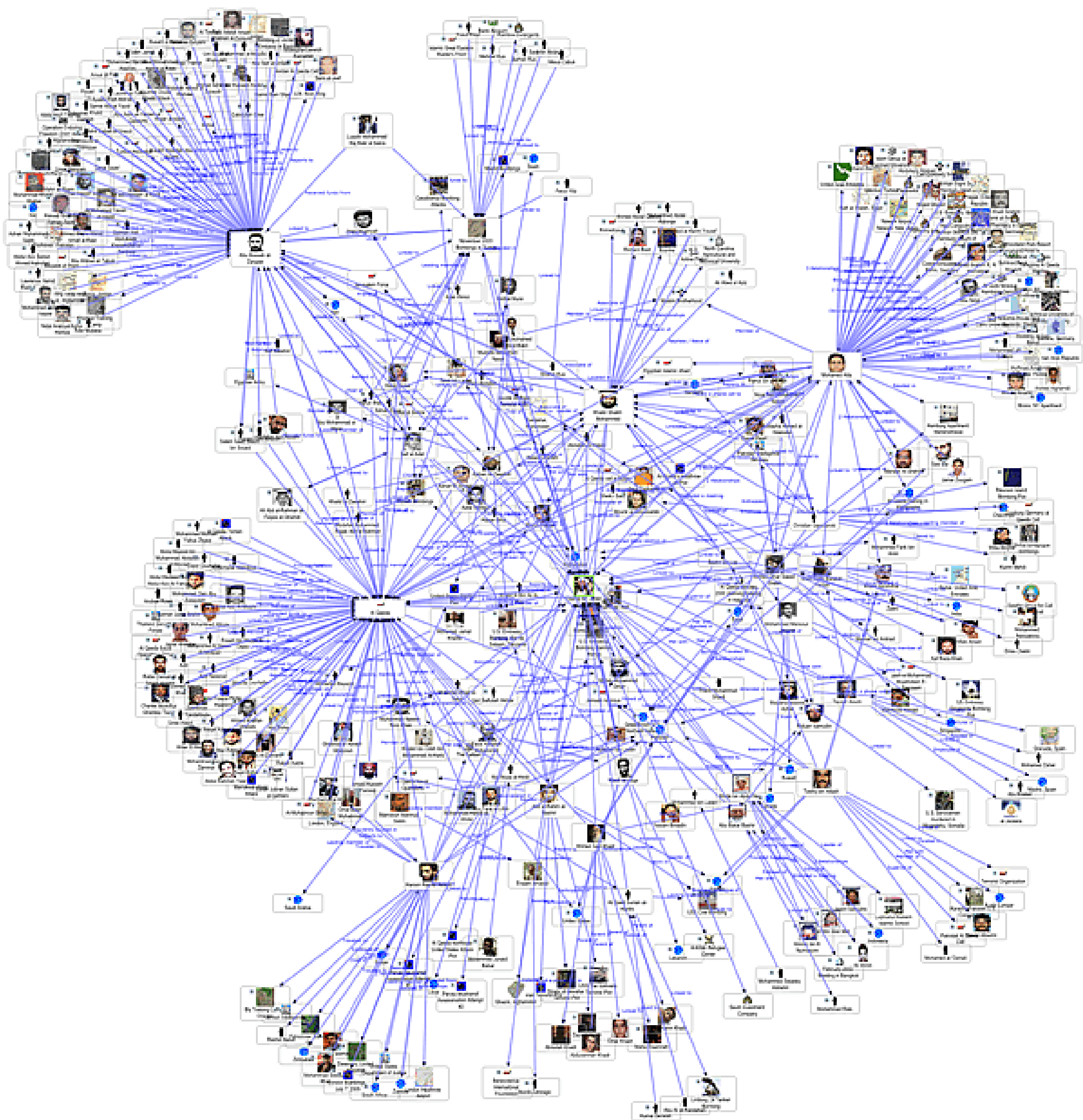
Social Network Analysis: Hub and Authority



- Entities that many other entities point to are called Authorities. In Sentinel Visualizer, relationships are directional—they point from one entity to another.
- If an entity has a high number of relationships pointing to it, it has a high authority value, and generally:
  - Is a knowledge or organizational authority within a domain.
  - Acts as definitive source of information.

Source: http://www.fmsasg.com/SocialNetworkAnalysis/

Social Network Analysis



Source: http://www.fmsasg.com/SocialNetworkAnalysis/

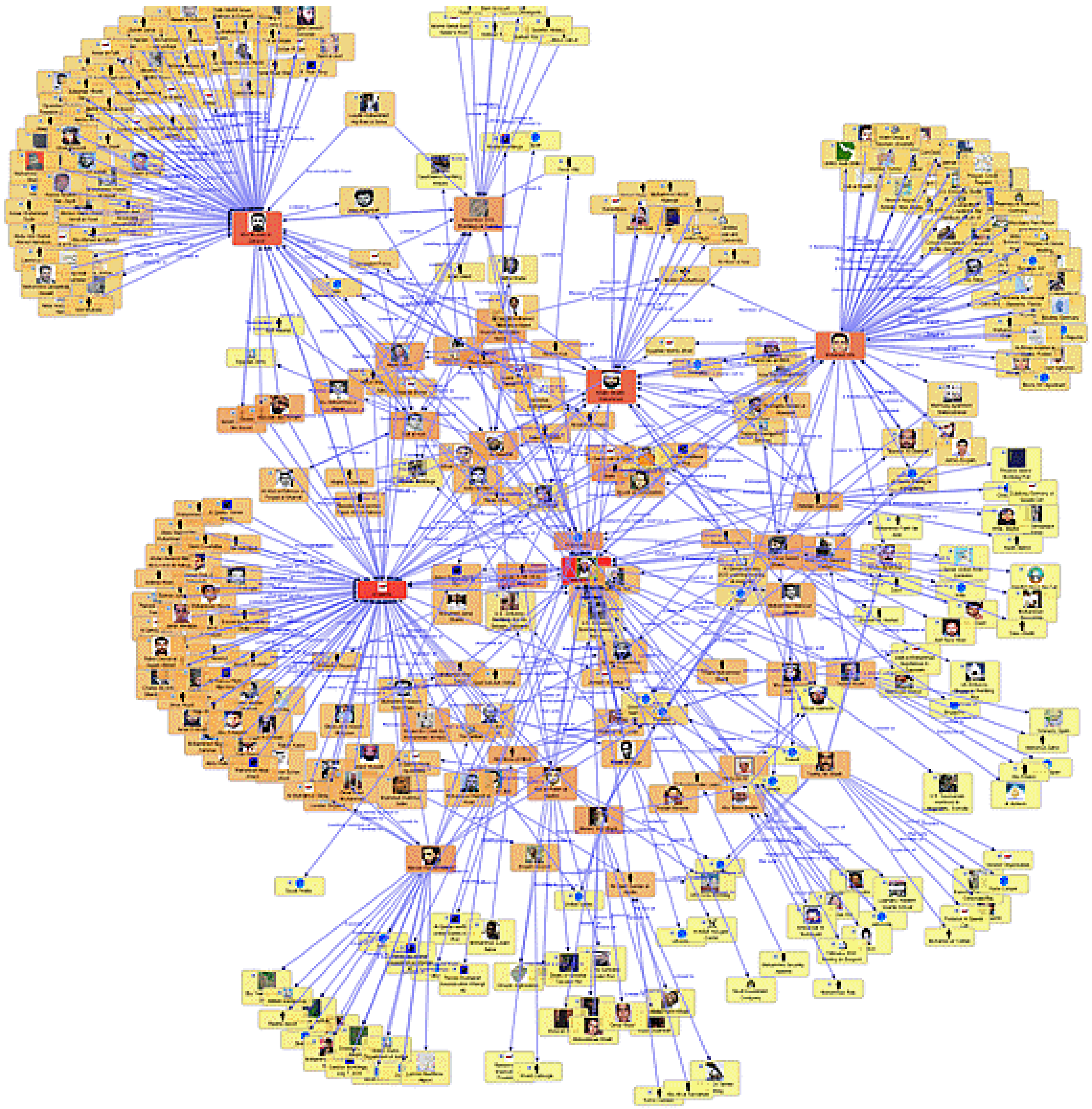
Social Network Analysis

Network Metrics

Calculate ○ CardView ◉ TableView ☐ Group area Expand groups Collapse groups

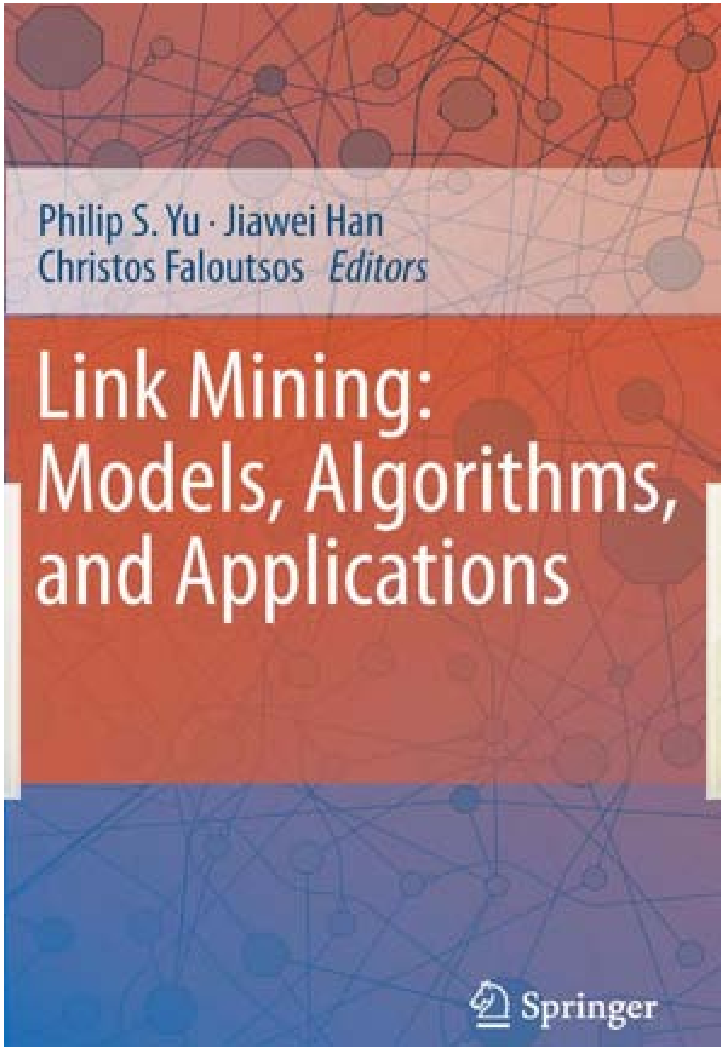
Name	Type	Degree	Betweenness	Closeness	Eigenvalue	Hub	Authority
Osama bin Laden	Person	44	0.920492092358...	1	0.0271	0	0.011
Abdallah Al-Halabi	Person	2	0	0.654867256637...	0.0001	0	0
Abu Mussab al-Zarqawi	Person	84	0.934887847326...	0.869451697127...	0.7028	0.6572	0.1076
Al Qaeda	Terrorist Organiz...	85	1	0.962427745664...	0.0416	0.3941	0.0166
Ayman Al-Zawahiri	Person	14	0.045794908783...	0.716129032258...	0	0	0.0173
Enaam Arnaout	Person	4	0.031189325814...	0.656804733727...	0.0001	0	0
Imad Eddin Barakat Yarbas	Person	11	0.065049589038...	0.704016913319...	0.0015	0	0.0025
Khalid Shaikh Mohammed	Person	32	0.339916464724...	0.866059817945...	0.002	0	0.1528
Mohamed Atta	Person	61	0.666268740074...	0.820197044334...	0.0015	0	0.6816
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Social Network Analysis



Source: http://www.fmsasg.com/SocialNetworkAnalysis/

Link Mining



http://www.amazon.com/Link-Mining-Models-Algorithms-Applications/dp/1441965149

Link Mining
(Getoor & Diehl, 2005)

- Link Mining
  - Data Mining techniques that take into account the links between objects and entities while building predictive or descriptive models.
- Link based object ranking, Group Detection, Entity Resolution, Link Prediction
- Application:
  - Hyperlink Mining
  - Relational Learning
  - Inductive Logic Programming
  - Graph Mining

Characteristics of Collaboration Networks

(Newman, 2001; 2003; 3004)

- Degree distribution follows a power-law
- Average separation decreases in time.
- Clustering coefficient decays with time
- Relative size of the largest cluster increases
- Average degree increases
- Node selection is governed by preferential attachment

Social Network Techniques

- Social network extraction/construction
- Link prediction
- Approximating large social networks
- Identifying prominent/trusted/expert actors in social networks
- Search in social networks
- Discovering communities in social network
- Knowledge discovery from social network

Social Network Extraction

- Mining a social network from data sources
- Three sources of social network (Hope et al., 2006)
  - Content available on web pages
    - E.g., user homepages, message threads
  - User interaction logs
    - E.g., email and messenger chat logs
  - Social interaction information provided by users
    - E.g., social network service websites (Facebook)

Social Network Extraction

- IR based extraction from web documents
  - Construct an “actor-by-term” matrix
  - The terms associated with an actor come from web pages/documents created by or associated with that actor
  - IR techniques (TF-IDF, LSI, cosine matching, intuitive heuristic measures) are used to quantify similarity between two actors’ term vectors
  - The similarity scores are the edge label in the network
    - Thresholds on the similarity measure can be used in order to work with binary or categorical edge labels
    - Include edges between an actor and its k-nearest neighbors
- Co-occurrence based extraction from web documents

Link Prediction

- Link Prediction using supervised learning (Hasan et al., 2006)
  - Citation Network (BIOBASE, DBLP)
  - Use machine learning algorithms to predict future co-authorship
    - Decision three, k-NN, multilayer perceptron, SVM, RBF network
  - Identify a group of features that are most helpful in prediction
  - Best Predictor Features
    - Keywork Match count, Sum of neighbors, Sum of Papers, Shortest distance

Identifying Prominent Actors in a Social Network

- Compute scores/ranking over the set (or a subset) of actors in the social network which indicate degree of importance / expertise / influence
  - E.g., Pagerank, HITS, centrality measures
- Various algorithms from the link analysis domain
  - PageRank and its many variants
  - HITS algorithm for determining authoritative sources
- Centrality measures exist in the social science domain for measuring importance of actors in a social network

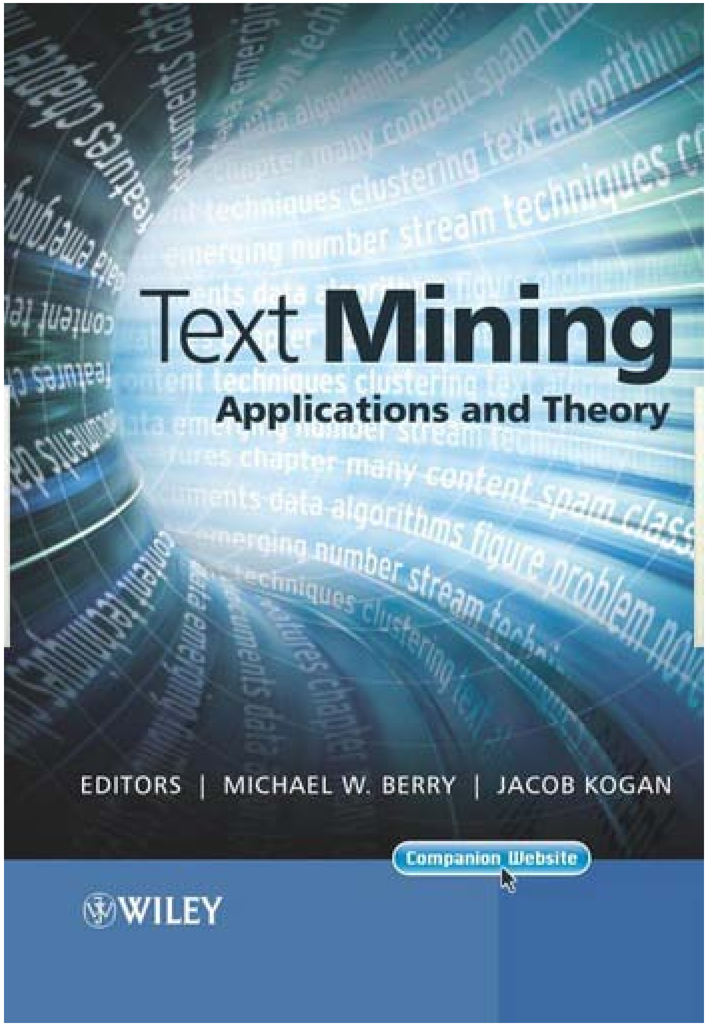
Identifying Prominent Actors in a Social Network

- Brandes, 2011
- Prominence→ high betweenness value
- Betweenness centrality requires computation of number of shortest paths passing through each node
- Compute shortest paths between all pairs of vertices

Text and Web Mining

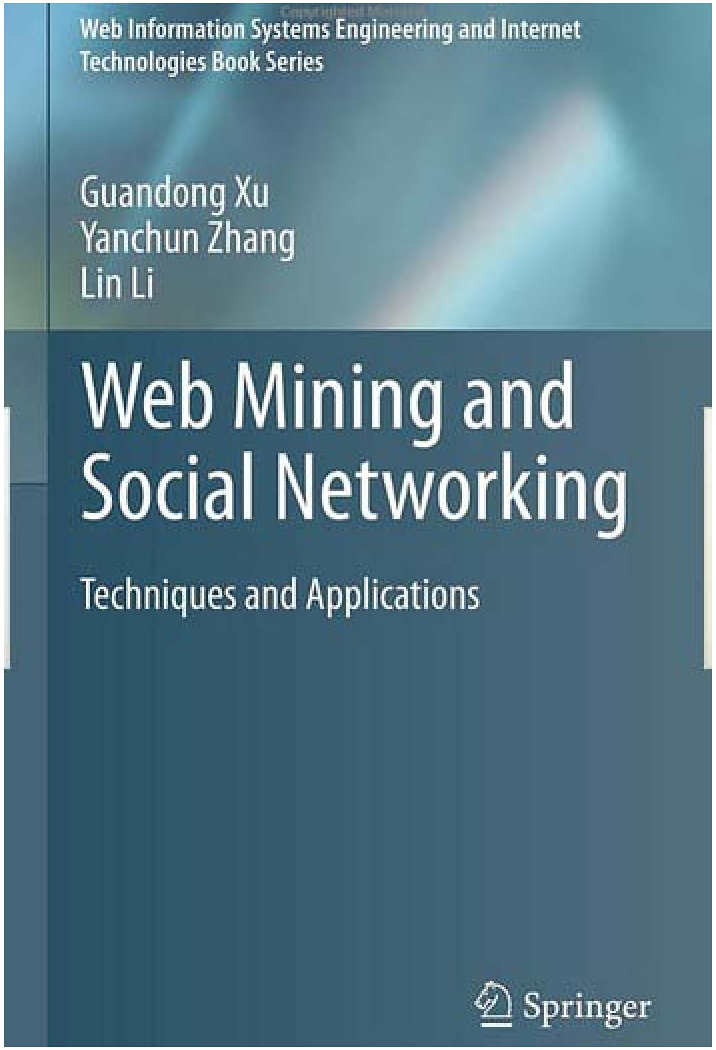
- Text Mining: Applications and Theory
- Web Mining and Social Networking
- Mining the Social Web: Analyzing Data from Facebook, Twitter, LinkedIn, and Other Social Media Sites
- Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data
- Search Engines – Information Retrieval in Practice

Text Mining



http://www.amazon.com/Text-Mining-Applications-Michael-Berry/dp/0470749822/

Web Mining and Social Networking

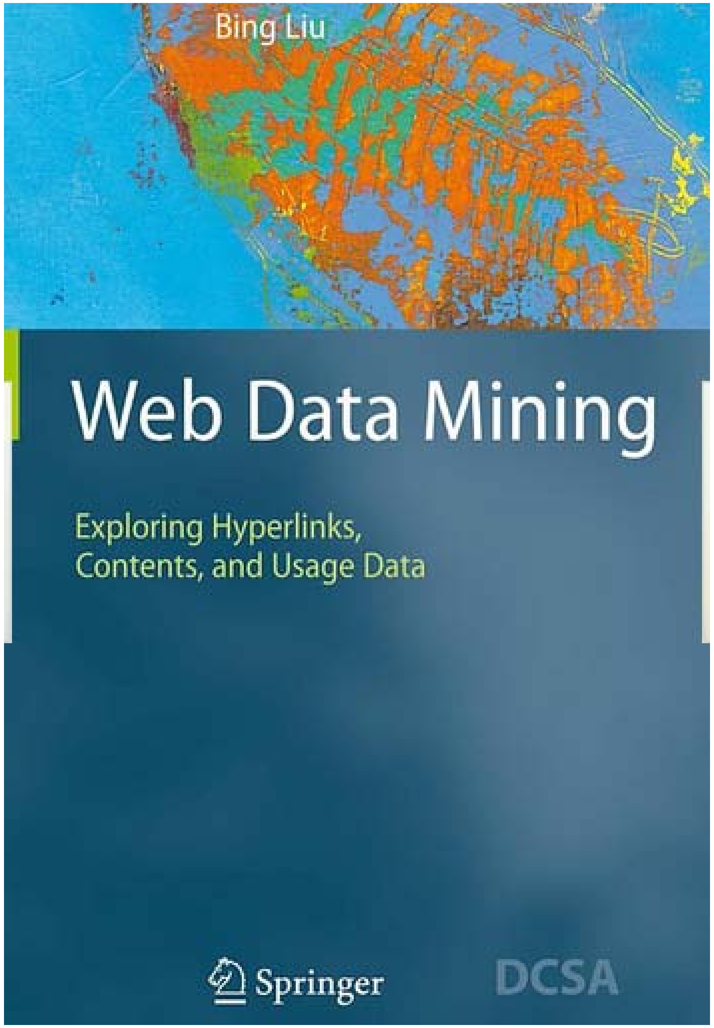


http://www.amazon.com/Web-Mining-Social-Networking-Applications/dp/1441977341

Mining the Social Web: Analyzing Data from Facebook, Twitter, LinkedIn, and Other Social Media Sites

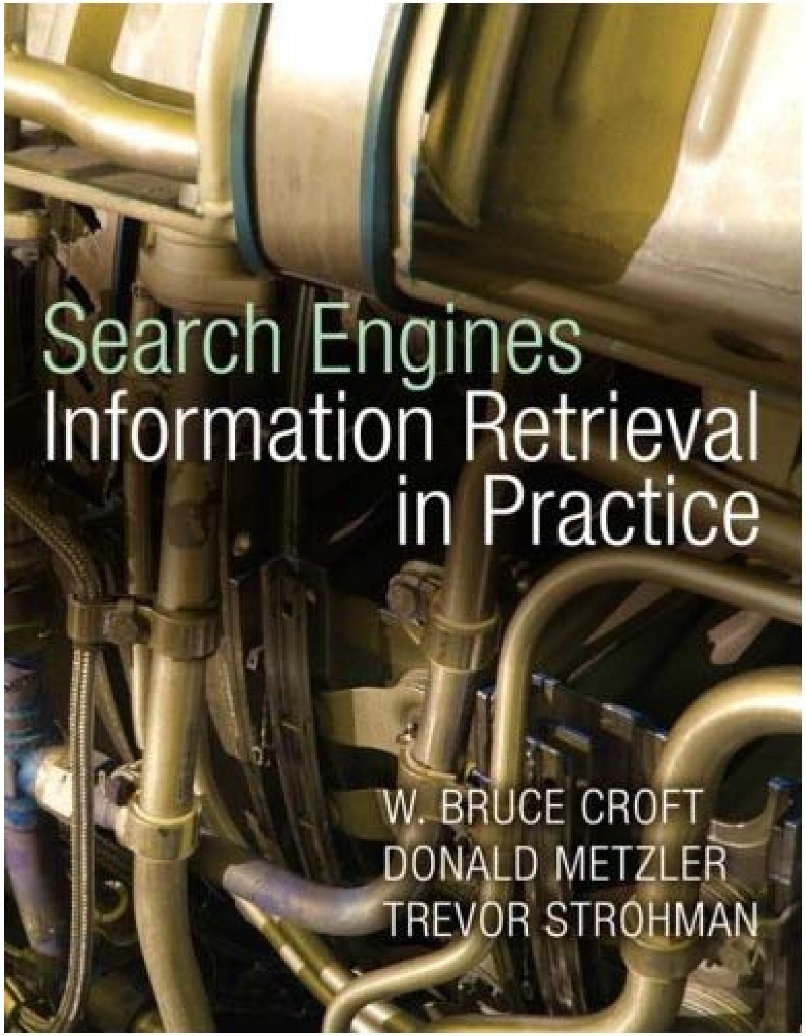
http://www.amazon.com/Mining-Social-Web-Analyzing-Facebook/dp/1449388345

Web Data Mining:
Exploring Hyperlinks, Contents, and Usage Data



http://www.amazon.com/Web-Data-Mining-Data-Centric-Applications/dp/3540378812

Search Engines: Information Retrieval in Practice



http://www.amazon.com/Search-Engines-Information-Retrieval-Practice/dp/0136072240

Text Mining

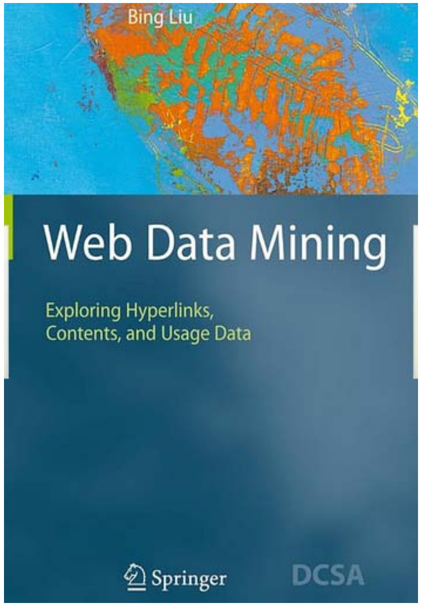
- Text mining (text data mining)
  - the process of deriving high-quality information from text
- Typical text mining tasks
  - text categorization
  - text clustering
  - concept/entity extraction
  - production of granular taxonomies
  - sentiment analysis
  - document summarization
  - entity relation modeling
    - i.e., learning relations between named entities.

http://en.wikipedia.org/wiki/Text_mining

Web Mining

- Web mining
  - discover useful information or knowledge from the **Web hyperlink structure, page content, and usage data.**
- Three types of web mining tasks
  - Web structure mining
  - Web content mining
  - Web usage mining

Source: Bing Liu (2009) Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data



Opinion Mining and Sentiment Analysis:

NLP Meets Social Sciences

Bing Liu
Department of Computer Science
University Of Illinois at Chicago

http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

Source: Bing Liu, Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences . Talk given at the Invited Workshop on Social Theory and Social Computing, Honolulu, Hawaii, May 22-23, 2010

Opinion Mining

- Two main types of textual information.
  - Facts and Opinions
    - Note: factual statements can imply opinions too.
- Most current text information processing methods (e.g., web search, text mining) work with factual information.
- Sentiment analysis or opinion mining
  - computational study of opinions, sentiments and emotions expressed in text.
- Why opinion mining now? Mainly because of the Web; huge volumes of opinionated text.

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Opinion Mining
user-generated media

- Importance of opinions:
  - Opinions are important because whenever we need to make a decision, we want to hear others' opinions.
  - In the past,
    - Individuals: opinions from friends and family
    - businesses: surveys, focus groups, consultants …
- Word-of-mouth on the Web
  - User-generated media: One can express opinions on anything in reviews, forums, discussion groups, blogs ...
  - Opinions of global scale: No longer limited to:
    - Individuals: one's circle of friends
    - Businesses: Small scale surveys, tiny focus groups, etc.

A Fascinating Problem!

- Intellectually challenging & major applications.
  - A popular research topic in recent years in NLP and Web data mining.
  - 20-60 companies in USA alone
- It touches every aspect of NLP and yet is restricted and confined.
  - Little research in NLP/Linguistics in the past.
- Potentially a major technology from NLP.
  - But "not yet" and not easy!
  - Data sourcing and data integration are hard too!

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

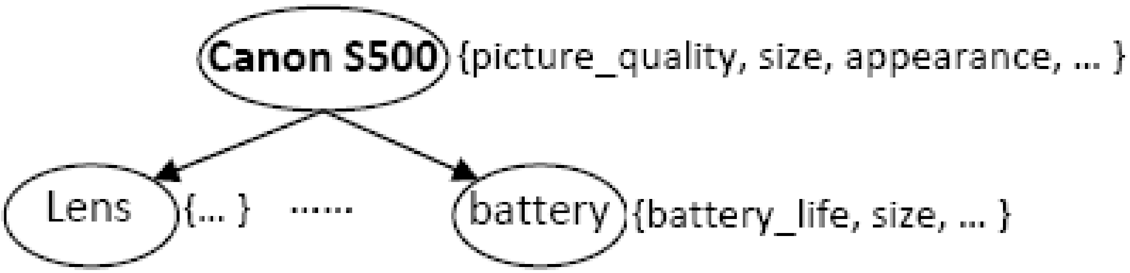
An Example Review

- *"I bought an iPhone a few days ago. It was such a nice phone. The touch screen was really cool. The voice quality was clear too. Although the battery life was not long, that is ok for me. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, and wanted me to return it to the shop. …"*
- What do we see?
  - **Opinions**, **targets of opinions**, **and** **opinion holders**

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Target Object (Liu, Web Data Mining book, 2006)

- **Definition** (**object**): An *object o* is a product, person, event, organization, or topic. *o* is represented as
  - a hierarchy of components, sub-components, and so on.
  - Each node represents a component and is associated with a set of attributes of the component.



- An opinion can be expressed on any node or attribute of the node.
- To simplify our discussion, we use the term ***features*** to represent both components and attributes.

What is an Opinion?

(Liu, a Ch. in NLP handbook)

- An *opinion* is a quintuple

  $(o_j, f_{jk}, so_{ijkl}, h_i, t_l)$,

  where

  – o_j is a target object.

  – f_{jk} is a feature of the object o_j.

  – so_{ijkl} is the sentiment value of the opinion of the opinion holder h_i on feature f_{jk} of object o_j at time t_l. so_{ijkl} is +ve, -ve, or neu, or a more granular rating.

  – h_i is an opinion holder.

  – t_l is the time when the opinion is expressed.

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Objective – structure the unstructured

- Objective: Given an opinionated document,
  - Discover all quintuples (o_j, f_{jk}, so_{ijkl}, h_i, t_l),
    - i.e., mine the five corresponding pieces of information in each quintuple, and
  - Or, solve some simpler problems
- With the quintuples,
  - Unstructured Text → Structured Data
    - Traditional data and visualization tools can be used to slice, dice and visualize the results in all kinds of ways
    - Enable qualitative and quantitative analysis.

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Sentiment Classification: doc-level

(Pang and Lee, et al 2002 and Turney 2002)

- Classify a document (e.g., a review) based on the overall sentiment expressed by opinion holder
  - Classes: Positive, or negative (and neutral)
- In the model, (o_j, f_{jk}, so_{ijkl}, h_i, t_l),
- It assumes
  - Each document focuses on a single object and contains opinions from a single opinion holder.
  - It considers opinion on the object, o_j (or $o_j = f_{jk}$)

Subjectivity Analysis
(Wiebe et al 2004)

- Sentence-level sentiment analysis has two tasks:
  - Subjectivity classification: Subjective or objective.
    - Objective: e.g., *I bought an iPhone a few days ago.*
    - Subjective: e.g., *It is such a nice phone.*
  - Sentiment classification: For subjective sentences or clauses, classify positive or negative.
    - Positive: *It is such a nice phone.*
- However. (Liu, Chapter in NLP handbook)
  - subjective sentences ≠ +ve or –ve opinions
    - E.g., *I think he came yesterday.*
  - Objective sentence ≠ no opinion
    - Imply –ve opinion: *My phone broke in the second day.*

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Feature-Based Sentiment Analysis

- Sentiment classification at both document and sentence (or clause) levels are not sufficient,
  - they do not tell what people like and/or dislike
  - A positive opinion on an object does not mean that the opinion holder likes everything.
  - An negative opinion on an object does not mean .....
- Objective: Discovering all quintuples

  $(o_j, f_{jk}, so_{ijkl}, h_i, t_l)$

- With all quintuples, all kinds of analyses become possible.

Feature-Based Opinion Summary

(Hu & Liu, KDD-2004)

"I bought an iPhone a few days ago. It was such a nice phone. The touch screen was really cool. The voice quality was clear too. Although the battery life was not long, that is ok for me. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, and wanted me to return it to the shop. …"

Feature Based Summary:

Feature1: **Touch screen**

Positive: 212

- *The touch screen was really cool.*
- *The touch screen was so easy to use and can do amazing things.*

…

Negative: 6

- The screen is easily scratched.
- I have a lot of difficulty in removing finger marks from the touch screen.

…

Feature2: **battery life**

…

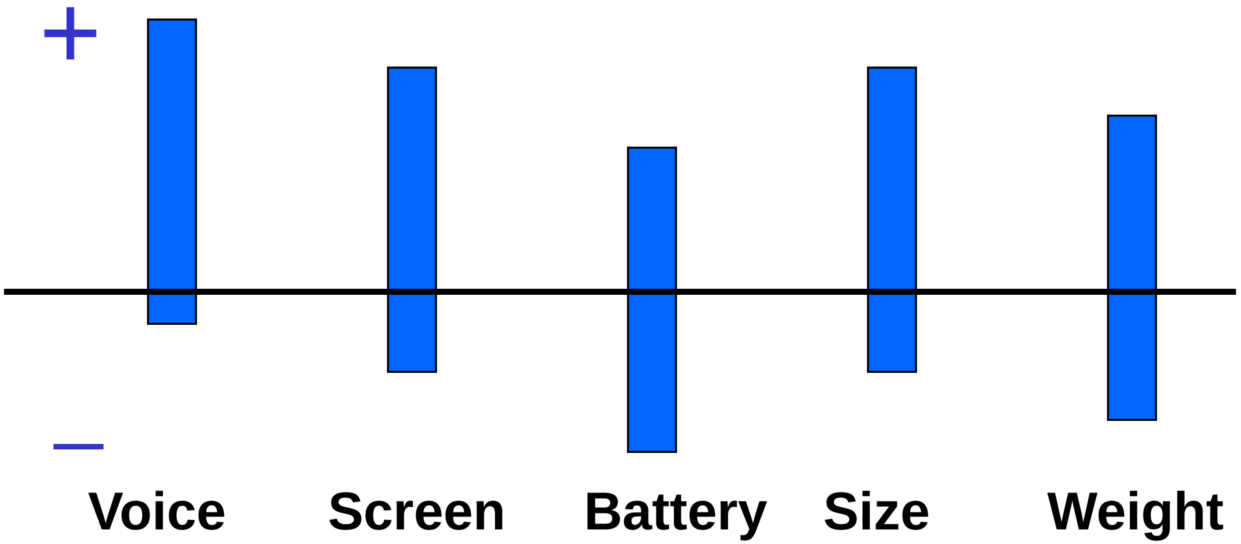
Note: We omit opinion holders

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Visual Comparison (Liu et al. WWW-2005)

- Summary of reviews of

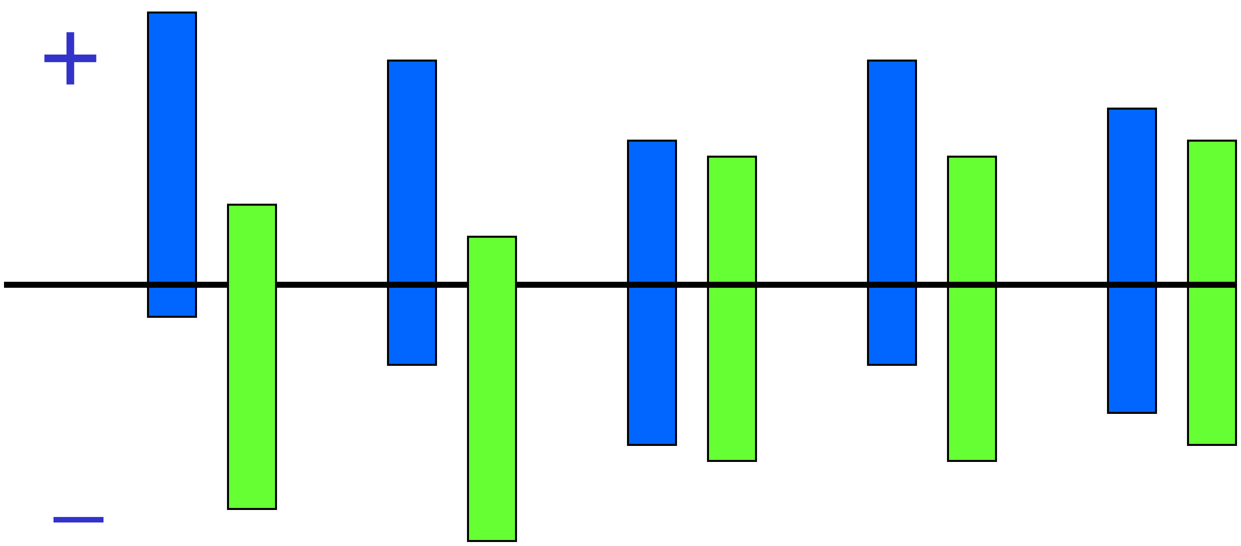
Cell Phone 1



- Comparison of reviews of

Cell Phone 1

Cell Phone 2



Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Live Demo: OpinionEQ

(I gave a live demo of the OpinionEQ system.
Some screensdumps from the demo are shown here)

- It performs feature-based sentiment analysis.

Demo 1: Compare consumer opinions on three GPS systems, Garmin, Magellan, Tomtom.

- Based on a set of features, price, map, software, quality, size, etc.

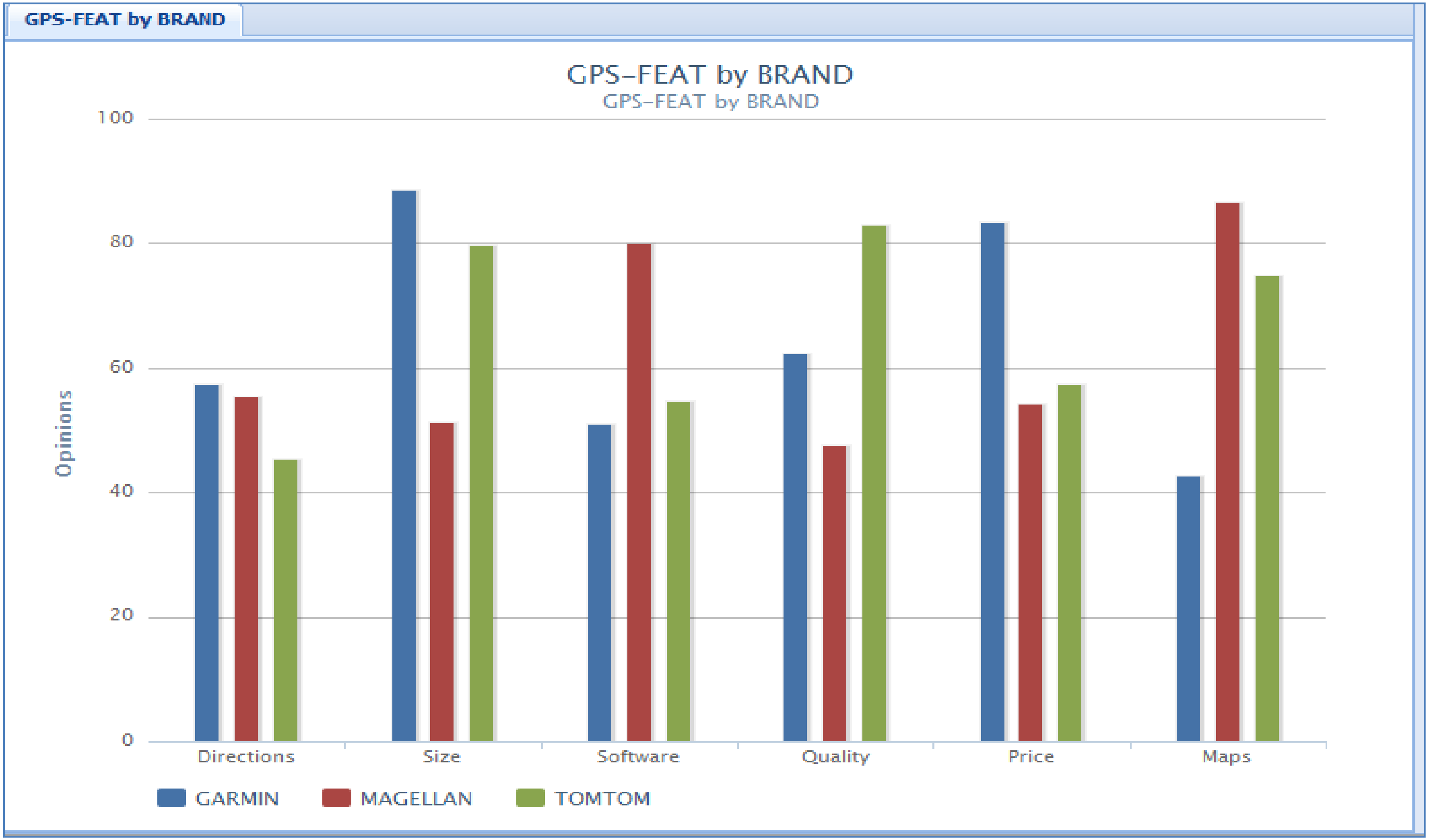
Demo 2: Instant page analysis

- The user gives a URL, and the system identifies opinions on the page instantly.

- We also have a Twitter opinion monitoring system (not demo-ed)

Demo 1: Compare 3 GSPs on different features

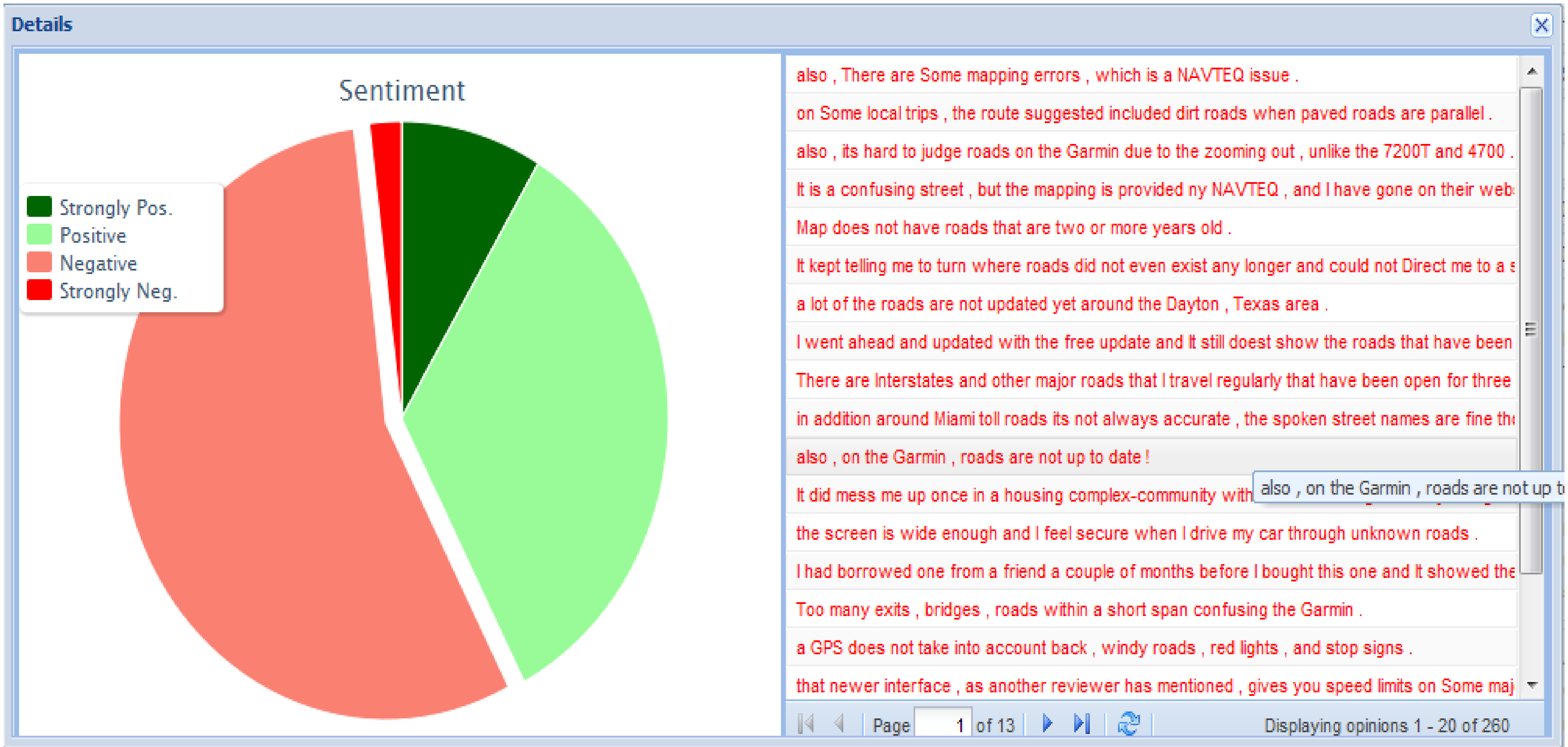
- Each bar shows the proportion of +ve opinion



Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

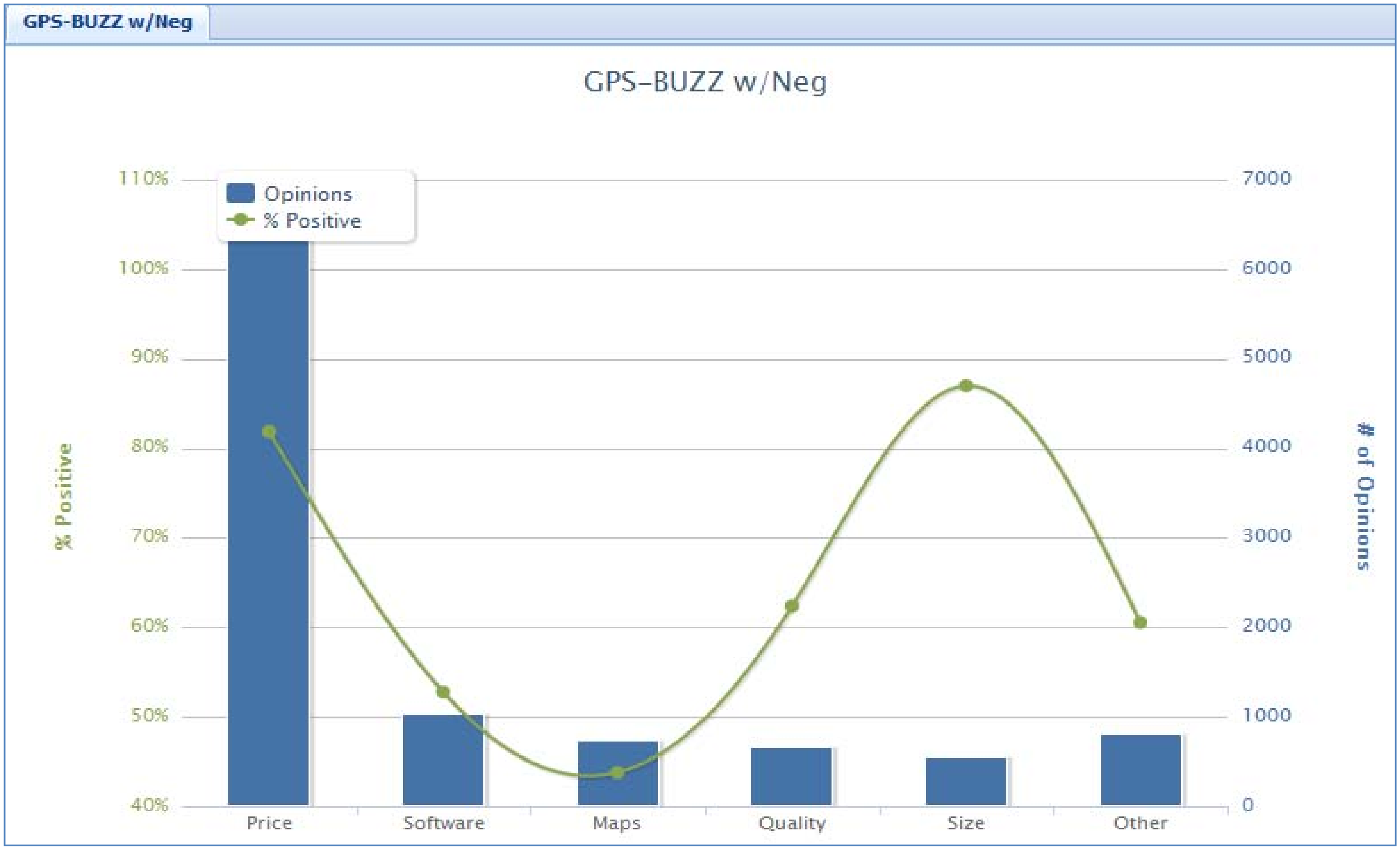
Demo 1: Detail opinion sentences

- You can click on any bar to see the opinion sentences. Here are negative opinion sentences on the maps feature of Garmin.
- The pie chart gives the proportions of opinions.



Demo 1: # of feature mentions

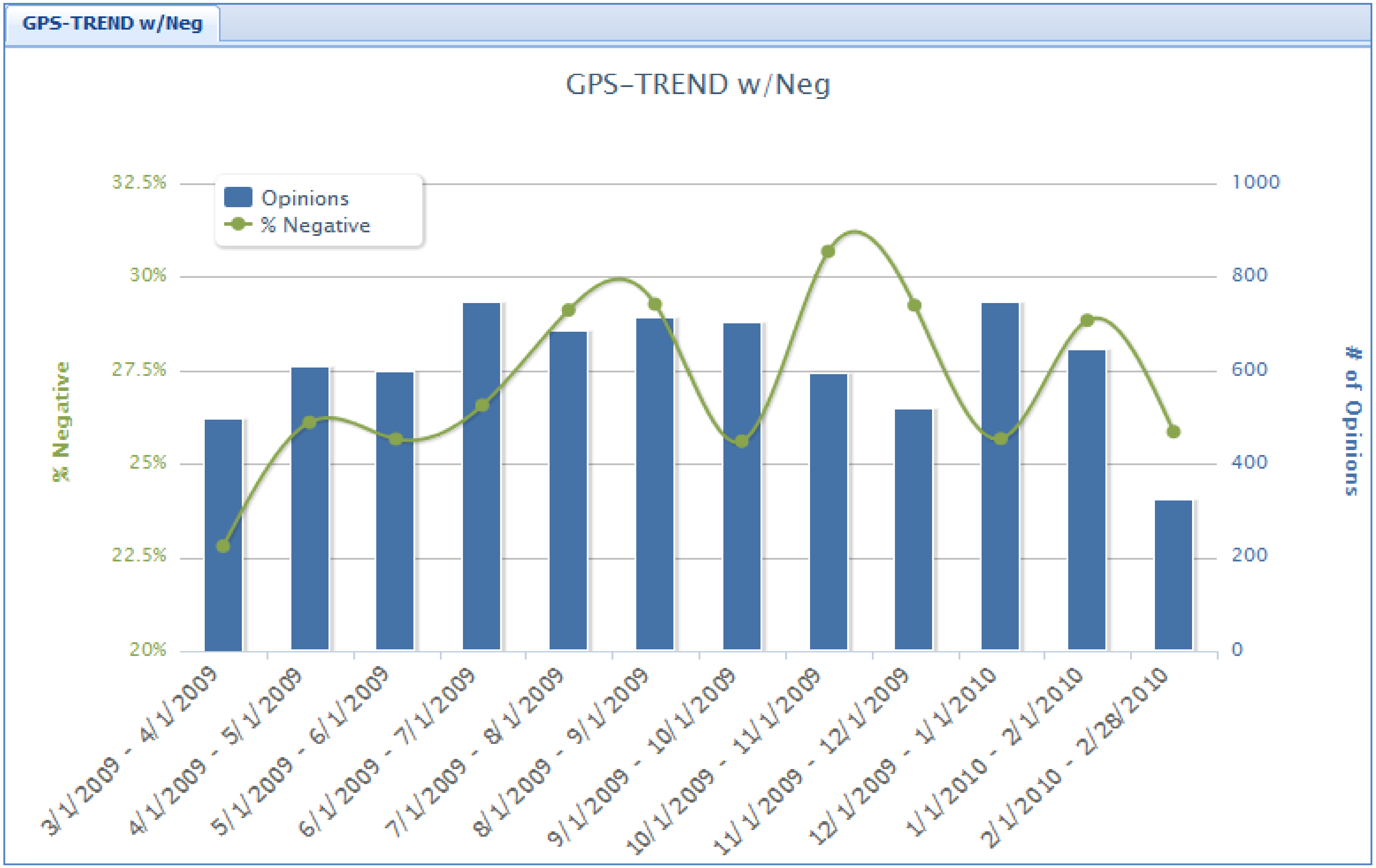
- People talked a lot about prices than other features. They are quite positive about price, but not bout maps and software.



Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Demo 1: Aggregate opinion trend

- More complains in July - Aug, and in Oct – Dec!



Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

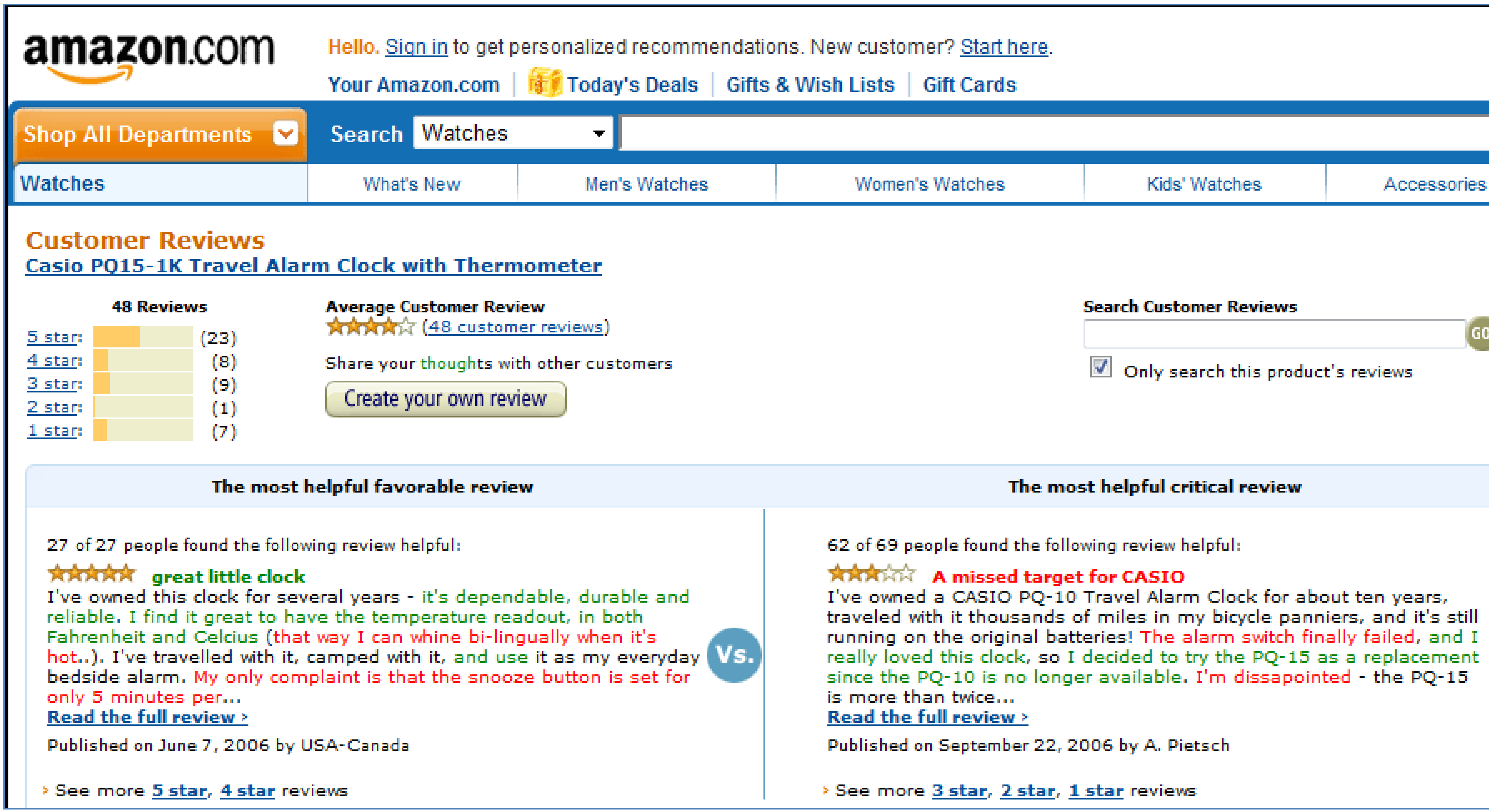
Other goodies of OpinionEQ

- Allow the user to choose
  - Products/brands,
  - Features
  - Sites
  - Time periods

  for opinion comparison.
- Work on an individual feature for detailed analysis.
- Allow the user to see the full opinion text and also the actual page in the site from where the opinion text was extracted.

Demo 2 – Instant page analysis

- Given a URL, it automatically identifies opinions on the page. Green: +ve, and red: -ve



Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Demo 2 – Instant page analysis

- It also extract the opinions in the page and list them.

Pros	Cons
1. FREE 2-Day Shipping: See details. . (details)	1. I find it great to have the temperature readout, in both Fahrenheit and Celcius (that way I can whine bi-lingually when it's hot. . (details)
2. great little clock. . (details)	2. My only complaint is that the snooze button is set for only 5 minutes per. . (details)
3. I've owned this clock for several years - it's dependable, durable and reliable. (details)	3. A missed target for CASIO. . (details)
4. I find it great to have the temperature readout, in both Fahrenheit and Celcius (that way I can whine bi-lingually when it's hot. . (details)	4. The alarm switch finally failed, and I really loved this clock, so I decided to try the PQ-15 as a replacement since the PQ-10 is no longer available. . (details)
5. The alarm switch finally failed, and I really loved this clock, so I decided to try the PQ-15 as a replacement since the PQ-10 is no longer available. . (details)	5. I'm dissapointed - the PQ-15 is more than twice. . (details)
6. love it!, May 10, 2010. . (details)	6. I always seem to loose track of time on the computer and phone and needed something.. . (details)
7. While the digits of the display are decent enough, the operations to set the clock for time, alarm or any other of the settings, are horrific. (details)	7. Not worth my time or money to return the clock, and I DO NOT recommend this clock at all.. . (details)
8. LLBean has a much nicer, user friendly travel clock for less and I could kick myself for not having taken the time to buy another of those.. . (details)	8. LLBean has a much nicer, user friendly travel clock for less and I could kick myself for not having taken the time to buy another of those.. . (details)
9. I bought from Amazon due to the ease of billing, which was the ONLY reason I bought this instead of the LLBean clock.. . (details)	9. While you can't please everyone with a product, I would not recommend this to anyone.. . (details)
10. Very accurate timing but tempreture is off, April 9, 2010. (details)	10. Bought it in December 1996 wholesale for $13 (more than 13 years ago)and i'm still using it EVERYDAY.. Bottom line: Very Very Very accurate and durable BUT tempreture show

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Sentiment Analysis is Challenging!

- *"This past Saturday, I bought a Nokia phone and my girlfriend bought a Motorola phone with Bluetooth. We called each other when we got home. The voice on my phone was not so clear, worse than my previous phone. The battery life was long. My girlfriend was quite happy with her phone. I wanted a phone with good sound quality. So my purchase was a real disappointment. I returned the phone yesterday."*

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

An Example Practice of Review Spam

Belkin International, Inc

- Top networking and peripherals manufacturer | Sales ~ $500 million in 2008
- Posted an ad for writing fake reviews on amazon.com (65 cents per review)

Timer: 00:00:00 of 60 minutes

Want to work on this HIT? Accept HIT

Want to see other HITs? Skip HIT

Write Product Reviews 25-50 Words

Requester: Mike Bayard

Qualifications Required: HIT approval rate (%) is not less than 95

Jan 2009

Write a Positive 5/5 Review for Product on Website

Positive review writing.

- Use your best possible grammar and write in US English only
- Always give a 100% rating (as high as possible)
- Keep your entry between 25 and 50 words
- Write as if you own the product and are using it
- Tell a story of why you bought it and how you are using it
- Thank the website for making you such a great deal
- Mark any other negative reviews as "not helpful" once you post yours

Instructions:

The link below leads to a product on a website. Read-through the product's features and write a positive review for it using the guidelines above to the best of your ability. I have also provided the part number for this product and you can click on the links below to see it on several alternative websites. In order to post some reviews you will need to create an account on the site. You can use your own email address or open a new free webmail account (gmail, yahoo...) and use it to post with.

Experiments with Amazon Reviews

- June 2006
  - 5.8mil reviews, 1.2mil products and 2.1mil reviewers.
- A review has 8 parts
  - *<Product ID> <Reviewer ID> <Rating> <Date> <Review Title> <Review Body> <Number of Helpful feedbacks> <Number of Feedbacks> <Number of Helpful Feedbacks>*
- Industry manufactured products "*mProducts*"

  e.g. electronics, computers, accessories, etc
  - 228K reviews, 36K products and 165K reviewers.

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Some Tentative Results

- Negative outlier reviews tend to be heavily spammed.
- Those reviews that are the only reviews of some products are likely to be spammed
- Top-ranked reviewers are more likely to be spammers.
- Spam reviews can get good helpful feedbacks and non-spam reviews can get bad feedbacks.

Meeting Social Sciences

- Extract and analyze political opinions.
  - Candidates and issues
- Compare opinions across cultures and lang.
  - Comparing opinions of people from different countries on the same issue or topic, e.g., Internet diplomacy
- Opinion spam (fake opinions)
  - What are social, culture, economic aspects of it?
- Opinion propagation in social contexts
- How opinions on the Web influence the real world
  - Are they correlated?
- Emotion analysis in social context & virtual world

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

Opinion Mining and Sentiment Analysis

- We briefly defined sentiment analysis problem.
  - Direct opinions: focused on feature level analysis
  - Comparative opinions: different types of comparisons
  - Opinion spam detection: fake reviews.
    - Currently working with Google (Google research award).
- A lot of applications.
- Technical challenges are still huge.
  - But I am quite optimistic.
- Interested in collaboration with social scientists
  - opinions and related issues are inherently social.

Source: Bing Liu (2010) Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences

More details can be found in

- B. Liu, “Sentiment Analysis and Subjectivity.” A Chapter in *Handbook of Natural Language Processing*, 2nd Edition, 2010.
  - (An earlier version) B. Liu, “Opinion Mining”, A Chapter in the book: Web Data Mining, Springer, 2006.
- Download from: http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

Processing Text

- Converting documents to *index terms*
- Why?
  - Matching the exact string of characters typed by the user is too restrictive
    - i.e., it doesn't work very well in terms of effectiveness
  - Not all words are of equal value in a search
  - Sometimes not clear where words begin and end
    - Not even clear what a word is in some languages
      - e.g., Chinese, Korean

Text Statistics

- Huge variety of words used in text <u>but</u>
- Many statistical characteristics of word occurrences are predictable
  - e.g., distribution of word counts
- Retrieval models and ranking algorithms depend heavily on statistical properties of words
  - e.g., important words occur often in documents but are not high frequency in collection

Tokenizing

- Forming words from sequence of characters
- Surprisingly complex in English, can be harder in other languages
- Early IR systems:
  - any sequence of alphanumeric characters of length 3 or more
  - terminated by a space or other special character
  - upper-case changed to lower-case

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Tokenizing

- Example:
  - "Bigcorp's 2007 bi-annual report showed profits rose 10%." becomes
  - "bigcorp 2007 annual report showed profits rose"
- Too simple for search applications or even large-scale experiments
- Why? Too much information lost
  - Small decisions in tokenizing can have major impact on effectiveness of some queries

Tokenizing Problems

- Small words can be important in some queries, usually in combinations
    - xp, ma, pm, ben e king, el paso, master p, gm, j lo, world war II
- Both hyphenated and non-hyphenated forms of many words are common
  - Sometimes hyphen is not needed
    - e-bay, wal-mart, active-x, cd-rom, t-shirts
  - At other times, hyphens should be considered either as part of the word or a word separator
    - winston-salem, mazda rx-7, e-cards, pre-diabetes, t-mobile, spanish-speaking

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Tokenizing Problems

- Special characters are an important part of tags, URLs, code in documents
- Capitalized words can have different meaning from lower case words
  - Bush, Apple
- Apostrophes can be a part of a word, a part of a possessive, or just a mistake
  - rosie o'donnell, can't, don't, 80's, 1890's, men's straw hats, master's degree, england's ten largest cities, shriner's

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Tokenizing Problems

- Numbers can be important, including decimals
  - nokia 3250, top 10 courses, united 93, quicktime 6.5 pro, 92.3 the beat, 288358
- Periods can occur in numbers, abbreviations, URLs, ends of sentences, and other situations
  - I.B.M., Ph.D., cs.umass.edu, F.E.A.R.
- Note: tokenizing steps for queries must be identical to steps for documents

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Tokenizing Process

- First step is to use parser to identify appropriate parts of document to tokenize
- Defer complex decisions to other components
  - word is any sequence of alphanumeric characters, terminated by a space or special character, with everything converted to lower-case
  - everything indexed
  - example: 92.3 → 92 3 but search finds documents with 92 and 3 adjacent
  - incorporate some rules to reduce dependence on query transformation components

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Tokenizing Process

- Not that different than simple tokenizing process used in past
- Examples of rules used with TREC
  - Apostrophes in words ignored
    - o’connor → oconnor bob’s → bobs
  - Periods in abbreviations ignored
    - I.B.M. → ibm Ph.D. → ph d

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Stopping

- Function words (determiners, prepositions) have little meaning on their own
- High occurrence frequencies
- Treated as *stopwords* (i.e. removed)
  - reduce index space, improve response time, improve effectiveness
- Can be important in combinations
  - e.g., “to be or not to be”

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Stopping

- Stopword list can be created from high-frequency words or based on a standard list
- Lists are customized for applications, domains, and even parts of documents
  - e.g., "click" is a good stopword for anchor text
- Best policy is to index all words in documents, make decisions about which words to use at query time

Stemming

- Many morphological variations of words
  - *inflectional* (plurals, tenses)
  - *derivational* (making verbs nouns etc.)
- In most cases, these have the same or very similar meanings
- Stemmers attempt to reduce morphological variations of words to a common stem
  - usually involves removing suffixes
- Can be done at indexing time or as part of query processing (like stopwords)

Stemming

- Generally a small but significant effectiveness improvement
  - can be crucial for some languages
  - e.g., 5-10% improvement for English, up to 50% in Arabic

kitab	*a book*
kitabi	*my book*
al**kitab**	*the book*
kitabuki	*your book* (f)
kitabuka	*your book (m)*
kitabuhu	*his book*
kataba	*to write*
ma**ktaba**	*library, bookstore*
ma**ktab**	*office*

Words with the Arabic root **ktb**

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Stemming

- Two basic types
  - Dictionary-based: uses lists of related words
  - Algorithmic: uses program to determine related words
- Algorithmic stemmers
  - *suffix-s:* remove ‘s’ endings assuming plural
    - e.g., cats → cat, lakes → lake, wiis → wii
    - Many *false negatives*: supplies → supplie
    - Some *false positives*: ups → up

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Porter Stemmer

- Algorithmic stemmer used in IR experiments since the 70s
- Consists of a series of rules designed to the longest possible suffix at each step
- Effective in TREC
- Produces *stems* not *words*
- Makes a number of errors and difficult to modify

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Porter Stemmer

- Example step (1 of 5)

Step 1a:

- Replace ***sses*** by ***ss*** (e.g., stresses → stress).
- Delete ***s*** if the preceding word part contains a vowel not immediately before the ***s*** (e.g., gaps → gap but gas → gas).
- Replace ***ied*** or ***ies*** by ***i*** if preceded by more than one letter, otherwise by ***ie*** (e.g., ties → tie, cries → cri).
- If suffix is ***us*** or ***ss*** do nothing (e.g., stress → stress).

Step 1b:

- Replace ***eed***, ***eedly*** by ***ee*** if it is in the part of the word after the first non-vowel following a vowel (e.g., agreed → agree, feed → feed).
- Delete ***ed***, ***edly***, ***ing***, ***ingly*** if the preceding word part contains a vowel, and then if the word ends in ***at***, ***bl***, or ***iz*** add ***e*** (e.g., fished → fish, pirating → pirate), or if the word ends with a double letter that is not ***ll***, ***ss*** or ***zz***, remove the last letter (e.g., falling→ fall, dripping → drip), or if the word is short, add ***e*** (e.g., hoping → hope).
- Whew!

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Porter Stemmer

False positives	*False negatives*
organization/organ	european/europe
generalization/generic	cylinder/cylindrical
numerical/numerous	matrices/matrix
policy/police	urgency/urgent
university/universe	create/creation
addition/additive	analysis/analyses
negligible/negligent	useful/usefully
execute/executive	noise/noisy
past/paste	decompose/decomposition
ignore/ignorant	sparse/sparsity
special/specialized	resolve/resolution
head/heading	triangle/triangular

- Porter2 stemmer addresses some of these issues
- Approach has been used with other languages

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Krovetz Stemmer

- Hybrid algorithmic-dictionary
  - Word checked in dictionary
    - If present, either left alone or replaced with “exception”
    - If not present, word is checked for suffixes that could be removed
    - After removal, dictionary is checked again
- Produces words not stems
- Comparable effectiveness
- Lower false positive rate, somewhat higher false negative

Stemmer Comparison

Original text:

Document will describe marketing strategies carried out by U.S. companies for their agricultural chemicals, report predictions for market share of such chemicals, or report market statistics for agrochemicals, pesticide, herbicide, fungicide, insecticide, fertilizer, predicted sales, market share, stimulate demand, price cut, volume of sales.

Porter stemmer:

document describ market strategi carri compani agricultur chemic report predict market share chemic report market statist agrochem pesticid herbicid fungicid insecticid fertil predict sale market share stimul demand price cut volum sale

Krovetz stemmer:

document describe marketing strategy carry company agriculture chemical report prediction market share chemical report market statistic agrochemic pesticide herbicide fungicide insecticide fertilizer predict sale stimulate demand price cut volume sale

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Phrases

- Many queries are 2-3 word phrases
- Phrases are
  - More precise than single words
    - e.g., documents containing “black sea” vs. two words “black” and “sea”
  - Less ambiguous
    - e.g., “big apple” vs. “apple”
- Can be difficult for ranking
    - e.g., Given query “fishing supplies”, how do we score documents with
      - exact phrase many times, exact phrase just once, individual words in same sentence, same paragraph, whole document, variations on words?

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Phrases

- Text processing issue – how are phrases recognized?
- Three possible approaches:
  - Identify syntactic phrases using a *part-of-speech* (POS) tagger
  - Use word *n-grams*
  - Store word positions in indexes and use *proximity operators* in queries

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

POS Tagging

- POS taggers use statistical models of text to predict syntactic tags of words
  - Example tags:
    - NN (singular noun), NNS (plural noun), VB (verb), VBD (verb, past tense), VBN (verb, past participle), IN (preposition), JJ (adjective), CC (conjunction, e.g., “and”, “or”), PRP (pronoun), and MD (modal auxiliary, e.g., “can”, “will”).
- Phrases can then be defined as simple noun groups, for example

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Pos Tagging Example

Original text:
Document will describe marketing strategies carried out by U.S. companies for their agricultural chemicals, report predictions for market share of such chemicals, or report market statistics for agrochemicals, pesticide, herbicide, fungicide, insecticide, fertilizer, predicted sales, market share, stimulate demand, price cut, volume of sales.

Brill tagger:
Document/NN will/MD describe/VB marketing/NN strategies/NNS carried/VBD out/IN by/IN U.S./NNP companies/NNS for/IN their/PRP agricultural/JJ chemicals/NNS ,/, report/NN predictions/NNS for/IN market/NN share/NN of/IN such/JJ chemicals/NNS ,/, or/CC report/NN market/NN statistics/NNS for/IN agrochemicals/NNS ,/, pesticide/NN ,/, herbicide/NN ,/, fungicide/NN ,/, insecticide/NN ,/, fertilizer/NN ,/, predicted/VBN sales/NNS ,/, market/NN share/NN ,/, stimulate/VB demand/NN ,/, price/NN cut/NN ,/, volume/NN of/IN sales/NNS ./.

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Example Noun Phrases

TREC data		Patent data	
Frequency	*Phrase*	*Frequency*	*Phrase*
65824	united states	975362	present invention
61327	article type	191625	u.s. pat
33864	los angeles	147352	preferred embodiment
18062	hong kong	95097	carbon atoms
17788	north korea	87903	group consisting
17308	new york	81809	room temperature
15513	san diego	78458	seq id
15009	orange county	75850	brief description
12869	prime minister	66407	prior art
12799	first time	59828	perspective view
12067	soviet union	58724	first embodiment
10811	russian federation	56715	reaction mixture
9912	united nations	54619	detailed description
8127	southern california	54117	ethyl acetate
7640	south korea	52195	example 1
7620	end recording	52003	block diagram
7524	european union	46299	second embodiment
7436	south africa	41694	accompanying drawings
7362	san francisco	40554	output signal
7086	news conference	37911	first end
6792	city council	35827	second end
6348	middle east	34881	appended claims
6157	peace process	33947	distal end
5955	human rights	32338	cross-sectional view
5837	white house	30193	outer surface

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Word N-Grams

- POS tagging too slow for large collections
- Simpler definition – phrase is any sequence of *n* words – known as *n-grams*
  - *bigram*: 2 word sequence, *trigram*: 3 word sequence, *unigram*: single words
  - N-grams also used at character level for applications such as OCR
- N-grams typically formed from *overlapping* sequences of words
  - i.e. move n-word "window" one word at a time in document

N-Grams

- Frequent n-grams are more likely to be meaningful phrases
- N-grams form a Zipf distribution
  - Better fit than words alone
- Could index all n-grams up to specified length
  - Much faster than POS tagging
  - Uses a lot of storage
    - e.g., document containing 1,000 words would contain 3,990 instances of word n-grams of length $2 \leq n \leq 5$

Google N-Grams

- Web search engines index n-grams
- Google sample:

Number of tokens:	1,024,908,267,229
Number of sentences:	95,119,665,584
Number of unigrams:	13,588,391
Number of bigrams:	314,843,401
Number of trigrams:	977,069,902
Number of fourgrams:	1,313,818,354
Number of fivegrams:	1,176,470,663

- Most frequent trigram in English is “all rights reserved”
  – In Chinese, “limited liability corporation”

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Document Structure and Markup

- Some parts of documents are more important than others
- Document parser recognizes structure using markup, such as HTML tags
  - Headers, anchor text, bolded text all likely to be important
  - Metadata can also be important
  - Links used for *link analysis*

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Example Web Page

Tropical fish

From Wikipedia, the free encyclopedia

Tropical fish include fish found in tropical environments around the world, including both freshwater and salt water species. Fishkeepers often use the term *tropical fish* to refer only those requiring fresh water, with saltwater tropical fish referred to as *marine fish*.

Tropical fish are popular aquarium fish , due to their often bright coloration. In freshwater fish, this coloration typically derives from iridescence, while salt water fish are generally pigmented.

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Example Web Page

```
<html>
<head>
<meta name="keywords" content="Tropical fish, Airstone, Albinism, Algae eater,
Aquarium, Aquarium fish feeder, Aquarium furniture, Aquascaping, Bath treatment
(fishkeeping),Berlin Method, Biotope" />
…
<title>Tropical fish - Wikipedia, the free encyclopedia</title>
</head>
<body>
 …
<h1 class="firstHeading">Tropical fish</h1>
…
<p><b>Tropical fish</b> include <a href="/wiki/Fish" title="Fish">fish</a> found in <a
href="/wiki/Tropics" title="Tropics">tropical</a> environments around the world,
including both <a href="/wiki/Fresh_water" title="Fresh water">freshwater</a> and <a
href="/wiki/Sea_water" title="Sea water">salt water</a> species. <a
href="/wiki/Fishkeeping" title="Fishkeeping">Fishkeepers</a> often use the term
<i>tropical fish</i> to refer only those requiring fresh water, with saltwater tropical fish
referred to as <i><a href="/wiki/List_of_marine_aquarium_fish_species" title="List of
marine aquarium fish species">marine fish</a></i>.</p>
<p>Tropical fish are popular <a href="/wiki/Aquarium" title="Aquarium">aquarium</a>
fish , due to their often bright coloration. In freshwater fish, this coloration typically
derives from <a href="/wiki/Iridescence" title="Iridescence">iridescence</a>, while salt
water fish are generally <a href="/wiki/Pigment" title="Pigment">pigmented</a>.</p>
…
</body></html>
```

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Link Analysis

- Links are a key component of the Web
- Important for navigation, but also for search
  - e.g., Example website
  - "Example website" is the anchor text
  - "http://example.com" is the destination link
  - both are used by search engines

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Anchor Text

- Used as a description of the content of the *destination page*
  - i.e., collection of anchor text in all links pointing to a page used as an additional text field
- Anchor text tends to be short, descriptive, and similar to query text
- Retrieval experiments have shown that anchor text has significant impact on effectiveness for *some types of queries*
  - i.e., more than PageRank

PageRank

- Billions of web pages, some more informative than others
- Links can be viewed as information about the *popularity* (*authority*?) of a web page
  – can be used by ranking algorithm
- *Inlink* count could be used as simple measure
- Link analysis algorithms like PageRank provide more reliable ratings
  – less susceptible to link spam

Random Surfer Model

- Browse the Web using the following algorithm:
  - Choose a random number *r* between 0 and 1
  - If $r < \lambda$:
    - Go to a random page
  - If $r \geq \lambda$:
    - Click a link at random on the current page
  - Start again
- PageRank of a page is the probability that the "random surfer" will be looking at that page
  - links from popular pages will increase PageRank of pages they point to

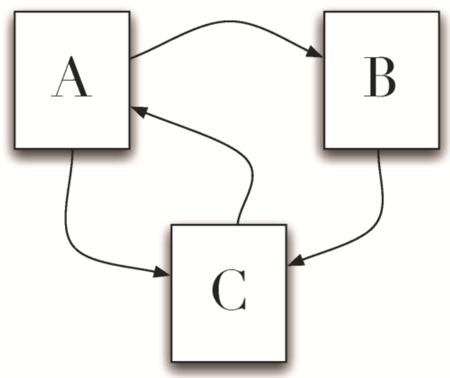
Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Dangling Links

- Random jump prevents getting stuck on pages that
  - do not have links
  - contains only links that no longer point to other pages
  - have links forming a loop
- Links that point to the first two types of pages are called *dangling links*
  - may also be links to pages that have not yet been crawled

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

PageRank



- PageRank (*PR*) of page C = *PR*(A)/2 + *PR*(B)/1
- More generally,

$$PR(u) = \sum_{v \in B_u} \frac{PR(v)}{L_v}$$

  – where B_u is the set of pages that point to *u*, and L_v is the number of outgoing links from page *v* (not counting duplicate links)

PageRank

- Don’t know PageRank values at start
- Assume equal values (1/3 in this case), then iterate:
  – first iteration: *PR*(C) = 0.33/2 + 0.33 = 0.5, *PR*(A) = 0.33, and *PR*(B) = 0.17
  – second: *PR*(C) = 0.33/2 + 0.17 = 0.33, *PR*(A) = 0.5, *PR*(B) = 0.17
  – third: *PR*(C) = 0.42, *PR*(A) = 0.33, *PR*(B) = 0.25
- Converges to *PR*(C) = 0.4, *PR*(A) = 0.4, and *PR*(B) = 0.2

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

PageRank

- Taking random page jump into account, 1/3 chance of going to any page when $r < \lambda$
- $PR(\mathrm{C}) = \lambda/3 + (1 - \lambda) \cdot (PR(\mathrm{A})/2 + PR(\mathrm{B})/1)$
- More generally,

$$PR(u) = \frac{\lambda}{N} + (1 - \lambda) . \sum_{v \in B_u} \frac{PR(v)}{L_v}$$

  – where N is the number of pages, λ typically 0.15

```
procedure PageRank(G)
        ▷ G is the web graph, consisting of vertices (pages) and edges (links).
    (P, L) ← G                                  ▷ Split graph into pages and links
    I ← a vector of length |P|                  ▷ The current PageRank estimate
    R ← a vector of length |P|                  ▷ The resulting better PageRank estimate
    for all entries I_i ∈ I do
        I_i ← 1/|P|                             ▷ Start with each page being equally likely
    end for
    while R has not converged do
        for all entries R_i ∈ R do
            R_i ← λ/|P|                         ▷ Each page has a λ/|P| chance of random selection
        end for
        for all pages p ∈ P do
            Q ← the set of pages such that (p, q) ∈ L and q ∈ P
            if |Q| > 0 then
                for all pages q ∈ Q do
                    R_q ← R_q + (1 − λ)I_p/|Q|  ▷ Probability I_p of being at page p
                end for
            else
                for all pages q ∈ P do
                    R_q ← R_q + (1 − λ)I_p/|P|
                end for
            end if
            I ← R                               ▷ Update our current PageRank estimate
        end for
    end while
    return R
end procedure
```

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

A PageRank Implementation

- Preliminaries:
  - 1) Extract links from the source text. You'll also want to extract the URL from each document in a separate file. Now you have all the links (source-destination pairs) and all the source documents
  - 2) Remove all links from the list that do not connect two documents in the corpus. The easiest way to do this is to sort all links by destination, then compare that against the corpus URLs list (also sorted)
  - 3) Create a new file I that contains a (url, pagerank) pair for each URL in the corpus. The initial PageRank value is 1/#D (#D = number of urls)
- At this point there are two interesting files:
  - [L] links (trimmed to contain only corpus links, sorted by source URL)
  - [I] URL/PageRank pairs, initialized to a constant

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

A PageRank Implementation

- Preliminaries - Link Extraction from .corpus file using Galago

```
DocumentSplit -> IndexReaderSplitParser -> TagTokenizer
split = new DocumentSplit ( filename, filetype, new byte[0], new byte[0] )
index = new IndexReaderSplitParser ( split )
tokenizer = new.TagTokenizer ( )
tokenizer.setProcessor ( NullProcessor ( Document.class ) )
doc = index.nextDocument ( )
tokenizer.process ( doc )
```

  - doc.identifier contains the file's name
  - doc.tags now contains all tags
  - Links can be extracted by finding all tags with name "a"
  - Links should be processed so that they can be compared with some file name in the corpus

A PageRank Implementation

Iteration:

- Steps:
  1. Make a new output file, R.
  2. Read L and I in parallel (since they're all sorted by URL).
  3. For each unique source URL, determine whether it has any outgoing links:
  4. If not, add its current PageRank value to the sum: T (terminals).
  5. If it does have outgoing links, write (source_url, dest_url, $I_p/|Q|$), where I_p is the current PageRank value, $|Q|$ is the number of outgoing links, and dest_url is a link destination.
     Do this for all outgoing links. Write this to R.
  6. Sort R by destination URL.
  7. Scan R and I at the same time. The new value of R_p is:
     (1 - lambda) / #D (a fraction of the sum of all pages)
     plus: lambda * sum(T) / #D (the total effect from terminal pages),
     plus: lambda * all incoming mass from step 5. ()
  8. Check for convergence
  9. Write new R_p values to a new I file.

A PageRank Implementation

- Convergence check
  - Stopping criteria for this types of PR algorithm typically is of the form ||new - old|| < tau where new and old are the new and old PageRank vectors, respectively.
  - Tau is set depending on how much precision you need. Reasonable values include 0.1 or 0.01. If you want really fast, but inaccurate convergence, then you can use something like tau=1.
  - The setting of tau also depends on N (= number of documents in the collection), since ||new-old|| (for a fixed numerical precision) increases as N increases, so you can alternatively formulate your convergence criteria as ||new – old|| / N < tau.
  - Either the L1 or L2 norm can be used.

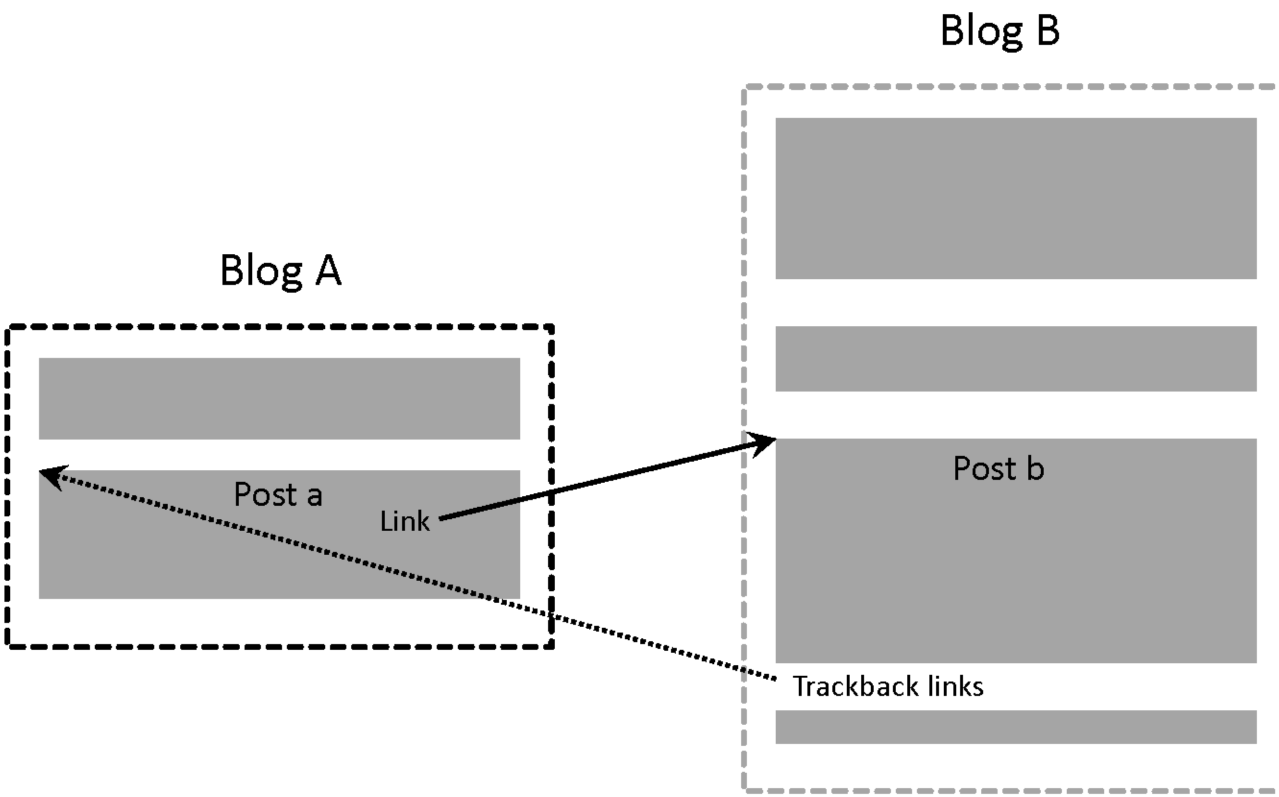
Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Link Quality

- Link quality is affected by spam and other factors
  - e.g., *link farms* to increase PageRank
  - *trackback links* in blogs can create loops
  - links from comments section of popular blogs
    - Blog services modify comment links to contain `rel=nofollow` attribute
    - e.g., "Come visit my <a `rel=nofollow` href="http://www.page.com">web page."

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Trackback Links



Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Information Extraction (IE)

- Automatically extract structure from text
  - annotate document using tags to identify extracted structure
- *Named entity recognition (NER)*
  - identify words that refer to something of interest in a particular application
  - e.g., people, companies, locations, dates, product names, prices, etc.

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Named Entity Recognition (NER)

Fred Smith, who lives at 10 Water Street, Springfield, MA, is a long-time collector of **tropical fish.**

<p ><PersonName><GivenName>Fred</GivenName> <Sn>Smith</Sn> </PersonName>, who lives at <address><Street >10 Water Street</Street>, <City>Springfield</City>, <State>MA</State></address>, is a long-time collector of tropical fish.</p>

- Example showing semantic annotation of text using XML tags
- Information extraction also includes document structure and more complex features such as *relationships* and *events*

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Named Entity Recognition

- *Rule-based*
  - Uses *lexicons* (lists of words and phrases) that categorize names
    - e.g., locations, peoples' names, organizations, etc.
  - Rules also used to verify or find new entity names
    - e.g., "<number> <word> street" for addresses
    - "<street address>, <city>" or "in <city>" to verify city names
    - "<street address>, <city>, <state>" to find new cities
    - "<title> <name>" to find new names

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Named Entity Recognition

- Rules either developed manually by trial and error or using machine learning techniques
- S*tatistical*
  - uses a probabilistic model of the words in and around an entity
  - probabilities estimated using *training data* (manually annotated text)
  - Hidden Markov Model (HMM)
  - Conditional Random Field (CRF)

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Named Entity Recognition

- Accurate recognition requires about 1M words of training data (1,500 news stories)
  - may be more expensive than developing rules for some applications
- Both rule-based and statistical can achieve about 90% effectiveness for categories such as names, locations, organizations
  - others, such as product name, can be much worse

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Internationalization

- 2/3 of the Web is in English
- About 50% of Web users do not use English as their primary language
- Many (maybe most) search applications have to deal with multiple languages
  - *monolingual search*: search in one language, but with many possible languages
  - *cross-language search*: search in multiple languages at the same time

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Internationalization

- Many aspects of search engines are language-neutral
- Major differences:
  - Text encoding (converting to Unicode)
  - Tokenizing (many languages have no word separators)
  - Stemming
- Cultural differences may also impact interface design and features provided

Source: Croft et al. (2008) Search Engines: Information Retrieval in Practice

Chinese "Tokenizing"

1. Original text

旱灾在中国造成的影响

(the impact of droughts in China)

2. Word segmentation

旱灾	在	中国	造成	的	影响
drought	at	china	make		impact

3. Bigrams

旱灾 灾在 在中 中国 国造

造成 成的 的影 影响

Summary

- Social Network Analysis
- Link Mining
- Text Mining
- Web Mining
- Opinion Mining in Social Media

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