Finding High-Quality Content in Social Media

Proceedings of the 2008 International Conference on Web Search and Data Mining. ACM, 2008.

Eugene Agichtein et al.

Identifying Topical Authorities in Microblogs

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Aditya Pal and Scott Counts

Presented by Matt Chaney

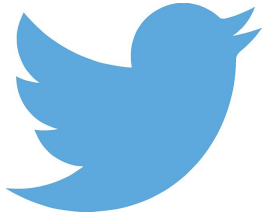
CS 834 - Presentation 5

Web is Changing

1990s - traditional content producers / consumers

2000s - user-generated content ➔ “pro-sumers”

- Blogs
- Photo/Video sharing
- Social Networking
- **Question / Answer**
  - **Yahoo! Answers**



Focus on Question/Answer

- Quality of content - traditional content quality range is much narrower than unmediated, user-generated content

- Additional content sources
  - Document content
  - Link analysis
  - User-to-document relation types
  - User-to-user interactions

- How to find high quality question/answer content?

Study Outline

- Three key questions:
  1. What are the elements of social media that can be used to facilitate automated discovery of high-quality content?
  2. How are these different factors related? Is content alone enough for identifying high-quality items?
  3. Can community feedback approximate judgments of specialists?
- First large-scale study combining content analysis with user-generated content
- Model user-interactions with graph-based framework
- Combine evidence from many sources into overall quality classification

Yahoo! Answers

- Users ask questions / provide answers on *any* topic

- Actively regulate the system through democratic quality management
  - Mark an “interesting” question
  - Vote on answers - thumbs up / down
  - Report offensive / inappropriate behavior

- Users have threefold role
  1. Asker
  2. Answerer
  3. Regulator

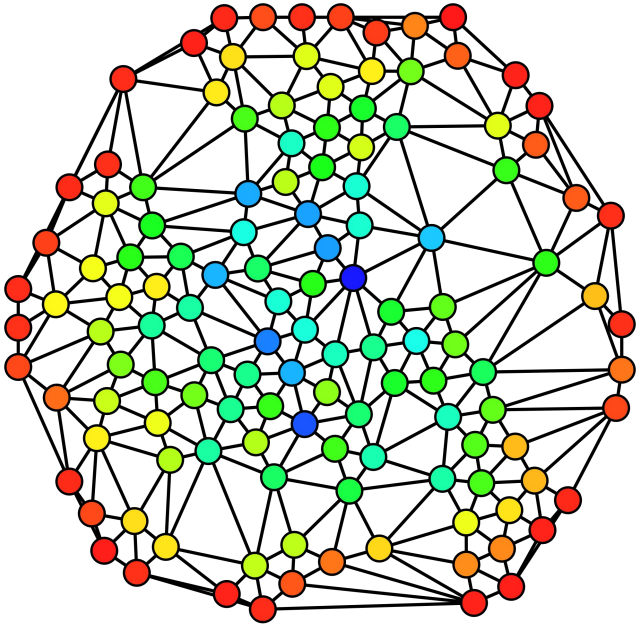
- Results in a heterogeneous web of social interactions

Question Lifecycle

- Question is **Open** - about 90,000 questions *per day*
- Other users submit answers
- Question becomes **Closed**
  - Asker closes question to more answers
  - Time limit reached - 4 (or 8) days
- Question becomes **Resolved**
  - Other users vote on the best answer
  - Asker selects best answer

Related Work

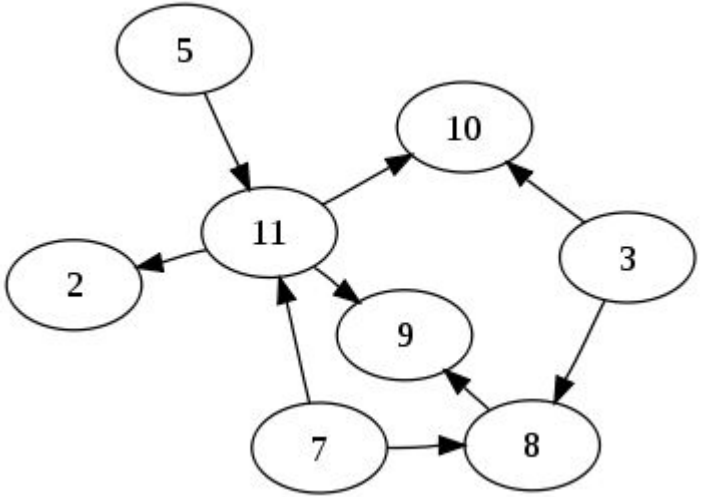
- Link Analysis in Social Media
- Propagating Reputation
- Question / Answering Portals
- Expert Finding
- Content Quality Text Analysis
- Implicit Feedback Ranking



Hue scale representing node betweenness on a graph.
Claudio Rocchini. CC-BY 2.5. 2007.

Identifying Quality Content

- Intrinsic content quality, primarily text-related
  - Punctuation / typos
  - Syntactic and semantic complexity
  - Grammaticality
- User relationships
  - Answerer (u) answers user (v) question $U \rightarrow V$
- Usage statistics
  - Click count / dwell time
- **Classification → High Quality vs The Rest**



A directed, acyclic graph (DAG).
Maat. Public Domain. 2010.

User Relationships

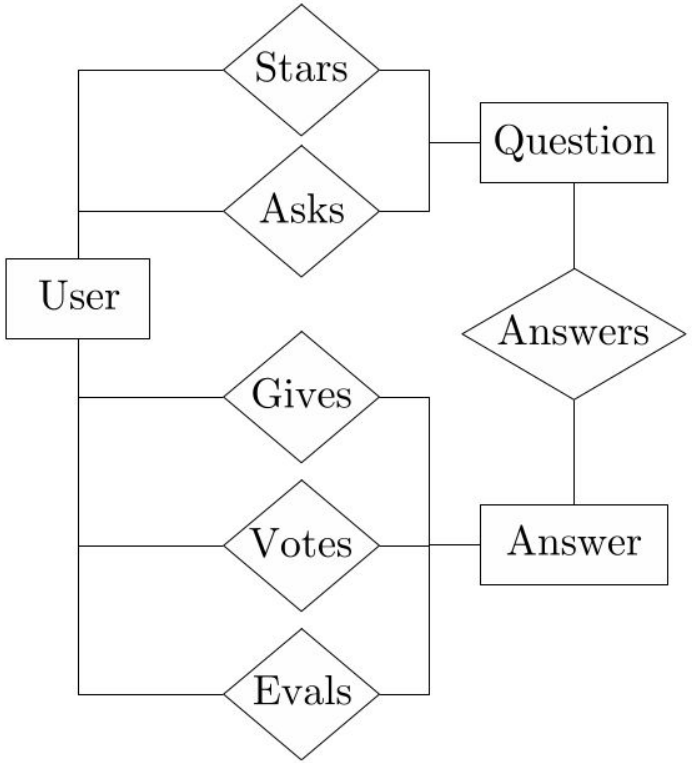


Figure 1. Partial entity-relationship diagram of answers.
Finding High-Quality Content in Social Media. Eugene Agichtein et al. 2008.

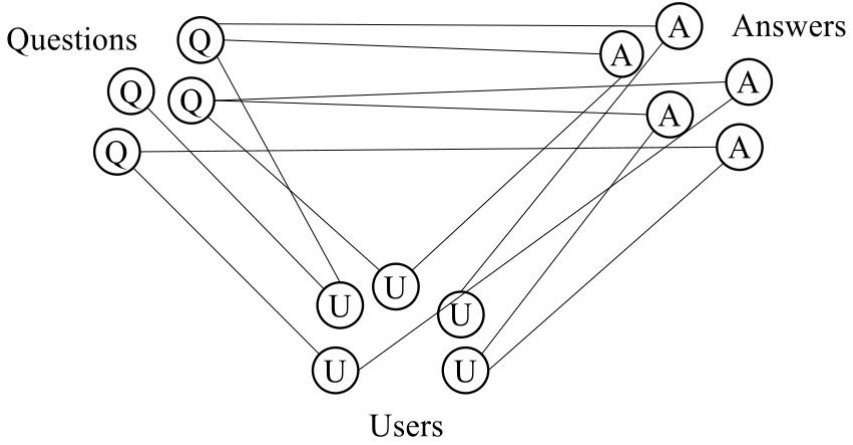


Figure 2: Interaction of users-questions-answers modeled as a tri-partite graph.
Finding High-Quality Content in Social Media. Eugene Agichtein et al. 2008.

Answer Feature Space

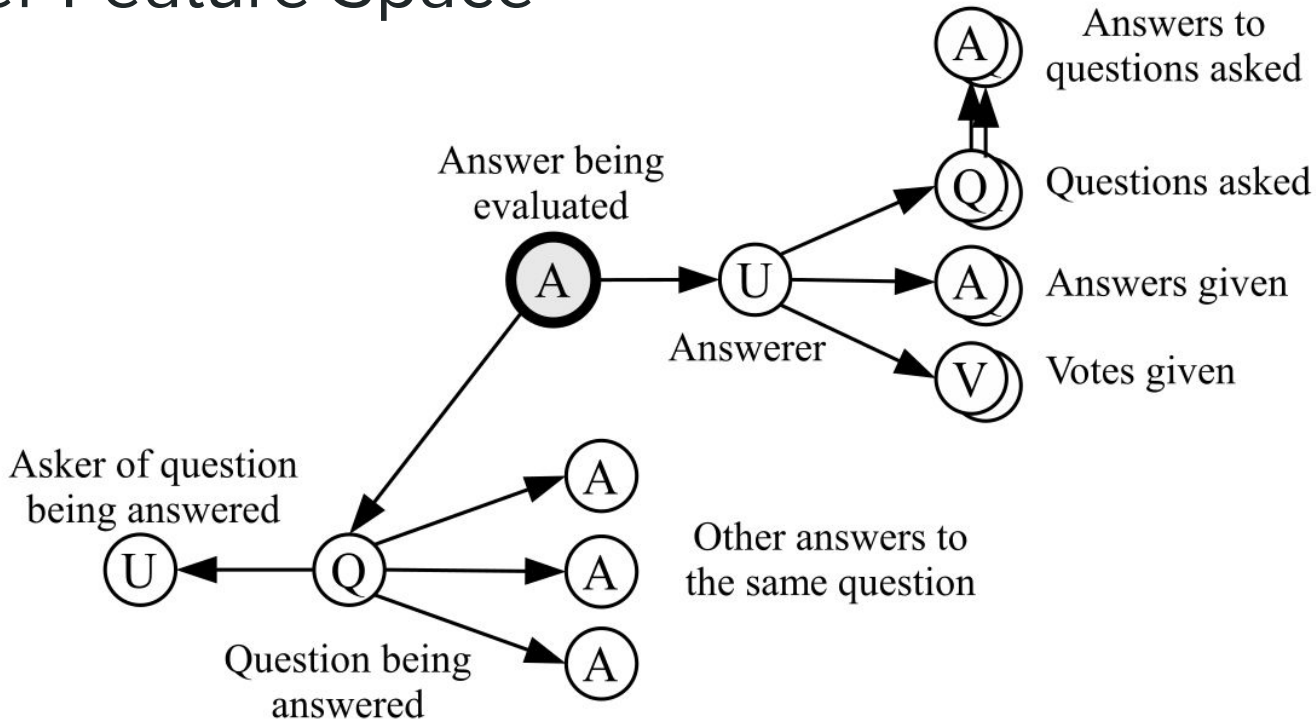


Figure 3: Types of features available for inferring the quality of an answer.
Finding High-Quality Content in Social Media. Eugene Agichtein et al. 2008.

Question Feature Space

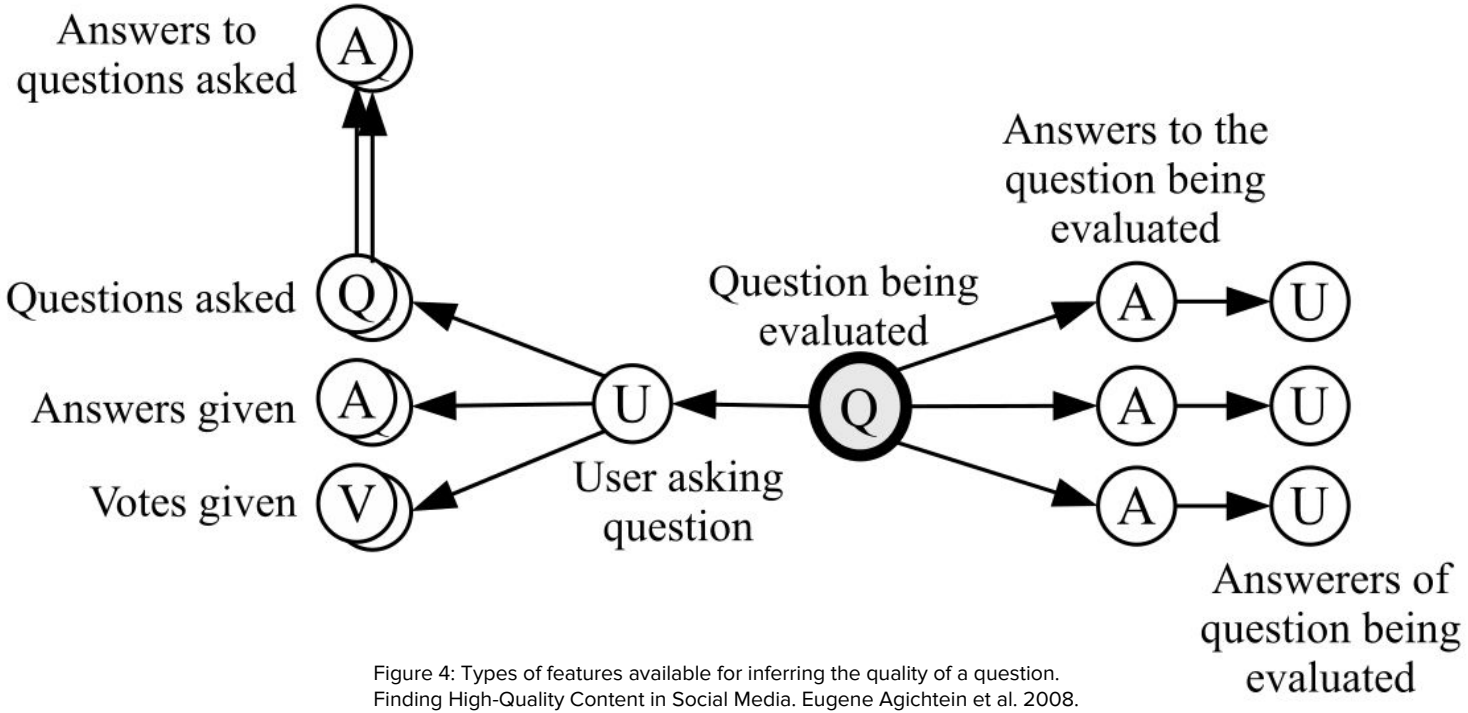


Figure 4: Types of features available for inferring the quality of a question.
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Implicit User-User Relationships

Graph G = (V, E)

- V = users
- E = edges connecting users → $E = \{ E_a \cup E_b \cup E_v \cup E_s \cup E_+ \cup E_- \}$
- Apply HITS and PageRank on each graph

Graph $G_x = (V, E_x)$

- h_x → HITS Hub scores
- a_x → HITS Authority scores
- p_x → PageRank scores

QA Features

- Content
  - Directly use semantic features
  - Rely on classifier to identify the *most salient* features
  - Model the relationship between *question* and *answer*
    - KL-divergence between LM of two texts
    - Non-stopword overlap
    - Ratio between lengths

- Usage Features
  - Question-Answer page click count
  - Temporal statistics
  - Categorical click expectations

Experimental Setup

- 6,665 questions
- 8,366 Question-Answer pairs
- Labeled for quality by human editors
  - Well-formedness
  - Readability
  - Utility
  - Interestingness
  - Answers ➔ Correctness
  - Type association ➔ Informational, advice, opinion, poll

- Agreement for “question quality” ➔ κ = 0.68
- 10-Fold cross validation
- 80% used as training

Graph Analysis for Finding Relationships

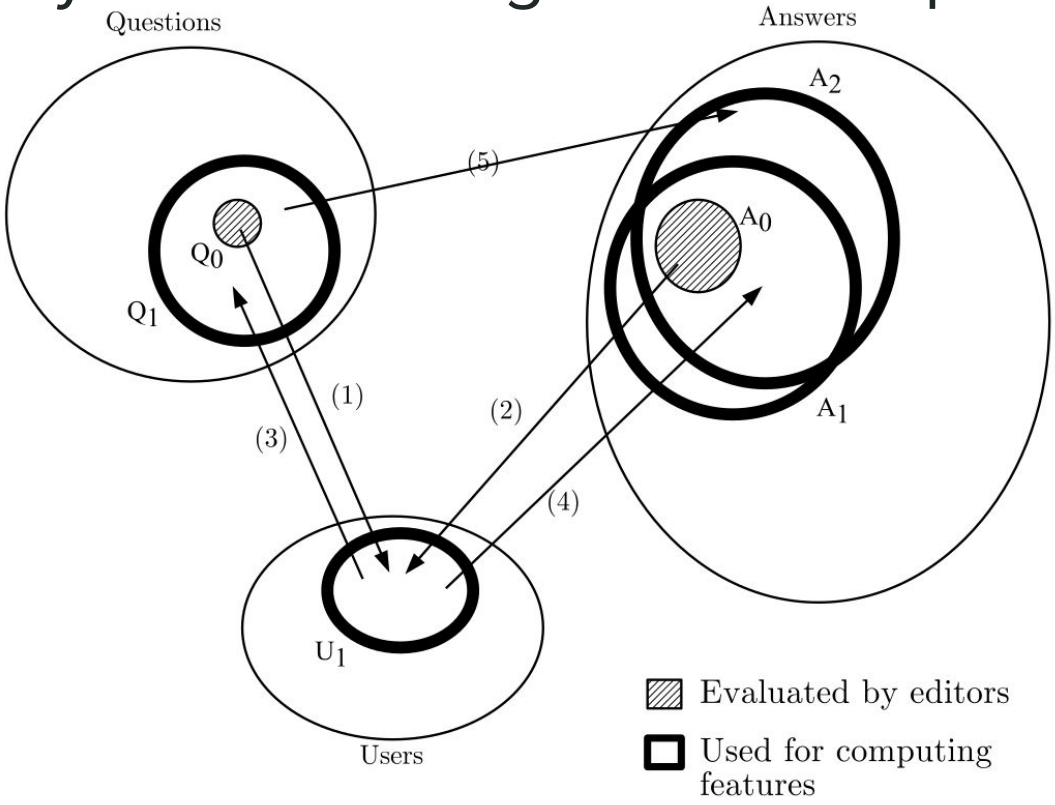

Figure 5: Sketch showing how do we find related questions and answers.
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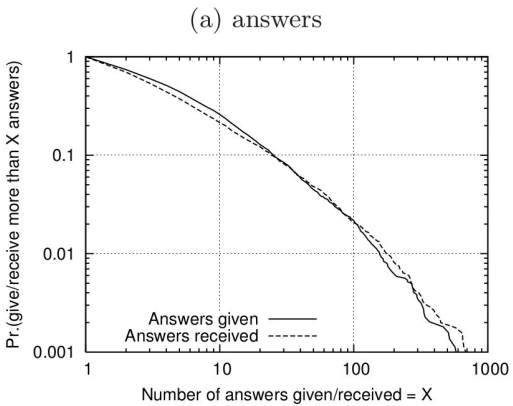
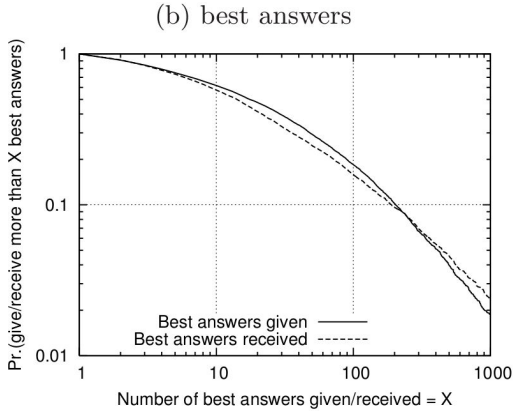
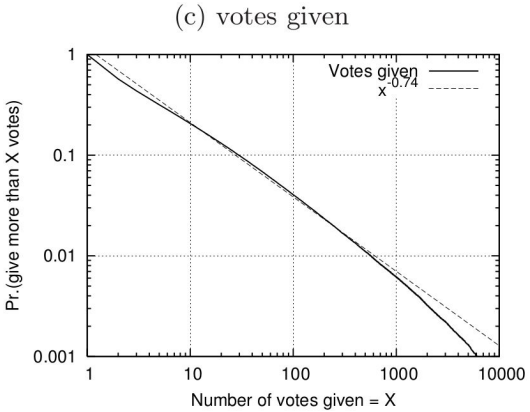
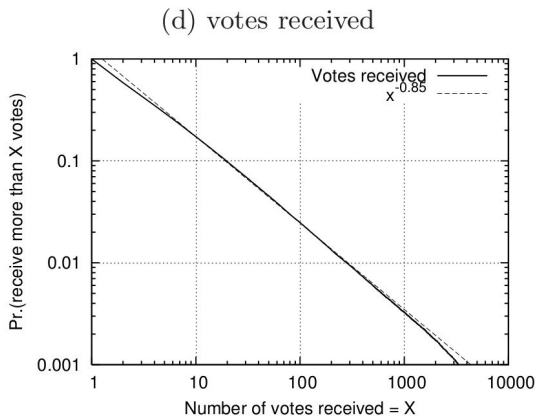
Statistics


(a) answers
Pr.(give/receive more than X answers)
Number of answers given/received = X
Answers given
Answers received
1
0.1
0.01
0.001
1
10
100
1000


(b) best answers
Pr.(give/receive more than X best answers)
Number of best answers given/received = X
Best answers given
Best answers received
1
0.1
0.01
1
10
100
1000


(c) votes given
Pr.(give more than X votes)
Number of votes given = X
Votes given
x^-0.74
1
0.1
0.01
0.001
1
10
100
1000
10000


(d) votes received
Pr.(receive more than X votes)
Number of votes received = X
Votes received
x^-0.85
1
0.1
0.01
0.001
1
10
100
1000
10000

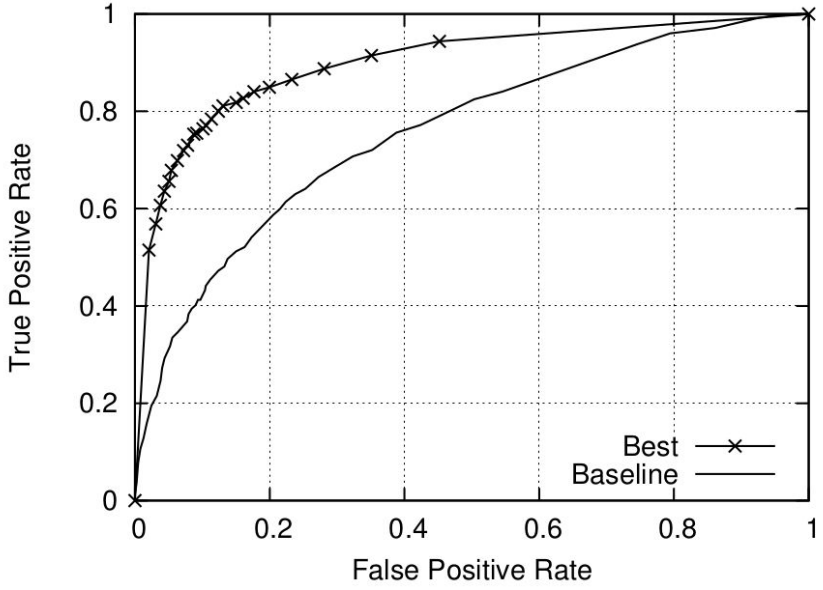
Question Quality Results

Method	High qual. P	High qual. R	Normal/low qual. P	Normal/low qual. R	AUC
Text (Baseline)	0.654	0.481	0.762	0.867	0.523
Usage	0.594	0.470	0.755	0.836	0.508
Relation	0.694	0.603	0.806	0.861	0.614
Intrinsic	0.746	0.650	0.829	0.885	0.645
T+Usage	0.683	0.571	0.798	0.865	0.575
T+Relation	0.739	0.647	0.828	0.881	0.659
T+Intrinsic	0.757	0.650	0.830	0.891	0.648
T+Intr.+Usage	0.717	0.690	0.845	0.861	0.686
T+Relation+Usage	0.722	0.690	0.845	0.865	0.679
T+Intr.+Relation	**0.798**	0.752	0.874	**0.901**	0.749
All	0.794	**0.771**	**0.885**	0.898	**0.761**

Table 2: Precision P, Recall R, and Area Under the ROC Curve for the task of finding high-quality questions.
Finding High-Quality Content in Social Media. Eugene Agichtein et al. 2008.

Receiver Operating Characteristic (ROC) Results

Questions



Answers

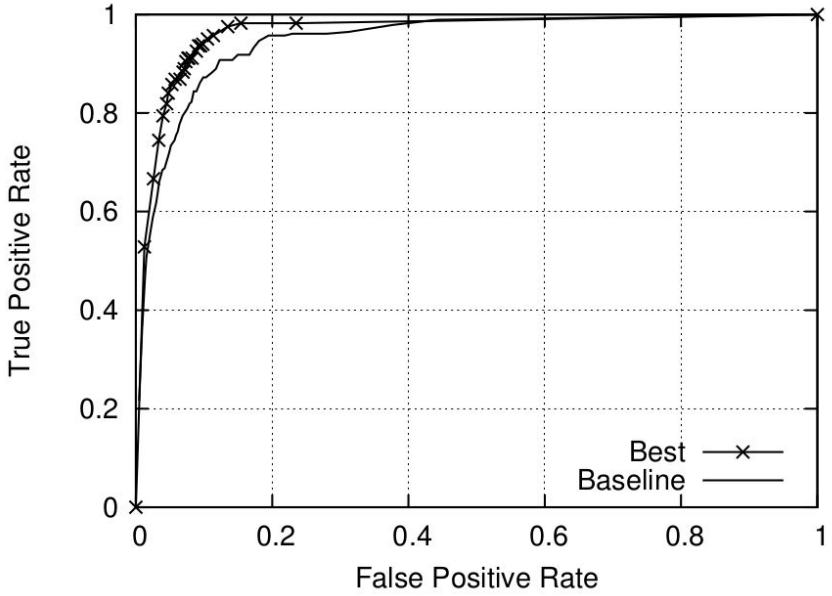


Figure 8. ROC curve for the best-performing classifier, for the task of finding high-quality questions (left) and high-quality answers (right).
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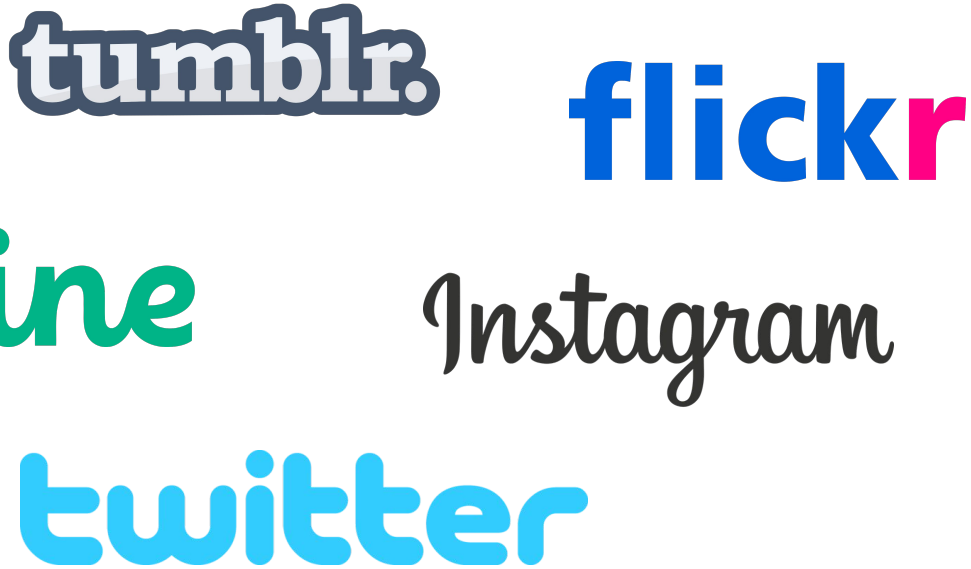
CS 834 - Presentation 5

Advent of Microblogging

Short, simple messaging services, in the form of a blog, but on a much smaller scale



Study Goals

- Huge number of content producers
  - \+ Great diversity
  - − Finding quality difficult
- Identify *topical* authorities
  - Avoid overgeneralized, well-known authorities, e.g. news outlets
  - Topical authority authors may not exist until an event occurs
- Graph analysis metrics insufficient
  - Sensitive to celebrity authors
  - Computationally infeasible for large-sized datasets in real time
- Algorithm that finds topical authorities automatically in near real-time using clustering

Related Work

- TwitterRank
  - Latent Dirichlet Allocation
  - Weighted user graph ➔ weight = topical similarity
  - Variant of PageRank
  - Method differs in using **clustering** over graph analysis and using additional **author features**
- PageRank; HITS
- Prior automatic authority identification
  - **Community Question and Answering**
- Most prior work dominated by computationally expensive **network analysis** approaches

Authority Features

- Focus on message impact metrics
  - Original Tweet (OT)
  - Conversational Tweet (CT)
  - Repeated Tweet (RT)
  - Mentions (M)
  - Graph Characteristics (G)

- Self Similarity $S(s1, s2) = \frac{|s1 \cap s2|}{|s1|}$

$$S(a) = \frac{2 \cdot \sum_{i=1}^{n} \sum_{j=1}^{i-1} S(s_i, s_j)}{(n-1) \cdot n}$$

ID	Feature
$OT1$	Number of original tweets
$OT2$	Number of links shared
$OT3$	Self-similarity score that computes how similar is author's recent tweet w.r.t. to her previous tweets
$OT4$	Number of keyword hashtags used
$CT1$	Number of conversational tweets
$CT2$	Number of conversational tweets where conversation is initiated by the author
$RT1$	Number of retweets of other's tweet
$RT2$	Number of unique tweets ($OT1$) retweeted by other users
$RT3$	Number of unique users who retweeted author's tweets
$M1$	Number of mentions of other users by the author
$M2$	Number of unique users mentioned by the author
$M3$	Number of mentions by others of the author
$M4$	Number of unique users mentioning the author
$G1$	Number of topically active followers
$G2$	Number of topically active friends
$G3$	Number of followers tweeting on topic after the author
$G4$	Number of friends tweeting on topic before the author

Table 1: List of metrics of potential authorities.
Finding High-Quality Content in Social Media. Eugene Agichtein et al. 2008.

Feature List

$$\text{Topical signal } (TS) = \frac{OT1 + CT1 + RT1}{|\#\text{ tweets}|}$$

$$\text{Signal strength } (SS) = \frac{OT1}{OT1 + RT1}$$

$$\text{Non-Chat signal } (\bar{C}S) = \frac{OT1}{OT1 + CT1} + \lambda \frac{CT1 - CT2}{CT1 + 1}$$

$$\lambda < \frac{OT1}{OT1 + CT2} \cdot \frac{CT1 + 1}{OT1 + CT1}$$

ID	Feature
$OT1$	Number of original tweets
$OT2$	Number of links shared
$OT3$	Self-similarity score that computes how similar is author's recent tweet w.r.t. to her previous tweets
$OT4$	Number of keyword hashtags used
$CT1$	Number of conversational tweets
$CT2$	Number of conversational tweets where conversation is initiated by the author
$RT1$	Number of retweets of other's tweet
$RT2$	Number of unique tweets ($OT1$) retweeted by other users
$RT3$	Number of unique users who retweeted author's tweets
$M1$	Number of mentions of other users by the author
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Feature List

$$\text{Retweet impact } (RI) = RT2 \cdot \log(RT3)$$

$$\text{Network score } (NS) = \log(G1+1) - \log(G2+1)$$

$$\text{Information diffusion } (ID) = \log(G3+1) - \log(G4+1)$$

$$\text{Mention impact } (MI) = M3 \cdot \log(M4) - M1 \cdot \log(M2)$$

ID	Feature
$OT1$	Number of original tweets
$OT2$	Number of links shared
$OT3$	Self-similarity score that computes how similar is author's recent tweet w.r.t. to her previous tweets
$OT4$	Number of keyword hashtags used
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$CT2$	Number of conversational tweets where conversation is initiated by the author
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Gaussian Mixture Model

- Group users into two clusters over entire feature space
- Probabilistic model
- Reduce the size of the target cluster (most authoritative users)
- Less sensitive to outliers (celebrities)

Maximizing Likelihood of the data

Consider n data points $x = \{ x_1, x_2, \ldots, x_n \}$ in *d*-dimensional space
density of a point x:

$$p(x|\pi, \Theta) = \sum_{z=1}^{k} p(z|\pi) \cdot p(x|\theta_z)$$

With $\Theta = \{ \theta_z : 1 \leq z \leq k \}$ as model parameters of k Gaussian distributions
i.e. $\theta_z = \{ \mu_z , \Sigma_z \}$

$$p(x|\theta_z) = \frac{1}{((2\pi)^d |\Sigma_z|)^{\frac{1}{2}}} \exp\{-\frac{1}{2}(x-\mu_z)^T \Sigma_z^{-1} (x-\mu_z)\}$$

Expectation Maximization Overview

Assuming points are independent and identically distributed (i.i.d.), likelihood is:

$$p(\mathbf{x}|\pi,\Theta) = \prod_{i=1}^{n} P(x_i|\pi,\Theta)$$
$$= \prod_{i=1}^{n}\sum_{z=1}^{k} p(z|\pi)\cdot p(x_i|\theta_z)$$

Expectation Maximization (EM) - Iterative algorithm with 2 steps

1. E-Step ➔ Compute probability of *k* Gaussian components given data points using Bayes' theorem

2. M-Step ➔ Compute model parameters to maximize the likelihood of the data

Expectation Maximization Steps

1. E-Step

$$p(z|x_i, \pi, \Theta) = \frac{p(x_i|\theta_z) \cdot p(z|\pi)}{\sum_{z=1}^{k} p(x_i|\theta_z) \cdot p(z|\pi)}$$

2. M-Step

$$\mu_z = \frac{\sum_{i=1}^{n} x_i \cdot p(z|x_i, \pi, \Theta)}{\sum_{i=1}^{n} p(z|x_i, \pi, \Theta)}$$

$$\Sigma_z = \frac{\sum_{i=1}^{n} (x_i - \mu_z) \cdot (x_i - \mu_z)^T \cdot p(z|x_i, \pi, \Theta)}{\sum_{i=1}^{n} p(z|x_i, \pi, \Theta)}$$

$$p(z|\pi) = \frac{\sum_{i=1}^{n} p(z|x_i, \pi, \Theta)}{\sum_{z=1}^{k} \sum_{i=1}^{n} p(z|x_i, \pi, \Theta)}$$

Ranking within clusters

Gaussian Ranking Algorithm

$$R_G(x_i) = \prod_{f=1}^{d} \int_{-\infty}^{x_i^f} N(x; \mu_f, \sigma_f)$$

- N (x; μ_f , σ_f) is the univariate Gaussian distribution with model parameters as μ_f and σ_f

- Computes Gaussian Cumulative Distribution (GCD)
  - Monotonically increasing function, useful for ranking
  - Scoring can be high or low with modification to the integral

Dataset

- All tweets posted from June 6th 2010 to June 10th 2010
- 89,622,039 tweets in total
- Three topics

	$\|U\|$	$\|OT\|$	$\|CT\|$	$\|RT\|$
iphone	430,245	658,323	242,000	129,560
oil spill	64,892	111,000	8,140	29,224
world cup	44,387	308,624	28,612	47,837

Table 2: Dataset statistics. |U|, |OT|, |CT|, |RT| are overall count of users, original tweets, conversational tweets and retweets, respectively.
Identifying Topical Authorities in Microblogs. Aditya Pal and Scott Counts. 2011.

Baselines for Comparison

- ***our*** - The authors' model
- ***b1*** - Graph Properties { RI, MI, ID, NS }
- ***b2*** - Textual Properties { TS, SS, CS }
- ***b3*** - Random selection of authors that fall outside target cluster

Evaluation - User Study

- Comparison of ***our*** vs three baselines ***b1***, ***b2***, and ***b3***

- 48 participants

- Users presented with 40 screens
  - 20 anonymous author
  - 20 author shown

- Validated statistical significance of results using **one-sided paired t-tests**

Results

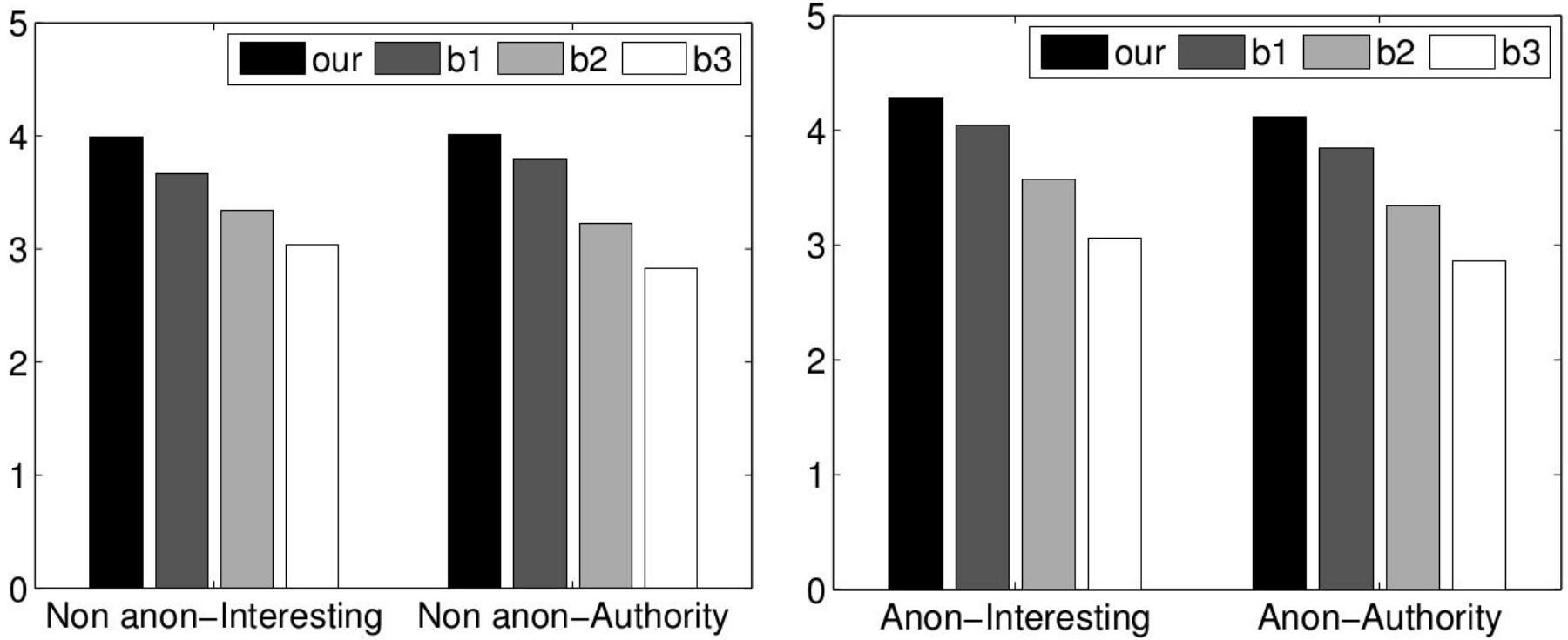

Figure 3: Average ratings per model per participating user.
Identifying Topical Authorities in Microblogs. Aditya Pal and Scott Counts. 2011.