A Computational Approach to Media Bias Mitigation

Souneil Park
29 June 2011

TIMES group, KAIST
(https://nclab.kaist.ac.kr/TIMES/index.html)
Motivation

- Media is inherently biased

Korea-US Summit
2006. Sep. 15
Media Bias from a Computational Journalism View

**News Service Framework For Media Bias Mitigation (NLP/IR Studies)**

- Understanding data: what is diversity in news discourse?
- Technical solution to capture diversity?
- Difference from related work?
- ...

**User Behavior & Cognition (HCI & Psychological studies)**

- Can interfaces influence news reading and opinion?
- Is the interface proper?
- Observations & Implications?
- ...

**Bias in News Production Process (Communication studies)**

- Causes of bias
- Forms of bias
- Current efforts and potential solutions?
- ...

**News Service Framework**

**ARTICLE COLLECTION**

**ASPECT CLASSIFICATION**

**ASPECT PRESENTATION**

- News Page Crawler
- Article Extractor
- Aspect Analyzer
- Cluster Generator
- Article Preprocessor
- News Page Crawler

**News Cube Service Interface**

**Aspect Presenter**

**Browsing Pattern Monitor**

**Article Type Filter**

**News Providers**

**NewsCube**
Structural view to Media Bias Problem

“News production is a continuous subjective valuation process” (Son, 2006)
Review of available approaches

Bias Diagnosis Approaches

PREAMBLE
Members of the Society of Professional Journalists of the journalist are to be familiar with the following guidelines.

SEEK TRUTH AND REPORT IT
Journalists should endeavor to:
1. Tell the truth, the entire truth and nothing but the truth.
2. Be fair and impartial.
3. Be objective and analytical.
4. Be thorough in investigating and verifying information.
5. Be precise in language and description.
6. Be accountable for their work.

BE ACCOUNTABLE
Journalists are accountable to their readers, fellow journalists, and the society.

Journalists should:
1. Clearly and explicitly discuss coverage and editorial decisions.
2. Encourage the public to voice grievances against news media.
3. Disclose sources and reveal hidden interests.
4. Display ethical practices of journalism and the news media.
5. Commit to the same high standards to which they hold others.
Media Bias Mitigation

- Mitigate *effects* of bias from readers perspective
- Provide a classified view on multiple news frames
  - Help readers develop balanced views
- Practical solution
Potential Solution Space

- Provides an basis upon which to compare solutions of different disciplines

**Production stage**
Avoid bias creation

<table>
<thead>
<tr>
<th>Journalism ethics &amp; standards</th>
<th>Adversarial reporting formats</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objectivity, Fairness, …</td>
<td>Deliver multiple biased views</td>
</tr>
</tbody>
</table>

**Post-Production stage**
Deal with already generated bias in news

<table>
<thead>
<tr>
<th>Bias Diagnosis</th>
<th>Bias Measurement</th>
<th>Bias Correction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Analyze &amp; notify bias (Frame analysis)</td>
<td>Quantitatively measure &amp; notify bias</td>
<td>Revise biased news (e.g. Wikipedia)</td>
</tr>
</tbody>
</table>

**Bias Mitigation**
Deal with readers’ experience

- Deliver multiple biased views
Overview of the thesis

News Frames in articles

Fact selection
Source selection
Presentation

Discourse types

Straight News
Contentious Issues
Political News

Techniques

Domain Knowledge for News analysis
Collective Intelligence in Social Annotation

Interface
Aspect-level News Browsing
...
NewsCube for Aspect-level Browsing

• Fact selection bias – Aspect-level News Browsing

• Reading experience of NewsCube

• Aspect-level Classification
  ▫ Development & Evaluation

• User study
Fact selection bias in news events

- Major type of bias in the news gathering stage
  - Important in straight news articles
    - E.g., “Announcement of a new property tax plan”

Fact selection bias in news events

- Kim, “normalization of property tax”
- “Tax increase for high-priced houses”
- The plan doesn’t affect houses in most districts
- Loopholes in the plan

Kim, “normalization of property tax”

"Tax increase for high-priced houses"

The plan doesn’t affect houses in most districts

Loopholes in the plan
News Reading Experience of NewsCube

• New media interaction method for media bias mitigation

Tax increase 11.8 times for billion won apt.

Tax increase from 2 mil. to 7 mil. for 0.68 billion won apt.

Tax increase from 3.48 mil to 11.51 million for apt. in …

Tax increase from 250K to 2.95 mil. for billion won apt.

"Tax Bomb" Tax increase from …

Title

Keywords

Snippet

Group of articles with different aspects

Aspect traversal cue

그룹 1. 다수 가사가 겸하는 내용 (예: 올 그룹)

그룹 2. 소수 가사가 겸하는 내용

그룹 3. 소수 가사가 겸하는 내용

그룹 4. 소수 가사가 겸하는 내용

http://newscube.kaist.ac.kr/cluster.php?tid=11060503b


Home | NewsCube | Help | NewsCube 말고 크게 어긋나요?
Related work

• TDT and Event threading [Allan et al. BNTUW-98]
  ▫ Coarser level organization
    • Topic: set of news stories on related real-world events
    • Event: something that happens at a certain place at a certain time
    • E.g., “Oklahoma city bombing in 1995” (TDT corpus)

• Opinion Mining & Sentiment Analysis
  ▫ Product review [Dasgupta et al. ACL-06]
  ▫ Positive vs. negative [Pang et al. EMNLP-02]
NewsCube for Aspect-level Browsing

- Fact selection bias – Aspect-level News Browsing
- Reading experience of NewsCube
- Aspect-level Classification
  - Development & Evaluation
- User study
Interpretation of news frames

- Definition of news frames
  - “select some aspects of a perceived reality and make them more salient ...” (Entman’ 93)
  - Aspect: thematic proposition describing the topic
    - agent, action, agency, background, implication (Rhee’ 97)
  - Definition from the “information selection” view

---

“Tax increase for high-priced houses”

Kim, “normalization of property tax”

loopholes in the plan

The plan doesn’t affect houses in most districts
Agreement in aspect interpretation

- 4 participants select (multiple) sentences
- Metric: F-measure
- 103/120 articles: 0.8, on average
Agreement in article classification

- 5 participants performed classification
- 30 news topics
- Kappa value between 0.6 – 0.92

Completely same

Not at all
Characteristic of our approach

- Based on observation of the news production process
  - Behavior of reporters, news outlets

- Apply new features & heuristics
  - News writing rule of journalists
  - Framing cycle
    - Aspect coverage pattern

- Complementary to IR, NLP techniques
**News Structure-based Aspect Extraction**

- Utilize “Inverted pyramid style of news writing”
  - Head-lead: saliently covered aspects
  - Main text: ordered in diminishing importance

![Diagram of inverted pyramid]

**Keywords from (head-lead)**

**Give weight based on Main text**

---

Excerpt from news article:

"Police have been investigating 524 demonstrators after farmers and activists Friday collided violently in the area, seeking to protest against plans to construct a military base."

"The deployment of riot police and military personnel was anticipated after area residents rejected a proposed construction plan for a military base,Ro.
Framing cycle-aware clustering

• Framing cycle
  ▫ Aspect coverage pattern of news producers
  ▫ Head: similar aspects ➔ Tail: different aspects
  ▫ Similar observations in [Miller’03][Curtin’99]

  **Head stage**: press releases, news agency reports, …

  **Tail stage**: experts, stakeholders, …

- **A**: Civic groups file complaint against Samsung
- **B**: Increasing suspicion, responses of stakeholders
- **C**: Kim, “Fake director meeting in 1996”
- **F**: Samsung, “unproductive and exhausting disputes”

<Framing Cycle Example, “Complaint against Samsung Corp.”>
2 phase classification using *Head-Tail* characteristic

- **1st phase**: Head-Tail partitioning
  - Utilize the *long-tail distribution*
  - View keywords based on *Common vs. Uncommon* frame
    - Overcome limitation of direct term-matching

**Common**
- Samsung.
- Civic group
- PSPD
- Complaint
- Slush fund
- Bribery
- ...

**Uncommon**
- Kim Yongchul
- Secret safe
- Fake meeting
- Dispute
- Prosecution
- ...

*<Frequency distribution of keywords>*
2 phase classification using *Head-Tail* characteristic

- 2\textsuperscript{nd} phase: Tail-side clustering
  - Classify articles of the non-head group
  - Focus on the *similarity in uncommon keywords*

![Frequency distribution of keywords]

- Non-Head group (Tail groups)

![Head-Tail characteristic of the example event]

<Frequency distribution of keywords>
Overall accuracy of classification

- **Ground truths**
  - Manual classification results of 30 news topics

- **Comparison methods**
  - Extraction: Simple TF
  - Clustering: Hierarchical Clustering (HC), K-means, Spectral

<table>
<thead>
<tr>
<th>Clustering (Extraction)</th>
<th>Average (F-mes.)</th>
<th># of winning sets</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCAC(NSE)</td>
<td>0.777</td>
<td>21</td>
</tr>
<tr>
<td>HC(NSE)</td>
<td>0.683</td>
<td>6</td>
</tr>
<tr>
<td>HC(TF)</td>
<td>0.654</td>
<td>3</td>
</tr>
<tr>
<td>K-means(NSE)</td>
<td>0.587</td>
<td>0</td>
</tr>
<tr>
<td>K-means(TF)</td>
<td>0.567</td>
<td>0</td>
</tr>
<tr>
<td>Spectral(NSE)</td>
<td>0.542</td>
<td>0</td>
</tr>
<tr>
<td>Spectral(TF)</td>
<td>0.527</td>
<td>0</td>
</tr>
</tbody>
</table>
NewsCube for Aspect-level Browsing

- Fact selection bias – Aspect-level News Browsing
- Reading experience of NewsCube
- Aspect-level Classification
  - Development & Evaluation
- User study
News Browsing Trace

- 3 User groups: NewsCube, GoogleNews, RandomCube
  - 25 participants each (75 in total)
- Measure
  - # of read articles
  - # of article groups (according to NewsCube)
Questionnaire

• NewsCube vs. GoogleNews (Each 33 participants)
• Questions (5 point scale)

  ▫ “Encourage readers to read multiple articles”
  ▫ “actually read multiple articles covering different aspects”
  ▫ “could easily access multiple articles..”
  ▫ “helped me to have a more balanced view”
Semi-structured Interview

Protest Against U.S Military Base Relocation

New Property Tax Plan

GN NC

Opinion group

GN NC

Neutral

: GoogleNews (Gn)

: NewsCube (NC)
Semi-structured Interview

• Better awareness of news events
  ▫ NewsCube users mention more diverse aspects

• Opinion Development
  ▫ Neutral-NC: Mostly hesitate to develop a specific views
  ▫ Neutral-GN: Mostly develop clear views
  ▫ Opinion-NC: Read articles of challenging views (Some acknowledge)
  ▫ Opinion-GN: Most reaffirm their views
Implications & Discussion

• News reading interfaces can influence behavior & opinion

• Different depending on ideological preference & personal Interest
  ▫ Chance exist even to people with a predetermined view

• Further implications from [Munson et al. CHI 10]
  ▫ People w/ Political Preference
  ▫ Political News & Commentary
  ▫ Not organized based on topic
Interface strategy for diversity?

- Study different motivations of readers
  - More information, Different viewpoints, ?

- Interface strategy
  - Presentation of topically related
  - Non-explicit presentation of viewpoints
  - Fact based articles
  - Use of personal interest
Overview of the thesis

News Frames in articles
- Fact selection
- Source selection
- Presentation
- ...

Discourse types
- Straight News
- Contentious Issues
- Political News
- ...

Techniques
- Domain Knowledge for News analysis
- Collective Intelligence in Social Annotation
- ...

Interface
- Aspect-level News Browsing
- ...

Sources
Contentious issues

- Various stakeholders participate and make arguments against each other

- "act of invasion, violation of North-South Agreement"
- "accept North Korean inspection team"
- "Scientific investigation, China should support it"
- "stop exploiting the situation politically"
Outline

- Related work - Opinion mining

- Characteristics of contentious news discourse
  - Comparison to corpus used for opinion mining

- Study of argument frame

- Disputant relation-based method

- Experiments
Related work in opinion mining

• Issues
  ▫ Document-level sentiment classification (TREC, Turney ACL02, …)
    • Product reviews
  ▫ Subjective sentence detection (NTCIR-7, Wiebe ACL99, …)
    • Opinion holder, target detection
  ▫ Opinion polarity analysis: Positive, Neutral, Negative

• Debate stance recognition
  ▫ Classification of debate posts (Somasundaran et al ACL09, Lin et al. CoNLL06)
    • Ideological debate, product comparison debate
Difference characteristics of news discourse

- Centered to a common topic
  - A specific entity

- Involves diverse topics
  - Schon et al. 94

Healthcare debate

- Government deficit
- Medicare
- Tax increase
- President's leadership
- Effect on election
- ...
Difference characteristics of news discourse

• Structure is predictable to some extent

• Hardly predictable
  ▫ Changes over time

Positive vs. Negative

Healthcare debate

Healthcare reform may not reduce medical bankruptcies
there will be tax increases
Reduce U.S. deficit over 10 years and sharply expand insurance coverage
A repeal would have a negative impact on patient care
Difference characteristics of news discourse

- Positive vs. Negative
  - or Pro vs. Con
- Many forms of arguments
  - Negative vs. Negative
  - Neglect opponents’ argument
  - Emphasize a different topic
  - w/o explicit opinion
  - ...
Disputant oriented view (↔ topic-oriented view)

- Competing disputants express opposing views
  - Disputants take position and compete for media coverage (Miller 01)
- Intuitively recognize contentions through opponents

U.S. considering financial sanctions against NK
Lee "act of invasion, violation of North-South Agreement"

VS.

NK “we will dispatch an inspection team”
China held back from any assessment
**Opponent-based frame vs. Pos-Neg Frame**

- Task: classify news articles based on each frame
  - 3 participants
  - 250 articles 14 contentious issues

- 2 subtasks
  - Pos-Neg Frame: identify main topic ➔ classification (POS,NEG,OTHER)
  - Opponent Frame: identify opponents ➔ classification (Side1,Side2,Other)

<table>
<thead>
<tr>
<th>Issue #</th>
<th>Free-marginal kappa</th>
<th>Issue #</th>
<th>Free-marginal kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pos.-Neg.</td>
<td>Opponent</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.83</td>
<td>0.67</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>0.57</td>
<td>0.48</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>0.44</td>
<td>0.95</td>
<td>10</td>
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<tr>
<td>4</td>
<td>0.75</td>
<td>0.87</td>
<td>11</td>
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<tr>
<td>5</td>
<td>0.36</td>
<td>0.64</td>
<td>12</td>
</tr>
<tr>
<td>6</td>
<td>0.30</td>
<td>0.70</td>
<td>13</td>
</tr>
<tr>
<td>7</td>
<td>0.18</td>
<td>0.96</td>
<td>14</td>
</tr>
<tr>
<td><strong>Avg.</strong></td>
<td><strong>0.50</strong></td>
<td><strong>0.78</strong></td>
<td></td>
</tr>
</tbody>
</table>

Annotator 1 Pos vs. Neg: 191, Opponent frame: 86
Annotator 2 Pos vs. Neg: 150, Opponent frame: 99
Annotator 3 Pos vs. Neg: 141, Opponent frame: 102
Disputant relation-based Classification Overview

Disputant Extraction

Disputant Partitioning

Article Classification

VS.

VS.

VS.
Disputant relation-based Classification

• Key ideas
  ▫ Utilize the nature of contention: attacking opponents
    • Identify opposing disputant groups
  ▫ Focus on major type of bias in contentious issues
    • Analyze to which an article is slanted

• Features of the method
  ▫ Unsupervised
  ▫ Primitive tools and resource
    • NER, POS Tagger, Wilson lexicon (Translated)
  ▫ Use news web search to extract disputant relations
Disputant Extraction

- Use quoting patterns in news articles

- Extract subjects from direct & indirect quotes
  - e.g., 정부는 북한이 사과하지 않는 이상 대화는 없다고 밝혔다.
  - (The government clarified that there won’t be any talks unless North Korea apologizes for the attack.)

- Identification of subjects
  - Named Entity + (topic particle | subject particle)
    - Named Entity: Organization, Name, Country, Media, Position
  - Anaphora resolution
    - E.g., “이 대통령” → “이명박 대통령” (“President Lee” → “President Lee Myung Bak”)
Disputant Partitioning

- Use criticizing structure among disputants
  - There are **key opponents**
  - Disputants target key opponents
  - Minor disputants are rarely targeted
Detecting key opponents

• Criticizing relationship → Graph model

  e.g., the *government* defined that “the *attack* of *North Korea* is an act of *invasion* ...”

  ![Graph model diagram]

• Modified HITS algorithm
Partitioning minor disputants

- Use key opponent as pivots
  - Analyze to which side is close

- Features from article set
  - Positive quote rate
  - Negative quote rate
  - Frequency of ‘Standing Together’
    - e.g., *South Korea* and *U.S.* both criticized...
  - Frequency of division

- Features from news search results
  - Two queries: “M-D, KO1”, “M-D, KO2”
  - Same features from the titles
Article Classification

- Analyze which side is more centrally covered

Two Parameters

Quotes (Direct, indirect)

From which side quotes came

Similarity to quotes of each side

Non quote sentences

SVM trained with quotes of each side

α: Quote bias Threshold

β: Biased sentence Threshold
Evaluation

• Disputant Partitioning

<table>
<thead>
<tr>
<th></th>
<th>Side 1</th>
<th>Side 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pr.</td>
<td>Re.</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.71</td>
<td>0.59</td>
</tr>
</tbody>
</table>

• Article Classification

<table>
<thead>
<tr>
<th></th>
<th>Sim.*</th>
<th>DrC</th>
<th>DrC (upper bound)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. wF</td>
<td>0.48</td>
<td>0.68</td>
<td>0.76</td>
</tr>
</tbody>
</table>

*Sim.: TF.IDF + K-means (k=3)

- Error analysis
  - Articles w/ few quotes
  - Criticizing the quoted disputants
Overview of the thesis

News Frames in articles
- Fact selection
- Source selection
- Presentation
- ...

Discourse types
- Straight News
- Contentious Issues
- Political News
- ...

Techniques
- Domain Knowledge for News analysis
- Collective Intelligence in Social Annotation
- ...

Interface
- Aspect-level News Browsing
- ...

Collective Intelligence in Social Annotation
Text Analysis Approach

[Lin et al. ECML/PKDD 08]
[Somasundaran et al. NAACL 10]

• Select a few specific issues

• Study texts expressing explicit opposing opinions
Social Annotation Analysis

• Collective knowledge of commenters
  ▫ language, issues, political context

• Potential of active political commenters
  ▫ A clear and strong political preference
  ▫ Either as liberal or conservative
  ▫ Consistent over time and issues
Sentiment Pattern

- Benefits of Comments
  - Concise
  - Explicit expression of sentiments
  - Explicit words
Data set
(Source: Naver.com)

General Set (1395 articles)

Popular Set (3385 articles)
Questions

- Existence of active commenters
- Political orientation of commenters
- Commenters with a regular sentiment pattern
Questions

- Existence of active commenters
- Political orientation of commenters
- Commenters with a regular sentiment pattern
Article set coverage

Commentators rank

Popular News Set
General News Set
Popular set

Distribution of Commenting Periods

- 6 months ~
- 5 ~ 6 months

26%

74%
General set

Distribution of Commenting Periods

- 9 months ~: 66%
- 6 ~ 9 months: 14%
- 3 ~ 6 months: 10%
- Etc.: 10%
Questions

- Existence of active commenters
- Political orientation of commenters
- Commenters with a regular sentiment pattern
Clarity of Political Preference

- General Set
- Popular Set

- ≥9/10
- ≥8/10
- ≥7/10
- ≥6/10
Consistency of Political Preference

Liberal

- Oppose revision
- Criticize government
- Oppose nomination
  - Criticize conservatives
  - Revision of sejong city bill
  - 4 river project
  - Prime minister nomination
  - Revision of the media bill

Conservative

- Criticize opponents
- Defend the project
- Defend the nominee
  - Criticize opposition parties
Consistency of Political Preference

50 commenters of General Set
- Liberal: 54%
- Conservative: 38%
- Others: 8%

50 commenters of Popular Set
- Liberal: 24%
- Conservative: 62%
- Others: 14%
Questions

- Existence of active commenters
- Political orientation of commenters
- Commenters with a regular sentiment pattern
Analysis process

20 comment samples

Positive Match

Negative Match

Love you!

Bad move!

Sarkozy under pressure as French protests hit streets

Thu Mar 19, 2009 7:12pm EDT

By James Mackenzie

PARIS (Reuters) - Up to three million people took to the streets of France on Thursday for a second round of protests against President Nicolas Sarkozy’s handling of the economic crisis and to demand more help for struggling workers.

The rallies, which polls say are backed by three-quarters of the French public, reflect growing disillusion with Sarkozy’s reforms as tens of thousands lose their jobs.
| [0.75, 1)  | 18 | 44 |
| [0.5, 0.75) | 43 | 3  |
| [0.25, 0.5) | 24 | 3  |
| [0, 0.25)  | 0  | 2  |
| No sample  | 0  | 37 |
Commenter as Classifier

Sentiment (S)
- Negative
- Positive
- Vague

Bayes Classifier

Article Class (C)
- Liberal
- Conservative
- Vague
Comparison methods

1. Manual Sentiment Analysis
2. Auto Sentiment Analyzer
3. TF.IDF + SVM Classifier

# of commenters: 14 (G: 7, P: 7)
Training data: 20 comment sample / commenter
Test data: 20 comment sample / commenter
Performance

- **Accuracy**

  - General Set
    - Overall: 76% (67%)
    - Conservative & Liberal: 83% (75%)

  - Popular Set
    - Overall: 74% (66%)
    - Conservative & Liberal: 80% (75%)

- **Coverage**

<table>
<thead>
<tr>
<th></th>
<th>General Set (≥ 5 comments)</th>
<th>Popular Set</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PC</strong></td>
<td>5% (21%)</td>
<td>31%</td>
</tr>
</tbody>
</table>
2\textsuperscript{nd} round

1. Manual Sentiment Analysis
2. Auto Sentiment Analyzer
3. TF.IDF + SVM Classifier

# of commenters: 14 (G: 7, P: 7) + 25 (G: 14, P: 11)
Training: 20 comment sample / commenter
Test: 20 comment sample / commenter
**Performance**

- **Accuracy**

<table>
<thead>
<tr>
<th>General Set</th>
<th>Popular Set</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Overall</strong></td>
<td><strong>Overall</strong></td>
</tr>
<tr>
<td>67%</td>
<td>67%</td>
</tr>
<tr>
<td>56%</td>
<td>57%</td>
</tr>
<tr>
<td>42%</td>
<td>48%</td>
</tr>
<tr>
<td><strong>Conservative &amp; Liberal</strong></td>
<td><strong>Conservative &amp; Liberal</strong></td>
</tr>
<tr>
<td>75%</td>
<td>74%</td>
</tr>
<tr>
<td>69%</td>
<td>68%</td>
</tr>
<tr>
<td>51%</td>
<td>57%</td>
</tr>
</tbody>
</table>

- **Coverage**

<table>
<thead>
<tr>
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<th>General Set (≥ 5 comments)</th>
<th>Popular Set</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PC+CC</strong></td>
<td>11% (46%)</td>
<td>54%</td>
</tr>
</tbody>
</table>
Learning curve
After Grueling Battle, Obama Claims Nomination

Next on Agenda Is Clinton’s Role

By ADAM NAGRANSKI

Senator Barack Obama heads onto the general election with obvious advantages. His campaign’s ability to build a nationwide organization will be crucial. Whether he can lift the atmosphere for Republicans,  in a country where many see

are hungry for change, and commit-

ing one of the parties to a divisive campaign, will also be a focus.

We write to see if he can shift the
towards more moderate and
tenable positions. Mr. Obama has

proven in his own party that

he can bridge divides. It

remains to be seen how well he can do that in national politics.

First Black to Lead

The Ticket for a

Major Party

BY JEFF ZELNY

Senator Barack Obama started the Democratic nominat-

ional campaign as looking

to be a long shot. But

over the course of the pri-

mary season, he has
geroused New York and

stoked the enthusiasm

of a generation of voters.

“I think he’s going to

win,” Barack Obama

said last week.

“I think he’s going to

win.”
Evaluation Results (Multi commenter-based)

- Prediction accuracy

- Coverage

MV, WV, MPP: different combination techniques of the Multi commenter-based method

![Accuracy Graph]

![Coverage Graph]
Discussion

- Advanced modeling of commenters’ behavior
- Applications
- Use in other domains
- Potential for automation
- Combining w/ other social annotations
Conclusion

• Study media bias problem from a computational perspective
  ▫ Viewpoint in news production
  ▫ Media bias mitigation approach

• Computational framework for media bias mitigation
  ▫ Methods to presenting diversity for three article domains
    • Classification methods specific to the article domains

• Comprehensive understanding of news events

• Observations of readers’ (balanced) viewpoint
Future work

• Effect on readers’ views (opinion)
  ▫ Whole news reading process
  ▫ Long term study
  ▫ Readers’ motivations

• Other article domains
  ▫ Columns, Editorials

• Other solution than classification of views
  ▫ Summary
  ▫ Highlighting

• Other bias types
  ▫ Presentation
  ▫ Topic or Issue selection