OPINION MINING ON TRAVELER REVIEWS AND RANKING HOTELS

CSE-4250: PROJECT AND THESIS-II

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Introduction

What is Opinion?

Opinions are thoughts influencing decision making.

- *Which schools should I apply to?*
- *Which professor to work for?*
- *Whom should I vote for?*
- *Which hotel should I book?*

Whom shall I ask for opinions?

Pre Web

- *Friends and relatives*
- *Acquaintances*

Post Web

- *Blogs (google blogs, livejournal)*
- *E-commerce sites (amazon, ebay)*
- *Review sites (CNET, PC Magazine)*
- *Discussion forums (forums.craigslist.org, forums.macrumors.com)*

Have enough opinions!

Now that I have got enough opinions, I can take decisions…

Is it really enough?

…Having opinions is not enough

- Searching for reviews is quite difficult
  - *Searching for opinions is not as convenient as general web search*

- Huge amounts of information available on one topic
  - *Difficult and quite impossible to analyze each and every review separately*
  - *Expression of reviews are different in many ways*

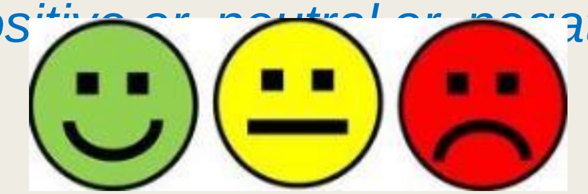
"overall, this hotel is my first choice at Cox's Bazar…"
"the facilities are good but the service isn't so…"
"best in Cox's Bazar by quality and value"
"…disappointing"

What is Opinion Mining?

Computational study of *opinions*, *sentiments* and *emotions* expressed in text.

- Detects the contextual polarity of text

  (positive or neutral or negative)



- Derives the opinion, or the attitude of an opinion holder.

Tasks of Opinion Mining

Opinion mining is a complex task that is why it is divided into sub classes.

- Subjectivity Classification
- Opinion Classification
- Optional Tasks

Subjectivity Classification

- Raw data contains opinionated and non-opinionated texts, punctuations etc.

- In this classification opinionated text is separated from the raw document.

  For Example: A review is such that,

“we arrived at the long beach hotel yesterday, me and my brother planned this short trip to Cox’s Bazar. This hotel is near to the beach so the view from the balcony is amazing.”

Opinion Classification

- From the opinionated text using this classification we get polarity of the text.

- It can be binary classification
  (*positive or negative*)

- It can be multiclass classification
  (*extremely negative, negative, neutral, positive, extremely positive*)

Optional Tasks

There are various optional tasks. Such as,

- Opinion Holder Extraction

  e.g. getting the ranks of the contributor

- Feature Extraction

  e.g. extracting a specific feature like room service, food court etc.

Research Challenges

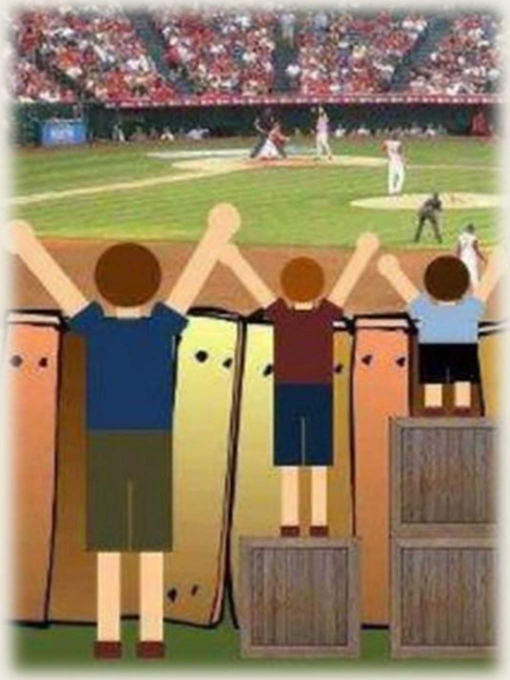
- Integrity of the *reviews* can not be *ensured*

Research Challenges(Cont.)

- Due to *competition* among the hotels high possibility of *false reviews*

Research Challenges(Cont.)

- *Amount* of reviews highly *varies* which sometimes results in *inaccurate ratings* of hotels



Literature Review

Mining and Summarizing Customer Reviews [6]

- Minqing Hu and Bing Liu , “Mining and Summarizing Customer Reviews”

- Main objective of this work:

  (1) Mining product features commented by the customer

  (2) Identifying opinion sentences in each review and deciding polarity

  (3) Summarizing the results.

Drawbacks

- In this paper the authors didn't summarize the reviews by selecting a subset of reviews.

- Summarization didn't take any original sentences from the reviews. So it cannot idealize the main points as the classic text summarization does

Reviews, Reputation, and Revenue: The Case of Yelp.com [7]

- Michael Luca, “Reviews, Reputation and Revenue: The Case of Yelp.com”

- In this research paper, the author proposed,

  (1) a one-star increase in Yelp rating leads to a 5-9 percent increase in revenue,

  (2) this criteria only applies to single independent restaurants

  (3) Chain restaurants plays neutral role even if yelp rating increases

Drawbacks

- Chain restaurant revenue increment cannot be extracted from this research
- Data set was small for this work because extracting data from Yelp.com is prohibited from using web crawler *(i.e. tools for scraping data from web)*

Domain of Our Research

Problem Domain

Mining traveler experiences/reviews expressed on services provided by hotels in Bangladesh

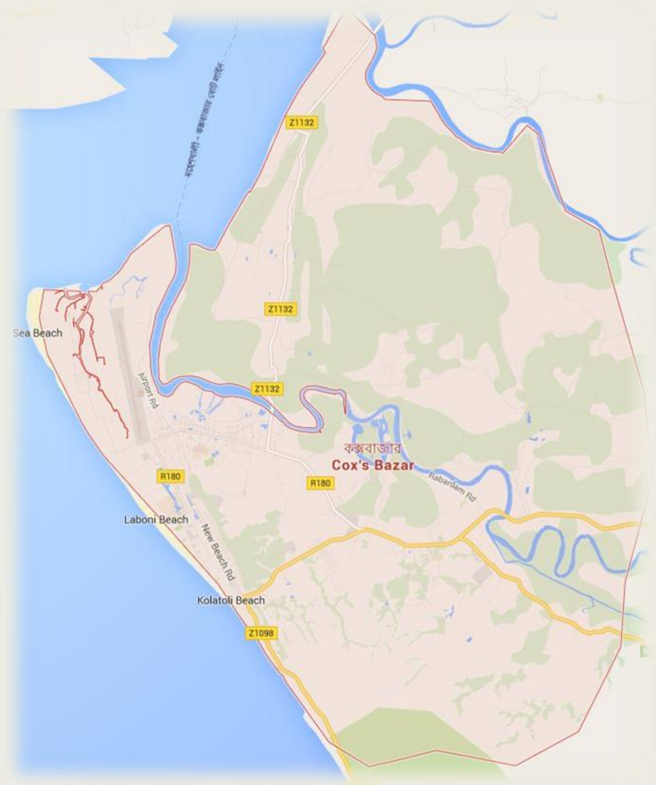
Problem Domain (Cont.)

- We are mining reviews from the travelling guide, “TripAdvisor”

  *www.**tripadvisor**.com*

- We are starting our work from the district
  that attracts tourists the most which is Cox’s Bazar

- Primarily we are mining reviews of travelers
  visiting various hotels in this tourist gathering area



Problem Domain (Cont.)

Problem Domain (Cont.)

1) Name and residence of the reviewing traveler
   e.g. MUHassan, Dhaka City, Bangladesh

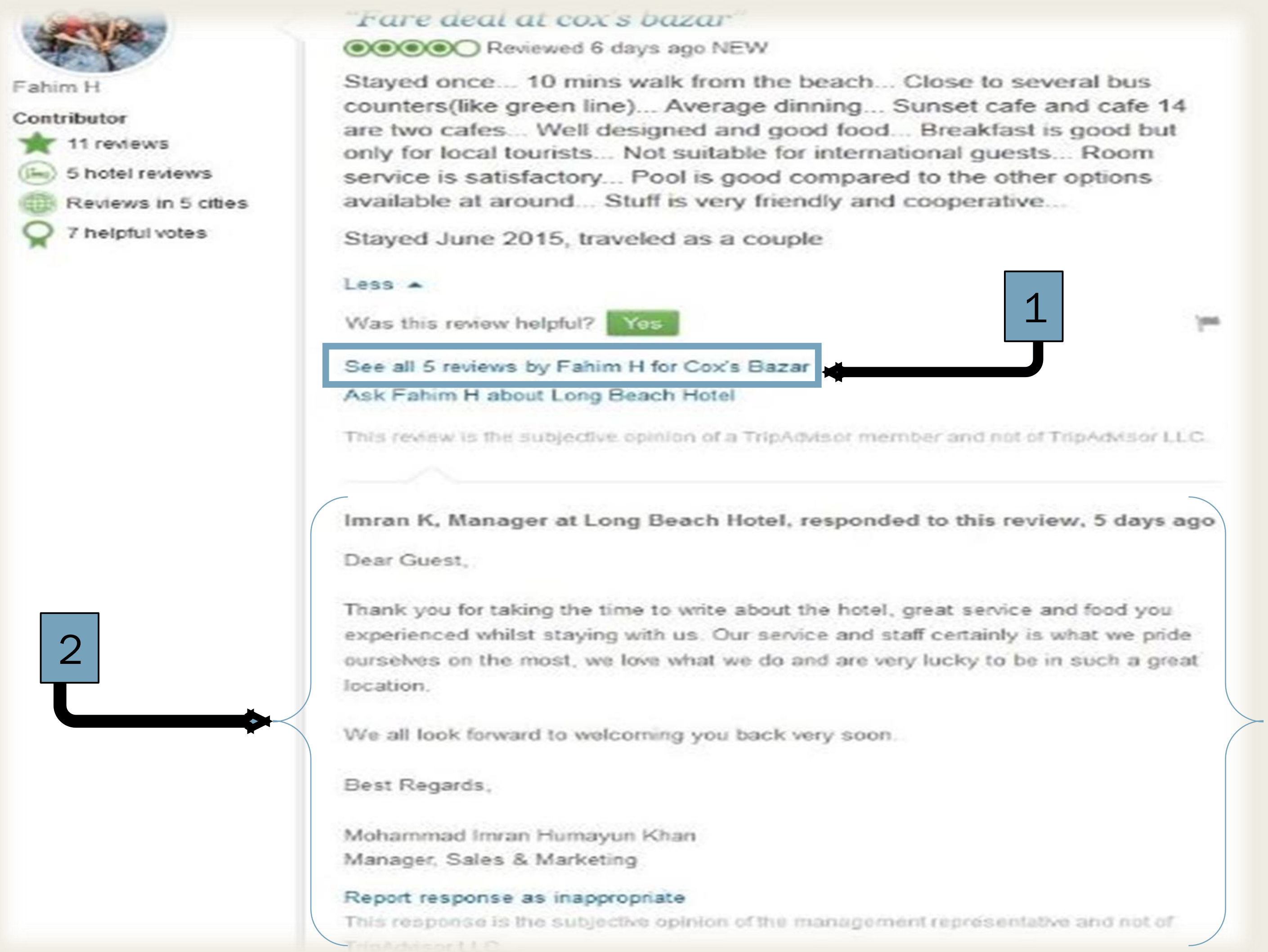
2) Information about the profile of the reviewer on "TripAdvisor" site
   e.g. Top Contributor, 50 Reviews, 19 helpful votes etc.

3) Rating provided by the reviewer and the time of the review
   e.g. 5 out of 5 stars, Reviewed 12,June,2015 etc.

4) The review of the traveler in a large opinioned paragraph

5) Voting panel for other users to vote a review if it is helpful or not!

Problem Domain (Cont.)



Problem Domain (Cont.)

1) All the reviews provided by a certain reviewer on the site

2) Feedback given by a hotel manager upon reviewing of a traveler

Proposed Framework

Working Procedure

- We followed the below mentioned steps to achieve our goal
    1. SentiWordNet based score retrieval
    2. Score retrieval using Naïve Bayes method
    3. Weight assignment to individual opinion holder
    4. Final calculation of two approaches

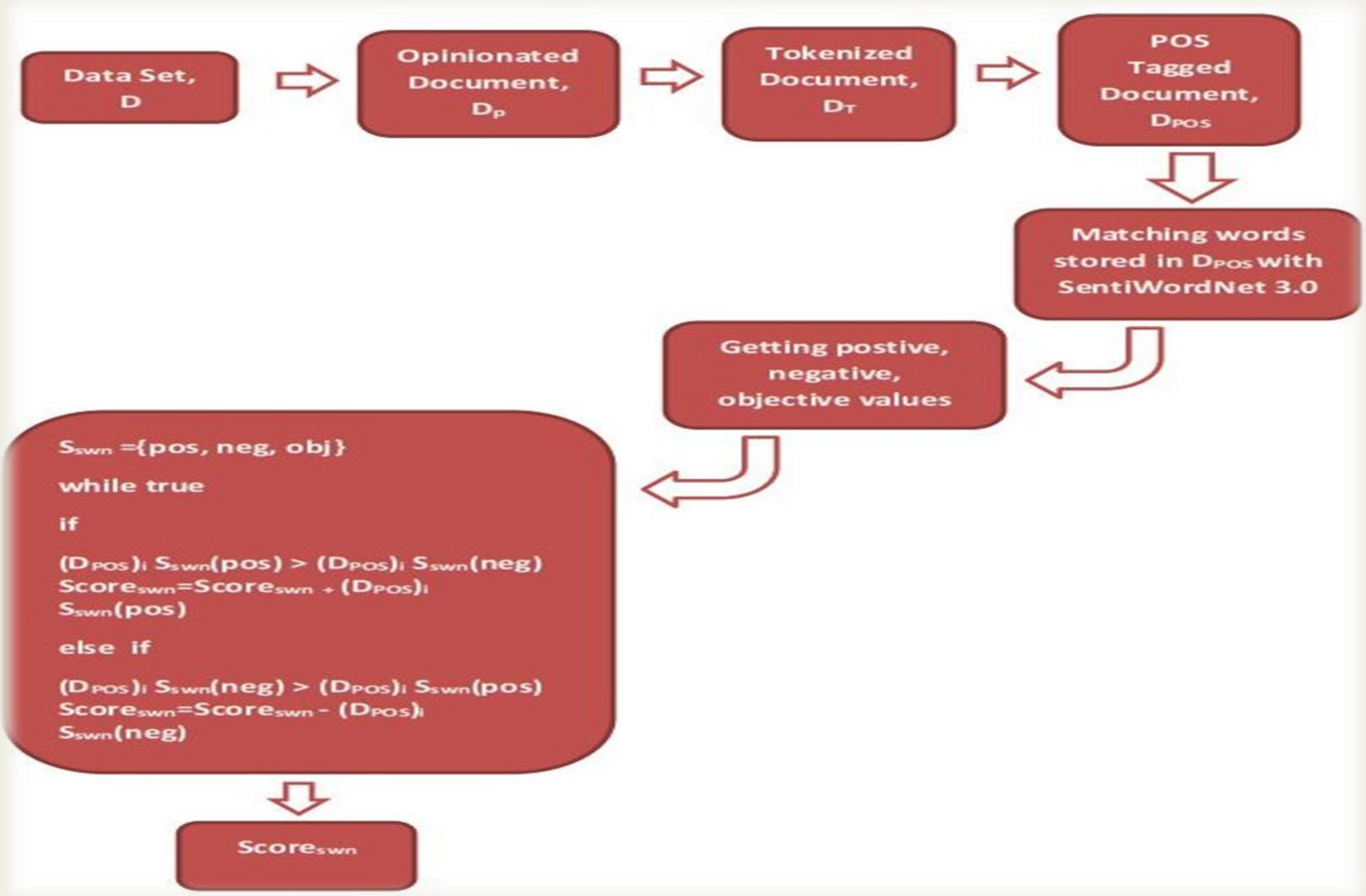
Score Retrieval

SentiWordNet:

- SentiWordNet is a lexical resource for opinion mining.

- It assigns each synsets of WordNet with three sentiment score.
  (Positive, negative and objective)

Score Retrieval (Cont.)



Score Retrieval (Cont.)

Naïve Bayes Method:

- Naïve Bayes is a Supervised learning approach which gives probabilistic result of unlabeled data based on trained labeled data set.

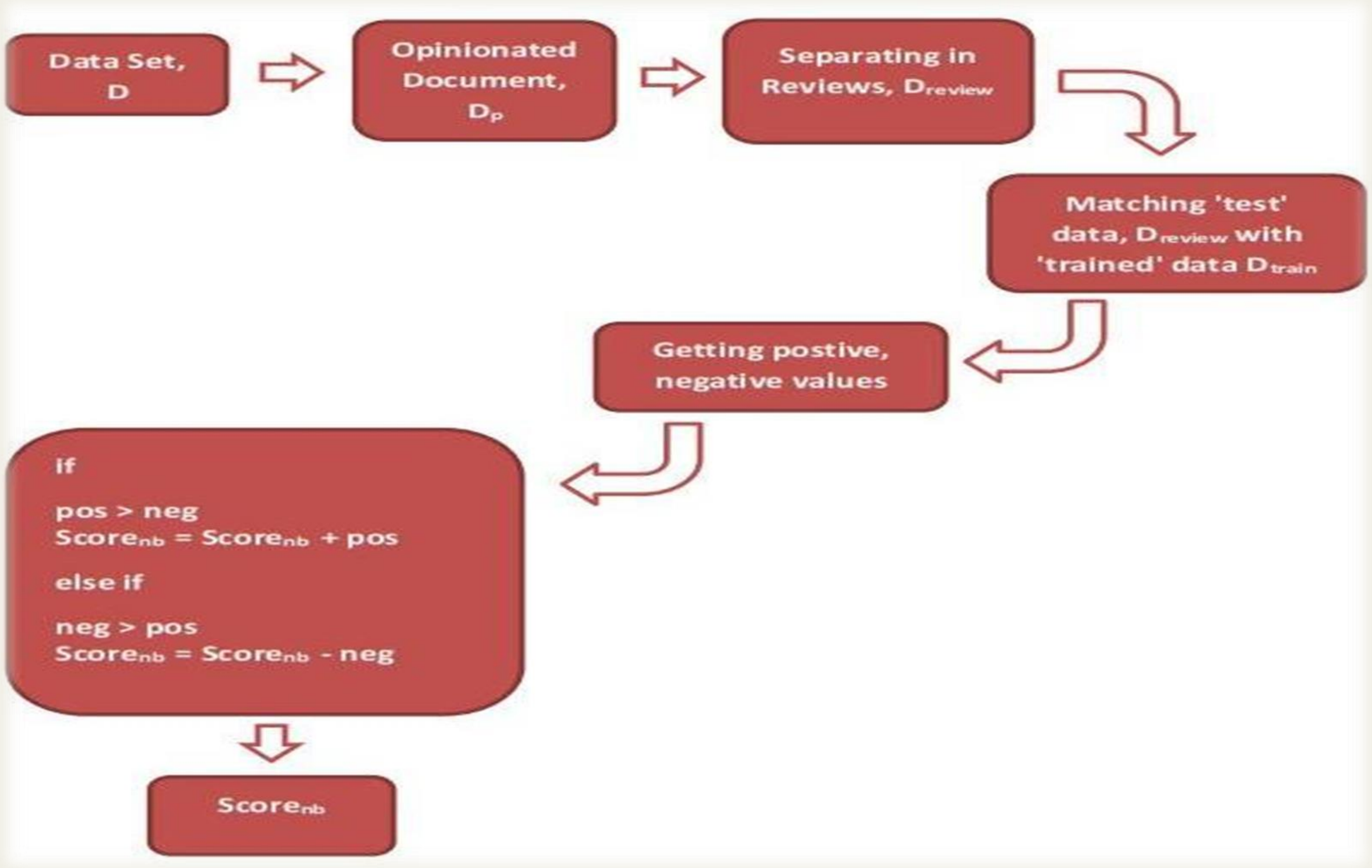
$$P(c \mid d) = \frac{P(c)P(d \mid c)}{P(d)},$$

Where,

P(c) = Probability of Unlabeled data*(c)*

P(d) = Probability of Labeled data*(d)*

Score Retrieval (Cont.)



Weight Assignment

Why weight assignment is necessary?

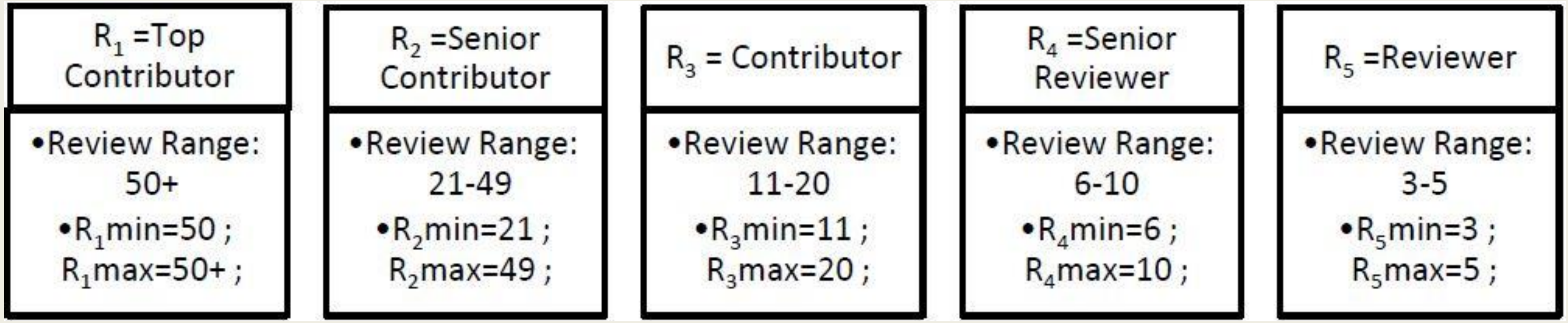
- Opinion *prioritizing* is a *must* in order to distinguish *mature and professional* reviewers opinion from an *amateur* reviewers opinion.

- A *professionals* point of view and interest will definitely *make a difference* in case of *ranking* a hotel.

- There will always be some *integrity/accuracy* issues when it comes to *opinions* as someone stating a feature as *satisfactory* while other will state *otherwise* (*Whose opinion to choose?*)

Weight Assignment (Cont.)

- In TripAdvisor, there is already a priority rating system available for the reviewers!



Weight Assignment (Cont.)

- The equation we proposed for assigning weight of each individual opinion holder is,

$$W_i^j = \frac{S_{review} - R_5min}{R_1min - R_5min}$$

Where,

W_i^j = Weight of ith number of reviewer in a document and jth number of title of opinion holder.

S_{review} = Amount of reviews that reviewer has given in entire TripAdvisor.

R_5min = Lowest rank that is 'Reviewer' category's minimum value *(i.e. 3)*

R_1min = Highest rank that is 'Top Contributor' category's minimum value *(i.e. 50)*

Weight Assignment (Cont.)

- W_i^j returns a value within the range of (0 – 1)
- If an opinion holder's title is 'Reviewer' then W_i^j will return a value close to '0'
- If an opinion holder's title is 'Top Contributor' then W_i^j will return a value of '1'
- By getting the value of W_i^j we can control the flow of final score.

Final Calculation

- For *SentiWordNet* approach, final score of a hotel is,

$$\mathrm{Score}_{\mathrm{hotel}} = \sum_{i=0}^{n} Score_{swn} * W_i^j$$

Where,

$Score_{swn}$ = Score of each opinionated review by using SentiWordNet.

W_i^j = Weight of that opinion holder.

Final Calculation (Cont.)

- For *Naïve Bayes* approach, final score of a hotel is-

$$\text{Score}_{\text{hotel}} = \sum_{i=0}^{n} Score_{NB} * W_i^j$$

Where,

$Score_{nb}$ = Score of each opinionated review by using Naïve Bayes.

W_i^j = Weight of that opinion holder.

Achievement of Our Research

- We have implemented the dictionary based approach using SentiWordNet and supervised machine learning approach using Naïve Bayes method
- Based on the output results of this two methods we ranked the hotels
- Compared our ranking with the original ranking done by TripAdvisor
- We yielded considerable amount of accurate results comparing to the original

Performance Evaluation

Tools Used

- The language we used for parsing data,
  -python(2.7.8)
- We used python shell as IDLE (Integrated Development and Learning Environment)
- NLTK (Natural language Tool Kit)
- We used a library for extracting data from HTML and XML files,
  -beautifulsoup (vers. 4.3.2)
- We used a library for training and testing data sets
  -Textblob (vers. 0.11.0)
- SentiWordNet(3.0)

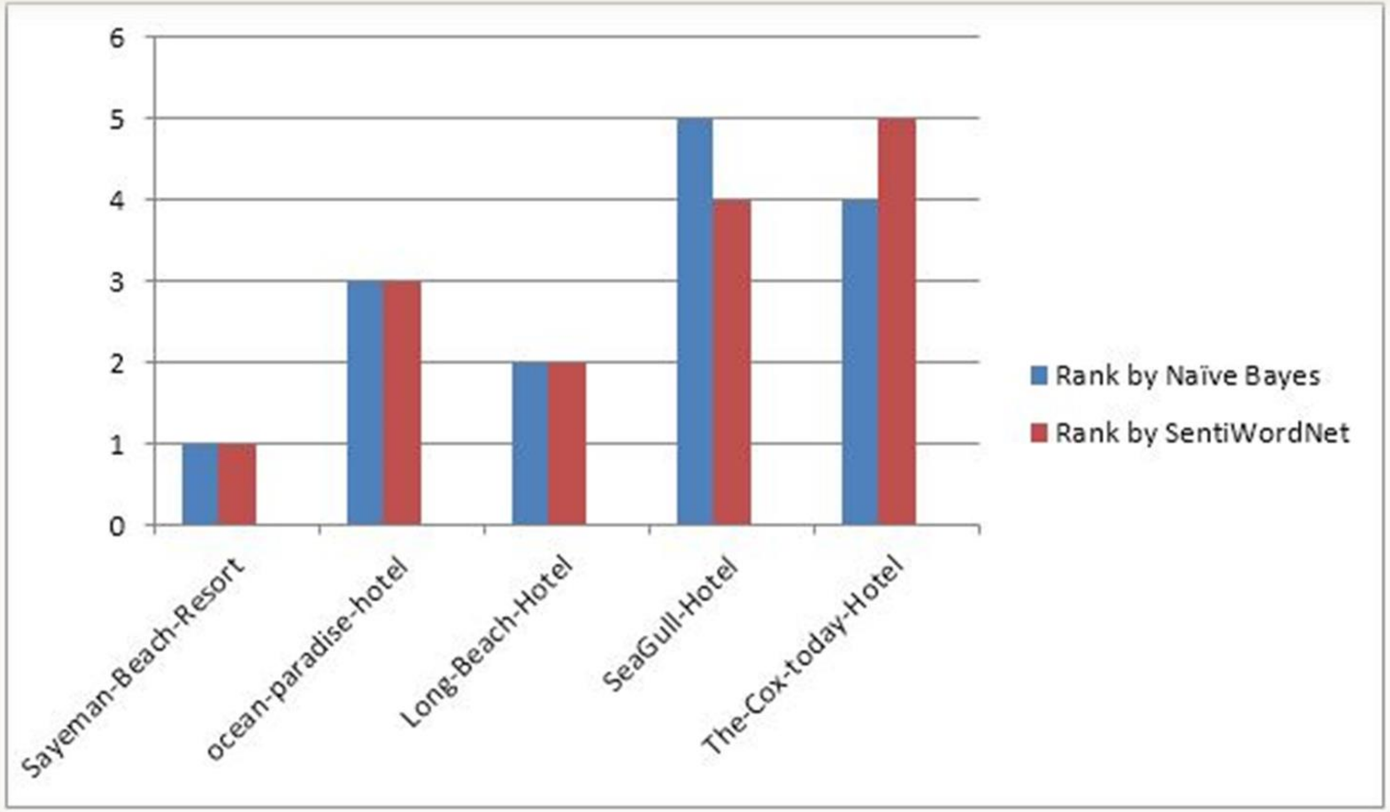
Comparison of Scores

In here we compared the output results we got from the approaches used

Hotels	Tripadvisor Ranking	Sentiwordnet score	Naïve Bayes Score
Sayeman-Beach-Resort	1	0.24103	8.407036572
Ocean-paradise-hotel	2	3.09725	65.15086523
Long-Beach-Hotel	3	1.841837	32.30790236
SeaGull-Hotel	4	3.638370	128.7505741
The-Cox-today-Hotel	5	4.211528	82.40988736

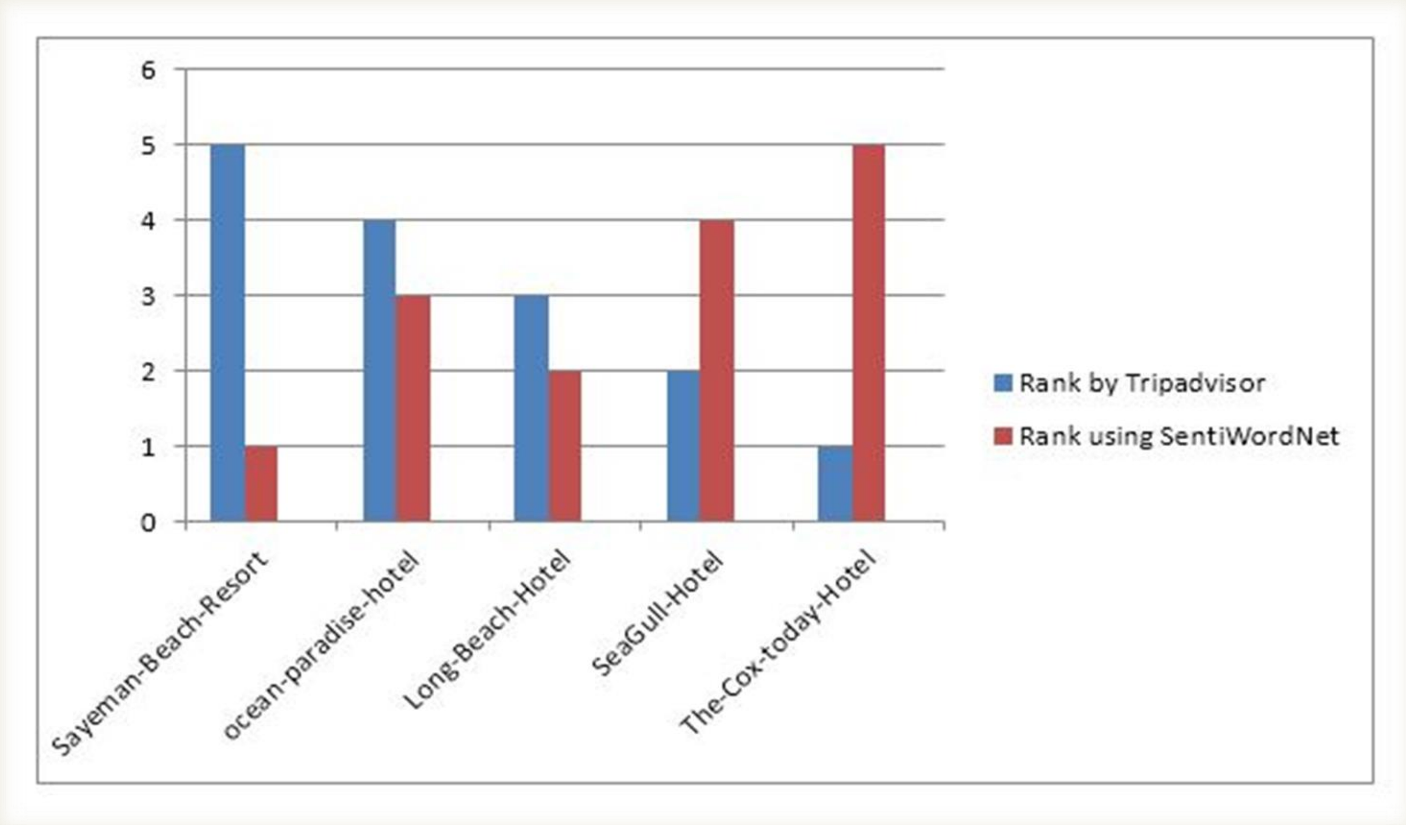
Comparison of Ranks

- Comparison of ranking depending on the score of Naïve Bayes and SentiWordNet



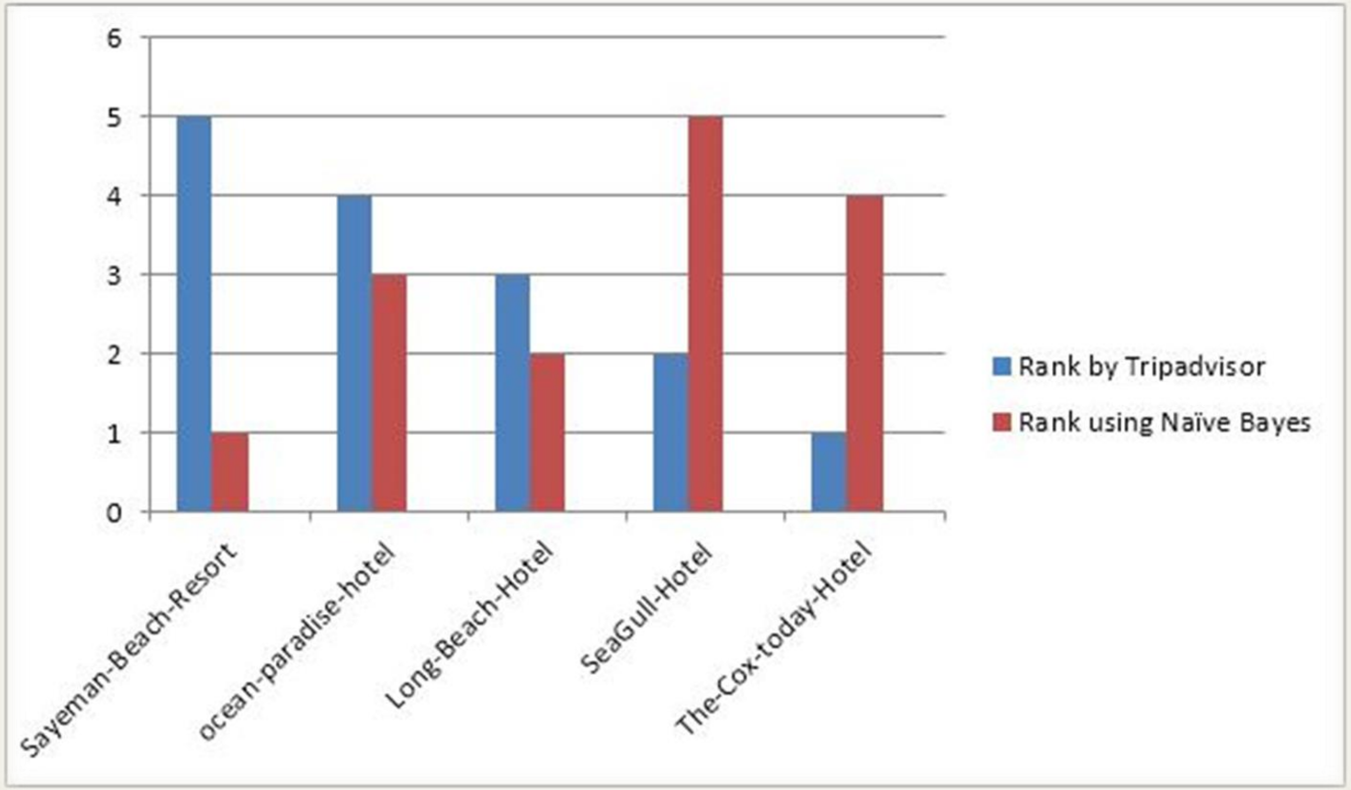
Comparison of Ranks (Cont.)

- Comparison of ranking of TripAdvisor and score of SentiWordNet



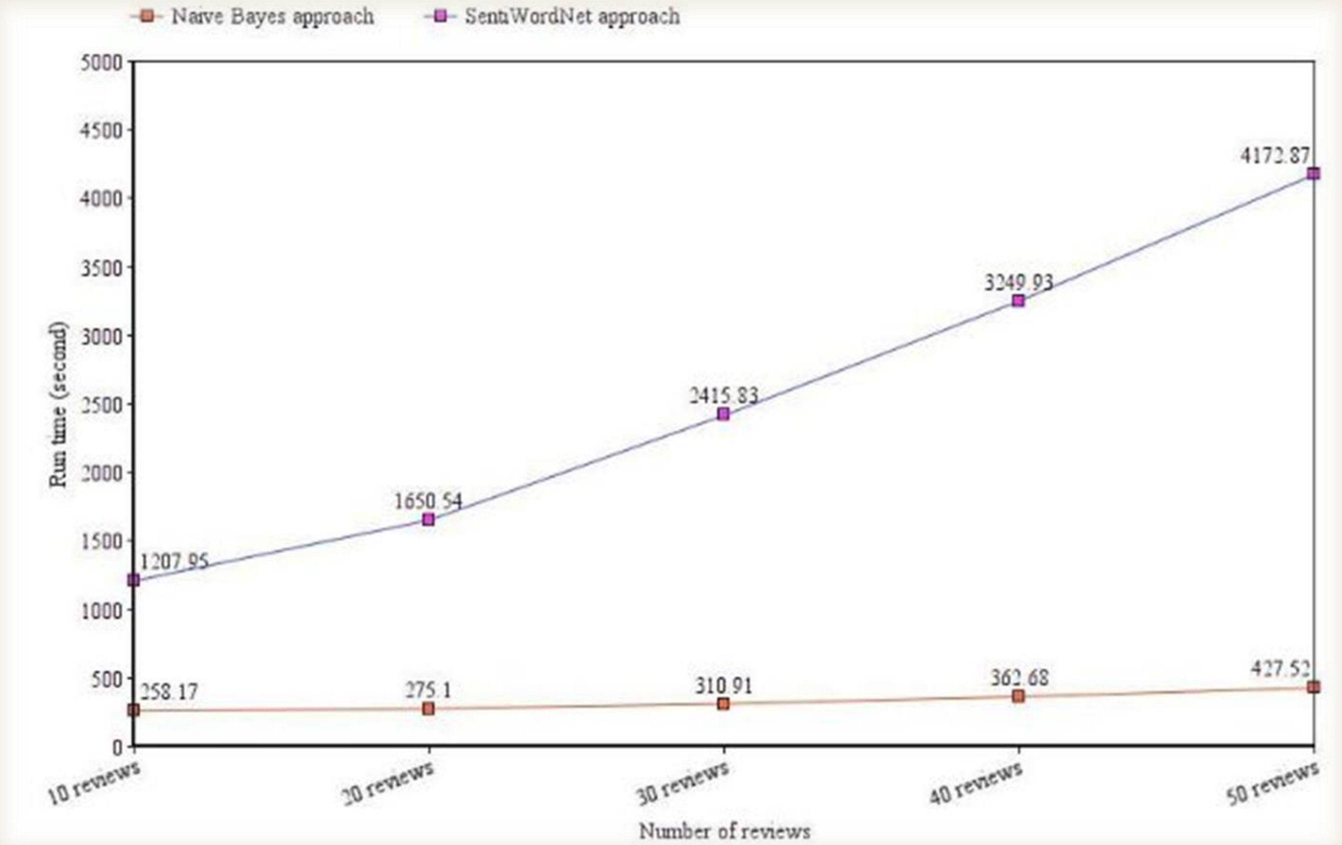
Comparison of Ranks (Cont.)

- Comparison of ranking of TripAdvisor and score of Naïve Bayes



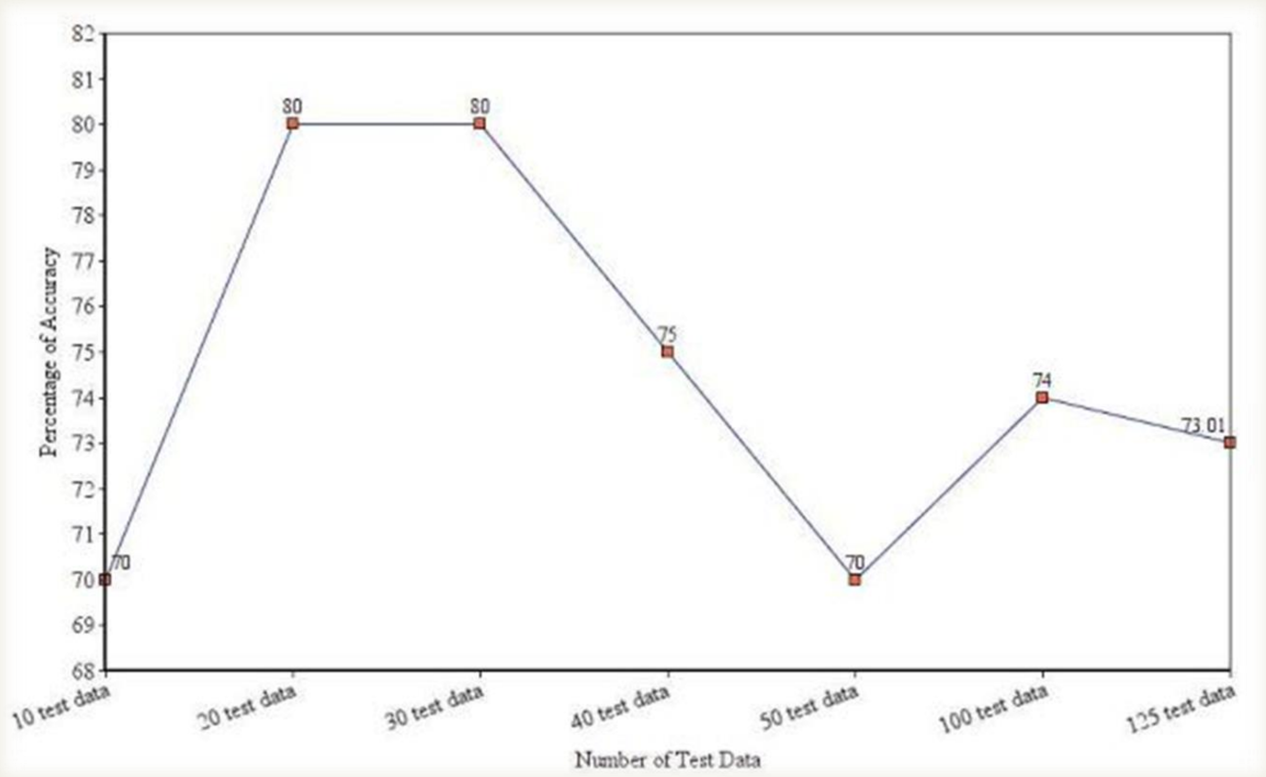
Comparison of Run Time Performance

- Comparison of time needed to run each of the approaches we used



Accuracy

- Accuracy can vary depending on test data set while using Naïve Bayes approach



Conclusion

Summary

- We used the methods which are dictionary based SentiWordNet and supervised machine learning method Naïve Bayes
- Successfully implementing these two methods we collected scores
- Based on the scores we established a ranking system of our own which prioritizes user opinions
- Compared our output with the original ranking done by TripAdvisor
- Our ranking proves to be better than that of the original with higher accuracy

Limitations

- Our context of research is hotel reviews. We could not ensure the integrity of the reviews we used for our purpose.
- Due to the competition among the hotels to become the best there is a possibility of finding false reviews.
- Monotonous type of reviews given in large quantity can affect the polarity of the desired result
- We had to take equal amount of reviews from each hotels otherwise uneven amount of reviews would have resulted in inaccurate ratings
- We have chosen Naïve Bayes classifier as our machine learning method. We could have gotten more accurate result if we used other machine learning approaches such as Support Vector Machine (SVM) or Maximum Entropy (ME).

Future Work

- We have ranked hotels based on user opinions in this research of ours. In future we want rank hotels based on individual features of particular hotels.
- We want to implement other approaches to yield better accuracy in future.
- The system of user contribution has changed in TripAdvisor since our research. We want to take on the new system to research further.

References

- [1]B.Liu Sentiment Analysis and Subjectivity. Handbook of Natural Language Processing, Second edition, 2010

- [2]https://en.wikipedia.org/wiki/Sentiment_analysis

- [3]J. Wiebe, T. Wilson and C. Cardie. Annotating expressions of opinions and emotions in language. *Language Resources and Evaluation*, 1(2), 2005.

- [4]J. Wiebe, T. Wilson, R. Bruce, M. Bell, and M. Martin, “Learning subjective language,” Computational Linguistics, vol. 30, pp. 277–308, September 2004.

- [5]Pang, B and Lee L. Opinion mining and sentiment analysis. Foundations and Trends in Information Retrieval 2008,(1-2),1–135

References (Cont.)

- [6] Minqing Hu and Bing Liu, “Mining and Summarizing Customer Reviews”
- [7] Michael Luca, Reviews, “Reputation and Revenue: The Case of Yelp.com”
- [8]E. Riloff, S. Patwardhan, and J. Wiebe, “Feature subsumption for opinion analysis,” Proceedingsof the Conference on Empirical Methods in Natural Language Processing (EMNLP), 2006.
- [9]J. Wiebe, “Learning subjective adjectives from corpora,” Proceedings of AAAI, 2000.
- [10]Teeja Mary Sebastian, Akshi Kumar, Sentiment Analysis: A Perspective on its Past, Present and Future, 2012
- [11]Pang B. and Lee L. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales, Proceedings of the Association for Computational Linguistics (ACL),2005:115–124

References (Cont.)

- [12]Choi, Y., Cardie, C., Riloff, E., and Patwardhan, S., Identifying sources of opinions with conditional random fields and extraction patterns. Proceedings of the Human Language Technology Conference and the Conference on Empirical Methods in Natural Language Processing (HLT/EMNLP), 2005.
- [13]Bethard, S., Yu, H., Thornton, A., Hatzivassiloglou, V., and Jurafsky, D., Automatic extraction of opinion propositions and their holders. Proceedings of the AAAI Spring Symposium on Exploring Attitude and Affect in Text, 2004.
- [14]Yi, J., Nasukawa, T., Niblack, W., & Bunescu, R., Sentiment analyzer: extracting sentiments about a given topic using natural language processing techniques. Proceedings of the 3rd IEEE international conference on data mining (ICDM 2003):427–434
- [15]Hu, M. and Liu, B. Mining opinion features in customer reviews. In Proceedings of AAAI, 2004:755–760.

References (Cont.)

- [16]Popescu A-M. andEtzioni O., Extracting product features and opinions from reviews, Proceedings of the Human Language Technology Conference and the Conference on Empirical Methods in Natural Language Processing (HLT/EMNLP),2005
- [17]Dave K., Lawrence S, and Pennock D.M. Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In Proceedings of the 12th international conference on World Wide Web(WWW), 2003, pp.:519–528
- [18]Turney P. Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. In Proceedings of the Association for Computational Linguistics (ACL), 2005: 417–424
- [19]Yu H. and Hatzivassiloglou V., Towardsanswering opinion questions: Separating factsfrom opinions and identifying the polarity ofopinion sentences.In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), 2003.

References (Cont.)

- [20]Liu, B., Hu, M.,& Cheng, J. Opinion observer: Analyzing and comparing opinions on the web. In Proceedings of the 14th international world wide web conference (WWW-2005). ACM Press: 10–14.
- [21]Wilson T., Wiebe J., and Hoffmann P.,Recognizing contextual polarity in phrase-level sentiment analysis. In Proceedings of the Human Language Technology Conference and the Conference on Empirical Methods in NaturalLanguage Processing (HLT/EMNLP) 2005:347–354
- [22]Esuli, A., &Sebastiani, F. Determining the semantic orientation of terms through gloss classification.In Proceedings of CIKM-05, the ACM SIGIR conference on information and knowledge management, Bremen, DE, 2005.
- [23]Aue, A. and Gamon, M., Customizing sentiment classifiers to new domains: A case study. Proceedings of Recent Advances in Natural Language Processing (RANLP),2005.

References (Cont.)

- [24]Hatzivassiloglou, V. and McKeown, K., Predicting the semantic orientation of adjectives. In Proceedings of the Joint ACL/EACL Conference,2004: 174–181
- [25]Kim, S. and Hovy, E., Determining the sentiment of opinions.In Proceedings of the International Conference on Computational Linguistics (COLING) ,2004
- [26] Melville, P., Gryc, W., and Lawrence, R.D. Sentiment analysis of blogs by combining lexical knowledge with text classification. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining.2009: 1275-1284.
- [27] Annett, M. and Kondrak, G. A comparison of sentiment analysis techniques: Polarizing movie blogs. Advances in Artificial Intelligence,2008, 5032:25–35
- [28] Heerschop, B., Hogenboom, A., and Frasincar, F. Sentiment lexicon creation from lexical resources, Springer, In 14th International Conference on Business Information Systems (BIS 2011), volume 87 of Lecture Notes in Business Information Processing: 185–196.

References (Cont.)

- [29] Julia Kreutzer & Neele Witte, Semantic Analysis, Opinion Mining Using SentiWordNet
- [30] Baccianella, Stefano, Andrea Esuli, and Fabrizio Sebastiani. "SentiWordNet 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining." LREC. Vol. 10. 2010.
- [31] Alexander Pak, Patrick Paroubek, Twitter as a Corpus for Sentiment Analysis and Opinion Mining


THANK YOU!


Any
Questions