USING TEXT SUMMARIES FOR PREDICTING RATING SCALES

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Overview

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- Related Work
- Text Summarization Approaches
- The Rating Inference Process
- Experimental Setup
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  - Experiments and evaluation
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- Conclusion and Future Work

Introduction

CONTEXT

- Web 2.0 ➔ emergence of new types of websites (wikis, blogs, social networks, …)
  - Users express their opinions
  - Studies show that 73%-87% of users take into account the Internet reviews before making any decision (Pang and Lee, 2008)
  - Companies are interested in monitoring public perceptions on products, services, policies, etc.
- Problem ➔ exponential and fast growth of information

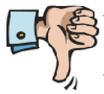
Introduction

CONTEXT

- NLP groups a series of tasks capable of providing methods and tools to efficiently deal with all this available information
  - ***Sentiment Analysis*** detects and classifies opinions in text
  - ***Text summarization*** provides a brief but accurate representation of the contents of a document
- <u>Rating Inference</u> is the task of identifying the author's textual evaluation of an entity
  - Users normally rate a service, product, ... (1=worst,...5=best)

Introduction

CONTEXT

- Rating Inference
  - Subtask of sentiment analysis
  - More challenging than binary classification (e.g. thumbs up , thumbs down )
    - Fine-grained granularity (e.g. 5-star rating)
    - With short documents the results are quite good (74% of accuracy), but not for long documents (40%)
- Text Summarization has been proven to be useful to other NLP tasks
  - Information Retrieval
  - Question Answering
  - Text Classification

Introduction

OBJECTIVES

- Preliminary analysis of the usefulness of different types of text summaries for the rating inference task
  - What type of summary and compression rate could be used instead of the full document for the rating inference task?
- We present a limited set of extractive summary types that have a widespread use in the NLP community

Related Work

- Previous work on Rating Inference
  - 1-4 star rating prediction for movie reviews (Pang and Lee, 2005)
  - 1-5 star rating prediction for product reviews (very short texts) (Saggion and Funk, 2009)
  - Rating of different aspects of hotels given in reviews (Baccianella et al., 2009)
  - Simplification of the task into binary classification (Devitt and Ahmad, 2007)
- To the best of our knowledge Text Summarization has not been analyzed within this task

Text Summarization

TECHNIQUES

- Techniques for detecting relevant information
  - **Term Frequency** (TF) → the most frequent words of a document are indicative of its topic
  - **Code Quantity Principle** (CQP) → the length of a noun-phrase may indicate important information
  - **Textual Entailment** (TE) → avoids incorporating redundancy in summaries
- Different combinations of techniques are analyzed
  - TF
  - TE+TF
  - CQP+TF
  - TE+CQP+TF

Text Summarization

APPROACHES

- Summarization types
  - **Generic** → the summary contains the main ideas
  - **Query-focused** → the summary contains the most important facts related to a query/topic/entity
  - **Sentiment-based** → the summary contains the most relevant subjective information of a document
- Baselines
  - ***LEAD*** → extracts the first sentences
  - ***FINAL*** → extracts the last sentences
  - ***QF*** → extracts the most similar sentences to a query
    - using SUMMA toolkit (Saggion, 2008)
  - ***SENT*** → extracts the strongest opinionated sentences

The Rating Inference Process

TOOLS

- General Archiecture for Text Engineering (GATE)
  - Tokenization and lemmatization (root of the word)
  - Part of speech tagging (pos)
  - Morphological analysis
  - Sentiment features using SentiWordnet (Esuli and Sebastiani, 2006) (sentiWN)
  - SVM
    - 10-fold cross validation
    - Features to train the full review and summaries
      - Root
      - Root+pos+sentiWN

Experimental Setup

DATASET

- Small corpus
  - 89 bank reviews rated from 1 to 5 gathered from *Ciao* Website (*http://www.ciao.co.uk*)
- Corpus statistics

# Reviews	89
Avg. Length	2,603
Max. Length	5,730
Min. length	1,491

- Class distribution

Star-rating	#Reviews	%
1-star	17	19
2-star	11	12
3-star	9	10
4-star	28	32
5-star	24	27

Experimental Setup

EXPERIMENTS & EVALUATION

- Summaries vs. Full review
- 7,120 summaries
  - 3 approaches (generic, query-focused, sentiment-based)
  - 4 combination of techniques (tf, cqp+tf, te+tf, te+cqp+tf)
  - 4 baselines (lead, final, qf, sent)
  - 5 compression rates (10%, 20%, 30%, 40%, 50%)
- Evaluation
  - Mean Squared Error (MSE)

$$MSE = \frac{\sum_{i=1}^{n} (Y_i - \widehat{Y}_i)^2}{n}$$

Experimental Setup

RESULTS

- Results using only ***root*** as feature for the rating classification

Approach	Compression Rate					
Full document		**10%**	**20%**	**30%**	**40%**	**50%**
Full review	MSE	2.59	2.59	2.59	2.59	2.59
4 star-rating	MSE	2.58	2.58	2.58	2.58	2.58
Summarization strategy						
LEAD	MSE	3.10	3.00	3.10	3.30	3.10
FINAL	MSE	2.74	3.00	**2.13**	2.64	**2.48**
QF	MSE	**2.49**	2.70	3.58	3.78	3.88
SENT	MSE	3.89	3.16	3.03	2.90	2.66
Generic-TF	MSE	3.21	**2.33**	**2.39**	**2.37**	**2.44**
Generic-TE+TF	MSE	3.39	3.23	**2.52**	**2.38**	**2.29**
Generic-CQP+TF	MSE	3.01	3.34	2.61	3.17	3.03
Generic-TE+CQP+TF	MSE	2.70	2.93	3.00	3.10	2.71
QF-TF	MSE	**2.11**	**2.19**	**2.18**	**2.46**	**2.37**
QF-TE+TF	MSE	**2.44**	**2.08**	**2.30**	**2.27**	**2.42**
QF-CQP+TF	MSE	2.83	3.00	2.70	**1.80**	**2.00**
QF-TE+CQP+TF	MSE	**2.11**	**2.51**	**2.28**	**2.40**	**2.10**
SENT-TF	MSE	2.83	**2.16**	**2.47**	**2.43**	**2.29**
SENT-TE+TF	MSE	3.20	2.80	**2.40**	2.69	2.71
SENT-CQP+TF	MSE	3.01	3.27	2.62	3.21	3.10
SENT-TE+CQP+TF	MSE	2.69	3.21	3.46	2.90	2.93

Experimental Setup

RESULTS

- Results using ***root+pos+sentiWN*** as features for the rating classification

Approach	Compression Rate					
Full document		**10%**	**20%**	**30%**	**40%**	**50%**
Full review	MSE	2.59	2.59	2.59	2.59	2.59
4 star-rating	MSE	2.58	2.58	2.58	2.58	2.58
Summarization strategy						
LEAD	MSE	2.63	2.68	2.72	2.86	2.60
FINAL	MSE	3.20	2.90	**2.16**	**2.13**	**2.50**
QF	MSE	**2.45**	3.45	2.90	2.91	2.81
SENT	MSE	3.69	2.87	**2.44**	**2.34**	**2.27**
Generic-TF	MSE	3.21	2.68	**2.19**	**2.29**	**2.33**
Generic-TE+TF	MSE	3.98	2.90	2.79	3.06	2.64
Generic-CQP+TF	MSE	3.37	3.45	3.31	3.19	2.84
Generic-TE+CQP+TF	MSE	3.02	2.87	2.83	3.18	**2.53**
QF-TF	MSE	**2.44**	**2.56**	**2.37**	2.77	**2.50**
QF-TE+TF	MSE	3.21	**2.52**	**2.26**	2.62	2.72
QF-CQP+TF	MSE	2.73	3.48	**2.51**	**2.48**	**2.27**
QF-TE+CQP+TF	MSE	2.60	2.83	**2.52**	**2.44**	**2.53**
SENT-TF	MSE	3.02	**2.47**	**2.16**	**2.12**	**2.31**
SENT-TE+TF	MSE	2.99	3.07	**2.21**	2.93	2.64
SENT-CQP+TF	MSE	3.54	2.81	**2.51**	**2.43**	2.70
SENT-TE+CQP+TF	MSE	2.77	**2.31**	**2.14**	2.82	**2.47**

Experimental Setup

DISCUSSION

- Sentiment-based summaries when not using sentiment features is not of great help
- Query-focused summaries seem to be appropriate in all cases
- 30% compression rate obtains on average better MSE values
- The combination of techniques TE+CQP+TF of 10% compression rate might be useful for other NLP tasks
  - its MSE is lower than for other techniques with the same compression rate

Conclusion and Future Work

CONCLUSIONS

- **Rating inference task** → predict the correct rating associated to a document based on the language expressed
- Extensive **analysis of summarization strategies** for the rating inference task instead of using full reviews
  - Generic vs. Query-focused vs. Sentiment-based
  - Combination of techniques for detecting relevant information (term frequency, the code quantity principle, textual entailment)
  - Analysis of baselines (lead, final, qf, sent)
- Results show that **query-focused** and **sentiment-based** summaries are the **most appropriate** for tackling this task

Conclusion and Future Work

FUTURE WORK

- Extend the size of the dataset
- Replicate the experimnents in another domain
  - E.g. Movie reviews
- Analyze the problems of such a fine-granularity classification (1-5 labels)
  - Simplifying the problem considering only 3 classes instead of 5

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Thank you very much for your attention!

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NLP NATURAL LANGUAGE PROCESSING

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