Spotting Sentiments with Semantic Aware Multilevel Cascaded Analysis

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Outline

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Content generated on the Web

- Numerous individuals express opinions and feelings in the Web.
- Continuous use of popular Social Networks and Web 2.0 technologies has pushed the need for understanding crowd's opinions.

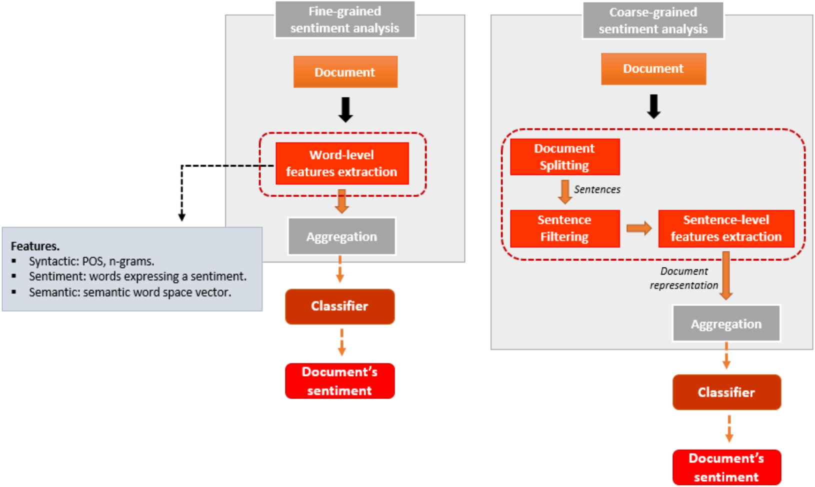
Laptop X is more expensive than laptop Y.

Laptop X is the best laptop in the market!

Capturing sentiment out of textual resources (1/2)

- Machine learning is a popular approach for spotting the sentiment expressed in documents (i.e. document-based sentiment analysis).
- Typically, document-based sentiment analysis processes operate at a particular level:
  - Fine-grained approach: word-level process (i.e. sentiment-based, syntactic-based, semantic-based).
  - Coarse-grained approach: sentence-level process.
- Sentiments' extraction only either out of separated sets of words or at lined sentences leads to information loss.

Capturing sentiment out of textual resources (2/2)



Our goals

- **Given:** a set of documents D; a sentiment label and a representation for each document;
- **Predict:** the expressed sentiment for any new document.

G1. Exploit effectively diverse information from each individual sentence of a document.

G2. Design an effective approach for combining information arising from different text-levels.

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Recursive Neural Tensor Network

- **RNTN:** suitable for capturing the compositional effects in sentences.
- It learns a semantic vector space & generates a sparse tree to represent a document at different levels.
- Each sentence is represented with a **semantic information vector**.
- It can classify individual sentences and produce a **sentiment probability distribution vector**. **In our case:**
  - A 5-value sentiment probability distribution vector is produced (1 - very negative, 2 - negative, 3 - neutral, 4 - positive, 5 - very positive).

Sentiment probability distribution: $sent_i(s)$, where $i = 1, ..., 5$ and s a sentence of a document.
Semantic space vector: $vec(s)$.

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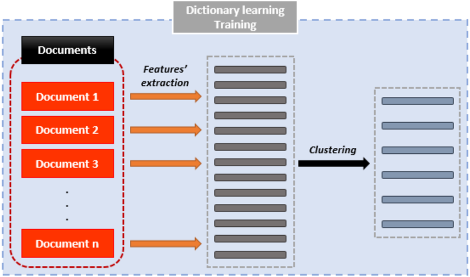
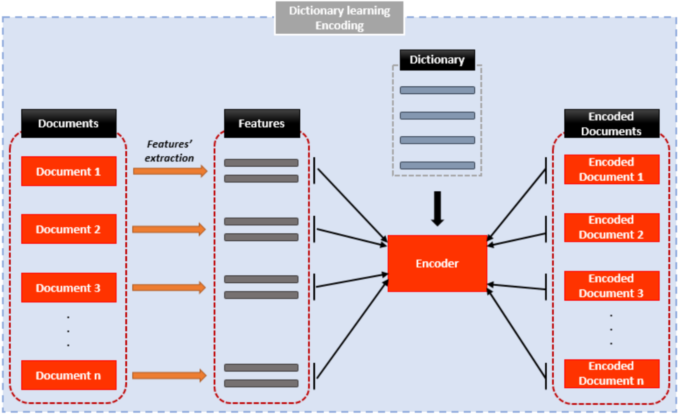
Dictionary learning (1/2)

- Use of a clustering process to construct a dictionary.
- Clustering is applied on the feature vectors that represent the documents' sentences.
- Each "word" of the dictionary corresponds to a set of similar feature vectors.
- K-means and variants are usually used to perform the clustering.



Dictionary learning (2/2)

Encoding of a new document.



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Problem definition

Multilevel sentiment analysis

- **Given:** a training dataset D, a word-level feature extractor $f(w)$, a sentence-level feature extractor $g(s)$, and a sentiment label for each document $t_i \in \{pos, neg\}$;
- **Extract:** the word level and the sentence level features of each document d.
- **Predict:** the sentiment of any new document $d_{test} \notin D$.

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Word level analysis (1/3)

Step 1. Features extraction: word to vector mapping.
Step 2. The document-level vectors aggregation via a weighting scheme (e.g. term-frequency tf).

Step 1. Features extraction: word to vector mapping.

- A word w is modeled as a vector $v \in \mathbb{R}^k$, where k equals the size of the used dictionary.
- All the elements of v are zero except for the one that corresponds to the word w.

Word-level features.

- Both Bag of Words (BoW) and Naive Bayes bigrams (NB) features were examined.

Word level analysis (2/3)

Step 2. Word vectors aggregation.

- All the vectors of the words in a document are combined into one that describes the whole document.

Word-level feature extractor

The word-level feature extractor f maps each word w of a document d to a vector $f(w) \in \mathbb{R}^l$ (l is the dimensionality of the (output) vector).

Word level analysis (3/3)

Aggregation Example (BoW features).

- Dictionary: $\{bag, of, words\}$.

Word	Vector
bag	(1,0,0)
of	(0,1,0)
words	(0,0,1)

- Binary weighting scheme.
  - Vector of the phrase *bag bag words*: (1,0,1).
- Term-frequency weighting scheme.
  - Vector of the phrase *bag bag words*: (2,0,1).

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Sentence level analysis (1/6)

Step 1. Features extraction.
Step 2. Aggregation phase under a weighting scheme.

Step 1. **Features extraction.**

- Use of the RNTN model as a sentence-level feature extractor.
  - Sentiment distribution vector, $sent(s)$.
  - Semantic vector, $vec(s)$.
- Other methods could also be used for extracting the sentiment distribution and the semantic vector for each sentence.
- RNTN was the first to achieve 85.4% accuracy on binary sentence-level classification.

Sentence level analysis (2/6)

Step 2. Aggregation phase.

Two approaches were examined:

- Sentiment center estimation.
- Semantic center estimation.

Sentence level analysis: Sentiment center estimation (3/6)

Sentiment center vector.

$$sent_{center}(d) = \sum_{s \in d} sent(s)/|d|$$

where $|d|$ is the number of sentences of document d.

Sentiment variance vector.

$$sent_{var}(d) = \sum_{s \in d} (sent(s) - sent_{center}(d))^2/|d|$$

which contains the squared differences from the document's center.

Sentence level analysis: Semantic center estimation (4/6)

Semantic center vector.

$$vec_{center}(d) = \sum_{s \in d} vec(s)/|d|$$

where $|d|$ is the number of sentences of document d.

Semantic variance vector.

$$vec_{var}(d) = \sum_{s \in d} (vec(s) - vec_{center}(d))^2/|d|$$

which contains the squared differences from the document's center.

Sentence level analysis: Semantic CenterBook (5/6)

- Builds on vectors that merge semantically similar sentences.

CenterBook process.

Given a training set of documents $D = \{d_1, d_2, ..., d_n\}$
Do

- Split all documents into a set of sentences.
- Clustering the set of all sentences appearing in D.

Done
Output: a collection of clusters.

Sentence level analysis: Semantic CenterBook (6/6)

- Each sentence in a document is represented by its nearest cluster.
- The overall document is modeled by the set of centroids.

Sentence encoding function, $h(s)$.

$$h(s) = y_i = \begin{cases} 1, & i == arg_j min(||c_j - vec(s)||_2^2) \\ 0, & otherwise \end{cases}$$

where y_i is the i-th element of $y(s)$ vector.

Document representation, CenterBook.

$$code(d) = \sum_{s \in S_d} h(s)$$

where s is each sentence of a document d and S_d the set of all sentences of document d.

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MultiSpot pipeline (1/2)

Given a document d

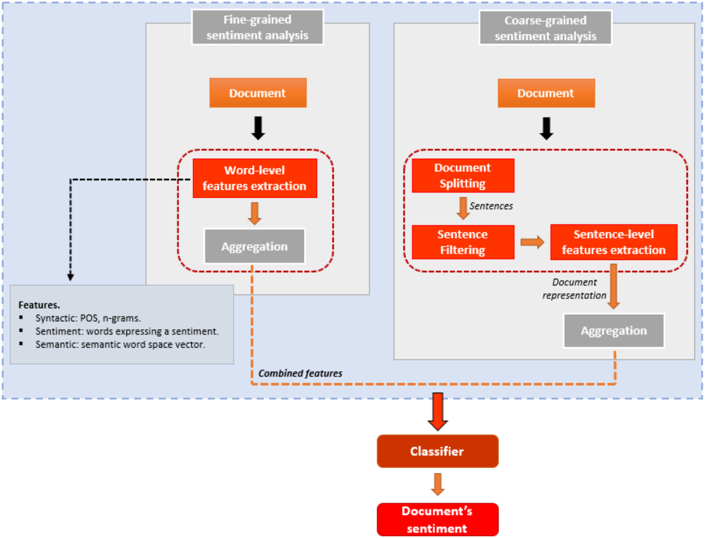
Do

- **Phase 1.** Word level analysis (*Fine-grained word features*).
- **Phase 2.** Sentence level analysis (*Coarse-grained word features*).
- **Phase 3.** Combination of word and sentence level aggregated features.

Done

Spot the document's sentiment.

MultiSpot pipeline (2/2)



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Dataset overview

- Both datasets contain movie reviews collected from the Internet Movie Database (IMDB).

Dataset	# Reviews	Pos / Neg
Large Movie Review Dataset (IMDB)	50k + 50k (unlab)	50% - 50%
Polarity dataset v2.0 (RT-2k)	2.000	50% - 50%

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Fundamental Characteristics

- **Extracted word-level features.**
  - BoW (*top 10.000 unigrams*) & NB bigrams.
  - Weighting scheme: Term-frequency for the IMBD dataset, Binary weighting for the RT-2k.
- **Extracted sentence-level features:** Sentiment distribution & Semantic vector based on RNTN model.
- **Clustering:** k-means algorithm for 15 iterations, 10 times repetition of the clustering process and selection of the minimum energy configuration.
- **Classification:** linear SVM, selection of best SVM model based on 10-fold cross validation.

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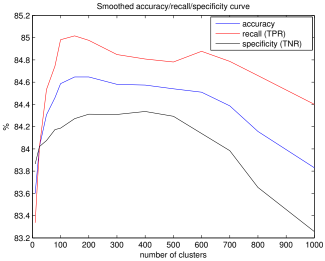
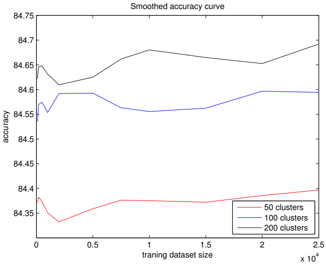
CenterBook evaluation

How is the classification quality affected by:

Q1. the number of the clusters?

Q2. the size of available training data?





Results for the IMDB dataset.

Go

Evaluation of sentence-based approaches

Parameters.

- Use of 200 clusters for the IMDB dataset and 100 clusters for the RT-2k dataset.

Features	**IMDB**			**RT-2k**		
	Accuracy	**Recall**	**F1**	**Accuracy**	**Recall**	**F1**
Rule-based	76.21	56.36	70.32	59.7	19.80	32.95
Sentiment Center	84.02	80.97	83.52	83.30	86.10	83.75
Sentiment Center (var)	84.01	80.96	83.51	83.05	86.30	83.58
Semantic Center	84.90	83.45	84.68	**85.10**	86.80	**85.35**
Semantic Center (var)	85.27	83.53	85.01	84.90	85.50	84.99
CenterBook	84.76	85.05	84.80	83.15	84.10	83.34
Sentiment Center (var) + Semantic Center	85.27	83.53	85.01	85.05	85.40	85.10
Sentiment Center (var) + Semantic Center + CenterBook	**85.35**	84.30	**85.20**	84.85	87.10	85.18

- Approaches that involve semantic features yield better classification results.

Evaluation of the MultiSpot method using BoW and NB bigrams features (1/2)

Features	IMDB			RT-2k		
	Accuracy	**Recall**	**F1**	**Accuracy**	**Recall**	**F1**
BoW	87.77	88.01	87.80	87.15	88.40	87.31
BoW + Sentiment Center	88.99	89.01	88.99	87.45	88.70	87.60
BoW + Semantic Center (var)	89.36	89.18	89.34	88.20	89.60	88.36
BoW + CenterBook	89.29	89.26	89.29	88.85	90.80	89.06
BoW + Sentiment Center + Semantic Center (var)	89.38	89.22	89.36	88.25	89.70	88.42
BoW + Sentiment Center + Semantic Center (var) + CenterBook	**89.48**	89.19	**89.45**	**89.05**	91.50	**89.31**

- 1.71% improvement for the IMDB dataset and 1.9% improvement for the RT-2k dataset.

Features	IMDB			RT-2k		
	Accuracy	**Recall**	**F1**	**Accuracy**	**Recall**	**F1**
NB bi	91.43	92.13	91.49	89.45	90.80	89.59
NB bi+ Sentiment Center	91.72	91.77	91.73	90.00	91.30	90.13
NB bi+ Semantic Center (var)	91.76	91.49	91.73	90.90	91.90	90.99
NB bi+ CenterBook	91.72	91.90	91.73	**91.30**	93.50	**91.49**
NB bi+ Sentiment Center + Semantic Center (var)	**91.78**	91.53	**91.76**	90.85	91.90	90.95
NB bi+ Sentiment Center + Semantic Center (var) + CenterBook	91.60	91.33	91.58	90.65	93.10	90.87

- 0.35% improvement for the IMDB dataset and 1.85% improvement for the RT-2k dataset.

Evaluation of the MultiSpot method using BoW and NB bigrams features (2/2)

Observations.

- The combination of word & sentence level features improves the classification accuracy.
- The quality of the word-level features significantly affects the overall classification accuracy.

Friedman test.

- It is used to explore differences in treatments across multiple test attempts.
- **Null hypothesis:** Multilevel cascaded sentiment analysis does not increase the accuracy of the baseline (BoW / NB bigrams) classifier ➔ Rejected.

Comparison of MultiSpot with state-of-the-art approaches

Method	IMDB	RT-2k
MultiSpot method		
NB bi + CenterBook	91.72	**91.30**
NB bi + Sentiment Center (var) + Semantic Center (var)	**91.78**	90.85
State-of-the-art approaches		
Full + Unlabeled + BoW (Maas2011)	88.89	88.90
BoW SVM (Pang2004)	-	87.15
tfΔidf (Martineau2009)	-	88.10
Appr. Taxonomy (Whitelaw2005)	-	**90.20**
Word Repr. RBM + BoW (Dahl2012)	89.23	-
NB SVM bigrams (Wang2012)	91.22	89.45
Paragraph Vector (Le2014)	**92.58**	-

- **RT-2k:** exceeds the existing classification accuracy by 1.1%.
- **IMDB:** surpasses the existing classification accuracy for 0.8% (not combined with the paragraph vector method).

Outline

Conclusions

G1. Exploit effectively diverse information from each individual sentence of a document.

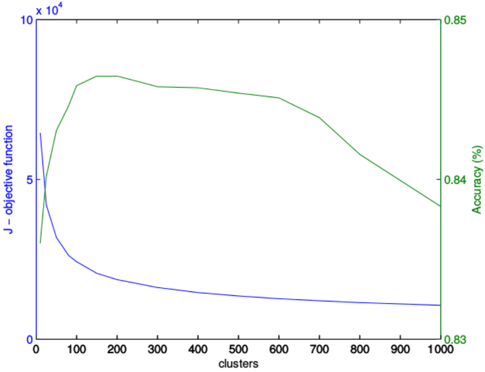
- Exploitation of sentiment and/or semantic information via the center-based methodologies.

G2. Design an effective approach for combining information arising from different text-levels.

- MultiSpot is an affective pipeline which combines both word and sentence level information.

Questions?

Evaluation of the k-means objective function.



Results for the IMDB dataset.

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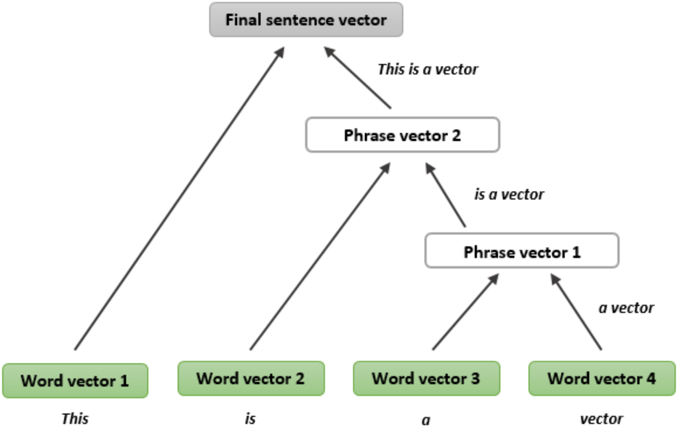
Appendix: Tree structure



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