

# SENTIMENT RETRIEVAL ON WEB REVIEWS USING SPONTANEOUS NATURAL SPEECH

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## ABSTRACT

This paper addresses the problem of document retrieval based on sentiment criteria. A query based on *natural spontaneous speech* expressing an opinion about a certain topic, is used to search a repository of documents containing favorable or unfavorable opinions on many topics. The goal is to retrieve documents whose opinions more closely resemble the one in the query. A semantic system based on spontaneous speech transcripts is augmented with information from another modality. This information is collected from a repository of reviews on technological products. Spontaneous speech transcriptions and full text article reviews are mapped to a sentiment space, where posterior probabilities extracted from the article are used to *regularize* their transcriptions counterparts. This paper makes three important contributions. First, we introduce a framework for sentiment analysis that can accommodate combinations of different modalities, while maintaining the flexibility of a unimodal system, i.e. capable of dealing with the absence of any modality. Second, we show that it is possible to improve average precision on *speech transcriptions' sentiment retrieval* by means of regularization. Third, we demonstrate the strength and generalization of our approach by training regularizers on one dataset, while performing sentiment retrieval experiments with significant gains on two other publicly available datasets of YouTube clips.

**Index Terms**— Sentiment analysis, spontaneous speech reviews, polarity, subjectivity, information retrieval.

## 1. INTRODUCTION

The advent of social media acted as an immense highway for a continuous flow of opinionated information accessible to all. Every minute, people share personal feelings on the web; e.g. reviews on recently acquired items, gastronomical experiences, emotional events in their lives, religious beliefs, or simpler matters of opinion on everyday issues. Platforms like Twitter, Youtube, Facebook or Google+ are on the epicenter

of these sentimental waves of information.<sup>1</sup> The availability of this user-centric data allied to commercial interests has spurred research efforts in many directions. For example, the fashion industry is interested in knowing what are the trends for next season, governmental agencies need to detect potential security threats, technology companies want to measure the acceptance of their products and detect market-specific issues with implications on their sales strategy. All of these share an underlying need to “feel the pulse” of an audience. This is broadly known as sentiment analysis or opinion mining and is usually split into two smaller tasks: subjectivity [5] and polarity [?]. While subjectivity measures *how much sentiment* information a user opinion contains, polarity focuses on analyzing whether the opinion is *positive or negative*.

Previous work on sentiment analysis has been predominantly unimodal, mostly in the text domain [1, 2, 3]. Traditional natural language processing (NLP) tasks (e.g. text classification) often rely on topic models [4]. Subjectivity or polarity analysis typically use earlier NLP models, such as bag-of-words (BoW) [5]. It is also considered a more challenging task, when compared to text classification, and often requires domain-specific data. This has led to the development of many sentiment lexicons [6, 7, 8] and large annotated datasets [5, 9, 10]. A challenging area that, in our opinion, has not received enough attention, is how to incorporate multiple sources of information for sentiment analysis. To the best of our knowledge only a couple of studies have been made along that direction [11, 12]. In particular, an important area of research, is the task of automatic sentiment extraction from natural audio streams containing spontaneous speech. In the present work, we aim to address this issue by performing sentiment analysis on speech transcriptions extracted from video reviews. With regards to previous multimodal sentiment analysis work, we would emphasize the following key distinctions: in our work different data sources are mapped onto a common space where sentiment is extracted, and although our retrieval framework can incorporate multimodal data, we note that it is robust enough to work in the absence of any modality.

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<sup>1</sup>YouTube alone claims that more than 100 hours of video are being uploaded every minute, <http://www.youtube.com/yt/press/statistics.html>

In this paper, we propose a feature regularizer suitable for sentiment analysis through modal expansion. A set of reviews for small electronic appliances was collected, containing a small video clip and a full text article on each product. A linear operator is then learned to minimize the average similarity of data across the two modalities. This acts as a feature regularizer for samples belonging to the noisier of the modalities. Among other results, we show in section ??, how the regularization of transcriptions extracted from spontaneous natural speech contained in a video review is able to produce over 5% gains on retrieval accuracy of *unseen* YouTube transcriptions.

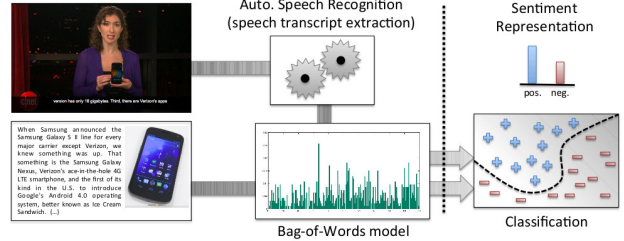
## 2. SENTIMENT ANALYSIS

In the present work we focus on automatic sentiment analysis in a scenario where multiple sources of information are available during the training stage (but not for testing). This does in fact exist in many practical applications; e.g. specialized review sites, social media, personal product review blogs. One example is the CNET database [13], a repository of product reviews with information available in two formats: a video with someone reviewing a consumer electronics product, and a full text article, not necessarily written by the same person, where a more thorough evaluation of the product is presented. We are interested in consolidating the prevailing sentiment about a certain product expressed through these multiple sources (e.g. video, audio, textual).

### 2.1. Sentiment space

The simplest approach to represent multi-modal data consists in concatenation of features from different sources. This however raises questions on how to deal with missing modalities (features). Another approach is to map data onto a common space, where heterogeneous modalities are represented with the same features [?]. This space *made by design*, is tailored to the task at hand and is the approach we follow in this work. For opinion mining we leverage heterogenous sources of information into a *sentiment space*. This is done by building classifiers for each modality that map a low-level feature space,  $\mathcal{R}$ , onto a vector of class posterior probabilities in the sentiment space,  $\mathcal{S}$ ; where dimensions stand for positive or negative sentiments.

Figure 1 summarizes how to obtain the sentiment polarity representation for both modalities: text and video reviews. In the case of a text snippet, the bag-of-words model can be obtained directly from low-level features (e.g. words, bigrams). For the video review, an automated speech recognition (ASR) system is first used to estimate the corresponding transcriptions. These are usually noisy text features, and are used as low-level representation for this modality. As expected, the accuracy of a sentiment detector based solely on speech transcriptions is lower than one based on a full length textual

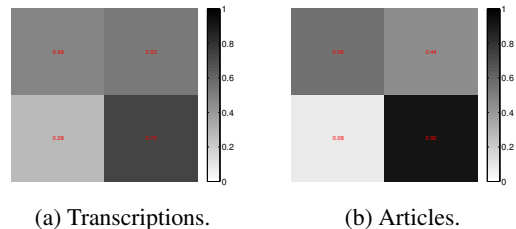


**Fig. 1:** To obtain the sentiment representation low-level features are first extracted to obtain a bag-of-words representation. A text classifier maps this to the sentiment space.

review. The existing gap between the accuracy of the two modalities allows for significant gains on sentiment retrieval by means of regularization. A framework that is introduced in the following section.

### 2.2. Polarity regularization

The principle of modal expansion relies on the fact that one (auxiliar) modality may contain more information about the sentiment than the data in which we are interested [14]. In the present study, the data extracted by an ASR is not as informative in predicting the polarity of the prevalent sentiment as a full text article. This can be noted by inspection of the confusion matrices on the individual modalities, as shown on Figure 2. We use this principle to find a transformation that *morphs* posterior probabilities obtained from the less accurate modality (Fig. 2a) to the ones obtained through the more accurate data (Fig. 2b); e.g. speech transcriptions and full text article, respectively.



**Fig. 2:** Confusion matrices for the two modalities on CNET dataset.

More formally, given a set of observations for product reviews in two modalities  $(\mathbf{x}_s^i, \mathbf{x}_t^i)$  with  $i = 1 \dots n$ , where  $\mathbf{x}_s^i$  is the  $i^{th}$  sample of the speech transcription, and  $\mathbf{x}_t^i$  the corresponding observation of the text article, we first obtain their representation onto the space of sentiment class posteriors through suitable unimodal classifiers,

$$\boldsymbol{\pi}_s^i \leftarrow \Gamma(\mathbf{x}_s^i) \quad \text{and} \quad \boldsymbol{\pi}_t^i \leftarrow \Psi(\mathbf{x}_t^i)$$

where  $\Gamma(\cdot)$  and  $\Psi(\cdot)$  stand for the classifier function for speech transcriptions and text articles respectively.  $\boldsymbol{\pi}_{s,t}^i$  is

the  $i^{th}$  2-dimensional posterior vector obtained as a result of applying the respective classifier. Then, we partition the observations in two groups, positive (+) and negative (-) reviews. Using reviews that exhibit similar sentiment, we learn two transformations  $\Phi^j, j \in \{+, -\}$

$$\begin{aligned} \Phi^j : \mathcal{S} &\rightarrow \mathcal{S} & j \in \{+, -\} \\ \pi_s &\rightarrow \pi_t \end{aligned}$$

A solution for each  $\Phi^j$  can be found in the least squares sense

$$\min \|\Phi^j(\pi_s^j) - \pi_t^j\|_2^2 \quad (1)$$

where positive sample pairs  $(\pi_s^+, \pi_t^+)$  are used to learn  $\Phi^+$ , and negative pairs are used to learn  $\Phi^-$ . Restricting  $\Phi^j$  to the class of linear operators, it can be shown that equation (1) can be mapped to a quadratic programming problem with affine constraints. These constraints enforce the *range space* of  $\Phi^j$  to lie on the simplex, making any transformed point a valid probability vector. Furthermore, under certain mild conditions, the feasible set and the optimization problem are convex and a global minimum can be obtained using the approach described in [14].

After this procedure two matrices are obtained;  $\Phi^+$  and  $\Phi^-$  regularize towards positive and negative sentiment classes by linear projection of the original probability posterior vectors. Now we focus on the problem of applying these projections to *any speech transcript sample* given on the sentiment space,  $\pi_s$ .

### 2.3. Weighting the transformations

The regularization introduced in the previous section is a class-dependent linear transformation. Where the classes considered are the two polarities a review can exhibit: positive (+) and negative (-). The procedure provides the learning for positive ( $\Phi^+$ ) and negative ( $\Phi^-$ ) sentiment transformations. For a given speech transcript,  $\pi_s$ , we use the following convex combination to yield the regularized features:

$$\hat{\pi}_s = \sum_{j \in \{+, -\}} w^j \Phi^j(\pi_s) \quad (2)$$

In equation (2) a vector of weights,  $\mathbf{w}$ , is used to interpolate the regularization transformations. To determine  $\mathbf{w}$  we consider two different scenarios: either the sample point  $\mathbf{x}_s$  has an associated text review,  $\mathbf{x}_t$ , in which case we set  $\mathbf{w} = \pi_t$ , or if there is no associated text review then we perform a cross-modal search [?] operation using  $\mathbf{x}_s$  to find the most suitable  $\mathbf{w}$ . In such operation, a similarity measure is computed in a pairwise comparison of the  $\pi_s$  point to each available text article reviews  $\mathcal{T} = \{\pi_t^1, \pi_t^2, \dots, \pi_t^n\}$ . Then,  $\mathbf{w}$  is fixed as follows:

$$\begin{aligned} \mathbf{w} &= \pi_{j^*} \\ j^* &= \arg \max_j S(\pi_j, \pi_s) \quad \forall j = 1 \dots n. \end{aligned}$$

In this work  $S(a, b)$  is the *Kulback-Leibler* divergence, but any suitable similarity measure between  $a$  and  $b$  can be applied.

## 3. EXPERIMENTAL SETUP AND RESULTS

In this section experiments are conducted to assess whether an additional source of information can be used to improve results on the task of retrieving reviews that express similar sentiment to a given query. All experiments refer to a query-by-example (QBE) retrieval scenario in the sentiment space; where speech transcripts are used as queries. Different scenarios are considered; namely when only one modality is present in the retrieval set in which case regularization transforms are learned on a different dataset.

**Datasets:** The CNET [13] dataset is a public collection of consumer electronic product reviews available in two modalities: 1) a full text article about the product, written by one of CNET’s editors, and 2) a video where CNET people describe their evaluation on that product. In particular, we restrict to the set of product reviews whose videos contained closed captions representing the speech transcriptions. In both – transcriptions and text reviews – the pros and cons of each product are detailed and an overall editor rating of the product is made. The rating ranges from 1 to 5 stars<sup>2</sup>. Although the reviews tend to be somewhat lenient, we have set the threshold between a good and bad review at the mean point 2.5, i.e. any product rated 2.5 or below would be considered “negative” and the rest are considered “positive” reviews. Our final CNET collection contains 50 reviews on both modalities, 25 from each “sentiment” as summarized in Table 1.

source	words	sentences	samples
speech transcripts	475	22	50
text articles	2330	85	50

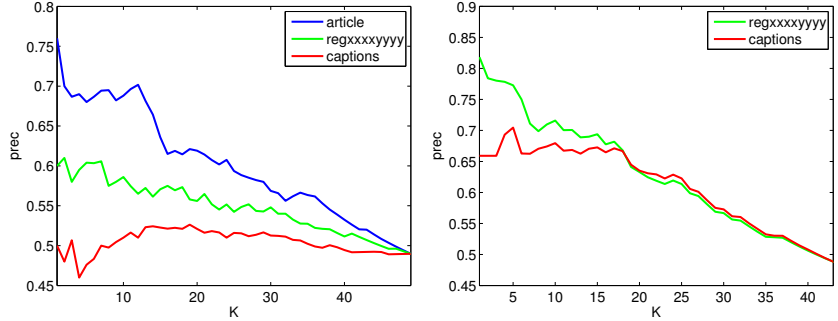
**Table 1:** CNET document statistics: words per document, sentences per document, split per source of information.

The other dataset used in this work, is a collection of YouTube videos where people express opinions about a wide variety of topics. This dataset results from the concatenation of positive and negative reviews available in [12, 15]. From the 28 labelled videos of [15], we used 20 videos that were still available online at the time of the experiments. From [12] we use a total of 24 videos, 12 videos from each class. This yields a total of 44 sentiment videos for the YouTube experiments. Please refer to the original papers [12, 15] for more details on each set of videos.

**Representation:** Both text articles and speech transcripts are english written reviews. The popular BoW model is used to

<sup>2</sup>1 and 5 star rated products are hard to find. Our final collection contains products ranging 2 to 4.5 stars.

	Dataset	
	CNET	Youtube
Article	0.678	n/a
Transc. <sub>reg</sub>	0.624	0.726
Transcript	0.546	0.689
random	0.5	0.5



(a) CNET reviews

(b) YouTube reviews

**Table 2:** Mean average precision (mAP) scores for retrieval on both datasets.

**Fig. 3:** Precision @K for both datasets (CNET and YouTube). Note that text article reviews are not available on the YouTube data.

represent them at a low-level space. We follow the best practices in text representation for sentiment analysis [5] and consider both unigrams and bigrams, no stop-word list, no stemming nor lemmatization.

**Classification:** To obtain the representation on the sentiment space we train a Naïve Bayes classifier using the software package of [16]. The choice of the “best” model lies outside the scope of this work, nevertheless we note that more complex models can be used without implications in the current framework [5]. The training data is a random sample of 3,000 observations from the Amazon reviews dataset of [17]. 1,500 samples from reviews rated with 5 stars and the same amount for reviews rated with 1 star. We note that the same classifier is used throughout the experiments, regardless of the dataset being tested, i.e. CNET or YouTube. This shows a fair amount of generalization on our framework. The classifier yields the 2-dimensional vector,  $\pi$ , that expresses the belief that a certain review contains positive (negative) sentiments.

### 3.1. Results

Speech transcriptions are used as queries on a QBE retrieval scenario. The first set of experiments uses CNET reviews [13]. We consider three retrieval database scenarios: (1) full text articles, (2) speech transcripts from the video clip, and (3) regularized transcripts. For the second set of experiments we use the YouTube video reviews collected by [15, 12]. In this dataset there is no corresponding text article associated with the videos. Hence, we consider retrieval experiments on speech transcripts data, and on regularized transcript features. Standard information retrieval metrics [?] are used to assess performance. Table 2 shows mean average precision (mAP) for each scenario. Summarizing retrieval precision in a single number. Figure 3 shows precision for all values of  $K$  on each experiment.

**CNET:** Regularization of the speech transcripts achieves a gain of 14% relative to the non-regularized transcripts, raising

mAP from 0.55 to 0.62. “Transc.<sub>reg</sub>” features are around 9% below the upper bound mAP achieved when retrieving on the full text articles; we note, however, that the full article reviews are seldom available in real life applications. From Figure 3a one sees that the overwhelming gain on precision comes from lower values of  $K$ . This favors a scenario where people only look at the first few results of a query.

**YouTube:** Retrieval accuracy for the YouTube dataset is shown on the rightmost column of Table 2. Note that only one modality exists in this dataset. It is worth mentioning the higher mAP for transcriptions obtained for this dataset as compared to the previous dataset. This is likely due to the more lenient reviews made by CNET professionals. The same operators learned with CNET data are used here to achieve regularized transcript features. For the weighting we use the search strategy introduced in section 2.3. The mAP gains are relatively (5.5%) more modest when compared to the previous experiment, going from 0.69 to 0.73. As for the precision@K curve of Figure 3b we see the same (good) effect as before, i.e. higher gains for lower values of  $K$ .

## 4. CONCLUSIONS AND FUTURE WORK

More recent works in sentiment analysis show benefits in joining several sources of information [12]. We present a learning framework that transfers knowledge across modalities, and show that this improves accuracy of similar-sentiment retrieval. Benefits are achieved in the overall average precision, more specifically for lower values of retrieved documents. As noted by [18], ignoring word order in the treatment of a semantic task is not plausible, and it may result in serious damage of sentiment analysis in hard cases of negation. In the future, it is planned the extension of this sentiment analysis framework in order to accommodate more modalities, e.g. acoustic and visual related features, and to explore text articles at the sentence level with a coherent analysis transferred to the whole document.

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