A LDA-Based Topic Classification Approach from Highly Imperfect Automatic Transcriptions

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Abstract

Although the current transcription systems could achieve high recognition performance, they still have a lot of difficulties to transcribe speech in very noisy environments. The transcription quality has a direct impact on classification tasks using text features. In this paper, we propose to identify themes of telephone conversation services with the classical Term Frequency-Inverse Document Frequency using Gini purity criteria (TF-IDF-Gini) method and with a Latent Dirichlet Allocation (LDA) approach. These approaches are coupled with a Support Vector Machine (SVM) classification to resolve theme identification problem. Results show the effectiveness of the proposed LDA-based method compared to the classical TF-IDF-Gini approach in the context of highly imperfect automatic transcriptions. Finally, we discuss the impact of discriminative and non-discriminative words extracted by both methods in terms of transcription accuracy.

Keywords: Speech analytics; Topic identification; Latent Dirichlet Allocation

1. Introduction

The application considered in this paper concerns the automatic analysis of telephone conversations between an agent and a customer in a customer care service of the Paris transportation system. The agent follows a conversation protocol to address customer requests or complaints. One purpose of the application is to identify themes that appear in the conversation. A conversation may contain more than one semantically related theme, but not all of them are relevant for the application task. For example, a customer may inquire about an object lost on a transportation mean that was late. In such a case, the loss is a much more relevant theme than the traffic state. In this situation, agents annotate a conversation with what they consider the major theme of the customer request. This leads to annotate a theme for each conversation.

This paper presents a system for the automatic extraction of themes from conversations acquired during the daily operation of a call centre in Paris. The system generates hypotheses about the most relevant theme of each conversation. The major difficulty of this classification task concerns the unpredictable behavior of the customers. Conversations may contain very noisy segments and are decoded by an Automatic Speech Recognition (ASR) component. In the context of Information Retrieval (IR) tasks, the main feature used is the word term frequency. This specific feature allows to obtain a subset of discriminative words for a considered class (a “theme” in this study). The term “discriminative” is associated to a word if it permits to discern a class from the others. Finally, this set of discriminative words should permit to compose a vector representation of conversation themes in the semantic space.

While the term frequency is a performant feature in the context of manually written texts, its application to automatic transcriptions seems to be more difficult since transcription errors are inevitable. Indeed, these errors would lead to an incorrect representation of the discriminative words. For this reason, the projection of the automatically transcribed words in a more abstracted space could increase the robustness to the ASR errors.

In this paper, we propose to compare two unsupervised representations of discriminative words to automatically identify themes of telephone conversations in different configurations of highly imperfect transcriptions. The classical Term Frequency-Inverse Document Frequency with Gini purity criteria (TF-IDF-Gini) method (Robertson, 2004) is firstly applied to extract discriminative words for each theme to identify from transcriptions. We secondly propose to explore a topic space representation of discriminative words with the use of the Latent Dirichlet Allocation (LDA) approach (Blei et al., 2003). Each representation is finally used to train a Support Vector Machine (SVM) classifier to automatically associate a theme to a conversation. We also propose in this article a discussion about the classification performance impact of discriminative and non-discriminative words chosen by both methods in terms of transcription accuracy.

2. Related work

Recent reviews for spoken conversation analysis, speech analytics, topic identification and segmentation can be found in (Tur and De Mori, 2011), (Melamed and Gilbert, 2011), (Hazen, 2011) and (Purver, 2011) respectively. The classical Term Frequency-Inverse Document Frequency (TF-IDF) (Robertson, 2004) has been widely used for extracting discriminative words from texts. Works also found improvements associating TF-IDF with the Gini purity criteria (Dong et al., 2011).

Other approaches proposed to consider the document as a mixture of latent topics. These methods, such as Latent Semantic Analysis (LSA) (Deerwester et al., 1990; Bellegard, 1997), Probabilistic LSA (PLSA) (Hofmann, 1999) or Latent Dirichlet Allocation (LDA) (Blei et al., 2003), build a higher-level representation of the document in a topic space. All of these methods are commonly used in the Information Retrieval (IR) field. They consider documents as a bag-of-words (Salton, 1989) without taking ac-
count of word order; nevertheless, they demonstrated their performance on various tasks.

LDA is a generative model which considers a document, seen as a bag-of-words, as a mixture probability of latent topics. In opposition to a multinomial mixture model, LDA considers that a theme is associated to each occurrence of a word composing the document, rather than associate a topic with the complete document. Thereby, a document can change of topics from a word to another. However, the word occurrences are connected by a latent variable which controls the global respect of the distribution of the topics in the document. These latent topics are characterized by a distribution of word probabilities which are associated with them. PLSA and LDA models have been shown to generally outperform LSA on IR tasks (Hofmann, 2001). Moreover, LDA provides a direct estimate of the relevance of a topic knowing a word set.

Support Vector Machines (SVM) are a set of supervised learning techniques. Knowing a sample, SVMs determine a separation plan between parts of the sample called support vector. Then, a separating hyperplane that maximizes the margin between the support vectors and the hyperplane separator (Vapnik, 1963) is calculated. SVMs were used for the first time by (Boser et al., 1992) both in regression (Müller et al., 1997) and in classification (Joachims, 1999) tasks. The SVM popularity is due to the good results achieved in these two specific tasks and the low number of parameters requiring adjustment.

A LDA-based approach combined with a SVM classification process has recently been studied in various domains, such as biology (hua Yeh and hsing Chen, 2010), text classification (Zrigui et al., 2012), stylometry (Arun et al., 2009), audio information retrieval (Kim et al., 2009), social event detection (Morchid et al., 2013a) or image detection (Tang et al., 2009). To our knowledge, a combined LDA-SVM approach has not yet been applied to theme classification of highly imperfect automatic transcriptions but was used in the context of keyword and keyphrase extraction in automatic transcriptions (Sheeba and Vivekanandan, 2012). The TF-IDF extraction method coupled with a SVM classification, which constitutes our baseline system, has been widely studied in text classification such as (Lan et al., 2005; Georgescul et al., 2006).

3. Theme identification methods

This section presents the proposed theme classification system using discriminative words extracted from highly imperfect transcriptions. The system is composed of two main parts. The first one creates a vector representation of words with two different unsupervised approaches: a term frequency Okapi/BM25 vector (Robertson, 2004) with the TF-IDF-Gini method (Dong et al., 2011) and a topic space representation with the LDA approach (Blei et al., 2003). The second part uses the extracted vectors to learn SVM classifiers. Figure 1 presents the global architecture of the proposed classification system using manual (TRS) and automatic (ASR) transcriptions.

Figure 1: General approach of the classification system.

3.1. Description of dialogue features

To perform the classification task, a features representation of each dialogue is needed. Thus, the next sections describe two different representations of a dialogue using a discriminative terms list and a topic space.

3.1.1. Discriminative terms

Let’s consider a corpus \(D\) of dialogues \(d\) with a word vocabulary \(V = \{w_1, \ldots, w_N\}\) of size \(N\) where \(d\) is seen as a bag-of-words (Salton, 1989). A term of \(V\) is chosen according to its importance \(\delta_t\) in the theme \(t\) by calculating its Term Frequency (TF), its Inverse Document Frequency (IDF) (Robertson, 2004) and the Gini purity criteria (Dong et al., 2011) that is common for all the themes. This set of scores \(\delta\) composes the frequency model \(f\):

\[
\delta_t^w = tf_t(w) \times idf_t(w) \times gini_t(w)
\]

Then the words with highest scores \(\Delta\) for all themes \(\mathbf{T}\) are extracted and constitute a discriminative word subset \(V_\Delta\) (each theme \(t \in \mathbf{T}\) has its own score \(\delta_t\)) and its own frequency \(\gamma\) in the model \(f\) (Morchid et al., 2013b):

\[
\gamma_f = \frac{\#d \in t}{\#d \in D}
\]

Note that a same word \(w\) can be present in different themes, but with different scores (TF-IDF-Gini) depending of its relevance in the theme:

\[
\Delta(w) = P(w|f) = \int P(w|t)P(t|f) dt = \sum_{t \in \mathbf{T}} P(w|t)P(t|f) = \sum_{t \in \mathbf{T}} \delta_t^w \times \gamma_f = \left\langle \delta, \gamma_f \right\rangle
\]

3.1.2. Semantic representation

For each dialogue \(d \in D\), a semantic feature vector \(V_d^\gamma\) is determined. The \(n^{th}\) (\(1 \leq n \leq |V_\Delta|\)) feature \(V_d^\gamma[n]\), is composed with the number of occurrences of the word
binary classifier
together binary classifiers
kernel for every pair of distinct theme. As a result, all to-
denotes the number of themes and
method (Yuan et al., 2012). For this multi-theme problem,
gives a better testing accuracy than the
method is chosen with a linear kernel. This method
sations requires a multi-class classifier. The
in this part, classifiers are trained with the vector represen-

3.1.3. Topic representation
The topic representation is performed using a Latent
Dirichlet Allocation (LDA) based approach (see section 2.).
A thematic space \( m \) of \( n \) topics is then obtained with, for
each theme \( z \), the probability of each word \( w \) of \( V \) knowing
\( z (P(w|z) = V^w) \) and for the entire model \( m \), the
probability of each theme \( z \) knowing the model \( m \) (\( P(z|m) = V^z \)).
For every dialogue \( d \) of a corpus \( D \), a first parameter \( \theta \) is
drawn according to a Dirichlet law of parameter \( \alpha \). A second
parameter \( \phi \) is drawn according to the same Dirichlet
law of parameter \( \beta \). Then, to generate every word \( w \) of
the document \( d \), a latent topic \( z \) is drawn from a multinomial
distribution on \( \theta \). Knowing this topic \( z \), the distribution of
the words is a multinomial of parameters \( \phi \). The parameter
\( \theta \) is drawn for all the documents from the same prior pa-
rameter \( \alpha \). This allows to obtain a parameter binding the
documents all together (Blei et al., 2003).

Mapping of conversations/topic space
The Gibbs sampling algorithm (Griffiths and Steyvers,
2002) was used to infer a dialogue \( d \) with the \( n \) topics of
the thematic space \( m \). This algorithm is based on the
Markov Chain Monte Carlo (MCMC) method. Thus, the
Gibbs sampling allows to obtain samples of the distribution
parameters \( \theta \) knowing a word \( w \) of a test document and a
given topic \( z \). A feature vector \( V^d_\theta \) of the topic represent-
of \( d \) is then obtained. The \( k^{th} \) feature \( V^d[k] \) (where
1 \( \leq k \leq n \)) is the probability of the topic \( z_k \) knowing the
dialogue \( d \):

\[
V^d[k] = P(z_k|d)
\]  

3.2. SVM classification
In this part, classifiers are trained with the vector representa-
tion of words to automatically assign the most relevant
theme to each conversation. The classification of conversa-
tions requires a multi-class classifier. The one-against-
one method is chosen with a linear kernel. This method
gives a better testing accuracy than the one-against-rest
method (Yuan et al., 2012). For this multi-theme problem,
\( T \) denotes the number of themes and \( t_i, i = 1, \ldots, T \) de-
notes the \( T \) themes. A binary classifier is used with a linear
kernel for every pair of distinct theme. As a result, all to-
gether binary classifiers \( T(T - 1)/2 \) are constructed. The
binary classifier \( C_{i,j} \) is trained from example data where
\( t_i \) is a positive class and \( t_j \) a negative class (\( i \neq j \)).
For a new vector representation (semantic eq. 2 or topic
eq 3) of a dialogue \( d \) from the test corpus, if \( C_{i,j} \) means that
\( d \) is in the theme \( t_i \), then the vote for the class \( t_i \) is added
by one. Otherwise, the vote for the theme \( t_j \) is increased
by one. The dialogue \( d \) is finally assigned with the theme
having the highest number of votes.

4. Experiments
The next sections describe the experimental protocol and evaluate both dialogue representations and classification
methods. Furthermore, a short study gives some interesting
perspectives for WER consideration and determination
knowing a task.

4.1. Experimental protocol
In order to perform experiments on the conversation theme
identification, the corpus of the DECODA project was
used (Bechet et al., 2012). This corpus is composed of
1,067 telephone conversations split into a train set (740 di-
alogues) and a test set (327 dialogues), and manually
notated with 8 conversation themes: problems of itinerary,
lost and found, time schedules, transportation cards, state
of the traffic, fares, infractions and special offers.

The train set is used to compose a subset of discriminative
words (section 3.1.). This set allows to elaborate a semantic
space for each conversation of the test corpus with the
basic TF-IDF-Gini method. In the experiments, the num-
er of discriminative words has been varied from 800 to the
total number of words contained in the train corpus (7,920
words). The test corpus contains 3,806 words (70.8% occur-
in the train corpus).

In the same way, a topic vector is calculated by mapping
each dialogue of the test corpus with each topic space.
A set of 25 topic spaces with a different topic number
\((\{5, \ldots, 600\})\) is elaborated by using a LDA model in the
train corpus (example: test = TRS \( \rightarrow \) LDA train corpus =
TRS). The topic spaces are made with the Mallet Java im-
plementation (McCallum, 2002) of LDA.

Then, for both configurations (semantic or topic vector), a
SVM classifier is learned with the LIBSVM library (Chang
and Lin, 2011). SVM parameters are optimized by cross
validation on train corpus.

The LIA-Speeal ASR system is used for the experi-
ments (Linarès et al., 2007). This system results in an
overall Word Error Rate (WER) of 45.8% (train set) and
of 58.0% (test set). These high error rates are mainly due to
speech disfluencies and to adverse acoustic environments.
A “stop list” of 126 words\(^1\) was used to remove unneces-
sary words which results in a WER of 33.8% (train set) and
of 49.5% (test set).

Experiments are conducted with the two unsupervised
methods (TF-IDF-Gini / LDA) on the manual (TRS) and
the automatic transcriptions only (ASR). We also propose
to study the combination of both manual and automatic
transcriptions (TRS+ASR) in order to see if ASR errors can
be supplied by the correct reference words.

4.2. Theme classification performance
Figure 2 presents the theme classification accuracy ob-
tained by the TF-IDF-Gini and the LDA approaches on the
test corpus for all transcription configurations (TRS/ASR)
when varying the word extraction conditions (number of
discriminative words and number of topics). We can see
that the LDA-based method outperforms the best theme
classification accuracies obtained by the TF-IDF-Gini ap-
proach (see table 1).

As expected, the TRS train / TRS test configuration
(TRS \( \rightarrow \) TRS) gives the best classification results with a

\(^1\)http://code.google.com/p/stop-words/
Figure 2: Theme classification performance by varying the number of discriminative words (a) and the number of topic spaces (b).

Figure 3: Word Error Rate of the $n$ most discriminative words using TF-IDF-Gini (a) and LDA (b) approaches.

| DATA          | BEST ACCURACY (%) |
|---------------|-------------------|
| Train | Test | #words | TF-IDF-Gini | Topics | LDA  |
| TRS    | TRS   | 800     | 79.7        | 100    | 86.6 |
| TRS    | ASR   | 8000    | 69.7        | 40     | 77.0 |
| ASR    | ASR   | 800     | 73.5        | 60     | 81.4 |
| ASR+TRS | ASR   | 2400    | 72.2        | 100    | 78.7 |

Table 1: Theme classification accuracy (Confidence interval of ±3.69% for the LDA system)

gain of 6.9 points with the LDA method. When comparing the training corpus types, we can also note that best performance on the ASR test is obtained with the ASR training data. A gain of 10.9 points is noted with the LDA method compared to the TF-IDF-Gini approach on the automatic transcriptions of conversations. It seems clear that using comparable training and testing configurations allows to achieve the best classification performance, whether it be on manual or on automatic transcriptions.

We can finally note that the LDA approach performance has a tendency to fluctuate when varying the number of topics. This could be explained by the high Word Error Rate (WER) of the targeted corpus: indeed, the words chosen as discriminative in particular topic number conditions could be wrongly transcribed in a high proportion. We can support this assumption by analyzing results obtained using 90 topics on the figure 2. An important performance drop is observed for the ASR training conditions (ASR $\rightarrow$ ASR and ASR $\rightarrow$ TRS) while a smaller performance lost is seen when including the reference transcriptions during the training process (ASR+TRS $\rightarrow$ ASR and TRS $\rightarrow$ TRS).

4.3. Transcription accuracy of discriminative words

While the performance with the TF-IDF-Gini approach is clearly better on manual transcriptions (table 1), the performance is almost identical on manual and on automatic transcriptions with the LDA method (respectively 86.6% and 81.4% of classification accuracy). We think that the LDA-based approach can better manage the errors contained in the automatic transcriptions by choosing discriminative words depending on their transcription accuracy. Figure 3 compares the Word Error Rates (WER) of the $n$
most discriminative words using TF-IDF-Gini and LDA approaches on all the configurations (TRS/ASR). The score \( s(w) \) used to find the most relevant words for the LDA approach is computed with:

\[
s(w) = P(w|m) = \int_z P(w|z)P(z|m)\,dz = \sum_{z\in m} P(w|z)P(z|m) = \sum_{z\in m} V^w_z \times V^z_m = \left\langle V^w, V^m \right\rangle
\]

where \( V^w \) is the vector representation of a word \( w \) in all topics \( z \) of the topic space \( m \), \( V^m_z \) is the vector representation of all the topics \( z \) in \( m \) and \( \langle \cdot, \cdot \rangle \) is the inner product. The WER is then classically computed on the most discriminative words (weight of 1 for each word).

If we firstly compare the different configurations (TRS/ASR), we can note that the higher the theme classification accuracy is (table 1), the lower the WER is. This can be observed on both methods. More, we can see that the WER obtained with the LDA approach is slightly lower than the one obtained with the TF-IDF-Gini method, no matter the configuration considered. This means that a better transcription accuracy is associated to the discriminative words extracted with the LDA approach in comparison to the one obtained with the TF-IDF-Gini method, which could explain the higher classification performance reached by the LDA-based configuration.

5. Conclusions

In this paper, we presented an architecture to identify conversation themes from highly imperfect transcriptions using two different conversation representations coupled with a SVM classification step. We shown that the proposed topic representation using a LDA-based method outperforms the classification results obtained by the classical TF-IDF-Gini approach. The classification accuracy reaches 86.6% on manual transcriptions and 81.4% on automatic transcriptions with a respective gain of 6.9 and 10.9 points.

We also discussed the possible link between classification performance and transcription accuracy. The proposed analysis showed that the best classification results are obtained on configurations which extract the discriminative words having a lower Word Error Rate. The promising observations will lead to a more detailed qualitative study in a future work. Indeed, this preliminary study could be greatly extended with new analysis by taking into account, for example, the discriminative word weights in the transcription accuracy evaluation. A general perspective would be to propose a solution to estimate the classification performance depending on the transcription accuracy. In the context of evaluation metrics, it would also be interesting to find another way to estimate the accuracy of automatic transcriptions in the context of a specific task since the classical WER is not a good indicator of transcription quality in an applicative context.

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