Dialog Act classification using utterance embeddings

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Abstract

Traditionally, automatic Dialog Act Tagging has been based on training machine learning classifiers using hand-crafted features extracted from data. In this work, we experiment with a new feature representation for dialog act tagging by learning distributional embeddings for utterances. We train a distributional semantic model that allows us to infer vector representations for entire utterances and use them to train several classifiers in order to tag utterances in the Switchboard corpus.

1 Introduction

Discourse structure analysis is essential for understanding spontaneous dialogs and developing human-computer dialog systems. An essential part of discourse structure analysis is the identification of dialog act classes (e. g. *questions*, *self-talks*, *statements*, *backchannels*). As defined by Austin (1962), dialog acts present linguistic abstractions of the illocutionary force of speech acts and model the communicative intention of an utterance in a conversation. There are several tasks that have dialog acts as an input for their computations. Examples of these include speech recognition, speech synthesis, summarization, and of course, human-machine dialog systems. As a result, correctly identifying dialog act tags is fundamental for such tasks.

Table 1 shows an example of dialog acts from the Switchboard corpus we are trying to classify. The table already gives an idea that some of the 43 dialog acts might have a rather closed set of possibilities (e.g. the classes Agree or Acknowledge) whereas classes like Statement can contain any content. Although the individual words in an utterance are important cues, we argue that the meaning of an utterance as a whole is essential for tagging it correctly.

Tag	Speaker / Utterance
Wh-Question	A: how old is your daughter?
Statement-non-opinion	B: she's three.
Summarize	oh , A: so she's a little one.
Agree	B: yes.
Acknowledge	A: yeah.
Statement-non-opinion	B: she's, she's little.

Table 1: SWDA dialog excerpt.

For the purpose of this work, we extract feature representations for entire utterances in an unsupervised fashion. For that we build a distributional semantic model that learns vector representations for entire utterances and then use these vector features as inputs for different machine learning classifiers, expecting that the embeddings can model the meaning of an entire utterance. Several techniques can be used for mapping text units to a high dimensional real value space. Utterance embeddings have the attractive property of representing an entire textual sequence as a vector while taking word order into account, as opposed to the classical *Bag-of-words* approach in which word order is not preserved and in which resulting vectors show no semantic relations. We expect this encapsulated extra information to play an important role in the classification task. In order to infer those embeddings we use the *paragraph2vec* framework recently introduced by (Le and Mikolov, 2014), which is based on the previous word embedding models by (Mikolov et al., 2013).

For the actual dialog act tagging we treat the problem as a multi-class classification task and classify utterances both in isolation as well as in the context of the previous utterances. We evaluate the tagging accuracy and compare different models. Besides the baselines set up by previous work, we compare the results against a simple baseline that uses a bag-of-words (BOW) representation for each utterance.

The outline of this report is set as follows: in Section 2, we present relevant approaches that aim

at classifying dialog acts and briefly describe their main characteristics and results. In Section 3, we specify the datasets used in our experiments, present the model to infer utterance embeddings and we detail the properties of our classification pipeline. An exhaustive analysis of the results of the experiments is presented in Section 4. Finally, Section 5 includes conclusions drawn from this work as well as issues and future work. [LQ: check]

2 Related Work

Several approaches have been proposed for classifying dialog acts. Most of them rely on supervised trained models, and use hand crafted features extracted for all utterances. Some recent work shows that using distributional representations for dialog act classification outperforms these methods. We briefly present some of the most relevant work in this section.

The authors of Stolcke et al. (2000) predict dialog acts by modeling a conversation as a Hidden Markov Model (HMM). A sequence of dialog acts is represented as a *discourse model* where the probability of the next dialog act depends on the *n* previous dialog acts. They integrate this model with a *language model* for each separate dialog act, which computes the possibility of the occurrence of all *word n-grams* in an utterance given a certain dialog act tag. In Stolcke et al. (2000) models are also trained on the actual speech signals, where the 'language model' is trained on prosodic and acoustic evidence. [DW: do we need to tell this last bit?] When considering the models trained on the dialog transcripts we can see that in this an utterance is represented as a bag of n-grams. We will try to find a representation that captures the composition of an utterance in a better way.

In Kalchbrenner and Blunsom (2013) a Recurrent Convolutional Neural Network (RCNN) is trained in a supervised manner on a corpus, which achieves state of the art results on the dialog act tagging task. The RCNN learns both a *discourse model* and a *sentence model* from a specific corpus, where the utterance representation is derived from individual word vectors, which are chosen randomly. We feel that this representation can become a lot richer if it is learned as in Le and Mikolov (2014), where word vectors have some distributional meaning. Another strength of this approach is that it is possible to train these utterance embeddings in an unsupervised manner, making it possible to additional, possibly unannotated, corpora.

An investigation on the contribution of distributional semantic information to the dialog act tagging task was conducted in Milajevs and Purver (2014). It was found that such information did improve tagging when compared to simple bag of words approaches. However only very simple distributional representations were investigated in this research, words were represented as a vector of their co-occurrences. Utterances as point wise multiplications or additions of these vectors, which implicates the loss of any compositional features. The work of Milajevs and Purver (2014) was not able to outperform the earlier work on dialog act tagging presented before.

In our work we will use the same *discourse model* as Stolcke et al. (2000) and represent the entire dialog as an HMM. However for our *sentence model* we will train different classifiers based on the embeddings, which are learned using the techniques from Le and Mikolov (2014). We will explain how we construct utterance embeddings in the next section. In section 4 we explain how we use these representations to build a *sentence model* as well and briefly repeat the *discourse model* as an HMM.

[DW: This ok?] [RW: I agree. And then this can serve as a transition to the utt2vec explanation in the next section.]

3 Utterance Embeddings

[RW: This section still contains some redundant parts and needs to be restructured.] [DW: I did a first attempt at fixing it, but it still needs some (small) updates]

3.1 Word Embeddings

Neural networks for distributional semantics has gained relevant importance in the past years since the publication of the first neural network word embedding models. One of the main reasons for that was the discovery that dense high-dimensional vector representations of words are able to capture semantic relations between words Mikolov et al. (2013). Figure 1 shows a typical example where simple vector addition and subtraction lead to analogies such as, the vector difference between *woman* and *man* is the same as between

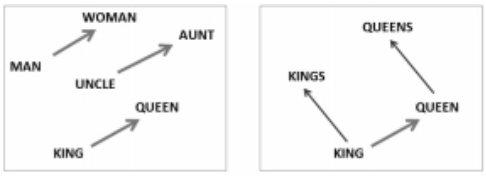

Figure 1: Word2vec semantic relations.

aunt and *uncle*.

In distributional semantic models, word embeddings are learned by predicting words within a context of other words. Based on the fact that similar words occur in similar contexts, these models are capable of successfully representing words in high-dimensional vectors Mikolov et al. (2013).

Originally, these networks had two main architectures, know as *Continuous-bag-of-words* and *Skip-gram*. In the first case, the networks were optimized to predict the next word given its context, while in the latter, the context is predicted given a certain word. Due to word co-occurrences, these models are able to effectively capture the meaning of the words.

3.2 Paragraph embeddings

The approach from Mikolov et al. (2013) is no longer feasible on a sentence level, as the vocabulary of all observed sentences is larger [DW: isn't it infinitely large? as we can construct a sentence of any lenght?] than the word-based vocabulary leading to sparse contexts. Therefore, a slightly different neural network approach for learning representations of sentences has been proposed by (2014), in which sentence vectors are learned from the words within the sentences. In this case, sentence embeddings are trained together with word embeddings. The latter are shared for the entire model.

In this case, two structures are maintained one for words, and one for sentence representations. The word structure is shared across all sentences, while the sentence structure is only valid for the current paragraph. The training task is the same as before: given a certain window, the model is optimized to predict the missing word. However this time, the context representation is constructed using the individual word vectors together with the paragraph vector. This training schema is called *Paragraph Vector Distributed memory (PV-DM)*, and it is the one we use to train our model. Figure 2 shows the *PV-DM* architecture.

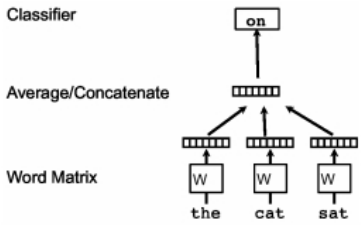

Figure 2: Paragraph vector PV-DM architecture.

This model makes it possible to map word sequences of any length to vectors of fixed dimensionality. Moreover, its unsupervised nature allows any unannotated corpus to be used for training.

Once the model is trained, it can be queried in order to get the vector representations for each previously seen sentence. It can also be used to *infer* vector mappings of *unseen* sentences. This second step will be crucial to get representations for utterances in our test dataset.

The approach presented by Le and Mikolov (2014) has two very nice advantages. Firstly it is completely unsupervised, and thus, we can use any amount of unannotated data that is available.

[DW: i dont think we need this as a spererate subsubsection? but alternatively merge the previous and next paragraph talking about the advantages of the model]

Moreover we can use pretrained word embeddings. This can be summarized as follows: (a) No new words are added to the vocabulary; (b) Intersecting words adopt pretrained values ; (c) Non intersecting words are left alone. [DW: maybe explain this a bit better/more in depth?] For our experiments, we try different alternatives, training word and paragraph embeddings from scratch using several different dialog corpora as input, and also using freely available pretrained word embeddings[1]. In the next section we specify the different ways and corpora we used for learning utterance embeddings. [DW: this ok?]

4 Methodology

[DW: This needs a brief introduction with set up of this section]

[1] https://code.google.com/p/word2vec/

4.1 Dialog datasets

[LQ: Describe the switchboard corpus. It's 42 tags.] [LQ: Describe the BNC corpus.] Throughout the classification pipeline, we make use use different dialog corpora. With the purpose of training word embedding models, options include training using a combination of: the Switchboard corpus, the British National corpus, and pretrained word vectors.

For the evaluation step is mandatory to utilize labelled data, for this reason, we train and evaluate our classifiers on the Switchboard corpus. We divide the dataset into a training and a test set, containing % and % of the total length, respectively. [LQ: add percentages]

In the next subsections we present a description of each dataset.

The Switchboard corpus

The Switchboard Dialog Act corpus (SwDA) consists of a compilation of telephone transcripts between two interlocutors. It contains a total 205.000 utterances and 1.4 million words While many features are defined for each utterance unit, the most important for our work is the tag attribute. Each utterance is associated to a label, which summarizes syntactic, semantic, and pragmatic information. The corpus contains a total of 200 tags, which can be further aggregated into 44 main classes. Table 2 shows examples for the five most common tags. Table 3 present examples of utterances contained in the SwDA corpus.

[LQ: add cite to SWDA]

Tag	Description	Example	%
st	Statement-non-opinion	Me, I'm in the legal department.	36
b	Acknowledge	Acknowledge Uh-huh.	19
sv	Statement-opinion	I think it's great.	13
aa	Accept	That's exactly it.	5
%	Turn exit	So,-	5

Table 2: SWDA's 5 most frequent tags.

The British National corpus

The British National corpus (BNC) is a collection of 100 million words sampled from different written and spoken sources, with the intention of representing the British English language. Some of the sources of these data include newspapers, articles, journals, books, letter, transcription of informal conversations, among others. This dataset contains a huge amount of unlabelled sentences. Table 4 presents sentence examples extracted from the BNC.

qrr B.34.utt2: C or do you think that [we're, + we're,] F uh, all trying to keep up with a certain standard of living?
sv A.35.utt1: I think that's part of it too.
sv A.35.utt2: C But I do think, -
qy B.36.utt1: E I mean do you think,

Table 3: SwDA utterance examples.

ADR 172 The kind of girl that even if you didn't know well you always said "hello" to and got a cheery wave and a smile back.
B72 966 For example, the sedimentary rocks that form the top geological layer in much of southern Britain may be only a few hundred metres thick in a few isolated sites.
B2E 714 Then Fulham got one of her worst raids of the war.

Table 4: BNC sentence examples.

4.2 Discourse Model

[DW: Please check the following on readability]

Just like Stolcke et al. (2000) we will model a dialog as an HMM. The hidden states will be the dialog acts and the observed quantities the uttered words and their speaker. To find the most likely tag for a single utterance we will find the best dialog act tag t for an utterance using equation 1.

$$\begin{aligned} t^* &= \underset{t}{argmax} P(t|u) \\ &= \underset{t}{argmax} \frac{P(u|t)P(t)}{P(u)} \\ &= \underset{t}{argmax} \underbrace{P(u|t)}_{\text{sentence model}} \underbrace{P(t)}_{\text{discourse model}} \end{aligned} \quad (1)$$

We discuss the sentence model in detail in section 4.3. As a discourse model we will assume that the *prior probability* of a tag depends on the preceding tags and their speakers. $P(t_i) = P(t_i|t_{i-1}...t_0, s_{i-1}...s_0)$. Where we assume that the discourse is a Markov Model of order k: $P(t_i) = P(t_i|t_{i-1}...t_{i-k}, s_{i-1}...s_{i-k})$.

Different dynamic programming techniques can be used to find the most probable sequence of tags $\mathbf{t}$ given a sequence of utterances $\mathbf{u}$ and their

speaker s, we will use the Viterbi decoding algorithm Ryan and Nudd (1993).

[DW: the following could go to the discussion, but i think it is good to note these assumptions straight away] An assumption made in this model is that two sequential utterances u_i and u_{i+1} are independent of each other. We know that in conversation interlocutors tend to align on different levels including lexical choices Danescu-Niculescu-Mizil et al. (2012). Also it is very likely that the same words will be used in the answer to a question as in the question. However we count on the fact that the dependence of u_i and t_i will be stronger than the is stronger than the independence violation of u_i and u_{i+1} Stolcke et al. (2000).

4.3 Sentence Models

[DW: Do we want to do this before or after the discourse model?] [LQ: Mention which classifiers we use, and with which params]

5 Results

5.1 Evaluating Sentence Models

[DW: results from the huge table we have online, find a nice way to summarize this]

5.2 Intersecting Sentence and Discourse Models

[DW: Baseline]

[DW: Using 'best' sentence models from last subsection]

5.3 Error Analysis

Utterance embeddings have the property of encapsulating the meaning of utterances from the words that compose them; as with the case of word embeddings, these representations present appealing relations from which similar words (in a semantic sense) appear close by in the high dimension space. We being by extracting samples from the SwDA corpus belonging to clear unrelated tags, and applying dimensionality reduction to their vector representations and plotting the results in 2 and 3 dimensions. The sampled utterances belong to the following categories: *Wh-question*, *Thanking*, *Reject*, and *Apology*. Considering the words that are used in these kind of units, sample points should be clearly separated. The utterance embeddings were extracted using a 300-dimensional model trained on the SwDA corpus interjected with Google pretrained vectors. Figure 5 and Figure 6 show scatter diagrams of the utterance embeddings after applying PCA.

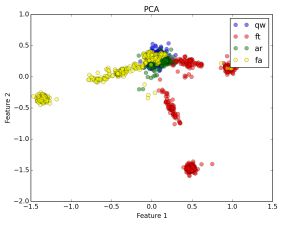

Figure 3: 2D PCA.

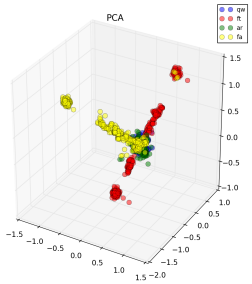

Figure 4: 3D PCA.

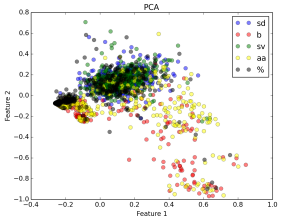

Figure 5: 2D PCA.

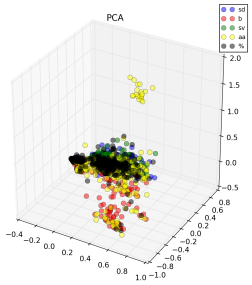

Figure 6: 3D PCA.

Though, the classification task seems easy considering the previous tag examples, it gets more complicated when we handle other utterance choices. Figure 5 and Figure 6 show the scatter diagram after applying PCA to utterance embedding of the 5 most frequent tags (*Statement-non-opinion*, *Acknowledge*, *Statement-opinion*, *Accept*, *Turn exit*), which account for 78% of the corpus.

6 Conclusion

- repeat results, what do they imply for hypotheses?
- criticisms to what we did
- possible future work
- ...

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