Deep Dialog Act Recognition using Multiple Token, Segment, and Context Information Representations

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Abstract

A dialog act is a representation of an intention transmitted in the form of words. In this sense, when someone wants to transmit some intention, it is revealed both in the selected words and in how they are combined to form a structured segment. Furthermore, the intentions of a speaker depend not only on her intrinsic motivation, but also on the history of the dialog and the expectation she has of its future. In this article we explore multiple representation approaches to capture cues for intention at different levels. Recent approaches on automatic dialog act recognition use Word2Vec embeddings for word representation. However, these are not able to capture segment structure information nor morphological traits related to intention. Thus, we also explore the use of dependency-based word embeddings, as well as character-level tokenization. To generate the segment representation, the top performing approaches on the task use either RNNs that are able to capture information concerning the sequentiality of the tokens or CNNs that are able to capture token patterns that reveal function. However, both aspects are important and should be captured together. Thus, we also explore the use of an RCNN. Finally, context information concerning turn-taking, as well as that provided by the surrounding segments has been proved important in previous studies. However, the representation approaches used for the latter in those studies are not appropriate to capture sequentiality, which is one of the most important characteristics of the segments in a dialog. Thus, we explore the use of approaches able to capture that information. By combining the best approaches for each aspect, we achieve results that surpass the previous state-of-the-art in a dialog system context and similar to human-level in an annotation context on the Switchboard Dialog Act Corpus, which is the most explored corpus for the task.

1. Introduction

In order to interpret its conversational partners’ utterances, it is valuable for a dialog system to identify the generic intention behind the uttered words, as it provides an important clue concerning how each segment should be interpreted. That intention is revealed by dialog acts, which are the minimal units of linguistic communication (Searle, 1969). Similarly to other text classification tasks, such as news categorization and sentiment analysis (Kim, 2014; Conneau, Schwenk, Barrault, & Lecun, 2017), most of the recent approaches on
dialog act recognition take advantage of different Neural Network (NN) architectures. In that context, and considering the findings of previous studies on dialog acts, there are three main aspects of the task to be explored. First, at what level should a segment be tokenized and how can those tokens be represented in order to provide maximum information? Then, how can those token representations be combined to generate a representation of the whole segment, while keeping information about the original tokens and the relations between them? Finally, how can relevant context information from different sources, such as the surrounding segments or the speaker, be combined with the segment representation to achieve the best possible performance on the task?

Not much effort has been put into the first aspect and most NN-based dialog act recognition approaches perform tokenization at the word-level and generate the token representations using pre-trained Word2Vec embeddings (Mikolov et al., 2013). This approach captures information concerning words that commonly appear together and is able to map semantic relations between different words in the embedding space. However, many dialog acts are related to word functions or segment structure, which this approach is not adequate to capture. Furthermore, there are cues for intention at a sub-word level, both in lemmas and affixes, as well as in word abstractions, such as syntactic units. However, none of these have been explored in previous studies.

The second aspect is that on which most variations between existing approaches occur. Multiple Deep Neural Network (DNN) architectures have been explored to combine the token representations into a single segment representation that captures relevant information for the task. Of the two state-of-the-art approaches on dialog act recognition, one uses a deep stack of Recurrent Neural Networks (RNNs) (Schmidhuber, 1990) to capture long distance relations between tokens (Khanpour et al., 2016), while the other uses multiple parallel temporal Convolutional Neural Networks (CNNs) (Fukushima, 1980) to capture relevant functional patterns with different length (Liu et al., 2017). Although these approaches focus on capturing different information, both have been proved successful on the task. Thus, an approach able to capture both kinds of information is expected to outperform both of these approaches.

Finally, concerning the third aspect, a dialog act is not only related to the words in a segment, but also to the whole dialog context. That is, the intention of a speaker is influenced by the dialog history, as well as the expectation of its future direction. Furthermore, it is also influenced by the speaker’s intrinsic characteristics. The latter are hard to capture and are usually not available for a dialog system. Thus, only speaker information that is directly related to the dialog, such as turn-taking (Liu et al., 2017), is typically considered. Concerning information from the surrounding segments, its influence, especially that of preceding segments, has been thoroughly explored in at least two studies (Ribeiro et al., 2015; Liu et al., 2017). However, in both cases, although it is one of its most important characteristics, that information was represented in ways that are not appropriate to capture its sequentiality.

In this article we use the Switchboard Dialog Act Corpus (Jurafsky et al., 1997), which is the most explored corpus for dialog act recognition, to study and compare different solutions concerning the three aspects. To do so, we focus on exploring different representations at the three-levels – token, segment, and context –, taking previous studies and the previously referred limitations into account.
In the remainder of the article we start by describing the Switchboard corpus and its
dialog act annotations in Section 2. Then, Section 3 provides an overview of related work
on dialog act recognition on that corpus using DNNs. In Section 4 we describe our exper-
imental setup, which defines a common ground for the multiple experiments in the study.
In Section 5, we start by exploring different segment representation approaches, since it is
the step that introduces higher variation in the network. Then, in Section 6, we explore
token representation at different levels. To conclude the experiments, in Section 7, we assess
the influence of context information on the task and explore different representations for
that information. Finally, Section 8 states the most important conclusions of this work and
provides pointers for future work.

2. Dataset

Switchboard (Godfrey et al., 1992) is a corpus consisting of about 2,400 telephone conver-
sations among 543 American English speakers (302 male and 241 female). Each pair of
speakers was automatically attributed a topic for discussion, from 70 different ones. Fur-
thermore, speaker pairing and topic attribution were constrained so that no two speakers
would be paired with each other more than once and no one spoke more than once on
a given topic. The Switchboard Dialog Act Corpus (Jurafsky et al., 1997) is a subset of
this corpus, consisting of 1,155 manually transcribed conversations, containing 223,606 seg-
ments. An excerpt of a transcription is shown in Figure 1. The corpus was annotated for
dialog acts using the SWBD-DAMSL tag set, which was structured so that the annota-
tors were able to label the conversations from transcriptions alone. It contains over 200
unique tags. However, in order to obtain a higher inter-annotator agreement and higher
example frequencies per class, a less fine-grained set of 44 tags was devised. As shown in
Table 1, the class distribution is highly unbalanced, with the three most frequent classes
– *Statement-opinion*, *Acknowledgement*, and *Statement-non-opinion* – covering 68% of the
corpus. The set can be reduced to 43 or 42 categories (Stolcke et al., 2000; Rotaru, 2002;
Gambäck et al., 2011), if the *Abandoned* and *Uninterpretable* categories are merged, and
depending on how the *Segment* category, used when the current segment is the continuation
of the previous one by the same speaker, is treated. By analyzing the data, we came to
the conclusion that merging segments labeled as *Segment* with the previous segment by the
same speaker is the best approach, since some of the attributed labels only make sense when
the segments are merged. Also, it makes sense to merge the *Abandoned* and *Uninterpretable*
categories, because both represent disruptions in the dialog flow, which interfere with the
typical dialog act sequence. There is also a 41-category variant of the tag set (Webb & Fer-
guson, 2010), which merges the *Statement-opinion* and *Statement-non-opinion* categories,
making this the most frequent class, covering 49% of the corpus. Jurafsky et al. (1997) report an average pairwise Kappa (Carletta, 1996) of .80, while Stolcke et al. (2000) refer to
an inter-annotator agreement of 84%, which we assume to be the average pairwise percent
agreement.

As previously stated, we selected this corpus for our experiments because it is the most
explored for the dialog act recognition task, since it contains a large amount of annotated
data which can lead to solid results. Furthermore, since its tag set is domain-independent,
the probability of drawing conclusions that depend on the domain of the corpus is reduced.
SPK A: Okay. /  
SPK A: {D So, }  
SPK B: [ { I guess, +  
SPK A: What kind of experience [ do you, + do you ] have, then with child care?  
SPK B: I think, ] + { F uh, } I wonder ] if that worked. /  
SPK A: Does it say something? /  
SPK B: I think it usually does. /  
SPK B: You might try, { F uh, } /  
SPK B: I don’t know, /  
SPK B: hold it down a little longer, /  
SPK B: { C and } see if it, { F uh, } -/  
SPK A: Okay <beep>. /  

Figure 1: An excerpt of a Switchboard Dialog Act Corpus transcription. Brackets are used to annotate different phenomena. Square brackets signal repetitions and corrections. Curly brackets signal disfluencies.

Stolcke et al. (2000) describe a data partition of the corpus into a training set of 1,115 conversations, a test set of 19 conversations, and a future use set of 21 conversations. In our experiments, we use the latter as a validation set.

3. Related Work

Dialog act recognition on the Switchboard Dialog Act Corpus has been widely explored using multiple machine learning approaches. The primordial approach by Stolcke et al. (2000) relied on Hidden Markov Models (HMMs) (Baum & Petrie, 1966) using word n-grams as features. This approach achieved 71.0% accuracy when applied to the manual transcriptions and 64.8% when applied to automatic transcriptions with 41% Word Error Rate (WER) on the test set. Since then, many other approaches have been explored. For instance, Rotaru (2002) used the k-Nearest Neighbors (k-NN) algorithm (Cover & Hart, 1967), with the distance between neighbors being measured as the number of common bigrams between segments. Sridhar et al. (2009) used a maximum entropy model combining lexical, syntactic, and prosodic features with context information from the surrounding segments. Webb and Ferguson (2010) applied a classification approach based on cue phrases, that is, phrases that are highly indicative of a particular dialog act. Gambäck et al. (2011) used Support Vector Machines (SVMs) (Cortes & Vapnik, 1995) with word n-grams, wh-words, punctuations, and context information from the preceding segments as features, together with an Active Learning (AL) approach to select the most informative subset of the training data. The article by Král and Cerisara (2010) provides an overview of most of these approaches.

Here, we focus on the most recent studies, which take advantage of DNNs. To our knowledge, the first to do so was that by Kalchbrenner and Blunsom (2013). The described
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| Label                      | Count | %  |
|----------------------------|-------|----|
| Statement-non-opinion      | 72,824| 36 |
| Acknowledgement            | 37,096| 19 |
| Statement-opinion          | 25,197| 13 |
| Agreement                  | 10,820| 5  |
| Abandoned                  | 10,569| 5  |
| Appreciation               | 4,663 | 2  |
| Yes-No-Question            | 4,624 | 2  |
| Non-verbal                 | 3,548 | 2  |
| Yes Answer                 | 2,934 | 1  |
| Conventional Closing       | 2,486 | 1  |
| Uninterpretable            | 2,158 | 1  |
| Wh-Question                | 1,911 | 1  |
| No Answer                  | 1,340 | 1  |
| Response Acknowledgement   | 1,277 | 1  |
| Hedge                      | 1,182 | 1  |
| Declarative Yes-No-Question| 1,174 | 1  |
| Other                      | 1,074 | 1  |
| Backchannel-Question       | 1,019 | 1  |
| Quotation                  | 934   | .5 |
| Summarization              | 919   | .5 |
| Affirmative Non-yes Answer | 836   | .4 |
| Action Directive           | 719   | .4 |

Table 1: Label distribution in the Switchboard Dialog Act Corpus (Jurafsky et al., 1997).

The approach uses a Hierarchical Convolutional Neural Network (HCNN) to generate segment representations from randomly initialized 25-dimensional word embeddings. Then, it uses a RNN-based discourse model that combines the sequence of segment representations with speaker information and outputs the corresponding sequence of dialog acts. By limiting the discourse model to consider information from the two preceding segments only, this approach achieved 73.9% accuracy on the test set.

Lee and Dernoncourt (2016) compared the performance of a Long Short-Term Memory (LSTM) unit against that of a CNN to generate segment representations from 200-dimensional Global Vectors for Word Representation (GloVe) embeddings (Pennington, Socher, & Manning, 2014) pre-trained on Twitter data. In order to generate the corresponding dialog act classifications, the segment representations were then fed to a 2-layer feed-forward network, in which the first layer normalizes the representations and the second selects the class with higher probability. In their experiments, the CNN-based approach consistently led to better results than the LSTM-based one. The architecture was also used to provide context information from up to two preceding segments at two levels. The first level refers to the concatenation of the representations of the preceding segments with that of the current segment before providing it to the feed-forward network. The second refers to the concatenation of the normalized representations before providing them to the output network.
The previous studies explored the use of a single recurrent or convolutional layer to generate the segment representation from those of its words. However, as stated in Section 1, the approaches which currently have top performance on the task explore the use of multiple of those layers. On the recurrent side, Khanpour et al. (2016) achieved their best results using a segment representation generated by concatenating the outputs of a stack of 10 LSTM units at the last time step. This way, the model is able to capture long distance relations between tokens. On the convolutional side, Liu et al. (2017) generated the segment representation by combining the outputs of three parallel CNNs with different context window sizes, in order to capture different functional patterns. In both cases, pre-trained word-embeddings were used as input to the network. Khanpour et al. (2016) compared the performance of embeddings with different dimensionality trained on multiple corpora using GloVe and Word2Vec (Mikolov et al., 2013). The best results were achieved when using 150-dimensional embeddings trained on Wikipedia data using Word2Vec. Liu et al. (2017) used 200-dimensional Word2Vec embeddings trained on Facebook data. Overall, from the reported results, it is not possible to state which is the top performing segment representation approach since the evaluation was performed on different subsets of the corpus. Still, Khanpour et al. (2016) reported 73.9% accuracy on the validation set and 80.1% on the test set, while Liu et al. (2017) reported 74.5% and 76.9% accuracy on the two sets used to evaluate their experiments.

Additionally, Liu et al. (2017) explored the use of context information concerning speaker changes and from the surrounding segments. The first was provided as a flag and concatenated to the segment representation. Concerning the latter, they explored the use of discourse models, as well as of approaches that concatenated the context information directly to the segment representation. The discourse models transform the model into a hierarchical one by generating a sequence of dialog act classifications from the sequence of segment representations. Thus, when predicting the classification of a segment, the surrounding ones are also taken into account. However, when the discourse model is based on a CNN or a bidirectional LSTM unit, it considers information from future segments, which is not available for a dialog system. Still, even when relying on future information,
the approaches based on discourse models performed worse than those that concatenated the context information directly to the segment representation. In this sense, similarly to our previous study using SVMs (Ribeiro et al., 2015), Liu et al. (2017) concluded that providing that information in the form of the classification of the surrounding segments leads to better results than using their words, even when those classifications are obtained automatically. Furthermore, both studies have shown that the first preceding segment is the most important and that the influence decays with the distance. Using the setup with gold standard labels from three preceding segments, Liu et al. (2017) achieved 79.6% and 81.8% on the two sets used to evaluate the approach.

4. Experimental Setup

In order to set a common ground for result comparison, we use the generic architecture shown in Figure 2, which is based on those of the top performing approaches referred to in Section 3. Below, we describe each of its components, as well as the training and evaluation procedures.

![Figure 2: The generic architecture of the network. $t_i$ corresponds to the $i$-th token.](image)

4.1 Embedding Layer

The input of the network is a tokenized segment, which is passed to an embedding layer. As a baseline, we perform the tokenization at the word level and do not use pre-trained word embeddings. Thus, the weights of the embedding layer are initialized randomly and updated along with the rest of the network. The resulting word embeddings are 200-dimensional as in the study by Liu et al. (2017). Different tokenization and embedding approaches are explored in Section 6.

4.2 Segment Representation

The segment representation step processes and combines the token embeddings to generate a vectorial representation of the segment. This is the step that introduces higher variability in the network and in which the main differences between previous dialog act recognition approaches occur. Initially, we reduce this step to a max pooling operation over the token
embeddings, that is, the representation of a segment is the area in the embedding space that contains it. Section 5 explores the use of the complex state-of-the-art approaches, as well as a Recurrent Convolutional Neural Network (RCNN)-based approach which has not been applied to the task before.

### 4.3 Dimensionality Reduction Layer

In order to avoid result differences caused by using representations with different dimensionality, the network includes a dimensionality reduction layer. This is a dense layer which maps the segment representations into a 100-dimensional space, as in the study by Liu et al. (2017). Furthermore, during the training phase, we use dropout with 50% probability in this layer, in order to reduce the probability of overfitting. Before passing the segment representation to this layer, additional features can be concatenated to it. The approaches described in Section 7 take advantage of this to provide context information to the network.

### 4.4 Output Layer

Finally, the output layer maps the 100-dimensional representation into a dialog act label. To do so, we use a dense layer with number of units equal to the number of labels. This layer uses the softmax activation to obtain the class probabilities. The class with higher probability is then selected for the segment. Since this is a multiclass classification problem, we use the categorical cross entropy loss function. Furthermore, for performance reasons, we use the Adam optimizer (Kingma & Ba, 2015).

### 4.5 Training & Evaluation

We used Keras (Chollet et al., 2015) with the TensorFlow (Abadi et al., 2015) backend to implement our networks. We used a fixed random seed to avoid result differences caused by different initializations. However, there is still some non-determinism introduced by the optimization of certain operations for running on Graphics Processing Unit (GPU). Thus, the results we present in this paper refer to the average (μ) and standard deviation (σ) of the results obtained by training and testing the networks over 10 runs. The mini-batch size was 512. The training phase stopped after 10 epochs without improvement on the validation set. In this sense, although we present results on both the validation and test sets, all the decisions were based on the results on the validation set. Considering the baseline described in this section, it achieves an average of 75.60% accuracy on the validation set and 71.78% on the test set.

### 5. Segment Representation

As stated in the previous section, the segment representation step is the one which introduces higher variability in the network. Consequently, it is where the main differences between previous dialog act recognition approaches occur. Thus, we start our study by exploring different approaches for this step. As stated in Section 3, of the two state-of-the-art approaches on dialog act recognition, one uses a RNN-based approach (Khanpour et al., 2016) for segment representation, while the other uses one based on CNNs (Liu et al., 2017). Both have their own advantages, as while the first focuses on capturing information from
relevant sequences of tokens, the latter focuses on the context surrounding each token and, thus, captures information concerning neighboring tokens. Concerning the task at hand, this is relevant since, among other aspects, while some dialog acts are distinguishable due to the order of the tokens in the segment (e.g. subject-auxiliary inversion in questions), others are distinguishable due to the presence of certain tokens or sequences of tokens independently of where they occur in the segment (e.g. greetings). Thus, and since the two approaches were not compared directly and were evaluated on different sets, we included both of them in our experiments. However, since each approach is expected to capture a different kind of information, but both kinds are relevant for the task, a third approach that merges at least some of the capabilities of the other two is expected to perform better on the task. That is exactly what the RCNN-based approach by Lai et al. (2015) was designed to do. This approach achieved state-of-art performance on text classification tasks, such as document topic classification and movie review rating, but was not applied to dialog act recognition before. Thus, we also included it in our experiments. The characteristics of each approach and our adaptations of their original versions are described below.

5.1 RNN-Based Segment Representation

As described in Section 3, the recurrent approach by Khanpour et al. (2016) uses a stack of 10 LSTM units. The segment representation is given by the concatenation of the outputs of the 10 LSTM units at the last time step, that is, after processing all the tokens in the segment. This process is shown in Figure 3. Using the output at the last time step instead of other pooling operation makes sense, since the recurrent units process the tokens sequentially. Thus, that output contains information from the whole segment. In our experiments we attempted to replace the LSTM units with Gated Recurrent Units (GRUs) (Chung et al., 2014), in order to reduce the amount of memory required. However, the results were not satisfactory. Furthermore, we attempted to use bidirectional LSTM units, but there were no benefits. Still, contrarily to what Khanpour et al. (2016) stated in their paper, we were able to improve the results by applying dropout with 50% probability to the input of each LSTM unit during the training phase.

5.2 CNN-Based Segment Representation

As described in Section 3, the convolutional approach by Liu et al. (2017) uses a set of parallel temporal CNNs with different window size, each followed by a max pooling operation. The segment representation is given by the concatenation of the results of the pooling operations. This way, the representation contains information concerning groups of tokens with different sizes. To achieve the results presented in their paper, Liu et al. (2017) used three CNNs with 100 filters and 1, 2, and 3 as context window sizes. In a previous study using the same architecture for different tasks, Kim (2014) used 3, 4, and 5 as window sizes. Both setups performed similarly in our experiments. However, their combination, that is, five parallel CNNs with window sizes between 1 and 5, led to better results, which means that both small and large groups of tokens provide relevant information. The process to generate a segment representation using this approach is shown in Figure 4.
5.3 RCNN-Based Segment Representation

As previously stated, the previous approaches focus on capturing different kinds of information, both of them relevant for the task. The RCNN-based approach by Lai et al.
(2015) combines some of the advantages of RNN- and CNN-based segment representation approaches in order to capture both kinds of information. This approach achieved interesting results on multiple text classification tasks but had not been applied to dialog act recognition yet. Thus, we included it in our study with some adaptations. One of its advantages is that it removes the need for selecting an appropriate context window size for convolution by using a bidirectional recurrent approach which captures context information from all the tokens that appear before and after each token. The embedding representation of each token is then extended by surrounding it with that context information. A linear transformation together with the tanh activation is applied to each of those token embeddings to reduce their dimensionality and normalize their representation. Finally, a max pooling operation is performed over the sequence of token representations to obtain the segment representation. As shown in Figure 5, we replaced the simple RNNs used to obtain token context information with GRUs, which are able to capture the importance of distant tokens. In our experiments we obtained the best results when using a GRU with a number of neurons in each direction equal to the dimensionality of the embedding space. We also explored the use of LSTM units, as well as of a stack of recurrent units to extract context information at different levels. However, that did not improve the results. Furthermore, we explored the use of different number of neurons in the token representation dimensionality reduction layer. In this aspect, the best results were achieved when using a number of neurons equal to the dimensionality of the embedding space. Finally, applying dropout with 50% probability to the input of each GRU also improved the results.

5.4 Results

In Table 2 we can see that the RNN and CNN approaches perform similarly, with a difference of .15 percentage points between average accuracy results on the validation set and .02 on the test set. However, it is important to refer that the training of the RNN approach is much more resource consuming than the CNN counterpart. It requires around 9 times more memory and each training epoch takes around 31 times longer.

|               | Validation | Test       |
|---------------|------------|------------|
|               | \(\mu\)   | \(\sigma\) | \(\mu\)   | \(\sigma\) |
| Max Pooling   | .7560      | .0019      | .7178      | .0024      |
| RNN           | .7625      | .0028      | .7274      | .0046      |
| CNN           | .7640      | .0024      | .7272      | .0036      |
| RCNN          | .7696      | .0021      | .7277      | .0026      |

Table 2: Accuracy results using different segment representation approaches.

Considering the RCNN approach, we can see that, as expected, it is able to improve the results of the remaining approaches. On the validation set, the improvement is of .56 percentage points. However, that improvement is not reflected on the test set. Still, the RCNN approach is that with lowest standard deviation results among the three, which suggests that the model is more stable and less prone to variation than those generated by the other approaches.
Figure 5: The RCNN-based segment representation approach. \( e_i \) corresponds to the embedding representation of the \( i \)-th token.

The average accuracy difference between the best approach and the much simpler max pooling baseline is just 1.36 percentage points on the validation set and .99 percentage points on the test set. These differences are not very expressive, which suggests that the overall improvement that can be achieved by improving the segment representation is reaching a saturation point and that improvement should be sought on the other steps.

Since the RCNN approach is that with best performance, we selected it for the segment representation step when exploring the approaches for the remaining steps described in the following sections.

6. Token Embedding

A segment is formed by multiple constituents. Thus, as shown in the previous section, its representation is obtained through a combination of the representations of those constituents. In this section we explore different means to represent those constituents or tokens. First, it is important to refer that, as revealed by the studies described in Section 3,
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A segment is typically seen as a sequence of words. However, it can be also be seen at other levels. For instance, from a finer-grained point of view, a segment can be seen as a sequence of characters. On the other hand, it can also be seen as a sequence of syntactic units, or other abstractions from words. Below, we explore these three levels. Since we are focusing on the multiple steps of dialog act recognition approaches using DNNs, we only approach embedding representations, that is, those that represent a token as a vector of coordinates in a certain embedding space (Lavelli et al., 2004).

6.1 Word-Level Embedding

As previously stated, segments are typically seen as sequences of words. Thus, there has been extensive research on means to generate word-embedding representations that capture relevant word semantics (Collobert et al., 2011; Mikolov et al., 2013; Pennington et al., 2014; Levy & Goldberg, 2014). In addition to the methods themselves, this effort has led to the generation of sets of publicly available pre-trained word embeddings, which can be used to obtain baseline or benchmark results. Below, we discuss which word-embedding approaches we used in our experiments and why they are relevant for the task. However, first, we explore the dimensionality of the embedding space, that is, the relation between ambiguity and sparseness.

6.1.1 Embedding Space Dimensionality

The dimensionality of the embedding space is the factor that defines the trade-off between ambiguity and sparseness. On the one hand, higher dimensionality leads to increased sparseness and memory requirements. At the limit, one can have dimensionality equal to the number of words in the vocabulary and use a one-hot approach to represent words. On the other hand, lower dimensionality leads to ambiguity in the representation. However, up to a certain level, ambiguity is not necessarily harmful. As stated in Section 3, Khanpour et al. (2016) explored embedding spaces with dimensionality 75, 150, and 300 together with different embedding approaches. In every case, the embedding space with dimensionality 150 led to the best results. Liu et al. (2017) used a different dimensionality value, 200, in their study. In our experiments we explored the use of the four different dimensionality values.

6.1.2 Pre-Trained Embeddings

As previously stated, there has been extensive research on means to generate word-embedding representations. The most common approaches are the Continuous Bag of Words (CBOW) model (Mikolov et al., 2013), commonly known as Word2Vec, and the GloVe (Pennington et al., 2014). Khanpour et al. (2016) used pre-trained embeddings using both approaches in their study and achieved their best results using Word2Vec embeddings trained on Wikipedia data. Liu et al. (2017) also used Word2Vec embeddings, but trained on Facebook data. Since we have access to the embeddings trained on Wikipedia data, but not to those trained on Facebook data, we used the first in our experiments.

The CBOW model generates word representations based on the co-occurrence of adjacent words. However, as previously stated, many dialog acts are related to the structure of the segment and not sequences of specific words. Thus, we also explored the dependency-
based embedding approach by Levy and Goldberg (2014), which takes that structure into account and not only word co-occurrences. It does so by introducing information concerning syntactic dependencies between words in the embedding generation process. First, it generalizes the Skip-Gram model (Mikolov et al., 2013) by allowing it to use arbitrary contexts instead of just those based on adjacent words. Then, it uses the syntactic contexts derived from automatically produced dependency parse-trees. That is, the embedding generated for a given word is based on the syntactic relations it participates in. Thus, embeddings generated using this approach seem appropriate for the dialog act recognition task. In our experiments we used the pre-trained set provided by Levy and Goldberg (2014), which was trained on Wikipedia data.

Using pre-trained embeddings typically leads to results that generalize better, since they are trained on large amounts of data and not only on a reduced set focused on a particular domain. However, this also means that their generation does not take their future use on a specific task into account. In their study, Liu et al. (2017) used pre-trained embeddings but let them adapt to the task during the training phase. However, they did not perform a comparison with the case where the embeddings are not adaptable. Thus, in our study we experimented with both fixed and adaptable embeddings.

6.1.3 Embedding Combinations

In the previous section, we have discussed that different embedding approaches capture different kinds of information. For instance, while the CBOW model captures information concerning sets of words that occur together frequently, the dependency-based approach captures information concerning syntactic dependencies. Furthermore, if no pre-trained embeddings are used, the generated representation is task specific, while when pre-trained embeddings are used, the representation captures information from larger amounts of data and is more generic. Adaptable embeddings attempt to balance the trade-off between the two. However, all those kinds of information may be complementary and relevant for the task. Thus, we assessed whether it is advantageous to combine multiple embedding representations. To do so, we used the approach suggested by Kim (2014) in the paper that inspired the CNN approach used by Liu et al. (2017). Considering the architecture in Figure 2, our approach replicates all the steps up to segment representation, inclusively, for each embedding approach, and then concatenates the generated segment representations before passing them to the dimensionality reduction layer. In our experiments, we combined both the fixed Word2Vec and dependency-based embeddings with their adaptable counterparts, as well as with each other and the version without pre-trained embeddings.

6.2 Character-Level Embedding

Although the majority of models used in Natural Language Processing (NLP) are word-based, there are also character-based models achieving interesting performance on text classification tasks, such as news article categorization and review rating (Zhang et al., 2015). The main advantage of these models is that they are able to capture information concerning the morphology of words, such as their lemmas and affixes. Furthermore, they typically generalize better since they do not have to deal with the out-of-vocabulary prob-
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lem. On the other hand, when using an embedding space with the same dimensionality, character models are much slower, since the number of tokens largely increases.

Considering the task at hand, dialog acts are related to an intention which is transmitted in the form of words. Thus, the selected words are expected to have a function related to that intention. In this sense, the function of a word is typically related to its morphology. For instance, there are cases, such as adverbs of manner and negatives, in which the function, and hence the intention, of a word is related to its affixes. On the other hand, there are cases in which considering multiple forms of the same lexeme independently does not provide additional information concerning intention and the lemma suffices. Since a character-level model is able to capture that information, we decided to assess its performance on the task. To do so, we performed an experiment using the same segment representation approach as for the word-level approach, but using the characters as tokens.

6.3 Functional-Level Embedding

As previously stated, there are some dialog acts that are more related to the structure of the segment or the functions of its words than to the presence of specific words or sets of words. Thus, it makes sense to explore tokenization at a level that abstracts those words. Considering what was said in the previous sections concerning the importance of suffixes, it is interesting to assess how important they are for the task. Since automatic suffix extraction is not straightforward, we performed the negative experiment, that is, we replaced the words with their lemmas and assessed the loss of performance of both word- and character-level embedding in comparison to the case when the original words were used. In order to obtain the lemmas we used the spaCy parser (Honnibal & Montani, 2017).

A replacement of the words by the corresponding syntactic units in the form of Part of Speech (POS) tags leads to a representation that captures the syntactic function of each word, as well as the structure of the segment when sets of words are considered together. Thus, we performed experiments with embedding at the POS-tag level. We used both the course-grained Google Universal POS tag set (Petrov et al., 2012) and the fine-grained Penn Treebank tag set (Marcus et al., 1993). While the first only covers the word type, the latter also includes information regarding morphological features of the words. Similarly to the lemmas, the POS tags were obtained using the spaCy parser.

Note that, as previously stated, there are also dialog acts that are related to specific words or sets of words. Thus, the described replacement of words with POS tags impairs the detection of such dialog acts, since those tags are only able to capture information that is generic to the class and not that which is specific to the words. To avoid this problem it is important to understand which classes of words can be abstracted with the corresponding POS tags and which cannot. We hypothesize that nouns, proper nouns, numerals, and adjectives are the classes that fall in the first category. Still, in addition to replacing this set of classes, we performed experiments replacing each word class to assess the relevance of specific words of that class.

6.4 Results

Starting with the dimensionality of the embedding space, in Table 3 we can see that using an embedding space with 200 dimensions, such as in the study by Liu et al. (2017), leads to
better results than any of the dimensionality values used by Khanpour et al. (2016). Furthermore, considering the three values they used, our experiments revealed better performance when using 300 dimensions than when using 150 dimensions, which was the best value in their study. However, their experiments on dimensionality also considered pre-trained embeddings, while we used a random initialization. We also performed some experiments that compared different values for the embedding space dimensionality while using pre-trained embeddings and, in every case, the embedding space with 200 dimensions led to better results.

| Dim  | Validation | Test |
|------|------------|------|
| 75   | .7645 .0025 | .7231 .0028 |
| 150  | .7650 .0015 | .7257 .0029 |
| 200  | .7696 .0021 | .7277 .0026 |
| 300  | .7662 .0029 | .7277 .0015 |

Table 3: Accuracy results according to embedding space dimensionality.

Concerning the use of different kinds of pre-trained embeddings, in Table 4 we can see that dependency-based embeddings outperform the widely used Word2Vec embeddings. Furthermore, both embeddings were trained on the English Wikipedia. Thus, the result difference was not caused by different training data. This confirms that the segment structure information included in the dependency-based representation is relevant for the task. The original embeddings had dimensionality 300. Since we use dimensionality 200 in our experiments, we discarded the exceeding dimensions, as was done by Khanpour et al. (2016) in their study.

|            | Validation | Test |
|------------|------------|------|
| CBOW       | .7757 .0015 | .7378 .0038 |
| Adaptable CBOW | .7667 .0015 | .7334 .0043 |
| Dependency-based | .7781 .0010 | .7432 .0028 |
| Adaptable Dependency-based | .7649 .0022 | .7277 .0032 |

Table 4: Accuracy results using pre-trained word embeddings.

Still in Table 4 we can see that, in both cases, using adaptable embeddings impairs performance. This was partially expected since the dialogs in the Switchboard corpus do not have a common domain nor common participants. Thus, since the separation into training, validation, and test sets is performed at the dialog level, what happens is that by letting the embeddings adapt, they overfit to the training dialogs and do not generalize well. Furthermore, since our embedding layer corresponds to a matrix of weights that is initialized with the values of the pre-trained embeddings, it does not reproduce the architectures used to produce the pre-trained embeddings, but only their output. Thus, the advantages of those architectures are not considered during the adaptation. This explains
the larger performance decay of dependency-based embeddings in comparison to that of CBOW embeddings.

A surprising result was that, as shown in Table 5, none of the embedding combinations led to better performance. In fact, all of those including an adaptable approach led to performance decreases above .90 percentage points in comparison to the simpler fixed embedding scenarios. This was unexpected since each embedding approach in the combinations was supposed to provide relevant information. Still, it can be explained by the overfitting of the adaptable embedding approaches. The concatenation of the representations generated by each approach before the dimensionality reduction layer contains the information provided by the fixed embedding representation and any additional relevant information provided by the adaptable representation. However, the dimensionality reduction layer ends up selecting information that is overfit to the training examples. This phenomenon can be assessed by removing that layer or by increasing the final dimensionality. We leave that for future work.

On the other hand, the combination of the fixed versions of the CBOW and dependency-based embeddings led to results above those obtained using the CBOW embeddings alone, but below the ones obtained using the dependency-based embeddings alone, which suggests that the latter cover all the information provided by the first.

|                              | Validation | Test    |
|------------------------------|------------|---------|
|                              | $\mu$      | $\sigma$| $\mu$  | $\sigma$ |
| CBOW + Adaptable             | .7667      | .0020   | .7305  | .0031    |
| CBOW + Random                | .7644      | .0033   | .7293  | .0021    |
| Dependency-based + Adaptable | .7659      | .0024   | .7310  | .0027    |
| Dependency-based + Random    | .7616      | .0012   | .7286  | .0028    |
| CBOW + Dependency-based      | .7767      | .0026   | .7410  | .0029    |

Table 5: Accuracy results using word embedding combinations.

Less surprising was the fact that character-level embeddings led to better results than word-level embeddings with random initialization. The concrete results are shown in Table 6. This confirms that there is relevant information for the task at a sub-word level. The results in Table 7 further confirm that part of that information is provided by affixes. However, the character-level embeddings were not able to achieve the performance of the pre-trained word embeddings. Furthermore, as explained in Section 6.2, the training and prediction processes are slower given the larger amount of tokens. Still, it is important to refer that we used the same embedding space dimensionality at the character and word levels. However, dimensionality 200 is higher than that required to use a one-hot representation at the character level, especially considering the English language. Thus, embedding at the character-level can be performed using a lower dimensionality, which hastens the process. Furthermore, we did not explore whether the RCNN-based segment representation approach is the best when using character-level tokenization, nor whether the information captured by character- and word-level approaches is complementary. Still, we leave a thorough study of these aspects for future work.

As previously stated, the experiments using lemmatized segments have shown that affixes provide relevant information for the task. In Table 7 we can see the results obtained.
Table 6: Accuracy results using character-level embeddings.

| Validation | Test |
|------------|------|
| µ   | σ   | µ   | σ   |
| Character-level | .7735 | .0008 | .7348 | .0021 |

when using both word and character-level tokenization. It is interesting to see that the accuracy losses between the four results and their non-lemmatized counterparts vary between 1.56 and 1.91 percentage points which, given the standard deviation of the results when using lemmatized segments, can be considered similar values. This means that affixes are as important for the task when using word-level tokenization as when using character-level tokenization. Still, the fact that information provided by affixes accounts for less than 2 percentage points accuracy shows that most of the information concerning intention is in the lemmas and that the affixes only provide additional information in specific cases.

Table 7: Accuracy results using lemmatized words.

| Validation | Test |
|------------|------|
| µ   | σ   | µ   | σ   |
| Word-level | .7510 | .0035 | .7086 | .0025 |
| Character-level | .7579 | .0037 | .7175 | .0053 |

Finally, considering embeddings at the POS tag-level, in Table 8 we can see that the fine-grained set leads to better results than the course-grained one. However, they are both far from the results obtained using word-level embeddings with random initialization. This shows that, as expected, there are specific words that are relevant for the correct identification of dialog acts and that it cannot be performed based on the structure of the segment alone. In fact, this is consistent with the findings of previous studies on other discourse-related tasks (Marcu, 2000). Still, our experiments replacing a single class of words at each time have shown that there are classes for which the specific words have no influence on the task. In this sense, similar or better results than those of the word-level embeddings with random initialization were achieved for nouns, proper nouns, conjunctions, numerals, determinants, adpositions, and particles. However, replacing all of these classes at once led to worse results. Furthermore, the set of classes we hypothesized that could be replaced, consisting of nouns, proper nouns, numerals, and adjectives, also led to worse results, as shown in the last row of Table 8. Still, as future work, we want to pre-train embeddings using this replacement and assess whether the information provided from larger amounts of data can improve the performance.

7. Context Information

Although a dialog act represents the intention behind a set of words, that intention is not constrained to a specific segment and its context provides relevant cues. As described in Section 3, previous studies have shown that the most important source of context information
for dialog act recognition is the dialog history, with influence decaying with distance (Ribeiro et al., 2015; Lee & Dernoncourt, 2016; Liu et al., 2017). However, information concerning the speakers and, more specifically, turn-taking has also been proved important (Liu et al., 2017). Thus, in our study, we explore both the surrounding segments and speaker information as sources of context information.

### 7.1 Surrounding Segments

A dialog is a structured sequence of segments, in which each segment typically depends on both what has been said before and what is expected to be said in future. Thus, the surrounding segments are the most important sources of context information for dialog act recognition. In the context of a dialog system identifying its conversational partner’s intention, the system only has access to the preceding segments. Thus, we focus on approaches able to capture information from those segments. Still, in order to assess the importance of future information and simulate the annotation environment, we also performed some experiments using that information.

As stated in Section 3, considering the preceding segments, we have shown in a previous study (Ribeiro et al., 2015) that providing information in the form of segment classifications leads to better results than in the form of words. Liu et al. (2017) further showed that using a single label per segment is better than using the probability of each class. Furthermore, both studies showed that using automatic predictions leads to a decrease in performance around 2 percentage points in comparison to using the manual annotations. Thus, in order to simplify the experiments and obtain an upper bound for the approach, in this study we just use the manual annotations. In our previous study, we have used up to five preceding segments and showed that the gain becomes smaller as the number of preceding segments increases, which supports the claim that the closest segments are the most relevant. Liu et al. (2017) stopped at three preceding segments, but noticed a similar pattern. In this study we explore up to five preceding segments, as well as the entire dialog history.

Although both our previous study and that by Liu et al. (2017) used the classifications of preceding segments as context information, none of them took into account that those segments have a sequential nature and simply flattened the sequence before appending it to the segment representation. However, as previously stated, both studies have shown that each label in that sequence is related to those that precede it. Thus, an approach that captures that information is expected to lead to better performance. To do so, we introduce a recurrent layer that processes the label sequence before appending it to the segment representation. Since the closest segments are expected to have more influence but

|          | Validation | Test  |
|----------|------------|-------|
|          | $\mu$  | $\sigma$ | $\mu$  | $\sigma$ |
| Coarse-grained | .6771 | .0026 | .6300 | .0023 |
| Fine-grained   | .6985 | .0022 | .6528 | .0033 |
| Selected      | .7424 | .0028 | .7136 | .0044 |

Table 8: Accuracy results using POS tags.
there still may be important information in distant segments, we use a GRU to process the label sequence. We used a number of neurons equal to the number of classes and no dropout. Each element in the sequence outputted by the recurrent layer consists of information about the sequence of labels up to that element. Thus, on the one hand, even if it is flattened in a similar manner to the label sequence in the previous approaches, it now contains sequentiality information. On the other hand, the last element of the sequence outputted by the recurrent layer can be seen as a summary of the sequence of labels of the preceding segments. We performed experiments using both approaches.

Finally, concerning future information, in terms of representation, the sequence of labels of the following segments can be seen as a mirrored version of the sequence of labels of the preceding segments. Thus, we propose using the same approach based on the processing of the sequence by a recurrent layer. However, in this case, the sequence is processed backwards. To assess the impact of this future information on the task, we performed experiments both independently of and in combination with the use of preceding segment information.

7.2 Speaker Information

As previously stated, information concerning the speakers is also relevant for dialog act recognition. However, specific information about speaker characteristics may not be available. Still, information about the speaker of each segment, that is, who said what, is always available. In this sense, intentions may vary if two sequential segments are uttered by the same or different speakers. Thus, turn-taking information is relevant for dialog act recognition. In fact, this has been confirmed in the study by Liu et al. (2017). Thus, we also use turn-taking information in this study. It is provided as a flag that states whether the speaker is different from that of the preceding segment.

7.3 Results

Starting with the reproduction of the flat label sequence approach, in Table 9 we can see that the results follow the same pattern as in our previous study and that by Liu et al. (2017). The first preceding segment is the most important, leading to a 3.21 percentage point improvement on the validation set and 3.56 on the test set. An additional .85 percentage points on the validation set and .94 on the test set can be obtained adding additional segments, up to the fourth. However, adding the second preceding segment accounts for an improvement of .61 and .83 percentage points, respectively. This supports the claim that the influence of preceding segments decays with distance. Adding the fifth preceding segment decreases performance by .1 percentage points on the validation set and .31 on the test set. Using the whole dialog history further harms the performance by 1.36 percentage points on the validation set and 2.92 on the test set. When looking at these results, one may be tempted to assume that using large context windows not only does not provide relevant information but also harms the performance. However, the decay in performance is due to the adaptations required to use this approach in the context of a NN, as when using a context window of a given size, in order to obtain sequences with the same length, the preceding label sequence for segments which do not have enough preceding segments must be padded. The amount of required padding increases with the size of the context
window, leading to a reduction in the percentage of relevant information included in the representation provided to the dimensionality reduction layer. However, the results achieved when using the whole dialog history still surpass those obtained without information from the preceding segments.

| #Preceding Segments | Validation   | Test        |
|----------------------|--------------|-------------|
|                      | $\mu$ | $\sigma$  | $\mu$ | $\sigma$  |
| 0                    | .7781 | .0010 | .7432 | .0028 |
| 1                    | .8102 | .0020 | .7788 | .0028 |
| 2                    | .8163 | .0030 | .7871 | .0032 |
| 3                    | .8171 | .0005 | .7879 | .0018 |
| 4                    | .8187 | .0031 | .7882 | .0032 |
| 5                    | .8177 | .0028 | .7851 | .0030 |
| All                  | .8041 | .0012 | .7559 | .0026 |

Table 9: Accuracy results using a flat label sequence of the preceding segments.

Table 10 shows the results obtained when using the recurrent layer to process the preceding label sequence before concatenating it with the segment representation. Using the flattened version of the outputted sequence also suffers from the previously described padding problem. Still, comparing both approaches when using the whole dialog history shows that the recurrent layer captures relevant information. The approach that uses only the last element of the sequence outputted by the recurrent layer as a summary of the preceding context minimizes the padding problem, as when generating the output for the last element of the sequence, the GRU is able to discard that information. This is the scenario that proves the importance of the recurrent layer to capture sequentiality information between the labels, leading to results above the best obtained by the approach that does not take the sequentiality information into account.

|               | Validation   | Test        |
|---------------|--------------|-------------|
|               | $\mu$ | $\sigma$  | $\mu$ | $\sigma$  |
| Flatten       | .8061 | .0011 | .7571 | .0043 |
| Last Pooling  | .8213 | .0018 | .7901 | .0014 |

Table 10: Accuracy results using a recurrent layer to generate preceding segment information.

Concerning context information from future segments, we ended up using the representation approach that uses the last element outputted by the recurrent layer, as it was the one with best performance for preceding segments. That is, we provide future context information in the form of a summary of the sequence of labels of the following segments. The results in Table 11 confirm that future information is also able to provide important cues for the task, with an improvement of 2.77 percentage points on the validation set and 2.98 on the test set, in comparison to when no context information is used. However, these
improvement values are lower than the 4.32 and 4.69 obtained when using context information from the preceding segments. This is consistent with the fact that when a segment is uttered, its speaker is aware of the dialog history, but only has an expectation of its future direction. Furthermore, when information from both preceding and future segments is used, the improvement in comparison with the case when only the preceding segments are used is of 1.46 percentage points on the validation set and 1.55 on the test set. Since the values are lower than the improvement provided by future information in comparison with the case without context information, this shows that there are some dialog acts that can be identified both by those that precede it and those that follow it.

| Validation | Test  |
|------------|-------|
| µ          | σ     | µ    | σ     |
| Future     | .8058 | .0024| .7730 | .0014 |

Table 11: Accuracy results using future segment information.

As for speaker information concerning turn-taking, it had been proved important for the task before. The results in Table 12 further confirm that importance. However, it leads to better results in conjunction with context information from the surrounding segments. On its own, speaker change information accounts for a .16 percentage point improvement on the validation set, but actually harms performance on the test set. When combined with information from the preceding segments, it accounts for an improvement of .27 percentage points on the validation set and .41 on the test set. Finally, when used in combination with context information from all surrounding segments it accounts for an improvement of .74 percentage points on the validation set and .53 on the test set. This improved importance in combination with information from the surrounding segments supports the claim that similar sequences of segments may have different intentions according to the involved speakers. As future work, we intend to explore the use of information concerning the whole turn-taking history instead of a single flag stating whether the speaker is different from that of the preceding segment.

| Validation | Test |
|------------|------|
| µ          | σ    | µ    | σ    |
| Speaker    | .7797| .0019| .7423| .0036 |
| Speaker + Preceding | .8240| .0021| .7942| .0025 |
| Speaker + Preceding + Future | .8433| .0021| .8109| .0021 |

Table 12: Accuracy results using speaker information.

Finally, considering that during the segment annotation process the annotators had access to the complete dialogs and to information about the speakers, the scenario that includes information from all the surrounding segments and turn-taking information is the one closest to the annotation environment. In this sense, on the validation set, our approach reached the 84% inter-annotator agreement, which means that our classifier has performance similar to that of a human annotator.
8. Conclusions

In this paper we explored multiple approaches on token, segment, and context information representation in the context of automatic dialog act recognition using DNNs. All the experiments were performed on the Switchboard Dialog Act Corpus (Jurafsky et al., 1997), which is the most explored for the task. We started with the segment representation approaches, since that is the step with higher variation among the previous studies described in Section 3 and that which introduces more changes in the overall architecture. We used adaptations of the approaches with top performance in previous studies, namely the RNN-based approach by Khanpour et al. (2016) and the CNN-based approach by Liu et al. (2017). However, those approaches focus on capturing different kinds of information, both of which are relevant for the task. Thus, we introduced the use of the RCNN-based approach by Lai et al. (2015) and adapted it to capture relevant relations between distant tokens. This approach outperformed the other two, proving that both token sequences and the contexts that surround each token are relevant for the task.

In terms of token embedding, we have explored approaches at the character, word, and functional levels. Starting with the typically used word-level, we have shown that using an embedding space with 200 dimensions as used by Liu et al. (2017) in their study leads to better results than any of the dimensionality values used by Khanpour et al. (2016). Furthermore, we have shown that, since the dialogs in the Switchboard Dialog Act Corpus have multiple domains, using fixed pre-trained word embeddings leads to better results than letting them be trained along with the network. In this sense, we have shown that dependency-based embeddings outperform those generated by Word2Vec, which is the most used embedding approach. This is in accordance with the task, since many dialog acts are related to the structure of the segment and, thus, the dependencies between tokens. However, the experiments that replaced the words with the corresponding POS tags did not perform as well as the word-based approaches, which shows that dialog acts are also related to specific words. Furthermore, our experiments at the character-level produced results similar to those of word-level approaches using pre-trained embeddings. This proves that there is important information for the task at a sub-word level. More specifically, the character-level approach is able to capture morphological aspects of the words, such as affixes and lemmas, which reveal their function and provide an important cue to identify intention.

Concerning context information, we focused on that provided by preceding segments, since those are the ones available to a dialog system attempting to identify its conversational partner’s intention. In this sense, previous dialog act recognition studies have shown that the best way to represent relevant context information from preceding segments is in the form of their classifications and not their words. However, in those studies, the sequentiality of the preceding segments, which is one of their main characteristics, was not appropriately represented. We approached this gap by reducing the representation of information from preceding segments to a summary of the sequence of their classifications, generated by a recurrent approach. Additionally, to simulate the annotation environment, in which the annotators have access to the whole dialog, we performed experiments that provided information from future segments in the same manner. In this sense, when information concerning turn-taking was combined with that extracted from all surrounding segments,
our approach reached the inter-annotator agreement of 84% on the validation set, which means that our classifier has performance similar to that of a human annotator.

Direct comparison with the results reported in previous studies is not straightforward. The results presented by Khanpour et al. (2016) should be comparable with ours, since we use the same test set. However, although we replicated their RNN-based approach achieving results in line with those reported for the validation set, we were not able to achieve the results they reported for the test set. Thus, we assume that the discrepancy of over 6 percentage points between the results presented for the two sets in their paper was due to the fact they considered the outcome of a single run, with a specific initialization. Furthermore, our study has shown that their approach can be improved in many aspects. In the case of the study by Liu et al. (2017), direct result comparison with those reported is not possible since they were obtained on different sets. However, the result differences between overlapping steps in our experiments are consistent with those described in their paper. Thus, we can safely state that their approach can be improved by using five parallel CNNs, dependency-based word embeddings, and the summary representation of context information. Still, it does not perform as well as the RCNN-based approach in the same conditions.

In terms of future work, there are still some aspects that can be explored, especially in terms of token representation. These are mainly related to the character- and functional-level approaches. Considering the first, we intend to perform a more in-depth study to assess the information that character-level approaches are able to capture and whether it can be combined with that captured by word-level approaches. As for the latter, we intend to explore the use of pre-trained embeddings on a large amount of data with specific word classes replaced by the corresponding POS tags. In terms of segment representation, we believe that the room for improvement is reduced, since our best approach only leads to an improvement of a single percentage point in comparison to the much simpler max pooling baseline, which suggests that the overall improvement that can be achieved by improving the segment representation is reaching a saturation point. Finally, concerning context information, we intend to explore the use of the whole turn-taking history, as well as other sources that may be relevant for the task, such as the domain and context of the dialog.

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