General-Purpose Communicative Function Recognition using a Hierarchical Network with Cascading Outputs and Maximum a Posteriori Path Estimation

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Abstract
ISO 24617-2, the standard for dialog act annotation, defines a hierarchically organized set of general-purpose communicative functions. The automatic recognition of these functions, although practically unexplored, is relevant for a dialog system, since they provide cues regarding the intention behind the segments and how they should be interpreted. In this paper, we explore the recognition of general-purpose communicative functions in the DialogBank, which is a reference set of dialogs annotated according to the standard. To do so, we adapt a state-of-the-art approach on flat dialog act recognition to deal with the hierarchical classification problem. More specifically, we propose the use of a hierarchical network with cascading outputs and maximum a posteriori path estimation to predict the communicative function at each level of the hierarchy, preserve the dependencies between the functions in the path, and decide at which level to stop. Furthermore, since the amount of dialogs in the DialogBank is reduced, we rely both on additional dialogs annotated using mapping processes and on transfer learning to improve performance. The results of our experiments show that the hierarchical approach outperforms a flat one and that maximum a posteriori estimation outperforms an iterative prediction approach based on masking.

1 Introduction
From the perspective of a dialog system, it is important to identify the intention behind the segments in a dialog, since it provides an important cue regarding the information that is present in the segments and how they should be interpreted. According to Searle [1969], that intention is revealed by dialog acts, which are the minimal units of linguistic communication. Consequently, automatic dialog act recognition is an important task in the context of Natural Language Processing (NLP), which has been widely explored over the years. In an attempt to set the ground for more comparable research in the area, a standard for dialog act annotation, ISO 24617-2, was developed [Bunt et al., 2012; Bunt et al., 2017]. However, annotating dialogs according to this standard is an exhaustive process, especially since the annotation does not consist of a single dialog act label, which in the standard nomenclature is called a communicative function, but rather of a complex structure which includes information regarding the semantic dimension of the dialog act and relations with other segments, among others. Consequently, the amount of data annotated according to the standard is still small and the automatic recognition of its communicative functions is practically unexplored.

We explore the automatic recognition of communicative functions in the English dialogs available in the DialogBank [Bunt et al., 2016; Bunt et al., 2019], which is the only publicly available source of dialogs fully annotated according to the standard. We focus on general-purpose communicative functions, since, contrarily to the dialog act labels of widely explored corpora in dialog act recognition research, they pose a hierarchical classification problem, with paths that may not end on a leaf communicative function. Furthermore, we focus on the Task dimension, since it is the one in which general-purpose communicative functions are predominant.

To approach the problem, we propose adaptations of a state-of-the-art approach on dialog act recognition that allow it to deal with the hierarchical problem posed by the general-purpose communicative functions of the standard. The adaptations focus on the ability to predict communicative functions at the multiple levels of the hierarchy, identify when the available information is not enough to predict more specific functions, and preserve the dependencies between the functions in the path. Furthermore, given the reduced amount of dialogs in the DialogBank, we explore the use of additional dialogs annotated using mapping processes, as well as of transfer learning processes to improve performance.

In the remainder of the paper, we start by providing an overview on the standard and dialog act recognition approaches in Section 2. Then, in Section 3, we describe our approach for predicting the general-purpose communicative functions of the standard. Section 4 describes our experimental setup, including the datasets, evaluation methodology, and implementation details. Finally, Section 5 presents and discusses the results of our experiments and Section 6 summarizes the contributions and provides pointers for future work.
2 Related Work

Since we are exploring the automatic recognition of the communicative functions defined by the standard for dialog act annotation, in this section we start by providing an overview on that standard. Then, we discuss state-of-the-art approaches on dialog act recognition and the few which have been applied to communicative function recognition.

2.1 ISO Standard for Dialog Act Annotation

ISO 24617-2, the ISO standard for dialog act annotation [Bunt et al., 2012; Bunt et al., 2017], states that, in order to isolate intentions, the annotation should not be performed on turns or utterances, but rather on functional segments [Carroll and Tanenhaus, 1978]. Furthermore, according to the standard, the dialog act annotation of a segment does not consist of a single label, but rather of a complex structure containing information about the participants, relations with other functional segments, the semantic dimension of the dialog act, its communicative function, and optional qualifiers concerning certainty, conditionality, partiality, and sentiment.

The standard defines nine semantic dimensions – Task, Auto-Feedback, Allo-Feedback, Turn Management, Time Management, Discourse Structuring, Own Communication Management, Partner Communication Management, and Social Obligations Management – in which different communicative functions may occur. These communicative functions are the standard equivalent to the dialog act labels used to annotate dialogs before the introduction of the standard. They are divided into general-purpose and dimension-specific functions. The former can occur in any semantic dimension and are organized hierarchically as shown in Figure 1. The latter can only occur in the corresponding dimension and are at the same level. We do not explicit dimension-specific communicative functions because they are outside the focus of our work. However, of the nine semantic dimensions, only the Task dimension does not have specific functions.

2.2 Dialog Act Recognition

Automatic dialog act recognition is a task that has been widely explored over the years, using both classical machine learning and deep learning approaches. In both cases, the approaches differ mainly on how the representation of a segment is generated from the representations of its tokens and how they are able to weigh context information in the decision process. The article by Král and Cerisara [2010] provides a comprehensive overview on classical machine learning approaches on the task, except for the more recent Support Vector Machine (SVM)-based approaches [Gambäck et al., 2011; Ribeiro et al., 2015]. Regarding deep learning approaches, both Recurrent Neural Networks (RNNs) [Lee and Dernoncourt, 2016; Ji et al., 2016; Khanpour et al., 2016; Tran et al., 2017] and Convolutional Neural Networks (CNNs) [Kalchbrenner and Blunsom, 2013; Lee and Dernoncourt, 2016; Liu et al., 2017] have been used to generate segment representations by combining the embedding representations of their words. While the first focus on capturing information from relevant sequences of tokens, the latter focus on the context surrounding each token and, thus, on capturing relevant token patterns independently of where they occur in the segment. Ribeiro et al. [2019b] have compared the RNN- and CNN-based approaches with top performance and concluded that a set of parallel CNNs with different window sizes generates more informative segment representations than a stack of RNNs, while also consuming less resources.

Regarding the representation of words, most approaches on dialog act recognition using deep learning have relied on pre-trained uncontextualized embedding representations generated by Word2Vec [Mikolov et al., 2013] or GloVe [Pennington et al., 2014]. However, Ribeiro et al. [2019b] have shown that, similarly to what happens on most NLP tasks, using contextualized embeddings, especially those generated by BERT [Devlin et al., 2019], leads to higher performance. Furthermore, they have shown that there are also important cues for intention at a sub-word level which can only be captured when using a finer-grained tokenization, such as at the character-level [Ribeiro et al., 2019a].

Regarding context information, previous studies have shown that the influence of preceding segments decreases with the distance and that their dialog act classification is more informative than their words [Ribeiro et al., 2015; Liu et al., 2017]. Furthermore, Ribeiro et al. [2019b] have shown that sequentiality information and long distance dependencies between the preceding segments can be captured by using a RNN to generate a summary of their classifications. These studies have also shown that turn-taking information is also relevant, albeit to a lesser extent.

To the best of our knowledge, only Anikina and Kruijff-Korbayová [2019] have explored the automatic recognition of the communicative functions defined by the standard. More specifically, they have explored the recognition of a compressed set of eight communicative functions on the TRADR corpus [Kruijff-Korbayová et al., 2015]. This compressed set merges functions in the Task, Turn Management, and Feedback dimensions and does not consider the hierarchical nature of general-purpose functions. Thus, the task was approached as a flat classification problem. The authors compared the performance of several Deep Neural Network (DNN) architectures and uncontextualized embedding approaches and observed the highest performance when the representation of the segment was generated by passing GloVe embeddings through an Long Short-Term Memory Unit (LSTM). However, the use of parallel CNNs was not explored and only large window sizes were considered. Furthermore, similarly to what was observed in previous studies on dialog act recognition, using context information regarding the dialog history led to improved performance. However, in this case, it was summarized as the average of the embedding representations of all the words in the dialog history.

3 Communicative Function Recognition

The main difference between general-purpose communicative function recognition and traditional dialog act recognition is that the former poses a hierarchical classification problem, with paths that may not end on a leaf. However, both are intention recognition problems at their core. Thus, as summarized in Figure 2, we approach the problem by adapting the
state-of-the-art approach on dialog act recognition by Ribeiro et al. [2019b] to deal with hierarchical problems.

Since the target is still the intention behind a segment, we use the same approaches to capture relevant information from the segment and its context. That is, two representations of the segment are generated in parallel, one based on its characters and another on contextualized embedding representations of its words, generated by BERT [Devlin et al., 2019]. In both cases, the representation of the segment is generated by concatenating the outputs of three parallel CNNs with different window sizes. At the character level, we use windows of size three, five, and seven, in order to focus on affixes, lemmas, and inter-word relations. At the word level, we use windows of size one, two, and three, in order to focus on independent words and short word patterns. The two representations are then concatenated and decorated with context information. Since the number of dialogs in the DialogueBank is small, in order to avoid overfitting, we do not rely on a summary of the whole dialog history. Instead, we use a flattened sequence of classifications and turn-taking information of the three preceding segments, which have been proved the most important in previous studies [Ribeiro et al., 2015; Liu et al., 2017]. The classification of each preceding segment is represented as a concatenation of the one-hot representations of the communicative functions at each level of the hierarchy. Turn-taking information is provided as flags stating whether the speaker changed.

The adaptation to the communicative function recognition problem refers to how the output is generated from the representation of the segment decorated with context information. The original approach features a dimensionality reduction layer to capture the most important information from the decorated representation and reduce the probability of overfitting by applying dropout during the training phase. Then, the most probable dialog act is predicted by passing the reduced representation through an output layer with the softmax activation. By flattening the hierarchy, we can use the same approach to predict the general-purpose communicative functions of the standard. However, that means that the relations between each communicative function and its ancestors and descendants are not considered.

In order to capture the relations between levels, instead of using a single output layer, we introduce the use of an output layer per level, connected as an output cascade. Furthermore, since the information that allows the distinction between communicative functions varies according to the level of the hierarchy, we also use a dimensionality reduction per level, which specializes the segment representation accordingly. Overall, this means that the output at each level is concatenated to the segment representation before it is passed through the dimensionality reduction layer of the next level.

Since the general-purpose communicative functions of the standard follow a strict hierarchy, the classification of a segment does not necessarily end on a leaf, and the leaves are not all at the same level, the network must be able to predict paths with variable length. To approach this problem, we add an additional label to each level of the hierarchy to represent that there is no label attributed to the segment at that level. This way, we are able to simulate paths with fixed length, while introducing minimal impact on the network during the training phase. These additional labels are also considered when providing context information to the network.

During the inference phase, the parent-child relations between the communicative functions must be considered. That is, when selecting the label at a given level, only the children of the label selected for the level above it can be considered. This restriction can be enforced using an iterative approach that starts by selecting the communicative function with highest probability at the top level and then applies a mask on the predictions of the level below it, in order to discard the communicative functions that are not children of the selected one. This process is then repeated for each level of the hierarchy. However, the performance of this approach is highly impaired when misclassifications occur in the upper levels of the hierarchy. To attenuate this problem, we explore a prediction approach based on Maximum a Posteriori (MAP) estimation. That is, we compute the posterior probability of all possible paths in the hierarchy according to the softmax
outputs at each level and select that with highest probability. In our experiments, we compare the performance of the flat classification approach with that of the hierarchical approach with both iterative and MAP prediction.

4 Experimental Setup

This section describes our experimental setup, including the datasets, the evaluation methodology, and implementation details to allow future reproduction of our experiments.

4.1 Datasets

We used three datasets in our experiments: one as gold standard, one to provide additional data during the training phase, and another for transfer learning. They are described below.

The DialogBank

To the best of our knowledge, the DialogBank [Bunt et al., 2016; Bunt et al., 2019] is the only publicly available source of dialogs annotated fully according to the standard guidelines. It features (re-)annotated dialogs from four English corpora and four Dutch corpora. There is a total of 17 annotated dialogs in English and 9 in Dutch. Of the English dialogs, five are from MapTask [Anderson et al., 1991], four are from Switchboard [Godfrey et al., 1992], three are from TRAINS [Allen and Schubert, 1991], and five are from DBOX [Petukhova et al., 2014].

Although it includes dialogs from multiple corpora, the amount of data provided by the DialogBank is too small for drawing solid conclusions from the results of DNN-based approaches trained solely on it, especially considering the hierarchical nature of the general-purpose communicative functions that we intend to recognize automatically. However, since these dialogs are the closest we have to a gold standard annotation, the evaluation of our approaches is based on the performance on the DialogBank.

LEGO-ISO

LEGO-ISO [Ribeiro et al., 2016] consists of 347 dialogs from the Let’s Go Bus Information System [Raux et al., 2006] annotated with the standard’s communicative functions. Each dialog features the system and a human user. Since system utterances are generated through slot filling of fixed templates, they have no errors and contain casing and punctuation information. In contrast, the transcriptions of user utterances were obtained using an Automatic Speech Recognition (ASR) system and, thus, are subject to recognition errors and contain no casing nor punctuation information.

The annotation with the standard’s communicative functions was obtained through the mapping of the original dialog act annotations of the LEGO corpus [Schmitt et al., 2012]. The mapping was based solely on the original labels and the transcriptions of the turns. This means that the annotation is performed on turns rather than on functional segments and that it does not cover every semantic dimension. Consequently, this dataset cannot be used as a gold standard. Still, it is 20 times larger than the DialogBank in number of English dialogs. Thus, it provides a significant amount of data that can be used during the training phase to improve the performance on general-purpose communicative function recognition.

Switchboard Dialog Act Corpus

The Switchboard Dialog Act Corpus [Jurašky et al., 1997] is an annotated subset of the Switchboard [Godfrey et al., 1992] corpus. It is the largest and most explored corpus annotated with dialog act information, consisting of 1,155 manually transcribed conversations, containing 223,606 segments. The conversations are between pairs of humans and cover multiple domains. The corpus is annotated for dialog acts using the domain-independent SWBD-DAMSL tag set, which features over 200 unique labels. However, most studies use a reduced set of 42 labels to obtain a higher inter-annotator agreement and higher example frequencies per class. Although the corpus is not annotated according to the standard, its dialog act annotations and the communicative functions of the standard reveal similar intentions. Thus, we use it in our experiments to train a dialog act recognition model for transfer learning.

4.2 Evaluation Methodology

In this study, we focus on the recognition of general-purpose communicative functions in the DialogBank. Furthermore,
we focus on the Task dimension, since the number of occurrences in the remaining dimensions is not representative. In this context, we defined two scenarios. The first focuses on the recognition of the different general-purpose functions in the segments that have communicative functions in the Task dimension. Thus, the remaining segments are discarded. On the other hand, the second scenario also considers the identification of segments which have communicative functions in the Task dimension. Thus, all segments are considered and a new label, None, is given to those which do not have communicative functions in that dimension.

Given the reduced amount of dialogs in the DialogBank, we evaluate the performance of the approaches using leave-one-dialog-out cross-validation. Additionally, and since the DialogBank features dialogs from multiple corpora, we also evaluate it using leave-one-corpus-out cross-validation, in order to assess cross-corpora generalization capabilities. In each fold, we train an ensemble of classifiers by using each dialog as a validation set for adjusting the parameters of the network, while training on the remainder. Furthermore, the LEGO-ISO dialogs are included in the training set of every classifier. The predicted classification of each segment in the left out dialog/corpus is then given by a majority vote of the classifiers in the ensemble, with ties broken randomly.

Additionally, in every scenario, we also assess the influence of applying a transfer learning process that presets the weights of the layers that generate the representation of the segment to those of a flat dialog act recognition model trained on the Switchboard Dialog Act Corpus. In this case, only the dimensionality reduction and output layers are trained on the dialogs annotated according to the standard.

Since we are dealing with a hierarchical classification problem, we report results in terms of exact match ratio (MR), as well as the hierarchical versions of precision (hP), recall (hR), and F-measure (hF) as proposed by Kiritchenko et al. [2005]. These hierarchical metrics are relevant, since they consider the whole path and, thus, capture the difference between predicting a label that shares part of its path with the correct label and one that follows a completely different path. We report the values of every metric in percentage form.

### 4.3 Implementation Details

To implement the networks, we used Keras [Chollet and others, 2015] with the TensorFlow [Abadi and others, 2015] backend. During the training phase, we used the Adam optimizer [Kingma and Ba, 2015] to update the weights, mini-batches with size 512, and early stopping with 10 epochs of patience. That is, the training phase stopped after ten epochs without improvement on the validation set.

To obtain contextualized word representations, we used the output of the last layer of the large uncased BERT model [Devlin et al., 2019]. When using character-level tokenization, embedding representations of the characters were trained together with the network to capture relations between them. To generate the segment representations, we used 100 filters in each CNN and aggregated the results using the max pooling operation. Finally, the dimensionality reduction layers were implemented as Rectified Linear Units (ReLUs) with 200 neurons and 50% dropout probability.

### 5 Results

Table 1 shows the results of our experiments. First of all, we can see that using transfer learning improves the performance of every approach, in every scenario, and in terms of every metric. The average improvement is of 12.26 percentage points in terms of exact match ratio and 10.95 percentage points in terms of hierarchical F-measure. This shows that, given the reduced amount of data, training the layers that generate the segment representations solely on the dialogs annotated according to the standard leads to overfitting. On the other hand, since the Switchboard Dialog Act Corpus is sufficiently large, a model trained on its dialogs generates representations that capture information regarding generic intention that is not specific to a single set of labels. The specificities of different sets are then captured by the dimensionality reduction and output layers. In the remainder of this discussion, we focus on the results achieved using transfer learning.

Starting with the scenario in which only segments with communicative functions in the Task dimension are considered, we can see that there is a gap of at least 17.78 percentage points between the results in terms of exact match ratio and hierarchical F-measure. This shows that even when the classifiers fail to predict the correct communicative function of a segment, they still predict part of the path correctly. Furthermore, the higher precision than recall suggests that the classifiers avoid predicting communicative functions that are deeper in the hierarchy. This can be justified by the reduction of number of examples with depth, which biases the classifiers towards the prediction of shallower functions.

When evaluating using leave-one-dialog-out cross-validation, we can see that the hierarchical classifier outperformed the flat one by 4.03 percentage points in terms of exact match ratio and 3.36 in terms of F-measure. This confirms that the per-level dimensionality reduction layers are able to capture the information that is most important for distinguishing the communicative functions at a given level and that the output cascade is able to capture information regarding the hierarchical relations. Furthermore, the MAP prediction approach outperformed the iterative one by 3.23 percentage points in terms of exact match ratio and 1.33 in terms of F-measure, which confirms that the impact of misclassifications in the top levels can be attenuated by correct predictions in the lower levels.

When evaluating using leave-one-corpus-out cross-validation, we can observe similar patterns. However, the exact match ratio and F-measure of the best approach decrease by 18.43 and 11.90 percentage points, respectively. In addition to the lower number of segments used to train the classifiers, part of this drop in performance is explained by the fact that some communicative functions only occur in one of the corpora. Thus, the drop is higher in terms of recall than precision. This reveals the importance of having a representative amount of dialogs for training.

Finally, when also considering the segments which do not have communicative functions in the Task dimension, we can see that the gap between exact match ratio and hierarchical F-measure no longer exists. The exact match ratio is higher than when those segments are not considered because in most
Table 1: Results achieved while predicting Task dimension communicative functions in the DialogBank. TL refers to transfer learning.

cases they are easy to identify. However, the F-measure is lower since misclassifying a segment as not having communicative functions in the Task dimension means that all the functions in the correct path are missed. Furthermore, since the segments without communicative functions have the None label in every level of the hierarchy, the classifiers become even more biased towards the prediction of shallower communicative functions. This is confirmed by the higher performance drop in terms of recall than precision.

6 Conclusions

In this paper, we have explored the automatic recognition of the general-purpose communicative functions defined by the ISO standard for dialog act annotation. To do so, we adapted a state-of-the-art approach on flat dialog act recognition to deal with the hierarchical classification problem posed by these communicative functions.

Our experiments on the DialogBank, which is a reference set of dialogs annotated according to the standard, have shown that the flat approach is outperformed by a hierarchical approach that specializes the representation of the segment for each level of the hierarchy, while also considering the outputs of the levels above it. Furthermore, a prediction approach based on MAP estimation outperforms an iterative one based on masking according to the prediction of the previous level, since it is more robust to misclassifications in individual levels. Finally, since the number of dialogs annotated according to the standard is reduced, the performance can be improved by pre-training the segment representation approach on a large corpus for dialog act recognition.

To the best of our knowledge, this was the first study to address the automatic recognition of the complete hierarchy of general-purpose communicative functions. However, the standard also defines dimension-specific communicative functions and a complete dialog act annotation includes additional information. Thus, the automatic recognition of all relevant aspects should be explored as future work.

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