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Publication date:
2018

Citation for published version (APA):

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A Dual-Attention Hierarchical Recurrent Neural Network for Dialogue Act Classification

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Abstract

Recognising dialogue acts (DA) is important for many natural language processing tasks such as dialogue generation and intention recognition. In this paper, we propose a dual-attention hierarchical recurrent neural network for dialogue act classification. Our model is partially inspired by the observation that conversational utterances are normally associated with both a dialogue act and a topic, where the former captures the social act and the latter describes the subject matter. However, such a dependency between dialogue acts and topics has not been utilised by most existing systems for DA classification. With a novel dual task-specific attention mechanism, our model is able, for utterances, to capture information about both dialogue acts and topics, as well as information about the interactions between them. We evaluate the performance of our model on two publicly available datasets, i.e., Switchboard and DailyDialog. Experimental results show that by modelling topic as an auxiliary task, our model can significantly improve DA classification.

Introduction

Dialogue Acts (DA) are semantic labels of utterances, which are crucial to understanding communication: much of a speaker’s intent is expressed, explicitly or implicitly, via social actions (e.g., questions or requests) associated with utterances (Searle 1969). Recognising DA labels is important for many natural language processing tasks. For instance, in dialogue systems, knowing the DA label of an utterance supports its interpretation as well as the generation of an appropriate response. In the security domain, being able to detect intention in conversational texts can effectively support dialogue act classification. In the security domain, being able to detect intention in conversational texts can effectively support dialogue act classification.

A wide range of techniques have been investigated for DA classification. Early works on DA classification are mostly based on general machine learning techniques such as Hidden Markov models (HMM) (Stolcke et al. 2000), dynamic Bayesian networks (Dielmann and Renals 2008), and Support Vector Machines (SVM) (Liu 2006). Recent studies to the problem of DA classification have seen an increasing uptake of deep learning techniques, where promising results have been obtained. Kalchbrenner and Blunsom (2013) model a DA sequence with a recurrent neural network (RNN), where sentence representations are constructed by means of a convolutional neural network (CNN). Kumar et al. (2017) propose a hierarchical, bidirectional long short-term memory (Bi-LSTM) model with a conditional random field (CRF) for DA classification, achieving an overall accuracy of 79.2% on the SWDA dataset. There is also work exploring different deep learning architectures (e.g., hierarchical CNN or RNN/LSTM) to incorporate context information for DA classification, showing that incorporating context information improves DA classification (Liu et al. 2017).

Most of the deep learning approaches to DA classification utilise the dependencies from data, e.g., the dependency between adjacent utterances (Ji, Haffari, and Eisenstein 2016) as well as the implicit and intrinsic dependencies among DAs (Kumar et al. 2017). It has been observed that conversational utterances are normally associated with both a dialogue act and a topic, where the former captures the social act (e.g., promising) and the latter describes the subject matter (Wallace et al. 2013). In addition, the set of DAs associated with a conversation is likely to be affected by the topic of the conversation. For instance, DAs such as request and suggestion might appear more frequently in conversations relating to topics about work. However, such a reasonable source of information, surprisingly, has not been explored in the deep learning literature for DA classification. We hypothesise that modelling the topics of utterances as an auxiliary task may effectively support dialogue act classification.

In this paper, we propose a dual-attention hierarchical recurrent neural network for dialogue act classification. Our model is distinguished from existing methods in a few aspects. First, compared to the flat structure employed by existing models (Khanpour, Guntakandla, and Nielsen 2016; Ji, Haffari, and Eisenstein 2016; Tran, Zukerman, and Haffari 2017), our hierarchical recurrent neural network can represent the input at the word, utterance, and conversation levels, preserving the natural hierarchical structure of a conversation. Second, our model is able to incorporate rich context information for DA classification with a novel task-specific dual-attention mechanism. Employing attention into our model sheds light on the observation that different di-
Dialogue acts are semantically related to different words in an utterance (Tran, Zukerman, and Haffari 2017a). Third, apart from incorporating the commonly used dependencies between utterances, our dual-attention mechanism can further capture, for utterances, information about both dialogue acts and topics. This is a useful source of context information which has not previously been explored in existing deep learning models for DA classification.

We evaluate our model against several strong baselines (Kalchbrenner and Blunsom 2013; Lee and Dernoncourt 2016; Khanpour, Guntakandla, and Nielsen 2016; Ji, Haffari, and Eisenstein 2016; Kumar et al. 2017) on the task of dialogue act classification. Extensive experimentation conducted on two publicly available datasets (namely Switchboard (Jurafsky 1997) and DailyDialog (Li et al. 2017)) shows that by modelling the topic information of utterances as an auxiliary task, our model can significantly improve DA classification, yielding comparable performance to state-of-the-art deep learning methods (Kumar et al. 2017) in classification accuracy.

Related Work

Dialogue Act (DA) recognition is a supervised classification task, where each utterance in a conversation is assigned with a DA label. Broadly speaking, methods for DA classification can be divided into two categories, i.e., instance-based methods and sequence labelling methods. Instance-based methods treat each utterance as an independent data point and predict the DA label for each utterance separately, e.g., naive Bayes (Grau et al. 2004) and maximum entropy (Ang, Liu, and Shriberg 2005). In contrast, sequence labelling methods cast DA recognition as a sequence labelling task where the dependency among consecutive utterances are taken into consideration, where example methods include Hidden Markov Models (HMM) (Stolcke et al. 2000) and Conditional Random Fields (CRF) (Kim, Cave- don, and Baldwin 2010).

Recently, deep learning has been widely applied in many natural language processing tasks, including DA classification. Kalchbrenner and Blunsom (2013) proposed to model a DA sequence with a recurrent neural network (RNN) where sentence representations were constructed by means of a convolutional neural network (CNN). Lee and Dernoncourt (2016) tackled DA classification with a model built upon RNNs and CNNs. Specifically, their model can leverage the information of preceding texts, which can effectively help improve the DA classification accuracy. More recently, a latent variable recurrent neural network was developed for jointly modelling sequences of words and discourse relations between adjacent sentences (Ji, Haffari, and Eisenstein 2016). In their work, the shallow discourse structure is represented as a latent variable and the contextual information from preceding utterances are modelled with a RNN. Kumar et al. (2017) proposed a hierarchical, bidirectional long short-term memory (Bi-LSTM) model with a CRF for DA classification, where the inter-utterance and intra-utterance information are encoded by a hierarchical Bi-LSTM and the dependency between DA labels is captured by a CRF.

In addition to modelling dependency between utterances, various contexts have also been explored for improving DA classification or modelling DA under multi-task learning. For instance, Wallace et al. (2013) proposed a generative joint sequential model to classify both DA and topics of patient-doctor conversations. Their model is similar to the factorial LDA model (Paul and Dredze 2012), which generalises LDA to assign each token a K-dimensional vector of latent variables. The model of Wallace et al. (2013) only assumed that each utterance is generated conditioned on the previous and current topic/DA pairs. In contrast, our model is able to model the dependencies of all utterances of a conversation, and hence can better capture the effect between DAs and topics. Qin, Wang, and Kim (2017) introduced a joint model for identifying salient discussion points in spoken meetings as well as labelling discourse relations. They assumed that the interaction between content and discourse relations might improve the classification performance on both phrase selection and DA classification. A tree-structured discourse was constructed to jointly model the content and discourse relations. Lexical and syntactic features were utilised for the two tasks, such as TF-IDF scores for words, part of speech (POS) tags, etc. Shen and Lee (2016) proposed a neural attention model for DA detection and key term extraction, where their model shows that the attention mechanism is effective for sequence classification.

Methodology

Given a training corpus $D = \langle(C_n, Y_n, Z_n)\rangle_{n=1}^{N}$, where $C_n = \langle u_i^n \rangle_{i=1}^{T}$ is a conversation consisting of a sequence of T utterances, $Y_n = \langle y_i^n \rangle_{i=1}^{T}$, and $Z_n = \langle z_i^n \rangle_{i=1}^{K}$ are the corresponding sequences of dialogue act (labels) and topics for $C_n$, respectively. Each utterance $u_i = \langle w_i^t \rangle_{t=1}^{K}$ of a conversation $C_n$ is a sequence of K words. Our goal is to learn a model from $D$, such that, given an unseen conversation $C_u$, the model can predict the dialogue act (labels) of the utterances of $C_u$.

Figure 1 gives an overview of the proposed Dual-Attention Hierarchical recurrent neural network (DAH). We adopt a shared utterance encoder for the input, which encodes each word $w_i^t$ of an utterance $u_i$ into a vector $h_i^t$. The dialogue act attention and topic attention mechanisms capture DA and topic information as well as the interactions between them. The outputs of the dual-attention are then encoded in the corresponding conversation-level sequence tags (i.e., $g_i$ and $s_i$), based on the corresponding utterance representations and target labels.

Shared Utterance Encoder

In our model, we adopt a shared utterance encoder to encode the input utterances. Such a design is based on the rationale that the shared encoder can transfer knowledge between two tasks and reduce the risk of overfitting. Specifically, the shared utterance encoder is implemented using the bidirectional gated recurrent unit (BiGRU) (Cho et al. 2014), which encodes each utterance $u_i = \langle w_i^t \rangle_{t=1}^{K}$ of a conversation $C_n$ as a series of hidden states $\langle h_i^t \rangle_{t=1}^{K}$. Here, $i$ indicates the
tors, and calculated as follows,

\[ h^i_t = \text{concat} \left( \vec{h}^i_t, \vec{h}^i_t \right), \]

where \( \text{concat}(\cdot, \cdot) \) is an operation for concatenating two vectors, and \( \vec{h}^i_t \) and \( \vec{h}^i_t \) are the \( i \)-th hidden state of the forward gated recurrent unit (GRU) (Cho et al. 2014) and backward GRU for \( w^i_t \), respectively. Formally, the forward GRU \( \vec{h}^i_t \) is calculated as follows,

\[
\begin{align*}
  r_t &= \sigma \left( W_{er} e_t^i + W_{hr} \vec{h}^i_{t-1} + b_r \right) \\
  z_t &= \sigma \left( W_{ez} e_t^i + W_{hz} \vec{h}^i_{t-1} + b_z \right) \\
  n_t &= \tanh \left( W_{en} e_t^i + r_t \odot \left( W_{hn} \vec{h}^i_{t-1} + b_n \right) \right) \\
  \vec{h}^i_t &= (1 - z_t) \odot n_t + z_t \odot \vec{h}^i_{t-1} 
\end{align*}
\]

where \( \vec{h}_{t-1}^i \) is the hidden state for word \( w_{t-1}^i \), \( e_t^i \) is the word embedding of \( w_t^i \), and \( r_t, z_t, n_t \) are the reset, update, and new gates, respectively. Sigmoid (denoted as \( \sigma \)) and \( \tanh \) functions are applied to each element of their vector arguments as pointwise operations, and \( \odot \) denotes element-wise multiplication. \( W_{er}, W_{hr}, W_{ez}, W_{hz}, W_{en}, W_{hn}, b_r, b_z, b_n \) are parameters that need to be estimated. Finally, the backward GRU encodes \( u_t \) from the reverse direction (i.e., \( w^K_t, \ldots, w_1^i \)) and generates \( (\vec{h}^i_t)_{i=1}^K \), following the same formulation as the forward GRU.

**Task-specific Attention**

Recall that one of the key challenges of our model is to capture for each utterance, information about both dialogue acts and topics, as well as information about the interactions between them. We address this challenge by incorporating into our model a novel task-specific dual-attention mechanism, which accounts for both DA and topic information extracted from utterances. In addition, DAs and topics are semantically relevant to different words in an utterance. With the proposed attention mechanism, our model can also assign different weights to the words of an utterance by learning the degree of importance of the words to the DA or topic labelling task, i.e., promoting the words which are important to the task and reducing the noise introduced by less important words.

For each utterance \( u_t \), the dialogue act attention calculates a weight vector \( \langle \alpha_t^i \rangle_{i=1}^K \) for \( (\vec{h}^i_t)_{i=1}^K \), the hidden states of \( u_t \), \( u_t \) can then be represented as a weighted combination vector

\[
  l_t = \sum_{i=1}^K \alpha_t^i h^i_t. \tag{3}
\]

In contrast to the traditional attention mechanism (Bahdanau, Cho, and Bengio 2014), which only depends on one set of hidden vectors from the Seq2Seq decoder, the dialogue act attention in DAH relies on two sets of hidden vectors, i.e., \( g_{t-1} \) of the conversation-level DA tagger and \( s_{t-1} \) of the conversation-level topic tagger, where the interaction between DAs and topics in each task-specific attention mechanism can capture, for utterances, information about both DAs and topics. Specifically, the weights \( \langle \alpha_t^i \rangle_{i=1}^K \) for the dialogue act attention are calculated by

\[
  \alpha_t^i = \text{softmax} \left( e_t^i \right) \tag{4}
\]

where

\[
  e_t^i = \tanh \left( W_{(act)}^i \cdot s_{t-1} + V_{(act)}^i \cdot g_{t-1} + U_{(act)}^i \cdot h_t^i + b_{(act)}^i \right). \tag{5}
\]

The topic attention layer has a similar architecture to the dialogue act attention layer, which takes as input both \( s_{t-1} \) and \( g_{t-1} \). Similar to the dialogue act attention, the weight vector \( \langle \beta_t^i \rangle_{i=1}^K \) for the topic attention output \( v_t \) can be calculated as follows

\[
  v_t = \sum_{i=1}^K \beta_t^i h_t^i. \tag{6}
\]

\[
  \beta_t^i = \text{softmax} \left( c_t^i \right), \tag{7}
\]
where
\[ c_i^t = \tanh \left( W^{\text{topic}} \cdot s_{t-1} + V^{\text{topic}} \cdot g_{t-1} + U^{\text{topic}} \cdot h_i^t + b^{\text{topic}} \right). \]  (8)

Note that \( W^{\text{act}}, V^{\text{act}}, U^{\text{act}}, b^{\text{act}}, W^{\text{topic}}, V^{\text{topic}}, \) and \( b^{\text{topic}} \) are vectors of parameters that need to be learned during training.

**Conversational Sequence Tagger**

**Dialogue act sequence tagger.** The conversational dialogue act sequence tagger predicts the next DA \( y_t \) conditioned on the attention vector \( l_t \) and all previous predicted DAs \( \langle y_t \rangle_{t=1}^{T-1} \) (c.f. Figure 1). Formally, this conditional probability can be formulated as
\[
p(y_1, \ldots, y_T|C) = p(y_1|l_1) \prod_{t=2}^T p(y_t|l_t, y_1, \ldots, y_{t-1}),
\]
where
\[
p(y_t|l_t, y_1, \ldots, y_{t-1}) = \text{softmax}(g(g_t, l_t)) \quad (10)
\]
\[
g(g_t, l_t) = A \text{concat}(g_t, l_t) + b. \quad (11)
\]
Here \( C = \langle u_t \rangle_{t=1}^T \) is the sequence of all utterances seen so far, \( T \) is the length of a conversation, \( l_t \) is the hidden state of the conversational DA tagger for the \( t \)-th utterance, \( z_t \) is the attention vector of \( u_t \), and \( g(\cdot) \) is a linear transformation function. \( A \) and \( b \) are model parameters which need to be learned during training.

Vector \( g_t \) is calculated in a GRU (denoted as \( f \)):
\[
g_t = f(y_{t-1}, g_{t-1}, l_t). \quad (12)
\]

In training, teacher forcing (Williams and Zipser 1989) with a value of 0.5 is used for label \( y_{t-1} \) in order to avoid accumulation of false prediction.

**Topic sequence tagger.** The conversational topic sequence tagger is designed to predict \( z_t \) conditioned on \( v_t \) and all previous predicted topics \( \langle z_t \rangle_{t=1}^{T-1} \). Similar to the formulation of the dialogue act tagger, we have
\[
p(z_1, \ldots, z_T|C) = p(z_1|v_1) \prod_{t=2}^T p(z_t|v_t, z_1, \ldots, z_{t-1}),
\]
\[
p(z_t|v_t, z_1, \ldots, z_{t-1}) = \text{softmax}(g(s_t, v_t)) \quad (13)
\]
\[
g(s_t, v_t) = A' \text{concat}(s_t, v_t) + b' \quad (14)
\]
\[
s_t = f(z_{t-1}, s_{t-1}, v_t). \quad (15)
\]
Here \( C = \langle u_t \rangle_{t=1}^T \) is also the sequence of all utterances seen so far, \( s_t \) is the hidden state of the conversational topic tagger for the \( t \)-th utterance, \( v_t \) is the attention vector of \( u_t \), and \( A' \) and \( b' \) are model parameters.

Let \( \Theta \) be all the model parameters that need to be estimated for the DAH model. We can then estimate \( \Theta \) based on \( \mathcal{D} = \langle \langle C_n, Y_n, Z_n \rangle \rangle_{n=1}^N \) by minimising the objective function below, which seeks to jointly optimise the prediction for both dialogue acts and topics
\[
\hat{\Theta} = \arg \min_{\Theta} - \sum_{n=1}^N \left[ \log (p(y^n_1, \ldots, y^n_T|C_n)) + \alpha \log (p(z^n_1, \ldots, z^n_T|C_n)) \right]. \quad (17)
\]

The hyper-parameter \( \alpha \) controls the contribution of the conversational topic tagger towards the objective function. In our experiments, \( \alpha = 0.1 \) is determined empirically.

**Experimental Settings**

**Datasets**

We evaluate the performance of our model on two publicly available dialogue datasets, namely, Switchboard (Jurafsky 1997) and Dailydialog (Li et al. 2017).

**Switchboard Dialogue Act Corpus (SWDA).** The SWDA dataset consists of 1,155 two-sided telephone conversations labelled with 66 conversation-level topics (e.g., weather climate, air pollution, etc.) and 42 utterance-level dialogue acts (e.g., statement-opinion, statement-non-opinion, wh-question). The average speaker turns per conversation, tokens per conversation, and tokens per utterance are 195.2, 1,237.8, and 7.0, respectively.

**DailyDialog Corpus (DYDA).** The DyDA dataset contains 13,118 human-written daily conversations, which are labelled with 10 different topics (e.g., tourism, politics, finance) at the conversation-level as well as four dialogue act classes at the utterance level, i.e., inform, question, directive and commissive. The former two classes are information transfer acts, while the latter two are action discussion acts. The average speaker turns per conversation, tokens per conversation, and tokens per utterance are 7.9, 114.7, and 14.6, respectively. The definition of the four mutually-exclusive categories of dialogue acts is as follows (Li et al. 2017):

- “Inform” class contains all statements and questions by which the provider is giving information”;
- “Questions” class is labelled when the speaker wants to know something and seeks for some information”;
- “Directives” class contains dialogue acts like request, instruct, suggest and accept/reject offer”;
- “Commissive” class is about accept/reject request or suggestion and offer”.

**Implementation Details**

For both experimental datasets (SWDA and DyDA), the top 15,000 words with the highest frequency are indexed. For SWDA, the standard split is adopted based on (Stolcke et al. 2000), utilising 1,115 conversations for training and 19 conversations for testing. We select 112 conversations from the training dataset as the validation dataset following (Lee and Dernoncourt 2016). For DyDA, we also use the standard

- [http://comppragma.christopherpotts.net/swda.html](http://comppragma.christopherpotts.net/swda.html)
- [http://yanran.li/dailydialog](http://yanran.li/dailydialog)
The input data is represented with 300-dimensional Glove word embeddings (Pennington, Socher, and Manning 2014) in order to capture the word similarity and accelerate model training. The shared encoder is a BiGRU with two layers, whereas the conversational sequence tagger is a GRU containing a single layer. We set the dimension of the hidden layers (i.e., $h_t$, $g_t$, and $s_t$) to 100 and applied a dropout layer (Srivastava et al. 2014) to both the shared encoder and the sequence tagger at a rate of 0.2. The Adam optimiser (Kingma and Ba 2014) is used for training with an initial learning rate of 0.001 and a weight decay of 0.0001. Each utterance in a mini-batch was padded to the maximum length for that batch and the maximum batch-size allowed is 10.

### Experimental Results

#### Dialogue Acts Classification

We compare our Dual-Attention Hierarchical RNN model (DAH) against several state-of-the-art models for dialogue act classification. In order to show the effectiveness of DAH, we also report the performance of the Single-Attention Hierarchical RNN model (SAH), i.e., a simplified version of DAH that only models dialogue acts, with topical information omitted.

**Results on the SWDA dataset.** For the SWDA dataset, we compare our models against the following baselines:

- **HMM:** A Hidden Markov Model for the discourse structure of a conversation (Stolcke et al. 2000);
- **JAS:** A generative joint, additive, sequential model of topics and speech acts in patient-doctor communication (Wallace et al. 2013);
- **CNN:** A CNN containing contextual information (Lee and Démoncourt 2016);
- **RCNN:** A hierarchical CNN modelling utterances followed by a RNN capturing contextual information (Kalchbrenner and Blunsom 2013);
- **LSTM-Softmax:** A deep bidirectional LSTM to classify dialogue acts via a softmax classifier (Khanpour, Gunatakandla, and Nielsen 2016);
- **DRLM-Cond:** A latent variable recurrent neural network for dialogue act classification (Ji, Haffari, and Eisenstein 2016);
- **Bi-LSTM-CRF:** A hierarchical bidirectional LSTM with a CRF as the top layer to classify dialogue acts (Kumar et al. 2017).

Note that while all the aforementioned baselines model the dependency between the dialogue acts of a sequence of utterances, only the JAS model has attempted to model both dialogue acts and topics. All baselines above use the same test dataset as our model.

Table 2 shows the dialogue act classification results of our model and the baselines on the SWDA dataset. Among the baseline models, Bi-LSTM-CRF achieved the best classification performance with 79.2% accuracy. It can also be observed that the deep learning models (e.g., Bi-LSTM-CRF, DRLM-Cond) in general give better performance than the traditional statistical models (i.e., HMM and JAS).

The SAH model, that only models dialogue acts, obtains 74.1% accuracy, which is better than JAS and RCNN. By jointly modelling dialogue act and topics, the DAH model achieves an overall accuracy of 78.3%, which is a significant performance boost over SAH (i.e., 4.2% higher; paired t-test $p < 0.01$). This result shows that the performance of DAH classification can be improved significantly by using topic information. When comparing DAH with the baselines models, we can see that DAH achieves comparable performance to the state-of-the-art model Bi-LSTM-CRF (i.e., 78.3% vs. 79.2%). Although Bi-LSTM-CRF outperforms DAH, the architecture of DAH is simpler: Bi-LSTM-CRF employs a bidirectional LSTM in the conversational layer, and the DA classifier is a CRF which is more complicated than the softmax of DAH.

**Results on the DyDA dataset.** We also evaluated our models on the DyDA dataset. As for the baselines, we ran and reported the results for JAS and DRLM-Cond as only the source code for these two models is publicly available. Nevertheless, one should note that DRLM-Cond is the second-best performing baseline on the SWDA dataset. We fine-tuned the model parameters for both JAS and DRLM-Cond to perform the comparison as fair as possible.

As can be seen from Table 3, DRLM-Cond performs better than JAS and achieves an overall accuracy of 81.1%. Our DAH and SAH models, in contrast, give much better performance where both models outperform DRLM-Cond for more than 3.2% on utterance-level dialogue act classification. As with the SWDA dataset, DAH outperforms the SAH model on DyDA. By examining the classification per-
Figure 2: The normalized confusion matrix of 10 DAs using SAH (left) and DAH (right) in SWDA.

<table>
<thead>
<tr>
<th>Models</th>
<th>DA Type</th>
<th>P (%)</th>
<th>R (%)</th>
<th>F1 (%)</th>
<th>Acc. (%)</th>
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<tbody>
<tr>
<td>JAS</td>
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<td>74.5</td>
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<td></td>
<td>Avg.</td>
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<td>77.3</td>
<td>75.6</td>
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<tr>
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<tr>
<td></td>
<td>Questions</td>
<td>93.8</td>
<td>95.2</td>
<td>94.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Directives</td>
<td>76.9</td>
<td>70.4</td>
<td>73.5</td>
<td>86.5</td>
</tr>
<tr>
<td></td>
<td>Commissive</td>
<td>72.8</td>
<td>60.9</td>
<td>66.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Avg.</td>
<td>86.1</td>
<td>86.5</td>
<td>86.2</td>
<td></td>
</tr>
</tbody>
</table>

Table 3: DA classification results on the DyDA dataset.

formance of DAH and SAH on each dialogue act type, we see that both models achieve fairly similar performance on the Info, Questions classes, but DAH outperforms SAH on Directives and Commissive by more than 4% in F1 scores. This again proves that conversation-level topic information is helpful for dialogue act recognition.

To summarise, our DAH model achieves comparable performance to the state-of-the-art for dialogue act classification on the SWDA dataset; it also gives the best classification performance on the DyDA dataset. Experimental results demonstrate that modelling conversational topic information as an auxiliary task does improve the classification on dialogue acts.

Analysing the Effectiveness of Joint Modelling Dialogue Act and Topic

In this section, we provide detailed analysis on why DAH can yield better performance than SAH by jointly modelling dialogue acts and topics.

Figure 3 shows the normalized confusion matrix derived from 10 DA classes of SWDA for both the DAH and SAH models. It can be observed that DAH yields improvement on recall for many DA classes compared to SAH. For example, 17.8% improvement on bk and 7% on sv. For bk (Response Acknowledge) which has the highest improvement level, we see that the improvement largely comes from the reduction of misclassifying bk to b (Acknowledge Backchannel). The key difference between bk and b is that an utterance labelled with bk has to be produced within a question-answer context, whereas b is a "continuer" simply representing a response to the speaker.

It is not surprising that SAH makes poor prediction as the utterances of these two DAs: they share many syntactic cues, e.g., indicator words such "okay", "oh", and "uh-huh", which can easily confuse the model. When comparing the topic dis-
Figure 4: Topic distribution (the distribution of topic \( k \) under a DA label \( d \) is calculated by using the number of utterances associated with topic \( k \) and DA label \( d \) divided by the total number of utterances associated with the DA label \( d \)) of \( b \), \( bk \), \( qw \) and \( qo \) on 12 most prominent topics (1: gun control, 2: air pollution, 3: music, 4: universal public service, 5: crime, 6: pets, 7: Latin America, 8: exercise and fitness, 9: basketball, 10: gardening, 11: space flight and exploration, 12: ethics in government).

Figure 5: DA Attention visualisation using SAH (upper) and DAH (lower). The true label of the utterance above is \( sd \); SAH predicts DA as \( sv \) and DAH predicts DA as \( sd \).

In Figure 3, DAH obtains improvement over SAH for all the four DA classes of DyDA. In particular, Directives and Commisive achieve higher improvement margin compared to the other two classes, where the improvement are largely attributed to less number of instances of the Directives and Commisive classes being mis-classified into Inform and Questions. Examining the topic distribution reveals that Directives and Commisive classes are more relevant to the topics such as tourism, health, and work. In contrast, the topics of Inform and Questions classes are more about relationship, emotion, and politics.

Finally, we show in Figure 5 a DA attention visualisation example of SAH and DAH for an utterance from SWDA. It can be seen that SAH gives very high weight to the word “because” and de-emphasizes other words. By modelling both DAs and topics with the dual-attention mechanism, DAH can capture more important words for the task (e.g., “reasonable”, “ever”, etc.) and correctly predicts the DA label as \( sd \).

**Conclusion**

In this paper, we developed a dual-attention hierarchical recurrent neural network for dialogue act classification. Compared to the flat structure employed by existing models, our hierarchical model can better preserve the hierarchical structure of natural language conversations. More importantly, with the proposed task-specific dual-attention mechanism, our model is able to capture information about both dialogue acts and topics, as well as information about the interactions between them. Experimental results based on two public benchmark datasets show that modelling conversational topic information as an auxiliary task can effectively improve dialogue act classification, and that our model is able to achieve comparable performance to the state-of-the-art deep learning methods for DA classification.

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3NB: topic distribution not shown for DyDA due to page limit.
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