MIDAS, A Dialog Act Annotation Scheme for Open-Domain Human-Machine Spoken Conversations

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Abstract

Dialog act prediction is an essential language comprehension task for both dialog system building and discourse analysis. Previous dialog act schemes, such as SWBD-DAMSL, are designed for human-human conversations, in which conversation partners have perfect language understanding ability. In this paper, we design a dialog act annotation scheme, MIDAS (Machine Interaction Dialog Act Scheme), targeted on open-domain human-machine conversations. MIDAS is designed to assist machines which have limited ability to understand their human partners. MIDAS has a hierarchical structure and supports multi-label annotations. We collected and annotated a large open-domain human-machine spoken conversation dataset (consists of 24K utterances). To show the applicability of the scheme, we leverage transfer learning methods to train a multi-label dialog act prediction model and reach an F1 score of 0.79.

1 Introduction

Previous popular dialog act annotation schemes, such as MapTask (Thompson et al., 1993), SWBD-DAMSL (Jurafsky et al., 1997), and ISO (Bunt et al., 2010) are designed to understand human-human dialogs. Despite the fact that these dialog act schemes are not designed for human-machine conversations, state-of-the-art social conversational systems still use them to train automatic dialog act predictors (Chen et al., 2018; Mezza et al., 2018). We believe that an annotation scheme designed specifically for human-machine conversations that addresses their unique features would improve dialog system performance further.

Human-human and human-machine conversations are very different. Because of the limitation of the machine, humans use different syntax and semantics when talking to a machine than a human. For example, requests such as “dim the light” are much more frequently seen in human-machine conversations. On the other hand, some labels designed in human-human schemes are not needed in human-machine schemes for machine understanding tasks. For example, separating Summarize-Reformulate (e.g. “Who know what they’re doing with that”) and Rhetorical-Questions (e.g.“Who would steal a newspaper”) (Jurafsky et al., 1997) in SWBD-DAMSL is not necessary for dialog systems. Moreover, previous schemes annotate conversations on human transcriptions, while in real-time human-machine conversation, transcriptions are not available. Therefore schemes for human-machine dialogs have to operate on unsegmented automatic speech recognition (ASR) outputs. We trained a dialog act predictor model using The Switchboard Dialog Act Corpus (SwDA) annotated with SWBD-DAMSL (Jurafsky et al., 1997) and tested on human-spoken dialog system conversations. Even with BERT pre-training, the model’s performance is only 47.38% in prediction accuracy. This low score suggests that only using existing dataset to train models for spoken dialog systems are not applicable. We therefore propose a new annotated human-machine data to solve this problem.

In this paper, we propose a hierarchical multi-label dialog act annotation scheme, MIDAS, specifically designed for real-time open-domain human-machine spoken conversations. We annotate real-world human-machine social conversations using the MIDAS scheme. The scheme is easy for human to follow. Two annotators achieve an inter-annotated agreement of \( \kappa = 0.94 \). We train a multi-label dialog act classifier using transfer learning methods and reached a 0.79 in F1 score. We also share our annotated data and trained models with the research community for
the hope of pushing dialog system performance ¹.

2 Related Work

Previous dialog act annotation schemes are mostly designed for dialogs with a specific task, such as MapTask (Thompson et al., 1993) and Verbmo-obil (Alexandersson et al., 1998). There are a few dialog act schemes designed for task-independent conversations, such as the Discourse Annotation and Markup System of Labeling (DAMSL) (Core and Allen, 1997) and SWBD-DAMSL (Jurafsky et al., 1997). SWBD-DAMSL is used to annotate Switchboard (Godfrey et al., 1992) corpus, a task-independent telephone conversation corpus. However, the conversation topics in Switchboard are still limited to 70 pre-defined topics, such as “air pollution”. In this paper, we design a dialog annotation scheme specifically for social chitchat conversations without any topic constraints.

Most dialog schemes are designed for human-human conversations in the previous research. Because of the recent developments of ASRs and natural language understanding (NLU) technologies, dialog systems, such as Amazon Alexa, have been more and more popular among general users. Therefore, given the discrepancy between human-human and human-machine conversations, there is a need to design dialog act schemes for human-machine conversations in order to analyze and support dialog system building. Khatri (2018) introduces a human-machine dialog act annotation scheme with 14 tags. However, the scheme is designed for modeling conversation topics instead of training dialog act predictors. The scheme has tags such as Information Request, General Chat, and Multiple Goals, and the annotation is done on unsegmented user utterances. Even though the limited number of tag categories makes annotation more reliable, it may not provide enough information for understanding user intents. For example, tags such as Multiple Goals do not provide explicit information on any conversation topic to a dialog manager. We propose a dialog act annotation scheme that focuses on improving open-domain dialog system understanding. We also build a dialog act predictor based on the annotated corpus which reached a 0.79 in F1 score.

Previously, most popular annotation schemes, such as DAMSL, use mutually-exclusive tags (Mezza et al., 2018) to make annotation process easy and reliable. However, Bunt (2009) argues that conversation utterances are complex. Each functional segment can have four to five functions on average, so dialog act tags should serve multiple functions. Dynamic Interpretation Theory (DIT) (Bunt, 1997) and its extension, DIT++ (Bunt, 2009) try to solve this problem by supporting multi-dimension and multi-function. The 88 tags are organized in a hierarchically structure and separated into dimension-specific and general-purpose functions. The fifth version of DIT++, ISO (Bunt et al., 2010, 2017), is introduced to incorporate not only linguistic theory but also empirical discourse analysis on real domain-independent conversations. Although much effort has been put in designing ISO, no large dataset annotated using it exists, probably due to the complexity of the scheme and the lack of clear guidelines on how to use contextual information (Mezza et al., 2018). Because of the intricacy of open domain social conversations, we propose to build the dialog act scheme to have a hierarchical structure and multi-dimension tags. We also limit the number of dialog acts (23 tags) to make the annotation process feasible (two annotators reached 0.94 in Kapa). We publish the annotated human-machine chatbot corpus that has 24,000 utterances.

3 MIDAS Annotation Scheme

We design MIDAS, a contextual hierarchical multi-label dialog act annotation scheme. MIDAS follows DIT++ and ISO (Bunt, 2009; Bunt et al., 2010) to ensure that the scheme is easy to both annotate and train automatic dialog act predictors. MIDAS focuses on assisting dialog systems to understand their human users, while previous schemes mainly focus on analyzing human-human dialog. Therefore, besides inheriting labels from previous schemes (such as SWBD-DAMSL and ISO), MIDAS also creates a set of new labels that adapt to the human-machine setting. A complete description of MIDAS is in Appendix 9.1. We discuss the three main features of MIDAS: context completeness, hierarchical structure, and multi-label, respectively as follows.

3.1 Contextual completeness

MIDAS relies on contextual information in the annotation process. Specifically, annotators are asked to fill in the ellipsis based on the previous
Figure 1: Semantic request tree. Scheme types, classes, categories, and sub-categories are in green, blue, purple, and yellow, respectively. Dialog act tags are leaf nodes in red. Tags can co-occur in one utterance, except tags under opinion and statement non-opinion, question and answer categories due to semantic and syntactic conflicts. For example, “User1: Do you watch TV shows? User2: I prefer watching movies.” User2 is labeled both general opinion and negative answer.

utterances before assigning dialog act tags. For instance, in “User1: have you read any book recently. User2: the great gatsby”, the latter utterance will be completed as “i read the great gatsby recently”. The completion process is only for annotators while the original utterances remain unchanged. We leave automatic completion before machine prediction to future work.

Capturing contextual information is more difficult for automated methods compared to human annotators (Bunt et al., 2010). When building dialog act predictor models, we also add the previous user utterances as feature representations. See Section 5 for details.

3.2 Hierarchical structure

We design MIDAS to have a tree structure. It has two sub-trees: semantic request type (Figure 1) and functional request type (Figure 2). Under each type, there are classes, categories, and tags arranged in a hierarchical tree structure. Please refer to Figure 1 and 2 for detailed organization. Utterances will be labeled with dialog act tags, which are the leaf nodes. The non-leaf nodes are used to help annotators find the correct dialog act tags.

3.2.1 Semantic request

Semantic request type captures dialog content, therefore they are essential for dialog topic planning. Semantic request separates into initiative class and responsive class based on whether the user is proposing or continuing a topic. Initiative class is especially important in the human-machine setting, because in such unbalanced power setting, the machine has to follow the topic that its human partner proposes. Therefore, understanding whether the user is proposing a new topic with its specific intent is the first step for the system to be coherent. There are two categories, question and command in the initiative class, that are designed to distinguish information request from action request.

MIDAS first separate question into yes/no question and open-ended question based on syntax. Such separation helps the system to generate coherent response. For example, system responses are more natural to start with words, such as “yes” or “no” when replying to yes/no question. Then MIDAS further separates open-ended question into factual question and opinion question based on different types of information that users seek. The system need to search different knowledge bases based on the tag. For example, factual questions requires factual information from knowledge
graphs such as Wikipedia, while opinion question requires information from corpora with opinionated material such as Twitter database.

Different from question, command conveys orders and is particularly popular in human-machine dialogs. The system needs to follow users’ command, whether implicit or explicit, because the system has less power in the conversation with human. Therefore, unlike ISO and other schemes, MIDAS combines command types, such as direct request, indirect request, and suggestion. Combining these tags also simplifies the annotation scheme. In addition, we add an extra tag under command, invalid command, which tailors to smart devices. Users sometimes produce commands that are out of the system’s capability. For example, users may want to control the device hardware that the dialog system does not have access to currently. The system will want to identify these utterances and handle them separately.

Responsive class indicates that the utterance is a continuation of the previous topic. SWBD-DAMSL notices that opinions are often followed by other opinions, whereas statements are followed by backchannels (Jurafsky et al., 1997). This distinction may not be beneficial to human-human conversations (Jurafsky et al., 1997) as humans do not need to explicitly distinguish between the two tags to generate corresponding responses. However, knowing whether an utterance is a statement or an opinion is essential for a system to generate appropriate responses. In addition, a quick and definite reply to the previous utterance proposal or question can benefit dialog planning. Hence, MIDAS further breaks the responsive class into opinion, statement non-opinion, and answer, based on conversation history.

MIDAS separates the opinion category into the additional opinion subcategory and the comment tag because we observed examples such as “User1: my friend thinks we are living in matrix. User2: she’s probably right”. User2 comments on the previous utterance without contributing extra information. Comment often indicates an utterance of simply reply, without explicit feedbacks. MIDAS separates three types of opinions: appreciation, complaint, and general opinion, because having the sentiment valence of the opinion can help the system plan the dialog better. For dialog systems, understanding whether the user is complaining or praising them is essential information to plan for dialog policies.

We also break down answer into positive answer, negative answer, and other answer, based on utterance sentiment. One caveat is that utterances, such as “why not”, contain negative words but are actually positive answer for questions such as “can we talk about movies”. Such phenomena suggests that automatic dialog act prediction models require semantic understanding and need to incorporate context in feature representation.
3.2.2 Functional request

Functional request type helps dialog systems achieve discourse level coherence. We define incomplete, social convention, and other classes under the functional request type.

Incomplete class describes utterances that are not complete. There are two types of incomplete, abandon and nonsense. In real-world settings, human users can be cut off due to issues such as background noises and long pauses. These cases are labeled as abandon. In comparison, nonsense is used to label utterances that human annotators cannot understand. These utterances usually have many ASR errors. The system can understand both abandon and nonsense utterances better by asking users to repeat. However, MIDAS still separates the two, because if the utterance has an abandon tag, such as “i think”, the system can give users more specific instructions such as “take your time”. Such instructions are not applicable for nonsense utterances.

Social convention class is similar to the social obligations management and discourse structure management dimensions in ISO (Bunt et al., 2010). There are opening, closing, thanks, apology, apology response, hold, and back channeling to provide discourse level information.

Finally, utterances that cannot be assigned to any other tag in this hierarchical structure are labeled as an other tag.

3.3 Multi-label support

Compared to single-label schemes, multi-label schemes capture different dimensions and functions, which support dialog system building and discourse analysis better. For example,

User1: what books have you read recently
User2A: i haven’t read any
User2B: i don’t want to talk about books
User2C: i prefer watching movies

Users may use different sentences to express a negative answer intent. If the annotation scheme is single-label, the above three sentences cannot be differentiated. Having an extra label to capture other semantic information besides negative answer will benefit dialog system building. For instance, User2B has the additional task command intent to end the current topic compared to User2A. User2C has the general opinion intent to initiate a different topic. While the dialog system may not need to change the topic if the utterance is User2A, but will have to change if it is User2B.

SWBD-DAMSL allows a utterance to be tagged as double labels and lists the preferred tag first (Jurafsky et al., 1997). However, the rules designed to order these tags rely on heuristics and are not explicit to follow. Our proposed scheme, MIDAS, also allows multiple tags with a clear priority but do not require annotators to order the tags. The scheme is thus easier to follow and more reliable.

In MIDAS, except for two exclusive category pairs (opinion and statement non-opinion, question and answer), labels in each category can co-occur with another. However, we restrict the maximum number of tags for each utterance to be two, in order to reduce the complexity in the annotation process, as well as machine prediction.

If there are more than two dialog act tags applicable to an utterance, we choose the two that are most useful for dialog planning (without ordering). Due to the unbalanced power of human-machine conversations, MIDAS prefers dialog act categories in the following order: answer, command, opinion, statement non-opinion, and question. For example, “User1: what do you want to talk about? User2: how about the financial market”. User2’s utterance can be tagged as task command, opinion question, and other opinion. Among the three tags, task command and opinion question are more important for the system to direct the conversation towards a specific topic so we only keep these two.

4 Dataset and Annotation Process

We collected 380K human-machine conversations using Gunrock, the 2018 Alexa Prize winning social bot (Chen et al., 2018). Table 1 shows an example conversation. Two annotators reached an inter-annotator agreement of $\kappa = 0.94$ on 1,185 segmented utterances. Then they annotated the rest of the data separately. In total, they annotated 468 conversations, including 24K segmented sentences on both user and system, among which 12.9K segments are from users. general opinion and statement non_opinion are the most frequent tags. For multiple labels, (positive_answer, command) and (negative_answer, command) are the most frequent co-occur tags. Detailed annotation results including dialog act tags distribution are shown in Appendix 9.1 and Appendix 9.2.
what do you want to talk about
what can you tell me what the top books are right now
i am so excited to talk to you about books. i’m actually a pretty big bookworm, and i love to read when i’m not chatting
oh [SEG] what are some titles of the books you’ve read
recently, i’m reading the great gastby. it’s really thought provoking, and i can see why some people call it the great american novel. how about you? what book do you like?
what are some titles of the books you’ve read recently, i’m reading the great gastby. it’s really thought provoking, and i can see why some people call it the great american novel. how about you? what book do you like?
not read a book in a while [SEG] do you have recommendations in the sci fi
i have {not} read a book in a while [SEG] do you have recommendations in the sci fi

Table 1: An example conversation between a machine (USER1) and a human (USER2). The word “not” is dropped in the last sentence due to ASR errors.

For dialog act prediction, user utterances in human-machine dialogs are ASR outputs and have no punctuation. Therefore, we train a model to segment utterances into complete semantic units for pre-process. We then perform dialog act prediction on each segmented unit (Stolcke et al., 2000). Previous research detects sentence boundaries by predicting the exact punctuation in the training dataset (Cho et al., 2015). However, correct punctuation also relies on deep semantic understanding beyond the sentence surface forms. A misused question mark can lead the dialog act model to predict a sentence as a question. So following Favre et al. (2008), we only predict the boundary of the sentence instead of predicting punctuation to avoid introducing errors.

Because it is expensive to annotate sentence boundaries, we use the Cornell Movie-Quotes Corpus (Danescu-Niculescu-Mizil and Lee, 2011) to train a sentence segmentation model. The Cornell dataset contains 300K utterances from movie transcripts. We reformat the transcripts by replacing punctuation to sentence breaker tokens (denotes as [SEG]). We then trained a sequence-to-sequence (seq2seq) model to predict sentence breaker tokens similarly to Klejch et al. (2017) and Peitz et al. (2011). Both the encoder and the decoder are 2-layer 500-dimension bi-LSTM. In addition, the decoder uses global attention and input feed (Luong et al., 2015) with beam search. The input of the model is a reformatted sentence, and the output is the same sentence with added sentence breaker tokens. An example can be seen in the last USER2 utterance in Table 1. Word embeddings are pre-trained with fastText (Mikolov et al., 2018) using Common Crawl. We evaluate the segmentation model on human labeled 2K human utterances of collected data. The segmentation model achieves 84.43% in micro F1 score, 84.97% in precision, and 84.57% in recall. We apply the trained segmentation model on the entire collected dataset to obtain segmented sentences. All the dialog act annotation and predictions are done on the automatic segmentation results.

5 Dialog Act Prediction

We formulate the dialog act prediction problem as a multi-label classification problem. Building on previous work on text classification, we use an encoder-decoder model with two major modifications. We incorporate context in feature design and have one or two labels as output. In addition, we leverage both unlabeled data and annotated data in the transfer learning process.

5.1 Baseline model

RNN models have shown promising results on text classification (Rojas-Barahona et al., 2016). Our baseline model uses a 2-layer Bi-LSTM to encode the context representation and a multi-layer perceptron (MLP) to decode the output. For multi-label prediction, we use a binary cross-entropy objective function. During testing, we choose the labels with the highest two values predicted from the MLP as the potential output and filter them with an empirical threshold (0.5) to decide to keep both labels or just the one with the highest probability.

5.2 Context representation

Contextual information plays an important role in dialog act prediction (Liu et al., 2017; Khatri et al., 2018). We consider two methods to represent previous turns: the actual utterance (text), and the dialog act of the utterance (DA). For each method, the most recent segmented sentence unit from each speaking party is considered as the history. We append the last segmented system unit (sys_unit), the previous segmented user unit (user_prev), and the current segmented user unit (user_cur) as sys_unit <u_p> user_prev <u_c> user_cur where <u_p> and <u_c> are special tokens to separate utterances. For instance, to predict the dialog act for the segment “do you have recommendations in the sci fi” in the last USER2 utterance in Table 1, the context representation is formed as what book do you like <u_p> i haven’t read a book in a while <u_c> do you have rec-
ommendations in the sci fi. However, if the current utterance is the first one in the current turn, i.e. there is no contextual information, we use an empty token for \(usr_{prev}\) instead.

Another method to incorporate history is to replace the actual previous segment unit with its dialog act labels (if there are two labels for one segment, we combine both labels). The results for these two methods are shown in Table 2.

5.3 Transfer learning

We experimented with two methods to leverage more data. One is an unsupervised task on domain adaption and the other is a supervised dialog act predictor trained on SwDA (Jurafsky et al., 1997).

For domain adaption, we started with the BERT based model trained on Wikipedia (Devlin et al., 2018) to leverage contextual word embeddings from a large language model. However, one potential drawback of using BERT pre-trained on textual data is its domain difference from conversational data. Inspired by Siddhant et al. (2018), we use 50 million unlabeled segmented utterances collected from 380K conversations from Gunrock to fine-tune the BERT language model before training on the classification task.

In addition to pre-trained word-embeddings from language models, we leverage annotated datasets. We automatically map 42 tags from SWBD-DMSL to our 23 tags. The detailed mapping can be found in Appendix 9.3. We remove all the punctuation (except apostrophes) and non-verbal information such as “<laugh>” from the carefully annotated dataset. We also drop sentences with dialog act that is not applicable to ours such as 3rd-party-talk. Because there are only 4 utterances labeled with two tags out of 386K original utterances in SwDA, we consider this as a single-label dataset. After pre-processing, we extract a total of 200K annotated utterances using context representation explained in Section 5.2. We train a single-label prediction model based on BERT before fine-tuning it on multi-label prediction with our annotated data.

6 Experiments

Setting Unlike human-human conversations, in which the interlocutors share common patterns, machine and user utterances in a dialog system are very different from each other. For instance, machine utterances may have punctuation, contain no ASR errors, and have limited vocabulary and syntax compared to user utterances. Due to the differences between user and machine utterances in human-machine conversations, we cannot combine them during prediction. The main purpose of having a dialog act predictor is for dialog system to understand user intent better. Therefore, we build a dialog act prediction model on user utterances only. After pre-processing (refer to Section 5.2 for details), there are 12.9K user segments. 13.78% of them have two labels. We use 10.3K for training and 2.6K for testing. The rest 11.1K annotated machine segments are used as context.

Models. We implemented 11 models as follows:

We use LSTM to represent the baseline model trained with LSTMs. We use BERT to represent transformer models with a pre-trained BERT language model. According to different transfer learning methods described in Section 5.3, BERT\_F is a pre-trained BERT language model fine-tuned on unlabeled in-domain data, whereas BERT\_SwDA is a pre-trained BERT language model fine-tuned on labeled SwDA task. Combining these two methods, BERT-SwDA\_F fine-tunes on both the unlabeled and labeled tasks. After fine-tuning, the models are trained on our annotated data with MIDAS scheme. To evaluate the impact of context representation for the above models, we use -text and -DA to represent using text and dialog act as the context, respectively. In addition, we denote -no\_context to predict on the current utterance only without using any context.

Implementation details. The baseline dialog act prediction model uses a 2-layer Bi-LSTM with a hidden size of 500. The LSTM layers use a dropout rate of 0.3. We optimize the model with Adam optimizer (Kingma and Ba, 2014). For the transformer models, we use 12 layers with 12 attention heads and a hidden size of 768. All the fully connected layers use a dropout rate of 0.1.

Because one data sample may have two labels in our annotation, we calculate precision, recall, and F1 on each sample and then average them across all samples (micro F1).

7 Results and Analysis

Table 2 describes the experimental results on all 11 models. Transformer models using BERT embeddings (BERT-text) outperform Bi-LSTM models with pre-trained word embeddings (LSTM-text) by a large margin (from 75.51% to 79.11%
Table 2: BERT_F-DA+text achieves the best precision and F1 score. Results reported are an averaged score of six different random seed runs.

| Model                | Pre(%) | Rect(%) | F1(%) |
|----------------------|--------|---------|-------|
| LSTM-text            | 75.94  | 75.91   | 75.51 |
| LSTM-DA              | 75.83  | 73.48   | 73.77 |
| BERT-text            | 79.57  | 79.31   | 79.11 |
| BERT-DA              | 79.29  | 76.12   | 76.87 |
| BERT-no_context      | 73.88  | 70.43   | 71.30 |
| BERT-DA+text         | 79.79  | 79.47   | 79.28 |
| BERT_F-text          | 79.83  | 79.64   | 79.40 |
| BERT_F-DA            | 79.30  | 76.15   | 76.89 |
| BERT_F-DA+text       | **79.93** | 79.61   | **79.44** |
| BERT-SwDA            | 79.26  | 76.43   | 78.98 |
| BERT-SwDA_F          | 79.58  | **79.76** | 79.28 |

In F1. If we further fine tune the BERT language model on an unsupervised training task with similar data distribution (BERT_F-text), the classification result further improves from 79.11% to 79.40% in F1. This is consistent with previous research on in-domain pre-training (Siddhant et al., 2018). However, the performance improvement is not statistically significant. One possible reason is that models pre-trained on a very large text dataset, such as Wikipedia, already encodes sufficient semantics for dialog act prediction. Therefore, fine-tuning the model on a more domain aligned data set does not improve the performance drastically.

We found that incorporating context improves the model performance. Adding text information as context improves the BERT model from 71.30% to 79.11% in F1. We also compare the impact of different context embedding methods on dialog act classification performance. The results show that replacing text with dialog act achieves a high precision, but suffers from a low recall. This is because an utterance can have multiple intents while dialog act itself does not provide enough context information to achieve accurate prediction. For example, when “i don’t think so” is a response to a simple yes/no question such as “have you read the book”, it is a negative_answer. But if it is a response to a more complex yes/no question, such as “do you want to talk about books”, then it has two tags, command and negative_answer. The latter conveys user’s implicit request on changing the topic. Therefore, only using dialog act as context could lead to high recall but low F1. We found combining both previous segment’s dialog act label and its surface text together achieves the best performance in F1 (79.44%). However the performance improvement over including text only is not statistically significant. This suggests that dialog act and text may have more overlapped information than complimentary information.

We also found that fine-tuning the model using the supervised dialog act prediction task on the SwDA data did not improve performance in F1 but improved recall slightly. The reduced performance may be due to the data difference. Even though both datasets are open domain conversational data, SwDA task uses pre-processed Switchboard data that does not have ASR errors. Moreover, SwDA is human-human conversations, and they are more coherent and consistent compared to human-machine conversations. Another reason is that SwDA dataset has exactly one label for each utterance. When fine-tuning on our multi-label task, the pre-trained single-label model may tend to predict more labels to quickly reduce loss but fail to learn better representations.

We further looked into the errors from the best model (BERT_F-DA+text) and found that the model confuses statement non-opinion and general opinion. This is most likely caused by only including one turn context. Sometimes, users would have questions that breaks the conversation flow, such as “can you say it again clearly”. The model needs to consider not only this utterance but also the turns before that to perform dialog act prediction. We plan to incorporate longer context in future work. In addition, some of the nonsense sentences are misclassified as statement non_opinion such as “it doesn’t outside break a car”. It is also worth noting that some incorrectly segmented units resulted in inaccurate dialog act prediction.

8 Conclusion and Future Work

We propose a dialog act scheme designed for open-domain human-machine conversational systems, MIDAS. MIDAS is a hierarchical annotation scheme that supports multiple labels. We annotated 24K sentences from a human-machine social conversation data using MIDAS. We also trained dialog act classification models based on the annotated dataset. We tested different transfer learning techniques to improve model performance. We found that fine-tuning using the pre-trained BERT embedding plus the unannotated target human-machine conversation improved model.
performance. But fine-turning the model on a supervised dialog act task with human-human data did not improve model performance.

In the future, we plan to combine dialog act and parsing in a multi-task learning setting, so the dialog act model can borrow information from syntactic and semantic parsing representations. In addition, we would like to test if training the utterance segmentation and dialog act prediction together can improve model performance.

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## Appendices

### 9.1 Dialog Act Scheme

| Dialog Act Tag       | Description                                      | Example                                                                 | Count in user utterances (single label only) |
|----------------------|---------------------------------------------------|-------------------------------------------------------------------------|---------------------------------------------|
| factual question     | factual questions                                 | How old is Tom Cruise; How’s the weather today                          | 360                                         |
| opinion question     | opinionated questions                             | What’s your favorite book; what do you think of disney movies           | 236                                         |
| yes/no question      | yes or no questions                               | Do you like pizza; did you watch the game last night                    | 325                                         |
| task command         | commands/requests (can be in a question format)   | can i ask you a question; let’s talk about the immigration policy; repeat | 651                                         |
| invalid command      | general device/system commands that cannot be handled by the social bot | show me a picture; cook food for me                                      | 87                                          |
| appreciation         | appreciation towards the previous utterance       | that’s cool; that’s really awesome                                       | 201                                         |
| general opinion      | personal view with polarized sentiment            | dogs are adorable; (A: How do you like Tom) B: i think he is great       | 2157                                        |
| complaint            | complaint about the response from another party   | I can’t hear you; what are you talking about; you didn’t answer my question | 239                                         |
| comment              | comments on the response from another conversation party | (A: my friend thinks we live in the matrix) B1: she is probably right; B2: you are joking, right; B3: i agree; (A: ... we can learn a lot from movies ...) B: there is a lot to learn; (A: He is the best dancer after michael jackson. What do you think) B: michael jackson | 430                                         |
| statement non-opinion| factual information                               | I have a dog named Max; I am 10 years old; (A: what movie have you seen recently) B: the avengers | 1717                                        |
| other answer         | answers that are neither positive or negative     | I don’t know; i don’t have a favorite; (A: do you like listening to music) B: occasionally | 428                                         |
| positive answer      | positive_answers                                  | yes; sure; i think so; why not                                         | 1278                                        |
| negative answer      | negative response to a previous question          | no; not really; nothing right now                                       | 867                                         |
| Dialog Act Tag | Description | Example | Count in user utterances (single label only) |
|----------------|-------------|---------|--------------------------------------------|
| abandon        | not a complete sentence | So uh; I think; can we | 440 |
| nonsense       | utterances that do not make sense to humans | he all out | 129 |
| hold           | a pause before saying something | let me see; well | 272 |
| opening        | opening of a conversation | hello my name is tom; hi; | |
| closing        | closing of a conversation | nice talking to you; goodbye | 540 |
| thanks         | expression of thankfulness | thank you | 80 |
| back-channeling| acknowledgement to the previous utterance | Uh-huh; (A: I learned that ...) B: okay/yeah/right/really? | 427 |
| apology        | apology | I’m sorry | 29 |
| apology response| response to apologies | That’s all right | 6 |
| other          | utterances that cannot be assigned to other tags | | 12 |
## 9.2 Multi-functionality schemes

| Dialog Act Tags                               | Example                                                                 | Count in User Utterances |
|-----------------------------------------------|-------------------------------------------------------------------------|--------------------------|
| *positive answer, task command*              | (A: wanna know something interesting about it?) B: sure; (A: do you want to talk about some games) B: minecraft | 698                      |
| *negative answer, task command*              | (A: would you like to know more about it?) B: I don’t want to hear more | 328                      |
| *task command, general opinion*              | (A: what do you want to talk about) B: harry potter stuff              | 192                      |
| *task command, statement non_opinion*        | let’s talk about mario kart                                           | 141                      |
| *positive answer, statement non_opinion*     | (A: have you read any books recently?) B: I’m reading the great gatsby | 133                      |
| *task command, yes/no question*              | do you know tom brady; (A: what do you want to talk about?) B: how about movies | 116                      |
| *negative answer, statement non_opinion*     | (A: do you have pets) B: I don’t have any                              | 66                       |
| *positive answer, general opinion*           | (A: do you like animals) B: My favorite animals is panda               | 35                       |
| *invalid command, yes/no question*           | can you speak louder                                                  | 15                       |
| *task command, factual question*             | what do you know about dodgers                                         | 12                       |
| *negative answer, general opinion*           | (A: do you watch sports) B: I’m not into sports                         | 10                       |
| *task command, opinion question*             | (A: what did you find interesting recently) B: what do you think of the new movie | 9                       |
| *task command, complaint*                    | I don’t want to hear you talk about anything; would you stop asking me that question | 5                       |
| *other answer, general opinion*              | (A: what’s your favorite movie) B: there are so many to choose from    | 5                        |
| *positive answer, comment*                   | (A: don’t you think so) B: it’s true                                   | 4                        |
| *general opinion, yes/no question*           | (A: what would you imagine doing in such situation) B: can we just sleep all day | 3                       |
| *negative answer, comment*                   | (A: isn’t that interesting) B: that’s ridiculous                        | 3                        |
| *general opinion, opinion question*          | (A: what book would you recommend me to read) B: how about antifragile   | 3                        |
### Dialog Act Tag Mapping

| SWBD-DAMSL         | SWBD   | MIDAS             |
|--------------------|--------|-------------------|
| statement_non-opinion | sd     | statement non_opinion |
| Acknowledge (Backchannel) | b      | back-channeling   |
| Statement-opinion   | sv     | general opinion   |
| Agree/Accept        | aa     | pos answer        |
| Abandoned or Turn-Exit | %     | abandon           |
| Appreciation        | ba     | appreciation      |
| Yes-No-Question     | qy     | yes-no question   |
| Non-verbal          | x      | pos answer        |
| Yes answers         | ny     | pos answer        |
| Conventional-closing | fc    | closing           |
| Uninterpretable     | %      | abandon           |
| Wh-Question         | qw     | pos answer        |
| No answers          | nn     | neg answer        |
| Response Acknowledge | bk   | back-channeling   |
| Hedge               | h      | other answers     |
| Declarative Yes-No-Question | qy’d | yes-no question |
| Other               | o,fo,bc,by-fw | other             |
| Backchannel in question form | bh | back-channeling |
| Quotation           | ˆq | other opinion     |
| Summarize/reformulate | bf  | other opinion     |
| Affirmative non-yes answers | na, ny’e | pos answer |
| Action-directive    | ad     | task command      |
| Collaborative Completion |ˆ2 | general opinion   |
| Repeat-phrase       | b’m   | general opinion   |
| Open-Question       | qo    | general opinion   |
| Rhetorical-Questions |qh  | other opinion     |
| Hold before answer/agreement | ˆh | hold              |
| Reject              | ar     | neg answer        |
| Negative non-no answers | ng,nn’e | neg answer      |
| Signal-non-understanding | br   | complaint         |
| other_answers       | no     | other answer      |
| Conventional-opening | fp   | opening           |
| Or-Clause           | qrr   | other             |
| Dispreferred answers | arp,nd | neg answer |
| 3rd-party-talk      | t3     | other             |
| Offers, Options Commits | oo,cc,co | other          |
| Self-talk           | t1     | other             |
| SWBD-DAMSL | SWBD | MIDAS          |
|------------|------|---------------|
| Downplayer | bd   | apology response |
| Maybe/Accept-part | aap/am | pos answer |
| Tag-Question | 'g | other |
| Declarative Wh-Question | qw’d |       |
| Apology | ja | apology |
| Thanking | ft | thanking |