Improving Named Entity Recognition in Spoken Dialog Systems by Context and Speech Pattern Modeling

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Abstract

While named entity recognition (NER) from speech has been around as long as NER from written text has, the accuracy of NER from speech has generally been much lower than that of NER from text. The rise in popularity of spoken dialog systems such as Siri or Alexa highlights the need for more accurate NER from speech because NER is a core component for understanding what users said in dialogs. Deployed spoken dialog systems receive user input in the form of automatic speech recognition (ASR) transcripts, and simply applying NER model trained on written text to ASR transcripts often leads to low accuracy because compared to written text, ASR transcripts lack important cues such as punctuation and capitalization. Besides, errors in ASR transcripts also make NER from speech challenging. We propose two models that exploit dialog context and speech pattern clues to extract named entities more accurately from open-domain dialogs in spoken dialog systems. Our results show the benefit of modeling dialog context and speech patterns in two settings: a standard setting with random partition of data and a more realistic but also more difficult setting where many named entities encountered during deployment are unseen during training.

1 Introduction

Named entity recognition (NER) is the task of extracting proper names of people, locations, and so on from text or speech (Grishman and Sundheim, 1996). There has been a lot of work on NER from written text with many systems achieving impressive results (Devlin et al., 2019; Akbik et al., 2019). Although, NER from speech has been around for the same time as NER from text (starting with work by Kubala et al. (1998)), accuracy of NER from speech still lags behind the accuracy of NER from text. The rise in popularity of spoken dialog systems such as Siri or Alexa highlights the need for more accurate NER from speech because NER is a core component for understanding what users said in dialogs. In spoken dialog systems, humans interact with the systems using natural speech to accomplish certain tasks (task-oriented dialog) or just to be entertained (chitchat or open-domain dialog) (Jurafsky and Martin, 2009). These systems require speech transcripts as input in real-time and the transcripts are obtained using automatic speech recognition (ASR) components (Turmo et al., 2009).

Much previous work on NER from speech data, such as broadcast news, applied text-based NER systems to the output of an ASR system (Palmer and Ostendorf, 2001). However, NER performance degraded significantly (20 points drop in F1 score) when applying a NER trained on written data to transcribed speech (Kubala et al., 1998). This could be because applying text-based NER system to ASR output ignores the differences in styles and conventions in written and spoken language (Palmer and Ostendorf, 2001). For example, spoken utterances in spontaneous speech are usually much shorter than written prose so the utterances could be ambiguous when taken out of context. In addition, speech also contains disfluencies, repetitions, restarts and corrections (Turmo et al., 2009). Besides, text-based NER system may depend on cues such as sentence punctuation and capitalization which are not present in ASR transcripts (Shriberg et al., 2000). Furthermore, ASR is not error-free and errors in ASR transcripts lead to cascading errors in NER (Turmo et al., 2009). Due to factors such as greater variation in speakers, greater variation in content because of the open-ended nature of open-domain dialogs, and less professional recording environment, ASR transcripts from spoken dialog systems often contain more errors than that from broadcast news, making NER in dialogs a much more challenging task.
We propose two models that exploit dialog context and speech patterns which are available in open-domain dialogs from spoken dialog systems to achieve more accurate NER. Our results show the benefit of modeling dialog context and speech patterns in two settings: a standard setting with random partition of data and a more realistic but also more difficult setting where there is little overlap between named entities during training and testing.

2 Related Work

Recent NER models perform well on clean text datasets such as CoNLL (Tjong Kim Sang and De Meulder, 2003) and OntoNotes (Hovy et al., 2006), but less well on noisy data (Mayhew et al., 2020) such as the WNUT dataset (Derczynski et al., 2017). In term of F1 score, the current state-of-the-art model (Akbik et al., 2019) achieves 93% on the CoNLL dataset but only 49% on the WNUT dataset. The overreliance of NER models on the convention of capitalizing named entities (Derczynski et al., 2017) partly explains why they perform poorly on text where capitalization is absent or noisy. In spoken dialog systems, inputs to NER models are ASR transcripts which not only lack capitalization and punctuation but also contain transcription errors (Sundheim, 1995; Lenzi et al., 2012). Although, joint decoding of ASR transcript and NER output (Caubrière et al., 2020) partly lessens the impact of ASR errors on NER, detecting named entities in ASR transcripts remains a challenging problem (Galibert et al., 2014).

Prior work on NER from ASR transcripts focus on reducing ASR errors (Palmer and Ostendorf, 2001), exploiting multiple ASR hypotheses (Horlock and King, 2003; Béchet et al., 2004), or exploiting additional information such as speech pattern features (Katerenchuk and Rosenberg, 2014). Examples of speech pattern features are ASR confidence (Sudoh et al., 2006), pauses, and word durations (Hakkani-Tür et al., 1999). Recently, Cervantes and Ward (2020) used solely prosodic speech features to spot location mentions. Our work is similar to Katerenchuk and Rosenberg (2014) in that we also utilize speech pattern features. However, while Katerenchuk and Rosenberg (2014) focused on broadcast news speech, our work focuses on spoken dialogs. Thus, besides speech pattern features, our models also exploit dialog context for more accurate NER. In addition, Katerenchuk and Rosenberg (2014) used a separate classifier trained on data from a small set of speakers to derive speech pattern features, so the predicted features may not generalize to more diverse populations. In contrast, our approach is more integrated since the speech pattern features encoder is part of the proposed models thereby encouraging the models to learn features that are more generalizable.

3 Methods

3.1 Motivation

Dialog utterances are usually short and ambiguous when taken out of context, therefore identifying named entities in dialog utterances can be challenging. Figure 1 shows two challenging cases where dialog context and speech patterns can aid NER. Although users’ utterances are similar, the phrase “her” is a named entity in the second case but not in the first case. Without knowing what the bot said (i.e. dialog context), the best guess is that “her” refers to a person and therefore not a named entity. However, when “i like her” is a response to the question “What is your favorite sci-fi movie?”, “her” is a named entity (the 2013 sci-fi movie Her). Examples are not actual interaction data.
ers were choosing their words (Goldman-Eisler, 1958), so pauses might indicate subsequent named entities in utterances. Figure 1b shows the user pausing prior to uttering the named entity “her” as the user might have been considering different named entities. In contrast, in Figure 1a, there was no pause probably because the user was saying a set phrase so there was no difficult choice involved. Furthermore, pauses could signal boundaries (punctuation) between grammatical structures within utterances (Reich, 1980; Chen, 1999). Since punctuation is an important feature in NER (Nadeau and Sekine, 2007) and punctuation is missing in ASR transcript, pauses could potentially replace the missing punctuation. Exaggerated variation in word durations and pauses could be present when pronouncing non-native names (Fitt, 1995; Rangarajan and Narayanan, 2006). Tokens’ confidence might also predict the presence of named entities since named entities appear less often than other words in ASR training data. Tokens’ confidence have been used previously in NER task (Palmer and Ostendorf, 2001; Sudoh et al., 2006).

3.2 Model

We propose two NER models for dialog which take a dialog exchange as input. A dialog exchange consists of a bot’s utterance followed by an user’s utterance, and the models must label named entities in the user’s utterance, taking into account the context (the bot’s utterance). The user’s utterance includes lexical features (i.e. word tokens or word pieces) and speech pattern features which are pauses’ duration, words’ duration, and tokens’ ASR confidence. Both models have three components: (1) a context encoder, (2) a speech pattern encoder, and (3) a sequence tagger. The context encoder and speech pattern encoder are the same in both models and the encoders provide additional clues for the sequence tagger to accurately label named entities. The first model’s sequence tagger is a widely used model for NER from written text based on BiLSTM-CRF (Ma and Hovy, 2016; Lample et al., 2016), which combines bidirectional LSTM (Graves and Schmidhuber, 2005) with conditional random field (Lafferty et al., 2001). The second model’s sequence tagger is based on BERT (Devlin et al., 2019), which achieved state-of-the-art result for the CoNLL dataset.

Figure 2 shows the models’ structure. The context encoder is a bag-of-embedding model (Figure 2a), which encodes the bot’s utterance and outputs a single context vector. Specifically, the tokens’ embeddings (concatenation of word and character embeddings) in the bot’s utterance are fed through a max-pooling layer to produce the context vector. The context vector and the lexical vectors (Figure 2b) are combined as models’ input using element-wise addition (Figure 2d). The speech pattern encoder is a BiLSTM (Figure 2c), which encodes speech pattern features as vectors. These vectors are concatenated with the outputs from the last hidden layer of BiLSTM or BERT. While BiLSTM uses a conditional random field to tag the tokens, BERT uses a fully-connected layer instead (similar to (Devlin et al., 2019)).

Since BERT uses sub-word tokens, some words may be split into multiple tokens. For example, “interstellar” is split into “inter” and “#stellar”. However, as the speech pattern features are only available for individual words and not for word pieces, these features have to be split up for multi-token words. In particular, the sub-word tokens have the same ASR confidence and duration as the word’s ASR confidence and duration. Although the durations of the sub-word tokens should be shorter than the word’s duration, it is not clear how to derive the correct durations. For the pauses, the preceding pause value is assigned to the first sub-word token while the succeeding pause value is
Table 1: Data statistics. The data were collected during the period from December 2019 to May 2020. The data are divided into two different splits (standard and hard) with a shared training set. The hard split is used to test the robustness of the proposed model while the standard split is common practice in machine learning.

|          | Train          | Dev          | Test          |
|----------|----------------|--------------|---------------|
| Number of Tokens | 22,908        | 3,000        | 3,000         |
| Average Length | 146,858       | 19,585       | 19,279        |
| Train | 22,908 | 624,168 | 146,858 | 27.2 | 6.4 |
| Standard Split | | | | |
| Dev | 3,000 | 80,749 | 19,585 | 26.9 | 6.5 |
| Test | 3,000 | 81,668 | 19,279 | 27.2 | 6.4 |
| Hard Split | | | | |
| Dev | 3,000 | 81,585 | 19,984 | 27.1 | 6.6 |
| Test | 3,000 | 82,137 | 20,583 | 27.3 | 6.8 |

Table 2: Number of unique named entities that are also in the training set (vocabulary transfer)

|          | CoNLL | OntoNotes | WNUT |
|----------|-------|-----------|------|
| Number of Tokens | 203,621 | 1,088,503 | 62,730 |
| Number of Entities | 23,499 | 81,829 | 1,975 |
| Standard split | 7,402 | 934 | 952 |
| Hard split | 7,402 | 1,254 | 1,391 |

Table 3: Comparing the dataset used in this paper against public NER datasets.

4 Experiments

4.1 Data

The data are from conversations between humans and the Gunrock chatbot (Liang et al., 2020), which participated in the 2019 Amazon Alexa Prize. Conversations were collected during the period from December 2019 to May 2020. Each data sample consists of one chatbot utterance and the following human utterance (Figure 1). Chatbot utterances are in mixed-case while human utterances are output from an ASR system and are in lower case.

The data are divided into two different splits: a standard split and a hard split, and the two splits share the same training set (Table 1). While the training, development, and test set of the standard split are formed by randomly partitioning the data, the development and test set of the hard split are created such that they have more named entities that are not seen in the training set (i.e., little named entity overlap). Table 2 illustrates the difference in term of named entity overlap measured using vocabulary transfer rate (Palmer and Day, 1997). Vocabulary transfer is the proportion of unique named entities appearing in both training and test set, and as expected, the development and test sets of the hard split have much lower vocabulary transfer than that of the standard split. Although standard split is a common practice in machine learning, deep learning models can perform well on the standard split by exploiting the spurious patterns in the data (Jia and Liang, 2017). Thus, the hard split is necessary for measuring how well the models can generalize, since NER models relying heavily on surface patterns will underperform when there are a lot of unseen named entities (Augenstein et al., 2017). Furthermore, the test set of the hard split more closely resembles the test data during deployment because the data the models see during deployment usually differ from the data collected during training (little overlap of named entities). Thus, the performance on the hard split is a more realistic reflection of the models performance during deployment. A comparison between the size of the dataset used in this paper and that of popular public NER datasets is shown in Table 3.

Although named entities are typically classified into three big types: Person, Location, and Organization (Nadeau and Sekine, 2007), fine-grained typing may be more useful, especially for question-answering and information retrieval (Fleischman, 2001). For example, Location can be subdivided into City, State, and Country (Lee and Lee, 2005). Similarly, Person can be subdivided into Politician
and Entertainer (Fleischman and Hovy, 2002). In addition, special types may be used to address systems’ specific needs, for example Film (Etzioni et al., 2005), Book title (Brin, 1998; Witten et al., 1999), Brand (Bick, 2004), Protein (Shen et al., 2003; Tsuruoka and Tsujii, 2003; Settles, 2004), Drug (Rindflesch et al., 1999), and Chemical (Narayanaswamy et al., 2002).

Since the Gunrock chatbot needs to converse with users in different topics, fine-grained typing is more useful for accurately retrieving information about named entities. Named entities in data samples were manually labelled by Gunrock team members using 6 named entity types: Movie, Book, Song, Person, Character, and Other. The BIO scheme was used for labeling the data. Figure 3 and Table 4 show the distribution of named entities by types and the average entity length by types respectively. The Movie, Book, and Song types are for names of movies and TV shows, books, and songs respectively. The Person type includes names of real people or musical groups (e.g. Tom Hanks or Imagine Dragons). The Character type includes names of fictional people in movies or stories (e.g. Anna and Elsa in the movie Frozen). The Other type is for the other named entities (e.g. US or Siri) that do not belong to any of the previous 5 types. For labeling polysemous entities, context (i.e. chatbot utterance) is taken into account to determine the correct type. For example, for the human response “yes harry potter”, “harry potter” is a Character with regard to the question “Do you have a favorite character in the book?”. However, when the question is “Did you watch any movie recently?”,” harry potter” is labeled as a Movie.

### 4.2 Implementation Details

The models are implemented using PyTorch (Paszke et al., 2019) and transformers (Wolf et al., 2020) libraries. For BiLSTM-CRF models, word embeddings and character embeddings were concatenated to form the context input and lexical input. The size of word embeddings and character embeddings are 300 and 100 respectively. Word embeddings were initialized using GloVe word vectors from (Pennington et al., 2014). For BERT models, lexical input only includes sub-word embeddings. The size of the context encoder’s word embedding and character layer are 600 and 168 respectively (so that the concatenated size is 768, matching the dimension of BERT). The parameters of the BERT model were initialized using the pre-trained uncased BERT base model. The speech pattern encoder is a two-layer BiLSTM with the hidden state size of 256. The dropout (Srivastava et al., 2014) rate of the speech pattern encoder was set at 0.3. The input to the encoder are speech pattern features which include: token ASR confidence, token duration, the pauses preceding and succeeding the token. Due to constraints in the Alexa data collection, other acoustic/prosodic speech features are unavailable. The token duration is thresholded at 1.5 second which is the 99th percentile value. The preceding (succeeding) pause is a binary variable, indicating whether there is a gap more than 30 milliseconds before (after) the token.

All models were trained for 100 epochs with the batch size of 128. BiLSTM-CRF models were trained using Adam (Kingma and Ba, 2014), while BERT models were trained using AdamW (Loshchilov and Hutter, 2018). Linear learning rate schedule is used for training BERT.

| Type | Movie | Book | Song |
|------|-------|------|------|
| Length | 2.3   | 3.0  | 2.7  |

| Type | Person | Character | Other |
|------|--------|-----------|-------|
| Length | 2.0   | 1.3      | 1.6   |

Table 4: Average entity length (tokens) by entity types

![Figure 3: Entities by types, S: Standard, H: Hard](image-url)

- **(a)** Name entities occurrence (All)

|       | Movie | Book | Song | Person | Character | Other |
|-------|-------|------|------|--------|-----------|-------|
| Test (H) | 354   | 170  | 94   | 447    | 157       | 169   |
| Dev (H)  | 246   | 328  | 80   | 328    | 97        | 175   |
| Test (S) | 221   | 181  | 60   | 310    | 66        | 94    |
| Dev (S)  | 210   | 172  | 67   | 347    | 55        | 82    |
| Train    | 1652  | 1330 | 538  | 2566   | 591       | 725   |

- **(b)** Name entities occurrence (Unique)

|       | Movie | Book | Song | Person | Character | Other |
|-------|-------|------|------|--------|-----------|-------|
| Test (H) | 153   | 133  | 73   | 263    | 77        | 87    |
| Dev (H)  | 147   | 140  | 68   | 229    | 48        | 82    |
| Test (S) | 177   | 164  | 77   | 258    | 60        | 78    |
| Dev (S)  | 156   | 145  | 65   | 279    | 49        | 62    |
| Train    | 971   | 922  | 468  | 1426   | 544       | 427   |

The preceding (succeeding) pause is a binary variable, indicating whether there is a gap more than 30 milliseconds before (after) the token.
whereby learning rate peaks after 10% of the training steps and then decreases to 0. We find models’ hyperparameters using random search (Bergstra and Bengio, 2012) in 80 trials (see Table 5).

### 4.3 Results

Following CoNLL evaluation method, the models are evaluated using F1 score computed using complete spans of named entities. As shown in Figure 4, modeling context consistently leads to significant gain in F1 score, regardless of the data split or the model structure. For the standard split, the BiLSTM-CRF’s F1 improved from 62.8% to 70.8% while BERT’s F1 improved from 67.3% to 72.4%. Similarly for the hard split, the BiLSTM-CRF’s F1 improved from 48.0% to 56.1% while BERT’s F1 improved from 59.2% to 64.7%.

Adding speech pattern features did not lead to notable changes in F1 score when testing on the standard split. BiLSTM-CRF’s F1 improved by 0.2% (62.8% to 63.0%) while BERT’s F1 improved by 0.6% (67.3% to 67.9%) (see Table 6). However, when testing on the hard split, the gap between using and not using speech pattern features is more noticeable. BiLSTM-CRF’s F1 improved by 1.0% (48.0% to 49.0%) while BERT’s F1 improved by 0.9% (59.2% to 60.1%). This is perhaps unsurprising since the lexical overlap (i.e. number of shared named entities) between the standard split’s training and test set is quite high (see Table 2), so exploiting complementary features like speech pattern may be less beneficial.

In all setups, combining speech pattern features with context resulted in the highest F1 scores. Besides, BERT models outperformed BiLSTM-CRF models as the former were pre-trained on a large amount of data while the latter were trained from scratch. Lastly, performance on the hard split is still lower than that on the standard split, indicating room for improving the models’ robustness.

### 4.4 Ablation

In order to determine the usefulness of different speech pattern features, we conducted ablation by 0.6% (67.3% to 67.9%) (see Table 6). However, when testing on the hard split, the gap between using and not using speech pattern features is more noticeable. BiLSTM-CRF’s F1 improved by 1.0% (48.0% to 49.0%) while BERT’s F1 improved by 0.9% (59.2% to 60.1%). This is perhaps unsurprising since the lexical overlap (i.e. number of shared named entities) between the standard split’s training and test set is quite high (see Table 2), so exploiting complementary features like speech pattern may be less beneficial.

Figure 4: Context is always beneficial while speech pattern features are more beneficial in the hard split evaluation. Detailed results are in Table 6.

| BiLSTM-CRF          | Learning rate | Dropout | Dimension | BiLSTM layers | Weight decay |
|---------------------|---------------|---------|-----------|---------------|--------------|
|                     | 3e-3, 1e-3, 3e-4, 1e-4, 3e-5 | 0.0, 0.1, 0.2, 0.3, 0.4, 0.5 | 128, 256, 512 | 1, 2, 3, 4 | 1e-7, 1e-6, 1e-5 |

| BERT                | Learning rate | Weight decay |
|---------------------|---------------|--------------|
|                     | 1e-4, 6e-5, 3e-5, 1e-5 | 0.01 |

Table 5: Hyperparameter grids for random search

| Standard Split | Lx. | Ct. | SP | P | R | F1  |
|----------------|-----|-----|----|---|---|-----|
| LSTM           | Y   | 59.8| 66.1| 62.8|
| LSTM           | Y   | 69.2| 72.4| 70.8|
| LSTM           | Y   | 58.3| 68.6| 63.0|
| LSTM           | Y   | 69.5| 73.2| 71.3|

| Hard Split     | Lx. | Ct. | SP | P | R | F1  |
|----------------|-----|-----|----|---|---|-----|
| LSTM           | Y   | 42.5| 55.1| 48.0|
| LSTM           | Y   | 51.3| 62.0| 56.1|
| LSTM           | Y   | 42.6| 57.6| 49.0|
| LSTM           | Y   | 51.8| 65.6| 57.9|

| BERT           | Y   | 56.0| 62.8| 59.2|
| BERT           | Y   | 62.9| 66.7| 64.7|
| BERT           | Y   | 55.6| 65.3| 60.1|
| BERT           | Y   | 62.5| 69.0| 65.6|

Table 6: Context and speech pattern features improve NER performance. Lx.: Lexical, Ct.: Context, SP: Speech pattern features
Tables 7 and 8 show the performance of different models on the standard and hard splits. The tables include metrics such as precision (P), recall (R), and F1 score. The models compared are BERT and LSTM, with variations to study the impact of different features and pre-training. The standard split shows that BERT 4F outperforms BERT 3F and BERT 2F, while the hard split shows that BERT 4F performs better than BERT 3F and BERT 2F.

The performance of the models on the standard and hard splits is presented in Table 7 and Table 8. The tables show that BERT 4F generally outperforms BERT 3F and BERT 2F, indicating that all features are useful, especially ASR confidence and token duration.

The 5th section discusses the roles of context and speech patterns. It notes that context and speech patterns can help resolve the type of an entity when it belongs to multiple types. Speech pattern features can be used to locate named entities, even if the predicted type is incorrect. BERT, after pre-training, may gain world knowledge that helps in identifying names, whereas BiLSTM-CRF may miss such entities. Users have given consent for the release of these examples, and some parts have been anonymized to protect users' privacy.

5 Discussion

5.1 Roles of context and speech patterns

Although unknown words may pose a challenge to NER systems, entities that have multiple types are harder to deal with than unknown words (Bernier-Colborne and Langlais, 2020). Dialog context can help resolve the type of an entity when the entity belongs to multiple types. For example, without context, BiLSTM-CRF and BERT predicted “lord of the rings” as Book (incorrect) instead of Movie. Knowing dialog context also helps when named entities are common phrases. Without context, BiLSTM-CRF missed the entity “the notebook”, while BERT misclassified it as Book.

In contrast, speech pattern features can help locating the named entities. For example, BiLSTM-CRF and BERT predicted the wrong text spans as named entities (e.g. “jonas brothers once” instead of “jonas brothers”). Interestingly, although the predicted type is not correct, the type of “mclovin” predicted by BERT is more plausible than BiLSTM-CRF. This might be because BERT gained some world knowledge after pre-training, and NER models usually benefit from external sources of knowledge (Ratinov and Roth, 2009; Passos et al., 2014).

Table 7: Speech pattern features ablation. 4F: all features, 3F: without ASR confidence, 2F: without ASR confidence and token duration. Lx.: Lexical, Ct.: Context, SP: Speech pattern features

Table 8: Effect of pre-training. Lx.: Lexical, Ct.: Context, SP: Speech pattern, †: trained from scratch
Figure 5: Without context, both models either predicted the wrong entity type or missed the named entity.

Figure 6: Speech pattern helps locating named entities. Without speech pattern, models predicted the wrong entity spans (e.g., “jonas brothers once” and “with mclovin”). SP: speech patterns.

5.2 Towards robust NER in dialog system

Current ASR systems still perform poorly in domains that require special vocabulary and under noisy conditions (Georgila et al., 2020). Unfamiliar words or recording noise may lead to ASR errors that affect downstream tasks such as NER. Although continuously retraining the ASR and NER models can reduce these errors, such effort may be costly. Integrating features such as speech pattern features, which are less affected by changing vocabulary and recording conditions, could make NER models more robust and reduce the frequency of having to retrain the models.

Speech pattern features have been used for NER in spoken broadcast news although this did not lead to improvement in performance (Hakkani-Tür et al., 1999). In contrast to (Hakkani-Tür et al., 1999) where the features encoder and the NER tagging model were trained, we trained the models jointly so they are more sensitive to cases when speech pattern features are indicative of named entities. Our proposed models show consistent improvement over lexical-features-only baselines, especially when training and testing data are significantly different, demonstrating that it is possible to combine lexical and speech pattern features to achieve more robust NER system.

5.3 Future work

We show that short context and minimal speech pattern features can improve NER performance. Better performance might be achieved by modeling longer context and more features (e.g. prosodies, parts of speech, punctuation) from a SOTA ASR system. Prosodic features can also be extracted automatically to better align to sub-word tokens (Tran et al., 2018). It would also be interesting to see how robust NER would improve entity linking especially when entity mentions contain ASR errors.

Since our work only explored open-domain conversations between humans and a chatbot, it is important to validate the benefits of modeling context and speech pattern features in other settings. Examples of other settings include open-domain conversations between humans or task-oriented conversations between humans or between humans and chatbots. For these different settings, NER models might need longer context or speech pattern features other than what were used in this paper. However, many previous studies have shown the usefulness of these additional features in other tasks so there are reasons to believe that the findings should translate to other datasets and settings.

6 Conclusions

Named entity recognition for dialogs is difficult because utterances are ambiguous out of context and ASR transcripts are noisy due to ASR errors and the lack of punctuation and capitalization. We proposed two NER models exploiting dialog context and speech patterns to address the ambiguity issue and ASR noise. Our results show that context usually improves NER accuracy while speech patterns help in the more difficult but more realistic scenario with many unseen named entities. Further studies on exploiting features from non-text modalities are warranted to enhance NER in dialog systems.
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