Learning ASR-Robust Contextualized Embeddings for Spoken Language Understanding

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Abstract

Employing pre-trained language models (LM) to extract contextualized word representations has achieved state-of-the-art performance on various NLP tasks. However, applying this technique to noisy transcripts generated by automatic speech recognizer (ASR) is concerned. Therefore, this paper focuses on making contextualized representations more ASR-robust. We propose a novel confusion-aware fine-tuning method to mitigate the impact of ASR errors to pre-trained LMs. Specifically, we fine-tune LMs to produce similar representations for acoustically confusable words that are obtained from word confusion networks (WCNs) produced by ASR. Experiments on the benchmark ATIS dataset show that the proposed method significantly improves the performance of spoken language understanding when performing on ASR transcripts.

1 Introduction

A spoken language understanding (SLU) module serves an important role in a spoken dialogue system, which aims at extracting semantic concepts from spoken utterances and provides structured information for accessing the backend database. Typical tasks of SLU include intent detection and slot filling. These two tasks focus on predicting speaker’s intent and extracting semantic concepts as constraints for the natural language. A movie-related example utterance “find comedies by James Cameron” shown in Figure 1 has two slot-value labels and a specific intent for the whole utterance.

Applying deep learning techniques has been shown to boost the performance of SLU (Yao et al., 2014; Gao et al., 2014; Mesnil et al., 2014; Goo et al., 2018). Most prior work focused on applying understanding models on manual transcripts, ignoring the errors introduced by automatic speech recognizers (ASR). Hence, several methods were proposed to address this problem. Simonnet et al. (2018) simulated ASR errors and trained SLU models for better handling the errors. The prior work leveraged information from lattices or word confusion networks (Hakkani-Tür et al., 2006; Tür et al., 2013; Ladhak et al., 2016; Shivakumar and Georgiou, 2018; Shivakumar et al., 2019), and Zhu et al. (2018) also applied domain adversarial training for ASR-error adaptation, demonstrating the importance of incorporating ASR errors for better SLU performance.

Deep contextualized word representations recently have achieved great success among language understanding tasks (Peters et al., 2018; Devlin et al., 2018; Siddhant et al., 2018). Nevertheless, they may be less robust to noisy texts, such as the recognized results. In this paper, we investigate the impact of ASR errors in contextualized embeddings and further propose a novel confusion-aware fine-tuning method to alleviate this problem. To our best knowledge, there is no prior work that learned contextualized word embeddings and considered the errors produced from spoken language for better robustness. The contributions are 3-fold:

• This is the first attempt of learning contextualized word embeddings specifically for spoken language.
• The proposed approach achieves better performance on the benchmark spoken language understanding task.
• The proposed method shows the better robustness in the ASR transcripts.

| Word | find comedies by james cameron |
|------|--------------------------------|
| Slot | genre: comedy                  |
|      | director: James Cameron        |
| Intent| find_movie                    |

Figure 1: An annotated utterance example.
2 Learning ASR-Robust Contextualized Embeddings

To enable the embeddings to adapt ASR errors for improving SLU, our proposed method consists of three stages: 1) language model pre-training on general domain corpora, 2) confusion-aware language model fine-tuning on SLU data, and 3) training a language understanding model with the fine-tuned LM on SLU data.

In the problem formulation, we treat both intent detection and slot prediction as multi-label sequence classification problems. More formally, given an utterance \( x = \{w_1, w_2, ..., w_{|x|}\} \), the goal is to predict its corresponding intents \( I_x = \{i_1, i_2, ..., i_{|I_x|}\} \) and the associated slots \( S_x = \{s_1, s_2, ..., s_{|S_x|}\} \).

The input utterance \( x \) can be either manually transcribed texts, denoted as \( x_{\text{trs}} \), or ASR-recognized results, denoted as \( x_{\text{asr}} \). The proposed approach is detailed below.

2.1 Embeddings from Language Model (ELMo)

Peters et al. (2018) proposed ELMo to extract context-dependent word embeddings from a pre-trained LM, and the contextualized embeddings were proved to be able to improve the performance of downstream NLP tasks. In this paper, we adopt the same model architecture as in the original work, which consists of a CNN character encoder and two bidirectional LSTMs (Hochreiter and Schmidhuber, 1997). Same strategy of combining hidden states from different layers is applied (Peters et al., 2018), which computes the representation \( e_t \) for a word \( w^t \) in the sentence \( x \) as:

\[
e_t = \gamma \sum_{i=0}^{2} \alpha_i \cdot h^t_{i,i},
\]

where \( h^t_{i,i} = [h^t_{i,i}; h^t_{i,i}] \) is the concatenation of the \( i \)-th layer output from both directions at the time \( t \), \( \alpha_i \) is the weight for the \( i \)-th layer, and \( \gamma \) is a scaling factor. \( \alpha_i \) and \( \gamma \) are scalar parameters learned along with downstream tasks. The ELMo model is pre-trained on the general-domain textual data.

2.2 Language Model Fine-Tuning

One advantage of pre-training a language model is that it can leverage large amounts of unlabeled text corpora. Usually the data is general such as Wikipedia. However, the data distribution of the target task may be different from that used in pre-training, posing a domain mismatch problem. Howard and Ruder (2018) proposed to fine-tune the pre-trained LM with sentences from the downstream dataset and showed that it boosts the performance of the downstream task. Chronopoulou et al. (2019) also demonstrated the effectiveness of the fine-tuning method.

In order to adapt the pre-trained LM to the target data, the fine-tuning technique is applied. Given an utterance \( x = \{w_1, w_2, ..., w_{|x|}\} \), the bidirectional language modeling loss can be written as:

\[
L_{\text{LM}} = \frac{1}{|x|} \sum_{t=1}^{|x|} - \log p(w_t \mid w_{<t}) - \log p(w_t \mid w_{>t}),
\]

where \( p(w_t \mid w_{<t}) \) and \( p(w_t \mid w_{>t}) \) are probabilities of \( w_t \) predicted by the forward LM and the backward LM respectively.

Language model fine-tuning can be performed on both manual transcription and recognized results, because it does not require labels but sentences only.

2.3 Confusion-Aware Fine-Tuning

Taking ASR transcripts as inputs may introduce an issue that words in an utterance may be misrecognized. For instance, \( \text{fair} \) and \( \text{fear} \) are acoustically similar, so an ASR system may fail to distinguish between them, resulting in a substitution error. Such recognition errors might be recovered by human, because human are aware of the acoustic confusability of words. However, the errors may significantly degrade the testing performance when the models are trained on manual transcripts. In order to enhance the ASR robustness in contextualized word embeddings, this section integrates the acoustic confusion into our LM.

We propose a confusion-aware fine-tuning method to mitigate this problem from pre-trained LMs, which aims at making the LM consider multiple acoustically confusable words. Let \( C = \{w^x_{1,i}, w^x_{2,i}\} \) denote an acoustic confusion, i.e., two words with similar pronunciation in two different utterances \( x_1 \) and \( x_2 \). We introduce a new loss term called confusion loss:

\[
L_{\text{conf}} = \sum_{i=0}^{1} 1 - \frac{h^{x_1}_{i,i} \cdot h^{x_2}_{i,i}}{\|h^{x_1}_{i,i}\| \|h^{x_2}_{i,i}\|},
\]

which is the cosine distance between the LM hidden states corresponding to words. Note that we

\[\text{Values of slots are not measured, because they are difficult to evaluate on ASR transcripts.}\]
empirically find that including only the first two layers in loss computation works the best. Two approaches are designed for extracting acoustic confusions.

### 2.3.1 Supervised Confusion Extraction

Assuming that both ASR transcripts $x_{asr}$ and manual transcripts $x_{trs}$ of a spoken utterance are accessible, we align $x_{asr}$ with $x_{trs}$ to extract acoustic confusions as shown in Figure 2a. By minimizing $L_{conf}$, we directly force the LM to produce representations for an erroneous word similar to its correct counterpart. This method is called supervised confusion extraction considering that it requires ground truth transcripts of utterances.

### 2.3.2 Unsupervised Confusion Extraction

Considering the scenario where only audio recording of a spoken utterance is available, we can apply an ASR on the recording and construct a word confusion network (WCN). Then a list of n-best hypotheses is generated and aligned using WCN, and the acoustic confusions can be obtained as depicted in Figure 2b.

An important advantage of this approach is that it does not require any labeled utterances; therefore, we can leverage unlabeled audio recordings to fine-tune LMs in an unsupervised fashion.

### 2.4 Joint Objective Function for Fine-tuning

In the fine-tuning stage, we minimize the joint objective function including the LM loss and confusion-aware loss:

$$L_{FT} = L_{LM} + \beta L_{conf},$$

where $\beta$ is a hyperparameter to balance the contribution of two loss functions. The procedure enables our model to incorporate not only the target domain information but the acoustic information for better robustness to ASR errors.

### 2.5 Spoken Language Understanding (SLU)

To further build an SLU model that leverages ASR-robust contextualized embeddings, we employ a biLSTM as our SLU model, where the biLSTM takes contextualized word embeddings $\{e_t\}_{t=1}^{|x|}$ as the input, and the outputs of the last biLSTM layer are max-pooled and linearly transformed to obtain the predicted probabilities. The overall architecture is illustrated in Figure 3. During training, the loss function for SLU is defined as binary cross entropy. Weights of the ELMo model are fixed during this stage except for $\alpha_i$ and $\gamma$. The trained SLU is expected to tolerate the ASR errors for better performance due to the integration of ASR-robust contextualized word embeddings.

### 3 Experiments

The experiments are performed to measure the effectiveness of the proposed model for SLU.

#### 3.1 Setup

ATIS (Airline Travel Information Systems) (Hemphill et al., 1990; Dahl et al., 1994; Tur et al., 2010) is the benchmark dataset widely used in language understanding research. The dataset contains audio recordings of people making flight reservations with corresponding manual transcripts. The training set contains 4,478 utterances.
Table 1: F1-scores (%) on ATIS. Manual and ASR indicate evaluating on \( x_{\text{trs}} \) and \( x_{\text{asr}} \) respectively. Joint considers both tasks and reports utterance-level accuracy. sup-conf stands for supervised confusion extraction, and unsup-conf stands for unsupervised confusion extraction. † indicates the significant improvement over the compared baselines.

| Model                          | Intent Manual | Intent ASR | Slot Manual | Slot ASR | Joint Manual | Joint ASR |
|-------------------------------|---------------|------------|-------------|----------|--------------|-----------|
| (a) Oracle_1                  | 97.97         | 97.23      | 92.02       | 91.27    | 66.89        |           |
| (b) Oracle_2                  | 98.48         | 97.35      | 93.97       | 92.67    | 74.65        |           |
| (c) Context-independent       | 97.12         | 93.21      | 92.94       | 88.01    | 60.44        |           |
| (d) Pre-trained ELMo          | 98.38         | 94.75      | 93.84       | 90.47    | 66.43        |           |
| (e) (d) + fine-tune, \( L_{\text{LM}} \) only | 98.05         | 97.06†     | 93.75       | 91.88†   | 68.60        |           |
| (f) (d) + fine-tune, \( L_{\text{FT}} \) (sup-conf) | 98.28         | 97.73†     | 93.89       | 92.45†   | 72.31†       |           |
| (g) (d) + fine-tune, \( L_{\text{FT}} \) (unsup-conf) | 98.27         | 97.47†     | 93.80       | 92.28†   | 70.25†       |           |

and the test set contains 893 utterances. There are 81 slot labels and 18 intents in the training set.

Our ASR is trained on WSJ (Paul and Baker, 1992) using the s5 recipe from Kaldi (Povey et al., 2011). We use the ASR system to recognize audio recordings in ATIS and extract acoustic confusions for fine-tuning. The word error rate (WER) of ASR results is 16.36% in the ATIS test set.

3.2 Model and Training Details
The pre-trained weights of ELMo from Peters et al. (2018) are adopted. The size of contextualized representations is 1024. Our SLU model has two layers with 300-dimensional hidden states.

In the fine-tuning stage, acoustic confusions that contain stop words are excluded, and \( \beta \) is set to 0.1. We set batch size to 64 and use Adam as the optimizer (Kingma and Ba, 2014) with learning rate 0.001 for all stages. We fine-tune ELMo for 3 epochs and train the SLU model for 50 epochs.

3.3 Baselines
We compare our method with some baselines and oracle systems as below.

- Context-independent: replaces the contextualized representations with traditional context-independent word embeddings. The embedding matrix is initialized randomly.
- Pre-trained ELMo: uses pre-trained ELMo weights without fine-tuning.
- Oracle_1: trains SLU on \( x_{\text{asr}} \) with pre-trained ELMo embeddings.
- Oracle_2: trains SLU on \( x_{\text{asr}} \) and \( x_{\text{asr}} \) with pre-trained ELMo embeddings.

Note that our model does not utilize the information the oracle systems use, so it can be simply viewed as the upperbound of the performance.

4 Results
Table 1 shows the experimental results, where the reported numbers are F1-scores averaged over three runs. All models are trained on \( x_{\text{trs}} \) except for the oracle systems, and they all perform great when evaluated on \( x_{\text{trs}} \). Rows (c) and (d) show that ASR errors degrade SLU performance considerably for both context-independent and context-dependent embeddings. When testing on \( x_{\text{asr}} \), the performance drops 3.63% for intent detection and 3.37% for slot prediction using pre-trained ELMo embeddings.

Our proposed method, confusion-aware language model fine-tuning, outperforms baselines by a large margin on both tasks (rows (e)-(g)), while it maintains identical performance on \( x_{\text{trs}} \). Results in row (e) can be viewed as an ablation to rows (f) and (g), where we exclude \( L_{\text{conf}} \) from the joint objective. Row (e) shows that while \( L_{\text{LM}} \) provides significant improvement alone, adding \( L_{\text{conf}} \) further boosts performance notably. The results demonstrate the effectiveness of the proposed confusion-aware fine-tuning and the robustness of our SLU model.

5 Conclusion
This paper proposes a novel confusion-aware language model fine-tuning method for learning ASR-robust contextualized embeddings. We introduce supervised and unsupervised methods for extracting acoustic confusions and integrate a confusion loss that forces LMs to consider acoustically confusable words. The experiments on SLU demonstrate that our proposed method learns contextualized embeddings that are robust to ASR errors.
References

Alexandra Chronopoulou, Christos Baziotis, and Alexandros Potamianos. 2019. An embarrassingly simple approach for transfer learning from pretrained language models. *arXiv preprint arXiv:1902.10547*.

Deborah A Dahl, Madeleine Bates, Michael Brown, William Fisher, Kate Hunnicke-Smith, David Pallett, Christine Pao, Alexander Rudnicky, and Elizabeth Shriberg. 1994. Expanding the scope of the atis task: The atis-3 corpus. In *Proceedings of the workshop on Human Language Technology*, pages 43–48. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Chih-Wen Goo, Guang Gao, Yun-Kai Hsu, Chih-Li Huo, Tsung-Chieh Chen, Keng-Wei Hsu, and Yun-Nung Chen. 2018. Slot-gated modeling for joint slot filling and intent prediction. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 753–757, New Orleans, Louisiana. Association for Computational Linguistics.

Daniel Guo, Gokhan Tur, Wen-tau Yih, and Geoffrey Zweig. 2014. Joint semantic utterance classification and slot filling with recursive neural networks. In *2014 IEEE Spoken Language Technology Workshop (SLT)*, pages 554–559. IEEE.

Dilek Hakkani-Tür, Frédéric Béchet, Giuseppe Riccardi, and Gokhan Tur. 2006. Beyond asr 1-best: Using word confusion networks in spoken language understanding. *Computer Speech & Language*, 20(4):495–514.

Charles T. Hemphill, John J. Godfrey, and George R. Doddington. 1990. The ATIS spoken language systems pilot corpus. In *Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania*, June 24–27,1990.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9(8):1735–1780.

Jeremy Howard and Sebastian Ruder. 2018. Universal language model fine-tuning for text classification. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 328–339, Melbourne, Australia. Association for Computational Linguistics.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Faisal Ladhad, Ankur Gandhe, Markus Dreyer, Lambert Mathias, Ariya Rastrow, and Björn Hoffmeister. 2016. Latticernn: Recurrent neural networks over lattices. *Interspeech 2016*, pages 695–699.

Grégoire Mesnil, Yann Dauphin, Kai Sheng Yao, Yoshua Bengio, Li Deng, Dilek Hakkani-Tur, Xiaodong He, Larry Heck, Gokhan Tur, Dong Yu, et al. 2014. Using recurrent neural networks for slot filling in spoken language understanding. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 23(3):530–539.

Douglas B. Paul and Janet M. Baker. 1992. The design for the wall street journal-based csr corpus. In *Proceedings of the Workshop on Speech and Natural Language, HLT ’91*, pages 357–362, Stroudsburg, PA, USA. Association for Computational Linguistics.

Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In *Proc. of NAACL*.

Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukas Burget, Ondrej Glembek, Nagendra Goel, Mirko Hannemann, Petr Motlicek, Yanmin Qian, Petr Schwarz, et al. 2011. The kaldi speech recognition toolkit. Technical report, IEEE Signal Processing Society.

Prashanth Gurunath Shivakumar and Panayiotis Georgiou. 2018. Confusion2vec: Towards enriching vector space word representations with representational ambiguities. *arXiv preprint arXiv:1811.03199*.

Prashanth Gurunath Shivakumar, Mu Yang, and Panayiotis Georgiou. 2019. Spoken language intent detection using confusion2vec. *arXiv preprint arXiv:1904.03576*.

Aditya Siddhant, Anuj Goyal, and Angeliki Metallinou. 2018. Unsupervised transfer learning for spoken language understanding in intelligent agents. *arXiv preprint arXiv:1811.05370*.

Edwin Simonnet, Sahar Ghannay, Nathalie Camelin, and Yannick Esteve. 2018. **Simulating ASR errors for training SLU systems.** In *Proceedings of the 11th Language Resources and Evaluation Conference*, Miyazaki, Japan. European Language Resource Association.

Gökhan Tür, A-noop Deoras, and Dilek Z. Hakkani-Tür. 2013. Semantic parsing using word confusion networks with conditional random fields. In *INTERSPEECH*.

Gokhan Tur, Dilek Hakkani-Tür, and Larry Heck. 2010. What is left to be understood in ATIS? In *Proceedings of 2010 IEEE Spoken Language Technology Workshop (SLT)*, pages 19–24. IEEE.

Kaisheng Yao, Baolin Peng, Yu Zhang, Dong Yu, Geoffrey Zweig, and Yangyang Shi. 2014. Spoken language understanding using long short-term memory neural networks. In *2014 IEEE Spoken Language Technology Workshop (SLT)*, pages 189–194. IEEE.
Su Zhu, Ouyu Lan, and Kai Yu. 2018. Robust spoken language understanding with unsupervised asr-error adaptation. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 6179–6183. IEEE.