On the Use of External Data for Spoken Named Entity Recognition

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Abstract

Spoken language understanding (SLU) tasks involve mapping from speech audio signals to semantic labels. Given the complexity of such tasks, good performance might be expected to require large labeled datasets, which are difficult to collect for each new task and domain. However, recent advances in self-supervised speech representations have made it feasible to consider learning SLU models with limited labeled data. In this work we focus on low-resource spoken named entity recognition (NER) and address the question: Beyond self-supervised pre-training, how can we use external speech and/or text data that are not annotated for the task? We draw on a variety of approaches, including self-training, knowledge distillation, and transfer learning, and consider their applicability to both end-to-end models and pipeline (speech recognition followed by text NER model) approaches. We find that several of these approaches improve performance in resource-constrained settings beyond the benefits from pre-trained representations alone. Compared to prior work, we find improved F1 scores of up to 16%. While the best baseline model is a pipeline approach, the best performance when using external data is ultimately achieved by an end-to-end model. We provide detailed comparisons and analyses, showing for example that end-to-end models are able to focus on the more NER-specific words.

1 Introduction

Named entity recognition (NER) is a popular task in natural language processing (NLP), which involves detecting the named entities and their categories in a given text sequence. NER can be used as a way to extract information from unstructured data, which can also be used as features for other NLP tasks like question answering (Chen et al., 2017) and slot filling for task-oriented dialogues (Louvan and Magnini, 2018).

When it comes to recognizing named entities from speech inputs, the task becomes even more strenuous. Thanks to pre-trained text representations such as BERT (Devlin et al., 2019), text-based NER has recently improved greatly, for example achieving about 95% F1 score on the CoNLL 2003 dataset (Sang and De Meulder, 2003) and 92% on the Ontonotes 5 dataset (Pradhan et al., 2013). However, a recent study (Shon et al., 2021) shows that there is still a 10-20% absolute degradation in F1 score between spoken NER models and text-based NER using gold transcripts (see Figure 1) when unsupervisedly pre-trained models are used. How to close this gap remains a critical problem. In addition to addressing the performance gap due to poor speech-to-text conversion, there are additional opportunities in spoken NER for taking advantage of acoustic cues in addition to the word sequence.

In this paper, we study the potential benefits of using external data of different types and from
different domains. External data for spoken NER can be classified into (a) plain speech audio, (b) plain text, (c) speech with transcripts, and (d) text-based NER data.

We conduct extensive experiments and benchmark our findings against recently published baselines for NER on the VoxPopuli dataset of European Parliament speech recordings (Shon et al., 2021) and also introduce baselines of our own. We observe improvement from leveraging every type of external data. Our analysis also quantifies pros and cons of pipeline (speech recognition followed by text NER) and end-to-end (E2E) approaches. Some key results are summarized in Figure 1. Specific contributions include:

(i) Unlike previous work, we devote equal effort to improving both pipeline and E2E approaches for spoken NER. Prior work has typically focused on improving either pipeline or E2E approaches.
(ii) We explore a wide range of external data types and corresponding relevant methods for their use. We hope this will help guide future work on spoken NER conducted in settings with different data availability.
(iii) Overall, we obtain F1 improvements of up to 16% for the E2E model and 6% for the pipeline model, over previously published baselines, setting a new state of the art for NER on this dataset.
(iv) We also benchmark the improvement obtained from using self-supervised representations, compared to a baseline model that directly uses standard spectrogram features. Self-supervised representations give an absolute boost of 19 and 16 points for pipeline and E2E models respectively. To our knowledge, prior work has not directly measured the improvement from self-supervised representations over competitive baselines tuned for the task.
(v) We establish that E2E models outperform pipeline approaches on this task, given access to external data, while the baseline models without the external data have the opposite relationship.
(vi) Our analyses show that end-to-end models are able to focus on the more NER-specific words, and are better at semantic understanding even while having slightly poorer speech-to-text conversion ability than pipeline models.

2 Related work
2.1 Spoken named entity recognition
While named entity recognition in text has been studied extensively in the NLP community (Mikheev et al., 1999; Florian et al., 2003; Nadeau and Sekine, 2007; Ratnov and Roth, 2009; Ritter et al., 2011; Lampe et al., 2016; Chiu and Nichols, 2016; Akbik et al., 2019; Wang et al., 2021b; Yamada et al., 2020), relatively little work has been conducted on extracting named entities from speech (Kim and Woodland, 2000; Sudoh et al., 2006; Parada et al., 2011; Ghannay et al., 2018; Caubrière et al., 2020; Yadav et al., 2020; Shon et al., 2021). Recognizing named entities from speech is a more challenging task which is commonly done through a pipeline approach: combining an automatic speech recognition (ASR) system with a text-based NER model (Sudoh et al., 2006; Raymond, 2013; Jannet et al., 2015). There is rising interest in end-to-end (E2E) approaches in the speech community and several E2E speech NER models have been introduced (Ghannay et al., 2018; Caubrière et al., 2020; Yadav et al., 2020; Shon et al., 2021).

To the best of our knowledge, Ghannay et al. (2018) introduced the first E2E speech NER model and studied it on a French speech dataset. The approach is based on the DeepSpeech2 (Amodei et al., 2016) ASR architecture, with the addition of special characters for NER labels around the named entities in the transcription, and is trained with character-level connectionist temporal classification (CTC; Graves et al., 2006). This E2E method outperforms their pipeline baseline, and pre-training the model on ASR improves the final NER performance. Yadav et al. (2020) introduce an English speech NER dataset and propose an E2E approach based on DeepSpeech2 model and CTC objective (similar to (Ghannay et al., 2018)) combined with language model (LM) fusion. They show that LM fusion significantly improves the performance of the E2E approach, outperforming a pipeline baseline when trained on 150 hrs of labelled audio. Caubrière et al. (2020) provide a detailed comparison between E2E and pipeline models; however, they focus on small RNN/CNN models and do not use state-of-the-art self-supervised pretrained models.

While (Ghannay et al., 2018; Caubrière et al., 2020; Yadav et al., 2020) have shown that E2E models can outperform pipeline approaches in a fully
supervised setting, they do not account for improvements in both speech and NLP from self-supervised pre-training and semi-supervised approaches. Shon et al. (2021) have introduced new speech NER annotations for the public VoxPopuli corpus (Wang et al., 2021a) and show that E2E models still do not rival pipeline approaches when state-of-the-art pre-trained models such as DeBERTa (He et al., 2020) and wav2vec 2.0 (Baevski et al., 2020) are used. However, their E2E speech NER models are at a disadvantage, since both their E2E and pipeline models use the same pre-trained speech representations while the pipeline also has access to a text model trained on 78GB of text. This inspires us to study the benefits of using additional unlabelled data.

2.2 Unsupervised pre-training of speech models

There is a long history of using unsupervised pre-training in NLP to improve performance over purely supervised training (with much smaller labeled datasets) on a broad range of tasks, including pre-trained models like context-independent word embeddings (e.g., (Mikolov et al., 2013; Pennington et al., 2014)), contextualized word representations (e.g., (McCann et al., 2017; Peters et al., 2018)), and most recently sub-word based pre-trained models like BERT (Devlin et al., 2019), GPT (Radford et al., 2018), and their variants (Yang et al., 2019; Liu et al., 2019; Lan et al., 2020; Clark et al., 2020; Radford et al., 2019; Brown et al., 2020). Unsupervised pre-training has started to make an impact on speech tasks as well, with the first improvements seen in large-scale ASR with wav2vec (Schneider et al., 2019). More recently, improvements have been seen on more tasks with wav2vec 2.0 (Baevski et al., 2020) and other models (Conneau et al., 2020; Hsu et al., 2021a; Chung et al., 2021; Hsu et al., 2021b; Wu et al., 2021; Ling and Liu, 2020; Yang et al., 2021).

However, it is not yet clear how universal pre-trained representations are for speech tasks, and in particular for understanding tasks like NER. Although some pre-trained models achieve impressive performance across a variety of tasks including some understanding tasks (Yang et al., 2021), and analyses show that they contain at least some word meaning information (Pasad et al., 2021), they have not yet been tested on a broad range of challenging understanding tasks. We believe our work is the first to test the effect of unsupervised pre-training specifically on spoken NER.

2.3 Leveraging external data

Self-training (Scudder, 1965; Yarowsky, 1995; Riloff, 1996) is a popular approach to improve the performance of a supervised model when some unannotated data is available in addition to the labeled training set. The unannotated data is first labeled by the task-specific trained model, producing “pseudo-labels”, and then the final system is trained with the additional pseudo-labeled data. This process can be repeated iteratively until performance saturates. Self-training can improve ASR (Parthasarathi and Strom, 2019; Xu et al., 2021) and is also complementary to pre-training (Xu et al., 2021). To the best of our knowledge, this is the first work to introduce it to spoken NER while also studying its effects on both E2E and pipeline approaches.

Knowledge distillation is a procedure widely used by the model compression community (Cheng et al., 2017). The method is to train a smaller student network using the supervision signals from some intermediate output, such as the softened softmax (Hinton et al., 2015), from the teacher network. In the context of our work, the student and teacher networks are two different approaches for solving NER tasks, and the student network is trained on the final output tags of the teacher network. For instance, in the presence of external unlabeled speech, we can utilize a pipeline model to generate pseudo-labels from audio, and then train an E2E model on this new, larger dataset.

Transfer learning has been widely employed for SLU tasks (Lugosch et al., 2019; Jia et al., 2020), including spoken NER (Ghannay et al., 2018; Caubrière et al., 2020). ASR is a typical choice of task to pre-train the model with, before fine-tuning it on SLU task-specific data. Since transcribed speech is more widely available than SLU-specific tags, this approach is practical. Intuitively, we can think of ASR pre-training as helping to do the speech-to-text “portion” of the E2E model’s work.

3 Methods

NER involves detecting the entity phrases along with their tags. The annotations include the text transcripts for the audio along with the entity phrases and corresponding tags. Spoken NER, like
any other SLU task, is typically tackled using one of two types of approaches: (i) Pipeline, and (ii) End-to-end (E2E). As shown in Fig. 2, a pipeline approach decodes speech to text using automatic speech recognition (ASR) and then passes the decoded text through a text NER module; whereas an E2E system directly maps the input speech to the output task labels. Each approach has its own set of advantages and shortcomings. Pipeline systems can enjoy the individual advances from both the speech and the text research communities, since ASR is also a more common task than NER; while combining two modules increase inference time, and propagation of ASR errors can have unexpected detrimental effects on the text NER module performance. On the other hand, E2E models directly optimize the task-specific objective and also have smaller inference time; but such models typically require a large amount of task-specific labeled data to perform well. This can be seen from previous papers on E2E NER (Yadav et al., 2020; Ghannay et al., 2018), where at least 100 hours of labeled data is typically used.

3.1 Baseline models

The baselines we use for E2E and pipeline models are taken from Shon et al. (2021). Similarly to previous work (Shon et al., 2021; Ghannay et al., 2018; Yadav et al., 2020), we formulate E2E NER as character-level prediction with tag-specific special characters delimiting entity phrases. For example, the phrases “irish” and “eu” are tagged as NORP ($) and GPE (%) respectively in “the $ irish \] system works within a legal and regulatory policy directive framework dictated by the % eu \]”. The E2E NER and ASR modules are initialized with the wav2vec2.0 base (Baevski et al., 2020) pre-trained speech representation, while the text NER module is pre-trained with DeBERTa base (He et al., 2020). These are then fine-tuned for ASR/NER where a linear layer is added on top of the final hidden-state output. Note that since text transcripts are typically a part of the NER annotations, we can train a separate NER model using the grand-truth text as input. This text NER model serves roughly as a topline, which is also further used in experiments with external data.

It is to be expected that using self-supervised representations gives a significant boost in limited labeled data settings. In order to quantify the benefits of the pre-trained representations in our setting, we also report the performance of E2E and pipeline baselines that are trained from scratch.

3.2 Utilizing external data

Next we describe our approaches that use data external to this task-specific labeled data, in order to improve both the pipeline and E2E models for spoken NER. We use three types of external data: (i) unlabeled speech (Un-Sp), (ii) unlabeled text (Un-Txt), and (iii) transcribed speech (Sp-Txt).

The majority of the techniques we consider involve labeling the external data with a labeling model (typically one of the baseline models) to produce pseudo-labels. The target model is then trained on these generated pseudo-labels along with the original labeled NER data. Tables 1 and 2 present a detailed list of all methods we consider for improving pipeline and E2E models respectively. Details and definitions of terms in the tables are given below.

When the labeling model is same as the target model, this is a well established process called self-training (Scudder, 1965; Yarowsky, 1995; Riloff,
Table 1: Methods for using external data for pipeline models. Details in Sec. 3.2.

| External data type | Method             | Labeling model | Target model | LM for decoding |
|--------------------|--------------------|----------------|--------------|-----------------|
| Unlabeled speech   | SelfTrain-ASR      | ASR            | ASR          | T3 3-gram       |
| Unlabeled text     | SelfTrain-txtNER  | text NER       | text NER     |                 |
| Transcribed speech | Pre-ASR            | n/a            | n/a          |                 |

Table 2: Methods for using external data for E2E models. Details in Sec. 3.2.

| External data type | Method             | Labeling model | Target model | LM for decoding |
|--------------------|--------------------|----------------|--------------|-----------------|
| Unlabeled speech   | SelfTrain-NER      | E2E-NER        | E2E-NER      | pLabel 4-gram   |
| Distill-Pipeline   | Pipeline-NER (after SelfTrain-ASR) | E2E-NER | E2E-NER | pLabel 4-gram |
| Unlabeled text     | Distill-NLP-lm     | text NER       | n/a          | pLabel 4-gram   |
| Transcribed speech | Distill-NLP        | text NER       | E2E-NER      | pLabel 4-gram   |
|                    | Pre-ASR            | n/a            | n/a          | ftune 4-gram    |

1996; Xu et al., 2020, 2021). In our setting, the ASR and E2E NER models both use word-level language models (LM) for decoding and Shon et al. (2021) observe consistent boosts from LM decoding in all the baseline models. Since LM decoding improves the generated output over the vanilla model output, self-training from pseudo-labels is expected to improve the target models by distilling the LM information into all layers of the model.

When the two models are different, we refer to it as knowledge distillation (Hinton et al., 2015), where the information is being distilled from the labeling model to the target model. This approach enables the target model to learn from the better-performing labeling model via pseudo-labels. Among the baseline models, the pipeline performs better than E2E approaches, presumably since the former use strong pre-trained text representations. So for instance, distilling from Pipeline (labeling model) into the E2E model (target model) is expected to boost performance of the E2E model.

The generated pseudo-labels also provide additional annotated data for LM training, which can be used in E2E models. 4-gram LMs trained on these are referred to as \textit{plabel 4-gram} (for “pseudo-label 4-gram”) in Tab. 2. The language model used in baseline E2E NER experiments is trained on the 15hr finetune set (\textit{ftune 4-gram}). All the ASR experiments use language models trained on the TED-LIUM 3 LM corpus (Hernandez et al., 2018) as in Shon et al. (2021) (T3 3-gram).

3.2.1 Unlabeled speech

The unlabeled speech is used to improve the ASR module of the pipeline approach via self-training (\textit{SelfTrain-ASR}).

For improving the E2E model, the improved pipeline can be used as the labelling model, followed by training the E2E model on the generated pseudo-labels (\textit{Distill-Pipeline}). Alternatively, the unlabeled audio can be directly used to improve the E2E model via self-training (\textit{SelfTrain-NER}).

3.2.2 Unlabeled text

The text NER module in the pipeline approach is improved by self-training using the unlabeled text data (\textit{SelfTrain-txtNER}).

The E2E model uses the pseudolabels generated form text NER baseline module on the unlabeled text to update the language model used for decoding (\textit{Distill-NLP-lm}).

3.2.3 Transcribed speech data

The pipeline approach is improved by using the additional transcribed speech data to improve the ASR module (\textit{Pre-ASR}).

The E2E model uses the updated ASR as an initialization (\textit{Pre-ASR}), in a typical transfer learning setup. Alternatively, in the presence of paired speech text data, the pseudo-labels generated from the text NER model can be used for training the E2E model, thus distilling information from a stronger model into it (\textit{Distill-NLP}).
The Irish system works within a legal and regulatory policy directive framework dictated by the EU.

| Speech-to-text conversion | Language understanding |
|---------------------------|------------------------|
| The Irish system works within a legal and regulatory policy directive framework dictated by the EU | (iris, NORP) (eu, GPE) |
| The Irish system works with Eastern European framework dictated by the EU | (eastern european, NORP) (eu, ORG) |

| Metric      | A | B | Comments                                      |
|-------------|---|---|-----------------------------------------------|
| F1 (%)      | 50 | 50 | Quantifies overall performance but misses the nuances of the errors |
| label-F1 (%)| 100 | 50 | Measures success despite speech-to-text conversion errors |

Figure 3: Illustration of the F1 and label-F1 evaluation metrics on two example sentences.

3.3 Evaluation metrics

Similarly to previous work (Ghannay et al., 2018; Yadav et al., 2020), we evaluate performance using micro-averaged F1 scores on two aspects of the output. F1 score is the harmonic mean of precision and recall. The first score, referred to as F1, evaluates an unordered list of named entity phrase and tag pairs predicted for each sentence. An entity prediction is considered correct if both the entity text is correct and the entity tag is correct. The second score, label-F1, considers only the tag predictions. Label-F1 is useful for understanding NER accuracy despite the possible misspellings and segmentation errors in speech-to-text conversion. Fig. 3 shows how two sample outputs are evaluated on this measure.

4 Experimental setup

4.1 Dataset

VoxPopuli (Wang et al., 2021a) is a large multilingual speech corpus consisting of European Parliament event recordings with audio, transcripts and timestamps from the official Parliament website. The English subset of the corpus has 540 hours of spoken data with text transcripts. Shon et al. (2021) recently published NE annotations for a 15-hour subset of the train set and the complete standard dev and test sets. We use the remainder of the train set that lacks NER annotations, and a uniformly sampled a 100-hour subset of it, for our experiments with external in-domain data. The statistics for these splits are reported in Tab. 3.

| Data split | # utt | Duration (hours) | # entity phrases |
|------------|-------|------------------|-----------------|
| fine-tune  | 5k    | 15               | 5820            |
| dev        | 1.7k  | 5                | 1862            |
| test       | 1.8k  | 5                | 2006            |
| external   | 350k  | 101              | N/A             |
|            | 177k  |                  | 508             |

Table 3: Data statistics. The “external” data does not have named entity annotations.

4.2 Baseline models

The setup for E2E and pipeline baselines is the same as in Shon et al. (2021). For baselines that don’t use pre-trained representations, we utilize the DeepSpeech2 (DS2) toolkit1 (Amodei et al., 2016). DS2 converts audio files into normalized spectrogram features. The model is a combination of two 2-D convolutional layers followed by five bidirectional LSTM layers, and a softmax layer. The softmax layer outputs the probabilities for a sequence of characters. The model is trained with SpecAugment data augmentation (Park et al., 2019) and a connectionist temporal classification (CTC) objective (Graves et al., 2006).

4.3 Utilizing external data

For experiments involving fine-tuning wav2vec2.0 models on pseudo-labels for either E2E NER or ASR tasks, the fine-tuning is done using the fairseq library (Ott et al., 2019). The model is trained for 80k (160k) updates when training on 100hrs (500hrs) pseudo-labeled data. For experiments involving training the text NER model on pseudo-labels, HuggingFace’s transformers toolkit (Wolf et al., 2019) is used. The detailed config files can be found in the public codebase.2

5 Results

5.1 Baseline models

Results from all the baseline models are reported in Tab 4. The models here are trained on the fine-tune set. We see that self-supervised pre-training gives a significant performance boost over no pre-training (E2E-baseline). The NLP topline is far better than

1https://github.com/SeanNaren/deepspeech.pytorch
2codebase link to be added
Table 4: Dev set % f-score performance of baseline models. All models here are trained on the fine-tune set. The pre-trained speech and text models are mentioned wherever used or applicable.

| NER system | Pretrained model | Speech | Text | F1  |
|------------|------------------|--------|------|-----|
| Pipeline   |                  |        |      | 52.4|
| E2E        |                  |        |      | 51.8|
| Pipeline   | W2V2-B           | DeBERTa-B | 71.3 | 68.1|
| E2E        | W2V2-B           |        |      |     |
| Text NER   |                  | DeBERTa-B |     | 86.0|

The baseline results are not surprising: The limited labeled data is not enough for the baseline E2E approach, but the pipeline model is able to leverage a strong text representation model, which gives it an edge. When we use external unlabeled speech or transcribed speech, we are able to distill knowledge from the pipeline or text NER models, respectively, and improve the E2E model. Both of these labelling models have a stronger semantic component than the E2E baseline because of their strong text NER module. On the other hand, the baseline pipeline model already takes advantage of the text NER module, which leaves little room for improvement in the semantic understanding component; only the speech-to-text conversion is improved by using external data.

In the presence of unlabeled text, the pipeline model uses a better text NER component obtained after self-training. For the E2E model, the improvement is from a better LM trained on pseudo-labels. It is unclear why one should perform better than the other, and surprisingly, SelfTrain-txtNER performs worse using 500h than on 100h (see Tab. 5).

5.3 Analysis

In Tab. 7, we look at the word error rates (WER) of ASR and text generated from NER models alongside the F1 and label-F1 scores. When evaluating WER for the E2E NER models, we strip off the tag-specific special character tokens. We observe that (i) label-F1 is always much better than F1, suggesting that a good fraction of spoken NER errors are caused by missed detection and segmentation errors even when the entity tag prediction is correct. (ii) Even when E2E is better than pipeline in terms
of F1 (for Un-Sp and Sp-Txt), label-F1 has a reverse trend, albeit by only 0.5 points absolute. However, the difference in F1 and label-F1 performance for pipeline models is larger than that for E2E. This suggests that misspellings or segmentation errors are much more detrimental to the pipeline models’ performance.

(iii) Additionally, from the WER we see that the ASR used in pipeline models is typically better performing than the speech-to-text conversion of E2E models, even when the former has a poorer F1. This collectively implies that E2E models tend to learn more entity-specific words, despite being generally poorer at speech-to-text conversion. This is despite the fact that we do not give those words or labels extra weight in the training objective. On the other hand, the kinds of errors made by the ASR module, although fewer than those made by E2E, are detrimental to the text NER module’s performance.

6 Conclusion

We have explored a variety of approaches for using external data to improve both pipeline and E2E approaches for spoken NER. We note that E2E approaches are better able to take advantage of the external data by distilling information from the more semantically mature pre-trained text representations. On the other hand, pipeline approaches show minimal improvements from the use of external data. Our analysis also hints at E2E models’ capability to focus on more entity-specific words despite being poorer at speech-to-text conversion than pipeline models.

We hope that our work provides guiding principles for researchers working on spoken language understanding in similar low-resource domains, when some form of external data is found in abundance. This work also leaves open some interesting research questions for future work. For example, we see minor improvements between 100h and 500h of external data (see Tab. 5 and 6), which suggests the question “what is the smallest amount of external data needed to obtain significant improvements in NER performance?”. One preliminary experiment with external, out-of-domain text NER data (OntoNotes 5.0) fails to improve the text NER performance, suggesting the challenges of dealing with out-of-domain datasets. This more practical setting where we have access to out-of-domain external data is expected to be challenging also because of possible differences between the entity label sets used for the in-domain and external data. This area warrants an in-depth study. From the modeling perspective, better fine-tuning strategies for wav2vec2.0 in low supervision settings have been proposed for ASR (Pasad et al., 2021); it would be interesting to explore how these findings may transfer to a spoken language understanding task.

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