



Three-Module Modeling For End-to-End Spoken Language Understanding Using Pre-trained DNN-HMM-Based Acoustic-Phonetic Model

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Abstract

In spoken language understanding (SLU), what the user says is converted to his/her intent. Recent work on end-to-end SLU has shown that accuracy can be improved via pre-training approaches. We revisit ideas presented by Lugosch et al. using speech pre-training and three-module modeling; however, to ease construction of the end-to-end SLU model, we use as our phoneme module an open-source acoustic-phonetic model from a DNN-HMM hybrid automatic speech recognition (ASR) system instead of training one from scratch. Hence we fine-tune on speech only for the word module, and we apply multi-target learning (MTL) on the word and intent modules to jointly optimize SLU performance. MTL yields a relative reduction of 40% in intent-classification error rates (from 1.0% to 0.6%). Note that our three-module model is a streaming method. The final outcome of the proposed three-module modeling approach yields an intent accuracy of 99.4% on FluentSpeech, an intent error rate reduction of 50% compared to that of Lugosch et al. Although we focus on real-time streaming methods, we also list non-streaming methods for comparison.

Index Terms: spoken language understanding (SLU), end-to-end SLU, automatic speech recognition (ASR).

1. Introduction

In conventional DNN-HMM hybrid speech recognition systems, acoustic models use (sub)phonetic units generated by phonetic-context decision trees [1, 2]. Potentially large vocabulary systems can be built using pronunciation lexicons that contain a relatively small number of such units. Such acoustic-phonetic modeling is prevalent in real-time commercial ASR systems for the following two reasons. It facilitates fast and accurate speech decoding via a weighted finite state transducer (WFST) with an N -gram language model (LM), as well as a pronunciation lexicon. Also, it accounts for the out-of-vocabulary (OOV) problem—words unseen during acoustic-model training—simply by adding them into the lexicon and adding their training sentences into N -gram learning. However, OOVs are still a problem for end-to-end models which use word-level units. Far more speech data for training would be needed to account for unseen events when modeling word-level units. Moreover, decoding with advanced end-to-end models such as those involving Transformers [3] can lead to increased decoding latency, as such models require much longer input contexts. One partial solution to these problems is to leverage the advantages of DNN-HMM-based acoustic-phonetic models. In this paper, we study the use of phonetic models and add a phoneme-to-word conversion module to build end-to-end models.

Traditionally, spoken language understanding systems are formulated as a pipelined ASR component and text-based natu-

ral language understanding (NLU) component. The ASR component converts speech to word sequences which the NLU component then parses into intents and slots. The trend toward end-to-end modeling has also entered the SLU domain. End-to-end SLU approaches map speech audio directly to the speaker intent without explicitly producing a text transcript [4, 5, 6, 7, 8, 9, 10, 11, 12, 13]. These thus eliminate the need for an independent ASR decoder and reduce overall computational times in SLU decoding. In traditional pipelined systems, however, the hard decisions made by the ASR component during decoding discard the acoustical distances from confusing words, which may contain the true hypothesis, resulting in a final decision of the pipeline NLU component that is suboptimal. In contrast, an end-to-end SLU model can retain acoustical information for all possible words in the middle layers, and hence allow these to compete with each other via both acoustic and semantic scores in the final layers.

Studies have been done on pre-training for end-to-end SLU modeling. Of studies which use FluentSpeech open-source data [9], approaches without Transformer-based models [9, 10, 11] showed substantial improvements from pre-training, whereas those with Transformers (or self-attention) [11, 12, 13] showed no such improvements. Here we do not use Transformers, primarily because of their use of long input contexts and increased decoding times, and secondarily because of their weakness when using pre-training. However, we found that with a highly accurate Transformer ASR component, the pipelined NLU component's intent accuracy may outperform the other non-streaming end-to-end methods using Transformer. Our finding is presented in the final comparing table. It may suggest room to further improve current end-to-end approaches.

For the proposed end-to-end SLU system, we use the three-module architecture from Lugosch et al. [9]. The scope and context length of each module are different, ranging from phoneme to word to sentence. Also, the context lengths range from short to long, requiring optimization using different modeling approaches and data. The first module is for units at the phoneme or sub-phoneme level. Such units can compose all spoken words of different pronunciations. A conventional acoustic-phonetic model from a DNN-HMM hybrid ASR system may already work well for this purpose. The second module is for units at the word or sub-word level. In a conventional DNN-HMM or GMM-HMM hybrid system, the decoder uses an explicit mechanism with WFST and a pronunciation lexicon. In end-to-end models, this should be replaced by layers with phoneme-to-word conversion effects, as in our second module. The third module is for units at the sentence level. In SLU, this converts word sequences to intents. For these three modules, we use pre-training approaches with out-of-domain speech data to learn the first and second modules with phoneme and word targets.

2. Related Work

2.1. End-to-end SLU architecture of Lugosch et al.

Lugosch et al. [9] use a three-module modeling approach for end-to-end SLU that involves two major steps: phoneme and word module training using speech data, and intent module training using SLU data. They achieve 98.8% intent classification accuracy on their publicly released FluentSpeech data. Both phoneme and word modules are pre-trained using MTL on out-of-domain speech data, that is, LibriSpeech [14]. pre-training reduces their intent classification error by 65%: from 3.4% without pre-training to 1.2% with pre-training. We adopt their three-module architecture but use different methods for pre-training and MTL. We replace the phoneme module with a well-trained, open-source speech model, as described in the next section. Also, we use MTL on word and intent modules with SLU data to jointly optimize SLU performance.

2.2. Pre-trained Kaldi LibriSpeech model

In this study we use the publicly available LibriSpeech Kaldi chain model¹ as the phonetic module. This is a 16-layer factored time-delayed neural network (TDNN-F) model trained with lattice-free maximum mutual information (LF-MMI) criteria [15] on 960 hours of LibriSpeech data [14] with a $3\times$ speed perturbation. A total of 6024 pdf-ids are generated via decision-tree clustering over Gaussian mean vectors of tri-phone states [16]. As input acoustic features, used are 40-dimensional mel-frequency cepstral coefficients (MFCC) with i-vector speaker normalization [17]. In the experiments reported here, the parameters of this module were used unmodified.

3. End-to-end SLU

SLU maps a T -length speech feature sequence, $X = \{\mathbf{x}_t \in \mathbb{R}^D | t = 1, \dots, T\}$, to a semantic intent u . Here, \mathbf{x}_t is a D -dimensional speech feature vector (e.g., MFCC) at frame t , and u is an intent.

SLU is mathematically formulated using Bayesian decision theory, where the most probable intent, \hat{u} , is estimated among all possible intents, U , with the whole model Θ as

$$\hat{u} = \arg \max_{u \in U} p_{\Theta}(u|X). \quad (1)$$

The main problem of SLU is thus obtaining the posterior distribution $p_{\Theta}(u|X)$. When learning this we attempt to find the optimal parameters, $\hat{\Theta}$, that minimize the cross entropy (CE) between its posterior distribution and the data distribution in the training set, \mathcal{D} :

$$\hat{\Theta} = \arg \min_{\Theta} \sum_{(X,u) \in \mathcal{D}} -\log p_{\Theta}(u|X). \quad (2)$$

Traditionally, the SLU decoding problem as illustrated by Eq. (1) is factorized into two distributions— $p_{\Theta_W}(W|X)$ for ASR and $p_{\Theta_U}(u|W)$ for NLU—as

$$\begin{aligned} \hat{u} &= \arg \max_{u \in U} \sum_{W \in V} \{p_{\Theta_W}(W|X) \cdot p_{\Theta_U}(u|W)\} \\ &\approx \arg \max_{u \in U} \max_{W \in \text{N-best}(X)} \{p_{\Theta_W}(W|X) \cdot p_{\Theta_U}(u|W)\}, \end{aligned} \quad (3)$$

¹<http://www.kaldi-asr.org/models/m13>

where the ASR module, Θ_W , first decodes a speech feature sequence, X , into a word sequence, $W = \{\mathbf{w}_i \in V | i = 1, \dots, M\}$; followed by the NLU module, Θ_U , to decode the word sequence, W , into an intent, u . Here, V is the decoding vocabulary, and \mathbf{w}_i is the i -th word in the word sequence of length M , which may differ from the length of the speech sequence.

In the two-model approach, ASR and NLU are typically trained on different types of data without joint optimization over end-to-end speech-to-intent data. Decoding using the maximum over the N -best ASR sentences is a fast way to replace summing probabilities over all probable word sequences, W . Many pipeline systems streamline calculations by using only the 1-best ASR result to decode intents, as

$$\begin{cases} \hat{W} &= \arg \max_{W \in V} p_{\Theta_W}(W|X) \\ \hat{u} &= \arg \max_{u \in U} p_{\Theta_U}(u|\hat{W}). \end{cases} \quad (4)$$

Note that using only the 1-best ASR result likely reduces decoding accuracy.

There are thus two advantages in using end-to-end SLU models: end-to-end speech-to-intent probabilities can be jointly optimized, and SLU decoding is speeded up by reducing computational times in separate speech decoding phrases.

3.1. Three-module stepwise modeling

As illustrated in Table 1, the SLU end-to-end models here are constructed using acoustic-phonetic, pronunciation, and language understanding (LU) modules, with target units ranging from phoneme to word to sentence and context lengths ranging from short to long. Such an end-to-end model can be expressed as a cascaded model: $[\Theta_U, \Theta_W, \Theta_P]$. Equation (2) can thus be rewritten as

$$\begin{aligned} [\hat{\Theta}_U, \hat{\Theta}_W, \hat{\Theta}_P] &= \\ \arg \min_{[\Theta_U, \Theta_W, \Theta_P]} \sum_{(X,u) \in \mathcal{D}} &-\log p_{[\Theta_U, \Theta_W, \Theta_P]}(u|X). \end{aligned} \quad (5)$$

Stepwise learning is used to build the three modules one by one: first $\hat{\Theta}_P$, then $\hat{\Theta}_W$, and last $\hat{\Theta}_U$.

The first module, $\hat{\Theta}_P$, is constructed with alignments of all the phone-level labels, $P = \{\mathbf{p}_t \in \mathbb{R} | t = 1, \dots, T\}$, as

$$\hat{\Theta}_P = \arg \min_{\Theta_P} \sum_{(X,P) \in \mathcal{D}} -\log p_{\Theta_P}(P|X). \quad (6)$$

Based on $\hat{\Theta}_P$, the second module, $\hat{\Theta}_W$, is constructed given transcription word sequences of length L , $W = \{\mathbf{w}_l \in V | l = 1, \dots, L\}$, as

$$\hat{\Theta}_W = \arg \min_{\Theta_W} \sum_{(X,W) \in \mathcal{D}} -\log p_{[\Theta_W, \hat{\Theta}_P]}(W|X). \quad (7)$$

Table 1: Modules in end-to-end SLU

Module	Symbol	Function
Acoustic-phonetic	Θ_P	Waveforms to phones
Pronunciation	Θ_W	Phones to words
LU	Θ_U	Words to intents

Last, based on $\hat{\Theta}_P$ and $\hat{\Theta}_W$, given their annotated intent, u , the third module, $\hat{\Theta}_U$, is trained as

$$\hat{\Theta}_U = \arg \min_{\Theta_U} \sum_{(X,u) \in \mathcal{D}} -\log p_{[\Theta_U, \hat{\Theta}_W, \hat{\Theta}_P]}(u|X). \quad (8)$$

As described below, pre-training approaches using out-of-domain data are used in the proposed method for three-module stepwise learning. For example, the training of the first two modules uses out-of-domain speech data without intent annotations. It is also possible to jointly optimize all modules with in-domain SLU data. We conduct experiments on both configurations, as described below.

3.1.1. Acoustic-phonetic (wave-to-phone) module, Θ_P

With the first module, Θ_P , formulated as $\tilde{P} = \text{Emb}_{\Theta_P}(X)$, we convert a speech feature sequence, X , to a phoneme-level embedding vector sequence, \tilde{P} , as the output of the last hidden layer. The resultant softmax values, $\text{softmax}(\text{linear}(\tilde{P}))$, are the posterior probabilities used in Eq. (6) to compute the training error.

Unlike Lugosch et al.’s training of the speech model with MTL using both phoneme and word targets, we adopt the publicly available non-end-to-end model for use in our end-to-end SLU model, as mentioned in Section 2.2. The underlying expectation for the first module is to leverage the strengths of conventional DNN-HMM-based acoustic-phonetic models. For instance, such phoneme-level modules work around OOVs by using thousands of phoneme-level units from which any word may be constructed, even words unseen during acoustic training; in addition, these modules achieve good accuracy with only hundreds of hours of speech training data. By contrast, end-to-end models using word-level units typically require far more data and cannot recognize OOVs without complicated workarounds.

3.1.2. Pronunciation (phone-to-word) module, Θ_W

With the second module, Θ_W , formulated as $\tilde{W} = \text{Emb}_{\Theta_W}(\tilde{P})$ given \tilde{P} , we convert a phoneme-level embedding sequence, \tilde{P} , to a word-level embedding sequence, \tilde{W} , as the output of the last hidden layer. The resultant softmax values, $\text{softmax}(\text{linear}(\tilde{W}))$, are the posterior probabilities used in Eq. (7) to compute the training error.

Despite the advantages of the conventional DNN-HMM model described above, to decode speech such a model requires hidden Markov models (HMMs), a pronunciation lexicon, a language model, and a weighted finite state transducer (WFST). As the HMM mechanism is too simple to represent all pronunciation variations, directly using a neural network to map phone-level representations to word-level representations is one way to improve performance.

Our second module for phoneme-to-word conversion is an LSTM recurrent neural network [18] trained using connectionist temporal classification (CTC) loss [19, 20] over byte pair encoding (BPE) [21] wordpieces from BERT [22].

We use LibriSpeech for pre-training, followed by FluentSpeech for fine-tuning. By using the phoneme-level embedding vectors from the first module as input, less data may be required to converge when training the second module than training directly using the speech data as input, because the underlying phoneme embeddings provide more converged distributions than the raw speech data.

3.1.3. LU (word-to-intent) module, Θ_U

With the last module, Θ_U , formulated as an intent classifier $\hat{u} = \arg \max_{u \in U} p_{\Theta_U}(u|\tilde{W})$, we convert a word-level embedding sequence, \tilde{W} , to an intent, \hat{u} .

This module handles sentence-scope information to make decisions. It is better to include the whole sentence as context and ignore the word order if not important. Currently, similar to Lugosch et al. [9], we use a recurrent neural network for this with the output of the second module as its input, followed by a linear-projection layer from the output of the last recurrent layer to all classification targets before the softmax computation for the final classification decisions. The model is fully trained on the small amount of target SLU data. In addition to stepwise training, we use MTL in order to jointly optimize SLU, as described in the next section.

3.2. Multi-target learning (MTL) for joint optimization

As mentioned above, in all of our experiments we use an open-source model as the first module, without further tuning on the target SLU data. The parameters of the second and third modules however, can be learned jointly on the SLU data with multi-target learning (MTL) approach [23] to optimize their SLU performance. We modify Eq. (8) as

$$\begin{aligned} [\hat{\Theta}_U, \hat{\Theta}_W] = \\ \arg \min_{[\Theta_U, \Theta_W]} \sum_{(X,W,u) \in \mathcal{D}} -\log p_{[\Theta_U, \Theta_W, \hat{\Theta}_P]}(u, W|X), \end{aligned} \quad (9)$$

where $\hat{\Theta}_P$ is fixed. Here, the joint loss is computed as a weighted sum over logarithms of intent posterior probabilities and word-sequence posterior probabilities with weight α , as

$$\begin{aligned} \log p_{[\Theta_U, \Theta_W, \hat{\Theta}_P]}(u, W|X) = \\ \alpha \log p_{[\Theta_U, \Theta_W, \hat{\Theta}_P]}(u|X) + (1 - \alpha) \log p_{[\Theta_W, \hat{\Theta}_P]}(W|X). \end{aligned} \quad (10)$$

4. Experiments

4.1. Data sets

We are grateful for the open-source FluentSpeech SLU data,² a corpus of SLU data for spoken commands to smart homes or virtual assistants, for instance, “put on the music” or “turn up the heat in the kitchen”. Each audio utterance is labeled with three slots: action, object, and location. A slot takes one of multiple values: for instance, the “location” slot can take the values “none”, “kitchen”, “bedroom”, or “washroom”. In the paper, we follow Lugosch et al. [9], i.e., we refer to the combination of slot values as the intent of the utterance, without distinguishing between domain, intent, and slot prediction. The dataset contains 31 unique intents and 30,043 utterances, or 19 hours of speech in total, spoken by 97 speakers, and is split into three parts: 23,132 utterances from 77 speakers for training, 3,118 utterances from another 10 speakers for validation, and 3,793 utterances from the remaining 10 speakers for testing.

We used another open-source data source, the LibriSpeech ASR corpus³ [14], to pre-train the first two modules of our end-to-end SLU models. This is a corpus of read speech derived from audiobooks, comprising approximately 1000 hours

²fluent.ai/research/fluent-speech-commands/

³http://www.openslr.org/12

Table 2: *Speech datasets*

Dataset	Speakers	Utterances	Hours
LibriSpeech Train	2,338	-	960.7
FluentSpeech Train	77	23,132	14.7
FluentSpeech Valid	10	3,118	1.9
FluentSpeech Test	10	3,793	2.4

of 16kHz read English speech. We used its 960 hours of speech in the training set to pre-train our phone-to-word module. Table 2 describes the datasets used in our experiments.

4.2. Pronunciation (phone-to-word) module modeling

The second module converts (sub)phonetic units to (sub)word units. We used BERT’s 32K byte pair encoding (BPE) word-piece vocabulary [21, 22] as our word-level units to facilitate future text-based pre-training approaches. For this module we created a network with 4 layers of 768 UniLSTM units. Its input was the output of the above-mentioned first module of Kaldi LibriSpeech model. Thus each frame of speech was first fed into the Kaldi TDNN-F LF-MMI model to obtain its intermediate acoustic-phonetic embedding vector. This module was trained over PyTorch platform using CTC loss [19, 20] with a linear projection of $768 \times 32K$ before applying softmax to compute the posteriors, using the Adam optimization algorithm [24] with an initial learning rate of 0.001 (or 0.000125 in the fine-tuning phase) and 0.1 dropout. The learning rate was cut in half when the validation set loss increased, and learning was terminated when the loss did not decrease for three continuous epochs. The second module was trained first on the LibriSpeech corpus, followed by fine-tuning with FluentSpeech SLU data for acoustic adaptation.

The wave-to-phone module and phone-to-word module together form an end-to-end speech model which converts speech to words. Additionally, as mentioned before, our third module for LU can be fine-tuned together with the second module to jointly optimize SLU performance. Table 3 compares the ASR of the models in each modeling step. Clearly, fine-tuning reduces word error rates (WER) considerably and MTL yields a similar WER while improving its SLU intent accuracy.

4.3. End-to-end SLU Modeling

The third intent module was added as a network with 2 layers of 768 UniLSTM units, and trained after the above pronunciation module was ready. This module was trained using the PyTorch platform using cross-entropy (CE) loss with a linear projection of 768×31 before applying softmax to compute the posteriors, and also used Adam optimization. In addition to the above stepwise LU module training, the MTL LU modules with various α for the joint loss in Eq. (10) are trained, too. In Table 3, we compare the SLU intent accuracy of stepwise training and MTL with $\alpha = 0.5$: the latter outperforms the former. Table 4 lists MTL experiments with different α . MTL with $\alpha = 0.6$ yields the best intent accuracy: 99.4%, which is currently the best result with the streaming approach. We also see in Table 3 that the intent accuracy of all end-to-end models is superior to that of the pipeline approach. Obvious superiority is observed over the ‘pre-trained’ line, where its ASR WER is very high but its SLU intent accuracy for the end-to-end model is much better than for the pipeline approach. This demonstrates the superiority of end-to-end modeling.

Table 3: *ASR tests on FluentSpeech without language model, and two SLU tests (left: pipeline approach on ASR output, right: end-to-end approach)*

Pronunciation module	ASR WER	SLU Intent acc. Pipe.	E2E
LibriSpeech pre-trained	29.70%	62.8%	96.5%
+FluentSpeech fine-tuned	1.84%	97.0%	99.0%
+FluentSpeech MTL 0.5	1.82%	97.1%	99.2%

Table 4: *SLU intent accuracy of tests on FluentSpeech with MTL end-to-end models trained with different weights*

MTL model	α in Eq. (10)				
	0.4	0.5	0.6	0.7	0.8
E2E	99.1%	99.2%	99.4%	99.3%	99.2%

4.4. Advanced non-streaming approaches

Because SLU experiments using Transformer methods in Radfar et al. [11] and Rongali et al. [13] do not benefit from pre-training, we are interested in whether end-to-end SLU is as necessary as using advanced end-to-end models. We trained a CTC/attention Transformer ASR model using LibriSpeech following [25] with ESPNet⁴ and experimented on pipeline decoding with FluentSpeech. Our Transformer has a 12-layer encoder and a 6-layer decoder, as well as a 2-layer CNN in front that reduces the frame rate to one fourth. This yields an intent accuracy of 99.6% on FluentSpeech, outperforming the other methods. The SLU accuracies for these streaming and non-streaming methods are all listed in Table 5.

Table 5: *Intent classification accuracy on FluentSpeech across various systems*

SLU approach	Intent acc.
Streaming systems	
Pipeline: ‘+FluentSpeech.fine-tuned’ + NLU	97.0%
E2E: Lugosch’s et al. [9]	98.8%
E2E: Our MTL 0.6 (w/ UniLSTM)	99.4%
Non-streaming systems	
E2E: Wang et al. [10]	99.0%
E2E: Price [12]	99.5%
E2E: Rongali et al. [13]	99.5%
Pipeline: Our CTC/attn Transformer + NLU	99.6%

5. Conclusion

Using a publicly available phonetic module, we simplify the construction of an end-to-end SLU model. Our pronunciation model for phoneme-to-word conversion is pre-trained and fine-tuned for the SLU domain. We jointly optimize the LU module for word-to-intent conversion with the above phone-to-word module using MTL, yielding the superior streaming-method intent accuracy of 99.4% on FluentSpeech. A CTC/attention Transformer model including long contexts results in the overall best intent accuracy, 99.6%, even with the pipeline decoding approach. This suggests end-to-end SLU still has room to improve.

⁴<http://github.com/espnet/espnet>

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