A Study of Different Ways to Use The Conformer Model For Spoken Language Understanding

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Abstract

SLU combines ASR and NLU capabilities to accomplish speech-to-intent understanding. In this paper, we compare different ways to combine ASR and NLU, in particular using a single Conformer model with different ways to use its components, to better understand the strengths and weaknesses of each approach. We find that it is not necessarily a choice between two-stage decoding and end-to-end systems which determines the best system for research or application. System optimization still entails carefully improving the performance of each component. It is difficult to prove that one direction is conclusively better than the other. In this paper, we also propose a novel connectionist temporal summarization (CTS) method to reduce the length of acoustic encoding sequences while improving the accuracy and processing speed of end-to-end models. This method achieves the same intent accuracy as the best two-stage SLU recognition with complicated and time-consuming decoding but does so at lower computational cost. This stacked end-to-end SLU system yields an intent accuracy of 93.97% for the SmartLights far-field set, 95.18% for the close-field set, and 99.71% for FluentSpeech.

Index Terms: spoken language understanding (SLU), Conformer, connectionist temporal classification (CTC)

1. Introduction

There has been a recent rise in the study of end-to-end SLU methods [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12], which have a common goal of finding more accurate and rapid approaches to solving the problem of recognizing the intent in an utterance directly from the voice without using ASR to produce the text. One of the primary difficulties of NLU is ASR errors; thus the lack of ASR textual output is likely to reduce certain errors in intent recognition. However, it is yet uncertain whether end-to-end approaches are more effective in reducing errors. Therefore, we compare the end-to-end approach with the traditional two-stage approach. In particular, to account for the differences from different ASR components, in the experiments here we use a single ASR model. After controlling for ASR variables, we seek to understand the differences in accuracy and speed that arise from differences in system design.

The complexity of sentence expressions in SLU application scenarios varies greatly. These include simple command and control scenarios, where some include fixed expressions only and some are more open. SLU recognition with fixed expressions is easier, but dialogue systems are typically characterized by more complex utterances. Not only are there no fixed expressions, but sentence lengths vary greatly, and the fluency and speed of speech vary, making overall SLU recognition more difficult. However, the recognition ability of neural networks depends heavily on the training corpus. Different setups of test data against training data may also highly influence to the evaluation results, especially in the SLU systems that are composed of multiple sub-task components [13]. Different setups of test data against training data may also highly influence to the evaluation results, especially in the SLU systems that are composed of multiple sub-task components [13]. For simple SLU applications, it is easier to collect training speech that covers all expressions with rich pronunciation variations among different speakers. In contrast, it is difficult to collect data for complex scenarios, or even to collect a sufficient number of sentence patterns. For simple scenarios, neural networks can be trained as data is sufficient: a simple type of neural network may fit the data and work quickly. For complex scenarios where there is not enough training data, neural networks are needed that provide more accurate language prediction capability in situations where there is not enough data. The design of a good SLU system must account for all of these issues. Different to [13] designing different challenge test sets with held-out speaker or utterance for precise evaluation, we in this paper use the same ASR component to reduce biases in comparing different SLU combination methods.

Current end-to-end studies in the literature show that SLU models trained using multi-objective learning that includes text and phoneme annotations outperform single models that target intent alone [3, 4, 5, 6, 7]. That is, using ASR annotations to compute loss and to perform error back-propagation learning for the associated neural network parameters still improves the intent recognition of end-to-end SLU. However, current end-to-end SLU models still use a simple stack of ASR models with NLU, and most of these stacked models are RNNs. In contrast, we use Conformer as the ASR model [14] Conformer uses self-attention instead of RNN. In addition, in order to perform hybrid-loss training, Conformer contains CTC- and attention-based decoders, which increases the richness of our comparisons with two different ASR decoding methods. CTC decoding is based on conditional independent probability, whereas attention decoding is based on conditional dependent probability. The latter might be useful as applying on SLU with insufficient training utterances to cover all testing ones.

From an ASR perspective, the Conformer model structure is currently state-of-the-art. As already mentioned, it effectively utilizes the hybrid loss of CTC and attention to train the model parameters. CTC, the first end-to-end technique developed for ASR [15, 16], automatically aligns sounds to words via dynamic programming and requires no pre-given alignment. Compared with the cross-entropy (CE) training for a given path, it enriches the neural network training with different alignment results, especially in the SLU systems that are composed of multiple sub-task components [13]. Different setups of test data against training data may also highly influence to the evaluation results, especially in the SLU systems that are composed of multiple sub-task components [13]. For simple SLU applications, it is easier to collect training speech that covers all expressions with rich pronunciation variations among different speakers. In contrast, it is difficult to collect data for complex scenarios, or even to collect a sufficient number of sentence patterns. For simple scenarios, neural networks can be trained as data is sufficient: a simple type of neural network may fit the data and work quickly. For complex scenarios where there is not enough training data, neural networks are needed that provide more accurate language prediction capability in situations where there is not enough data. The design of a good SLU system must account for all of these issues. Different to [13] designing different challenge test sets with held-out speaker or utterance for precise evaluation, we in this paper use the same ASR component to reduce biases in comparing different SLU combination methods.
hand, incorporates rich sentence-wide attention [17, 18, 19]. CTC/attention multi-target learning (MTL) further combines the strengths of CTC and attention [20, 21]. The Conformer design includes all of these advances and uses convolution blocks in the encoder to improve its robustness to speech dynamics [14].

Below, we describe how this study utilizes the various Conformer components to construct different SLU systems.

2. Research Methods

In all of the experiments in this paper, we use Conformer as the ASR model. This uses a hybrid CTC/attention loss to train the model parameters, which yields high accuracy and robust recognition capability. Since it adopts both CTC and attention decoding, we take advantage of both to put together two two-stage SLU systems. In addition, the CTC decoding method only uses the encoder component, which facilitates the comparison of stacked end-to-end systems by using this encoder to form a cascaded end-to-end SLU model and ignore ASR decoding. These two systems differ only in their ASR decoding. This comparison thus affords a fair view into the difference between pipelined and end-to-end systems without ASR biases. Additional details are provided later.

To construct each system, we take the following steps. First, for each dataset the Conformer model is trained and evaluated for ASR. Section 3.2 compares the accuracy of the two decoding methods on each dataset. Then, the Conformer encoder works as an acoustic encoding unit to convert speech from a sequence of Mel-frequency filter bank coefficients, \( \mathbf{X} = \{x_1, \ldots, x_T\} \), to a sequence of acoustic latent representations, \( \mathbf{Y} = \text{Enc}(\mathbf{X}) \), where \( T \) denotes the number of frames. Sequence \( \mathbf{Y} \) is then decoded via the CTC algorithm to a sequence of word-pieces, \( \hat{\mathbf{W}}_{\text{CTC}} \), as

\[
\hat{\mathbf{W}}_{\text{CTC}} = \arg\max_{\mathbf{W} \in \mathcal{V}} \text{CTC}(\text{Enc}(\mathbf{X})|\theta_{\text{CTC}}), \tag{1}
\]

after which comes the second stage of word NLU recognition, described in Section 2.1. The Conformer encoder is ideal for acoustic coding of speech: its outcome sequence represents a set of acoustic feature vectors that can be used to recognize words or even to recognize the embedded intent carried in these words. Therefore, a stacked end-to-end SLU approach could feed these vectors as input to an NLU module to classify the intent directly, skipping ASR decoding, as in the system described in Section 2.2. In addition, we propose a connectionist time summary (CTS) component to shorten the acoustic sequence before sending it to the RNN LU module in end-to-end methods, as described in Section 2.3. The last comparison is of the pipeline approach using Conformer’s attention-rescoring decoding. Equation 2 predicts \( \hat{\mathbf{W}}_{\text{AT}} \) using both the encoder and the decoder:

\[
\hat{\mathbf{W}}_{\text{AT}} = \arg\max_{\mathbf{W} \in \mathcal{V}} \text{Att}(\text{Enc}(\mathbf{X})|\theta_{\text{Dec}}), \tag{2}
\]

The attention mechanism utilizes a conditional dependent distribution which treats previously decoded labels as the condition when predicting the next word. If it produces better ASR output than CTC decoding, we expect that it would form a better pipeline system, as described in Section 2.4. However, computational cost may be a concern, as when using a larger beamwidth, as discussed in Section 3.4. The various ways of using the Conformer components are illustrated in Fig. 1.

2.1. Pipeline P1: Conformer encoder, CTC decoding, and text-based NLU

P1 is a pipelined system that accomplishes ASR decoding using Conformer’s encoder and a CTC component, depicted as ‘CTC decoder’ in the upper-left of Fig. 1. The ASR decoding outcome, \( \hat{\mathbf{W}}_{\text{CTC}} \), is fed into a text-based NLU model to produce the final SLU result, NLU(\( \hat{\mathbf{W}}_{\text{CTC}} \)).

Conformer is pretrained with LibriSpeech and fine-tuned with target SLU data, either FluentSpeech or SmartLights. The text-based NLU network is trained with the SLU data only.

2.2. End-to-end E1: stacked Conformer encoder and RNN LU

E1 is an end-to-end SLU system that skips ASR decoding and produces latent sequences, \( \mathbf{Y} = \{y_t|\text{Enc}(x_t), t = 1 \ldots T\} \). The text-based NLU network is trained with the SLU data processed by the Conformer encoder.

2.3. End-to-end E2: stacked Conformer encoder, connectionist temporal summarization (CTS), and RNN LU

In the third system, we add a component to the well-trained E1 system: connectionist temporal summarization (CTS). Its function is to shorten the sequence \( \mathbf{Y} \) to a shorter one, \( \mathbf{Y}' = \text{CTS}(\mathbf{Y}) \), to reduce the RNN-LU computational complexity. NLU is then fed with the resulting sequence, \( \text{LNU}(\mathbf{Y}') \). The algorithm is described in detail in Section 2.3.1. Since the input to NLU has changed, a fine-tuning step for RNN-LU is necessary. This is done using the pre-trained parameters from E1.
2.3.1. Connectionist temporal summarization (CTS)

CTS processing shortens the latent sequence \( Y \) from frame-wise to segment-wise. We compute the softmax distributions for each frame \( y_i \) in the acoustic encoding sequence with the help of the linear transformation matrix \( H_{\text{CTC}} \) in the CTC-loss component. This maps \( y_i \) from the dimension of the latent representation vector for each frame to the size of the word-piece labels in vocabulary \( V \) as

\[
p_{w,t} = \text{softmax}(H_{\text{CTC}} \cdot y_i).
\]

We then determine the label with the maximal softmax score for each frame using

\[
\hat{w}_t = \arg\max_{w \in V} p_{w,t},
\]

after which we perform the following two steps:

- **Segmentation**: we aggregate as one segment all contiguous frames with the same maximum label \( \hat{w}_t = \cdots = \hat{w}_{t+k} \).

- **Representation**: for each segment, we find the frame \( \hat{t} \) with the maximal softmax score via Eq. (5) and select its vector \( y_{\hat{t}} \) to represent the whole segment.

\[
\hat{t} = \arg\max_{t \leq \hat{t}} p_{\hat{t},t}
\]

Note that the CTS shortening resembles the max-pooling effect over time for its segmental selection and representation processing as illustrated in Eq. 6:

\[
Y' = \text{CTS}(Y) \simeq \{ y_{\hat{t}} \mid \text{maxpool}(y_{\hat{t}}), i = 1 \ldots S \},
\]

where \( i \) is the segment index. After shortening, the CTS sequence lengths are usually twice as long as the number of word-pieces in each utterance, which may help LU to be more efficient than when using acoustic sequences as input.

2.4. Pipeline P2: Conformer encoder-decoder, attention-rescoring decoding, and text-based NLU

The fourth system is a pipeline system that uses Conformer’s attention-rescoring decoding. Compared with CTC decoding, this requires at least doubles the running time. Its larger beam widths dramatically increase its time consumption. It uses the previous decoded labels as conditions. As in P1, its decoding outcome, \( \hat{W}_{\text{ATT}} \), is fed to a text-based NLU model to decide the final intent decision, \( \text{NLU}(\hat{W}_{\text{ATT}}) \). Both Conformer and the text-based NLU network are exactly as the same as in P1: only ASR decoding is different.

3. Experiments

3.1. Datasets

In our experiments we used the open-source Librispeech ASR corpus [22] as the primary dataset when training Conformer. This is a corpus of read speech derived from audiobooks, comprising approximately 1000 hours of 16kHz read English speech. We used the 960-hour training set of clean and noisy speech, the 5.4-hour dev-clean set for validation, and the 5.4-hour test-clean set for testing.

Fluent Speech Commands,\(^2\) or FluentSpeech, is 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, location can take the values “none”, “kitchen”, “bedroom”, or “washroom”. Here, we follow Lugosch et al. in referring to the combination of slot values as the intent of the utterance, without distinguishing between domain, intent, and slot prediction [4]. The dataset contains 31 unique intents.

Snips SmartLights [23], another corpus of SLU data for spoken commands to smart homes, contains both close-field and far-field acoustic recording conditions. The latter was recorded via the replay-and-record approach with a microphone at a distance of 2 meters. The dataset contains 6 unique intent classes. Because SmartLights does not define training and test sets, we selected the first, second, third, fourth, and fifth entries of every five utterances as five different training and evaluation sets for our five-fold cross validation experiments.

Table 1: Speech datasets

| Dataset   | Intents | Spkrs | Uts  | Hours |
|-----------|---------|-------|------|-------|
| LibriSpeech | train   | 2,338 | 281,241 | 281,241 | 960.7 |
|           | dev-clean | 97    | 2,703 | 5.4   |
|           | test-clean | 87    | 2,620 | 5.4   |
| FluentSpeech | train    | 31    | 23,132 | 14.7  |
|           | valid    | 31    | 3,118 | 1.9   |
|           | test     | 31    | 3,789 | 2.4   |
| SmartLights | close-field | 6    | 52    | 1,660 | 1.4   |
|           | far-field | 6    | 52    | 1,660 | 1.4   |

3.2. ASR accuracy

We started with ASR training and testing. The Conformer model was pre-trained with LibriSpeech and fine-tuned with SLU data. All models were built using the ESPNet toolkit\(^3\) using Mel-frequency filter bank (Fbank) feature vectors as input; this is a sequence of 83-dimensional feature vectors with a 25-ms window size and 10-ms window shifts. The model used 2-layer convolutional neural networks (CNN) as the frontend, each of which had 256 filters with \( 3 \times 3 \) kernel size and \( 2 \times 2 \) stride; thus the time reduction of the frontend was \( 1/4 \). Our vocabulary was a list of 5000 byte-pair-encoded [24] word-piece labels. The model contained 12 layers of self-attention encoder blocks and 6 layers of decoder blocks, each of which contained a self-attention layer and an encoder-decoder cross-attention layer. The multi-head attentions in both models had four heads, and attention-rescoring decoding on each test set. The results are listed in Table 2. As mentioned above, the SmartLights experiments were conducted using 5-fold cross validation.

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\(^2\)https://fluent.ai/research/fluent-speech-commands/

\(^3\)https://github.com/espnet/espnet
Table 2: Word error rate (WER %) evaluation of ASR using CTC decoding and attention-rescoring decoding on different datasets

| Decoding Method | CTC | ATR | Beamwidth |
|-----------------|-----|-----|-----------|
| LibriSpeech     | 4.04| 4.75| 3.78      |
| FluentSpeech    | 1.18| 1.09| 1.10      |
| SmartLights     | 5.75| 5.66| 5.78      |
| SmartLights     | 7.32| 7.14| 7.09      |

3.3. SLU accuracy

We built RNN LU modules for systems E1 and E2 using the acoustic latent-sequence input from the Conformer encoder, instead of using text labels. The end-to-end RNN LU networks and the text-based NLU networks were identical in their sizes and types. We used a two-layer bidirectional LSTM network with 256 neurons per layer and per direction. E2 used the pre-trained NLU network inherited from E1, as CTS sequences were summarized from those sequences used to train the NLU network in E1. All end-to-end models were trained using PyTorch by adding the NLU network on top of the Conformer encoder. In our experiments, as with the training NLU parameters, the parameters for the Conformer encoder were all fixed without change.

The intent classification accuracy of all compared SLU systems is reported in Table 3. As mentioned above, the SmartLights experiments used 5-fold cross validation. As these used the Conformer for ASR, all SLU accuracies were high. The best systems were the P2 pipeline system using attention-rescoring ASR decoding and the E2 end-to-end system using CTS sequences. Although E2 was derived from E1 by shortening acoustic encoding sequences, it yielded even better accuracy with less input data. Also, note that while attention-rescoring ASR decoding makes use of sentence-wide word-association probabilities, the E2 end-to-end system does not. This supports the use of the CTS encoding sequence as a compact representation form in end-to-end SLU applications.

As for the comparison between pipeline and end-to-end methods, it is unclear which is better. While end-to-end E1 is outperformed by pipeline P1, E2 is better than P1. Everything is important in each recognition step over the whole SLU process, including the input representation ability, the neural network capability, and the training approach. Whether we proceed from speech to textual words or to latent acoustic sequences, and whether we go from textual words or from latent acoustic sequences to intent, every step counts.

Table 3: SLU intent classification accuracy (%) using CTC decoding and full Conformer decoding on different datasets

| System          | Beamwidth | P1   | E1   | E2   | E2       | P2   |
|-----------------|-----------|------|------|------|----------|------|
| FluentSpeech    | no        | 99.55| 99.68| 99.71| 99.55    | 99.68|
| SmartLights     | close-field| 94.52| 92.83| 95.18| 94.88    | 95.12|
|                 | far-field | 93.61| 84.81| 93.97| 94.03    | 94.22|

3.4. Decoding time

We then evaluated the decoding real-time factor (RTF) of all systems on FluentSpeech, as presented in Table 4.

Table 4: Real-time factors (RTF) of FluentSpeech decoded with different systems using an Intel Xeon® Gold 6130 CPU @ 2.10GHz:

| System | Beamwidth | P1   | E1   | E2   | E2       | P2   |
|--------|-----------|------|------|------|----------|------|
|        |           | CPU  | 0.028| 0.036| 0.028    | 0.047| 0.140|

System E2 is as efficient as P1, as its acoustic encoding sequences are shortened to a length of approximately twice the number of word-pieces in an utterance.

4. Conclusion

We compare four different SLU systems—both pipelines and end-to-end systems—over two different SLU corpora. To rule out ASR biases and ensure a fair comparison, all use the same Conformer ASR model. For the pipeline approach, better ASR accuracy naturally yields better SLU accuracy in general. Hence, the Conformer attention-rescoring decoding outperforms CTC decoding; likewise, the pipeline system using attention-rescoring outperforms that using CTC decoding. Impressively, the end-to-end E2 method beats E1 in terms of both speed and accuracy. Interestingly, in terms of SLU accuracy for E1, E2, and P1, E1 loses to P1 and P1 loses to E2. There is no evidence for consistent two-stage superiority over end-to-end, or vice versa.

As far as the integration of ASR and NLU functions goes, current end-to-end SLU research is likely still at its early stage, and no approach has been developed that differs substantially from stacking two separate ASR and NLU modules together. The authors propose a bold conjecture: future SLU research might go even deeper in language modeling by integrating an ASR word-association language model and an NLU word-to-intent language model. Equipped with such a sophisticated language model, the acoustic encoding model would be able to aggressively model more modalities of speech, emotions, and so on.

5. References

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