INTEGRATING SOURCE-CHANNEL AND ATTENTION-BASED SEQUENCE-TO-SEQUENCE MODELS FOR SPEECH RECOGNITION

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ABSTRACT
This paper proposes a novel automatic speech recognition (ASR) framework called Integrated Source-Channel and Attention (ISCA) that combines the advantages of traditional systems based on the noisy source-channel model (SC) and end-to-end style systems using attention-based sequence-to-sequence models. The traditional SC system framework includes hidden Markov models and connectionist temporal classification (CTC) based acoustic models, language models (LMs), and a decoding procedure based on a lexicon, whereas the end-to-end style attention-based system jointly models the whole process with a single model. By rescoring the hypotheses produced by traditional systems using end-to-end style systems based on an extended noisy source-channel model, ISCA allows structured knowledge to be easily incorporated via the SC-based model while exploiting the complementarity of the attention-based model. Experiments on the AMI meeting corpus show that ISCA is able to give a relative word error rate reduction of up to 21\% over an individual system, and by 13\% over an alternative method which also involves combining CTC and attention-based models.

Index Terms— DNN-HMM, CTC, sequence-to-sequence, end-to-end, model combination, ASR

1. INTRODUCTION
Recently, automatic speech recognition (ASR) systems have obtained significant performance improvements due to the rapid development of deep learning [1]. Instead of traditional Gaussian mixture model (GMM)-based hidden Markov model (HMM) acoustic models and n-gram language models (LMs), state-of-the-art systems nowadays often use deep neural networks (DNNs) for acoustic and language modelling in the statistical ASR framework based on the modular noisy source-channel model (SC) [2]. Along with the statistical models, an SC-based system also incorporates acoustic, phonetic, and lexical knowledge etc. via feature extraction, subword unit construction and decoding, which have demonstrated their significance in improving ASR accuracy and robustness over the years. Despite its good performance, building SC-based ASR systems is considered to be complex and usually requires additional resources such as a phonetic lexicon created by experts.

The attention-based encoder-decoder or sequence-to-sequence networks (referred to as attention-based models below) provide a promising alternative to the SC-based models. Shortly after their success in machine translation [3], attention-based models have been applied to ASR [4, 5]. This approach is considered to be end-to-end because the attention-based model serves as an integrated acoustic and language model that does not require a lexicon when modelling with grapheme-based units. As the attention-based end-to-end approach greatly simplifies construction of an ASR pipeline, various ASR-specific techniques have been subsequently proposed to improve performance. Different encoder architectures have been explored to better handle the input acoustic features [6, 11]. Improvements to the loss functions [12, 14], data augmentation [15, 16], and other optimisation related methods [17, 20] have been found to be effective. Meanwhile, some speaker-related knowledge has been integrated into the end-to-end system [21, 22]. Alternative subword units have been studied to incorporate richer information [23, 25]. Recurrent neural network language models (RNNLMs) trained on additional text data have been integrated into the attention-based systems during training or testing [26, 28]. Together, despite having a large numbers of parameters and requiring a considerable amount of training data, recent attention-based systems have achieved state-of-the-art results on some ASR tasks [16, 29, 30], which makes the end-to-end approach increasingly competitive and encouraging.

Besides the attention-based systems, end-to-end ASR approaches also include connectionist temporal classification (CTC)-based methods [31, 32]. CTC is a sequence-level objective function which does not require frame-level alignments produced by an existing ASR system for DNN acoustic model training. Hence with context-independent graphemic output units, these systems are considered to be end-to-end as lexicons and context-dependent subword unit clustering are not needed. Since CTC is almost mathematically equivalent to HMM-based models [33, 34], this paper treats CTC-based models as one special class of SC-based systems.

In this paper, a framework, Integrated Source-Channel and Attention (ISCA), is proposed to combine the advantages from both the SC-based models and the attention-based models for ASR. By extending the noisy source-channel model that covers both DNN-HMMs and CTC models, the attention-based model can be used as an additional complementary module to rescore each hypothesised word sequence from the (speech) frame-synchronous decoding procedure of the SC-based system. This enables the joint use of attention models with phonetic and linguistic knowledge in a simple way. Inspired by [35, 36], the hidden layers of the acoustic model in the SC-based system and the encoder of the attention-based system can be shared via multi-task learning. Alternatively, the two systems can be constructed independently, which makes ISCA a general approach that combines a traditional ASR system with an attention-based end-to-end system. First, commonly used setups of both the attention-based model and the CTC model baselines are improved by drawing techniques from DNN-HMM acoustic models. Then, experimental results using the augmented multi-party interaction (AMI) dataset show that ISCA improves the word error rates (WERs) over both component systems by significant margins.

This paper is organised as follows. Sections 2 and 3 describe the SC and attention-based frameworks. Section 4 presents the details of the ISCA framework. Experimental setup and results are given in Sec 5 and Sec 6 with conclusions in Sec 7.
2. NOISY SOURCE-CHANNEL MODEL

Speech recognition can be viewed as a noisy source-channel modelling problem [2] where speech is produced and encoded via a noisy channel and the recogniser is to find the most probable source text \( W \) given the output of the noisy channel \( O \). According to Bayes’ rule, decoding follows the maximum a posteriori (MAP) rule to search over each possible hypothesis \( W \) by

\[
P(W|O) \propto p(O|W)P(W),
\]

where \( p(O|W) \), estimated by an acoustic model, is the likelihood of generating the observation through the channel; \( P(W) \), approximated by an LM, describes the underlying probabilistic distribution of the source. In this way, an SC-based ASR system consists of several independent modules.

2.1. HMM Acoustic Models

In acoustic modelling, HMMs, together with GMMs or DNNs, are used to model the generative process of the observation sequences with respect to the subword units. The parameters of the HMMs are estimated using the maximum likelihood (ML) criterion:

\[
F_{ML} = \ln \sum_{S} \prod_{t=1}^{T} P(s_{t+1}|s_{t})p(o_{t}|s_{t}),
\]

where \( [s_1, s_2, \ldots, s_T] \) is a possible HMM state sequence for the given transcription \( W^{ref} \) of an utterance, whose observation \( O \) is \( [o_1, o_2, \ldots, o_T] \). The observation probability \( p(o_{t}|s_{t}) \) is estimated by a GMM or a DNN, and \( P(s_{t+1}|s_{t}) \) is the transition probability.

The GMM-HMM parameters are often trained at the sequence-level by using the forward-backward procedure to find the alignments between time steps and all possible state sequences \( S \) corresponding to \( W^{ref} \) [1][2]. For DNN-HMMs, the DNN is often trained as a classifier to estimate the state posterior probability \( P(s_{t}|o_{t}) \), whose training alignments are generated by a pre-trained system. Such frame-level DNN training allows better data shuffling which was found to be important for efficient training with stochastic gradient descent (SGD) [38]. The log-likelihood \( \log p(o_{t}|s_{t}) \) is calculated according to Bayes’ rule by

\[
\ln p(o_{t}|s_{t}) = \ln P(s_{t}|o_{t}) - \ln P(s_{t}) + \ln p(o_{t}),
\]

where \( P(s_{t}) \) is the prior probability estimated by the frequency of \( s_{t} \) from the training alignments and \( p(o_{t}) \) is the observation prior. Alternatively, the forward-backward procedure can also be applied to train DNN-HMMs at the sequence-level [39][40].

Since phones often serve as natural units to define word pronunciations, phonetic-based units are commonly used in conjunction with a lexicon. Although the first-order Markovian property of HMMs assumes the transition to each HMM state only depends on its immediate preceding one, the effect of the assumption can be reduced by introducing more contextual information, e.g. DNN models taking the current and adjacent frames as input [41][42], and context-dependent phones clustered by phonetic decision trees [43]. Minimum error rate discriminative sequence training is also useful for acoustic models to learn information beyond the scope of individual frames [44][45]. LMs provide word-level contextual information estimated using a text corpus where supplementary text data is often available in addition to speech transcriptions. Many state-of-the-art ASR systems are SC-based that combines information from all the aforementioned sources [46].

2.2. CTC Acoustic Model

CTC is a method that trains a DNN acoustic model with a blank output symbol at the sequence-level without any explicit HMM structure [31]. The training objective function is

\[
F_{CTC} = \ln \sum_{S} \prod_{t=1}^{T} P(s_{t}|o_{t}),
\]

where \( S \) are all possible symbol sequences that can map to \( W^{ref} \) by removing repeated symbols and the blanks. During training, alignments and losses are computed by the forward-backward procedure.

Fig. 1: A CTC-equivalent HMM topology. The white and grey cycles are emission and non-emission states. \( \emptyset \) is the blank symbol.

By comparing Eqn. (4) to Eqns. (2) and (3), CTC is equivalent to a special instantiation of the 2-state HMM structure where \( P(s_1) \), \( p(o_{1}) \), and \( P(s_{t+1}|s_{t}) \) are ignored [54]. As shown in Fig. 1, the first emission state of the HMM is the skippable blank state (\( \emptyset \) with a self-loop and the second one corresponds to the subword unit. The blank state is shared across all HMMs.

In practice, \( p(o_{1}) \) is a constant and \( P(s_{t+1}|s_{t}) \) makes little difference when being forced to set to 1.0 [37]. At test time, the posterior probability of the CTC blank symbol can be penalised by an extra empirical value [47][48], which can be seen as a rough approximation of the prior \( P(s_{t}) \). As a result, it is reasonable to view CTC as an acoustic modelling method in the SC framework, which combines the HMM topology in Fig. 1 the ML training criterion and the forward-backward procedure. In addition, the RNN-transducer [32] can be viewed as an SC-based system, since it extends CTC by introducing an extra prediction network as a language model trained in parallel with the CTC acoustic model.

3. ATTENTION-BASED MODEL

3.1. Attention-based Sequence-to-sequence Model

Originating from machine translation, the attention-based sequence-to-sequence model maps the input sequence of a source language to the output sequence of a target language [3]. For ASR, the attention model maps a \( T \)-length input observation sequence \( O \) to an \( I \)-length output subword unit sequence \( C \). Instead of decomposing into an acoustic model and a language model as in Sec. 2, attention-based models compute the posterior distribution \( P(C|O) \) directly following the chain rule of conditional probability:

\[
P(C|O) = P(c_1|O)P(c_2|c_1,O)\ldots P(c_I|c_{I-1},\ldots,c_2,O),
\]

where \( C \) is converted from \( W^{ref} \) for training. Compared to Eqn. (4), the attention-based systems hold some theoretical advantages over the SC-based systems: they do not necessarily rely on the first-order Markovian assumption during decoding, and the acoustic and language information is jointly learned using a single model without making any independence assumptions.

The attention-based model consists of a neural encoder, a neural decoder, and an attention mechanism. The neural encoder maps the variable-length input sequence \( O \) to an intermediate embedding
At each decoding step \(i\), the encoded information \(E\) is first transformed into a context vector \(h_i\) based on the annotation vector \(a_i\) produced by the attention mechanism. Then, the neural decoder transforms the hidden information \(h_i\) to the posterior distribution on the current subword unit \(c_i\) based on the previous output and the previous decoder state \(d_{i-1}\). The procedure stops when the end-of-sentence symbol is decoded, which allows output sequences to have variable lengths. More specifically,

\[
E = \text{NeuralEncoder}(O)
\]

\[
a_i = \text{AttentionMechanism}(a_{i-1}, d_{i-1}, E)
\]

\[
h_i = E \cdot a_i
\]

\[
d_i = \text{NeuralDecoder}(c_{i-1}, d_{i-1}, h_i).
\]

Despite the elegance of this framework, there are some differences when applying it to ASR. For machine translation, the attention mechanism is particularly effective because the input and output sequences generally have similar lengths and irregular alignments. For ASR, the input observation sequence is often much longer than the output subword unit sequence, and their alignment is relatively local and strictly monotonic [19]. Thus the strength of the attention mechanism may not be brought fully into play, while making it challenging to process streaming data [50]. Furthermore, the attention-based systems often require more training data and model parameters than the SC-based systems [16,30] since it is not straightforward to incorporate rule-based knowledge such as a lexicon [51]. Moreover, since the previous decoding output needs to be fed into the neural decoder to obtain the probability distribution over the next subword unit, it is very expensive to search over a large hypothesis space and store rich decoding results in the form of a lattice. As described in Sec. 3.1 various changes have been made to the attention-based end-to-end framework to address some of the issues above.

3.2. Multi-task Training of Hybrid CTC and Attention Models

Within the scope of end-to-end speech recognition, a hybrid CTC and attention architecture has been proposed to take advantage of both CTC and attention models during both training and decoding [56]. This architecture adopts the multi-task training method with one output branch using the CTC loss and the other branch using the loss of the attention-based decoder. The rest of the acoustic model and the neural encoder share the same parameters. During decoding, a beam search is performed on the attention branch, where the prefix score of the current partial hypothesis is obtained from the CTC branch. The CTC prefix score and the attention score are then interpolated for ranking and pruning during the search [35]. A score from a multi-level RNNLM or a look-ahead word-based RNNLM [25] can also be added to the joint score during the beam search. The benefits of this architecture are that each branch provides a certain degree of regularisation for the other branch and the score interpolation during decoding refines the search space. However, this framework requires both branches to use identical subword units as well as the same encoder parameters, which reduces their complementarity to some extent. Optimising the interpolation coefficients for both training and decoding is very important for the performance, which requires the model to be re-trained and the dev set to be decoded multiple times to achieve near-optimal results.

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The proposed ISCA framework that combines both an SC-based model and an attention-based model is described in this section. Compared to the hybrid CTC and attention architecture reviewed in

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Fig. 2. Integrated source-channel and attention (ISCA) framework. Modules in rounded boxes are trainable.

Sec. 3.2 ISCA performs frame-synchronous decoding using the SC-based model first and then rescoring hypotheses with the attention-based model. This integration of an SC-based model means ISCA both easily incorporates extra phonetic and linguistic knowledge, and is capable of handling streaming data in the first decoding pass.

4.1. Framework Overview

In the system described in Sec. 3.2 the decoding process is based on the attention-based model where the CTC branch plays an auxiliary role. Owing to the advantages of SC-based models, especially the relative ease of integrating structured knowledge into the pipeline, the ISCA framework focuses on the SC-based system and then establishes the dependence between the SC-based model and the attention-based model. Given an SC-based model that maximises the posterior probabilities of a word sequence \(W\) with an acoustic model \(p(O|W)\) and a language model \(P(W)\), ISCA is an extended noisy source-channel model that includes an extra attention-based model trained to maximise the probability of the corresponding correct subword unit sequence \(C\). The posterior probabilities given by the extended SC can be obtained as follows:

\[
P(W|O) = \sum_{C} P(W, C | O) = \sum_{C} P(C | W, O) P(W | O) \propto p(O|W) P(W) \sum_{C} P(C|W, O).
\]

Since an attention-based model directly computes \(P(C|O)\) from Eqn. (5), it can be further conditioned on \(W\) to compute \(P(C|W, O)\) by rescoring \(W\) with the attention model. If \(C\) is a subword unit sequence obtained by converting \(W\) using a lexicon, there is \(P(C|W, O) = P(C|O)\); otherwise \(P(C|W, O) = 0\). If the subword units are graphemic, then there is often only one \(C\) for each \(W\). If the subword units are phonetic, there are often multiple \(C\)s due to multiple pronunciations, and \(\sum_{C} P(C|O)\) is the sum of posteriors of all possible phonetic sequences for a given \(W\). The attention-based model can also be viewed as a special language model conditioned on acoustics.

In contrast to ISCA, standard combination methods, such as confusion network combination [52] and ROVER [53], are not suitable for attention-based models, since they normally require decoding lattices or confidence scores from both systems, in order to work well.
4.2. Subword Unit Selection

Although graphemic lexicons are very easy to construct, phonetic lexicons often help reduce the acoustic modelling complexity, especially for languages like English with irregular orthography. Context-dependent modelling can be applied to both graphemes and phones, and due to a large number of possible context-dependent units, decision-tree-based clustering is often needed to reduce the number of classes [43].

Compared to the multi-task trained CTC and attention-based framework where the subword units from both branches have to be identical, the ISCA framework allows the SC-based model and the attention-based system to have different modelling units, either graphemic or phonetic, context-independent or -dependent, and the scores from the two models are integrated at the word-level regardless of their respective lexicons. It is predictable that for SC-based models, context-dependent modelling is more significant since it reduces the effect of the first-order Markovian assumption by conditioning on the preceding and/or succeeding subword units. For the attention-based models, the effectiveness of using context-dependent units is questionable as it has already conditioned on all previous subword units from Eqn. (5).

4.3. Training

As shown in Fig. 2, the SC-based model and the attention-based model can be trained separately or together in a multi-task fashion by sharing the neural encoder parameters with the hidden layers of the acoustic model. For multi-task trained models, the total number of parameters in the entire system may be much smaller due to parameter sharing. Although multi-task training can be an effective type of regularisation, setting the interpolation weights between the two losses and configuring the learning rate to achieve good performance for both models may not be straightforward. For separately trained models, each one can have an individual configuration for model architecture and training hyperparameters. Some advanced training techniques more suitable for one type of model can be applied to its training procedure independently. For example, discriminative sequence training for the SC model [44, 45] and sequence-level objectives for the attention model [12, 14].

4.4. Decoding

The MAP decoding rule still applies to ISCA to find the 1-best decoding result $W^*$ based on Eqn. (10).

$$W^* = \arg \max_{W} \left\{ p(O|W)P(W) \sum_{C} P(C|W, O) \right\}$$  \(11\)

$$\approx \arg \max_{W} \left\{ \ln p(O|W) + \alpha \ln P(W) + \beta \ln \sum_{C} P(C|W, O) \right\},$$

where $\alpha$ is the language model scaling factor and $\beta$ is the attention model scaling factor. The use of these scaling factors are necessary for these log-scores to fall within reasonable dynamic ranges. To simplify the implementation of ISCA, only a limited number of hypotheses $(n$-best) obtained from the SC-based model are combined with scores from the attention-based model in this paper.

5. EXPERIMENTAL SETUP

5.1. Data and Features

In this paper, the individual headset microphone (IHM) from the AMI meeting corpus [52] is used. The dataset contains around 80 hours of speech for training, and 8 hours for both development (dev) and evaluation (eval). The inputs used are 80-dim filter-bank features at a 10ms frame rate concatenated with 3-dim pitch features.

5.2. Model Configurations

The pipeline is based on the ESPnet setup [35, 55]. The default configurations for the acoustic model for the SC model and the encoder of the attention model are both 8-layer bi-directional long short-term memory models (BLSTMs) with a projection layer. The BLSTM has 320 units in each direction and the projection size is also 320. For the SC model, an additional fully connected layer of size 320 is added before softmax output. The attention model uses a location-aware attention mechanism connecting to the decoder with a one-layer 300-unit LSTM. The n-gram LMs are trained using both AMI and Fisher data. The RNNLM is trained purely based on the text transcriptions of AMI data. The RNNLM has one LSTM layer with 1000 hidden units, whose perplexities on the dev and eval data are 73 and 64 respectively.

5.3. Training and Decoding Setups

To train the HMM-based model, the CE objective function is used with alignments produced by a pre-trained DNN-HMM system. Unigram label-smoothing [56] is applied before computing the CE loss of the attention model. The numbers of graphemes, monophones and triphones are 31, 48 and 4016. The ADADelta [57] optimiser is used and the batch size is 30 utterances for all models.

For decoding of SC-based models, PyHTK [58] is used to set up the corresponding HMM structures and the decoding pipeline. HTK [59] tools are used for lattice generation, lattice rescoring with a trigram LM, and $n$-best list generation. For decoding of attention models, the width of the beam search is 30.

6. EXPERIMENTS

In this section, several improvements to the CTC and attention-based model baselines are made to narrow the gap between the traditional DNN-HMM models and the end-to-end models. Next, within the scope of SC-based models, different subword units and objective functions are compared. Under the ISCA framework, both multi-task training and separate training performance are reported. After the exploratory experiments on the AMI dev set, key findings are summarised and the models are tested on the AMI eval set.

6.1. Improvements on Multi-task Trained Baseline Systems

In the baseline setup [35], both the CTC model and the attention-based model use the same set of graphemes as their output units and the effective frame rate is 1/4. Frame rate reduction is achieved by skipping some time steps in the LSTM layer. The first LSTM layer has a full frame rate and the next two layers skip one step at every other frame. Statistics on the training data shows that the input/output length ratio is more than four for 95.0% of all utterances but is more than three for 99.9% of the data. For phones, 99.9% of the utterances have an input/output length ratio higher than four. For attention-based models where frame-synchronicity is not required, a higher ratio of frame rate reduction may be appropriate. However, for SC-based models, the frame rate should not be less than 1/3 of the full frame rate.

In experiments shown in Table 1, the frame rate is reduced at the input feature level, which is more similar to the setup from SC-based systems [60, 61]. By sampling one in every three frames, the performance of the model improves despite two-thirds of training data not being used. Offsets on the starting point of the input sequence by one or two frames allow the model to be trained on every frame, which
reduces the WER by another 2% absolute. By stacking two adjacent frames with the current as the input, the WER is further reduced by 2% since the test-time unused frames are covered [62]. Overall, a 6-7% absolute reduction of WER is observed over the baseline.

6.2. Improvements on CTC Models

By treating CTC models as a class of SC-based models, the decoding procedure of the traditional HMM-based systems can be used, where various sources of structured information are incorporated. The baseline uses the prefix search decoding procedure and improvements are made using the lexical-tree-based decoding procedure.

As shown in Table 2, the addition of a graphemic lexicon that prevents decoding words with incorrect spelling reduces the WER by 2.7% absolute. However, some words in the lexicon can be decomposed into shorter word-pieces, which happen to also be legal words in the lexicon. The introduction of the trigram LM greatly reduces the fragmentation of words and reduces the WER significantly (5.4% absolute). One of the many assumptions made by CTC is that all output units have equal prior probabilities. Computed by accumulating the output posteriors from the DNN, the estimated priors are very imbalanced. For example, in the case of 1/3 frame rate, the priors for the blank symbol, the letter ‘A’ and ‘Z’ are 0.43, 0.03, 0.0001 respectively. By using the graphemic unit priors similarly to HMMs as in Eqn. (3), the WER improves by another 5.3% absolute. By stacking two adjacent frames with the current as the input, the WER is further reduced by 2% since the test-time unused frames are covered [62]. Overall, a 6-7% absolute reduction of WER is observed over the baseline.

6.3. ISCA for Multi-task Trained Models

Following the multi-task training scheme where the acoustic model (SC-based model) and the encoder (attention-based model) are shared, the following experiments vary the modelling units and objective functions of the SC-based model, while keeping those of the attention-based model unchanged. In the following ISCA results, 20-best hypotheses from the SC-based models are used as an approximation to Eqn. (11). This simplified ISCA ranks the 20-best list by optimally interpolating the acoustic scores, trigram LM scores, the attention-based model scores, and optionally the RNNLM scores. A derivative-free stochastic global search algorithm, named covariance matrix adaptation evolution strategy (CMA-ES) [63], is used to optimise the interpolation weights.

| subword units | loss | SC | Att. | ISCA (+RNNLM) |
|---------------|------|----|-----|---------------|
| grapheme      | CTC  | 32.1| 31.7| 28.6 (28.4)   |
| monophone     | CTC  | 28.8| 31.6| 26.7 (26.3)   |
|               | CE   | 28.8| 31.8| 26.5 (26.0)   |
| triphone      | CTC  | 28.3| 31.4| 26.2 (25.6)   |
|               | CE   | 26.4| 31.6| 25.3 (24.7)   |

Table 3: AMI dev set WERs of multi-task trained systems. CE systems use single-state HMMs. A trigram LM is used for SC-based model decoding. RNNLM is not used except for results in brackets.

The model in the first row in Table 3 corresponds to the model of the last rows in both Tables 1 and 2. For this multi-task trained grapheme/CTC and attention-based model, the performance of the ISCA framework is similar to the joint decoding result in Table 1.

Given that the joint decoding method only applies to a CTC model and an attention-based model with the same graphemic units, one of the major advantages of the ISCA framework is that the SC model can have any subword units and any loss functions. The next two rows change the modelling units of SC-based systems to monophones, and the WER of the SC-based system reduces by 10.3% relative to the grapheme/CTC model. This is mainly due to the orthographic irregularity in English where phonetic-based units reduce the difficulty of modelling significantly. The mapping between pronunciation and text is achieved by the lexicon embedded in the decoding graph. For these two monophone SC models, improved CTC and CE models have similar performance. However, this observation does not hold for triphone systems. This is possibly because triphone systems are more sensitive to the quality of the training alignments since there are many more confusing triphone units than the monophone units. On the scale of AMI data set, the CTC system requires more training data to learn the triphone alignments properly by itself, whereas the CE system shows its advantage whose alignments were produced by a pre-trained high-performance system.

Further experiments show that multi-task trained SC-based models perform marginally better than their standalone counterparts. However, the expected benefits of multi-task training are not observed for the attention-based models. The last column in Table 3 shows that the ISCA approach yields consistent reduction in WER while the SC-based model improves, with or without an external RNNLM. However, as the performance gap between the SC-based model and the attention-based model widens, the relative improvement w.r.t. the SC-based model shrinks. In the extreme case where the triphone/CE model outperforms the attention-based model by 15.8% relative, ISCA with 20-best rescoring can still improve the WER of the SC-based model by 4.8% relative.

1 A decision tree is used to tie 93k triphone models (or states) to 4k.
2 An HTK acoustic model can yield similar WERs with only a fifth of the parameters due to better data shuffling, larger batch size etc. For results to be comparable, all models in this paper are trained using ESPnet.
3 It is a multi-task trained model with graphemic CTC and attention. Systems in Table 1 have an RNNLM while Tables 2 and 3 do not. Tables 1 and 3 shows comparable results for joint decoding (28.1) and ISCA (28.4).
Since the ISCA framework integrates two models at the word-level, attempts have also been made to change the modelling units of the attention-based model. Similar to the findings in [51][54], using monophone for the attention-based model is not as helpful as graphemes for ISCA, which shows that the complementarity of graphemic and phonetic models is essential. Since the neural decoder directly conditions on the previous output as in Eqn. (9), using context-dependent units for the attention-based model yields essentially no improvement compared to their context-independent counterparts as expected. For the attention-based models, modelling context-dependent phones is even a harder task than context-independent ones as the model also needs to learn the tying results found by phonetic decision trees. Another issue of using phonetic units for attention-based models is that, as a result of multiple pronunciations, there may be an exponential number of possible sequences $C$ in Eqn. (11) when the utterance gets longer.

### 6.4. ISCA for Models Trained Separately

Since the triphone/CE model outperforms the attention-based model significantly under the multi-task training setup and only 20-best hypotheses are used for ISCA, two more questions remain. First, how ISCA performs when the attention-based model improves. Second, if the first approximation in Eqn. (11) becomes more accurate, i.e., the $n$-best list becomes longer, how much more improvement ISCA can make. In order to answer these questions, three separate models are trained whose configurations are listed in Table 4.

| model                  | BLSTM config. | WER (+RNNLM)       |
|------------------------|---------------|--------------------|
| SC(triphone/CE)        | 8-layer, 320 units | 27.0 (25.8)        |
| Att.(small)            | 8-layer, 320 units | 31.6 (30.2)        |
| Att.(large)            | 4-layer, 1024 units | 26.3 (25.8)        |

Table 4: Configs. and WERs of three separately trained models.

![Fig. 3: ISCA between a separately trained triphone/CE model and attention-based models of different sizes.](image)

As shown in Fig. 5, the reduction in WER by an external RNNLM stagnates after an $n$-best list of length 20 is used. However, the WER of ISCA continues to drop, especially for the large attention-based model where two systems have similar WERs. Though the attention-based models the acoustic and language model jointly, an RNNLM trained using the AMI transcription only is still useful. The improvement by the RNNLM is expected to be greater when additional text corpora in similar domains are used for training. For the 100-best list, small and large attention-based models with the RNNLM reduces the WER by 7.1% and 10.5% relative to the triphone/CE model rescored by the RNNLM.

### 6.5. Summary and Discussions

Key results are summarised in Table 5. The total number of model parameters and performance on the AMI eval set are also reported for the following models and setups. By changing the encoder frame rate and arrangement of input acoustic features, the joint decoding WER of the multi-task trained CTC and the attention-based model drops from 37.4% to 29.2%. For standalone SC-based models, triphone/CE models consistently outperform other types of SC-based models. The standalone attention-based model requires five-fold more model parameters to reach competitive performance against the triphone/CE model. Although having more parameters combined, separately trained models outperform the multi-task trained model with a similar model size per branch. And the flexibility of individual optimisation leads to greater improvement when the performance of the two models are closer. Comparing to the improved baseline, ISCA reduces the WER by 13% relative for the multi-task trained system. For separately trained models, ISCA achieves relative WER reductions of 8.6% and 21% w.r.t. the triphone/CE model and the small attention-based model; 11.2% and 8.1% w.r.t. the triphone/CE model and the large attention-based model. Further improvement is expected if longer $n$-best lists are used or using ISCA for lattice rescoring [65][66], and if speaker adaptation is applied to both SC-based systems [67][68] and attention-based systems [21].

| model                  | #params. | dev | eval |
|------------------------|----------|-----|------|
| multi-task             | baseline | 15.6M | 34.5 | 37.4 |
|                        | improved baseline | 16.1M | 28.1 | 29.2 |
| separate               | SC (triphone/CE)  | 16.0M | 25.8 | 26.8 |
|                        | Att.(small)    | 15.9M | 30.2 | 31.0 |
|                        | Att.(large)    | 84.0M | 25.8 | 25.9 |
| ISCA                   | multi-task    | 17.3M | 24.4 | 25.4 |
|                        | SC + Att.(small) | 31.9M | 24.0 | 24.5 |
|                        | SC + Att.(large) | 100.0M | 23.1 | 23.8 |

Table 5: The number of parameters and WERs of some key models on both dev and eval sets, with RNNLM included. All ISCA systems use a 100-best list produced by the triphone/CE SC-based model.

In this paper, we have proposed a flexible framework called ISCA that combines a source-channel model system with an attention-based system viewed as a special language model conditioned on acoustic information. Since the two highly complementary models are integrated at the word-level, each one can be trained independently with different objective functions and/or lexicons, or they can be optimised in a multi-task training fashion. As the performance gap between attention-based systems and the traditional hybrid systems narrows, ISCA is expected to yield the state-of-the-art performance when combining the best system from both sides, while improving the robustness of the overall system.

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*The best performing system reported on AMI dev and eval sets is SC-based with WER about 19%, where speaker adaptive training, sequence training, speed perturbation and many other techniques have been used [65].*
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