

SEQUENCE-TO-SEQUENCE MODELS FOR SMALL-FOOTPRINT KEYWORD SPOTTING

Haitong Zhang Junbo Zhang Yujun Wang

Xiaomi Inc., Beijing, China
{zhanghaitong, zhangjunbo, wangyujun}@xiaomi.com

ABSTRACT

In this paper, we propose a sequence-to-sequence model for keyword spotting (KWS). Compared with other end-to-end architectures for KWS, our model simplifies the pipelines of production-quality KWS system and satisfies the requirement of high accuracy, low-latency, and small-footprint. We also evaluate the performances of different encoder architectures, which include LSTM and GRU. Experiments on the real-world wake-up data show that our approach outperforms the recently proposed attention-based end-to-end model. Specifically speaking, with $\sim 73\text{K}$ parameters, our sequence-to-sequence model achieves $\sim 3.05\%$ false rejection rate (FRR) at 0.1 false alarm (FA) per hour.

Index Terms— sequence-to-sequence, keyword spotting, recurrent neural networks

1. INTRODUCTION

Keywords Spotting (KWS), recently used as a wake-up trigger in the mobile devices, has become popular. As a wake-up trigger, KWS should satisfy the requirement of small memory and low CPU footprint, with high accuracy.

There are extensive researches on KWS, although most of them do not satisfy the requirements mentioned. For example, some systems [1, 2] are used to process the audio database offline. They generate the rich lattices using large vocabulary continuous speech recognition system (LVCSR) and search for the keyword. Another commonly used technique for KWS is the keyword/filler Hidden Markov Model (HMM) [3–5]. In these models, HMMs are trained separately for the keyword and non-keyword segments. The Viterbi decoding is used to search for the keyword at runtime.

Recently, [6] proposes a Deep KWS model, whose output is the probability of the sub-word of the keyword. Posterior probability handling is proposed to come up with a confidence score for the detection decision. Other neural networks, such as convolutional neural network (CNN) [7], are used in the similar model

architecture to improve the KWS performance. To further simplify the pipelines of the KWS model, some end-to-end models proposed can predict the probability of the whole keyword directly [8–10].

In [9], the model uses the combination of the convolution layer and recurrent layer to exploit both local temporal/spatial relation and long-term temporal dependencies. But the latency introduced by the window shifting makes it unpractical. [10] solves the problem by adopting an attention mechanism. However, there are two potential problems: (1) the sequence-to-one training is different from sequence-to-sequence decoding; (2) the pre-setting of the sliding window of 100 frame is arbitrary. To handle the problems, we propose a sequence-to-sequence KWS model. With the frame-wise alignments, we can train the model in the sequence-to-sequence framework, and simultaneously get rid of the sliding window.

The attention-based model in [10] is used as the baseline model and described in Section 2. Our proposed sequence-to-sequence models are detailed in Section 3. The experiment data, setup, and results follow in section 4. Section 5 closes with the conclusion.

2. THE BASELINE MODEL

The baseline model, as shown in Fig. 1, mainly consists of two parts: the encoder and the attention mechanism.

The encoder learns the higher representation $h = \{h_1, h_2, \dots, h_T\}$ from the input features $x = \{x_1, x_2, \dots, x_T\}$. $T = 189$ is applied when training. Only LSTM [11] and GRU [12] are used in our experiments for pair comparison. An attention mechanism [13] is applied to come up with an attention weight vector $a = \{a_1, a_2, a_3, \dots, a_T\}$. Then C is the feature representation for the whole sequential input, which is computed as the weighted sum of $h = \{h_1, h_2, \dots, h_T\}$. Finally the probability of the keyword $P(y)$ is predicted by a linear transformation and softmax function.

At runtime, the attention mechanism is applied to only 100 frames of input, but only one frame is fed into the network at each time-step since the others are computed already.

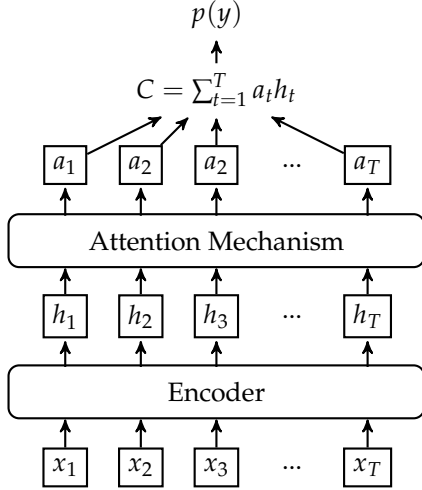


Fig. 1: The baseline model, which is proposed in [10].

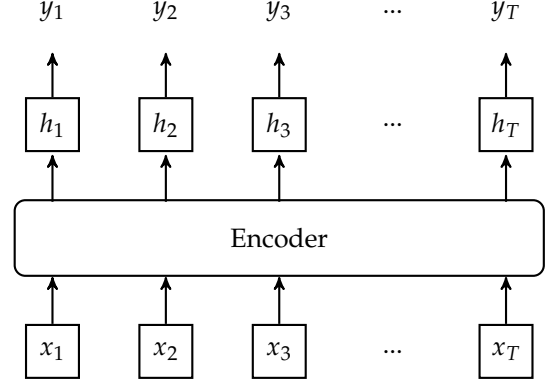


Fig. 2: The proposed sequence-to-sequence model.

3. THE PROPOSED MODEL

The proposed model is illustrated as Fig.2, which mainly includes the sequence-to-sequence training and the decode smoothing.

3.1. Sequence-to-sequence Training

The proposed model adopts the sequence-to-sequence training [14, 15], where the inputs are the features, and the outputs are the one-hot labels which indicate whether the current frame (together with the previous frames) includes the keyword or not.

An example of labeling the keyword is provided as Fig. 3. Tier one in Fig. 3 shows the phone-state alignments generated by the TDNN-LSTM model, which is trained using ~ 3000 hours of speech. Then the alignments are converted into the one-hot labels. As a result, the frames, which do not include the entire keyword, are labeled as 0. Otherwise, they are 1. The frames are labeled as -1 if they contain three and a half characters. Since these frames are ambiguous, labeling them as -1 and attaching zero weight to them can avoid the potential impact of labeling mistakes.

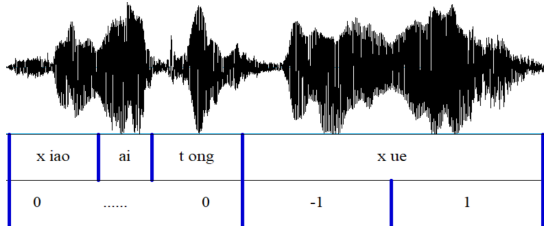


Fig. 3: The example labeling of the keyword, where the first tier are the alignments and the second the labels.

3.2. Decoding

When testing, the model takes the features for a single frame as input, and directly outputs the probability of detecting the keyword y_t . While it is fine to rely on the probability for a single frame, we adopt a smoothing method to come up with a more reliable probability \hat{y}_t , namely the average probability of probabilities of n consecutive frames:

$$\hat{y}_t = \frac{\sum_{i=t-n+1}^t y_i}{n} \quad (1)$$

4. EXPERIMENT

4.1. Dataset

The keyword in our experiments is a four-Chinese-character term ("xiao-ai-tong-xue"). The training data consists of ~ 188.9 k examples of the keyword (~ 99.8 h) and ~ 1007.4 k negative examples (~ 1581.8 h). The development data includes ~ 9.9 K positive examples and ~ 53.0 K negative examples. The testing data includes ~ 28.8 k keyword examples (~ 15.2 h) and ~ 32.8 k non-keyword (~ 37 h). The data is all collected from MI AI Speaker¹.

4.2. Experiment setup

40-dimensional filterbank features are computed from each audio frame, with 25ms window size and 10ms frameshift. Then the filterbank features are converted into the per-channel energy normalization (PCEN) [16] Mel-spectrograms.

¹<https://www.mi.com/aispeaker/>

Table 1: Performance comparison between the baseline models and the proposed seq-to-seq models, False Reject Rate (FRR) is at 0.1 false alarm (FA) per hour.

Model	FRR(%)	Params(K)
Baseline GRU	4.47	77.5
Baseline LSTM	11.86	103
Seq-to-seq GRU	3.05	73.3
Seq-to-seq LSTM	6.08	86.8

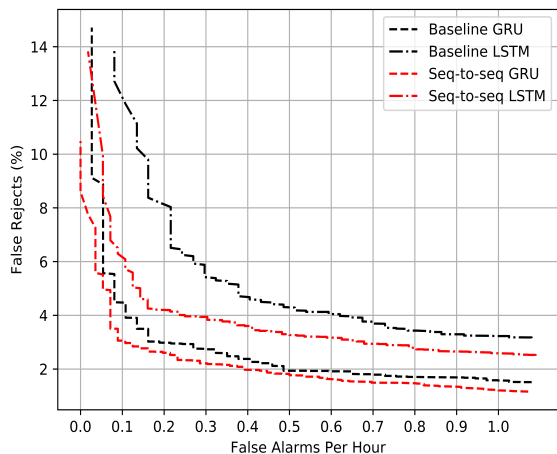


Fig. 4: The ROC of the baseline models and the proposed sequence-to-sequence model with the smoothing frame $n=12$.

The cross entropy is used as the loss function in the experiments. While training, all the weight matrices are initialized with the normalized initialization, and the bias vectors are initialized to 0 [17]. Adam optimizer [18] is used to update the training parameters, with the initialize learning rate of $1e-3$. The batch size is 64. Gradient norm clipping to 1 is applied, and L2 weight decay is $1e-5$.

4.3. Baseline vs Sequence-to-sequence

The experimental results are reported in the form of Receiver Operating Characteristic (ROC) curve, which is created by plotting the false reject rate (FRR) against false alarm (FA) number per hour at various thresholds. Lower curve represents the better result.

Fig. 4 illustrates the performance of the baseline models and the proposed models. In this experiment, the encoder is the 1-128 RNN layer, which is found to be the best architecture in [10]. It is clearly shown that our proposed model outperforms the baseline models

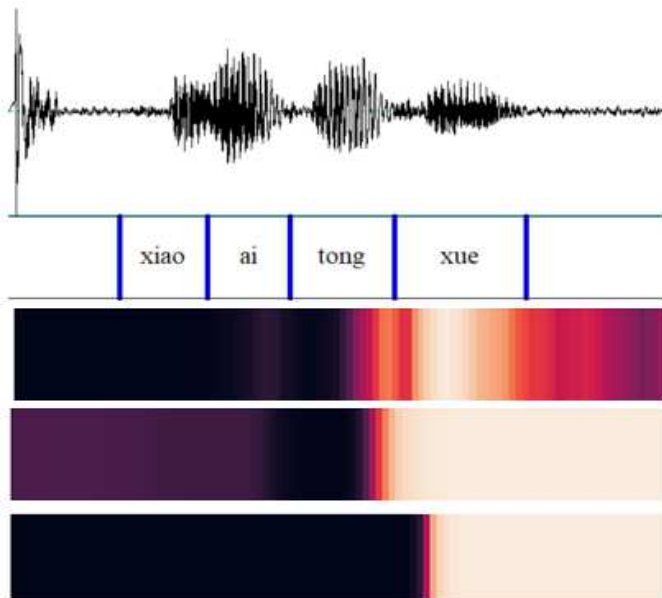


Fig. 5: The representative example for the keyword with four tiers of annotation. The first one is the alignment for the keyword; the second is the heatmap for the attention weights learned in Baseline GRU; the third and fourth are the heatmaps for the output probabilities given by Baseline GRU and Seq-to-seq GRU, respectively. Larger values are illustrated lighter.

in both LSTM and GRU architectures. The Seq-to-seq GRU achieves $\sim 3\%$ FFR at 0.1 FA per hour, with an $\sim 20\%$ improvement over Baseline GRU. The similar situation is observed in the LSTM architecture.

The second tier in Fig. 5 shows that the attention weights concentrate around the last character of the keyword. This distribution indicates that the attention mechanism is strengthening the role of RNN in learning the long-term dependency, rather than focusing on the keyword "with high resolution" [10].

The last heat-mat in Fig. 5 illustrates that sequence-to-sequence model is modeling the human auditory attention. As people wake up when the entire keyword is perceived, the probability gets large at present of the whole keyword. Although the second heat-mat in Fig. 5 shows a similar picture, the probabilities at the beginning are unreasonably larger than those for the third character, and the wake-up is triggered before the last character is perceived. These impacts can be attributed to two potential problems (Section 1). Instead of using human intervention to set the sliding window for the attention mechanism, our proposed models learn the information implicitly in the sequence-to-sequence architecture.

Table 2: Performance comparison between different encoder architectures, False Reject Rate (FRR) is at 0.1 false alarm (FA) per hour.

Type	Layer	Unit	FRR(%)	Params(K)
LSTM	1	64	7.71	27.0
LSTM	2	64	7.16	60.0
LSTM	3	64	6.55	93.1
LSTM	1	128	6.08	86.8
GRU	1	64	7.79	24.5
GRU	2	64	6.40	49.2
GRU	3	64	4.04	74.0
GRU	2	128	3.05	73.3

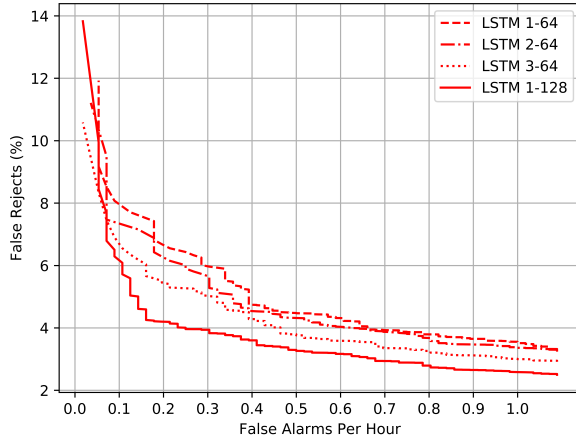


Fig. 6: The ROC of the seq-to-seq model with LSTM layer, with the smoothing frame $n = 12$.

4.4. Impact of encoder

We also explore the impact of the encoder on the model performance. As shown in Fig. 6 and Fig. 7, and Table 2, the models with more parameters tend to perform better than those with fewer parameters. The best models are LSTM 1-128 and GRU 1-128, respectively. As shown in Fig. 6 and Fig. 7, the 1-128 models outperform all the models with only 64 units by a large margin, which indicates that getting the network wider results in a better performance than getting it deeper in our experiment.

4.5. Impact of smoothing frame

The results of different settings of the smoothing frame n are illustrated in Table 3. Compared with no smoothing, the application of smoothing frame $n = 12$ can gain an absolute $\sim 0.15\%$ and $\sim 0.06\%$, respectively in LSTM 1-128 and GRU 1-128. Although the performance dif-

Table 3: Performance differences due to the smoothing frame, False Reject Rate (FRR) is at 0.1 false alarm (FA) per hour.

Model	Smooth Frame	FRR(%)
LSTM 1-128	1	6.23
LSTM 1-128	2	6.23
LSTM 1-128	5	6.25
LSTM 1-128	12	6.08
GRU 1-128	1	3.11
GRU 1-128	2	3.11
GRU 1-128	5	3.12
GRU 1-128	12	3.05

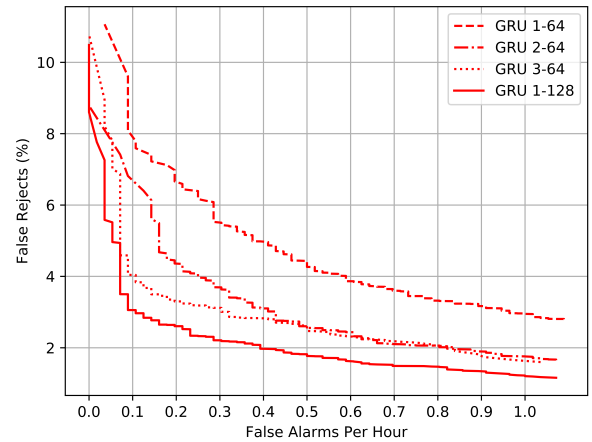


Fig. 7: The ROC of the seq-to-seq models with GRU layer, with the smoothing frame $n = 12$.

ference is minor, we insist that the smoothing strategy is reasonable and pragmatic. It is reasonable because in our sequence-to-sequence model, the detection of the keyword must be kept triggered for several frames once triggered. It is pragmatic since it is computationally cheap to take an average operation.

5. CONCLUSION

To conclude, the sequence-to-sequence model is more flexible than the attention-based one, because no sliding window is used and the training and decoding strategies are the same. As a result, the proposed sequence-to-sequence model outperforms the other in our real-world data, even with less model parameters. In addition, a computationally-cheap probability smoothing method can improve the performance's robustness.

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