PREDICTING DETECTION FILTERS FOR SMALL FOOTPRINT OPEN-VOCABULARY KEYWORD SPOTTING

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ABSTRACT
In many scenarios, detecting keywords from natural language queries is sufficient to understand the intent of the user. In this paper, we propose a fully-neural approach to open-vocabulary keyword spotting, allowing a user to include a voice interface to its device without having to retrain a model on task-specific data. We present a keyword detection neural network weighing less than 550KB, in which the topmost layer performing keyword detection is predicted by an auxiliary network, that may be run offline to generate a detector for any keyword.

Index Terms— keyword spotting, automatic speech recognition, meta learning, convolutional network

1. INTRODUCTION
The recent advances in automatic speech recognition (ASR), reaching close to human recognition performance [1], paved the way to natural language interaction in everyday life, making voice become a natural interface for the communication with objects. Yet such ASR systems demand a lot of resources and computing power, and mainly rely on a connection to the cloud. Nonetheless, it was observed that spoken language understanding (SLU) on the edge was possible when the tasks are known, in a closed-ontology setting (e.g. with a task-specific language model [2]). There has been a surge of interest lately in running neural networks on micro-controllers (MCUs), which are cheaper and less energy-consuming [3]. To fit in such hardware, the ASR systems should still be reduced by several orders of magnitude. However for many interactions a full ASR system is not necessary: simple commands are sufficient. For example, in a washing machine one would only need to detect the different programs, temperatures, start/stop commands, etc.

We aim at building a “mini-SLU” system, to which the user can address in natural language, and in which the language understanding part is straightforwardly derived from the detection of specific keywords in the query. For this system to be practical and easy to adapt to any use-case, we assume that it should adapt to situations where the set of keywords is not known in advance, and for which no specific training data is available. In this work, we aim at creating a keyword spotting (KWS) model that is generic (can adapt to any keywords set, without specific training data), tiny (fit on MCUs), fast (should run in real-time), easy to use (so that SLU and subsequent actions are straightforward to implement on top of it), accurate and robust to noise.

We propose a fully neural architecture made of three components. An acoustic encoder, composed of a stack of recurrent layers, is pretrained as a quantized ASR acoustic model. Its intermediate features are fed to a convolutional keyword detector network trained to output keyword confidences. The weights of the latter are predicted by a keyword encoder neural network. We experimented this approach on two tasks: a “mini-SLU” task where keywords are detected inside queries formulated in natural language, and a speech command task where the goal is to predict one speech command among a predefined set. We compare this system to a baseline ASR-based method.

We give an overview of related approaches in Section 2. The proposed model is described in Section 3. We report the experimental results on the two tasks in Section 4 and conclude the paper in Section 5.

2. RELATED WORK
A significant amount of work has been proposed to classify speech commands in a predefined set or to detect wakewords with tiny neural networks under 500KB [4, 5]. However, these methods require specific training data, and are not suited to scenarios where training data is not readily available. Keyword spotting methods may be divided into two categories: query-by-example scenarios where the system is configured with example audios of the keywords, or query-by-string, where the system is configured by typing keywords. We are interested in the second type. Query-by-string scenarios can be further divided into ASR-based systems in which the keyword is detected from a transcription of the audio into words, characters or phones, or ASR-free systems which directly perform the detection from intermediate representations of the audio input and keywords, without relying on the transcription. Our model belongs to the latter category.

Traditional ASR-based keyword spotting approaches consist in building models for keywords and “background” and computing likelihood ratios between the two [6]. More recently, new approaches based on end-to-end neural speech
The first layers of an acoustic model pretrained with CTC serve as an acoustic encoder. The intermediate features are fed to a keyword detector, predicting a detection confidence for each of the keywords. The weights of its last layer (convolutions kernels with size $k$ and $N$ input channels) are predicted by an auxiliary network from the keyword phone sequence.

Recognizing systems trained to predict phone sequences emerged. They look for the keyword phone sequence in the network predictions, for example by trying to match the keywords in predicted phones lattices [7] or from the transcription directly, taking into account the confusions of the network [8, 9].

ASR-free approaches generally consist in computing embeddings for both the audio and the keyword pronunciation [10, 11]. In [10], the whole spoken utterance is embedded into a single vector with a recurrent auto-encoder. Similarly, the keyword is embedded into a vector using an auto-encoder of the phone sequence. The concatenation of both vectors is fed to a small neural network predicting whether the keyword appears in the utterance. In [11], different recurrent neural networks are trained to predict the word and phone embeddings. The classification is based on the distance between the keyword and utterance embedding. This method seems to be only applicable to isolated words and cannot handle keywords in a natural language utterance.

In the model we propose, a recurrent neural network is applied to the keyword pronunciations to predict the weights of the topmost convolution kernel of the keyword detector network. This idea is similar to other works on dynamic convolution filters in computer vision for weather prediction [12], visual question answering [13], or video and stereo prediction [14].

### 3. A GENERIC KEYWORD DETECTION NEURAL NETWORK

The proposed neural network, depicted in Fig. 1, has three main components.

The **acoustic encoder** is a small stack and skip LSTM network [15], trained with CTC [16] on a large generic speech corpus such as Librispeech [17] to predict the sequence of phonemes from an audio utterance. Although its final performance may be quite poor compared to a state-of-the-art ASR model, the intermediate features it learned while trained to recognize the phones should still be relevant for arbitrary keyword detection. After training, the last classification layer is removed, and the final intermediate features are fed to the keyword detector.

The **keyword detector** is a small two-layer convolutional neural network. From a context window of past intermediate feature frames, it predicts the probability of detection of each keyword in the keyword set. The first layer aggregates a small context of five frames of intermediate features with a convolution followed by a tanh activation. The weights of this layer are generic and shared by all potential keywords. The obtained representations are pooled and sub-sampled to provide some invariance. The last layer is a convolution followed by a sigmoid activation. There is one convolutional kernel for each keyword. Its weights are predicted by a third network: the keyword encoder.

The **keyword encoder** predicts the convolution kernel for the keyword detector from a phone sequence representation of the keyword. It consists of a bi-directional LSTM layer applied to a sequence of one-hot vector encoding each phone of the keyword, and an affine transform applied to the concatenation of the last output of the LSTM in each direction. The result of this affine transform is interpreted as the weights of the last convolutional layer in the keyword detector.

The set of keywords that we want to detect is defined at inference time. First, the topmost convolutional layer from the keyword set is generated. It can be done offline, once for each keyword. The pronunciation of each keyword is first retrieved from a lexicon or a grapheme-to-phoneme converter. Each phone sequence is fed to the keyword encoder, which predicts the convolution kernel for the corresponding keyword. They are used to build the top layer of the keyword detector.

During inference we stream the audio features to the acoustic encoder and the created keyword detector. This network produces a sequence of detection scores for each keyword. At each frame, the keyword with the maximum...
detection confidence is selected, if the confidence is higher than a pre-defined threshold.

At training time, we do not know yet what the final keywords will be. Thus for every batch we generate a set of synthetic keywords. First, we use the pretrained acoustic model to perform a CTC alignment of the whole dataset. After alignment, each intermediate feature frame is associated with a ground-truth phone (or blank). At every timestep of a given utterance, we extract a window of $W$ past frames, and a sequence of the last $N$ ground-truth phone at this timestep. The first layers of the acoustic model will remain frozen and will not be further trained.

During training, we create batches of $B$ samples. For each sample, we create $K$ synthetic keywords. Each keyword is a suffix of the extracted phone sequence, with a length uniformly sampled between 3 and $N$. The $K \times B$ keywords are fed to the keyword encoder, which predicts the $K \times B$ kernels of the last convolution layer, for each synthetic keyword. The obtained keyword detector is applied to the $B$ acoustic samples of $W$ frames each. It results in $K \times B$ prediction outputs for each of the $B$ samples.

The network is trained with a cross-entropy loss, to predict 1 for the keywords that match a suffix of the $N$ phones extracted for the samples, and 0 everywhere else. In general, there will be $K$ positive keywords, and $K(B - 1)$ negative ones for each training sample in the batch, as illustrated in Fig. 2.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig2.png}
\caption{Mini-batch creation for the training of the generic keyword spotting model (here, $K = 2$ and $B = 4$).}
\end{figure}

4. EXPERIMENTAL RESULTS

4.1. Experimental setup

We compute 40 MFCC features from the audio with a sliding window of 25ms shifted by 10ms. The inputs of the model are stacks of five frames every three frames following [15]. The acoustic encoder has a first linear layer with 128 tanh units, followed by three LSTM layers of 128 units each. Overall, it contains 442k parameters. All weights and activations are quantized to 8 bits [18]. The keyword detector is made of a first convolutional layer with a kernel of five frames, and 128 output tanh units, followed by a max-pooling over three consecutive frames every two frames. The last convolutional layer has a kernel size of 12. The receptive field of the detector has a size of $W = 30$ frames. The keyword encoder is made of a bidirectional LSTM layer with 128 units in each direction, followed by a linear transform, predicting $12 \times 128 = 1536$ weights for each keyword.

The base acoustic model is trained on Librispeech [17], augmented 4 times using a room simulator with different amounts of noise and reverberation [19]. It is trained with CTC to predict the phone sequence, using minibatches of 32 samples, and the Adam optimizer with a learning rate of $1e-3$. The quantized mode is activated during training after about 30 epochs, and the model is further trained for one epoch. The phone error rate on the whole development set of Librispeech is 24.5%.

After aligning the acoustic model predictions on the training and development sets with CTC, we extract training samples for 15% of the frames (to limit the dataset size): a context window of 30 frames of last intermediate features of the acoustic model and the last 10 ground-truth phones at the considered timestep. On the development set, we extract the same samples for 5% of the frames. The keyword detector and encoder are jointly trained using minibatches of 128 samples, two synthetic commands of lengths randomly sampled between three and 10 for each training example, for three epochs using the Adam optimizer and a learning rate of 1e-4.

4.2. ASR-lite baseline

The ASR-lite baseline performs a detection of the keyword from sequences of phone predictions. It is an ASR-based method using the base acoustic model neural network that was pre-trained with CTC to output phone probabilities for each frame (Section 4.1). At inference, the CTC score for every keyword is computed for every possible audio segment. A confidence score is derived from the total probability associated with the segment and the length of that segment. When the confidence of a keyword exceeds a predefined threshold, the keyword is output and the corresponding segment will not be included in the search for the next keyword.

4.3. Mini-SLU results

|                  | lights | washing |
|------------------|--------|---------|
| Samples          | 564    | 545     |
| Unique keywords  | 8      | 8       |
| Speakers (M/F)   | 32 (22/10) | 33 (23/11) |
| Samples/speaker - avg (min/max) | 18 (8/60) | 17 (5/50) |
| Duration (s) - avg (min/max) | 2.6 (1.6/6.1) | 3.4 (1.8/6.7) |

Table 1: Mini-SLU datasets statistics.
For the mini-SLU task, we crowd-sourced queries for two use-cases: a smart light scenario and a washing machine scenario (Table 1). Each dataset was re-recorded in clean and noisy, reverberated far-field conditions with a SNR of 5dB. Each query contains between one and four keywords, and are expressed in natural language (e.g., “could you [turn on] the lights for the [bedroom]?”). We measure the ratio of exactly parsed queries, i.e., those for which the sequence of detected keywords exactly match the expected one, and the F1 score as a measure of performance at the keyword level. We compare the results of the proposed generic KWS neural network to the ASR-lite approach presented in Section 4.2. The latter uses the acoustic model that is subsequently included in the proposed method. We also perform a standard (cheating) ASR decoding using a closed vocabulary containing all words in the test sets. In practice, the full vocabulary is not known and that method cannot be applied to tiny devices use cases, and the results are only provided as a point of comparison.

|                      | lights clean | lights noisy | washing clean | washing noisy |
|----------------------|--------------|--------------|---------------|---------------|
| ASR (closed)         | 70.9 (89.6)  | 45.3 (77.8)  | 68.1 (90.2)   | 47.5 (81.3)   |
| ASR lite             | 44.3 (77.1)  | 34.9 (70.0)  | 52.6 (85.9)   | 34.9 (75.6)   |
| Proposed             | 48.8 (82.6)  | 26.7 (68.7)  | 62.6 (88.2)   | 36.3 (77.8)   |

Table 2: Ratio of exactly parsed queries (and F1 score, in %) of the proposed model on two mini-SLU tasks in clean and noisy conditions.

The results are reported in Table 2. Not surprisingly, the best results are achieved by the ASR decoding. Among the keyword spotting methods, the one proposed in this paper almost always performs best in terms of F1 score, and outperforms the other in terms of exact match rate by a large margin. Most of the weights of the neural networks are actually shared by the ASR-lite model and the proposed one. The main difference lies in the fact that the ASR-lite method relies on the local phone predictions to detect keywords, whereas in the proposed method, a neural network directly predicts whether the keyword appears in a given segment. The neural network has a high phone error rate (24.5%) which may greatly compromise the detection of the phone sequence in the former approach. The neural network in the latter approach may learn from the acoustic model’s confusions at the sequence level. This could explain its superior performance. Moreover, since we reused most of the network of the ASR-lite approach in the proposed one without retraining its weights, the two methods could be combined at a quite small additional cost.

4.4. Speech commands results

For the speech command task, the goal is to detect a single command among a pre-defined set. We evaluate our approach on Google’s speech command dataset and on a proprietary dataset of audio control commands. We measure the false rejection rate across all commands on the command datasets and a false alarm rate on a big dataset of negative data for the audio control commands, and on the commands not included in the positive set for Google’s speech command dataset. We compare our results with a model trained on specific training data, similar in size (240K parameters) and performance to the res15 ResNet architecture of [21], and to the ASR-lite approach.

![Fig. 3: Results on speech commands datasets](image)

The results are depicted in Fig. 3. As expected, the model trained on specific training data is much better than the other two open-vocabulary approaches. Nonetheless, the method we propose largely outperforms the ASR-lite baseline. It is worth noting that the models labeled “with data” are models trained on specific training data for each of the command sets, whereas the other two models can readily be applied to any command set, without retraining. The ASR-lite approach relies on the phone prediction and might not gain much from fine-tuning on the command-specific dataset. In the proposed approach, however, the weights generated by the keyword encoder could serve as a starting point for re-training on command-specific data and could probably benefit from it, even with a smaller training set than the “with data” approach. This will be experimented in a future work.

5. CONCLUSION

We proposed a method to generate a small-footprint keyword spotting neural network predicting the presence of a keyword, that can run on micro-controllers, without requiring specific training data for the keyword. The weights of the neural network are partially generated by an auxiliary neural network operating on the phone sequence of the keyword. We have shown that it outperforms an ASR-based method on a mini-SLU and a speech command detection task.

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1The datasets will be made publicly available, should the paper be accepted.

2evaluating on the same 12 commands as in [4, 21]

3with 10 commands: “turn on, turn off, play, pause, start, stop, next track, previous track, volume up, volume down”.
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