Spoken Term Detection and Relevance Score Estimation using Dot-Product of Pronunciation Embeddings

Jan Švec , Luboš Šmídl , Josef V. Psutka , Aleš Pražák

Department of Cybernetics, University of West Bohemia, Pilsen, Czech Republic

{honzas,smidl,psutka_j,aprazak}@kky.zcu.cz

Abstract

The paper describes a novel approach to Spoken Term Detection (STD) in large spoken archives using deep LSTM networks. The work is based on the previous approach of using Siamese neural networks for STD and naturally extends it to directly localize a spoken term and estimate its relevance score. The phoneme confusion network generated by a phoneme recognizer is processed by the deep LSTM network which projects each segment of the confusion network into an embedding space. The searched term is projected into the same embedding space using another deep LSTM network. The relevance score is then computed using a simple dot-product in the embedding space and calibrated using a sigmoid function to predict the probability of occurrence. The location of the searched term is then estimated from the sequence of output probabilities. The deep LSTM networks are trained in a self-supervised manner from paired recognition hypotheses on word and phoneme levels. The method is experimentally evaluated on MALACH data in English and Czech languages.

Index Terms: spoken term detection, relevance-score estimation, speech embeddings

1. Introduction

The task of spoken term detection (STD) for large spoken archives typically employs a large vocabulary continuous speech recognition (LVCSR). By recognizing and pre-indexing the spoken utterances the in-vocabulary (IV) queries could be directly found in the word index. The handling of out-of-vocabulary (OOV) terms consists of a much wider spectrum of methods [1] including recognition and indexing of sub-word units (phonemes, syllables or word fragments) [2, 3, 4], the use of IV proxy words [5, 6] or the use of acoustic embeddings and similarity metrics in a vector space [7, 8]. The acoustic embeddings often play a role also in the query-by-example (QbE) task in the low-resourced setup but the idea of neural-network-based projection of the query and the utterance into a single space could be reused in the more general STD task employing the standard speech recognition models [9, 10, 11].

In the QbE task the recurrent neural networks (RNNs) are usually used in the Siamese configuration – two similar networks handle both the utterance and the query. The networks are often trained using the triplet loss function [12, 13, 8]. The use of RNNs to process the signal and the query is also present in the wakeup word detection task [14, 15, 16].

Since we are targeting the large spoken archives for which the LVCSR system exists and is used for searching the IV terms, we focused on the methods where the STD is performed using the phoneme recognizer (in a structure similar to LVCSR) to search the OOV terms. The idea is not new and we used it in a mostly heuristic search presented in [2] and subsequently we adopted the approach of Siamese networks [17] to robustly estimate the term relevance scores. In this work we modified the Siamese architecture presented in [17] with the goal to simplify the network architecture and further improve the STD performance:

STD process – while the original Siamese architecture was proposed to relevance score estimation only and the localization of terms was performed using the index of phoneme triplets, the proposed approach allows both to localize and score the putative hits of the searched term. The proposed method does not need any kind of DTW [18, 19] nor subsequence matching [10].

Network structure – we keep the dual structure of the network where we map the recognized sequence and searched term into an embedding space using recurrent neural networks with the same architecture [13, 7]

Loss function – the loss function based on normalized cosine similarity [18, 13] was replaced with a simple binary cross-entropy which allows the network outputs to be interpreted as probabilities of occurrence improving the calibration of the relevance scores [20].

Network training – the idea of self-supervised learning from "blindly" recognized hypotheses on word and phoneme levels was used in a similar way. This way a large amount of training data could be easily generated from large spoken archives [11, 17]. Moreover, such training data match exactly the speech recognizer used and the neural network could model and partially compensate the errors of the recognizer.

Pronunciation embeddings – both the recognition output in the form of phoneme confusion network (sausage) and the graphemic representation of the searched term are projected into the same embedding space [7, 11, 18, 8]. In this space, the probability of occurrence is computed as a dot-product of two vectors and calibrated using a simple sigmoid function.

The above-mentioned ideas like the unsupervised transformation of the utterance into the latent embedding space using wav2vec method [21], mapping of words into the phonetic embedding space [10, 9] or the calibration of the relevance scores [22] are broadly used. This paper presents a novel application of such methods to the STD task in an integrated seamless way.

2. Deep LSTM for Spoken Term Detection

The proposed network architecture reuses some ideas from [17] especially the mapping from the graphemic representation of a searched term and from recognized phonemes into a shared embedding space where the relevance score is easily computed. The key difference from the previous work is that the sequence of recognized phonemes is mapped to a sequence of embedded vectors of the same length while the Siamese network used the mapping to a single vector. This way the scores between the searched term and the phoneme sequence are computed on a per-phoneme basis (or per confusion network segment if using
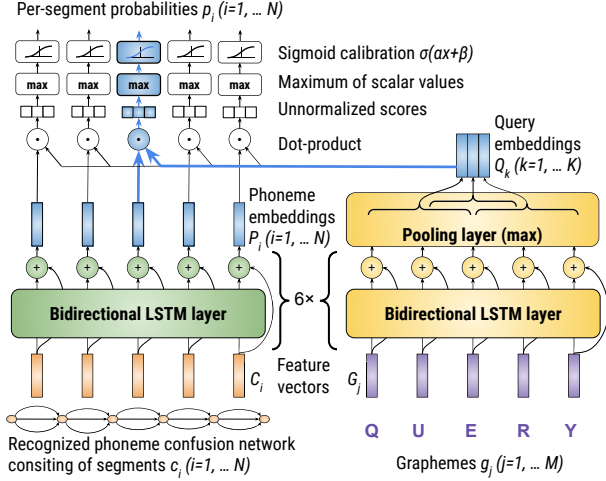
Figure 1: *Deep LSTM network architecture. In blue color the scoring for a single confusion network segment is highlighted (see Eq. (1) for details). The network for estimation of the minimal number of segments for the query is omitted for clarity.*

multiple phoneme hypotheses). Because the scores are computed for each phoneme we can easily determine locations of the putative hits using simple thresholding of scores. The overall relevance score of the putative hit is determined as an average of per-phoneme scores. To avoid the matches of query substrings the minimum length of the putative hit is also estimated by the network and all putative hits shorter than this minimum length are ignored.

2.1. Network architecture

The overall network consists of two independent processing pipelines implemented using deep LSTM networks: (1) the recognition output projection and (2) the searched term projection and minimum length estimation (Fig. 1). In each pipeline, we use a stack of bidirectional LSTM layers with skip connections. In our experiments, we used 6 such bidi-LSTM layers but the number of layers (and the number of trainable parameters) could be easily adjusted according to the amount of training data available. We used the dimensionality 300 (concatenated forward and backward LSTM outputs) for both processing pipelines.

To process the recognition output in the form of a phoneme-confusion network we use the features computed on the segments of the confusion network (i.e. on the transitions between two subsequent states). In our experiments, we used the top 3 transitions and the following features: time duration of the segment, probability of the transition, phoneme associated with the transition. If the segment contains less than 3 transitions we use padding transitions with zero probability and labeled with a special padding symbol. Alongside the padding symbol, we also use a special epsilon symbol which means transition without any phoneme associated. Such transitions are generated by the phoneme recognizer as part of the confusion network. The phonemes and special symbols are mapped to a continuous space using an embedding layer shared by all confusion network segments and by all symbols in the top 3 transitions of the segment. Segment duration and transition probabilities are processed using two independent stacks of two dense layers with *tanh* activation function each having 15 hidden units. The dimensionality of the phoneme embedding layer is 90. This way
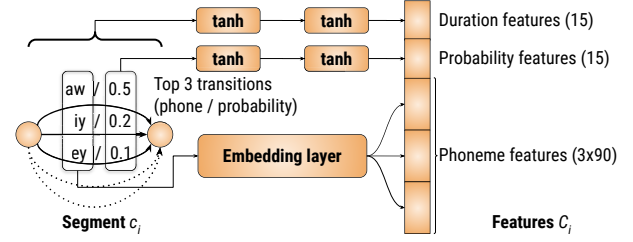

Figure 2: *Extraction of features from a segment of a phoneme confusion network.*

we obtain 300 features ($15 + 15 + 3 \times 90$) for the phoneme processing pipeline (Fig. 2).

Let's denote the segments of the phoneme confusion network as $c_i, i = 1, \ldots N$ and the graphemic representation consists of graphemes $g_j, j = 1, \ldots M$ (see Fig 1 for graphical explanation). The segments of the network are mapped to a sequence of feature vectors C_i using the feature extractor described above. The graphemes are mapped using an input embedding to features G_j.

The feature vectors C_i are mapped using the phoneme processing pipeline (6 layers of bidirectional LSTM with skip connections, green blocks in Fig. 1) to the sequence of pronunciation embeddings P_i. For the graphemes the same architecture is used followed by the maximum pooling layer (yellow blocks in Fig. 1). The output of the pooling are vectors $Q_k, k = 1, \ldots K$ where the number K depends on the configuration of the pooling layer (pooling size and stride). The final probability $p_i, i = 1, \ldots N$ is computed as:

$$p_i = \sigma\left(\alpha \cdot \max_{k=1}^{K}(P_i \cdot Q_k) + \beta\right) \quad (1)$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$ denotes the sigmoid function and α and β are trainable calibration parameters.

Since we are using the additive skip connections of the LSTM layers, the dimensionality of C_i, G_j, P_i, and Q_k have to be the same. In our experiments, we used 300-dimensional vectors. The embedding vectors P_i are independent of the query and could be pre-computed ahead of time to speed up the STD. The pooling layer of the grapheme processing pipeline allows extracting the query embeddings Q_k for different parts of the query word, for example, if $K = 3$ (pool size 8 and stride 4), the Q_1 represents the first half of the query, Q_2 the middle of the query and Q_3 the second half. It extends the expressive power of the model without increasing the number of trainable parameters. We illustrated the matches of particular Q_k for different queries in Fig. 3. It could be clearly seen that the overall maximum envelope of the peak consists of three partial peaks for particular Q_k vectors. By using the maximum in Eq. (1) we do not explicitly split the target probability between different Q_k vectors, we only say that on some location in the training chunk at least one of the query embeddings Q_k have to match the phoneme confusion network.

The sequence of graphemic embeddings G_i is also used to predict the expected minimum number of confusion network segments for the query. For this part of the network, we use a simple bidirectional LSTM with 20 units for each direction and the final outputs in each direction are combined using a dense linear layer.
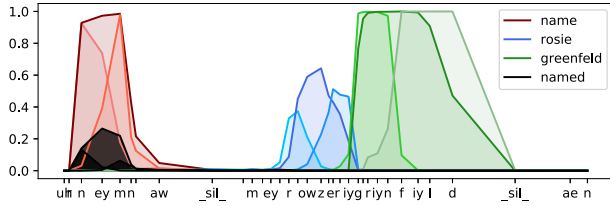
Figure 3: *Per-segment STD probabilities of a selected utterance, x-axis show the time and the 1-best phoneme sequence from the confusion network. The figure highlights three words used as separate queries:* name, rosie, greenfeld *while the fourth term* named *is used as a counterexample to the query* name. *Each query was represented as three pronunciation vectors (pooling size 8, stride 4) and the matches for each vector are shown in different shades.*

2.2. Network training

To train the neural network we use the self-supervised scheme where the network is trained not from the ground-truth human-annotated data but from the data produced by the speech recognizer. We recognize the data using two recognition engines, one working on word level and the second one on the phoneme level. The "blind" two-level recognition allows access to a large collection of training data, even much larger than the training data for speech recognizer and the data include the typical representatives of recognition errors.

The training data consist of the phoneme-level transcriptions (represented by phoneme confusion networks) segmented into chunks containing at most N segments. From the word-level representation of each chunk, the graphemic representation of the query is randomly sampled. We randomly select a single word with a probability of 0.5, two consecutive words with a probability of 0.25, etc. To avoid training from very noisy examples, we sample only words with a confusion score better than 0.95. If there is no such word, we randomly sample the recognition vocabulary to provide also negative examples during training. The selected words are joined together without space to form a query and therefore randomly simulate the OOV terms. Only queries longer than 4 graphemes and shorter than the maximum length $M = 16$ are allowed.

The target value is set to 1 if the confusion segment corresponds to the sampled query, 0 otherwise. If the negative example is used, the target consists of all 0's. Then the network is trained using a standard ADAM algorithm and binary cross-entropy loss function.

The network for predicting the minimum number of confusion network segments is trained using the mean-square-error loss function. As the target value, we use the 5th percentile of the number of segments seen in the training data for the query. If the query consists of multiple subsequent words, the target value is the sum of 5th percentiles for each word in the query.

2.3. STD algorithm

The spoken term detection using the deep LSTM approach consists of straightforward application of the two processing pipelines. The recognized phoneme confusion network is mapped to a sequence of embedding vectors P_i just once because the embedding vectors do not depend on the searched term. Each searched term graphemic representation is mapped to a set of K embedding vectors Q_k. The number of embedding vectors depends on the structure of the pooling layer used at the end of the query pipeline.

Table 1: *Statistics of development and test sets [17].*

	English		Czech	
	Dev	Test	Dev	Test
LVCSR vocabulary	243,699		252,082	
#speakers	10	10	10	10
OOV rate	0.5%	3.2%	0.3%	2.6%
LVCSR WER	24.10	19.66	23.98	19.11
#IV terms	597	601	1680	1673
#OOV terms	31	6	1145	948
dataset length [hours]	11.1	11.3	20.4	19.4

The sequence of embedding vectors P_i from the recognized phoneme confusion network is then combined using a dot-product with the embedding vectors of the query Q_k and calibrated to probabilities according to Eq. (1).

The last step is to convert the sequence of probability scores to a set of hits with combined scores assigned. In this step, the estimate of the minimum number of confusion network segments is used. The algorithm gradually lowers the threshold from 1.0 to 0.0 and searches for peaks of probability scores above this threshold and longer than the minimum number of segments. If such a peak occurs the time span is extracted from the corresponding segments of the confusion network the combined score is computed as an arithmetic mean of probability scores forming the peak. If the peak is evaluated as a hit the corresponding probability scores are zeroed and the threshold lowering process continues. This way we avoid including the peak multiple times in the results with different thresholds.

In the experiments, we observed that filtering the probability scores with a moving average filter of window width W and uniform weights $\frac{1}{W}$ improves the STD performance. The effect of this filtering is evaluated in Sec. 4.

3. Dataset description

The presented method was evaluated on the data from a USC-SFI MALACH archive in two languages – English [23] and Czech [24]. The archive for each language was recognized using the word- and phoneme-level recognizers. The phoneme confusion networks are aligned with the word-level hypothesis and the words with a confidence score (generated by a recognition engine) higher than 0.95 were used in training. More exactly the words were used to generate the queries and the phoneme confusion networks were used entirely for training regardless of the confidence of the corresponding words.

Speech recognition. We followed a typical Kaldi training recipe for a time delay neural network (TDNN) acoustic model training. This recipe supports layer-wise RBM pre-training, stochastic gradient descent training supported by GPUs and sequence-discriminative training optimizing sMBR criterion. We applied the standard 6 layers topology (5 hidden layers, each with 2048 neurons) with a softmax layer. The output dimension was equal to the number of context-dependent states (4521 for English, 4557 for Czech). We used features based on standard 12-dimensional Cepstral Mean Normalized (CMN) PLP coefficients with first and second derivatives. In total, the English acoustic model was trained from 217 hours and the Czech from 84 hours of the signal. We used our in-house real-time decoder both for the word- and phoneme recognition with trigram word- and 5-gram phoneme language model.

Table 2: *Results on the development dataset (MTWV) using phoneme-based STD.*

	English	Czech
Empirical method [2]	0.4636	0.6225
Siamese neural network [17]	0.5012	0.6547
Deep LSTM network (proposed method)		
pool size 16 ($K = 1$, $W = 5$)	0.6389	0.7505
pool size 8, stride 8 ($K = 2$, $W = 5$)	0.6676	0.7682
pool size 8, stride 4 ($K = 3$, $W = 5$)	**0.6703**	**0.7723**
larger filtering window ($W = 7$)	0.6567	0.7696
smaller filtering window ($W = 3$)	0.6646	0.7714
w/o output filtering ($W = 1$)	0.6433	0.7595
w/o LSTM skip connections	0.6666	0.7401
In-vocabulary terms	0.6726	0.7755
Out-of-vocabulary terms	0.6345	0.7671

Table 3: *Results on the test dataset (ATWV).*

All terms	English	Czech
Empirical method [2]	0.4435	0.6564
Siamese neural network [17]	0.4956	0.6873
Deep LSTM network	**0.5823**	**0.7531**
LVCSR+Empirical method	0.7191	0.6840
LVCSR+Siamese neural network	0.7263	0.7703
LVCSR+**Deep LSTM network**	**0.7275**	**0.8283**

two reasons: (1) the deep LSTM network is trained from recognized IV words and (2) the language model of the phoneme recognizer (5-gram) is trained from textual transcriptions and therefore better modeling the IV words than the OOV words.

5. Conclusions

To conclude the paper we used the trained networks with meta parameters and decision thresholds evaluated on development data (Tab. 2) to perform the STD on the test data. We present the results for both the pure phoneme-based search (top part of Tab. 3) and for the case where the IV terms are searched using the LVCSR hypothesis and OOV terms using the proposed method (bottom part of Tab. 3). In both cases, the ATWV metric on test data outperforms the baseline methods [17, 2].

The improvement is not only from the better modeling of the underlying data and task but also from the ability of the model to distinguish between similar terms in different contexts. This is illustrated on a real part of an utterance (Fig. 3) where the red and black peaks represent the per-segment probabilities of terms *name* vs. *named*. The probability of the second term is substantially lower despite being very similar to the first term.

The method outperforms the baseline and at the same time provides an integrated neural-network-based solution to the STD task. We introduced modifications that contribute to the improved performance: (1) the computation of calibrated per-segment probabilities and optimization of the binary cross-entropy loss, (2) representation of the query using multiple grapheme embeddings, (3) introducing the skip connections in the LSTM architecture and (4) the STD process employing gradual thresholding of output probabilities. In future work, we would like to focus on improving this method in different ways: *Large spoken archives* – since we can pre-compute the per-segment phoneme embeddings P_i, we would like to experiment with quantization of such embeddings followed by indexation. By using the quantized embeddings we will be able to directly select the set of the embeddings matching the query based on the grapheme embeddings Q_k and the quantization codebook. We would like to explore it together with the decimation of phoneme embeddings P_i, i.e. with using one embedding for every n-th only.

Query-by-example – the method is suitable for jointly training the QbE system employing grapheme/audio queries and phoneme/audio representation of utterances. The only change is in replacing the phoneme confusion network feature extractor with an acoustic feature extractor.

4. Experimental evaluation

The experimental evaluation was performed in the same setup as in [17]. To directly compare the results we reused the recognition models used in this paper. The baseline for the experiments was the empirical method from [2] and the Siamese neural network from [17]. In the experiments, we compared different setups of the proposed method (see Tab. 2) using the development dataset. We report the ATWV using the optimal decision threshold on development data (virtually MTWV) and the optimal decision thresholds used for STD on test data (true ATWV) [25]. Because the loss function used in network training is not necessarily correlated with the ATWV metric, we trained multiple networks using the same data and we stored all weights across the first 32 epochs. Each epoch consisted of 10k batches of 32 examples. Each example contained a chunk of $N = 256$ confusion network segments. Then we used these trained networks to perform the STD on the development data and we selected the best performing network in terms of the ATWV metric (Tab. 2). This network was then used in STD over the test data (Tab. 3).

First, we show the results for different configurations of the query pooling layer. We experimented with a single global maximum pooling (pool size 16 and $K = 1$ query embedding vectors), maximum pooling of the first and second half (pool size 8, stride 8 and $K = 2$) and maximum pooling with three output vectors (pool size 8, stride 4 and $K = 3$). The results clearly show that using more than one grapheme embedding vector brings a substantial improvement in the performance. The increase in MTWV from $K = 2$ to $K = 3$ is smaller than the step from $K = 1$ to $K = 2$.

Then, for the optimal pooling configuration, we tried different sizes of the output probability filtering window (W). The optimal size of the window is $W = 5$ and again the results are substantially better for any $W > 1$, i.e. in comparison with the case where no filtering is used.

We also performed the experiments with a pure LSTM network without the skip connections. In this case, we used the optimal pooling and filtering window configuration ($K = 3$, $W = 5$). The MTWV metric shows worse performance in both languages. We also observed much slower convergention of the training process.

The last two lines in Tab. 2 compares the MTWV values for IV and OOV terms. This illustrates the expectation that the IV terms are easier to detect using the proposed method due to

6. Acknowledgements

7. References

[1] D. Karakos and R. M. Schwartz, "Combination of search techniques for improved spotting of oov keywords," in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2015, pp. 5336–5340.

[2] J. Psutka, J. Švec, J. V. Psutka, J. Vaněk, A. Pražák, L. Šmídl, and P. Ircing, "System for Fast Lexical and Phonetic Spoken Term Detection in a Czech Cultural Heritage Archive," *EURASIP Journal on Audio, Speech, and Music Processing*, vol. 2011, no. 1, p. 10, 2011.

[3] Y. He, P. Baumann, H. Fang, B. Hutchinson, A. Jaech, M. Ostendorf, E. Fosler-Lussier, and J. Pierrehumbert, "Using pronunciation-based morphological subword units to improve oov handling in keyword search," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 24, no. 1, pp. 79–92, 2016.

[4] C. van Heerden, D. Karakos, K. Narasimhan, M. Davel, and R. Schwartz, "Constructing sub-word units for spoken term detection," in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2017, pp. 5780–5784.

[5] L. Zhiqiang, J. Kang, W.-Q. Zhang, and J. Liu, "An LSTM-CTC Based Verification System for Proxy-Word Based OOV Keyword Search," in *Proceedings of ICASSP 2017*, 2017, pp. 5655–5659.

[6] G. Chen, O. Yilmaz, J. Trmal, D. Povey, and S. Khudanpur, "Using proxies for OOV keywords in the keyword search task," in *2013 IEEE Workshop on Automatic Speech Recognition and Understanding, ASRU 2013 - Proceedings*, 2013, pp. 416–421.

[7] S. Settle and K. Livescu, "Discriminative Acoustic Word Embeddings: Recurrent Neural Network-Based Approaches," *IEEE Workshop on Spoken Language Technology (SLT)*, pp. 503–510, 2016. [Online]. Available: http://arxiv.org/abs/1611.02550

[8] Y. Yuan, L. Xie, C. Leung, H. Chen, and B. Ma, "Fast query-by-example speech search using attention-based deep binary embeddings," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 28, pp. 1988–2000, 2020.

[9] N. Sacchi, A. Nanchen, M. Jaggi, and M. Cernak, "Open-Vocabulary Keyword Spotting with Audio and Text Embeddings," in *Proc. Interspeech 2019*, 2019, pp. 3362–3366. [Online]. Available: http://dx.doi.org/10.21437/Interspeech.2019-1846

[10] Y. Wang, H. Lee, and L. Lee, "Segmental audio word2vec: Representing utterances as sequences of vectors with applications in spoken term detection," in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2018, pp. 6269–6273.

[11] H. Kamper, W. Wang, and K. Livescu, "Deep convolutional acoustic word embeddings using word-pair side information," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, vol. 2016-May, 2016, pp. 4950–4954.

[12] B. Gündoğdu, B. Yusuf, and M. Saraçlar, "Joint learning of distance metric and query model for posteriorgram-based keyword search," *IEEE Journal of Selected Topics in Signal Processing*, vol. 11, no. 8, pp. 1318–1328, 2017.

[13] Z. Zhu, Z. Wu, R. Li, H. Meng, and L. Cai, "Siamese recurrent auto-encoder representation for query-by-example spoken term detection," in *Proc. Interspeech 2018*, 2018, pp. 102–106. [Online]. Available: http://dx.doi.org/10.21437/Interspeech.2018-1788

[14] Y. Wang, H. Lv, D. Povey, L. Xie, and S. Khudanpur, "Wake Word Detection with Alignment-Free Lattice-Free MMI," in *Proc. Interspeech 2020*, 2020, pp. 4258–4262. [Online]. Available: http://dx.doi.org/10.21437/Interspeech.2020-1811

[15] G. Chen, C. Parada, and T. N. Sainath, "Query-by-example keyword spotting using long short-term memory networks," in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2015, pp. 5236–5240.

[16] M. Bulín, L. Šmídl, and J. Švec, "On using stateful lstm networks for key-phrase detection," in *Text, Speech, and Dialogue*, K. Ekštein, Ed. Cham: Springer International Publishing, 2019, pp. 287–298.

[17] J. Švec, J. V. Psutka, L. Šmídl, and J. Trmal, "A relevance score estimation for spoken term detection based on rnn-generated pronunciation embeddings," in *Proc. Interspeech 2017*, 2017, pp. 2934–2938. [Online]. Available: http://dx.doi.org/10.21437/Interspeech.2017-1087

[18] W. He, W. Wang, and K. Livescu, "Multi-view Recurrent Neural Acoustic Word Embeddings," *ICLR*, pp. 1–12, nov 2016. [Online]. Available: http://arxiv.org/abs/1611.04496

[19] B. Gundogdu, B. Yusuf, and M. Saraclar, "Generative rnns for oov keyword search," *IEEE Signal Processing Letters*, vol. 26, no. 1, pp. 124–128, 2019.

[20] J. van Hout, L. Ferrer, D. Vergyri, N. Scheffer, Y. Lei, V. Mitra, and S. Wegmann, "Calibration and multiple system fusion for spoken term detection using linear logistic regression," in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2014, pp. 7138–7142.

[21] S. Schneider, A. Baevski, R. Collobert, and M. Auli, "wav2vec: Unsupervised Pre-Training for Speech Recognition," in *Proc. Interspeech 2019*, 2019, pp. 3465–3469. [Online]. Available: http://dx.doi.org/10.21437/Interspeech.2019-1873

[22] D. Karakos, R. Schwartz, S. Tsakalidis, L. Zhang, S. Ranjan, T. Ng, R. Hsiao, G. Saikumar, I. Bulyko, L. Nguyen, J. Makhoul, F. Grezl, M. Hannemann, M. Karafiat, I. Szoke, K. Vesely, L. Lamel, and V. B. Le, "Score normalization and system combination for improved keyword spotting," in *2013 IEEE Workshop on Automatic Speech Recognition and Understanding*, vol. 26, no. 3, 2013, pp. 210–215.

[23] B. Ramabhadran, S. Gustman, W. Byrne, J. Hajič, D. Oard, J. S. Olsson, M. Picheny, and J. Psutka, "USC-SFI MALACH Interviews and Transcripts English LDC2012S05," 2012. [Online]. Available: https://catalog.ldc.upenn.edu/LDC2012s05

[24] J. Psutka, V. Radová, P. Ircing, J. Matoušek, and L. Müller, "USC-SFI MALACH Interviews and Transcripts Czech LDC2014S04," 2014. [Online]. Available: https://catalog.ldc.upenn.edu/LDC2014S04

[25] S. Wegmann, A. Faria, A. Janin, K. Riedhammer, and N. Morgan, "The TAO of ATWV: Probing the mysteries of keyword search performance," pp. 192–197, 2013.