Learning Efficient Representations for Keyword Spotting with Triplet Loss

Roman Vygon  
*Higher IT School, Tomsk State University & NTR Labs*  
Tomsk, Russia  
rvygon@ntr.ai

Nikolay Mikhaylovskiy  
*Higher IT School, Tomsk State University & NTR Labs*  
Moscow, Russia  
nickm@ntr.ai

Abstract—In the past few years, triplet loss-based metric embeddings have become a de-facto standard for several important computer vision problems, most notably, person reidentification. On the other hand, in the area of speech recognition the metric embeddings generated by the triplet loss are rarely used even for classification problems. We fill this gap showing that a combination of two representation learning techniques: a triplet loss-based embedding and a variant of kNN for classification instead of cross-entropy loss significantly (by 26% to 38%) improves the classification accuracy for convolutional networks on a LibriSpeech-derived LibriWords datasets. To do so, we propose a novel phonetic similarity based triplet mining approach. We also match the current best published SOTA for Google Speech Commands dataset V2 10+2-class classification with an architecture that is about 6 times more compact and improve the current best published SOTA for 35-class classification on Google Speech Commands dataset V2 by over 40%.

Keywords— keyword spotting, spoken term detection, triplet loss, kNN, representation learning, audio classification

I. INTRODUCTION

The goal of keyword spotting is to detect a relatively small set of predefined keywords in a stream of user utterances, usually in the context of small-footprint device [1]. Keyword spotting (KWS for short) is a critical component for enabling speech-based user interactions for such devices [2]. It is also important from an engineering perspective for a wide range of applications [3].

Since a KWS system is always-on, it should have very low power consumption to maximize battery life. On the other hand, it should detect the keywords with high accuracy and low latency [2]. Thus, the key problem in a KWS system design is to improve its accuracy and speed while keeping the footprint of the system very low. In this article we show how the use of the triplet loss-based embeddings allows us to improve the classification accuracy of the existing small-footprint neural network architectures.

A. Previous work on KWS

The first work on KWS was most likely published in 1967 [4]. Over years, a number of machine learning architectures for small-footprint KWS have been proposed (see, for example [5][6][7][8][9]).

With the renaissance of neural networks, they become the architecture class of choice for KWS systems (see, for example, [1][2][10][11][12][13][14])

Publication of the Google Speech Command dataset [15] have provided a common ground for KWS system evaluation and allowed for accelerating research. Further, we denote V1 and V2 versions 1 and 2 of the dataset, respectively. Since the publication of the Google Speech Command dataset led to a vast corpus of relevant work appearing in the past three years, we will only briefly discuss the most relevant recent work.

When publishing the dataset, Warden [15] have also provided a baseline model based on the convolutional architecture of Sainath and Parada [11], achieving the accuracy of 85.4% and 88.2% on V1 and V2, respectively. The respective Kaggle competition winner has achieved 91% accuracy on V1.

Jansson [16] suggested an interesting fully-convolutional model working out of raw waveforms, but, probably, a bit ahead of time and did not improve on previous accuracy results.

de Andrade et al. [3] have proposed an attention-based recurrent network architecture and achieved the SOTA on 2, 10, 20-word and full-scale versions of the dataset.

Majumdar and Ginsburg [17] have published a lightweight separable convolution residual network architecture MatchboxNet, achieving the new SOTA of 97.48 on V1 and 97.63 on V2.

Rybakov, Kononenko et al. [18] tested many of the existing models and proposed a multihead attention-based recurrent neural network architecture, achieving a new SOTA of 98% on V2.
Most recently, Tang et al. [19] have released Howl - a productionalized, open-source wake word detection toolkit, explored a number of models and achieved nearly-SOTA accuracy with a residual convolutional network architecture.

B. Previous work on the use of triplet loss for the metric embedding learning

The goal of metric embedding learning is to learn a function \( f : R^F \rightarrow R^D \), which maps semantically similar points from the data manifold in \( R^F \) onto metrically close points in \( R^D \), and semantically different points in \( R^F \) onto metrically distant points in \( R^D \) [20].

The triplet loss for this problem was most likely first introduced in [21] in the framework of image ranking:

\[
l(p_i; p_i^+, p_i^-) = \{0, g + D(f(p_i), f(p_i^+)) - D(f(p_i), f(p_i^-))\} \tag{1}
\]

where \( p_i, p_i^+, p_i^- \) are the anchor image, positive image, and negative image, respectively, \( g \) is a gap parameter that regularizes the gap between the distance of the two image pairs: \((p_i, p_i^+)\) and \((p_i, p_i^-)\), and \( D \) is a distance function that can be, for example, Euclidean distance in the image embedding space:

\[
D(f(P), f(Q)) = \|f(P) - f(Q)\|^2 \tag{2}
\]

A similar loss function was earlier proposed by Chechik et al. in [22], but the real traction came to the triplet loss in the area of face re-identification after the works of Schroff, Kalenichenko, and Philbin on FaceNet [23] and Hermans, Beyer, and Leibe [20].

In the speech domain, the use of triplet loss is more limited, but there still are several important works we need to mention. In particular, Huang J. et al. [24], Ren et al. [25], Kumar et al. [26], and Harvill et al. [27] use triplet loss with varied neural network architectures for the task of the speech emotion recognition. Bredin [28] and Song et al. [29] use triplet-loss based learning approaches for the speaker diarization, and Zhang and Koshida [30] and Li et al. [31] – for the related task of speaker verification.

Turpault et al. [32] propose a strategy for augmenting data with transformed samples, in line with more recent works in varied machine learning areas.

The most similar works to ours are probably [33], [34], [35] and [36], but there are many important differences:

- Sacchi et al. [33] operate in the open-vocabulary setting, which required the authors to design a system with a common embedding for text and speech, while we concentrate on improving the quality of existing low-footprint architectures for closed-vocabulary keyword spotting
- Shor et al. [34] concentrate on building an unified embedding that works well for non-semantic tasks, while we concentrate on the semantic task of keyword spotting
- Yuan et al. [35] operate in a two-stage detection/classification framework and use a BLSTM network with a mix of triplet, reverse triplet and hinge loss
- Huh et al. [36] start from the same res15 model as we do, but primarily focus on detection metrics and use SVM for classification, so our classification metrics are significantly better

C. Our contributions

Our contributions in this work are the following:

- We show that combining two representation learning methods: triplet-loss based metric embeddings and a kNN classifier allows us to significantly improve the accuracy of CNN-based models that use cross-entropy to classify audio information
- We propose a novel batch sampling approach based on phonetic similarity that allows to improve F1 metric when classifying highly imbalanced datasets

II. MODEL ARCHITECTURES

Most of the current state-of-the-art keyword spotting architectures are present in the work of Rybakov et al. [18], with the best model to date being the Bidirectional GRU-based Multihead attention RNN. It takes a mel-scale spectrogram and convolves it with a set of 2D convolutions. Then two bidirectional GRU layers are used to capture two-way long term dependencies in the audio data. The feature in the center of the bidirectional LSTM’s output sequence is projected using a dense layer and is used as a query vector for the multi-head attention (4 heads) mechanism. Finally, the weighted (by attention score) average of the bidirectional GRU output is processed by a set of fully connected layers for classification.

We have mostly experimented with ResNet-based models res8 [19] and res15 [37]. The initial experiments have shown that RNN-based architectures show significantly worse results when trained for the triplet loss, so they were discarded in our later work.

We used the encoder part of each of the models above to generate triplet-loss based embeddings, that are later classified using the K-Nearest Neighbor (kNN) algorithm.

TABLE I. Encoder model sizes for the key models studied.

| Model       | Embedding dimension | Model encoder size, [K] |
|-------------|---------------------|-------------------------|
| Mh-Att-RNN  | 256                 | 743                     |
| res8        | 128                 | 885                     |
| res15       | 45                  | 109                     |
| Att-RNN     | 128                 | 202                     |
III. EXPERIMENTS

A. Datasets and tasks

1) SpeechCommands

Google Speech Commands dataset Version 1 has 65K utterances from various speakers, each utterance 1 second long. Each of these utterances belongs to one of 30 classes corresponding to common words like “Go”, “Stop”, “Left”, “Down”, etc. Version 2 has 105K utterances, each 1 second long, belonging to one of 35 classes. The sampling rate of both datasets is 16kHz.

In our experiments we have considered the following tasks based on these datasets [3][15]:

- Recognition of all 35 words using Google Speech Dataset V2
- Recognition of 10 words (“Yes”, “No”, “Up”, “Down”, “Left”, “Right”, “On”, “Off”, “Stop”, and “Go”) and additional labels for “Unknown” and “Silence”.

For these tasks and each architecture studied we have measured top-1 classification accuracy.

2) LibriWords Datasets

To further explore the possibilities of triplet loss models we needed a dataset that consists of a large number of different words to classify.

Thus, we have used LibriSpeech [38] - a collection of 1,000 hours of read English speech. The dataset was split on the word level by Lugosch et al. [39]. Since LibriSpeech is aligned on sentence level only, the Montreal Forced Aligner [40] was used to obtain intervals for individual words. The alignments are available online [39]. Further we call this derived dataset LibriWords.

We have created four different versions of the dataset (LibriWords10k, LibriWords100, LibriWords1000, LibriWords10000) that correspond to the first 10, 100 etc. words by popularity in the librispeech-train-clean-360 dataset. For example, the LibriWords10 words are: “the”, “and”, “of”, “to”, “a”, “in”, “he”, “I”, “that”, “was”.

Durations of the words range from 0.03 seconds to 2.8 seconds, with mean duration of 0.28 seconds. The details on the datasets metrics are available in the Appendix 1. We have split the dataset into train/val/test in 9:1:1 proportion, and tried to keep this proportion holds for each word in the dataset. We release NeMo-like manifests for ease of use and reproduction.

Since the motivation behind the dataset is to model real-life speech recognition scenarios, there was no further quality assurance on the data.

B. Approach to training models

1) Batch sampling

When working with Speech Commands and LibriWords10 datasets, to ensure a meaningful representation of the anchor-positive distances, following [23], we sample an equal number of objects from all the classes available.

For unbalanced datasets with a large number of words, we also needed an efficient class-sampling method, otherwise the network will often train on irrelevant batches where embeddings of the words are already far from each other. To achieve better class selection we have used three sampling approaches:

- Uniform: sample batch\_size classes randomly from a uniform distribution.
- Proportional: sample batch\_size classes randomly from a distribution proportional to the word distribution in the dataset. Motivation behind this approach is twofold. First, the popular words are short (the, a, I) so they are not easy to distinguish from the rest. Second, if you equally train on them, there will be the same amount of errors, and that’s a lot in terms of the absolute value. (If we classify 2% of a popular word incorrectly, this would significantly spoil the metric for the entire dataset).
- Phonetic: Calculate a matrix of phonetic similarity for all the words in the dataset, sample batch\_size/2 classes, then, for each sampled class add a random phonetically similar word to the batch. Similarity score is calculated using SoundEx, Caverphone, Metaphone and NYSIIS algorithms [42].

These sound similarity algorithms were all developed with tasks different from ours in mind. To achieve a baseline applicable to LibriWords we used a weighted average of distances calculated using all 4 algorithms. The weights go as follows:

$$D_{\text{ Phonetic}} = D_{\text{Soundex}} \times 0.2 + \frac{D_{\text{Caverphone}} + D_{\text{Metaphone}} + D_{\text{NYSIIS}}}{3} \times 0.1$$

The metapone algorithm has a bigger weight due to its original task being the nearest to ours. The optimal use of these algorithms is a matter of future research, for example, we had to adjust manually the distances of a handful of pairs of words: e.g. the pair “know-no” had a large distance while being similar. The problem was found while analyzing the confusion matrix.

We have evaluated these three triplet mining approaches alone and in combinations, mixing them with equal probabilities. The results in the TABLE II. show that the proportional sampling method improves the accuracy by increasing the score of more popular words while the phonetic sampling method improves the F1 metric due to better classification of difficult pairs like “at”-“ate”, “an”-“ame”. Uniform sampling usage is essential as one of the sampling strategies, as it provides the proper class coverage.

2) Triplet selection

An important part of TL models is the selection of triplets used to calculate the loss, since taking all possible triplets from a batch is computationally expensive. We have used a randomized approach to the online batch triplet mining based on [20], where the negative sample to a hard pair of the anchor and a positive sample is selected randomly from the set of negative samples resulting in non-zero loss. Our initial experiments have shown that this modification of the online batch triplet mining performs better than hard or semi-hard batch loss options.
The effects of the different sampling strategies for triplet loss of res15 model on LibriWords10000

| Method(s)          | Accuracy | F1  |
|--------------------|----------|-----|
| Uniform            | 79.4     | 0.72|
| Proportional       | 77.1     | 0.61|
| Phonetic           | 76.9     | 0.73|
| Uniform+Phonetic   | 78.9     | 0.76|
| Uniform+Proportional | 81.2   | 0.74|
| Proportional+Phonetic | 80.0   | 0.72|
| Uniform+Proportional +Phonetic | 80.8 | 0.75|

3) Optimization and training process

Baseline models were trained until they reached a plateau on a validation set. We monitored the validation accuracy of triplet loss models each 1k batches and stopped the training process if the accuracy didn't increase for more than .1% for 3 consecutive times. The number of epochs is listed in the TABLE III. below.

The decrease in epochs for larger datasets is due to class-imbalance – triplet models sample classes directly, so instead of seeing all objects in the dataset it sees the same number of objects, but distributed more evenly between classes. The baseline, cross-validation based models converge to predict the most popular words well, while ignoring the rest. One can see this from the low F1 metric on LibriWords10000 dataset. The batch size was 35*10 for TL-res8, 35*4 for TL-res15 and 128 for the baseline models.

Training was done using the Novograd [43] algorithm with initial learning rate of 0.001 and cosine annealing decay to 1e-4.

4) Influence of kNN

We have tested kNN for several values of k, and have found that for LibriWords the best performing value varies depending on the dataset size, while for Speech Commands the best performing value was k=5 (see TABLE IV. ).

As the model size is of a great concern for the keyword spotting application, and for the larger datasets kNN part of the model can take a lot of memory, we have also studied the effect of kNN quantization available from [44] on the size, speed and accuracy of the resulting model, varying the number of segments for the Product Quantizer.

| Task                        | Triplet Loss | Crossentropy | Relative improvement |
|-----------------------------|--------------|--------------|----------------------|
|                            | Accuracy | F1 | Accuracy | F1 | Accuracy, % | F1, %    |
| Speech Commands V2 / 35     | 96.4     | 0.957 | 95.7    | 0.953 | 16.28     | 8.51     |
| Speech Commands V2 / 12     | 98.02    | 0.966 | 97.7    | 0.963 | 13.91     | 8.11     |
| LibriWords10                 | 91.7     | 0.90  | 88.8    | 0.88  | 26.25     | 16.67    |
| LibriWords100                | 86.9     | 0.87  | 82.3    | 0.81  | 25.99     | 31.58    |
| LibriWords1000               | 84.3     | 0.86  | 78.2    | 0.78  | 27.94     | 36.36    |
| LibriWords10000              | 81.2     | 0.75  | 69.3    | 0.41  | 38.66     | 57.63    |
TABLE VI. MODEL ACCURACY COMPARISON ON GOOGLE SPEECH COMMANDS DATASET TASKS

| Model          | Loss  | Model Size, KB | V2 35 accuracy | V2 12 accuracy |
|----------------|-------|----------------|----------------|----------------|
| res8           | Triplet | 901            | 95.6           | 96.7           |
|                | Crossentropy | 885           | 93.9           | 96.1           |
| res15          | Triplet | 252            | 96.4           | 98.02          |
|                | Crossentropy | 237           | 95.7           | 97.7           |
| Mh-Att-RNN [18]| Crossentropy | 743           |                | 98.0           |
| Attention RNN [3] | Crossentropy | 202           | 93.9           |                |

V. ACKNOWLEDGMENTS

The authors are grateful to

- colleagues at NTR Labs Machine Learning Research group for the discussions and support;
- Prof. Sergey Orlov and Prof. Oleg Zmeve for the computing facilities provided;
- Nikolay Shmyrev for pointing out to the works [35], [36].

VI. REFERENCES

[1] Tang, R., and J. Lin, “Deep residual learning for small-footprint keyword spotting.” ArXiv 1710.10361.
[2] Zhang, Y., N. Suda, L. Lai, and V. Chandra, “Hello Edge: Keyword Spotting on Microcontrollers.” ArXiv 1711.07128.
[3] de Andrade, D., L. Sabato, M. Viana, and C. Bernkopf, “A neural attention model for speech command recognition.” ArXiv 1808.08929
[4] Teacher, C., Kellett, y., and Focht L., “Experimental, limited vocabulary, speech recognizer.” IEEE Transactions on Audio and Electroacoustics, 15(3):127–130, 1967.
[5] Rohlicek, J.R., Russell, W., Roukos, S., Gish, H., “Continuous hidden Markov modeling for speaker-independent word spotting.” In: Acoustics, Speech, and Signal Processing 1989, pp. 627–630. IEEE
[6] Szoke I., Schwarz P., Matejka P., et al., “Phoneme based acoustics keyword spotting in informal continuous speech.” In: Matousek V., Mautner P., Pavelka T. Text, Speech and Dialogue, Berlin: Springer-Verlag, 2005:302-309 doi: 10.1007/11551874_39.
[7] Zhang, S., Shuang, Z., Shi, Q., Qin, Y., “Improved mandarin keyword spotting using confusion garbage model.” In: 2010 20th International Conference on Pattern Recognition (ICPR), pp. 370–3703.
[8] Greibus M., Telksnys L., “Speech Keyword Spotting with Rule Based Segmentation.” In: Skersys T., Butleris R., Butkiene R. (eds) Information and Software Technologies. ICIST 2013. Communications in Computer and Information Science, vol 403. Springer, Berlin, Heidelberg.
[9] Principi, S., Squartini, R., Bonfigli, G. Ferroni, and F. Piazza, “An integrated system for voice command recognition and emergency detection based on audio signals,” Expert Syst. Appl., vol. 42, no. 13, pp. 5668–5683, Aug. 2015, doi: 10.1016/j.eswa.2015.02.036.
[10] Chen G., Parada C., and Heigold G., “Small-footprint keyword spotting using deep neural networks.” In Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on, pages 4087–4091.
[11] Sainath T. N. and Parada C., “Convolutional neural networks for small-footprint keyword spotting.” In Sixteenth Annual Conference of the International Speech Communication Association, 2015.
[12] Arik S. O., Kleigl M., Child R., Hestness J., Ghibiansky A., Fougnier C., Prenger R., and Coates A., “Convolutional recurrent neural networks for small-footprint keyword spotting.” ArXiv:1703.05390, 2017.
[13] Sun M., Raju A., Tucker G., Panchapagesan S., Fu G., Mandal A., Matsoukas S., Strom T., and Vitaladevuni S., “Max-pooling loss training of long short-term memory networks for small-footprint keyword spotting.” In Spoken Language Technology Workshop (SLT), 2016 IEEE, pages 474–480. IEEE, 2016.
[14] He, Y., Prabhavalkar, R., Rao, K., Li, W., Bakhitn, A., and McGraw, I., “Streaming Small-Footprint Keyword Spotting using Sequence-to-Sequence Models.” ArXiv:1710.09617
[15] Warden P., “Speech commands: A public dataset for single-word speech recognition.” ArXiv:1804.03209.
[16] Jansson, P., “Single-word speech recognition with Convolutional Neural Networks on raw waveforms”. Degree Thesis, Information technology, ARCADIA University, Finland
[17] Majumdar S., and Ginsburg B., “MatchboxNet: 1D Time-Channel Separable Convolutional Neural Network Architecture for Speech Commands Recognition” ArXiv:2004.08531
[18] Rybakov O., Kononenko N., Subrahmanya N., Visontai M., and Laurenzo S., “Streaming keyword spotting on mobile devices” arXiv:2005.06720
[19] Tang, R., Lee, J., Razi, A., Cambre, J., Bicking, I., Kaye, J., and Lin, J., “Howl: A Deployed, Open-Source Wake Word Detection System.” arXiv:2008.09606.
[20] Hermans A., Beyer L, and Leibe B., “In Defense of the Triplet Loss for Person Re-Identification” arXiv:1703.07737.
[21] Wang J., Song Y., Leung T., Rosenberg C., Wang J., Philbin J., Chen B., and Wu Y., “Learning fine-grained image similarity with deep ranking.” arXiv:1404.4661.
[22] Chechik, G., Sharma, V., Shalit, U., and Bengio, S., “Large scale online learning of image similarity through ranking.” The Journal of Machine Learning Research, 11:1109–1135, 2010.
[23] Schroff F., Kalenichenko D., and Philbin J., “FaceNet: A Unified Embedding for Face Recognition and Clustering.” arXiv:1503.03832
[24] Huang J., Li Y., Tao J., and Lia Z., “Speech Emotion Recognition from Variable-Length Inputs with Triplet Loss Function.” INTERSPEECH 2018: 3673-3677.
[25] Ren M., Nie W., Liu A., Su Y., “Multi-modal Correlated Network for emotion recognition in speech”, Visual Informatics, Volume 3, Issue 3, 2019, Pages 150-155.
[26] Kumar P., Jain S., Raman B, Roy P.P., and Iwamura M., “End-to-end Triplet Loss based Emotion Embedding System for Speech Emotion Recognition”, arXiv:2010.06200
[27] Harvill J., AbdelWahab M., Lotfian R, and Bussu C., “Retrieving speech samples with similar emotional content using a Triplet loss function”, ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Brighton, United Kingdom, 2019, pp. 7400-7404, doi: 10.1109/ICASSP.2019.8683273.
[28] Bredin H., “Tristounet: triplet loss for speaker turn embedding” arXiv:1609.04301
[29] Song H., Willi M., Thiagarajan J.J., Berisha V., Spanias A., “Triplet Network with Attention for Speaker Diarization” arXiv:1808.01535
[30] Zhang, C., Koishida, K., “End-To-End Text-Independent Speaker Verification with Triplet Loss on Short Utterances.” Proc. Interspeech 2017, 1487-1491, DOI: 10.21437/Interspeech.2017-1608.
[31] Li C., Ma X., Jiang B., Li X., Cao Y., Kannan A., Zhu Z., “Deep Speaker: an End-to-End Neural Speaker Embedding System” arXiv:1705.02304
[32] Turpault N, Serizel R, Vincent E., “Semi-supervised triplet loss based learning of ambient audio embeddings,” ICASSP 2019, May 2019, Brighton, United Kingdom. hal-02025824
[33] Sacchi, N., Nanchen, A., Jaggi, M. and Cerrah, M., “Open-Vocabulary Keyword Spotting with Audio and Text Embeddings.” 3362-3366. 10.21437/Interspeech.2019-1846.
[34] Shor J., Jansen A., Maor R., Lang O., Tuval O., de Chaumont Quiry F., Tagliasacchi M., Shavitt I., Emanual D., Havivi Y., “Towards Learning a Universal Non-Semantic Representation of Speech” arXiv:2002.12764
[35] Yuan, Y., Zhang, Z., Xu, S., Huang, and L. Xie, “Verifying Deep Keyword Spotting Detection with Acoustic Word Embeddings.” 2019 IEEE Autom. Speech Recognit. Underst. Work. ASRU 2019 - Proc., no. 61571363, pp. 613–620, 2019, doi: 10.1109/ASRU.2019.9003781.
J. Huh, M. Lee, H. Heo, S. Mun, and J. S. Chung, “Metric learning for keyword spotting,” arXiv:2005.08776 2020.

R. Tang and J. Lin, “Honk: A PyTorch reimplementation of convolutional neural networks for keyword spotting,” arXiv. arXiv, Oct. 17, 2017. Accessed: Jan. 02, 2021. http://arxiv.org/abs/1710.06554.

V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: An ASR corpus based on public domain audio books,” in ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, Aug. 2015, vol. 2015-August, pp. 5206–5210.

Lugosch L., Ravanelli M., Ignoto P., Tomar V. S., and Bengio Y., “Speech model pre-training for end-to-end spoken language understanding,” in Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH, 2019, vol. 2019-Sept, pp. 814–818.

M. McAuliffe, M. Socolof, S. Mihuc, M. Wagner, and M. Sonderegger, “Montreal forced aligner: Trainable text-speech alignment using kaldi,” Proc. Annu. Conf. Int. Speech Commun. Assoc. INTERSPEECH, vol. 2017-Aug, pp. 498–502, 2017, doi: 10.21437/Interspeech.2017-1386.

https://zenodo.org/record/2619474, last retrieved on Jan 2nd, 2021.

A. F. Ahmed, M. A. Sherif, and A. C. N. Ngomo, “Do your resources sound similar?: On the impact of using phonetic similarity in link discovery,” in K-CAP 2019 - Proceedings of the 10th International Conference on Knowledge Capture, 2019, vol. 8, no. 19, pp. 53–60, doi: 10.1145/3360901.3364426.

B. Ginsburg et al., “Stochastic Gradient Methods with Layer-wise Adaptive Moments for Training of Deep Networks,” arXiv: http://arxiv.org/abs/1905.11286.

J. Johnson, M. Douze, and H. Jégou, “Billion-scale similarity search with GPUs,” arXiv. arXiv:1702.08734v1 doi: 10.1109/tbdata.2019.2921572.

APPENDIX 1. WORD DISTRIBUTIONS IN LIBRIWORDS DATASETS

![Distribution of words in LibriWords10](image)
Fig. 2. Distribution of words in LibriWords100

Fig. 3. Distribution of words in LibriWords1000.

|           | Total words | Most popular word | Least popular word | Class imbalance |
|-----------|-------------|-------------------|--------------------|-----------------|
| libri10   | 875 043     | the 224 240       | was 42 757         | 5.2             |
| libri100  | 1 890 091   | the 224 240       | never 4 121        | 54.4            |
| libri1000 | 2 723 023   | the 224 240       | path 329           | 681.6           |
| libri10000| 3 394 530   | the 224 240       | parade 21          | 10678           |
### APPENDIX 2. Influence of KNN Quantization on Speed, Memory Consumption and Accuracy of Classifiers

#### Table VIII. Memory Consumption, Test Set Predict Time and Accuracy for Different KNN Quantization Segment Number for LibriWords10 Dataset.

| Segment Number for LibriWords | Memory, MB | Time, s | Accuracy, % |
|-------------------------------|------------|---------|-------------|
| Basic                         | 246        | 17.15   | 91.74       |
| 4                             | 5.95       | 0.53    | 91.34       |
| 8                             | 7.87       | 0.62    | 91.48       |
| 16                            | 11.7       | 0.73    | 91.56       |
| 32                            | 19.4       | 1.1     | 91.61       |
| 64                            | 34.8       | 2.33    | 91.58       |

#### Table IX. Memory Consumption, Test Set Predict Time and Accuracy for Different KNN Quantization Segment Number for LibriWords100 Dataset.

| Segment Number for LibriWords | Memory, MB | Time, s | Accuracy, % |
|-------------------------------|------------|---------|-------------|
| Basic                         | 638        | 118.6   | 86.9        |
| 4                             | 15.1       | 1.72    | 91.34       |
| 8                             | 20.1       | 2.08    | 85.23       |
| 16                            | 30.1       | 2.7     | 86.11       |
| 32                            | 50         | 4.18    | 86.24       |
| 64                            | 90         | 8.98    | 86.22       |

#### Table X. Memory Consumption, Test Set Predict Time and Accuracy for Different KNN Quantization Segment Number for LibriWords1000 Dataset.

| Segment Number for LibriWords | Memory, MB | Time, s | Accuracy, % |
|-------------------------------|------------|---------|-------------|
| Basic                         | 977        | 272.37  | 84.2        |
| 4                             | 23.1       | 2.85    | 78.75       |
| 8                             | 30.7       | 3.87    | 81          |
| 16                            | 46         | 4.92    | 82.18       |
| 32                            | 76.5       | 8.13    | 82.5        |
| 64                            | 138        | 17.54   | 82.65       |

#### Table XI. Memory Consumption, Test Set Predict Time and Accuracy for Different KNN Quantization Segment Number for LibriWords10000 Dataset.

| Segment Number for LibriWords | Memory, MB | Time, s | Accuracy, % |
|-------------------------------|------------|---------|-------------|
| Basic                         | 1260       | 440.66  | 79.4        |
| 4                             | 29.8       | 4.27    | 68.56       |
| 8                             | 39.6       | 5.69    | 73.33       |
| 16                            | 59.4       | 7.23    | 75.51       |
| 32                            | 98.8       | 12.03   | 76.35       |
| 64                            | 178        | 27.15   | 76.59       |

#### Table XII. Performance of the Best KNN Quantizations for Different Datasets

| Commands | Memory, MB | Accuracy, basic | Memory, quantization | Accuracy, quantization | Memory economy, times | Accuracy degradation, % |
|----------|------------|-----------------|----------------------|------------------------|-----------------------|-------------------------|
| Commands | 15.7       | 96.19           | 95.98                | 95.98                  | 10.13                 | 5.51                    |
| LW10     | 246        | 91.74           | 91.61                | 91.61                  | 12.68                 | 1.57                    |
| LW100    | 638        | 86.9            | 86.24                | 86.24                  | 12.76                 | 5.04                    |
| LW1000   | 977        | 84.2            | 82.65                | 82.65                  | 7.08                  | 9.81                    |
| LW10000  | 1260       | 79.4            | 76.59                | 76.59                  | 7.08                  | 13.64                   |