

# Improving Label-Deficient Keyword Spotting Using Self-Supervised Pretraining

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## Abstract

In recent years, the development of accurate deep keyword spotting (KWS) models has resulted in KWS technology being embedded in a number of technologies such as voice assistants. Many of these models rely on large amounts of labelled data to achieve good performance. As a result, their use is restricted to applications for which a large labelled speech data set can be obtained. Self-supervised learning seeks to mitigate the need for large labelled data sets by leveraging unlabelled data, which is easier to obtain in large amounts. However, most self-supervised methods have only been investigated for very large models, whereas KWS models are desired to be small. In this paper, we investigate the use of self-supervised pretraining for the smaller KWS models in a label-deficient scenario. We pretrain the Keyword Transformer model using the self-supervised framework Data2Vec and carry out experiments on a label-deficient setup of the Google Speech Commands data set. It is found that the pretrained models greatly outperform the models without pretraining, showing that Data2Vec pretraining can increase the performance of KWS models in label-deficient scenarios. The source code is made publicly available.

## 1 Introduction

Personal assistants like Google Assistant, Amazon’s Alexa and Apple’s Siri have become commonplace in day-to-day life. Common for all is that they make use of advanced Automatic Speech Recognition (ASR) systems, which are activated by keywords in order to save resources when the ASR sys-

tem is not needed [1]. Keyword activation is done through a so-called Keyword Spotting (KWS) system, which is used to detect keywords in speech. Apart from voice assistants KWS also has other use cases such as speech data mining and phone call routing [2].

Early KWS systems were based on Large-vocabulary Continuous Speech Recognition [3] and later on keyword/filler Hidden Markov Model (HMM) models [4], whereas modern KWS systems use Deep Neural Networks (DNNs) to determine the existence of keywords. These systems are known as deep KWS systems and have shown significant improvements in accuracy over keyword/filler HMM approaches [1]. While deep KWS systems have improved the accuracy of KWS systems, they still need large amounts of labelled data to generalize well. As data labelling is a costly and time-consuming process, the need for labelled data is a considerable bottleneck for KWS systems.

The need for labelled data has long been a constraint for the further development in the area of deep learning [5]. Recently, much effort has been put towards the development of self-supervised methods which can learn good representations using the data itself as supervision. This movement is partly inspired by the fact that humans do not need to be shown thousands of examples to learn meaningful patterns, and instead learn good representations of the world primarily through observation [6].

### 1.1 Keyword Spotting Systems

A deep KWS system can usually be divided into three parts, namely a feature extractor, a DNN acoustic model and posterior handling as illustrated in Figure 1.

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Figure 1: Illustration of a typical deep KWS system.

The feature extractor in a KWS system is used to generate a compact representation of the input signal. Feature extraction can both be done using handcrafted features, such as Mel-frequency cepstral coefficients (MFCCs), or they can be extracted using learned filter banks or neural networks [7].

The extracted features are fed into the acoustic model, which is the core element of a KWS system. The acoustic model is responsible for modelling keywords from the extracted speech features, and producing posterior probabilities of the keyword being present. The goal of the acoustic model is to provide high accuracy, while being computationally efficient [1]. Both Convolutional Neural Network (CNN) [8], Recurrent Neural Network (RNN) [2] and transformer [9] architectures have been used for acoustic modelling of keywords in deep KWS systems.

The acoustic model typically outputs posteriors  $\mathbf{y}^{(i)}$ , which are the posteriors over  $N_c$  classes. Posterior handling is thus the process of choosing an appropriate classification from the posteriors, and can be divided into a streaming and a non-streaming setting. Here, the streaming setting describes the case where the KWS system has to handle a continuous stream of audio sequences as opposed to the more simple case of individual unrelated audio sequences. While the streaming setting better represents a real-world application, we focus on the non-streaming setting, as the non-streaming and streaming performance have been shown to be highly correlated [1].

## 1.2 Self-supervised Learning

In the search for more generalizable deep learning models that do not rely on large amounts of labelled data, self-supervised learning has shown great promise. Self-supervised learning describes methods in which the data itself is used for supervision, e.g., by removing some part of the data and

training the model to fill in the missing part [6], or by predicting future data from the past [10]. By pretraining models on a self-supervised pretext task the model learns a good representation of the data. After pretraining, the pretrained model can then be used for downstream tasks such as classification, e.g., by using the extracted representations as input to a smaller model which requires less labelled data to train [6]. As a result, self-supervised learning can be used to improve model performance in the case of label-deficiency.

While promising, many self-supervised methods have only been investigated for very large models with several million parameters using large data sets, such as LibriSpeech [11], for pretraining. Consequently, training these models require numerous high-end GPUs and several weeks of training. This makes training these models infeasible in many cases, e.g., due to limited time or restricted computing resources. Additionally, for many use cases, such as KWS for voice assistants, it is desired that the models are small [1].

The use of knowledge distillation methods [12] have been investigated to transfer knowledge from a large model to a smaller one [13, 14, 15]. However, while knowledge distillation makes it possible to transfer the representations learned by a large model to a smaller model, it does not deal with the original problem of initially needing to train a large model. [16] studied the use of self-supervised learning to train smaller models without distillation from a large pretrained model using contrastive self-supervised learning. Here, they found that, contrary to former assumptions, small models were able to solve the self-supervised pretext tasks without overfitting. Additionally, they were able to improve the performance of five different small image recognition models, ranging from 2.5 to 11 million parameters, suggesting that training small self-supervised models is feasible.

In this paper, we investigate the use of self-supervised learning for KWS using the non-contrastive self-supervised framework Data2Vec [17]. We implement three variations of the Keyword Transformer (KWT) model [9], varying from  $607 \times 10^3$  to  $5361 \times 10^3$  parameters, and pretrain the models using Data2Vec. The models are evaluated on a label-deficient setup of the Google Speech Commands data set [18], and the results show that self-supervised pretraining significantly improves

the KWS performance when only a sparse amount of labelled data is available. The source code used to produce the results of this paper is made publicly available<sup>1</sup>.

## 2 Methodology and Materials

### 2.1 Keyword Spotting Model

The Data2Vec framework uses a transformer encoder and as a result, we choose to use the transformer based KWT model [9], which achieves state-of-the-art performance on the Google Speech Commands KWS benchmark data set and fits directly into the Data2Vec framework. The KWT model is based on a vision transformer [19], substituting images with MFCCs.

Feature extraction is done by first computing the MFCCs of the input audio sequence frame by frame. Here, we use a window length of 480, a hop length of 160, and we use the first 40 MFCCs. Each MFCC vector is then passed through a linear layer to yield embeddings matching the transformer input dimension.

The acoustic model consists of 12 identical transformer blocks, which are followed by a Multilayer Perceptron (MLP) classification head. As in the vision transformer [19], the KWT [9] model concatenates a CLS (i.e., classification) token to the input, yielding a global encoding of all time steps. This global encoding is then used as input for the classification head. However, we found that instead of using a global encoding, using the mean of the individual encodings for each time step (i.e., MFCC vector) as the input for the classification head yields better performance, both with and without self-supervised pretraining. An illustration of the KWS model used in this study is seen in Figure 2

Following (author?) [9], the encoder dimension of each transformer block,  $d$ , is set such that  $\frac{d}{k} = 64$ , where  $k$  is the number of attention heads in the multi-head attention block.

### 2.2 Data2Vec Pretraining

Self-supervised learning methods are generally modality specific, i.e., self-supervised methods for image recognition do not translate to time-series

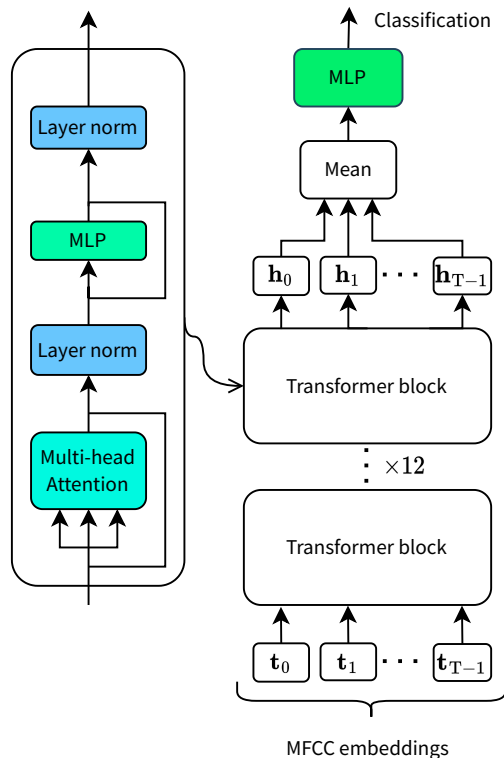


Figure 2: Illustration of the Keyword Spotting model.

processing. Recently, the general self-supervised learning framework Data2Vec was proposed, with the goal of unifying the self-supervised task for multiple modalities, inspired by the fact that humans seem to use similar mechanisms for understanding language as they do for vision [17]. The Data2Vec framework achieves state-of-the-art performance on common benchmarks for self-supervised methods in vision, audio and natural language modelling. Data2Vec makes use of a student teacher paradigm in which the teacher model receives the full input and the student model receives a masked version of the input, i.e., a version where some input is hidden. The student model then tries to predict the hidden state representation of the teacher model using a linear regression head.

In Data2Vec, the student and teacher models are identical transformer encoders and the teacher model weights are an Exponential Moving Average (EMA) of the student model weights. A general

<sup>1</sup><https://github.com/HolgerBovbjerg/data2vec-KWS>

overview of the Data2Vec framework is illustrated in Figure 3.

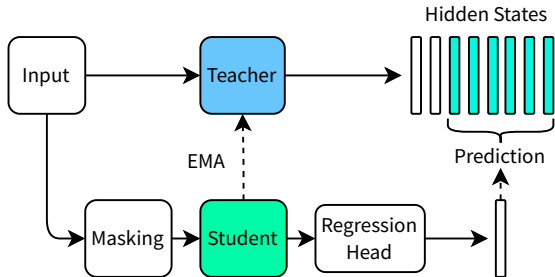


Figure 3: Illustration of the Data2Vec framework.

The teacher model weights are updated using an EMA of the student model weights such that

$$\Delta = \tau\Delta + (1 - \tau)\theta \quad (1)$$

where  $\Delta$  is the teacher weights,  $\tau$  is an exponential decay constant, and  $\theta$  is the student weights.

As  $\tau$  controls how often the teacher model is updated, a linear schedule is used which increases  $\tau$  from an initial value  $\tau_0$  to a target value  $\tau_{\text{end}}$  over  $n_\tau$  updates. This is done to have the teacher update more frequently in the beginning where the model is random and less frequently when the model has learned a good representation of the data.

In the Data2Vec framework [17], standard transformer encoders are used, and the objective of the student is to predict the output representations from the top  $K$  transformer blocks of the teacher. (author?) [17] found that predicting the average of the normalized hidden state representations instead of having individual predictions for each layer performed equally well, while the former is more computationally efficient. As a result, the targets are formed as

$$y_t = \frac{1}{K} \sum_{l=L-K+1}^L \hat{\mathbf{h}}_t^l \quad (2)$$

where  $y_t$  is the target at time step  $t$ ,  $L$  is the total number of transformer blocks and  $\hat{\mathbf{h}}_t^l$  is the normalized hidden state representation from transformer block  $l$  at time step  $t$ .

Target normalization serves to prevent the model from model collapse, i.e., finding a trivial solution such as a constant representation [17, 20].

The learning objective in the Data2Vec framework is to minimize the difference between the student prediction  $f_t(x)$  and the target  $y_t$  given by (2). Following the Data2Vec study for audio data, we use an MSE loss as well.

## 2.3 Data Set

For evaluation of the KWS model, we use the openly available Google Speech Commands V2 data set [18], which has become the most-used benchmark data set for KWS systems and is also used in the KWT study [9]. The Speech Commands V2 data set consist of 105 829 labelled keyword sequences of clean audio with a duration of 1 s and a sampling rate of 16 kHz. It consists of a total of 35 different keywords. The full set of audio sequences in the Speech Commands V2 data set are originally split into a training, validation and test set of 80 %, 10 % and 10 %, respectively.

In order to simulate a label-deficient scenario where most of the data is unlabelled and only a small amount of labelled data is available, a label-deficient version of the Speech Commands V2 data set is created. This is done by randomly splitting the training set such that 80 % of the training set is set aside for unlabelled pretraining and the remaining 20 % is used as the labelled training set. The resulting splits and their number of examples are summarized in Table 1.

Table 1: Reduced label Google Speech Commands V2 splits.

Split	Examples
Pretrain	67 731
Train	16 932
Validation	10 583
Test	10 583

In addition to the Speech Commands pretraining set, we also carry out experiments using Librispeech 100-hour clean [11] training set for pretraining, in order to test the effect of using data that is not domain-specific for pretraining.

### 3 Experiments

In the KWT study [9], the number of attention heads in the transformer blocks,  $k$ , is varied from 1 to 3, and the encoder dimension,  $d$ , from 64 to 192, yielding three models of varying size. We follow the same choice and the experiments are thus carried out for three KWT model variations, which are summarized in Table 2. This is done to gain insight into how model size influences the performance with and without pretraining.

All experiments have been carried out on a virtual machine with 10 CPUs, 40 GB RAM and one NVIDIA T40 GPU with 16 GB Random Access Memory (RAM). With this setup, pretraining and fine-tuning for the KWT-3 model takes approximately 10 h and 1 h respectively.

#### 3.1 Baseline

In order to evaluate the benefit of Data2Vec pretraining, a baseline without pretraining has been established. For both baseline and fine-tuning, all three KWT variations are trained on the label-deficient Speech Command training set. In addition, we also establish a baseline on the full training data.

During training, we apply SpecAugment [21] following the same approach as the KWT study [9]. We train the KWT model for 140 epochs using a batch size of 512, and we use Cross Entropy as the learning objective. The weights are optimized using the AdamW optimizer [22] with a two-step learning schedule. Here, the learning rate is initially “warmed up” by linearly increasing it from  $\eta_0 = \eta_{\max}/(\text{batch size} \cdot n_{\text{epochs}})$  to  $\eta_{\max}$  over the first 10 epochs, with  $\eta_{\max} = 0.001$ , after which it follows a cosine annealing schedule [23] for the remaining 130 epochs. A weight decay of  $\lambda = 0.1$  is used, as well as label smoothing [24] with a smoothing weight of  $\epsilon = 0.1$ .

A simple classification accuracy metric is used as the KWS performance metric, for evaluation of the KWS system. While the accuracy metric can be deceiving for imbalanced data sets, the Speech Commands V2 data set is rather balanced in terms of different keywords, thus accuracy is a useful measure of system performance [1].

The baseline results on the test set for all three KWT variations are seen in Table 4. All three mod-

els achieve performance comparable to the training and validation set scores, indicating that the models all generalize well to new data. As expected, due to the limited amount of labelled training data (20%), all models perform significantly worse than on the full training set. Interestingly, the KWT-1 model achieves the best performance when trained on the full training set, while the larger KWT-2 and KWT-3 models perform better on the label-deficient training set.

#### 3.2 Pretraining

During pretraining, the classification head in Figure 2 is replaced by a linear regression head, which predicts the hidden state representations of the teacher model. Following the choice of (author?) [17], a time-domain masking strategy identical to the one used in Wav2Vec [6] is used. Specifically, MFCC vectors are sampled with a probability  $p_{\text{mask}}$ , and the following  $N_{\text{mask}}$  MFCC vectors are replaced by a MASK token embedding. During pretraining, the inputs are first converted to MFCC embeddings and a mask is generated for each embedding. The student model then encodes the masked embeddings, and the teacher model encodes the unmasked embeddings.

Most of the hyperparameters for pretraining are chosen according to the settings used for speech in the original Data2Vec study [17], with some slight alterations due to differences in data set and hardware setup. A summary can be seen in Table 3.

After Data2Vec pretraining, the regression head is replaced with the original classification head in order to fine-tune the model for KWS. Fine-tuning is done following the same procedure as used for the baseline.

The test set accuracy for the fine-tuned models are seen in Table 4 along with the baseline scores. All three models achieve significantly better performance when using Data2Vec pretraining than without, when trained on the label-deficient training set. Additionally, the KWT-2 and KWT-3 models also outperform the baseline on the full training set. The models pretrained using Speech Commands data show absolute improvements in accuracy over the baseline between 6.72% to 11.31%, with the KWT-3 model having the best accuracy, achieving a score of 95.29%. The two smaller models, KWT-1 and KWT-2, also achieve similar performance,

Table 2: KWT model variations.

Model Name	Transformer MLP Dim.	Encoder Dim.	Attn. Heads	Parameters
KWT-1	256	64	1	$607 \times 10^3$
KWT-2	512	128	2	$2394 \times 10^3$
KWT-3	768	192	3	$5361 \times 10^3$

Table 3: Summary of settings used for Data2Vec pretraining.

$\tau_0$	$\tau_{\text{end}}$	$n_\tau$	$p_{\text{mask}}$
0.999	0.9999	1000	0.65
$N_{\text{mask}}$	$K$	Weight decay	Loss
10	8	0.1	MSE
Epochs	Batch Size	Optimizer	Scheduler
200	512	Adam	1-cycle

with an accuracy of 92.94 % and 95.07 %. The models pretrained using Librispeech data achieve similar performance as models pretrained using Speech Commands data, with the KWT-1 model showing an improvement in accuracy of 1.42 %, whereas the KWT-2 and KWT-3 models show a decrease in accuracy of 0.60 % and 0.71 % respectively. This suggests that the learned representations from pretraining are not specific to the data set, and that the representations learned during pretraining on one data set are transferable to a new data set.

Interestingly, the pretrained models perform similar to or even outperform the models trained on the full training set, while only using 20 percent of the training set for labelled training. Generally, the results show that for all three model sizes, pretraining using Data2Vec can significantly improve the label-deficient KWS performance. Additionally, models pretrained on Librispeech data perform similarly to the models pretrained on Speech Commands, showing that pretraining does not need to be done using domain specific data. This indicates that self-supervised pretraining is also beneficial for small KWS models in label-deficient scenarios.

Table 4: Summary of results for the three KWT models. Full indicates model trained on the full training set without pretraining. SC denotes Data2Vec pretraining using Speech Commands pretraining set, and LS denotes pretraining using Librispeech 100-hour clean training set.

Model	Test accuracy			
	Baseline	Full	Data2Vec	
			SC	LS
KWT-1	0.8622	<b>0.9638</b>	0.9294	0.9436
KWT-2	0.8575	0.9498	<b>0.9507</b>	0.9447
KWT-3	0.8398	0.9079	<b>0.9529</b>	0.9458

## 4 Conclusion

In this paper, we investigated the use of the self-supervised learning methods, Data2Vec, in order to improve the performance of KWS models in label-deficient scenarios. We implemented a self-supervised keyword spotting system using three variations of the KWT model which were pretrained using Data2Vec, and the system was tested on a label-deficient setup of the Google Speech Commands data set. The results show that pretraining using Data2Vec significantly improved the KWS performance for all three implemented models, with absolute improvements in test set accuracy between 6.72 % to 11.31 %. Moreover, when trained using only 20 % of the total training data, the pretrained models achieved performance comparable to models trained on the full training set, regardless of whether the models were pretrained on domain-specific data. These significant improvements in accuracy suggest that self-supervised pretraining can greatly improve the performance of KWS models. Further investigation into the application of various self-supervised learning methods for KWS thus serves as an interesting direction of future research.

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