

TensorFlow Speech Recognition Challenge

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Abstract: We are witnessing the significant development of the blooming relationship between science and technology. Humanity is striving on making everyday life easier and more controllable by the integration of the intelligent machines. We want to control those machine easier, such as by spoken commands. This is where this project comes in and answers that question.

Keywords: tensorflow, speech recognition, audio recognition, feature extraction, MFCC.

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I. INTRODUCTION

...for which our code can be found at our GitHub repository¹.

II. DATA

This project was given by Kaggle as Tensorflow challenge, where the task is to correctly classify the audio recording. Dataset was given by Tensorflow as one second audio clips of different words spoken by different people. Dataset can automatically be downloaded when starting the train part of machine learning solution to the problem. The goal is to have a model that tries to classify a one second audio clip as either silence, an unknown word, "yes", "no", "up", "down", "left", "right", "on", "off", "stop" and "go", even though more words can be found in the dataset and included in the training process. Each of the words is separated into files named as the recordings of the word they present. In order to make these clips as realistic as they would be in real life, the background noise is added in preprocess part of the code. There is a file of few background noises within the dataset that is downloaded. Each audio file is encoded with the id of the person who recorded the word, followed by nohash and a number from 0, specifying the time the same person recorded the word. Apart from the audio files that take up the majority of the data file, testing and validation lists can be found too. Each of those text file contains a list of the audio clips so that dataset can be partitioned in training, validation and test set.

i. Preprocessing

In order to feed our neural network with the data, we first need to process it. Neural network is fed by the image, so we need to transform the audio file to a spectrogram. Spectrogram is a visual representation of the spectrum of frequencies of sound or other signal as they vary in time. Spectrograms can be generated by an optical spectrometer, a bank of

band-pass filters or by Fourier transform. First, let us observe what the data looks like after reading the audio file.

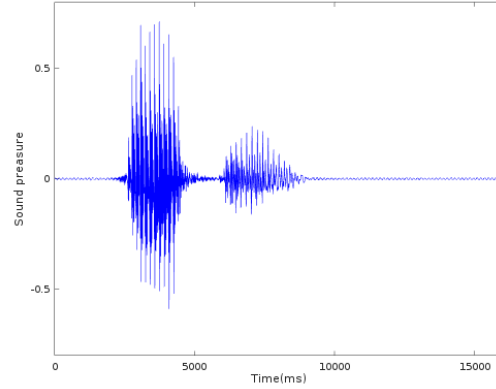


Figure 1: Waveform for audio 'happy'

Creating a spectrogram using FFT is a digital process. Digitally sampled data (which ours is), in time domain, is broken up into chunks, which usually overlap, and Fourier transformed to calculate the magnitude of the frequency spectrum for each chunk. Each chunk then corresponds to a vertical line in the image; a measurement of magnitude versus frequency for a specific moment in time (the midpoint of the chunk). These spectrums or time plots are then laid side by side to form the image or a three-dimensional surface, or slightly overlapped in various ways, i.e. windowing. This process essentially corresponds to computing the squared magnitude of the short-time Fourier transform (STFT) of the signal $x(t)$ - that is, for a window ω ,

$$\text{spectrogram}(t, \omega) = |\text{STFT}(t, \omega)|^2,$$

where

$$\begin{aligned} \text{STFT}\{x[n]\}(m, \omega) &\equiv X(m, \omega) \\ &= \sum_{n=-\infty}^{\infty} x[n] \omega[n - m] e^{-j\omega n}. \end{aligned}$$

The STFT is performed on a computer so it uses the FFT (Fast Fourier Transform), so all the variables are discrete and quantized.

After running our code in Octave to generate

¹<https://github.com/Qkvad/SpeechRecognition>

spectrogram yield the figure ??

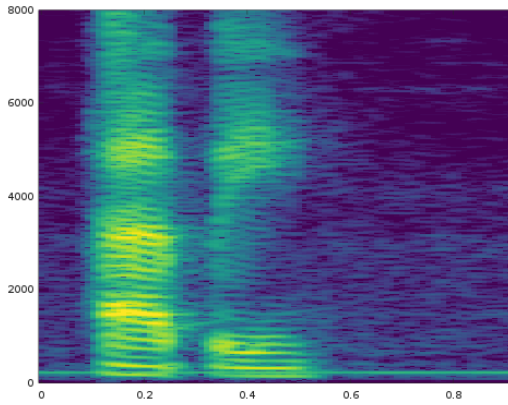


Figure 2: Spectrogram for audio 'happy'

III. MACHINE LEARNING

In order to classify processed audio data into known classes ("up", "down", ...), we use a neural network model, specifically - a convolutional neural network (CNN). It is important to notice that audio samples corresponding to the same word need not to "look" the same. For example, one speaker may have begun speaking later than the other. CNNs have had the most success in dealing with classifying such data and we say that CNN model is thus *spatially invariant*.

Specifically, as is reported in [?], CNNs outperform Deep Neural Networks which outperform Hidden Markov Model system, which is a commonly used technique for keyword spotting.

To put it simply and stress this fact's importance, we can write

$$CNN > DNN > HMM$$

where $> = \{(x, y) : x, y \text{ are classifiers}\}$ and $(x, y) \in >$ if and only if x performs better than y on a given dataset.

i. Convolutional Neural Network

We use a convolutional neural network model described in [?], with two layers of convolution.

The task of convolution layers is to extract features in a spatially invariant manner and it is their output that finally goes into fully connected hidden layers such as in ordinary neural network.

ii. Training

To be honest, training a convolutional neural network with our dataset of over 100000 audio samples was not a walk in the park. On a fairly strong laptop, it took us about 19 hours for 15000 training steps with learning rate of 0.001 and 3000 training steps with learning rate 0.0001 for finner descent.

Some of the important parameters for training the model are: `wanted_words`, `batch_size`, `learning_rate`, `how_many_training_steps`, `clip_duration_ms`, `data_dir`, ...

Most important parameters that control the preprocessing are: `background_volume`, `silence_percentage`, `unknown_percentage`, `time_shift_ms`, `window_size_ms`, `window_stride_ms`, `dct_coefficient_count`, ...

Let us observe the confusion matrices and accuracy of our model after 4000 steps and at the end of training. Classes are listed in order: silence, unknown, yes, no, up, down, left, right, on, off, stop, go.

[363	2	1	0	4	0	0	1	0	0	0	0]
[6	185	14	14	14	12	31	35	25	8	15	12]
[5	8	350	8	2	1	21	1	0	0	0	1]
[1	9	15	274	18	24	14	0	3	1	9	38]
[4	2	1	0	308	0	14	1	2	1	15	2]
[5	9	5	23	5	297	7	0	4	3	11	8]
[4	5	32	0	7	0	284	12	1	5	2	0]
[3	6	0	0	8	0	18	326	1	1	0	0]
[6	14	0	0	27	2	0	6	289	17	2	0]
[6	2	0	0	68	0	9	6	8	267	6	1]
[5	8	0	2	69	6	4	0	0	6	249	1]
[2	14	2	62	13	51	3	3	4	2	6	210]

Figure 3: Confusion matrix after 4000 train steps

[365	2	0	0	1	0	0	2	0	0	1	0]
[6	267	6	3	8	11	19	16	11	0	11	13]
[1	3	377	4	0	1	8	2	0	0	0	1]
[3	8	4	341	4	7	10	1	2	2	4	20]
[3	2	0	0	327	0	3	0	1	3	9	2]
[4	2	5	20	0	333	3	0	0	1	3	6]
[2	3	15	3	3	0	318	6	0	0	1	1]
[2	4	1	0	1	0	8	345	1	0	0	1]
[5	12	0	1	9	1	1	0	328	6	0	0]
[4	3	0	0	37	0	3	2	6	310	7	1]
[4	4	0	0	16	0	2	0	0	1	323	0]
[3	17	0	29	3	16	1	1	2	1	2	297]

Figure 4: Confusion matrix after 18000 train steps

We obtained total accuracy of 88,4%. As expected, the two classes hardest to distinguish are "no" and "go".

iii. Application

Now, to see this trained model in action, we give it some easy and also some hard audio files to classify to demonstrate it's power.

First, the easy part, let's predict a word "yes" without much background noise. It's read audio file and corresponding MFCC that our model obtains are given in figure ??

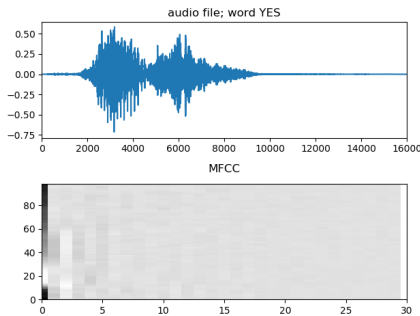


Figure 5: Audio recording of a word "yes"

The model prediction is as follows:

- yes (score = 0.99882)
- _unknown_ (score = 0.00062)
- left (score = 0.00052)

Now we feed our model with extremely noised and shifted audio data for "yes".

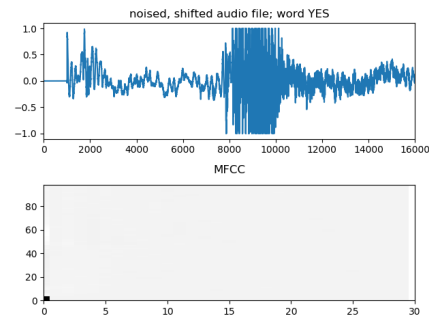


Figure 6: Extreme audio recording of a word "yes"

Although this is extremely distorted and noised, it seems that our model is pretty confident predicting the following:

- yes (score = 0.85262)
- left (score = 0.07611)
- _unknown_ (score = 0.02981)

IV. DIFFERENT APPROACHES

REFERENCES

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