Speech Command Project

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MA18BTECH11004

EE5600- Speech Command Model

Aim

Speech Command Recoginition Model.

Table of Contents

Table of Contents

Generating Data and Storing Data

In this Part we generate data.I used audacity to generate many samples and preprocess the data so that I get each audio sample length to 2 seconds.

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- To do so, We set Sampling Rate to 16kHz.
- Generated 80 Samples of each command and saved them in respective folder.
- I used soundfile package to read .wav files.
- Now, we Store sound-data in data_x array and corresponding command in data_y array.

Table of Contents

Splitting the data

We need to divide data into train and test samples.So that we train the model with train data and test the accuracy with test data so that we can check performance of our model.

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- To do so,we did Stratified Sampling.
- Stratified Sampling is performed instead of random Sampling because Stratified Sample can provide greater precision (or less biased data that is to get equal proportions of each command) than random sample of same size.

Table of Contents

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- I took steps of 1000 to create 18 files per sample.

Table of Contents

Extracting Features

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- We will divide our data into segments of 1024 length and then we perform various operations and we end up with 39 mel-coefficients.
- So our data is ready for modelling!

Table of Contents

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- Then applied fully connected layer with Softmax Activation, (Since we need to classify our data into 5 classes(multinomial)) Since we need to find the command.

Table of Contents

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- Adam Optimizer is combination of RMSprop and Stochastic gradient descent with momentum.It Uses both advantages of both methods.
- At the end of Training we will end up with Optimal Coefficients/solution.

Table of Contents

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- we can observe that it is decreasing.

Table of Contents

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- Then we plotted log of Attention Scores and corresponding input vector before taking MFCC on other axes.
- We can see that attention are high at high informative parts.

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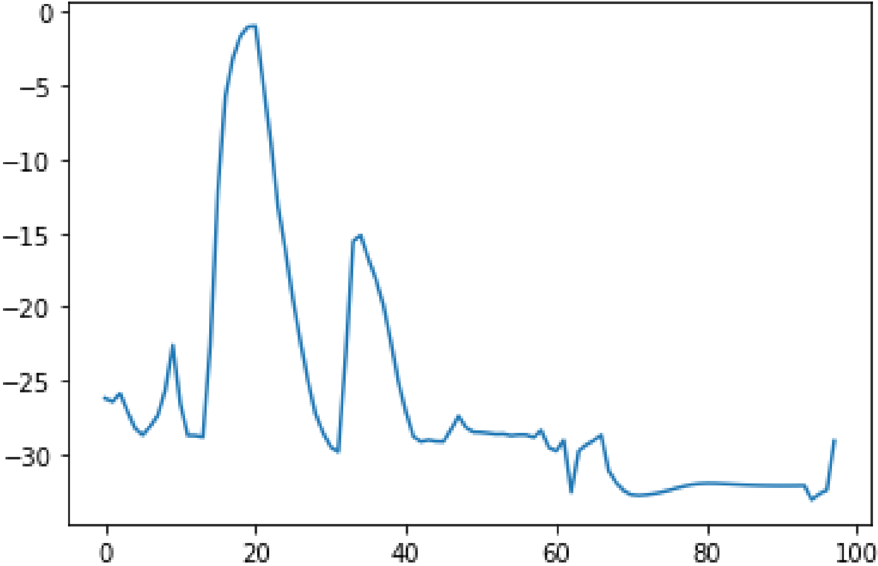

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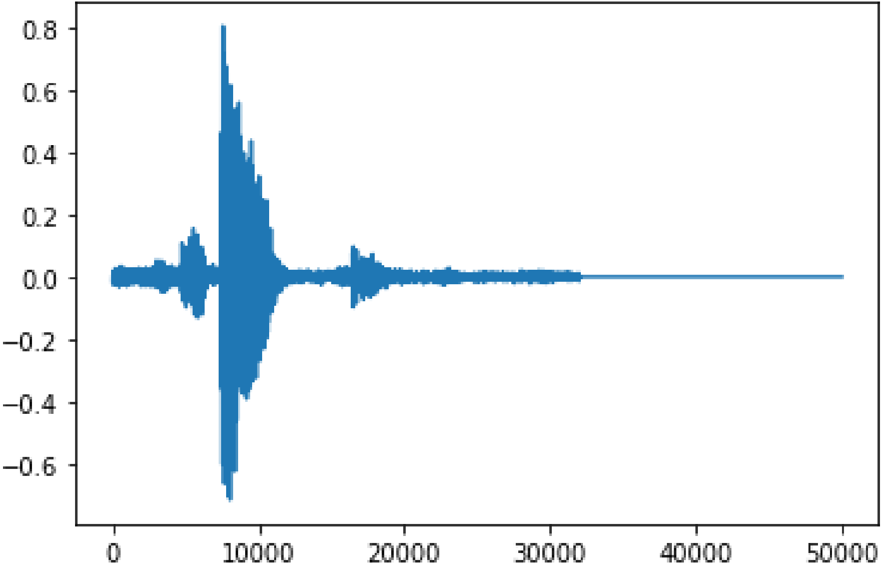

END

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