Voice Recognition through Machine Learing

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Abstract—This manual shows how to develop a voice recognition algorithm and use it to control a toycar.

1 Dataset

- 1.1 Record 'forward' 80 times in your laptop and save as 'forwardi.wav' for i = 1, ..., 80.
- 1.2 Repeat by recording 'left', 'right', 'back' and 'stop'. Make sure that the audio files for each command are in separate directories. Download the following directory for reference

https://github.com/gadepall/EE1390/trunk/AI-ML/audio dataset

1.3 Use the following script to generate a dataset for 'back' command. Explain through a block diagram.

https://raw.githubusercontent.com/gadepall/ EE1390/master/AI-ML/codes/250files.py

Solution: to generate the dataset needed for training. The following diagram explains how this is done for the back command. back (80 files) $\xrightarrow{25 \text{ files.py}} 2000 \text{ files}$.

1.4 After creating 2000 back files rename all 3.1.1 Consider \mathbf{x} be 4043×1 to be human voice the files in the format 'backi.way' for i = $1, \ldots, 2000$. Use the given link for renaming.

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https://raw.githubusercontent.com/gadepall/ EE1390/master/AI-ML/codes/250files.pv

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- 1.5 Suitably modify the above script to generate similar datasets for 'left', 'right', 'stop' and 'forward'. So now we have 10000 audio files in total.
- 1.6 Store the complete dataset in a directory and run code.py from within the directory. Note that this should be done on a powerful workstation.

https://raw.githubusercontent.com/gadepall/ EE1390/master/AI-ML/codes/code.py

1.7 This will generate two files **W1.out** and **b.out**. Save the files in same directory.

2 Implementation

2.1 Execute **record.py** and issue any of the commands 'forward', 'left', 'right', 'back' and 'stop'. The output will be as per the following table.

back	0
forward	1
left	2
right	3
stop	4

- 2.2 Now Save the files 'W1.out' and 'b.out' in raspberry pi.
- 2.3 Implementation on raspberry pi.(yet to be done

3 Building the neural network

- 3.1 Problem Statement
- issuing either 'forward', 'left', 'right', 'back' and 'stop'. Let W be 4043×5 and b be 1×5 . W and b are the machine parameters. Then the machine makes a decision based on

$$\mathbf{v1} = \mathbf{x}^T \mathbf{W} + \mathbf{b} \tag{3.1}$$

3.1.2 Now, apply the sigmoid function to all the elements of the output matrix (y1) to scale the values between 0 and 1.

$$\hat{\mathbf{y}} = 1 \div (1 + exp(-\mathbf{y1})) \tag{3.2}$$

3.1.3 The problem is to estimate **W** and **b**. This is done by considering the error(cost) function,

$$J(\mathbf{W}, \mathbf{b}) = \frac{1}{2} ||\mathbf{y} - \hat{\mathbf{y}}||^2$$
 (3.3)

- 3.1.4 We need to find the minimum of error function for optimising the equations.
- 3.2 Solution: Gradient Descent
- 3.2.1 W and b can be estimated from (3.3) using

$$\mathbf{W}(n+1) = \mathbf{W}(n) - \frac{\alpha}{2} \frac{\partial J(\mathbf{W}, \mathbf{b})}{\partial \mathbf{W}} \mathbf{W}(n) \quad (3.4)$$
$$\mathbf{b}(n+1) = \mathbf{b}(n) - \frac{\alpha}{2} \frac{\partial J(\mathbf{W}, \mathbf{b})}{\partial \mathbf{b}} \quad (3.5)$$

Show that (3.4) can be expressed as

$$\mathbf{W}(n+1) = \mathbf{W}(n) - \alpha \left[\mathbf{x}^{T}(n)\mathbf{x}(n)\mathbf{W}(n) + \mathbf{x}^{T}(n)\mathbf{b}(n) - \mathbf{x}^{T}(n)\mathbf{y}(n) \right]$$
(3.6)
$$\mathbf{b}(n+1) = \mathbf{b}(n) - \alpha \left[\mathbf{x}\mathbf{W} - \mathbf{b} - \mathbf{y} \right]$$
(3.7)

Solution: From (3.3) and (3.2),

$$J(\mathbf{W}, \mathbf{b}) = \frac{1}{2} ||\mathbf{y} - \hat{\mathbf{y}}||^{2}$$

$$= (\mathbf{x}\mathbf{W} + \mathbf{b} - \mathbf{y})^{T} (\mathbf{x}\mathbf{W} + \mathbf{b} - \mathbf{y}) \quad (3.9)$$

$$= (\mathbf{W}^{T}\mathbf{x}^{T} + \mathbf{b}^{T} - \mathbf{y}^{T}) (\mathbf{x}\mathbf{W} + \mathbf{b} - \mathbf{y}) \quad (3.10)$$

$$= \mathbf{W}^{T}\mathbf{x}^{T}\mathbf{x}\mathbf{W} + \mathbf{W}^{T}\mathbf{x}^{T}\mathbf{b} - \mathbf{W}^{T}\mathbf{x}^{T}\mathbf{y} \quad (3.11)$$

$$+ \mathbf{b}^{T}\mathbf{x}\mathbf{W} + \mathbf{b}^{T}\mathbf{b} - \mathbf{b}^{T}\mathbf{y} - \mathbf{y}^{T}\mathbf{x}\mathbf{W} \quad (3.12)$$

$$- \mathbf{y}^{T}\mathbf{b} + \mathbf{y}^{T}\mathbf{y} \quad (3.13)$$

Using

$$\frac{\partial}{\partial \mathbf{W}} \mathbf{W}^T \mathbf{x}^T \mathbf{x} \mathbf{W} = \tag{3.14}$$

- 3.3 Dataset
- 3.3.1 Record as many audio files of each of the words given below.
 - 1)Forward
 - 2)Left

- 3)Right
- 4)Back
- 5)Stop
- 3.3.2 Recreate these by adding empty elements in the front and back in many different cobinations to create a dataset.
- 3.4 Training
- 3.4.1 Import these soundfiles to an array in a python program using *soundfile* library and convert to mfcc format using *pythonspeechfeatures* library.
- 3.4.2 Extend the program to train the data, taking help from *1.6*. Also add a function to test the accuracy.
- (3.4) 3.4.3 Note the accuracy.
 - 3.4.4 Add to the program, some code to store the generated weights(W1) and biases(b).