

# DIGITAL SPEECH RECOGNITION HOMEWORK 1

## Discrete Hidden Markov Model Implementation

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### Environment

Macbook Pro 2013

CPU - Intel Core i5 2.4 GHz

RAM - 4GB DDR3 MHz 1600

OS - OSX Yosemite 10.10.2

Compiler - Apple LLVM version 6.1.0 (clang-602.0.53) (based on LLVM 3.6.0svn)

### Implementation

Baum-Welch Algorithm and Viterbi Algorithm using C.

### Install and Run

```
make
./train $iter model_init.txt seq_model_num.txt
      model_num.txt
./test modellist.txt testing_data.txt result.txt
```

- \$iter is the number of training iterations
- model\_init.txt is the initial model file
- seq\_model\_num.txt is the training data for model #num
- model\_num.txt is the file to store trained model #num
- modellist.txt is the file containing filenames for all models to be tested
- testing\_data.txt is the testing data file
- result.txt prints the prediction and probability for the most probable model

Use the following code for cross-validation during training:

```
FILE *ground_truth_file = open_or_die("testing_answer.txt",
    "r");
testing_result_file = open_or_die(argv[3], "r");
double testing_accuracy = accuracy(testing_result_file,
    ground_truth_file);
printf("Testing complete, accuracy = %f", testing_accuracy);
```

## Experiments

#Iterations	Accuracy
10	0.5372
50	0.8244
100	0.7976
500	0.8528
1000	0.8616

### Additional Experiments

1. Batch size: 1000 ( for( $s = \text{epoch} \% 10$ ;  $s < \text{num\_samples}$ ;  $s += 10$  ) )  
Iterations: 50 Accuracy: 0.8192  
Performance: Training is significantly faster
2. Update after evaluating each sample, averaging into current parameter  
$$\pi_i / a_{ij} / b_j(k) = 0.9999 \pi_i / a_{ij} / b_j(k) + 0.0001 \pi_i' / a_{ij}' / b_j(k)'$$
  
Iterations: 50 Accuracy: 0.7948  
Performance: Training is fastest, but accuracy is lower.

## Problems to Discuss

1. Compare the performance of straightforward version and log version of viterbi algorithm.
2. Compare the performance of the EM version and convex optimization version of Baum-Welch.
3. Compare the computational complexity and prediction accuracy of HMMs and RNN's (i.e. with LSTM/GRU units).
4. The correct way to calculate  $P(O | \Lambda)$
5. Auto adjust of HMM parameters. (To avoid overfitting)
6. Will using small batch update or averaging update into current parameters for each sample still converge? (like mini-batch & stochastic gradient descent)

## References

1. L. Rabiner and B.H. Juang, Fundamentals of Speech Recognition.
2. D. Jurafsky and J. Martin. Speech and Language Processing.
3. C. Bishop, Pattern Recognition and Machine Learning.