CS224S Assignment 3

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1 Improving the monophone acoustic model

Initially, we tried various values for the five parameters to determine the optimal values for the male-only training set using *Mel-frequency cepstral coefficients (MFCCs)*, with no normalization or triphone features. In this section we describe our method for tuning the parameters, present the results, and include a discussion as to why certain parameter adjustments showed improved test results with respect to the baseline system.

1.1 Parameters

Number of iterations (`num_iters`) We tried 10, 20 and 30 iterations and found 20 iterations to show the lowest word and sentence error rate. 10 iterations was not sufficient for the Gaussian HMM model to converge, whereas after 30 iterations the improvement seen at 20 has plateaued and begun to worsen.

Silence boost factor (`boost_silence`) The default value for this parameter was 1, indicating no special treatment being given to the likelihoods of GMMs corresponding to the silence phones. By increasing this parameter, we are indicating it is more likely for a silence phone to occur, and a decrease in the parameter makes the model less likely to choose a silence phone. We tried values between 0.3 and 1.5, and found the best performance results by setting `boost_silence` to 0.5. This is equivalent to halving the weights for all models that correspond to the silence decreased.

The silence class is of very different nature than the other phone classes. When we train the phones well, we need not to reduce the silence likelihood. However, since we do not have much training data in this scenario and we know the training data does not fit the test data well—because we are only training on males and the test set is mixed gender (as is discussed later)—reducing the likelihood helps the system, as otherwise a lot of phones get mapped to the less distinct silence class. It essentially requires one to be *more than certain* that a segment corresponds to silence before actually choosing it.

Total number of Gaussians (`totgauss`) We experimented with Gaussian sizes between 100 and 612, finding that 256 performed the best. The total number of Gaussians is the largest possible number of Gaussians in the GMM which models each subphone. Too few Gaussians (e.g 100) underfits the data, while too large a value (e.g. 612) overfits. Comparing a system with the optimal parameters and one with all the optimal parameters except totgauss which is doubled, the training error decreases for both WER by 0.04 and 0.13 while the test error increases by 3.53 and 4.14: confirming that we are indeed overfitting.

Last iteration to increase number of Gaussians at (`max_iter_inc`) We found that allowing the number of Gaussians to be increased until the final iteration performed the best. In this training scenario we have limited data, so when the number of Gaussians are split they are a better representation of the data compared to fitting them perfectly to the training data and do not need more iterations to be re-fit.

Iterations to realign frames at (`realign_iters`) We found that regardless of the other parameter values, the system performs best when the forced alignment is performed at every iteration. This is not surprising as it repeatedly re-estimating the HMM parameters ensures the HMMs are fitting the training data as closely as possible. Whichever number of iterations we chose for the system, we did forced alignment at every iteration.

1.2 Final adjustments

Once we determined the best value for a parameter keeping the others fixed, we adjusted the other parameters while keeping the given one at its best value. By doing this we found the best performing setup to be 20 iterations, silence boosted by 0.5, a maximum of 256 Gaussians, Gaussians allowed to split until iteration 19 and realignment iterations $[1, 2, \ldots, 19]$ (after every iteration).

This gave us the error rates summarized in Table 1. On the test set, this model gave 554 insertions, 383 deletions, and 1688 substitutions.

	train	test
WER	0.67	9.18
SER	2.21	18.96

Table 1: Error rates for improved monophone acoustic model.

2 Improving feature extraction

The next step was to improve feature extraction by adding a normalization step after the extraction was done to filter out environmental noise. With the male-only training set this step lowers both the WER and the SER by approximately a quarter to 6.79% and 14.86%, respectively.

While the number of deletions did not change a lot, we saw a significant drop in the number of insertions and substitutions. This indicates that, on the one hand, background noise is less frequently mapped to a phone and, on the other hand, that the model is better at distinguishing between phones as without the noise it should be easier to map the features to a certain phone.

We also tried some other model parameter combinations but consistently got the best results with the parameters from Section 1.

By optimizing the model parameters and by including the noise filtering step, we were able to lower the error rate by almost 50% over our baseline. However, a seemingly low WER of 6.79% still implies that one has to repeat a 16 digit number sequence approximately 67.5% of the time which is clearly not practical. In the next section, we try to improve our system by using different and more training data.

3 Different training data

We first used our optimal parameters from Part 1 and trained new models using the following training sets: 1) 10 male speakers, 2) 10 female speakers, 3) 5 male and 5 female speakers, and 4) 55 male and 57 female speakers.

The results are presented in Table 2. First, we can see that training only on female speakers seems to work better than training only on male speakers. There are two possible explanations for that. Either the test set contains more female speakers than male speakers or the set of female speakers has more variability than the set of male speakers. In such a small random sample it is not unlikely that there is for example a greater variety of accents in the female sample.

Further, we can see that including both male and female speakers decreases the error rate by more than 70% compared to only using female speakers. This is not surprising as we have speakers of both gender in our test set, so the training data is more similar to the test data.

If we include a lot more training examples as it is the case in training set 4, we see another small gain over the small mixed-gender set. The larger training error is probably caused by the larger variety in the training set but the fact that the training error and the test error are almost the same indicates that the training data is well suited to train a model that works well on a large test set.

We also did some parameter tuning for test sets 2 through 4. The optimal parameters and the corresponding test WER and SER are presented in Table 3.

These results indicate a few trends. First, the more data we add and the more representative data we have, the more Gaussians we can use to estimate the model. Also, we got better results in case we set the last iteration at which the number of Gaussians is increased to a lower value for the more general data sets 3 and 4. This indicates that if the training data is more representative, then we want to fit the Gaussians for more iterations to the training data instead of generating more and more Gaussians that we only fit for fewer iterations. Lastly, in case we have better data to train the phones on, it seems to help to increase the `boost_silence` parameter.

By using a larger and more representative data set we were able to lower the WER to 0.83. At this error rate, a bank customer would have to repeat a 16-digit number on average in only 12% of the cases which makes the system a lot more practical.

4 Adding triphone features

The final enhancement to our model was to enable an additional training step: the generation of triphone features. Since triphone features provide context and capture changes in formant and signal nature across phones, they can provide useful cues towards phone identity. We thus expected them to provide improved performance.

We tuned two parameters in the triphone training step: the number of leaves in the triphone decision tree (`numleaves`) and the maximum number of final Gaussians (`totgauss`). In general, we found that a much

Dataset	train		test				
	WER	SER	WER	SER	Ins	Del	Sub
male	1.55	1.82	6.79	14.86	367	376	1198
female	0.76	2.11	5.35	12.34	204	420	905
mixed	0.55	1.82	1.51	4.57	116	200	115
full	1.04	3.11	1.47	4.23	138	128	154

Table 2: Error rates for all datasets.

Dataset	`num_iterations`	`boost_silence`	`totgauss`	`realign_iters`	`max_iter_inc`	WER	SER
male	20	0.5	256	1:1:19	19	6.79	14.86
female	20	0.5	512	1:1:19	19	5.2	11.72
mixed	20	0.75	256	1:1:19	19	1.7	4.95
full	20	1.5	2048	1:1:19	10	0.83	2.57

Table 3: Error rates with various parameters tuned.

larger number of final Gaussians was required for an improvement over the simple monophone model (values of `totgauss` smaller than the ones chosen previously obviously resulted in a worse WER).

We also observed a diminishing returns effect with perfecting the values of the triphone model parameters, in that the marginal improvement obtained with higher values of parameters was not significant.

Eventually, we found that the best choice for the parameters was:

- Maximum number of Gaussians (`totgauss`): 8000
- Number of leaves (`numleaves`): 100

With these parameters, we obtained a slight improvement in our system's performance, as summarized in Table 5.

	train	test
WER	0.17	0.54
SER	0.55	1.7

Table 5: Error rates for model with triphone features.

4.1 Benefits of using triphone features

To determine qualitatively where triphone features helped, we compared the output of the monophone-only model, the model including triphone features, and the gold set of decodings in the test set. We made a few interesting observations:

- With triphone features, the model was able to differentiate "1" and "9" better in a few cases. For example, the gold sequence "7 7 8 9 7 1 9" was mistakenly decoded as "7 7 8 9 7 1 1" by the monophone-only model, but was correctly decoded by the triphone-enhanced model. We surmise that the ability to capture formant changes across frames allowed the latter model to observe the forceful dental "release" at the beginning of "nine", even if the vowel pronunciation may have sounded similar to "one".

- The triphone-enhanced model was also able to distinguish sequences of similar, vowel-only phones better. For example, in a sequence involving two consecutive "oh" digits ("4 2 8 0 0 9"), the monophone-only model observed only one digit, while the triphone-enhanced model observed both. Again, this is probably due to the improved ability to capture the subtle formant change between two utterances of "oh".

- However, triphone features did not always improve recognizability. The triphone-enhanced model inserted an extraneous "8" in the sequence "3 5 4 4 z 6 z", making it "3 5 4 4 8 z 6 z", while the monophone-only model recognized the sequence correctly. It appears that the same ability to better identify forceful releases at the beginning of a phone that allowed the model to distinguish "one" and "nine" caused the model to be overly cautious and detect a transition from an "eight", which ends in a dental sound, to a "zero", which begins with a sibilant.

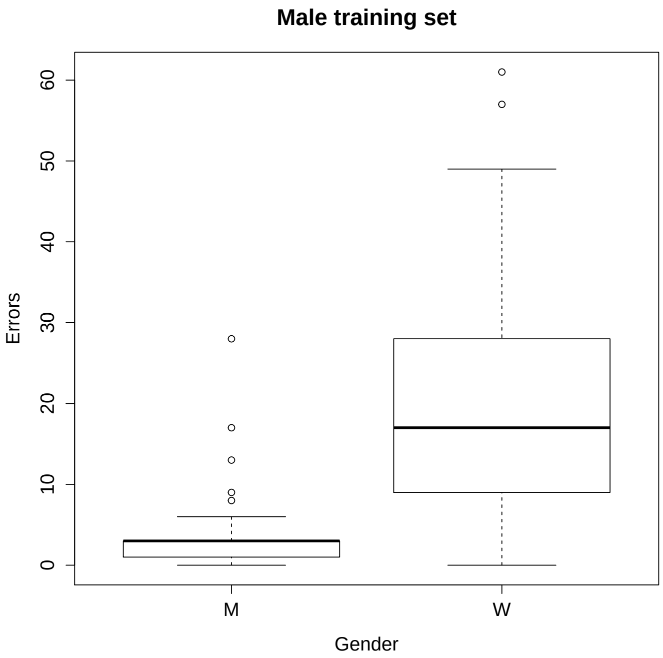
Dataset	not tuned		tuned	
	no norm.	norm.	no norm.	norm.
male	12.32/24.39	9.50/20.49	9.18/18.95	6.79/14.86
female	9.06/20.41	7.7/17.61	6.39/15.03	5.35/12.34
mixed	3.99/11.36	3.27/9.29	1.8/5.16	1.51/4.57
full	3.17/8.97	2.59/7.33	1.61/4.75	1.47/4.23

Table 4: Error rates for combinations of tuning, normalization and datasets (written as WER/SER).

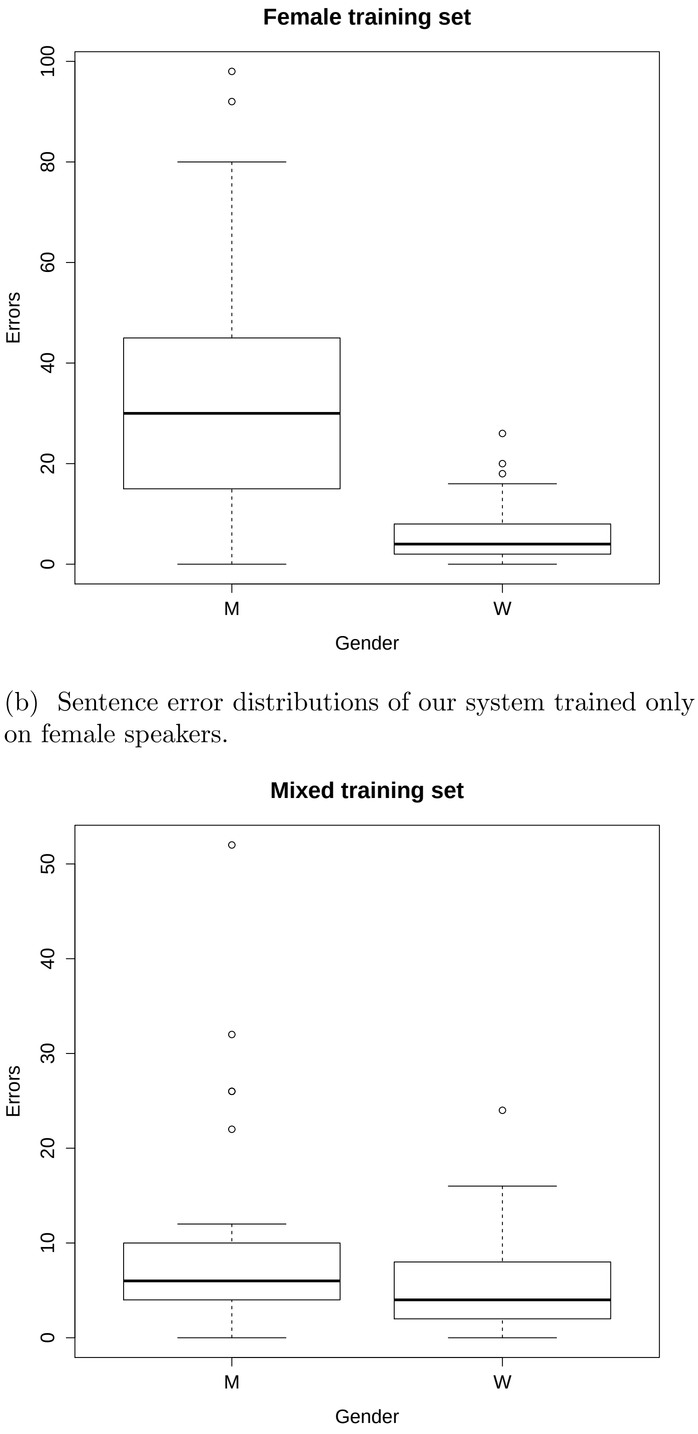
5 Extra Credit: Influence of Speaker Gender in the Training Set

In order to confirm our intuitions from Section 3 that a system trained only on male or only on female speakers makes more mistakes on the other gender, we took the output of our systems trained with training set 1, 2 and 3 and counted for each speaker the number of sentences which contained at least one error. Then we mapped the speaker IDs to their gender using the mapping information in the TIDIGITS corpus. Figure 1 shows the distributions of the sentence error count for each gender for the different training sets. These figures exactly match the intuitions we gave earlier: If we train only on male speakers, we make significantly more errors on female speech and vice versa. Further, if we train on female and male speakers, there is hardly a gender difference in terms of the sentence error distributions.

In Figure 1c, we can see that there are still some speakers with very high error counts. These cases can be easily explained if we look at the dialect of the speaker. All the speakers with very high error rates have very strong dialects, namely African-American Vernacular English, a Southern dialect or a Chicago dialect which is known to have the northern cities vowel shift.



(a) Sentence error distributions of our system trained only on male speakers.



(b) Sentence error distributions of our system trained only on female speakers.

(c) Sentence error distributions of our system trained on speakers of both genders.

Figure 1: Sentence error distributions for different datasets.