Natural Language Processing Homework 3

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README

1 Perplexity per Word

First, we get that the $\log_2$-probability of each of the sample files is as follows:

-12111.3 ../../speech/sample1
-7388.84 ../../speech/sample2
-7468.29 ../../speech/sample3
Word count for each sample file (found with wc -w)
sample1: 1686
sample2: 978
sample3: 985
Cross-Entropy for each sample:
sample1: 7.18345
sample2: 7.55505
sample3: 7.58202
Calculating the perplexity per word for each of the sample files:
$2^{-\frac{1}{N} * log_2 p(x)}$
sample1: $2^{\frac{-1}{1686} * (-12111.3)} = 2^{7.18345} = 145.3565$
sample2: $2^{\frac{-1}{978} * (-7388.84)} = 2^{7.55505} = 188.0602$
sample3: $2^{\frac{-1}{985} * (-7468.29)} = 2^{7.58202} = 191.6088$
log2 probabilities on the bigger switchboard corpus...
-12561.5 ../../speech/sample1
-7538.27 ../../speech/sample2
-7938.95 ../../speech/sample3

A larger corpus results in a more positive value of the log2 probability. This shows that the larger corpus results in a better fitting model as it has a higher probability of predicting the future. Furthermore, this results in the perplexities per word decreases. This is due to the larger training corpus gives more training data . The perplexity going down means that the model is less confused on the sample text, and is able to choose from a smaller number of possibilities for each word.

2 textcat.py

textcat.py included in submission.

3 Categorizing

3.1

Lowest error is 0.09259259..., or an accuracy of 0.90740740...

3.2

The value of 0.00035 was used for lambda.

3.3

An error rate of .13148... was observed when our value of lambda was used on the test data.

3.4 Graphs

Graphs are included in the submission. One graph shows a comparison between the length of the test file and its accuracy rate. The second graph shows a comparison between the size of the training corpus with its resulting accuracy rate.

3.5 Increasing training size

Graph is included.

4 Questions

V the size of the vocabulary including OOV

4.1

UNIFORM estimate $\hat{p}(z|xy) = 1/V$

ADDL estimate $\hat{p}(z|xy) = \frac{c(xyz)+\lambda}{c(xy)+\lambda V}$

If we mistakenly take V to equal 19,999, then the UNIFORM estimate would be larger than it is suppose to be, since V is the denominator. Having a lower-than-expected denominator would give more weight to smaller, more novel events.

For the ADDL estimate, having V equal 19,999 would result in a similar situation where the estimation would be larger than expected because V is in the denominator and give more weight to novel events. However, we would see less of an impact with ADDL estimation depending on what λ is.

For both, by having V equal a smaller number than it is supposed to be means that the sum of all probabilities would not equal 1.

4.2

Setting $\lambda = 0$ would give the naive historical estimate. This would mean that no smoothing is occurring at all.

Beyond that, if it happens that $c(xy) = 0$, (in other words, we didn't see xy in training) then we get that $\hat{p}(z|xy)$ has no value at all / is undefined.

4.3

If c(xyz) = c(xyz') = 0, then:

$\hat{p}(z|xy) = \frac{\lambda V \hat{p}(z|y)}{c(xy)+\lambda V}$

$\hat{p}(z'|xy) = \frac{\lambda V \hat{p}(z'|y)}{c(xy)+\lambda V}$

If c(xyz) = c(xyz') = 1, then:

$\hat{p}(z|xy) = \frac{1+\lambda V \hat{p}(z|y)}{c(xy)+\lambda V}$

$\hat{p}(z'|xy) = \frac{1+\lambda V \hat{p}(z'|y)}{c(xy)+\lambda V}$

4.4

BACKOFF ADDL estimate $\hat{p}(z|xy) = \frac{c(xyz)+\lambda V * \hat{p}(z|y)}{c(xy)+\lambda V}$

Increasing lambda will make it so that the trigram probabilities will be more like the corresponding bigram's probability because we're putting less weight on the trigram's count.

5 Other Smoothing

5.1 add-l smoothing

Implemented

5.2 ADDL vs BACKOFF_ADDL

With the same lambda value as in 3.c (0.00035), switching to BACKOFF_ADDL improved the performance. This resulted in an error rate of 0.09444, smaller than our error rate of 0.13148 from 3.c.

Basically running fileprob.py as in Q1, but using backoff_add0.01 as the smoothing method.

-9898.16 ../../speech/sample1 -6048.05 ../../speech/sample2 -6105.56 ../../speech/sample3

Cross Entropy:

sample1: 5.87079

sample2: 6.1841

sample3: 6.1985

Calculating the perplexity per word for each of the sample files:

sample1: $2^{\frac{-1}{1686}*(-9898.16)} = 2^{5.87079} = 58.5174$

sample2: $2^{\frac{-1}{978}*(-6048.05)} = 2^{6.1841} = 72.7109$

sample3: $2^{\frac{-1}{985}*(-6105.56)} = 2^{6.1985} = 73.4422$

6 The Long Question

6.1

See code

6.2

See code

6.3

Training from corpus en.1K

.
Vocabulary size is 30 types including OOV and EOS
Start optimizing.
finished one epoch: -2998.76590608
finished one epoch: -2923.93611832
finished one epoch: -2884.8817791
finished one epoch: -2861.08771739
finished one epoch: -2845.19134998
finished one epoch: -2833.85038073
finished one epoch: -2825.36942636
finished one epoch: -2818.80193777
finished one epoch: -2813.57736719
finished one epoch: -2809.33075972
Finished training on 992 tokens

6.4

Command: python textcat.py loglinear1 lexicons/chars-10.txt speech/train/switchboard All_Training/en.1K All_Training/sp.1K

Results:
Command:
Results:
When loglinear5,
When loglinear.05,
Of course, with more training (a larger lexicon), the accuracy would improve.

7 a-priori

When adding the prior probability that P(spam) = 1/3, this obviously means that P(gen) = 2/3. Text categorizing is looking at the probability of the

model (whether an email is *gen* or *spam*) given the data (a test email text file), and looking for the data that has the greatest resulting probability.

Using Bayes Theorem, this means that determining the maximum probability out of all of the models given the data =

$\frac{P(data|model)*P(model)}{P(data)}$

= P(data — model) * P(model)

Since P(data) doesn't help us to find the maximum probability. Rather, we use the a-priori that was given to us.

The number is used only at test time, where it's used to help predict the test file.

8 Speech Recognition

8.1

We are trying to maximize the probability of the utterance U given the intentional statement someone was trying to say $\overrightarrow{w}$. In other words, we want to maximize:

$P(U|\overrightarrow{w})$

$= \frac{P(\overrightarrow{w}|U)P(U)}{P(\overrightarrow{w})}$, by Bayes'.

We can get $P(\overrightarrow{w}|U)P(U)$ from the sample file, where the second column provides the value of $\log_2(P(U|\overrightarrow{w}) = P(\overrightarrow{w}|U)P(U)$.

We can get P(U) from the trigram model.

8.2

speechrec.py is included in the submission.

8.3 Error Rates

Chosen smoothing method, and why: We tested all of the smoothings (just on one n-gram model) and selected the one that gave us the best error rates. This experiment is described in Table 1. We used the words-10 lexicon.

Table 2 shows the overall error rate on easy and unrestricted for each of the three N-gram models. We are using the smoothing $backoff\_add0.1$.

Used overleaf.com to generate LaTeX document.

Smoothing	errorRate [Easy]	errorRate [unrestricted]
Uniform	0.202	0.360
add10	0.187	0.362
add1	0.183	0.355
add0.1	0.166	0.360
add0.01	0.160	0.353
backoff_add10	0.184	0.358
backoff_add1	0.168	0.356
backoff_add0.1	0.156	0.363
backoff_add0.01	0.157	0.356

Table 1: Error Results from speechrec.py, used to decide which smoothing method to pick.

N-Gram	Overall errorRate [Easy]	Overall errorRate [unrestricted]
1-Gram	0.203	0.390
2-Gram	0.163	0.373
3-Gram	0.150	0.362

Table 2: Overall error results for speechrec.py