

Hw2: Language Modeling across Domains with Various Smoothing Methods

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Abstract

Language modeling has been prominent in natural language processing (NLP) for decades and takes its roots in probabilistic modeling. However, modeling long-range dependencies with n-gram models explicitly is intractable since larger contexts become less and less likely to be observed in data. In turn, n-grams rely on Markovian assumptions; conditioning on the previous n-words in a context is considered a sufficient statistic of future likelihood. This homework explores language modeling across three corpora from different timeframes and domains. Several methods of probability smoothing are applied to these models to improve generalization, including Laplacian, add-k, and stupid backoff (Brants et al., 2007) smoothing.

Our findings indicate that across all corpora, stupid backoff smoothing was most effective at ensuring generalization for n-grams. Moreover, bigram models were best suited for generalizing across all corpora, though for more homogenous corpora (reuters, gutenber) benefitted from additional context via higher order n-grams (namely, trigrams).

We also applied our tuned n-gram models for each corpus across domains. Using the same set of basic prefixes, we compared generated sentences between these models as well as perplexity scoring. Our high level observations include that the brown and gutenber corpora were most similar lexically, and that the brown corpus appeared to be most diverse. In general, natural sounding sentences scored lower perplexities on n-gram models with $n > 1$, but with poetic or syntactically jumbled sentences, unigram models scored lower values. Due to the length of some generated sentences, extra information is stored in the Appendix 5.

1 Related Work: Language Model Implementations

Language modeling addresses the challenge of generating predictions from sparse data. Language in any dialect is diverse, ambiguous, and generally full of syntax flexibility. As a result, effective

methods tend to make use of intelligent forms of probability smoothing (Chen and Goodman, 1999). Without probabilistic smoothing, n-gram models will see certain vocabulary combinations as impossible (Jelinek, 1980) and be infinitely surprised when a combination of tokens not witnessed during training is observed at test time.

In addition, language model capacity is heavily influenced by their n-gram cardinality. Trigram models tend to incorporate higher capacity than bigram models, and so on. Our hyperparameter tuning also focuses on identifying the optimal n-gram cardinality for generalization as well as the correct regularization to assist in the prevention of overfitting.

2 Experimental Setup

Our language model was implemented from scratch and is defined by the following characteristics.

1. Our package can accommodate an arbitrary context (n) and produces padding when necessary for modeling short phrases with the token immediately preceding sentence start represented as SOS and, as necessary, padding tokens placed before it.
2. Our package can implement arbitrary add-k smoothing (including Laplacian) as well as stupid backoff smoothing.
3. No centralization of tokens with low counts into Unk tokens is undertaken. We made this design choice in an effort to reasonably model rare tokens without excluding them entirely.

With this language model package, we implemented three rounds of hyperparameters tuning. First, we explore the performance of different add-k smoothing methods on the bigram model. Using the results of this ablation, we examine the impact

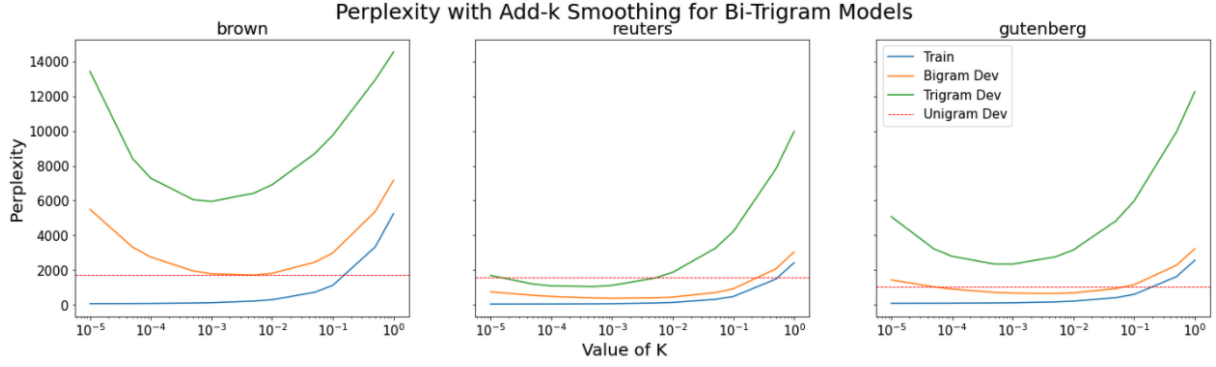


Figure 1: Train and dev-set perplexity for bi- and tri-gram language models with vary k in add- k smoothing. A $k=1$ represents Laplacian smoothing while dropping k represents weakening the Dirichlet prior based on the data. Referenced is dev-set perplexity for unigram models.

higher-order n -grams on our performance. Thirdly, we restarted this two-step process with stupid backoff smoothing, tuning the n -gram cardinality as well as the backoff parameter λ . Other, more sophisticated methods of smoothing including Katz (Katz, 1987) and Kneser-Ney (Kneser and Ney, 1995) were not attempted due to time constraints.

3 Hyperparameter Tuning

Perhaps the most simple smoothing mechanism for n -gram language models is Laplacian smoothing (MacKay and Peto, 1995). In general, conditional token probabilities given context are derived from frequentist estimates (counts) of instances seen during training. If a token is not seen with a given context at this time, its probability of occurring at test time is set to zero. This is an unreasonable assumption solved by smoothing in general. Laplacian smoothing addresses this by adjusting all count-derived probabilities to the following:

$$p_{\text{laplace}}(w_i) = \frac{C(w_i, w_{i-1}, \dots, w_{i-n+1}) + k}{C(w_{i-1}, \dots, w_{i-n+1}) + kV} \quad (1)$$

where k for Laplacian smoothing is equal to 1 and V refers to the size of the vocabulary. Another way of thinking of Laplacian smoothing is by converting what was originally a maximum likelihood estimate into a maximum a-posteriori by adding a Dirichlet prior to the data, defined in this project as a categorical distribution. In this context, k represents the strength of the prior. With this change, the behavior for modeling a completely unknown token by assigning it a very low but positive probability is the same.

Initial experiments with a Laplacian prior yielded poor results, defined in terms of develop-

ment (dev) set perplexity. We determined this issue to be the result of a prior that was too strong and overpowered the witnessed data, even for a bigram model. Figure 1 explores the impact of scaling down the strength of our prior, determining that optimal $k = 0.01$ for all datasets. For all data, the transition from underfitting to overfitting as k is decreased is clearly seen.

In addition, Figure 1 includes the same ablation conducted on a trigram model. It appears that the additional capacity of the trigram led it to overfit more easily, resulting in poor generalization relative to the bigram model. Interestingly, the optimal add- k smoothing for bigrams only improved the *brown* slightly from its unigram baseline, while the other corpora improves substantially. We believe this is due to the diversity of content in the corpus (poetry, sports, plays, etc.).

Curious on if the tendency for higher-order n -grams to overfit could be resolved with a different method of smoothing, we applied an implementation of stupid backoff. Stupid (naive) backoff (name defined by authors) (Brants et al., 2007) operated by querying an n -gram corpus for a given context-word pair. If no occurrence exist, then the algorithm conducts the same query, but this time on a lower-order n -gram corpus. This iteration continues until a match for the word is found (even if it is a unigram). A heuristic penalty of $\lambda = 0.4$ is applied as a multiplier after each backoff iteration to improve generalization and keep the resulting probabilities relatively valid. If the word is never found, a very low default probability is returned in the same manner as it is for add- k smoothing.

3.1 In-Domain Text Analysis: Empirical

Empirically, we found stupid backoff to work exceedingly well relative to the current best add- k

performance. For every corpus, dev set perplexity dropped substantially. However, the `brown` corpus again was quick to overfit when higher-order n-gram models were applied to it. Trigram models

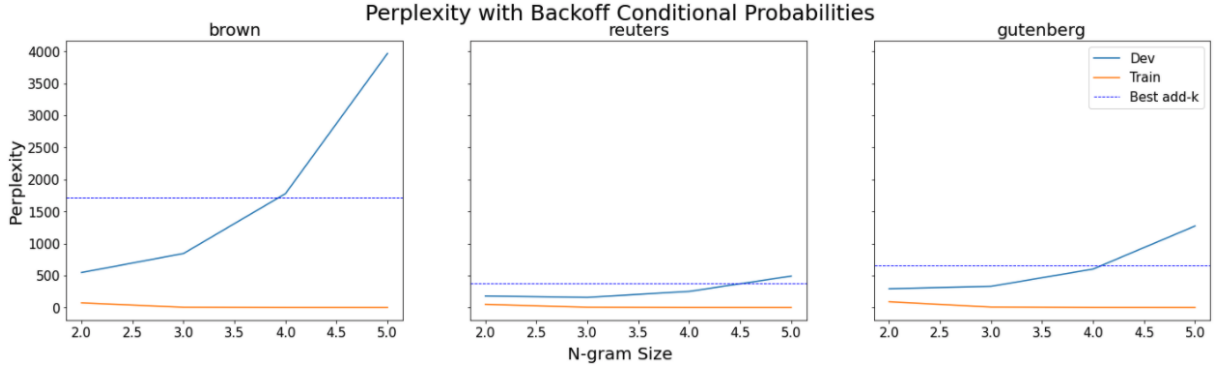


Figure 2: Dev-set perplexity across corpora with stupid backoff smoothing implemented with $\lambda = 0.4$ and varying number of context sizes (n-gram length). Referenced is current best performance from add-k smoothing (dotted).

yielded small but notable performance jumps for the other corpora, but the `brown` corpus saw a substantial increase in perplexity. Because the performance jump from bigram to trigram models in the other two corpora was modest, and with an intention to maximize generalization, we chose a bigram model implemented with stupid backoff as our tuned model. The baseline unigram performance, along with the performance of our tuned add-k and backoff models is shown in Table 1.

Though not shown, varying numbers of λ were tested. We found that $\lambda = 0.4$ worked best across all corpora at balancing off underfitting (low λ) and overfitting (high λ). With our hyperparameter search complete, we then explored the behavior of our train bigram models on out of domain data.

3.2 Out-of-Domain Text Analysis: Empirical

An insightful way to explore differences between data corpora is to train a language model on one and have it run inference on another. We have conducted this exact experiment below in Table 2 by scoring the test set perplexity of each language model - corpus pair. As expected, each model determined its own corpus to be the most natural sounding. More interesting was the similarity between the `brown` and `gutenberg` corpora. The test-set perplexity of the `gutenberg` corpus when

	brown	reuters	gutenberg
uni.	1514 / 1758	1467 / 1577	981 / 1036
add-k	128 / 1822	72 / 378	124 / 650
b-off	75 / 559	51 / 180	92 / 285

Table 1: Hyperparameter tuning results. Train and dev-set perplexity across all three corpora with different smoothing. add-k and backoff (b-off) running optimal $k=0.01$ and $n=2$ for ngram models

evaluated under the `brown` language model was 841, while `reuters` was scored over 2100 in the same setting. Furthermore, When these were evaluated under the `gutenberg` model, the `reuters` corpus was seen as four times more perplexing than the `brown` corpus. This led us to believe that the lexical characteristic of the `brown` and `gutenberg` corpora were most similar.

	brown	reuters	gutenberg
brown	558.59	2118.33	840.811
reuters	1500.02	180.312	2159.68
gutenberg	1098.51	4240.6	285.342

Table 2: Test set perplexity for each language model with stupid backoff smoothing applied. Each model is applied to every corpus.

The `reuters` corpus was also unique for how well its language model could generalize to test data. with a perplexity of 180 it was by far the most successful in-domain bigram model. We feel this is due to the `reuters` corpus being domain specific (finance, business) and therefore more homogenous than the other corpora. By contrast, the `brown` corpus was by far the most lexically diverse; its test-set perplexity was over 3 times higher than the other corpora and nearly 8 times higher than its train-set perplexity. The difficulty of modeling diverse language for downstream tasks is a particularly well explored phenomenon (Ponte and Croft, 1998). To take a closer look at the differences in these models, we feed each model both human and machine generated sentences and observe perplexity scoring a lower level.

3.3 Qualitative Analysis: Language Scoring

As displayed in Table 3, we have created several sentences (indexed to appendix A) to score under our three language models. Sentences 0, 1,

sen.	brown	reuters	gutenberg
0	6836 / 5268	490 / 1571	4012 / 6455
1	1901 / 1997	1765 / 2670	519 / 1325
2	621 / 1081	5685 / 2628	2094 / 1572
3	1011 / 687	1353 / 1334	1884 / 1473
4 ^g	1270 / 1663	2296 / 2656	124 / 1271
5 ^r	110 / 335	245 / 882	111 / 361
6 ^r	1498 / 2288	846 / 1430	3863 / 4466

Table 3: Perplexity scoring of sentences (bigram / unigram) (indexed in appendix A) by backoff language models. Columns represent the domain of the model used for scoring. Superscripts denote the domain of the model that generated the sentence, if not human.

and 2 were created by the authors to appear most natural under the `reuters`, `gutenberg`, and `brown` corpuses, respectively. As expected, the perplexity of our models reflected this intention. Sentence 0, a comment on the financial forecast of Dow Chemical, was given a perplexity score of 490 by the `reuters` model, 8x and 10x smaller than the scores given by the `gutenberg` and `brown` datasets, respectively.

By contrast, sentence 1 - a Shakespearean question of resisting temptation - appears most natural under the `gutenberg` language model, though the contrast between other models is not as stark as sentence 0. Sentence 2, a casual discussion about a football game, was seen as most natural by the `brown` language model, was seen as nearly 10x more perplexing by `reuters` but only 3x more perplexing by `gutenberg`, providing further evidence that the `brown` and `gutenberg` corpuses are most similar. Lastly, sentence 3 is most unique because the unigram model for all corpuses scored a lower perplexity.

A short but modern poetic phrase, sentence 3 seemed most natural under the unigram model because unigrams do not model context. Since all of the words in the phrase are relatively common independently (but not in their present order), n-gram models saw this phrase as unnatural. This demonstrates one of the fundamental challenges of language modeling across domains such as poetry or other literature. The definition of what is a "natural" language phrase is difficult to model holistically.

Aside from human-generated sentences, we also included three machine generated sentences to compare the `reuters` and `gutenberg` corpuses. All sentences were seeded with the prefix `It was like`. Sentence 4^g was generated by the

`gutenberg` corpus and also categorized as most natural under the same. Sentence 6^r depicts the same trend for the `reuters` corpus. Alternatively, 5^r was generated by the `reuters` corpus but scored as more natural under the `brown` and `gutenberg` corpuses. This is likely due to how short the sentence is; with only a few tokens, the sentence also contains few words that can be solely considered economic terms. These two features together made 5^r appear unnatural under the domain-specific `reuters` corpus. We explore this domain specificity in the next section.

Prefix: The forecast

Brown: **The forecast** by an age
could flash gangling man found
to suppose we have established
rapport and payments shall be
adjusted Richards of Russia does
the at Portsmouth Haverhill and
wild

Reuters: **The forecast** on stocks
and preferred their trade has led
some 11 Pechiney this CBT floor
price index has pared severely
impair efficiency to elaborate

Gutenberg: **The forecast** of Israel
21 say is falleth virtue summon
all our servants and his own
hands moment they thank them Why
did you

Prefix: Who hath

Brown: **Who hath** according
to whatever substantial ups
unconsciously keeping the could
pilots took pride or disquietude
he told between eleven at the
synergism between 1930

Reuters: **Who hath** QTR NET Shr 28
producing area

Gutenberg: **Who hath** failed of
up into the man shall hiss What
chinn value not your game with
thine By at once more in them
will Jerusalem saying The mound
torrid suns

3.4 Qualitative Analysis: Text Generation

In our final set of experiments, we qualitatively assess the performance of our language models by seeding them with several prefixes and observing the output. Shown above in examples 3.3 and 3.3, we seeded sentences with `The forecast` and `Who hath`, respectively. Other experiments like this were completed and can be found in our [supporting materials](#). We highlight these two prefixes to demonstrate the domain adaptation of our models even when given an out-of-domain prefix. For example, the prefix `Who hath` originates from old-English that is found in the Gutenberg corpus, forcing the other models to adapt. The `reuters` model converts this prefix into a question of if someone has shares of stock or assets. Additionally, the sentence also appears most unnatural of all three. The `brown` corpus does a much better job of generating a natural sentence, but still lacks compared to `gutenberg` which produced a near-biblical phrase.

As a comparison, we also fed each model a more general seed of `The forecast`, one that could yield multiple interpretations. The language models took advantage of this ambiguity to resolve the prefix into its domain. The `reuters` model discussed the forecast of basic and preferred stocks, `brown` quoted something that vaguely resembles historical prose, and again `gutenberg` interprets the forecast as "Israel 21," a pseudo-biblical passage. Though qualitative, the extent to which each generated sentence appears domain specific seems indicative of the lexical homogeneity of the training corpus. From this lense, the `brown` corpus appears the most linguistically diverse, and `reuters` the least, mirroring quantitative findings.

Included in appendix B, generated sentences from unigram models loosely replicate the findings of our tuned n-gram models, with a few notable exceptions. First, unigram models are poor at conjugating phrases and developing coherent thoughts due to their lack of conditioning on history and sampling from the marginal distributions of words. N-gram models are far better at this even with only single word context (bigrams), though long phrases tend to progressively lose coherence.

4 Discussion and Conclusion

Considered together, our quantitative and qualitative findings yielded several insights. Regarding the `brown` corpus, we found it surprising that our

add-k smoothing struggled to even slightly outperform the unigram baseline compared to the other corpuses. After further examination, we feel this is because this corpus is far more linguistically diverse than its counterparts. This is confirmed by the tendency for language models to overfit to testing data for the `brown` corpus and the discovery that this corpus includes many different forms of language, from sports to poetry. Even with a more sophisticated smoothing method, stupid backoff, language models struggled to fit well to the data and not overfit 2.

Most likely, this linguistic diversity was part of the reason why the `brown` corpus generalized much better to the `gutenberg` texts than `reuters`. Full of domain-specific terminology, the `reuters` corpus was considered an almost completely foreign dialect when viewed from the other models. This observation is partially true, which many terms in the `reuters` unambiguously financial and business related. Though each corpus observes some domain-specificity (e.g. biblical references and old-English from `gutenberg`), the concentration of domain-specific terms is most pronounced in `reuters`. Evidence of this homogeneity can be seen with the incredibly low perplexity values `reuters` had on its testing corpus relative to other models. However, this excellent in-domain generalization came at the cost of poor out-of-domain adaptation.

In a sense, the `reuters` model intended to capture business-centric phrases more so than English. In `reuters`-generated phrases that included little business jargon, the `brown` and `gutenberg` corpuses scored the statement as more natural. At the same time, it proved nearly impossible to generate a sentence using the `brown` or `gutenberg` models that scored a lower perplexity with `reuters`. Generally, this lends the insight that language models for domain-specific tasks can be improved by training on a subset of only relevant language, but may subsequently struggle to generalize in out-of-domain tasks. In several cases, the in-domain benefit may justify this trade-off.

5 Statement of Collaboration

I solicited the help of Anthony Chen in asking a few questions about issues I was having with my smoothing techniques and the assignment in general. Beyond this discussion and perusing Campus Wire, I completed this independently.

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A Sentence Reference

Below is a reference for table with generated sentences. As noted above, the sentences indexed in 3 with an additional superscript were generated by the reuters model while *g* references gutenbergs.

index	sentence
0	This third quarter fiscal forecast for DOW Chemical is bearish according to financial analysts.
1	Who hath such scuples as to remain untrod- den by the perils of temptation?
2	Hey did hear about that fight the football team got in to after practice?
3	Walked alone did she, on to tomorrow.
4 ^g	It was like fire sent them and new psycho- logical influences set in stone brought the Holy Ghost
5 ^r	It was like the workforce body
6 ^r	It was like a loss for Bahrain Oman and current residents are packing said company spokesman

B Unigram Generated Sentences

Prefix: The forecast

Brown: The forecast blanket
royalty was least is limited
story cases heading present
be payments movement its two
possible the unmistakably

Reuters: The forecast sales late
and practices

Gutenberg: The forecast point
blossoms blossoms out won mark is
natured incommodiously

Prefix: Who hath

Brown: Who hath the
automatically the efficiency

Reuters: Who hath to Ray agency
was

Gutenberg: Who hath said she Till
the the at there and the news you
and hands mouse shall 28 strength
entrance assistants my from
