LANGUAGE MODELING

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ABSTRACT

This exercise is a guide with destination the model of a language with the SRILM - The SRI Language Modeling Toolkit. The training corpus used will be some journal-style writings from a translation shared task, Machine Translation of News, and the test corpus will be taken from the assignment proposal. Also, some code in order to prepare the data will be token from it. The process of this exercise will be to use the N-gram language model kind, to check it with different n values (monogram, bigram, trigram, . . .), two different corpora and a mix of them. Finally, the best language model will be selected.

0.1. Github

The whole project could be downloaded from the `git` repository

`https://github.com/Gonaco/language-modeling`

1. INTRODUCTION

The problem of building a language model could be approached by defining the set of rules that the language follows (the grammar), but this is a very complex and computationally inefficient solution and it needs directly the work of a human. Instead, using Machine Learning, the probabilistic relationship between words or sequence of words can be directly derived and modeled from an already created text or set of texts (a **corpus**). The models that behave like described before are known as the **Stochastic Language Models** and the avoid the need to create broad grammars, therefore, they are often used.

1.1. N-gram model

The N-gram model is a kind of Stochastic Language Model that are also termed Markov models, because of its behaviour. The N-gram model take into account the probability of a single word or a string of them (of length n) in order to calculate the probability of a word to appear or to after some string of length n. When $n = 1$ the probability of a single word is calculated (monogram), when $n = 2$ it calculated the probability of appearing a word after another (bigram), . . .

The N-gram model follows the concept of the Naive Bayes Estimator, that consider each event independent from the rest. Although it seems an idiotic and unrealistic assumption, it works quite well in practice. Therefore, the probability distribution that defines a language model will be:

$$P(\boldsymbol{W}) = P(\mathrm{w}_1, \mathrm{w}_2, ..., \mathrm{w}_n) = \prod_{i=1}^{n} P(\mathrm{w}_i | \mathrm{w}_1, \mathrm{w}_2, ..., \mathrm{w}_{i-1})$$

The conditional probabilities are calculated as the **Maximum Likelihood**

$$P(\mathrm{w}_i | \mathrm{w}_{i-(n-1)}, \mathrm{w}_{i-(n-2)}, ..., \mathrm{w}_{i-1} = \\ = \frac{C(\mathrm{w}_{i-(n-1)}, \mathrm{w}_{i-(n-2)}, ..., \mathrm{w}_{i-1}, \mathrm{w}_i)}{C(\mathrm{w}_{i-(n-1)}, \mathrm{w}_{i-(n-2)}, ..., \mathrm{w}_{i-1})}$$

where $C(\cdot)$ represents the number of times that the words appear all together.

1.1.1. *Smoothing*

The previous model is unlikely to generalize well to new sentences as soon as if some word does not appear in the corpus, the model gives 0 probability for it. For the same reason, with n-gram models the amount of training data is of million of words. Thus, smoothing is critical to make estimated probabilities robust for unseen data. Smoothing techniques adjust the maximum likelihood for unseen data, although the likelihood for the training data may be hurt slightly. They tend to make distributions more uniform adjusting low probabilities upward and high probabilities downward.

There are two different Smooth N-Gram models:

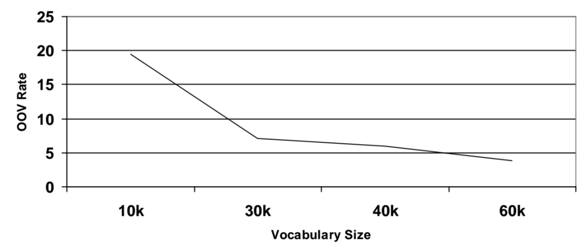
- Backoff models
- Interpolated models

The difference between them lies in that the backoff models do the distinction between the 0 probability words and the rest, besides the interpolated do not. As soon as the SRILM software only has backoff model, just this model will be considered. All the backoff algorithms follow the next equation

$$P_{smooth}(\mathrm{w}_i \mid \mathrm{w}_{i-(n-1)} \cdots \mathrm{w}_{i-1}) =$$
$$= \begin{cases} \alpha(\mathrm{w}_i | \mathrm{w}_{i-(n-1)} \ldots \mathrm{w}_{i-1}) & \text{if } C(\mathrm{w}_{i-(n-1)} \cdots \mathrm{w}_i) > 0 \\ \gamma(\mathrm{w}_{i-(n-1)} \cdots \mathrm{w}_{i-1}) \cdot & \\ \cdot P_{smooth}(\mathrm{w}_i \mid \mathrm{w}_{i-(n-2)} \cdots \mathrm{w}_{i-1}) & \text{if } C(\mathrm{w}_{i-(n-1)} \cdots \mathrm{w}_i) = 0 \end{cases}$$

1.2. Quality Measure

In order to know how good a language model could be, without fully testing it, two measures are used **Out-Of-Vocabulary (OOV)** range and **Perplexity**. The OOV range is the number of words that are not in the vocabulary of the language model. The higher the OOV range the less words will be predicted in a correct way. Also, the shorter the corpus, the higher the OOV range.



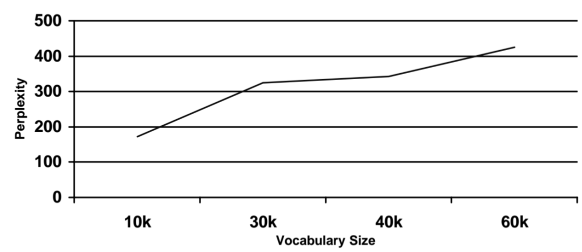
The Perplexity ($PP(\boldsymbol{W})$ is the complexity measure for a language model, the higher, the more complex. The perfect perplexity for a language model is when it is the same that the real language perplexity.

$$PP(\boldsymbol{W}) = 2^{\frac{1}{N_{\boldsymbol{W}}} log_2(\frac{1}{P(\boldsymbol{W})})}$$

where $N_{\boldsymbol{W}}$ is the number of different words in the corpora. By the other hand, the perplexity measure done by the SRILM software is calculated as

$$PP_{SRILM}(\boldsymbol{W}) = 10^{\frac{-log_2(P(\boldsymbol{W}))}{N_{\boldsymbol{W}} + \#\text{sentences} - OOV}}$$

Therefore, the higher the corpus length, the higher the perplexity.



2. LANGUAGE MODELS STUDY

Now, the study will be done with the Good-Turing discounting and Katz backoff for smoothing because they are algorithms often used and with very good results. They will be executed with the `ngram-count` and `ngram` functions.

Two corpora will be used from the news database: Europarl v7/v8 (corpus A) and News Crawl: articles from 2007 (corpus B). Both of them will be compared and mixed in order to seek the best result possible.

2.1. Commands

2.1.1. Corpus tokenization

First, the data should be tokenize, as soon as the break marks have to be analyzed separated from the word and not having different probabilities for a word and the same word with the break mark.

```
# From the st2 folder

./tokenizer.perl -l en < ../corpus/europarl-v7.en >
  ↪  ../corpus/europarl-v7.en.tok
./tokenizer.perl -l en < ../corpus/news.2007.en.shuffled
  ↪  > ../corpus/news.2007.en.shuffled.tok
./tokenizer.perl -l en < newstest2016-deen-ref.en >
  ↪  newstest2016-deen-ref.en.tok
```

2.1.2. 1-Gram

Doing the model with monograms is the same as doing the model without taking into account the previous words. In order to do that for both corpora, the next code should be run.

```
srilm-1.7.2/bin/i686-m64/ngram-count -order 1 -text
  ↪  corpus/europarl-v7.en.tok  -lm
  ↪  lang_models/model_A-1.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 1 -lm
  ↪  lang_models/model_A-1.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_A-1.ppl

srilm-1.7.2/bin/i686-m64/ngram-count -order 1 -text
  ↪  corpus/news.2007.en.shuffled.tok  -lm
  ↪  lang_models/model_B-1.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 1 -lm
  ↪  lang_models/model_B-1.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_B-1.ppl
```

2.1.3. 2-Gram

This time the same will be done, but with bigrams.

```
srilm-1.7.2/bin/i686-m64/ngram-count -order 2 -text
  ↪  corpus/europarl-v7.en.tok  -lm
  ↪  lang_models/model_A-2.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 2 -lm
  ↪  lang_models/model_A-2.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_A-2.ppl

srilm-1.7.2/bin/i686-m64/ngram-count -order 2 -text
  ↪  corpus/news.2007.en.shuffled.tok  -lm
  ↪  lang_models/model_B-2.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 2 -lm
  ↪  lang_models/model_B-2.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_B-2.ppl
```

2.1.4. 3-Gram

The trigram model will be executed.

```
srilm-1.7.2/bin/i686-m64/ngram-count -order 3 -text
  ↪  corpus/europarl-v7.en.tok  -lm
  ↪  lang_models/model_A-3.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 3 -lm
  ↪  lang_models/model_A-3.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_A-3.ppl

srilm-1.7.2/bin/i686-m64/ngram-count -order 3 -text
  ↪  corpus/news.2007.en.shuffled.tok  -lm
  ↪  lang_models/model_B-3.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 3 -lm
  ↪  lang_models/model_B-3.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_B-3.ppl
```

2.1.5. 4-Gram

For a model with order four, the next code is requires.

```
srilm-1.7.2/bin/i686-m64/ngram-count -order 4 -text
  ↪  corpus/europarl-v7.en.tok  -lm
  ↪  lang_models/model_A-4.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm
  ↪  lang_models/model_A-4.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_A-4.ppl

srilm-1.7.2/bin/i686-m64/ngram-count -order 4 -text
  ↪  corpus/news.2007.en.shuffled.tok  -lm
  ↪  lang_models/model_B-4.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm
  ↪  lang_models/model_B-4.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_B-4.ppl
```

2.1.6. 5-Gram

And finally, for an order of five:

```
srilm-1.7.2/bin/i686-m64/ngram-count -order 5 -text
  ↪  corpus/europarl-v7.en.tok  -lm
  ↪  lang_models/model_A-5.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 5 -lm
  ↪  lang_models/model_A-5.arpa -ppl
  ↪  st2/newstest2016-deen-ref.en.tok -debug 2 >
  ↪  lang_models/model_A-5.ppl
```

```
srilm-1.7.2/bin/i686-m64/ngram-count -order 5 -text corpus/news.2007.en.shuffled.tok -lm lang_models/model_B-5.arpa
srilm-1.7.2/bin/i686-m64/ngram -order 5 -lm lang_models/model_B-5.arpa -ppl st2/newstest2016-deen-ref.en.tok -debug 2 > lang_models/model_B-5.ppl
```

2.2. N-Gram models results

After executing the code, some results can be seen. It will be seen that for both the best results come for the fourth order and, also, that the OOV range of the second corpus is quite better than the first one.

2.2.1. `europarl-v7.en` *Corpus (A)*

Using this corpus, the OOV range is 2375. It is a very big number of words that are outside the range.

Order (n)	Perplexity
1	1892,86
2	634,99
3	579,51
4	577,87
5	578,88

2.2.2. `news.2007.en.shuffled` *Corpus (B)*

With this corpus, an OOV range of 829 is achieved. It is better than the language model before.

Order (n)	Perplexity
1	1438,85
2	303,81
3	243,37
4	242,76
5	245,23

2.3. Best Mix

A mix is done because it is often the best solution for the high OOV and, also, it could help with the perplexity problem reducing the model complexity. As soon as the 4-gram has had the best results, the mix model will be computed with order four.

Moreover, the mix will not be done just by half and half. The λ parameter is the mixture percentage of the first model (and $\lambda-1$ is the mixture percentage of the second one). So, in order to calculate the best model some different λ will checked. In order to analyze the progression of the mixture of models the next commands should be executed.

```
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm lang_models/model_A-4.arpa -mix-lm lang_models/model_B-4.arpa -lambda 0.1 -write-lm lang_models/mix_model_lambda_01.arpa
srilm-1.7.2/bin/i686-m64/ngram -lm lang_models/mix_model_lambda_01.arpa -ppl st2/newstest2016-deen-ref.en.tok
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm lang_models/model_A-4.arpa -mix-lm lang_models/model_B-4.arpa -lambda 0.2 -write-lm lang_models/mix_model_lambda_02.arpa
srilm-1.7.2/bin/i686-m64/ngram -lm lang_models/mix_model_lambda_02.arpa -ppl st2/newstest2016-deen-ref.en.tok
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm lang_models/model_A-4.arpa -mix-lm lang_models/model_B-4.arpa -lambda 0.3 -write-lm lang_models/mix_model_lambda_03.arpa
srilm-1.7.2/bin/i686-m64/ngram -lm lang_models/mix_model_lambda_03.arpa -ppl st2/newstest2016-deen-ref.en.tok
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm lang_models/model_A-4.arpa -mix-lm lang_models/model_B-4.arpa -lambda 0.4 -write-lm lang_models/mix_model_lambda_04.arpa
srilm-1.7.2/bin/i686-m64/ngram -lm lang_models/mix_model_lambda_04.arpa -ppl st2/newstest2016-deen-ref.en.tok
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm lang_models/model_A-4.arpa -mix-lm lang_models/model_B-4.arpa -lambda 0.5 -write-lm lang_models/mix_model_lambda_05.arpa
srilm-1.7.2/bin/i686-m64/ngram -lm lang_models/mix_model_lambda_05.arpa -ppl st2/newstest2016-deen-ref.en.tok
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm lang_models/model_A-4.arpa -mix-lm lang_models/model_B-4.arpa -lambda 0.7 -write-lm lang_models/mix_model_lambda_07.arpa
srilm-1.7.2/bin/i686-m64/ngram -lm lang_models/mix_model_lambda_07.arpa -ppl st2/newstest2016-deen-ref.en.tok
srilm-1.7.2/bin/i686-m64/ngram -order 4 -lm lang_models/model_A-4.arpa -mix-lm lang_models/model_B-4.arpa -lambda 0.9 -write-lm lang_models/mix_model_lambda_09.arpa
srilm-1.7.2/bin/i686-m64/ngram -lm lang_models/mix_model_lambda_09.arpa -ppl st2/newstest2016-deen-ref.en.tok
```

The OOV rate of the mixture results on 782 words out of vocabulary, that is quite better than the rates of both corpora alone. It is proved that the best mix is with a higher percentage of the second corpus (that was the best one) and, also, that a mixture (even with a not very good corpus) is better than just one corpus.

λ	Perplexity
0.1	231,2
0.2	228,78
0.3	230,32
0.4	235,03
0.5	243,09
0.7	273,81
0.9	358,36

For future works with the SRILM software, an experiment with a mixture of even more corpora could be done in order to test if the more mixed are the corpora the better language model results.

Finally, the best mix will be defined by

```
srilm-1.7.2/bin/i686-m64/ngram -lm lang_models/mix_model_lambda_02.arpa -ppl st2/newstest2016-deen-ref.en.tok
```