

Homework 1*Handed Out: 09/07/2018**Due: 11:59pm, 09/28/2018*

Please submit an archive of your solution (including code) on Compass by 11:59pm on the due date. Please document your code where necessary.

Getting started

All files that are necessary to do the assignment are contained in a tarball which you can get from:

http://courses.engr.illinois.edu/cs447/HW/cs447_HW1.tar.gz

You need to unpack this tarball (`tar -zxvf HW1.tar.gz`) to get a directory that contains the code and data you will need for this homework.

Part 1: Language models and smoothing (6 points)

1.1 Goal

The first part of the assignment requires you to train some simple n-gram language models on a corpus of movie reviews and to test them on two smaller corpora: a collection of positive reviews, and one of negative reviews.

1.2 Data

The corpora are stored as text files, where each line is one sentence from a review:

1. `train.txt`: contains the training corpus of movie reviews (30k sentences)
2. `pos_test.txt`: contains the test corpus of positive reviews (1k sentences)
3. `neg_test.txt`: contains the test corpus of negative reviews (1k sentences)

Tokens (this includes words and punctuation marks, which you should treat like regular tokens) are separated by whitespaces.

1.3 Provided Code

To get you started, we have provided the module `hw1_lm.py`. This file contains code for reading in the corpora (as in HW0) and maintaining a basic probability distribution (`UnigramDist`).

We have also defined a parent `LanguageModel` class, along with subclass definitions for the five language models we'd like you to implement. Your main task (described in section 1.4) is to implement the high-level methods of these models, specifically: generating sentences, calculating the probability of sentences, and computing the perplexity of a corpus.

Internally, we recommend that you treat each sentence as a list of tokens; this is the same representation returned by our `input` method.

1.4 What you need to implement

1.4.1 Preprocessing

To make your models more robust, it is necessary to perform some basic preprocessing on the corpora.

Sentence markers For all corpora, each sentence must be surrounded by a start of sentence and end of sentence marker (`<s> . . . </s>`). These markers will allow your models to generate sentences that have realistic beginnings and endings, if you train your model properly.

Handling unknown words In order to deal with unknown words in the test corpora, all words that appear only once in the training corpus must be replaced with a special token for unknown words (e.g. 'UNK') before estimating your models. When unknown words are encountered in the test corpora, they should be treated as that special token instead.

These preprocessing steps have been provided for you in the assignment code.

1.4.2 The LanguageModel classes

In order to compare the effects of using different-order n-grams and smoothing, we require you to implement the following five models:

1. **UnigramModel**: an unsmoothed unigram model, with probability distribution $\hat{P}(w)$
2. **SmoothedUnigramModel**: a unigram model smoothed using Laplace (add-one) smoothing, with probability distribution $P_L(w)$
3. **BigramModel**: an unsmoothed bigram model, with probability distribution $\hat{P}(w'|w)$
4. **SmoothedBigramModelAD**: a bigram model smoothed using absolute discounting, with probability distribution $P_{AD}(w'|w)$
5. **SmoothedBigramModelKN**: a bigram model smoothed using Kneser-Ney, with probability distribution $P_{KN}(w'|w)$

Laplace Smoothing For the **SmoothedUnigramModel** we want you to use Laplace smoothing, also known as add-one smoothing, on the unigram model $\hat{P}(w)$. Remember that in Laplace smoothing we increase the counts of all events by one and renormalize. This takes probability mass away from seen events and reserves it for unseen events (see Lecture 4)

In order to smooth your unigram model, you will need the number of words in the corpus, N , and the number of word types, S . The distinction between these is meaningful: N indicates the number of word instances, where S refers to the size of our vocabulary. The sentence “the cat saw the dog” has four word types (*the*, *cat*, *saw*, *dog*), but five word tokens (the, cat, saw, the, dog). The token “the” appears twice in the sentence, but they share the same type *the*.

If $c(w)$ is the frequency of w in the training data, you can compute $P_L(w)$ as follows:

$$P_L(w) = \frac{c(w) + 1}{N + S}$$

Absolute Discounting Smoothing In order to produce the **SmoothedBigramModel**, we want you to use absolute discounting on the bigram model $\hat{P}(w'|w)$.

You need to compute a discounting factor D . If n_1 are the number of bigrams w_1w_2 that appear only once, and n_2 are the number of bigrams w_1w_2 that appear exactly twice, compute D as

$$D = \frac{n_1}{n_1 + 2n_2}.$$

For each distribution $P(w'|w)$, you need to then also compute the number of seen bigram types ww' , S_w (this captures how many different w' occur after w in the training data).

$$S(w) = |w' : c(ww') > 0|$$

If $c(w)$ is the frequency of w in the training data, and $c(ww')$ the frequency of ww' in the training data, compute $P_{AD}(w'|w)$ as follows:

$$P_{AD}(w'|w) = \frac{\max(c(ww') - D, 0)}{c(w)} + \frac{D}{c(w)} \times S_w \times P_L(w')$$

Kneser-Ney Smoothing For the `SmoothedBigramModelKN`, Kneser-Ney augments absolute discounting with another way of handling lower order unigram distribution. Instead of directly using the Laplace smoothed unigram in absolute discounting, here you can replace the MLE unigram distribution with the continuation probability P_C , that estimates how likely the unigram is to continue a new context, normalized by the total number of unique bigrams. You can then compute P_C as follows (here i is a free variable):

$$P_C(w') = \frac{|w : c(ww') > 0|}{|w_{i-1}w_i : c(w_{i-1}w_i) > 0|}$$

Then compute P_{KN} as,

$$P_{KN}(w'|w) = \frac{\max(c(ww') - D, 0)}{c(w)} + \frac{D}{c(w)} \times S_w \times P_C(w')$$

1.4.3 Generating sentences

For each of the four language models, you need to implement the following methods:

`generateSentence(self)`: returns a sentence `sent` that is generated by the language model. `sent` is a list of the form `[<s>, w1, ..., wn, </s>]`, where w_1 to w_n are words in your vocabulary (including UNK, but excluding `<s>` and `</s>`). You can assume that `<s>` starts each sentence (with probability 1). The following words $(w_1, \dots, w_n, </s>)$ are generated according to your language model's distribution. The number of words (n) is not fixed. Instead, you stop generating a sentence as soon as you generate the end of sentence symbol `</s>`.

`getSentenceProbability(self, sen)`: returns the probability of the sentence `sen` (which is again a list of the form `[<s>, w1, ..., wn, </s>]`) according to the model.

Please use the provided `generateSentencesToFile` method and your unigram and bigram language models to generate 20 sentences (saved as `unigram_output.txt`, `smooth_unigram_output.txt`, `bigram_output.txt`, `smooth_bigram_ad_output.txt`, and `smooth_bigram_kn_output.txt`).

Implementation hint In order to avoid underflow, your implementation may have to use log-probabilities internally. That is, once you have computed each (smoothed) probability from your relative frequency estimates (counts), you need to convert it to its logarithm (use `math.log(p)` for natural logs or `math.log(p, 2)` for base-2 log, but make sure you always use the same base).

1.4.4 Computing the perplexity of the test corpora

You need to compute the perplexity (normalized inverse log probability) of the two test corpora according to all five of your models (unsmoothed unigram, smoothed unigram, unsmoothed bigram, smoothed bigram ad and smoothed bigram kn). Implement the following method to evaluate a whole corpus:

`getCorpusPerplexity(self, corpus)`: given a corpus `corpus`, calculate and return its perplexity

For a corpus W with N words, Jurafsky and Martin tells you to compute perplexity as follows:

$$\text{Perplexity}(W) = \sqrt[N]{\prod_{i=1}^N \frac{1}{P(w_i|w_{i-1})}}$$

Since this is prone to underflow issues, you may be better off computing it using logarithms:

$$\text{Perplexity}(W) = \exp\left(-\frac{1}{N} \sum_{i=1}^N \log P(w_i|w_{i-1})\right)$$

Evaluate the models on the test corpora. Do you see a difference between the two test domains?

1.5 What you will be graded on

You will be graded based on the files you submit and the answers you provide to the questions on Compass. Each of your models (excluding the unsmoothed unigram model) is worth 1 point (4 points total), and the Compass questions are worth 0.5 points (2 points total). Keep in mind that we must be able to run your submitted code or you will receive 0 points.

To help you identify errors, we have included a test script `hw1_lm_test.py`. This script will use the classes you implement in `hw1_lm.py` and test their methods against a simple corpus, `test.txt`, which we have also included.

1.6 What to submit

See the end of this document for full submission guidelines, but the files you must submit for this portion are:

1. `hw1_lm.py`: your completed Python module for language models (see all of section 1.4)
2. Four text files, containing sentences generated by your language models (see section 1.4.3). For each sentence, include the probability your model assigns to that sentence.
 - `unigram_output.txt`: a text file containing the 20 sentences generated by your unsmoothed unigram language model
 - `smooth_unigram_output.txt`: a text file containing the 20 sentences generated by your smoothed unigram language model
 - `bigram_output.txt`: a text file containing the 20 sentences generated by your unsmoothed bigram language model
 - `smooth_bigram_ad_output.txt`: a text file containing the 20 sentences generated by your smoothed bigram language model using Absolute Discounting Smoothing
 - `smooth_bigram_kn_output.txt`: a text file containing the 20 sentences generated by your smoothed bigram language model using Kneser-Ney Smoothing

Additionally, you must answer the following discussion questions on Compass when you submit your assignment. These questions can be found by navigating to *Course Content* → *Homeworks* → *Homework 1* → *Homework 1 Language Model Discussion Questions*

1. When generating sentences with the unigram model, what controls the length of the generated sentences? How does this differ from the sentences produced by the bigram models?
2. Consider the probability of the generated sentences according to your models. Do your models assign drastically different probabilities to the different sets of sentences? Why do you think that is?
3. Generate additional sentences using your bigram and smoothed bigram models. In your opinion, which model produces better / more realistic sentences?
4. For each of the four models, which test corpus has a higher perplexity? Why? Make sure to include the perplexity values in the answer.

Part 2: Finite-State Transducers (4 points)

2.1 Goal

Your task is to implement a finite-state transducer (or FST; see Lecture 2) which transduces the infinitive form of verbs to their correct *-ing* form. You will be graded according to how many verbs your transducer handles correctly.

2.2 Data

The input to your program is a text file with a single (infinitive) verb per line. For each verb, your program should compute the correct translation (e.g. `walk ==> walking`) and print it as a line in the output file.

1. `360verbs.txt`: sample input file containing a list of 360 infinitive verbs, one verb per line.
2. `360verbsCorrect.txt`: sample output file containing the correct translation (infinitive to *-ing* form) for each of the 360 verbs in order, one translation per line.

2.3 Provided Code

To help you with your task, we've provided `fst.py`, a module for constructing and evaluating FSTs. You shouldn't modify any of the code in this file. Below, we describe the most useful methods provided by this module:

`FST(self, initialStateName)`: instantiate an FST with an initial (non-accepting) state named `initialStateName`

`addState(self, name, isFinal)`: add a state named `name` to the FST; by default, `isFinal=false` and so the state is not an accepting state.

`addTransition(self, inStateName, inString, outString, outStateName)`: adds a transition between state `inStateName` and state `outStateName`, where both of these states already exist in the FST. The FST can traverse this transition after reading `inString`¹, and outputs `outString` when it does so.

`addSetTransition(self, inStateName, inStringSet, outStateName)`: adds a transition between state `inStateName` and state `outStateName` for each character in `inStringSet`. For each transition, the FST outputs the same character it reads.

You will need to implement your solution by modifying the file `hw1_fst.py`. This file uses the function `buildFST()` to define a rudimentary (and buggy) FST for translating verbs. Your task is to modify this function (using the methods in `fst.py`) to produce a better FST. You are free to define your own character sets (we've started out with some useful ones at the beginning of the file) and any helper methods you require. The main method evaluates the sample FST on an input file. When implementing your FST, you can save your results to another file (e.g. `360verbsGuess.txt`) and run `diff` against `360verbsCorrect.txt` to see how well you're doing:

```
python hw1_fst.py 360verbs.txt > 360verbsGuess.txt
```

```
diff -U 0 360verbsCorrect.txt 360verbsGuess.txt | grep ^@ | wc -l
```

This will print the number of incorrect translations.

¹`inString` can be at most one character long

2.4 What you need to implement

Your task is to fix the implementation of `buildFST()` by replacing the sample FST with a better FST for translating infinitive verbs to their correct *-ing* form. Your FST can be non-deterministic (that is, a state may have multiple transitions for the same input character), but each accepted string should only have one analysis.² It will accept a string if it reaches a final state after having read its last character. If it accepts a string, it will output its translation. If it does not accept a string, it will output FAIL. All verb stems are at least three letters long. In many cases, the *-ing* form just consists of *stem + ing*:

```
walk ==> walking    fly ==> flying
```

But there are a number of exceptions. In particular, in order to correctly translate the 360 verbs we've provided, your FST must implement the following rules:

- 1. Dropping the final -e:** Drop the final *-e* if and only if it is preceded by a consonant or by the letter *u*:

```
ride ==> riding      make ==> making      see ==> seeing
argue ==> arguing    seize ==> seizing
```

- 2. Double the final consonant:** Double a final single *-n*, *-p*, *-t*, *-r* if and only if it is preceded by a single vowel³:

```
stop ==> stopping   admit ==> admitting   stoop ==> stooping
occur ==> occurring set ==> setting       leap ==> leaping
halt ==> halting    bar ==> barring
```

Exceptions to this rule are verbs ending in *-er*, *-en*:⁴

```
gather ==> gathering  happen ==> happening
```

- 3. Change final *-ie* to *-y* :**

```
die ==> dying
```

Notes: When you define a transition, the input strings can only be zero ("") or one character long, and your FST can't have more than 30 states (you shouldn't need that many).

2.5 What to submit

For this portion, you only need to submit one file:

1. `hw1fst.py`: your completed Python module for translating verb forms using FSTs (see section 2.4)

We will use our own copy of the `fst` module and input files to test your program during grading.

2.6 What you will be graded on

You will be graded according to the number of verbs in `360verbs.txt` that your FST correctly translates (100% is 4 points; the provided FST starts at 78%). You need to make sure that the function definition of `buildFST()` remains the same, so that we can check your results and verify that your FST adheres to the specification.

²If your FST accepts a string along multiple paths, all of the outputs will all be printed out and the translation will be marked incorrect: e.g. `appeal --> appealingappealing`

³This is a simplified version of the actual spelling rule. Our data set does not contain verbs like *pardon*, where this rule does not apply. It also does not contain verbs that end in other letters like *stab*, *slam*, where this rule also applies.

⁴We are assuming American English spelling for *labeling*, etc.

Submission guidelines

You should submit your solution as a compressed tarball on Compass. To do this, save your files in a directory called *abc123_hw1* (where *abc123* is your NetID) and create the archive from its parent directory (`tar -zcvf abc123_hw1.tar.gz abc123_hw1`). Do not include the corpora themselves, but do include the following files:

1. `hw1_lm.py`: your completed Python module for language models (see all of section 1.4)
2. Five text files, containing sentences generated by your language models (see section 1.4.3). For each sentence, include the probability your model assigns to that sentence.
 - `unigram_output.txt`: a text file containing the 20 sentences generated by your unsmoothed unigram language model
 - `smooth_unigram_output.txt`: a text file containing the 20 sentences generated by your smoothed unigram language model
 - `bigram_output.txt`: a text file containing the 20 sentences generated by your unsmoothed bigram language model
 - `smooth_bigram_ad_output.txt`: a text file containing the 20 sentences generated by your smoothed bigram language model using Absolute Discounting Smoothing
 - `smooth_bigram_kn_output.txt`: a text file containing the 20 sentences generated by your smoothed bigram language model using Kneser-Ney Smoothing
3. `hw1_fst.py`: your completed Python module for translating verb forms using FSTs (see section 2.4)

Additionally, you must answer the discussion questions on Compass when you submit your assignment. These questions can be found by navigating to *Course Content* → *Homeworks* → *Homework 1* → *Homework 1 Language Model Discussion Questions*