EECS 595 / SI 561 / LING 541 – Natural Language Processing

Assignment 4

Machine Translation

(version 5.0)

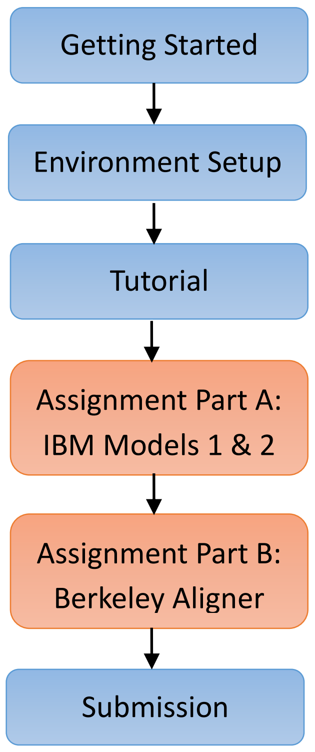
Due: December 13, 2015, 11:59 pm

Introduction

In this assignment we will:

1. Go through the basics of Machine Translation models;
2. Implement IBM models 1 and 2;
3. Create an implementation of the Berkeley Aligner;
4. Analyze data output from all models.

This document is structured in the following sequence:


Getting Started
Environment Setup
Tutorial
Assignment Part A: IBM Models 1 & 2
Assignment Part B: Berkeley Aligner
Submission

Basic introduction to Machine Translation and IBM models 1 & 2

Set up everything to start working on the assignment

Overview of NLTK commands to be used in the assignment

Implement and examine IBM models 1 & 2

Implement and analyze the Berkeley Aligner; optional extra credit

Files to be submitted

Getting Started

The goal of this assignment is to understand and implement various models for machine translation. We will be using the German-English corpus from Comtrans. The corpus contains roughly 100,000 pairs of equivalent sentences--one in German and one in English. Our objective will be to determine the alignments between these sentences using various machine translation models and compare the results.

Assume we are given a parallel corpus of training sentences in two languages. For example, the first pair in the corpus is:

e = Wiederaufnahme der Sitzungsperiode

f = Resumption of the session

For each pair of sentences, we want to determine the alignment between them. Since we do not have any alignment information in our training set, we will need to determine a set of parameters from the corpus, which will enable us to predict the alignments.

For IBM Model 1, we need to determine one parameter set: t(f | e). The t parameter represents the translation probability of word f being translated from word e. This results in a simple model that produces alignments based on the most probable translation of each word.

For IBM Model 2, we need to determine two parameter sets: q(j | i, l, m) and t(f | e). The q parameter represents the alignment probability that a particular word position i will be aligned to a word position j, given the sentence lengths l and m. This results in a model that examines both the word translations and the position distortion of a word in the target sentence. The q parameters will be initialized to the uniform distribution, meaning that q (j | i, l, m) = 1 / (l + 1).

A great explanation of the IBM Models by Michael Collins can be found here:

http://www.cs.columbia.edu/~mcollins/courses/nlp2011/notes/ibm12.pdf

In order to compute these parameters, we use the EM algorithm. The EM algorithm takes an initial set of parameters and attempts to find the maximum likelihood estimates of these parameters under the model. There are 2 steps: the Expectation step, which computes the likelihood of the current parameters, and the Maximization step, which updates these parameters to maximize the likelihood. A very detailed explanation with some intuition behind it can be found here:

http://www.isi.edu/natural-language/mt/wkbk.rtf

In this assignment, you will implement a simplified version of the Berkeley Aligner model. This model uses the concept of alignment by agreement. Essentially, you will be training two IBM model 2s simultaneously: one from the source language to the target language and one from the target language to the source language. The idea is that intersecting these two models will eliminate some of the errors that unidirectional translation models would produce. In order to accomplish this, the EM algorithm initializes two models and maximizes the combined probability of both models. More information can be found here:

http://cs.stanford.edu/~pliang/papers/alignment-naacl2006.pdf

Environment Setup

Step 1: Confirm that your link to the NLTK files is working

To test that you have successfully linked to the nltk directory, open the python interpreter and run:

```
from nltk.corpus import comtrans
```

This should not produce any errors. If you get the error:

```
Resource u'corpora/comtrams' not found
```

It is likely an error from linking in assignment 1. To fix this, go back to your home directory:

```
cd ~/
```

Remove the symbolic link:

```
rm -r nltk_data
```

Run the linking command.

```
ln -s ../595/nltk_data/ nltk_data
```

Test again. You should get no errors.

Step 2: Copy the homework files to your hidden directory under Homework4 folder

Use the following command:

```
cp -r /home/595/Homework4/student_files/ ~/hidden/$PIN/Homework4
```

Be sure to replace $PIN with your pin.

Tutorial

In this assignment, you will be using many of the alignment tools available within NLTK.

One important object is AlignedSent, which is given in the ComTrans corpus object.

```
>>> from nltk.corpus import comtrans

>>> my_aligned_sent = comtrans.aligned_sents('alignment-en-fr.txt')[0]

>>> my_aligned_sent

AlignedSent(['Resumption', 'of', 'the', 'session'], ['Reprise', 'de',
'la', 'session'], Alignment([(0, 0), (1, 1), (2, 2), (3, 3)]))
```

The original sentence can be obtained using: aligned_sent.words. The translated sentence can be obtained with aligned_sent.mots. The alignment array can be obtained with aligned_sent.alignment. Each tuple (i, j) in the alignment indicates that words[i] is aligned to mots[j].

An IBMModel1 object can be created with:

```
>>> from nltk.align import IBMModel1

>>> ibm = IBMModel1(list_of_aligned_sents, num_iters)
```

where “list_of_aligned_sents” is a list of AlignedSent objects and “num_iters” is the number of iterations you want the EM algorithm to make. (Note that the object name has a lowercase “l” followed by the number “1,” not two “l”s.) The model automatically trains on initialization. You can then call the model’s align method to predict the alignment for an AlignedSent object.

Each AlignedSent object in the corpus contains the correct alignments. In order to evaluate the results of the model, use the AlignedSent.alignment_error_rate() function.

Provided Files and Report

The assignment can be found in:

> */home/595/Homework4/student_files*

It contains the following files:

> *A.py* – contains skeleton code for Part A
>
> *B.py* – contains skeleton code for Part B
>
> *EC.py* – contains skeleton code for Part B extra credit
>
> *main.py* – runs the assignment [do not modify this file]

You must use the skeleton code we provide you. Do not rename these files. Inside, you will find our solutions with most of the code removed. In the missing code's place, you will find comments to guide you to a correct solution.

We have provided code that creates all output files (main.py). Do not modify this code in any way, and pay close attention to the instructions in the comments. If you modify this code it may be very difficult to evaluate your work and this will be reflected in your grade. You may add helper functions if you would like.

Report

You are required to create a brief report about your work. The top of the report should include your Uniqname and the time you expect each of your programs to complete. Throughout the assignment, you will be asked to include specific output or comment on specific aspects of your work.

Part A – IBM Models 1 & 2

In this part, we will be using NLTK to examine IBM models 1 & 2. You will need to implement the methods compute_average_aer(), save_model_output(), create_ibm1(), and create_ibm2(). When creating the text files, do not worry about encoding.

1) In the create_ibm1 function, initialize an instance of IBM Model 1, using 10 iterations of EM. Train it on the corpus that is passed into the function. Then, implement save_model_output to save the model’s predicted alignments for the first 20 sentence pairs in the corpus to “ibm1.txt” (we are training and testing on the same data). Use the following format for each sentence pair:

Source sentence	[as given by AlignedSent.words]
Target Sentence	[as given by AlignedSent.mots]
Alignments	[as given by AlignedSent.alignment]
(blank line)	

Ex:
[u’Frau’, u’Pr\xe4sidentin’, u’,’ u’zur’, u’Gesch\xe4ftsordnung’, u’.’]
[u’Madam’, u’President’, u’,’, u’on’, u’a’, u’point’, u’of’, u’order’, u’.’]
0-0 1-0 2-2 3-7 4-7
(blank line)

2) In the create_ibm2 function, initialize an instance of IBM Model 2 using 10 iterations of EM. Train it on the corpus that is passed into the function. Then, save the model’s predicted alignments for the first 20 sentences in the corpus to “ibm2.txt”. Use the same sentence pair format as above.

3) Implement the compute_avg_aer function. For each of the first 50 sentence pairs in the corpus, compute the alignment error rate (AER). Compute the average AER over the first 50 sentences for each model. You can use the AER that exists in NLTK, but you must implement your own averaging scheme. In your report, compare the results between the two models. Specifically, highlight a sentence pair from the development set where one model outperformed the other. Comment on why one model computed a more accurate alignment on this pair.

4) Experiment with the number of iterations for the EM algorithm. Try to find a number of iterations that provides the lowest error rate, but still runs in a reasonable amount of time. Discuss how the number of iterations is related to the AER. These number may not be the same for each of the IBM models.

Part B – Berkeley Aligner

In this part we will improve upon the performance of the IBM models using a simplified version of the BerkeleyAligner Model. In this model, we will train two separate models simultaneously such that we maximize the agreement between them. Here, we will be digging a bit more into the machine translation algorithms and implementing the EM algorithm.

You will need to complete the implementation of the class BerkeleyAligner, which will support the same function calls as the NLTK implementations of the IBM models.

For the EM algorithm, initialize the translation parameters to be the uniform distribution over all possible words that appear in a target sentence of a sentence containing the source word. Words should be treated as case sensitive. Initialize the alignment parameters to be the uniform distribution over the length of the source sentence.

We will be using a simplified quantification of agreement between the two models (in comparison to that proposed in the paper). When you compute the expected counts, use the average expected count with respect to the two models' parameters.

Both models' parameters can be stored in the same dictionary. However, the translation and distortion parameters should be stored in separate dictionaries. Null alignments should be dealt with in the same fashion that IBM models 1 and 2 handle them. When creating the text file, do not worry about encoding. Note: The iteration should be left at 10 when the code is submitted, but feel free to alter it while testing, if needed, to find convergence.

1) Implement the train() function. This function takes in a training set and the number of iterations for the EM algorithm. You will have to implement the EM algorithm for this new model. Return the parameters in the following format:

   (translation, distortion)

2) Implement the align() function. This function uses the trained model's parameters to determine the alignments for a single sentence pair.

3) Train the model and determine the alignments for the first 20 sentences. Save the results to "ba.txt". Use the same format as in part A. Note that the main function of B.py calls A.save_model_output(aligned_sents, ba, "ba.txt") for you, so this step should not require any additional coding.

4) Compute the average AER for the first 50 sentences. Note that the main function of B.py calls A.compute_avg_aer(aligned_sents, ba, 50) for you, so this step should not require any additional coding. Compare the performance of the BerkeleyAligner model to the IBM models.

5) In your report, give an example of a sentence pair that the Berkeley Aligner performs better on than the IBM models, and explain why you think this is the case.

6) **(Extra Credit)** Think of a way to improve upon the Berkeley Aligner model. Specifically examine the way we quantify agreement between the two models. In our implementation, we computed agreement as the average expected count of the two models. Implement an improved Berkeley Aligner model that computes agreement in a better way. There is skeleton code in EC.py (same as for B.py) Compute the average AER for the first 50 sentences. Compare to the other models. Again, this part is optional but if your implementation is interesting and shows improved performance, you will be eligible for bonus points.

Submission

A.py – methods implemented

Ibm1.txt – contains the first 20 sentence pairs and their alignments for IBM Model 1

Ibm2.txt – contains the first 20 sentence pairs and their alignments for IBM Model 2

B.py – methods implemented

ba.txt – contains the first 20 sentence pairs and their alignments for Berkeley Aligner

EC.py – improved Berkeley Aligner code [optional]

README.txt – writeup of all written portions as well as general comments about your code and how it works or any issues that occur while running it

Make sure running main.py does not fail and that all output is printed correctly. The output of main.py will make up a large portion of your grade.

Make sure all files are within the folder:

~/hidden/<YOUR_PIN>/Homework4/

As a final step, run the permissions script to set correct permissions for your homework files:

/home/595/Homework4/hw4_set_permissions.sh <YOUR_PIN>

Additional Resources

Here are some NACLO problems related to translation:

http://www.nacloweb.org/resources/problems/2012/N2012-C.pdf

http://www.nacloweb.org/resources/problems/2010/C.pdf