Homework #9: Machine Translation (MT)

Deadline: 11:59pm Monday 16 December 2013

Please present a report with all your answers, explanations, and sample images or plots. Submit also a soft copy of the source code and binaries used to generate these results. Please note that copying of any results or source code will result in ZERO credit for the whole homework.

Acknowledgment: This homework is adapted from Michael Collins' Coursera NLP class from 2013.

The goal of this homework is to implement two translation models, IBM model 1 and IBM model 2, and apply these models to predict English/Spanish word alignments. Both models estimate the conditional probability of a foreign sentence $f_1 \dots f_m$ and an alignment $a_1 \dots a_m$ given a particular English sentence $e_1 \dots e_l$ and length m. The simpler model, IBM model 1, defines the conditional probability with a single set of parameters t as

$$p(f_1 \dots f_m, a_1 \dots a_m | e_1 \dots e_l, m) = \frac{1}{(1+l)^m} \prod_{i=1}^{m} t(f_i | e_{a_i})$$

while the richer IBM Model 2 defines the same conditional probability with two sets of parameters t and q

$$p(f_1 \dots f_m, a_1 \dots a_m | e_1 \dots e_l, m) = \prod_{i=1}^{m} q(a_i | i, l, m) t(f_i | e_{a_i})$$

Training Data

The main task of this assignment is to estimate these parameters from data. We estimate the parameters from a parallel corpus of aligned sentences. Each entry in the corpus contains two versions of the same sentence, one in English and one in Spanish. The parallel corpus we are using is a subset of the Europarl corpus [Koehn, 2005] accessed from http://www.statmt.org/europarl/ which contains aligned sentences from the proceedings of the European Parliament. The training corpus is split into two files, `corpus.en` and `corpus.es`, which contain English and Spanish sentences respectively. The i-th sentence in the English file is a translation of the i-th sentence in the Spanish file. The files are in UTF-8, contain one sentence per line, and words are separated by a space.

```
> head -n 3 corpus.en
resumption of the session
i declare resumed the session of the european parliament adjourned on ...
Although , as you will have seen , the dreaded ' millennium bug ' failed ...
```

```
> head -n 3 corpus.es
```

```
reanudaci´on del per´ıodo de sesiones
declaro reanudado el per´ıodo de sesiones del parlamento europeo ...
como todos han podido comprobar , el gran " efecto del año 2000 " no se ...
```

IBM Model 1

The full algorithm for IBM model 1 is given on page 21 in the notes on machine translation http://www.cs.columbia.edu/~mcollins/ibm12.pdf. We recommend closely reading those notes for a full description of the problem. The core portion of the algorithm is summarized here.

Recall that IBM model 1 only has word translation parameters $t(f \mid e)$, which can be interpreted as the conditional probability of generating a foreign word f from an English word e (or from NULL). We can estimate $t(f \mid e)$ using the EM algorithm, which iterates through the parallel corpus repeatedly. For the k-th sentence pair and each index i in the foreign sentence $f^{(k)}$ and j in the English sentence $e^{(k)}$, we define:

$$\delta(k,i,j) = \frac{t(f_i^{(k)} | e_j^{(k)})}{\sum_{j=0}^{l_k} t(f_i^{(k)} | e_j^{(k)})}$$

where l_k is the length of the English sentence. The delta function is used to update the expected counts for the current iteration:

$$c(e_j^{(k)}, f_i^{(k)}) \leftarrow c(e_j^{(k)}, f_i^{(k)}) + \delta(k,i,j)$$
$$c(e_j^{(k)}) \leftarrow c(e_j^{(k)}) + \delta(k,i,j)$$

After each iteration through the parallel corpus, we revise our estimate for t parameters:

$$t(f|e) = \frac{c(e,f)}{c(e)}$$

for all possible foreign words f and English words e (and NULL).

IBM Model 2

The complete algorithm for estimating IBM model 2 parameters is given on page 13 of the notes. Be sure to understand the details of this algorithm before beginning to code the assignment. We note here that IBM model 2 extends the implementation of the EM algorithm for IBM model 1. The main additional step is adapting the delta function to include $q(j \mid i, l, m)$ parameters:

$$\delta(k,i,j) = \frac{q(j|i,l_k,m_k) t(f_i^{(k)} | e_j^{(k)})}{\sum_{j=0}^{l_k} q(j|i,l_k,m_k) t(f_i^{(k)} | e_j^{(k)})}$$

and computing expected counts $c(j \mid i, l, m)$ and $c(i, \ l, m)$

After each iteration through the corpus we re-estimate the $t(f_i, e_j)$ parameters as before and add new updates for the q parameters:

$$q(j|i,l,m) = \frac{c(j|i,l,m)}{c(i,l,m)}$$

Evaluation

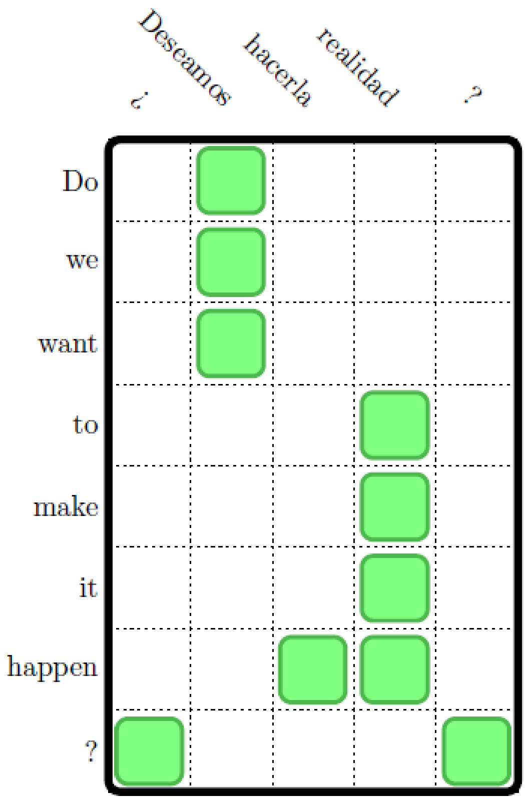
We provide aligned development and test data, `dev.en / dev.es` and `test.en / test.es` in order to evaluate alignment accuracy. The format of these files is identical to the corpus training files, one sentence per line with aligned sentences.

We also provide a file, `dev.key`, which contains the manually annotated gold alignments for the development sentences. The key is adapted from Lambert et al. [2005] and accessed at http://gps-tsc.upc.es/veu/LR/epps_ensp_alignref.php3. The file contains lines of the form:

...
6 7 3
6 7 4
6 8 5
...
Each line specifies a word alignment of the form

```
SentenceIndex EnglishIndex ForeignIndex
```

The first line of the example specifies that in the 6th pair of sentences the 7th English word is aligned to the 3rd Spanish word. Note that the gold alignments do not include NULL word alignments, all three indices start from 1, and unlike previous assignments there are no blank lines between sentences.



As an example, consider the 6th sentence pair in the development set:

```
e = Do we want to make it happen ?
f = ¿ Deseamos hacerla realidad ?
```

The gold word alignment, 6 7 3, indicates that the English word "happen" is aligned with the Spanish word "hacerla". The full alignment of the sentence pair is as in the figure.

For all of the questions in this assignment you should output predicted alignments in this format. We have included a script `eval_alignment.py` to evaluate the accuracy of these alignments. Assuming that you have written alignments to a file `dev.out`, running python `eval_alignment.py dev.key dev.out` will give the F-Score of the predicted alignments compared to the gold alignments.

Note: The alignments given in the key file often map single English words to multiple foreign words, whereas our models do not. For this reason it is impossible to get perfect recall or F-Score on this data set. For parts 1 and 2 we ignore this issue.

Part 1

The first problem is to estimate the parameters of IBM model 1 using corpus.en and corpus.es as input. Before implementing please read the following notes carefully.

- Your implementation should only store *t* parameters for possible pairs of foreign and English words, i.e. words that occur together in some parallel translation, and the special English word NULL. We recommend implementing *t* as a collection of sparse maps for each English word *e* where the keys of the map are the words *f* that are occur with *e* and the values are the corresponding parameters *t*(*f* | *e*). Using a non-sparse implementation will likely result in memory issues.
- In the initialization step, set *t*(*f* | *e*) to be the uniform distribution over all foreign words that could be aligned to e in the corpus. More specifically

$$t(f|e) = \frac{1}{n(e)}$$

  where *n*(*e*) is the number of different words that occur in any translation of a sentence containing *e*. Note that the special English word NULL can be aligned to any foreign word in the corpus.
- Starting from the initial *t*(*f* | *e*) parameters, run **5 iterations** of the EM algorithm for IBM model 1 (this may take a while). When your model is completed, save your *t* parameters to a file, as you will need them for the next problem.
- Finally, use your model to find alignments for the development sentence pairs `dev.en` / `dev.es`. For each sentence, align each foreign word f_i to the English word with the highest *t*(*f* | *e*) score, i.e.

$$a_i = \arg \max_{j \in \{0 \cdots l\}} t(f_i|e_j)$$

  Write your alignments to a file in the format of `dev.key` described above. Check the accuracy with `eval_alignments.py`.

Part 2

We now extend the alignment model to IBM model 2 by adding alignment parameters $q(j \mid i, l, m)$. Initialize the q parameters to the uniform distribution over all j for each i, l, and m, i.e.

$$q(j|i,l,m) = \frac{1}{l+1}$$

You only need to store parameters for pairs of sentence lengths l and m that occur in the corpus.

- To initialize the $t(f \mid e)$ parameters, use the last set of parameters (after 5 iterations) produced by your implementation of IBM model 1.
- Run 5 iterations of EM for IBM model 2.
- As before, use the model to compute alignments for the development sentence pairs in the corpus. For each foreign word f_i, the best alignment is

  $$a_i = \arg\max_{j \in \{0 \cdots l\}} q(j|i,l,m) t(f_i|e_j)$$

  Write your alignments to a file in the format of `dev.key` described above. Check the accuracy with `eval_alignments.py`.

Requirements

You are required to implement EM training for IBM Models 1 & 2.

Please submit your code and report in one zip file, named **CMPN463.HW03.firstname.lastname.zip**. For example, if your name is Mohamed Aly, your file should be named **CMPN463.HW03.Mohamed.Aly.zip**.

Grading

1 pts: report and submission file name
3 pts: correct implementation of EM training for IBM Model 1 (F-score >= 0.42)
6 pts: correct implementation of EM training for IBM Model 2 (F-score >= 0.449)

References

Philipp Koehn. Europarl: A parallel corpus for statistical machine translation. In MT summit, volume 5, 2005.

Patrik Lambert, Adri`a De Gispert, Rafael Banchs, and Jos´e B Mari˜no. Guidelines for word alignment evaluation and manual alignment. Language Resources and Evaluation, 39(4):267–285, 2005.