Assignment 2: IBM Model 1

CSC401/2511 Tutorial, Winter 2015
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Based on slides by Jackie Cheung, Alex Fraser and Frank Rudzicz
Noisy Channel Model

We need a language model, a translation model, and a decoder.
A Translation Model

**Problem**: calculating $P(F|E)$.

**Solution**: Introducing word alignments.
- Possible Mappings between source words (English) and target words (French).

**Assumptions**:  
- Translating from French $F$ into English $E$.  
- Each French word comes from one English word.  
- No many-to-one or many-to-many mappings.
IBM Model 1

\[ P(F|E) = \sum_A P(F,A|E) \]

\[ P(F,A|E) = \prod_j P(f_j | e_{a(j)}) \]

\( f_j \) & \( e_i \): jth & ith words of sentences F and E.
\( a \) is an alignment function that maps each French word \( f_j \) to an English word \( e_i \).
All alignments are equally likely.
EM Algorithm

Parameters to learn: \( P(f_j | e_{a(j)}) \)

Could learn if we had word-aligned corpus (M-step)

La maison bleue \( \rightarrow \) Le chat blanc
The blue house \( \rightarrow \) The white cat

Could decode if we had parameters (E-step)
EM Algorithm

• Initialize model parameters
• Iterate:
  • Assign probabilities to missing data (alignments)
  • Estimate model parameters from completed data

*Could learn if we had word-aligned corpus (M-step)*

| La maison bleue | \( P(f|e_k) = ??? \) |
|-----------------|------------------|
| The blue house  |                  |

*Could decode if we had parameters (E-step)*

| Le chat blanc  | \( P(f|e_k) = 0.16 \) |
|----------------|------------------|
| The white cat  |                  |
Initialization

• Need to start the cycle somewhere.
• Make up (reasonable) values for the parameters.
• Assume uniform distribution over all word pairs that occur together in some sentence.
Initialization Example

the blue cat  le chat bleu
the red dog   le chien rouge

but,
P(rouge|cat) = 0

P(le|the),
P(chat|the),
P(bleu|the),
P(chien|the),
P(rouge|the) = 1 / 5

P(le|red)
P(rouge|red)
P(chien|red) = 1 / 3
Expectation Step

Calculating $P(A|F, E)$ for all word alignments

\[
P(A|E, F) = \frac{P(F, A|E)}{P(F|E)}
\]

\[
P(F|E) = \sum_A P(F, A|E)
\]

IBM Model 1
Expectation Step

\[ P(A|E,F) = \frac{\prod_j P(f_j|e_{a(j)})}{\sum_{A'} \prod_j P(f_j|e_{a'(j)})} \]

\[ P(A|E,F) = \prod_j \frac{P(f_j|e_{a(j)})}{\sum_i P(f_j|e_i)} \]
Expectation Step

Given ‘t’ parameters

For each sentence pair:
  - For every possible alignment of this sentence pair, simply work out the equation of Model 1
  - Sum the Model 1 alignment scores, over all alignments of a sentence pair
  - Divide the alignment score of each alignment by this sum to obtain a normalized score
  - The resulting normalized score is the posterior probability of the alignment
Maximization Step

Collect counts to estimate new parameter values:

\[ P(f \mid e) = \frac{tcount(f, e)}{total(e)} \]

Number of cases in training corpus where f is aligned to e, weighted by the probability of that alignment.

\[ tcount(f, e) = \sum_{(E,F)} c(f \mid e; F, E) \]

aligned sentence-pairs \((E,F)\) in training corpus

\[ c(f \mid e; F, E) = \sum_a P(a \mid E, F) \cdot count(f, e, a) \]

number of times f aligned to e in a
Maximization Step

\[
c(f|e; F, E) = \sum_a P(a|E, F) \ \text{count}(f, e, a)
\]

- Parameters come from previous iteration
- Ways to align f to e

\[
c(f|e; F, E) = \frac{P(f|e)}{\sum_i P(f|e_i)} \ \text{count}(f, e)
\]
initialize $P(f|e)$
for a number of iterations:
  set $tcount(f, e)$ to 0 for all $f, e$
  set $total(e)$ to 0 for all $e$
for each sentence pair $(F, E)$ in training corpus:
  for each unique word $f$ in $F$:
    $\text{denom}_c = 0$
    for each unique word $e$ in $E$:
      $\text{denom}_c += P(f|e) \times F\.count(f)$
    for each unique word $e$ in $E$:
      $tcount(f, e) += P(f|e) \times F\.count(f) \times E\.count(e) / \text{denom}_c$
      $total(e) += P(f|e) \times F\.count(f) \times E\.count(e) / \text{denom}_c$
for each $e$ in domain($total(:)$):
  for each $f$ in domain($tcount(:,e)$):
    $P(f|e) = tcount(f, e) / total(e)$
Decoding

\[ E_{\text{best}} = \operatorname{argmax} P(F|E)P(E) \]

Finding the sentence that maximize the translation and language model probabilities: A Search Problem
Decoder

Greedy transformation:
- Find most likely word $e$ for word $f$ by $P(f|e)$
- Greedily reorder words to maximize $P(E)$
- Take the highest probability output at each step

Stack decoding: (25.8 in Jurafsky & Martin)
- $A^*$ search
- Maintain a priority queue of partial translations
- Each partial translation has a score calculated based on translation and language model probabilities
Bonus Marks

- Decoder
- Good-Turing smoothing
- IBM Model 2
- Null word
- Error analysis
Good-Turing Smoothing

- Assign the probability mass of n-grams with frequency of \( r+1 \) to the ones with frequency of \( r \).

- Probability mass of n-grams that were never seen comes from the ones that occurred once.
Good-Turing Smoothing

Fixed probability for unseen n-grams:

1. \( P_0 = \frac{N_1}{N} \)
2. \( P_0 \): total probability of all unseen events
3. \( N_1 \): number of events that occurred once
4. \( N \): number of all events

Probability of other events are adjusted to fit inside probability space (M&S, Section 6.2.5)
IBM Model 2

\[ P(F,a|E) = \prod_j P(f_j | e_{a(j)}) P(a(j) | j, \text{len}(F), \text{len}(E)) \]

The probability that the \( i \)th English word is aligned to the \( j \)th French word, given lengths of the sentences.
Null Word

- Not all words may have an alignment:
  Canada's program
  Le programme du Canada
- Add NULL word
  NULL Canada's program
  Le programme du Canada
- Fixed probability of aligning with NULL.
Q: The preprocessing rules in the handout don't handle this particular case (e.g. punctuation, French sentences in the English corpus, etc.). Can I fix it?
A: Yes, as long as it is reasonable and you document it. However, first check your CDF forum.

No bonus marks for extra work on this part. You are not required to do anything beyond what is described in the handout. Do not spend too much time on this part!
Q: How long should calculating the language model/training EM take?

A: Each should take at most a couple of hours even on the most resource-intensive settings. More marks are allocated for correctness. Efficiency is a secondary concern—if you can finish running it by the deadline, you're probably OK!
Q: How accurate should the final translations be?

A: The accuracy will vary wildly depending on the decoder and model you use. Marks for task 5 will not be based on the accuracy result you get, but rather the correctness of the evaluation code and your written report.