Natural Language Processing

Anoop Sarkar
anoopsarkar.github.io/nlp-class

Simon Fraser University

October 16, 2014

Natural Language Processing

Anoop Sarkar
anoopsarkar.github.io/nlp-class

Simon Fraser University

Part 1: Statistical Machine Translation

Introduction to Statistical Machine Translation

Generative Model of Word Alignment

Word Alignments: IBM Model 3

Word Alignments: IBM Model 1

Basic Terminology

Translation

We will consider translation of

- a source language string in French, called $\mathbf{f}$
- into a target language string in English, called $\mathbf{e}$.

A priori probability: $\Pr(\mathbf{e})$

The chance that $\mathbf{e}$ is a valid English string.
What is better? Pr(*I like snakes*) or Pr(*snakes like I*)

Conditional probability: $\Pr(\mathbf{f} \mid \mathbf{e})$

The chance of French string $\mathbf{f}$ given $\mathbf{e}$.
What is the chance of French string *maison bleue* given the English string *I like snakes*?

Basic Terminology

Joint probability: $\Pr(\mathbf{e}, \mathbf{f})$

The chance of both English string **e** and French string **f** occuring together.

- If **e** and **f** are independent (do not influence each other) then
$$\Pr(\mathbf{e}, \mathbf{f}) = \Pr(\mathbf{e}) \Pr(\mathbf{f})$$

- If **e** and **f** are not independent (they do influence each other) then
$$\Pr(\mathbf{e}, \mathbf{f}) = \Pr(\mathbf{e}) \Pr(\mathbf{f} \mid \mathbf{e})$$

Which one should we use for machine translation?

Statistical Machine Translation

Given French string $\mathbf{f}$ find the English string $\mathbf{e}$ that maximizes $\Pr(\mathbf{e} \mid \mathbf{f})$

$$\mathbf{e}^* = \arg\max_{\mathbf{e}} \Pr(\mathbf{e} \mid \mathbf{f})$$

This finds the *most likely* translation $\mathbf{e}^*$

Alignment Task

$$
\begin{tikzcd}
\mathbf{e} \arrow[dr] & \\
 & \text{Program} \arrow[r] & \Pr(\mathbf{e} \mid \mathbf{f}) \\
\mathbf{f} \arrow[ur] &
\end{tikzcd}
$$

Translation Task

$$
\begin{tikzcd}
 & & \mathbf{e}_1 : \Pr(\mathbf{e}_1 \mid \mathbf{f}) \\
\mathbf{f} \arrow[r] & \text{Program} \arrow[ur] \arrow[dr] & \vdots \\
 & & \mathbf{e}_n : \Pr(\mathbf{e}_n \mid \mathbf{f})
\end{tikzcd}
$$

Bayes' Rule

Bayes' Rule

$$\Pr(\mathbf{e} \mid \mathbf{f}) = \frac{\Pr(\mathbf{e}) \Pr(\mathbf{f} \mid \mathbf{e})}{\Pr(\mathbf{f})}$$

Exercise

Show the above equation using the definition of $P(\mathbf{e}, \mathbf{f})$ and the chain rule.

Noisy Channel Model

Use Bayes' Rule

$$
\begin{aligned}
\mathbf{e}^* &= \arg\max_{\mathbf{e}} \Pr(\mathbf{e} \mid \mathbf{f}) \\
&= \arg\max_{\mathbf{e}} \frac{\Pr(\mathbf{e}) \Pr(\mathbf{f} \mid \mathbf{e})}{\Pr(\mathbf{f})} \\
&= \arg\max_{\mathbf{e}} \Pr(\mathbf{e}) \Pr(\mathbf{f} \mid \mathbf{e})
\end{aligned}
$$

Noisy Channel

- Imagine a French speaker has **e** in their head
- By the time we observe it, **e** has become "corrupted" into **f**
- To recover the most likely **e** we reason about
  1. What kinds of things are likely to be **e**
  2. How does **e** get converted into **f**

Statistical Machine Translation

Noisy Channel Model

$$\mathbf{e}^* = \arg\max_{\mathbf{e}} \underbrace{\Pr(\mathbf{e})}_{\textbf{Language Model}} \cdot \underbrace{\Pr(\mathbf{f} \mid \mathbf{e})}_{\textbf{Alignment Model}}$$

Training the components

- **Language Model**: *n*-gram language model with smoothing.
  Training data: lots of monolingual **e** text.
- **Alignment Model**: learn a mapping between **f** and **e**.
  Training data: lots of translation pairs between **f** and **e**.

Word reordering in Translation

Candidate translations

Every candidate translation $\mathbf{e}$ for a given $\mathbf{f}$ has two factors:

$$\Pr(\mathbf{e}) \Pr(\mathbf{f} \mid \mathbf{e})$$

What is the contribution of $\Pr(\mathbf{e})$?

Exercise: Bag Generation

Put these words in order:
have programming a seen never I language better

Exercise: Bag Generation

Put these words in order:
actual the hashing is since not collision-free usually the is less perfectly the of somewhat capacity table

Word reordering in Translation

Candidate translations

Every candidate translation $\mathbf{e}$ for a given $\mathbf{f}$ has two factors:

$$\Pr(\mathbf{e}) \Pr(\mathbf{f} \mid \mathbf{e})$$

What is the contribution of $\Pr(\mathbf{f} \mid \mathbf{e})$?

Exercise: Bag Generation

Put these words in order:
love John Mary

Exercise: Word Choice

Choose between two alternatives with similar scores $\Pr(\mathbf{f} \mid \mathbf{e})$:
she is in the end zone
she is on the end zone

Statistical Machine Translation

Noisy Channel Model

Every candidate translation $\mathbf{e}$ for a given $\mathbf{f}$ has two factors:

$$\Pr(\mathbf{e}) \Pr(\mathbf{f} \mid \mathbf{e})$$

Translation Modeling

- $\Pr(\mathbf{f} \mid \mathbf{e})$ does not need to be perfect because of the $\Pr(\mathbf{e})$ factor.
- $\Pr(\mathbf{e})$ models **fluency**.
- $\Pr(\mathbf{f} \mid \mathbf{e})$ models the transfer of **content**.
- This a *generative model* of translation.

$\Pr(\mathbf{f} \mid \mathbf{e})$: How does English become French?

English $\Rightarrow$ Meaning $\Rightarrow$ French

- English to meaning representation:
  John must not go $\Rightarrow$ $\textsc{obligatory}(\textsc{not}(\textsc{go}(\textsc{john})))$
  John may not go $\Rightarrow$ $\textsc{not}(\textsc{permitted}(\textsc{go}(\textsc{john})))$
- Meaning representation to French

English $\Rightarrow$ Syntax $\Rightarrow$ French

- Parsed English:
  Mary loves soccer $\Rightarrow$ *(S (NP Mary) (VP (V loves) (NP soccer)))*
- Parse tree to French parse tree:
  (S (NP Mary) (VP (V loves) (NP soccer))) $\Rightarrow$ *(S (NP Mary) (VP (V aime) (NP le football)))*

$\Pr(\mathbf{f} \mid \mathbf{e})$: How does English become French?

English words $\Rightarrow$ French words

- Simplest model, map English words to French words
- Corresponds to an alignment between English and French:

$$\Pr(\mathbf{f} \mid \mathbf{e}) = \Pr(f_1, \ldots, f_I, a_1, \ldots, a_I \mid e_1, \ldots, e_J)$$

Statistical Machine Translation

The IBM Models

- The first statistical machine translation models were developed at IBM Research (Yorktown Heights, NY) in the 1980s
- The models were published in 1993:
  Brown et. al. The Mathematics of Statistical Machine Translation.
  Computational Linguistics. 1993.
  `http://aclweb.org/anthology/J/J93/J93-2003.pdf`
- These models are the basic SMT models, called:
  IBM Model 1, IBM Model 2, ..., IBM Model 5
  as they were called in the 1993 paper.
- We still use **e** and **f** in the equations because their system translated from French to English.

Natural Language Processing

Anoop Sarkar
anoopsarkar.github.io/nlp-class

Simon Fraser University

Part 2: Generative Model of Word Alignment

Introduction to Statistical Machine Translation

Generative Model of Word Alignment

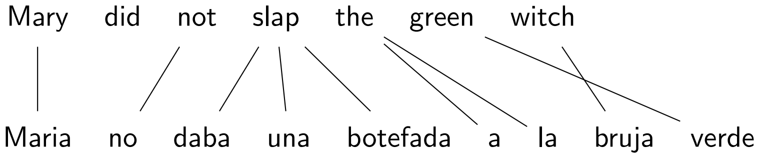
Word Alignments: IBM Model 3

Word Alignments: IBM Model 1

Generative Model of Word Alignment

- English **e**: Mary did not slap the green witch
- "French" **f**: Maria no daba una botefada a la bruja verde
- Alignment **a**: $\{1, 3, 4, 4, 4, 5, 5, 7, 6\}$
  e.g. $(f_8, e_{a_8}) = (f_8, e_7) =$ (bruja, witch)

Visualizing alignment **a**



Generative Model of Word Alignment

Data Set

- Data set $\mathcal{D}$ of N sentences:
$$\mathcal{D} = \{(\mathbf{f}^{(1)}, \mathbf{e}^{(1)}), \ldots, (\mathbf{f}^{(N)}, \mathbf{e}^{(N)})\}$$
- French $\mathbf{f}$: $(f_1, f_2, \ldots, f_I)$
- English $\mathbf{e}$: $(e_1, e_2, \ldots, e_J)$
- Alignment $\mathbf{a}$: $(a_1, a_2, \ldots, a_I)$

Generative Model of Word Alignment

Find the best alignment for each translation pair

$$\mathbf{a}^* = \arg\max_{\mathbf{a}} \Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e})$$

Chain rule revisited

$$\begin{aligned} \Pr(\mathbf{f}, \mathbf{a}) &= \Pr(\mathbf{f}) \Pr(\mathbf{a} \mid \mathbf{f}) \\ \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) &= \Pr(\mathbf{f} \mid \mathbf{e}) \Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) \end{aligned}$$

Alignment probability

$$\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) = \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\Pr(\mathbf{f} \mid \mathbf{e})} = \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}$$

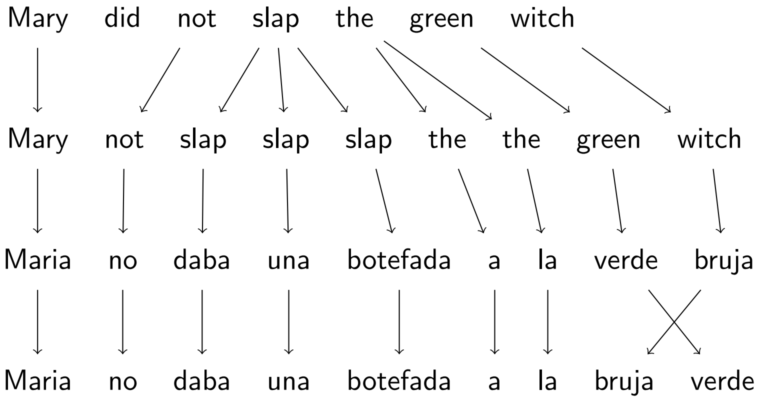
Introduction to Statistical Machine Translation

Generative Model of Word Alignment

- Word Alignments: IBM Model 3
- Word Alignments: IBM Model 1

Word Alignments: IBM Model 3

Generative "story" for $P(\mathbf{a} \mid \mathbf{f}, \mathbf{e})$



Word Alignments: IBM Model 3

Fertility parameter

$$n(\phi_j \mid e_j) : n(3 \mid slap)$$

Translation parameter

$$t(f_i \mid e_j) : t(bruja \mid witch)$$

Distortion parameter

$$d(f_{pos} \mid e_{pos}, I, J) : d(8 \mid 7, 8, 6)$$

Introduction to Statistical Machine Translation

Generative Model of Word Alignment

- Word Alignments: IBM Model 3
- Word Alignments: IBM Model 1

Word Alignments: IBM Model 1

Alignment probability

$$\Pr(\mathbf{a} \mid \mathbf{f}, \mathbf{e}) = \frac{\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}{\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})}$$

Example alignment

1	2	3	4
das	Haus	ist	klein
|	|	|	|
1	2	3	4
the	house	is	small

$$\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = \prod_{i=1}^{I} t(f_i \mid e_{a_i})$$

$$\begin{aligned}\Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) = {} & \\ & t(\text{das} \mid \text{the}) \times \\ & t(\text{Haus} \mid \text{house}) \times \\ & t(\text{ist} \mid \text{is}) \times \\ & t(\text{klein} \mid \text{small})\end{aligned}$$

Word Alignments: IBM Model 1

Sum over all alignments

$$\sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e}) \quad = \quad \sum_{a_1=1}^{J} \sum_{a_2=1}^{J} \cdots \sum_{a_I=1}^{J} \prod_{i=1}^{I} t(f_i \mid e_{a_i})$$

Assume (f_1, f_2, f_3) and (e_1, e_2)

$$\sum_{a_1=1}^{2} \sum_{a_2=1}^{2} \sum_{a_3=1}^{2} t(f_1 \mid e_{a_1}) \times t(f_2 \mid e_{a_2}) \times t(f_3 \mid e_{a_3})$$

Word Alignments: IBM Model 1

Assume (f_1, f_2, f_3) and (e_1, e_2): $I = 3$ and $J = 2$

$$\sum_{a_1=1}^{2} \sum_{a_2=1}^{2} \sum_{a_3=1}^{2} t(f_1 \mid e_{a_1}) \times t(f_2 \mid e_{a_2}) \times t(f_3 \mid e_{a_3})$$

$J^I = 2^3$ terms to be added:

$t(f_1 \mid e_1)$	$\times$	$t(f_2 \mid e_1)$	$\times$	$t(f_3 \mid e_1)$	$+$
$t(f_1 \mid e_1)$	$\times$	$t(f_2 \mid e_1)$	$\times$	$t(f_3 \mid e_2)$	$+$
$t(f_1 \mid e_1)$	$\times$	$t(f_2 \mid e_2)$	$\times$	$t(f_3 \mid e_1)$	$+$
$t(f_1 \mid e_1)$	$\times$	$t(f_2 \mid e_2)$	$\times$	$t(f_3 \mid e_2)$	$+$
$t(f_1 \mid e_2)$	$\times$	$t(f_2 \mid e_1)$	$\times$	$t(f_3 \mid e_1)$	$+$
$t(f_1 \mid e_2)$	$\times$	$t(f_2 \mid e_1)$	$\times$	$t(f_3 \mid e_2)$	$+$
$t(f_1 \mid e_2)$	$\times$	$t(f_2 \mid e_2)$	$\times$	$t(f_3 \mid e_1)$	$+$
$t(f_1 \mid e_2)$	$\times$	$t(f_2 \mid e_2)$	$\times$	$t(f_3 \mid e_2)$	$+$

Word Alignments: IBM Model 1

Factor the terms:

$$\begin{array}{lcll}
(t(f_1 \mid e_1) \times t(f_2 \mid e_1)) & \times & (t(f_3 \mid e_1) + t(f_3 \mid e_2)) & + \\
(t(f_1 \mid e_1) \times t(f_2 \mid e_2)) & \times & (t(f_3 \mid e_1) + t(f_3 \mid e_2)) & + \\
(t(f_1 \mid e_2) \times t(f_2 \mid e_1)) & \times & (t(f_3 \mid e_1) + t(f_3 \mid e_2)) & + \\
(t(f_1 \mid e_2) \times t(f_2 \mid e_2)) & \times & (t(f_3 \mid e_1) + t(f_3 \mid e_2)) &
\end{array}$$

$$(t(f_3 \mid e_1) + t(f_3 \mid e_2)) \left(\begin{array}{lcll}
t(f_1 \mid e_1) & \times & t(f_2 \mid e_1) & + \\
t(f_1 \mid e_1) & \times & t(f_2 \mid e_2) & + \\
t(f_1 \mid e_2) & \times & t(f_2 \mid e_1) & + \\
t(f_1 \mid e_2) & \times & t(f_2 \mid e_2) &
\end{array} \right)$$

$$(t(f_3 \mid e_1) + t(f_3 \mid e_2)) \left(\begin{array}{lcll}
t(f_1 \mid e_1) & \times & (t(f_2 \mid e_1) + t(f_2 \mid e_2)) & + \\
t(f_1 \mid e_2) & \times & (t(f_2 \mid e_1) + t(f_2 \mid e_2)) &
\end{array} \right)$$

Word Alignments: IBM Model 1

Assume (f_1, f_2, f_3) and (e_1, e_2): $I = 3$ and $J = 2$

$$\prod_{i=1}^{3} \sum_{a_i=1}^{2} t(f_i \mid e_{a_i})$$

$I \times J = 2 \times 3$ terms to be added:

$$\begin{array}{lcll}
(t(f_1 \mid e_1) & + & t(f_1 \mid e_2)) & \times \\
(t(f_2 \mid e_1) & + & t(f_2 \mid e_2)) & \times \\
(t(f_3 \mid e_1) & + & t(f_3 \mid e_2)) &
\end{array}$$

Acknowledgements

Many slides borrowed or inspired from lecture notes by Michael Collins, Chris Dyer, Kevin Knight, Adam Lopez, and Luke Zettlemoyer from their NLP course materials. All mistakes are my own.