



Natural Language Processing

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Part 1: Machine Translation

Introduction to Machine Translation

Basic Terminology

Translation

We will consider translation of

- ▶ a source language string in French, called **f**
- ▶ into a target language string in English, called **e**.

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

The chance that **e** is a valid English string.

What is better? $\Pr(I \text{ like snakes})$ or $\Pr(\text{snakes like } I)$

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

The chance of French string **f** given **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 $\mathbf{e}$ and French string $\mathbf{f}$ occurring together.

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

$$\Pr(\mathbf{e}, \mathbf{f}) = \Pr(\mathbf{e}) \Pr(\mathbf{f})$$

- ▶ If $\mathbf{e}$ and $\mathbf{f}$ are not independent (they do influence each other) then

$$\Pr(\mathbf{e}, \mathbf{f}) = \Pr(\mathbf{e}) \Pr(\mathbf{f} | \mathbf{e})$$

Which one should we use for machine translation?

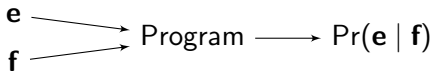
Machine Translation

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

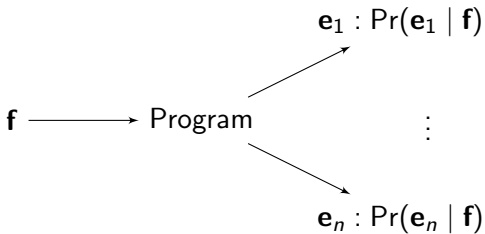
$$\mathbf{e}^* = \arg \max_{\mathbf{e}} \Pr(\mathbf{e} \mid \mathbf{f})$$

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

Alignment Task



Translation Task



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 $\mathbf{e}$ in their head
- ▶ By the time we observe it, $\mathbf{e}$ has become “corrupted” into $\mathbf{f}$
- ▶ To recover the most likely $\mathbf{e}$ we reason about
 1. What kinds of things are likely to be $\mathbf{e}$
 2. How does $\mathbf{e}$ get converted into $\mathbf{f}$

Machine Translation

Noisy Channel Model

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

Training the components

- ▶ **Language Model:** n -gram language model with smoothing.
Training data: lots of monolingual $\mathbf{e}$ text.
- ▶ **Alignment/Translation Model:** learn a mapping between $\mathbf{f}$ and $\mathbf{e}$.
Training data: lots of translation pairs between $\mathbf{f}$ and $\mathbf{e}$.

Word reordering in Translation

Candidate translations

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

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

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:

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

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

Exercise: Bag Generation

Put these words in order:

love John Mary

Exercise: Word Choice

Choose between two alternatives with similar scores $\Pr(\mathbf{f} | \mathbf{e})$:

she is in the end zone

she is on the end zone

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(f | e): How does English become French?

English $\Rightarrow$ Meaning $\Rightarrow$ French

- ▶ English to meaning representation:

John must not go $\Rightarrow$ OBLIGATORY(NOT(GO(JOHN)))

John may not go $\Rightarrow$ NOT(PERMITTED(GO(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:

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

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 3, IBM Model 4,
IBM Model 5
as they were called in the 1993 paper.
- ▶ We use **e** and **f** in the equations in honor of their system
which translated from French to English.
Trained on the Canadian Hansards (Parliament Proceedings)

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