



# Natural Language Processing

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[anoopsarkar.github.io/nlp-class](http://anoopsarkar.github.io/nlp-class)

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Part 1: Statistical Machine Translation

## Introduction to Statistical 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?

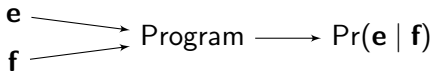
# Statistical Machine Translation

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

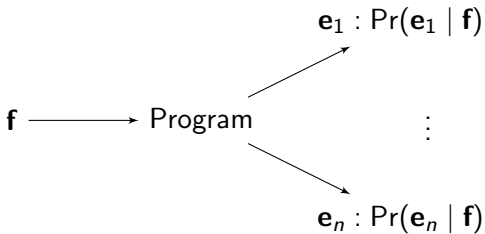
$$\mathbf{e}^* = \arg \max_{\mathbf{e}} \Pr(\mathbf{e} \mid \mathbf{f})$$

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

## Alignment Task



## 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  $\mathbf{f}$

# Statistical 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 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*

# 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(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:

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

# 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 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)



## Acknowledgements

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