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 $\mathbf{f}$
- 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?

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**

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/Translation 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 **e** for a given **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

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 ⇒ Meaning ⇒ French

- English to meaning representation:
  John must not go ⇒ OBLIGATORY(NOT(GO(JOHN)))
  John may not go ⇒ NOT(PERMITTED(GO(JOHN)))
- Meaning representation to French

English ⇒ Syntax ⇒ French

- Parsed English:
  Mary loves soccer ⇒ *(S (NP Mary) (VP (V loves) (NP soccer)))*
- Parse tree to French parse tree:
  (S (NP Mary) (VP (V loves) (NP soccer))) ⇒ *(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:

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

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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