Machine Translation

Michael Collins, Columbia University

Sign in

Translate

From: Arabic - detected To: English Translate

English Spanish French Arabic - detected

كما أوضح أن الإنفاق الاستهلاكي كان المحرك الرئيسي للاقتصاد الذي تضرر جراء عامين من الاضطرابات السياسية

وأشار إلى أن هناك شبه غياب للاستثمارات الأجنبية المباشرة في النصف الأول من السنة المالية، وأنه لتحقيق نمو اقتصادي بنسبة 7% تحتاج البلاد إلى معدل استثمار لا يقل عن 22%

English Spanish Arabic

He also explained that consumer spending was the main engine of the economy that has been hit by two years of political turmoil

He pointed out that there is a near absence of foreign direct investment (FDI) in the first half of the fiscal year, and that to achieve economic growth of 7% country needs investment rate of at least 22%

Overview

- Challenges in machine translation
- Classical machine translation
- A brief introduction to statistical MT

Challenges: Lexical Ambiguity

(Example from Dorr et. al, 1999)

Example 1:

book the flight $\Rightarrow$ reservar

read the book $\Rightarrow$ libro

Example 2:

the box was in the pen

the pen was on the table

Example 3:

kill a man $\Rightarrow$ matar

kill a process $\Rightarrow$ acabar

Challenges: Differing Word Orders

- English word order is *subject – verb – object*
- Japanese word order is *subject – object – verb*

English:	IBM bought Lotus
Japanese:	*IBM Lotus bought*

English:	Sources said that IBM bought Lotus yesterday
Japanese:	*Sources yesterday IBM Lotus bought that said*

Syntactic Structure is not Preserved Across Translations (Example from Dorr et. al, 1999)

The bottle floated into the cave

$\Downarrow$

La botella entro a la cuerva flotando
(the bottle entered the cave floating)

Syntactic Ambiguity Causes Problems

(Example from Dorr et. al, 1999)

John hit the dog with the stick

$\Downarrow$

John golpeo el perro con el palo/que tenia el palo

Pronoun Resolution (Example from Dorr et. al, 1999)

The computer outputs the data; it is fast.

$\Downarrow$

La computadora imprime los datos; es rapida

The computer outputs the data; it is stored in ascii.

$\Downarrow$

La computadora imprime los datos; estan almacendos en ascii

Overview

- Challenges in machine translation
- Classical machine translation
- A brief introduction to statistical MT

Direct Machine Translation

- Translation is word-by-word
- Very little analysis of the source text (e.g., no syntactic or semantic analysis)
- Relies on a large bilingual directionary. For each word in the source language, the dictionary specifies a set of rules for translating that word
- After the words are translated, simple reordering rules are applied (e.g., move adjectives after nouns when translating from English to French)

An Example of a set of Direct Translation Rules

(From Jurafsky and Martin, edition 2, chapter 25. Originally from a system from Panov 1960)

Rules for translating *much* or *many* into Russian:

if preceding word is *how* **return** *skol'ko*
else if preceding word is *as* **return** *stol'ko zhe*
else if word is *much*
    if preceding word is *very* **return** nil
    else if following word is a noun **return** *mnogo*
else (word is many)
    if preceding word is a preposition and following word is noun **return** *mnogii*
    else return *mnogo*

Some Problems with Direct Machine Translation

- Lack of any analysis of the source language causes several problems, for example:
  - Difficult or impossible to capture long-range reorderings

    English: Sources said that IBM bought Lotus yesterday
    Japanese: *Sources yesterday IBM Lotus bought that said*

  - Words are translated without disambiguation of their syntactic role
    e.g., *that* can be a complementizer or determiner, and will often be translated differently for these two cases

    They said *that* ...

    They like *that* ice-cream

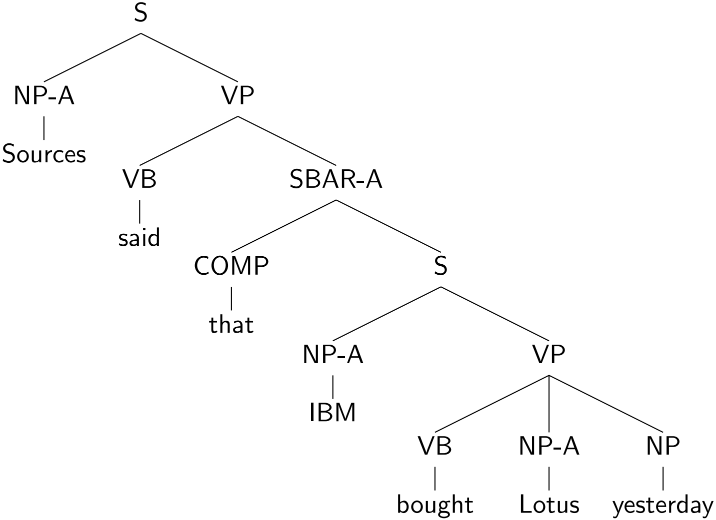
Transfer-Based Approaches

Three phases in translation:

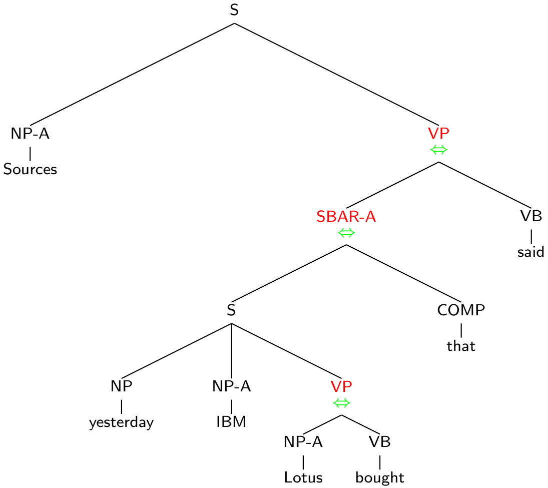
- Analysis: Analyze the source language sentence; for example, build a syntactic analysis of the source language sentence.
- Transfer: Convert the source-language parse tree to a target-language parse tree.
- Generation: Convert the target-language parse tree to an output sentence.

Transfer-Based Approaches

- The “parse trees” involved can vary from shallow analyses to much deeper analyses (even semantic representations).
- The transfer rules might look quite similar to the rules for direct translation systems. But they can now operate on syntactic structures.
- It’s easier with these approaches to handle long-distance reorderings
- The *Systran* systems are a classic example of this approach



⇒ Japanese: *Sources yesterday IBM Lotus bought that said*


S
NP-A
Sources
VP
⇔
SBAR-A
⇔
VB
said
S
COMP
that
NP
yesterday
NP-A
IBM
VP
⇔
NP-A
Lotus
VB
bought

Interlingua-Based Translation

Two phases in translation:

- Analysis: Analyze the source language sentence into a (language-independent) representation of its meaning.
- Generation: Convert the meaning representation into an output sentence.

Interlingua-Based Translation

One Advantage: If we want to build a translation system that translates between n languages, we need to develop n analysis and generation systems. With a transfer based system, we'd need to develop $O(n^2)$ sets of translation rules.

Disadvantage: What would a language-independent representation look like?

Interlingua-Based Translation

- How to represent different concepts in an interlingua?
- Different languages break down concepts in quite different ways:

  German has two words for *wall*: one for an internal wall, one for a wall that is outside

  Japanese has two words for *brother*: one for an elder brother, one for a younger brother

  Spanish has two words for *leg*: *pierna* for a human's leg, *pata* for an animal's leg, or the leg of a table
- An interlingua might end up simple being an intersection of these different ways of breaking down concepts, but that doesn't seem very satisfactory...

Overview

- Challenges in machine translation
- Classical machine translation
- A brief introduction to statistical MT

A Brief Introduction to Statistical MT

- Parallel corpora are available in several language pairs
- Basic idea: use a parallel corpus as a training set of translation examples
- Classic example: IBM work on French-English translation, using the Canadian Hansards. (1.7 million sentences of 30 words or less in length).
- Idea goes back to Warren Weaver (1949): suggested applying statistical and cryptanalytic techniques to translation.

... one naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography. When I look at an article in Russian, I say: "This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode."

(Warren Weaver, 1949, in a letter to Norbert Wiener)

The Noisy Channel Model

- Goal: translation system from French to English
- Have a model $p(e \mid f)$ which estimates conditional probability of any English sentence e given the French sentence f. Use the training corpus to set the parameters.
- A Noisy Channel Model has two components:

$$\begin{array}{rl} p(e) & \textbf{the language model} \\ p(f \mid e) & \textbf{the translation model} \end{array}$$

- Giving:

$$p(e \mid f) = \frac{p(e, f)}{p(f)} = \frac{p(e)p(f \mid e)}{\sum_e p(e)p(f \mid e)}$$

  and

$$\text{argmax}_e p(e \mid f) = \text{argmax}_e p(e)p(f \mid e)$$

More About the Noisy Channel Model

- The **language model** $p(e)$ could be a trigram model, estimated from any data (parallel corpus not needed to estimate the parameters)
- The **translation model** $p(f \mid e)$ is trained from a parallel corpus of French/English pairs.
- Note:
  - The translation model is backwards!
  - The language model can make up for deficiencies of the translation model.
  - Later we'll talk about how to build $p(f \mid e)$
  - Decoding, i.e., finding

    $$\text{argmax}_e p(e) p(f \mid e)$$

    is also a challenging problem.

Example from Koehn and Knight tutorial

Translation from Spanish to English, candidate translations based on $p(Spanish \mid English)$ alone:

Que hambre tengo yo

$\rightarrow$

What hunger have $\quad p(s|e) = 0.000014$

Hungry I am so $\quad p(s|e) = 0.000001$

I am so hungry $\quad p(s|e) = 0.0000015$

Have i that hunger $\quad p(s|e) = 0.000020$

...

Example from Koehn and Knight tutorial (continued)

With $p(Spanish \mid English) \times p(English)$:

Que hambre tengo yo

$\rightarrow$

What hunger have	$p(s\|e)p(e) = 0.000014 \times 0.000001$
Hungry I am so	$p(s\|e)p(e) = 0.000001 \times 0.0000014$
I am so hungry	$p(s\|e)p(e) = 0.0000015 \times 0.0001$
Have i that hunger	$p(s\|e)p(e) = 0.000020 \times 0.00000098$

...