CS 6120/CS4120: Natural Language Processing

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Machine Translation

- Automatically translate one natural language into another.

Mary didn't slap the green witch.

Maria no dió una bofetada a la bruja verde.
(Mary do not gave a slap to the witch green.)

[Some slides are borrowed from Raymond Mooney, Kevin Knight, and Alan Ritter]

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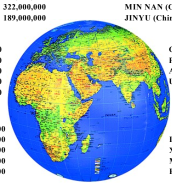
Thousands of Languages Are Spoken

MANDARIN	885,000,000	TURKISH	59,000,000
SPANISH	332,000,000	URDU	58,000,000
ENGLISH	322,000,000	MIN NAN (China)	49,000,000
BENGALI	189,000,000	JINYU (China)	45,000,000
HINDI	182,000,000	GUJARATI	44,000,000
PORTUGUESE	170,000,000	POLISH	44,000,000
RUSSIAN	170,000,000	ARABIC	42,500,000
JAPANESE	125,000,000	UKRAINIAN	41,000,000
GERMAN	98,000,000		
WU (China)	77,175,000	ITALIAN	37,000,000
JAVANESE	75,500,800	XIANG (China)	36,015,000
KOREAN	75,000,000	MALAYALAM	34,022,000
FRENCH	72,000,000	HAKKA (China)	34,000,000
VIETNAMESE	67,662,000		
TELUGU	66,350,000	KANNADA	33,663,000
YUE (China)	66,000,000	ORIYA	31,000,000
MARATHI	64,783,000	PANJABI	30,000,000
TAMIL	63,075,000	SUNDA	27,000,000



Source: Ethnologue

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Word Alignment

- Shows mapping between words in one language and the other.

Mary didn't slap the green witch.
Maria no dió una bofetada a la bruja verde.
(Mary do not gave a slap to the witch green.)

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Translation Quality: what's the current status?

- Achieving literary quality translation is very difficult.
- Existing MT systems can generate rough translations that frequently at least convey the gist of a document.
- High quality translations possible when specialized to narrow domains, e.g. weather forecasts.
- Some MT systems used in ***computer-aided translation*** in which a bilingual human post-edits the output to produce more readable accurate translations.

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Outline

- Issues in machine translation (MT)
- Direct transfer and syntactic transfer
- Statistical MT and noisy channel model
- MT evaluation

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Ambiguity Resolution is Required for Translation

- Syntactic and semantic ambiguities must be properly resolved for correct translation:
  - "John **plays** the guitar." → "John **toca** la guitarra."
  - "John **plays** soccer." → "John **juega** el fútbol."
- An apocryphal story is that an early MT system gave the following results when translating from English to Russian and then back to English:
  - "The spirit is willing but the flesh is weak." ⇒ "The liquor is good but the meat is spoiled."
  - "Out of sight, out of mind." ⇒ "Invisible idiot."

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Issues: Lexical Gaps

- Some words in one language do not have a corresponding term in the other.
  - Rivière (river that flows into ocean) and fleuve (river that does not flow into ocean) in French
  - Schadenfraude (feeling good about another's pain) in German.
  - Oyakoko (filial piety) in Japanese

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Issues: Differing Word Orders

- English word order is subject – verb – object (SVO)
- Japanese word order is subject – object – verb (SOV)

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

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Issues: Differing Word Orders

- English word order is subject – verb – object (SVO)
- Japanese word order is subject – object – verb (SOV)

Word order	English equivalent	Proportion of languages	Example languages
SOV	"She him loves."	45%	Sanskrit, Hindi, Ancient Greek, Latin, Japanese, Korean
SVO	"She loves him."	42%	Chinese, English, French, Hausa, Italian, Malay, Russian, Spanish
VSO	"Loves she him."	9%	Biblical Hebrew, Arabic, Irish, Filipino, Tuareg-Berber, Welsh
VOS	"Loves him she."	3%	Malagasy, Baure
OVS	"Him loves she."	1%	Apalaí, Hixkaryana
OSV	"Him she loves."	0%	Warao, (certain dialects of) Korean

Subject, **O**bject, **V**erb

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Issues: Syntactic Structure is not Preserved Across Translations

The bottle floated into the cave

⇓

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

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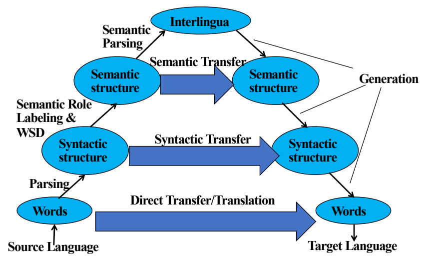
Vauquois Triangle



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Direct Transfer/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 dictionary. For each word in the source language, the dictionary specifies a set of rules for translating that word.

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CLASSIC SOUPS

			Sm.	Lg.
清燉雞湯	57.	House Chicken Soup (Chicken, Celery, Potato, Onion, Carrot)	1.50	2.75
雞飯湯	58.	Chicken Rice Soup	1.85	3.25
雞麵湯	59.	Chicken Noodle Soup	1.85	3.25
廣東雲吞	60.	Cantonese Wonton Soup	1.50	2.75
蕃茄蛋湯	61.	Tomato Clear Egg Drop Soup	1.65	2.95
雲吞湯	62.	Regular Wonton Soup	1.10	2.10
酸辣湯	63.	Hot & Sour Soup	1.10	2.10
蛋花湯	64.	Egg Drop Soup	1.10	2.10
雲蛋湯	65.	Egg Drop Wonton Mix	1.10	2.10
豆腐菜湯	66.	Tofu Vegetable Soup	NA	3.50
雞玉米湯	67.	Chicken Corn Cream Soup	NA	3.50
蟹肉玉米湯	68.	Crab Meat Corn Cream Soup	NA	3.50
海鮮湯	69.	Seafood Soup	NA	3.50

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Direct Transfer/Translation

- Morphological Analysis
  - Mary didn't slap the green witch. →
    Mary DO:PAST not slap the green witch.
- Lexical Transfer
  - Mary DO:PAST not slap the green witch.
  - Maria no dar:PAST una bofetada a la verde bruja.
- Lexical Reordering
  - Maria no dar:PAST una bofetada a la bruja verde.
- Morphological generation
  - Maria no dió una bofetada a la bruja verde.

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An Example of a set of Direct Translation Rules

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*

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Lack of any analysis of the source language causes several problems

- 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

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Possible Solution

- 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.

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Syntactic Transfer

- Simple lexical reordering does not adequately handle more dramatic reordering such as that required to translate from an SVO to an SOV language.

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Syntactic Transfer

- Simple lexical reordering does not adequately handle more dramatic reordering such as that required to translate from an SVO to an SOV language.
- Need syntactic transfer rules that map parse tree for one language into one for another.
  - English to Spanish:
    - NP → ADJ Nom ⇒ NP → Nom ADJ
  - English to Japanese:
    - VP → V NP ⇒ VP → NP V
    - PP → P NP ⇒ PP → NP P

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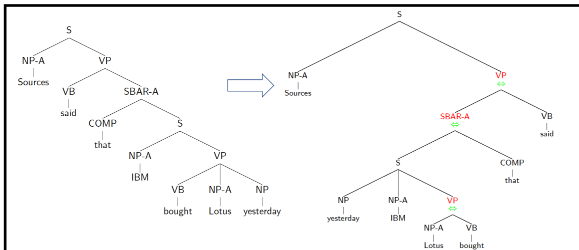

⇒ Japanese: *Sources yesterday IBM Lotus bought that said*

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Statistical MT

- Manually encoding comprehensive bilingual lexicons and transfer rules is difficult.
- SMT acquires knowledge needed for translation from a ***parallel corpus*** or ***bitext*** that contains the same set of documents in two languages.
- The Canadian Hansards (parliamentary proceedings in French and English) is a well-known parallel corpus.
- First align the sentences in the corpus based on simple methods that use coarse cues like sentence length to give bilingual sentence pairs.
- Then align the words in parallel sentences

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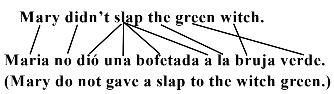
Word Alignment



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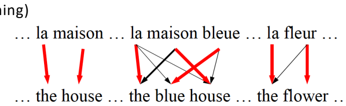
Word Alignment

- Basic idea: co-occurrence between words and phrases (like a bipartite matching)



- The IBM models (will not be discussed in class, but reference here: http://www.cs.columbia.edu/~mcollins/courses/nlp2011/notes/ibm12.pdf)

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English	French	P(f | e)
national	nationale	0.47
	national	0.42
	nationaux	0.05
	nationales	0.03
the	le	0.50
	la	0.21
	les	0.16
	l'	0.09
	ce	0.02
	cette	0.01
farmers	agriculteurs	0.44
	les	0.42
	cultivateurs	0.05
	producteurs	0.02

[Brown et al 93]

After aligning a large number of sentences, we get a probabilistic translation table

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Next: Picking a Good Translation

- A good translation should be ***faithful*** and correctly convey the information and tone of the original source sentence.
- A good translation should also be ***fluent***, grammatically well structured and readable in the target language.
- Final objective:

$$T_{best} = \underset{T \in \text{Target}}{\operatorname{argmax}} \text{ faithfulness}(T, S) \text{ fluency}(T)$$

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Noisy Channel Model

- Based on analogy to information-theoretic model used to decode messages transmitted via a communication channel that adds errors.
- Assume that source sentence was generated by a "noisy" transformation of some target language sentence and then use Bayesian analysis to recover the most likely target sentence that generated it.

Translate foreign language sentence $F = f_1, f_2, \ldots f_m$ to an English sentence $\hat{E} = e_1, e_2, \ldots e_I$ that maximizes $P(E \mid F)$

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Bayesian Analysis of Noisy Channel

$$\begin{aligned}\hat{E} &= \underset{E \in English}{\operatorname{argmax}} P(E \mid F) \\ &= \underset{E \in English}{\operatorname{argmax}} \frac{P(F \mid E) P(E)}{P(F)} \\ &= \underset{E \in English}{\operatorname{argmax}} \underbrace{P(F \mid E)}_{\text{Translation Model}} \underbrace{P(E)}_{\text{Language Model}}\end{aligned}$$

A decoder determines the most probable translation $\hat{E}$ given F

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

Que hambre tengo yo
$\rightarrow$

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

...

(This is where the translation table comes in!)

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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	$p(s\|e)p(e) = 0.000020 \times 0.00000098$

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Evaluating MT

- Human subjective evaluation is the best but is time-consuming and expensive.
- Automated evaluation comparing the output to multiple human reference translations is cheaper and correlates with human judgements.

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Human Evaluation of MT

- Ask humans to estimate MT output on several dimensions.
  - **Fluency**: Is the result grammatical, understandable, and readable in the target language.
  - **Fidelity**: Does the result correctly convey the information in the original source language.

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Computer-Aided Translation Evaluation

- **Edit cost**: Measure the number of changes that a human translator must make to correct the MT output.
  - Number of words changed
  - Amount of time taken to edit
  - Number of keystrokes needed to edit

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Automatic Evaluation of MT

- Collect one or more human ***reference translations*** of the source.
- Compare MT output to these reference translations.
- Score result based on similarity to the reference translations.
  - BLEU

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BLEU

- Determine number of *n*-grams of various sizes that the MT output shares with the reference translations.
- Compute a modified precision measure of the *n*-grams in MT result.

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BLEU Example

Cand 1: Mary no slap the witch green
Cand 2: Mary did not give a smack to a green witch.

Ref 1: Mary did not slap the green witch.
Ref 2: Mary did not smack the green witch.
Ref 3: Mary did not hit a green sorceress.

Cand 1 Unigram Precision: 5/6

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BLEU Example

Cand 1: Mary no slap the witch green.
Cand 2: Mary did not give a smack to a green witch.

Ref 1: Mary did not slap the green witch.
Ref 2: Mary did not smack the green witch.
Ref 3: Mary did not hit a green sorceress.

Cand 1 Bigram Precision: 1/5

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BLEU Example

Cand 1: Mary no slap the witch green.
Cand 2: Mary did not give a smack to a green witch.

Ref 1: Mary did not slap the green witch.
Ref 2: Mary did not smack the green witch.
Ref 3: Mary did not hit a green sorceress.

Clip match count of each *n*-gram to maximum count of the *n*-gram in any single reference translation

Cand 2 Unigram Precision: 7/10

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BLEU Example

Cand 1: Mary no slap the witch green.
Cand 2: Mary did not give a smack to a green witch.

Ref 1: Mary did not slap the green witch.
Ref 2: Mary did not smack the green witch.
Ref 3: Mary did not hit a green sorceress.

Cand 2 Bigram Precision: 4/9

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Modified *N*-Gram Precision

- Average *n*-gram precision over all *n*-grams up to size *N* (typically 4, 2 in this example) using geometric mean.

$$p_n = \frac{\sum_{C \in corpus} \sum_{\text{n-gram} \in C} \text{count}_{\text{clip}}(\text{n-gram})}{\sum_{C \in corpus} \sum_{\text{n-gram} \in C} \text{count}(\text{n-gram})} \qquad p = \sqrt[N]{\prod_{n=1}^{N} p_n}$$

Cand 1: $p = \sqrt[2]{\frac{5}{6}\frac{1}{5}} = 0.408$

Cand 2: $p = \sqrt[2]{\frac{7}{10}\frac{4}{9}} = 0.558$

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Brevity Penalty

- Not easy to compute recall to complement precision since there are multiple alternative gold-standard references and don't need to match all of them.
- Instead, use a penalty for translations that are shorter than the reference translations.
- Define effective reference length, *r*, for each sentence as the length of the reference sentence with the largest number of *n*-gram matches. Let *c* be the candidate sentence length.

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \le r \end{cases}$$

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BLEU Score

- Final BLEU Score: BLEU = *BP* × *p*

Cand 1: Mary no slap the witch green.
Best Ref: Mary did not slap the green witch.

$$c = 6, \quad r = 7, \quad BP = e^{(1-7/6)} = 0.846$$

$$BLEU = 0.846 \times 0.408 = 0.345$$

Cand 2: Mary did not give a smack to a green witch.
Best Ref: Mary did not smack the green witch.

$$c = 10, \quad r = 7, \quad BP = 1$$

$$BLEU = 1 \times 0.558 = 0.558$$

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BLEU Score Issues

- BLEU has been shown to correlate with human evaluation when comparing outputs from different SMT systems.
- However, it is does not correlate with human judgments when comparing SMT systems with manually developed MT (Systran) or MT with human translations.
- Other MT evaluation metrics have been proposed that claim to overcome some of the limitations of BLEU (e.g. METEOR, NIST, etc).

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