Machine Translation

- Introduction
- Why is MT hard?
- Approaches to MT
  - Direct Translation
  - Syntactic Transfer
  - Interlingua
- Parallel Texts
- Statistical Machine Translation
- Computer Aided Translation

Introduction

- Goal: Automate of some or all of the task of translation.
  - Fully-Automated Translation
  - Computer Aided Translation
- What is "translation"?
  - Transformation of utterances from one language to another that *preserves "meaning"*.
- What is "meaning"?
  - Depends on how we intend to use the text.

Machine Translation Uses

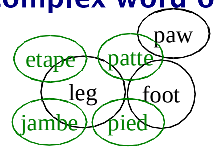
- Fully automated translation
  - Informal translation
    - babelfish
    - e-mail
  - Translating technical writing
    - Manuals
    - Proceedings
  - Translating literary writing
- Computer aided translation
- Deciding what to translate "properly"

Why is MT hard?

- Languages differ from each other in many ways.
  - Lexical Differences
  - Syntactic Differences
  - Semantic Differences
  - Pragmatic Differences
- Ambiguity in the source language
  - Need to resolve ambiguity before we can translate

Why is MT hard:
Lexical Difficulties

- One word can have multiple translations
  - e.g., "know" in English: "savoir" or "connaitre" in French
- Complex word overlap



- Lexical gap: word with no (simple) translation
- Idioms

Why is MT hard:
Syntactic Difficulties

- Different languages use different syntactic structures.
  - SVO vs SOV vs VSO
  - Free word order languages
- To translate, we need to find the correct syntactic structure:
  - Resolve ambiguities
- Some syntactic forms are not possible in some languages
  - Center embedding

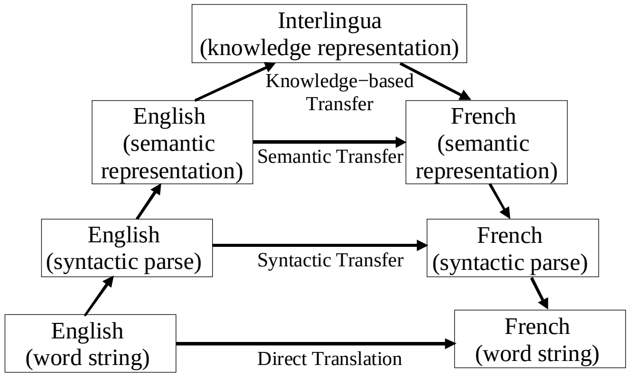
Why is MT hard:
Semantic and Pragmatic Difficulties

- Literal translation does not produce fluent speach:
  - Ich esse gern: *I eat readily.*
  - La botella entro a la cueva flotando: *The bottle entered the cave floating.*
- Literal translation does not preserve semantic information
  - eg., "I am full" translates to "I am pregnant" in French.
- Literal translation does not preserve pragmatic information.
  - e.g., focus, sarcasm

Approaches to MT

- Machine translation makes use many NLP technologies.
  - Word sense disambiguation
  - Tagging
  - Parsing
  - Collocations
  - Document classification

Approaches to MT



Direct Translation

- Series of processing stages
  - Each focused on a single problem (e.g., morphological analysis)
- Stages manipulate strings of tokens
  - No parsing or syntactic structures.
- Each stage performs a uni-directional transformation on the input.

Direct Translation: Example

- Input
  - watashihatsukuenouenopenwojonniageta
- Morphological Analysis
  - watashi ha tsuke no ue no pen wo jon ni ageru PAST
- Lexical transfer of content words
  - I ha desk no ue no pen wo John ni give PAST.
- Preposition re-arrangement
  - I ha pen on desk wo John to give PAST
- SVO rearrangements & determiners
  - I give PAST the pen on the desk to John
- Morphological Generation
  - I gave the pen on the desk to John

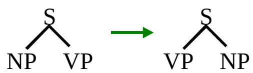
Syntactic Transfer

Three steps:

- Parse the source text.
- Transform the source language syntax tree into the target language.
- Use the target language syntax tree to generate a sentence.

Syntactic Transfer

- Define transformational rules on syntax trees



  - Context-free rules
  - Context-sensitive rules
- Apply rules to the source language syntax tree.
  - Top-down or bottom-up

Interlingua

- Two steps:
  - Translate source text into a universal knowledge representation.
  - Use the knowledge representation to generate a target text.
- Advantages:
  - For *n* languages, we need *n* components (not n^2)
  - Other programs can use the interlingua

Interlingua: Difficulties

- Universal lexicon
  - How do we construct a universal lexicon?
  - Must include all distinctions made by *any* language.
  - How to differentiate similar terms?
    - e.g., "shake" vs "vibrate"
- Universal knowledge format
  - How do we encode "knowledge"
  - What to include? (e.g., pragmatic information?)
- Unnecessary disambiguation
- Preserving ambiguity

Robustness Issues

- Machine translation should usually be robust
  - Always produce a sensible output
- Ways to achieve robustness:
  - Use robust components (robust parsers, etc.)
  - Use fallback mechanisms (e.g., to word-for-word translation)
  - Use statistical techniques to find the translation that is *most likely* to be correct.

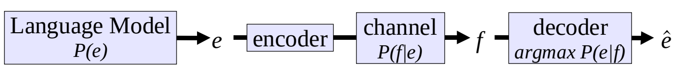
Text Alignment

- Statistical techniques need training data.
- *Parallel texts* (or *bitexts*): one text in multiple languages.
  - Produced by human translation
  - Readily available
- The alignment problem:
  - Which sentences in one language correspond with which sentences in another?
  - One-to-one alignment doesn't work: translators don't translate each sentence separately.

Text Alignment

- Types of alignment
  - "n:m" → n sentences are translated into m sentences.
  - Common types of alignment
    - 1:1 (90%), 1:2, 2:1, 1:3, 3:1
- Algorithms:
  - Dictionary-based methods
  - Length-based methods
  - Arrival vectors
  - Lexical algorithms

Statistical MT



- Noisy Channel Model
  - Assume that we *started* with an English sentence.
  - The sentence was then translated to french.
  - We want to translate it back.
- Use bayes rule:

$$\mathrm{argmax}_e P(e|f) = \mathrm{argmax}_e \frac{P(e)P(f|e)}{P(f)}$$

$$\mathrm{argmax}_e P(e|f) = \mathrm{argmax}_e P(e)P(f|e)$$

Statistical MT (Continued)

$$\mathrm{argmax}_e P(e|f) = \mathrm{argmax}_e P(e)P(f|e)$$

- Two components:
  - P(e): Language Model
  - P(f|e): Translation Model
- Task:
  - P(f|e) translates words
  - P(e) helps puts them in the correct order
- Estimate *P(f|e)* using a parallel corpus.

Problems with Statistical ML

- No notion of syntactic phrases
  - Words often get scrambled
- Difficulties with idioms
- Non-local dependancies
  - N-gram models cannot encode non-local dependancies.
  - Transform sentences to remove non-local dependencies (e.g., un-do movement)
- Sparse data problems

Computer Assisted Translation

- Machine translation performs tedious work for human translators.
  - Provide correct translation for "easy" sentences
  - Provide noisy translation for "difficult" sentences
- Post-editing: human cleans up the output of the machine translator.
  - Often required for human translation, as well.

CAT (continued)

We can make the translation task easier:

- Sublanguages:
  - If we can identify the genre of the text precisely, MT can use more specialized algorithms.
- Pre-editing:
  - Edit source text to use constrained vocabulary and constrained syntactic forms.
- Interactive Systems:
  - The computer can ask a human to help it make better choices.
  - Translation Memory