Why is (machine) translation hard?

- Typological differences
- Translational differences

Evaluation in MT

- Human evaluation of MT Quality
- Automatic evaluation in Language Technology
- Word precision and recall
- BLEU
Why (machine) translation is hard.

Why can’t we just use a dictionary?

Because:

- Languages are constructed differently (typology)
- Translation is not one-to-one
Language typology: morphology

- **Number of morphemes per word**
  - **Isolating**: 1,
    - Chinese, Vietnamese
  - **Synthetic**: >1
  - **Polysynthetic**: >>1

- **Morphemfusion**:
  - **Agglutinative**
    - putting morphemes after each other
    - Japanese, Turkish, Finnish, Sami
  - **Fusion**
    - Russian

Washakotya'tawitsherahetkvhta'se
"He made the thing that one puts on one's body ugly for her"
"He ruined her dress"
(Mohawk, polysynthetic, Src: Wikipedia)

(3.1) uygarlaştıramadıklarımızdanmışsınızımızcasına
uygar +laş+tir +ama +dik +lar+ımız +dan+miş +simz+casr
 civilized +BEC +CAUS +NABL +PART +PL +P1PL +ABL +PAST +2PL +AsIf
“(behaving) as if you are among those whom we could not civilize”

Turkish, agglutinative, polysynthetic J&M, Ch. 3
Language typology: Syntax

- **Word order:**
  - Subject-Verb-Object, SVO
  - SOV
  - VSO

- **Prepositions vs postpositions**

- **Modifiers before or after:**
  - Red wine vs. vin rouge

- **Verb-framed vs. satellite-framed**
  - Marking of direction
  - Marking of manner

Jorge swam across the river.
Jorge cruzó a nado el río.
One language may contain a marker which is lacking — or very different — in another language:

- Tense
- Aspect:
  - She smiles vs she is smiling
- Case
- Definiteness
Translational discrepancies

- Translation is not only about typological differences
- Even between typologically similar languages, the translation is not always one-to-one
# Lexical ambiguities in SL

<table>
<thead>
<tr>
<th>Word form</th>
<th>Norw: &quot;dekket&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>POS</td>
<td>Noun</td>
</tr>
<tr>
<td>Base form</td>
<td>&quot;dekk&quot;</td>
</tr>
<tr>
<td>Homonymy</td>
<td>&quot;dekk på båt&quot;</td>
</tr>
<tr>
<td>Polysemy</td>
<td></td>
</tr>
<tr>
<td>Gloss</td>
<td>&quot;deck&quot;</td>
</tr>
</tbody>
</table>

## More examples

<table>
<thead>
<tr>
<th>Norw</th>
<th>English</th>
</tr>
</thead>
<tbody>
<tr>
<td>Verb/noun  løp, løper, bygg, bygget</td>
<td>fish, run, runs, ring</td>
</tr>
<tr>
<td>Homonymy bygg (Noun), ball</td>
<td>bank, ball, bass</td>
</tr>
<tr>
<td>Polysemy hode</td>
<td>head, bass (music)</td>
</tr>
</tbody>
</table>
Lexical choice in transfer

- The TL may make more distinctions than SL
  - No: tak, Eng: ceiling/roof
  - Eng: grandmother, No: farmor/mormor

- Context dependent choice in TL
  - Strong tea, powerful government
  - Dekke på bordet → set the table
  - Dekke bordet → set/cover the table

- Languages may draw different distinctions
  - Morgen – morning, legg – leg
Syntactic ambiguities in SL

- **Global ambiguities**
  - De kontrollerte bilene → They controlled the cars
  - De kontrollerte bilene er i orden → The controlled cars are OK

- **Local ambiguities:**
  - I saw a star with a telescope.
Structural mismatch

- Thematic divergence/argument switching
  - E: I like Mary.
  - S: Mary me gusta.

- Head switching:
  - E: Kim likes to swim.
  - G: Kim schwimmt gern.

- More divergence:
  - N: Han heter Paul.
  - E: His name is Paul.
  - F: Il s’appell Paul.

- Idiomatic expressions
Beyond sentence meaning

- Tracking the referent,
  No: den/det han/hun
- Metaphors, idioms

- Changre,
- Rhime, rythm
- Deliberate ambiguity, humor
- ...

...
Why is (machine) translation hard?
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- BLEU
Israeli officials are responsible for airport security.
Israel is in charge of the security at this airport.
The security work for this airport is the responsibility of the Israel government.
Israeli side was in charge of the security of this airport.
Israel is responsible for the airport’s security.
Israel is responsible for safety work at this airport.
Israel presides over the security of the airport.
Israel took charge of the airport security.
The safety of this airport is taken charge of by Israel.
This airport’s security is the responsibility of the Israeli security officials.
Translation quality – Human eval.

- Given output of MT system + either
  1. Source text + reference translation (bilingual evaluator)
  2. Source text only (bilingual evaluator)
  3. Reference translation only (monolingual evaluator)
  4. Nothing (output only) (only fluency)

- Rate the translations (one sentence a time)

- Across several dimensions, typically
  - Adequacy: Does the output convey the same as the original/reference translation?
  - Fluency: Is this good target language?
  - and maybe several other dimensions
Judge Sentence

You have already judged 14 of 3064 sentences, taking 86.4 seconds per sentence.

**Source:** les deux pays constituent plutôt un laboratoire nécessaire au fonctionnement interne de l’UE.

**Reference:** rather, the two countries form a laboratory needed for the internal working of the EU.

<table>
<thead>
<tr>
<th>Translation</th>
<th>Adequacy</th>
<th>Fluency</th>
</tr>
</thead>
<tbody>
<tr>
<td>both countries are rather a necessary laboratory the internal operation of the EU.</td>
<td><img src="https://example.com" alt="Adequacy" /></td>
<td><img src="https://example.com" alt="Fluency" /></td>
</tr>
<tr>
<td>both countries are a necessary laboratory at internal functioning of the EU.</td>
<td><img src="https://example.com" alt="Adequacy" /></td>
<td><img src="https://example.com" alt="Fluency" /></td>
</tr>
<tr>
<td>the two countries are rather a laboratory necessary for the internal workings of the EU.</td>
<td><img src="https://example.com" alt="Adequacy" /></td>
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</tr>
<tr>
<td>the two countries are rather a laboratory for the internal workings of the EU.</td>
<td><img src="https://example.com" alt="Adequacy" /></td>
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</tr>
</tbody>
</table>

**Annotator:** Philipp Koehn  
**Task:** WMT06 French-English

Instructions: 5= All Meaning  
4= Most Meaning  
3= Much Meaning  
2= Little Meaning  
1= None  
5= Flawless English  
4= Good English  
3= Non-native English  
2= Disfluent English  
1= Incomprehensible
Challenges in human TQ eval.

- What’s in a number?
  - People use the scales differently
  - Normalize?

- More reliable alternative:
  - Evaluate several systems at once
  - Which translation is better?
Why is (machine) translation hard?
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Evaluation in MT
- Human evaluation of MT Quality
- **Automatic evaluation in Language Technology**
- Word precision and recall
- BLEU
Example 1: Tagging
- Task: Assign part of speech tags to words in text
  - *The/DT grand/JJ jury/NN commented/VBD* ...
- **Gold standard**: A hand-annotated corpus
- Run your tagger on the gold standard
- Compare the results with the gold standard
- **Accuracy**: #(correct tags)/#words

Experimental set up:
- Split an annotated corpus in two parts:
  - Training
  - Testing (=gold standard) not used in training
Common evaluation measures in LT

- **Recall** = \( \frac{tp}{tp + fn} \)

- **Precision** = \( \frac{tp}{tp + fp} \)

- **F-score** = \( \frac{1}{\alpha \frac{1}{P} + (1 - \alpha) \frac{1}{R}} \)

- **F₁** = \( \frac{1}{0.5 \frac{1}{P} + (1 - 0.5) \frac{1}{R}} = \frac{2PR}{R + P} \)

<table>
<thead>
<tr>
<th>System perform</th>
<th>selected</th>
<th>tp: True positive</th>
<th>fp: False positive</th>
</tr>
</thead>
<tbody>
<tr>
<td>target</td>
<td>tp</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not target</td>
<td>fn: False negative</td>
<td>tn: True negative</td>
<td></td>
</tr>
</tbody>
</table>
Some remarks

- Precision and recall:
  - Comes from Information Retrieval (IR)
  - Have become (too?) popular in language technology

- Useful when:
  - There is more than one target/correct answer
  - The targets are known
  - The true negatives are many, uninteresting or unknown
  - The targets are not ranked

- Statistical significance tests are more easily available for accuracy than for P, R, F
Why is (machine) translation hard?
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Adapting P, R, F to MT-eval

- **Precision** = \( \frac{\text{correct}}{\text{output.length}} \)
- **Recall** = \( \frac{\text{correct}}{\text{ref.length}} \)
- **F\(_1\)** = \( \frac{2}{\frac{1}{P} + \frac{1}{R}} = \frac{2}{\frac{\text{correct}}{\text{ref.length}} + \frac{\text{correct}}{\text{output.length}}} = \frac{2 \text{correct}}{\text{output.length} + \text{ref.length}} \)
Precision and Recall of Words

SYSTEM A: Israeli officials responsibility of airport safety

REFERENCE: Israeli officials are responsible for airport security

- Precision
  \[
  \frac{\text{correct}}{\text{output-length}} = \frac{3}{6} = 50\%
  \]

- Recall
  \[
  \frac{\text{correct}}{\text{reference-length}} = \frac{3}{7} = 43\%
  \]

- F-measure
  \[
  \frac{\text{precision} \times \text{recall}}{(\text{precision} + \text{recall})/2} = \frac{.5 \times .43}{(.5 + .43)/2} = 46\%
  \]
Precision and Recall

SYSTEM A: **Israeli officials responsibility of airport safety**

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: **airport security Israeli officials are responsible**

<table>
<thead>
<tr>
<th>Metric</th>
<th>System A</th>
<th>System B</th>
</tr>
</thead>
<tbody>
<tr>
<td>precision</td>
<td>50%</td>
<td>100%</td>
</tr>
<tr>
<td>recall</td>
<td>43%</td>
<td>100%</td>
</tr>
<tr>
<td>f-measure</td>
<td>46%</td>
<td>100%</td>
</tr>
</tbody>
</table>

$\frac{6}{7} \approx 0.86$

$\frac{12}{13} \approx 0.92$

flaw: no penalty for reordering

Chapter 8: Evaluation
Position-independent error rate

- Similar measure to (word) recall + precision
- Reports mistakes – not correctness
- We skip the details - formula
Word Error Rate

- Minimum number of editing steps to transform output to reference
  - **match**: words match, no cost
  - **substitution**: replace one word with another
  - **insertion**: add word
  - **deletion**: drop word

- Levenshtein distance

\[
\text{WER} = \frac{\text{substitutions} + \text{insertions} + \text{deletions}}{\text{reference-length}}
\]

Chapter 8: Evaluation

Levenshtein distance used in
- spell-checking
- OCR
- Translation memory
Example

<table>
<thead>
<tr>
<th>Israeli officials responsible of airport safety</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Israeli officials</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>are</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>responsible</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>for airport security</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Metric</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>word error rate (WER)</td>
<td>57%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System B</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Chapter 8: Evaluation
Why is (machine) translation hard?
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Evaluation in MT
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- Word precision and recall
- **BLEU**
BLEU

- A Bilingual Evaluation Understudy Score
- Main ideas:
  - Use several reference translations
  - Count precision of n-grams:
    - For each n-gram in output: does it occur in at least one reference?
  - Don’t count recall but use a penalty for brevity
    - Why not recall?
$$p_n = \frac{\sum_{C \in \{\text{Candidates}\}} \sum_{n\text{-gram} \in C} \text{Count}_{\text{clip}}(n\text{-gram}, C, C.\text{refs})}{\sum_{C \in \{\text{Candidates}\}} \sum_{n\text{-gram} \in C} \text{Count}(n\text{-gram}, C)}$$

- **Candidates:**
  - the set of sentences output by trans. system
- **Count(n-gram, C):**
  - the number of times $n$-gram occurs in C
- **Count$_{\text{clip}}$(n-gram, C, C.refs):**
  - the number of times the $n$.gram occurs in both
    - C and
    - the reference translation for the same sentence where $n$.gram occurs most frequent
Technicality:

If the same n-gram has several occurrences in a candidate translation sentence, it should not be counted more times than the number of occurrences in the reference sentence with the largest number of occurrences of the same n-gram.
Example, p₃

- Hyp, C:
  - One of the girls gave one of the boys one of the boys.

- C-Refs:
  - A girl gave a boy one of the toy cars
  - One of the girls gave a boy one of the cars.

#
Example, $p_3$

- Hyp, C:
  - *One of the girls gave one of the boys one of the boys.*

- C-Refs:
  - *A girl gave a boy one of the toy cars*
  - *One of the girls gave a boy one of the cars.*

- $\text{Count}_{\text{clip}}(\text{one of the, C, C-refs}) = 2$

<table>
<thead>
<tr>
<th>one of the</th>
<th>of the girls</th>
<th>the girls gave</th>
<th>girls gave one</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 (3)</td>
<td>1</td>
<td>1</td>
<td>0 (1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>gave one of</th>
<th>of the boys</th>
<th>the boys one</th>
<th>boys one of</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 (1)</td>
<td>0 (2)</td>
<td>0 (1)</td>
<td>0 (1)</td>
</tr>
</tbody>
</table>

- $P_3 = 4/11$
How to combine the n-gram precisions?

\[ p_1 \times p_2 \times \cdots \times p_n = \prod_{i=1}^{n} p_i \]

Remember

\[ \ln(\prod_{i=1}^{n} p_i) = \ln(p_1 \times p_2 \times \cdots \times p_n) = \ln(p_1) + \ln(p_2) + \cdots + \ln(p_n) = \sum_{i=1}^{n} \ln p_i \]

One can add weights, typically \( a_i = 1/n \)

\[ \ln(p_1^{a_1} \times p_2^{a_2} \times \cdots \times p_n^{a_n}) = a_1 \ln(p_1) + a_2 \ln(p_2) + \cdots + a_n \ln(p_n) \]

How long n-grams?

- Max 4-grams seems to work best
Brevity penalty

- **c** is the length of the candidates
- **r** is the length of the reference translations:
  - for each C choose the R most similar in length
- **Penalty applies if** **c** < **r**:
  - **BP** = 1 if **c** ≥ **r**
  - **BP** = \( e^{(1-r/c)} \) otherwise

- **BLEU** = **BP** \( \cdot \exp \sum_{i=1}^{n} w_n \ln p_i \)

- \( \ln \text{BLEU} = \min \left(1 - \frac{r}{c}, 0\right) + \sum_{i=1}^{n} w_n \ln p_i \)

\[
c = \sum_{C \in \text{Candidates}} \text{length}(C)
\]
\[
r = \sum_{C \in \text{Candidates}} \text{length}(R \cdot \text{sim} \cdot C)
\]

This is correct
Error in K:SMT