CSCI 1470/2470
Spring 2023

Ritambhara Singh

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Friday

# Deep Learning

DALL-E 2 prompt “a painting of deep underwater with a yellow submarine in the bottom right corner”

# Review: Natural Language Prediction Tasks

*"They went to the grocery store and* **bought…** **bread?**

**milk?**

**rock?**

**Generating artificial sentences:** Here each word is a discrete unit; predicting the next part of the sequence means predicting words

# Review: Natural Language Prediction Tasks

Input: X

**"The story telling was erratic and, at times, slow"**

**"Loved the diverse cast of this movie"**

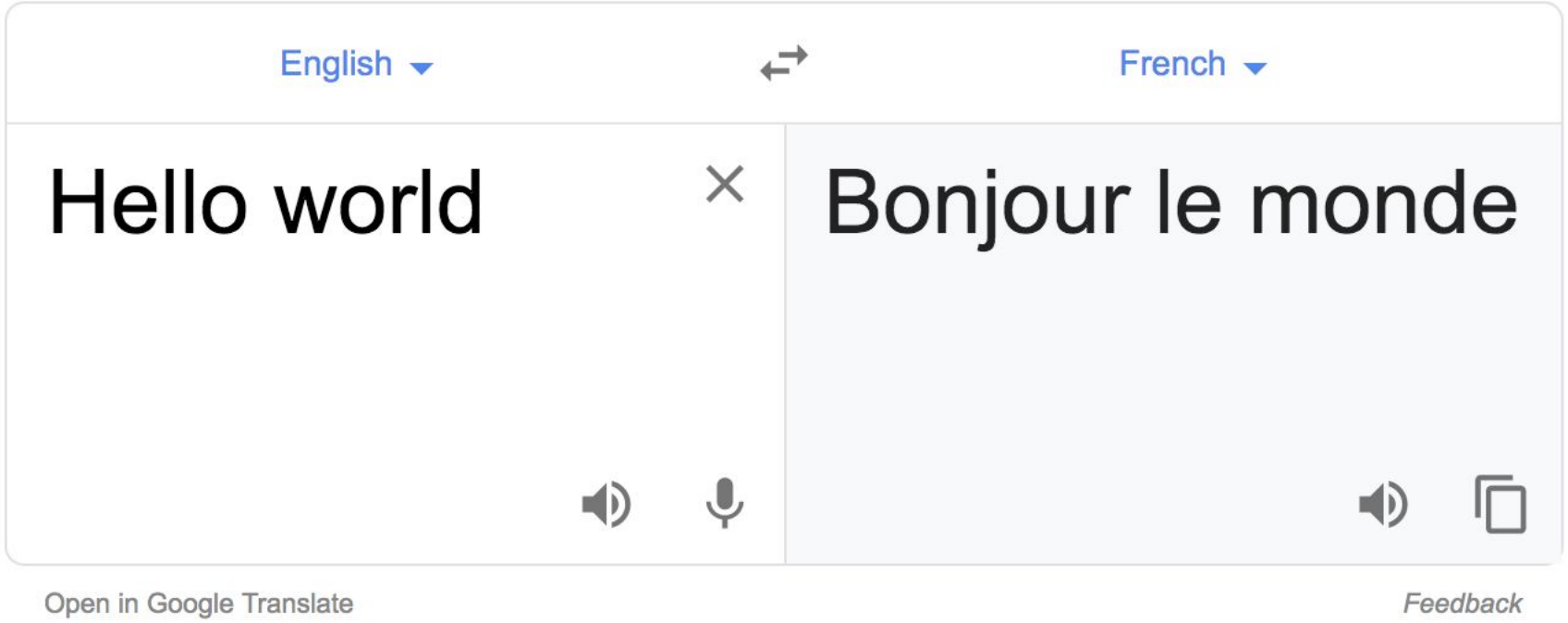
Function: f

Output: Y

"Good review?"

# Machine Translation (MT)

Software that transforms text in a source language into text in a target language



# Why is this an interesting problem to solve?

- **Complex:** languages evolve rapidly and don't have a clear and well-defined structure
  - Example of language change: "awful" originally meant "full of awe", but is now strictly negative

- **Important**: billions per year spent on translation services
  - >CA$2.4 billion spent per year by Canadian government
  - >£100 million spent per year by UK government

- Original approach: create rule-based MT programs

- ***Why doesn't this work?***

# Why rule-based MT doesn’t work (1/3)

Basic rules are regularly broken

Example rule: in English, adjectives come before nouns

“black cat”, “large building”, etc.

Exception: “something”

“something black”, “something large”, etc.

# Why rule-based MT doesn’t work (2/3)

Too many language pairs: Google Translate has 133 languages, or 8,778 pairs

Thus would require 8,778 sets of rules to cover all that Google Translate does

| | | | | | |
|---|---|---|---|---|---|
| ✓ Detect language | Czech | Hebrew | Latin | Portuguese | Tajik |
| Afrikaans | Danish | Hindi | Latvian | Punjabi | Tamil |
| Albanian | Dutch | Hmong | Lithuanian | Romanian | Telugu |
| Amharic | English | Hungarian | Luxembourgish | Russian | Thai |
| Arabic | Esperanto | Icelandic | Macedonian | Samoan | Turkish |
| Armenian | Estonian | Igbo | Malagasy | Scots Gaelic | Ukrainian |
| Azerbaijani | Filipino | Indonesian | Malay | Serbian | Urdu |
| Basque | Finnish | Irish | Malayalam | Sesotho | Uzbek |
| Belarusian | French | Italian | Maltese | Shona | Vietnamese |
| Bengali | Frisian | Japanese | Maori | Sindhi | Welsh |
| Bosnian | Galician | Javanese | Marathi | Sinhala | Xhosa |
| Bulgarian | Georgian | Kannada | Mongolian | Slovak | Yiddish |
| Catalan | German | Kazakh | Myanmar (Burmese) | Slovenian | Yoruba |
| Cebuano | Greek | Khmer | Nepali | Somali | Zulu |
| Chichewa | Gujarati | Korean | Norwegian | Spanish | |
| Chinese | Haitian Creole | Kurdish (Kurmanji) | Pashto | Sundanese | |
| Corsican | Hausa | Kyrgyz | Persian | Swahili | |
| Croatian | Hawaiian | Lao | Polish | Swedish | |

# Why rule-based MT doesn’t work (3/3)

Translations depend on context, and words shouldn’t always be translated literally

| | Spanish | English |
|---|---|---|
| Apertium (rule-based) | Me llamo John | I call me John |

# Why rule-based MT doesn’t work (3/3)

Translations depend on context, and words shouldn’t always be translated literally

| | Spanish | English |
|---|---|---|
| Apertium (rule-based) | Me llamo John | I call me John |
| Google Translate | Me llamo John | My name is John |

- Original approach: create rule-based MT programs (doesn't work well!)

- **Deep learning can help!**
  - Instead of telling the computer rules, it could learn them for itself

What is the first thing we need?

# Parallel Corpora

- We need pairs of equivalent sentences in two languages, called ***parallel corpora***

# Canadian Hansards

- Hansards are transcripts of parliamentary debates
- Canada's official languages are English and French, so everything said in parliament is transcribed in both languages

# Canadian Hansards: Examples

| English | French |
| --- | --- |
| What a past to celebrate. | Nous avons un beau passé à célébrer. |
| We are about to embark on a new era in health research in this country. | Le Canada est sur le point d'entrer dans une nouvelle ère en matière de recherche sur la santé. |

# Canadian Hansards

- We can use this as a dataset for MT!
- Not perfect:
  - *Translations aren't literal*: in the example, "this country" is translated to "Le Canada"
  - *Biased in style*: not everyone speaks like politicians in parliamentary debate
  - *Biased in content*: some topics are never discussed in parliament

# Other parallel corpora

- Europarl, a parallel corpus of 21 languages used in the European Parliament
- EUR-Lex, a parallel corpus of 24 languages used in EU law and public documents
- Japanese-English Bilingual Corpus of Wikipedia's Kyoto Articles

Any questions?

# Problems with parallel corpora

- Expensive to produce
- Tend to be biased towards particular types of text – e.g. government documents containing formal language
- Translations aren't necessarily literal - e.g. "this country" -> "Le Canada"
- Parallel corpora are necessary, **but never perfect**

# Implementing learning-based MT

We have our dataset!

# Example from Hansards

- For example, take the first entry in Hansard's:

edited hansard number 1

hansard révisé numéro 1

# LM approach

- Language modelling works on a word-by-word basis, taking only previous words as input

$$P(w_{t,i}) = P(w_{t,i} \mid w_{s,i-1}, w_{s,i-2}, \dots, w_{s,0})$$

- Where $w_{t,i}$ is the $i^{th}$ word in the target sentence, and $w_{s,i}$ is the $i^{th}$ word in the source sentence

Will it work for MT task?

# Why our LM approach doesn't work for MT

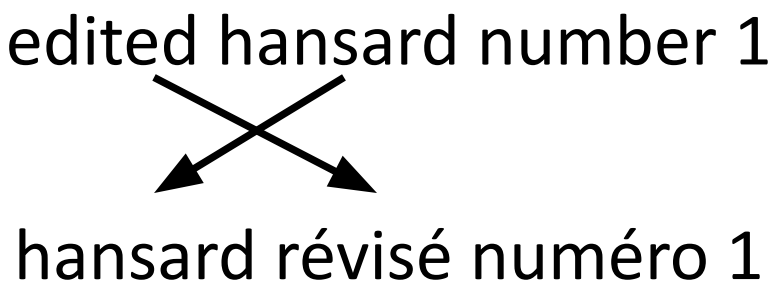
- Language modelling works on a word-by-word basis, taking only previous words as input

$$P(w_{t,i}) = P(w_{t,i} \mid w_{s,i-1}, w_{s,i-2}, \dots, w_{s,0})$$

- Where $w_{t,i}$ is the $i^{th}$ word in the target sentence, and $w_{s,i}$ is the $i^{th}$ word in the source sentence
- However, **it is not a given that the information we need comes in the preceding words**
- The order and length of the source and target sentences are not necessarily equal

# Example from Hansards

- For example, take the first entry in Hansard's:



What should we do?

# Further examples

French: “Londres me manque”

Naive translation: “London I miss”

Correct translation: “I miss London”

French: “Je viens de partir”

Naive translation: “I come of to go”

Correct translation: “I just left”

# Sequence to Sequence (seq2seq)

Thus, we cannot simply use the previous words – we need to ***summarize the source sentence first***

This is called sequence to ***sequence to sequence learning***, or ***seq2seq***

# Sequence to Sequence (seq2seq)

- Instead of:

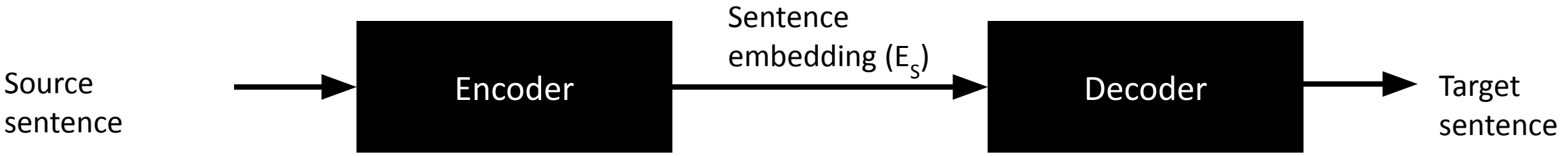
$$P(w_{i,t}) = P(w_{i,t} \mid w_{i-1,s}, w_{i-2,s}, \dots, w_{0,s})$$

Let's do:

$$P(w_{i,t}) = P(w_{i,t} \mid E_S, w_{i-1,t}, w_{i-2,t}, \dots, w_{0,t})$$

Where $E_S$ is a summary, or ***embedding***, of the sentence taken from the source language, and $w_i$ is the $i^{th}$ word of the sentence in the target language

# What will the neural net look like?

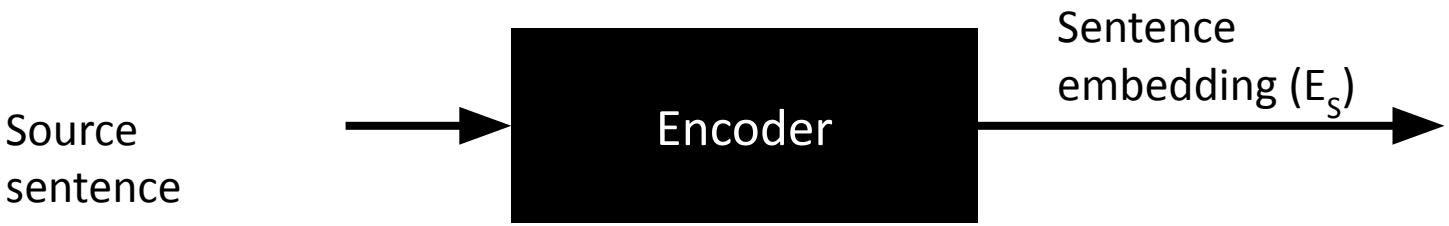



Origin of the encoder/decoder terminology: information theory

- The encoder “compresses” the source sentence into a compact “code”
- The decoder recovers the sentence (but in the target language) from this code

# What will the neural net look like?

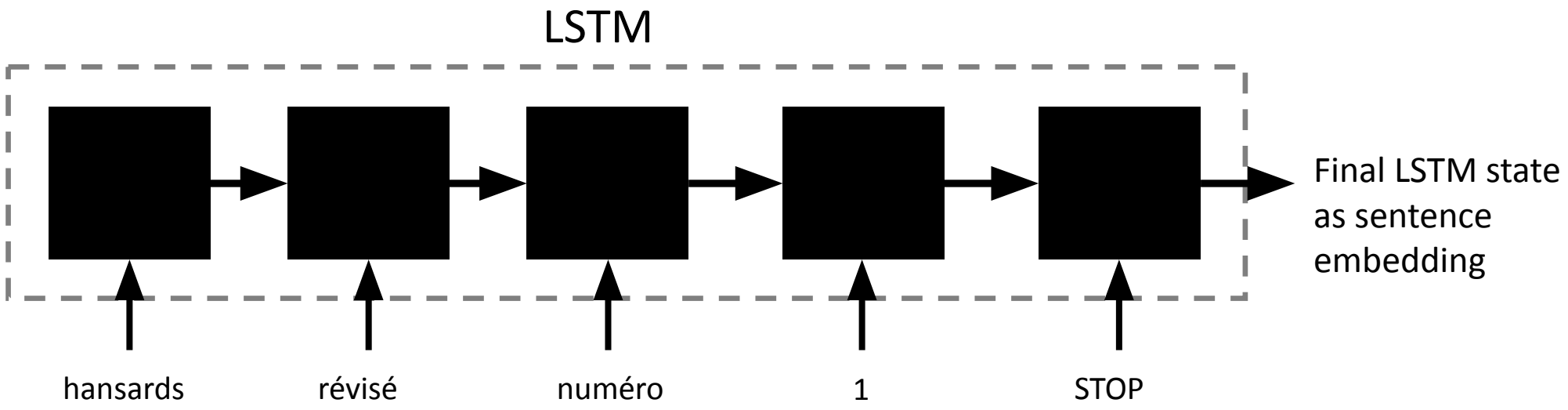
Any ideas?



# Encoder

- To generate the sentence embedding, we need an encoder
- Use an LSTM
- Feed in the source sentence
- Take the final LSTM state as the sentence embedding
- This will be a ***language-agnostic*** representation of the sentence
  - i.e. it will represent the *meaning* of the sentence without being tied to any particular language

# Encoder architecture



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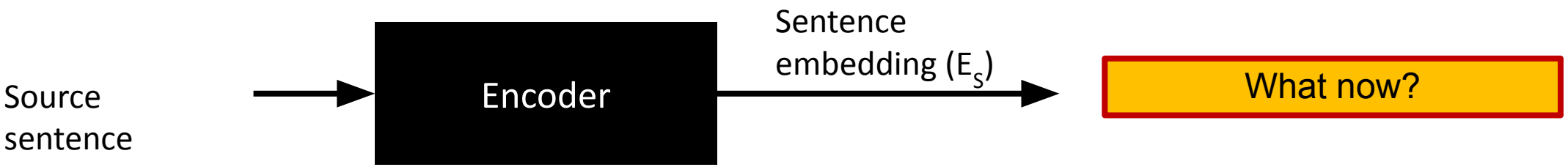
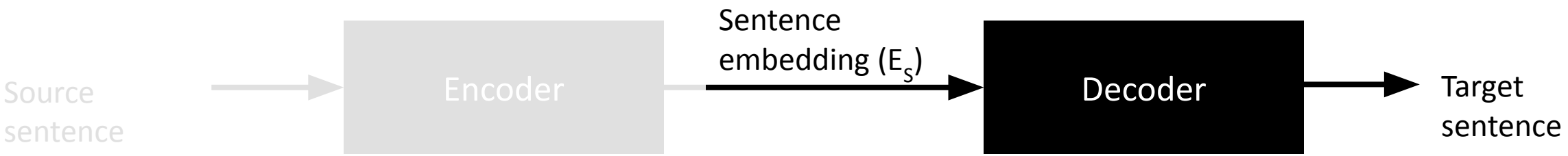


# What will the neural net look like?

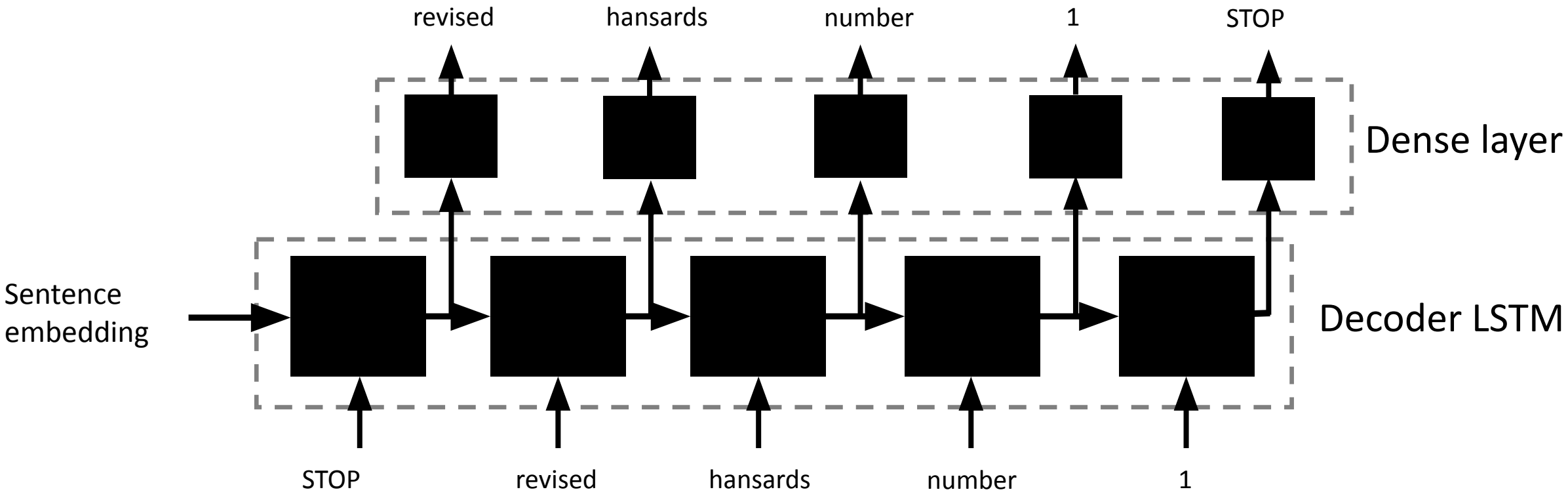
Any ideas?



# Decoder

- We now have a sentence embedding representing the meaning of the source sentence
- Now, let's generate a sentence in the target language with the same meaning
- Use an LSTM again, **with the sentence embedding** as its initial hidden state
- The rest is just like language modeling:
  - Input to the LSTM is the previous word from the target sentence
  - Take each LSTM output and put it through a fully connected layer
  - Softmax to convert to probability distribution over next word in target language

# Decoder architecture



# Putting it all together...

Any questions?

revised hansards number 1 STOP

Dense layer

Decoder LSTM

STOP revised hansards number 1

Encoder LSTM

Final LSTM state as sentence embedding

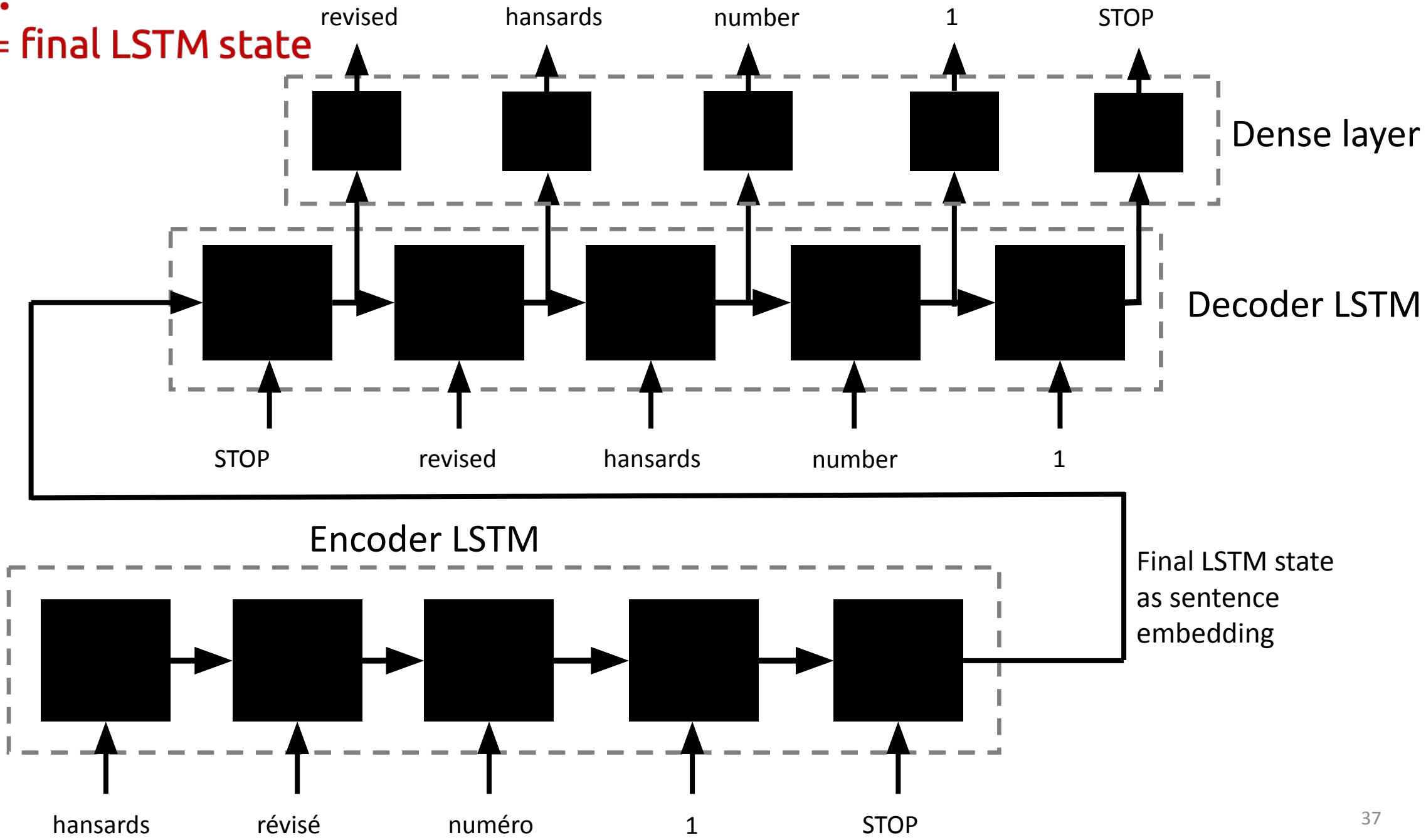
hansards révisé numéro 1 STOP

# Architecture variations

- No one correct answer on how to produce the sentence embedding
- One improvement: instead of taking the final state as the sentence embedding, sum the LSTM states
- Advantage: Less bias towards later words

**Old:**

$E_s$ = final LSTM state



**New:**

$E_s$ = sum of LSTM states

revised hansards number 1 STOP

Dense layer

Decoder LSTM

Sum of LSTM states as sentence embedding

+

STOP revised hansards number 1

Encoder LSTM

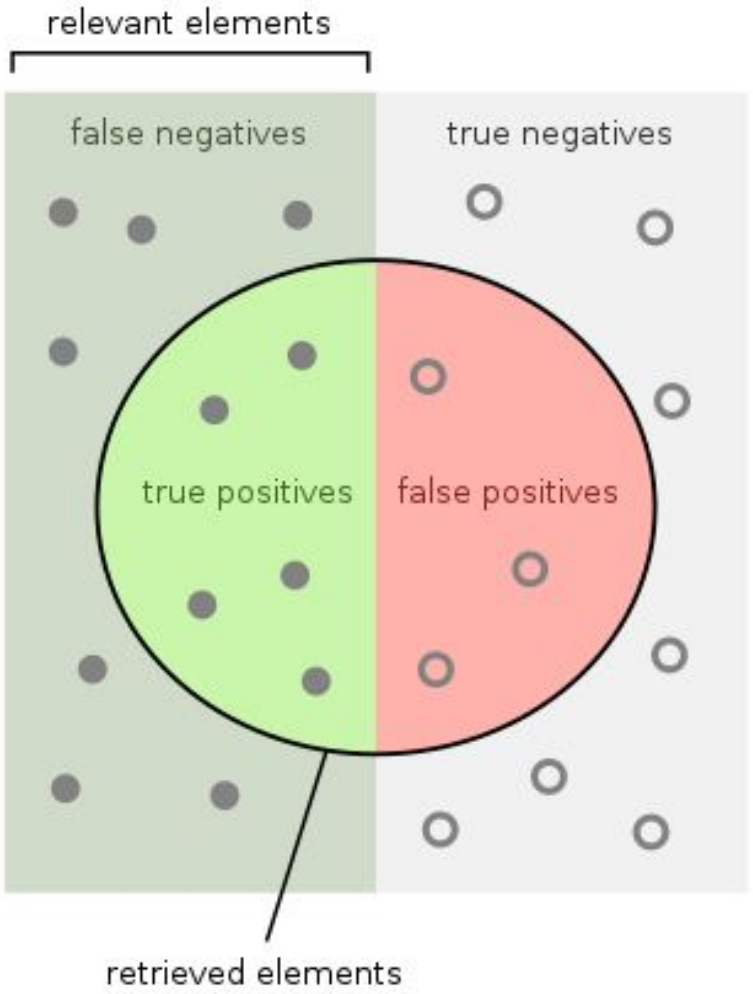
hansards révisé numéro 1 STOP

Any questions?

# Evaluating MT models

i.e. How do we know if a translation is good?

# Precision and Recall




How many retrieved items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are retrieved?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

https://en.wikipedia.org/wiki/Precision_and_recall

# BLEU

- **B**i-**L**ingual **E**valuation **U**nderstudy

- Based on ***precision***:
  fraction of words generated that are in a given ground-truth ("correct" translated sentence)
  - Or, more commonly, that are in one of several given correct translations

- Instead of naïve precision (per word), use n-grams of each sentence
  - For example, in "Sam saw the black cat", check for "Sam saw the", "saw the black", etc. instead of "Sam", "saw", etc.

# ROUGE

- **R**ecall-**O**riented **U**nderstudy for **G**isting **E**valuation

- Based on ***recall***:
  fraction of words in the correct translated sentence that are generated
  - Or, more commonly, that are in one of several given correct translations

- Like BLEU, also looks for n-grams instead of individual words

# Calculate BLEU and ROGUE scores (naively!)

Generated: “BLEU prefers shorter sentences”

Ground-Truth: “BLEU prefers shorter sentences more than ROUGE”

Generated: “BLEU prefers shorter sentences more than ROUGE”

Ground-Truth: “BLEU prefers shorter sentences”

# Do we prefer BLEU or ROUGE?

Generated: “BLEU prefers shorter sentences”

Ground-Truth: “BLEU prefers shorter sentences more than ROUGE”

BLEU score:

ROUGE score:

# Do we prefer BLEU or ROUGE?

Generated: “BLEU prefers shorter sentences more than ROUGE”

Ground-Truth: “BLEU prefers shorter sentences”

BLEU score:

ROUGE score:

# Both are biased

- BLEU favors shorter sentences
- ROUGE favors longer sentences

What should we do?

# Both are biased

- BLEU favors shorter sentences
- ROUGE favors longer sentences

- So, let's use a metric that combines both BLEU and ROUGE
  - i.e. a single metric that tries to assess ***both*** precision and recall (a common thing to do in information retrieval)

How?

# $F_1$ score

- BLEU favors shorter sentences
- ROUGE favors longer sentences
- $F_1$ score is the ***harmonic mean*** of BLEU and ROUGE
- $0 \leqq F_1 \leqq 1$
- **The higher the $F_1$ score, the better the translation**

$$F_1 = \frac{2}{\frac{1}{BLEU} + \frac{1}{ROUGE}} = \frac{2(BLEU \cdot ROUGE)}{BLEU + ROUGE}$$

# Why combine using the harmonic mean?

- More appropriate than arithmetic mean for ***rate*** quantities
  - Precision and recall are both rates (i.e. percentage of matching words)
- More info on why: On Average, You're Using the Wrong Average
- Added benefit: punishes extreme values --- a BLEU score of 0 and a ROUGE score of 1 would result in an $F_1$ score of 0, not 0.5
  - Note that it's not actually possible for one sentence to have both a BLEU of 0 and a ROUGE of 1, but you get the idea...

# Problems with $F_1$

- Does the “correct” translation even exist?
  - Sam saw a cat which was black
  - Sam saw a black thing which was a cat
  - A black cat was seen by Sam
  - Sam saw a black cat
- All above sentences are valid – but some are more or less “natural”
- $F_1$ cannot know this
  - And it may give high scores to unnatural translations if they have high word overlap with known good translations!

# Problems with $F_1$
# Morphologically rich languages

- Here are two translations of “Her village is large” into Shipibo, which is spoken in Peru:

  Jawen jemara ani iki

  Jawen jemaronki ani iki

- Sentence 1: The speaker is claiming the village is large because they have seen it with their own eyes
- Sentence 2: The speaker is claiming the village is large because they were told so by someone else

# Problems with $F_1$
# No understanding of meaning

Target: “F1 score is a flawed metric for evaluating machine translation systems”

Generated 1: “F1 score is an imperfect metric for evaluating machine translation systems”

$F_1$ score: 0.599

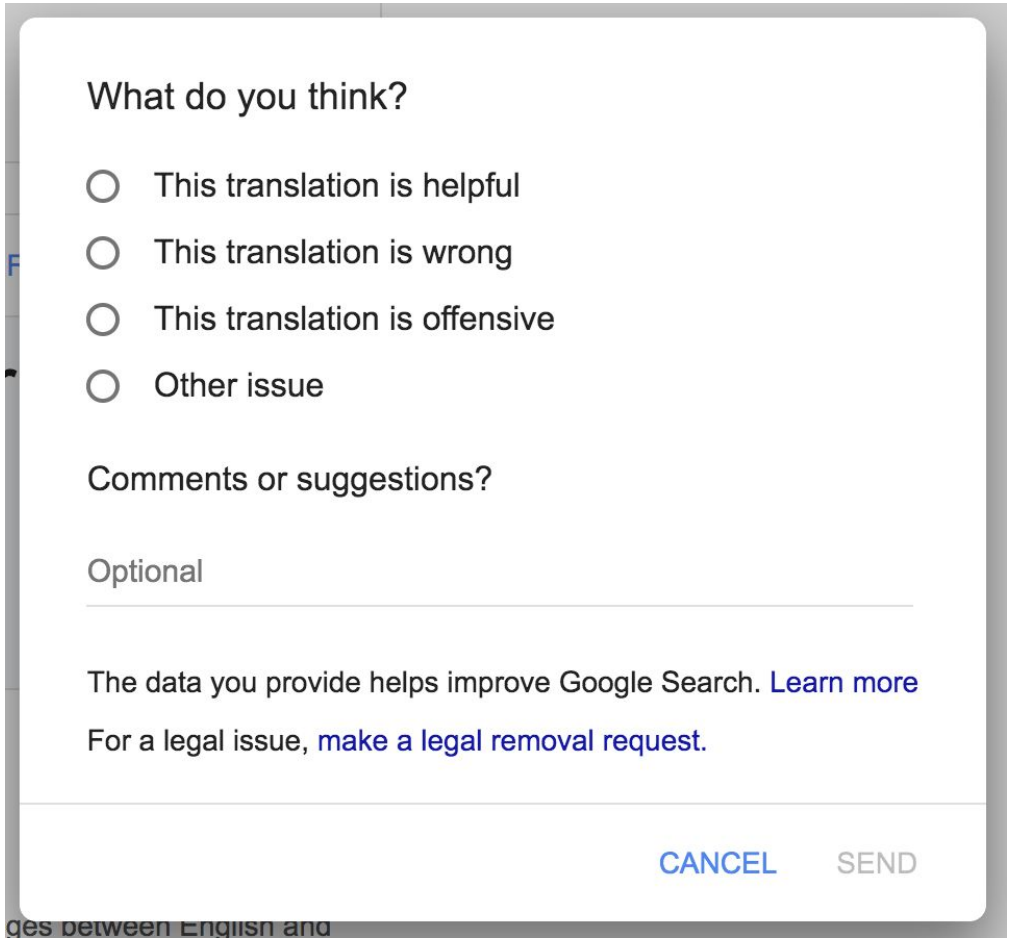
Generated 2: “F1 score is a ***great*** metric for evaluating machine translation systems”

$F_1$ score: 0.710

Is this accurate?

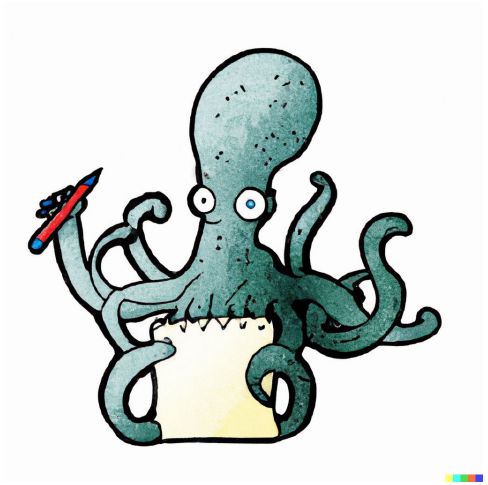
# Human evaluation

- The alternative is to have humans evaluate each translation
- However, this is very time consuming
- Google Translate attempts this with its “Translate Community” – volunteers who rate translations and suggest improvements



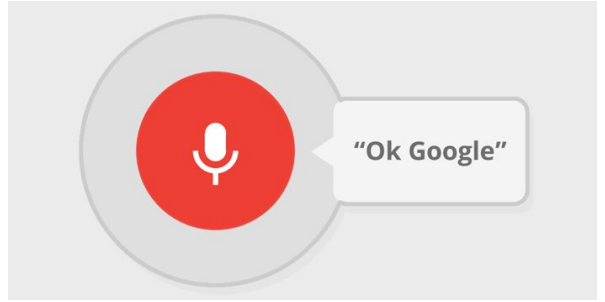
# Recap

Machine translation



Evaluation

- Can train DL models using Parallel Corpora
- Seq-2-seq prediction (encoder-decoder)
- Various applications




- BLEU
- ROGUE
- F1 SCORE

$$F_1 = \frac{2}{\frac{1}{BLEU} + \frac{1}{ROUGE}} = \frac{2(BLEU \cdot ROUGE)}{BLEU + ROUGE}$$

# Extra: Other Applications of seq2seq

- **Text summarization**

- Source: Long text pessage
- Target: Shortened version of input text passage

**Source Text:** Peter and Elizabeth took a taxi to attend the night party in the city.

While in the party, Elizabeth collapsed and was rushed to the hospital.

**Summary:** Elizabeth was hospitalized after attending a party with Peter.

https://blog.floydhub.com/gentle-introduction-to-text-summarization-in-machine-learning/

# Extra: Other Applications of seq2seq

- Text summarization
- **Chatbots**

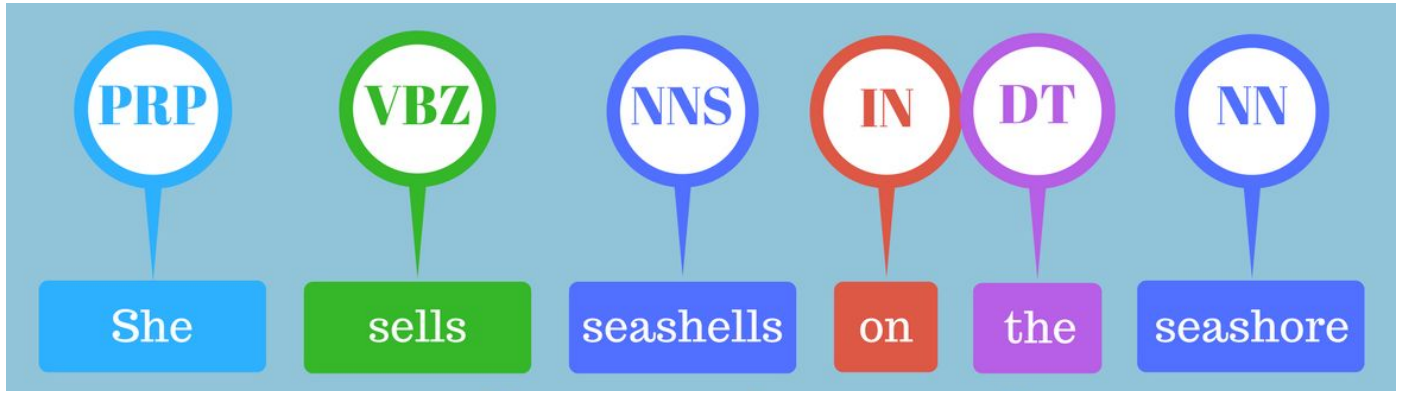
- Source: user question
- Target: chatbot response


https://www.yodlee.com/blog/chatbots-in-banking/

# Extra: Other Applications of seq2seq

- Text summarization
- Chatbots
- **Part of speech tagging**

- Source: natural language sentence
- Target: part-of-speech labels for each word in the input sentence

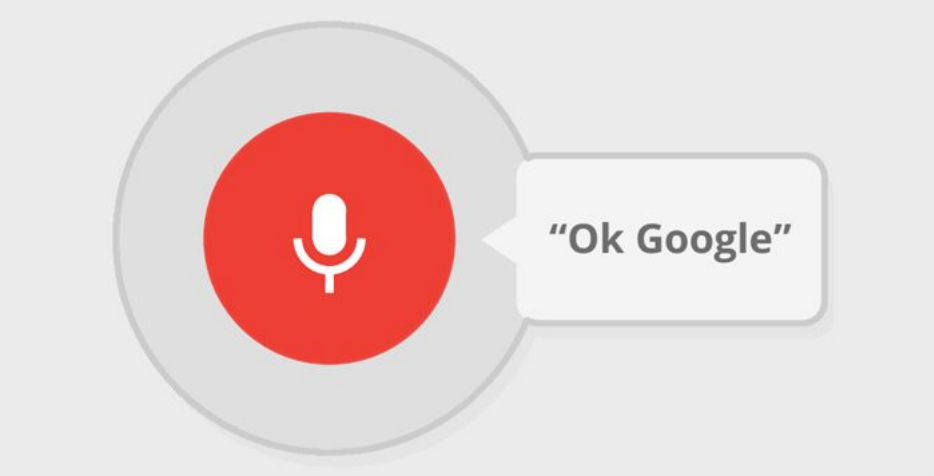



https://medium.com/analytics-vidhya/pos-tagging-using-conditional-random-fields-92077e5eaa31

# Extra: Other Applications of seq2seq

- Text summarization
- Chatbots
- Part of speech tagging
- **Speech recognition**

- Input: sequence of audio samples
- Output: sequence of text words



# Extra: Other Applications of seq2seq

- Text summarization
- Chatbots
- Part of speech tagging
- Speech recognition
- **Speech generation**

- Input: sequence of text words
- Output: sequence of audio samples

- Google Cloud Text to Speech