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Natural Language Processing
IN2361

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Chapter 13
Machine Translation and Encoder-Decoder Models

- content is based on [1] and [2]
- certain elements (e.g. equations or tables) were taken over or taken over in a modified form from [1] and [2]
- citations of [1] and [2] or from [1] and [2] are omitted for legibility
- errors are fully in the responsibility of Georg Groh
- BIG thanks to Dan and James for a great book!
- BIG thanks to Richard and all the guys at Stanford for excellent lecture materials!

Machine Translation

- task: translate sentence from source language to target language

L'homme est né libre, et partout il est dans les fers

⇩

Man is born free, but everywhere he is in chains

- 1950- … : early machine translation: rule-based systems based on bilingual dictionaries

[3]

Machine Translation

Use cases:

- Information access: translate instructions on web (e.g. recipes, newspaper articles or Wikipedia articles)

- Post-editing: produce draft translation for post-editing by human translator (computer-aided translation (CAT))
- Localization: adapt content to particular language community
- In-the-moment communication: incremental translation, translating speech on-the-fly, image-centric translation

Machine Translation: Statistical Models

- 1990s-2010s: core idea: learn probabilistic model from data

- find best sentence y in target language given a source language sentence x:

$$\mathrm{argmax}_y P(y|x)$$

$$= \mathrm{argmax}_y \underbrace{P(x|y)}\underbrace{P(y)}$$

Translation Model

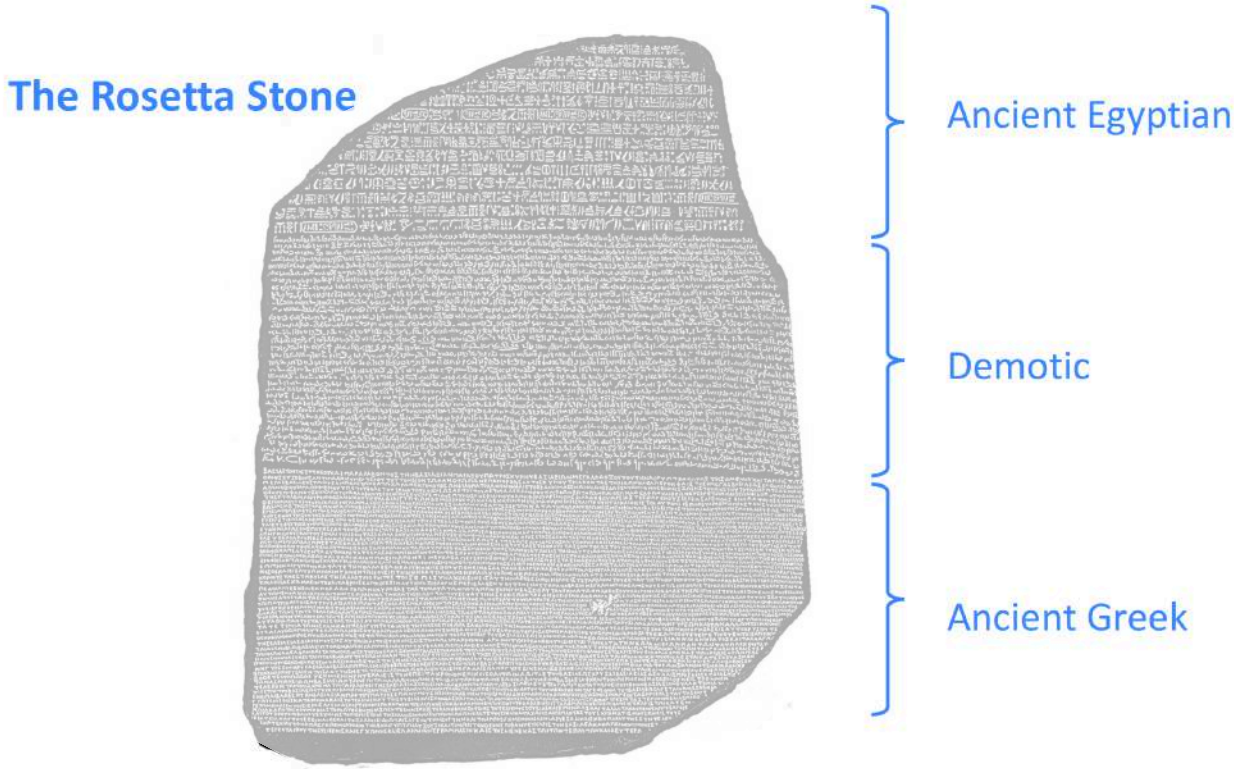
Models how words and phrases should be translated.
Learnt from parallel data.

Language Model

Models how to write good English.
Learnt from monolingual data.

Machine Translation: Statistical Models

- translation model $P(x|y)$: large amounts of parallel data required

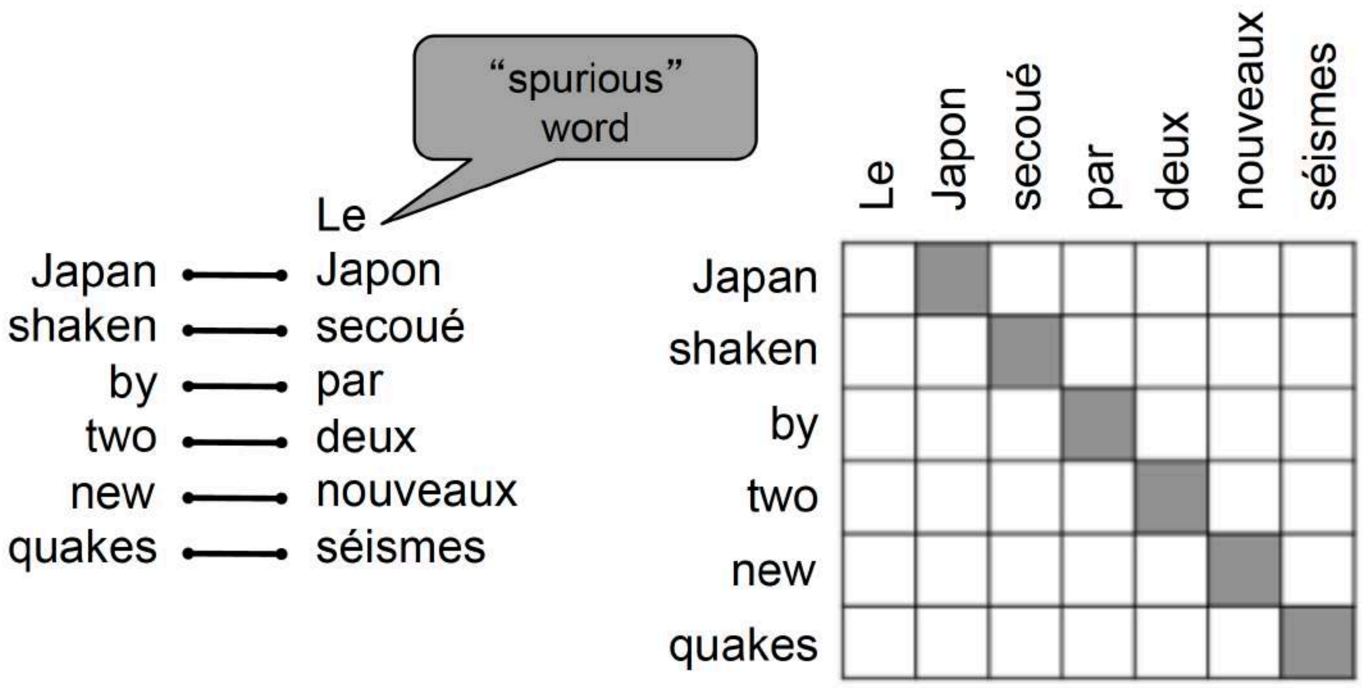


- more accurately, we need to learn $P(x, a|y)$, where a is an alignment between source sentence x and target sentence y

Alignment

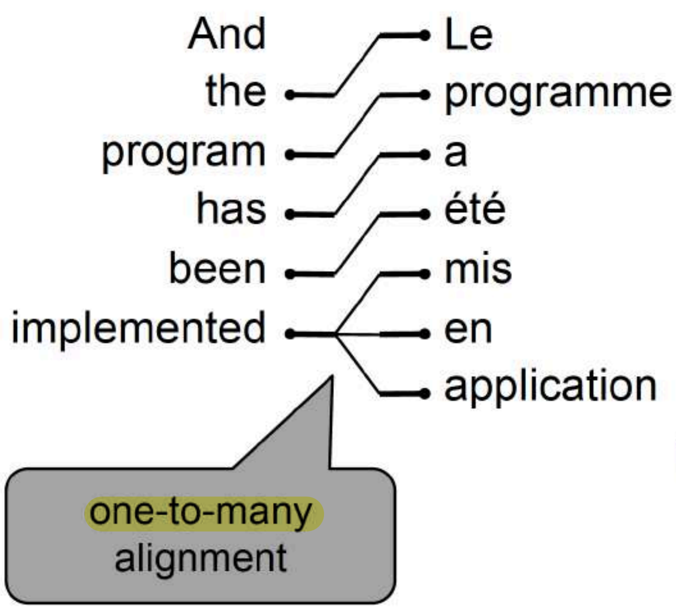
- alignment: correspondence between particular words in translated sentence pair

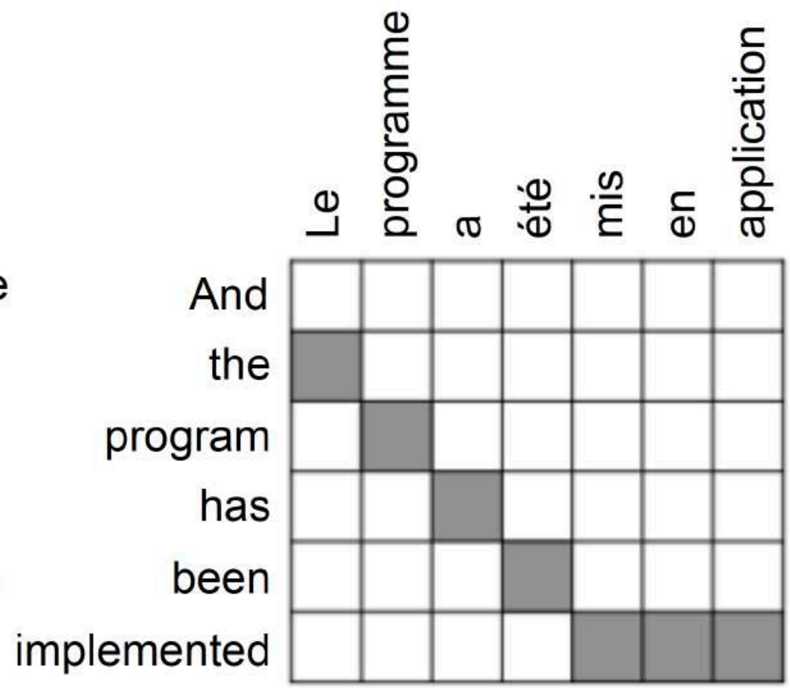
- some words may have no counterpart



Alignment

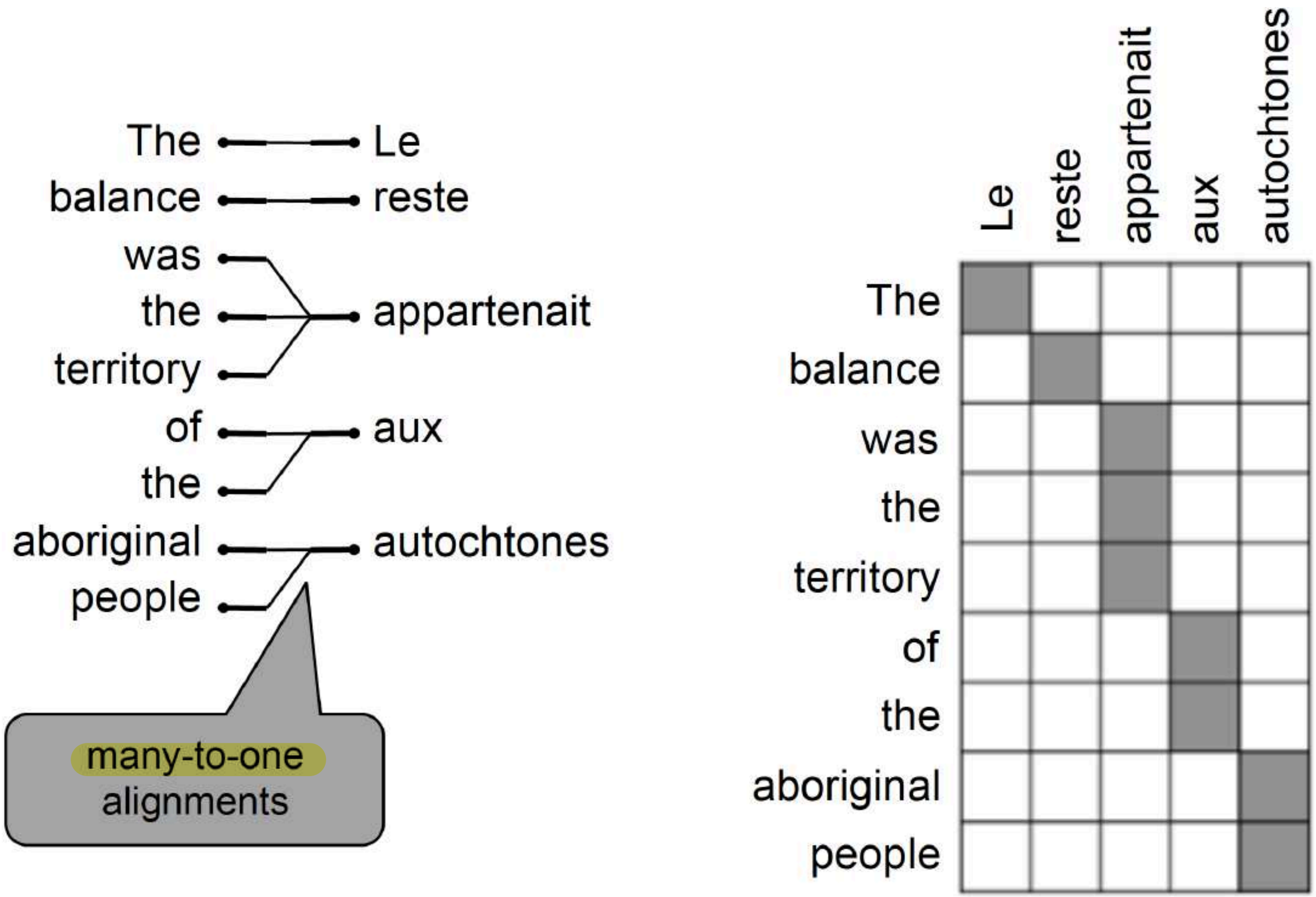
can be one-to-many ("fertile" words)





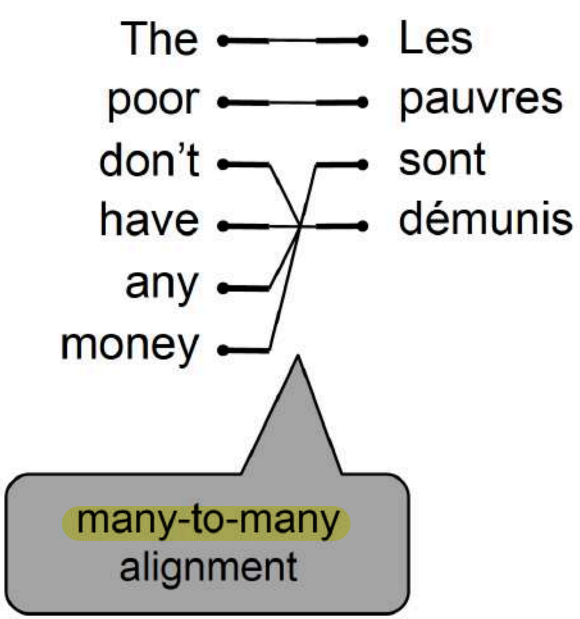
Alignment

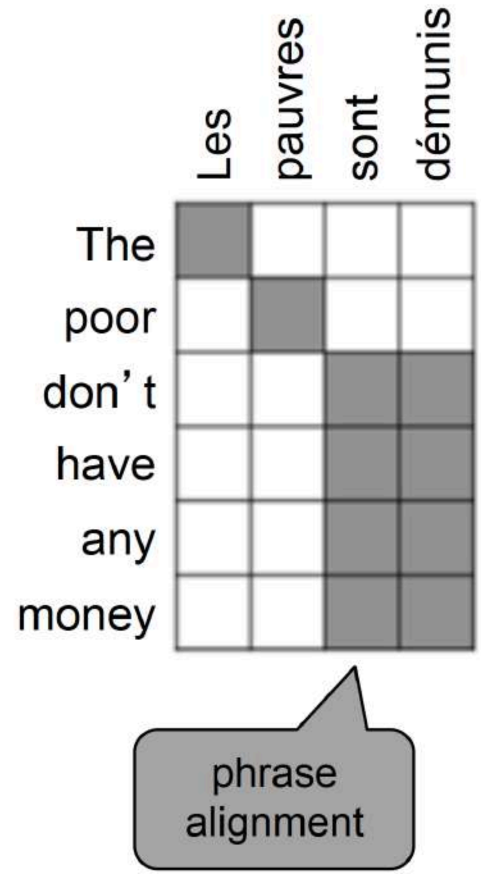
or many-to-one



Alignment

or many-to-many (phrase level)





Statistical Models

- best systems extremely complex
- lots of important details
- many separately-designed subcomponents
- lots of feature engineering
  - need to design features to capture particular language phenomena
- require compiling and maintaining extra resources: e.g. tables of equivalent phrases
- → lots of human effort to maintain for each language pair

→ use **Neural Machine Translation (NMT)**

Sequence to Sequence (seq2seq)/ Encoder-Decoder Networks

- In previous chapters:
  - Map input sequence to single score (e.g. sentiment classification)
  - Sequence labelling: map each word to label (e.g. part-of-speech labelling)
- Seq2seq/Encoder-Decoder Networks: Output is complex function of entire input → no direct mapping between words
- Seq2seq in Machine translation:
  - English: *He wrote a letter to a friend*

    Japanese: *tomodachi ni tegami-o kaita*

    friend to letter wrote
  - 大会/General Assembly 在/on 1982年/1982 12月/December 10日/10 通过了/adopted 第37号/37th 决议/resolution ， 核准了/approved 第二次/second 探索/exploration 及/and 和平peaceful 利用/using 外层空间/outer space 会议/conference 的/of 各项/various 建议/suggestions 。

    On 10 December 1982 , the General Assembly adopted resolution 37 in which it endorsed the recommendations of the Second United Nations Conference on the Exploration and Peaceful Uses of Outer Space .

Encoder-Decoder Networks

- In general: Encoder-decoder networks solve seq2seq problems, such as:
  - Machine translation
  - Summarization (map long text to short)
  - Dialogue generation (map user input to system output)
  - Semantic parsing (map string of words to semantic representation)
  - …..

Language Divergences and Typology

- Models need to consider linguistic differences among languages

- Word Order Typology
  - Position of verb compared to subject/object

    S V O
    - English: *He wrote a letter to a friend*

    S O V
    - Japanese: *tomodachi ni tegami-o kaita*
      friend to letter wrote

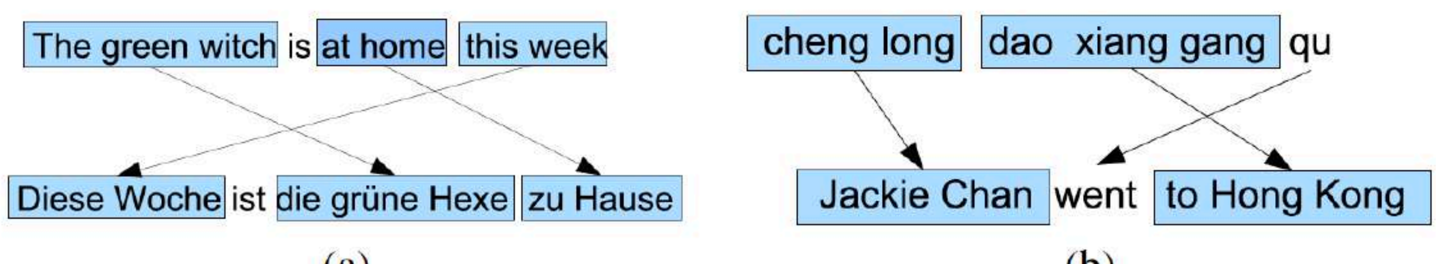
    V S O
    - Arabic: *katabt risāla li ṡadq*
      wrote letter to friend

  - Adjective before/after noun

    Spanish *bruja verde*

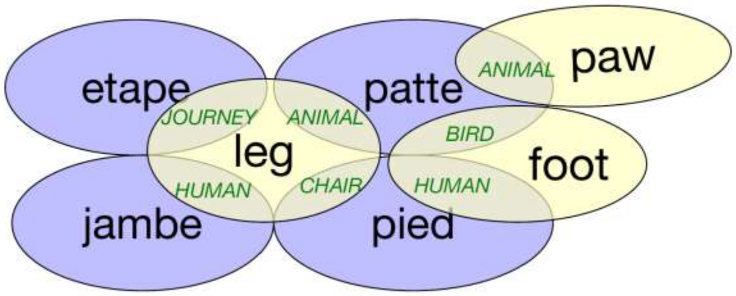
    English *green witch*

  - Adverb positions:



Language Divergences and Typology

- Lexical Divergences
  - Words with multiple meanings
  - Lexical gap: specific word not existing



- or more than one word:

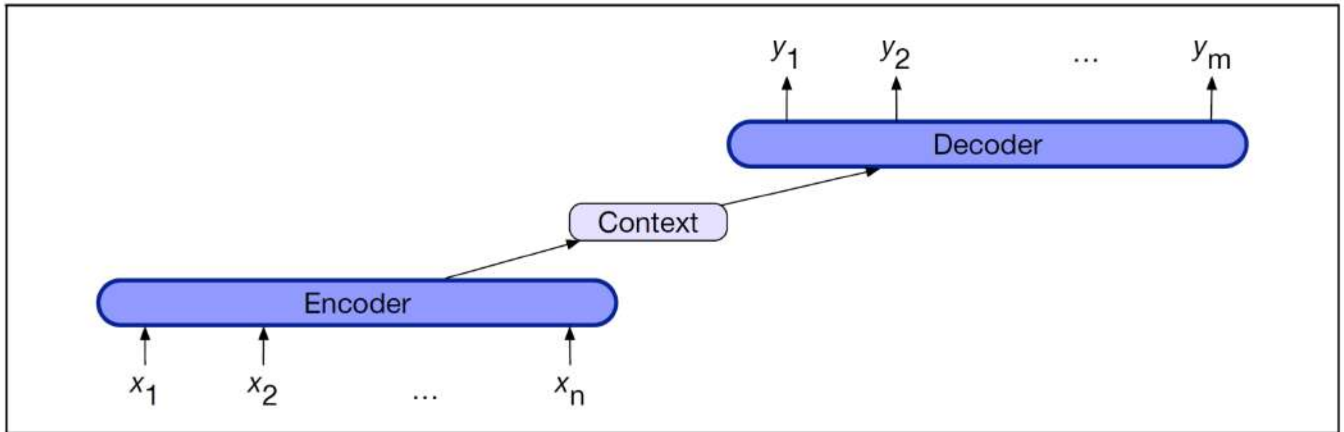
  English: heaven, sky; German: Himmel
  English: wall; German: Mauer, Wand
  English: Brother; Chinese: gege *older brother*, didi *younger brother*

- Referential density: Languages with implicit pronouns and references

  [El jefe]$_i$ dio con un libro. $\emptyset_i$ Mostró a un descifrador ambulante.
  [The boss] came upon a book. [He] showed it to a wandering decoder.

Encoder-Decoder Networks

- models capable of generating contextually appropriate, arbitrary length, output sequences
- 3 parts:
  - Encoder: accepts input sequence x_1^n
    → generates contextualized representation h_1^n
  - Context vector c: function of h_1^n, conveys essence of input to decoder
  - Decoder: accepts input c
    → generates hidden states h_1^m, from which output sequence y_1^m can be obtained
- Can use RNNs / LSTMs, CNNs or Transformer architectures



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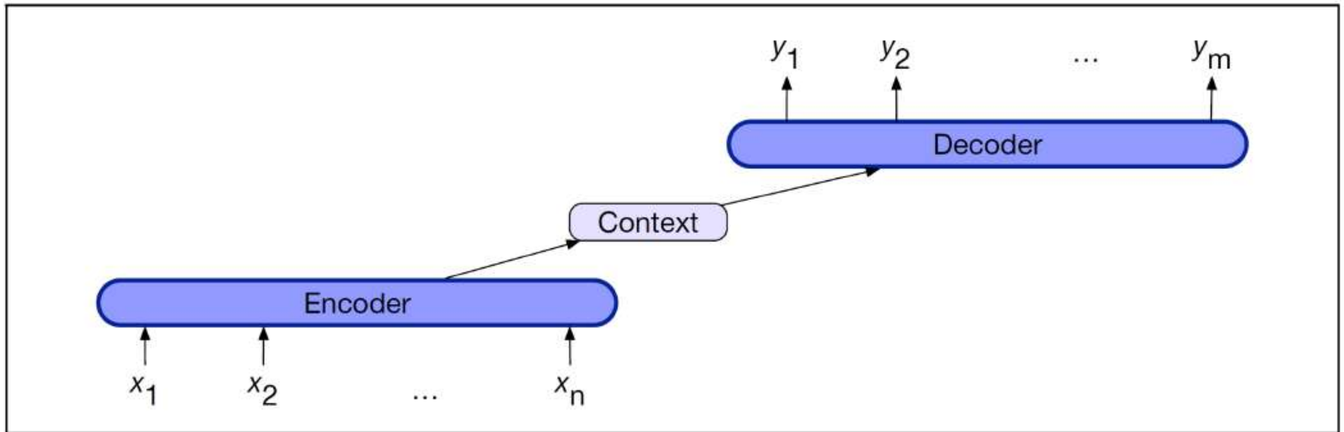
Older notation from Jurafsky: $x_1^n == x_{1:n}$



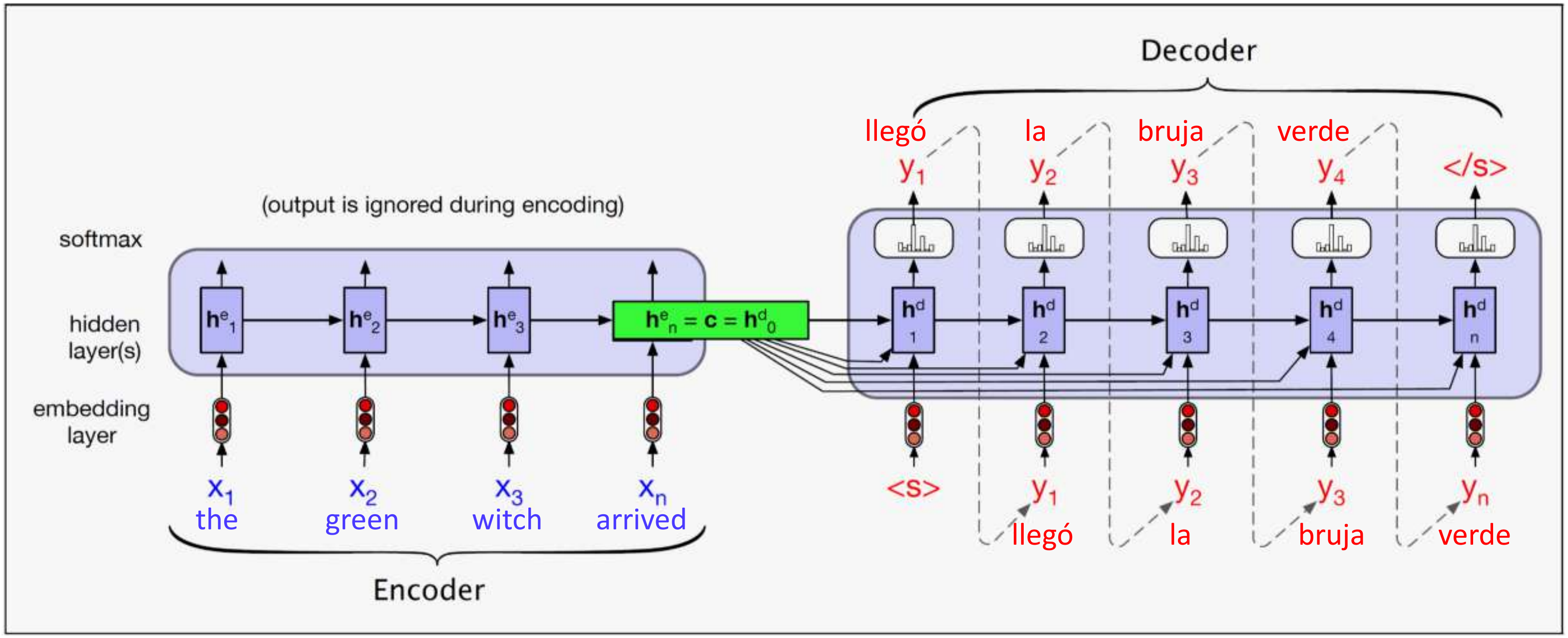
Encoder-Decoder with RNNs

- Recap: Autoregressive language model:

$$p(y) = p(y_1)p(y_2|y_1)p(y_3|y_1, y_2) \dots p(y_m|y_1, \dots, y_{m-1})$$

- Adaptions for translation model from source to target language:
  - add sentence separation at end of source text
  - Conditional language model: condition on source text

$\rightarrow p(y|x) = p(y_1|x)p(y_2|y_1, x)p(y_3|y_1, y_2, x) \dots p(y_m|y_1, \dots, y_{m-1}, x)$



Training Encoder-Decoder Networks

- Training data: tuples of source-target pairs
- Approach
  - Give source text to model
  - Starting with separator token: train autoregressively to predict next target word
  - Calculate loss for each token
  - Average token losses for sentence level loss

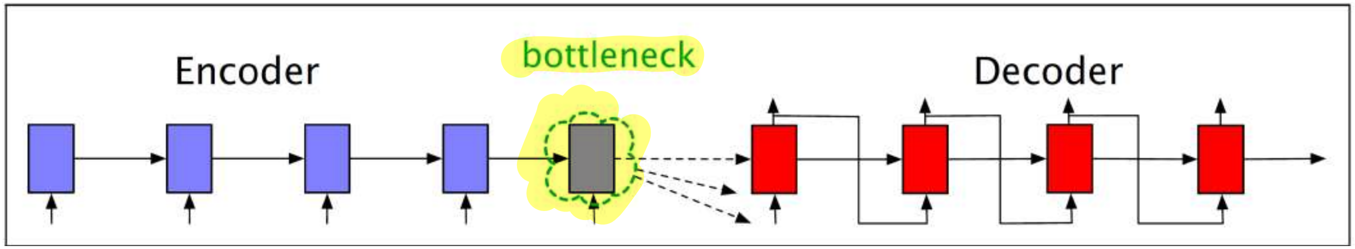
- Teacher forcing
  - Inference: Previous prediction as input for next word
  - Training: Gold target token instead of prediction as input

  → not propagate wrong predictions

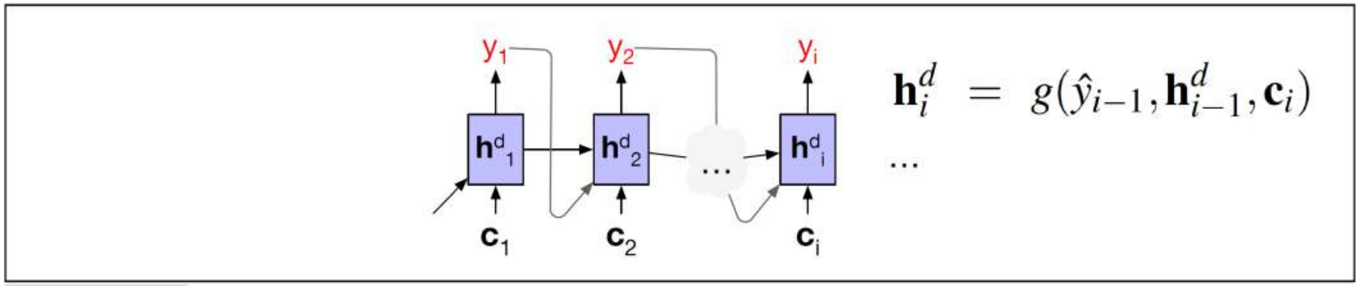
  → speed up training

Attention

- Bottleneck problem:
  - Encoder final state only info about source sentence for decoder
  - → must encode ALL information in one neuron



- Attention mechanism: Include all encoder hidden states in context vector
  - Weighted sum of encoder hidden states
    → focus on relevant part in source text
  - Context vector different for each decoding step



Dot-Product Attention

- Calculate relevance of each encoder state to i-th decoder state:
  - Similarity score between *j*-th encoder and *i*-th decoder hidden states:

$$score(\mathbf{h}^d_{i-1}, \mathbf{h}^e_j) \;=\; \mathbf{h}^d_{i-1} \cdot \mathbf{h}^e_j$$

→ Normalize score and repeat for each encoder state

$$\begin{aligned}\alpha_{ij} &= \boxed{\mathrm{softmax}}(score(\mathbf{h}^d_{i-1}, \mathbf{h}^e_j)\ \boxed{\forall j \in e}) \\ &= \frac{\exp(score(\mathbf{h}^d_{i-1}, \mathbf{h}^e_j))}{\sum_k \exp(score(\mathbf{h}^d_{i-1}, \mathbf{h}^e_k))}\end{aligned}$$

- Possibility to include weights in score function: $score(\mathbf{h}^d_{i-1}, \mathbf{h}^e_j) \;=\; \mathbf{h}^d_{t-1} \mathbf{W}_s \mathbf{h}^e_j$
  - Weights optimized during training

→ Learn aspects relevant in current application

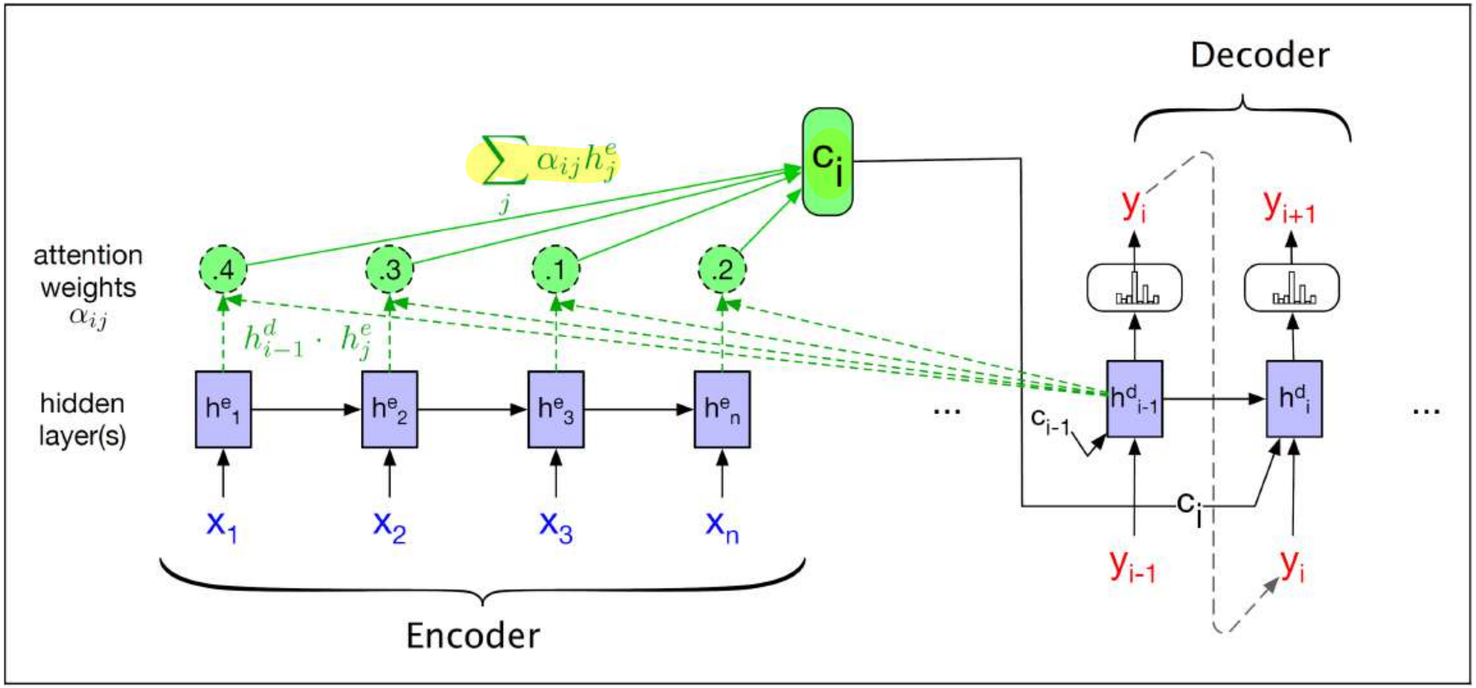
→ Allow different dimensions in encoder and decoder

Dot-Product Attention

- Given distribution α, calculate fixed-length context vector for i-th decoder hidden state

$$\mathbf{c}_i = \sum_j \alpha_{ij} \mathbf{h}^e_j$$

- Encoder-decoder with dynamic context vector:



Advantages and Disadvantages of NMT

Advantages of NMT

Compared to SMT, NMT has many advantages:

- Better performance
  - More fluent
  - Better use of context
  - Better use of phrase similarities
- A single neural network to be optimized end-to-end
  - No subcomponents to be individually optimized
- Requires much less human engineering effort
  - No feature engineering
  - Same method for all language pairs

Advantages and Disadvantages of NMT

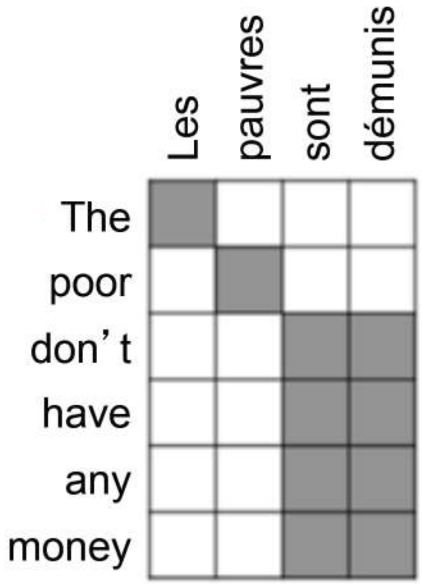
Disadvantages of NMT?

Compared to SMT:

- NMT is less interpretable
  - Hard to debug
- NMT is difficult to control
  - For example, can't easily specify rules or guidelines for translation
  - Safety concerns!

Advantages of Attention

- significantly improves NMT performance
  - very useful to allow decoder to focus on certain parts of the source
- solves the bottleneck problem
  - allows decoder to look directly at source; bypass bottleneck
- helps with vanishing gradient problem
  - Provides shortcut to faraway states
- provides some interpretability
  - by inspecting attention distribution, we can see what the decoder was focusing on
  - we get alignment for free! (we never explicitly trained an alignment system; network just learned alignment by itself)

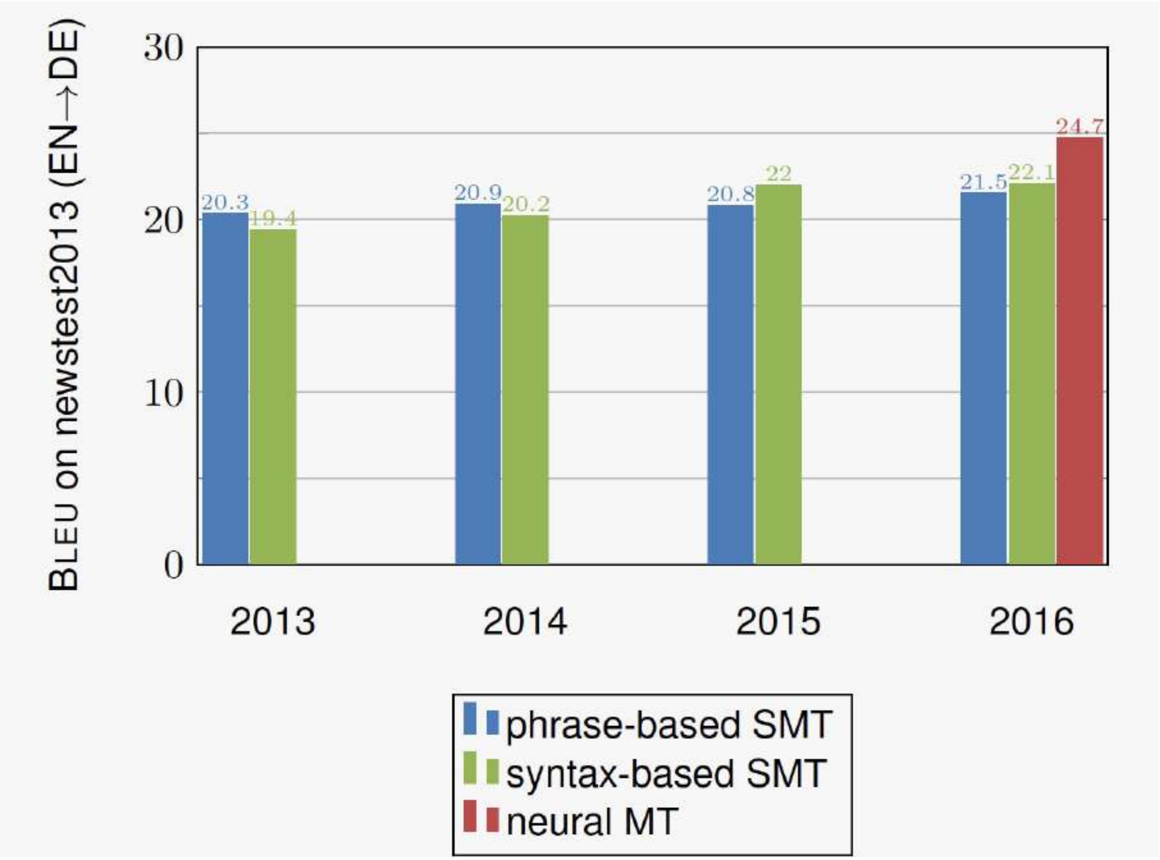


Evaluation of Machine Translation

- BLEU (Bilingual Evaluation Understudy): compare machine translation to one or more human translations & compute similarity score based on:
  - n-gram precision (usually n=3 or 4)
  - & extra penalties for too short machine translations

- disadvantages of BLEU: many valid translations exist → poor BLEU score of an otherwise good translation that just differs in n-gram overlap from the available human translations in corpus

Progress in Machine Translation

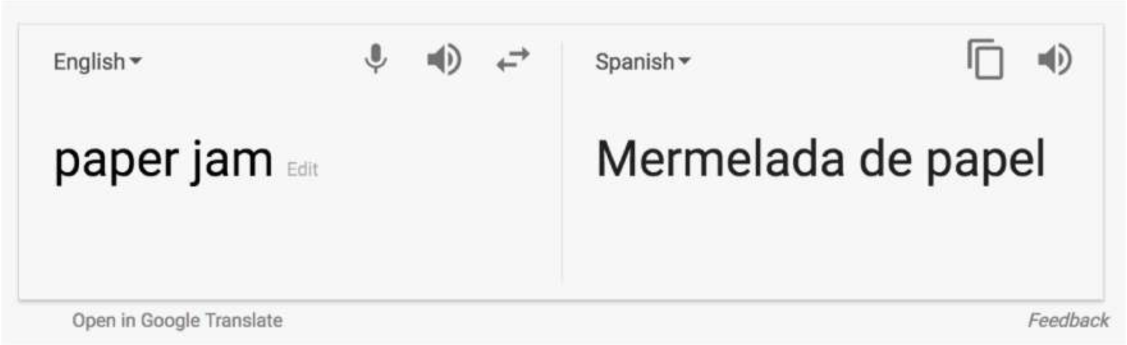


[4]

- 2014: first seq 2 seq paper
- 2016: Google translate switches from SMT to NMT

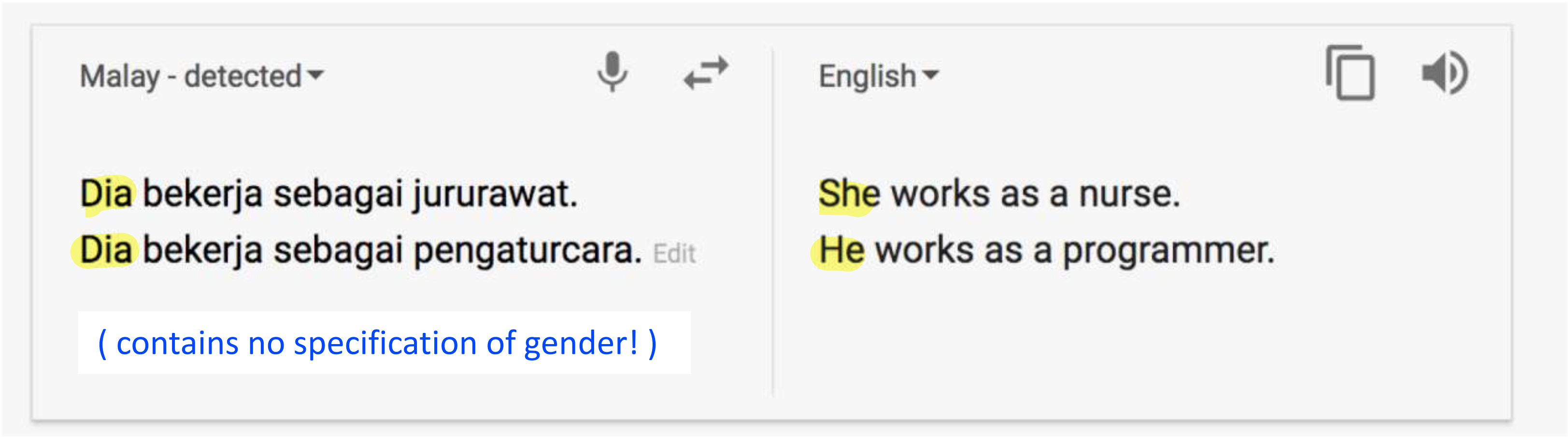
Prevailing Problems

- out-of-vocabulary words
- domain mismatch between train and test data
- maintaining context over longer text
- low-resource language pairs
- using common sense still hard:



Prevailing Problems

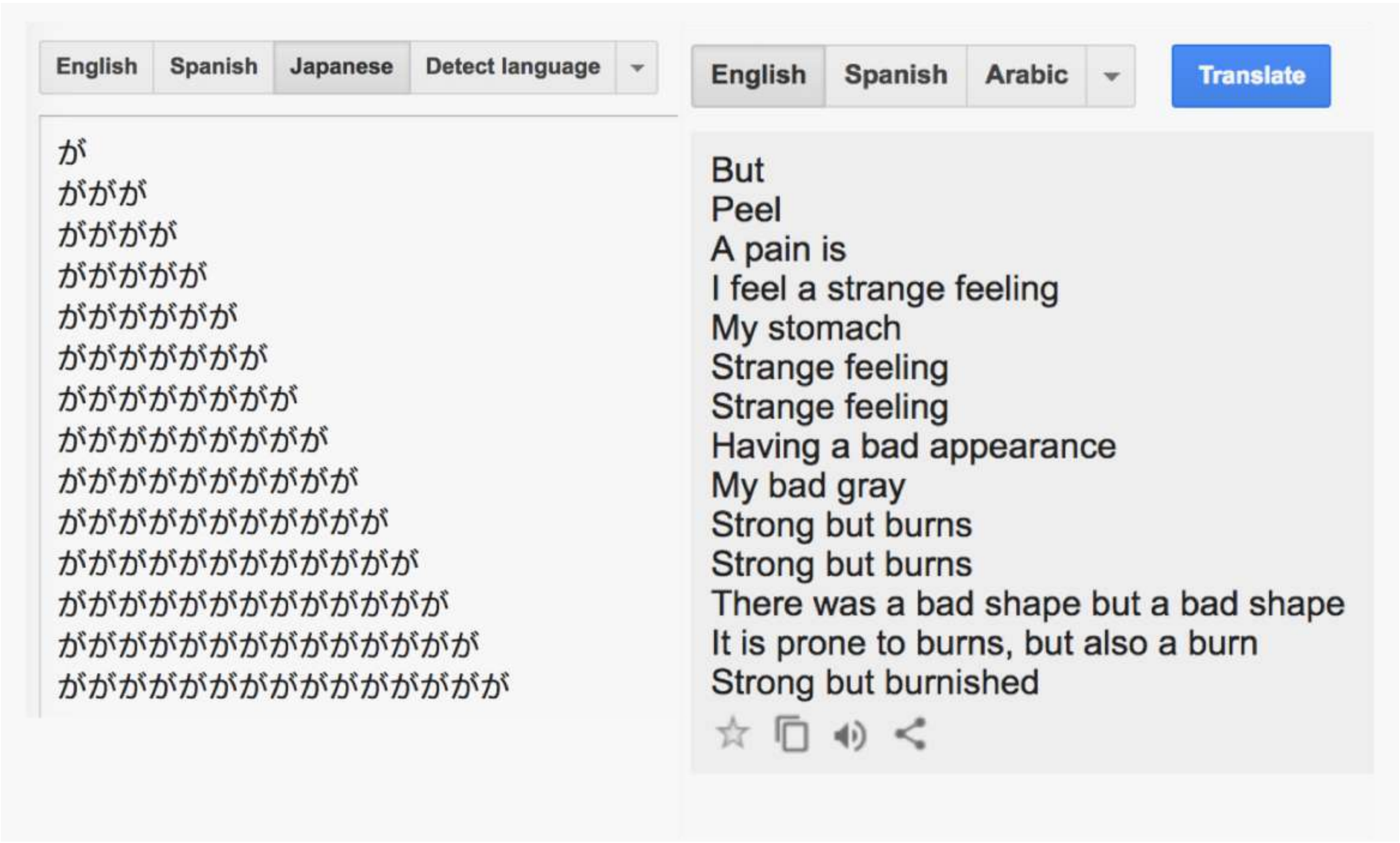
- NMT picks up cultural bias in training data:



[5]

Prevailing Problems

- Uninterpretable systems do strange things (1) :

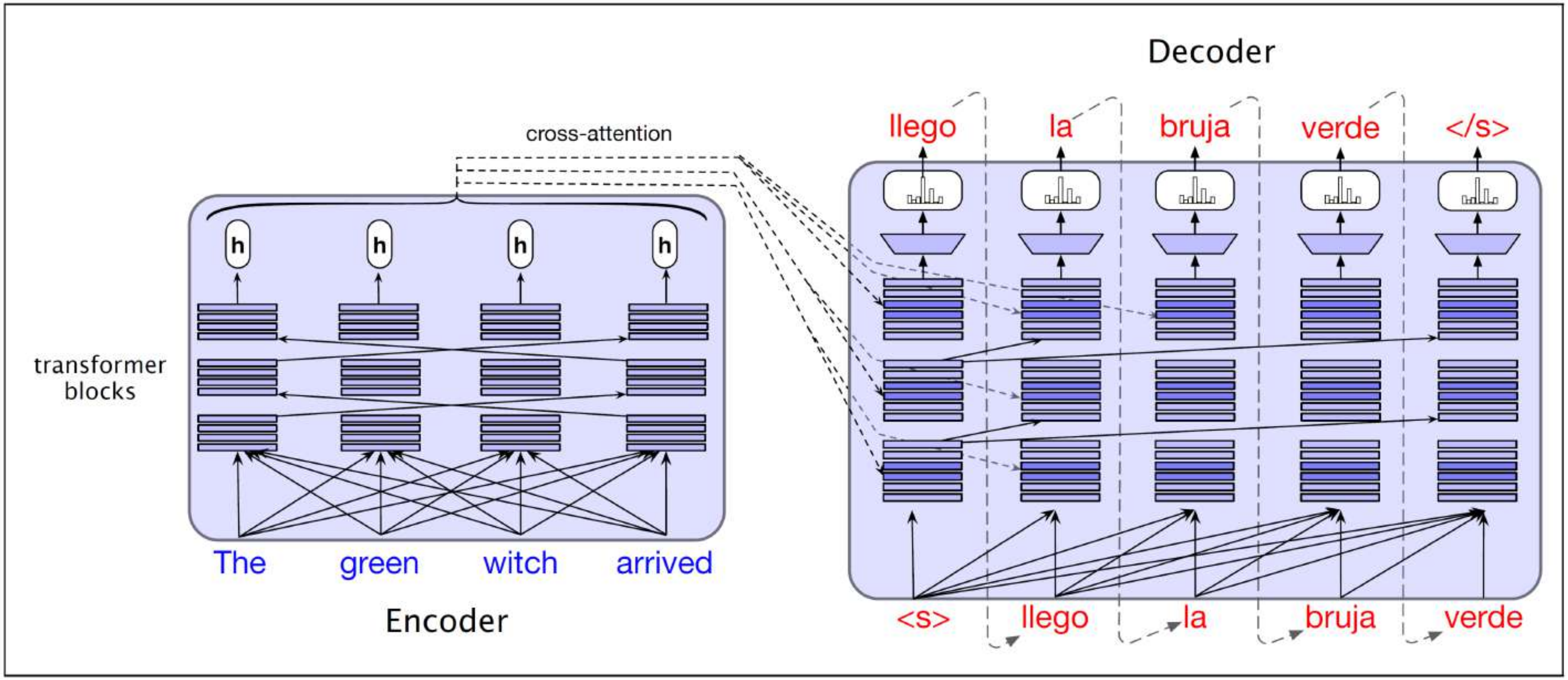


[6]

(1) : philosophical question: is this really a problem? would humans perform systematically better?

Encoder-Decoder with Transformers

- Replace RNN (sequential input) with transformer blocks (parallel input)
- Dot product attention → cross-attention layer



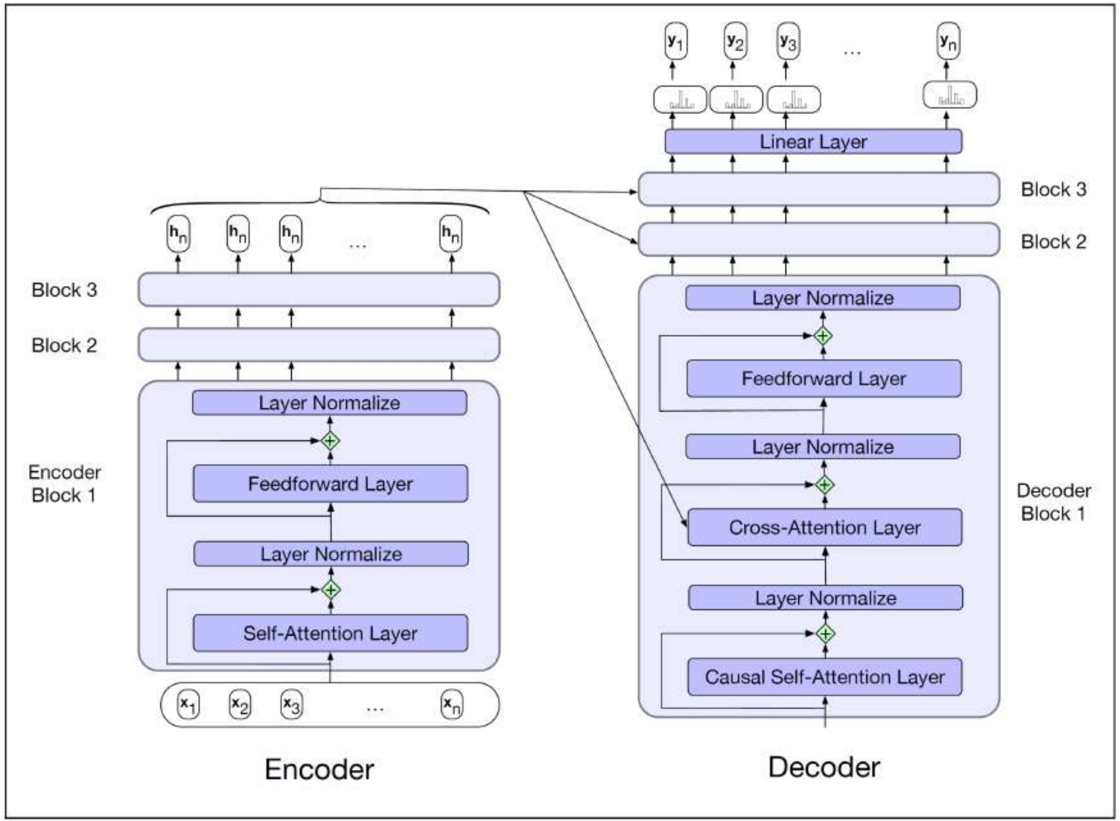
Cross-Attention

- Recap self-attention: queries, keys and values from previous decoder layer
- Cross-attention: keys and values from encoder output

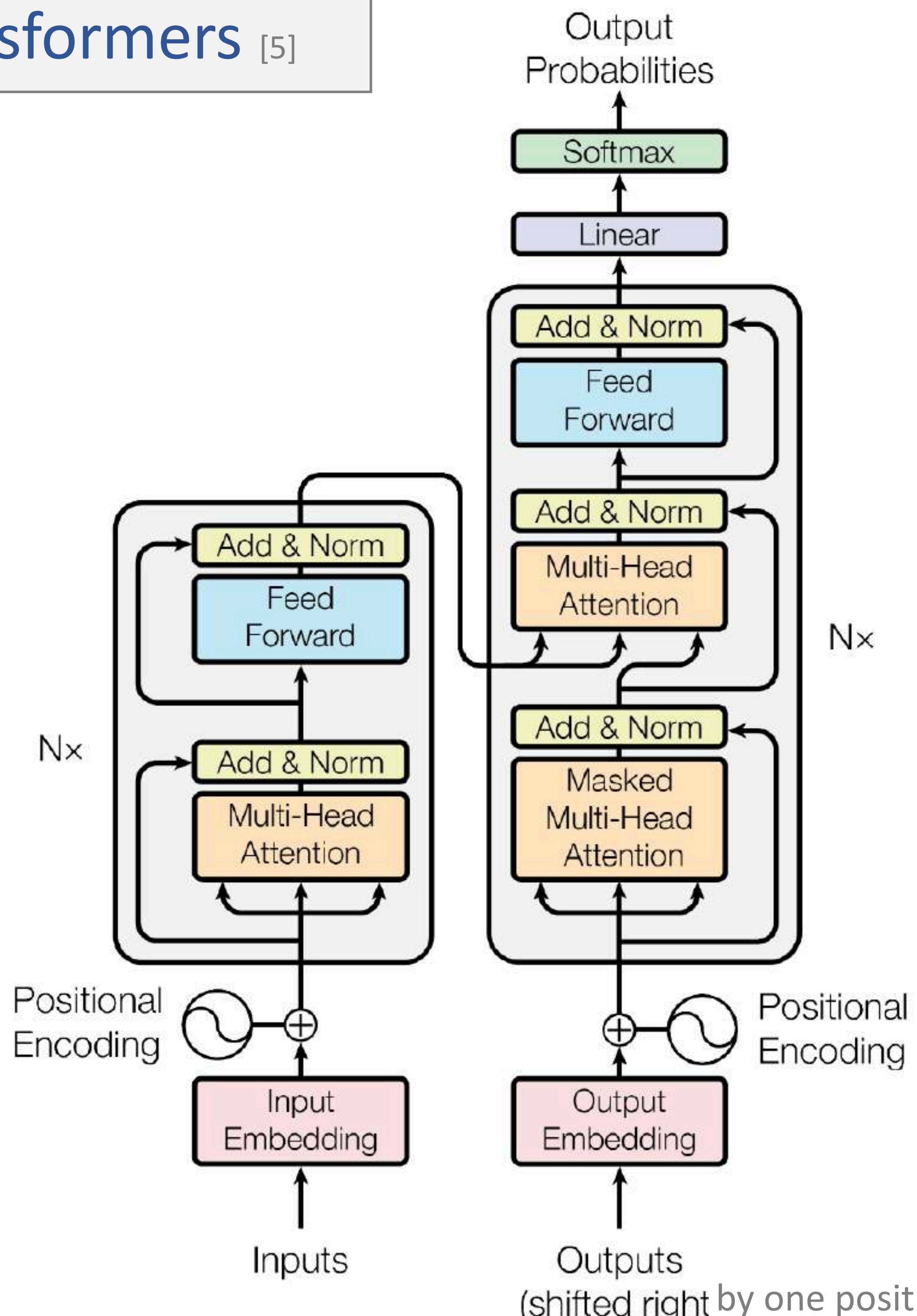
$$\mathbf{Q} = \mathbf{W^Q H}^{dec[i-1]}; \quad \mathbf{K} = \mathbf{W^K H}^{\boxed{enc}}; \quad \mathbf{V} = \mathbf{W^V H}^{\boxed{enc}}$$

$$\boxed{CrossAttention(\mathbf{Q},\mathbf{K},\mathbf{V}) \;=\; \text{softmax}\left(\frac{\mathbf{QK}^\intercal}{\sqrt{d_k}}\right)\mathbf{V}}$$

- → decoder attends to all source words



Encoder-Decoder with Transformers [5]



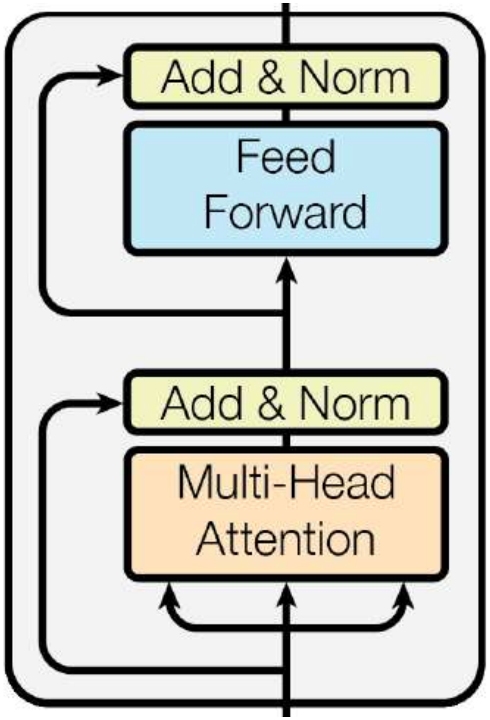
by one position)

Complete Block of Encoder [5]

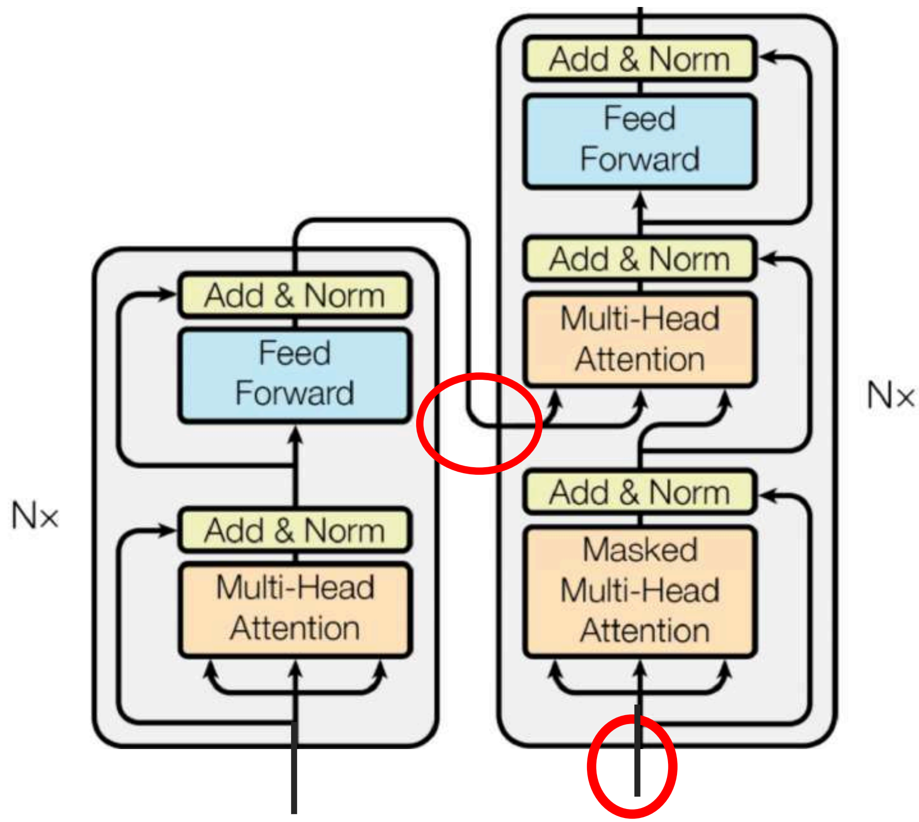
- each block: two "sublayers":
  - unmasked multihead self attention
  - two-layer fully connected feed forward (C)NN with ReLu:

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

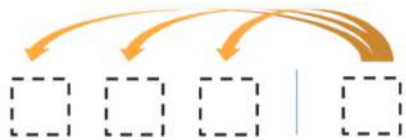
- each sublayer:
  - residual (short-circuit) connection and Layer Norm:
  - Layer Norm(x + Sublayer(x))
  - Layer Norm changes input to have mean 0 and variance 1



Decoder [5]



encoder decoder attention : queries from previous decoder layer; keys & values from encoder output



decoder self attention on previously generated outputs; masked to prevent information flow from future to past (ensure auto-regressive property)

Tokenization

- Fixed vocabulary built by BPE or wordpiece algorithms
  → corpus with tokens from both languages (enables copying)

- Wordpiece algorithm:
  - Input: Training corpus and desired vocabulary size *V*
  - 1. Init lexicon with all characters
  - 2. Repeat until *V* wordpieces in lexicon
    - Train n-gram LM on training corpus using current lexicon
    - New wordpieces by concatenating two from current lexicon
      → add most probable piece according to language model to lexicon

words: Jet makers feud over seat width with big orders at stake

wordpieces: _J et _makers _fe ud _over _seat _width _with _big _orders _at _stake

Backtranslation to increase parallel data

- Problem: for some language pairs only limited amount of parallel data but large monolingual corpus available in target language (e.g. English)
  → translate to source language
  → add synthetic data to parallel corpus

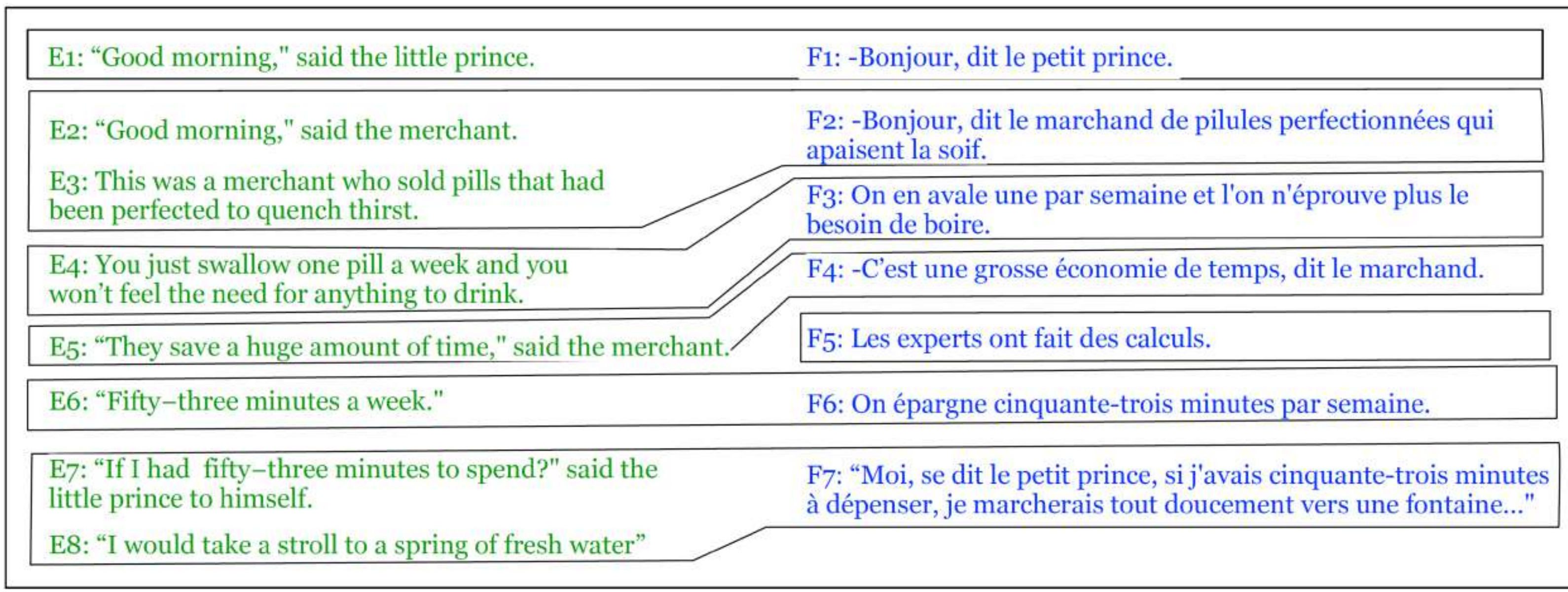
- Backtranslation parameters:
  - Generation of backtranslation
  - Decoding strategy: greedy inference, sampling, Monte Carlo search, ..
  - Ratio of back-translated to natural data

- Monte Carlo search: useful for underfitted decoders
  - Previous approaches: take most probable word
  - Here: sample words according to probabilities

    Softmax probability distribution: {*the*: 0.6; *green*: 0.2; *a*: 0.1; *witch*: 0.1}
    → weighted die with 4 sides weighted 0.6, 0.2, 0.1, 0.1
    → small amount of improbable words in data

Sentence alignment

- Parallel corpora for training
  → align sentences from both languages
- Score function to measure likelihood of two spans being translations
  e.g. cosine similarity between multilingual embeddings
- Alignment algorithm to find alignment based on scores



Evaluation of Machine Translation

- Evaluation along two dimensions:
  - **Adequacy / Faithfulness**: Preservation of exact meaning
  - **Fluency**: quality of target language text

- Human evaluators
  - Often online crowdworkers
  - Multilingual: rate criterion on defined scale
  - Monolingual: Compare to reference translation or rank pairs of candidate translations
  - Disagreement between raters → normalize and exclude outliers

Automatic Evaluation Metrics: Character overlap

- Compared to humans: less expensive but less accurate
- Assumption: High overlap between MT and human gold translation desired
- **Character F-score (chrF)**: rank candidate by character n-gram overlaps

chrP percentage of character 1-grams, 2-grams, ..., k-grams in the hypothesis that occur in the reference, averaged.

chrR percentage of character 1-grams, 2-grams,..., k-grams in the reference that occur in the hypothesis, averaged.

→ combine precision and recall in weighted F-score
($\beta = 2$ weights recall twice as much as precision)

$$\text{chrF}\beta = (1+\beta^2)\frac{\text{chrP}\cdot\text{chrR}}{\beta^2\cdot\text{chrP}+\text{chrR}}$$

chrF example

- chrF2,2 → 2-grams and $\beta = 2$

REF: `witness for the past,`		
HYP1: `witness of the past,`	chrF2,2 = .86	
HYP2: `past witness`	chrF2,2 = .62	

- 1. Remove whitespaces

REF: `witnessforthepast,` (18 unigrams, 17 bigrams)
HYP1: `witnessofthepast,` (17 unigrams, 16 bigrams)

- 2. Count matching unigrams and bigrams

unigrams that match: `w i t n e s s f o t h e p a s t ,` (17 unigrams)
bigrams that match: `wi it tn ne es ss th he ep pa as st t,` (13 bigrams)

- 3. Calculate precision and recall

unigram P:	17/17 = 1	unigram R:	17/18 = .944
bigram P:	13/16 = .813	bigram R:	13/17 = .765

- 4. Combine to F-Score

$$\begin{aligned} \text{chrP} &= (17/17 + 13/16)/2 = .906 \\ \text{chrR} &= (17/18 + 13/17)/2 = .855 \\ \text{chrF2,2} &= 5\frac{\text{chrP} * \text{chrR}}{4\text{chrP} + \text{chrR}} = .86 \end{aligned}$$

Automatic Evaluation Metrics: Practical Considerations

- chrF used to compare performances of two models
  → statistical significance test

- More common metric: **BiLingual Evaluation Understudy (BLEU)**
  - Word instead of character n-gram overlap
    → sensitive to tokenization
  - Purely precision-based

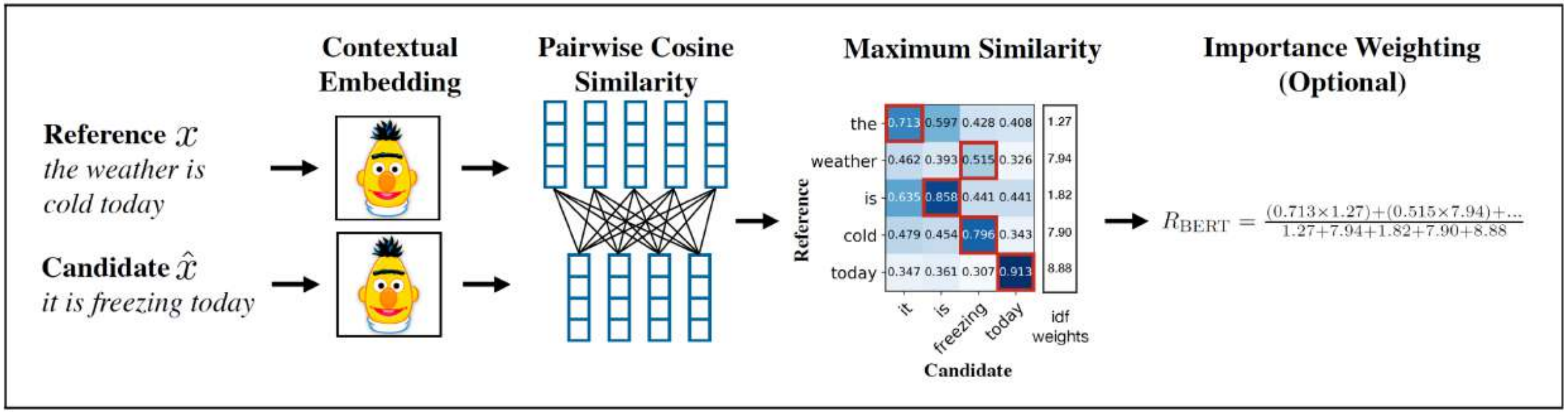
- N-gram overlap limitations:
  - No synonym awareness
  - Robust to position changes → bad word order evaluation
  - No coverage of cross-sentence properties
  - Reference summary needed

Automatic Evaluation Metrics: Embedding Based

- Embeddings to include knowledge about synonyms and paraphrases
- Given dataset with (reference translation, candidate translation, human ranking) triplets

  → train predictor by passing reference and candidate through e.g. BERT

- BERTScore: no supervised training data → token-wise cosine similarity of embedding representations



- Token in x matched to $\hat{x}$ → recall
- Tokens in $\hat{x}$ matched to x → precision

$$R_{\mathrm{BERT}} = \frac{1}{|x|} \sum_{x_i \in x} \max_{\tilde{x}_j \in \tilde{x}} x_i \cdot \tilde{x}_j$$

$$P_{\mathrm{BERT}} = \frac{1}{|\tilde{x}|} \sum_{\tilde{x}_j \in \tilde{x}} \max_{x_i \in x} x_i \cdot \tilde{x}_j$$

Bias and Ethical Issues

- Translation Hungarian (gender neutral pronoun ő) to English

Hungarian (gender neutral) source	English MT output
ő egy ápoló	she is a nurse
ő egy tudós	he is a scientist
ő egy mérnök	he is an engineer
ő egy pék	he is a baker
ő egy tanár	she is a teacher
ő egy esküvőszervező	she is a wedding organizer
ő egy vezérigazgató	he is a CEO

- Results difficult to control and interpret → Confidence score of prediction

- Focus on high-resource languages to English
  → efforts to increase low-resourced language corpora

Bibliography

(1) Dan Jurafsky and James Martin: Speech and Language Processing (3rd ed. draft, version Jan, 2022); Online: https://web.stanford.edu/~jurafsky/slp3/ (URL, Oct 2022) (this slideset is especially based on chapter 10)

(2) Richard Socher et al: "CS224n: Natural Language Processing with Deep Learning", Lecture Materials (slides and links to background reading) http://web.stanford.edu/class/cs224n/ (URL, May 2018), 2018

(3) https://youtu.be/K-HfpsHPmvw (URL, Aug 2018) (in [2])

(4) Rico Sennrich (University of Edinburgh): Neural Machine Translation: Breaking the Performance Plateau, Talk July 2016; http://www.meta-net.eu/events/meta-forum-2016/slides/09_sennrich.pdf (URL, Aug 2018) (in [2])

(5) Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L. and Polosukhin, I., 2017. Attention is all you need. In Advances in Neural Information Processing Systems (pp. 5998-6008) and arXiv:1706.03762v5

Recommendations for Studying

- minimal approach:

  work with the slides and understand their contents! Think beyond instead of merely memorizing the contents

- standard approach:

  minimal approach + read the corresponding pages in Jurafsky [1]

- interested students

  == standard approach + study the corresponding parts of the Stanford lecture CS224n on the latest trends in NMT.