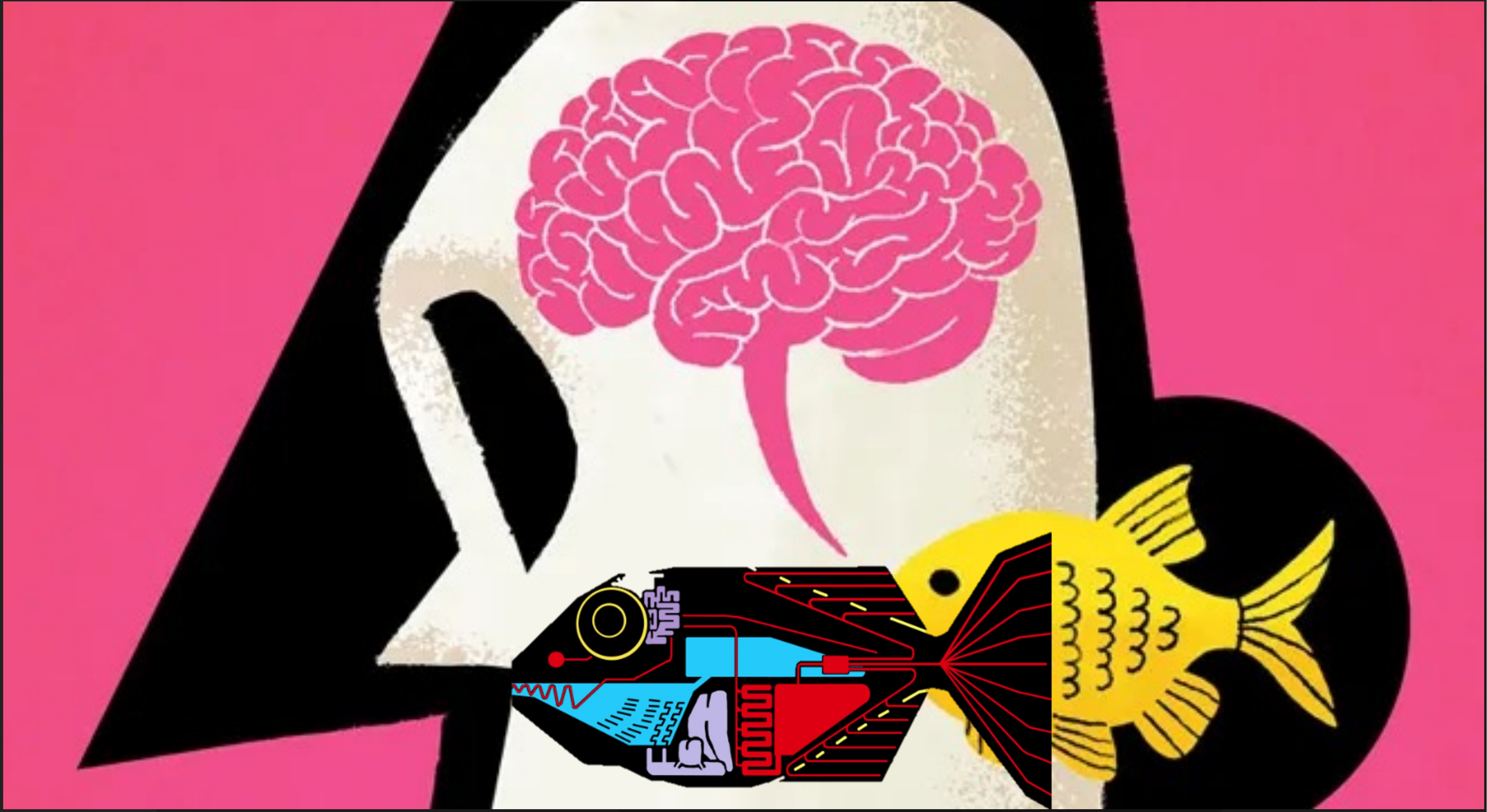

Image: Trawling for Babel fish. Concept and juxtaposition: Raeid Saqur.

Statistical + **Neural machine translation**

CSC401/2511 – Natural Language Computing – Winter 2024

Gerald Penn, Sean Robertson & Raeid Saqur

Lecture 5

University of Toronto

Logistics

- Office hours: Mon 12 noon – 13h (over zoom, note the channel)
- Course drop deadline: ~Feb 19, 2024 (see SGS calendar)

- A1: due Feb 9, 2024. Final A1 tutorial/OH on Feb 9
- A2: release Feb 10, 2024
- No tutorials this Friday (Feb 2, 2024)

- Please do **NOT** be this person

- Lecture feedback:
  - Anonymous
  - Please share any thoughts/suggestions
- **Questions?**

Machine Translation (MT)

- Introduction & History
- L5 (1/3) - Statistical MT:
  - Noisy Channel model
  - Alignment based models
- L5 (2/3) Neural MT:
  - Seq2seq (encoder-decoder) architectures
  - Attention mechanisms
  - Transformers intro.
- L5 (3/3) Decoding & Evaluation:
  - Beam Search
  - BLEU

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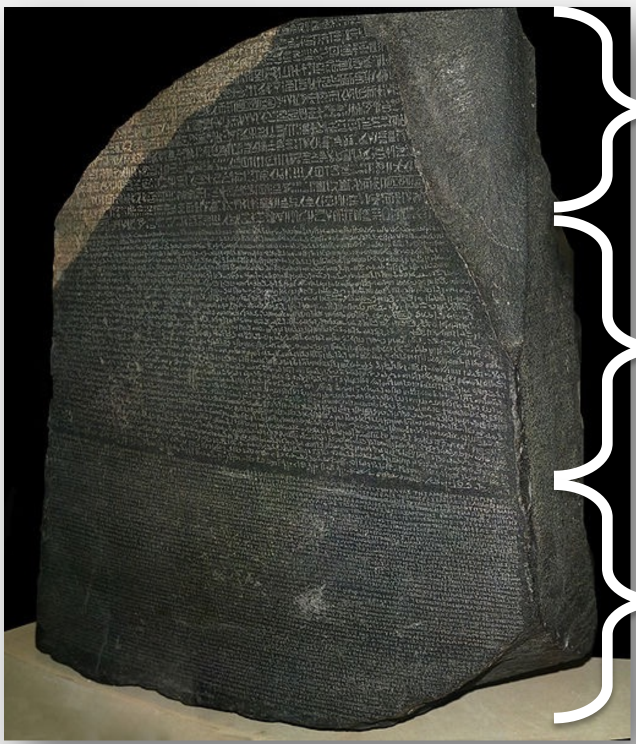
The Rosetta Stone

- The **Rosetta Stone** dates from 196 BCE.
  - It was re-discovered by French soldiers during Napoleon's invasion of Egypt in 1799 CE.



Ancient Egyptian hieroglyphs

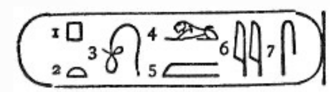
Egyptian Demotic

Ancient Greek

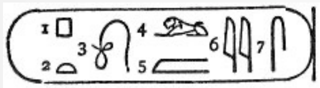
- It contains three **parallel** texts in different languages, only the **last** of which was understood.

- *By 1799, ancient Egyptian had been forgotten.*

Deciphering Rosetta

- During 1822–1824, **Jean-François Champollion** worked on the Rosetta stone. He noticed:
    1. The circled Egyptian symbols  appeared in roughly the same positions as the word ‘*Ptolemy*’ in the Greek.
    2. The number of Egyptian hieroglyph tokens were **much larger** than the number of Greek words → Egyptian seemed to have been partially phonographic.
    3. Cleopatra’s cartouche was written 

Aside – deciphering Rosetta

- So if  was '*Ptolemy*' and  was '*Cleopatra*' and the symbols corresponded to sounds – can we match up the symbols?

P	T	O	L	M	E	S		
C	L	E	O	P	A	T	R	A

- This approach demonstrated the value of working from **parallel texts** to decipher an unknown language:
  - *It would not have been possible without* ***aligning*** *unknown words (hieroglyhs) to known words (Greek)…*

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Today

- Introduction to statistical machine translation (SMT).
  - What we want is a system to take utterances/sentences in one language and transform them to another:

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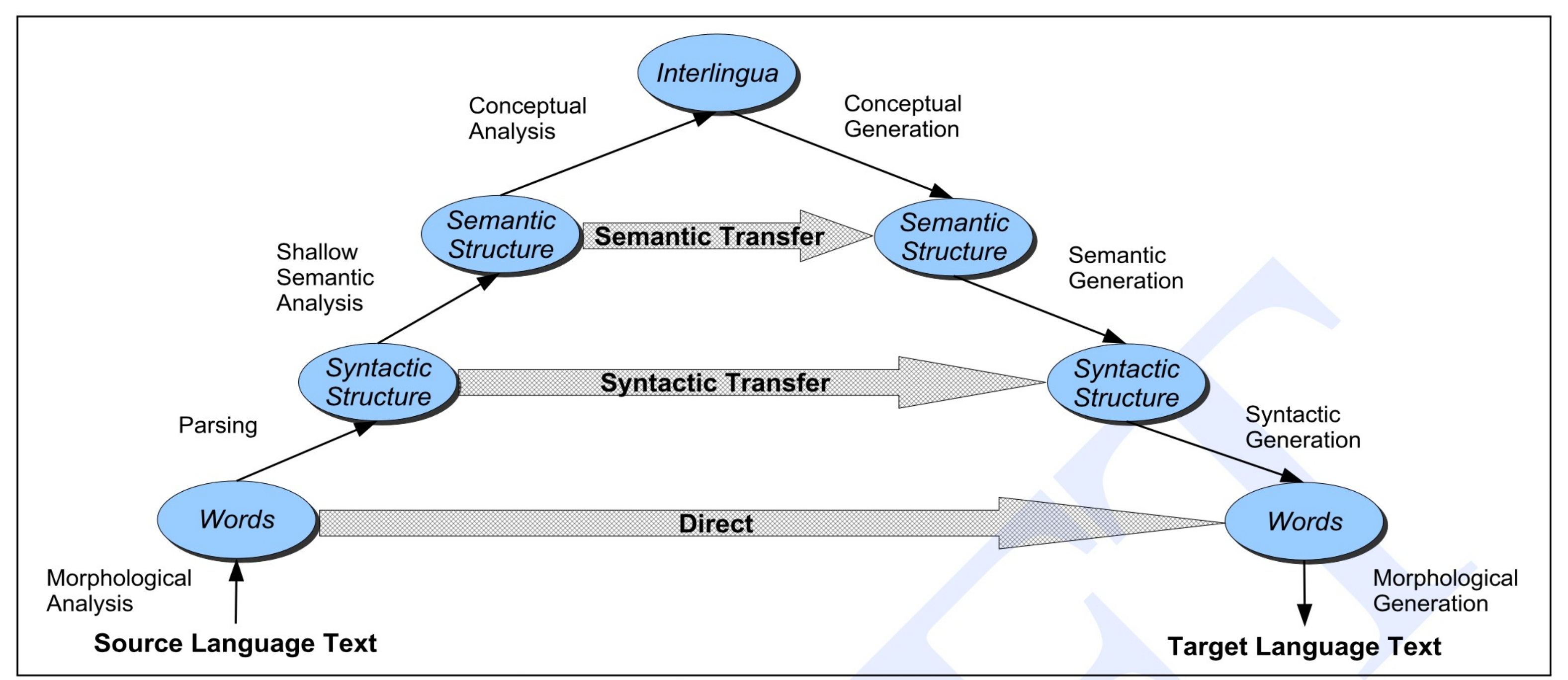
MT Approaches

- High-level classes of methodologies:
  - Direct Translation
  - Syntactic Transfer
  - Semantic Transfer
  - Interlingua

Vauquois (1968) Triangle



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Direct translation

- A bilingual dictionary that aligns words across languages can be helpful, but only for simple cases.

¿	*Dónde*	*está*	*la*	*biblioteca*	*?*
	Where	*is*	*the*	*library*	*?*
	Où	*est*	*la*	*bibliothèque*	*?*

Mi	*nombre*	*es*	*T-bone*
My	*name*	*is*	*T-bone*
Mon	*nom*	*est*	*T-bone*

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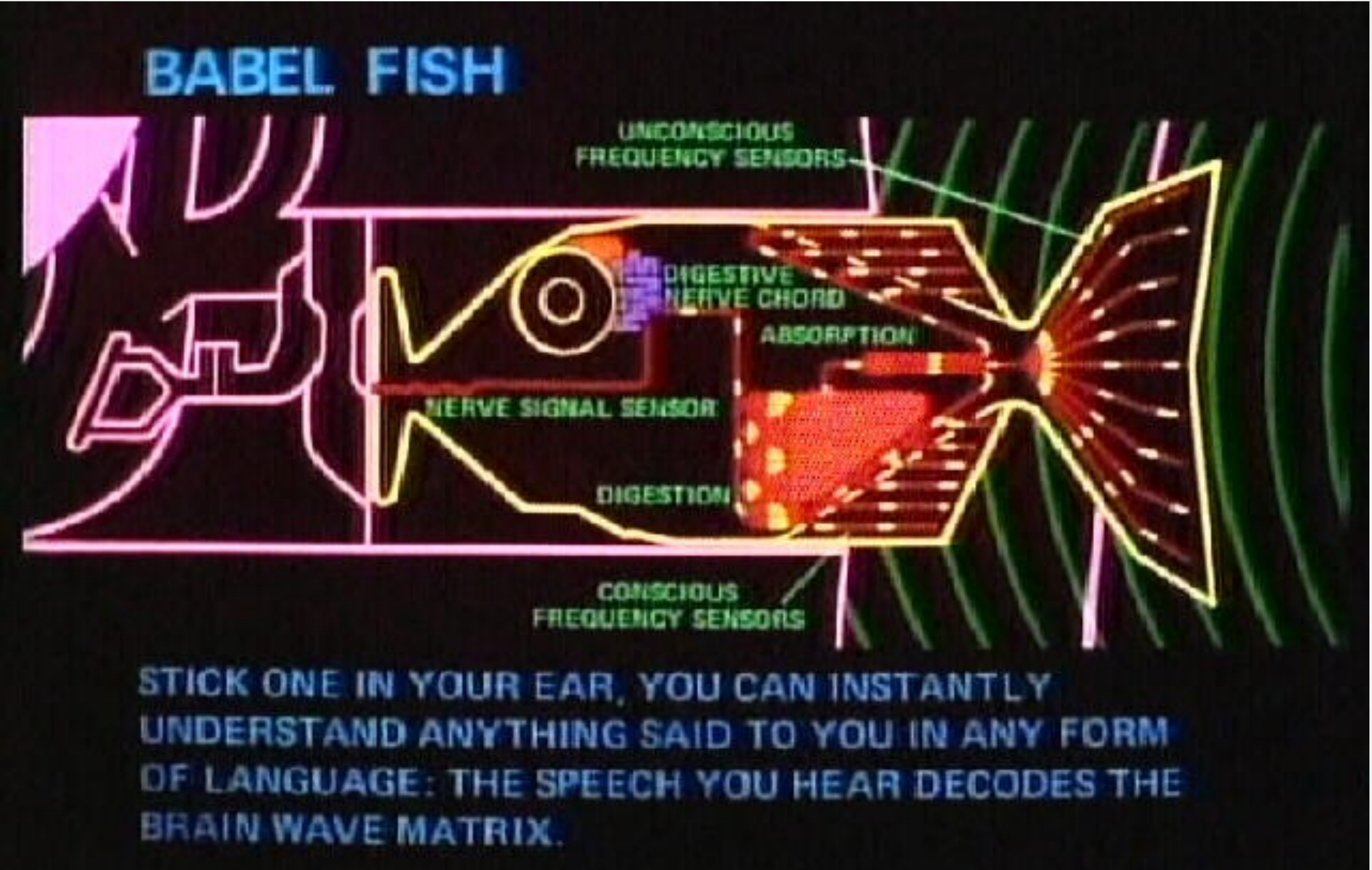
Difficulties in MT: typology

- Different **morphology** → difficult **mappings**, *e.g.*
  - Many (*polysynthetic*) vs one (*isolating*) morphemes per word
    e.g., Yupik e.g., Cantonese
  - Many (*fusion*) vs few (*agglutinative*) *features* per morpheme
    e.g., Russian e.g., Turkish
- Different **syntax** → **long-distance effects**, *e.g.*
  - SVO vs. SOV vs. VSO (e.g. English vs. Japanese vs. Arabic)
    - He listens to music / kare ha ongaku wo kiku
      Subject Verb Object Subject Object Verb
  - Verb vs. satellite-framed (e.g. Spanish vs. English)
    - La botella salió flotando / The bottle floated out

Difficulties in MT: ambiguity

- **Ambiguity** makes it hard to pick one translation
  - Lexical: many-to-many word mappings

    Paw Patte Foot Pied
  - Syntactic: same token sequence, different structure
    - Rick hit the Morty [with the stick]$_{PP}$ / Rick golpeó el Morty con el palo
    - Rick hit the Morty [with the stick]$_{PP}$ / Rick golpeó el Morty que tenia el palo
  - Semantic: same structure, different meanings
    - I'll pick you up / {Je vais te chercher, Je vais te ramasser}
  - Pragmatic: different contexts, different interpretations
    - Poetry vs technical report



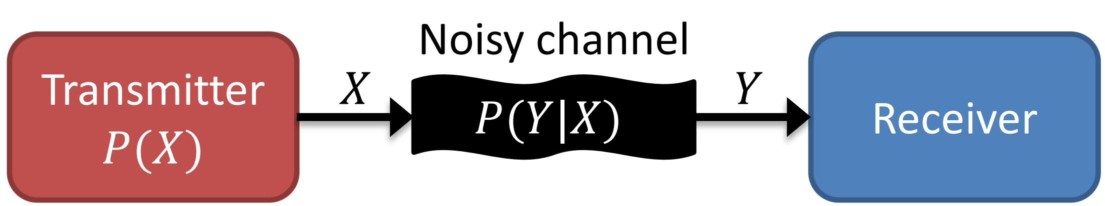
THE NOISY CHANNEL

Statistical machine translation

- Machine translation seemed to be an intractable problem until a change in perspective…

When I look at an article in Russian, I say: ‘This is really written in English, but it has been **coded** in some strange symbols. I will now proceed to **decode**.’

Warren Weaver March, 1947



Claude Shannon July, 1948

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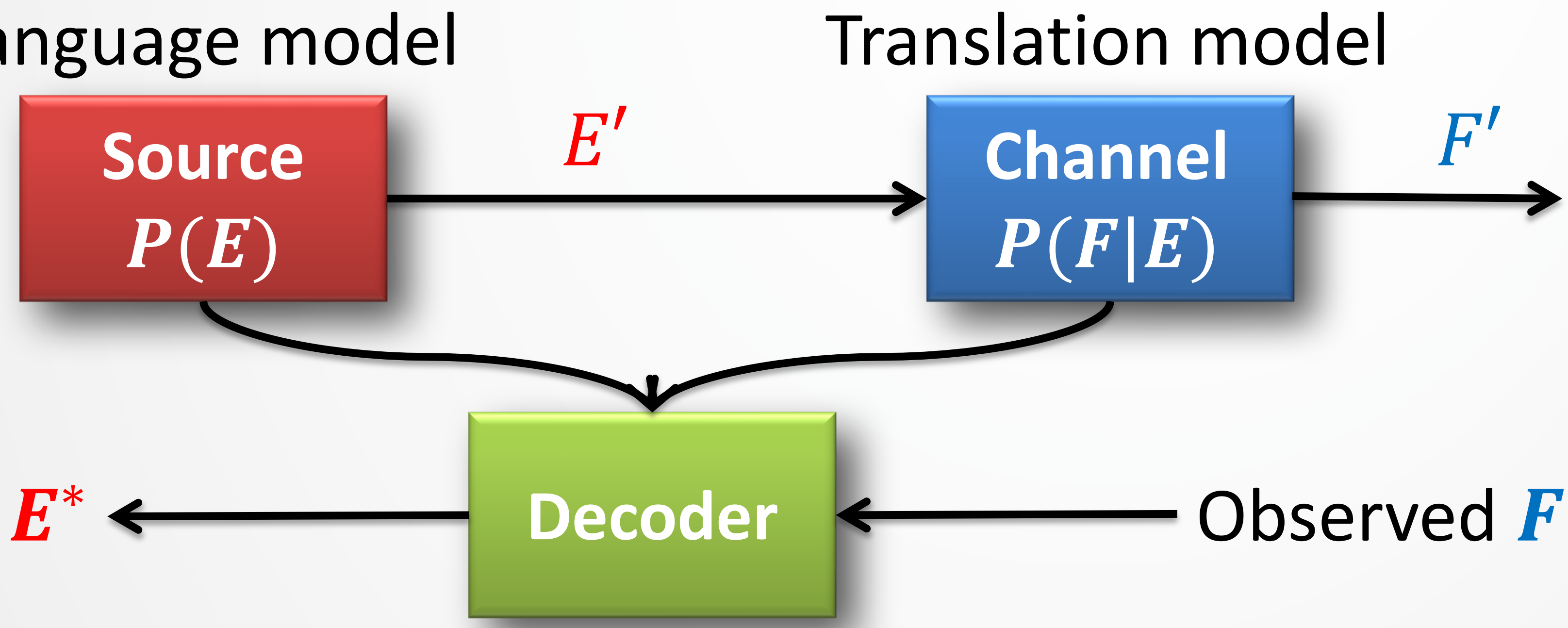
The noisy channel model

- Imagine that you're given a French sentence, F, and you want to convert it to the best corresponding English sentence, E^*
  - i.e., $E^* = \underset{E}{\operatorname{argmax}} P(E|F)$
- Use Bayes' Rule:

$$E^* = \operatorname{argmax}_E \frac{P(F|E)P(E)}{P(F)}$$

- $P(F)$ doesn't change argmax (besides, French isn't anything but noisy English anyway)

The noisy channel



$$E^* = \underset{E}{\operatorname{argmax}}\, P(F|E)P(E)$$

How to use the noisy channel

- How does this work?

$$E^* = \underset{E}{\operatorname{argmax}} \underbrace{P(F|E)}_{\text{Translation model}} \overbrace{P(E)}^{\text{Language model}}$$

- $P(E)$ is a **language model** (e.g., *N*-gram) and encodes knowledge of word order.
- $P(F|E)$ is a **word- (or phrase-)level translation model** that encodes only knowledge on an *unordered* basis.
- **Combining** these models can give us **naturalness** and **fidelity**, respectively.

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How to use the noisy channel

- Example from Koehn and Knight using only conditional likelihoods of Spanish words given English words.

- *Que hambre tengo yo*

  →

  What hunger have I $P(S|E) = 1.4E^{-5}$

  Hungry I am so $P(S|E) = 1.0E^{-6}$

  I am so hungry $P(S|E) = 1.0E^{-6}$

  Have I that hunger $P(S|E) = 2.0E^{-5}$

  …

Best translation using only the translation model

How to use the noisy channel

- … and with the English language model

- *Que hambre tengo yo*

  →

What hunger have I	$P(S\|E)P(E) = 1.4E^{-5} \times 1.0E^{-6}$
Hungry I am so	$P(S\|E)P(E) = 1.0E^{-6} \times 1.4E^{-6}$
I am so hungry	$P(S\|E)P(E) = 1.0E^{-6} \times 1.0E^{-4}$
Have I that hunger	$P(S\|E)P(E) = 2.0E^{-5} \times 9.8E^{-7}$

  …

How to learn $P(F|E)$?

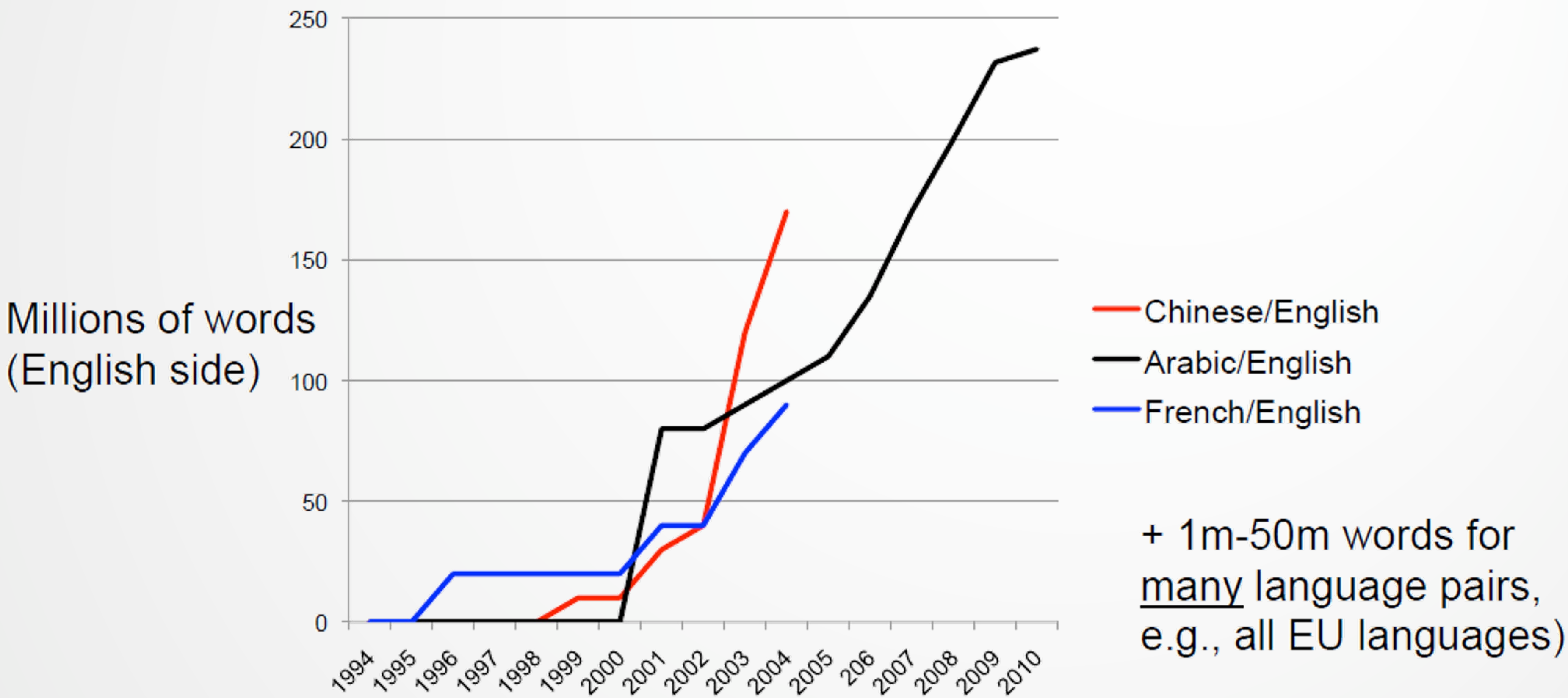
- Solution: collect statistics on vast parallel texts

… **<u>citizen</u>** of Canada has the **<u>right</u>** to vote in an election of members of the House of Commons or of a legislative assembly and to be qualified for membership …

… **<u>citoyen</u>** canadien a le **<u>droit</u>** de vote et est éligible aux élections législatives fédérales ou provinciales …

e.g., the *Canadian Hansards*:
bilingual Parliamentary proceedings

Bilingual data



Source: Chris Manning's lecture slide

- Data from Linguistic Data Consortium (LDC) at University of Pennsylvania.

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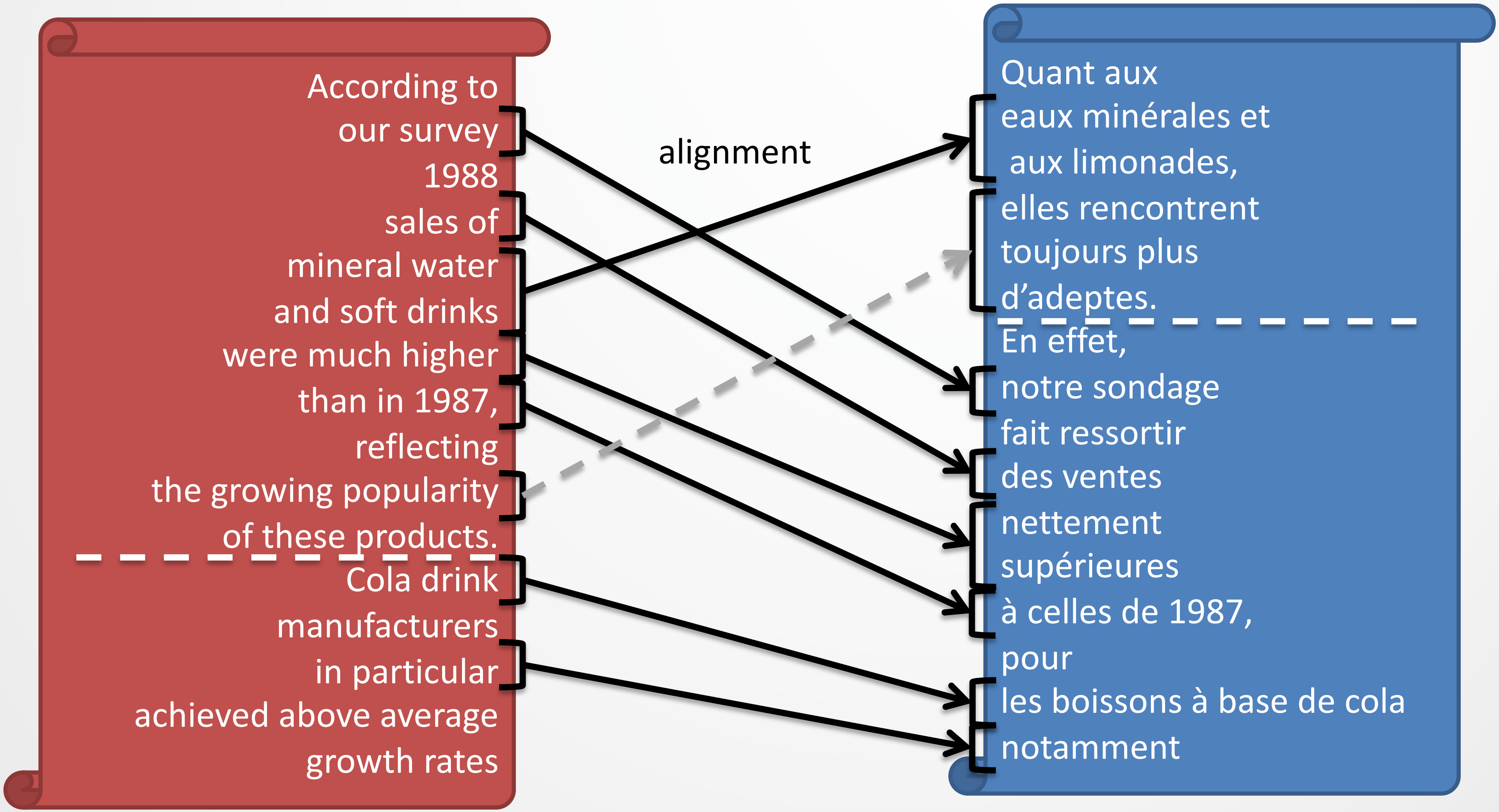
Alignments

- Alignments at different granularities
  - Word, phrase, sentence, document
- SMT makes alignments explicit
  - One block of text entirely responsible for a translated block (conditional independence)
- Letting A index pairs of aligned blocks in bitext

$$P(F|E) = \sum_A P(F, A|E) = \sum_A P(A|E) \prod_i P\left(F_{A_{i,1}} \middle| E_{A_{i,2}}\right)$$

Alignment

- In practice, words and phrases can be out of order.



From Manning & Schütze

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Alignment

- Also in practice, we're usually not given the alignment.

According to
our survey
1988
sales of
mineral water
and soft drinks
were much higher
than in 1987,
reflecting
the growing popularity
of these products.
Cola drink
manufacturers
in particular
achieved above average
growth rates

?

Quant aux
eaux minérales et
aux limonades,
elles rencontrent
toujours plus
d'adeptes.
En effet,
notre sondage
fait ressortir
des ventes
nettement
supérieures
à celles de 1987,
pour
les boissons à base de cola
notamment

From Manning & Schütze

Sentence alignment

- Sentences can also be **unaligned** across translations.
  - E.g., *He was happy.*$_{E1}$ *He had bacon.*$_{E2}$ $\rightarrow$
    Il était heureux parce qu'il avait du bacon.$_{F1}$

E_1	F_1
E_2	F_2
E_3	F_3
E_4	F_4
E_5	F_5
E_6	F_6
E_7	F_7
…	

E_1 E_2	F_1
E_3	F_2
E_4	F_3
E_5	F_4 F_5
E_6	F_6
E_7	F_7

Recalling
$\prod_i P\left(F_{A_{i,1}} \middle| E_{A_{i,2}}\right)$:
$A_1 = (\{1\},\{1,2\})$
$A_2 = (\{2\},\{3\})$
$A_3 = (\{3\},\{4\})$
$A_4 = (\{4,5\},\{5\})$
Etc…

Sentence alignment

- We often need to align **sentences** before moving forward.
- Goal: find $A^* = \text{argmax}_A P(A|F, E)$
- We'll look at two broad classes of methods:
  1. Methods that only look at **sentence length**,
  2. Methods based on **lexical matches**, or "cognates".
- Most machine translation (including neural) relies on sentence-level alignments of bitexts

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1. Sentence alignment by length

(Gale and Church, 1993)

- **Idea**: lengths of aligned sentences are correlated
- Assuming the paragraph alignment is known,
  - $\mathcal{L}_E$ is the # of characters in an English sentence,
  - $\mathcal{L}_F$ is the # of characters in a French sentence.
- Define cost/penalty function $Cost(\mathcal{L}_E, \mathcal{L}_F)$
  - Lowest when $\mathcal{L}_E = c\mathcal{L}_F$ for learned/guessed c
- Also define "prior" fixed cost $C_{i,j}$ of aligning i English sentences to j French sentences

1. Sentence alignment by length

E_1	F_1
E_2	
E_3	F_2
E_4	F_3
E_5	F_4
	F_5
E_6	F_6

$$
\begin{aligned}
Cost = \; & Cost\left(\mathcal{L}_{E_1} + \mathcal{L}_{E_2}, \mathcal{L}_{F_1}\right) + C_{2,1} + \\
& Cost\left(\mathcal{L}_{E_3}, \mathcal{L}_{F_2}\right) + C_{1,1} + \\
& Cost\left(\mathcal{L}_{E_4}, \mathcal{L}_{F_3}\right) + C_{1,1} + \\
& Cost\left(\mathcal{L}_{E_5}, \mathcal{L}_{F_4} + \mathcal{L}_{F_5}\right) + C_{1,2} + \\
& Cost\left(\mathcal{L}_{E_6}, \mathcal{L}_{F_6}\right) + C_{1,1}
\end{aligned}
$$

It's a bit more complicated – see paper on course webpage (**aside**)

Find distribution of sentence breaks with minimum cost using **dynamic programming**

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2. Sentence alignment by cognates

- **Cognates**: *n.pl.* Words that have a common **etymological** origin.
- **Etymological**: *adj.* Pertaining to the historical derivation of a word. E.g., *porc*→*pork*

- The intuition is that words that are **related** across languages have similar **spellings**.
  - e.g., *zombie*/*zombie*, *government*/*gouvernement*
  - Not always: *son* (male offspring) vs. *son* (sound)

- Cognates can "anchor" sentence alignments between related languages.

2. Sentence alignment by cognates

- Cognates should be spelled similarly…

- ***N*-graph**: *n.* Similar to *N*-grams, but computed at the **character-level**, rather than at the word-level.

  E.g., $Count(s, h, i)$ is a **trigraph** model

- Church (1993) tracks all **4-graphs** (*quadrigraph*) which are identical across two texts.
  - He calls this a 'signal-based' approximation to cognate identification.
  - Better for noisy data, like the results of optical character recognition

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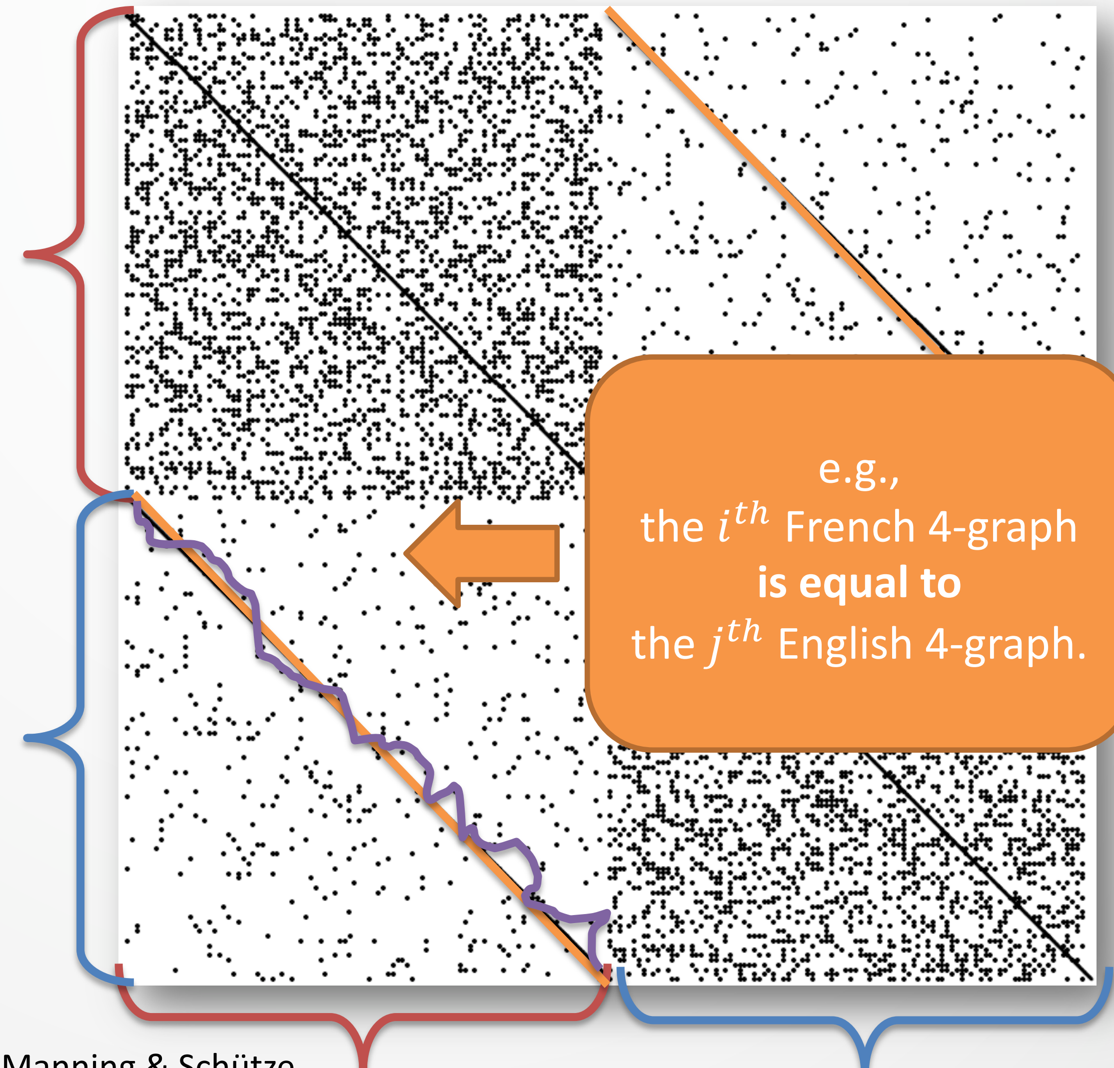
2. Church's method

1. Concatenate paired texts on both axes.

2. **Dot-plot**: place a 'dot' where the i^{th} French and the j^{th} English 4-graph are **equal**.

3. Search for a short path 'near' the bilingual diagonals.



From Manning & Schütze

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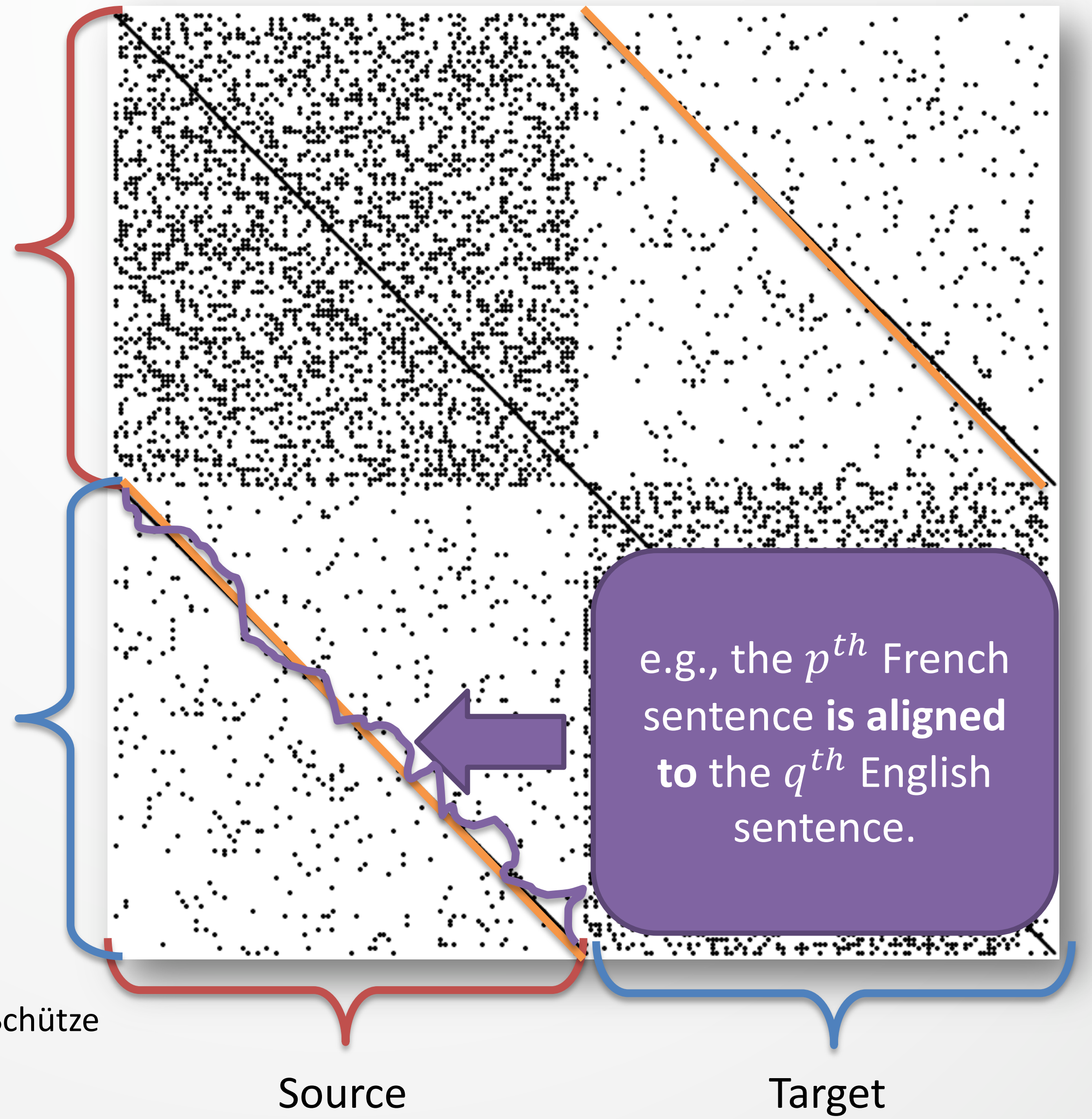
2. Church’s method

- Each point along **this path** is considered to represent a **match** between languages.
- The relevant French and English sentences are ∴ **aligned**.



From Manning & Schütze

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Aligning other granularities

- Recall: $P(F|E) = \sum_A P(A|E) \prod_i P\left(F_{A_{i,1}} \middle| E_{A_{i,2}}\right)$

- A_i can be pairs of sets of sentences if F, E are documents

- If F, E are sentences, A_i are pairs of sets of words

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Word alignment models

- Make a simplifying assumption that every word in F maps to one E (i.e. $A_i = (\{i\}, \{j\}) \mapsto j$)
- E.g. IBM-1: $P(F|A, E) \propto \prod_i P\left(F_i \middle| E_{A_i}\right)$ $\frac{Count\left(F_i, E_{A_i}\right)}{Count\left(E_{A_i}\right)}$
- Trained via Expectation Maximization (see HMM lecture)

	Maria	no	dió	una	bofetada	a	la	bruja	verde
Mary	A_1								
did						A_6			
not		A_2							
slap			A_3	A_4	A_5				
the							A_7		
green									A_9
witch								A_8	

A **word alignment matrix** From J&M 2nd Ed.

Problems with word alignments

- What if some E_j isn't aligned anywhere?
- Need more flexible context!

	Maria	no	dió	una	bofetada	a	la	bruja	verde
Mary	A_1								
did		A_2							
not		A_3							
slap					A_4				
the							A_5		
green									A_6
witch								A_7	

$P(E|F)$

(For English to Spanish)

NP

Phrase-based translation

- Suppose beads are pairs non-empty, contiguous spans of words that partition $F \times E$

$$A_i = \left(\left(\ell_1^{(i)} : u_1^{(i)}\right), \left(\ell_2^{(i)} : u_2^{(i)}\right)\right)$$

- Call each span an indivisible phrase $\left(F_{A_{i,1}}, E_{A_{i,2}}\right) \mapsto (\bar{F}_i, \bar{E}_i)$ and assume phrases sequential in E, then:

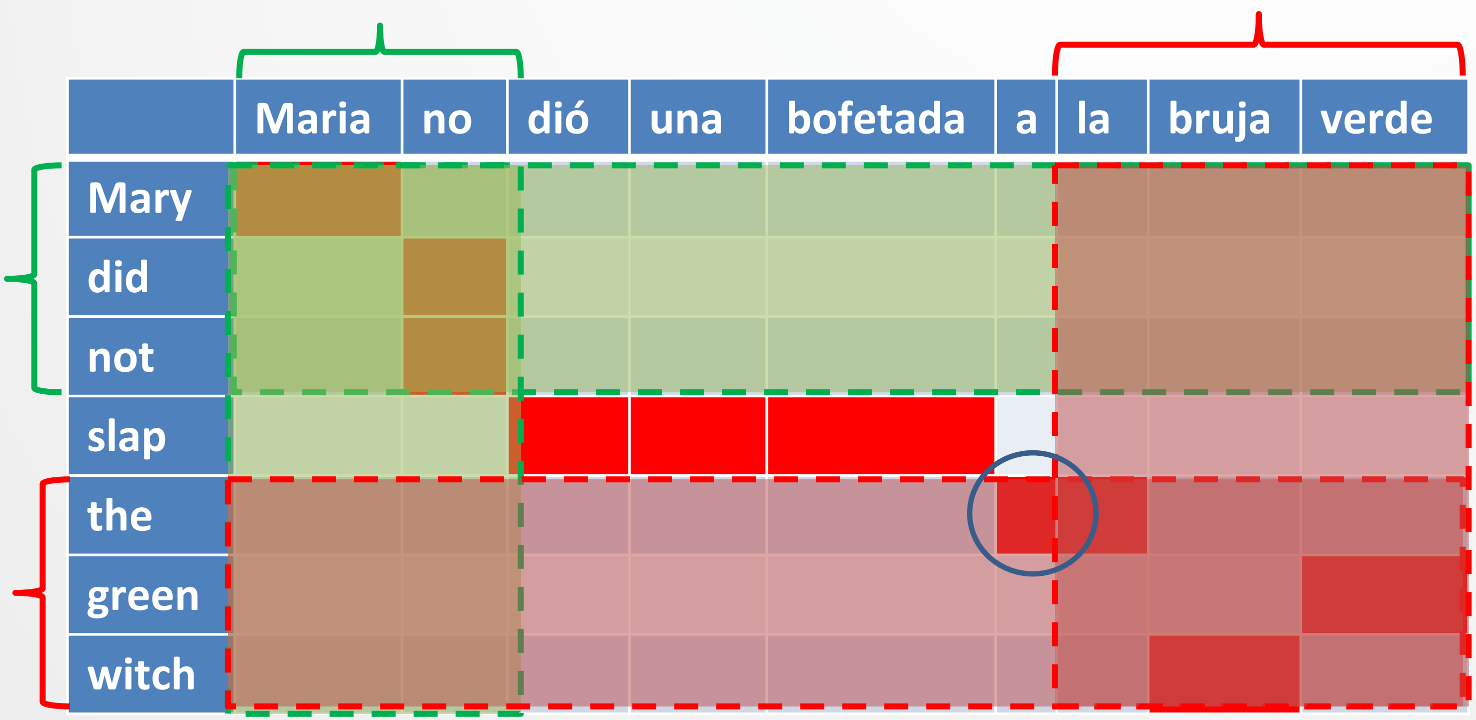
$$P(F, A|E) \propto \prod_i \phi(\bar{F}_i, \bar{E}_i) \overbrace{d\left(u_1^{(i-1)} - \ell_1^{(i)} - 1\right)}^{\text{'d' is penalizing } \phi \text{ for being distorted}}$$

- $\phi(\bar{F}, \bar{E}) = Count(\bar{F}, \bar{E}) / \sum_{\bar{F}'} Count(\bar{F}', \bar{E})$ is the phrase translation probability
- $d(\cdot)$ is the distortion metric/distance (e.g. $d(x) = \alpha^{|x|}$)
  where α is a distortion constant
  - Since $\bar{E}_i, \bar{E}_{i+1}$ are sequential, penalizes when $\bar{F}_i, \bar{F}_{i+1}$ aren't

Bilingual phrase pairs

Recall:
$\phi(\bar{F},\bar{E}) = \frac{Count(\bar{F},\bar{E})}{\sum_{\bar{F}'} Count(\bar{F}',\bar{E})}$

- Count the pair $(\bar{F},\bar{E}) = \left(F_{\ell_1:u_1}, E_{\ell_2:u_2}\right)$ if "consistent"
  1. At least one A_i is in the box $[\ell_1:u_1]\times[\ell_2:u_2]$
  2. All A_i containing any word in $[\ell_1:u_1]$ or any word in $[\ell_2:u_2]$ must be in the box as well



(Re)using a **word alignment matrix** seen earlier to extract phrases

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Decoding with phrases

- Decoding is the process of deriving E given F
  $E^* = \text{argmax}_E P(F|E)P(E) \approx \text{argmax}_E P(F, A|E)P(E)$
- Checking all E, A is infeasible
- Instead, use a (heuristic) **beam search**
  1. Choose partial translation (E', A') with highest score ($\propto P(F', A'|E')P(E')$)
  2. Increment that by appending bilingual phrase pairs
  3. Prune set of resulting partial translations by score
- We'll see **beam search** in more detail in NMT

NEURAL MACHINE TRANSL-ATION

SMT - Summary

- 1990s-2010s SMT: huge research field
- So far, we only discussed the high-level ideas (e.g. *alignment*), omitting lots of details and caveats
- Best systems were extremely complex with many separately designed sub-components
- Lots of human effort & hand-engineered feature design (e.g. capturing specific language phenomenon)
- Required compiling and maintaining large rules engine

NMT – biggest success story of NLP Deep Learning?

- Circa 2016, NMT became the leading standard method for MT starting with a fringe research attempt in 2014!
- **2014**: First seq2seq paper published [1,2]
- **2016**: Google Translate switches from SMT to NMT – and by 2018, everyone has!
- NMT systems trained by a small group of engineers in a few months outperforms the (then) SOTA SMT systems, built by hundreds of engineers over decades!
- NMT is a flagship task for NLP deep learning
- In 2024, NMT research continues to thrive, with many improvements to the vanilla *seq2seq* model we'll discuss

[1] **Sutskever, Ilya**, et al. "Sequence to sequence learning with neural networks." *NeurIPS* (2014).

[2] Bahdanau, Dzmitry, et al. "Neural machine translation by jointly learning to align and translate." *arXiv preprint arXiv:1409.0473* (2014).

What is NMT?

- Machine translation with neural networks
- *Usually* drops noisy channel: $E^* = \text{argmax}_E P(E|F)$
  - Some NMT researchers (e.g. "Simple and effective noisy channel modeling for neural machine translation," 2019. Yee *et al.*) use the noisy channel objective
- No (explicit) alignments – *end-to-end* training
- Outperforms "SMT" by a large margin

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Solving the alignment problem

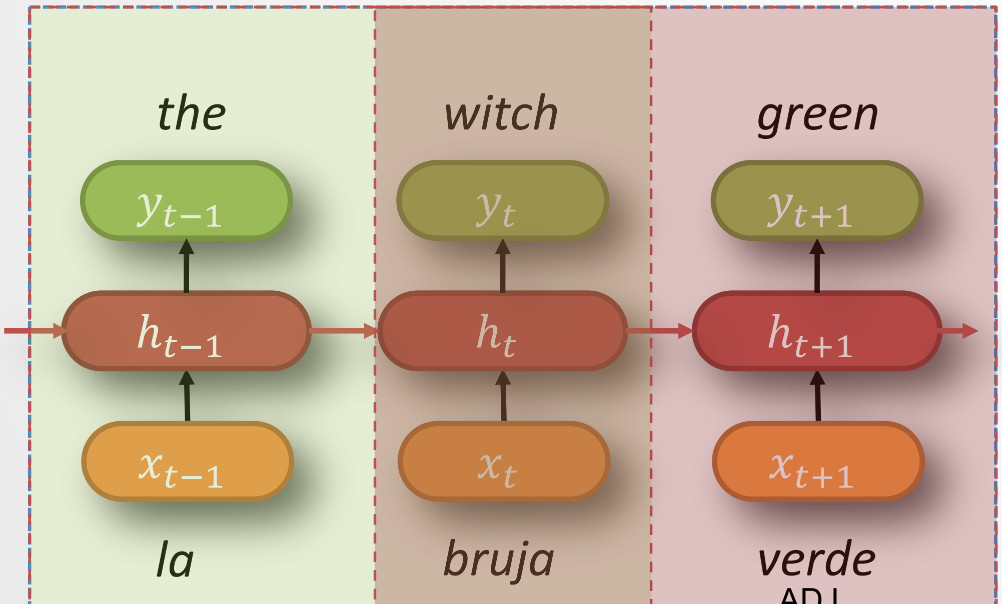
- Recall that source and target words (or, sentences) are not always one-to-one
- SMT solution is to marginalize explicit alignments
  - $E^* = \text{argmax}_E \sum_A P(F, A|E)P(E)$
- NMT uses sequence-to-sequence (seq2seq) encoder/decoder architectures
  - An **encoder** produces a representation of F
  - A **decoder** interprets that representation and generates an output sequence E

Seq2seq motivation

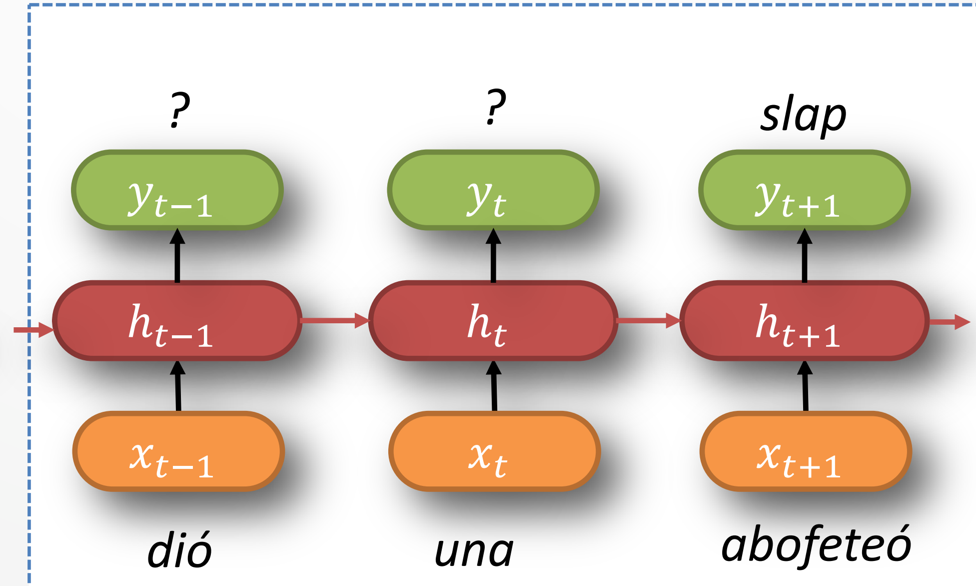
Why do we need seq2seq encoder/decoder architecture?

Why not train a RNN to output a translated token from source token?

*"Mary no **dió una abofeteó** a la bruja verde." -> "Mary did not **slap** the green witch."*



Different morphology: Adj, NN order not same



- len(src) == len(tgt) is an extreme restriction:
- Mapping is not always 1:1 (e.g. many:1)

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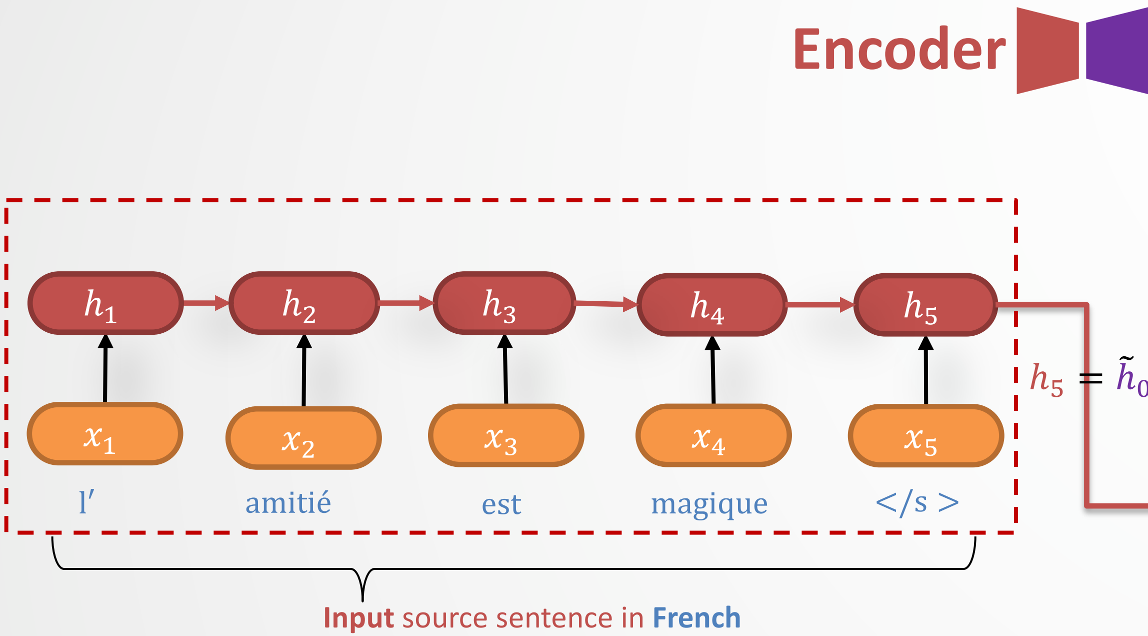
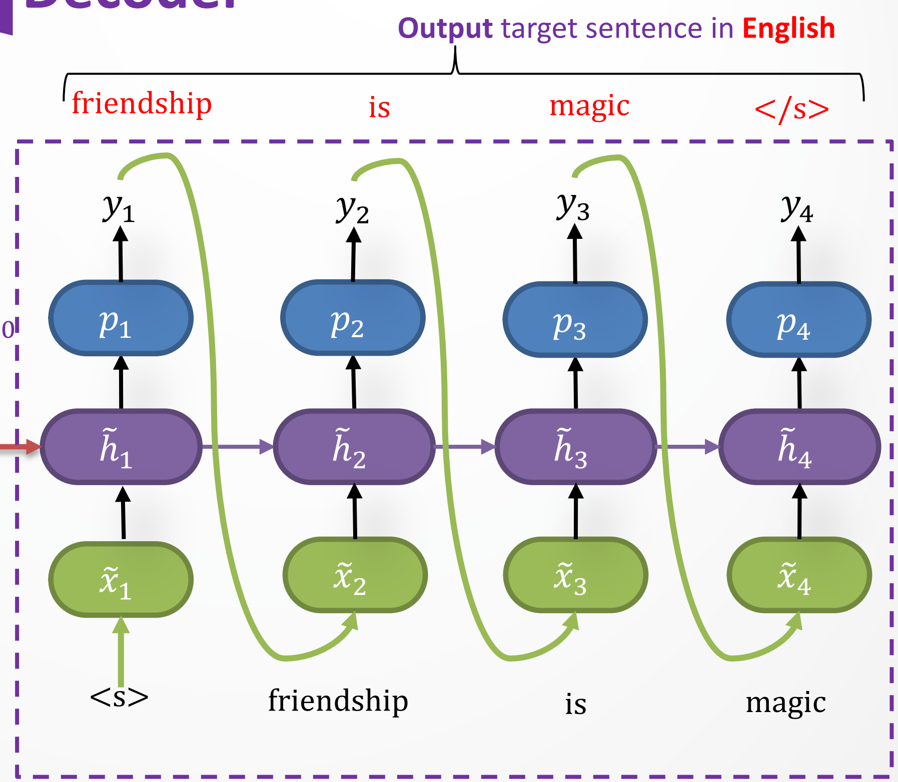
NMT: the seq2seq model



Encoder (RNN) produces an encoding of the source (French) sentence



Decoder (RNN) generates target sentence (in English), conditioned on the encoding

Decoder is predicting the next word of the target sentence y

Prediction is **conditioned** on the source sentence **x**

$$P(y|x) = P(y_1|x)P(y_2|y_1, x) \dots P\left(y_T\middle|y_1, \dots y_{(T-1)}, x\right)$$

- The *seq2seq* model is an example of conditioned language model (LM)
- Many variants exists. The classical (vanilla) seq2seq model outlined here
- NMT directly calculates $y^* = \text{argmax}_y P(y|x)$
- I.e. with our formulation:

$$E^* = \text{argmax}_E P(E|F)$$

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Notation

Term	Meaning
$F_{1:S}$	Source sequence (translating from)
$E_{1:T}$	Target sequence (translating to)
$x_{1:S}$	Input to encoder RNN (i.e. source embeddings $x_s = T_F(F_s)$)
$h_{1:S}^{(\ell,n)}$	Encoder hidden states (w/ optional layer index ℓ or head n)
$\tilde{x}_{1:T}$	Input to decoder RNN
$\tilde{h}_{1:T}^{(\ell,n)}$	Decoder hidden states (w/ optional layer index ℓ or head n)
$p_{1:T}$	Decoder output token distribution parameterization $p_t = f\left(\tilde{h}_t\right)$
$y_{1:T}$	Sampled output token from decoder $y_t \sim P(y_t \mid p_t)$
$c_{1:T}$	Attention context $c_t = Attend\left(\tilde{h}_t, h_{1:S}\right) = \sum_s \alpha_{t,s} h_s$
$e_{1:T,1:S}$	Score function output $e_{t,s} = score\left(\tilde{h}_t, h_s\right)$
$\alpha_{1:T,1:S}$	Attention weights $\alpha_{t,s} = \exp e_{t,s} \,/ \sum_{s'} \exp e_{t,s'}$
$\tilde{z}_{1:T}^{(\ell)}$	Transformer decoder intermediate hidden states (after self-attention)

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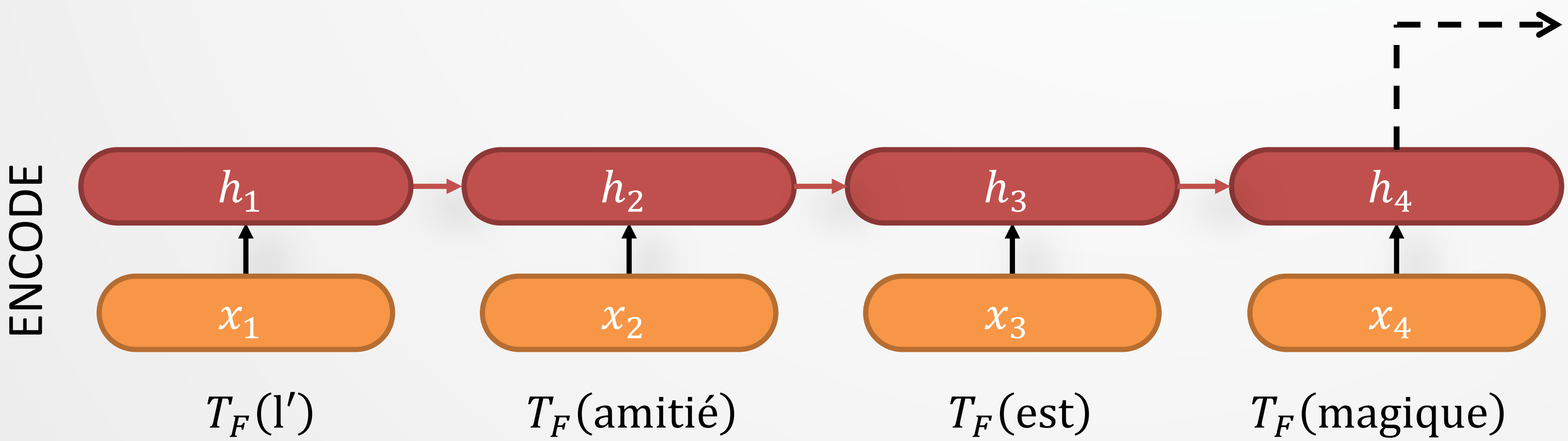
Encoder

- Encoder given source text $x = (x_1, x_2, \ldots)$
  - $x_s = T_F(F_s)$ a source word embedding
- Outputs last hidden state of RNN
- Note $h_S = f(F_{1:S})$ conditions on entire source

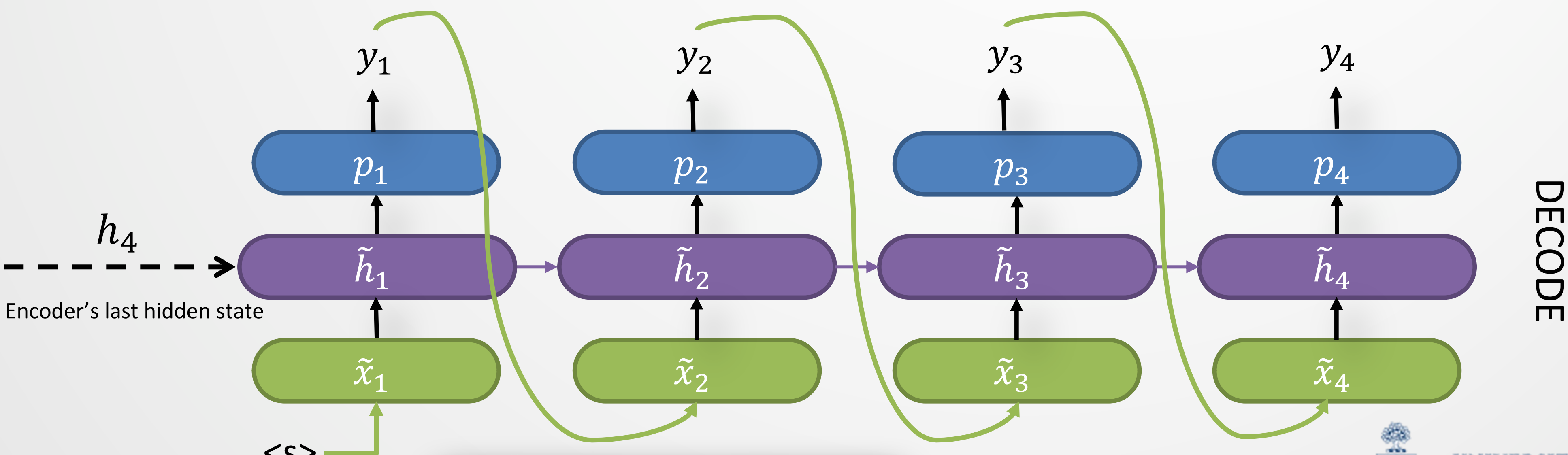


Source sentence (French): *L' amitié est magique*

Target sentence (English): *Friendship is magic* [Ground truth output]

Decoder

- **Sample** a target sentence word by word $y_t \sim P(y_t|p_t)$
- Set input to be embedding of **previously generated word** $\tilde{x}_t = T_E(\boldsymbol{y_{t-1}})$
- $p_t = f(\tilde{h}_t) = f\left(g(\tilde{x}_t, \tilde{h}_{t-1})\right)$ is **deterministic**
- Base case: $\tilde{x}_1 = T_E(\text{<s>}),\ \tilde{h}_0 = h_S$
- $P(y_{1:T}|F_{1:S}) = \prod_t P(y_t|y_{<t}, F_{1:S}) \rightarrow$ **auto-regressive**



N.B.: Implicit $y_0 = \text{<s>}, P(y_0) = 1$

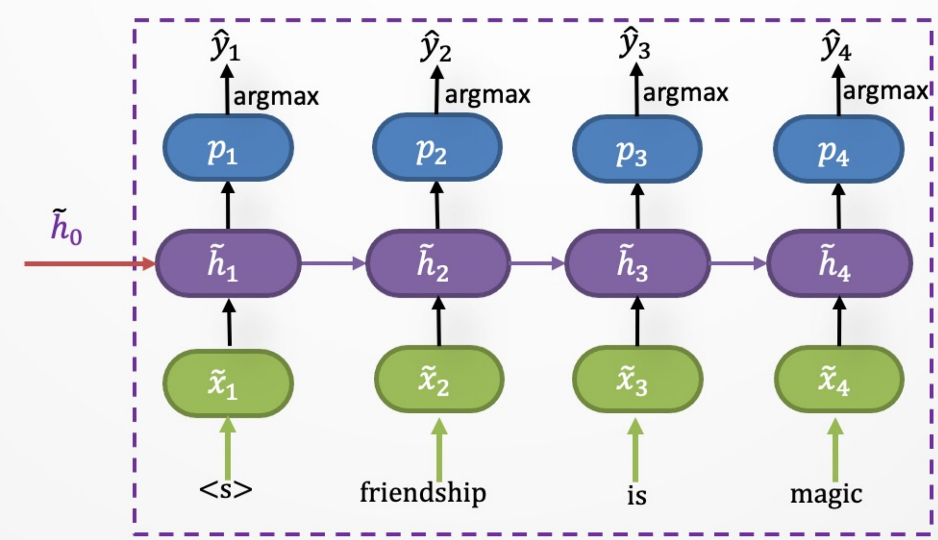
NMT: Training a MT system

- Train towards maximum likelihood estimate (MLE) against **one** translation E
- Auto-regression simplifies independence

MLE: $\theta^* = \text{argmin}_\theta \mathcal{L}(\theta|E,F)$

$$\mathcal{L}(\theta|E,F) = -\log P_\theta(y = E|F)$$
$$= -\sum_t \log P_\theta(y_t = E_t|E_{<t}, F_{1:S})$$

$$\mathcal{L} = -\log P(\text{friendship}|\cdots) - \log P(\text{is}|\cdots) - \log P(\text{magic}|\cdots) - \log P(\text{</s>}|\cdots)$$



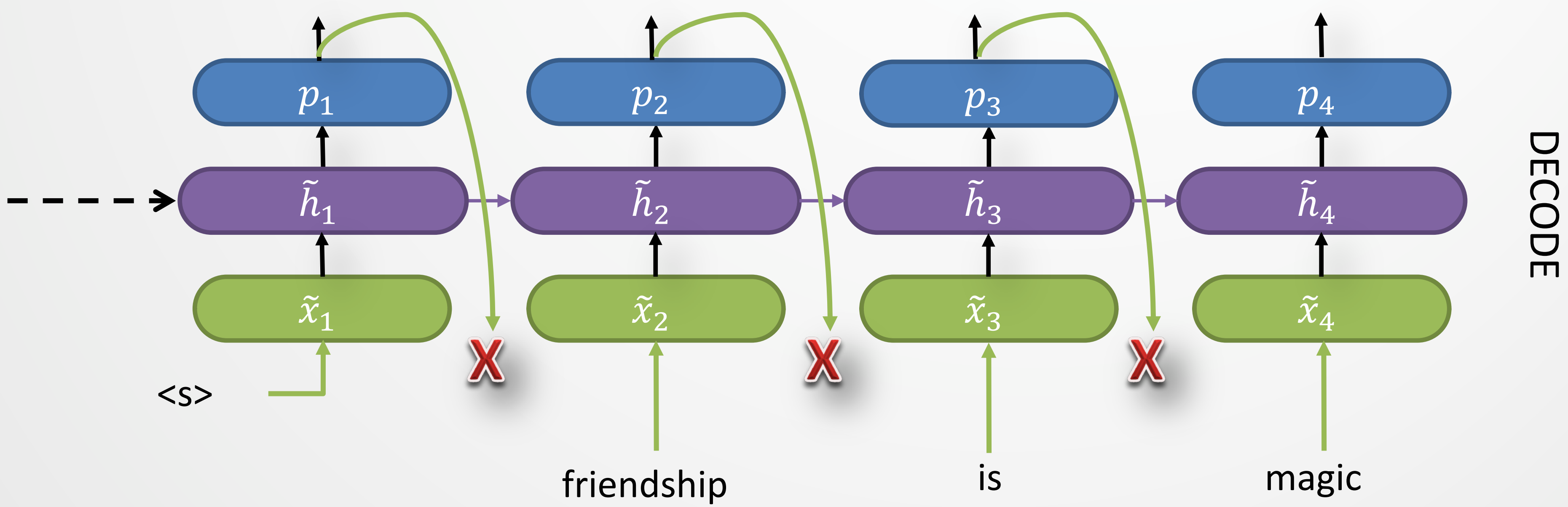
Teacher forcing

Core Idea

Remove feed-forward **recurrence** from the previous output to the hidden units at a time step and **replace** with ground-truth values for faster training

- Teacher forcing = maximum likelihood estimate (MLE)
- Replace $\tilde{x}_t = T(\underbrace{y_{t-1}}_{\text{Predicted output}})$ with $\tilde{x}_t = T(\underbrace{E_{t-1}}_{\text{target or ground truth}})$
- Caveat: since $y_{t-1} \neq E_{t-1}$ in general, causes **exposure bias**

$$\mathcal{L} = -\log P(\text{friendship}|\cdots) - \log P(\text{is}|\cdots) - \log P(\text{magic}|\cdots) - \log P(</s>|\cdots)$$



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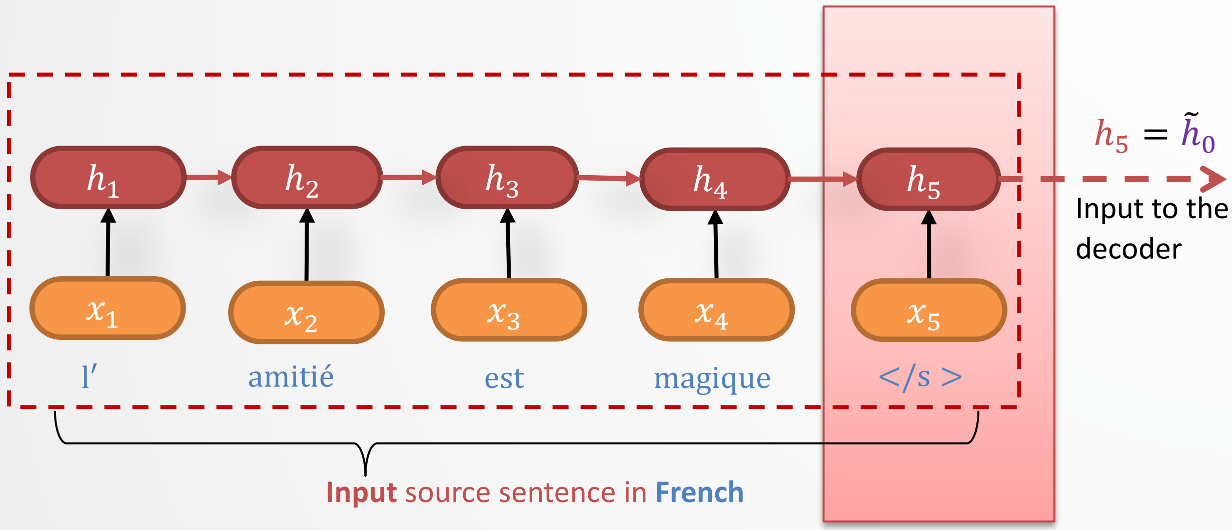
Attention motivations - I

- The information bottleneck problem with vanilla *seq2seq* model



The encoder RNN output h_5 has to encode information from all preceding time steps.

Creates a bottleneck at h_5, due to the *vanishing gradient problem* for longer sequences

- **Solution**: sequence to sequence with **attention** (*seq2seq+attn*)[2] model

Core Idea

Use **direct connection** to the encoder states and **focus** on selective, **relevant parts** of the **source sequence** at every step of the decoder

[1] Sutskever, Ilya, et al. "Sequence to sequence learning with neural networks." *NeurIPS* (2014).
[2] Bahdanau, Dzmitry, et al. "Neural machine translation by jointly learning to align and translate." *arXiv preprint arXiv:1409.0473* (2014).

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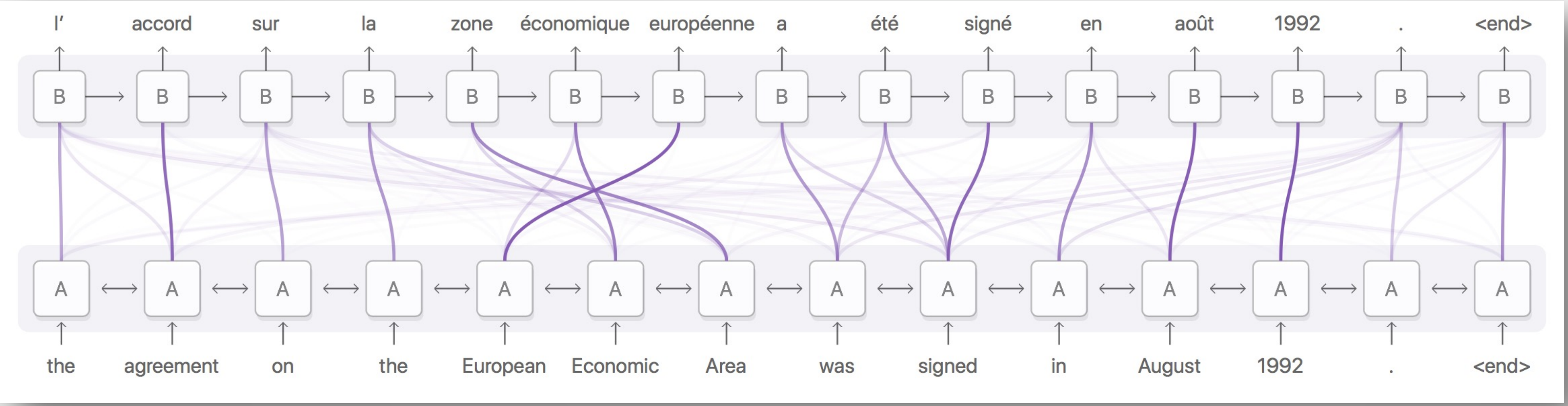
Attention motivations - II

- Allow decoder to “**attend**” (or, *query*) to certain areas of input (*values*) when making decisions. (Warning: correlation ≠ causation!) [1,2]
- Combines input from sequence dimension $h_{1:S}$ in a context-dependent way



Imagery from the excellent https://distill.pub/2016/augmented-rnns/#attentional-interfaces .

[1] Jain, Sarthak, and Byron C. Wallace. "Attention is not explanation." *arXiv preprint arXiv:1902.10186* (2019)
[2] Wiegreffe, Sarah, and Yuval Pinter. "Attention is not not explanation." *arXiv preprint arXiv:1908.04626* (2019)

Attention mechanisms

- Input to decoder a weighted sum of **all** encoder states
- Weights determined **dynamically by decoder previous hidden state**
- $\tilde{x}_t = [c_{t-1}; T_E(y_{t-1})]$
  - 1. Attention scores $a_{t,1:S} = score(\tilde{h}_t, h_{1:S})$
  - 2. Weights $\alpha_{t,s} = softmax(a_{t,1:S}, s) = {}^{\exp a_{t,s}}/_{\sum_{s'} \exp a_{t,s'}}$
  - 3. Context vector $c_t = \; Attend(\tilde{h}_t, h_{1:S}) = \sum_s \alpha_{t,s} h_s$
- Score function, usually $score(a, b) = |a|^{-1/2} \langle a, b \rangle$ (scaled **dot-product** attention).

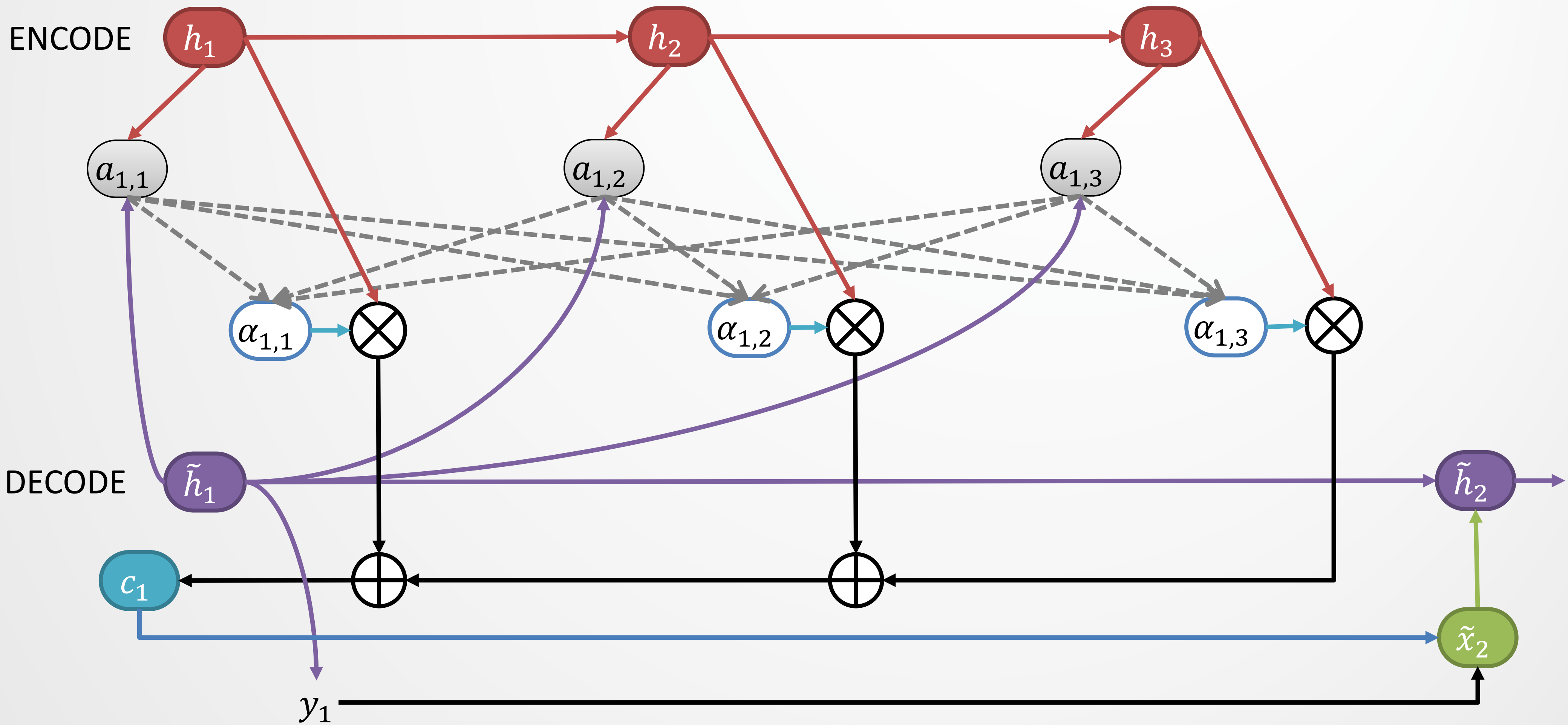
Score function variants

- Attention scores $a_{t,1:S} = score(\tilde{h}_t, h_{1:S})$
- Many variants of the score function for calculating attention scores between decoder's $\tilde{h}_t$ and encoder's $h_{1:S}$
- Basic dot-product attention $a_{t,s} = \tilde{h}_t^{\ T}.\, h_s \in \mathbb{R}$
  - Assumption: $\tilde{h}_{(t)}, h_{(s)} \in \mathbb{R}^d$
- Multiplicative (bilinear) attention $a_{t,s} = \tilde{h}_t^{\ T}.\, \boldsymbol{W}.\, h_s \in \mathbb{R}$
  - Assumption: $\tilde{h}_{(t)} \in \mathbb{R}^{d_1}, h_{(s)} \in \mathbb{R}^{d_2}$,
    $W \in \mathbb{R}^{d_1 \times d_2}$ is a weight matrix

Mind Map: the decoder hidden state at time t, $\tilde{h}_t$, is a **query** that attends to all the encoder hidden states, $h_{1:S}$, the **values**!

Attention example

$a_{t,s} = score(\tilde{h}_t, h_s) \quad \alpha_{t,s} = softmax(a_{t,1:S}, s) \qquad c_t = \sum_s \alpha_{t,s} h_s \qquad \tilde{x}_t = [c_{t-1}; T_E(y_{t-1})] \in \mathbb{R}^{2d}$



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Multi-headed attention (in *seq2seq*)

Core Idea We want to "attend to different things" for a given time step → use **multi-headed attention**

1. Split N heads (with $W^{(n)}, \tilde{W}^{(n)} \in \mathbb{R}^{(d \times \frac{d}{N})}$)

$$\underbrace{\tilde{h}_{t-1}^{(n)}}_{\in \mathbb{R}^{\frac{d}{N}}} = \underbrace{\tilde{h}_{t-1}^{T}}_{\in \mathbb{R}^{d}} \underbrace{\tilde{W}^{(n)}}_{\in \mathbb{R}^{(d \times \frac{d}{N})}}$$

$$\underbrace{h_{s}^{(n)}}_{\in \mathbb{R}^{\frac{d}{N}}} = \underbrace{h_{s}^{T}}_{\in \mathbb{R}^{d}} \underbrace{W^{(n)}}_{\in \mathbb{R}^{(d \times \frac{d}{N})}}$$

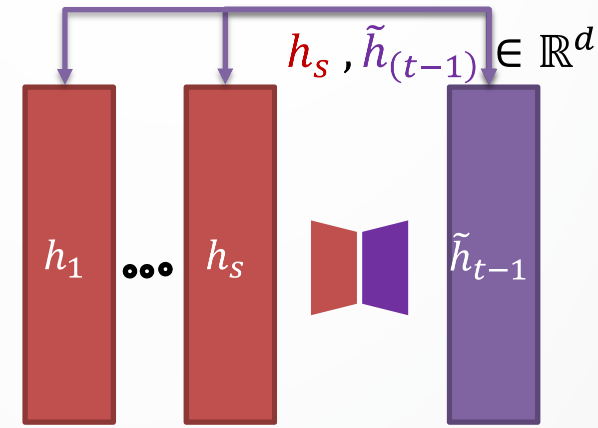
Think of the $W, \tilde{W}$ as transformation matrices projecting hidden states $h, \tilde{h}$ to a more compact dimension $\in \mathbb{R}^{\frac{d}{N}}$

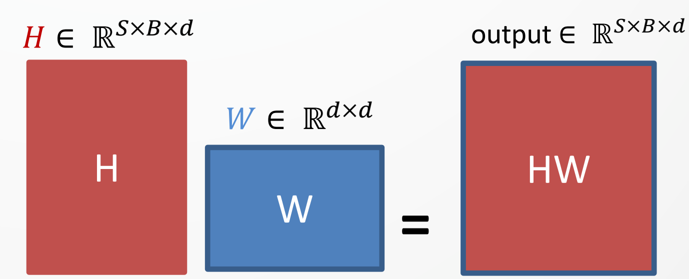
2. Use attention: $c_{t-1}^{(n)} = Att\left(\tilde{h}_{t-1}^{(n)}, h_{1:S}^{(n)}\right)$

3. Combine for result:

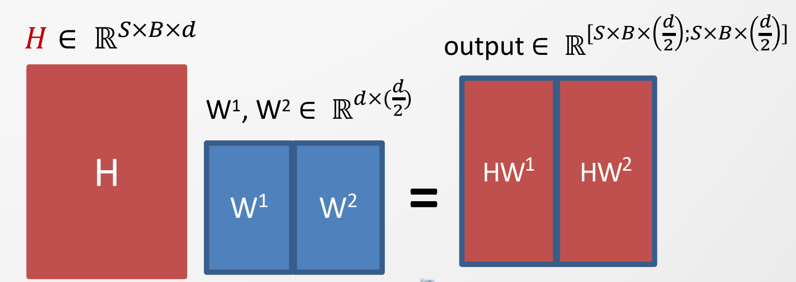
$$\tilde{x}_t = \left[\underbrace{Q c_{t-1}^{(1:N)}}_{\in \mathbb{R}^{?}}; \underbrace{T_E(y_{t-1})}_{\in \mathbb{R}^{d}}\right]$$

here **Q** is a parameter matrix for transforming the concatenated multi-head context vectors $c_{t-1}^{(1:N)}$





Single-head attention



Multi-head attention (N=2)

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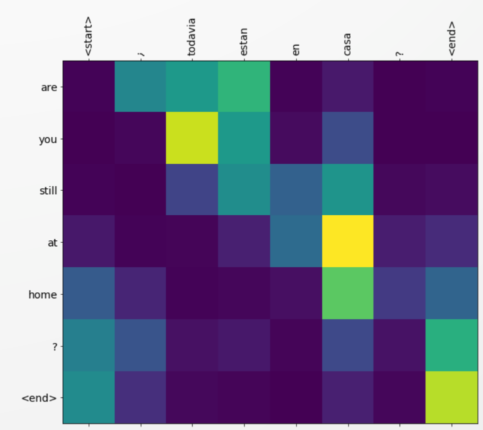
Attention advantages

- Improves NMT performance significantly
- Solves the bottleneck problem
  - Allows the decoder to look at the source sentence directly, circumventing the bottleneck
- Helps with the long-horizon (vanishing gradient) problem – by providing shortcut to distant states
- Makes the model (somewhat) interpretable
  - We can examine the attention distribution to see what the decoder was focusing on
- We get (soft) alignment for free
  - Compare w/ the '*word alignment*' matrix from SMT
  - The network learns alignment by itself even w/o any explicit training



Transformer networks

- Breakout paper in 2017: *Attention is all you need* [1]
- **Core idea**: replace recurrent connections with attention

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

- Empirical results showcased using machine translation (WMT'14)
- Deep dive in lecture L6: Transformers

[1] Vaswani, Ashish, et al. "Attention is all you need." *NeuIPS* (2017).

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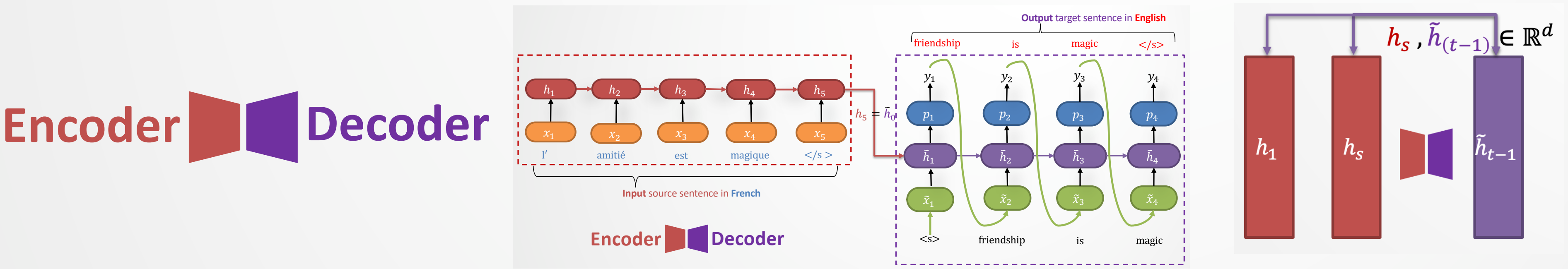
RNNs to Transformers

- **Transformers** is the underlying architecture for all state-of-the-art deep neural models – not just in NLP, but across other modalities too
- So far, we have seen encoder-decoder models using *Seq2Seq* RNNs (and variant) architectures using *attention* for memory bottlenecks

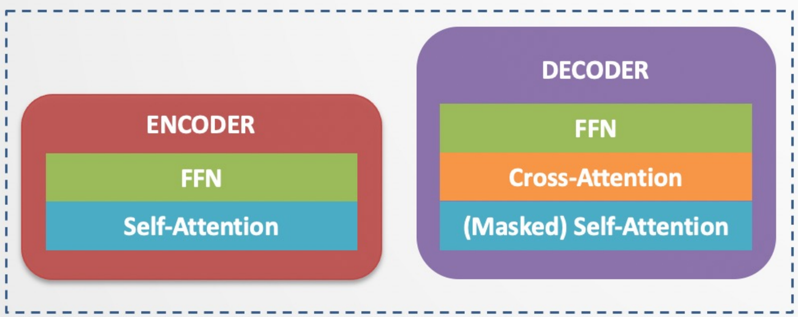


- With Transformers, we use the same (enc-dec) paradigm, updating the building blocks by removing recurrence with parallelizable blocks
- Why?

[1] Vaswani, Ashish, et al. "Attention is all you need." *NeuIPS* (2017).

Transformer networks (high-level)

Core Idea Replace recurrence (RNN) with attention



- Encoder uses self-attention

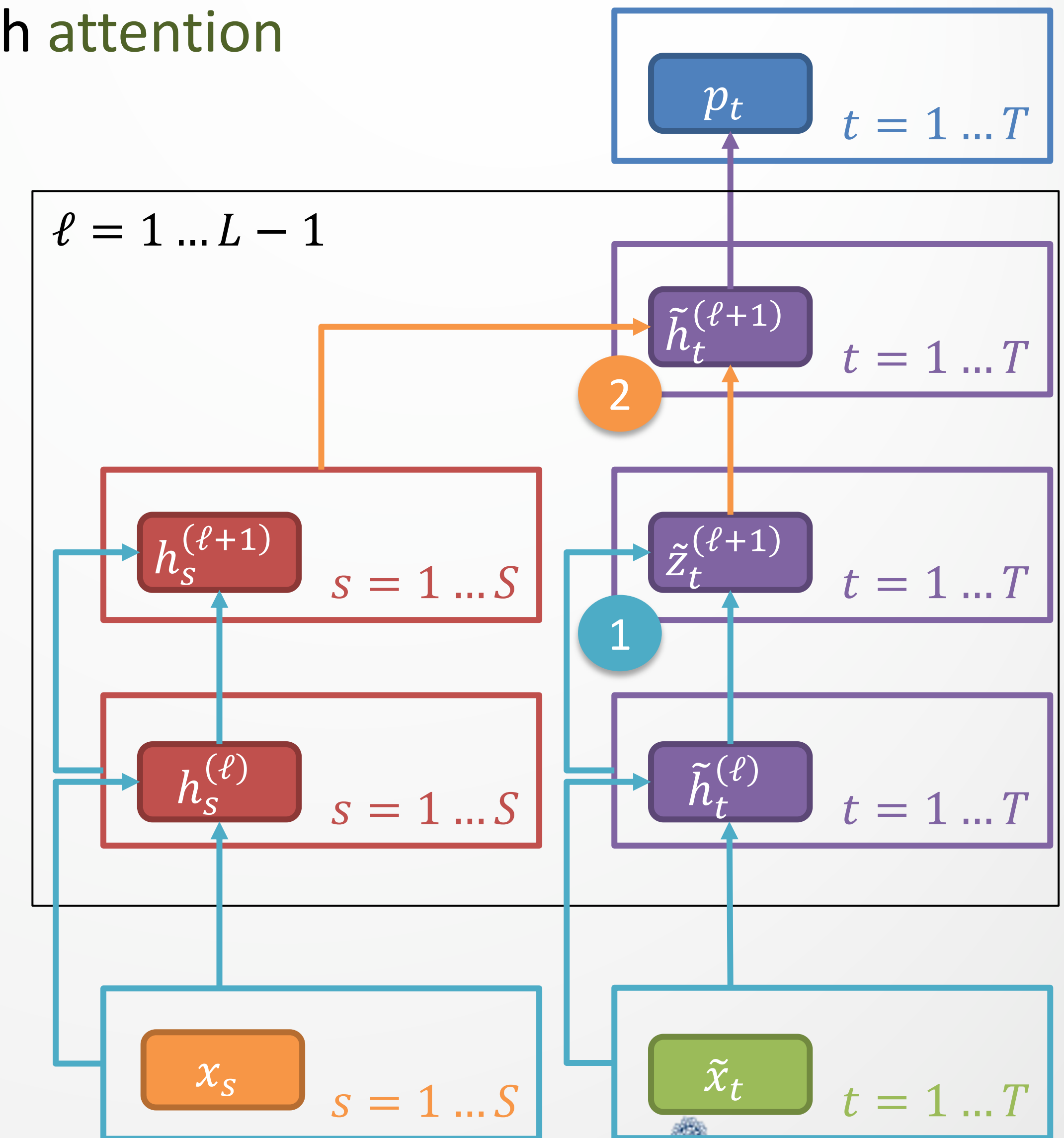
$$h_s^{(\ell+1)} \leftarrow Att_{Enc}\left(h_s^{(\ell)}, h_{1:S}^{(\ell)}\right)$$

Decoder uses 1. self-attention*

$$\tilde{z}_t^{(\ell+1)} \leftarrow Att_{Dec1}\left(\tilde{h}_t^{(\ell)}, \tilde{h}_{1:t}^{(\ell)}\right)$$

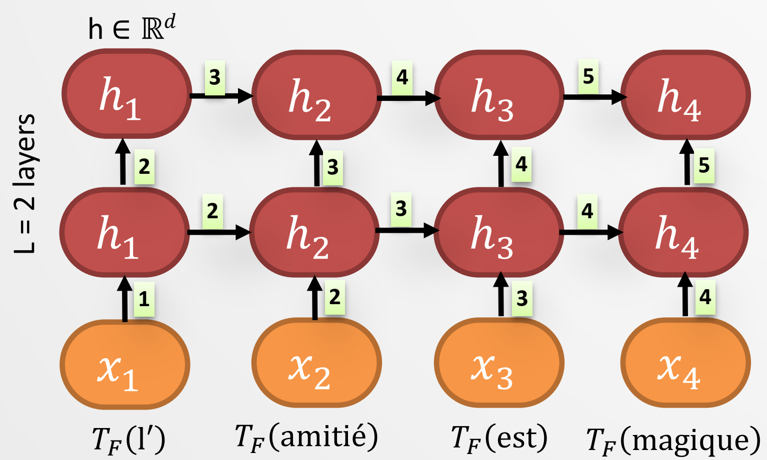
then 2. attention with encoder

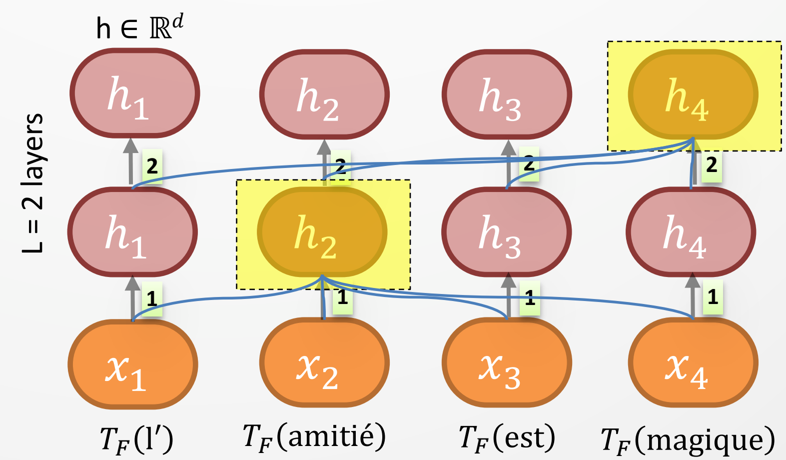
$$\tilde{h}_t^{(\ell+1)} \leftarrow Att_{Dec2}\left(\tilde{z}_t^{(\ell+1)}, h_{1:S}^{(\ell+1)}\right)$$



Transformer motivations

- Limitations of recurrent connections: long-term dependencies, lack of parallelizability, interaction distance (steps to distant tokens).
- Attention allows access to entire sequence
- Lots of computation can be shared, parallelized across sequence indices. Identical layers: [self, cross]-attention, feed-forward w/ tricks
  - Layer norm., residual connections, positional encodings, masking
  - See Vaswani *et al* (2017) for specific architecture





Source sentence (French): *L' amitié est magique*
Target sentence (English): *Friendship is magic*

Transformer auto-regression

$$\tilde{z}_t^{(\ell+1)} \leftarrow Att_{Dec1}\left(\tilde{h}_t^{(\ell)}, \tilde{h}_{\boxed{1:t}}^{(\ell)}\right)$$

- Decoder cannot attend to future: *masked self-attention*
- In teacher forcing, cannot see target directly if decoder input shifted $E_t \mapsto E_{t+1}$
- In order to decode during testing, you must
  - $y_1 \sim Decode([T_E(\text{<s>})])$
  - $y_2 \sim Decode([T_E(< s >), T_E(y_1)])$
  - Etc. until </s>

Position (in)dependence

- Attention mechanism is agnostic to sequence order
  - For permutation vector v s.t. $sorted(v) = (1,2,\ldots,V)$

$$Att(a, b_v) = Att(a, b_{1:V})$$

- **Caveat:** but the *word order* **matters** in language translation
- **Solution**: encode position in input:

$$x_s = T_F(F_s) + \phi(s)$$

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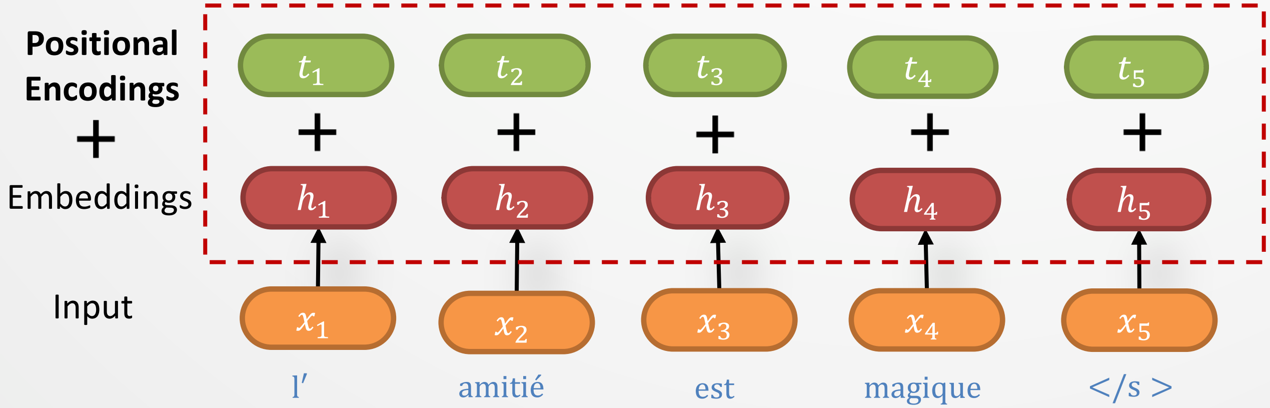
Transformer - Positional Encoding

Add positional information of an input token in the sequence into the input embedding vectors.

$$PE_{(pos,\ \mathbf{2i})} = \mathbf{sin}\left(\frac{pos}{10000^{\left(\frac{2i}{d_{model}}\right)}}\right);\ PE_{(pos,\ \mathbf{2i+1})} = \mathbf{cos}\left(\frac{pos}{10000^{\left(\frac{2i}{d_{model}}\right)}}\right)$$

- The *positional encodings* (PE) have the same dimension d_{model} as the embeddings (for summation)
- Many choices of PEs possible: learned or fixed.



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Runtime complexity

- Assume $S \approx T$

Model	Complexity	Reason
Without attention	$\boldsymbol{O(T)}$	Encoder, then decoder
With attention	$O(T^2)$	Decoder attends to all encoder states
Transformer	$O(T^2)$	Everyone attends to everyone else

- Parallelization caveats:
  - Quick to train, slow during decoding
  - Auto-regressive stacked RNN much slower than non-auto-regressive stacked RNNs
  - More details in CSC 413/2516

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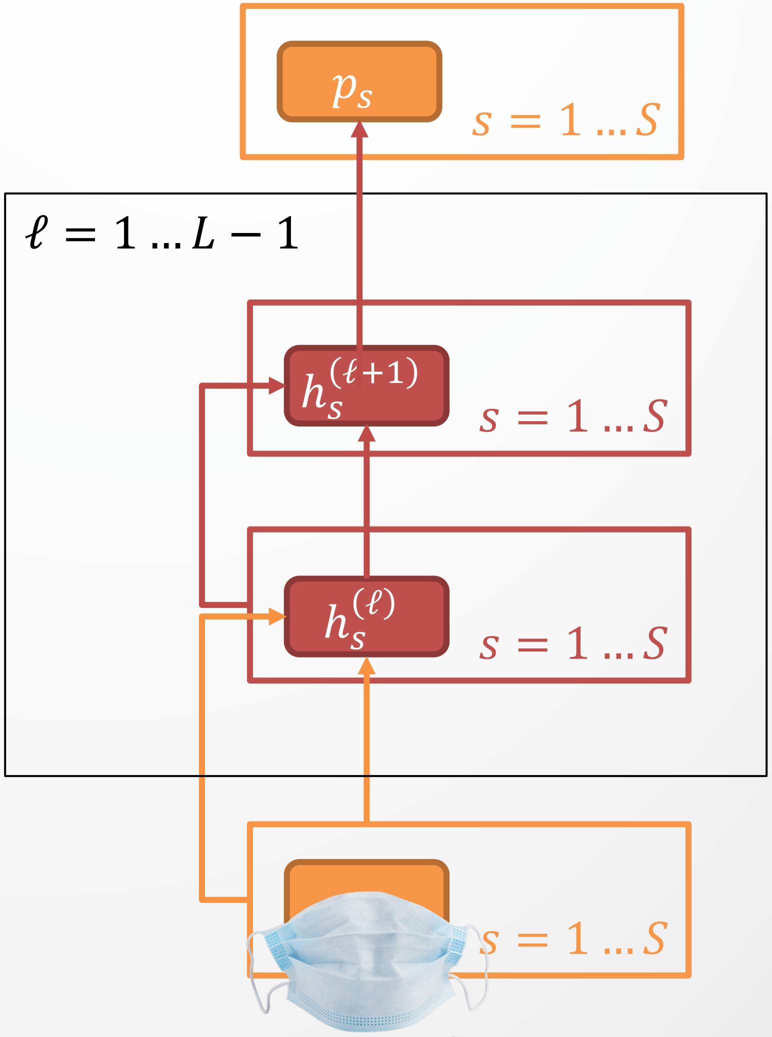
Intermezzo - BERT

(It's not an aside – it's testable!)

- **B**idirectional **E**ncoder **R**epresentations from **T**ransformers
- *Extremely* popular language representation + NLM
- Just the encoder part of the transformer model
- Learns the input that was masked



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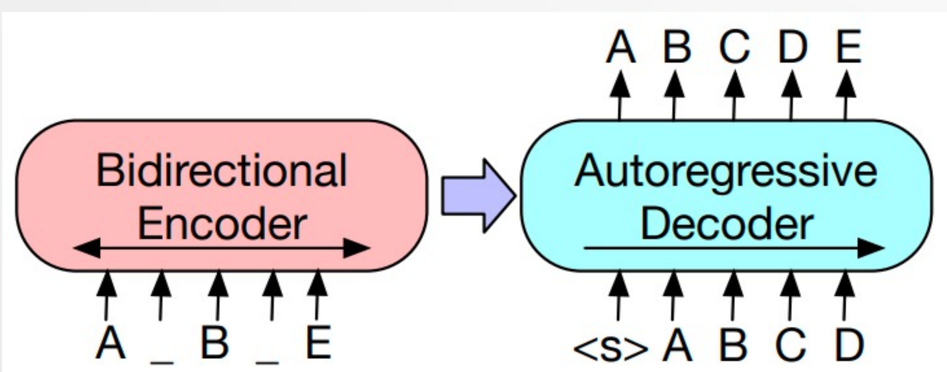
Aside – BERT → BART → NMT

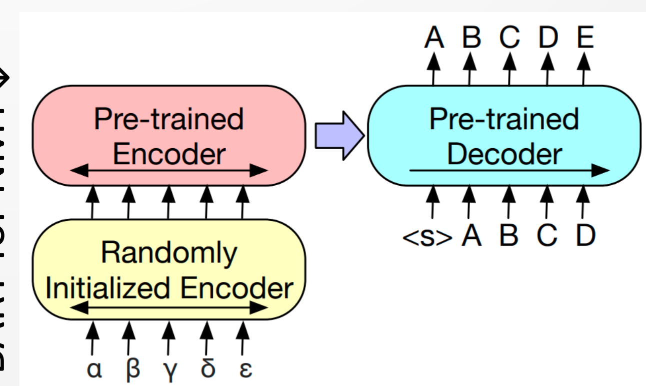
(This time it's not testable)

- Pretrained BERT language model used to re-score/fine-tune downstream NLP tasks
- Explosion of variants to BERT
- BART (Lewis *et al*, 2020) adds the decoder back to BERT, keeping the BERT objective
- Add some source language layers on top to train for NMT



BART↓

BART for NMT→



Decoding in NMT

Exhaustive search decoding

- Computationally intractable
- Maximize the probability of length T translation E_T

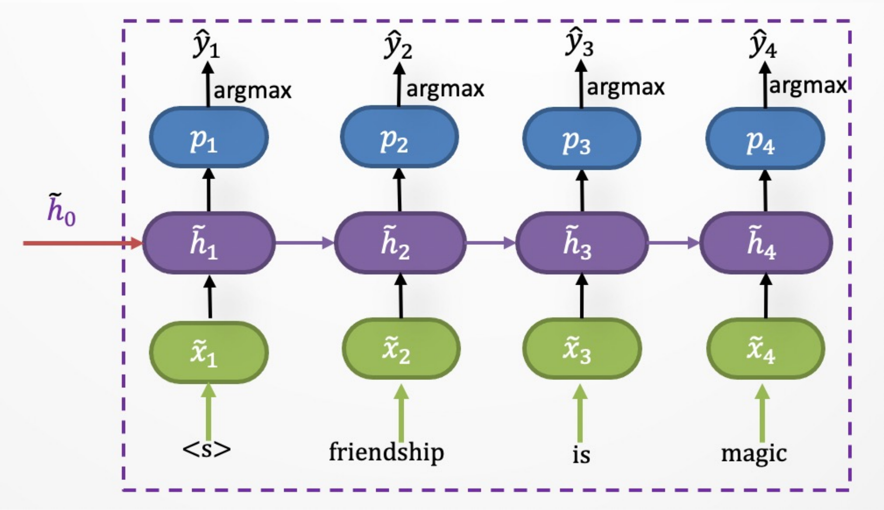
$$P(E|F_S) = (P(e_1|F_S)P(e_2|y_1, F_S), \dots, P(e_T|y_1, y_2 \dots, y_{T-1}, F_S)$$

- At each decoder time step *t*, with vocab size *V* :
  - there is *V* possibilities for the decoded token e^t
  - we are tracking V^t possible *partial translations*
- The $O(V^T)$ runtime complexity is infeasible

Greedy Decoding

- Core idea: take the **most probable** word on each step

$$y_t = \text{argmax}_i(p_{t,i})$$



- Problem: Can't recover from a prior bad choice (no '*undo*')

- Sub-optimal in an auto-regressive setup:
  - $\tilde{h}_t$ continuous, depends on y_{t-1}
  - DP (optimal sequence) solutions for discrete, finite state spaces (e.g. *Viterbi search* - HMM lecture) impossible

Beam search: top-*K* greedy

- **Core idea**: track the K top choices (most probable) of partial translations (or, hypotheses) at each step of decoding
- K is also called the '*beam width*' or '*beam size*'
  - Where, $5 \leq K \leq 10$ usually in practice
- The score of a hypothesis $(y_1, \ldots, y_t)$ is its log probability:

$$score(y_1, \ldots, y_t) = \log P_{LM}(y_1, \ldots, y_t | x) = \sum_{i=1}^{t} \log P_{LM}(y_i | y_1, \ldots, y_{i-1}, x)$$

  - We search and track the top k hypotheses based on the score
  - Scores are all negative, and higher is better
- Beam search is *not* guaranteed to find the optimal solution
- However, much more efficient and practical than exhaustive search

Beam search example (*t=1*)

$V = \{\mathrm{H}, \mathrm{A}, </\mathrm{s}>\}$, K=2

$b_{t,0}^{(k)}$: *k*-th path hidden state
$b_{t,1}^{(k)}$: *k*-th path sequence
$b_{t}^{(k\to v)}$: *k*-th path extended with token *v*

k	$b_{0,1}^{(k)}$	$P\left(b_0^{(k)}\right)$
1	[<s>]	1
2	[<s>]	0

k	$b_{0,1}^{(k\to v)}$	$P\left(b_0^{(k\to v)}\right)$
1*	[<s>,H]	1x0.1=0.1
1*	[<s>,A]	1x0.9=0.9
1*	[<s>,</s>]	1x0=0
2	[<s>,H]	0x0.1=0
2	[<s>,A]	0x0.9=0
2	[<s>,</s>]	0x0=0

k	$b_{1,1}^{(k)}$	$P\left(b_1^{(k)}\right)$
1	[<s>,A]	0.9
2	[<s>,H]	0.1

*Note $\forall k. \sum_v P\left(b_t^{(k\to v)}\right) = 1$

Beam search example (*t*=2)

$V = \{\text{H}, \text{A}, </\text{s}>\}$, K=2

k	$b_{1,1}^{(k)}$	$P\left(b_1^{(k)}\right)$
1	[<s>,A]	0.9
2	[<s>,H]	0.1

k	$b_{1,1}^{(k\rightarrow v)}$	$P\left(b_1^{(k\rightarrow v)}\right)$
1	[<s>,A,H]	0.9x0.5=0.45
1	[<s>,A,A]	0.9x0.3=0.27
1	[<s>,A,</s>]	0.9x0.2=0.18
2	[<s>,H,H]	0.1x0.9=0.09
2	[<s>,H,A]	0.1x0.0=0
2	[<s>,H,</s>]	0.1x0.1=0.01

k	$b_{2,1}^{(k)}$	$P\left(b_2^{(k)}\right)$
1	[<s>,A,H]	0.45
2	[<s>,A,A]	0.27

Problem 1: concentrated mass on a prefix creates near identical hypotheses

Beam search example (*t=3*)

$V = \{\mathrm{H}, \mathrm{A}, </\mathrm{s}>\}$, K=2

k	$b_{2,1}^{(k)}$	$P\left(b_2^{(k)}\right)$
1	[<s>,A,H]	0.45
2	[<s>,A,A]	0.27

k	$b_{2,1}^{(k\to v)}$	$P\left(b_2^{(k\to v)}\right)$
1	[<s>,A,H,H]	0.45x0.5=**0.225**
1	[<s>,A,H,A]	0.45x0.3=0.135
1	[<s>,A,H,</s>]	0.45x0.2=0.09
2	[<s>,A,A,H]	0.27x0.2=0.054
2	[<s>,A,A,A]	0.27x0.2=0.054
2	[<s>,A,A,</s>]	0.27x0.6=**0.162**

EOS token generated

k	$b_{3,1}^{(k)}$	$P\left(b_3^{(k)}\right)$
1	[<s>,A,H,H]	0.225
2	[<s>,A,A,</s>]	0.162

A complete hypothesis

Beam search: stopping criterion

- **Continue** decoding greedily **until** the model produces an end of sequence (</s>) token
- But '</s>' can be produced at different timesteps for each candidate hypotheses
  - Mark a hypothesis as **complete** when </s> is produced
  - The probability of a completed hypothesis **does not decrease**
  - Place it aside and continue exploring other hypotheses paths
- Usually we continue beam search until:
  - A pre-defined cutoff timestep *T* is reached
  - A pre-defined cutoff completed hypotheses *n* has been reached

Beam search example (*t=4*)

$V = \{\mathrm{H}, \mathrm{A}, </\mathrm{s}>\}$, K=2

k	$b_{3,1}^{(k)}$	$P\left(b_3^{(k)}\right)$
1	[<s>,A,H,H]	0.225
2	[<s>,A,A,</s>]	0.162

k	$b_{3,1}^{(k\to v)}$	$P\left(b_3^{(k\to v)}\right)$
1	[<s>,A,H,H,H]	0.225x0.9=**0.214**
1	[<s>,A,H,H,A]	0.225x0.05=0.01
1	[<s>,A,H,H,</s>]	0.18x0=0
2*	[<s>,A,A,</s>]	0.162x0=0
2*	[<s>,A,A,</s>]	0.162x0=0
2*	[<s>,A,A,</s>]	0.162x1=0.162

k	$b_{4,1}^{(k)}$	$P\left(b_4^{(k)}\right)$
1	[<s>,A,H,H,H]	0.214
2	[<s>,A,A,</s>]	0.162

*Since k=2 is finished

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Beam search example (*t=5*)

$V = \{\mathrm{H}, \mathrm{A}, </s>\}$, K=2

k	$b_{4,1}^{(k)}$	$P\left(b_4^{(k)}\right)$
1	[<s>,A,H,H,H]	0.214
2	[<s>,A,A,</s>]	0.162

k	$b_{4,1}^{(k\to v)}$	$P\left(b_4^{(k\to v)}\right)$
1	[<s>,A,H.H,H,H]	0.214x0.7=0.150
1	[<s>,A,H,H,H,A]	0.214x0.3=0.064
1	[<s>,A,H,H,H,</s>]	0.171x0=0
2	[<s>,A,A,</s>]	0.162x0=0
2	[<s>,A,A,</s>]	0.162x0=0
2	[<s>,A,A,</s>]	0.162x1=0.162

Winner!

k	$b_{5,1}^{(k)}$	$P\left(b_5^{(k)}\right)$
1	[<s>,A,A,</s>]	0.162
2	[<s>,A,H,H,H,H]	0.150

Problem 2: finished path probability doesn't decrease → preference for shorter paths

Solution: Normalize hypotheses score by length (1/t)

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Beam search: top-*K* greedy

$b_{t,0}^{(k)}$: *k*-th path hidden state
$b_{t,1}^{(k)}$: *k*-th path sequence
$b_{t}^{(k\to v)}$: *k*-th path extended with token *v*

Given vocab V, decoder σ, beam width K

$\forall k \in [1, K].\, b_{0,0}^{(k)} \leftarrow \tilde{h}_0, b_{0,1}^{(k)} \leftarrow [\text{<s>}], \log \mathrm{P}\left(b_0^{(k)}\right) \leftarrow -\mathbb{I}_{k\neq 1}\infty$

$f \leftarrow \emptyset$ # finished path indices

While $1 \notin f$:

$\forall k \in [1, K].\, \tilde{h}_{t+1}^{(k)} \leftarrow \sigma\left(b_{t,0}^{(k)}, last\left(b_{t,1}^{(k)}\right)\right)$ # $last(x)$ gets last token in x

$\forall v \in V, k \in [1, K] \backslash f.\, b_{t,0}^{(k\to v)} \leftarrow \tilde{h}_{t+1}^{(k)}, b_{t,1}^{(k\to v)} \leftarrow \left[b_{t,1}^{(k)}, v\right]$

Calculate hypothesis score $\log P\left(b_t^{(k\to v)}\right) \leftarrow \log P(y_{t+1} = v | \tilde{h}_{t+1}^{(k)}) + \log P\left(b_t^{(k)}\right)$

$\forall v \in V, k \in f.\, b_t^{(k\to v)} \leftarrow b_t^{(k)}, \log P\left(b_t^{(k\to v)}\right) \leftarrow \log P\left(b_t^{(k)}\right) - \mathbb{I}_{v\neq \text{</s>}}\infty$

$\forall k \in [1, K].\, b_{t+1}^{(k)} \leftarrow \operatorname{argmax}^k_{b_t^{(k'\to v)}} \log P\left(b_t^{(k'\to v)}\right)$ # *k-th max* $b_t^{(k'\to v)}$

$f \leftarrow \{k \in [1, K] | last\left(b_{t+1}^{(k)}\right) = \text{</s>}\}$

$t \leftarrow t + 1$

Return $b_{t,1}^{(1)}$

*Other completion criteria exist (e.g. $t \leq T$, finish some # of paths)

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Beam search: top-K greedy

In lecture annotations

$b_{t,0}^{(k)}$: k-th path hidden state
$b_{t,1}^{(k)}$: k-th path sequence
$b_t^{(k\to v)}$: k-th path extended with token v

Initialization

Given vocab V, decoder σ, beam width K

$\forall k \in [1,K].\, b_{0,0}^{(k)} \leftarrow \tilde{h}_0, \mathrm{b}_{0,1}^{(k)} \leftarrow [\text{<s>}], \log \mathrm{P}\left(b_0^{(k)}\right) \leftarrow -\mathbb{I}_{k\neq 1}\infty$

$f \leftarrow \emptyset$ # finished path indices

While $1 \notin f$: End search when the most probable of the K prefixes end with </s>

$\forall k \in [1,K].\, \tilde{h}_{t+1}^{(k)} \leftarrow \sigma\left(b_{t,0}^{(k)}, last\left(b_{t,1}^{(k)}\right)\right)$ # $last(x)$ gets last token in x

$\forall v \in V, k \in [1,K]\backslash f.\, b_{t,0}^{(k\to v)} \leftarrow \tilde{h}_{t+1}^{(k)}, b_{t,1}^{(k\to v)} \leftarrow \left[b_{t,1}^{(k)}, v\right]$

K paths excluding the finished ones

Calculate hypothesis score $\log P\left(b_t^{(k\to v)}\right) \leftarrow \log P(y_{t+1} = v|\tilde{h}_{t+1}^{(k)}) + \log P\left(b_t^{(k)}\right)$

$\forall v \in V, k \in f.\, b_t^{(k\to v)} \leftarrow b_t^{(k)}, \log P\left(b_t^{(k\to v)}\right) \leftarrow \log P\left(b_t^{(k)}\right) - \mathbb{I}_{v\neq \text{</s>}}\infty$

Pick top-K (sorted) $\forall k \in [1,K].\, b_{t+1}^{(k)} \leftarrow \mathrm{argmax}^k_{b_t^{(k'\to v)}} \log P\left(b_t^{(k'\to v)}\right)$ # k-th max $b_t^{(k'\to v)}$

$f \leftarrow \{k \in [1,K] | last\left(b_{t+1}^{(k)}\right) = \text{</s>}\}$ Write as finished path if </s> generated

$t \leftarrow t+1$ Go to next time-step

Return $b_{t,1}^{(1)}$ Return the most probable (index 1) finished path sequence

Sub-words

- Out-of-vocabulary words can be handled by breaking up words into parts
  - "abwasser+behandlungs+anlange" → "water sewage plant"
    [e.g. agglutinative (German)]
- Sub-word units are built out of combining characters (like phrases!)
- Popular (sub-word tokenization) approaches include
  - Byte Pair Encoding (BPE): "Neural machine translation of rare words with subword units," 2016. Sennrich *et al.*
  - Wordpieces: "Google's neural machine translation system: bridging the gap between human and machine translation," 2016. Wu *et al.*

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Aside – advanced NMT

- Modifications to beam search
  - "Diverse beam search," 2018. Vijayakumar *et al.*
- Exposure bias
  - "Optimal completion distillation," 2018. Sabour *et al.*
- Back translation
  - "Improving neural machine translation models with monolingual data," 2016. Senrich *et al*.
- **N**on-**a**utoregressive neural machine **t**ranslation, 2018. Gu *et al*.
- Unsupervised neural machine translation, 2018. Artetxe *et al*.
- + *Optional readings* listed on course webpage

Evaluation of MT systems

对外经济贸易合作部今天提供的数据表明，今年至十一月中国实际利用外资四百六十九点五九亿美元，其中包括外商直接投资四百点零七亿美元。

Human (Reference)	According to the data provided today by the Ministry of Foreign Trade and Economic Cooperation, as of November this year, China has actually utilized 46.959B US dollars of foreign capital, including 40.007B US dollars of direct investment from foreign businessmen.
IBM4 (Candidate 1)	The Ministry of Foreign Trade and Economic Cooperation, including foreign direct investment 40.007B US dollars today provide data include that year to November China actually using foreign 46.959B US dollars and
Yamada/ Knight (Candidate 2)	Today's available data of the Ministry of Foreign Trade and Economic Cooperation shows that China's actual utilization of November this year will include 40.007B US dollars for the foreign direct investment among 46.959B US dollars in foreign capital.

How can we objectively compare the quality of the two candidate translations?

Automatic evaluation

- We want an **automatic** and effective method to **objectively** rank competing translations.
  - Word Error Rate (WER) measures the number of erroneous word **insertions**, **deletions**, **substitutions** in a translation.
    - E.g., **Reference**: *how to recognize speech*
      Translation: *how understand a speech*
    - Works for Automatic Speech Recognition (ASR)
  - **Problem**: There are many possible valid translations.
    (There's no need for an exact match)

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Challenges of evaluation

- **Human judges**: expensive, slow, non-reproducible (different judges – different biases).

- Multiple valid translations, e.g.:
  - **Source**: *Il s'agit d'un guide qui assure que l'armée sera toujours fidèle au Parti*
  - **T1**: *It is a guide to action that ensures that the military will forever heed Party commands*
  - **T2**: *It is the guiding principle which guarantees the military forces always being under command of the Party*

BLEU evaluation

- **BLEU (BiLingual Evaluation Understudy)** is an automatic and popular method for evaluating MT.
  - It uses **multiple** human **reference** translations, and looks for local matches, allowing for phrase movement.

  - **Candidate:** *n.* a translation produced by a machine.

- There are a few parts to a **BLEU score**…

[1]Papineni, Kishore, et al. "Bleu: a method for automatic evaluation of machine translation." *Proceedings of the 40th ACL*. 2002. [link]

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Example of BLEU evaluation

- **<u>Reference 1</u>**: *It is a guide to action that ensures that the military will forever heed Party commands*
- **<u>Reference 2</u>**: *It is the guiding principle which guarantees the military forces always being under command of the Party*
- **<u>Reference 3</u>**: *It is the practical guide for the army always to heed the directions of the party*

- **<u>Candidate 1</u>**: *It is a guide to action which ensures that the military always obeys the commands of the party*
- **<u>Candidate 2</u>**: *It is to insure the troops forever hearing the activity guidebook that party direct*

BLEU: Unigram precision

- The **unigram precision** of a candidate is

$$\frac{C}{N}$$

where N is the number of words in the **candidate**
and C is the number of words in the **candidate** which are in **at least one reference**.

- e.g., **Candidate 1**: *It is a guide to action which ensures that the military always obeys the commands of the party*
  - **Unigram precision** $= \frac{17}{18}$
    (*obeys* appears in none of the three references).

BLEU: Modified unigram precision

- **Reference 1**: *The lunatic is on the grass*
- **Reference 2**: *There is a lunatic upon the grass*
- **Candidate**: *The the the the the the the*
  - Unigram precision $= \frac{7}{7} = 1$ 

- **Capped unigram precision:**

  A candidate word type w can only be correct a **maximum** of $cap(w)$ times.

  - e.g., with $\boldsymbol{cap(the) = 2}$, the above gives

    $p_1 = \frac{2}{7}$

BLEU: Generalizing to *N*-grams

- Generalizes to higher-order *N*-grams.
  - **Reference 1**: ***It is*** *a guide to action that ensures that the military will forever heed Party commands*
  - **Reference 2**: ***It is*** *the guiding principle which guarantees the military forces always being under command of the Party*
  - **Reference 3**: ***It is*** *the practical guide for the army always to heed the directions of the party*

  - **Candidate 1**: ***It is*** *a guide to action which ensures that the military always obeys the commands of the party*
  - **Candidate 2**: ***It is*** *to insure the troops forever hearing the activity guidebook that party direct*

Bigram precision, p_2

$p_2 = 10/17$

$p_2 = 1/13$

BLEU: Precision is not enough

- **Reference 1**: *It is a guide to action that ensures that the military will forever heed Party commands*
- **Reference 2**: *It is the guiding principle which guarantees the military forces always being under command* ***of the*** *Party*
- **Reference 3**: *It is the practical guide for the army always to heed the directions* ***of the*** *party*

- **Candidate 1**: ***of the***

Unigram precision, $p_1 = \frac{2}{2} = 1$ Bigram precision, $p_2 = \frac{1}{1} = 1$

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BLEU: Brevity

- Solution: Penalize brevity.
- **Step 1**: for each candidate,
  find the reference **most similar in length**.
- **Step 2**: $\boldsymbol{c_i}$ is the length of the i^{th} candidate, and
  $\boldsymbol{r_i}$ is the nearest length among the references,

$$brevity_i = \frac{r_i}{c_i}$$

Bigger = too brief

- **Step 3**: multiply precision by the (0..1) **brevity penalty**:

$$BP_i = \begin{cases} 1 & \text{if } brevity_i < 1 \\ e^{1-brevity_i} & \text{if } brevity_i \geq 1 \end{cases}$$

$(r_i < c_i)$

$(r_i \geq c_i)$

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BLEU: Final score

- On slide 87, $r_1 = 16, r_2 = 17, r_3 = 16$, and $c_1 = 18$ and $c_2 = 14$,

$$brevity_1 = \frac{17}{18} \qquad BP_1 = 1$$

$$brevity_2 = \frac{16}{14} \qquad BP_2 = e^{1-\left(\frac{8}{7}\right)} = 0.8669$$

- **Final score** of candidate C:

$$\boxed{BLEU_C = BP_C \times (p_1 p_2 \ldots p_n)^{1/n}}$$

where p_n is the n-gram precision. (You can set n empirically)

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Example: Final BLEU score

- **Reference 1:** *I am afraid Dave*
  Reference 2: *I am scared Dave*
  Reference 3: *I have fear David*
  Candidate: *I fear David*

Assume $cap(\cdot) = 2$ for all *N*-grams

Also assume BLEU order $n = 2$

- $brevity = \frac{4}{3} \geq 1$ so $BP = e^{1-\left(\frac{4}{3}\right)}$
- $p_1 = \frac{1+1+1}{3} = 1$
- $p_2 = \frac{1}{2}$
- $BLEU = BP(p_1 p_2)^{\frac{1}{2}} = e^{1-\left(\frac{4}{3}\right)}\left(\frac{1}{2}\right)^{\frac{1}{2}} \approx 0.5067$

Aside – Corpus-level BLEU

- To calculate BLEU over M source sentences (assuming one candidate per source)…
- $BLEU \neq \frac{1}{M}\sum_{m=1}^{M} BLEU_m$
- Sum statistics over *all* sources
  - m indexes m-th source sentence, drop candidate index i
  - $p_n = \frac{\sum_{m=1}^{M} capped\_true\_ngram\_count_m}{\sum_{m=1}^{M} N_m}$
  - $r = \sum_{m=1}^{M} r_m$
  - $c = \sum_{m=1}^{M} c_m$
  - $brevity = r/c$
- **We won't ask you to calculate it this way**

BLEU: summary

- BLEU is a **geometric mean** over n-gram precisions.
  - These precisions are **capped** to avoid strange cases.
    - E.g., the translation "*the the the the*" is not favoured.
  - This geometric mean is **weighted** (*brevity penalty*) so as not to favour unrealistically short translations, e.g., "*the*"
- Initially, evaluations showed that BLEU predicted human judgements very well, but:
  - People started **optimizing** MT systems to **maximize** BLEU. Correlations between BLEU and humans **decreased**.

When an evaluation metric becomes the target of optimization, it ceases to be an evaluation metric.

NMT - Advantages

NMT has many advantages over SMT:

- Better performance
- Superior design, simpler training:
  - A single neural network can be trained end-to-end
  - No sub-components need individual optimization/training
- Significantly less human engineering effort:
  - Same method for all language pairs
  - No feature engineering for specific requirements

NMT - Disadvantages

Compared to SMT:

- Interpretability: NMT is less interpretable
- NMT is harder to debug
- Less fine-grained control:
  - For e.g., can’t specify rules or guidelines for translation
  - More prone to biases

NMT – Research questions

- Morphological errors
- Biases in training data
- Low-resource languages
- Common-sense translations
- Contextual, multi-modally grounded reasoning
  - Instruction following by AI agents (EAI agents, robots) using non-expert language feedback
- Generalization to multiple domains