Statistical + **Neural machine translation**

CSC401/2511 – Natural Language Computing – Spring 2022
Lecture 6
University of Toronto

Logistics

- Office hours: Tuesdays 10 am – 11 am (over zoom, note the channel)
- Course drop deadline: Feb 20, 2022 (see SGS calendar)

- A1: due Feb 11, 2022
- A2: release Feb 12, 2022
- A2 tutorials planned schedule:
  - Feb 18: A2 tutorial – 1 (delivery: zoom)
  - Mar 4: A2 tutorial – 2 (delivery: in person)
  - Mar 11: A2 – Q/A and OH (*submission due at mid-night*)

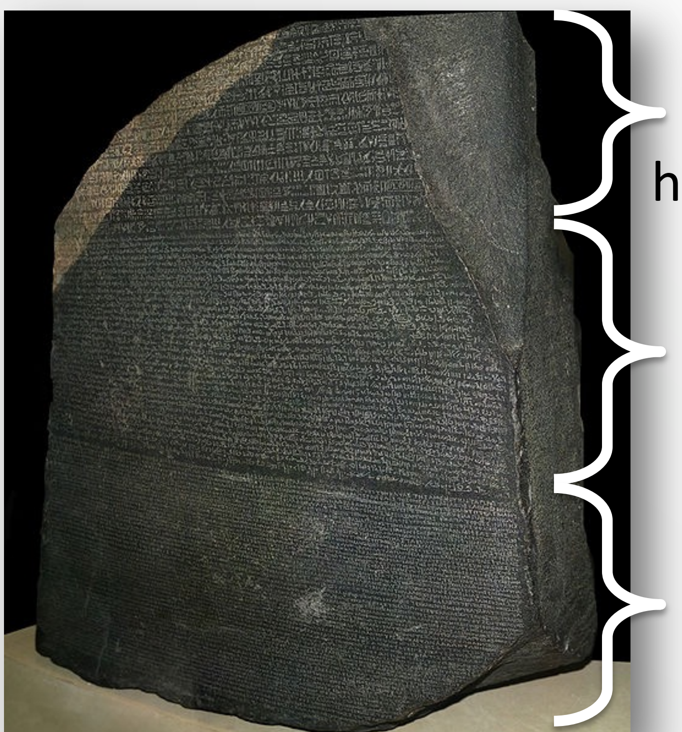
- Lecture delivery:
  - Online (*as is*) until Feb 18
  - Reading week break: Feb 21-25 (*no lectures or tutorials*)
  - In-person Feb 28th onwards
- Final exam: planned in-person

Machine Translation (MT)

- Introduction & History
- L6 (1/3) - Statistical MT:
  - Noisy Channel model
  - Alignments
- L6 (2/3) Neural MT:
  - Attention
  - Transformers
- L6 (3/3) Decoding & Evaluation:
  - Beam Search
  - BLEU

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

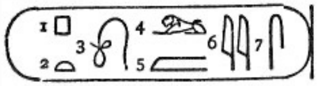
Egyptian Demotic

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 

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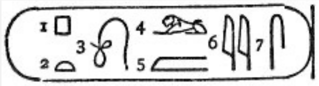
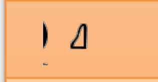
Aside – deciphering Rosetta

- 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)…*

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:

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*

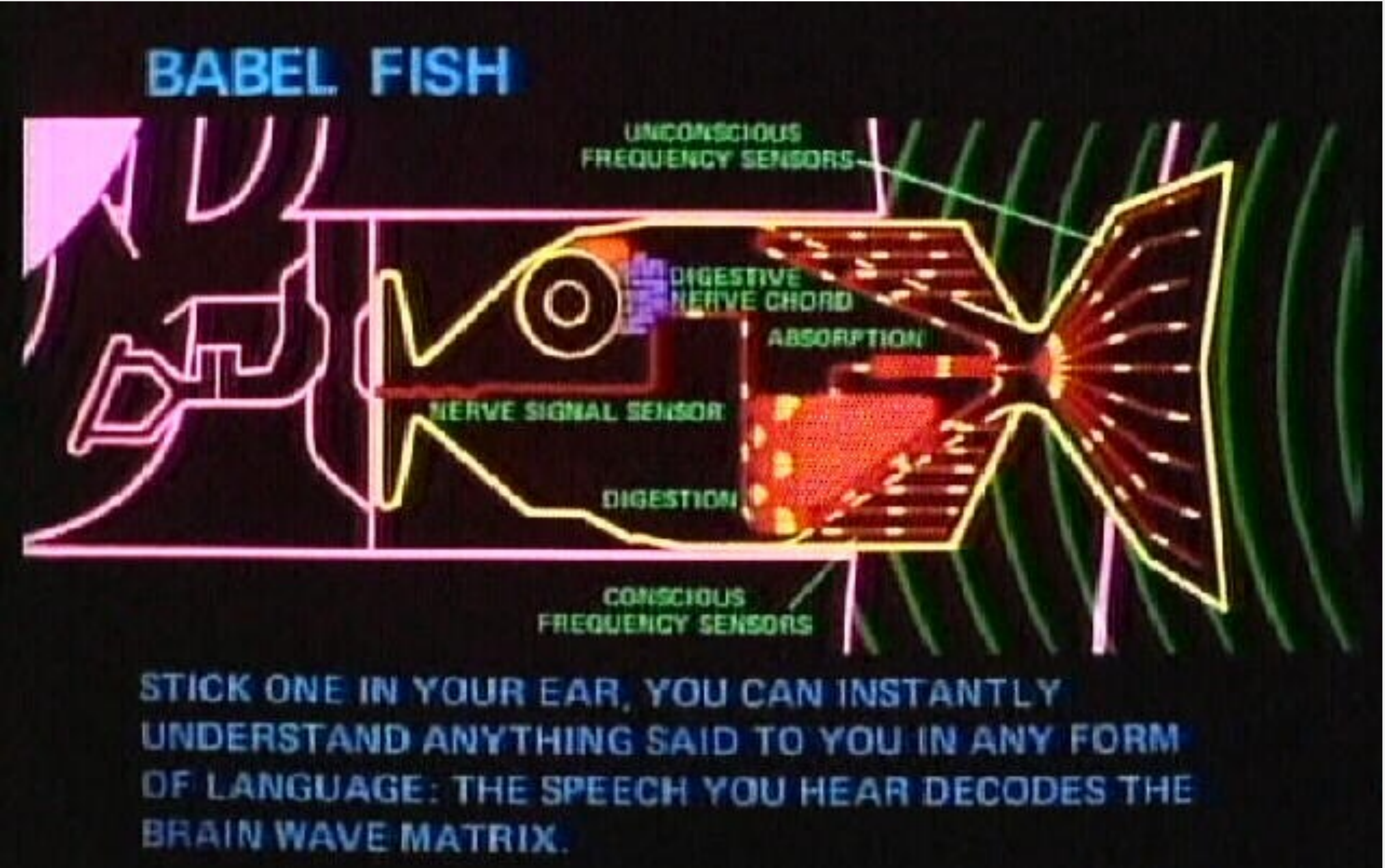
Difficulties in MT: typology

- Different **morphology** → difficult **mappings**, *e.g.*
  - Many (*polysynthetic*) vs one (*isolating*) morphemes per word
  - Many (*fusion*) vs few (*agglutinative*) features per morpheme
- Different **syntax** → **long-distance effects**, *e.g.*
  - SVO vs. SOV vs. VSO (e.g. English vs. Japanese vs. Arabic)
    - $\underbrace{\text{He}}_{\text{Subject}}$ $\underbrace{\text{listens to}}_{\text{Verb}}$ $\underbrace{\text{music}}_{\text{Object}}$ / $\underbrace{\text{kare ha}}_{\text{Subject}}$ $\underbrace{\text{ongaku wo}}_{\text{Object}}$ $\underbrace{\text{kiku}}_{\text{Verb}}$
  - 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



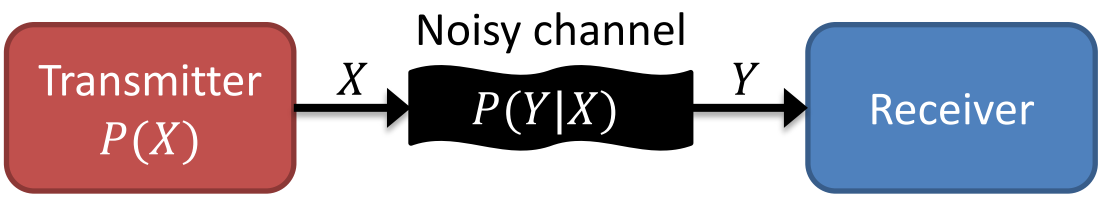
THE NOISY CHANNEL

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

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)

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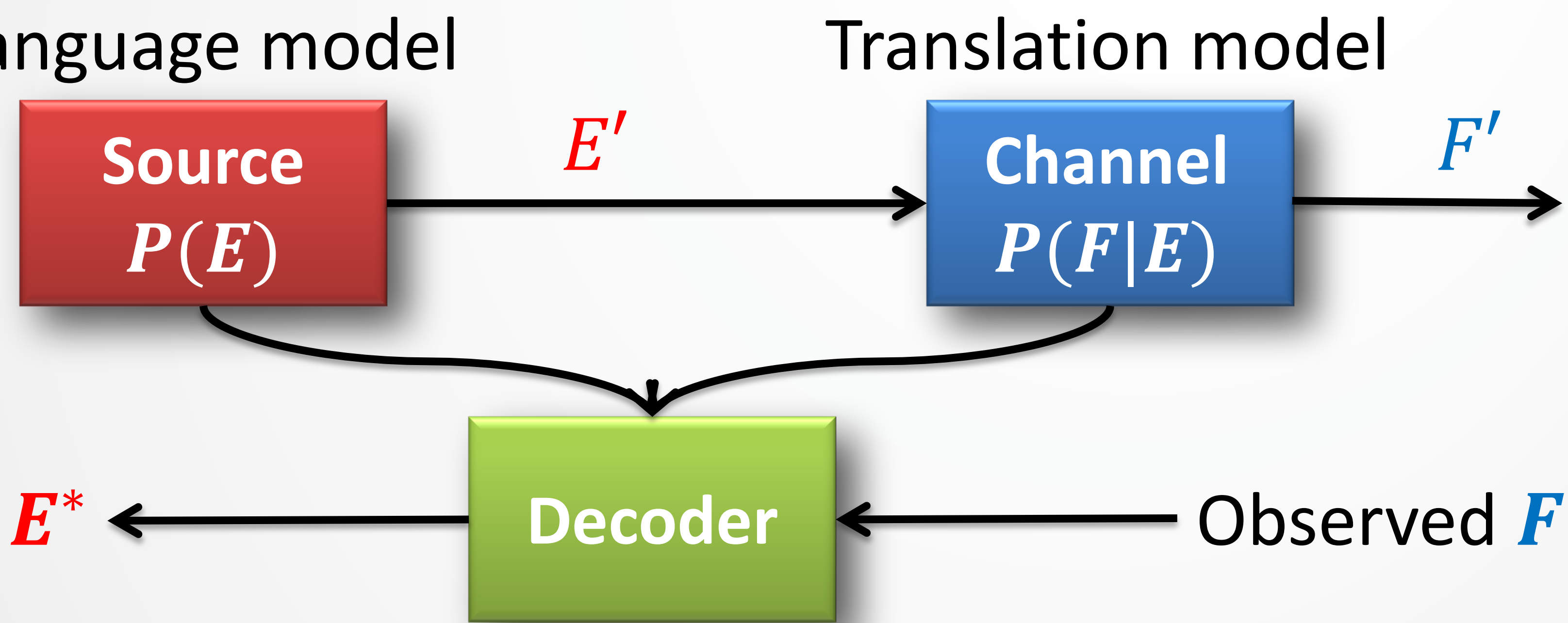
The noisy channel



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

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 $P(F|E)$?

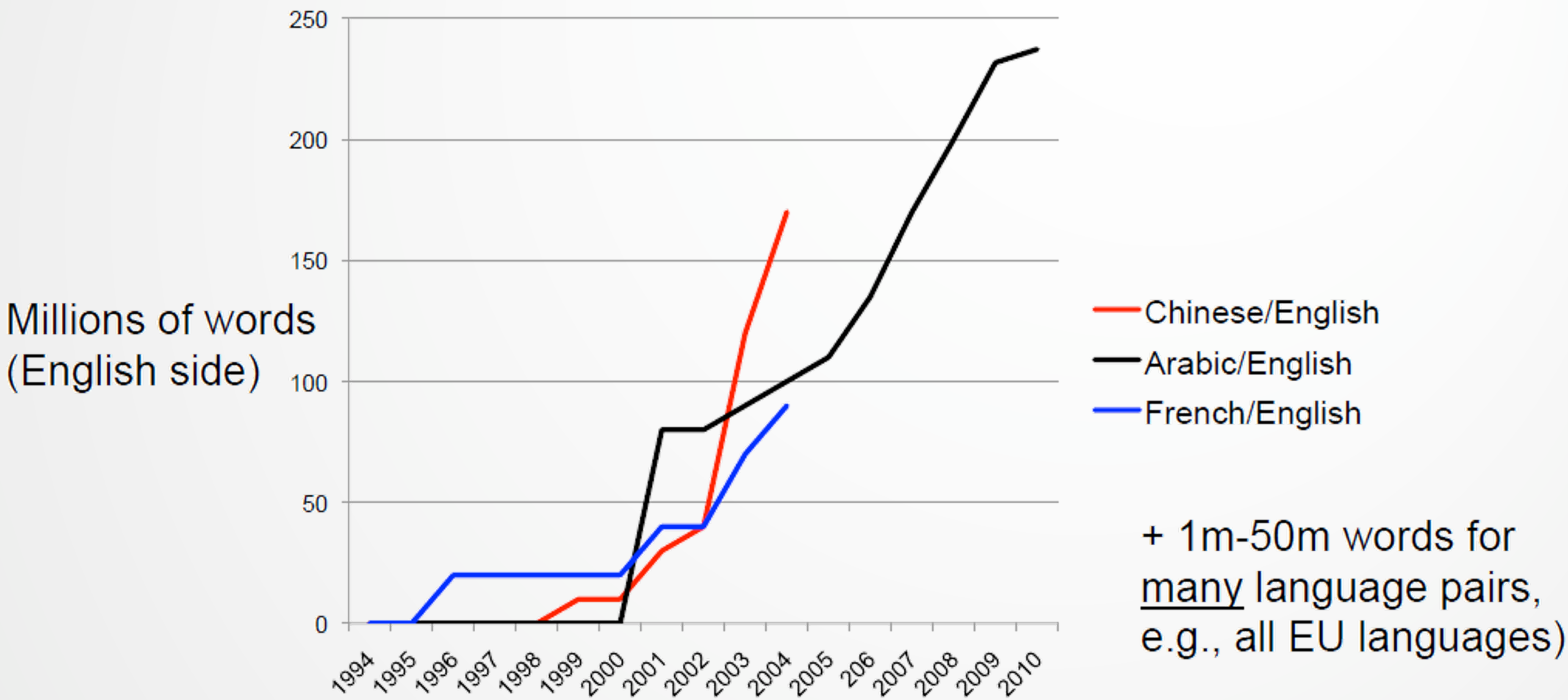
- Solution: collect statistics on vast parallel texts

… **<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



From Chris Manning's course at Stanford

- Data from Linguistic Data Consortium at University of Pennsylvania.

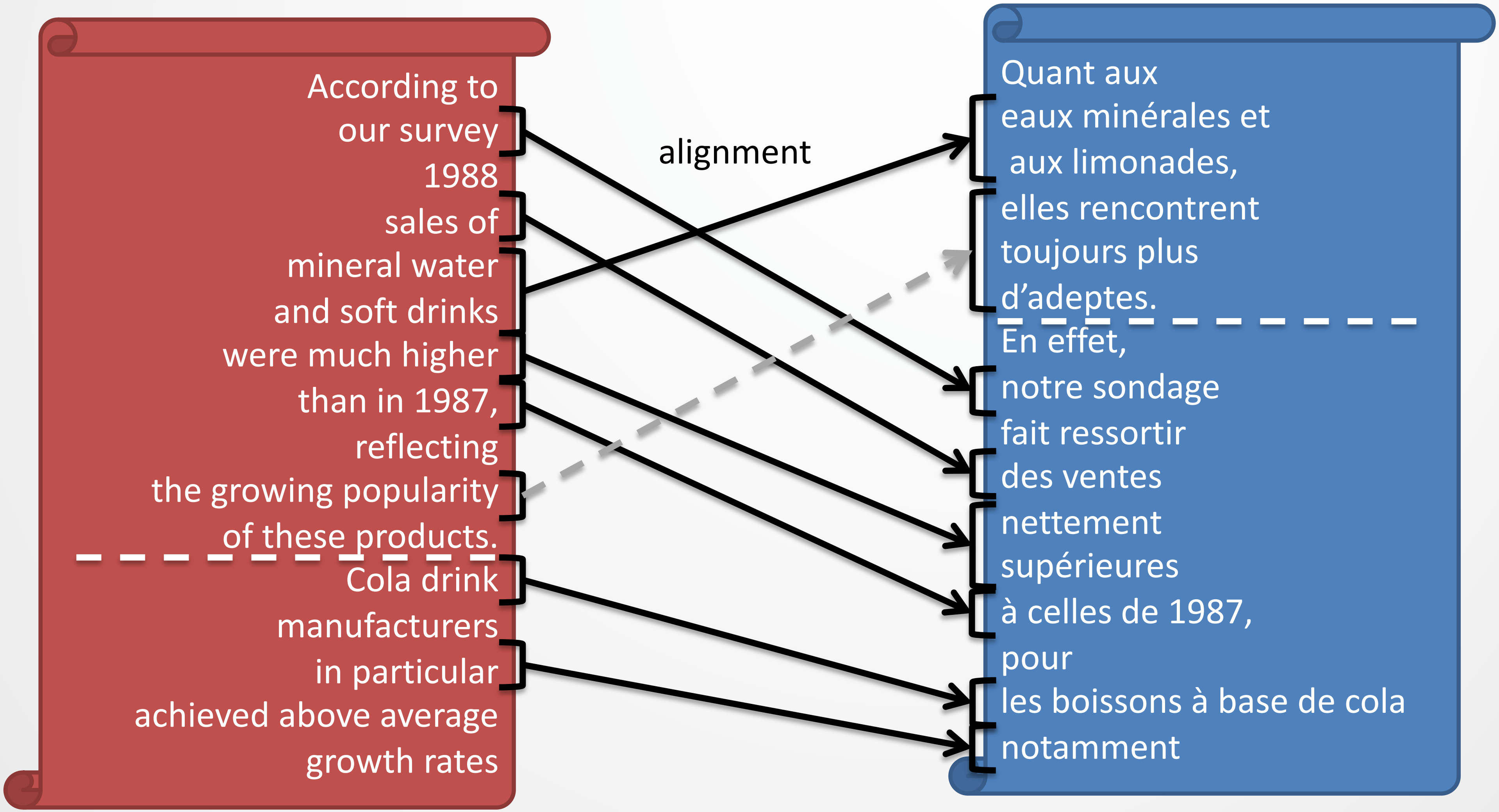
Alignments

- 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 MT (including neural) relies on sentence-level alignments of bitexts

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1. Sentence alignment <u>by length</u>

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

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

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

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

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

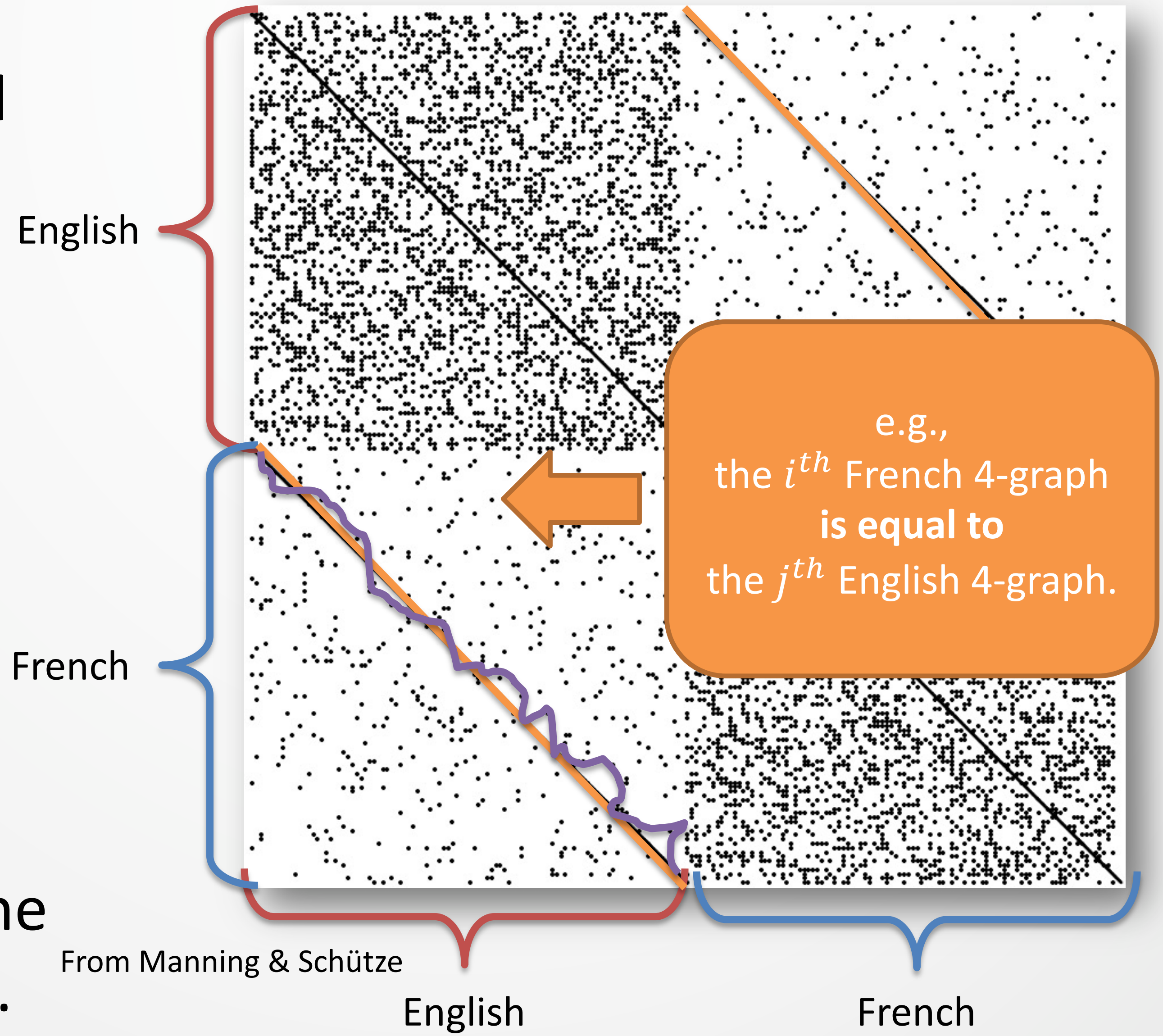
- Church (1993) tracks all **4-graphs** which are identical across two texts.
  - He calls this a 'signal-based' approximation to cognate identification.
  - Better for noisy data, like the results of optical character recognition

2. Church's method

1. Concatenate paired texts.

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

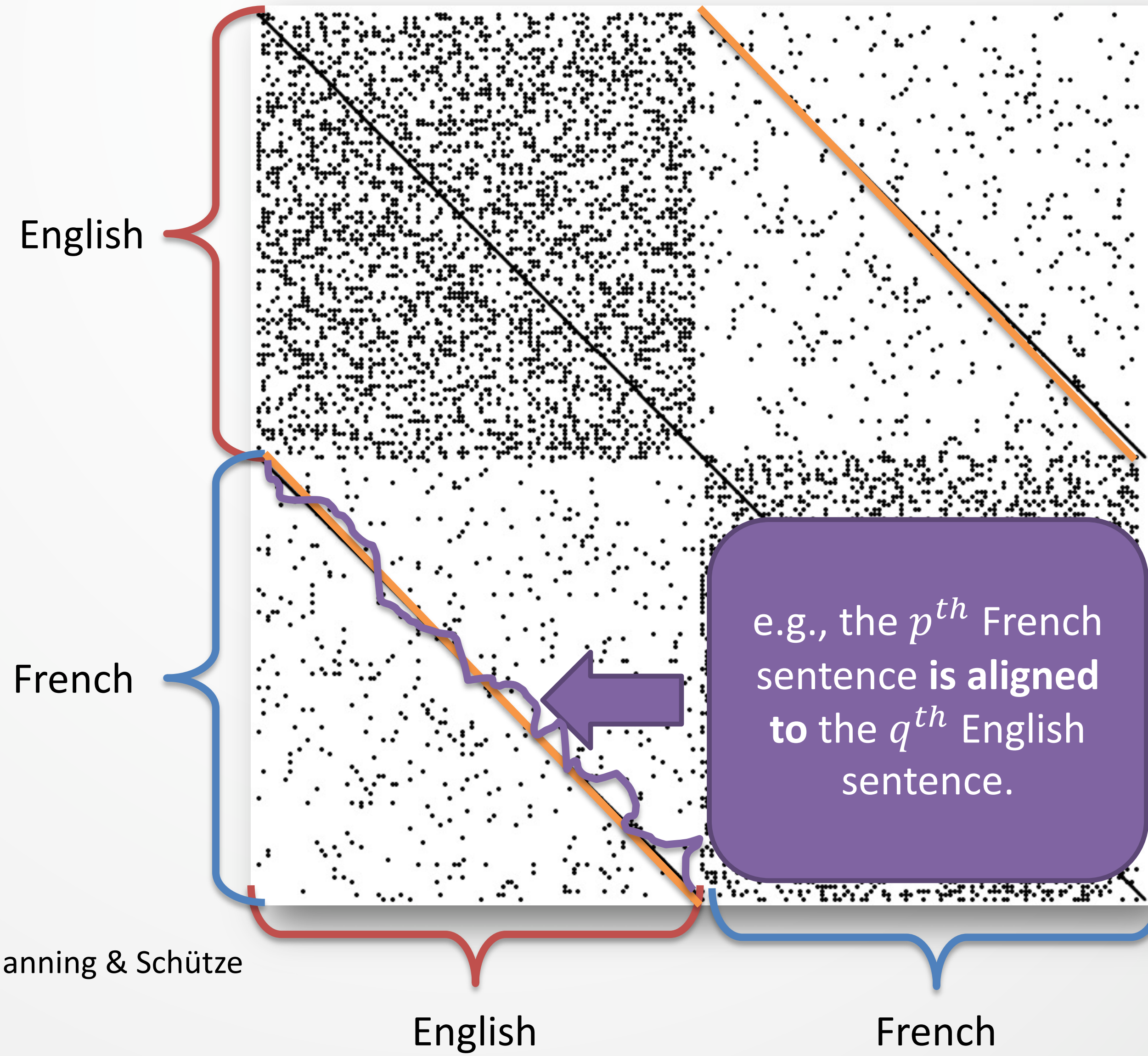
3. Search for a short path 'near' the bilingual diagonals.



From Manning & Schütze

2. Church's method

- Each point along **this path** is considered to represent a **match** between languages.
- The relevant English and French 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 E, F are documents

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

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	

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 $F \times E$

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

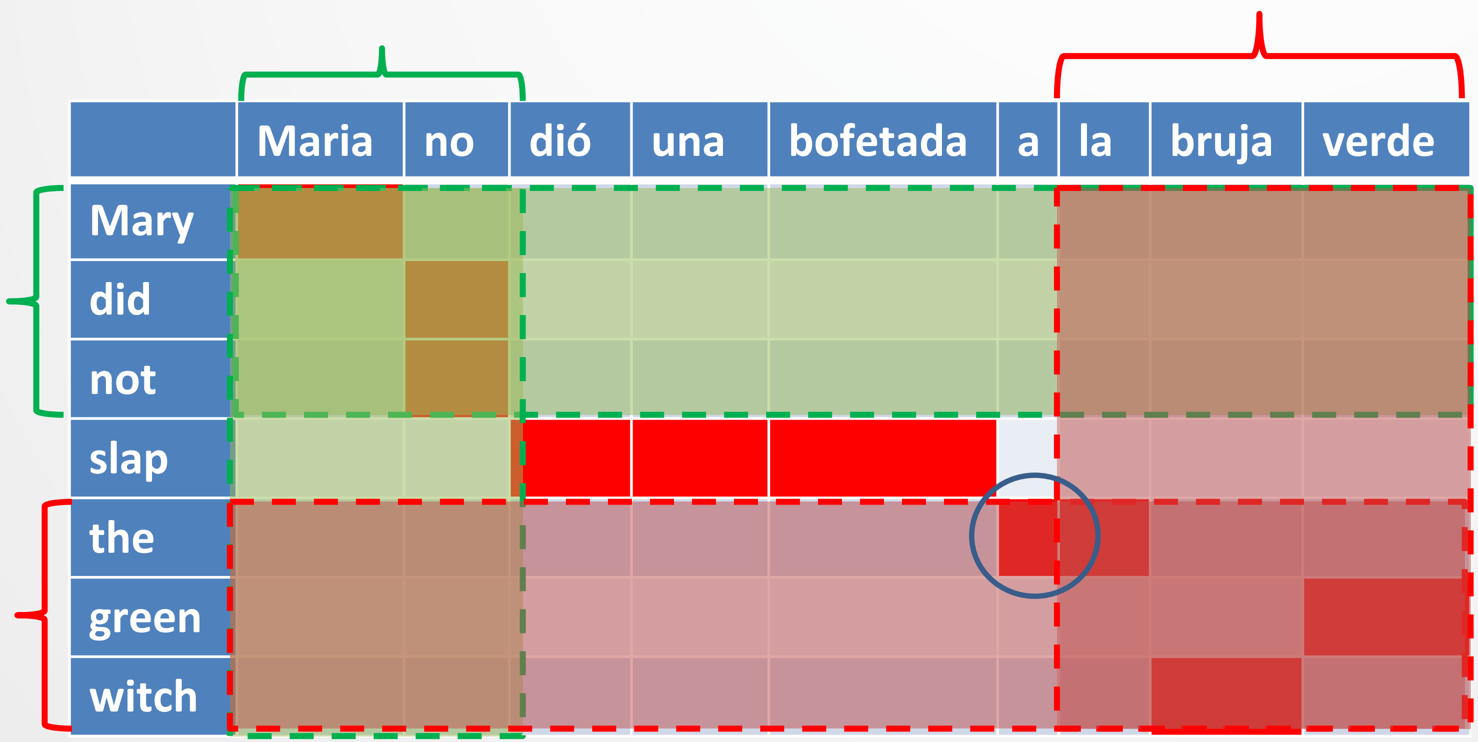
- Call each span an indivisible phrase $\left(F_{A_{i,1}}, E_{A_{i,2}}\right) \mapsto (\bar{F}_i, \bar{E}_i)$ and assume phrases sequential in E, then:

$$P(F, A|E) \propto \prod_i \phi(\bar{F}_i, \bar{E}_i)\, d\left(u_1^{(i-1)} - \ell_1^{(i)} - 1\right)$$

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

Bilingual phrase pairs

- 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



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 2022, 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).

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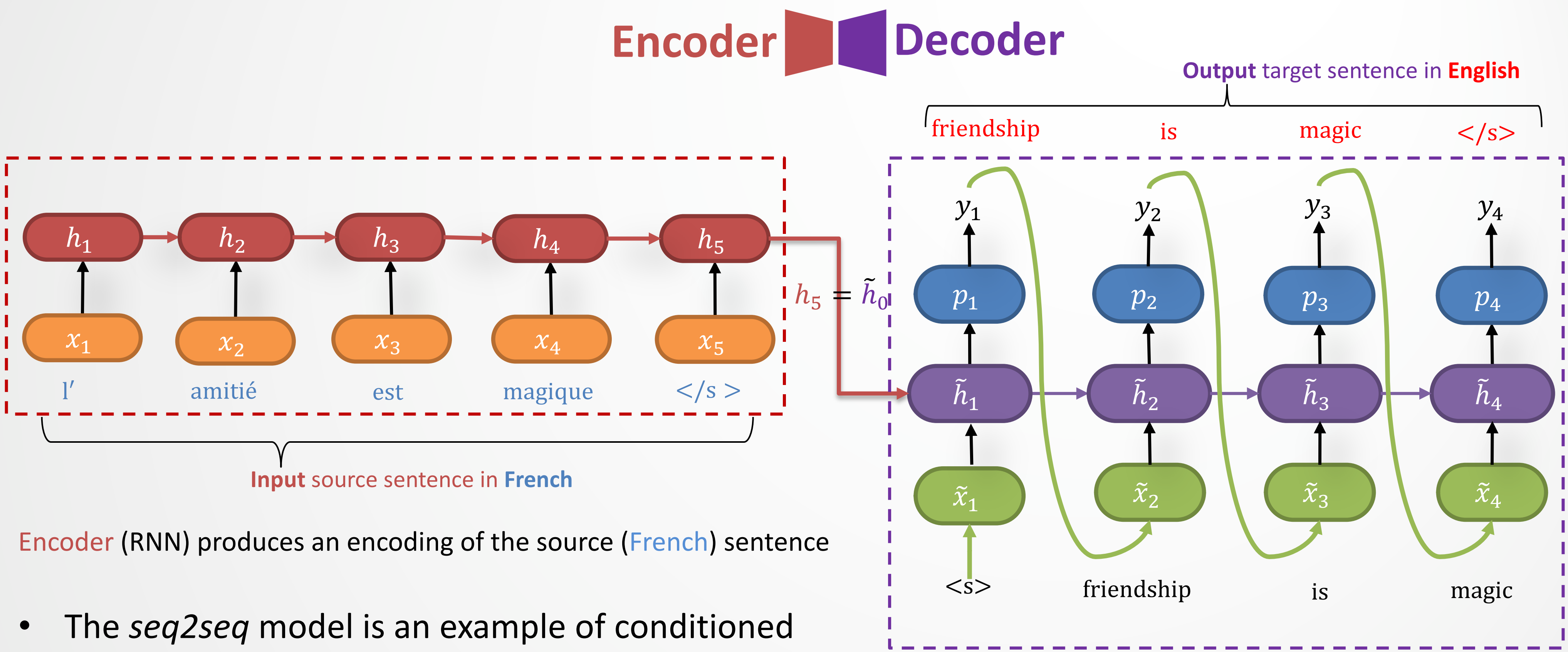
What is NMT?

- 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

Solving the alignment problem

- Recall that source and target words (/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

NMT: the seq2seq model



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

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

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**

$$P(y|x) = P(y_1|x)P(y_2|y_1, x) \ldots P(y_T|y_1, \ldots y_{(T-1)}, x)$$

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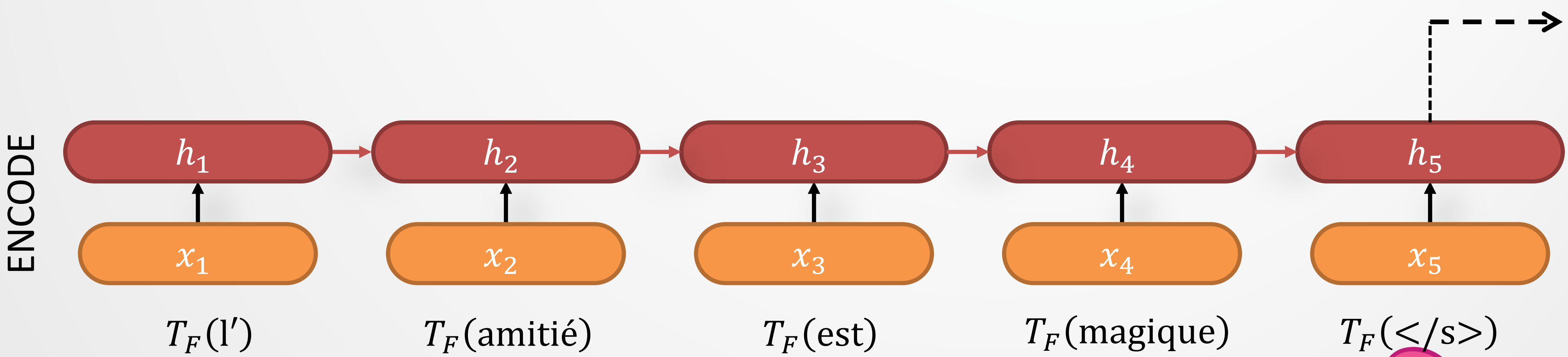
Notation

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 $y_t \sim P(y_t \vert p_t)$
$c_{1:T}$	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)

Encoder

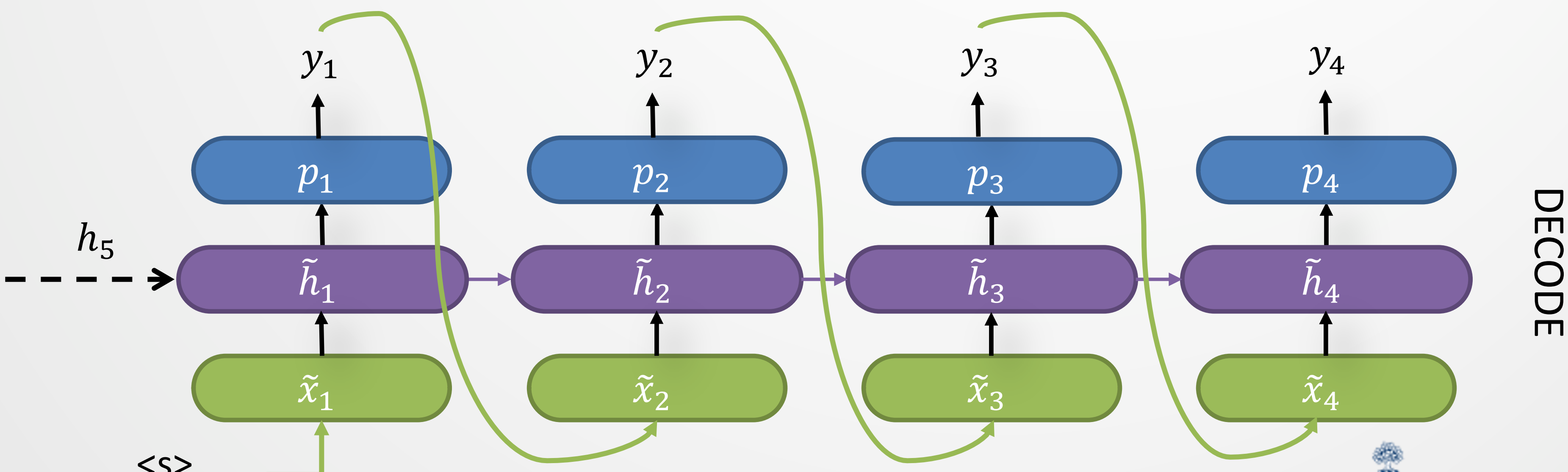
- Encoder given source text $x = (x_1, x_2, \ldots)$
  - $x_s = T_F(F_s)$ a source word embedding
- Outputs last hidden state of RNN
- Note $h_S = f(F_{1:S})$ conditions on entire source



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** $\tilde{x}_t = T_E(y_{t-1})$
- $p_t = f(\tilde{h}_t) = f\left(g(\tilde{x}_t, \tilde{h}_{t-1})\right)$ is **deterministic**
- Base case: $\tilde{x}_1 = T_E(<s>),\ \tilde{h}_0 = h_S$
- $P(y_{1:T}|F_{1:S}) = \prod_t P(y_t|y_{<t}, F_{1:S}) \rightarrow$ **auto-regressive**

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



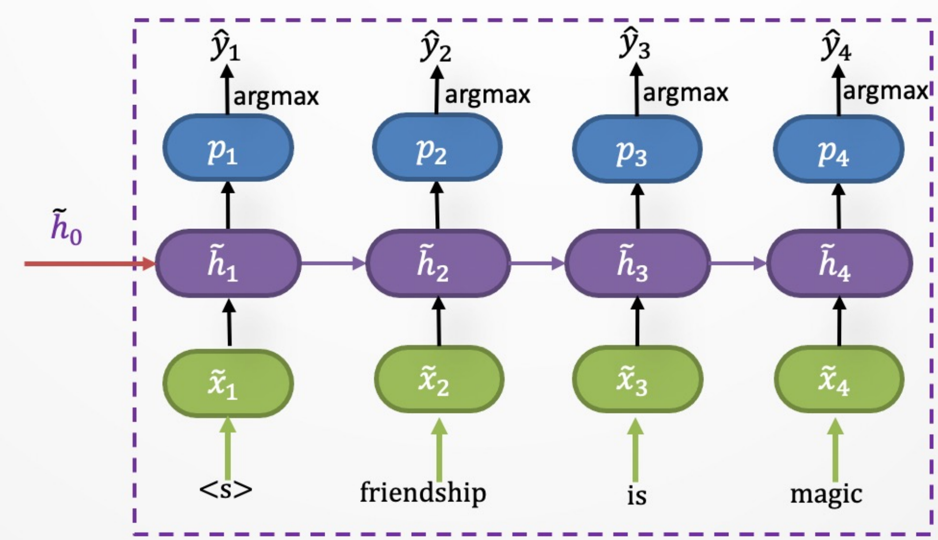
NMT: Training a MT system

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

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

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

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



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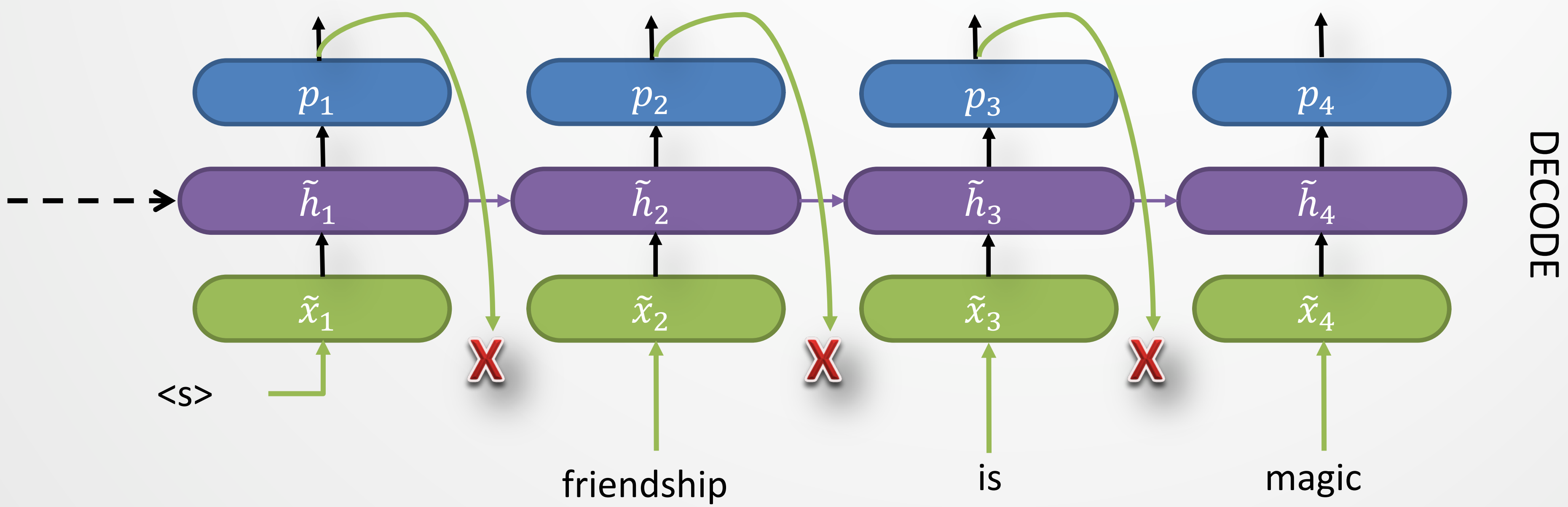
Teacher forcing

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

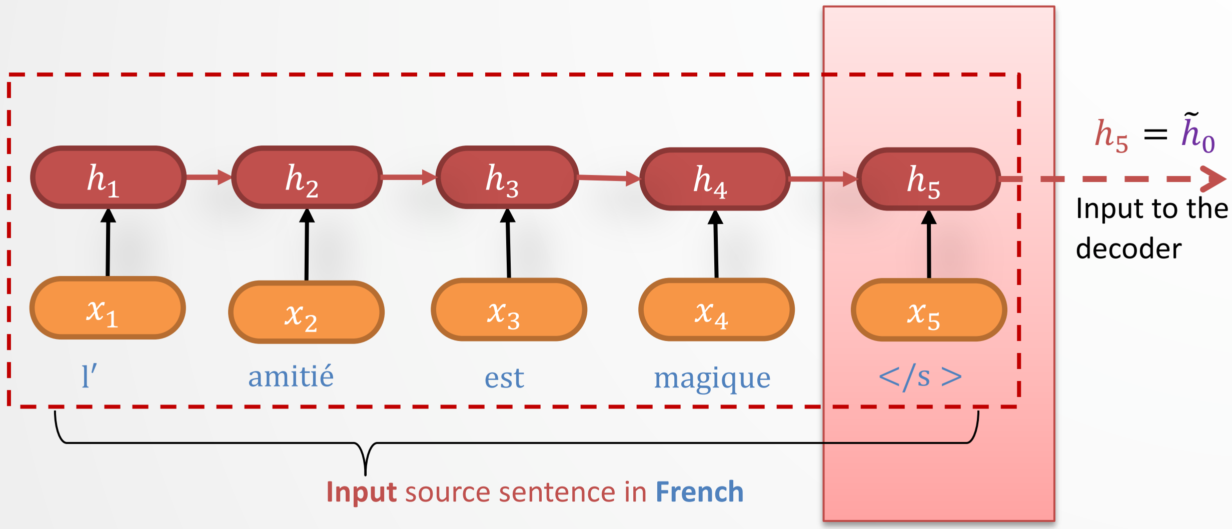
- Teacher forcing = maximum likelihood estimate (MLE)
- Replace $\tilde{x}_t = T(\underbrace{y_{t-1}}_{\text{Predicted output}})$ with $\tilde{x}_t = T(\underbrace{E_{t-1}}_{\text{target or ground truth}})$
- Caveat: since $y_{t-1} \neq E_{t-1}$ in general, causes **exposure bias**

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



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

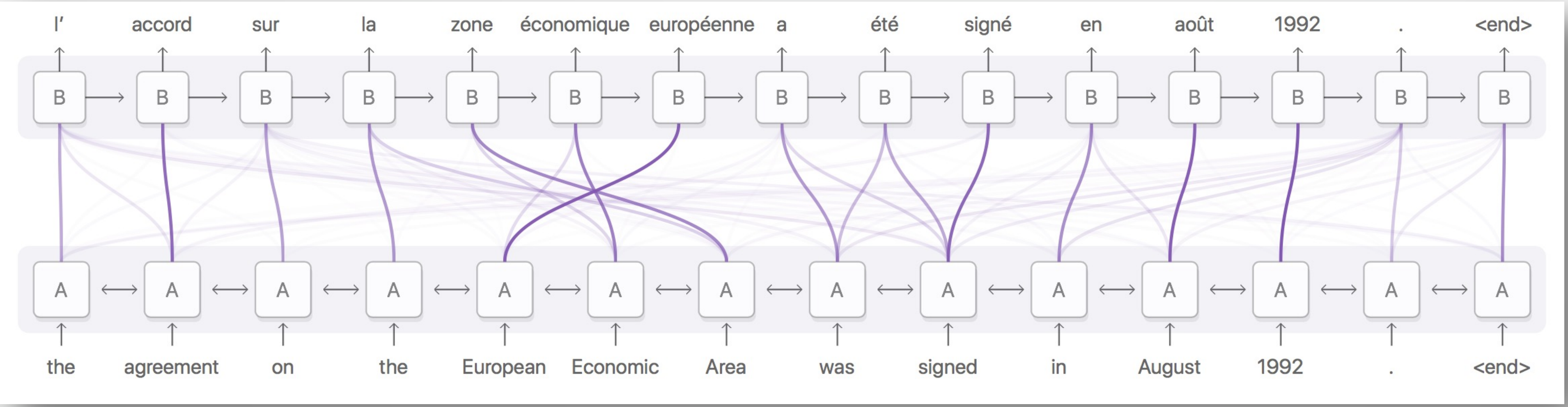
Core Idea

Use **direct connection** to the encoder states and **focus** on selective, **relevant parts** of the **source sequence** at <u>every step</u> 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).

Attention motivations - II

- Allow decoder to "**attend**" to certain areas of input 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)

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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 $e_{t,s} = score(\tilde{h}_t, h_s)$
  - 2. Weights $\alpha_{t,s} = softmax(e_{t,1:S}, s) = {}^{\exp e_{t,s}}\!/_{\sum_{s'} \exp e_{t,s'}}$
  - 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)

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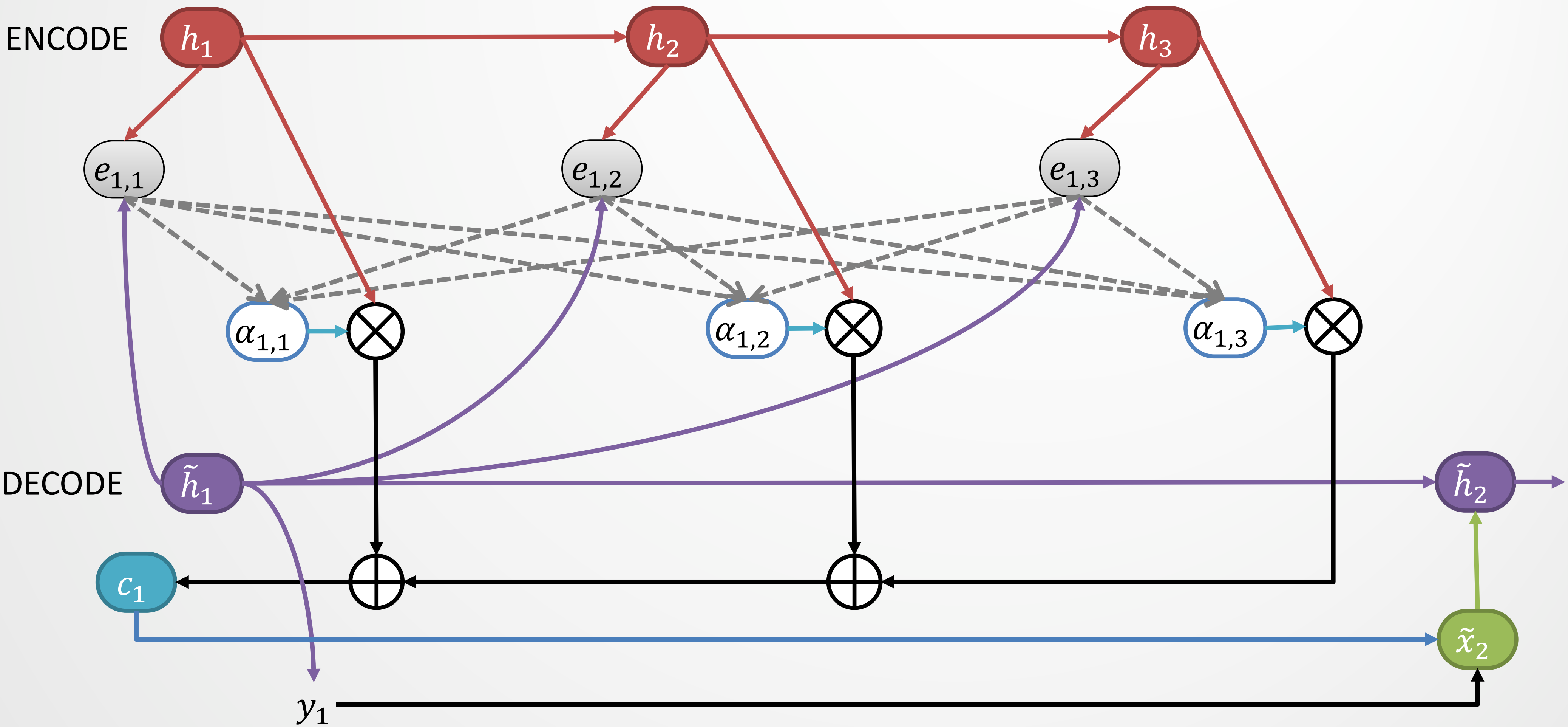
Attention example

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



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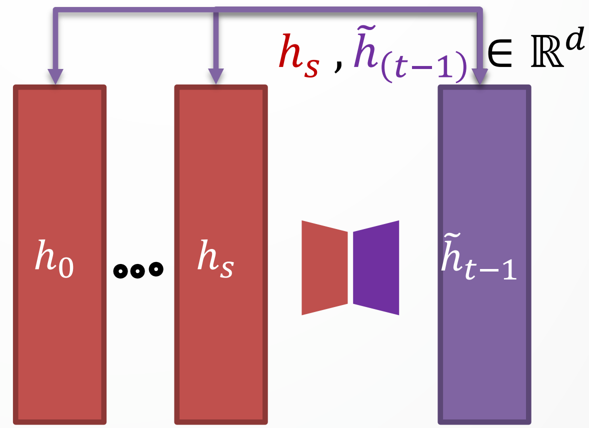
Multi-headed attention

Core Idea

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



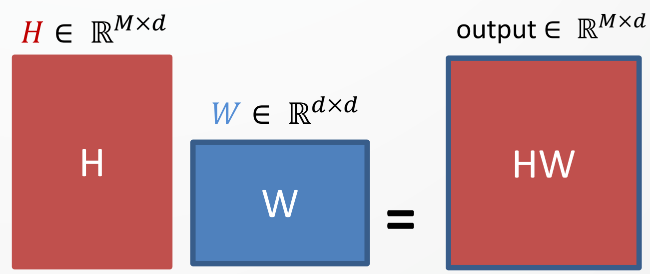
1. Split N heads (with $W^{(n)}, \widetilde{W}^{(n)}, Q \in \mathbb{R}^{(d \times \frac{d}{N})}$)

$$\tilde{h}_{t-1}^{(n)} = \widetilde{W}^{(n)} \tilde{h}_{t-1}$$
$$h_s^{(n)} = W^{(n)} h_s$$

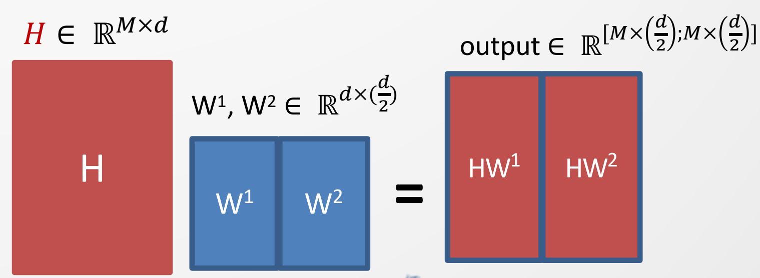
2. Use attention: $c_{t-1}^{(n)} = Att\left(\tilde{h}_{t-1}^{(n)}, h_{1:S}^{(n)}\right)$

3. Combine for result:

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



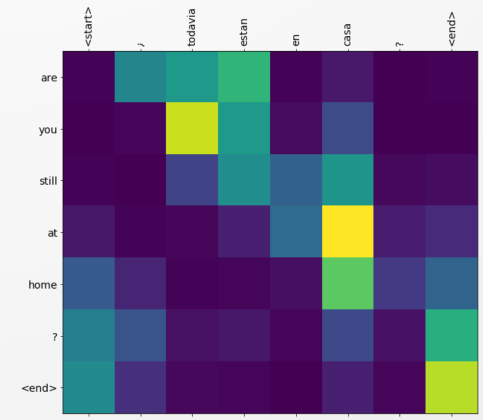
Single-head attention



Multi-head attention

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 RNN 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.

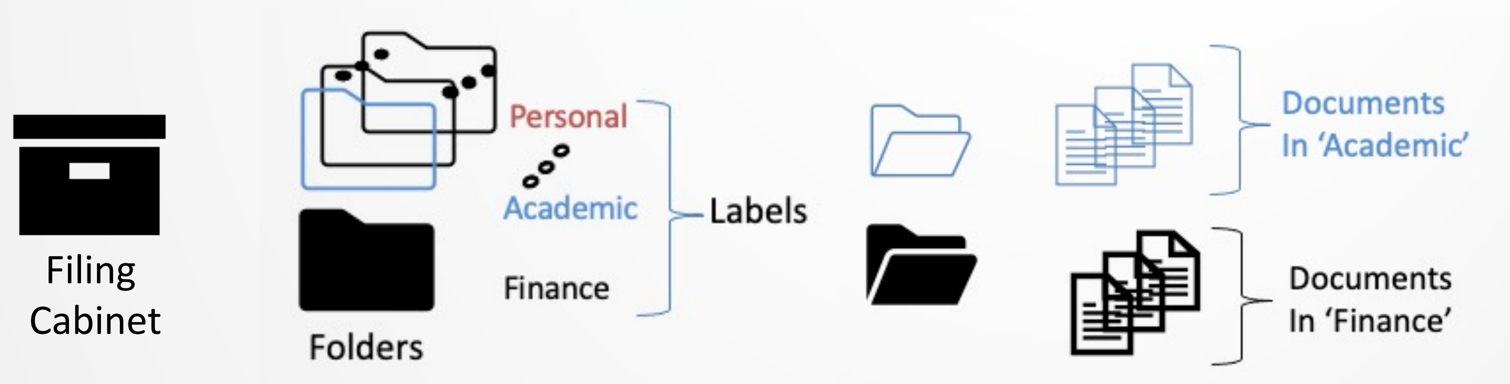
Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
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**	$2.3 \cdot 10^{19}$	

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

Transformer networks - Intuition

In the classical roboquity era (2100-2250 AD), humans are only allowed *filing cabinets* and *paper documents* to store information

ACORN doesn't exist, and UofT students' info (financial, academic, personal) retrieval works as follows:



K Keys

V Values

Similarity Measure Dot Product Attention

Q Queries

$$\text{Attention (Q,K,V)} = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

q1 What is the student's current academic standing?

q2 What is the student's current financial status?

q3 What is the student's residency status in Canada?

Transformer networks

Core Idea

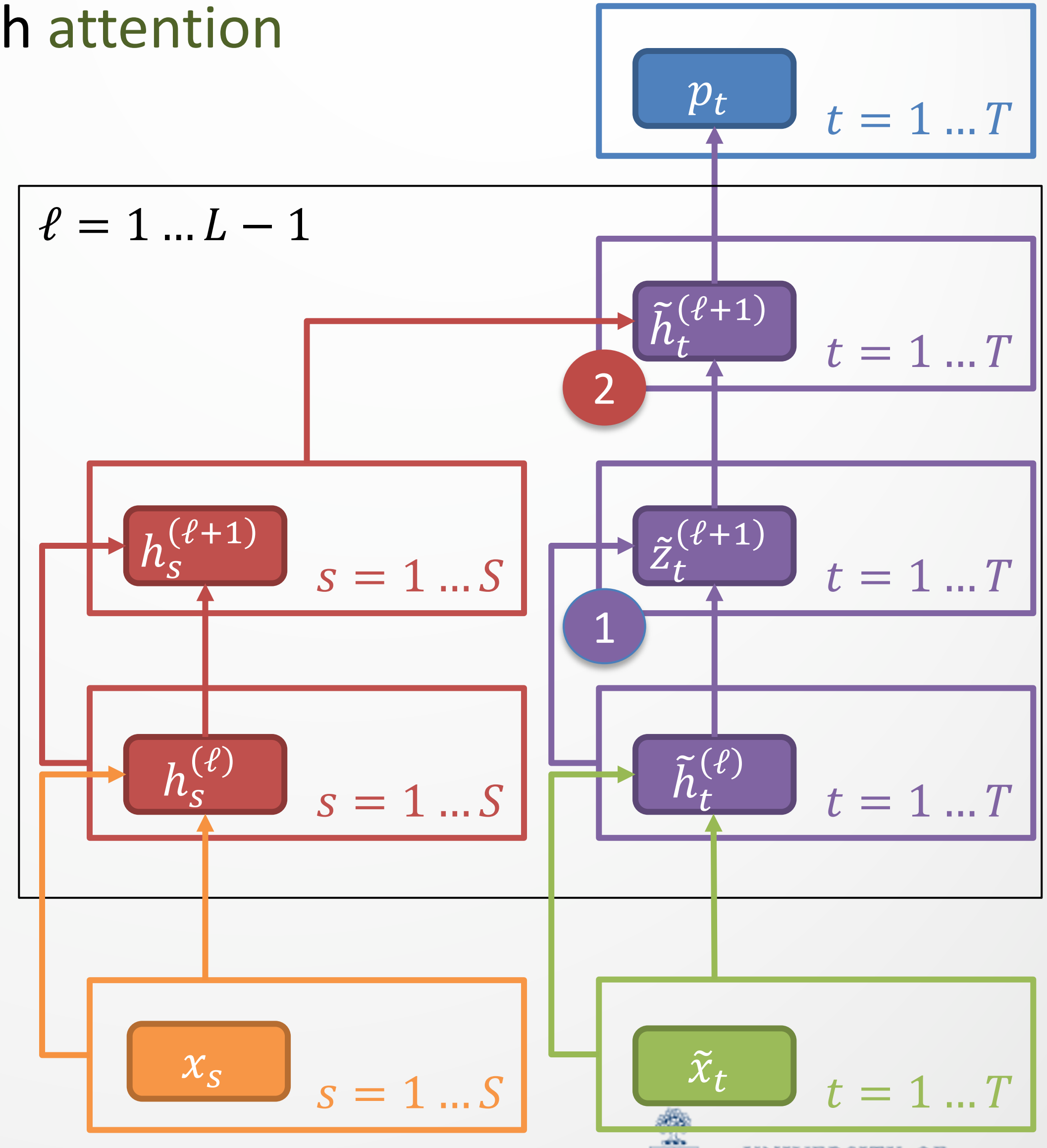
Replace recurrence (RNN) with attention

- Encoder uses self-attention

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

- Decoder uses self-attention, then attention with encoder

$$\tilde{z}_t^{(\ell+1)} \leftarrow Att_{Dec1}\left(\tilde{h}_t^{(\ell)}, \tilde{h}_{1:t}^{(\ell)}\right)$$
$$\tilde{h}_t^{(\ell+1)} \leftarrow Att_{Dec2}\left(\tilde{z}_t^{(\ell+1)}, h_{1:S}^{(\ell+1)}\right)$$



Transformer motivations

- RNN recurrences suffer from vanishing gradient
- Attention allows access to entire sequence
  - Better at long-term dependencies
- Lots of computation can be shared, parallelized across sequence indices
  - Feed-forward primarily + batch norm + residuals
  - See Vaswani *et al* (2017) for specific architecture

Position (in)dependence

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

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

- **Caveat:** but the order of words matters in a translation
- **Solution**: encode position in input

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

- What about decoder input?

Transformer auto-regression

- $\tilde{z}_t^{(\ell+1)} \leftarrow Att_{Dec1}\left(\tilde{h}_t^{(\ell)}, \tilde{h}_{\boxed{1:t}}^{(\ell)}\right)$
- Decoder can not attend to future
- 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
  - $y_1 \sim Decode([T_E(<s>)])$
  - $y_2 \sim Decode([T_E(< s >), T_E(y_1)])$
  - Etc. until </s>

Runtime complexity

- Assume $S \approx T$

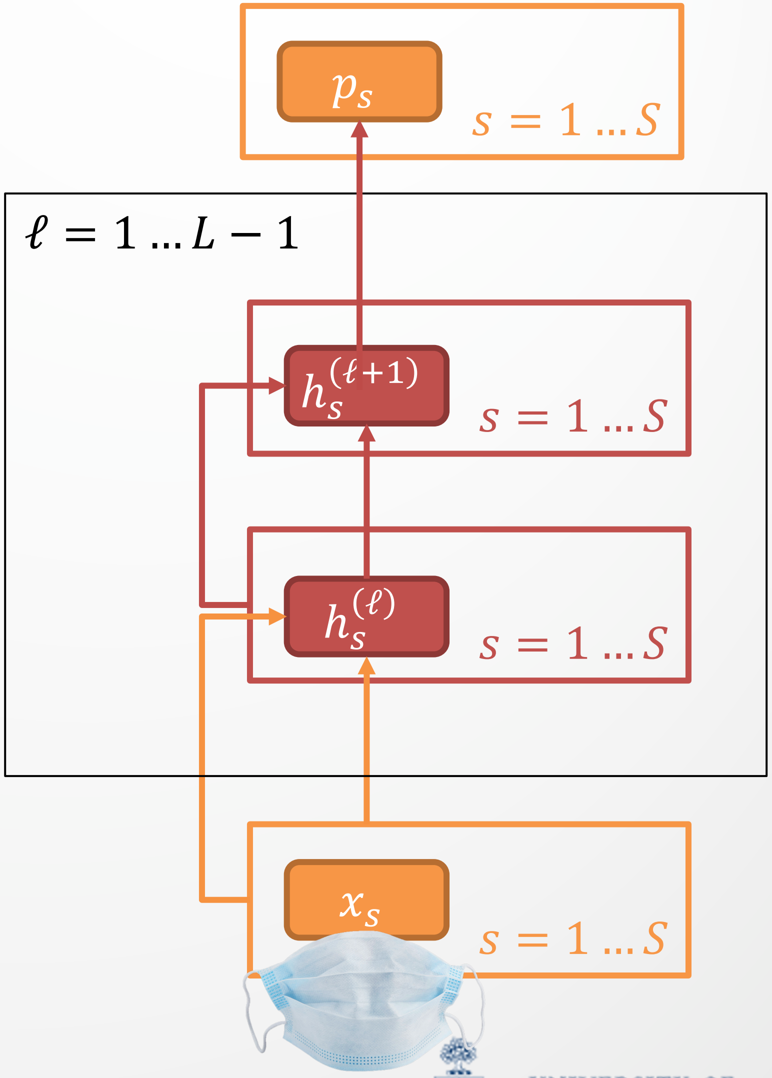
Model	Complexity	Reason
Without attention	$\boldsymbol{O(T)}$	Encoder, then decoder
With attention	$O(T^2)$	Decoder attends to all encoder states
Transformer	$O(T^2)$	Everyone attends to everyone else

- Parallelization leads to
  - Transformers quick to train, slow during decoding
  - Auto-regressive stacked RNN much slower than non-auto-regressive stacked RNNs
  - More details in CSC 421/2516

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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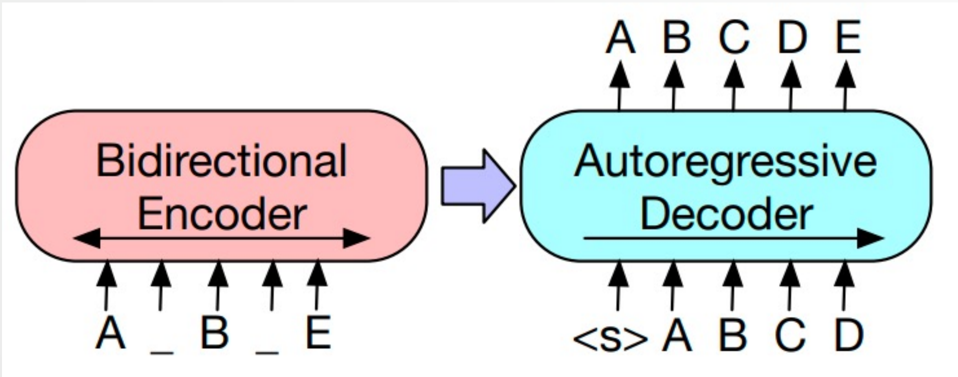
Aside – BERT → BART → NMT

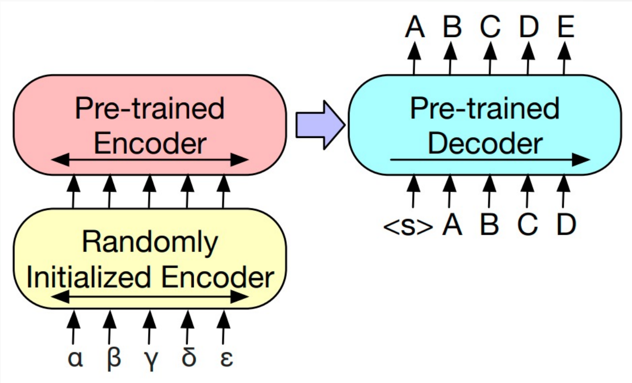
(This time it's not testable)

- 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→



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Logistics (Feb 14, 2022)

- **A2 released** on Feb 12, due Mar 11
- Please do not share assignment codes after you are done
- A2 tutorials planned schedule:
  - Feb 18: A2 tutorial – 1 (delivery: zoom)
  - Mar 4: A2 tutorial – 2 (delivery: in person)
  - Mar 11: A2 – Q/A and OH (*submission due at mid-night*)
- **Reading week break** next week (*no classes or tutorials*)

- Course drop deadline: Feb 20, 2022 (see SGS calendar)
- Office hours: Tuesdays 10 am – 11 am (zoom, note the channel)
- Lecture delivery:
  - Online (*as is*) until Feb 18
  - Reading week break: Feb 21-25 (*no lectures or tutorials*)
  - In-person Feb 28th onwards
- Final exam: planned in-person

Lecture plan

- [**Today**] L6 (3/3) Decoding & Evaluation:
  - Beam Search
  - BLEU
- Previously:
  - Introduction & History
  - L6 (1/3) - Statistical MT:
    - Noisy Channel model
    - Alignments
  - L6 (2/3) Neural MT:
    - Attention
    - Transformers

Decoding in NMT

Exhaustive search decoding

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

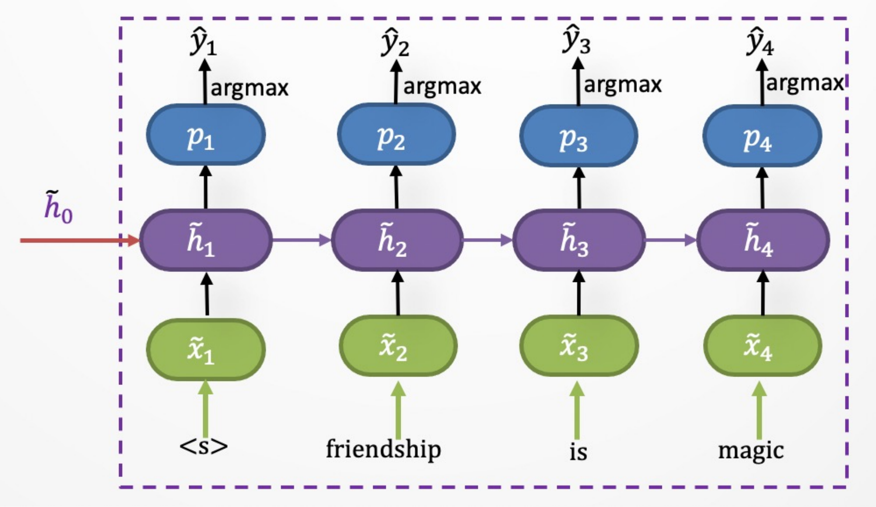
$$P(E|F_S) = (P(e_1|F_S)P(e_2|y_1, F_S), \dots, P(e_T|y_1, y_2 \dots, y_{T-1}, F_S)$$

- 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 <u>each step</u> 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 $(y_1, \dots, y_t)$ is its log probability:

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

  - 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

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Beam search example (*t=1*)

$V = \{\mathrm{H}, \mathrm{A}, </s>\}$, 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 $\forall k. \sum_v P\left(b_t^{(k\to v)}\right) = 1$

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Beam search example (*t*=2)

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

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

k	$b_{1,1}^{(k\to v)}$	$P\left(b_1^{(k\to v)}\right)$
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*)

$V = \{\mathrm{H}, \mathrm{A}, </s>\}$, 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 <u>different timesteps</u> for each candidate hypotheses
  - Mark a hypothesis as **complete** <u>when </s> is produced</u>
  - 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*)

$V = \{\text{H}, \text{A}, </\text{s}>\}$, 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*)

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

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

$f \leftarrow \emptyset$ `# finished path indices`

While $1 \notin f$:

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

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

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

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

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

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

$\quad t \leftarrow t+1$

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

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

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
```

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

$f \leftarrow \emptyset$ `# 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 approaches include
  - Byte Pair Encoding: “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.*

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*.
- Non-autoregressive neural machine translation, 2018. Gu *et al*.
- Unsupervised neural machine translation, 2018. Artetxe *et al*.
- BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension," 2020. Lewis *et al.*

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

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	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	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	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 two translations?

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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*
    - **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]

Example of BLEU evaluation

- **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*

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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).

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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**:

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

$(r_i < c_i)$

$(r_i \geq c_i)$

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:

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

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

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** 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**.