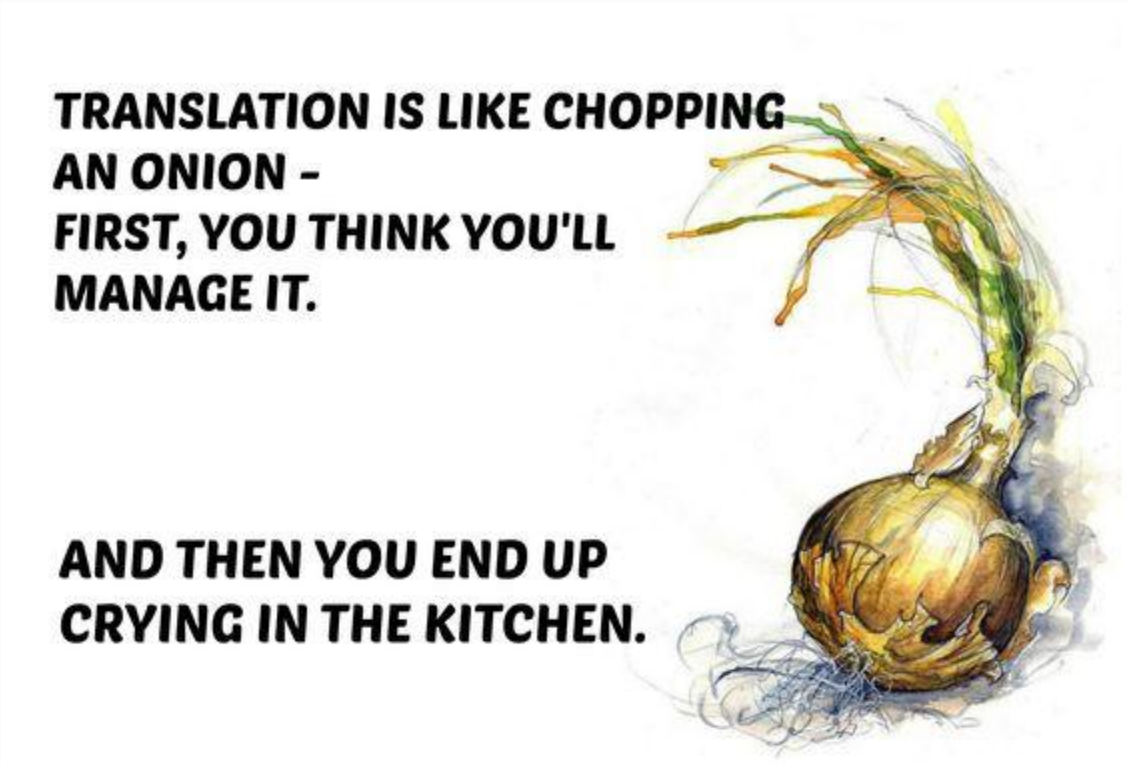

Source: Vera Hembitskaya

CS 1671 / CS 2071 / ISSP 2071
Human Language Technologies

Session 24: Machine translation

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April 13, 2026

University of Pittsburgh | School of Computing and Information

Assessments: homework

- Homework 3 is **due this Thu Apr 16**
- Run Jupyter notebooks from templates on the CRCD
- Part 1: LLM prompting
  - Use CRCD CPUs
- Part 2: Instruction tuning of an LLM
  - Use CRCD GPUs

Assessments: project

- Project final report is **due Tue Apr 28**
- Implement your proposed LLM system, compare with your baseline system
- There is a LaTeX or Word template available
- See project website for instructions of what to include

Structure of this course

MODULE 1	Prerequisite skills for NLP	text normalization, linear alg., prob., machine learning

	Approaches	How text is represented	NLP tasks
MODULE 2	statistical machine learning	n-grams	language modeling text classification
MODULE 3	neural networks	static word vectors	text classification
MODULE 4	transformers and LLMs	contextual word vectors	language modeling text classification

MODULE 5	NLP applications and ethics	machine translation, information retrieval, bias

Overview: Machine translation

- Translation in practice
- Why is translation difficult?
- Exercise: translate some Tajik
- Parallel corpora
- Encoder-decoder MT systems with transformers
- Beam search
- MT evaluation
- Bias and MT

Translation

- Mapping a “text” in a source language to a target language

“I went to the store to buy eggs” → “Eu fui à loja comprar ovos”

→

Slide adapted from Lori Levin

Translation in practice

Most translation is still done by human translators

Translation and Localization Industry Grows 11.8% in 2021 to USD 26.6bn

https://slator.com/translation-localization-industry-grows-in-2021-to-usd-26bn/

Image credit: AMN Healthcare

Slide adapted from Lori Levin

Post-editing and computer-assisted translation

- Checking and correcting of machine translation by humans is called **post-editing**

Evacuation Ladder

Do not yell

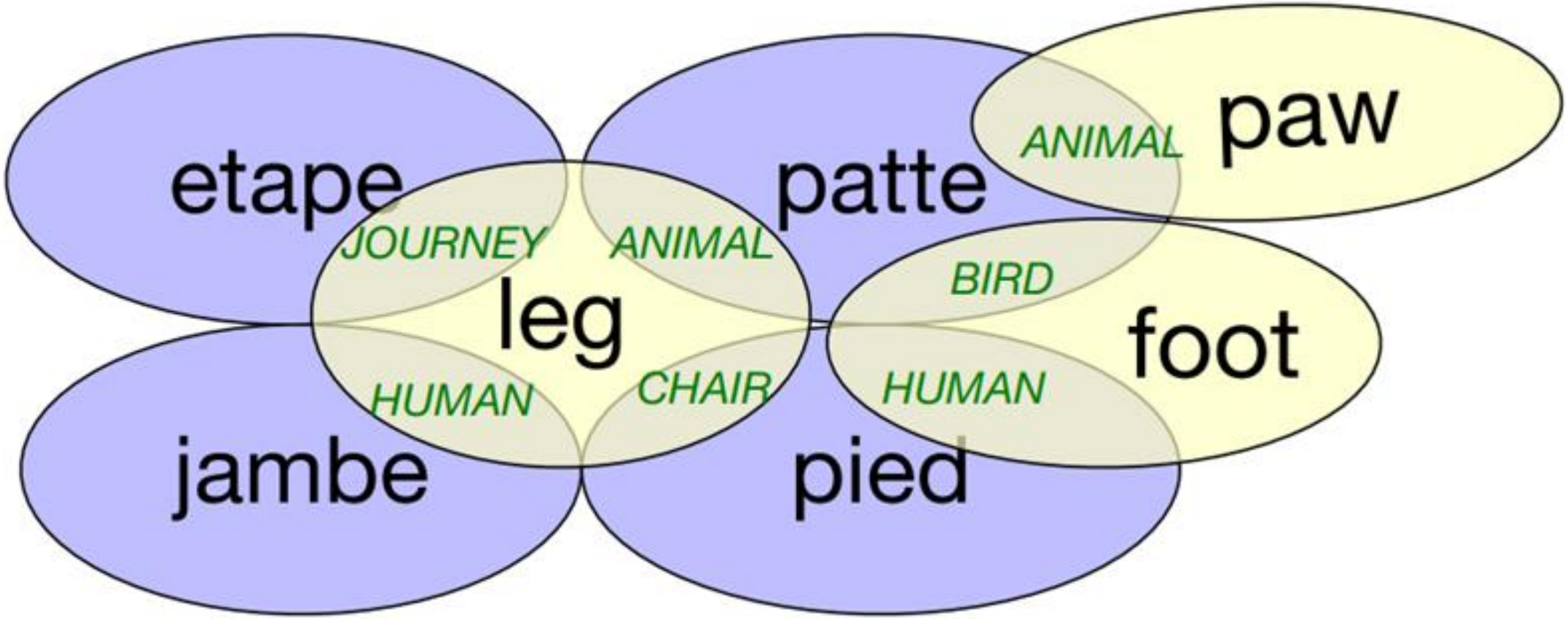
Slide adapted from Lori Levin

Images credit: https://www.languageconnections.com/blog/7-hilarious-machine-translation-mistakes/

Why is translation difficult?

Why not just look up each word in a dictionary and translate word-for-word?

Many-to-many mappings of words



Slide adapted from Lori Levin, Jurafsky & Martin, Hutchins & Somers

Why not translate word-for-word: grammar distinctions

The grammars of some languages make distinctions that other languages don't make:

- Russian *kniga* translates to English as *the book* or *a book*.
  - English grammar makes a distinction in definiteness
  - Russian grammar does not.
- English *it* translates to French *il*/*le* (masculine) or *elle*/*la* (feminine).
- English *a* translates to French as *un* (masculine) or *une* (feminine).
  - *Une chaise* (a chair) vs *un livre* (a book)
  - French grammar makes a distinction in gender
  - English grammar does not.

Slide adapted from Lori Levin

Why not translate word-for-word: Different numbers of words to say the same thing

uygarlaştıramadıklarımızdanmışsınızcasına

"(behaving) as if you are among those whom we were not able to civilize"

uygar	"civilized"
+laş	"become"
+tır	"cause to"
+ama	"not able"
+dık	past participle
+lar	plural
+ımız	first person plural possessive ("our")
+dan	ablative case ("from/among")
+mış	past
+sınız	second person plural ("y'all")
+casına	finite verb → adverb ("as if")

Slide adapted from Lori Levin

Why not translate word-by-word: word order

English: *He wrote a letter to a friend* ⟵ SVO (verb-medial)

Japanese: *tomodachi ni tegami-o kaita* ⟵ SOV (verb-final)
friend to letter wrote

Arabic: *katab risāla li ṡadq* ⟵ VSO (verb-initial)
wrote letter to friend

Slide adapted from Lori Levin, Jurafksy & Martin

Exercise: Tajik

There are 3,344,720 speakers of ***Tajik*** in Tajikistan (one of the Central Asian republics of the former Soviet Union) and another million speakers in surrounding countries.

дуусти хуби ҳамсояй сумо	a good friend of your neighbor
ҳамсояй дуусти хуби сумо	a neighbor of your good friend
ҳамсояй хуби дуусти сумо	a good neighbor of your friend

Above are three phrases in Tajik with their English translations. Your task is to give the English translations of all four Tajik words. The possibilities are simply "good," "friend," "neighbor," and "your." The order of the words – which is not the same order as in English! – does the rest.

дуусти	________
ҳамсояй	________
хуби	________
сумо	________

Problem by Adriana Solovyova
Slide adapted from Lori Levin

Why is translation difficult? Style and genre

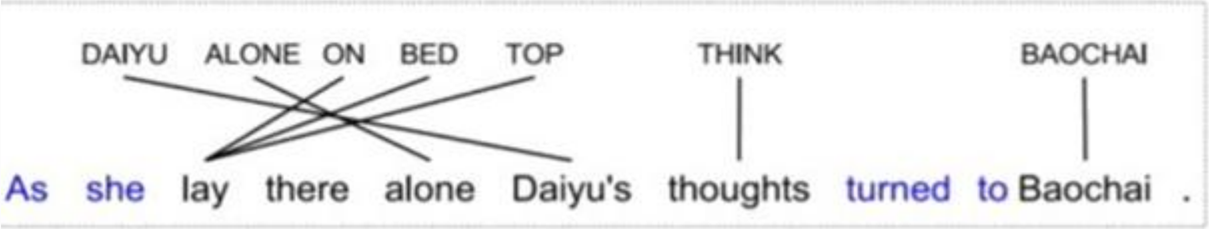
鍿玉自在枕上感念寶釵

dai yu zi zai zhen shang gan nian bao chai

From “Dream of the Red Chamber”, Cao Xue Qin (1792)

Chinese:

English:



Parallel data is more likely to match styles (like literary style) than be an “exact” translation

Slide adapted from Patrick Fernandez, Graham Neubig, Xinyi Wang, Lori Levin

Preparing for machine translation

1. Collect a parallel corpus
2. Align sentences

Slide adapted from Lori Levin

Parallel corpora

Buy Gift Cards   **Pickup** ASAP (20-25 minutes) **from** 114 Atwood St.   0

Bao - Pitt Campus

Food

Appetizers 头台

Tea Egg 茶叶蛋
$4.00

Pork Belly Slider 五花肉刈包
$7.95

Popcorn Chicken 盐酥鸡
$8.95

Cantonese Style Chicken Feet 广式风爪
$8.95

Rolled Pancakes w/Roast Beef 牛肉卷饼
$12.95

Pan Fried Radish Cake 萝卜糕
$7.95

Crab Rangoon 蟹角
$7.95

Indian Pan Fried Pancake 印度薄煎饼
$6.95

Parallel corpora examples

- Europarl: Proceedings of the European Parliament; 21 languages; up to 2 million sentences
- United Nations Parallel Corpus: 10 million sentences in Arabic, Chinese, English, French, Russian, Spanish
- OpenSubtitles: movie and TV subtitles
- ParaCrawl: 223 million sentences in 23 EU languages

Slide adapted from Lori Levin, Jurafsky & Martin

What about parallel corpora for the other 7000 languages?

- For many languages, the only parallel text is the Christian Bible.
- Low-resource MT is a large area of research
  - How to leverage monolingual texts (backtranslation)
  - Humans in the loop
  - Leverage multilingual models

Slide adapted from Lori Levin

Sentence alignment

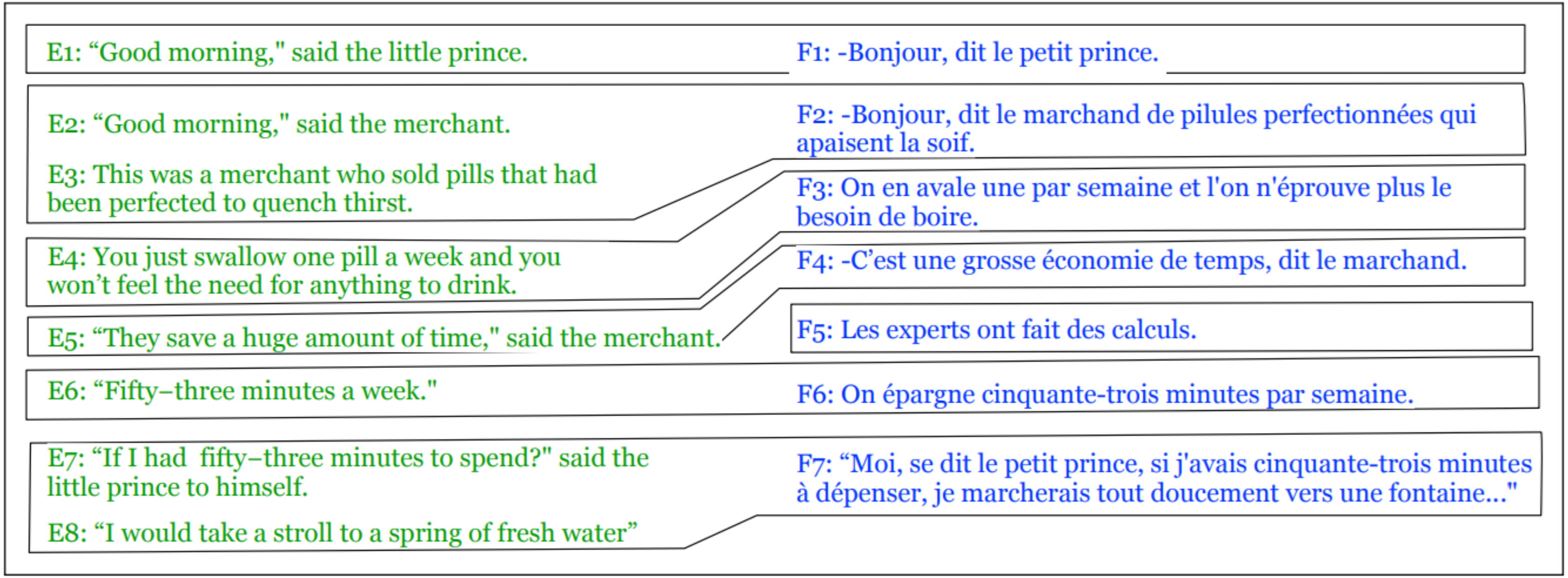


Figure 10.17 A sample alignment between sentences in English and French, with sentences extracted from Antoine de Saint-Exupery’s *Le Petit Prince* and a hypothetical translation. Sentence alignment takes sentences $e_1, \ldots, e_n$, and $f_1, \ldots, f_n$ and finds minimal sets of sentences that are translations of each other, including single sentence mappings like (e_1,f_1), (e_4,f_3), (e_5,f_4), (e_6,f_6) as well as 2-1 alignments (e_2/e_3,f_2), (e_7/e_8,f_7), and null alignments (f_5).

Figure credit: Jurafsky & Martin

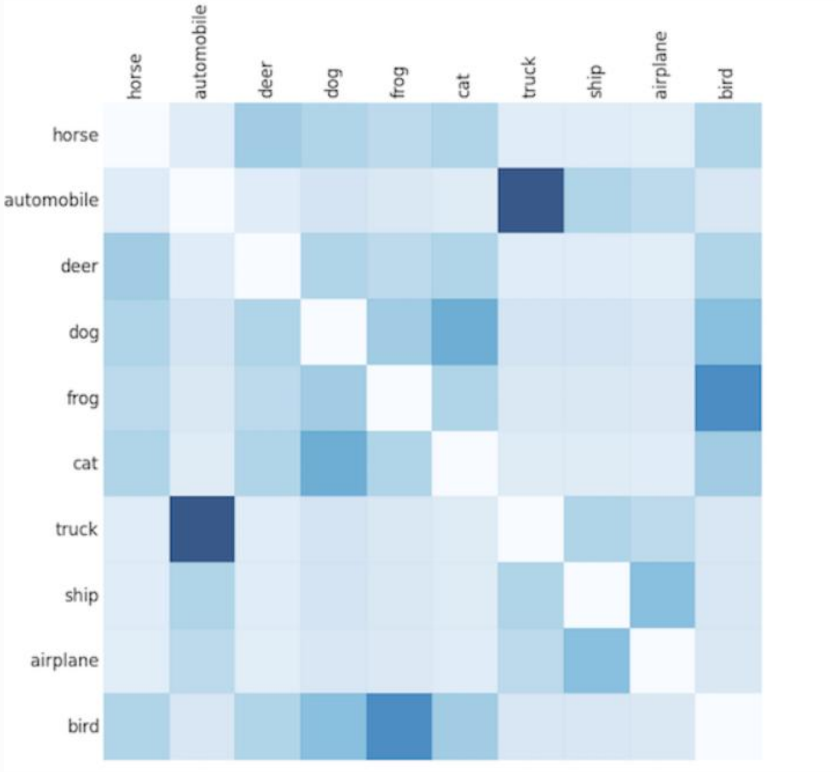
Encoder-decoder MT systems

Which model to train?

 of course. But why?

Slide credit: Sabit Hassan

Recap: Attention and Transformers



- Focus on different parts of input for each input and output
- Closer to how we humans may process language

Slide credit: Sabit Hassan

Encoder-decoder transformer architecture

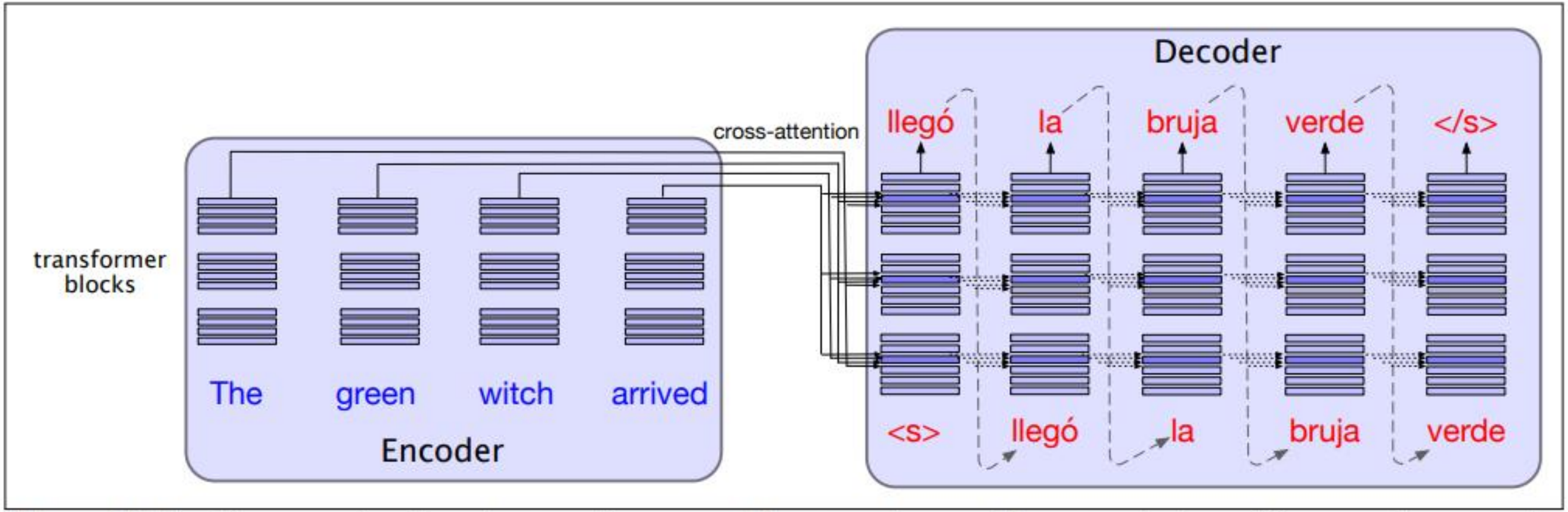
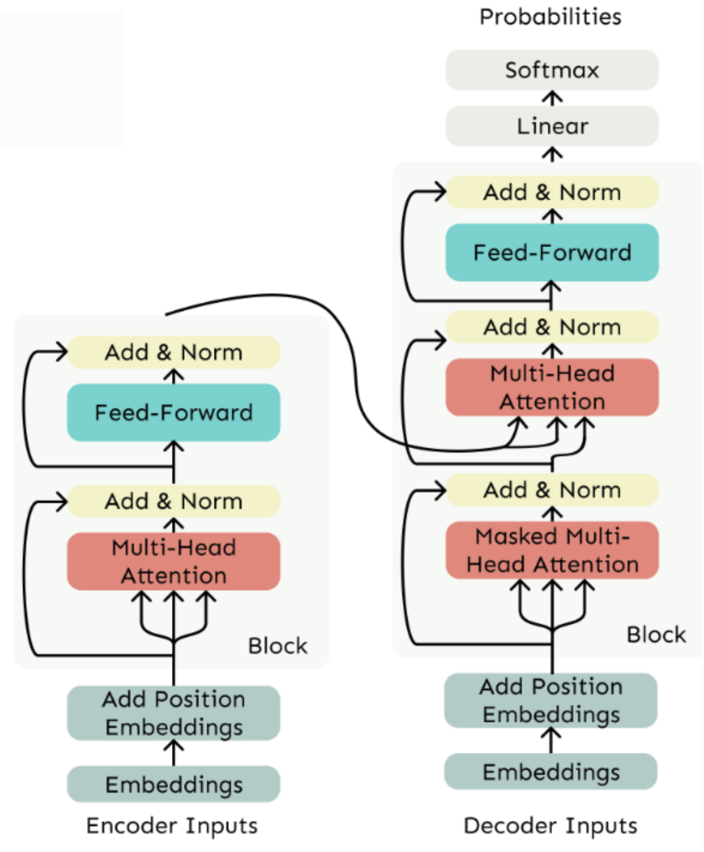


Figure 10.5 The encoder-decoder transformer architecture for machine translation. The encoder uses the transformer blocks we saw in Chapter 9, while the decoder uses a more powerful block with an extra **cross-attention** layer that can attend to all the encoder words. We'll see this in more detail in the next section.

Slide adapted from Jurafsky & Martin

The transformer encoder-decoder

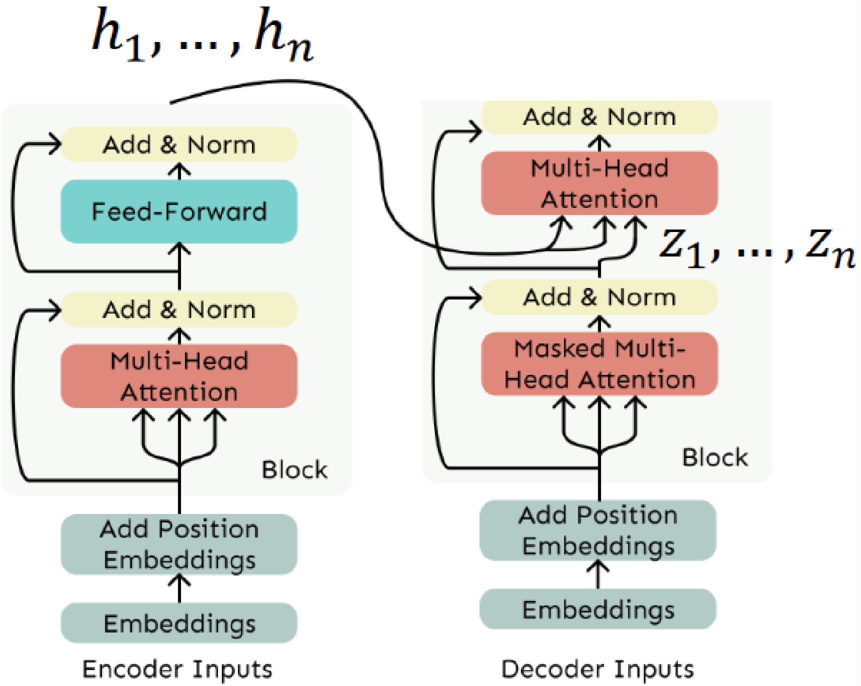
- Can use transformers for encoder-decoder (seq2seq) framework
- Transformer decoder modified to perform cross-attention to the output of the encoder



Slide adapted from John Hewitt

Cross-attention

- We saw that self-attention is when keys, queries, and values come from the same source.
- In the decoder, we have attention that looks more like what we saw last week.
- Let $h_1, \ldots, h_n$ be **output** vectors **from** the Transformer **encoder**; $x_i \in \mathbb{R}^d$
- Let $z_1, \ldots, z_n$ be input vectors from the Transformer **decoder**, $z_i \in \mathbb{R}^d$
- Then keys and values are drawn from the **encoder** (like a memory):
  - $k_i = K h_i, v_i = V h_i$.
- And the queries are drawn from the **decoder**, $q_i = Q z_i$.



Slide adapted from John Hewitt

Beam search

Beam search improves on greedy decoding

- Traditional encoder-decoder framework involves generating highest probability word (argmax) at each timestep in the decoding
- But this greedy approach suffers from issues if choosing early high-probability tokens leads to low-probability sequences!
- **Solution**: Don't commit to just the 1 highest probability word, but keep multiple options in a "beam"
- Prune to *k* highest-probability sequences after each timestep

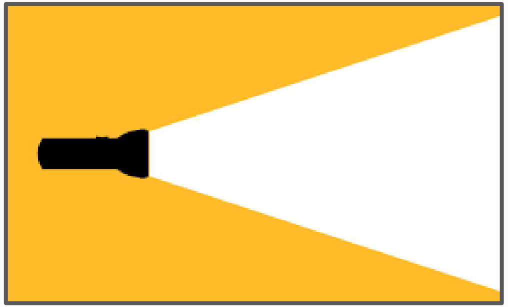
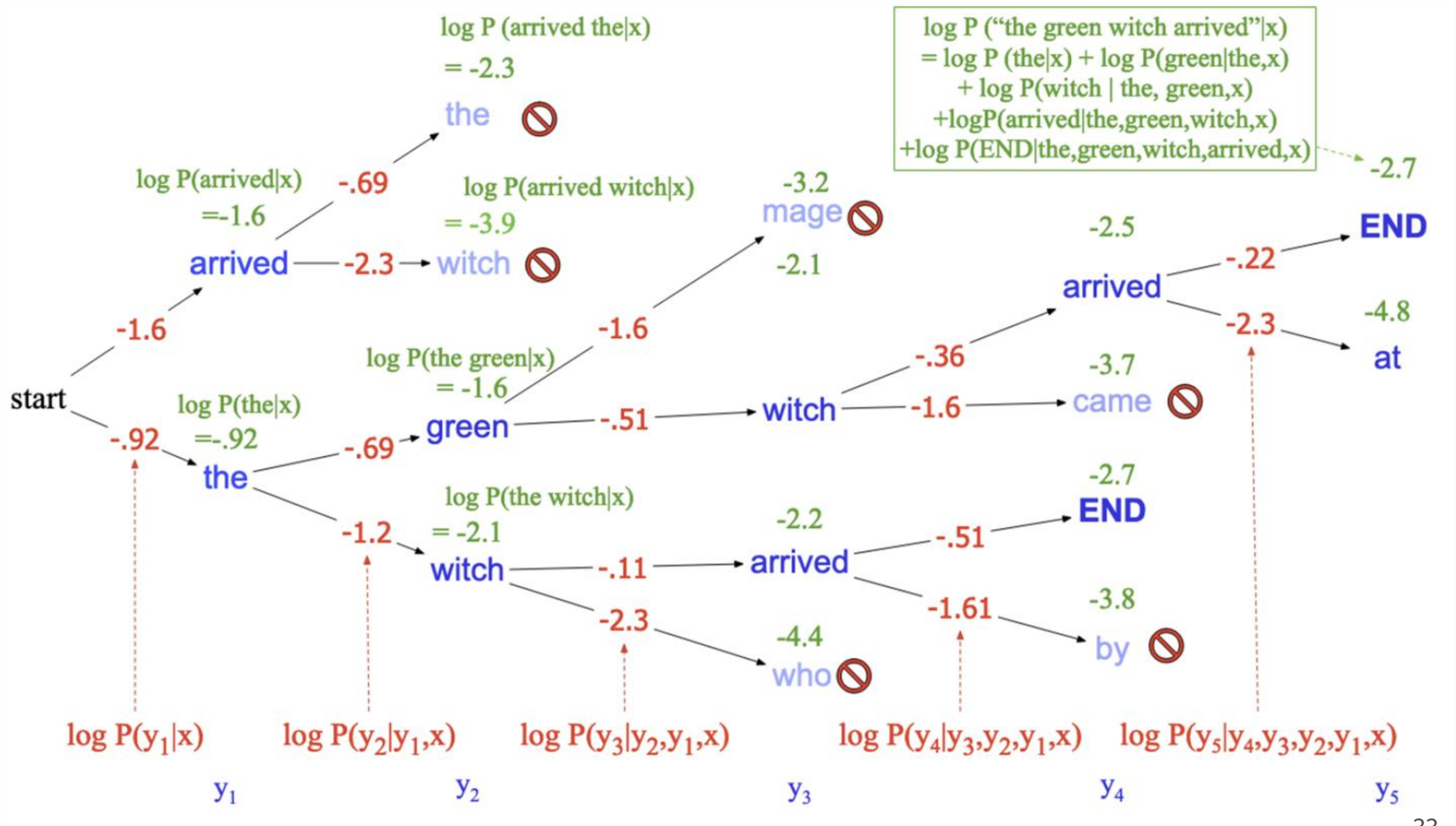


Image: iStock

Beam search example

Find highest probability English sentence for x = “llegó la bruja verde”



Slide adapted from Jurafsky & Martin

MT evaluation

Human evaluation of MT

Human evaluation: Rate/edit translations. Expensive but the best.

- Can ask bilingual raters to compare original source text with prediction
- Can ask monolingual raters to compare predicted translation with reference translation

SOURCE: On Tuesday, we went to the zoo.

REFERENCE: El martes, fuimos al zoológico.

PREDICTED: Martes, nos fuimos al zoo

Slide adapted from Sabit Hassan

Two aspects of human evaluation of MT

- **Adequacy**: how well translation captures exact meaning of the source sentence
- **Fluency**: how fluent/readable/natural the translation is in the target language

Slide adapted from Sabit Hassan

Automatic evaluation of MT

- Character or word **overlap-based**
  - chrF, BLEU
- **Embedding-based**: measure distance between embeddings of tokens
  - Trying to capture synonyms
  - METEOR, BERTScore
- **Classifier-based:** train a classifier to predict human ratings between predicted translations and reference translations
  - COMET, BLEURT

Slide adapted from Sabit Hassan

chrF score

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

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

Slide adapted from Sabit Hassan

Bias in MT

Example: gender bias in pronoun translation

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

Figure 13.12 When translating from gender-neutral languages like Hungarian into English, current MT systems interpret people from traditionally male-dominated occupations as male, and traditionally female-dominated occupations as female (Prates et al., 2019).

Figure from Jurafsky & Martin

Fixing MT: bias

- Expand definitions of bias
  - Bias is multifaceted. Gender, racial, cultural, linguistic
- Identify existence of bias
- Identify sources of bias: annotations? Embedding space?
- Involve native speakers in evaluation

Slide credit: Sabit Hassan

Conclusion

- MT is often used in conjunction with human translators
- Language divergences (in word meaning, syntax structure, etc) make MT difficult
- Parallel corpora are used for training MT systems
- Encoder-decoder transformer MT systems use cross-attention to attend to the source language input when generating the target language output
- Automatic overlap methods (chrF, BLEU) are popular MT evaluations, though can be poor proxies for adequacy and fluency ratings by humans
- Like any NLP task, social biases (e.g. gender in pronouns) must be considered in MT

Questions?