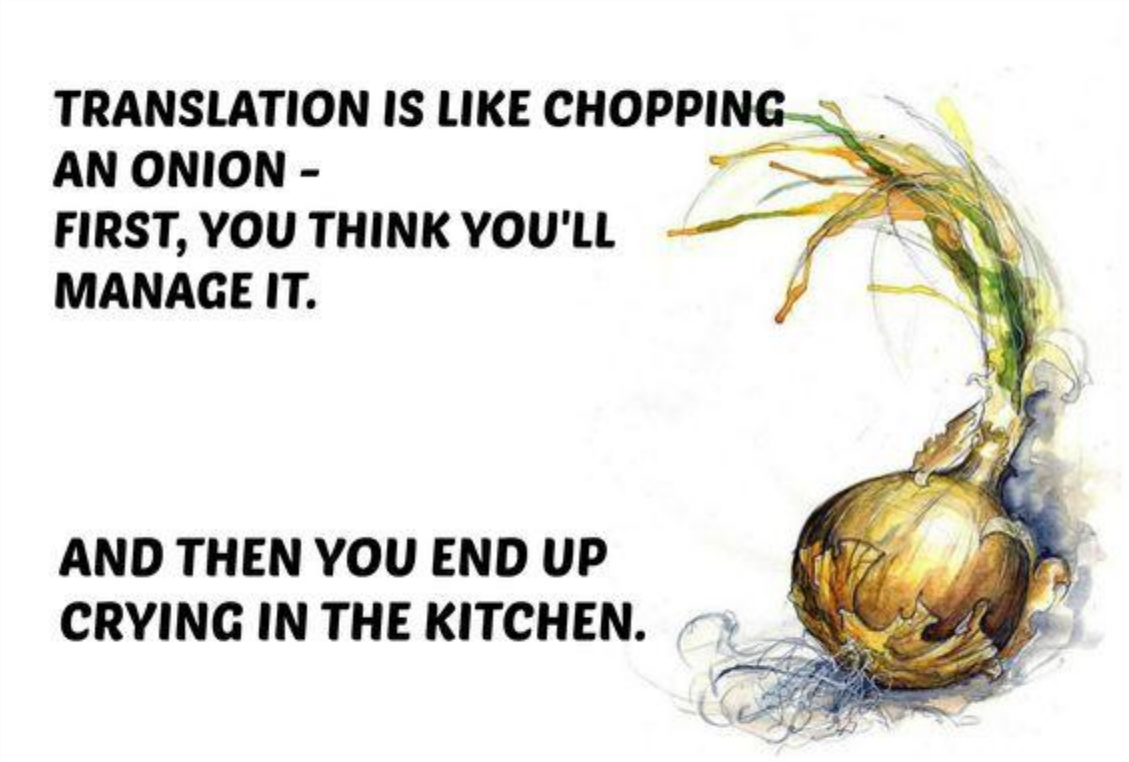


TRANSLATION IS LIKE CHOPPING AN ONION –
FIRST, YOU THINK YOU'LL MANAGE IT.

AND THEN YOU END UP CRYING IN THE KITCHEN.

Source: Vera Hembitskaya

CS 2731
Introduction to Natural Language Processing

Session 23: Machine translation

Michael Miller Yoder

November 11, 2025

University of Pittsburgh | School of Computing and Information

Course logistics: project

- Project progress report **due tomorrow, Thu Nov 13**
- Part 1: Task and dataset
  - Address the questions on basic dataset statistics, as well as how you will use your dataset to address your task
  - If you do not have a "traditional" dataset, present rough equivalents
- Part 2: Some kind of a result
  - Options: Baseline system evaluation on your dataset, a result from your own system, an example output from your system
- Part 3: Open questions and challenges
  - Need any help or additional resources?

Course logistics: homework

- Homework 4 is **due next Thu Nov 20**
  - More Hugging Face, this time BERT-based models for part-of-speech tagging

Structure of this course

MODULE 1 Introduction and text processing: text normalization, machine learning, NLP tasks

	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 Sequence labeling and parsing: named entity recognition, dependency parsing

MODULE 6 NLP applications and ethics: machine translation, chatbots, search engines, bias

Review

1. What is syntax?
2. What is the output format of syntactic parsing (like dependency parsing) tasks?

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

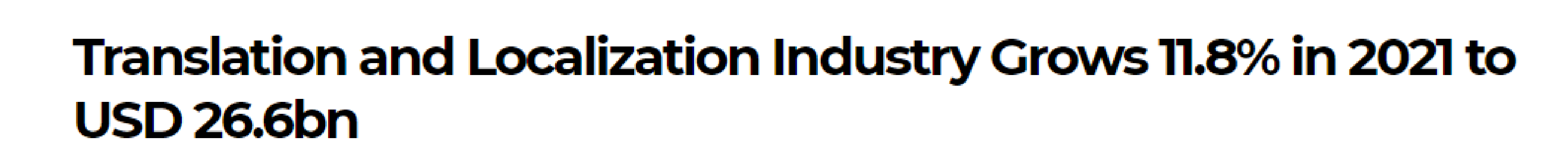
“I went to the store to buy eggs” → “Eu fui à loja comprar ovos”

→

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

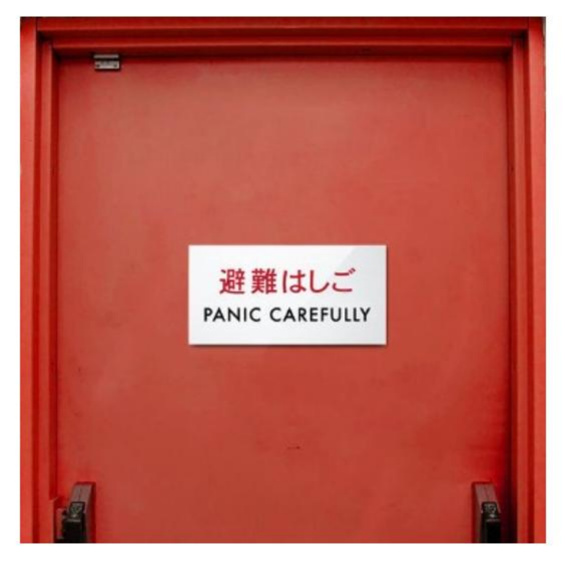
https://slator.com/translation-localization-industry-grows-in-2021-to-usd-26bn/

Image credit: AMN Healthcare

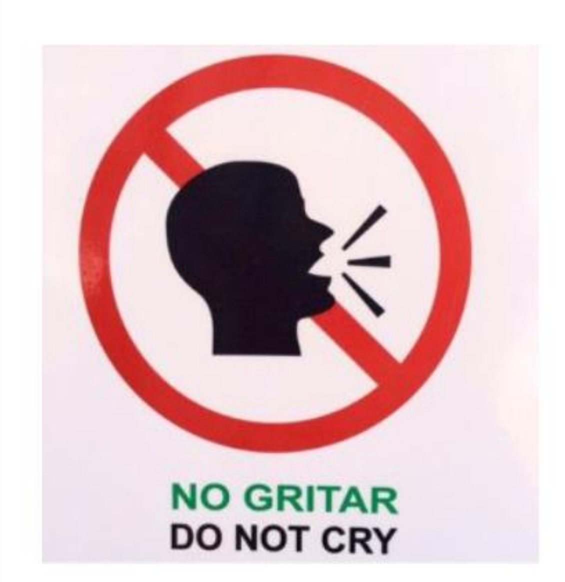
Slide adapted from Lori Levin

Post-editing and computer-assisted translation

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



Evacuation Ladder



Do not yell

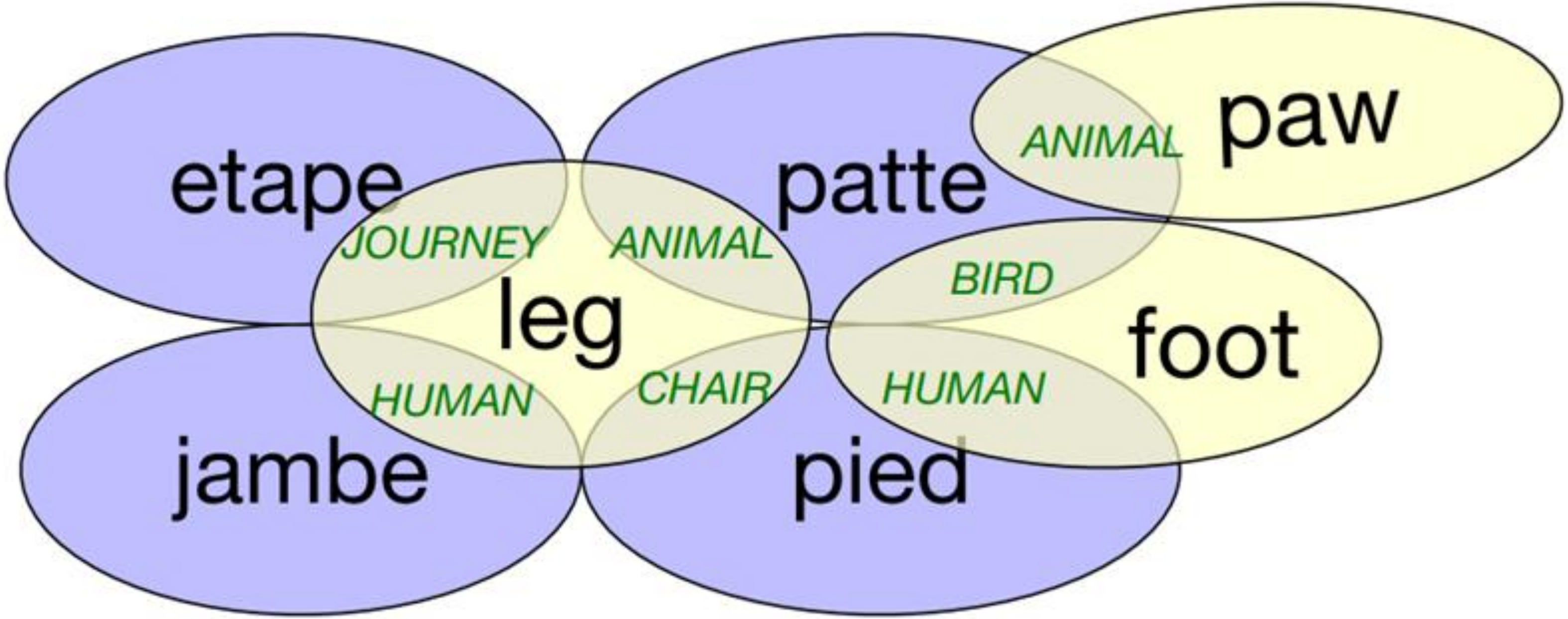
Slide adapted from Lori Levin

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

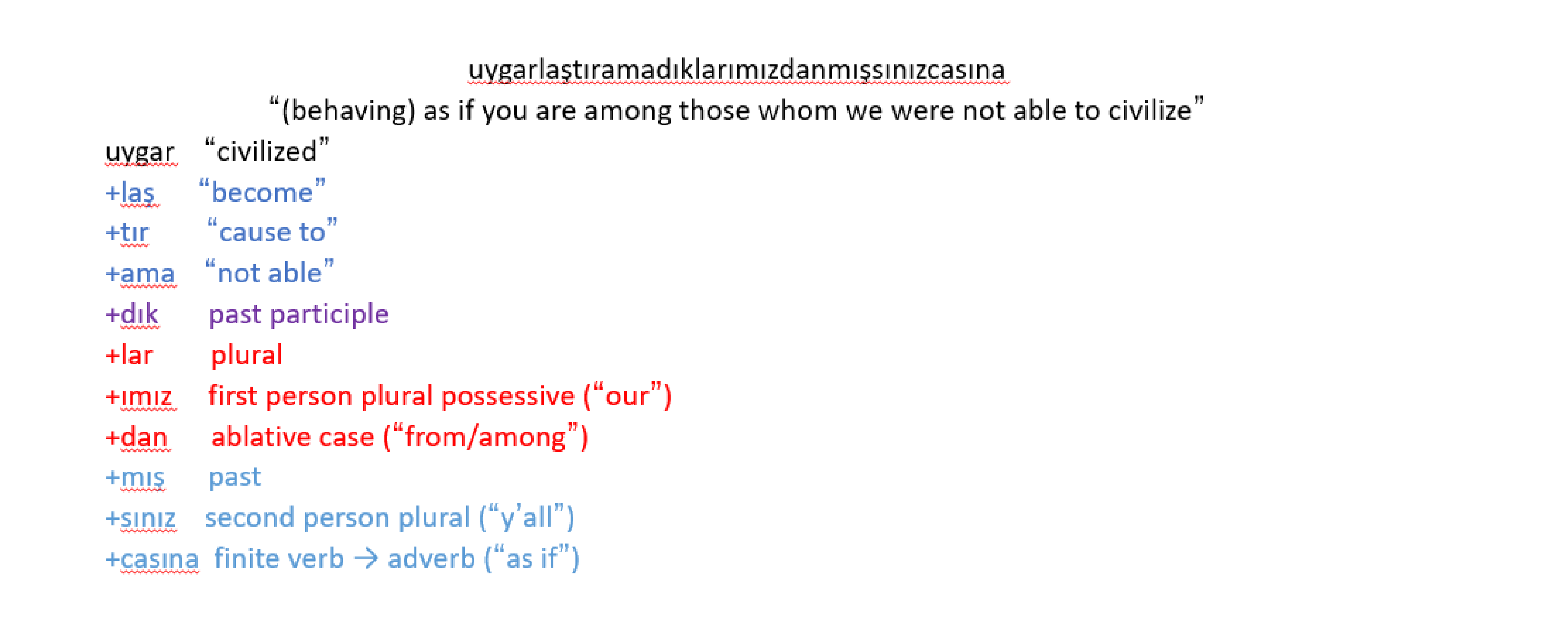
Why not translate word-for-word: grammar distinctions

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



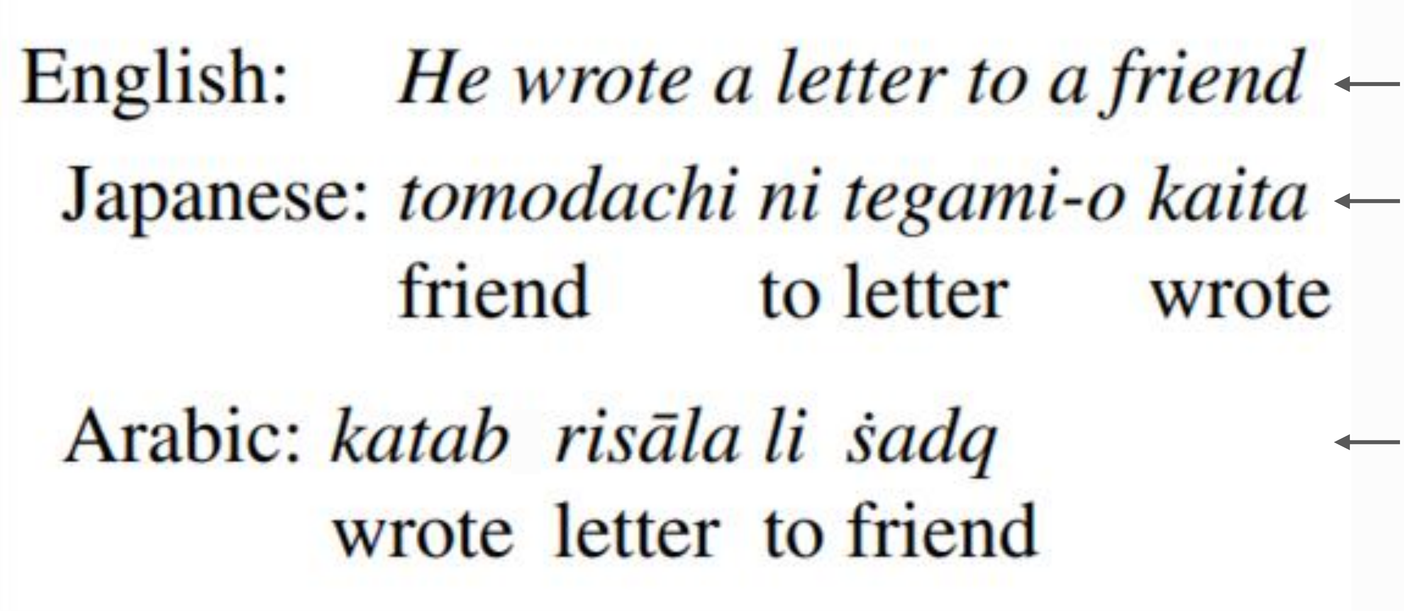
uygarlaştıramadıklarımızdanmışsınızcasına

"(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*

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

Arabic: *katab risāla li ṡadq*
wrote letter to friend

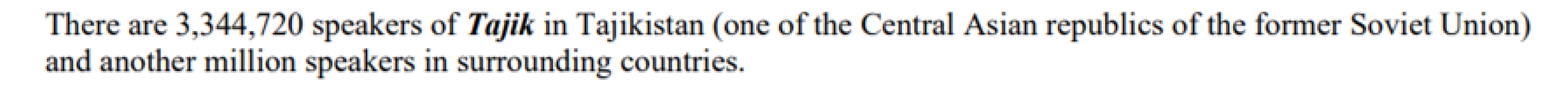
← SVO (verb-medial)

← SOV (verb-final)

← VSO (verb-initial)

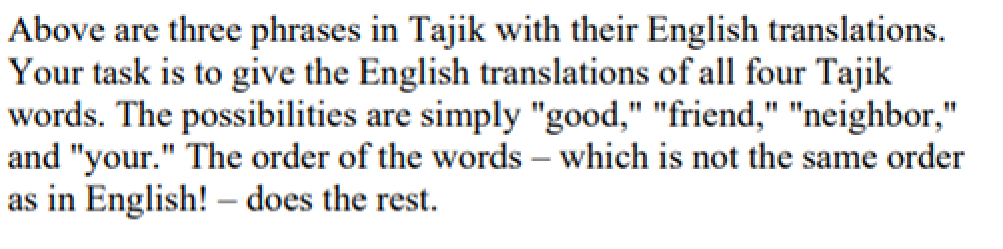
Slide adapted from Lori Levin, Jurafksy & Martin

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 ________

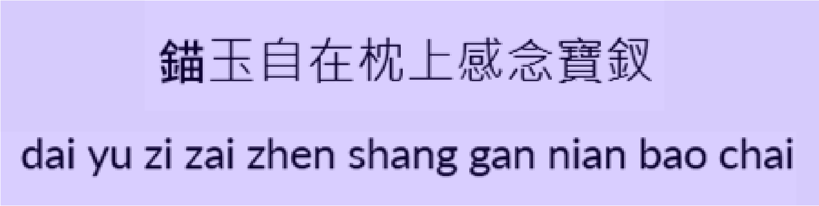
ҳамсояй ________

хуби ________

сумо ________

Problem by Adriana Solovyova
Slide adapted from Lori Levin

Why is translation difficult? Style and genre



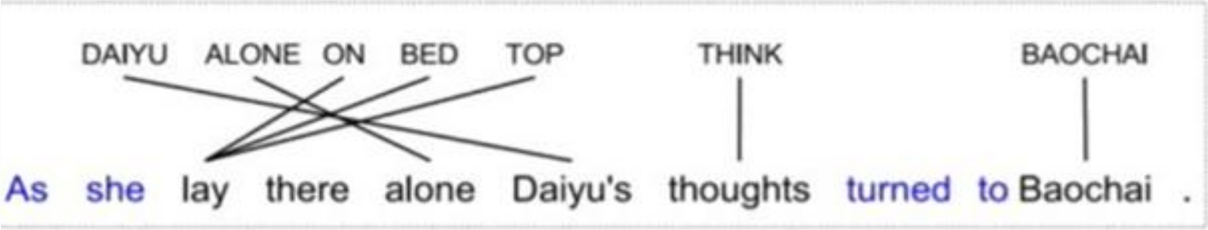
錨玉自在枕上感念寶釵

dai yu zi zai zhen shang gan nian bao chai

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

Chinese:

English:



DAIYU ALONE ON BED TOP THINK BAOCHAI

As she lay there alone Daiyu's thoughts turned to Baochai .

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

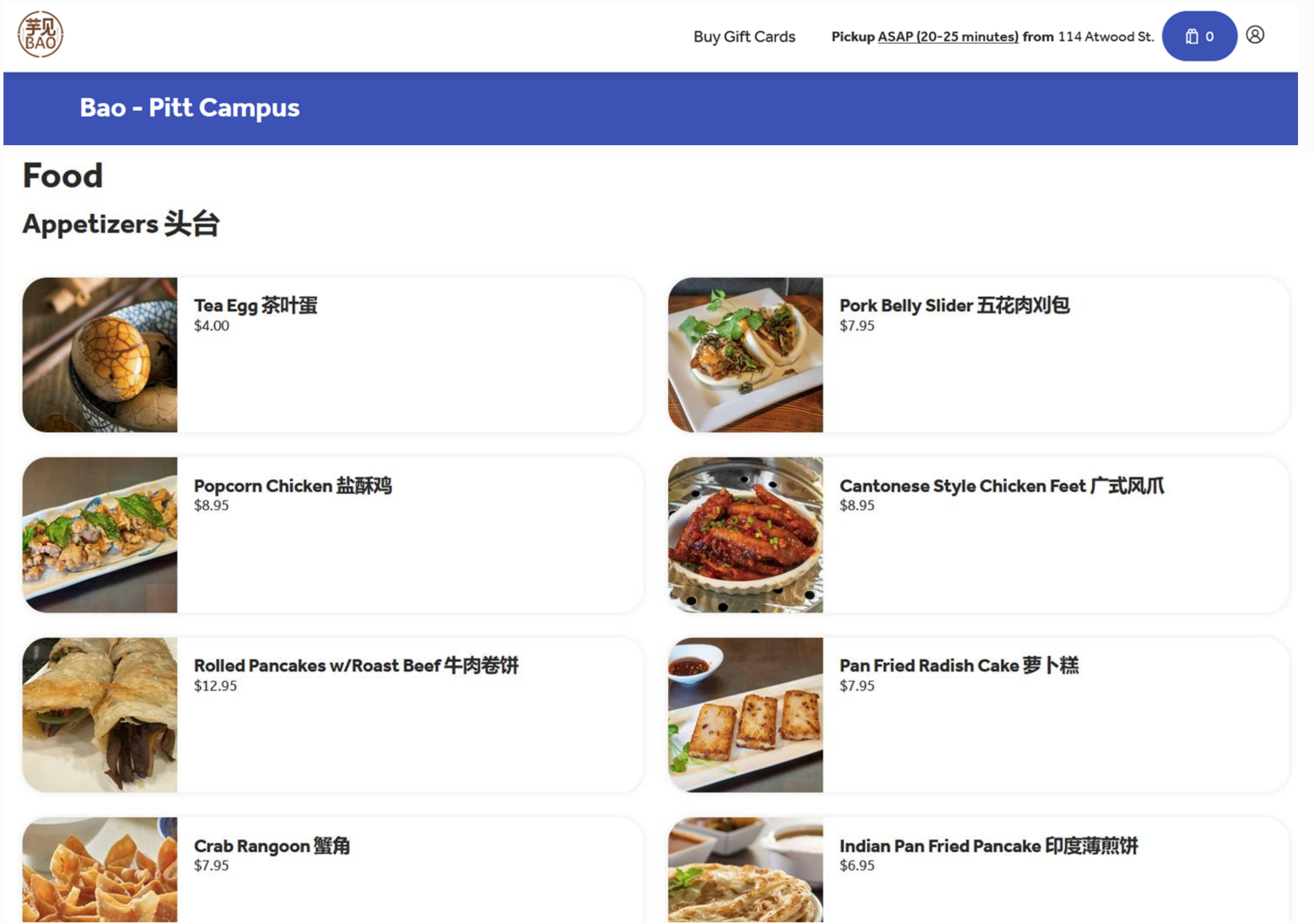
Slide adapted from Patrick Fernandez, Graham Neubig, Xinyi Wang, Lori Levin

Preparing for machine translation

1. Collect a parallel corpus
2. Align sentences

Slide adapted from Lori Levin

Parallel corpora



Pickup ASAP (20-25 minutes) **from** 114 Atwood St.

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

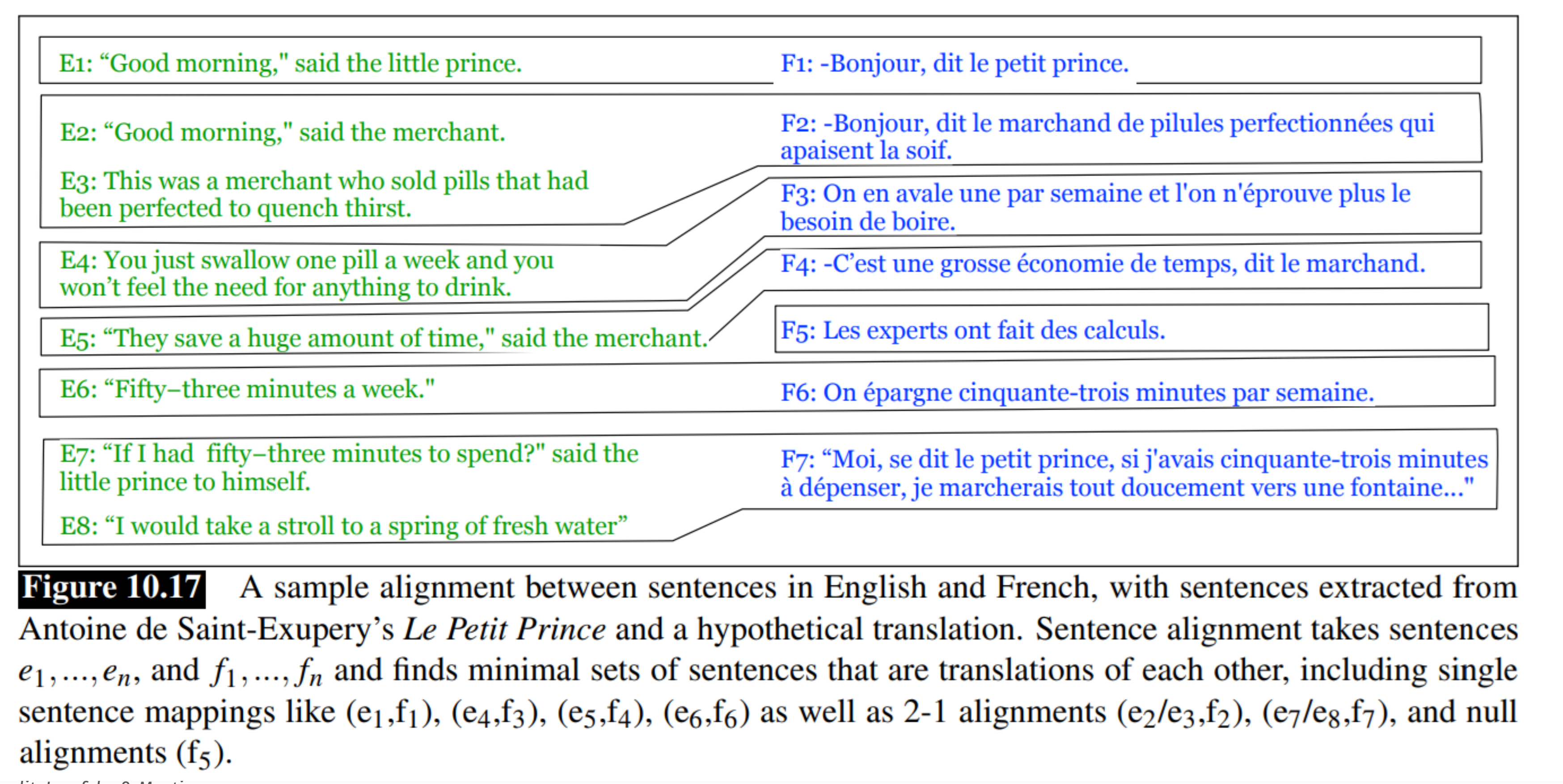
Slide adapted from Lori Levin, Jurafsky & Martin

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



E1: “Good morning," said the little prince.

F1: -Bonjour, dit le petit prince.

E2: “Good morning," said the merchant.

E3: This was a merchant who sold pills that had been perfected to quench thirst.

F2: -Bonjour, dit le marchand de pilules perfectionnées qui apaisent la soif.

E4: You just swallow one pill a week and you won’t feel the need for anything to drink.

F3: On en avale une par semaine et l'on n'éprouve plus le besoin de boire.

E5: “They save a huge amount of time," said the merchant.

F4: -C’est une grosse économie de temps, dit le marchand.

F5: Les experts ont fait des calculs.

E6: “Fifty–three minutes a week."

F6: On épargne cinquante-trois minutes par semaine.

E7: “If I had fifty–three minutes to spend?" said the little prince to himself.

E8: “I would take a stroll to a spring of fresh water”

F7: “Moi, se dit le petit prince, si j'avais cinquante-trois minutes à dépenser, je marcherais tout doucement vers une fontaine..."

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

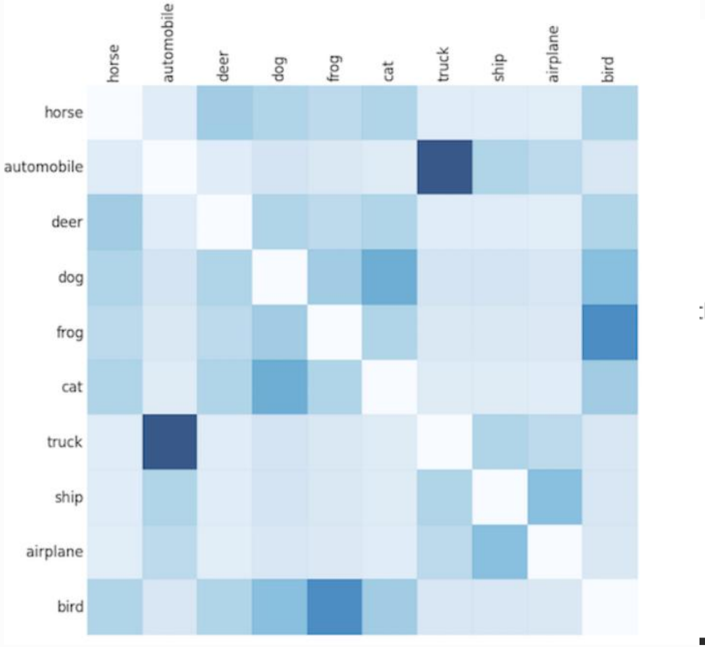
Encoder-decoder MT systems

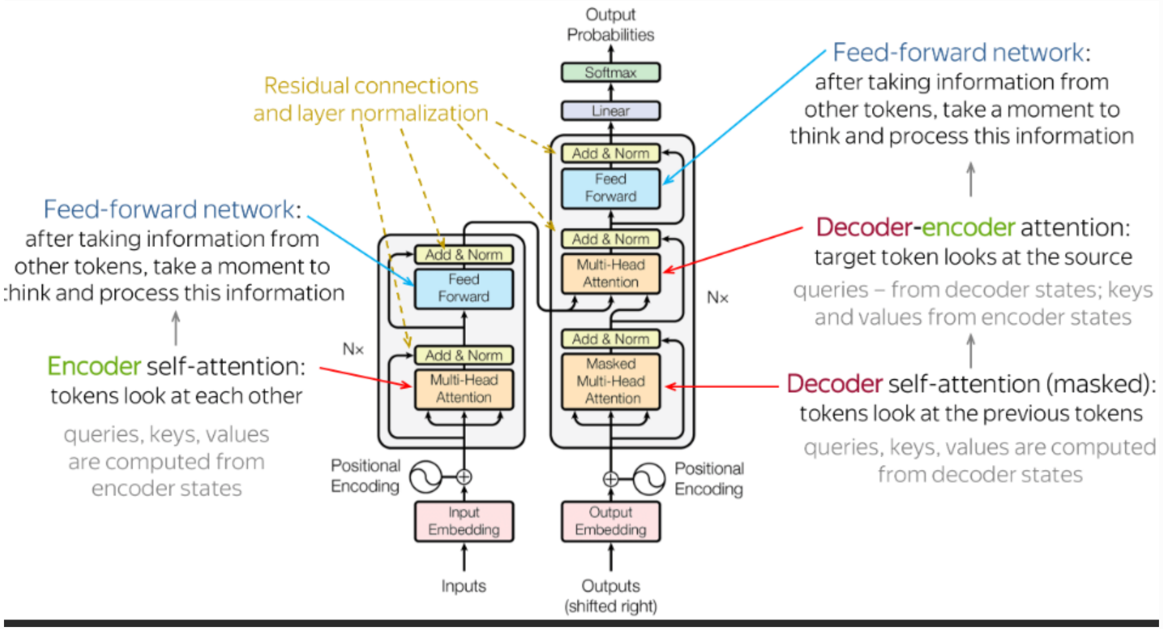
Which model to train?

of course. But why?

Slide credit: Sabit Hassan

Recap: Attention and Transformers





Residual connections and layer normalization

Feed-forward network: after taking information from other tokens, take a moment to think and process this information

Encoder self-attention: tokens look at each other

queries, keys, values are computed from encoder states

Feed-forward network: after taking information from other tokens, take a moment to think and process this information

Decoder-encoder attention: target token looks at the source

queries – from decoder states; keys and values from encoder states

Decoder self-attention (masked): tokens look at the previous tokens

queries, keys, values are computed from decoder states

- 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

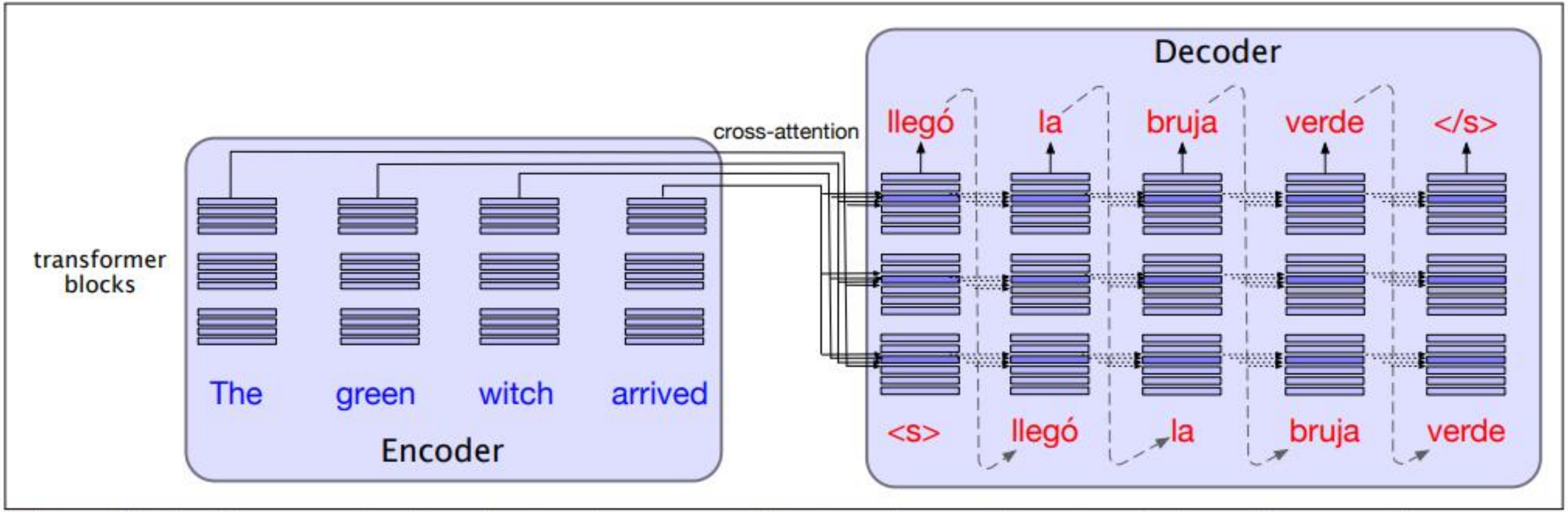
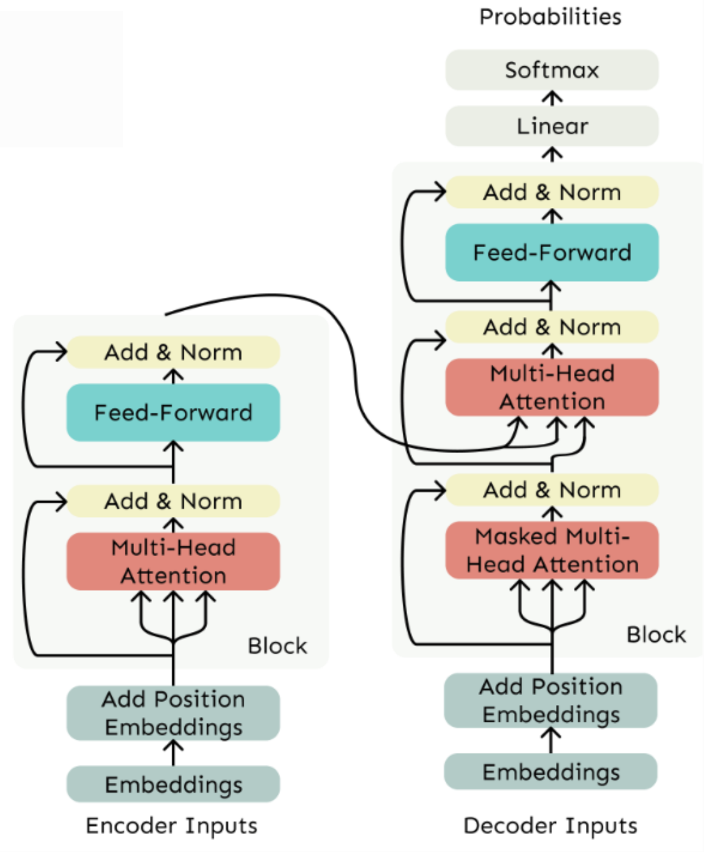


Figure 10.5 The encoder-decoder transformer architecture for machine translation. The encoder uses the transformer blocks we saw in Chapter 9, while the decoder uses a more powerful block with an extra **cross-attention** layer that can attend to all the encoder words. We'll see this in more detail in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

Slide adapted from Jurafsky & Martin

The transformer encoder-decoder

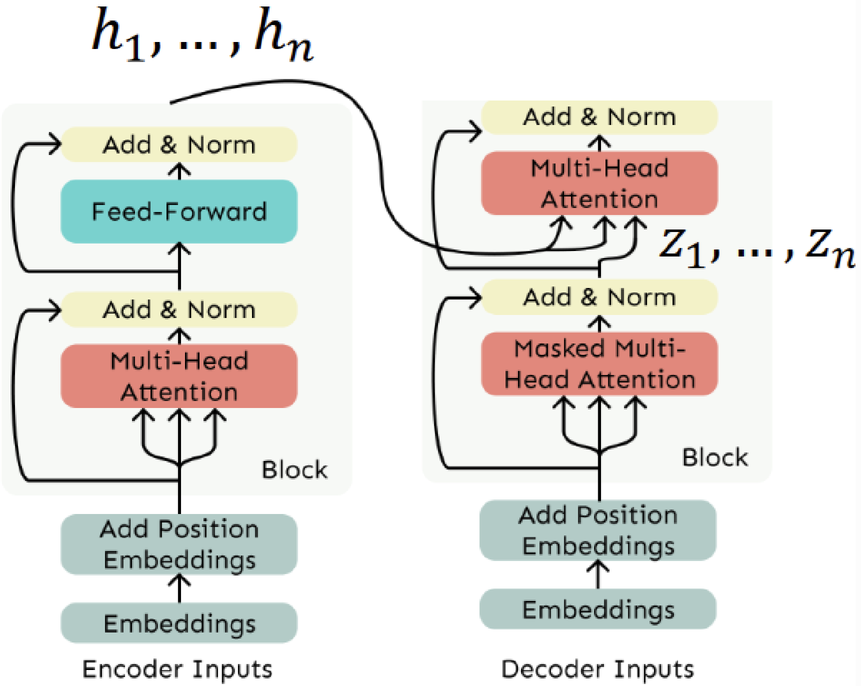
- Can use transformers for encoder-decoder (seq2seq) framework
- Transformer decoder modified to perform cross-attention to the output of the encoder



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 $h_1, \dots, h_n$ be **output** vectors **from** the Transformer **encoder**; $x_i \in \mathbb{R}^d$
- Let $z_1, \dots, z_n$ 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):
  - $k_i = Kh_i, v_i = Vh_i$.
- And the queries are drawn from the **decoder**, $q_i = Qz_i$.



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

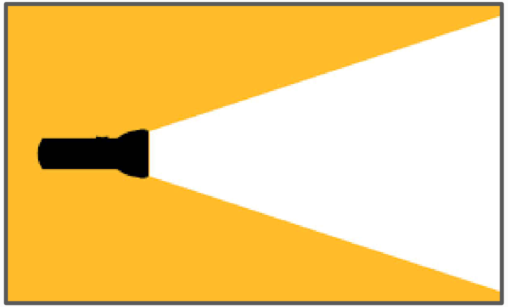
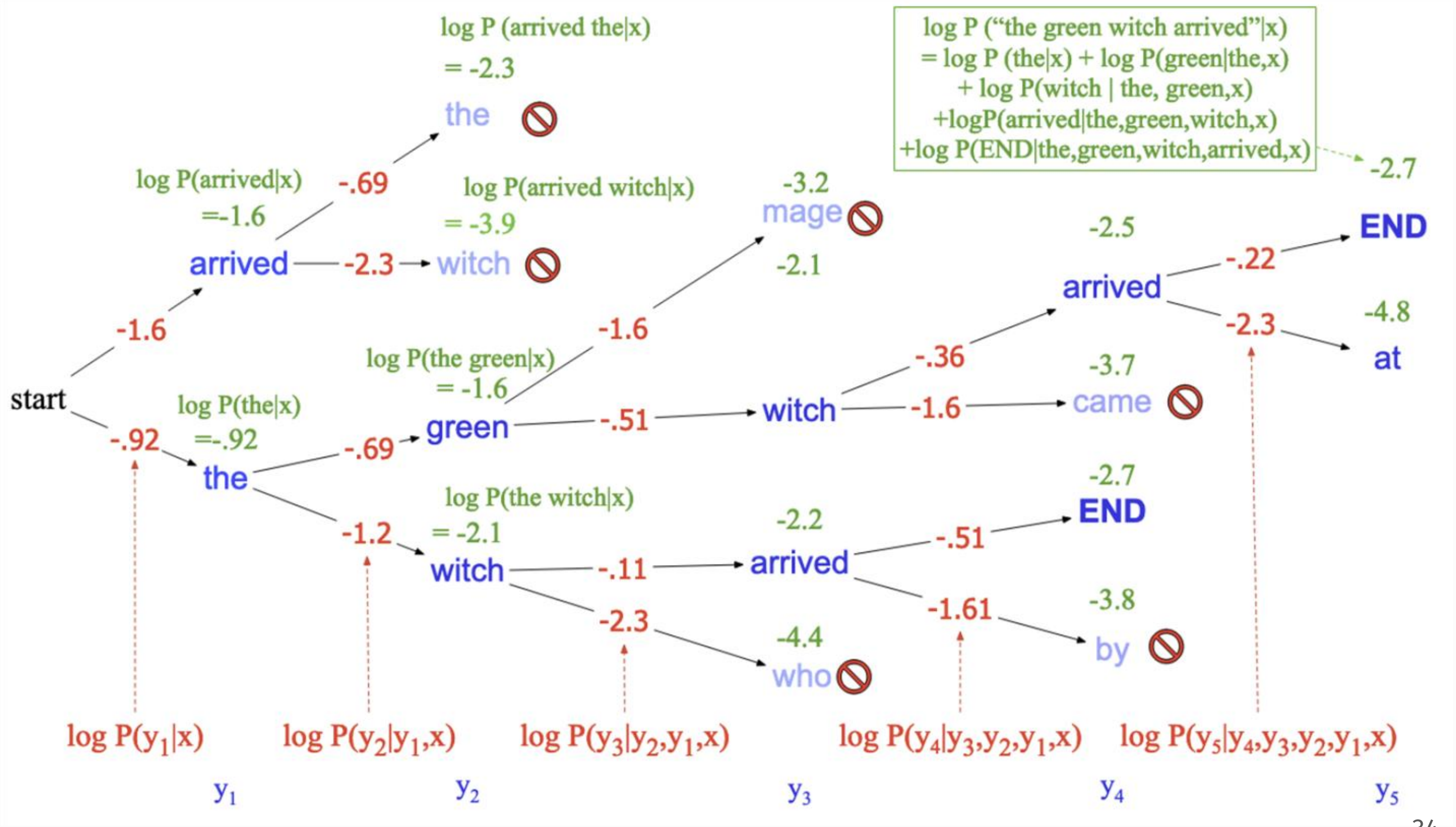


Image: iStock

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

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

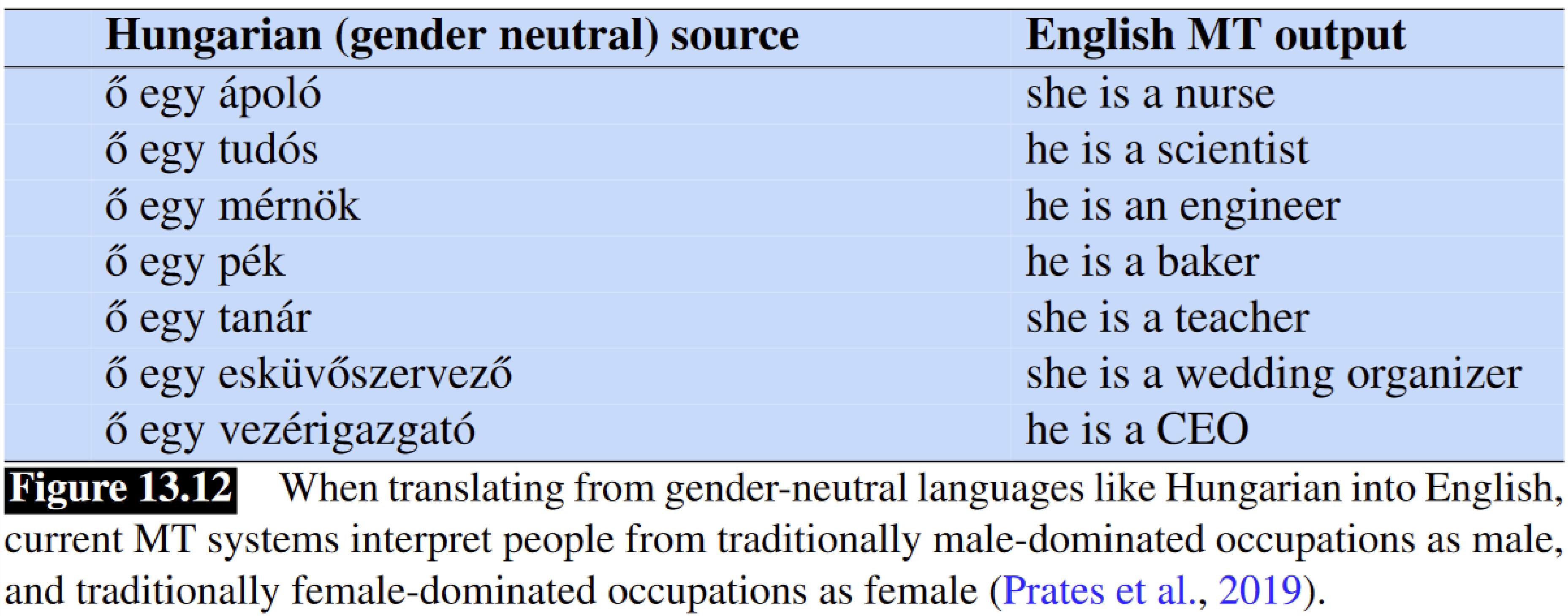
- **chrP**: percentage of character 1-grams, 2-grams, …, k-grams in the hypothesis that occur in the reference, averaged.
- **chrR**: percentage of character 1-grams, 2-grams,…, k-grams in the reference that occur in the hypothesis, averaged.

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

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?

How to align sentences

Need:

1. Cost function: how likely are a source language span and a target language span to be translations (matching sentences)?
2. Alignment algorithm: uses scores between spans to find a good alignment between documents

Multilingual embedding space

1. Cost function: score similarity of sentences across languages with cosine similarity of embeddings in **multilingual embedding space**

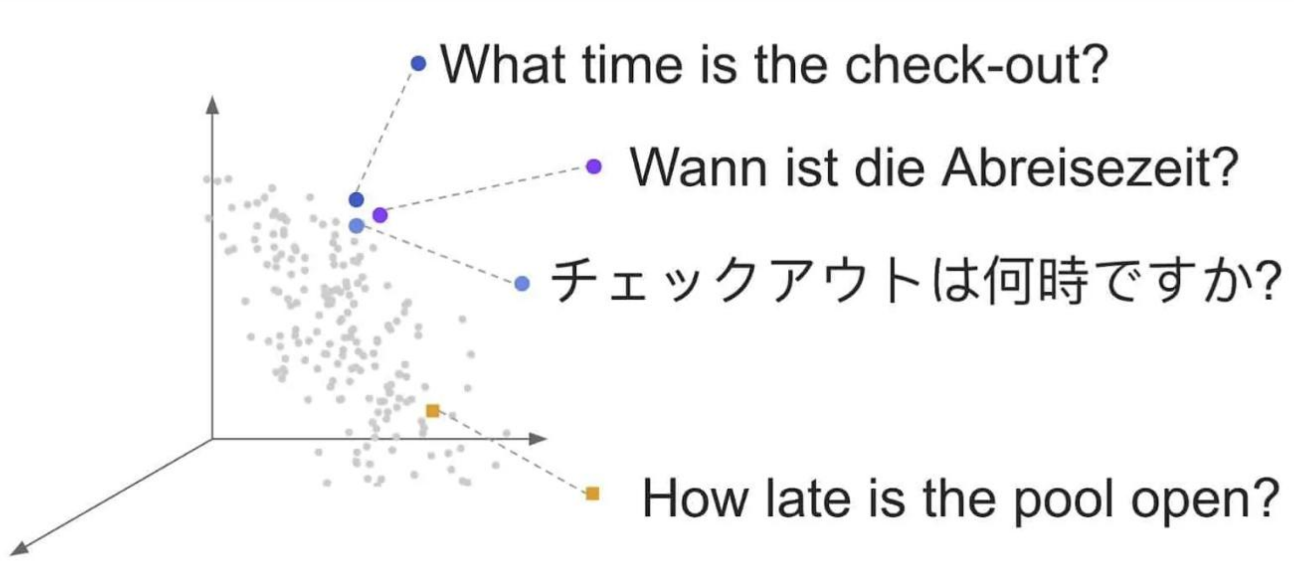

What time is the check-out?
Wann ist die Abreisezeit?
チェックアウトは何時ですか?
How late is the pool open?

Figure credit: Megagon Labs

Sentence alignment: cost function and alignment alg

1. Cost function using cosine similarity of embeddings in multilingual embedding space [Thompson + Koehn 2019]

$$c(x,y) = \frac{(1-\cos(x,y))\mathrm{nSents}(x)\ \mathrm{nSents}(y)}{\sum_{s=1}^{S} 1-\cos(x,y_s) + \sum_{s=1}^{S} 1-\cos(x_s,y)}$$

2. Dynamic programming algorithm [Gale + Church 1993] as the alignment algorithm
   - Minimize cost over the entire sequence of spans