Neural Machine Translation

CSCI 1460: Computational Linguistics

Lecture 9

Ellie Pavlick

Fall 2023

Topics

- SMT Followup: Putting it all together
- MT Evaluation
- Neural MT
  - Encoder-Decoder Models
  - Multilingual LMs and “Zero Shot” Cross-Lingual Transfer

Topics

- **SMT Followup: Putting it all together**
- MT Evaluation
- Neural MT
  - Encoder-Decoder Models
  - Multilingual LMs and “Zero Shot” Cross-Lingual Transfer

Full Phrase-Based MT System

$$\text{argmax}_{tgt \in TGT} P(src \mid tgt) P(tgt)$$

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1. Translation Model

Full Phrase-Based MT System

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1. Translation Model
2. Language Model

Full Phrase-Based MT System

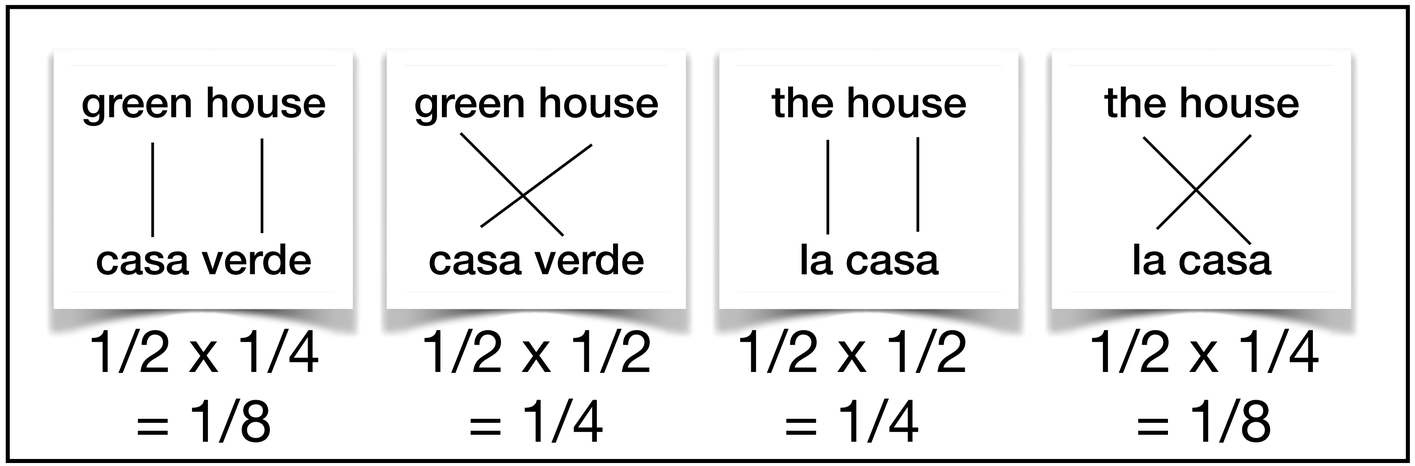
$$\text{argmax}_{tgt \in TGT} P(src \mid tgt) P(tgt)$$

1. Translation Model
2. Language Model
3. Decoder

Alignment: Produces a Translation Model

green house	casa verde
the house	la casa

a



t

		target		
		green	house	the
source	casa	1/2	1/2	1/2
	la	0	1/4	1/2
	verde	1/2	1/4	0

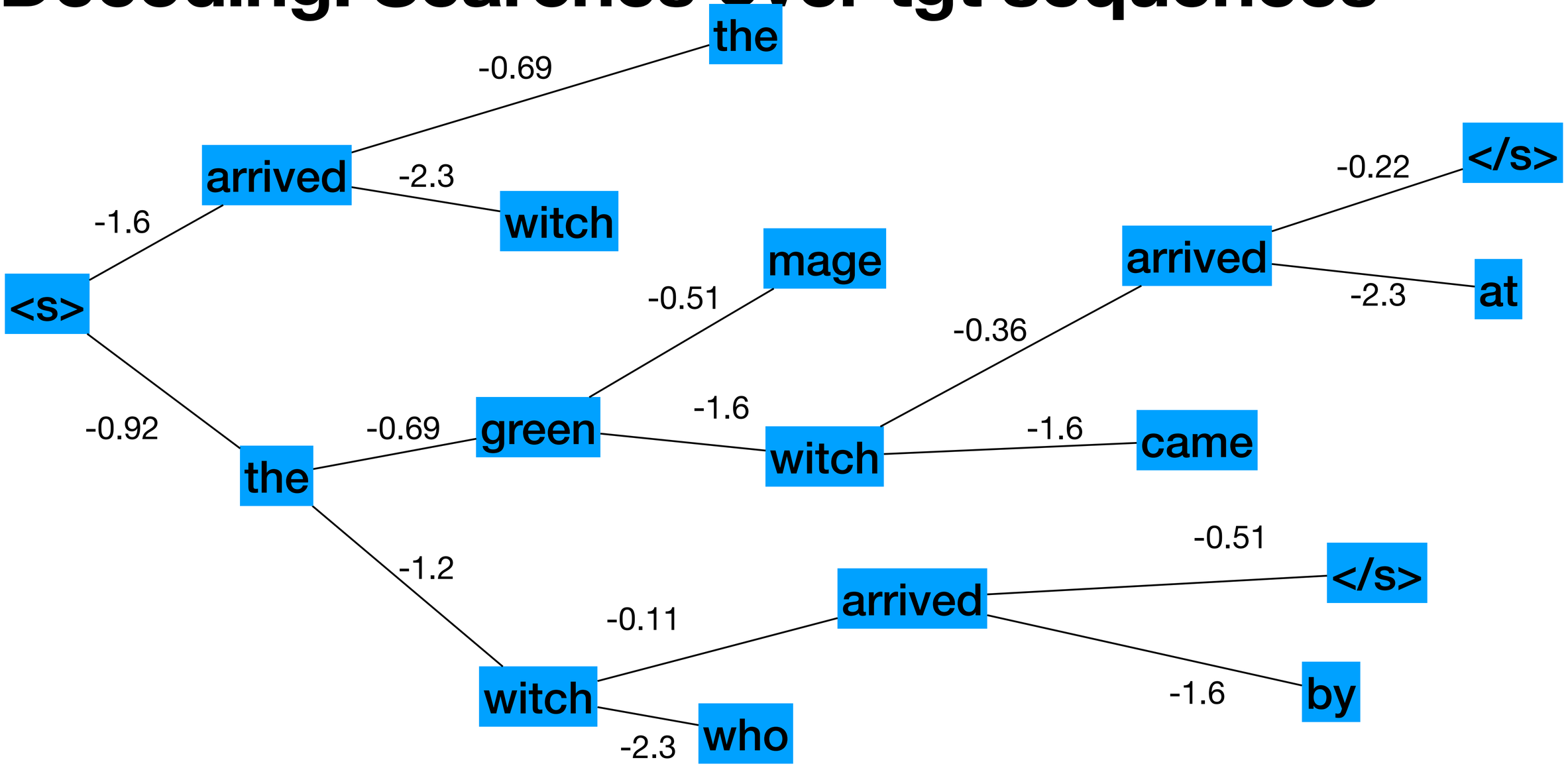
Lectures 9—12: Language Models

<s> can you tell me about any good cantonese restaurants close by </s>
<s> mid priced thai food is what i'm looking for </s>
<s> tell me about chez panisse </s>
<s> can you give me a listing of the kinds of food that are available </s>
<s> i'm looking for a good place to eat breakfast </s>
<s> when is caffe venezia open during the day </s>

$$P(w_0 \ldots w_n) \approx P(w_0 | \text{<s>}) \times P(w_1 | w_0) \times P(w_2 | w_1) \times \ldots \times P(w_n | w_{n-1})$$

P(tell me about caffe venezia) = P(tell|<s>) x P(me|tell) x P(about|me) x
P(caffe|about) x P(venezia|caffe) x P(</s>|venezia)

Decoding: Searches over tgt sequences



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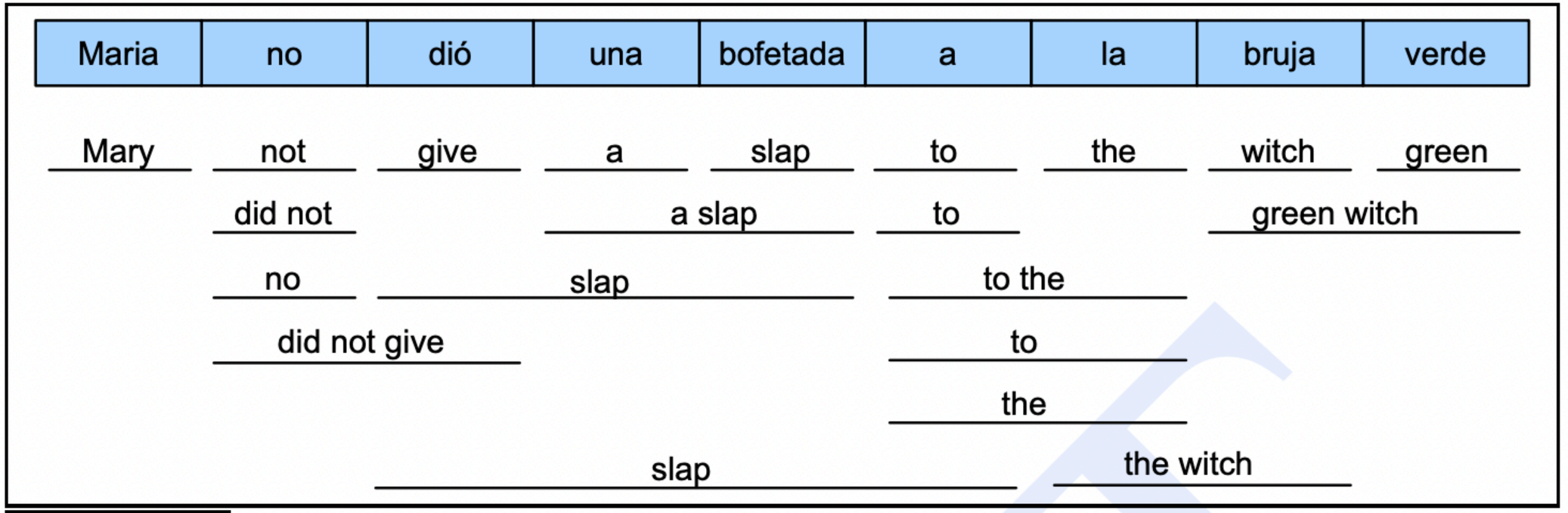
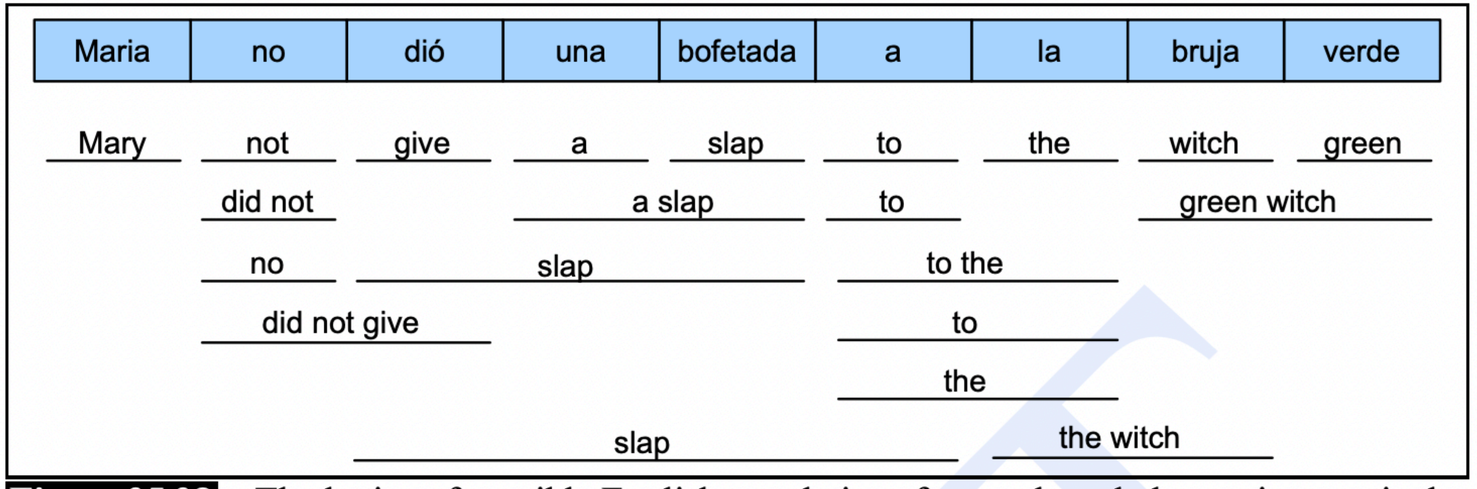


Figure 25.28 The lattice of possible English translations for words and phrases in a particular sentence F, taken from the entire aligned training set. After Koehn (2003a)



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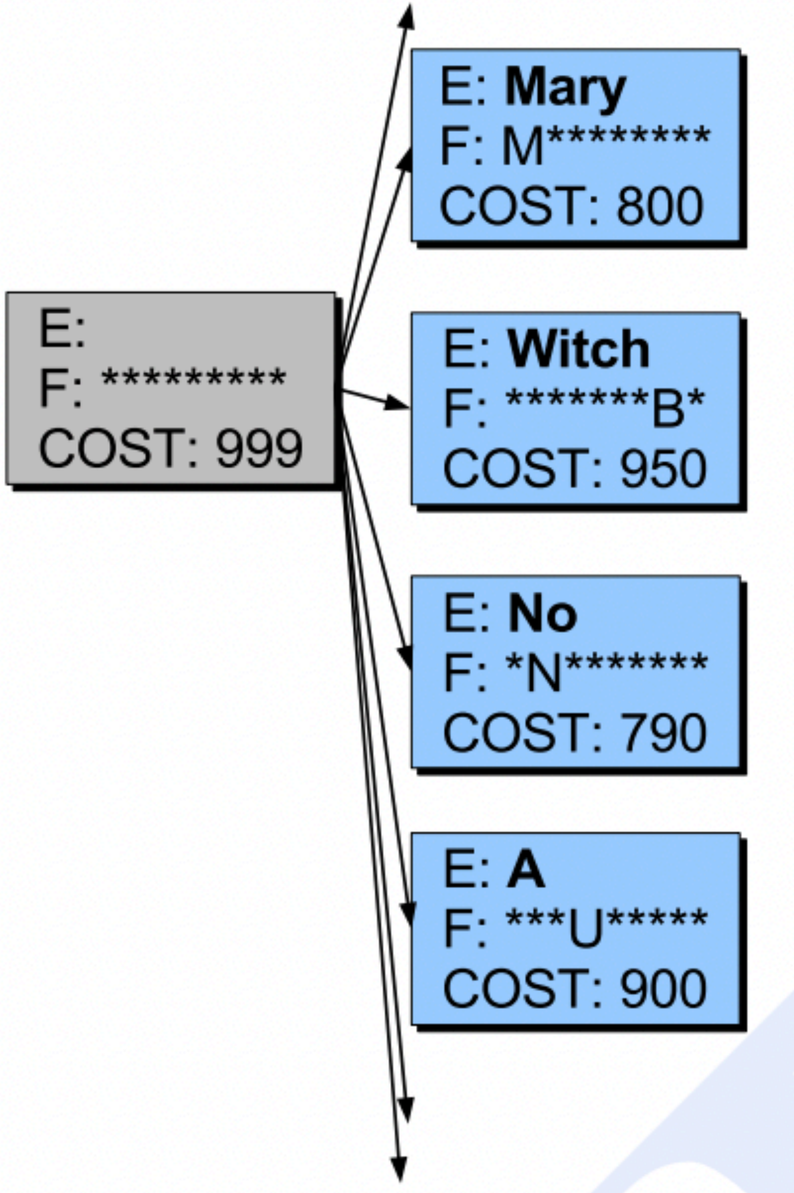

a) after expanding NULL

Maria	no	dió	una	bofetada	a	la	bruja	verde
Mary	not	give	a	slap	to	the	witch	green
	did not		a slap		to		green witch	
	no	slap			to the			
	did not give				to			
					the			
		slap				the witch		

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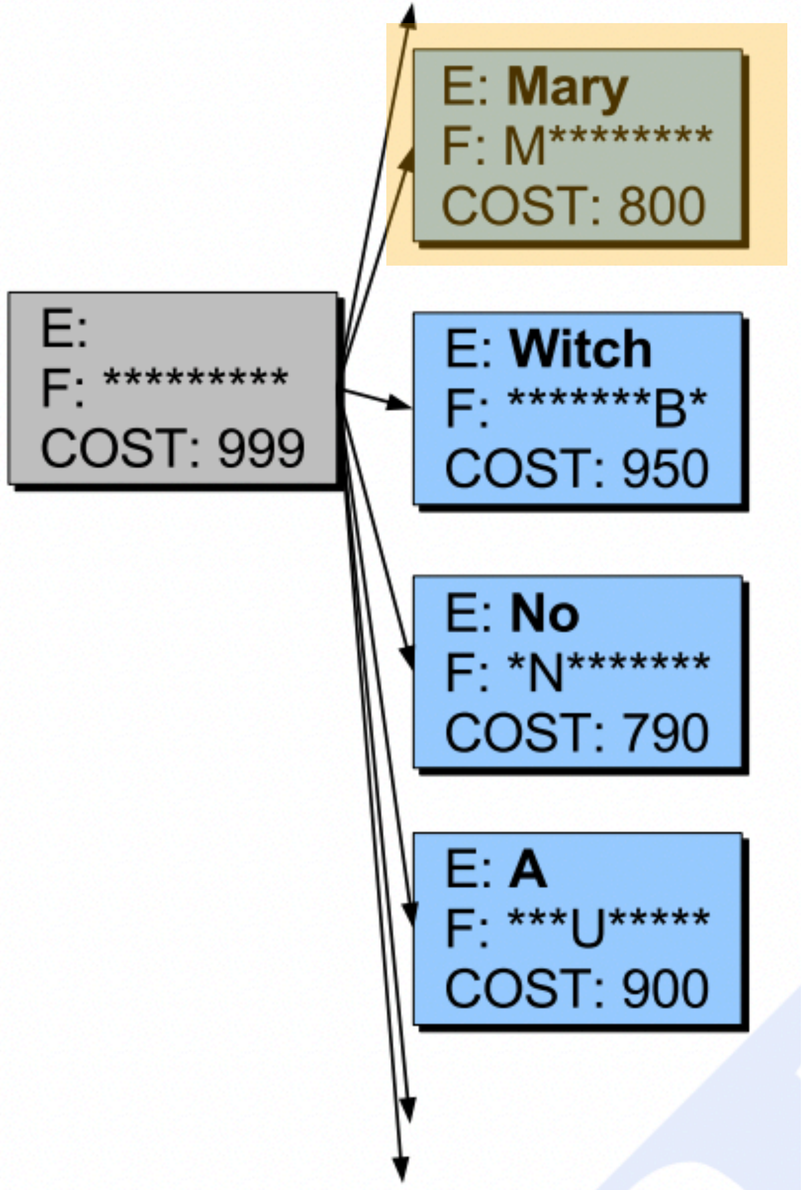

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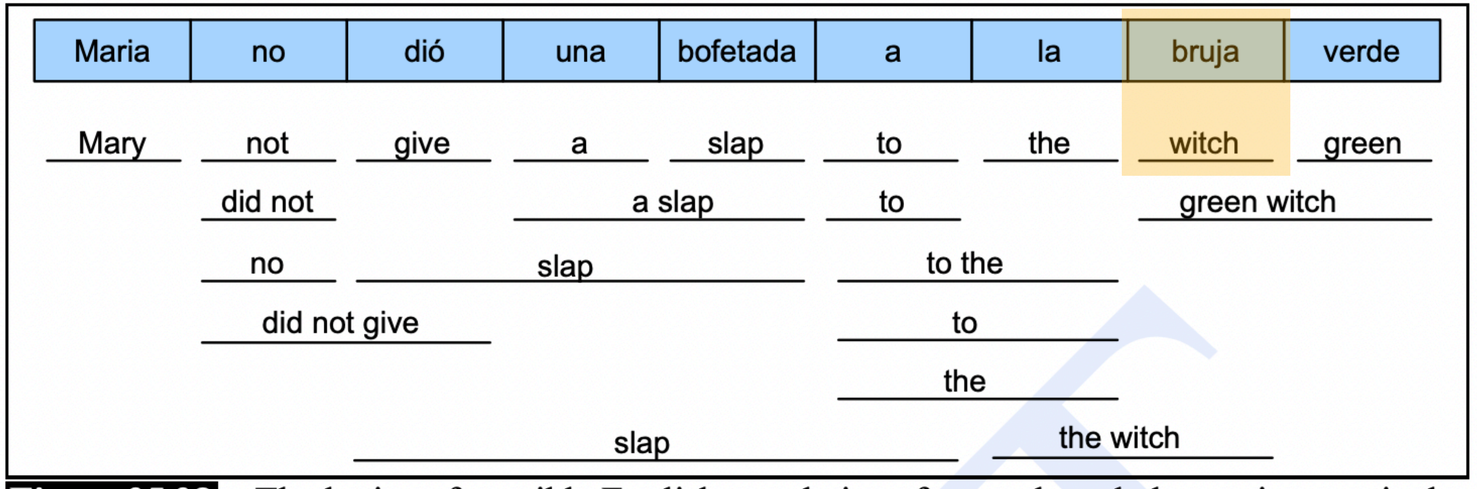

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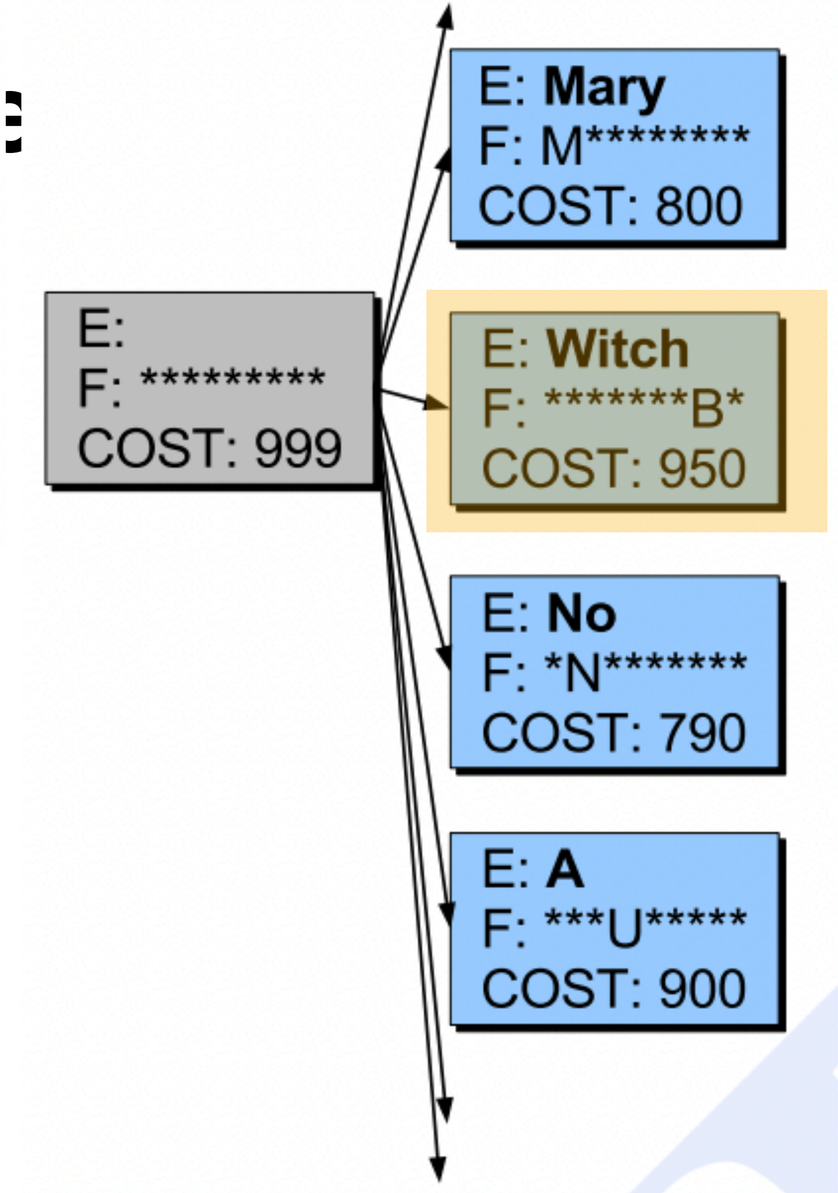

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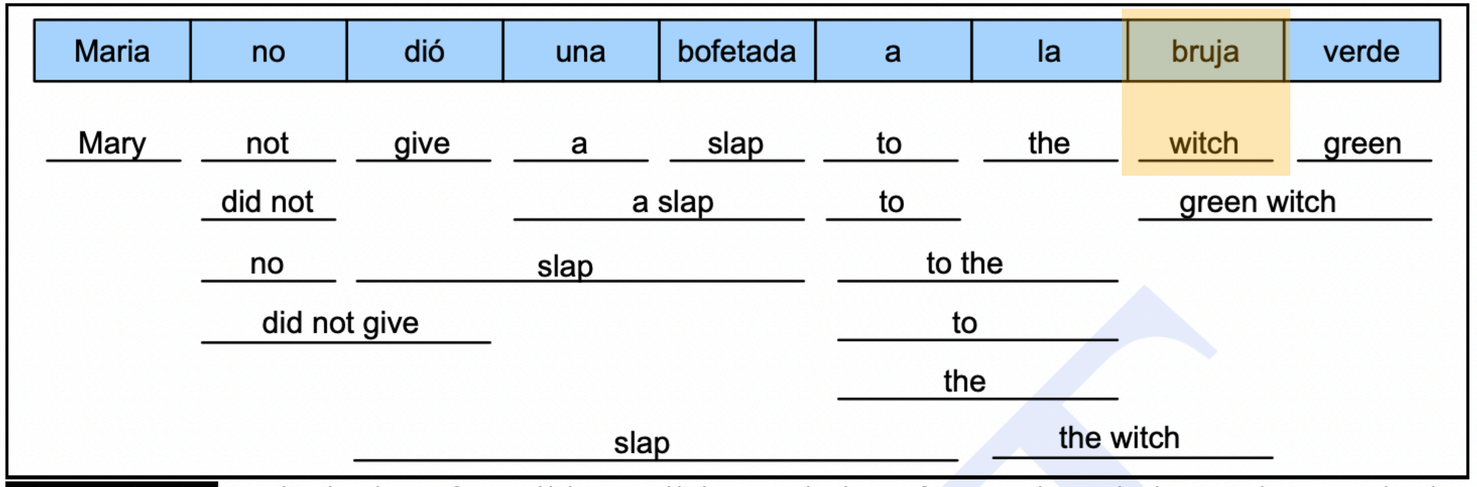

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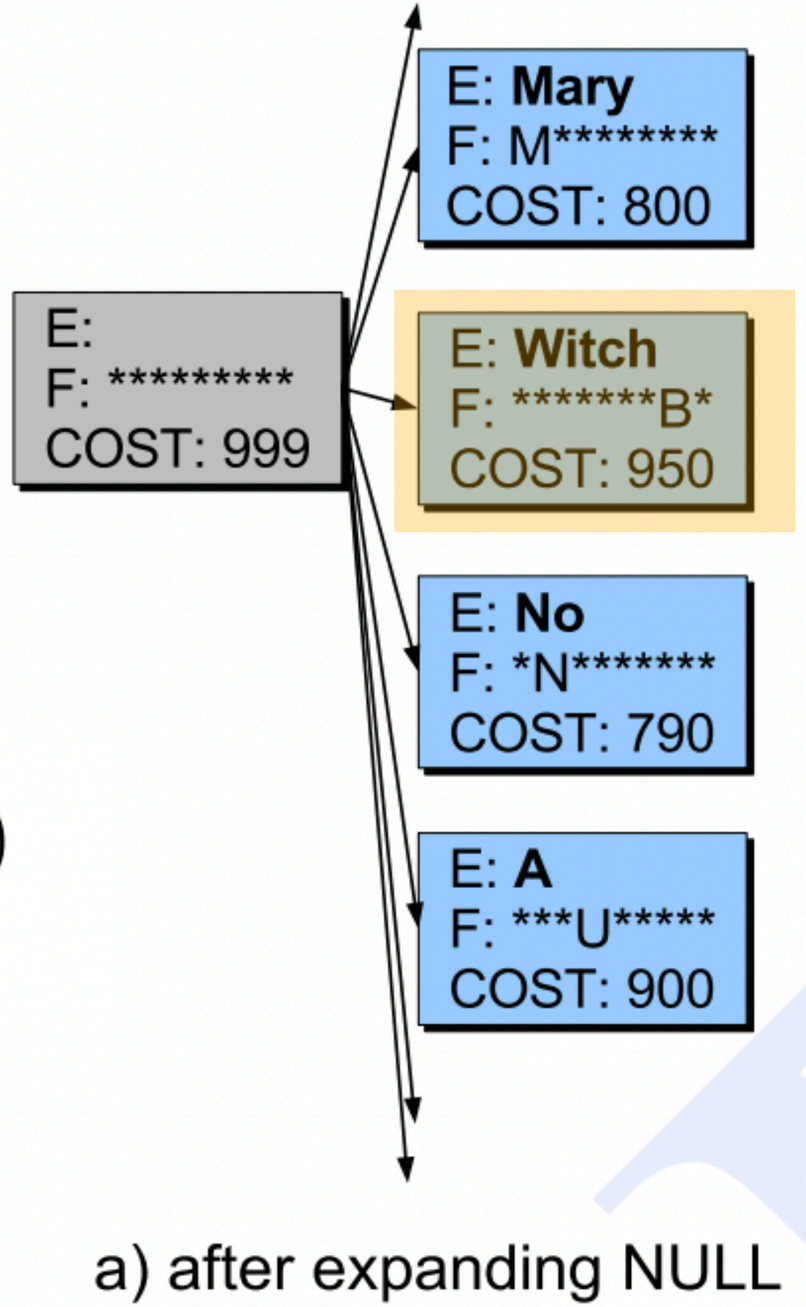
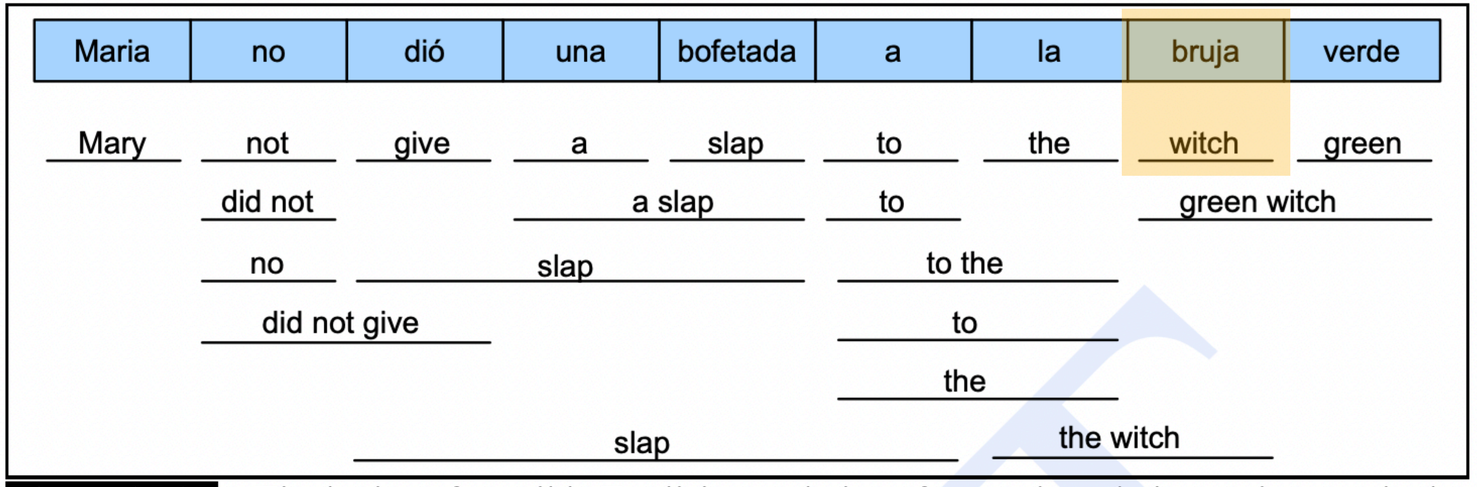


$$\text{cost}(E,F) = \prod_{i \in S} \phi(\bar{f}_i, \bar{e}_i) d(a_i - b_{i-1}) P(E)$$

product over all positions in the (partial) sentence



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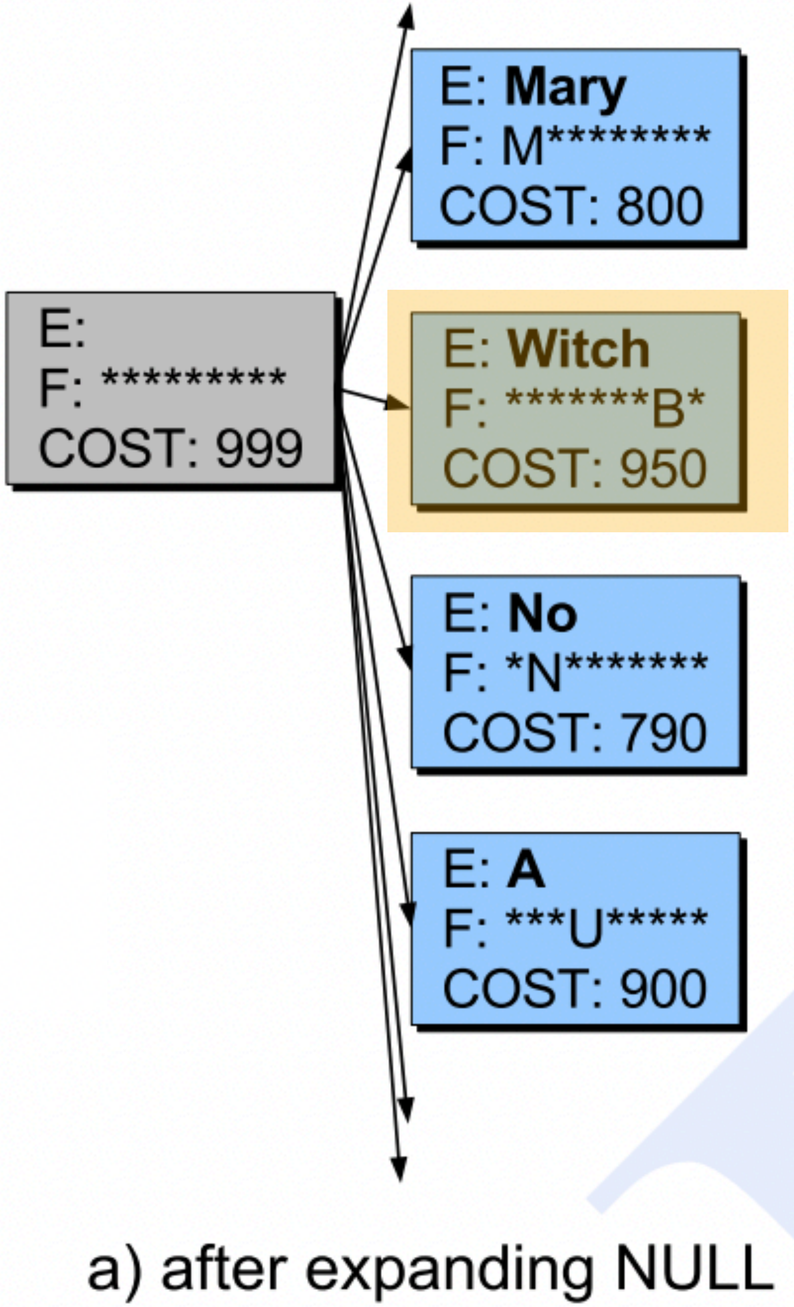
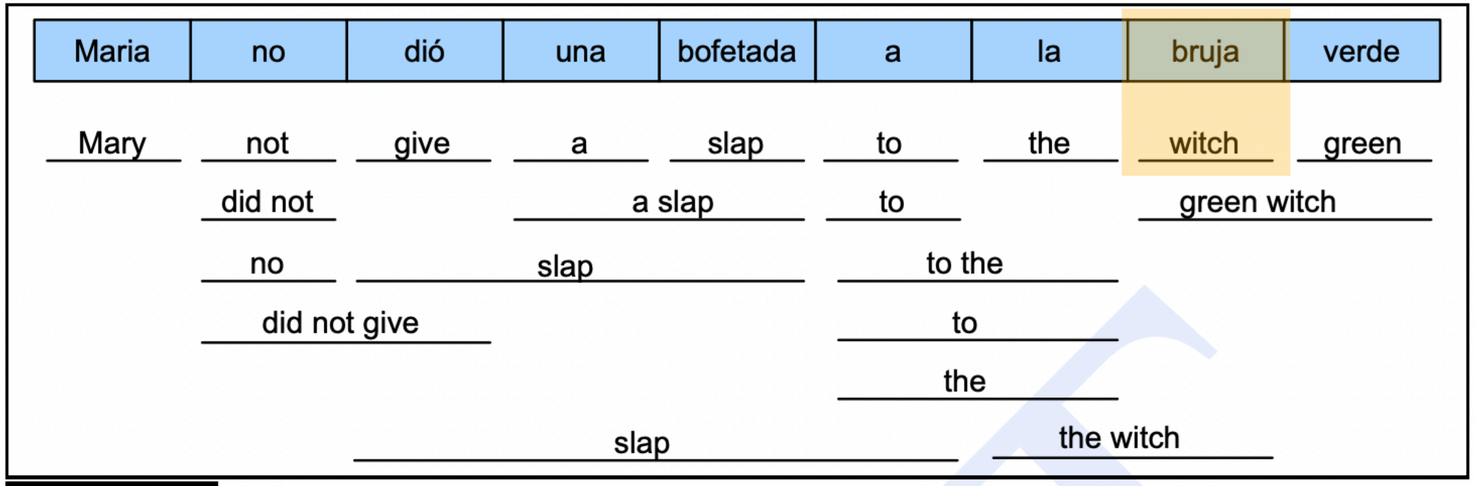


$$\text{cost}(E,F) = \prod_{i \in S} \phi(\overline{f}_i, \overline{e}_i) d(a_i - b_{i-1}) P(E)$$

translation probability
(e.g., from IBM alignment model)



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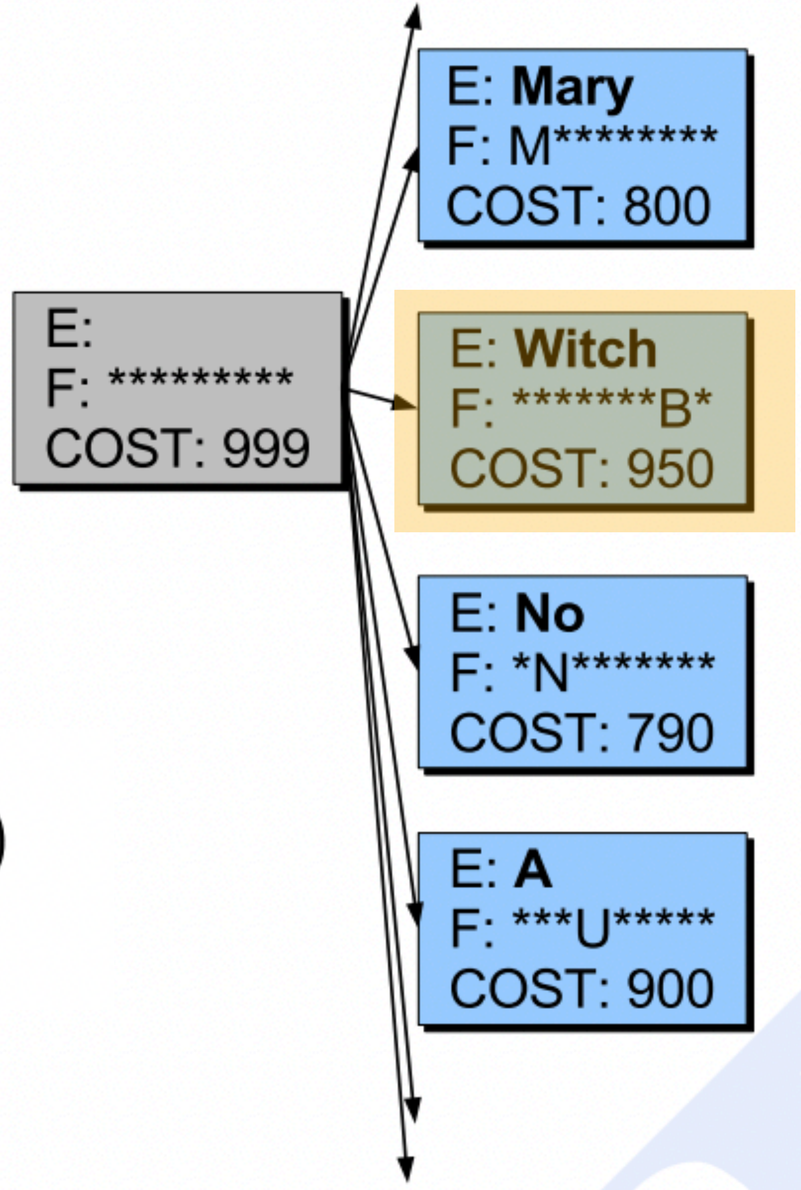
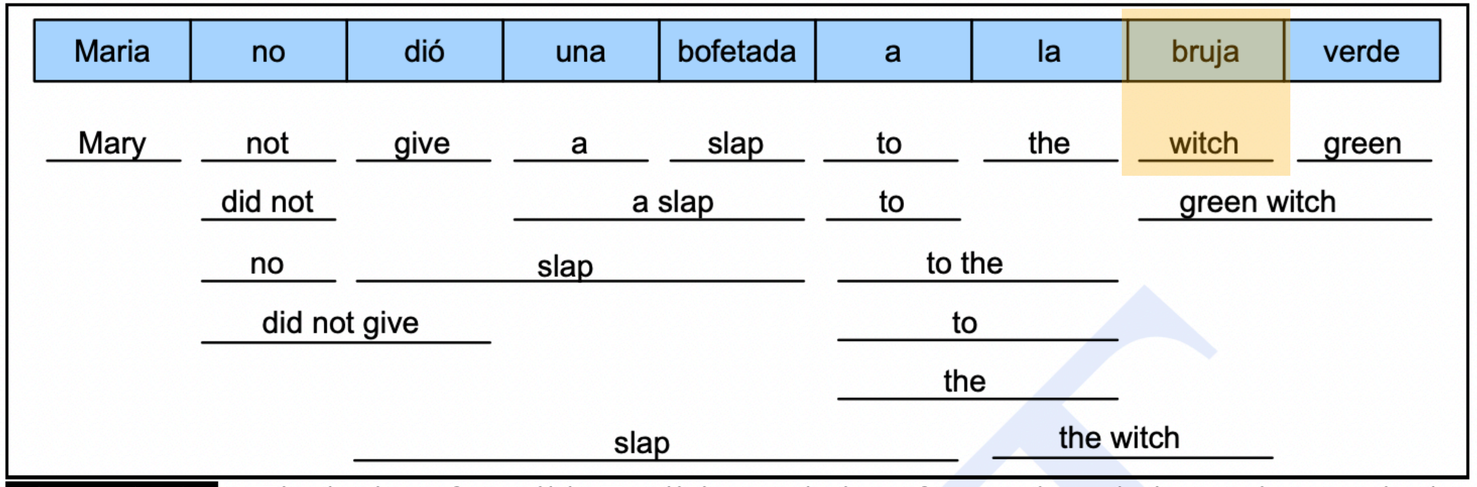


a) after expanding NULL

$$\text{cost}(E,F) = \prod_{i \in S} \phi(\bar{f}_i, \bar{e}_i) d(a_i - b_{i-1}) P(E)$$

distortion probability

(deals with offsets, e.g., probability of translating the 8th word first)



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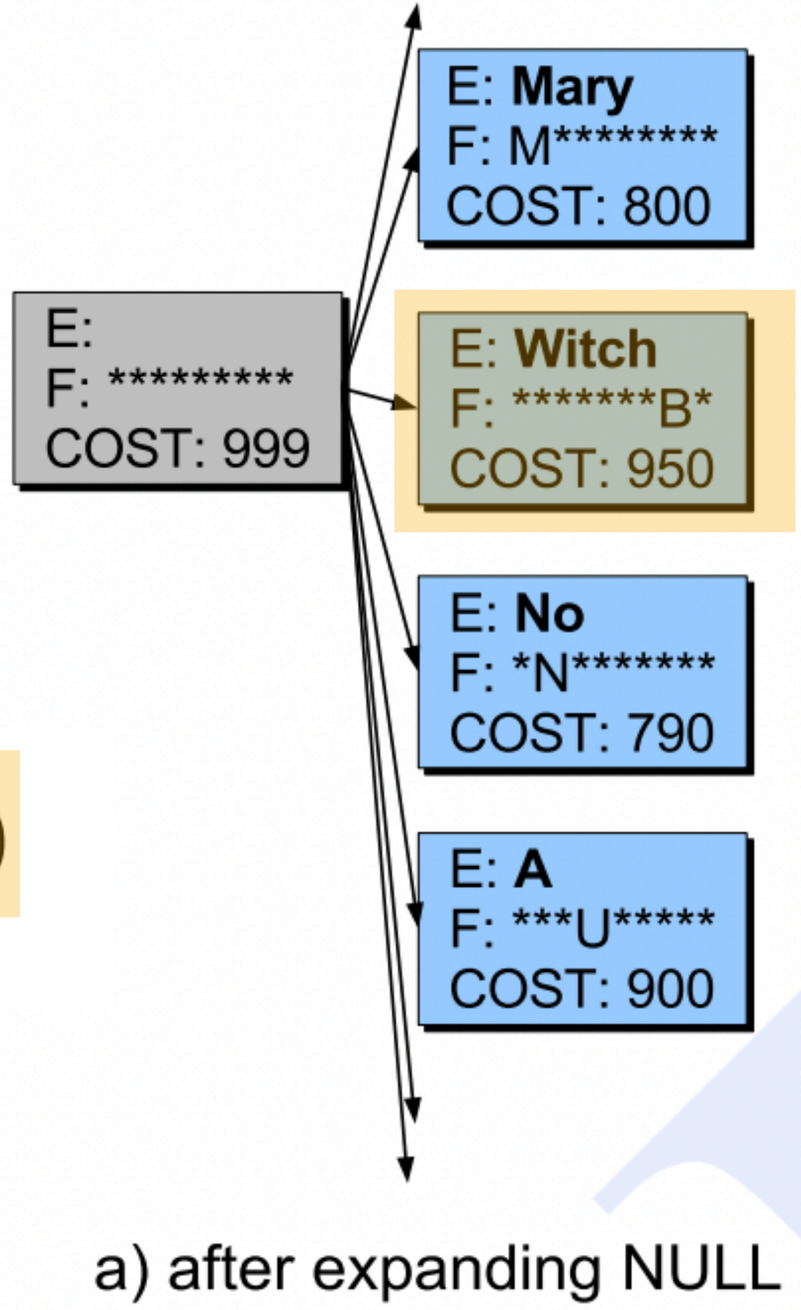
language model probability



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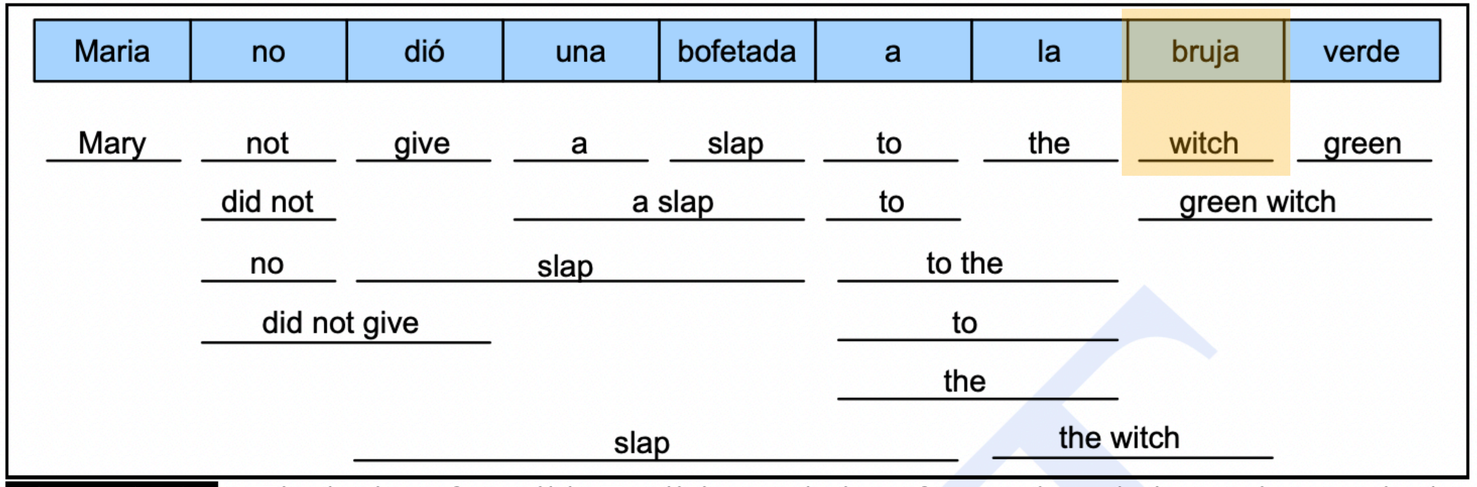

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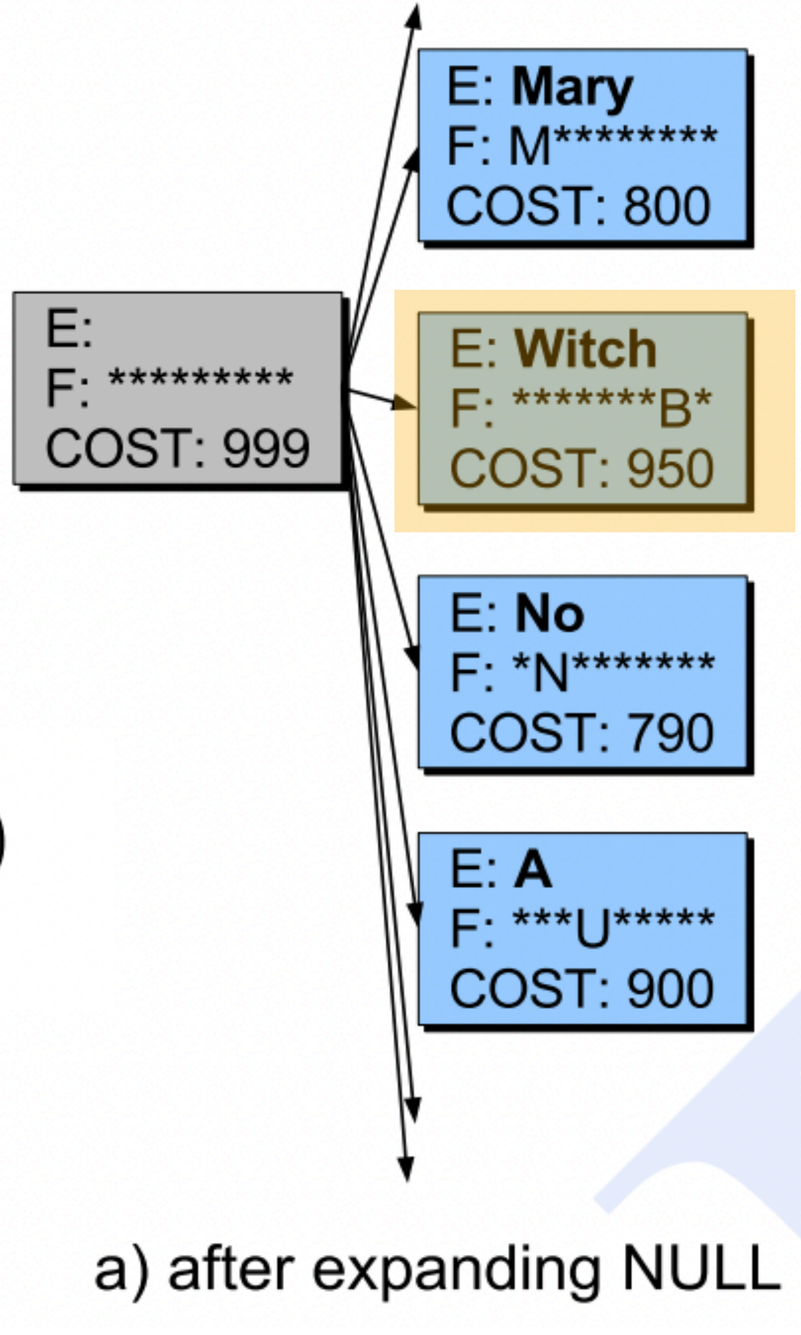

$$\text{cost}(E,F) = \prod_{i \in S} \phi(\bar{f}_i, \bar{e}_i) d(a_i - b_{i-1}) P(E)$$

(also combined with an estimated "future cost" of translating the remaining words.)

Topics

- SMT Followup: Putting it all together
- **MT Evaluation**
- Neural MT
  - Encoder-Decoder Models
  - Multilingual LMs and “Zero Shot” Cross-Lingual Transfer

MT Evaluation

- Human Evaluation:
  - Explicit ratings for fluency and faithfulness
  - Most reliable, but expensive to collect
  - Needs to be collected new for every system
  - Can’t be “hill climbed”

MT Evaluation

- Automatic Evaluations:
  - NLP likes automatic evals for standardization and optimization
  - Most popular metric for MT is **BLEU**

MT Evaluation

BLEU

- Assume we have an MT output (“candidate”) and are comparing against multiple human-generated “referent” translations
- Intuition: We should reward models for producing translations that contains lots of the same words/phrases as the references

MT Evaluation

BLEU

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

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

MT Evaluation

BLEU

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MT Evaluation

BLEU

- BLEU: Weighted n-gram precision with a length penalty

$$Bleu = BP \times exp\left(\frac{1}{N}\sum_{n=1}^{N} logp_n\right)$$

MT Evaluation
BLEU

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weighted
ngram
precision

MT Evaluation
BLEU

- BLEU: Weighted n-gram precision with a length penalty

$$Bleu = BP \times exp\left(\frac{1}{N}\sum_{n=1}^{N} logp_n\right)$$

"brevity penalty"

MT Evaluation

BLEU

weighted ngram precision

$$p_n = \frac{\sum_{c \in cand} \sum_{ngm \in c} count_{clip}(ngm)}{\sum_{c' \in cand} \sum_{ngm' \in c'} count(ngm')}$$

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MT Evaluation

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unigram precision = 1

MT Evaluation

BLEU

weighted ngram precision

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unigram precision = 2

MT Evaluation

BLEU

weighted ngram precision

$$p_n = \frac{\sum_{c \in cand} \sum_{ngm \in c} count_{clip}(ngm)}{\sum_{c' \in cand} \sum_{ngm' \in c'} count(ngm')}$$

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unigram precision = 3

MT Evaluation

BLEU

weighted ngram precision

$$p_n = \frac{\sum_{c \in cand} \sum_{ngm \in c} count_{clip}(ngm)}{\sum_{c' \in cand} \sum_{ngm' \in c'} count(ngm')}$$

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unigram precision = 4

MT Evaluation

BLEU

weighted ngram precision

$$p_n = \frac{\sum_{c \in cand} \sum_{ngm \in c} count_{clip}(ngm)}{\sum_{c' \in cand} \sum_{ngm' \in c'} count(ngm')}$$

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unigram precision = 17

(every word except "obeys")

MT Evaluation

BLEU

weighted ngram precision

$$p_n = \frac{\sum_{c \in cand} \sum_{ngm \in c} count_{clip}(ngm)}{\sum_{c' \in cand} \sum_{ngm' \in c'} count(ngm')}$$

Candidate 1	It is a guide to action which ensures that the military always obeys the commands of the party

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unigram precision = 17 / 18 = 0.94

(every word except "obeys")

MT Evaluation

BLEU

weighted ngram precision

$$p_n = \frac{\sum_{c \in cand} \sum_{ngm \in c} count_{clip}(ngm)}{\sum_{c' \in cand} \sum_{ngm' \in c'} count(ngm')}$$

Candidate 1	party party party party

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unigram precision = 4 / 4 = 1.0

(every word except "obeys")

MT Evaluation

BLEU

weighted ngram precision

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"clipped" unigram precision = 4 / 4 = 1.0

(every word except "obeys")

MT Evaluation
BLEU

- BLEU: Weighted n-gram precision with a length penalty

$$Bleu = BP \times exp\left(\frac{1}{N}\sum_{n=1}^{N} logp_n\right)$$

harmonic mean of unigram, bigram, trigram, 4-gram precisions

MT Evaluation

BLEU

- BLEU: Weighted n-gram precision with a length penalty

$$Bleu = BP \times exp\left(\frac{1}{N}\sum_{n=1}^{N} logp_n\right)$$

brevity penalty

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r)/c} & \text{if } c \leq r \end{cases}$$

MT Evaluation

- Automatic Evaluations:
  - NLP likes automatic evals for standardization and optimization
  - Most popular metric for MT is **BLEU**
  - Newer variations exist: e.g., ML models like ESIM and BLEURT
  - Controversial—once systems are sufficiently good, metrics stop correlating with human judgments

MT Evaluation

Tangled up in BLEU: Reevaluating the Evaluation of Automatic Machine Translation Evaluation Metrics

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The University of Melbourne
Victoria 3010, Australia

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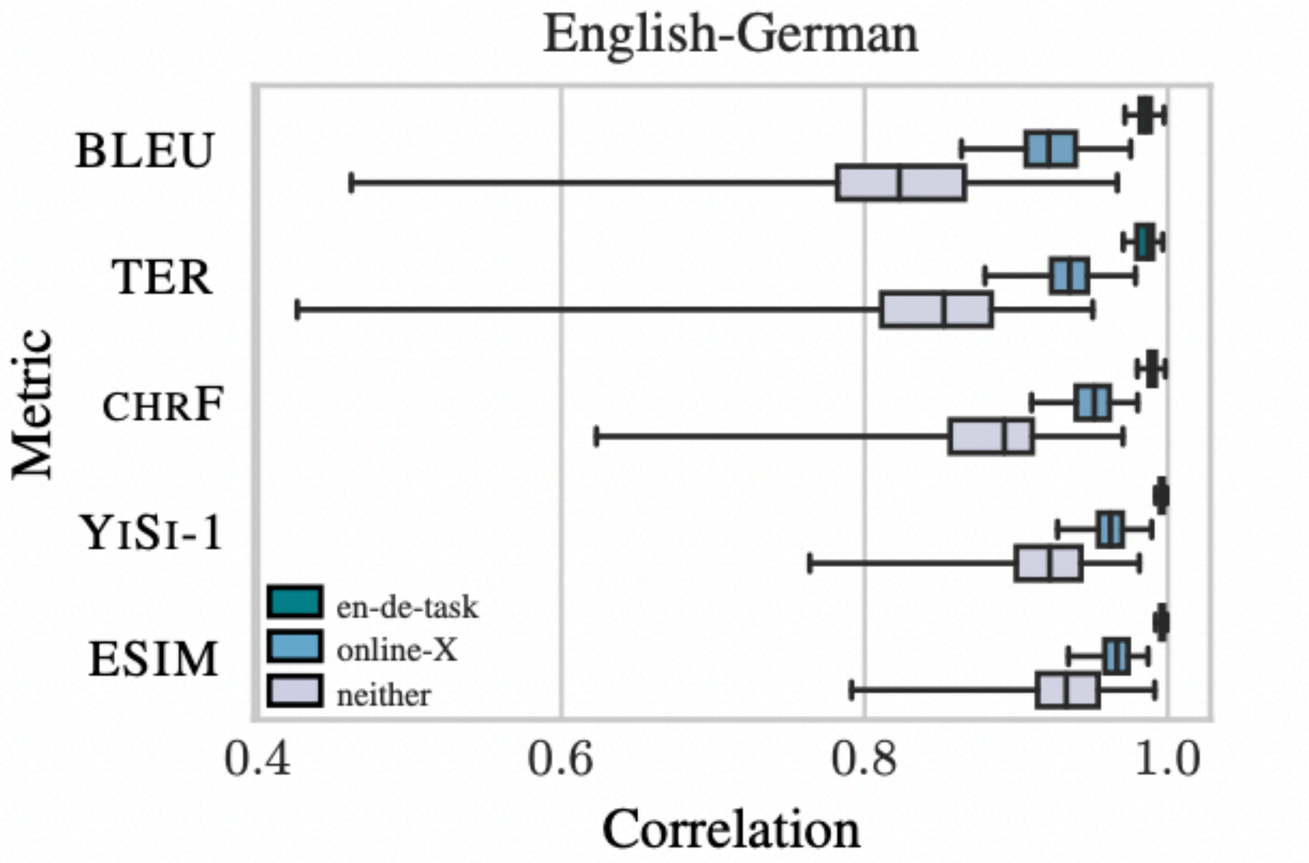
MT Evaluation



Baseline metrics

- BLEU (Papineni et al., 2002b) is the precision of n-grams of the MT output compared to the reference, weighted by a brevity penalty to punish overly short translations. BLEU has high variance across different hyper-parameters and pre-processing strategies, in response to which sacreBLEU (Post, 2018) was introduced to create a standard implementation for all researchers to use; we use this version in our analysis.
- TER (Snover et al., 2006) measures the number of edits (insertions, deletions, shifts and substitutions) required to transform the MT output to the reference.
- CHRF (Popović, 2015) uses character n-grams instead of word n-grams to compare the MT output with the reference. This helps with matching morphological variants of words.

Best metrics across language pairs

- YISI-1 (Lo, 2019) computes the semantic similarity of phrases in the MT output with the reference, using contextual word embeddings (BERT: Devlin et al. (2019)).
- ESIM (Chen et al., 2017; Mathur et al., 2019) is a trained neural model that first computes sentence representations from BERT embeddings, then computes the similarity between the two strings. [3]

Source-based metric

- YISI-2 (Lo, 2019) is the same as YISI-1, except that it uses cross-lingual embeddings to compute the similarity of the MT output with the source.

Topics

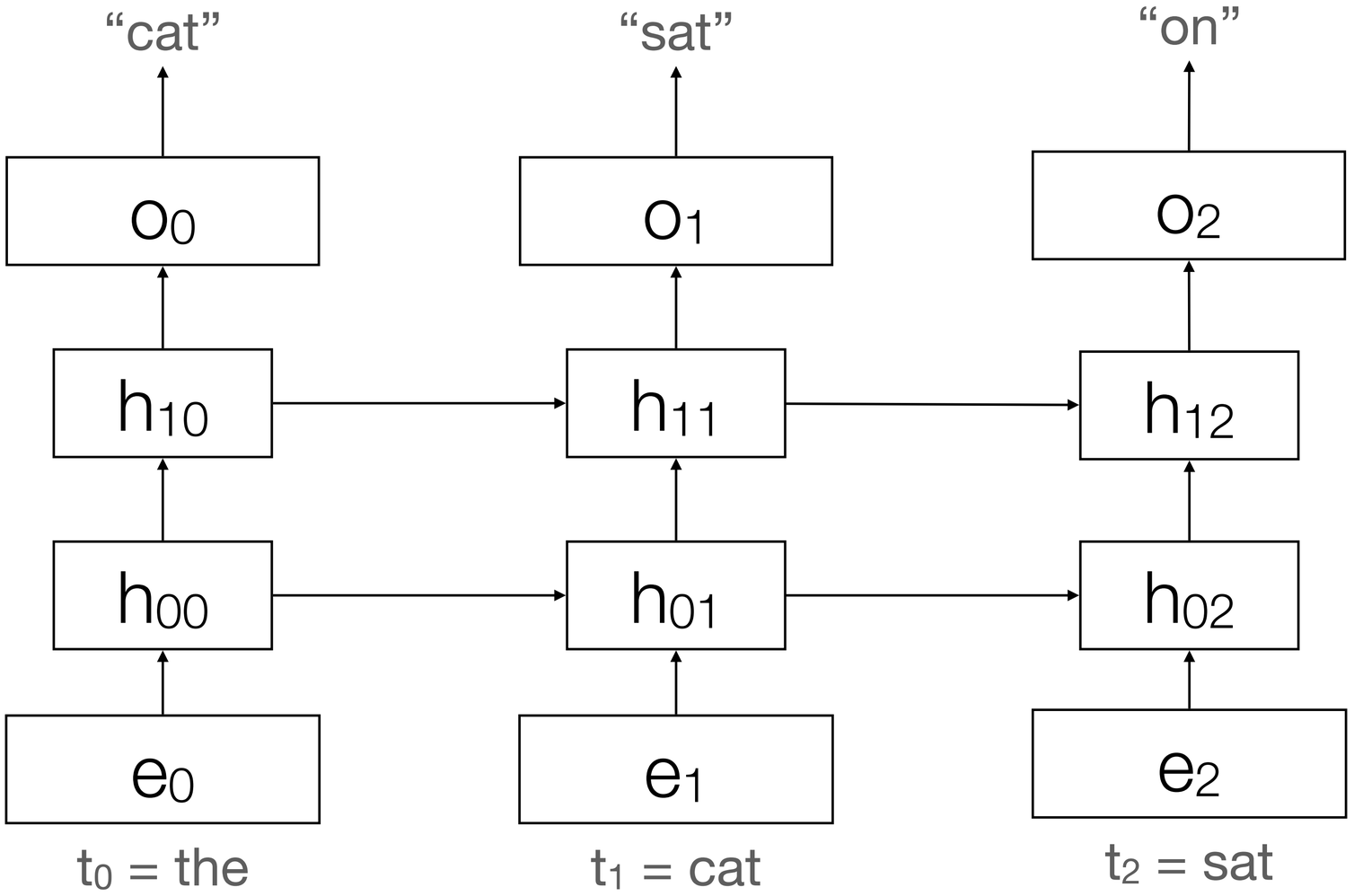
- SMT Followup: Putting it all together
- MT Evaluation
- **Neural MT**
  - **Encoder-Decoder Models**
  - Multilingual LMs and “Zero Shot” Cross-Lingual Transfer

Encoder-Decoder Models

- AKA “sequence to sequence” or seq2seq
- Intuition: “Conditional” text generation/language modeling
- Like language modeling, but output is dependent on some input, in this case, the source sentence
- seq2seqs were originally designed for MT, but have since been applied to many other tasks
  - E.g., summarization, parsing, etc…

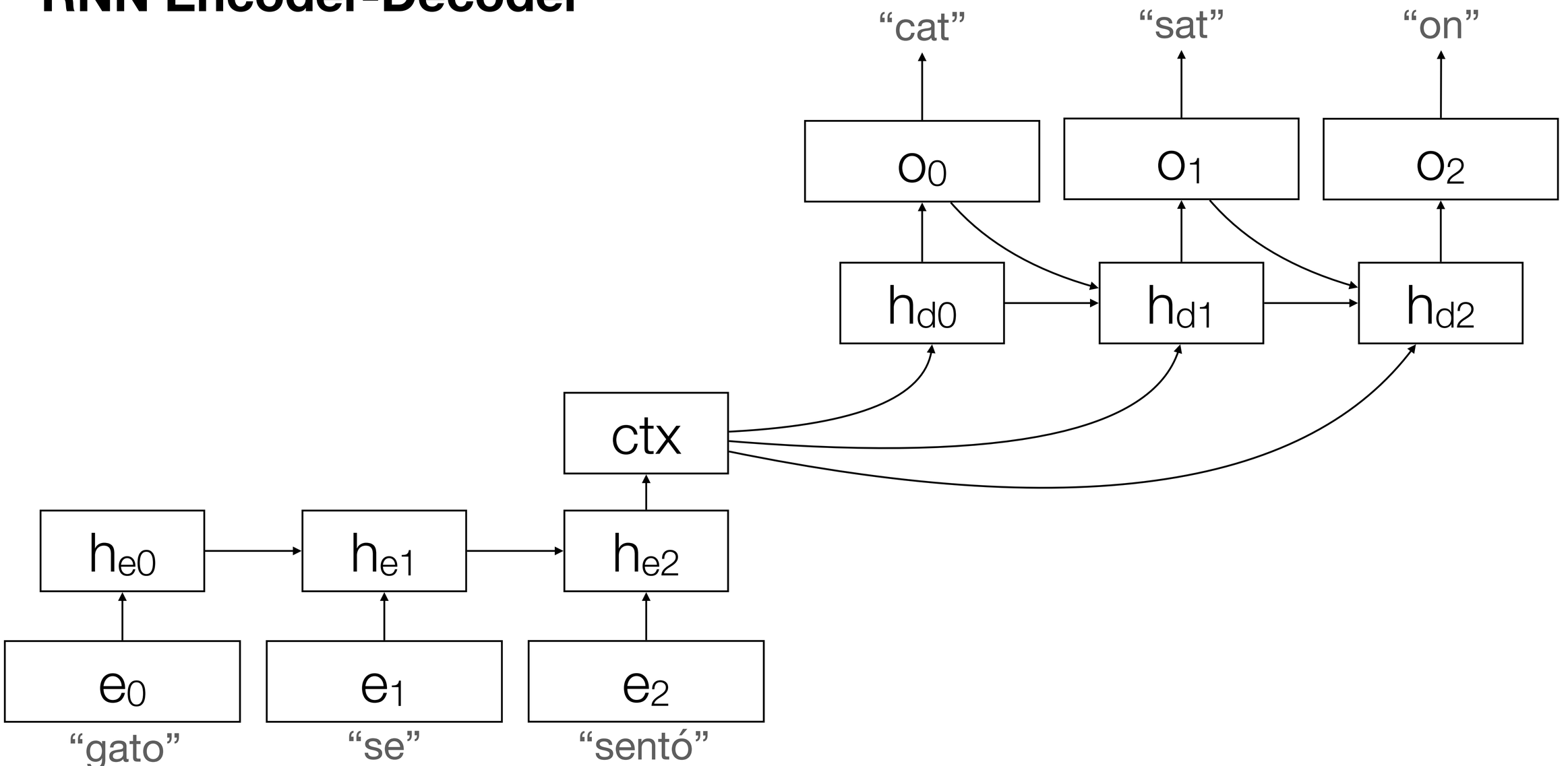
Encoder-Decoder Models

Basic RNN



Encoder-Decoder Models

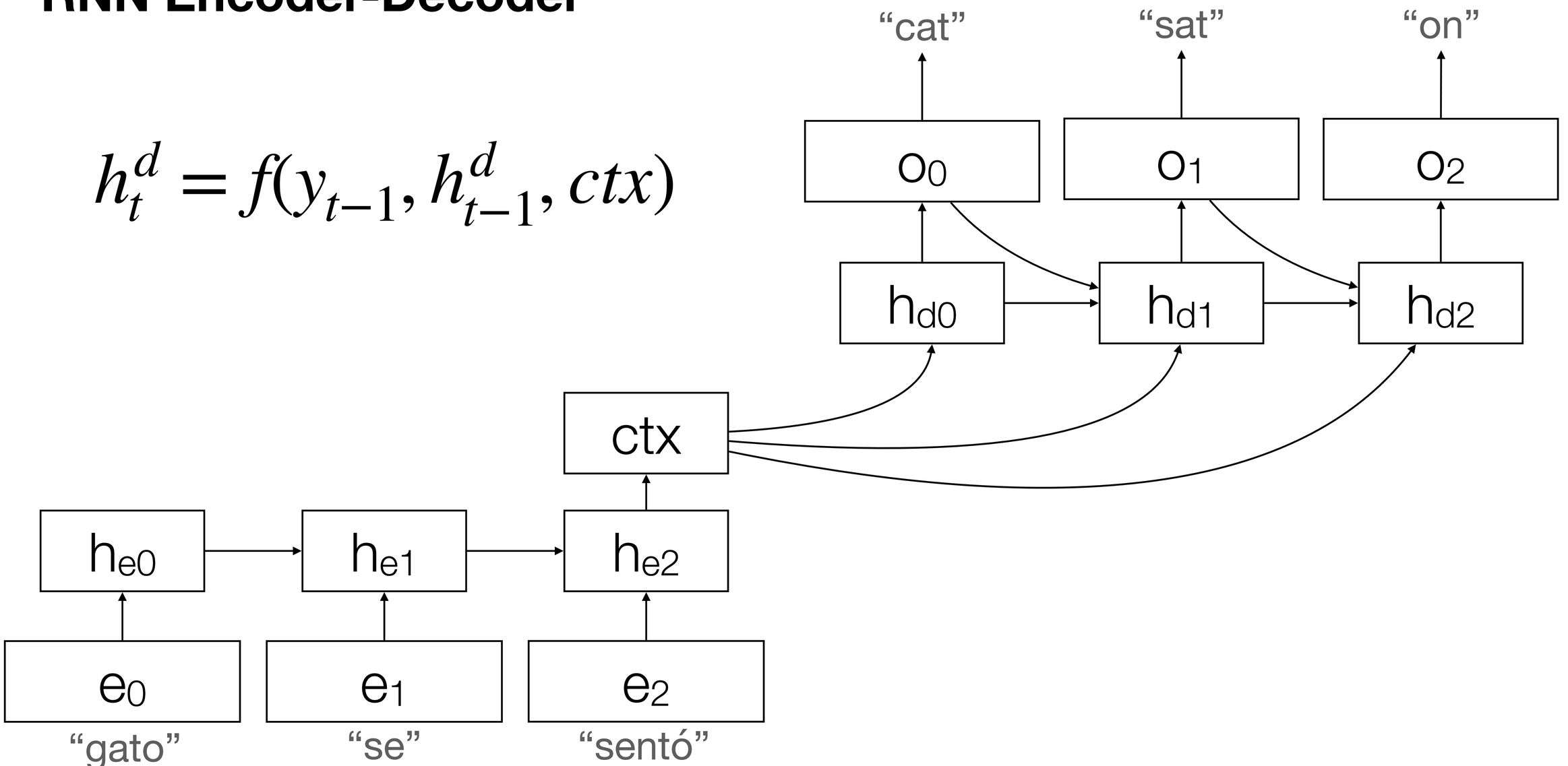
RNN Encoder-Decoder



Encoder-Decoder Models

RNN Encoder-Decoder

$$h_t^d = f(y_{t-1}, h_{t-1}^d, ctx)$$

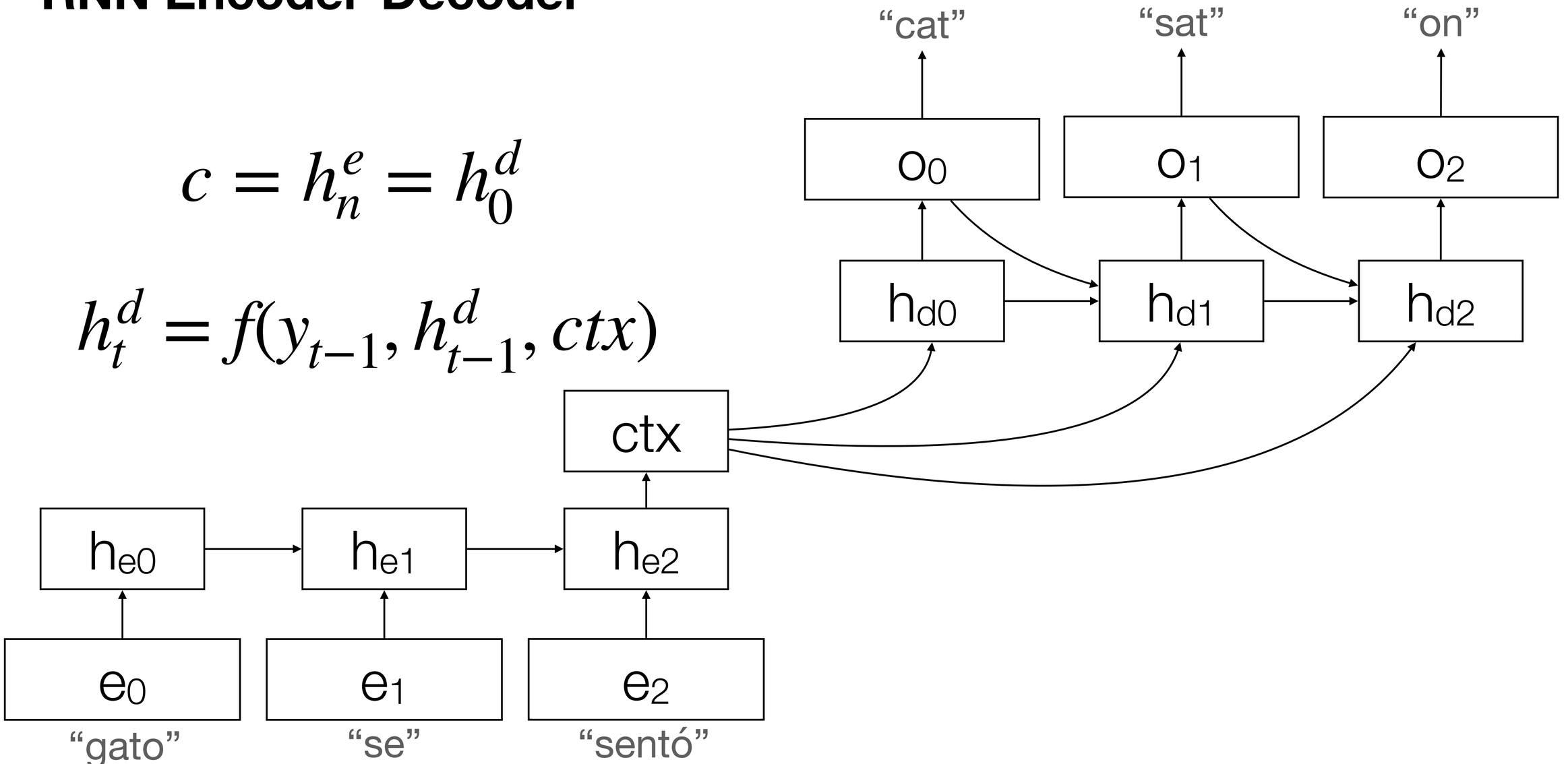


Encoder-Decoder Models

RNN Encoder-Decoder

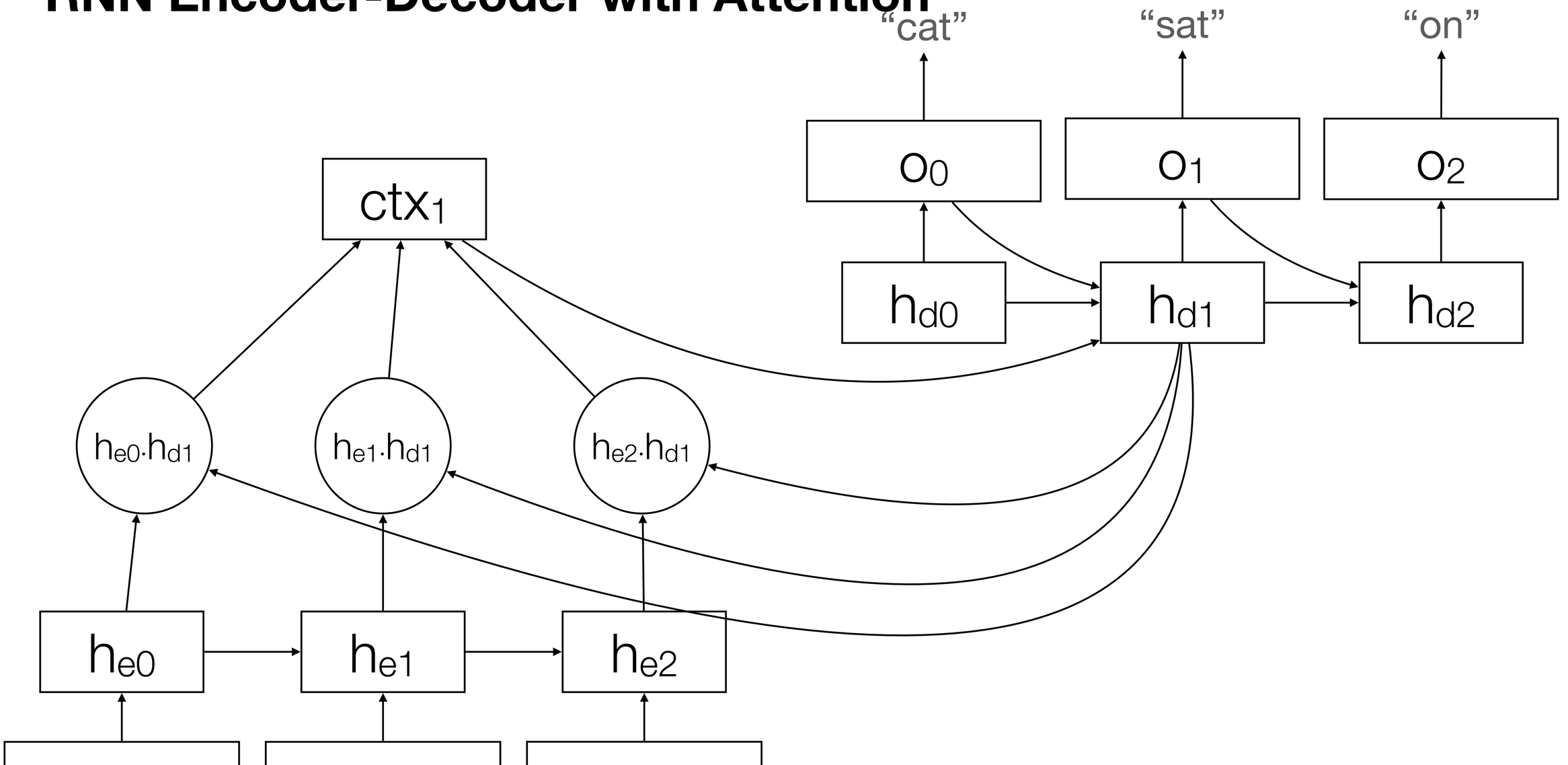
$$c = h_n^e = h_0^d$$

$$h_t^d = f(y_{t-1}, h_{t-1}^d, ctx)$$



Encoder-Decoder Models

RNN Encoder-Decoder with Attention



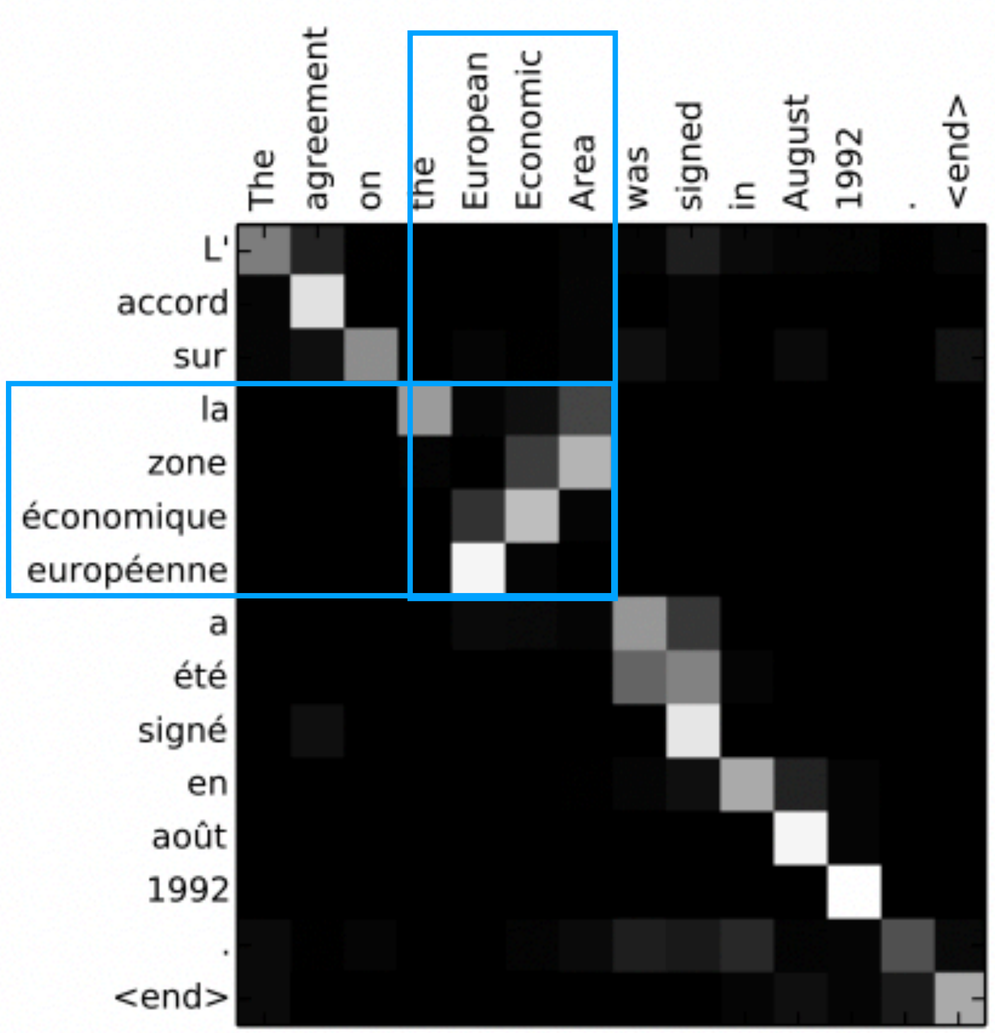
Encoder-Decoder Models

NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

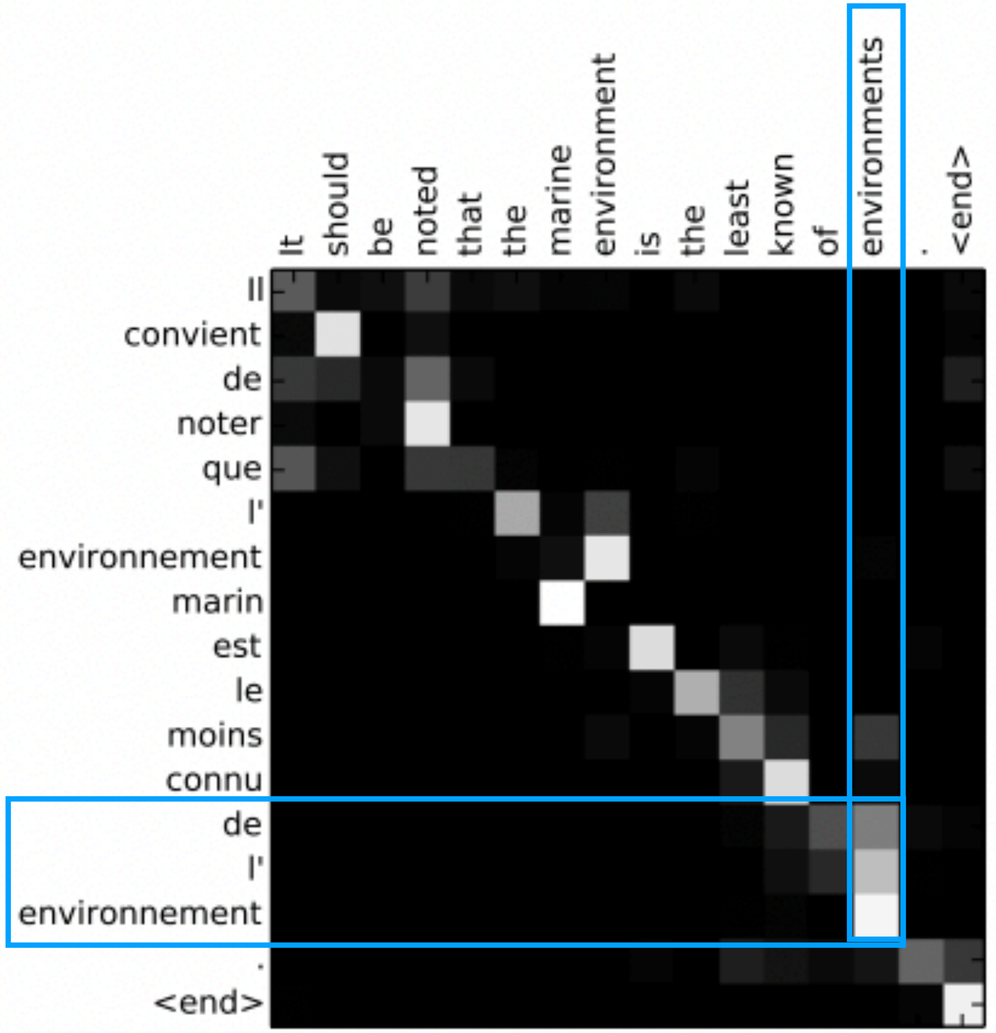
Dzmitry Bahdanau
Jacobs University Bremen, Germany

KyungHyun Cho **Yoshua Bengio***
Université de Montréal

Encoder-Decoder Models

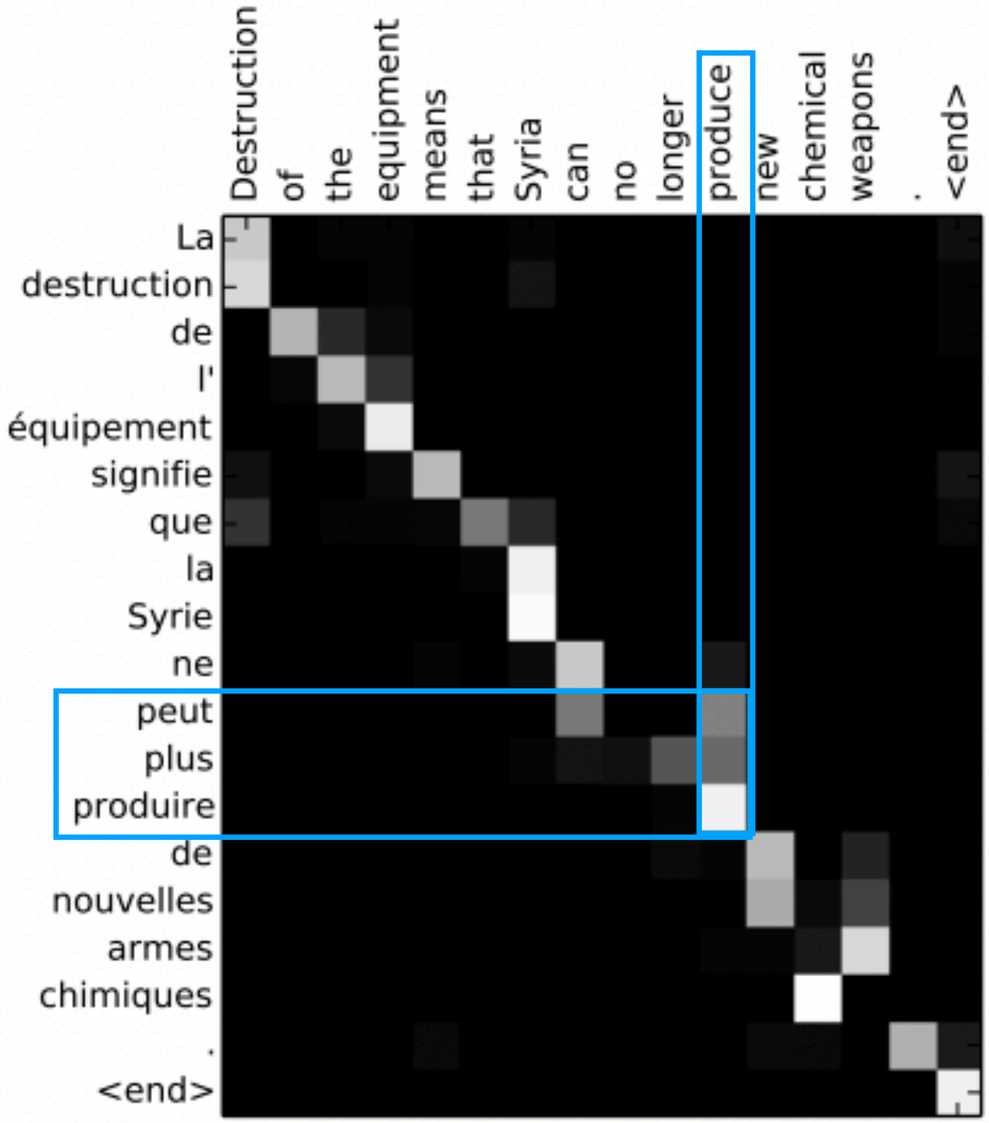


(a)

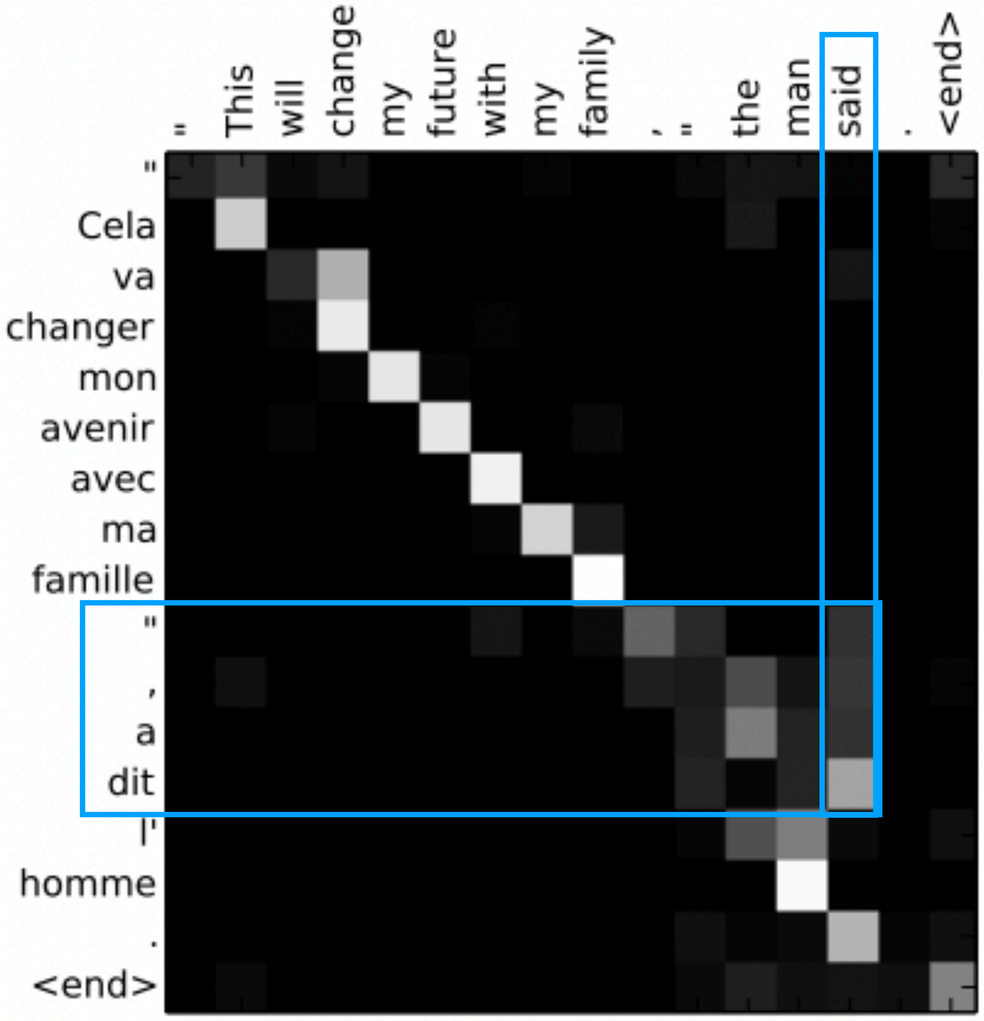


(b)

Encoder-Decoder Models



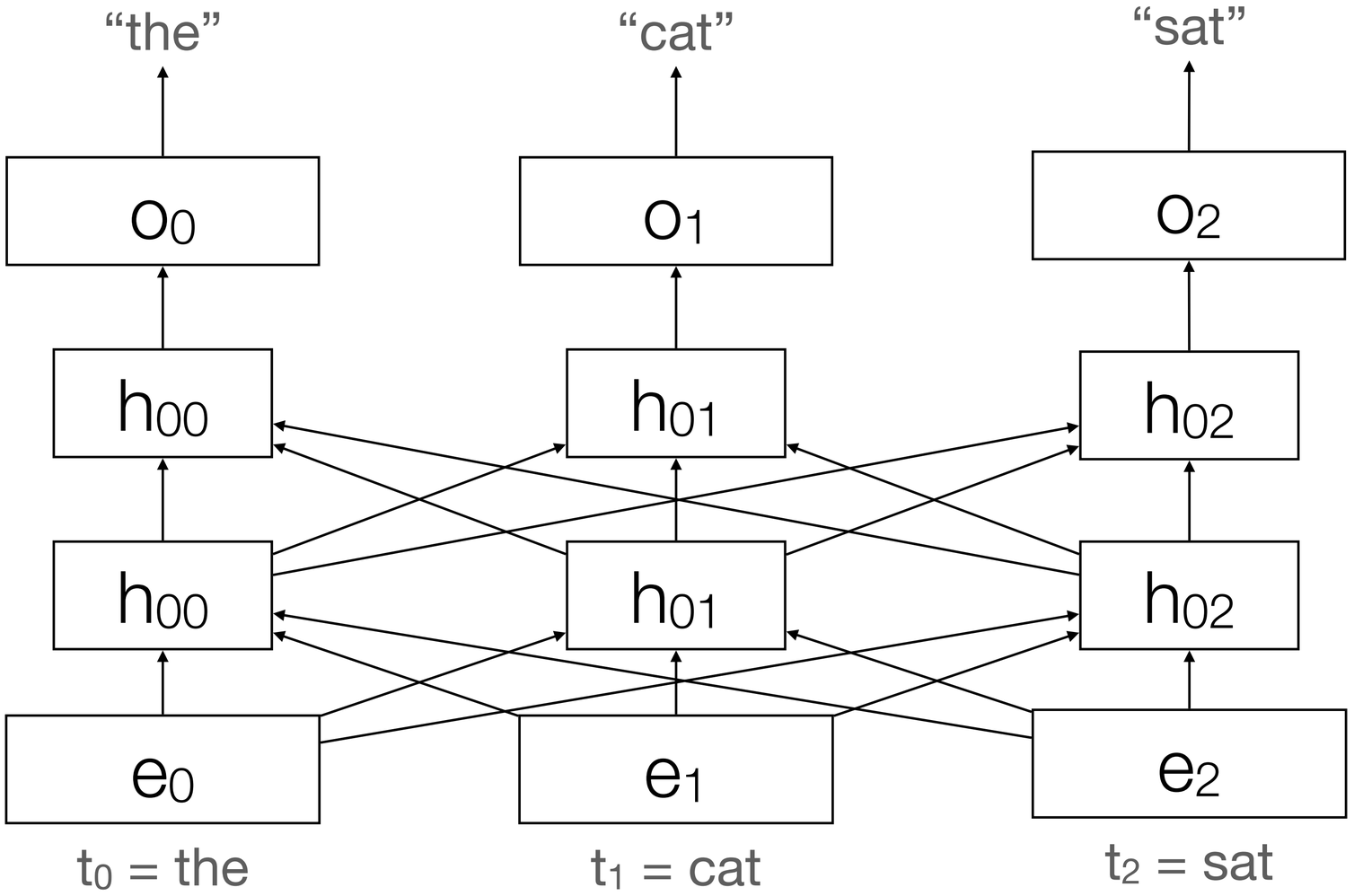
(c)



(d)

Encoder-Decoder Models

Transformer Encoder-Decoder



Encoder-Decoder Models

Recap: Transformer Blocks

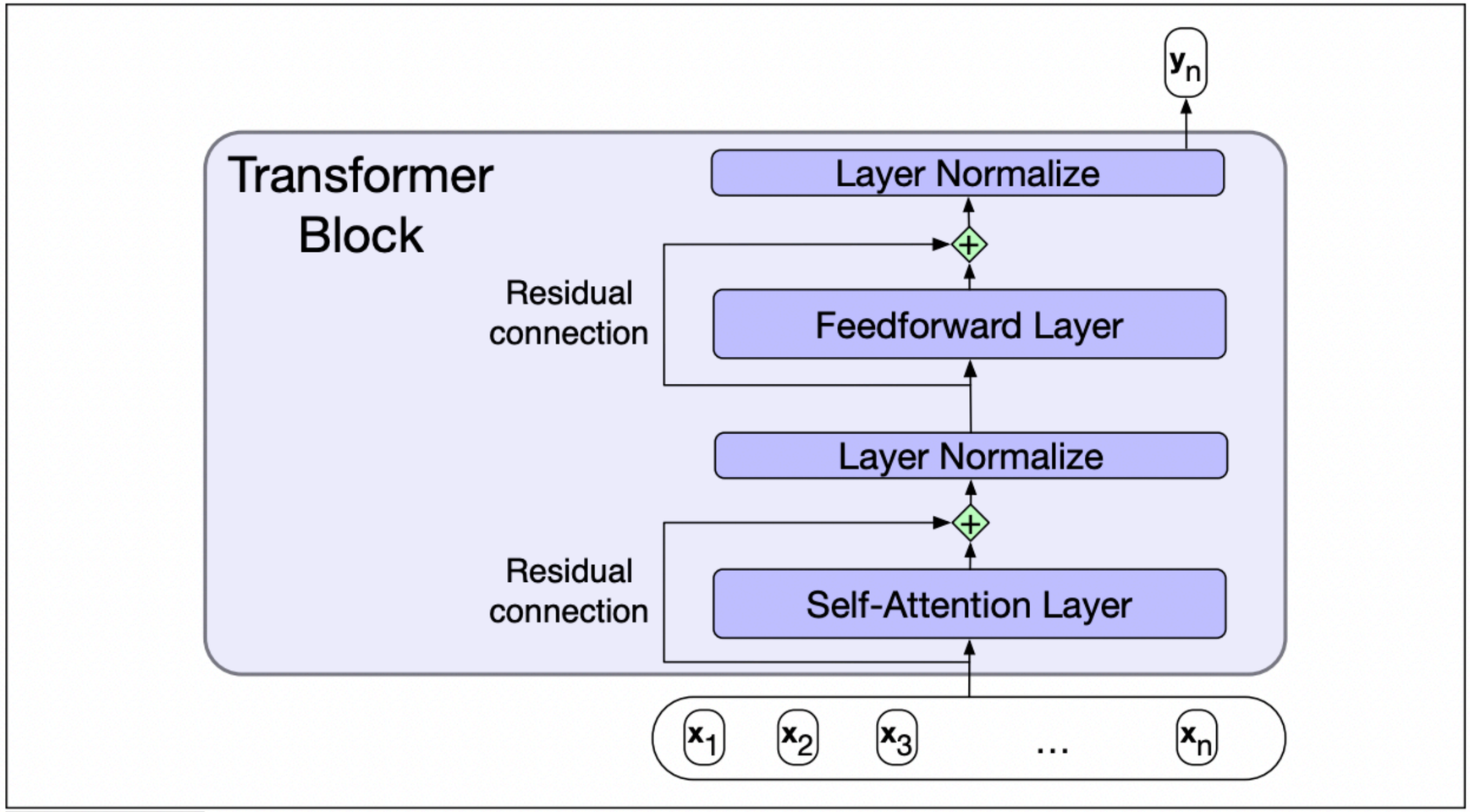
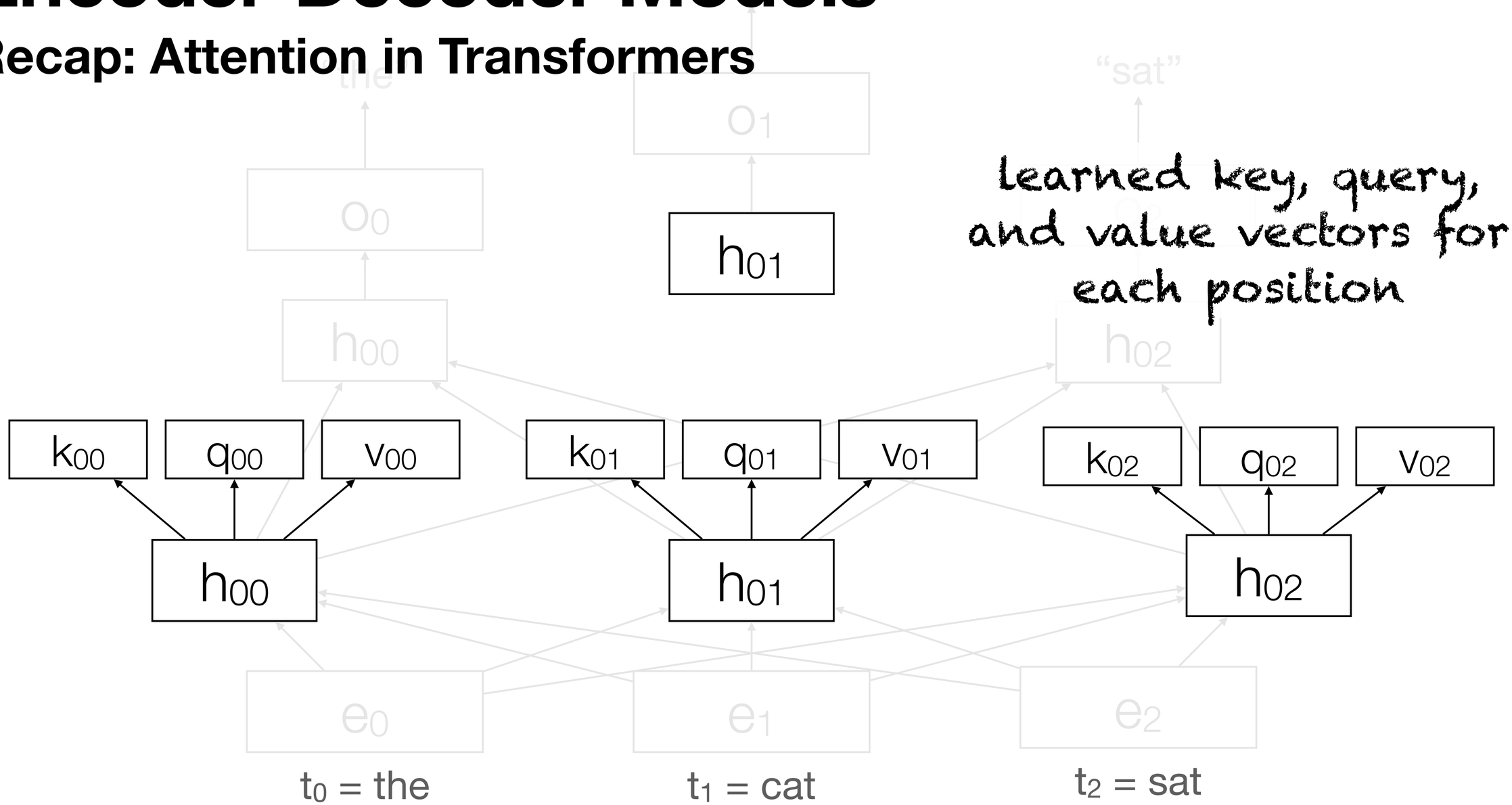


Figure 9.18 A transformer block showing all the layers.

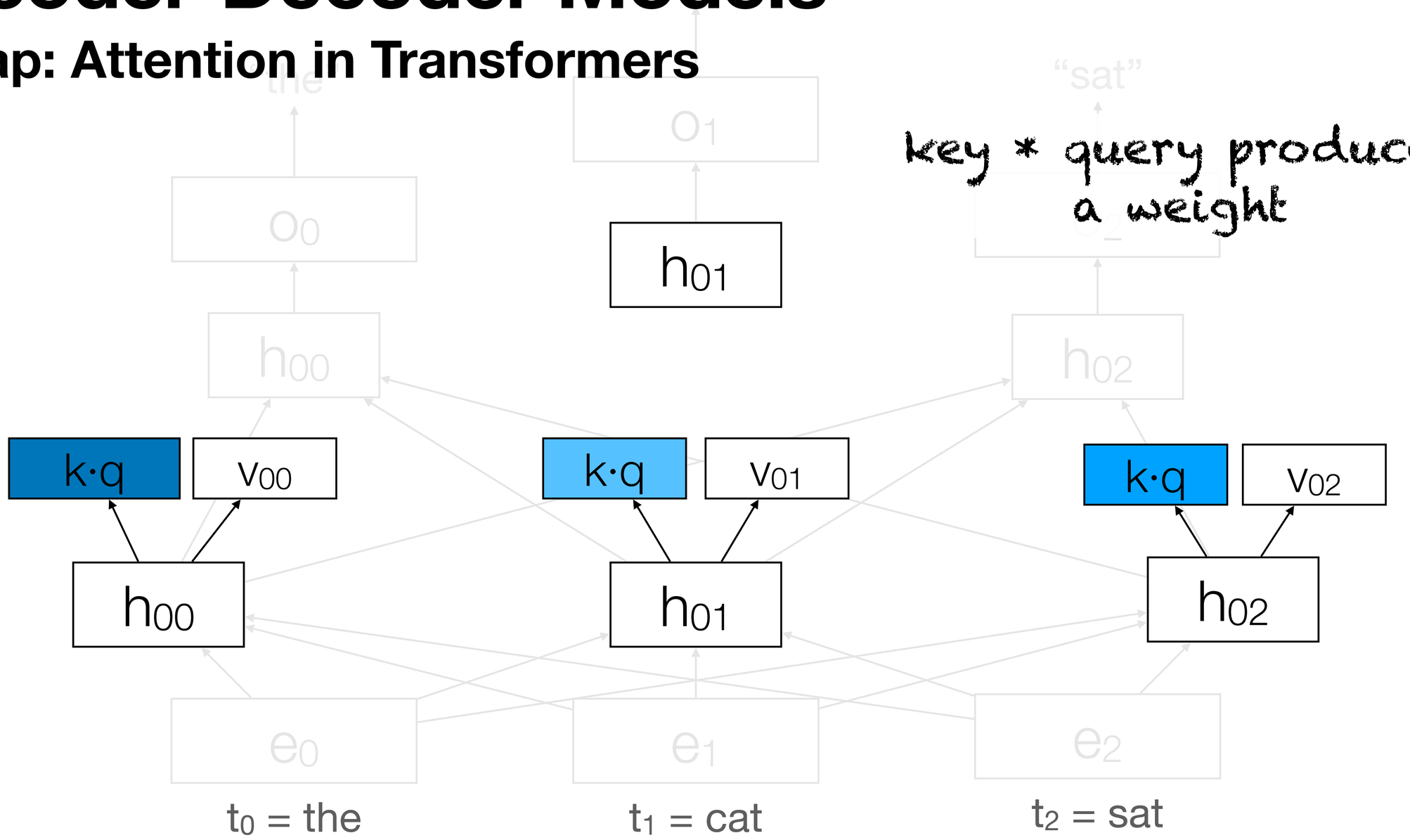
Encoder-Decoder Models

Recap: Attention in Transformers



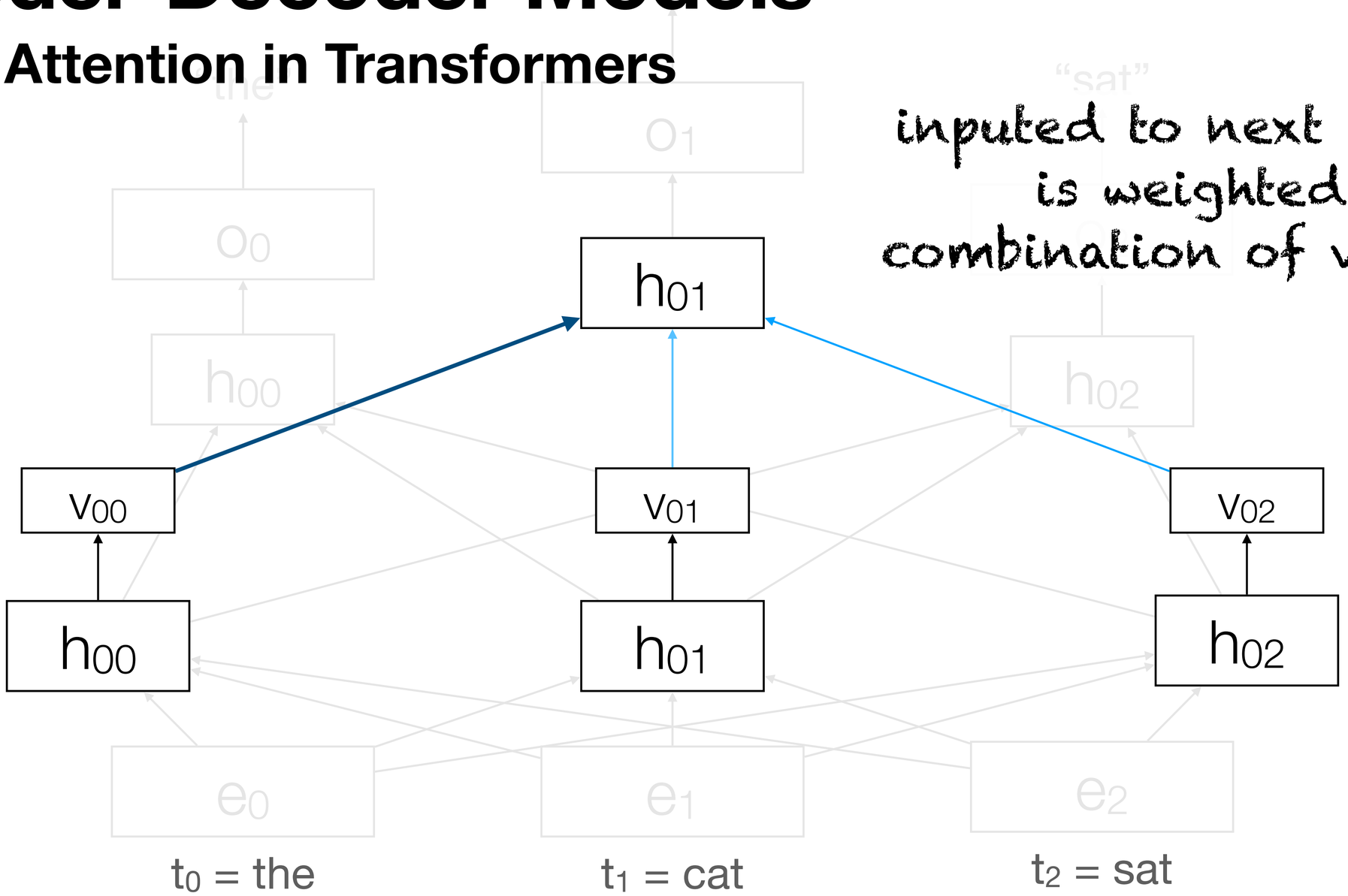
Encoder-Decoder Models

Recap: Attention in Transformers



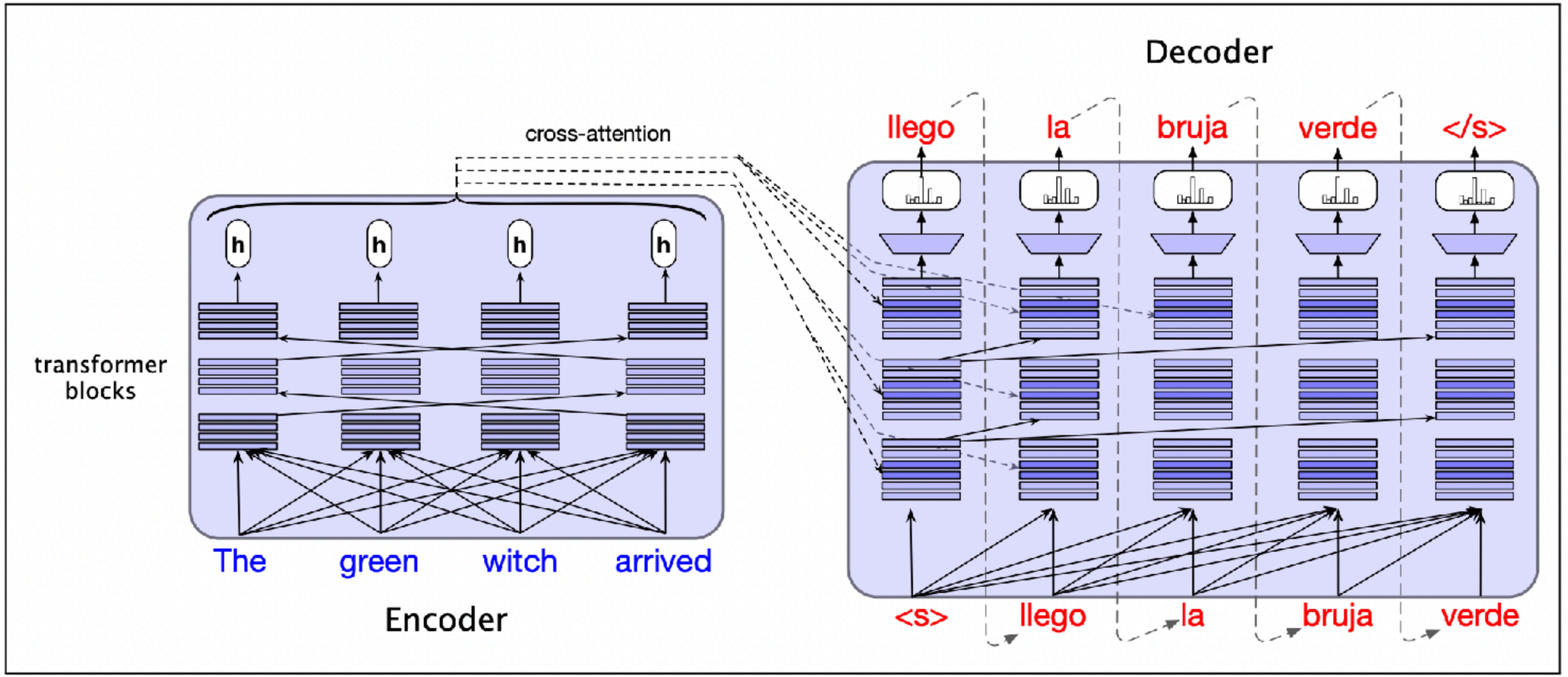
Encoder-Decoder Models

Recap: Attention in Transformers



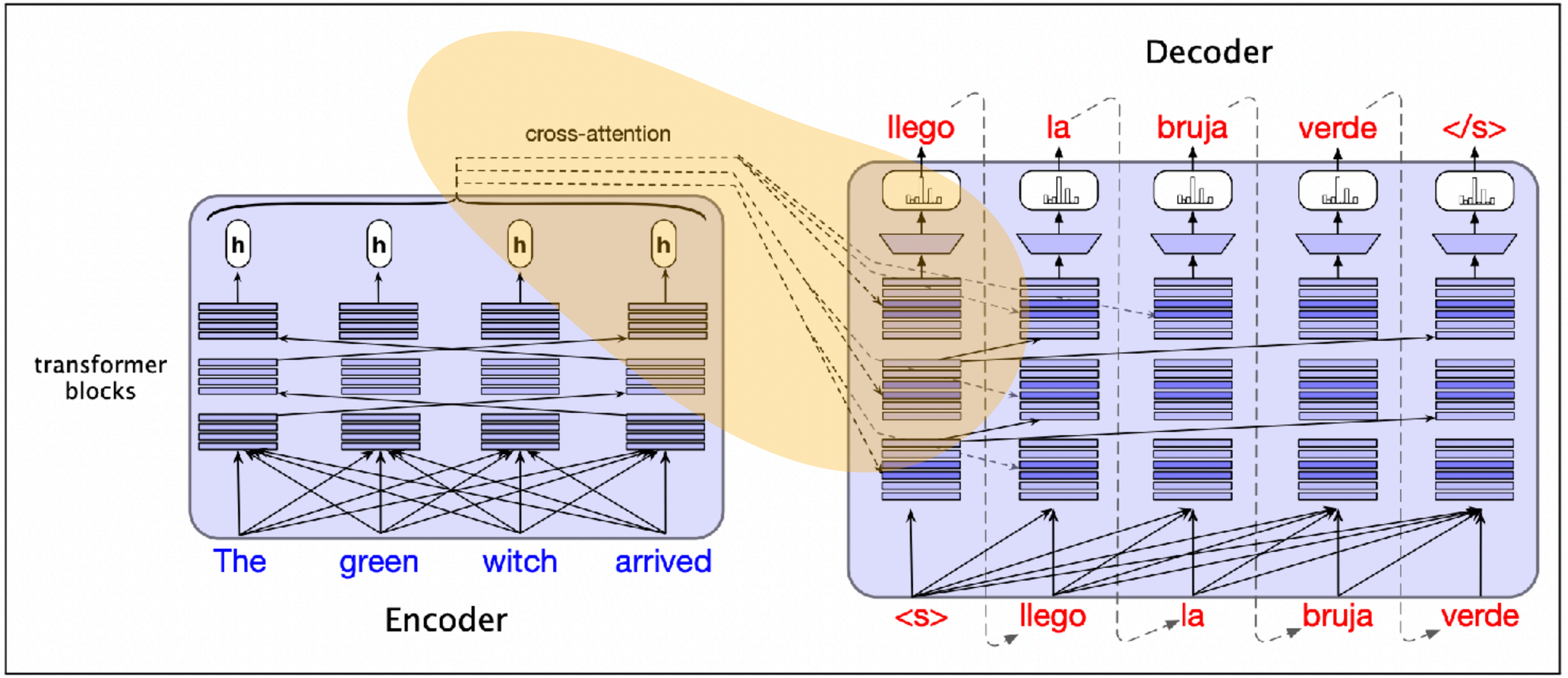
Encoder-Decoder Models

Transformer Encoder-Decoder



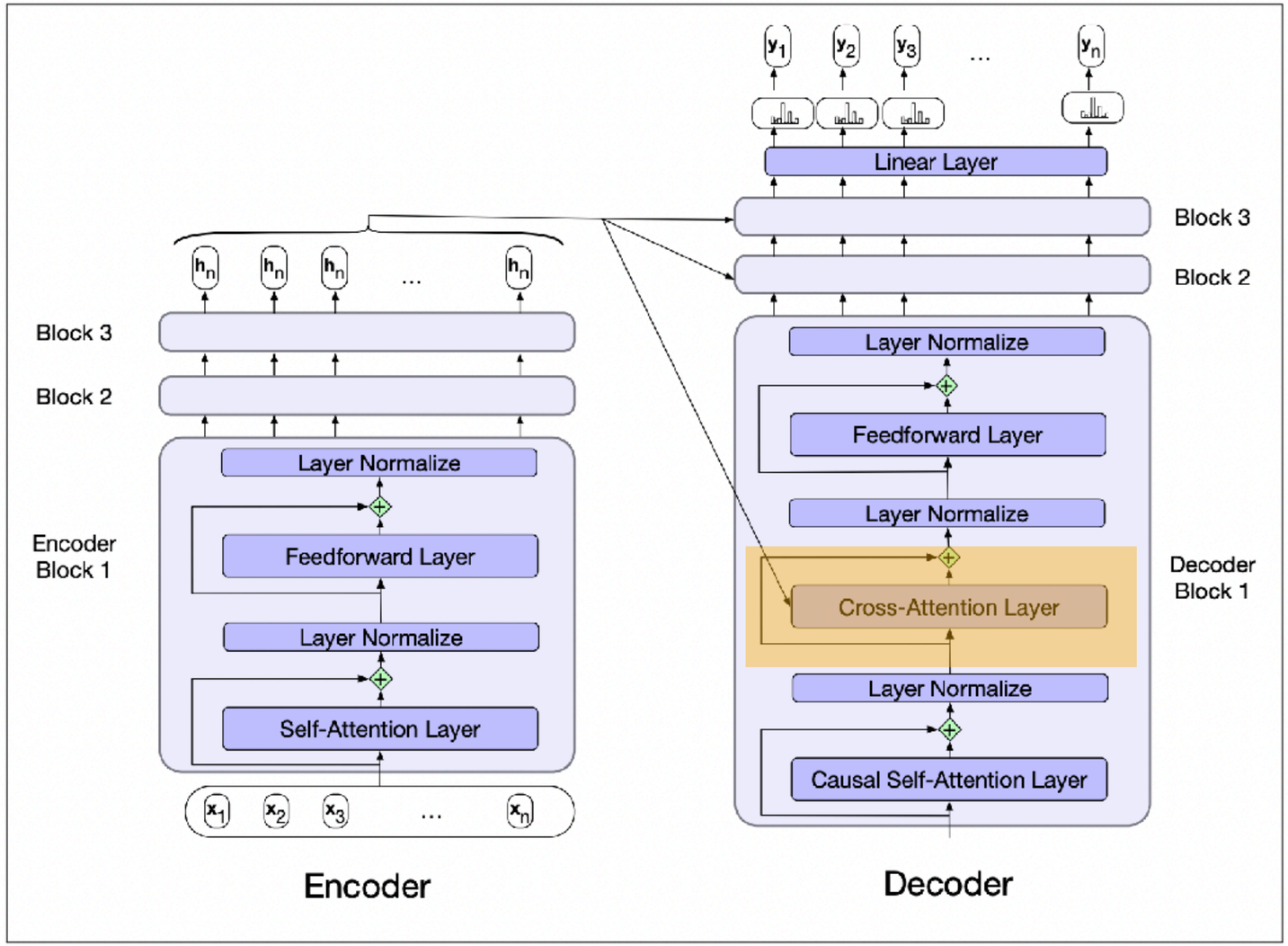
Encoder-Decoder Models

Transformer Encoder-Decoder



Encoder-Decoder Models

Transformer Encoder-Decoder

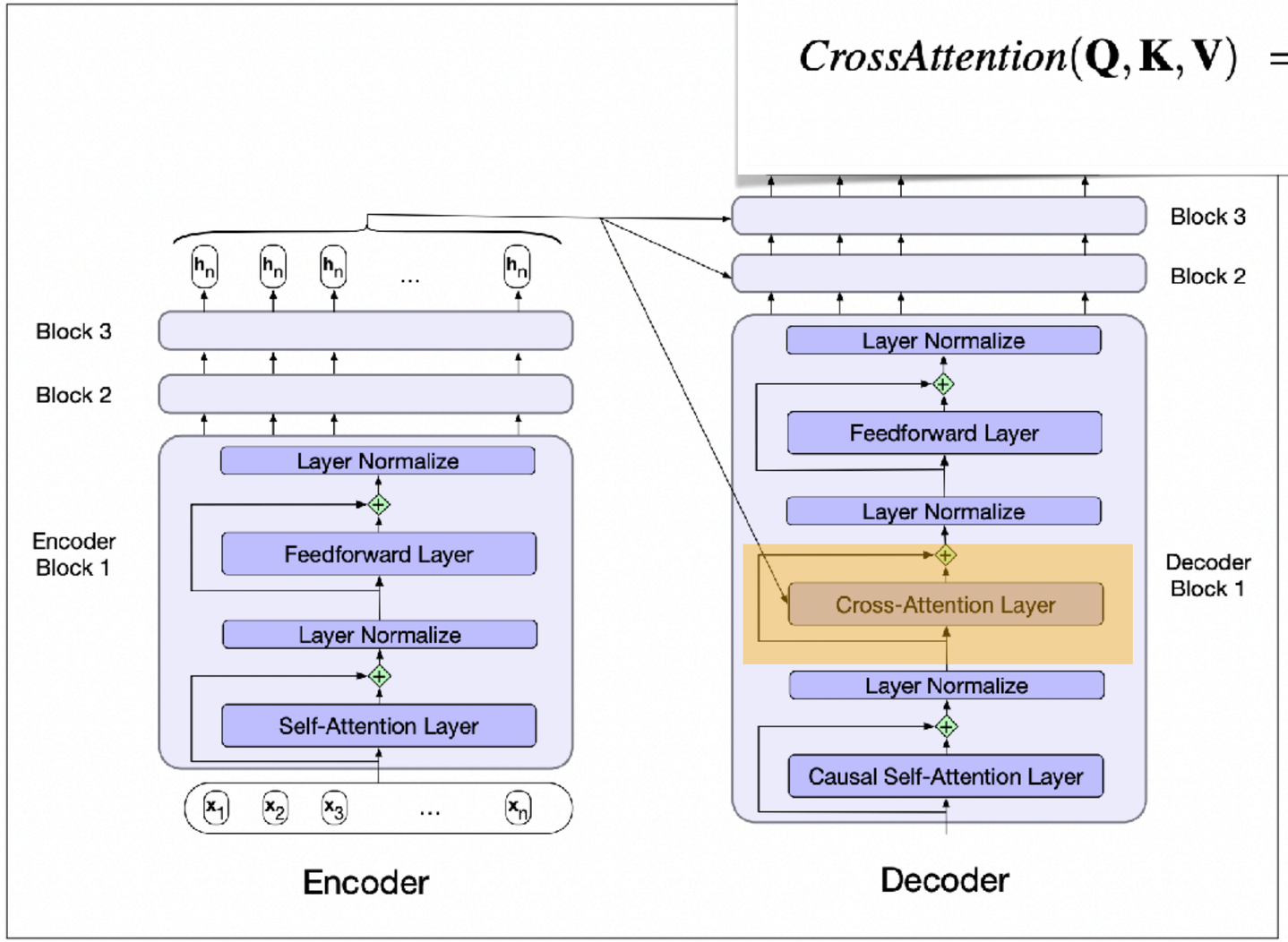


Encoder-Decoder Models

Transformer Encoder-Decoder

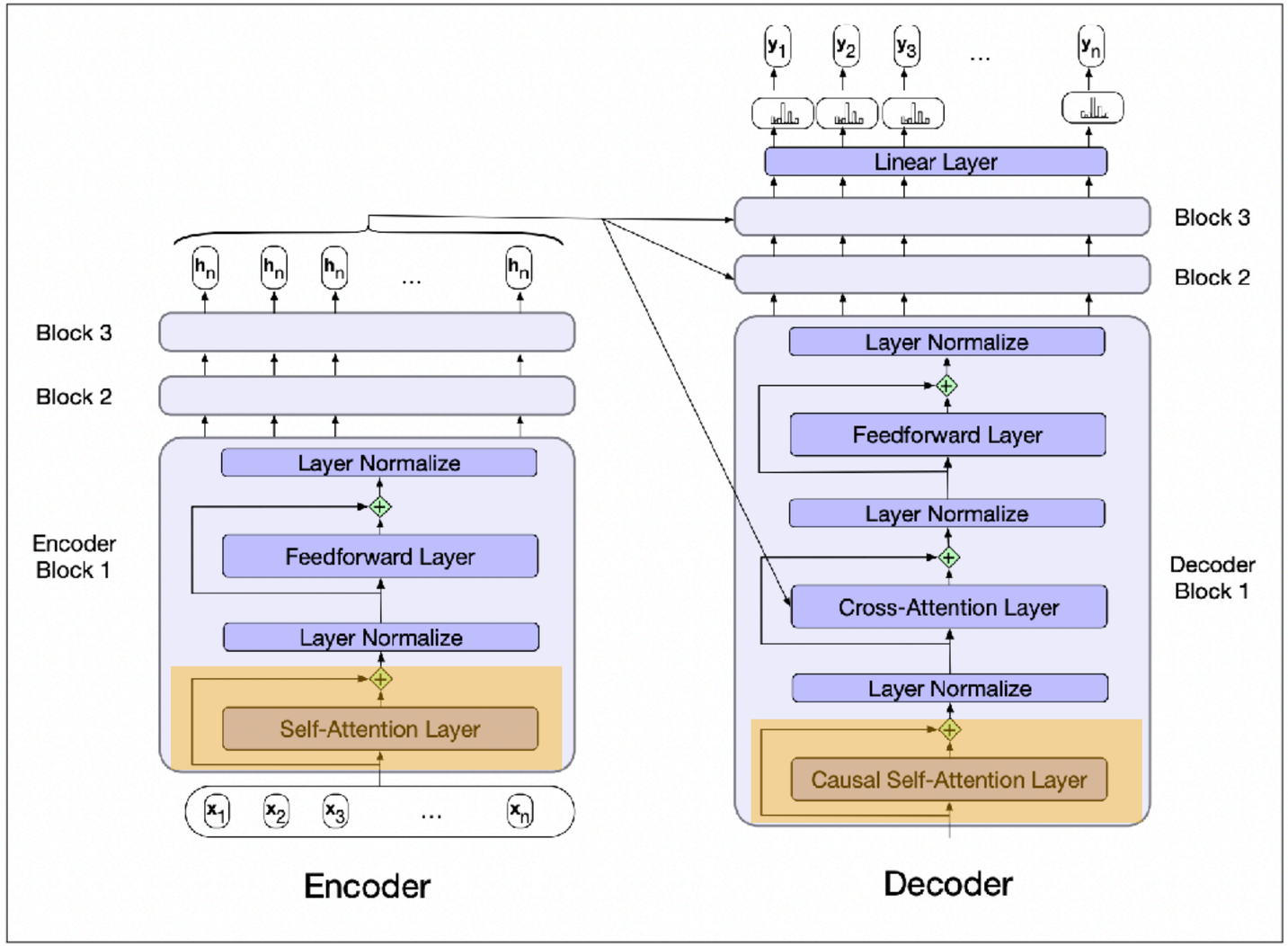
$$\mathbf{Q} = \mathbf{W}^{\mathbf{Q}}\mathbf{H}^{dec[i-1]};\ \mathbf{K} = \mathbf{W}^{\mathbf{K}}\mathbf{H}^{enc};\ \mathbf{V} = \mathbf{W}^{\mathbf{V}}\mathbf{H}^{enc}$$

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



Encoder-Decoder Models

Transformer Encoder-Decoder



Encoders? Decoders? Encoder-Decoders?

- The encoder-decoder model was first applied to MT and was one of the early big “successes” of neural language generation
- Many other models (namely, large LMs) are inspired by this architecture, but don’t “need” both the encoder and the decoder
  - Encoder-Decoder: Original Transformer Model (Vaswani et al, 2017)
  - Encoder-only: BERT and variants (ALBERT, DistilBERT, RoBERTa)
  - Decoder-only (i.e., auto-regressive): GPT

Topics

- SMT Followup: Putting it all together
- MT Evaluation
- **Neural MT**
  - Encoder-Decoder Models
  - **Multilingual LMs and “Zero Shot” Cross-Lingual Transfer**

Cross Lingual Transfer

- Goal: Train only on one language (English), but work in all languages
- Intuition: If the model learns a good representation of the languages under the hood (“interlingua”), it should be able to map the training it receives in one language to any other language

Multilingual Language Models

Cross-lingual Language Model Pretraining

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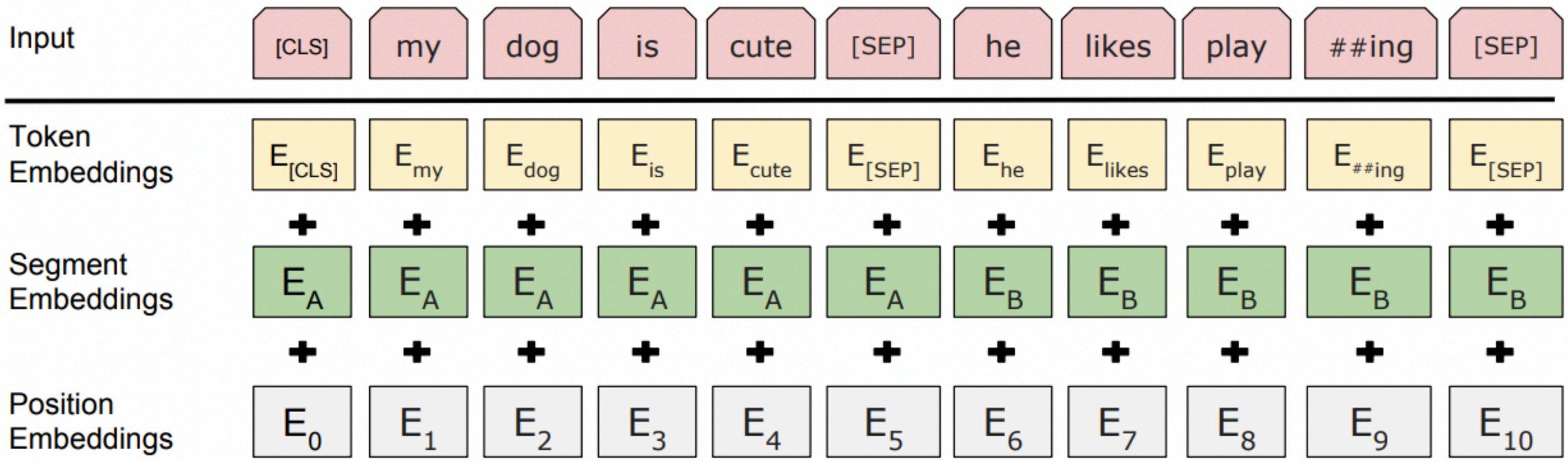
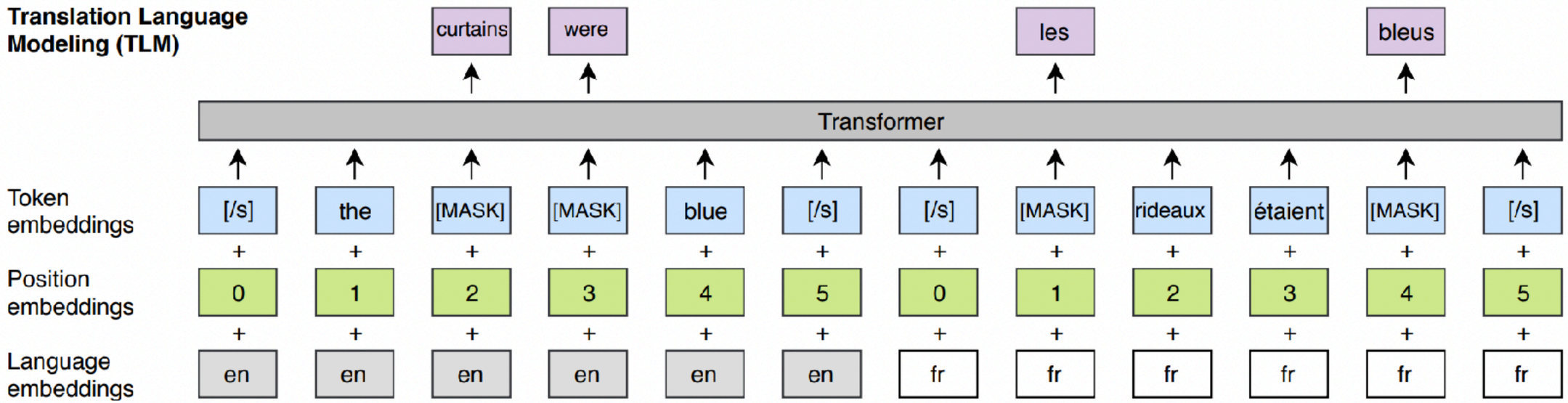
Multilingual Language Models

Recap: BERT



Multilingual Language Models

Multilingual MLM



Multilingual Language Models

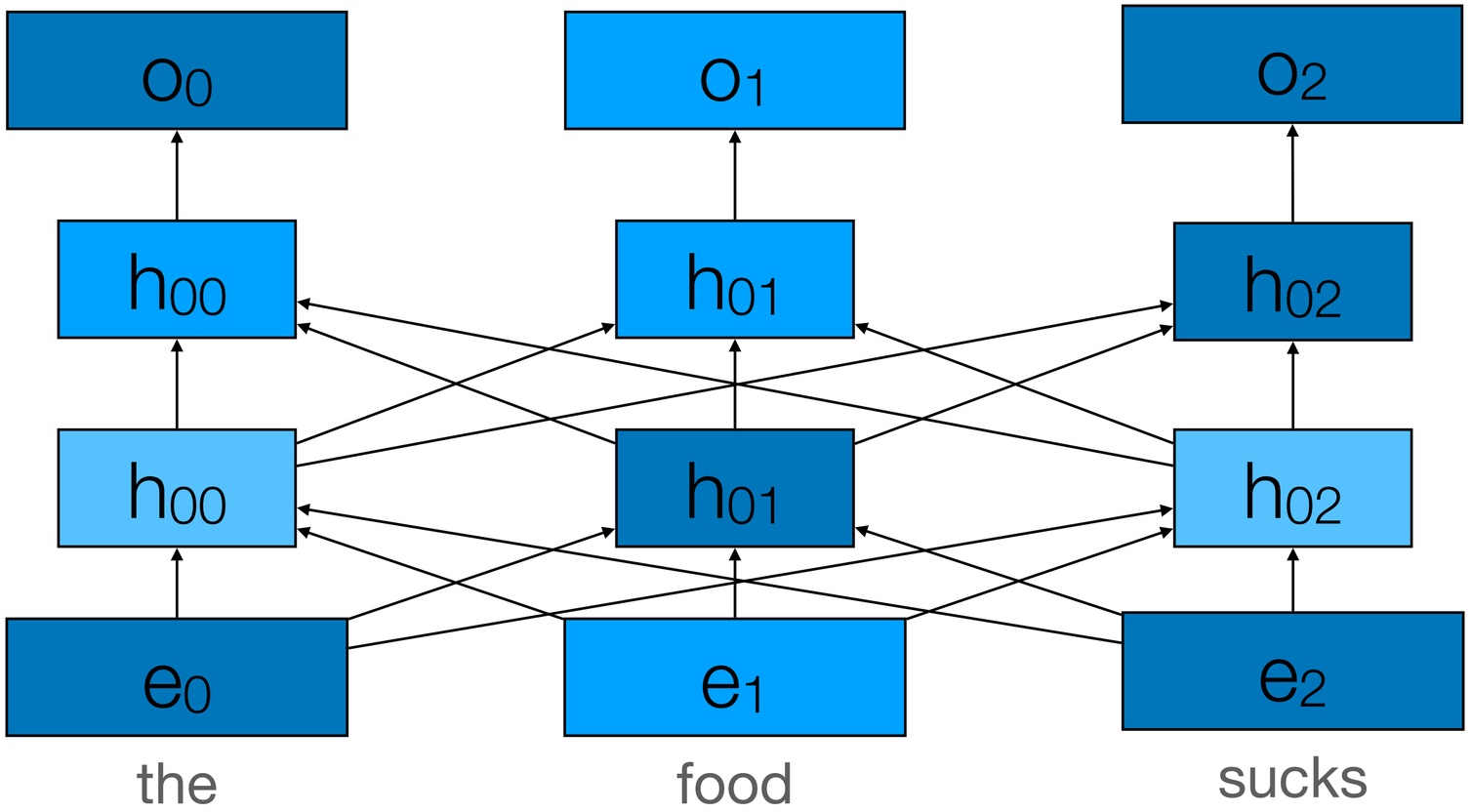
- Common multilingual models: mBERT, XLM-RoBERTa
- Just recently: mGPT, BLOOM
- Just monolingual data
- Shared wordpiece vocabulary
- No explicit mechanisms to encourage translation etc.

https://github.com/google-research/bert/blob/master/multilingual.md

Multilingual Language Models

Recap: Pretraining and Finetuning

Task: Sentiment Analysis
Input: “the food sucks”
Expected: Negative

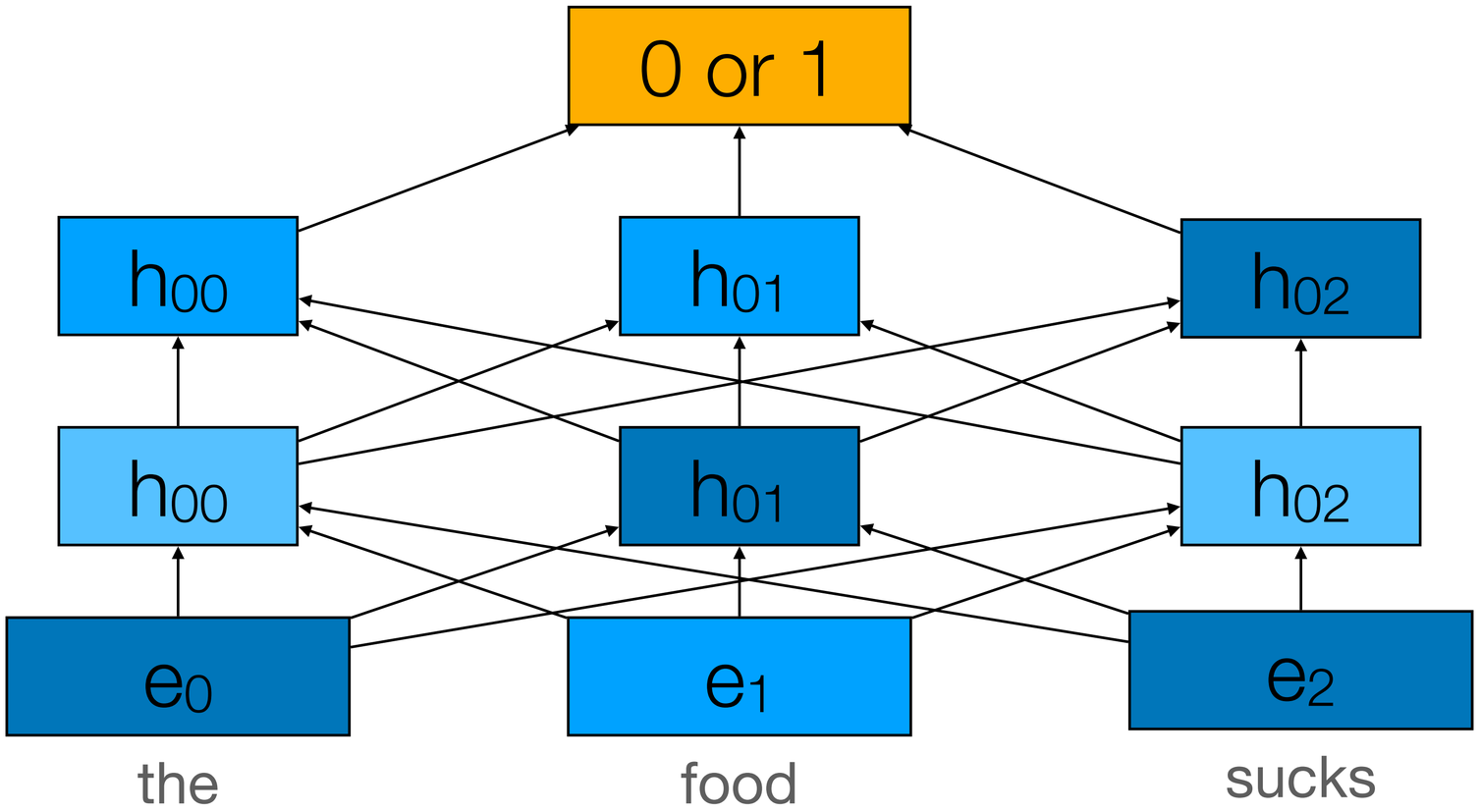


Multilingual Language Models

Recap: Pretraining and Finetuning

Task: Sentiment Analysis
Input: “the food sucks”
Expected: Negative

Adjust output layers to reflect target task

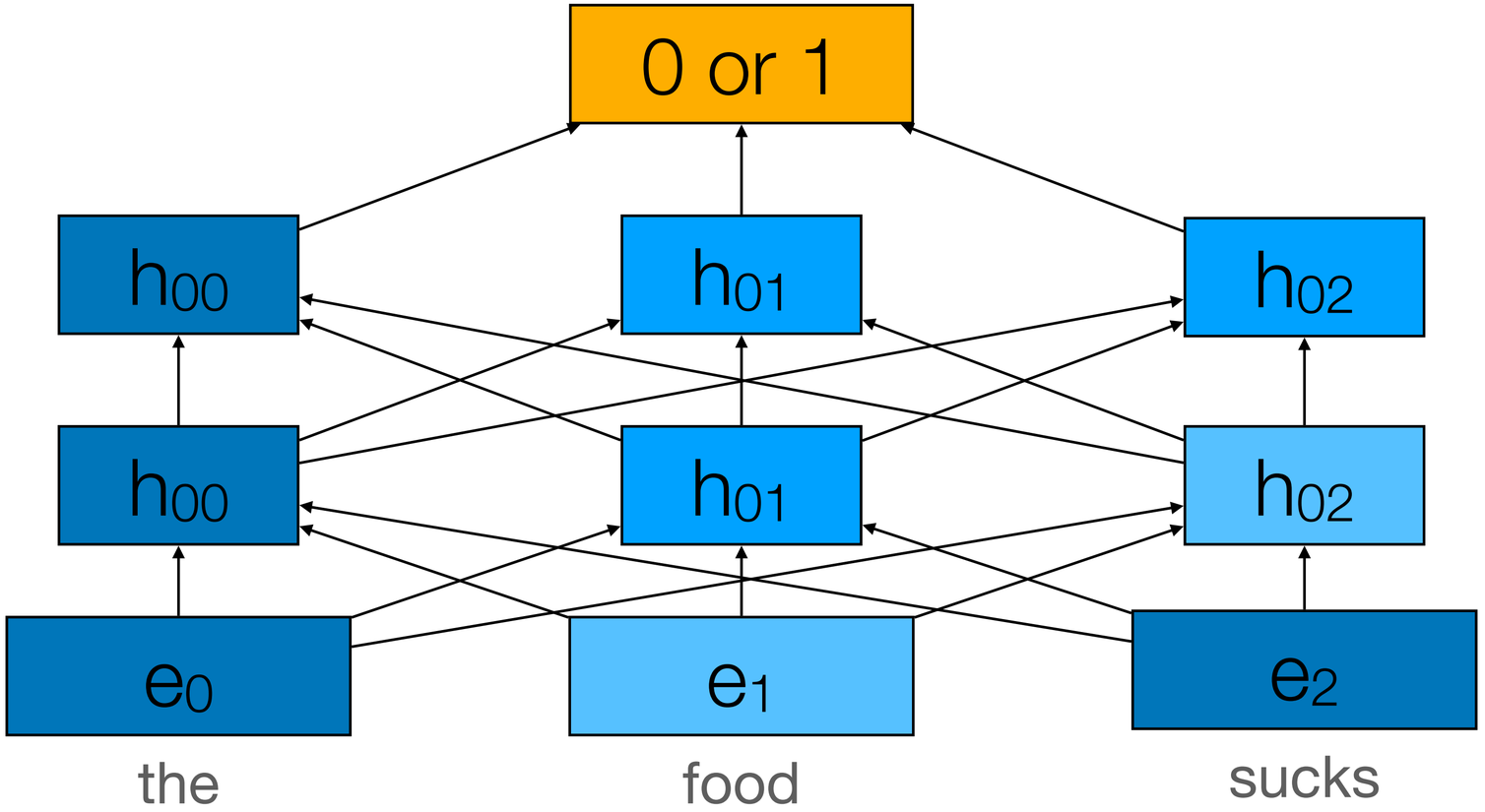


Multilingual Language Models

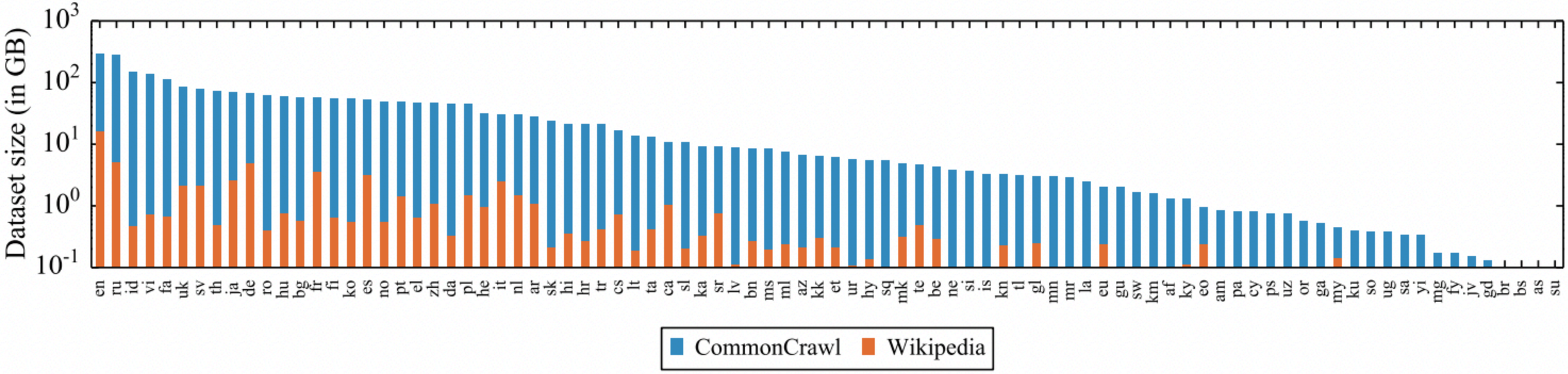
Recap: Pretraining and Finetuning

Task: Sentiment Analysis
Input: “the food sucks”
Expected: Negative

Keep training network, backproping through everything as needed.



Multilingual Language Models



Multilingual Language Models

Model	D	#M	#lg	en	fr	es	de	el	bg	ru	tr	ar	vi	th	zh	hi	sw	ur	Avg
Fine-tune multilingual model on English training set (Cross-lingual Transfer)																			
Lample and Conneau (2019)	Wiki+MT	N	15	85.0	78.7	78.9	77.8	76.6	77.4	75.3	72.5	73.1	76.1	73.2	76.5	69.6	68.4	67.3	75.1
Huang et al. (2019)	Wiki+MT	N	15	85.1	79.0	79.4	77.8	77.2	77.2	76.3	72.8	73.5	76.4	73.6	76.2	69.4	69.7	66.7	75.4
Devlin et al. (2018)	Wiki	N	102	82.1	73.8	74.3	71.1	66.4	68.9	69.0	61.6	64.9	69.5	55.8	69.3	60.0	50.4	58.0	66.3
Lample and Conneau (2019)	Wiki	N	100	83.7	76.2	76.6	73.7	72.4	73.0	72.1	68.1	68.4	72.0	68.2	71.5	64.5	58.0	62.4	71.3
Lample and Conneau (2019)	Wiki	1	100	83.2	76.7	77.7	74.0	72.7	74.1	72.7	68.7	68.6	72.9	68.9	72.5	65.6	58.2	62.4	70.7
XLM-R$_{\text{Base}}$	CC	1	100	85.8	79.7	80.7	78.7	77.5	79.6	78.1	74.2	73.8	76.5	74.6	76.7	72.4	66.5	68.3	76.2
XLM-R	CC	1	100	**89.1**	**84.1**	**85.1**	**83.9**	**82.9**	**84.0**	**81.2**	**79.6**	**79.8**	**80.8**	**78.1**	**80.2**	**76.9**	**73.9**	**73.8**	**80.9**
Translate everything to English and use English-only model (TRANSLATE-TEST)																			
BERT-en	Wiki	1	1	88.8	81.4	82.3	80.1	80.3	80.9	76.2	76.0	75.4	72.0	71.9	75.6	70.0	65.8	65.8	76.2
RoBERTa	Wiki+CC	1	1	**91.3**	82.9	84.3	81.2	81.7	83.1	78.3	76.8	76.6	74.2	74.1	77.5	70.9	66.7	66.8	77.8
Fine-tune multilingual model on each training set (TRANSLATE-TRAIN)																			
Lample and Conneau (2019)	Wiki	N	100	82.9	77.6	77.9	77.9	77.1	75.7	75.5	72.6	71.2	75.8	73.1	76.2	70.4	66.5	62.4	74.2
Fine-tune multilingual model on all training sets (TRANSLATE-TRAIN-ALL)																			
Lample and Conneau (2019)†	Wiki+MT	1	15	85.0	80.8	81.3	80.3	79.1	80.9	78.3	75.6	77.6	78.5	76.0	79.5	72.9	72.8	68.5	77.8
Huang et al. (2019)	Wiki+MT	1	15	85.6	81.1	82.3	80.9	79.5	81.4	79.7	76.8	78.2	77.9	77.1	80.5	73.4	73.8	69.6	78.5
Lample and Conneau (2019)	Wiki	1	100	84.5	80.1	81.3	79.3	78.6	79.4	77.5	75.2	75.6	78.3	75.7	78.3	72.1	69.2	67.7	76.9
XLM-R$_{\text{Base}}$	CC	1	100	85.4	81.4	82.2	80.3	80.4	81.3	79.7	78.6	77.3	79.7	77.9	80.2	76.1	73.1	73.0	79.1
XLM-R	CC	1	100	**89.1**	**85.1**	**86.6**	**85.7**	**85.3**	**85.9**	**83.5**	**83.2**	**83.1**	**83.7**	**81.5**	**83.7**	**81.6**	**78.0**	**78.1**	**83.6**

Multilingual Language Models

Model	D	#M	#lg	en	fr	es	de	el	bg	ru	tr	ar	vi	th	zh	hi	sw	ur	Avg
Fine-tune multilingual model on English training set (Cross-lingual Transfer)																			
Lample and Conneau (2019)	Wiki+MT	N	15	85.0	78.7	78.9	77.8	76.6	77.4	75.3	72.5	73.1	76.1	73.2	76.5	69.6	68.4	67.3	75.1
Huang et al. (2019)	Wiki+MT	N	15	85.1	79.0	79.4	77.8	77.2	77.2	76.3	72.8	73.5	76.4	73.6	76.2	69.4	69.7	66.7	75.4
Devlin et al. (2018)	Wiki	N	102	82.1	73.8	74.3	71.1	66.4	68.9	69.0	61.6	64.9	69.5	55.8	69.3	60.0	50.4	58.0	66.3
Lample and Conneau (2019)	Wiki	N	100	83.7	76.2	76.6	73.7	72.4	73.0	72.1	68.1	68.4	72.0	68.2	71.5	64.5	58.0	62.4	71.3
Lample and Conneau (2019)	Wiki	1	100	83.2	76.7	77.7	74.0	72.7	74.1	72.7	68.7	68.6	72.9	68.9	72.5	65.6	58.2	62.4	70.7
XLM-R$_{\text{Base}}$	CC	1	100	85.8	79.7	80.7	78.7	77.5	79.6	78.1	74.2	73.8	76.5	74.6	76.7	72.4	66.5	68.3	76.2
XLM-R	CC	1	100	**89.1**	**84.1**	**85.1**	**83.9**	**82.9**	**84.0**	**81.2**	**79.6**	**79.8**	**80.8**	**78.1**	**80.2**	**76.9**	**73.9**	**73.8**	**80.9**
Translate everything to English and use English-only model (TRANSLATE-TEST)																			
BERT-en	Wiki	1	1	88.8	81.4	82.3	80.1	80.3	80.9	76.2	76.0	75.4	72.0	71.9	75.6	70.0	65.8	65.8	76.2
RoBERTa	Wiki+CC	1	1	**91.3**	82.9	84.3	81.2	81.7	83.1	78.3	76.8	76.6	74.2	74.1	77.5	70.9	66.7	66.8	77.8
Fine-tune multilingual model on each training set (TRANSLATE-TRAIN)																			
Lample and Conneau (2019)	Wiki	N	100	82.9	77.6	77.9	77.9	77.1	75.7	75.5	72.6	71.2	75.8	73.1	76.2	70.4	66.5	62.4	74.2
Fine-tune multilingual model on all training sets (TRANSLATE-TRAIN-ALL)																			
Lample and Conneau (2019)†	Wiki+MT	1	15	85.0	80.8	81.3	80.3	79.1	80.9	78.3	75.6	77.6	78.5	76.0	79.5	72.9	72.8	68.5	77.8
Huang et al. (2019)	Wiki+MT	1	15	85.6	81.1	82.3	80.9	79.5	81.4	79.7	76.8	78.2	77.9	77.1	80.5	73.4	73.8	69.6	78.5
Lample and Conneau (2019)	Wiki	1	100	84.5	80.1	81.3	79.3	78.6	79.4	77.5	75.2	75.6	78.3	75.7	78.3	72.1	69.2	67.7	76.9
XLM-R$_{\text{Base}}$	CC	1	100	85.4	81.4	82.2	80.3	80.4	81.3	79.7	78.6	77.3	79.7	77.9	80.2	76.1	73.1	73.0	79.1
XLM-R	CC	1	100	**89.1**	**85.1**	**86.6**	**85.7**	**85.3**	**85.9**	**83.5**	**83.2**	**83.1**	**83.7**	**81.5**	**83.7**	**81.6**	**78.0**	**78.1**	**83.6**

Multilingual Language Models

Model	D	#M	#lg	en	fr	es	de	el	bg	ru	tr	ar	vi	th	zh	hi	sw	ur	Avg
Fine-tune multilingual model on English training set (Cross-lingual Transfer)																			
Lample and Conneau (2019)	Wiki+MT	N	15	85.0	78.7	78.9	77.8	76.6	77.4	75.3	72.5	73.1	76.1	73.2	76.5	69.6	68.4	67.3	75.1
Huang et al. (2019)	Wiki+MT	N	15	85.1	79.0	79.4	77.8	77.2	77.2	76.3	72.8	73.5	76.4	73.6	76.2	69.4	69.7	66.7	75.4
Devlin et al. (2018)	Wiki	N	102	82.1	73.8	74.3	71.1	66.4	68.9	69.0	61.6	64.9	69.5	55.8	69.3	60.0	50.4	58.0	66.3
Lample and Conneau (2019)	Wiki	N	100	83.7	76.2	76.6	73.7	72.4	73.0	72.1	68.1	68.4	72.0	68.2	71.5	64.5	58.0	62.4	71.3
Lample and Conneau (2019)	Wiki	1	100	83.2	76.7	77.7	74.0	72.7	74.1	72.7	68.7	68.6	72.9	68.9	72.5	65.6	58.2	62.4	70.7
XLM-R$_{\text{Base}}$	CC	1	100	85.8	79.7	80.7	78.7	77.5	79.6	78.1	74.2	73.8	76.5	74.6	76.7	72.4	66.5	68.3	76.2
XLM-R	CC	1	100	**89.1**	**84.1**	**85.1**	**83.9**	**82.9**	**84.0**	**81.2**	**79.6**	**79.8**	**80.8**	**78.1**	**80.2**	**76.9**	**73.9**	**73.8**	**80.9**
Translate everything to English and use English-only model (TRANSLATE-TEST)																			
BERT-en	Wiki	1	1	88.8	81.4	82.3	80.1	80.3	80.9	76.2	76.0	75.4	72.0	71.9	75.6	70.0	65.8	65.8	76.2
RoBERTa	Wiki+CC	1	1	**91.3**	82.9	84.3	81.2	81.7	83.1	78.3	76.8	76.6	74.2	74.1	77.5	70.9	66.7	66.8	77.8
Fine-tune multilingual model on each training set (TRANSLATE-TRAIN)																			
Lample and Conneau (2019)	Wiki	N	100	82.9	77.6	77.9	77.9	77.1	75.7	75.5	72.6	71.2	75.8	73.1	76.2	70.4	66.5	62.4	74.2
Fine-tune multilingual model on all training sets (TRANSLATE-TRAIN-ALL)																			
Lample and Conneau (2019)†	Wiki+MT	1	15	85.0	80.8	81.3	80.3	79.1	80.9	78.3	75.6	77.6	78.5	76.0	79.5	72.9	72.8	68.5	77.8
Huang et al. (2019)	Wiki+MT	1	15	85.6	81.1	82.3	80.9	79.5	81.4	79.7	76.8	78.2	77.9	77.1	80.5	73.4	73.8	69.6	78.5
Lample and Conneau (2019)	Wiki	1	100	84.5	80.1	81.3	79.3	78.6	79.4	77.5	75.2	75.6	78.3	75.7	78.3	72.1	69.2	67.7	76.9
XLM-R$_{\text{Base}}$	CC	1	100	85.4	81.4	82.2	80.3	80.4	81.3	79.7	78.6	77.3	79.7	77.9	80.2	76.1	73.1	73.0	79.1
XLM-R	CC	1	100	**89.1**	**85.1**	**86.6**	**85.7**	**85.3**	**85.9**	**83.5**	**83.2**	**83.1**	**83.7**	**81.5**	**83.7**	**81.6**	**78.0**	**78.1**	**83.6**

Cross Lingual Transfer

How multilingual is Multilingual BERT?

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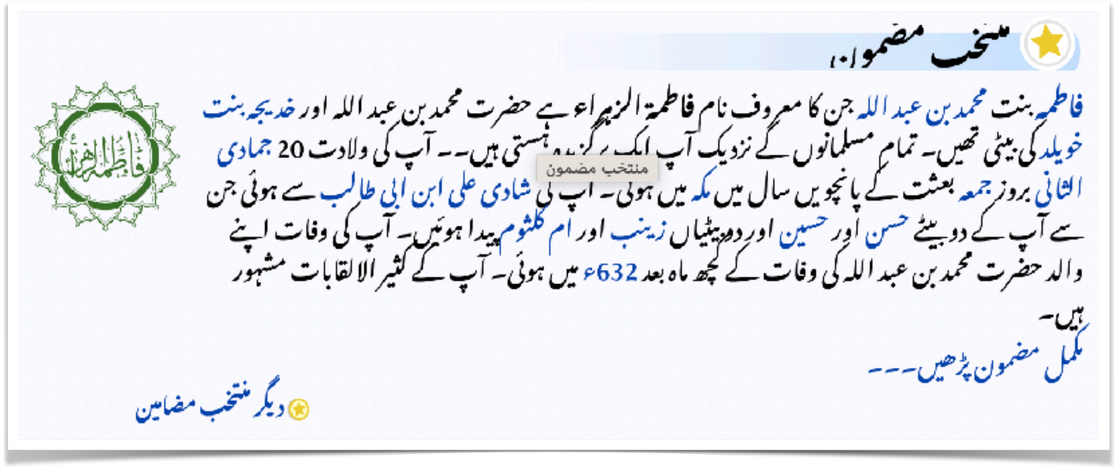
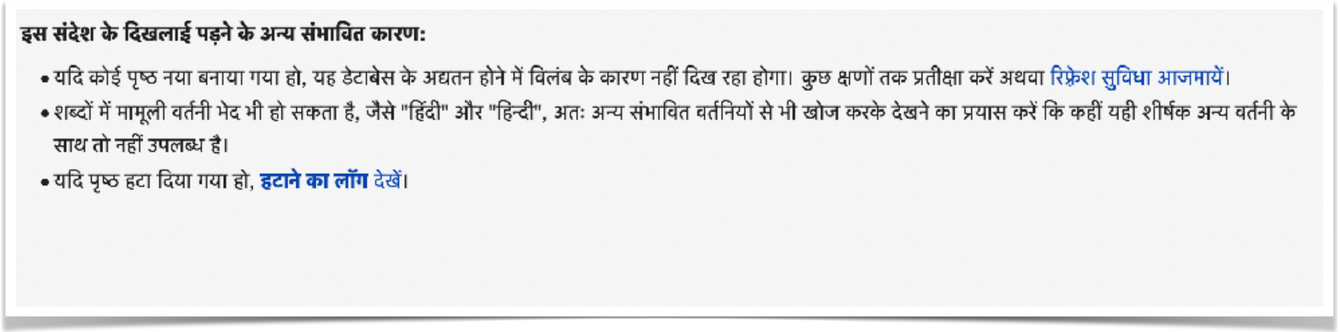
Cross Lingual Transfer

- What about transferring across languages with different scripts?
- I.e., zero overlap in vocabulary?
- E.g., train on Hindi (written in Devanagri), test on Urdu (written in Arabic)





Cross Lingual Transfer

	HI	UR
HI	**97.1**	85.9
UR	91.1	**93.8**

	EN	BG	JA
EN	**96.8**	87.1	49.4
BG	82.2	**98.9**	51.6
JA	57.4	67.2	**96.5**

Table 4: POS accuracy on the UD test set for languages with different scripts. Row=fine-tuning, column=eval.

Cross Lingual Transfer

Only ~6 points worse when trained on Urdu rather than Hindi

	HI	UR
HI	**97.1**	85.9
UR	91.1	**93.8**

	EN	BG	JA
EN	**96.8**	87.1	49.4
BG	82.2	**98.9**	51.6
JA	57.4	67.2	**96.5**

Table 4: POS accuracy on the UD test set for languages with different scripts. Row=fine-tuning, column=eval.

Cross Lingual Transfer

Larger performance drops for less similar language pairs

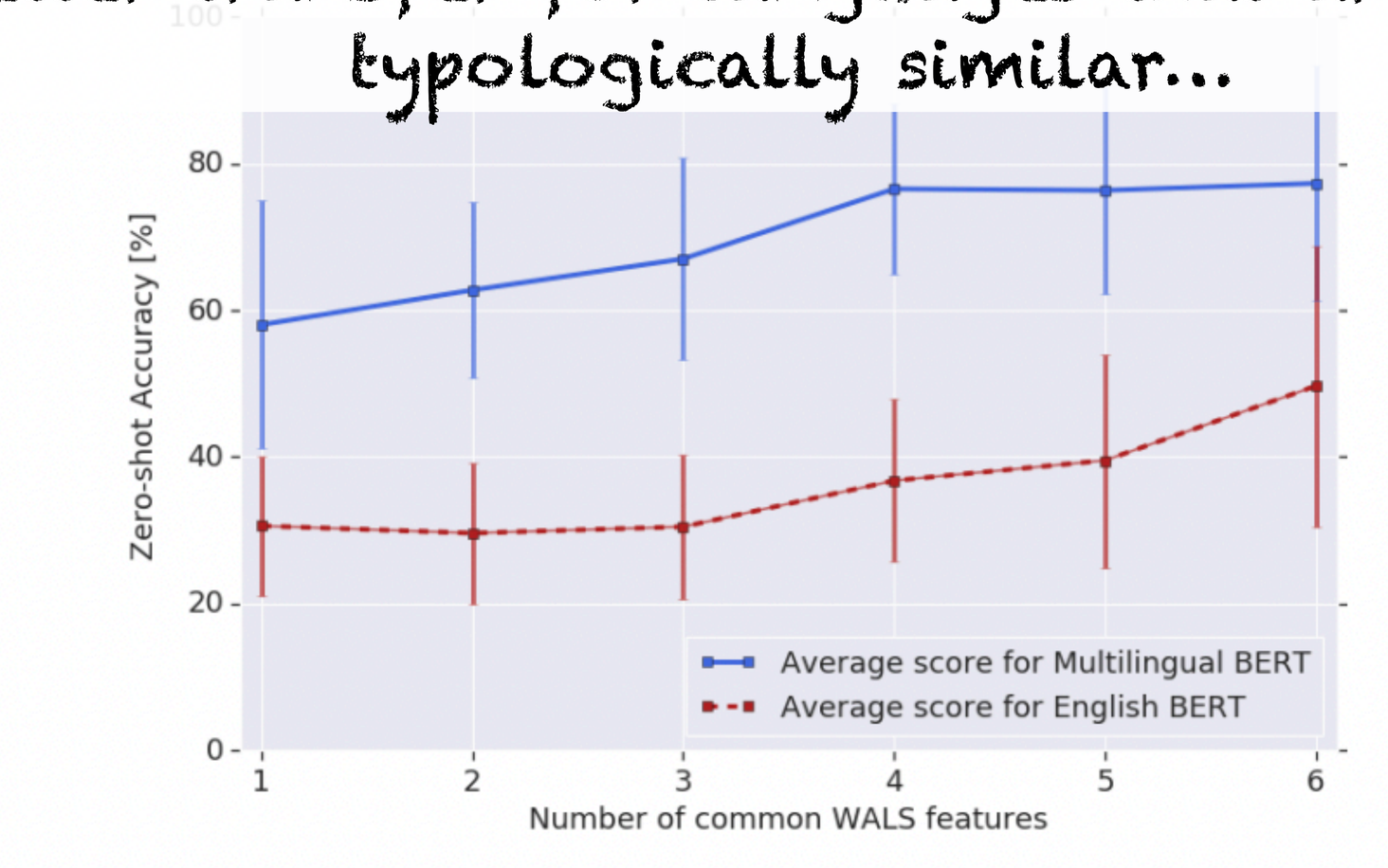
	HI	UR
HI	**97.1**	85.9
UR	91.1	**93.8**

	EN	BG	JA
EN	**96.8**	87.1	49.4
BG	82.2	**98.9**	51.6
JA	57.4	67.2	**96.5**

Table 4: POS accuracy on the UD test set for languages with different scripts. Row=fine-tuning, column=eval.

Cross Lingual Transfer

Better transfer for languages that are more typologically similar...



Cross Lingual Transfer

...e.g., more syntactically similar

	SVO	SOV
SVO	**81.55**	66.52
SOV	63.98	**64.22**

(a) Subj./verb/obj. order.

	AN	NA
AN	**73.29**	70.94
NA	75.10	**79.64**

(b) Adjective/noun order.

Table 5: Macro-average POS accuracies when transferring between SVO/SOV languages or AN/NA languages. Row = fine-tuning, column = evaluation.

Cross Lingual Transfer

- Training on the language you care about is still better, in general
- Why would we do cross-lingual transfer then?
- A few reasons:
  - You might not have training data in the language you care about
  - You might not even have enough data to train an MT system for the language you care about
  - Cross-lingual models require only unlabeled, monolingual data, so are more feasible to train

BLOOM: A 176B-Parameter Open-Access Multilingual Language Model

BigScience Workshop

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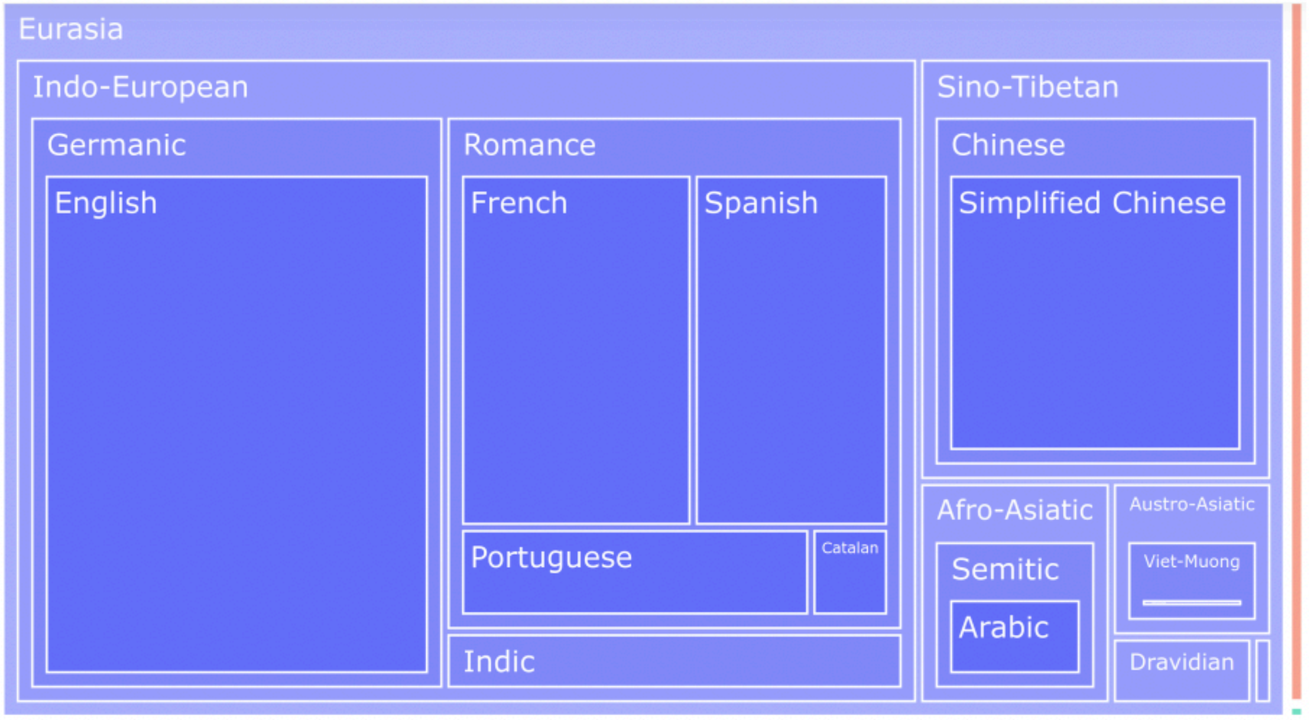
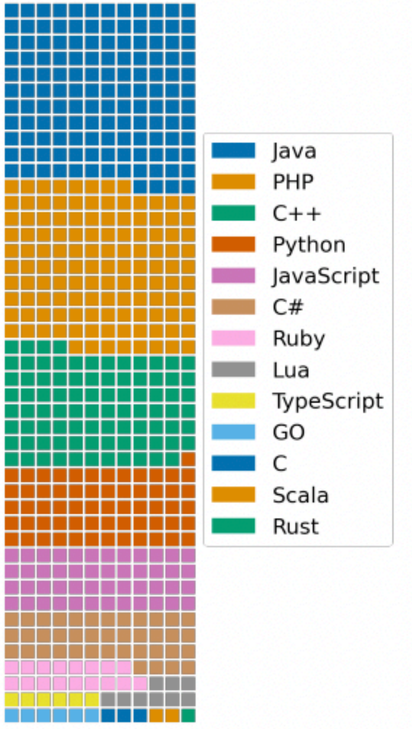
BLOOM: A 176B-Parameter Open-Access Multilingual Language Model





BLOOM: A 176B-Parameter Open-Access Multilingual Language Model

Src↓	Trg→	eng	ben	hin	swh	yor
eng	M2M	–	23.04	28.15	29.65	2.17
	BLOOM	–	25.52	27.57	21.7	2.8
ben	M2M	22.86	–	21.76	14.88	0.54
	BLOOM	30.23	–	16.4	–	–
hin	M2M	27.89	21.77	–	16.8	0.61
	BLOOM	35.40	23.0	–	–	–
swh	M2M	30.43	16.43	19.19	–	1.29
	BLOOOM	37.9	–	–	–	1.43
yor	M2M	4.18	1.27	1.94	1.93	–
	BLOOM	3.8	–	–	0.84	–

(a) Low-resource languages

Src↓	Trg→	cat	spa	fre	por
cat	M2M	–	25.17	35.08	35.15
	BLOOM	–	29.12	34.89	36.11
spa	M2M	23.12	–	29.33	28.1
	BLOOM	31.82	–	24.48	28.0
glg	M2M	30.07	27.65	37.06	34.81
	BLOOM	38.21	27.24	36.21	34.59
fre	M2M	28.74	25.6	–	37.84
	BLOOM	38.13	27.40	–	39.60
por	M2M	30.68	25.88	40.17	–
	BLOOM	40.02	28.1	40.55	–

(b) Romance languages

All done!
Questions?