Machine Translation

Yandex School of Data Analysis
David Talbot
October 2021

Outline

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- Why Machine Translation is hard

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- The Noisy Channel approach to MT (Statistical MT)

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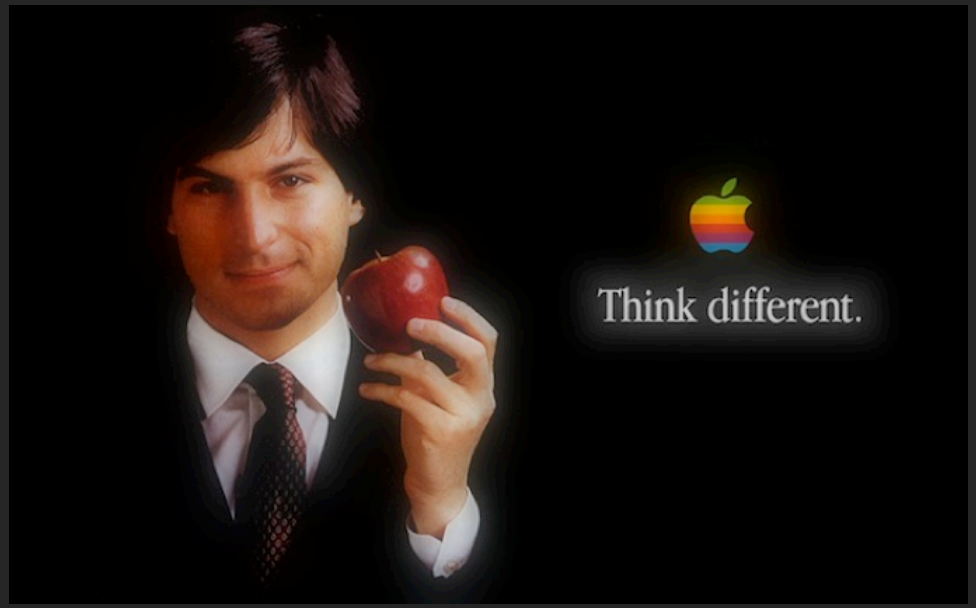
- Current challenges in NMT

Why Machine Translation is Hard

Ambiguity

“A computer that understands you like your mother”



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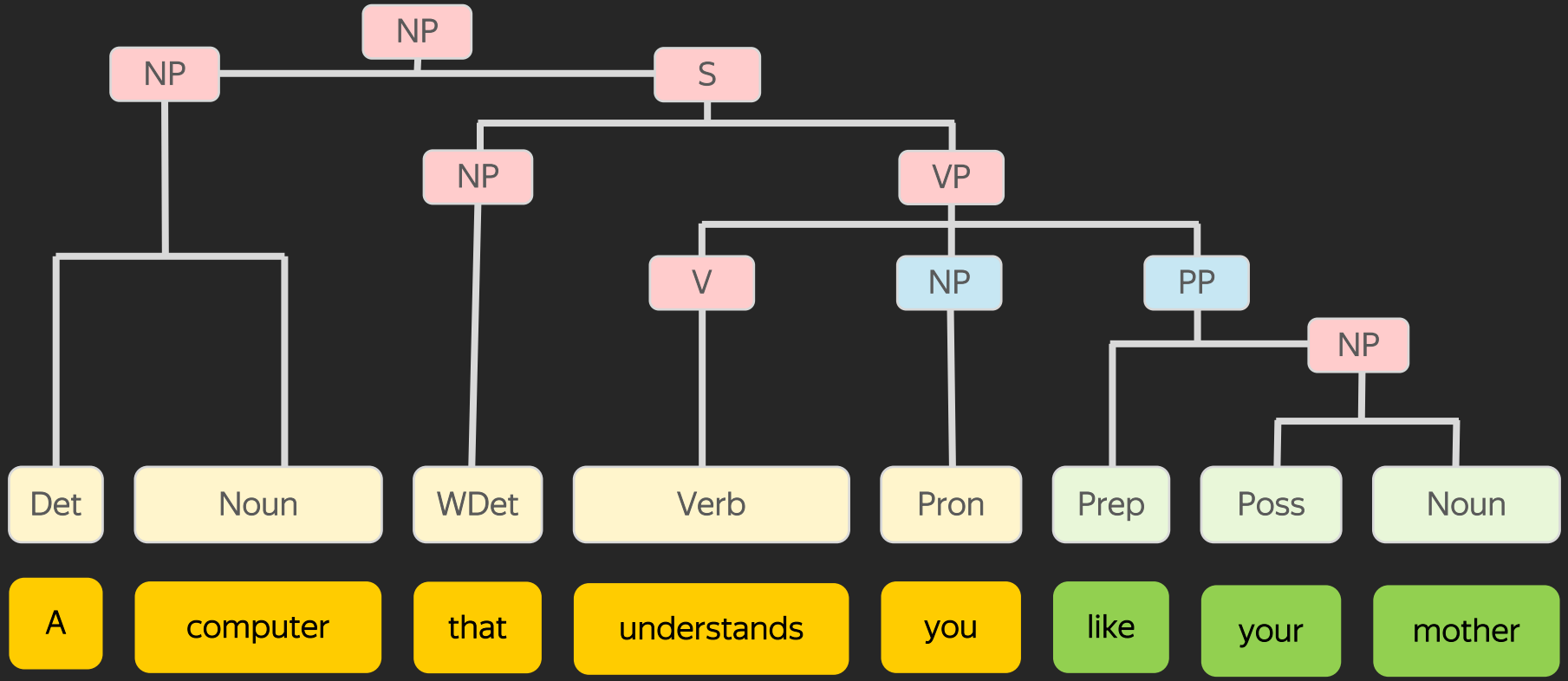
- Компьютер, который понимает тебя так же, как он понимает твою мать (?)

Syntactic Ambiguity



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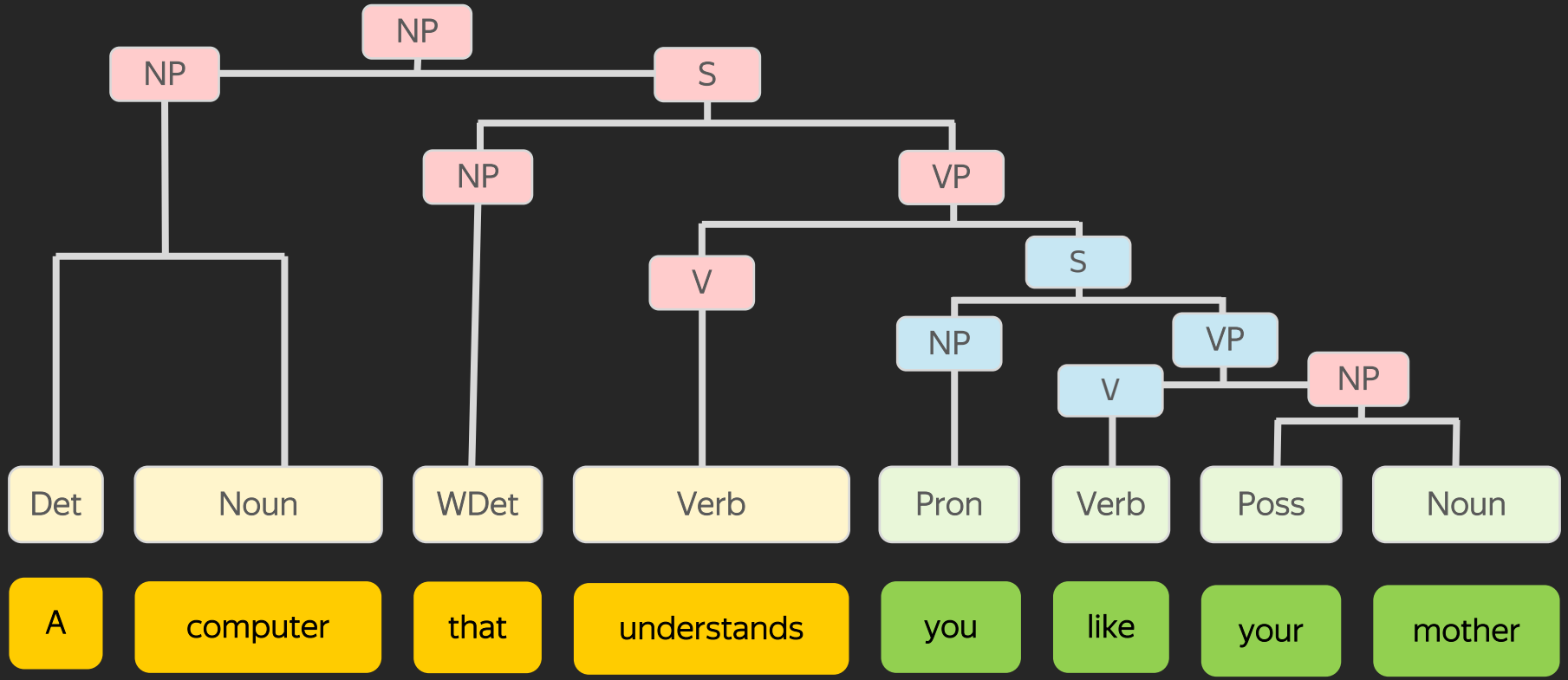

AI Completeness

What's the hardest word to translate in these sentences?

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Head-final Japanese

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お母さん　のように　理解してくれる　コンピュータ

mother [polite]	similar	understanding giving [inside group]	computer

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Progress in MT

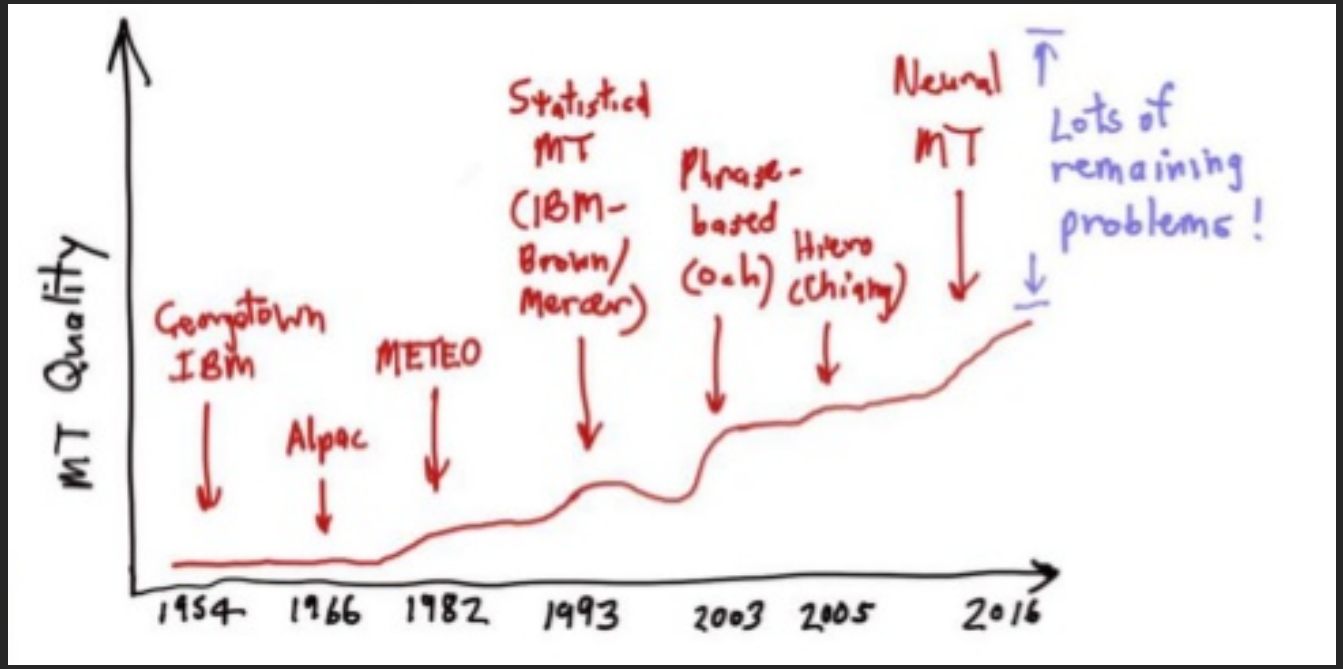
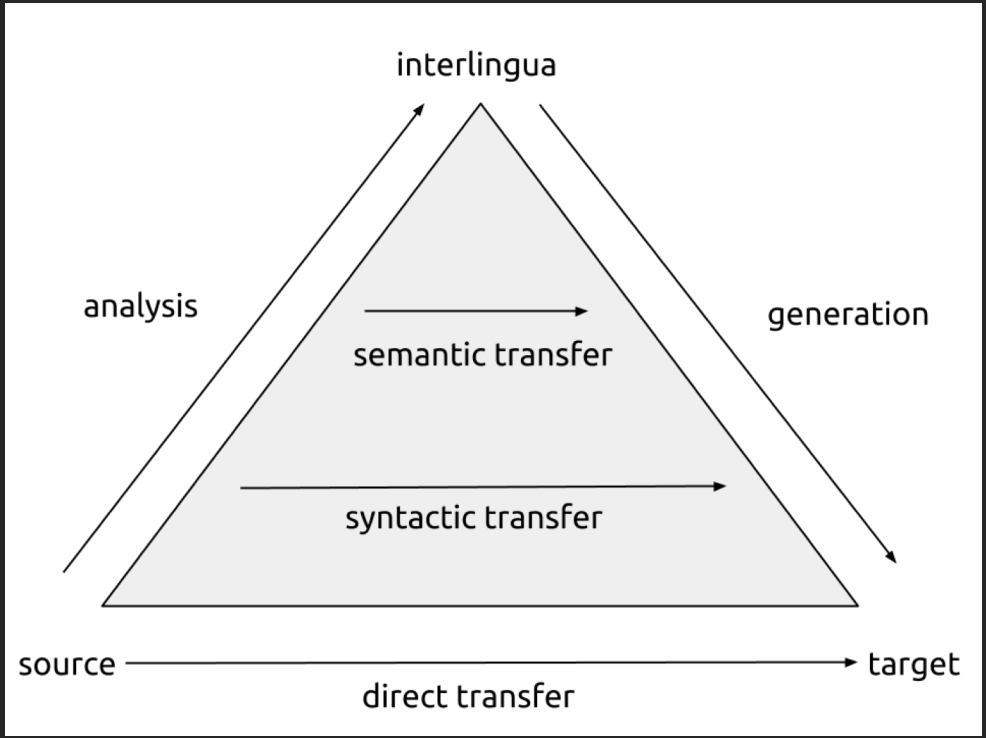


Image by Chris Manning

Vauquois Pyramid



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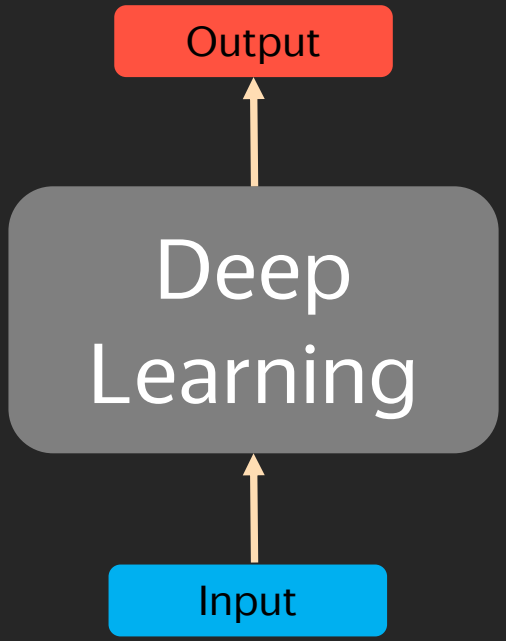

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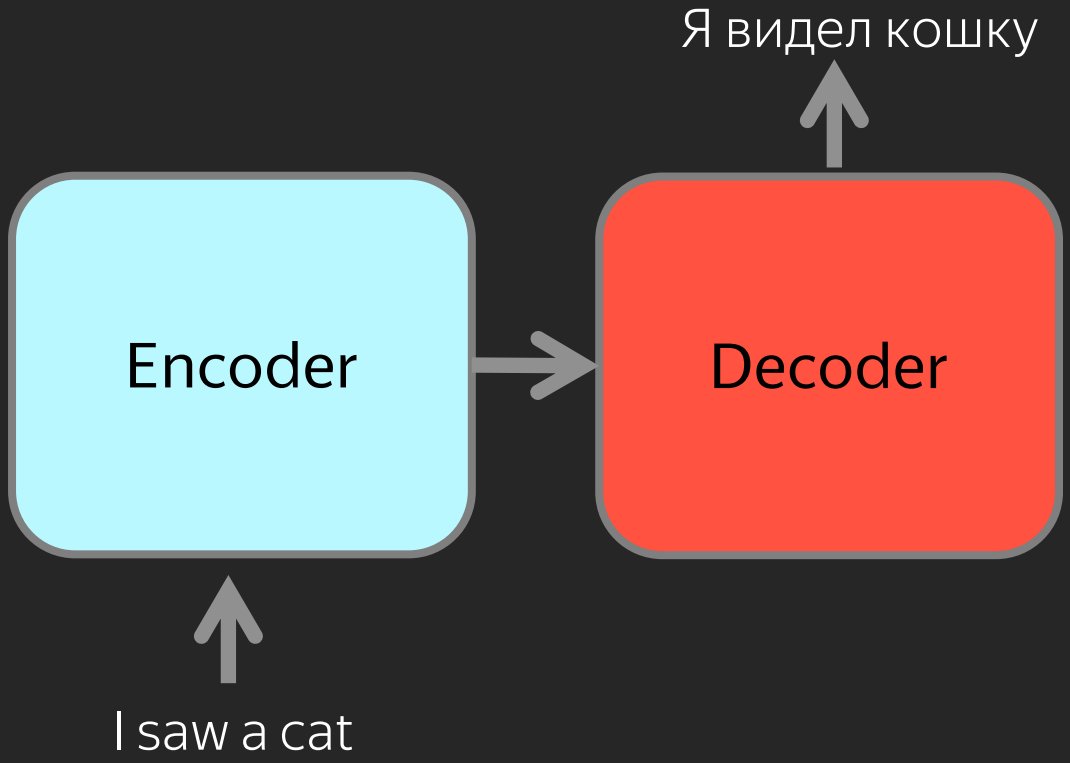

The Noisy Channel Approach to MT

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3. To estimate the ‘channel’ model from bilingual parallel corpora

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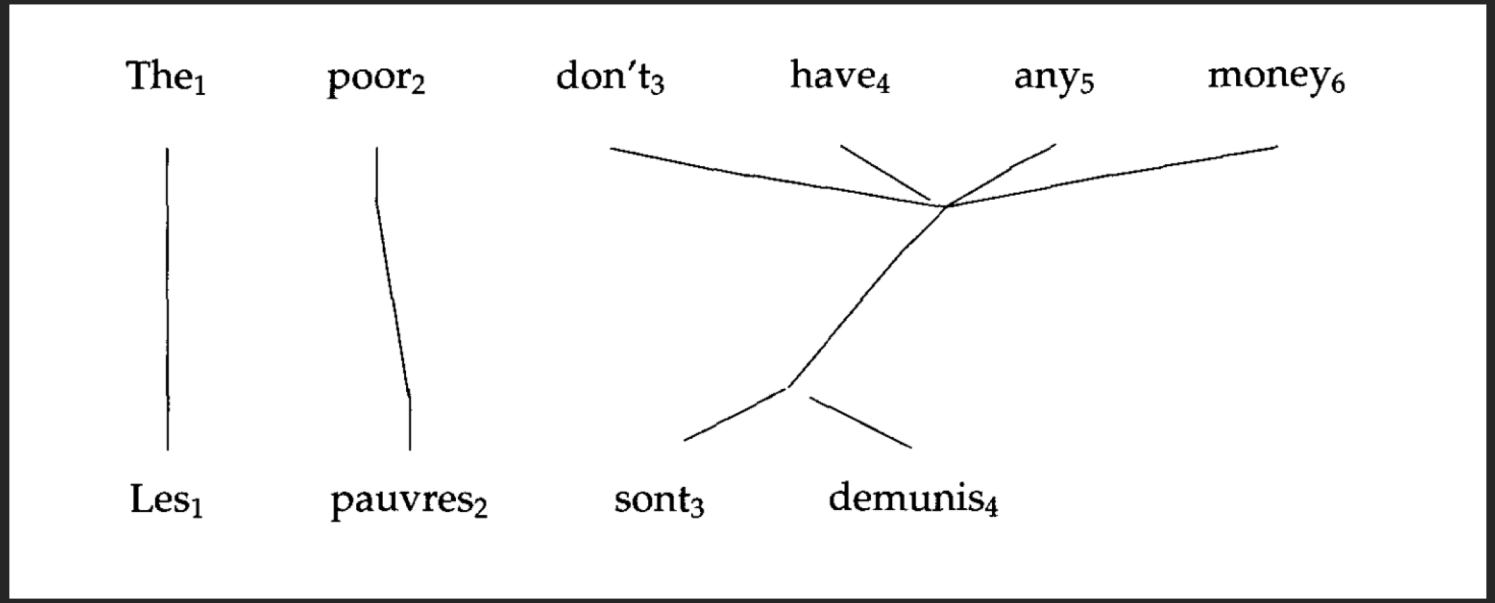

The Noisy Channel

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f

observation

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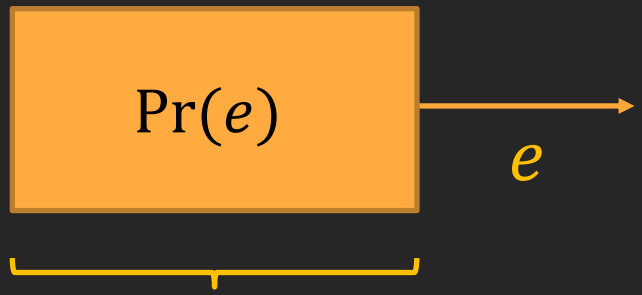

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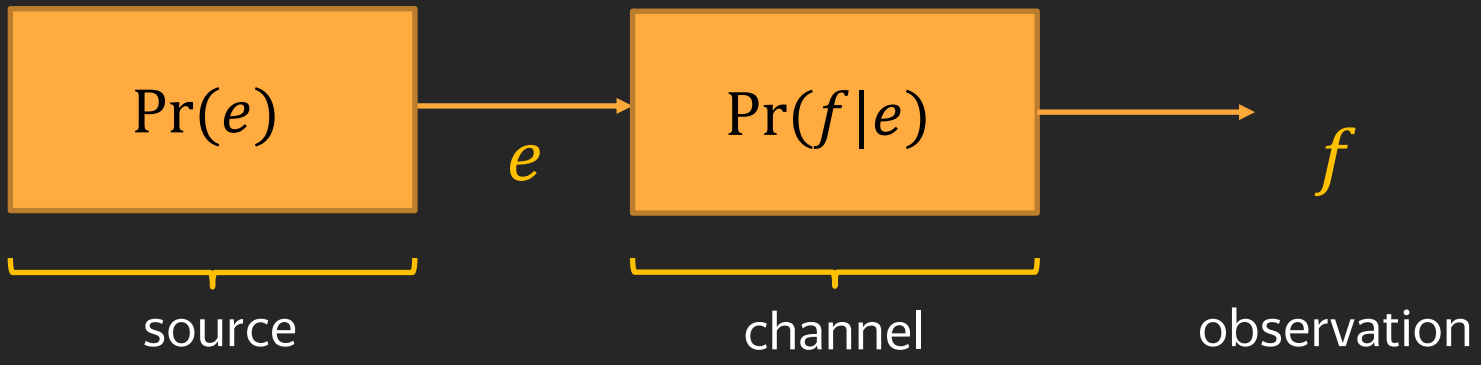

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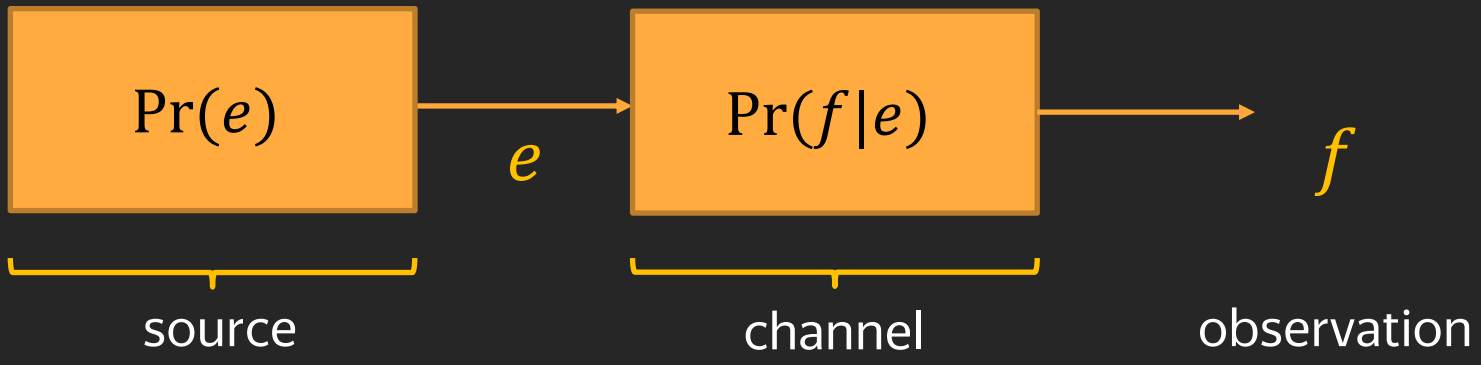

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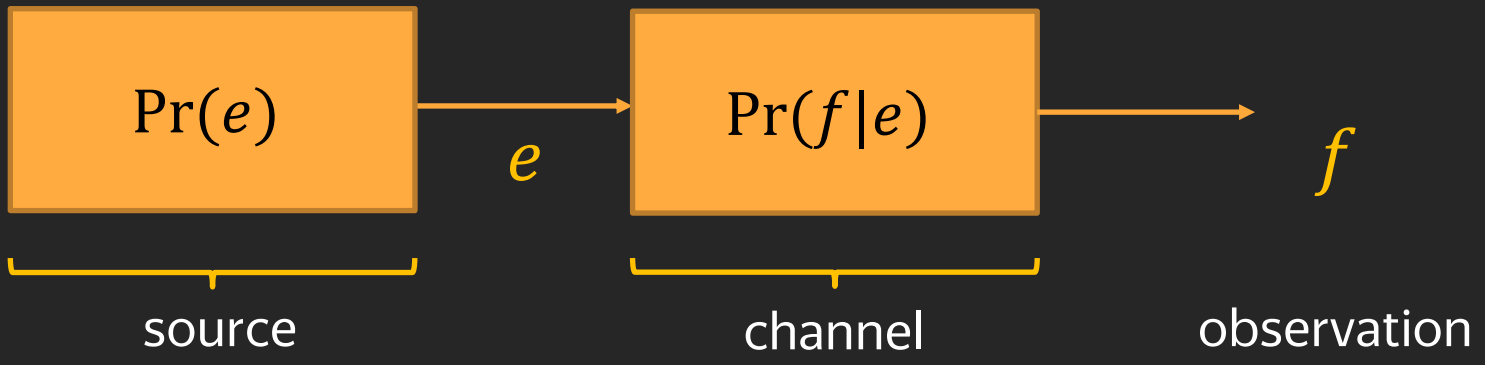

$$e^* = argmax_e \; Pr(e) \; \ldots$$

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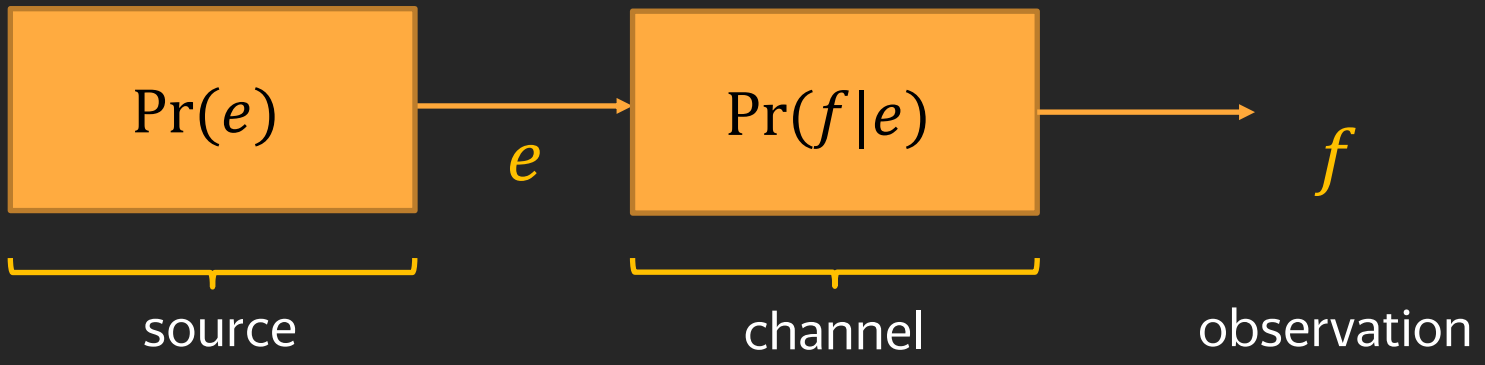

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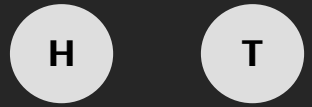

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$$\begin{aligned} e^* &= argmax_e \; Pr(e|f) \\ &\approx argmax_{e_i} \; \prod_{i=1}^{I} Pr(e_i|f) \end{aligned}$$

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Животное не прошло дорогу потому что оно был слишком устало

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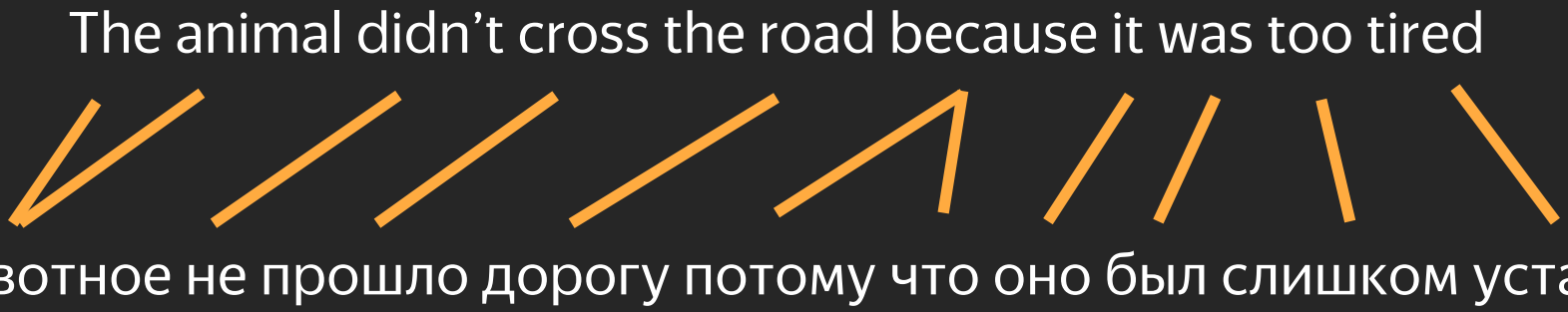

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E.g. $t(\text{животное}|\text{animal})$, $t(\text{прошло}|\text{cross})$, etc.

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2. Infer the posterior distribution over alignments $Pr(a|e,f)$ given $t(f|e)$

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5. Return to 2. until parameters $t(f|e)$ converge

Expectation Maximization Algorithm

Goal: Learn word level translation probabilities $t(f|e)$
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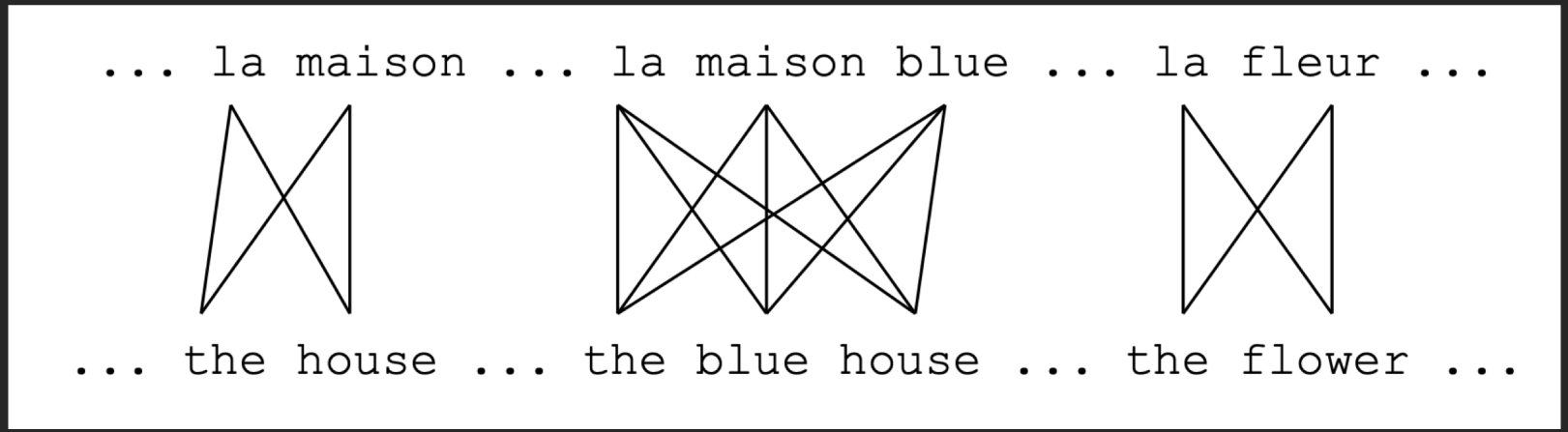

Image by Philipp Koehn

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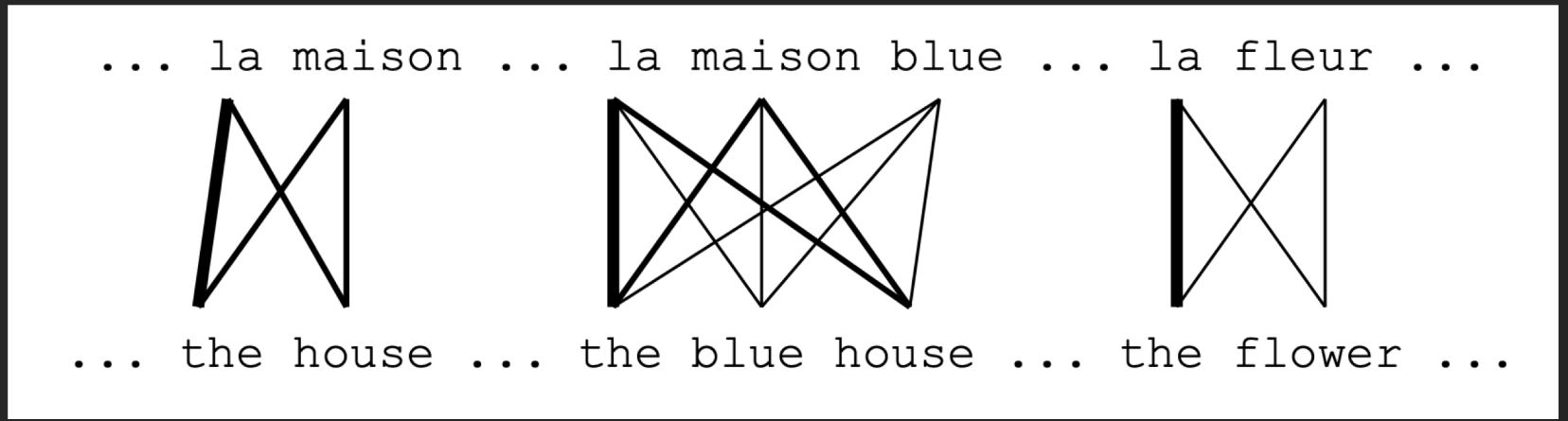

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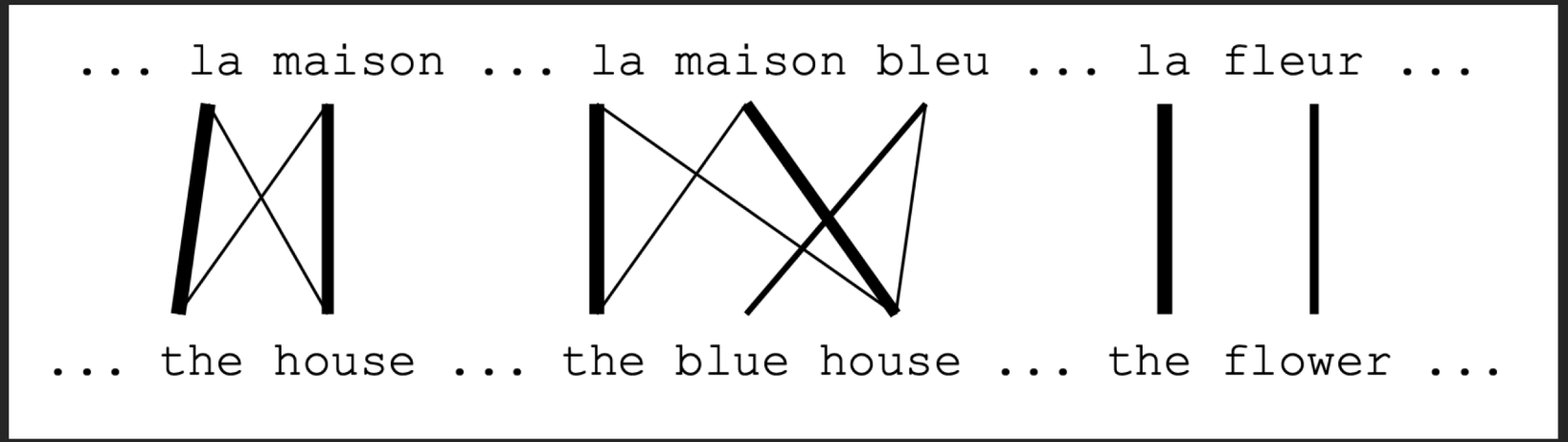

Expectation Maximization Algorithm

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Phrase-based Extensions (Koehn 2003)

Build phrasal models on top of word alignments

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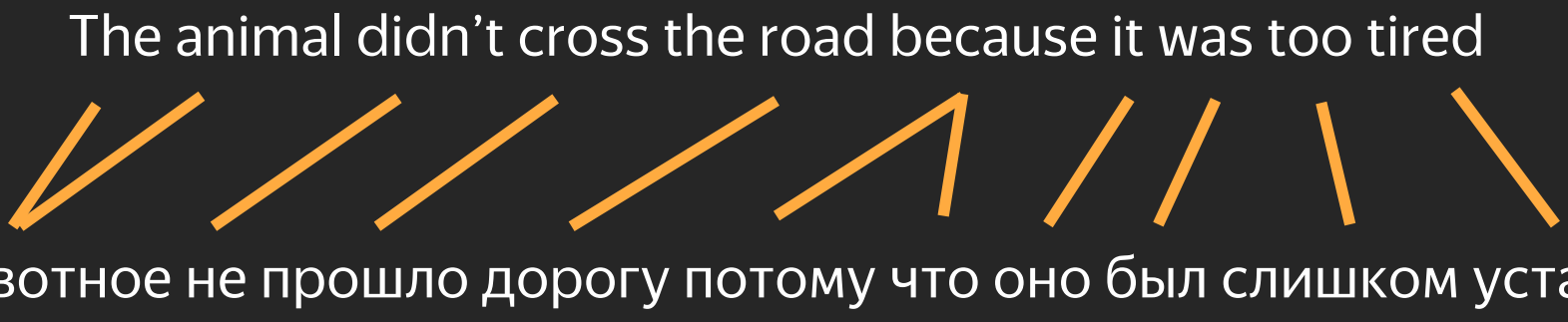
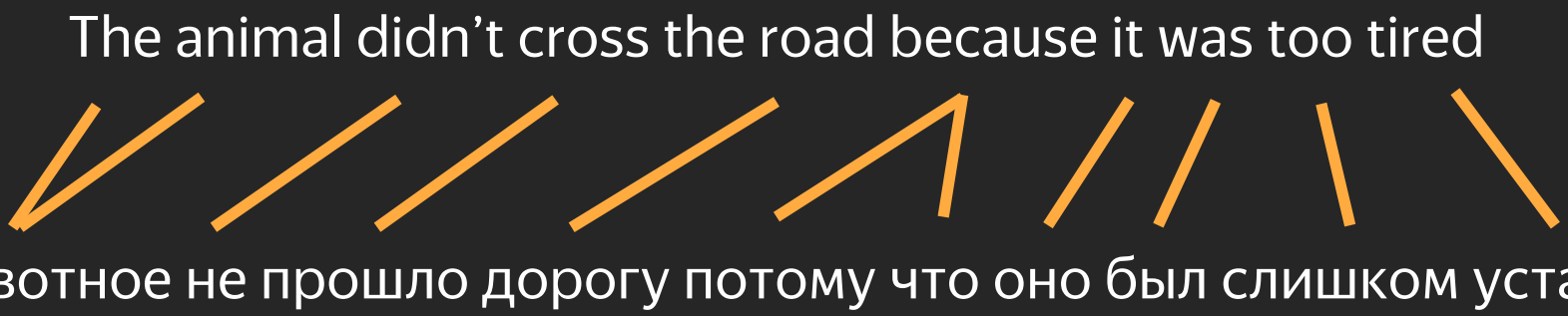


Phrase-based Extensions (Koehn 2003)

Build phrasal models on top of word alignments
Extract arbitrary phrases that are *more-or-less* mutually aligned



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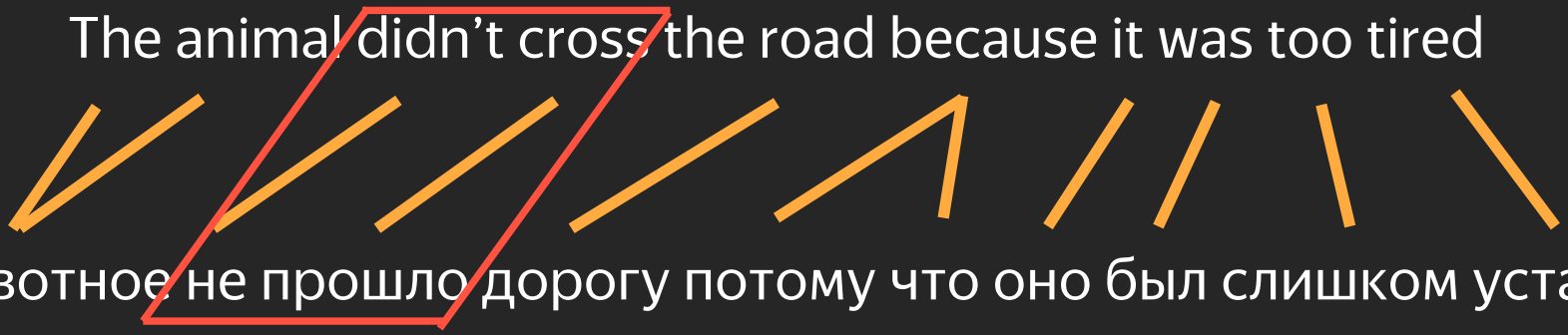

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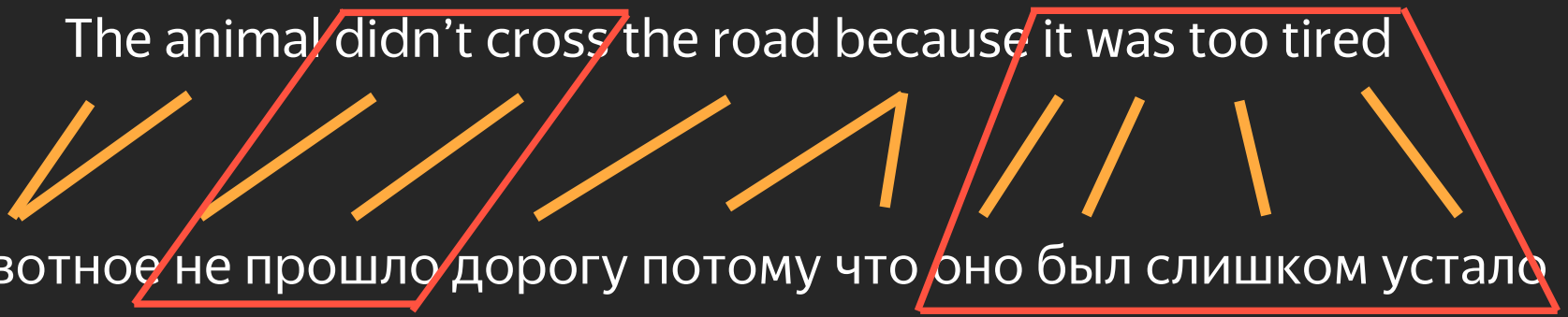

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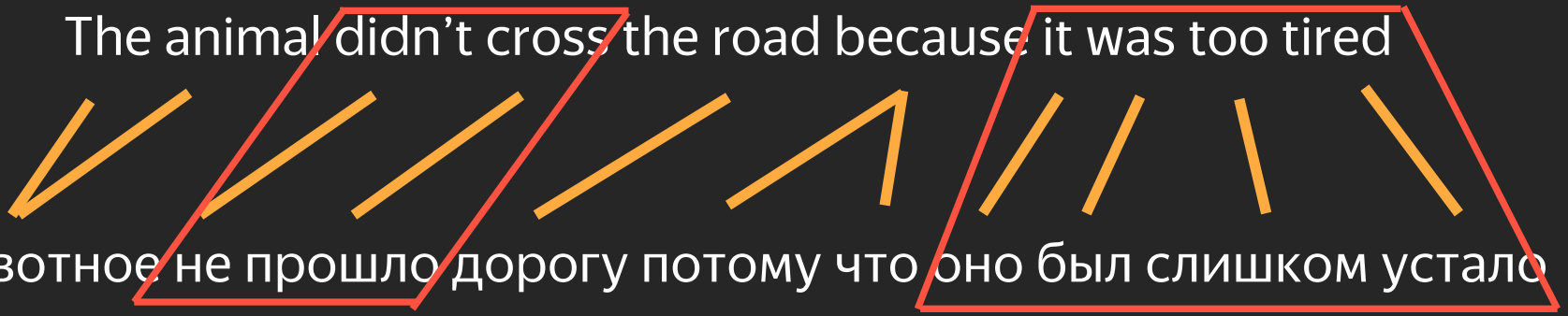
Estimate *phrase-level* translation probabilities



From Words to Phrases

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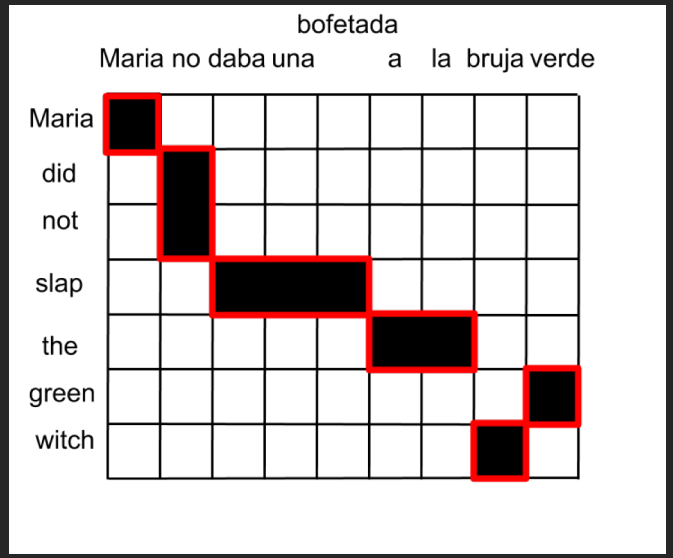

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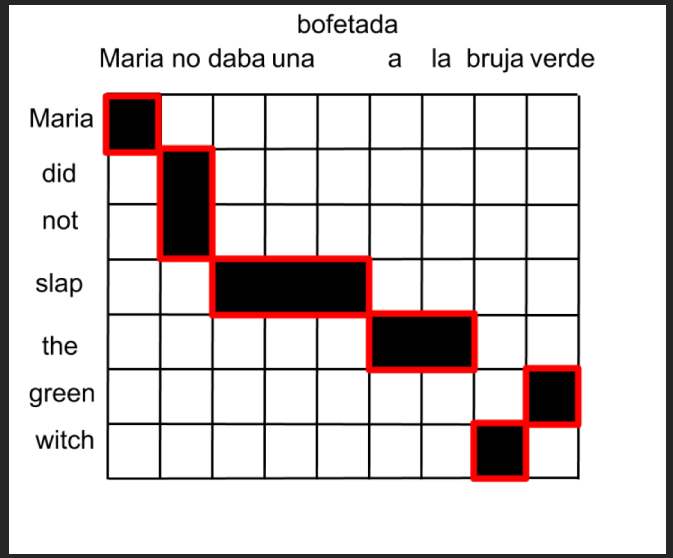
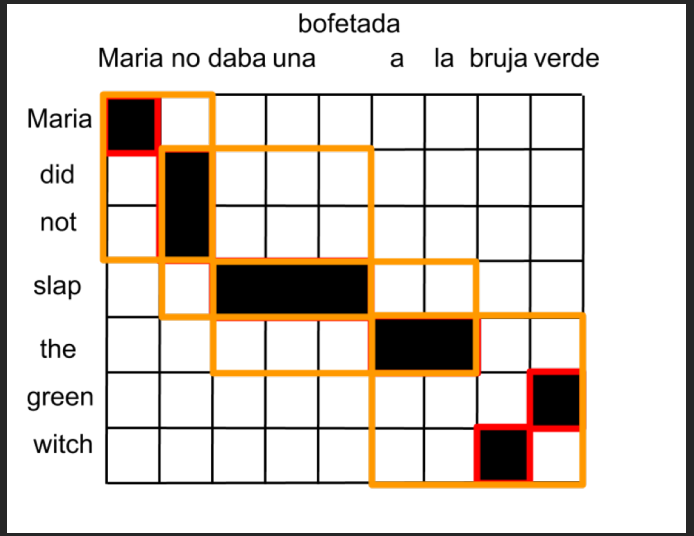
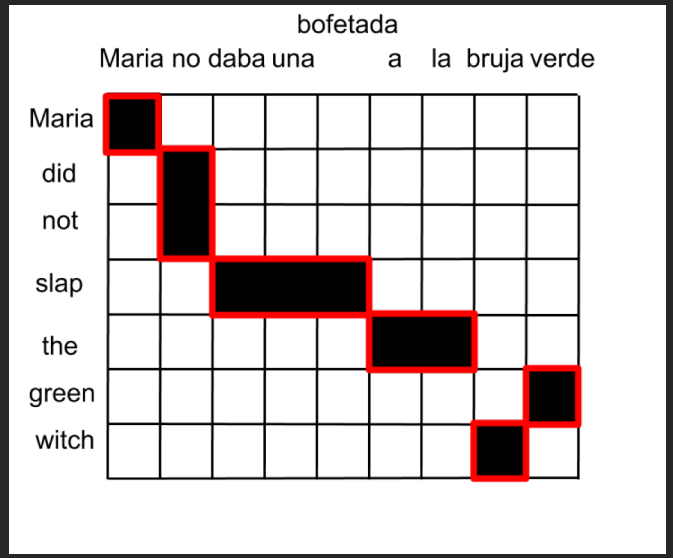
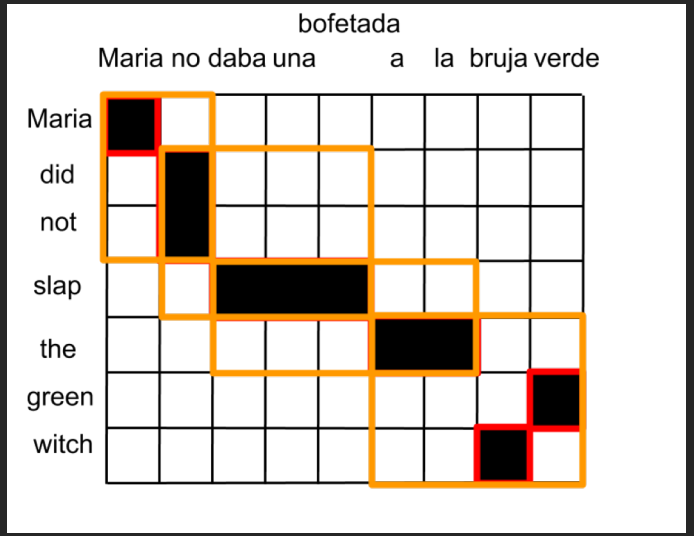




From Words to Phrases

- Estimate word alignments using EM





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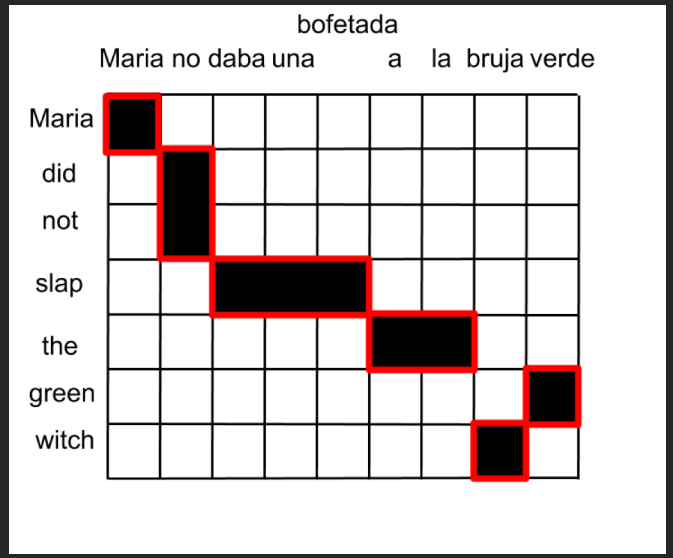
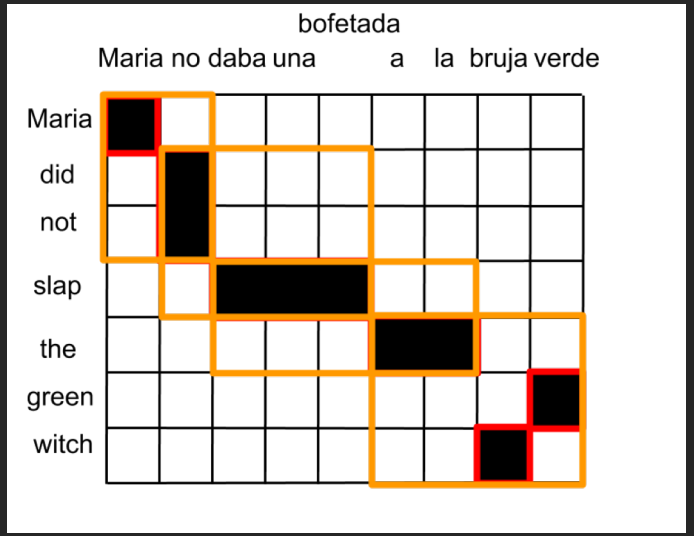
- Estimate word alignments using EM
- Use word alignments as constraints to align phrases





From Words to Phrases

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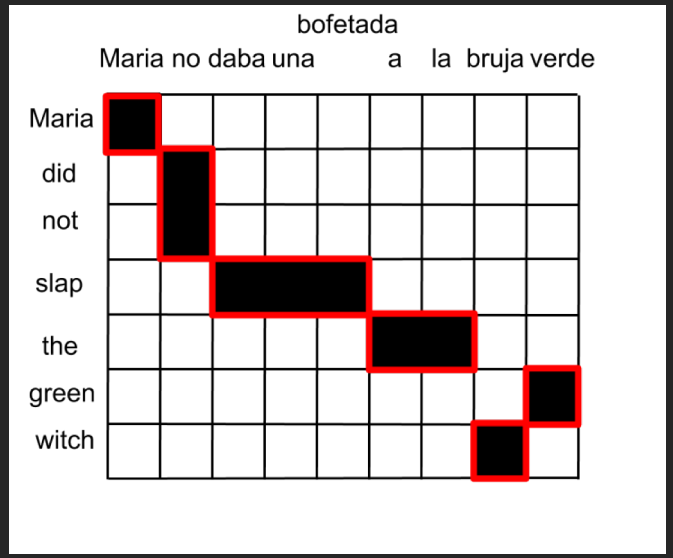
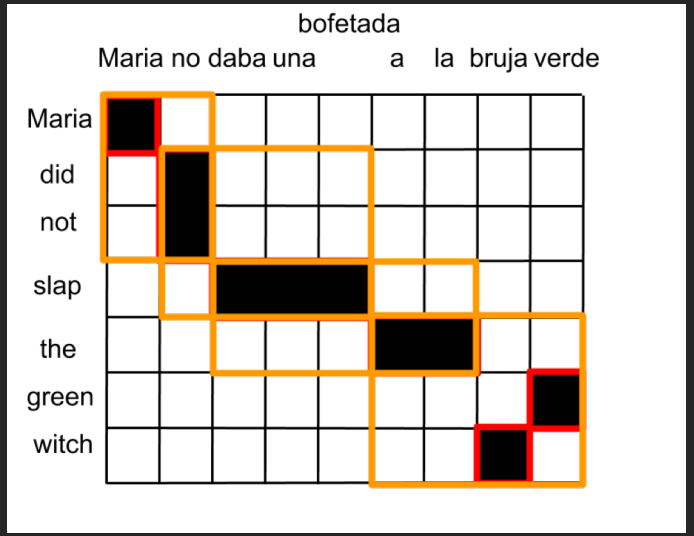
- Use word alignments as constraints to align phrases
- Build phrasal model of $\Pr(f|e)$





Phrasal Translation Model

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- Score phrase pairs based on counts of aligned phrase pairs

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- Score phrase pairs based on counts of aligned phrase pairs
- Add word level scores to smooth these

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- Score phrase pairs based on counts of aligned phrase pairs
- Add word level scores to smooth these
- Add arbitrary features to phrase, e.g. $Pr(e|f)$ in addition to $Pr(f|e)$

Phrase-based Translation Model

He	→	Он
stood	→	стоял, стояла, поставил, …
bank	→	берега, берегу, банк, банка …
He stood	→	Он стоял
by the bank	→	на берегу, рядом с банком …

Linear Translation Model

Linear Translation Model

- Arbitrary features $\phi_k(e, f)$: phrase-table, language model, length penalty, reordering costs, word-sense disambiguation, etc.

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Linear Translation Model

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- Optimize evaluation metric (BLEU) directly with beam search on dev

$$e^* = argmax_e \Sigma_k \lambda_k \phi_k(e, f)$$

Phrase-based Decoder

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Goal: Find the highest scoring translation **that translated all the input**

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Goal: Find the highest scoring translation **that translated all the input**

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- Backtrack from highest scoring hypothesis that translates all words

Phrase-based Translation

Phrase-based Translation

English

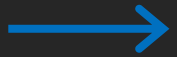
- He stood on the bank

Phrase-based Translation

English

- He stood on the bank

Phrase Table

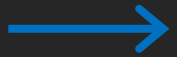


Phrase-based Translation

English *Pieces of Russian*

- He stood on the bank

Phrase Table



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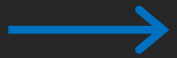

{Он | стояла | на | берегу ... }
Он | стоял | у | банка, ... }
Он | поставил | у берега, ... }

Phrase-based Translation

English *Pieces of Russian*

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Phrase Table → Language Model →

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Phrase-based Translation

English *Pieces of Russian* *Russian*

- He stood on the bank Он стоял на берегу

Phrase Table → Language Model →

{Он | стояла | на | берегу ... }
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Он | поставил | у берега, ... }

Phrase-based Extensions (Koehn 2003)

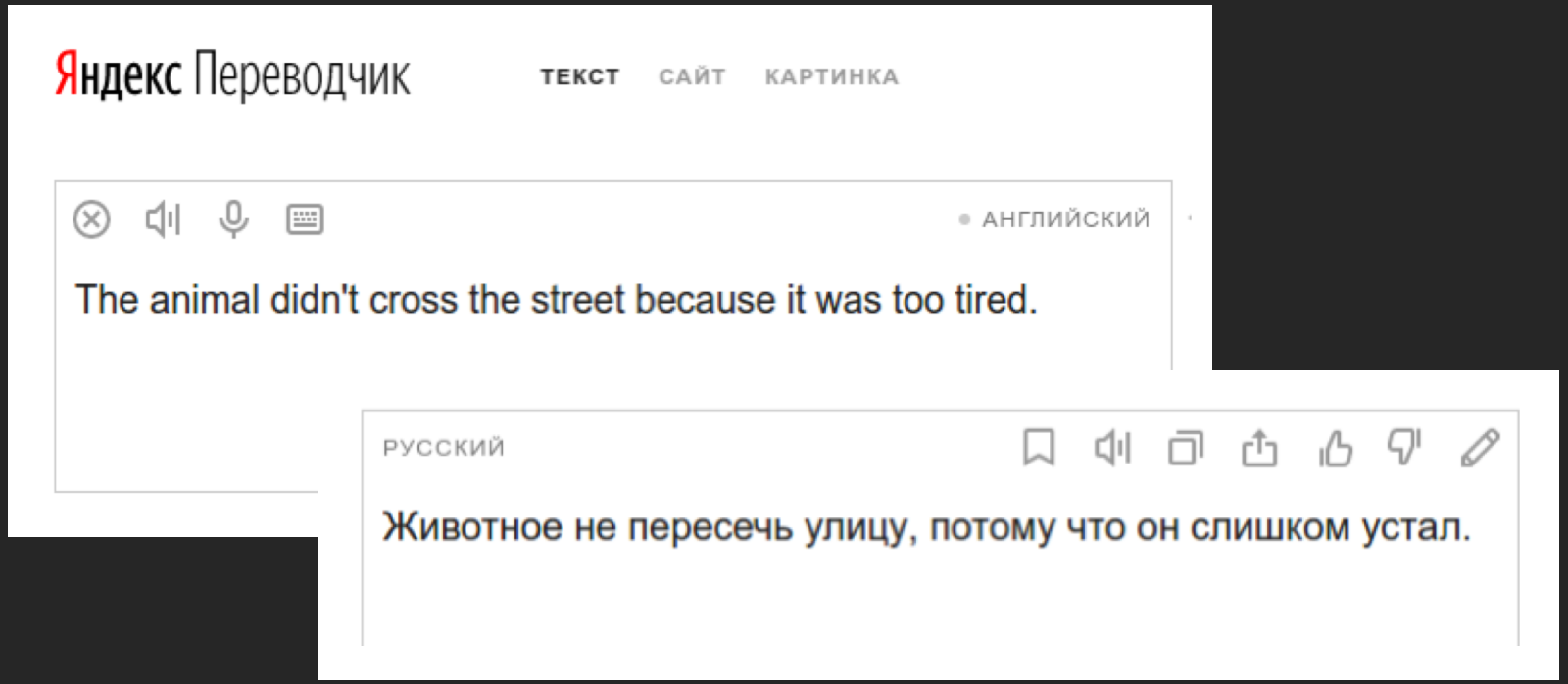
Phrase-based MT together with internet-scale parallel data mining enabled the first popular MT engines from mid-2000s

Яндекс Переводчик

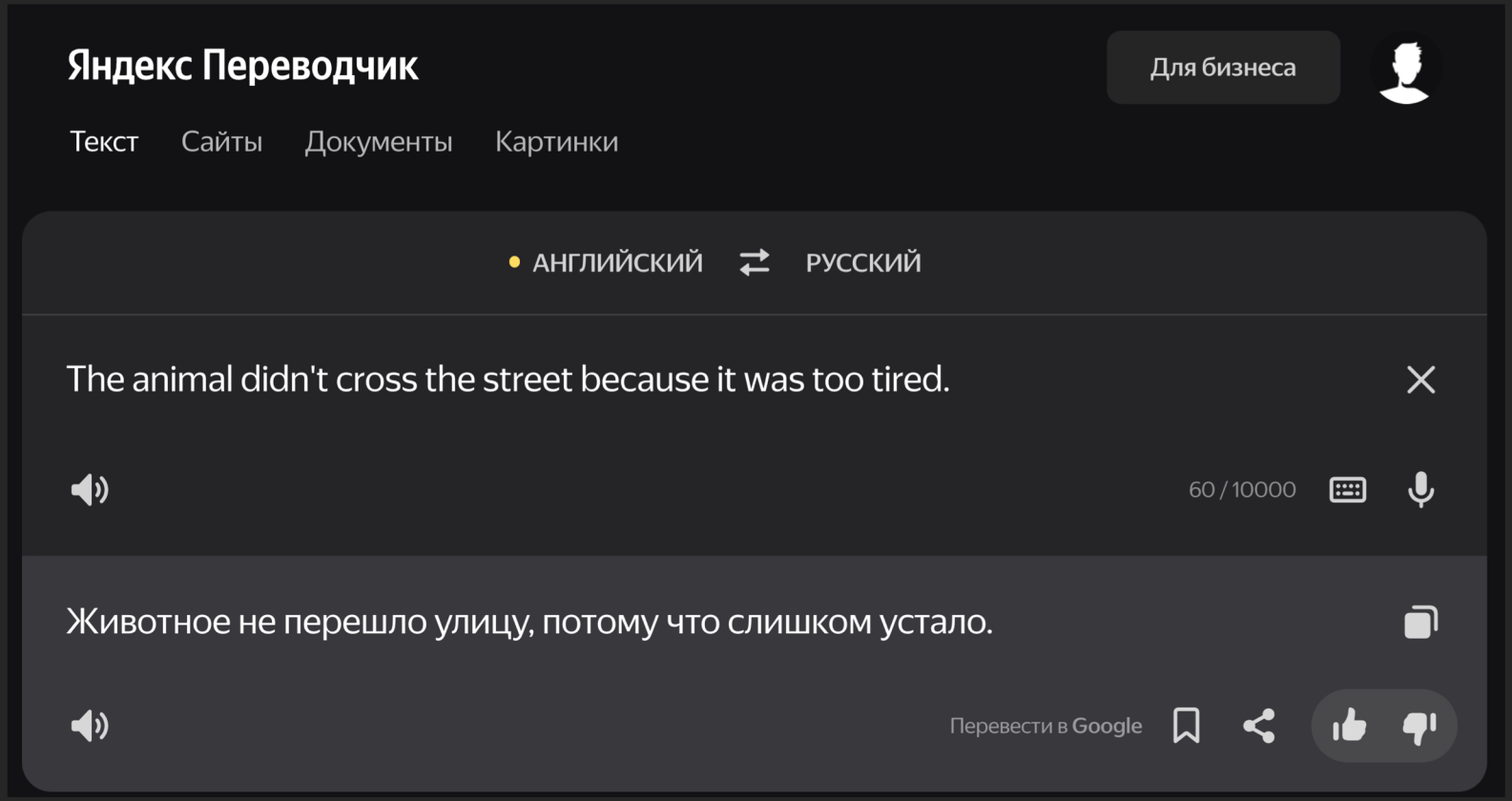
PROMT®

Phrase-based MT Quality (around 2016)

Great for getting the ‘gist’, not so great for sounding fluent or natural

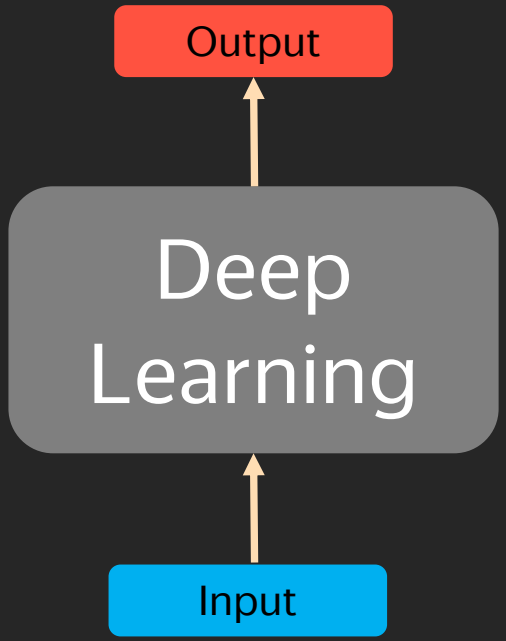


Something happened with MT Quality around 2017...

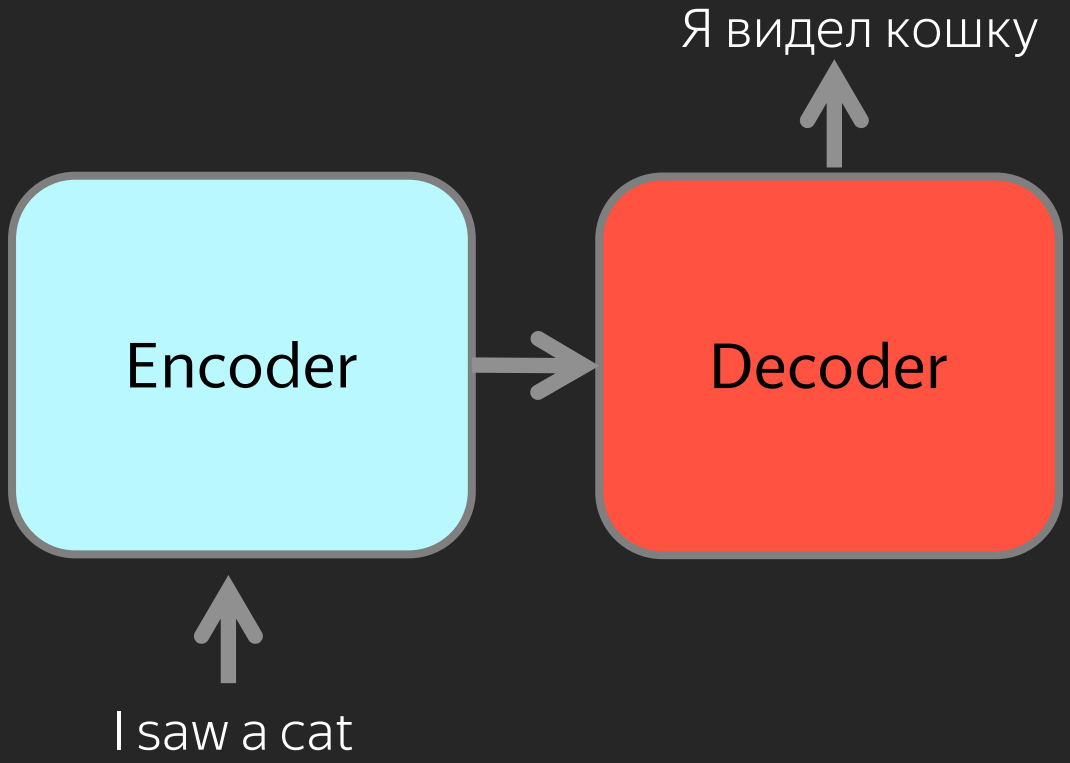


How Neural Machine Translation changed things

Neural Machine Translation



Encoder-Decoder



End-to-End Optimization

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- Direct optimization of conditional probability of translation in corpus

$$Pr(e|f)$$

End-to-End Optimization

- Direct optimization of conditional probability of translation in corpus

$$Pr(e|f)$$

- Optimize conditional probability of next word (locally normalized)

$$Pr(e|f) = \prod_{i=1}^{I} Pr(e_i|\, f,\ e_{<i}).$$

End-to-End Optimization

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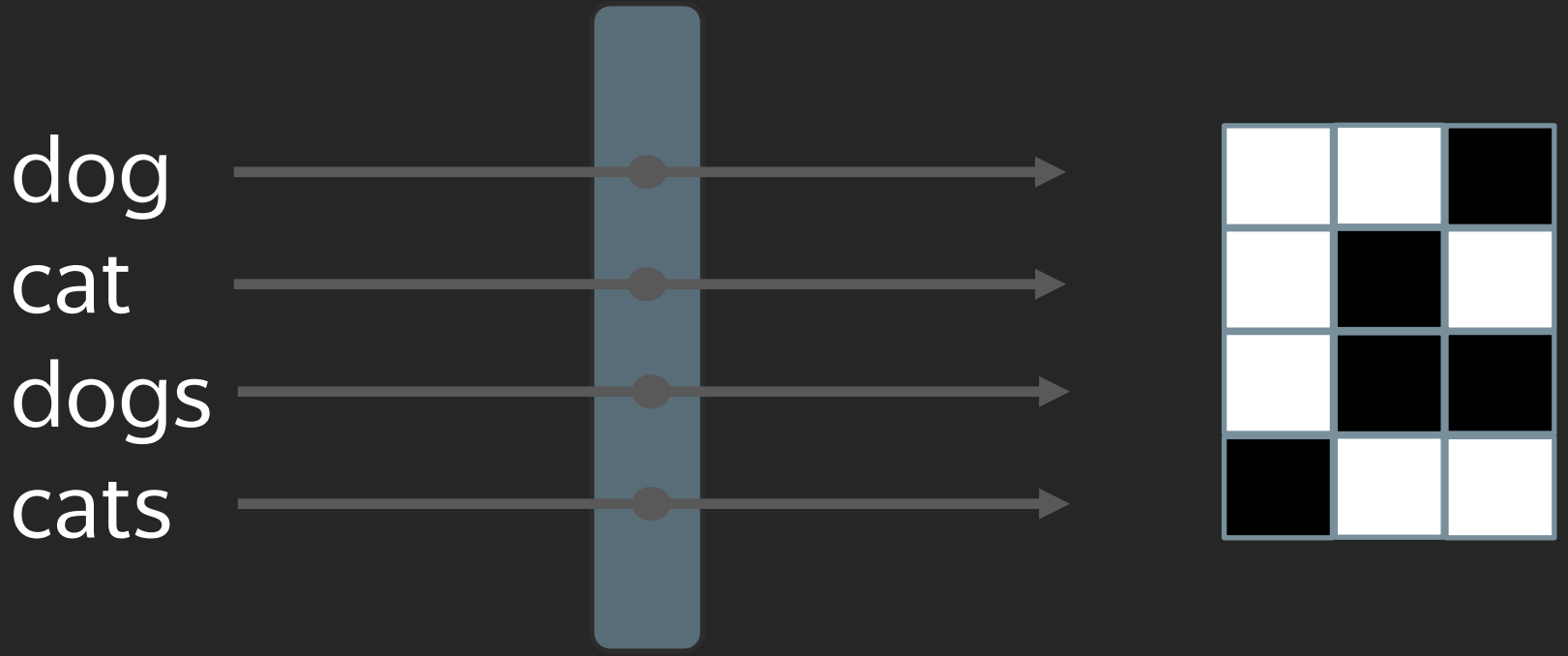
$$Pr(e|f) = \prod_{i=1}^{I} Pr(e_i|\, f,\ e_{<i}).$$

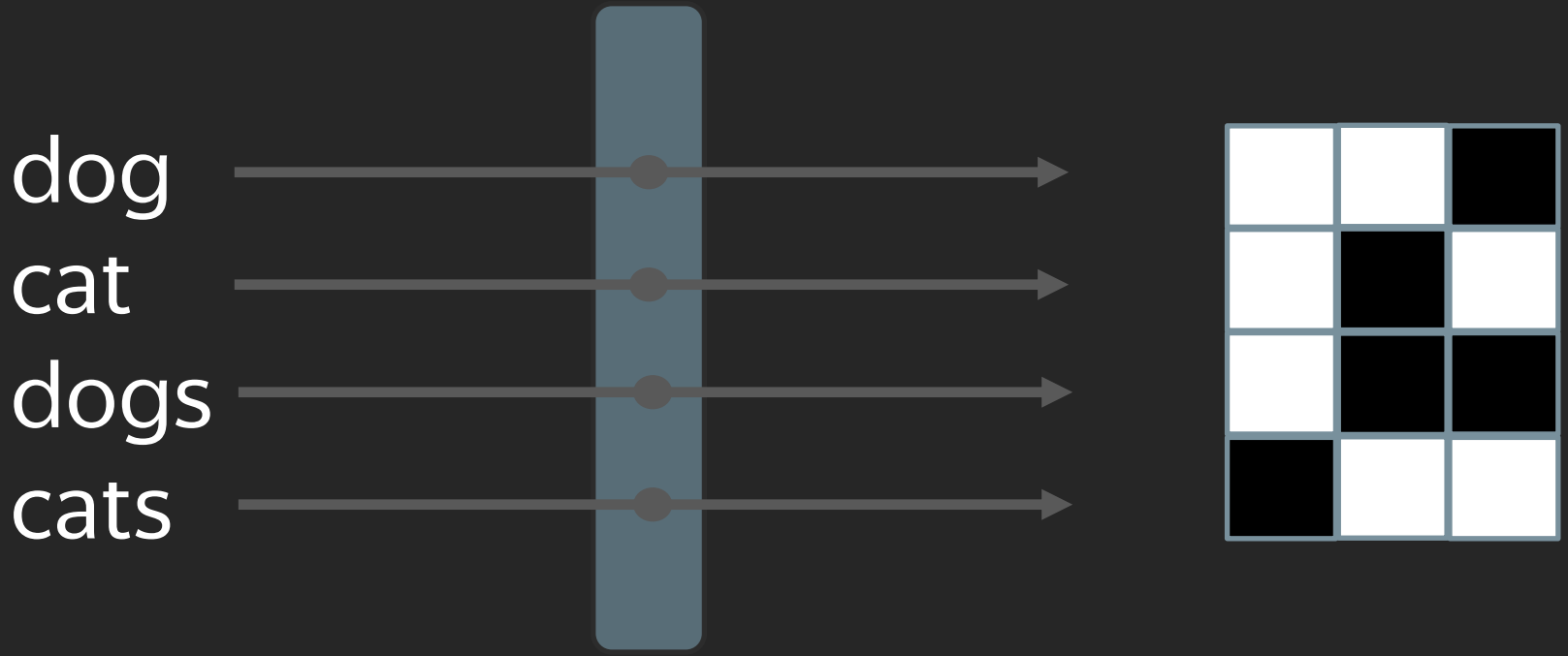
- Teacher forcing (i.e. provide reference prefix to model during training)

Representation Learning

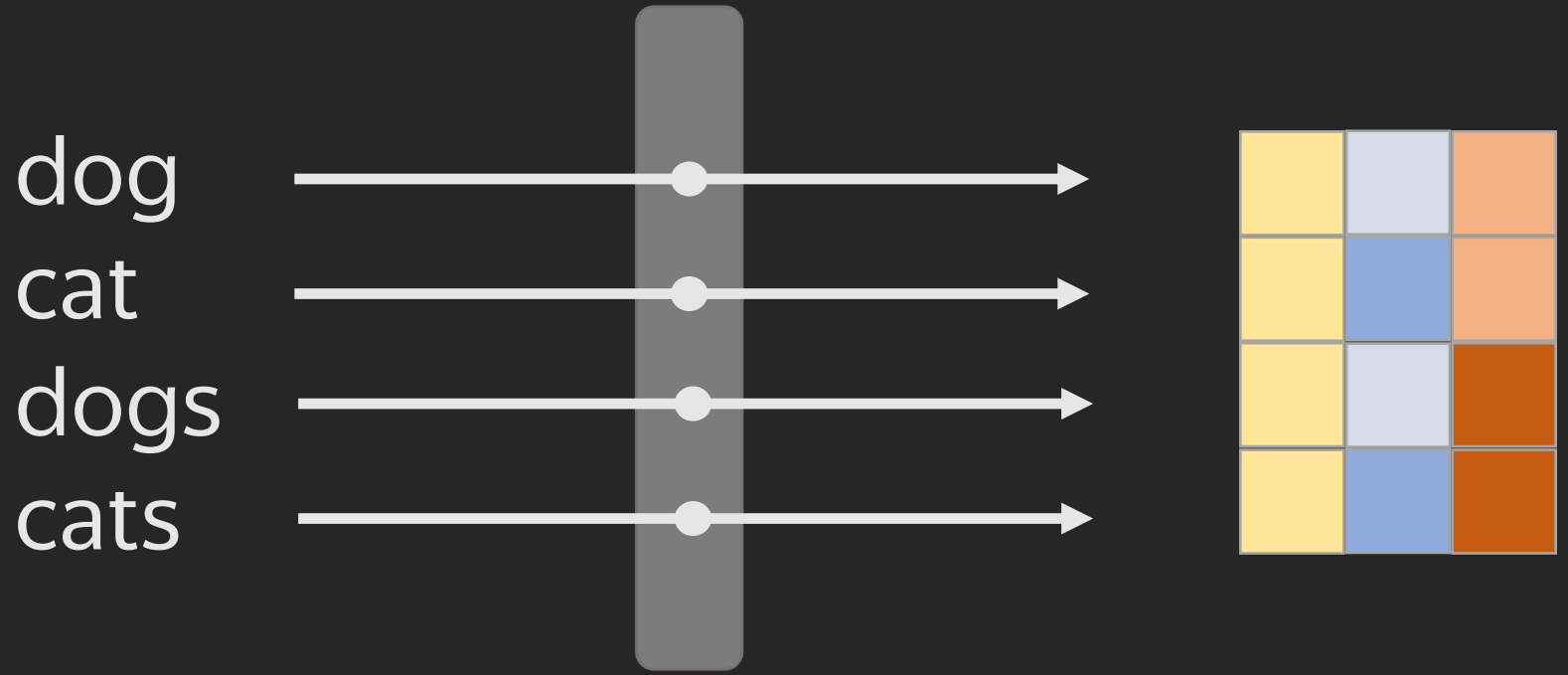
Non-learned Representations



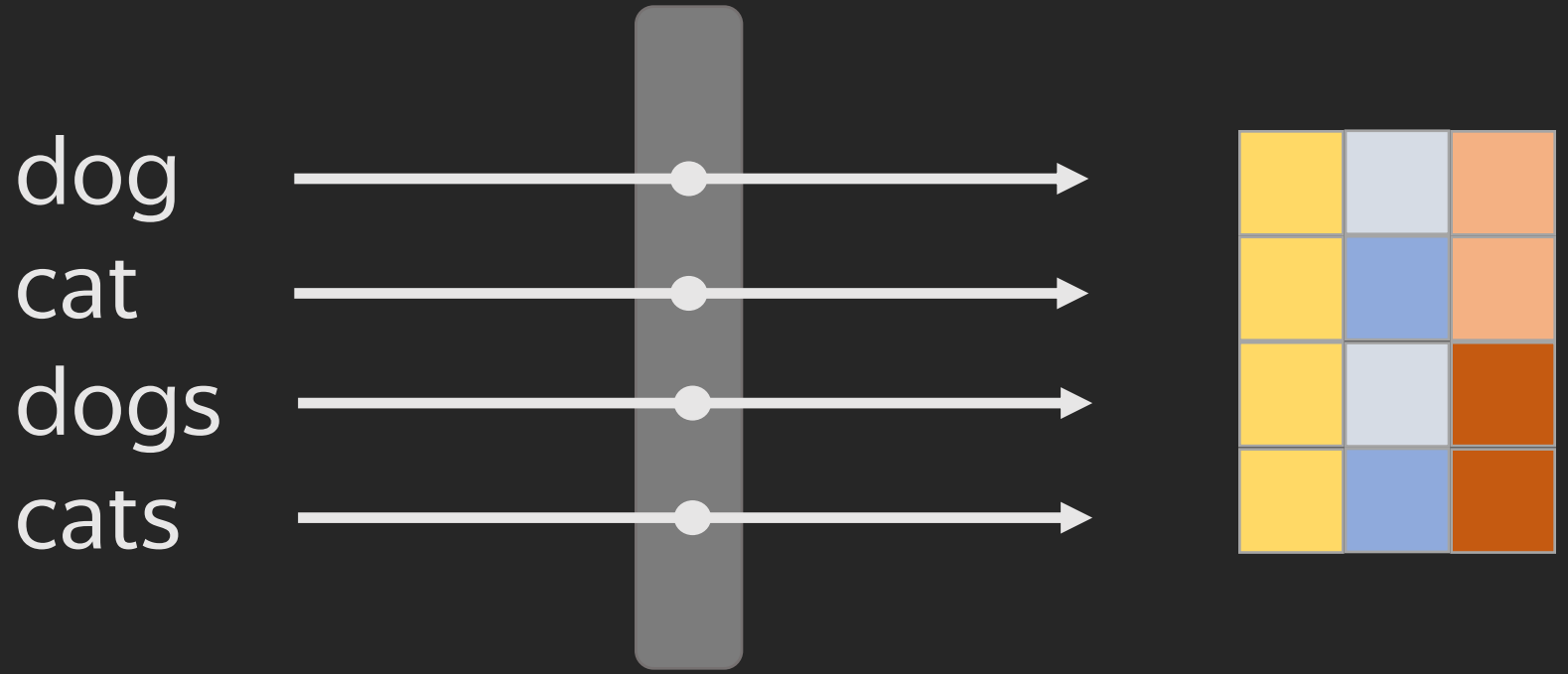
Non-learned Representations (Hamming Space)



Representation Learning



Representation Learning (Embedding space)



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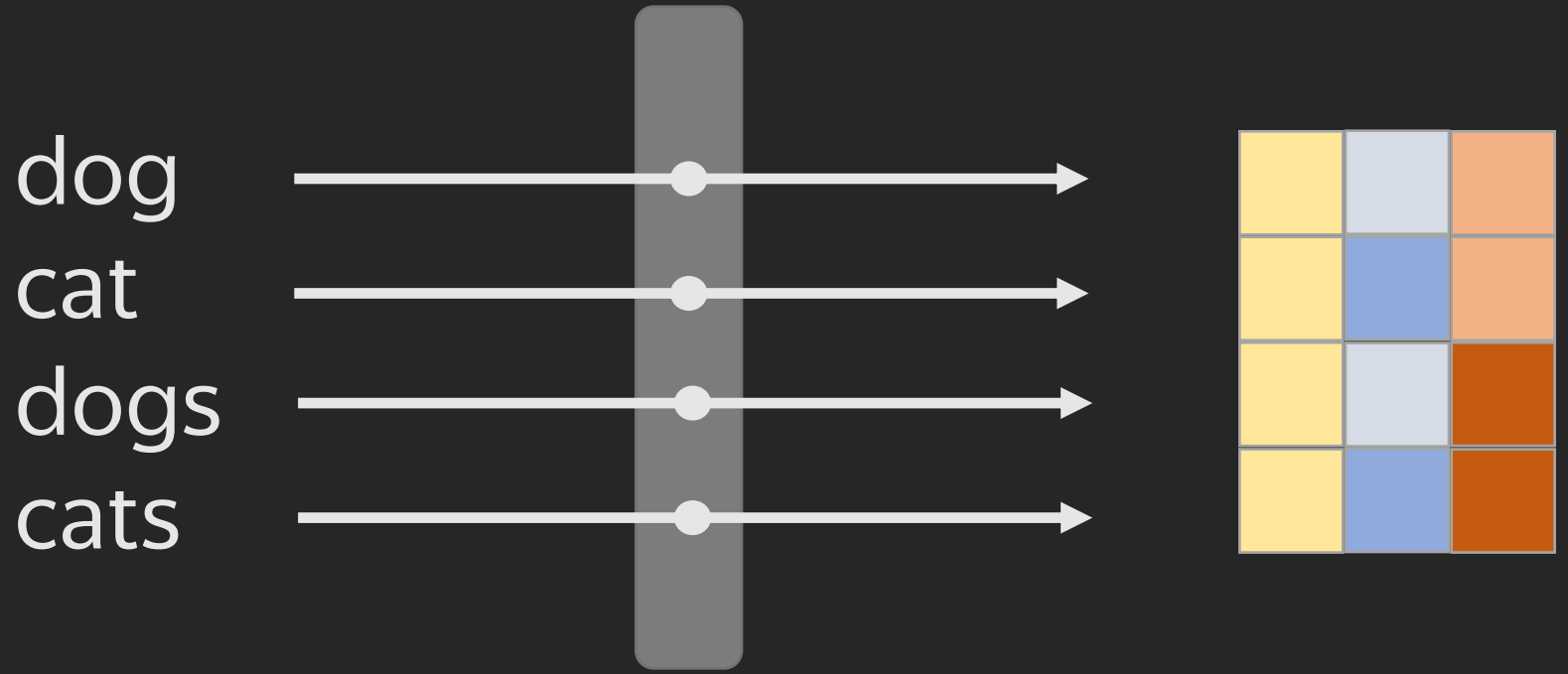

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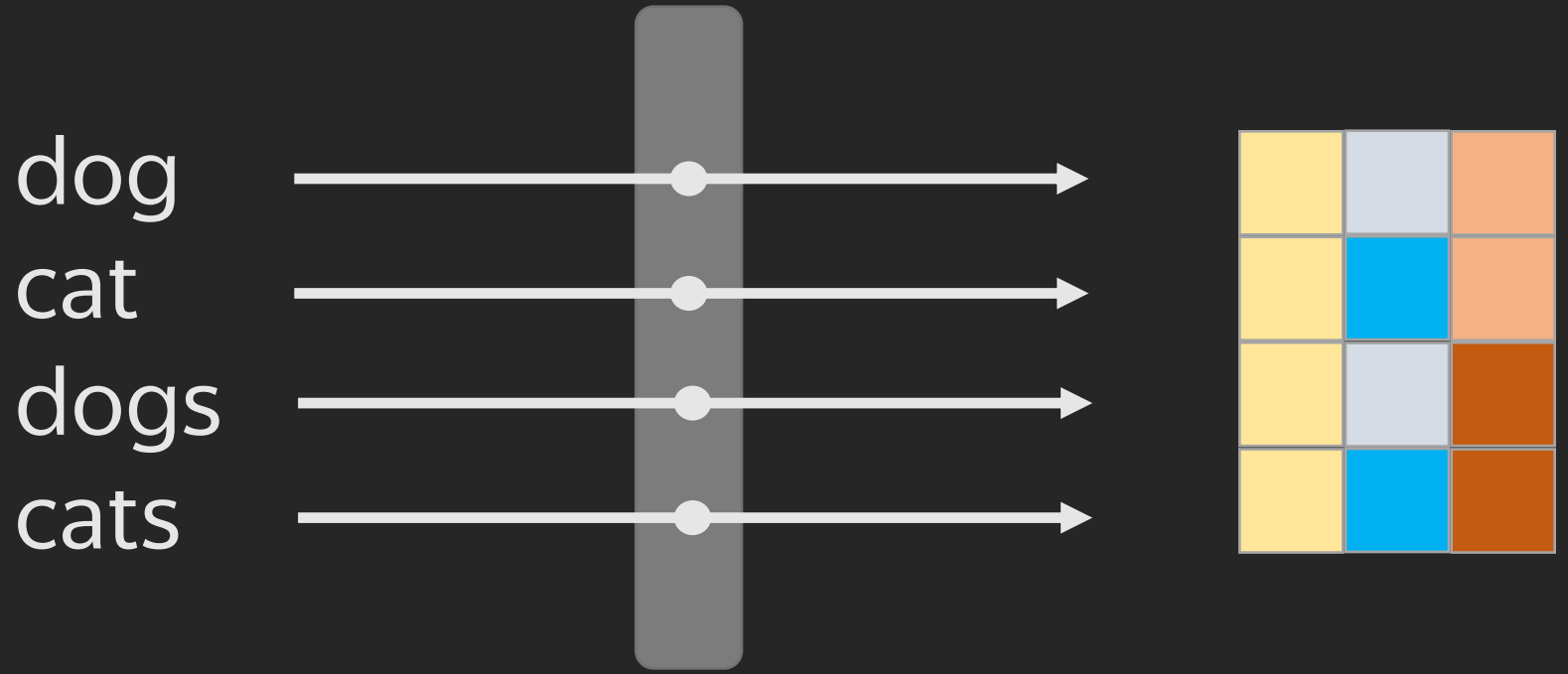

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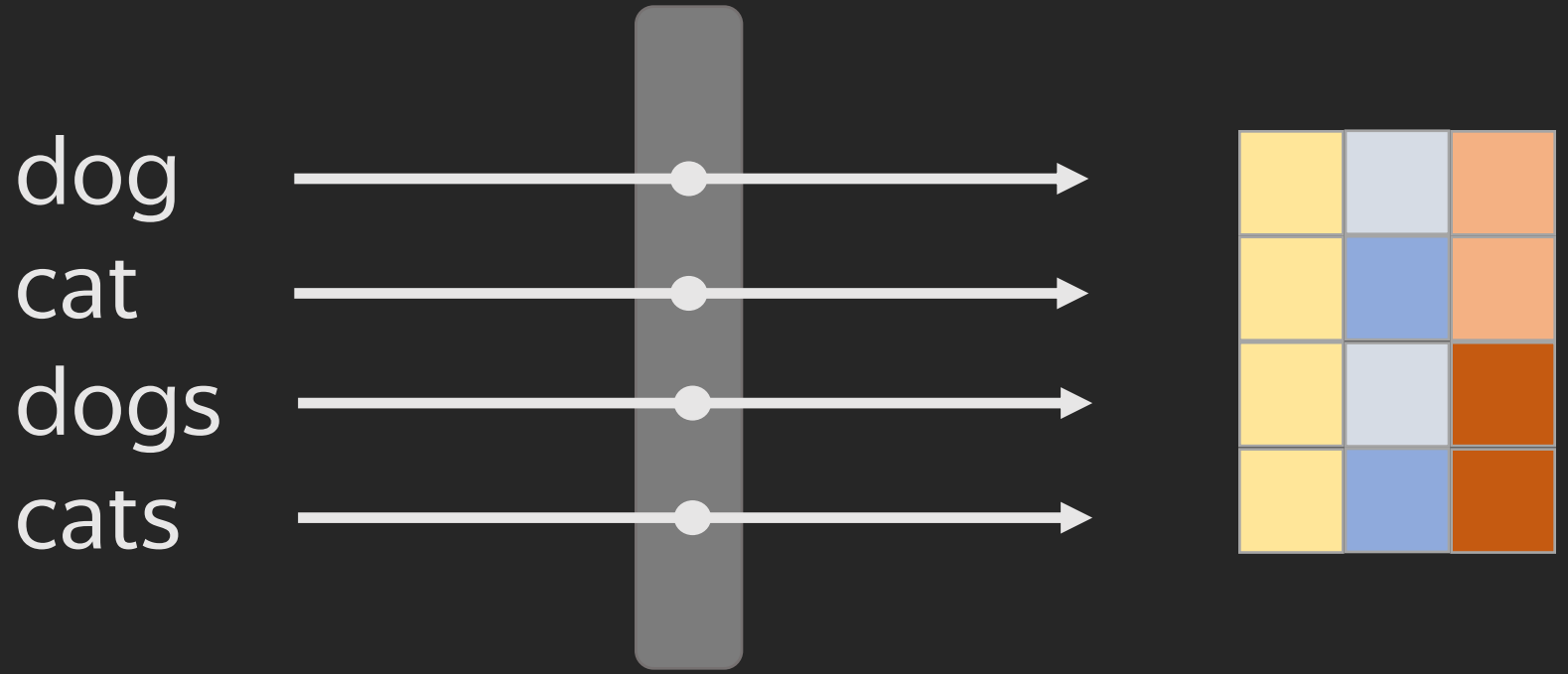

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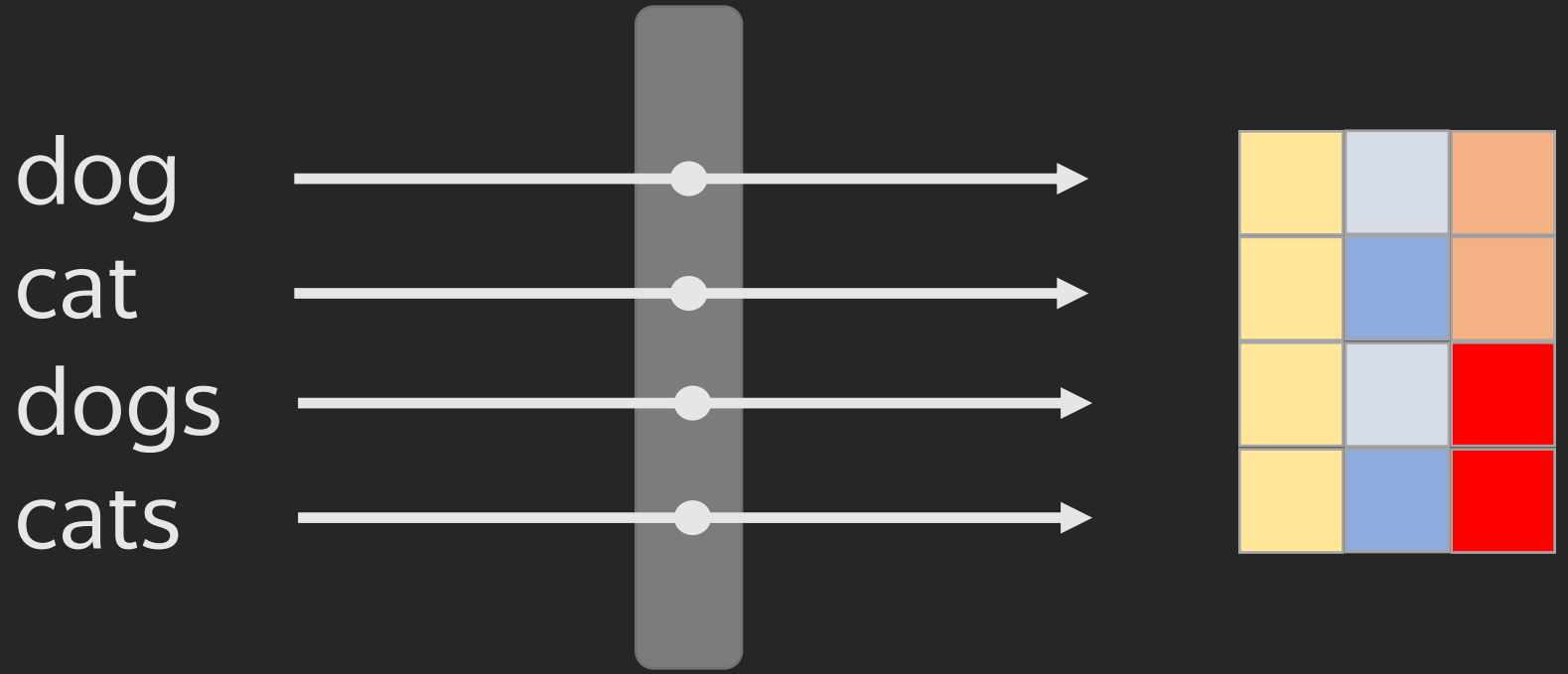

Independence Assumptions

- Chain-rule factorization (no explicit independence assumptions)

$$Pr(e|f) = \prod_{i=1}^{I} Pr(e_i|f,\ e_{<i}).$$

Conditional language model

Conditional language model

- Much more fluent output

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Source: The animal didn’t cross the street because it was too tired

Conditional language model

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PBMT: Животное не пересечь улицу потому, что он слишком устал

Conditional language model

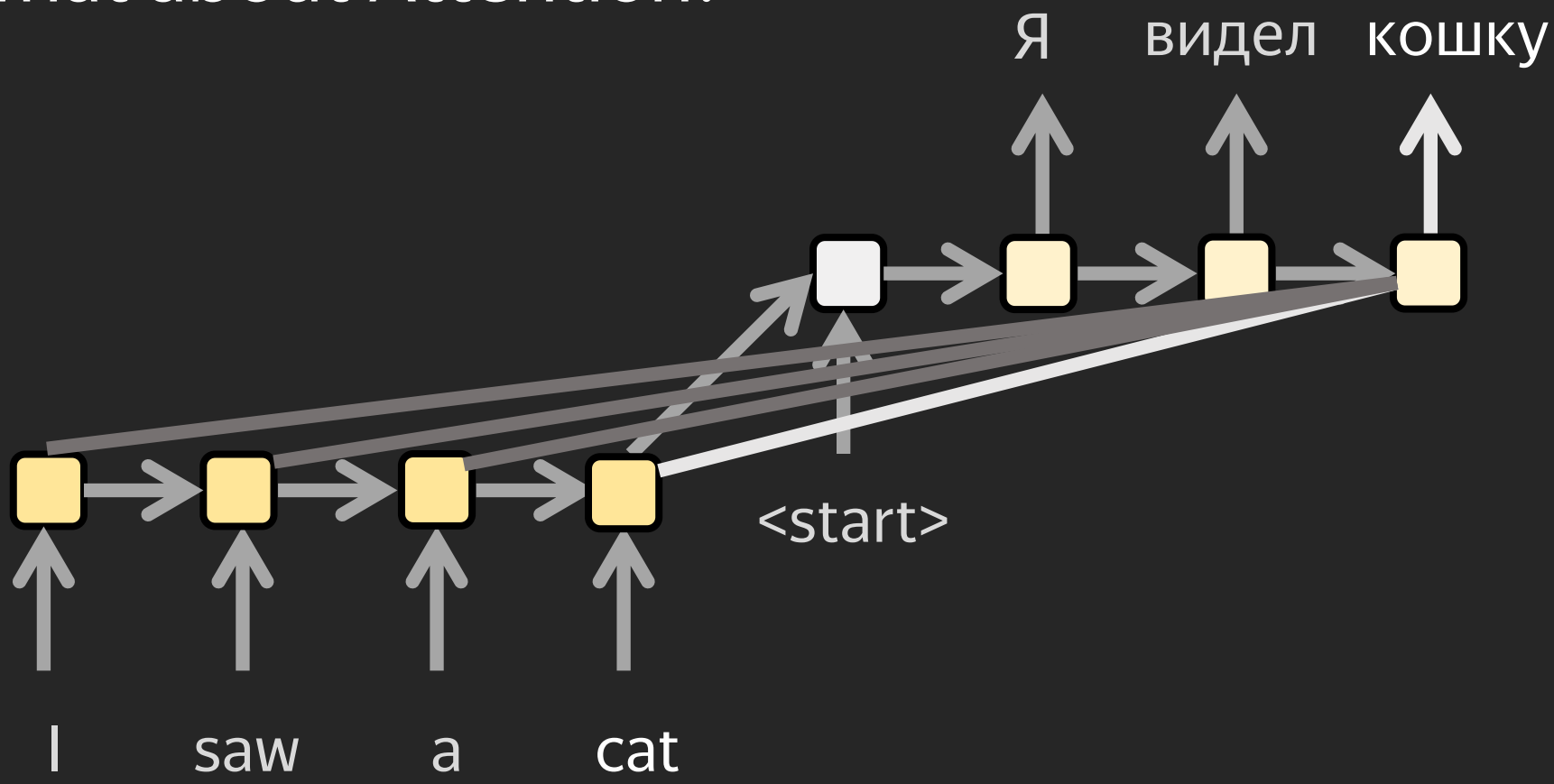
- Much more fluent output

Source: The animal didn't cross the street because it was too tired

PBMT: Животное не пересечь улицу потому, что он слишком устал

NMT: Животное не перешло улицу потому, что оно было слишком уставшим

What about Attention?



Attention vs. Independence

- Attention is a useful inductive bias

Attention vs. Independence

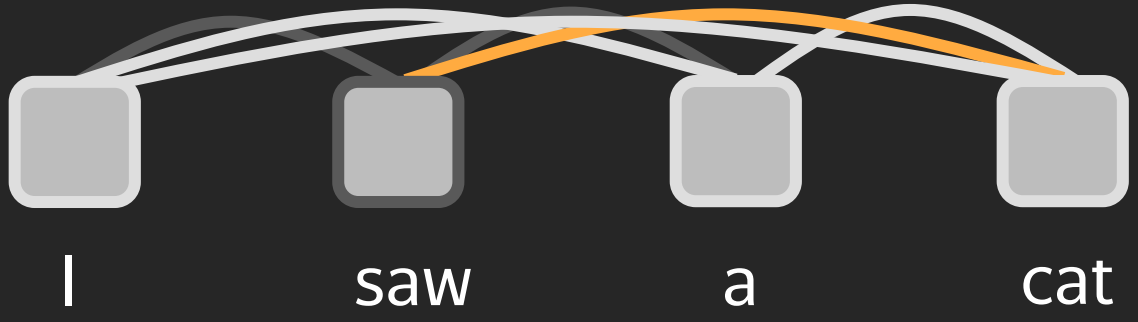
- Attention is a useful inductive bias
- Solves problem of constant capacity in sequence model

Attention vs. Independence

- Attention is a useful inductive bias
- Solves problem of constant capacity in sequence model
- Helps the model decompose the translation process

Multi-Head Self-Attention

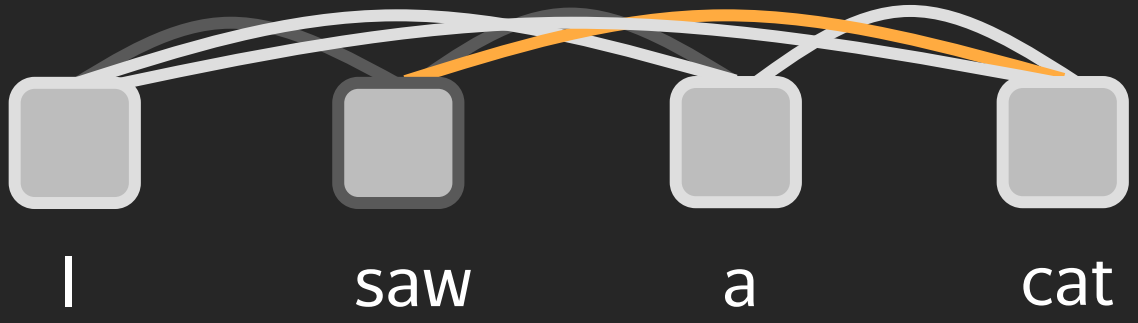
Attention can only really look at **one place** at a time



Multi-Head Self-Attention

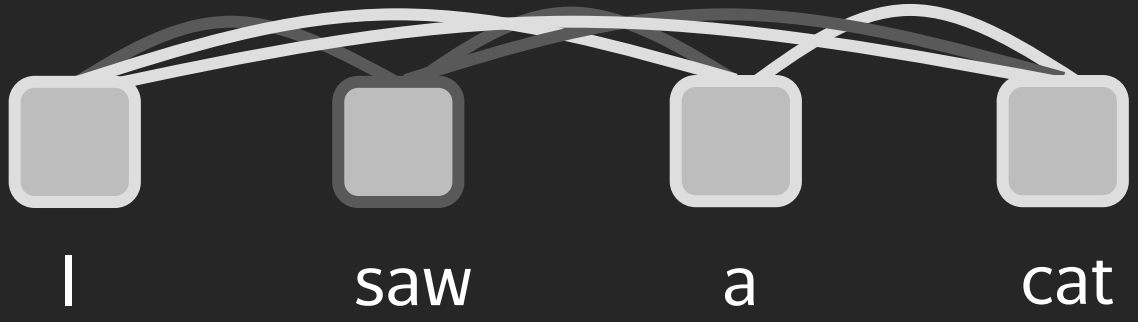
Attention can only really look at **one place** at a time

Attention pulls in information **uniformly** from all dimensions



Multi-Head Self-Attention

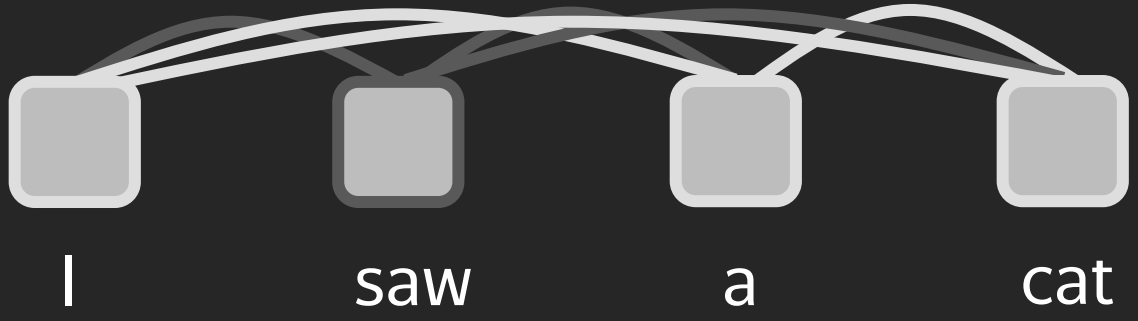
Compute attention in parallel using **different projections**



Multi-Head Self-Attention

Compute attention in parallel using different projections

$$Q_1 = xW_1^Q \qquad K_1 = xW_1^K \qquad V_1 = xW_1^V$$



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I	saw	a	cat
0.1	0.0	0.2	0.7

Multi-Head Self-Attention

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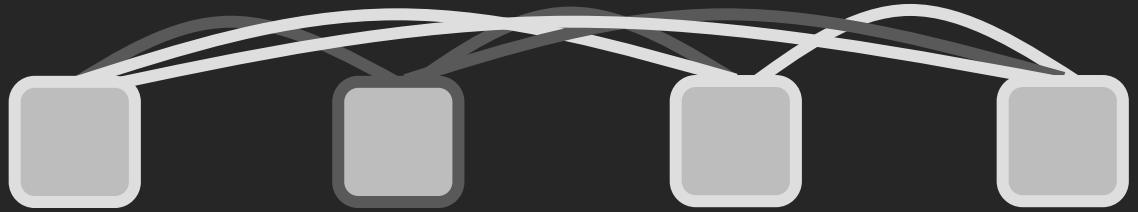

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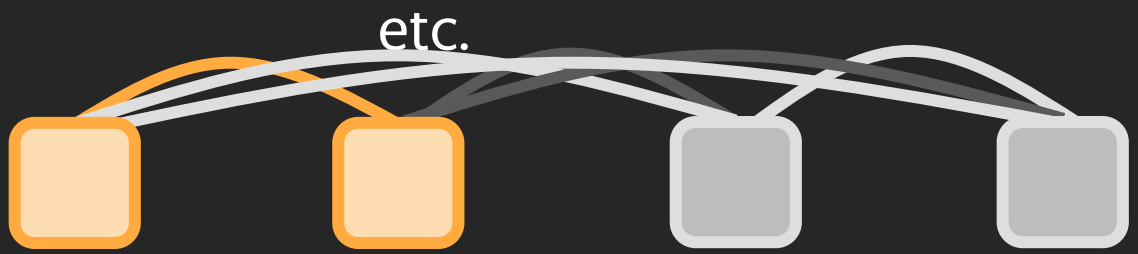

I	saw	a	cat	
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0.8	0.1	0.1	0.0	etc.

What can multi-head attention do?

- Each transformation can look at **different positions**

What can multi-head attention do?

- Each transformation can look at **different positions**
- Each transformation can focus on **different dimensions**

What does multi-head attention solve?

Она занимается **новым** проектом

- Gender and number agreement
- Case government

Monolingual data in NMT

Monolingual data in NMT

- Not immediately clear how to use it in a direct model of $Pr(e|f)$

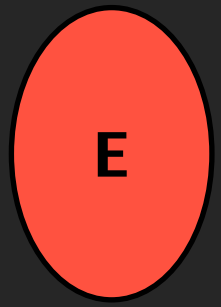
Monolingual data in NMT

- Not immediately clear how to use it in a direct model of $Pr(e|f)$
- Backtranslation most successful approach

Backtranslation in NMT

Backtranslation in NMT

Target language corpus



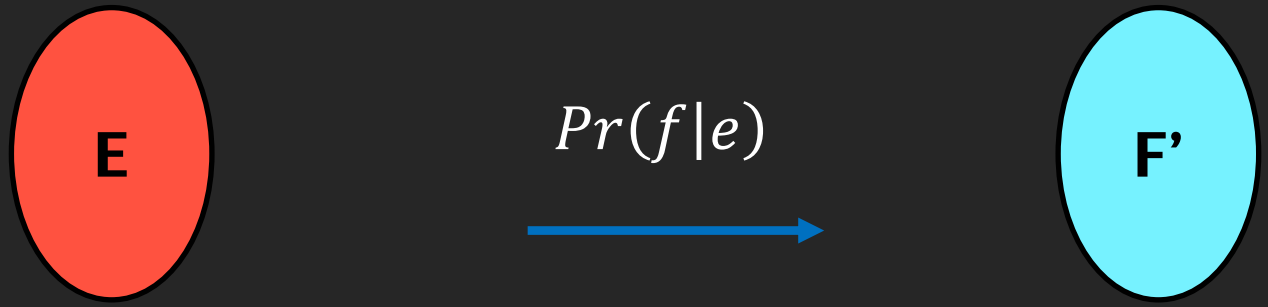
Backtranslation in NMT

Target language corpus

Backtranslation in NMT

Target language corpus

Synthetic source corpus



Backtranslation in NMT

Target language corpus

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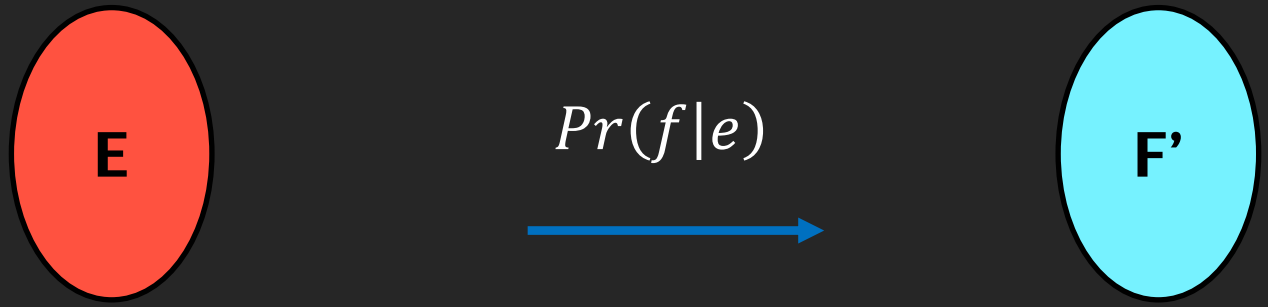

- Train $Pr(e|f)$ on synthetic parallel corpus (E, F')

Backtranslation in NMT

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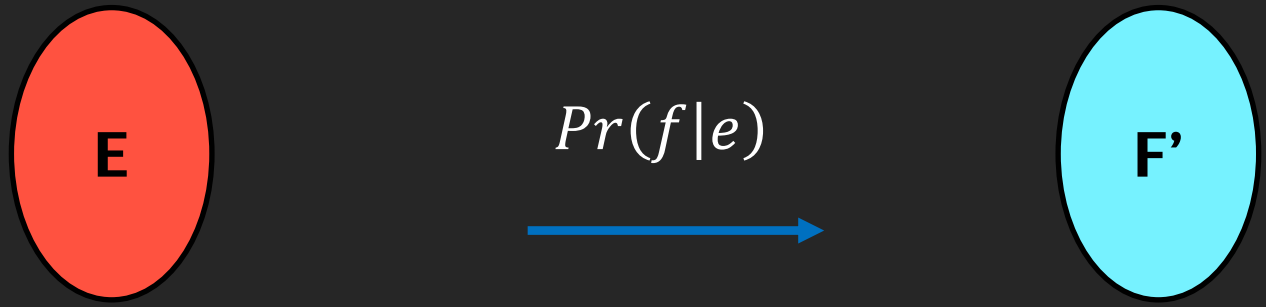

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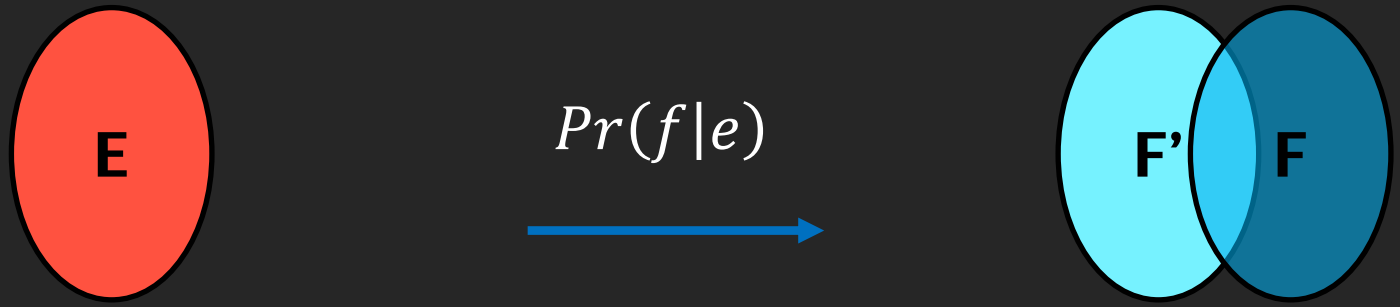

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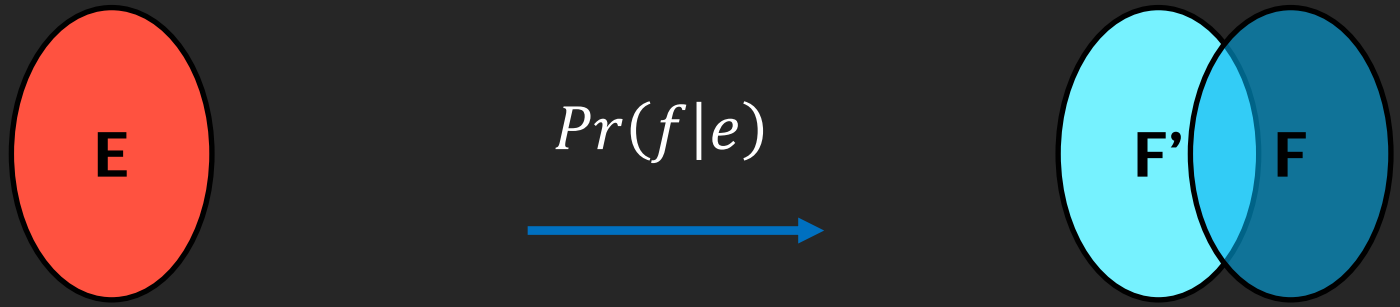

- Train $Pr(e|f)$ on synthetic parallel corpus (E, F')
- Errors in synthetic source corpus F' don't affect $Pr(e|f)$ for $f \in F$
- Sampling from $Pr(f|e)$ works better than greedy or beam search

Challenges for Neural Machine Translation

Hallucinations

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- Conditional language models can have minds of their own

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Hallucinations

- Conditional language models can have minds of their own
- No guarantee that all words are translated
- Deep neural models are very good are memorizing random noise
- Increasing NMT beam size beyond ~10 often hurts

Hallucinations - Detached

Source: das kann man nur feststellen , wenn die kontrollen mit einer großen intensität durchgeführt werden .

Correct: this can only be detected if controls undertaken are more rigorous .

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Source: das kann man nur feststellen , wenn die kontrollen mit einer großen intensität durchgeführt werden .

Correct: this can only be detected if controls undertaken are more rigorous .

Actual: blood alone moves the wheel of history , i say to you and you will understand , it is a privilege to fight .

Hallucinations - Oscillatory

Source: 1995 das produktionsvolumen von 30 millionen pizzen wird erreicht.

Correct: 1995 the production reached 30 million pizzas.

Hallucinations - Oscillatory

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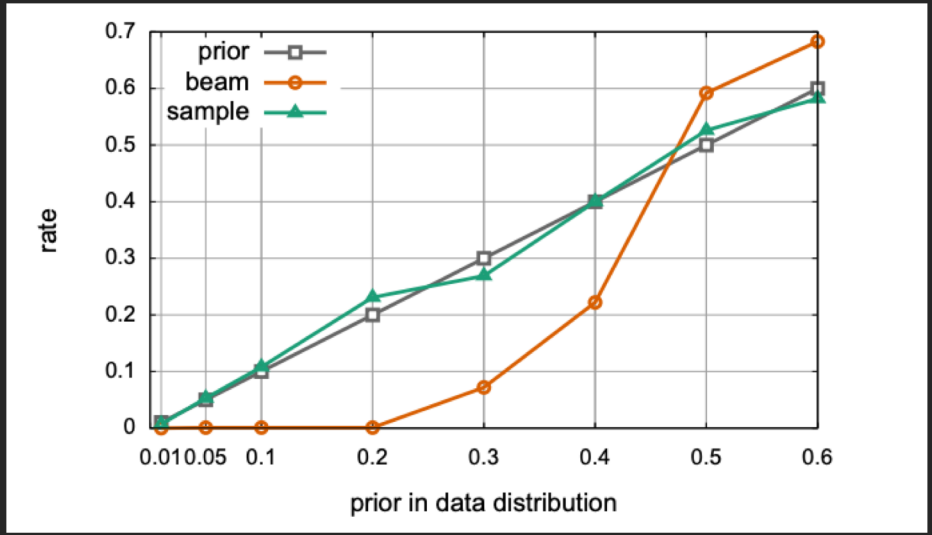
Correct: 1995 the production reached 30 million pizzas.

Actual: the us , for example , has been in the past two decades , but has been in the same position as the us , and has been in the united states .

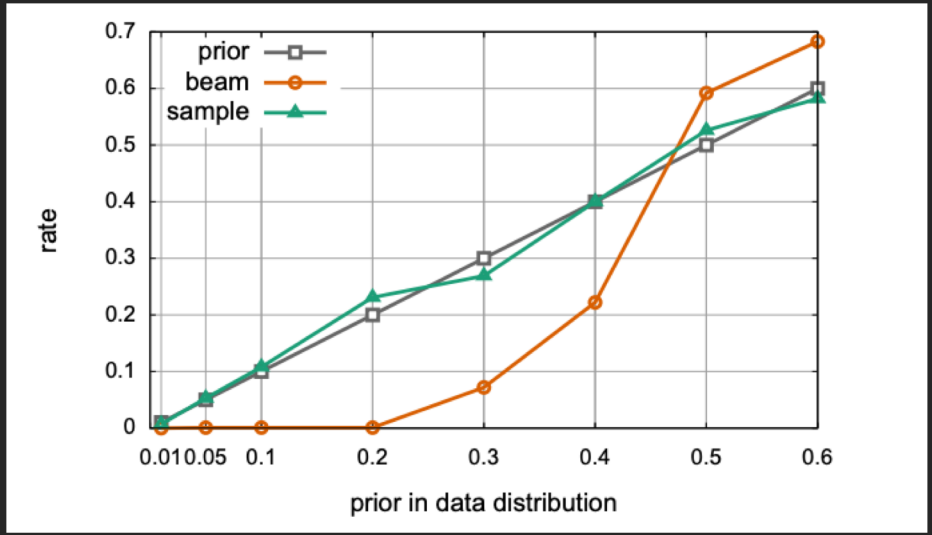
Problems with Beam Search

- Prefers very frequent tokens



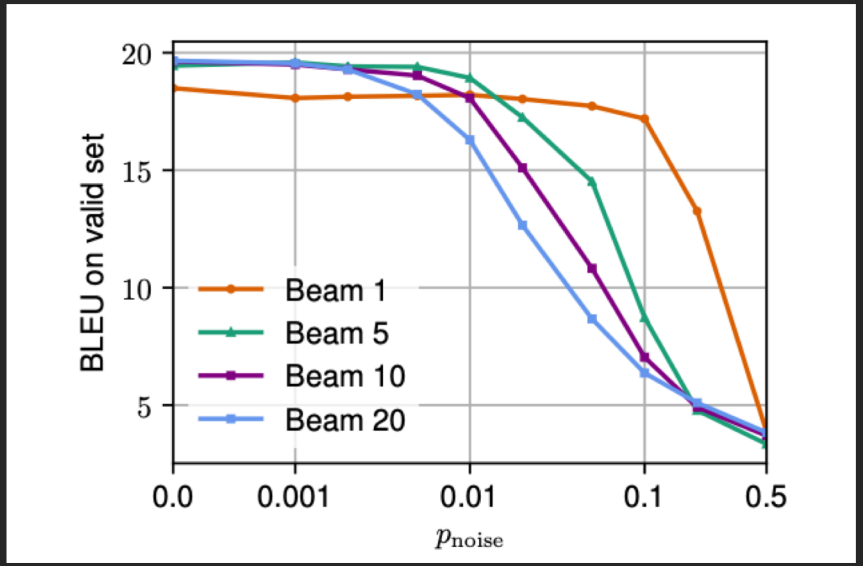
Problems with Beam Search

- Prefers very frequent tokens
- Doesn’t produce diverse hypotheses



Beam size and Noise

- Increasing beam-size hurts even more when training data is noisy (and it is)



Plausible Cause 1: Exposure Bias

Exposure Bias

- Training uses reference as prefix

Exposure Bias

- Training uses reference as prefix
- Inference uses generated result

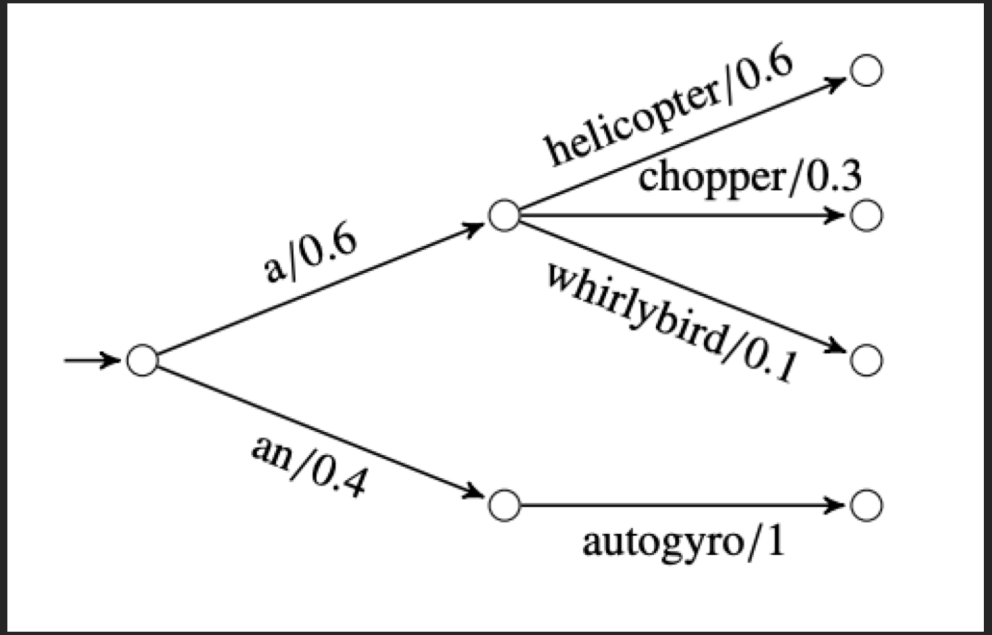
Exposure Bias

- Training uses reference as prefix
- Inference uses generated result
- Model learns to rely too heavily on prefix and then ignore the source

Plausible Cause 2: Label Bias

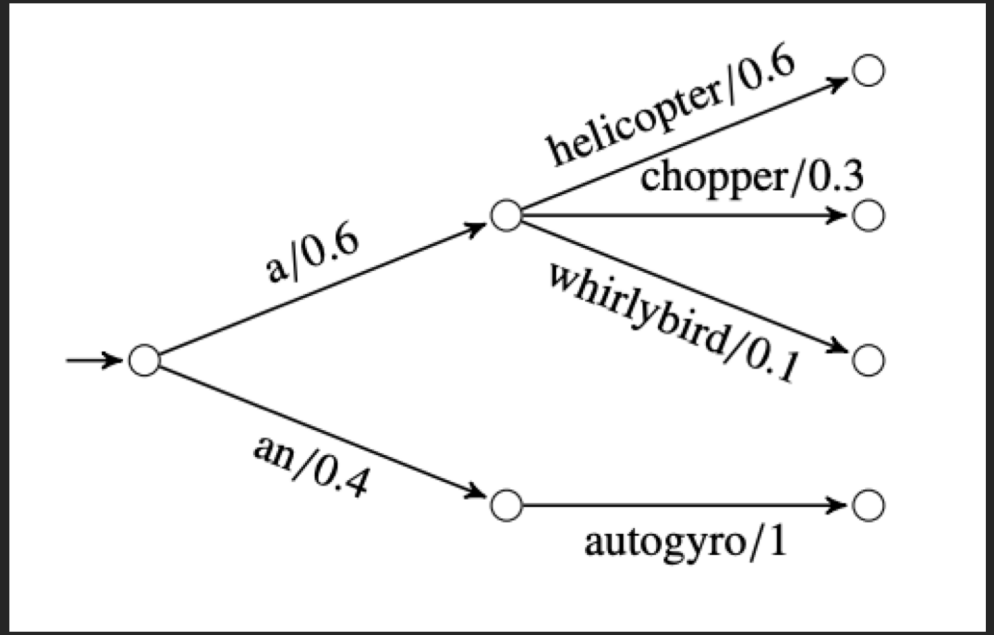
Label Bias

- Example toy word-to-word translation problem



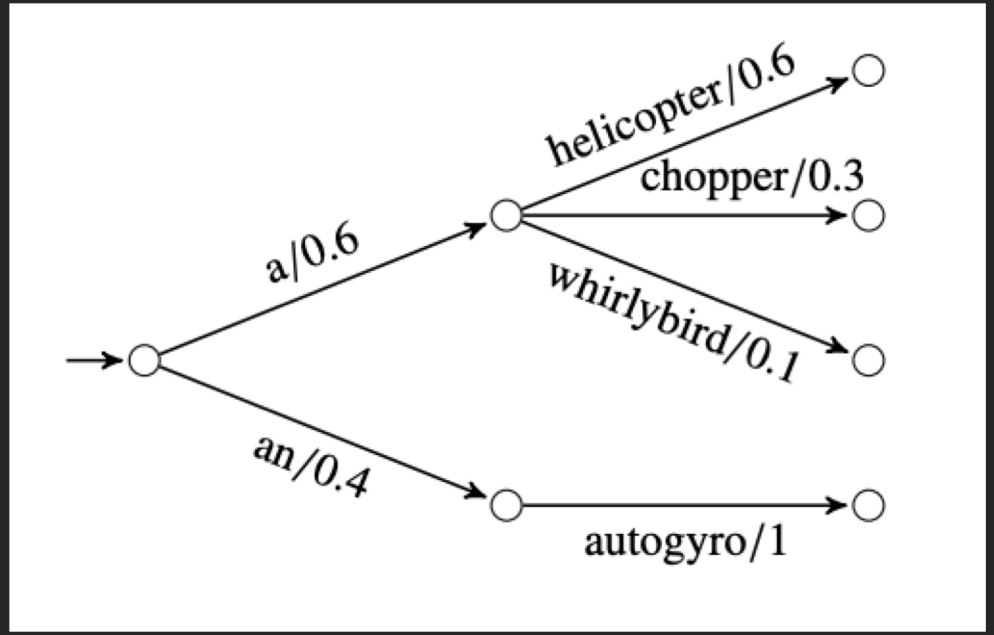
Label Bias

- Example toy word-to-word translation problem
- Locally normalized models can be biased towards states with low-entropy successors



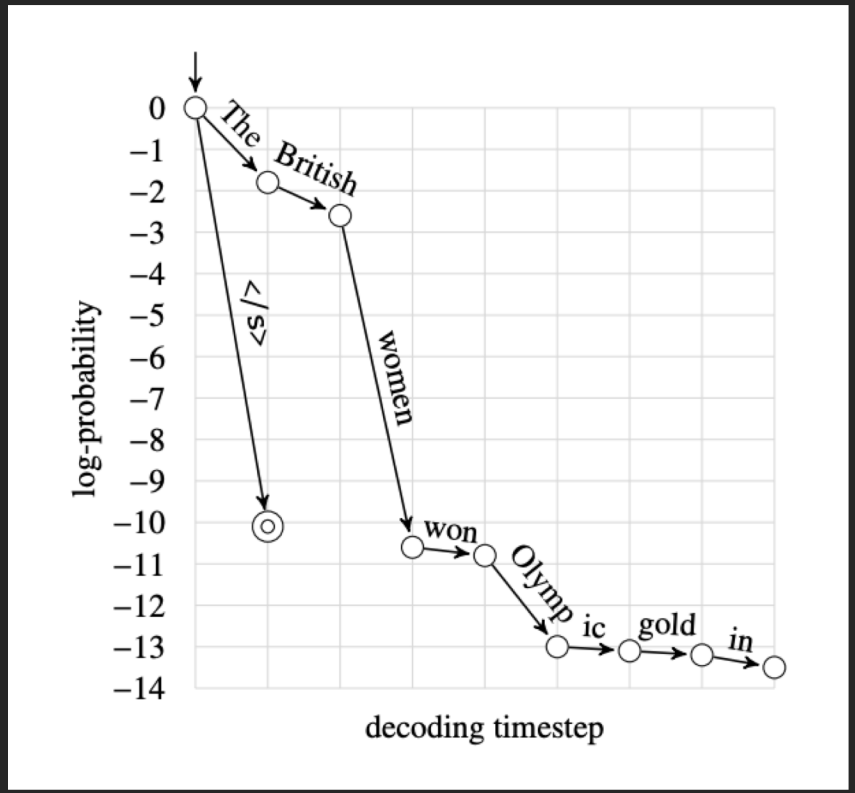
Label Bias

- Example toy word-to-word translation problem
- Locally normalized models can be biased towards states with low-entropy successors
- Current state *explains away* observations



Length Bias (extreme Label Bias)

- Empty hypothesis receives globally best score for >50% of standard test set (WMT15)



Neural Noisy Channel (Yu et al., 2017)

Neural Noisy Channel

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$$e^* = argmax_e \; Pr(e|f)$$
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Neural Noisy Channel

- Problems?

$$e^* = argmax_e \; Pr(e|f)$$
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Neural Noisy Channel

- Computationally challenging to use $Pr(f|e)$ model at inference time

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Neural Noisy Channel

- Computationally challenging to use $Pr(f|e)$ model at inference time
- Sample from proposal distribution then rescore with $Pr(f|e)$
- Enables significant improvements with larger beam sizes

$$e^* = argmax_e \; Pr(e|f)$$
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Document Context

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- NMT has gone a long way to approaching the *Bayes error* on the sentence translation problem
- Humans usually consume and translate text in context
- Current NMT doesn’t handle context well

Some things we can’t translate without more context

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- Anaphora

“I saw it yesterday”  {он, она, оно, они}

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  “I saw it yesterday” → {он, она, оно, они}

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Some things we can’t translate without more context

- Anaphora

  “I saw it yesterday” → {он, она, оно, они}

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- Consistency

  “Apple” → {Apple, компания Apple, Яблоко}

Document Level NMT

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- Parallel document data is not very abundant

Document Level NMT

- Parallel document data is not very abundant
- Solution: source-channel decomposition

Noisy Channel Document NMT

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- Train a source model on monolingual documents

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- Train a channel model on parallel sentence corpora

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Noisy Channel Document NMT

- Train a source model on monolingual documents
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$$
\begin{aligned}
e^* &= argmax_e \; Pr(e|f) \\
&= argmax_e \; Pr(e) \, Pr(f|e) \\
&\approx argmax_e \; Pr(e) \prod_{i=1}^{I} Pr(f_i|e_i)
\end{aligned}
$$

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\end{aligned}
$$

Noisy Channel Document NMT

- Train a source model on monolingual documents
- Train a channel model on parallel sentence corpora
- Independence assumptions in channel okay (remember why?)

$$
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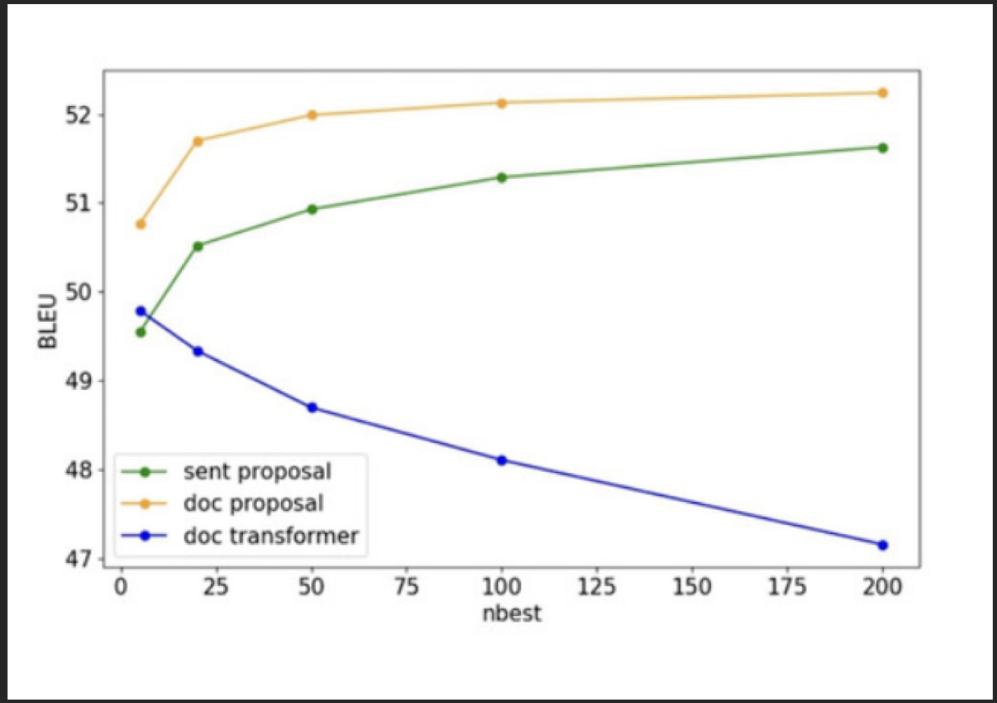
\end{aligned}
$$

Noisy Channel Document NMT

- Generate n-best list with direct model
- Re-rank with noisy channel



Noisy Channel Document NMT

- Increasing beam size no longer hurts