Real-Time Translation
Learning to Decode

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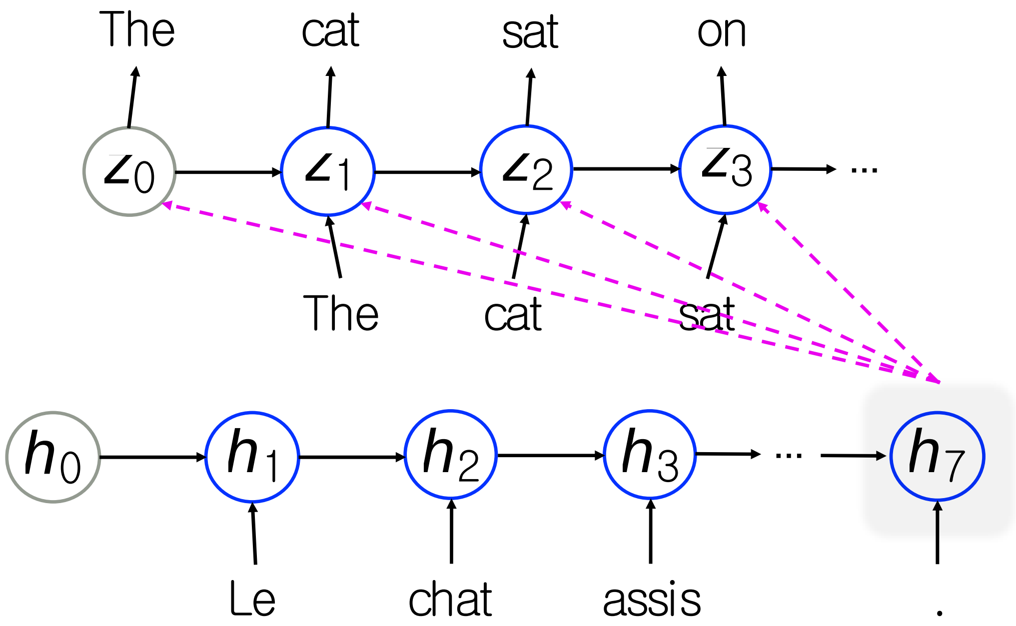
Jiatao Gu, Victor Li, Graham Neubig, Kyunghyun Cho.
Learning to translate in real-time with neural machine translation. EACL'17.

Decoding
from a recurrent language model

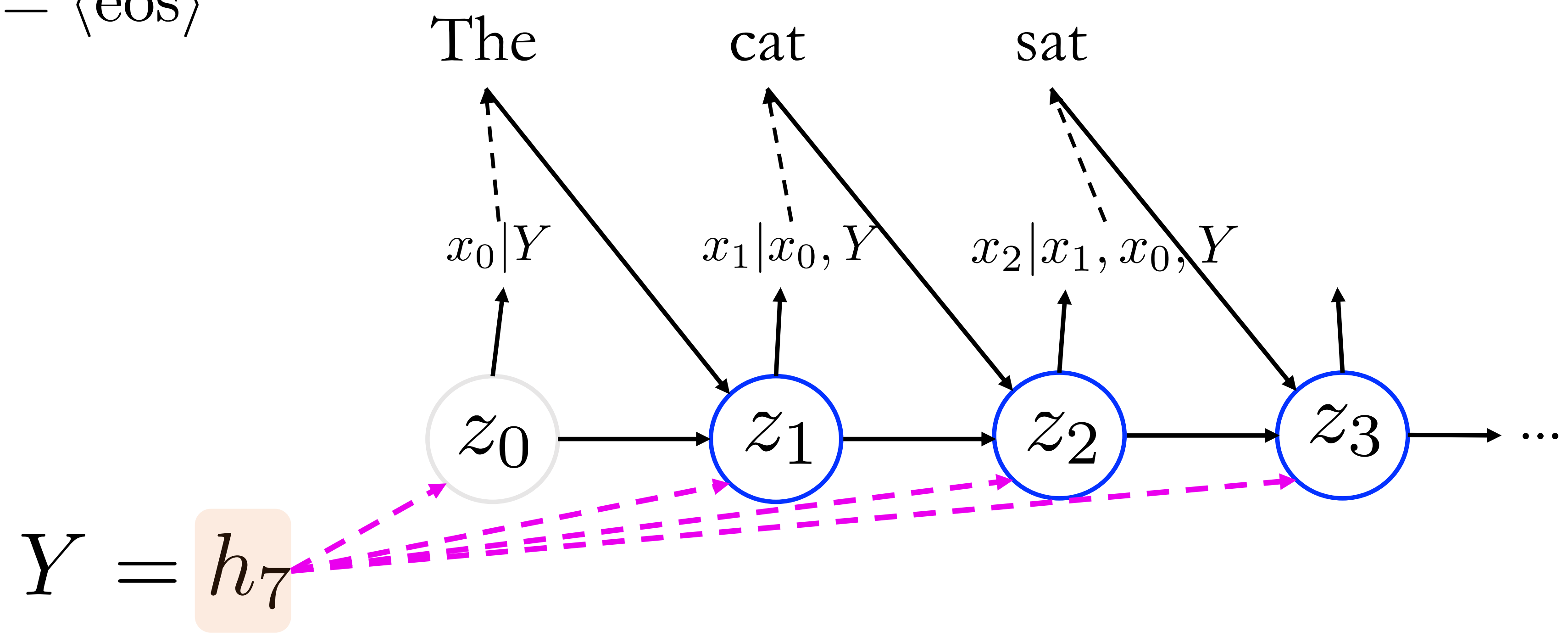
Decoding (0) – Exhaustive Search

- Simple and exact decoding algorithm
- Score each and every possible translation
- Pick the best one



Decoding (1) – Ancestral Sampling

- Efficient, unbiased sampling
- One symbol at a time from $\tilde{x}_t \sim x_t | x_{t-1}, \ldots, x_1, Y$
- Until $\tilde{x}_t = \langle \text{eos} \rangle$



Decoding (1) – Ancestral Sampling

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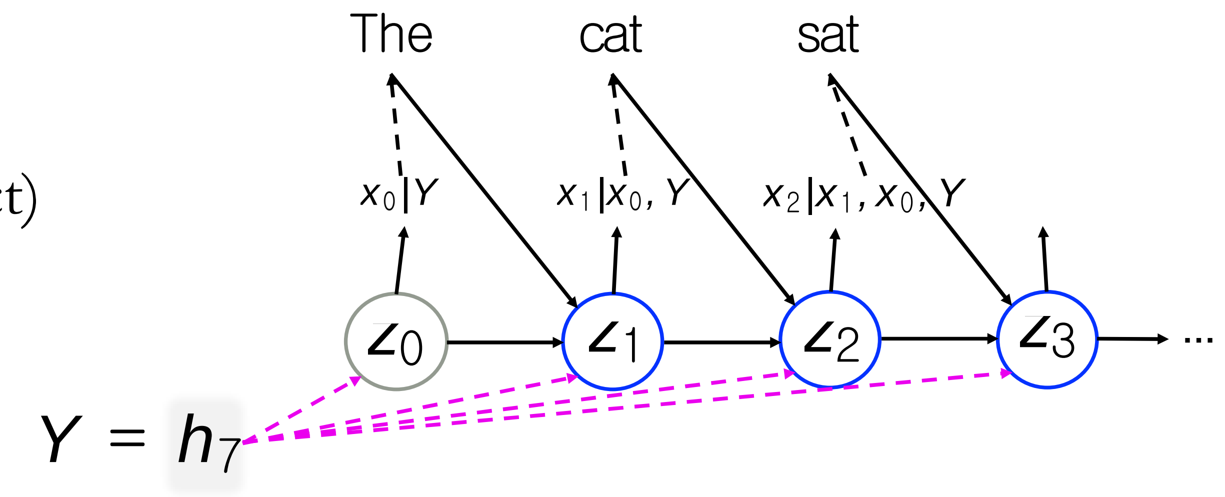
- One symbol at a time from $\tilde{x}_t \sim x_t | x_{t-1}, \ldots, x_1, Y$
- Until $\tilde{x}_t = \langle \text{eos} \rangle$
- Repeat this procedure for N times: $\left\{ \tilde{X}^1, \ldots, \tilde{X}^N \right\}$
- Choose $\arg\max_{\tilde{X}^n} \log p(\tilde{X}^n | Y)$
- Pros:
  1. Unbiased (asymptotically exact)
- Cons:
  1. High variance
  2. Pretty inefficient



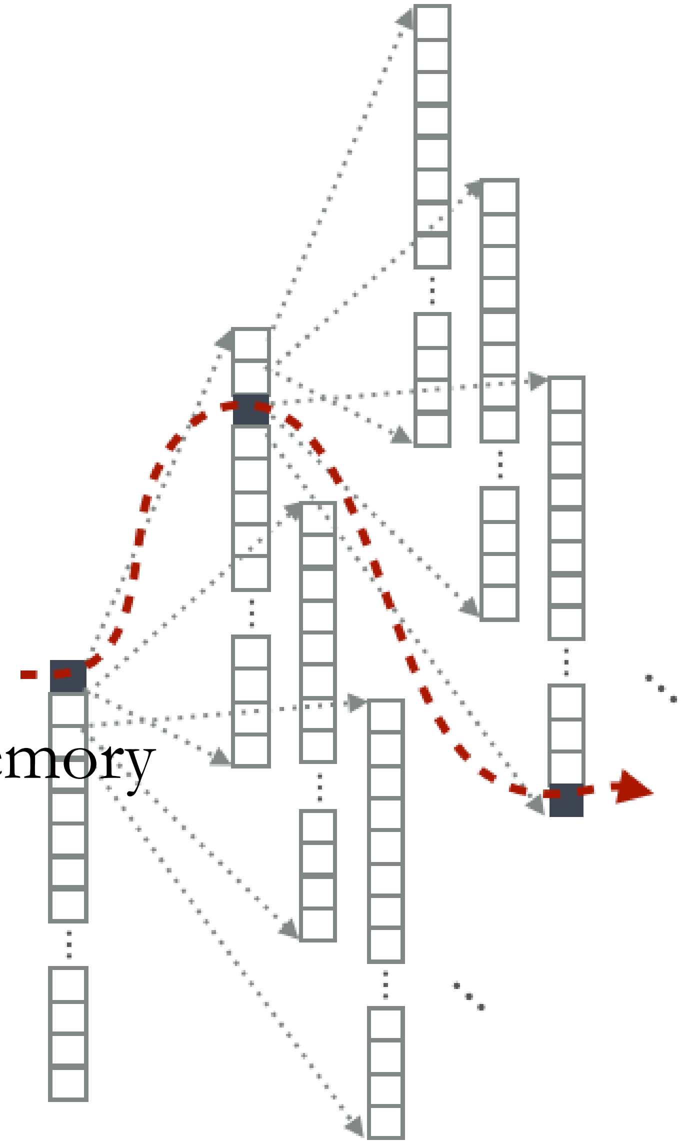
Decoding (2) – Greedy Search

- Efficient, but heavily suboptimal search
- Pick the most likely symbol each time

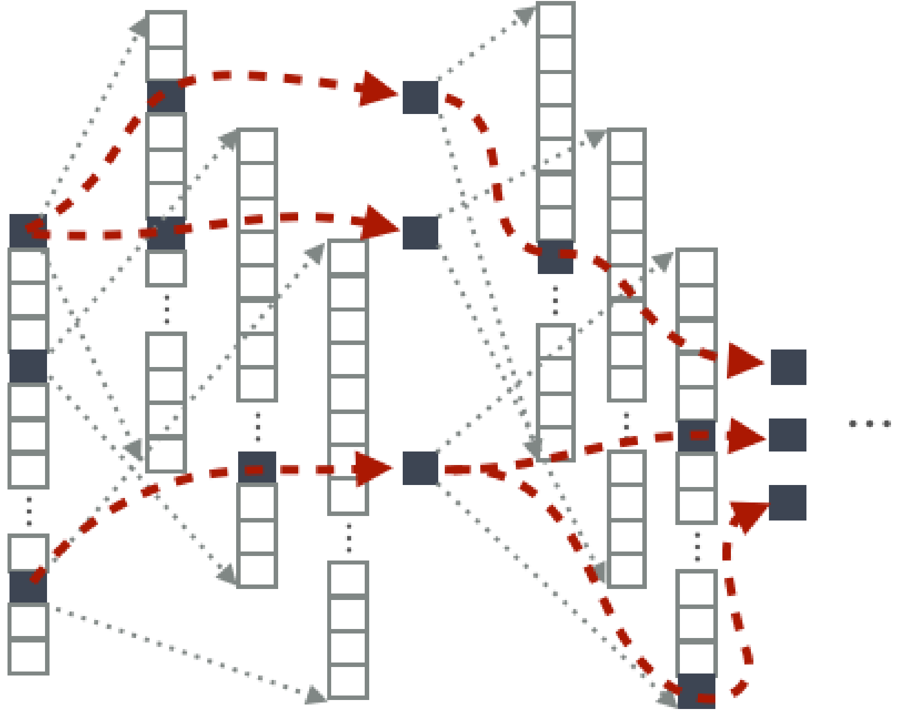
$$\tilde{x}_t = \arg\max_x \log p(x|x_{<t}, Y)$$

- Until $\tilde{x}_t = \langle \text{eos} \rangle$

- Pros:
  1. Super-efficient: both computation and memory
- Cons:
  1. Heavily suboptimal



Decoding (3) – Beam Search



- Pretty, but not quite efficient
- Maintain K hypotheses at a time

$$\mathcal{H}_{t-1} = \left\{(\tilde{x}_1^1, \tilde{x}_2^1, \ldots, \tilde{x}_{t-1}^1), (\tilde{x}_1^2, \tilde{x}_2^2, \ldots, \tilde{x}_{t-1}^2), \ldots, (\tilde{x}_1^K, \tilde{x}_2^K, \ldots, \tilde{x}_{t-1}^K)\right\}$$

- Expand each hypothesis

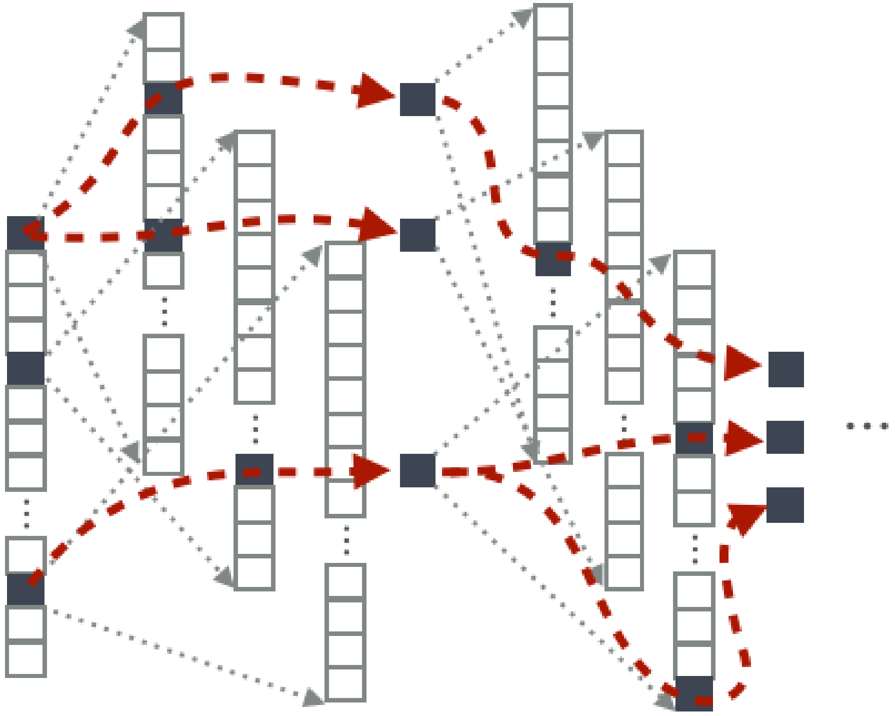
$$\mathcal{H}_t^k = \left\{(\tilde{x}_1^k, \tilde{x}_2^k, \ldots, \tilde{x}_{t-1}^k, v_1), (\tilde{x}_1^k, \tilde{x}_2^k, \ldots, \tilde{x}_{t-1}^k, v_2), \ldots, (\tilde{x}_1^k, \tilde{x}_2^k, \ldots, \tilde{x}_{t-1}^k, v_{|V|})\right\}$$

- Pick top-K hypotheses from the union $\mathcal{H}_t = \cup_{k=1}^K \mathcal{B}_k,$ where

$$\mathcal{B}_k = \arg\max_{\tilde{X} \in \mathcal{A}_k} \log p(\tilde{X}|Y), \ \mathcal{A}_k = \mathcal{A}_{k-1} - \mathcal{B}_{k-1}, \text{ and } \mathcal{A}_1 = \cup_{k'=1}^K \mathcal{H}_t^{k'}.$$

Decoding (3) – Beam Search

- Asymptotically exact, as $K \to \infty$
- Not necessarily monotonic improvement w.r.t. K
- K is selected to maximize the translation quality on a **validation** set.



Decoding

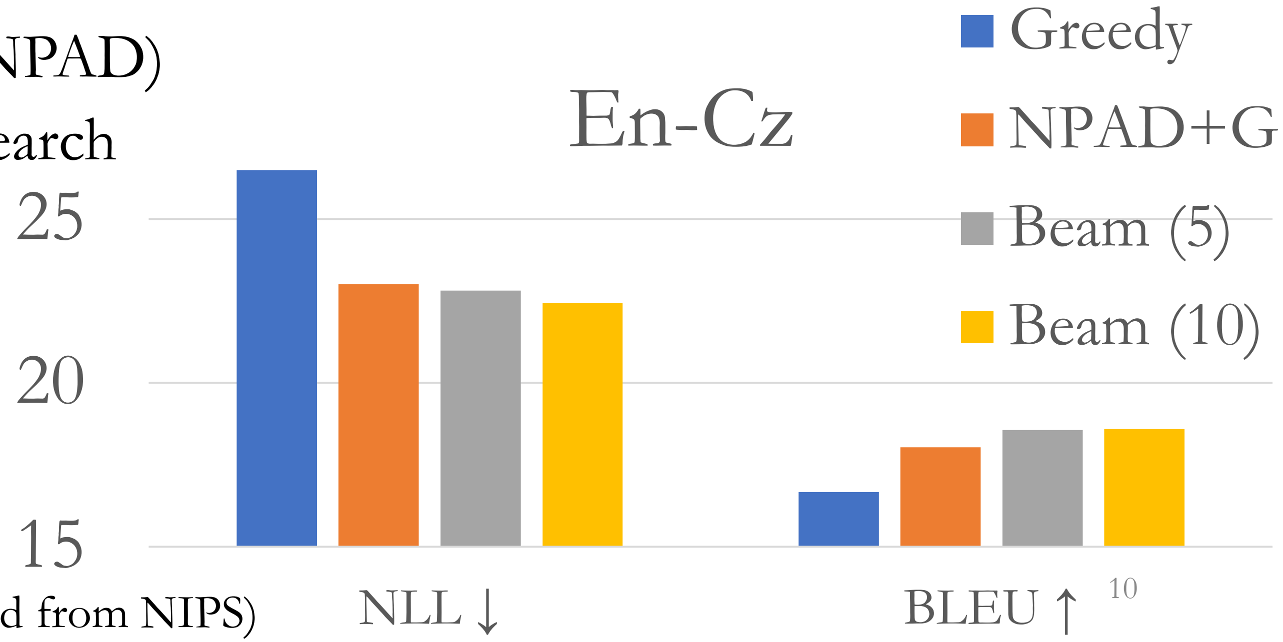
- English to Czech Translation: 12m training sentence pairs

Strategy	# Chains	Valid NLL↓	Valid BLEU↑	Test-1 NLL↓	Test-1 BLEU↑
Sto. Sampling	50	22.9818	15.64	26.2536	16.76
Greedy	-	27.879	15.5	26.4928	16.66
Beam	5	20.1842	17.03	22.8106	18.56
Beam	10	19.9173	17.13	22.4392	18.59

Cho (2016)

Inference is difficult and expensive (1)

- State space grows exponentially w.r.t. the (max) length of a sentence
  - $|V| + |V|^2 + \cdots + |V|^T$ possible sentences with $|V| \approx 10^3 \sim 10^6$ $T \approx 10 \sim 300$
  - No obvious way to reduce the search space: non-Markovian model
- Cheap, approximate search is often too approximate
  - Greedy decoding: cheap, approximate search
  - Noisy, parallel approximate decoding (NPAD)
  - Beam search: expensive, approximate search



(Cho, 2016 horribly rejected from NIPS)

Inference is difficult and expensive (2)

- *Is this what we want?*

$$\arg\max_{\theta} \sum_{t=1}^{T} \log p_{\theta}(x_t | x_{<t}, s)$$

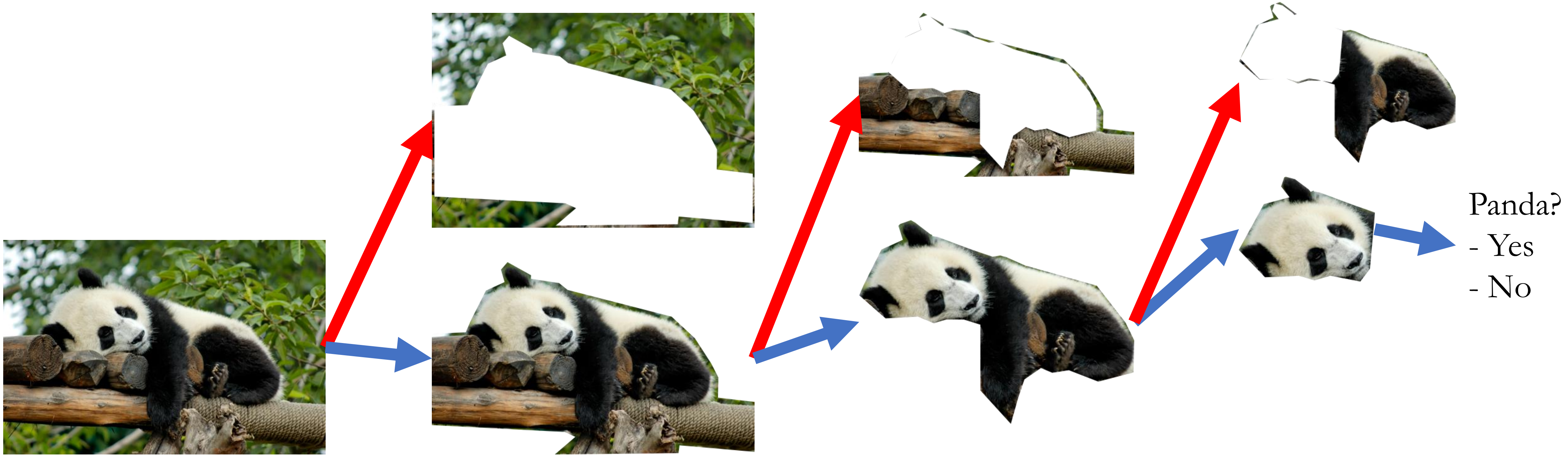
- Decoding objectives are *not known* in advance
  - MT for real-time conversation: quality ↑ vs. delay ↓
  - MT for K-12 students: quality ↑ vs. text difficulty ↓
  - On-device translation: quality ↑ vs. computational complexity ↓

- Even if so, little or no data available
  - Simultaneous interpretation: almost none with time stamps [He et al., 2016 NAACL]
  - Parallel corpora with controlled levels of difficulty: none

What can we do about it?

Learning to decode

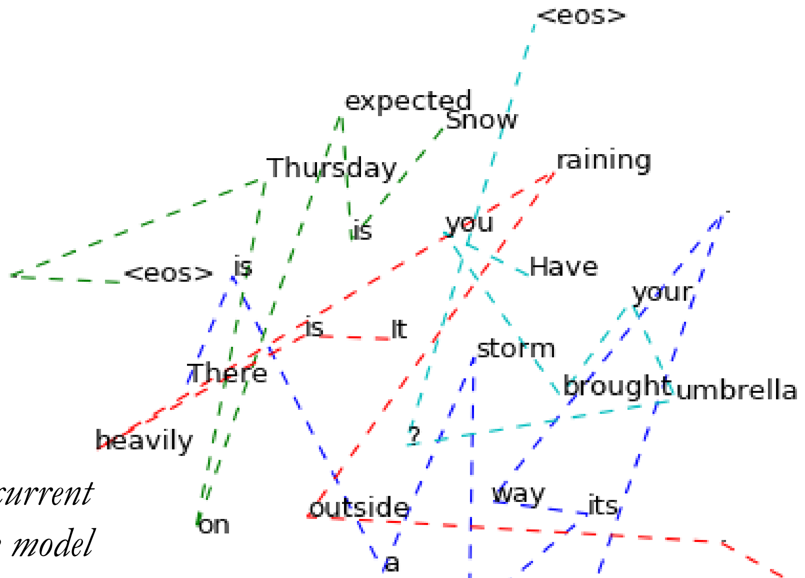
Neural network = Forgetting machine



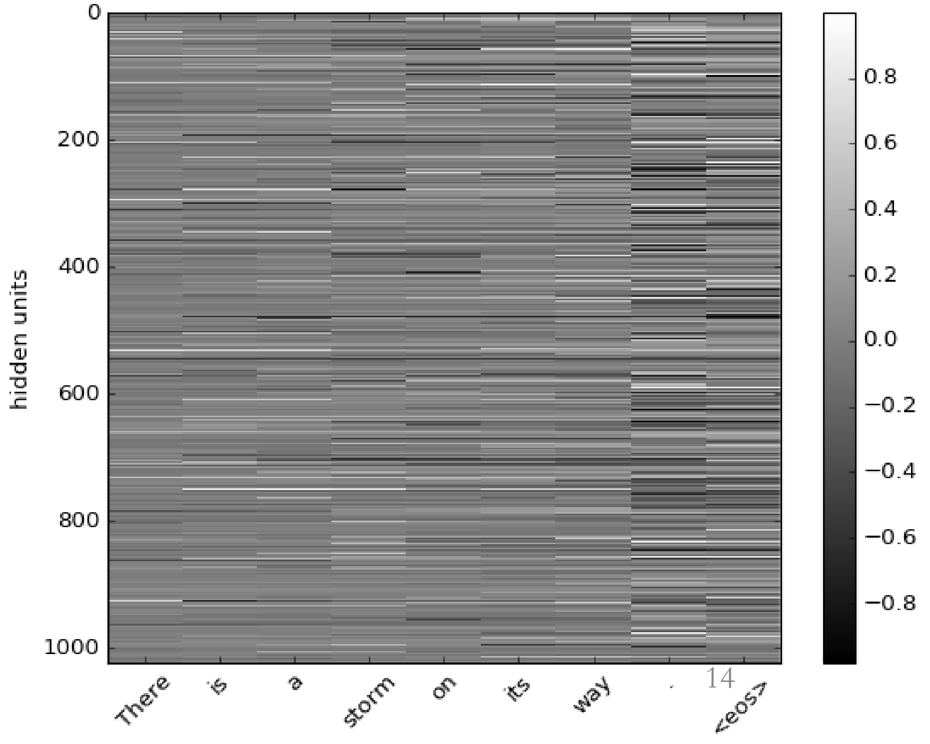
- A deep neural net iteratively disentangles relevant and irrelevant features
- Irrelevant features are discarded as information propagates
- In other words, *hidden layers contain rich info beyond the task*!

Exploiting the hidden activation

- What is captured by the hidden layers?
  - Deep Visualization: Edges/corners → textures → object parts → entire objects [Zeiler&Fergus, 2014 ECCV; Yosinski et al., 2016 DL; and many more]
  - Long-range dependency: closing brackets, agreement, … [Karpathy et al., 2015 arXiv; Tran et al., 2016 NAACL]
  - Sentiment! [Radford et al., 2017 OpenAI]
- Fairly limited understanding *especially* with text
- Why?

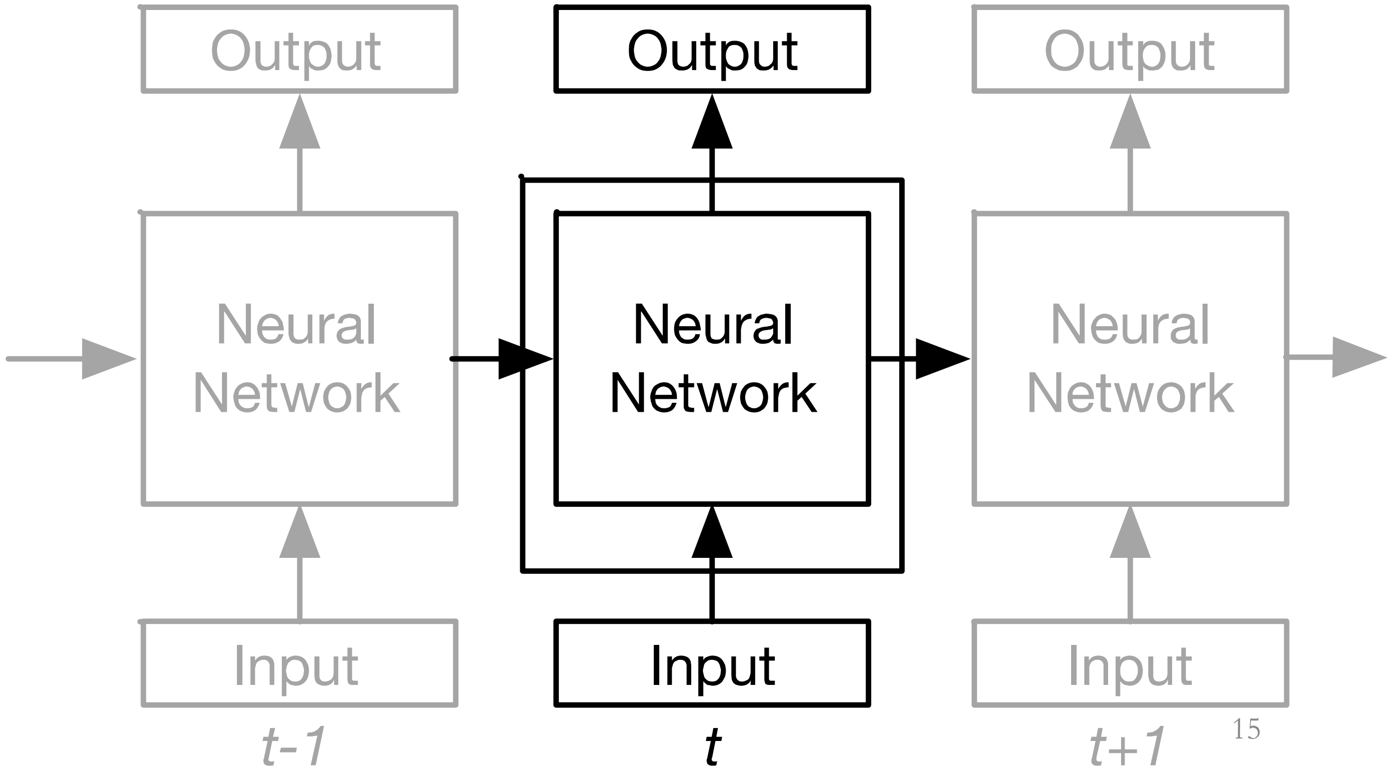


Hidden activations of a small recurrent language model



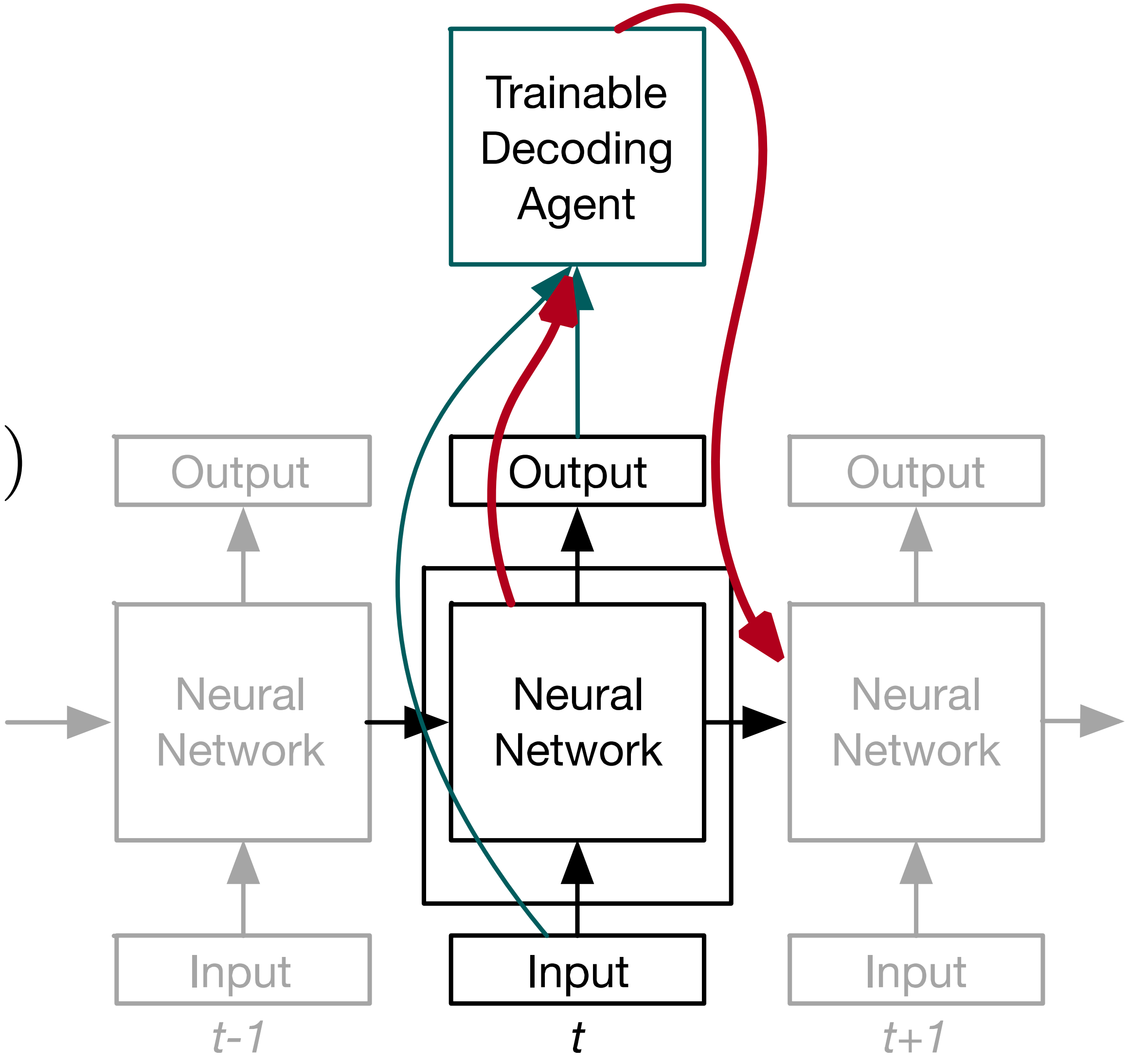
Trainable Decoding (1)

- A conditional recurrent neural net *defines* an environment
- State:
  - Previous hidden state h_{t-1}
  - Current input $\hat{x}_{t-1}$
  - Source context $c_t(s)$
- Action: any modification
  - Next input $\hat{x}_t$
  - Source s
- Reward: arbitrary



Trainable Decoding (2)

- A conditional recurrent neural net *defines* an environment
- A decoder is an agent:
  - Observes the state via $p(x_t|\hat{x}_{<t}, s)$
  - Acts by selecting $\hat{x}_t$
- Limited, because it doesn't exploit rich info captured in h_t
- *Can we extend it by training a neural network decoder?*



Yes, we can!

- Simultaneous Translation
  - Jiatao Gu, Kyunghyun Cho, Victor OK Li. Trainable greedy decoding for neural machine translation. EMNLP 2017
- Trainable Greedy Decoding
  - Jiatao Gu, Graham Neubig, Kyunghyun Cho, Victor OK Li. Learning to translate in real-time with neural machine translation. EACL 2017.
  - Yun Chen, Victor Li, Sam Bowman, Kyunghyun Cho. A Stable and Effective Learning Strategy for Trainable Greedy Decoding. (under review)

Simultaneous Translation (1)

- Inspired by simultaneous interpretation
- Source words arrive one at a time
- Translation starts before the complete sentence arrives
- Objective: quality ↑ delay ↓

Interpreters at the Nuremberg Trial (1945-1946)
https://www.pri.org/stories/2014-09-29/how-do-all-those-leaders-un-communicate-all-those-languages

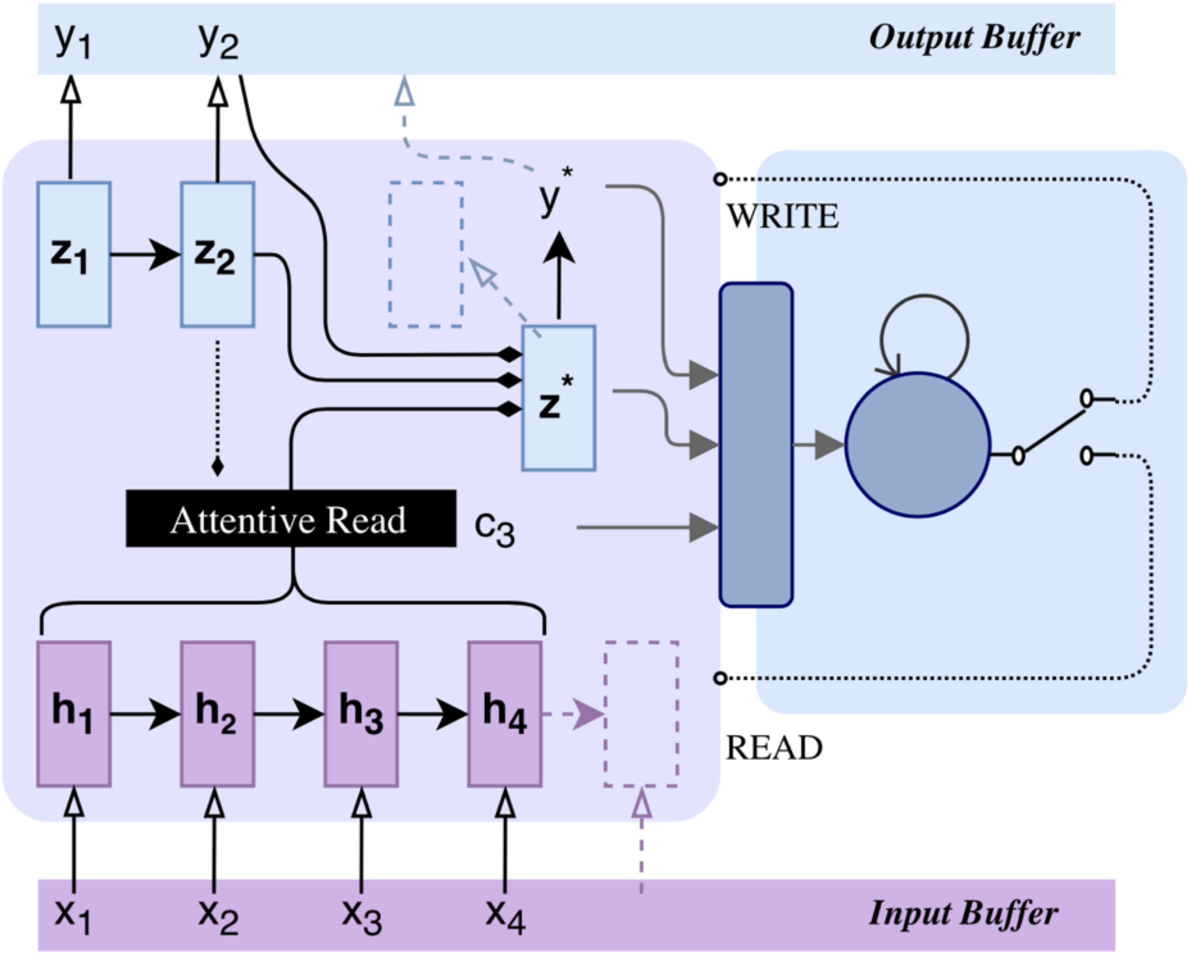
Simultaneous Translation (2)

Decoding

1. Start with a well-trained NMT
2. A simultaneous decoder intercepts and interprets the incoming signal
3. The simultaneous decoder forces the pretrained model to either
    1. output a target symbol, or
    2. wait for the next source symbol

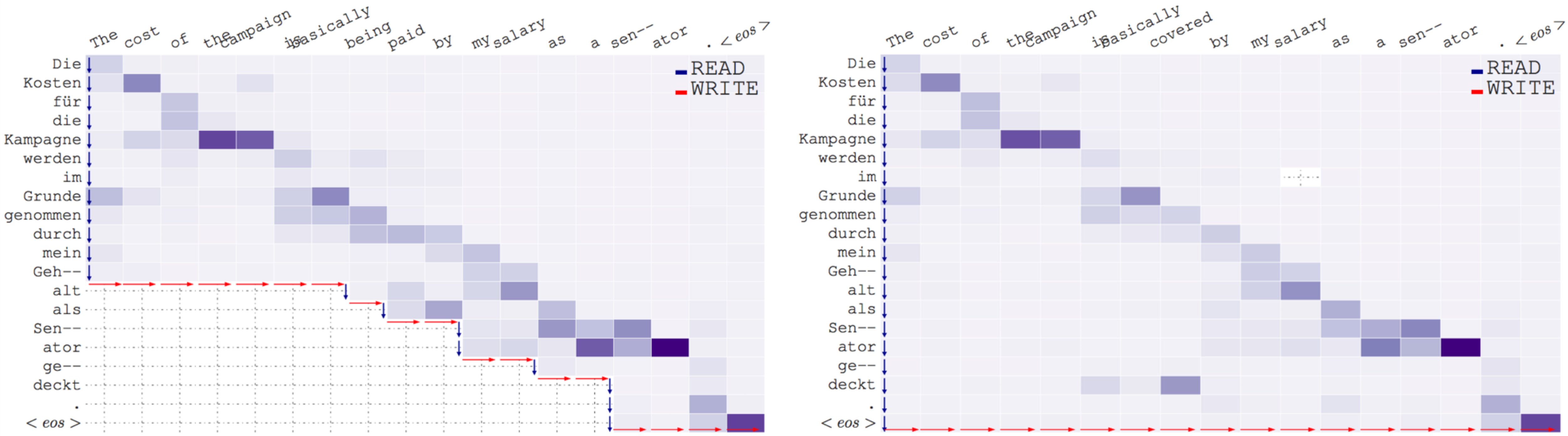
Learning

1. Trade-off between delay and quality
2. Policy gradient (REINFORCE)



[Gu, Neubig, Cho & Li, EACL 2017]

Simultaneous Translation (3)

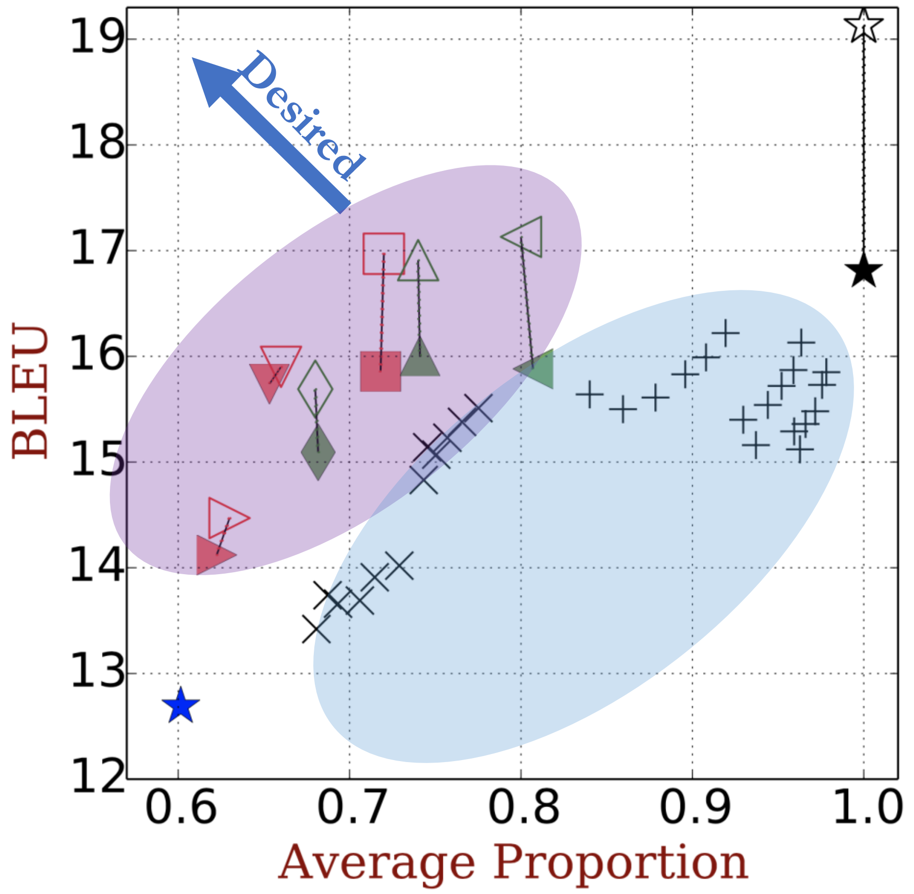


(a) Simultaneous Neural Machine Translation

(b) Neural Machine Translation

[Gu, Neubig, Cho & Li, EACL 2017]

Simultaneous Translation (4)



★ consecutive translation

★ word-by-word translation

+x simultaneous translation without using h_t

■ ▲ simultaneous translation (trainable decoding)

- *Better simultaneous translation by exploiting the rich info captured by the hidden state*

[Cho & Esipova, 2016 horribly rejected from EMNLP]
[Gu, Neubig, Cho & Li, EACL 2017]