What can Statistical Machine Translation teach Neural Machine Translation about Structured Prediction?

Graham Neubig

@ ICLR Workshop on Deep Reinforcement Learning Meets Structured Prediction
5/6/2019

Carnegie Mellon University
Language Technologies Institute

Types of Prediction

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- Two classes (**binary classification**)

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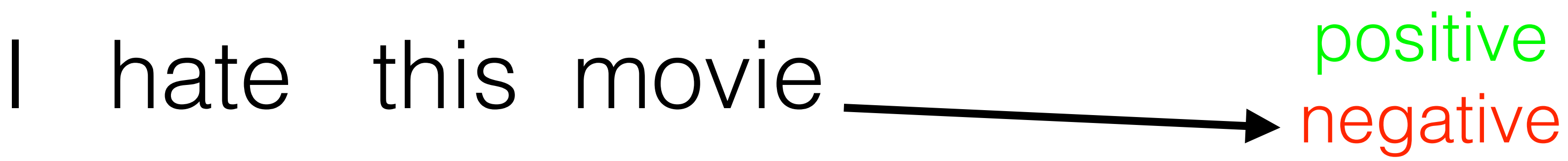

I hate this movie

positive

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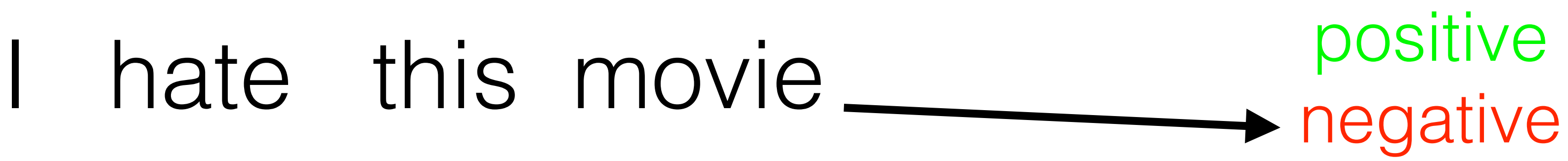

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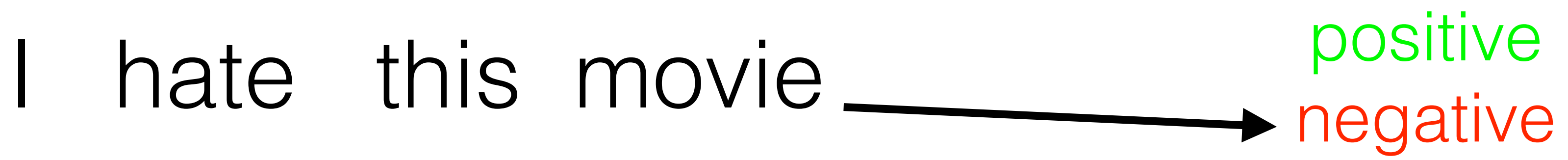

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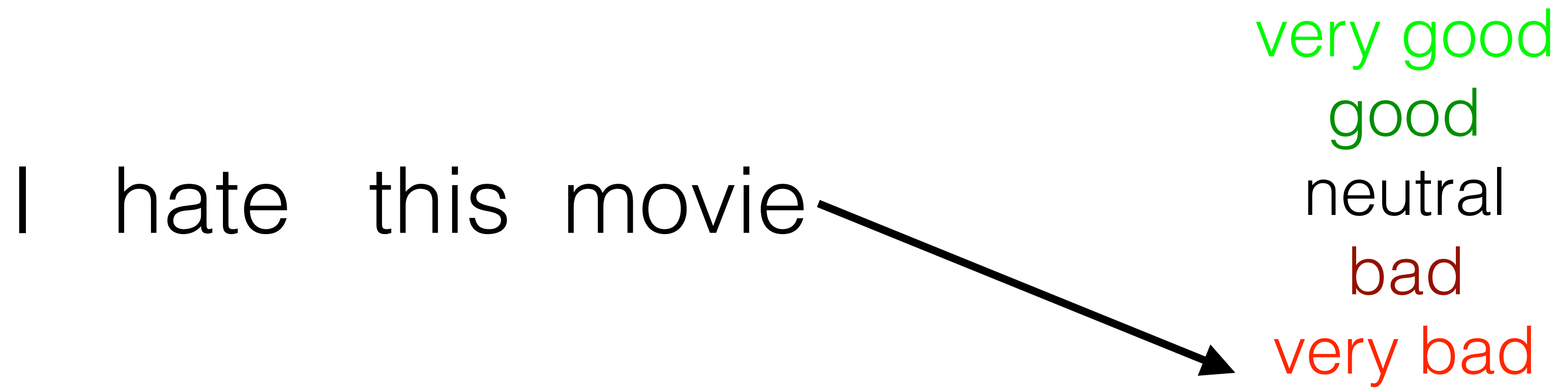

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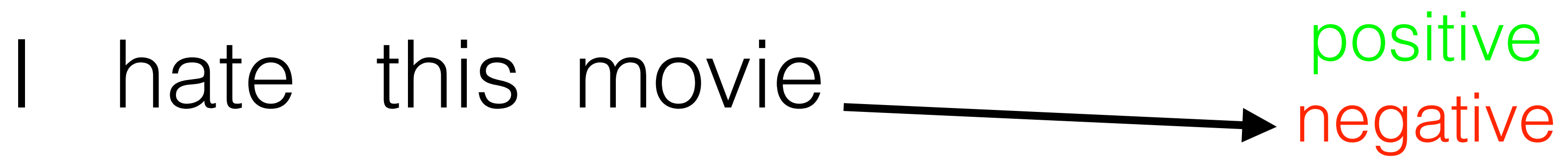

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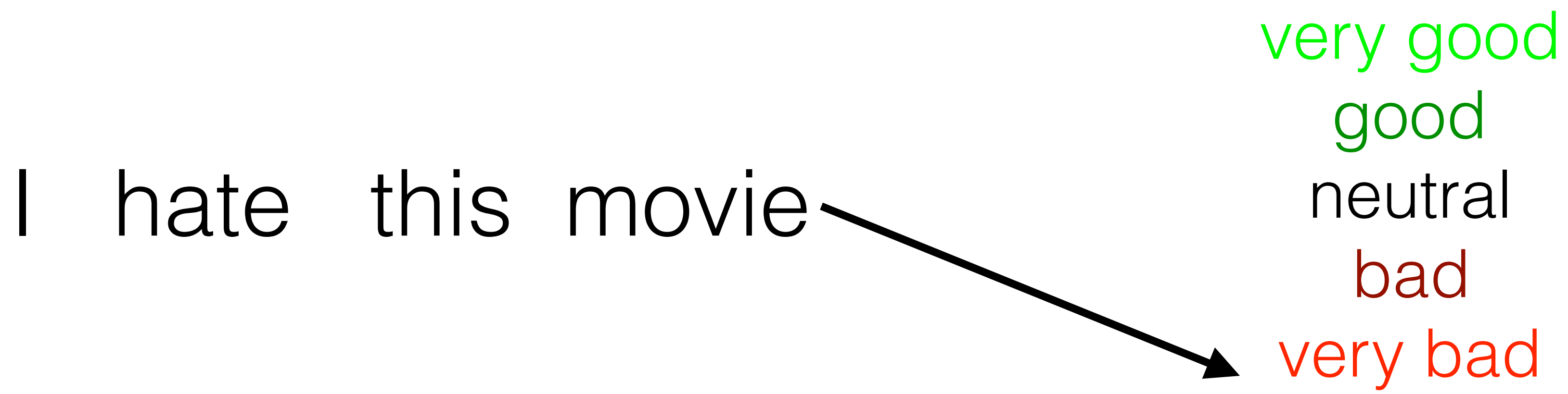

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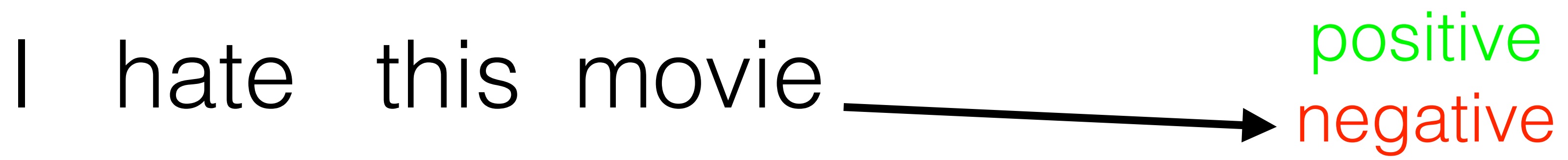

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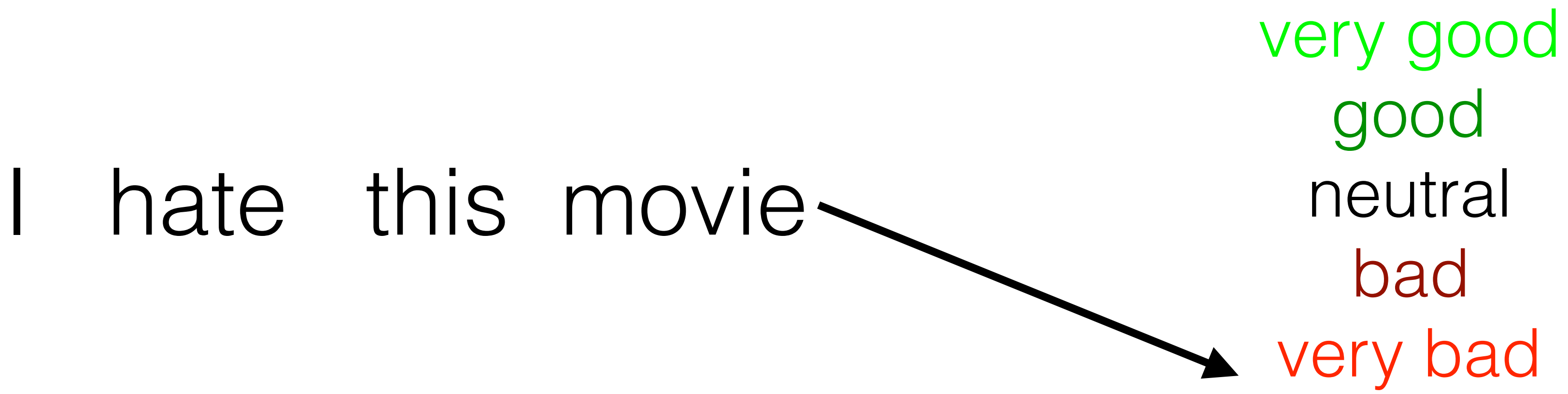

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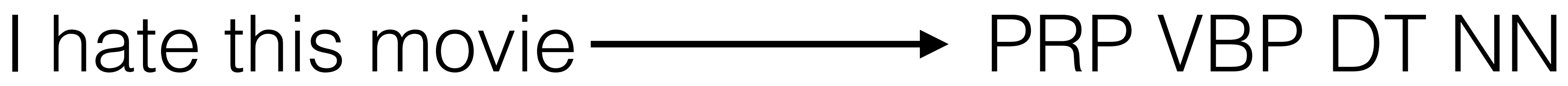

I hate this movie → PRP VBP DT NN

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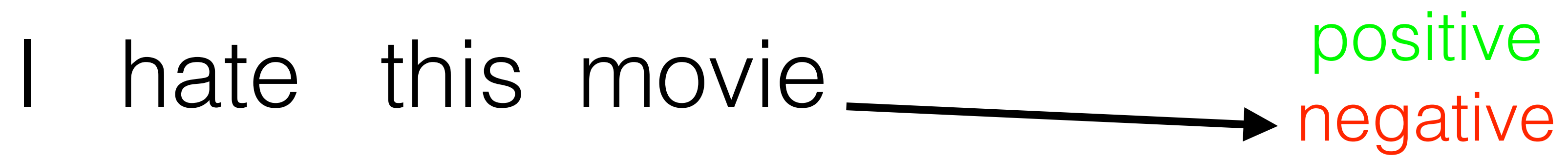

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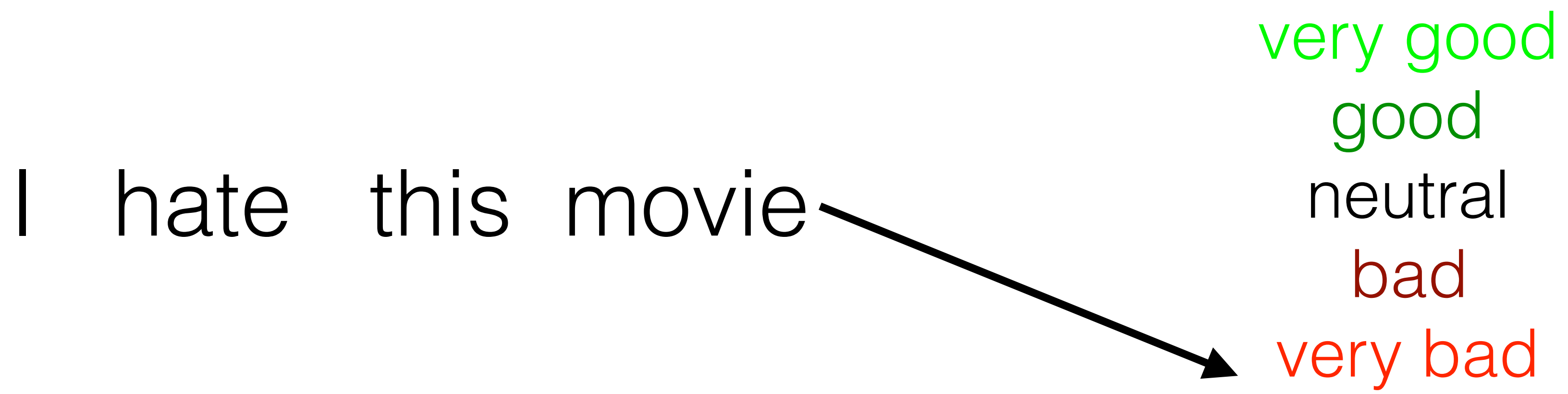

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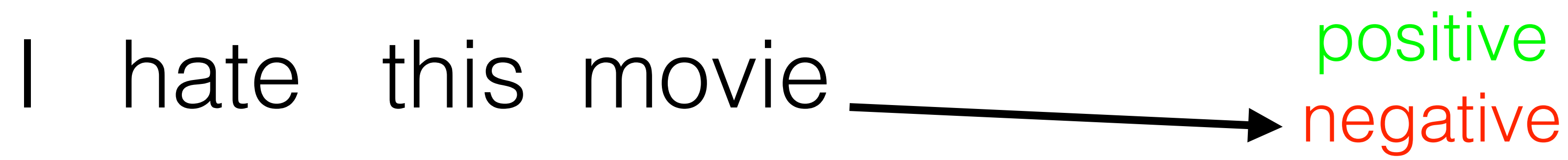

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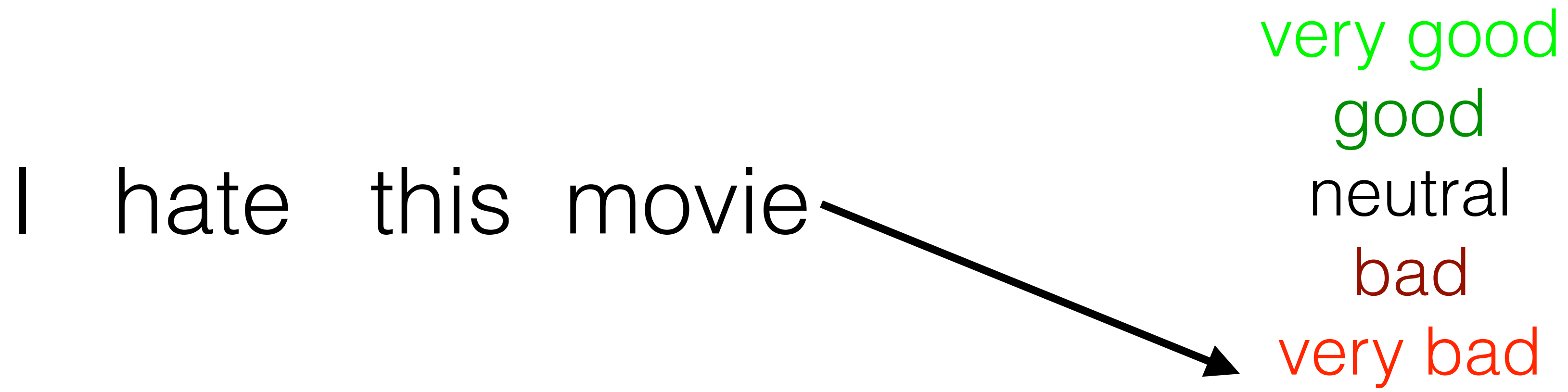

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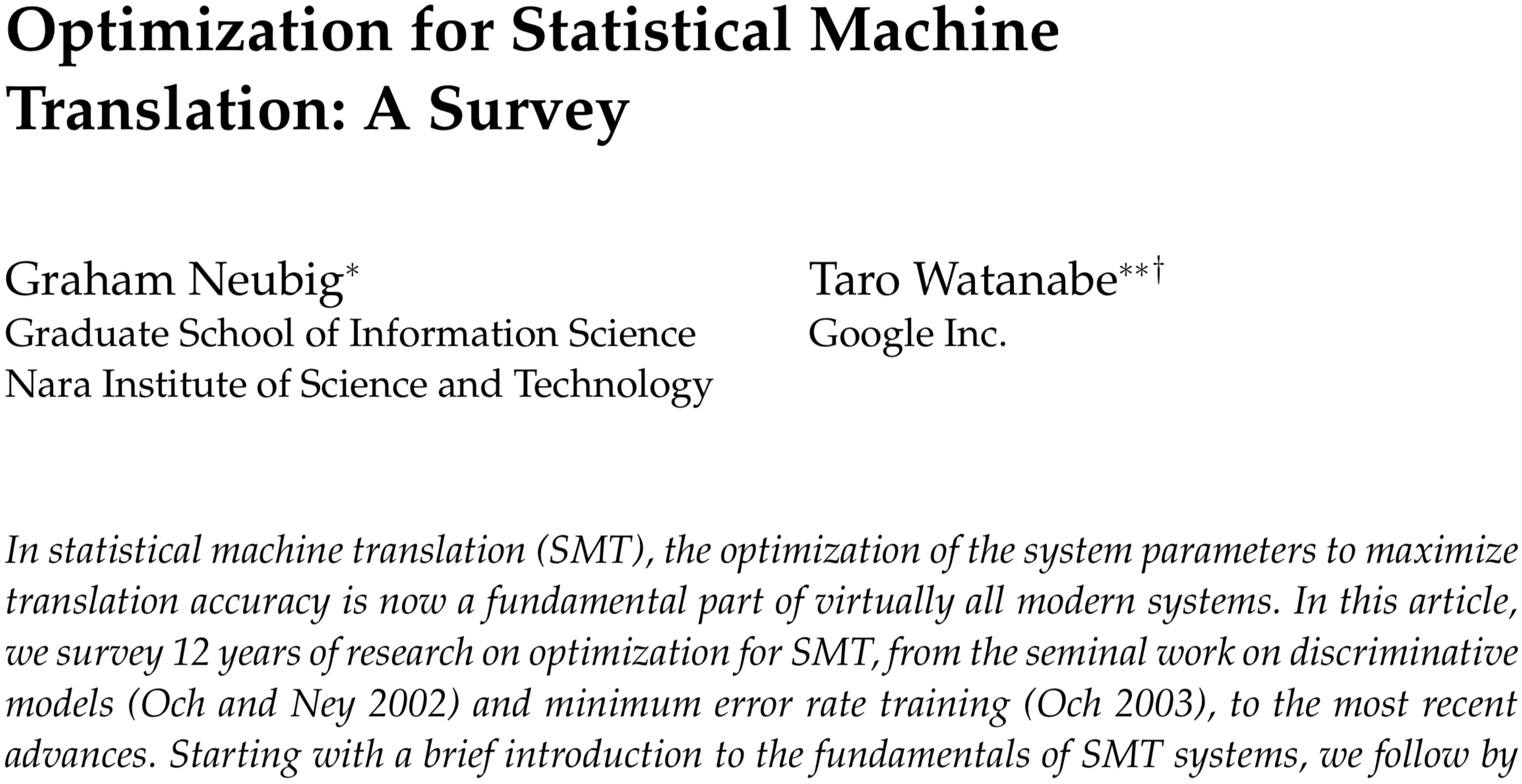

Optimization for Statistical Machine Translation: A Survey

Graham Neubig*
Graduate School of Information Science
Nara Institute of Science and Technology

Taro Watanabe**†
Google Inc.

In statistical machine translation (SMT), the optimization of the system parameters to maximize translation accuracy is now a fundamental part of virtually all modern systems. In this article, we survey 12 years of research on optimization for SMT, from the seminal work on discriminative models (Och and Ney 2002) and minimum error rate training (Och 2003), to the most recent advances. Starting with a brief introduction to the fundamentals of SMT systems, we follow by

...

Neubig & Watanabe, Computational Linguistics (2016)

Optimization for Statistical Machine Transl

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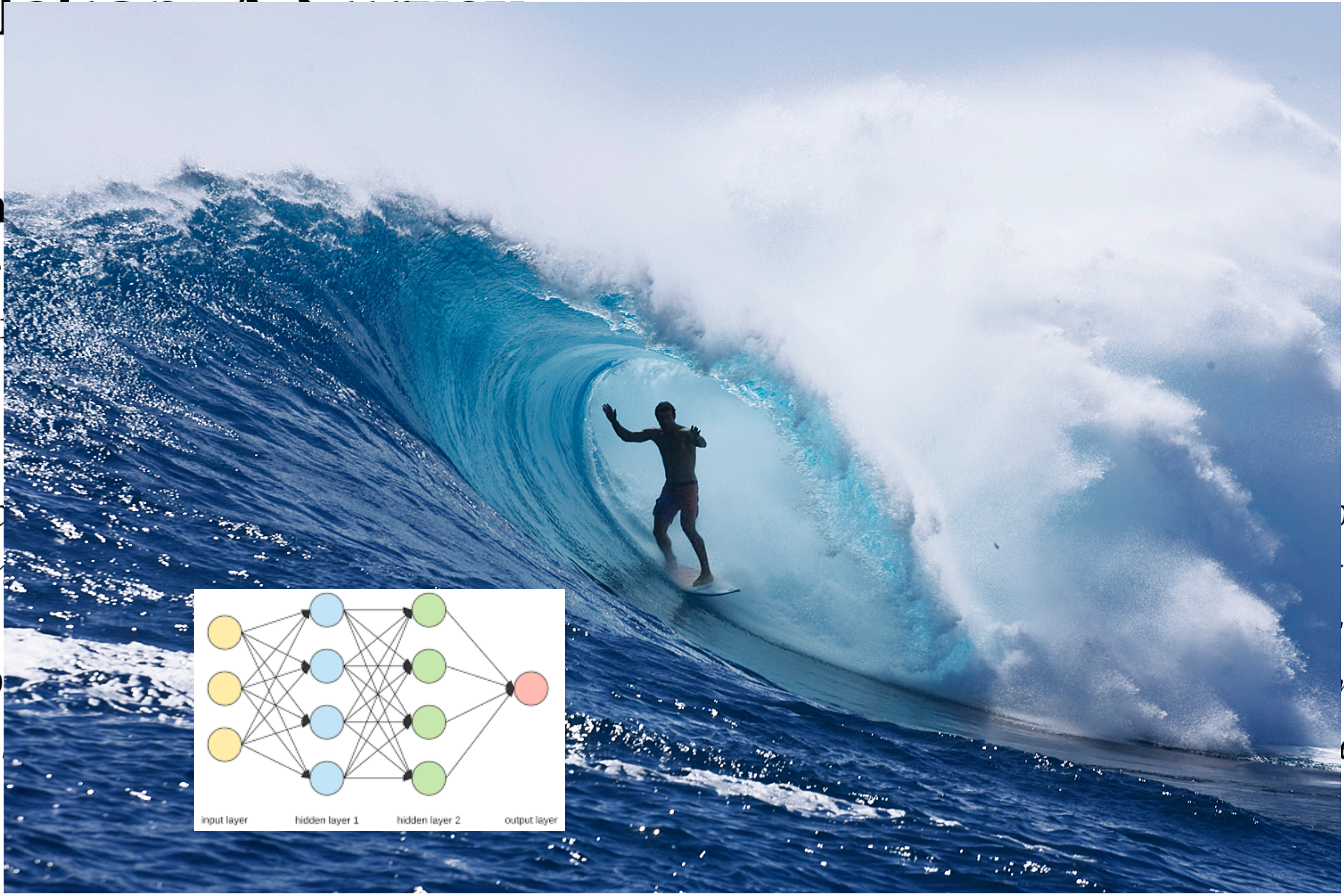
Graduate
Nara Inst

In statistic ... maximize translatior ... his article, we survey ... riminative models (O ... nost recent advances. ... e follow by



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Then: Symbolic Translation Models

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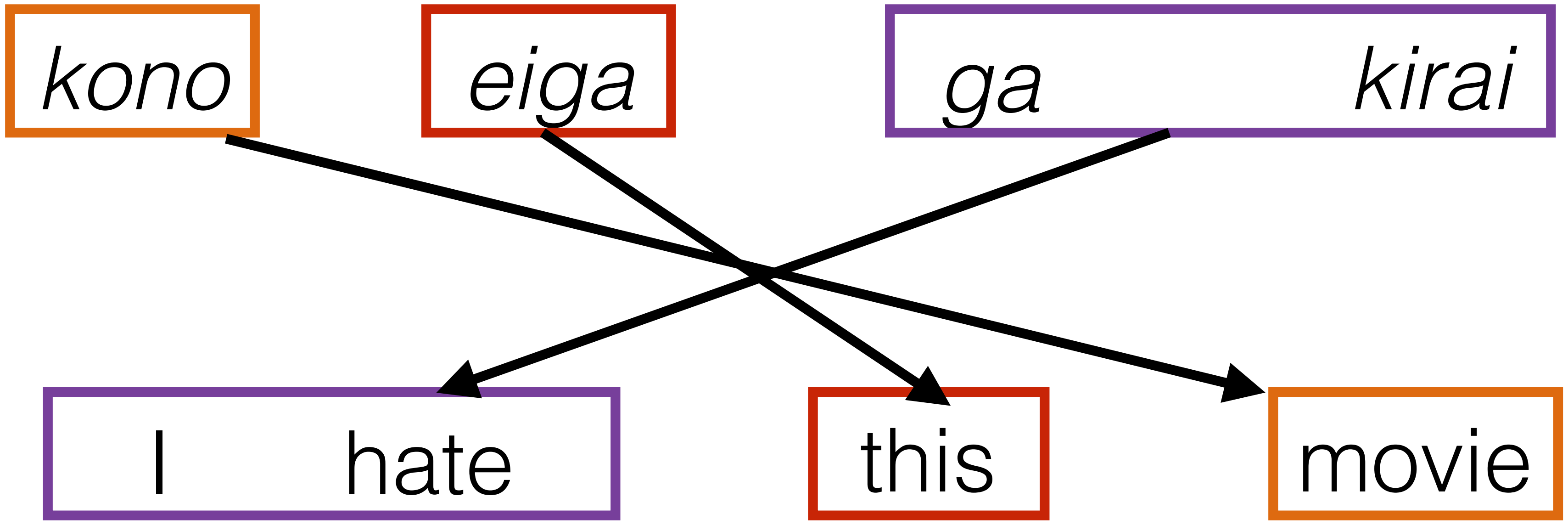

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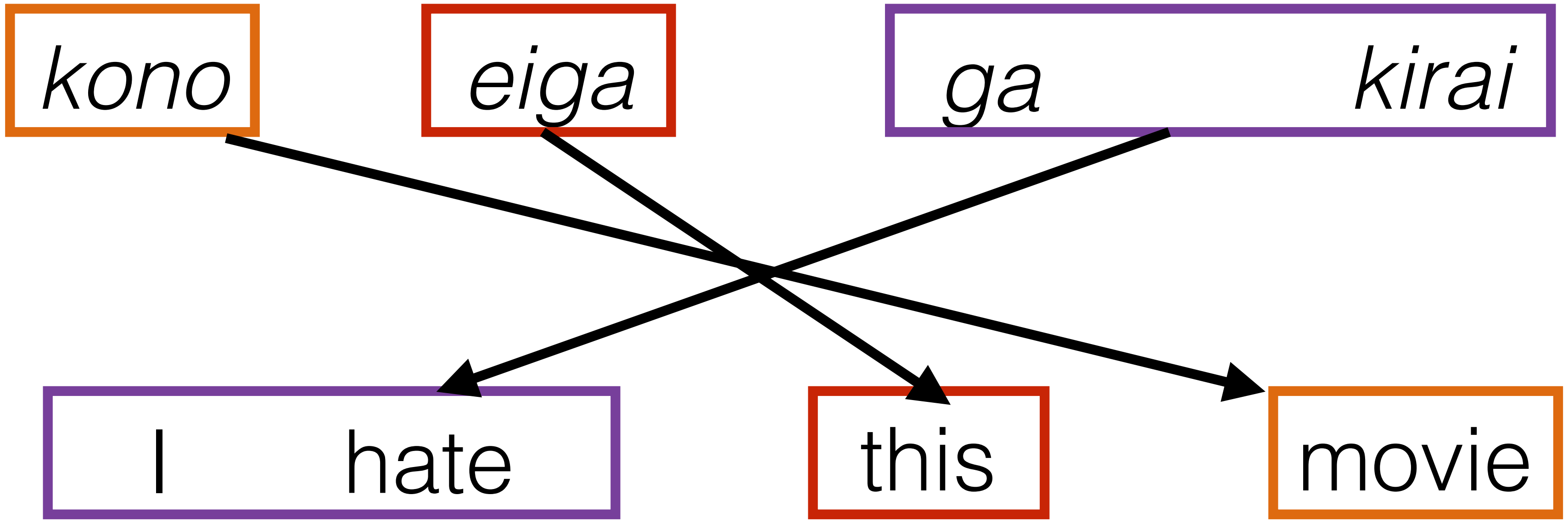

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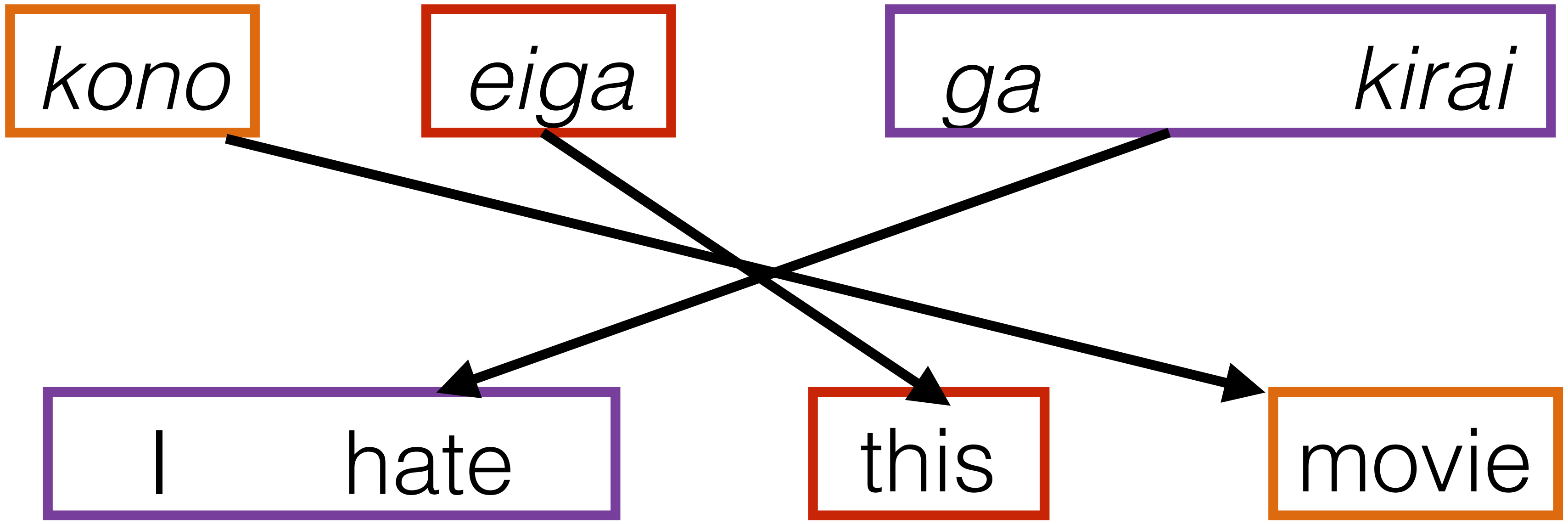

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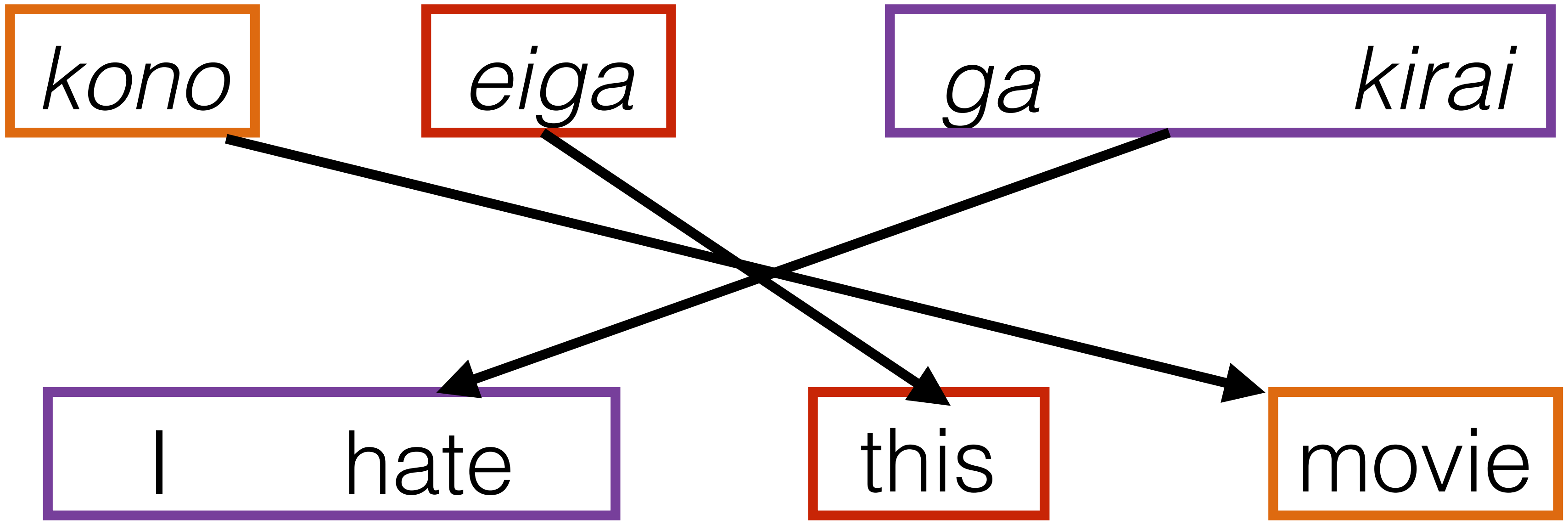

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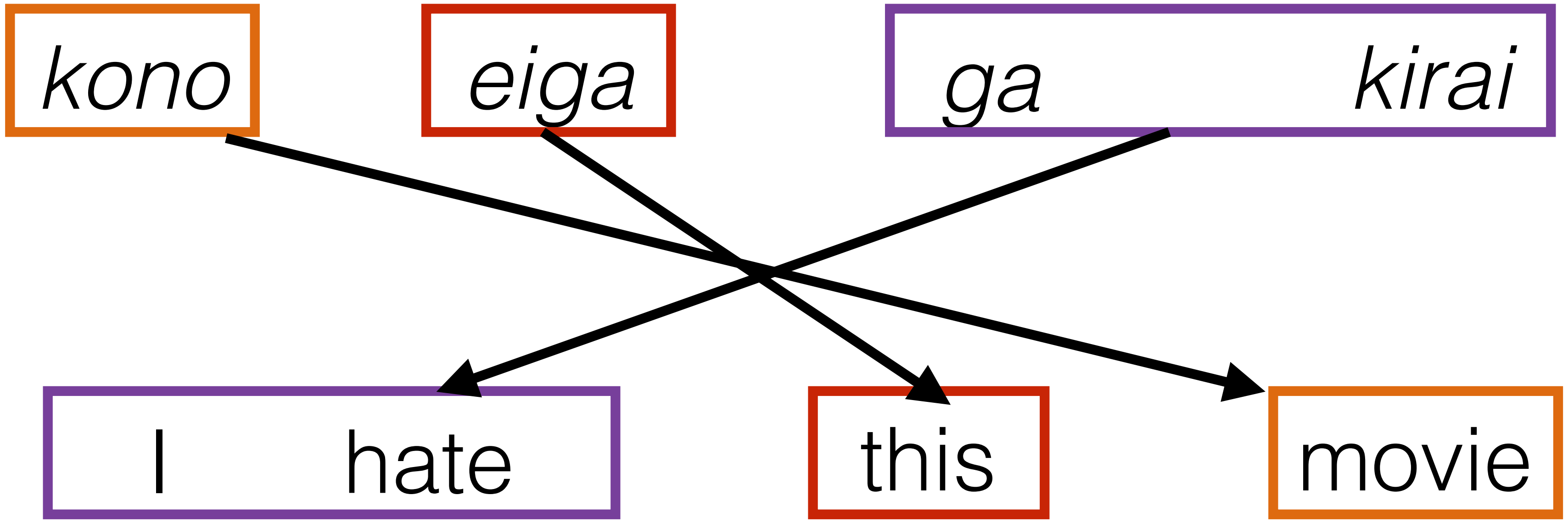

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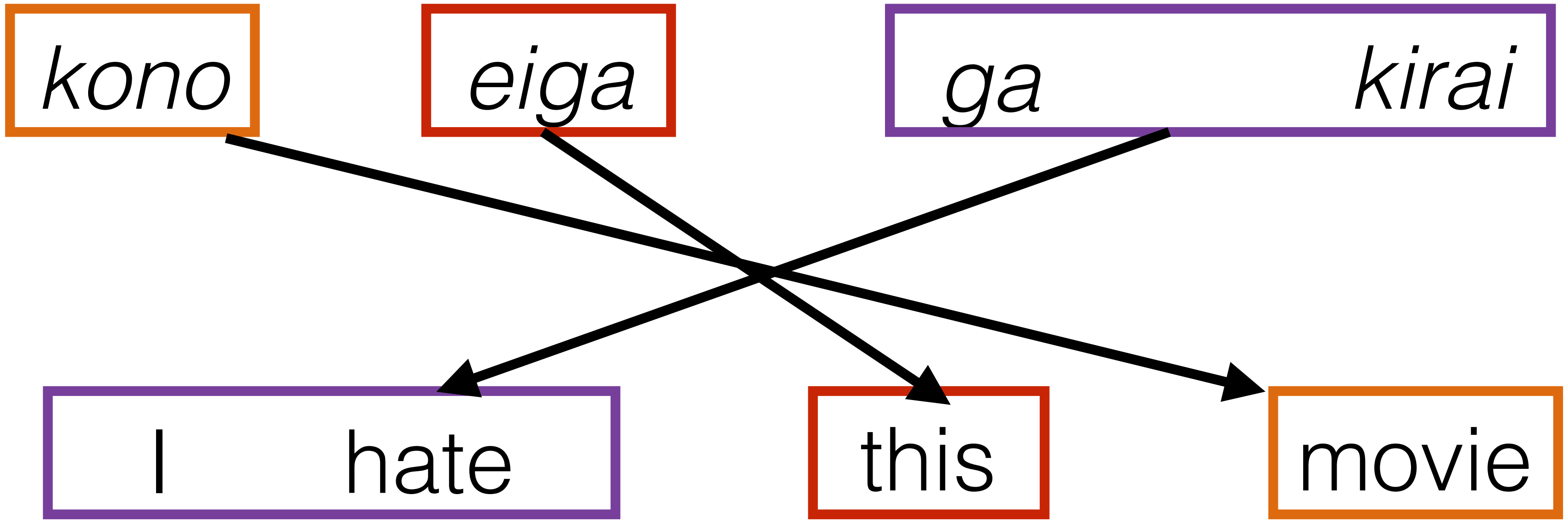

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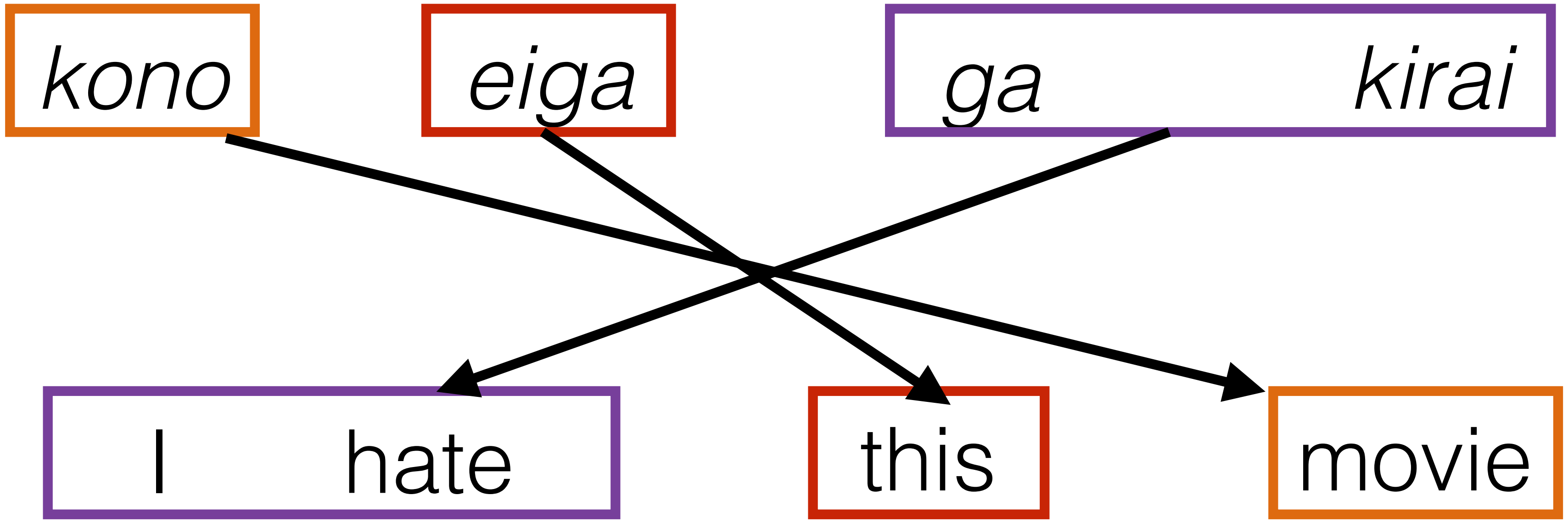

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  - **Length model P(|Y|)** -- e.g. word penalty for each word added
- **Second step:** learning log-linear combination to maximize translation accuracy [Och 2004]

$$\log P(Y \mid X) = \sum_i \lambda_i \phi_i(X, Y) / Z$$

Minimum Error Rate Training in Statistical Machine Translation (Och 2004)

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Auto-regressive Neural Networks

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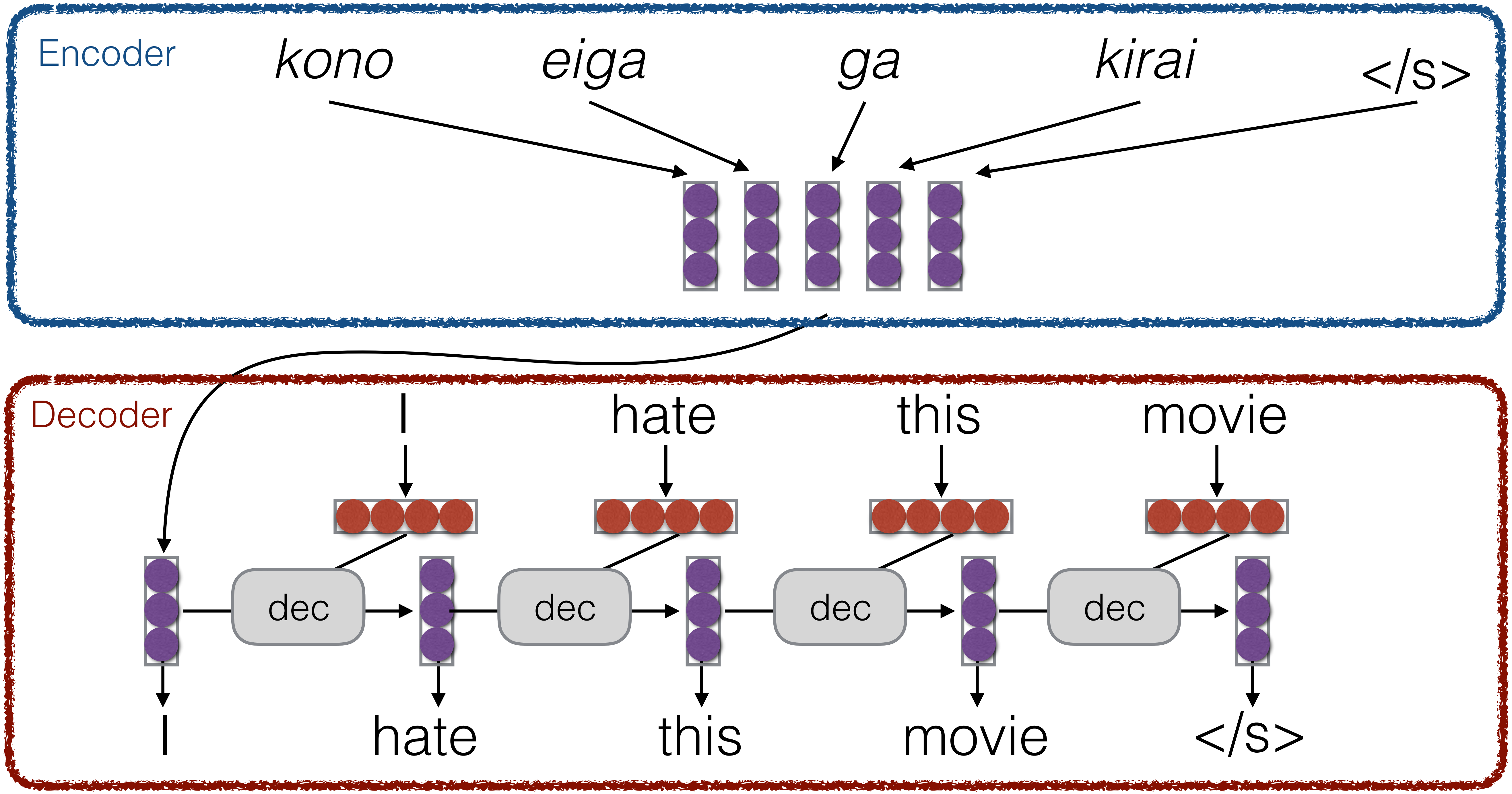

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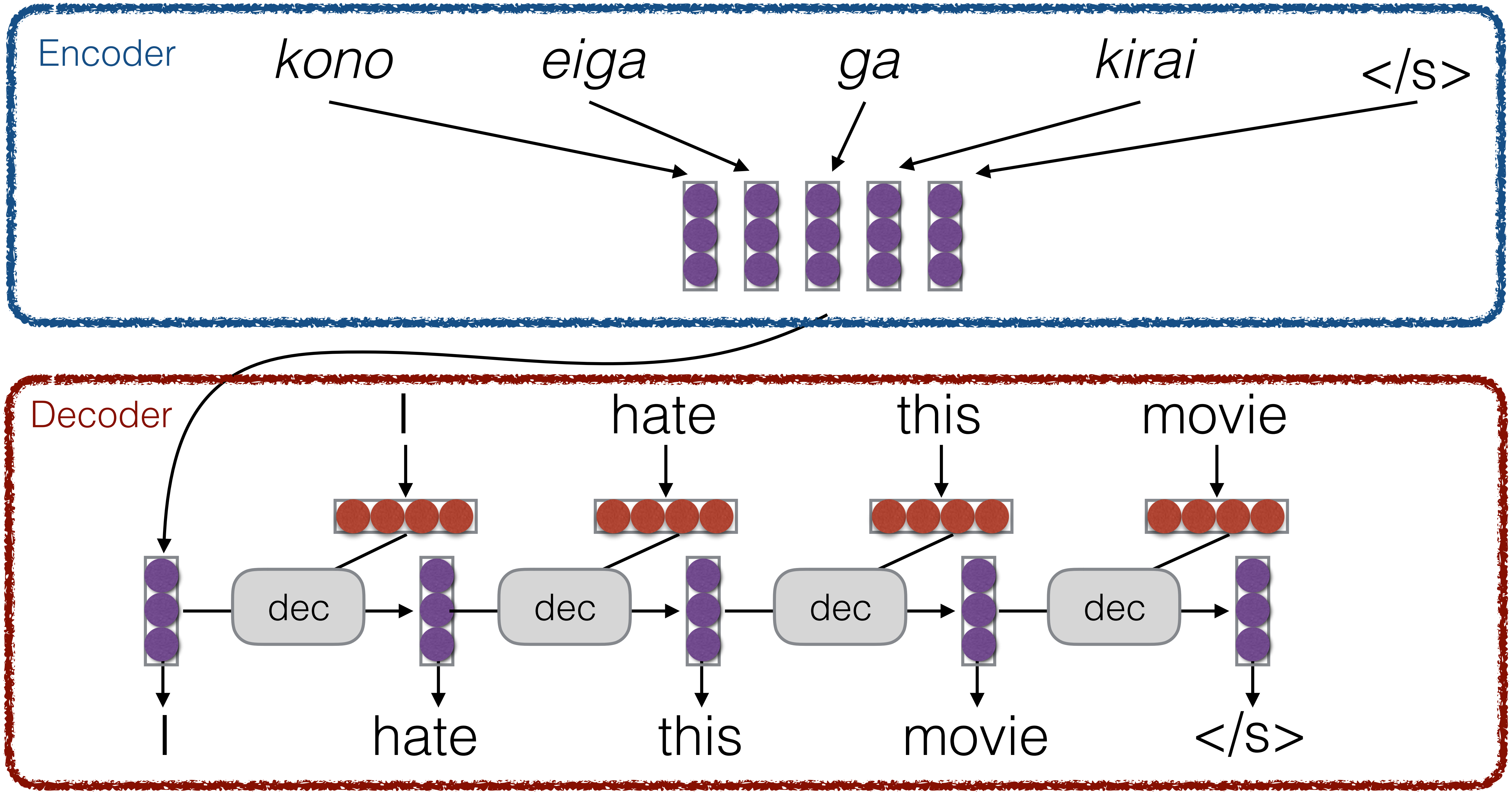
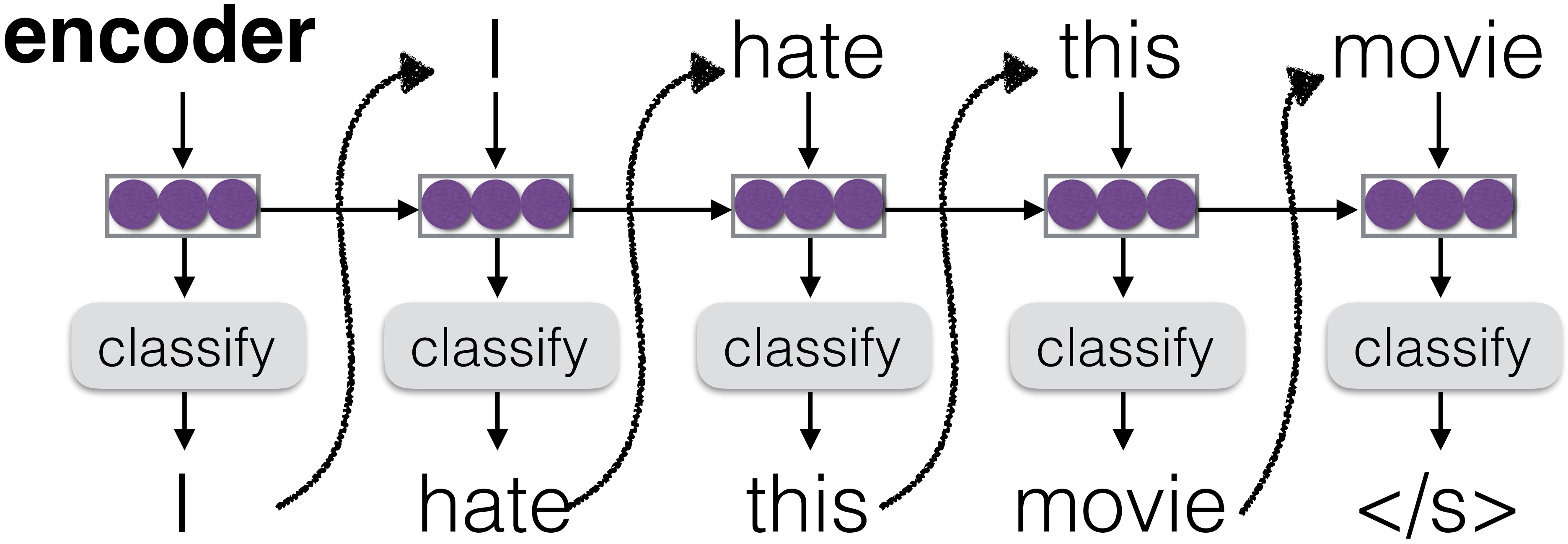


- All parameters trained end-to-end, **usually to maximize likelihood** (not accuracy!)

Standard MT System Training/Decoding

Decoder Structure



$$P(E \mid F) = \prod_{t=1}^{T} P(e_t \mid F, e_1, \ldots, e_{t-1})$$

Maximum Likelihood Training

- Maximum the likelihood of predicting the next word in the reference given the previous words

$$
\begin{aligned}
\ell(E \mid F) &= -\log P(E \mid F) \\
&= -\sum_{t=1}^{T} \log P(e_t \mid F, e_1, \ldots, e_{t-1})
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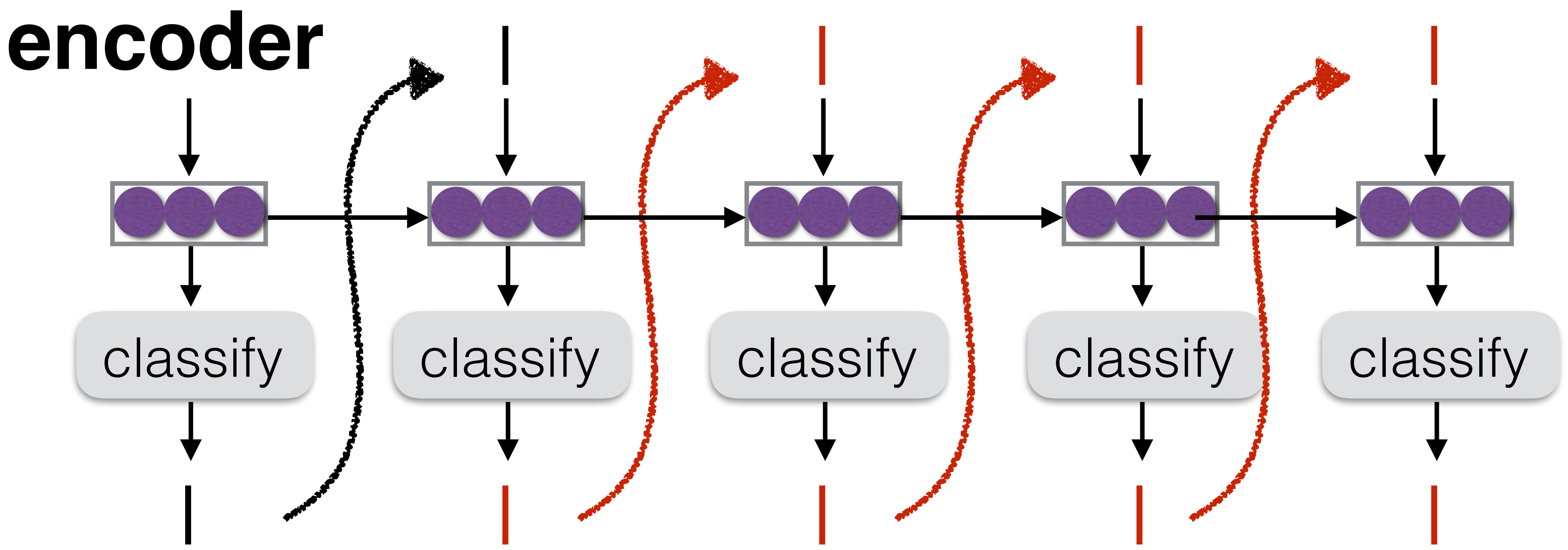
- Also called "teacher forcing"

Problem 1: Exposure Bias

- Teacher forcing assumes feeding correct previous input, but at test time we may make mistakes that propagate



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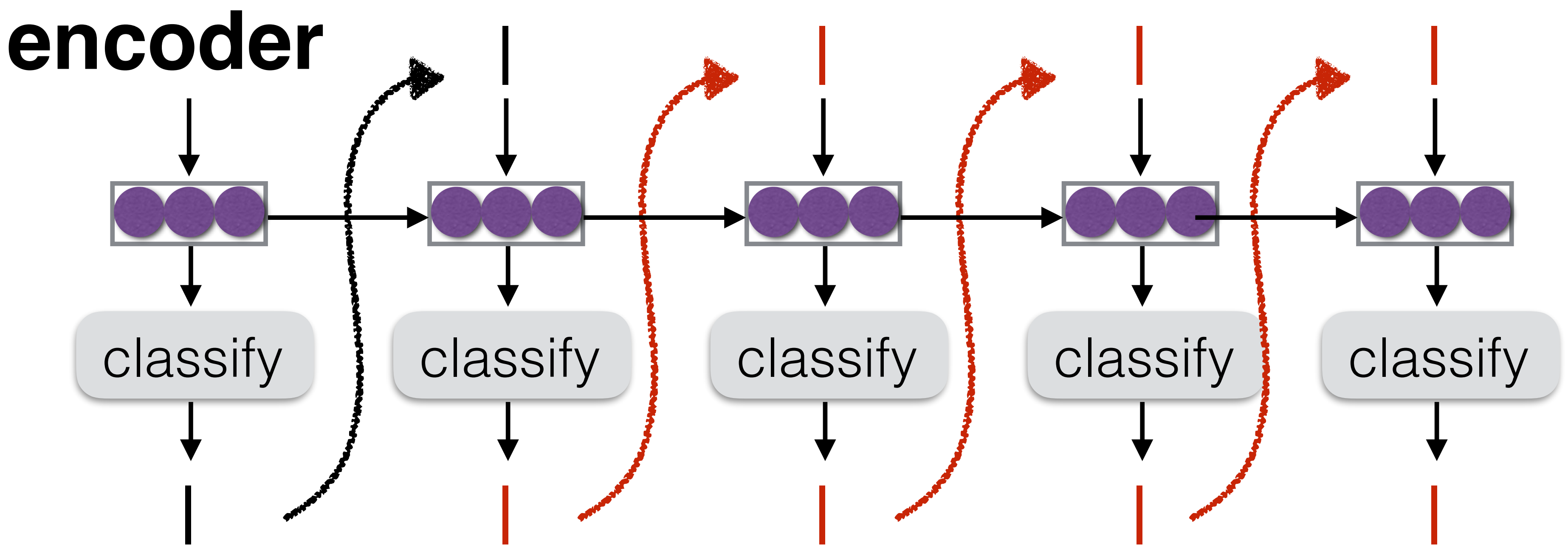

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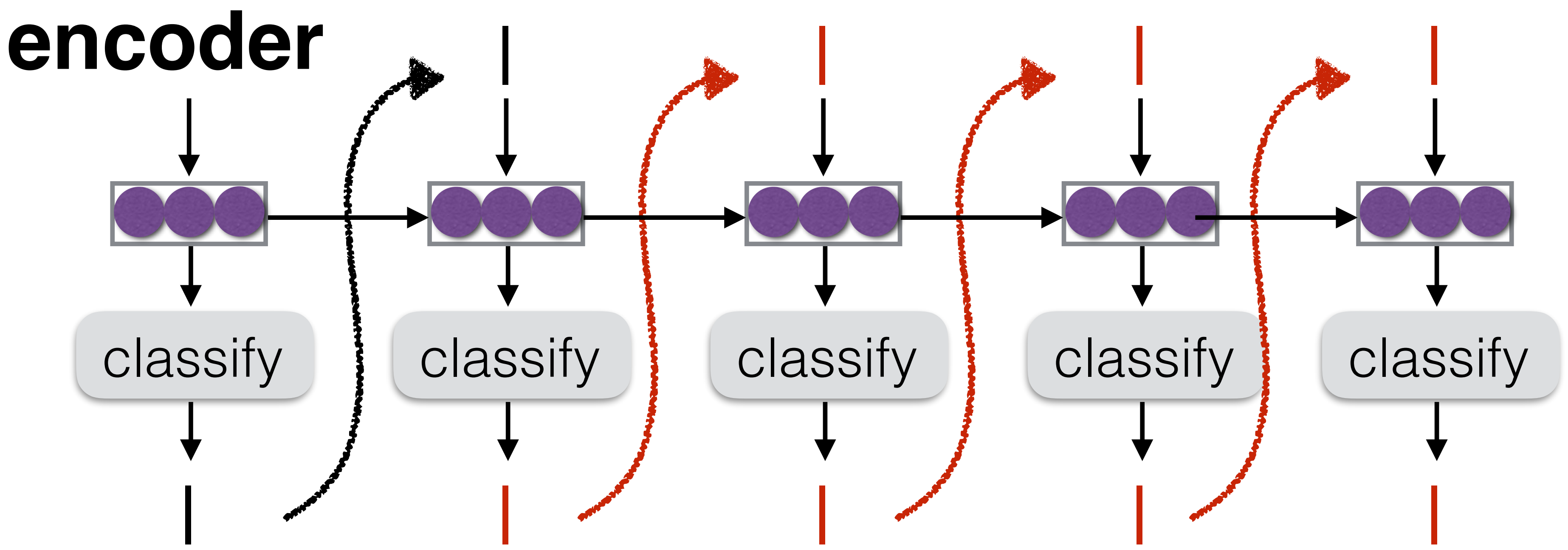

- **Exposure bias:** The model is not exposed to mistakes during training, and cannot deal with them at test
- **Really important!** One main source of commonly witnessed phenomena such as repeating.

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- In the end, we want good translations
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- **Really important!** Causes systematic problems:
  - Hypothesis-reference length mismatch
  - Dropped/repeated content

A Clear Example

- My (winning) submission to Workshop on Asian Translation 2016 [Neubig 16]

Lexicons and Minimum Risk Training for Neural Machine Translation: NAIST-CMU at WAT2016 (Neubig 16)

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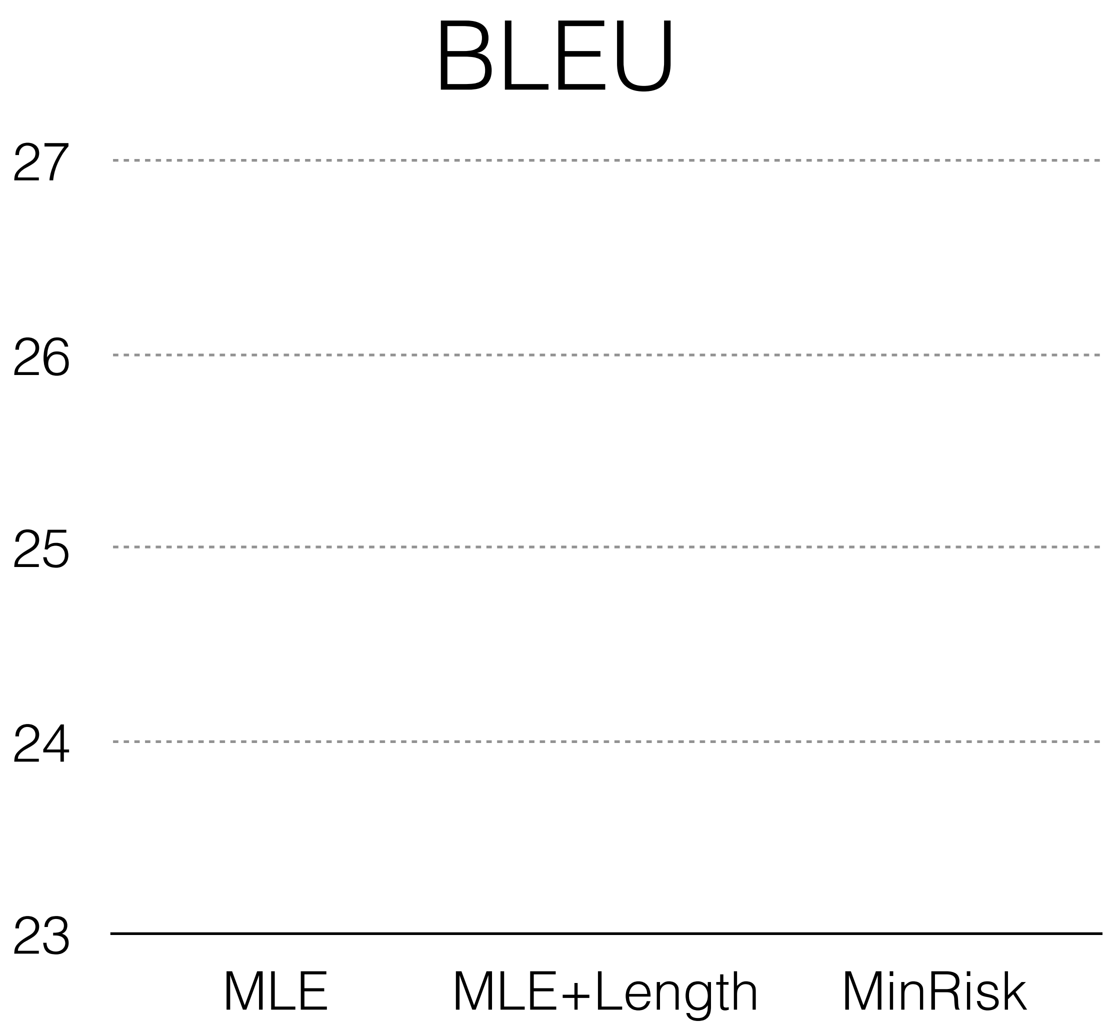

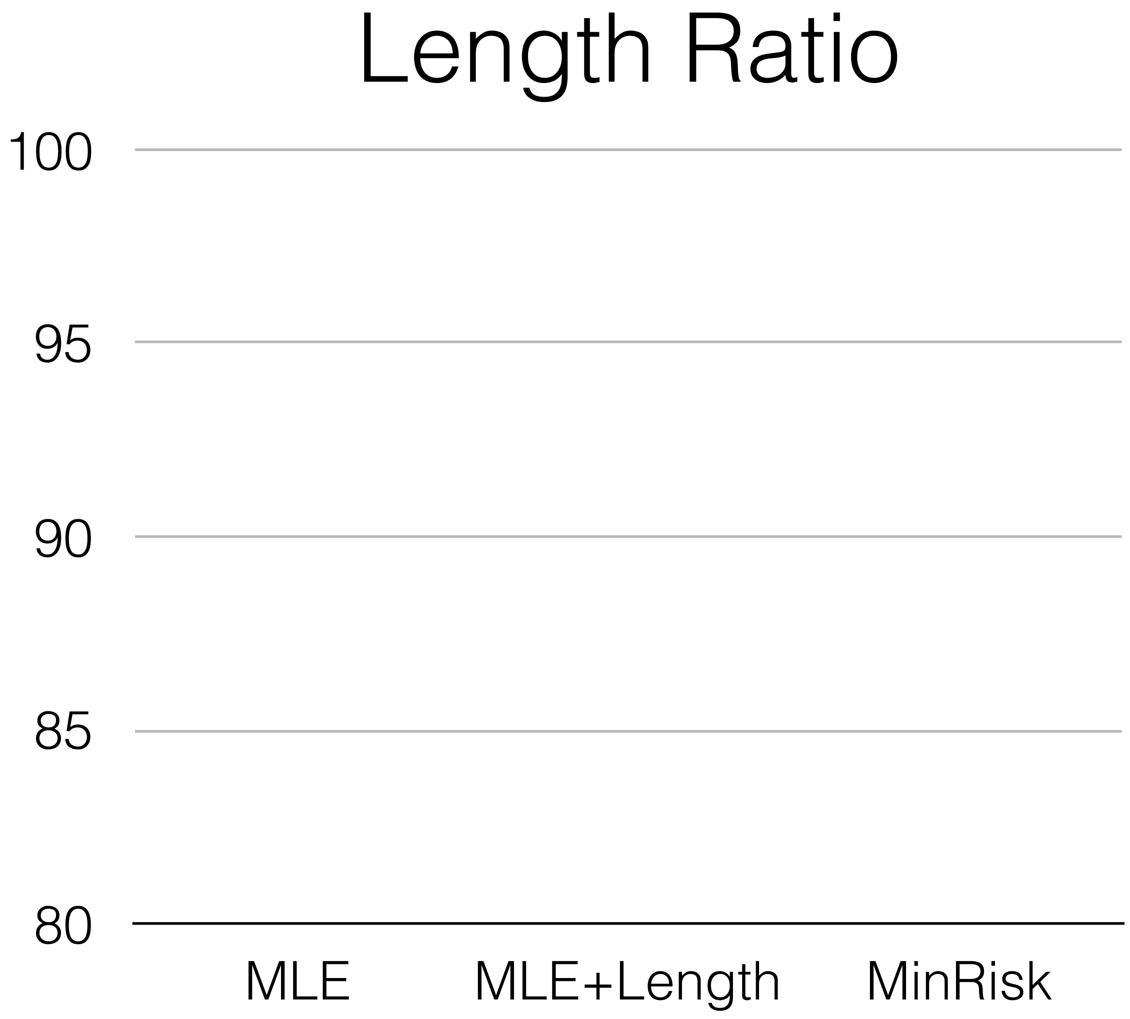

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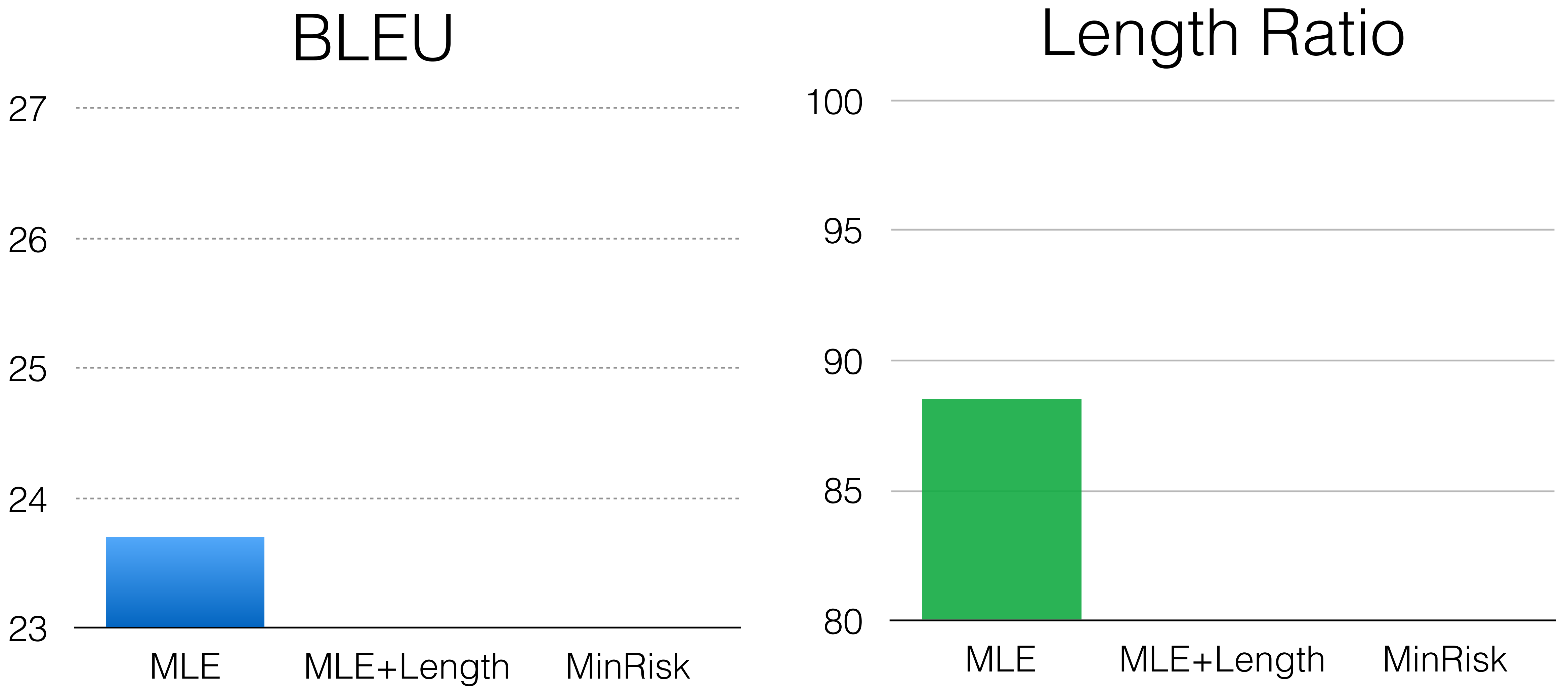

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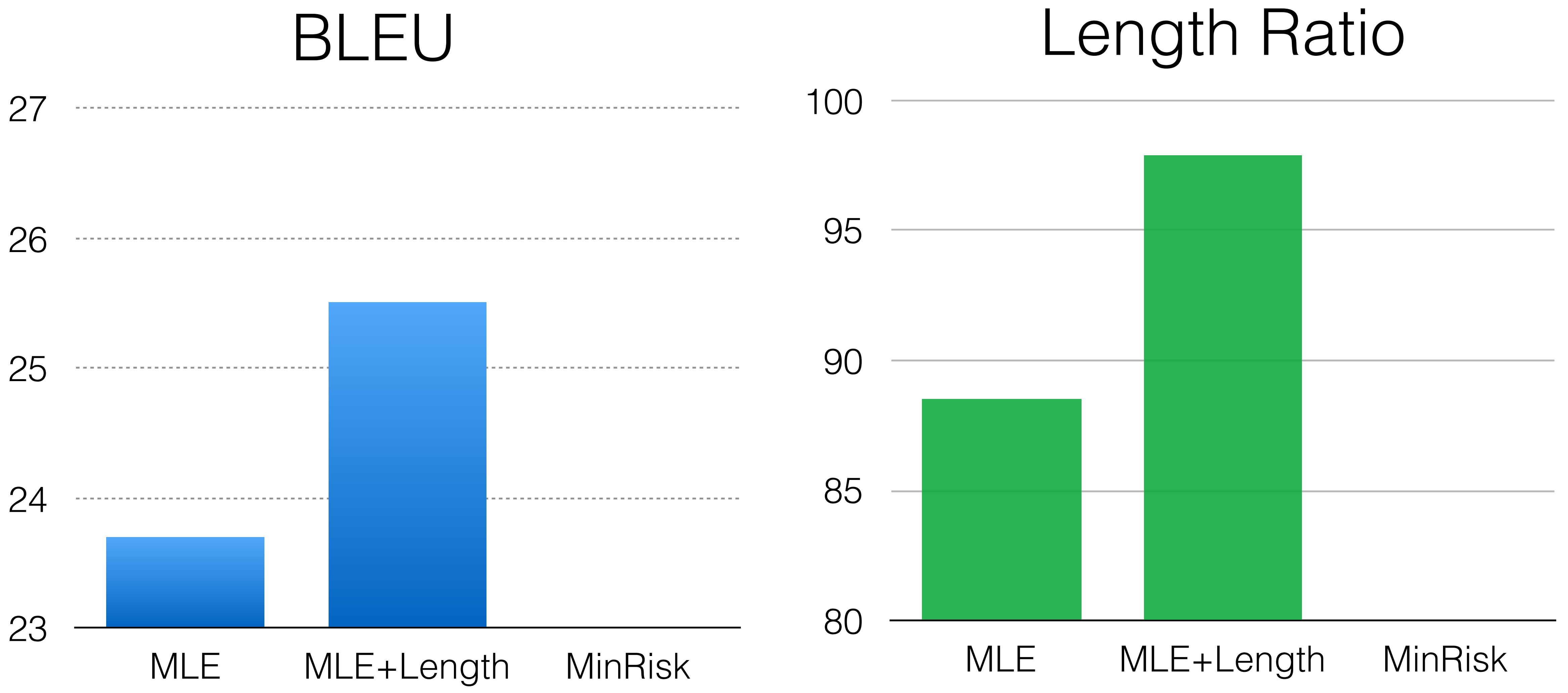

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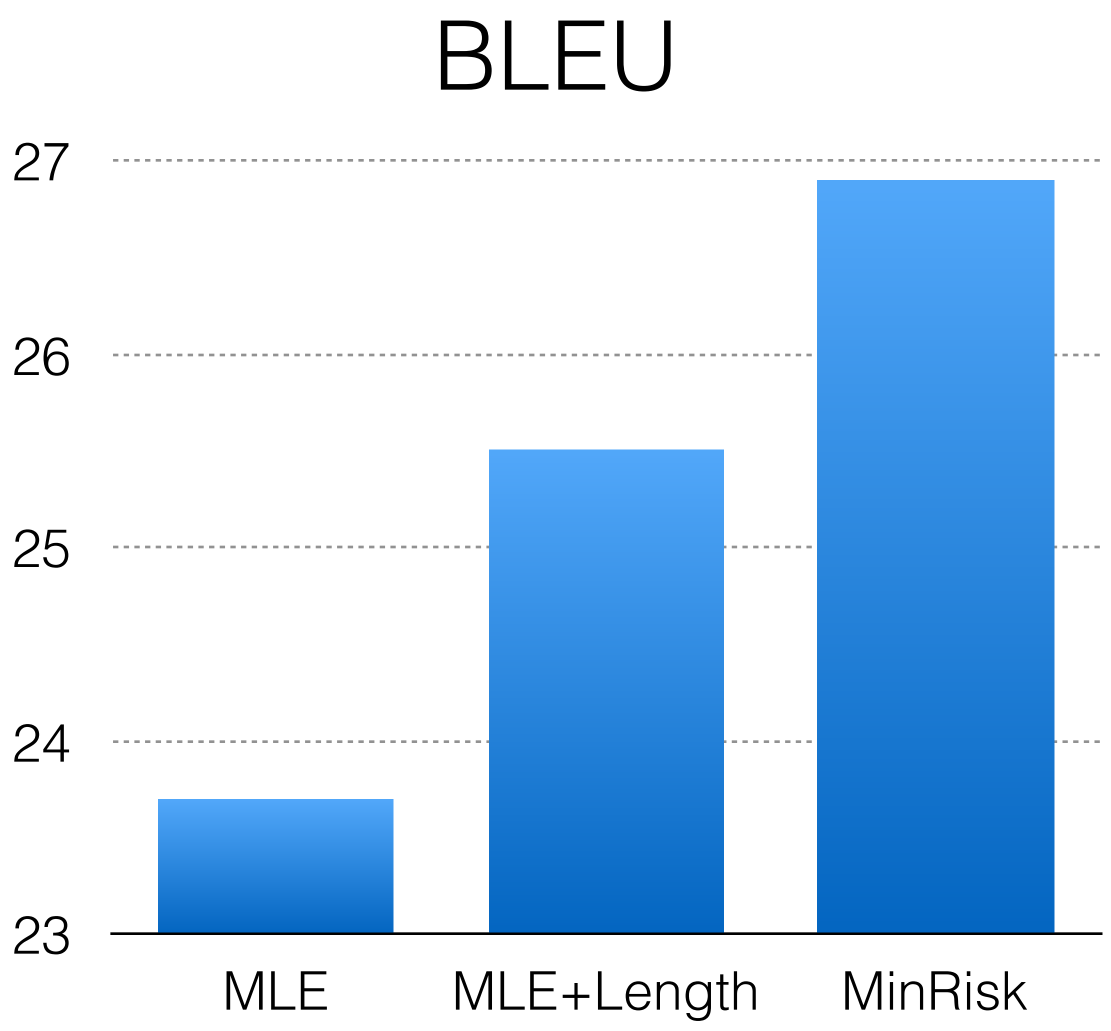

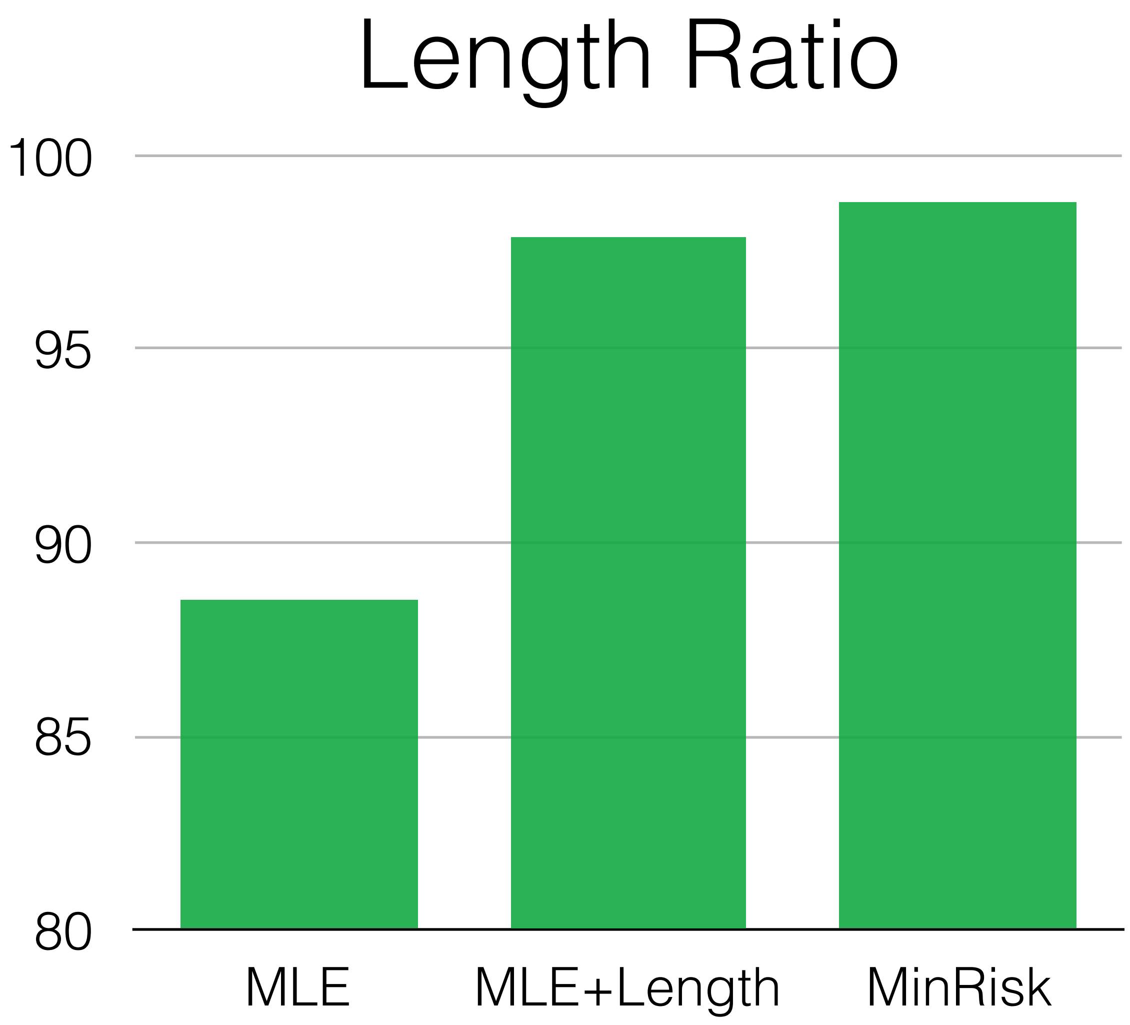

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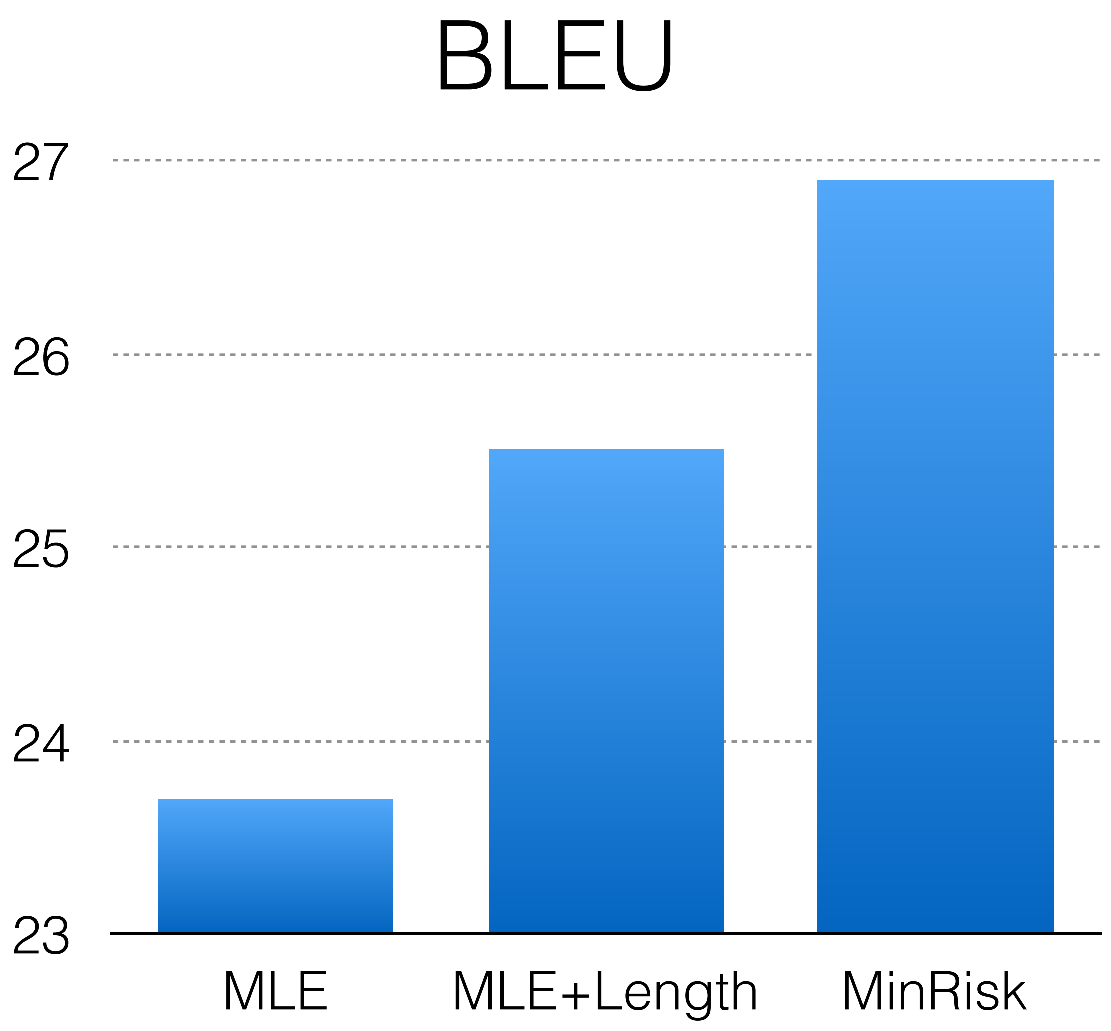

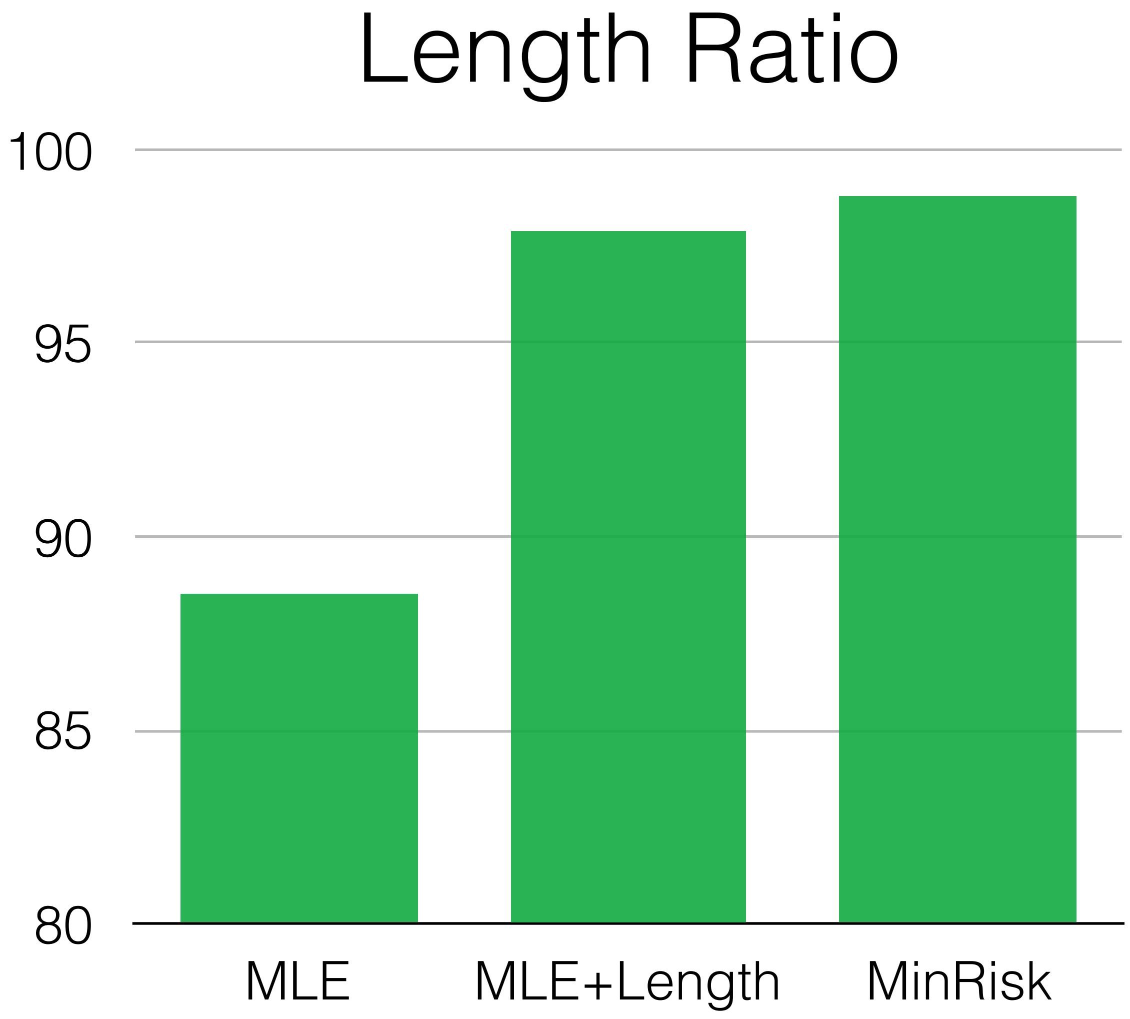

- Just training for (sentence-level) BLEU **largely fixes length problems, and does much better than heuristics**

Lexicons and Minimum Risk Training for Neural Machine Translation: NAIST-CMU at WAT2016 (Neubig 16)

Error and Risk

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- **Problem:** argmax is not differentiable, and thus not conducive to gradient-based optimization

In Phrase-based MT:
Minimum Error Rate Training

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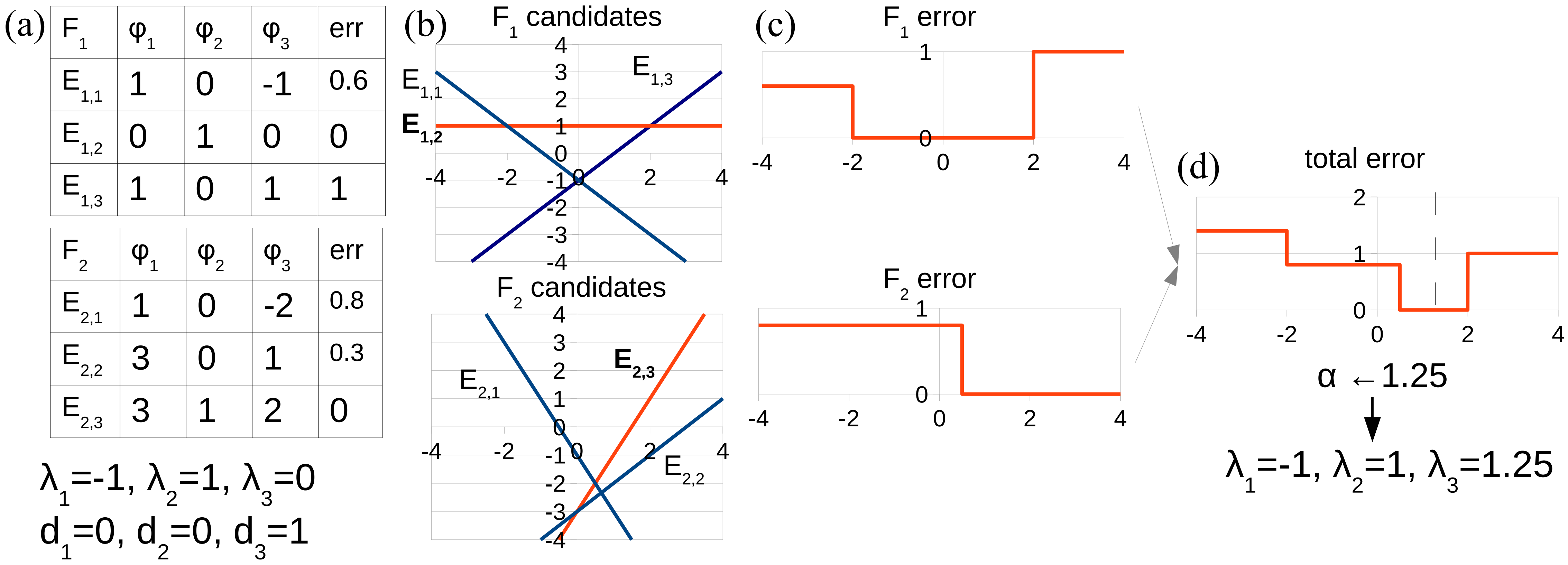

(a)

F_1	φ_1	φ_2	φ_3	err
$E_{1,1}$	1	0	-1	0.6
$E_{1,2}$	0	1	0	0
$E_{1,3}$	1	0	1	1

F_2	φ_1	φ_2	φ_3	err
$E_{2,1}$	1	0	-2	0.8
$E_{2,2}$	3	0	1	0.3
$E_{2,3}$	3	1	2	0

λ_1=-1, λ_2=1, λ_3=0
d_1=0, d_2=0, d_3=1

α ← 1.25

λ_1=-1, λ_2=1, λ_3=1.25

A Smooth Approximation: Risk [Smith+ 2006, Shen+ 2015]

Minimum Risk Annealing for Training Log-Linear Models (Smith and Eisner 2006)
Minimum risk training for neural machine translation (Shen et al. 2015)

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- This is includes the probability in the objective function -> **differentiable**!

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- If random sampling, make sure to deduplicate

Policy Gradient/REINFORCE

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- Alternative way of maximizing expected reward, minimizing risk

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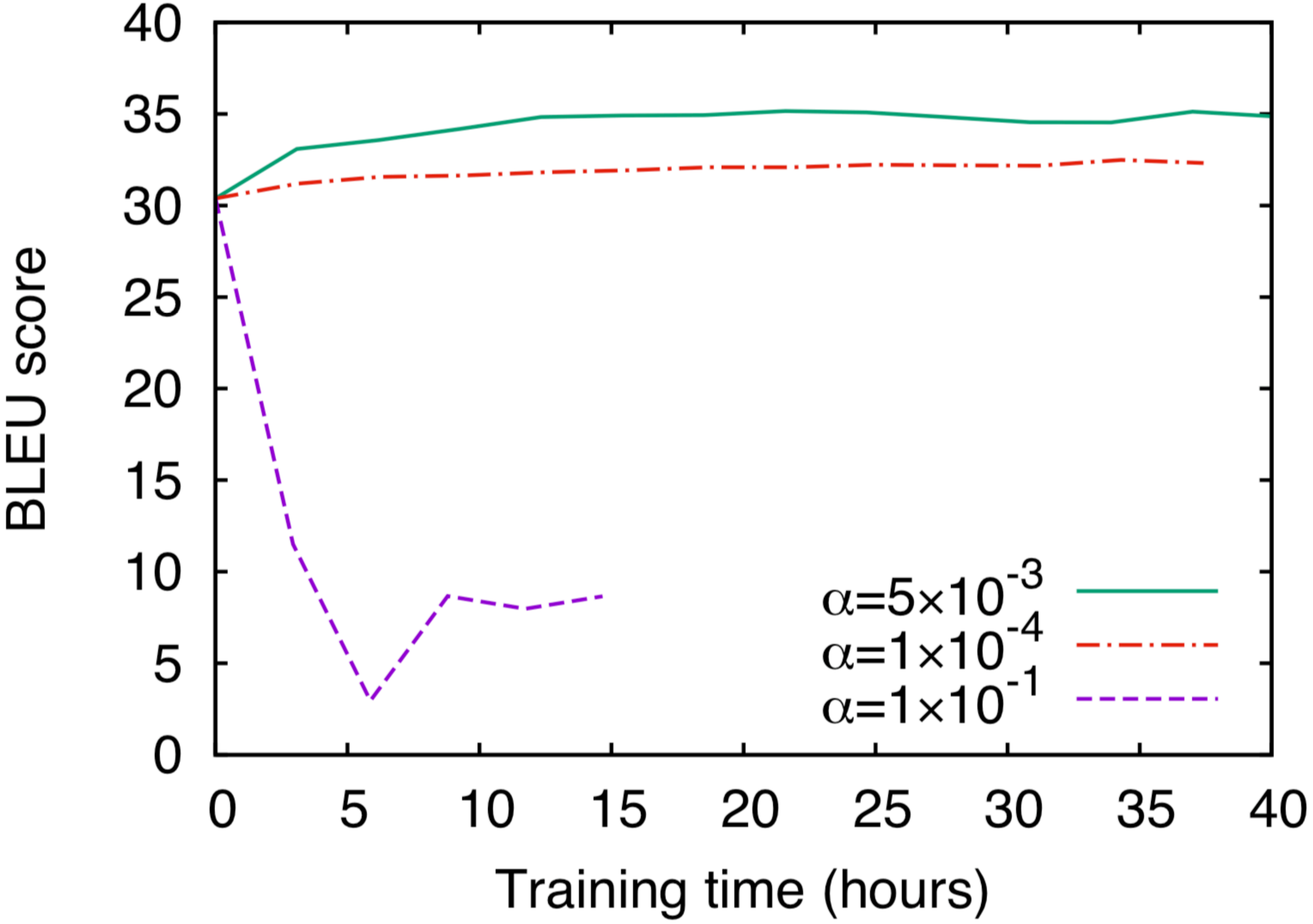
- Outputs that get a bigger reward will get a higher weight

- Can show this converges to minimum-risk solution

But Wait, why is Everyone Using MLE for NMT?

When Training goes Bad...



Minimum risk training for neural machine translation (Shen et al. 2015)

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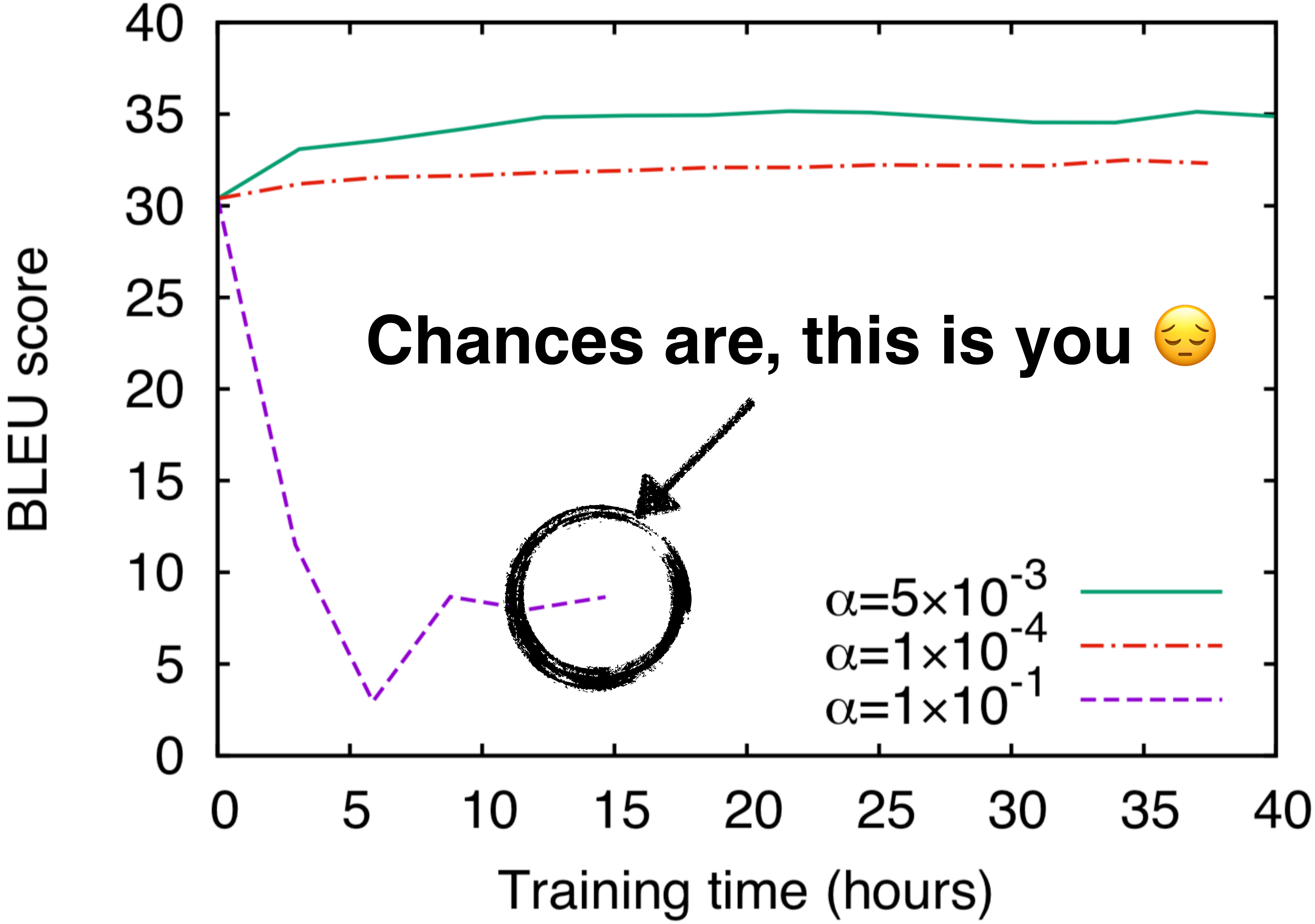

Chances are, this is you 😔

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It Happens to the Best of Us

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- Email from a famous MT researcher:

  "we also re-implemented MRT, but so far, training has been very unstable, and after a improving for a bit, our models develop a bias towards producing ever-shorter translations..."

My Current Recipe for Stabilizing MRT/Reinforcement Learning

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- MIXER (Ranzato et al. 2016) gradually transitions from MLE to the full objective

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- (Be careful to not backprop through the baseline)

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- We can also save previous roll-outs and re-use them when we update parameters (experience replay, Lin 1993)

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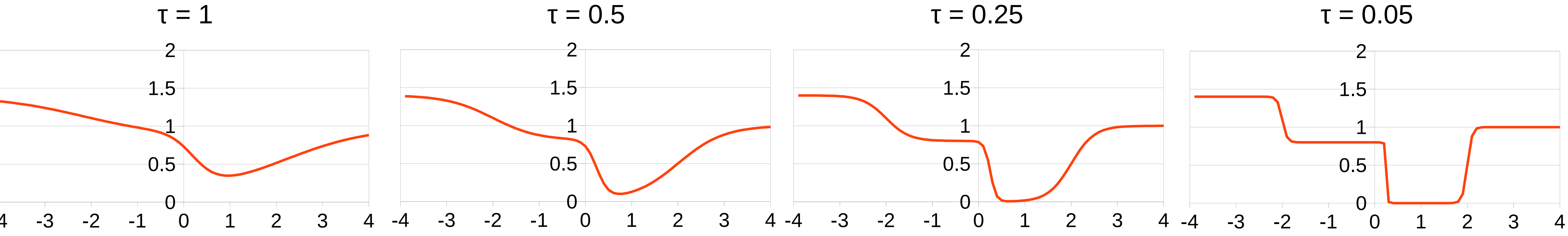

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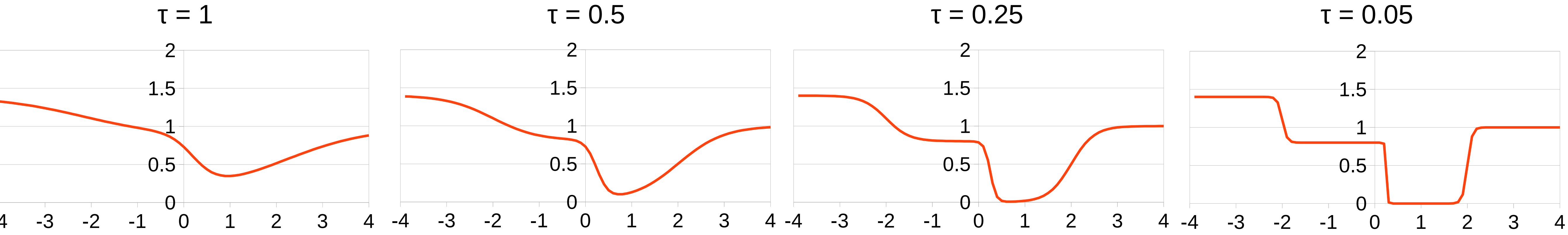

- With a small sample, setting temperature > 1 accounts for unsampled hypotheses that should be in the denominator

Contrasting Phrase-based SMT and NMT

Phrase-based SMT MERT and NMT MinRisk/REINFORCE

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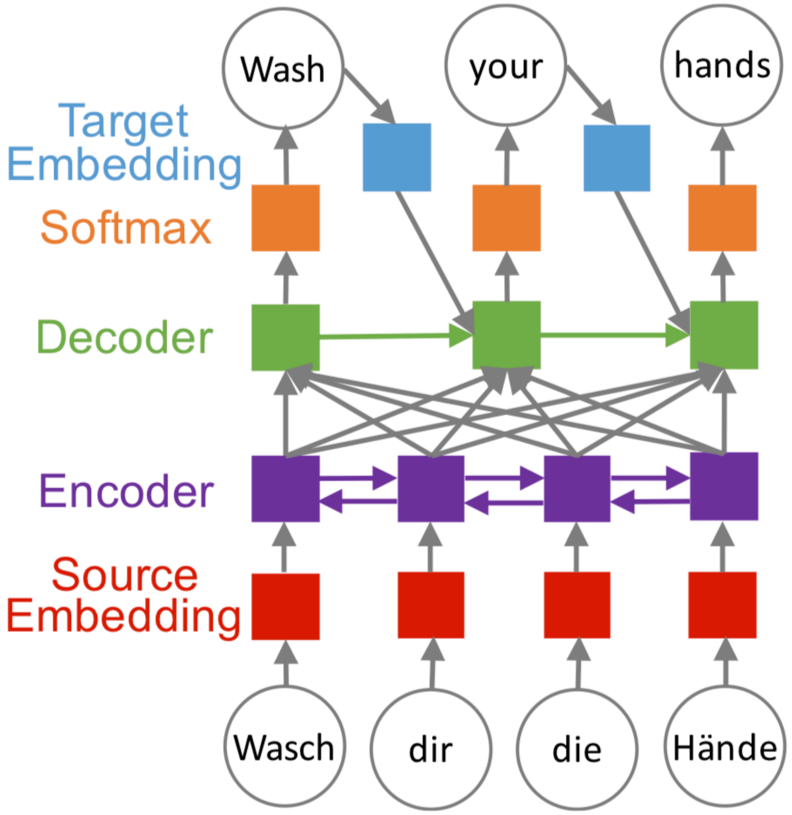

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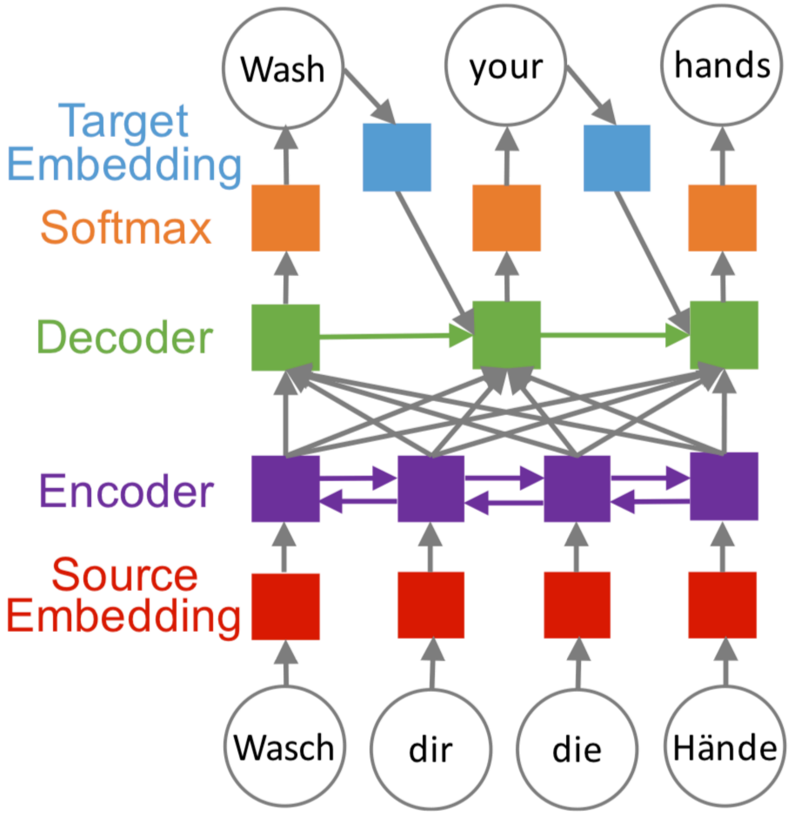

- Maybe we can **express models as a linear combination of a few hyper-parameters**?

  Contextualized Parameter Generation for Universal NMT. Platanios et al. 2018.

$$W = \sum_i \underline{\alpha_i} W_i$$

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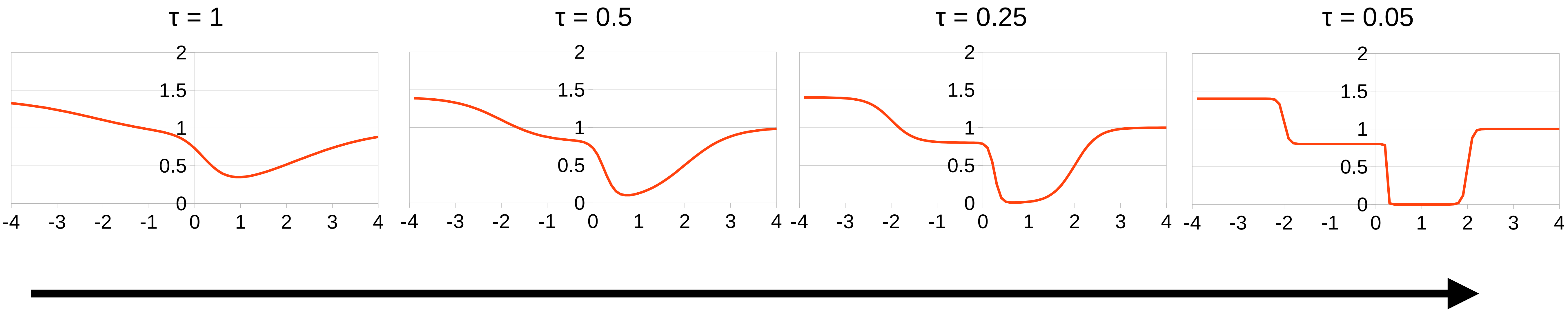
- Maybe we can **gradually anneal the temperature** to move towards a peakier distribution?
  Minimum risk annealing for training log-linear models. Smith and Eisner 2006.



Training progression

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- Maybe we can keep a running average of the sufficient statistics to approximate corpus BLEU?
  Online large-margin training of syntactic and structural translation features. Chiang et al. 2008.

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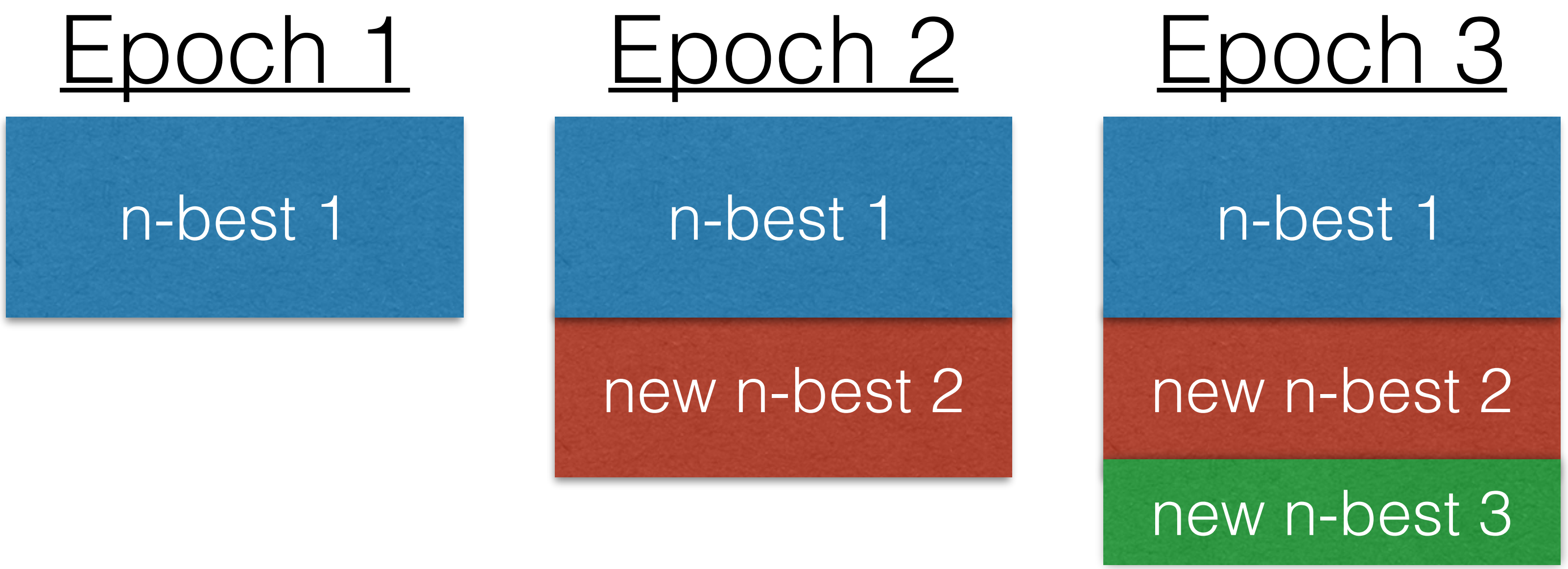

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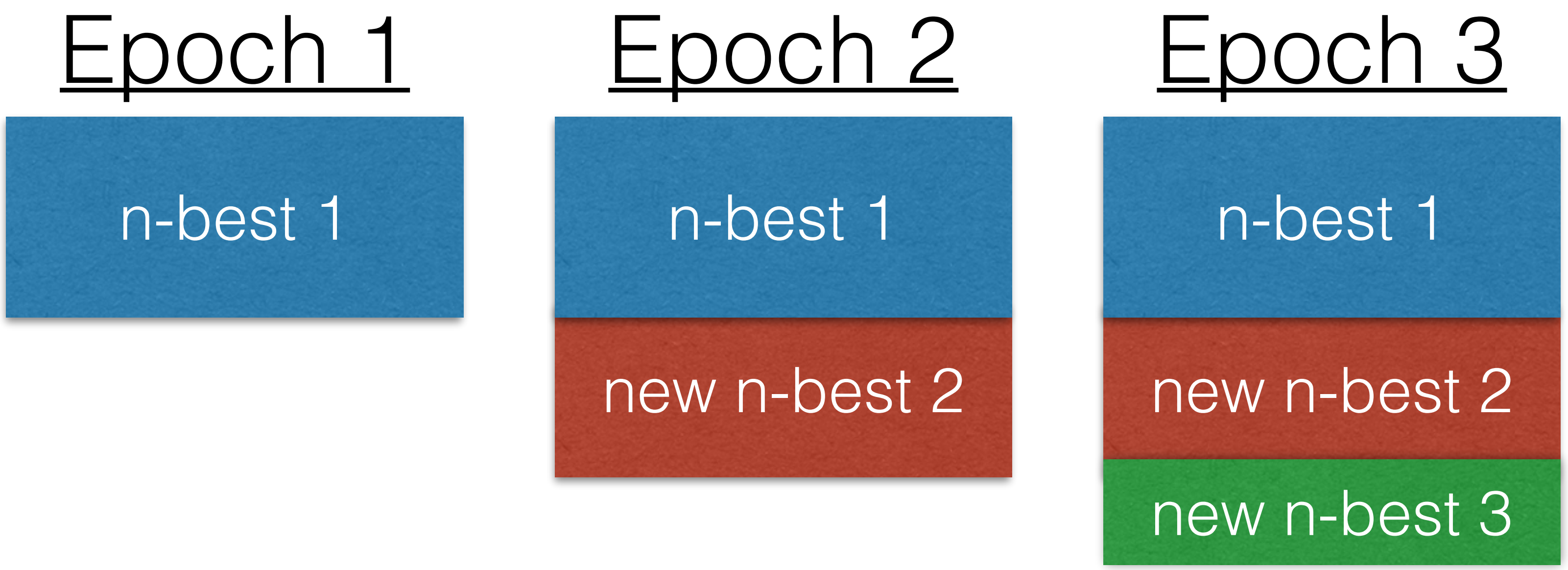

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Epoch 2

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new n-best 2

Epoch 3

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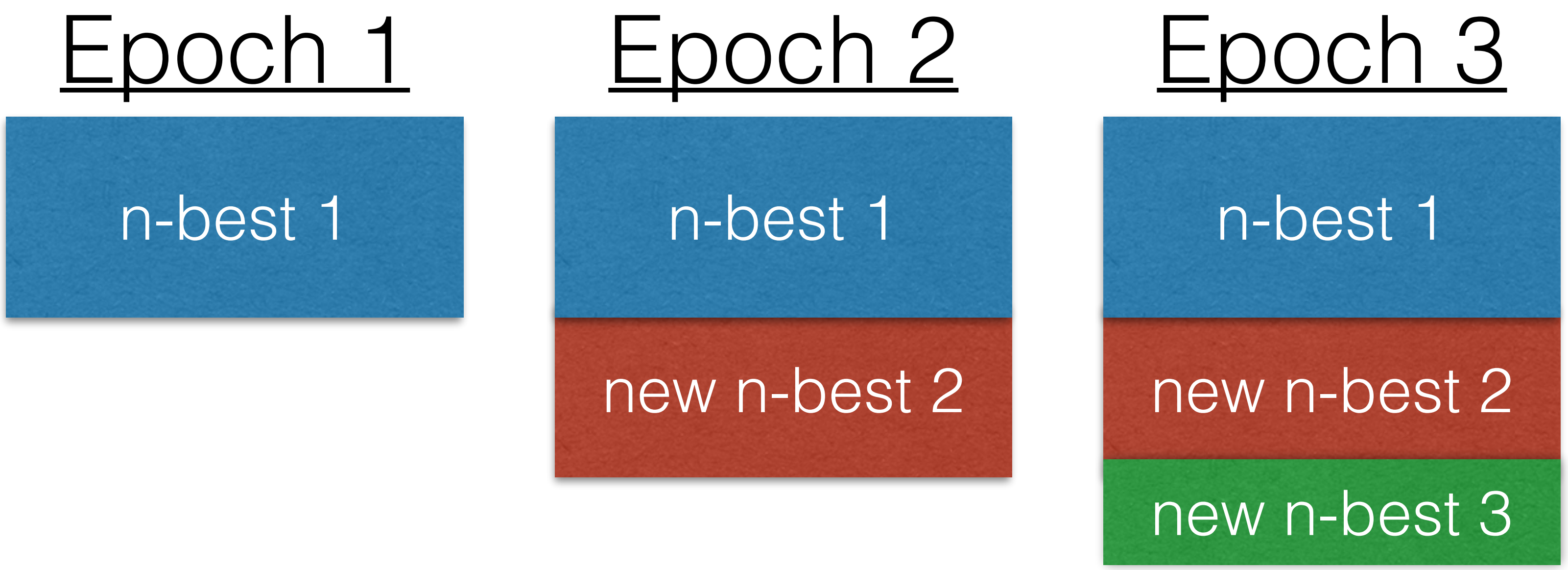

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- Maybe we could do the same for NMT? **Analogous to experience replay** in RL:
  Self-improving reactive agents based on reinforcement learning, planning and teaching. Lin 1992.

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Thanks! Questions?