Applied Deep Learning

Natural Language Generation

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Outline

- NLG Review
  - Language Modeling
  - Conditional Language Modeling
- Decoding Algorithm
  - Greedy
  - Beam Search
  - Sampling
- Evaluation
- Reinforcement Learning for NLG

Natural Language Generation

- Many tasks contain NLG
  - Machine Translation
  - Abstractive Summarization
  - Dialogue Generation
  - Image Captioning
  - Creative Writing
    - Storytelling, poetry generation
  - …

Language Modeling

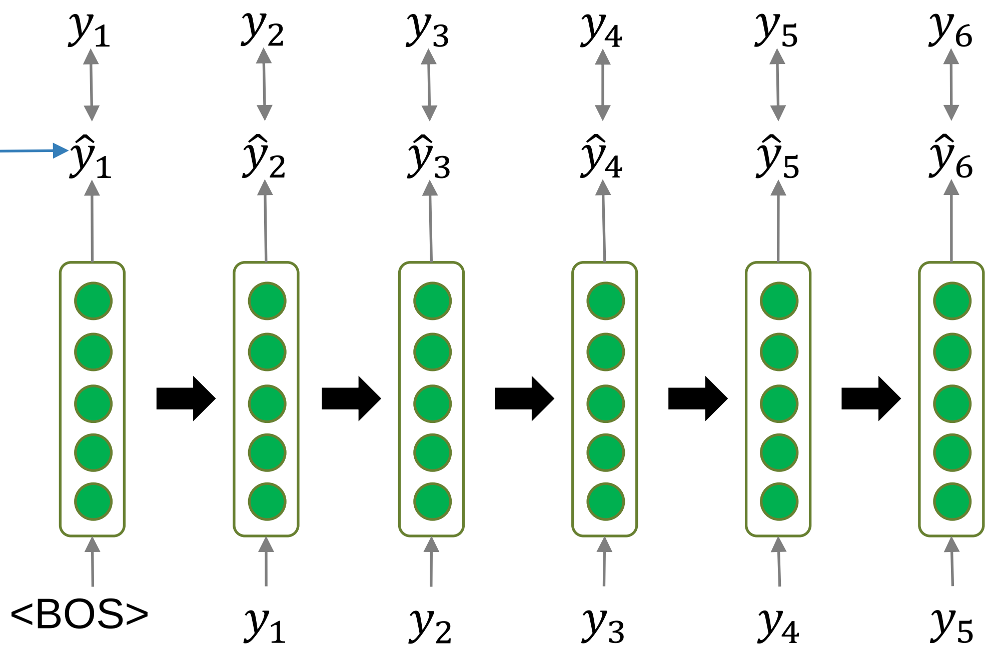
- Goal: predicting the next word given the words so far

$$P(y_i|y_1,\cdots,y_{i-1})$$

- **Language model** is to estimate the probability distribution
  - RNN-LM is to use RNN for modeling the distribution

5 RNN-LM

$P(y_i|y_1,\cdots,y_{i-1})$: probability distribution of the next word



Idea: pass the information from the previous hidden layer to leverage all contexts

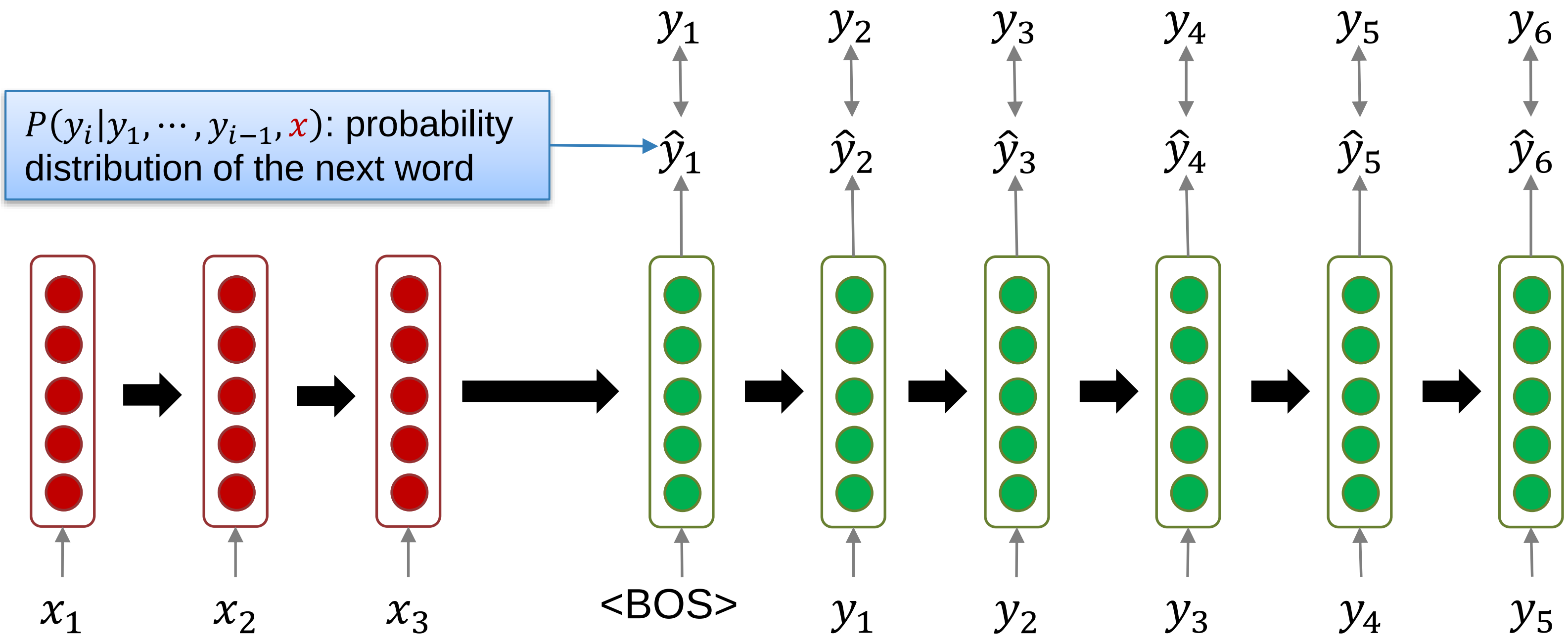
Conditional Language Modeling

- Goal: predicting the next word given the words so far, and other input x

$$P(y_i|y_1,\cdots,y_{i-1},x)$$

- Conditional language modeling tasks
  - Machine translation (x = source sentence, y = target sentence)
  - Summarization (x = document, y = summary)
  - Dialogue (x = dialogue context, y = response)
  - Image captioning (x = image, y = caption)
  - …

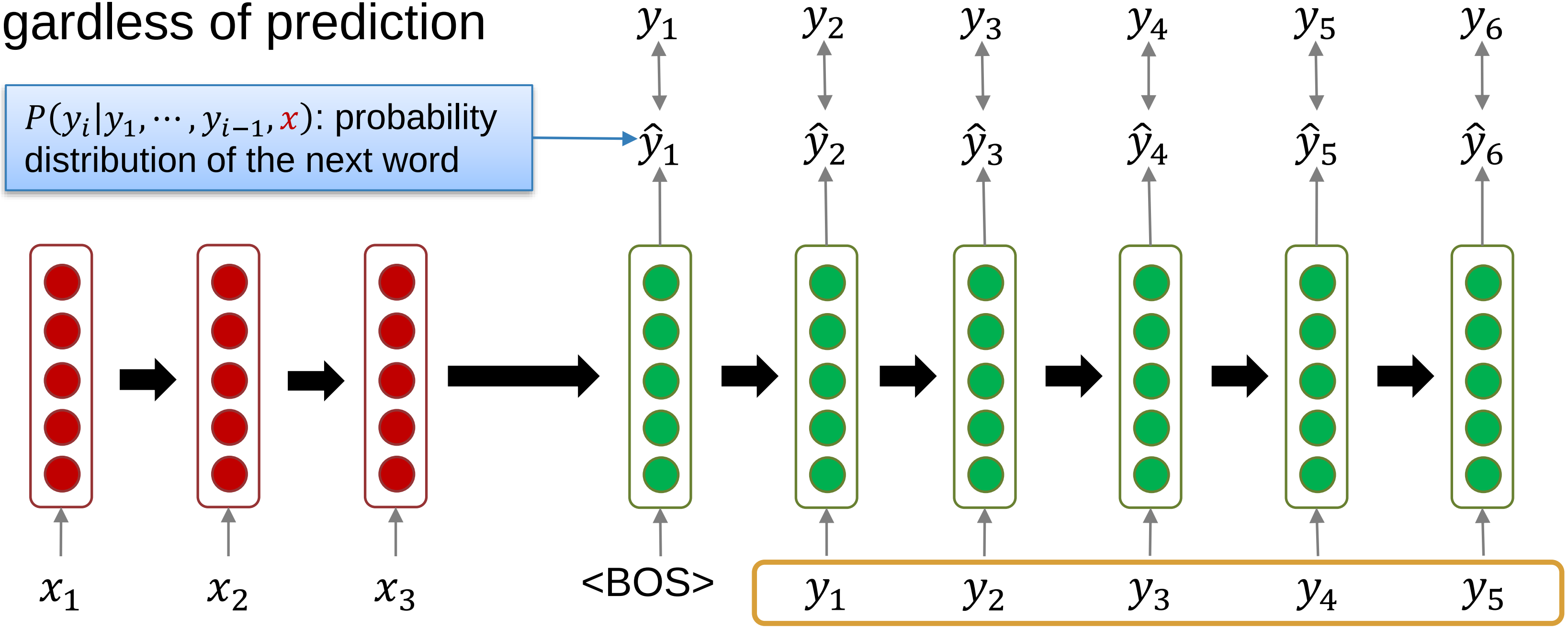
Sequence-to-Sequence Modeling



Training an encoder-decoder model that generate the next word with condition

Teacher Forcing

- During training, feeding the gold target sentence into the decoder regardless of prediction



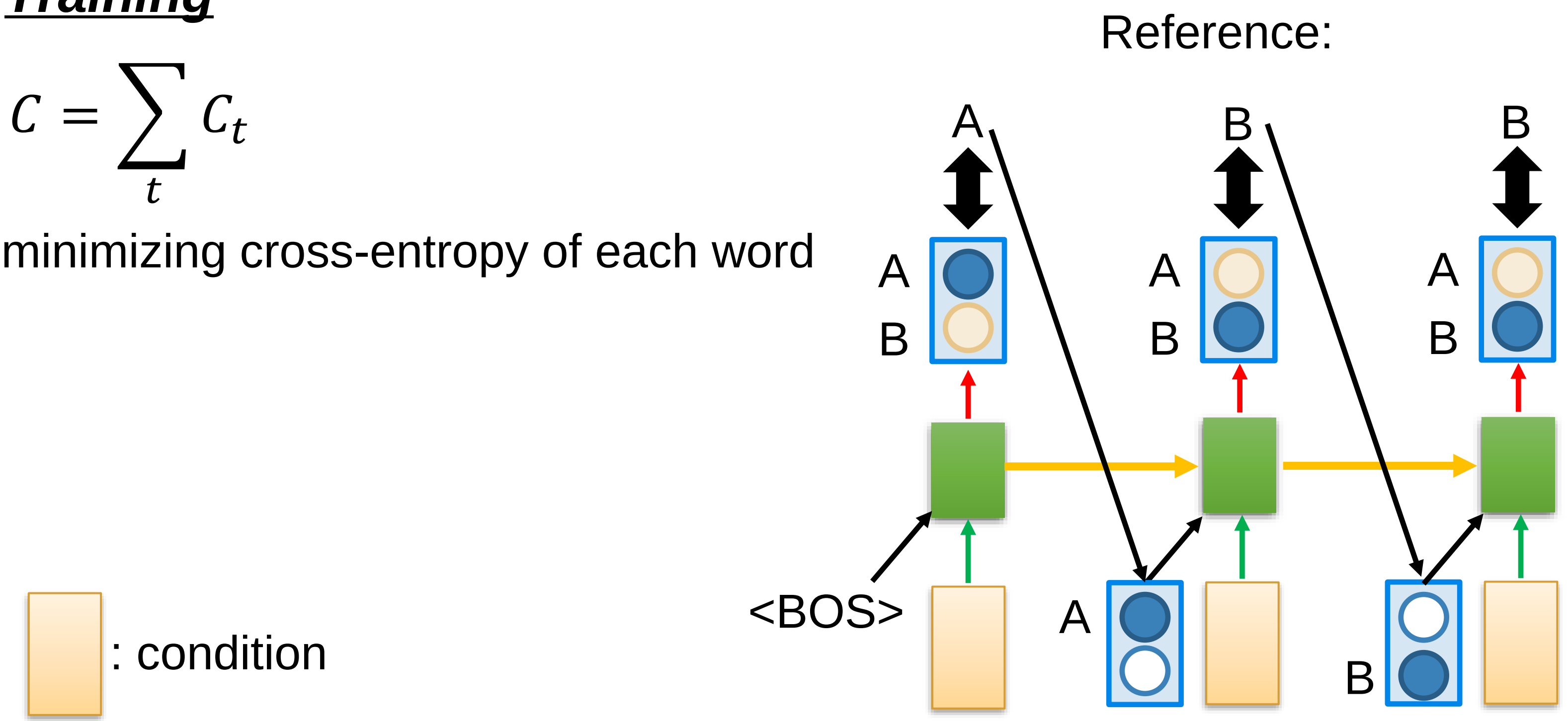
Issue: mismatch between training and testing

Mismatch between Train and Test

- ***Training***

$$C = \sum_t C_t$$

minimizing cross-entropy of each word

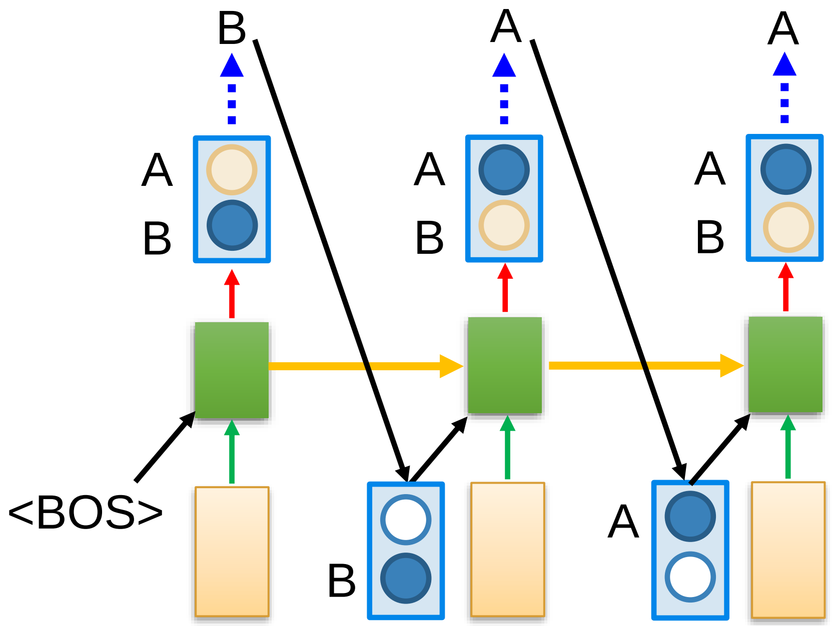


Mismatch between Train and Test

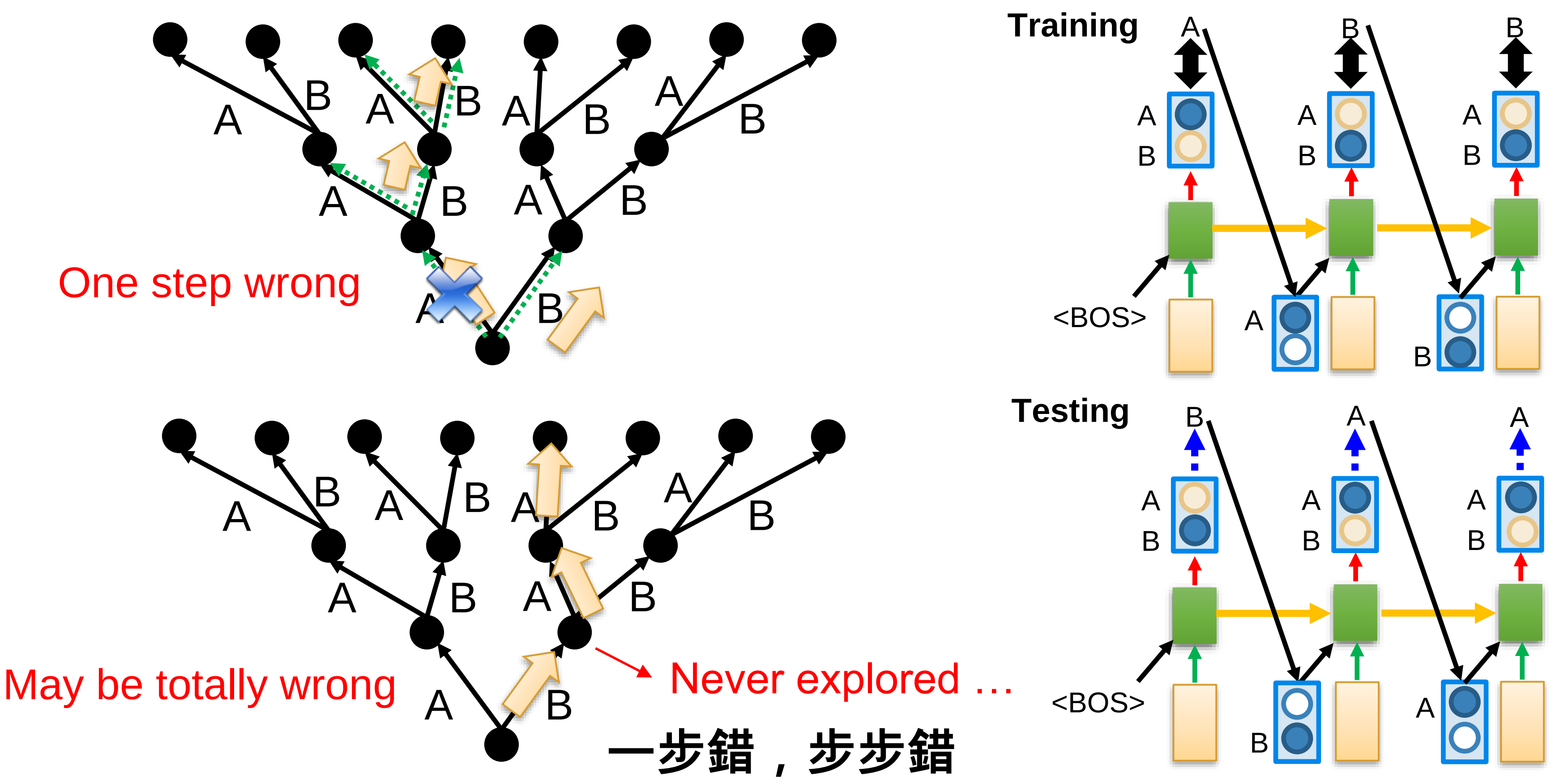
Generation

- Testing: Output of model is the input of the next step.
  - Reference is unknown
- Training: the inputs are reference.

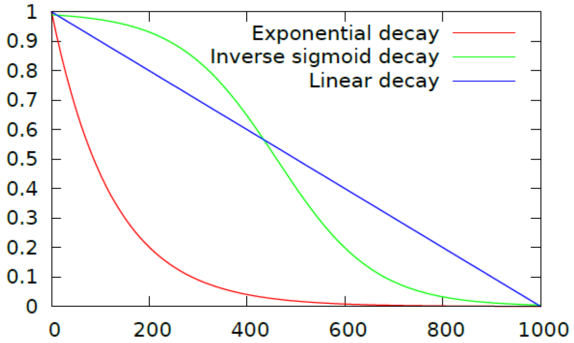
Exposure Bias

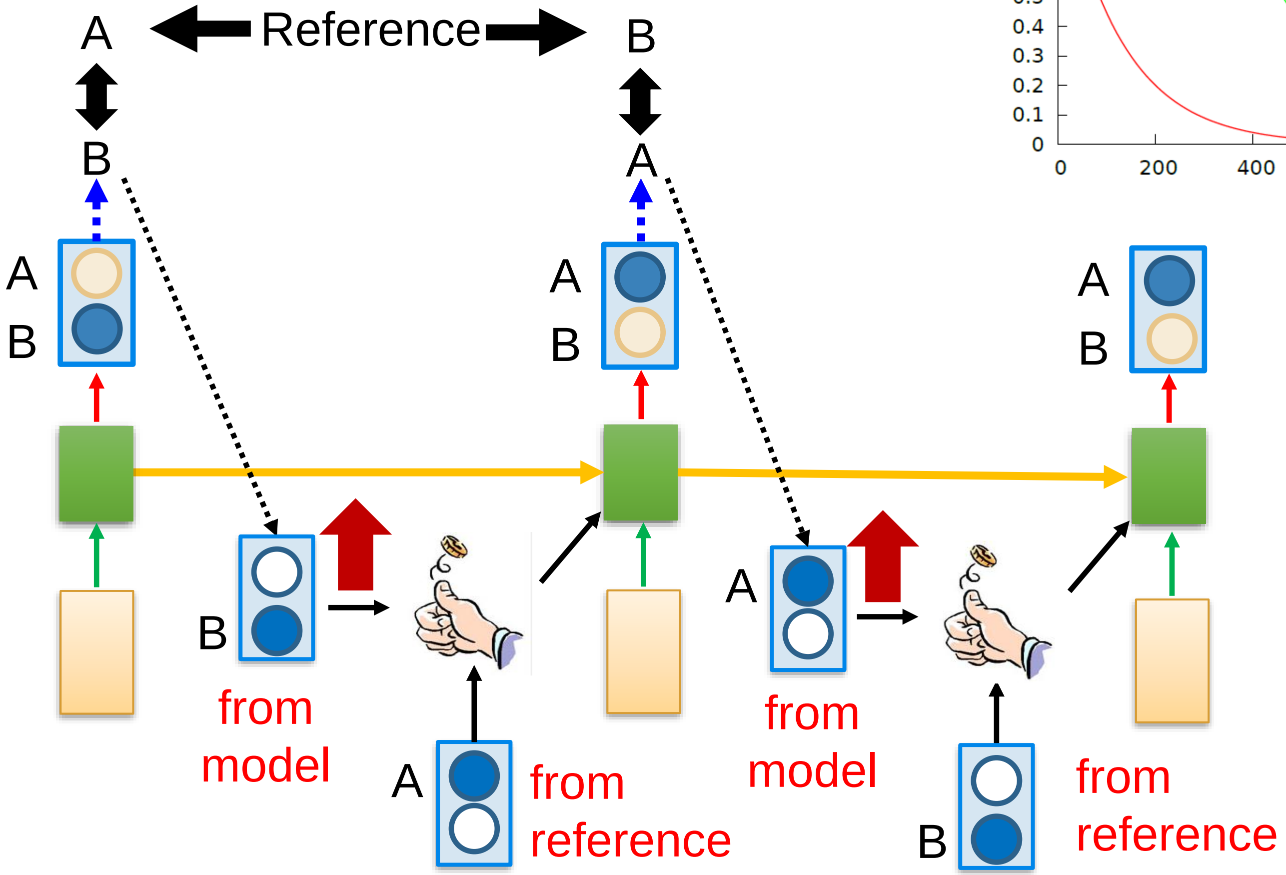


Exposure Bias



Scheduled Sampling





Scheduled Sampling

- Image captioning on MSCOCO

	BLEU-4	METEOR	CIDER
Always from reference	28.8	24.2	89.5
Always from model	11.2	15.7	49.7
Scheduled Sampling	30.6	24.3	92.1

Samy Bengio, Oriol Vinyals, Navdeep Jaitly, Noam Shazeer, Scheduled Sampling for Sequence Prediction with Recurrent Neural Networks, arXiv preprint, 2015

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Decoding Algorithm

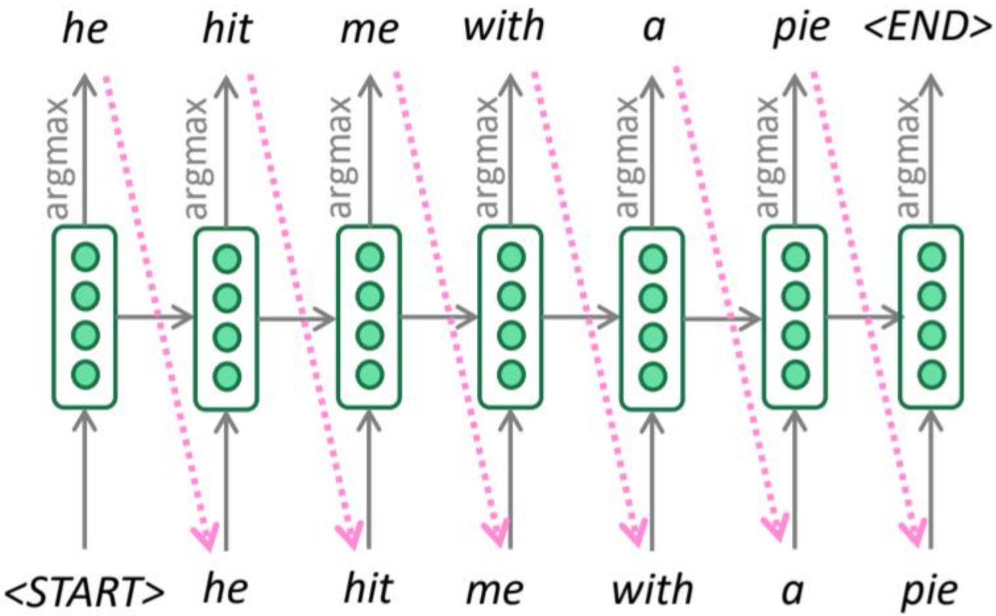
Strategy of Word Generation

Decoding Algorithm

- With a trained (conditional) LM, a *decoding algorithm* decides how to generate texts from the LM.
- Decoding Algorithms
  - Greedy
  - Beam Search
  - Sampling

Greedy

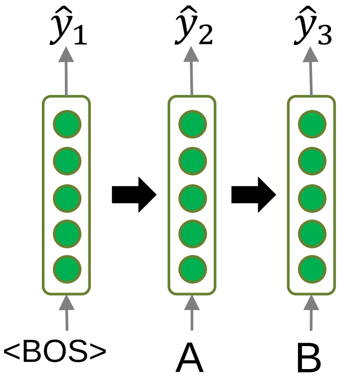
- Strategy: choosing the most probable word (argmax)

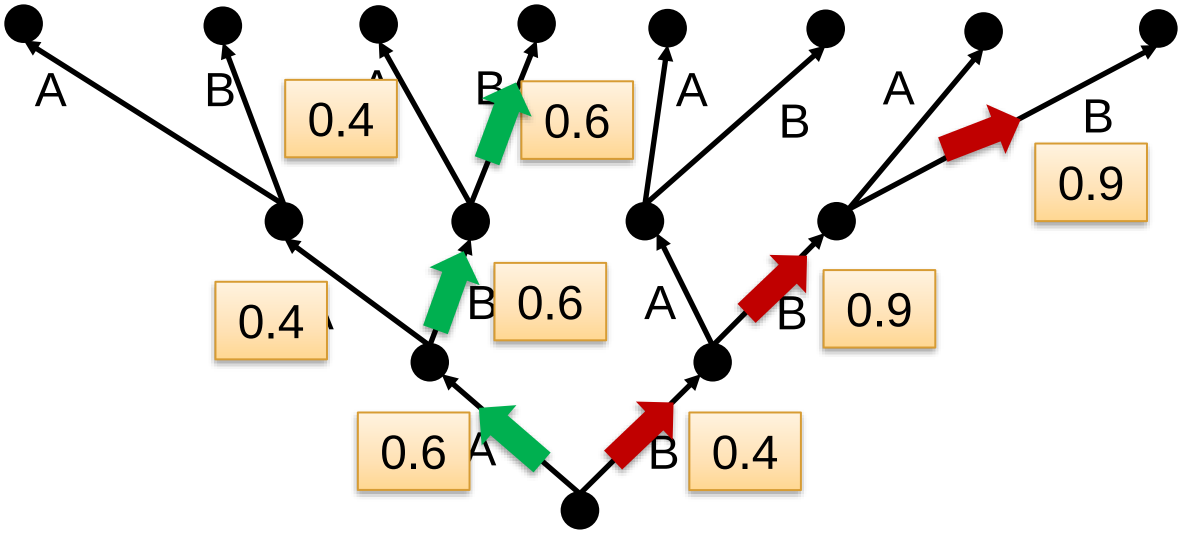


Output can be poor due to lack of backtracking

Suboptimal Issue

- Unexplored path may have higher probability.





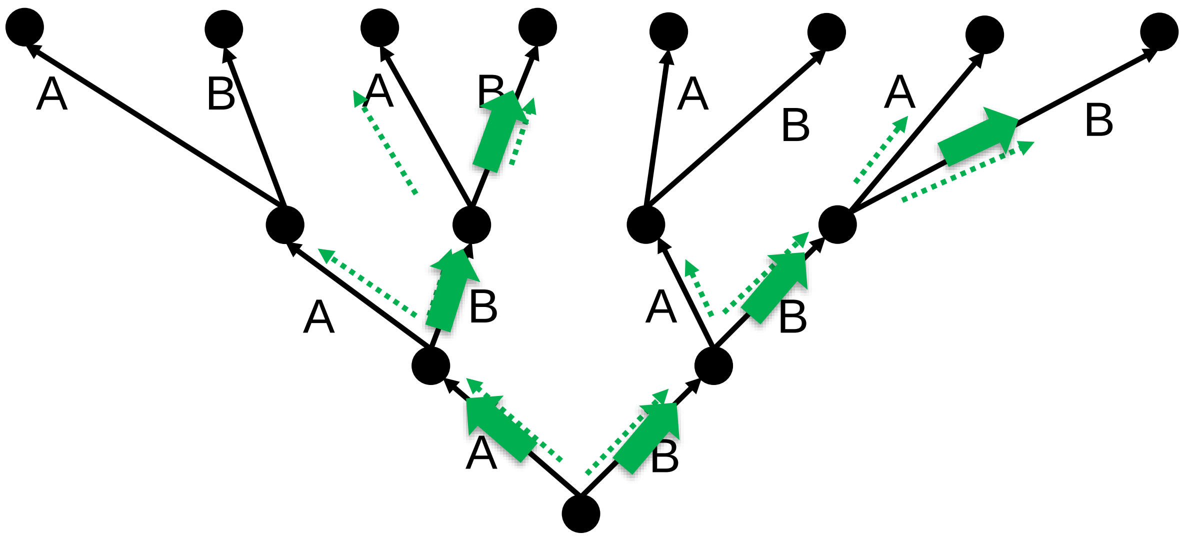
The red path has higher score.

Issue: Impossible to check all paths

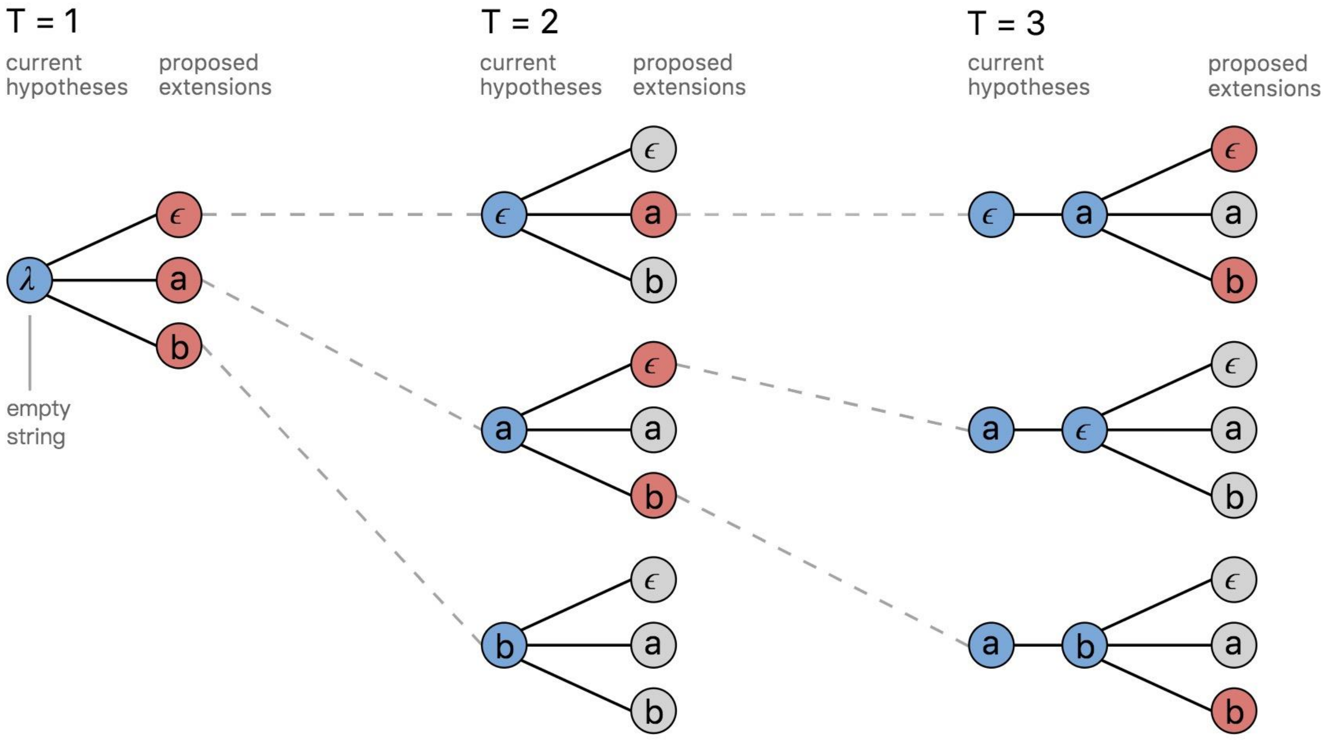
Beam Search

- Strategy: keeping track of the *k* most probable sequences and finding a better one

Keep several best paths at each step (beam size = 2)



Beam Search



A standard beam search algorithm with an alphabet of $\{\epsilon, a, b\}$ and a beam size of three.

The size of beam is 3 in this example.

Effect of Beam Size

- Small k
  - Ungrammatical, unnatural, incorrect, etc.

- Large k
  - Reduce some above issues
  - Computationally expensive
  - Introduce other issues
    - Chit-chat dialogues with large beam often generate generic sentences

Effect of Beam Size in Chit-Chat Dialogues

I mostly eat a fresh and raw diet, so I save on groceries

Beam Size	Model Response
1	*I love to eat healthy and eat healthy*
2	*That is a good thing to have*
3	*I am a nurse so I do not eat raw food*
4	*I am a nurse so I am a nurse*
5	*Do you have any hobbies?*
6	*What do you do for a living?*
7	*What do you do for a living?*
8	*What do you do for a living?*

Small Beam Size:
More on-topic but nonsensical; bad English

Large Beam Size:
safe, “correct” response, but generic and less relevant

Finding a proper beam size is not trivial

Sampling-Based Decoding

- Strategy: choosing the next word with randomness (from a distribution)
- Sampling
  - Randomly sample the word via the probability distribution instead of argmax
- Top-N Sampling
  - Sample the word via distribution but restricted to the top-N probable words
  - N=1 is greedy, N=V is pure sampling
  - Increasing N gets more diverse / risky output
  - Decreasing N gets more generic / safe output

Balancing between diversity and safety is an important direction

Probability Distribution

1. Softmax

$$P(w_t) = \frac{e^{s_w}}{\sum_{w' \in V} e^{s_{w'}}}$$

softmax: LM computes a prob dist by applying softmax to a vector of scores

2. Softmax temperature: applying a temperature hyperparameter τ to the softmax

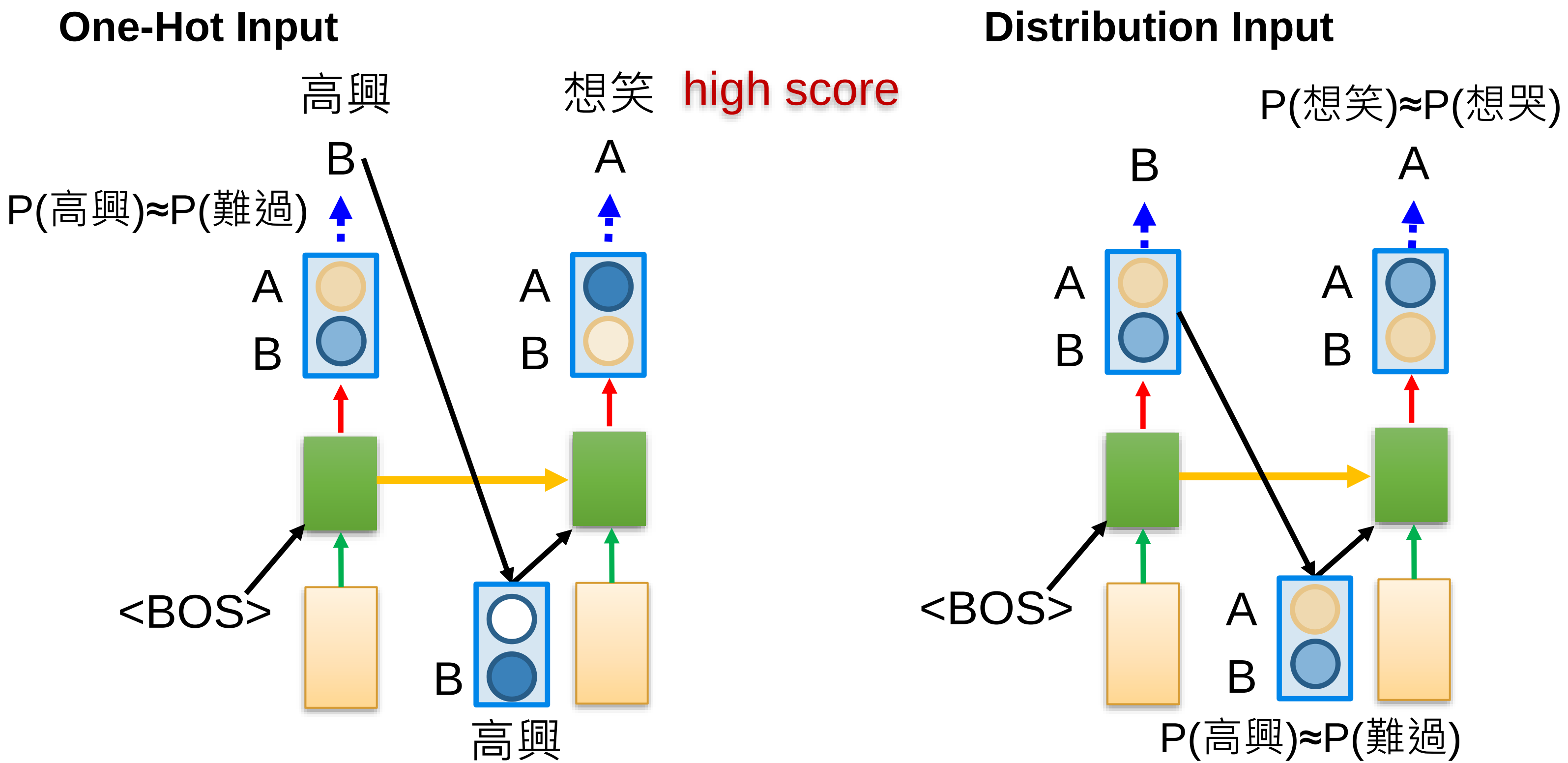
$$P(w_t) = \frac{e^{s_w/\tau}}{\sum_{w' \in V} e^{s_{w'}/\tau}}$$

- Higher temperature: $P(w_t)$ becomes more uniform → more diversity
- Lower temperature: $P(w_t)$ becomes more spiky → less diversity

softmax temperature is not a decoding algorithm, which is the way of controlling the diversity during testing via any decoding algorithm

Distribution Input

U: 你覺得如何?
M: 高興想笑 or 難過想哭



Distribution input may not be good for NLG

NLG Evaluation

How Good The Model Performs

BLEU

- N-Gram Precision

$$p_n = \frac{\sum_{ngram \in hyp} count_{clip}(ngram)}{\sum_{ngram \in hyp} count(ngram)}$$

highest count of n-gram in any reference sentence

- Brevity Penalty

$$B = \begin{cases} e^{(1-|ref|/|hyp|)}, \text{if } |ref| > |hyp| \\ 1 \quad , \text{otherwise} \end{cases}$$

- BLEU
  - Often used in machine translation

$$BLEU = \mathrm{B} \cdot exp\left[\frac{1}{\mathrm{N}} \sum_{n=1}^{N} p_n\right]$$

ROUGE

- ROUGE (Recall-Oriented Understudy for Gisting Evaluation)
  - Often used in summarization tasks

$$\text{ROUGE-N} = \frac{\sum_{S \in \{ReferemceSummaries\}} \sum_{gram_n \in S} Count_{match}(gram_n)}{\sum_{S \in \{ReferenceSummaries\}} \sum_{gram_n \in S} Count(gram_n)}$$

BLEU & ROUGE

- BLEU
  - Based on n-gram overlap
  - Consider precision
  - Reported as a single number
    - Combination of n = 1, 2, 3, 4 n-grams
- ROUGE
  - Based on n-gram overlap
  - Consider recall
  - Reported separately for each n-gram
    - ROUGE-1: unigram overlap
    - ROUGE-2: bigram overlap
    - ROUGE-L: LCS overlap

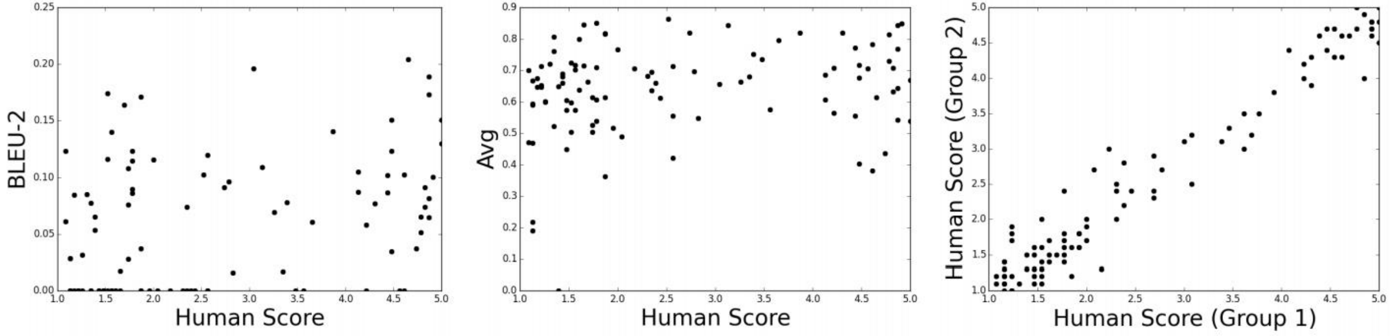
Automatic Evaluation Metrics

- Word overlap metrics: BLEU, ROUGE, METEOR, etc.
  - Not ideal for machine translation
  - Much worse for summarization
  - Even worse for dialogue, storytelling

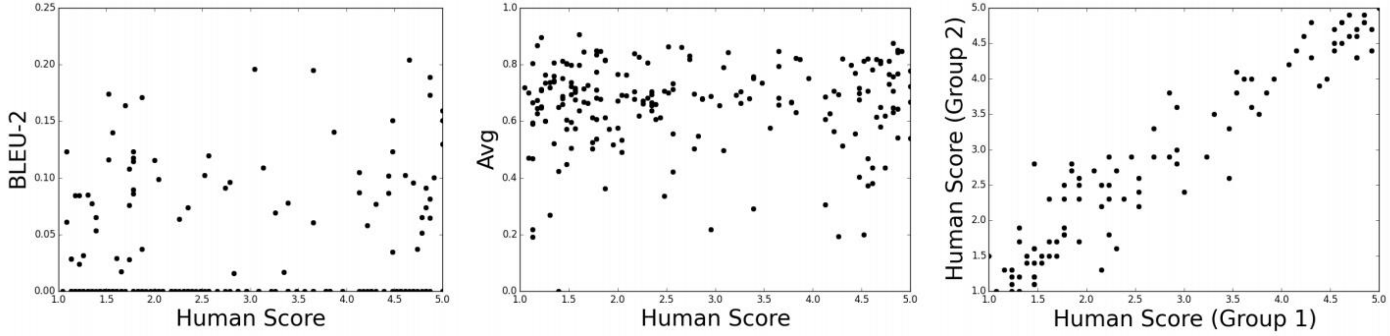
more open-ended

- Embedding metrics
  - Computing the similarity of word embeddings
  - Capturing semantics in a flexible way

Automatic Metrics v.s. Human Judgement



(a) Twitter



(b) Ubuntu

No agreement between automatic scores and human scores in dialogue quality

Focused Metrics for Particular Aspects

- Evaluating a single aspect instead of the overall quality
  - Fluency (compute probability w.r.t. well-trained LM)
  - Correct style (prob w.r.t. LM trained on target corpus)
  - Diversity (rare word usage, uniqueness of n-grams)
  - Relevance to input (semantic similarity measures)
  - Simple things like length and repetition
  - Task-specific metrics e.g. compression rate for summarization

Scores help us track some important qualities we care about

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Reinforcement Learning for NLG

Global Optimization

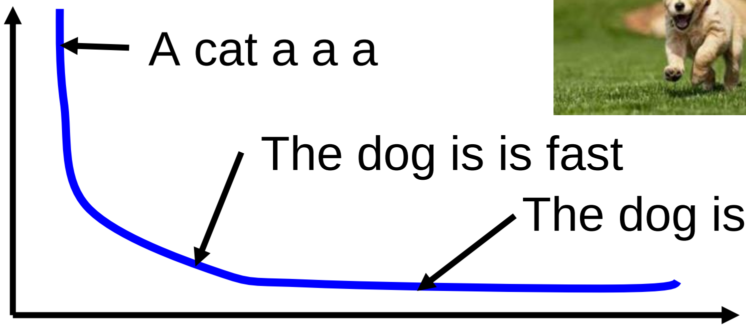
Global Optimization v.s. Local Optimization

- Minimizing the error defined on component level (local) is not equivalent to improving the generated objects (global)

Reference: The dog is running fast

$$C = \sum_t C_t$$

Cross-entropy of each step

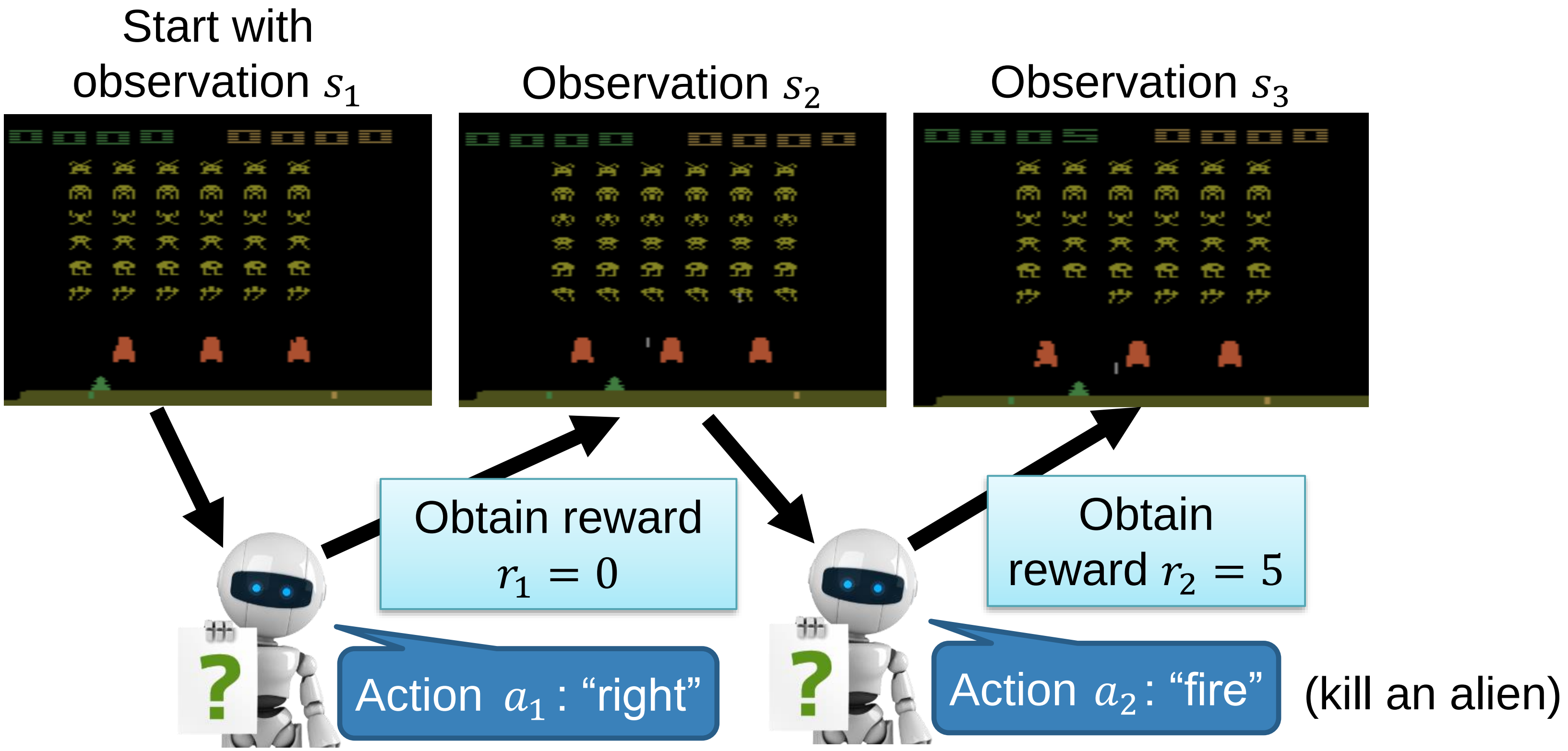


Optimize object-level criterion instead of component-level cross-entropy.

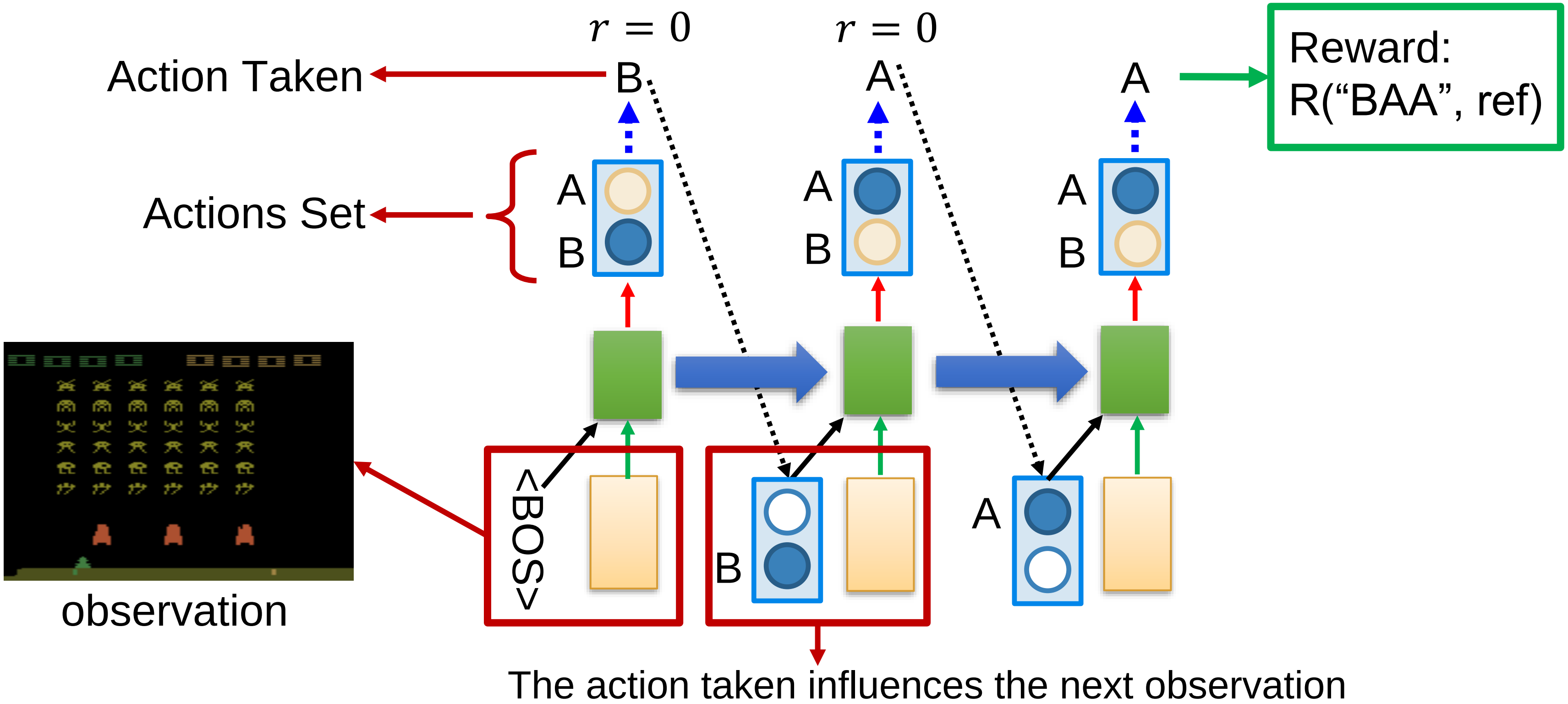
Object-level criterion: $R(y, \hat{y})$ y: ground truth, $\hat{y}$: generated sentence

Gradient Descent?

Reinforcement Learning

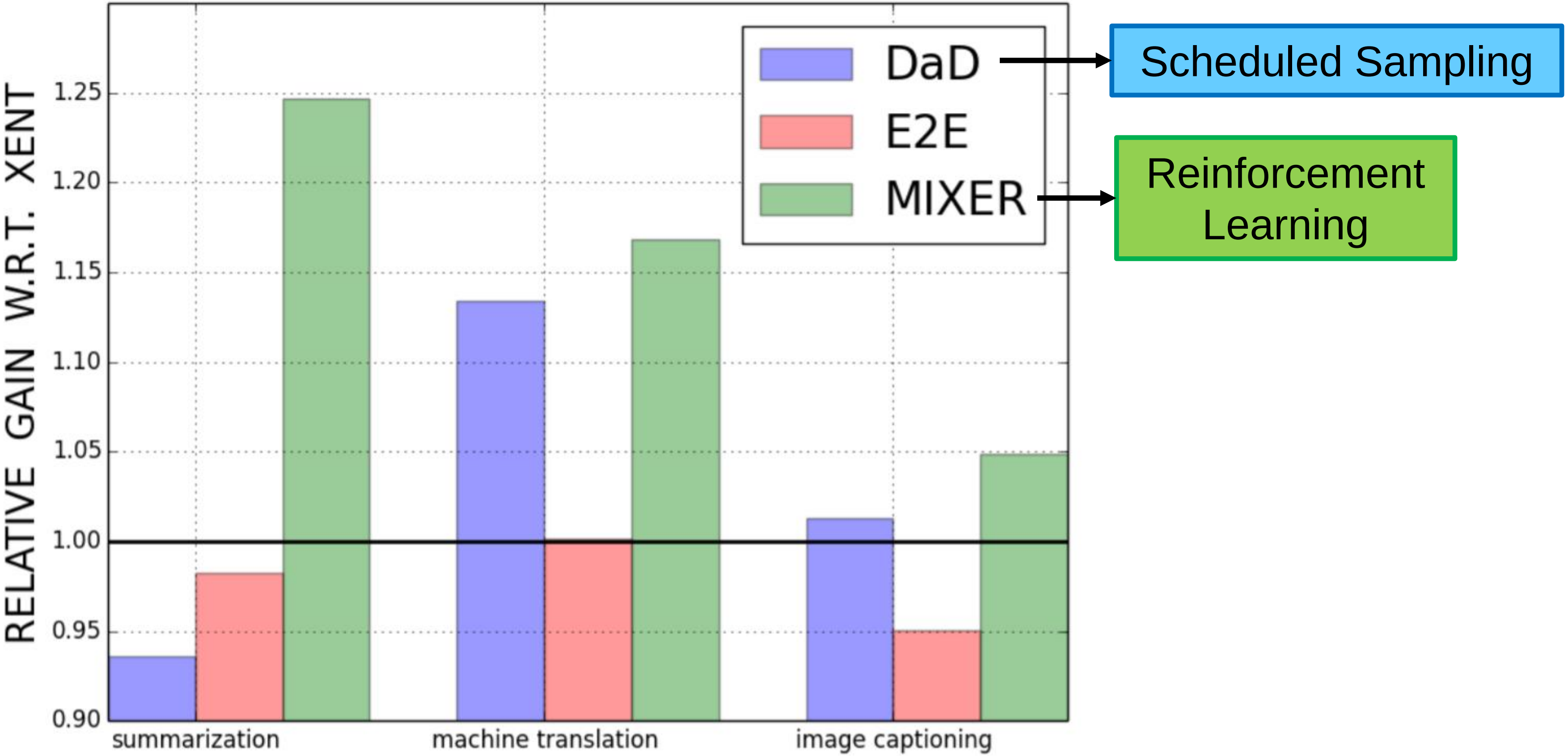


RL for NLG



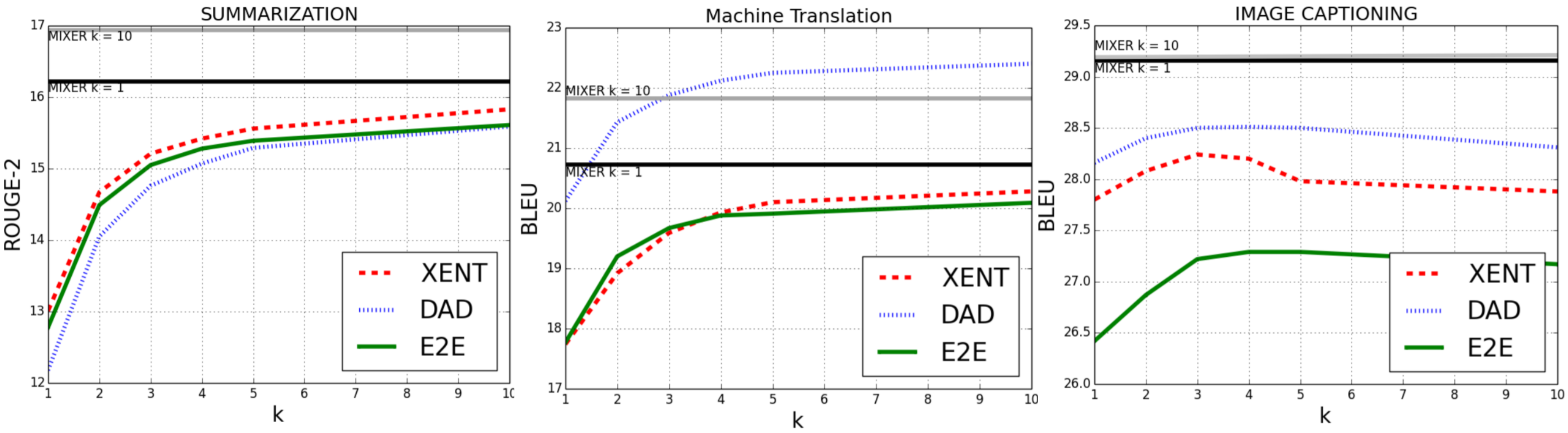
Marc'Aurelio Ranzato, Sumit Chopra, Michael Auli, Wojciech Zaremba, "Sequence Level Training with Recurrent Neural Networks", ICLR, 2016

RL for NLG



RELATIVE GAIN W.R.T. XENT
1.25
1.20
1.15
1.10
1.05
1.00
0.95
0.90
summarization
machine translation
image captioning
DaD
E2E
MIXER
Scheduled Sampling
Reinforcement Learning

RL for NLG


SUMMARIZATION
ROUGE-2
MIXER k = 10
MIXER k = 1
XENT
DAD
E2E
k
Machine Translation
BLEU
MIXER k = 10
MIXER k = 1
XENT
DAD
E2E
k
IMAGE CAPTIONING
BLEU
MIXER k = 10
MIXER k = 1
XENT
DAD
E2E
k

RL-Based Summarization

- RL: directly optimize ROUGE-L
- ML+RL: MLE + RL for optimizing ROUGE-L

Automatic

Model	ROUGE-1	ROUGE-2	ROUGE-L
ML, no intra-attention	44.26	27.43	40.41
ML, with intra-attention	43.86	27.10	40.11
RL, no intra-attention	**47.22**	30.51	**43.27**
ML+RL, no intra-attention	47.03	**30.72**	43.10

Human

Model	Readability	Relevance
ML	6.76	7.14
RL	4.18	6.32
ML+RL	**7.04**	**7.45**

Using RL instead of ML achieves higher ROUGE scores, but lower human scores.

Hybrid is the best.

Concluding Remarks

- NLG / Conditional NLG
- Decoding Algorithm
  - Greedy
  - Beam Search
  - Sampling
- Evaluation
  - Overall Quality → Specific Aspects
- Reinforcement Learning for NLG
  - Directly optimizing the target score