CS11-737 Multilingual NLP

Non-Autoregressive Generation

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https://lileicc.github.io/course/11737mnlp23fa/

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Outline

- Autoregressive & Non-autoregressive Generation
- Iterative NAT and Limitation
- Glancing Transformer
- Directed Acyclic Transformer

Transformer is Autoregressive

- Autoregressive models generate sentences sequentially

很多树 $\Rightarrow$ a lot of trees

- The conditional probability is factorized successively

$$p(Y|X;\theta) = \prod_{t=1}^{T} p(y_t|y_{<t}, X;\theta)$$

- Human-style translation is slow. Machine does not have to mimic human!

Wild idea: Parallel Generation?

- Non-autoregressive models generate all the tokens in parallel

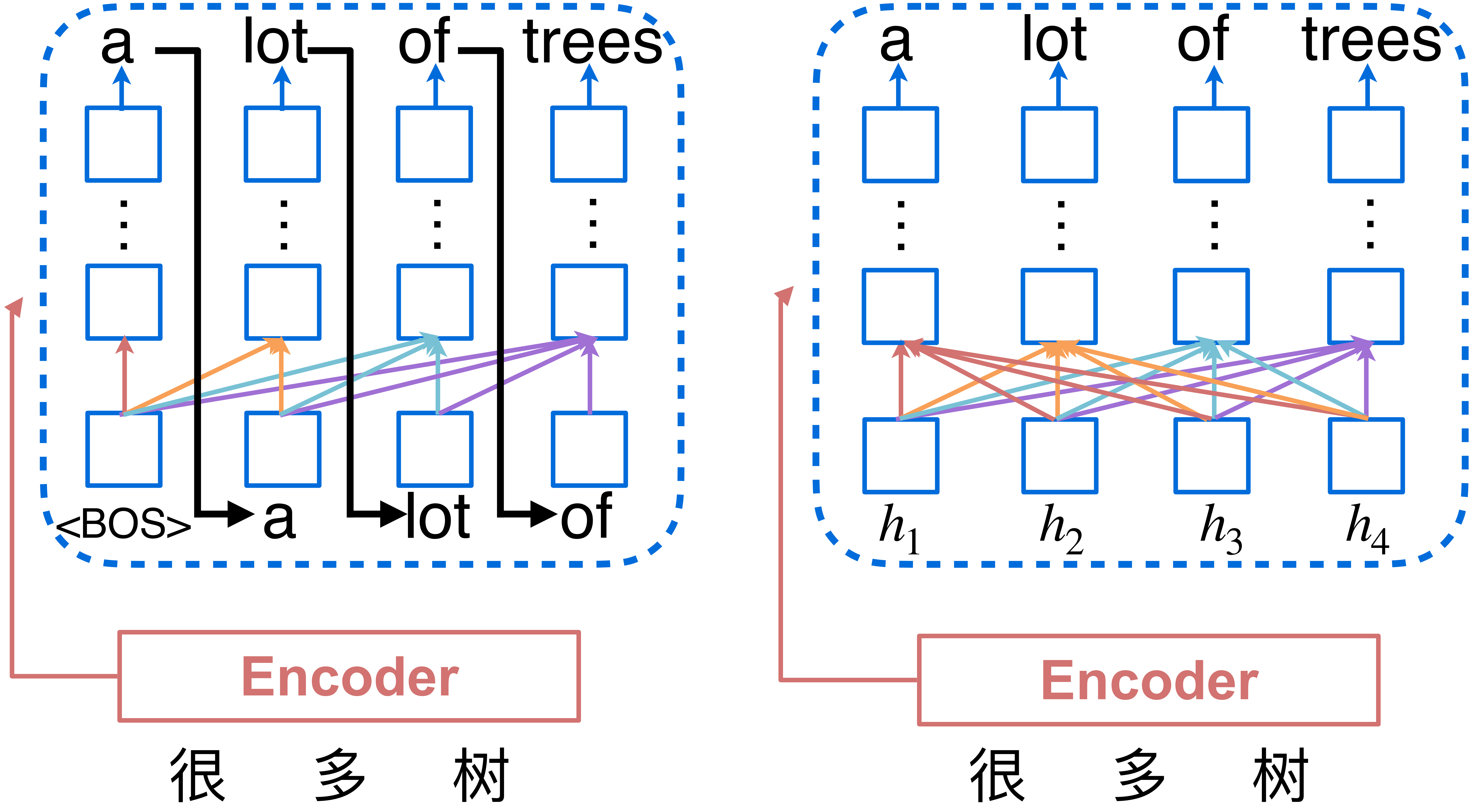
很多树 → a lot of trees

- Conditional independence assumption

$$p(Y|X;\theta) = \prod_{t=1}^{T} p(y_t|X;\theta)$$

Model architecture

Autoregressive decoder **Non-autoregressive decoder**



Training of vanilla NAT

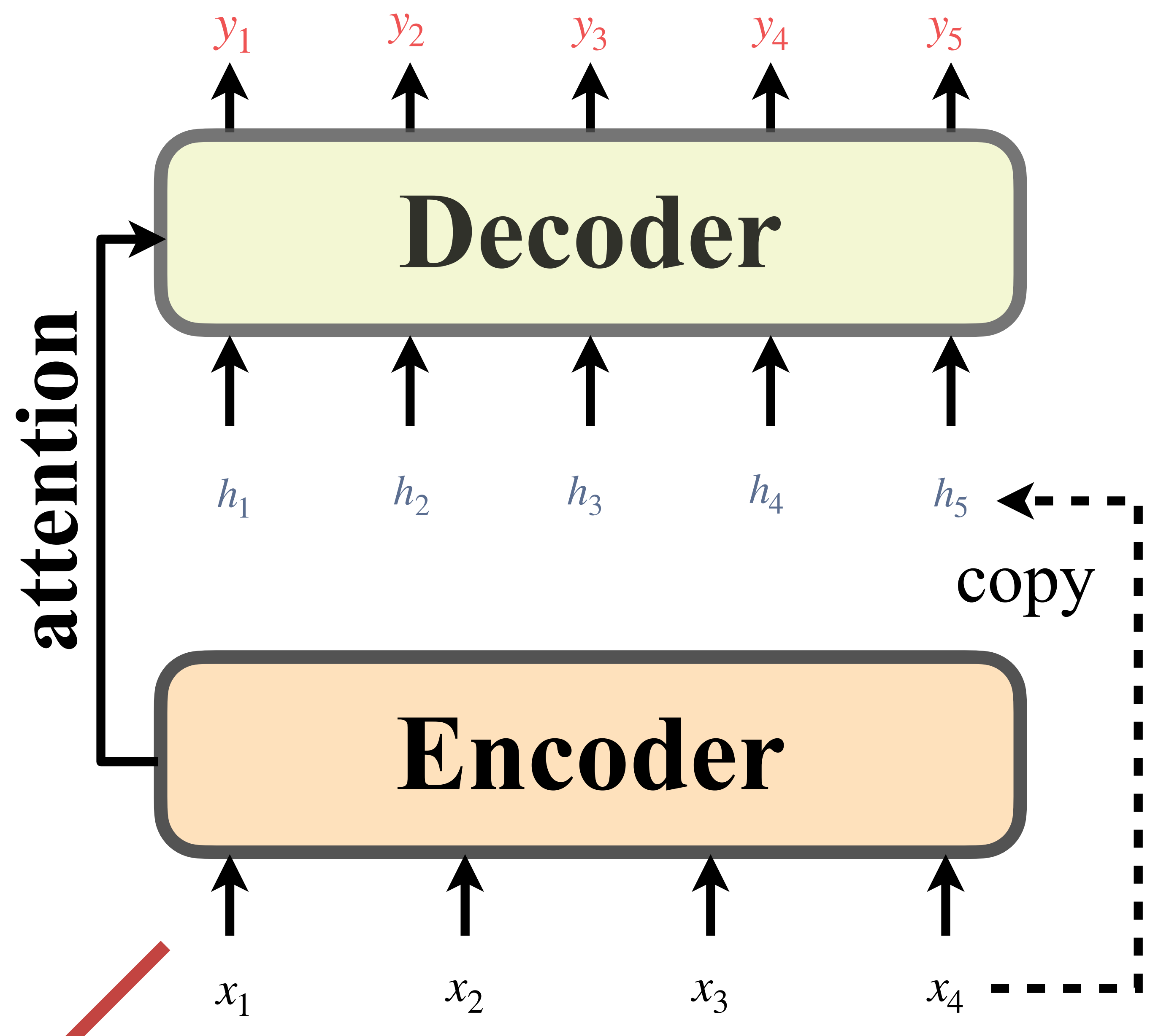
- Maximum likelihood estimation (MLE)

$$p(Y|X;\theta) = \prod_{t=1}^{T} p(y_t|X;\theta)$$

$$L_\theta = -\log p(Y|X;\theta)$$

directly follow autoregressive models

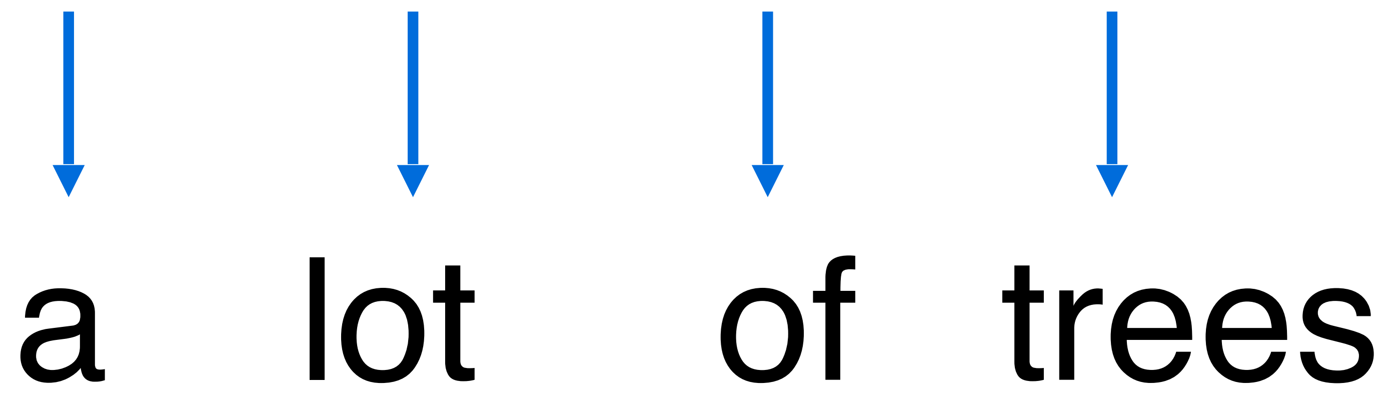
- Target length
  - predict before decoding
  - predefine max length



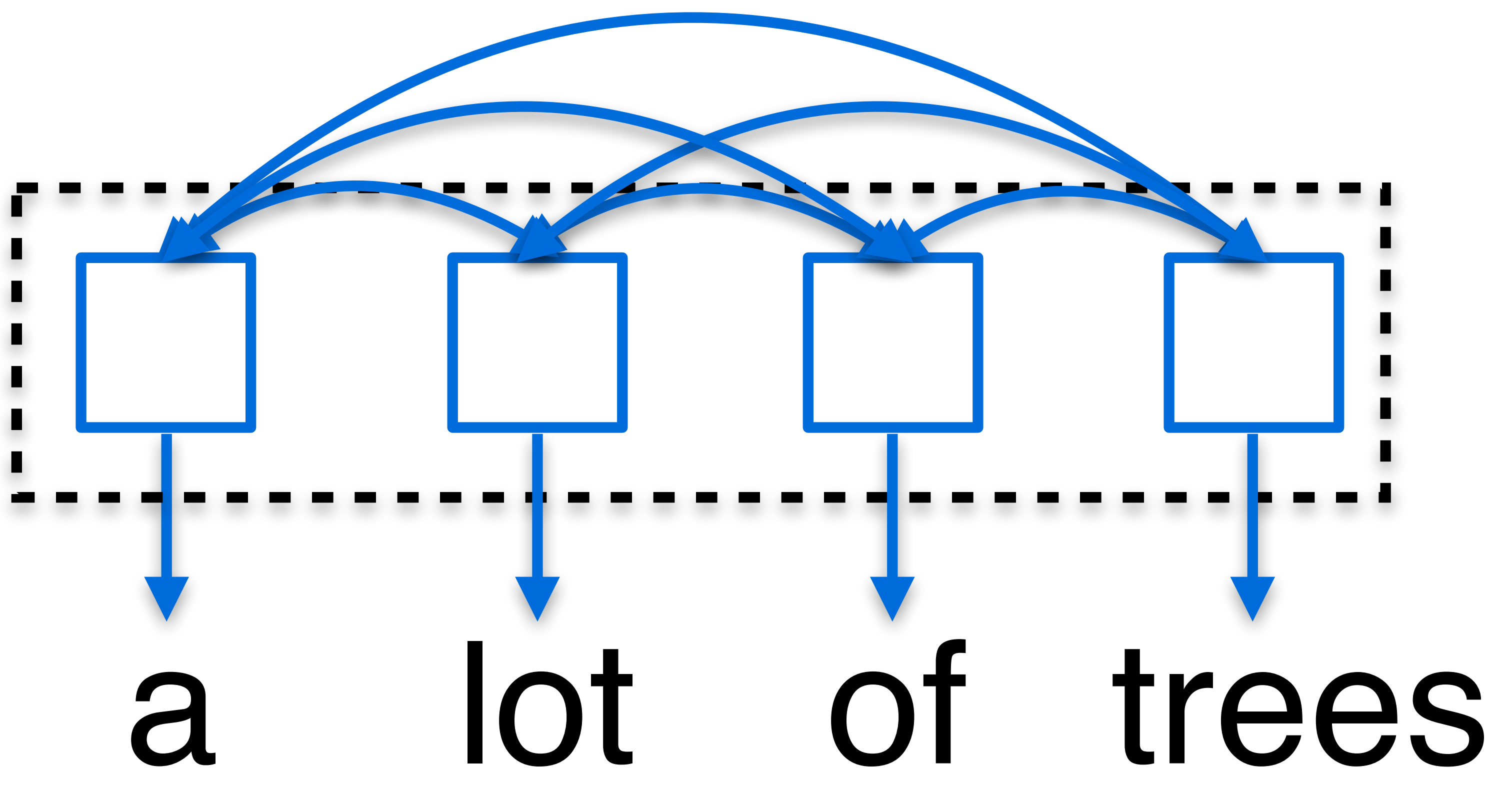
Lack explicit target word interdependency learning

Why Non-autoregressive?

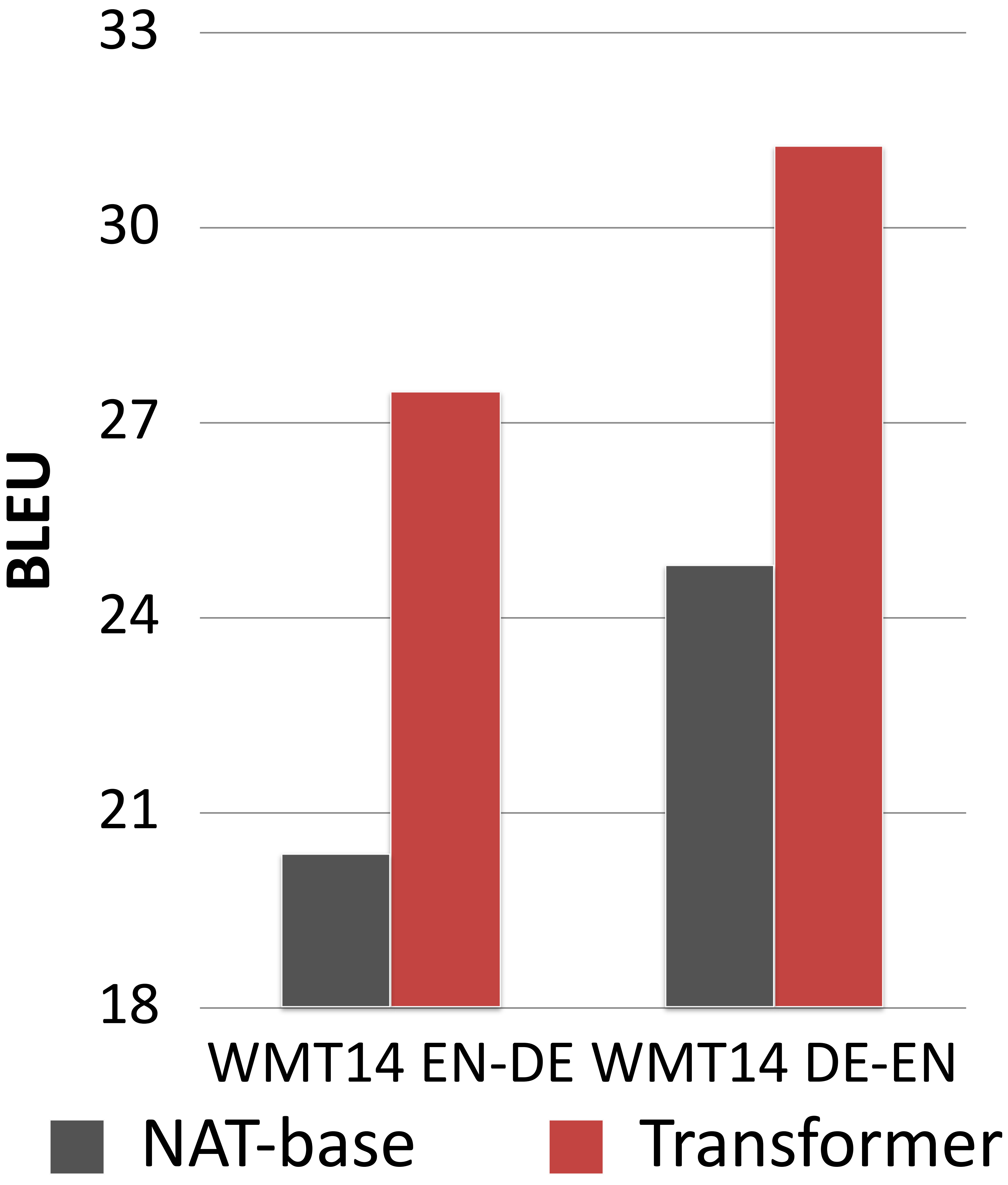
1. Faster decoding in non-autoregressive translation (NAT)



2. Capturing bidirectional context for generation



Challenge: Inferior Quality of NAT



- One input -> multiple target

很多树

a lot of trees

a great many trees

- Inconsistency problem in parallel generation

great many

lot of

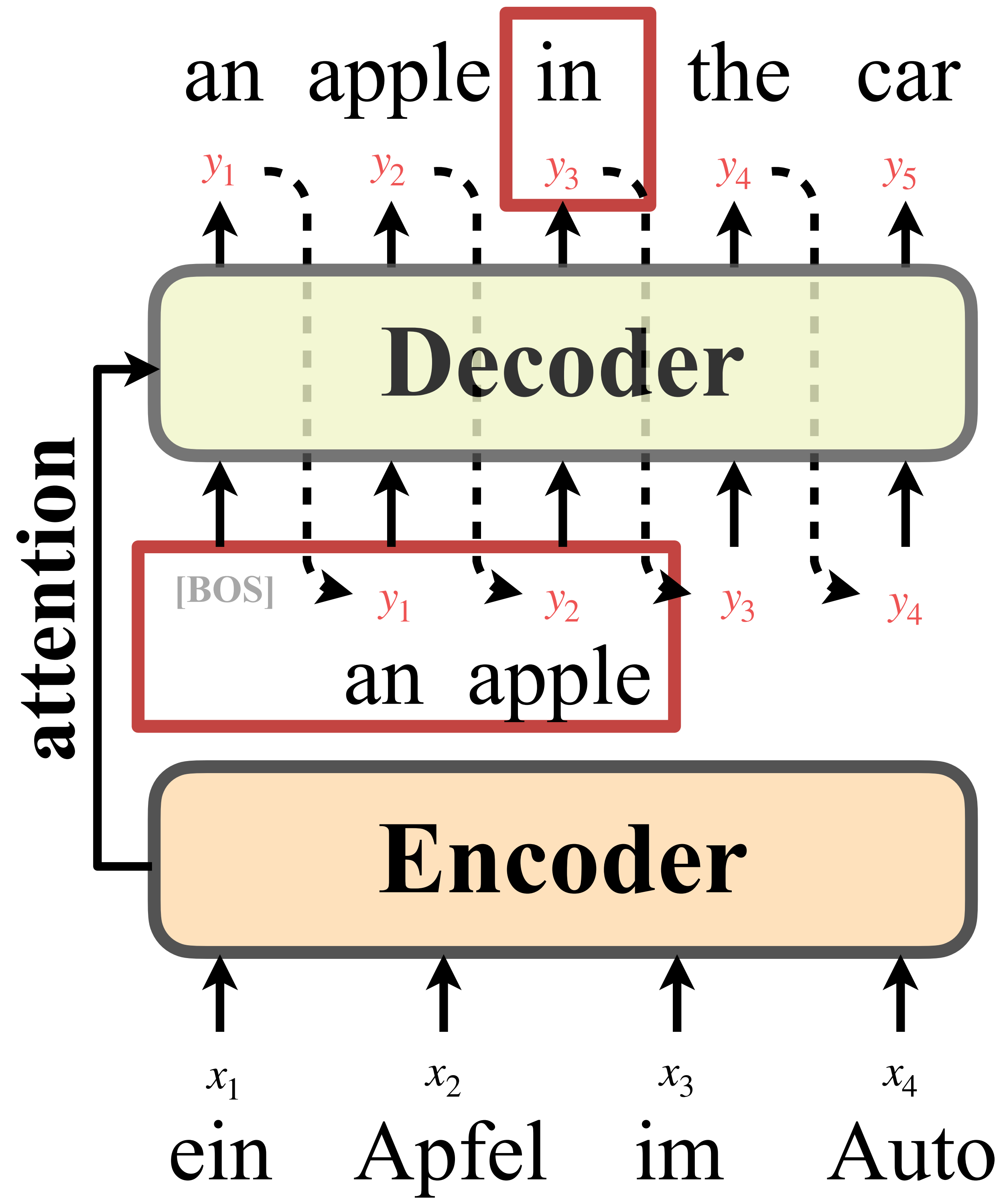
很多树

a great of trees

Key Intuition: Word interdependency

- Learning word interdependency in the target sentence is crucial for generating fluent sentences
- Non-autoregressive models lack a effective way of dependency learning

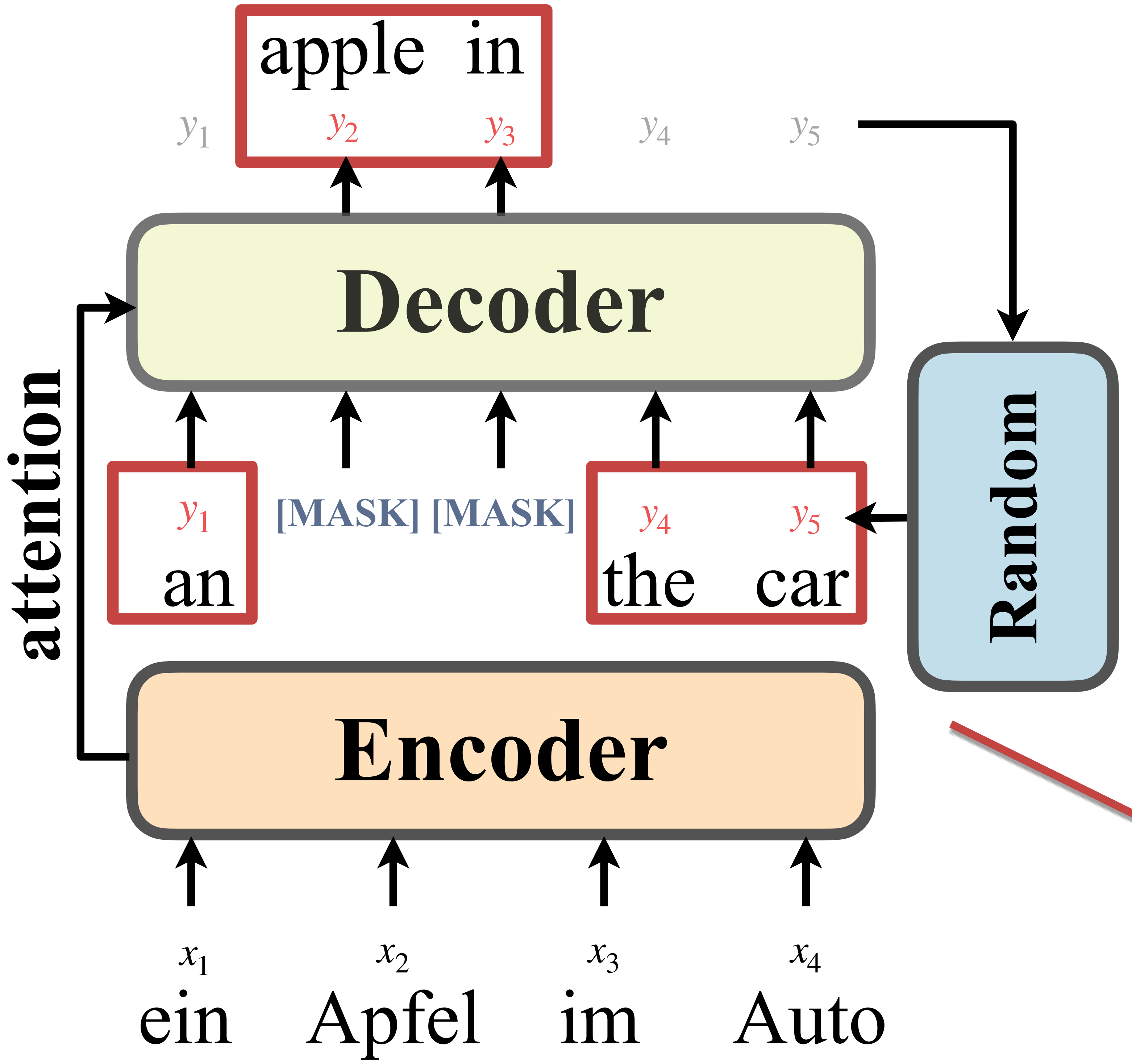
Learning Word Interdependency



Autoregressive models

- predict the next tokens conditioned on the input target tokens (left-to-right)

Iterative NAT



Iterative-NAT

- predict the randomly masked tokens based on unmasked tokens

rely on multiple decoding iterations, therefore does not gain speedup!

Lee et al. Deterministic Non-Autoregressive Neural Sequence Modeling by Iterative Refinement. EMNLP 2018.
Ghazvininejad et al. Mask-Predict: Parallel Decoding of Conditional Masked Language Models. EMNLP 2019.

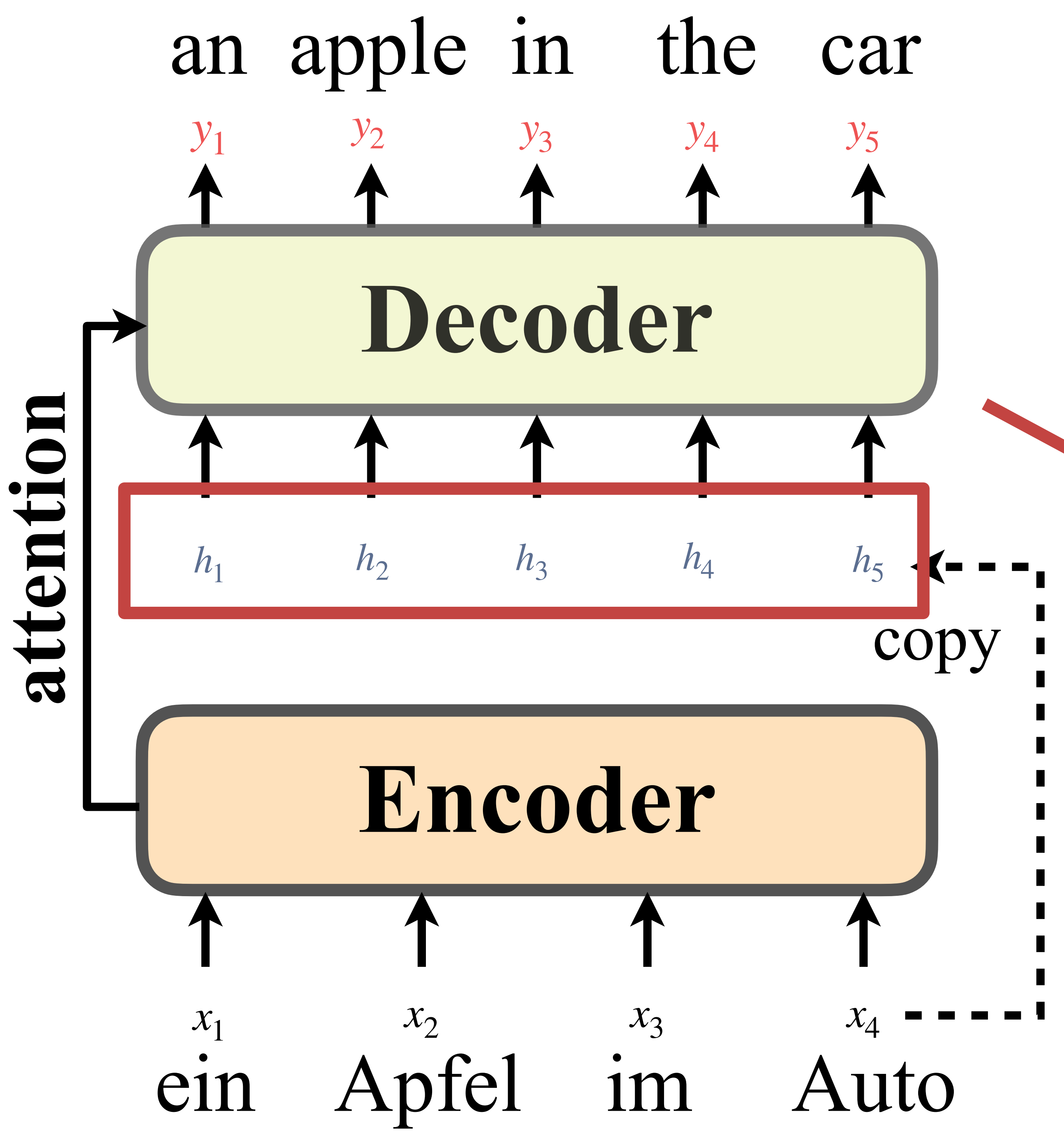
Dependency learning for NAT

- How to learn word interdependency for single-pass parallel generation?

- Contradiction
  - Word interdependency learning requires target word inputs
  - Single-pass parallel generation cannot obtain target words before prediction

- Glancing Language Model (GLM)
  - A gradual training method to achieve both

New Idea for Dependency learning



$$L_\theta = -\log p(Y|X;\theta)$$

Lack explicit target word interdependency learning

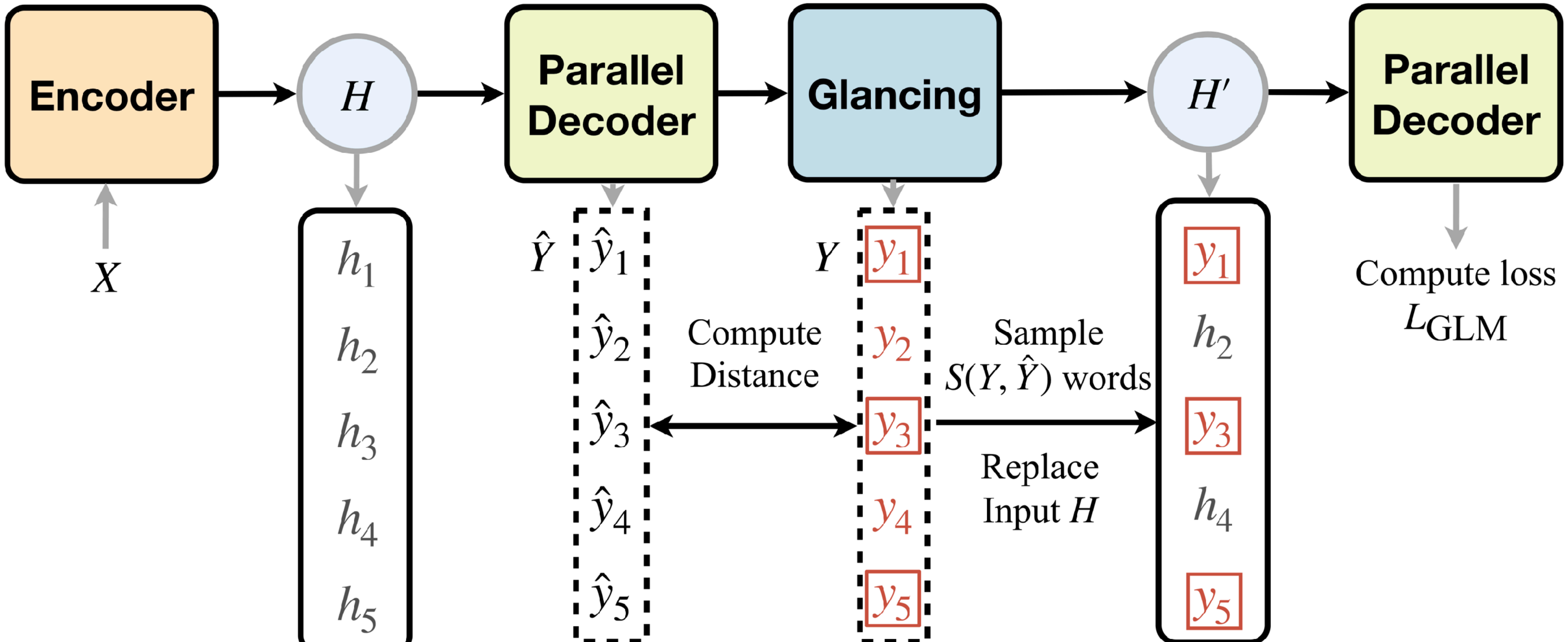
- Glancing Language Model (GLM)
  - A gradual training method
  - Learning word interdependency for **single-pass** parallel generation

Qian et al. Glancing Transformer for Non-autoregressive Neural Machine Translation. ACL 2021.

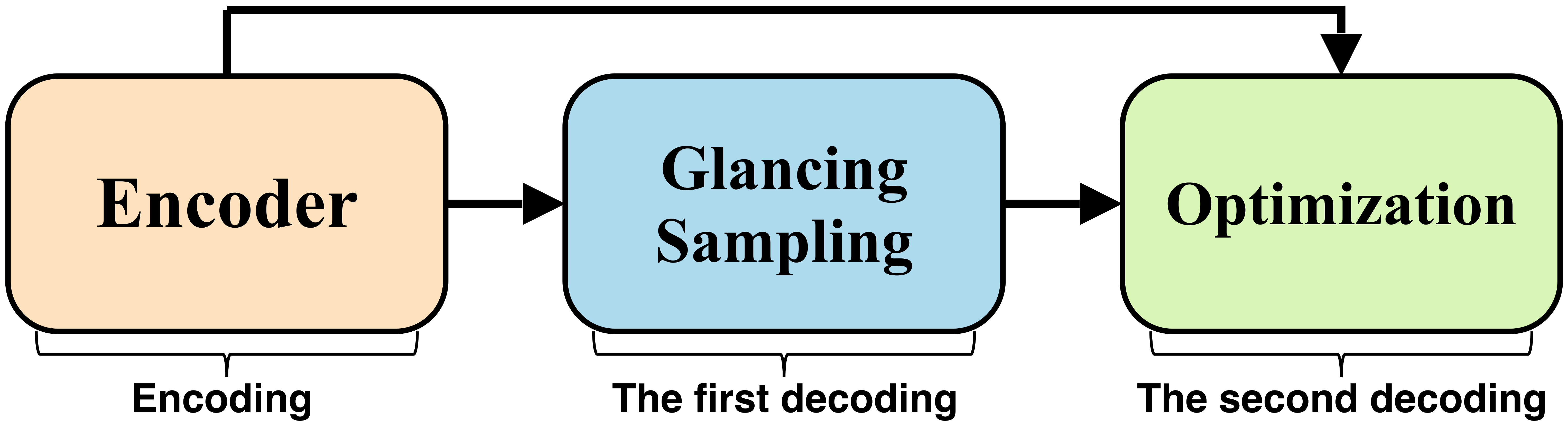
Glancing Language Model (GLM)

- An adaptive sampling strategy for gradual learning
  - From fragments to the whole sequence

- Learning target word interdependency for single-pass parallel generation



Glancing Language Model



only one-pass decoding in inference

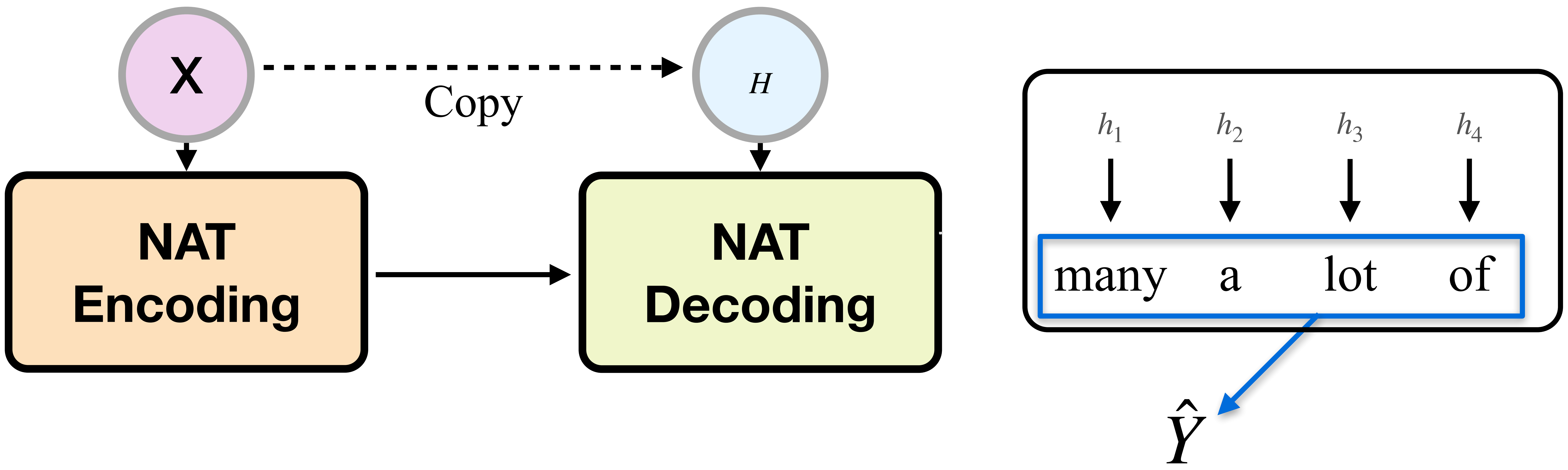
- Perform two decoding during training

1. Glancing Sampling (the first decoding):
   - Based on the prediction, replace part of the decoder inputs with sampled target words
2. Optimization (the second decoding):
   - Learn to predict the remaining words with the replaced decoder inputs

Qian et al. Glancing Transformer for Non-autoregressive Neural Machine Translation. ACL 2021.

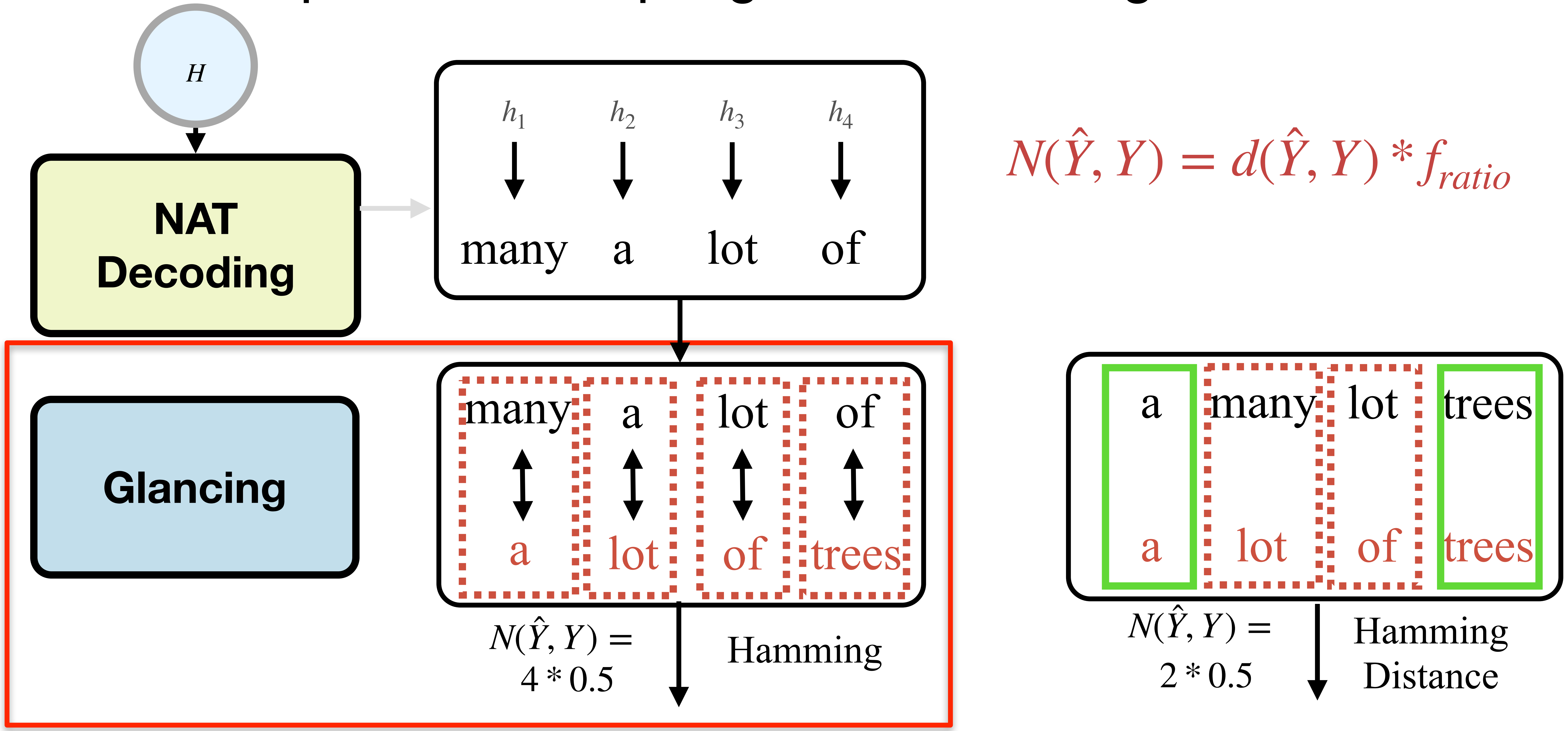
Glancing Sampling (1): NAT Decoding

- For input X, generate the whole sequence $\hat{Y}$ in parallel
- Training sample (X,Y)
  - X: 很多树
  - Y: a lot of trees

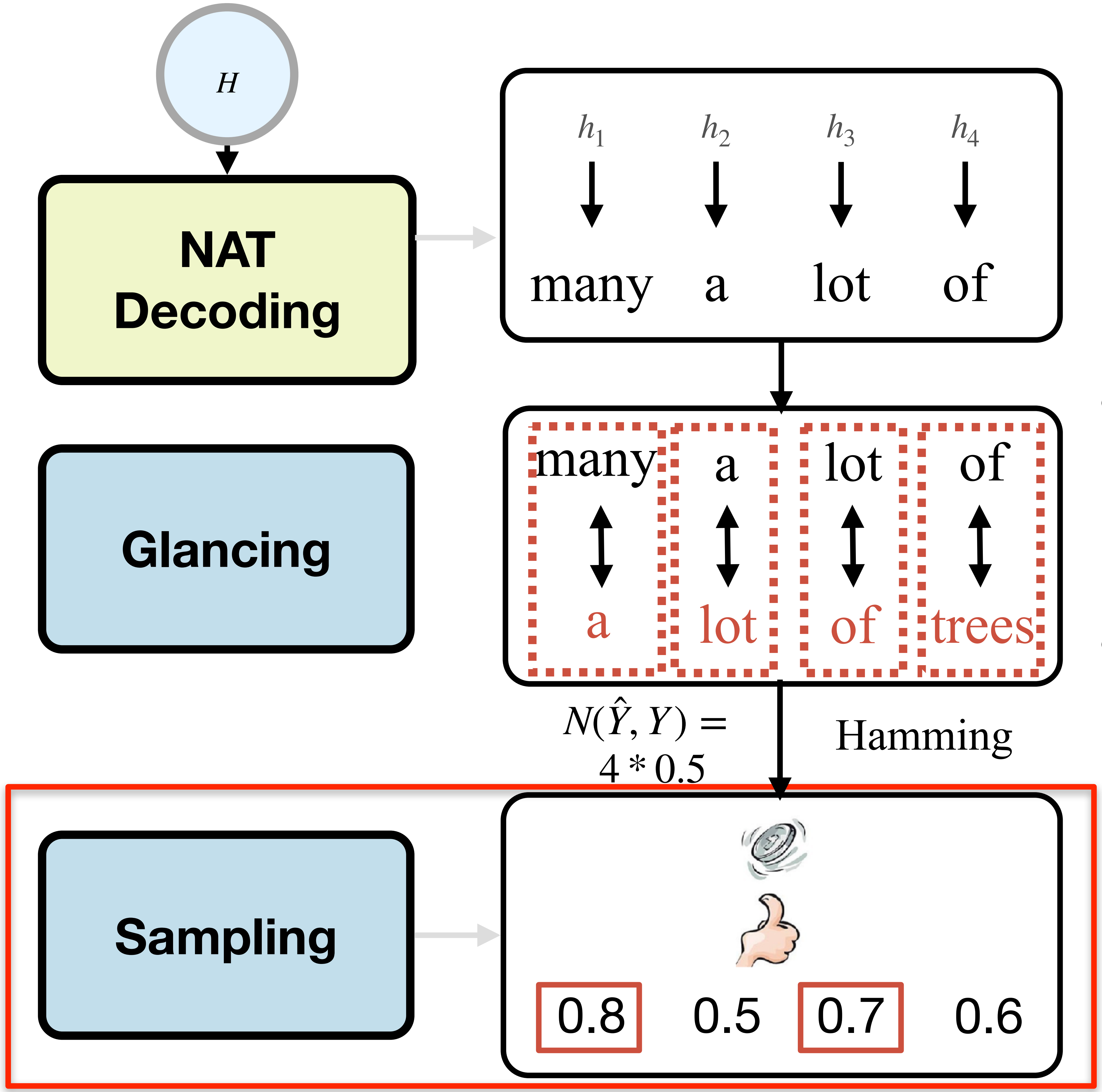


Glancing Sampling (2): Glancing

1. Measure the distance between the prediction and the reference
2. Compute the sampling number of target words

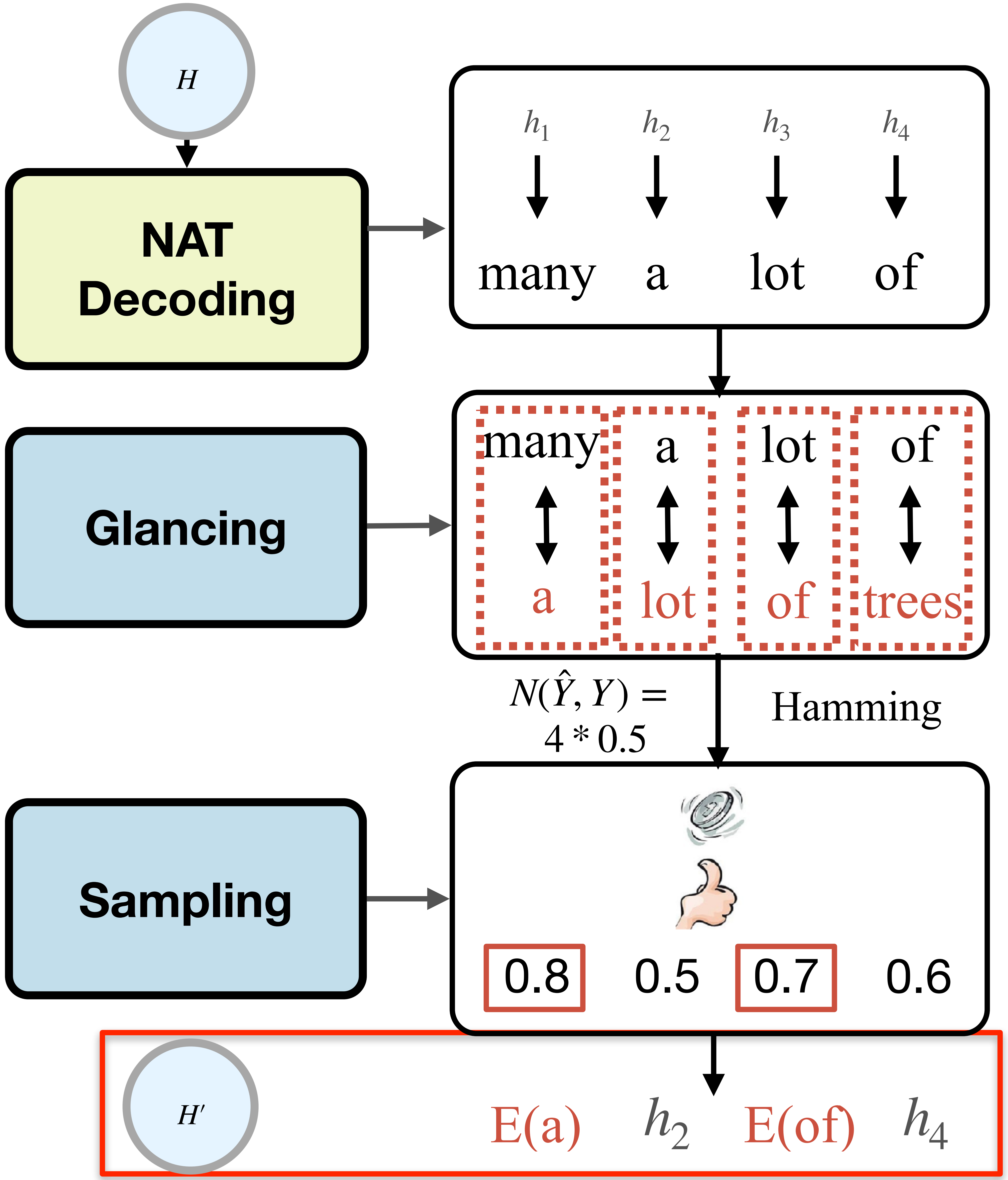


Glancing Sampling (3): Sampling



- Select $N(\hat{Y}, Y)$ target words for glancing
- Random target word selection strategy

Glancing Sampling (4): Replacing for prediction



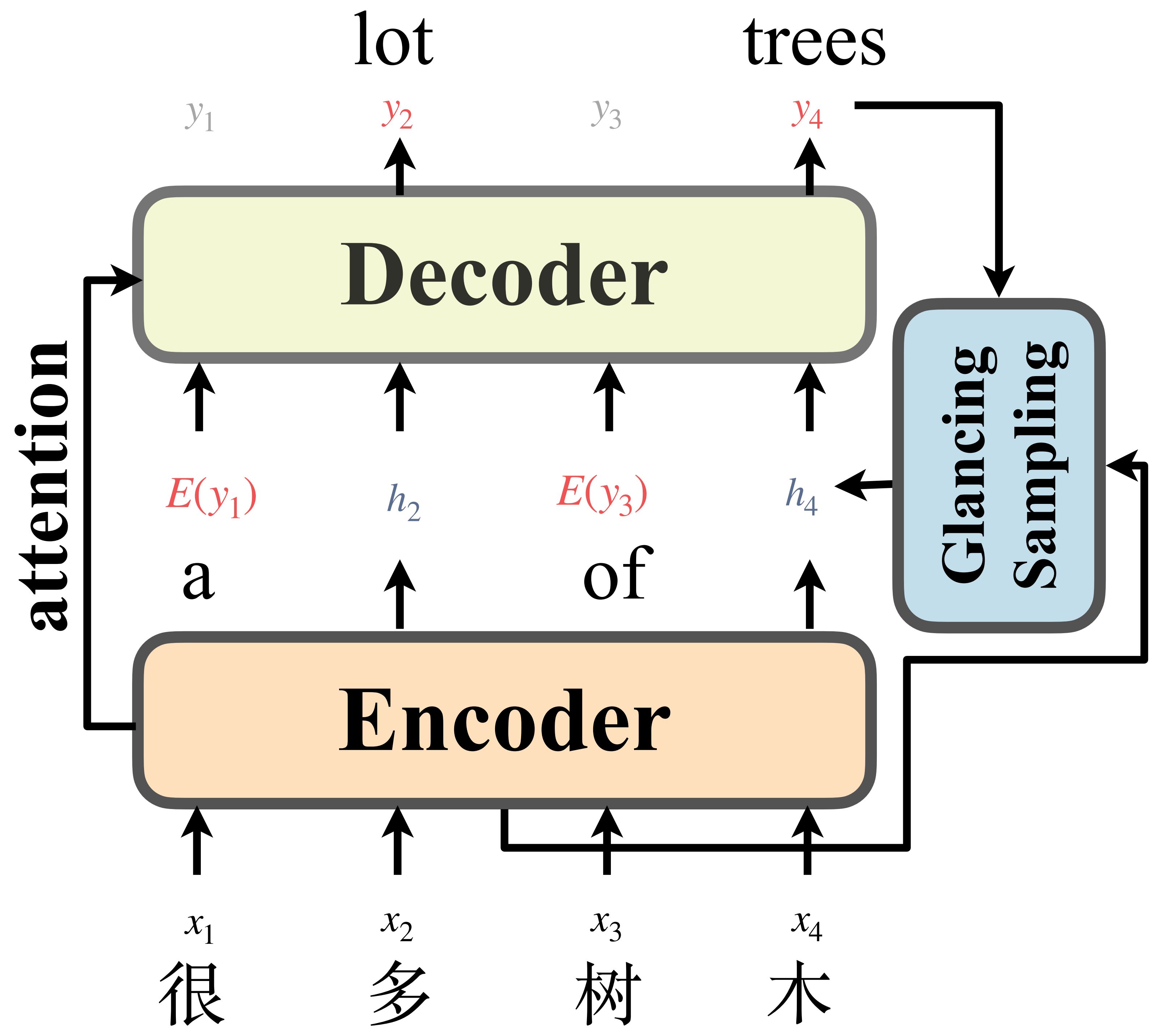
- Replace the original decoder inputs with the embedding of sampled target words

Methodology: Optimization

The second decoding:

- learn to predict the remaining words with the replaced decoder inputs

$$\mathcal{L}_{\text{GLAT}} = -\sum_{\{X,Y\}\in D} \sum_{y_t \in \{Y \setminus \mathbb{GS}(Y,\hat{Y})\}} \log p(y_t \mid \mathbb{GS}(Y,\hat{Y}), X; \theta)$$

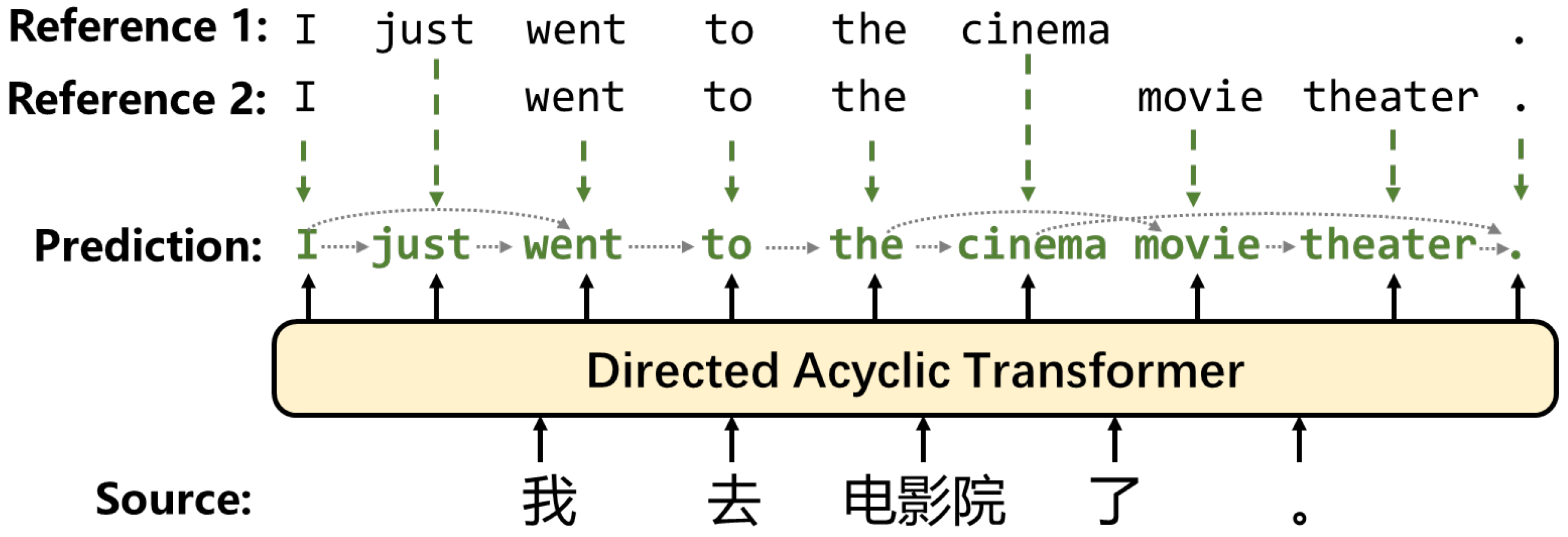


During training, the sampling number of target words decreases gradually.

Learn to generate longer fragments

Directed Acyclic Transformer (DA-Transformer)

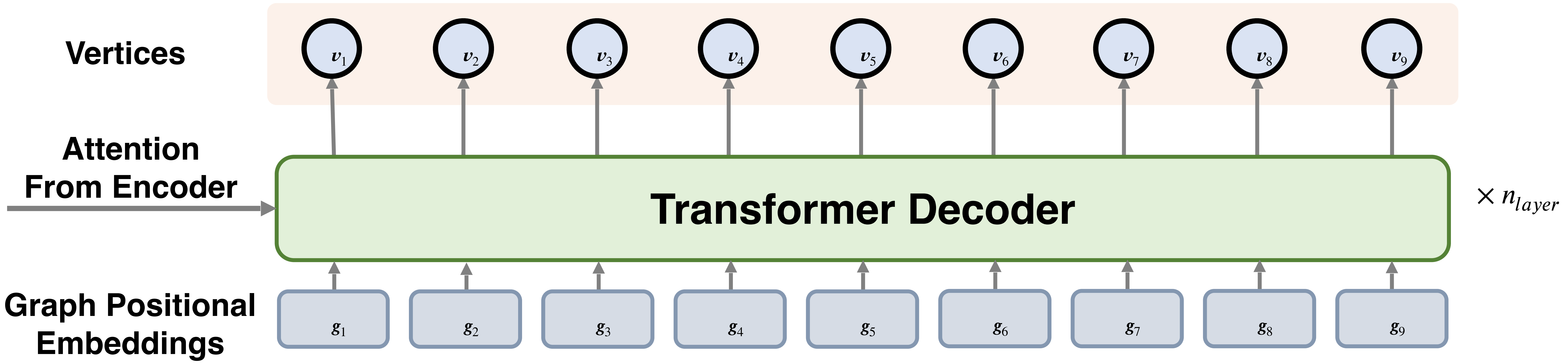
- Using directed acyclic graph (DAG)



Predicting a DAG containing multiple outputs in parallel

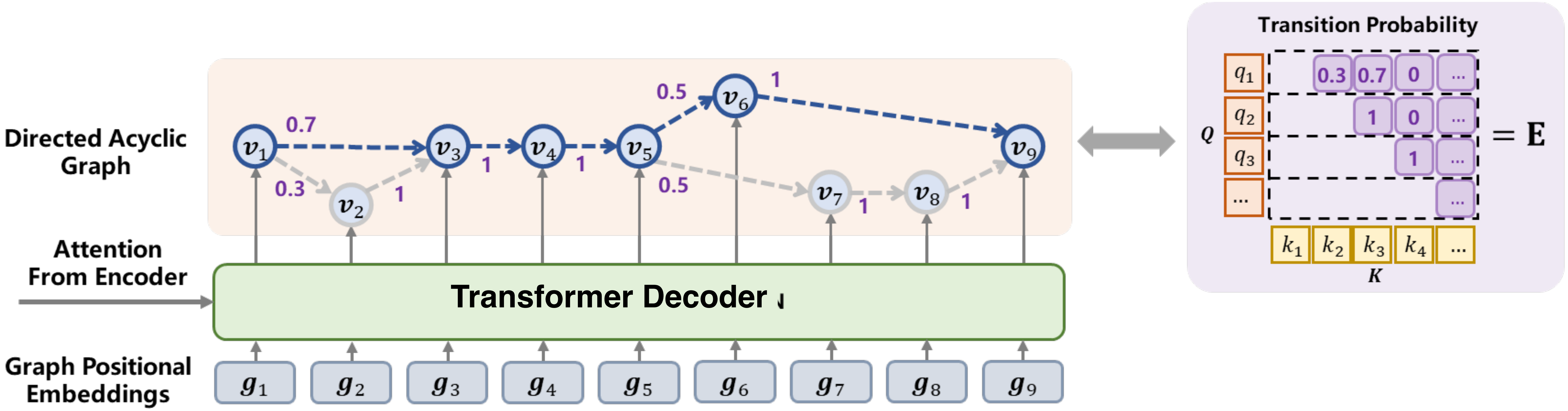
Directed Acyclic Transformer (DA-Transformer)

- Step 1: Obtaining the vertex states $\boldsymbol{V} = [\boldsymbol{v}_1, \cdots, \boldsymbol{v}_L]^T$



Directed Acyclic Transformer (DA-Transformer)

- Step 2: Predict the transition matrix E and sample a path A

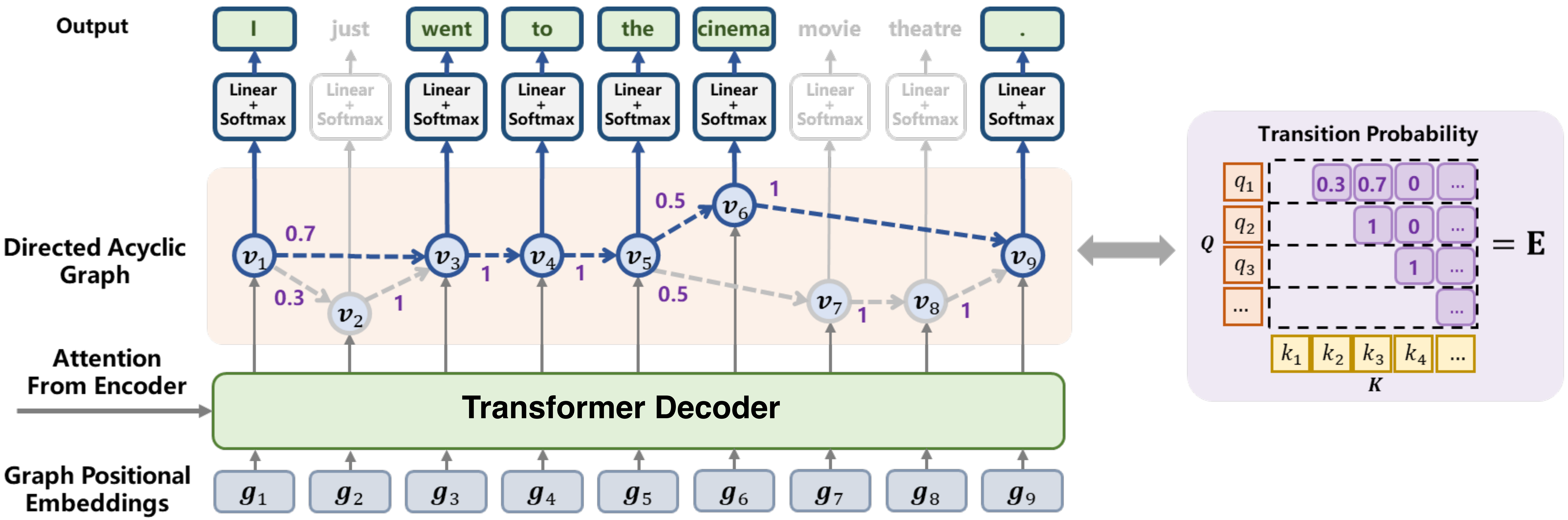


Path $A = \{1, 3, 4, 5, 6, 9\}$

$$P_\theta(A|X) = \prod_{i=1}^{M-1} P_\theta(a_{i+1}|a_i, X) = \prod_{i=1}^{M-1} \mathbf{E}_{a_i, a_{i+1}},$$

Directed Acyclic Transformer (DA-Transformer)

- Step 3: Predict the tokens on the selected path



Path $A = \{1, 3, 4, 5, 6, 9\}$ Reference $Y =$ `I went to the cinema .`

$$P_\theta(Y|A, X) = \prod_{i=1}^{M} P_\theta(y_i|a_i, X) = \prod_{i=1}^{M} \mathrm{softmax}(\mathbf{W}_\mathbf{P}\mathbf{v}_{a_i})$$

Directed Acyclic Transformer (DA-Transformer)

- Probability Modelling

$$P_\theta(Y|X) = \sum_{A\in\Gamma} P_\theta(Y, A|X) = \sum_{A\in\Gamma} P_\theta(A|X)P_\theta(Y|A, X),$$

All possible paths

Transition Probability

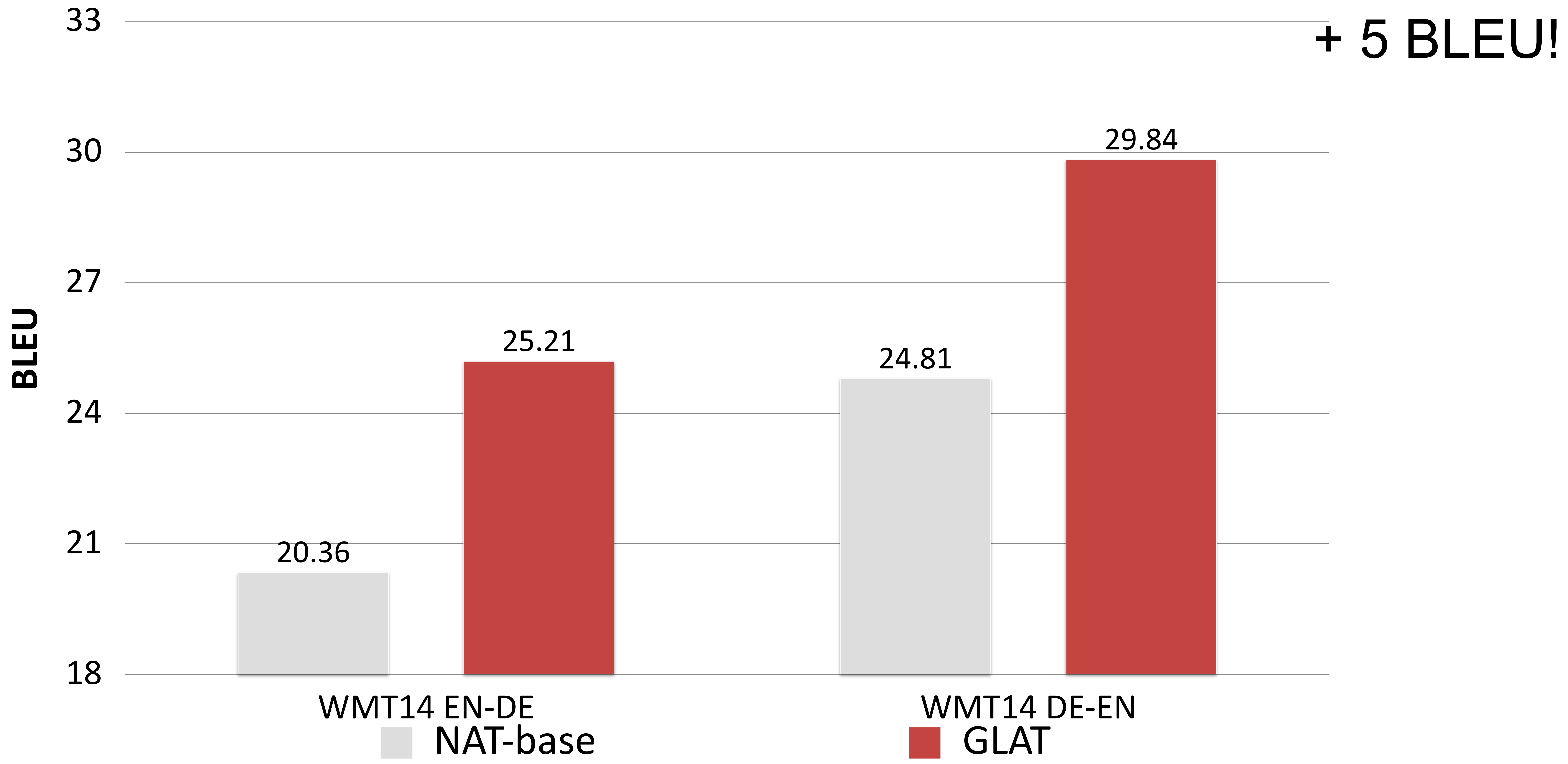
$$P_\theta(A|X) = \prod_{i=1}^{M-1} P_\theta(a_{i+1}|a_i, X) = \prod_{i=1}^{M-1} \mathbf{E}_{a_i,a_{i+1}},$$

Token Probability

$$P_\theta(Y|A, X) = \prod_{i=1}^{M} P_\theta(y_i|a_i, X) = \prod_{i=1}^{M} \mathrm{softmax}(\mathbf{W_P}\mathbf{v}_{a_i})$$

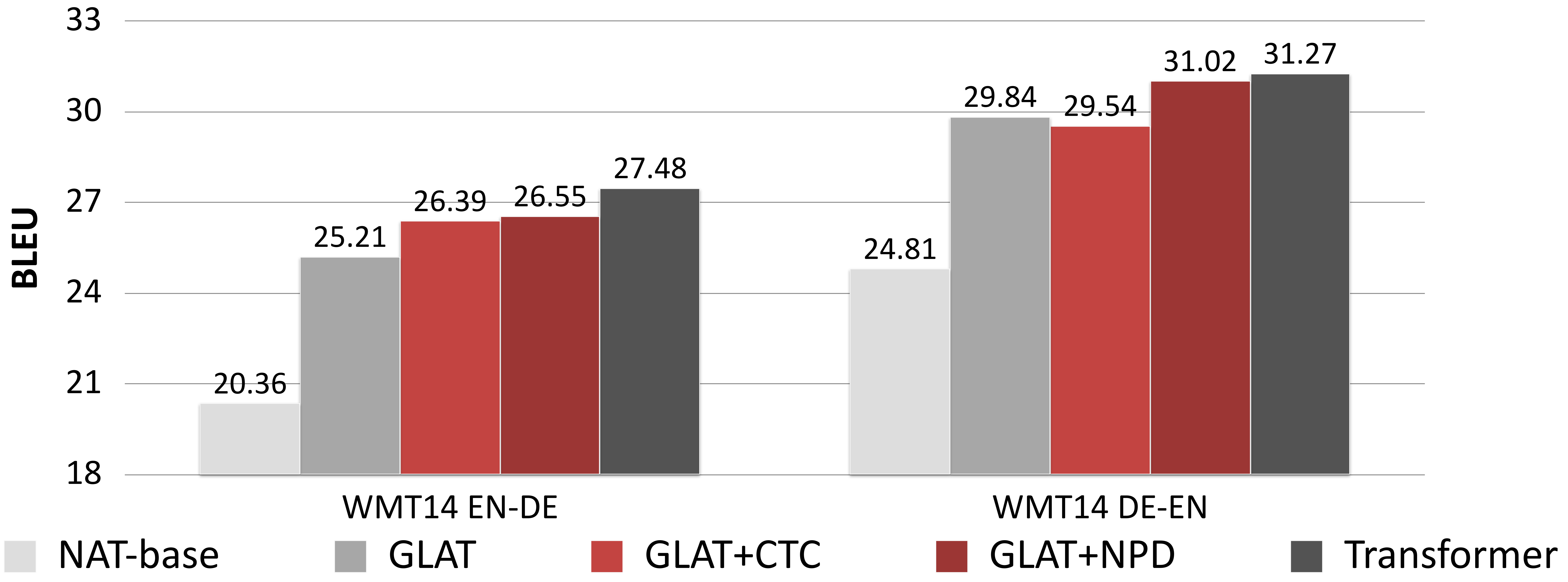
Experiments

GLAT boosts Translation Quality significantly!



Qian et al. Glancing Transformer for Non-autoregressive Neural Machine Translation. ACL 2021.

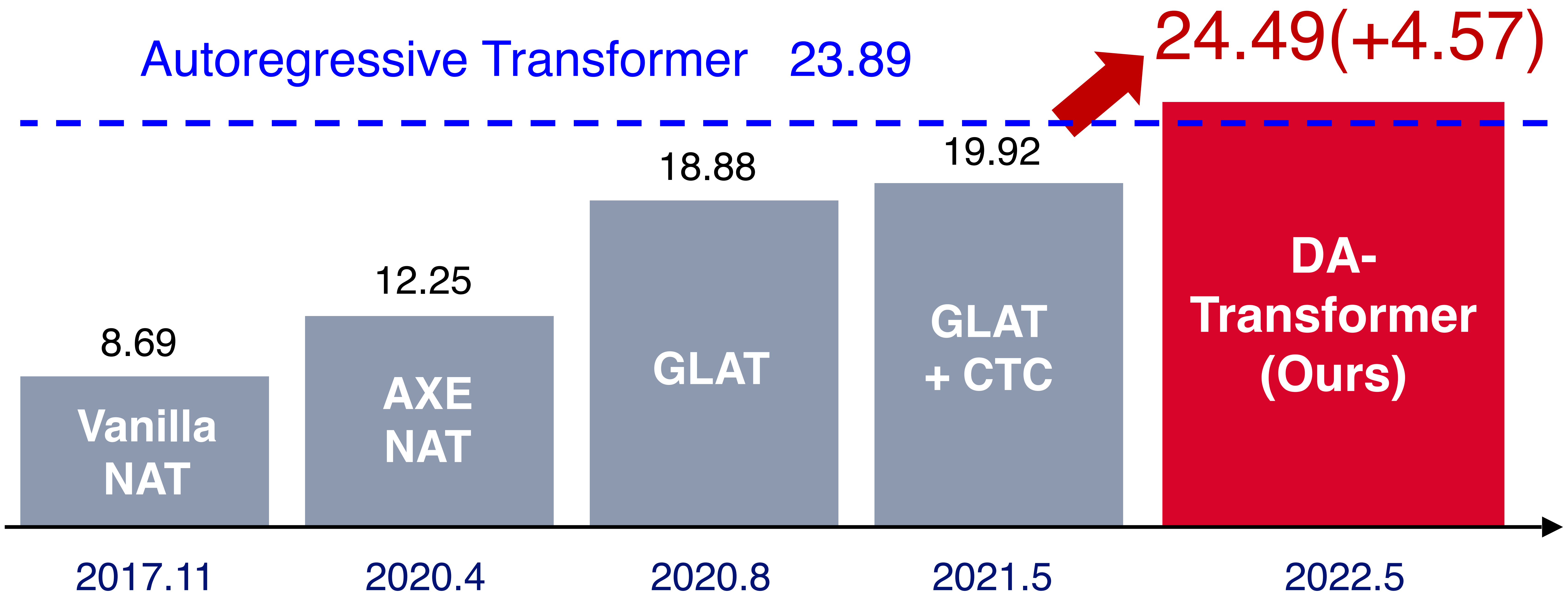
GLAT approaches Transformer quality!



- GLAT achieves high quality translation while keeping high inference speed-up (8x~15x)

Qian et al. Glancing Transformer for Non-autoregressive Neural Machine Translation. ACL 2021.

DA-Transformer gets Better Performance without KD!



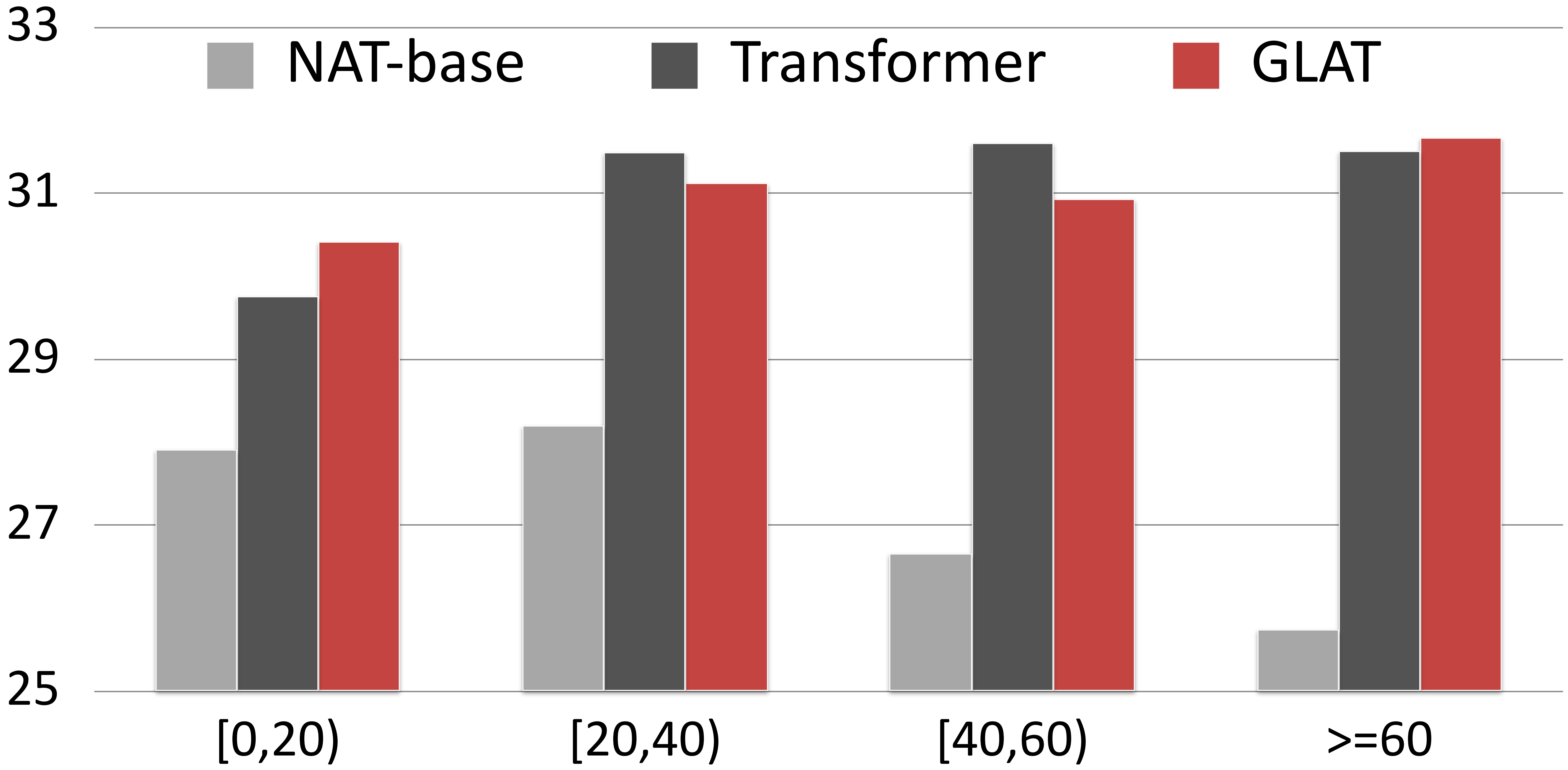
Translation Quality

(BLEU Score on WMT17 Zh-En)

Fei Huang, Hao Zhou, Yang Liu, Hang Li, Minlie Huang. Directed Acyclic Transformer for Non-Autoregressive Machine Translation. ICML 2022.

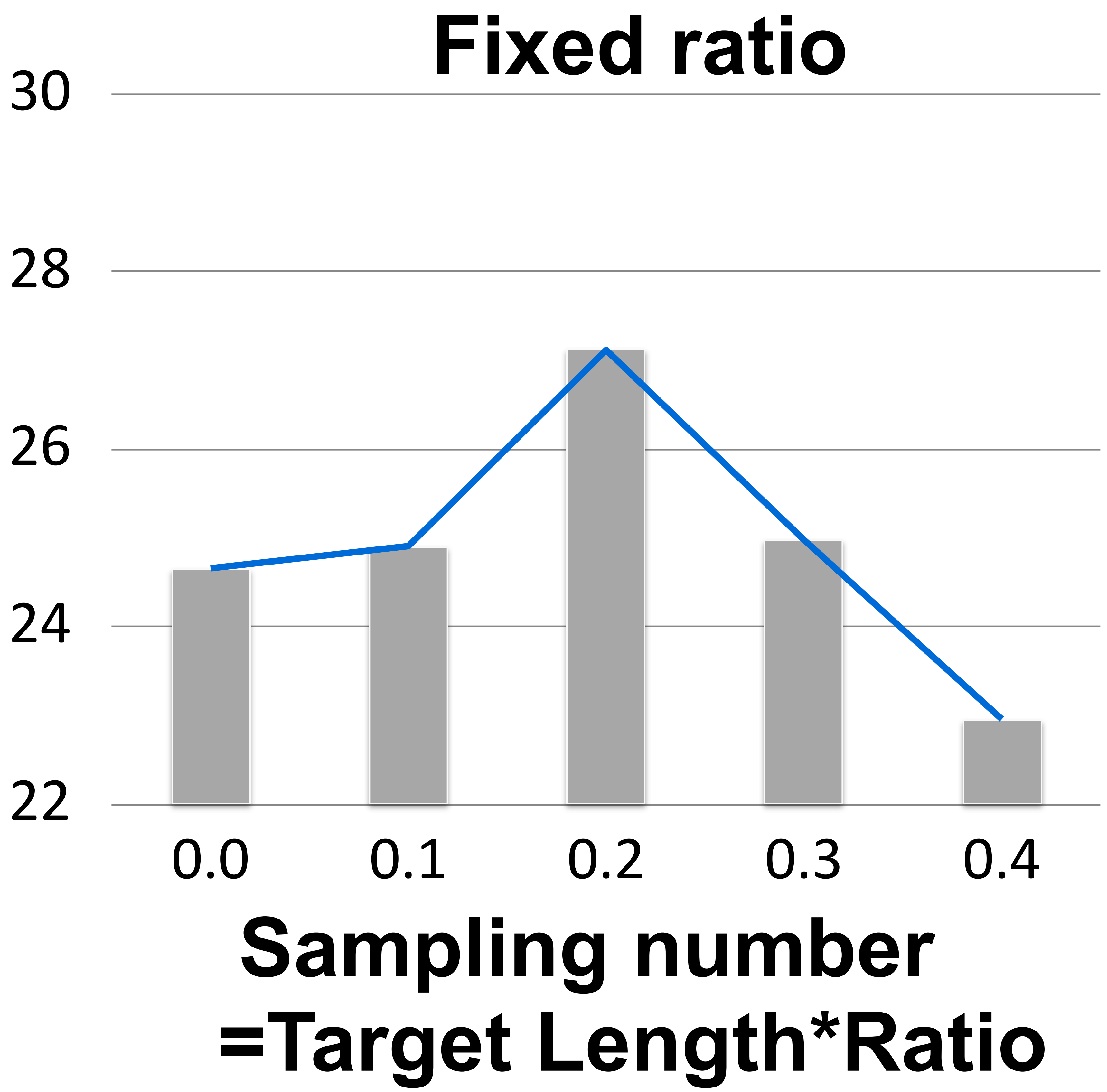
Performance for different lengths

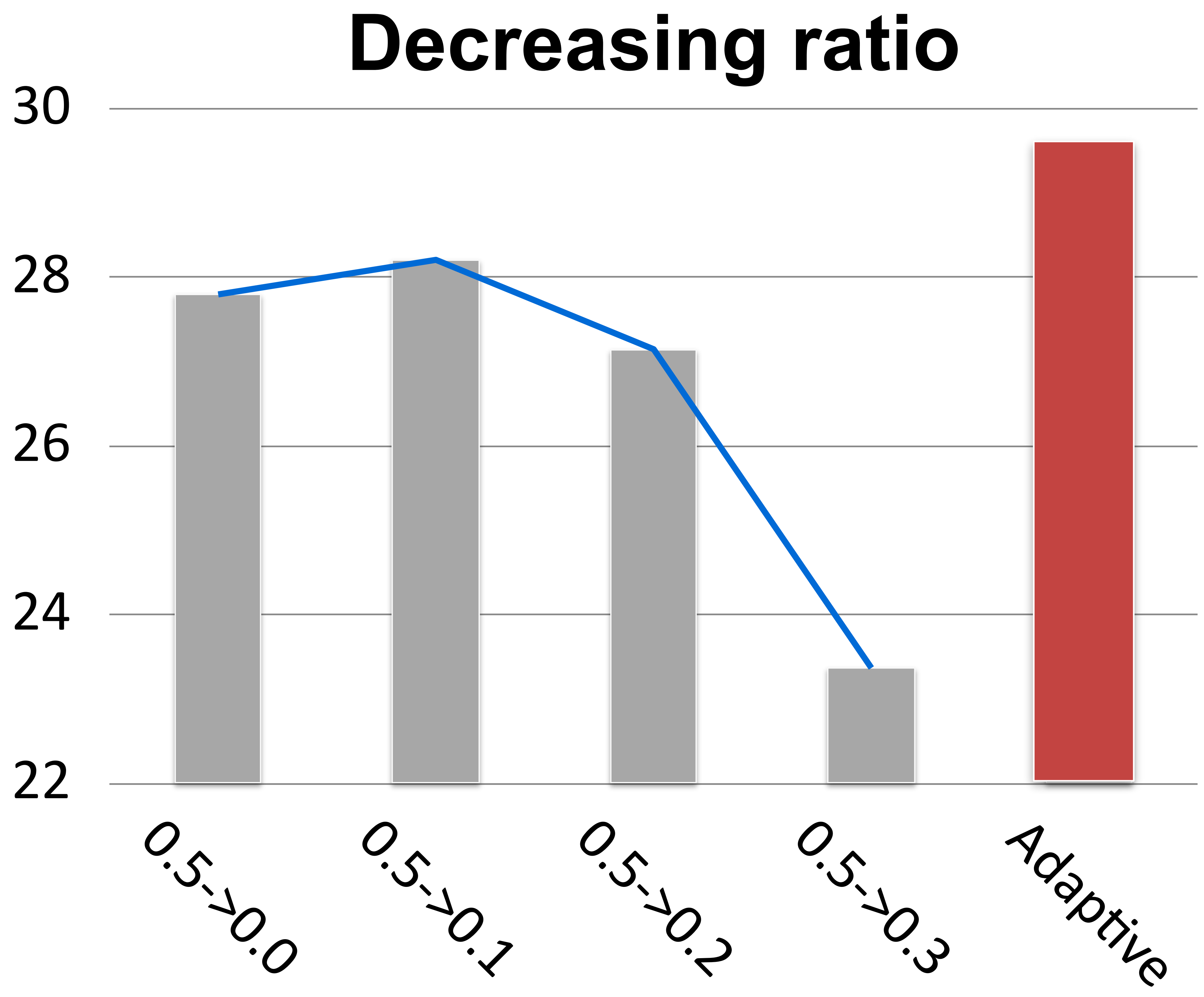
- The performance of NAT-base drops sharply as the input length becomes longer
- GLAT performs a little better than Transformer on WMT14 DE-EN when the input length is shorter than 20



Adaptive sampling number is effective

- The adaptive glancing sampling strategy significantly improves performance





GLAT in Real Competition

GLAT achieve the Top BLEU score in WMT21 En-De and De-En!

The first NAT system to do so!

newstest2021.de-en test set (de-en)

#	Name	BLEU
1	**Anonymous submission #1276**	35.0
2	**Anonymous submission #1284**	35.0
3	Anonymous submission #1304	34.9
4	Anonymous submission #1117	34.9
5	Anonymous submission #1258	34.9
6	**Anonymous submission #1124**	34.9
7	Anonymous submission #543	34.8
8	**Anonymous submission #963**	34.8
9	Anonymous submission #861	34.7
10	Anonymous submission #738	34.7

BLEU and ChrF are sacreBLEU scores. Systems in **bold face** are your submissior
validation errors denoted by -1.0 score.

newstest2021.en-de test set (en-de)

#	Name	BLEU
1	**Anonymous submission #1265**	31.3
2	Anonymous submission #1303	31.3
3	Anonymous submission #1291	31.3
4	Anonymous submission #804	31.3
5	Anonymous submission #368	31.3
6	Anonymous submission #1168	31.3
7	**Anonymous submission #1251**	31.2
8	**Anonymous submission #986**	31.2
9	Anonymous submission #1310	31.2
10	**Anonymous submission #1243**	31.2

BLEU and ChrF are sacreBLEU scores. Systems in **bold face** are your submissio
validation errors denoted by -1.0 score.

Qian et al. The Volctrans GLAT System: Non-autoregressive Translation Meets WMT21. 2021.

GLAT achieves Top-5 in WMT21 Human Evaluation

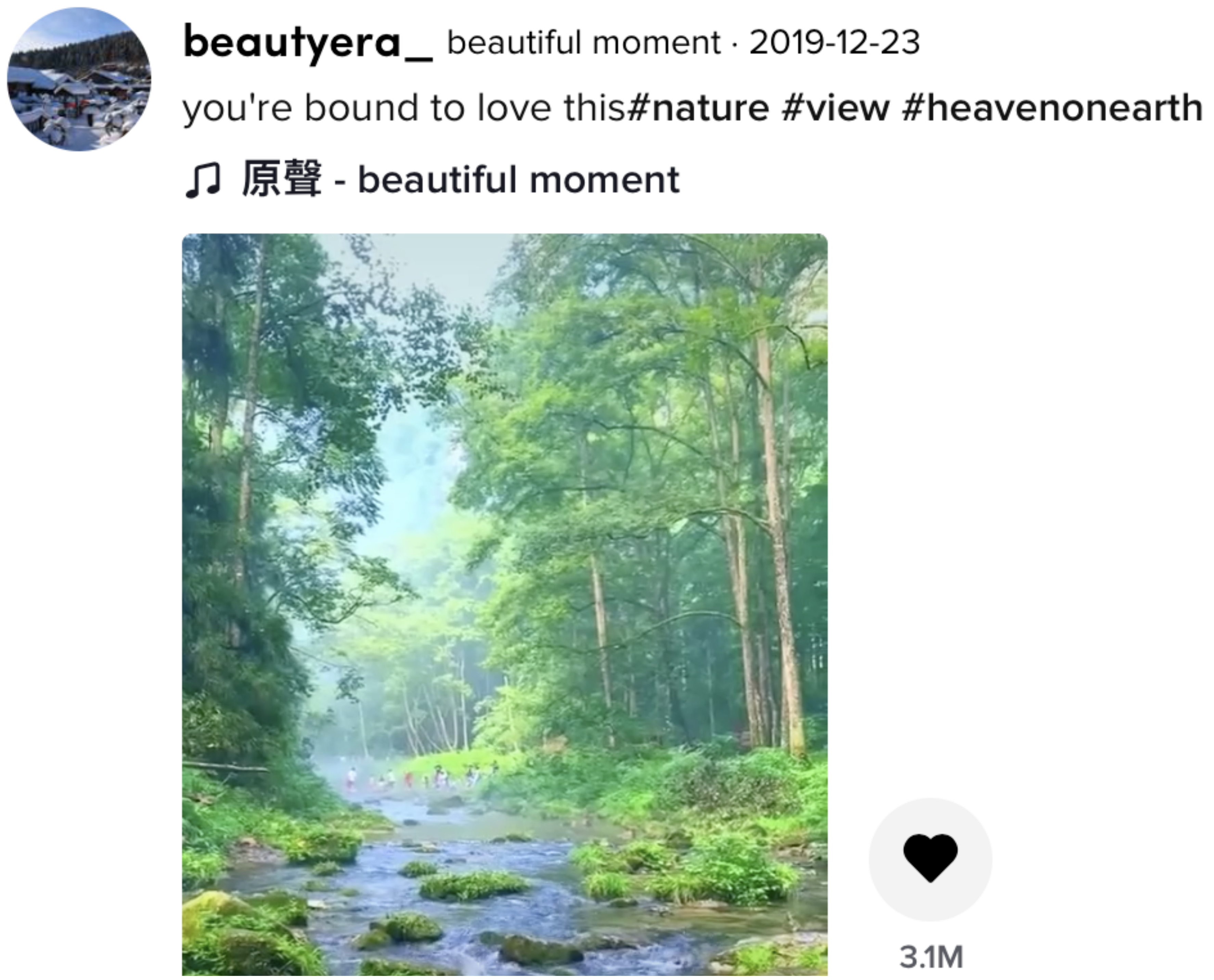
German→English

Rank	Ave.	Ave. z	System
1–5	71.9	0.126	Borderline
1–6	73.5	0.124	Online-A
1–4	78.6	0.122	Online-W
4	79.5	0.113	UF
3–8	73.2	0.106	VolcTrans-AT
4–9	77.5	0.100	Facebook-AI
5–12	75.8	0.068	ICL
4–12	73.4	0.048	Online-G
8–17	69.7	0.016	Online-B
7–17	71.3	0.016	Online-Y
7–17	71.6	0.010	VolcTrans-GLAT
5–16	69.6	0.007	P3AI
9–19	70.6	−0.008	SMU
9–17	73.1	−0.008	UEdin
9–17	69.1	−0.010	NVIDIA-NeMo
10–19	69.9	−0.035	Manifold
15–20	67.0	−0.043	Watermelon
7–17	71.8	−0.061	happypoet
16–20	66.8	−0.081	HUMAN-C
18–20	66.0	−0.120	HW-TSC

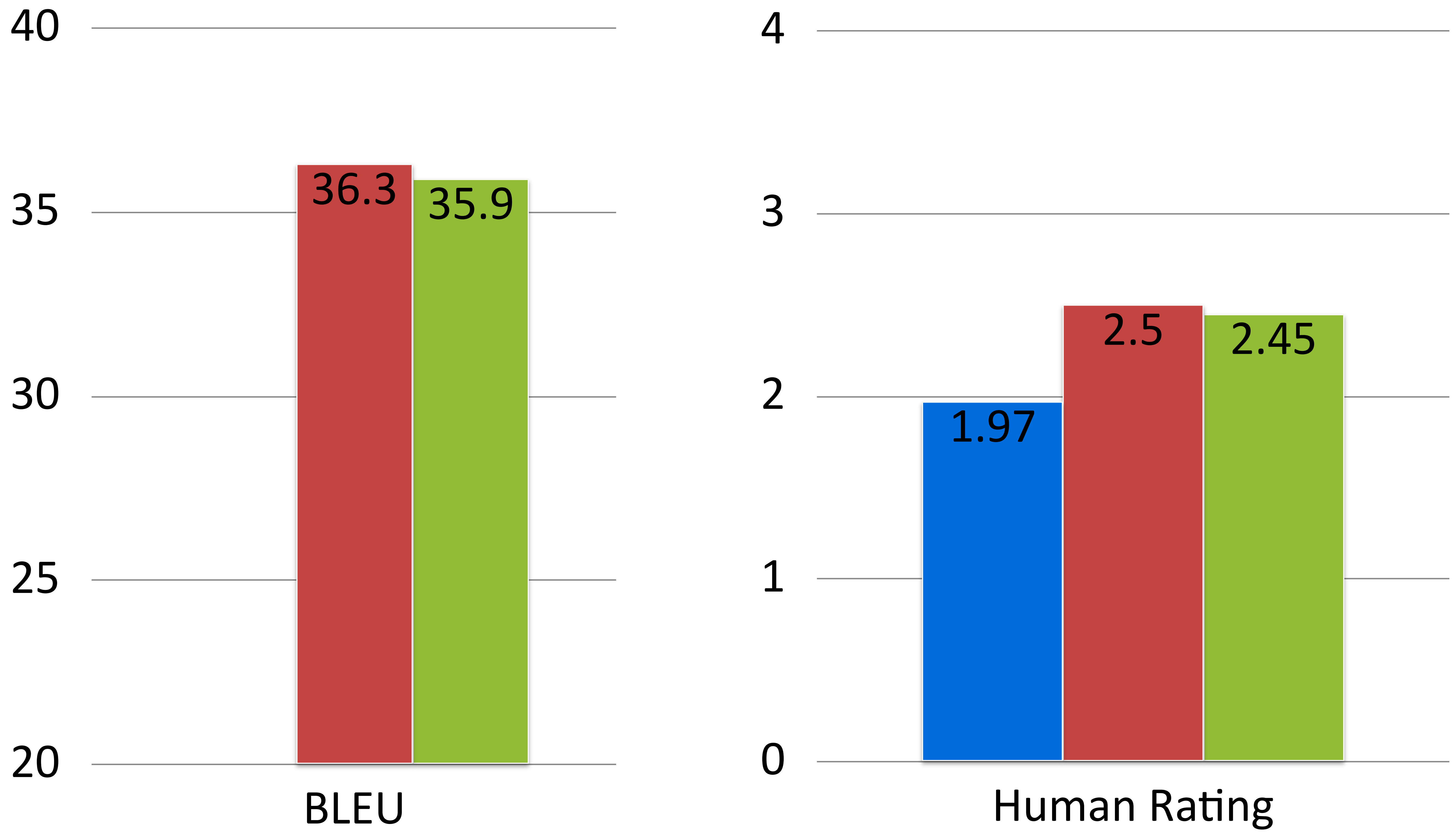
Findings of WMT21.

GLAT is the first production NAT system!

- Already deployed online in VolcTrans and serving English-Japanese



Tiktok caption translation



火山翻译
Volctrans

Summary

- Word interdependency learning is important
- GLAT can achieve comparable generation quality with autoregressive models
- A generation paradigm with great potential

Language Presentation

Course Evaluation and Feedback