達摩院
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Learning to Generalize to More: Continuous Semantic Augmentation for Neural Machine Translation

Xiangpeng Wei

Co-authors: Heng Yu, Yue Hu[†], Rongxiang Weng, Weihua Luo, Rong Jin

[†] From the University of Chinese Academy of Sciences (UCAS)

Neural Machine Translation

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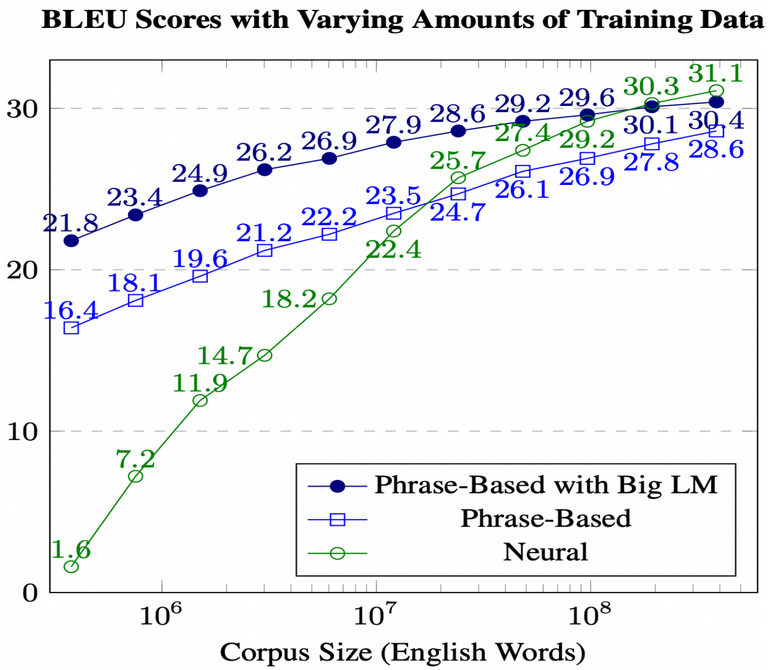

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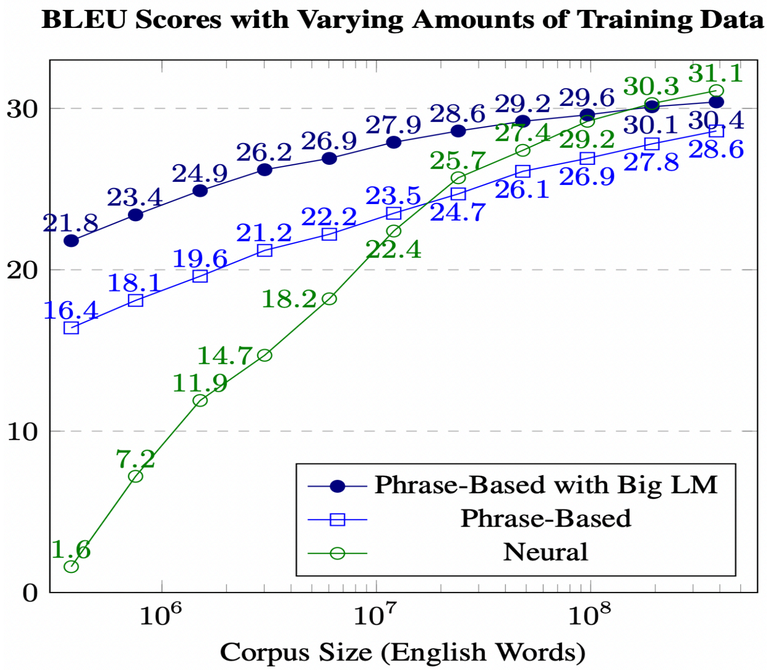

NMT benefits more from the increasing amounts of training data, but it is hard to warmup with access to a few training instances.

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Increasing the amount of training data through automatic data augmentation (DA) techniques has wide applications in NLP.

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- Back-Translation (Sennrich et al., 2016; Ott et al., 2018)
- Self-Supervised Learning (Cheng et al., 2016)
- SwitchOut (Wang et al., 2018)
- Soft Contextual Data Augmentation (Gao et al., 2019)
- Robust NMT (Cheng et al., 2018, 2019, 2020)
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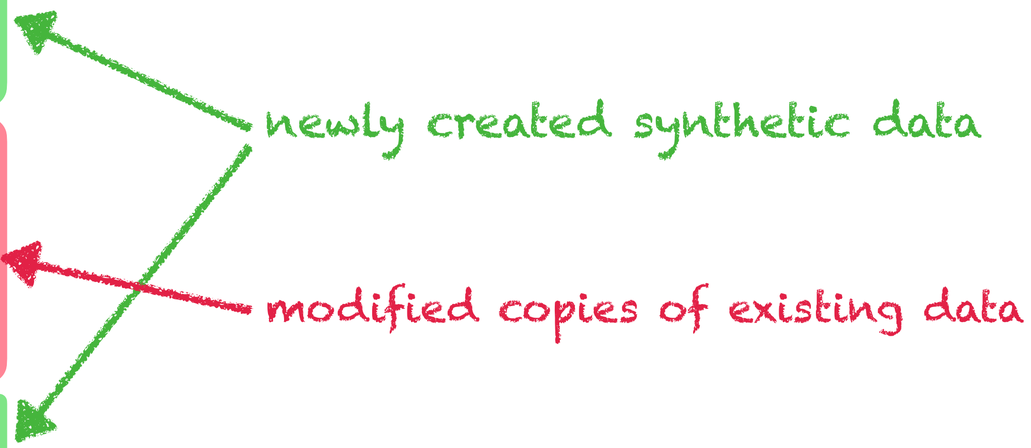

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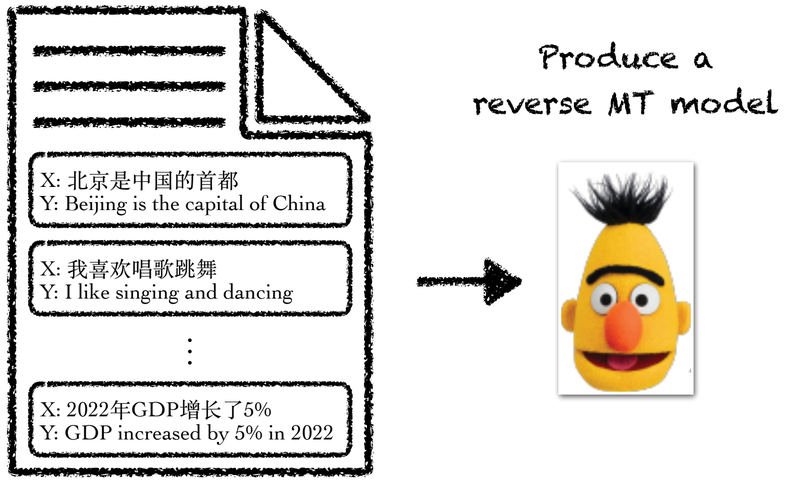

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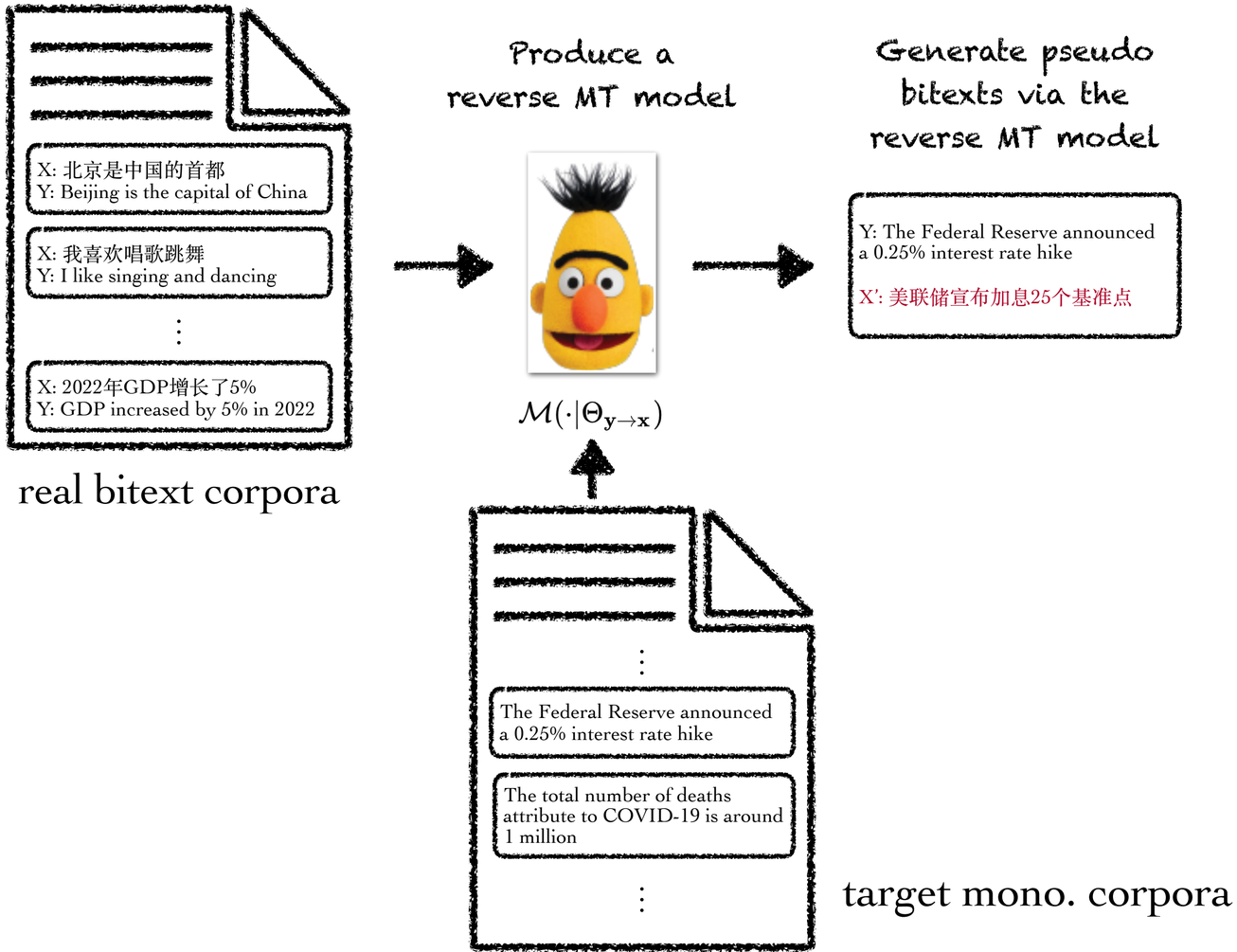

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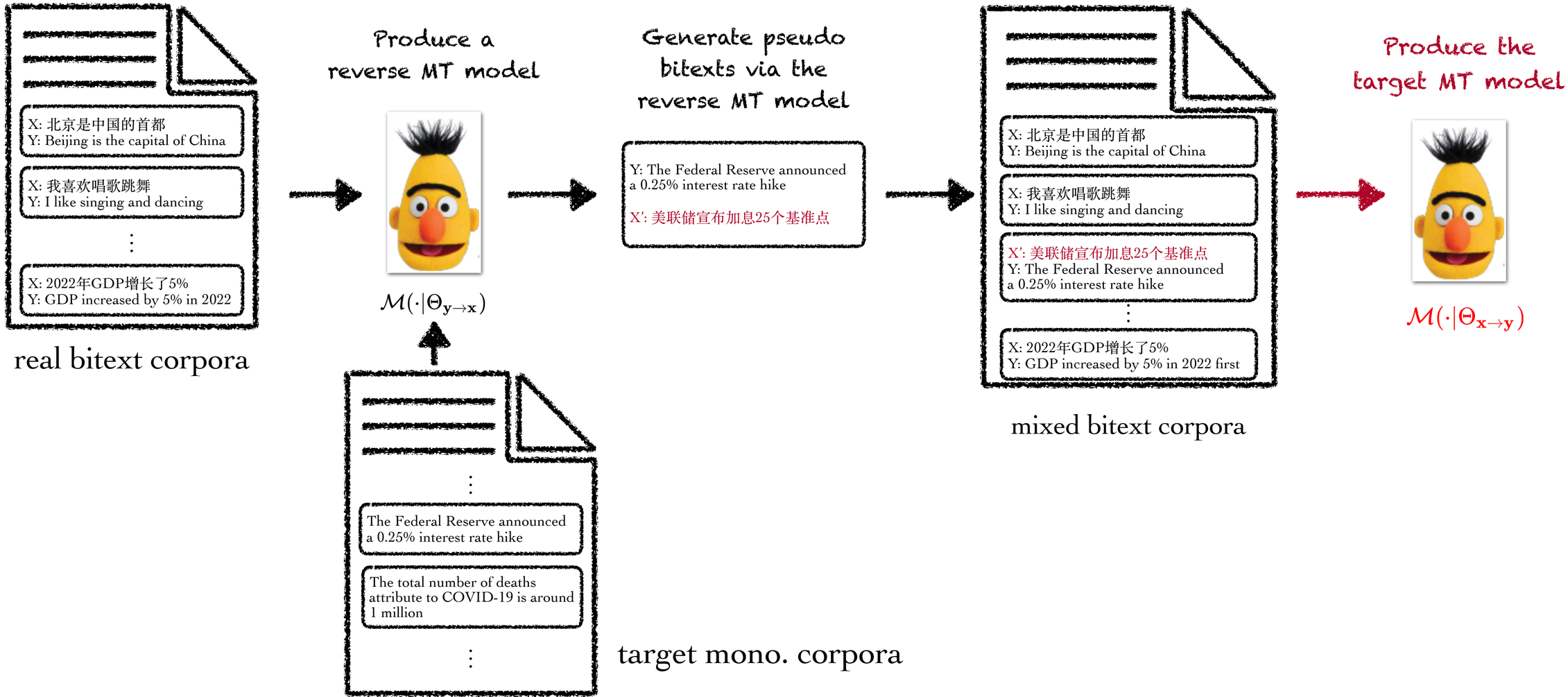

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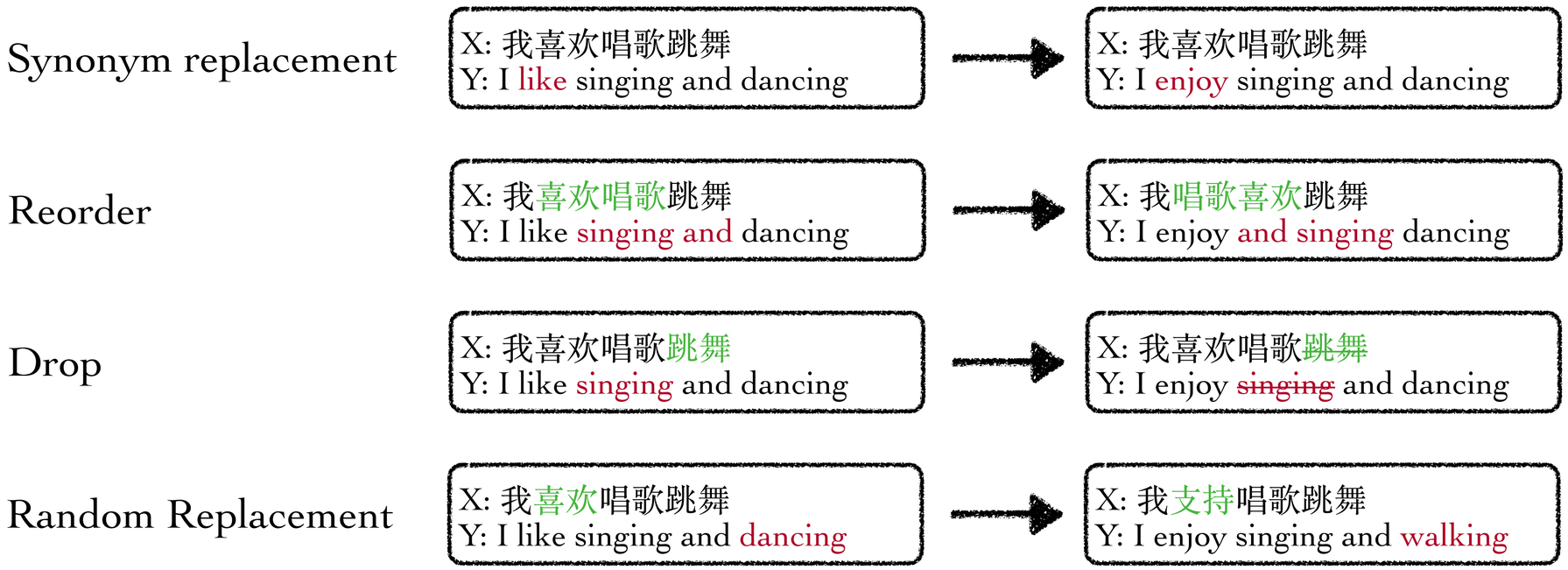

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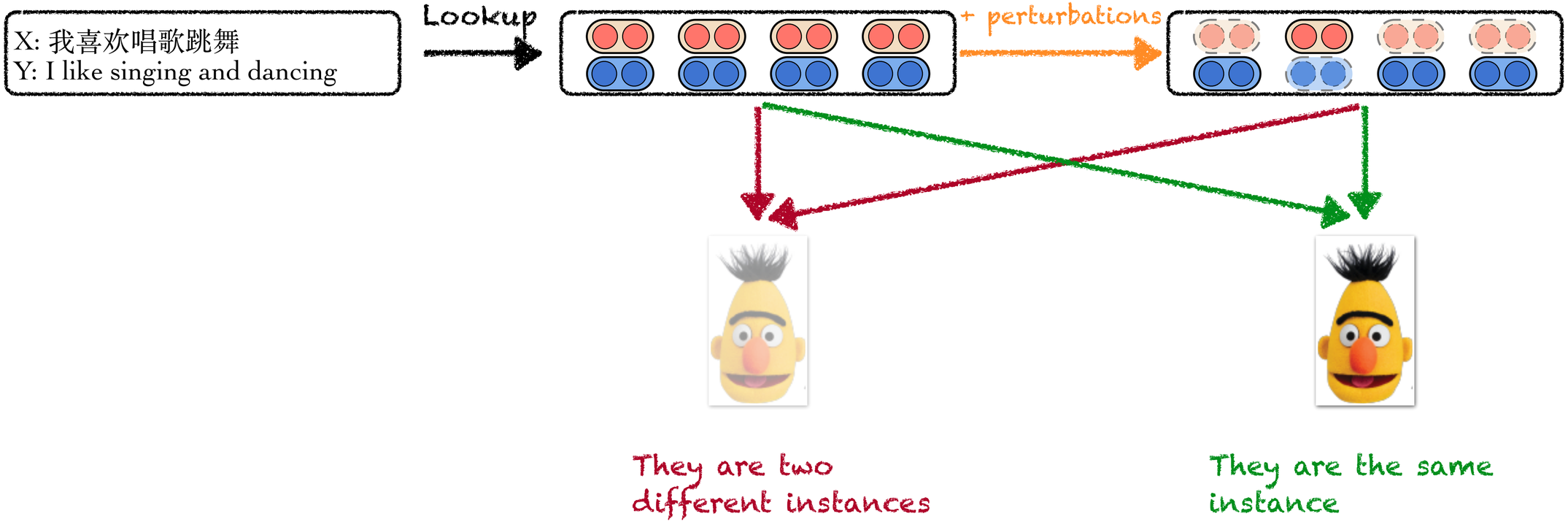

Cheng et al. 2018. Towards Robust Neural Machine Translation.

CsaNMT: Continuous Semantic Augmentation for NMT

- Learning a continuous semantic space to simulate the *real* distribution of semantic equivalence between source and target languages.
- Define a semantic vicinity for each observed training instance, which covers adequate variants of literal expression under the same meaning (many-to-many translation uncertainty).
- Optimizing the NMT model via vicinal risk minimization (i.e. maximize the log-likelihood of all training examples augmented with semantic vicinities).

Vicinal Risk Minimization

Formalizing data augmentation as enlarging the training set by drawing samples from a vicinity of existing training examples.

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Vicinal Risk Minimization (VRM): an extension of ERM with a vicinity per sample

$$R_{vrm}(f) = \frac{1}{n} \sum_{i=1}^{n} \int \ell(f(x), y_i) dP_{x_i}(x)$$

the vicinity

Formalization of CsaNMT

$(\mathbf{x}, \mathbf{y}) \in (X, Y)$ denotes a pair of two sentences with the same meaning, i.e. a parallel sentence pair

Maximum Likelihood Estimation

training corpora parameters

$$J_{mle}(\Theta) = \mathbb{E}_{(\mathbf{x},\mathbf{y})\sim\mathcal{C}}\big(\log P(\mathbf{y}|\mathbf{x};\Theta)\big)$$

decomposed to

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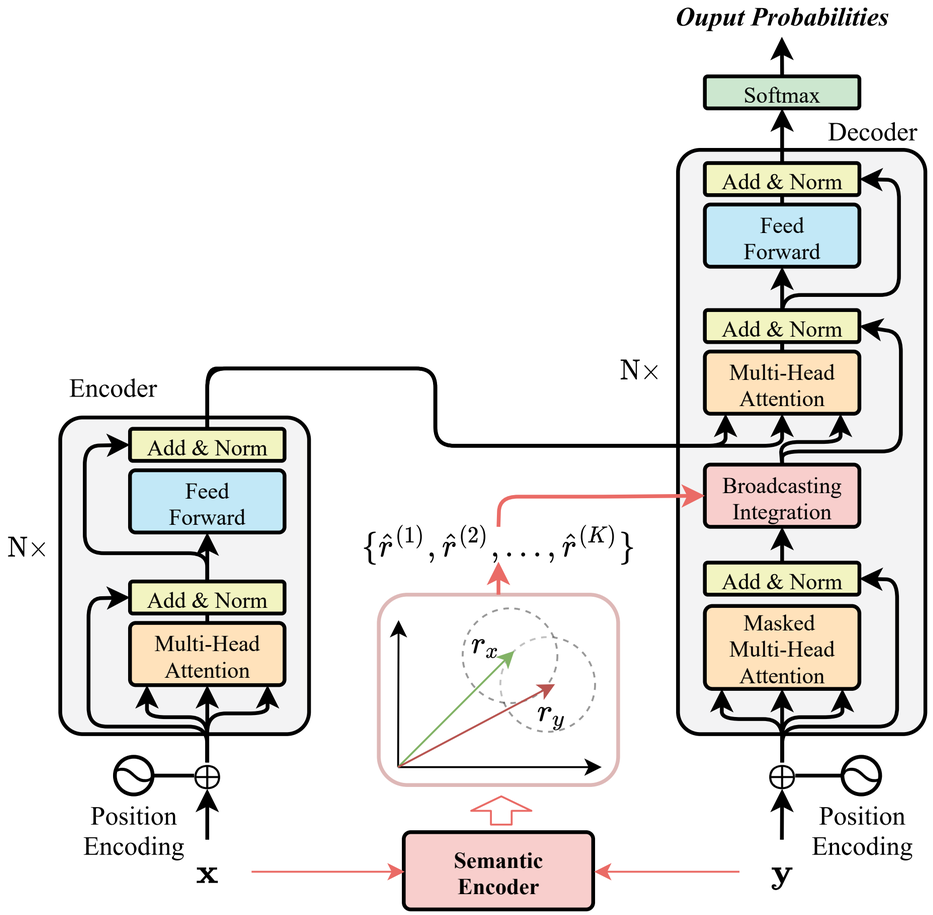
$$\mathcal{R} = \{\hat{r}^{(1)}, \hat{r}^{(2)}, \ldots, \hat{r}^{(K)}\}$$
$$\hat{r}^{(k)} \sim \nu(r_x, r_y)$$

a series of examples sampled from the vicinity

Graphical Illustration of CsaNMT

The model architecture consists of a vanilla encoder-decoder pipeline and an extra semantic encoder.



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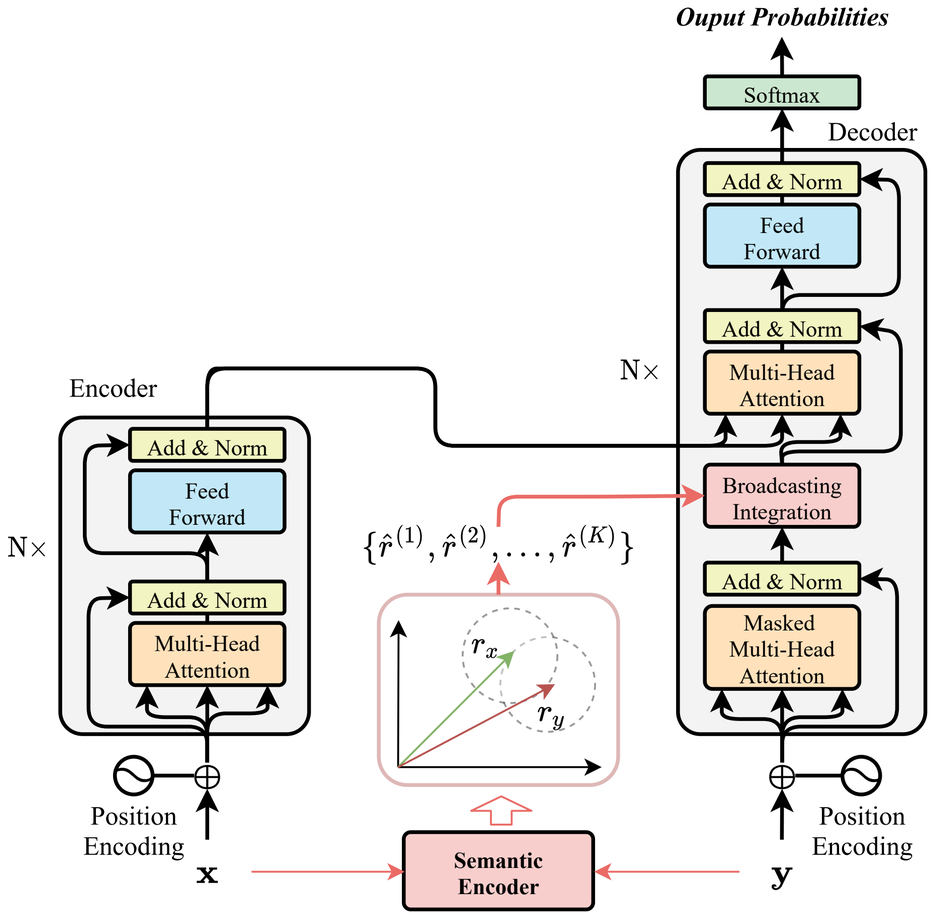

Definition 1. There is a universal semantic space among the source and the target languages for neural machine translation, which is established by a semantic encoder. It defines a forward function $\psi(\cdot\,;\Theta')$ to map discrete sentences into continuous vectors, that satisfies: $\forall(\mathbf{x},\mathbf{y}) \in (\mathcal{X},\mathcal{Y}) : r_x = r_y$. Besides, an adjacency semantic region $\nu(r_x, r_y)$ in the semantic space describes adequate variants of literal expression centered around each observed sentence pair $(\mathbf{x},\mathbf{y})$.

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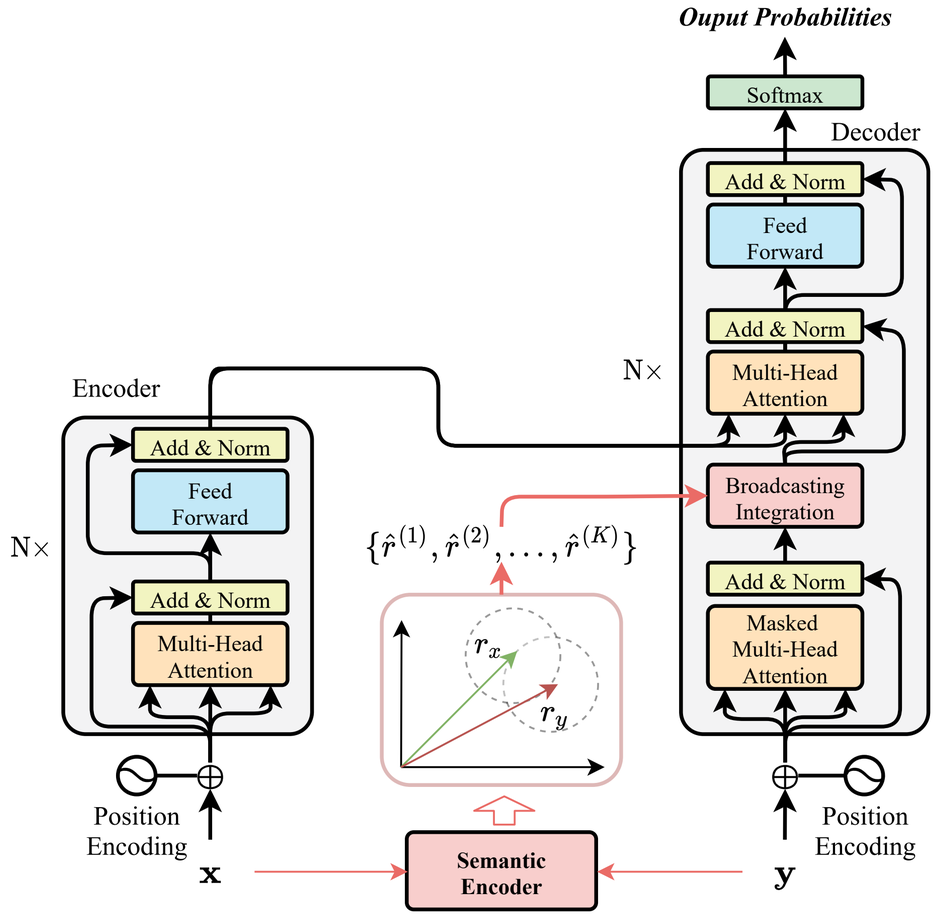

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- How to optimize the extra semantic encoder $\psi(\cdot\,;\Theta')$ so that it produces a meaningful vicinity $\nu(r_x, r_y)$ for each training instance?
- How to obtain samples from the adjacency semantic region in an efficient and effective way?

Tangential Contrastive Learning

Positive pairs: embeddings of each parallel two sentences are positives of each other

Negative pairs: (interpolated) embeddings of other sentences from the same mini-batch (in-batch negatives)

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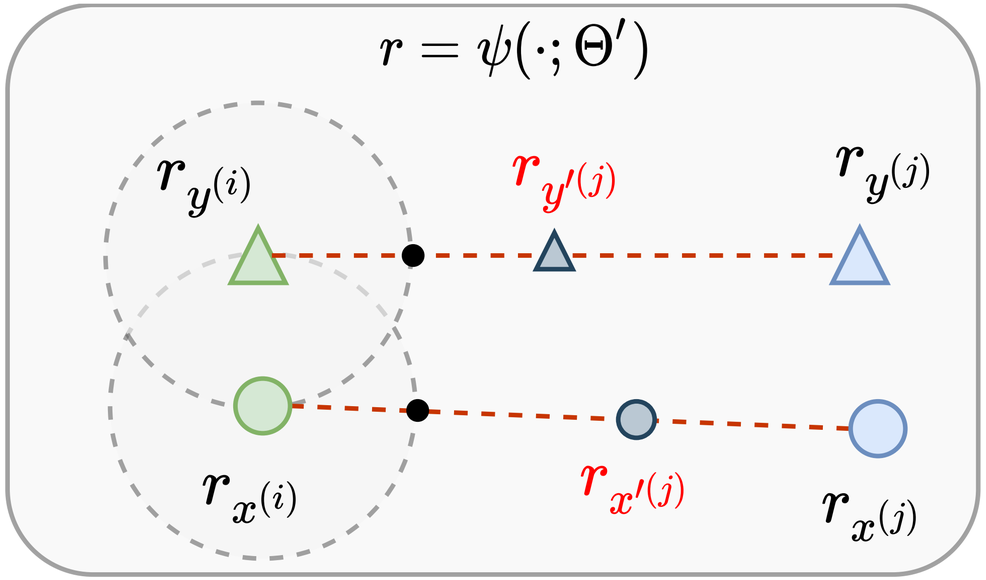

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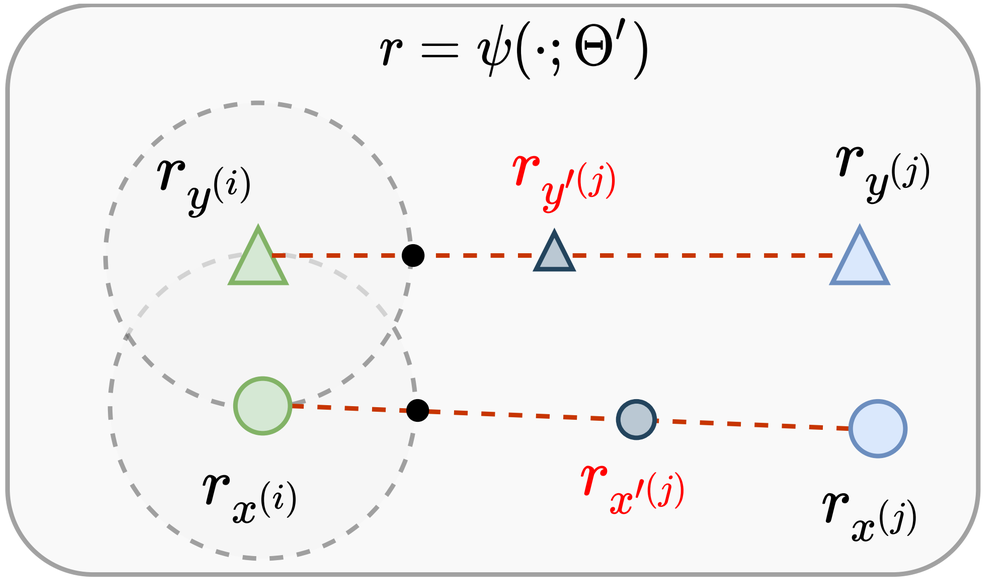

$\nu(\mathbf{r_x}, \mathbf{r_y})$: the union of two closed balls that are centered around r_x and r_y, the radius is $d = \| r_x - r_y \|_2$

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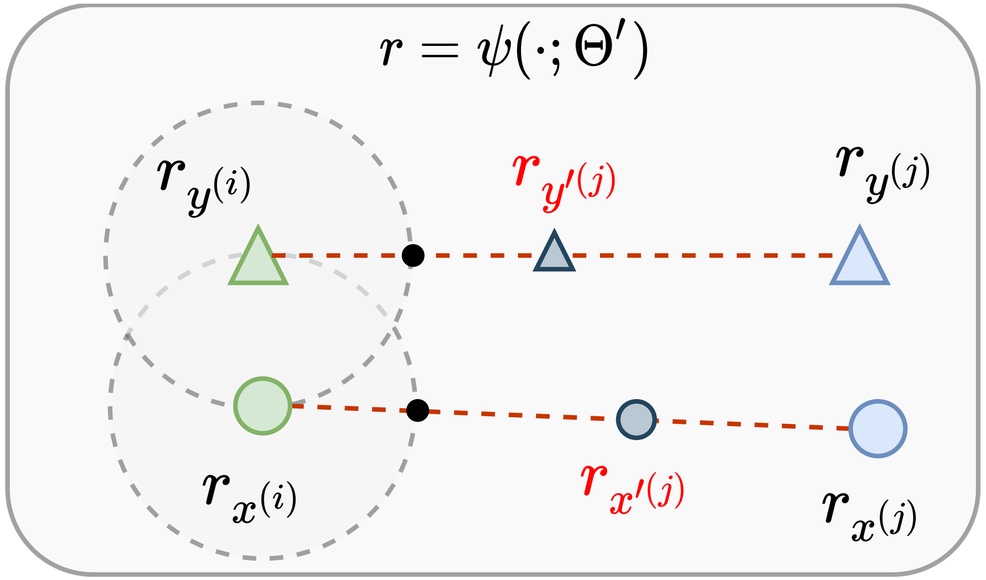

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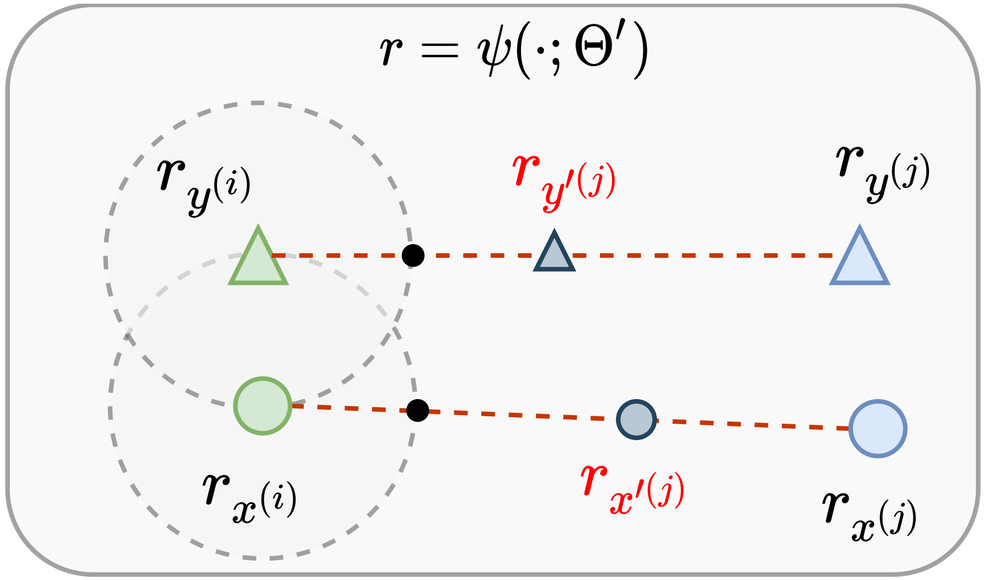

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Adaptively adjusted factors during training

Reasonable Negatives are walking between tangent points and in-batch ones

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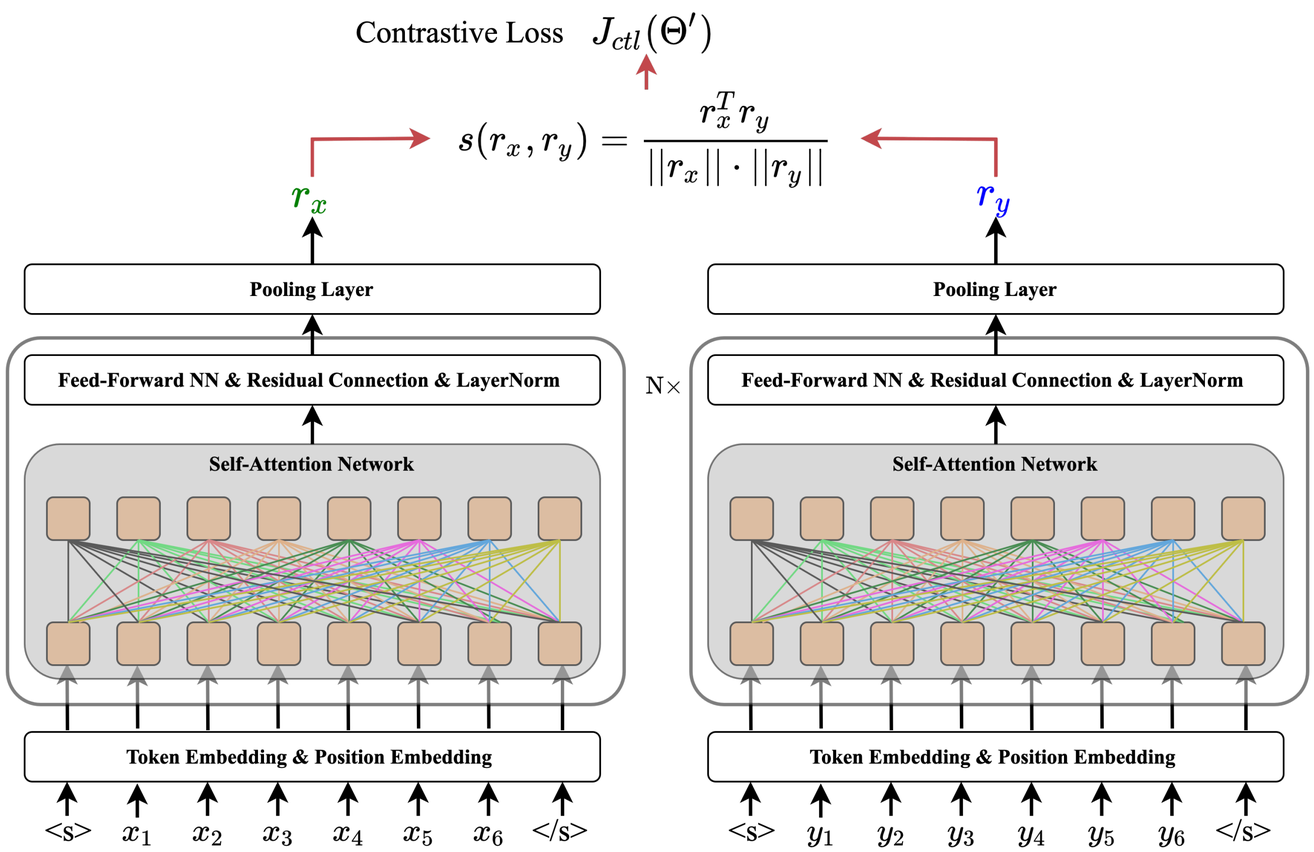

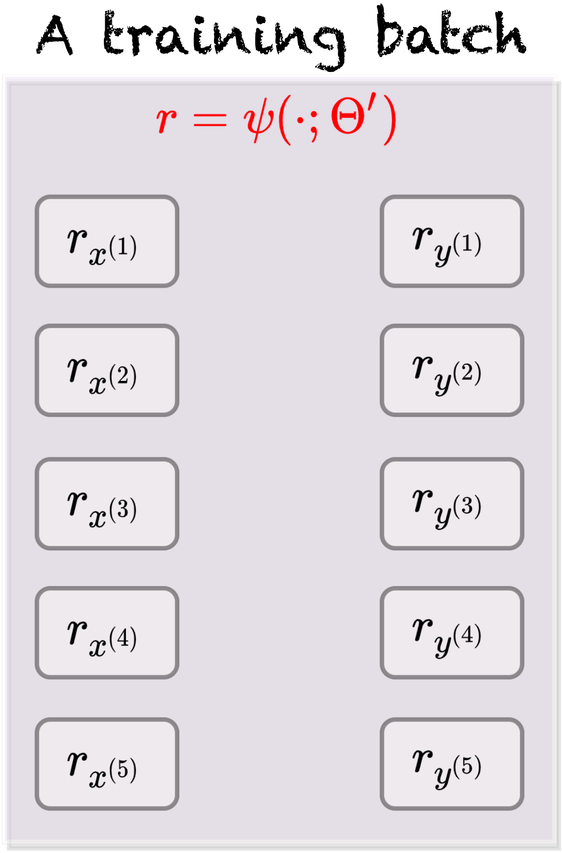

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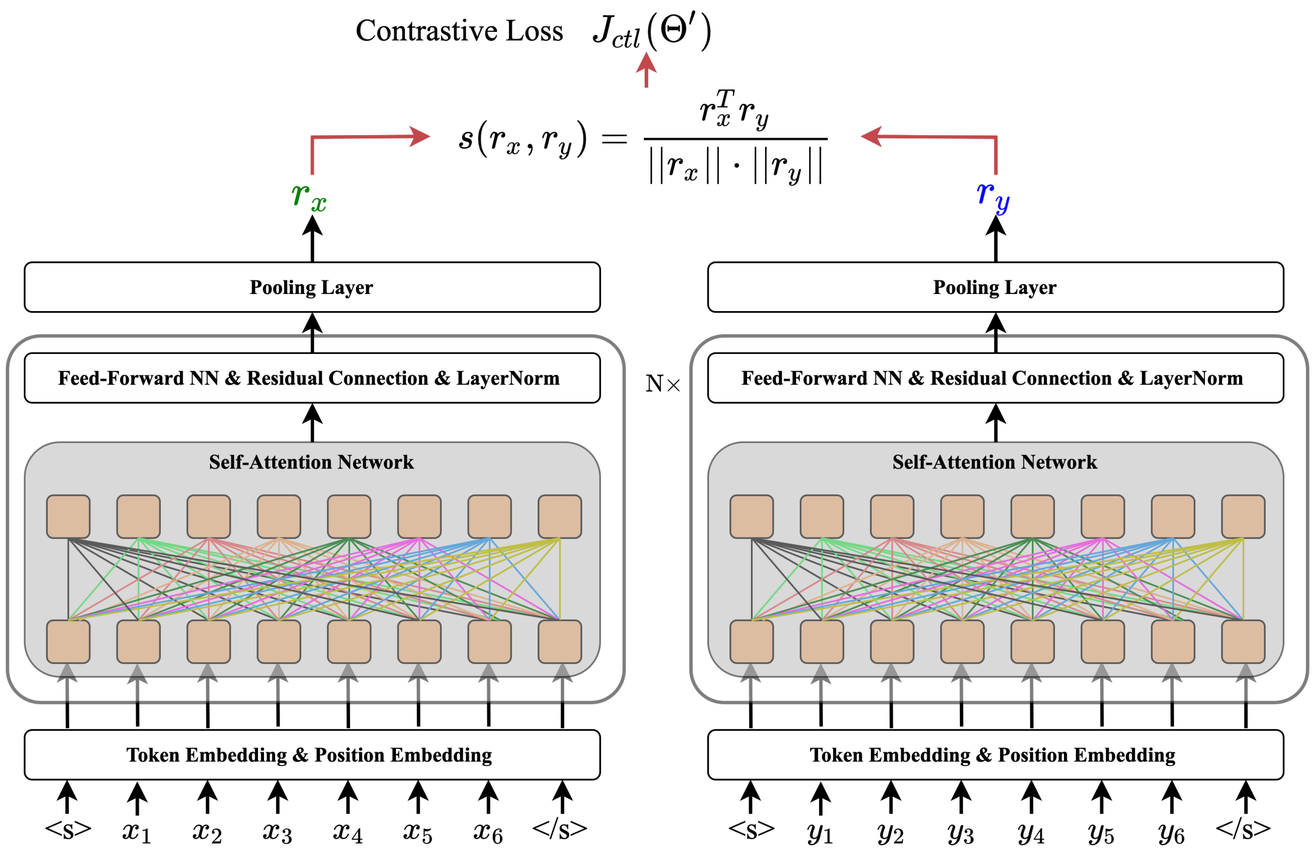

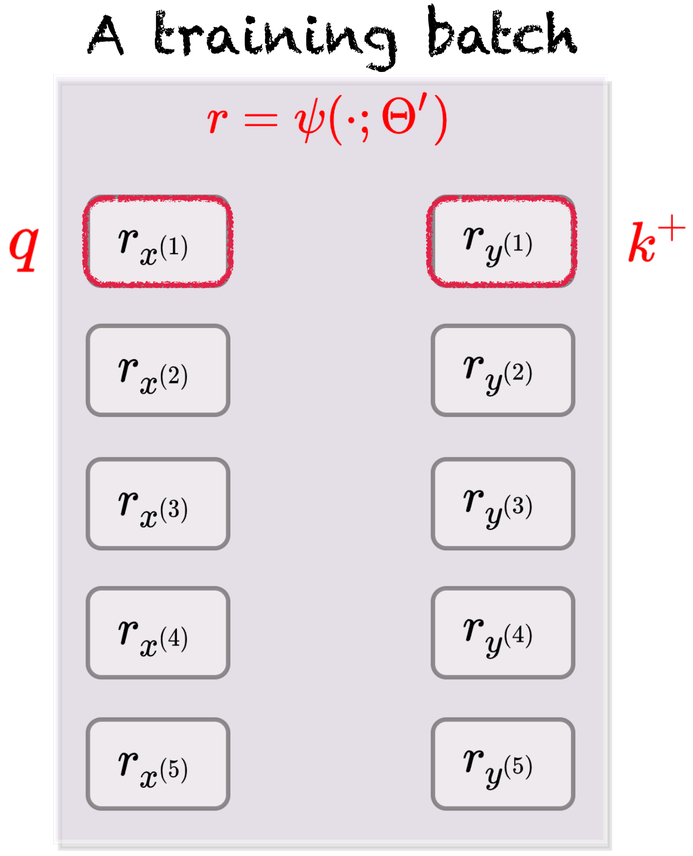

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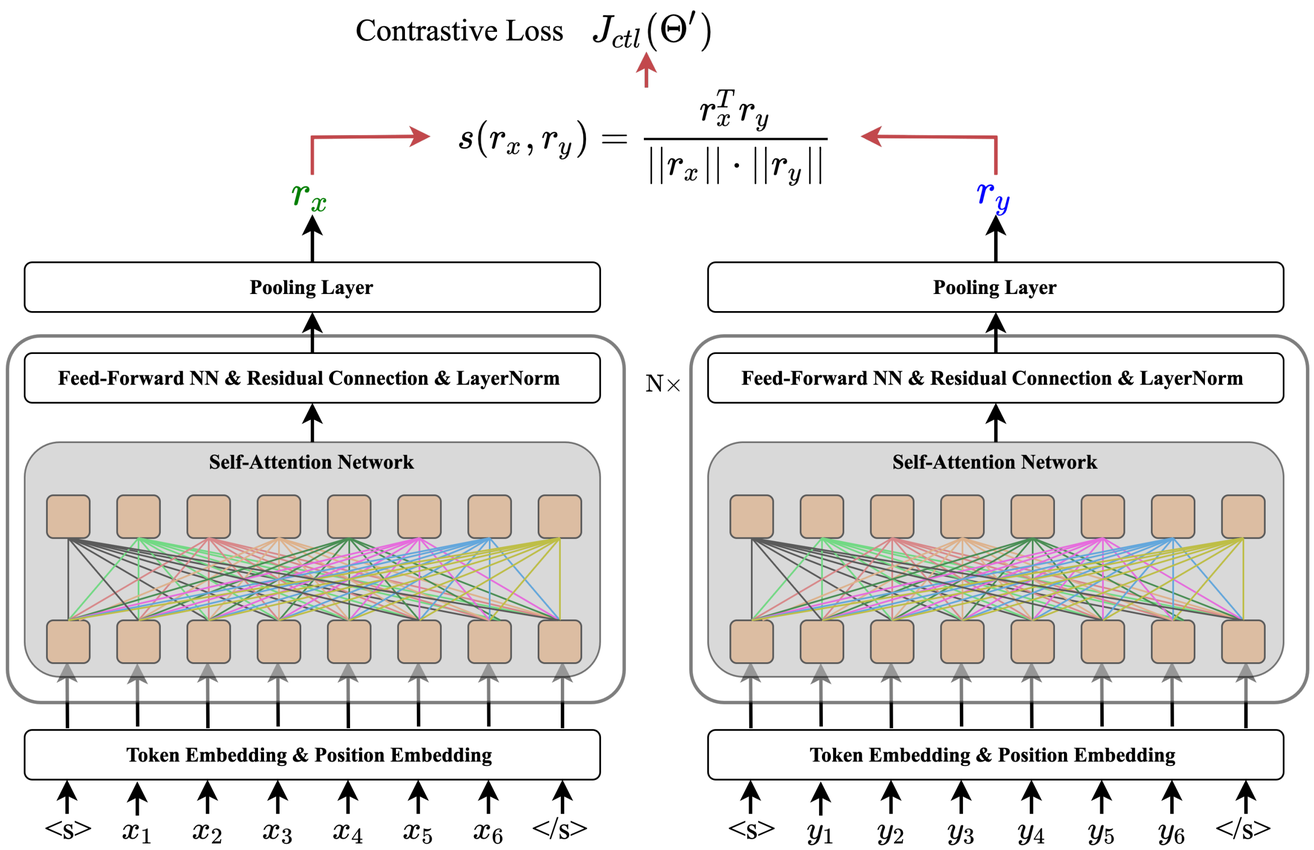

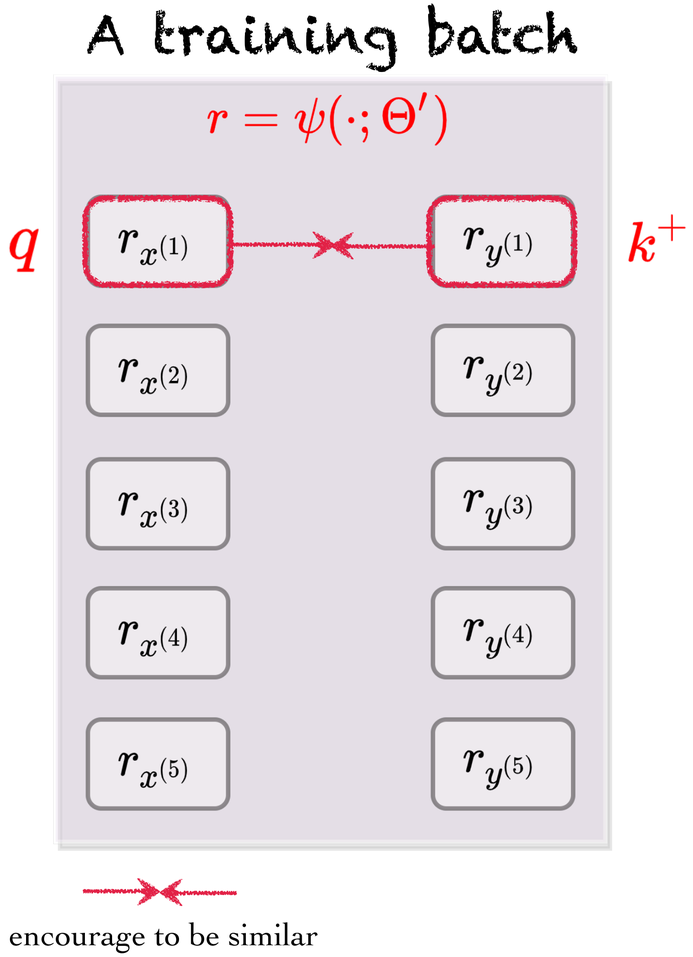

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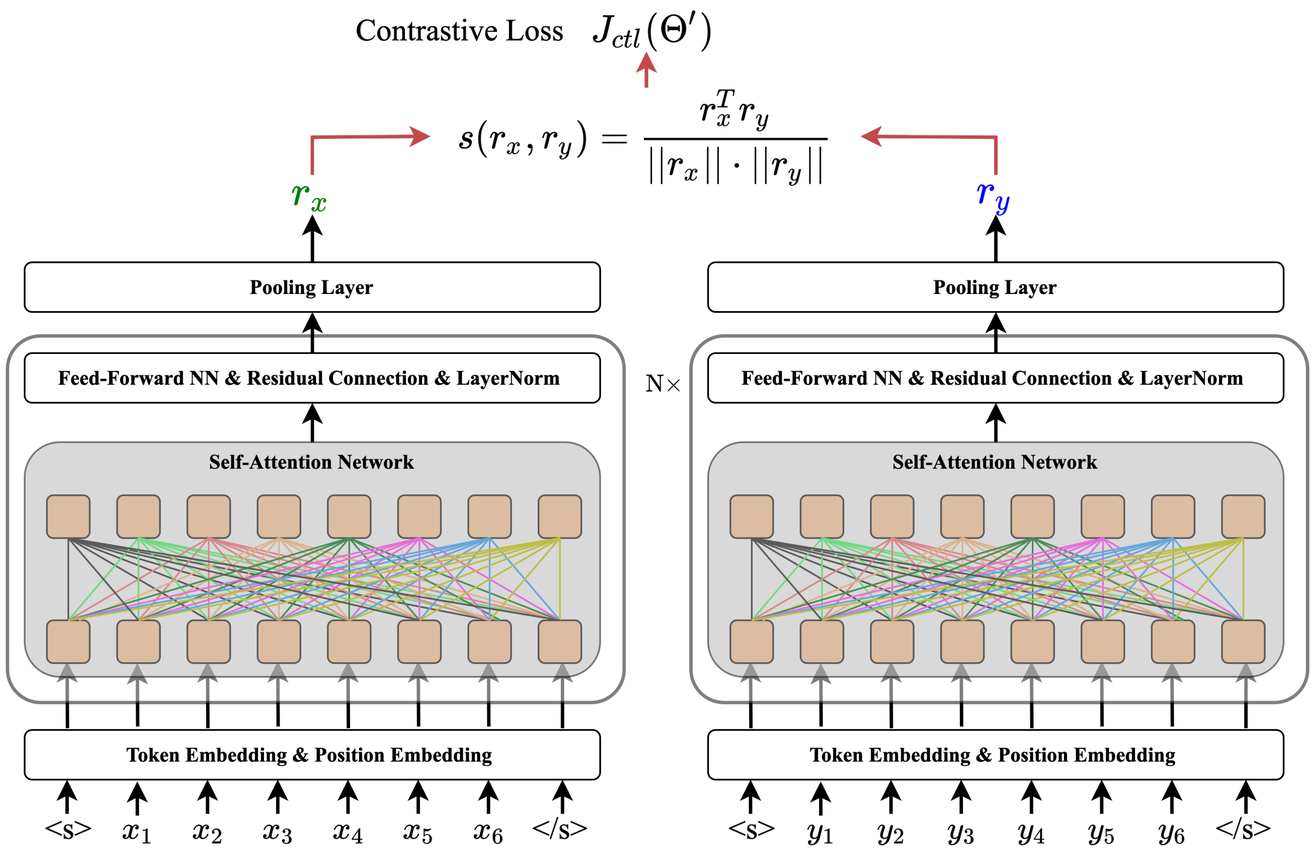

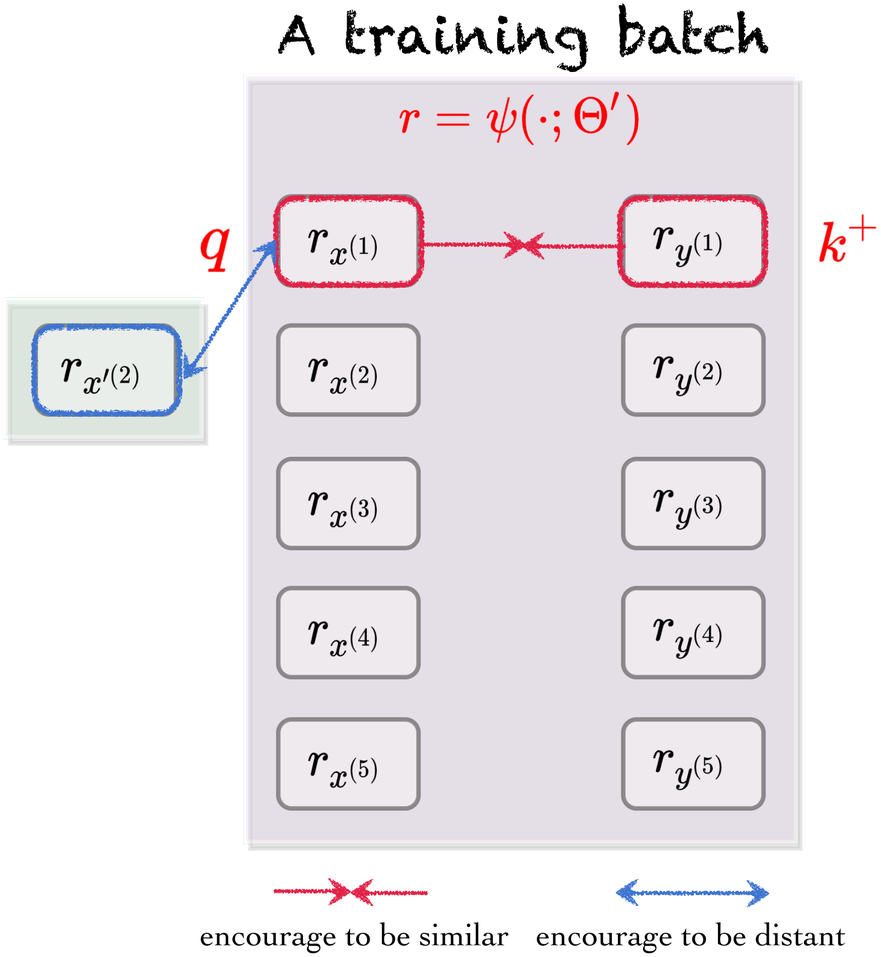

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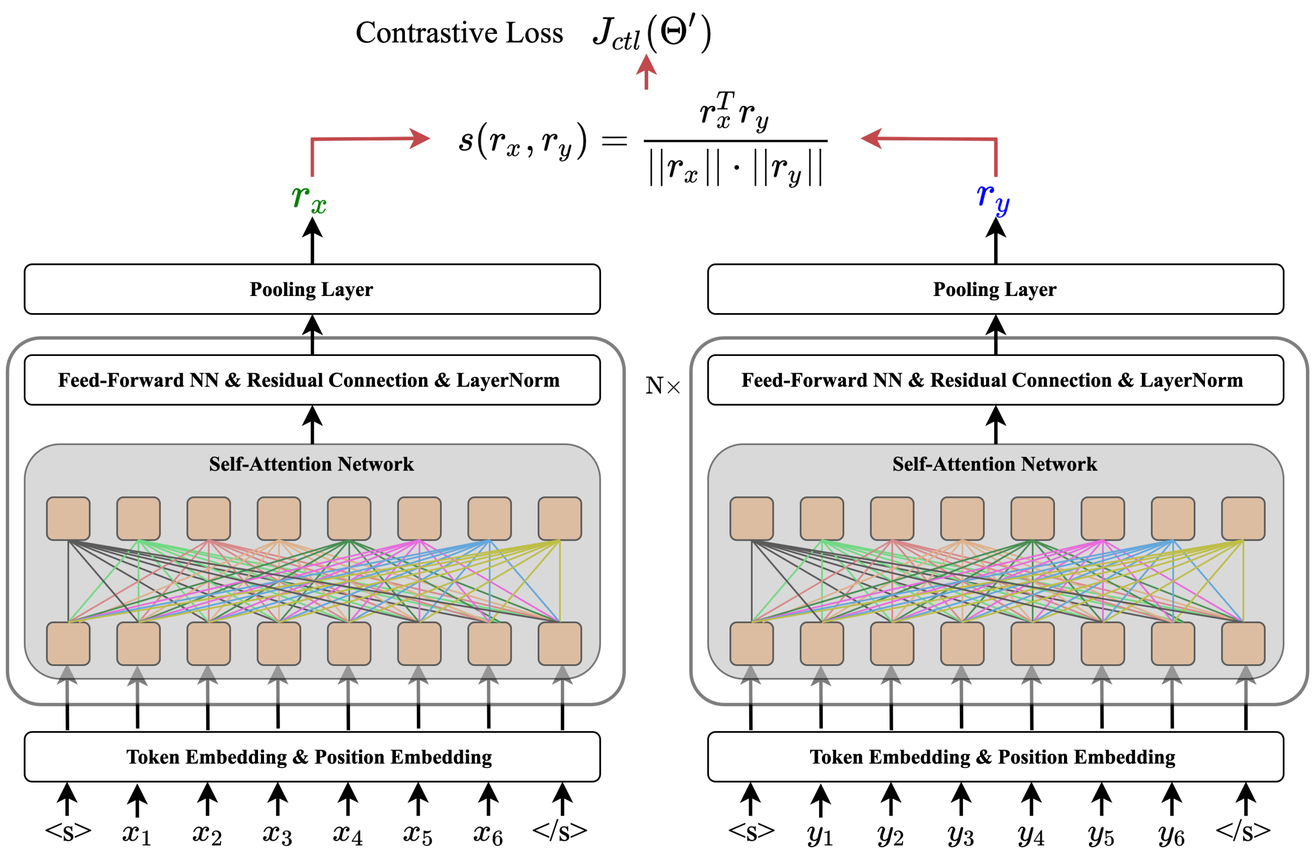

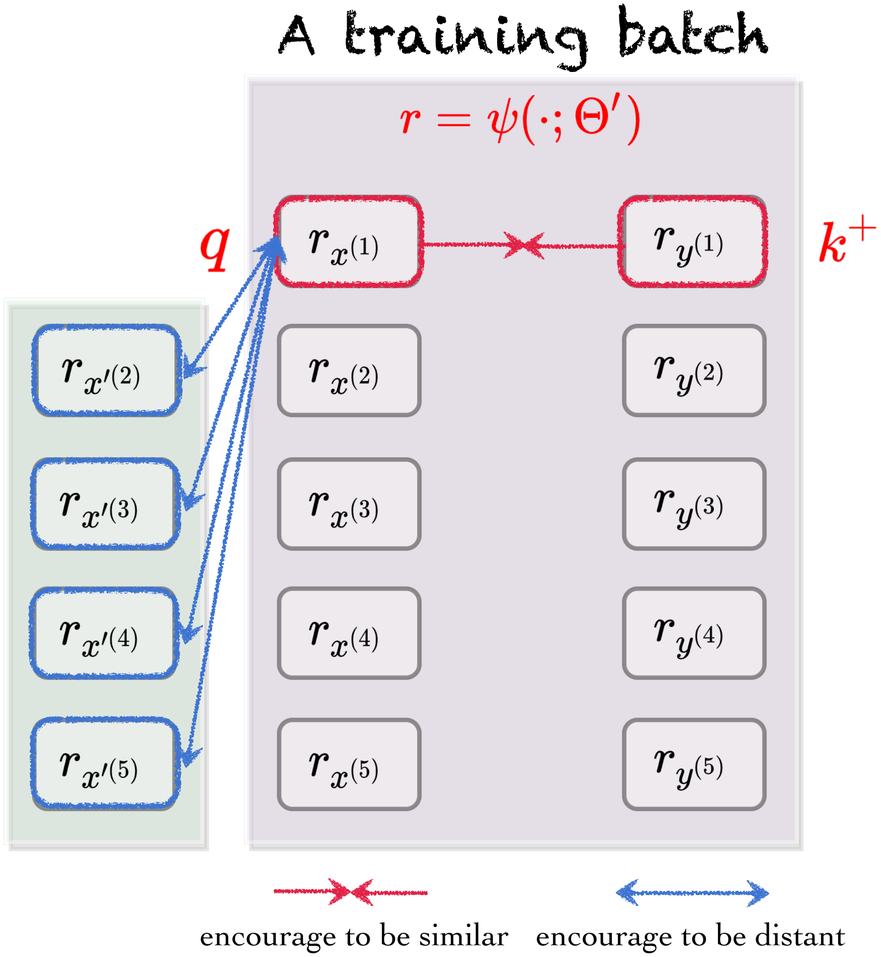

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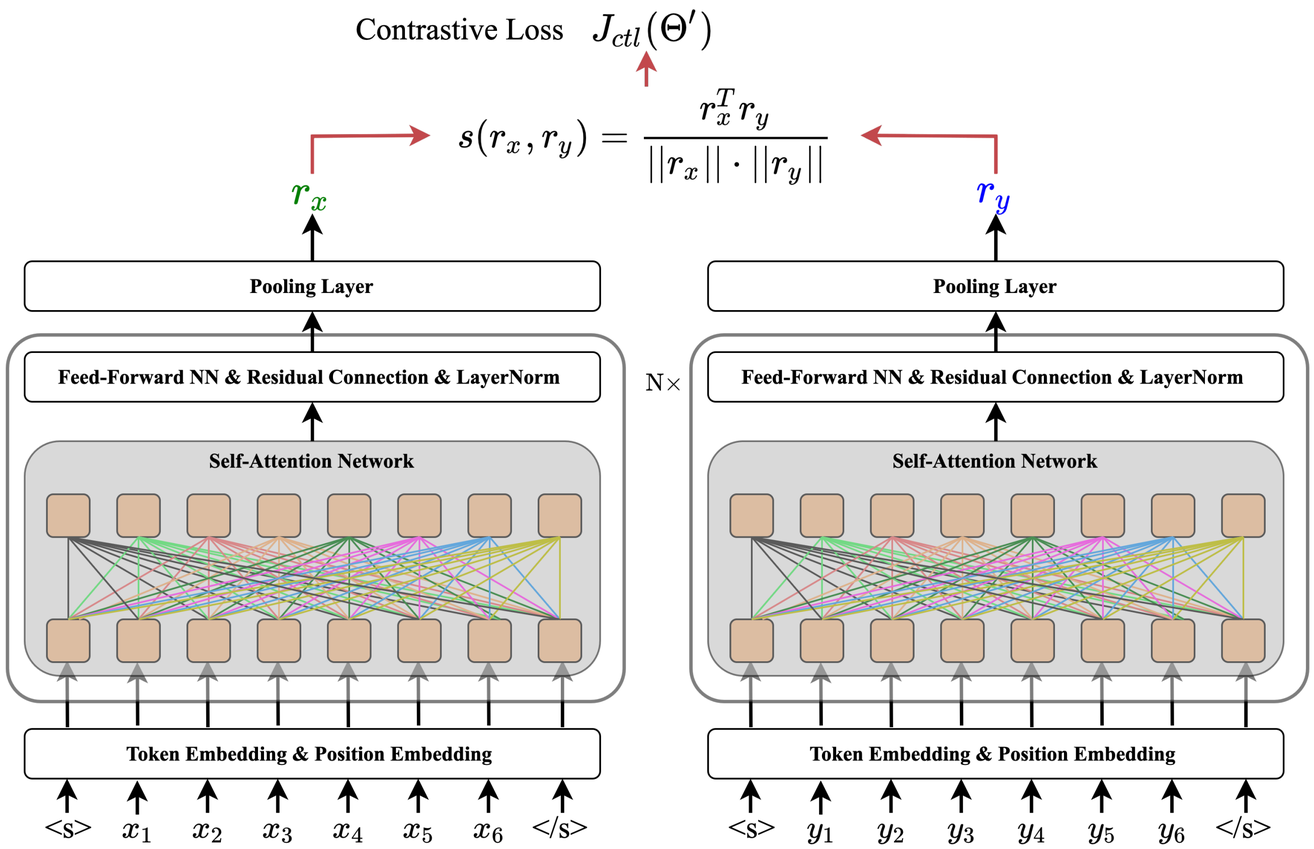

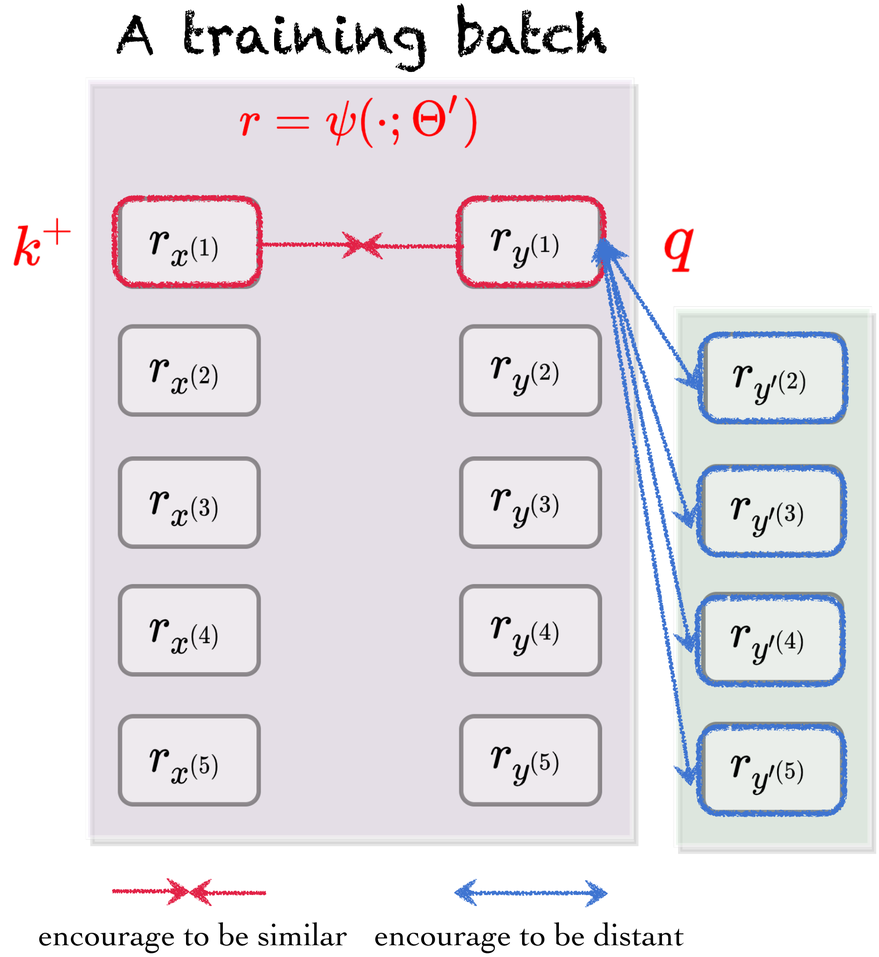

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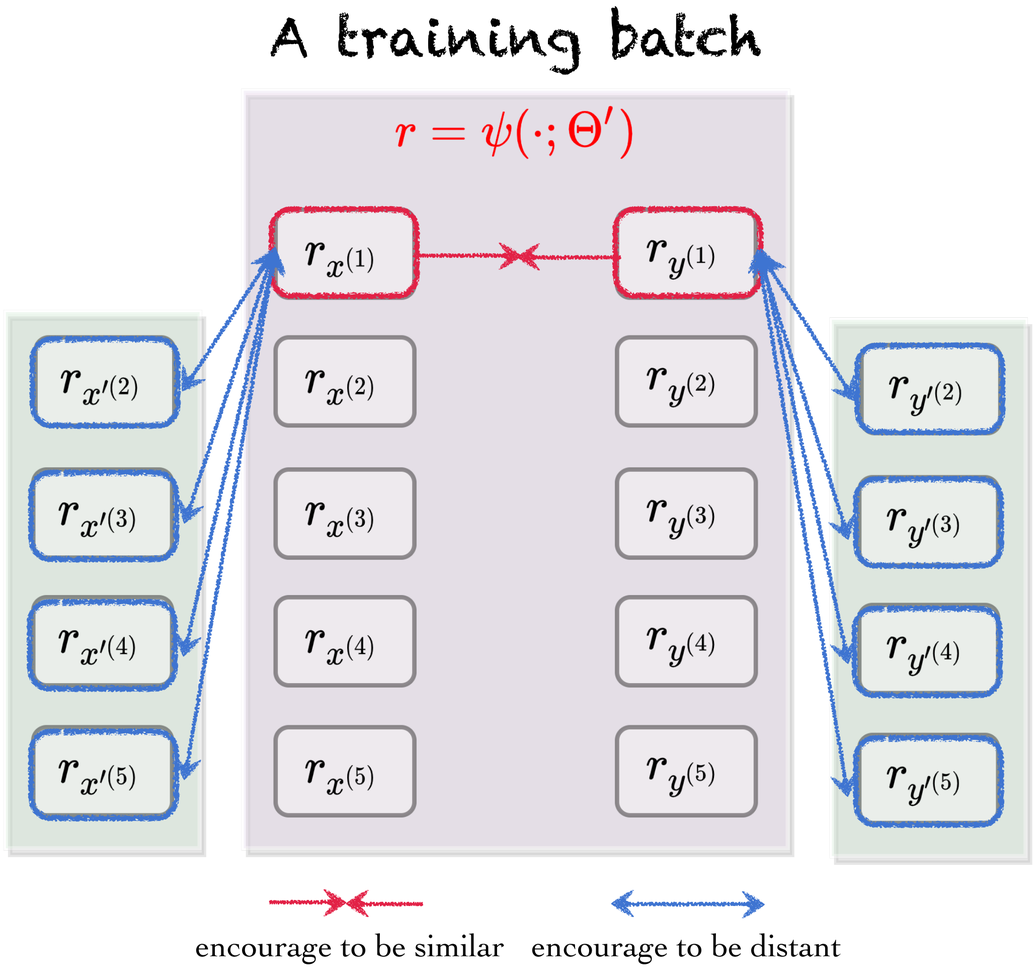

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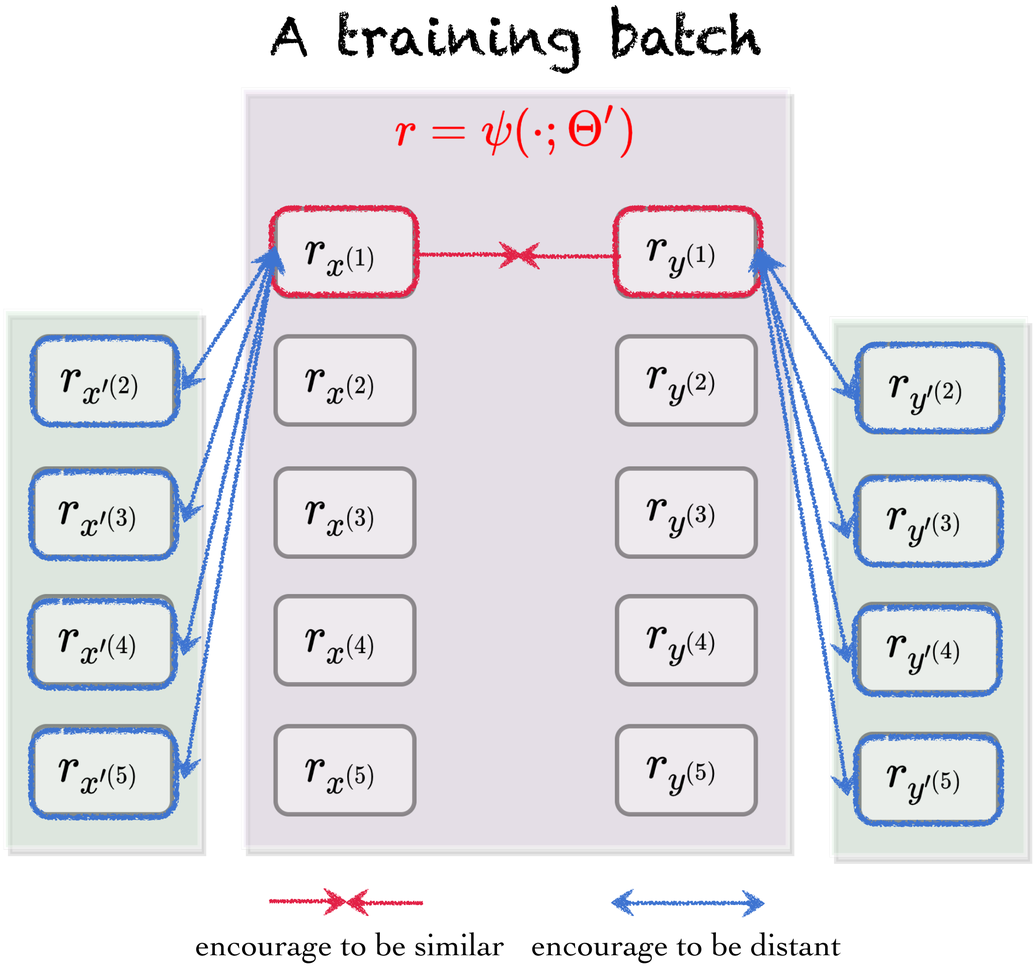

Parallel sentence pairs

$$J_{ctl}(\Theta') = \mathbb{E}_{(\mathbf{x}^{(i)},\mathbf{y}^{(i)})\sim\mathcal{B}}\left(\log \frac{e^{s\left(r_{x^{(i)}}, r_{y^{(i)}}\right)}}{e^{s\left(r_{x^{(i)}}, r_{y^{(i)}}\right)} + \xi}\right)$$

$$\xi = \sum_{j\&j\neq i}^{|\mathcal{B}|}\left(e^{s\left(r_{y^{(i)}}, r_{y'^{(j)}}\right)} + e^{s\left(r_{x^{(i)}}, r_{x'^{(j)}}\right)}\right)$$

Interpolated in-batch negatives

Sampling with Mixed Gaussian Recurrent Chain

Our scenario is that each training instance always accompanies with a cluster of vectors sampled from its continuous vicinity $\nu(r_x, r_y)$, to enable the NMT model to generalize to more.

Challenges: the vicinity of each instance follows an unknown probability distribution.

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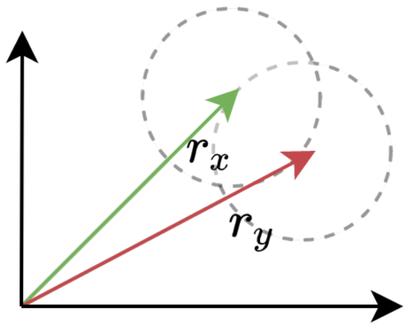
A possible solution with vector transform



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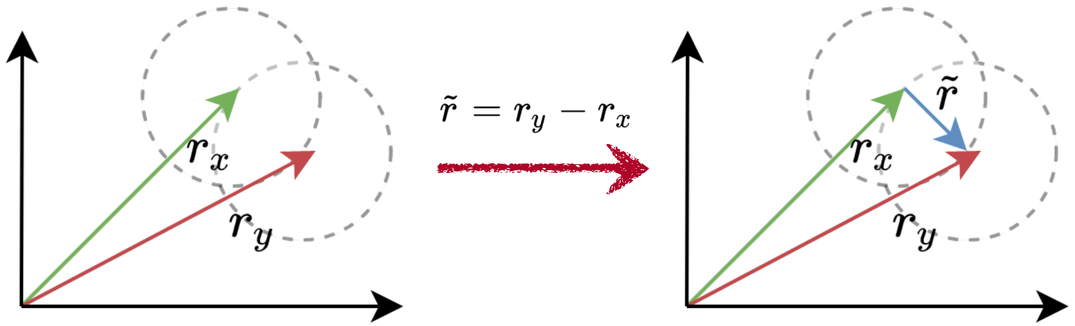

Compute the bias vector between the embeddings of two parallel sentences

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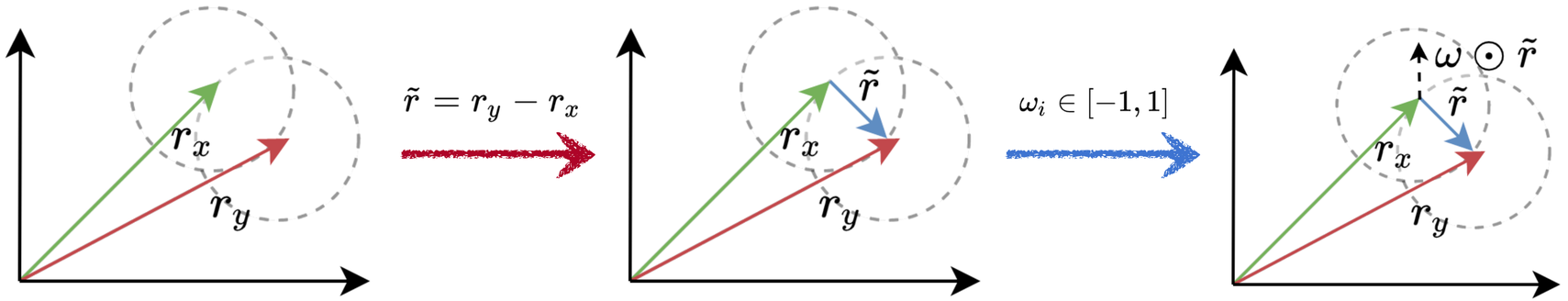

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Transform the norm or the direction of the bias vector

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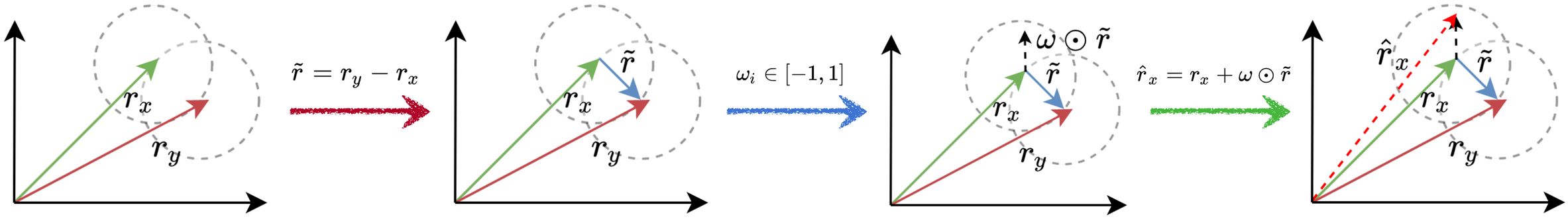

Compute the bias vector between the embeddings of two parallel sentences

Transform the norm or the direction of the bias vector

Newly construct a sample as the augmented instance

Sampling with Mixed Gaussian Recurrent Chain

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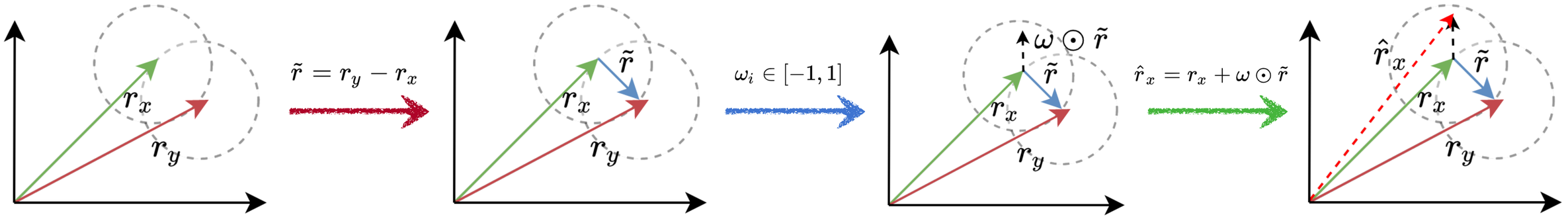

As a consequence, the goal of the sampling strategy turns into find a set of scale vectors:

$$\omega \in \{\omega^{(1)}, \omega^{(2)}, \ldots, \omega^{(K)}\}$$

Sampling with Mixed Gaussian Recurrent Chain

MGRC Sampling Algorithm

Input: The representations of the training instance $(\mathbf{x}, \mathbf{y})$, i.e. r_x and r_y.

Output: A set of augmented samples $\mathcal{R} = \{\hat{r}^{(1)}, \hat{r}^{(2)}, ..., \hat{r}^{(K)}\}$

Normalizing the importance of each element in $\tilde{r} = r_y - r_x$: $\mathcal{W}_r = \frac{|\tilde{r}| - min(|\tilde{r}|)}{max(|\tilde{r}|) - min(|\tilde{r}|)}$

Set $k = 1$, $\omega^{(1)} \sim \mathcal{N}(\mathbf{0}, \text{diag}(\mathcal{W}_r^2))$, $\hat{r}^{(1)} = r + \omega^{(1)} \odot (r_y - r_x)$

Initialize the set of samples as $\mathcal{R} = \{\hat{r}^{(1)}\}$.

while $k \leq (K - 1)$ **do**

  $k \leftarrow k + 1$

  Calculate the current scale vector: $\omega^{(k)} \sim p(\omega|\omega^{(1)}, \omega^{(2)}, ..., \omega^{(k-1)}$ according to Eq. (6).

  Calculate the current sample: $\hat{r}^{(k)} = r + \omega^{(k)} \odot (r_y - r_x)$.

  $\mathcal{R} \leftarrow \mathcal{R} \bigcup \{\hat{r}^{(k)}\}$.

end while

Sampling with Mixed Gaussian Recurrent Chain

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8: $\mathcal{R} \leftarrow \mathcal{R} \bigcup \{\hat{r}^{(k)}\}$.

9: **end while**

Limits the range of sampling to a subspace of the vicinity, and rejects to conduct sampling from the uninformative dimensions

$$p = \eta\mathcal{N}\left(\mathbf{0}, \mathrm{diag}(\mathcal{W}_r^2)\right) + (1.0 - \eta)\mathcal{N}\left(\frac{1}{k-1}\sum_{i=1}^{k-1}\omega^{(i)}, \mathbf{1}\right)$$

Describes the fact that the diversity of each training instance is not infinite

Training Strategy

① Tangential contrastive learning with adaptive negatives to optimize the semantic encoder:

$$\Theta'^{*} = \text{argmax}_{\Theta'} J_{ctl}(\Theta')$$

② Maximum likelihood estimation with vicinities to optimize the NMT model:

$$\Theta^{*} = \text{argmax}_{\Theta} J_{mle}(\Theta)$$

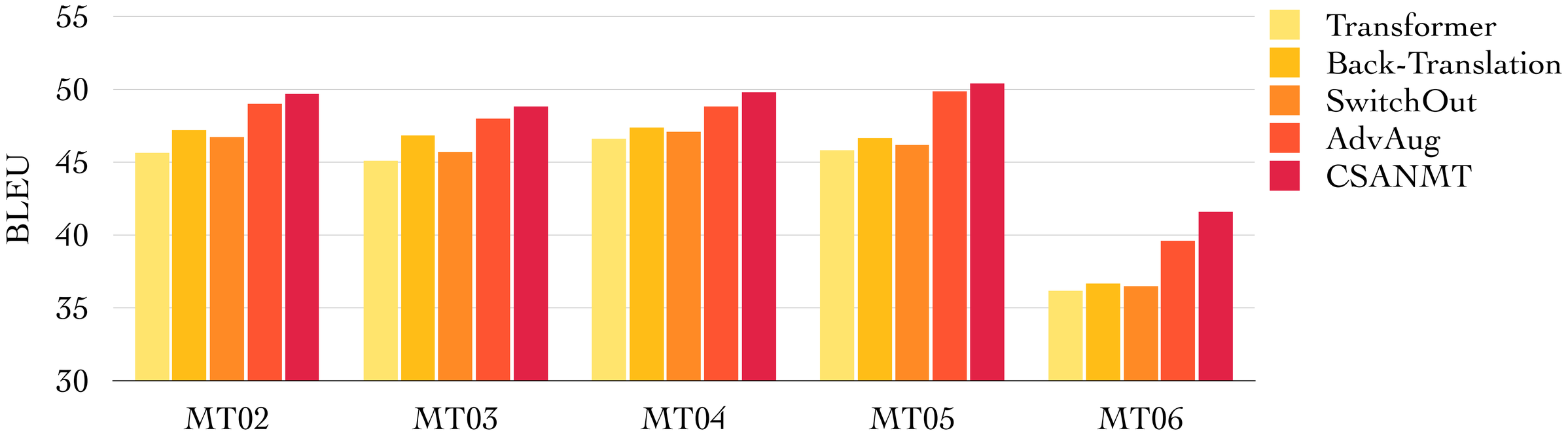
③ Jointly optimization while use a small learning rate to fine-tune the semantic encoder

$$\Theta = \Theta - \alpha_{mle} \cdot \nabla_{\Theta} J_{mle}(\Theta) \qquad \Theta' = \Theta' - \alpha_{ctl} \cdot \nabla_{\Theta'} J_{ctl}(\Theta')$$

a very small learning rate, e.g. 1e-5

CSANMT: Main Results

NIST Chinese-to-English, LDC corpus (1.25M) for training, MT06 (valid), MT02-05&08 (test)



CsaNMT: Main Results

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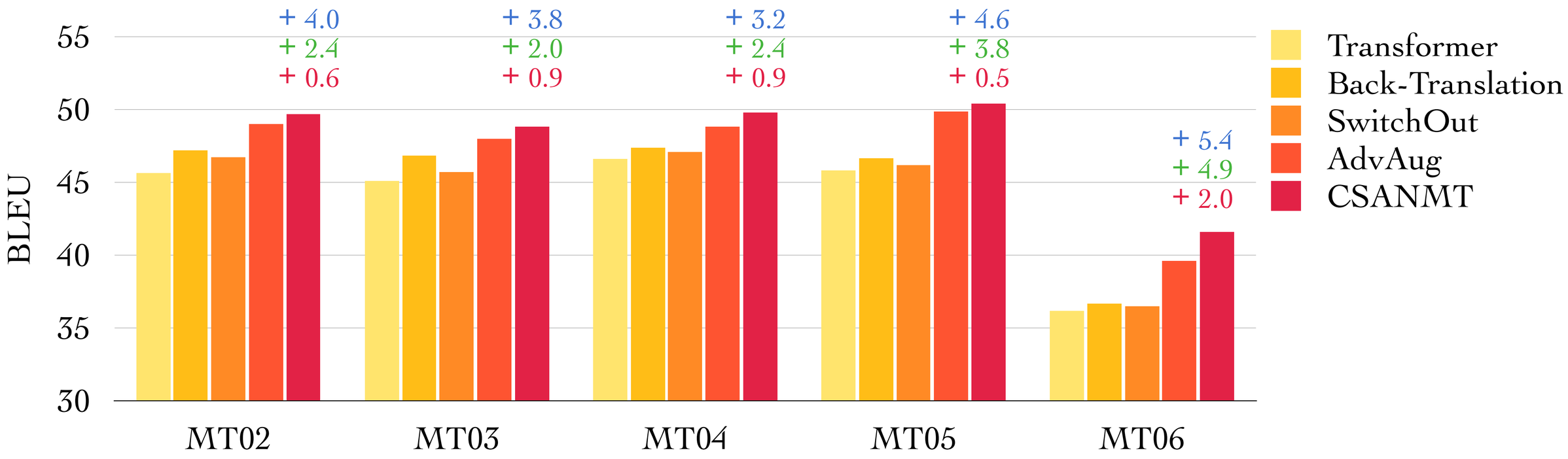


4.2 BLEU higher than Transformer

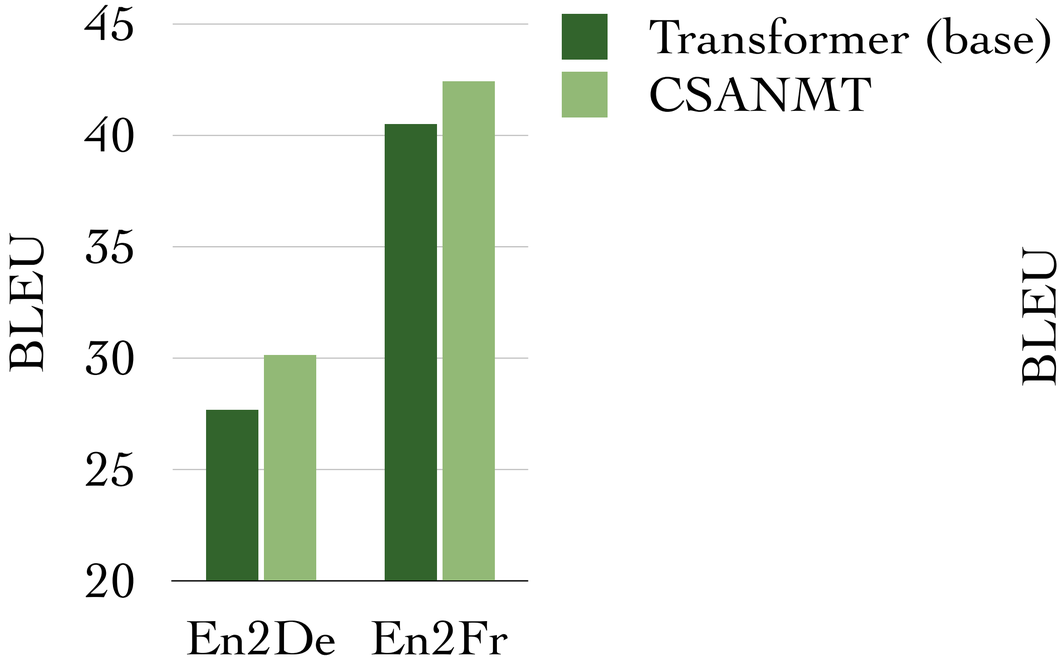
3.1 BLEU higher than Back-Translation

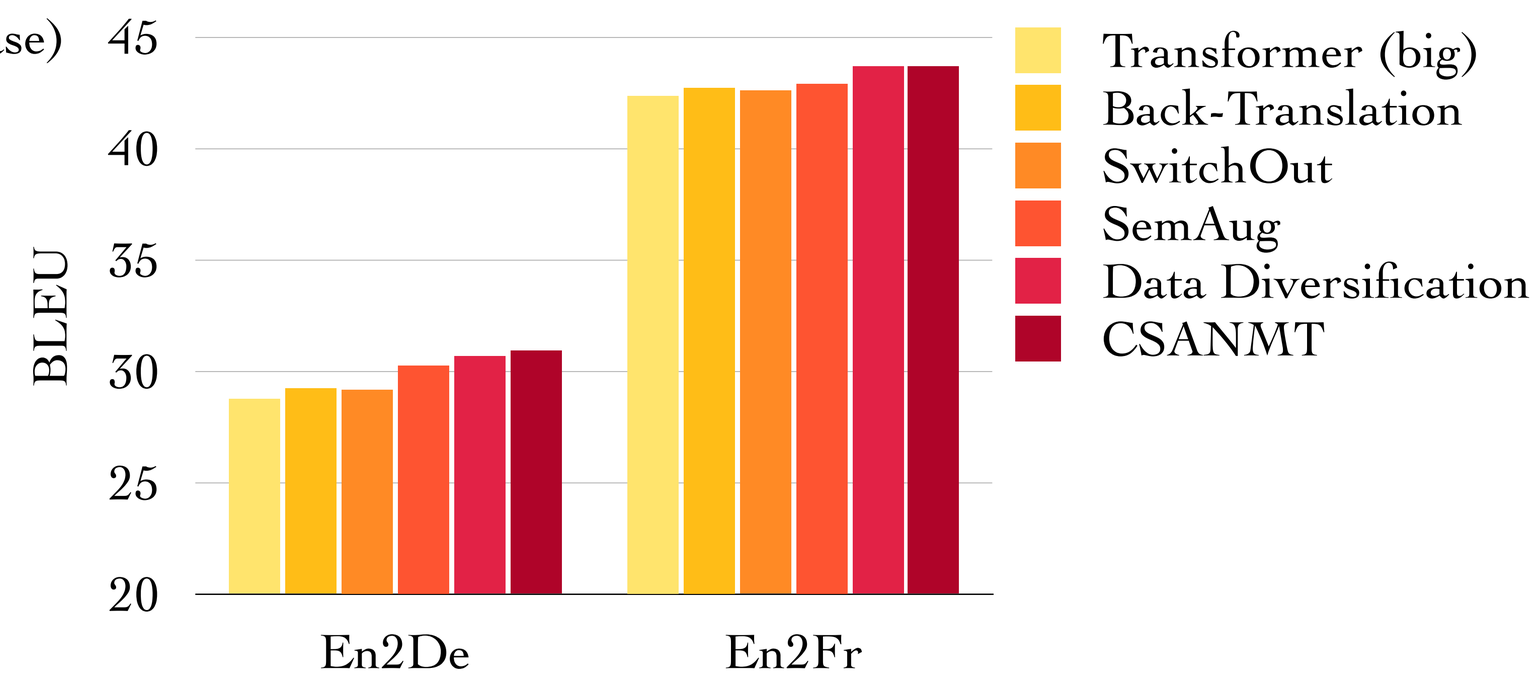
1.0 BLEU higher than AdvAug

CSANMT: Main Results

English-German, WMT'14 corpus (4.5M) for training, newstest2013 (valid), newstest2014 (test)

English-French, WMT'14 corpus (36M) for training, newstest2012 & 2013 (valid), newstest2014 (test)





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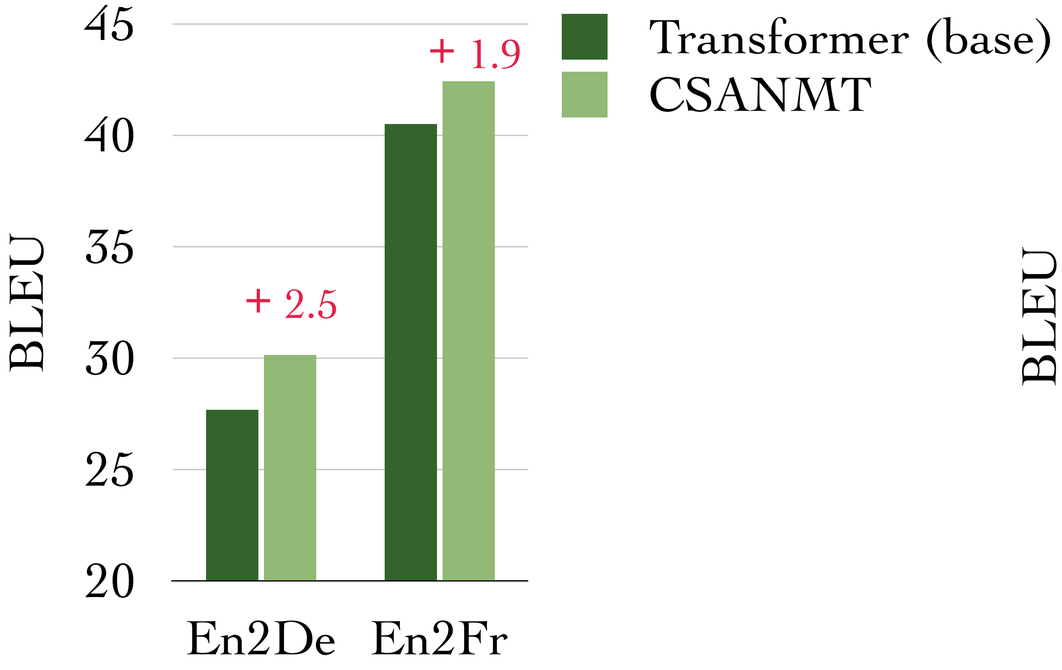

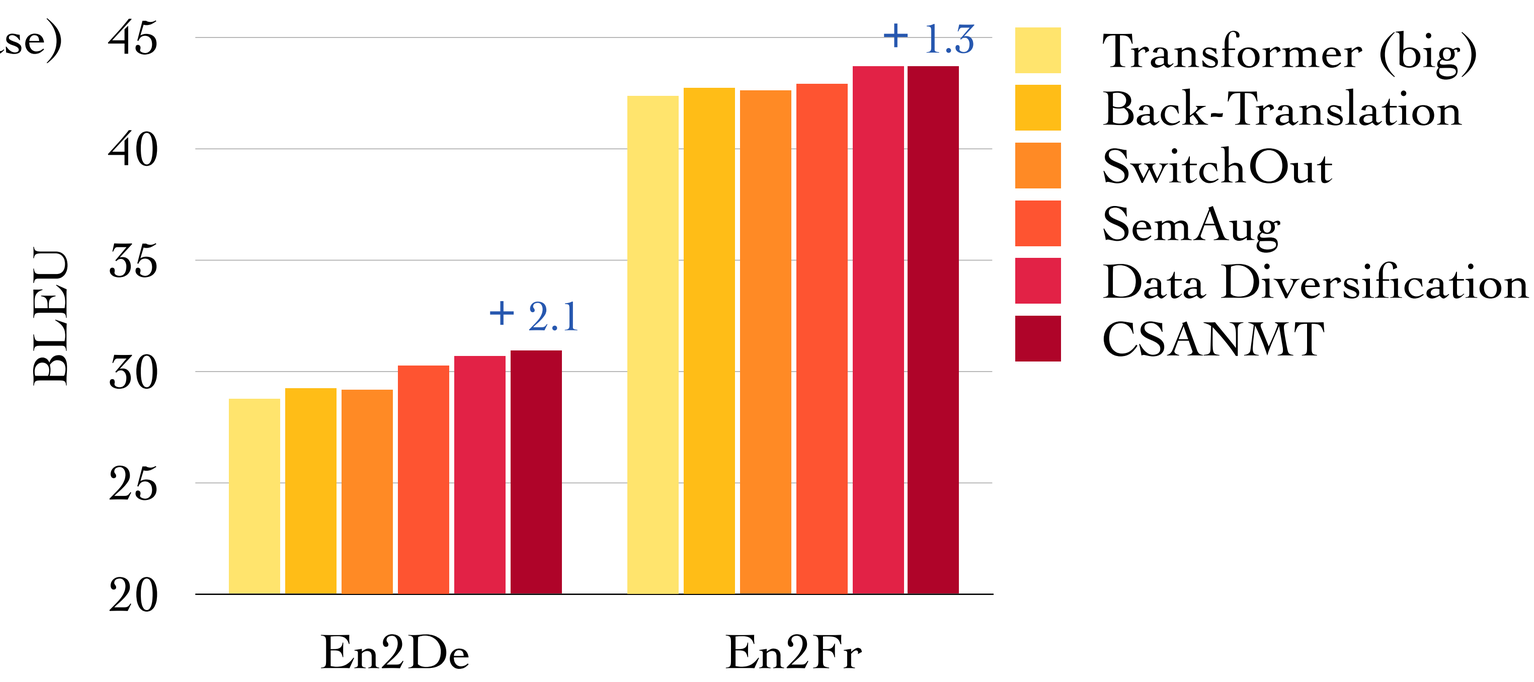

Significantly improves the vanilla Transformer, and performs comparably to the previous SOTA.

See more results in the paper

Why Does this Work?

Learning objective of semantic encoder and sampling algorithm

Tangential CTL

$$J_{ctl}(\Theta') = \mathbb{E}_{(\mathbf{x}^{(i)},\mathbf{y}^{(i)})\sim\mathcal{B}}\left(\log\frac{e^{s\left(r_{x^{(i)}},r_{y^{(i)}}\right)}}{e^{s\left(r_{x^{(i)}},r_{y^{(i)}}\right)}+\xi}\right)$$

MGRC

$$p = \eta\mathcal{N}\left(\mathbf{0},\mathrm{diag}(\mathcal{W}_r^2)\right) + (1.0-\eta)\mathcal{N}\left(\frac{1}{k-1}\sum_{i=1}^{k-1}\omega^{(i)},\mathbf{1}\right)$$

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Compare it to

Tangential CTL

$$J_{ctl}(\Theta') = \mathbb{E}_{(\mathbf{x}^{(i)},\mathbf{y}^{(i)})\sim\mathcal{B}}\left(\log\frac{e^{s\left(r_{x^{(i)}},r_{y^{(i)}}\right)}}{e^{s\left(r_{x^{(i)}},r_{y^{(i)}}\right)}+\xi}\right)$$

MGRC w/o recurrent chain

$$p = \eta\mathcal{N}\left(\mathbf{0},\mathrm{diag}(\mathcal{W}_r^2)\right) + (1.0-\eta)\mathcal{N}\left(\frac{1}{k-1}\sum_{i=1}^{k-1}\omega^{(i)},\mathbf{1}\right)$$

Tangential CTL

$$J_{ctl}(\Theta') = \mathbb{E}_{(\mathbf{x}^{(i)},\mathbf{y}^{(i)})\sim\mathcal{B}}\left(\log\frac{e^{s\left(r_{x^{(i)}},r_{y^{(i)}}\right)}}{e^{s\left(r_{x^{(i)}},r_{y^{(i)}}\right)}+\xi}\right)$$

Replace Gaussian with uniform dist.

$$\omega^{(k)} \sim \eta\mathcal{U}\left(-\mathcal{W}_r,\mathcal{W}_r\right) + (1.0-\eta)\mathcal{U}\left(\bar{\mathbf{a}}-\mathbf{1},\mathbf{1}-\bar{\mathbf{a}}\right)$$

Variational Inference

$$\mathbb{E}_{(\mathbf{x}^{(i)},\mathbf{y}^{(i)})\sim\mathcal{B}}\left(-KL\left(p(r_{x^{(i)}};\mu,\sigma^2)\parallel q(r_{x^{(i)}},r_{y^{(i)}};\mu',\sigma'^2)\right)\right)$$

Reparameterization

$$\hat{r}_x = \mu + \epsilon\odot\sigma \qquad \epsilon\sim\mathcal{N}(0,1)$$

Cosine similarity

$$\mathbb{E}_{(\mathbf{x}^{(i)},\mathbf{y}^{(i)})\sim\mathcal{B}}\left(\frac{r_{x^{(i)}}^T r_{y^{(i)}}}{\|r_{x^{(i)}}\|\cdot\|r_{y^{(i)}}\|}\right)$$

Default MGRC

$$p = \eta\mathcal{N}\left(\mathbf{0},\mathrm{diag}(\mathcal{W}_r^2)\right) + (1.0-\eta)\mathcal{N}\left(\frac{1}{k-1}\sum_{i=1}^{k-1}\omega^{(i)},\mathbf{1}\right)$$

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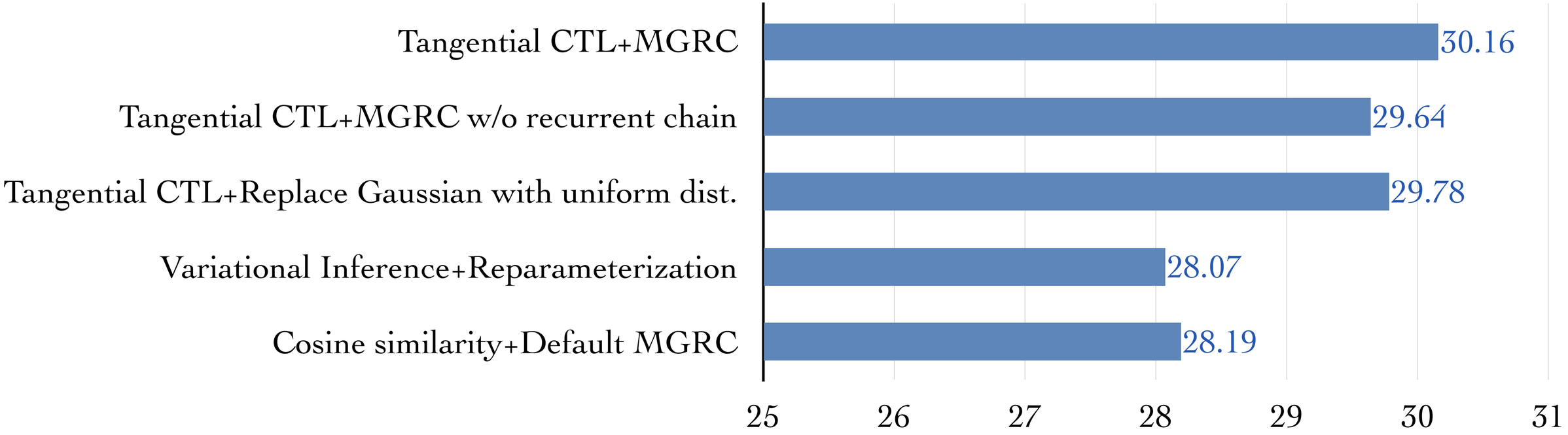
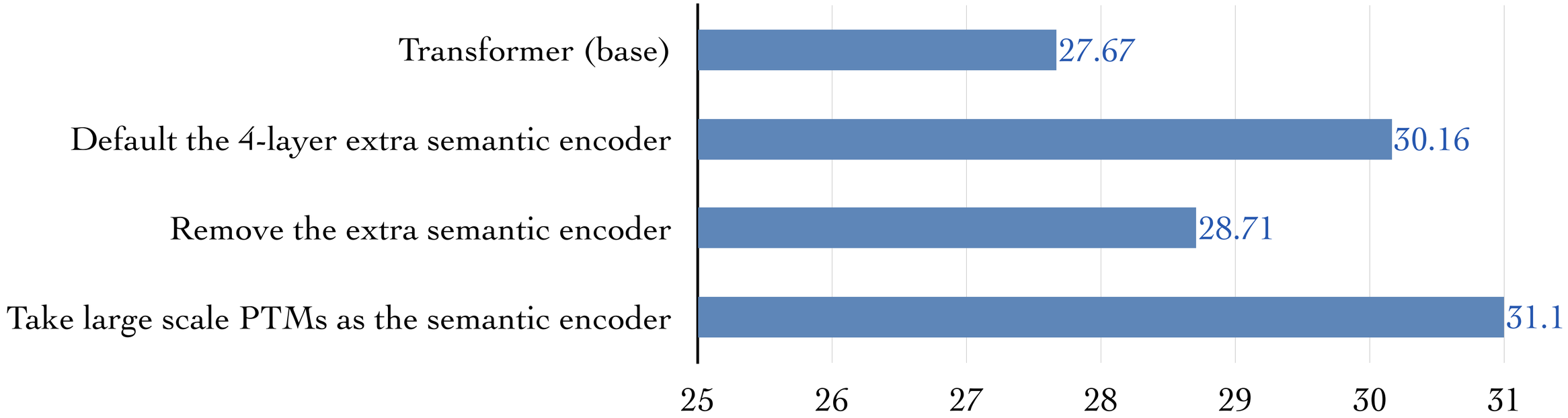
Learning objective of semantic encoder and sampling algorithm



- Tangential CTL ≫ Cosine similarity / Variational Inference (!)
- Tangential CTL + MGRC ≫ Variational Inference + Reparameterization (previous continuous generation)

Why Does this Work?

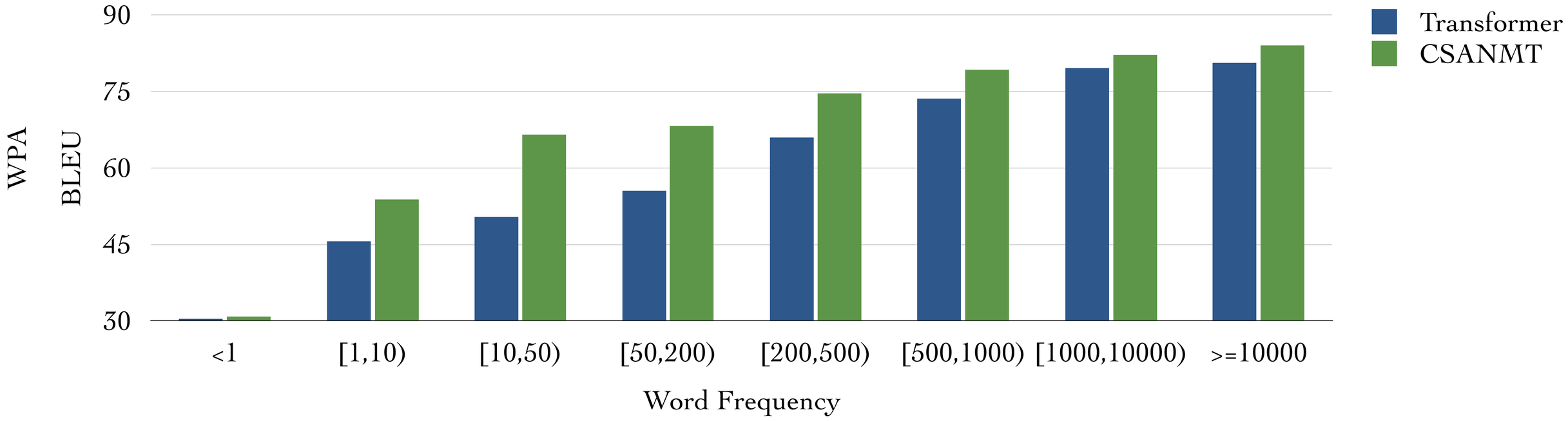
Effect of the semantic encoder variants



- The extra semantic encoder is necessary even it is small
- Take large scale pre-trained models (i.e., XLM-R) as the semantic encoder further improves ~1.0 BLEU

Why Does this Work?

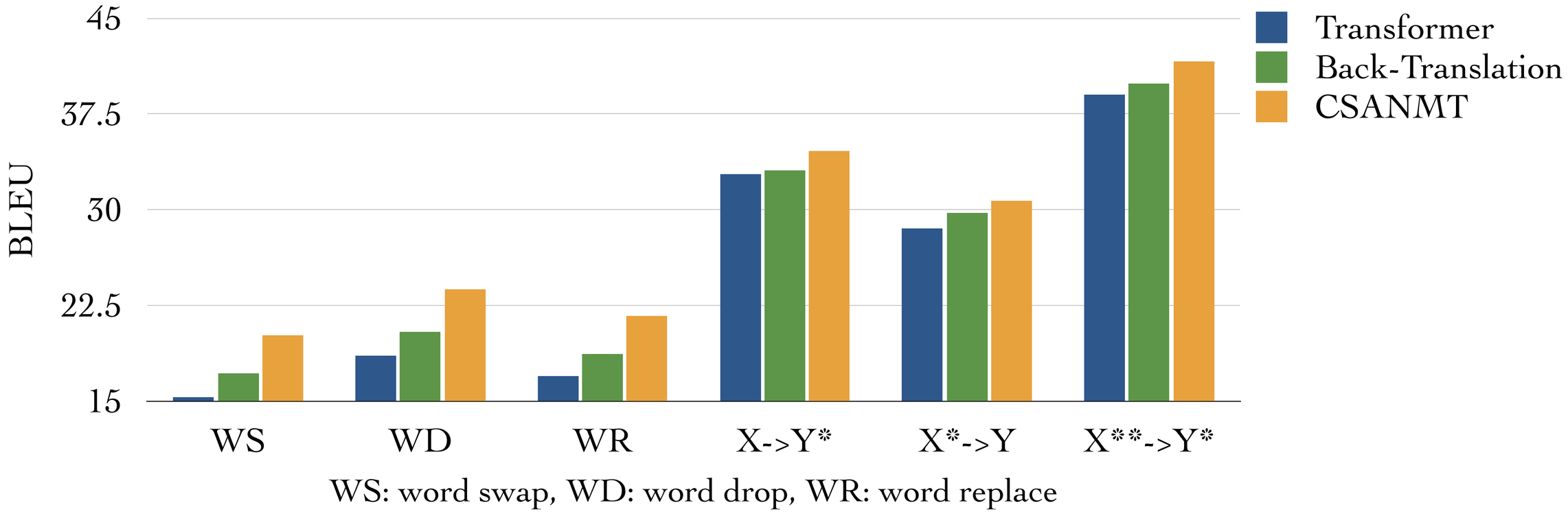
Word Prediction Accuracy (WPA)



- CSANMT generalizes to rare words better than the vanilla Transformer (gap of WPA up to 16%)

Why Does this Work?

Robustness towards Noisy Inputs and Translationese



WS: word swap, WD: word drop, WR: word replace

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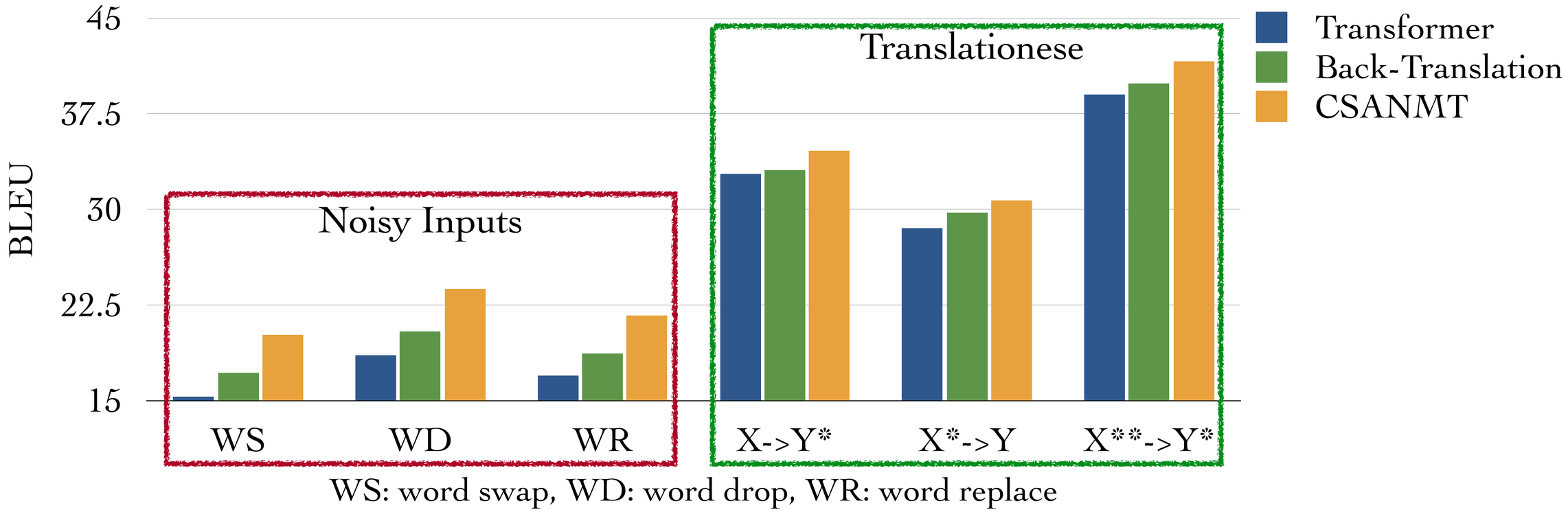


WS: word swap, WD: word drop, WR: word replace

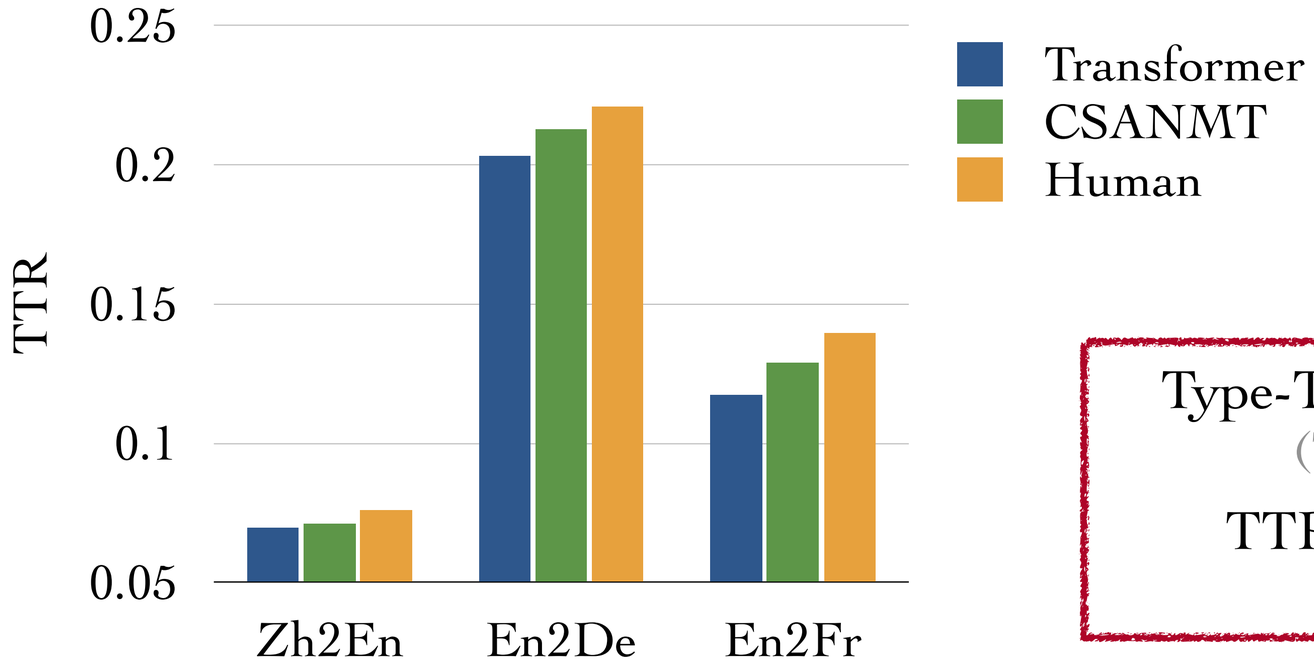
- Continuous semantic augmentation ≫ discrete data augmentation (i.e. back-translation)
- Continuous semantic augmentation benefits more (than discrete data augmentation) from natural parallel data to deal with the translationese inputs

Why Does this Work?

Lexical Diversity and Semantic Faithfulness

Why Does this Work?

Lexical Diversity and Semantic Faithfulness



Type-Token-Ratio (TTR)
(Templin, 1957)

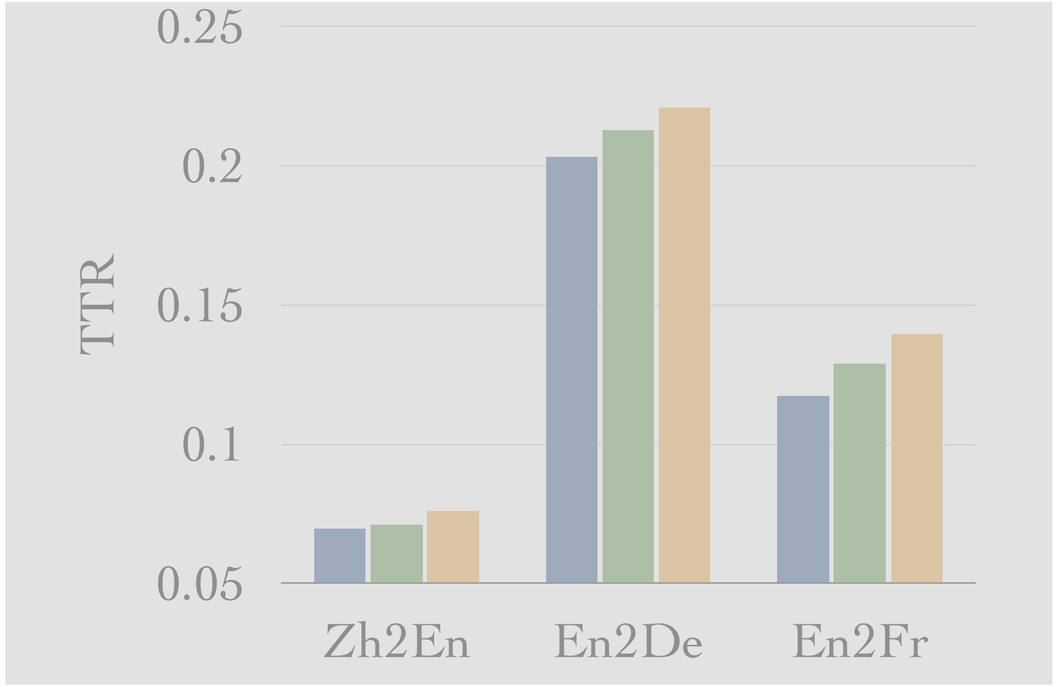
$$\text{TTR} = \frac{num.\ of\ types}{num.\ of\ tokens}$$

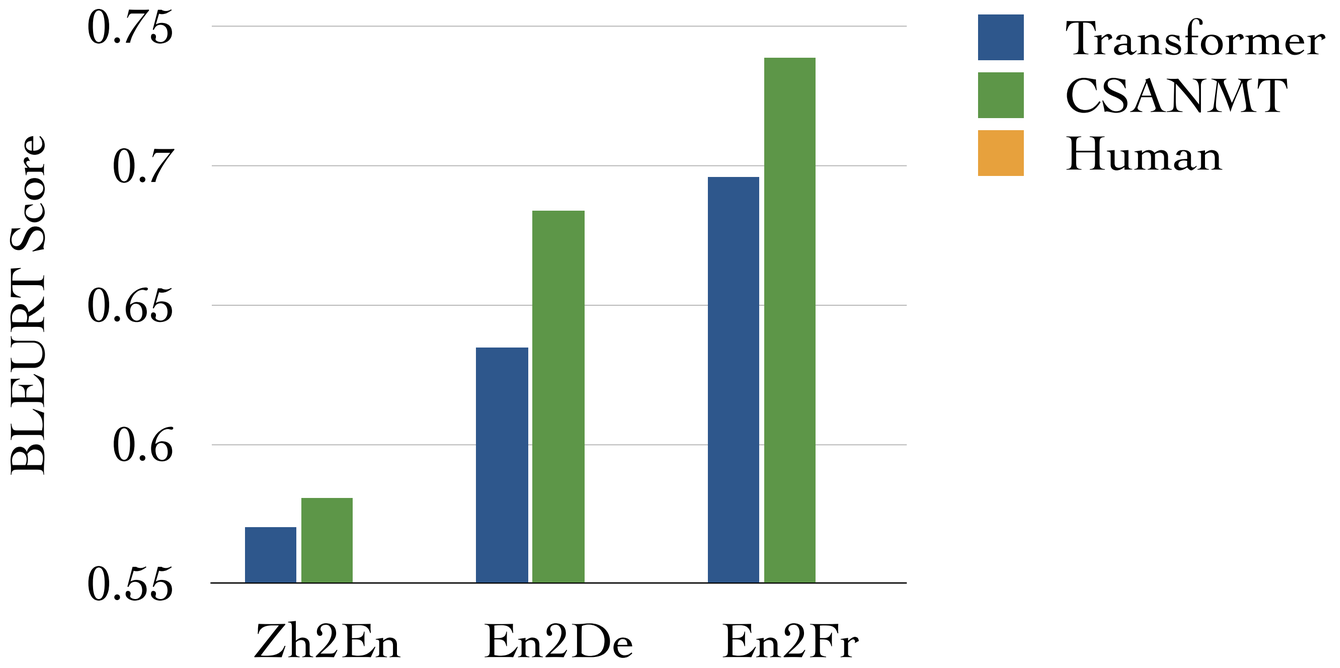
- Continuous semantic augmentation substantially bridges the gap of the lexical diversity between translations produced by human and machine.

Mildred C Templin. 1957. Certain language skills in children; their development and interrelationships.

Why Does this Work?

Lexical Diversity and Semantic Faithfulness

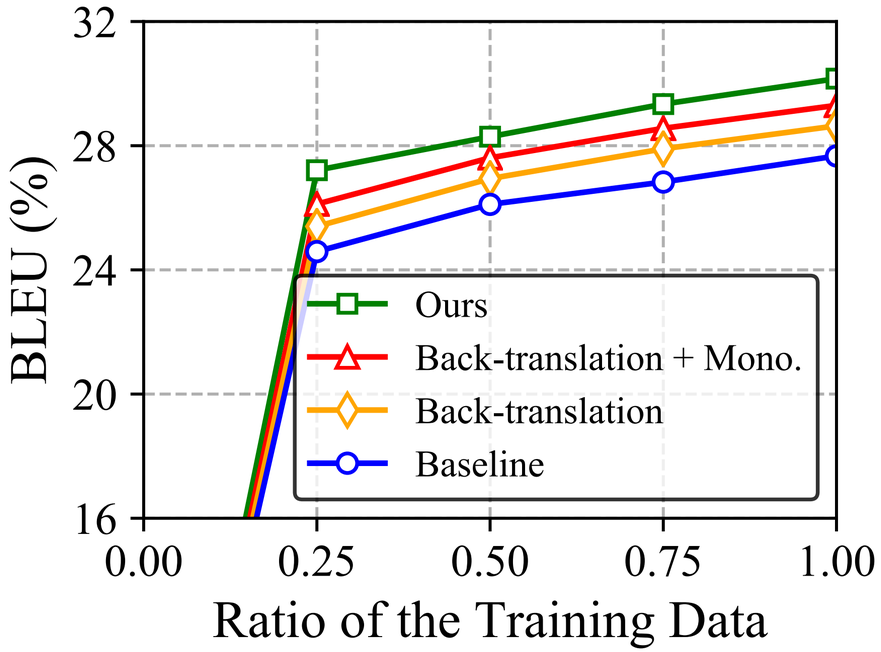




- Continuous semantic augmentation substantially bridges the gap of the lexical diversity between translations produced by human and machine.
- Continuous semantic augmentation shows a better capability on preserving the semantics of the generated translations than Transformer

Why Does this Work?

Data utilization and training efficiency



CSANMT achieves comparable performance with the baseline model with only 25% of training data, which indicates that our approach has great potential to achieve good results with very few data.

- Continuous semantic augmentation (without any extra monolingual data) consistently outperforms discrete data augmentation (even with extra 2M monolingual data) across different data ratios.

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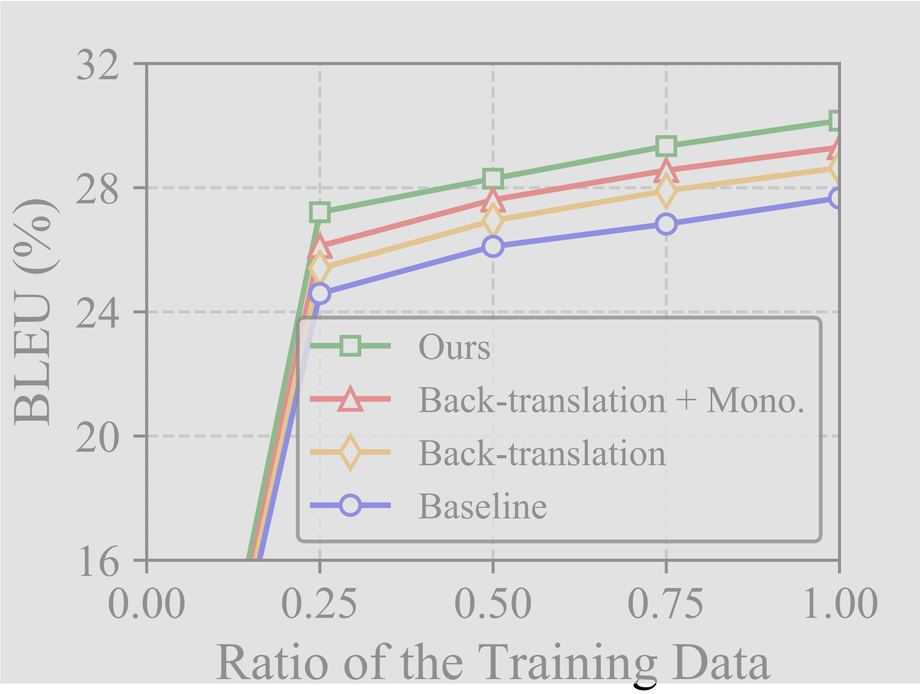
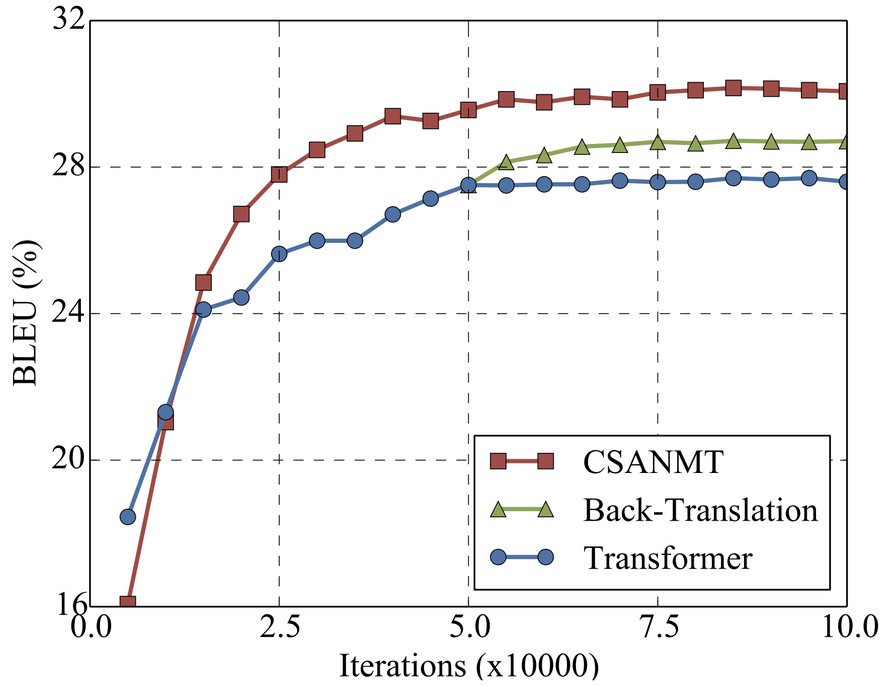
Data utilization and training efficiency





We need 44% more training costs than the vanilla Transformer, for the longer time to make the CSANMT model converge

- Continuous semantic augmentation (without any extra monolingual data) consistently outperforms discrete data augmentation (even with extra 2M monolingual data) across different data ratios.
- Continuous semantic augmentation performs consistently better than both the vanilla Transformer and the back-translation method at each iteration.

Summary

CSANMT A novel data augmentation paradigm for NMT, which achieves state-of-the-art results

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- **Tangential Contrastive Learning**: pre-train a semantic encoder, which forms an adjacency semantic region (i.e. the *vicinity*, cover adequate variants of literal expression under the same meaning) for each training example.

Summary

CSANMT A novel data augmentation paradigm for NMT, which achieves state-of-the-art results

- **Tangential Contrastive Learning**: pre-train a semantic encoder, which forms an adjacency semantic region (i.e. the *vicinity*, cover adequate variants of literal expression under the same meaning) for each training example.
- **Mixed Gaussian Recurrent Chain**: produce a series of diverse training data for each observed instance from its vicinity, i.e. a semantically-preserved continuous sub-space.

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CsaNMT A novel data augmentation paradigm for NMT, which achieves state-of-the-art results

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Next Step

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Next Step

- **Multilingual Scenario**: further study continuous semantic augmentation with the combination of large scale multilingual parallel and non-parallel corpora.
- **Model Architecture**: develop continuous semantic augmentation as a pure data augmentation merged into the vanilla Transformer.

Q & A

Code: https://github.com/pemywei/csanmt

Contact: pemywei@gmail.com