SwitchOut: An Efficient Data Augmentation for Neural Machine Translation

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November 2, 2018

*:equal contribution

Data Augmentation

- Neural models are data hungry, while collecting data is expensive

[1] image source:Medium

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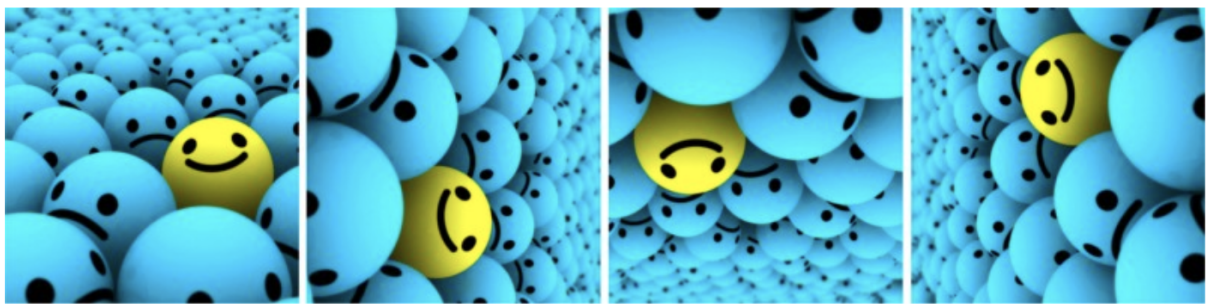
- Prevalent in computer vision[1]



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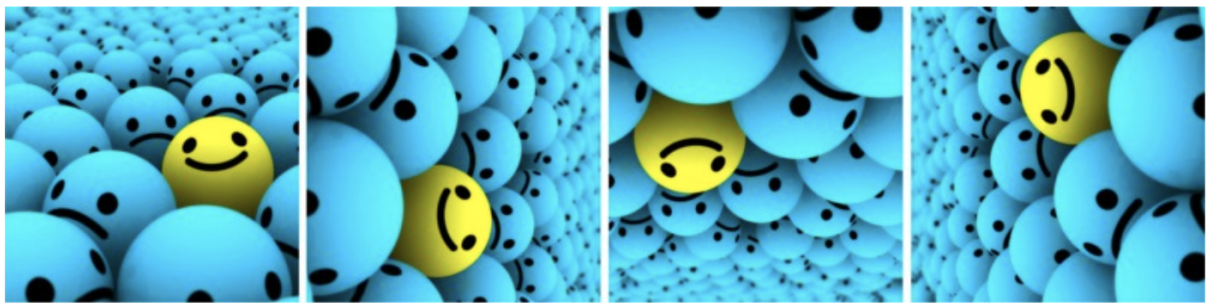

- More difficult for natural language
  - Discrete vocabulary
  - NMT sensitive to arbitrary noise

[1] image source:Medium

Existing Strategies

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Word replacement

wie geht es dir ? ⟶ How are you ?

Existing Strategies

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Word replacement

wie geht es dir ? ⟶ How are you ?

- Dictionary [Fadaee et al., 2017]
  wie geht es Tom ? ⟶ How is Tom ?

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  wie geht es dir ? ⟶ How are hello ?

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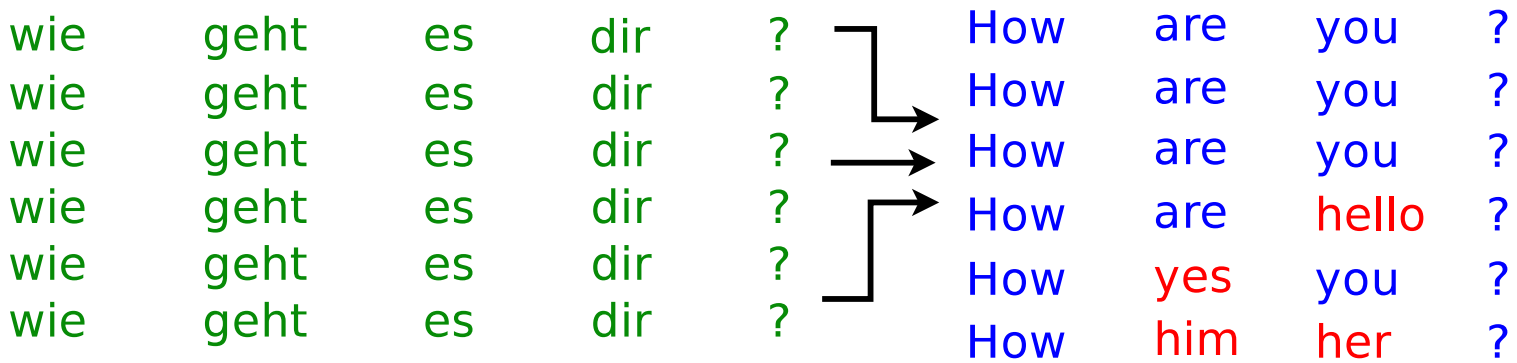
→ Can we characterize all of the related approaches together?

Existing Strategies: RAML

RAML [Norouzi et al., 2016]

- Motivation: NMT relies on imperfect partial translation at test time, but trained only on gold standard target



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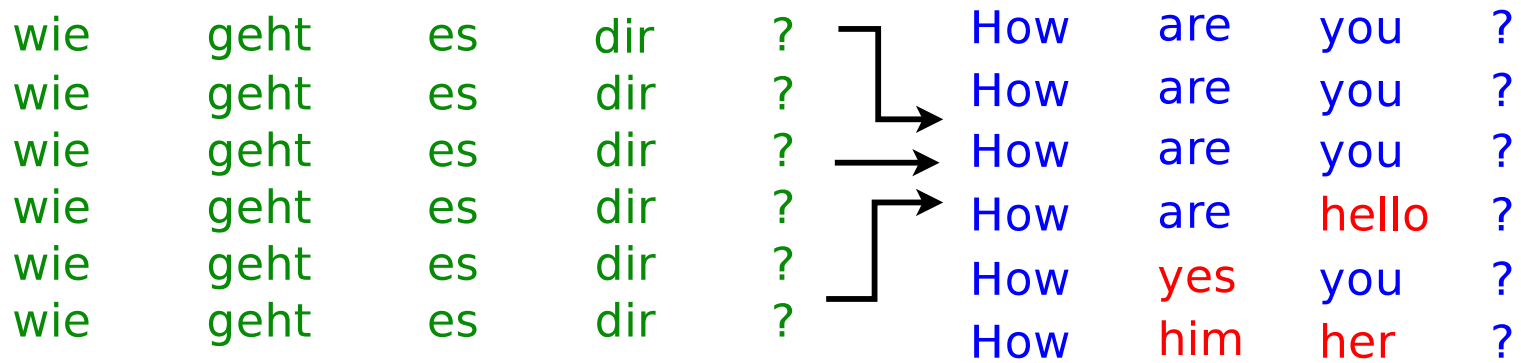

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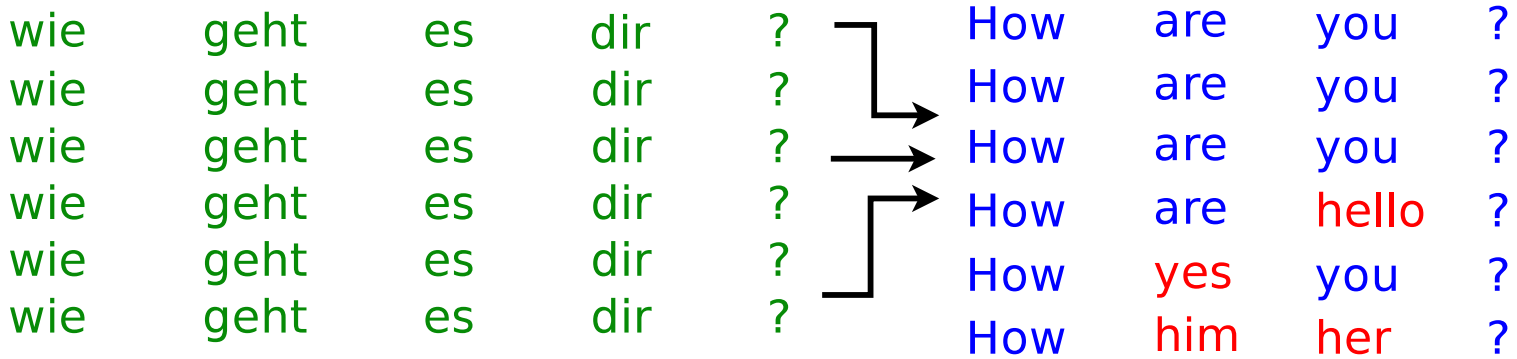
RAML [Norouzi et al., 2016]

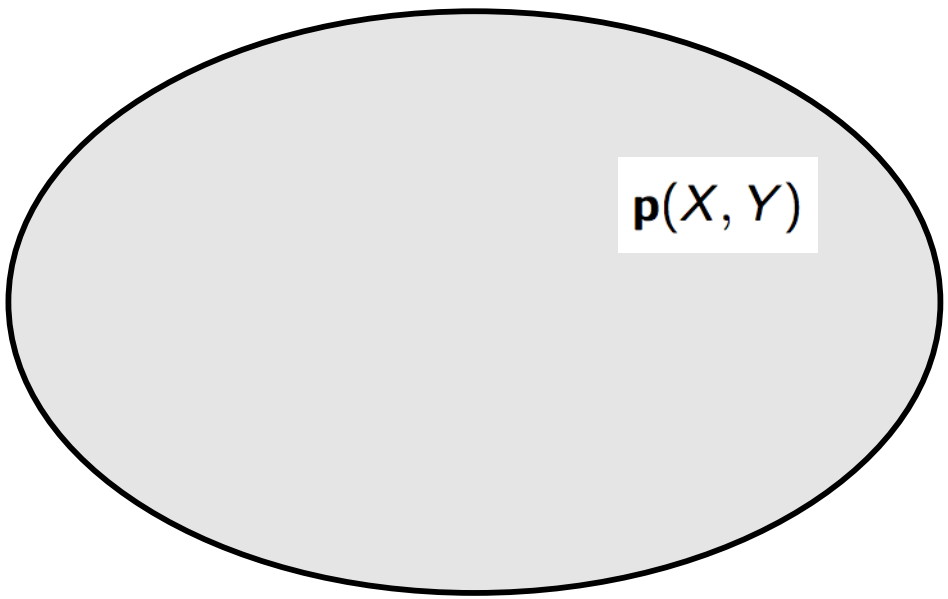
- Motivation: NMT relies on imperfect partial translation at test time, but trained only on gold standard target
- Solution: Sample corrupted target during training
- Gold target y, corrupted $\widehat{y}$, similarity measure r_y

$$\mathbf{q}^*(\widehat{y}|y,\tau) = \frac{\exp\{r_y(\widehat{y},y)/\tau\}}{\sum_{\widehat{y}'}\exp\{r_y(\widehat{y}',y)/\tau\}}$$



Formalize Data Augmentation

- **Real** data distribution: $x, y \sim \mathbf{p}(X, Y)$



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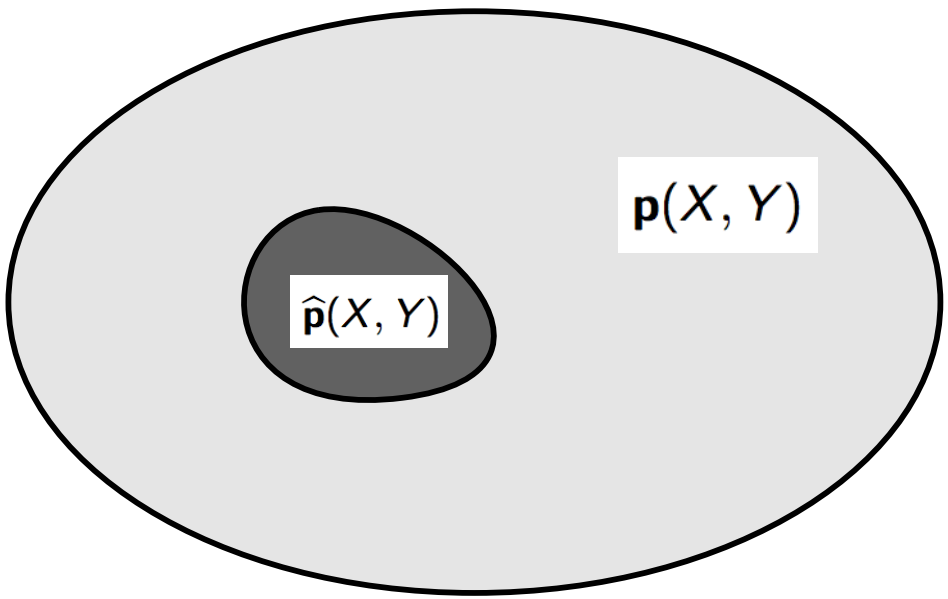

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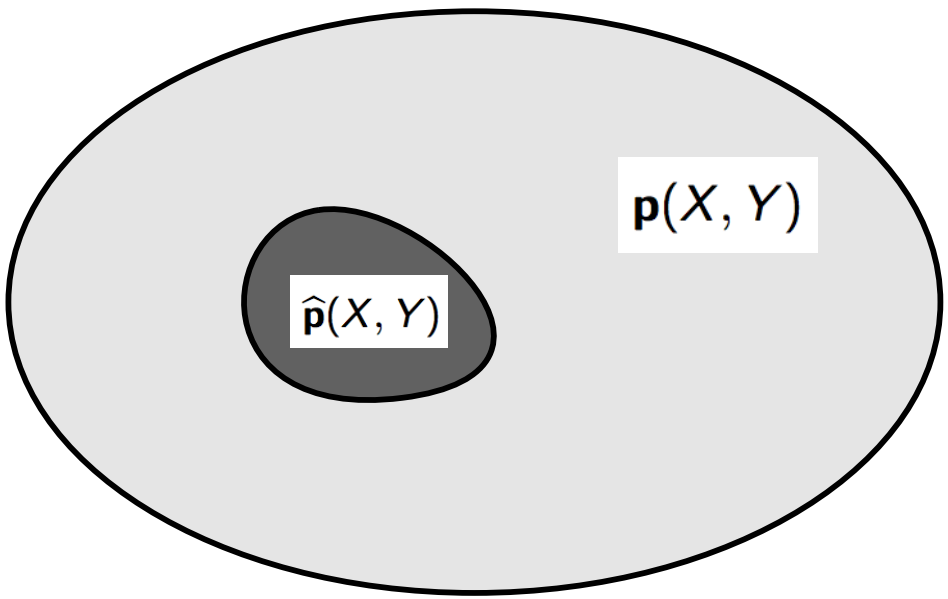

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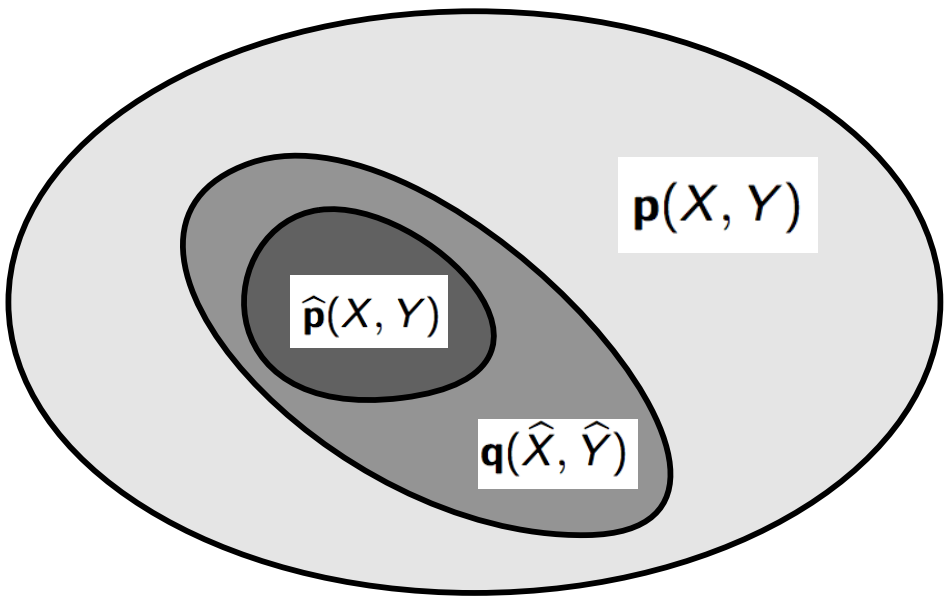
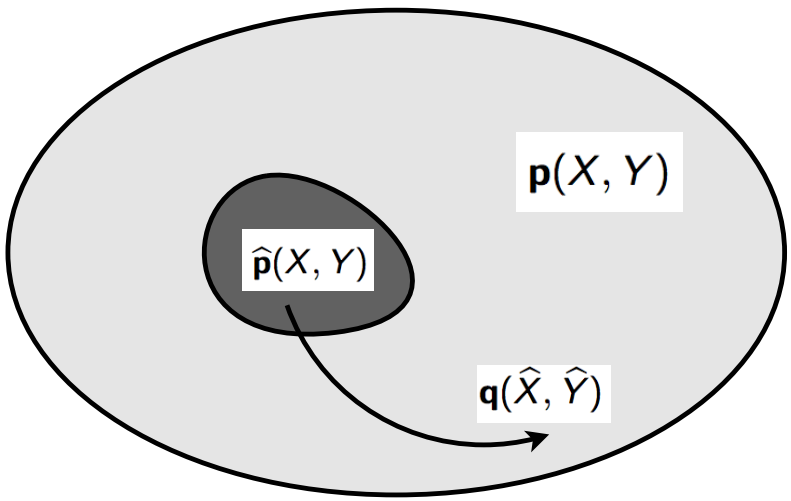
- Data augmentation: $\widehat{x}, \widehat{y} \sim \mathbf{q}(\widehat{X}, \widehat{Y})$



Design a good $\mathbf{q}(\widehat{X}, \widehat{Y})$

- **q**: function of **observed** (x, y)



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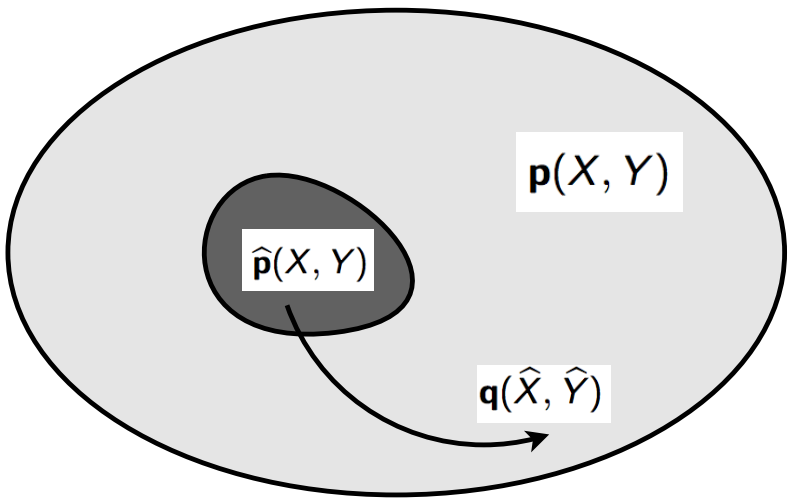

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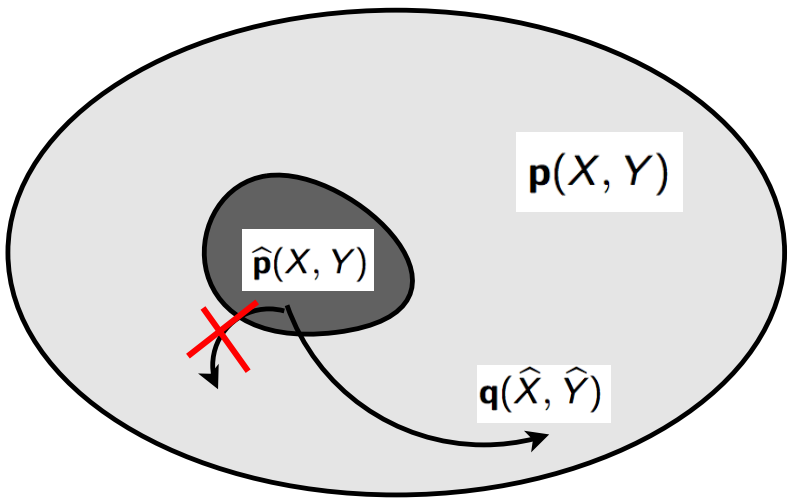

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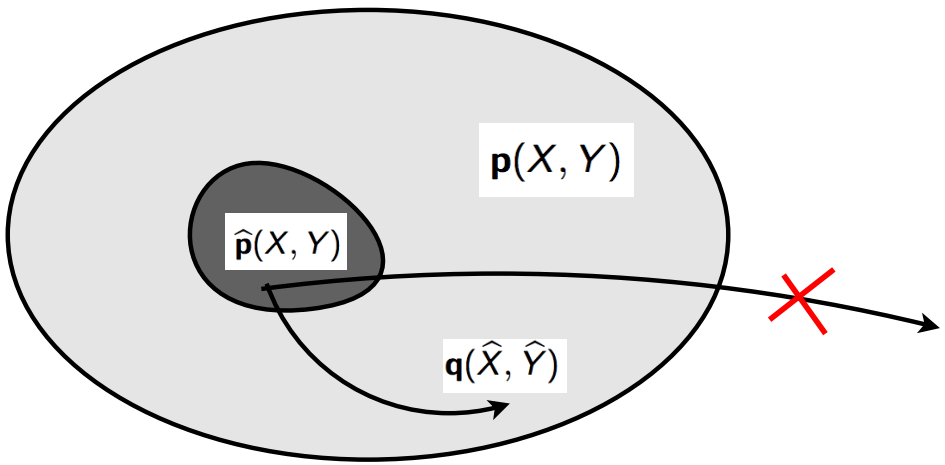

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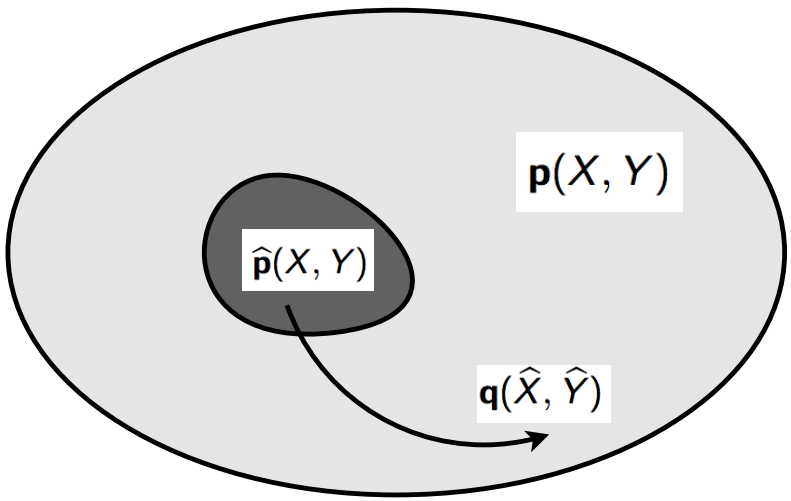
- τ: control effect of diversity; **q** should maximize

$$J(\mathbf{q}) = \tau \cdot \mathbb{H}\left[\mathbf{q}(\widehat{x}, \widehat{y}|x, y)\right] + \mathbb{E}_{\widehat{x},\widehat{y}\sim\mathbf{q}}\left[r_x(x, \widehat{x}) + r_y(y, \widehat{y})\right]$$



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- Decompose x and y

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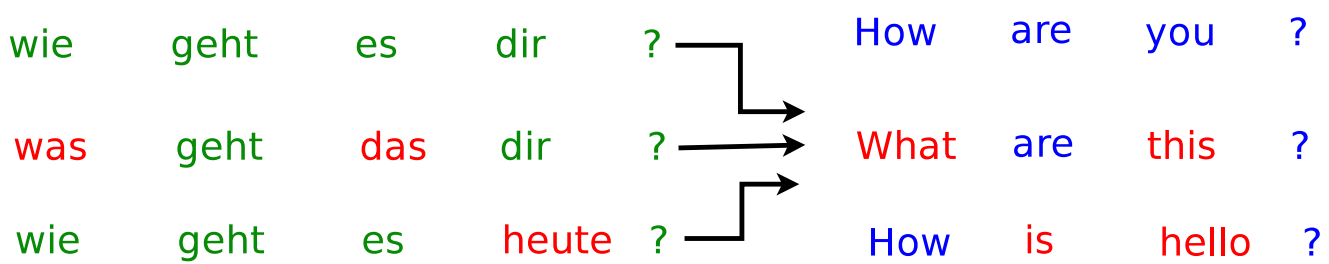
- Formulate existing methods
  - Dictionary: jointly on x and y, but deterministic and not diverse
  - Word dropout: **only** x side with null token
  - RAML: **only** y side

Formulate SwitchOut

- Augment **both** x and y!



Formulate SwitchOut

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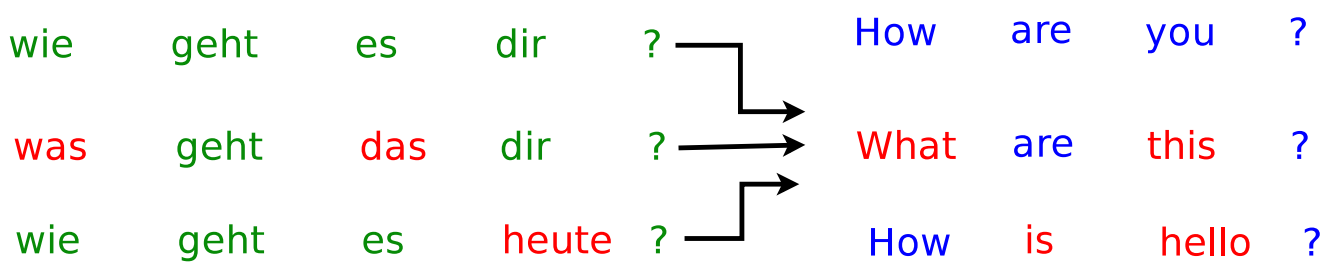
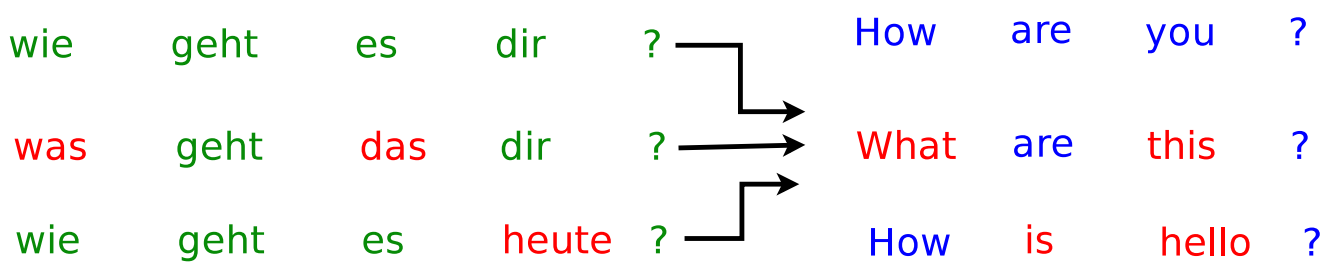


Formulate SwitchOut

- Augment **both** x and y!
- Sample for x, y **independently**
- Define $r_x(\widehat{x}, x)$ and $r_y(\widehat{y}, y)$
  - Negative Hamming Distance, following RAML



SwitchOut: Sample efficiently

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Given a sentence $s = \{s_1, s_2, ...s_{|s|}\}$

1. How many words to corrupt?
   Assumption: only one token for swapping.

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2. What is the corrupted sentence?

$$P(\text{randomly swap } s_i \text{ by another word}) = \frac{n}{|s|}$$

See Appendix: Efficient batch implementation in PyTorch and Tensorflow

Experiments

- Datasets
  - en-vi: IWSLT 2015
  - de-en: IWSLT 2016
  - en-de: WMT 2015
- Models
  - Transformer model
  - Word-based, standard preprocessing

Results: RAML and word dropout

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Method		en-de	de-en	en-vi
src	**trg**			
N/A	N/A	21.73	29.81	27.97
WordDropout	N/A	20.63	**29.97**	28.56
SwitchOut	N/A	**22.78**†	29.94	**28.67**†
N/A	RAML	22.83	30.66	28.88
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- SwitchOut on source > word dropout

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- SwitchOut on source > word dropout
- SwitchOut on source and target > RAML

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Where does SwitchOut help?

- More gain for sentences more different from training data

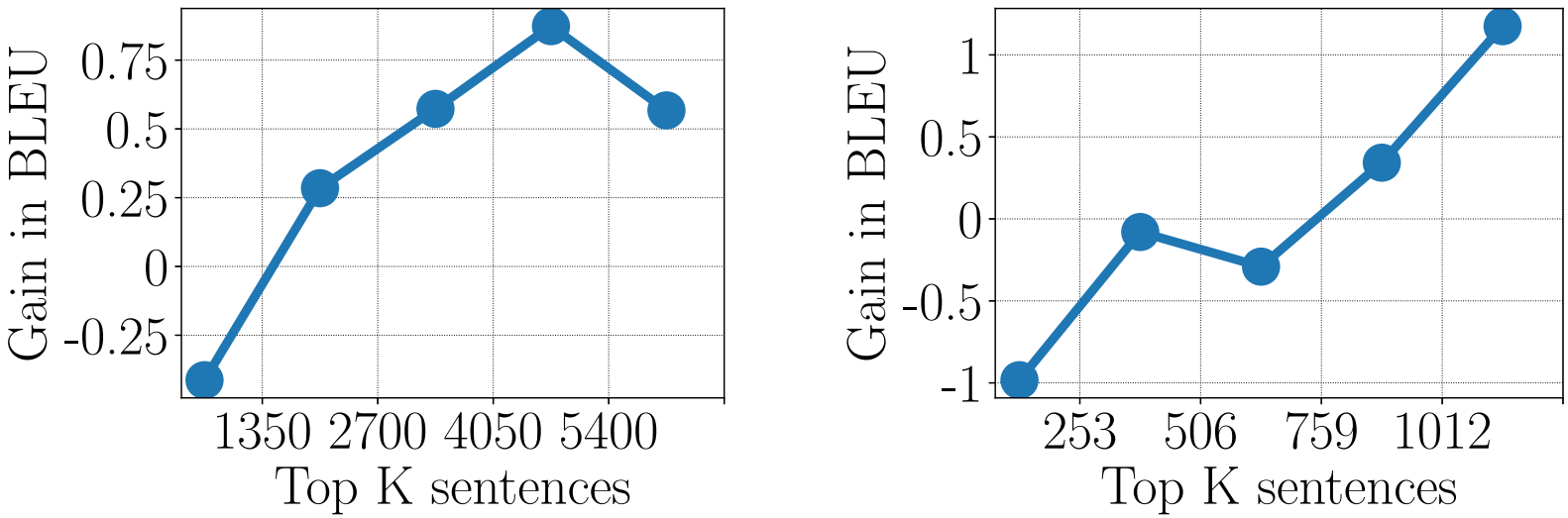

Figure: *Left*: IWSLT 16 de-en. *Right*: IWSLT 15 en-vi.

Final Thoughts

- SwitchOut sampling is efficient and easy-to-use

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Thanks a lot for listening! Questions?

References

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Results: Back Translation (WMT en-de 2015)

- SwitchOut $>$ Back Translation

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Transformer	21.73
+SwitchOut	22.78
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Results: Back Translation (WMT en-de 2015)

- SwitchOut > Back Translation
- Switchout + RAML + back translate wins

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