

Investigating Active Learning in Interactive Neural Machine Translation

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Outline of Presentation

- Overview on Machine Translation
- 2 Interactive MT
- Interactive Adaptive MT
- 4 Our Approach

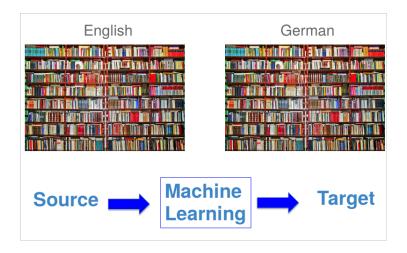


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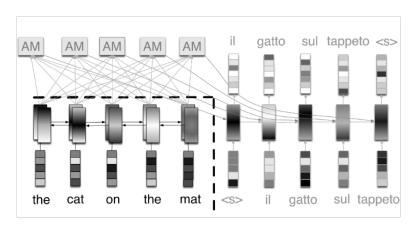
Machine Translation





Neural MT

Encoder-Decoder Architecture: Attention Model (Bahdunu et al., 2015)





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Interactive MT

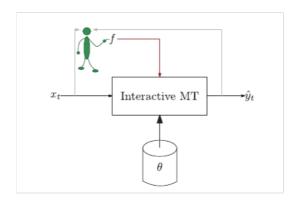


Figure source: Peris et al., 2017



Interactive MT

French (source sentence)

Nous décidons donc, citoyens, de prendre les choses en main

we decide therefore, citizens, to take things in hand.



we decide therefore, citizens, to take control of things



Interactive MT

- Why Interactive-predictive MT?
 - ► An effective way to improve **productivity gain** in translation
 - ► E.g. Lilt¹



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- Interactive MT
 - ▶ MT model used in interactive platform: **static**
 - ► Same mistakes would repeat
 - May negatively impact translation productivity
- Interactive Adaptive MT
 - Ability of MT models to change in response to customer's data
 - ▶ In other words, online **customisation** of MT models
 - This can counter the risk of encountering the same mistakes in future



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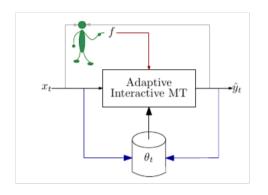


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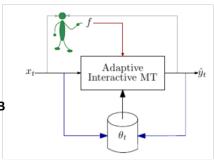
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S: input sentences for inference

B: block of sentences from S

C: chunk of sentences are sampled from B

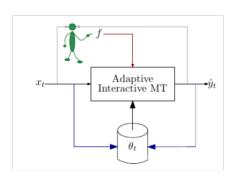




S: 50,000

B: 10,000

C: sample B; say 20% [2,000]

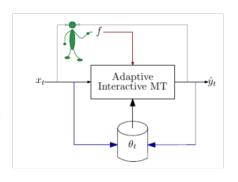




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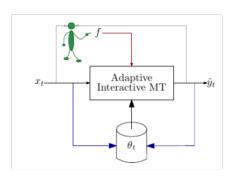
Uncertainty sampling: Labels those instances for which the model is least certain about the correct output to be generated



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Uncertainty sampling

1. Quality Estimation (QE)

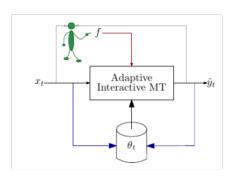
A process of evaluating the MT outputs without using gold-standard references.



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Uncertainty sampling

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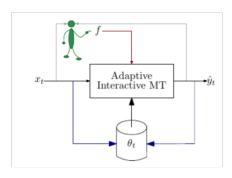
- A process of evaluating the MT outputs without using gold-standard references.
- E.g. translate 10,000 source sentences and using QE tool measure how good / bad the translations are
- Openkiwi toolkit (Kepler et al., 2019)



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Uncertainty sampling

2. Round-Trip Translation (RTT)

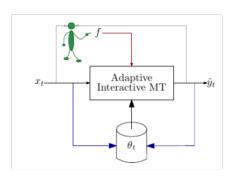
- A back-translation MT engine [target-to-source]
- Similarity between the Source Sentence and its RTT
- Sentences having the least similarity scores in B are sampled and supervised by the user



S: 50,000

B: 10,000

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Uncertainty sampling

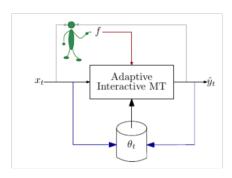
- 2. Round-Trip Translation (RTT)
 - Similarity 1
 - Sentence-embedding (Sim_{EMB})
 - S-BERT (Ramires and Gurevych, 2019)



S: 50,000

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Uncertainty sampling

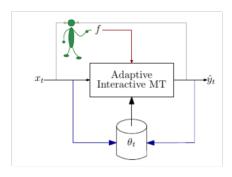
- 2. Round-Trip Translation (RTT)
 - Similarity 2
 - Edit distance (Sim_{fuzzy})
 - Fuzzywuzzy tool



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Uncertainty sampling

3. Named Entity (NEs) Count

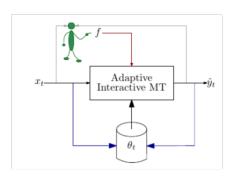
 Sentences having the most number of NE tokens in the block are considered as "difficult to translate" by the NMT model, and hence filtered for supervision



S: 50,000

B: 10,000

C: sample B; say 20% [2,000]



Uncertainty sampling

4. Query-by-committee (QbC)

- A voted entropy function: to calculate calculate the highest disagreement among the sampling techniques for a sample x
- Samples are then used for human supervision



- English-to-German
- German-to-English
- English-to-Hindi
- $\bullet \ \, \mathsf{Spanish}\text{-}\mathsf{to}\text{-}\mathsf{English} \\$

	English-German	English-Spanish	English-Hindi
Train	1.26m (Europarl)	1.9m (Europarl)	1.6m (IITB corpus)
Dev	1,057 (Europarl)	2000 (Europarl)	599 (IITB corpus)
Testset	59,975 (News-Commentary)	51,613 (News-Commentary)	47,999 (ILCI corpus)



	BLEU
Baseline	23.28
RS	23.88
QE	24.02
Sim_{Fuzzy}	24.55
Sim_{EMB}	24.35
NE Counting	25.22
QbC	25.51

Table: English-to-German (20%)



	BLEU
Baseline	24.08
RS	25.19
Sim_{Fuzzy}	25.98
Sim_{EMB}	26.18
NE Counting	25.50
QbC	26.53

Table: German-to-English (20%)



	BLEU
Baseline	25.76
RS	25.84
Sim_{Fuzzy}	25.97
Sim_{EMB}	25.88
NE Counting	25.92
QbC	26.18

Table: English-to-Hindi (20%)



	BLEU
Baseline	38.76
RS	39.16
Sim_{Fuzzy}	39.28
Sim_{EMB}	39.74
NE Counting	39.43
QbC	39.78

Table: Spanish-to-English (20%)



Conclusions

- Explored the applicability of various sampling techniques in active learning to update NMT models in interactive-predictive translation platform
- Novel sampling methods
 - QE
 - RTT
 - NE Counting
- QbC with proposed sampling methods provided us best results across all LPs



- Investigating Active Learning in Interactive Neural Machine Translation
- Kamal Gupta and Asif Ekbal from IIT Patna (India)
- Pushpak Bhattacharyay from IIT Bombay (India)
- MT-Summit 2021
- 16-20 August, Orlando, Florida, USA



Thanks for listening!



