Interactive Machine Translation

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System Demonstrations

(Demo)

Mixed-Initiative Experimental Studies

(Spence Green's Dissertation Slides)

Prefix-Constrained Decoding

Prefix Decoding

A user enters a prefix of the translation; the MT system predicts the rest.

Yemeni media report that there is traffic chaos in the capital.

Once the user has typed:
Jemenitische Medien berichten von einem Verkehrschaos

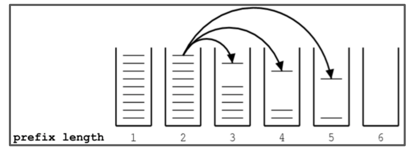
The system suggests:
in der Hauptstadt.

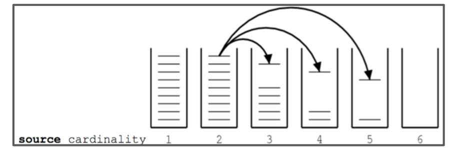
Suggestion is useful when:

- Sentence is completed in a way that a translator accepts,
- The next word suggestion is acceptable,
- Sentence is completed in a way that requires minimal post-editing.

Phrase-Based Prefix-Constrained Decoding

Early work [Barrachina et al. 2008; Ortiz-Martínez et al. 2009]: Standard phrase-based beam search, but discard hypotheses that don't match the prefix.





Better version [Wuebker et al. 2016]: While aligning the prefix to the source, use one beam per target cardinality. While generating the suffix of the translation, use one beam per source cardinality.

Also added:

- Different translation model weights for phrases in the prefix and suffix (lexical features are more relevant for alignment).
- Phrases extracted from the source and prefix to ensure coverage.

Neural Prefix-Constrained Decoding

State-of-the-art neural MT model from 2015 [Luong et al., 2015]:

- 4-layer stacked LSTM with attention.
- Embedding size & hidden unit size of 1000.
- 50-sentence mini-batches of sentences with length 50 or less; trained with SGD.
- Before layer normalization, residual connections, back translation, knowledge distillation, Transformer architecture, subwords, or label smoothing.
- Beam size of 12 for the suffix; beam size of 1 for the prefix (the constrained word).

Prefix Decoding: Phrase-Based vs Neural

En-De	autodesk		newstest2015	
	BLEU	**Next word accuracy**	**BLEU**	**Next word accuracy**
Phrasal baseline	**44.5**	37.8	22.4	28.5
Phrasal improved	**44.5**	46.0	22.4	41.2
NMT	40.6	52.3	23.2	50.4
NMT ensemble	44.3	**54.9**	**26.3**	**53.0**

Wuebker et al., 2016, "Models and Inference for Prefix-Constrained Machine Translation"

Online Adaptation

Online Fine-Tuning for Model Personalization

After sentence i is translated, take a stochastic gradient descent step with batch size 1 on (x_i, y_i) [Turchi et al., 2017].

Evaluation via simulated post-editing [Hardt and Elming, 2010]:

- Adaptation is performed incrementally on the test set.
- Translate x_i using model θ_{i-1} and compare it to reference y_i.
- Then, estimate θ_i from (x_i, y_i).

E.g., Autodesk corpus results using a small Transformer:

- Unadapted baseline: 40.3% BLEU
- Online adaptation: 47.0% BLEU

Recall of observed words goes up, but unobserved words goes down [Simianer et al., 2019]:

- R1 – % of words appearing for the second time in any reference that also appear in the corresponding hypothesis: 44.9% -> 55.0%
- R0 – % of words appearing for the first time in any reference that also appear in the corresponding hypothesis: 39.3% -> 35.8%

Turchi et al., 2017, "Continuous learning from human post-edits for neural machine translation."
Simianer et al., 2019, "Measuring Immediate Adaptation Performance for Neural Machine Translation"

Space-Efficient Model Adaptation

Inference for "personalized" (user-adapted) models:

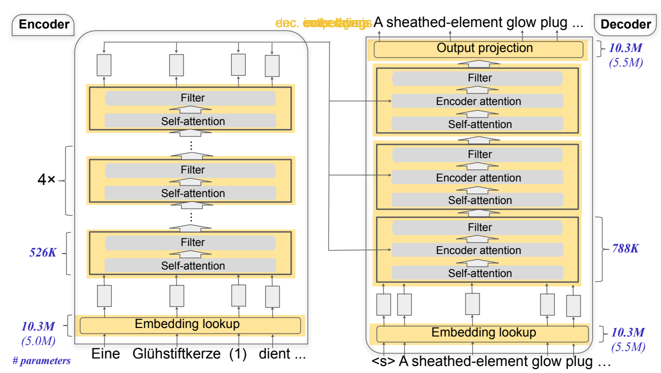
- Load User X's model from cache or persistent storage
- Apply model parameters to computation graph
- Perform inference

Example production constraint: latency budget of 300ms ⇒ maximum of ~10M parameters for a personalized model

Full (small transformer) model in 2019: ~36M parameters

Solution:

- Store models as offsets from baseline model: $W = W_b + W_u$
- Select sparse parameter subset W_u



	batch adaptation	online adaptation	# params
baseline	33.7		36.2M
full model	**41.7**	**39.0**	25.8M
outer layers	38.6	37.9	**2.2M**
inner layers	38.8	37.8	2.7M
enc. embeddings	36.3	35.7	5.0M
dec. embeddings	34.2	34.3	5.5M
output proj.	38.7	37.5	5.5M

Group Lasso Regularization for Sparse Adaptation

Simultaneous regularization and tensor selection

Regularize offsets Wu, define each tensor as one group g for L1/L2 regularization

$$R_{\ell_{1,2}}(W_u) = \sum_{g \in W_u} \sqrt{|g|}\ \|g\|_2$$

Total loss: $$\mathcal{L} = \mathcal{L}_{seq}(W_b + W_u) + \lambda R_{\ell_{1,2}}(W_u)$$

Cut off all tensors g with: $$\frac{1}{|g|} \sum_{w \in g} |w| < \theta$$

Define a group for each hidden layer and each embedding column

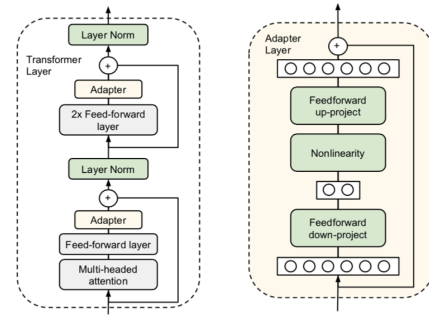
	en>fr	fr>en	en>ru	ru>en	en>zh	zh>en
Baseline	28.8	35.8	10.7	29.7	19.9	18.9
Full Adaptation	**36.6**	**49.6**	21.0	42.1	40.6	**46.6**
Sparse Adapt. (# params)	36.2 (16.5%)	49.2 (15.9%)	**21.2** (16.1%)	42.2 (15.8%)	**42.0** (15.6%)	46.5 (15.2%)

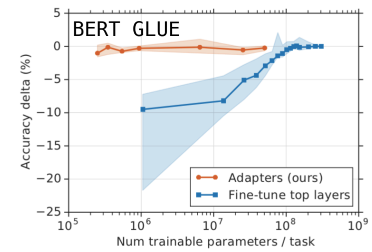
Wuebker et al., 2018, "Compact Personalized Models for Neural Machine Translation"

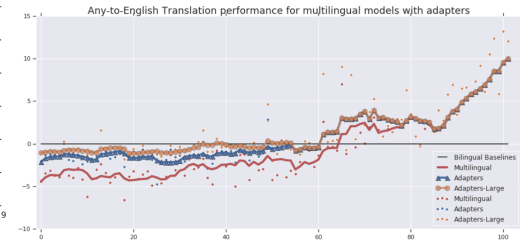
Bottleneck Adapter Modules

Adapter modules:

- Add offsets to activations by a combination of new adapter layers and residual connections.
- Initialize adapter layer weights near zero.
- During adaptation, freeze all model parameters except the adapter layers.







Houlsby et al., 2019, "Parameter-Efficient Transfer Learning for NLP"
Bapna & Firat, 2019. "Simple, Scalable Adaptation for Neural Machine Translation"

Tag Projection

Word Alignment Applications

Simple terminology-constrained inference:

- Users often specify termbases, which act as restrictions on the target translation.
- When attention focuses on a source term, add the corresponding target term to the translation hypothesis.

Tag projection:

- Strip markup tags before translation
- Project tags to final target sentence using word alignments

From Wikipedia: Translation is the communication of the <a1>meaning</a1> of a <a2>source-language</a2> text by means of an <a3>equivalent</a3> <a4>target-language</a4> text.^{<a5>[1]</a5>}

Google Translate: Übersetzung ist die Übermittlung der <a1>Bedeutung</a1> eines <a2>quellsprachlichen</a2> Textes mittels eines <a3>äquivalenten</a3> <a4>zielsprachlichen</a4> Textes.^{<a5>[1]</a5>}

Alignment by Attention in a Transformer

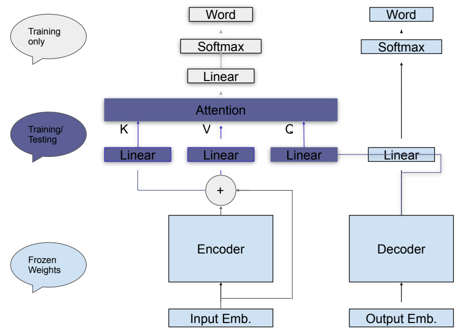
Train alignment attention to predict the next word.

Inference: find attention activations that maximize the likelihood of the observed next word.

Retrain: toward a self-supervised loss that maximizes the likelihood of inferred word alignments

Ensemble: inference under a bidirectional objective

Bias alignment configurations to have adjacent source words aligned to adjacent target words



Method	DeEn	EnFr	RoEn
Bidir. Att. Opt.	17.9%	8.4%	24.1%
+Guided	**16.3%**	**5.0%**	**23.4%**
Zenkel et al. (2019)	21.2%	10.0%	27.6%
Garg et al. (2019)	20.2%	7.7%	26.0%
GIZA++	18.7%	5.5%	26.5%

Zenkel et al., 2020. "End-to-End Neural Word Alignment Outperforms GIZA++"

Some Open Questions

Insertion Transformer

How can a translation model make suggestions about mid-sentence edits?

$$p(c, \ell | x, \hat{y}_t) = \text{InsertionTransformer}(x, \hat{y}_t)$$

$c \in \mathcal{C}$:a word to be inserted

$\ell \in [0, |\hat{y}_t|]$:an insertion location

x :Input sequence

$\hat{y}_t$:A sequence of output words inserted so far

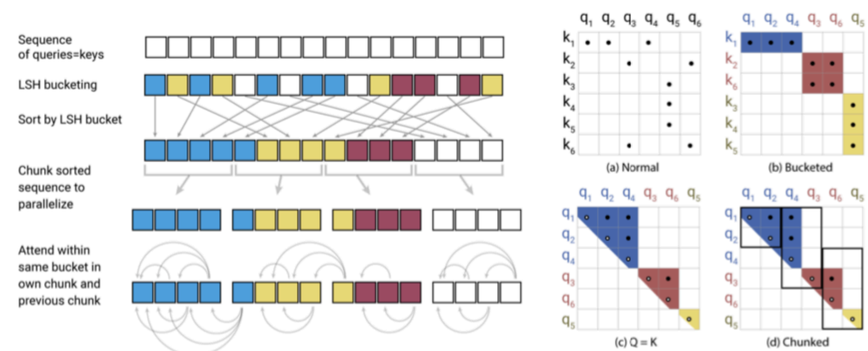
t	Canvas	Insertion
0	[]	(ate, 0)
1	[ate]	(together, 1)
2	[ate, together]	(friends, 0)
3	[friends, ate, together]	(three, 0)
4	[three, friends, ate, together]	(lunch, 3)
5	[three, friends, ate, lunch, together]	($\langle$EOS$\rangle$, 5)

Stern et al., 2019. "Insertion Transformer: Flexible Sequence Generation via Insertion Operations"

Reformer

Should document context be incorporated through learning or inference?

With some optimizations, a 64k-length sequence can be encoded on a GPU.



Kitaev et al., 2020. "Reformer: The Efficient Transformer"