Sequence Modeling with Unconstrained Generation Order

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TL;DR

- Sequence model that can **insert** tokens at an arbitrary position;
- Implicitly learn the most convenient decoding order from data;

left-to-right	mixed	right-to-left		
<u>a</u> cat sat on a mat .	a cat sat on a mat <u>.</u>	a cat sat on a mat <u>.</u>		
a <u>cat</u> sat on a mat .	a cat sat <u>on</u> a mat .	a cat sat on a <u>mat</u> .		
a cat <u>sat</u> on a mat .	a cat sat on <u>a</u> mat .	a cat sat on <u>a</u> mat .		
a cat sat <u>on</u> a mat .	a cat sat on a <u>mat</u> .	a cat sat <u>on</u> a mat .		
a cat sat on <u>a</u> mat .	a <u>cat</u> sat on a mat .	a cat <u>sat</u> on a mat .		
a cat sat on a <u>mat</u> .	a cat <u>sat</u> on a mat .	a <u>cat</u> sat on a mat .		
a cat sat on a mat .	<u>a</u> cat sat on a mat .	<u>a</u> cat sat on a mat .		

- Competitive results on Machine Translation, Im2Latex and Image Captioning tasks

Learning to Insert

Main idea: generate a sequence by inserting elements at arbitrary positions Hence, we generate a sequence of insertions: $\tau = (\tau_0, \tau_1, \tau_2, ..., \tau_T)$

Insertion: $\tau_t = (pos_t, token_t)$ insert $token_t$ at position $pos_t \in [0; t]$

Model: predict next insertion into partial output formed by previous inserts

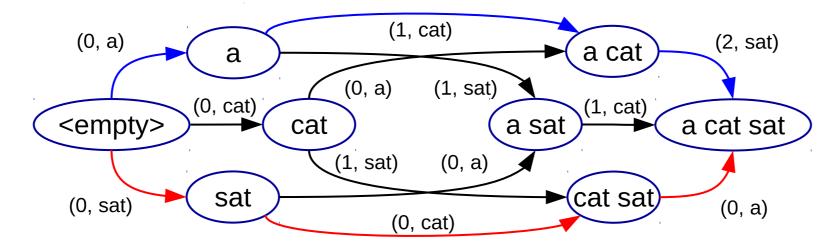
$$p(\tau|X,\theta) = \prod_t p(\tau_t|X,\tilde{Y}(\tau_{0:t-1}),\theta)$$
 $X-$ input (e.g. source sequence in MT) $\tilde{Y}(\tau_{0:t-1})-$ partial output sequence

Log-likelihood:
$$L = \sum_{\{X,Y\} \in D} \log p(Y|X,\theta) = \sum_{\{X,Y\} \in D} \log \sum_{\tau \in T^*(Y)} \prod_t p(\tau_t|X, \tilde{Y}(\tau_{0:t-1}), \theta)$$
 (1)

Lower bound:
$$L \ge \sum_{\{X,Y\} \in D} E_{\tau \sim p(\tau|X,\tau \in T^*(Y),\theta)} \log \prod_t p(\tau_t|X,\tilde{Y}(\tau_{0:t-1}),\theta)$$
 (2)

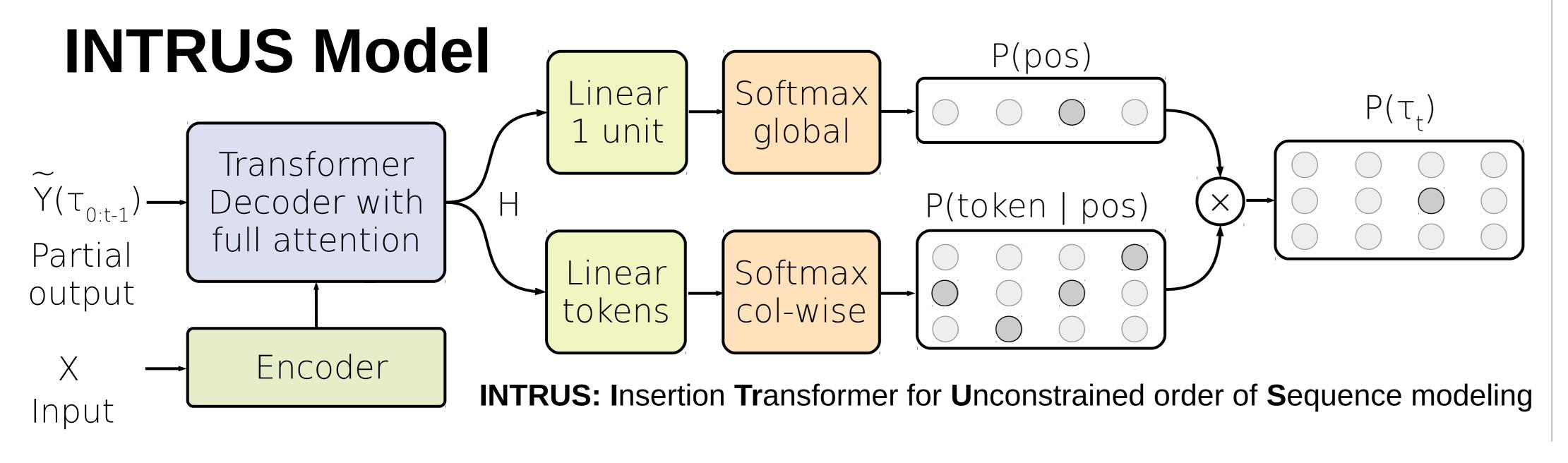
Training algorithm:

- **1)** Sample mini-batch of sequences (X, Y);
- 2) Generate a trajectory τ that produces Y proportionally to model probabilities;
- 3) Maximize lower bound (2) by backprop;

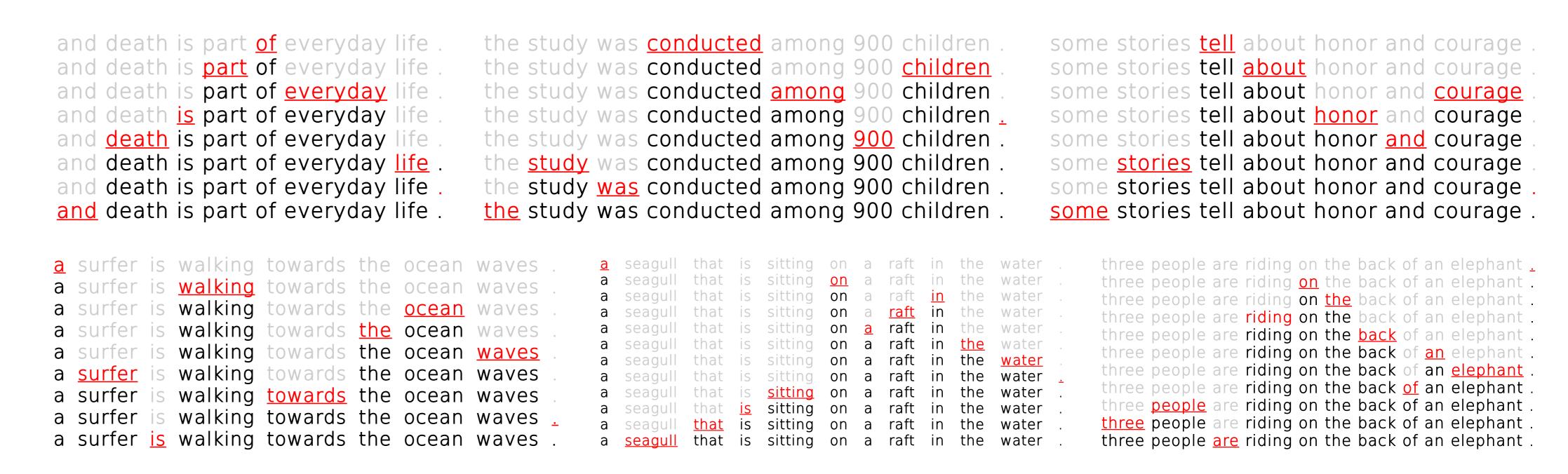


All trajectories that produce "a cat sat". Left-to-right is blue and right-to-left is red.

Pre-training: at step 2, sample generation order at random, ignoring model probabilities



Learned Decoding Orders:



Experiments

	En-Ru	Ru-En	En-Ja	En-Ar	En-De	De-En	Im2Latex	MSCOCO	
Model	BLEU						BLEU	CIDEr	
Left-to-right	31.6	35.3	47.9	12.0	28.04	33.17	89.5	18.0	56.1
Right-to-left	-	-	48.6	11.5	-	-	-	-	-
INTRUS	33.2*	36.4 *	50.3*	12.2	28.36 *	33.08	90.3*	25.6 *	81.0*

Tasks:

- Machine Translation WMT En-Ru, ASPEC En-Ja IWSLT En-De, En-Ar
- ImageToLatex-140K
- MSCOCO Image captioning

Ablation Analysis:

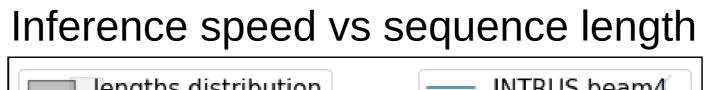
- Sampling lower bound is better than argmax -
- Pre-training greatly affects performance

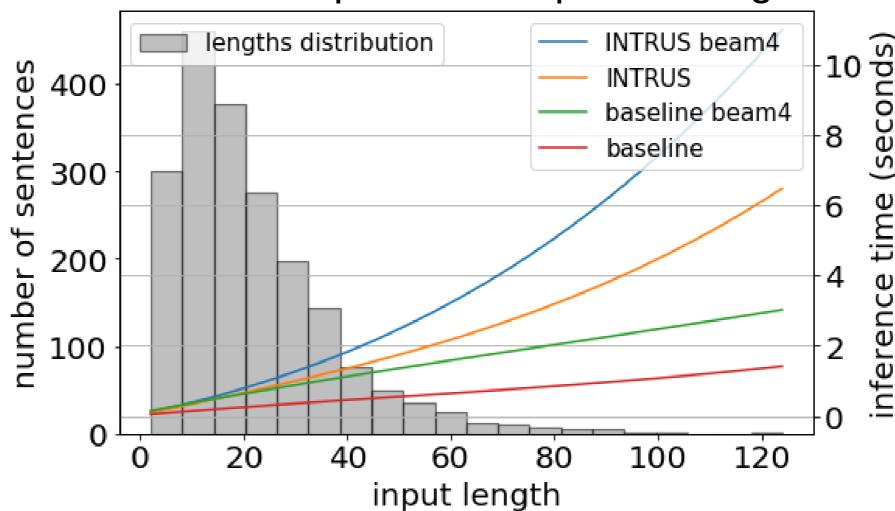
Training	INTRUS	Argmax	Pretraining	No pre-	Only pretraining		Baseline
strategy		8	left-to-right	training	uniform	left-to-right	left-to-right
BLEU	27.5	26.6	26.3	27.1	24.6	25.5	25.8

Ablation analysis on En-Ru translation task

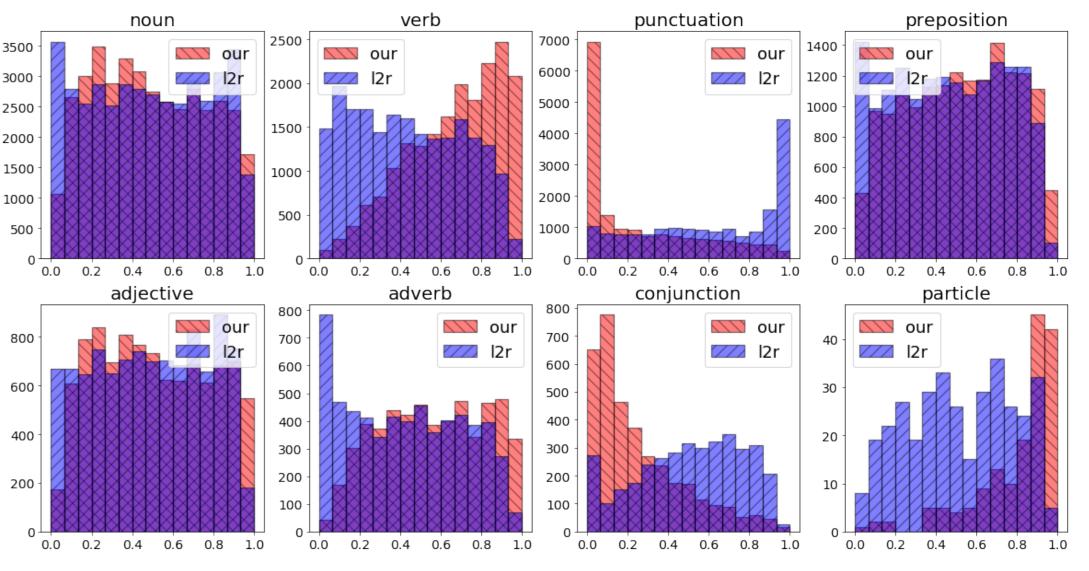
Brief summary:

- Learned decoding order meaningfully differs from left-to-right (right);
- In general, the model learned to insert "easy" tokens first;
- INTRUS is ~50% slower than base Transformer for most MT tasks (below);





Analysis noun 3500 3000 12r 250 200



Step on which different POS tags appear in sequences generated by INTRUS (our) and Transformer (I2r)

Links:

Code: https://github.com/TIXFeniks/neurips2019_intrus Yandex Research: https://research.yandex.com