Training and Distilling Seq2Seq Models

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(with Yoon Kim, Sam Wiseman, Yuntian Deng, Allen Schmaltz, Hendrik Strobelt)

at

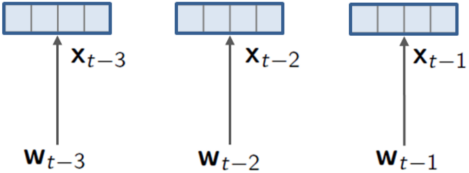
Sequence-to-Sequence

- Machine Translation (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014; Cho et al., 2014; Bahdanau et al., 2014; Luong et al., 2015)
- Question Answering (Hermann et al., 2015)
- Conversation (Vinyals and Le, 2015)
- Parsing (Vinyals et al., 2014)
- Argument Generation (Wang and Yang, 2015)
- Sentence Compression (Filippova et al., 2015)
- Speech (Chorowski et al., 2015)
- Summarization (Rush et al., 2015)
- Caption Generation (Karpathy and Fei-Fei, 2015; Xu et al., 2015)
- Video-to-Text (Venugopalan et al., 2015)

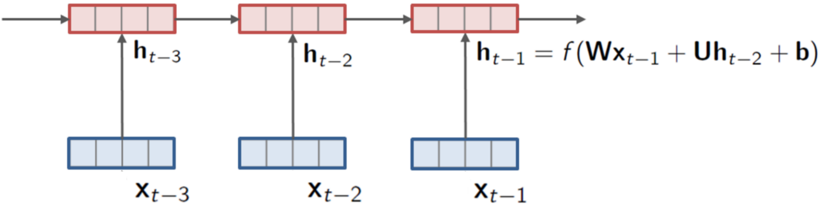
Seq2Seq Neural Network Toolbox

Embeddings	sparse features	$\Rightarrow$	dense features
RNNs	feature sequences	$\Rightarrow$	dense features
Softmax	dense features	$\Rightarrow$	discrete predictions

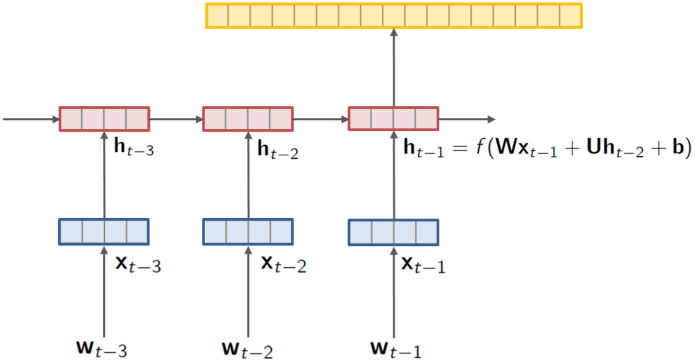
Embeddings sparse features $\Rightarrow$ dense features



RNNs/LSTMs feature sequences $\Rightarrow$ dense features

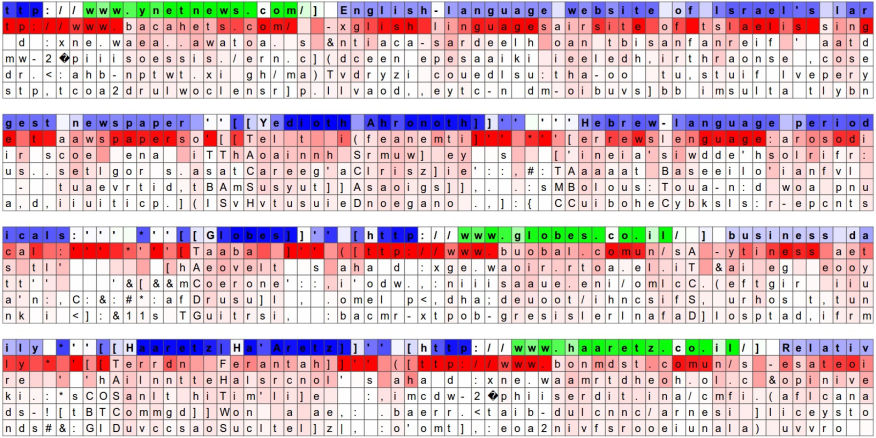


LM/Softmax dense features $\Rightarrow$ discrete predictions



$$p(\mathbf{w}_t|\mathbf{w}_1, \ldots, \mathbf{w}_{t-1}; \theta) = \mathrm{softmax}(\mathbf{W}_{out}\mathbf{h}_{t-1} + \mathbf{b}_{out})$$

$$p(\mathbf{w}_{1:T}) = \prod_t p(\mathbf{w}_t|\mathbf{w}_1, \ldots, \mathbf{w}_{t-1})$$



(Karpathy et al., 2015)

LSTMVis (Strobelt et al., 2016)

Example 1: Synthetic (Finite-State) Language

alphabet: ( ) 0 1 2 3 4

corpus: (1 (2) ()) 0 (((3)) 1)

- Numbers are randomly generated, must match nesting level.
- Train a predict-next-word language model (decoder-only).

$$p(\mathbf{w}_t | \mathbf{w}_1, \ldots, \mathbf{w}_{t-1})$$

[Parens Example]

(Strobelt et al., 2016)

LSTMVis (Strobelt et al., 2016)

Example 2: Real Language

alphabet: all english words

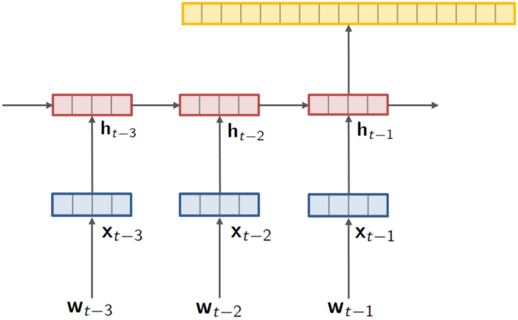
corpus: Project Gutenberg Children's books

- Train a predict-next-word language model (decoder-only).

$$p(\mathbf{w}_t | \mathbf{w}_1, \ldots, \mathbf{w}_{t-1})$$

[LM Example]

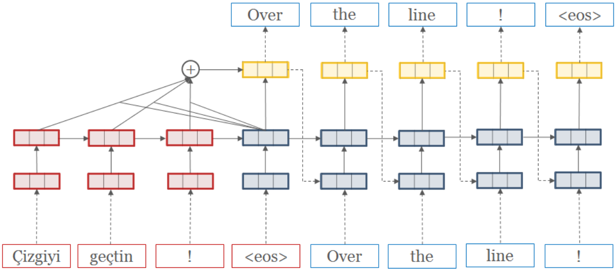
Contextual Language Model / "seq2seq"



- Key idea, contextual language model based on encoder $\mathbf{c}$:

$$p(\mathbf{w}_{1:T}|\mathbf{c}) = \prod_t p(\mathbf{w}_t|\mathbf{w}_1, \ldots, \mathbf{w}_{t-1}, \mathbf{c})$$

Actual Seq2Seq / Encoder-Decoder / Attention-Based Models



- Different encoders, attention mechanisms, input feeding, ...
- Almost all models use LSTMs or other gated RNNs
- Large multi-layer networks necessary for good performance.
  - 4 layer, 1000 hidden dims is common for MT

Seq2Seq Applications: Sentence Summarization (Rush et al., 2015)

Source

Russian Defense Minister Ivanov called Sunday for the creation of a joint front for combating global terrorism.

Target

Russia calls for joint front against terrorism.

- Used by Washington Post to suggest headlines (Wang et al., 2016)

Seq2Seq Applications: Grammar Correction (Schmaltz et al., 2016)

Source

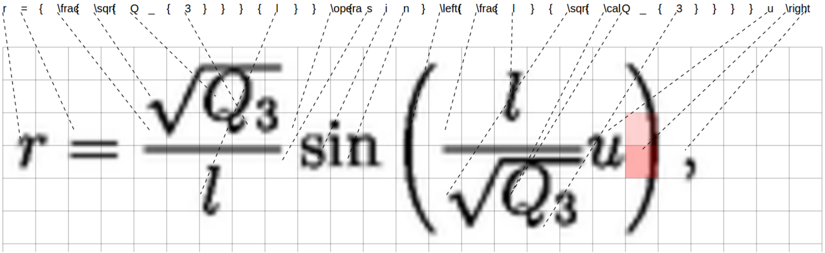
There is no a doubt, tracking systems has brought many benefits in this information age .

Target

There is no doubt, tracking systems have brought many benefits in this information age .

- First-place on BEA 11 grammar correction shared task
  (Daudaravicius et al., 2016)

Seq2Seq Applications: Im2Markup [In Submission]



[Latex Example]

This Talk

- How should we **train** these style of models?

  Sequence-to-Sequence Learning as Beam-Search Optimization

  (Wiseman and Rush, 2016)

- How can we **shrink** these models for practical applications (Kim and Rush, 2016)?

Some More Seq2Seq Details

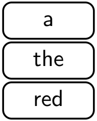
Training Objective: Local Multiclass NLL (for training targets $y_{1:T}$)

$$\mathsf{NLL}(\theta) = -\sum_t \log p(\mathbf{w}_t = y_t | \mathbf{w}_{1:t-1} = y_{1:t-1}, \mathbf{c}; \theta)$$

Test Objective: Structured prediction

$$\mathbf{w}_{1:T}^* = \arg\max_{\mathbf{w}_{1:T}} \sum_t \log p(\mathbf{w}_t | \mathbf{w}_{1:t-1}, \mathbf{c}; \theta)$$

Beam Search Example $(K = 3)$



For timesteps t from 1 to T:

1. Compute for all $k, \mathbf{w}_t$

$$s(\mathbf{w}_t, \mathbf{w}_{1:t-1}^{(k)}) \leftarrow \log p(\mathbf{w}_t | \mathbf{w}_{1:t-1}^{(k)}, \mathbf{c}) + \log p(\mathbf{w}_{1:t-1}^{(k)} | \mathbf{c})$$

2. Replace the K highest scoring target sequences

$$\mathbf{w}_{1:t}^{(1:K)} \leftarrow K \operatorname*{arg\,max}_{\mathbf{w}_{1:t}} s(\mathbf{w}_t, \mathbf{w}_{1:t-1}^{(k)})$$

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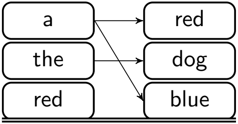

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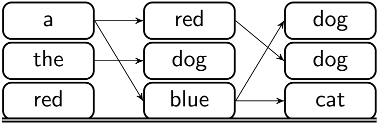

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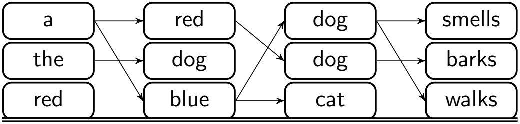

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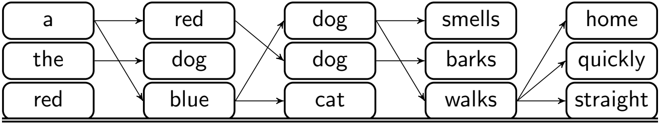

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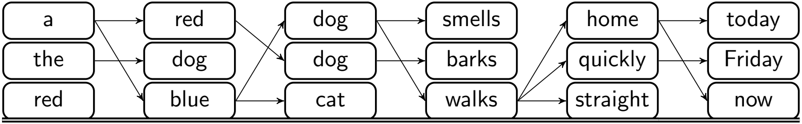

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Theoretical Issues with Standard Setup

- Exposure Bias
  - Training by conditioning on true $y_{1:t-1}$,

$$p(\mathbf{w}_t = y_t | \mathbf{w}_{1:t-1} = y_{1:t-1}, \mathbf{c}; \theta)$$

- Train/Test Loss Mismatch
  - Training with local NLL, evaluate with hamming-style losses (BLEU)
- Label Bias (Lafferty et al., 2001)
  - Locally normalized models have known pathological issues

Related Work:

- Data as Demonstrator (Venkatraman et al., 2015)
- Scheduled Sampling (Bengio et al., 2015)

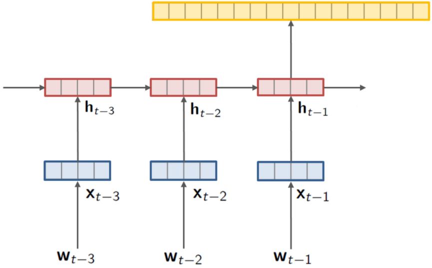
Explicit Reinforcement Learning

- MIXER (Ranzato et al., 2016)
- Actor-Critic (Bahdanau et al., 2016)

This Work: Seq2Seq Learning as Beam Search Optimization

- (Idea 1) Replace local softmax with sequence score f
- (Idea 2) Run beam search during training time
- (Idea 3) Train with cost-sensitive margin

(Idea 1) Replace local softmax with sequence scorer f



Normalized (Softmax)		Unnormalized
$\log p(\mathbf{w}_t \mid \mathbf{w}^{(k)}_{1:t-1}, \mathbf{c}; \theta)$	$\Rightarrow$	$f(\mathbf{w}_t, \mathbf{w}^{(k)}_{1:t-1}, \mathbf{c}; \theta)$

- Targets Label Bias

(Idea 2) Run beam search during training

1. For timesteps t from 1 to T:
   1. Compute for all $k, \mathbf{w}_t$

$$s(\mathbf{w}_t, \mathbf{w}_{1:t-1}^{(k)}) \leftarrow \log p(\mathbf{w}_t | \mathbf{w}_{1:t-1}^{(k)}, \mathbf{c}; \theta) + \log p(\mathbf{w}_{1:t-1}^{(k)} | \mathbf{c}; \theta)$$

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- Targets Exposure Bias

(Idea 2) Run beam search during training

1. For timesteps t from 1 to T:
    1. Compute for all $k, \mathbf{w}_t$

    $$s(\mathbf{w}_t, \mathbf{w}_{1:t-1}^{(k)}) \leftarrow f(\mathbf{w}_t, \mathbf{w}_{1:t-1}^{(k)}, \mathbf{c}; \theta)$$

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- Targets Exposure Bias

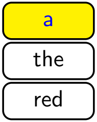
(Idea 3) Train with cost-sensitive margin

Objective: Margin between target seq y and last seq on beam $\mathbf{w}^{(K)}$

$$\mathcal{L}(\theta) = \sum_t \Delta(y_{1:t}, \mathbf{w}^K_{1:t}) \left[1 - f(y_t, y_{1:t-1}, \mathbf{c}) + f(\mathbf{w}^{(K)}_t, \mathbf{w}^{(K)}_{1:t-1}, \mathbf{c})\right]$$

- Slack-rescaled, margin-based sequence criterion, at each time step.
- When violation occurs, target replaces current beam (learning as search optimization (Daumé III and Marcu, 2005))
- Cost-sensitivity targets Train/Test Mismatch

Beam Search Optimization Example ($K = 3$)



- Color Gold: target sequence y
- Color Gray: violating sequence $\mathbf{w}^{(K)}$

Violation Criterion

$$\mathcal{L}(\theta) = \sum_t \Delta(y_{1:t}, \mathbf{w}^K_{1:t}) \left[1 - f(y_t, y_{1:t-1}, \mathbf{c}) + f(\mathbf{w}^{(K)}_t, \mathbf{w}^{(K)}_{1:t-1}, \mathbf{c}) \right]$$

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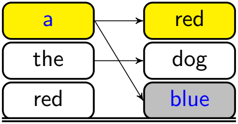

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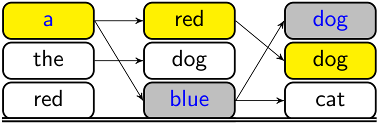

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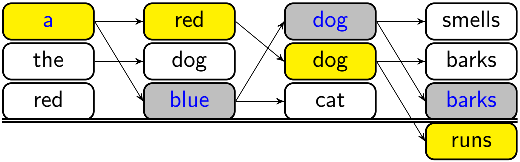

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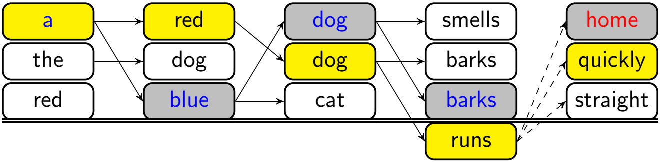
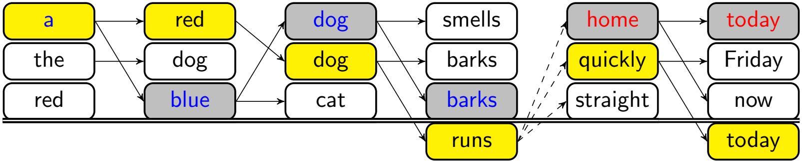


- Color Gold: target sequence y
- Color Gray: violating sequence $\mathbf{w}^{(K)}$

Violation Criterion

$$\mathcal{L}(\theta) = \sum_t \Delta(y_{1:t}, \mathbf{w}_{1:t}^K) \left[1 - f(y_t, y_{1:t-1}, \mathbf{c}) + f(\mathbf{w}_t^{(K)}, \mathbf{w}_{1:t-1}^{(K)}, \mathbf{c})\right]$$

Beam Search Optimization Example ($K = 3$)



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Violation Criterion

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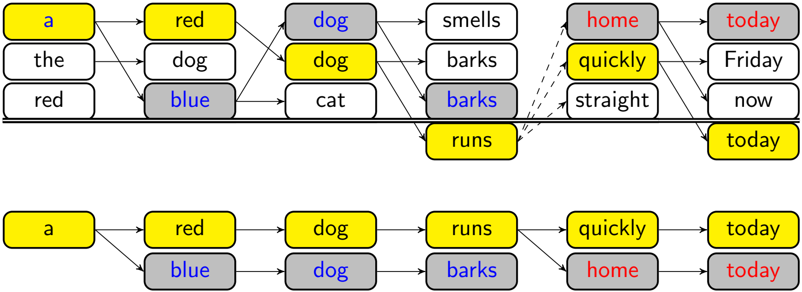
Backpropagation over Structure



- Margin gradients are sparse, only violating sequences get updates.
- Backprop only requires 2x time as standard methods.

Experiments

Experiments run on three small seq2seq baseline tasks

- Word Ordering (PTB, Liu et al, 15)
- Dependency Parsing (Stanford, setup as Chen and Manning, 14)
- Machine Translation (IWSLT 2014, DE-EN)

Details:

- Utilize our *seq2seq-attn* strong attention-based system
- Pretrained with NLL.
- Trained with a curriculum to gradually increase beam size.
- Additionally include BSO-Con with training-time constraints.
- All models trained with $K = 6$

	$K_e = 1$	$K_e = 5$	$K_e = 10$
	Word Ordering (BLEU)		
seq2seq	25.2	29.8	31.0
BSO	28.0	33.2	34.3
BSO-Con	**28.6**	**34.3**	**34.5**
	Dependency Parsing (UAS/LAS)		
seq2seq	**87.33/82.26**	88.53/84.16	88.66/84.33
BSO	86.91/82.11	91.00/**87.18**	91.17/**87.41**
BSO-Con	85.11/79.32	**91.25**/86.92	**91.57**/87.26
	Machine Translation (BLEU)		
seq2seq	22.53	24.03	23.87
BSO, SB-Δ, K_t=6	**23.83**	**26.36**	**25.48**
XENT	17.74	$\leq$ 20.5	$\leq$ 20.5
DAD	20.12	$\leq$ 22.5	$\leq$ 23.0
MIXER	20.73	-	$\leq$ 22.0

This Talk

- How should we **train** these style of models? (Wiseman and Rush, 2016)
- How can we **shrink** these models for practical applications?

Sequence-Level Knowledge Distillation

(Kim and Rush, 2016)

Issues

- Seq2Seq Models are really big
- Beam search can be quite slow

Related Work: Compressing Deep Models

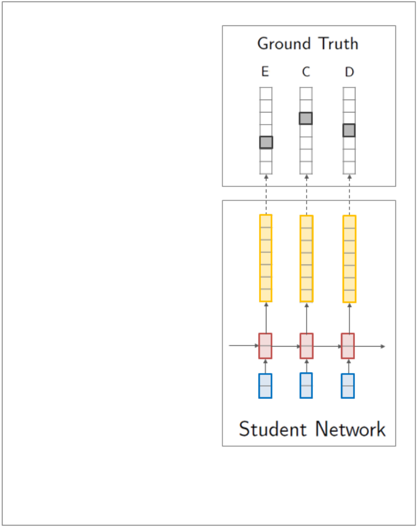
- **Pruning**: Prune weights based on importance criterion (LeCun et al., 1990; Han et al., 2016)
- **Knowledge Distillation**: Train a *student* model to learn from a *teacher* model (Bucila et al., 2006; Ba and Caruana, 2014; Hinton et al., 2015).

- Compressing NMT (See et al., 2016)

Baseline Model

Standard model minimize NLL(θ):

$$-\sum_t \log p(\mathbf{w}_t = y_t \mid \mathbf{w}_{1:t-1}, \mathbf{c}; \theta)$$

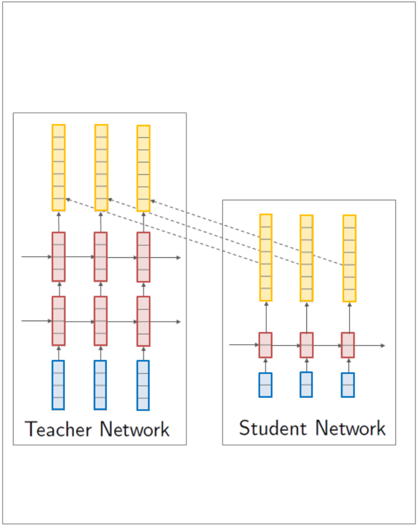


(Word-Level) Knowledge Distillation

Teacher network: $q(\mathbf{w}_t|\mathbf{w}_{1:t-1}, \mathbf{c}; \theta_T)$

Minimize cross-entropy with teacher

$$-\sum_t \sum_v q(\mathbf{w}_t = v \,|\, \mathbf{w}_{1:t-1}, \mathbf{c}; \theta_T) \times$$
$$\log p(\mathbf{w}_t = v \,|\, \mathbf{w}_{1:t-1}, \mathbf{c}; \theta)$$



This Work: Sequence-Level Knowledge Distillation

Instead of word NLL,

$$-\sum_{t}\sum_{v} q(\mathbf{w}_t = v \mid \mathbf{w}_{1:t-1}, \mathbf{c}; \theta_T) \times \log p(\mathbf{w}_t = v \mid \mathbf{w}_{1:t-1}, \mathbf{c}; \theta)$$

Minimize cross-entropy between q and p implied <u>sequence</u>-distributions

$$-\sum_{\mathbf{w}_{1:T}} q(\mathbf{w}_{1:T}|\mathbf{c}; \theta_T) \times \log p(\mathbf{w}_{1:T}|\mathbf{c}; \theta)$$

A Simple Approximation

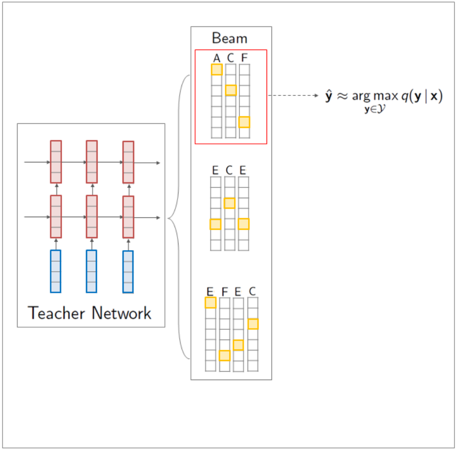
Approximate $q(\mathbf{w}_{1:T} \,|\, \mathbf{c})$ with mode

$$q(\mathbf{w}_{1:T} \,|\, \mathbf{c}) \approx \mathbf{1}\{\arg\max_{\mathbf{w}} q(\mathbf{w}_{1:T} \,|\, \mathbf{c})\}$$

Roughly obtained wtih beam search

$$\mathbf{w}^*_{1:T} \approx \arg\max_{\mathbf{w}_{1:T}} q(\mathbf{w}_{1:T} \,|\, \mathbf{c})$$

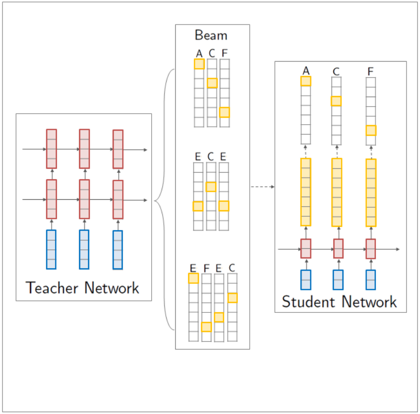
Empirically, point estimate captures significant mass



Sequence-Level Knowledge Distillation

Simple Model: train student on $\mathbf{w}^*$ with NLL

Local updating (Liang et al., 2006)



Results: English $\rightarrow$ German

Model	BLEU$_{K=1}$	$\Delta_{K=1}$	BLEU$_{K=5}$	$\Delta_{K=5}$	PPL	$p(\mathbf{w}^*)$
4×1000						
Teacher	17.7	–	19.5	–	6.7	1.3%
Seq-Inter	19.6	+1.9	19.8	+0.3	10.4	8.2%
2×500						
Student	14.7	–	17.6	–	8.2	0.9%
Word-KD	15.4	+0.7	17.7	+0.1	8.0	1.0%
Seq-KD	18.9	**+4.2**	19.0	+1.4	22.7	16.9%
Seq-Inter	18.9	**+4.2**	19.3	**+1.7**	15.8	7.6%

Combining Knowledge Distillation and Pruning (See et al., 2016)

Model	Prune %	Params	BLEU	Ratio
4×1000	0%	221 m	19.5	$1\times$
2×500	0%	84 m	19.3	$3\times$
2×500	50%	42 m	19.3	$5\times$
2×500	80%	17 m	19.1	$13\times$
2×500	85%	13 m	18.8	$18\times$
2×500	90%	8 m	18.5	$26\times$

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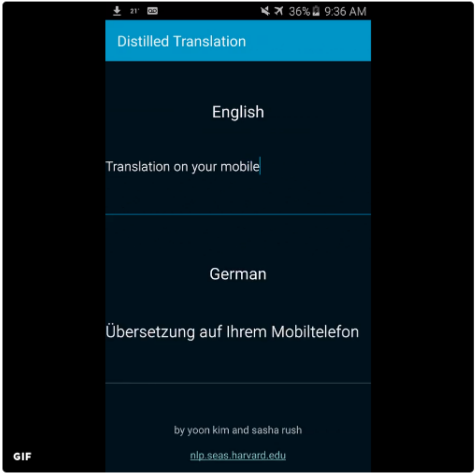
Seq KD (arxiv.org/abs/1606.07947): learn small LSTMs for fast translation. Runs on a phone (nlp.seas.harvard.edu/translation.apk)



Thank You

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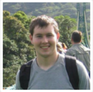
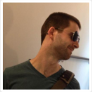
Graduate Students


Sebastian Gehrmann


Yoon Kim


Victoria Krakovna


Allen Schmaltz

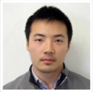

Sam Wiseman

Undergraduate Researchers


Jeffrey Ling


Keyon Vafa


Alex Wang


Mike Zhai

References I

Ba, L. J. and Caruana, R. (2014). Do Deep Nets Really Need to be Deep? In Proceedings of NIPS.

Bahdanau, D., Brakel, P., Xu, K., Goyal, A., Lowe, R., Pineau, J., Courville, A., and Bengio, Y. (2016). An Actor-Critic Algorithm for Sequence Prediction.

Bahdanau, D., Cho, K., and Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. CoRR, abs/1409.0473.

Bengio, S., Vinyals, O., Jaitly, N., and Shazeer, N. (2015). Scheduled Sampling for Sequence Prediction with Recurrent Neural Networks. NIPS, pages 1–9.

Bucila, C., Caruana, R., and Niculescu-Mizil, A. (2006). Model Compression. In Proceedings of KDD.

References II

Cho, K., van Merrienboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Y. (2014). Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. In Proceedings of EMNLP.

Chorowski, J., Bahdanau, D., and Serdyuk, D. (2015). Attention-based models for speech recognition. Advances in Neural.

Daudaravicius, V., Banchs, R. E., Volodina, E., and Napoles, C. (2016). A Report on the Automatic Evaluation of Scientific Writing Shared Task. NAACL BEA11 Workshop, pages 53–62.

Daumé III, H. and Marcu, D. (2005). Learning as search optimization: approximate large margin methods for structured prediction. In Proceedings of the Twenty-Second International Conference on Machine Learning {(ICML} 2005), pages 169–176.

References III

Filippova, K., Alfonseca, E., Colmenares, C. A., Kaiser, L., and Vinyals, O. (2015). Sentence Compression by Deletion with LSTMs. In Emnlp, volume lstmsen, pages 360–368.

Han, S., Mao, H., and Dally, W. J. (2016). Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding. In Proceedings of ICLR.

Hermann, K., Kocisky, T., and Grefenstette, E. (2015). Teaching machines to read and comprehend. Advances in Neural.

Hinton, G., Vinyals, O., and Dean, J. (2015). Distilling the Knowledge in a Neural Network. arXiv:1503.0253.

Kalchbrenner, N. and Blunsom, P. (2013). Recurrent continuous translation models. In EMNLP, pages 1700–1709.

References IV

Karpathy, A. and Fei-Fei, L. (2015). Deep visual-semantic alignments for generating image descriptions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3128–3137.

Karpathy, A., Johnson, J., and Li, F.-F. (2015). Visualizing and understanding recurrent networks. ICLR Workshops.

Kim, Y. and Rush, A. M. (2016). Sequence-Level Knowledge Distillation.

Lafferty, J., McCallum, A., and Pereira, F. (2001). Conditional random fields: Probabilistic models for segmenting and labeling sequence data. Proceedings of the eighteenth.

LeCun, Y., Denker, J. S., and Solla, S. A. (1990). Optimal Brain Damage. In Proceedings of NIPS.

Liang, P., Bouchard-Cote, A., Klein, D., and Taskar, B. (2006). An End-to-End Discriminative Approach to Machine Translation. In Proceedings of COLING-ACL.

References V

Luong, M.-T., Pham, H., and Manning, C. D. (2015). Effective Approaches to Attention-based Neural Machine Translation. In EMNLP, number September, page 11.

Ranzato, M., Chopra, S., Auli, M., and Zaremba, W. (2016). Sequence Level Training with Recurrent Neural Networks. ICLR, pages 1–15.

Rush, A. M., Chopra, S., and Weston, J. (2015). A Neural Attention Model for Abstractive Sentence Summarization. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), (September):379–389.

Schmaltz, A., Kim, Y., Rush, A. M., and Shieber, S. M. (2016). Sentence-Level Grammatical Error Identification as Sequence-to-Sequence Correction.

See, A., Luong, M.-T., and Manning, C. D. (2016). Compression of Neural Machine Translation via Pruning. In Proceedings of CoNLL.

References VI

Strobelt, H., Gehrmann, S., Huber, B., Pfister, H., and Rush, A. M. (2016). Visual Analysis of Hidden State Dynamics in Recurrent Neural Networks.

Sutskever, I., Vinyals, O., and Le, Q. V. (2014). Sequence to sequence learning with neural networks. In Advances in Neural Information Processing Systems, pages 3104–3112.

Venkatraman, A., Boots, B., Hebert, M., and Bagnell, J. (2015). DATA AS DEMONSTRATOR with Applications to System Identification. pdfs.semanticscholar.org.

Venugopalan, S., Rohrbach, M., and Donahue, J. (2015). Sequence to sequence-video to text. Proceedings of the.

Vinyals, O., Kaiser, L., Koo, T., Petrov, S., Sutskever, I., and Hinton, G. (2014). Grammar as a Foreign Language. In arXiv, pages 1–10.

Vinyals, O. and Le, Q. (2015). A neural conversational model. arXiv preprint arXiv:1506.05869.

References VII

Wang, S., Han, S., and Rush, A. M. (2016). Headliner. Computation+Journalism.

Wang, W. Y. and Yang, D. (2015). That ' s So Annoying !!!: A Lexical and Frame-Semantic Embedding Based Data Augmentation Approach to Automatic Categorization of Annoying Behaviors using # petpeeve Tweets . In EMNLP, number September, pages 2557–2563.

Wiseman, S. and Rush, A. M. (2016). Sequence-to-Sequence Learning as Beam-Search Optimization.

Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhutdinov, R., Zemel, R., and Bengio, Y. (2015). Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. ICML.