Interpreting, Training, and Distilling Seq2Seq Models

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(with Yoon Kim, Sam Wiseman, Allen Schmaltz, Sebastian Gehrmann, Hendrik Strobelt)

at

What's ML aspects have defined NLP problems?

1. Large, discrete input state spaces.
   - Vocabulary sizes in $10,000 - 100,000$
2. Long-term dependencies
   - *Sasha is giving a talk today at twitter, ..., he is excited.*
3. Variable-length output spaces
   - e.g. sentences, documents, conversations

> *Although current deep learning research tends to claim to encompass NLP, I'm (1) much less convinced about the strength of the results, compared to the results in, say, vision ...*

- Michael Jordan (2014) (quoted in Chris Manning, "Computational Linguistics and Deep Learning")

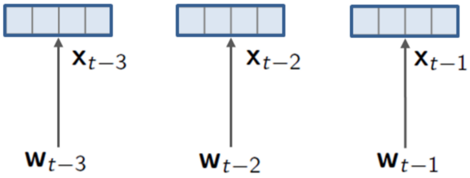
Sequence-to-Sequence is pretty convincing

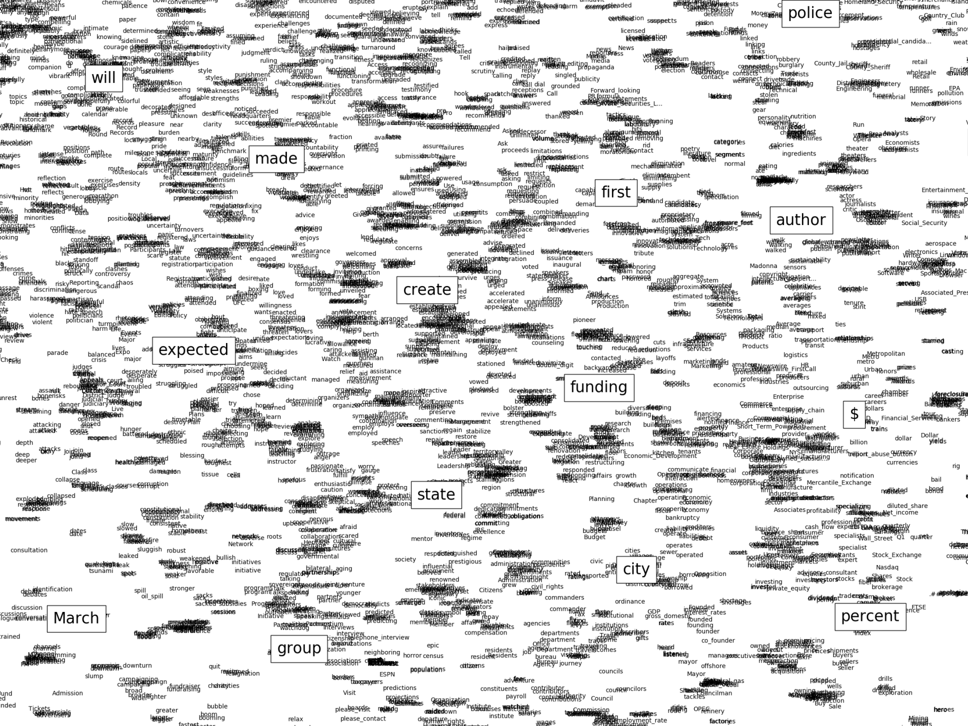
- Machine Translation (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014; Cho et al., 2014; Bahdanau et al., 2014; Luong et al., 2015)
- Question Answering (Hermann et al., 2015)
- Sentence Compression (Filippova et al., 2015)
- Parsing (Vinyals et al., 2014)
- *Summarization* (Rush et al., 2015)
- Conversation (Vinyals and Le, 2015)
- Argument Generation (Wang and Yang, 2015)
- *Grammar Correction* (Schmaltz et al., 2016)
- Speech (Chorowski et al., 2015)
- Caption Generation (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

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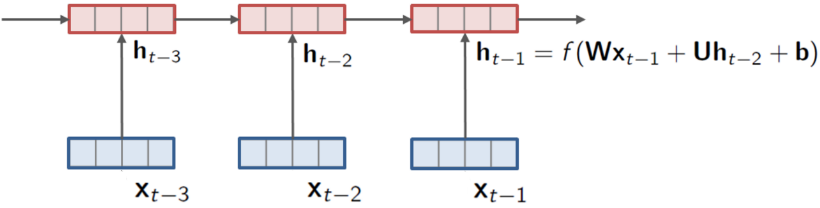
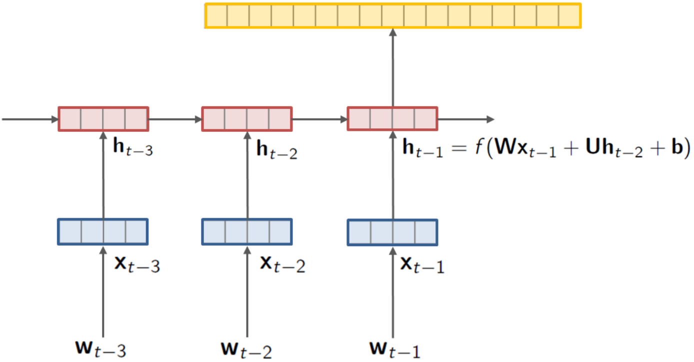
RNNs/LSTMs feature sequences $\Rightarrow$ dense features



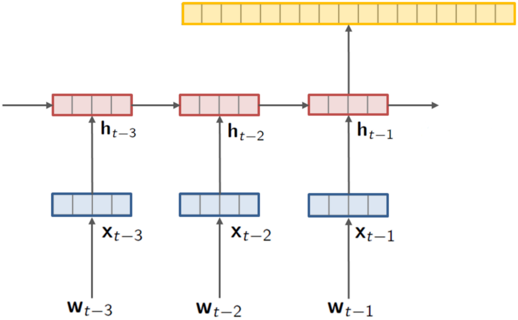
Softmax dense features $\Rightarrow$ discrete predictions



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

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

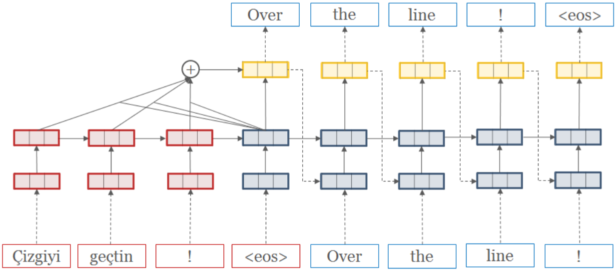
Contextual Language Model / “seq2seq”



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

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

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

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This Talk

- How can we **interpret** these learned hidden representations?
- How should we **train** these style of models?
- How can we **shrink** these models for practical applications?

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  LSTMVis

  (Strobelt et al., 2016)

- How should we **train** these style of models? (Wiseman and Rush, 2016)
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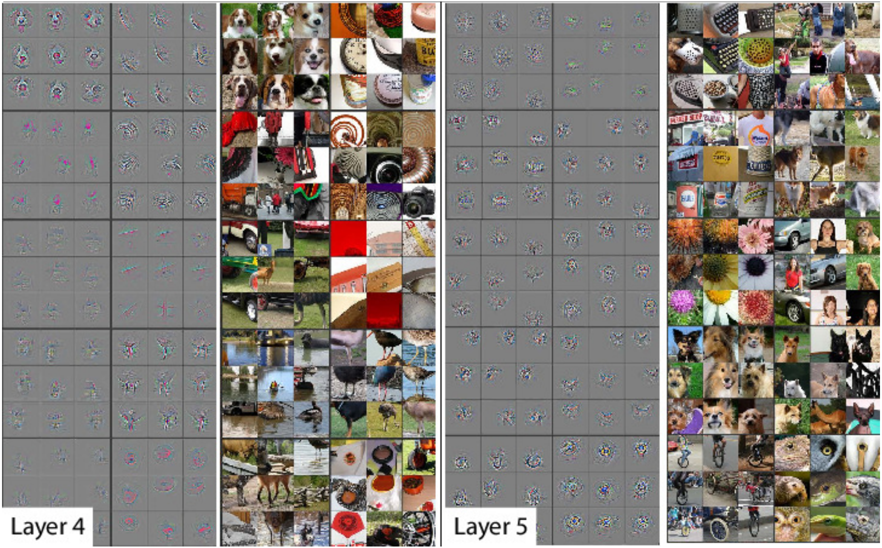
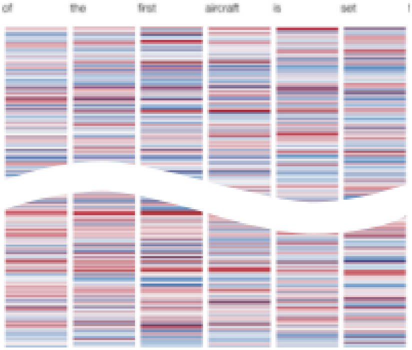
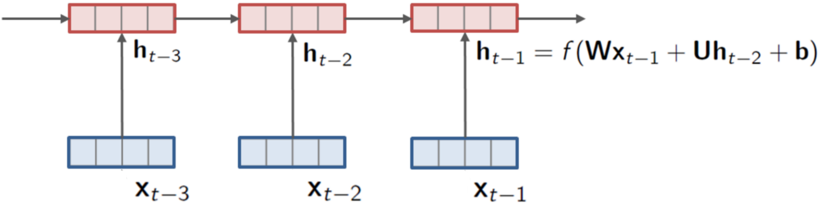
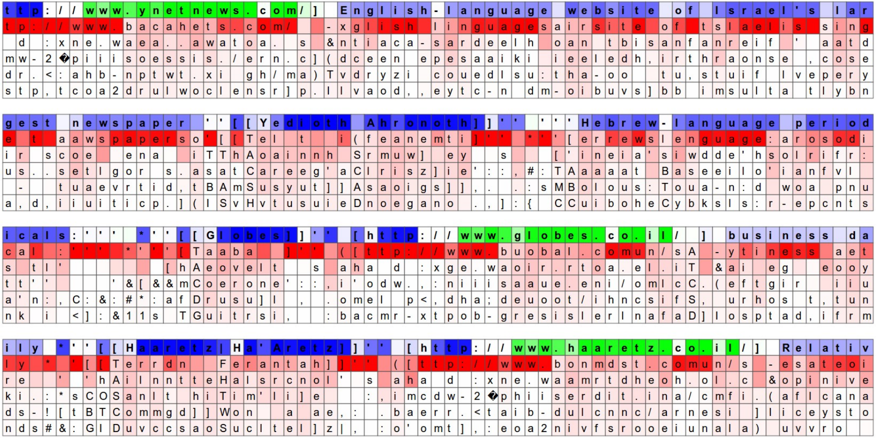


(Zeiler and Fergus, 2014)

Vector-Space RNN Representation







(Karpathy et al., 2015)

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]

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]

Example 3: Seq2Seq Encoder

alphabet: all english words

corpus: Summarization

- Train a full seq2seq model, examine *encoder* LSTM.

[Summarization Example]

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- How can we **interpret** these learned hidden representations? (Strobelt et al., 2016)
- 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: 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 output space

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

- Note: Completely intractable $O(\#\text{vocab}^T)$

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Standard Approach: Beam Search

1. Start with K partial starting hypotheses $\mathbf{w}^{(1:K)}$
2. For timesteps t from 1 to T:
    1. Compute for all $k, \mathbf{w}_t$

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

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Beam Search Example $(K = 3)$

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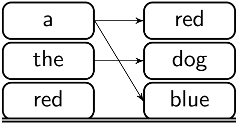

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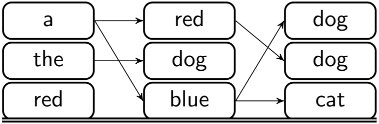

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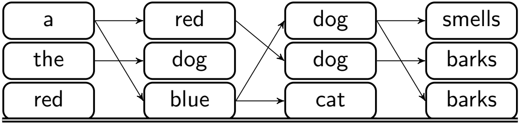

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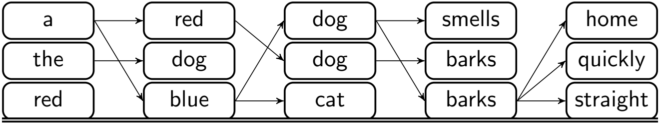

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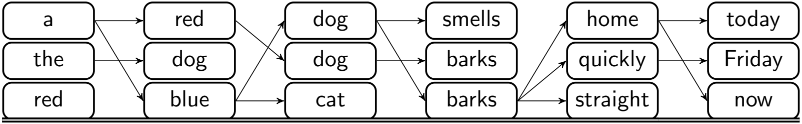

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Theoretical Issues with Standard Setup

- 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: Modify training data

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

Related Work: Use Reinforcement Learning

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

Opinion:

- DAD methods only address exposure bias,
- RL is too strong a hammer .

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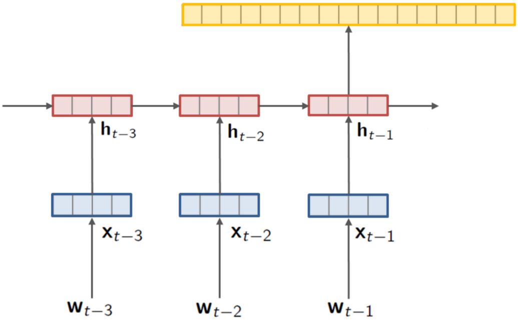
Our Proposal: Seq2Seq as Beam Search Optimization

New Setup: Run beam search at training.

- (Idea 1) Replace local softmax with sequence scorer f
- (Idea 2) Run beam search during training time
- (Idea 3) Replace local training objective with beam-search margin

(Idea 1) Replace local softmax with sequence scorer f



Same model, but replace $\log p(\mathbf{w}_t | \mathbf{w}^{(k)}_{1:t-1}, \mathbf{c}; \theta)$ with unnormalized $f(\mathbf{w}_t, \mathbf{w}^{(k)}_{1:t-1}, \mathbf{c}; \theta)$

(Idea 2) Run beam search during training

1. Start with K partial starting hypotheses $\mathbf{w}^{(1:K)}$
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(Idea 3) Replace local training objective with beam-search margin

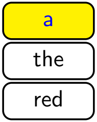
New Objective:

- 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))

Beam Search Optimization Example ($K = 3$)



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

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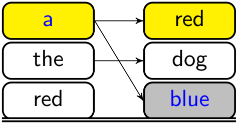

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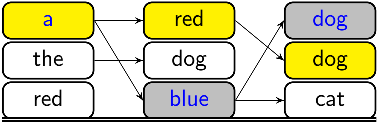

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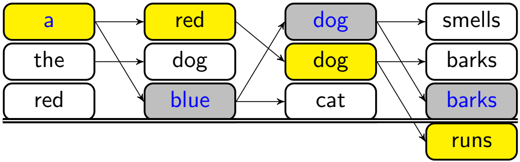

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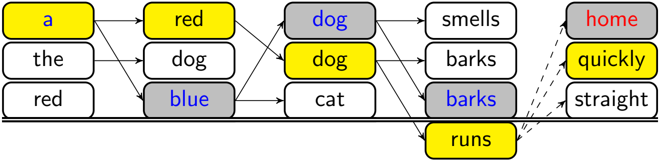

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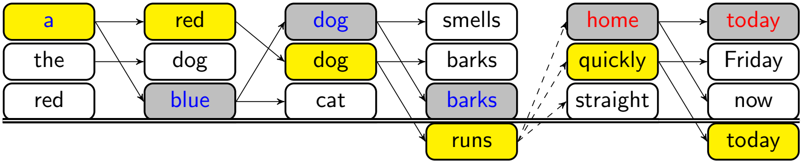

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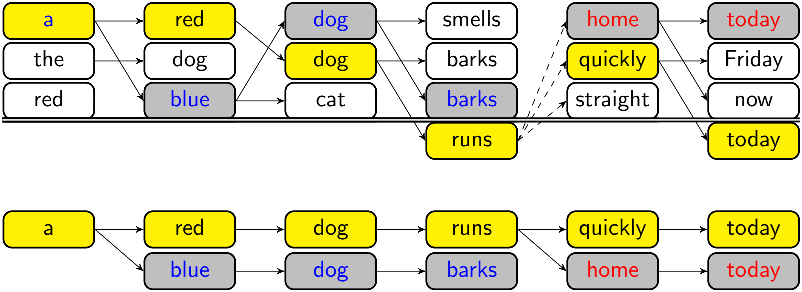
Structured Backpropagation



- Margin gradients are sparse, only violating sequences get updates.
- Backprop as efficient as standard models.

Theoretical Issues with Standard Setup

- Exposure Bias
  - Beam search at training
- Train/Test Loss Mismatch
  - Slack-rescaled margin can capture correct loss.
- Label Bias (Lafferty et al., 2001)
  - Sequence regression is not locally normalized

Experiments

Experiments run on three different seq2seq baseline tasks

- Word Ordering
- Dependency Parsing
- Machine Translation

Details:

- Utilize our *seq2seq-attn* code, very strong attention-based system
- Pretrained with NLL.
- Trained with a curriculum to gradually increase beam size.

	$K_e = 1$	$K_e = 5$	$K_e = 10$
	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

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- How can we **interpret** these learned hidden representations? (Strobelt et al., 2016)
- 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)

Seq2Seq In Practice

Benefits

- Very accurate
- General purpose
- Possibly interpretable

Downsides

- Models are really big (MT model is 4 layers each of 1000 units)
- 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).

Other methods:

- low-rank matrix factorization of weight matrices (Denton et al., 2014)
- weight binarization (Lin et al., 2016)
- weight sharing (Chen et al., 2015)

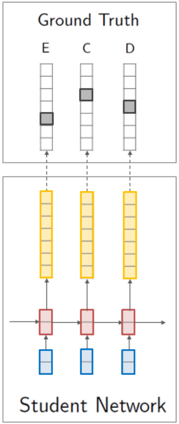
Baseline Model

Standard model minimize NLL(θ):

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

where y_t is the ground truth word at time t.

Cross-entropy with ground truth.

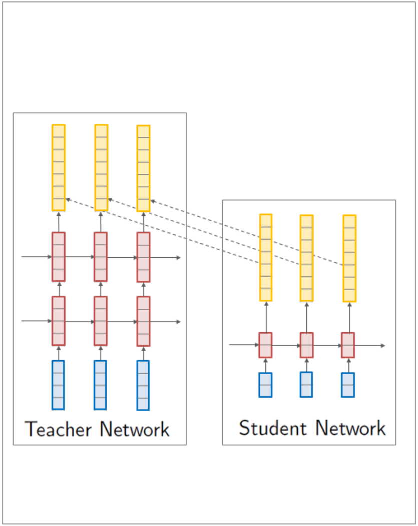


Word-Level Knowledge Distillation

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

Minimize cross-entropy between teacher and student distribution $\mathcal{L}_{\text{WORD-KD}}(\theta)$

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



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

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

Note: Exponential sum over possible $\mathbf{w}_{1:T}$.

A Simple Approximation

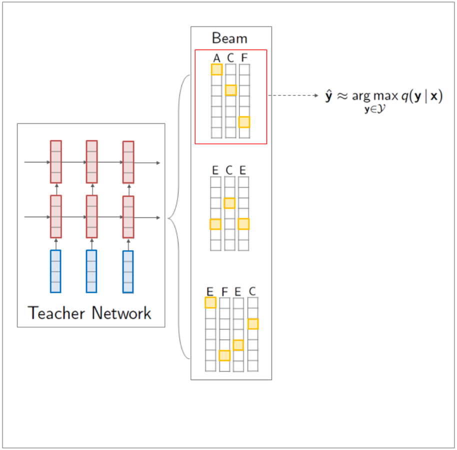
Approximate $q(\mathbf{w}_{1:T} \mid \mathbf{c})$ with mode

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

Roughly obtained wtih beam search

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

Empirically, point estimate captures significant mass



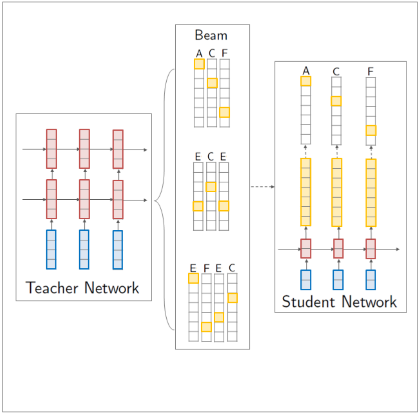
Sequence-Level Knowledge Distillation

$$\mathsf{L}_{\textsf{SEQ-KD}}(\theta) = -\log p(\mathbf{w}^*_{1:T} \mid \mathbf{c}; \theta)$$

$$\approx$$

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

Simplest model: train the student model on $\mathbf{w}^*$ with NLL



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

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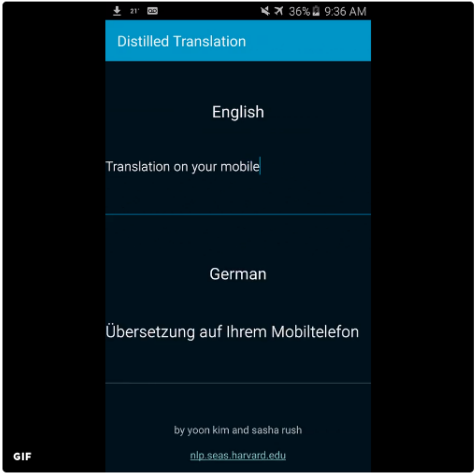
Seq KD (arxiv.org/abs/1606.07947): learn small LSTMs for fast translation. Runs on a phone (nlp.seas.harvard.edu/translation.apk)



Thank You

harvardnlp

Graduate Students

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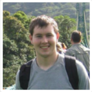
Yoon Kim

Victoria Krakovna



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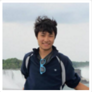
Sam Wiseman

Undergraduate Researchers



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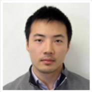
Keyon Vafa

Alex Wang



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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.

Chen, X., Xu, L., Liu, Z., Sun, M., and Luan, H. (2015). Joint learning of Character and Word Embeddings. In Proceedings of IJCAI.

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

Denton, E. L., Zaremba, W., Bruna, J., LeCun, Y., and Fergus, R. (2014). Exploiting Linear Structure within Convolutional Neural Networks for Efficient Evaluation. In Proceedings of NIPS.

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.

References IV

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

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.

Lin, Z., Coubariaux, M., Memisevic, R., and Bengio, Y. (2016). Neural Networks with Few Multiplications. In Proceedings of ICLR.

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.

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

References VI

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.

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.

Zeiler, M. D. and Fergus, R. (2014). Visualizing and understanding convolutional networks. In Computer Vision - ECCV 2014 - 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I, pages 818–833.