

Interpreting, Training, and Distilling Seq2Seq Models

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

<http://www.github.com/harvardnlp/seq2seq-talk/>



at



Carnegie Mellon University
Language Technologies Institute

Sequence-to-Sequence

- Machine Translation (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014b; Cho et al., 2014; Bahdanau et al., 2014; Luong et al., 2015)
- Question Answering (Hermann et al., 2015)
- Conversation (Vinyals and Le, 2015) (Serban et al., 2016)
- Parsing (Vinyals et al., 2014)
- Speech (Chorowski et al., 2015; Chan et al., 2015)
- Caption Generation (Karpathy and Li, 2015; Xu et al., 2015; Vinyals et al., 2015)
- Video-Generation (Srivastava et al., 2015)
- NER/POS-Tagging (Gillick et al., 2016)
- Summarization (Rush et al., 2015)

Sequence-to-Sequence

- **Machine Translation** (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014b; Cho et al., 2014; Bahdanau et al., 2014; Luong et al., 2015)
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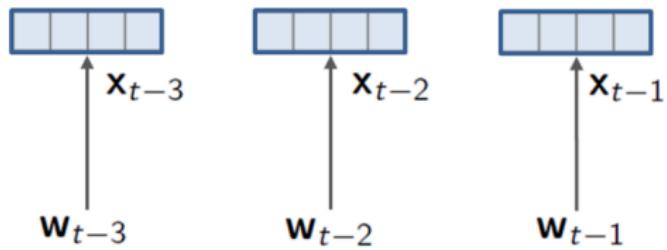
Seq2Seq Neural Network Toolbox

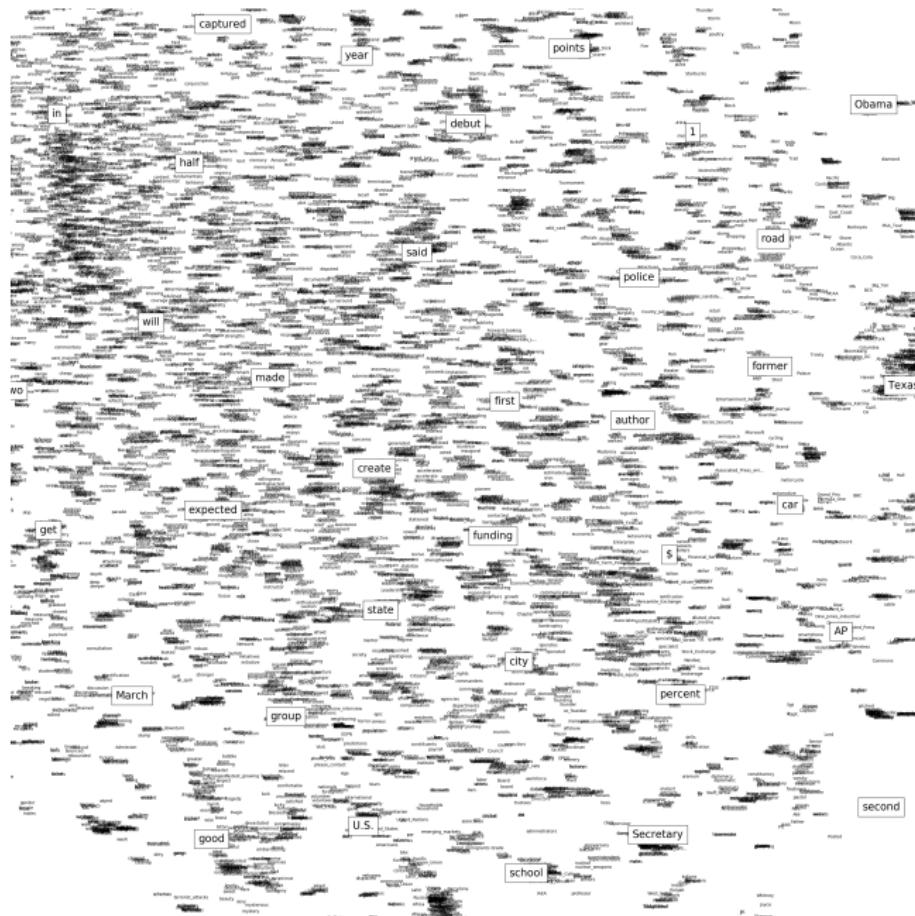
Embeddings sparse features \Rightarrow dense features

RNNs feature sequences \Rightarrow dense features

Softmax dense features \Rightarrow discrete predictions

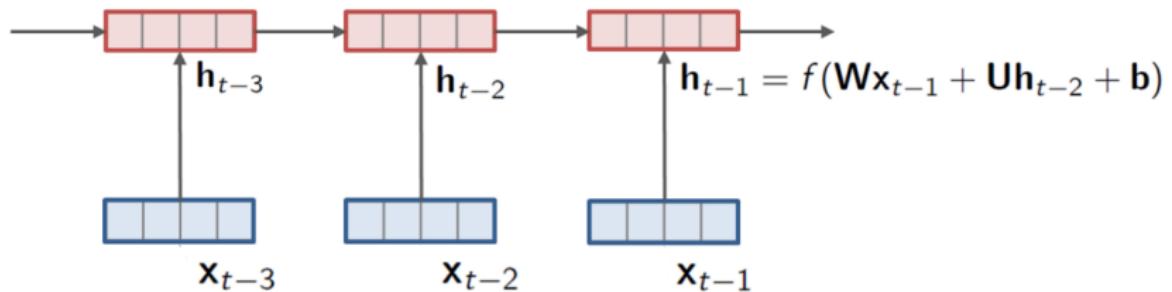
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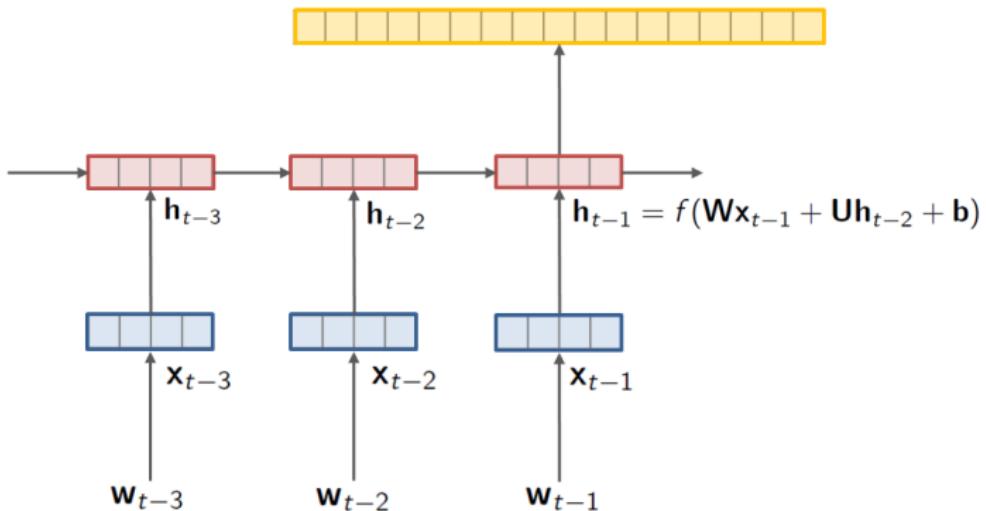


[Words Vectors]

RNNs/LSTMs feature sequences \Rightarrow dense features



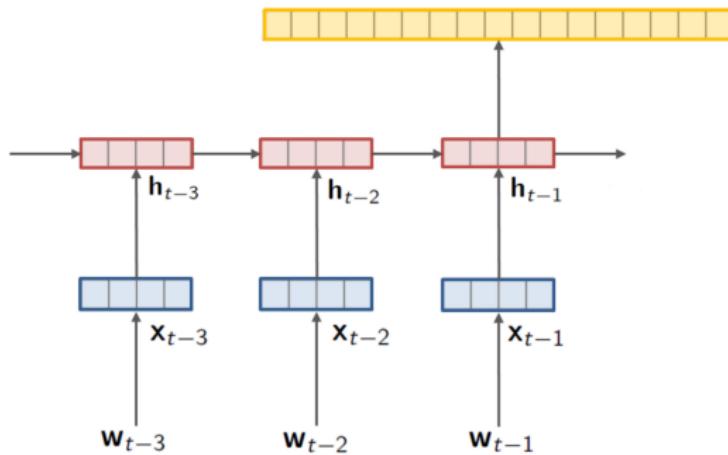
LM/Softmax dense features \Rightarrow discrete predictions



$$p(w_t | w_1, \dots, w_{t-1}; \theta) = \text{softmax}(\mathbf{W}_{out} \mathbf{h}_{t-1} + \mathbf{b}_{out})$$

$$p(w_{1:T}) = \prod_t p(w_t | w_1, \dots, w_{t-1})$$

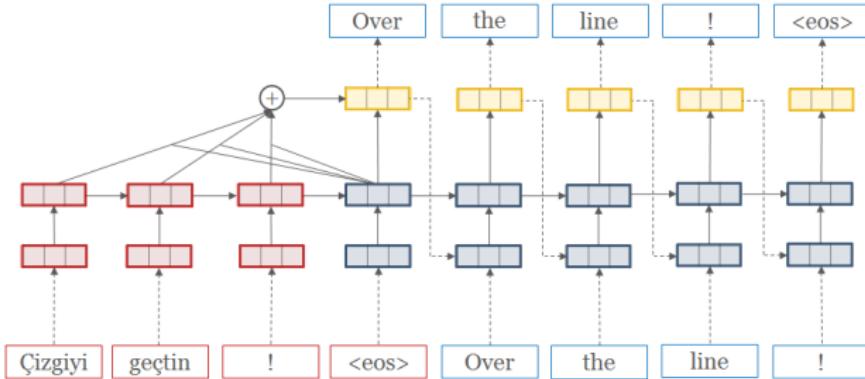
Contextual Language Model / “seq2seq”



- Key idea, contextual language model based on encoder x :

$$p(w_{1:T}|x) = \prod_t p(w_t|w_1, \dots, w_{t-1}, x)$$

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-Attn

- HarvardNLP's open-source system (Yoon Kim)
<http://github.com/harvardnlp/seq2seq-attn>
- Used by SYSTRAN for 32 language pairs (Crego et al., 2016)

Text Translation

This demo platform allows you to experience Pure Neural™ machine translation based on the last Research community's findings and SYSTRAN's R&D. You can translate up to 2000 characters of text in the languages proposed below. Check out the [information page](#) to learn more.

The screenshot shows a web-based text translation interface. At the top, there are input fields for "English" and "German", a "Filter" button, and a "Select a profile" dropdown. Below these, two text boxes show the source text "Translation on the internet" and its German translation "Übersetzung im Internet". To the right, a sidebar displays search results for the query "Translation on the internet". The results include:

- translation** [træn'zɪlefən] (↳ interpretation)
 - english translation
 - certified translation
 - French translation
 - machine translation
- on** [ən] /adv
 - darüber (↳ over)
 - spät (↳ late, subsequently)
 - daran (↳ most)
 - danach

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

Source (First Sentence)

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

Target (Title)

Russia calls for joint front against terrorism.

- (Mou et al., 2015) (Cheng and Lapata, 2016) (Toutanova et al., 2016) (Wang et al., 2016b) (Takase et al., 2016), among others
- Used by Washington Post to suggest headlines (Wang et al., 2016a)

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

Source (Original Sentence)

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

Target (Corrected Sentence)

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

- 1st on BEA'11 grammar correction task (Daudaravicius et al., 2016)

Seq2Seq Applications: Im2Markup (Deng and Rush, 2016)

The diagram illustrates the Seq2Seq process for generating XML markup from a mathematical equation. At the top, a sequence of tokens is shown in red: `r = { \frac{ \sqrt{Q} }{ l } \sin(\frac{ l }{ \sqrt{Q} } u) }`. Below this, a grid shows the mapping of these tokens to the corresponding XML structure. The tokens are connected by dashed lines to their respective parts in the XML output:

```
<math>r = \left\{ \frac{\sqrt{Q}}{l} \sin \left( \frac{l}{\sqrt{Q}} u \right) \right\}</math>
```

The XML structure is as follows:

```
<math>\left\{ \frac{\sqrt{Q}}{l} \sin \left( \frac{l}{\sqrt{Q}} u \right) \right\}</math>
```

The token `u` in the input sequence has a red background in the grid, indicating it is the target character being predicted at that step.

[Latex Example]

[Project]

This Talk

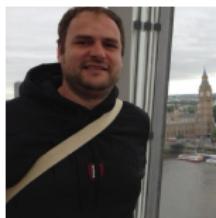
- How can we **interpret** these learned hidden representations?
- How should we **train** these style of models?
- How can we **shrink** these models for practical applications?

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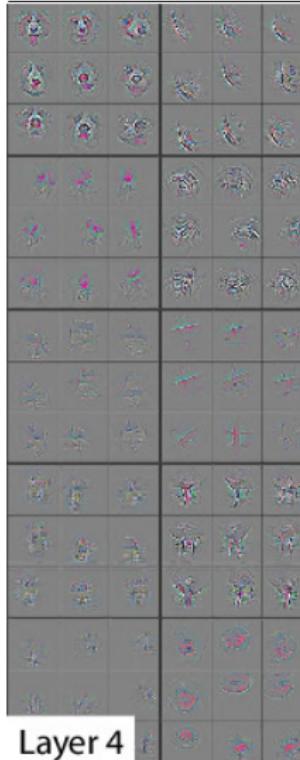
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LSTMVis lstm.seas.harvard.edu

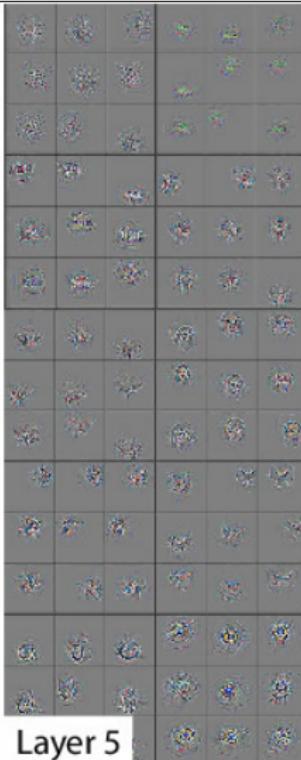
(Strobelt et al., 2016)



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



Layer 4

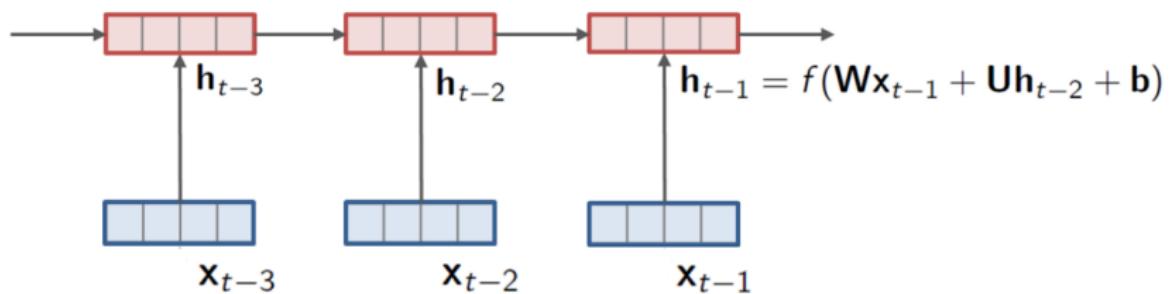
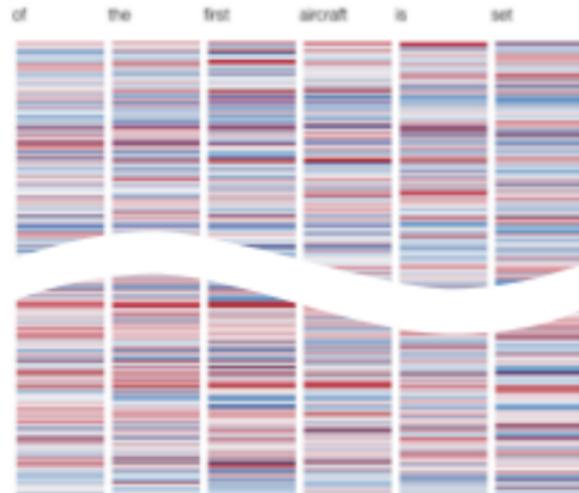


Layer 5



(?)

Vector-Space RNN Representation



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(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).

$$p(w_t | w_1, \dots, w_{t-1})$$

[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).

$$p(w_t | w_1, \dots, w_{t-1})$$

[LM Example]

Example 3: Seq2Seq Encoder

alphabet: all english words

corpus: Summarization

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

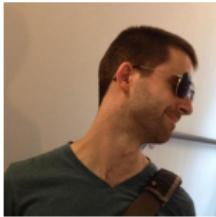
[Summarization Example]

This Talk

- 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)?

Seq2Seq Notation

- x ; source input
- \mathcal{V} ; vocabulary
- w_t ; random variable for the t -th target token with support \mathcal{V}
- $y_{1:T}$; ground-truth output
- $\hat{y}_{1:T}$; predicted output
- $p(w_{1:T} | x; \theta) = \prod_t p(w_t | w_{1:t-1}, x; \theta)$; model distribution

Seq2Seq Details

Train Objective: Given source-target pairs $(x, y_{1:T})$, minimize NLL of each word independently, conditioned on *gold* history $y_{1:t-1}$

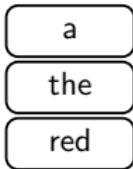
$$\mathcal{L}_{\text{NLL}}(\theta) = - \sum_t \log p(w_t = y_t | y_{1:t-1}, x; \theta)$$

Test Objective: Structured prediction

$$\hat{y}_{1:T} = \arg \max_{w_{1:T}} \sum_t \log p(w_t | w_{1:t-1}, x; \theta)$$

- Typical to approximate the arg max with beam-search

Beam Search ($K = 3$)



For $t = 1 \dots T$:

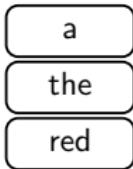
- For all k and for all possible output words w :

$$s(w, \hat{y}_{1:t-1}^{(k)}) \leftarrow \log p(\hat{y}_{1:t-1}^{(k)} | x) + \log p(w | \hat{y}_{1:t-1}^{(k)}, x)$$

- Update beam:

$$\hat{y}_{1:t}^{(1:K)} \leftarrow \text{K-arg max } s(w, \hat{y}_{1:t-1}^{(k)})$$

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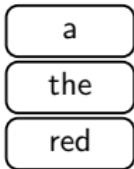
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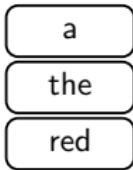
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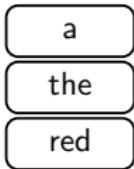
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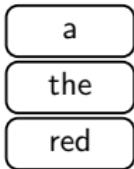
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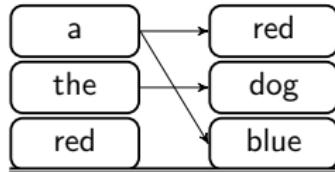
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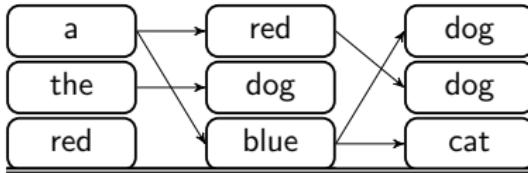
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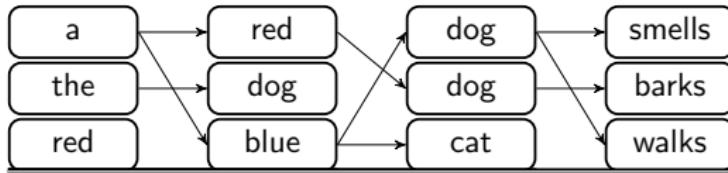
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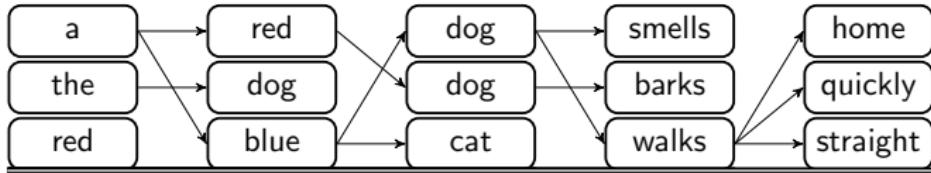
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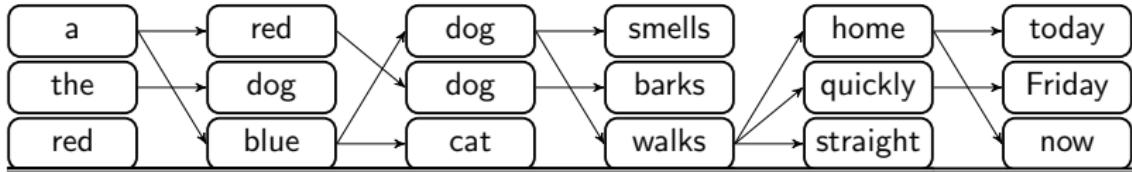
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Problem

How should we train sequence models?

Related Work

- Approaches to Exposure Bias, Label Bias:
 - Data as Demonstrator, Scheduled Sampling (Venkatraman et al., 2015; Bengio et al., 2015)
 - Globally Normalized Transition-Based Networks (Andor et al., 2016)
- RL-based approaches
 - MIXER (Ranzato et al., 2016)
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Issue #1: Train/Test Mismatch (cf., (Ranzato et al., 2016))

$$\text{NLL}(\theta) = - \sum_t \log p(w_t = y_t | y_{1:t-1}, x; \theta)$$

- (a) Training conditions on *true* history ("Exposure Bias")
- (b) Train with word-level NLL, but evaluate with BLEU-like metrics

Idea #1: Train with beam-search

- Use a loss that incorporates sequence-level costs

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BSO Idea #1: Use a loss that incorporates sequence-level costs

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

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Issue #2: Seq2Seq models next-word probabilities:

$$s(w, \hat{y}_{1:t-1}^{(k)}) \leftarrow \log p(\hat{y}_{1:t-1}^{(k)} | x) + \log p(w | \hat{y}_{1:t-1}^{(k)}, x)$$

- (a) Sequence score is sum of locally normalized word-scores; gives rise to “Label Bias” (Lafferty et al., 2001)
- (b) What if we want to train with sequence-level constraints?

Idea #2: Don't locally normalize

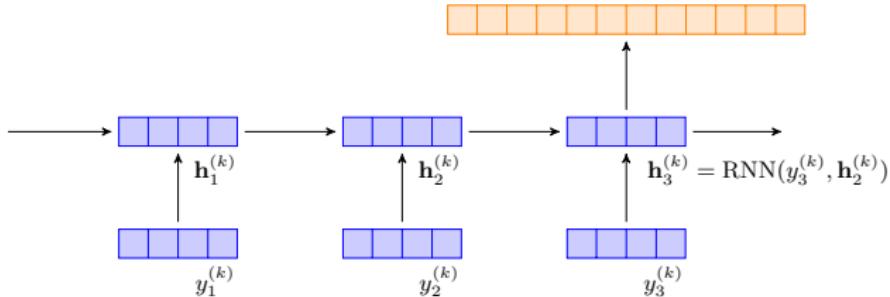
Issue #2: Seq2Seq models next-word probabilities:

$$s(w, \hat{y}_{1:t-1}^{(k)}) \leftarrow \log p(\hat{y}_{1:t-1}^{(k)} | x) + \log p(w | \hat{y}_{1:t-1}^{(k)}, x)$$

- (a) Sequence score is sum of locally normalized word-scores; gives rise to “Label Bias” (Lafferty et al., 2001)
- (b) What if we want to train with sequence-level constraints?

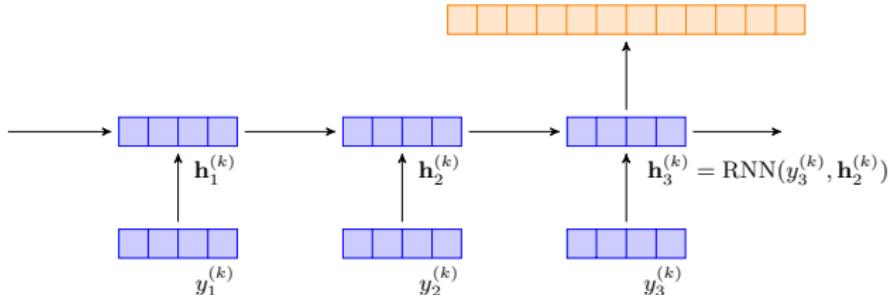
Idea #2: Don't locally normalize

BSO Idea #2: Don't locally normalize



$$s(w, \hat{y}_{1:t-1}^{(k)}) = \log p(\hat{y}_{1:t-1}^{(k)} | x) + \log \text{softmax}(\mathbf{W}_{out} \mathbf{h}_{t-1}^{(k)} + \mathbf{b}_{out})$$

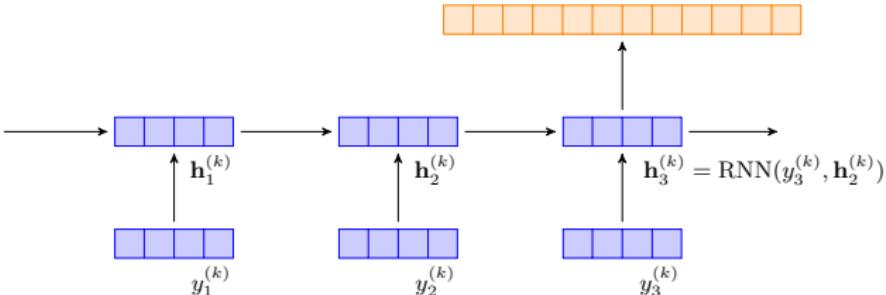
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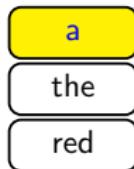


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- Can set $s(w, \hat{y}_{1:t-1}^{(k)}) = -\infty$ if $(w, \hat{y}_{1:t-1}^{(k)})$ violates a hard constraint

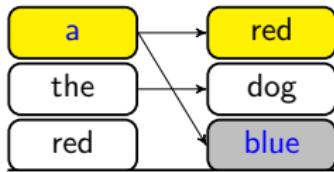
Beam Search Optimization



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

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

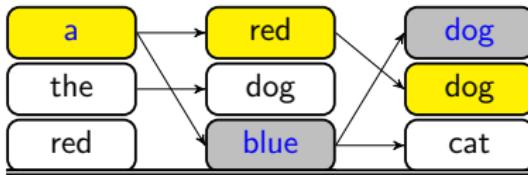
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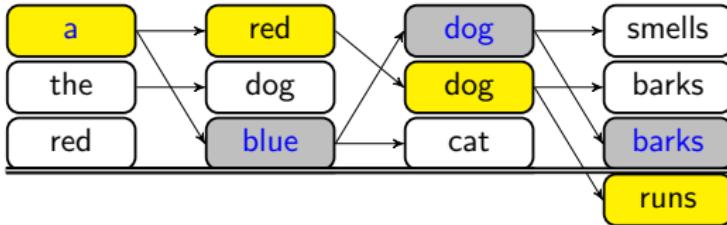
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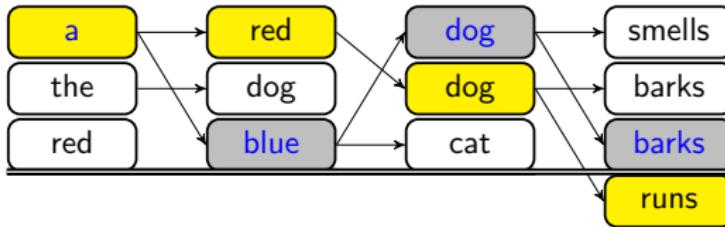
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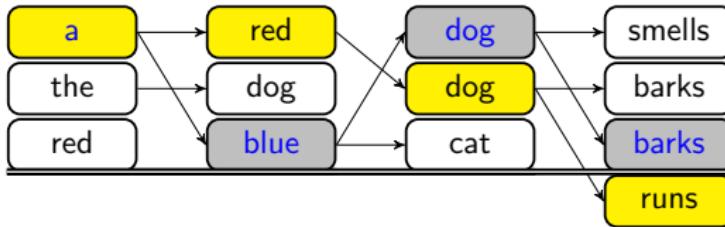


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- If no margin violation at $t - 1$, update beam as usual
- Otherwise, update beam with sequences prefixed by $y_{1:t-1}$

Beam Search Optimization

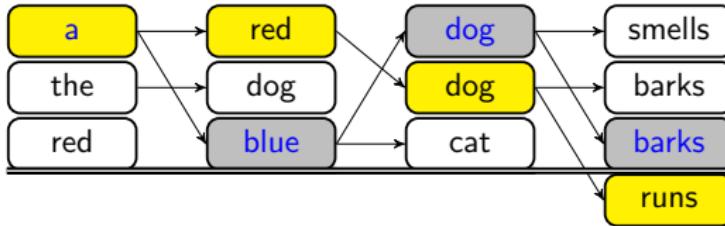


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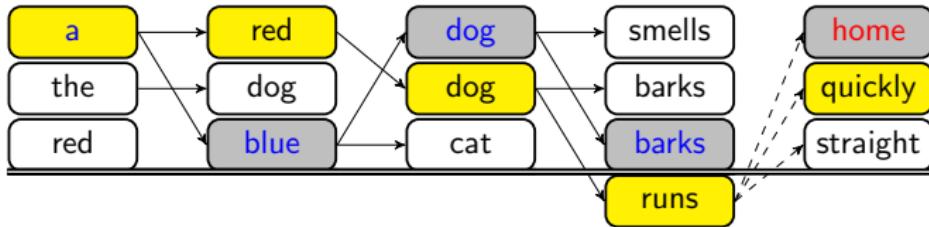


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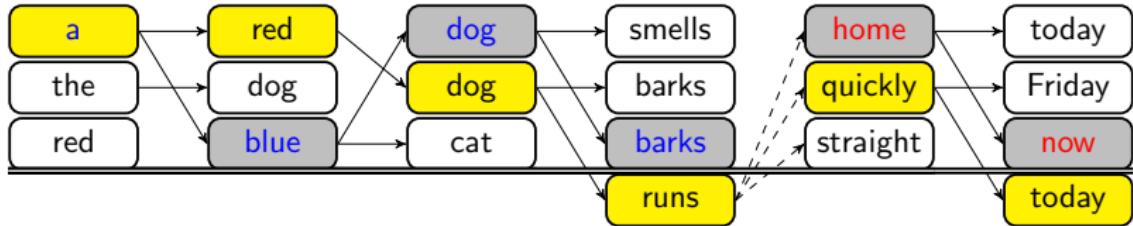


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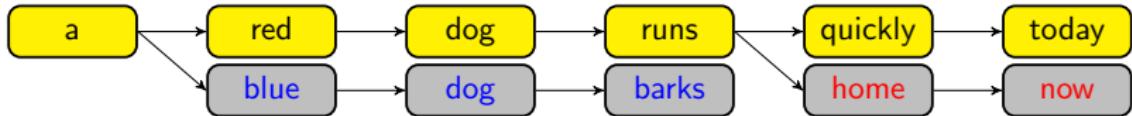
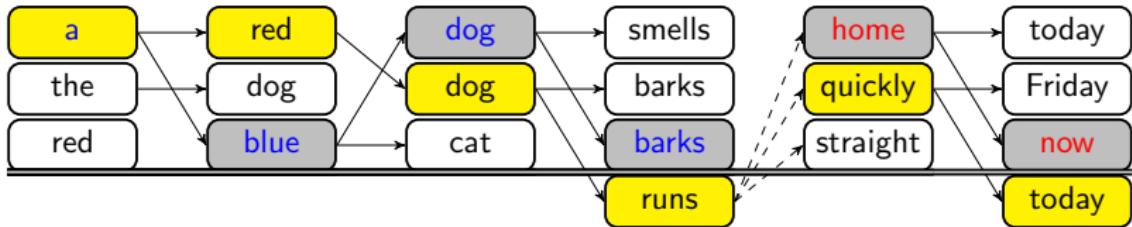


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Backpropagation over Structure



Experiments

- Word Ordering, Dependency Parsing, Machine Translation
- Uses LSTM encoders and decoders, attention, input feeding
- All models trained with Adagrad (Duchi et al., 2011)
- Pre-trained with NLL; K increased gradually
- “BSO” uses unconstrained search; “ConBSO” uses constraints

	$K_e = 1$	$K_e = 5$	$K_e = 10$
Word Ordering (BLEU)			
seq2seq	25.2	29.8	31.0
BSO	28.0	33.2	34.3
ConBSO	28.6	34.3	34.5
Dependency Parsing (UAS/LAS) ¹			
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
ConBSO	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	20.10	20.28
DAD	20.12	22.25	22.40
MIXER	20.73	21.81	21.83

¹Note Andor et al. (2016) have SOA, with 94.41/92.55.

This Talk

- 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)





Google unleashes deep learning tech on language with Neural ...

TechCrunch - Sep 27, 2016

Google has been working on a machine learning translation technique for years, and today is its official debut. The Google Neural Machine ...

Google Translate now converts Chinese into English with neural ...

VentureBeat - Sep 27, 2016

Google announces Neural Machine Translation

The Stack - Sep 28, 2016

Google announces Neural Machine Translation to improve Google ...

Highly Cited - ZDNet - Sep 27, 2016

Google is using Neural Networks for Chinese to English machine ...

Opinion - Firstpost - Sep 28, 2016

Google announces neural network to improve machine translation

In-Depth - Seeking Alpha - Sep 27, 2016



ZDNet



VentureBeat



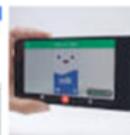
The Stack



Geektime



Geektime



Science Mag...

[View all](#)

SYSTRAN: 1st software provider to launch a Neural Machine ...

GlobeNewswire (press release) - Oct 17, 2016

In December, SYSTRAN will communicate the feedback received on Pure Neural™ Machine Translation, its roadmap and time to market plan ...

Iconic Integrates Custom Neural Machine Translation Into ...

Slator (press release) (subscription) - Oct 6, 2016

Dublin – October 6, 2016 – Iconic Translation Machines (Iconic), a leading Irish machine translation (MT) software and solutions provider, today ...



Iconic
Translation Machines

Neural Machine Translation

Excellent results on many language pairs, but need large models

- Original seq2seq paper (Sutskever et al., 2014a): 4-layers/1000 units
- Deep Residual RNNs (Zhou et al., 2016) : 16-layers/512 units
- Google's NMT system (Wu et al., 2016): 8-layers/1024 units

Beam search + ensemble on top

⇒ Deployment is challenging!

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Related Work: Compressing Deep Models

- **Pruning:** Prune weights based on importance criterion (LeCun et al., 1990; Han et al., 2016; See 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; Kuncoro et al., 2016). (Sometimes called “dark knowledge”)

Knowledge Distillation (Bucila et al., 2006; Hinton et al., 2015)

- Train a *larger teacher* model first to obtain teacher distribution $q(\cdot)$
- Train a *smaller student* model $p(\cdot)$ to mimic the teacher

Word-Level Knowledge Distillation

Teacher distribution: $q(w_t | y_{1:t-1})$

$$\mathcal{L}_{\text{NLL}} = - \sum_t \sum_{k \in \mathcal{V}} \mathbb{1}\{y_t = k\} \log p(w_t = k | y_{1:t-1}; \theta)$$

$$\mathcal{L}_{\text{WORD-KD}} = - \sum_t \sum_{k \in \mathcal{V}} q(w_t = k | y_{1:t-1}) \log p(w_t = k | y_{1:t-1}; \theta)$$

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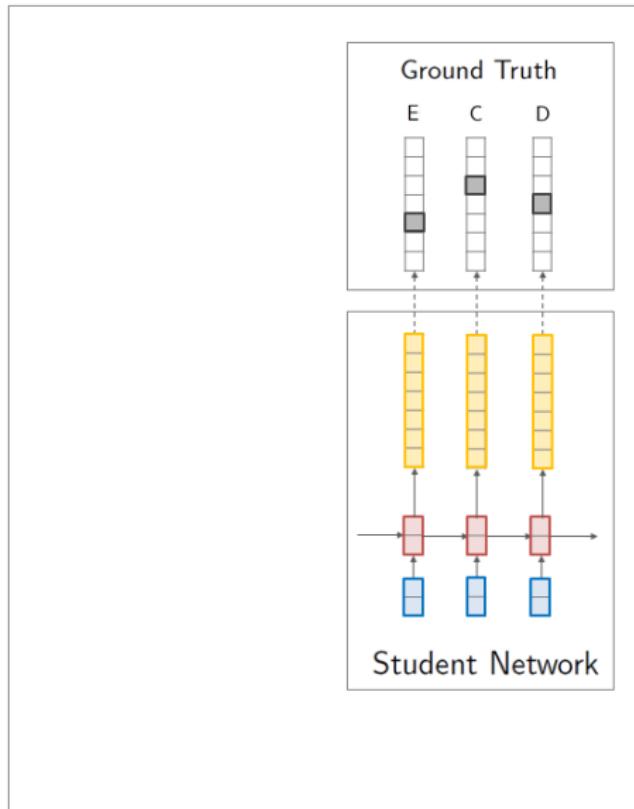
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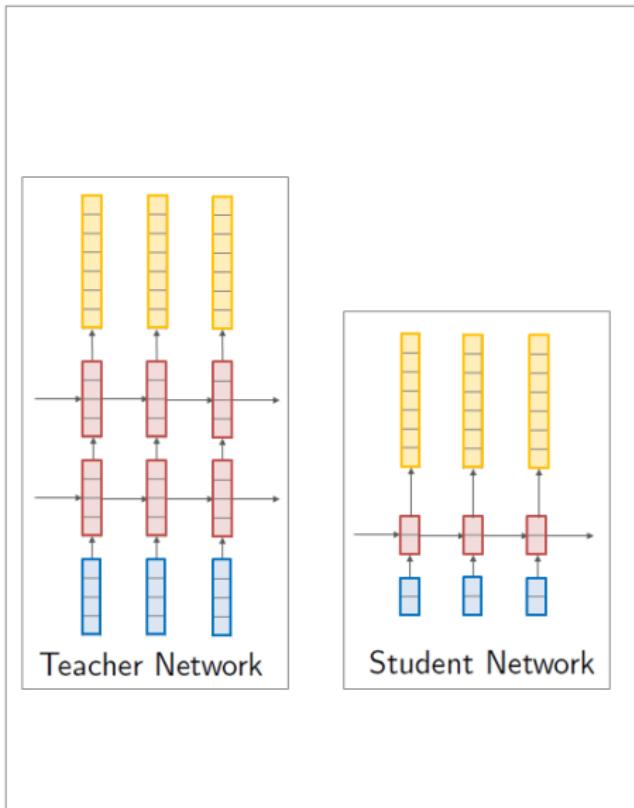
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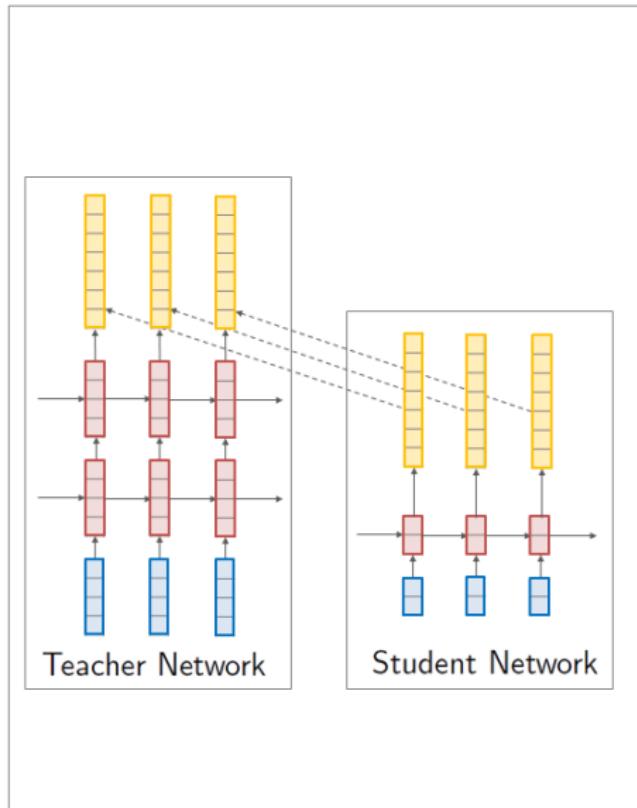
No Knowledge Distillation



Word-Level Knowledge Distillation



Word-Level Knowledge Distillation



Word-Level Knowledge Distillation Results

English → German (WMT 2014)

Model	BLEU
4 × 1000 Teacher	19.5
2 × 500 Baseline (No-KD)	17.6
2 × 500 Student (Word-KD)	17.7
2 × 300 Baseline (No-KD)	16.9
2 × 300 Student (Word-KD)	17.6

This Work: Sequence-Level Knowledge Distillation

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Instead minimize cross-entropy, between q and p implied sequence-distributions

$$\mathcal{L}_{\text{SEQ-KD}} = - \sum_{w_{1:T} \in \mathcal{V}^T} q(w_{1:T} \mid x) \log p(w_{1:T} \mid x)$$

Sum over an exponentially-sized set \mathcal{V}^T .

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Sequence-Level Knowledge Distillation

Approximate $q(w | x)$ with mode

$$q(w_{1:T} | x) \approx \mathbb{1}\{\arg \max_{w_{1:T}} q(w_{1:T} | x)\}$$

Approximate mode with beam search

$$\hat{y} \approx \arg \max_{w_{1:T}} q(w_{1:T} | x)$$

Simple model: train the student model on \hat{y} with NLL

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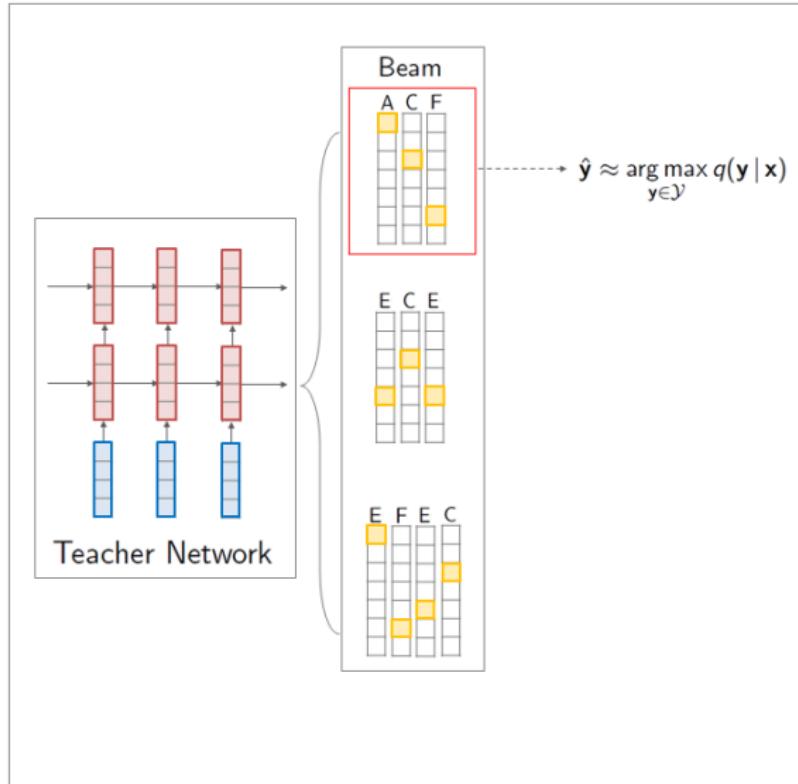
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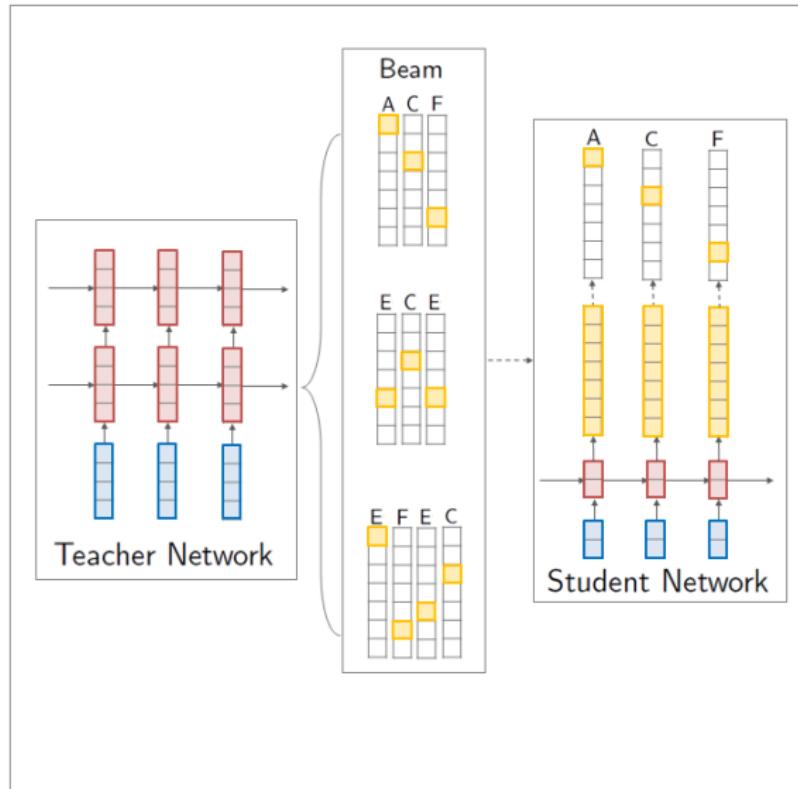
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Sequence-Level Knowledge Distillation



Sequence-Level Knowledge Distillation



Sequence-Level Interpolation

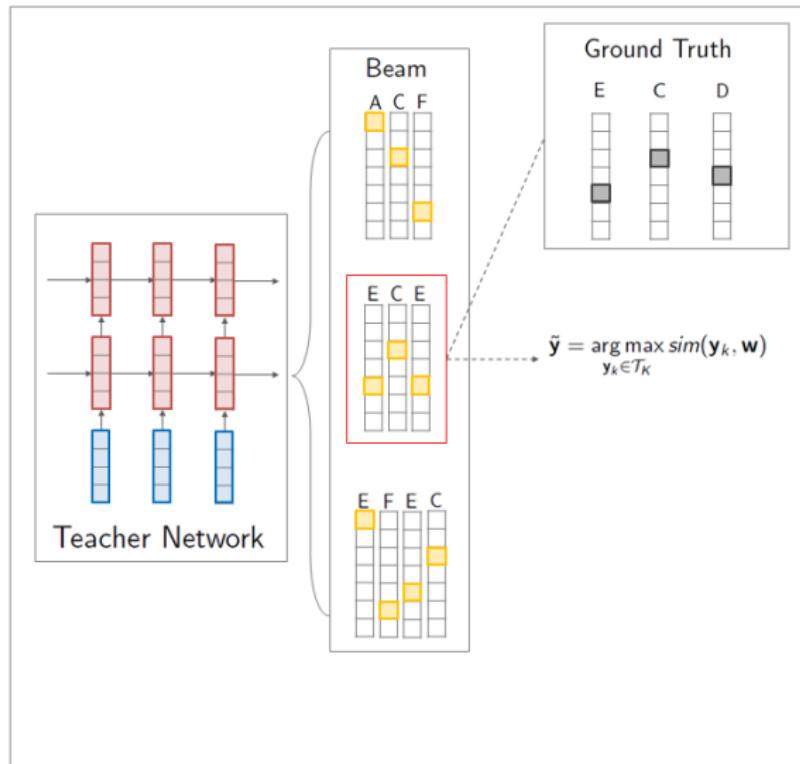
Word-level knowledge distillation

$$\mathcal{L} = \alpha \mathcal{L}_{\text{WORD-KD}} + (1 - \alpha) \mathcal{L}_{\text{NLL}}$$

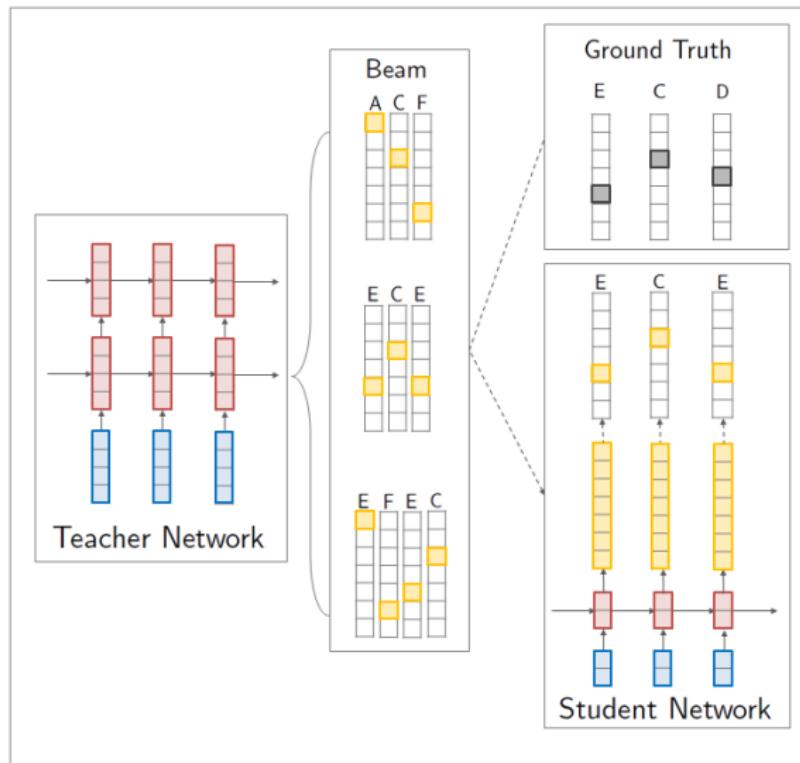
Training the student towards the mixture of teacher/data distributions.

How can we incorporate ground truth data at the sequence-level?

Sequence-Level Interpolation



Sequence-Level Interpolation



Experiments on English → German (WMT 2014)

- Word-KD: Word-level Knowledge Distillation
- Seq-KD: Sequence-level Knowledge Distillation with beam size $K = 5$
- Seq-Inter: Sequence-level Interpolation with beam size $K = 35$.
Fine-tune from pretrained Seq-KD (or baseline) model with smaller learning rate.

Results: English → German (WMT 2014)

Model	BLEU _{K=1}	$\Delta_{K=1}$	BLEU _{K=5}	$\Delta_{K=5}$	PPL	$p(\hat{\mathbf{y}})$
4 × 1000						
Teacher	17.7	—	19.5	—	6.7	1.3%
2 × 500						
Student	14.7	—	17.6	—	8.2	0.9%

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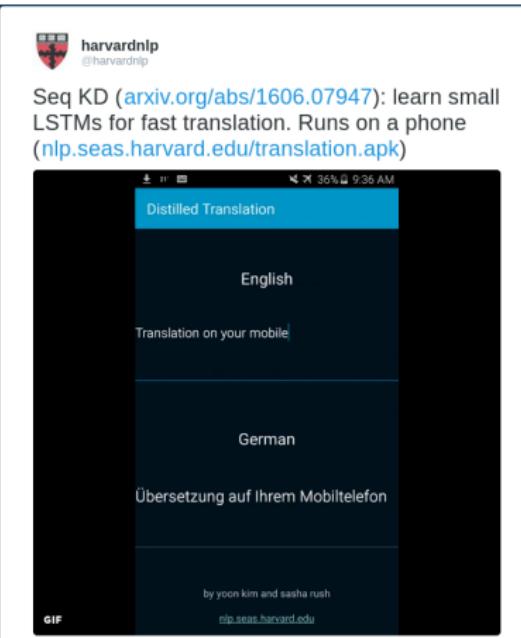
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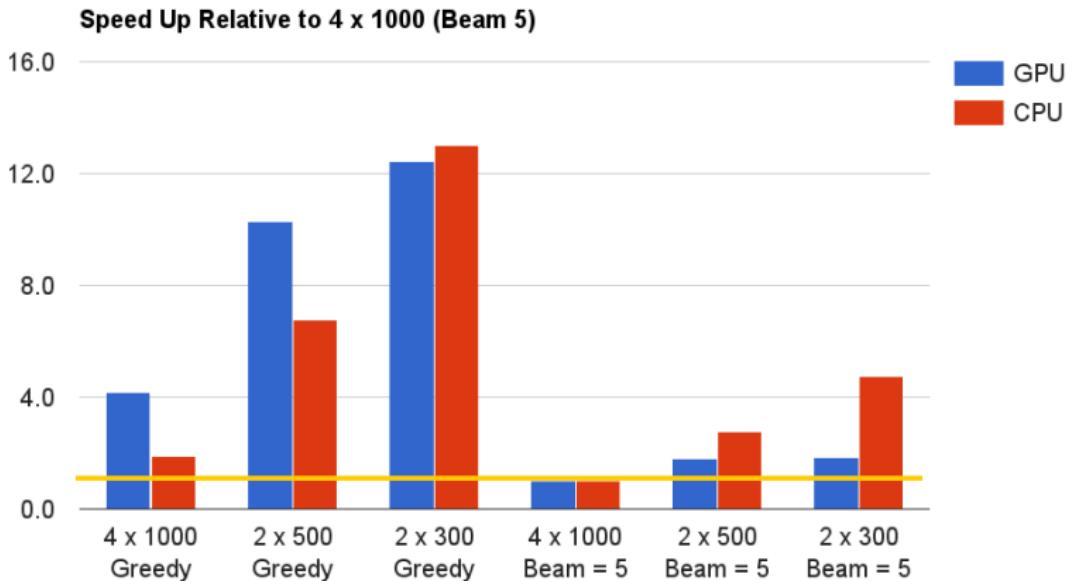
Many more experiments (different language pairs, combining configurations, different sizes etc.) in paper

An Application



[App]

Decoding Speed



Combining Knowledge Distillation and Pruning

Number of parameters still large for student models (mostly due to word embedding tables)

- 4×1000 : 221 million
- 2×500 : 84 million
- 2×300 : 49 million

Prune student model: Same methodology as See et al. (2016)

- Prune $x\%$ of weights based on absolute value
- Fine-tune pruned model (crucial!)

Combining Knowledge Distillation and Pruning

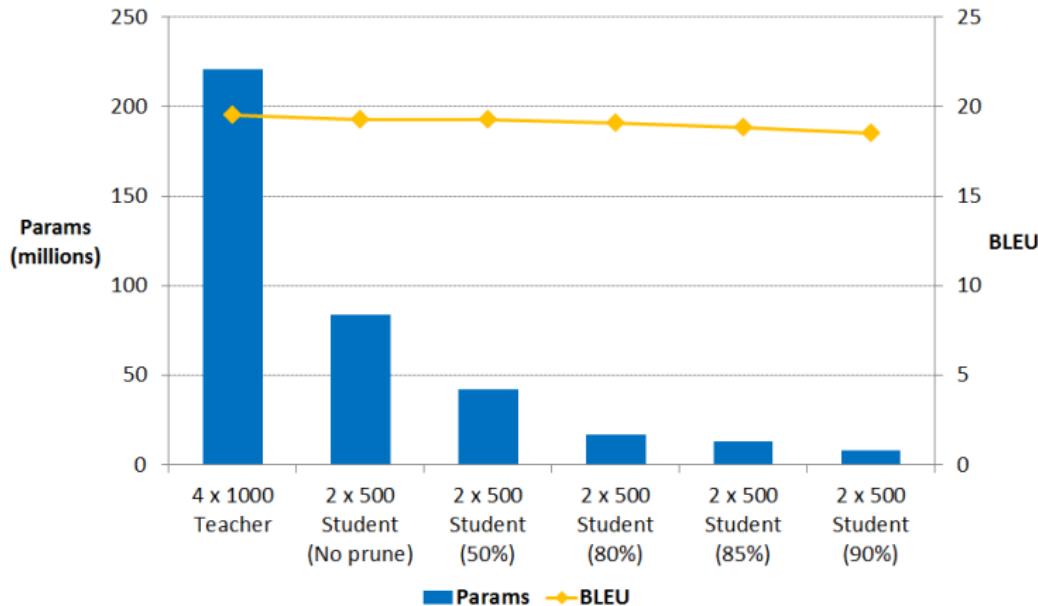
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Combining Knowledge Distillation and Pruning



Conclusion: Other work

- How can we **interpret** these learned hidden representations?
 - Lei et al. (2016) other methods for interpreting decisions (as opposed to states).
- How should we **train** these style of models?
 - Lee et al. (2016) CCG parsing (backprop through search is a thing now/again)
- How can we **shrink** these models for practical applications?
 - Live deployment: (greedy) student outperforms (beam search) teacher. (Crego et al., 2016)
 - Can compress an ensemble into a single model (Kuncoro et al., 2016)

Thanks!

References I

- Andor, D., Alberti, C., Weiss, D., Severyn, A., Presta, A., Ganchev, K., Petrov, S., and Collins, M. (2016). Globally Normalized Transition-Based Neural Networks. *arXiv*, cs.CL.
- 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. In *Advances in Neural Information Processing Systems*, pages 1171–1179.

References II

- Bucila, C., Caruana, R., and Niculescu-Mizil, A. (2006). Model Compression. In *Proceedings of KDD*.
- Chan, W., Jaitly, N., Le, Q., and Vinyals, O. (2015). Listen, Attend and Spell. *arXiv:1508.01211*.
- Cheng, J. and Lapata, M. (2016). Neural summarization by extracting sentences and words. *arXiv preprint arXiv:1603.07252*.
- Cho, K., van Merriënboer, 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*.
- Crego, J., Kim, J., and Senellart, J. (2016). Systran's pure neural machine translation system. *arXiv preprint arXiv:1602.06023*.

References III

- 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.
- Duchi, J., Hazan, E., and Singer, Y. (2011). Adaptive Subgradient Methods for Online Learning and Stochastic Optimization. *The Journal of Machine Learning Research*, 12:2121–2159.
- Gillick, D., Brunk, C., Vinyals, O., and Subramanya, A. (2016). Multilingual Language Processing from Bytes. In *Proceedings of NAACL*.

References IV

- 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., Kočiský, 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.
- Karpathy, A., Johnson, J., and Li, F.-F. (2015). Visualizing and understanding recurrent networks. *ICLR Workshops*.
- Karpathy, A. and Li, F.-F. (2015). Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3128–3137.

References V

- Kim, Y. and Rush, A. M. (2016). Sequence-Level Knowledge Distillation.
- Kuncoro, A., Ballesteros, M., Kong, L., Dyer, C., and Smith, N. A. (2016). Distilling an Ensemble of Greedy Dependency Parsers into One MST Parser. In *Proceedings of EMNLP*.
- Lafferty, J. D., McCallum, A., and Pereira, F. C. N. (2001). Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In *Proceedings of the Eighteenth International Conference on Machine Learning (ICML 2001)*, pages 282–289.
- LeCun, Y., Denker, J. S., and Solla, S. A. (1990). Optimal Brain Damage. In *Proceedings of NIPS*.
- Luong, M.-T., Pham, H., and Manning, C. D. (2015). Effective Approaches to Attention-based Neural Machine Translation. In *EMNLP*, number September, page 11.

References VI

- Mou, L., Yan, R., Li, G., Zhang, L., and Jin, Z. (2015). Backward and forward language modeling for constrained sentence generation. *arXiv preprint arXiv:1512.06612*.
- 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 VII

- Serban, I. V., Sordoni, A., Bengio, Y., Courville, A., and Pineau, J. (2016). Building End-to-End Dialogue Systems Using Generative Hierarchical Neural Network Models. In *Proceedings of AAAI*.
- Srivastava, N., Mansimov, E., and Salakhutdinov, R. (2015). Unsupervised Learning of Video Representations using LSTMs. *Proceedings of ICML*.
- Strobelt, H., Gehrman, 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. (2014a). Sequence to Sequence Learning with Neural Networks.
- Sutskever, I., Vinyals, O., and Le, Q. V. (2014b). Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems*, pages 3104–3112.
- Takase, S., Suzuki, J., Okazaki, N., Hirao, T., and Nagata, M. (2016). Neural headline generation on abstract meaning representation.

References VIII

- Toutanova, K., Tran, K. M., and Amershi, S. (2016). A dataset and evaluation metrics for abstractive compression of sentences and short paragraphs.
- Venkatraman, A., Boots, B., Hebert, M., and Bagnell, J. (2015). DATA AS DEMONSTRATOR with Applications to System Identification.
pdfs.semanticscholar.org.
- 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*.
- Vinyals, O., Toshev, A., Bengio, S., and Erhan, D. (2015). Show and Tell: A Neural Image Caption Generator. In *Proceedings of CVPR*.
- Wang, S., Han, S., and Rush, A. M. (2016a). Headliner.
Computation+Journalism.

References IX

- Wang, T., Chen, P., Amaral, K., and Qiang, J. (2016b). An experimental study of lstm encoder-decoder model for text simplification. *arXiv preprint arXiv:1609.03663*.
- Wiseman, S. and Rush, A. M. (2016). Sequence-to-Sequence Learning as Beam-Search Optimization.
- Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., Krikun, M., Cao, Y., Gao, Q., Macherey, K., Klingner, J., Shah, A., Johnson, M., Liu, X., Kaiser, L., Gouws, S., Kato, Y., Kudo, T., Kazawa, H., Stevens, K., Kurian, G., Patil, N., Wang, W., Young, C., Smith, J., Riesa, J., Rudnick, A., Vinyals, O., Corrado, G., Hughes, M., and Dean, J. (2016). Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation. *arXiv:1606.09.08144*.

References X

- 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*.
- Zhou, J., Cao, Y., Wang, X., Li, P., and Xu, W. (2016). Deep Recurrent Models with Fast-Forward Connections for Neural Machine Translation. In *Proceedings of TACL*.