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)

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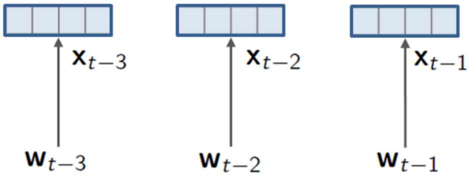
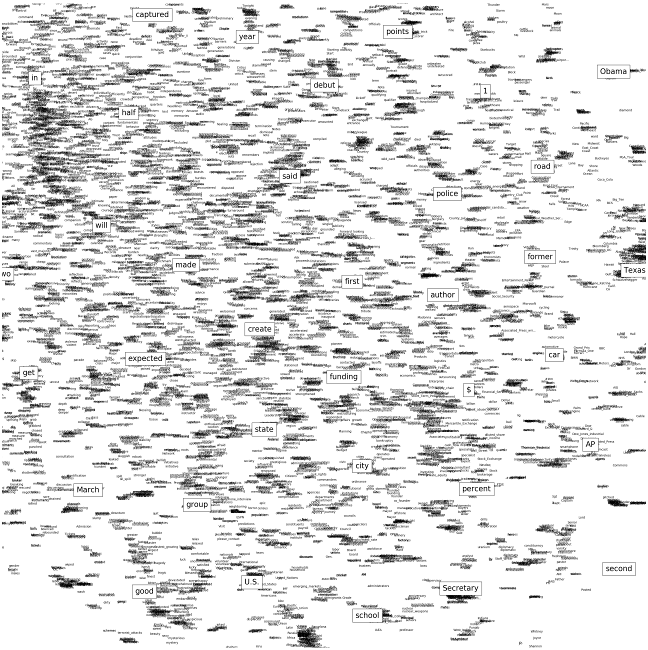
Seq2Seq Neural Network Toolbox

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

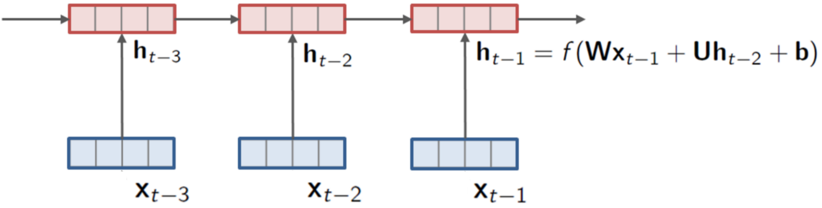
Embeddings sparse features $\Rightarrow$ dense features



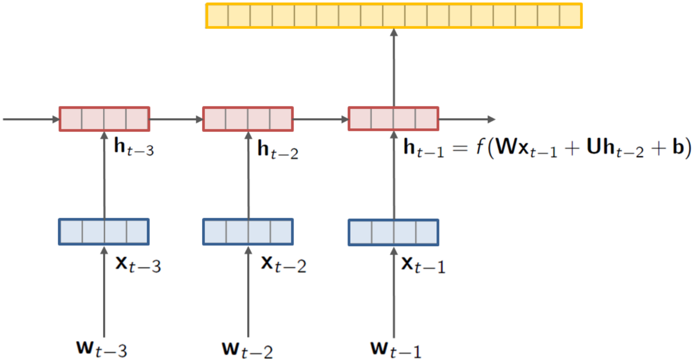


[Words Vectors]

RNNs/LSTMs feature sequences $\Rightarrow$ dense features



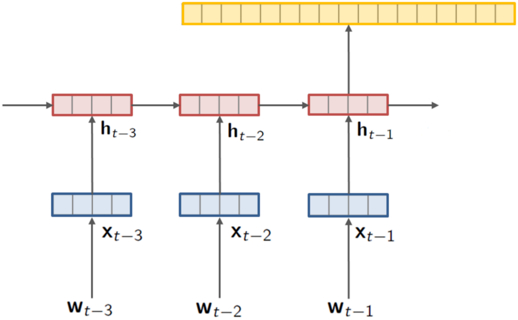
LM/Softmax dense features $\Rightarrow$ discrete predictions



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

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

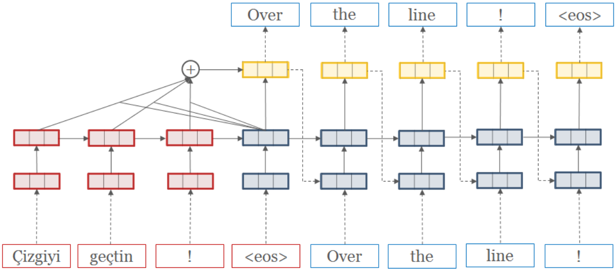
Contextual Language Model / “seq2seq”



- 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

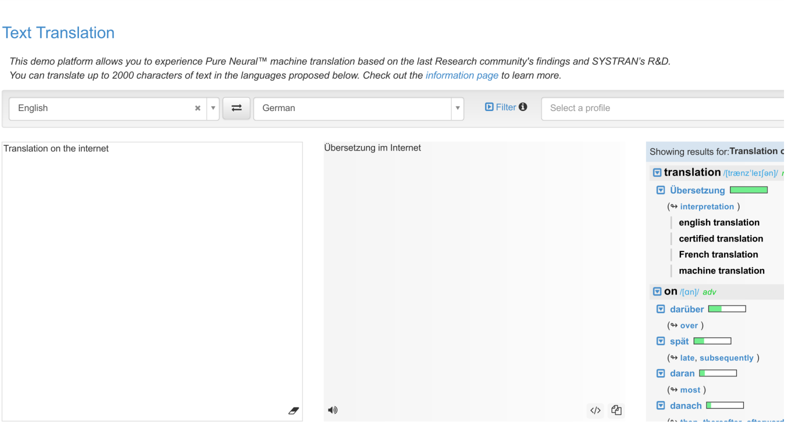


- Different encoders, attention mechanisms, input feeding, ...
- Almost all models use LSTMs or other gated RNNs
- Large multi-layer networks necessary for good performance.
  - 4 layer, 1000 hidden dims is common for MT

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)



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)

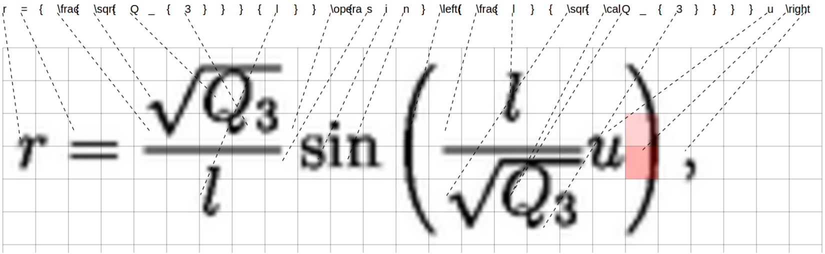
There is no a doubt, tracking systems has brought many benefits in this information age .

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)



[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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- How can we **interpret** these learned hidden representations?

LSTMVis lstm.seas.harvard.edu

(Strobelt et al., 2016)

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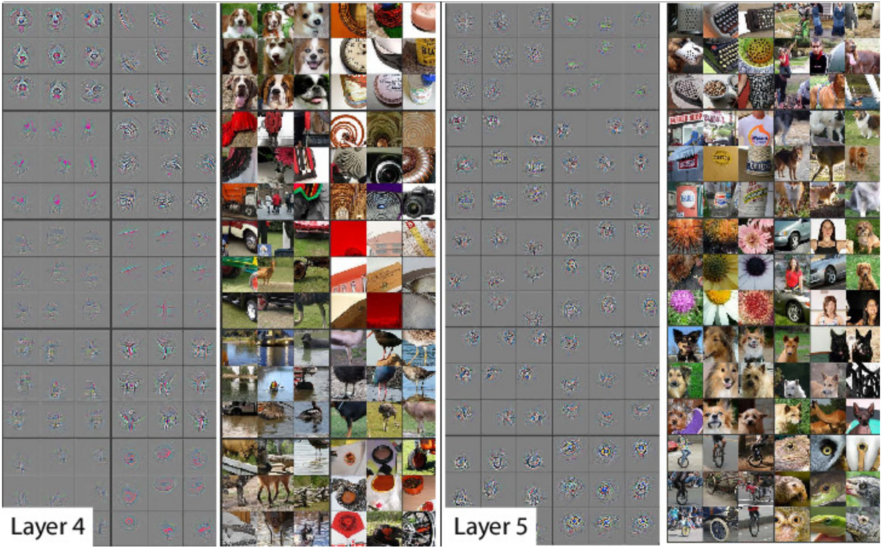
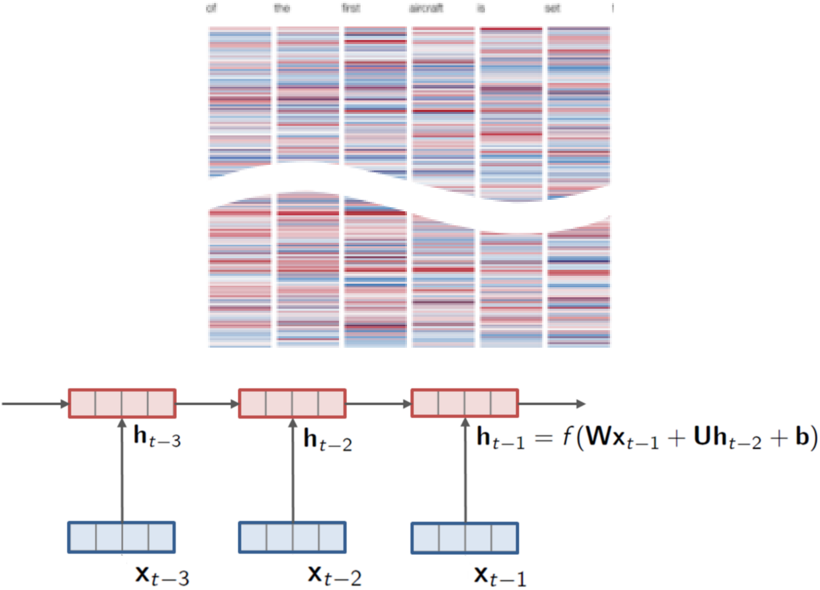
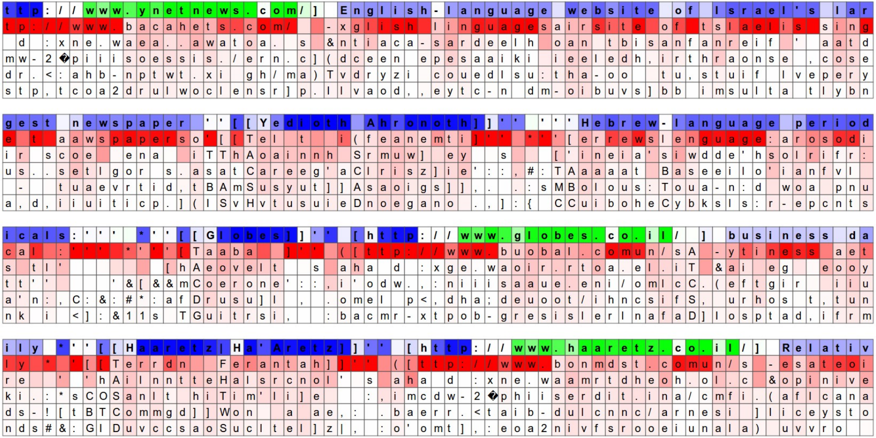

Layer 4
Layer 5

(?)

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).

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

[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).

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

[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 $y_{1:t-1}$

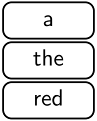
$$\mathcal{L}_{\text{NLL}}(\theta) = -\sum_{t} \log p(w_t = y_t | y_{1:t-1}, x; \theta)$$

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:

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

- Update beam:

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

Beam Search $(K = 3)$

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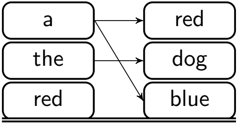

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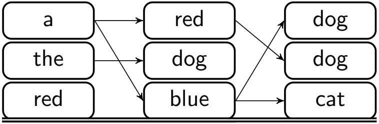

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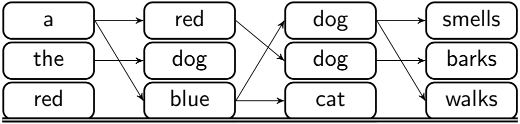

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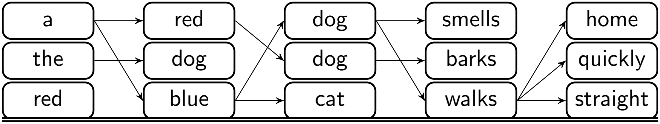

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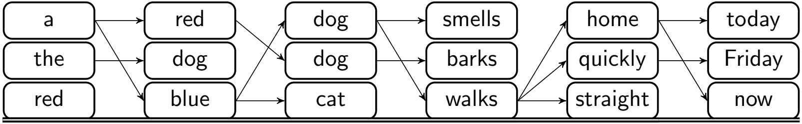

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Problem

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))

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

(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

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

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

- $y_{1:t}$ is the gold prefix; $\hat{y}_{1:t}^{(K)}$ is the K'th prefix on the beam
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Issue #2: Seq2Seq models next-word probabilities:

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(a) Sequence score is sum of locally normalized word-scores; gives rise to "Label Bias" (Lafferty et al., 2001)

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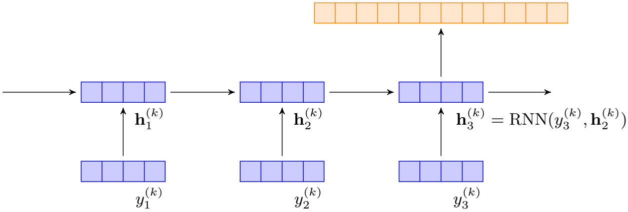

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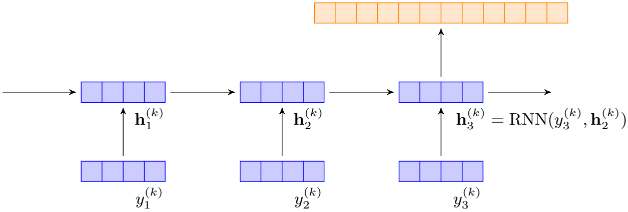

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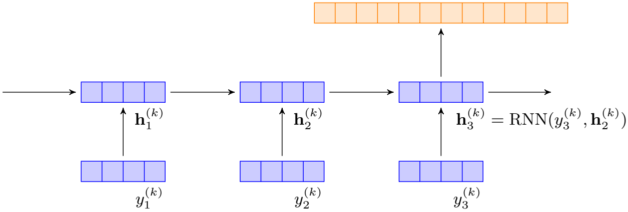

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$$= \mathbf{W}_{out}\,\mathbf{h}_{t-1}^{(k)} + \mathbf{b}_{out}$$

- 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

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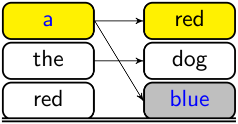
- Color Gold: target sequence y
- Color Gray: violating sequence $\hat{y}^{(K)}$

Beam Search Optimization



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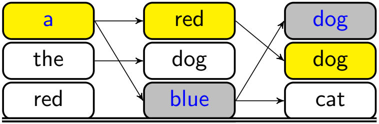

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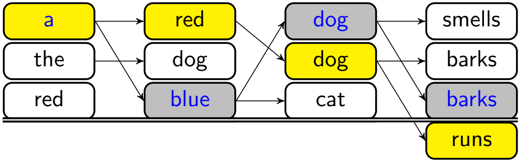
Beam Search Optimization



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

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

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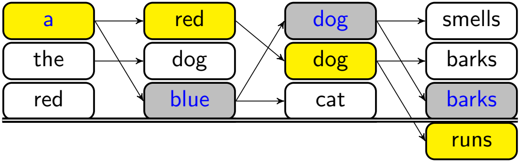

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LaSO (Daumé III and Marcu, 2005):

- If no margin violation at $t-1$, update beam as usual
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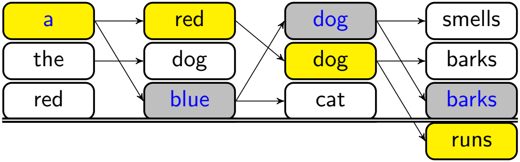

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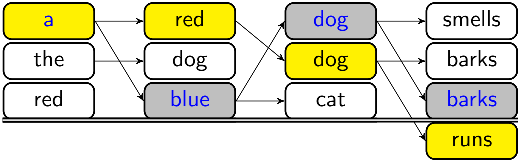

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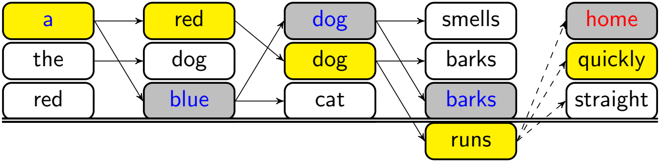

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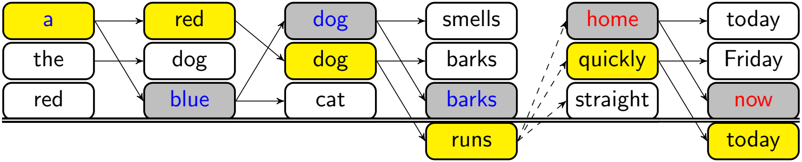

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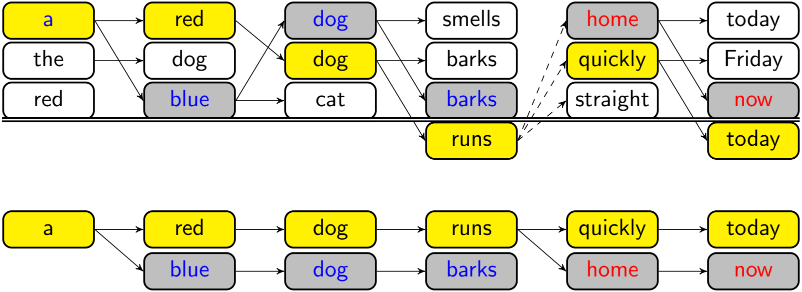
Backpropagation over Structure



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

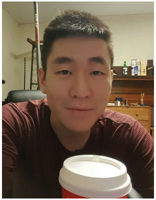
[1] Note Andor et al. (2016) have SOA, with 94.41/92.55.

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

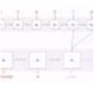
Google is using **Neural** Networks for Chinese to English **machine** ...
Opinion - Firstpost - Sep 28, 2016

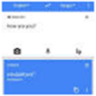
Google announces **neural** network to improve **machine translation**
In-Depth - Seeking Alpha - Sep 27, 2016


ZDNet


VentureBeat


The Stack


Geektime


Ubergizmo


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** TM **Machine Translation**, its roadmap and time to market plan ...

Iconic

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 ...

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

$\Longrightarrow$ Deployment is challenging!

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$\Longrightarrow$ Deployment is challenging!

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: $q(w_t \mid y_{1:t-1})$

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

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

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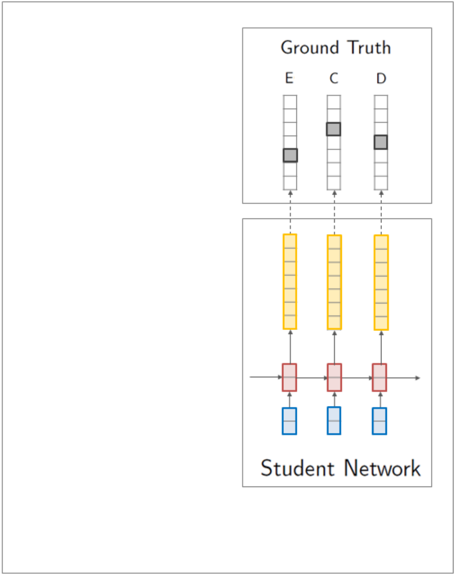
No Knowledge Distillation



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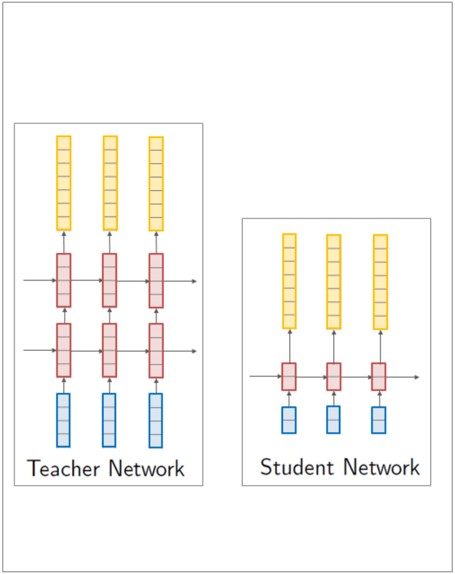

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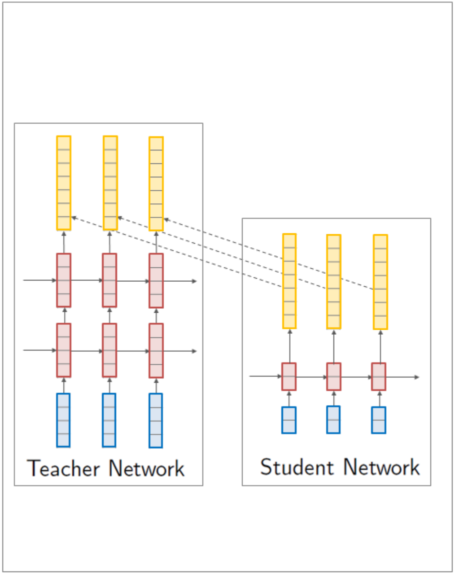

Word-Level Knowledge Distillation Results

English $\rightarrow$ 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

$$\mathcal{L}_{\mathsf{NLL}} = -\sum_{t}\sum_{k\in\mathcal{V}} \mathbb{1}\{y_t = k\} \log p(w_t = k \mid y_{1:t-1})$$

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

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

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

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

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

Sequence-Level Knowledge Distillation

Approximate $q(w \mid x)$ with mode

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

Approximate mode with beam search

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

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

Sequence-Level Knowledge Distillation

Approximate $q(w \,|\, x)$ with mode

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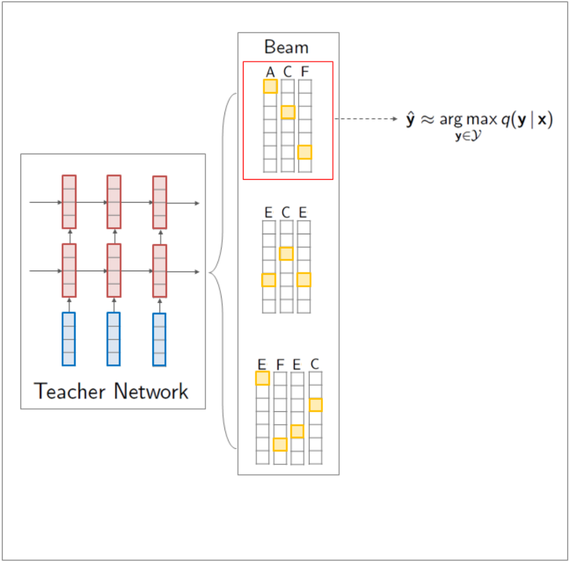

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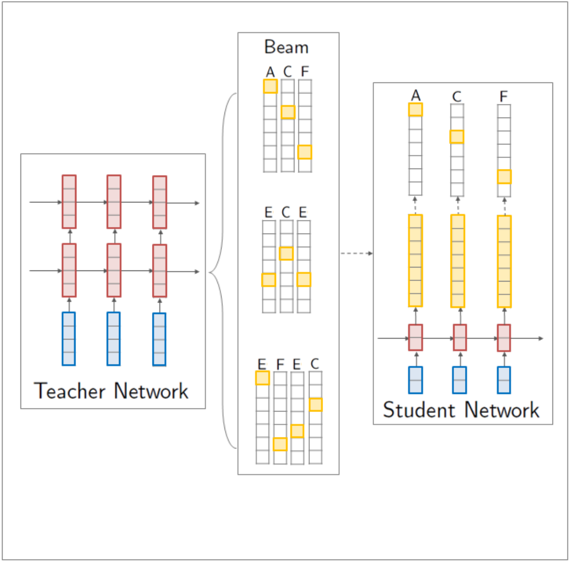


Sequence-Level Interpolation

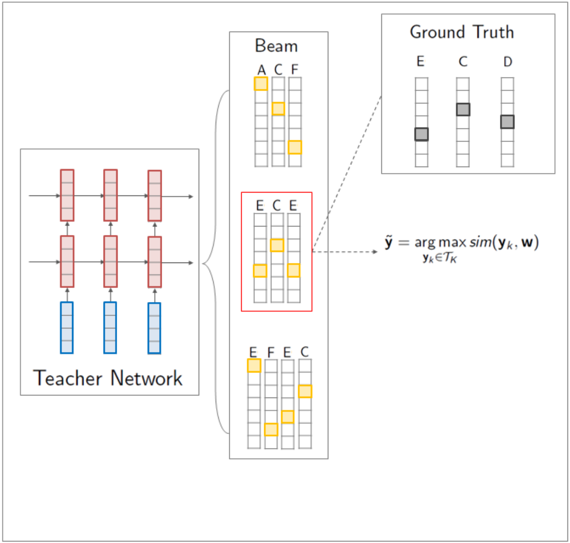
Word-level knowledge distillation

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

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

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

Sequence-Level Interpolation



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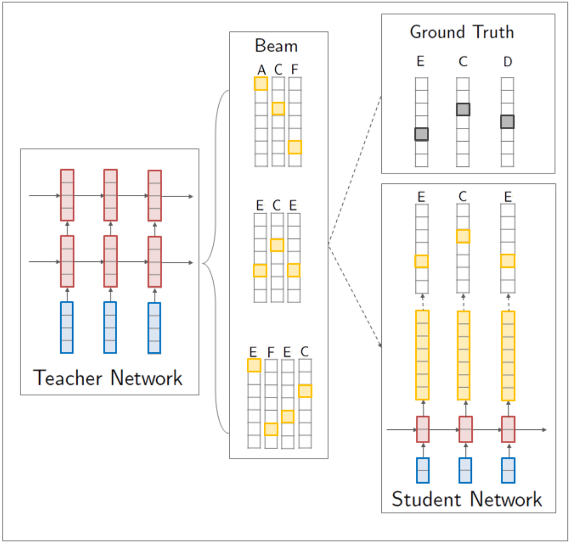

Experiments on English $\rightarrow$ German (WMT 2014)

- 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 $\rightarrow$ 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%

Results: English $\rightarrow$ German (WMT 2014)

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Word-KD	15.4	+0.7	17.7	+0.1	8.0	1.0%

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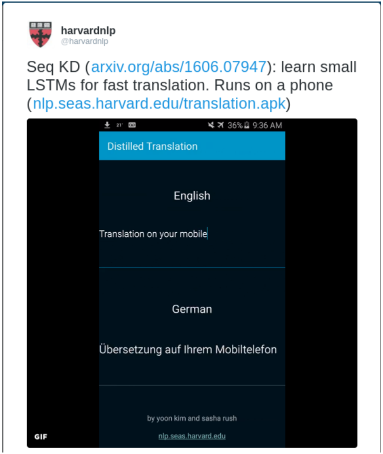
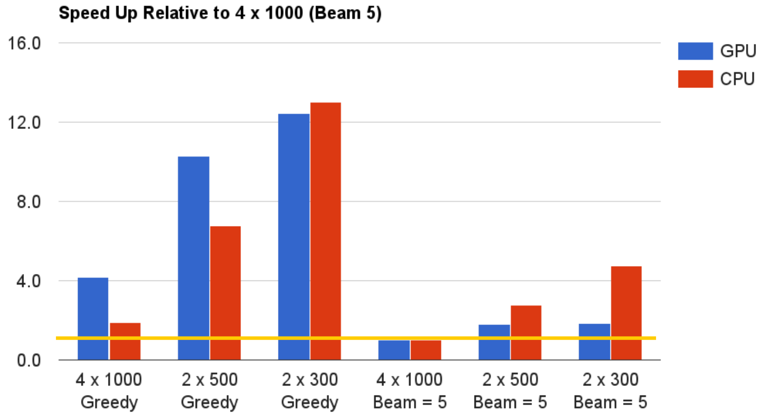
Many more experiments (different language pairs, combining configurations, different sizes etc.) in paper

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!)

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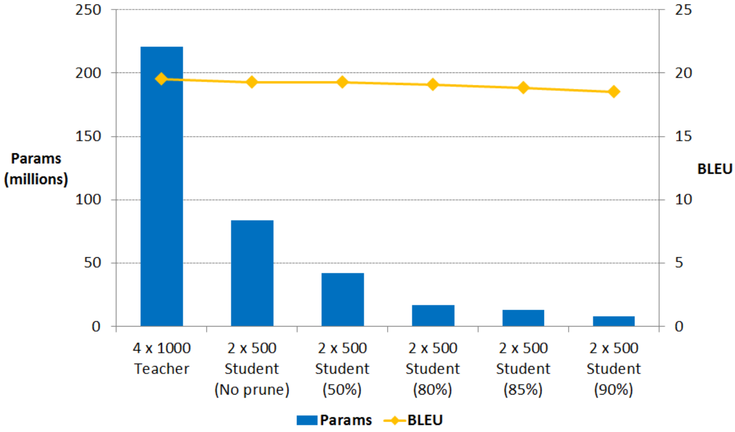
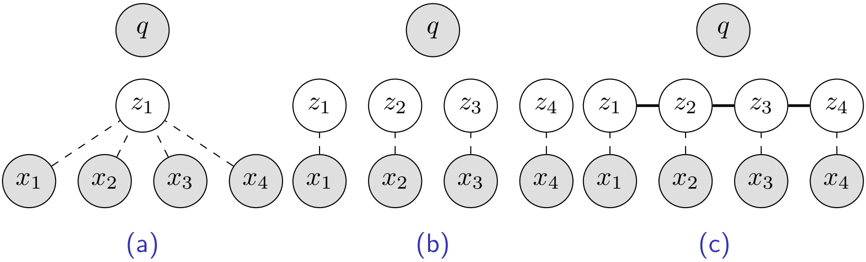


Conclusion: Other work

- 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)

Coming Work

- Structured Attention Networks (Kim et al 2016)



Thanks!

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