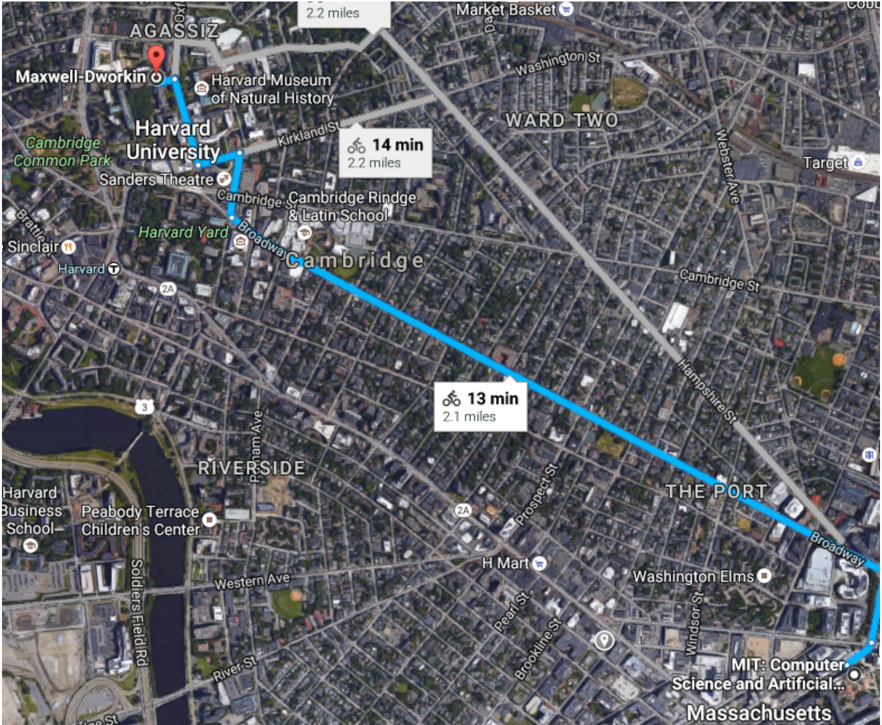
Interpreting, Training, and Distilling Seq2Seq Models

Alexander Rush (@harvardnlp)

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

at



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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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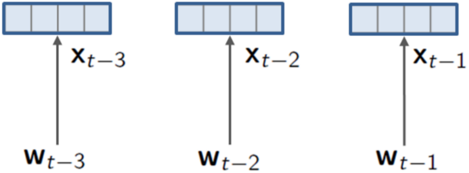
What's ML aspects have defined NLP problems?

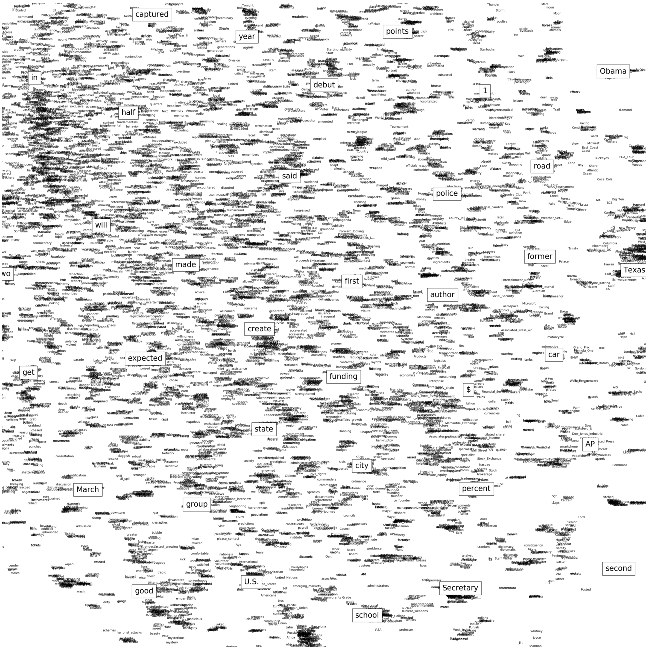
1. Large, discrete input state spaces.
   - Vocabulary sizes in $10,000 - 100,000$
2. Long-term dependencies
   - *Sasha is giving a talk today at MIT, ..., he is excited.*
3. Variable-length output spaces
   - e.g. sentences, documents, conversations

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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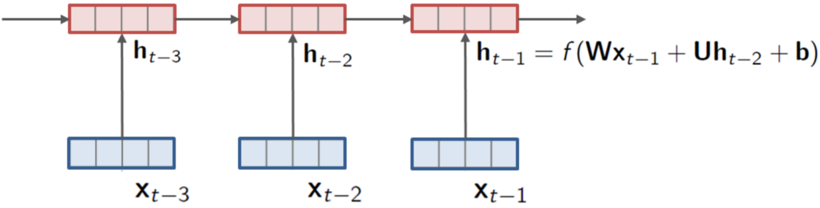
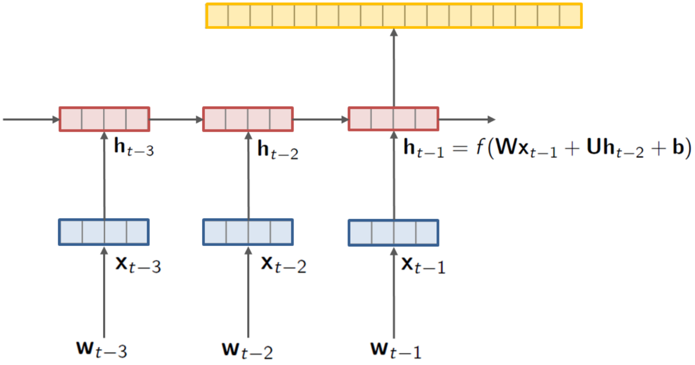
RNNs/LSTMs feature sequences $\Rightarrow$ dense features



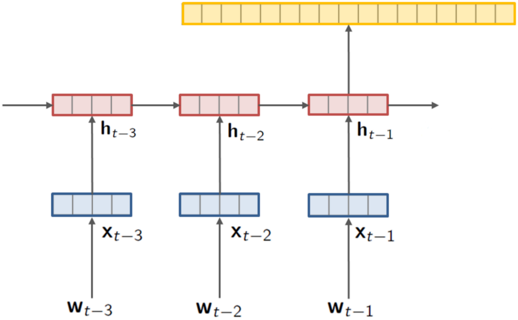
LM/Softmax   dense features $\Rightarrow$ discrete predictions



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

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

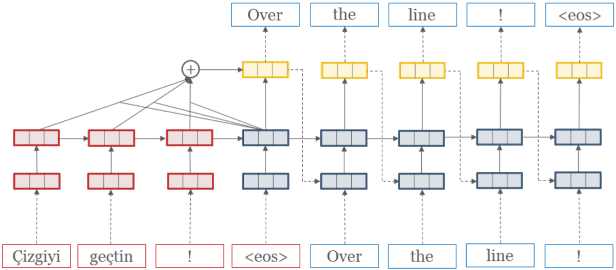
Contextual Language Model / “seq2seq”



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

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

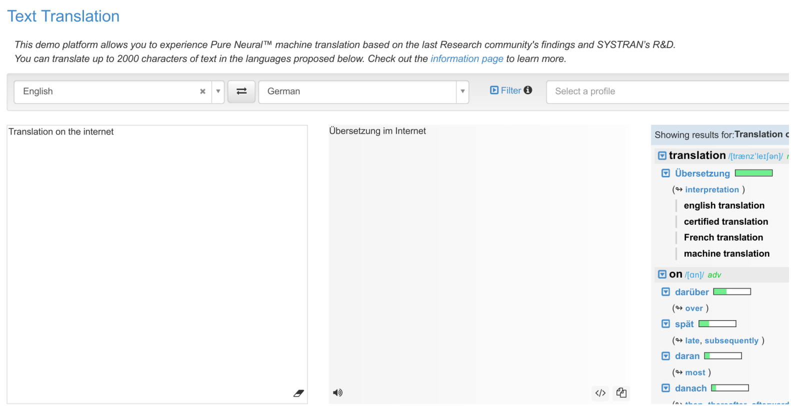
Actual Seq2Seq / Encoder-Decoder / Attention-Based Models



- 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-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)

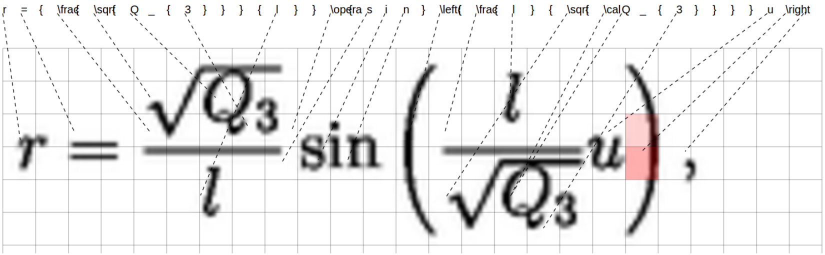
There is no a doubt, tracking systems has brought many benefits in this information age .

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]

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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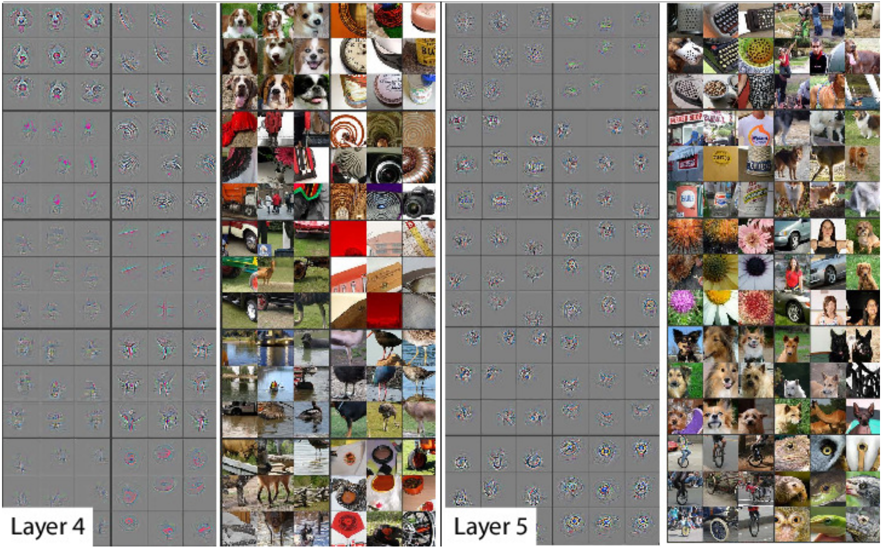
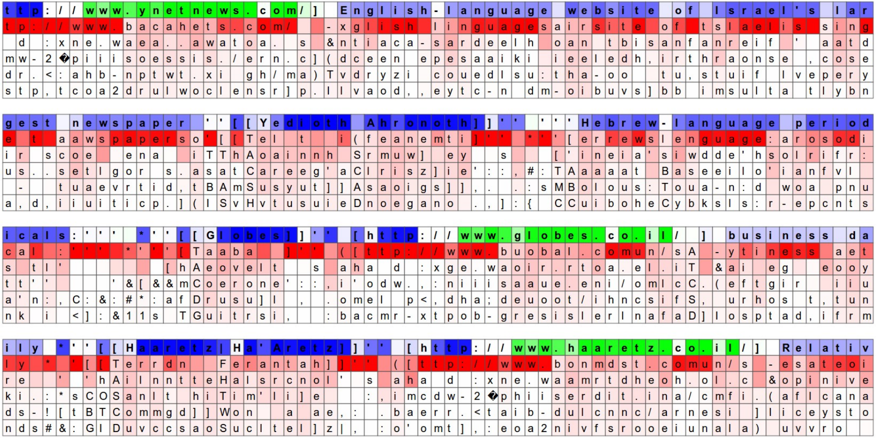
LSTMVis

(Strobelt et al., 2016)

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



(Zeiler and Fergus, 2014)



(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

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

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

Test Objective: Structured prediction

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

- Typical to approximate the $\arg\max$ with beam-search

Beam Search $(K = 3)$

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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:

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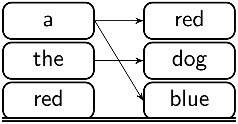

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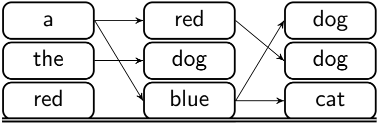

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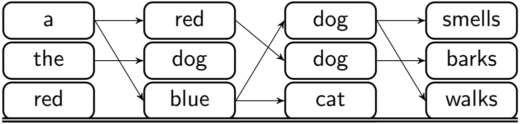

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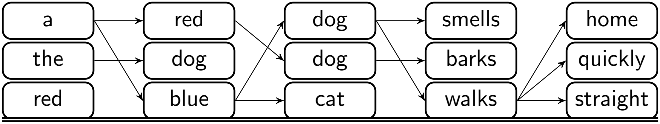

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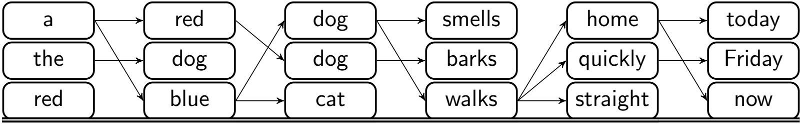

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Issue #1: Train/Test Mismatch (cf., (Ranzato et al., 2016))

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

(a) Training conditions on *true* history ("Exposure Bias")

(b) Train with word-level NLL, but evaluate with Hamming-like metrics

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- Use a loss that incorporates sequence-level costs

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

- $y_{1:t}$ 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:

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

(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?

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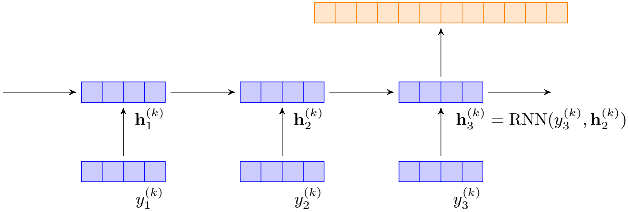

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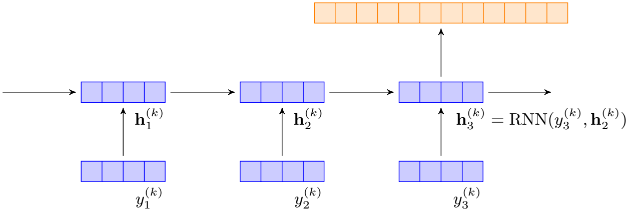

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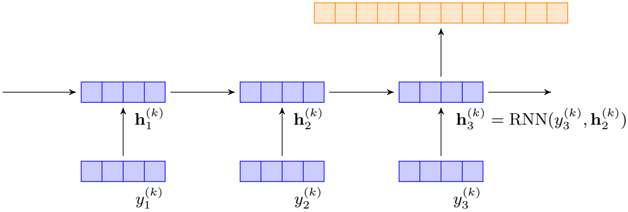

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$$= \mathbf{W}_{out}\, \mathbf{h}_{t-1}^{(k)} + \mathbf{b}_{out}$$

- 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 $\hat{y}^{(K)}$

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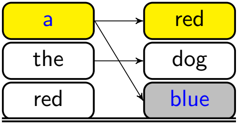

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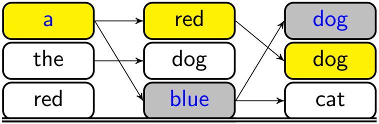

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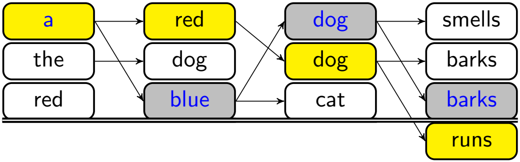
Beam Search Optimization



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

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

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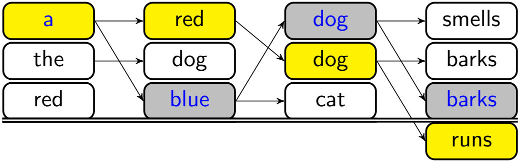

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LaSO (Daumé III and Marcu, 2005):

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

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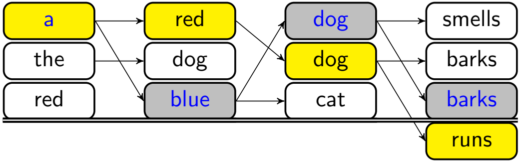

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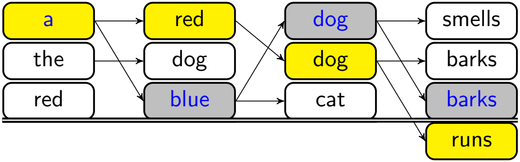

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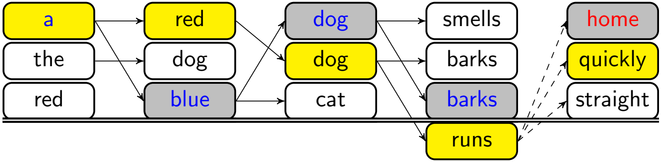

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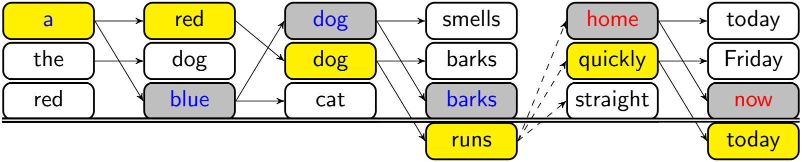
Beam Search Optimization



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

LaSO (Daumé III and Marcu, 2005):

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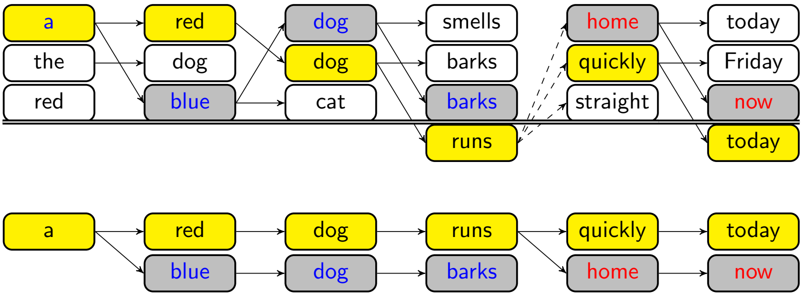
- Otherwise, update beam with sequences prefixed by $y_{1:t-1}$

Backpropagation over Structure



Recent Related Word

- 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)
  - Actor-Critic (Bahdanau et al., 2016)
- Training with beam-search attempts to offer similar benefits
  - Uses fact that we typically have gold prefixes in supervised text-generation to avoid RL

Experiments run on three Seq2Seq baseline tasks:

- 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

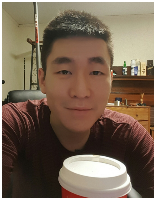
[1] Note Andor et al. (2016) have SOA, with 94.41/92.55.

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

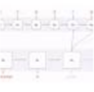
Google is using **Neural** Networks for Chinese to English **machine** ...
Opinion - Firstpost - Sep 28, 2016

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

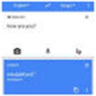
ZDNet

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 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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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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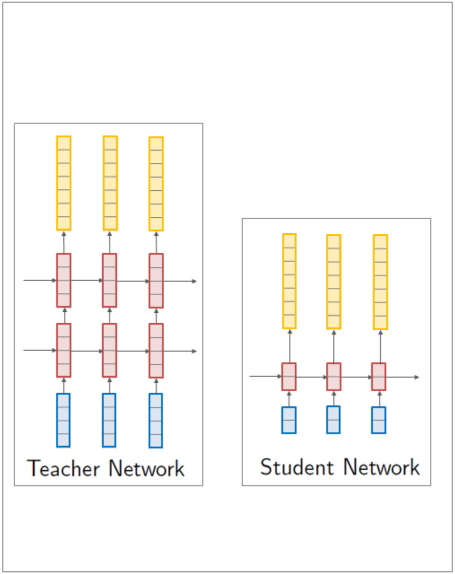

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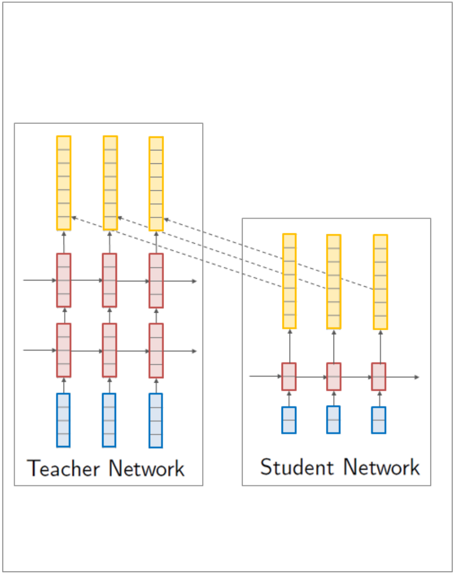

Word-Level Knowledge Distillation Results

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

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

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

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

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

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

This Work: Sequence-Level Knowledge Distillation

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

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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

$$q(w_{1:T} \,|\, x) \approx \mathbb{1}\{\operatorname*{arg\,max}_{w_{1:T}} q(w_{1:T} \,|\, x)\}$$

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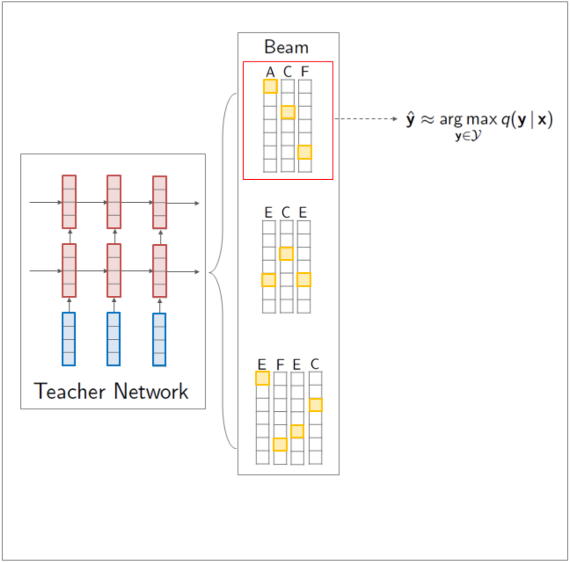

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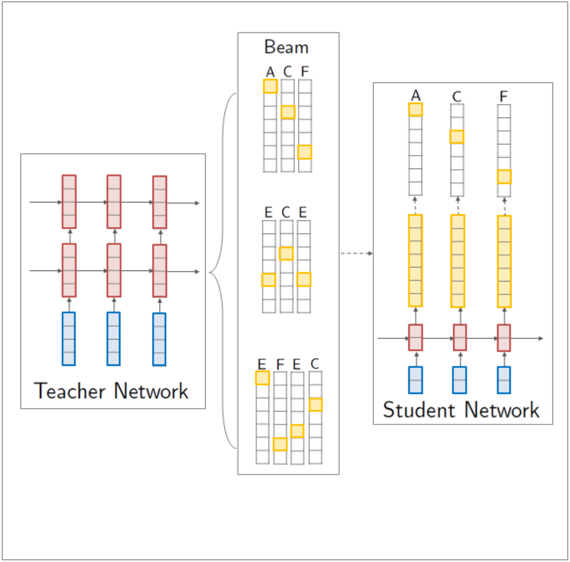

Experiments on English $\rightarrow$ German (WMT 2014)

- 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)

Model	BLEU$_{K=1}$	$\Delta_{K=1}$	BLEU$_{K=5}$	$\Delta_{K=5}$	PPL	$p(\hat{\mathbf{y}})$
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Word-KD	15.4	+0.7	17.7	+0.1	8.0	1.0%

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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%

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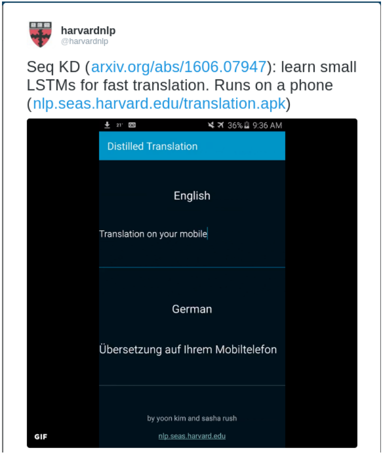
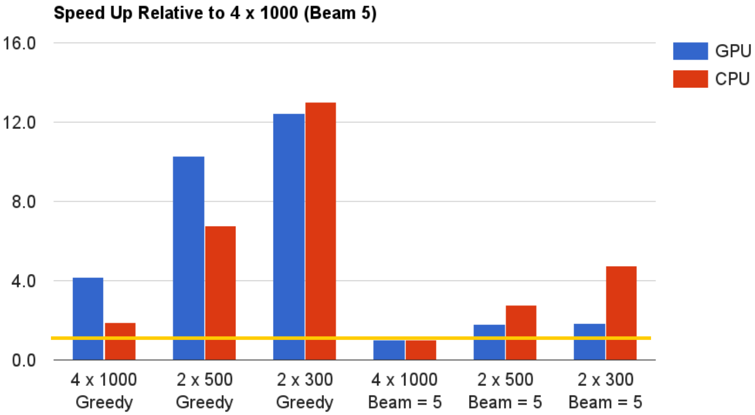
Seq-Inter	18.9	+4.2	19.3	+1.7	15.8	7.6%

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

An Application



Decoding Speed



Thank You

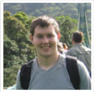
harvardnlp

Graduate Students

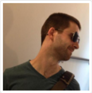
Sebastian Gehrmann

Yoon Kim

Victoria Krakovna



Allen Schmaltz



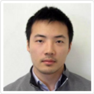
Sam Wiseman

Undergraduate Researchers

Jeffrey Ling

Keyon Vafa

Alex Wang



Mike Zhai

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