Interpreting, Training, and Distilling Seq2Seq Models

Alexander Rush (@harvardnlp)

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

at

Sequence-to-Sequence

- Machine Translation (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014; Cho et al., 2014; Bahdanau et al., 2014; Luong et al., 2015)
- Question Answering (Hermann et al., 2015)
- Conversation (Vinyals and Le, 2015) (Serban et al., 2016)
- Parsing (Vinyals et al., 2014)
- Argument Generation (Wang and Yang, 2015)
- Sentence Compression (Filippova et al., 2015)
- Speech (Chorowski et al., 2015)
- Summarization (Rush et al., 2015)
- Caption Generation (Karpathy and Li, 2015; Xu et al., 2015)
- Video-to-Text (Venugopalan et al., 2015)

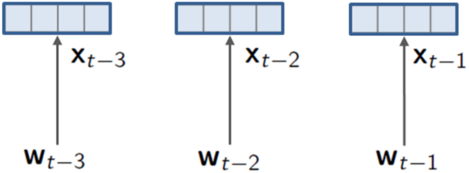
What's ML aspects have defined NLP problems?

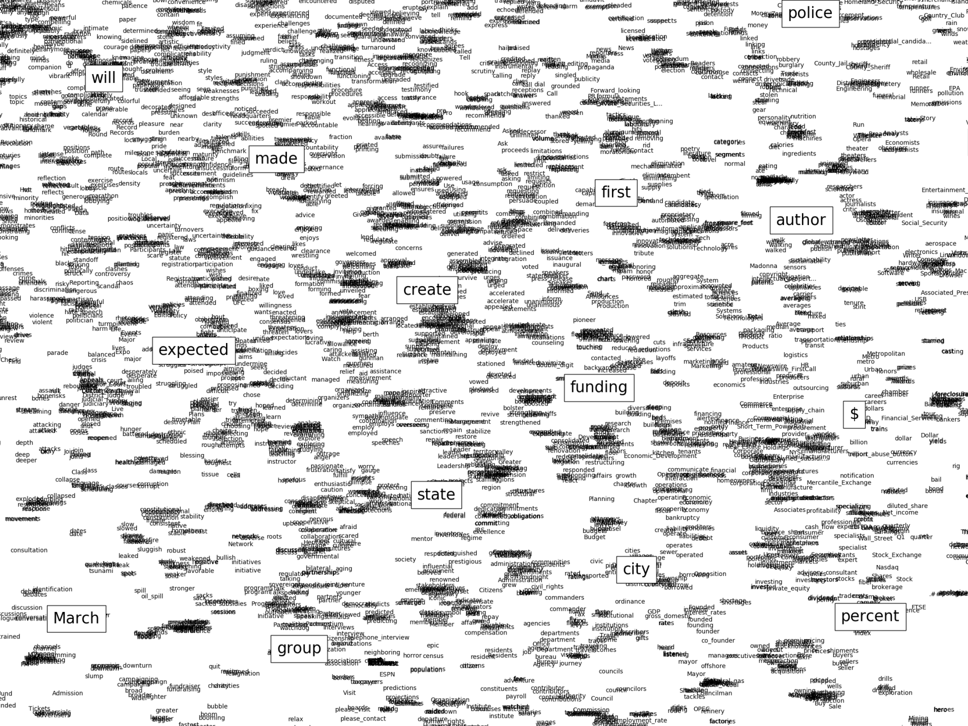
1. Large, discrete input state spaces.
   - Vocabulary sizes in $10,000 - 100,000$
2. Long-term dependencies
   - *Sasha is giving a talk today at IBM, ..., he is excited*.
3. Variable-length output spaces
   - e.g. sentences, documents, conversations

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




police
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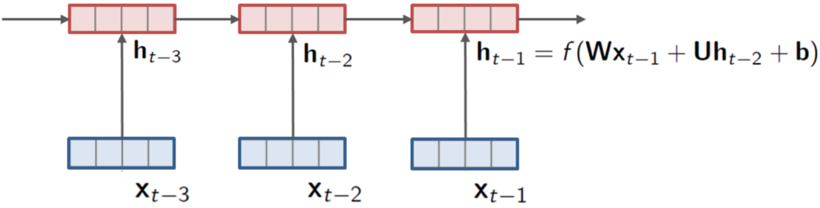
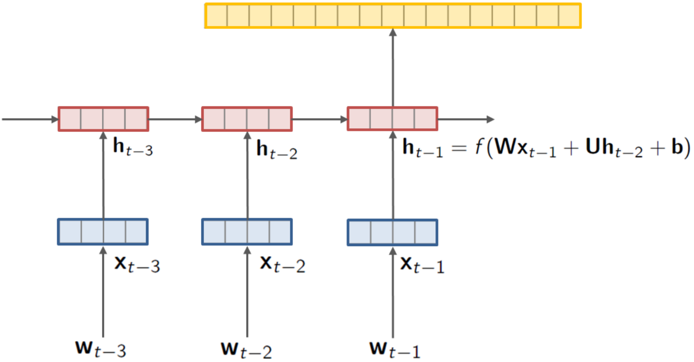
RNNs/LSTMs feature sequences $\Rightarrow$ dense features



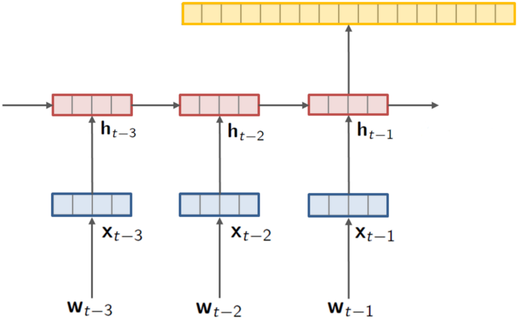
LM/Softmax dense features $\Rightarrow$ discrete predictions



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

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

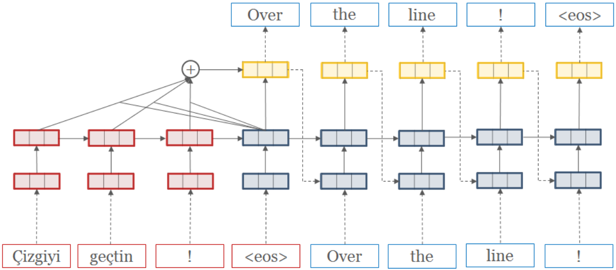
Contextual Language Model / "seq2seq"



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

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

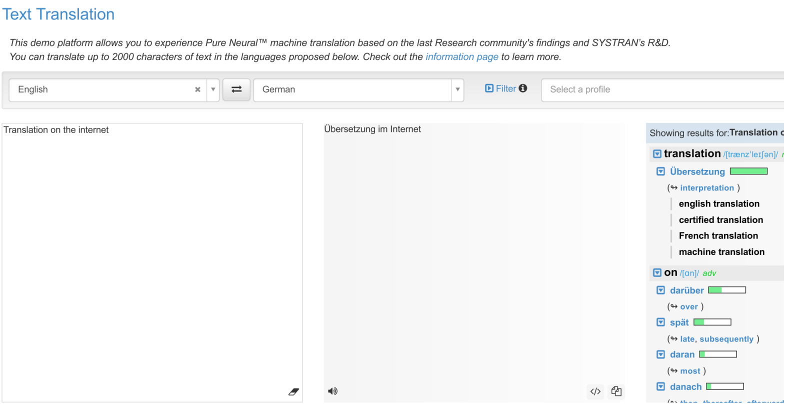
Actual Seq2Seq / Encoder-Decoder / Attention-Based Models



- 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-Attn: (Yoon Kim)

- HarvardNLP's open-source seq2seq/NMT implementation.



- Used by SYSTRAN to release NMT in 32 language (Crego et al., 2016)

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.

- Improved upon by researchers here at IBM (Nallapati et al., 2016)
- Used by Washington Post to suggest headlines (Wang et al., 2016)

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

Source

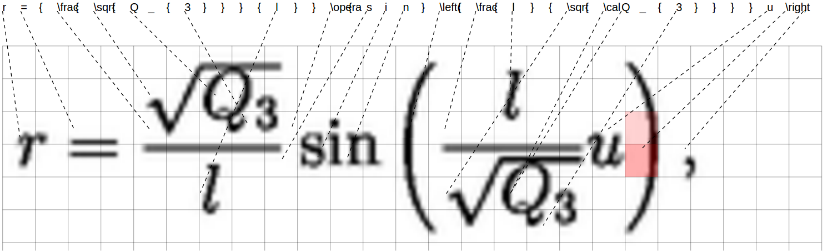
There is no a doubt, tracking systems has brought many benefits in this information age .

Target

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

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

Seq2Seq Applications: Im2Markup [In Submission]



[Latex Example]

This Talk

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

This Talk

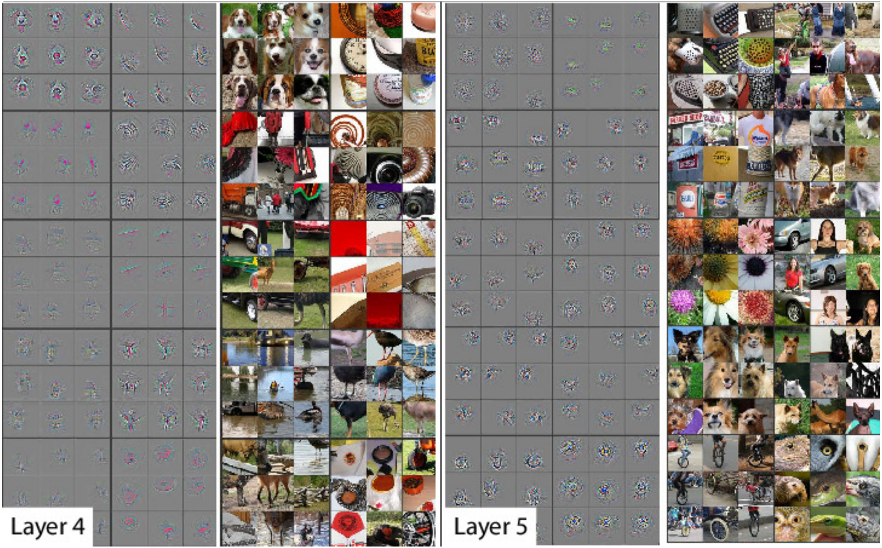
- How can we **interpret** these learned hidden representations?

  LSTMVis (Future IBMer!)

  (Strobelt et al., 2016)

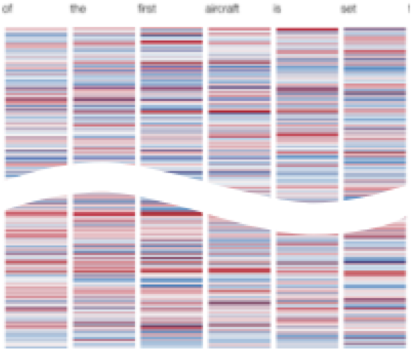
- How should we **train** these style of models? (Wiseman and Rush, 2016)

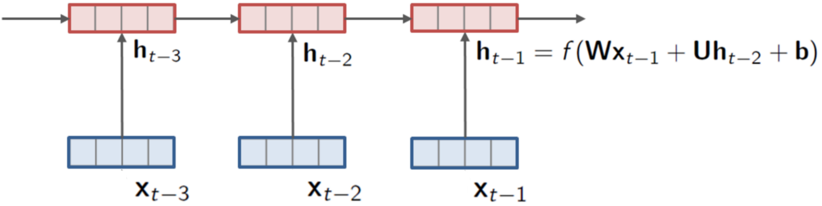
- How can we **shrink** these models for practical applications? (Kim and Rush, 2016)

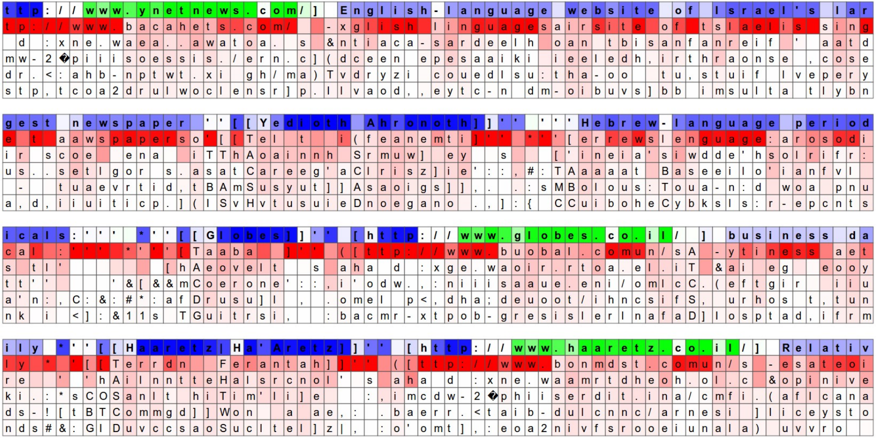


(Zeiler and Fergus, 2014)

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]

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)?

Some More Seq2Seq Details

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

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

Test Objective: Structured prediction

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

Beam Search Example $(K = 3)$

a

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For timesteps t from 1 to T:

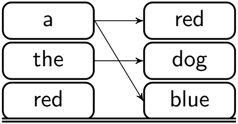
1. Compute for all $k, \mathbf{w}_t$

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

2. Replace the K highest scoring target sequences

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

Beam Search Example ($K = 3$)



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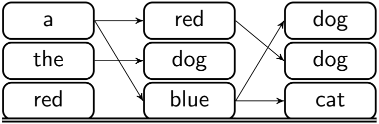

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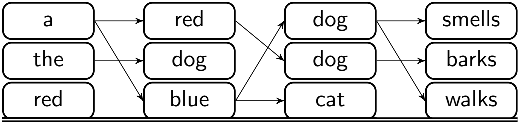

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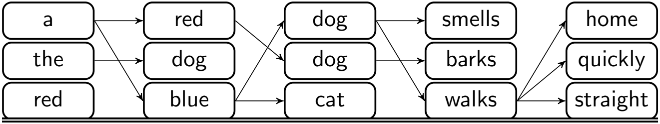

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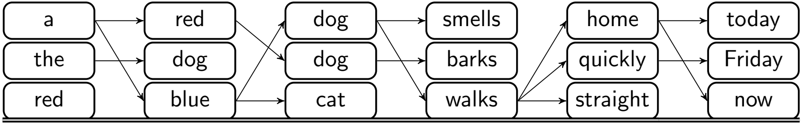

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Theoretical Issues with Standard Setup

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

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

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

Related Work:

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

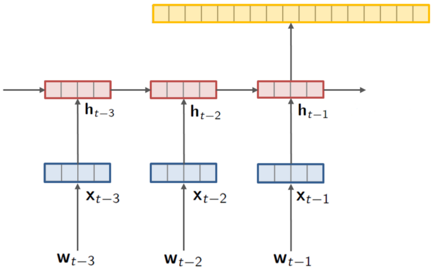
Explicit Reinforcement Learning

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

This Work: Seq2Seq Learning as Beam Search Optimization

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

(Idea 1) Replace local softmax with sequence scorer f



Normalized (Softmax) Unnormalized

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

- Targets Label Bias

(Idea 2) Run beam search during training

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

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

    2. Replace the K highest scoring target sequences

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

- Targets Exposure Bias

(Idea 2) Run beam search during training

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

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

   2. Replace the K highest scoring target sequences

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

- Targets Exposure Bias

(Idea 3) Train with cost-sensitive margin

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

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

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

Beam Search Optimization Example ($K = 3$)

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

Violation Criterion

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

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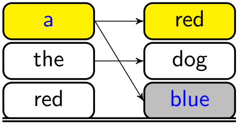
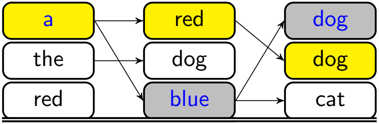


- Color Gold: target sequence y
- Color Gray: violating sequence $\mathbf{w}^{(K)}$

Violation Criterion

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

Beam Search Optimization Example ($K = 3$)



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Violation Criterion

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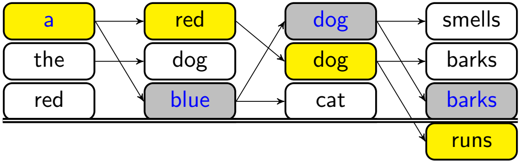

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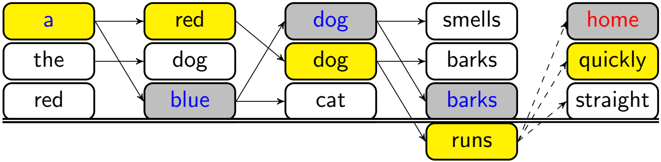

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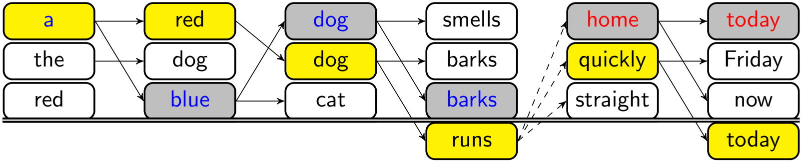

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Violation Criterion

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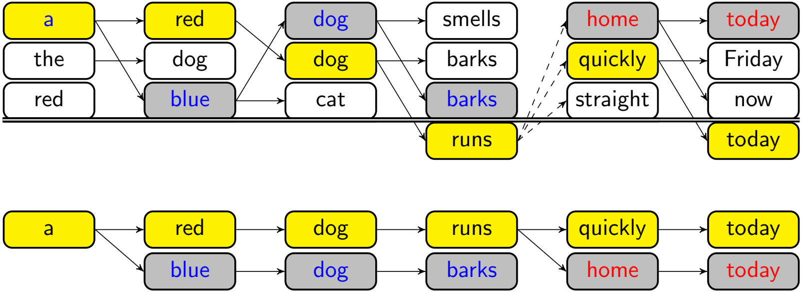
Backpropagation over Structure



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

Experiments

Experiments run on three small seq2seq baseline tasks

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

Details:

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

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

This Talk

- How 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)

Issues

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

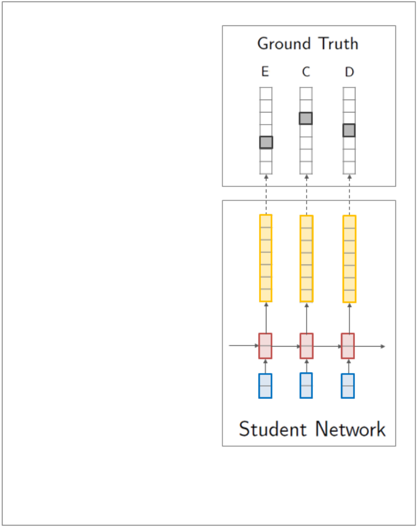
Related Work: Compressing Deep Models

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

Baseline Model

Standard model minimize NLL(θ):

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



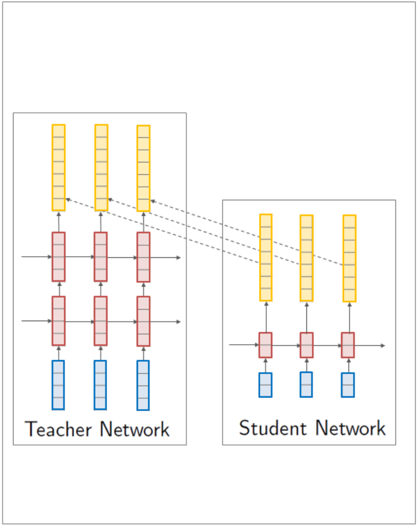
(Word-Level) Knowledge Distillation

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

Minimize cross-entropy with teacher

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

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



This Work: Sequence-Level Knowledge Distillation

Instead of word NLL,

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

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

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

A Simple Approximation

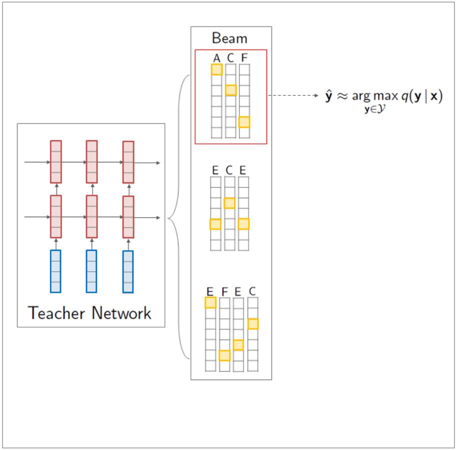
Approximate $q(\mathbf{w}_{1:T} \mid \mathbf{c})$ with mode

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

Roughly obtained wtih beam search

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

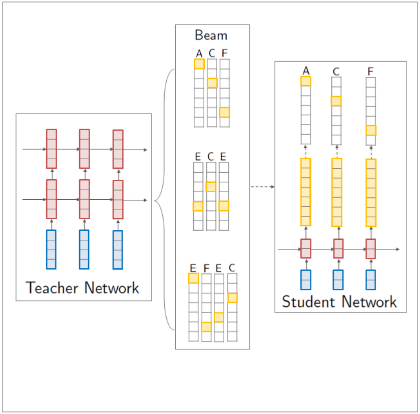
Empirically, point estimate captures significant mass



Sequence-Level Knowledge Distillation

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

Local updating (Liang et al., 2006)



Results: English $\rightarrow$ German

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

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

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

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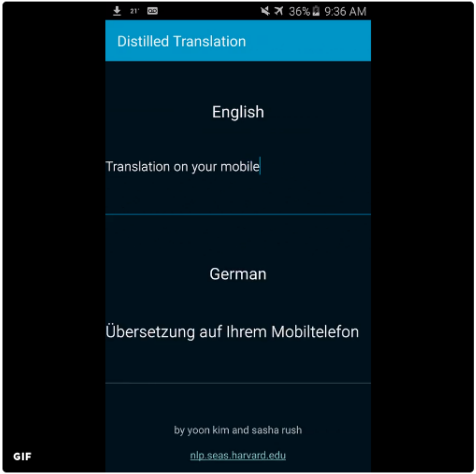
Seq KD (arxiv.org/abs/1606.07947): learn small LSTMs for fast translation. Runs on a phone (nlp.seas.harvard.edu/translation.apk)



Thank You

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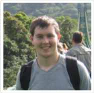
Graduate Students

Sebastian Gehrmann

Yoon Kim

Victoria Krakovna



Allen Schmaltz

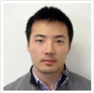
Sam Wiseman

Undergraduate Researchers

Jeffrey Ling

Keyon Vafa

Alex Wang



Mike Zhai

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