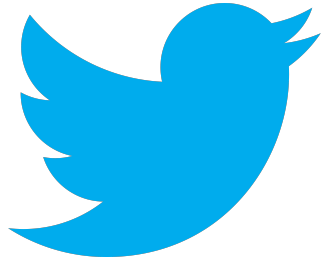
Interpreting, Training, and Distilling Seq2Seq Models

Alexander Rush (@harvardnlp)

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

at



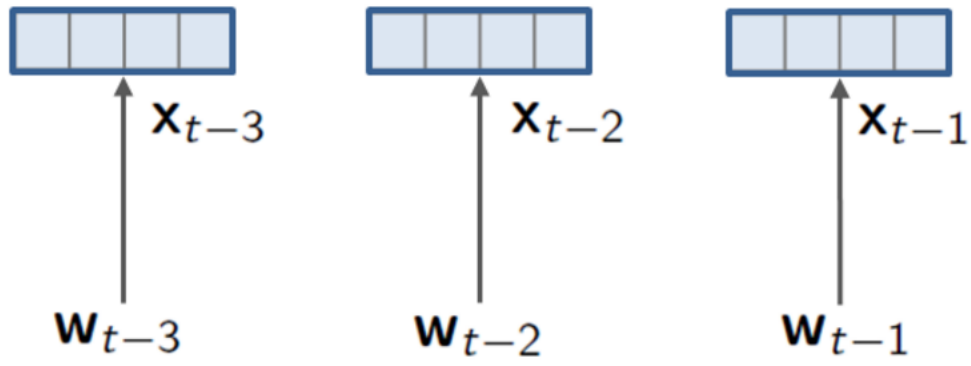
Sequence-to-Sequence is pretty convincing

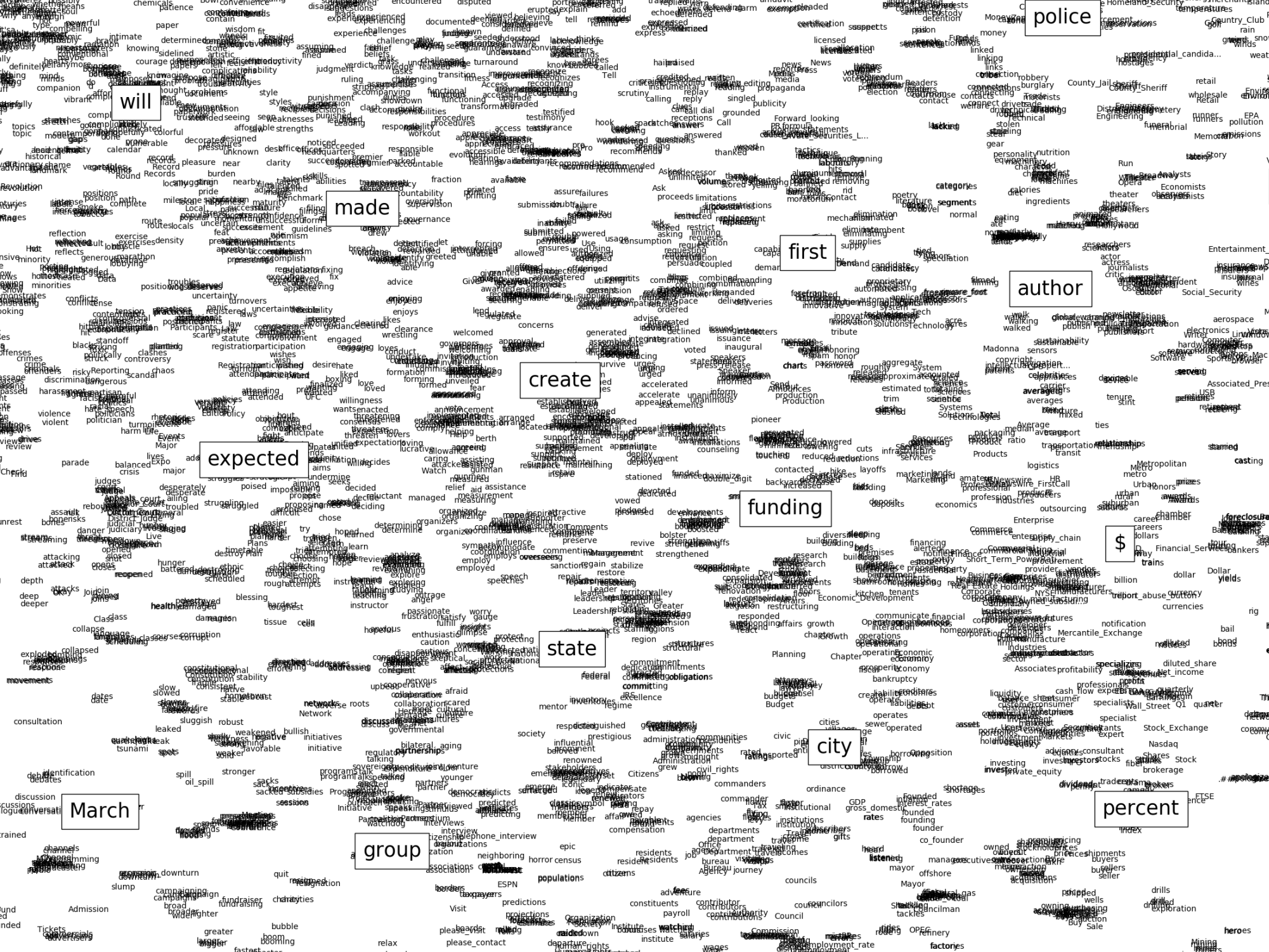
- Machine Translation (**?????**)
- Question Answering (**?**)
- Sentence Compression (**?**)
- Parsing (**?**)
- *Summarization* (**?**)
- Conversation (**?**)
- Argument Generation (**?**)
- *Grammar Correction* (**?**)
- Speech (**?**)
- Caption Generation (**?**)
- Video-to-Text (**?**)

Seq2Seq Neural Network Toolbox

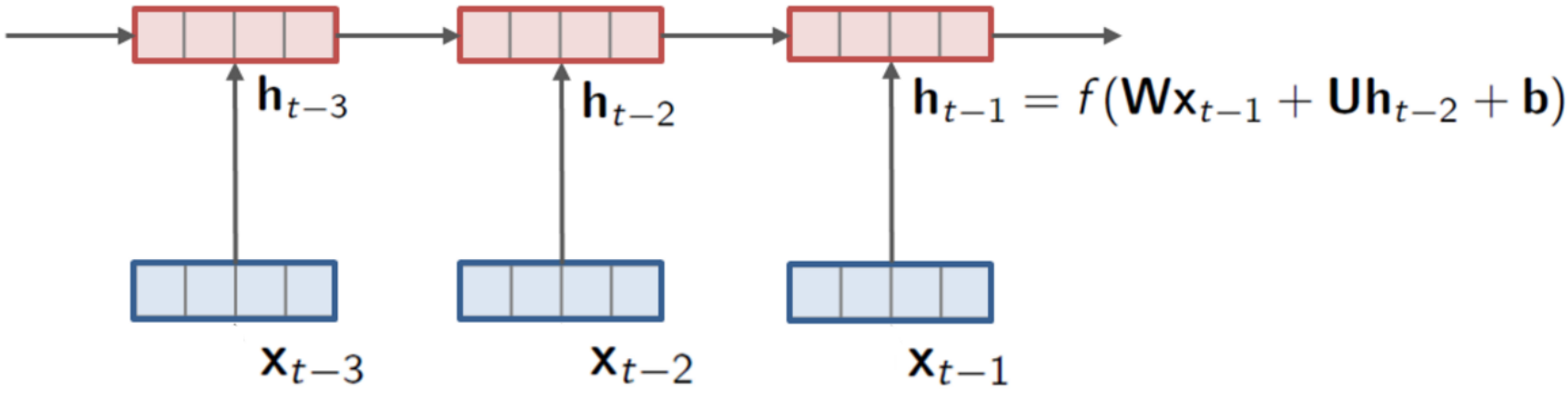
Embeddings	sparse features	$\Rightarrow$	dense features
RNNs	feature sequences	$\Rightarrow$	dense features
Softmax	dense features	$\Rightarrow$	discrete predictions

Embeddings sparse features $\Rightarrow$ dense features

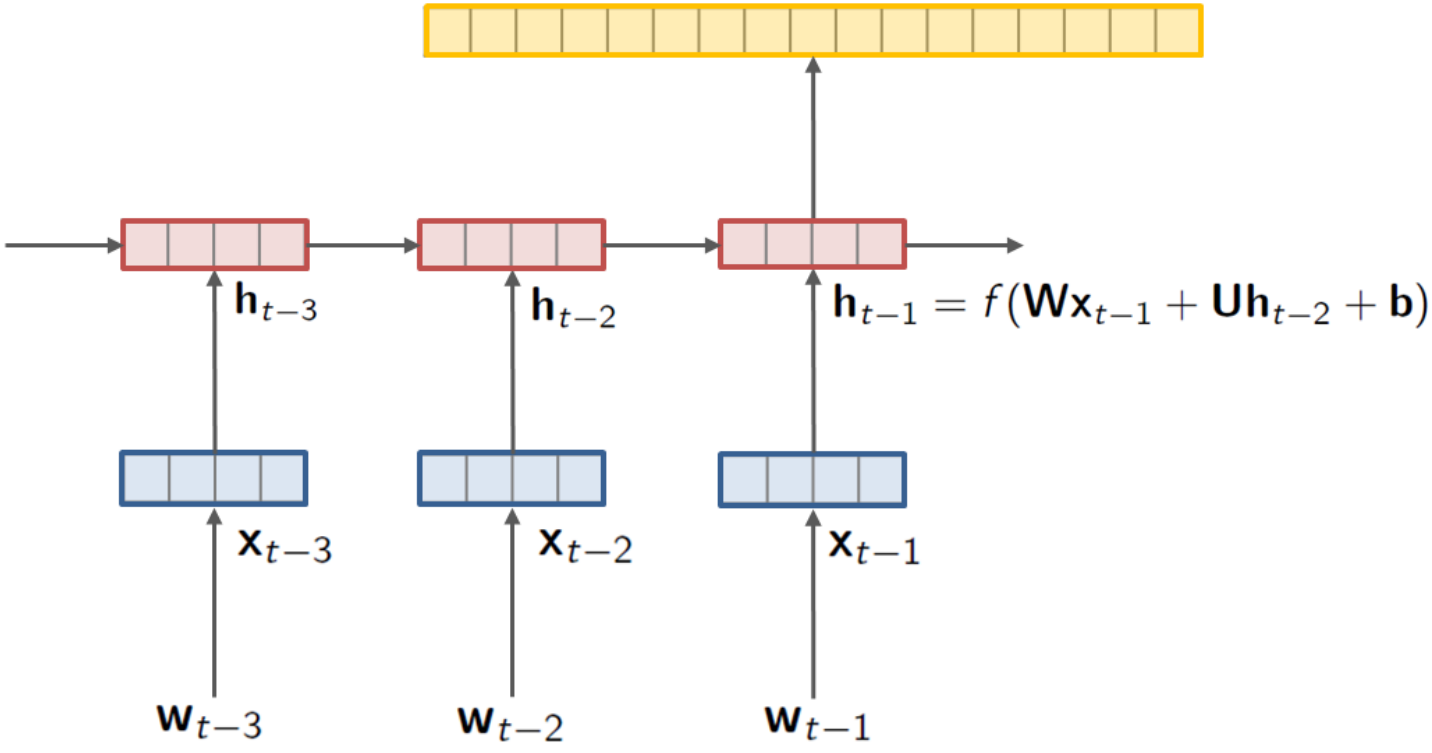



will
made
police
first
author
create
expected
funding
$
state
city
March
percent
group

RNNs/LSTMs feature sequences $\Rightarrow$ dense features



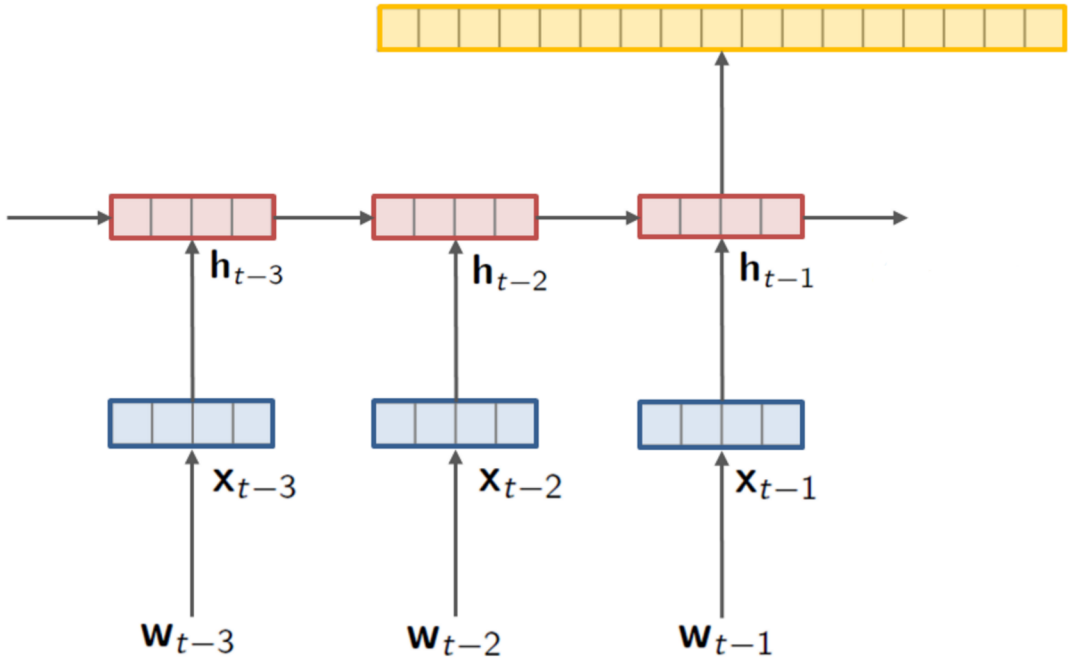
Softmax dense features $\Rightarrow$ discrete predictions



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

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

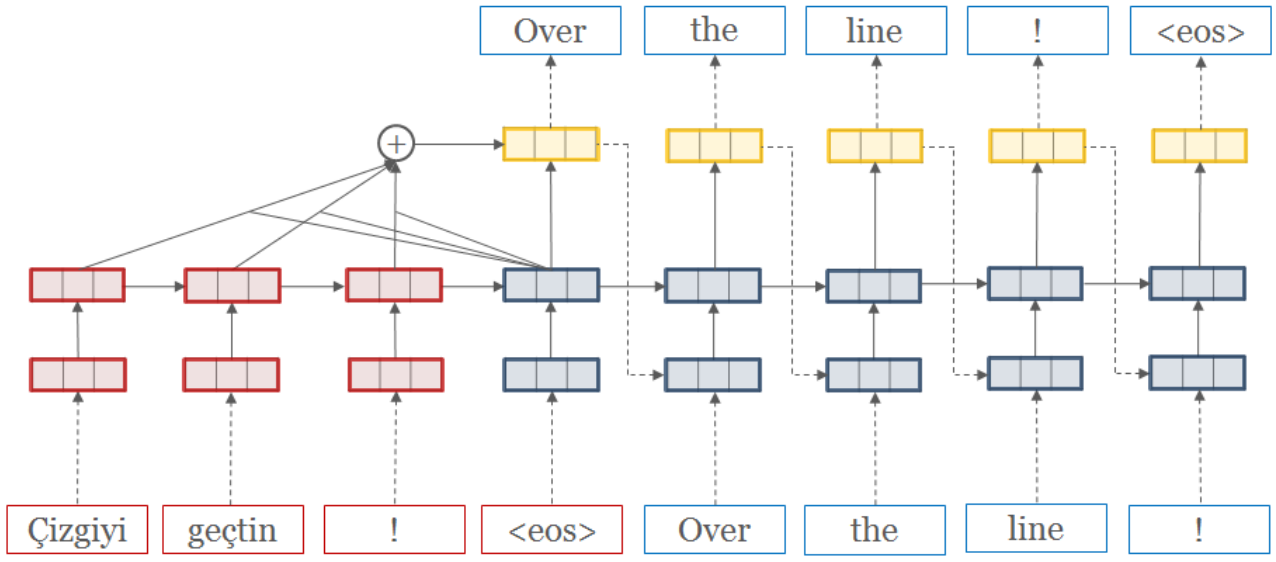
Contextual Language Model / "seq2seq"



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

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

Actual Seq2Seq / Encoder-Decoder / Attention-Based Models



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

Seq2Seq Applications: Sentence Summarization (?)

Source

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

Target

Russia calls for joint front against terrorism.

- Used by The Washington Post to suggest headlines (?)

Seq2Seq Applications: Sentence Summarization (?)

Source

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

Target

Russia calls for joint front against terrorism.

- Used by The Washington Post to suggest headlines (?)

Seq2Seq Applications: Grammar Correction (?)

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 (?)

Seq2Seq Applications: Grammar Correction (?)

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 (?)

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?

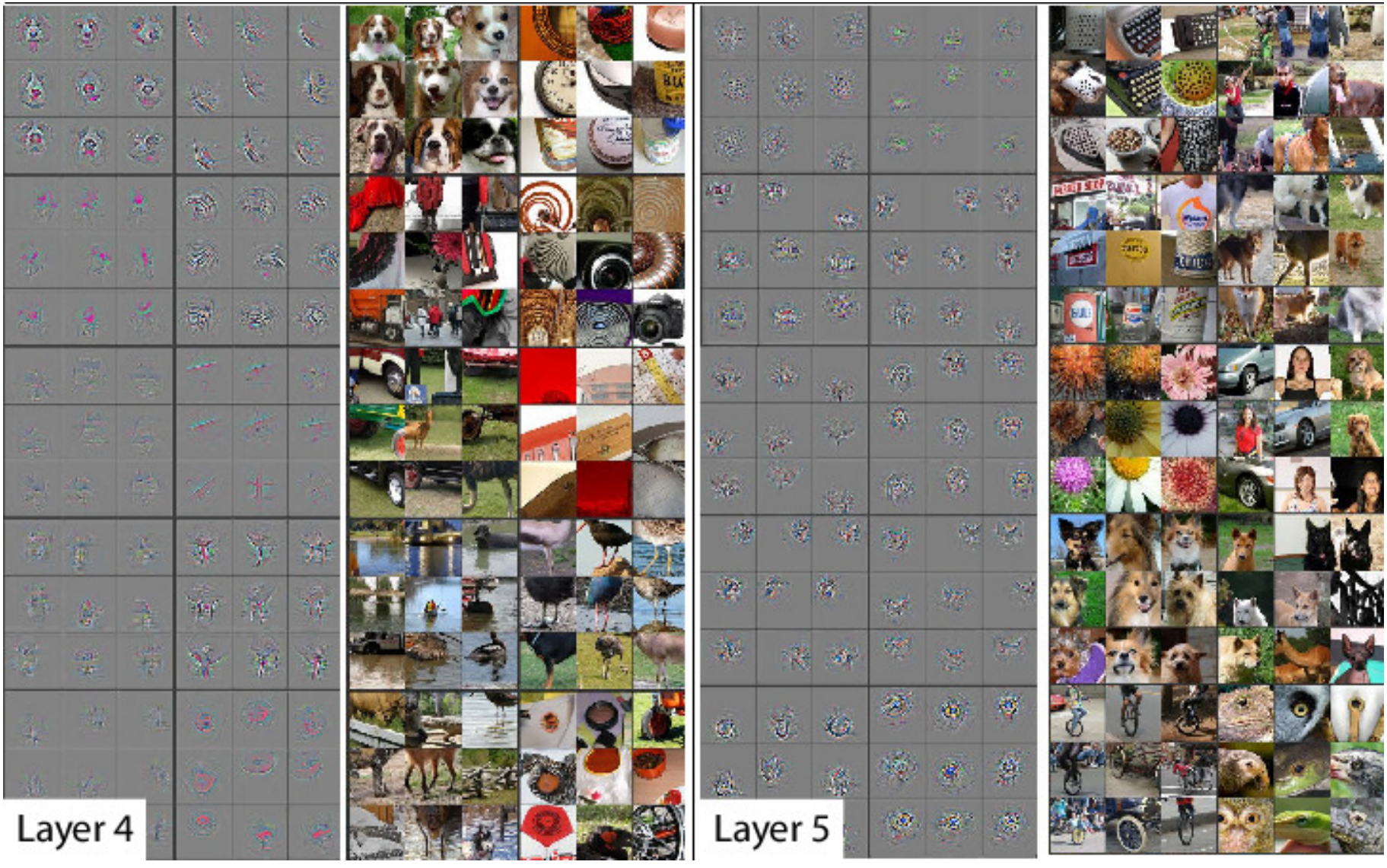
This Talk

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

  LSTMVis

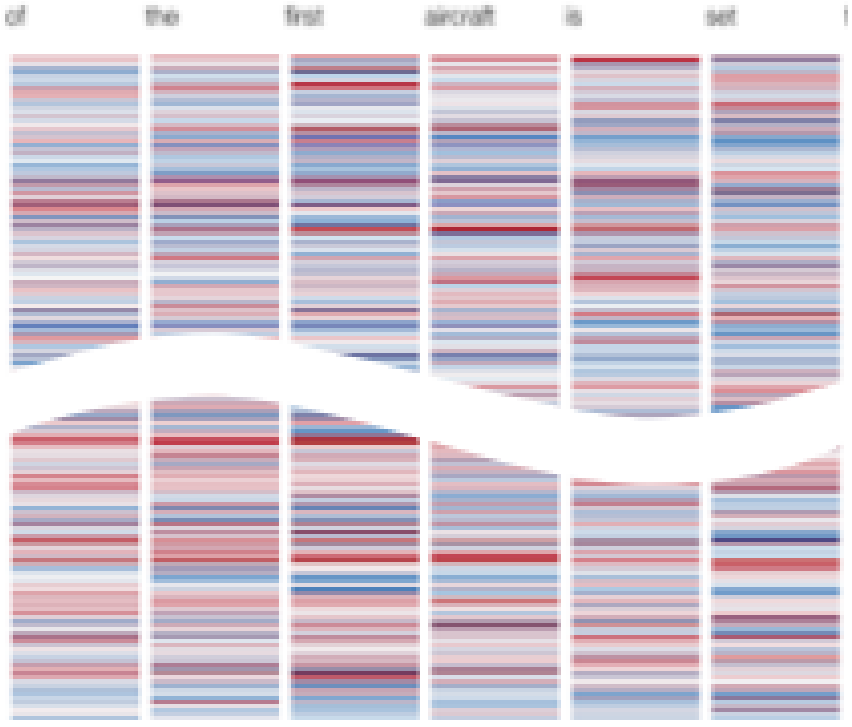
  (?)

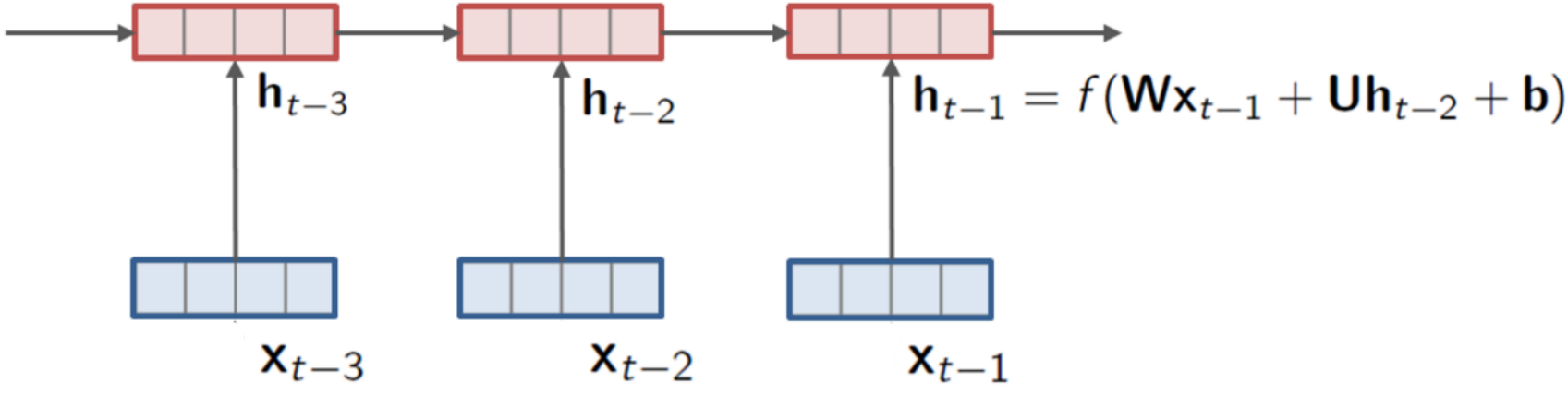
- How should we **train** these style of models? **(?)**
- How can we **shrink** these models for practical applications? **(?)**

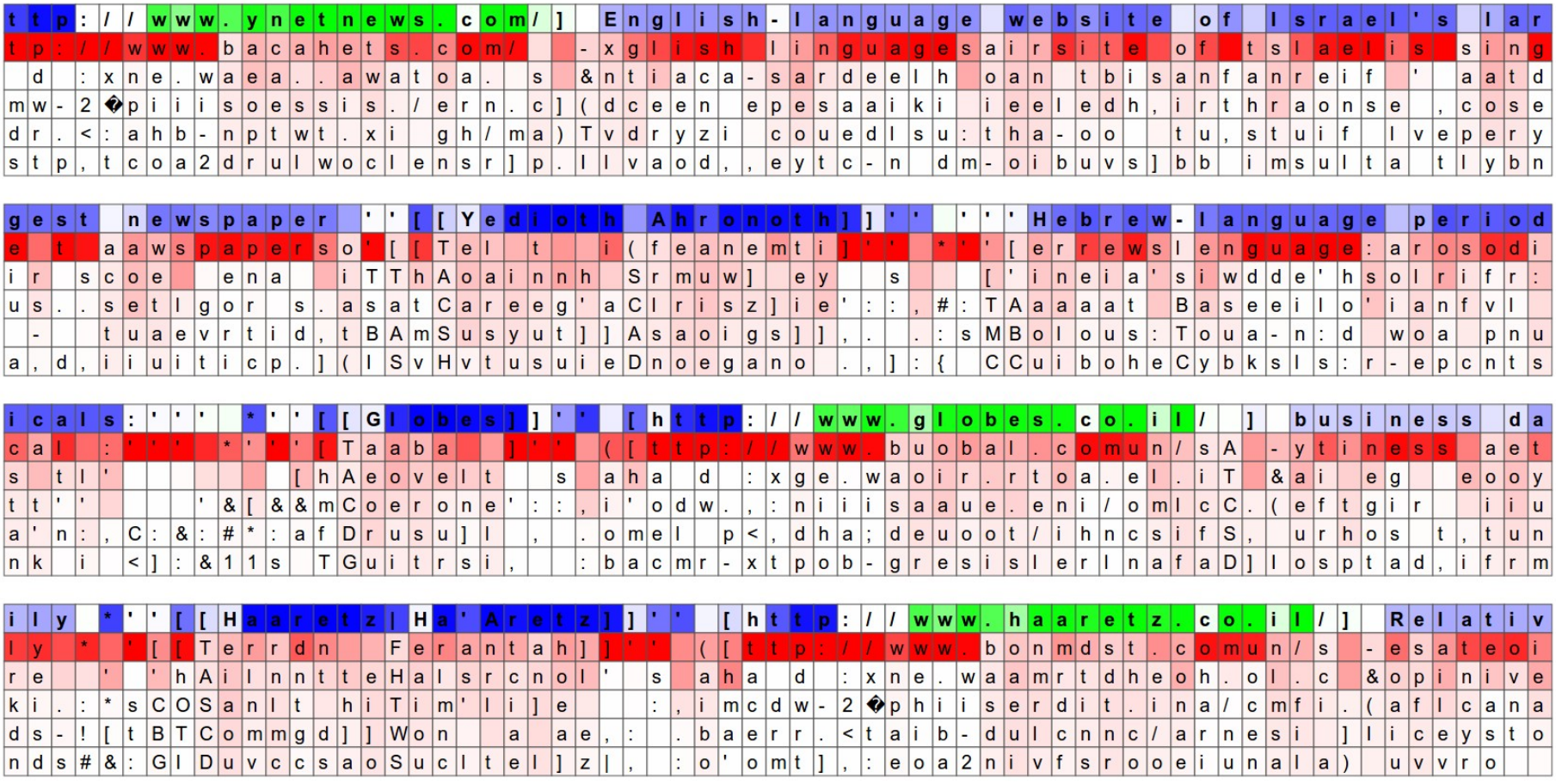

Layer 4
Layer 5

(?)

Vector-Space RNN Representation







(?)

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? (**?**)
- How should we **train** these style of models?

  Sequence-to-Sequence Learning as Beam-Search Optimization

  (**?**)

- How can we **shrink** these models for practical applications (**?**)?

Some More Seq2Seq Details

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

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

Test Objective: Structured output space

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

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

Some More Seq2Seq Details

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

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

Test Objective: Structured output space

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

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

Standard Approach: Beam Search

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

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

   2. Replace the K highest scoring target sequences

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

Standard Approach: Beam Search

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

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

   2. Replace the K highest scoring target sequences

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

Standard Approach: Beam Search

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

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

   2. Replace the K highest scoring target sequences

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

Standard Approach: Beam Search

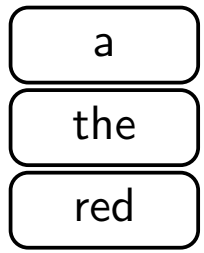
1. Start with K partial starting hypotheses $\mathbf{w}^{(1:K)}$
2. For timesteps t from 1 to T:
   1. Compute for all $k, \mathbf{w}_t$

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

   2. Replace the K highest scoring target sequences

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

Beam Search Example ($K = 3$)



For timesteps t from 1 to T:

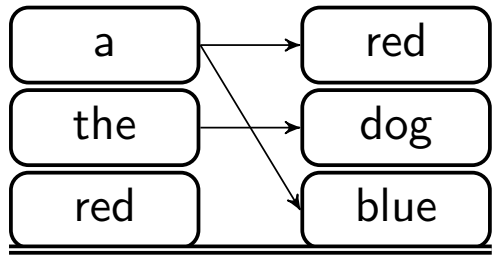
1. Compute for all $k, \mathbf{w}_t$

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

2. Replace the K highest scoring target sequences

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

Beam Search Example ($K = 3$)



For timesteps t from 1 to T:

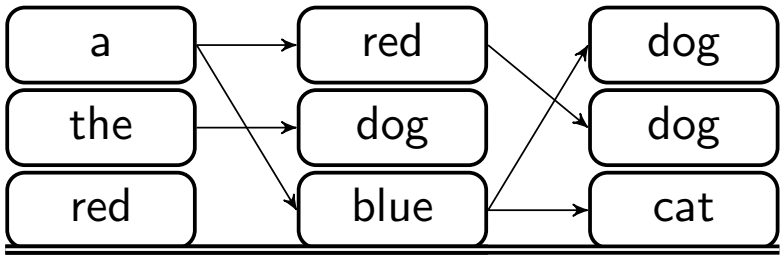
1. Compute for all $k, \mathbf{w}_t$

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

2. Replace the K highest scoring target sequences

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

Beam Search Example ($K = 3$)



For timesteps t from 1 to T:

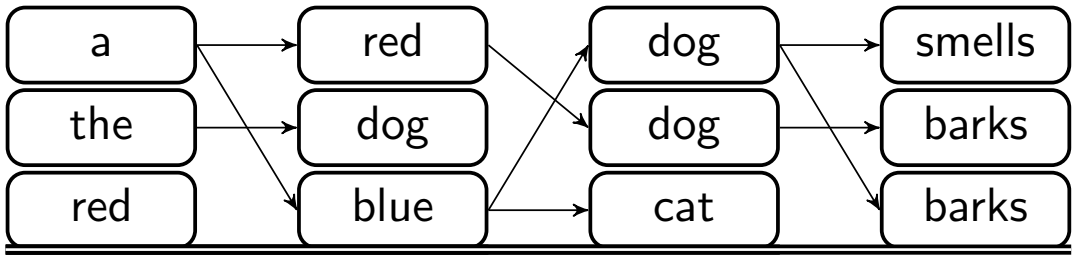
1. Compute for all $k, \mathbf{w}_t$

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

2. Replace the K highest scoring target sequences

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

Beam Search Example ($K = 3$)



For timesteps t from 1 to T:

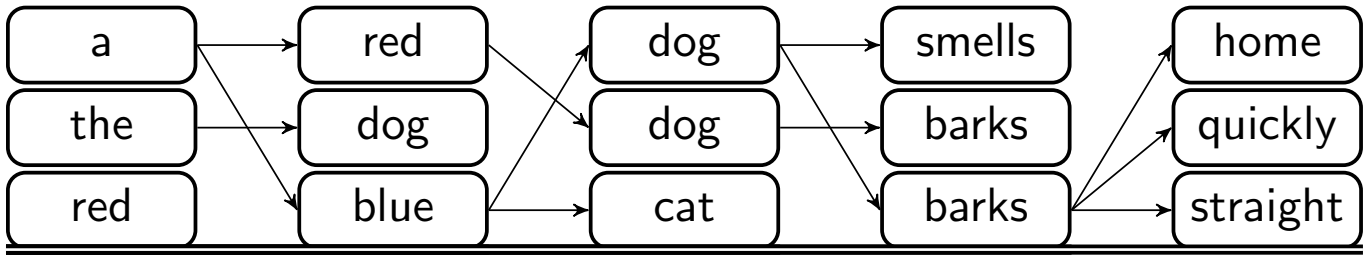
1. Compute for all $k, \mathbf{w}_t$

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

2. Replace the K highest scoring target sequences

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

Beam Search Example ($K = 3$)



For timesteps t from 1 to T:

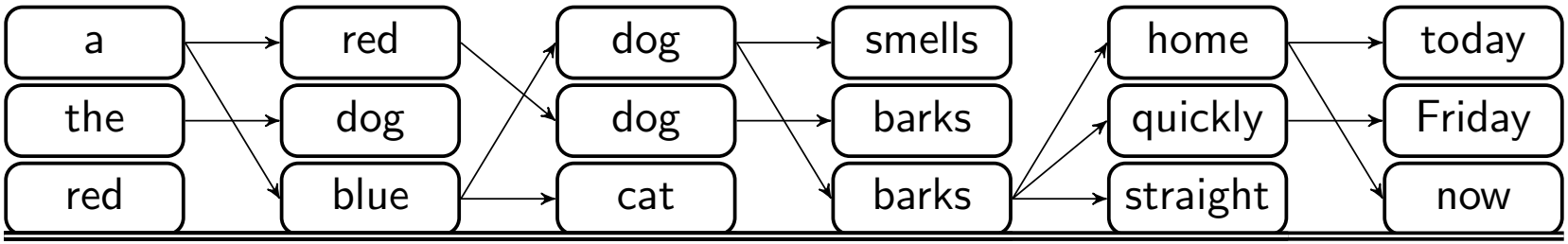
1. Compute for all $k, \mathbf{w}_t$

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

2. Replace the K highest scoring target sequences

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

Beam Search Example ($K = 3$)



For timesteps t from 1 to T:

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

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

2. Replace the K highest scoring target sequences

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

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 (**?**)
  - Locally normalized models have known pathological issues

Related Work: Modify training data

- Data as Demonstrator (**?**), Scheduled Sampling (**?**)

Related Work: Use Reinforcement Learning

- MIXER (**?**)
- Actor-Critic (**?**)

Opinion:

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

Related Work: Modify training data

- Data as Demonstrator (**?**), Scheduled Sampling (**?**)

Related Work: Use Reinforcement Learning

- MIXER (**?**)
- Actor-Critic (**?**)

Opinion:

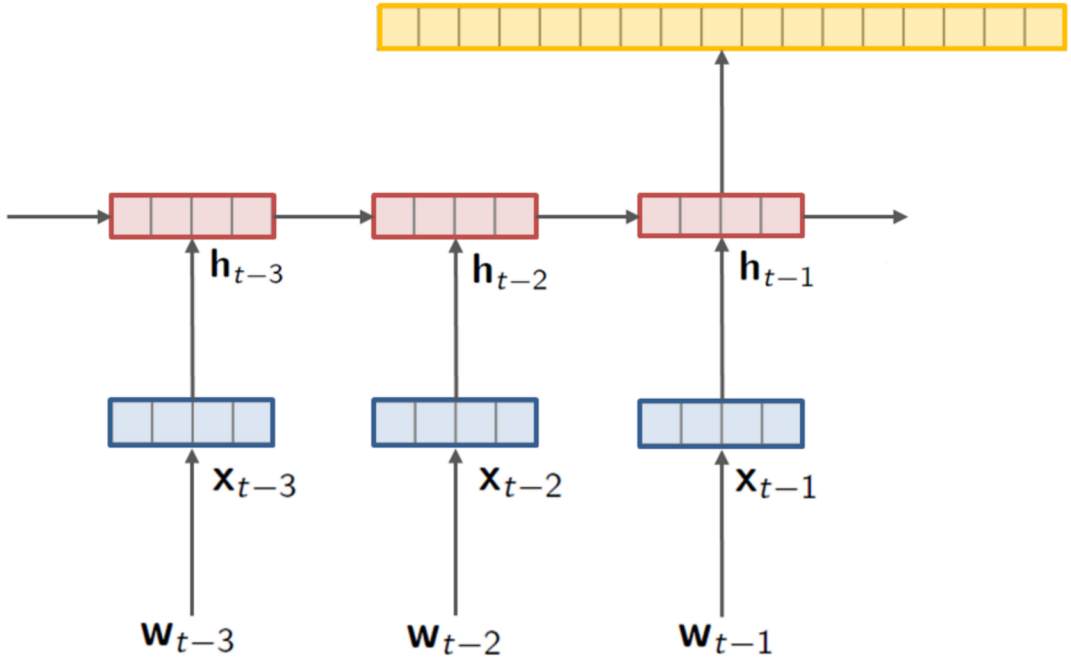
- DAD methods only address exposure bias,
- RL is too strong a hammer .

Our Proposal: Seq2Seq as Beam Search Optimization

New Setup: Run beam search at training.

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

(Idea 1) Replace local softmax with sequence scorer f



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

(Idea 2) Run beam search during training

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

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

   2. Replace the K highest scoring target sequences

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

(Idea 2) Run beam search during training

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

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

   2. Replace the K highest scoring target sequences

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

(Idea 3) Replace local training objective with beam-search margin

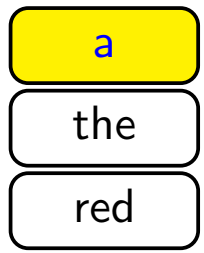
New Objective:

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

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

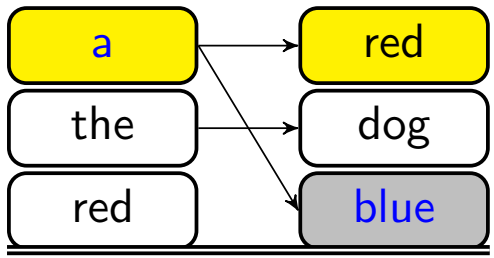
- Slack-rescaled, margin-based sequence criterion, at each time step.
- When violation occurs, target replaces current beam (learning as search optimization (**?**))

Beam Search Optimization Example ($K = 3$)



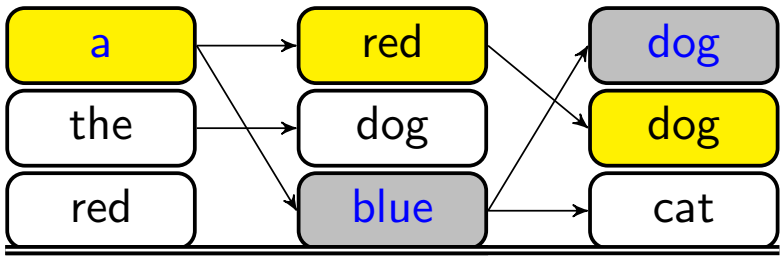
- Color Gold: target sequence y
- Color Gray: violating sequence $\mathbf{w}^{(K)}$

Beam Search Optimization Example ($K = 3$)



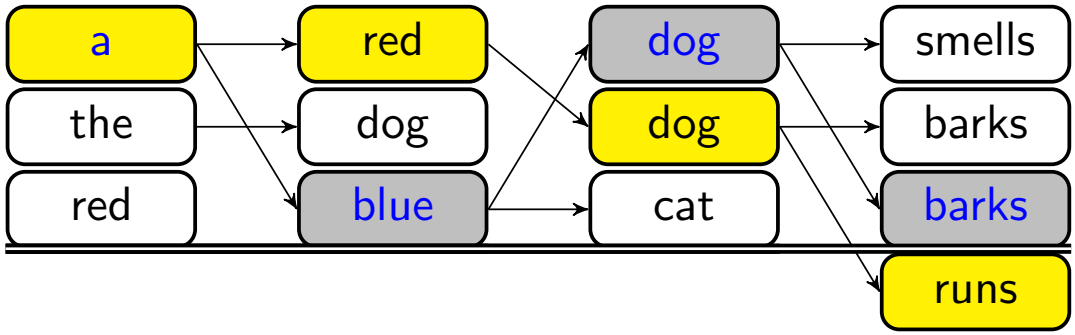
- Color Gold: target sequence y
- Color Gray: violating sequence $\mathbf{w}^{(K)}$

Beam Search Optimization Example ($K = 3$)



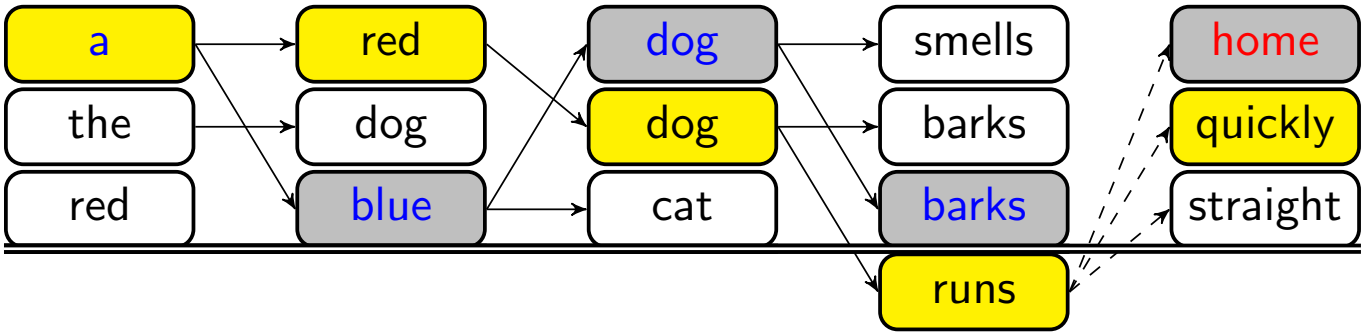
- Color Gold: target sequence y
- Color Gray: violating sequence $\mathbf{w}^{(K)}$

Beam Search Optimization Example ($K = 3$)



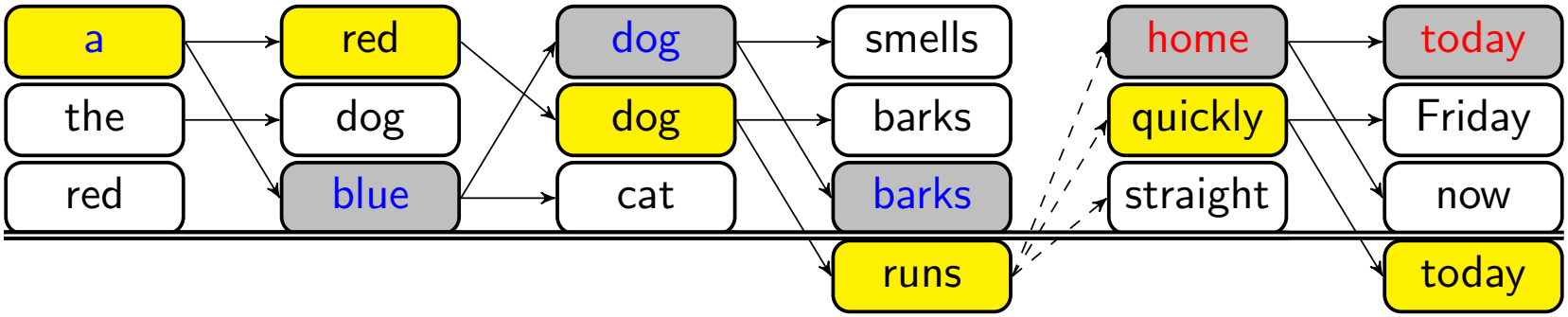
- Color Gold: target sequence y
- Color Gray: violating sequence $\mathbf{w}^{(K)}$

Beam Search Optimization Example ($K = 3$)



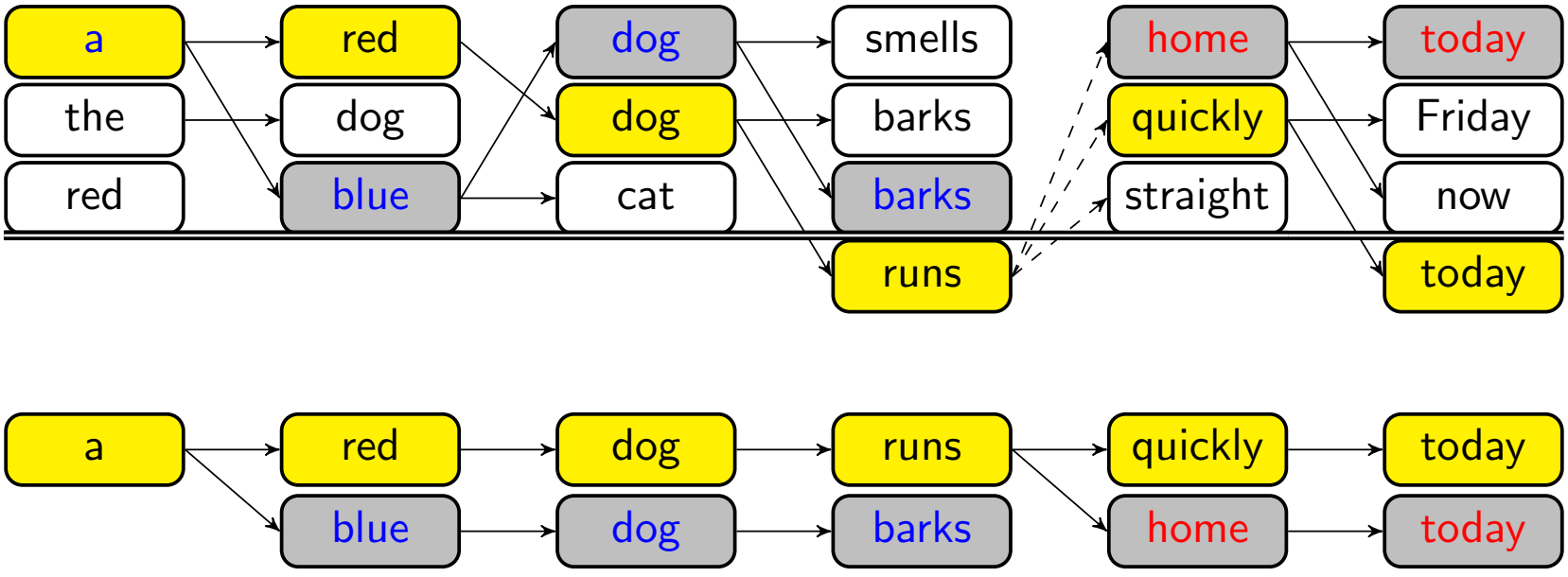
- Color Gold: target sequence y
- Color Gray: violating sequence $\mathbf{w}^{(K)}$

Beam Search Optimization Example ($K = 3$)



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

Structured Backpropagation



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

Theoretical Issues with Standard Setup

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

Experiments

Experiments run on three different seq2seq baseline tasks

- Word Ordering
- Dependency Parsing
- Machine Translation

Details:

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

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

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?

Sequence-Level Knowledge Distillation

(**?**)

Seq2Seq In Practice

Benefits

- Very accurate
- General purpose
- Possibly interpretable

Downsides

- Models are really big (MT model is 4 layers each of 1000 units)
- Beam search can be quite slow

Related Work: Compressing Deep Models

- **Pruning**: Prune weights based on importance criterion (**??**)
- **Knowledge Distillation**: Train a *student* model to learn from a *teacher* model (**???**).

Other methods:

- low-rank matrix factorization of weight matrices (**?**)
- weight binarization (**?**)
- weight sharing (**?**)

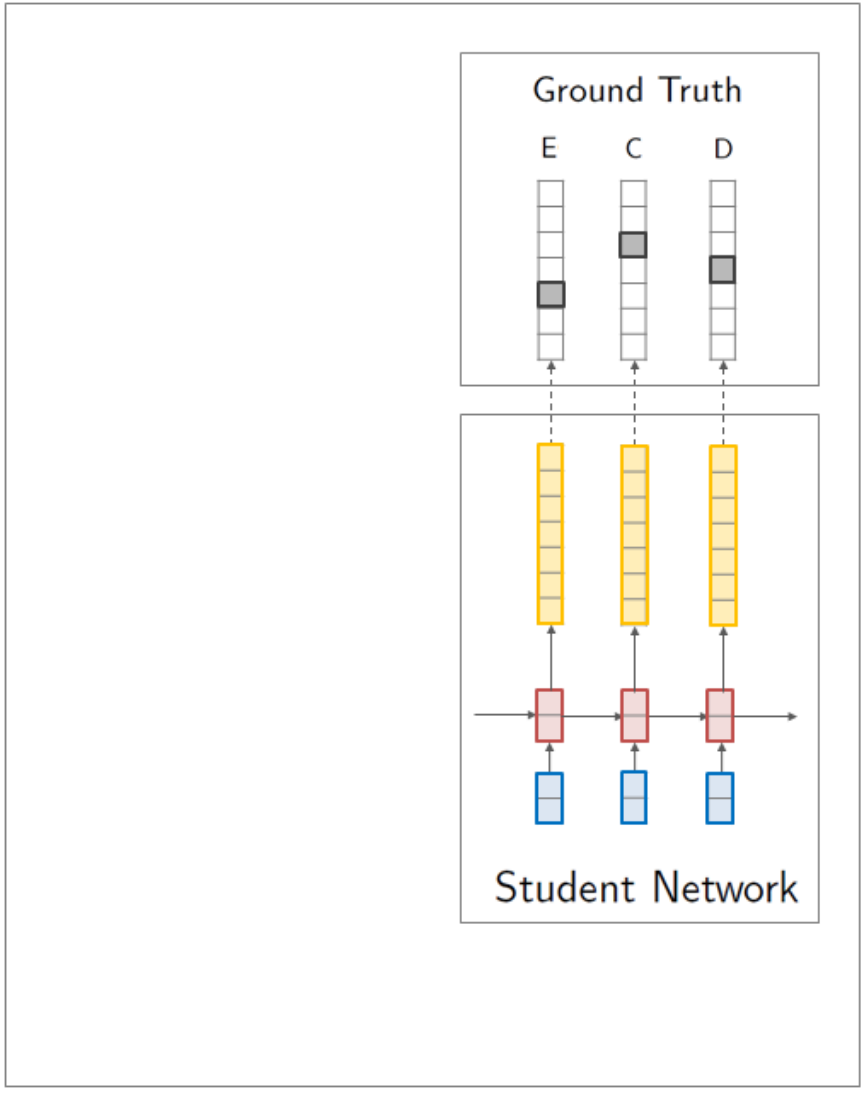
Baseline Model

Standard model minimize NLL(θ):

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

where y_t is the ground truth word at time t.

Cross-entropy with ground truth.



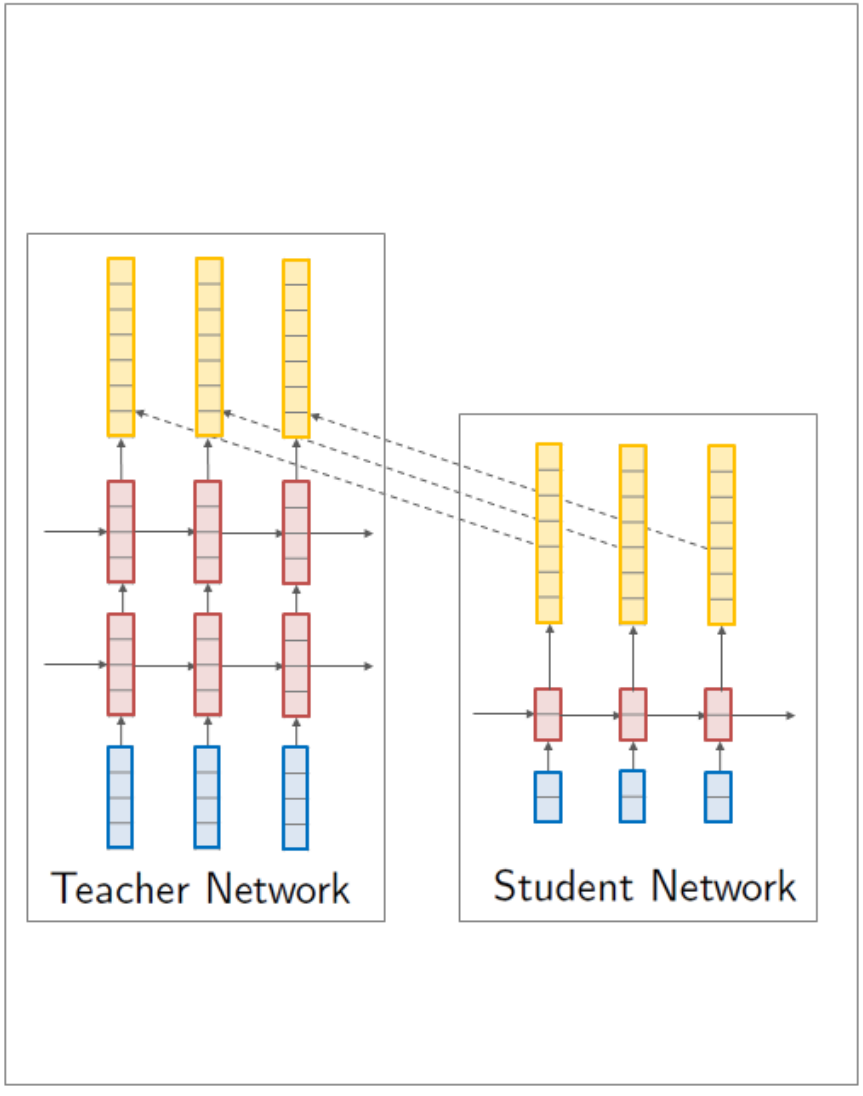
Word-Level Knowledge Distillation

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

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

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

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



This Work: Sequence-Level Knowledge Distillation

Instead of word NLL,

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

Minimize cross-entropy between q and p implied sequence-distributions

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

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

A Simple Approximation

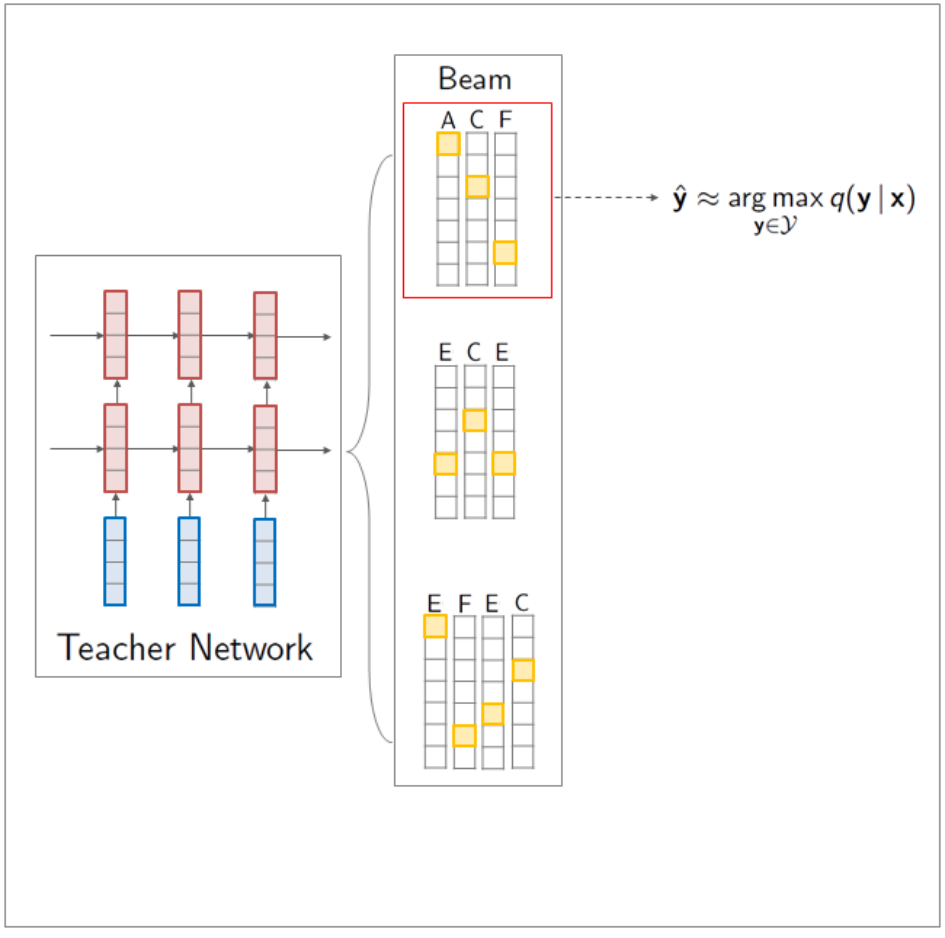
Approximate $q(\mathbf{w}_{1:T} \mid \mathbf{c})$ with mode

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

Roughly obtained wtih beam search

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

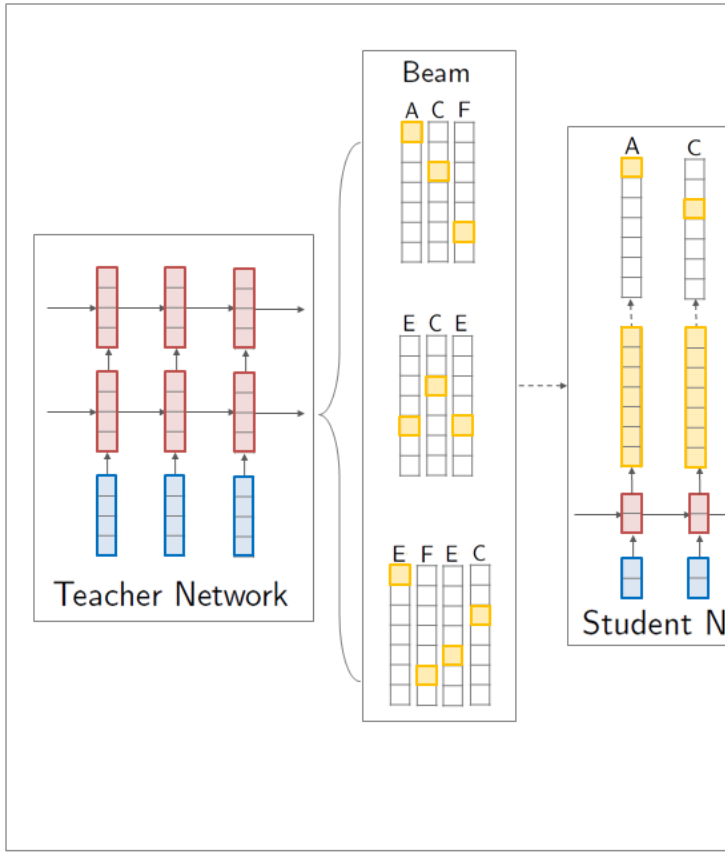
Empirically, point estimate captures significant mass



Sequence-Level Knowledge Distillation

$$\mathcal{L}_{\text{SEQ-KD}}(\theta) = -\log p(\mathbf{w}^*_{1:T} \mid \mathbf{c}; \theta)$$
$$\approx -\sum_{\mathbf{w}_{1:T}} q(\mathbf{w}_{1:T}|\mathbf{c}; \theta_T) \log p(\mathbf{w}_{1:T}|\mathbf{c}; \theta)$$

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



Results: English $\rightarrow$ German

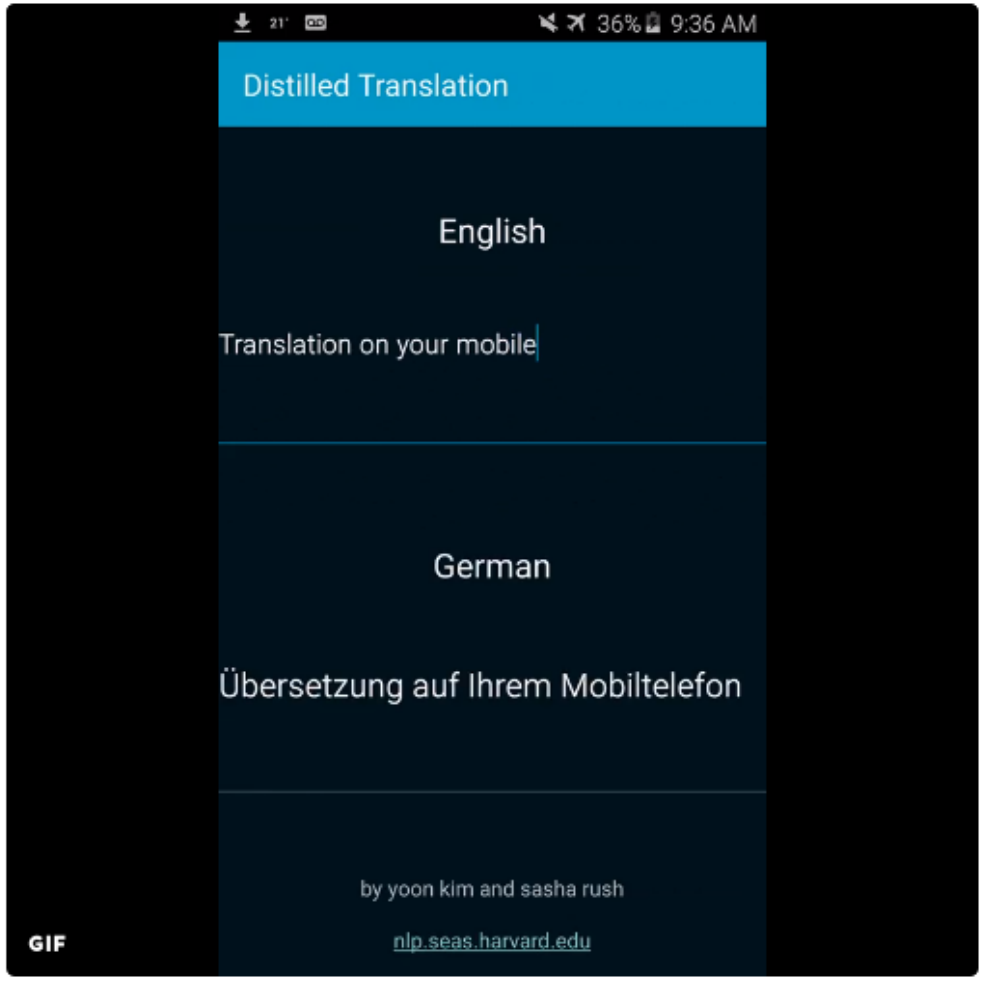
Model	BLEU$_{K=1}$	$\Delta_{K=1}$	BLEU$_{K=5}$	$\Delta_{K=5}$	PPL	$p(\mathbf{w}^*)$
4×1000						
Teacher	17.7	–	19.5	–	6.7	1.3%
Seq-Inter	19.6	+1.9	19.8	+0.3	10.4	8.2%
2×500						
Student	14.7	–	17.6	–	8.2	0.9%
Word-KD	15.4	+0.7	17.7	+0.1	8.0	1.0%
Seq-KD	18.9	**+4.2**	19.0	+1.4	22.7	16.9%
Seq-Inter	18.9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

Combining Knowledge Distillation and Pruning

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

harvardnlp
@harvardnlp

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

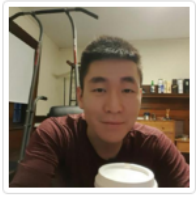


Thank You

harvardnlp

Graduate Students

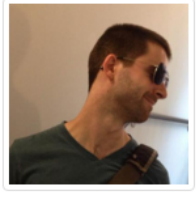
Sebastian Gehrmann



Yoon Kim

Victoria Krakovna

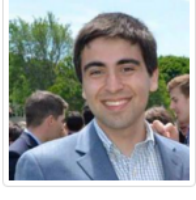
Allen Schmaltz



Sam Wiseman

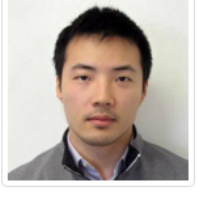
Undergraduate Researchers

Jeffrey Ling



Keyon Vafa

Alex Wang



Mike Zhai

References I