Training and Distilling Seq2Seq Models

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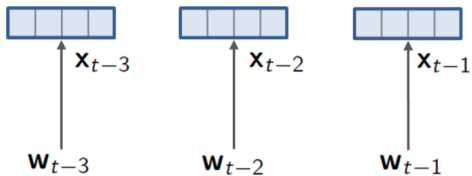
Sequence-to-Sequence

- 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)
- 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 (Xu et al., 2015)
- Video-to-Text (Venugopalan et al., 2015)
- Grammar Correction (Schmaltz et al., 2016)
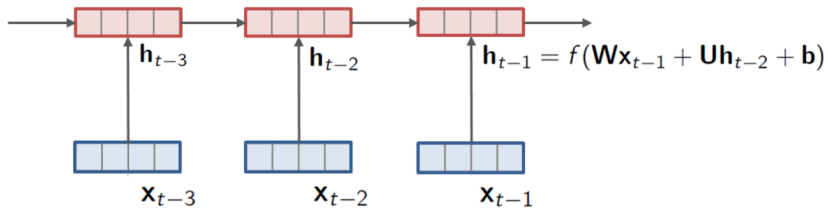
Seq2Seq Neural Network Toolbox

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

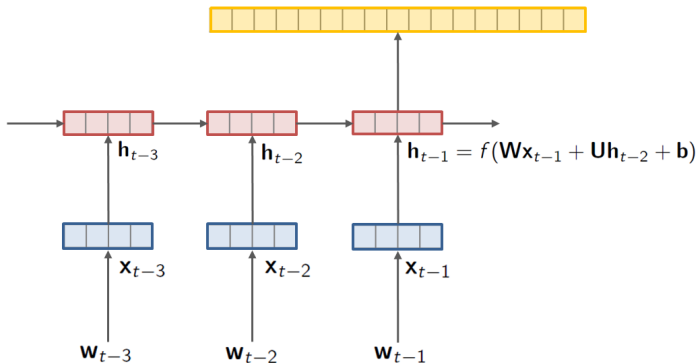Embeddings   sparse features $\Rightarrow$ dense features

$\mathbf{x}_{t-3}$ $\mathbf{x}_{t-2}$ $\mathbf{x}_{t-1}$

$\mathbf{w}_{t-3}$ $\mathbf{w}_{t-2}$ $\mathbf{w}_{t-1}$

RNNs/LSTMs   feature sequences   ⇒   dense features

$$\mathbf{h}_{t-1} = f(\mathbf{W}\mathbf{x}_{t-1} + \mathbf{U}\mathbf{h}_{t-2} + \mathbf{b})$$

LM/Softmax   dense features $\Rightarrow$ discrete predictions

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

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

(Karpathy et al., 2015)

LSTMVis (Strobelt et al., 2016)

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]

(Strobelt et al., 2016)

LSTMVis (Strobelt et al., 2016)

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]

Contextual Language Model / "seq2seq"
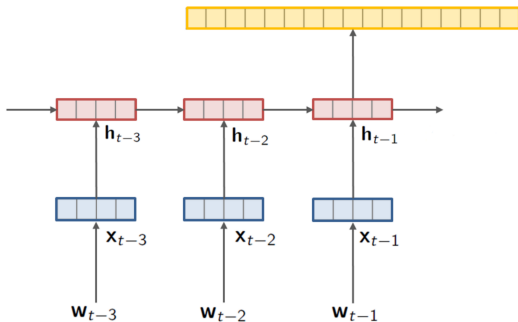
- Key idea, contextual language model based on encoder $\mathbf{c}$:

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

Actual Seq2Seq / Encoder-Decoder / Attention-Based Models
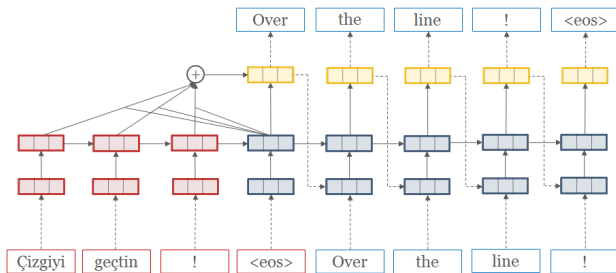
- Different encoders, attention mechanisms, input feeding, …

- 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 (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.

- 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]

$$r = { \frac{ \sqrt{ Q _ { 3 } } } { l } } \operatorname{ s i n } \left(\frac{ l } { \sqrt{ \cal Q _ { 3 } } } u \right) ,$$

[Latex Example]

This Talk

- 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 $y_{1:T}$)

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

Test Objective: Structured prediction

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

$$\boxed{\begin{array}{c} \text{a} \\ \hline \text{the} \\ \hline \text{red} \end{array}}$$

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

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

For timesteps t from 1 to T:

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Beam Search Example ($K = 3$)
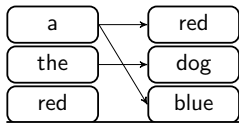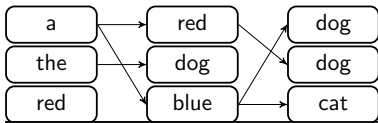

For timesteps t from 1 to T:

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 (Lafferty et al., 2001)
  - Locally normalized models have known pathological issues

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

- Scheduled Sampling (Bengio et al., 2015)

- Globally Normalized Transition-Based Networks (Andor et al., 2016)

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
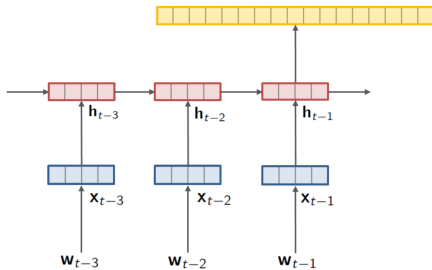
Normalized (Softmax)   Unnormalized

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

- Targets Label Bias

(Idea 2) Run beam search during training
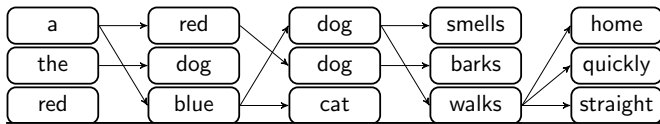
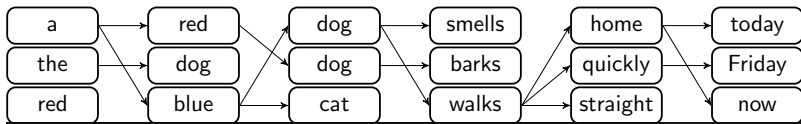1. For timesteps t from 1 to T:
   1. Compute for all $k, \mathbf{w}_t$

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

- Targets Exposure Bias

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   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 $\mathbf{w}^{(K)}$

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

- 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 ($K = 3$)

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

Violation Criterion

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

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Beam Search Optimization Example ($K = 3$)

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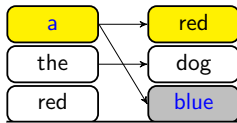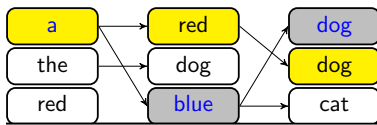# Beam Search Optimization Example ($K = 3$)

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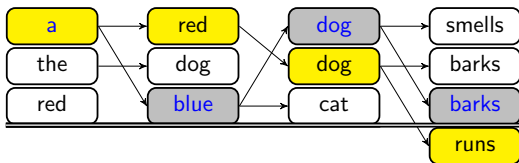
Backpropagation over Structure
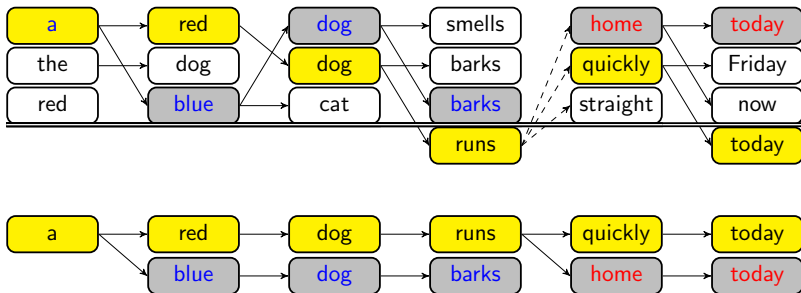
- Margin gradients are sparse, only violating sequences get updates.
- Backprop only requires 2x time as standard methods.

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)[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**
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	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 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)

- 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 $\text{NLL}(\theta)$:

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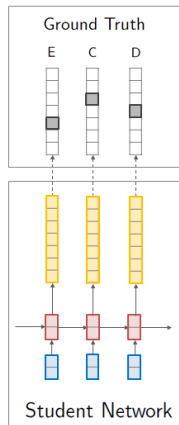
(Word-Level) Knowledge Distillation

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

Minimize cross-entropy with teacher

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

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

Teacher Network   Student Network
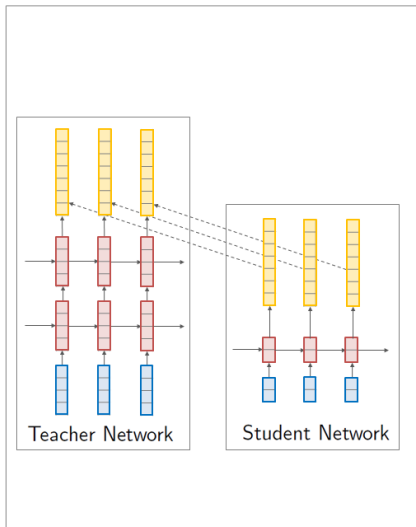
This Work: Sequence-Level Knowledge Distillation

Instead of word NLL,

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

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
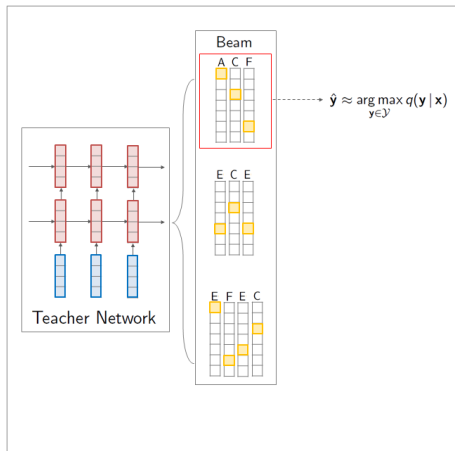
Sequence-Level Knowledge Distillation

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

Local updating (Liang et al., 2006)
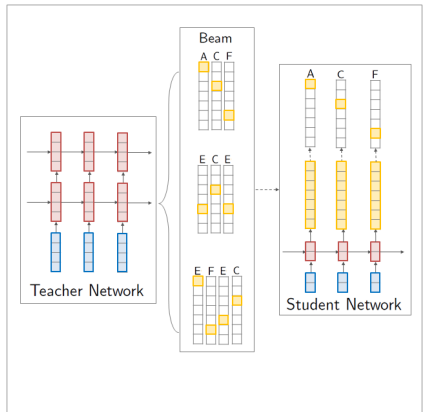
Results: English $\rightarrow$ German

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	$+\mathbf{4.2}$	19.0	$+1.4$	22.7	16.9%
Seq-Inter	18.9	$+\mathbf{4.2}$	19.3	$+\mathbf{1.7}$	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

harvardnlp
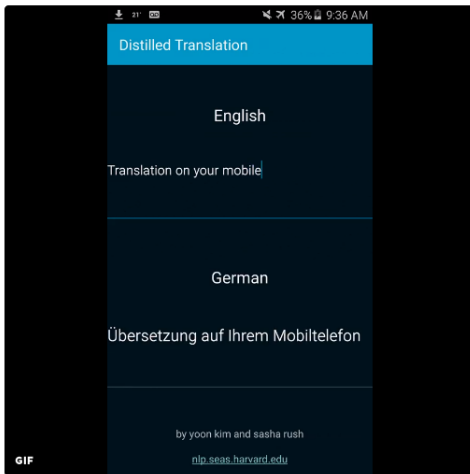
Graduate Students

Sebastian Gehrmann

Yoon Kim

Victoria Krakovna

Allen Schmaltz

Sam Wiseman

Undergraduate Researchers

Jeffrey Ling

Keyon Vafa

Alex Wang

Mike Zhai

Andor, D., Alberti, C., Weiss, D., Severyn, A., Presta, A., Ganchev, K., Petrov, S., and Collins, M. (2016). Globally Normalized Transition-Based Neural Networks. arXiv, cs.CL.

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