Learning How to Say It: Language Generation and Deep Learning

Alexander M Rush

Machine Learning for Multiclass Classification

x

Machine Learning for Multiclass Classification

x

$g(\cdot;\theta)$

Machine Learning for Multiclass Classification

x

$g(\cdot;\theta)$

y

Moped

Machine Learning for Multiclass Classification

x

$g(\cdot; \color{red}{\theta})$

y

Moped

Machine Learning for Text Generation

$$y^*_{1:T} = \arg\max_{y_{1:T}} f(y_{1:T}, x; \theta)$$

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- Input x, *what to talk about*
- Output text $y^*_{1:T}$, *how to say it*
- Model $f(.; \theta)$, learned from data

Part 1: Generating Text

Applications

Machine Translation

x

Yalitza Aparicio acababa de graduarse de una escuela para maestros y aun no tenia empleo cuando el proceso de busqueda de actrices para la ultima pelicula de Alfonso Cuaron llego a su natal Tlaxiaco, Oaxaca.

f

Machine Translation

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f

$y^*_{1:T}$

Yalitza Aparicio had just finished her teaching degree and didn't yet have a job when the Mexican director Alfonso Cuaron held a casting call in her home of Tlaxiaco, Oaxaca, for the lead role in his semi-autobiographical drama, "Roma."

Translation Performance

Evaluation Metric:

Target: `[Yalitza Aparicio had] just [finished her] teaching [degree] .`

Predict: `[Yalitza Aparicio had] recently [finished her] [degree].`

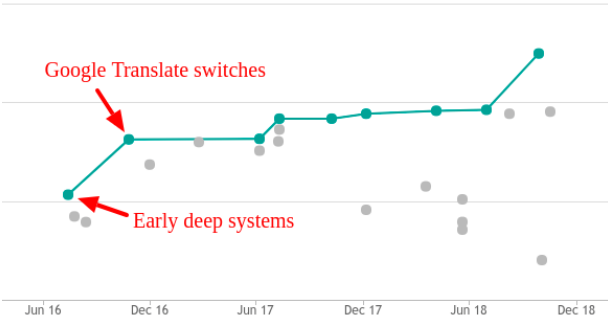
Translation Performance

Evaluation Metric:

Target: `[Yalitza Aparicio had] just [finished her] teaching [degree] .`

Predict: `[Yalitza Aparicio had] recently [finished her] [degree].`

Deep Learning Performance:



Sentence Summarization

x

Cambodian leader Hun Sen on friday rejected opposition parties' demands for talks outside the country, accusing them of trying to "internationalize" the political crisis.

f

Sentence Summarization

x

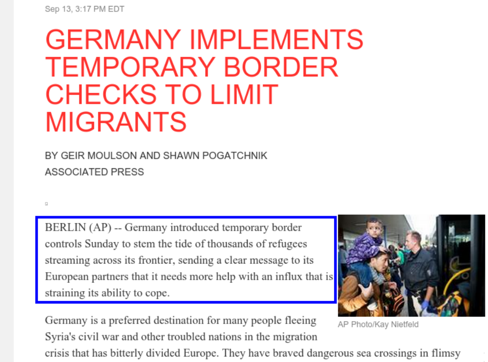
Cambodian leader Hun Sen on friday rejected opposition parties' demands for talks outside the country, accusing them of trying to "internationalize" the political crisis.

f

$y_{1:T}$

Cambodian government rejects opposition's call for talks abroad

GigaWord Dataset (Rush et al. [2015] w/ Facebook)


Sep 13, 3:17 PM EDT

GERMANY IMPLEMENTS TEMPORARY BORDER CHECKS TO LIMIT MIGRANTS

BY GEIR MOULSON AND SHAWN POGATCHNIK
ASSOCIATED PRESS

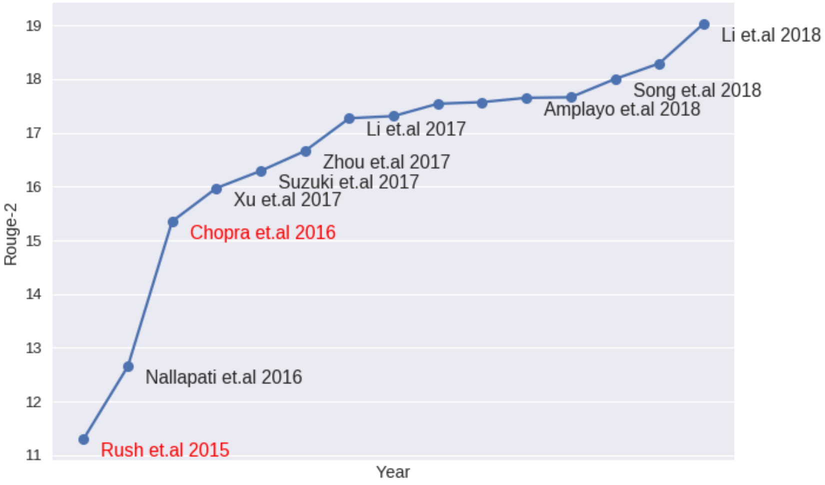
BERLIN (AP) -- Germany introduced temporary border controls Sunday to stem the tide of thousands of refugees streaming across its frontier, sending a clear message to its European partners that it needs more help with an influx that is straining its ability to cope.

AP Photo/Kay Nietfeld

Germany is a preferred destination for many people fleeing Syria's civil war and other troubled nations in the migration crisis that has bitterly divided Europe. They have braved dangerous sea crossings in flimsy

- Several million headlines paired with article leads.
- Simple model for abstractive summarization / compression.
- Benchmark dataset for early deep summarization work.

Sentence Summarization



Document Summary

London, England (reuters) – Harry Potter star Daniel Radcliffe gains access to a reported $20 million fortune as he turns 18 on monday, but he insists the money won't cast a spell on him. Daniel Radcliffe as harry potter in "Harry Potter and the Order of the Phoenix" to the disappointment of gossip columnists around the world , the young actor says he has no plans to fritter his cash away on fast cars , drink and celebrity parties . " i do n't plan to be one of those people who , as soon as they turn 18 , suddenly buy themselves a massive sports car collection or something similar , " he told an australian interviewer earlier this month . " i do n't think i 'll be particularly extravagant " . " the things i like buying are things that cost about 10 pounds – books and cds and dvds . " at 18 , radcliffe will be able to gamble in a casino , buy a drink in a pub or see the horror film " hostel : part ii , " currently six places below his number one movie on the uk box office chart . details of how he 'll mark his landmark birthday are under wraps . his agent and publicist had no comment on his plans . " i 'll definitely have some sort of party , " he said in an interview . . .

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Harry Potter star Daniel Radcliffe gets $20m fortune as he turns 18 monday. Young actor says he has no plans to fritter his cash away. Radcliffe 's earnings from first five potter films have been held in trust fund.

Document Summarization

Talk about Data

(Wiseman et al. [2017a])

TEAM	WIN	LOSS	PTS	FG_PCT	RB	AS ...
Heat	11	12	103	49	47	27
Hawks	7	15	95	43	33	20

PLAYER	AS	RB	PT	FG	FGA	CITY ...
Tyler Johnson	5	2	27	8	16	Miami
Dwight Howard	11	17	23	9	11	Atlanta
Paul Millsap	2	9	21	8	12	Atlanta
Goran Dragic	4	2	21	8	17	Miami
Wayne Ellington	2	3	19	7	15	Miami
Dennis Schroder	7	4	17	8	15	Atlanta
Rodney McGruder	5	5	11	3	8	Miami
...						

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The Atlanta Hawks defeated the Miami Heat, 103 - 95, at Philips Arena on Wednesday. Atlanta was in desperate need of a win and they were able to take care of a short-handed Miami team here. Defense was key for the Hawks, as they held the Heat to 42 percent shooting and forced them to commit 16 turnovers. Atlanta also dominated in the paint, winning the rebounding battle, 47 - 34, and outscoring them in the paint 58 - 26. The Hawks shot 49 percent from the field and assisted on 27 of their 43 made baskets. This was a near wire-to-wire win for the Hawks, as Miami held just one lead in the first five minutes. Miami (7 - 15) are as beat-up as anyone right now and it's taking a toll on the heavily used starters. Hassan Whiteside really struggled in this game, as he amassed eight points, 12 rebounds and one blocks on 4 - of - 12 shooting ...

E2E Challenge 2018

MR	name[The Golden Palace], eatType[coffee shop], food[Fast food], priceRange[cheap], customer rating[5 out of 5], area[riverside]
Reference	A coffee shop located on the riverside called The Golden Palace, has a 5 out of 5 customer rating. Its price range are fairly cheap for its excellent Fast food.

Submitter	Affiliation	System name	P?	BLEU	NIST	METEOR	ROUGE_L▲	CIDEr
HarvardNLP & Henry Elder	Harvard SEAS & Adapt	main_1_support_3		0.6737	8.6061	0.4523	0.7084	2.3056
Biao Zhang	Xiamen University	bzhang_submit	✓	0.6545	8.1840	0.4392	0.7083	2.1012
HarvardNLP & Henry Elder	Harvard SEAS & Adapt	main_1_support_2		0.6618	8.6025	0.4571	0.7038	2.3371
Shubham Agarwal	NLE	submission_third		0.6676	8.5416	0.4485	0.6991	2.2276
Shubham Agarwal	NLE	submission_second		0.6669	8.5388	0.4484	0.6991	2.2239
Thomson Reuters NLG	Thomson Reuters	NonPrimary_4_test_output_beam_5_model_13_post		0.6742	8.6590	0.4499	0.6983	2.3018

$$\mathcal{K}^L(\sigma=2)=\begin{pmatrix} -\frac{d^2}{dx^2}+4-\frac{3}{\cosh^2 x} & \frac{3}{\cosh^2 x} \\ \frac{3}{\cosh^2 x} & -\frac{d^2}{dx^2}+4-\frac{3}{\cosh^2 x} \end{pmatrix},$$

Talk about the Diagrams (Deng et al. [2016] w/ Bloomberg)

$$\mathcal{K}^L(\sigma = 2) = \left(\begin{array}{cc} -\frac{d^2}{dx^2} + 4 - \frac{3}{\cosh^2 x} & \frac{3}{\cosh^2 x} \\ \frac{3}{\cosh^2 x} & -\frac{d^2}{dx^2} + 4 - \frac{3}{\cosh^2 x} \end{array} \right) \qquad ,$$

```
{ \cal K } ^ { L } ( \sigma = 2 ) = \left( \begin{array}
{ c c } { - \frac { d ^ { 2 } } { d x ^ { 2 } } + 4 - \frac
{ 3 } { \operatorname { c o s h } ^ { 2 } x } } \& { \frac
{ 3 } { d x ^ { 2 } } }  { \frac { 3 } { \operatorname
{ c o s h } ^ { 2 } x } } \& { - \frac { d ^ { 2 } }
{ d x ^ { 2 } } + 4 - \frac { 3 } { \operatorname { c o s h }
^ { 2 } x } }  \end{array} \right) \qquad
```

Im2Latex

(Deng et al. [2016] w/ Bloomberg)

$$A_0^3(\alpha' \rightarrow 0) = 2g_d\,\varepsilon^{(1)}_\lambda \varepsilon^{(2)}_\mu \varepsilon^{(3)}_\nu \left\{ \eta^{\lambda\mu}\left(p_1^\nu - p_2^\nu\right) + \eta^{\lambda\nu}\left(p_3^\mu - p_1^\mu\right) + \eta^{\mu\nu}\left(p_2^\lambda - p_3^\lambda\right) \right\} .$$

```
(A_{0}^{3}(\alpha^{\prime }\rightarrow 0)=2g_{d}\,\,\varepsilon^{(1)}_{\lambda}\varepsilon^{(2)}
_{\mu }\varepsilon^{(3)}_{\nu }\left\{ \eta ^{\lambda \mu}\left( p_{1}^{\nu }-p_{2}^{\nu }\right) +
\eta ^{\lambda \nu }\left(p_{3}^{\mu }-p_{1}^{\mu }\right)+\eta ^{\mu \nu }\left( p_{2}^{\lambda}
-p_{3}^{\lambda }\right) \right\} . \label{17}
```

$$\left\{\begin{array}{rcl}\delta_{\epsilon} B & \sim & \epsilon F \, , \\ \delta_{\epsilon} F & \sim & \partial\epsilon + \epsilon B \, , \end{array}\right.$$

```
\left\{\begin{array}{rcl}\delta_{\epsilon} B & \sim & \epsilon F
\, , \\\delta_{\epsilon} F & \sim & \partial\epsilon + \epsilon B
\, , \\\end{array}\right.
```

$$\int\limits_{\mathcal{L}^d_{d-1}} f(H) d\nu_{d-1}(H) = c_3 \int\limits_{\mathcal{L}^A_2} \int\limits_{\mathcal{L}^L_{d-1}} f(H)[H,A]^2 d\nu^L_{d-1}(H) d\nu^A_2(L).$$

```
\int \limits_{{\cal L}^{d}_{d-1}}f(H)d\nu_{d-1}(H) =  c_{3} \int \limits_{{\cal L}^{A}_{2}}
\int \limits_{{\cal L}^{L}_{d-1}}f(H)[H,A]^{2}d\nu_{d-1}^{L}(H)d\nu_{2}^{A}(L).
```

$$J = \left(\begin{array}{cc} \alpha^t & \tilde{f}_2 \\ f_1 & \tilde{A} \end{array}\right) \left(\begin{array}{ll} 0 & 0 \\ 0 & L \end{array}\right) \left(\begin{array}{cc} \alpha & \tilde{f}_1 \\ f_2 & A \end{array}\right) = \left(\begin{array}{ll} \tilde{f}_2 L f_2 & \tilde{f}_2 L A \\ \tilde{A} L f_2 & \tilde{A} L A \end{array}\right)$$

```
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\left( \begin{array}{cc}\alpha & \tilde{f}_{1} \\ f_{2} & A\end{array}\right) =
\left( \begin{array}{ll}\tilde{f}_{2}Lf_{2} & \tilde{f}_{2}LA \\ \tilde{A}Lf_{2} &
\tilde{A}LA\end{array}\right)
```

$$\lambda^{(2)}_{n,1} = \frac{\partial \overline{H}_0}{\partial q_{n,0}} \ , lambda^{(2)}_{n,j_n} = \frac{\partial \overline{H}_0}{\partial q_{n,j_n-1}} - \mu_{n,j_n-1} \ , \quad j_n = 2,3,\cdots,m_n-1 \ .$$

```
\lambda_{n,1}^{(2)}=\frac{\partial\overline{H}_0}{\partial q_{n,0}}\ ,\ \\lambda_{n,j_n}^{(2)}=\frac{
\partial\overline{H}_0}{\partial q_{n,j_n-1}}-\mu_{n,j_n-1}\ ,\      \ j_n=2,3,\cdots,m_n-1\ .
```

$$(P_{ll'} - K_{ll'})\phi'(z_q)|\chi >= 0$$

```
(P_{ll'} - K_{ll'}) \phi '(z_{q})|\chi > = 0
```

Temporary

1 Introduction

What types of models get used for this equation?

$$\arg\max_{y_{1:T}} f(y_{1:T}, x; \theta)$$

State-of-the-Art Natural Language Processing, circa 2009

Task (x, y)

Syntax

Surface Structure

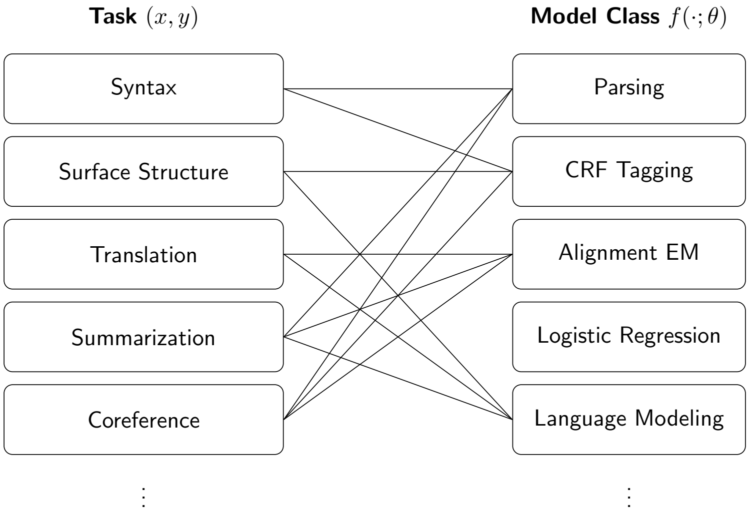
Translation

Summarization

Coreference

$\vdots$

State-of-the-Art Natural Language Processing, circa 2009



State-of-the-Art Natural Language Processing, circa 2019

Task (x, y)

Syntax
Surface Structure
Translation
Summarization
New Tasks

$\vdots$

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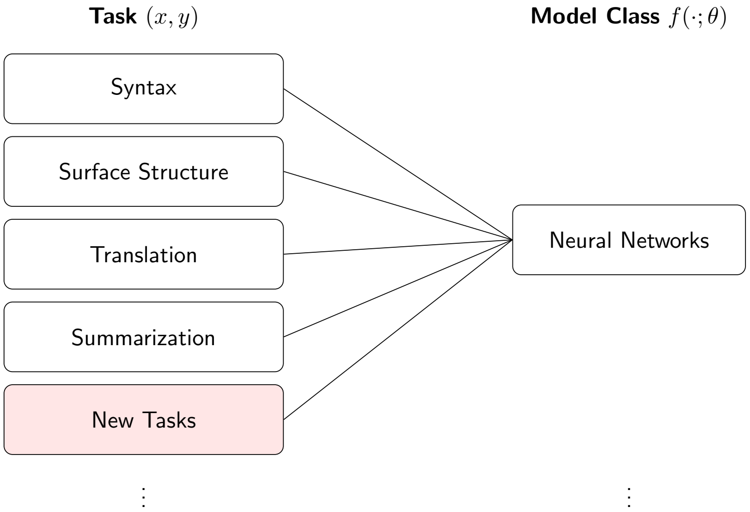

State-of-the-Art Natural Language Processing, circa 2019

Task (x, y)

Syntax

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Translation

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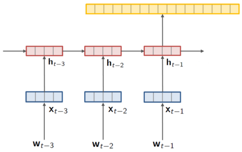
New Tasks

$\vdots$

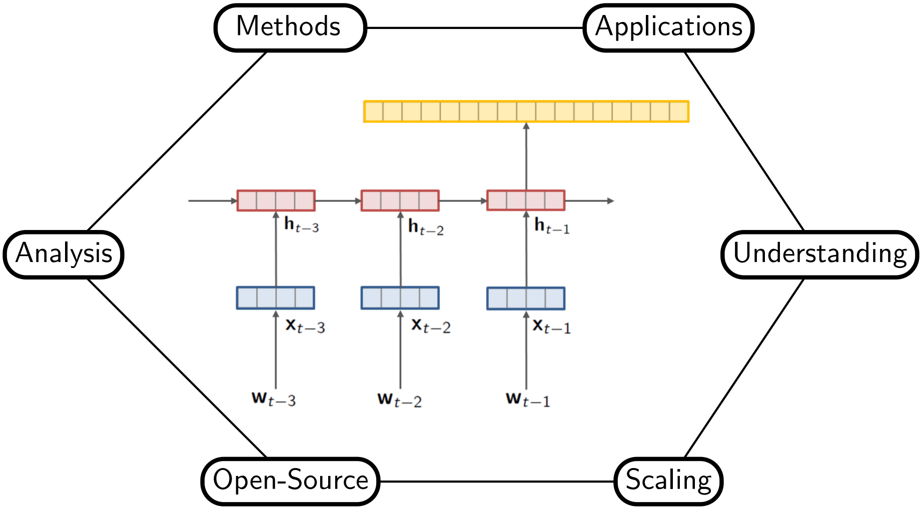
Model Class $f(\cdot; \theta)$

Neural Networks



$\vdots$

Harvard NLP Deep Learning Research



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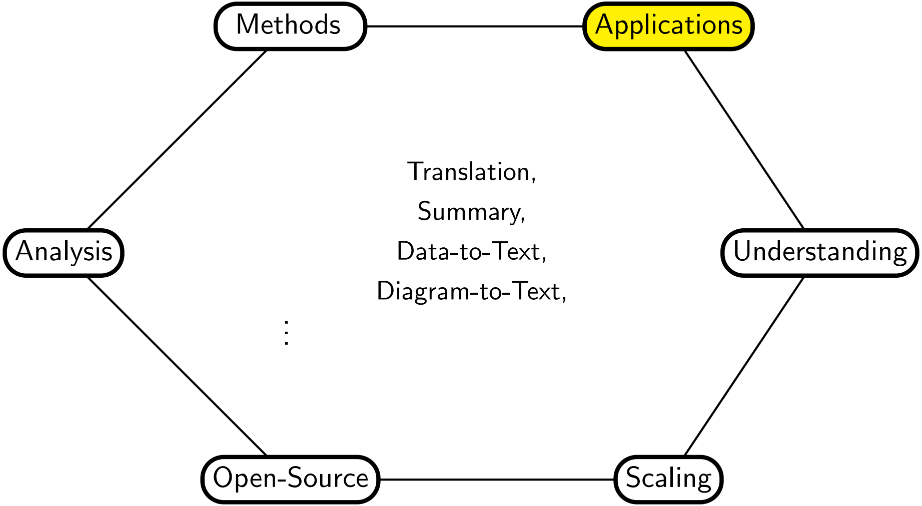
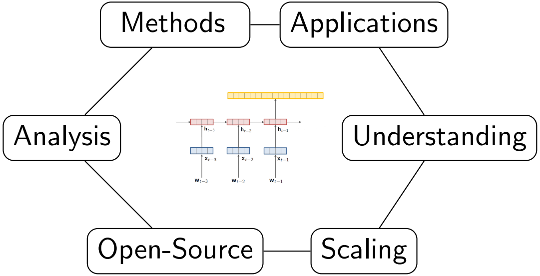


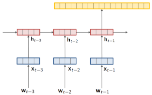
Selected Harvard NLP Deep Learning Research



Natural Lang. Processing
Machine Learning
Visualization

Selected Harvard NLP Deep Learning Research

Methods — Applications

Analysis  Understanding

Open-Source — Scaling

Strobelt et al. [2016]
Strobelt et al. [2019]
Wiseman et al. [2017b]

Natural Lang. Processing
Machine Learning
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Selected Harvard NLP Deep Learning Research

Kim et al. [2016]

Kim et al. [2017]

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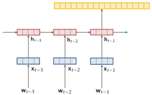
Methods — Applications

Analysis



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Deng et al. [2016]

Schmaltz et al. [2016]

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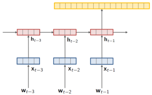

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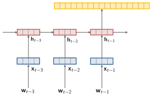

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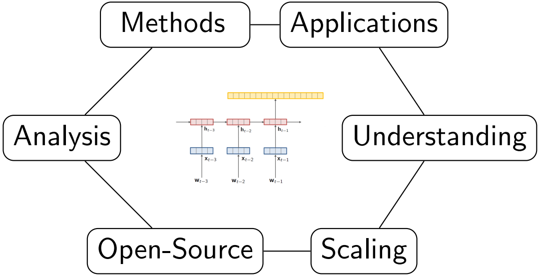

Kim and Rush [2016]
Senellart et al. [2018]
Reagen et al. [2017]

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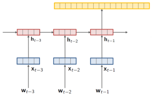

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Natural Lang. Processing

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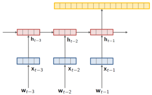

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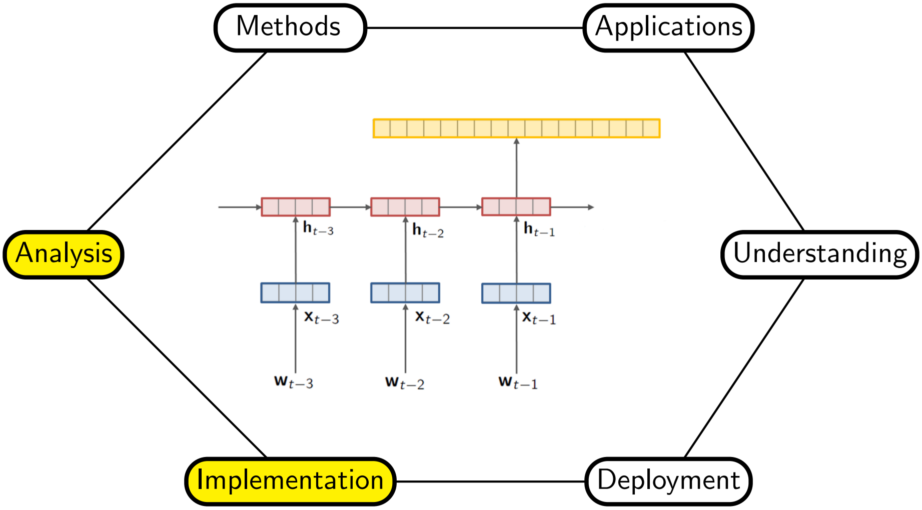
Natural Lang. Processing
Machine Learning
Visualization

Part 2: Deep Learning Internals



Machine Learning for Text Generation

$$y^*_{1:T} = \arg\max_{y_{1:T}} f(y_{1:T}; x, \theta)$$

- Input $x_{1:S}$, *what to talk about*
- Output text $y^*_{1:T}$, *how to say it*
- Model $f(.;\theta)$, learned from data

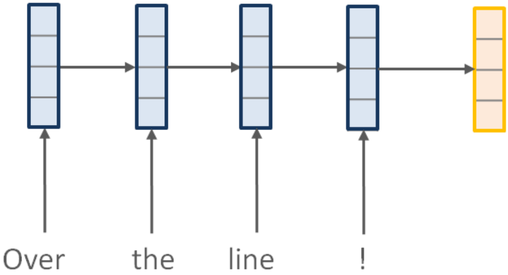
Recurrent Neural Network 1

$f(y_{1:T}, x_{1:T}; \theta)$

Over the line !

Recurrent Neural Network 1

$f(y_{1:T}, x_{1:T}; \theta)$



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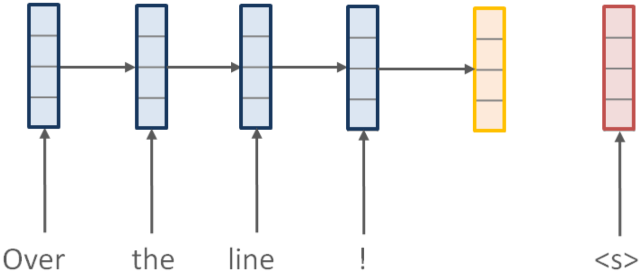
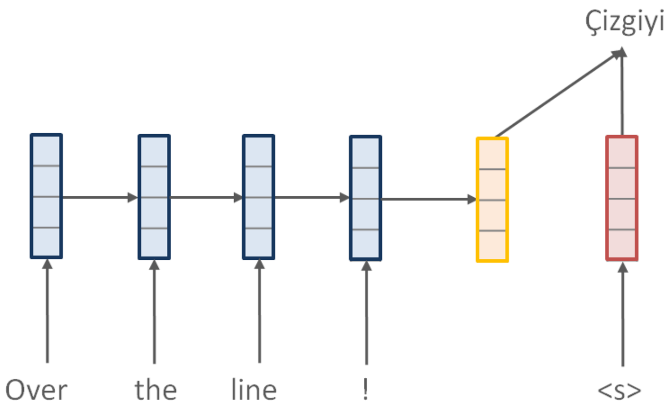


Recurrent Neural Network 1

$$f(y_{1:T}, x_{1:T}; \theta)$$



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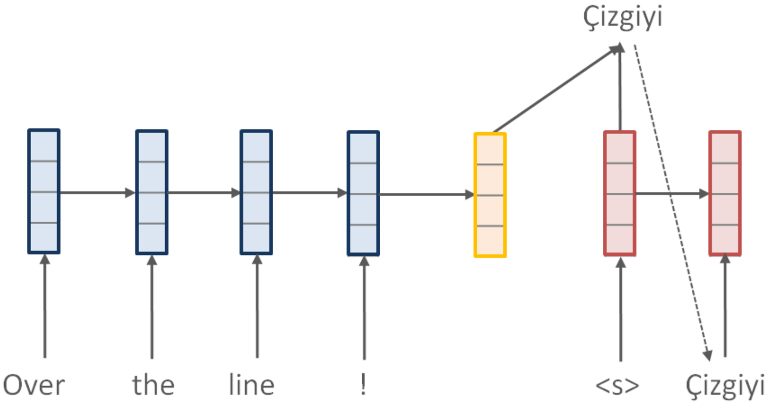

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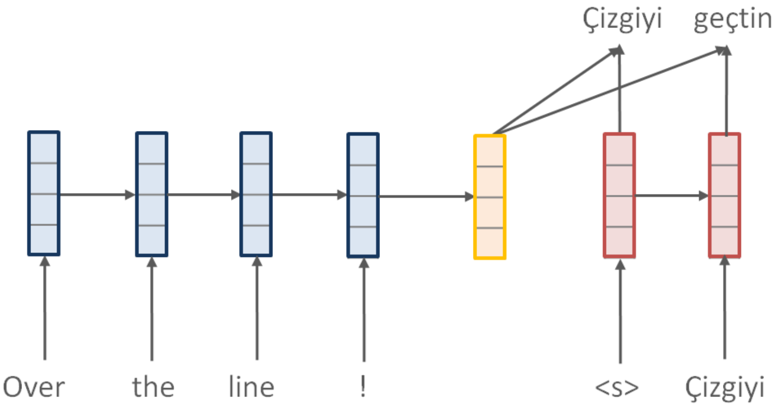

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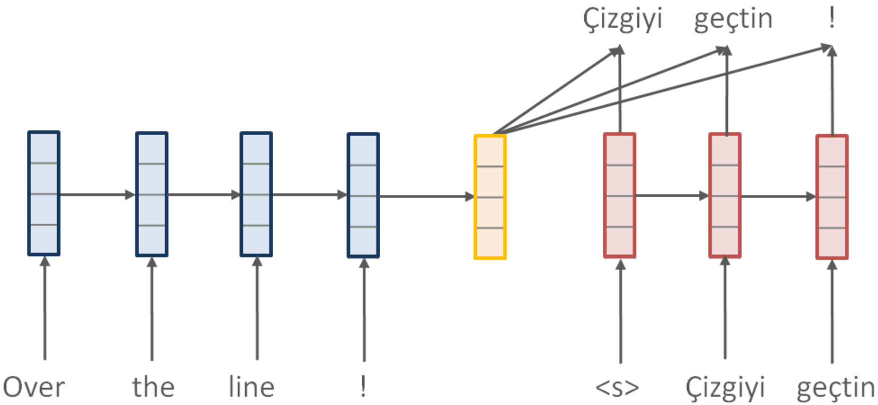

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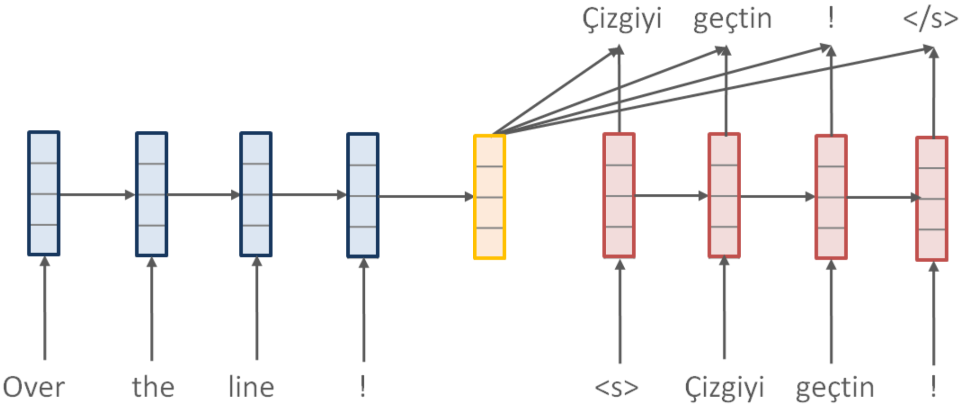


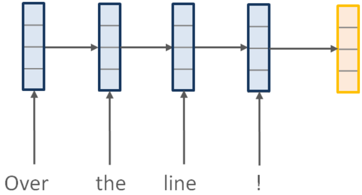
Recurrent Neural Network Math

Encoder:

$$\mathbf{h}_s^x \leftarrow \mathrm{RNN}(\mathbf{h}_{s-1}^x, x_s)$$

Context:

$$\mathbf{c} = \mathbf{h}_S^x$$



Recurrent Neural Network Math

Encoder:

$$\mathbf{h}_s^x \leftarrow \mathrm{RNN}(\mathbf{h}_{s-1}^x, x_s)$$

Context:

$$\mathbf{c} = \mathbf{h}_S^x$$

Decoder:

$$\mathbf{h}_t \leftarrow \mathrm{RNN}(\mathbf{h}_{t-1}, y_t)$$

Prediction:

$$p(y_{t+1} \mid y_{1:t}, x) = \mathrm{softmax}(\mathbf{W}[\mathbf{h}_t; \mathbf{c}])$$

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Generation Score:

$$f(y_{1:T}, x; \theta) = \log \sum_{t=1}^{T} p(y_t \mid y_{1:t-1}, x)$$

What can the decoder learn to say?

Decoder:

$$\mathbf{h}_t \leftarrow \mathrm{RNN}(\mathbf{h}_{t-1}, y_t)$$

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Toy Example:

Well-balanced parenthesis language with random nesting-level indicators,

- Vocabulary: ( ) 0 1 2 3 4
- Example String: 0 ((2) (((4 4 4) 3) . . .

Proxy Question: What does $\mathbf{h}_t$ look like over time?

LSTMVis - Parenthesis Language (Strobelt et al. [2016] w/ IBM)

Temporary

What can the decoder learn to say?

Decoder:

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Harder Example: Natural language outputs with complex syntax.

LSTMVis - Parenthesis Language (Strobelt et al. [2016] w/ IBM)

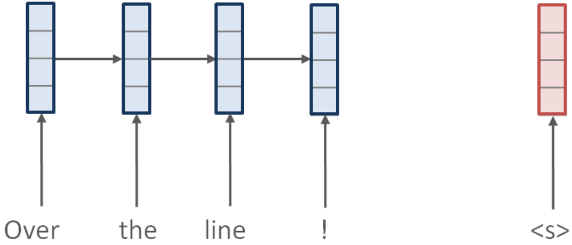
Temporary

LSTMVis - Natural Language (Strobelt et al. [2016] w/ IBM)

Temporary

Recurrent Neural Network 2 - Seq2Seq + Attention

$f(y_{1:T}, x_{1:T}; \theta)$



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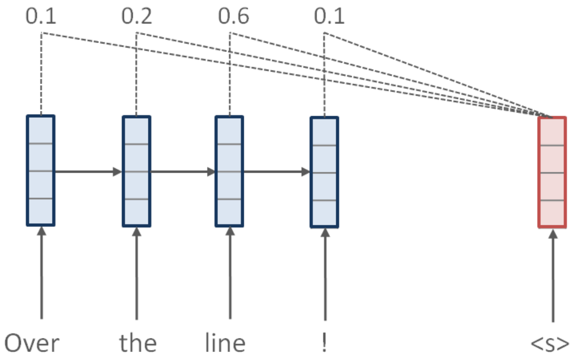

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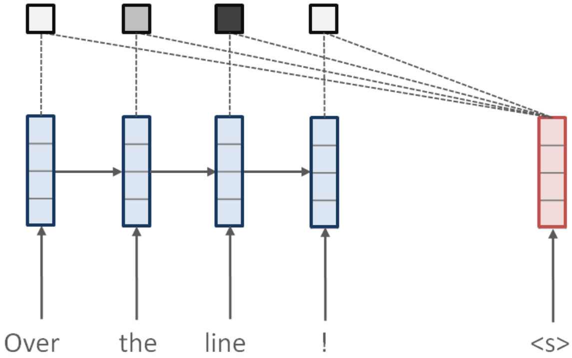

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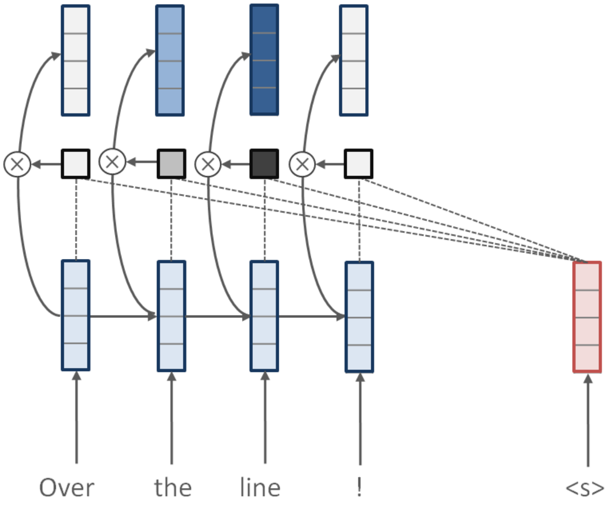

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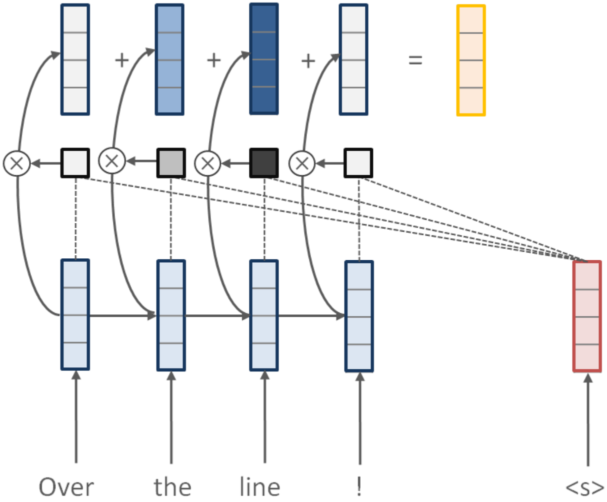

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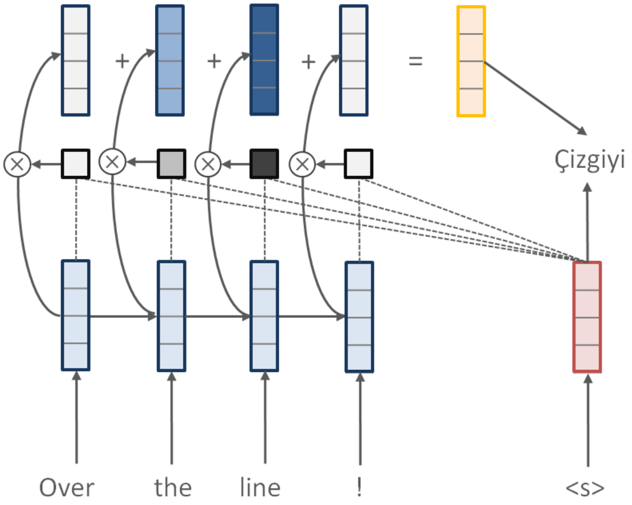

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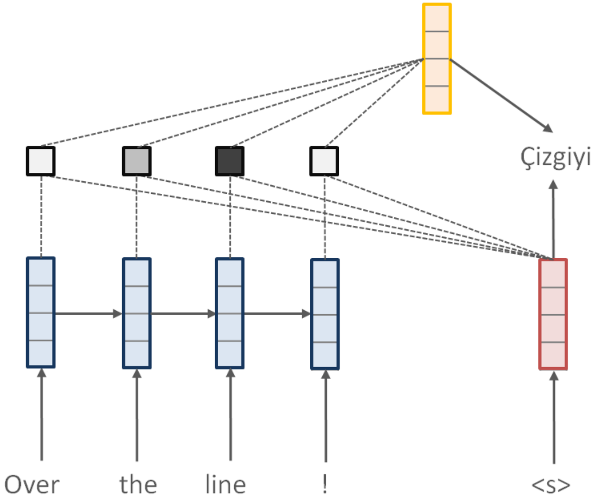

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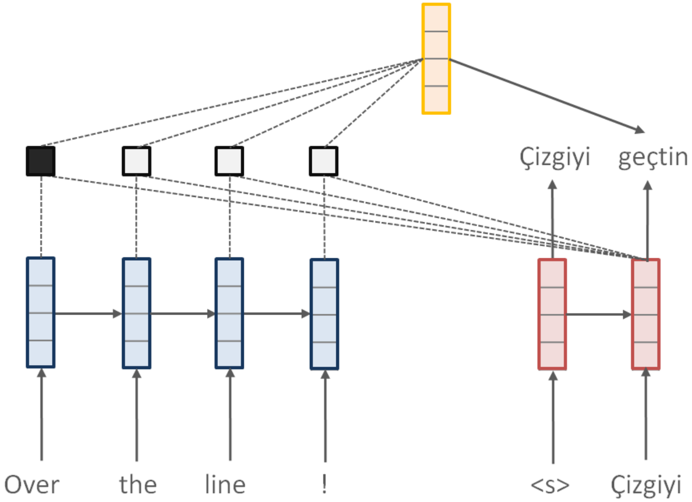

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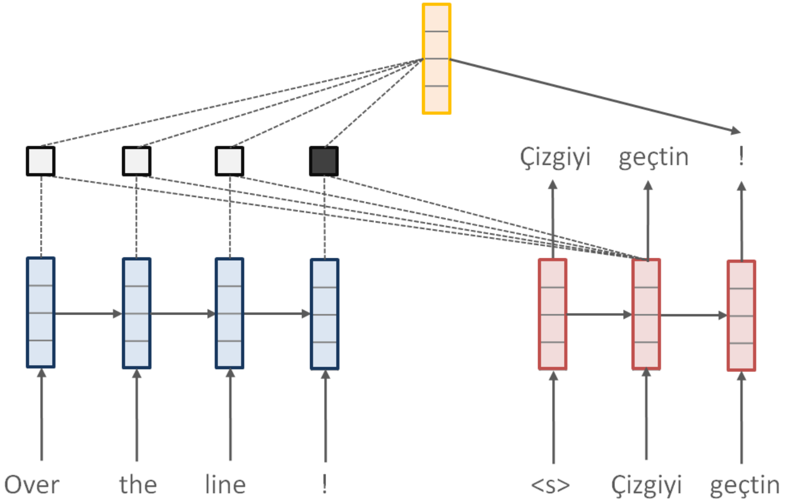

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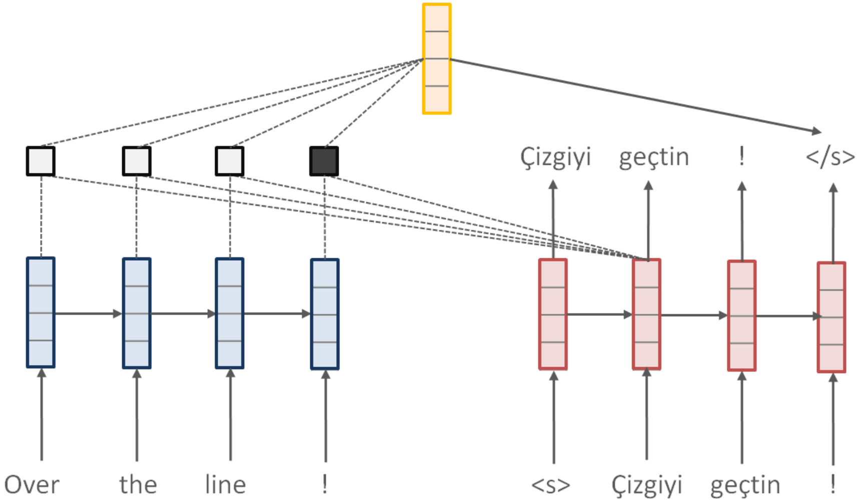


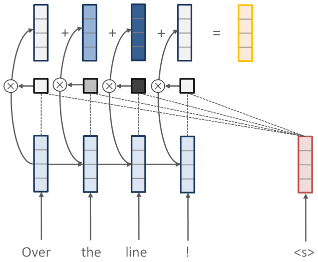
Attention Math

Encoder:

$$\mathbf{h}_s^x \leftarrow \mathrm{RNN}(\mathbf{h}_{s-1}^x, x_s)$$

Attention (Dynamic Context)

$$\alpha \leftarrow \mathrm{softmax}([\mathbf{h}_1^x; \dots; \mathbf{h}_S^x]^\top \mathbf{h}_t) \qquad \mathbf{c} \leftarrow \sum_{s=1}^{S} \alpha_s \mathbf{h}_s^x$$



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How does attention control what is said?

Attention (Dynamic Context)

$$\alpha \leftarrow \mathrm{softmax}([\mathbf{h}_1^x; \ldots; \mathbf{h}_S^x]^\top \mathbf{h}_t) \quad \mathbf{c} \leftarrow \sum_{s=1}^{S} \alpha_s \mathbf{h}_s^x$$

- Can we use this to control the output of the system?
- Can we examine how errors enter into translation?

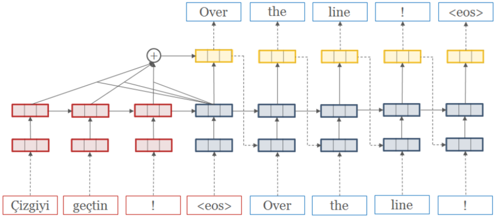
Temporary

An open-source neural machine translation system.

English Français 简体中文 한국어 日本語 Русский العربية

Home

OpenNMT is a industrial-strength, open-source (MIT) neural machine translation system utilizing the Torch/PyTorch mathematical toolkit.



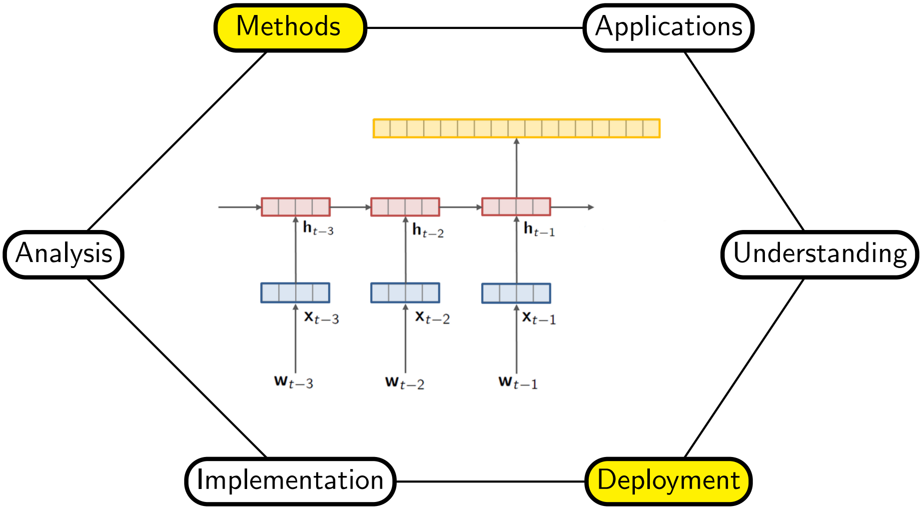
OpenNMT is used as provided in production by major translation providers. The system is designed to be simple to use and easy to extend, while maintaining efficiency and state-of-the-art translation accuracy.

- Collaborative open-source project started at Harvard, now self-sustaining.
- Used in production by Systran, Ubiqus, Booking.com, and others.
- Over 100 developers in France, China, Japan, Portugal, and the US.
- Designed to be research extensible to latest machine translation techniques.
- Pretrained models for translation as well as everything in this talk.

OpenNMT Workshop

Paris 2018

Part 3: Structured Modeling



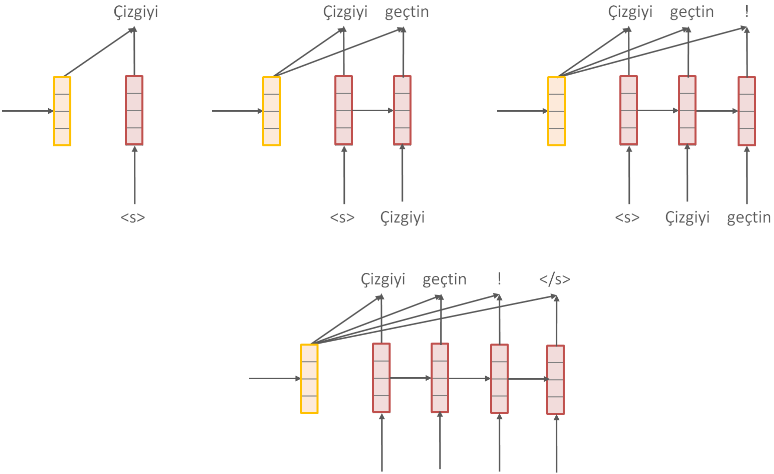
Machine Learning for Text Generation

$$y^*_{1:T} = \underset{y_{1:T}}{\arg\max}\, f(y_{1:T}; x, \theta)$$

- Input $x_{1:S}$, *what to talk about*
- Output text $y^*_{1:T}$, *how to say it*
- Model $f(.;\theta)$, learned from data

Training Seq2Seq

Parameters θ are trained to predict the next word *given the true history.*



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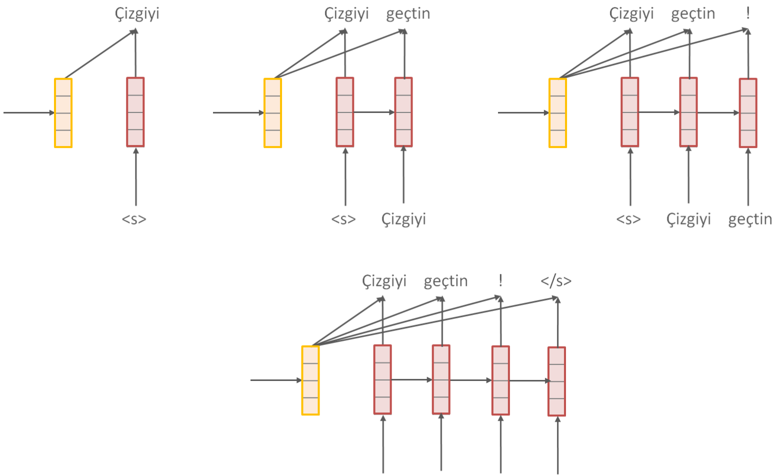
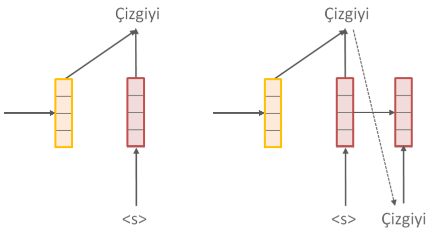
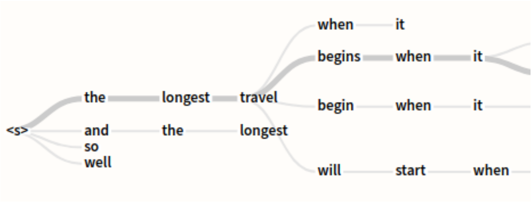


Deploying Seq2Seq

Parameters θ is deployed to predict a next word *given the predicted history*.





Requires predicting best sequence

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

However: Completely intractable for RNNs $O(\#\text{vocab}^T)$

Standard Heuristic Method: Beam Search

$K = 3$

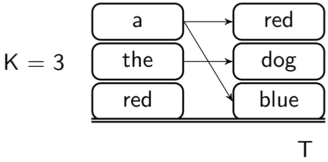
a

the

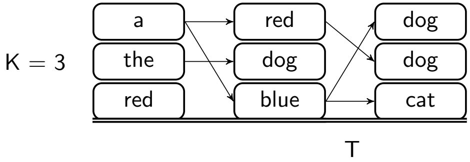
red

T

Standard Heuristic Method: Beam Search



Standard Heuristic Method: Beam Search



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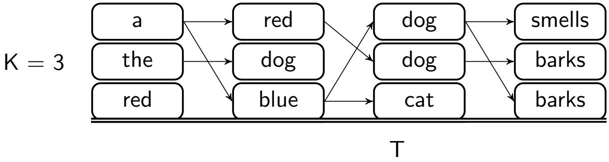

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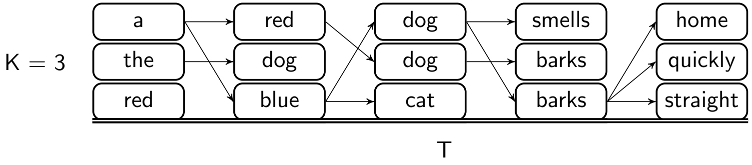

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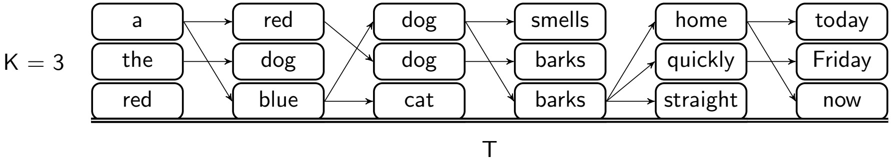

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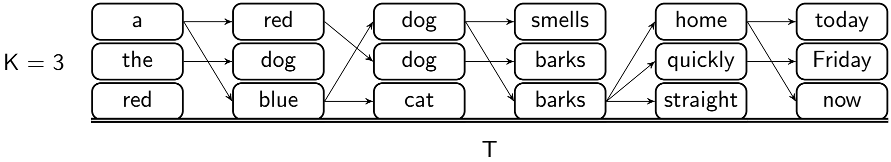

1. Compute the score of every possible next word.

$$f(y_t, y_{1:t-1}^{(k)}) \leftarrow \log p(y_t \mid y_{1:t-1}^{(k)}, x) + \log p(y_{1:t-1}^{(k)} \mid x)$$

2. Prune to only the K highest-scoring,

$$y_{1:t}^{(1:K)} \leftarrow K \operatorname*{arg\,max}_{y_{1:t}} f(y_t, y_{1:t-1}^{(k)})$$

Theoretical Issues with RNN-based Models

1. Label Bias
   - Training is locally discriminative, but prediction is over entire sequences.
2. Exposure Bias
   - Training conditions on true history ($y_{1:t-1}$) but generates with predicted history.

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Research

Can we better model discrete sequences for text generation?

Applications:

- (1) Improvements in training with less supervision.
- (2) Effective methods for downscaling translation models.

Sequence-to-Sequence Learning as Beam Search Optimization (Wiseman and Rush [2016])

Proposal: Directly modify the RNN training procedure to fix test biases.

1. Label Bias
2. Exposure Bias
3. Metric Bias

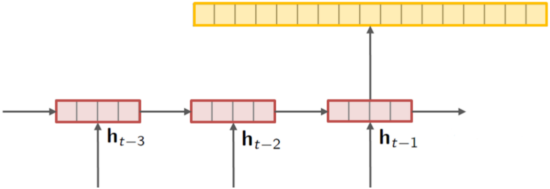
Modification 1: Global Scoring Function

Issue: Label Bias

- Training is locally discriminative, but prediction is over entire sequences.

Proposed Fix:

- Replace $\log p(y_t|y_{1:t-1}^{(k)}, \mathbf{c}; \theta)$ with a directly learned function $f(y_t, y_{1:t-1}^{(k)}, x; \theta)$



Modification 2: Beam Search at Training

Issue: Exposure Bias

- Training conditions on true history ($y_{1:t-1}$) but generates with predicted history.

Proposed Fix: During training:

1. Compute the score of every possible next word.

$$f(y_t, y_{1:t-1}^{(k)}) \leftarrow \log p(y_t \mid y_{1:t-1}^{(k)}, \mathbf{c}) + \log p(y_{1:t-1}^{(k)} \mid \mathbf{c})$$

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Modification 3: Train with Margin

Issue: Metric Bias

- Training uses multiclass classification, but evaluation uses n-gram match.

Proposed Fix: Use a structured SVM-style training loss:

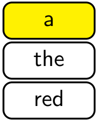
- Margin between ground truth sequence $\hat{y}$ and worst predicted sequence $y^{(K)}$

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

- Slack-rescaled, margin-based sequence criterion, at each time step.

- Δ is a task specific sequence cost, i.e. ngram-mismatch

Beam Search Optimization Example



- Color True: ground-truth sequence $\hat{y}$
- Color Red: last sentence $y^{(K)}$ upon violation

Strategy: upon violation, restart from ground truth (learning as search optimization **?**)

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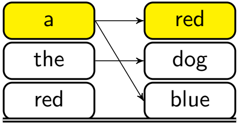

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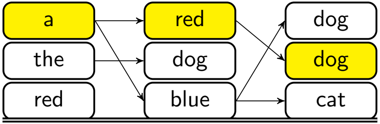

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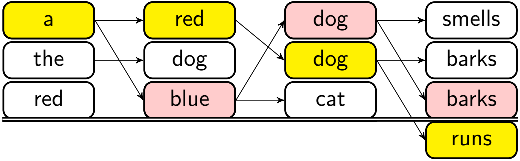

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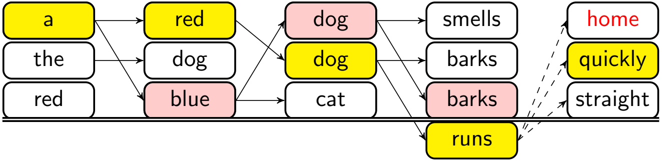

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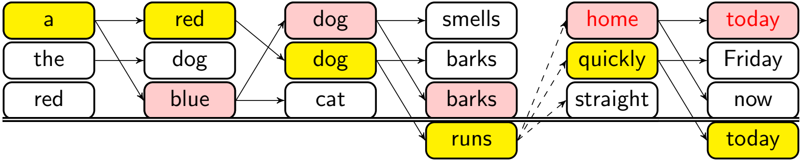

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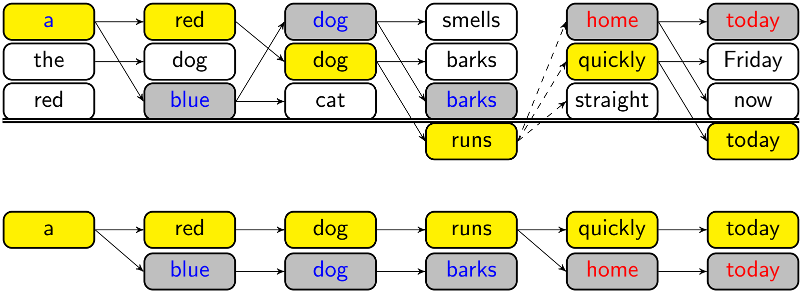
Parameter Updates: Structured Backpropagation



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

Results

Train Beam	$K = 1$	$K = 5$	$K = 10$
	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**

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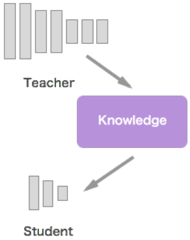
	Machine Translation (BLEU)		
seq2seq	22.53	24.03	23.87
BSO, SB-Δ	**23.83**	**26.36**	**25.48**
XENT	17.74	≤ 20.5	≤ 20.5
DAD	20.12	≤ 22.5	≤ 23.0
MIXER	20.73	-	≤ 22.0

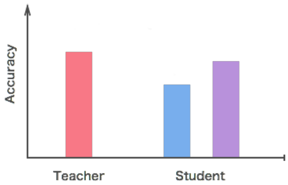
Sequence Knowledge Distillation (Kim and Rush [2016])

Proposal: Shrink the size of text generation models.

Goal: Replicate knowledge distillation results from multiclass image regcognition.

- **Knowledge Distillation**: Train a *student* model to learn from a *teacher* model **???**.





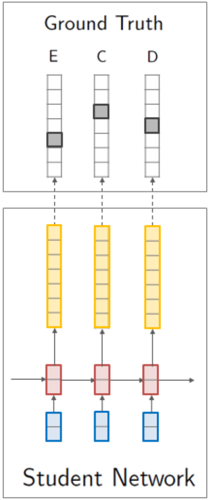
Baseline

Minimize :

$$\mathcal{L}(\theta) - \sum_{t} \log p(y_t = \hat{y}_t \mid \hat{y}_{1:t-1}, x; \theta)$$

where $\hat{y}_t$ is the ground truth word at time t.

Cross-entropy with ground truth.

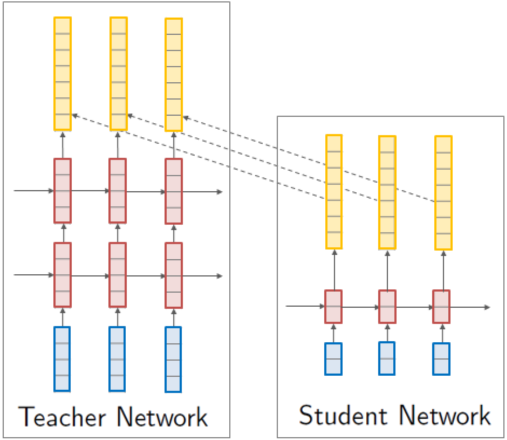


Multiclass Style: Word-Level Knowledge Distillation

Teacher model: $q(y_t|y_{1:t-1}, x; \theta_T)$

Cross-entropy between teacher and student

$$\mathcal{L}_{\text{WORD-KD}}(\theta) = -\sum_t \sum_v q(y_t = v \mid \hat{y}_{1:t-1}, x; \theta_T) \times$$
$$\log p(y_t = v \mid \hat{y}_{1:t-1}, x; \theta)$$



Sequence-Level Knowledge Distillation

Motivation: Replace multiclass with sequence-level cross-entropy.

$$\mathcal{L}_{\textsf{WORD-KD}}(\theta) = -\sum_{t}\sum_{v} q(y_t = v \mid \hat{y}_{1:t-1}, x; \theta_T) \times \log p(y_t = v \mid \hat{y}_{1:t-1}, \mathbf{c}; \theta)$$

$$\Downarrow$$

$$\mathcal{L}_{\textsf{SEQ-KD}}(\theta) = -\sum_{v_1} \dots \sum_{v_T} q(y_{1:T} = v_{1:T} | x; \theta_T) \times \log p(y_{1:T} = v_{1:T} | x; \theta)$$

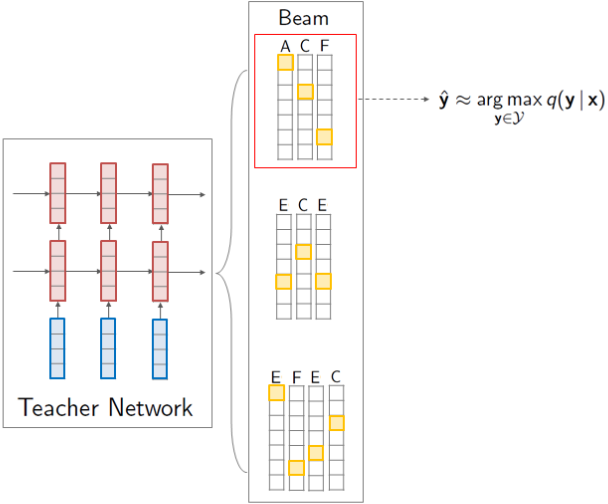
Mimic sequence output of teacher model.

Note: bottom distribution is again intractable.

Sequence Heusritic Approximation

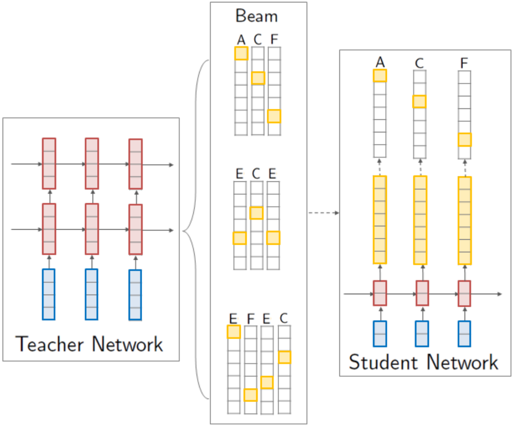
Approximate $q(y_{1:T} \mid x)$ with (beam search) mode sample

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



Sequence-Level Knowledge Distillation

$$\mathcal{L}_{\text{SEQ-KD}}(\theta) = -\log p(y^*_{1:T} \mid x; \theta)$$
$$\approx -\sum_{v_{1:T}} q(y_{1:T} = v_{1:t}|x; \theta_T) \log p(y_{1:T}|x; \theta)$$



Extension: $\mathcal{L}_{\text{SEQ-INTER}}(\theta)$ select sample based on ground truth $\hat{y}$ as well.

Results: WMT English $\rightarrow$ German Translation

Model	$\text{BLEU}_{K=1}$	$\Delta_{K=1}$	$\text{BLEU}_{K=5}$	$\Delta_{K=5}$
4×1000				
Teacher	17.7	–	19.5	–

Results: WMT English $\rightarrow$ German Translation

Model	BLEU$_{K=1}$	$\Delta_{K=1}$	BLEU$_{K=5}$	$\Delta_{K=5}$
4×1000				
Teacher	17.7	$-$	19.5	$-$
2×500				
Student	14.7	$-$	17.6	$-$
Word-KD	15.4	$+0.7$	17.7	$+0.1$

Results: WMT English $\rightarrow$ German Translation

Model	BLEU$_{K=1}$	$\Delta_{K=1}$	BLEU$_{K=5}$	$\Delta_{K=5}$
4×1000				
Teacher	17.7	$-$	19.5	$-$
2×500				
Student	14.7	$-$	17.6	$-$
Word-KD	15.4	$+0.7$	17.7	$+0.1$
Seq-KD	18.9	$+\mathbf{4.2}$	19.0	$+1.4$
Seq-Inter	18.9	$+\mathbf{4.2}$	19.3	$+\mathbf{1.7}$

Results: WMT English $\rightarrow$ German Translation

Model	BLEU$_{K=1}$	$\Delta_{K=1}$	BLEU$_{K=5}$	$\Delta_{K=5}$
4×1000				
Teacher	17.7	$-$	19.5	$-$
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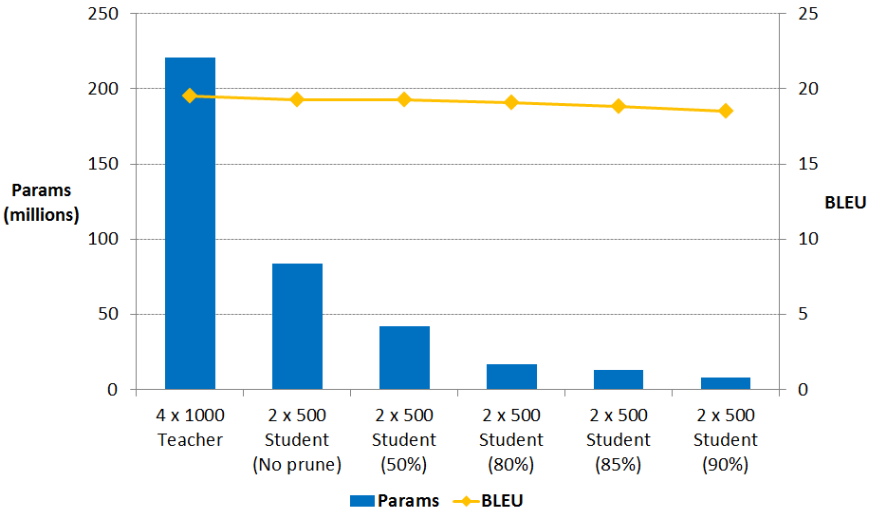
Seq-KD	18.9	$+\mathbf{4.2}$	19.0	$+1.4$
Seq-Inter	18.9	$+\mathbf{4.2}$	19.3	$+\mathbf{1.7}$
4×1000				
Seq-Inter	19.6	$+1.9$	19.8	$+0.3$

Combining Knowledge Distillation and Pruning



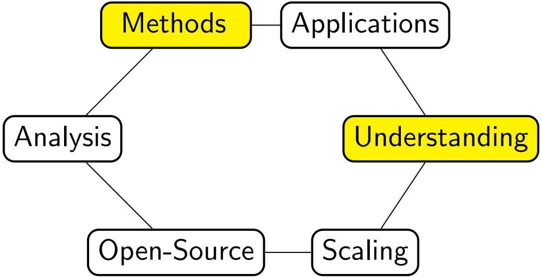
Application

Temporary

WNMT Translation Scaling Shared Task 2018

(Results)

Part 4: Deep Latent-Variable Mdoels



Deep Latent-Variable Models

Goal: Extent text generation to Expose specific choices as *discrete* latent variables.

$$p(y, z | x; \theta).$$

Deep Latent-Variable Models

Goal: Extent text generation to Expose specific choices as *discrete* latent variables.

$$p(y, z | x; \theta).$$

- y is our text output sequence
- z is a collection of latent variables
- θ are the neural network parameters.

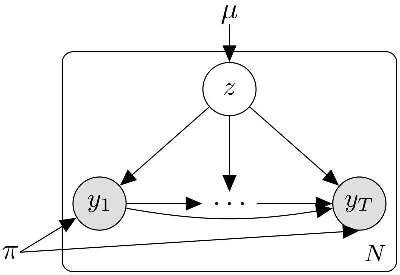
Example Model: Mixture of RNNs

Generative process:

1. Draw cluster $z \in \{1, \ldots, K\}$ from a Categorical.
2. Draw words $y_{1:T}$ from RNNLM with parameters π_z.

$$p(y, z | x; \theta) = \mu_z \times \mathrm{RNNLM}(y_{1:T}; \pi_z)$$

j



Posterior Inference

We'll be interested in the *posterior* over latent variables z:

$$p(z \mid y, x;\, \theta) = \frac{p(y, z|x;\, \theta)}{p(y|x;\, \theta)} = \frac{p(y \mid x, z;\, \theta) p(z|x;\, \theta)}{\sum_{z'} p(y \mid x, z';\, \theta) p(z'|x;\, \theta)}.$$

Posterior Inference

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How?

- Sum out over all discrete choices (e.g. run K RNNs).
- Variational inference based methods.

Application: Summary with Copy-Attention

(Gu et al, 2016) (Gulcehre et al, 2016)

Let z be a binary latent variable.

- If $z = 1$, let the model generate a new word.
- If $z = 0$, let the model copy a word from the source.

Inference:

Pointer-generator model + coverage summary

francis *saili* has signed a two-year deal to join munster later this year .
the 24-year-old was part of the new zealand under-20 side that won the junior world championship in italy in 2011 .
saili 's signature is something of a coup for munster and head coach anthony foley .

(See et al, 2017)

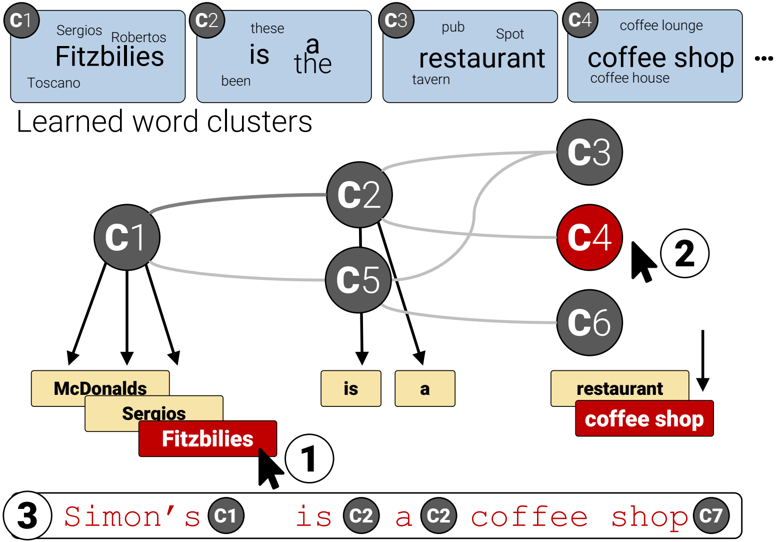
Latent Variable Models for Generation

Ongoing Work: Can we develop other discrete latent-variable models for generation?

Goals:

- Model Control
- Model Debugging
- Model Uncertainty

Example: Learning Neural Templates for Generation



MR	name[The Golden Palace], eatType[coffee shop], food[Fast food], priceRange[cheap], customer rating[5 out of 5], area[riverside]
Reference	A coffee shop located on the riverside called The Golden Palace, has a 5 out of 5 customer rating. Its price range are fairly cheap for its excellent Fast food.

Standard Approach

Step 1: Encode the Source

Fitzbillies,type[coffee shop],price[$<$ £20],food[Chinese],rate[3/5],area[city centre]

Step 2: Generate with RNN Decoder

Fitzbillies is a coffee shop providing Chinese food in the moderate price range . It is located in the city centre . Its customer rating is 3 out of 5.

Issues

1. Interpretable in its content selection?

   Decisions may come from anywhere in the source x.

2. Controllable in terms of style and form?

   Rely on a learned system to determine content.

Neural Template Generation Approach

Step 1: Encode the Source

Fitzbillies,ty[coffee shop],pr[$<$ £20],food[Chinese],cust[3/5],area[city centre]

Neural Template Generation Approach

Step 1: Encode the Source

Fitzbillies,ty[coffee shop],pr[< £20],food[Chinese],cust[3/5],area[city centre]

Step 2: Select a Template

The ___ ___ …	is a is an is an expensive …	___	providing serving offering …	___	food cuisine foods …	in the	high moderate less than average …	price price range …

.	It is	located in the located near near …	___	.	Its customer rating is Their customer rating is Customers have rated it …	___ out of ___	.

Neural Template Generation Approach

Step 1: Encode the Source

Fitzbillies,ty[coffee shop],pr[$<$ £20],food[Chinese],cust[3/5],area[city centre]

Step 2: Select a Template

The ___ ___ ...	is a is an is an expensive ...	___	providing serving offering ...	___	food cuisine foods ...	in the	high moderate less than average ...	price price range ...

.	It is	located in the located near near ...	___	.	Its customer rating is Their customer rating is Customers have rated it ...	___ out of ___	.

Step 3: Fill-in Each Segment

|| <u>Fitzbillies</u> ||

Neural Template Generation Approach

Step 1: Encode the Source

Fitzbillies,ty[coffee shop],pr[< £20],food[Chinese],cust[3/5],area[city centre]

Step 2: Select a Template

The ___ ___ …	is a is an is an expensive …	___	providing serving offering …	___	food cuisine foods …	in the	high moderate less than average …	price price range …
.	It is	located in the located near near …	___	.	Its customer rating is Their customer rating is Customers have rated it …	___ out of ___	.	

Step 3: Fill-in Each Segment

|| Fitzbillies || is a ||

Neural Template Generation Approach

Step 1: Encode the Source

Fitzbillies,ty[coffee shop],pr[$<$ £20],food[Chinese],cust[3/5],area[city centre]

Step 2: Select a Template

The ___ ___ …	is a is an is an expensive …	___	providing serving offering …	___	food cuisine foods …	in the	high moderate less than average …	price price range …

.	It is	located in the located near near …	___	.	Its customer rating is Their customer rating is Customers have rated it …	___ out of ___	.

Step 3: Fill-in Each Segment

‖ Fitzbillies ‖ is a ‖ coffee shop ‖

Neural Template Generation Approach

Step 1: Encode the Source

Fitzbillies,ty[coffee shop],pr[$<$ £20],food[Chinese],cust[3/5],area[city centre]

Step 2: Select a Template

The ___ ___ ...	is a is an is an expensive ...	___	providing serving offering ...	___	food cuisine foods ...	in the	high moderate less than average ...	price price range ...

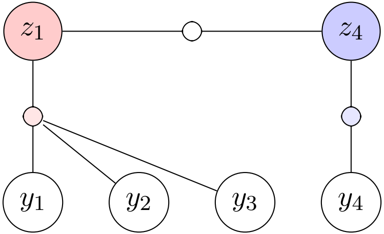
.	It is	located in the located near near ...	___	.	Its customer rating is Their customer rating is Customers have rated it ...	___ out of ___	.

Step 3: Fill-in Each Segment

‖ Fitzbillies ‖ is a ‖ coffee shop ‖ providing ‖ Chinese ‖ food ‖ in the ‖ moderate ‖ price range ‖ . ‖ It is ‖ located in the ‖ city centre ‖ . ‖

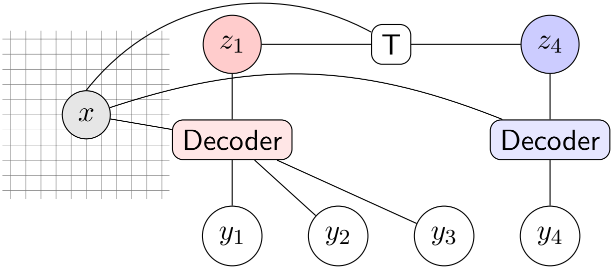
Technical Methodology: Hidden Semi-Markov Model

- HMM: discrete latent states with single emissions (e.g. words).
- HSMM: discrete latent states produce multiple emissions (e.g. phrases).
- Parameterized with *transition*, *emission*, and *length* distributions.



Technical Methodology: Neural Hidden Semi-Markov Model

- Employ HSMM as a conditional latent variable language model, $p(y_1, \ldots, y_T, z \mid x)$.
- Transition Distribution: NN between states.
- Emission Distribution: Seq2Seq+Attention, one per state k.



Technical Methodology: Learning Templates

- Fit model by maximizing log-marginal likelihood on training data.

$$\max_{\theta} \sum_{j} \log \sum_{z} p(y^{(j)}, z \mid x^{(j)}; \theta)$$

Details: Pre-score segmentations, HSMM forward algorithm for sum, backprop with autograd, all inference is exact.

Technical Methodology: Learning Templates

- Fit model by maximizing log-marginal likelihood on training data.

$$\max_{\theta} \sum_{j} \log \sum_{z} p(y^{(j)}, z \mid x^{(j)}; \theta)$$

Details: Pre-score segmentations, HSMM forward algorithm for sum, backprop with autograd, all inference is exact.

- Compute argmax segmentations to find common *templates*.

$$z^{(j)} = \arg\max_{z} p(y^{(j)}, z \mid x^{(j)}; \theta)$$

[The Wrestlers]$_{185}$ *[is a]*$_{29}$ *[coffee shop]*$_{164}$ *[that serves]*$_{188}$ *[English]*$_{139}$ *[food]*$_{18}$ *[in the]*$_{32}$ *[moderate]*$_{125}$ *[price range]*$_{180}$ *[.]*$_{90}$

Neural Template

The ___ ___ ...	is a is an is an expensive ...	___	providing serving offering ...	___	food cuisine foods ...	in the	high moderate less than average ...	price price range ...

.	It is	located in the located near near ...	___	.	Its customer rating is Their customer rating is Customers have rated it ...	___ out of ___	.

E2E Challenge

	BLEU	NIST
Test		
Substitution	43.78	6.88
Neural Template	56.72	7.63
Full Neural Model	65.93	8.59

	BLEU	NIST	ROUGE-4
Conditional KN-LM	19.8	5.19	10.7
NNLM (field)	33.4	7.52	23.9
NNLM (field & word)	34.7	7.98	25.8
Neural Template	33.8	7.51	28.2

Issue 1: Interpretability

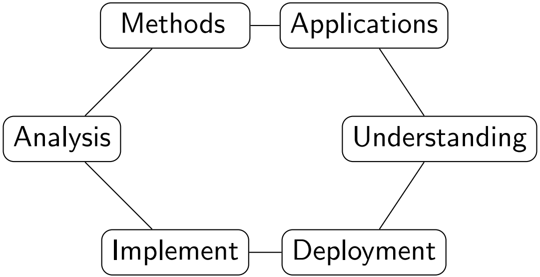
kenny warren
name: kenny warren, **birth date:** 1 april 1946, **birth name:** kenneth warren deutscher, **birth place:** brooklyn, new york, **occupation:** ventriloquist, comedian, author, **notable work:** book - the revival of ventriloquism in america
1. kenny warren deutscher (april 1, 1946) is an american ventriloquist. 2. kenny warren deutscher (april 1, 1946 , brooklyn,) is an american ventriloquist. 3. kenny warren deutscher (april 1, 1946) is an american ventriloquist, best known for his the revival of ventriloquism. 4. “kenny” warren is an american ventriloquist. 5. kenneth warren “kenny” warren (born april 1, 1946) is an american ventriloquist, and author.

Issue 2: Controllability

The Golden Palace
name[The Golden Palace], type[coffee shop], food[Chinese], priceRange[cheap] custRating[5 out of 5], area[city centre],
1. The Golden Palace is a coffee shop located in the city centre. 2. In the city centre is a cheap Chinese coffee shop called The Golden Palace. 3. The Golden Palace that serves Chinese food in the cheap price range. It is located in the city centre. Its customer rating is 5 out of 5. 4. The Golden Palace is a Chinese coffee shop. 5. The Golden Palace is a Chinese coffee shop with a customer rating of 5 out of 5.

Future Work

NLP post deep learning



Long-Form Generation with Explicit Reasoning

(2)

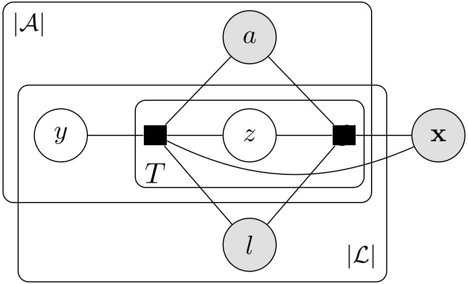
TEAM	WIN	LOSS	PTS	FG_PCT	RB	AS ...
Hawks	11	12	103	49	47	27
Heat	7	15	95	43	34	20

(3)

PLAYER	AS	RB	PT	FG	FGA	CITY ...
Tyler Johnson	5	2	27	8	16	Miami
Dwight Howard	11	17	23	9	11	Atlanta
Paul Millsap	2	9	21	8	12	Atlanta
Goran Dragic	4	2	21	8	17	Miami
Wayne Ellington	2	3	19	7	15	Miami
Dennis Schroder	7	4	17	8	15	Atlanta
Rodney McGruder	5	5	11	3	8	Miami
Hasan Whiteside	2	12	8	4	12	Miami
...						

(1)

[The Atlanta Hawks defeated the Miami Heat, 103 - 95, at Philips Arena on Wednesday.] [Defense was key for the Hawks, as they held the Heat to 42 percent shooting and forced them to commit 16 turnovers. Atlanta also dominated in the paint, winning the rebounding battle, 47 - 34, and outscoring them in the paint 58 - 26. The Hawks shot 49 percent from the field and assisted on 27 of their 43 made baskets.] [Miami (7 - 15) are as beat-up as anyone right now. Hassan Whiteside really struggled in this game, as he amassed eight points, 12 rebounds and one blocks on 4 - of - 12 shooting ...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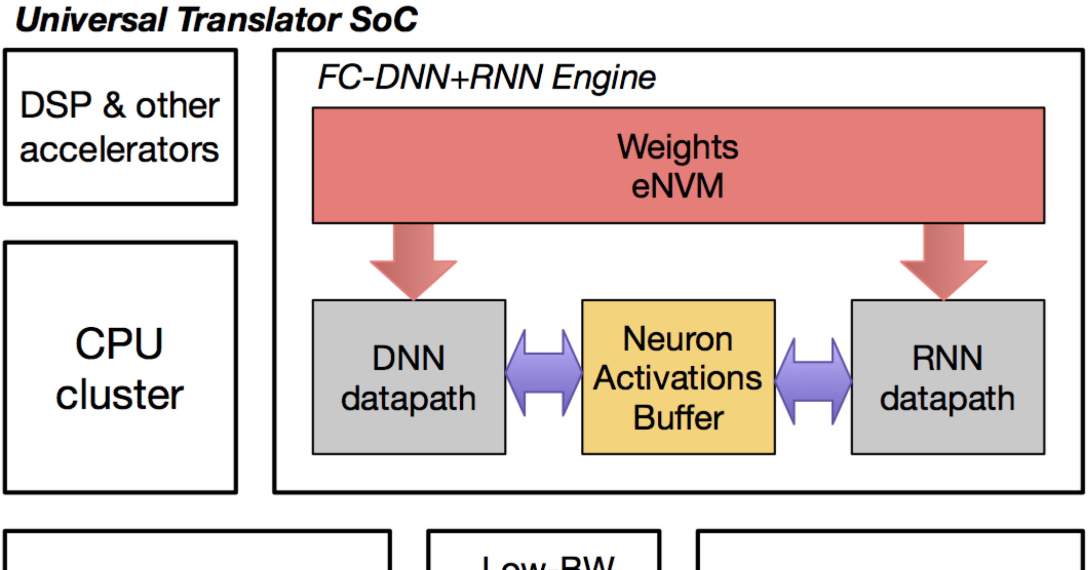
Learning Neural Reasoning-Based Models

Temporary


Universal Translator SoC
DSP & other accelerators
CPU cluster
FC-DNN+RNN Engine
Weights eNVM
DNN datapath
Neuron Activations Buffer
RNN datapath

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