Controlling Text Generation

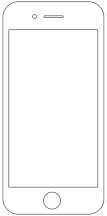
Alexander Rush / HarvardNLP

Machine Learning for Text Generation: 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.

p_θ



$y_{1:T}$

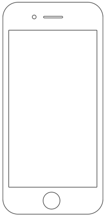
Yalitza Aparicio had just finished her teaching degree and didn't yet have a job when the Mexican director Alfonso Cuaron held a casting call in her home of Tlaxiaco, Oaxaca, for the lead role in his semi-autobiographical drama, "Roma."

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.

p_θ



$y_{1:T}$

Cambodian government rejects opposition's call for talks abroad

ENTERTAINMENT NEWS FEBRUARY 24, 2019 / 8:18 PM / A DAY AGO

Regina King wins supporting actress Oscar for 'Beale Street'

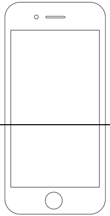
2 MIN READ

LOS ANGELES (Reuters) - Regina King won the Oscar for best supporting actress on Sunday for her role as a mother trying to look out for her pregnant daughter in "If Beale Street Could Talk."

It was the first Oscar for King, 48, who began her career in Hollywood more than three decades ago as a teenager on the 1980s sitcom "227." It was also her first nomination.

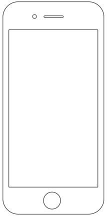
Document Summary

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 . . .



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.

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



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{ 3 } { \operatorname { c o s h } ^ { 2 } x } } \& { \frac
{ 3 } { d x ^ { 2 } } }  { \frac { 3 } { \operatorname
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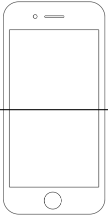
^ { 2 } x } }  \end{array} \right) \qquad
```

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
...						



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 shorthanded 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 ...

Machine Learning for Text Generation

$$y^*_{1:T} = \arg\max_{y_{1:T}} p_\theta(y_{1:T} \mid x)$$

- Input x, *what to talk about*

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- Input x, *what to talk about*
- Possible output text $y_{1:T}$, *how to say it*
- Scoring function p_θ, with parameters θ learned from data

Outline

Goal

Controllable Generation

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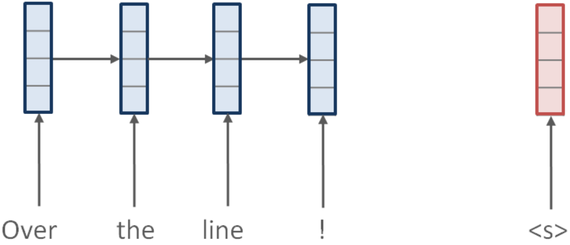
Goal

Controllable Generation

- **Model and Background**
- Work 1: Generation
- Work 2: Attention
- Challenges: Text Generation and Deep Learning

Seq2Seq + Attention

$$p(y_{1:T} \mid x_{1:T}; \theta)$$



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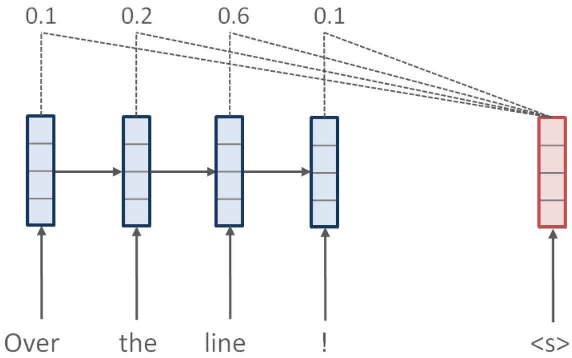

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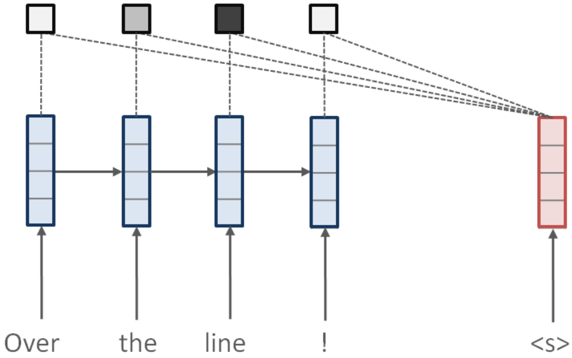

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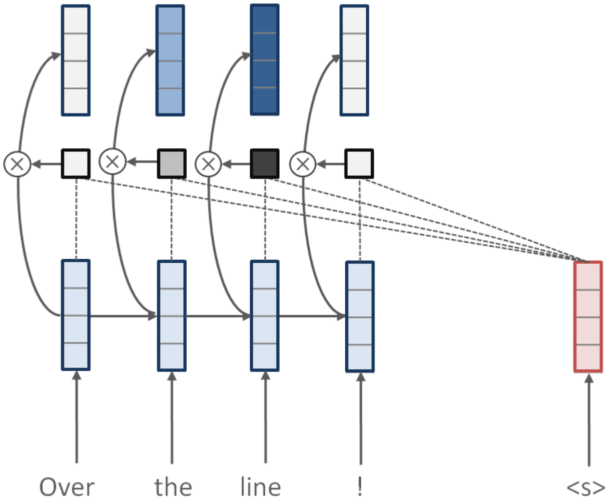

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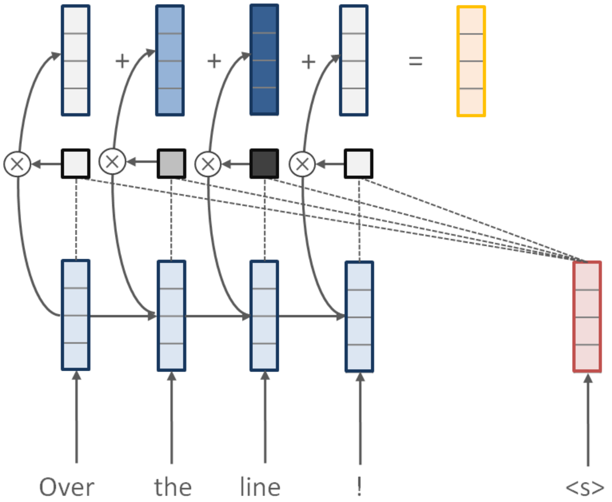

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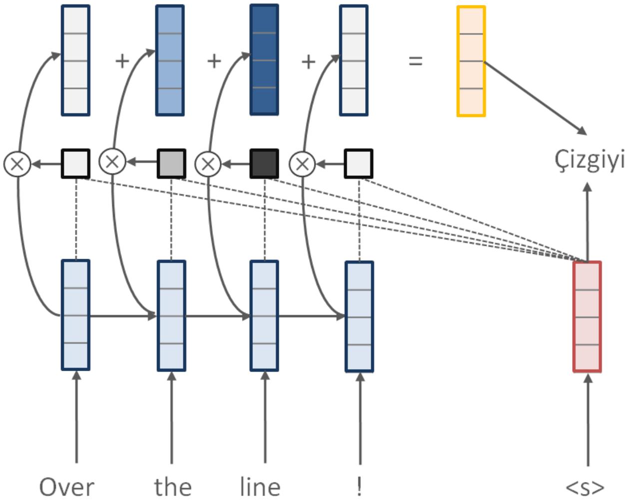

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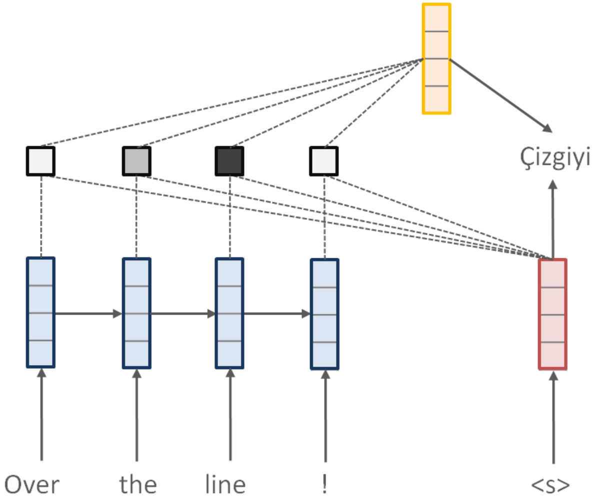

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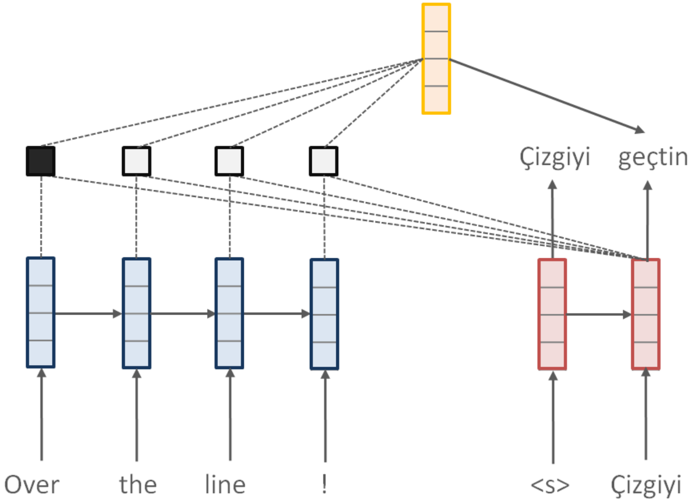

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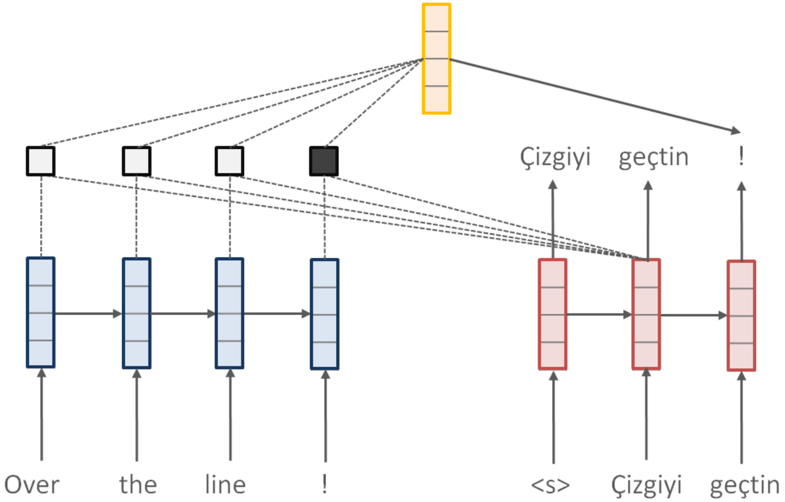

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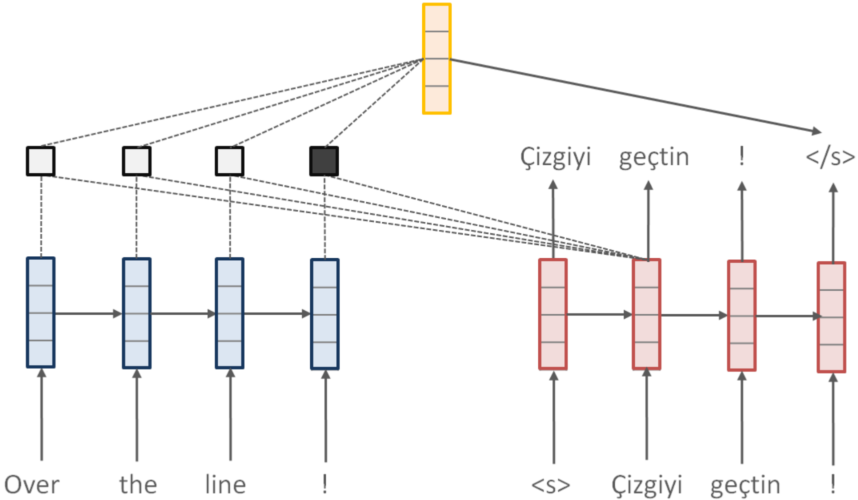


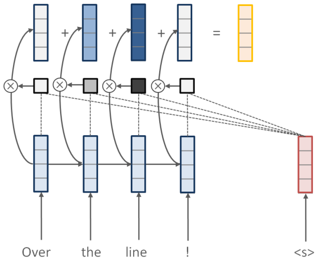
Attention Math

Encoder:

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

Attention (Dynamic Context)

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



Attention Math

Encoder:

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Decoder:

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

Prediction:

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

An open-source neural
machine translation system.

English Français 简体中文 한국어
日本語 Русский العربية

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Quickstart [Lua]

Quickstart [Python]

Advanced guide

Models and Recipes

FAQ

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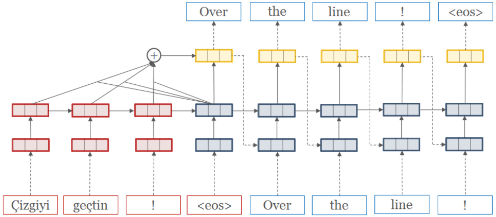
Documentation

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.

Outline

- Background: Core Model and Implementation
- **Work 1: Generation (Learning Neural Templates)**
- Work 2: Attention
- Challenges: Text Generation and Deep Learning

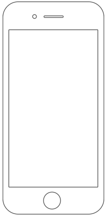
Can we learn to control text generation systems?

Talk about Data

x

Fitzbillies	
type	coffee shop
price	$<$ £20
food	Chinese
rating	3/5
area	city centre

p_θ



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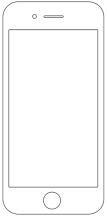


$y_{1:T}$

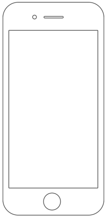
Fitzbillies is a coffee shop providing Chinese food in the moderate price range . It is located in the city centre . Its customer rating is 3 out of 5 .

Talking About Data

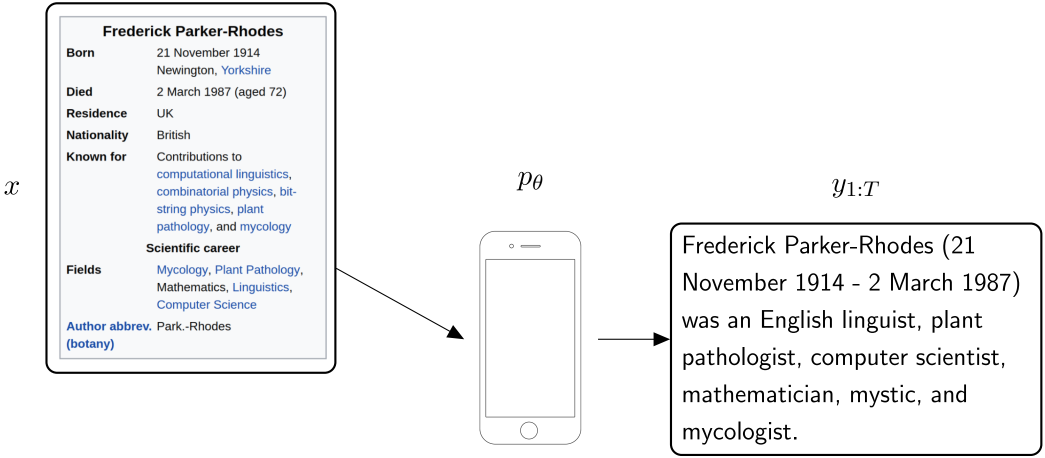
x

Frederick Parker-Rhodes	
Born	21 November 1914 Newington, Yorkshire
Died	2 March 1987 (aged 72)
Residence	UK
Nationality	British
Known for	Contributions to computational linguistics, combinatorial physics, bit-string physics, plant pathology, and mycology
Scientific career	
Fields	Mycology, Plant Pathology, Mathematics, Linguistics, Computer Science
Author abbrev. (botany)	Park.-Rhodes

p_θ



Talking About Data



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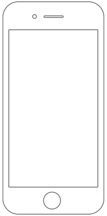
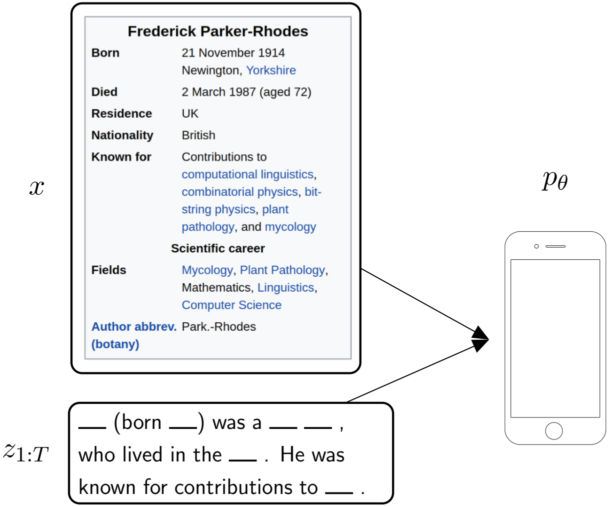


$y^*_{1:T}$

Frederick Parker-Rhodes (21 November 1914 - 2 March 1987) was an English mycology and plant pathology, mathematics at the University of UK.

Talking About Data



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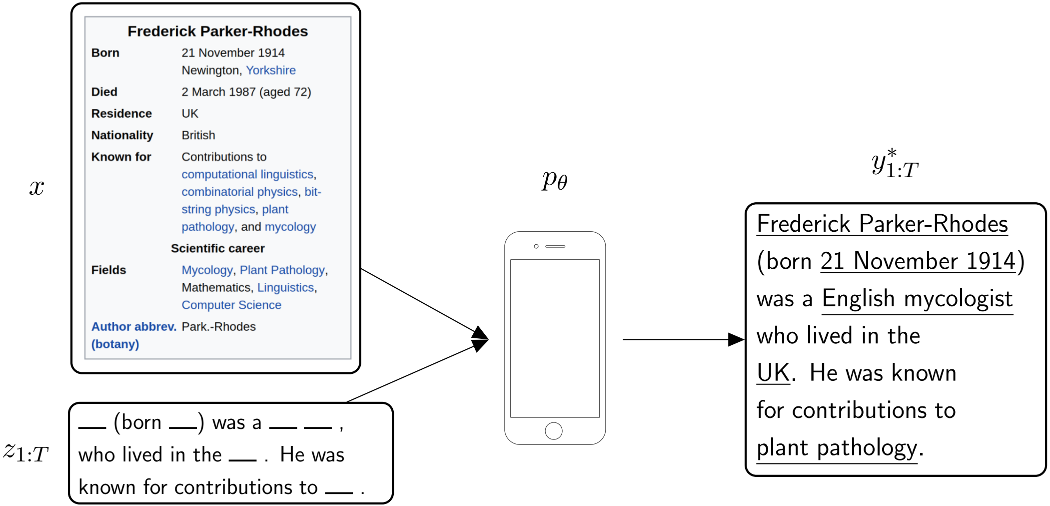

Arguments for Templated Generation

Guarantees about the quality, in particular,

- **Interpretable** in its factual content.
- **Controllable** in terms of style.

Can we achieve these criteria within a deep learning system?

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Can we achieve these criteria within a deep learning system?

Deep Latent-Variable Models

Strategy: Learn a probabilistic model and *extract* template-like constraints.

Expose specific choices as latent variables z.

$$p(y, z \mid x;\, \theta)$$

- x, y as before, *what to talk about, how to say it*
- z is a collection of problem-specific latent variables, *why we said it that way*

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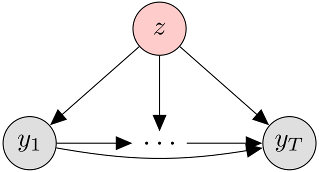
Challenge: Combine with deep learning approach, θ.

Motivating Example: Deep Clustering



The film is the first from ... $z = 1$

Allen shot four-for-nine ... $z = 2$

In the last poll Ericson led ... $z = 3$

1. Draw cluster $z \in \{1, \ldots, Z\}$.
2. Draw word sequence $y_{1:T}$ from decoder RNN z.

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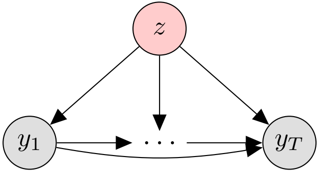

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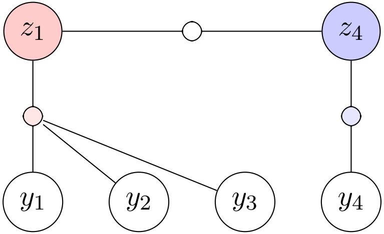
Time-Series Clustering

Similar approach can be employed with other probabilistic models.

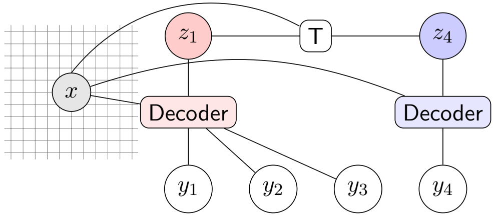
Hidden Semi-Markov Model

- Each discrete cluster produces multiple emissions (e.g. phrases).
- Parameterized with *transition* and *emission* distributions.



Model: A Deep Hidden Semi-Markov Model

Distribution: Encoder-Decoder, specialized per cluster $\{1, \ldots, Z\}$.



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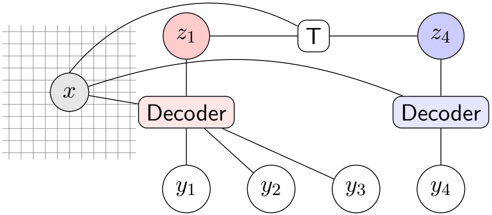

Probabilistic Model $\Rightarrow$ Templates

(Step 1) Train (Step 2) Match (Step 3) Extract

Step 1: Training HSMM

Training requires summing over clusters and segmentation of deep model.

$$\mathcal{L}(\theta) = \log \sum_{z_{1:T}} p(\hat{y}_{1:T}, z_{1:T} \mid x; \theta)$$

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Example

$$\hat{y}_{1:T} = \text{Frederick Parker-Rhodes was an English linguist, plant pathologist} \ldots$$

$$\Downarrow \sum_{z_{1:T}} p(\hat{y}_{1:T}, z_{1:T} \mid x; \theta)$$

Frederick Parker-Rhodes | was an English | linguist , | plant pathologist | ...

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Frederick | Parker-Rhodes was an English linguist , | linguist , | plant pathologist ...

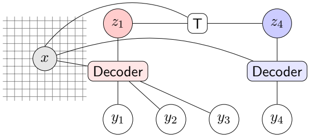
Step 1: Technical Methodology

Training is end-to-end, i.e. clusters and segmentation are learned simultaneously with encoder-decoder model on GPU.

- Backpropagation through dynamic programming.
- Parameters are trained by exactly marginalizing over segmentations.
- Utilize HSMM backward algorithm within standard training.

Step 2: Template Matching

Finding best cluster sequences for each training sentence.



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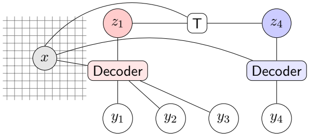

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Example

Frederick Parker-Rhodes was an English linguist, plant pathologist

$$\Downarrow \arg\max_{z_{1:T}}$$

Frederick Parker-Rhodes was an English linguist, plant pathologist . . .

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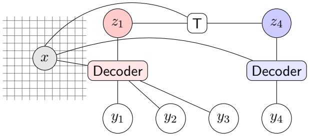

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Example

Frederick Parker-Rhodes was an English linguist, plant pathologist

$\Downarrow \arg\max_{z_{1:T}}$

Frederick Parker-Rhodes was an English linguist, plant pathologist ...

Step 3: Template Extraction

Find identical cluster sequences $z_{1:T}$ that occur most often.

Frederick Parker-Rhodes was an English linguist, plant pathologist ...

Bill Jones was an American professor, and well-known author ...

$\vdots$

$\Downarrow \arg\max_{z_{1:T}}$

Frederick Parker-Rhodes | was an English | linguist | , | plant pathologist | ...

Bill Jones | was an American | professor | , | and well-known author | ...

$\vdots$

Example Templates: Wikipedia

Example common extracted "templates".

aftab ahmed	(	born	1951	)	is an american	actor	.
anderson da silva	;	born on	1970	]	was an american	actress	
david jones	...	born 1	1974	...	is an english	cricketer	
...		...	...		...	...	

aftab ahmed	was a	world war i	member of the	austrian	house of representatives	.
anderson da silva	is a former	liberal	party member of the	pennsylvania	legislature	
david jones	is a	baseball	recipient of the	montana	senate	
...	...	...	...	...	...	

adjutant	aftab ahmed	was a	world war i	member of the	knesset	.
lieutenant	anderson da silva	is a former	liberal	party member of the	scottish parliament	
captain	david jones	is a	baseball	recipient of the	fc lokomotiv liski	
...	...	...	...	...	...	

william	" billy " watson	(	1913	–	1917	)	was an american	football player	.
john william	smith		c. 1900	in	surrey, england		was an australian	rules footballer	
james "	jim " edward		1913	-	british columbia		is an american	defenceman	
...	...		...	...	...		...	...	

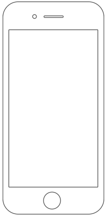
who plays for	collingwood	in the	victorial football league	(	vfl	)	.
who currently plays for	st kilda	of the	national football league		afl		
who played with	carlton	and the	australian football league		nfl		

Neural Template Generation Approach

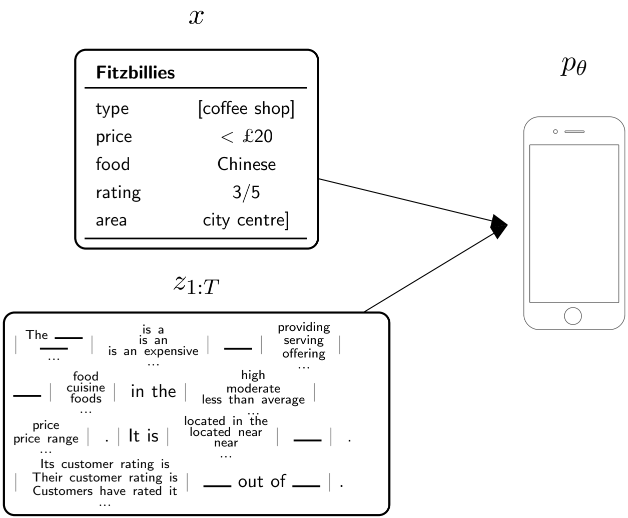
x

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

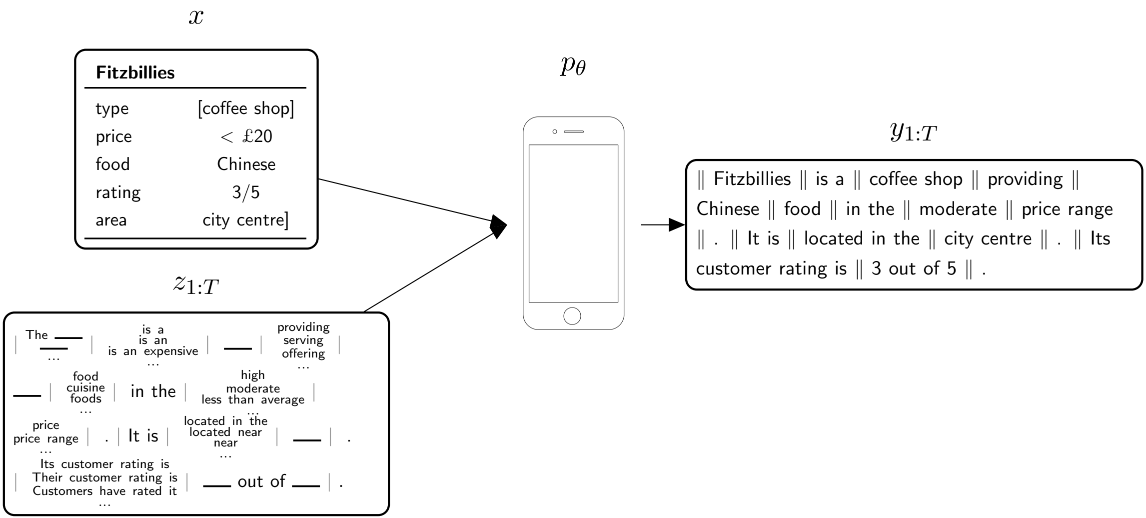
p_θ



Neural Template Generation Approach



Neural Template Generation Approach



Interpretable Output

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.

Controllable Style

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 is a Chinese coffee shop. 4. The Golden Palace is a Chinese coffee shop with a customer rating of 5 out of 5. 5. 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.

Automatic Metrics

	Reviews (ROUGE)
Template	54.6
Neural Template	65.0
Best Model	68.5

	WikiBio (BLEU)
Template	19.8
Neural Template	34.7
Best Model	34.8

Outline

- Background: Core Model and Implementation
- Work 1: Generation
- **Work 2: Attention (Latent Alignment and Variational Attention)**
- Challenges: Text Generation and Deep Learning

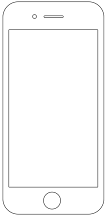
Can we learn to control what facts are used?

Machine Learning for Text Generation: 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.

p_θ



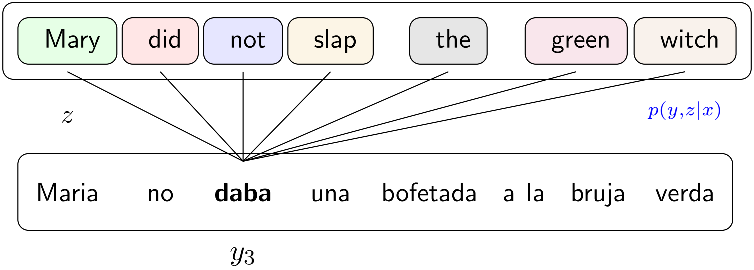
$y_{1:T}$

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."

Six Challenges for NMT (Koehn and Knowles 2017)

- **2: Requires large sample complexity**
- **5: The alignments learned by soft attention may not be interpreted as word alignments**

Latent-Variable Alignment Model



Latent Alignment: Motivation

If attention works so well, why study alignment?

- A latent variable approach facilitates compobility in a principled probabilistic manner. (Cohn et al, 2016)

- Posterior inference provides better post-hoc interpretability and analysis

- Modeling uncertainties might lead to better performance

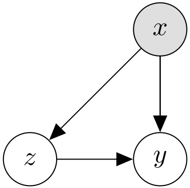
Problem Setup

- Let a be the prior alignment distribution of z
- Let $f(x, z; \theta)$ be the likelihood of x given z

$$z \sim a(x; \theta) \qquad y \sim f(x, z; \theta)$$

- Training Objective (maximizing marginal log-likelihood)

$$\mathcal{L}(\theta) = \log \sum_z p(y = \hat{y}, z \mid x) \quad = \quad \log \mathbb{E}_z[f(x, z; \theta)_{\hat{y}}]$$



Key Issue: Computational Cost

- Direct optimization is computationally expensive

$$\log \mathbb{E}_z [f(x, z; \theta)_{\hat{y}}]$$

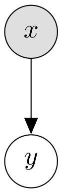
- Computing expectation requires summing over source for each target.
- Translation bottlenecked by training scale.

Workaround 1: Soft Attention

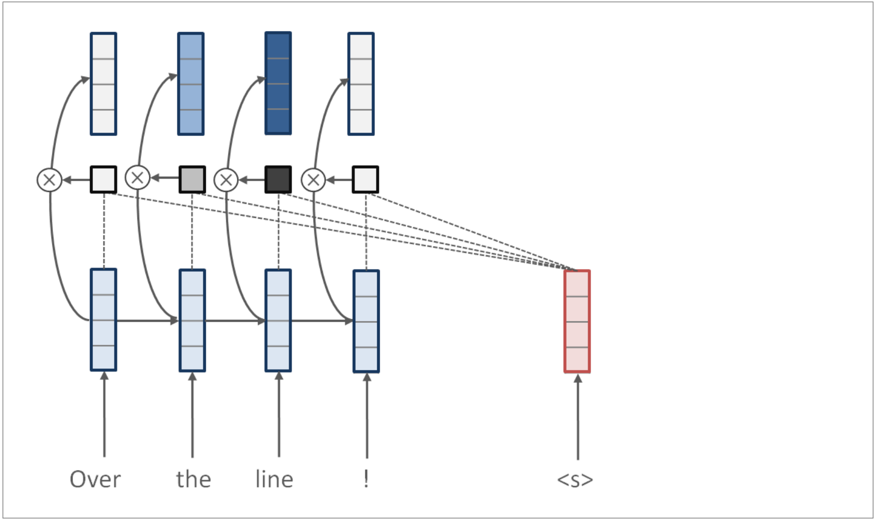
- Replace the joint distribution with a nested expectation [Bahdanau et al 2014]

$$\log \mathbb{E}_z[f(x,z)_{\hat{y}}] \approx \log f(x, \mathbb{E}_z[z])_{\tilde{y}}$$

- The corresponding graphical model is



Soft Attention



Workaround 2: Hard Attention

- [Xu et al 2015]: Directly apply Jensen's inequality and optimize with REINFORCE by sampling from the prior

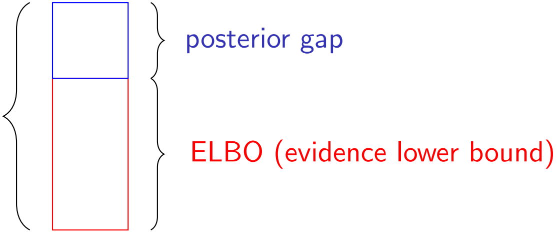
$$\log \mathbb{E}_z[f(x,z)_{\hat{y}}] \geq \mathbb{E}_z \log[f(x,z)_{\hat{y}}] \approx \log f(x,\tilde{z})_{\hat{y}}$$

- Problems:
  - The use of the prior in the expectation may result in a poor bound
  - Cannot directly use for posterior estimation $p(z \mid y, x)$

Marginal Likelihood: Variational Decomposition

For any* distribution $q(z)$ over z,

$$L(\theta) = \mathbb{E}_q\Big[\log p(y \mid x, z)\Big] - \mathrm{KL}[q(z) \,\|\, p(z \mid x)] + \mathrm{KL}[q(z) \,\|\, p(z \mid y, x)]$$



Since KL is always non-negative, $L(\theta) \geq \mathrm{ELBO}(\theta, \lambda)$.

Variational Attention

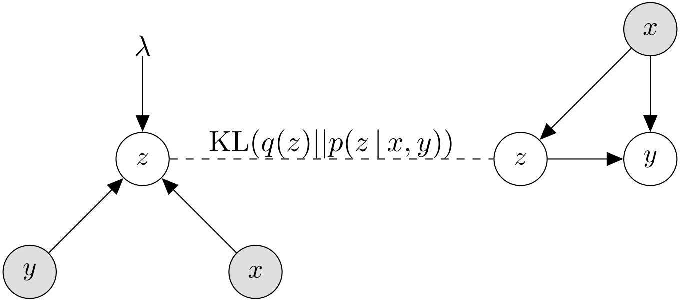
- Learn model and q to maximize the following lower bound

$$\begin{aligned}&\log \mathbb{E}_{z \sim p(z \,|\, x,)}[p(y \,|\, x, z)] \\ &\quad \geq \mathbb{E}_{z \sim q(z)}[\log p(y \,|\, x, z)] - \mathrm{KL}[q(z) \,\|\, p(z \,|\, x)]\end{aligned}$$

- We choose a $q(z)$ that affords analytic KL

- At test time, marginalize over z.

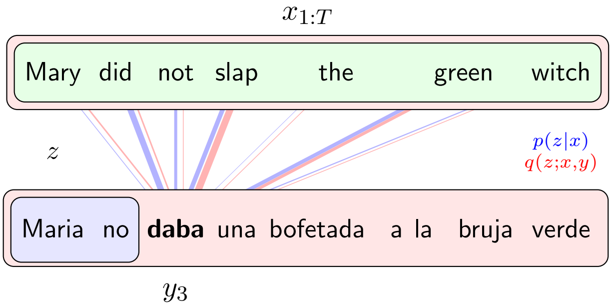
Example Form of q: Amortized Parameterization



λ parameterizes a global network (encoder) that is run over x, y to produce the local variational distribution, e.g.

$$q(z; \lambda) = \mathsf{enc}(x, y; \lambda)$$

Full Method



- The blue prior p is restricted to past information,
- The red variational posterior q may take into account future observations.

Technical Details: Categorical and Relaxed

- Categorical (Single Source Alignment Word)
  - z and $q(z)$: Categorical Distributions
  - Estimate gradients with REINFORCE

$$\mathbb{E}_{z \sim q(z)}[\nabla_\theta \log f(x, z) + \log f(x, z) \nabla_\phi \log q(z)]$$

Technical Details: Categorical and Relaxed

- Categorical (Single Source Alignment Word)
  - z and $q(z)$: Categorical Distributions
  - Estimate gradients with REINFORCE

$$\mathbb{E}_{z \sim q(z)}[\nabla_\theta \log f(x, z) + \log f(x, z) \nabla_\phi \log q(z)]$$

- Relaxed (Mixture Source Alignment)
  - z and $q(z)$: Dirichlet
  - Use reparameterization [Kingma et al 2013]
    - Sample u from a simple distribution $\mathcal{U}$, Apply transformation $g_\phi(\cdot)$ to obtain $z = g_\phi(u)$
  - The gradient estimator takes the form

$$\mathbb{E}_{u \sim \mathcal{U}}\left[\nabla_{\theta,\phi} \log f(x, g_\phi(u))\right]$$

Concurrent Experimental Work

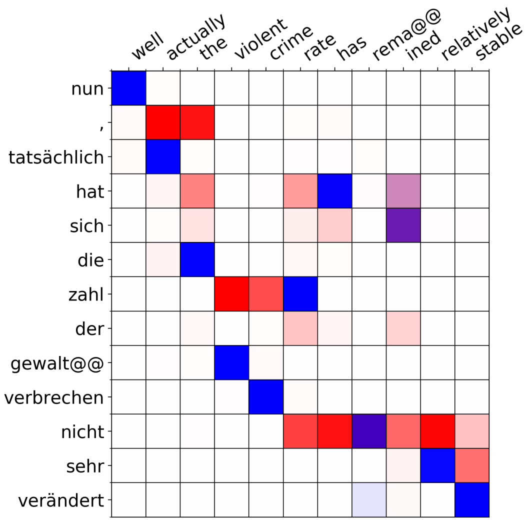
Many different researchers have recently explored the benefits of marginalization. Very similar results.

- Surprisingly Easy Hard-Attention for Sequence to Sequence Learning
- Hard Non-Monotonic Attention for Character-Level Transduction
- Posterior Attention Models for Sequence to Sequence Learning

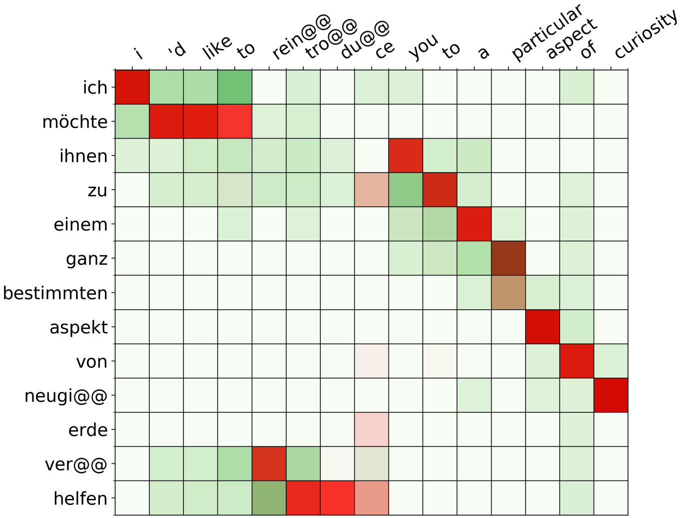
Experiments

- Full experiments on IWSLT and WMT using LSTM based NMT system.
- Model: Two layer attention based LSTM.
- Variational Model: Bidirectional LSTM model.

Example Alignments



Example Alignments



Results (MT: IWSLT)

Model	Objective	Exp	PPL	BLEU
Soft Attn	$\log p(y \mid \mathbb{E}[z])$	Softmax	7.17	32.77
Marg. Likelihood	$\log \mathbb{E}[p]$	Enum	6.34	33.29
Hard Attn	$\mathbb{E}_p[\log p]$	Enum	6.77	31.40
Hard Attn	$\mathbb{E}_p[\log p]$	Sample	6.78	30.42
Var Relaxed Attn	$\mathbb{E}_q[\log p] - \mathrm{KL}$	Sample	7.58	30.05
Var Attn	$\mathbb{E}_q[\log p] - \mathrm{KL}$	Enum	6.08	**33.69**
Var Attn	$\mathbb{E}_q[\log p] - \mathrm{KL}$	Sample	6.17	**33.30**

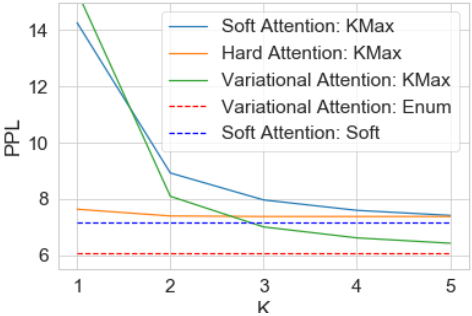
Results (MT: WMT)

Model	Objective	Exp	PPL	BLEU
Soft Attn	$\log p(y \mid \mathbb{E}[z])$	Softmax	-	24.10
Var Attn	$\mathbb{E}_q[\log p] - \mathrm{KL}$	Sample	-	24.98

Results (VQA)

Model	Objective	Exp	NLL	Eval
Soft Attn	$\log p(y \mid \mathbb{E}[z])$	Softmax	1.76	58.93
Marg. Likelihood	$\log \mathbb{E}[p]$	Enum	1.69	60.33
Hard Attn	$\mathbb{E}_p[\log p]$	Enum	1.78	57.60
Hard Attn	$\mathbb{E}_p[\log p]$	Sample	1.82	56.30
Var Attn	$\mathbb{E}_q[\log p] - \mathrm{KL}$	Enum	1.68	58.44
Var Attn	$\mathbb{E}_q[\log p] - \mathrm{KL}$	Sample	1.74	57.52

Inference



Soft Attention: KMax
Hard Attention: KMax
Variational Attention: KMax
Variational Attention: Enum
Soft Attention: Soft
PPL
14
12
10
8
6
1
2
3
4
5
K

Discussion: Alternative Inference Methods

Inference Method	#Samples	PPL	BLEU
REINFORCE	1	6.17	33.30
RWS	5	6.41	32.96
Gumbel-Softmax	1	6.51	33.08

- Gumbel-Softmax is a viable alternative
- RWS incurs higher memory cost

Outline

- Background: Core Model and Implementation
- Work 1: Controlling Generation
- Work 2: Controlling Attention (*Variational Attention*)
- **Challenges: Text Generation and Deep Learning**

Reasoning Systems for Long-Form Generation

(2)

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

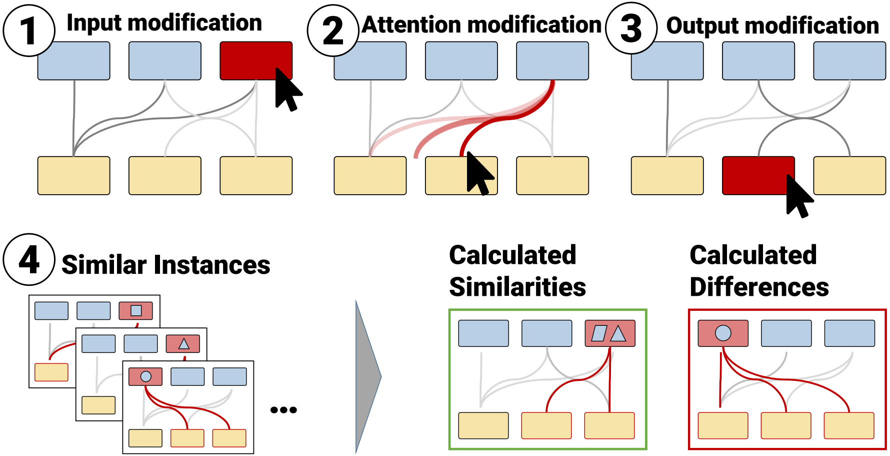
(3)

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)

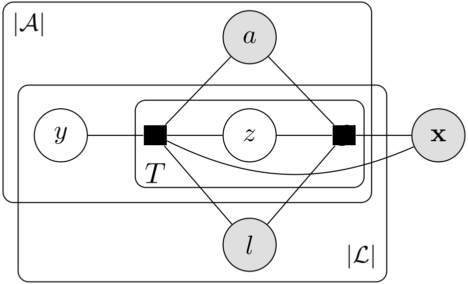
[The Atlanta Hawks defeated the Miami Heat, 103 - 95, at Philips Arena on Wednesday.] [Defense was key for the Hawks, as they held the Heat to 42 percent shooting and forced them to commit 16 turnovers. Atlanta also dominated in the paint, winning the rebounding battle, 47 - 34, and outscoring them in 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 ...

Controllable Deep Learning for Translation w/ IBM



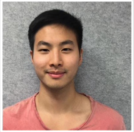
Prob. Programs for Language Understanding w/ Uber

```
def model(z):
  I, J = z.shape
  x = pyro.sample("x", Bernoulli(Px))
  with pyro.plate("I", I, dim=-2):
    y = pyro.sample("y", Bernoulli(Py))
    with pyro.plate("J", J, dim=-1):
      pyro.sample("z", Bernoulli(Pz[x,y]),
                        obs=z)
```



Harvard NLP

Graduate Students



Justin Chiu

Yuntian Deng

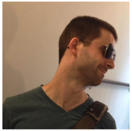
Sebastian Gehrmann

Yoon Kim

Kelly Zhang

Zachary Ziegler

Grad Alumni

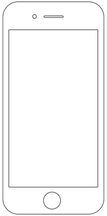


Sam Wiseman (TTIC)

http://lstm.seas.harvard.edu/client/lstmvis.html?project=00parens&source=states::states2&activation=0.3&cw=30&meta=..&pos=165

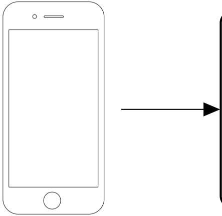
http://lstm.seas.harvard.edu/client/lstmvis.html?project=05childbook&source=states::states1&activation=0.3&cw=30&meta=..&pos=100&wordBrush=..20,23&wordBrushZero=..1,0&sc=..55,59,159,167,174,179

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



```
{ \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
```

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



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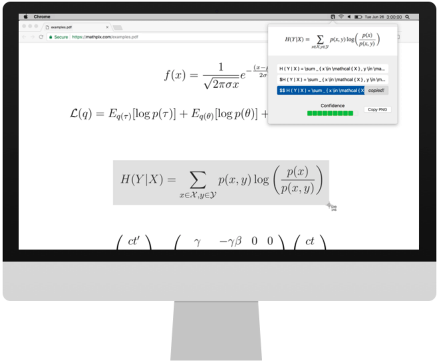
 { 3 } { d x ^ { 2 } } }  { \frac { 3 } { \operatorname
 { c o s h } ^ { 2 } x } } \& { - \frac { d ^ { 2 } }
{ d x ^ { 2 } } + 4 - \frac { 3 } { \operatorname { c o s h }
^ { 2 } x } }  \end{array} \right) \qquad
```

Convert images to LaTeX

Take a screenshot of math and paste the LaTeX into your editor, all with a single keyboard shortcut.

MacOS | Windows | Ubuntu



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