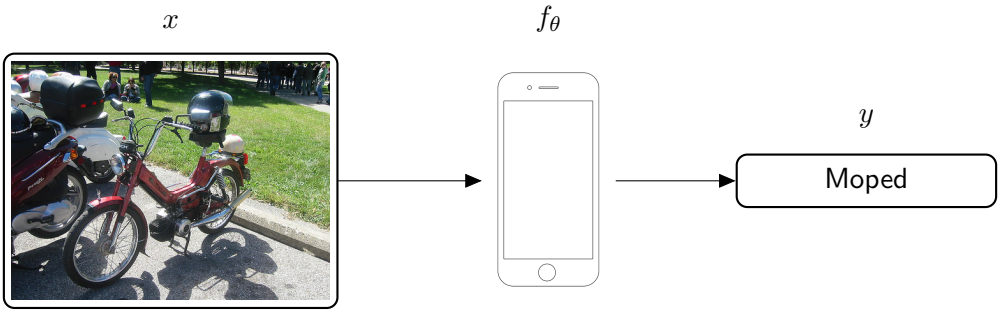
Learning How to Say It:
Language Generation and Deep Learning

Alexander M Rush

Machine Learning for Multiclass Classification



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.

f_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."

Machine Learning for Text Generation

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

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- Possible output text $y_{1:T}$, *how to say it*

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

Training and Evaluation

Training θ:

- Data consists of paired examples $(x, \hat{y})$, *how people say it*
- Typically as large as 100,000 to 10 million examples.

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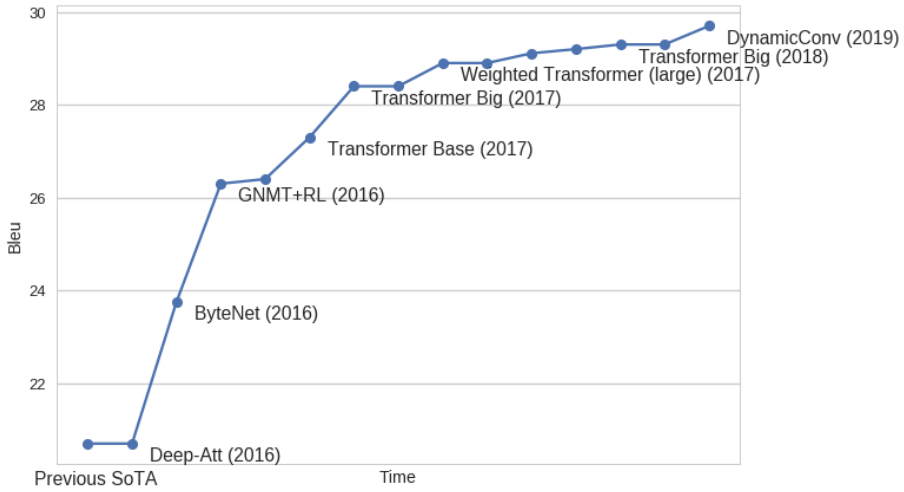
Evaluation:

- Truth: `[Yalitza Aparicio had] just [finished her] teaching [degree]`
- Prediction: `[Yalitza Aparicio had] recently [finished her] [degree]`

Machine Translation 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_θ

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f_θ

$y_{1:T}$

Cambodian government rejects opposition's call for talks abroad

Summarization Data

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

Sentence Summarization Performance

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.

Talk about the Diagrams

Deng et al. [2016] w/ Bloomberg

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

```
 { \cal K } ^ { L } ( \sigma = 2 ) = \left( \begin{array}
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 { 3 } { \operatorname { c o s h } ^ { 2 } x } } \& { \frac
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```
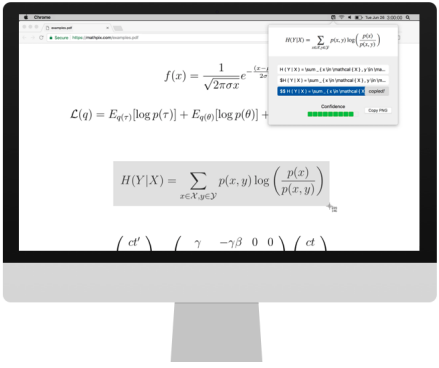

Convert images to LaTeX

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

MacOS Windows Ubuntu



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 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 ...

Outline

Goal

Learn How to Say It

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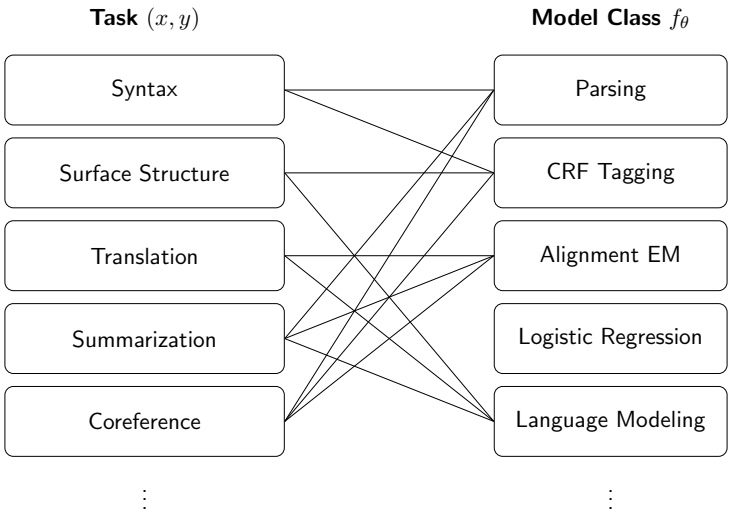
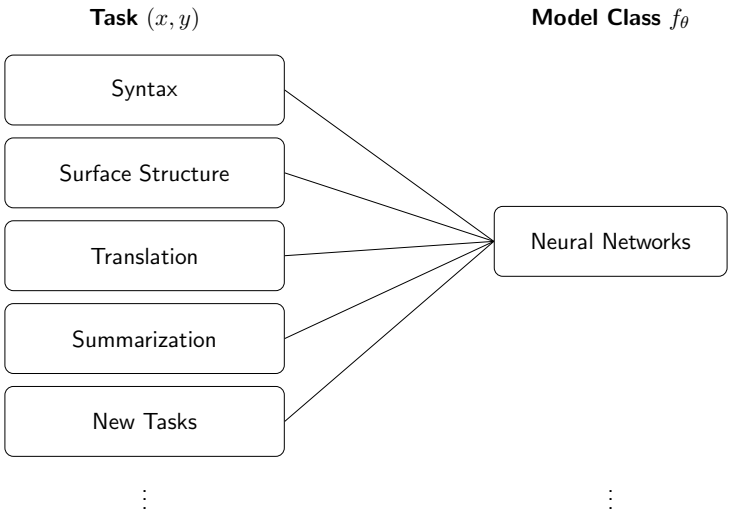
Learn How to Say It

- **Model: Structure and Implementation**
- Work 1: Rethinking Training
- Work 2: Rethinking Generation
- Challenges: Text Generation and Deep Learning

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



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



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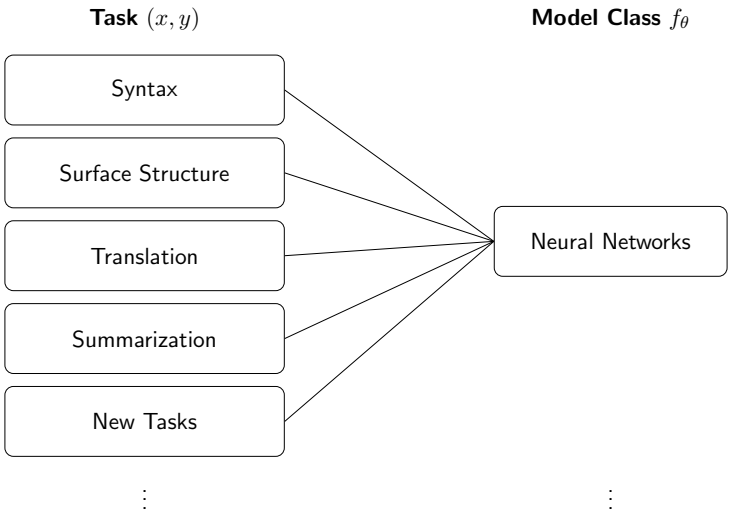

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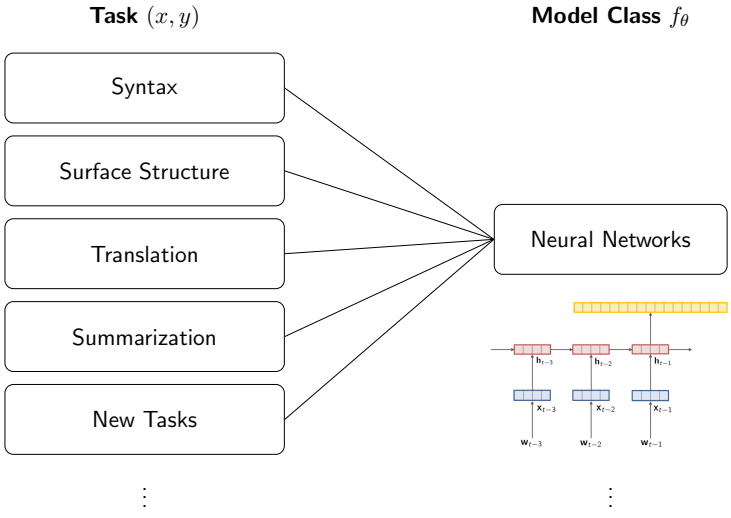

Encoder-Decoder

$$f_\theta(y_{1:T}, x_{1:S})$$

Over the line !

Encoder-Decoder

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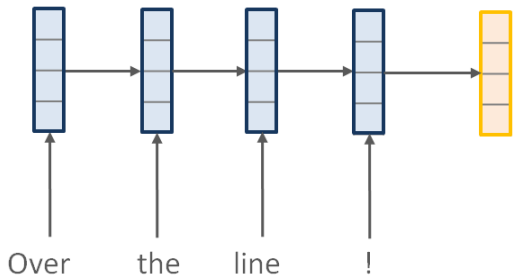

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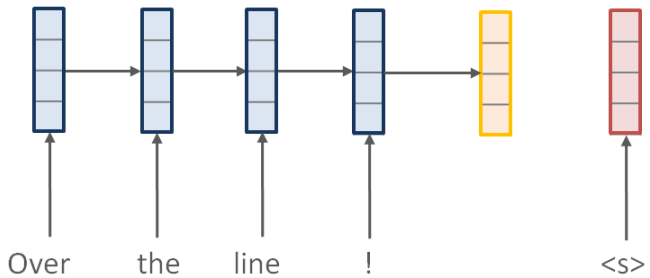

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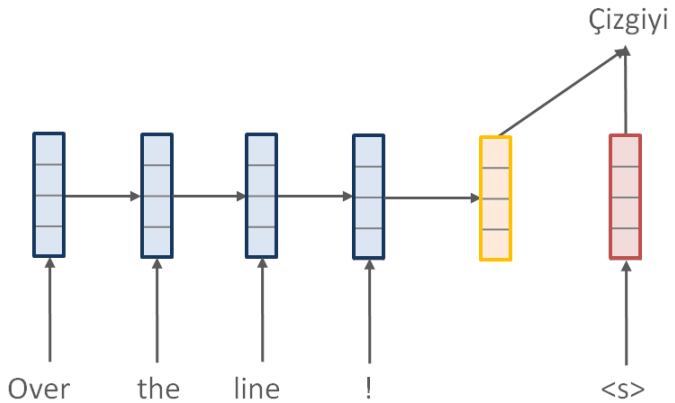

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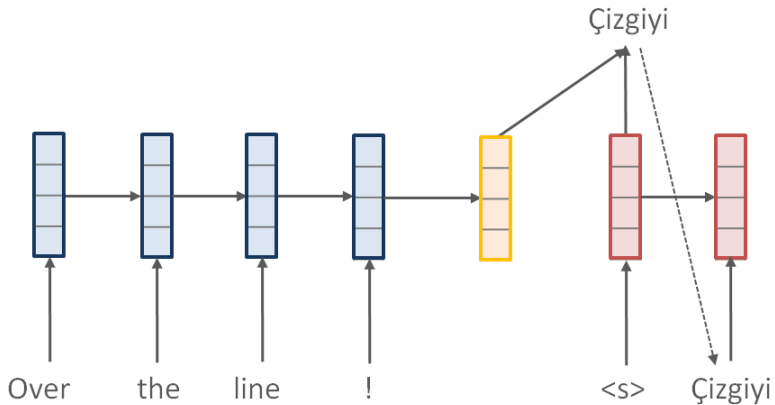

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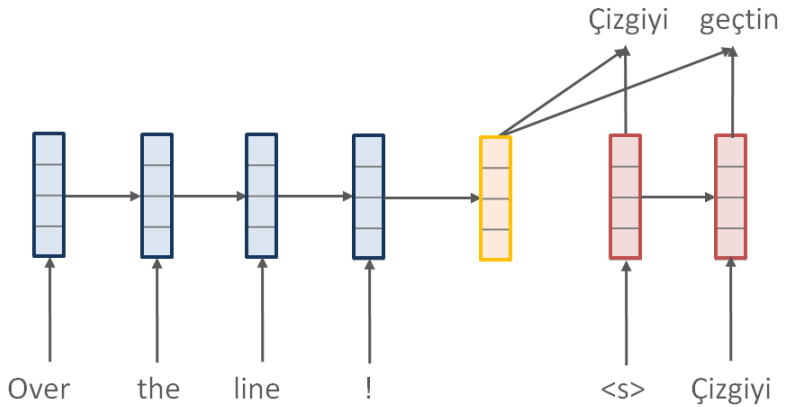

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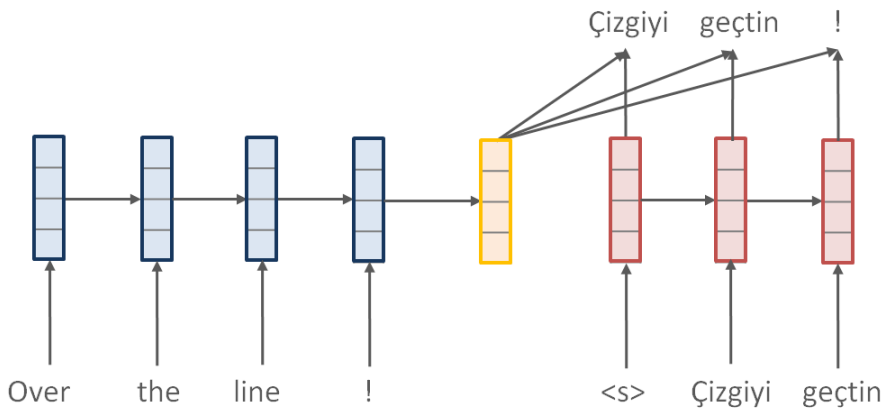

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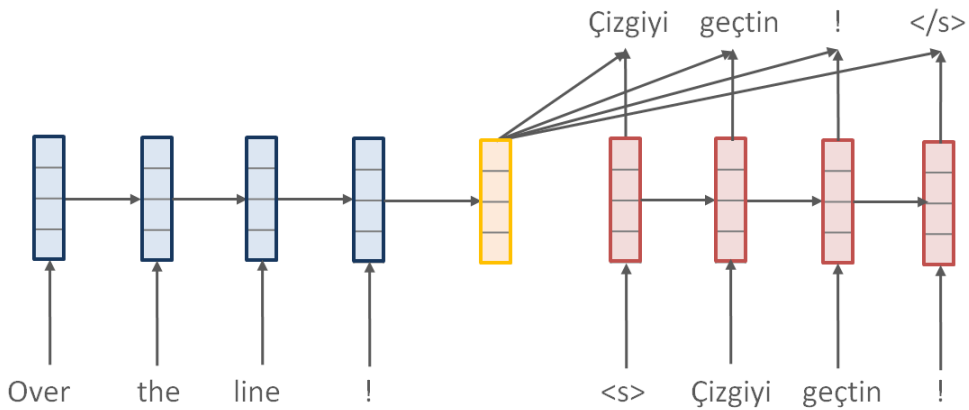


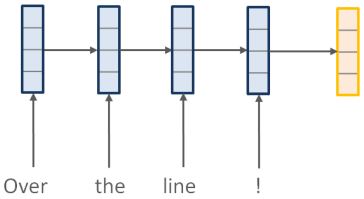
Encoder

Encoder:

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

Context:

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



Decoder

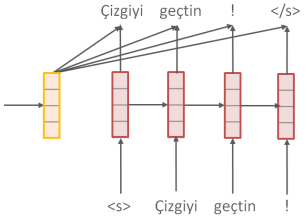
Decoder:

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

Scoring function:

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

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



Decoder Example

Decoder:

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

Language : Well-balanced parentheses (Dyck-1 Language) with nesting-levels,

- Vocabulary: ( ) 0 1 2 3 4

$$f(\text{“0 ((2) (((4 4 4) 3) } \ldots \text{”}, x)$$

$$>$$

$$f(\text{“0) (3)) (( ) 2 ( )) 2”} \ldots, x)$$

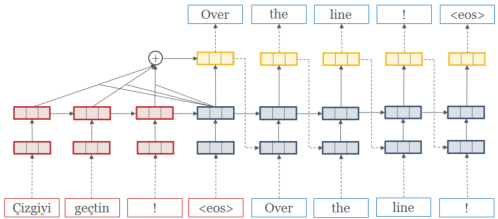
LSTMVis - Parenthesis Language Strobelt et al. [2016] w/ IBM

LSTMVis - Natural Language

Strobelt et al. [2016] w/ IBM

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.

Research Overview

Kim et al. [2016]
Kim et al. [2017]
Wiseman et al. [2017a]

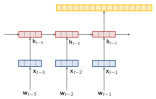
Rush et al. [2015]
Deng et al. [2016]
Schmaltz et al. [2016]

Methods

Applications

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

Analysis



Models

Wiseman et al. [2018]
Deng et al. [2018]
Kim et al. [2018]

Open-Source

Scaling

Klein et al. [2017]
Senellart et al. [2018]
Rush [2018]

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

Natural Lang. Processing
Machine Learning
Visualization

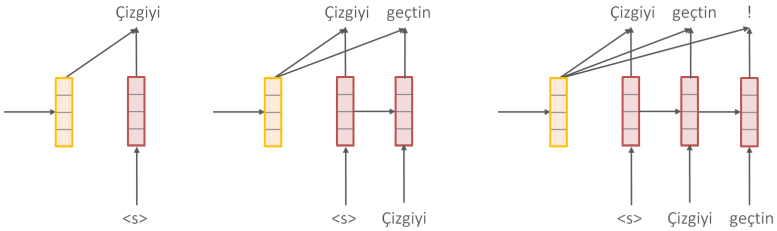
Outline

- Model: Structure and Implementation
- **Work 1: Rethinking Training (Beam Search Optimization)**
- Work 2: Rethinking Generation
- Challenges: Text Generation and Deep Learning

Can we learn parameters θ to better target text generation applications?

Baseline: Training Encoder-Decoder

Parameters θ are trained to score the next word given the *true* history, $(\hat{y}_{1:t-1})$

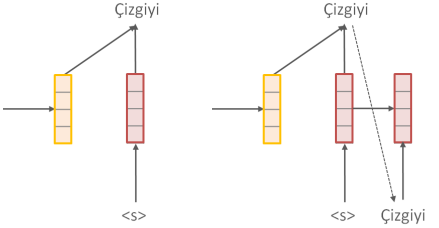


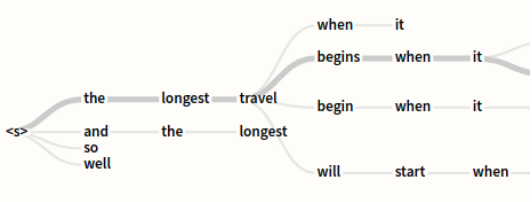
Training loss is identical to multiclass classification,

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

Generating with Encoder-Decoder

Parameters θ are used to score the next word given *any* history, $(y_{1:t-1})$



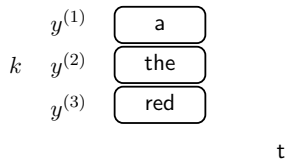


Generation aims to maximize over all sequences,

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

Standard Heuristic Method: Beam Search

$$y^*_{1:T} \approx \arg\max_{y_{1:T}} f_\theta(y_{1:T}, x)$$



Start with K sequences in beam.

1. For each k in beam, expand and score all possible next words y_t.
2. Prune all expansions ($K \times$ vocab) down to top K.

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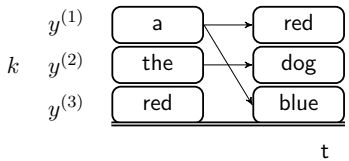

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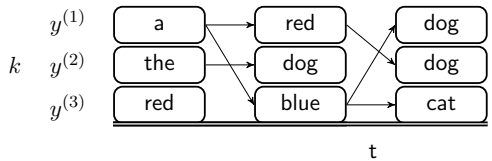

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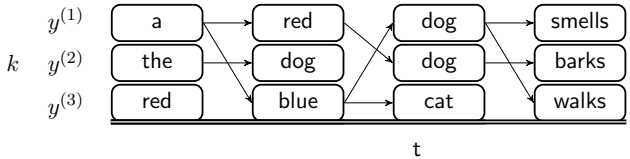

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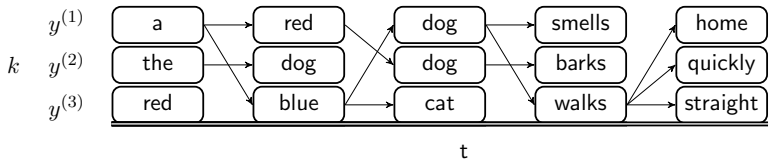

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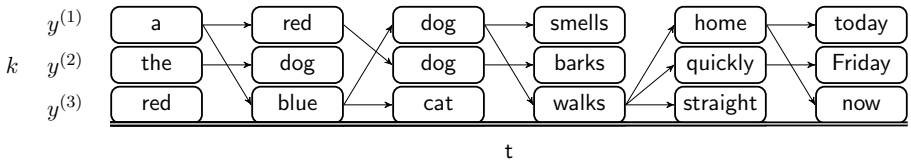

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Known Issues

Multiclass Training $\Rightarrow$ Structured Generation ?

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   - Training conditions on true history, but generation uses predicted history.

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Strategy: Modify model and training to target these issues.

Modification 1: Beam Search at Training

Fix: Exposure Bias

- Take prediction algorithm into account during training.

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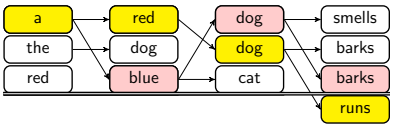

- Run our beam search procedure during training (structured training)

- Loss tied to mistakes, e.g. compare true sequence $\hat{y}_{1:t}$ to $y_{1:t}^{(K)}$ worst in beam

Modification 2: Global Scoring Function

Fix: Label Bias

- Use a global sequence scoring function.

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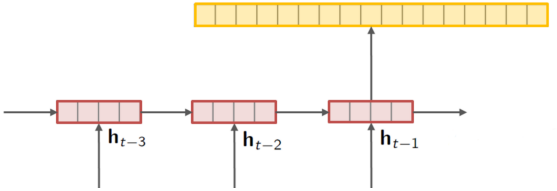
$$f_\theta(y_{1:t}, x) = \mathbf{W}[\mathbf{h}_{t-1}; \mathbf{c}]$$



- Replace local $\log p(y_t | y_{1:t-1}, x; \theta)$ with a global scoring model $f_\theta(y_{1:t}, x)$.

Modification 3: Train with Margin

Fix: Metric Bias

- Incorporate a metric specific term, e.g. n-gram mismatch

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$$\mathcal{L}(\theta) = \sum_t \Delta(\hat{y}_{1:t}, y^{(K)}_{1:t}) \left[1 - f_\theta(\hat{y}_{1:t}, x) + f_\theta(y^{(K)}_{1:t}, x)\right]_+$$

- Positive if true sequence $\hat{y}_{1:t}$ within margin of worst beam sequence $y^{(K)}_{1:t}$.
- Slack-rescaled margin takes problem-specific Δ into account.

Standard Training Example

True: ground-truth training sequence $\hat{y}_{1:T}$.

a

$$\mathcal{L}(\theta) = -\log p(\mathsf{a} \mid x; \theta)$$

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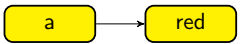

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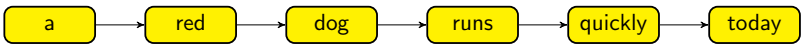

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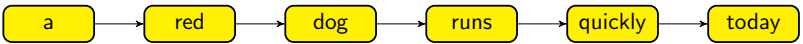

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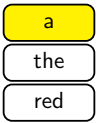
Beam Search Training Example



$$\mathcal{L}(\theta) = 0$$

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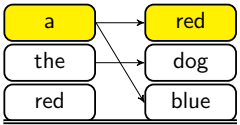

$$\mathcal{L}(\theta) \quad = \quad 0 + 0$$

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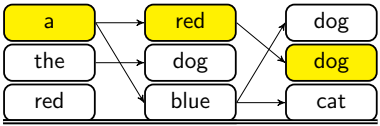

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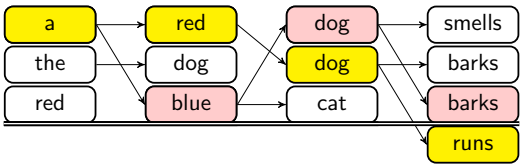

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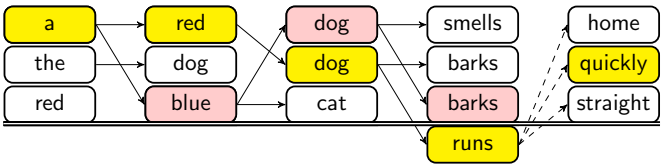

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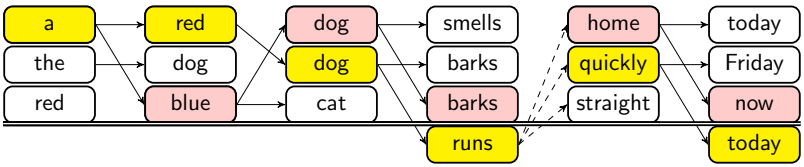

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Parameter Updates: Structured Backpropagation

$$\mathcal{L}(\theta) = \Delta\left[1 - f_\theta(\text{a red dog runs}, x) + f_\theta(\text{a blue dog barks}, x)\right]$$
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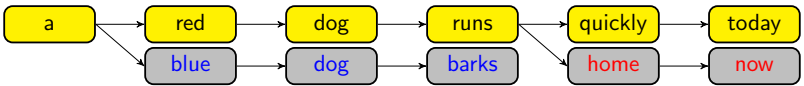

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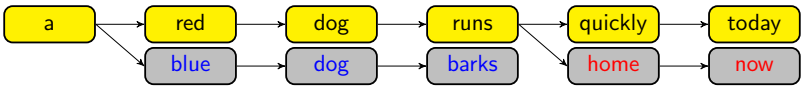


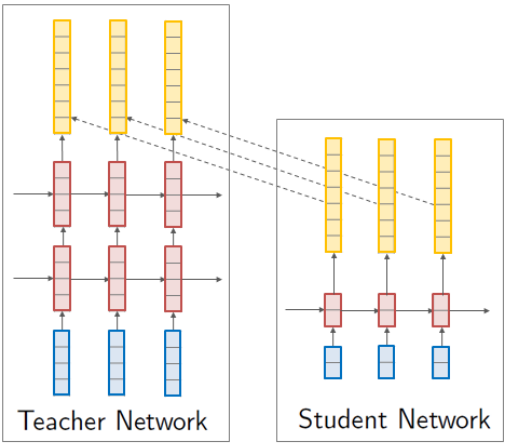
Key Modifications:

- Modification 1: $\mathcal{L}(\theta)$, loss determined by beam search procedure.
- Modification 2: $f_\theta(y_{1:t}, x)$, score determined by global model.
- Modification 3: Δ, scales loss by n-gram metric.

Results

Train Beam	$K = 5$	$K = 10$
	Word Ordering (BLEU)	
Encoder-Decoder	29.8	31.0
Beam Search Optimization	**34.3**	**34.5**
	IWSLT Machine Translation (BLEU)	
Encoder-Decoder	24.0	23.9
Beam-Search Optimization, Δ	**26.4**	**25.5**

Application: Sequence Compression Kim and Rush [2016]



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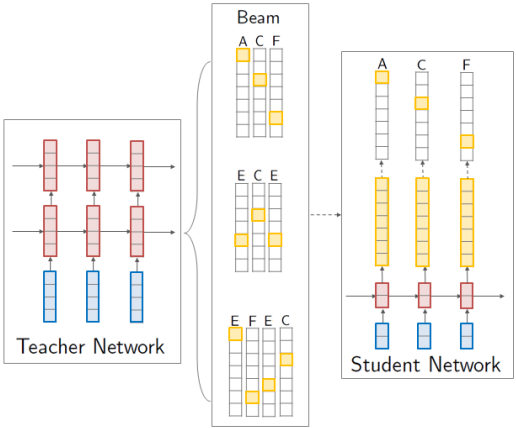


Scaling Translation Models

Outline

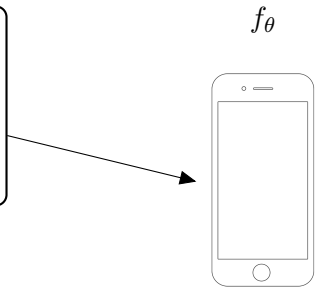
- Background: Core Model and Implementation
- Work 1: Rethinking Model Training
- **Work 2: Rethinking Generation (Learning Neural Templates)**
- Challenges: Text Generation and Deep Learning

Can we learn interpretable and controllable target text generation models?

Talk about Data (E2EGen)

x

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



f_θ

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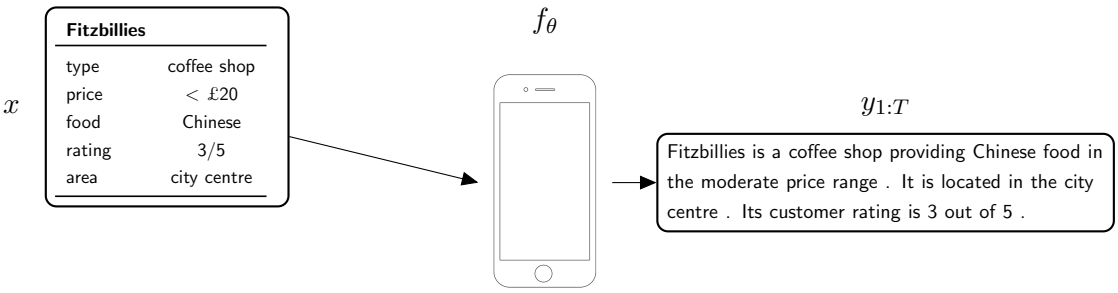

Talking About Data (WikiBio)

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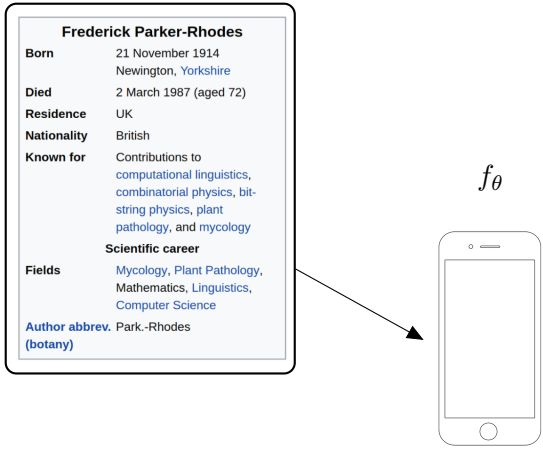

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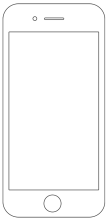

$y_{1:T}$

Frederick Parker-Rhodes (21 November 1914 - 2 March 1987) was an English linguist, plant pathologist, computer scientist, mathematician, mystic, and mycologist.

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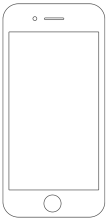

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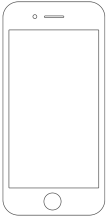

$z_{1:T}$

___ (born ___) was a ___ ___ , who lived in the ___ . He was known for contributions to ___ .

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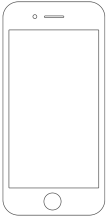

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Arguments for Templated Generation

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?

1. Model
2. Training
3. Template Extraction

Technical Approach: Deep Latent-Variable Models

Expose specific choices as latent variables z.

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

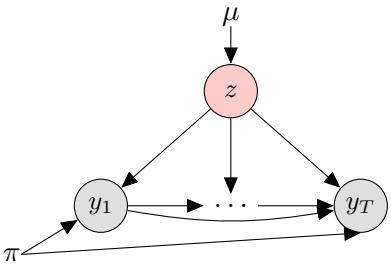
- x, y, θ as before, *what to talk about, how to say it*
- z is a collection of problem-specific latent variables

Example: Discrete Variables as Clusters

Generative process:

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

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



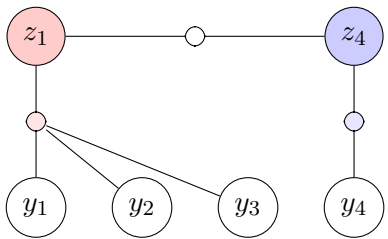
The film is the first from ... $z = 1$

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

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

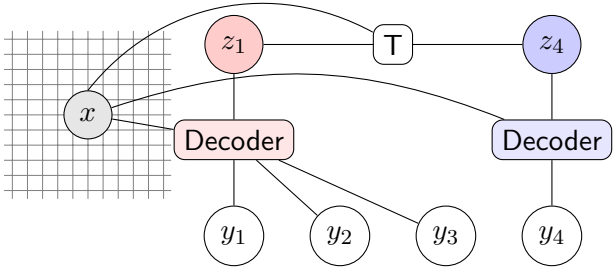
Hidden Semi-Markov Model

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



Model: A Deep Hidden Semi-Markov Model

- Employ HSMM as a conditional latent variable language model, $p(y_1, \ldots, y_T, z \mid x)$.
- Transition Distribution: neural network between clusters.
- Emission Distribution: Encoder-Decoder, specialized per cluster $\{1, \ldots, Z\}$.



Training

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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Frederick Parker-Rhodes was an English linguist, plant pathologist

$$\Downarrow \sum_{z_{1:T}}$$

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

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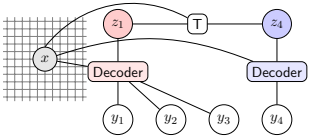
Template Extraction

Extract templates by finding most common, best latent sequences from training.



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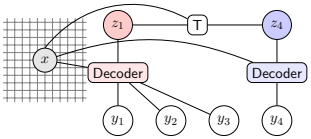

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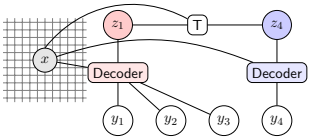

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Find templates $z_{1:T}$ that occur most often in the data.

Frederick Parker-Rhodes was an English linguist, plant pathologist

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

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

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

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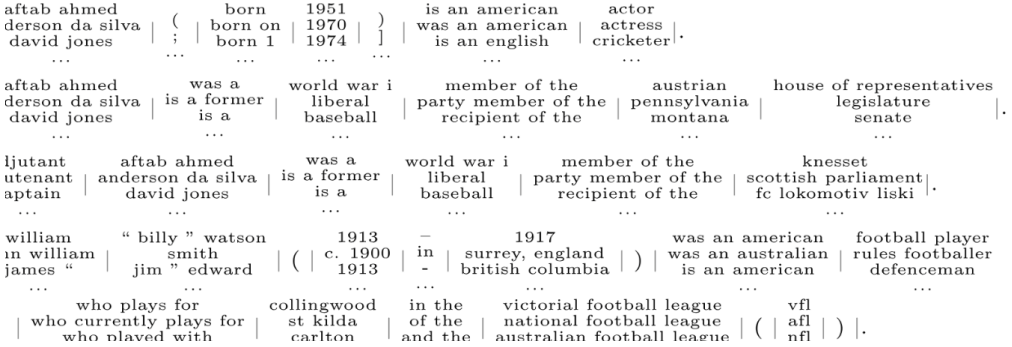
Example Templates: Wikipedia

Extracted templates $z^*_{1:T}$ and their generated words.



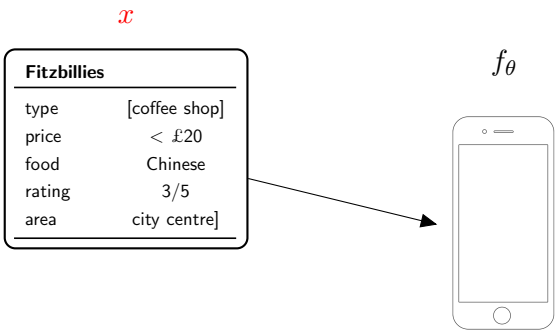
Technical Methodology

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

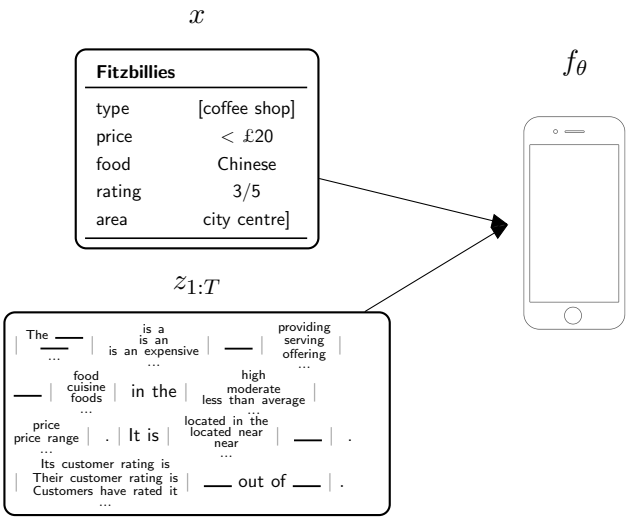
- Training Technique: Backpropagation through dynamic programming. Parameters are trained by exactly marginalizing over segmentations (HSMM backward algorithms)

- Extraction Technique: Viterbi algorithm over encoder-decoder potentials.

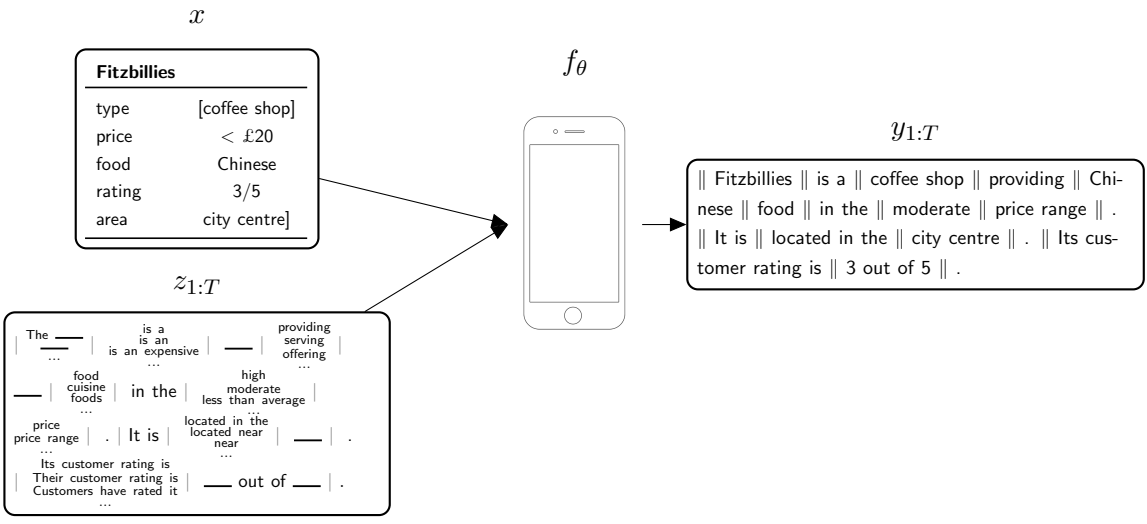
Neural Template Generation Approach



Neural Template Generation Approach



Neural Template Generation Approach



Arguments for Templated Generation

Guarantees about the quality, in particular,

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

Issue 1: Interpretable

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

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.

Results

E2E

(Val)	BLEU	NIST	ROUGE	CIDEr	METEOR
D&J (2017)	65.93	8.59	68.50	2.23	44.83
Substitution BL	43.78	6.88	54.64	1.39	37.35
Neural Template	59.80	7.56	65.01	1.95	38.75

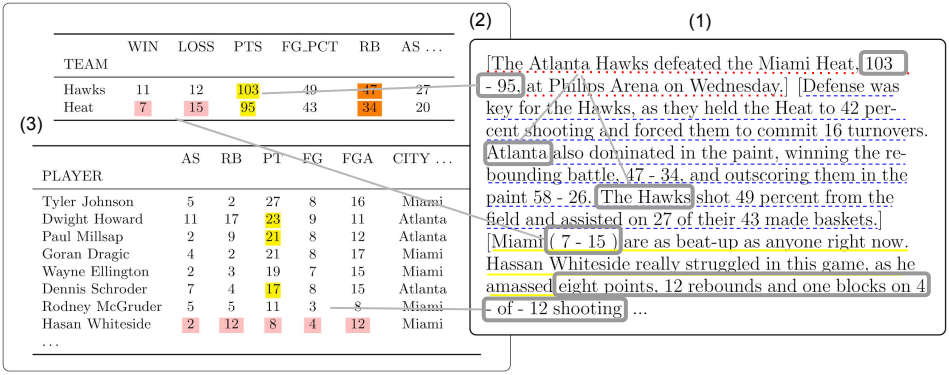
WikiBio

	BLEU	NIST	ROUGE-4
Template KN	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	34.8	7.59	38.6

Outline

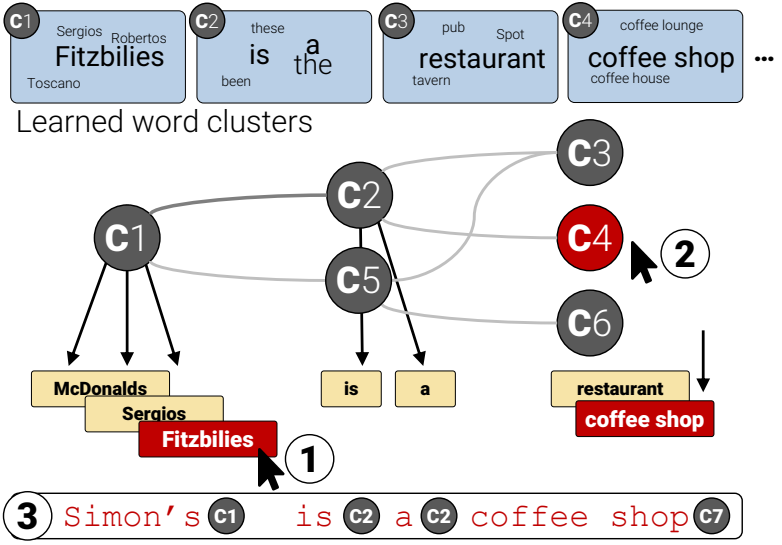
- Background: Core Model and Implementation
- Work 1: Rethinking Model Training (*Beam Search Optimization*)
- Work 2: Rethinking Generation (*Learning Neural Templates*)
- **Challenges: Text Generation and Deep Learning**

1) Long-Form Generation with Explicit Reasoning



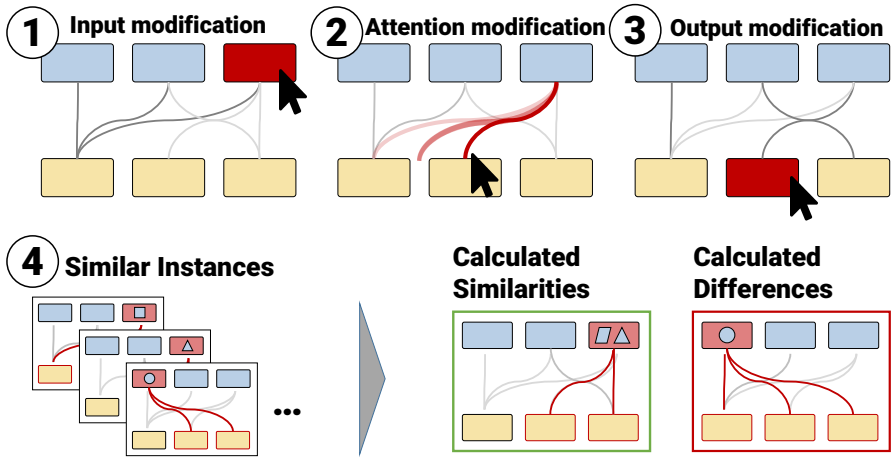
2) Controllable Interactive ML Systems

w/ IBM



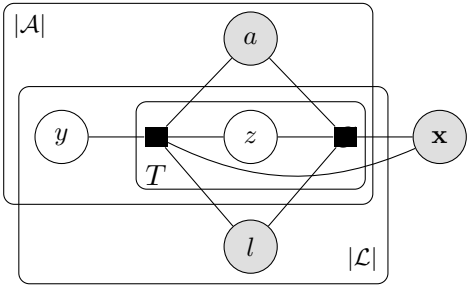
2) Controllable Interactive ML Systems

w/ IBM



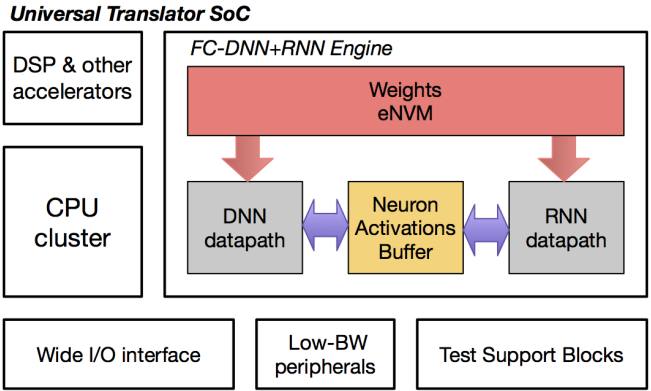
3) Prob. Programming & Deep Learning w/ Uber

```
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)
```



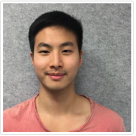
4) Hardware Co-Design

w/ ARM



Harvard NLP

Graduate Students



Justin Chiu

Yuntian Deng

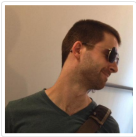
Sebastian Gehrmann

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

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