Breakthroughs in Neural Machine Translation

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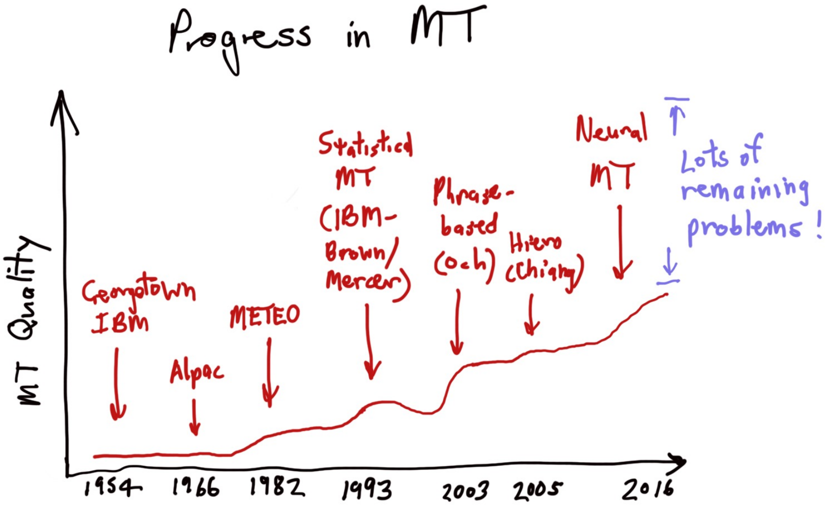
Coming seminars

- Today: Olof Mogren
  Neural Machine Translation
- October 6: John Wiedenhoeft
  Fast Bayesian inference in Hidden Markov Models using Dynamic Wavelet Compression
- October 10: Haris Charalambos Themistocleous
  Linguistic, signal processing, and machine learning approaches in eliciting information form speech

`http://www.cse.chalmers.se/research/lab/seminars/`


Progress in MT
MT Quality
Georgetown IBM
Alpac
METEO
Statistical MT (IBM-Brown/Mercer)
Phrase-based (Och)
Hiero (Chiang)
Neural MT
Lots of remaining problems!
1954
1966
1982
1993
2003
2005
2016

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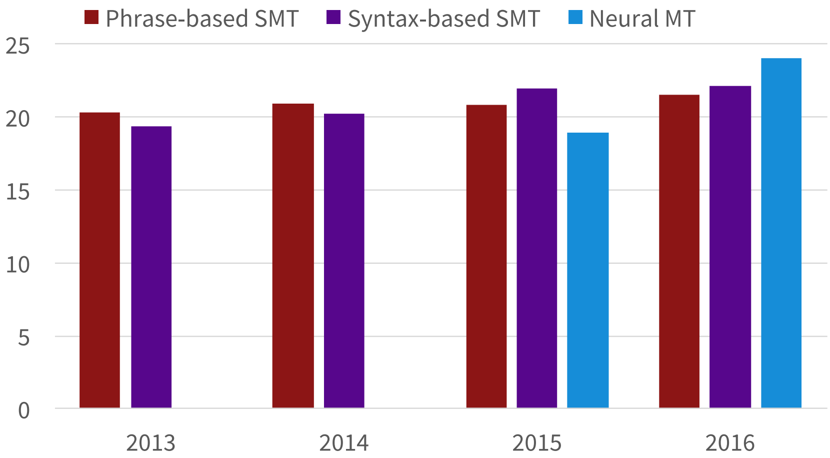
Progress in Machine Translation

[Edinburgh En-De WMT newstest2013 Cased BLEU; NMT 2015 from U. Montréal]



From [Sennrich 2016, http://www.meta-net.eu/events/meta-forum-2016/slides/09_sennrich.pdf]

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Phrase-based Statistical Machine Translation

A **marvelous** use of **big data** but … it's mined out?!?

1519年600名西班牙人在墨西哥登陆，去征服几百万人口的阿兹特克帝国，初次交锋他们损兵三分之二。

In 1519, six hundred Spaniards landed in Mexico to conquer the Aztec Empire with a population of a few million. They lost two thirds of their soldiers in the first clash.

translate.google.com (2009): 1519 600 Spaniards landed in Mexico, millions of people to conquer the Aztec empire, the first two-thirds of soldiers against their loss.

translate.google.com (2013): 1519 600 Spaniards landed in Mexico to conquer the Aztec empire, hundreds of millions of people, the initial confrontation loss of soldiers two-thirds.

translate.google.com (2014): 1519 600 Spaniards landed in Mexico, millions of people to conquer the Aztec empire, the first two-thirds of the loss of soldiers they clash.

translate.google.com (2015): 1519 600 Spaniards landed in Mexico, millions of people to conquer the Aztec empire, the first two-thirds of the loss of soldiers they clash.

translate.google.com (2016): 1519 600 Spaniards landed in Mexico, millions of people to conquer the Aztec empire, the first two-thirds of the loss of soldiers they clash.

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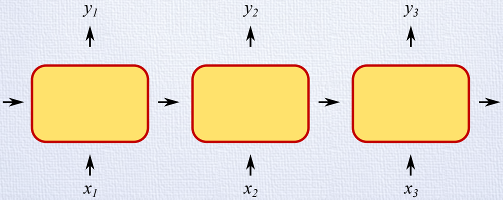
What is Neural MT (NMT)?

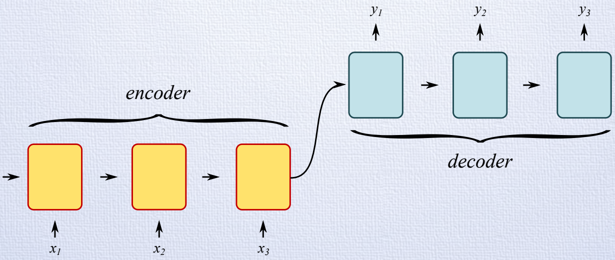
The approach of modelling the entire MT process
via one big artificial neural network.

Modelling language using RNNs



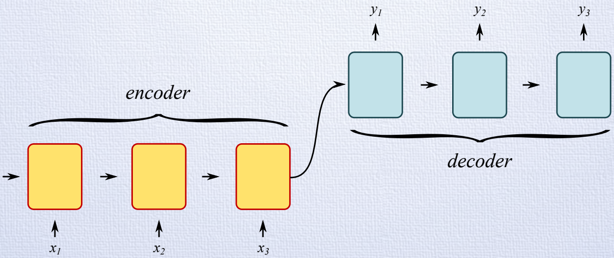
- Language models: $P(word_i | word_1, \ldots, word_{i-1})$
- Recurrent Neural Networks
- Gated additive sequence modelling:
  LSTM (and variants) details
- Fixed vector representation for sequences
- Use with beam-search for language generation

Encoder-decoder framework



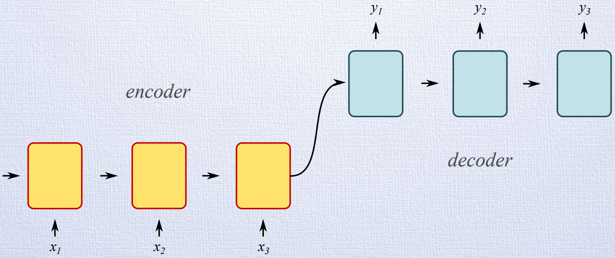
- Sequence to Sequence Learning with Neural Networks
  Ilya Sutskever, Oriol Vinyals, Quoc V. Le, NIPS 2014

Encoder-decoder framework



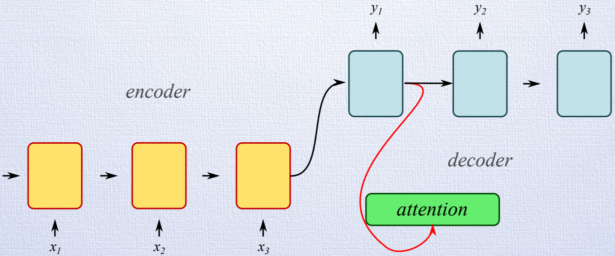
- Sequence to Sequence Learning with Neural Networks
  Ilya Sutskever, Oriol Vinyals, Quoc V. Le, NIPS 2014
- Reversed input sentence!

Encoder-decoder with attention



- Neural Machine Translation by Jointly Learning to Align and Translate
  Dzmitry Bahdanau, Kyunghyun Cho, Yoshua Bengio - ICLR 2015

Encoder-decoder with attention



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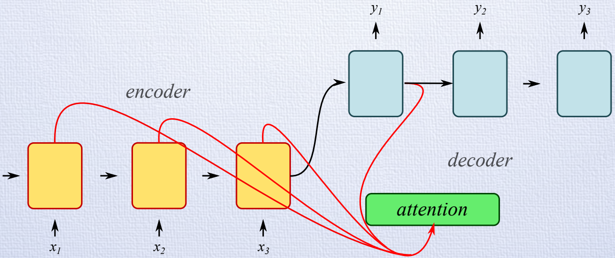
Encoder-decoder with attention



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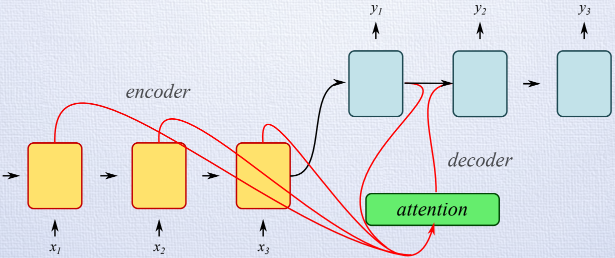
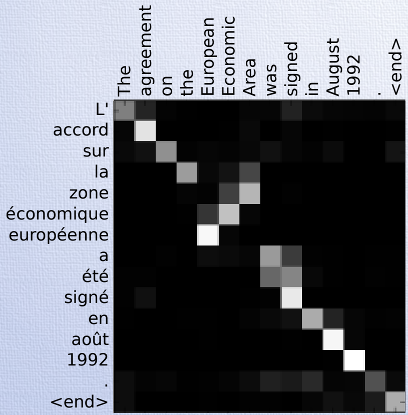
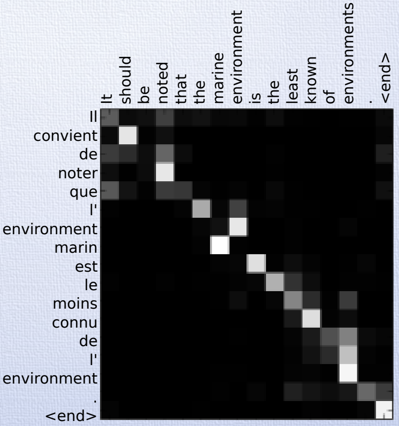
Encoder-decoder with attention



- Neural Machine Translation by Jointly Learning to Align and Translate
  Dzmitry Bahdanau, Kyunghyun Cho, Yoshua Bengio - ICLR 2015

Alignment - (more)





Neural Machine Translation, NMT

- End-to-end training
- Distributed representations
- Better exploitation of context

What's not on that list?

What's been holding NMT back?

- Limited vocabulary
  - Copying
  - Dictionary lookup
- Data requirements
- Computation
  - Training time
  - Inference time
  - Memory usage

Rare words 1: Subword units

- Neural machine translation of rare words with subword units
  Rico Sennrich and Barry Haddow and Alexandra Birch
- A character-level decoder without explicit segmentation for neural machine translation
  Junyoung Chung, Kyunghyun Cho, and Yoshua Bengio, ACL 2016

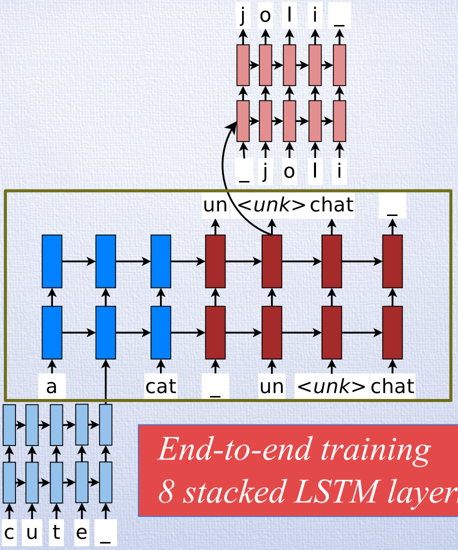
Byte-pair encoding (BPE):

`aaabdaaabac`	`ZabdZabac`	`ZYdZYac`	`XdXac`
	`Z=aa`	`Y=ab`	`X=ZY`
		`Z=aa`	`Y=ab`
			`Z=aa`

Rare words 2: Hybrid char/word NMT

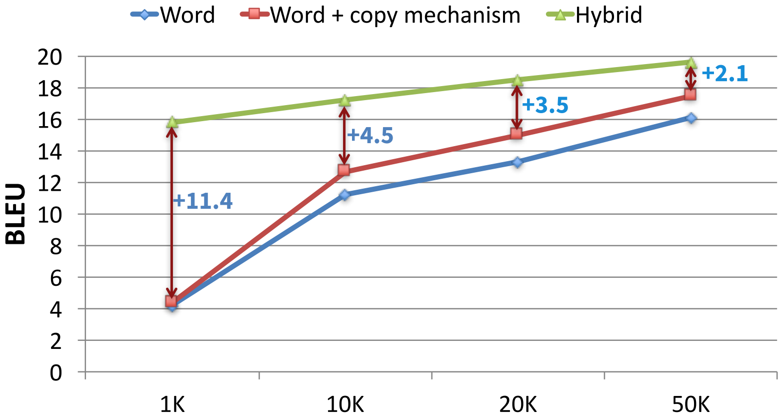
- Achieving open vocabulary neural machine translation with hybrid word-character models
  Thang Luong and Chris Manning, ACL 2016.
- Hybrid architechture:
  - Word-based for most words
  - Character-based for rare words
  - 2 BLEU points improvement over copy mechanism

Word-level
(4 layers)



End-to-end training
8 stacked LSTM layers

Effects of Vocabulary Sizes



More than +2.0 BLEU over copy mechanism!

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Rare Word Embeddings

- Word & character-based embeddings.

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Training with monolingual data

- Improving neural machine translation models with monolingual data
  Rico Sennrich, Barry Haddow, Alexandra Birch, ACL 2016.
- Backtranslate monolingual data (with NMT model)
- Use backtranslated data as parallell training data

Enriching parallel data

- *Dummy* source sentences

She loves cute cats	Elle aime les chats mignons	(parallel)
<null>	Elle aime les chiens mignons	(mono)

Small gain +0.4-1.0 BLEU.
Difficult to add more mono data.

Rico Sennrich, Barry Haddow, and Alexandra Birch. ***Improving Neural Machine Translation Models with Monolingual Data****. ACL 2016.*

Enriching parallel data

- *Synthetic* source sentences

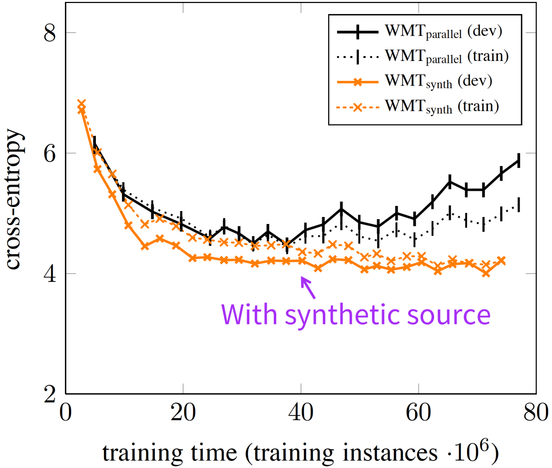
She loves cute cats	Elle aime les chats mignons	(parallel)
She likes cute cats	Elle aime les chiens mignons	(mono)

Back translated

Large gain +2.1-3.4 BLEU.

Rico Sennrich, Barry Haddow, and Alexandra Birch. ***Improving Neural Machine Translation Models with Monolingual Data****. ACL 2016.*

Prevent Over-fitting



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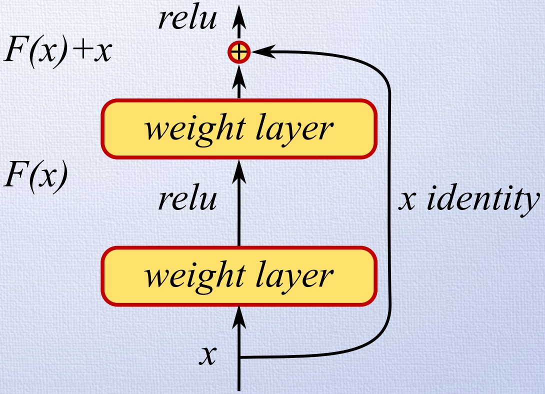
Residual deep LSTMs

- Deep recurrent models with fast-forward connections for neural machine translation: *Jie Zhou et.al., Baidu research, arXiv preprint, 1606.04199*
- Residual (skip) connections in depth
- 16 layers deep LSTM model

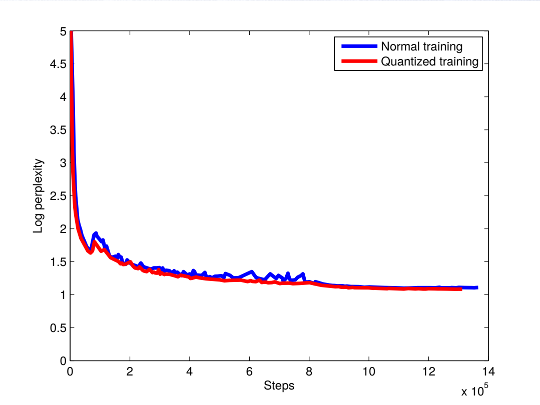


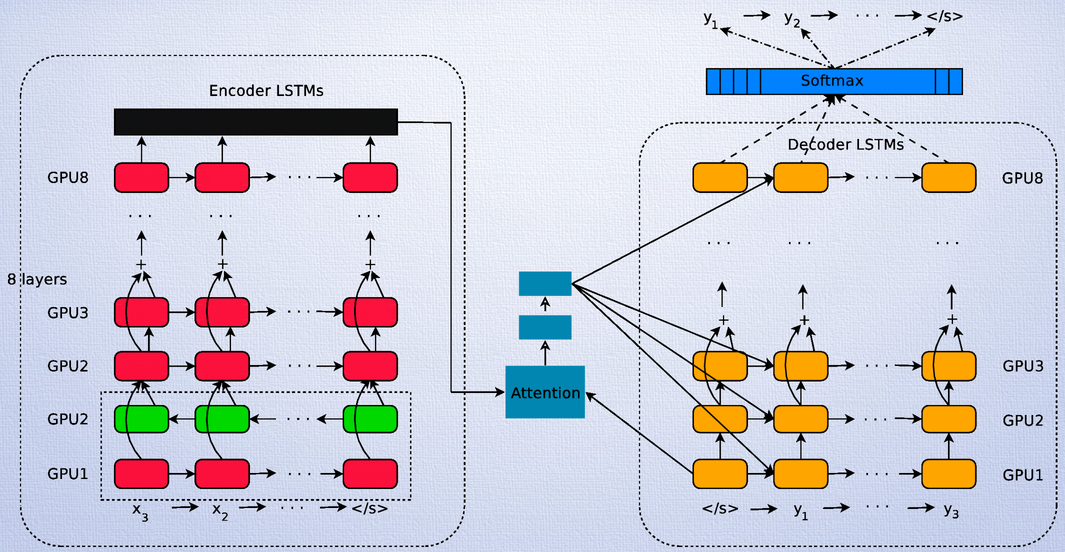
Putting it all together

- Google's neural machine translation system:
  Bridging the gap between human and machine translation
  Yonghui Wu, et.al., Google, arXiv preprint, 1609.08144
- Subwords like Sennrich et.al. (BPE)
- 8 layers deep LSTM model.
- Quantizised weights (see next slide)
- Downpour SGD: parallell training
- 8GPUs, one host.

Quantized inference

- Training: real-valued weights
- Limit precision:
  improved inference speed
- Weights $\in -1, 0, 1$
- Extra constraints on training:
  $x_t^i, c_t^i \in [-\delta, \delta]$
- Similar constraints on
  softmax layer.





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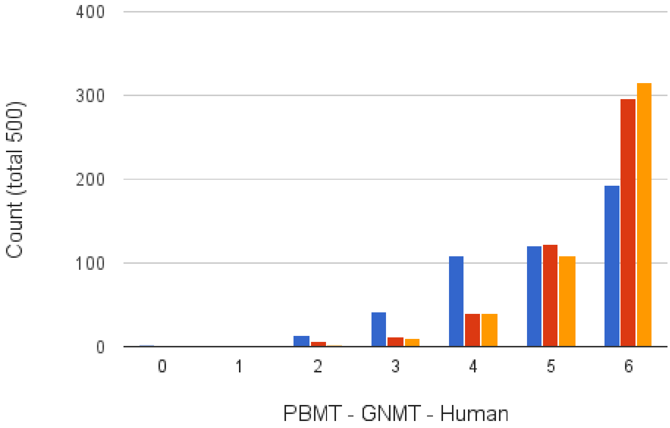

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Single model BLEU scores

Model	BLEU	Decoding time per sentence (s)
Word	37.90	0.2226
Character	38.01	1.0530
WPM-8K	38.27	0.1919
WPM-16K	37.60	0.1874
WPM-32K	38.95	0.1146
Mixed Word/Character	38.39	0.2774
PBMT [15]	37.0	
LSTM (6 layers) [30]	31.5	
LSTM (6 layers + PosUnk) [30]	33.1	
Deep-Att [43]	37.7	
Deep-Att + PosUnk [43]	39.2	

Ensemble model BLEU scores

Model	BLEU
WPM-32K (8 models)	40.35
RL-refined WPM-32K (8 models)	41.16
LSTM (6 layers) [30]	35.6
LSTM (6 layers + PosUnk) [30]	37.5
Deep-Att + PosUnk (8 models) [43]	40.4

Single model human evaluation

Model	BLEU	Side-by-side averaged score
PBMT [15]	37.0	3.87
NMT before RL	40.35	4.46
NMT after RL	41.16	4.44
Human		4.82

Future of (N)MT 1

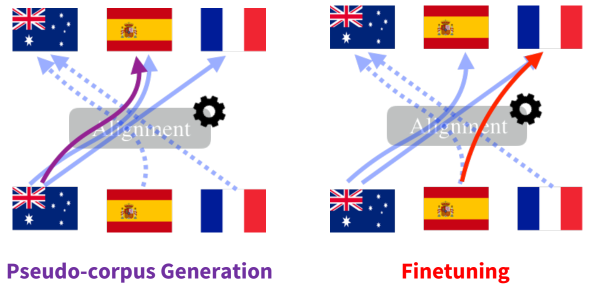
- Larger context (not only one sentence at a time)
  - Attention for long sequences in **speech**:
    Chan, Jaity, Le, Vinyals, ICASSP 2015
  - Tracking states over many sentences in **dialogue systems**:
    Serban, Sordoni, Bengio, Courville, Pineau , AAAI 2015

Future of (N)MT 2

- Multi-language translation models
  - Multi-Task Learning for Multiple Language Translation
    Dong, Wu, He, Yu, Wang, ACL 2015
  - Multi-Way, Multilingual Neural Machine Translation with a Shared Attention Mechanism
    Firat, Cho, Bengio, NAACL 2016
  - Improvement for low-resoursce languages
  - Not yet as good for high-resource languages
  - Zero-resource translation (some initial results)

Multilingual Translation: Looking Ahead

- Zero-resource translation
  - Finetuning with *pseudo*-parallel corpus
    [Sennrich et al., ACL2016]
  - Closely related to unsupervised learning



[Firat et al., EMNLP2016]

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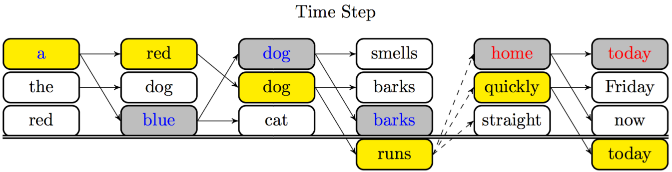
Beyond Maximum Likelihood

- Maximize the sequence-wise global loss
- Incorporate inference into training
  - Stochastic inference
    - Policy gradient [Ranzato et al., ICLR2016; Bahdanau et al., arXiv2016]
    - Minimum risk training [Shen et al., ACL2016]
  - Deterministic inference
    - Learning to search [Wiseman & Rush, arXiv2016]



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Appendix

by *ent362* , *ent300* updated 6:06 pm et , thu march 26 , 2015 (*ent300*) the `` *ent321* '' series will have to handcuff a new director . *ent201* , who directed `` *ent71* , '' told *ent286* that she wo n't be back for the sequel , `` *ent100* . '' `` directing ' *ent135* ' has been an intense and incredible journey for which i am hugely grateful , '' she said in a statement to the site . `` while i will not be returning to direct the sequels , i wish nothing but success to whosoever takes on the exciting challenges of films two and three . '' ' *ent71* ' : what fans hoped for ? the first film in the best - selling book series has been hugely successful , pulling in more than $ 550 million worldwide since it premiered in mid-february , but there have been rumbles that creative clashes were in the offing for the sequel . author *ent341* has a great deal of control in how her books are presented on screen , and she made it clear that she wanted to write the screenplay for the second film , *ent184* reported last month . *ent28* wrote the screenplay for `` *ent71* . '' the story behind mr. *ent289* 's suits the film stars *ent344* as billionaire *ent275* -- a man of certain sexual proclivities -- and *ent407* as his romantic partner , *ent389* .

X bows out of the `` *ent321* '' sequel

by *ent339* , *ent42* updated 2:59 pm et , thu march 26 , 2015 (*ent42*) call it `` *ent351* . '' a *ent396* state trooper caught a driver using a cardboard cutout of *ent421* , the *ent364* beer pitchman known as `` *ent397* . '' the driver , who was by himself , was attempting to use the *ent214* . `` the trooper immediately recognized it was a prop and not a passenger , '' trooper *ent367* told the *ent375* . `` as the trooper approached , the driver was actually laughing . '' *ent143* sent out a tweet with a photo of the cutout -- who was clad in what looked like a knit shirt , a far cry from his usual attire -- and the unnamed laughing driver : `` i do n't always violate the *ent303* lane law ... but when i do , i get a $ 124 ticket ! we 'll give him an a for creativity ! '' the driver was caught on *ent300* near *ent327* , *ent396* , just outside *ent53* . `` he could have picked a less recognizable face to put on his prop , '' *ent143* told the *ent375* . `` we see that a lot . usually it 's a sleeping bag . this was very creative . ''

a driver was caught in the **X** with a cutout of `` *ent7* ''

Teaching Machines to Read and Comprehend, Dec 2015

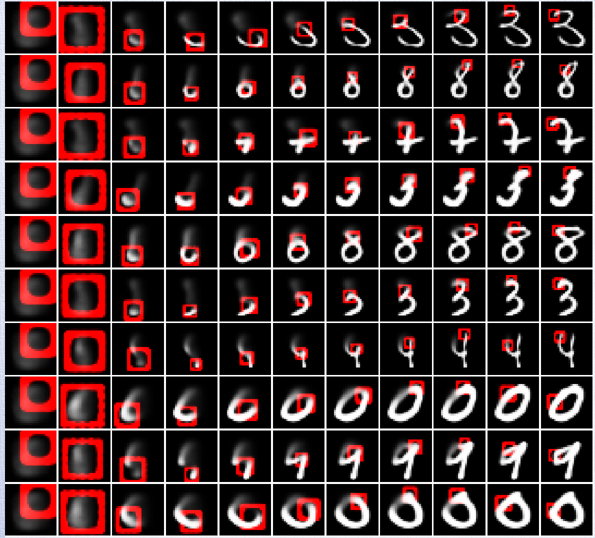
Hermann, Kocisky, Greffenstette,

Espeholt, Kay, Suleyman, Blunsom

What wasn't on that list?

- Explicit use of syntactic or semantic structures
- Explicit use of discourse structure, anaphora, etc.
- Black box component models for reordering, transliteration, etc

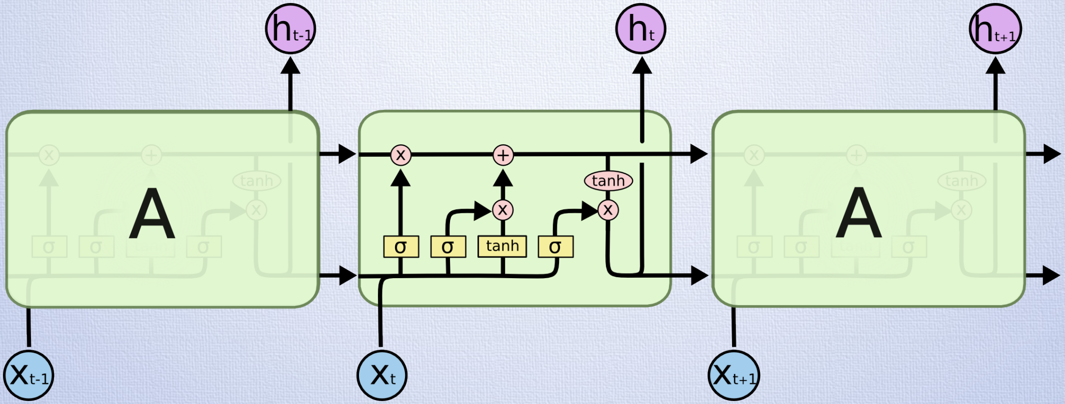
back



DRAW, A Recurrent Neural Network For Image Generation - 2015

Gregor, Danihelka, Graves, Rezende, Wierstra

LSTM



Christopher Olah

back