

# Deep Learning in NLP

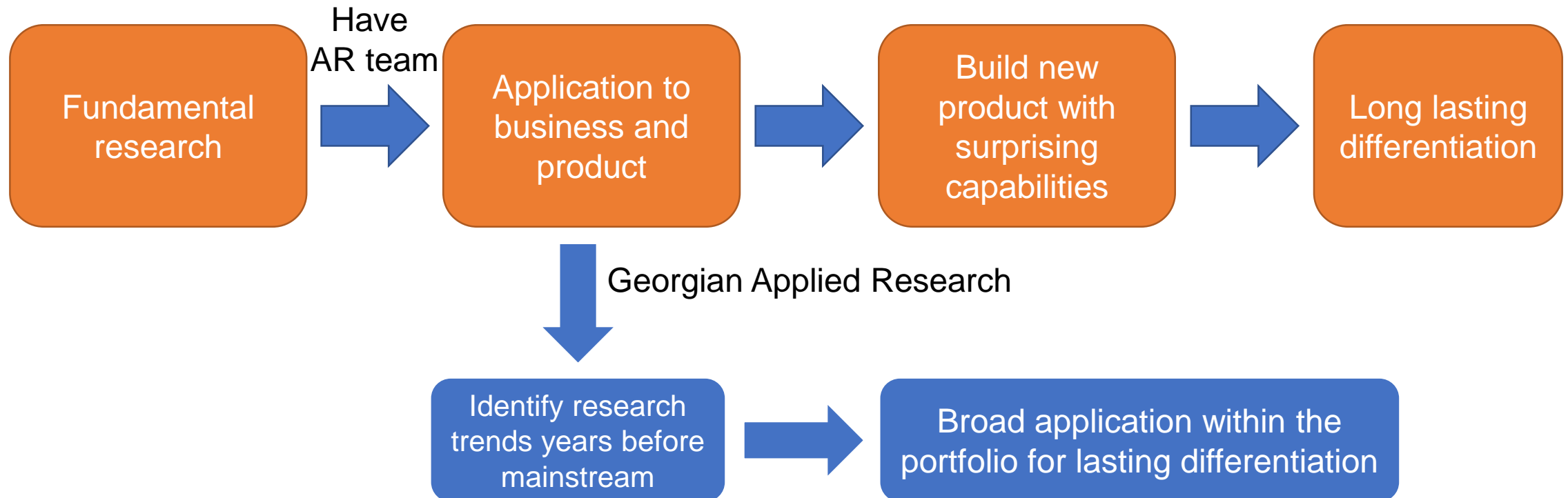
Parinaz Sobhani

# Bio

- Director, Machine Learning at Georgian Partners
- Ph.D. Computer Science (University of Ottawa)
- Research: NLP, DL, Sentiment and Stance Classification
- Previous affiliations:
  - Research Intern: Microsoft Research
  - Research Intern: NRC
  - Visiting Scholar: University of Copenhagen

# Impact Team in Georgian Partners

- Expertise in machine learning, security, privacy, natural language processing, software engineering.
- Enable portfolio companies to accelerate understanding and adoption of thesis areas.
- Act as an extension to a portfolio company's R&D capabilities.
- Engagements range from strategy workshops through to applied research.



# From Conventional Machine Learning to Deep Neural Networks

Although it is often valuable to approach problems with conventional machine learning,

✓ Easier to **implement, maintain** and **explain**

Current trends in the Machine Learning research community focus on deep neural networks.

What is **deep learning**?

*Deep Neural networks are stacked, multilayer networks where each layer provides nonlinear information processing and corresponds to a different level of abstraction.*

What are the advantages of DL over conventional Machine Learning?

- More **flexible** to capture rich and intricate patterns of data
- Easier **Transfer Learning** and better **Modularity**
- Automatically learn **high-level feature representations**

# Learning Representation

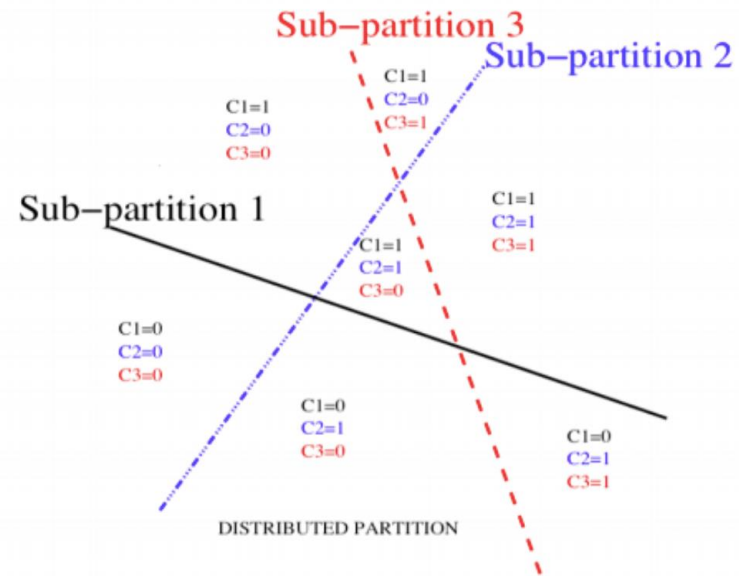
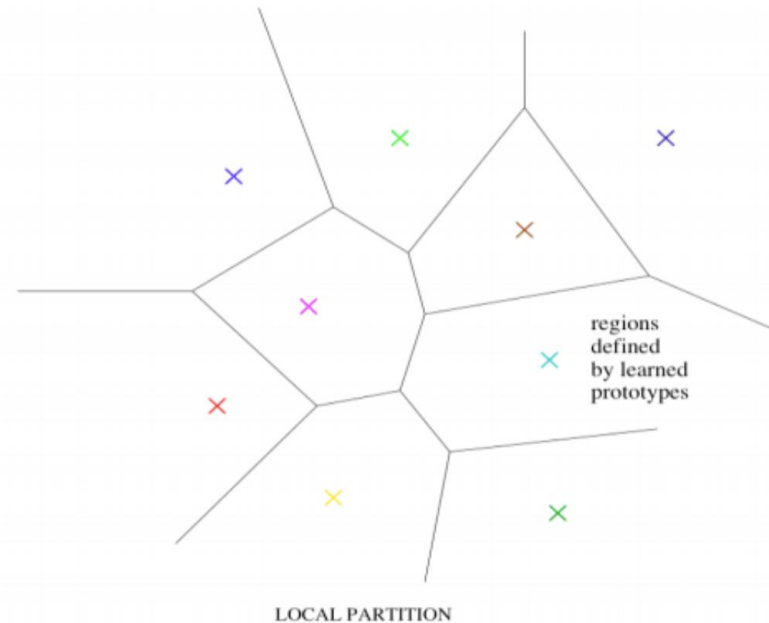
- Handcrafting features:
  - Are Domain/task dependent
  - Requires domain/language expertise
  - Might be over-specified or incomplete
- Why using deep learning to learn representation?
  - Automatic feature learning
  - Learning **distributed representation**
  - Learning **different-level of abstraction**

# One-hot Encoding Vs Distributed Representation

- One-Hot Encoding:

motel [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0] AND  
hotel [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0] = 0

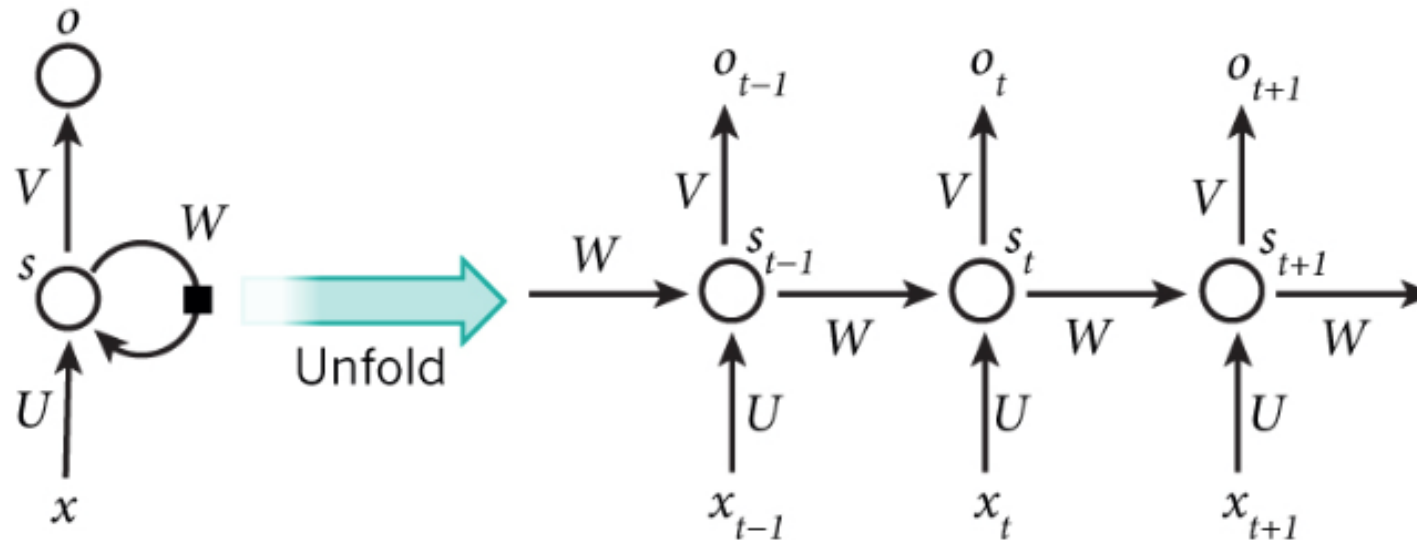
- Distributed Representation



# Why Neural Word Embedding?

- Soft clustering models, such as LSA or LDA, learn for each cluster/topic a distribution over words of how likely that word is in each cluster
- Advantages of the neural word embedding approach:
  - We can easily add supervision from one or many tasks to learn task-specific representation
  - We can build representations for large linguistic units

# Recurrent Neural Networks (RNN)



$$s_t = f(Ux_t + Ws_{t-1}),$$

$$o_t = \text{softmax}(Vs_t),$$

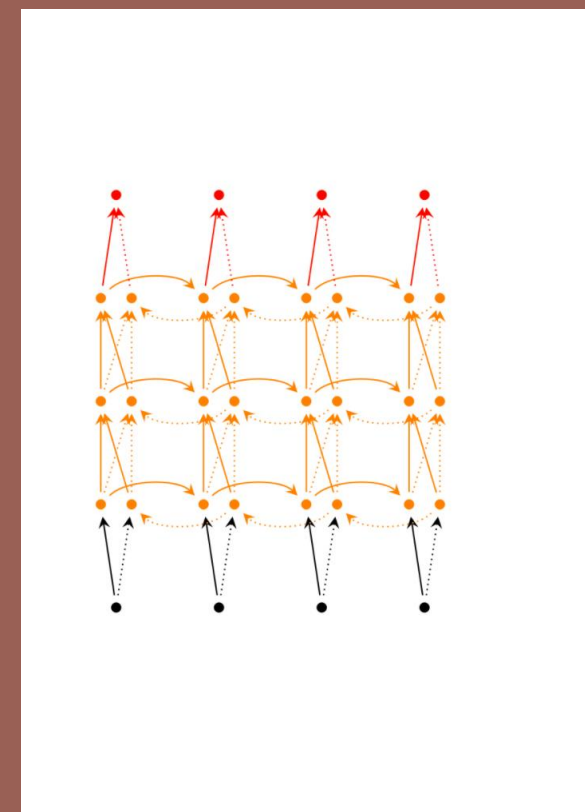
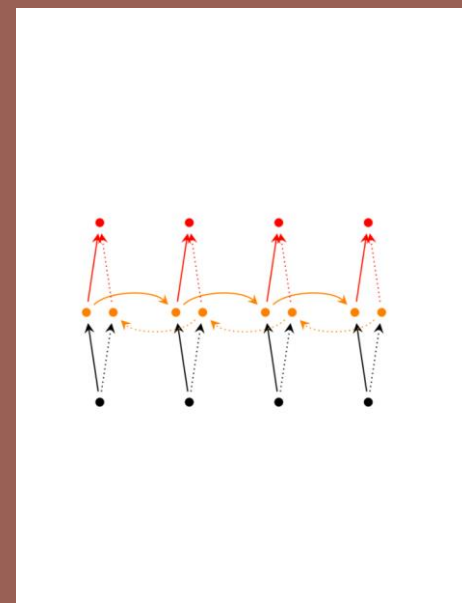
Figure from [WILDML](#)



# RNN Extensions

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- **Bidirectional RNNs**
  
  
  
  
  
  
  
  
  
  
- **Deep (Bidirectional) RNNs**



# Long Short-Term Memory (LSTM)

- LSTM [Hochreiter & Schmidhuber '97] has showed to be effective in a wide range problems:
  - handwriting recognition [Graves, '08],
  - machine translation [Sutskever, '14; Cho, '14],
  - speech recognition [Graves, '13],
  - image-to-text conversion [Vinyals, '14],
  - robot control [Mayer, '08],
  - etc.

# Long Short-Term Memory (LSTM)

- In conventional LSTM, history is summarized and encoded in *memory cells* in a **sequential** fashion.

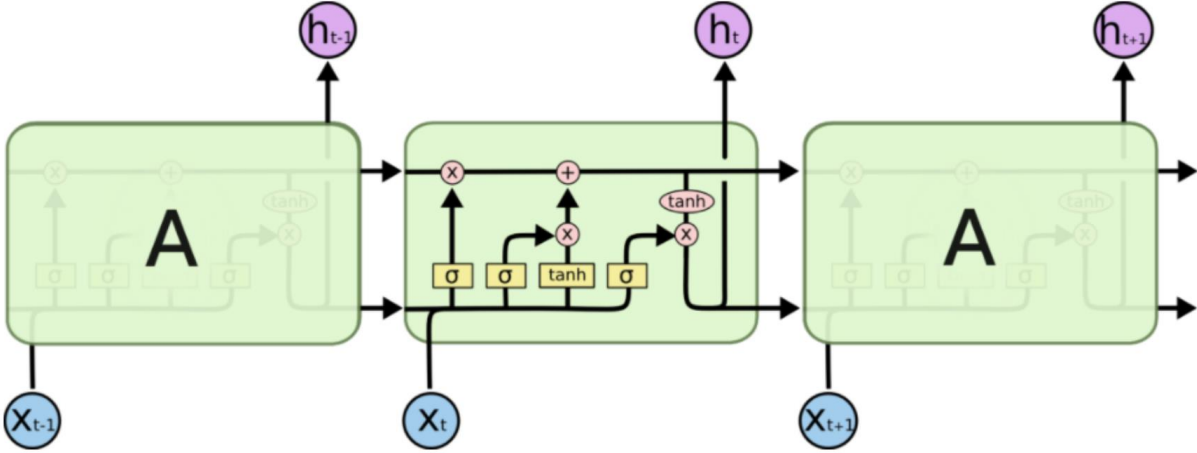
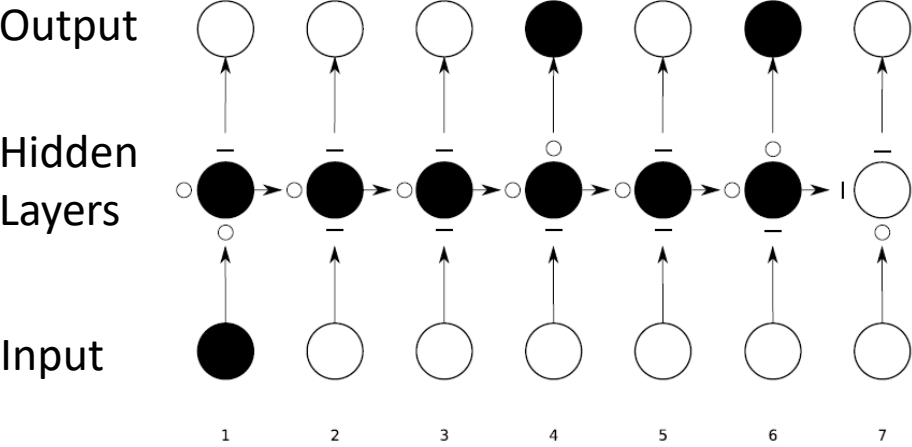
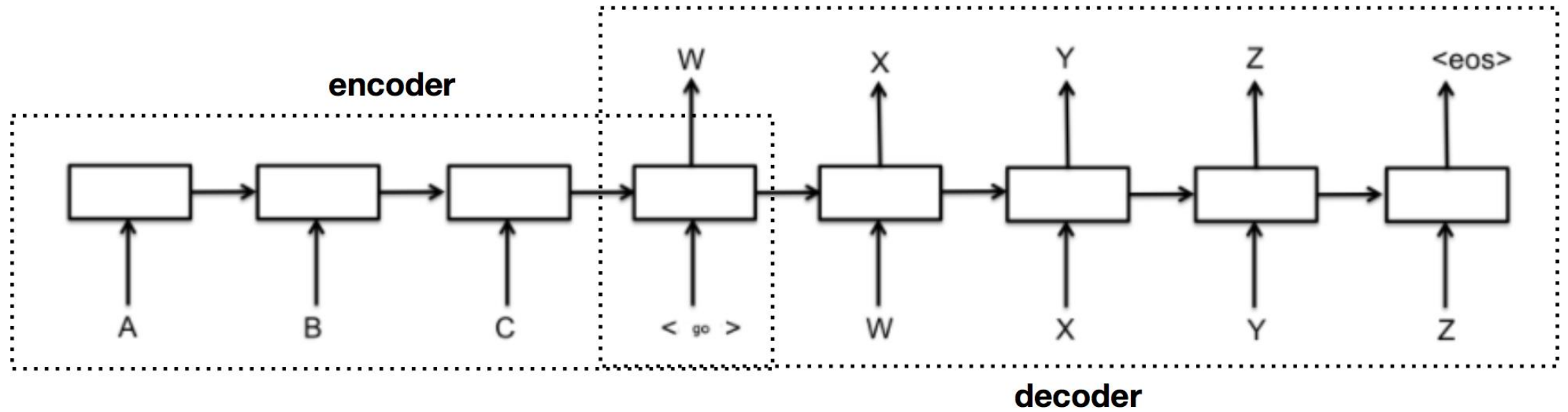


Figure from Christopher Olah

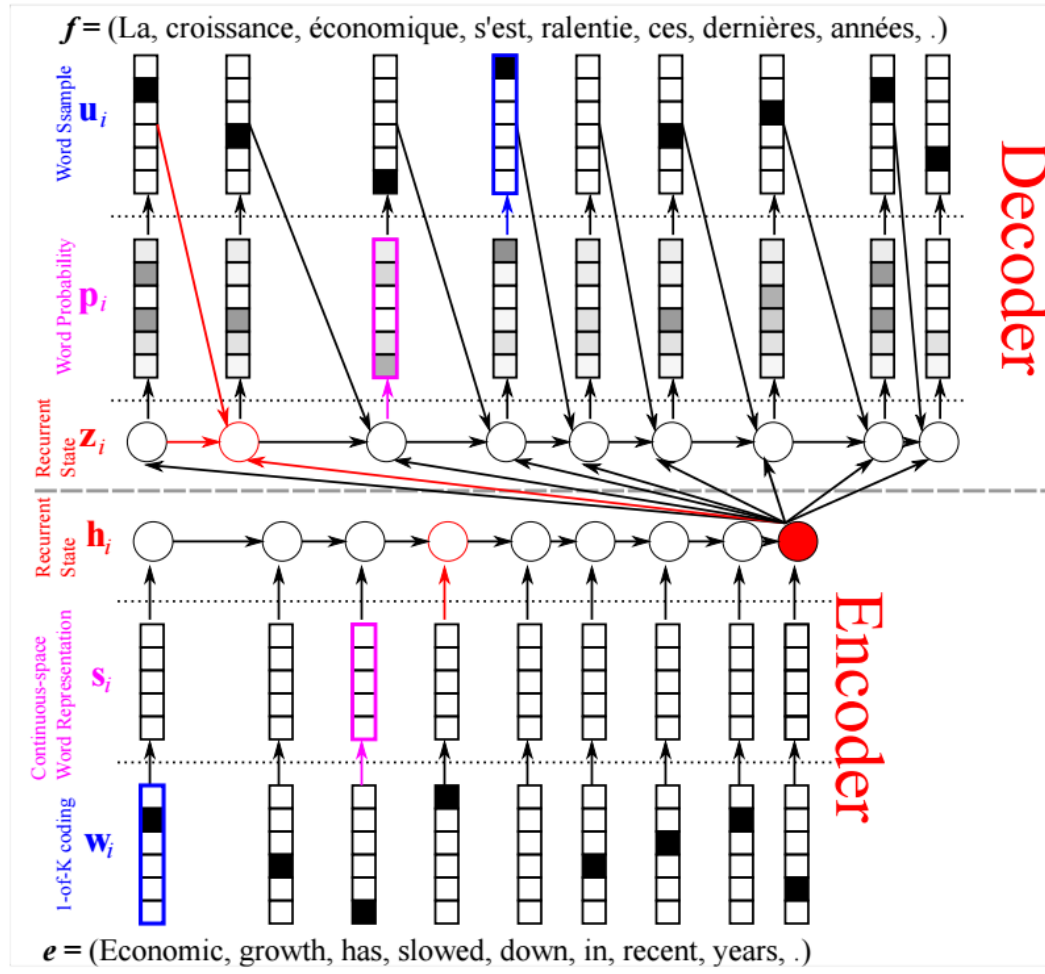
# Sequence-To-Sequence Model

[Sutskever et al. 2014, Cho et al. 2014]



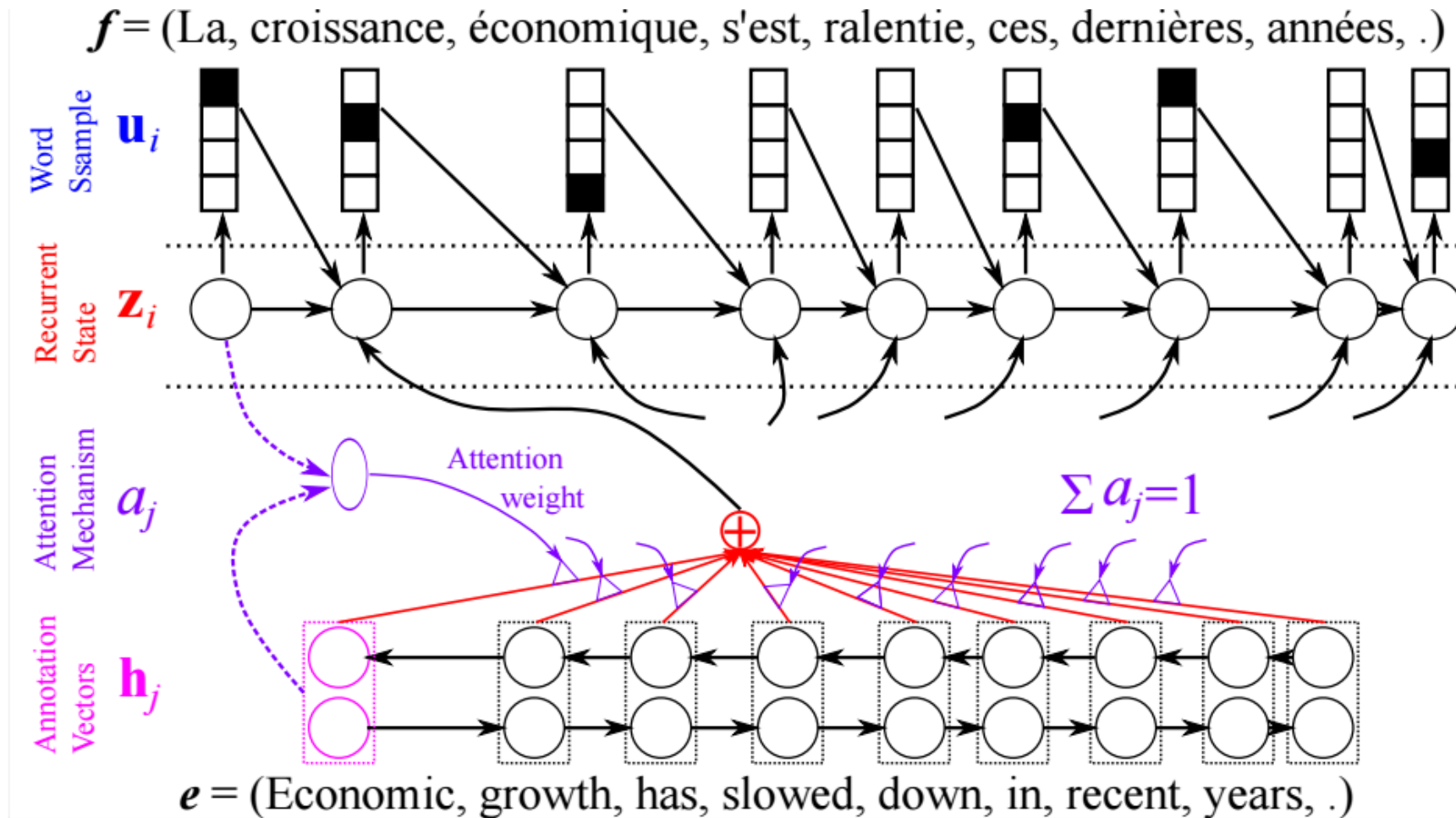
# Sequence-To-Sequence Model

[Sutskever et al. 2014, Cho et al. 2014]

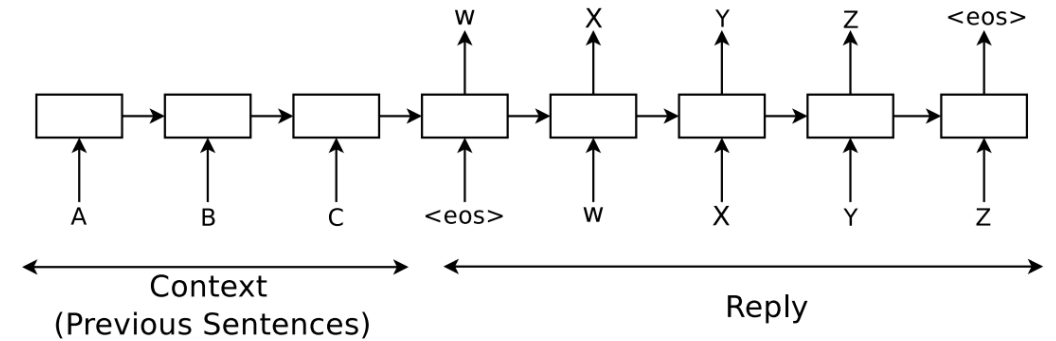


# Attention-based Model

[Bahdanau et al. 2015, Luong et al. 2015]



**Machine:** *hi*  
**Human:** *hello*  
**Machine:** *could you please let me know what are the operating systems you are using ?*  
**Human:** *i am using linux*  
**Machine:** *ok it was in the ssl vpn on which you stated it was broken*  
**Machine:** *please check if you are logged in to corp network*  
**Machine:** *what is the error that you are running please*  
**Human:** *i am seeing an error related to vpn*  
**Machine:** *what is the error message that you are getting when connecting to vpn using network connect ?*  
**Human:** *connection refused or something like that*  
**Machine:** *may i know the version of network connect you connect ?*  
**Human:** *i am not sure i know that*  
**Machine:** *is the network connect prompting for any user certificate*  
**Machine:** *?*  
**Human:** *yes*

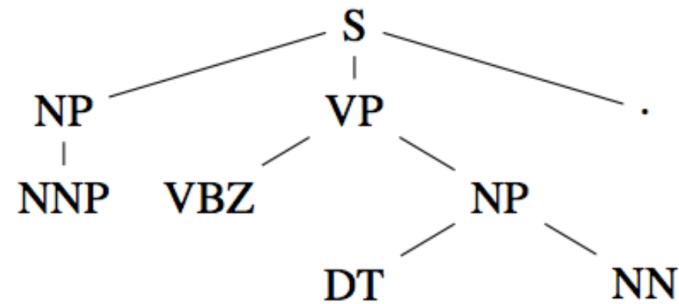


# Question Answering and Dialogue Generation

Vinyals et al. 2015

John has a dog .

→



Grammar as a foreign language

John has a dog .

→

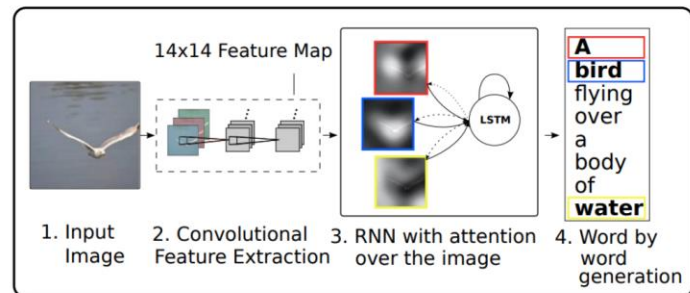
(S (NP NNP )<sub>NP</sub> (VP VBZ (NP DT NN )<sub>NP</sub> )<sub>VP</sub> . )<sub>S</sub>

Syntactic constituency parsing

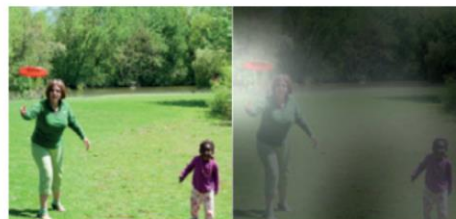
Vinyals et al. 2015



# Image Caption Generation (Xu et al, 2015)



- Images are just another language!



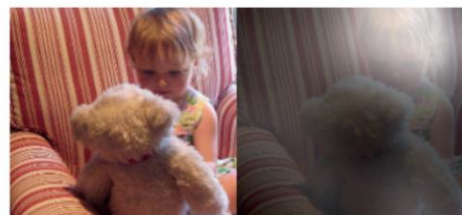
A woman is throwing a **frisbee** in a park.



A **dog** is standing on a hardwood floor.



A **stop** sign is on a road with a mountain in the background



A little **girl** sitting on a bed with a teddy bear.



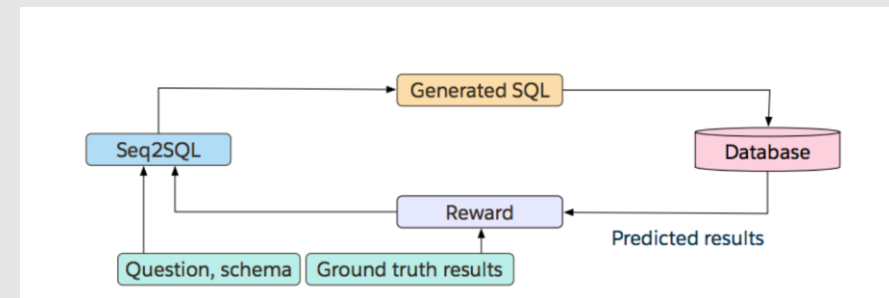
A group of **people** sitting on a boat in the water.



A giraffe standing in a forest with **trees** in the background.

# SQL Queries Generation (Zhong et al, 2017)

- Using policy-based reinforcement learning to generate the conditions of the query, which are unsuitable for optimization using cross entropy loss
- Seq2SQL leverages the structure of SQL to prune the space of generated queries and significantly simplify the generation problem



```
Q  how many voters from the bronx voted for the socialist party?  
P  SELECT MIN % party = socialist  
S' SELECT COUNT the bronx where the bronx = socialist  
S  SELECT COUNT the bronx WHERE the bronx = socialist  
G  SELECT the bronx WHERE party = socialist
```

# Neural-storyteller (Kiros et al, 2015)



Generated story about image  
Model: Romantic Novels

*“He was a shirtless man in the back of his mind, and I let out a curse as he leaned over to kiss me on the shoulder.”*

*He wanted to strangle me, considering the beautiful boy I’d become wearing his boxers.”*

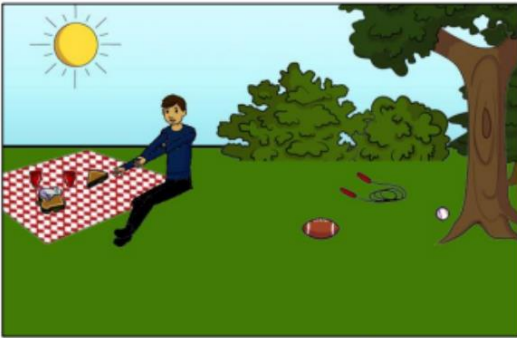
# Visual Question Answering (Agrawal et al, 2016)



What color are her eyes?  
What is the mustache made of?



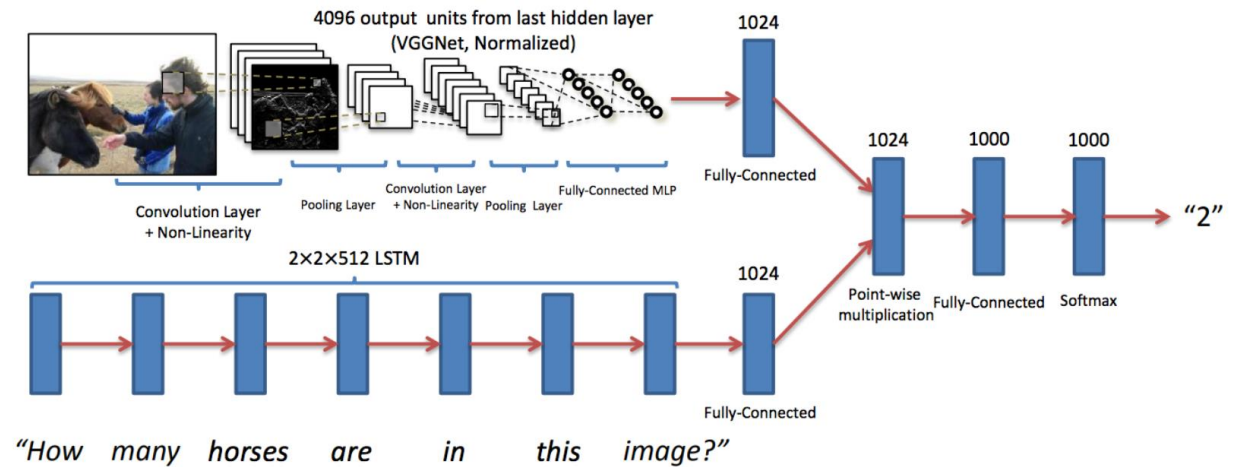
How many slices of pizza are there?  
Is this a vegetarian pizza?



Is this person expecting company?  
What is just under the tree?



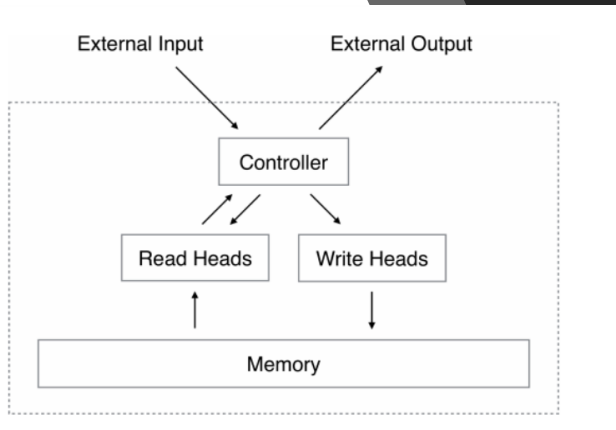
Does it appear to be rainy?  
Does this person have 20/20 vision?



# Other Approaches

- **Pointer Networks (Vinyals et al, 2015)**

It differs from the previous attention attempts in that, instead of using attention to blend hidden units of an encoder to a context vector at each decoder step, it uses attention as a pointer to select a member of the input sequence as the output.



- **Neural Turing Machines (Graves et al. 2014)**

A Neural Turing Machine (NTM) architecture contains two basic components: a neural network controller and a memory bank. Like most neural networks, the controller interacts with the external world via input and output vectors. Unlike a standard network, it also interacts with a memory matrix using selective read and write operations.

- **Memory networks (Sukhbaatar et al, 2015)**

# Other Resources

- DeeDeep Learning for NLP (without Magic)  
<https://nlp.stanford.edu/courses/NAACL2013/NAACL2013-Socher-Manning-DeepLearning.pdf>
- Recurrent Neural Networks Tutorial  
<http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/>
- Deep Learning for Machine Translation  
<https://drive.google.com/drive/folders/0B16RwCMQqrtda2toU29Za19qcWM>