

CSCI 599: Deep Learning and its Applications

Lecture 10

Spring 2019
Youngwoon Lee

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Attention

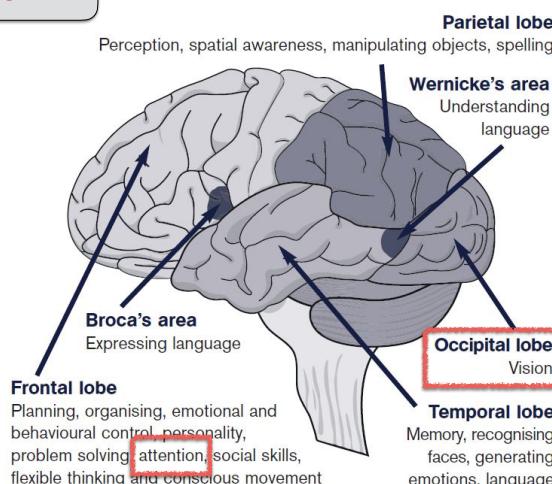


Image from <http://headwaythamesvalley.org.uk/about-brain-injury-2/about-the-brain/>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Cognitive Science inspired Deep Learning



Image from <http://clipart-library.com/clipart/695303.htm>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory

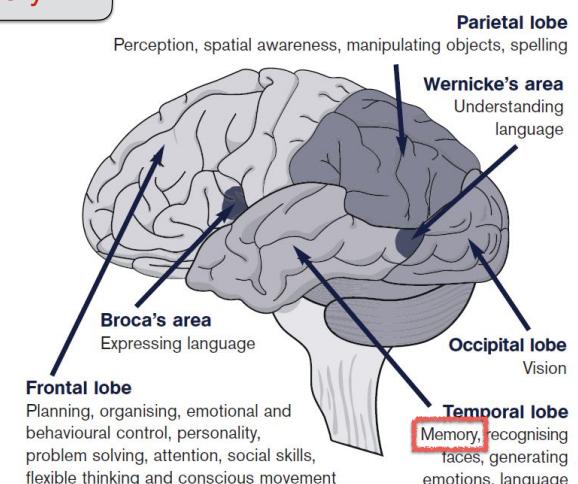


Image from <http://headwaythamesvalley.org.uk/about-brain-injury-2/about-the-brain/>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relationship

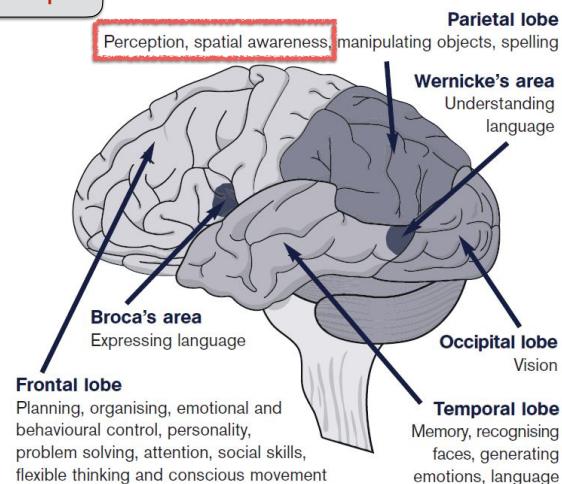


Image from <http://headwaythamesvalley.org.uk/about-brain-injury-2/about-the-brain/>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Today's agenda

- Part 1
 - Attention Model
- Part 2
 - Memory Network
- Part 3
 - Relation Network

Attention Model



Image from <http://clipart-library.com/clipart/695303.htm>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Cocktail party effect



Image from <https://www.sciencenews.org/article/new-ai-can-focus-one-voice-crowd>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

COMPOSING COMPLEX SKILLS BY LEARNING TRANSITION POLICIES

Yunqiang Lin¹, Hua-Hua Sun¹, Sriram Somasundaram¹, Edward S. Hs², Joseph J. Lim³
¹University of Southern California
²University of California, San Diego
³University of California, Los Angeles
E-mail: yunqiang.lin@usc.edu, huhua.sun@usc.edu, sriram.somasundaram@usc.edu, limj@ucsd.edu

ABSTRACT

humans acquire complex skills by exploiting previously learned transitions between them. To empower machines with this ability method that can learn from policies which effectively communicate future tasks without explicitly marking them. In this work, we introduce proximity predictions which indicate proximity to suitable initial states for the next skill. The algorithm is able to learn a sequence of skills using only visual and robotic arm manipulation which traditional policy gradient methods fail at. We demonstrate that transition policies enable us to learn sequences of skills faster and more robustly than previous methods using the proximity predictor further improving training time and fine-tuning time. We also show that using proximity predictions improve the spatial rewards from the task environment, primarily due to the increased speed of learning.

3. Derivatives

While features are typical of learning strategies used by memory-poor learners trained alone, comparing and contrasting strategies should not be as trivial as it might appear if considering the existing evidence. It requires a thorough examination because skills used in the final pool of trial items may not be the same as those used in the initial pool. In addition, the number of trials required to learn a skill may differ between training conditions. For example, in one study, a skill was learned in 10 trials for the beginner who had learned to catch people and randomly choose. To measure this skill, players must practice adjusting their movements and finely tune a coordination strategy prior to catching a player.

Can machines really learn new and complex tasks by solving simpler tasks and learning from their mistakes? This question has been asked since the first computer programs for learning from visual, auditory, and haptic feedback were developed. The answer is yes, but the process is not always smooth. For example, in 2008, researchers developed a robot that could learn to walk by observing a human and then applying the same principles to its own body (Perez et al., 2008; Miller et al., 2007; Miller et al., 2008). These model-based approaches assume that a task can be broken down into smaller components which are then learned sequentially. In this case, the robot learned to walk by first learning to stand, then the position of its starting point, and finally the movement of its legs. In the next section, we will discuss how robots learn to walk. However, these approaches do not hold in many real-world learning and control problems where a global skill may be necessary. In learning robotics, the best approach is learning by doing, and this, fail in failure, is often the key to success.

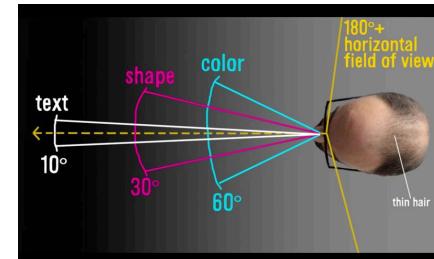
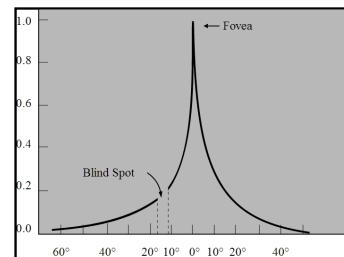
To bridge the gap between robots and humans, we propose a movement-based task scheme to examine participants' performance in a dynamic environment. We hypothesize that movement-based tasks will be more effective than static tasks for learning a movement skill. A movement task is a task that requires the participant to move his or her body in a different

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Human eyes cannot see everywhere in high resolution



Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Spatial attention



A woman is throwing a frisbee in a park.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Spatial attention



A woman is throwing a frisbee in a park.

- Humans only see specific regions in a higher resolution

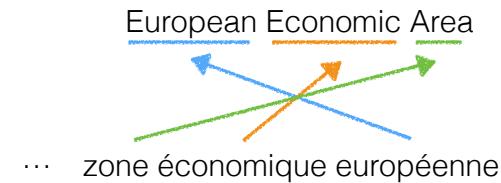
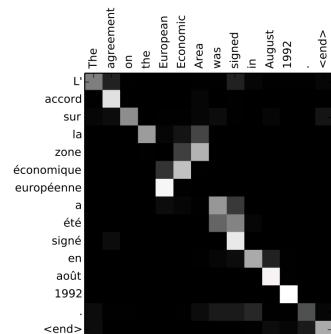
Xu et al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention, 2015

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Temporal attention



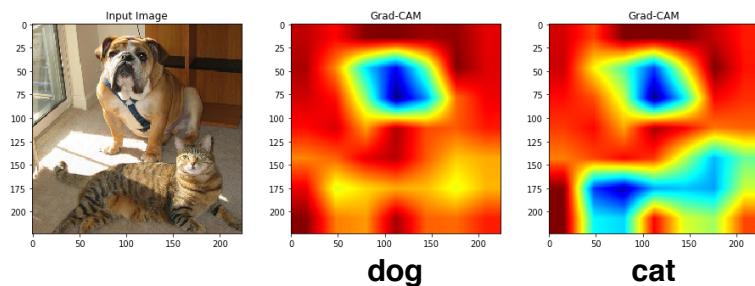
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Bahdanau et. al. Neural Machine Translation by Jointly Learning to Align and Translate. 2015.

Implicit attention in neural networks



- Deep neural networks naturally learn to focus more on some parts of the data than others

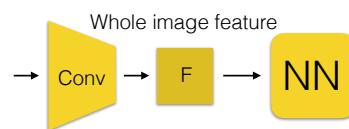
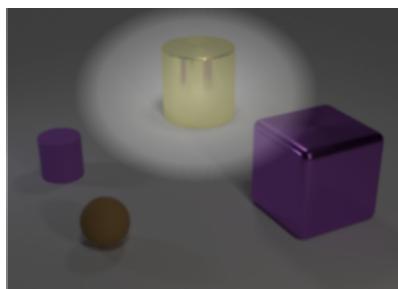
From assignment #1

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Implicit attention in neural networks



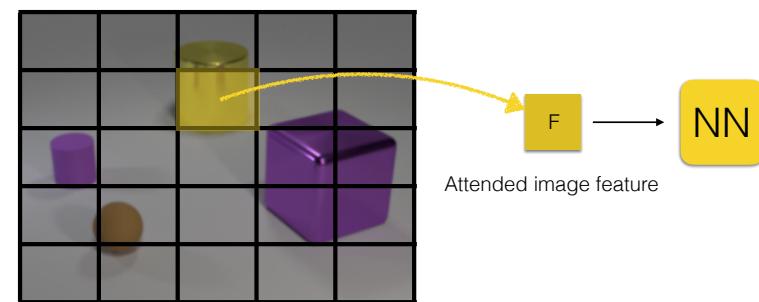
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image from Santoro et. al. A simple neural network module for relational reasoning. 2017.

Explicit attention in neural networks



- An explicit attention mechanism provides an inductive bias to a neural network

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Advantages of explicit attention

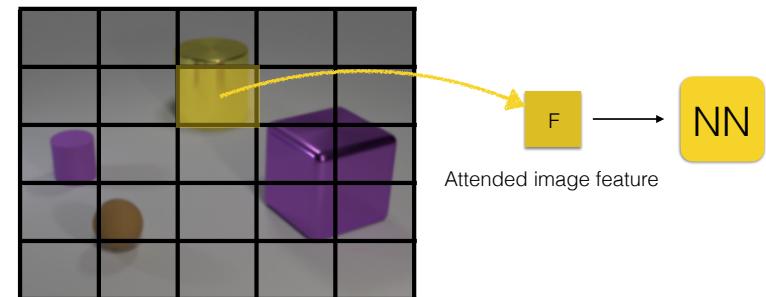
- Efficient computation
 - Extract important information and discard useless information
- Scalable to variable length inputs
- Can be applied to temporal domain (language, video)
- Easier to interpret where to focus

Joseph J. Lim

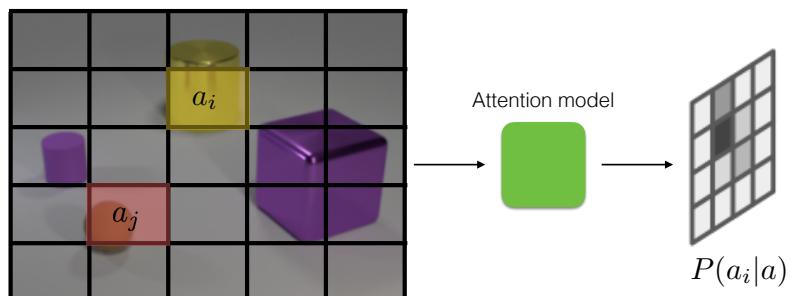
CSCI 599 @ USC

Lecture 10

Explicit attention in neural networks



Attention model



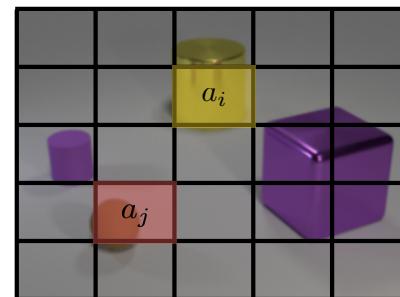
- Attention models predict a probability distribution over glimpses from an input \mathbf{a} : $P(a_i|a)$

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Attention model



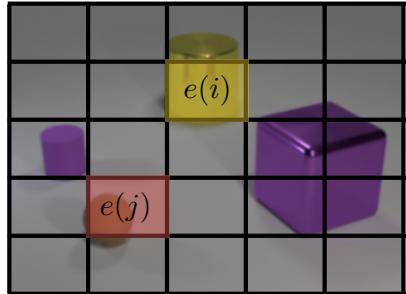
a_i : CNN feature of the cell i

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

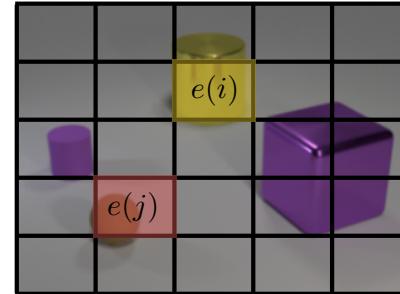
Attention model



Importance of each cell

$$e(i) = f_{\text{att}}(a_i, a)$$

a_i : CNN feature of the cell i



Importance of each cell

$$e(i) = f_{\text{att}}(a_i, a)$$

Attention probability of each cell

$$P(\cdot|a) = \text{softmax}(e(\cdot))$$

a_i : CNN feature of the cell i

Joseph J. Lim

CSCI 599 @ USC

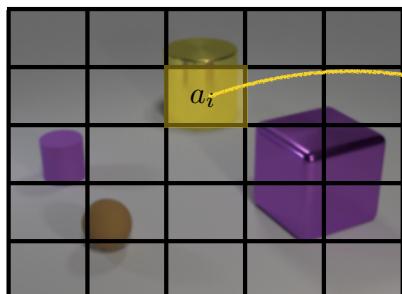
Lecture 10

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Attention model with RL



$$\pi(a_i|a) = P(a_i|a)$$

Attended image feature

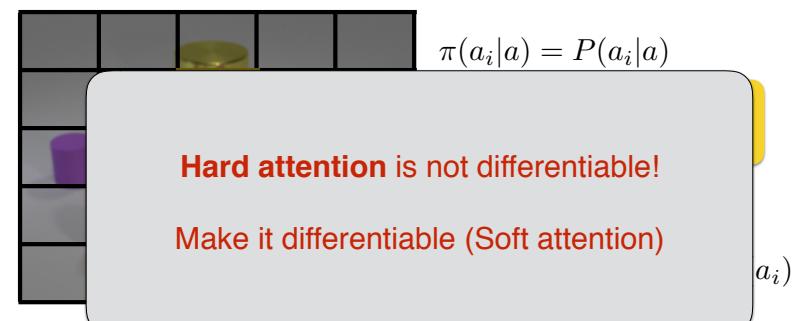
a_i

→ NN

$$Loss(a_i)$$

- We can learn a supervised task with RL by setting a task loss as a reward

Attention model with RL



- We can learn a supervised task with RL by setting a task loss as a reward

Joseph J. Lim

CSCI 599 @ USC

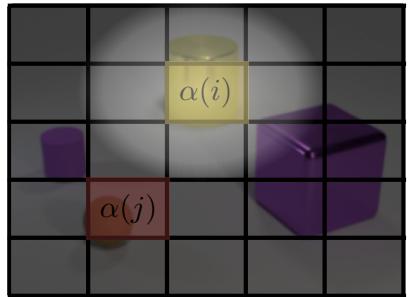
Lecture 10

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Soft attention



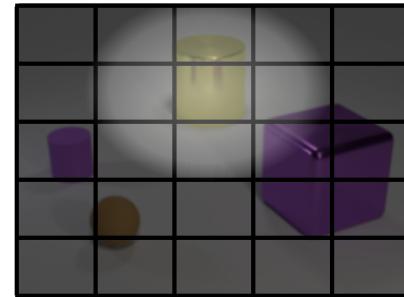
Importance of each cell

$$e(i) = f_{\text{att}}(a_i, a)$$

Attention probability of each cell

$$P(\cdot|a) = \text{softmax}(e(\cdot))$$

Soft attention



Importance of each cell

$$e(i) = f_{\text{att}}(a_i, a)$$

Attention probability of each cell

$$P(\cdot|a) = \text{softmax}(e(\cdot))$$

Attended feature

$$z = \sum_i P(a_i|a) \cdot a_i$$

Joseph J. Lim

CSCI 599 @ USC

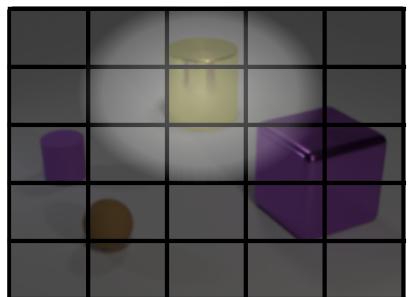
Lecture 10

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Soft attention



Weighted sum of features

z

NN

Attended feature

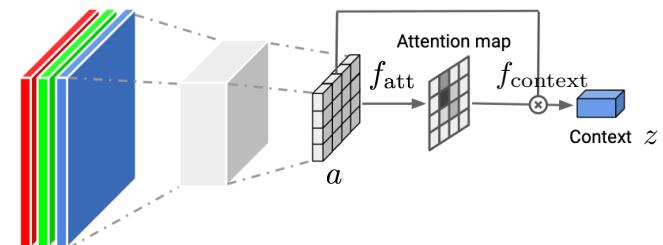
$$z = \sum_i P(a_i|a) \cdot a_i$$

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Attention model

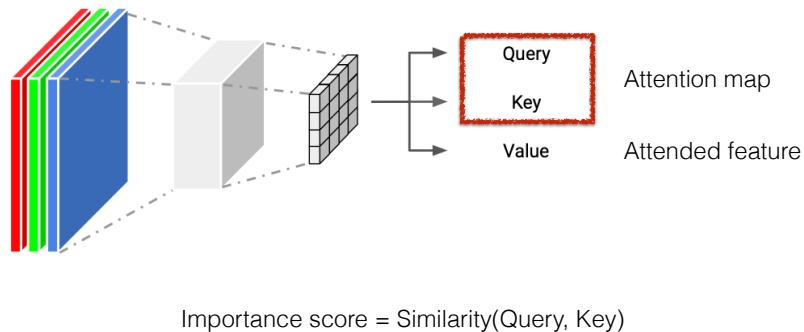


Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Associative Attention: attending by content

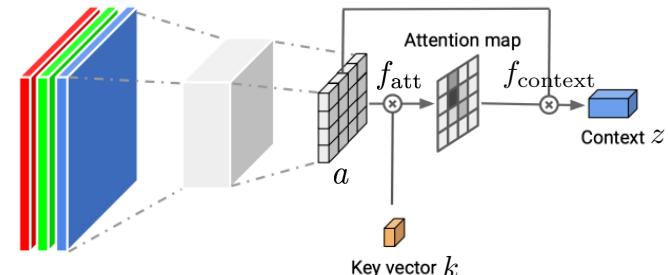


Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Associative Attention: attending by content



$$e(i) = f_{\text{att}}(a_i) \longrightarrow e(i) = f_{\text{att}}(a_i, a, k)$$

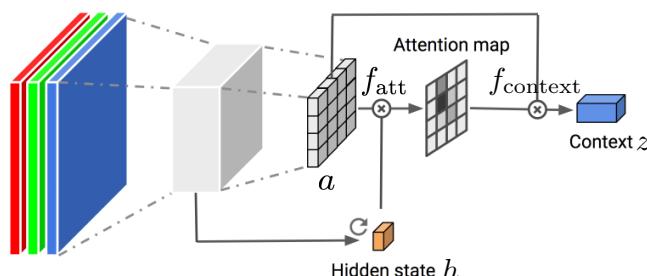
Similarity between the content and key

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Attention in recurrent networks



$$e(i) = f_{\text{att}}(a_i) \longrightarrow e(i) = f_{\text{att}}(a_i, h_{t-1})$$

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Applications of attention models

- Image captioning
- Image generation
- Language model and machine translation
- RL

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



A woman is throwing a frisbee in a park.

Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



A woman

Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



A woman **is throwing**

Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



A woman is throwing **a frisbee**

Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



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

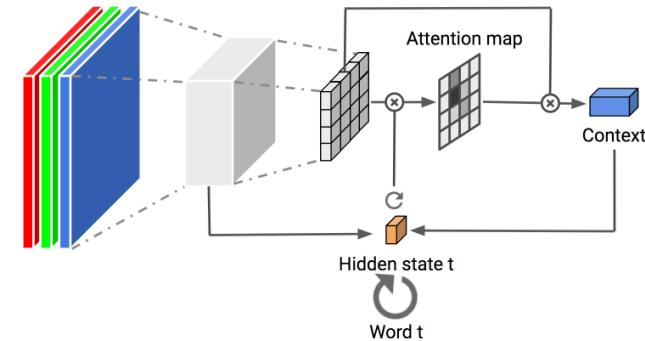
Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



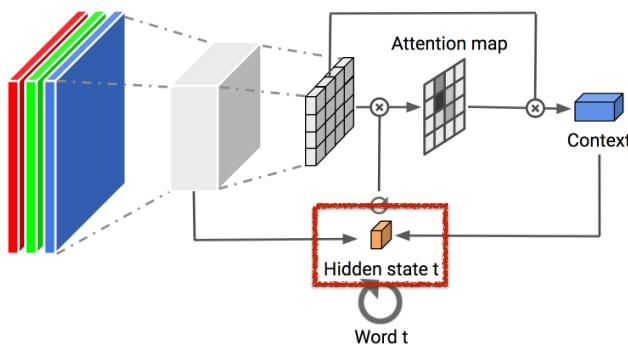
Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



Compute a hidden state based on the image

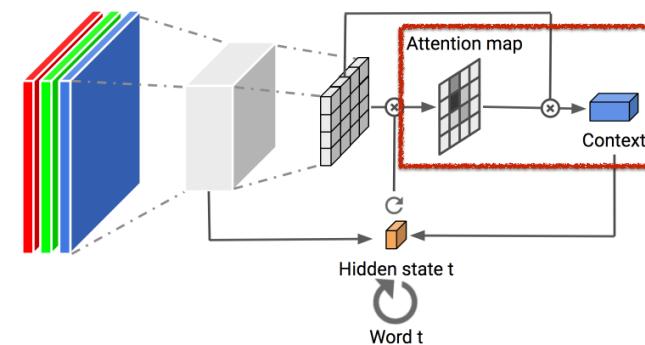
Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



Compute an attention map and context

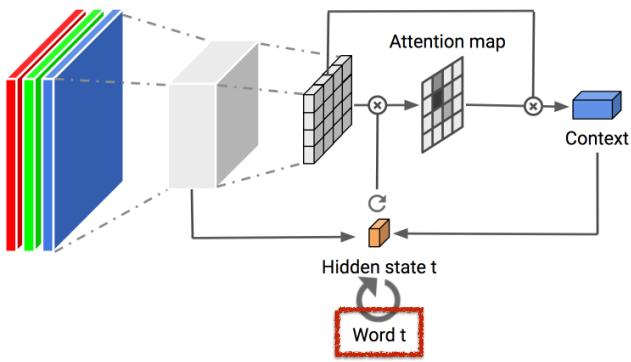
Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



Generate a word

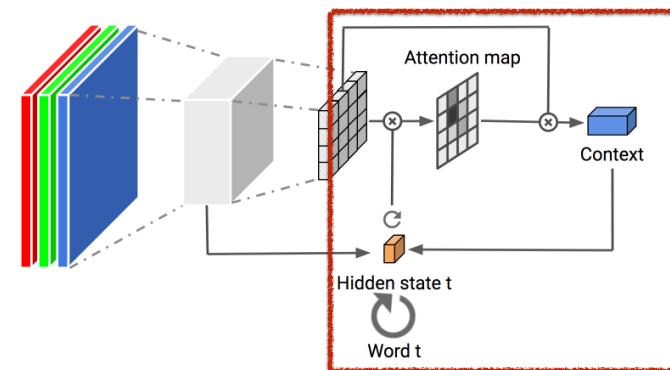
Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image captioning with Attention



Repeat this process to generate a sentence

Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Results



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.

Xu et. al., Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. 2015.

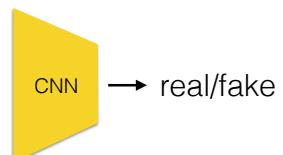
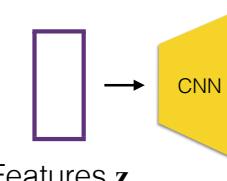
Joseph J. Lim

CSCI 599 @ USC

Lecture 12

Image generation

A convolutional network focuses on local features.
It is hard to preserve long-range dependency.



Zhang et. al., Self-Attention Generative Adversarial Networks. 2018.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Image generation

Add attention models to get details from **all feature locations**



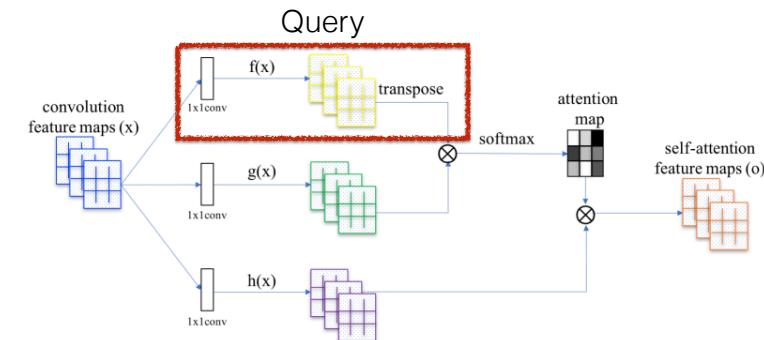
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Zhang et. al., Self-Attention Generative Adversarial Networks. 2018.

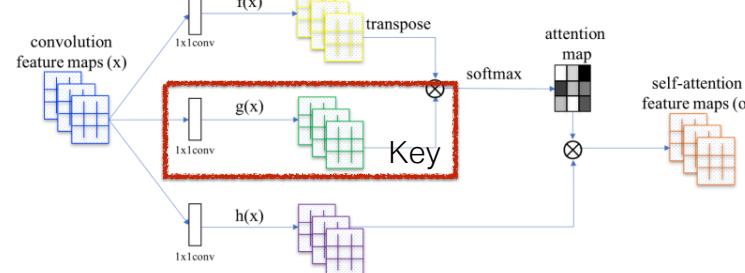
Self-Attention GAN



Use attention to share local features over the whole image

Zhang et. al., Self-Attention Generative Adversarial Networks. 2018.

Self-Attention GAN



Use attention to share local features over the whole image

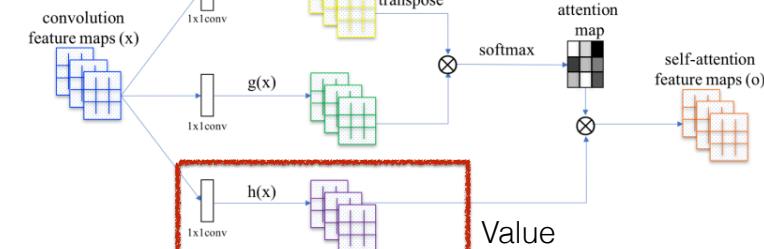
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Zhang et. al., Self-Attention Generative Adversarial Networks. 2018.

Self-Attention GAN



Use attention to share local features over the whole image

Zhang et. al., Self-Attention Generative Adversarial Networks. 2018.

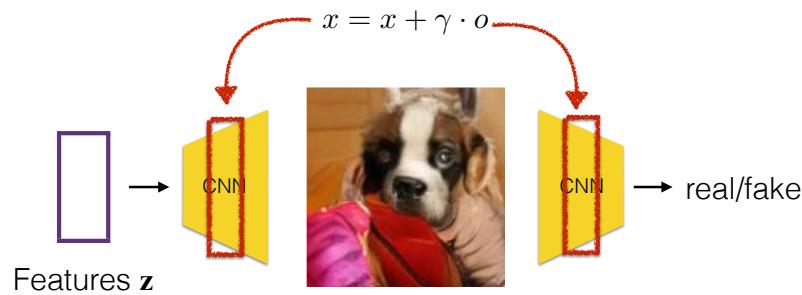
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Self-Attention GAN

Add attention models to get details from **all feature locations**



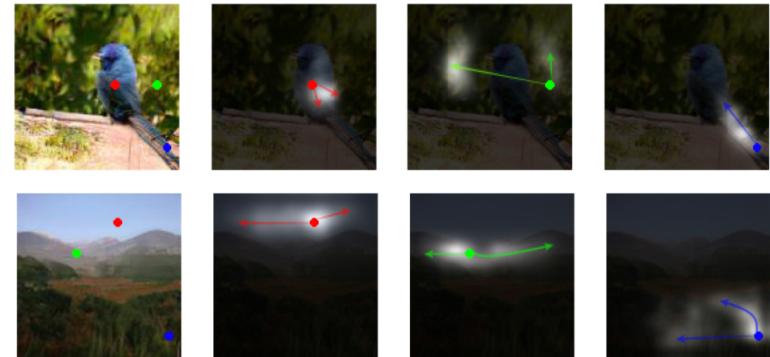
Zhang et al., Self-Attention Generative Adversarial Networks. 2018.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Results



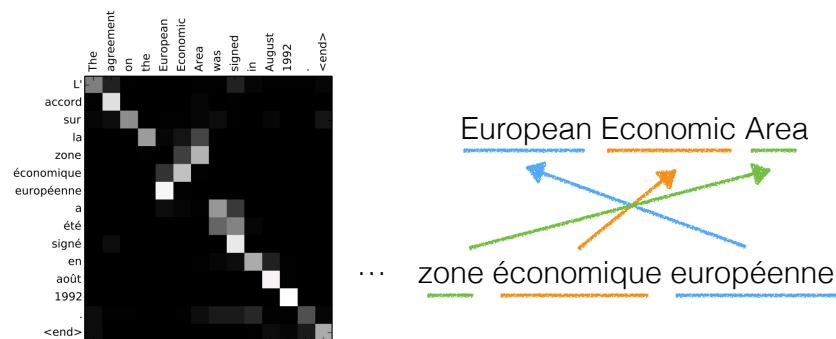
Zhang et al., Self-Attention Generative Adversarial Networks. 2018.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Neural machine translation



Bahdanau et al., Neural Machine Translation by Jointly Learning to Align and Translate. 2015.

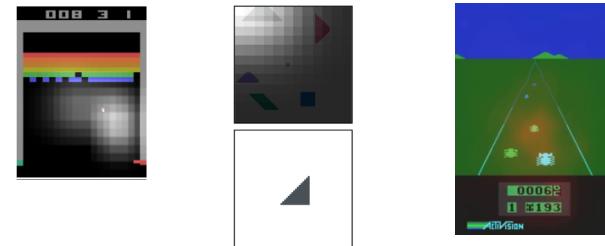
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

RL with Attention

When we play games, we only focus on important things



Sorokin et al., Deep Attention Recurrent Q-Network. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

RL with Attention

When humans play game, we only focus on important things

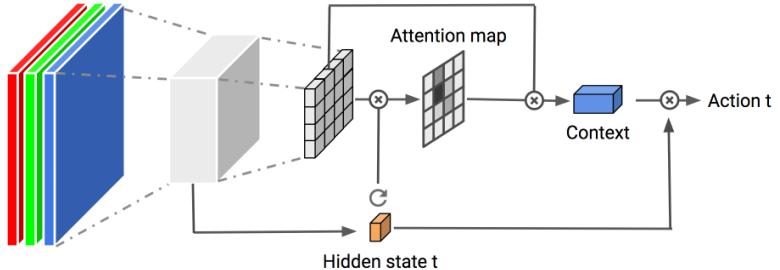


Joseph J. Lim

CSCI 599 @ USC

Lecture 10

RL with Attention



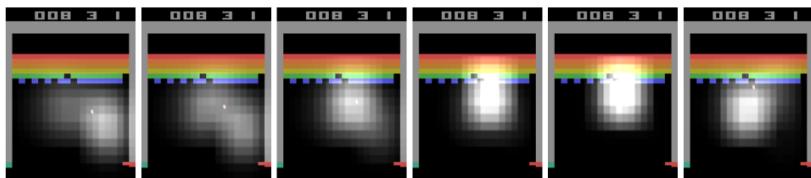
Sorokin et. al., Deep Attention Recurrent Q-Network, 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Results



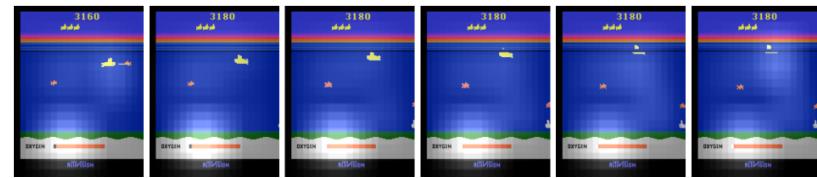
Focus on the ball

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Results



Focus on the Oxygen gauge

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Sorokin et. al., Deep Attention Recurrent Q-Network, 2015.

Sorokin et. al., Deep Attention Recurrent Q-Network, 2015.

Summary of attention model

- Attention models help deep neural networks to focus on important information
- Interpretability
- End-to-end training is possible using soft attention
- Many different attention models are possible depending on applications

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Today's agenda

- Part 1
 - Attention Model
- Part 2
 - Memory Network
- Part 3
 - Relation Network

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory Network



Slide credit: Graves et al. <http://people.idsia.ch/~rupeesh/rnnsymposium2016/slides/graves.pdf>
Graves et. al. Hybrid computing using a neural network with dynamic external memory, 2016.

Image from <http://clipart-library.com/clipart/695303.htm>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory network

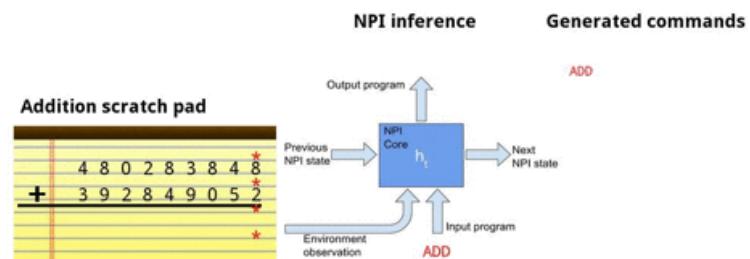


Image from <https://medium.com/near-ai/review-of-neural-programmer-interpreters-854a14a494fb>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory network

- A neural network is hardly storing data over long time

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory network

- A neural network is hardly storing data over long time
- Explicit memory can help to
 - Remember past events
 - Manipulate complex data (graph)
 - Construct a map (for navigation)

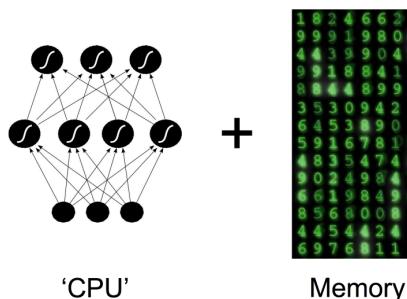
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory network

- Augment an external memory to a neural network



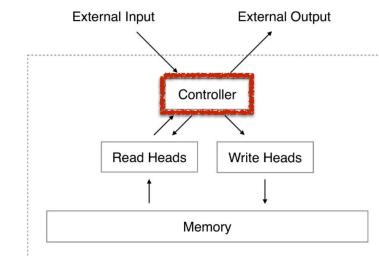
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory network overview

- The **Controller** is a main module



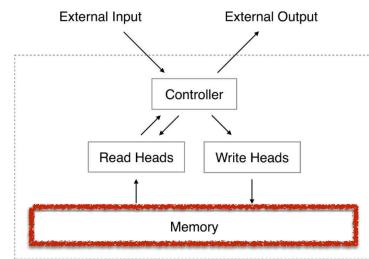
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory network overview

- The **Controller** is a main module
- The **Memory** can be
 - a list of values
 - key, value pairs
 - a map (2d grid, 3d grid)



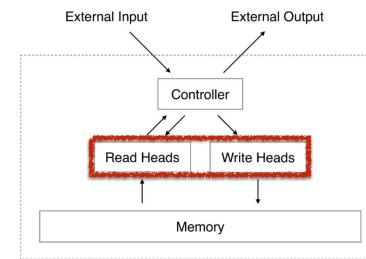
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Memory network overview

- The **Controller** is a main module
- The **Memory** can be
 - a list of values
 - key, value pairs
 - a map (2d grid, 3d grid)
- The controller can access the memory through **Read/Write Heads**



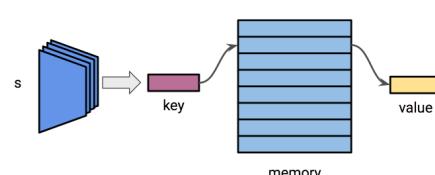
Joseph J. Lim

CSCI 599 @ USC

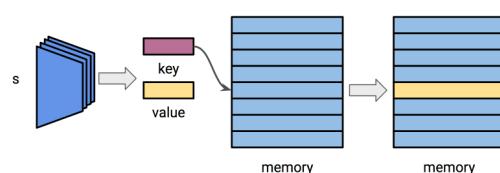
Lecture 10

Architecture

Read



Write



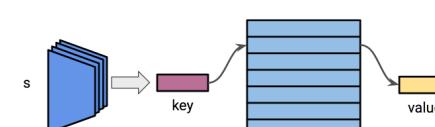
Joseph J. Lim

CSCI 599 @ USC

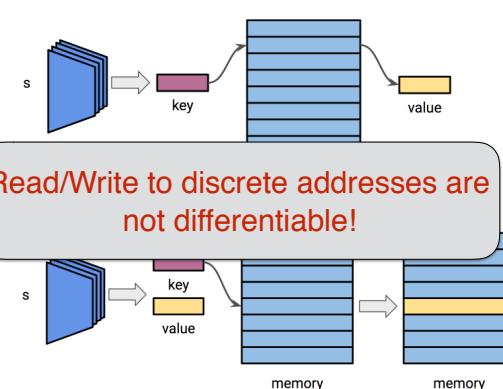
Lecture 10

Architecture

Read



Write



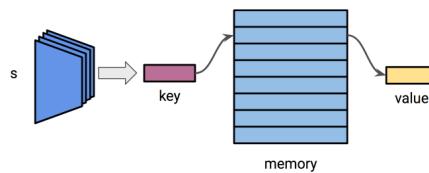
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Differentiable memory network

Read



Apply a soft attention when read

$$r = \sum_i w^r[i] \cdot \text{Memory}[i, \cdot]$$

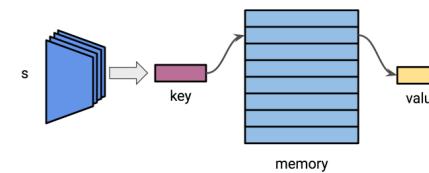
Joseph J. Lim

CSCI 599 @ USC

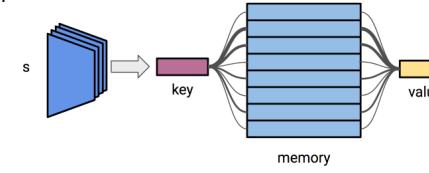
Lecture 10

Differentiable memory network

Read



Attention



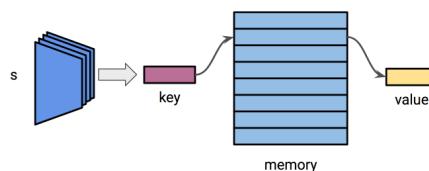
Joseph J. Lim

CSCI 599 @ USC

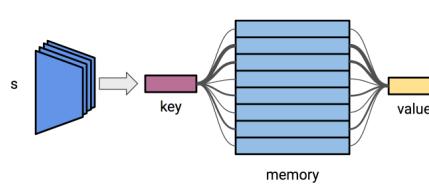
Lecture 10

Differentiable memory network

Read



Attention



Differentiable!

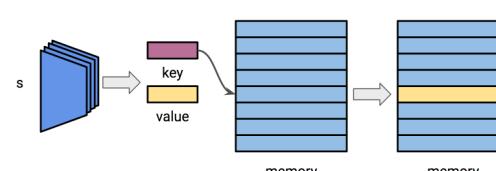
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Differentiable Memory Network

Write



Apply a soft attention when write

$$\text{Memory}[i, \cdot] = (1 - \gamma \cdot w^w[i]) \cdot \text{Memory}[i, \cdot] + w^w[i] \cdot \text{NewValue}$$

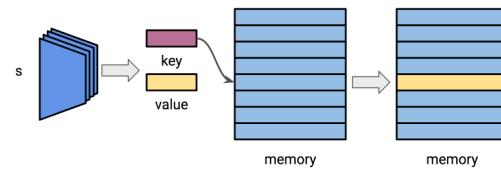
Joseph J. Lim

CSCI 599 @ USC

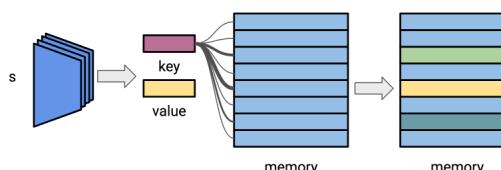
Lecture 10

Differentiable Memory Network

Write



Attention



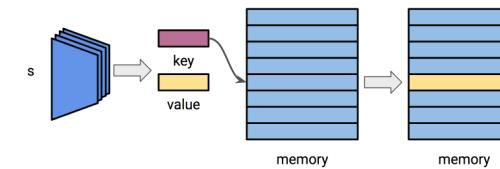
Joseph J. Lim

CSCI 599 @ USC

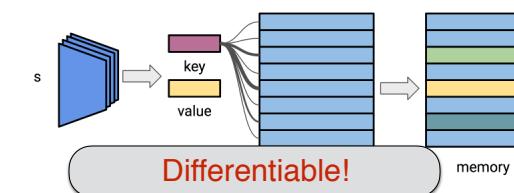
Lecture 10

Differentiable Memory Network

Write



Attention



Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Neural Turing Machine

NTM

Length 10, Repeat 20



Length 20, Repeat 10



LSTM

Length 10, Repeat 20



Length 20, Repeat 10

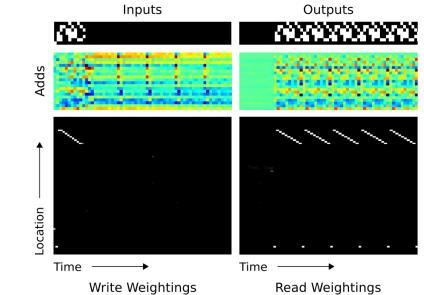


Time →
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Neural Turing Machine



Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Q&A task

Story (1: 1 supporting fact)	Support	Hop 1	Hop 2	Hop 3
Daniel went to the bathroom.		0.00	0.00	0.03
Mary travelled to the hallway.		0.00	0.00	0.00
John went to the bedroom.		0.37	0.02	0.00
John travelled to the bathroom.	yes	0.60	0.98	0.96
Mary went to the office.		0.01	0.00	0.00
Where is John? Answer: bathroom Prediction: bathroom				

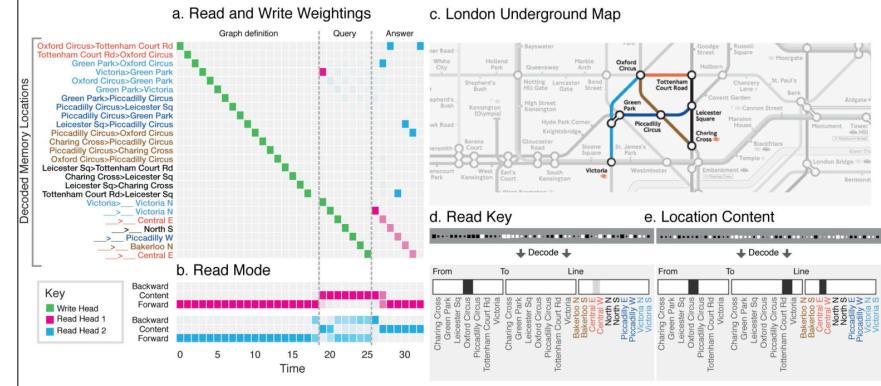
Sukhbaatar et. al. End-To-End Memory Networks. 2015.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Differentiable Neural Computers



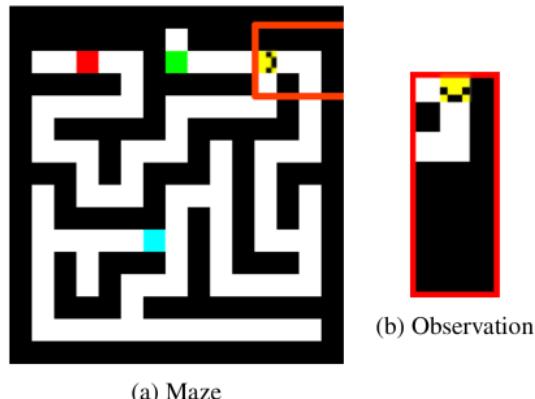
Graves et. al. Hybrid computing using a neural network with dynamic external memory. 2016.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Neural Map



Parisotto et. al. Neural Map: Structured Memory for Deep Reinforcement Learning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Summary of memory network

- The external memory can preserve data longer
- Soft attention can make a memory differentiable

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Today's agenda

- Part 1
 - Attention Model
- Part 2
 - Memory Network
- Part 3
 - Relation Network

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relation Network



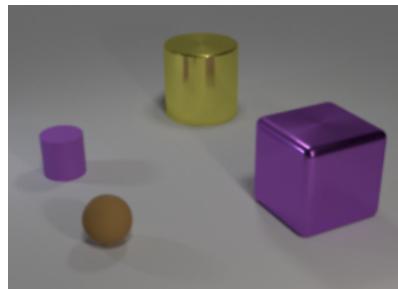
Image from <http://clipart-library.com/clipart/695303.htm>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Reasoning



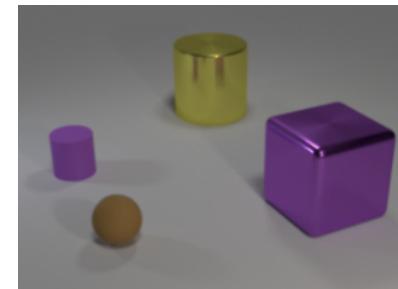
Santoro et. al. A simple neural network module for relational reasoning, 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Reasoning



Question:

What is the shape of the object that is farthest from the rubber sphere?

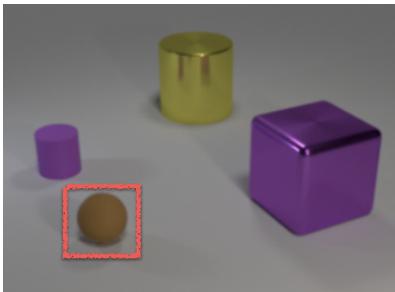
Santoro et. al. A simple neural network module for relational reasoning, 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Reasoning

**Question:**

What is the shape of the object that is farthest from the rubber sphere?

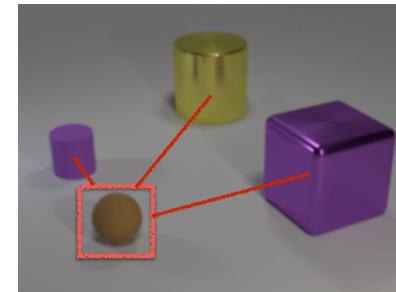
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Reasoning

**Question:**

What is the shape of the object that is farthest from the rubber sphere?

Santoro et. al. A simple neural network module for relational reasoning. 2017.

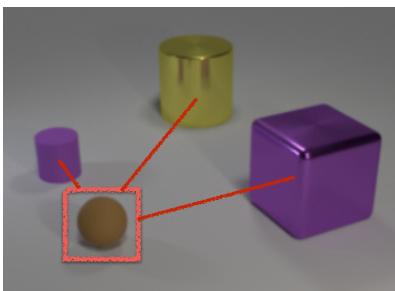
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Not efficient

Naive CNN

**Question:**

What is the shape of the object that is farthest from the rubber sphere?

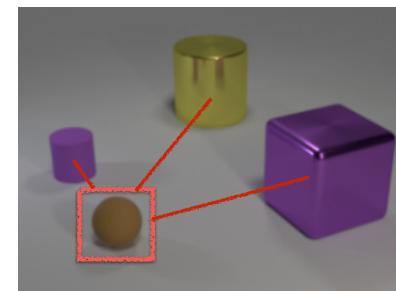
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Reasoning

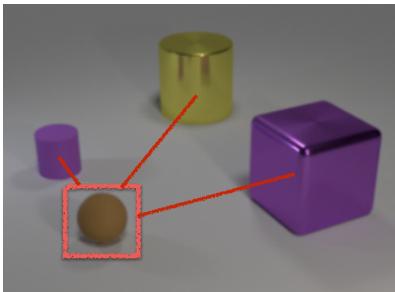
**How to understand spatial relationship between objects?**Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Reasoning



Object- and relation-centric state representation and relational reasoning need to be learned.

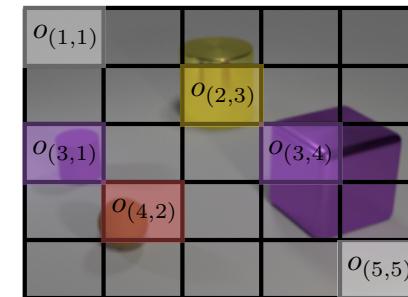
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational network



5 x 5 objects

Each cell is considered as an “object”

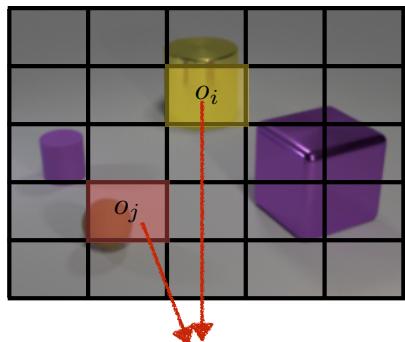
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational network



Infer relation between two objects

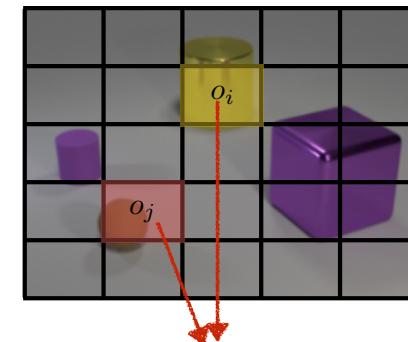
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational network



Infer relation between two objects

$$g_\theta(o_i, o_j)$$

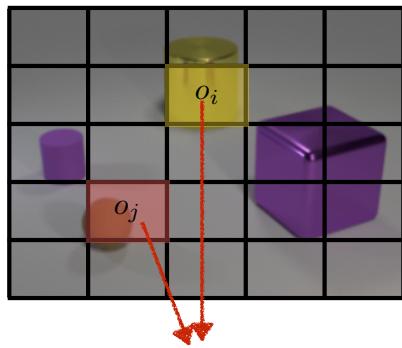
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational network



Infer relation between two objects

$$\sum_{i,j} g_\theta(o_i, o_j)$$

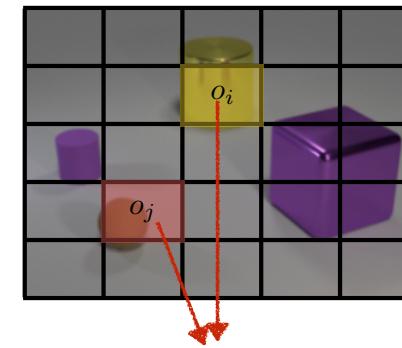
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational network



Infer relation between two objects w.r.t. a **question**

$$\sum_{i,j} g_\theta(o_i, o_j, q)$$

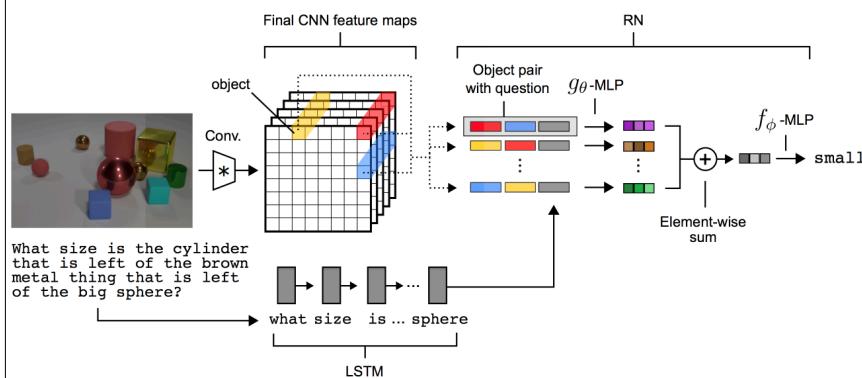
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

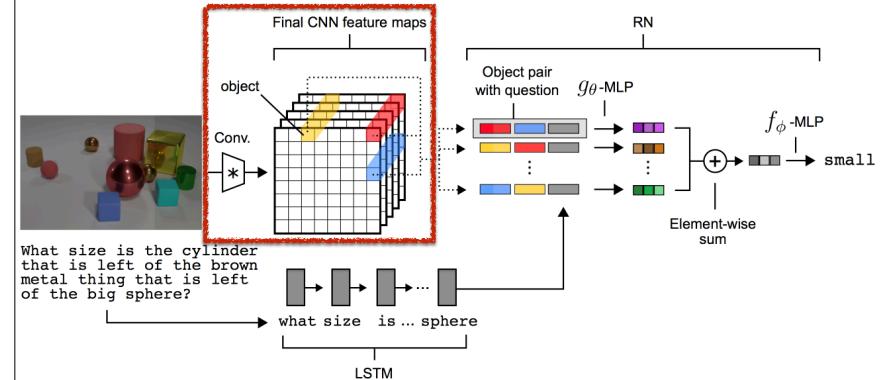
Relational Network



Code is available at <https://github.com/gilimlab/Relation-Network-Tensorflow>
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Relational Network

Features of objects



Joseph J. Lim

CSCI 599 @ USC

Lecture 10

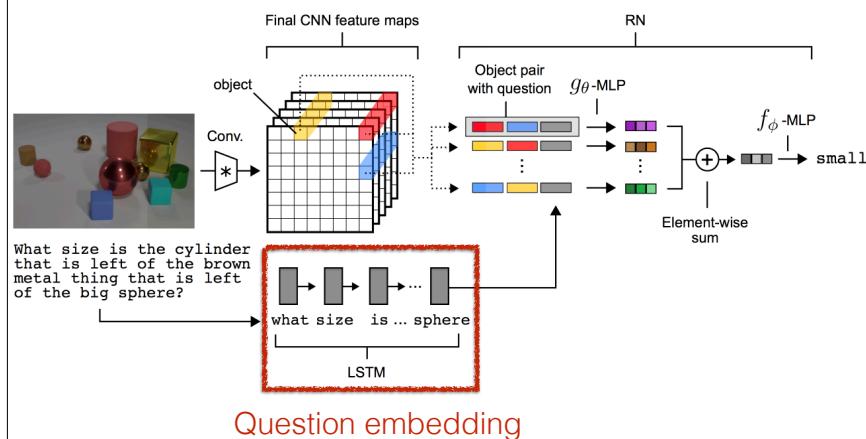
Code is available at <https://github.com/gilimlab/Relation-Network-Tensorflow>
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Network



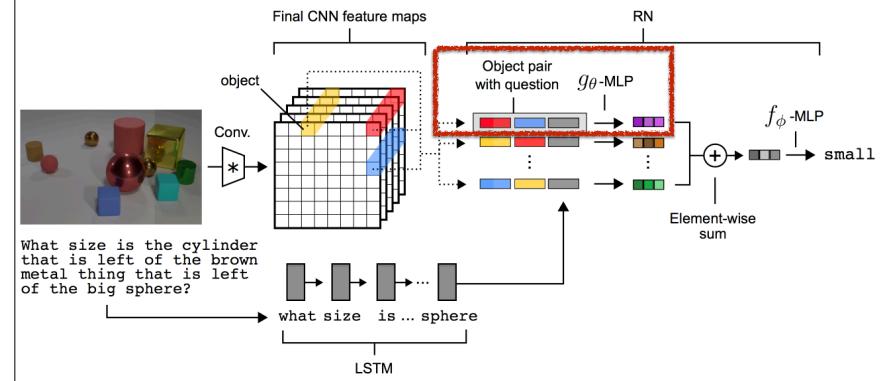
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Network

Relationship between objects

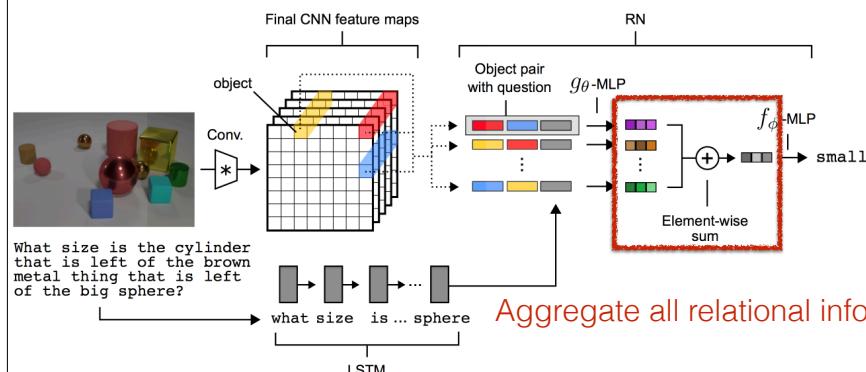


Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Network

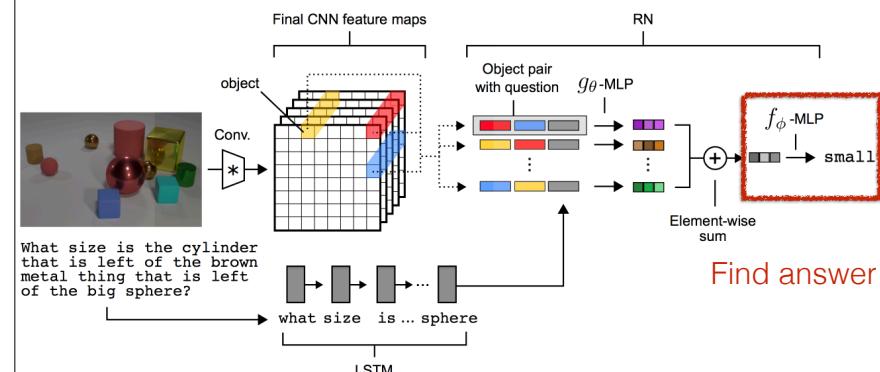


Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relational Network



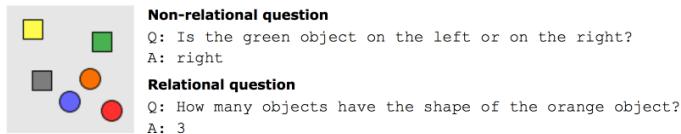
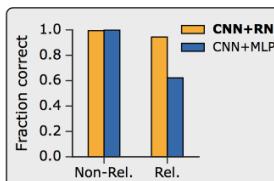
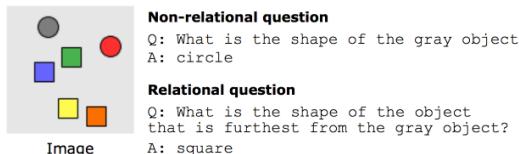
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Results

Sort-of-CLEVR



Santoro et. al. A simple neural network module for relational reasoning. 2017.

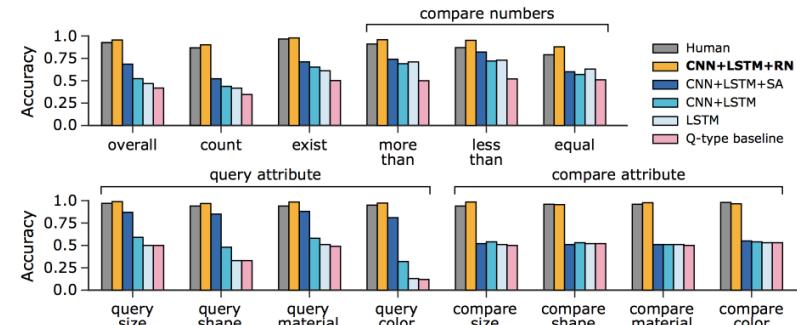
Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Results

CLEVR



Super-human performance

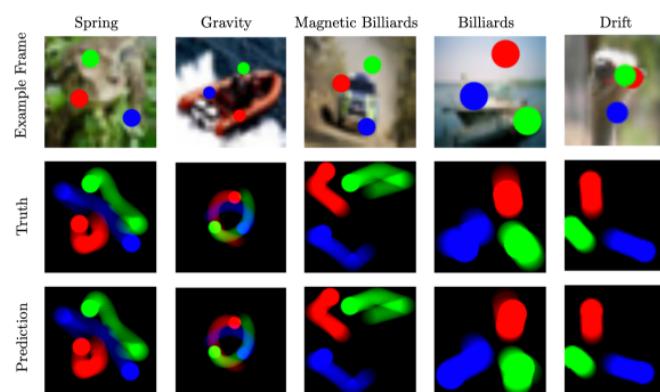
Santoro et. al. A simple neural network module for relational reasoning. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Results



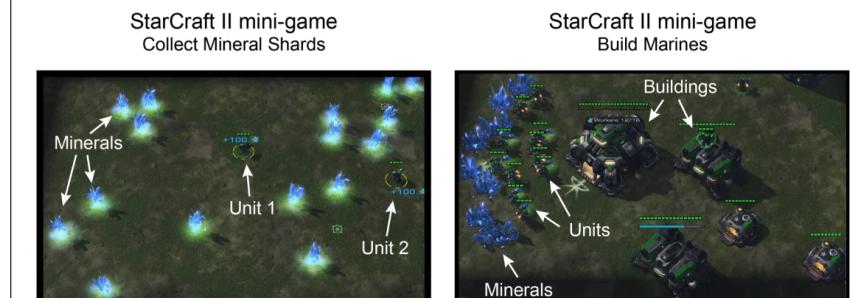
Watters et. al. Visual Interaction Networks. 2017.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Iterative relational reasoning



One-step relational reasoning is not enough to solve complicated tasks

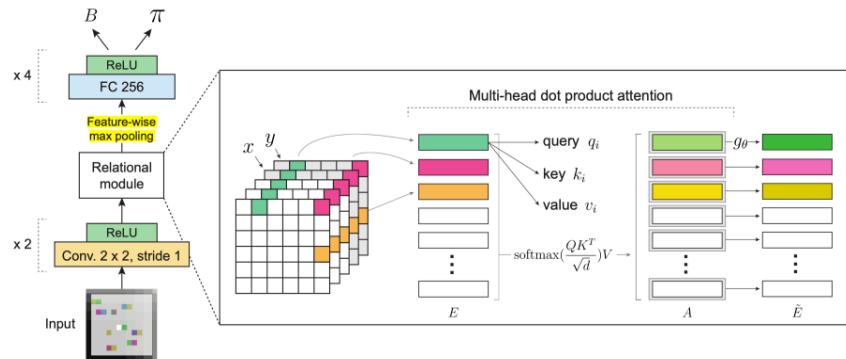
Zambaldi et. al. Deep reinforcement learning with relational inductive biases. 2019.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Relation network + Attention

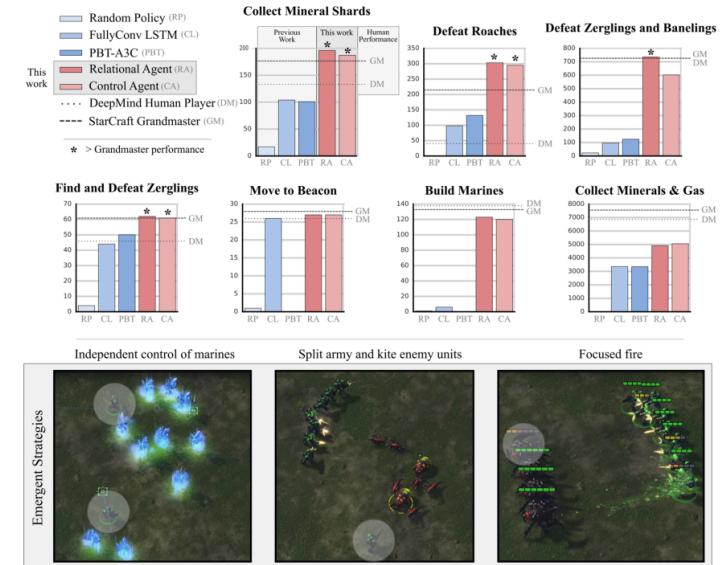


Zambaldi et. al, Deep reinforcement learning with relational inductive biases. 2019.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10



Zambaldi et. al, Deep reinforcement learning with relational inductive biases. 2019.

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Summary of relation network

- A relation network can efficiently represent relational information by sharing parameters over different pairs
- Relational reasoning is necessary to simplify a complexity of some problems with structures

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Cognitive Science inspired Deep Learning



Image from <http://clipart-library.com/clipart/695303.htm>

Joseph J. Lim

CSCI 599 @ USC

Lecture 10

Next lecture

- Resume Reinforcement Learning next class