Efficient Learning and Deep Reinforcement Learning

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Spring 2022

https://home.cs.colorado.edu/~DrG/Courses/NeuralNetworksAndDeepLearning/AboutCourse.html

Review

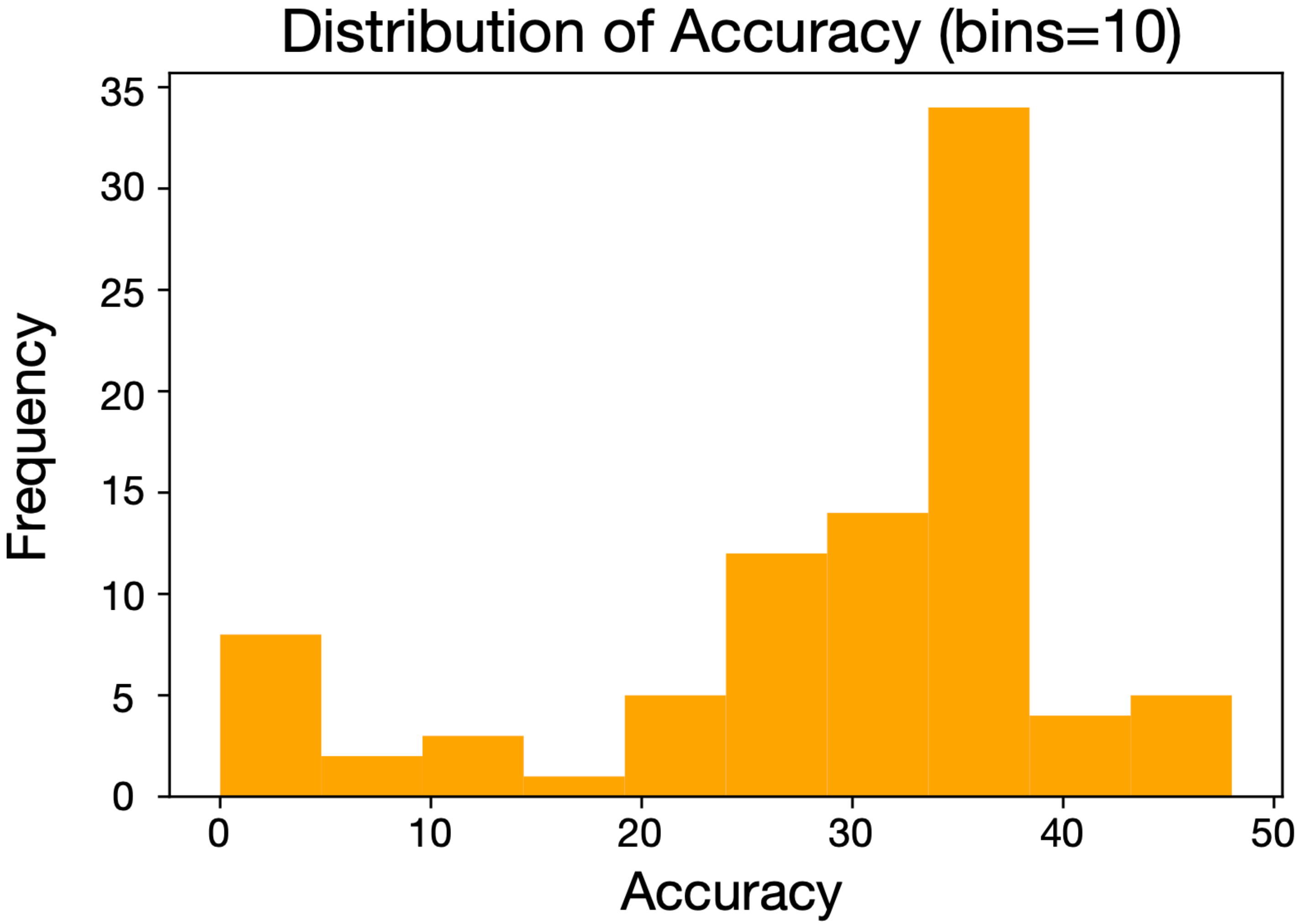
- Last week:
  - Motivation
  - Key idea: knowledge distillation
  - Knowledge distillation for CNNs (vision problems)
  - Knowledge distillation for Transformers (language problems)

- Assignments (Canvas):
  - Lab assignment 4 grades out
  - Final project outline due Friday

- Questions?

VQA Challenge Analysis

- 88 valid submissions
- Mean: 28.65%
- Naive model: 35.53%
  - Unanswerable predictions
- 2nd place: 44.93%
  - Cole Sturza
- 1rst place: 47.73%
  - Tushar Gautam



Today’s Topics

- Efficient learning: curriculum learning
- Efficient learning: active learning
- Reinforcement learning

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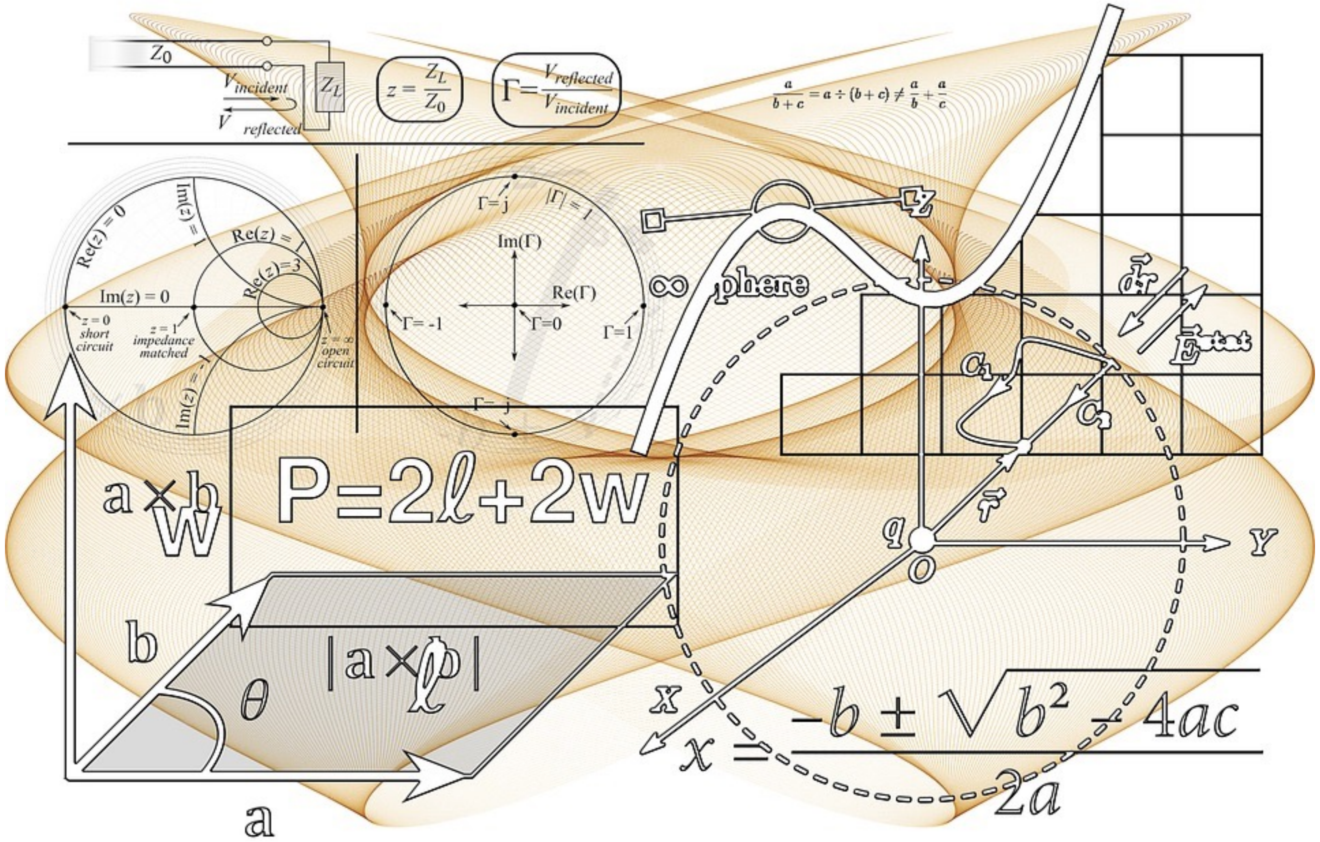
How to teach machines so they learn faster?

Intuition: How to Teach a Child Math?

Random Order of Examples



Meaningful Order of Examples


Table of Contents

Big Book of Math; Dinah Zike

Intuition: How to Teach a Child To Read

Random Order of Examples

Meaningful Order of Examples

Idea: Teach Machines As We Teach Humans

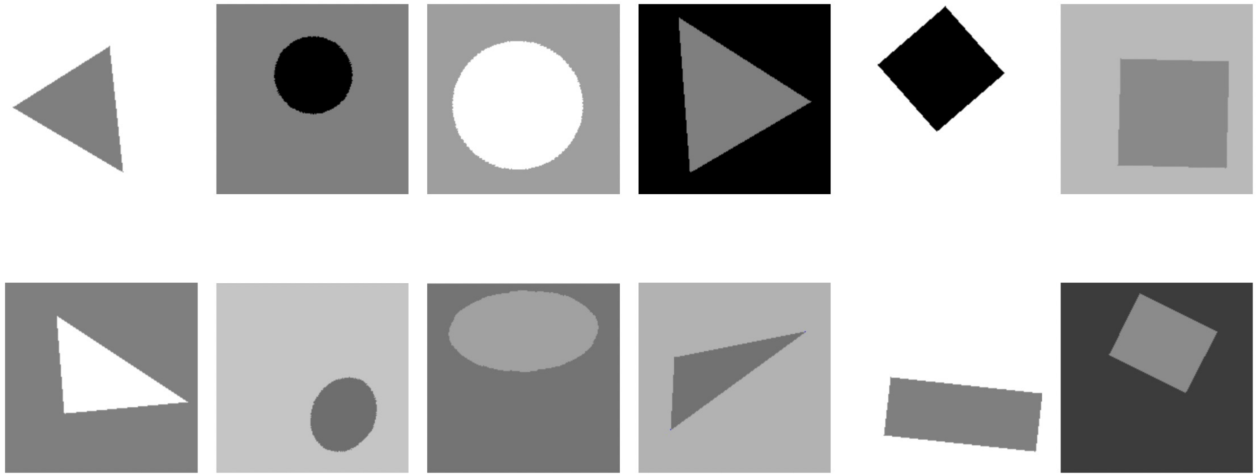
Curriculum

Train with simpler examples first and progressively harder examples over time

Jeffrey L. Elman. Learning and development in neural networks: The importance of starting small. Cognition, 1993.

Tasks

1. Classify each shape as rectangle, ellipse, or triangle



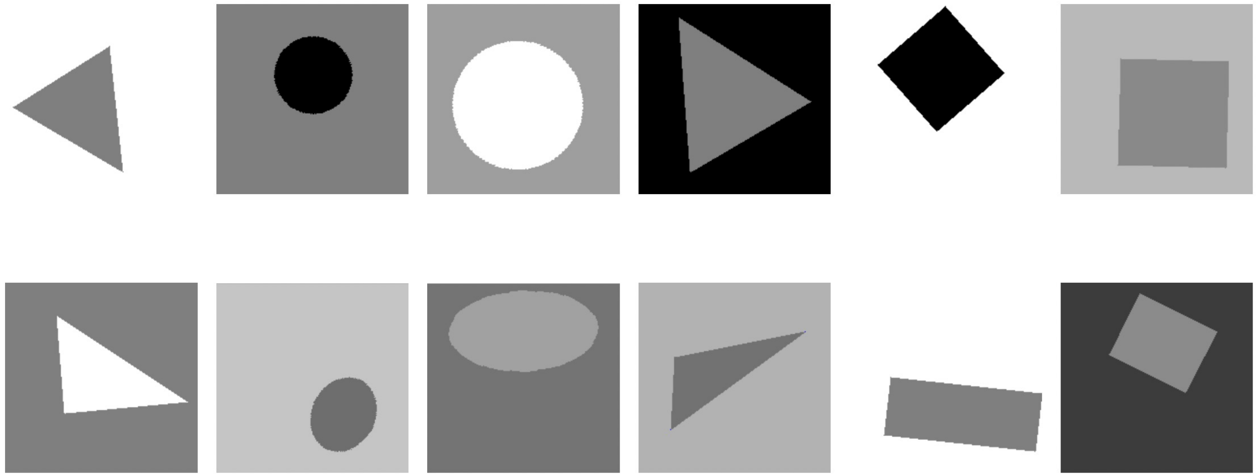
2. Predict the next word

Background music from a ________

Bengio et al., Curriculum Learning, 2009

Shape Prediction: Curriculum Learning

1. Classify each shape as rectangle, ellipse, or triangle



Architecture: 3-layer neural network

Easy (Basic): less shape variability (squares, circles, and equilateral triangles); 10,000 examples

Hard (Geom): more shape variability (rectangles, ellipses, and triangles); 10,000 examples

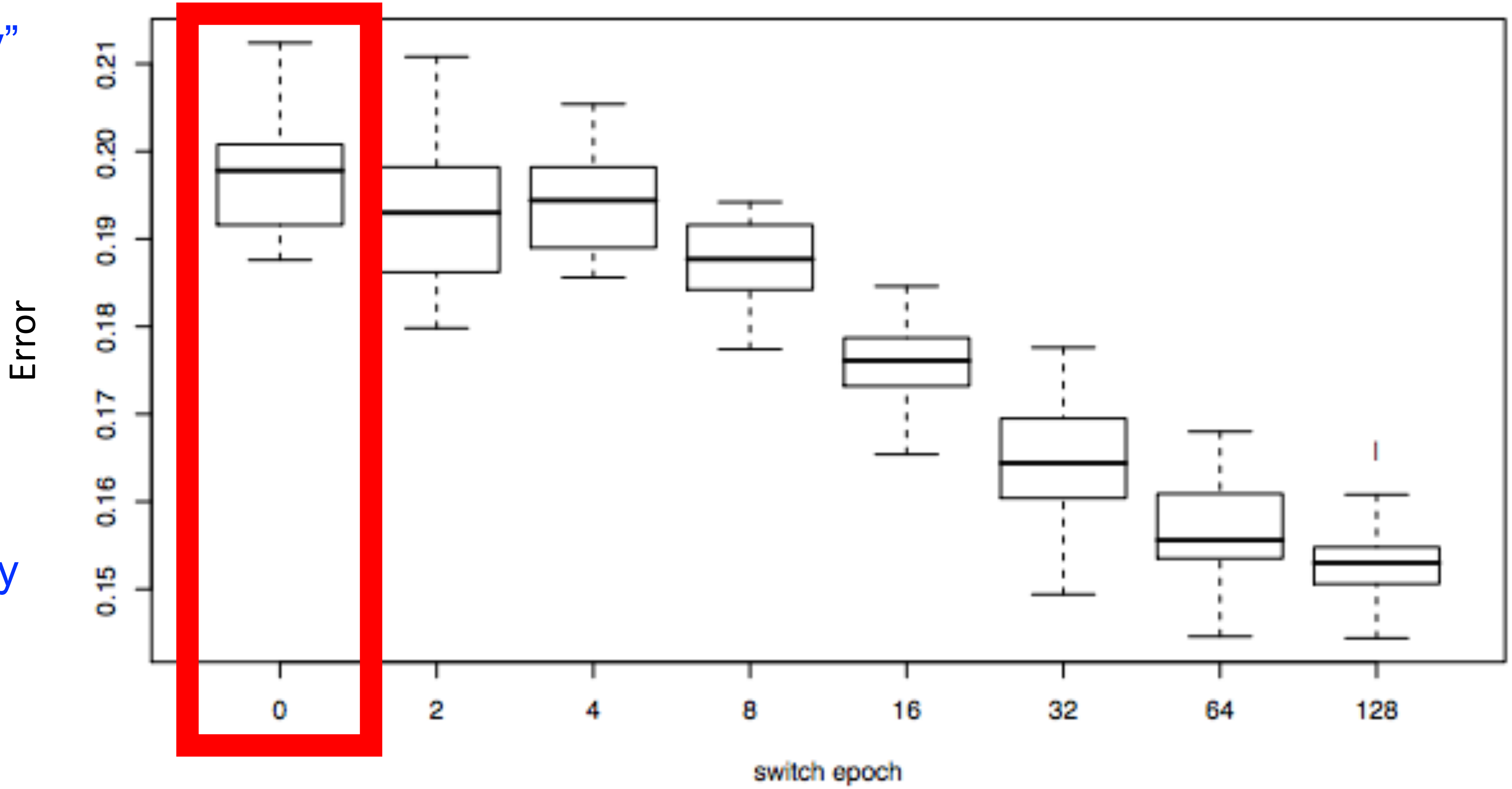
Bengio et al., Curriculum Learning, 2009

Shape Prediction: Curriculum Learning

Results of training on “easy” examples for *n* epochs and then training on “hard” examples.

What are benefits of curriculum learning?

How many epochs should the algorithm train with easy examples before switching to difficult examples?



No curriculum

Bengio et al., Curriculum Learning, 2009

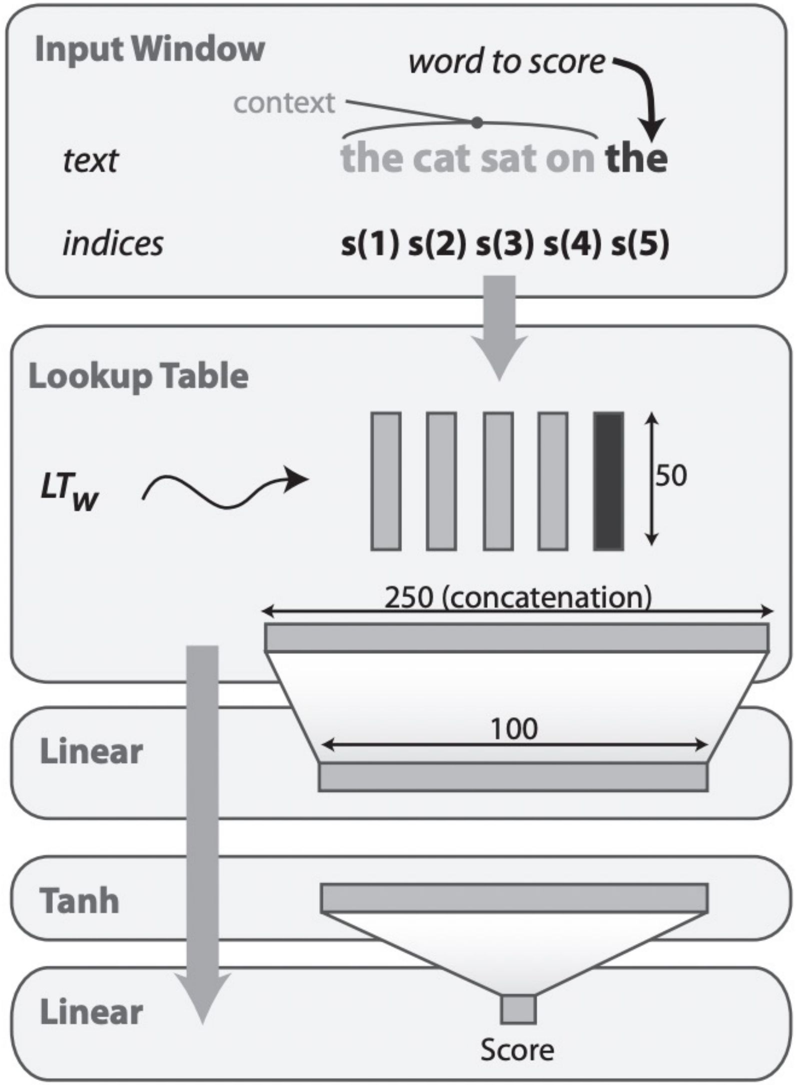
Next Word Prediction: Curriculum Learning

Architecture: context size set to 5

Easy: 5,000 most frequent words

Hard: additional 5,000 words at each epoch until 20,000 words

Examples with words not in the vocab were discarded from training



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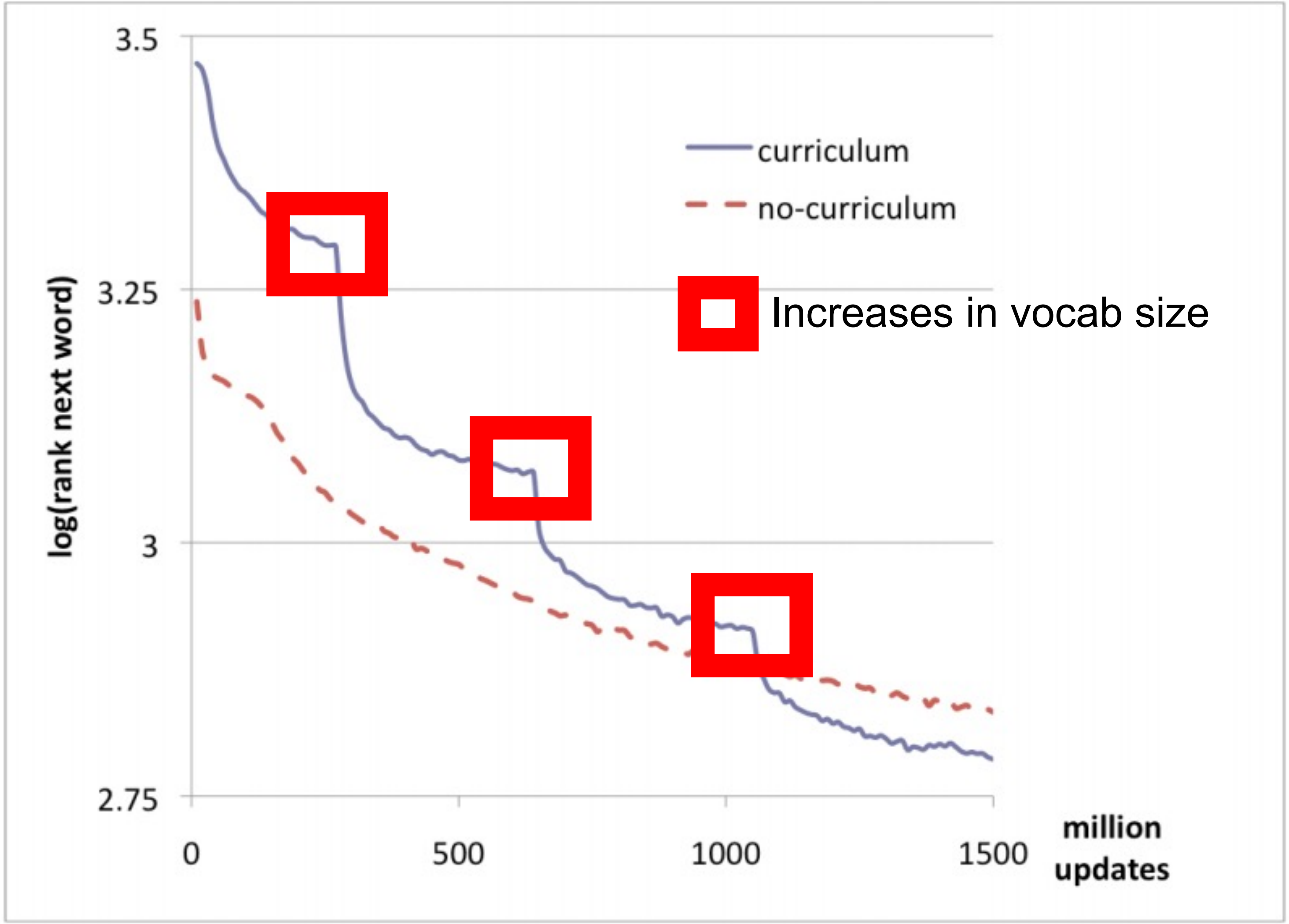
Next Word Prediction: Curriculum Learning

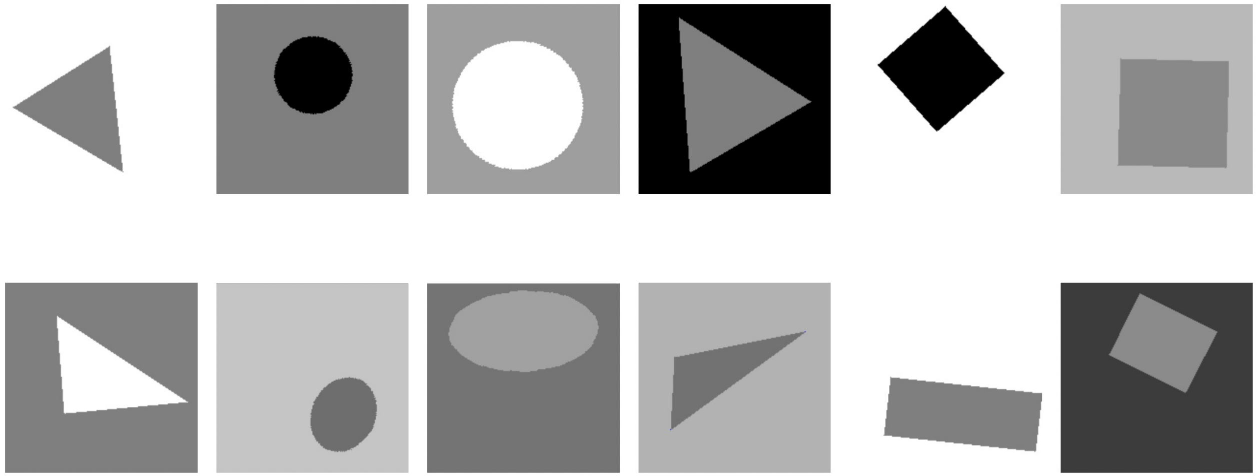
What are benefits of curriculum learning?



Bengio et al., Curriculum Learning, 2009

Summary: Curriculum Learning is a Form of Transfer Learning that Accelerates Optimization

1. Classify each shape as rectangle, ellipse, or triangle

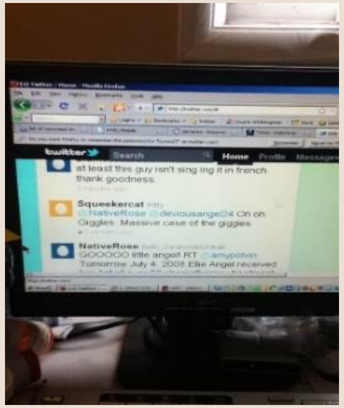


2. Predict the next word

Background music from a ________

Bengio et al., Curriculum Learning, 2009

Class Discussion: Curriculum Learning for Visual Question Answering



Is my monitor on?

Hi there can you please tell me what flavor this is?

Does this picture look scary?

Which side of the room is the toilet on?

Questions

1. What criteria should be used to order examples?
2. How would you update the training data (and how often)?

Today’s Topics

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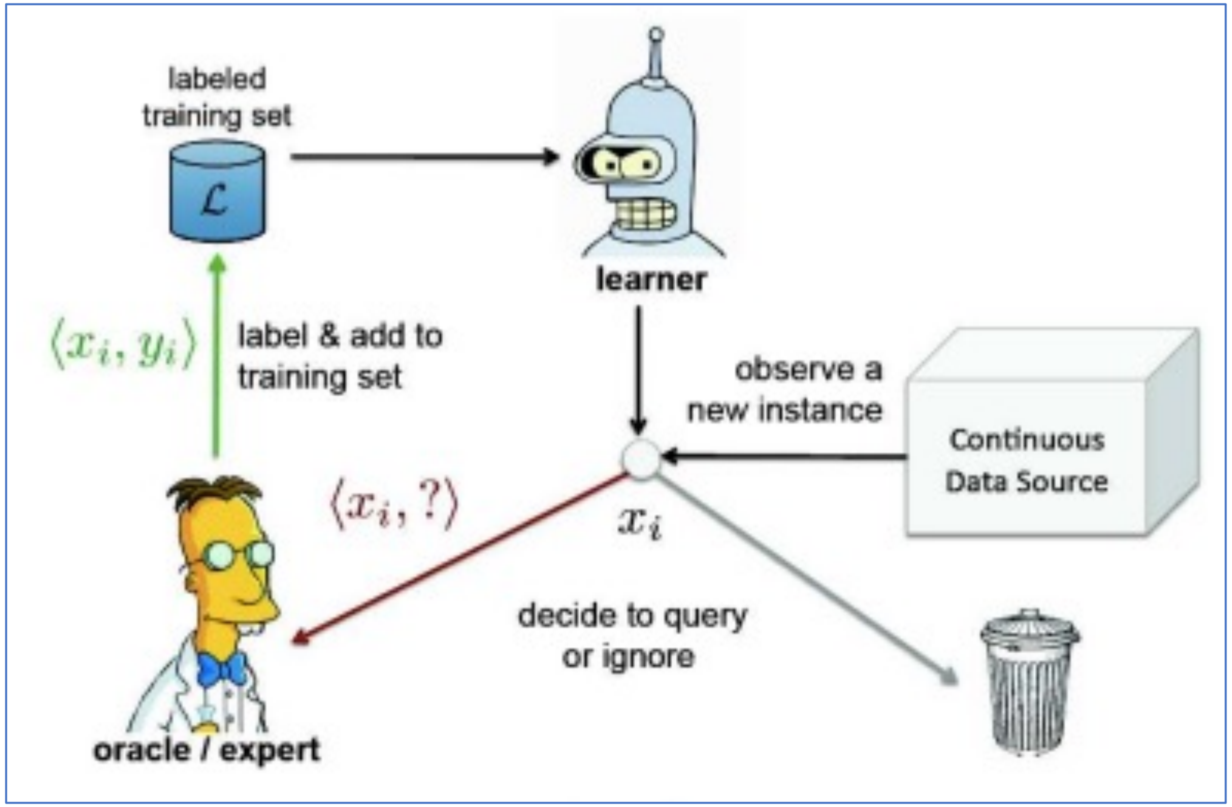
- Efficient learning: active learning
- Reinforcement learning

Actively select the examples to label that would be most effective for learning rather than labelling all available data

Types of Active Learning

1. Stream-Based

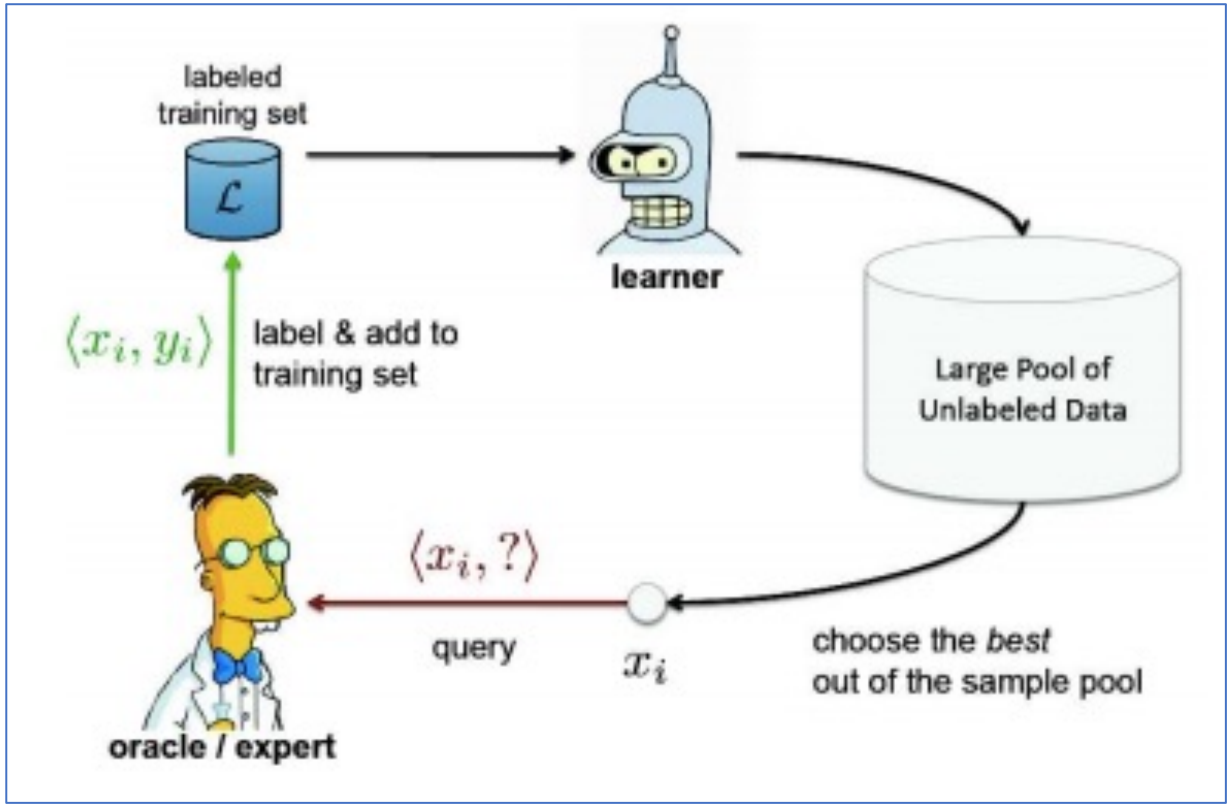


Consider one example at a time

Image Credit: https://www.cs.utah.edu/~piyush/teaching/10-11-slides.pdf

Types of Active Learning

2. Pool-Based

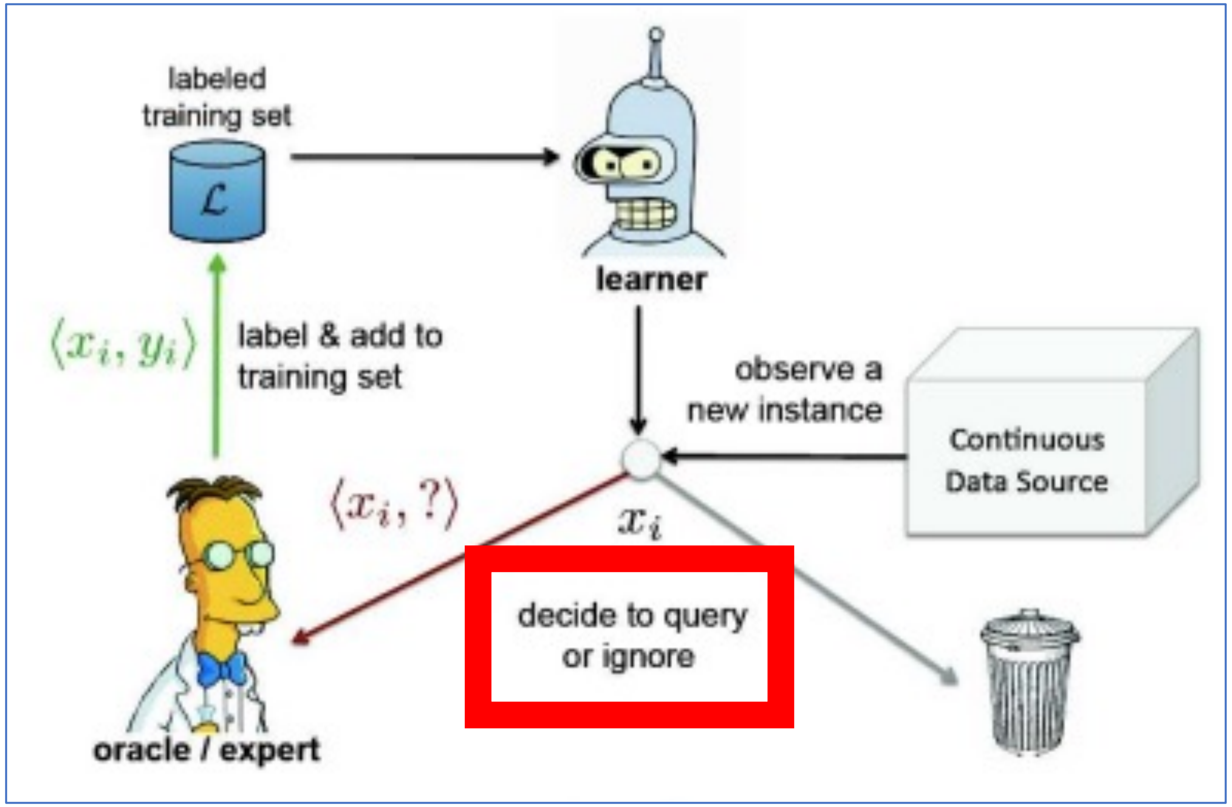


Consider many examples at a time

Image Credit: https://www.cs.utah.edu/~piyush/teaching/10-11-slides.pdf

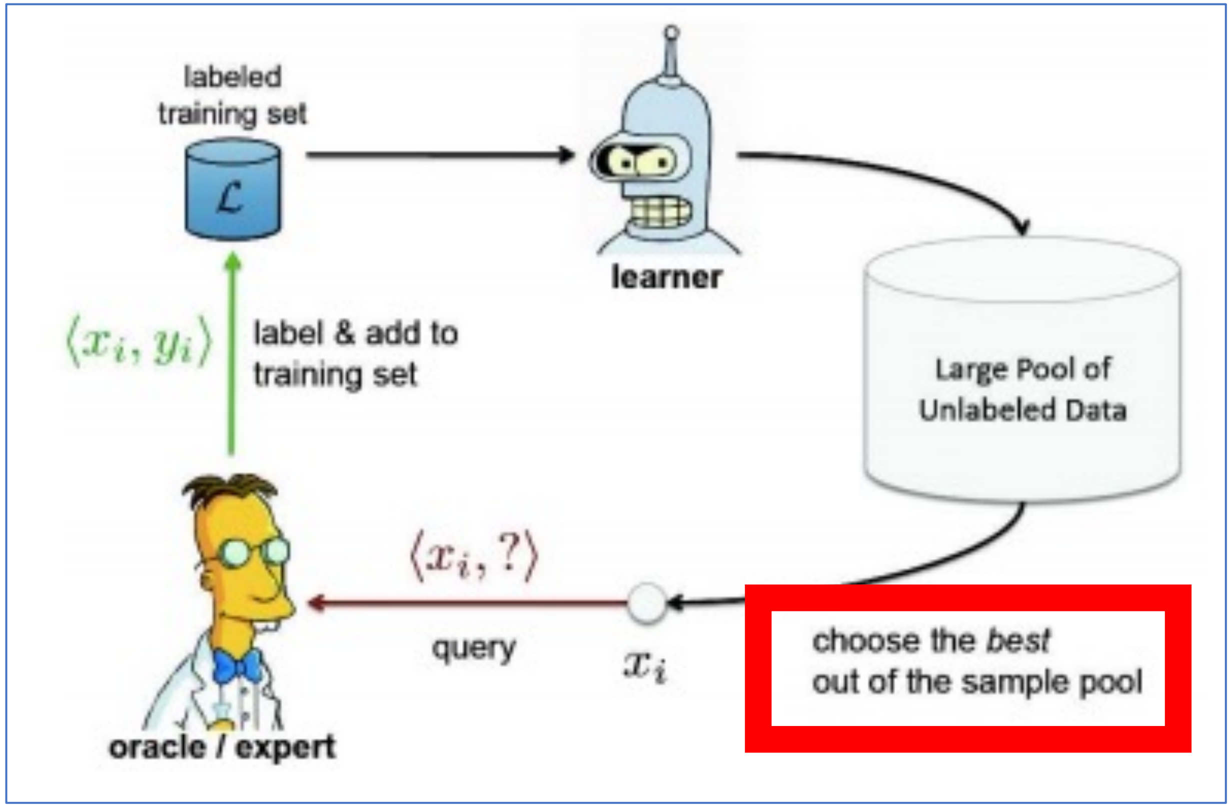
Types of Active Learning

Stream-Based



Consider one example at a time

Pool-Based



Consider many examples at a time

Image Credit: https://www.cs.utah.edu/~piyush/teaching/10-11-slides.pdf

Active Learning Approach

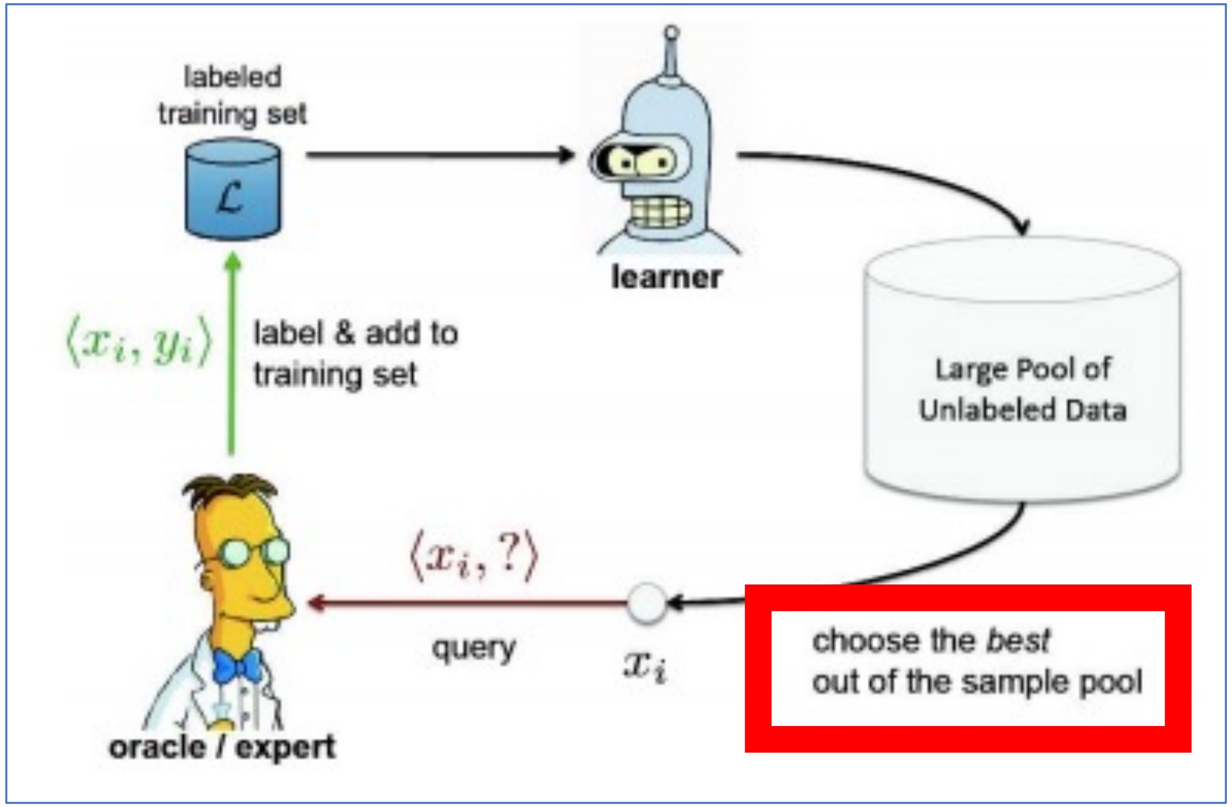
- Active Learning proceeds in rounds
- Each round has a current model (learned using the labeled data seen so far)
- The current model is used to assess informativeness of unlabeled examples
    - .. using one of the query selection strategies
- The most informative example(s) is/are selected
- The labels are obtained (by the labeling oracle)
- The (now) labeled example(s) is/are included in the training data
- The model is re-trained using the new training data

Image Credit: https://www.cs.utah.edu/~piyush/teaching/10-11-slides.pdf

Active Learning for Neural Networks: Status Quo

Iteratively add more labelled training examples after *n* epochs; different from curriculum learning because labels need to be collected for the added data

Pool-Based



Consider many examples at a time

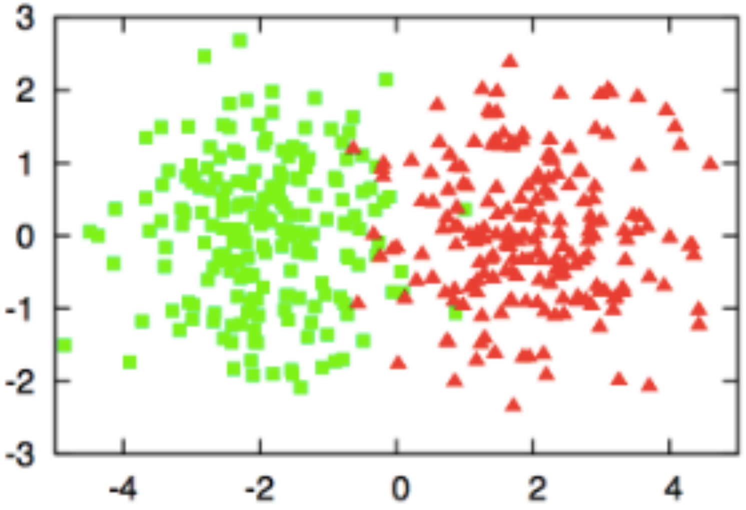
Image Credit: https://www.cs.utah.edu/~piyush/teaching/10-11-slides.pdf

Challenge: how to choose most informative example(s) to label?

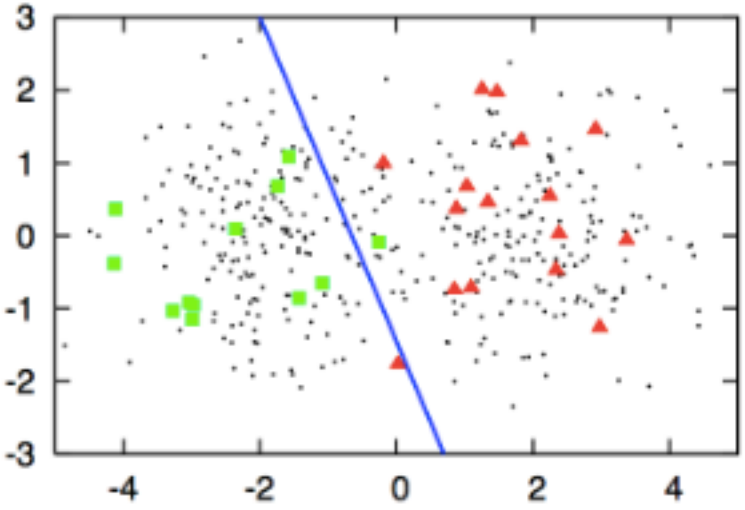
Common Approach: Uncertainty Sampling

Query instance(s) the classifier is most uncertain about.

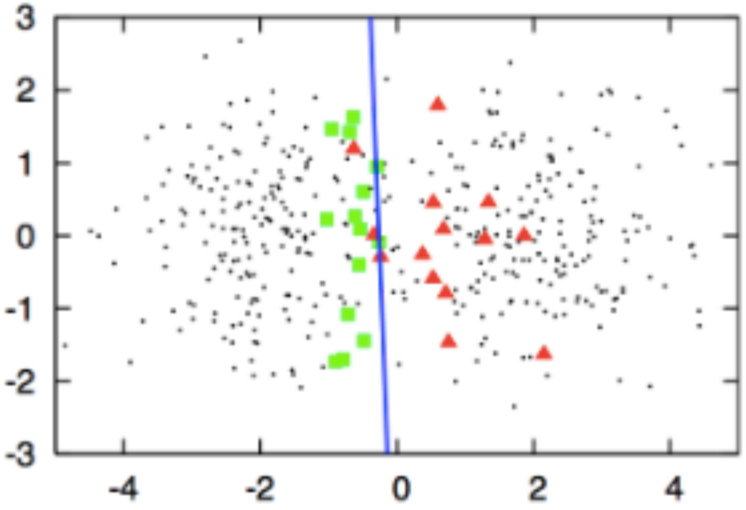
True Representation (Assume Labels Are Not Known)



Passive Learner (Random Selection)



Active Learner (Uncertainty Sampling)

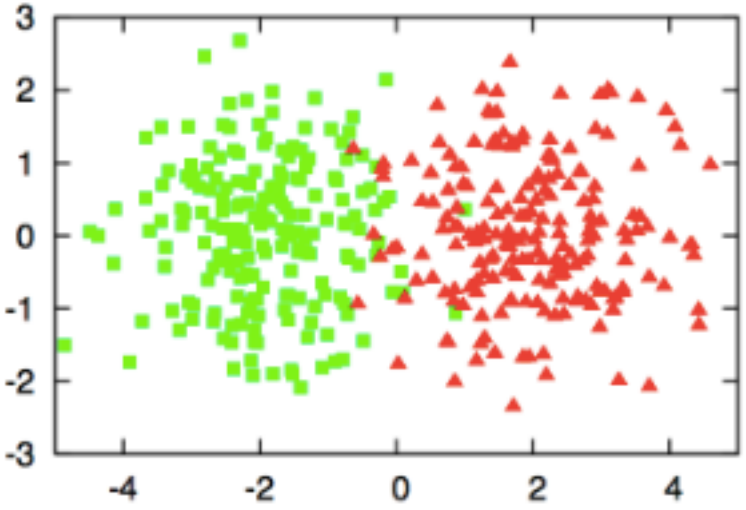


http://burrsettles.com/pub/settles.activelearning.pdf

Common Approach: Uncertainty Sampling

Why might this be a poor approach?

True Representation (Assume Labels Are Not Known)



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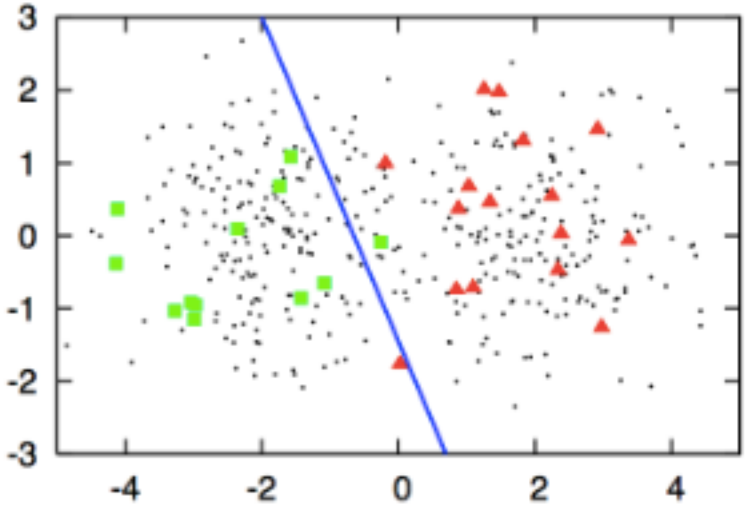
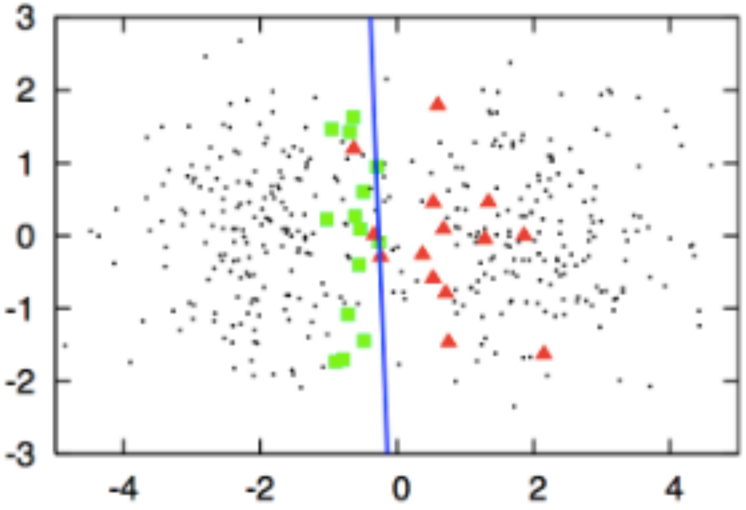


Active Learner (Uncertainty Sampling)



http://burrsettles.com/pub/settles.activelearning.pdf

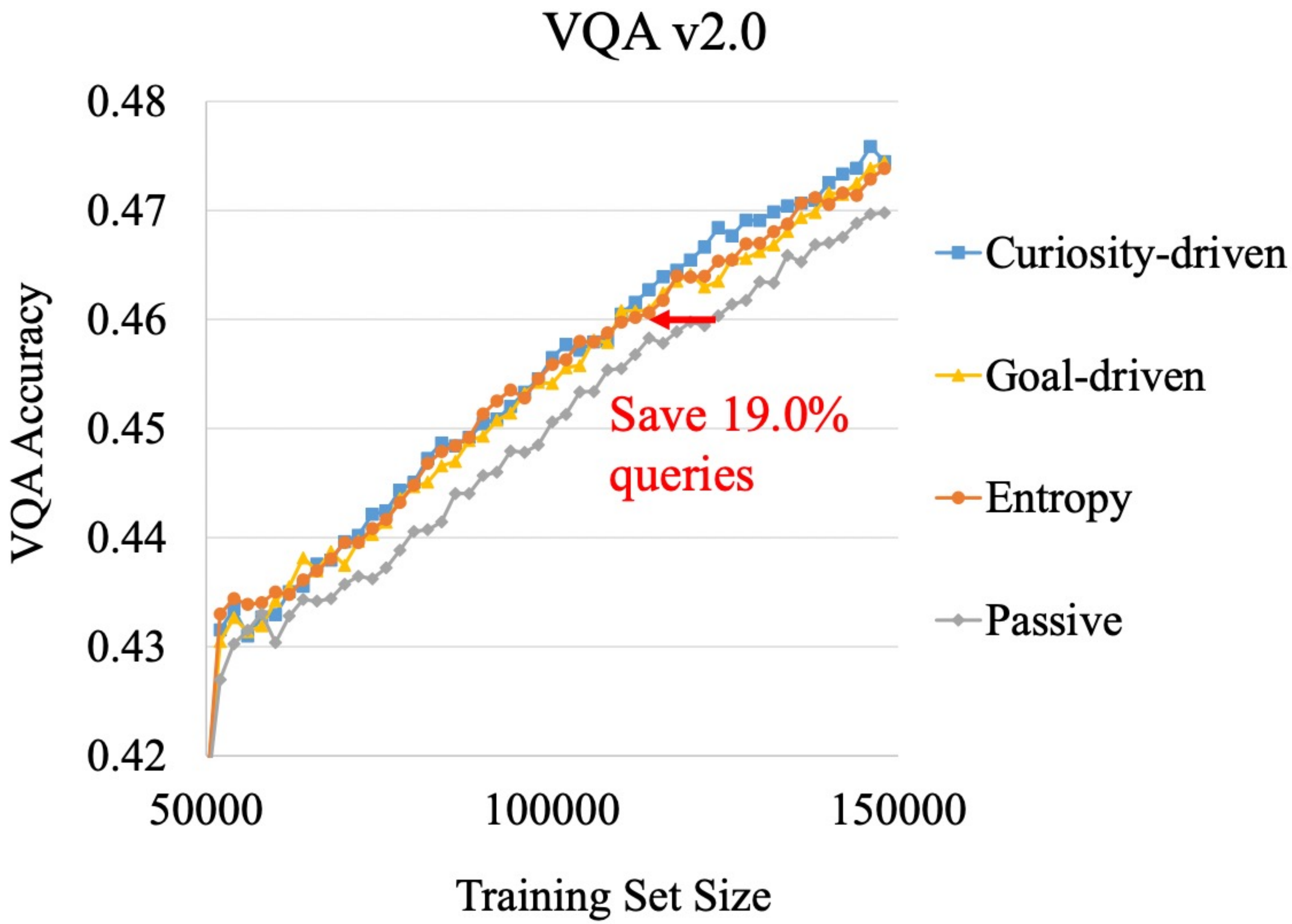
What Are Other Potential Active Learning Approaches?

- Select examples expected to:
  - meet a specific skill (e.g., learn to count in VQA)
  - boost model performance the most

Learning Curves: : Active vs Passive Learning

What are benefits of the active learning methods over passive learning?

- Learning is faster
- Reduces humans' annotation effort



Lin and Parikh. Active Learning for Visual Question Answering: An Empirical Study. 2017

Today’s Topics

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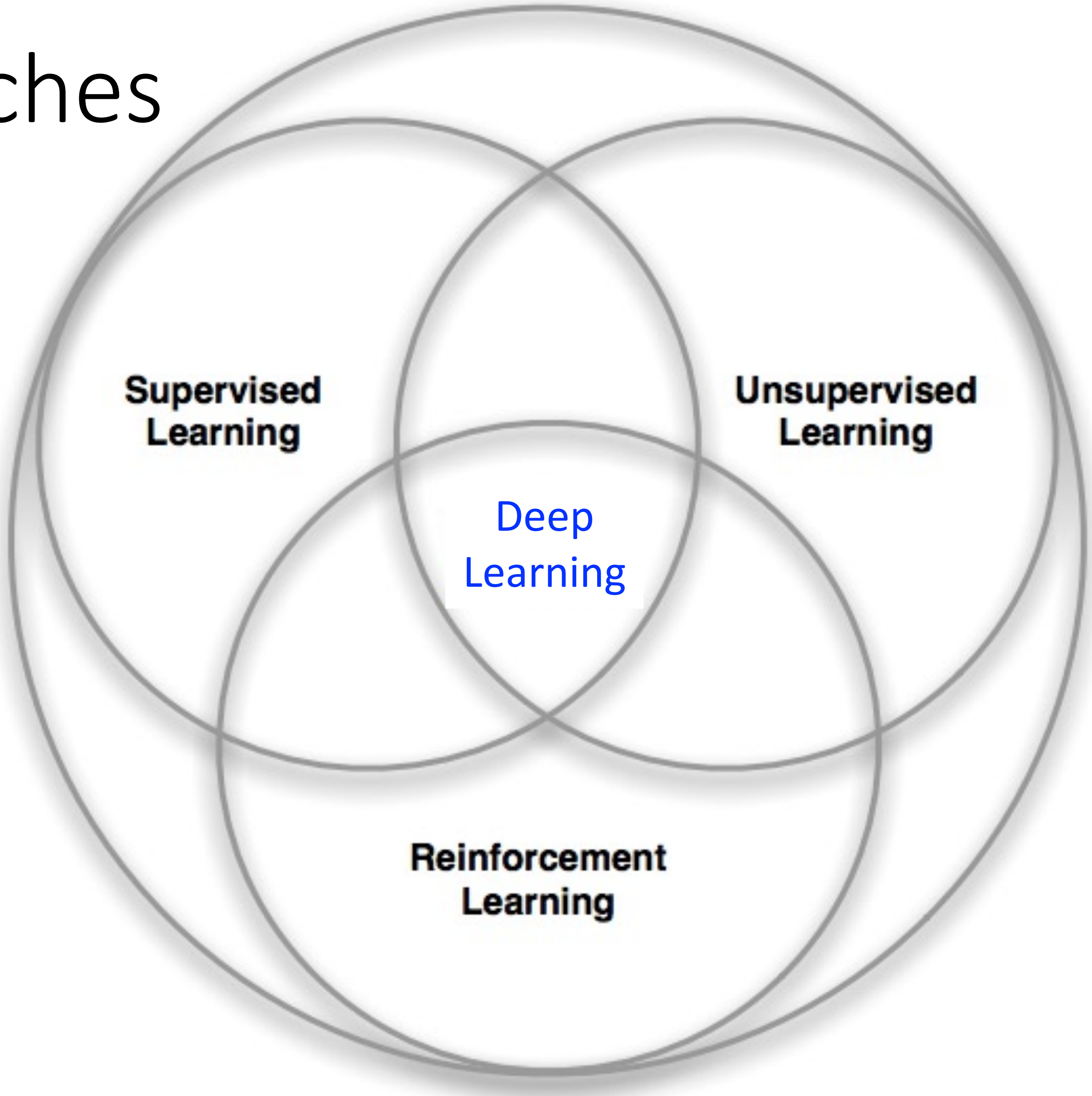
- Efficient learning: active learning
- Reinforcement learning

Deep Learning Approaches



http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching_files/intro_RL.pdf

Reinforcement Learning Overview

Agent takes actions in an environment to maximize the total reward

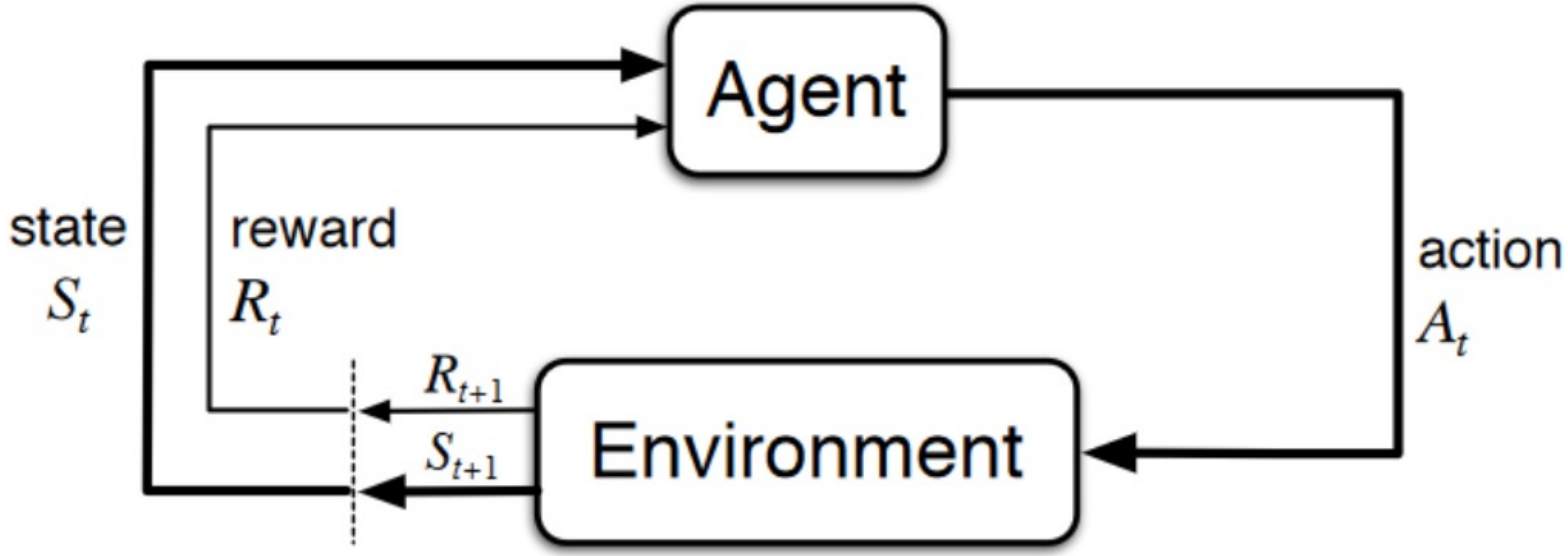


Figure Credit: https://towardsdatascience.com/applications-of-reinforcement-learning-in-real-world-1a94955bcd12

Intuition: Learning to Walk by Trial-and Error

https://en.wikipedia.org/wiki/Crawling_(human)

Reinforcement Learning Applications

Learning to Walk in 20 Minutes

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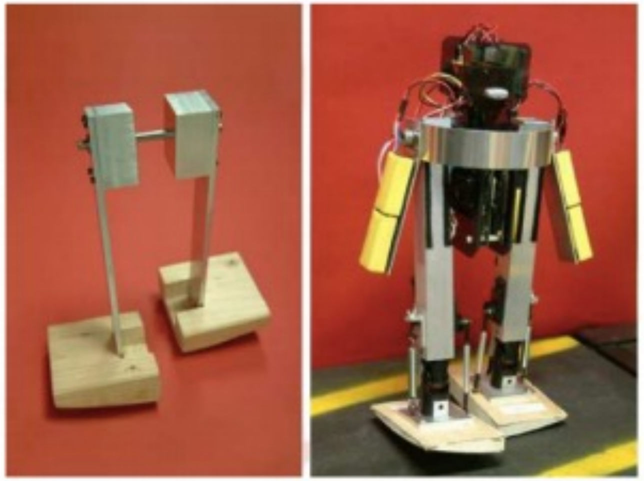

Reinforcement Learning Applications

Autonomous reinforcement learning on raw visual input data in a real world application

Sascha Lange, Martin Riedmiller
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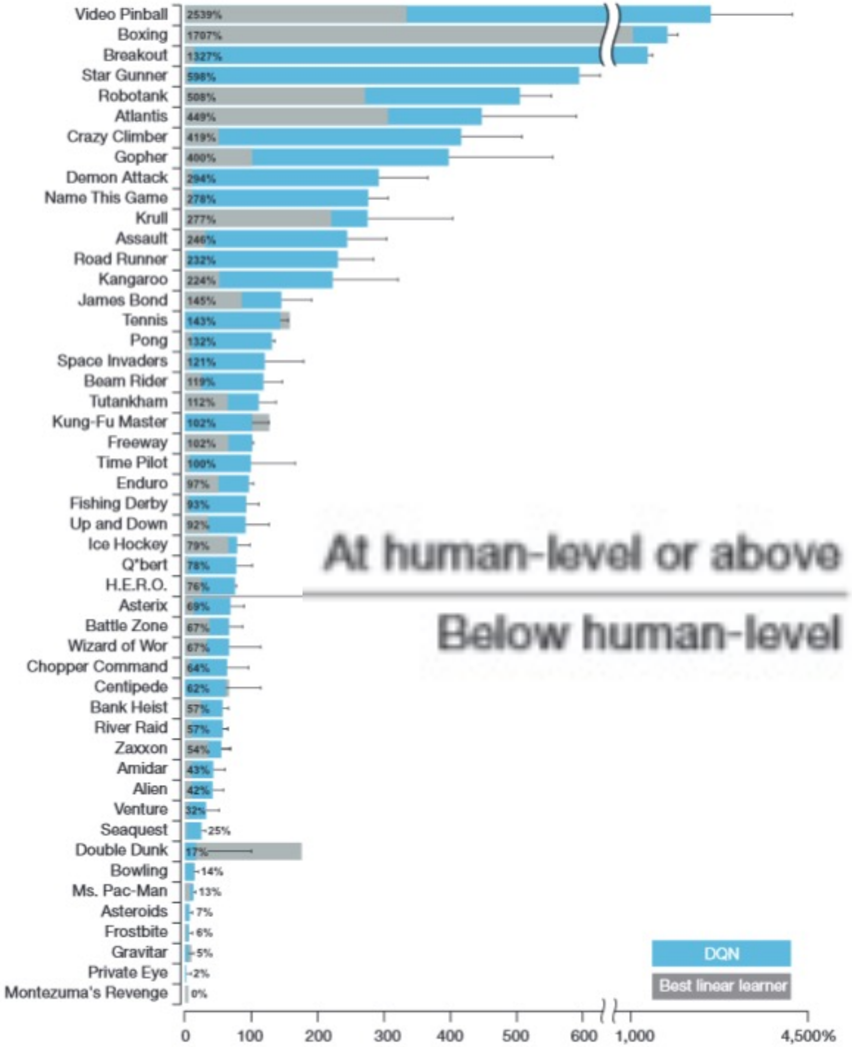
Albert-Ludwigs-Universität Freiburg
D-79110, Freiburg, Germany
Email: [slange,riedmiller]@informatik.uni-freiburg.de

Arne Voigtländer
Shoogee GmbH & Co. KG
Krögerweg 16a
D-48155 Münster, Germany
Email: arne@shoogee.com

Fig. 1. The visual slot car racer task. The controller has to autonomously learn to steer the racing car by raw visual input of camera images.

Reinforcement Learning Applications

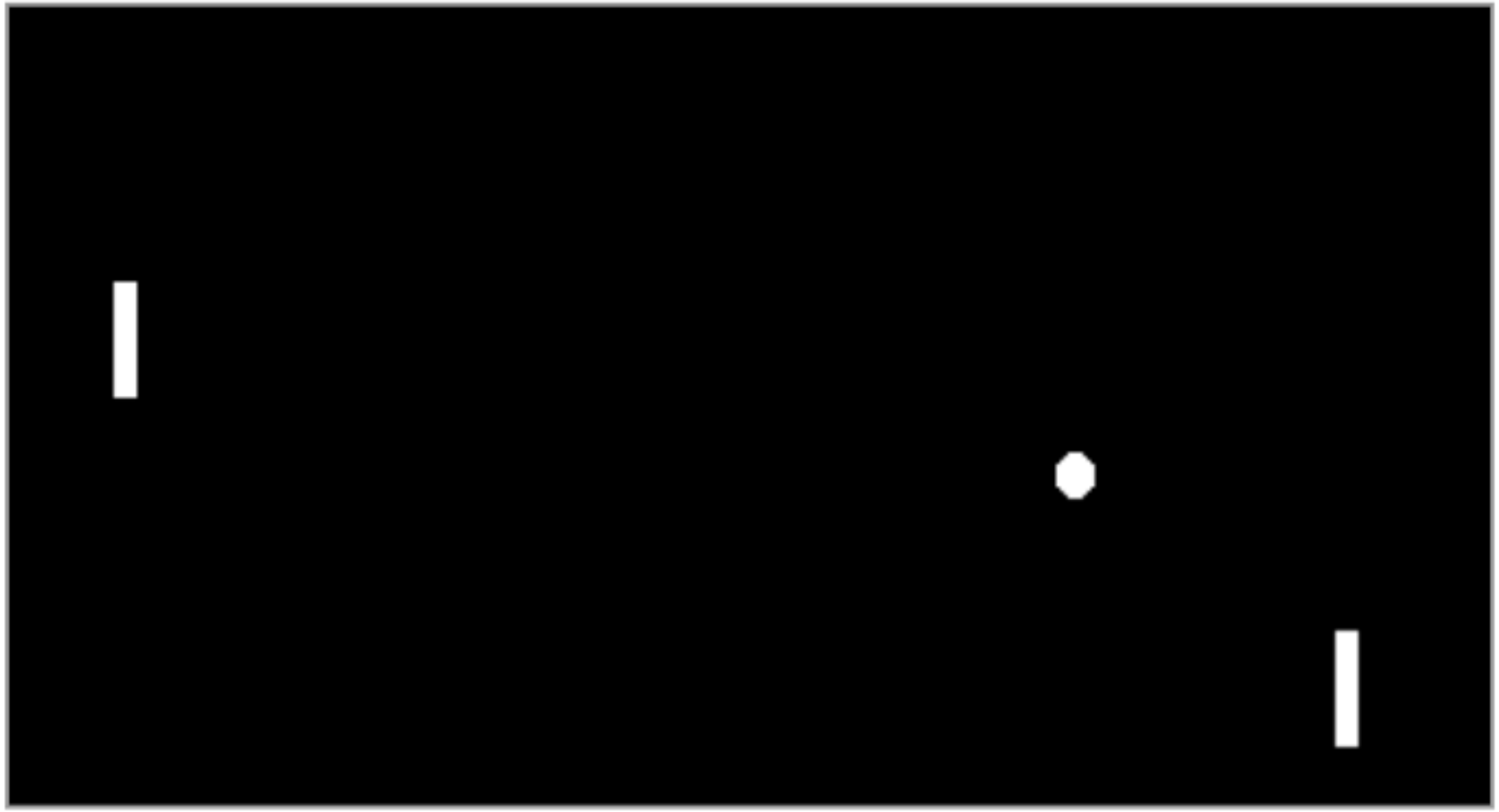


https://www.tastehit.com/blog/google-deepmind-alphago-how-it-works/

https://web.stanford.edu/class/psych209/Readings/MnihEtAlHassibis15NatureControlDeepRL.pdf

e.g., Pong Game Learning Example

Goal: compute optimal “up” and “down” paddle movements to maximize rewards



http://karpathy.github.io/2016/05/31/rl/

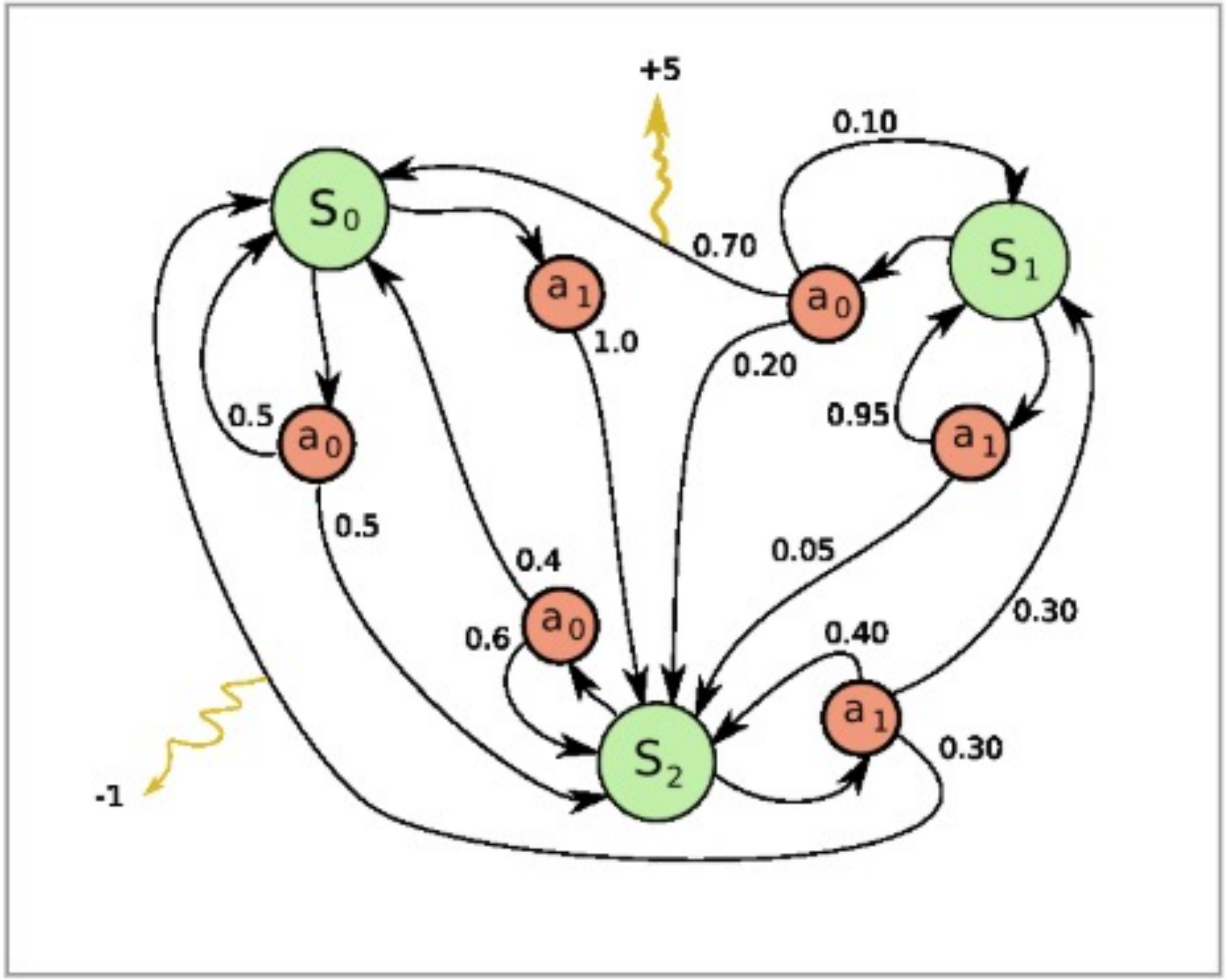
e.g., Pong Game Learning Example

Representation: graph where nodes are game states and edges are possible transitions with rewards

-1 if missed the ball

+1 reward if ball goes past opponent

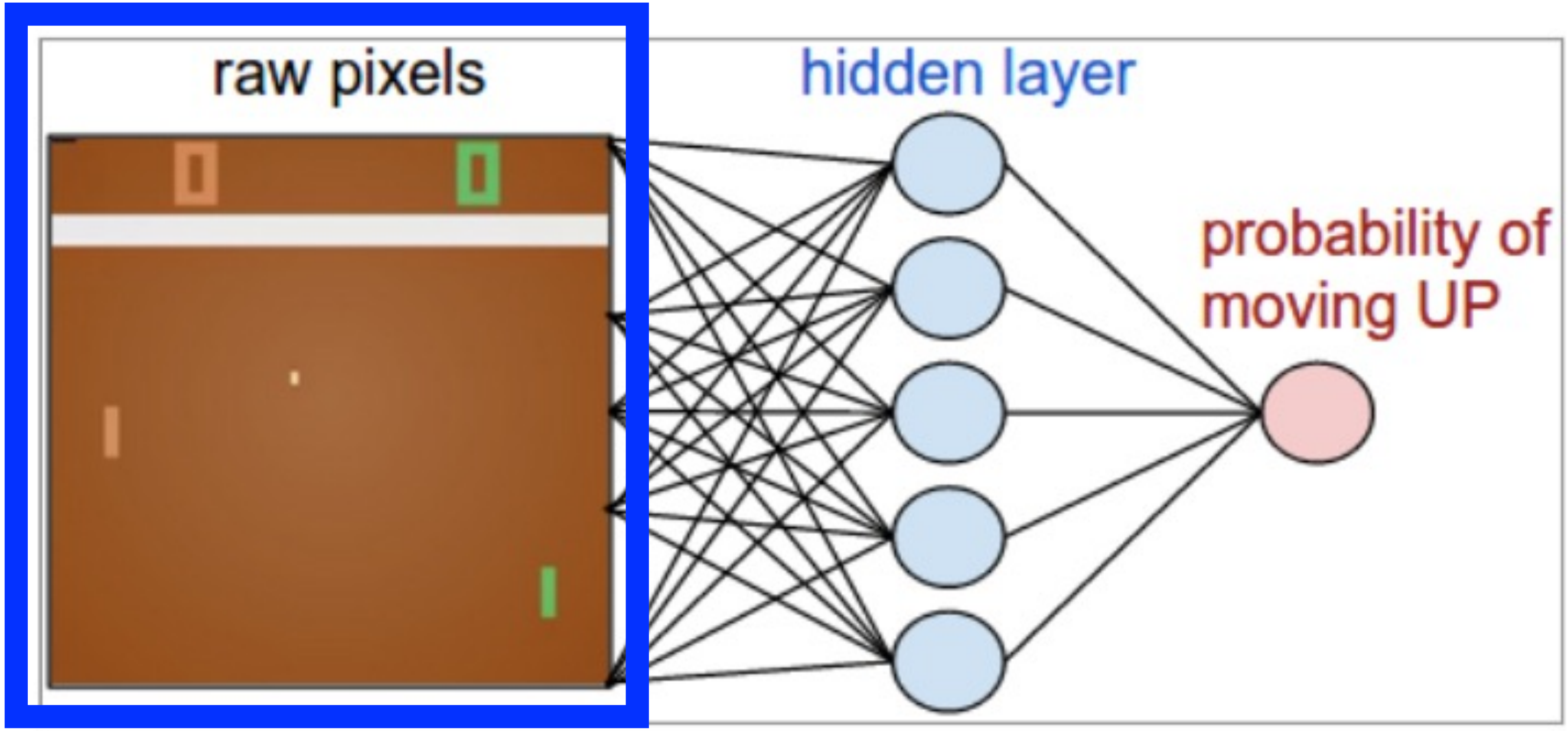
0 otherwise



http://karpathy.github.io/2016/05/31/rl/

e.g., Pong Game: Policy Network

Given game state (as image), decide if to move paddle up or down



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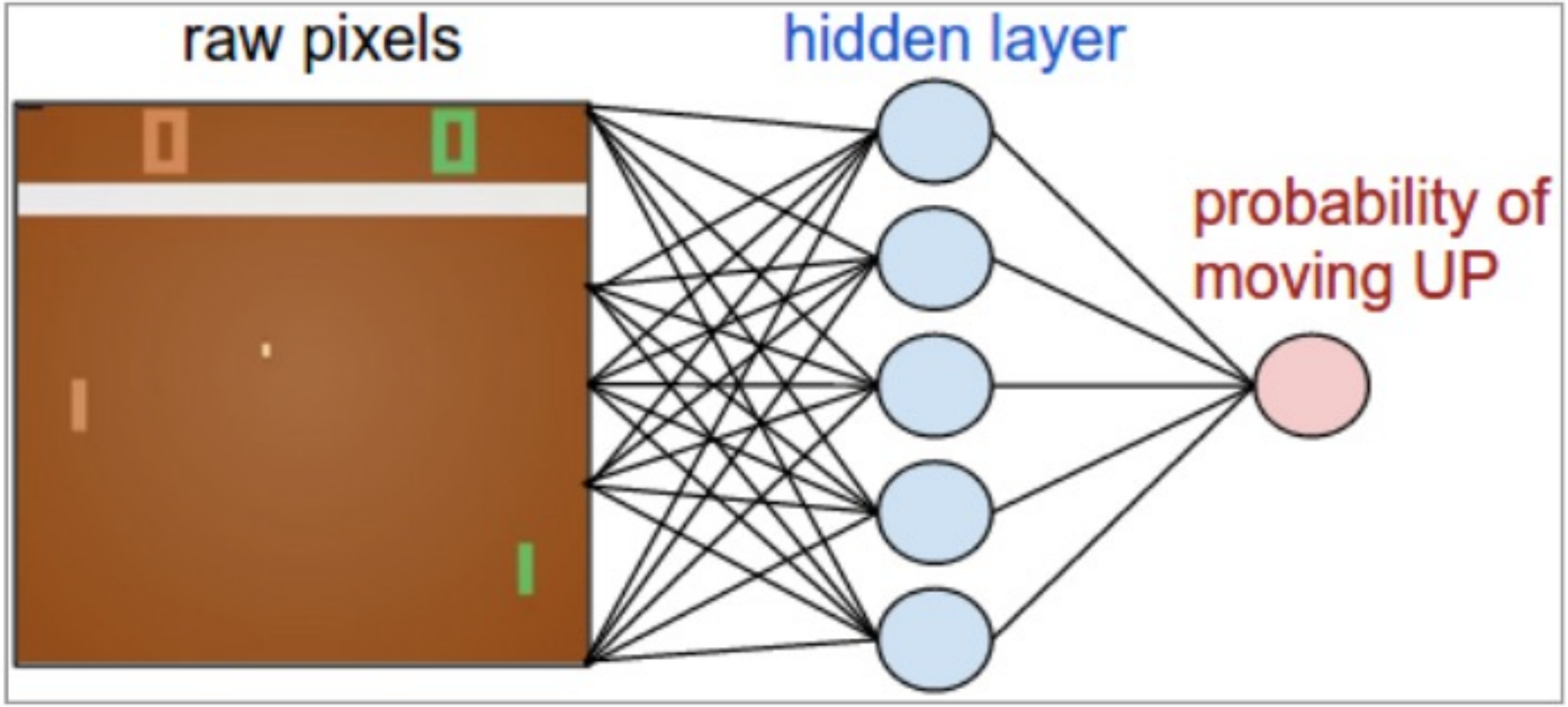
e.g., Pong Game: Policy Network

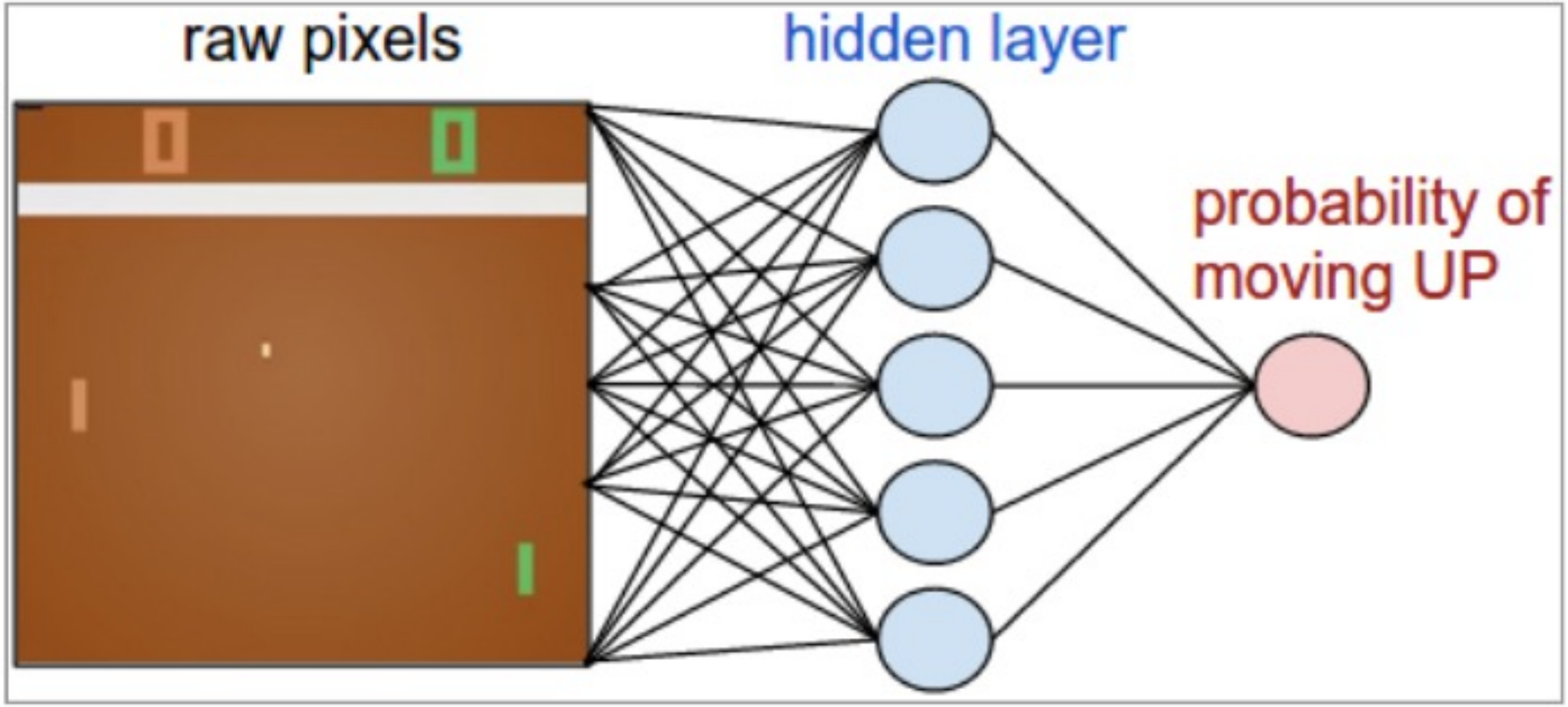
Reward provided after each game state of moving paddle up or down



http://karpathy.github.io/2016/05/31/rl/

e.g., Pong Game: Policy Network

Credit assignment problem: reward may be due to good action many steps ago



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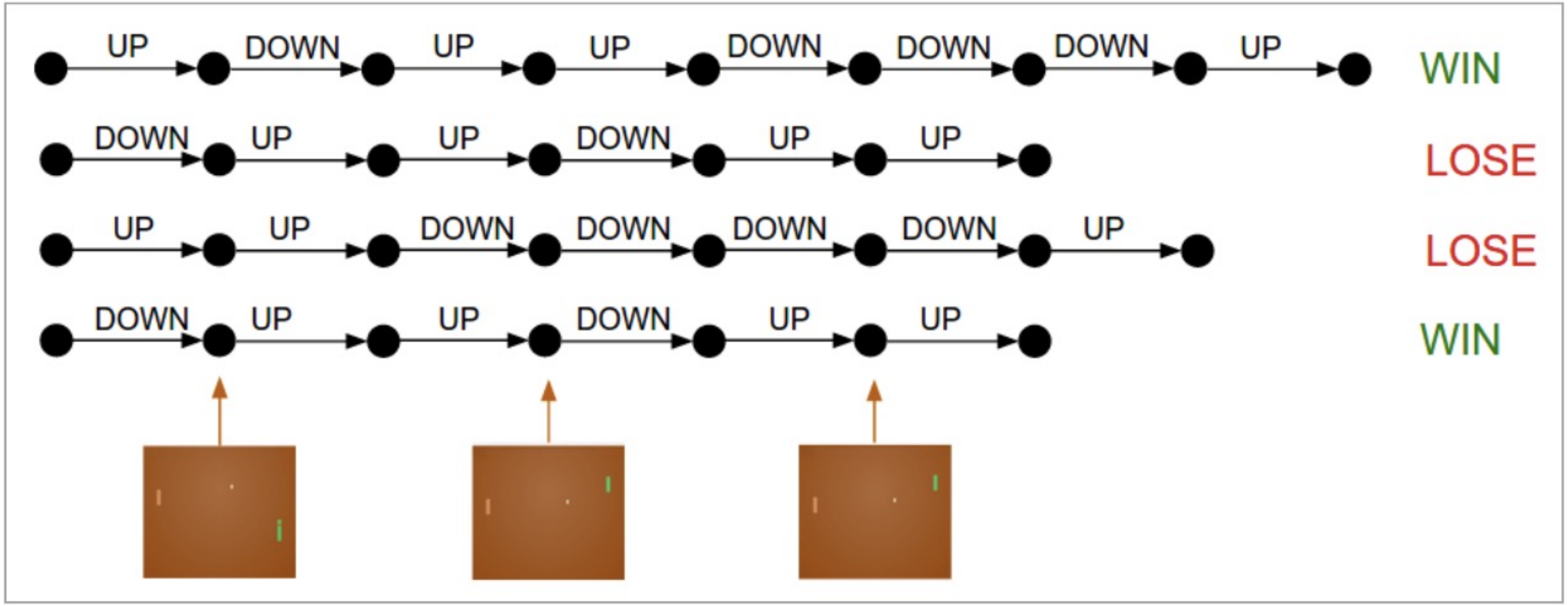
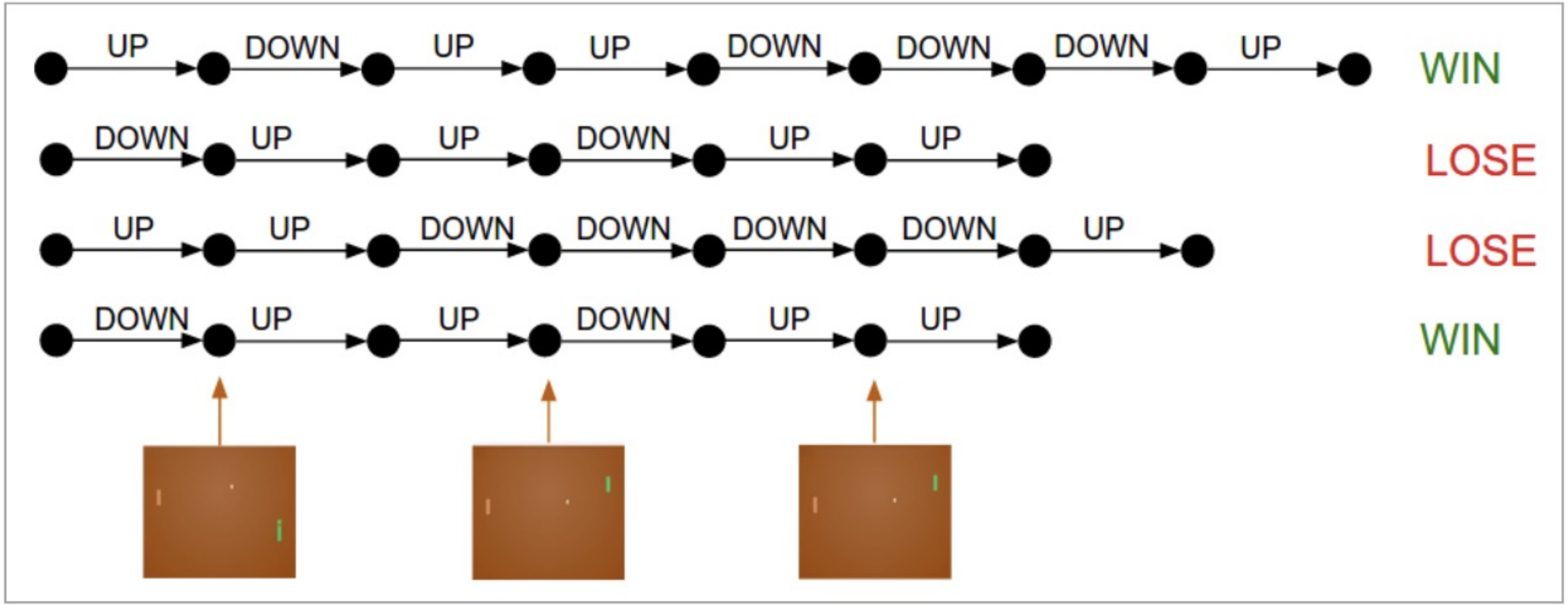
e.g., Pong Game: Training Protocol



Encourages actions that eventually lead to good outcomes and discourages actions that eventually lead to bad outcomes by updating gradients accordingly

http://karpathy.github.io/2016/05/31/rl/

e.g., Pong Game: Training Protocol



- 100 games played with 200 images/game
- Suppose: win 12 games, lose 88
  - # winning decisions = 200*12 = 2400 decisions; gradient updated to encourage each up/down action
  - # losing decisions: 200*88 = 17600; gradient updated to discourage each up/down action

http://karpathy.github.io/2016/05/31/rl/

e.g., Pong Game: Trained for Three Nights

Demo: https://www.youtube.com/watch?time_continue=16&v=YOW8m2YGtRg

e.g., Learning Dexterity

Demo: https://www.youtube.com/watch?v=jwSbzNHGflM

e.g., Learning to Flip Pancakes

Demo: https://www.youtube.com/watch?v=W_gxLKSsSIE&list=PL5nBAYUyJTrM48dViibyi68urttMlUv7e

e.g., Learning to Walk

Demo: https://www.youtube.com/watch?v=gn4nRCC9TwQ

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The End