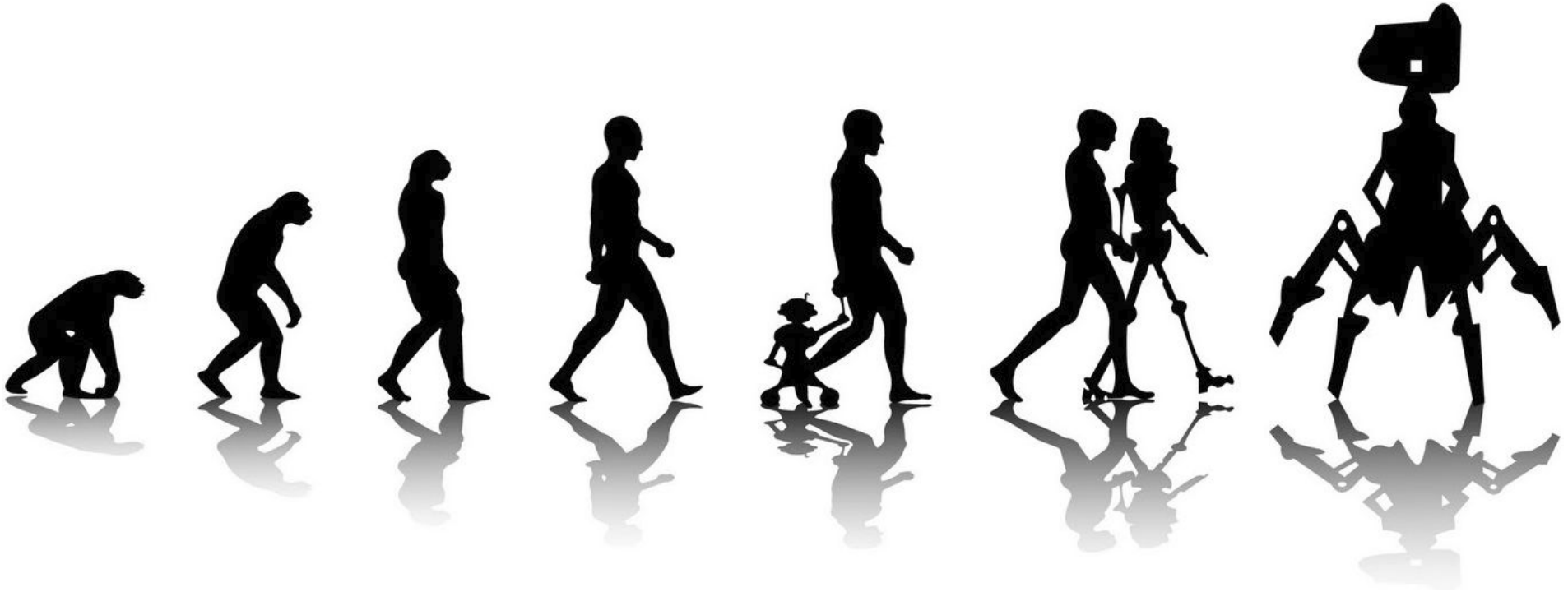


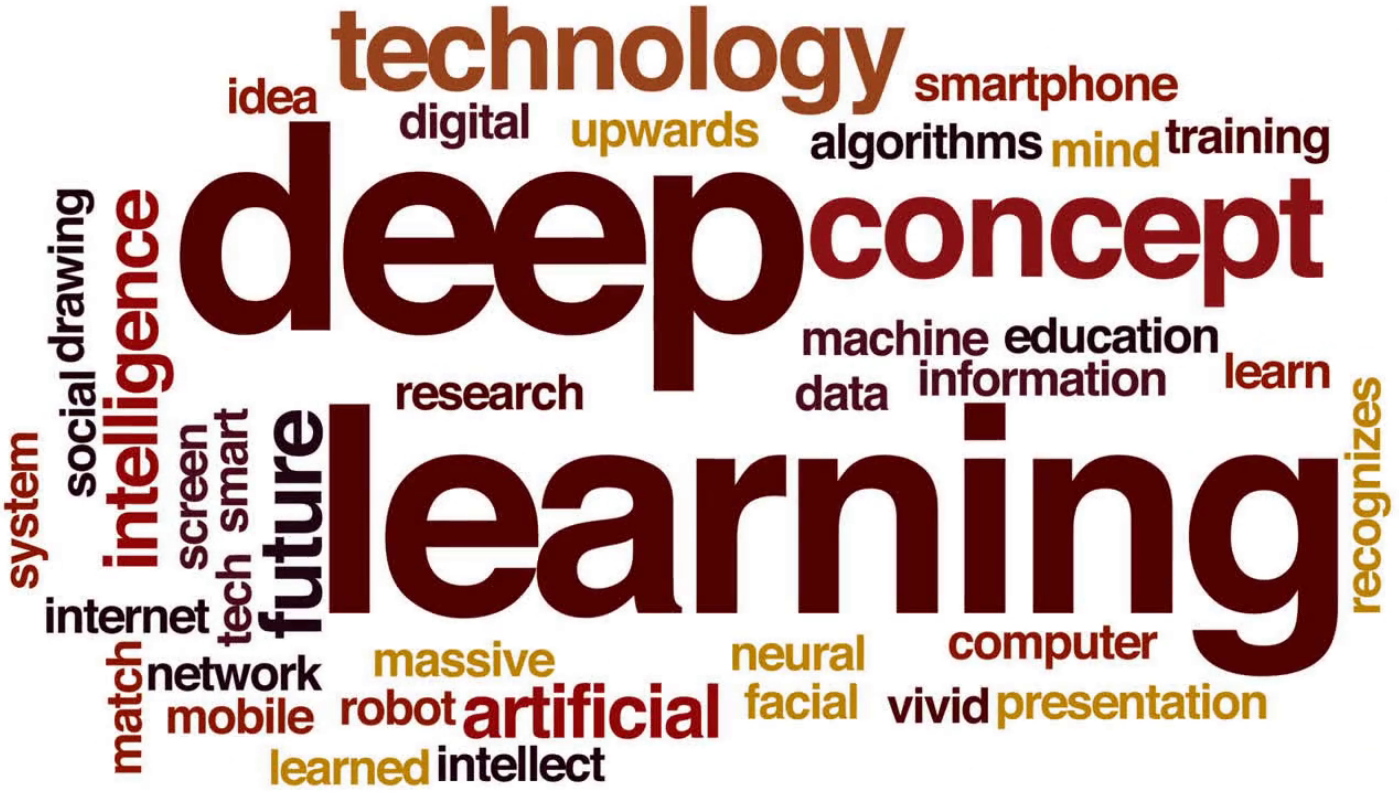
Modern Robotics: Evolutionary Robotics

COSC 4560 / COSC 5560

Professor Cheney

4/18/18

Tricks that make this work/scale!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research
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information
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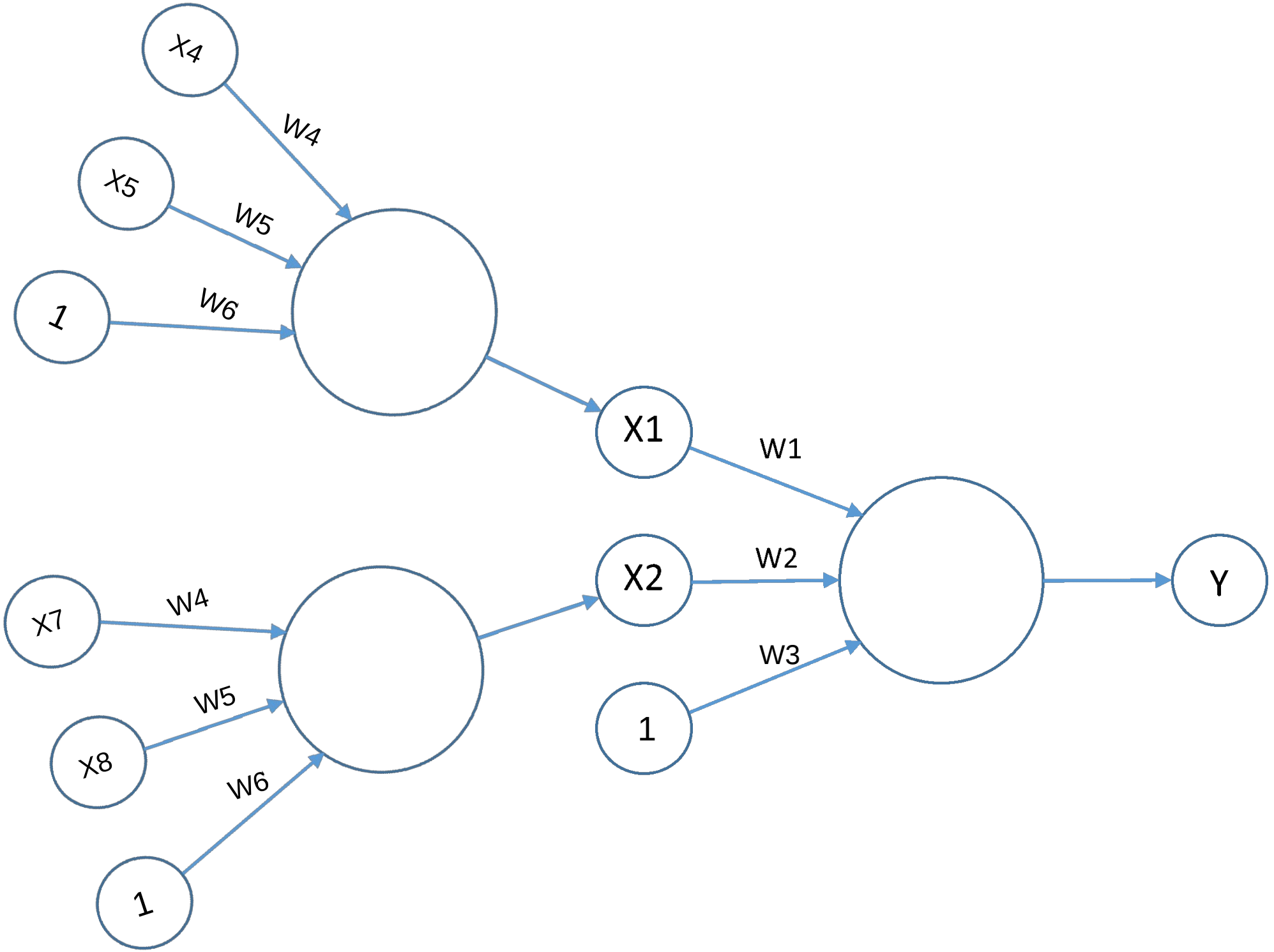
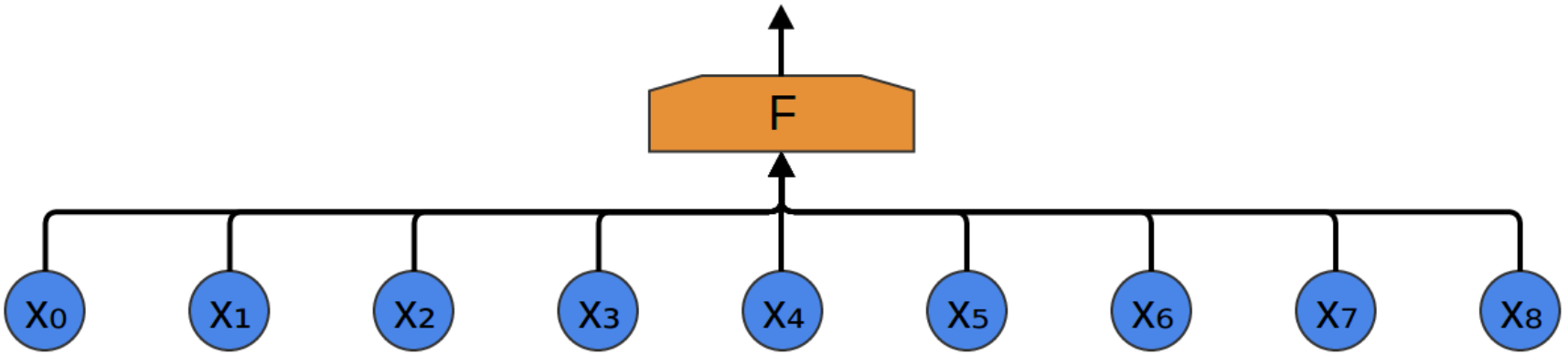
system
screen
smart
future
learning
recognizes
internet
tech
match
network
massive
neural
computer
mobile
robot
artificial
facial
vivid
presentation
learned
intellect

Weight Sharing (via convolution)


X4
W4
X5
W5
1
W6
X1
W1
X7
W4
X2
W2
Y
W5
X8
W3
1
W6
1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X2
X3
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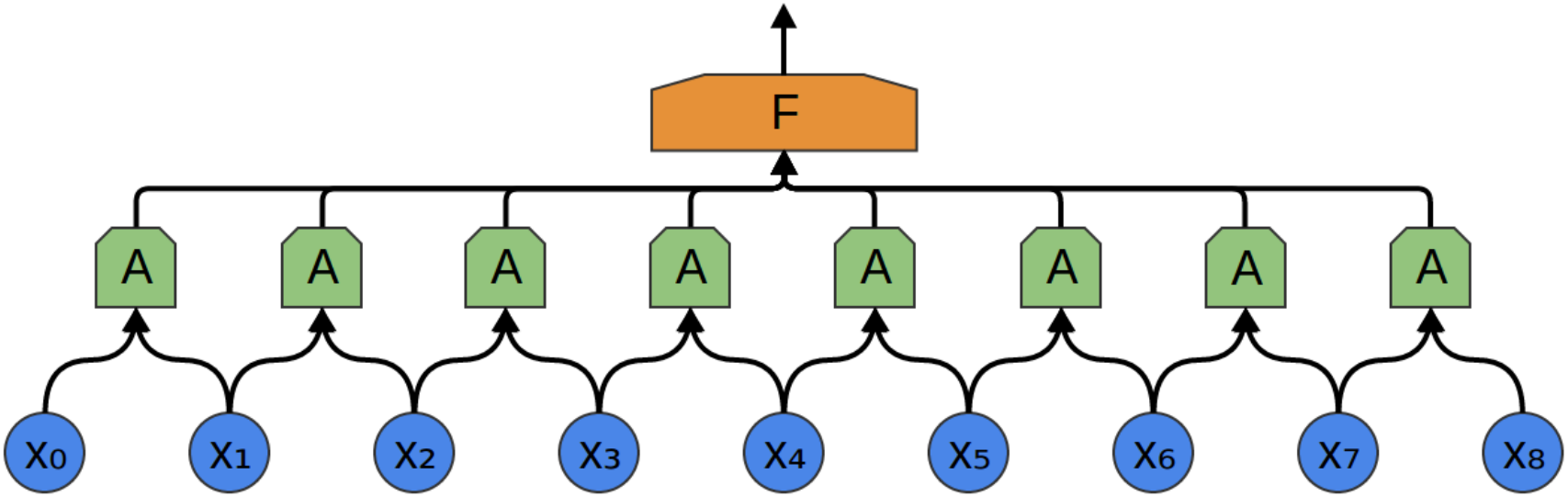
X7
X8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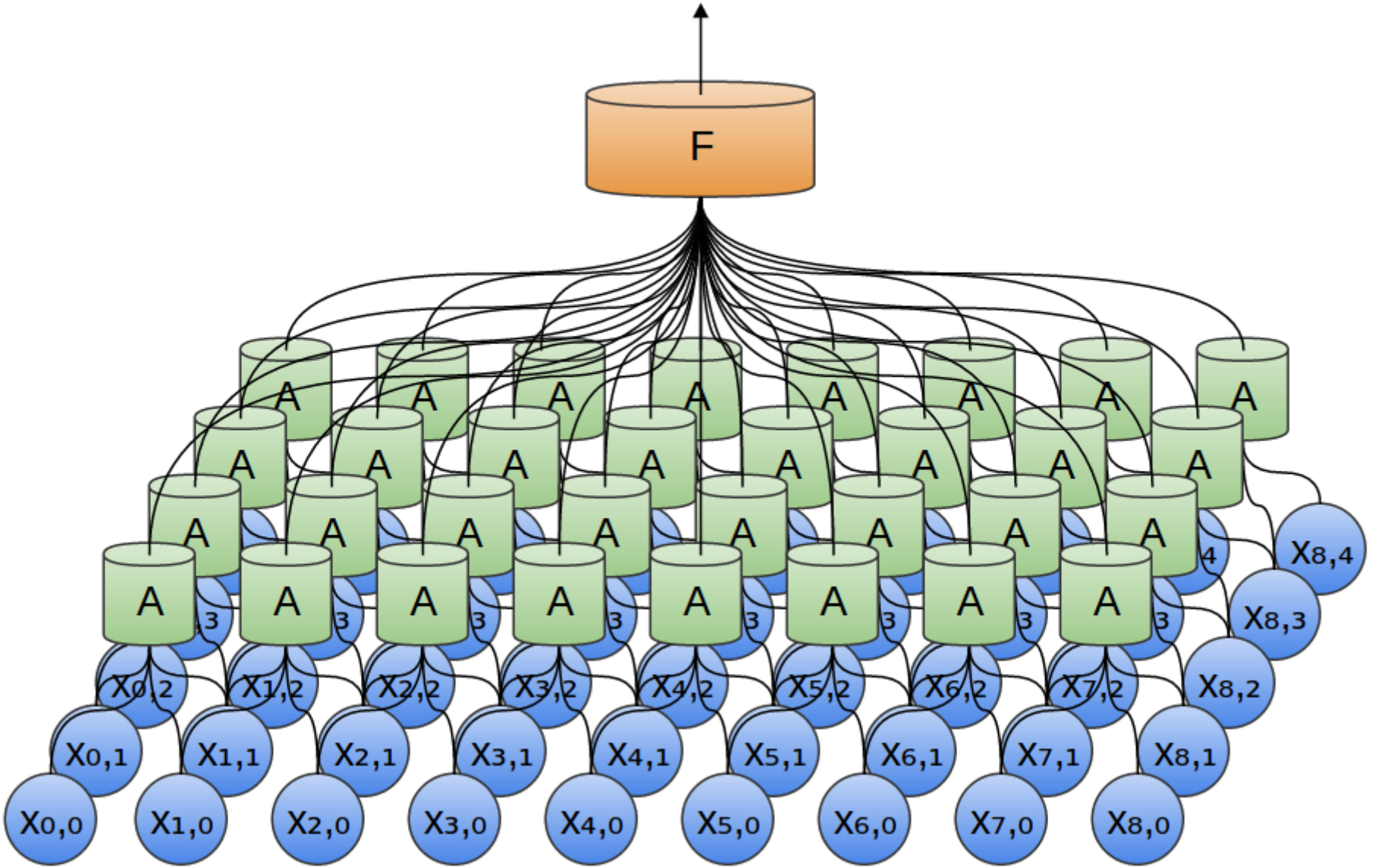
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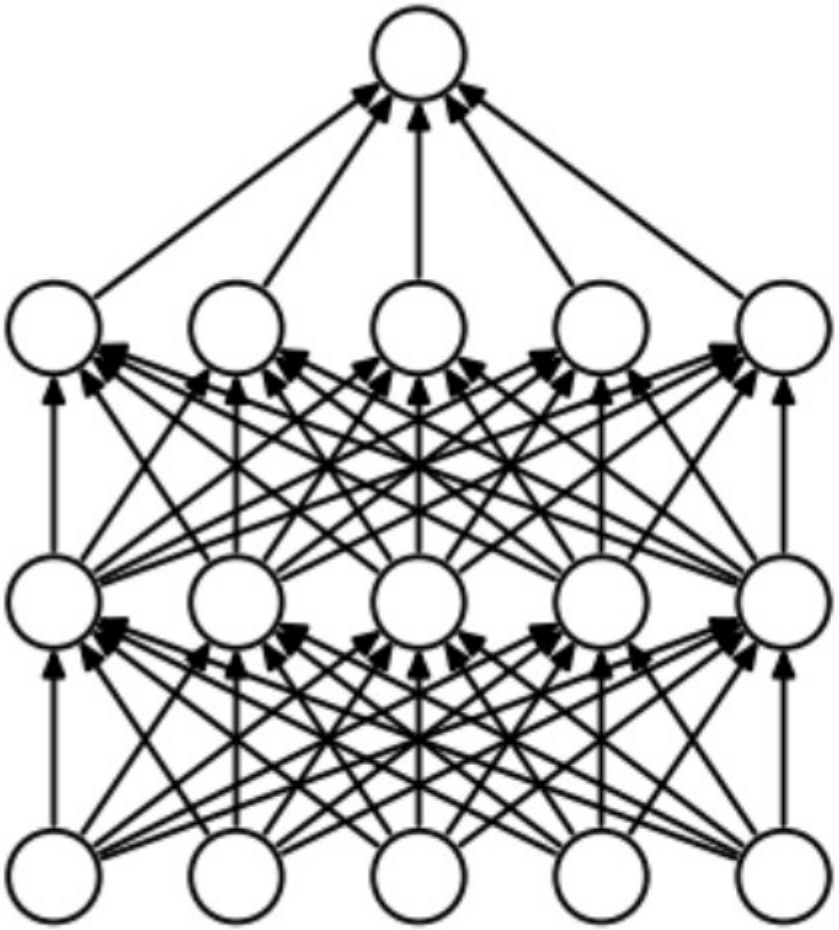
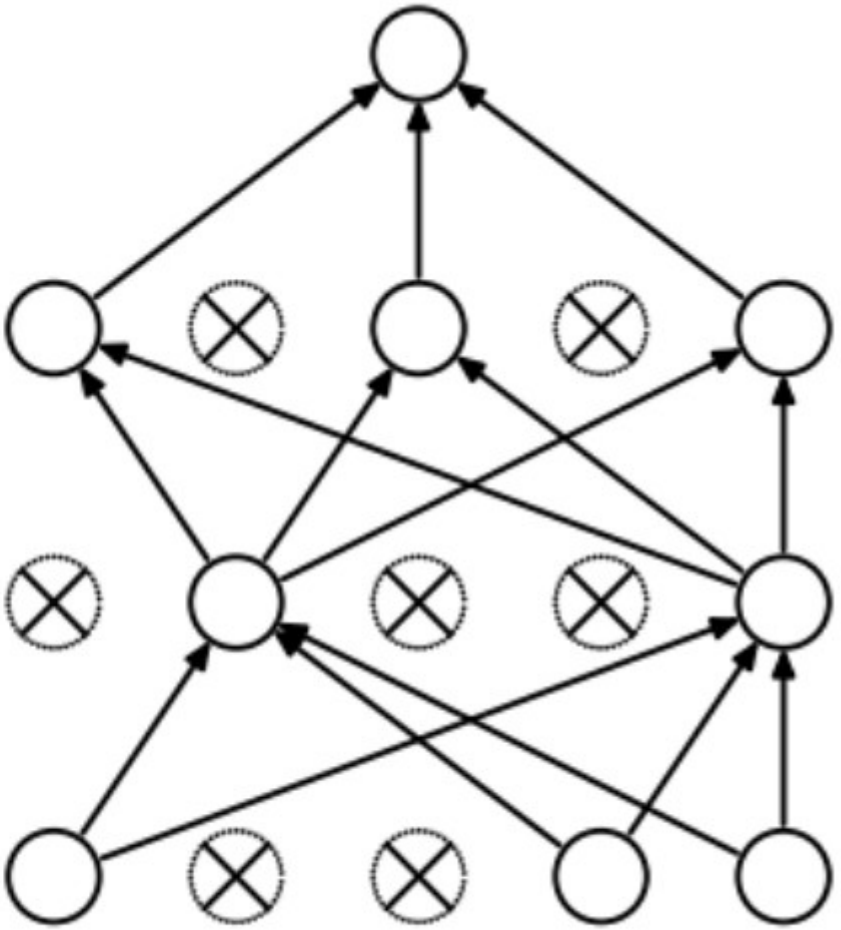
X7,1
X8,1
X0,2
X1,2
X2,2
X3,2
X4,2
X5,2
X6,2
X7,2
X8,2
X8,3
X8,4

Dropout



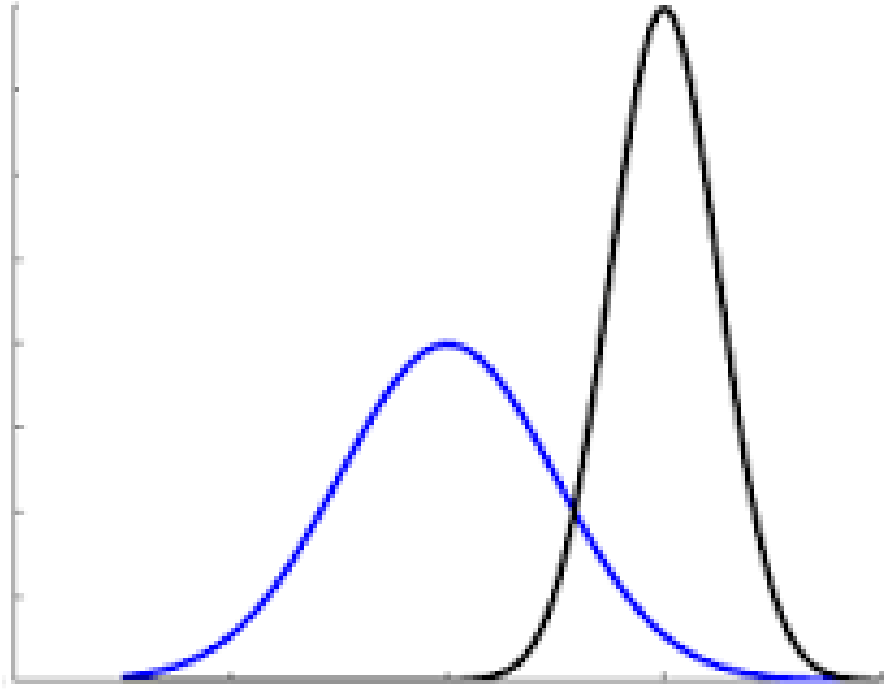
(a) Standard Neural Net



(b) After applying dropout.

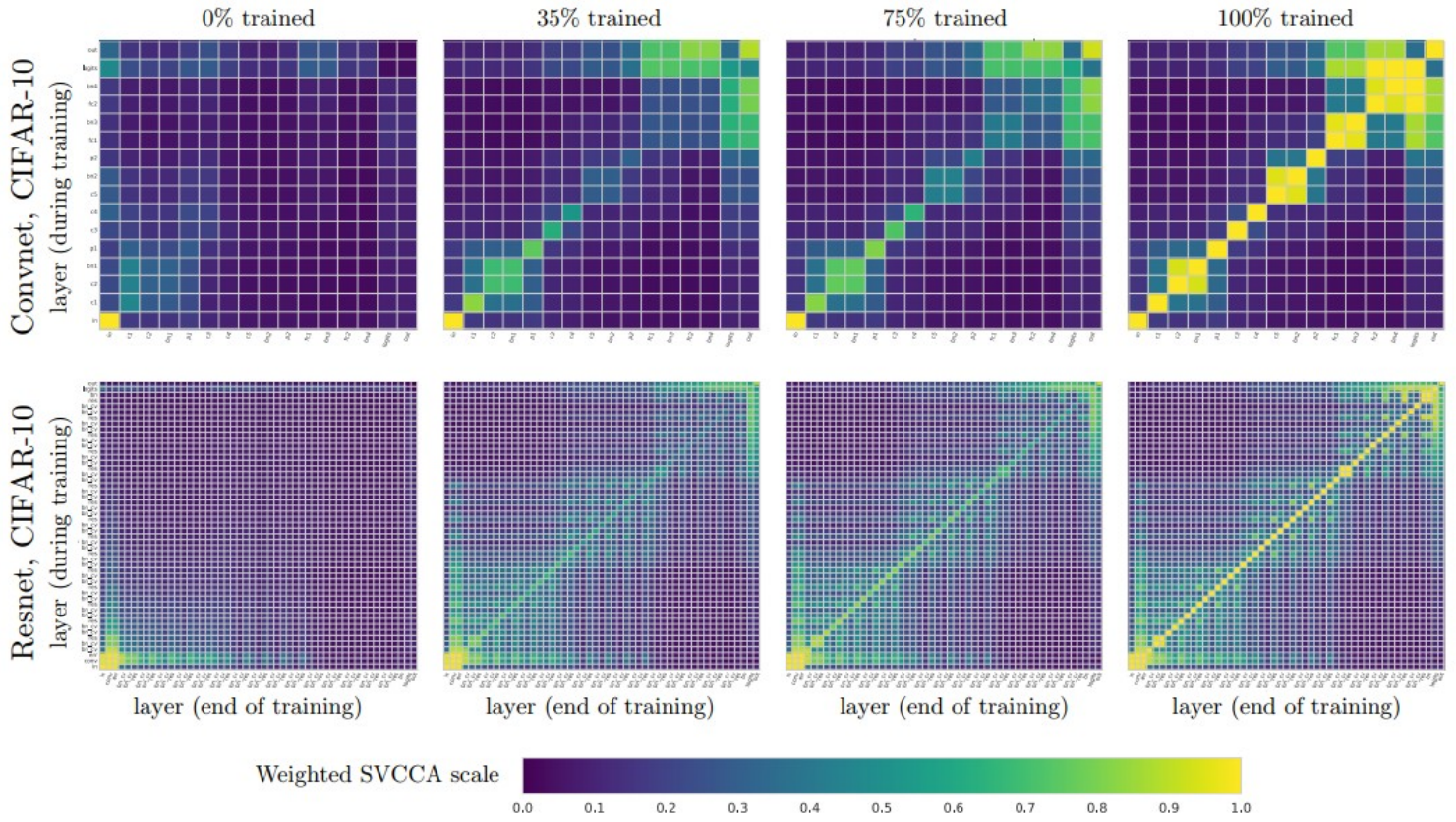
Batch Normalization

Internal Covariate Shift



SVCCA: Singular Vector Canonical Correlation Analysis for Deep Learning Dynamics and Interpretability

Maithra Raghu,[1,2] **Justin Gilmer,**[1] **Jason Yosinski,**[3] **& Jascha Sohl-Dickstein**[1]
[1]Google Brain [2]Cornell University [3]Uber AI Labs
maithrar@gmail.com, gilmer@google.com, yosinski@uber.com, jaschasd@google.com



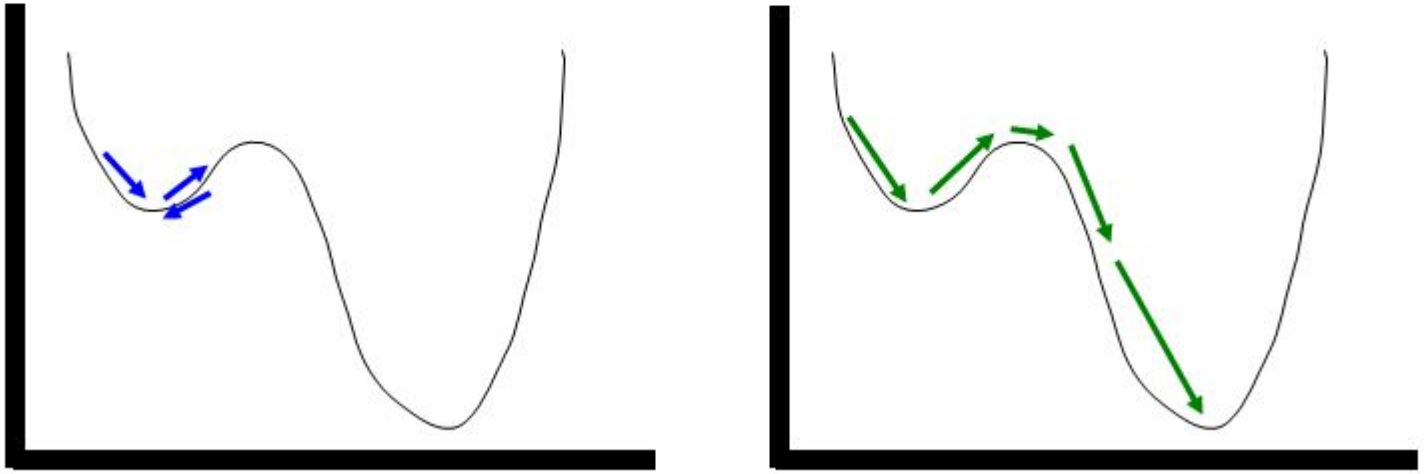
1. compute the empirical mean and variance independently for each dimension.

2. Normalize

$$\widehat{x}^{(k)} = \frac{x^{(k)} - \mathrm{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$

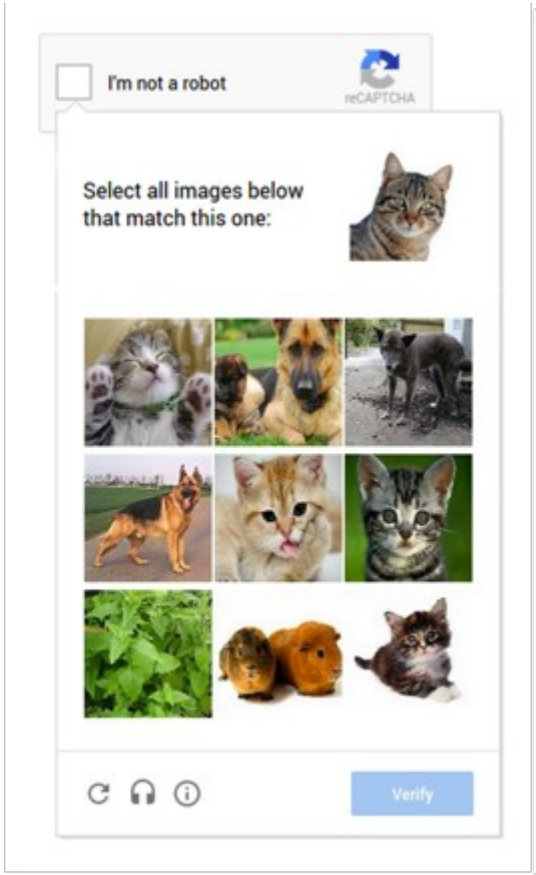
Momentum

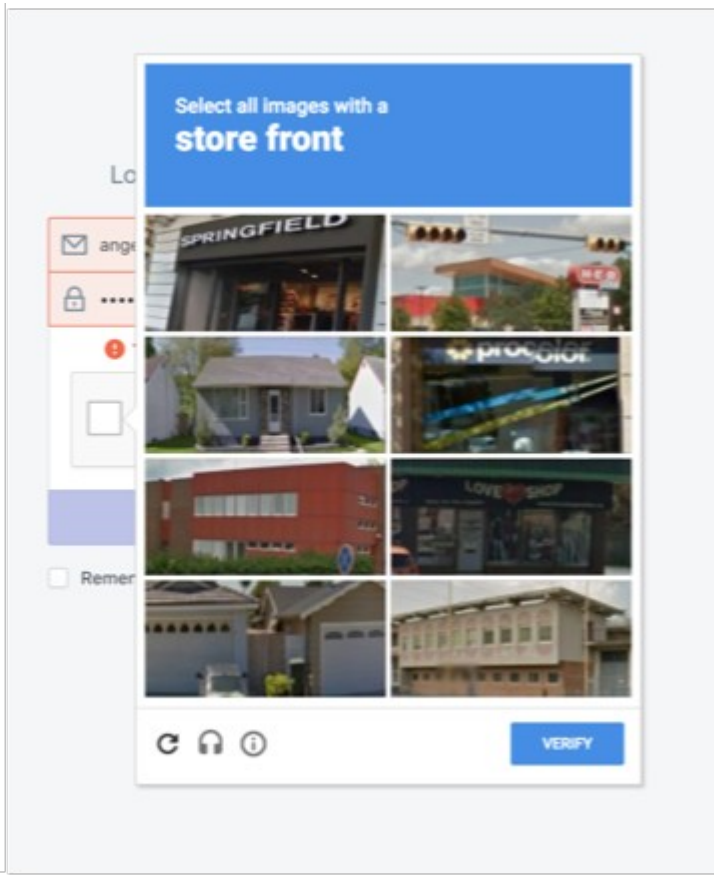
$$\Delta w_{ij}(k) = -\eta \nabla E + \beta \cdot \Delta w_{ij}(k-1)$$



Big Data


I'm not a robot
reCAPTCHA
Type the text
250
Verify


I'm not a robot
reCAPTCHA
Select all images below
that match this one:
Verify


Select all images with a
store front
SPRINGFIELD
VERIFY

ImageNet Challenge

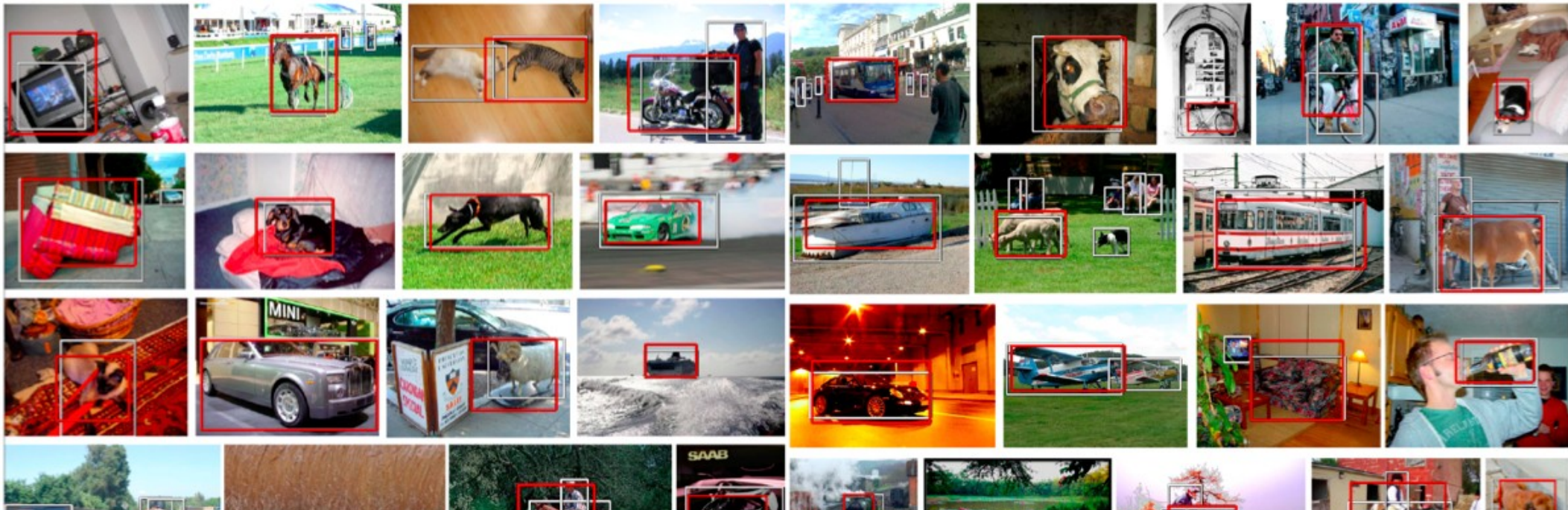
IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.

Visual Object Classes Challenge 2009 (VOC2009)

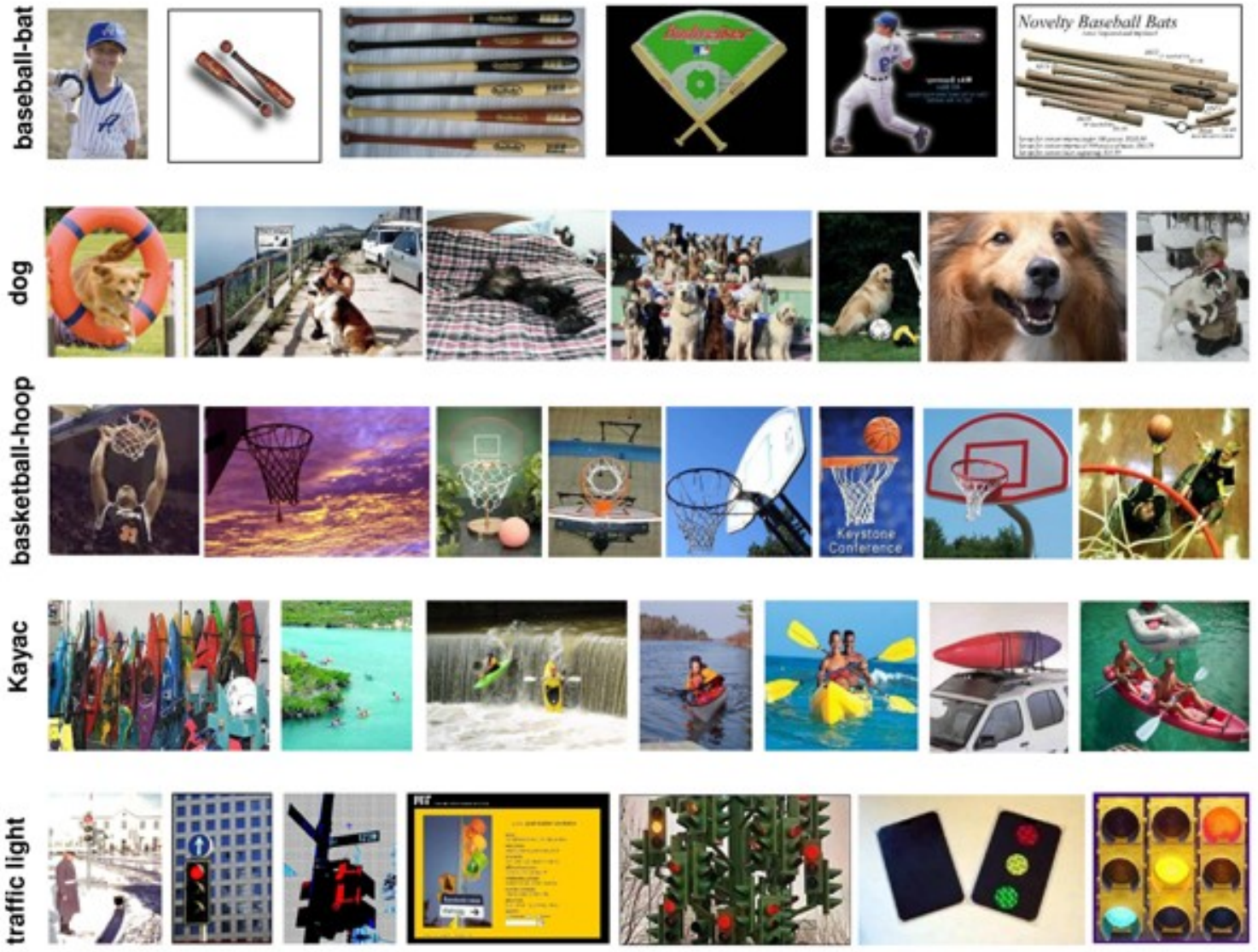
PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

20 classes. The train/val data has 11,530 images containing 27,450 ROI annotated objects and 6,929 segmentations.



Caltech 256

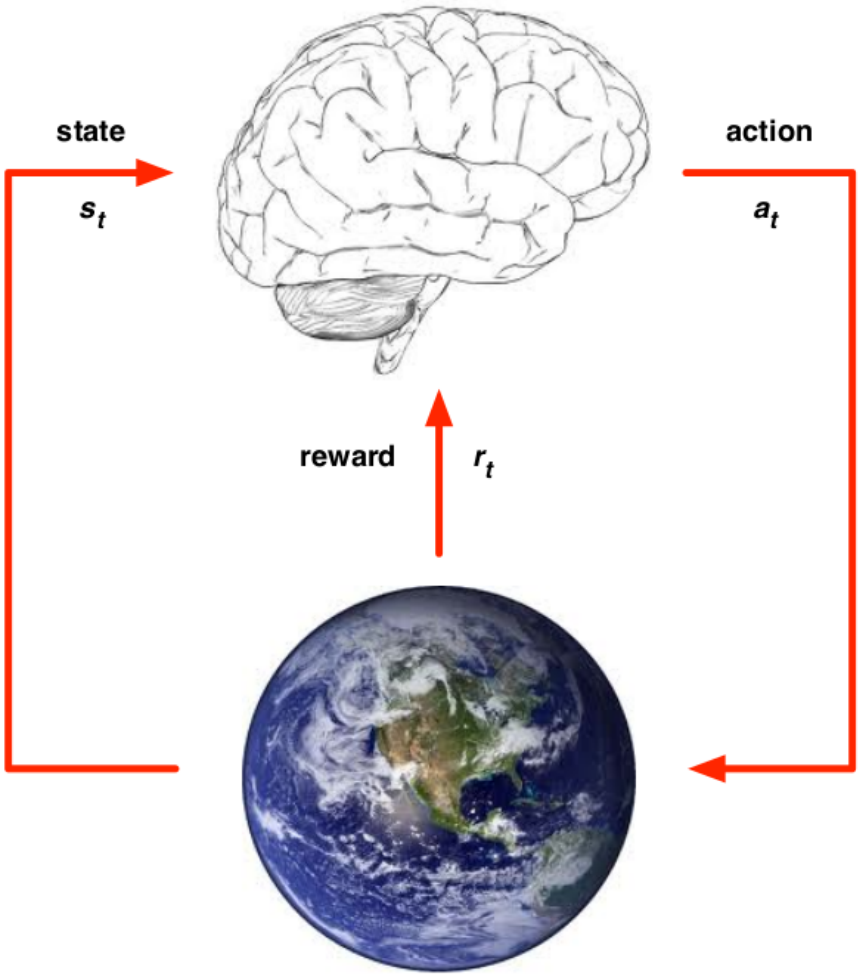
(256 object categories, 30607 images)



Deep Reinforcement Learning

David Silver, Google DeepMind

Agent and Environment



- At each step t the agent:
  - Receives state s_t
  - Receives scalar reward r_t
  - Executes action a_t
- The environment:
  - Receives action a_t
  - Emits state s_t
  - Emits scalar reward r_t

Approaches To Reinforcement Learning

Policy-based RL

- Search directly for the optimal policy π^*
- This is the policy achieving maximum future reward

Value-based RL

- Estimate the optimal value function $Q^*(s, a)$
- This is the maximum value achievable under any policy

Model-based RL

- Build a transition model of the environment
- Plan (e.g. by lookahead) using model

Deep Reinforcement Learning

- Can we apply deep learning to RL?
- Use deep network to represent value function / policy / model
- Optimise value function / policy /model end-to-end
- Using stochastic gradient descent

learning value networks

Bellman Equation

- Value function can be unrolled recursively

$$\begin{aligned} Q^{\pi}(s,a) &= \mathbb{E}\left[r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots \mid s, a\right] \\ &= \mathbb{E}_{s'}\left[r + \gamma Q^{\pi}(s', a') \mid s, a\right] \end{aligned}$$

- Optimal value function $Q^*(s,a)$ can be unrolled recursively

$$Q^*(s,a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q^*(s', a') \mid s, a\right]$$

- Value iteration algorithms solve the Bellman equation

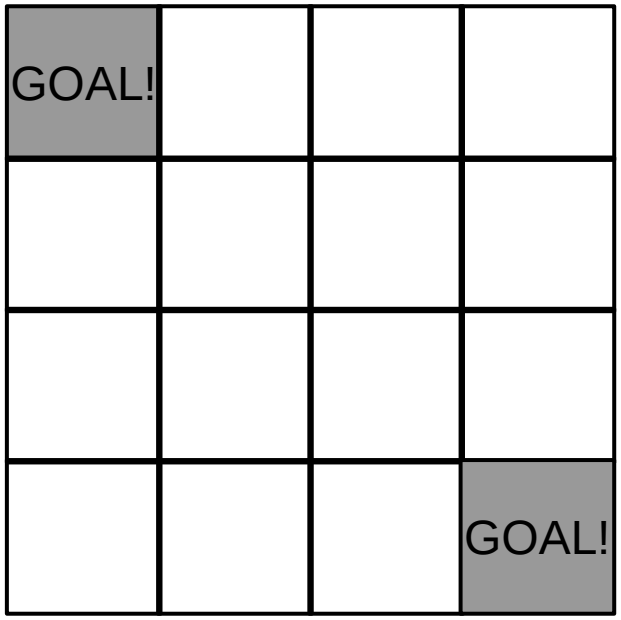
$$Q_{i+1}(s,a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q_i(s', a') \mid s, a\right]$$

grid world:

each timestep has -1 reward

the game terminates when
you reach a goal state

actions: N, S, E, W



intuitive description: “get to the goal as soon as possible”
(but let's pretend we're a robot, who doesn't know this!)

each value function (V) is defined
with respect to some behavioral policy (π)

V^{π}

let's iteratively find V^{π} for a random policy
in our mini grid world

current value (V_k) for a random policy

k=0

0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0

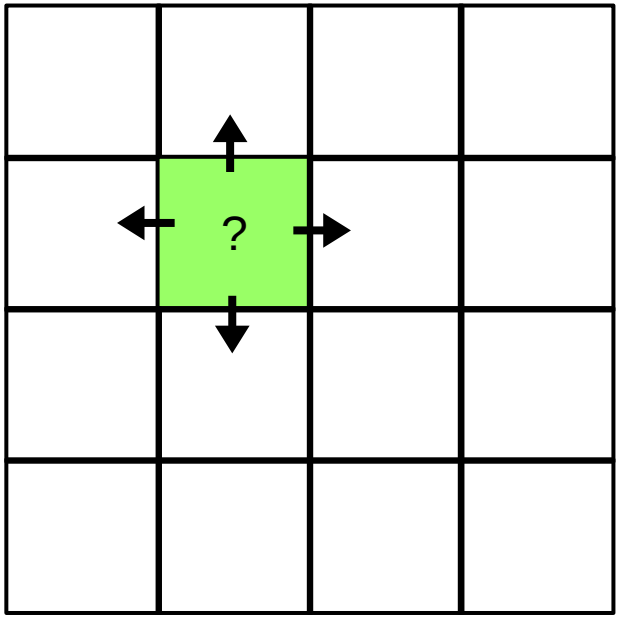
k=1

current value (V_k) for a random policy

k=0

0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0

k=1

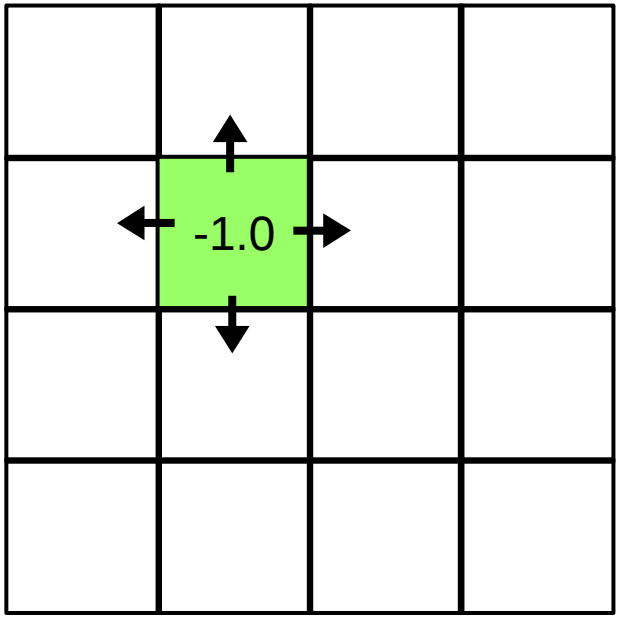


current value (V_k) for a random policy

k=0

0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0

k=1



current prediction for cumulative reward in new state

immediate reward

N: $V_{s,N} = -1 + 0 = -1$

S: $V_{s,S} = -1 + 0 = -1$

E: $V_{s,E} = -1 + 0 = -1$

W: $V_{s,W} = -1 + 0 = -1$

with a random policy,
we are equally likely to take any move,
so:

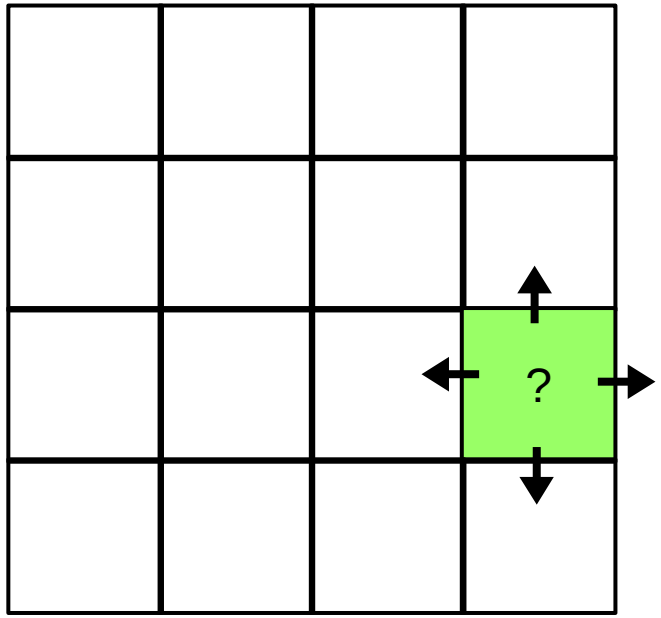
$V_s = (-1 + -1 + -1 + -1)/4 = -1$

current value (V_k) for a random policy

k=0

0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0

k=1



current value (V_k) for a random policy

k=0

0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0

k=1

			-1.0

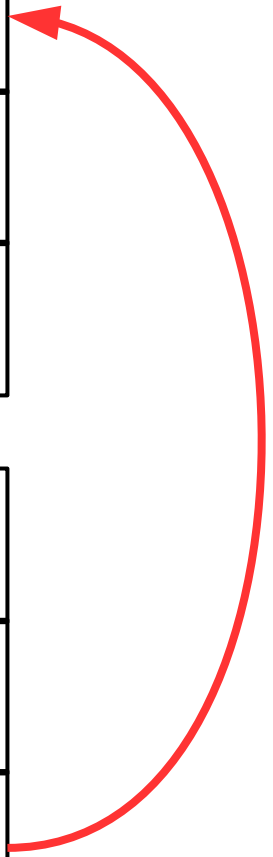
current value (V_k) for a random policy

k=0

0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0

k=1

0.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	0.0



next iteration…
new value function
becomes
old value function
(“current prediction
for cumulative reward”)

current value (V_k) for a random policy

k=1

0.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	0.0

k=2

current value (V_k) for a random policy

k=1

0.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	0.0

k=2

	-1.75		

N: $V_{s,N} = -1 + -1 = -2$
S: $V_{s,S} = -1 + -1 = -2$
E: $V_{s,E} = -1 + 0 = -1$
W: $V_{s,W} = -1 + -1 = -2$

$V_s = (-2 + -2 + -1 + -2)/4 = -1.75$

current value (V_k) for a random policy

k=1

0.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	0.0

k=2

0.0	-1.75	-2.0	-2.0
-1.75	-2.0	-2.0	-2.0
-2.0	-2.0	-2.0	-1.75
-2.0	-2.0	-1.75	0.0

current value (V_k) for a random policy

k=2

0.0	-1.75	-2.0	-2.0
-1.75	-2.0	-2.0	-2.0
-2.0	-2.0	-2.0	-1.75
-2.0	-2.0	-1.75	0.0

k=3

0.0	-2.4	-2.9	-3.0
-2.4	-2.9	-3.0	-2.9
-2.9	-3.0	-2.9	-2.4
-3.0	-2.9	-2.4	0.0

current value (V_k) for a random policy

k=10

0.0	-6.1	-8.4	-9.0
-6.1	-7.7	-8.4	-8.4
-8.4	-8.4	-7.7	-6.1
-9.0	-8.4	-6.1	0.0

k=∞

0.0	-14	-20	-22
-14	-18	-20	-20
-20	-20	-18	-14
-22	-20	-14	0.0

converged to true value function ($V^{\pi\text{-random}}$)