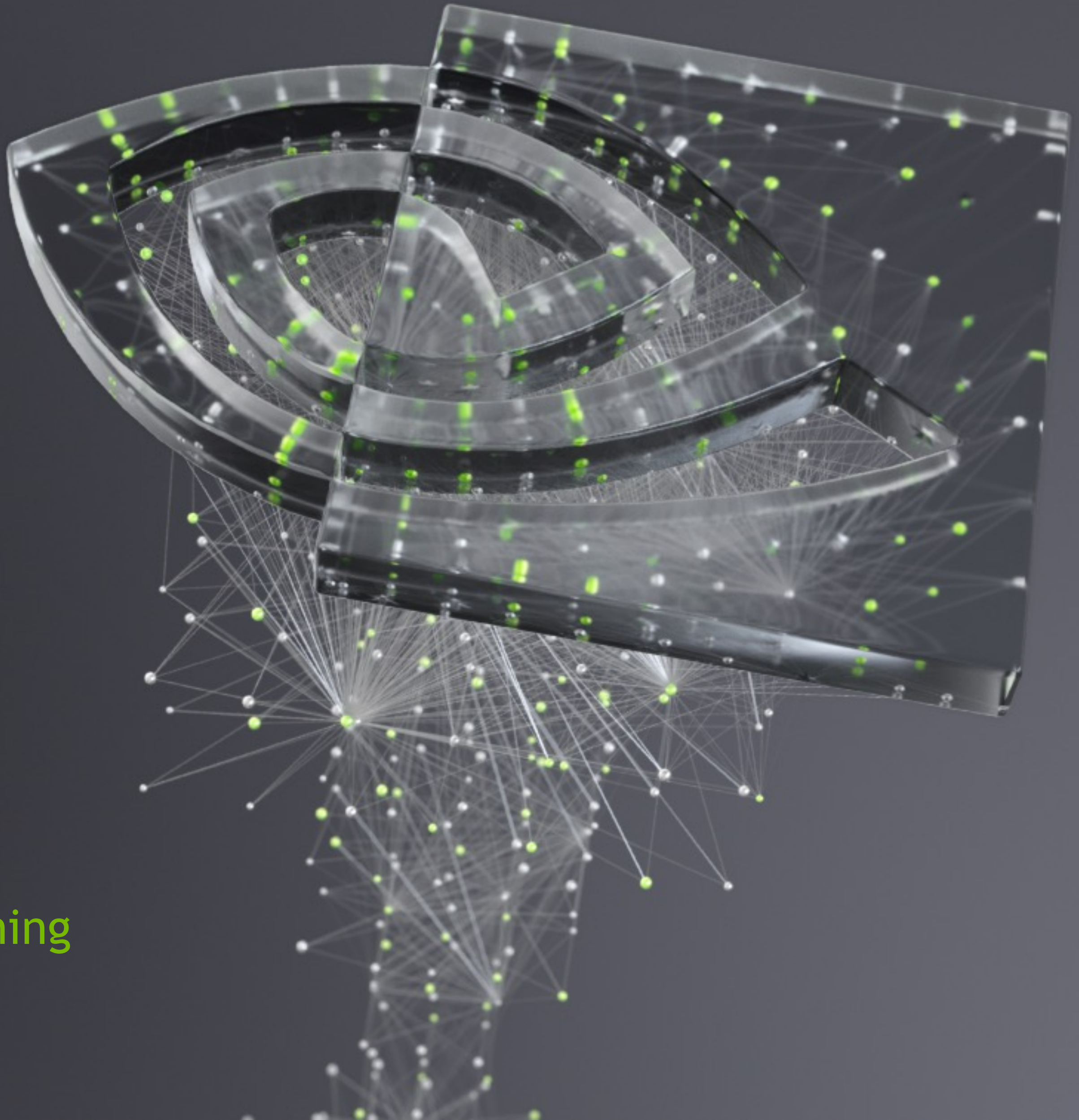
NVIDIA

DEEP LEARNING INSTITUTE

FUNDAMENTALS OF DEEP LEARNING

Part 1: An Introduction to Deep Learning



To see lecture notes, make full screen and click the “notes” button

WELCOME!

THE GOALS OF THIS COURSE

- Get you up and on your feet quickly
- Build a foundation to tackle a deep learning project right away
- We won't cover the whole field, but we'll get a great head start
- Foundation from which to read articles, follow tutorials, take further classes

AGENDA

- Part 1: An Introduction to Deep Learning
- Part 2: How a Neural Network Trains
- Part 3: Convolutional Neural Networks
- Part 4: Data Augmentation and Deployment
- Part 5: Pre-trained Models
- Part 6: Advanced Architectures

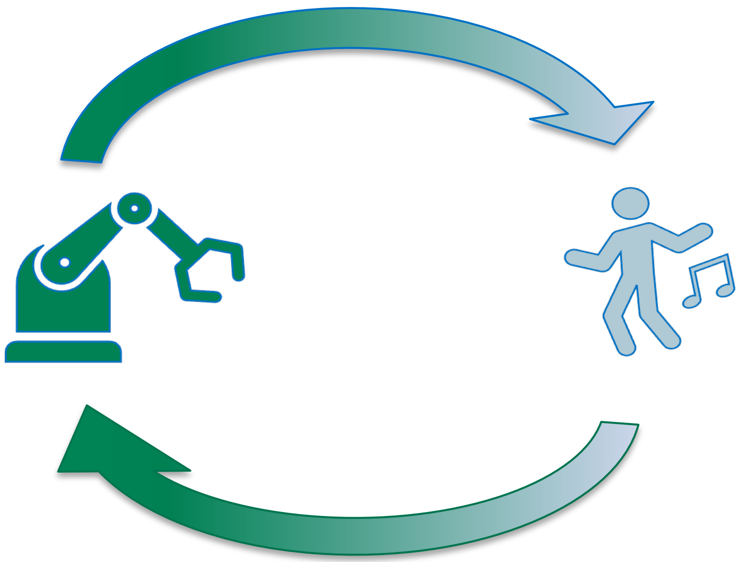
AGENDA – PART 1

- History of AI
- The Deep Learning Revolution
- What is Deep Learning
- How Deep Learning is Transforming the World
- Overview of the Course
- First Exercise

HAVE FUN!

HUMAN VS MACHINE LEARNING

Relaxed Alertness



Human	Machine
Rest and Digest	Training
Fight-or-flight	Prediction

LET’S GET STARTED

HISTORY OF AI

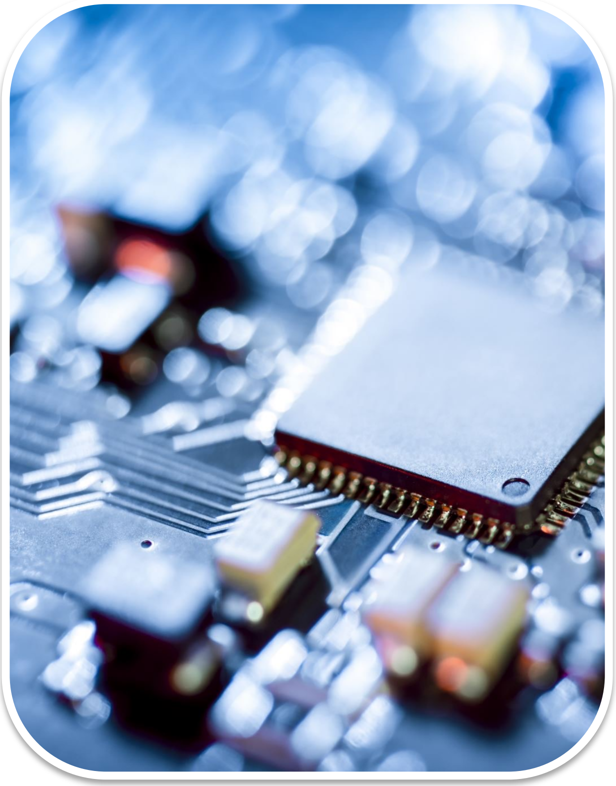
BEGINNING OF ARTIFICIAL INTELLIGENCE

COMPUTERS ARE MADE IN PART TO COMPLETE HUMAN TASKS

EARLY ON, GENERALIZED INTELLIGENCE LOOKED POSSIBLE

TURNED OUT TO BE HARDER THAN EXPECTED

EARLY NEURAL NETWORKS



Inspired by biology

Created in the 1950's

Outclassed by Von Neumann Architecture

EXPERT SYSTEMS

Highly complex

Programmed by hundreds of engineers

Rigorous programming of many rules

EXPERT SYSTEMS - LIMITATIONS

What are these three images?

HOW DO CHILDREN LEARN?

- Expose them to lots of data
- Give them the “correct answer”
- They will pick up the important patterns on their own

THE DEEP LEARNING REVOLUTION

DATA

- Networks need a lot of information to learn from
- The digital era and the internet has supplied that data

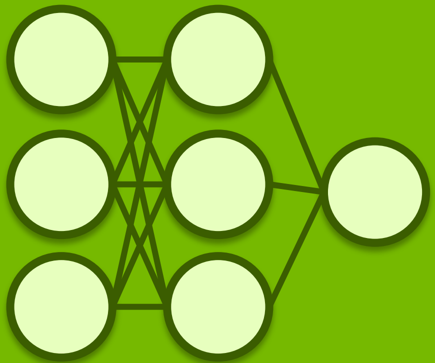
COMPUTING POWER

Need a way for our artificial “brain” to observe lots of data within a practical amount of time.

THE IMPORTANCE OF THE GPU

A Rendered Image

A Neural Network



WHAT IS DEEP LEARNING?

DEEP LEARNING FLIPS TRADITIONAL PROGRAMMING ON ITS HEAD

TRADITIONAL PROGRAMMING

Building a Classifier

1. Define a set of rules for classification
2. Program those rules into the computer
3. Feed it examples, and the program uses the rules to classify

MACHINE LEARNING

Building a Classifier

1

Show model the examples with the answer of how to classify

2

Model takes guesses, we tell it if it's right or not

3

Model learns to correctly categorize as it's training. The system learns the rules on its own

THIS IS A FUNDAMENTAL SHIFT

WHEN TO CHOOSE DEEP LEARNING

Classic Programming

If rules are clear and straightforward, often better to just program it

Deep Learning

If rules are nuanced, complex, difficult to discern, use deep learning

DEEP LEARNING COMPARED TO OTHER AI

- Depth and complexity of networks
- Up to billions of parameters (and growing)
- Many layers in a model
- Important for learning complex rules

HOW DEEP LEARNING IS TRANSFORMING THE WORLD

COMPUTER VISION

ROBOTICS AND MANUFACTURING

OBJECT DETECTION

SELF DRIVING CARS

NATURAL LANGUAGE PROCESSING

REAL TIME TRANSLATION

VOICE RECOGNITION

VIRTUAL ASSISTANTS

RECOMMENDER SYSTEMS

CONTENT CURATION

TARGETED ADVERTISING

SHOPPING RECOMMENDATIONS

REINFORCEMENT LEARNING

ALPHAGO BEATS WORLD CHAMPION IN GO

AI BOTS BEAT PROFESSIONAL VIDEOGAMERS

STOCK TRADING ROBOTS

OVERVIEW OF THE COURSE

HANDS ON EXERCISES

- Get comfortable with the process of deep learning
- Exposure to different models and datatypes
- Get a jump-start to tackle your own projects

STRUCTURE OF THE COURSE

- "Hello World" of Deep Learning
- Train a more complicated model
- New architectures and techniques to improve performance
- Pre-trained models
- Transfer learning

PLATFORM OF THE COURSE

- GPU powered cloud server
- JupyterLab platform
- Jupyter notebooks for interactive coding

SOFTWARE OF THE COURSE

- Major deep learning platforms:
  - TensorFlow + Keras (Google)
  - Pytorch (Facebook)
  - MXNet (Apache)
- We’ll be using TensorFlow and Keras
- Good idea to gain exposure to others moving forward

FIRST EXERCISE: CLASSIFY HANDWRITTEN DIGITS

HELLO NEURAL NETWORKS

Train a network to correctly classify handwritten digits

- Historically important and difficult task for computers

Try learning like a Neural Network

- Get exposed to the example, and try to figure out the rules to how it works

LET’S GO!

NVIDIA

DEEP
LEARNING
INSTITUTE

NVIDIA | DEEP LEARNING INSTITUTE

FUNDAMENTALS OF DEEP LEARNING

Part 2: How a Neural Network Trains

Part 1: An Introduction to Deep Learning

Part 2: How a Neural Network Trains

Part 3: Convolutional Neural Networks

Part 4: Data Augmentation and Deployment

Part 5: Pre-trained Models

Part 6: Advanced Architectures

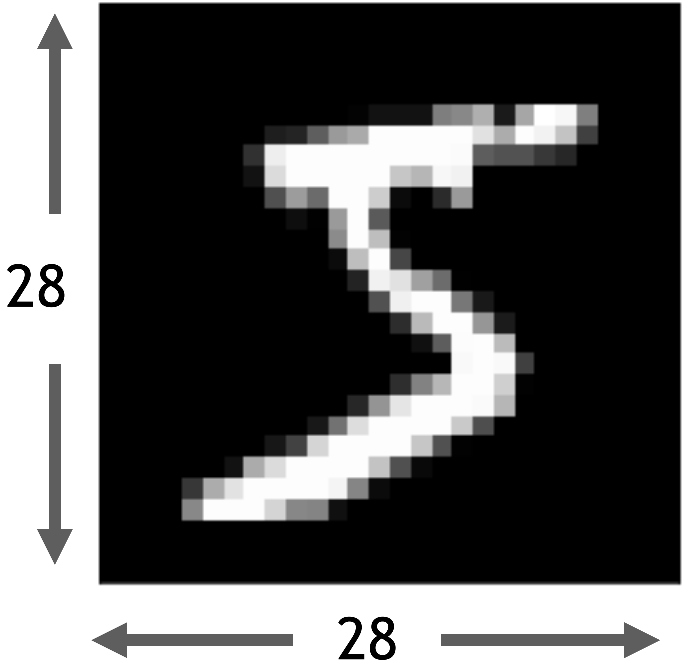
RECAP OF THE EXERCISE

What just happened?

1. Loaded and visualized our data
2. Edited our data (reshaped, normalized, to categorical)
3. Created our model
4. Compiled our model
5. Trained the model on our data

DATA PREPARATION

Input as an array



[0,0,0,24,75,184,185,78,32,55,0,0,0...]

DATA PREPARATION

Targets as categories

0 → [1,0,0,0,0,0,0,0,0,0]

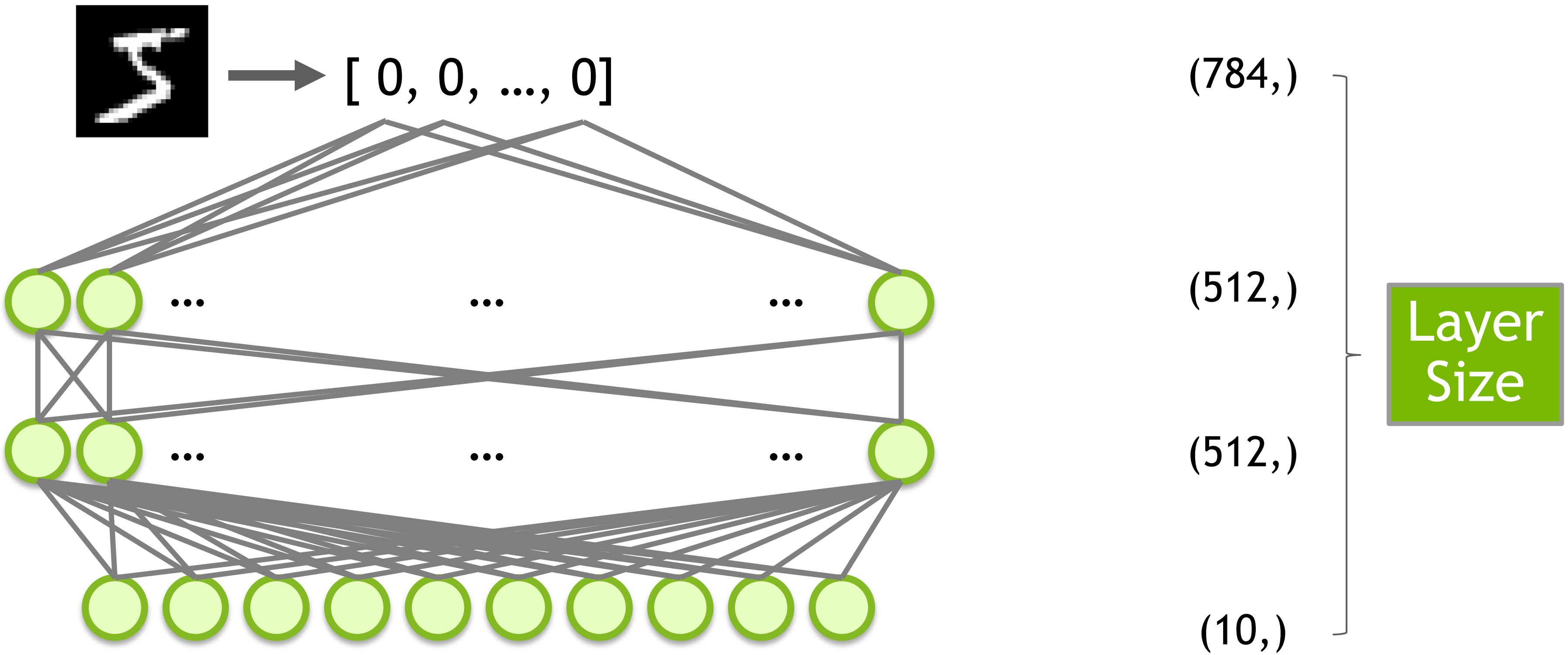
1 → [0,1,0,0,0,0,0,0,0,0]

2 → [0,0,1,0,0,0,0,0,0,0]

3 → [0,0,0,1,0,0,0,0,0,0]

⋮

AN UNTRAINED MODEL

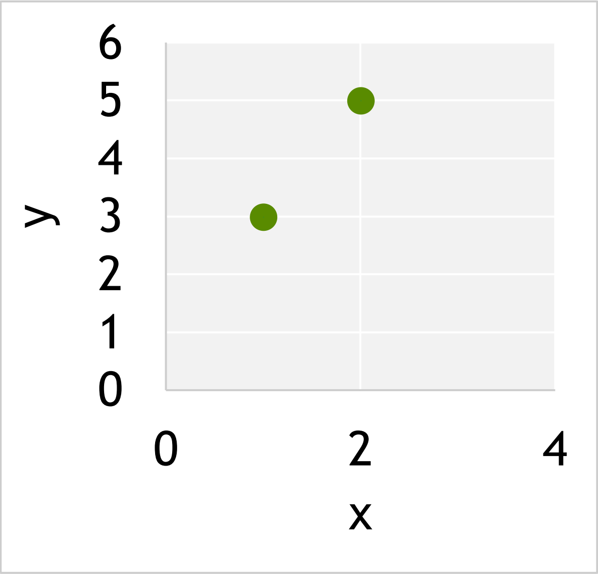


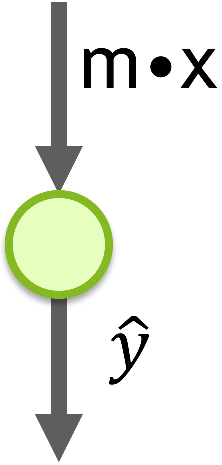
A SIMPLER MODEL

A SIMPLER MODEL

$$y = mx + b$$

x	y
1	3
2	5





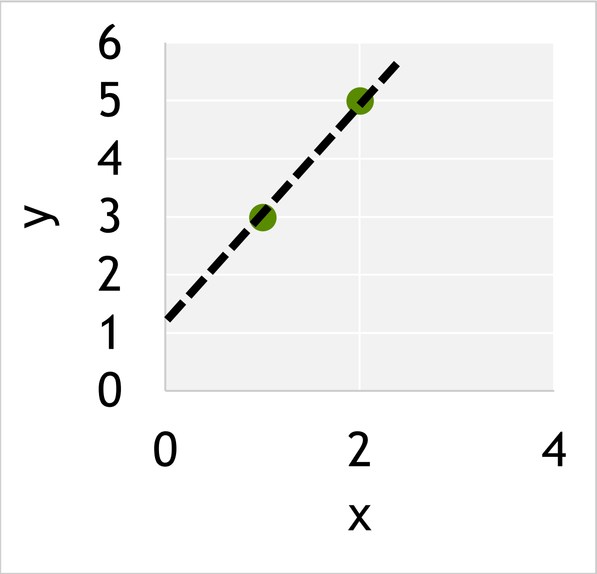
$m = ?$

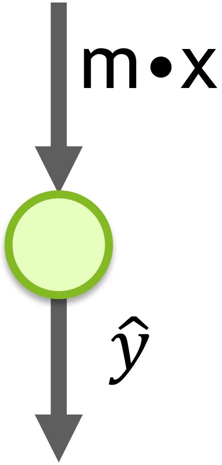
$b = ?$

A SIMPLER MODEL

$$y = mx + b$$

x	y
1	3
2	5





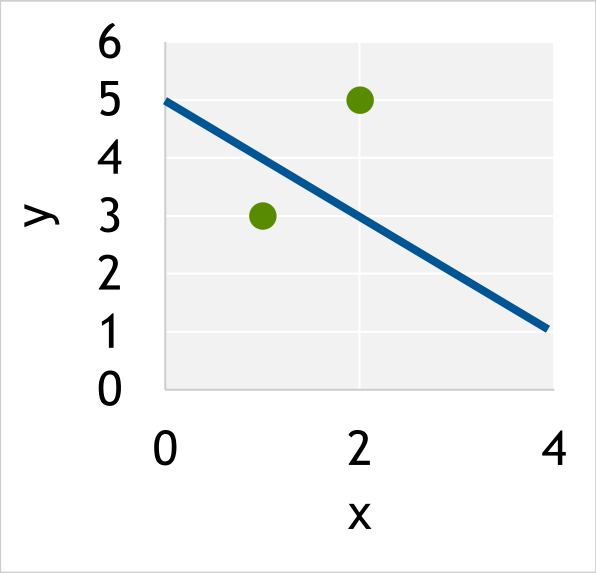
$$m = ?$$

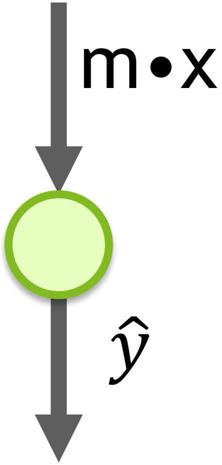
$$b = ?$$

A SIMPLER MODEL

$$y = mx + b$$

x	y	$\hat{y}$
1	3	4
2	5	3





Start Random

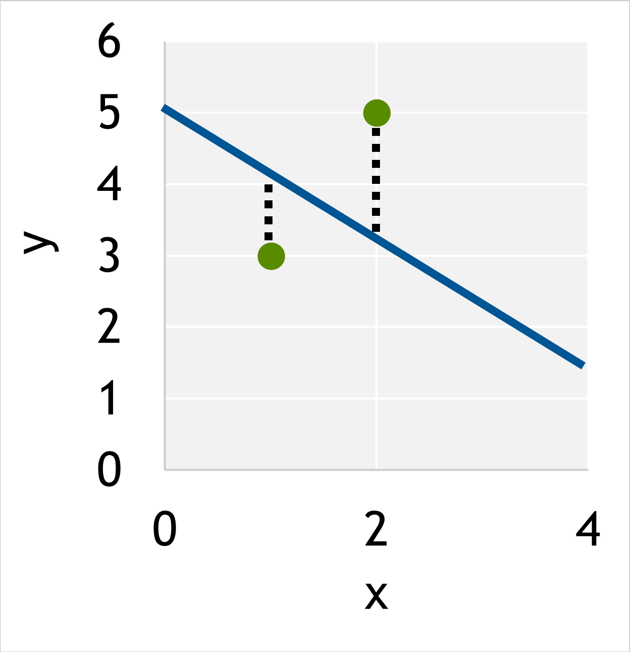
$$m = -1$$

$$b = 5$$

A SIMPLER MODEL

$$y = mx + b$$

x	y	$\hat{y}$	err^2
1	3	4	1
2	5	3	4
		MSE =	2.5
		RMSE =	1.6



$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

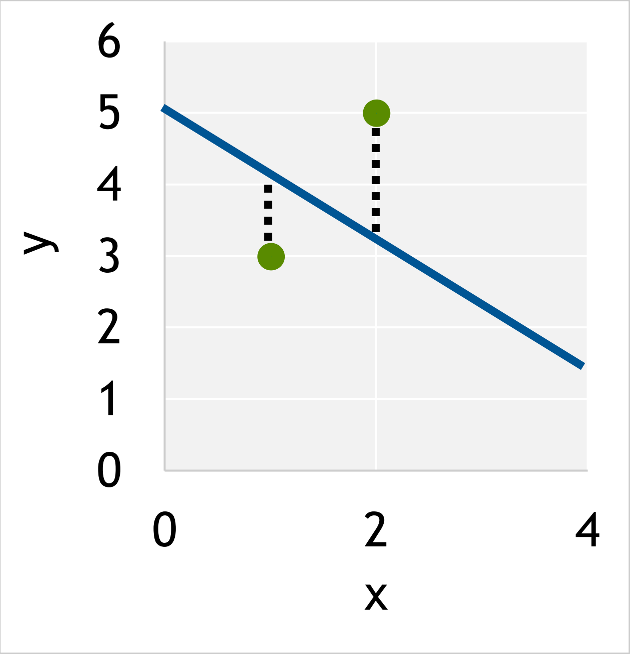
A SIMPLER MODEL

$$y = mx + b$$

x	y	$\hat{y}$	err^2
1	3	4	1
2	5	3	4

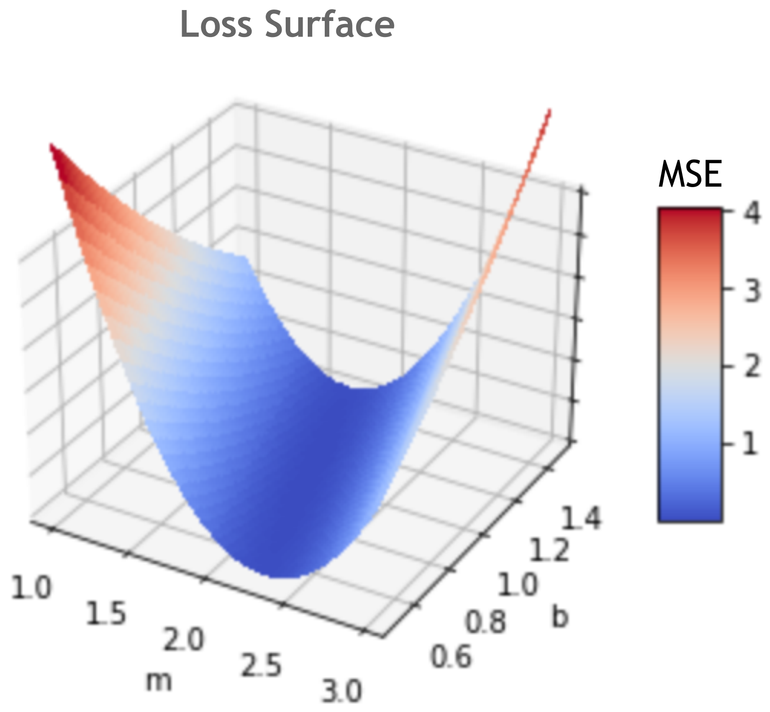
MSE = 2.5

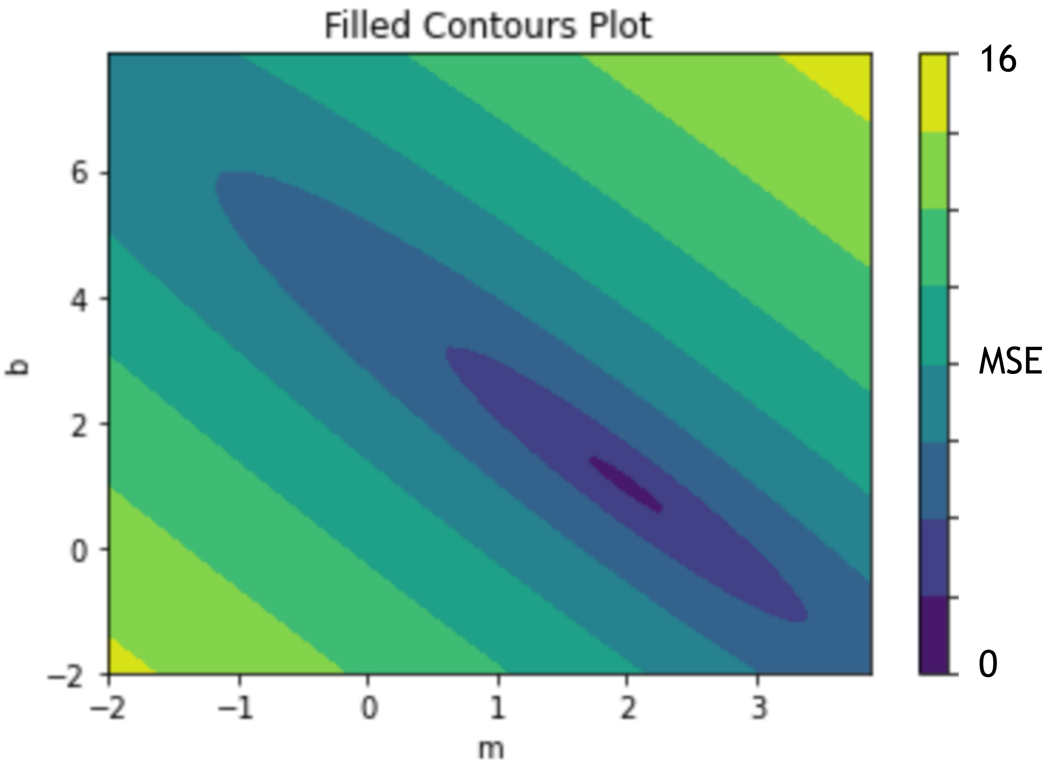
RMSE = 1.6



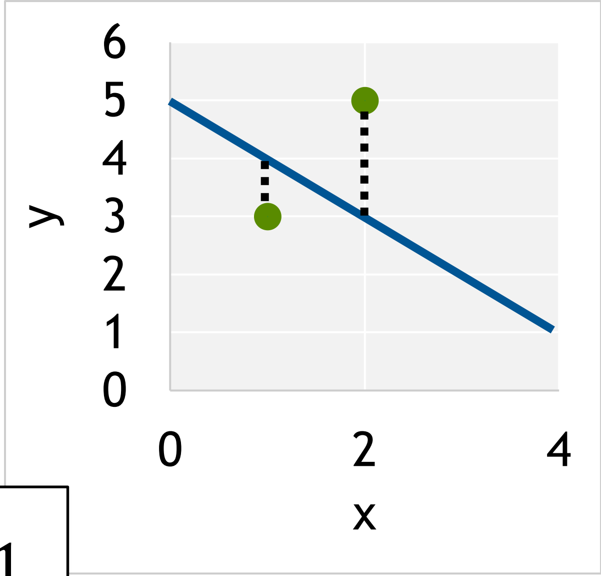

```python
data = [(1, 3), (2, 5)]
m = -1
b = 5


def get_rmse(data, m, b):
    """Calculates Mean Square Error"""
    n = len(data)
    squared_error = 0
    for x, y in data:
        # Find predicted y
        y_hat = m*x+b
        # Square difference between
        # prediction and true value
        squared_error += (
            y - y_hat)**2
    # Get average squared difference
    mse = squared_error / n
    # Square root for original units
    return mse ** .5
```

THE LOSS CURVE



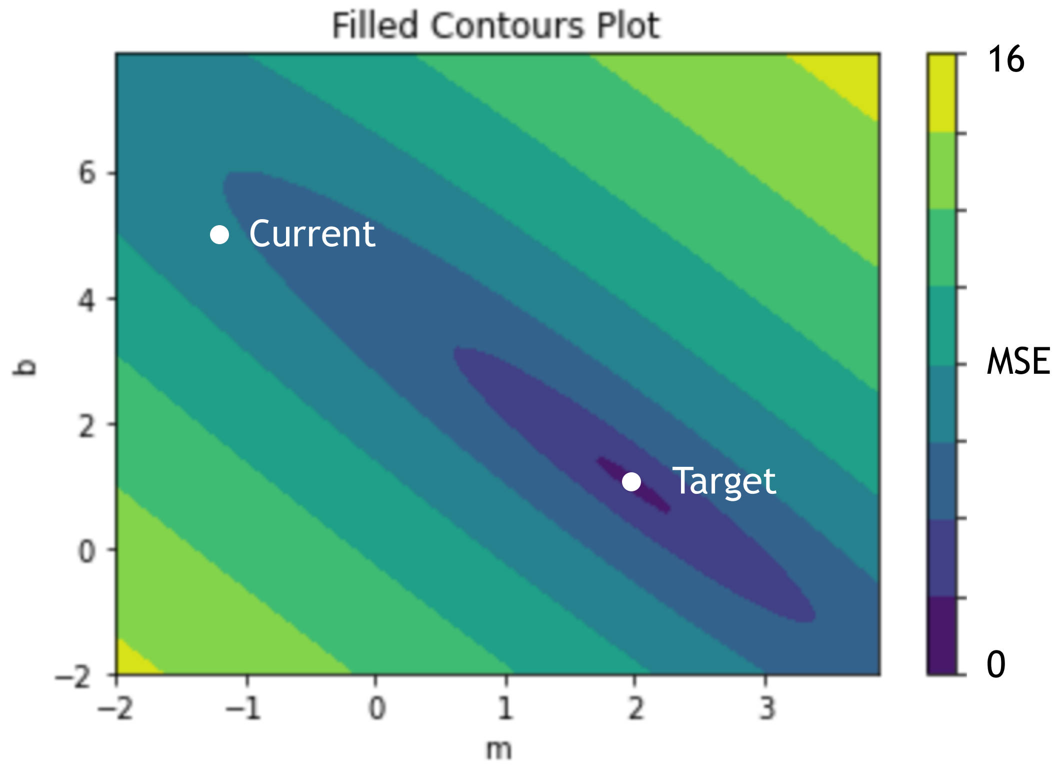


THE LOSS CURVE

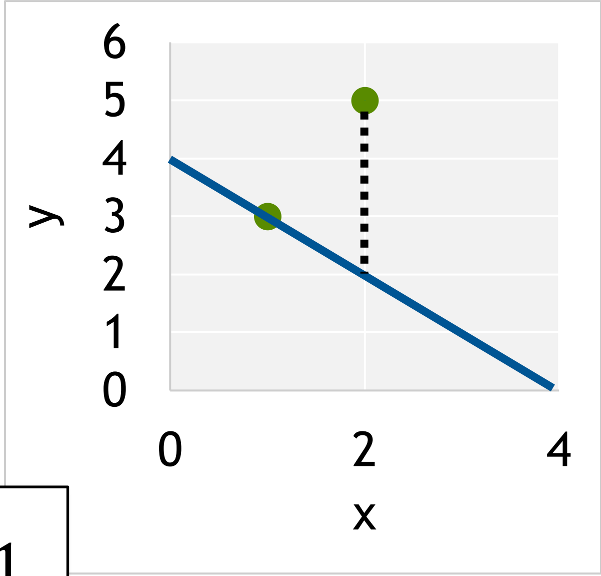


$m = -1$

$\mathrm{b} = 5$

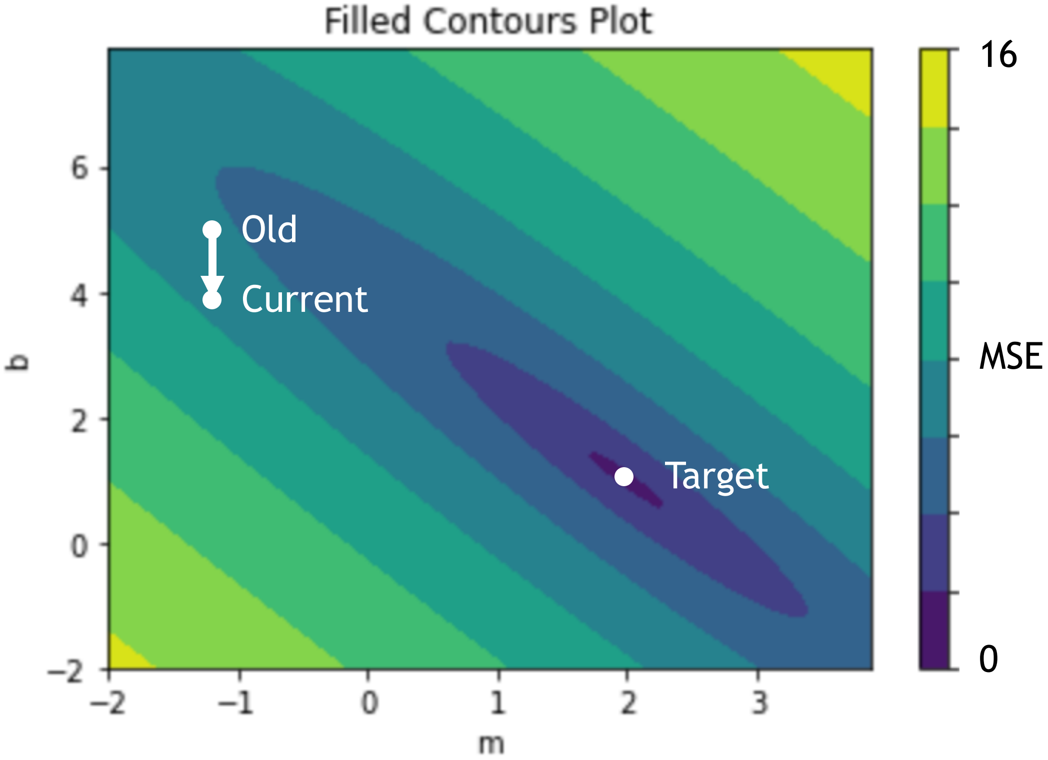


THE LOSS CURVE

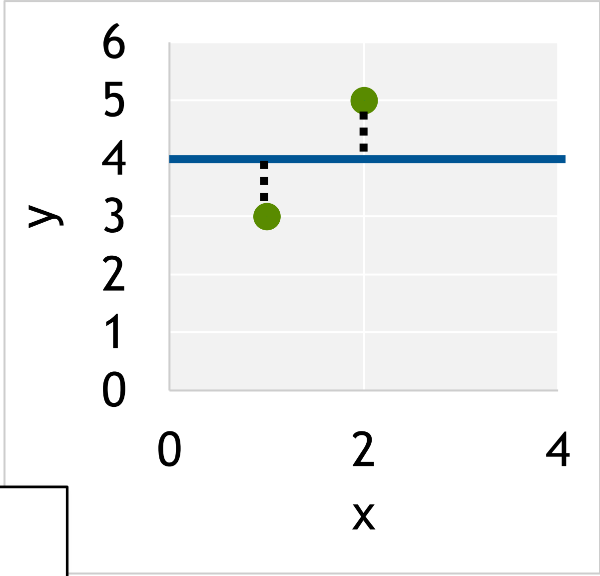


$$m = -1$$

$$\mathrm{b} = 4$$

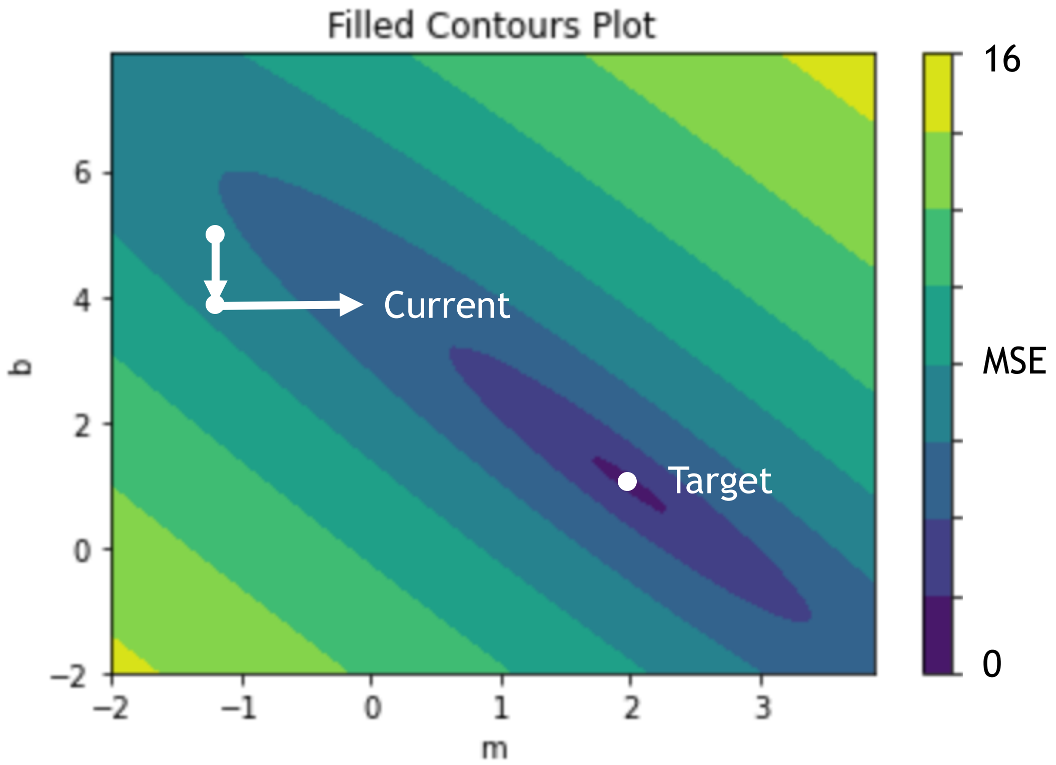


THE LOSS CURVE



$m = 0$

$b = 4$



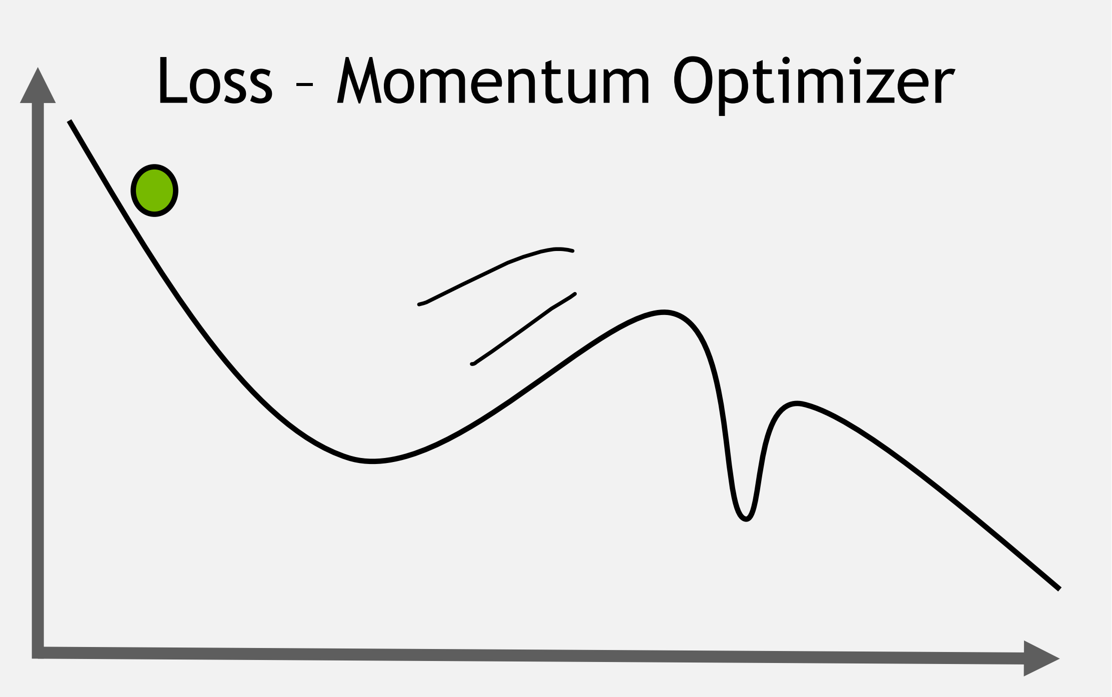
THE LOSS CURVE

The Gradient	Which direction loss decreases the most
λ: The learning rate	How far to travel
Epoch	A model update with the full dataset
Batch	A sample of the full dataset
Step	An update to the weight parameters

THE LOSS CURVE

The Gradient	Which direction loss decreases the most
λ: The learning rate	How far to travel
Epoch	A model update with the full dataset
Batch	A sample of the full dataset
Step	An update to the weight parameters

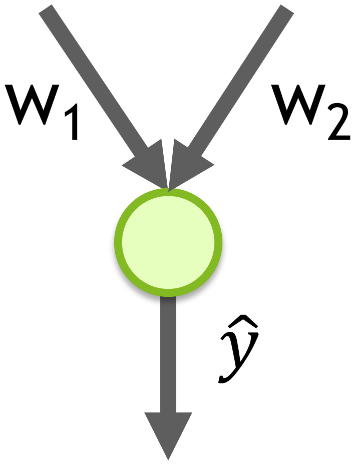
OPTIMIZERS



- Adam
- Adagrad
- RMSprop
- SGD

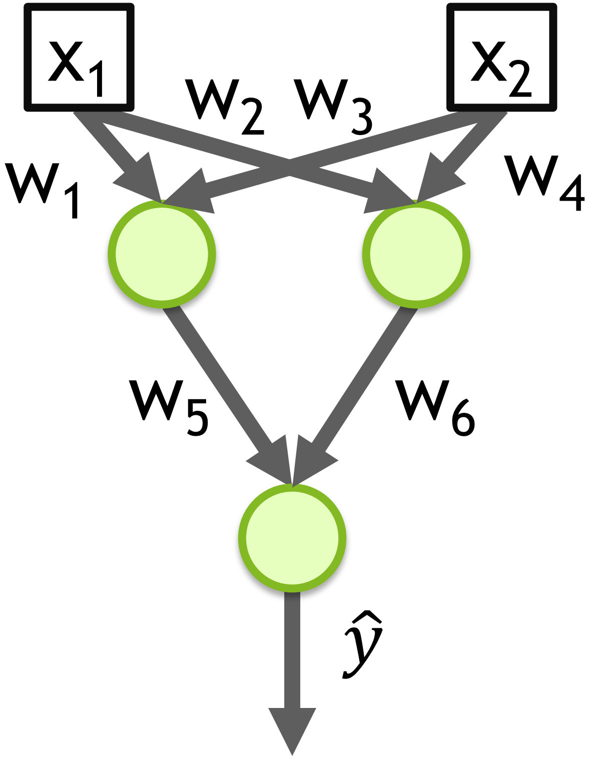
FROM NEURON TO NETWORK

BUILDING A NETWORK



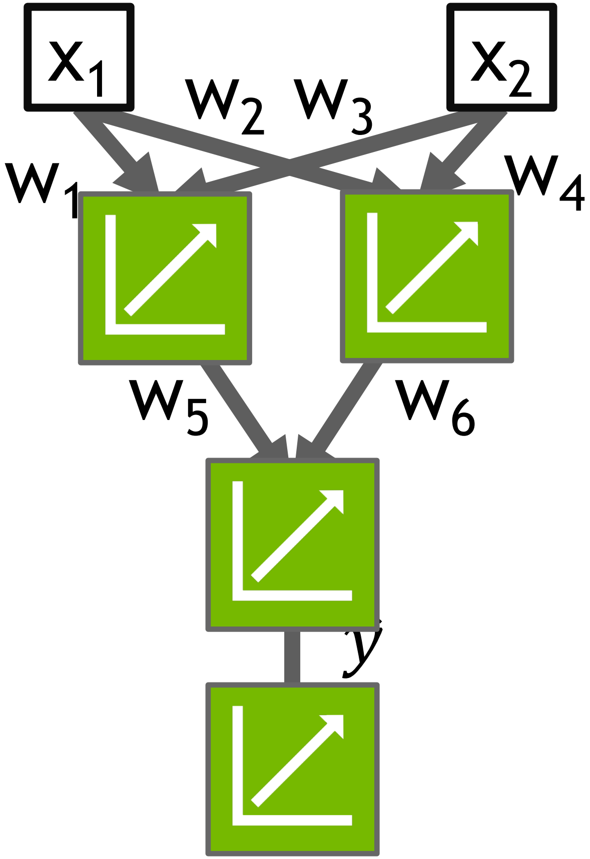
- Scales to more inputs

BUILDING A NETWORK



- Scales to more inputs
- Can chain neurons

BUILDING A NETWORK



- Scales to more inputs
- Can chain neurons
- If all regressions are linear, then output will also be a linear regression

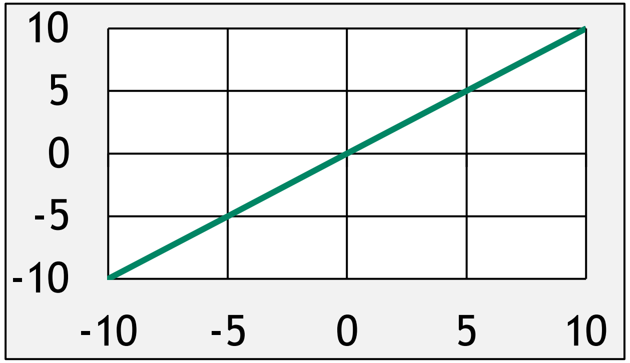
ACTIVATION FUNCTIONS

ACTIVATION FUNCTIONS

Linear

$$\hat{y} = wx + b$$

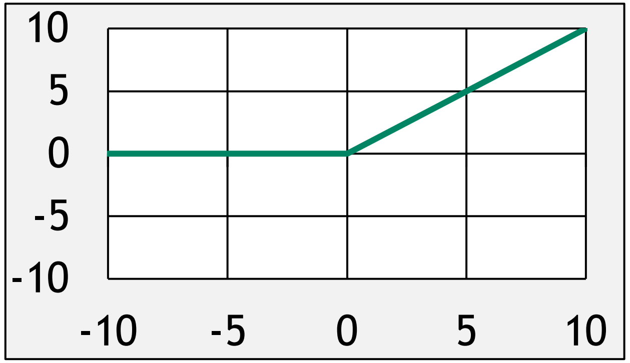
```python
# Multiply each input
# with a weight (w) and
# add intercept (b)
y_hat = wx+b
```



ReLU

$$\hat{y} = \begin{cases} wx + b \ if \ wx + b > 0 \\ 0 \ \ otherwise \end{cases}$$

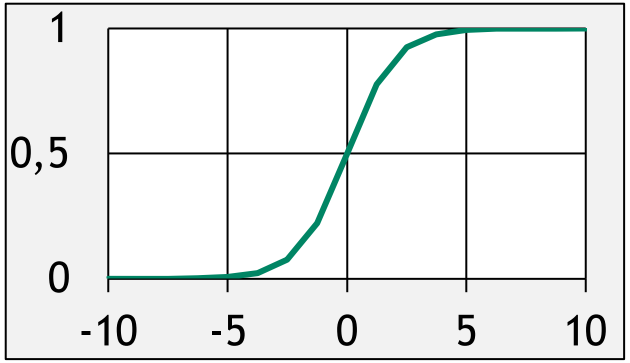
```python
# Only return result
# if total is positive
linear = wx+b
y_hat = linear * (linear > 0)
```



Sigmoid

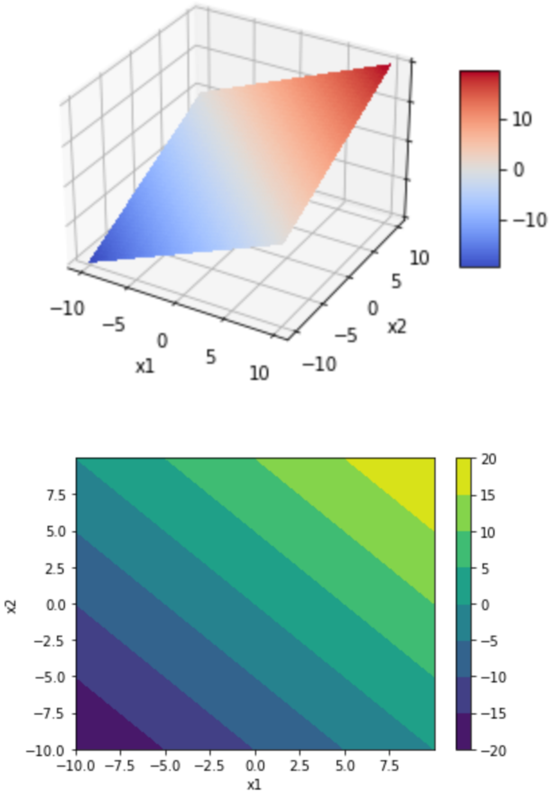
$$\hat{y} = \frac{1}{1 + e^{-(wx+b)}}$$

```python
# Start with line
linear = wx + b
# Warp to - inf to 0
inf_to_zero = np.exp(-1 * linear)
# Squish to -1 to 1
y_hat = 1 / (1 + inf_to_zero)
```

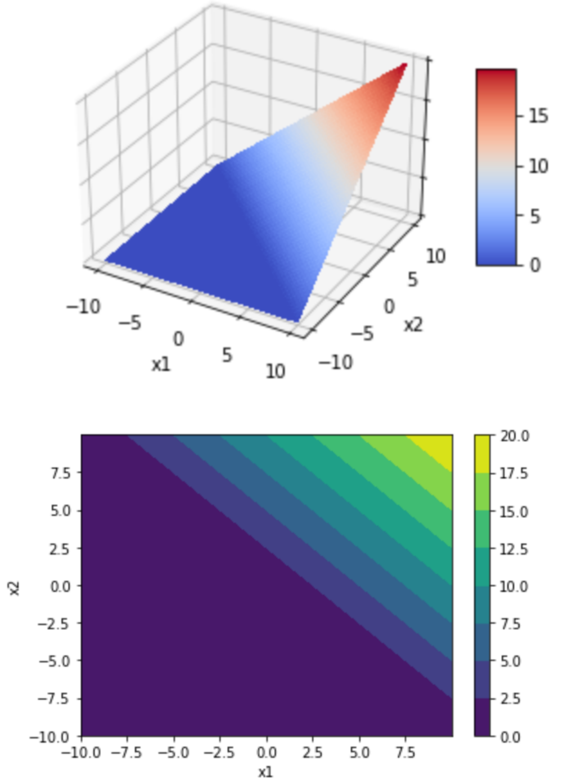


ACTIVATION FUNCTIONS

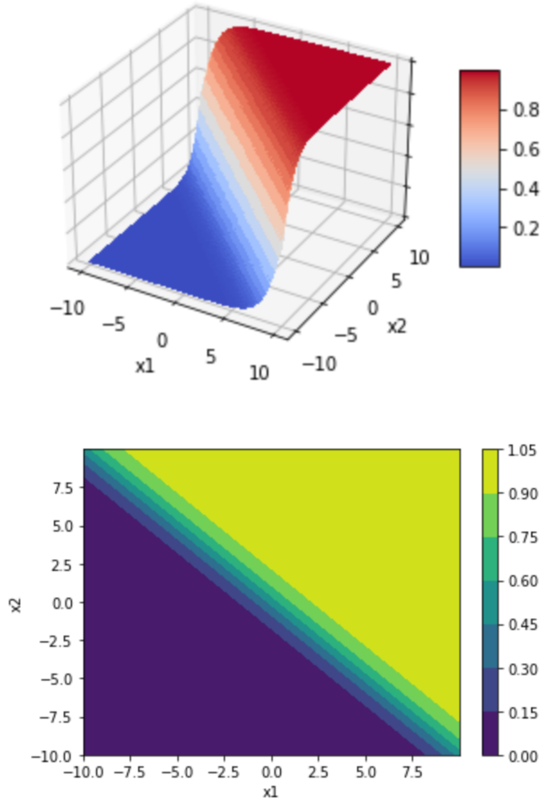
Linear



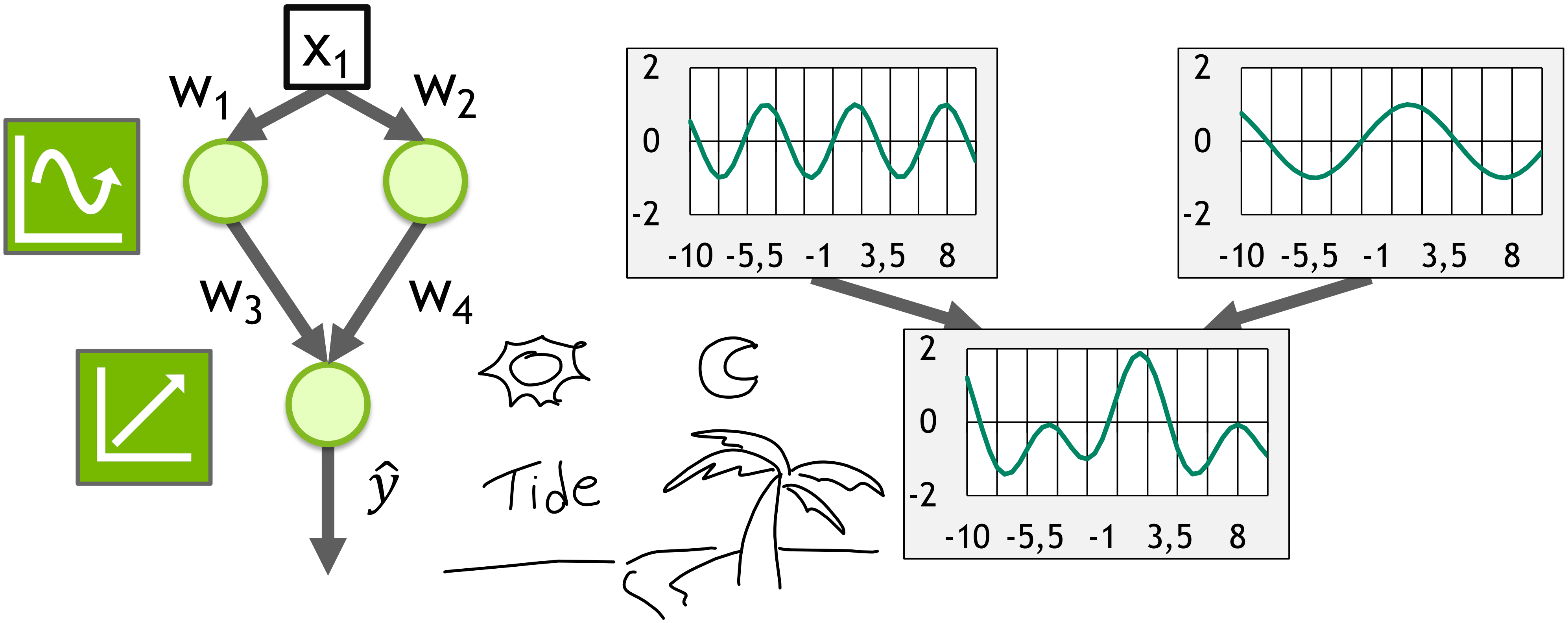
ReLU



Sigmoid



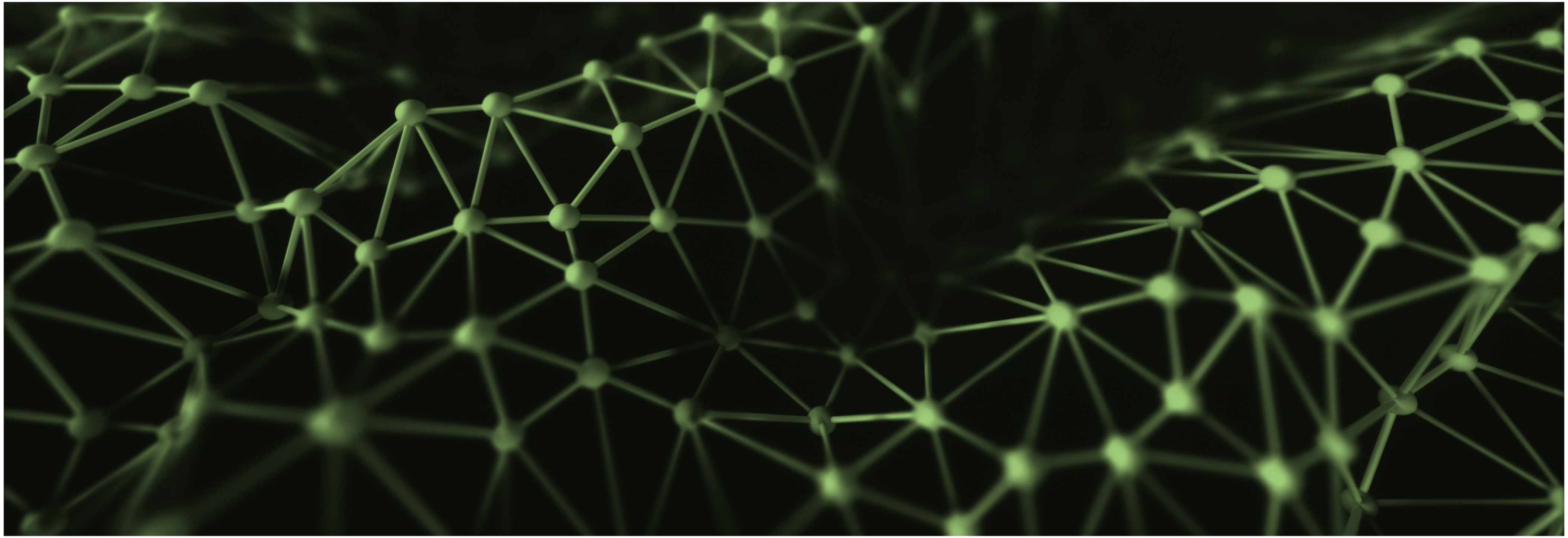
ACTIVATION FUNCTIONS



OVERFITTING

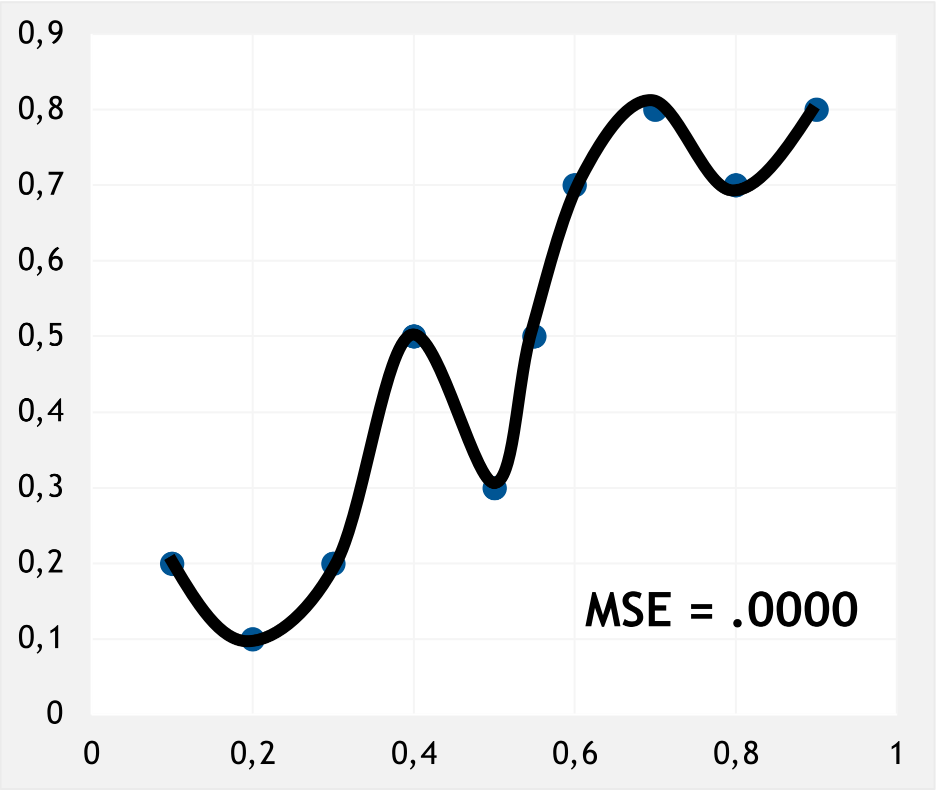
OVERFITTING

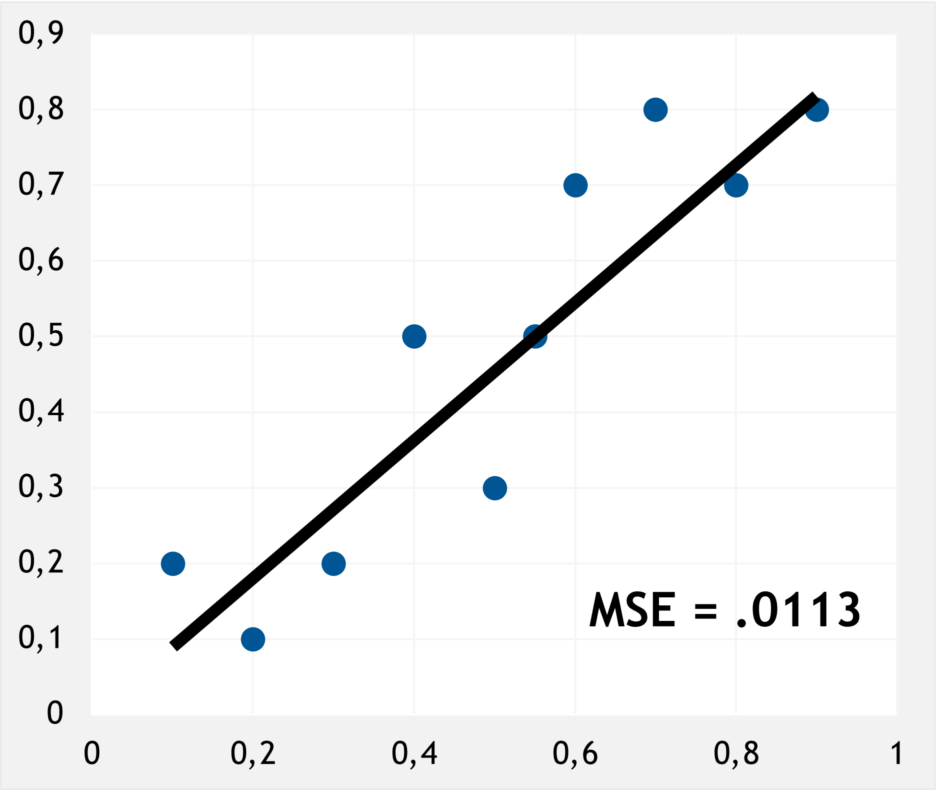
Why not have a super large neural network?



OVERFITTING

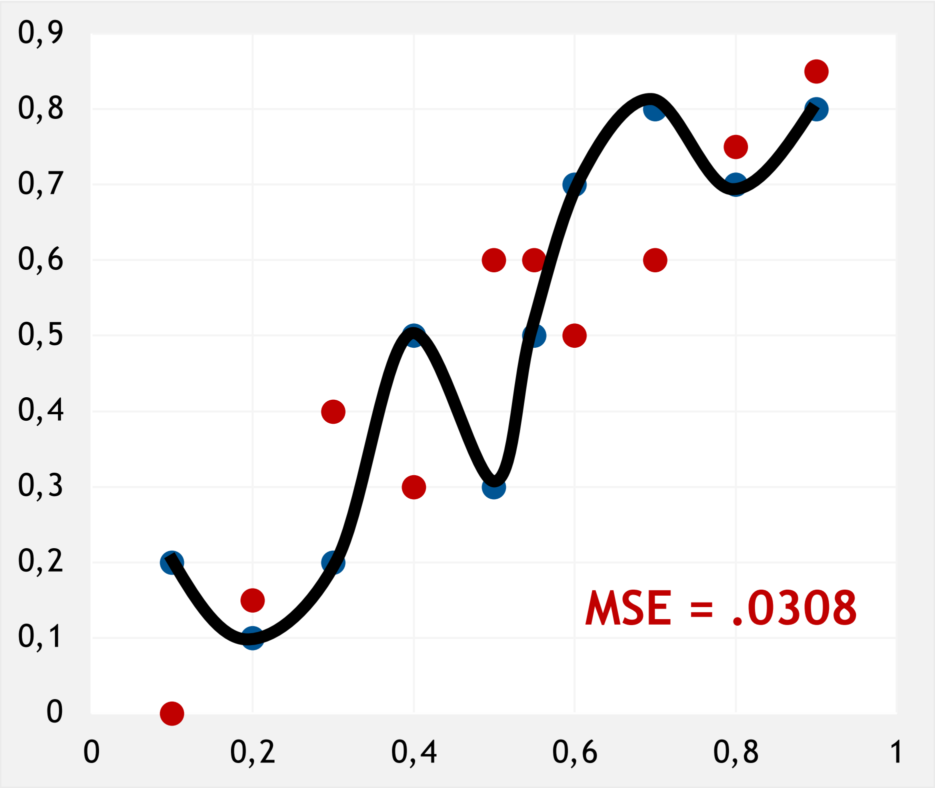
Which Trendline is Better?

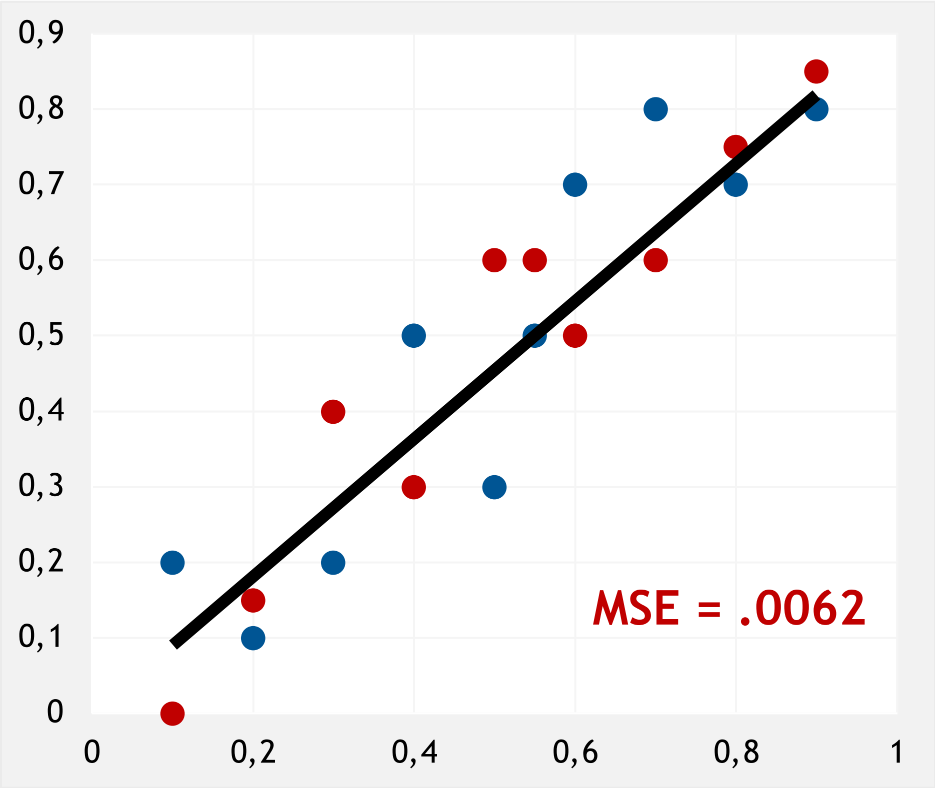




OVERFITTING

Which Trendline is Better?





DEEP LEARNING INSTITUTE

TRAINING VS VALIDATION DATA

Avoid memorization

Training data

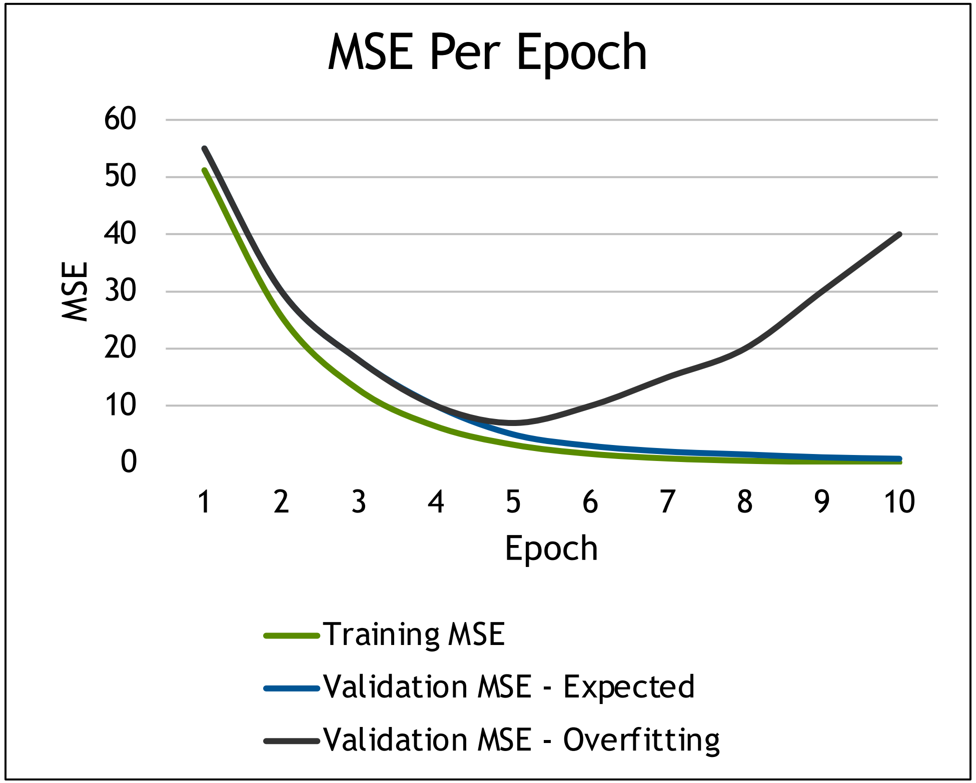
- Core dataset for the model to learn on

Validation data

- New data for model to see if it truly understands (can generalize)

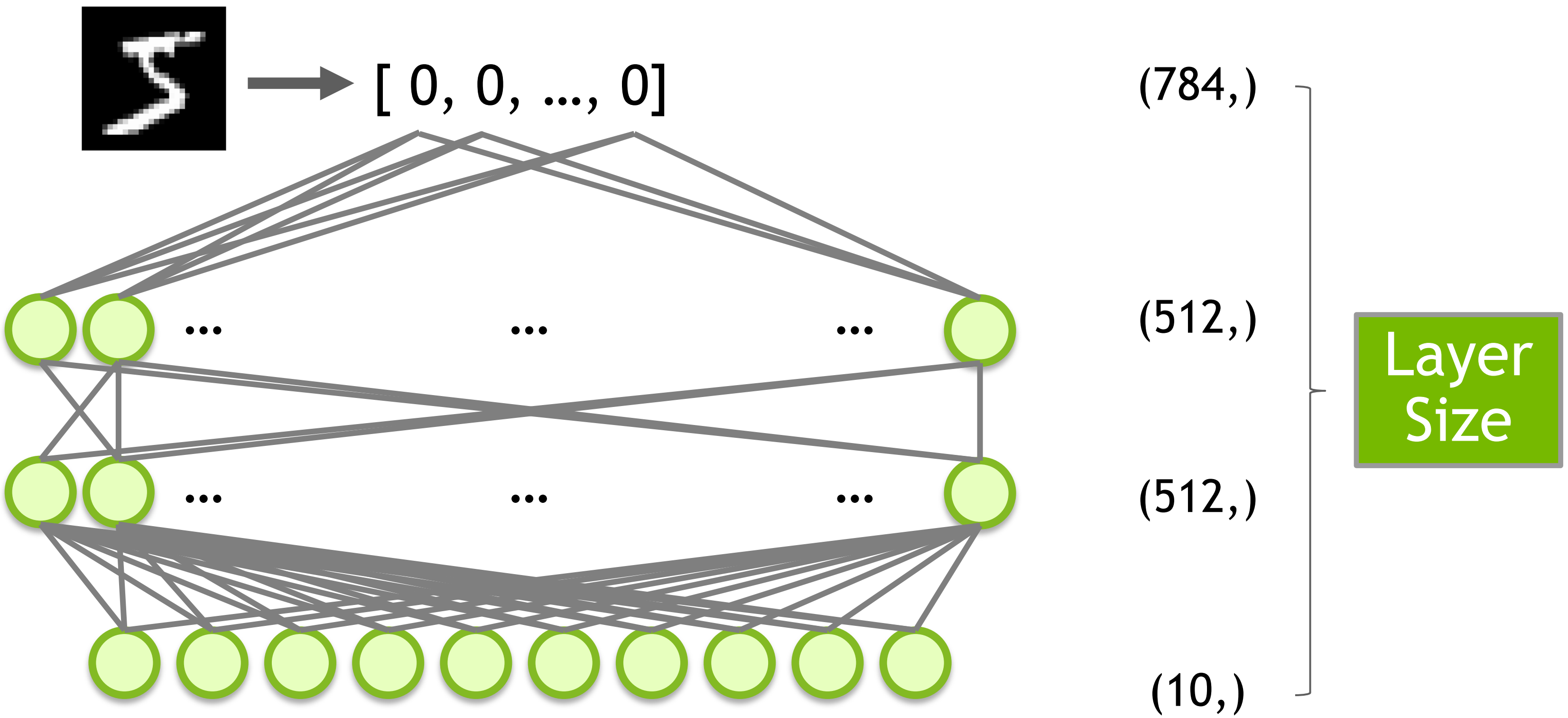
Overfitting

- When model performs well on the training data, but not the validation data (evidence of memorization)
- Ideally the accuracy and loss should be similar between both datasets

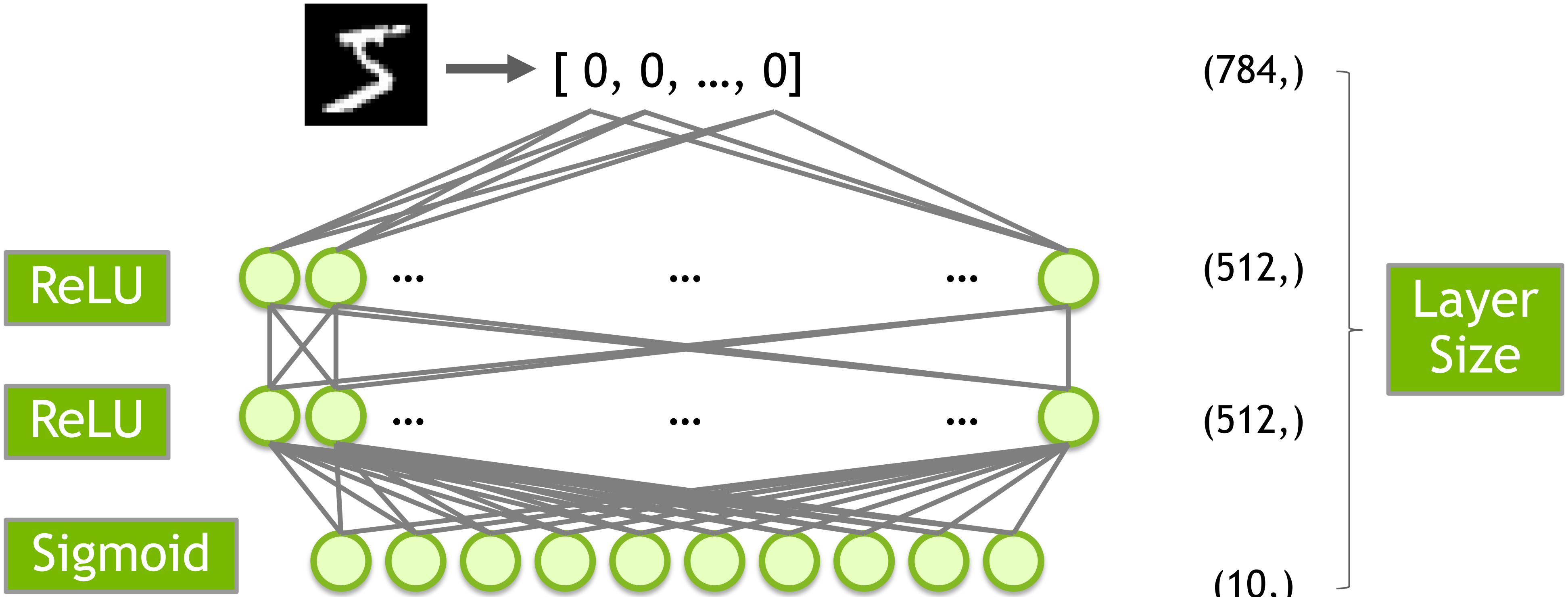


FROM REGRESSION TO CLASSIFICATION

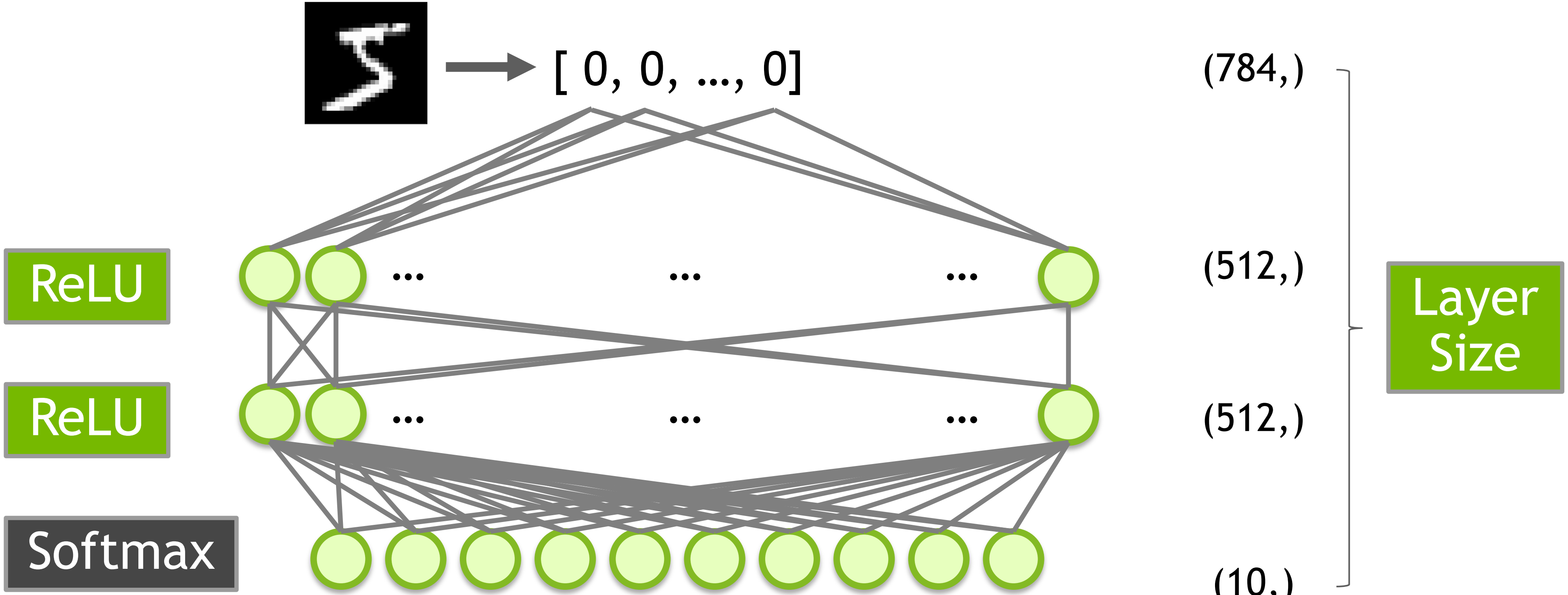
AN MNIST MODEL



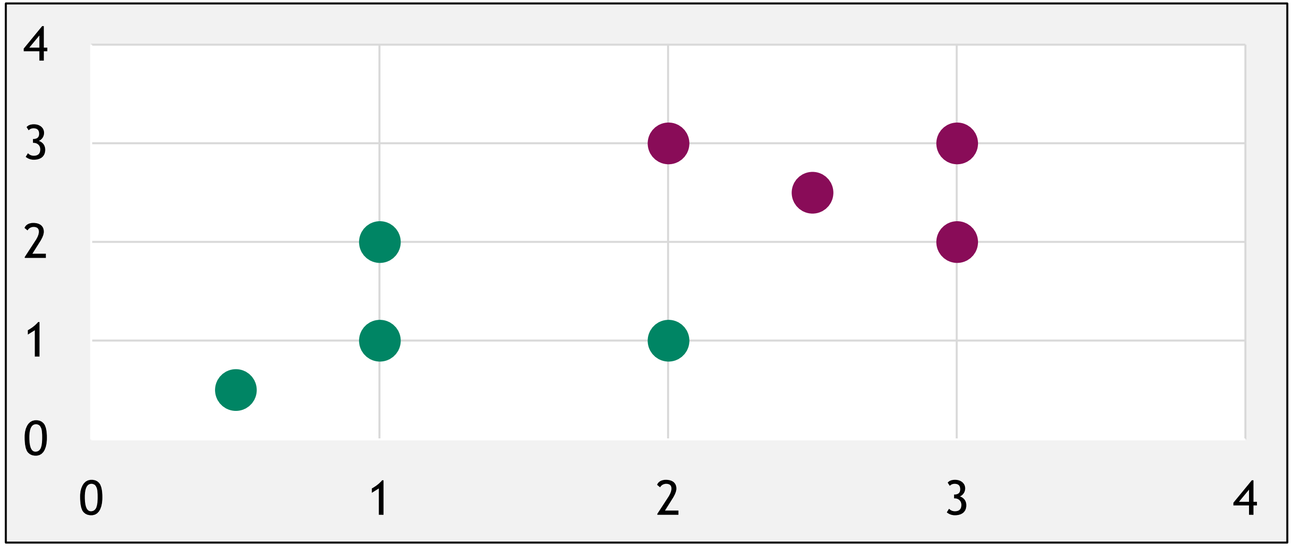
AN MNIST MODEL



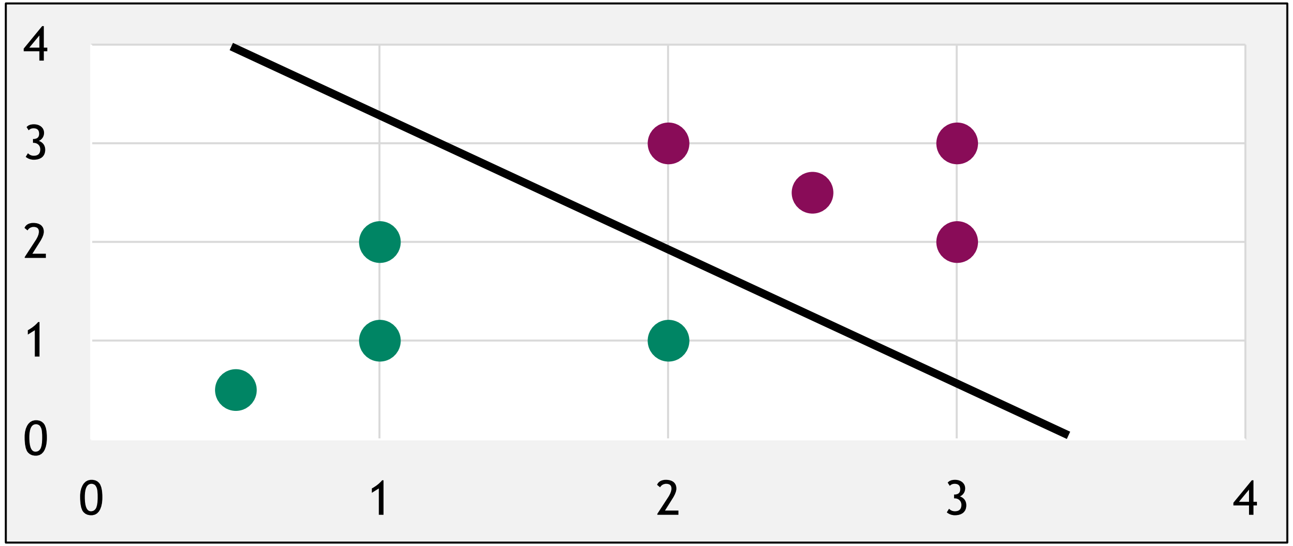
AN MNIST MODEL



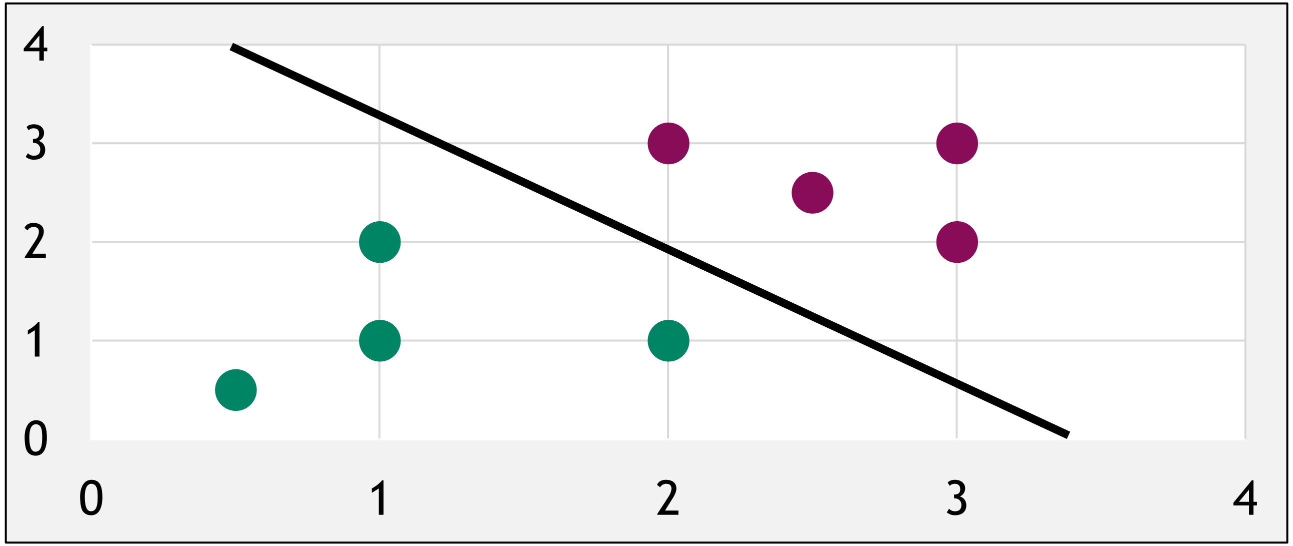
RMSE FOR PROBABILITIES?

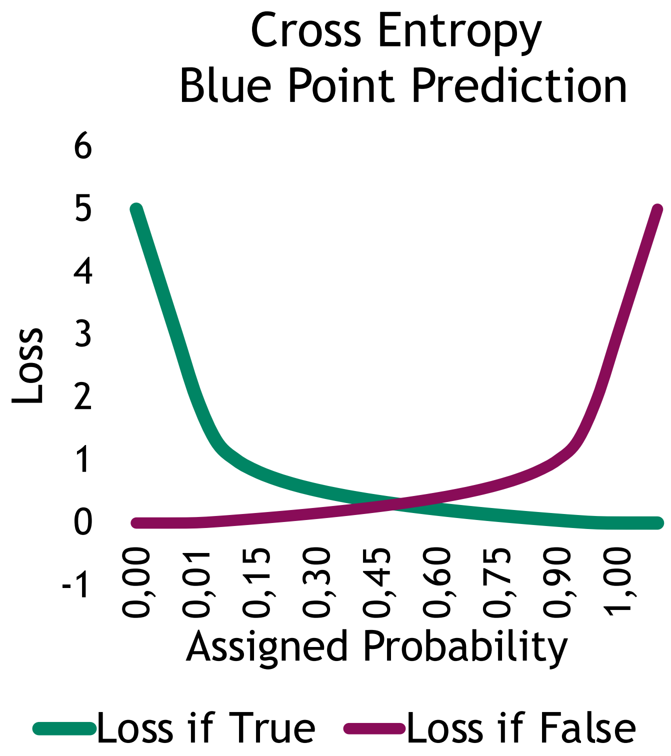


RMSE FOR PROBABILITIES?

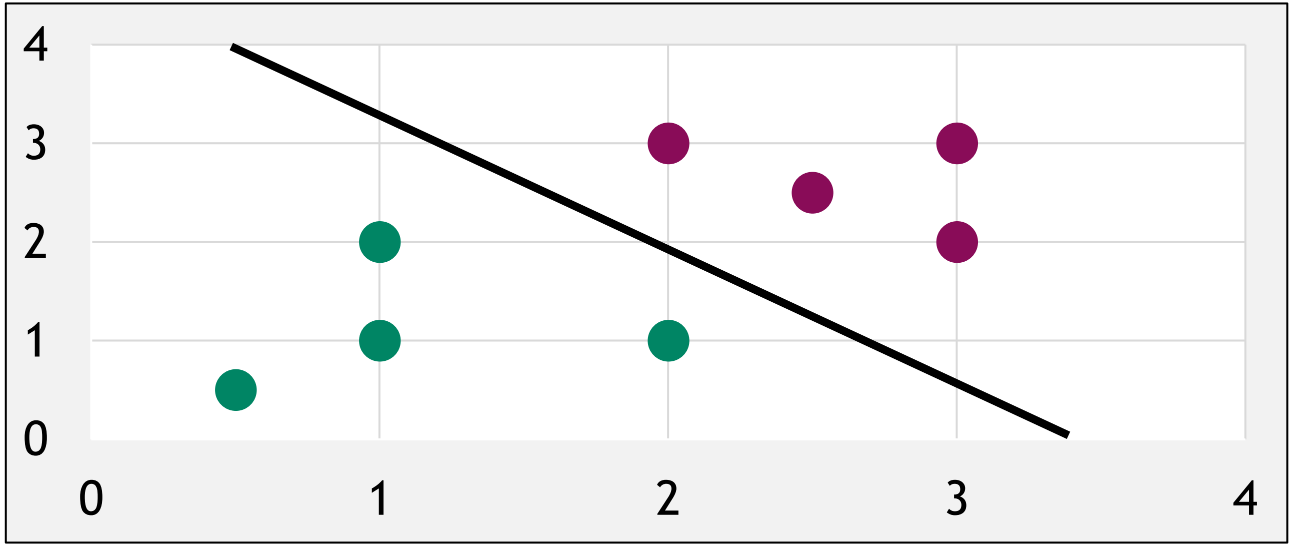


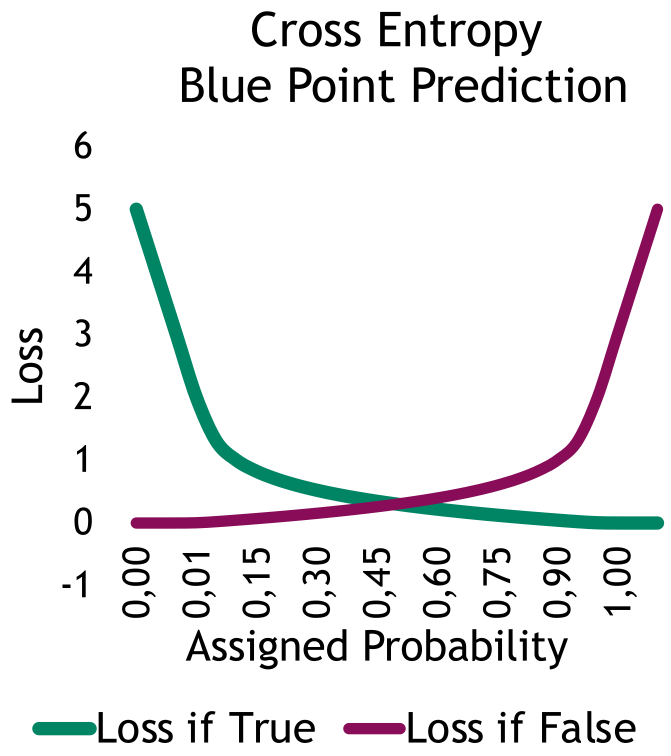
CROSS ENTROPY





CROSS ENTROPY



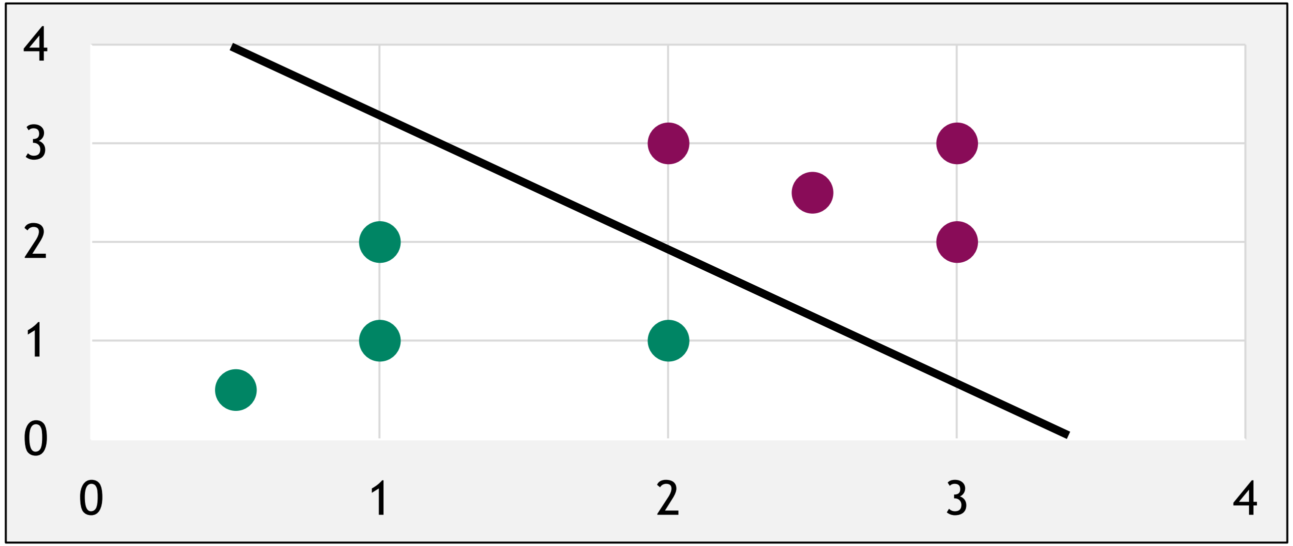


$$Loss = -\Big(\big(t(x) \cdot \log(p(x)) + \big(1 - t(x)\big) \cdot \log(1 - p(x)\big)\Big)$$

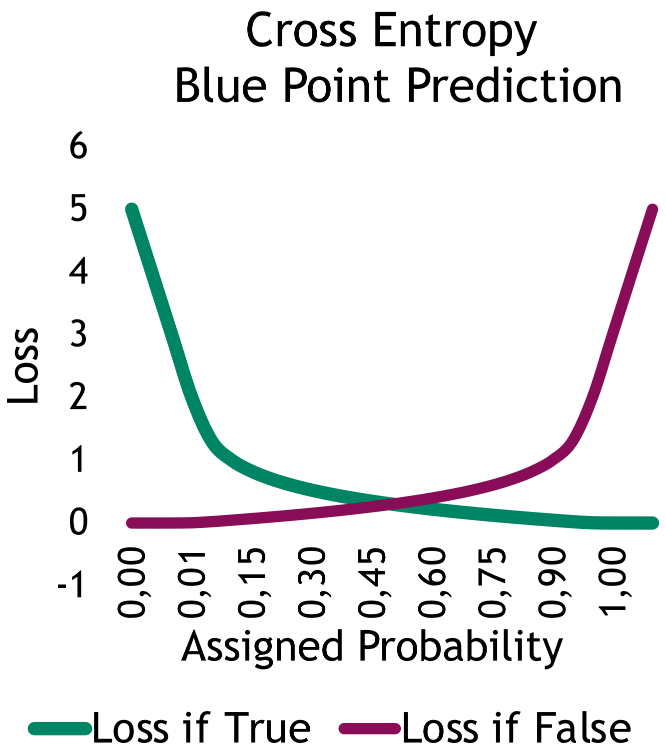
$$t(x) = target\ (0\ if\ False, 1\ if\ True)$$

$$p(x) = probability\ prediction\ of\ point\ x$$

CROSS ENTROPY



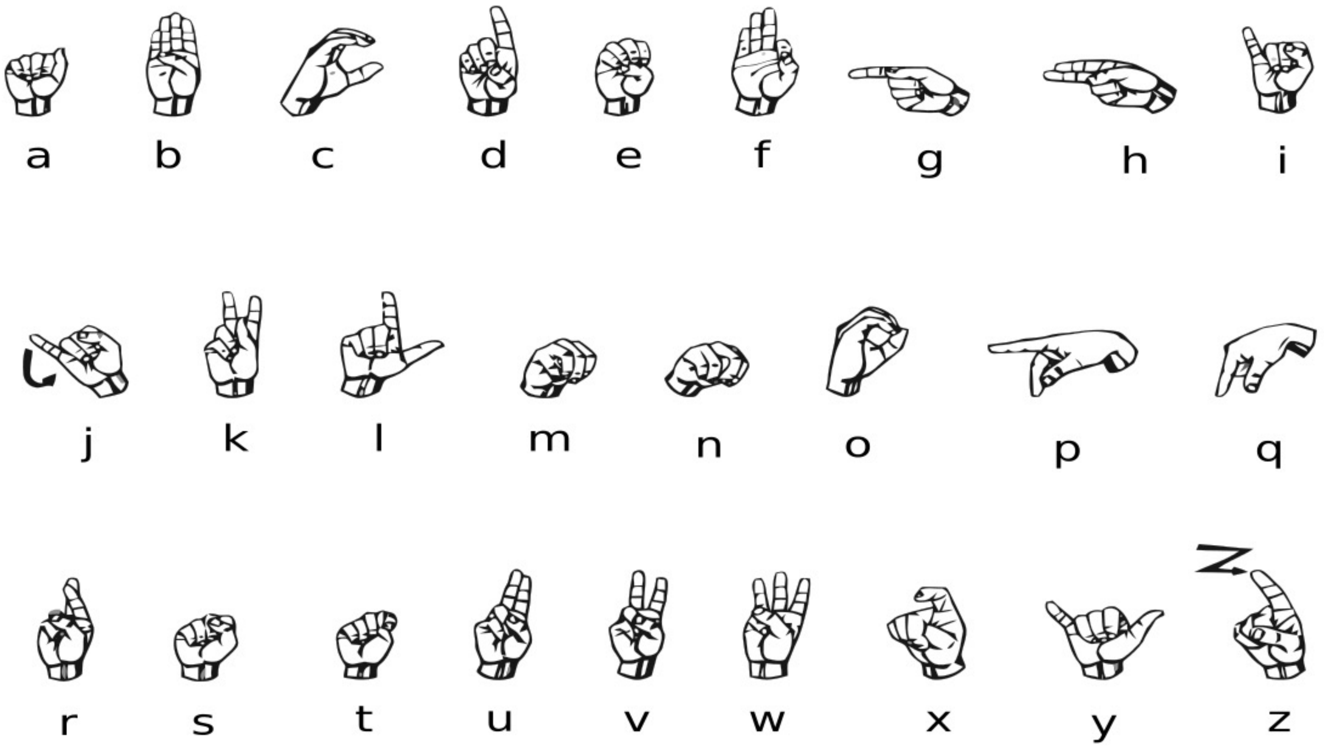

```python
def cross_entropy(y_hat, y_actual):
    """Infinite error for misplaced confidence."""
    loss = log(y_hat) if y_actual else log(1-y_hat)
    return -1*loss
```



BRINGING IT TOGETHER

THE NEXT EXERCISE

The American Sign Language Alphabet



LET’S GO!

NVIDIA | DEEP LEARNING INSTITUTE

APPENDIX: GRADIENT DESCENT

HELPING THE COMPUTER CHEAT CALCULUS

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y - \hat{y})^2 = \frac{1}{n}\sum_{i=1}^{n}(y - (mx + b))^2$$

$$MSE = \frac{1}{2}((3 - (m(1) + b))^2 + (5 - (m(2) + b))^2)$$

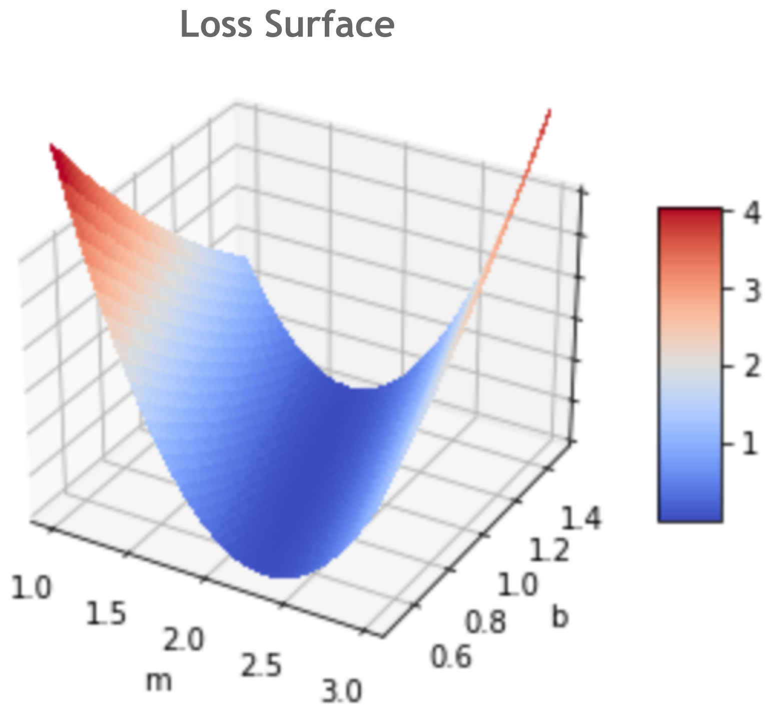
$$\frac{\partial MSE}{\partial m} = 5m + 3b - 13$$

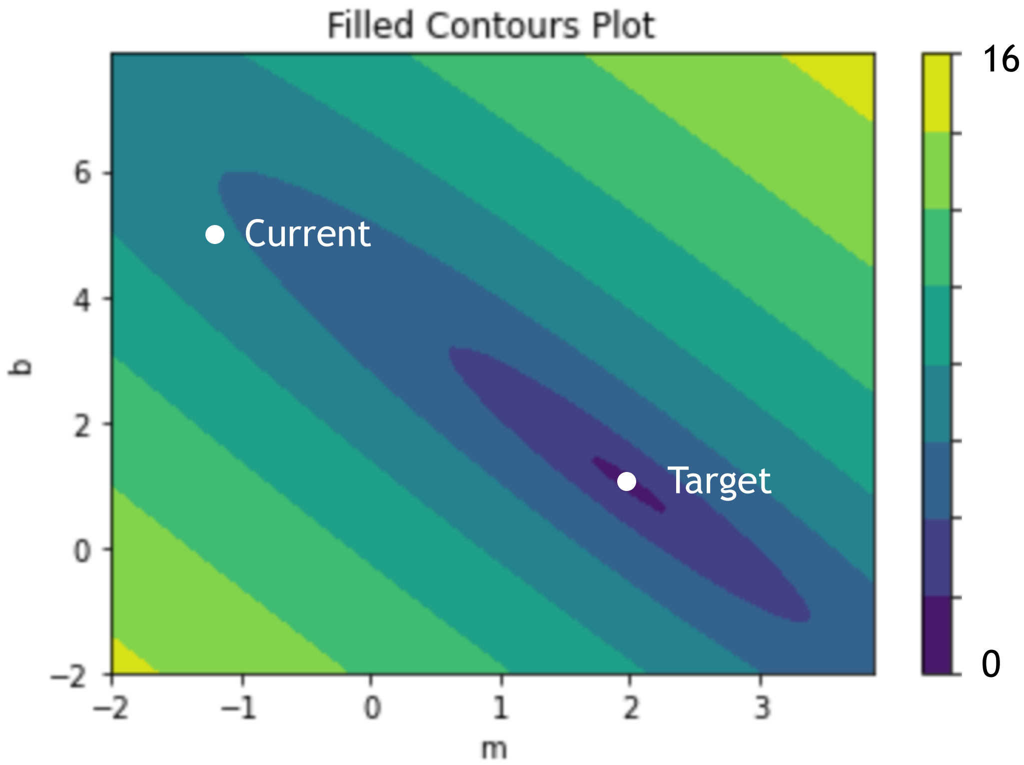
$$\frac{\partial MSE}{\partial b} = 3m + 2b - 8$$

$$\frac{\partial MSE}{\partial m} = -3$$

$$\frac{\partial MSE}{\partial b} = -1$$

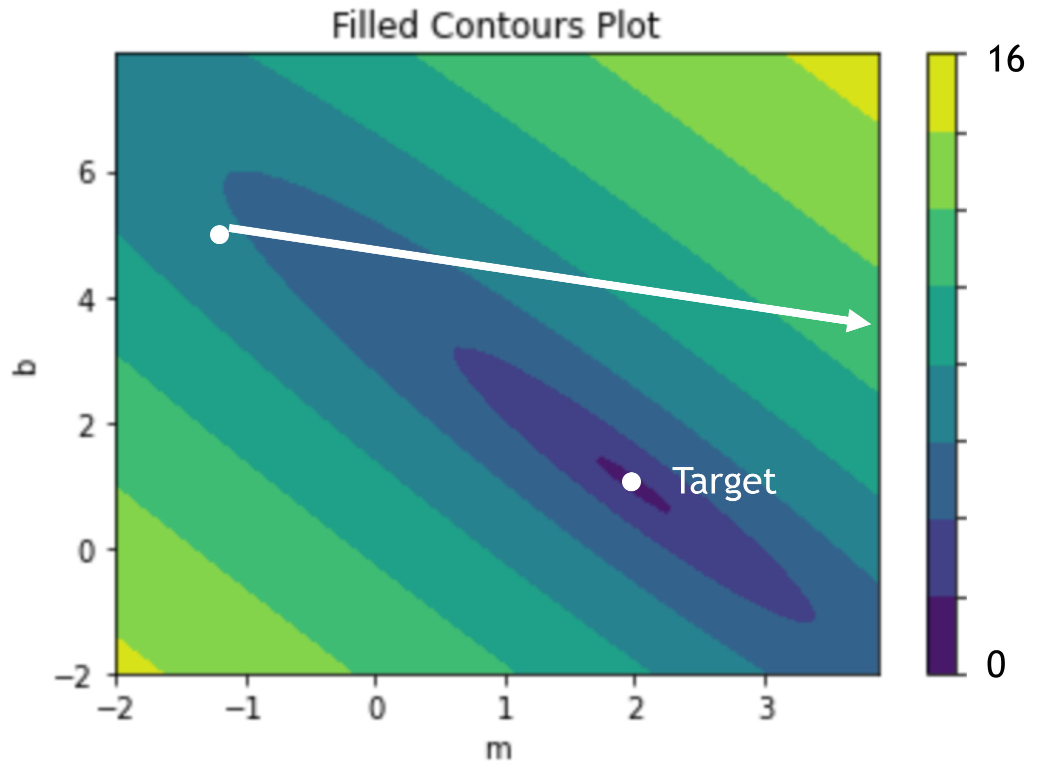
THE LOSS CURVE





THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7 \qquad \frac{\partial MSE}{\partial b} = -3$$



THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7 \qquad \frac{\partial MSE}{\partial b} = -3$$

$$\text{m} := \text{m} - \lambda \frac{\partial MSE}{\partial m}$$

$$\text{b} := b - \lambda \frac{\partial MSE}{\partial b}$$

THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7 \qquad \frac{\partial MSE}{\partial b} = -3$$

$$\mathrm{m} := \mathrm{m} - \lambda \frac{\partial MSE}{\partial m}$$

$$\lambda = .6$$

$$\mathrm{b} := b - \lambda \frac{\partial MSE}{\partial b}$$

THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7 \qquad \frac{\partial MSE}{\partial b} = -3$$

$$\mathrm{m} := \mathrm{m} - \lambda \frac{\partial MSE}{\partial m}$$

$$\lambda = .005$$

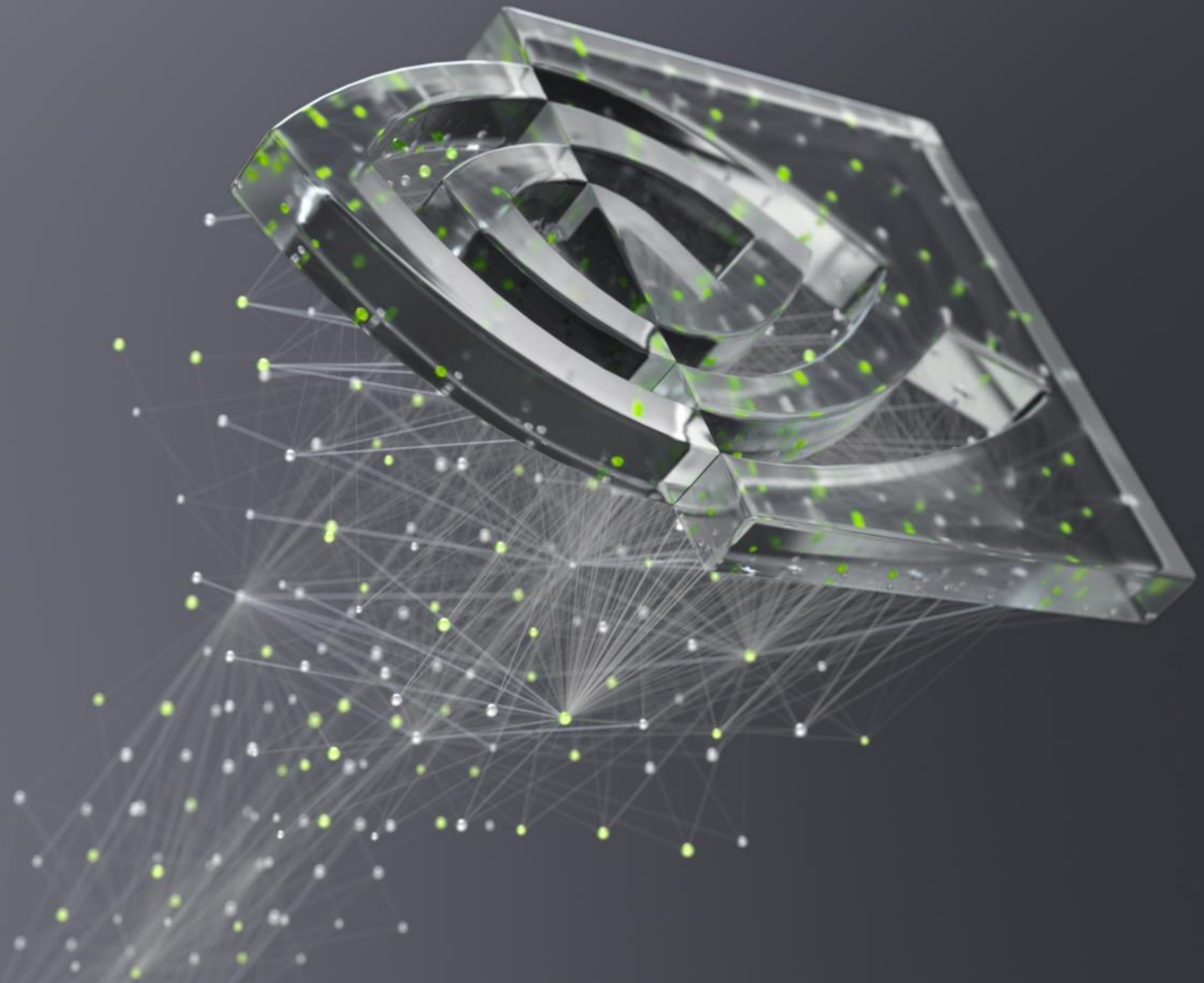
$$\mathrm{b} := b - \lambda \frac{\partial MSE}{\partial b}$$

THE LOSS CURVE

$$\lambda = .1$$

$$m := -1 + 7\,\lambda = -0.3$$

$$b := 5 + 3\,\lambda = 4.7$$



NVIDIA | DEEP LEARNING INSTITUTE

NVIDIA | DEEP LEARNING INSTITUTE

FUNDAMENTALS OF DEEP LEARNING

Part 3: Convolutional Neural Networks

Part 1: An Introduction to Deep Learning

Part 2: How a Neural Network Trains

Part 3: Convolutional Neural Networks

Part 4: Data Augmentation and Deployment

Part 5: Pre-trained Models

Part 6: Advanced Architectures

RECAP OF THE EXERCISE

- Trained a dense neural network model
- Training accuracy was high
- Validation accuracy was low
- Evidence of overfitting

KERNELS AND CONVOLUTION

KERNELS AND CONVOLUTION

Original Image

Blur

Sharpen

Brighten

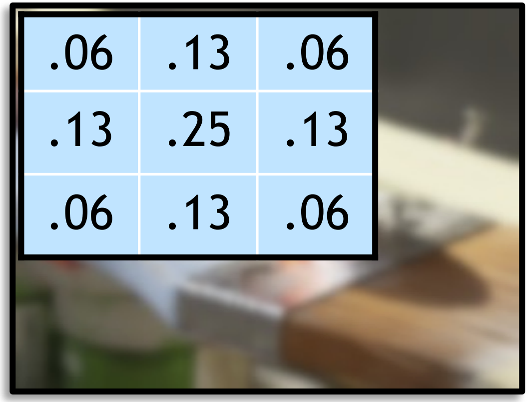
Darken

KERNELS AND CONVOLUTION

Original Image

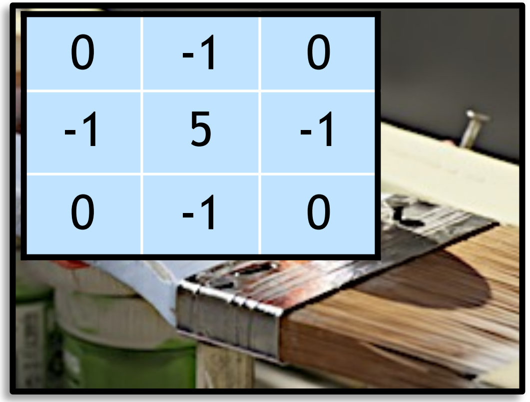
Blur

.06	.13	.06
.13	.25	.13
.06	.13	.06



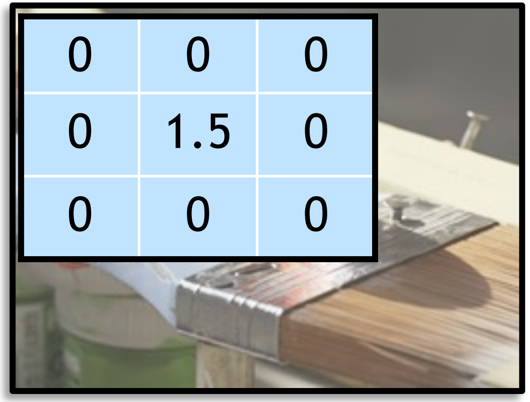
Sharpen

0	-1	0
-1	5	-1
0	-1	0



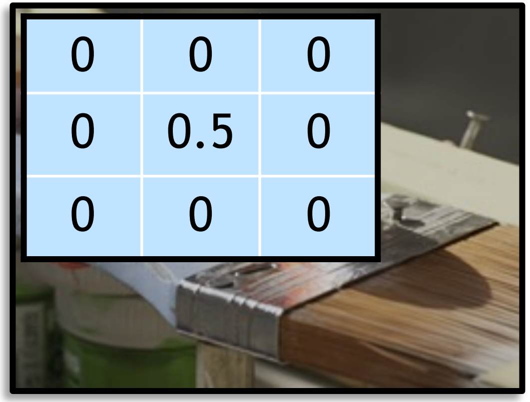
Brighten

0	0	0
0	1.5	0
0	0	0



Darken

0	0	0
0	0.5	0
0	0	0



KERNELS AND CONVOLUTION

Blur Kernel

.06	.13	.06
.13	.25	.13
.06	.13	.06

*

Original Image

1	0	1	1	0	1
0	1	0	0	1	0
0	1	1	1	1	0
0	1	1	1	1	0
1	0	1	1	0	1
1	1	0	0	1	1

=

Convolved Image

KERNELS AND CONVOLUTION

Blur Kernel

.06	.13	.06
.13	.25	.13
.06	.13	.06

*

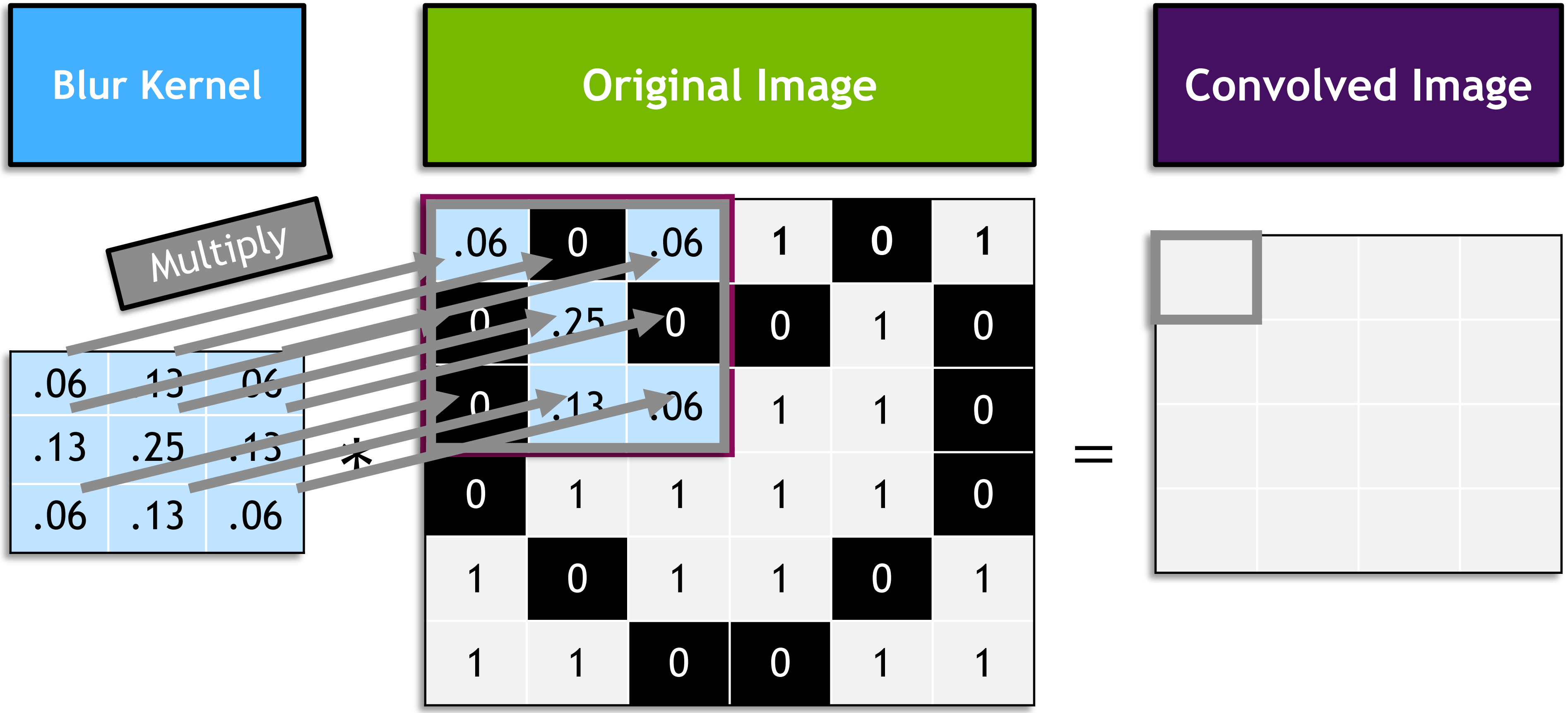
Original Image

1	0	1	1	0	1
0	1	0	0	1	0
0	1	1	1	1	0
0	1	1	1	1	0
1	0	1	1	0	1
1	1	0	0	1	1

=

Convolved Image

KERNELS AND CONVOLUTION



KERNELS AND CONVOLUTION

KERNELS AND CONVOLUTION

Blur Kernel

.06	.13	.06
.13	.25	.13
.06	.13	.06

*

Original Image

1	0	.13	.06	0	1
0	.13	0	0	1	0
0	.06	.13	.06	1	0
0	1	1	1	1	0
1	0	1	1	0	1
1	1	0	0	1	1

=

Convolved Image

.56	.57		

KERNELS AND CONVOLUTION

Blur Kernel

.06	.13	.06
.13	.25	.13
.06	.13	.06

*

Original Image

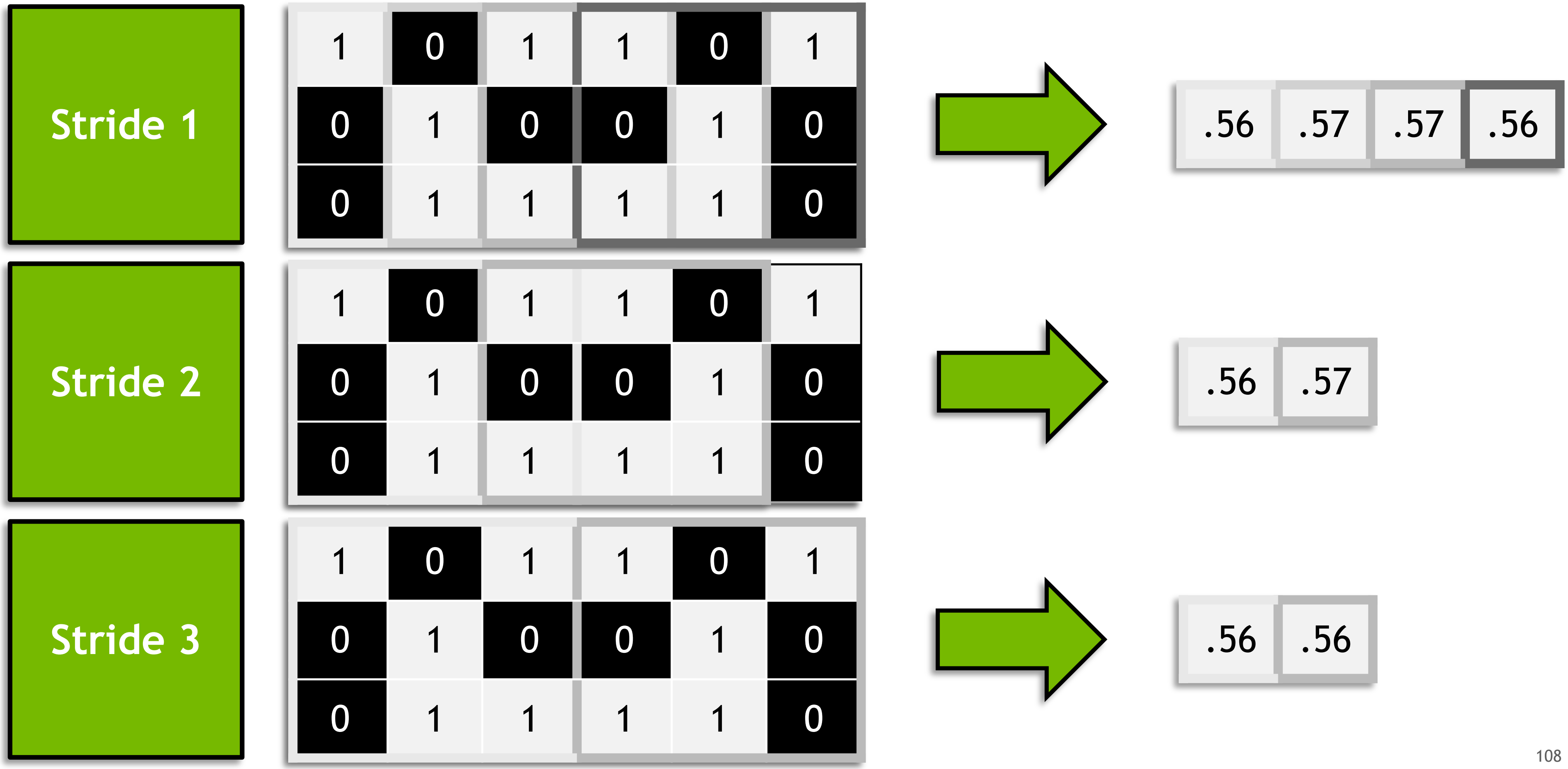
1	0	1	1	0	1
0	1	0	0	1	0
0	1	1	1	1	0
0	1	1	1	1	0
1	0	1	1	0	1
1	1	0	0	1	1

=

Convolved Image

.56	.57	.57	.56
.7	.82	.82	.7
.69	.95	.95	.69
.64	.69	.69	.64

STRIDE


Stride 1
1 0 1 1 0 1
0 1 0 0 1 0
0 1 1 1 1 0
.56 .57 .57 .56
Stride 2
1 0 1 1 0 1
0 1 0 0 1 0
0 1 1 1 1 0
.56 .57
Stride 3
1 0 1 1 0 1
0 1 0 0 1 0
0 1 1 1 1 0
.56 .56

PADDING

Original Image

1	0	1	1	0	1
0	1	0	0	1	0
0	1	1	1	1	0
0	1	1	1	1	0
1	0	1	1	0	1
1	1	0	0	1	1

Zero Padding

0	0	0	0	0	0	0	0
0	1	0	1	1	0	1	0
0	0	1	0	0	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	1	0	1	1	0	1	0
0	1	1	0	0	1	1	0
0	0	0	0	0	0	0	0

PADDING

Original Image

1	0	1	1	0	1
0	1	0	0	1	0
0	1	1	1	1	0
0	1	1	1	1	0
1	0	1	1	0	1
1	1	0	0	1	1

Mirror Padding

1	1	0	1	1	0	1	1
1	1	0	1	1	0	1	1
0	0	1	0	0	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
1	1	0	1	1	0	1	1
1	1	1	0	0	1	1	1
1	1	1	0	0	1	1	1

KERNELS AND NEURAL NETWORKS

KERNELS AND NEURAL NETWORKS

Kernel

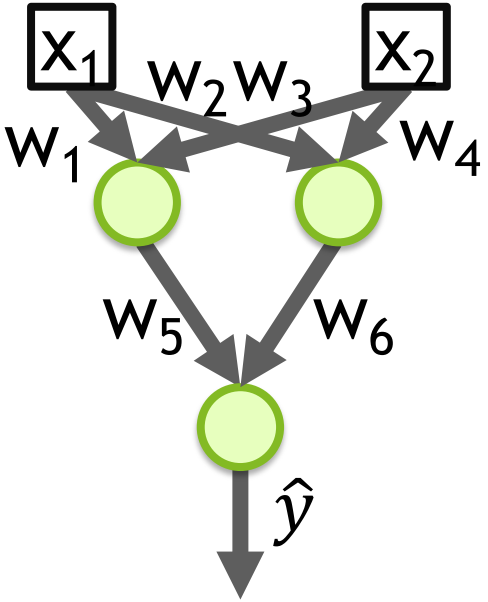
w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

KERNELS AND NEURAL NETWORKS

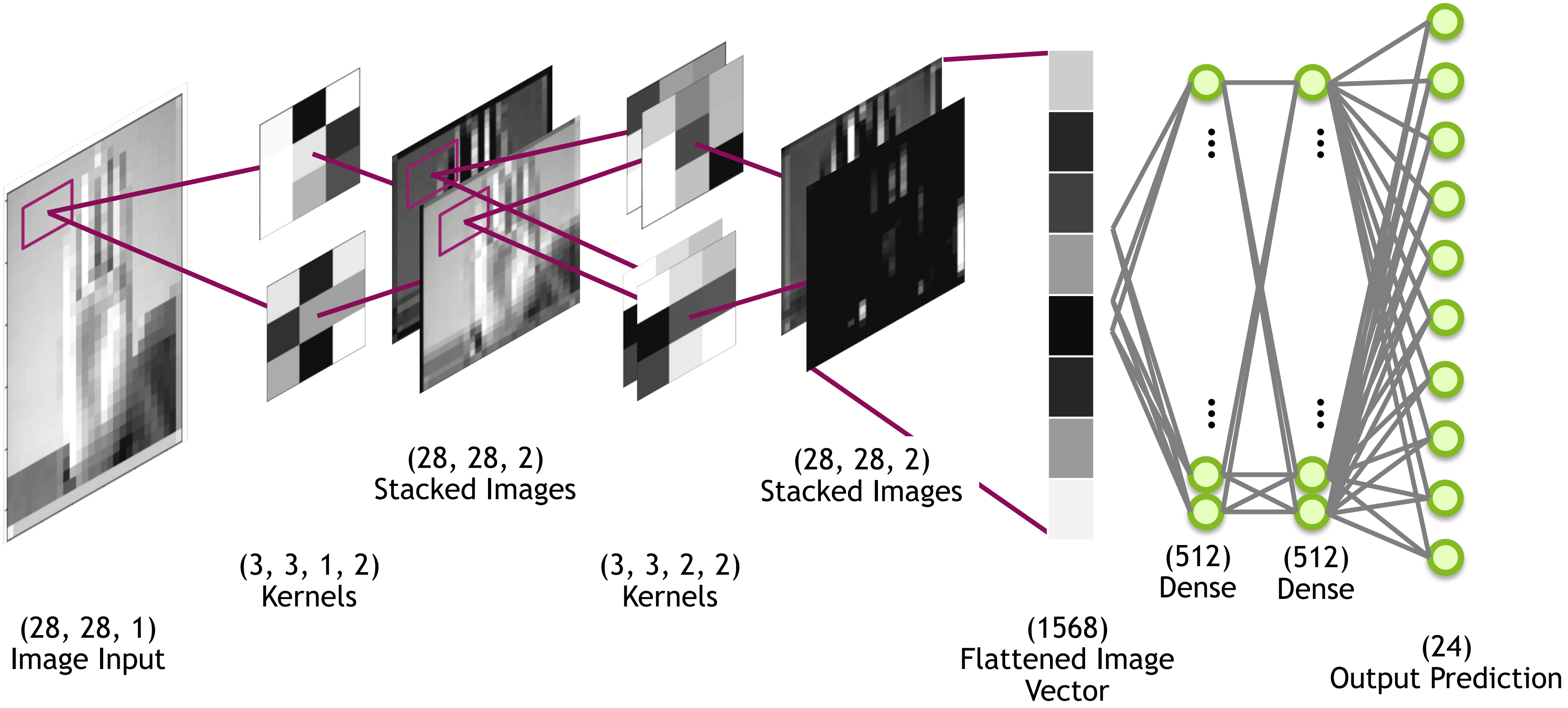
Kernel

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

Neuron

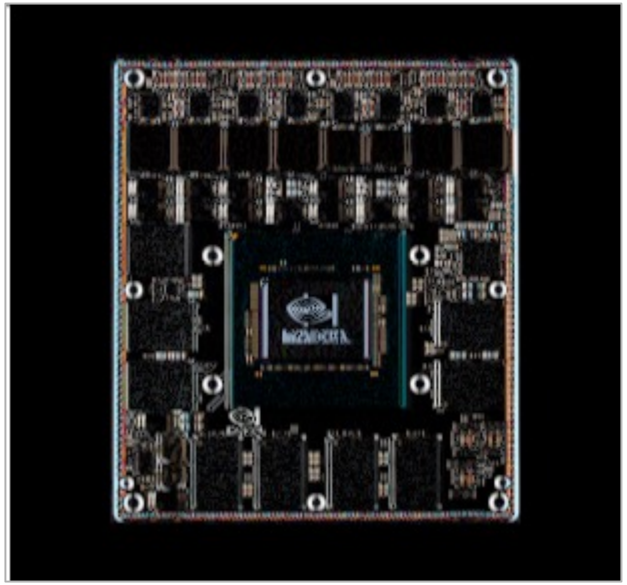


KERNELS AND NEURAL NETWORKS



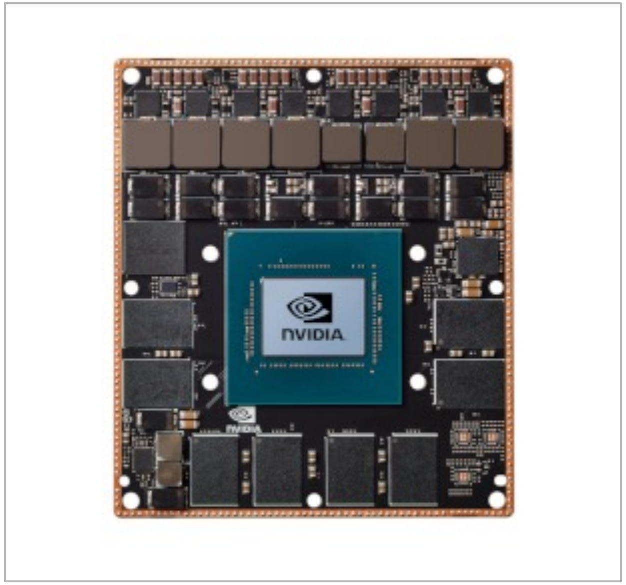
FINDING EDGES

Vertical Edges



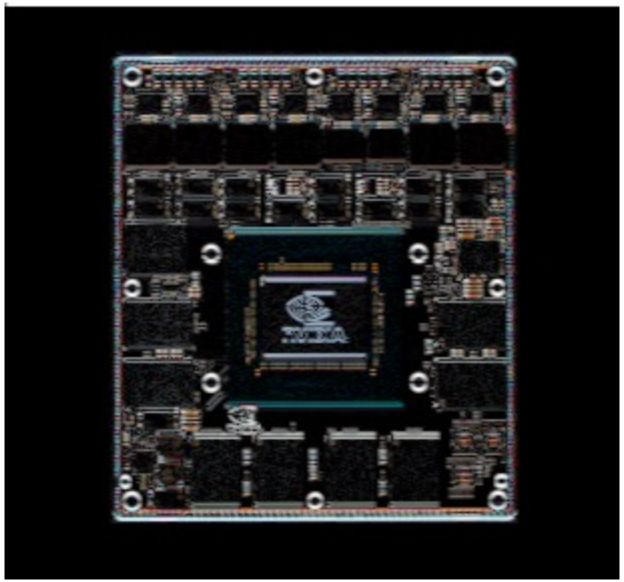
1	0	-1
2	0	-2
1	0	-1

Original Image



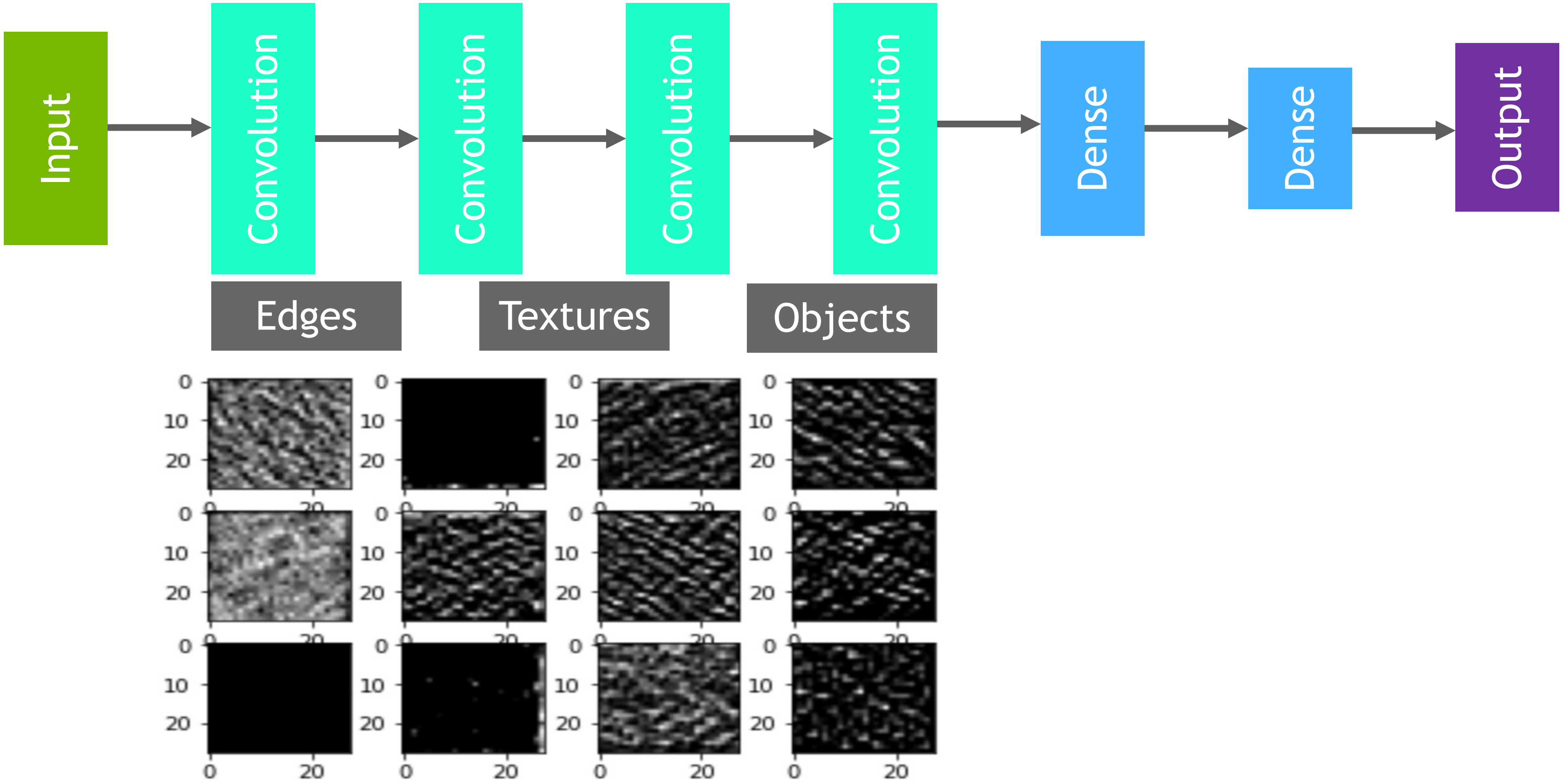
0	0	0
0	1	0
0	0	0

Horizontal Edges



1	2	1
0	0	0
-1	-2	-1

NEURAL NETWORK PERCEPTION



NEURAL NETWORK PERCEPTION

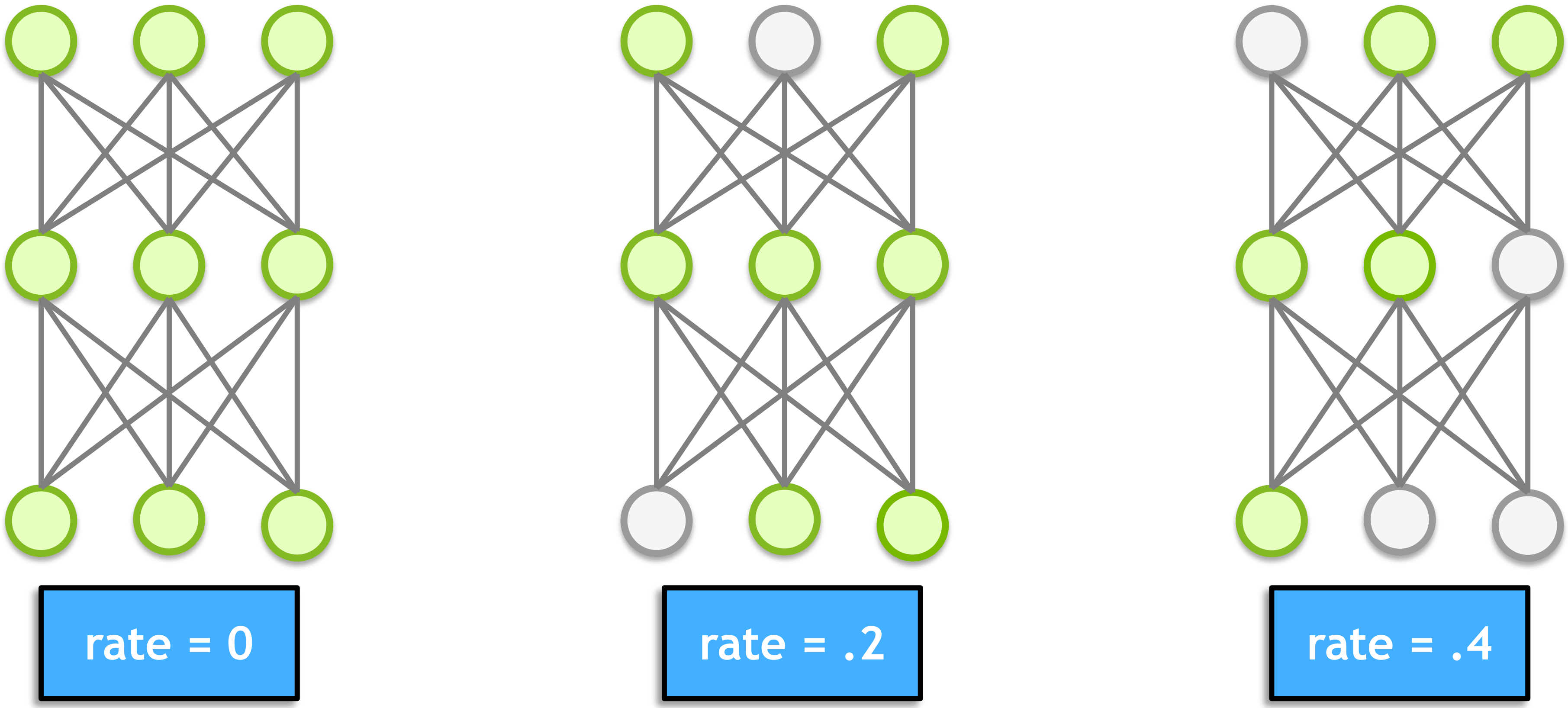
OTHER LAYERS IN THE MODEL

MAX POOLING

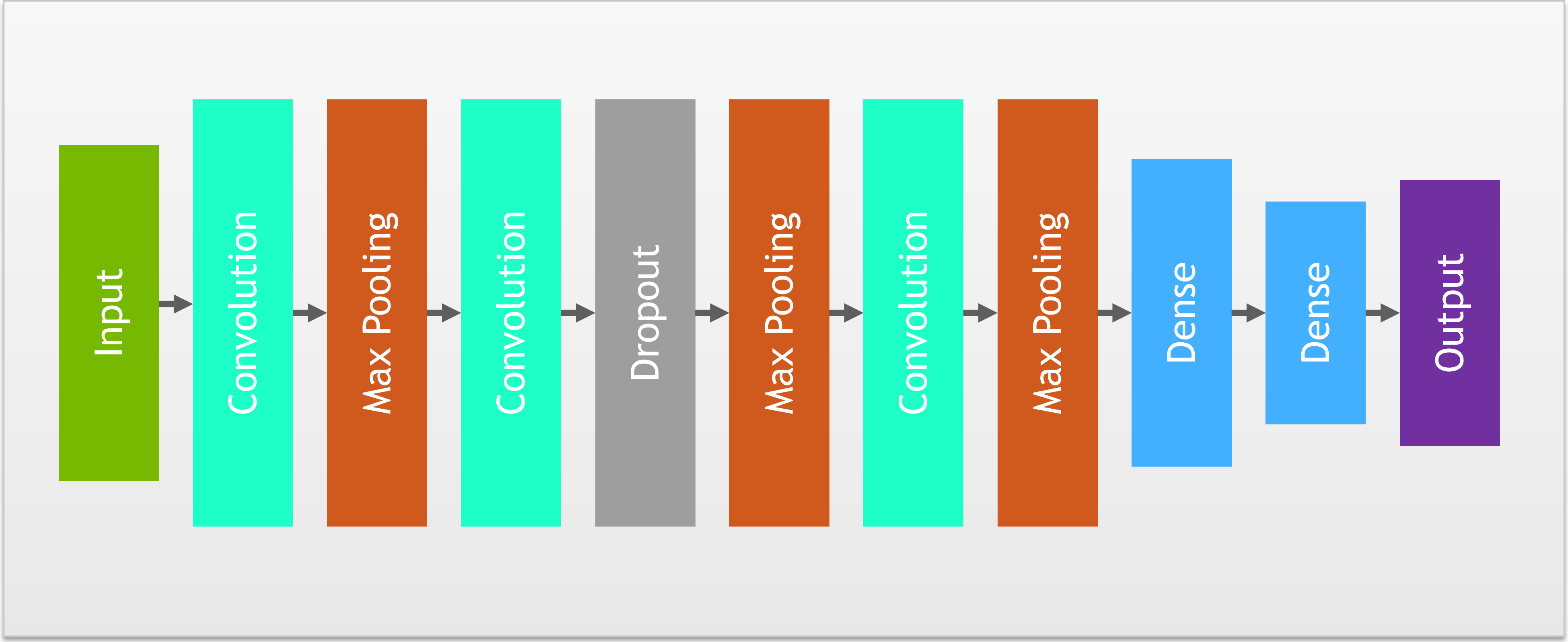
110	256	153	67
12	89	88	43
10	15	50	55
23	9	49	23

256	153
23	55

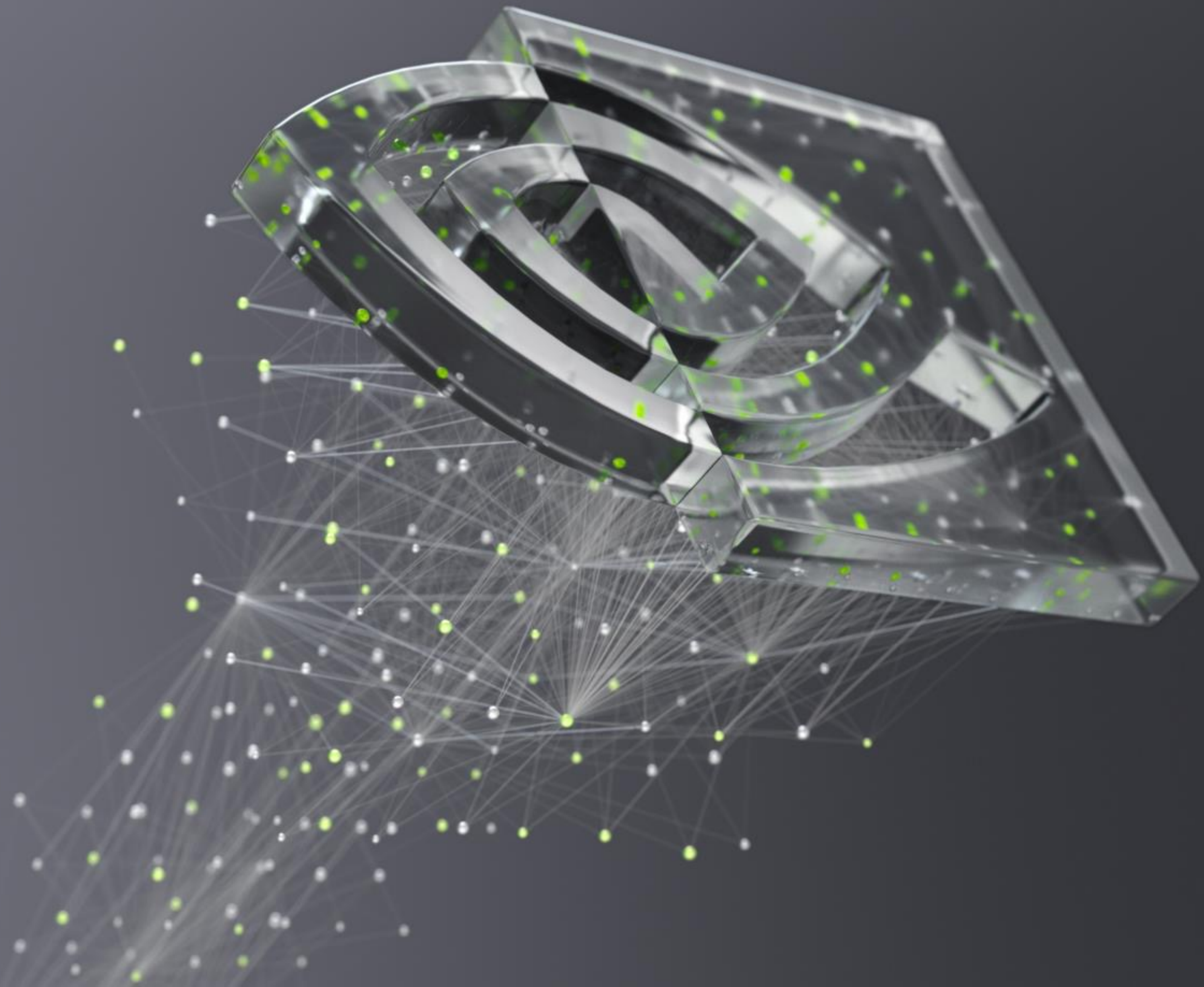
DROPOUT



WHOLE ARCHITECTURE



LET’S GO!



NVIDIA

DEEP
LEARNING
INSTITUTE

NVIDIA | DEEP LEARNING INSTITUTE

FUNDAMENTALS OF DEEP LEARNING

Part 4: Data Augmentation and Deployment

Part 1: An Introduction to Deep Learning

Part 2: How a Neural Network Trains

Part 3: Convolutional Neural Networks

Part 4: Data Augmentation and Deployment

Part 5: Pre-trained Models

Part 6: Advanced Architectures

RECAP OF THE EXERCISE

Analysis

- CNN increased validation accuracy
- Still seeing training accuracy higher than validation

Solution

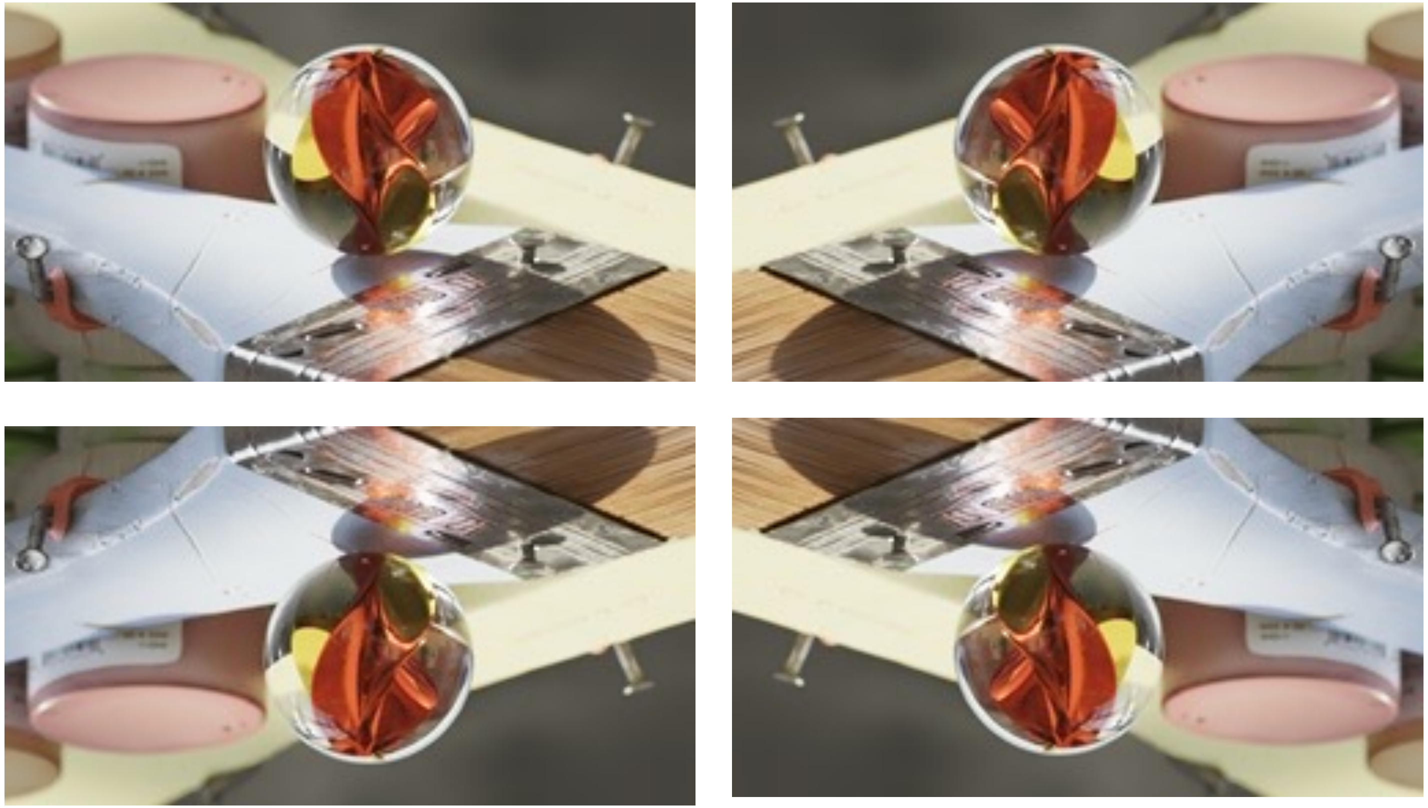
- Clean data provides better examples
- Dataset variety helps the model generalize

DATA AUGMENTATION

DATA AUGMENTATION

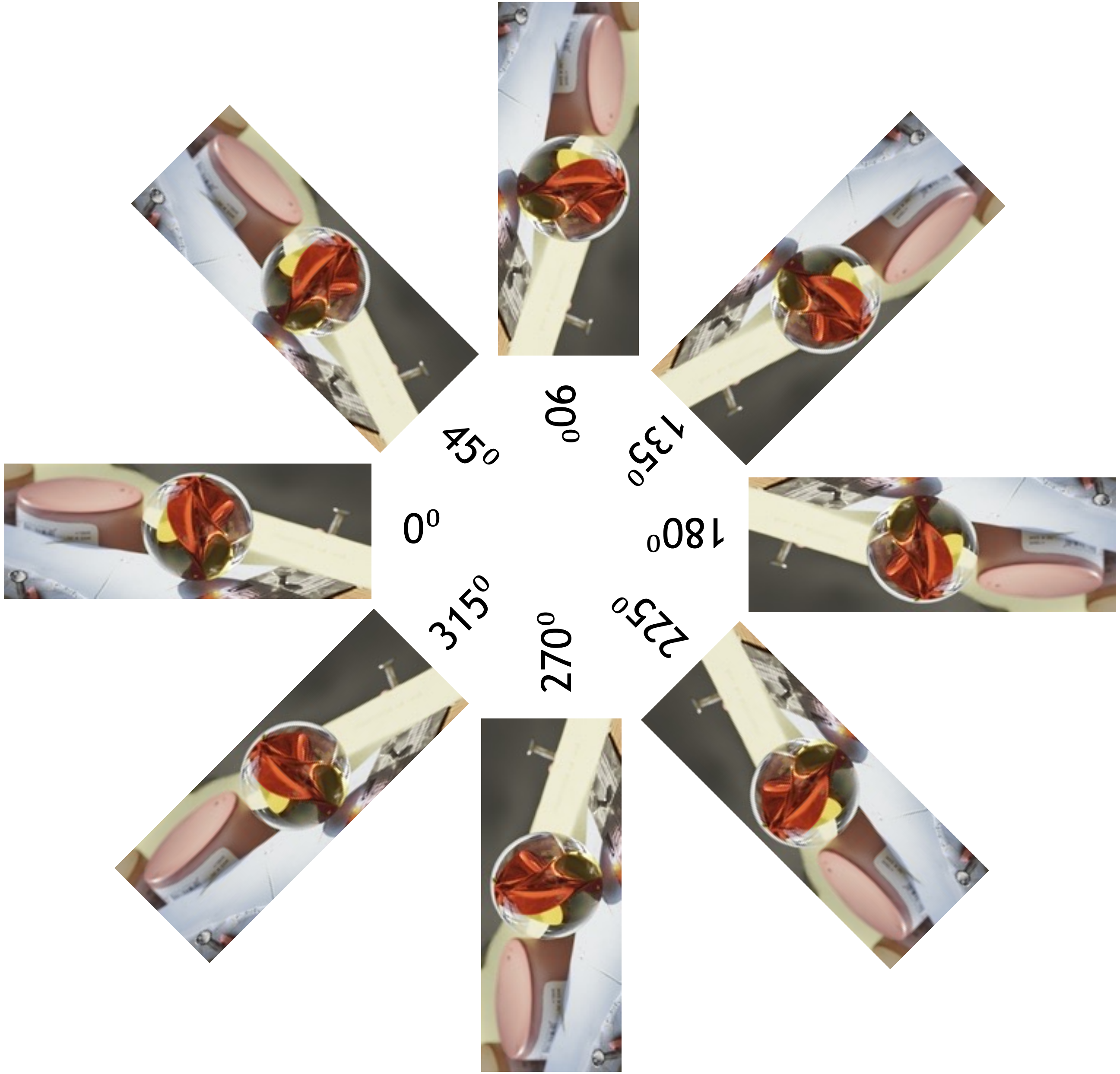
IMAGE FLIPPING

Horizontal Flip

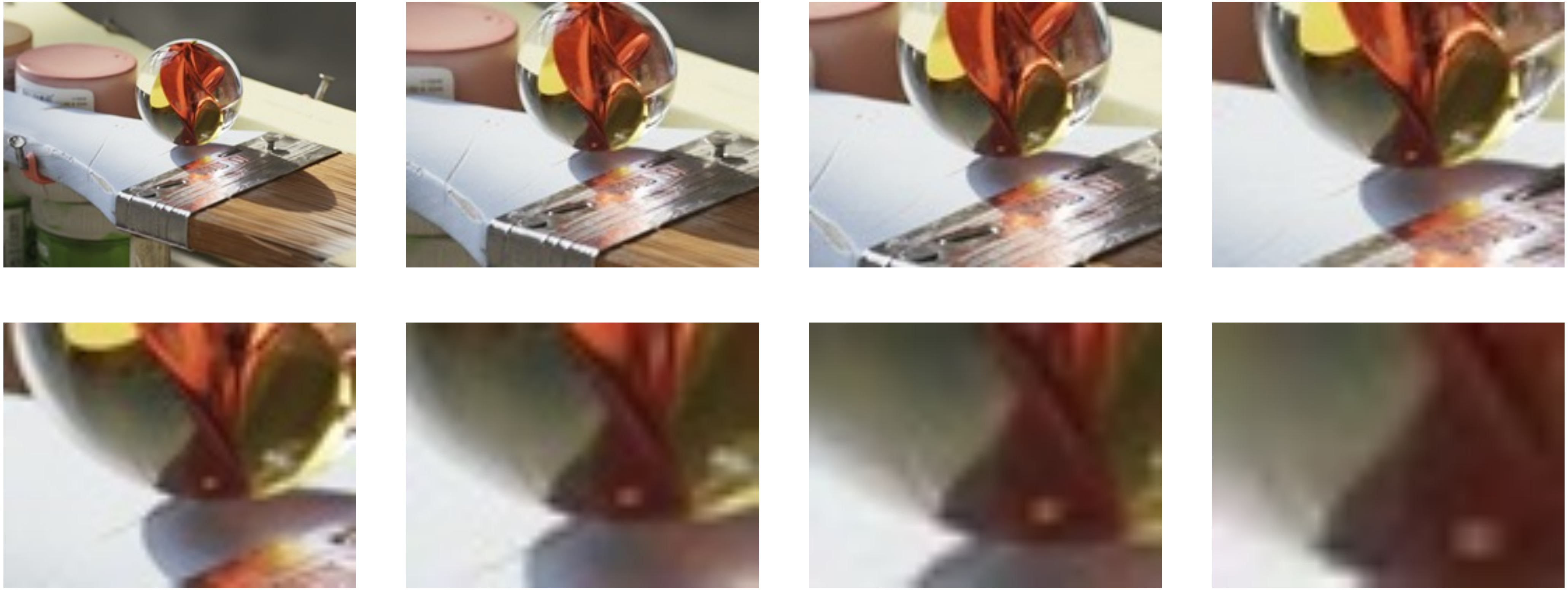


Vertical Flip

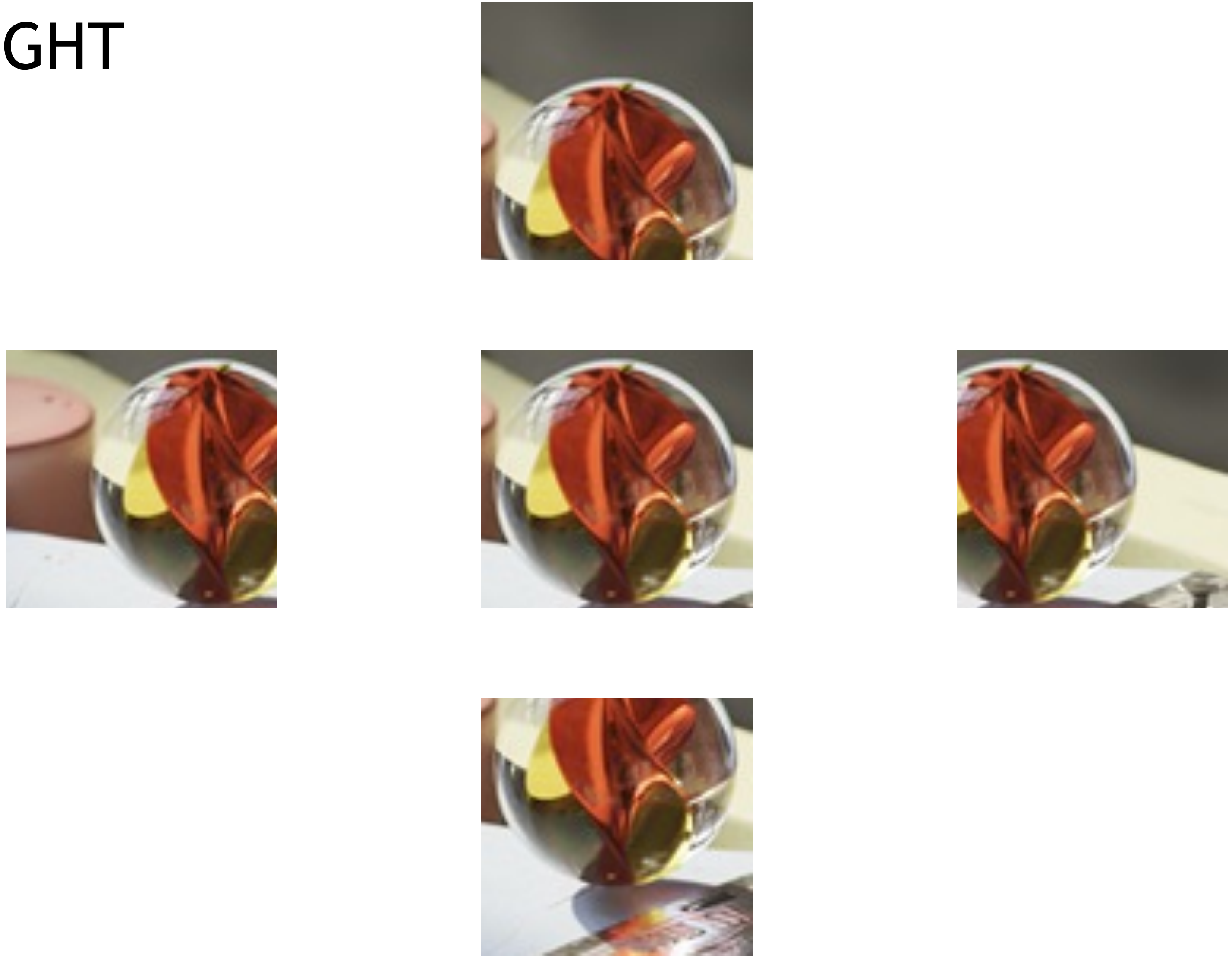
ROTATION



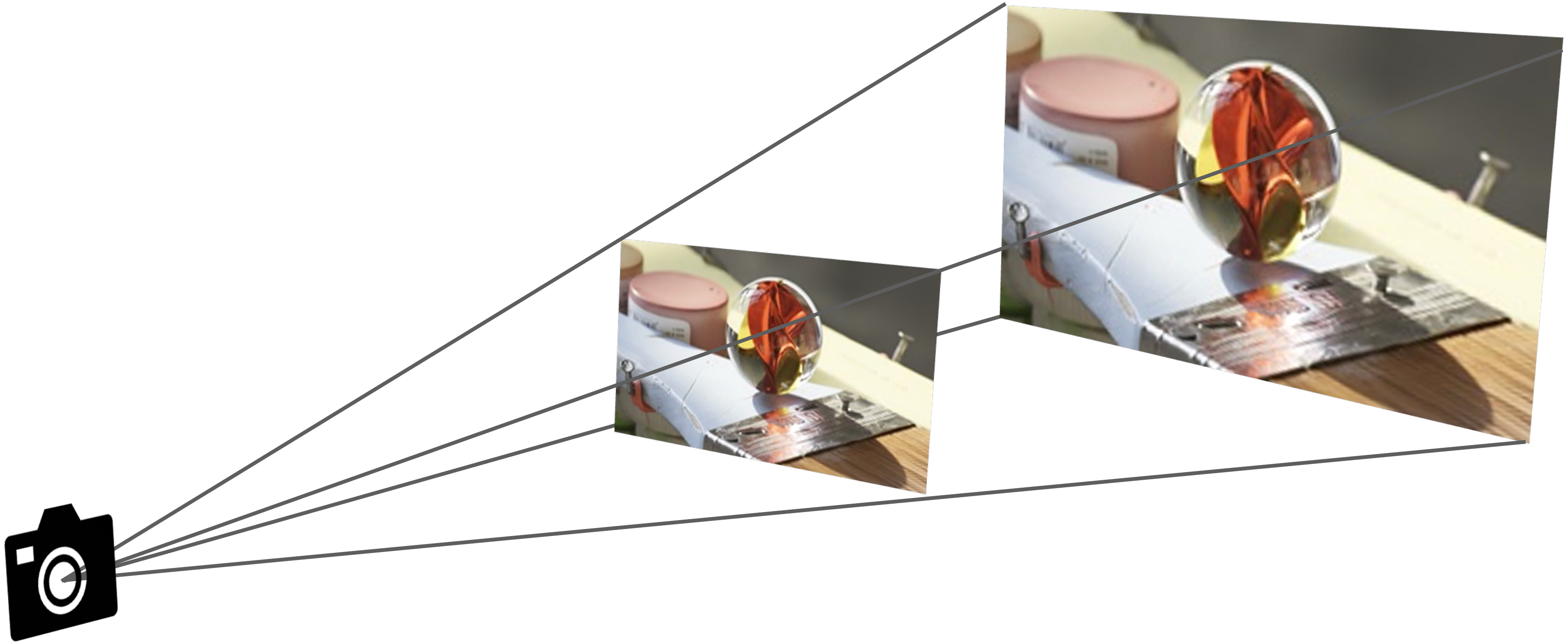
ZOOMING



WIDTH AND HEIGHT SHIFTING

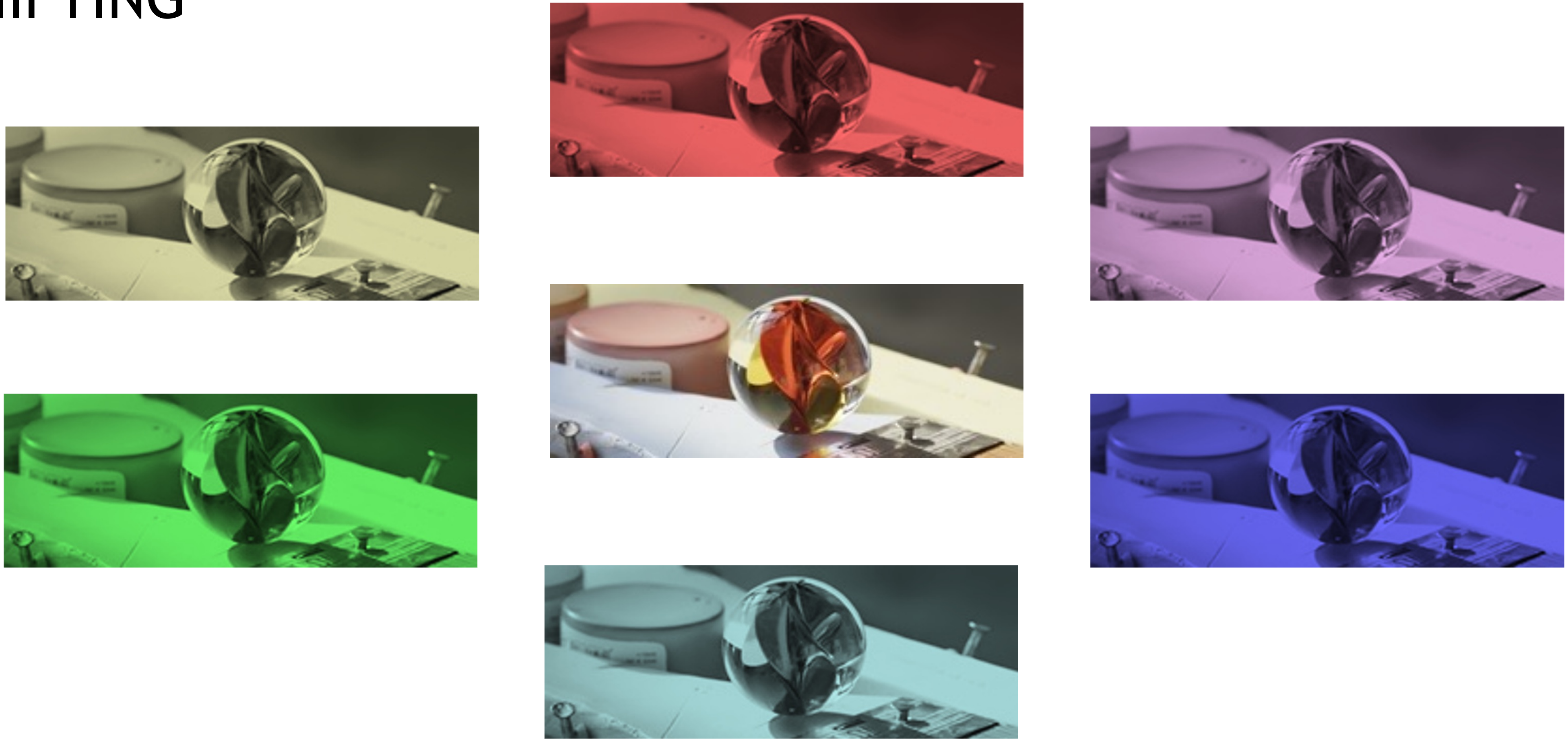


HOMOGRAPHY



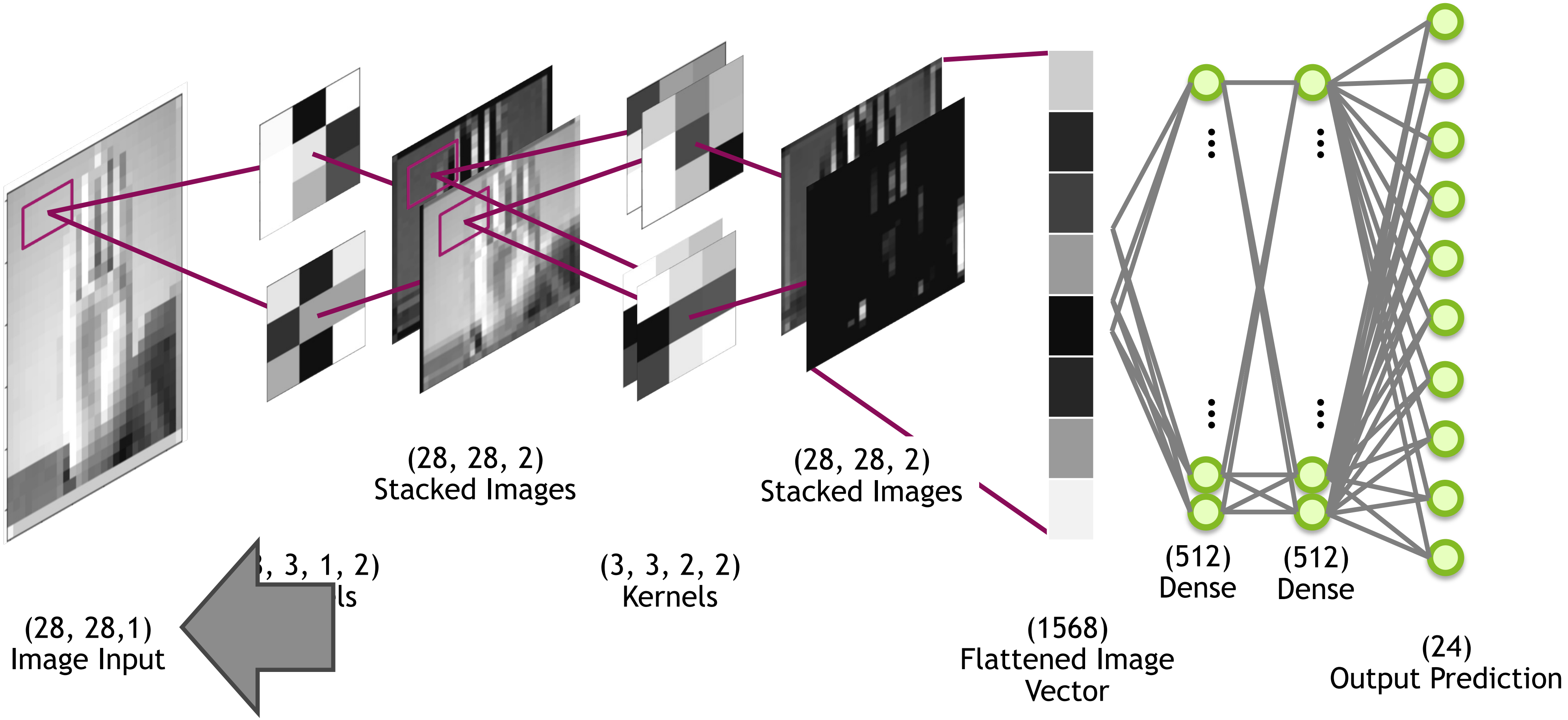
BRIGHTNESS

CHANNEL SHIFTING



MODEL DEPLOYMENT

MODEL DEPLOYMENT



MODEL DEPLOYMENT

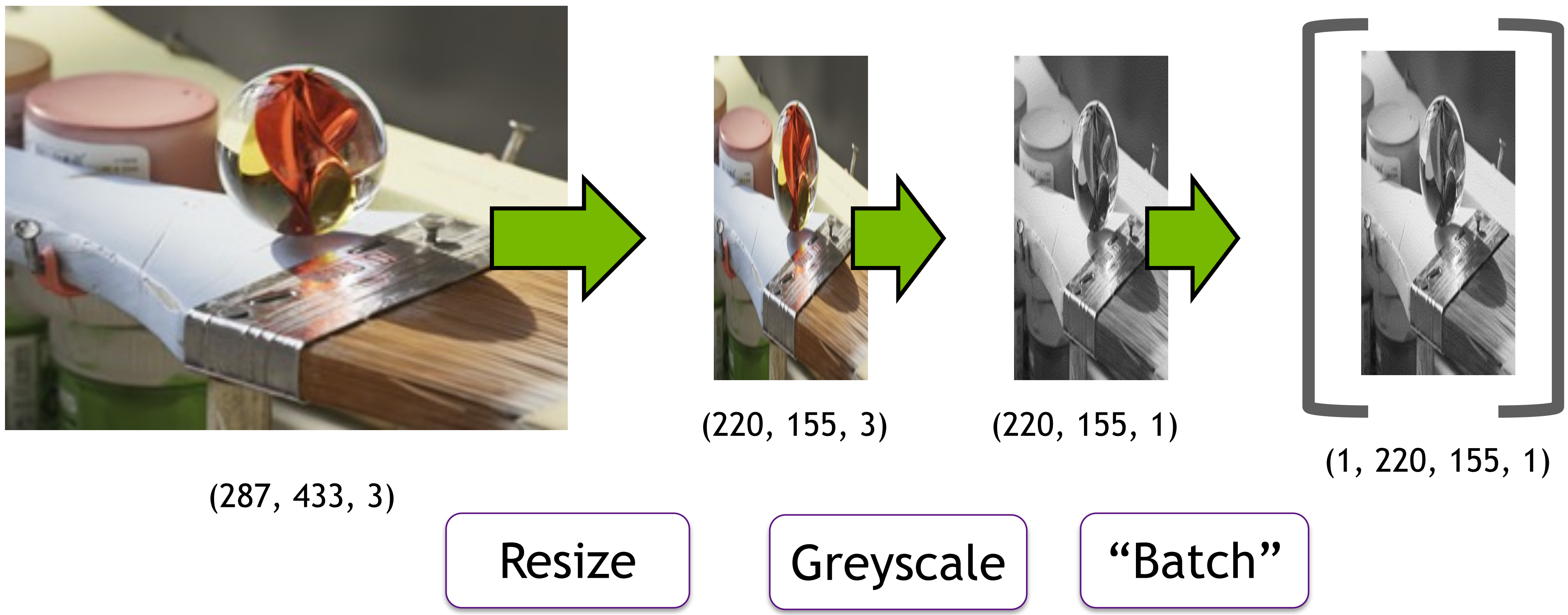
Training Batch Input

Convolution

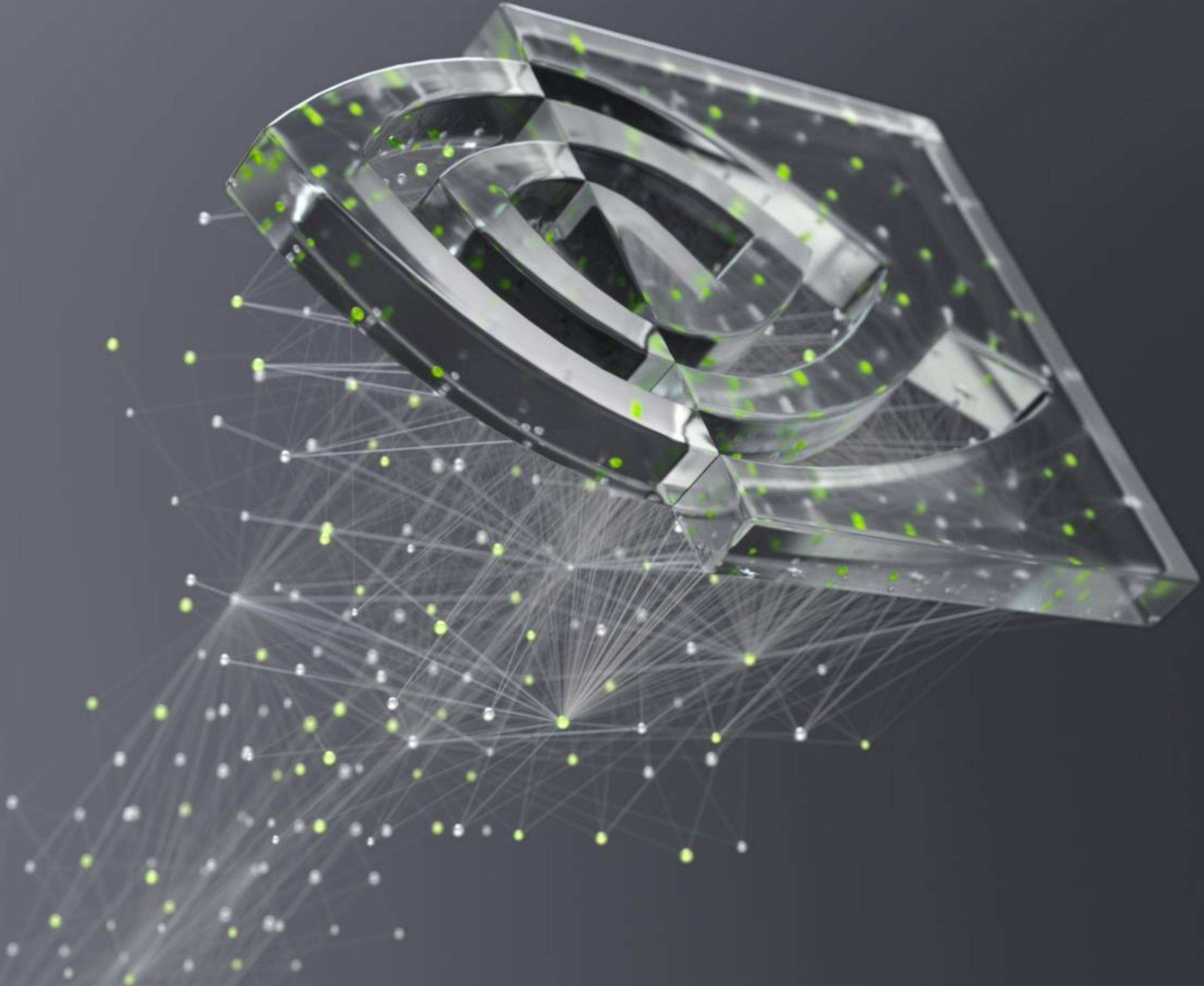
Max Pooling

...

MODEL DEPLOYMENT



LET’S TRY IT OUT!



NVIDIA

DEEP
LEARNING
INSTITUTE

DEEP LEARNING INSTITUTE

FUNDAMENTALS OF DEEP LEARNING

Part 5: Pre-trained Models

Part 1: An Introduction to Deep Learning

Part 2: How a Neural Network Trains

Part 3: Convolutional Neural Networks

Part 4: Data Augmentation and Deployment

Part 5: Pre-trained Models

Part 6: Advanced Architectures

REVIEW SO FAR

REVIEW SO FAR

- Learning Rate
- Number of Layers
- Neurons per Layer
- Activation Functions
- Dropout
- Data

PRE-TRAINED MODELS

PRE-TRAINED MODELS

TensorFlow Hub

Keras

NVIDIA NGC

PYTORCH HUB

PRE-TRAINED MODELS

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

Karen Simonyan* **& Andrew Zisserman**[+]
Visual Geometry Group, Department of Engineering Science, University of Oxford
{karen,az}@robots.ox.ac.uk

IMAGENET

THE NEXT CHALLENGE

An Automated Doggy Door

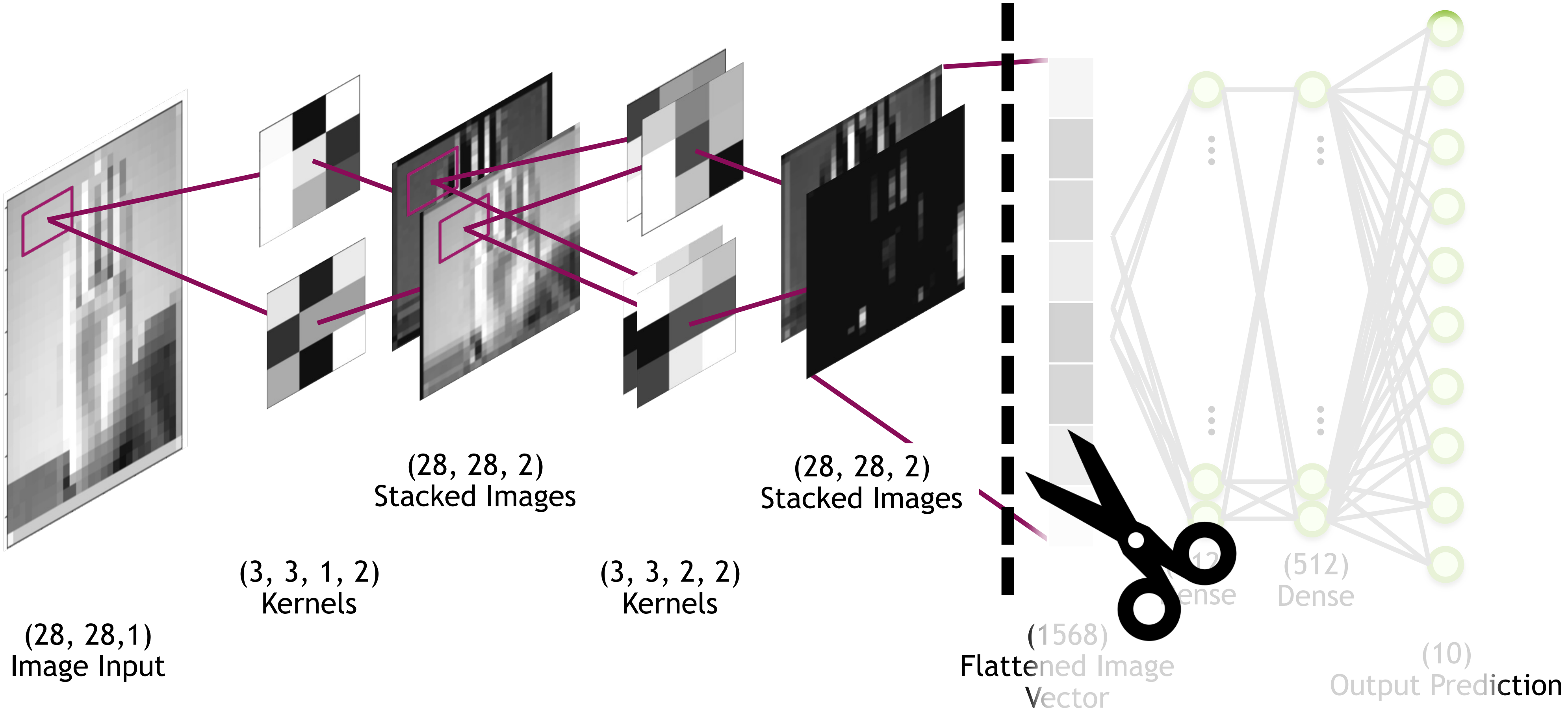
TRANSFER LEARNING

THE CHALLENGE AFTER

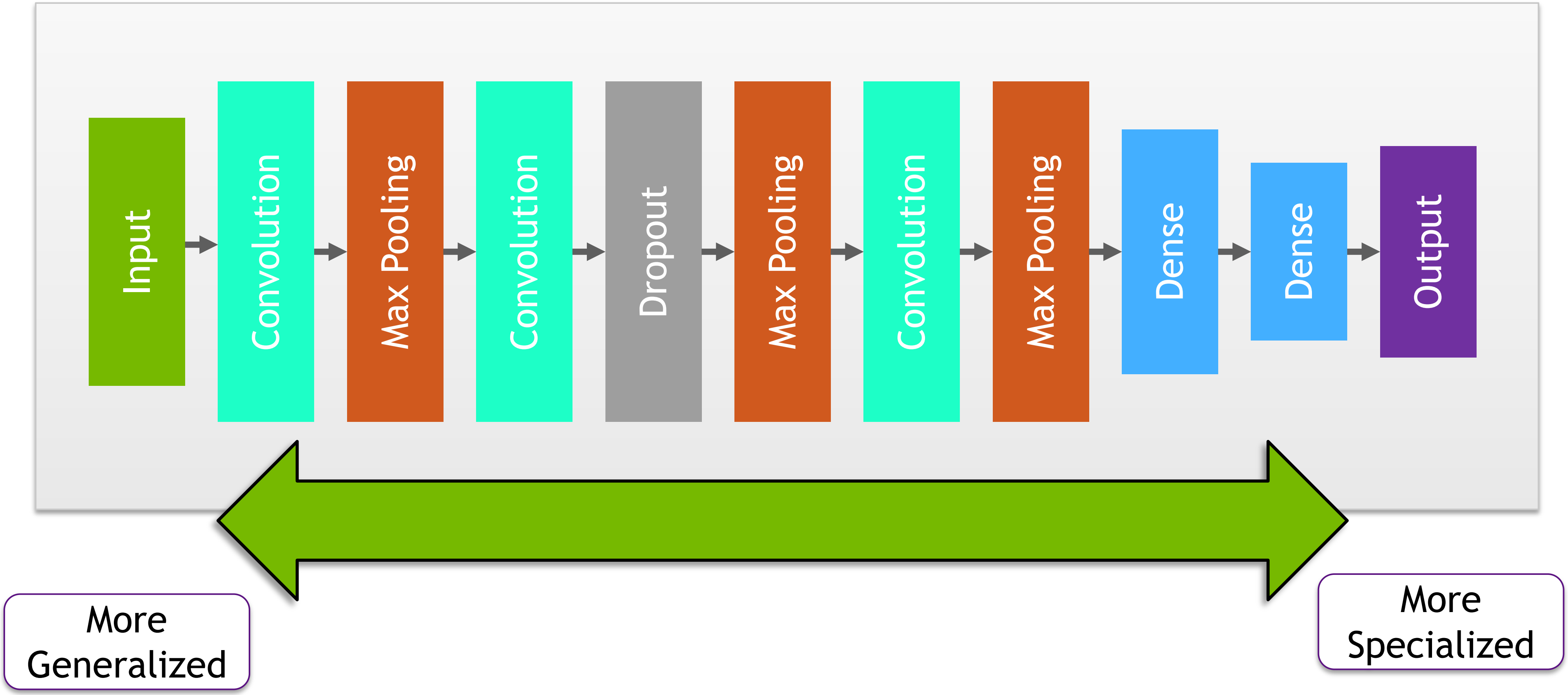
An Automated Presidential Doggy Door

TRANSFER LEARNING

TRANSFER LEARNING



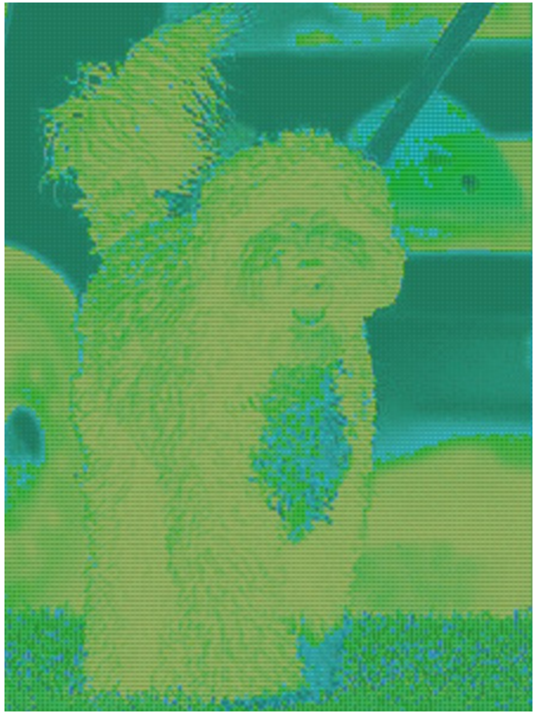
TRANSFER LEARNING

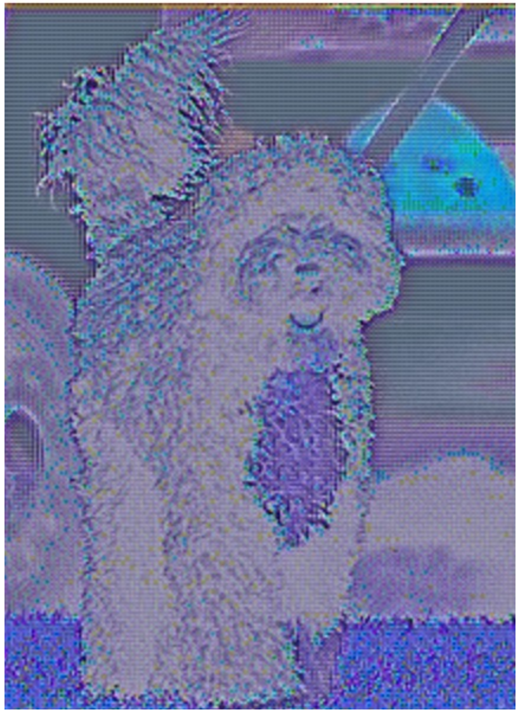


TRANSFER LEARNING

Freezing the Model?

TRANSFER LEARNING





LET’S GET STARTED!

NVIDIA

DEEP
LEARNING
INSTITUTE

NVIDIA | DEEP LEARNING INSTITUTE

FUNDAMENTALS OF DEEP LEARNING

Part 6: Advanced Architectures

Part 1: An Introduction to Deep Learning

Part 2: How a Neural Network Trains

Part 3: Convolutional Neural Networks

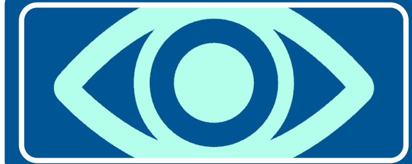
Part 4: Data Augmentation and Deployment

Part 5: Pre-trained Models

Part 6: Advanced Architectures

MOVING FORWARD

FIELDS OF AI

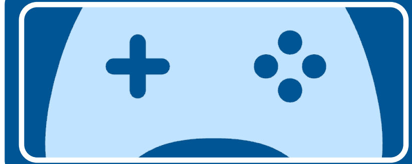


Computer Vision

- Optometry

Natural Language Processing

- Linguistics



Reinforcement Learning

- Game Theory
- Psychology

Anomaly Detection

- Security
- Medicine

FIELDS OF AI

Computer Vision

- Optometry

Natural Language Processing

- Linguistics

Reinforcement Learning

- Game Theory
- Psychology

Anomaly Detection

- Security
- Medicine

FIELDS OF AI

Computer Vision

- Optometry

Natural Language Processing

- Linguistics

Reinforcement Learning

- Game Theory
- Psychology

Anomaly Detection

- Security
- Medicine

NATURAL LANGUAGE PROCESSING

FROM WORDS TO NUMBERS

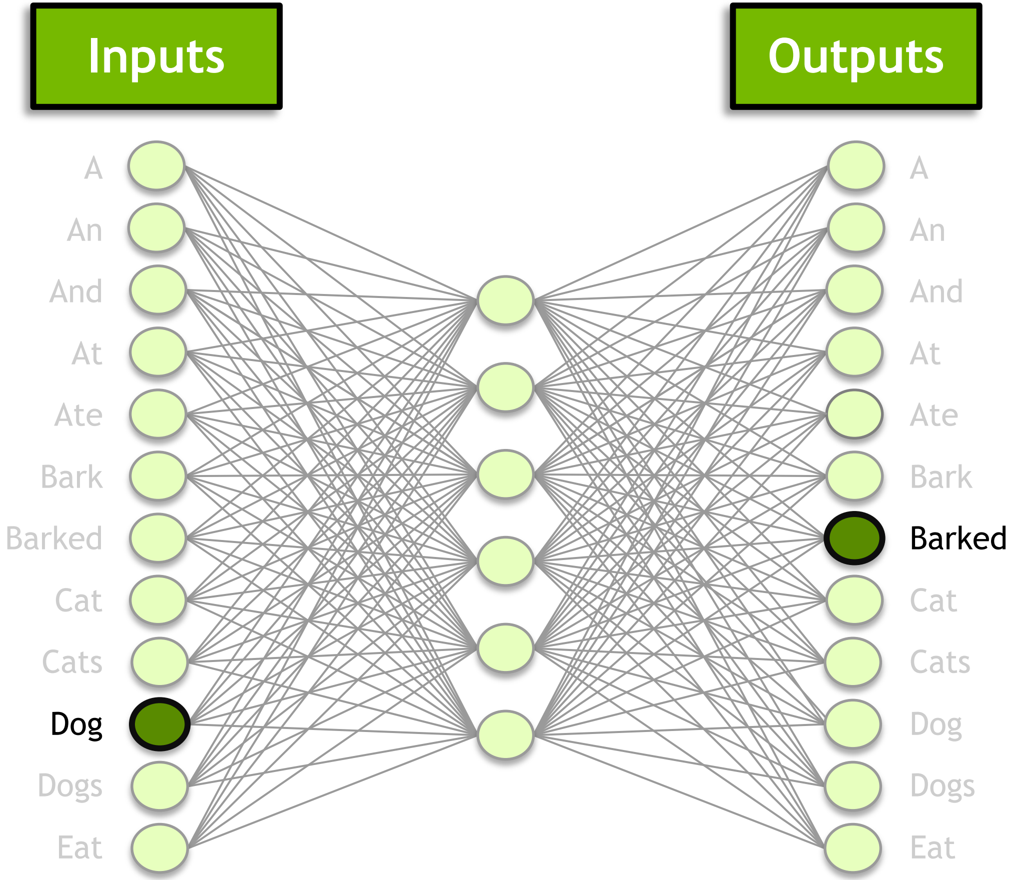
"A dog barked at a cat."

[1, 10, 7, 4, 1, 8]

Dictionary

1. A
2. An
3. And
4. At
5. Ate
6. Bark
7. Barked
8. Cat
9. Cats
10. Dog
11. Dogs
12. Eat

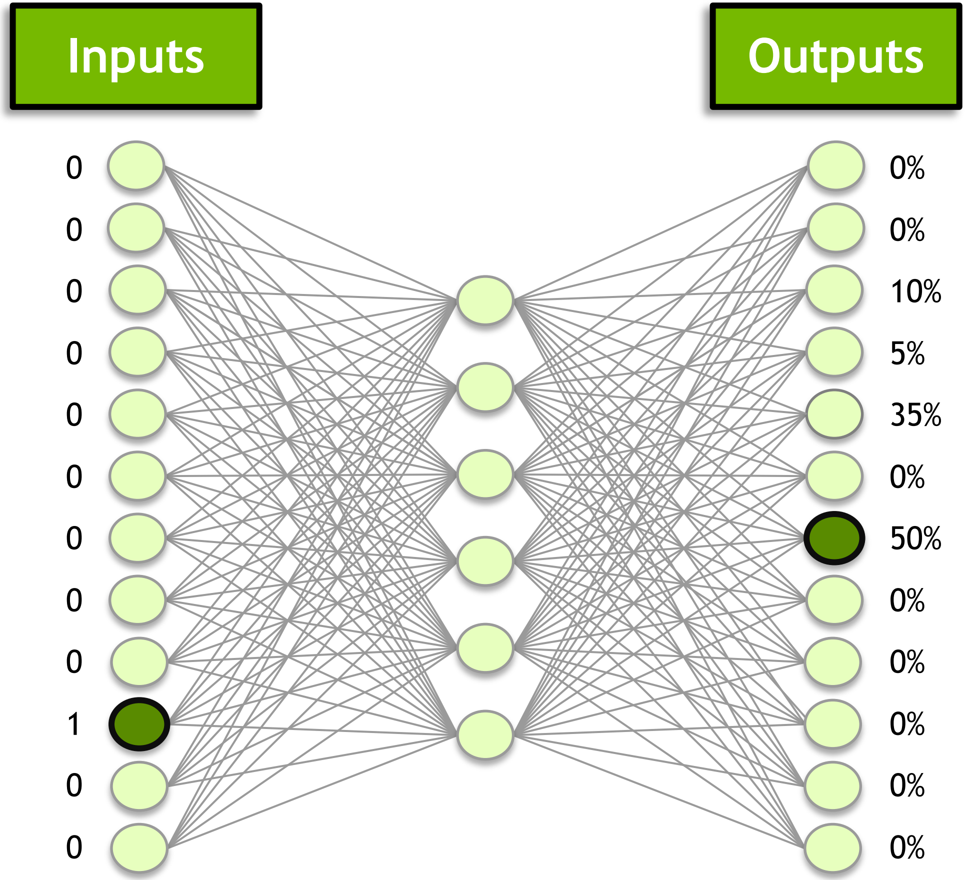
FROM WORDS TO NUMBERS



Dictionary

1. A
2. An
3. And
4. At
5. Ate
6. Bark
7. Barked
8. Cat
9. Cats
10. Dog
11. Dogs
12. Eat

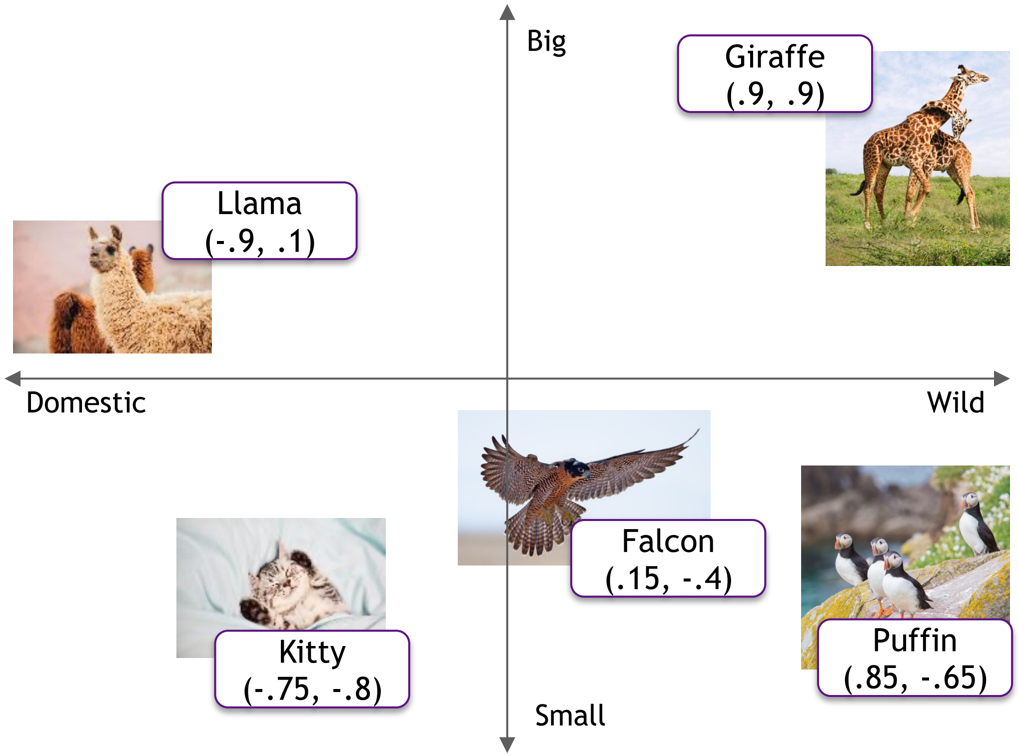
FROM WORDS TO NUMBERS



Dictionary

1. A
2. An
3. And
4. At
5. Ate
6. Bark
7. Barked
8. Cat
9. Cats
10. Dog
11. Dogs
12. Eat

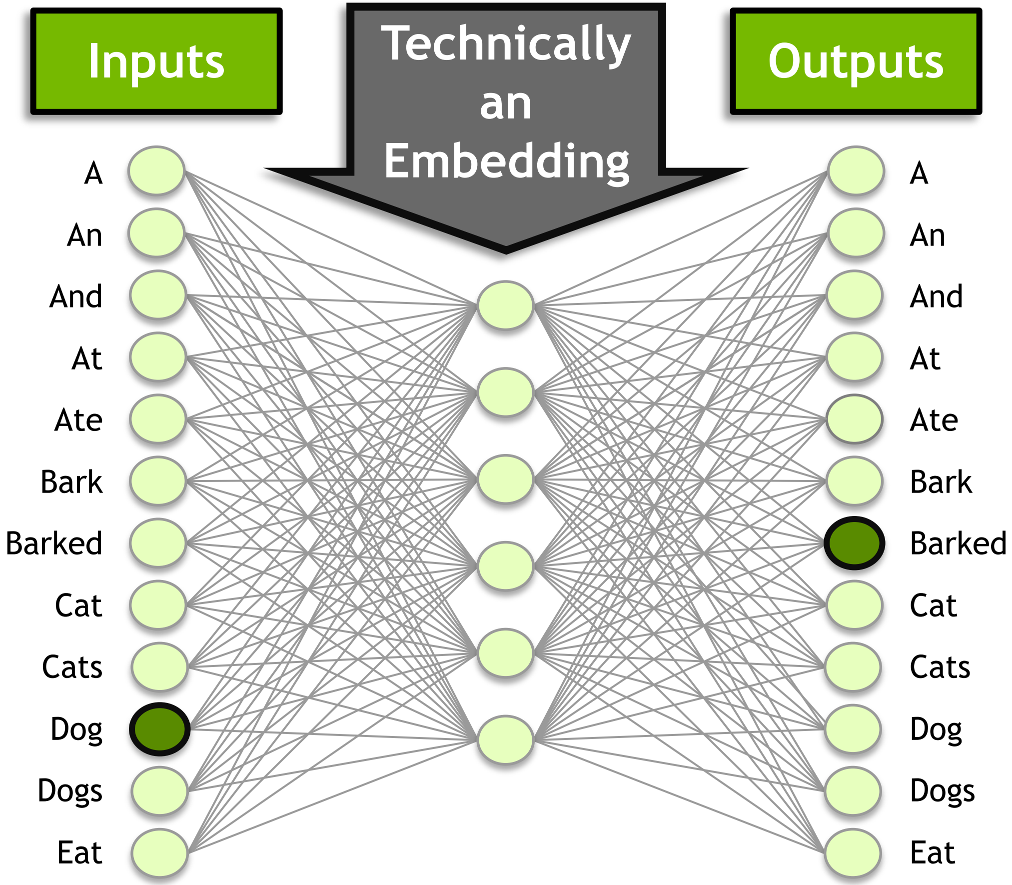
FROM WORDS TO NUMBERS



Bigger Dictionary

1.	A	31.	Ate	61.	Cats
2.	An	32.	Bark	62.	Dog
3.	And	33.	Barked	63.	Dogs
4.	At	34.	Cat	64.	Eat
5.	Ate	35.	Cats	65.	Eaten
6.	Bark	36.	Dog	66.	A
7.	Barked	37.	Dogs	67.	An
8.	Cat	38.	Eat	68.	And
9.	Cats	39.	Eaten	69.	At
10.	Dog	40.	A	70.	Ate
11.	Dogs	41.	An	71.	Bark
12.	Eat	42.	And	72.	Barked
13.	Eaten	43.	At	73.	Cat
14.	A	44.	Ate	74.	Cats
15.	An	45.	Bark	75.	Dog
16.	And	46.	Barked	76.	Dogs
17.	At	47.	Cat	77.	Eat
18.	Ate	48.	Cats	78.	Eaten
19.	Bark	49.	Dog	79.	…
20.	Barked	50.	Dogs	80.	…
21.	Cat	51.	Eat	81.	…
22.	Cats	52.	Eaten	82.	…
23.	Dog	53.	A		
24.	Dogs	54.	An		
25.	Eat	55.	And		
26.	Eaten	56.	At		
27.	A	57.	Ate		
28.	An	58.	Bark		
29.	And	59.	Barked		
30.	At	60.	Cat		

FROM WORDS TO NUMBERS



Dictionary

1. A
2. An
3. And
4. At
5. Ate
6. Bark
7. Barked
8. Cat
9. Cats
10. Dog
11. Dogs
12. Eat

RECURRENT NEURAL NETWORKS

RECURRENT NEURAL NETWORKS

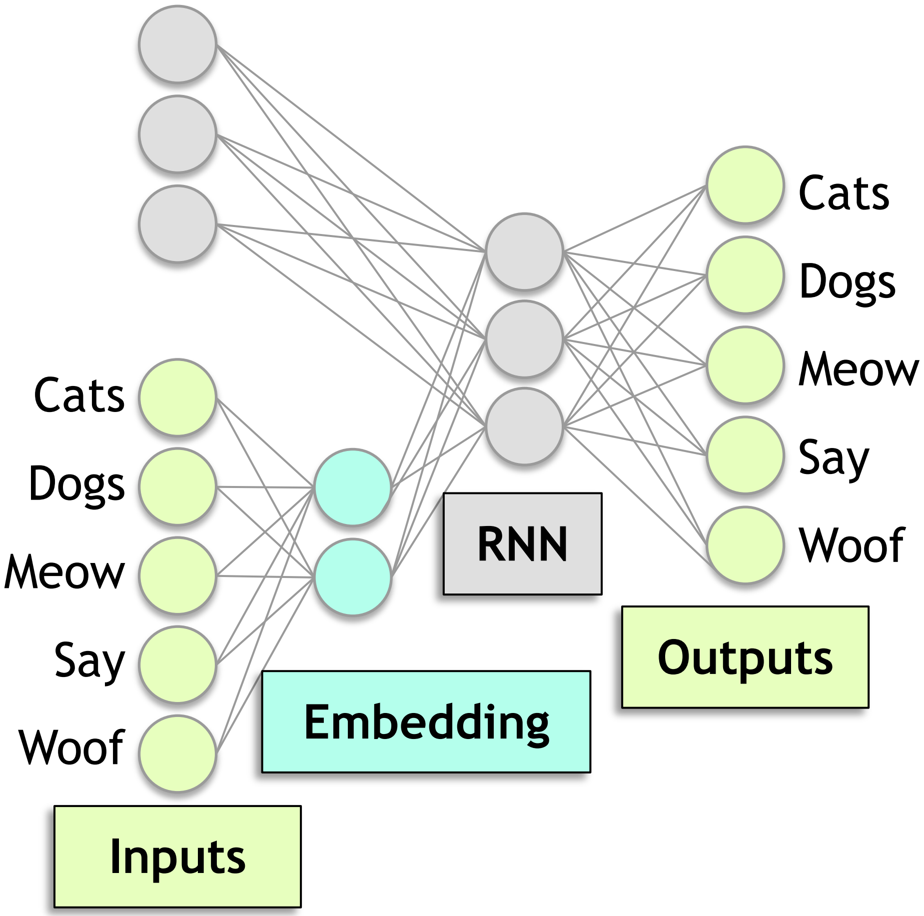
"Cats say ____."

"Dogs say ____."

Dictionary

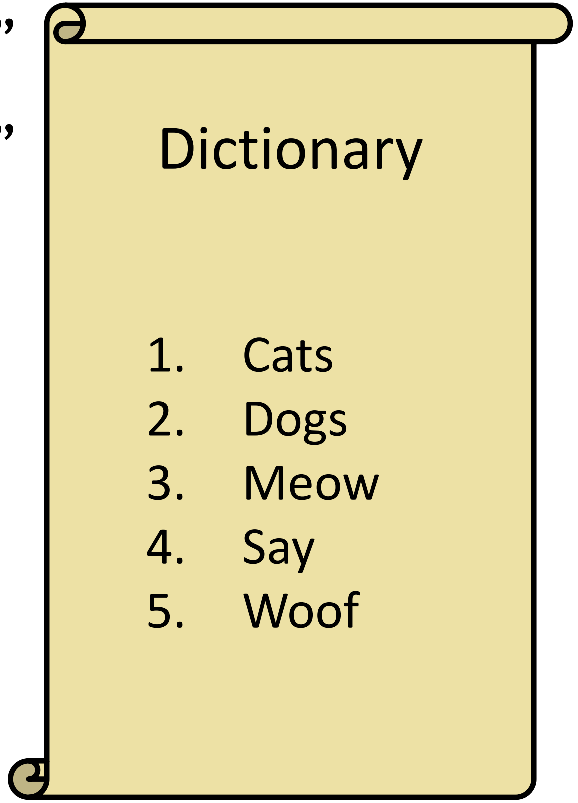
1. Cats
2. Dogs
3. Meow
4. Say
5. Woof

RECURRENT NEURAL NETWORKS

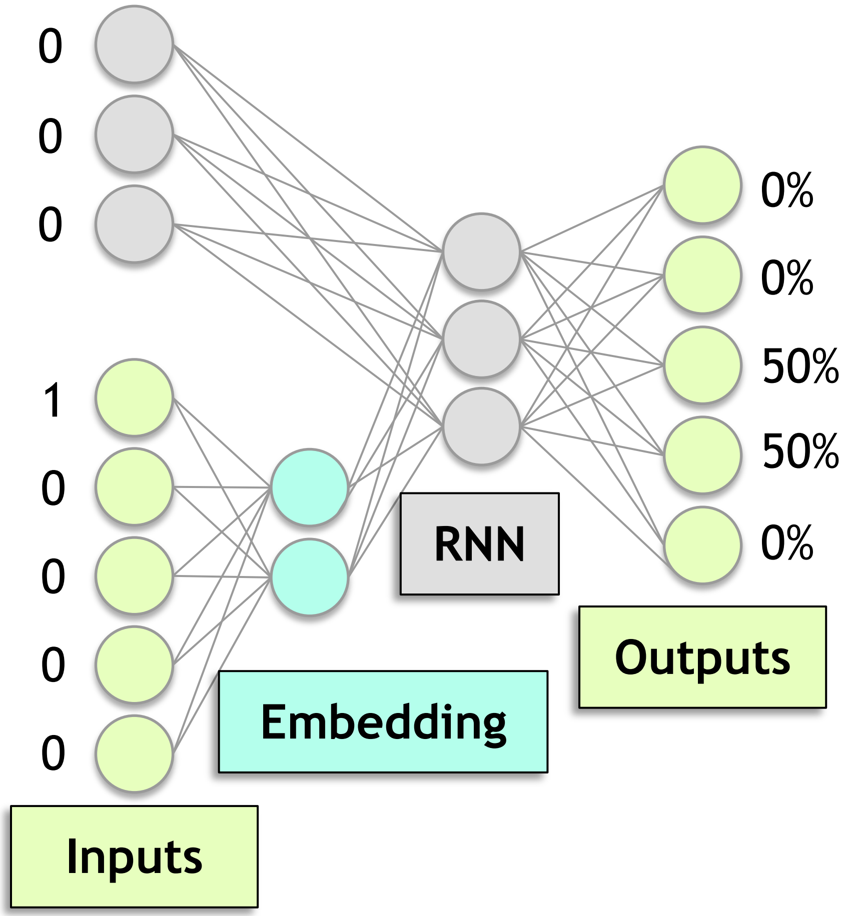


“Cats say ____.”

“Dogs say ____.”



RECURRENT NEURAL NETWORKS



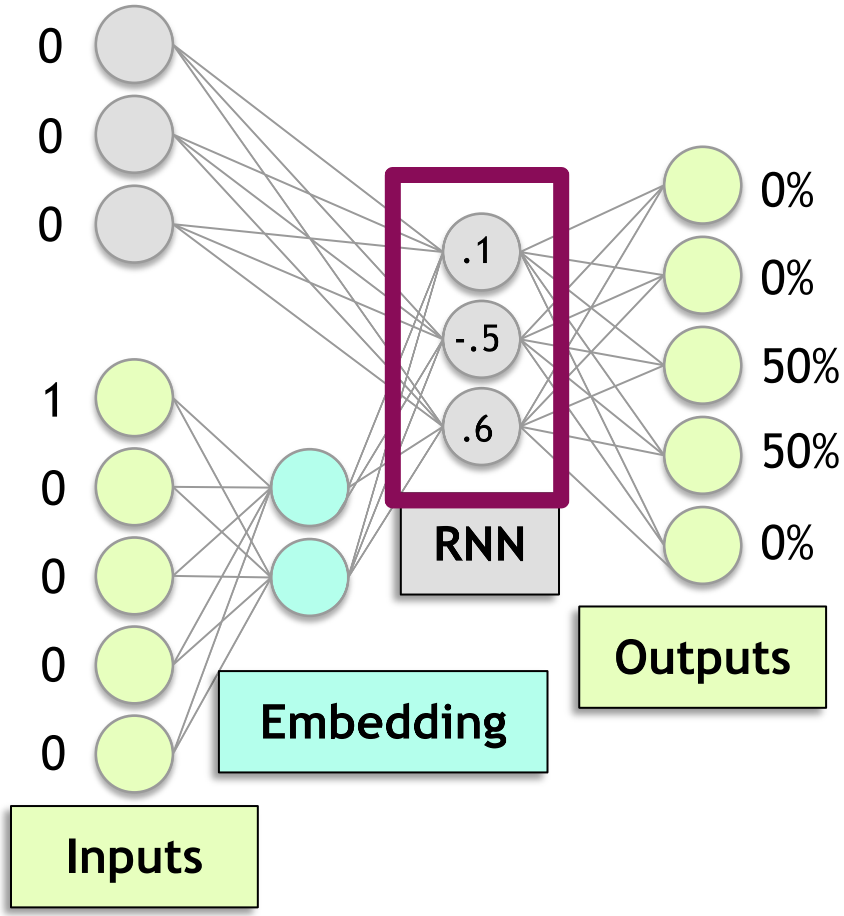
"Cats say ____."

"Dogs say ____."

Dictionary

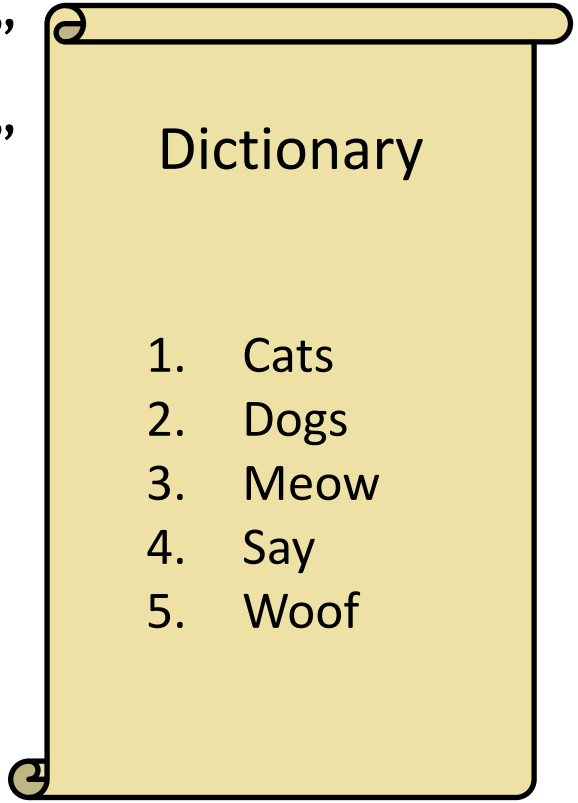
1. Cats
2. Dogs
3. Meow
4. Say
5. Woof

RECURRENT NEURAL NETWORKS

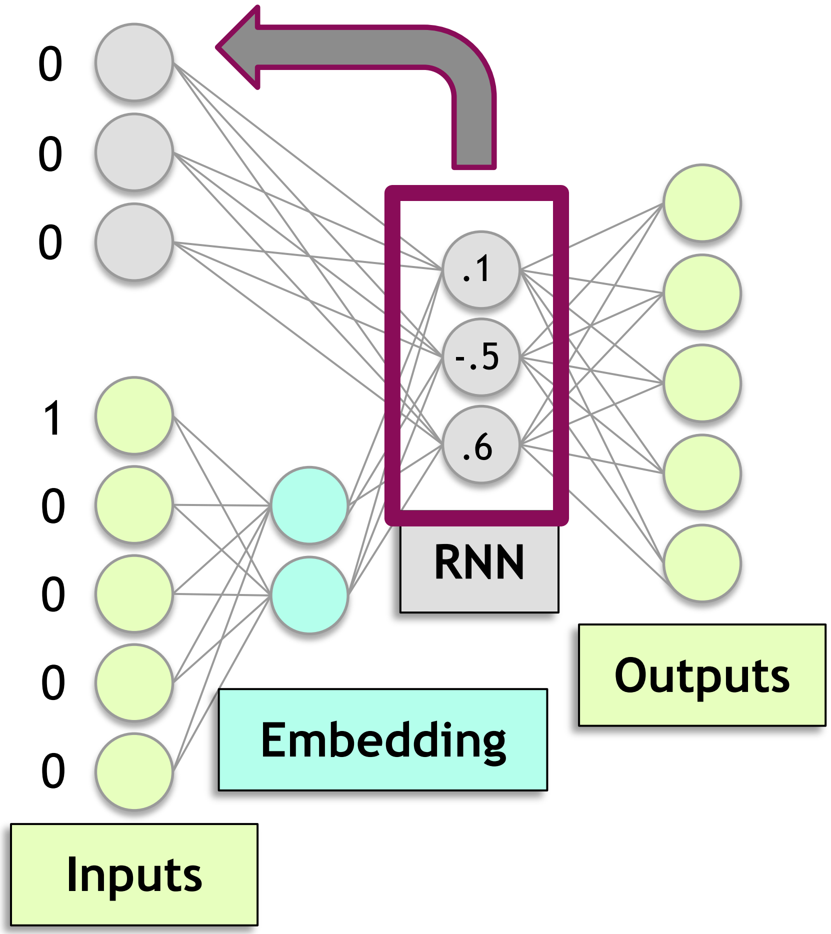


"Cats say ____."

"Dogs say ____."

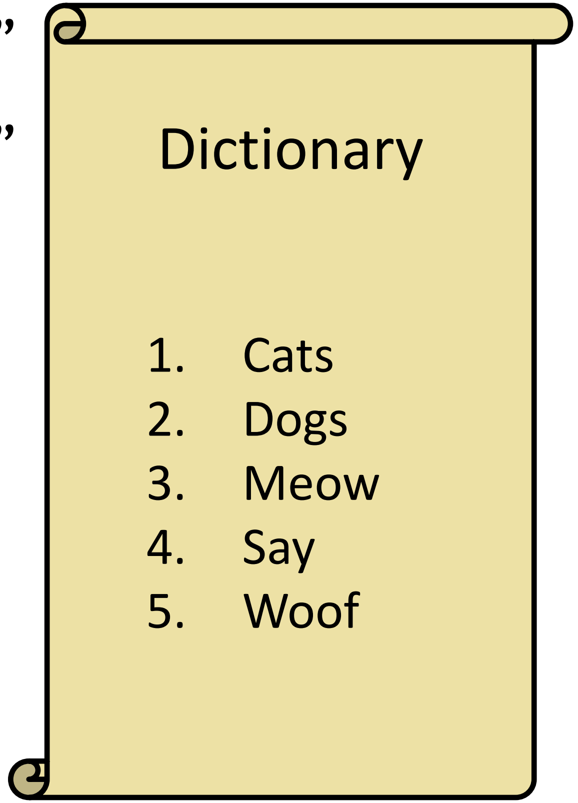


RECURRENT NEURAL NETWORKS

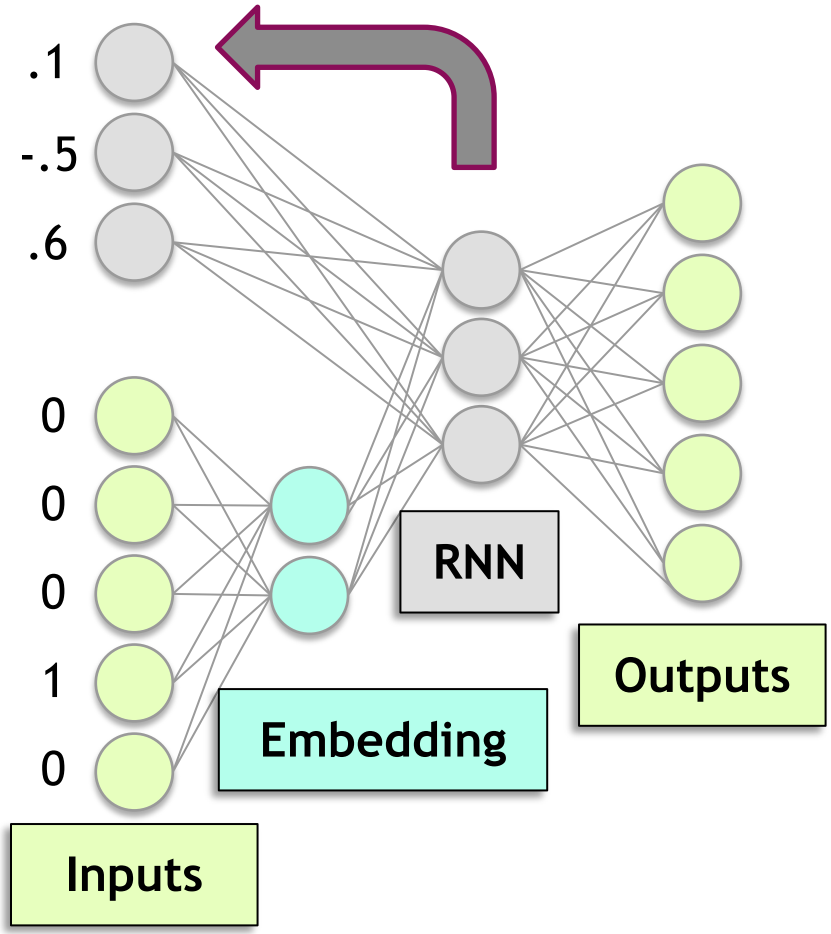


"Cats say ____."

"Dogs say ____."

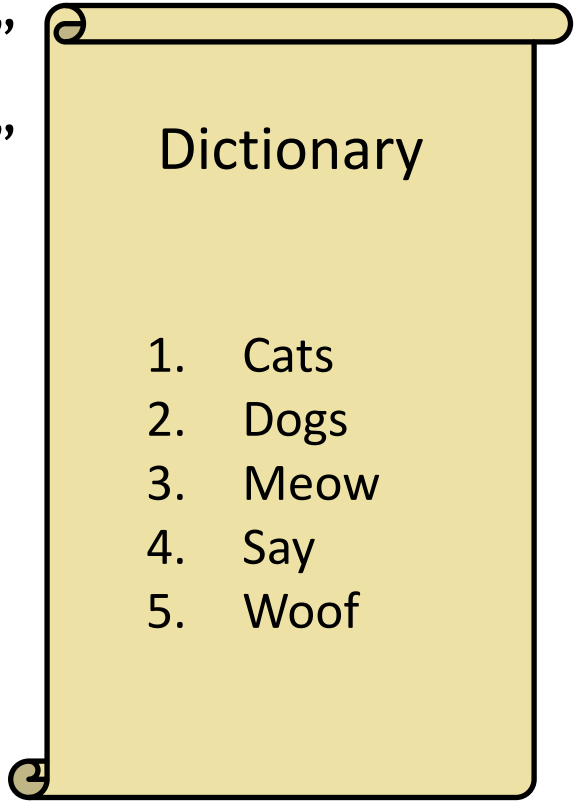


RECURRENT NEURAL NETWORKS

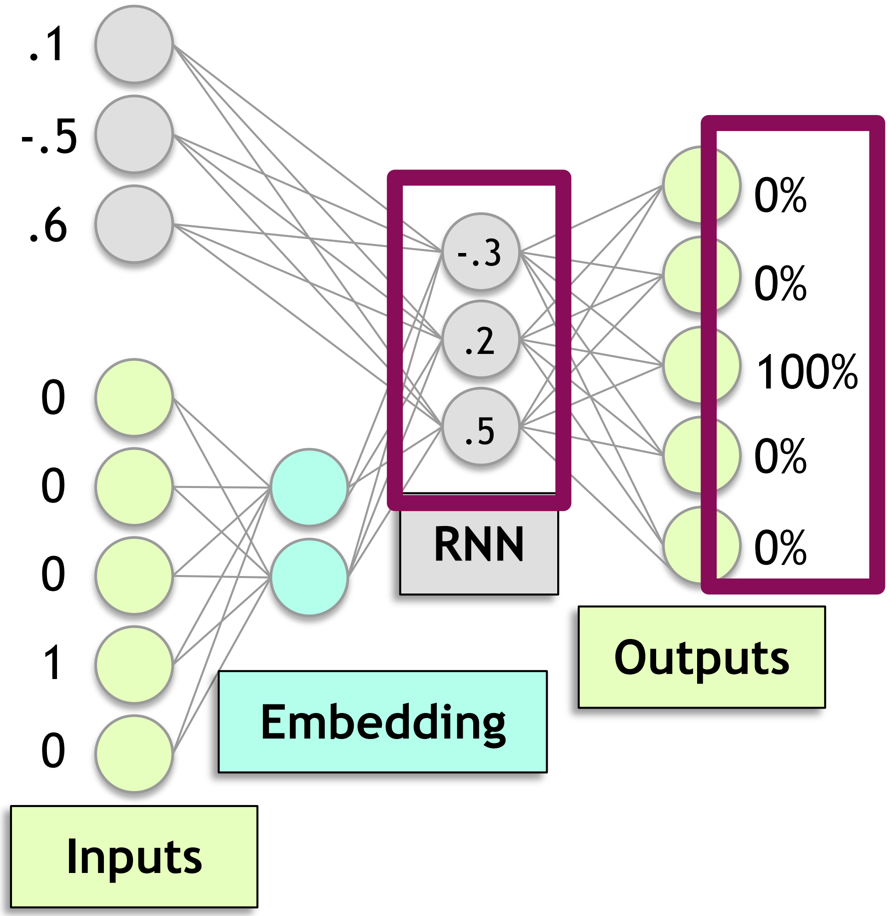


"Cats say ____."

"Dogs say ____."

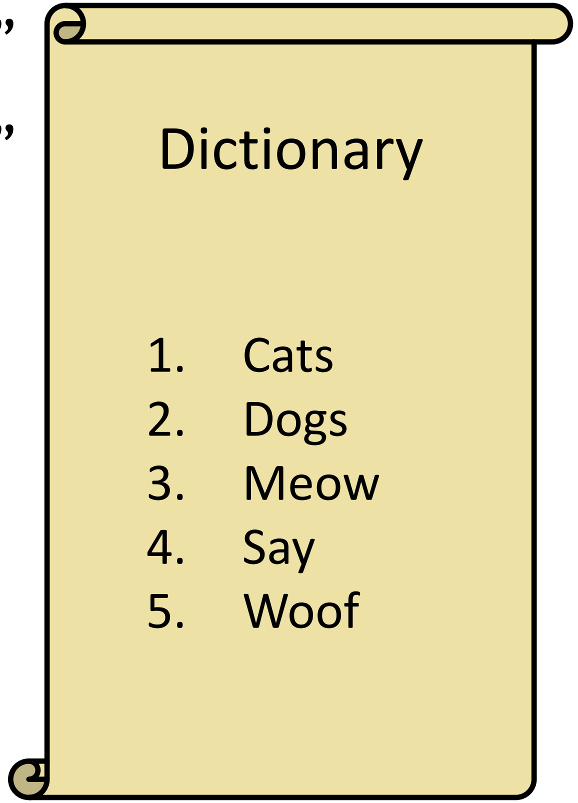


RECURRENT NEURAL NETWORKS

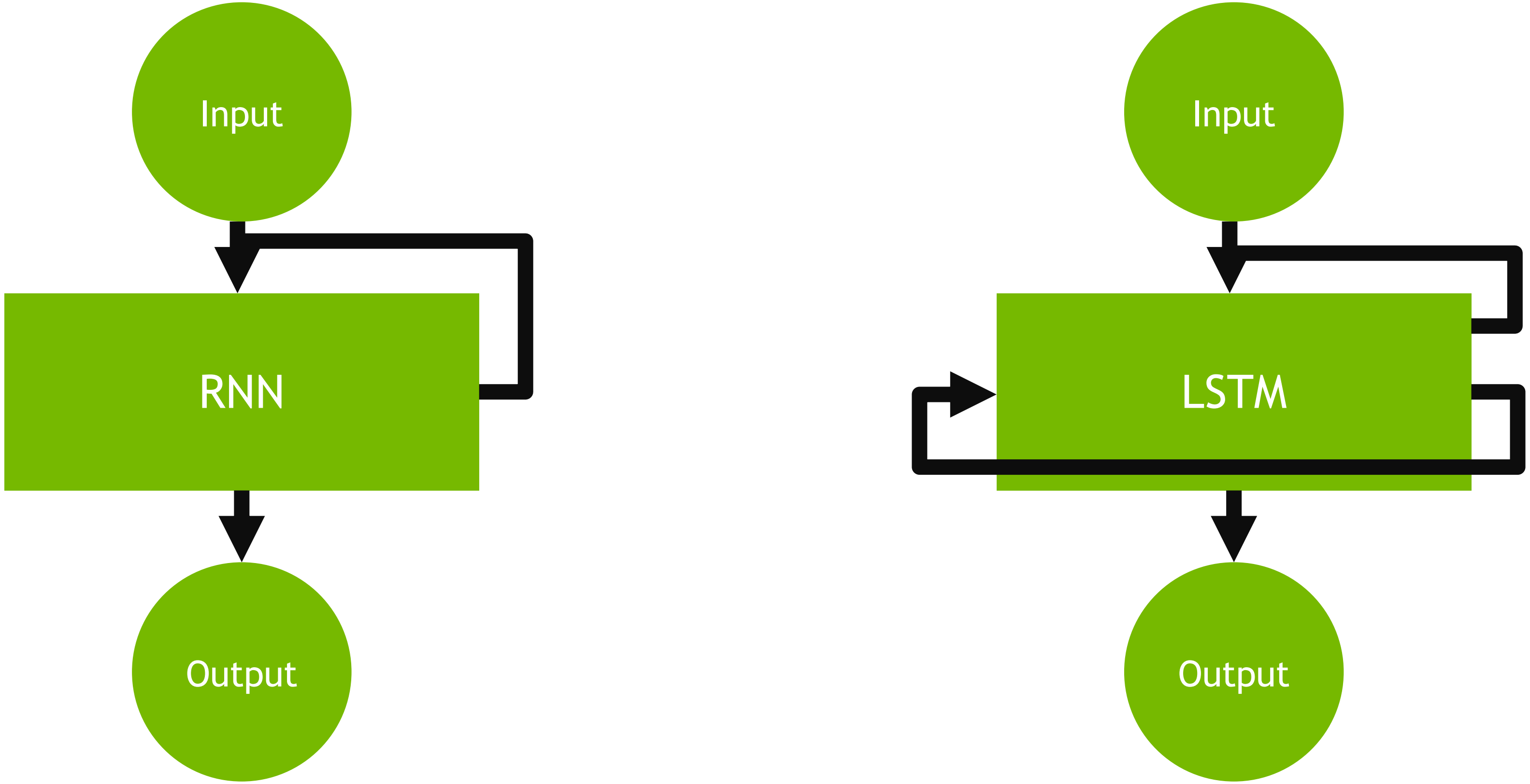


“Cats say ____.”

“Dogs say ____.”

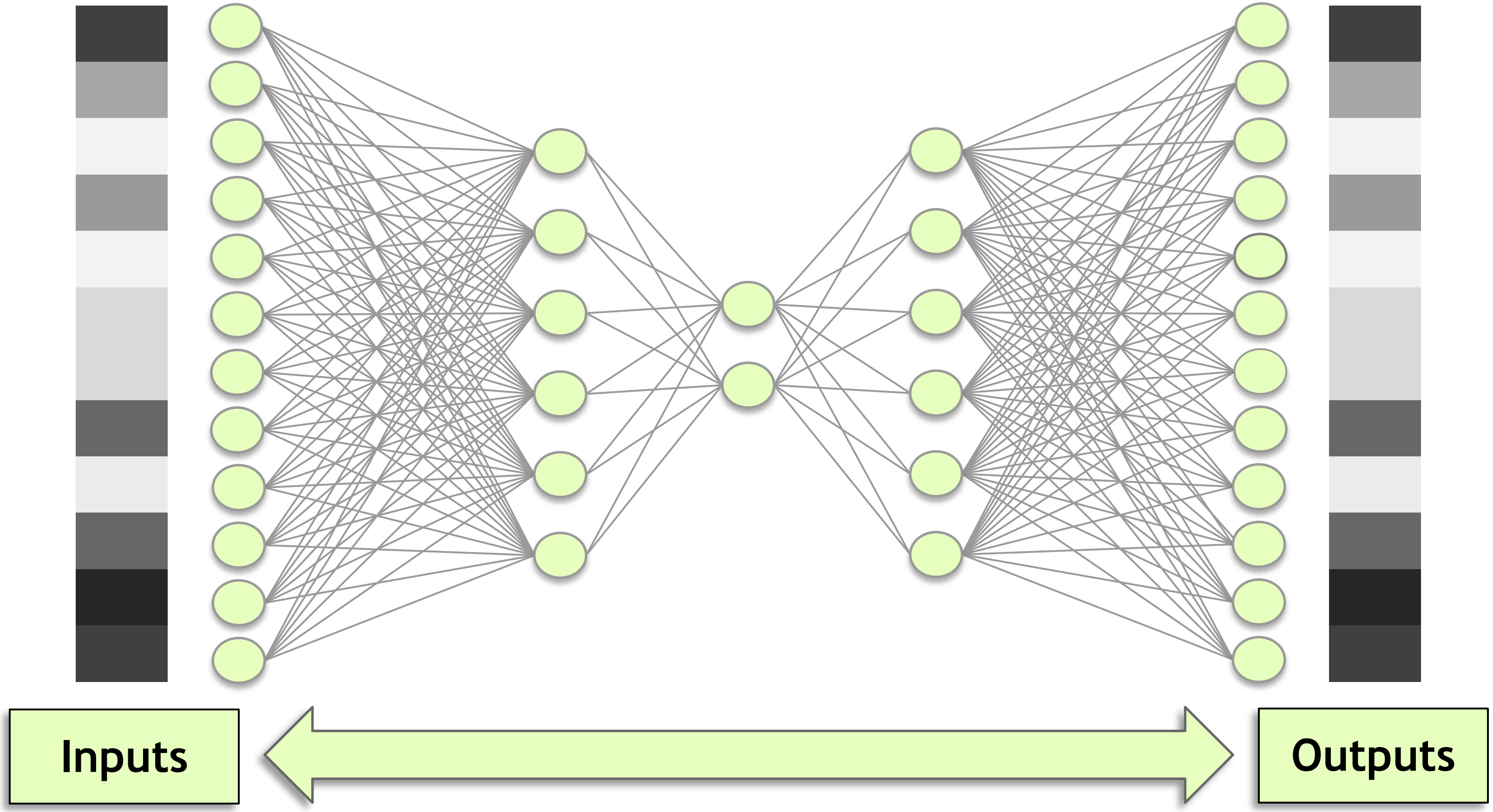


RECURRENT NEURAL NETWORKS

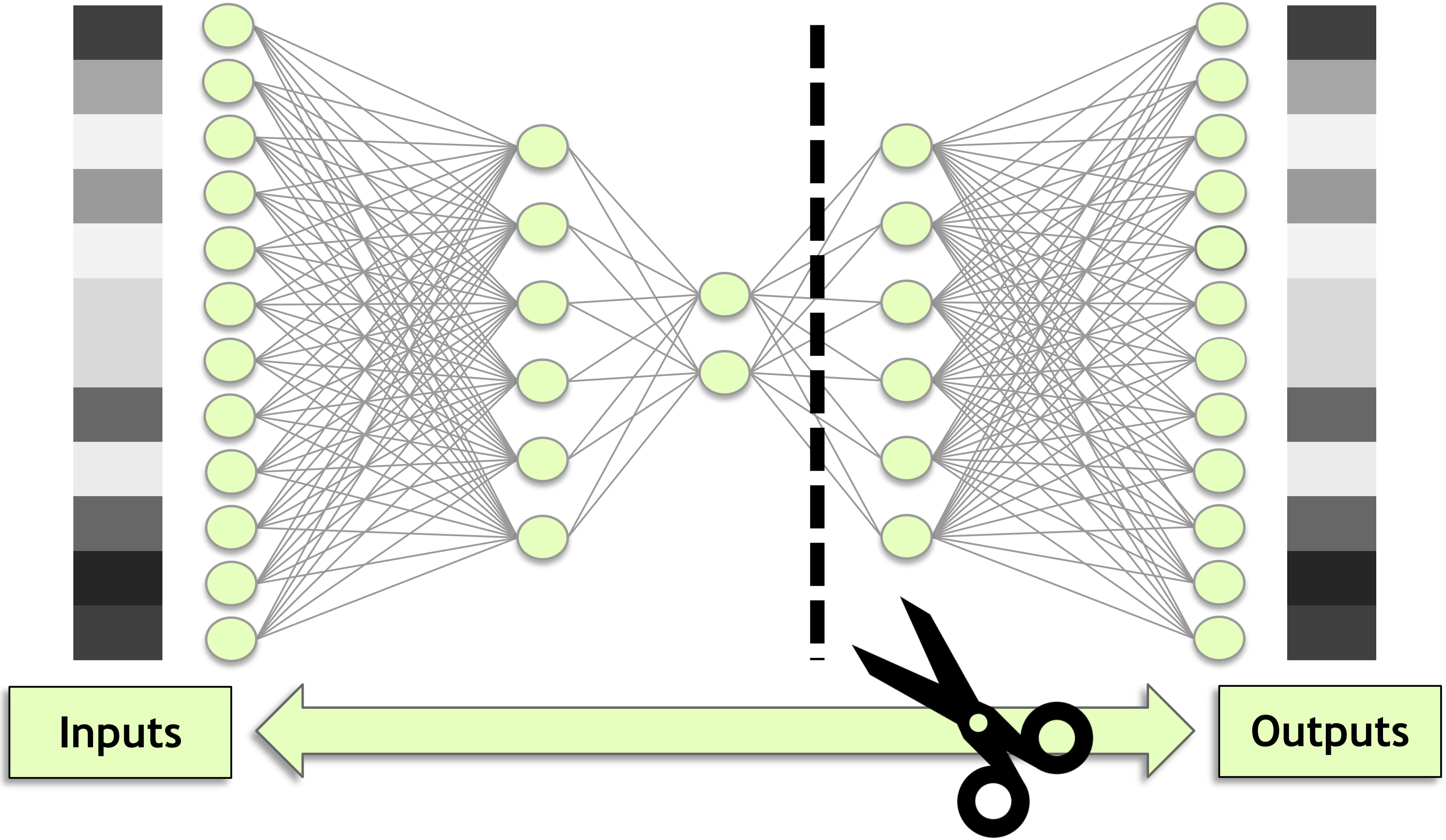


OTHER ARCHITECTURES

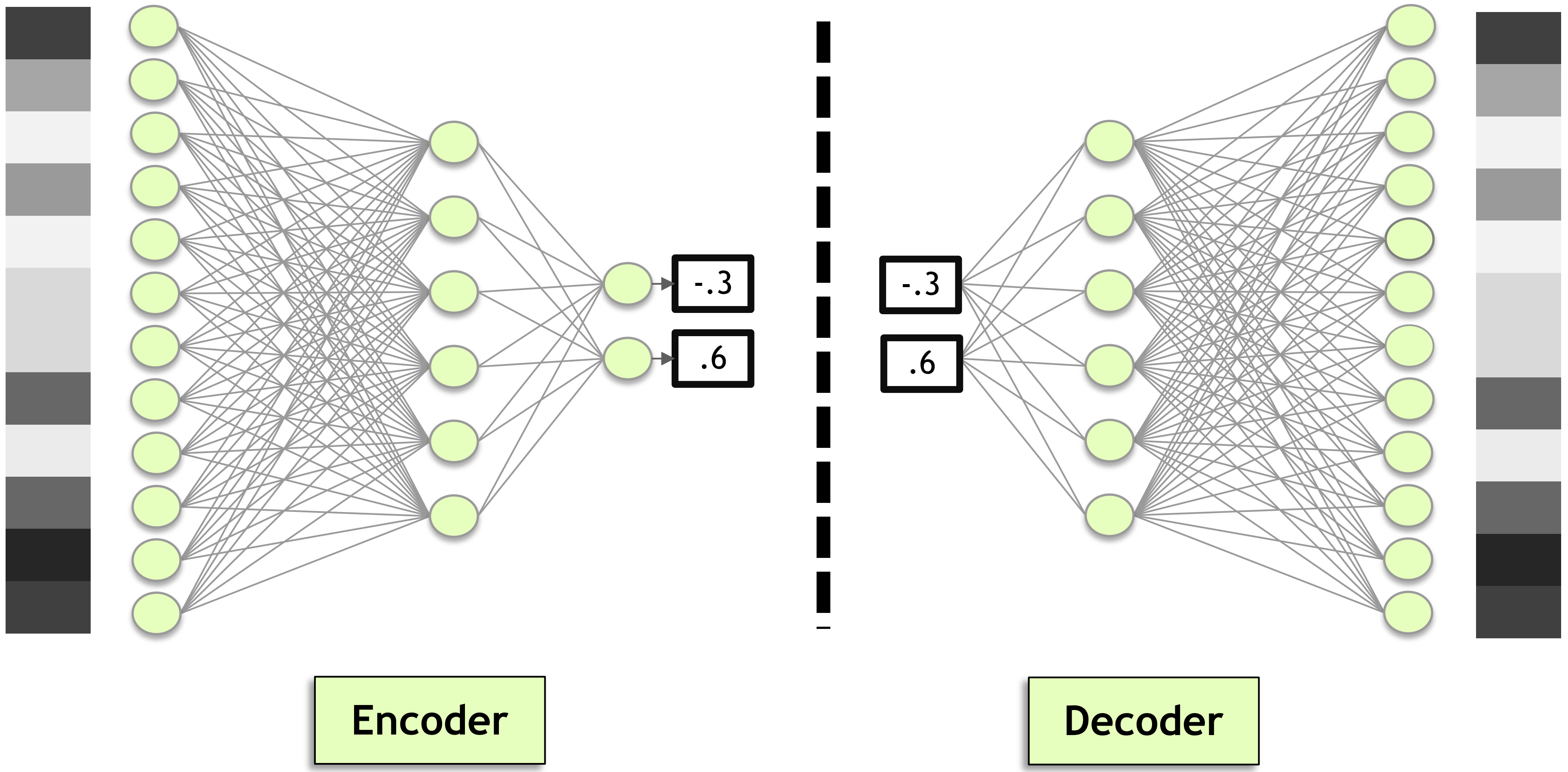
AUTOENCODERS



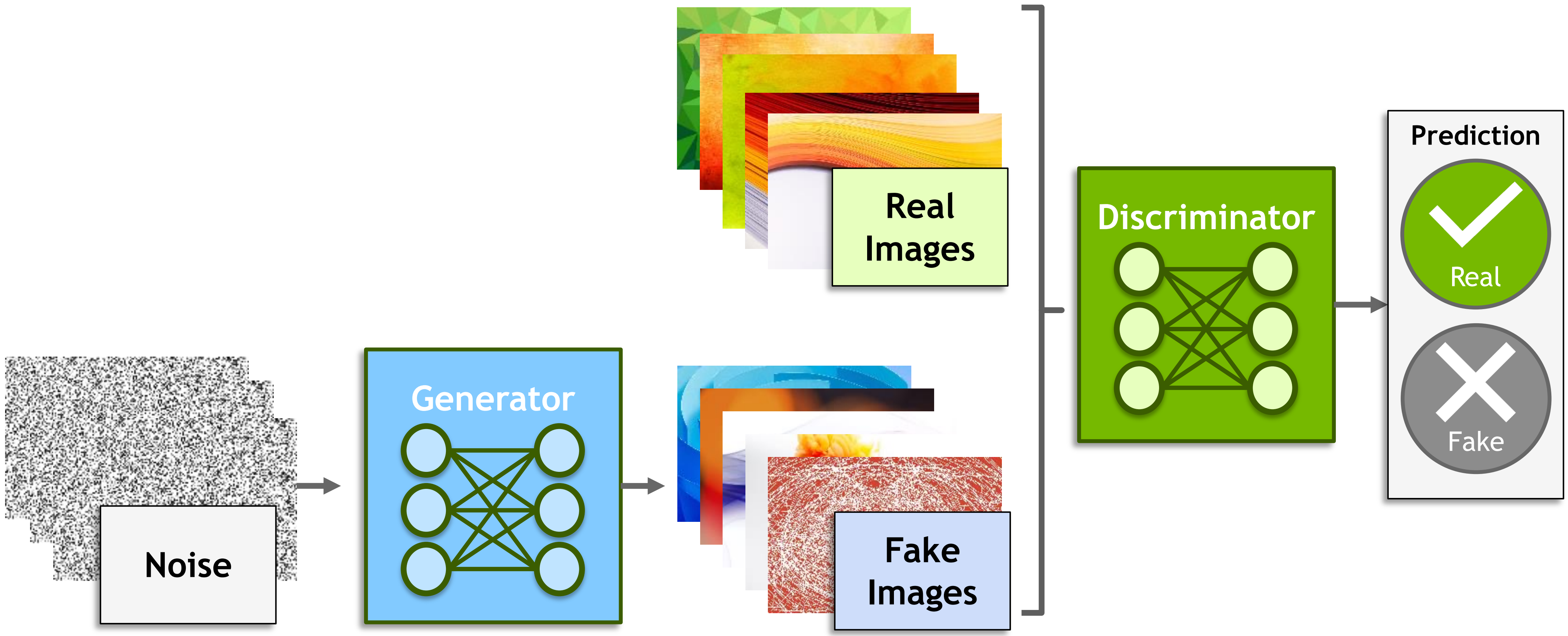
AUTOENCODERS



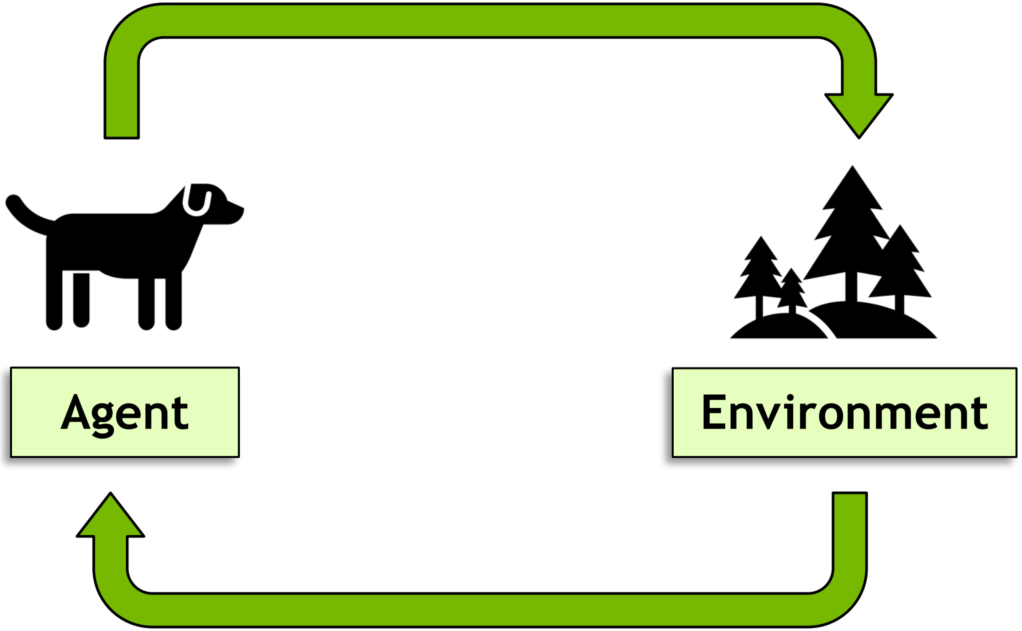
AUTOENCODERS



GENERATIVE ADVERSARIAL NETWORKS (GANS)



REINFORCEMENT LEARNING



NEXT STEPS

ENABLING PORTABILITY WITH NGC CONTAINERS

Extensive

- Diverse range of workloads and industry specific use cases

Optimized

- DL containers updated monthly
- Packed with latest features and superior performance

Secure & Reliable

- Scanned for vulnerabilities and crypto
- Tested on workstations, servers, & cloud instances

Scalable

- Supports multi-GPU & multi-node systems

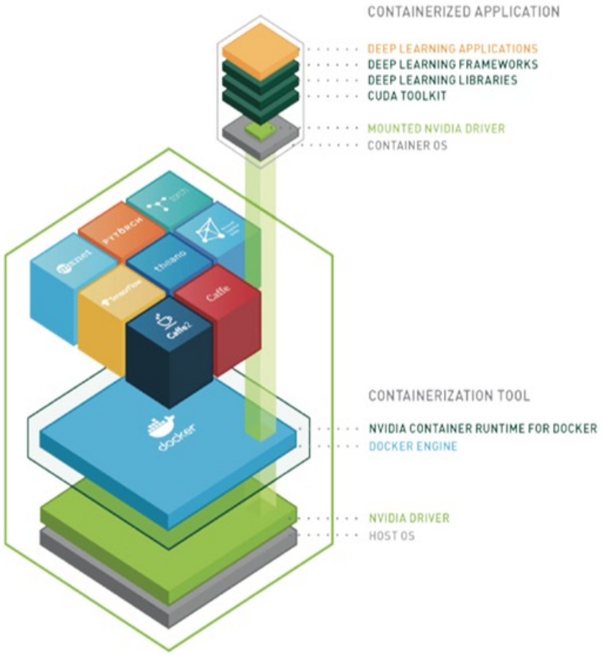
Designed for Enterprise & HPC

- Supports Docker, Singularity & other runtimes

Run Anywhere

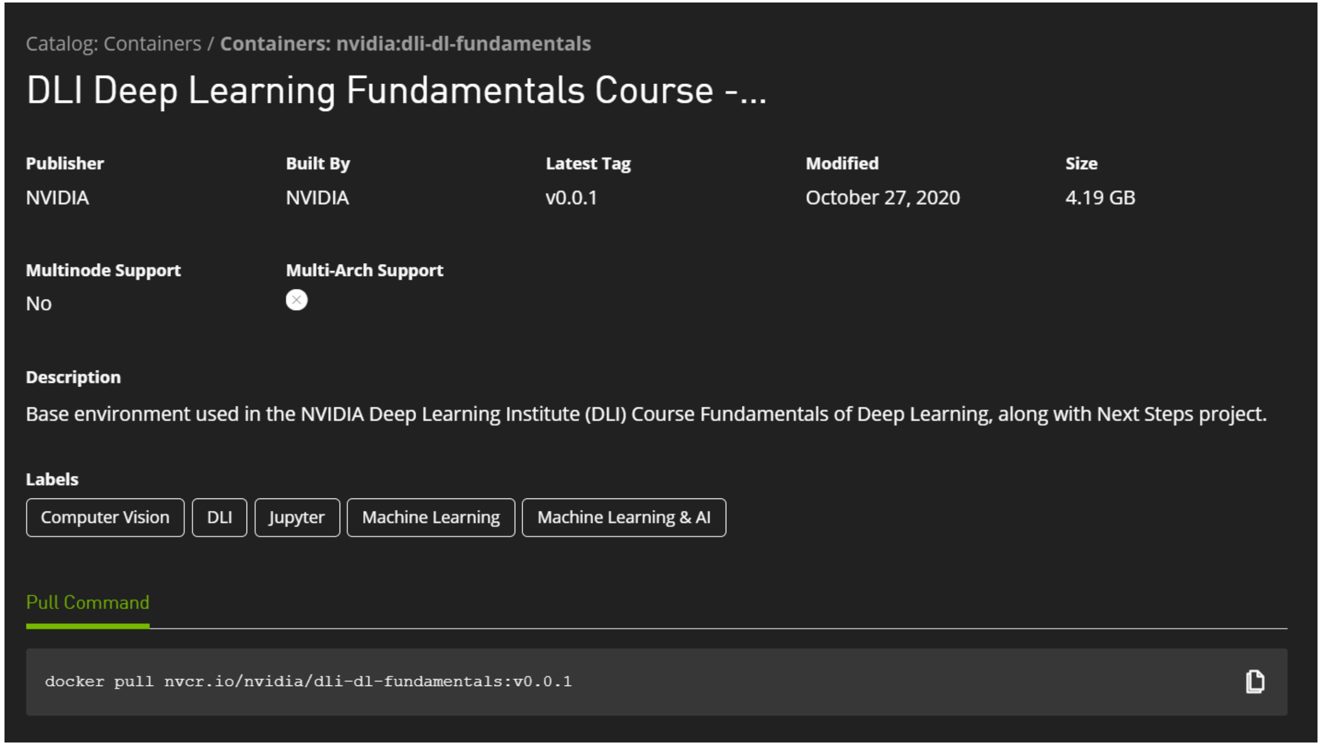
- Bare metal, VMs, Kubernetes
- x86, ARM, POWER
- Multi-cloud, on-prem, hybrid, edge

NGC Deep Learning Containers



Learn more about NGC Containers

NEXT STEPS FOR THIS CLASS



Step 1 Sign up for NGC

- https://docs.nvidia.com/dgx/ngc-registry-for-dgx-user-guide/index.html

Step 2 Visit NGC Catalog

- https://catalog.ngc.nvidia.com/orgs/nvidia/containers/dli-dl-fundamentals

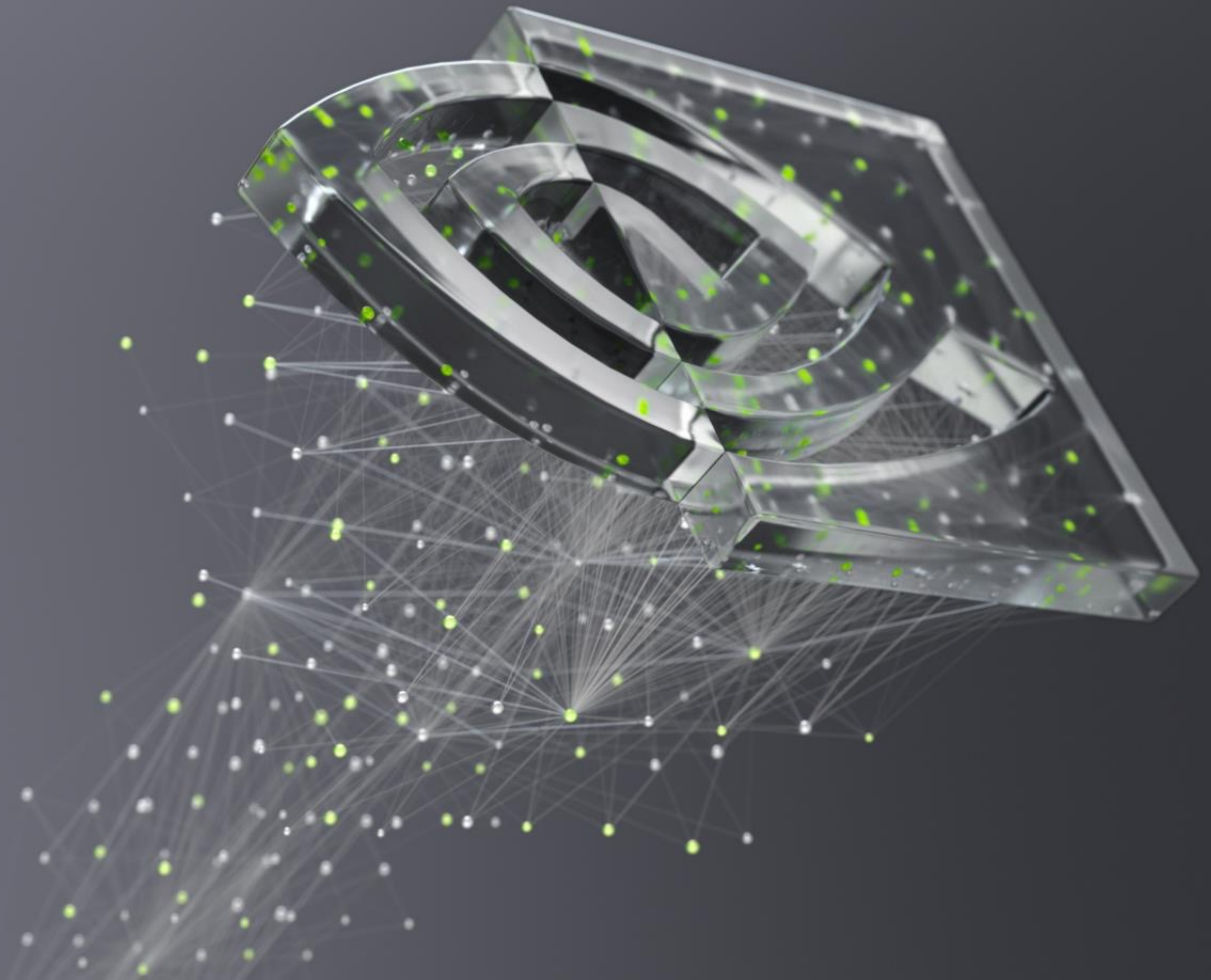
Step 3 Pull and Run Container

- Visit localhost:8888 to check out a JupyterLab environment with a Next Steps Project

CLOSING THOUGHTS

COPYING ROCKET SCIENCE

LET’S GET STARTED!



NVIDIA

DEEP LEARNING INSTITUTE