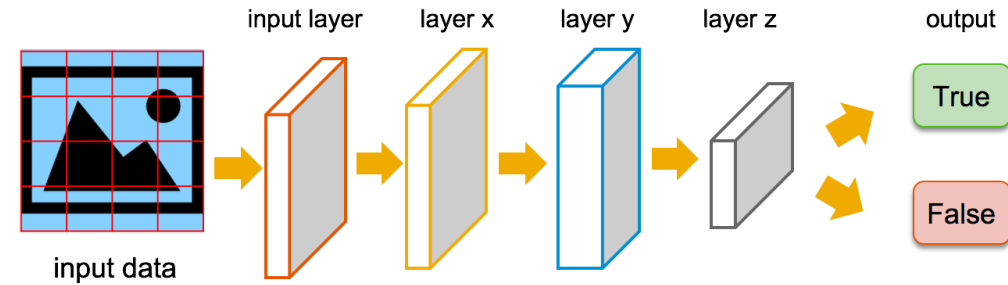


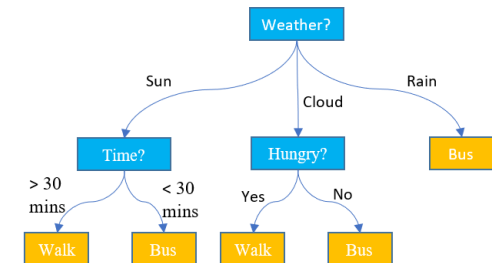
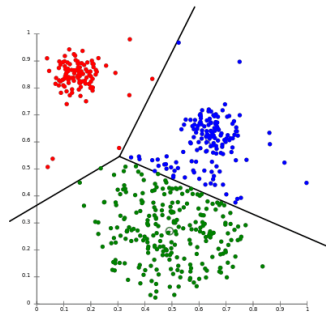
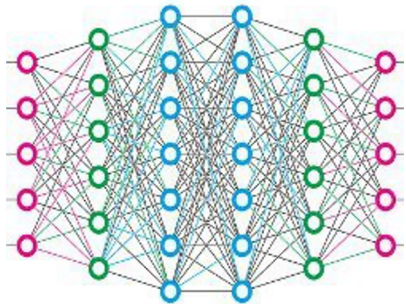
# CS 445

# Introduction to Machine Learning

## Softmax and One-Hot Encoding Convolution Neural Networks



Instructor: Dr. Kevin Molloy



# Announcements

## PA 3 Posted

- Due a week from Friday at 5:00 pm

# Learning Objectives

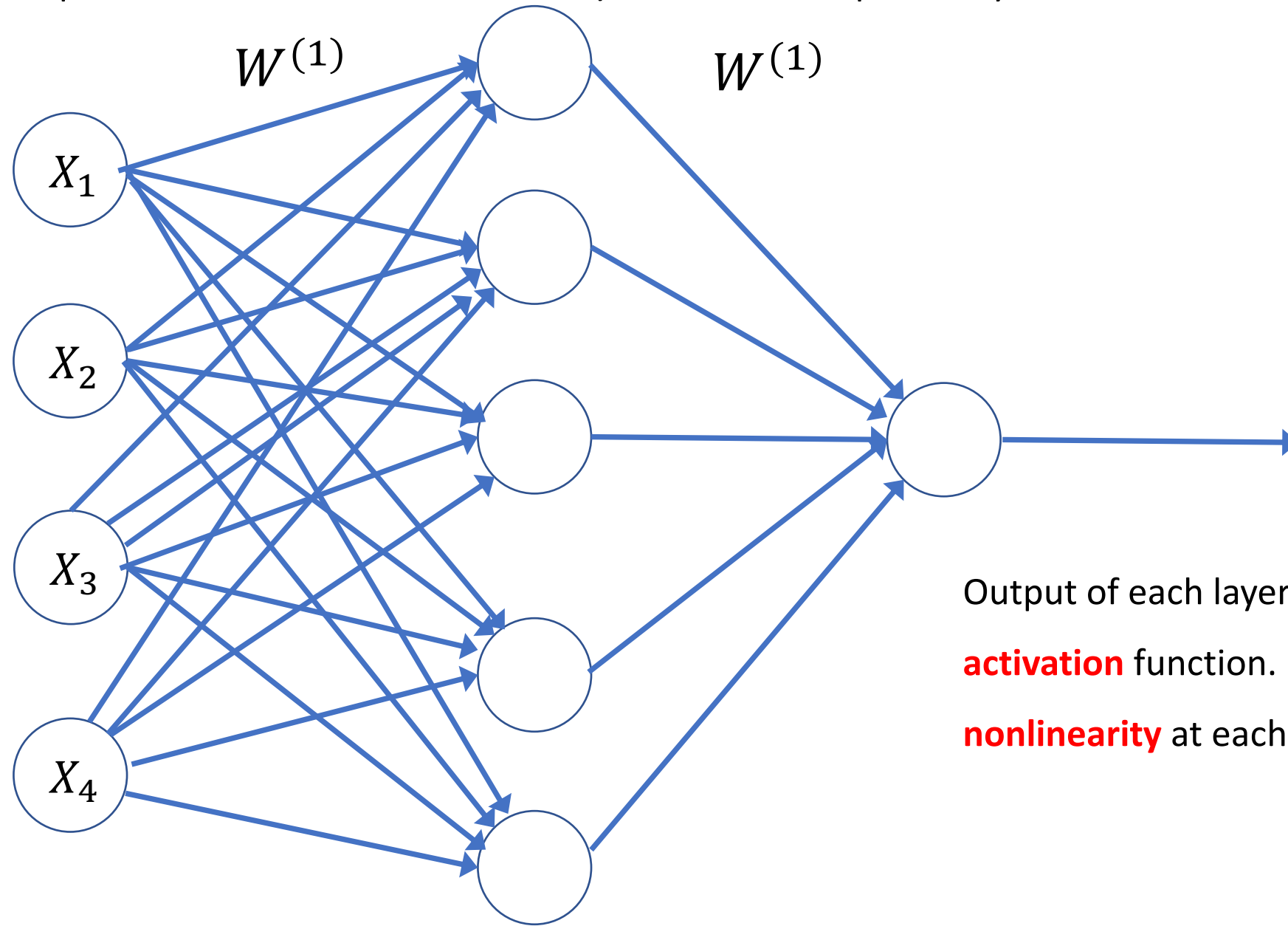
- Multiclass classification with NNs
- One hot encoding
- Monitoring Keras
- Sequential Networks and Image Recognition
- Utilize Convolution in NN (called CNNs)

# Binary Classification

Input

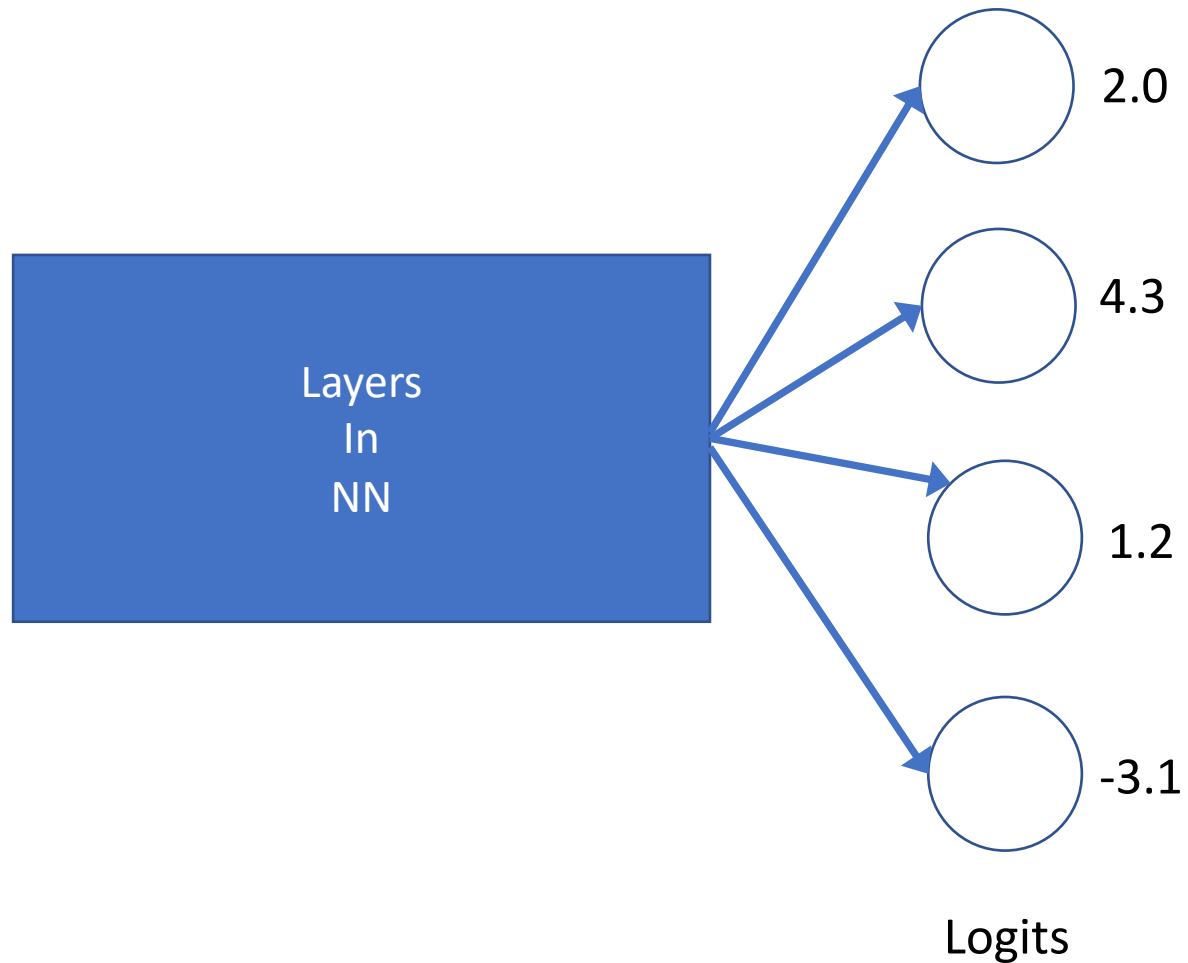
Hidden Layer

Output Layer



Output of each layer goes through an **activation** function. This introduces a **nonlinearity** at each node.

# Multiclass Classification



Logit – one per class. Each value tells us something about the target class. We would like to change these values to a probability distribution.

$$\textit{Softmax}(a_i) = \frac{\exp(a_i)}{\sum_j \exp(a_j)}$$

# Dealing with Categorical Data

- Problems like image (or digit) recognition have multiple categorical labels.
- Neural networks require all data (including the labels to be numeric).

How to Convert? In general, two steps are required

1. Convert labels to an integer encoding
2. One-hot encoding

# Integer and One-hot encoding

Classifying dogs, cats, and hamsters.

- "Dog" can be 1
- "Cat" can be 2
- Hamster can be "3".

Is this enough?

# Integer and One-hot encoding

Classifying dogs, cats, and hamsters.

- "Dog" can be 1
- "Cat" can be 2
- Hamster can be "3".

Is this enough? Turns out no. This encoding includes an ordinal relationship, which is not really applicable. One-hot encoding is the answer.

- Create a binary variable for each class, all variables are set to zero except for the actual class, which is set to 1.



# Keras Examples

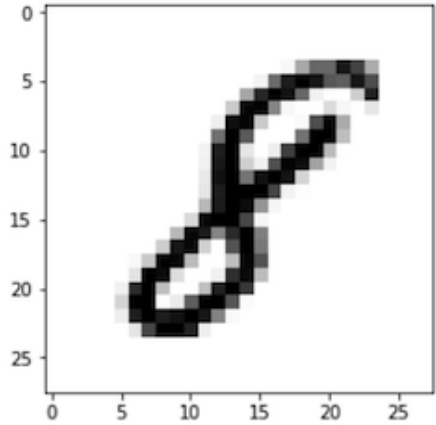
```
y_train = np_utils.to_categorical(y_train, 3) # 3 class problem

model.add(Dense(3, activation='softmax')) # add softmax layer as last layer

tensorboard = TensorBoard(log_dir='./logs', histogram_freq=1,
    write_images=True)

history = model.fit(X_train, y_train, epochs=10000, batch_size=1000,
    verbose=1, callbacks=[tensorboard])
```

# Images



$$28 \times 28 \times 1 = 784$$



$$3024 \times 4032 \times 3 = 36,578,304$$

A fully connected network with 1,000 hidden nodes in the first layer,  $W$  is a 36 million  $\times$  1000 (36 billion entries)

# Image Convolutions



Picture convolved with a "Canny edge detector".

How can we do this?

# Detecting Vertical Edges

3	0	1	2
1	5	8	9
2	7	2	5
0	1	3	1

Gray-scaled image

\*

1	0	-1
1	0	-1
1	0	-1

Filter or Kernel

=


# Detecting Vertical Edges

3	0	1	2
1	5	8	9
2	7	2	5
0	1	3	1

\*

1	0	-1
1	0	-1
1	0	-1

=

-5	

Gray-scaled image

Filter or Kernel

$$3*1 + 1*1 + 2*1 + 0*0 + 5*0 + 7*0 + 1*-1 + 8*-1 + 2*-1 = -5$$

# Detecting Vertical Edges

3	0	1	2
1	5	8	9
2	7	2	5
0	1	3	1

\*

1	0	-1
1	0	-1
1	0	-1

=

-5	-4

Gray-scaled image

Filter or Kernel

$$0*1 + 5*1 + 7*1 + 1*0 + 8*0 + 2*0 + 2*-1 + 9*-1 + 5*-1 = -4$$

# Detecting Vertical Edges

3	0	1	2
1	5	8	9
2	7	2	5
0	1	3	1

\*

1	0	-1
1	0	-1
1	0	-1

=

-5	-4
-10	

Gray-scaled image

Filter or Kernel

$$1*1 + 2*1 + 0*1 + 5*0 + 7*0 + 1*0 + 8*-1 + 2*-1 + 3*-1 = -10$$

# Detecting Vertical Edges

3	0	1	2
1	5	8	9
2	7	2	5
0	1	3	1

\*

1	0	-1
1	0	-1
1	0	-1

=

-5	-4
-10	-2

Gray-scaled image

Filter or Kernel

$$5*1 + 7*1 + 1*1 + 8*0 + 2*0 + 3*0 + 1*-1 + 3*-1 + 1*-1 = -2$$

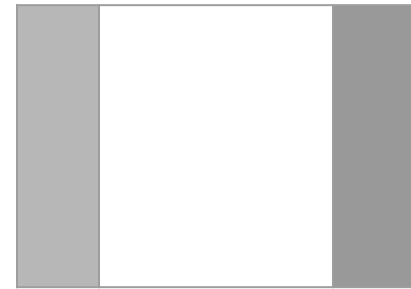
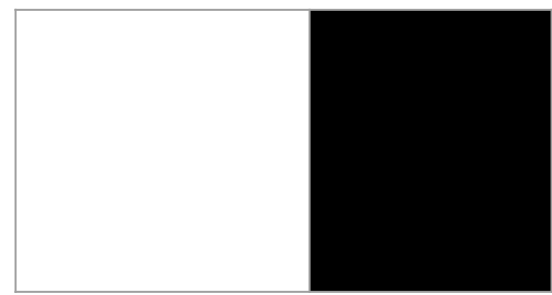


# Detecting Vertical Edges

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

1	0	-1
1	0	-1
1	0	-1

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0



# Other Filters

1	0	-1
1	0	-1
1	0	-1

Vertical Edges

1	1	1
0	0	0
-1	-1	-1

Horizontal Edges

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

Sobel Filter

# Novel Idea

1	0	-1
1	0	-1
1	0	-1

Vertical Edges

1	1	1
0	0	0
-1	-1	-1

Horizontal Edges

1	1	1
0	0	0
-1	-1	-1

Sobel Filter

How about **learning** a set of filters for edge/object characteristics?

$w_1$	$w_2$	$w_3$
$w_4$	$w_5$	$w_6$
$w_7$	$w_8$	$w_9$

# Losing Some Data Along the Way

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

6 x 6 (n x n)

1	0	-1
1	0	-1
1	0	-1

3 x 3 (f x f)

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0

4 x 4

In general  
(n - f + 1, n - f + 1)

- Notice corners only appear in 1 convolution computation.
- If you piece together several layers, you keep consolidating the signal/information

