# Machine Learning Live Session #4

# Review of Training Neural Networks

- Weights W are initialized randomly
  - Unless another initialization is specified (e.g., from a previous model or experience)
- Then, compare the predictions of the model with the actual labels in the training data
- Based on the comparison, update the weights to get the predictions closer to the actual labels
- Repeat the previous two steps until stopping criterion is met
- How do we make the comparison and update the weights to find the optimal values  $W^*$ ?

- How do we make the comparison?
  - This is the role of the loss function, which is *only* a function of the weights W, given the training data and architecture of the NN

Loss(W; training set, architecture of NN)

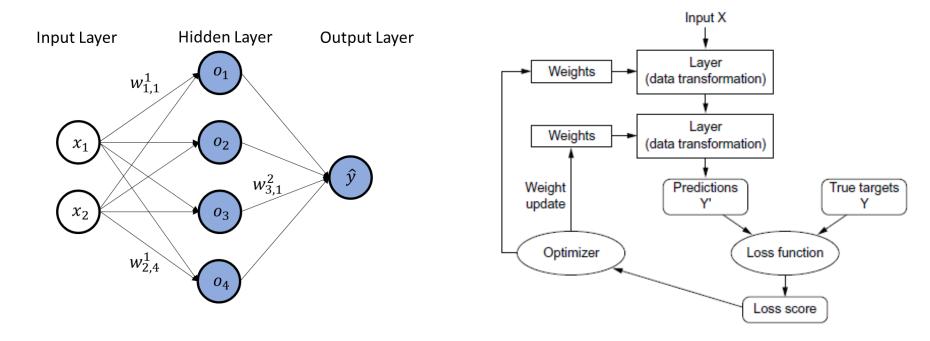
- Larger value of the loss means the compared values were further away
- Smaller value of the loss means the compared values were closer

#### Details of Training Process

• Important: for a particular training set and architecture, the loss is only a function of the weights  ${\cal W}$ 

Loss(W; training set, architecture of NN)

- The loss function is used along with an optimization algorithm to determine how to change the weights to improve the loss
- The goal of the optimization is to find the optimal weight values  $W^{st}$  that minimize the loss

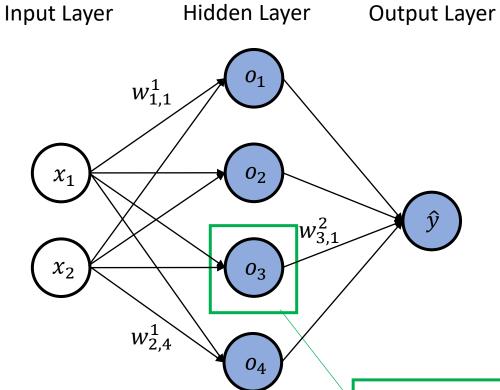


- ullet To calculate the loss for a given set of weight values W
  - 1. Each x in the training set is put through the network to obtain a prediction  $\hat{y}(x; W)$
  - 2. Calculate the loss function (example below using mean squared loss function for regression)

Loss(W; training set, architecture of NN) = 
$$\frac{1}{n} \sum_{i=1}^{n} (\hat{y}(x_i; W) - y_i)^2$$

 $x_1, x_2, \dots, x_n$  are training observations and  $y_1, y_2, \dots, y_n$  are actual labels

Age ( <i>x</i> <sub>2</sub> )
45
54
28
54
23
44
46

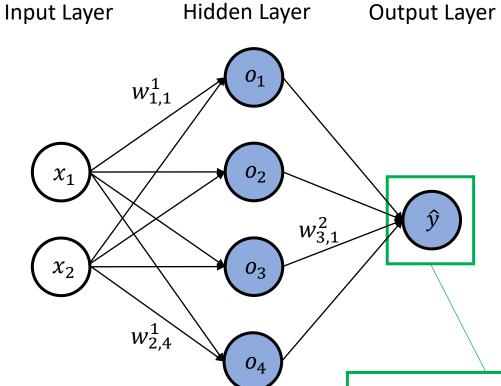


**Computation Node** 

 $o_3 = f_1(Weights \times Inputs + Bias)$ 

$$o_3 = f_1(w_{1,3}^1 \times x_1 + w_{2,3}^1 \times x_2 + w_{0,3}^1)$$

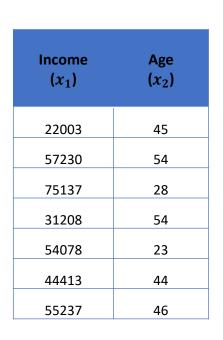
Income (x <sub>1</sub> )	Age ( <i>x</i> <sub>2</sub> )
22003	45
57230	54
75137	28
31208	54
54078	23
44413	44
55237	46

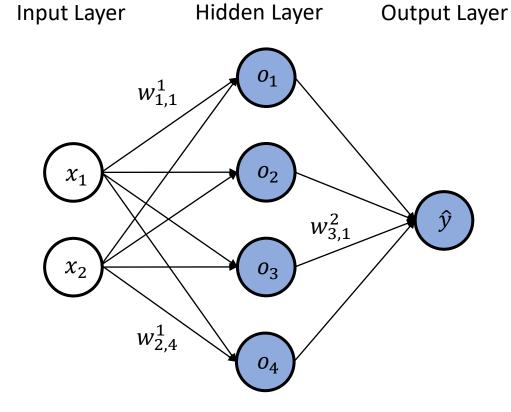


**Computation Node** 

$$\hat{y} = f_2(Weights * Inputs + Bias)$$

$$\hat{y} = f_2(w_{1,1}^2 o_1 + w_{2,1}^2 o_2 + w_{3,1}^2 o_3 + w_{4,1}^2 o_4 + w_0^2)$$

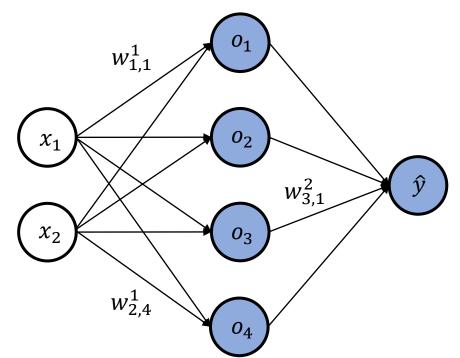




Predicted Revenue Given Set of Weights ${\cal W}$
$\hat{y}(22003,45;W)$
$\hat{y}(57230,54;W)$
$\hat{y}(75137,28;W)$
$\hat{y}(31208,54;W)$
$\hat{y}(54078,23;W)$
$\hat{y}(44413,44;W)$
$\hat{y}(55237,46;W)$

# Update weights based on loss function and Input Layer Hidden Layer Output Layer optimizer

Income (x <sub>1</sub> )	Age ( <i>x</i> <sub>2</sub> )
22003	45
57230	54
75137	28
31208	54
54078	23
44413	44
55237	46



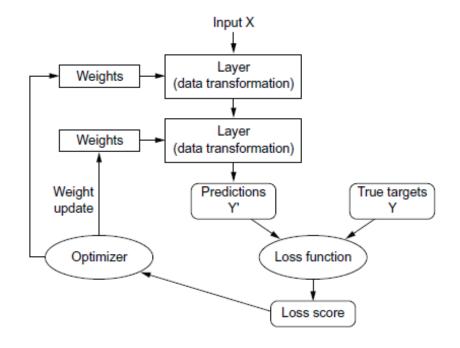
Predicted Revenue Given Set of Weights $\ensuremath{\mathcal{W}}$		Revenue from Customer
$\hat{y}(22003,45;W)$		14.03875
$\hat{y}(57230,54;W)$	The loss	23.31168
ŷ(75137,28; W)	function	24.05046
$\hat{y}(31208,54;W)$	compares these	18.5386
ŷ(54078,23; W)		18.50195
ŷ(44413,44; W)		20.63106
ŷ(55237,46; W)		22.32953

*Loss(W; training set, architecture of NN)* 

$$= \frac{1}{n} \sum_{i=1}^{n} (\hat{y}(x_i; W) - y_i)^2$$

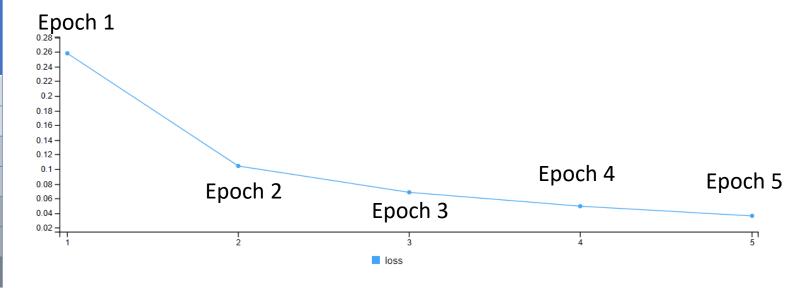
- When the training set is too large, it's not feasible to calculate the loss based on the entire training set every iteration
  - Solution: use batches consisting of subsets of rows of training data
  - Take for example a batch size of 2

Income (Customer Feature 1)	Age (Customer Feature 2)	Revenue from Customer	Predicted Revenue Given Set of Weights $\it W$
22003	45	14.03875	$\hat{y}(22003,45;W)$
57230	54	23.31168	$\hat{y}(57230,54;W)$
75137	28	24.05046	$\hat{y}(75137,28;W)$
31208	54	18.5386	$\hat{y}(31208,54;W)$
54078	23	18.50195	$\hat{y}(54078,23;W)$
44413	44	20.63106	ŷ(44413,44; W)
55237	46	22.32953	$\hat{y}(55237,46;W)$



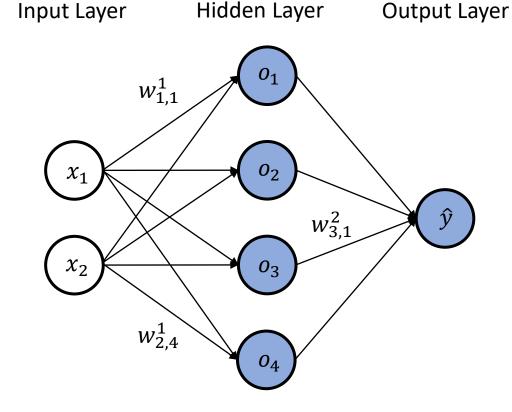
- Take for example a batch size of 2
  - Iterate through the training data taking two rows at a time
    - On each iteration, define the loss function Loss(W|selected two rows of training data, architecture of NN)
    - Use this loss function in conjunction with optimization algorithm to determine how to update weights
  - After iterating through the entire training set, we have completed an "epoch"
    - We specify the number of epochs in advance

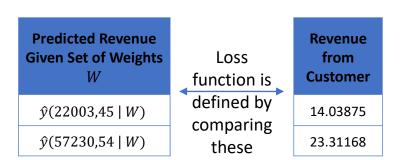
Income (Customer Feature 1)	Age (Customer Feature 2)	Revenue from Customer	Predicted Revenue Given Set of Weights $\ensuremath{\mathcal{W}}$
22003	45	14.03875	$\hat{y}(22003,45;W)$
57230	54	23.31168	$\hat{y}(57230,54;W)$
75137	28	24.05046	$\hat{y}(75137,28;W)$
31208	54	18.5386	$\hat{y}(31208,54;W)$
54078	23	18.50195	$\hat{y}(54078,23;W)$
44413	44	20.63106	ŷ(44413,44; W)
55237	46	22.32953	ŷ(55237,46;W)



#### Epoch #1, Step #1

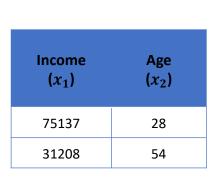


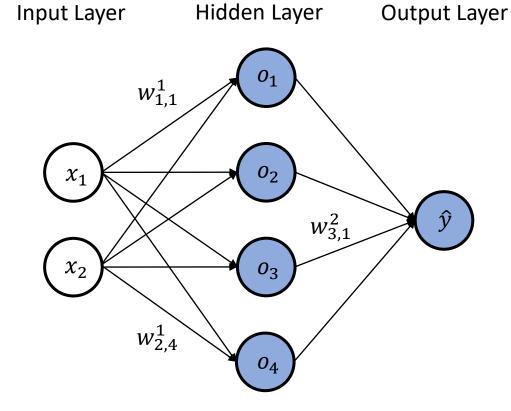




Update weights based on loss function and optimizer

#### Epoch #1, Step #2





Predicted Revenue Given Set of Weights  $\hat{y}$  (75137,28 | W)  $\hat{y}$  (31208,54 | W)

The set of Weights  $\hat{y}$  (31208,54 | W)  $\hat{y}$  (31208,54 | W)

Update weights based on loss function and optimizer

Revenue

from

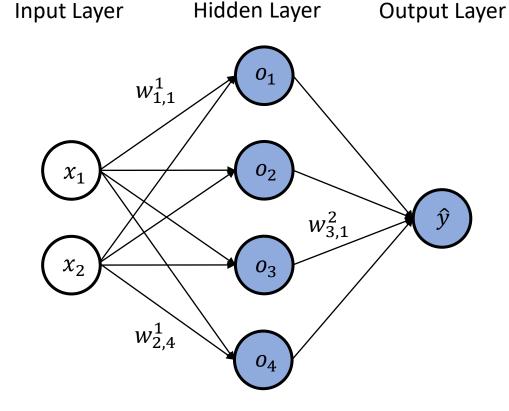
Customer

24.05046

18.5386

#### Epoch #1, Step #3





**Predicted Revenue Given Set of Weights** Loss function is WCustomer defined by  $\hat{y}(54078,23 \mid W)$ comparing  $\hat{y}(44413,44 \mid W)$ these

**Update** weights based on loss function and optimizer

Revenue

from

18.50195

20.63106

#### Epoch #1, Step #4

Income

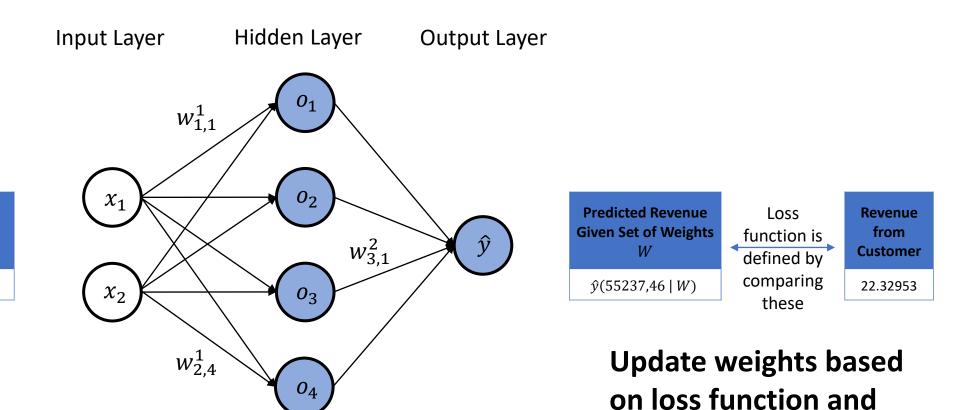
 $(x_1)$ 

55237

Age

 $(x_2)$ 

46



optimizer

- Finished iterating through the training set
  - Epoch #1 is now complete
- Shuffle the training set and start Epoch #2
- Continue in same manner until all epochs are completed

Income (Customer Feature 1)	Age (Customer Feature 2)	Revenue from Customer
22003	45	14.03875
57230	54	23.31168
75137	28	24.05046
31208	54	18.5386
54078	23	18.50195
44413	44	20.63106
55237	46	22.32953

