Neural Networks

Keras for Deep Learning Research

UMKC

Feedback is greatly appreciated!

Overview

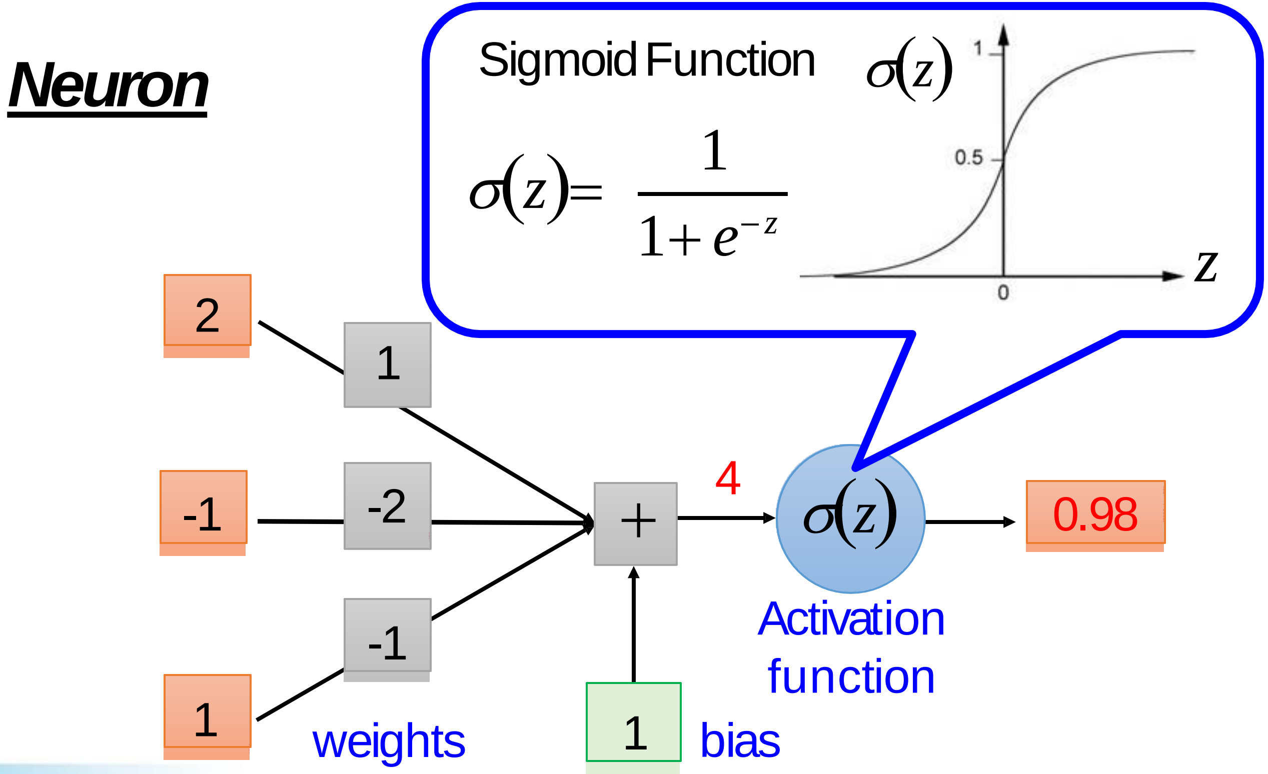
- Neural Network
- Backpropagation
- Gradient Descent (Optimization Algorithm)
- Cost/Loss Functions
- Activation Function
- Learning Rate

Artificial Neural Network

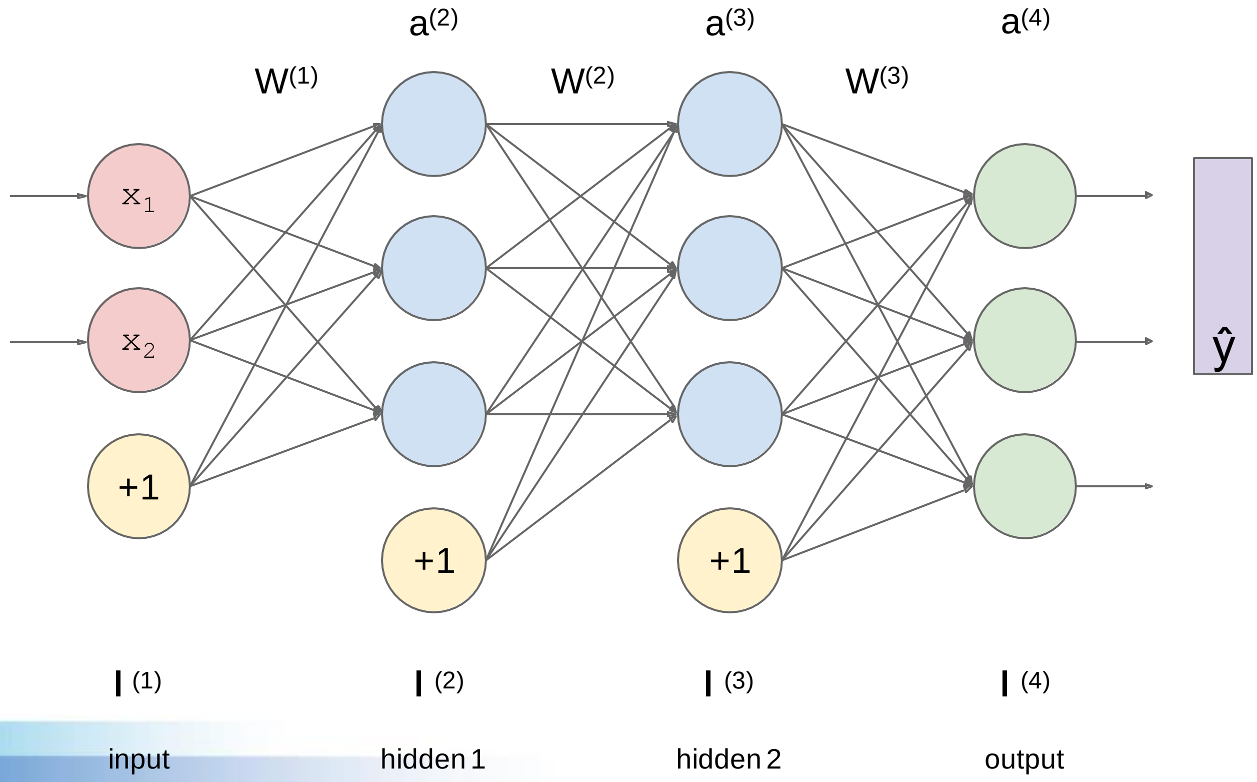
- What are artificial neural network?
  - A combination of a training method
  - An optimization method

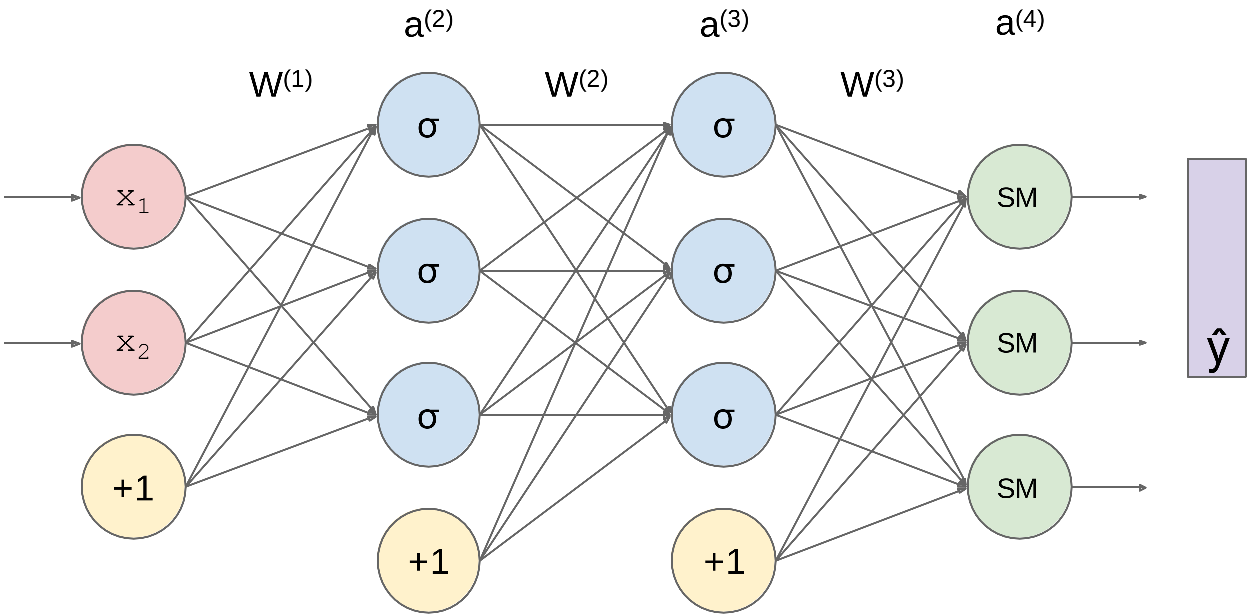
- A two phase cycle:
  - Propagation
  - Weight update

Neural Network



Feed forward neural network





x_i: input value
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SM: Softmax function
+1: bias (constant) unit
$a^{(l)}$: activation vector for layer l
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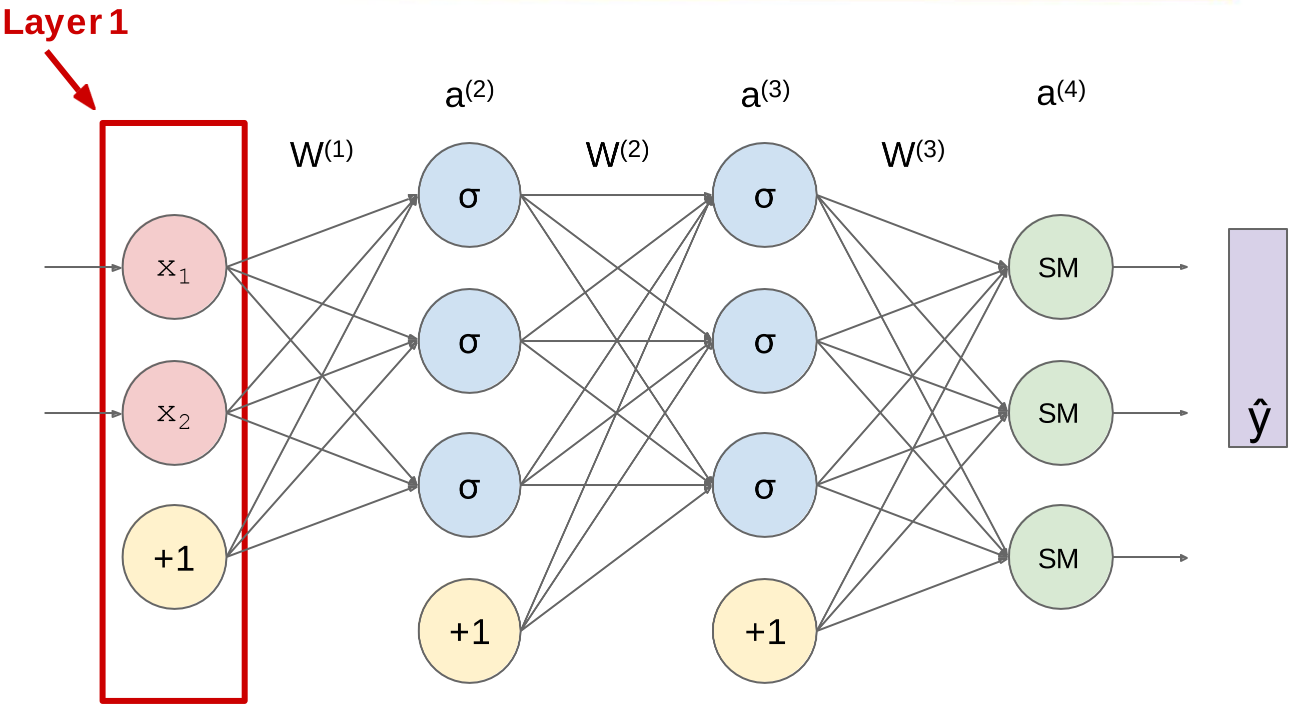

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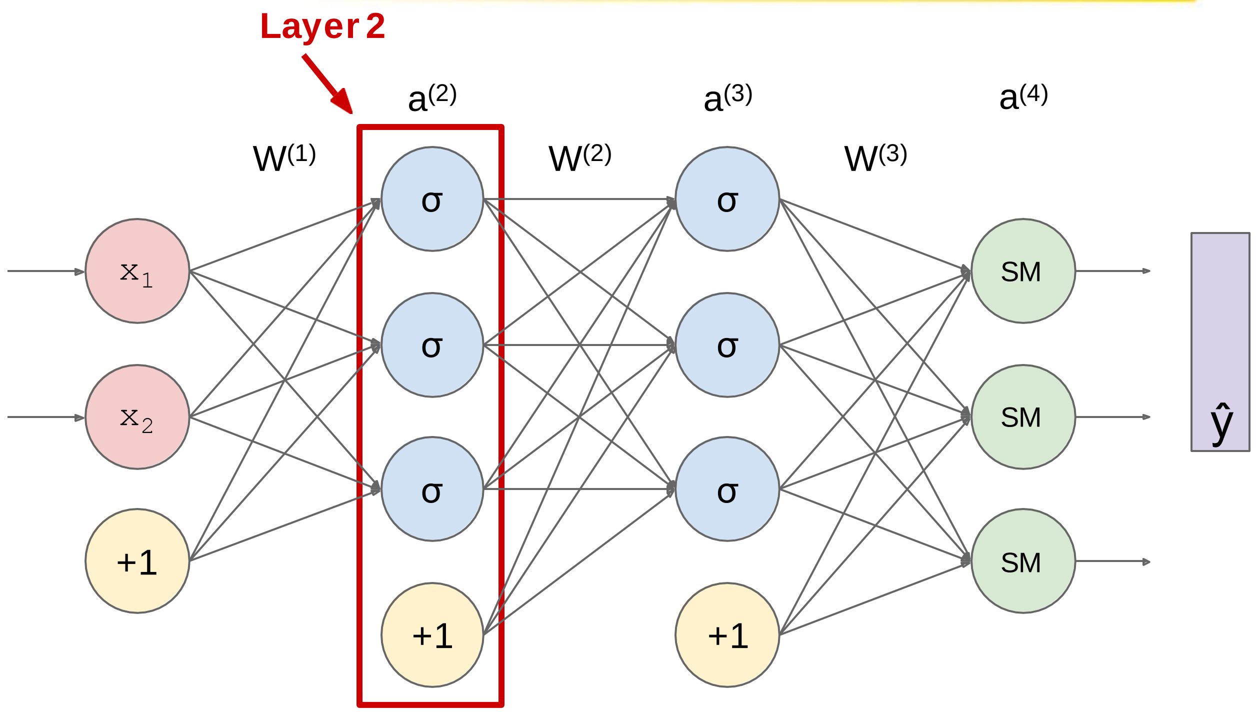

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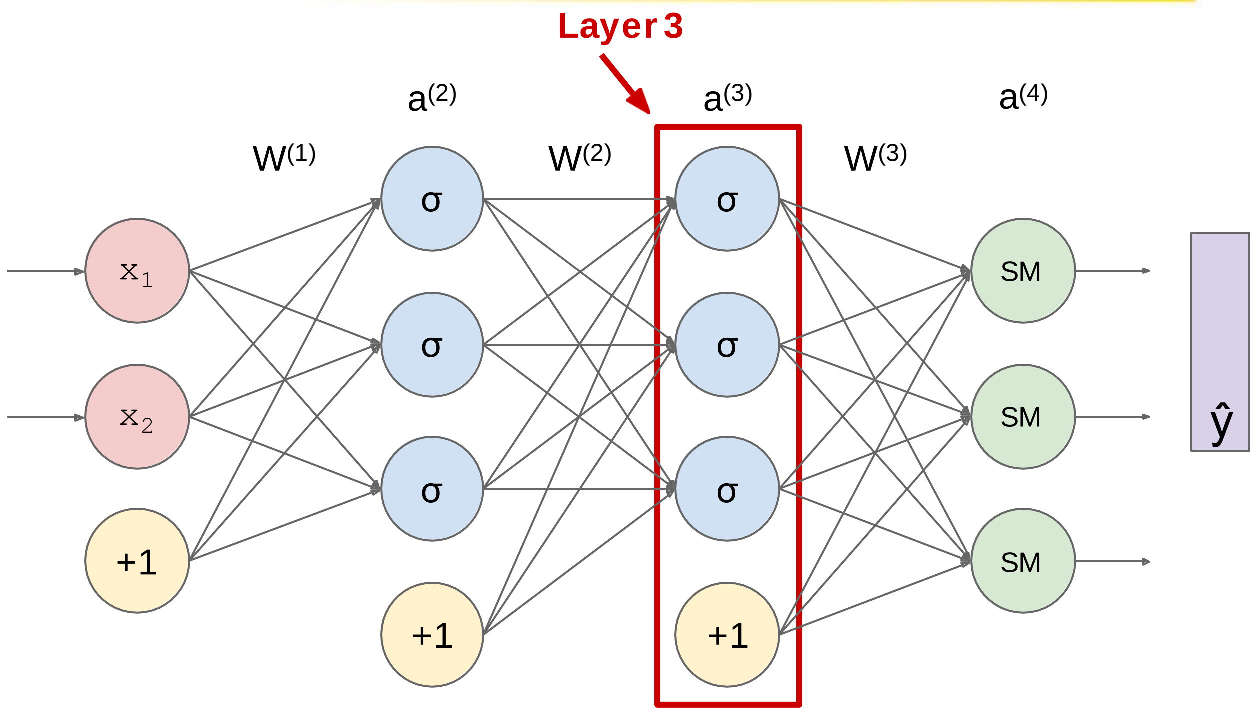

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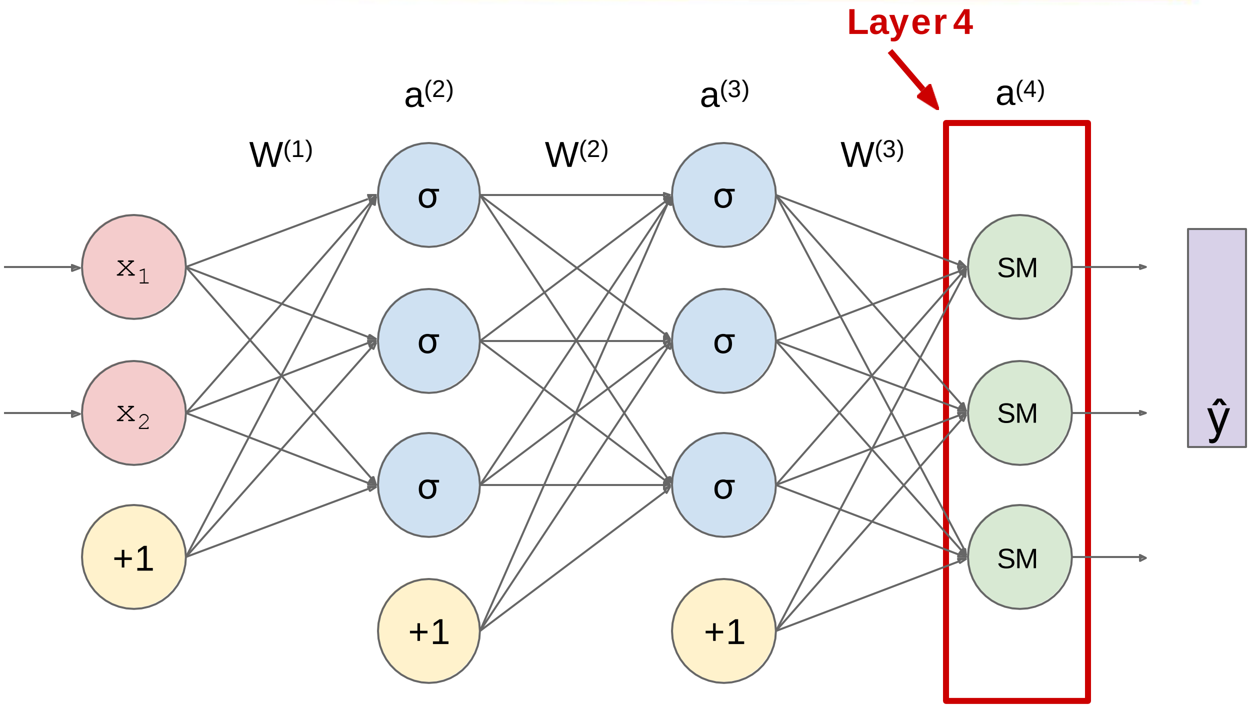

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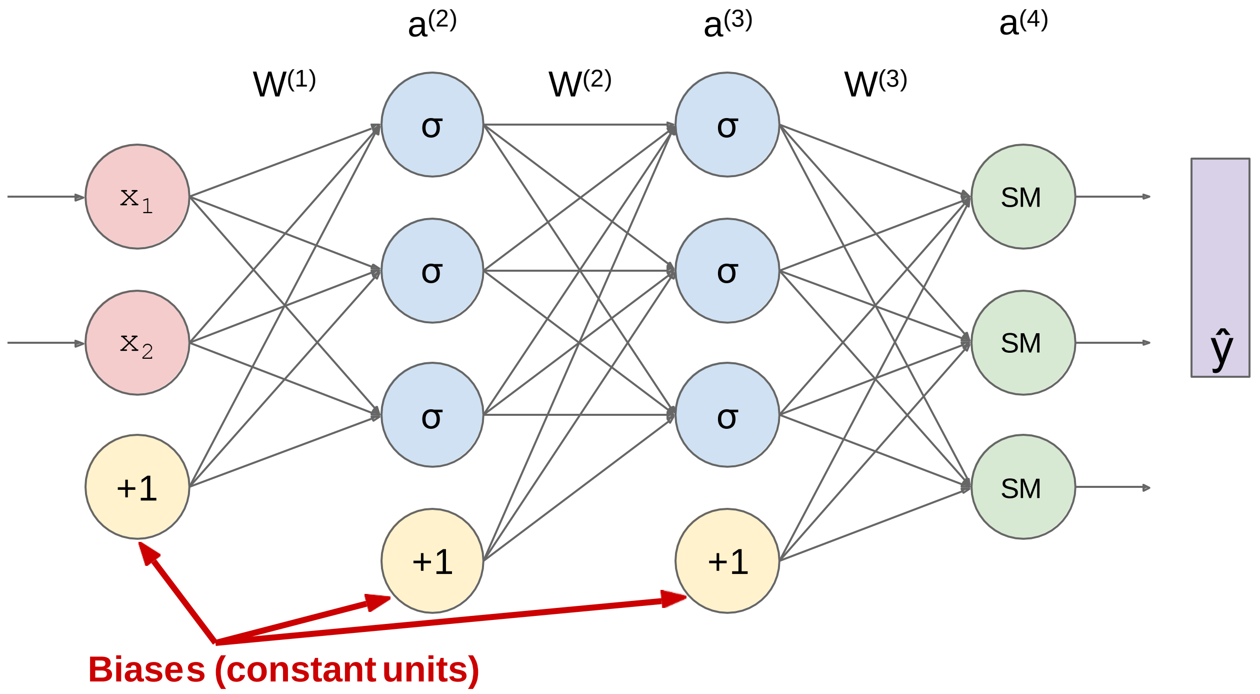

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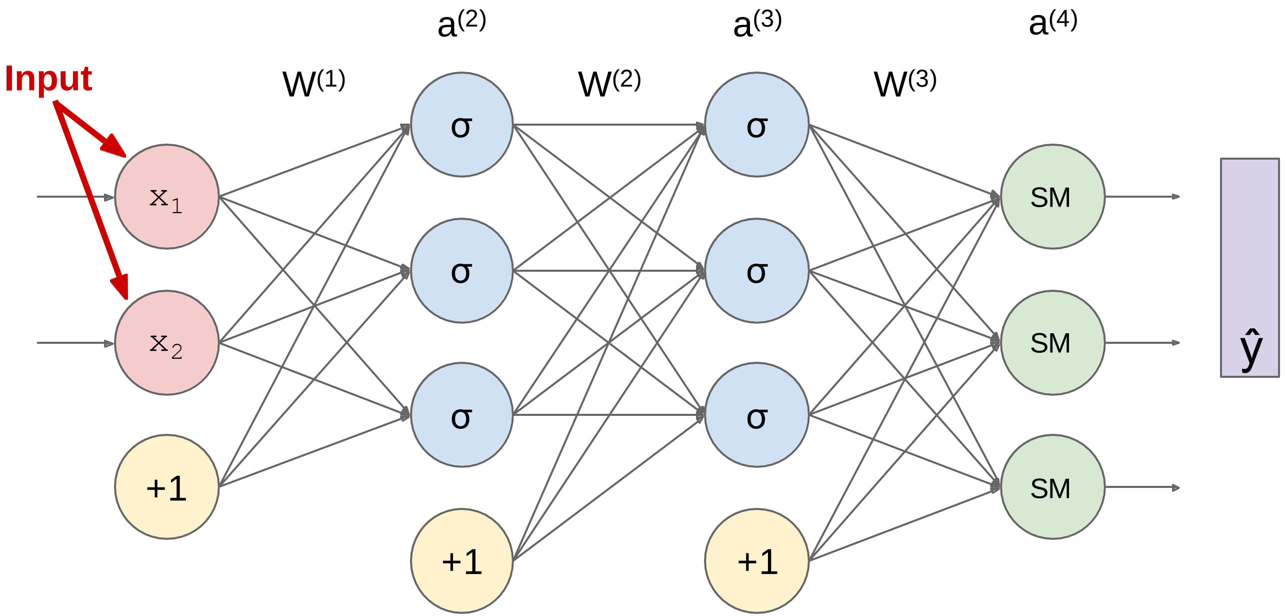

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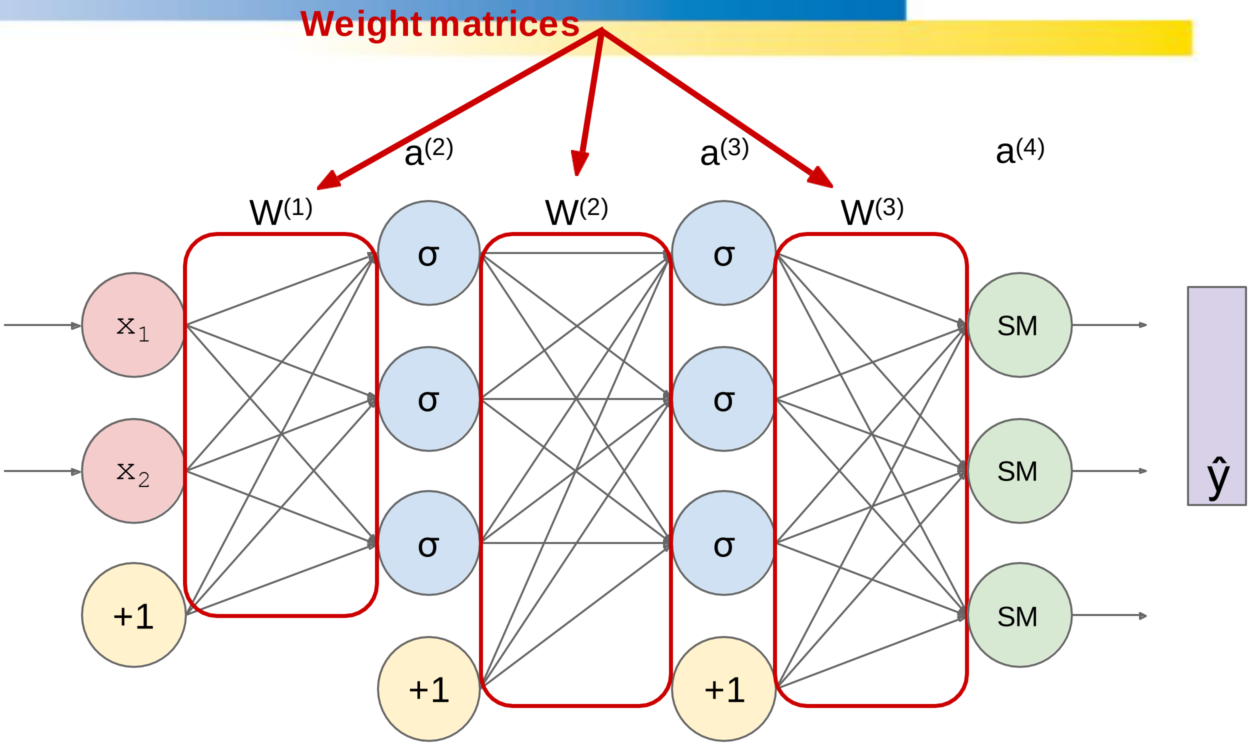

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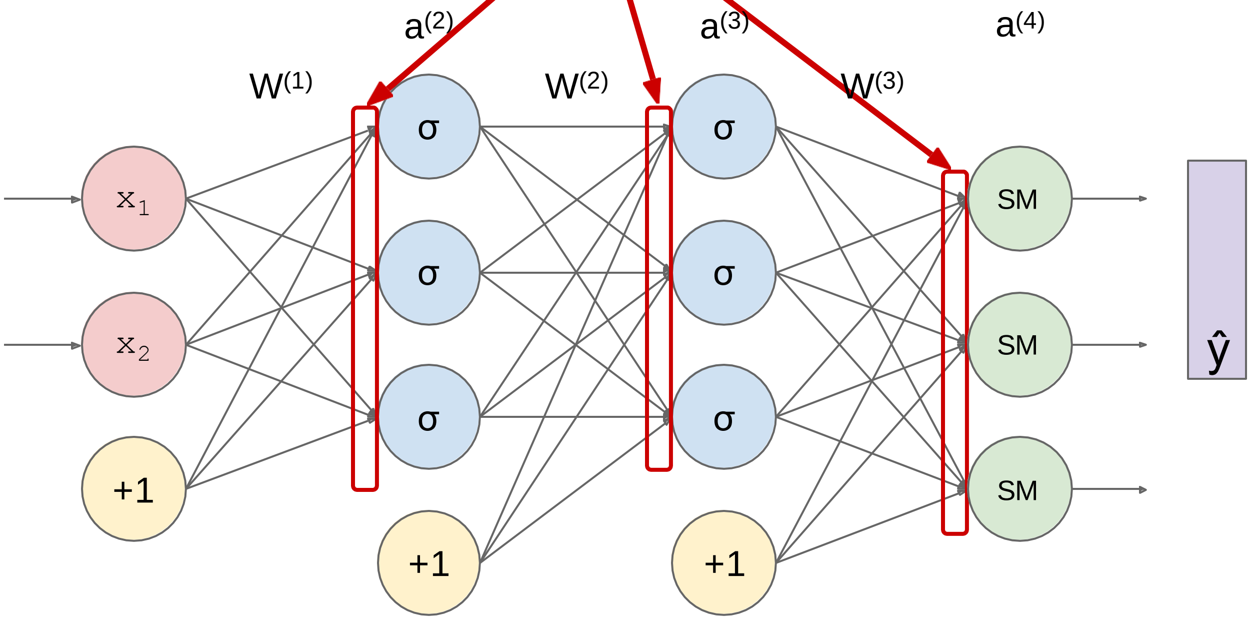
Layer inputs, $z^{(l)}$

$z^{(l)} = W^{(l-1)}a^{(l-1)} + b^{(l-1)}$



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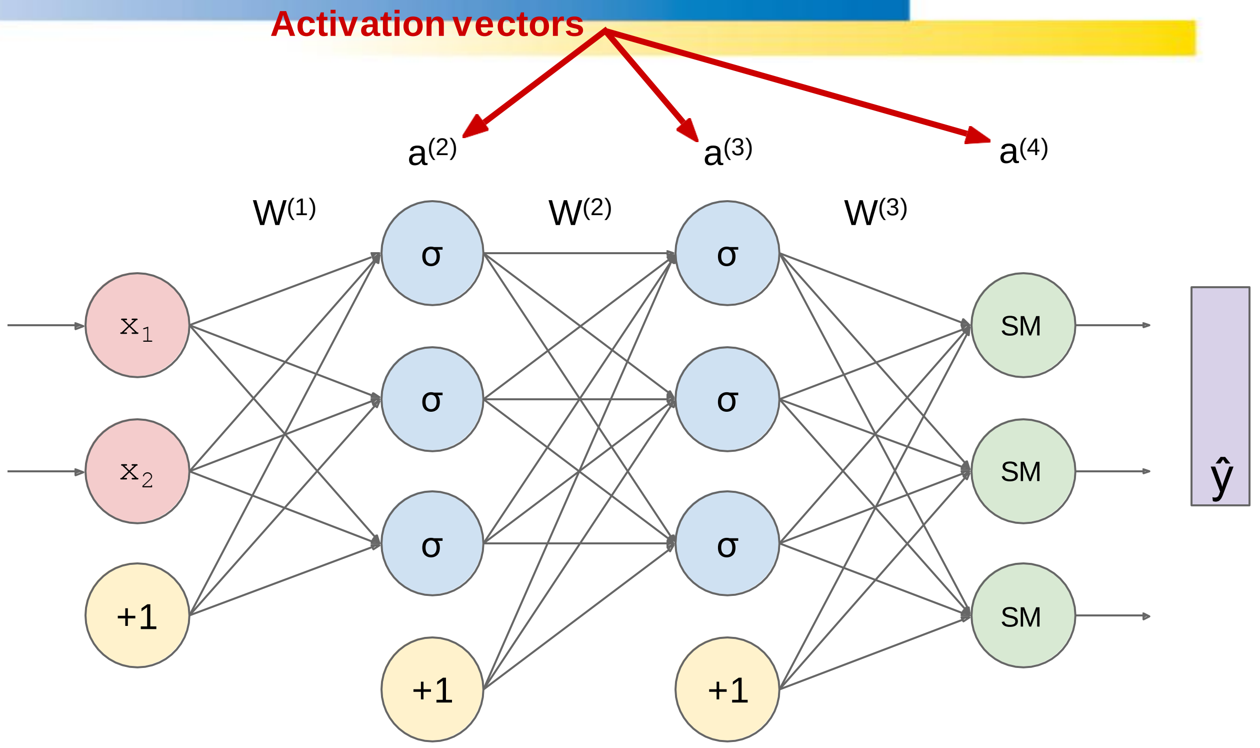

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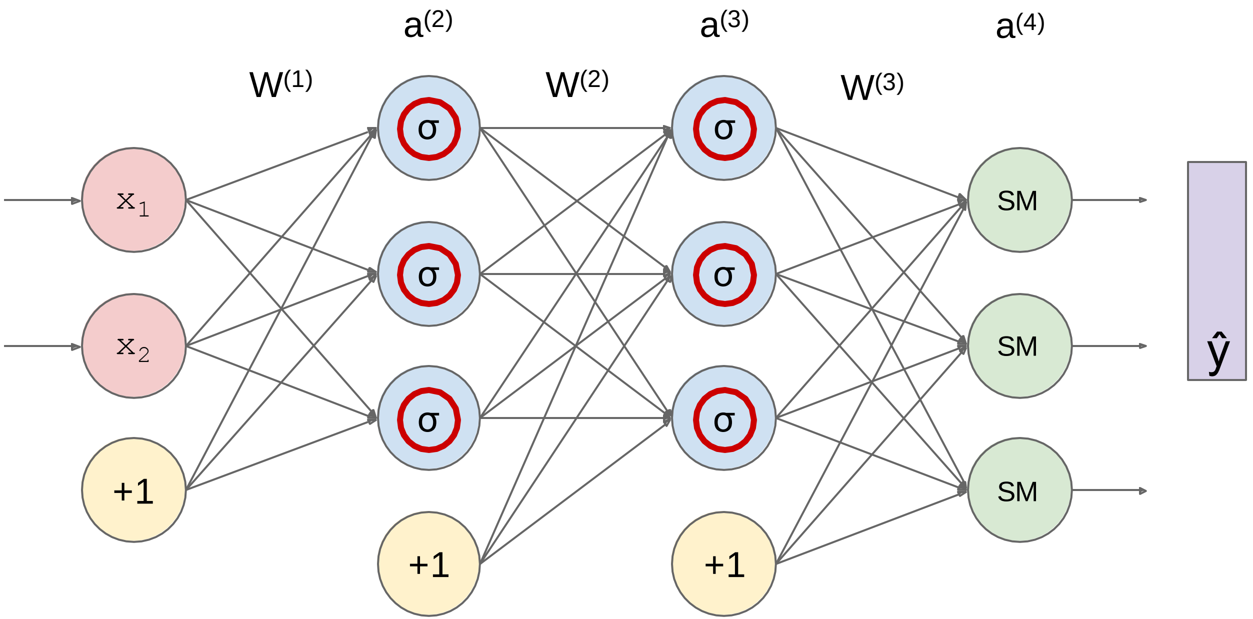
Sigmoid activation function



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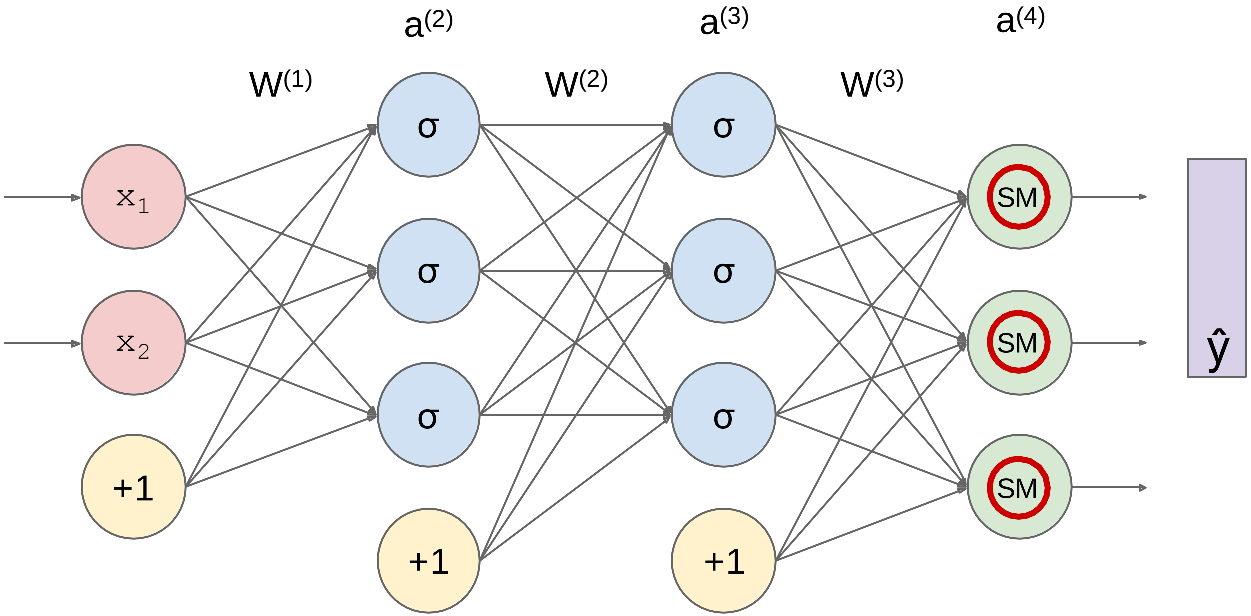
Softmax activation function



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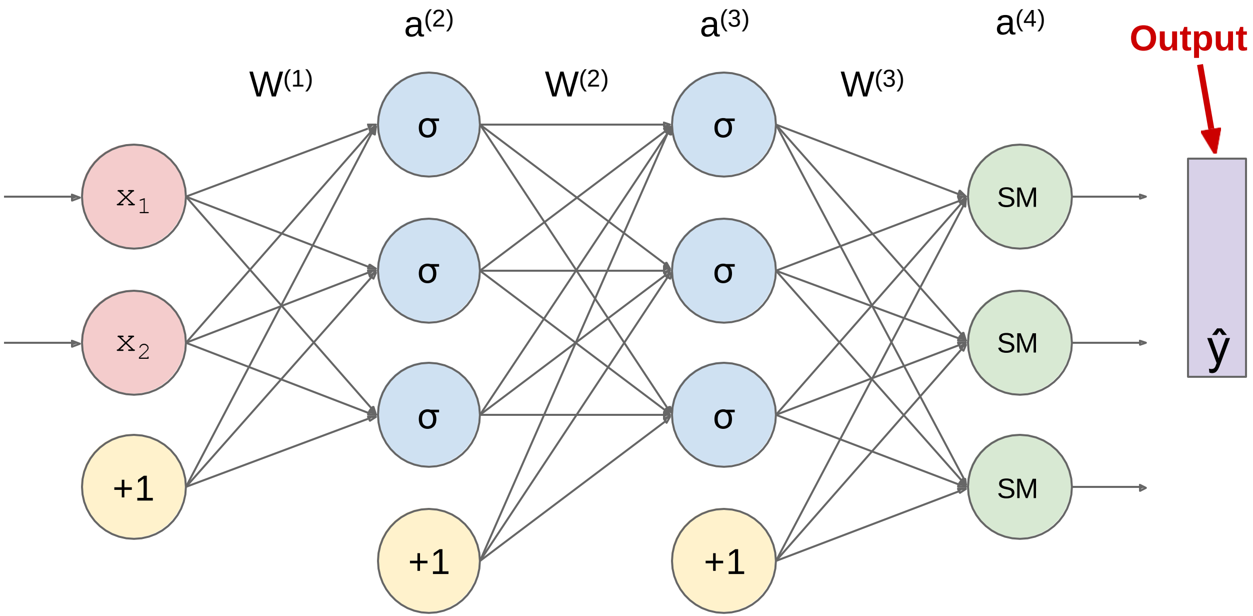

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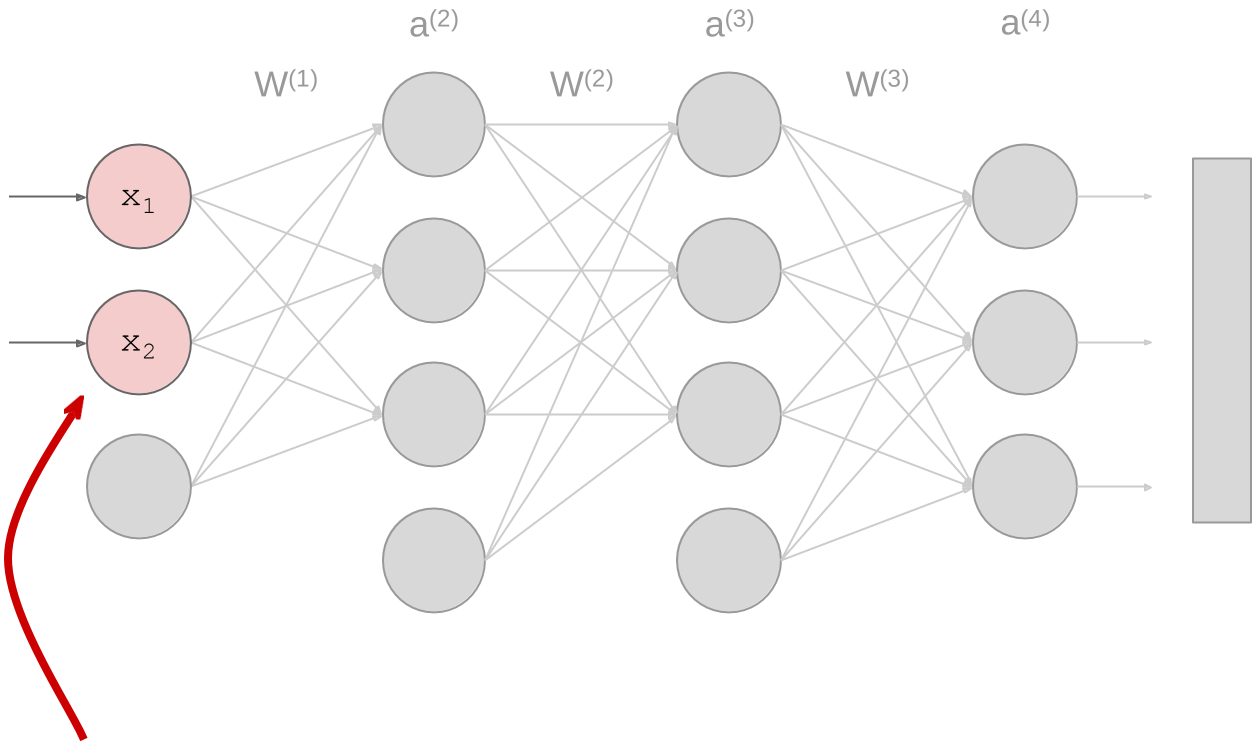
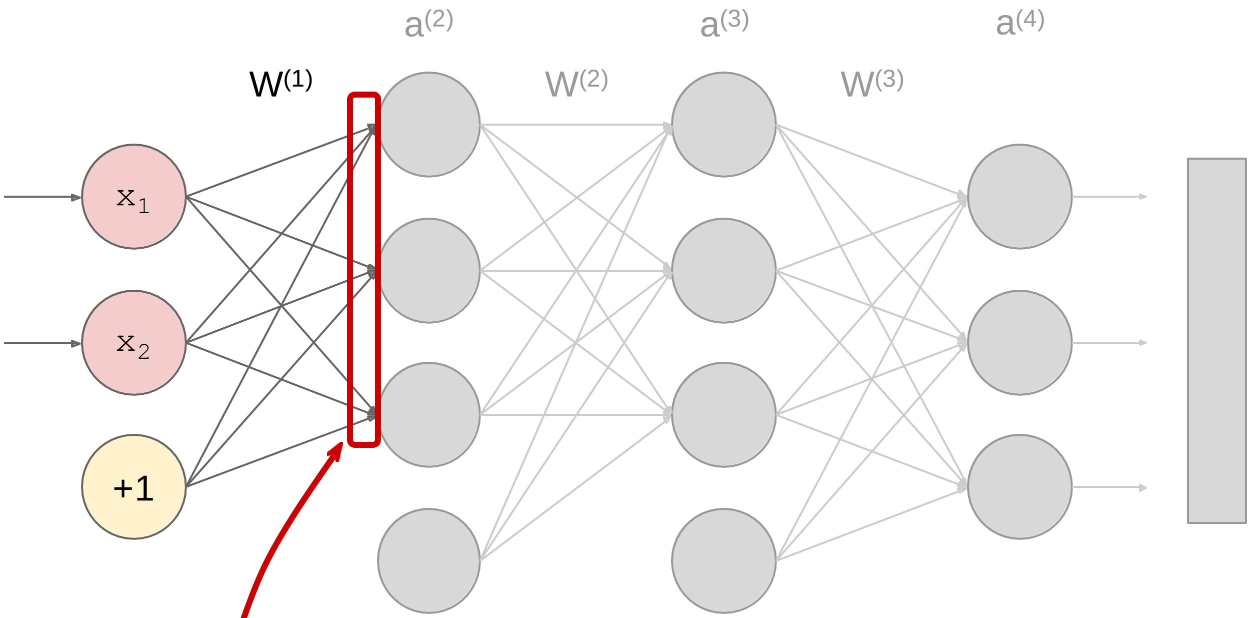
Forward Propagation



Input vector is passed into the network

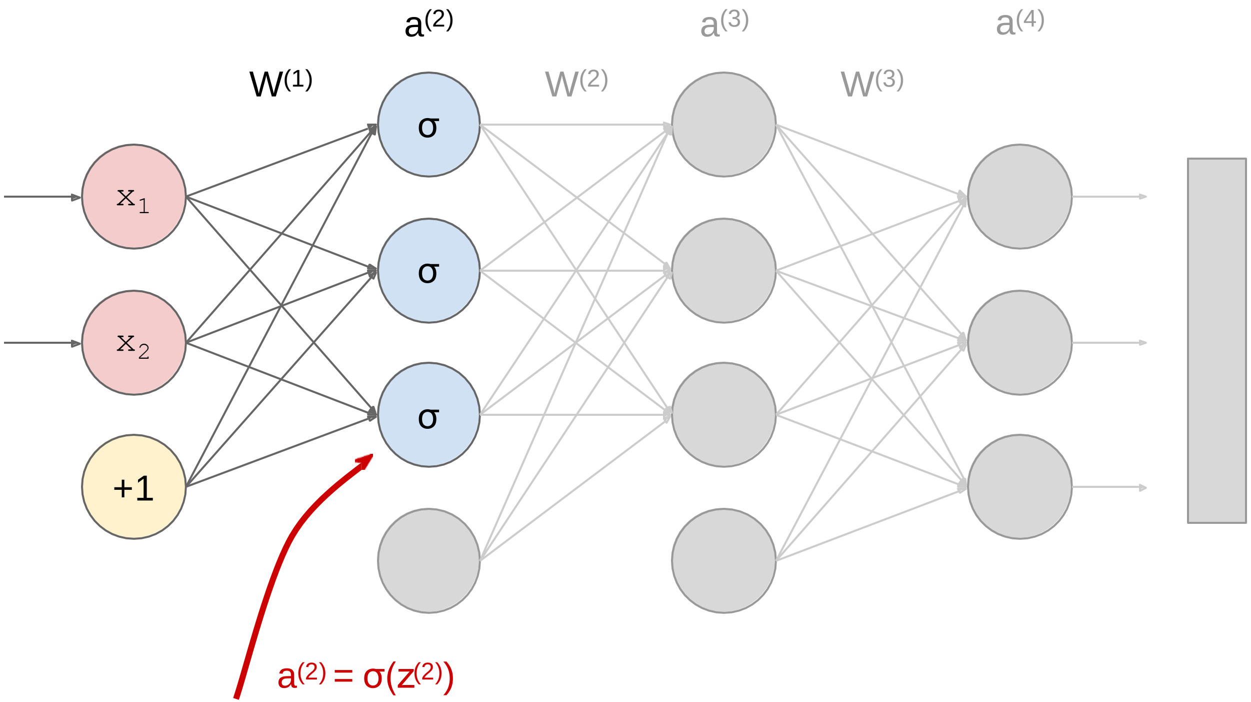
Forward Propagation



$z^{(2)} = W^{(1)}x + b^{(1)}$

Input is multiplied with $W^{(1)}$ weight matrix and added with layer 1biases to calculate $z^{(2)}$

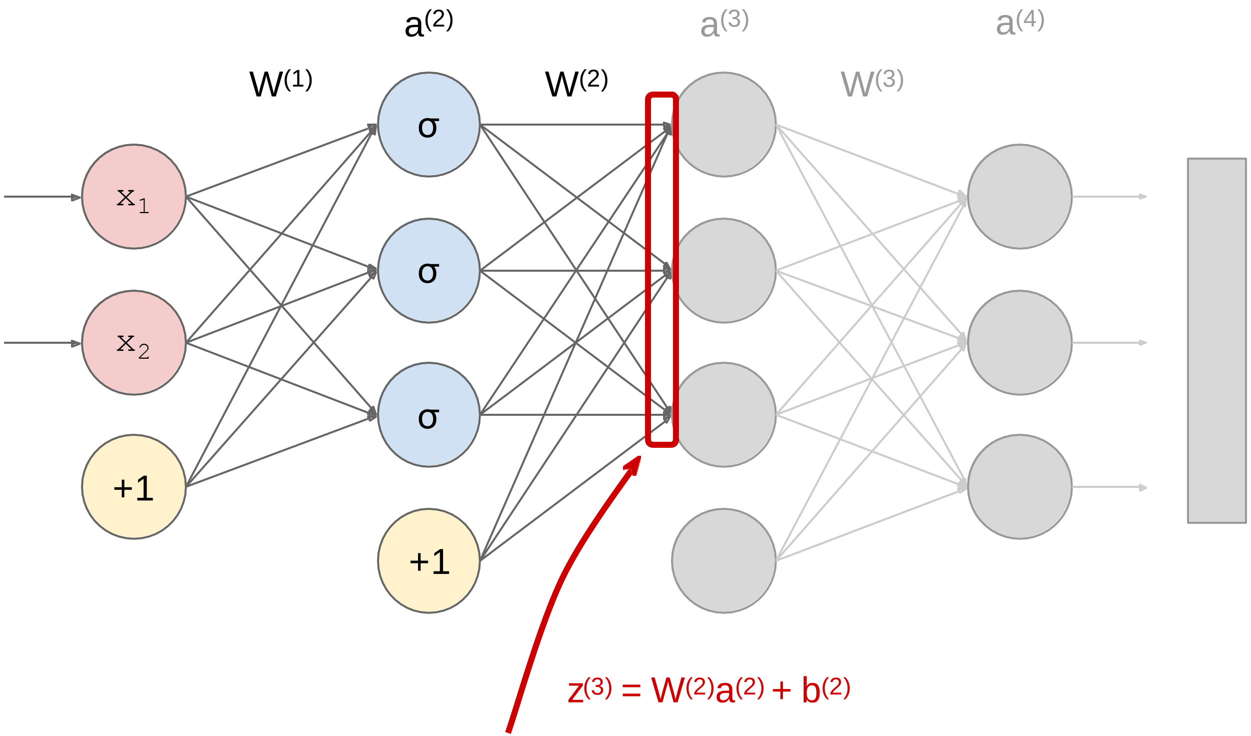
Forward Propagation



$a^{(2)} = \sigma(z^{(2)})$

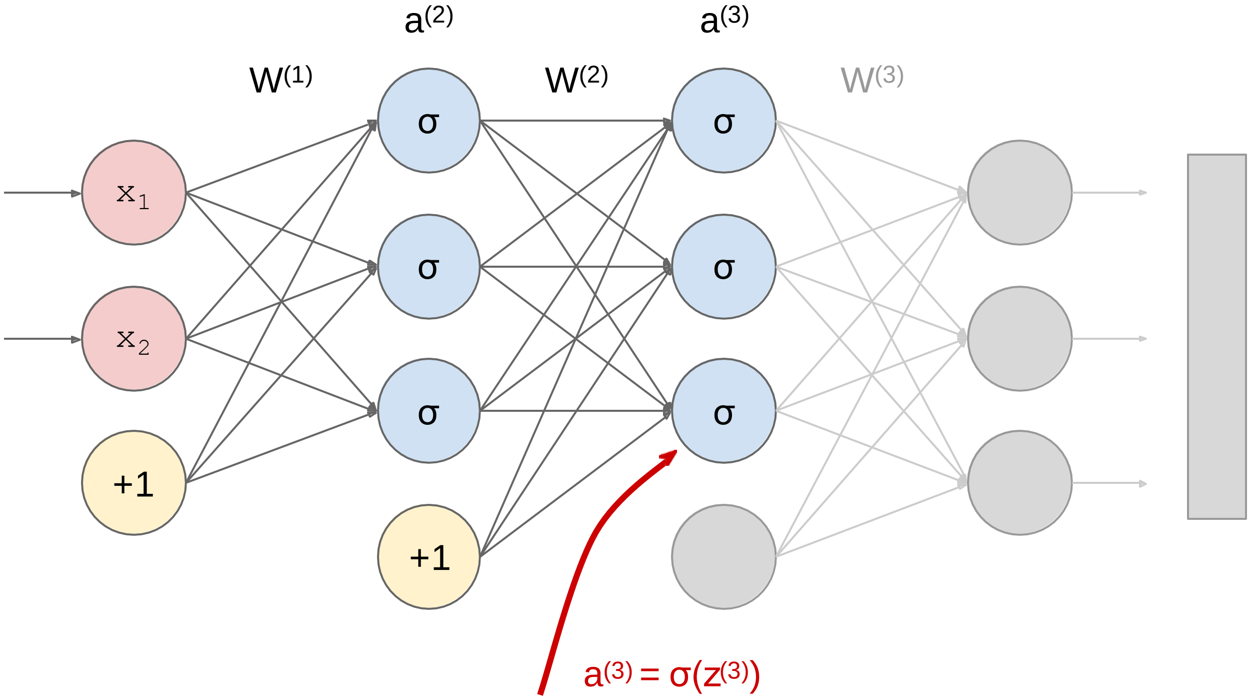
Activation value for the second layer is calculated by passing $z^{(2)}$ into some function. In this case, the sigmoid function.

Forward Propagation



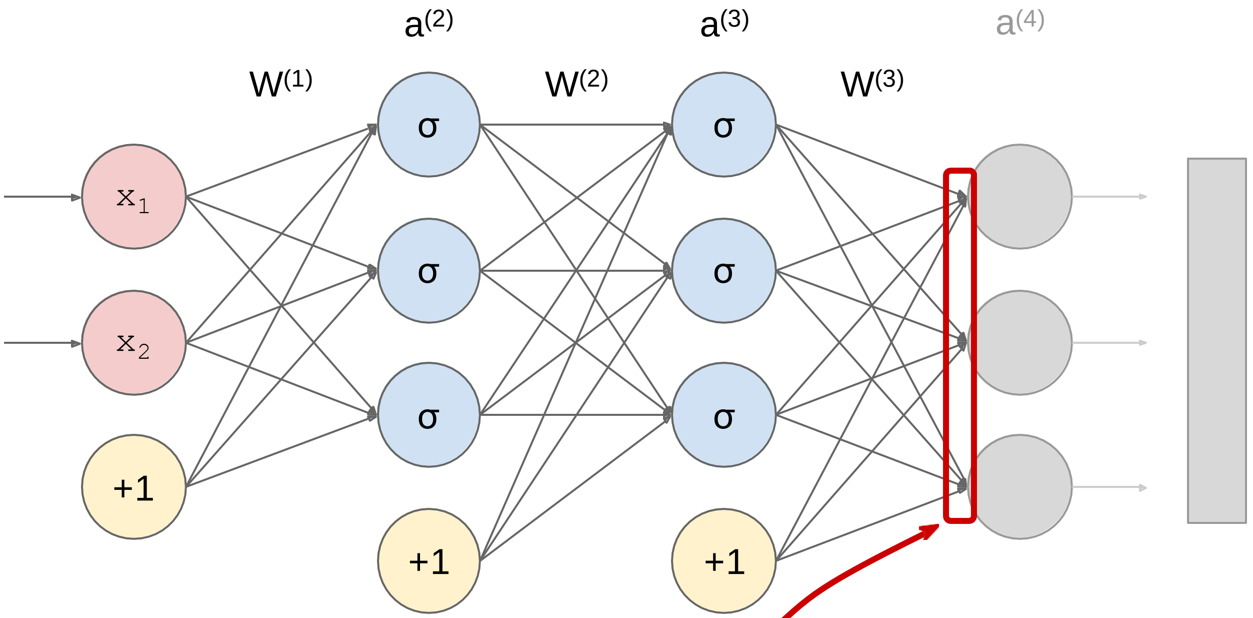
$z^{(3)}$ is calculated by multiplying $a^{(2)}$ vector with $W^{(2)}$ weight matrix and adding layer 2 biases

Forward Propagation



Similar to previous layer, $a^{(3)}$ is calculated by passing $z^{(3)}$ into the sigmoid function

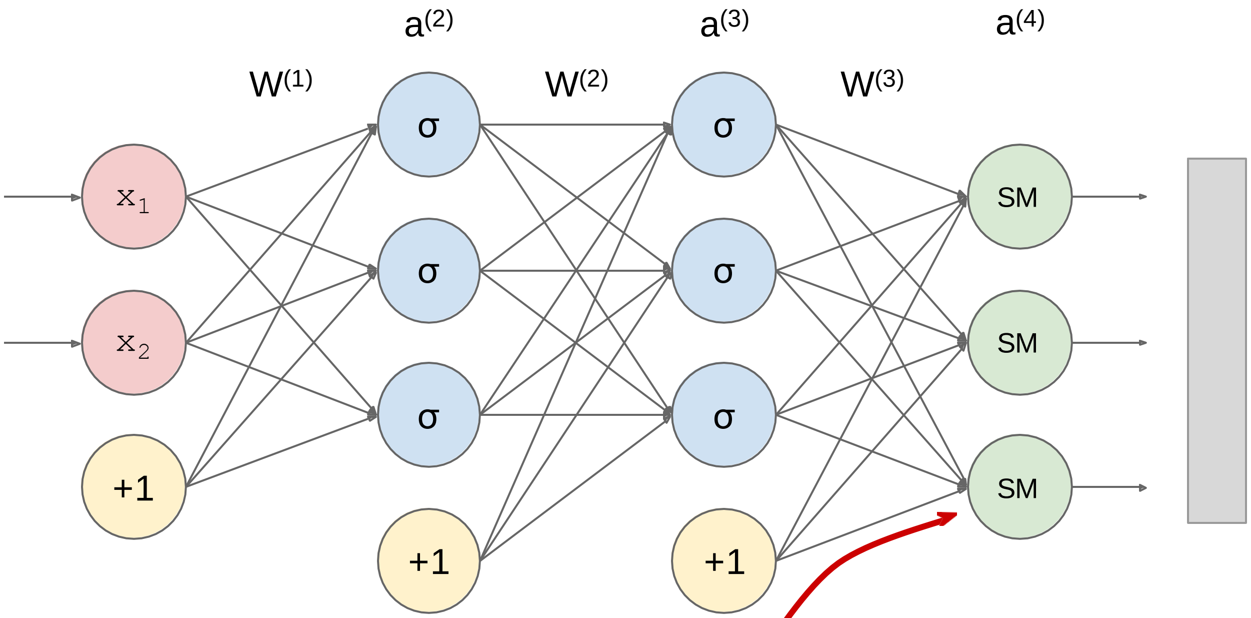
Forward Propagation



$z^{(4)} = W^{(3)}a^{(3)} + b^{(3)}$

$z^{(4)}$ is calculated by multiplying $a^{(3)}$ vector with $W^{(3)}$ weight matrix and adding layer 3 biases

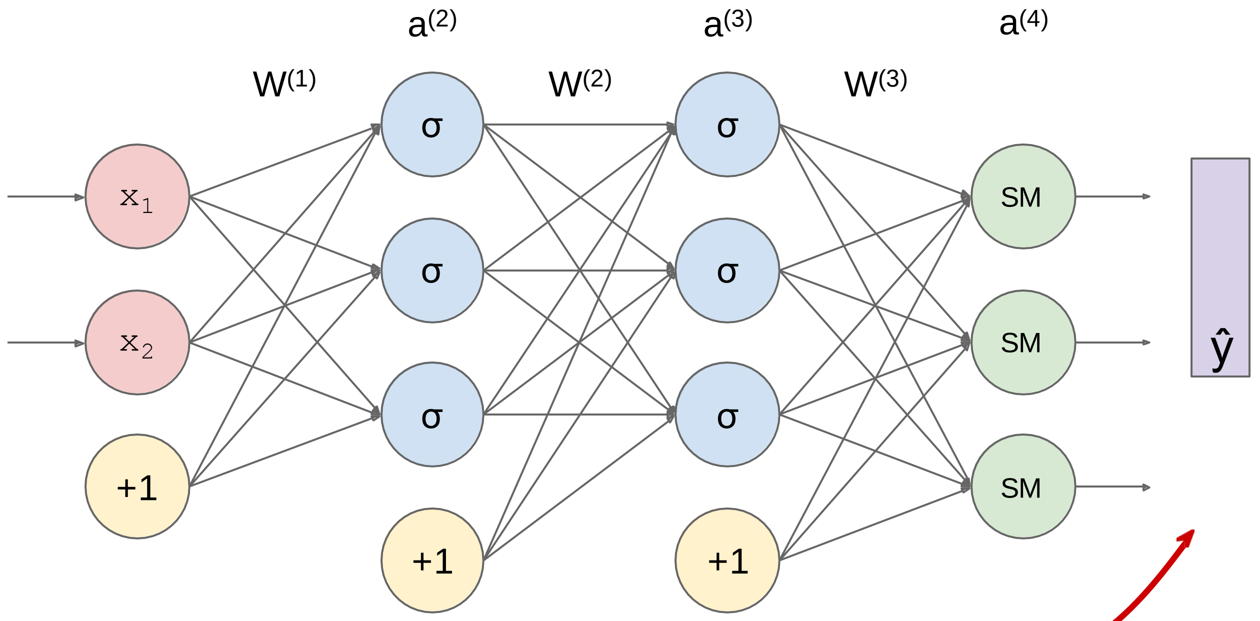
Forward Propagation



$a^{(4)} = SM(z^{(4)})$

For the final layer, we calculate $a^{(4)}$ by passing $z^{(4)}$ into the Softmax function

Forward Propagation



We then make our prediction based on the final layer's output

$$z^{(2)} = W^{(1)}x + b^{(1)}$$

$$z^{(3)} = W^{(2)}a^{(2)} + b^{(2)}$$

$$z^{(4)} = W^{(3)}a^{(3)} + b^{(3)}$$

$$a^{(2)} = \sigma(z^{(2)})$$

$$a^{(3)} = \sigma(z^{(3)})$$

$$a^{(4)} = \hat{y} = SM(z^{(4)})$$

Goal:

Find which direction to shift weights

How:

Find partial derivatives of the cost with respect to weight matrices

How (again):

Chain rule

Cost/ Loss Functions

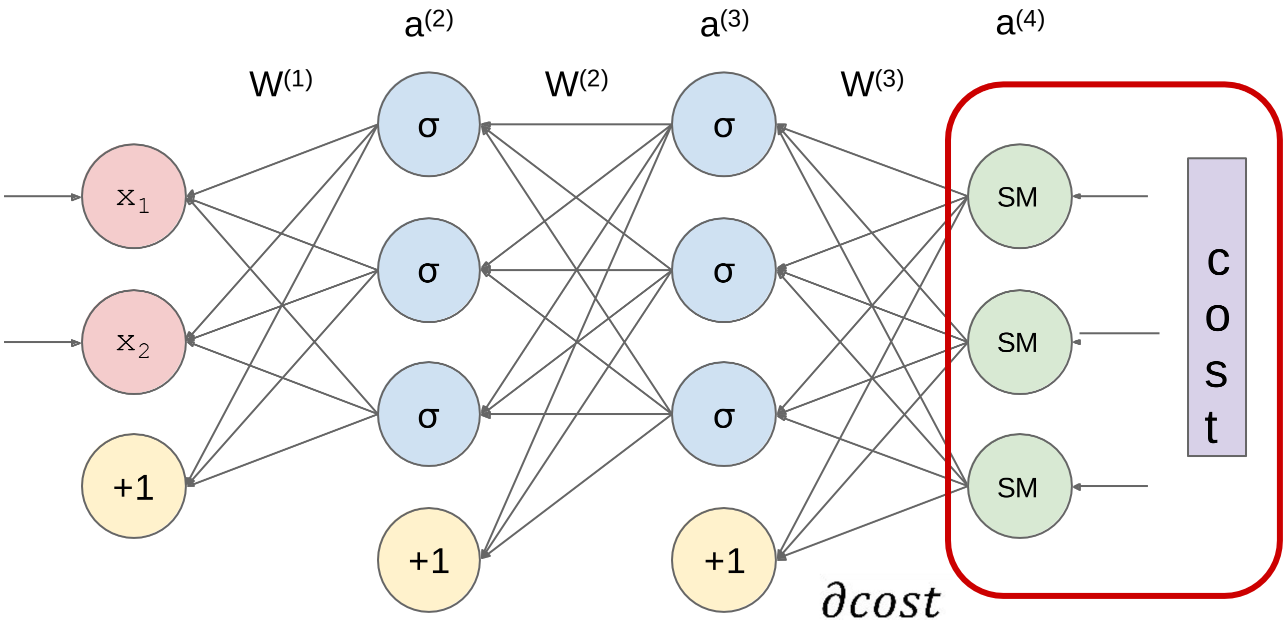
- We can use a cost function to measure how far off we are from the expected value.

- We'll use the following variables:
  - y to represent the true value
  - ŷ to represent the prediction value

Source: https://www.udemy.com/

Back Propagation

Want: $\frac{\partial cost}{\partial W^{(1)}}$ $\frac{\partial cost}{\partial W^{(2)}}$ $\frac{\partial cost}{\partial W^{(3)}}$



$\frac{\partial cost}{\partial z^{(4)}}$

x_i: input value
$\hat{y}$: output vector
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SM: Softmax function
+1: bias (constant) unit
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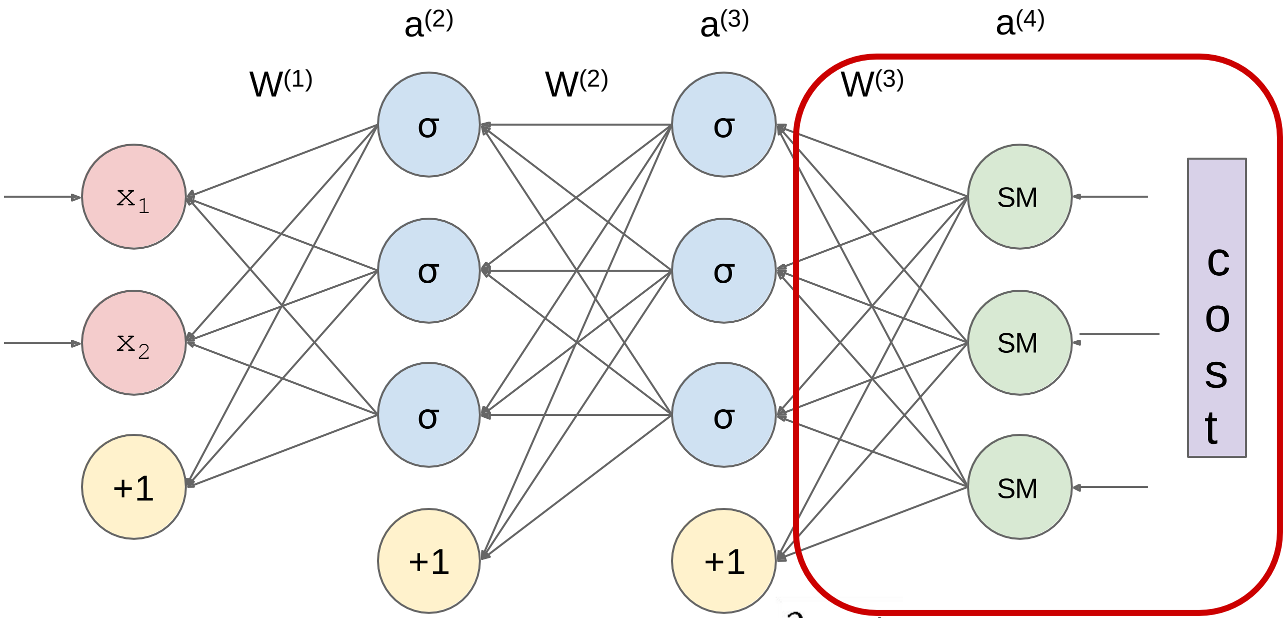
$W^{(l)}$: weight matrix for layer l
$z^{(l)}$: input into layer l

$$\frac{\partial z^{(4)}}{\partial W^{(3)}} = a^{(3)}$$

$$\frac{\partial cost}{\partial W^{(3)}} = \frac{\partial cost}{\partial z^{(4)}} \cdot \frac{\partial z^{(4)}}{\partial W^{(3)}} = \delta^{(4)} a^{(3)}$$

Back Propagation

Want: $\frac{\partial cost}{\partial W^{(1)}}$ $\frac{\partial cost}{\partial W^{(2)}}$ $\frac{\partial cost}{\partial W^{(3)}}$



$$\frac{\partial cost}{\partial W^{(3)}}$$

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$$\frac{\partial z^{(4)}}{\partial a^{(3)}} = W^{(3)}$$

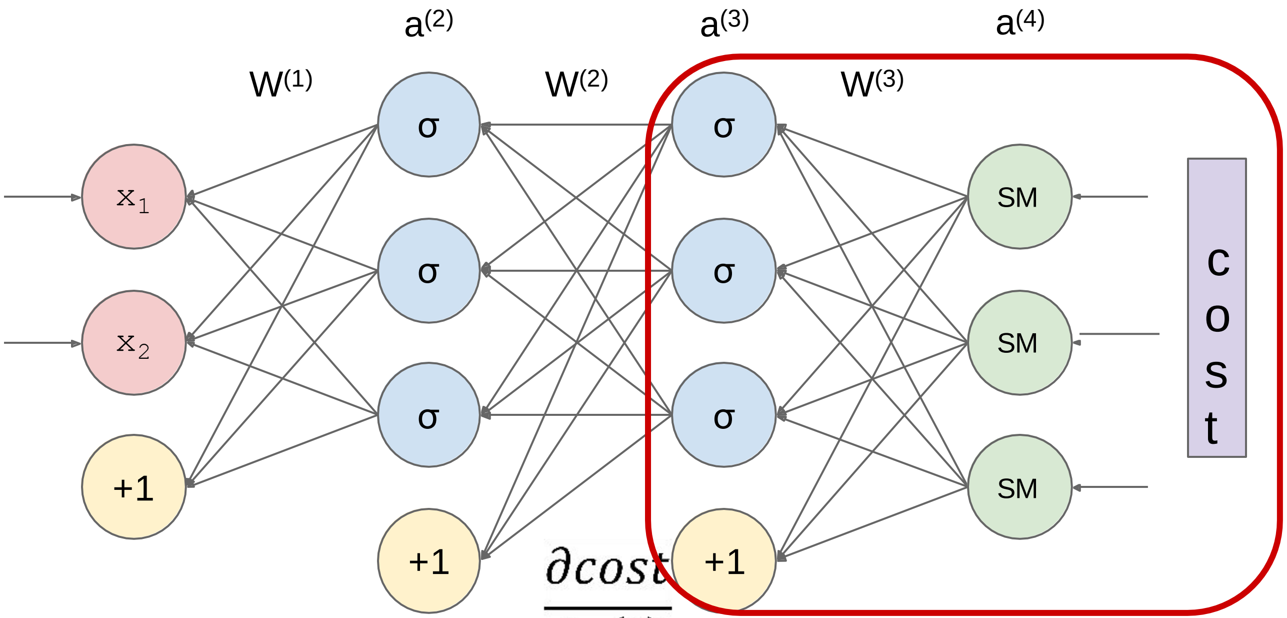
$$\frac{\partial a^{(3)}}{\partial z^{(3)}} = a^{(3)}(1 - a^{(3)})$$

$$\frac{\partial cost}{\partial z^{(3)}} = \frac{\partial cost}{\partial z^{(4)}} \cdot \frac{\partial z^{(4)}}{\partial a^{(3)}} \cdot \frac{\partial a^{(3)}}{\partial z^{(3)}} = \delta^{(3)}$$

Partials, step by step

Back Propagation

Want: $\frac{\partial cost}{\partial W^{(1)}}$ $\frac{\partial cost}{\partial W^{(2)}}$ $\frac{\partial cost}{\partial W^{(3)}}$



$\frac{\partial cost}{\partial z^{(3)}}$

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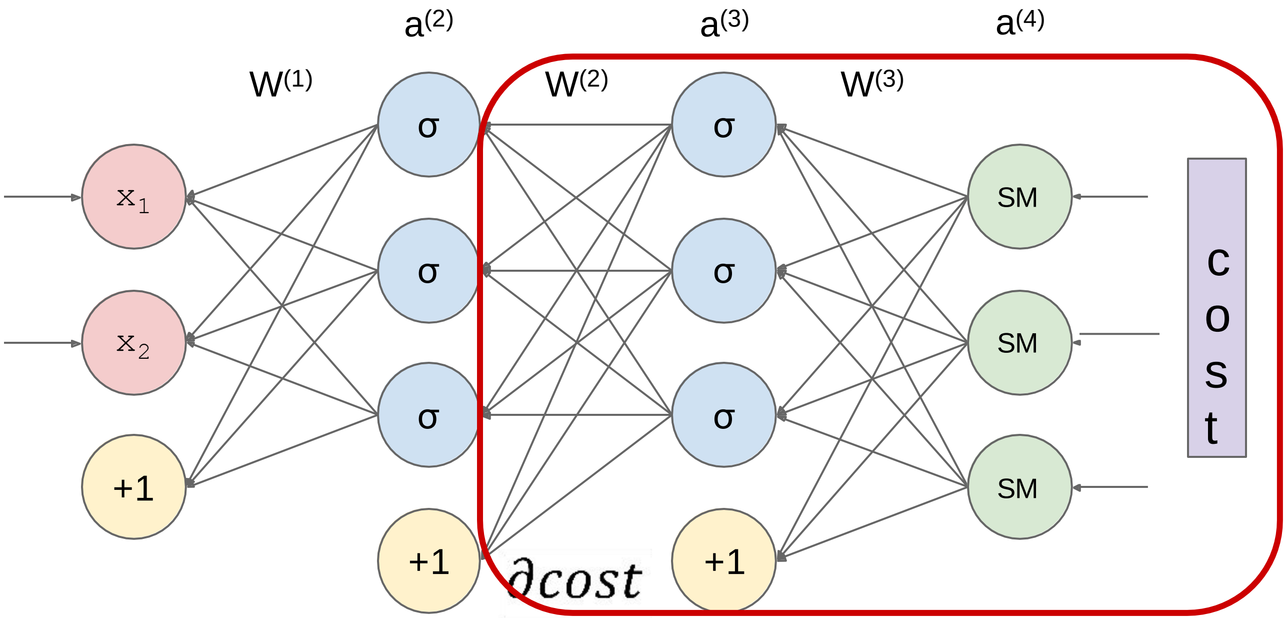
$$\frac{\partial cost}{\partial z^{(3)}} = \frac{\partial cost}{\partial z^{(4)}} \cdot \frac{\partial z^{(4)}}{\partial a^{(3)}} \cdot \frac{\partial a^{(3)}}{\partial z^{(3)}} = \delta^{(3)}$$

$$\frac{\partial cost}{\partial W^{(2)}} = \delta^{(3)} a^{(2)}$$

Back Propagation

Want: $\frac{\partial cost}{\partial W^{(1)}}$ $\frac{\partial cost}{\partial W^{(2)}}$ $\frac{\partial cost}{\partial W^{(3)}}$



$$\frac{\partial cost}{\partial W^{(2)}}$$

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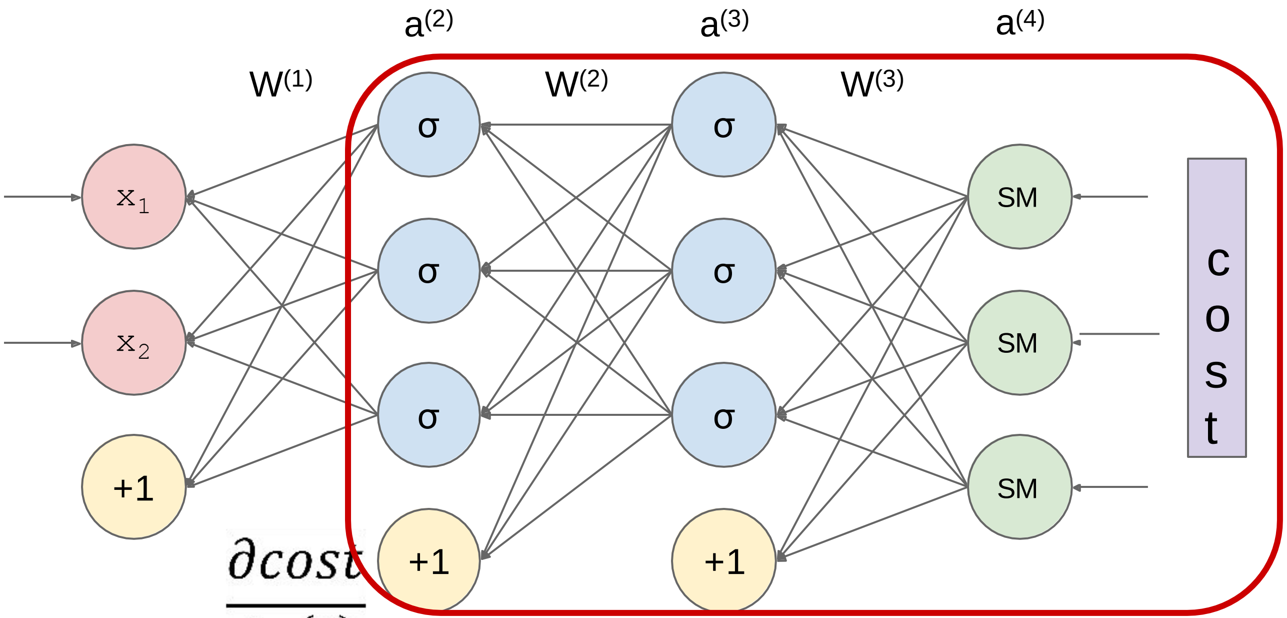
Back Propagation

Want: $\frac{\partial cost}{\partial W^{(1)}}$ $\frac{\partial cost}{\partial W^{(2)}}$ $\frac{\partial cost}{\partial W^{(3)}}$



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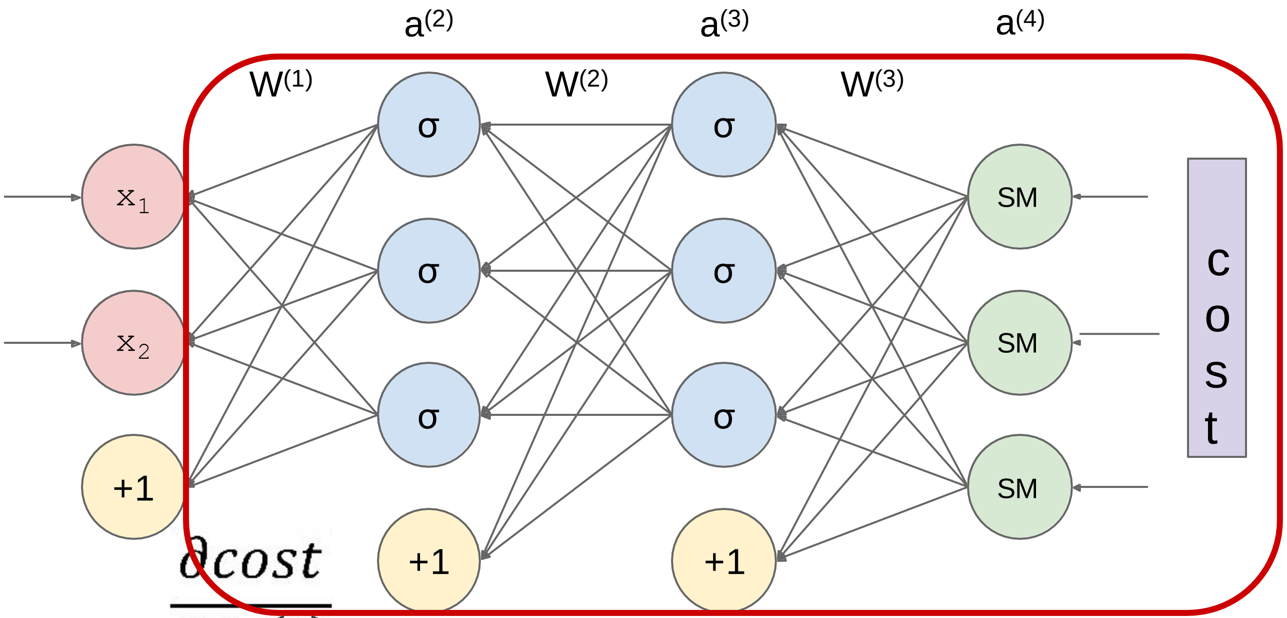

$\frac{\partial cost}{\partial W^{(1)}}$

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$$\delta^{(l)} = \frac{\partial cost}{\partial z^{(l)}}$$

$$\frac{\partial cost}{\partial W^{(l)}} = \delta^{(l+1)} a^{(l)}$$

$$\delta^{(l)} = \delta^{(l+1)} W^{(l)} a'^{(l)}$$

As programmers...

- How do we **NOT** do this ourselves?

We’re lazy by trade.

Automatic Differentiation

Auto-Differentiation: Idea

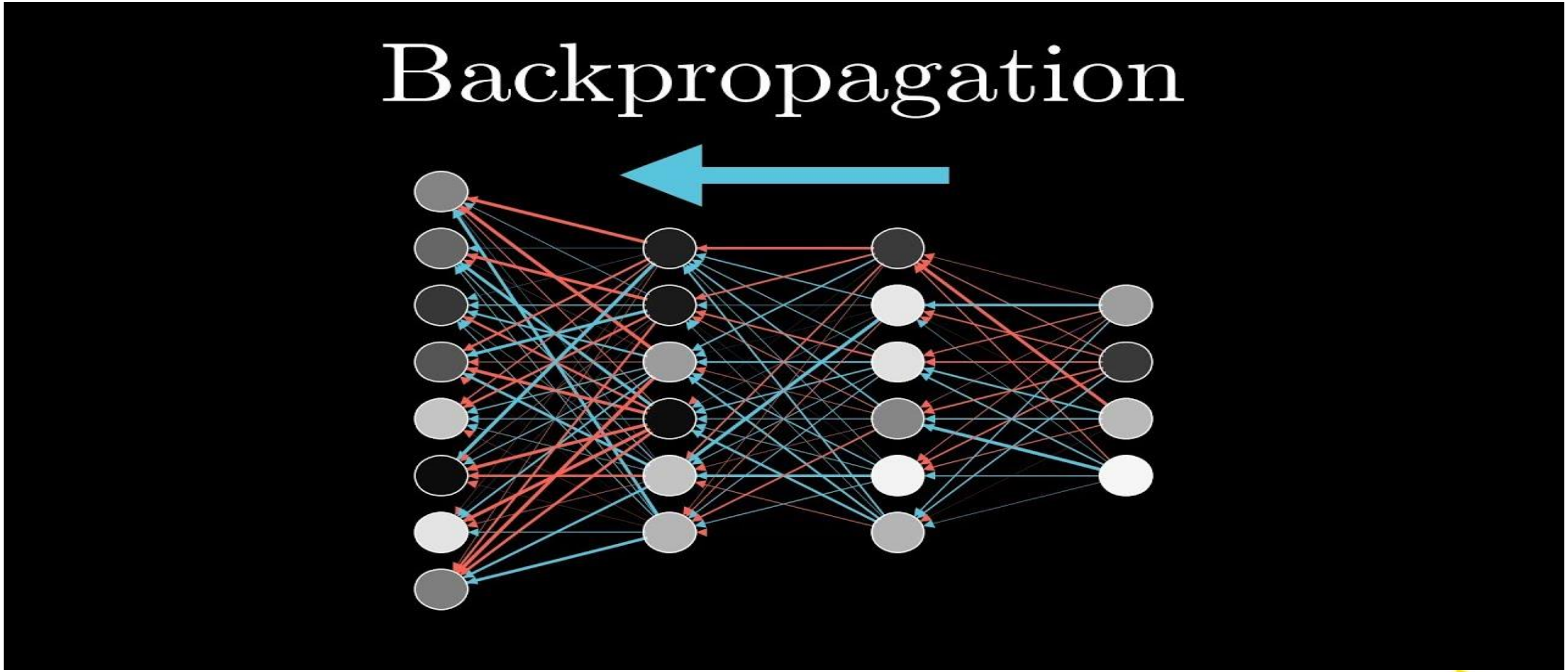
- Use functions that have easy-to-compute derivatives
- Compose these functions to create more complex super-model
- Use the chain rule to get partial derivatives of the model

What is Backpropagation

1. **Definition**

- Backpropagation is an algorithm for supervised learning of artificial neural networks using gradient descent.

Backpropagation



Backpropagation: Algorithm

The following steps is the recursive definition of algorithm:

1. Initialize weights and biases in neural network
2. Propagate input forward (by applying activation function)
3. Calculate the output for every neuron
4. Calculate the error at the outputs
5. Backpropagate the error

$$\frac{\partial J}{\partial W} = \frac{1}{n}\sum_{i}^{n} x^{(i)}\left(Wx^{(i)} + b - y^{(i)}\right)$$

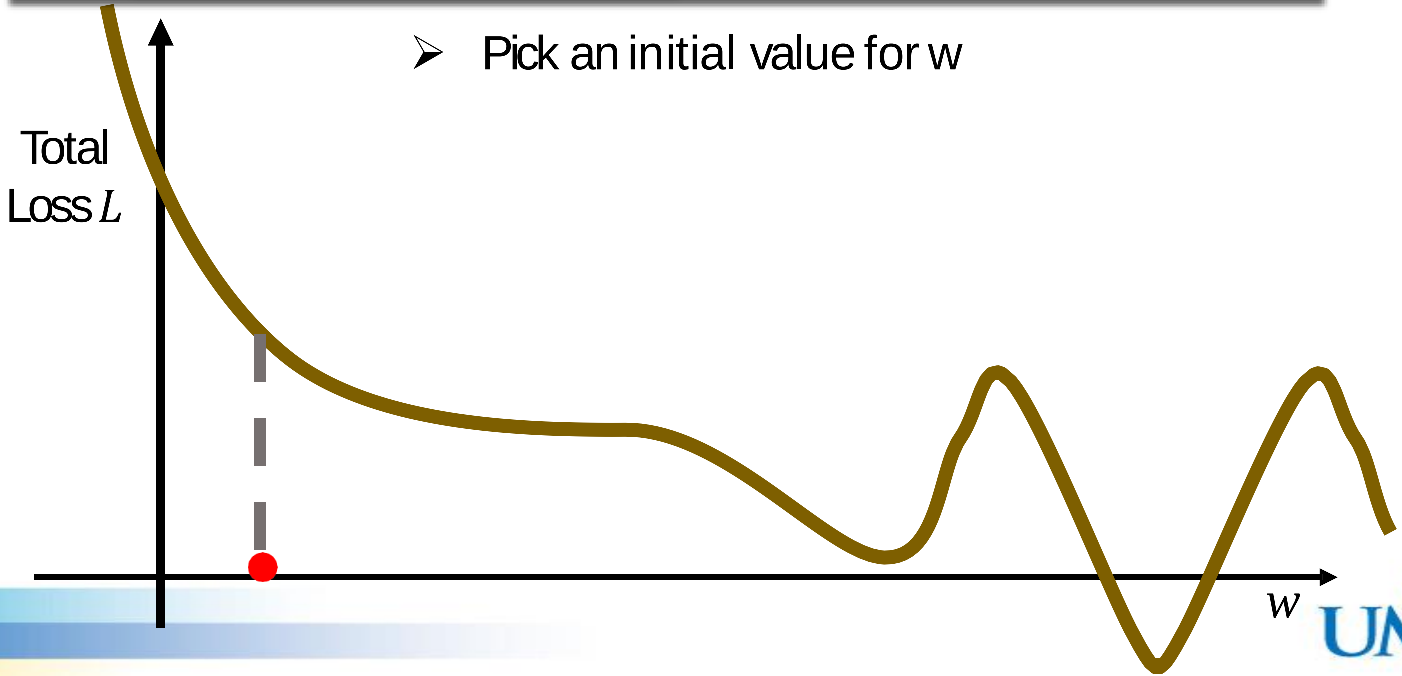
6. use the error signals to compute weight adjustments.

Gradient Descent

Network parameters $\theta = \{ w_1, w_2, \cdots, b_1, b_2, \cdots \}$

Find *network parameters θ^** that minimize total loss L

- Pick an initial value for w



Gradient Descent

Network parameters $\theta = \{w_1, w_2, \cdots, b_1, b_2, \cdots\}$

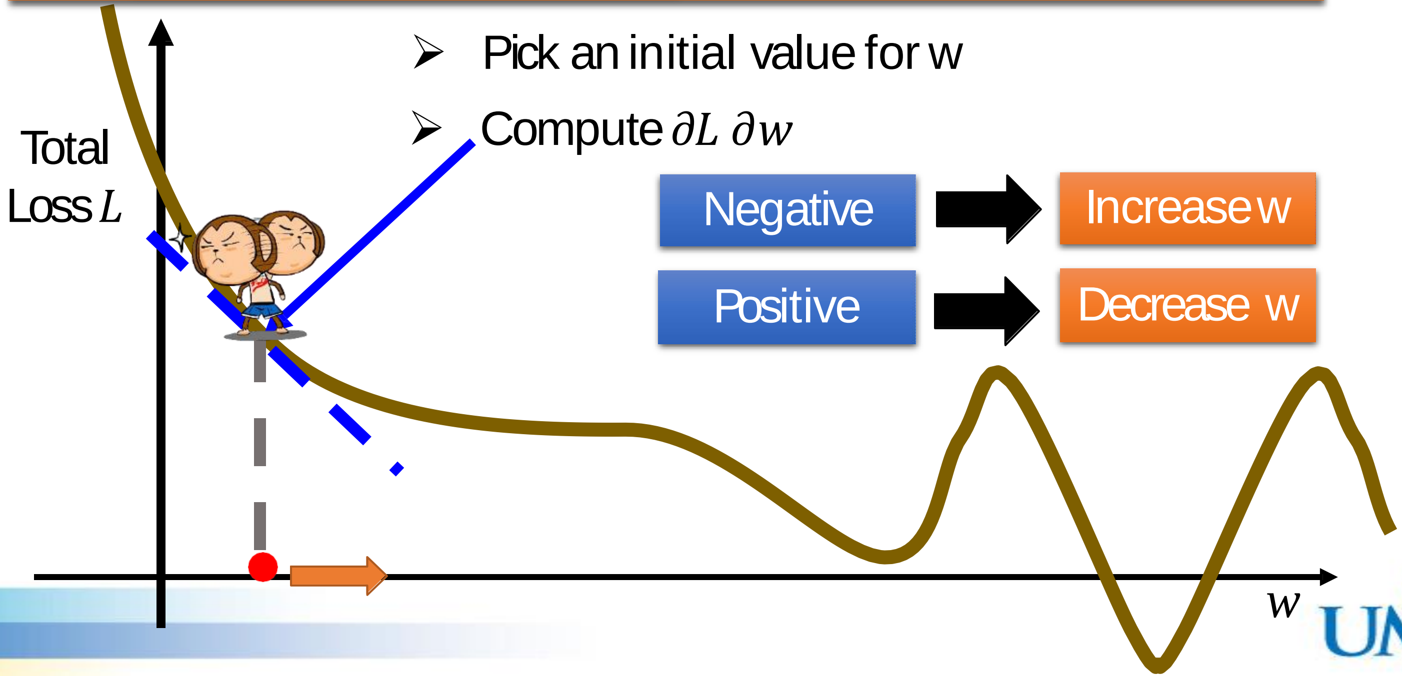
Find ***network parameters*** θ^* that minimize total loss L

➢ Pick an initial value for w

➢ Compute $\partial L / \partial w$

Negative → Increase w

Positive → Decrease w



Gradient Descent

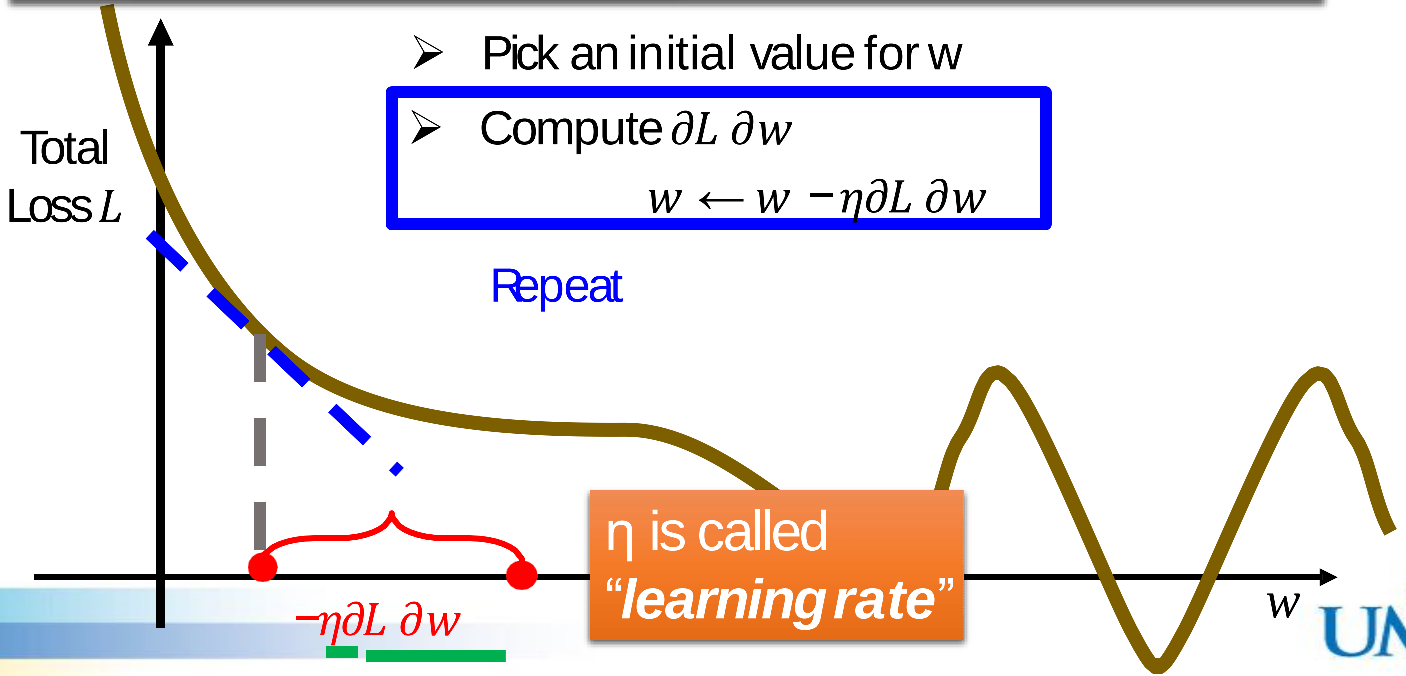
Network parameters $\theta = \{ w_1, w_2, \cdots, b_1, b_2, \cdots \}$

Find ***network parameters*** $\boldsymbol{\theta}^*$ that minimize total loss L

- Pick an initial value for w
- Compute $\partial L/\partial w$

  $w \leftarrow w - \eta \partial L/\partial w$

Repeat



Gradient Descent

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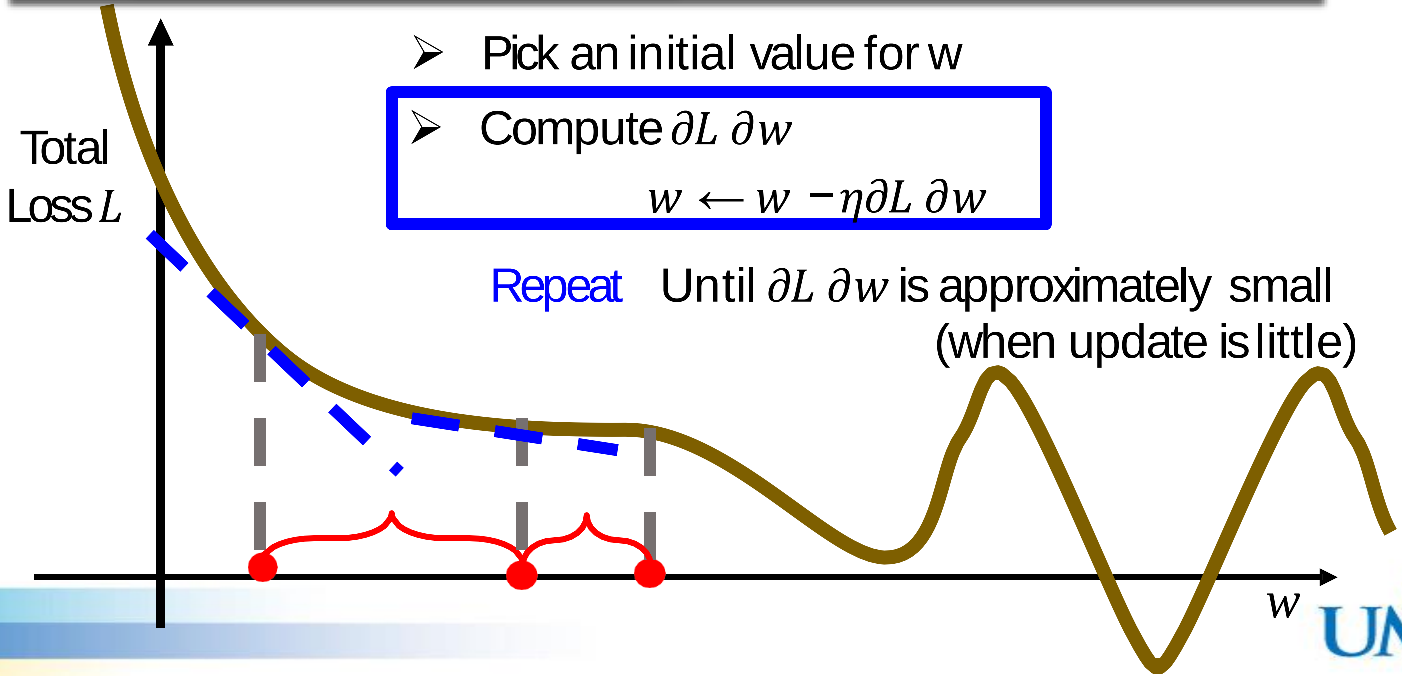


- Pick an initial value for w
- Compute $\partial L / \partial w$

  $w \leftarrow w - \eta \partial L / \partial w$

Repeat Until $\partial L / \partial w$ is approximately small (when update is little)

Learning Rate

- **Learning rate definition:**
  - learning rate determines **how fast** weights change.
- Learning rate = Trade-Off
  - Large values for ratio => Fast training
  - Lower ratios => Accurate training
- Question: How do *you* choose the learning rate?

Cost/ Loss Functions

- We can use a cost function to measure how far off we are from the expected value.

- We'll use the following variables:
  - y to represent the true value
  - ŷ to represent the prediction value

Source: https://www.udemy.com/

Common types of loss functions (1)

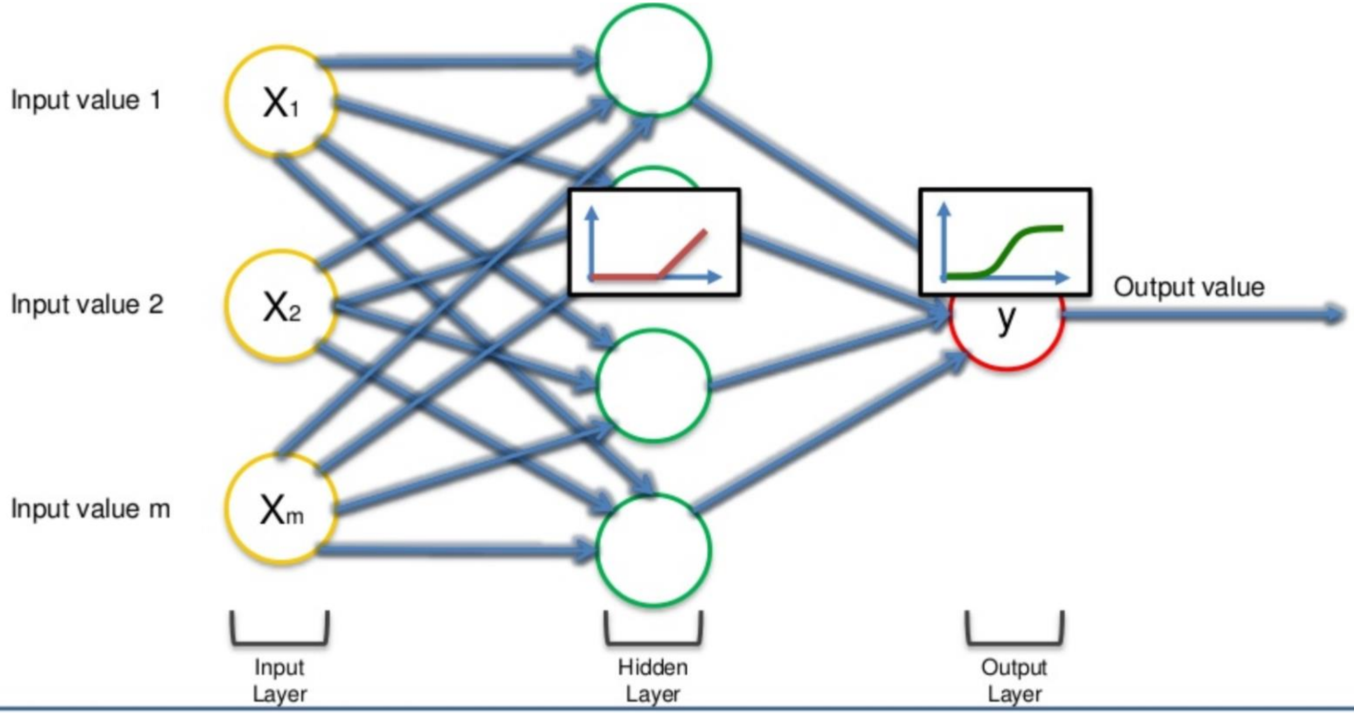
- Loss functions depend on the type of task:
  - Regression: the network predicts **continuous**, **numeric** variables
    - Example: Length of fishes in images, temperature from latitude/longitude or housing prices
    - Absolute value, square error

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}(y_i - f_\theta(x_i))^2$$

Common types of loss functions (2)

- Loss functions depend on the type of task:
  - Classification: the network predicts **categorical** variables (fixed number of classes)
    - Example: classify email as spam, predict student grades from essays.
    - hinge loss, Cross-entropy loss

Activation function

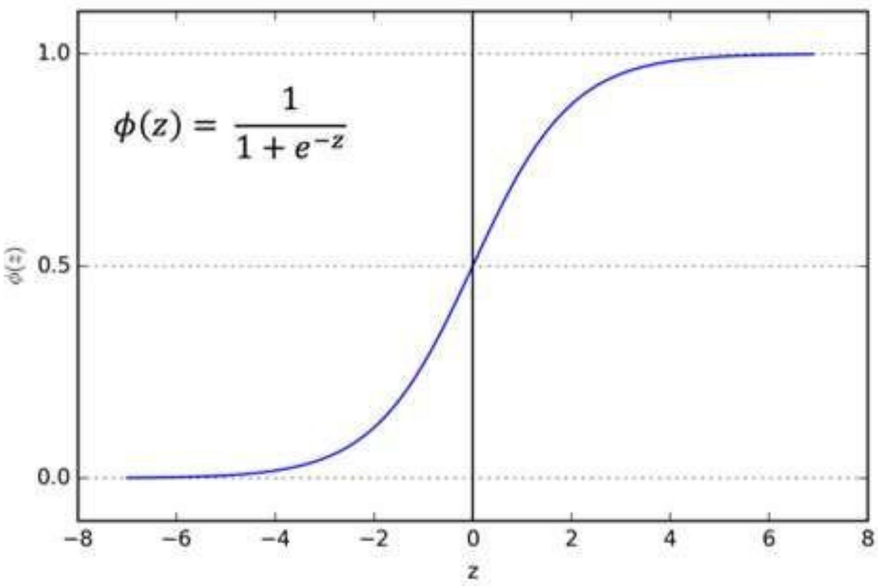


Activation Function

- They define the output of that node given an input or set of inputs
- They decide whether a neuron should be activated or not
- The activation function can be divided in two types:
  - Linear activation function
  - Non-Linear Activation Function
    - Sigmoid
    - Tanh
    - Relu

Non-Linear Activation Function - Sigmoid

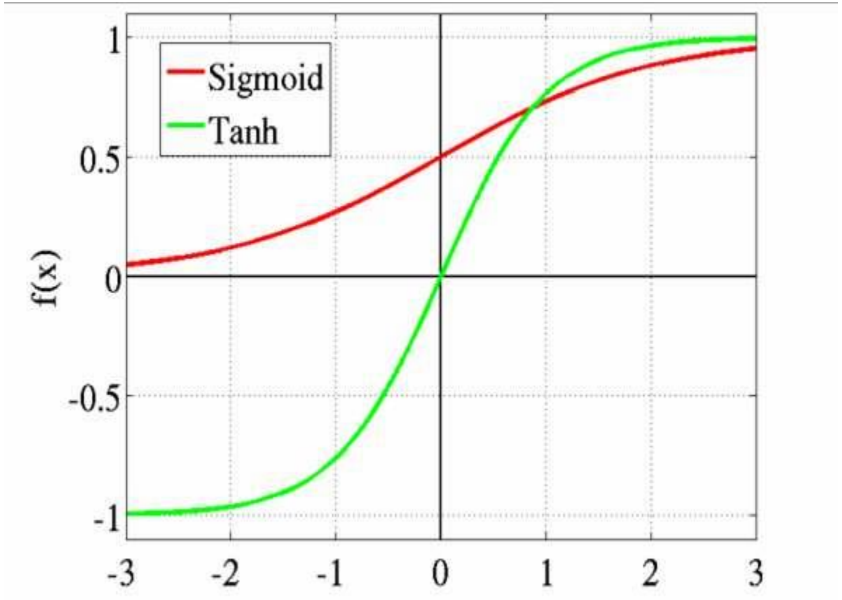
- It exists between (0 to 1).
- Used for models where we have to predict the probability as an output, sigmoid is the right choice.
- The function is differentiable, we can find the slope of the sigmoid curve at any two points.



Sigmoid Activation Function

Non-Linear Activation Function - Tanh

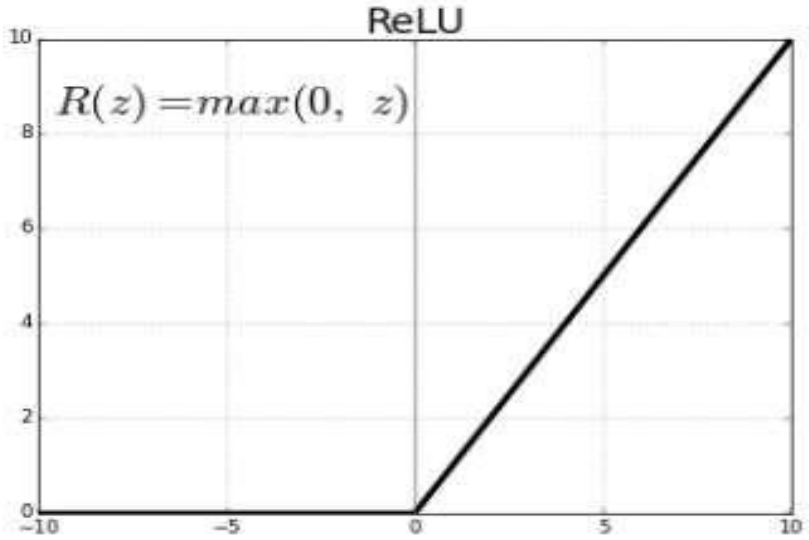
- The range of the tanh function is from (-1 to 1). Tanh is also sigmoidal
- Negative inputs will be mapped strongly negative and the zero inputs will be mapped near zero in the tanh graph.
- It is differentiable
- The tanh function is mainly used classification between two classes



Hyperbolic Tangent Activation Function

Non-Linear Activation Function - ReLU (Rectified Linear Unit)

- The ReLU is half rectified (from bottom). f(z) is zero when z is less than zero and f(z) is equal to z when z is above or equal to zero.
- **Range**: [0 to infinity)
- **Issue**: Negative values become zero immediately which decreases the ability of the model to fit or train from the data properly



Deep Learning Glossary

- Input: the first layer
- Output: what we want to compute
- Weight update: updating weight to decrease the cost function
- Bias: added to increase the flexibility of the model to fit the data
- Hidden layers: the neurons for the intermediate step
- Forward propagation: forwarding input through the neural network in order to generate network output value(s)
- Cost function: the difference between the targeted and actual output
- Activation function: They introduce non-linear properties to our Network
- Backward propagation: backward pass

Deep Learning Glossary

- Learning rate: a hyper-parameter that controls how much we are adjusting the weights of our **network** with respect the loss gradient
- Epochs: one forward pass and one backward pass of *all* the training examples
- Batch size: the number of training examples in one forward/backward pass
- Dropout: next class
- Regularization: next class

To recap: Keras Programming steps

- Importing Sequential class from keras.models
- Stacking layers using .add() method
- Configure learning process using .compile() method
- Train the model on train dataset using .fit() method

General layers

- Dense: implements the operation

  output = activation(dot(input, weight) + bias)

  – keras.layers.core.Dense(units, activation=None, use_bias=True, kernel_initializer='glorot_uniform', bias_initializer='zeros', kernel_regularizer=None, bias_regularizer=None, activity_regularizer=None, kernel_constraint=None, bias_constraint=None)

- Activations:
  – you can add one more new layer: model.add(Activation('tanh’))
  – or Activation argument in all forwarded layer: model.add(Dense(64, activation='tanh'))

Optimizers available in Keras

- How do we find the “best set of parameters (weights and biases)” for the given network ?
- Optimization
  - They vary in the speed of convergence,
  - ability to avoid getting stuck in local minima
  - SGD –Stochastic gradient descent
  - SGD with momentum
  - Adam
  - AdaGrad
  - RMSprop
  - AdaDelta

```
sgd = optimizers.SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
model.compile(loss='mean_squared_error', optimizer=sgd)
```

Loss functions available in Keras

- MSE –Mean square error: keras.losses.mean_squared_error(y_true, y_pred)
- MAE –Mean absolute error: keras.losses.mean_absolute_error(y_true, y_pred)
- Hinge: keras.losses.hinge(y_true, y_pred)
- Categorical_crossEntropy: keras.losses.categorical_crossentropy(y_true, y_pred)

Initializations

- Initialization define the way to set the initial random weights of keras layers
- Init→ model.add(Dense(64,init=‘uniform’))
- Uniform
- Lecun_uniform
- Normal
- Zero
- One
- Glorot_normal
- Glorot_uniform

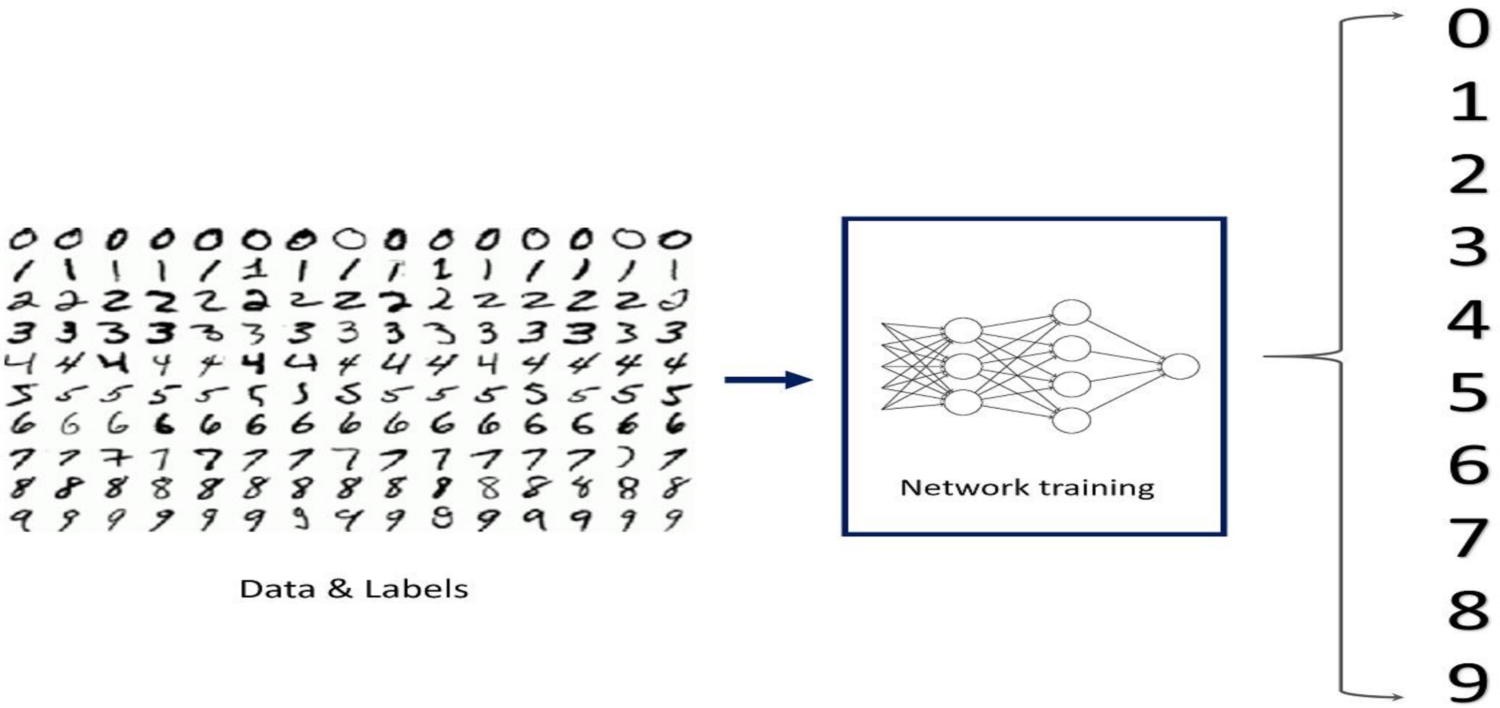
Evaluation in keras

- Usage of metrics:
  - A metrics is a function that is used to judge the performance of your model

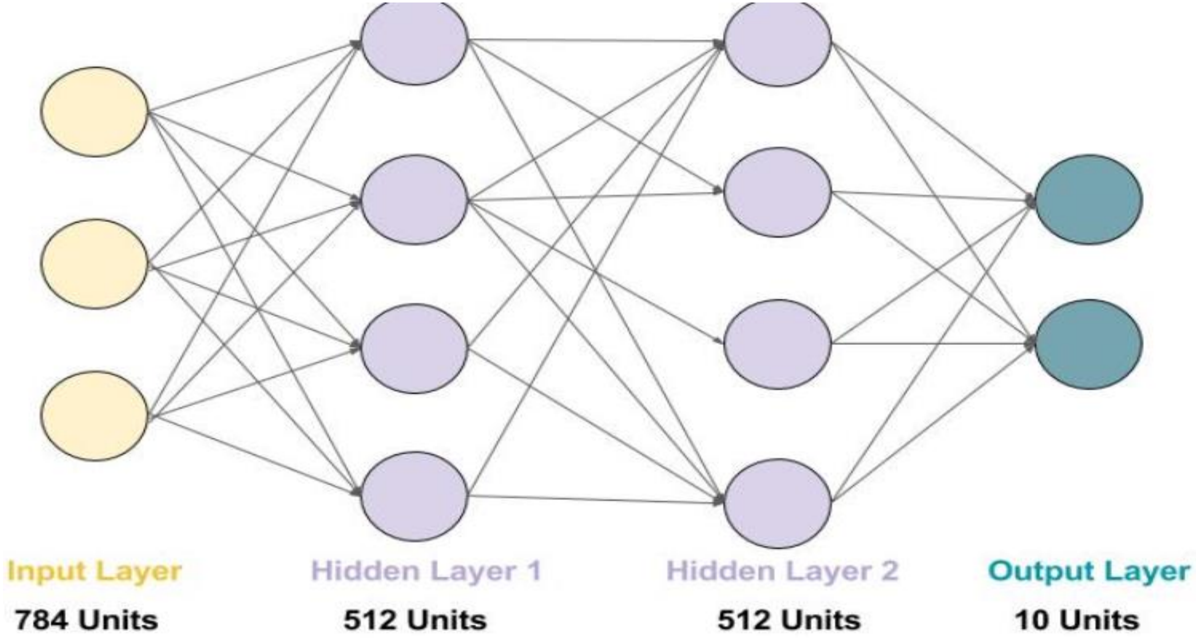
model.compile(loss='mean_squared_error', optimizer='sgd’

, metrics=['mae', 'acc'])

Use case: Image classification

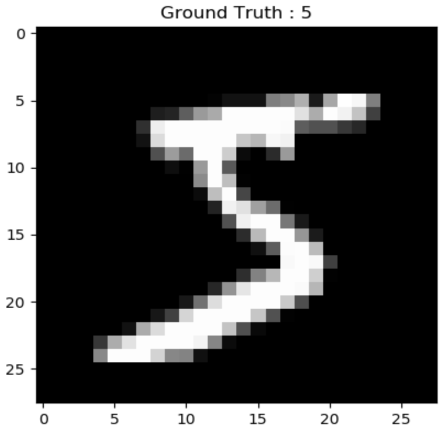


Model for image classification



Loading data and plotting the digit

```
(train_images,train_labels),(test_images, test_labels) = mnist.load_data()
#display the first image in the training data
plt.imshow(train_images[0,:,:],cmap='gray')
plt.title('Ground Truth : {}'.format(train_labels[0]))
# plt.show()
```



Processing the data

```
#1. convert each image of shape 28*28 to 784 dimensional which will be fed to the network as a single feature
dimData = np.prod(train_images.shape[1:])
train_data = train_images.reshape(train_images.shape[0],dimData)
test_data = test_images.reshape(test_images.shape[0],dimData)
#convert data to float and scale values between 0 and 1
train_data.astype('float')
test_data.astype('float')
#scale data
train_data //=255
test_data //=255
#change the labels frominteger to one-hot encoding
train_labels_one_hot = to_categorical(train_labels)
test_labels_one_hot = to_categorical(test_labels)
```

Creating the network & fitting

```
#creating network
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(dimData,)))
model.add(Dense(512, activation='relu'))
model.add(Dense(10, activation='softmax'))

model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
history = model.fit(train_data, train_labels_one_hot, batch_size=256, epochs=20, verbose=1,
                   validation_data=(test_data, test_labels_one_hot))
```

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Evaluation

```
[test_loss, test_acc] = model.evaluate(test_data, test_labels_one_hot)
print("Evaluation result on Test Data : Loss = {}, accuracy = {}".format(test_loss, test_acc))
```

Inference on the model

- model.predict_classes(test_data[[0],:])

Callbacks

- A callback is a set of functions to be applied at given stages of the training procedure.
- You can use callbacks to get a view on internal states and statistics of the model during training
- One of the default callbacks that is registered when training all deep learning models is the History callback
- It records training metrics for each epoch
- This includes the loss and the accuracy
- Metrics are stored in a dictionary in the history member of the object returned.
- # list all data in history
- print(history.history.keys()) → ['acc', 'loss', 'val_acc', 'val_loss’]

References

- https://www.youtube.com/watch?v=aircAruvnKk&t=866s


thank you!
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