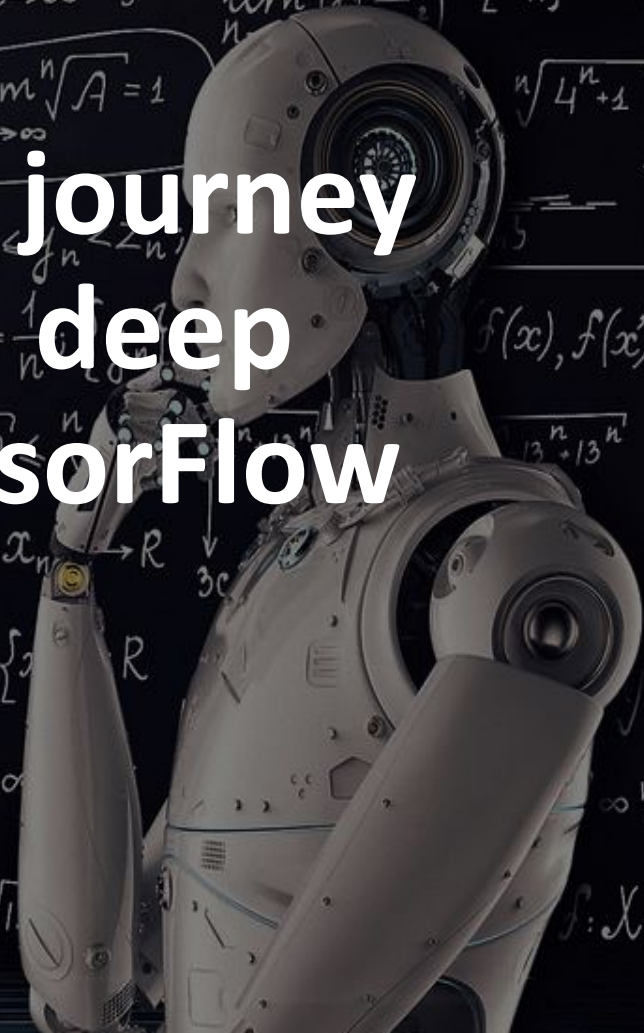


# How to start your journey in Machine and deep learning with TensorFlow

Osama Al-atraqchi



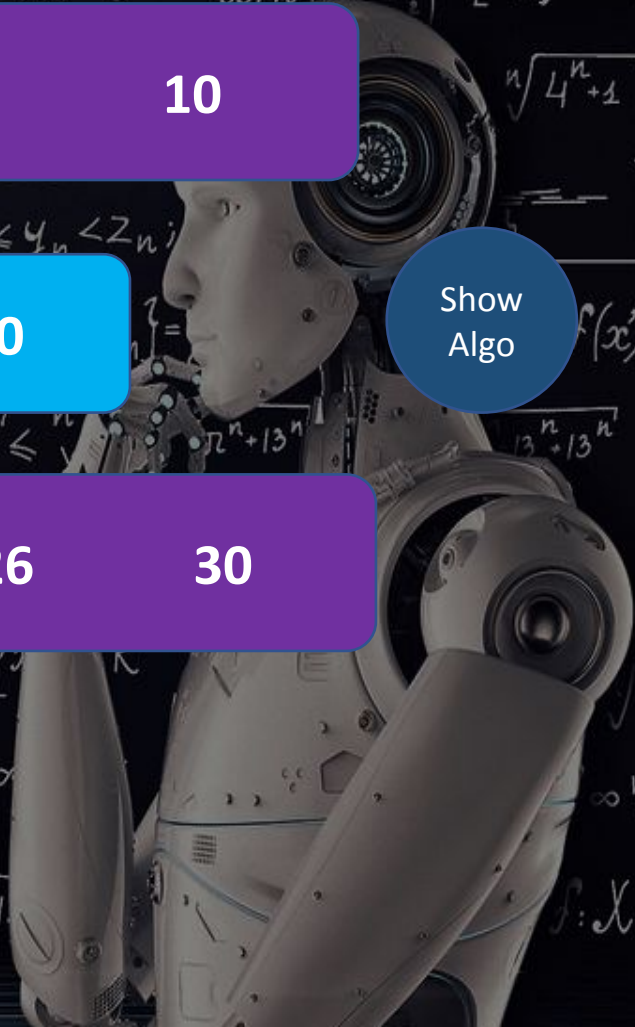
feature  
e

2 3 5 8 10

Result = Input \* 2 + 10

Show Algo

14 16 20 26 30



# Traditional Programming

Input

Algorithm

Output

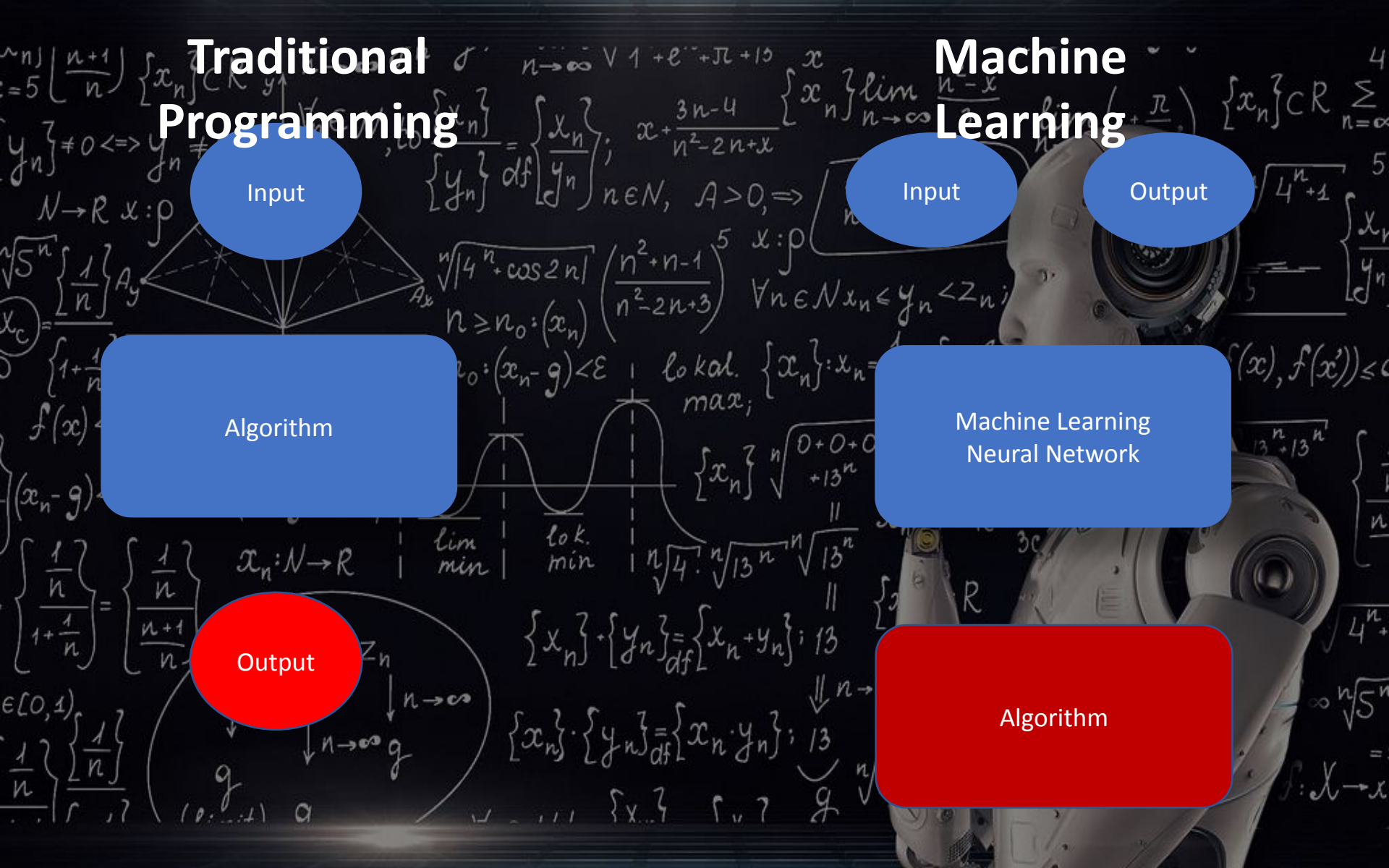
# Machine Learning

Input

Output

Machine Learning  
Neural Network

Algorithm



```
def function (input) :  
    output = input * 2 + 10  
return output
```

```
def function (input) :
```

```
    input= np.array([2, 3, 8, 5, 10], dtype=int)  
    output = np.array([14, 16, 26, 20, 30], dtype=int)  
  
    model = tf.keras.Sequential([  
        tf.keras.layers.Dense(units=1, input_shape=[1])  
    ])  
    model.compile(loss='mean_squared_error', optimizer=tf.keras.optimizers.Adam(0.  
1))  
    training = model.fit(input, output, epochs=500, verbose=False)  
    predict = model.predict([input])
```

```
Return predict
```

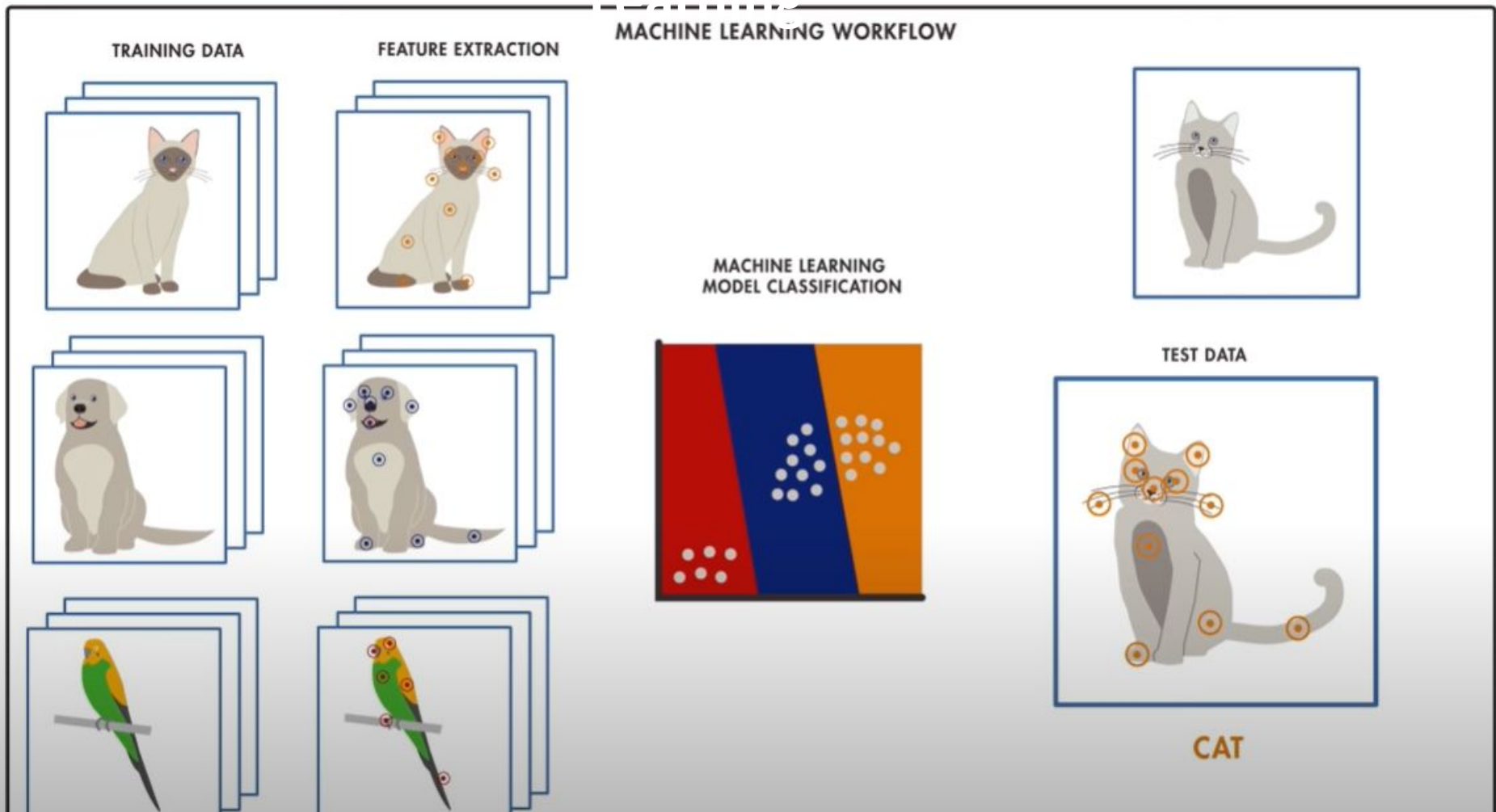
Math

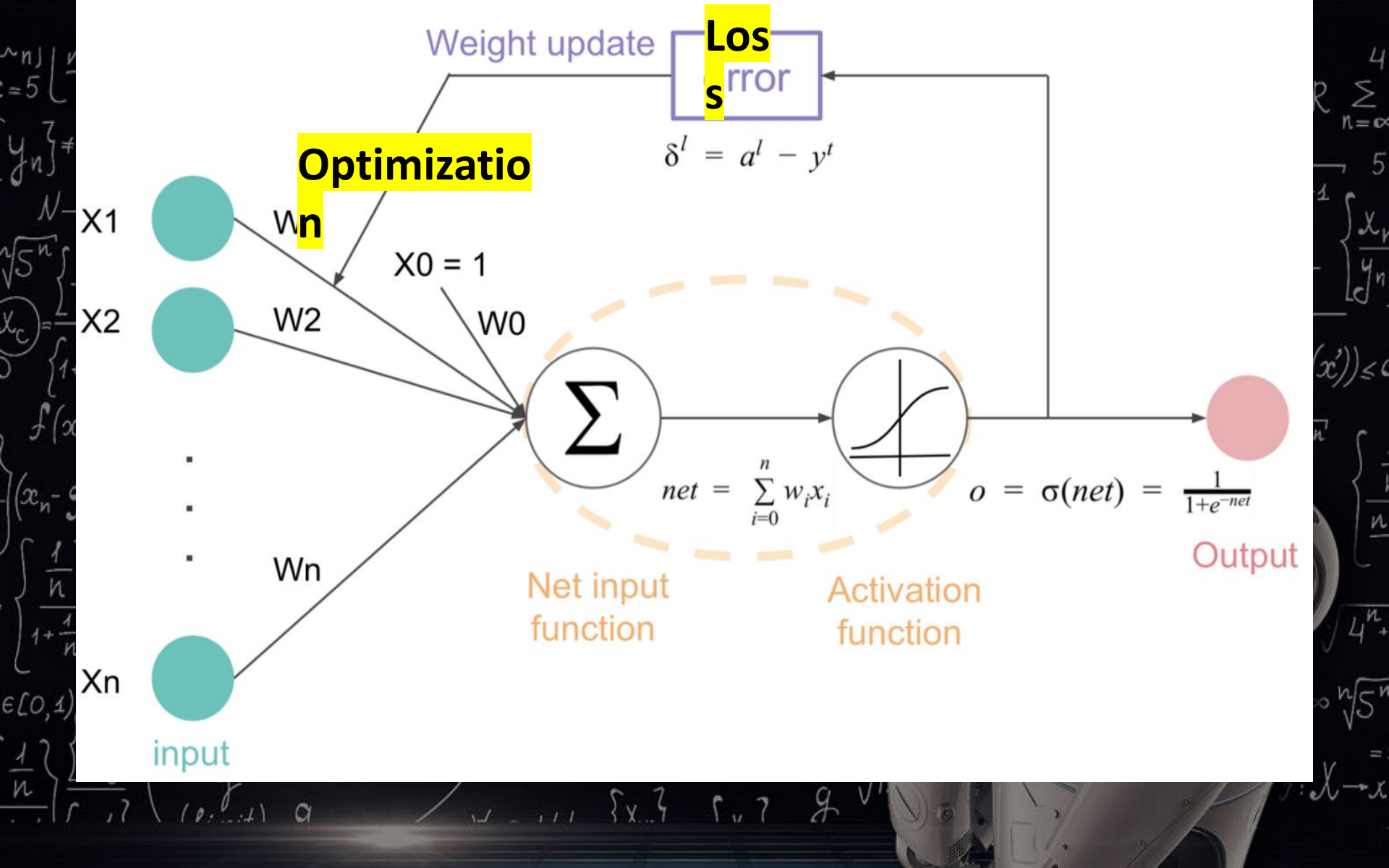
ML, DL

Coding



# Machine Learning VS Deep Learning





Weight update

Loss

Optimization

$$\delta^l = a^l - y^t$$

$X_1$

$W_1$

$X_0 = 1$

$W_0$

$X_2$

$W_2$

$\vdots$

$W_n$

$X_n$

input

$\Sigma$

$$net = \sum_{i=0}^n w_i x_i$$

Net input function



Activation function

$$o = \sigma(net) = \frac{1}{1+e^{-net}}$$

Output

# Activation Functions Types

Linear

$$F(x) = x *$$

Binary step

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$$

Sigmoid / Logistic

$$f(x) = \frac{1}{1 + e^{-x}}$$

Softmax

$$\text{softmax}(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

Parametric ReLU

$$f(x) = \max(ax, x)$$

# Losses: the difference between predicted output and desired output

- The mean squared error (MSE)

$$\text{MSE formula} = (1/n) * \Sigma(\text{actual} - \text{forecast})^2$$

- Cross-entropy:

$$H(P^* | P) = - \sum_i \underbrace{P^*(i)} \log \underbrace{P(i)}$$

# Optimizers

• **Optimizers are mathematical functions which are dependent on model's learnable parameters i.e Weights & Biases. Optimizers help to know how to change weights to reduce the losses.**

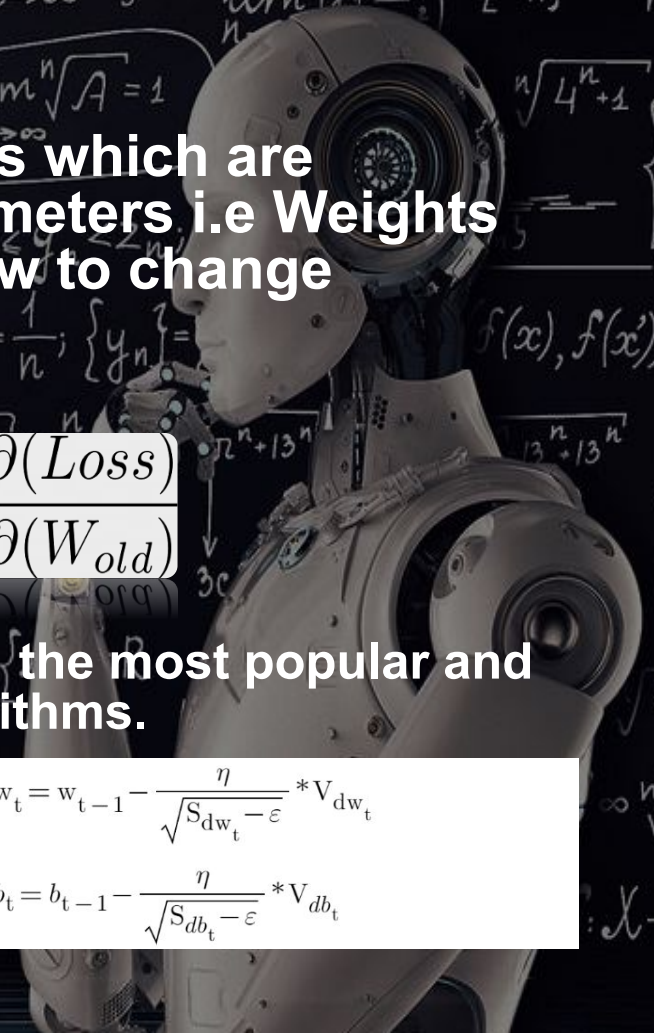
• **Gradient Descent:**

$$W_{new} = W_{old} - \alpha * \frac{\partial(Loss)}{\partial(W_{old})}$$

• **Adam(Adaptive Moment Estimation) : the most popular and famous gradient descent optimization algorithms.**

$$w_t = w_{t-1} - \frac{\eta}{\sqrt{S_{dw_t} - \epsilon}} * V_{dw_t}$$

$$b_t = b_{t-1} - \frac{\eta}{\sqrt{S_{db_t} - \epsilon}} * V_{db_t}$$



$$\{x_n\} \subset \mathbb{R} \quad \sum_{n=0}^{\infty} \left(\frac{n+1}{n}\right) \{x_n\}$$

$$\{y_n\} \neq 0 \Leftrightarrow y_n$$

$$N \rightarrow R \quad x: p$$

$$\sqrt[n]{5^n} \left\{ \frac{1}{n} \right\} A_y \leftarrow$$

$$x_c = \frac{1}{1 + \frac{1}{n}} x$$

$$f(x) \Leftrightarrow \exists q$$

$$(x_n - g) < \varepsilon \quad n \geq$$

$$\left\{ \frac{1}{n} \right\} = \left\{ \frac{1}{n} \right\}$$
$$\left\{ \frac{1}{1 + \frac{1}{n}} \right\} = \left\{ \frac{n}{n+1} \right\}$$

$$\in [0, 1) \left\{ \frac{1}{n} \right\}$$

$$\left\{ \frac{1}{n} \right\} \left\{ \frac{1}{n} \right\}$$

$$\{x_n\} \subset \mathbb{R} \quad \sum_{n=0}^{\infty} 4^n$$

$$\sqrt[n]{4^{n+1}} \left\{ \frac{1}{n} \right\} A_y \leftarrow$$

$$f(x), f(x') \leq c$$

$$\sqrt[n]{3^n + 3^n}$$

$$\left\{ \frac{1}{n} \right\}$$

$$\sqrt{4^n}$$

$$\infty \sqrt[n]{5^n}$$

$$=$$

$$f: X \rightarrow X$$

... (0, 1) a ... {x\_n} ... g ... v ...



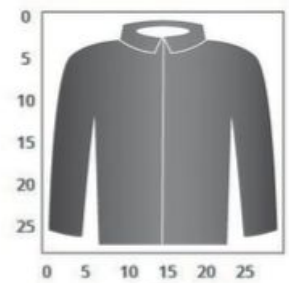
$y_n$   
 $= 5$   
 $y_n$

$\sqrt{5}$

)

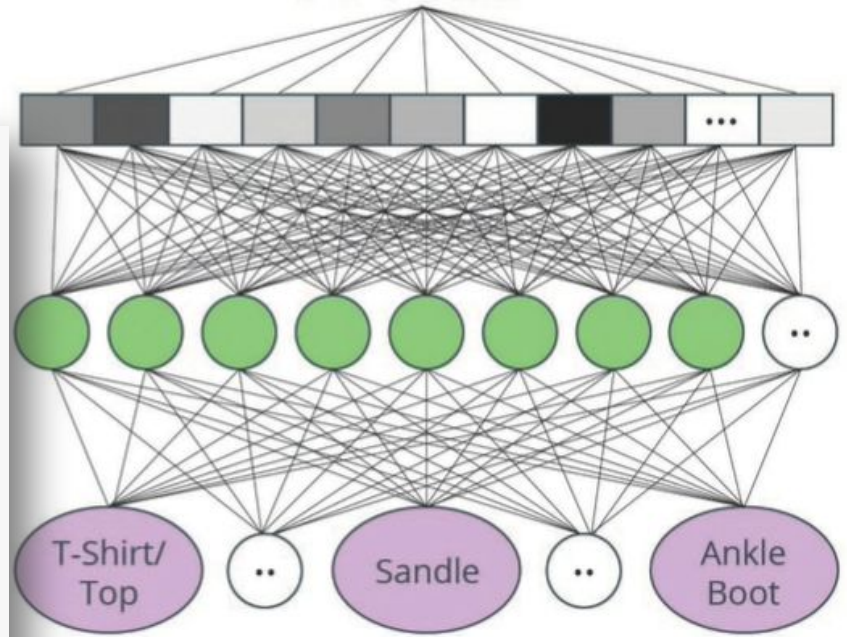
$\frac{1}{n}$   
 $\frac{2}{n}$   
 $\frac{3}{n}$   
 $\frac{4}{n}$   
 $\frac{5}{n}$   
 $\frac{6}{n}$   
 $\frac{7}{n}$   
 $\frac{8}{n}$   
 $\frac{9}{n}$   
 $\frac{10}{n}$   
 $\frac{11}{n}$   
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 $\frac{45}{n}$   
 $\frac{46}{n}$   
 $\frac{47}{n}$   
 $\frac{48}{n}$   
 $\frac{49}{n}$   
 $\frac{50}{n}$

Input image (28x28 = 784 pixels)

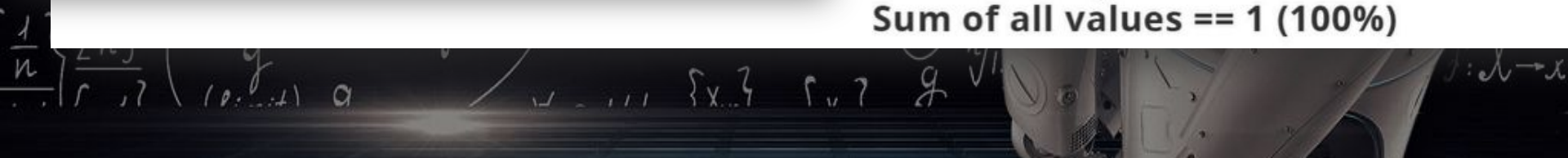


```
tf.keras.layers.Flatten(input_shape=(28, 28, 1))
```

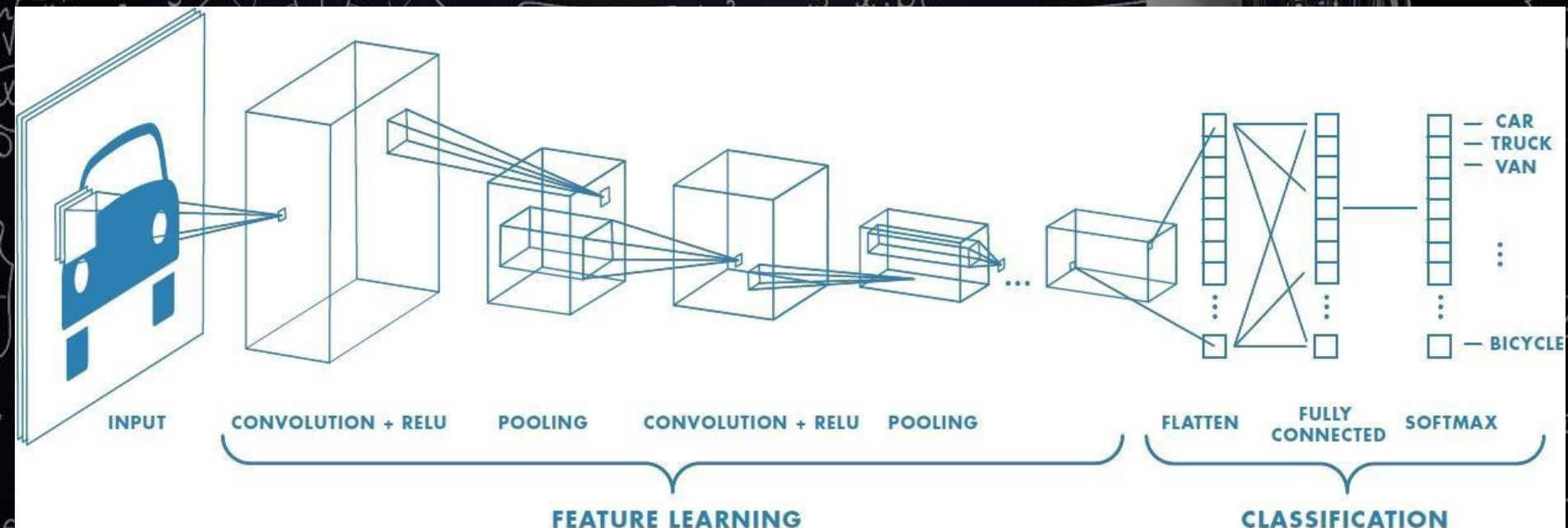
```
model = tf.keras.Sequential([  
    tf.keras.layers.Flatten(input_shape=(28, 28, 1)),  
    tf.keras.layers.Dense(500, activation=tf.nn.relu),  
    tf.keras.layers.Dense(10, activation=tf.nn.softmax)  
])  
  
model.compile(optimizer='adam',  
              loss=tf.keras.losses.SparseCategoricalCrossentropy(),  
              metrics=['accuracy'])
```



**Probability of each class**  
**Sum of all values == 1 (100%)**



# CNN

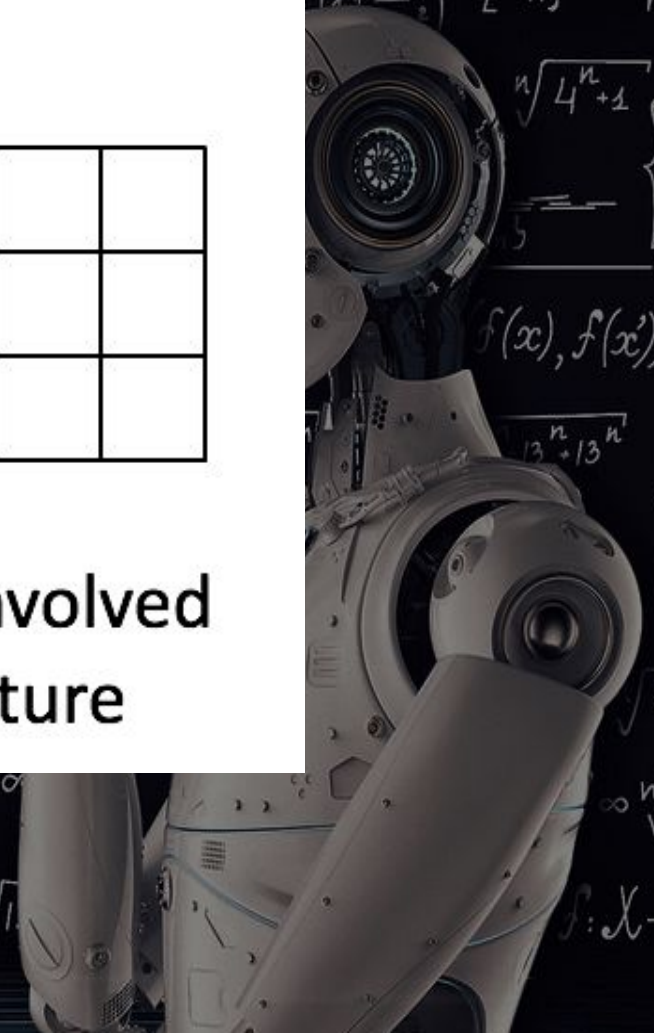


1 <small><math>\times_1</math></small>	1 <small><math>\times_0</math></small>	1 <small><math>\times_1</math></small>	0	0
0 <small><math>\times_0</math></small>	1 <small><math>\times_1</math></small>	1 <small><math>\times_0</math></small>	1	0
0 <small><math>\times_1</math></small>	0 <small><math>\times_0</math></small>	1 <small><math>\times_1</math></small>	1	1
0	0	1	1	0
0	1	1	0	0

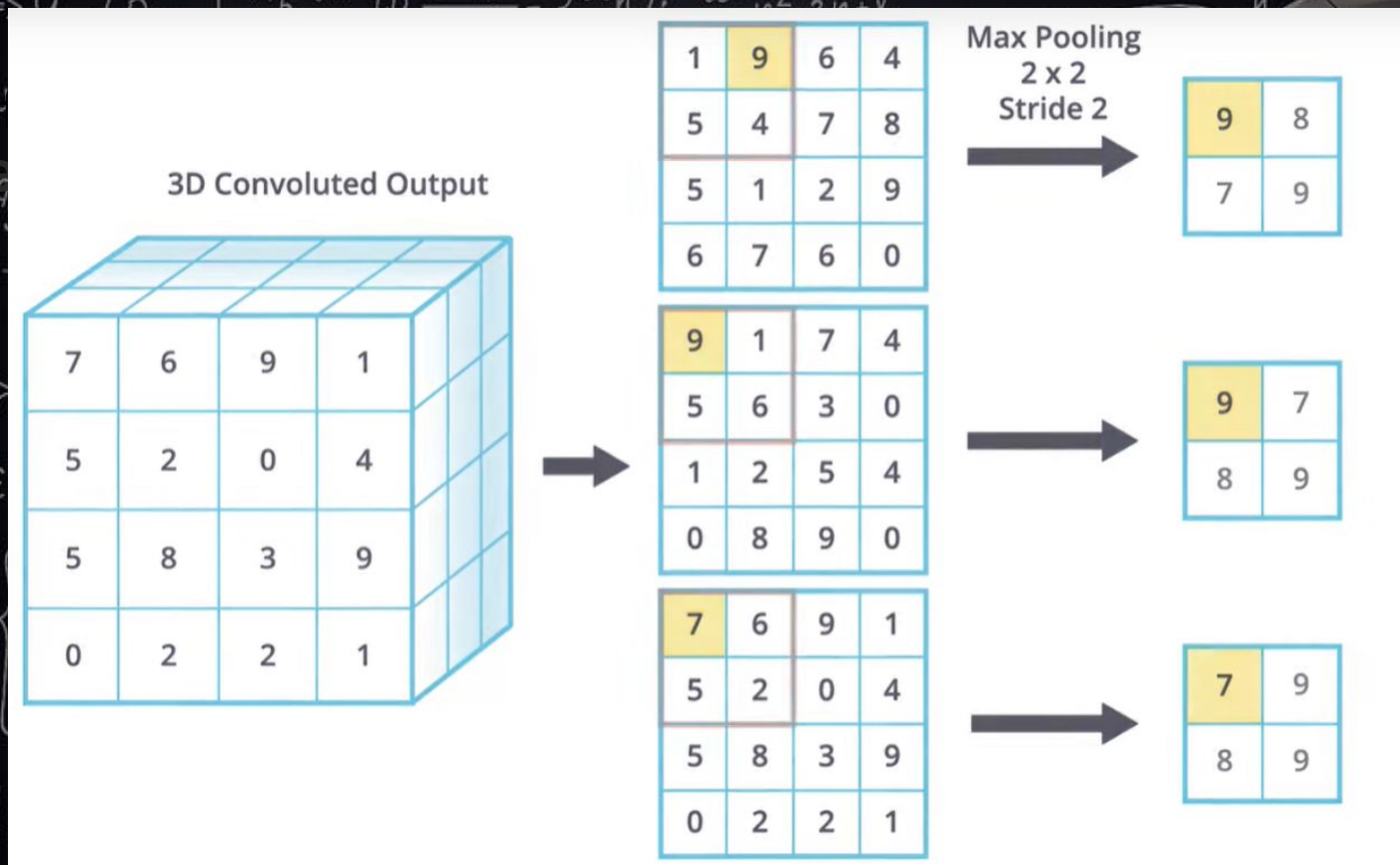
Image

4		

Convolved  
Feature



# Pooling Layer





# Transfer Learning

A technique that reuses a model that was created by machine learning experts and that has already been trained on a large dataset.

Freezing Parameters: Setting the variables of a pre-trained model to non-trainable. By freezing the model, only the variables

