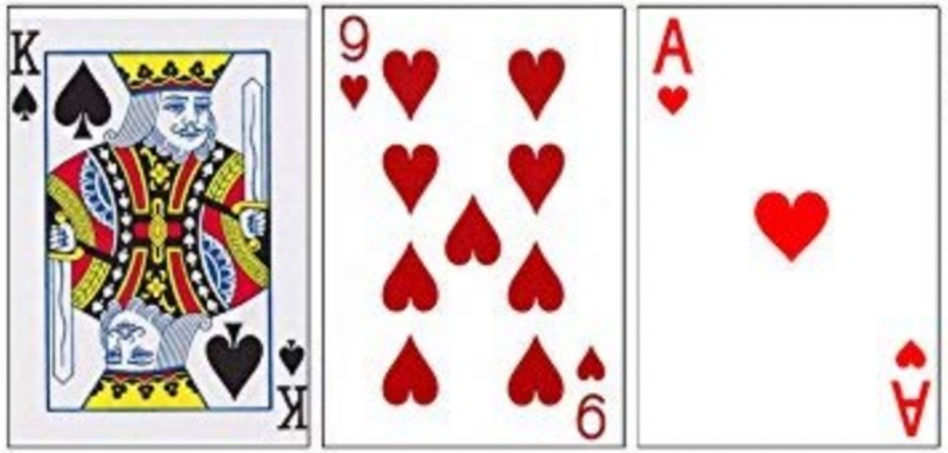
Why do We Learn Loss Functions?

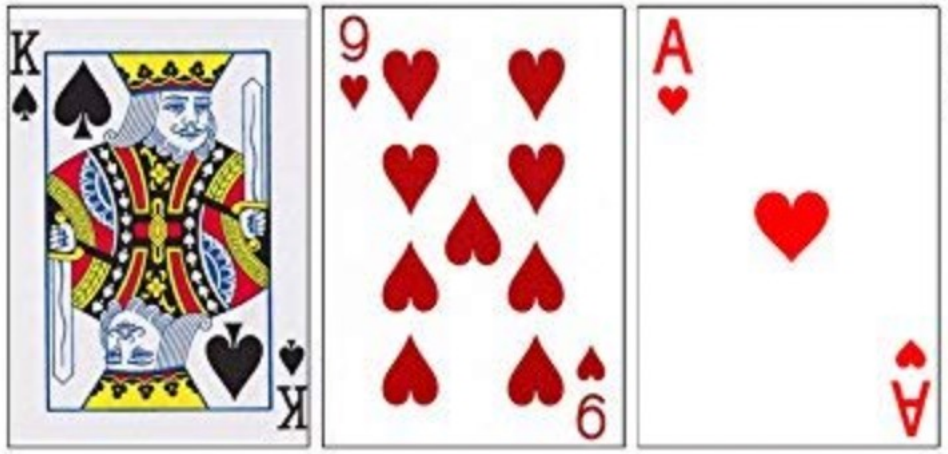
Loss functions are used in neural network training.

Loss Function

- Loss functions compute the distance between the current output of models and the expected output.
- Loss functions are important to optimize training models by minimizing loss.

Actual Values			
Guess	9	11	7
Absolute Error	4	2	6

Mean Absolute Error: (4+2+6)/3 = 4

Actual Values			
Guess	**9**	**11**	**7**
Squared Error	**16**	**4**	**36**

Mean Squared Error: $(4^2+2^2+6^2)/3 = 18.666666\ldots$

Binary Classification

Age	Have_Car	Have_Insurance
21	0	0
48	1	1
28	0	0
19	0	0
56	1	1
65	1	1
32	1	0
24	0	1
43	1	0
22	0	0
53	1	1

Binary Classification

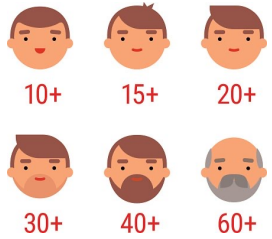
x

y

Age	Have_Car	Have_Insurance
21	0	0
48	1	1
28	0	0
19	0	0
56	1	1
65	1	1
32	1	0
24	0	1
43	1	0
22	0	0
53	1	1

$$y = f(x)$$

Age



X_1

w_1

$y = w_1 * X_1 + w_2 * X_2 + bias$

1 $y = \sum_{i=1}^{n} w_i x_i + b$

2 $z = \frac{1}{1 + e^{-y}}$

Have_Car

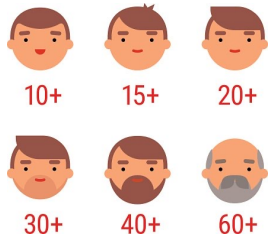
X_2

w_2

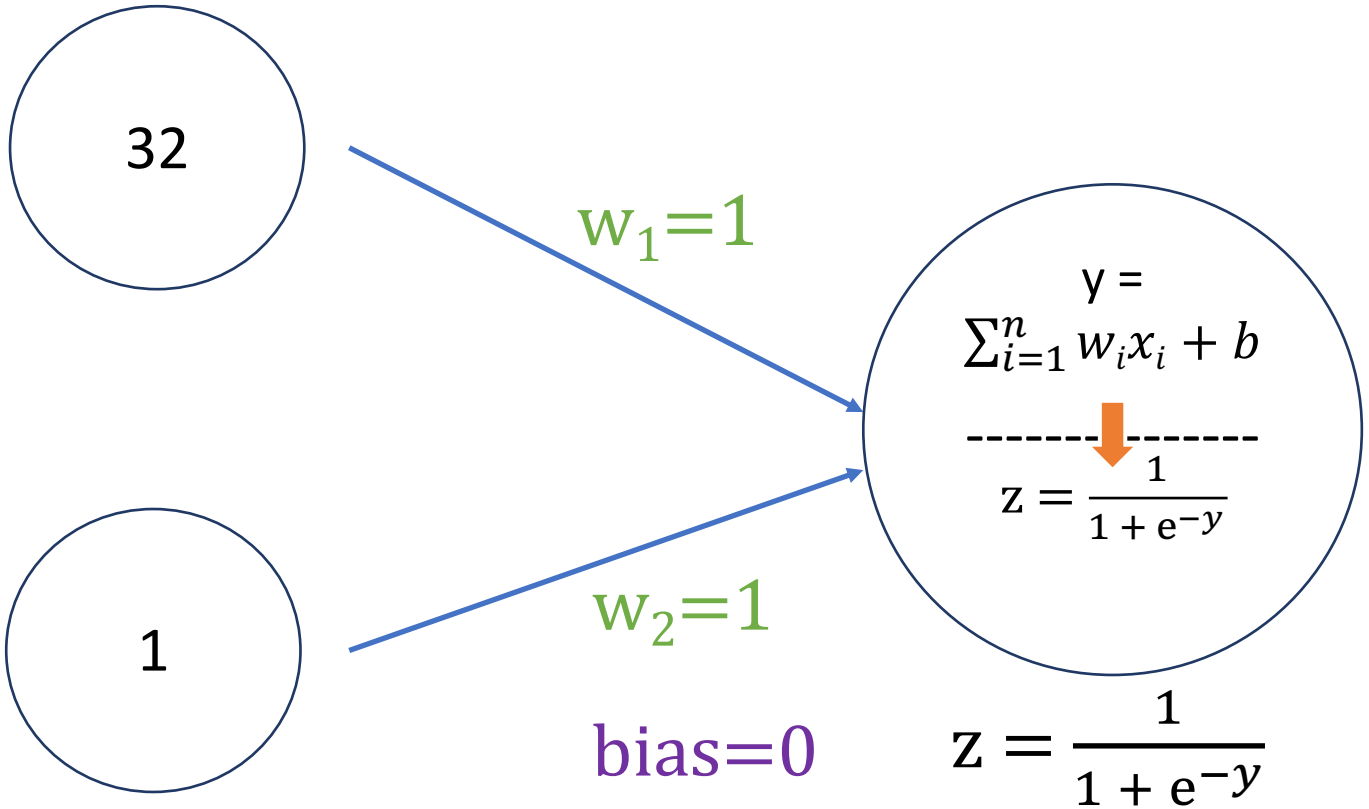
z, which is between 0 and 1, shows the probability of purchasing insurance

Age	Have_Car	Have_Insurance
21	0	0
48	1	1
28	0	0
19	0	0
56	1	1
65	1	1
32	1	0
24	0	1
43	1	0
22	0	0
53	1	1

Age



Have_Car



$$z = \frac{1}{1+e^{-y}}$$

$z = 0.\bar{9}$

Actual Value = 0

$y = w_1 * X_1 + w_2 * X_2 + bias$

$y = 1 * 32 + 1 * 1 + 0 = 33$

$error_1 = 0.99$

Mean Absolute Error

Loss

$$\text{Total Error} = \text{error}_1 + \text{error}_2 + \text{error}_3 + \ldots$$

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

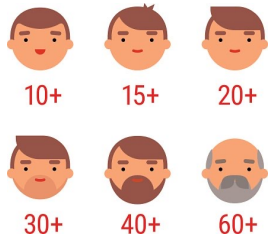
$$\textit{Mean Absolute Error} = \frac{1}{n}\sum_{i=1}^{n} abs(y_i - \hat{y}_i)$$

Cost Function

$$MAE = \frac{1}{n}\sum_{i=0}^{n} abs(y_i - \hat{y}_i)$$

Age	Have_Car	Have_Insurance
21	0	0
48	1	1
28	0	0
19	0	0
56	1	1
65	1	1
32	1	0
24	0	1
43	1	0
22	0	0
53	1	1

Age



Have_Car

32

1

$y = w_1 * X_1 + w_2 * X_2 + bias$

$w_1=1$

$w_2=1$

$bias=0$

$$y = \sum_{i=1}^{n} w^i x^i + b$$

$$z = \frac{1}{1 + e^{-y}}$$

Total Error = $error_1 + error_2 + error_3 + \ldots$

Mean Absolute Error = $\frac{1}{n}\sum_{i=1}^{n} abs(y_i - \hat{y}_i)$

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

Binary Cross Entropy (Log Loss) =

$$-\frac{1}{n}\sum_{i=1}^{n} \mathrm{y_i} * \log(\hat{y}_i) + (1 - yi) * \log(1 - (\hat{y}_i))$$


Python Practice

Mean Absolute Error

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

```
def mae(true_value, predicted_value):
    total_error = 0
    for t, p in zip(true_value, predicted_value):
        total_error += abs(t - p)
    print("Total Error:", total_error)
    mae = total_error / len(true_value)
    print("MAE:", mae)
```

Mean Squared Error

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

```
def mse(true_value, predicted_value):
    total_error = 0
    for t, p in zip(true_value, predicted_value):
        total_error += (t - p)**2
    print("Total Squared Error:", total_error)
    mse = total_error/len(true_value)
    print("Mean Squared Error:", mse)
```

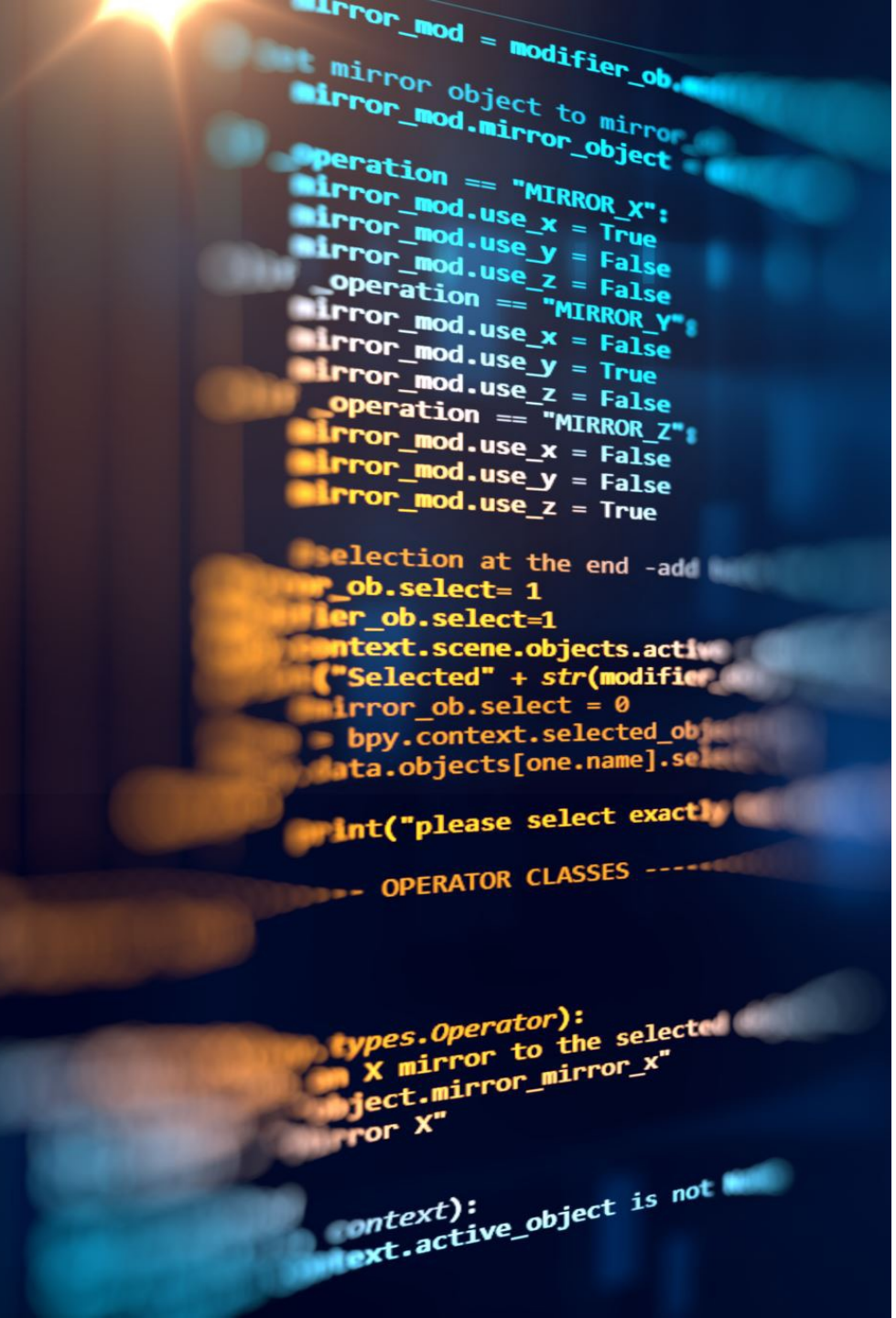
Binary Cross Entropy (Log Loss)

Binary Cross Entropy (Log Loss) =

$$-\frac{1}{n}\sum_{i=1}^{n} \mathrm{y_i} * \log(\hat{y}_i) + (1 - yi) * \log(1 - (\hat{y}_i))$$

```
def log_loss(true_value, predicted_value):
    predicted_new = [max(i, delta) for i in predicted_value]
    predicted_new = [min(i, 1-delta) for i in predicted_new]
    predicted_new = np.array(predicted_new)
    return -np.mean(true_value*np.log(predicted_new)+(1-true_value)*np.log(1-predicted_new))
```

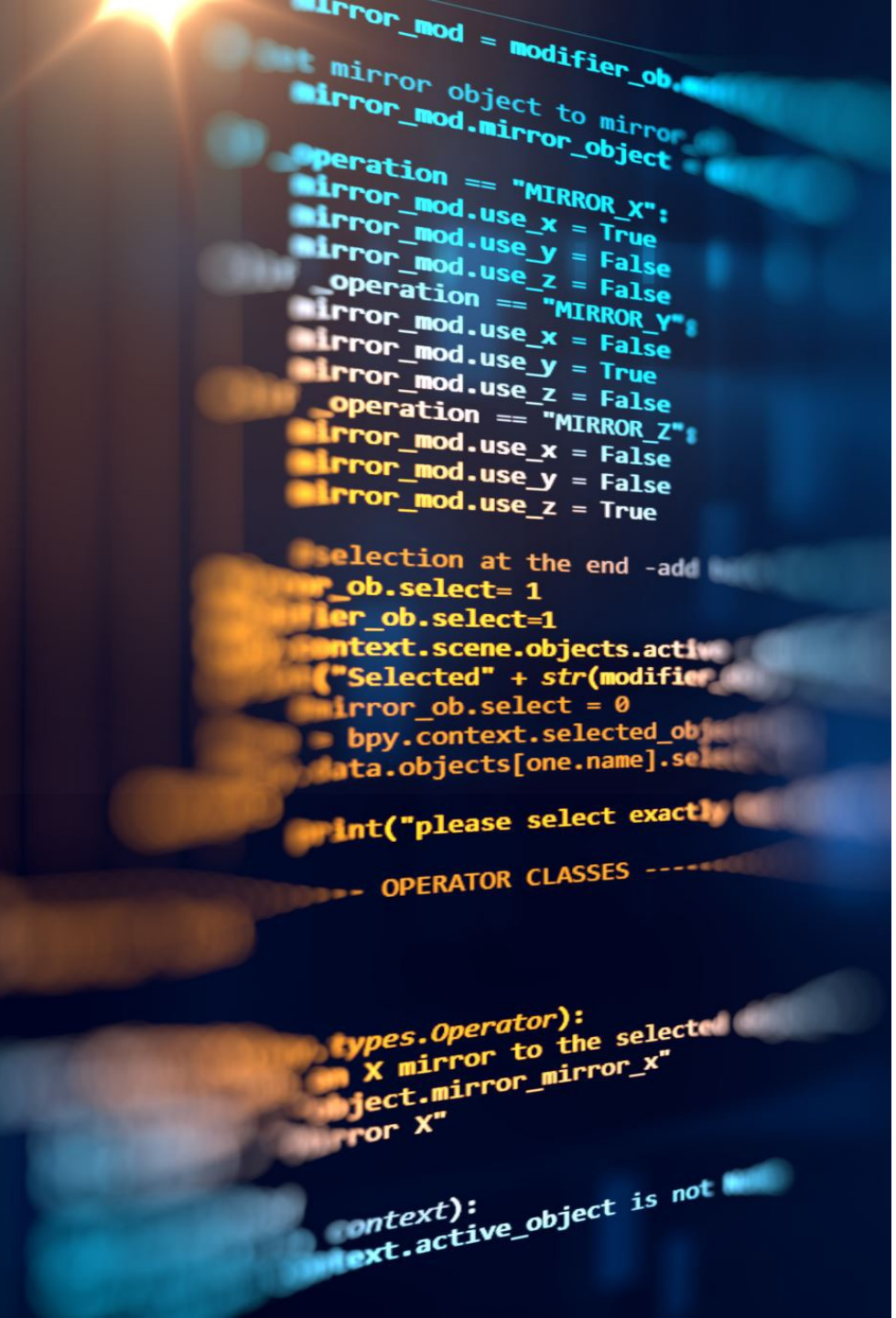
log_loss(true_value, predicted_value)



PyTorch Loss Function Examples

- nn.L1Loss
- nn.MSELoss
- nn.CrossEntropyLoss

(https://pytorch.org/docs/stable/nn.html)



TensorFlow-Keras Loss Function Examples

- tf.keras.losses.BinaryCrossentropy()
- tf.keras.losses.MeanAbsoluteError()
- tf.keras.losses.MeanSquaredError()

(https://www.tensorflow.org/api_docs/python/tf/keras/losses)