

# Optional Lab: Logistic Regression, Logistic Loss

In this ungraded lab, you will:

- explore the reason the squared error loss is not appropriate for logistic regression
- explore the logistic loss function

```
In [1]: import numpy as np
import matplotlib widget
import matplotlib.pyplot as plt
from plt_logistic_loss import plt_logistic_cost, plt_two_logistic_loss_curves, plt_simple_example
from plt_logistic_loss import soup_bowl, plt_logistic_squared_error
plt.style.use('./deeplearning.mplstyle')
```

## Squared error for logistic regression?

Squared Error Cost

$$J(\vec{w}, b) = \frac{1}{m} \sum_{i=1}^m \frac{1}{2} (y^{(i)} - \hat{y}^{(i)})^2$$

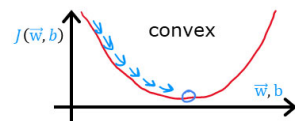
average of training set

$$L(\hat{y}^{(i)}, y^{(i)}) = \frac{1}{2} (y^{(i)} - \hat{y}^{(i)})^2$$

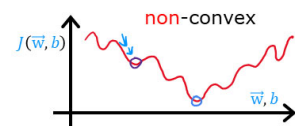
single training example

$$J(\vec{w}, b) = \frac{1}{m} \sum_{i=1}^m L(\hat{y}^{(i)}, y^{(i)})$$

linear regression  $f_{\vec{w}, b}(\vec{x}) = \vec{w} \cdot \vec{x} + b$



logistic regression  $f_{\vec{w}, b}(\vec{x}) = \frac{1}{1 + e^{-(\vec{w} \cdot \vec{x} + b)}}$



Recall for **Linear** Regression we have used the **squared error cost function**: The equation for the squared error cost with one variable is:

$$J(w, b) = \frac{1}{2m} \sum_{i=0}^{m-1} (f_{w, b}(x^{(i)}) - y^{(i)})^2 \quad (1)$$

where

$$f_{w, b}(x^{(i)}) = wx^{(i)} + b \quad (2)$$

Recall, the squared error cost had the nice property that following the derivative of the cost leads to the minimum.

