✨ Machine Learning

🚀 **Introduction to Linear Regression + Logistic Regression**

🤖 What is Machine Learning?

📜 Definition:

Machine Learning is a branch of Artificial Intelligence (AI) where computers **learn patterns from data** and make predictions without being explicitly programmed.

📊 Types of ML:

🧠 **Supervised Learning** → Model learns from ✅ **labeled data** (Input → Output).
Examples: House Price Prediction, Spam Detection.
Algorithms: Linear Regression, Logistic Regression, Decision Trees.
🔍 **Unsupervised Learning** → Model finds patterns in ❓ **unlabeled data**.
Examples: Customer Segmentation, Market Basket Analysis.
Algorithms: K-Means, PCA.
🏆 **Reinforcement Learning** → Agent learns by 🔥 **trial and error** with rewards.
Examples: Game Playing, Self-driving Cars.

⚠️ Overfitting vs Underfitting

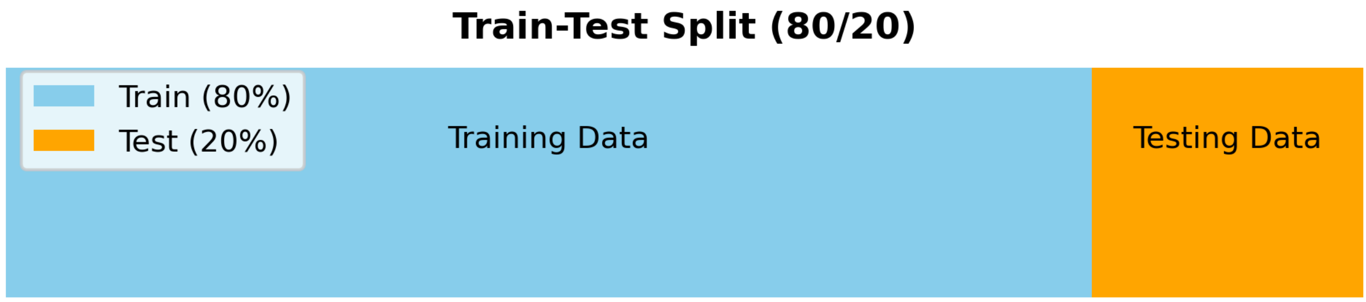
🤯 **Overfitting** → Model learns noise and performs badly on new data.
😔 **Underfitting** → Model too simple, fails to capture patterns.
💡 **Solution** → Regularization, Pruning, Cross-validation.

⚖️ Bias-Variance Tradeoff

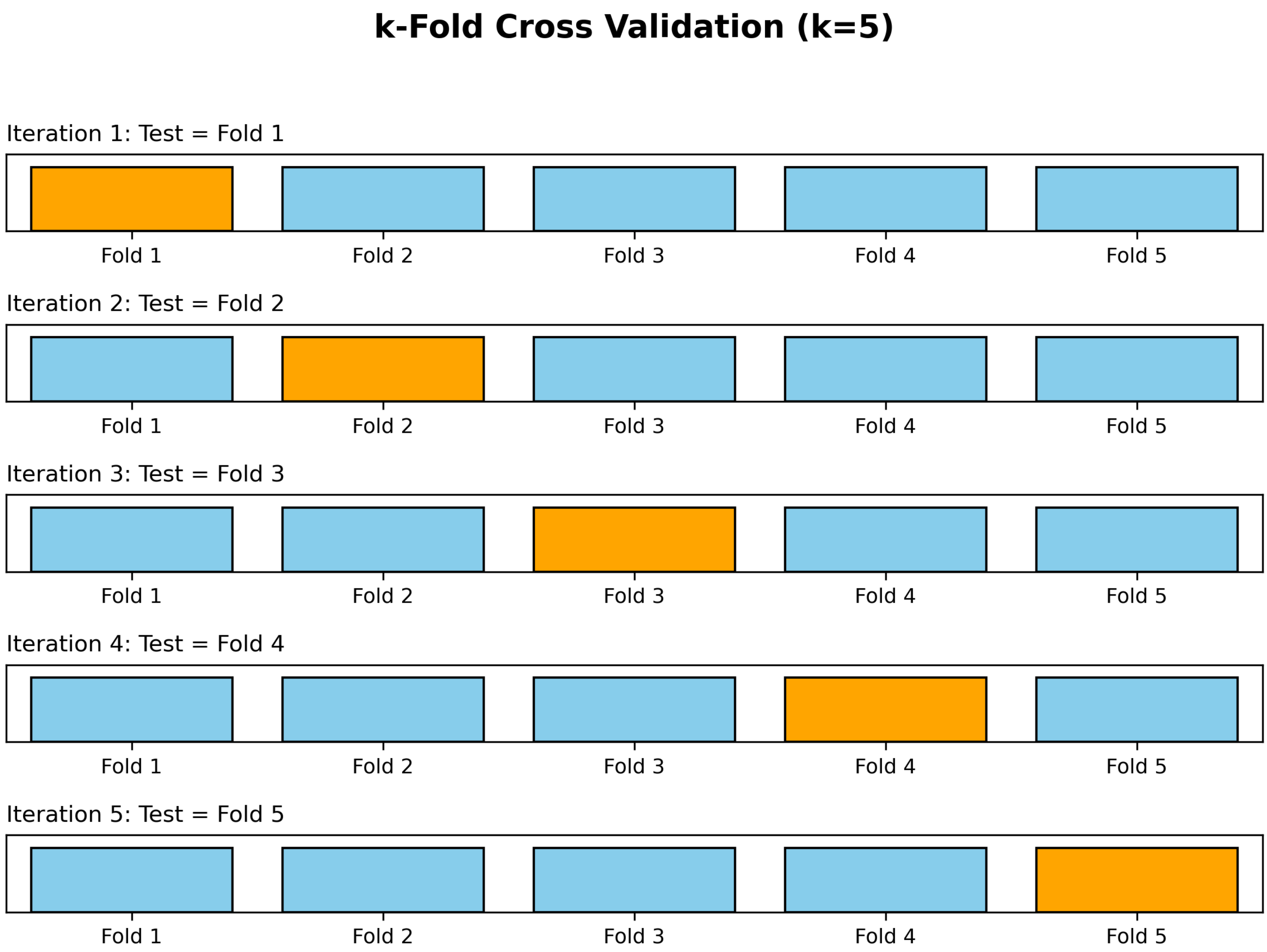
⬆️ **High Bias** → Underfitting (model too simple).
⬇️ **High Variance** → Overfitting (model too complex).
✅ Goal: Find a balance between bias & variance.

🔄 Train-Test Split & Cross-Validation

🚗 **Train-Test Split** → Divide dataset (e.g., 80% training, 20% testing).



➕ **Cross-Validation (k-fold)** → Split into k parts and train/test multiple times → better performance estimate.

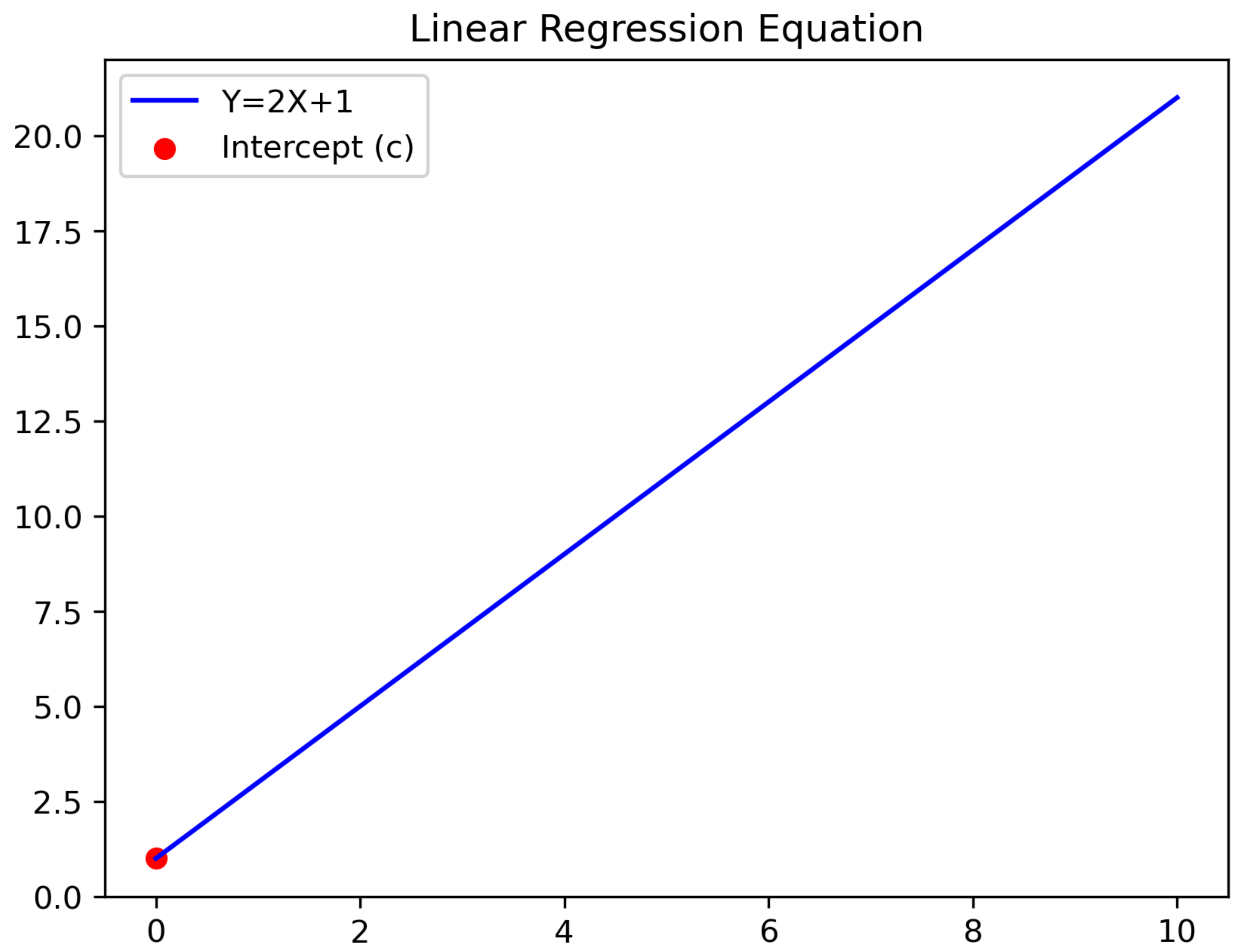


🟦 Part A: Linear Regression 📈

❓ What is Linear Regression?

📜 Definition:

Linear Regression predicts a 🎯 **continuous output variable (Y)** based on one or more input variables (X).



📌 Example: Predicting 🏠 **house price** based on size (sq. feet).

📏 Equation of Linear Regression

📝 Simple Linear Regression (one input):

```
Y = mX + c
```

Key:

- `Y` = Predicted output
- `X` = Input variable
- `m` = Slope (effect of X on Y)
- `c` = Intercept

📝 Multiple Linear Regression:

$$Y = b_0 + b_1 X_1 + b_2 X_2 + ... + b_n X_n$$

📉 Cost Function (Error Function)

We measure how far predictions are from actual values.

🎯 Mean Squared Error (MSE):

$J(m, c) = 1/n * \Sigma (Y_i - \hat{Y}_i)^2$

Our goal → 📉 **Minimize MSE**.

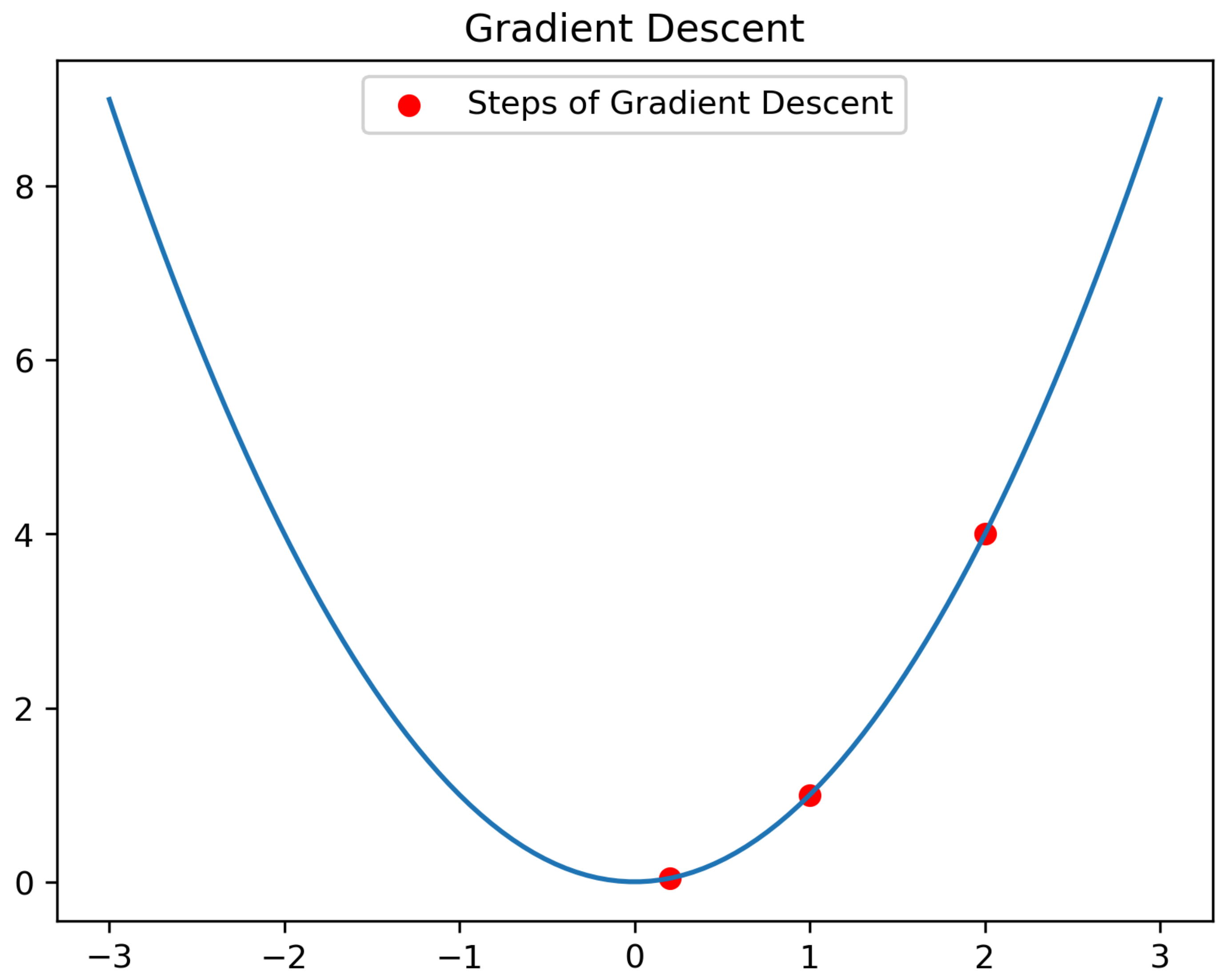
🚀 Optimization (Gradient Descent)

Update rules:

$m = m - \alpha * \partial J/\partial m$, $c = c - \alpha * \partial J/\partial c$

Where:

α = Learning rate



💡 Extra Concepts in Linear Regression

✅ Assumptions:

Linearity
No multicollinearity
Errors are normally distributed
Constant variance (Homoscedasticity)

📈 R^2 (Goodness of Fit):

Closer to 1 = better model.

📈 Adjusted R^2:

Adjusts for number of predictors (important in multiple regression).

✨ Regularization:

Ridge Regression (L2 penalty)
Lasso Regression (L1 penalty)
ElasticNet (L1 + L2)

🟩 Part B: Logistic Regression ⚖️

❓ What is Logistic Regression?

Logistic Regression is used for 🎯 **classification problems**.
It predicts the 📈 **probability** of belonging to a class (output = 0 or 1).
📌 Example: Spam vs Not Spam

⚖️ Equation of Logistic Regression

📝 Linear part:

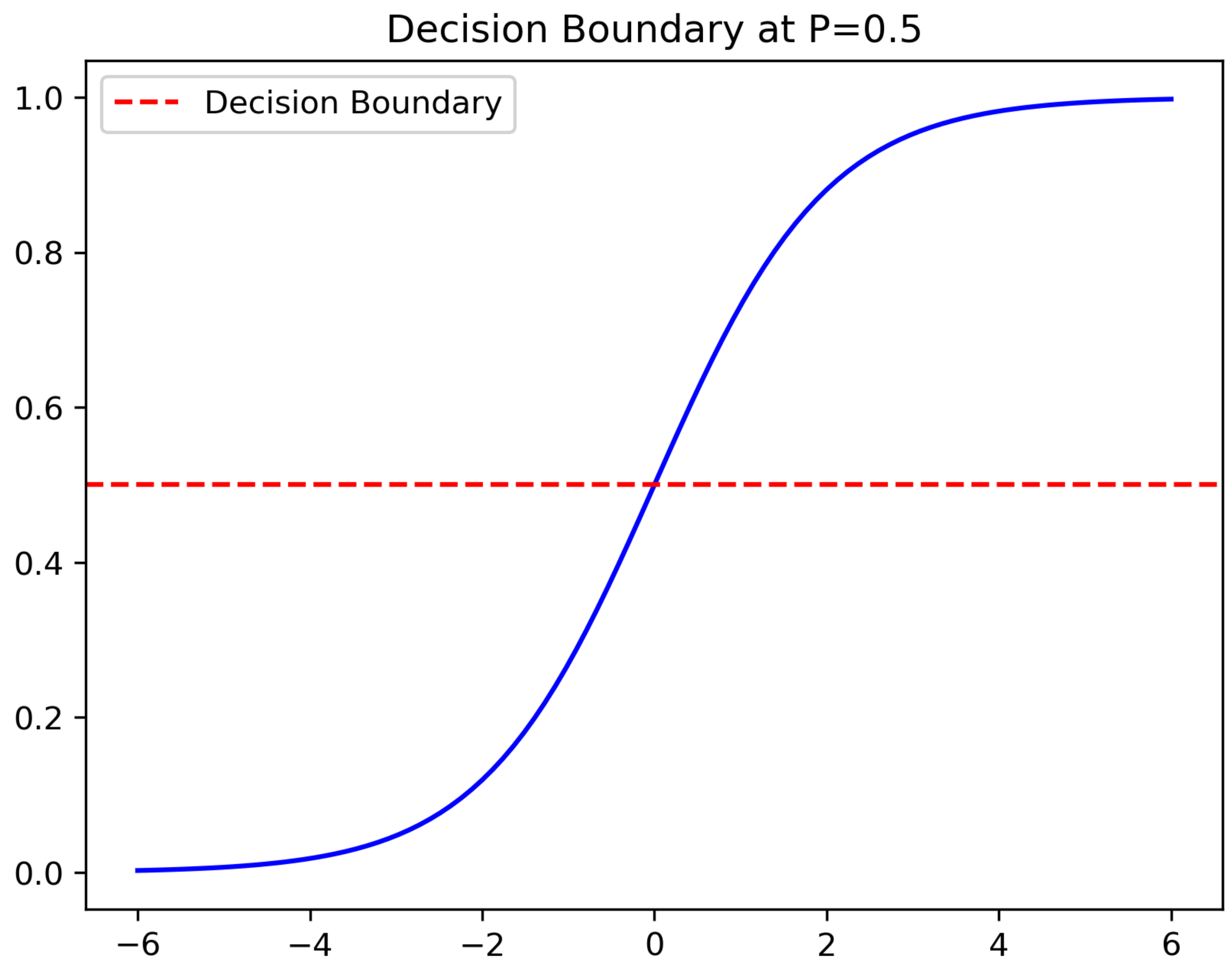
$Z = b_0 + b_1 X$

✨ Sigmoid Function:

$P(Y=1|X) = 1 / (1 + e^{-Z})$

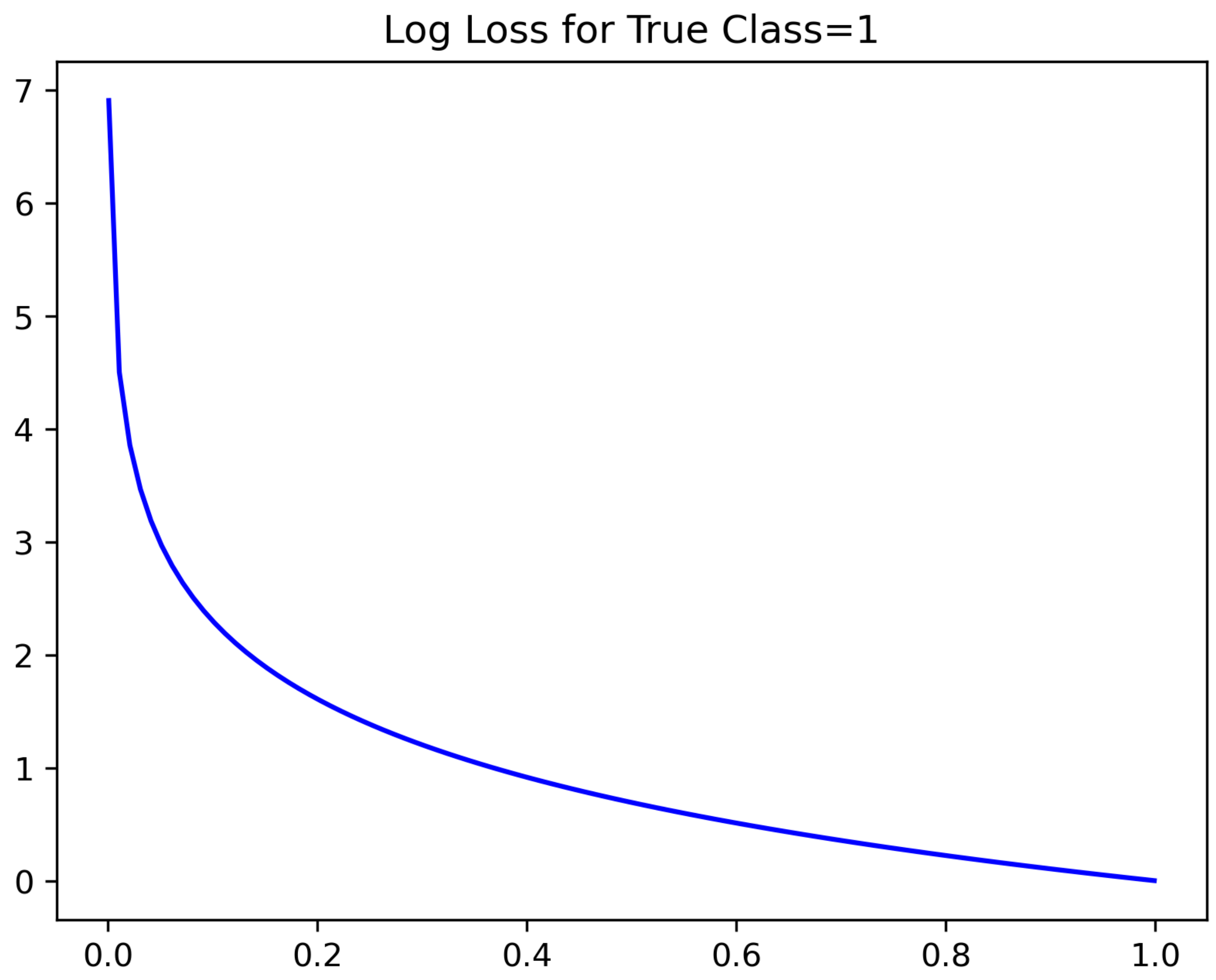
🎯 Decision Boundary

If $P > 0.5$ → Predict Class 1
If $P \le 0.5$ → Predict Class 0



📉 Cost Function (Log Loss)

$$J(\theta) = -\frac{1}{n} \cdot \Sigma [y_i \cdot \log(\hat{y}_i) + (1-y_i) \cdot \log(1-\hat{y}_i)]$$



💻 Example (Logistic Regression)

```
from sklearn.linear_model import LogisticRegression
import numpy as np

X = np.array([[1],[2],[3],[4],[5]])
y = np.array([0,0,0,1,1])

model = LogisticRegression()
model.fit(X,y)

print(model.predict([[1.5]]))  # Output -> 0
print(model.predict([[4.5]]))  # Output -> 1
```

💡 Extra Concepts in Logistic Regression

✅ Assumptions:

Binary dependent variable
No strong multicollinearity
Large dataset

📊 Odds & Logit:

```
Odds = p / (1-p)
log(p / (1-p)) = b₀ + b₁ X
```

📈 Evaluation Metrics:

Confusion Matrix (TP, TN, FP, FN)
Accuracy, Precision, Recall, F1-score
ROC Curve & AUC

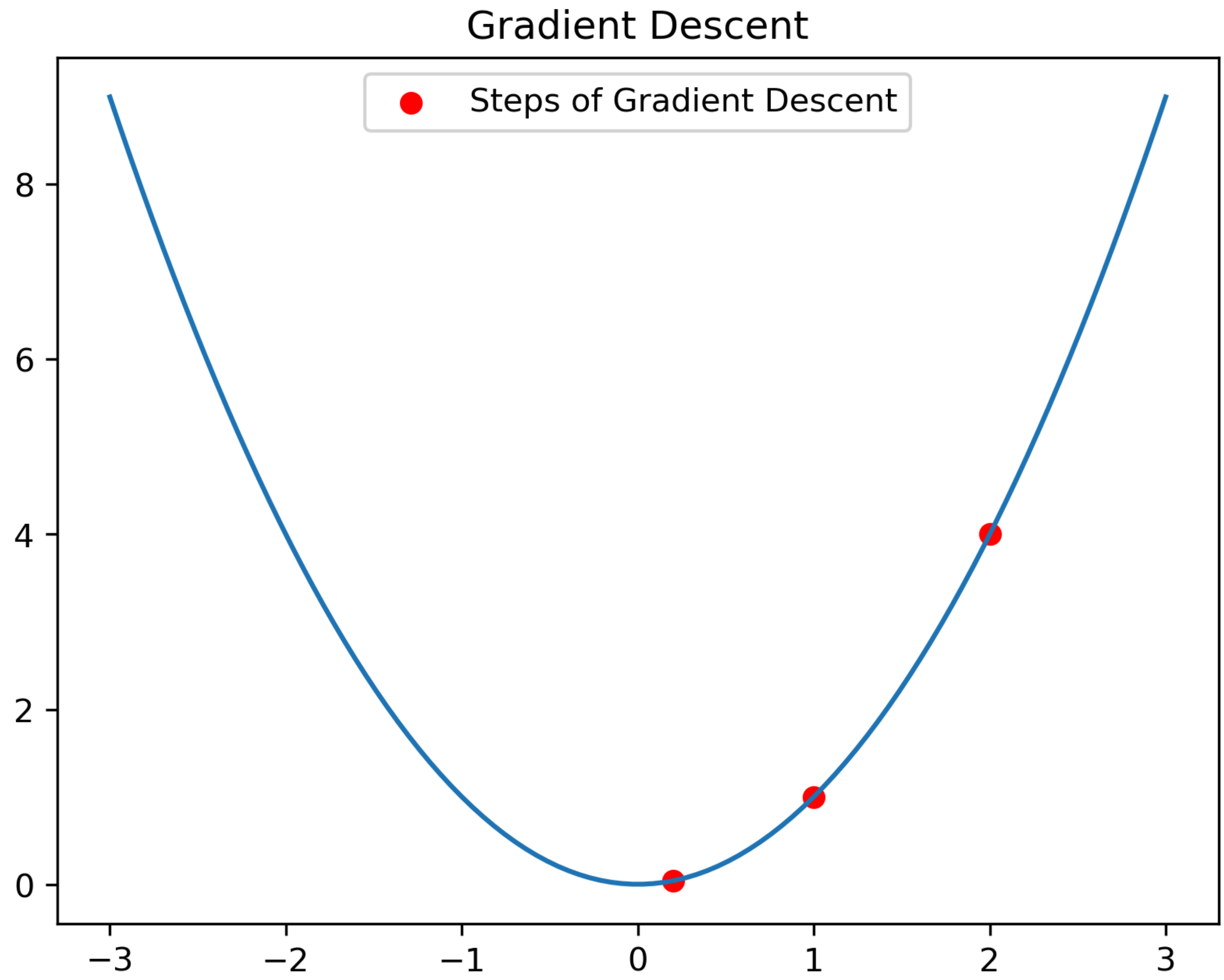
🔄 Multiclass Logistic Regression:

One-vs-Rest (OvR)
Softmax (Multinomial)

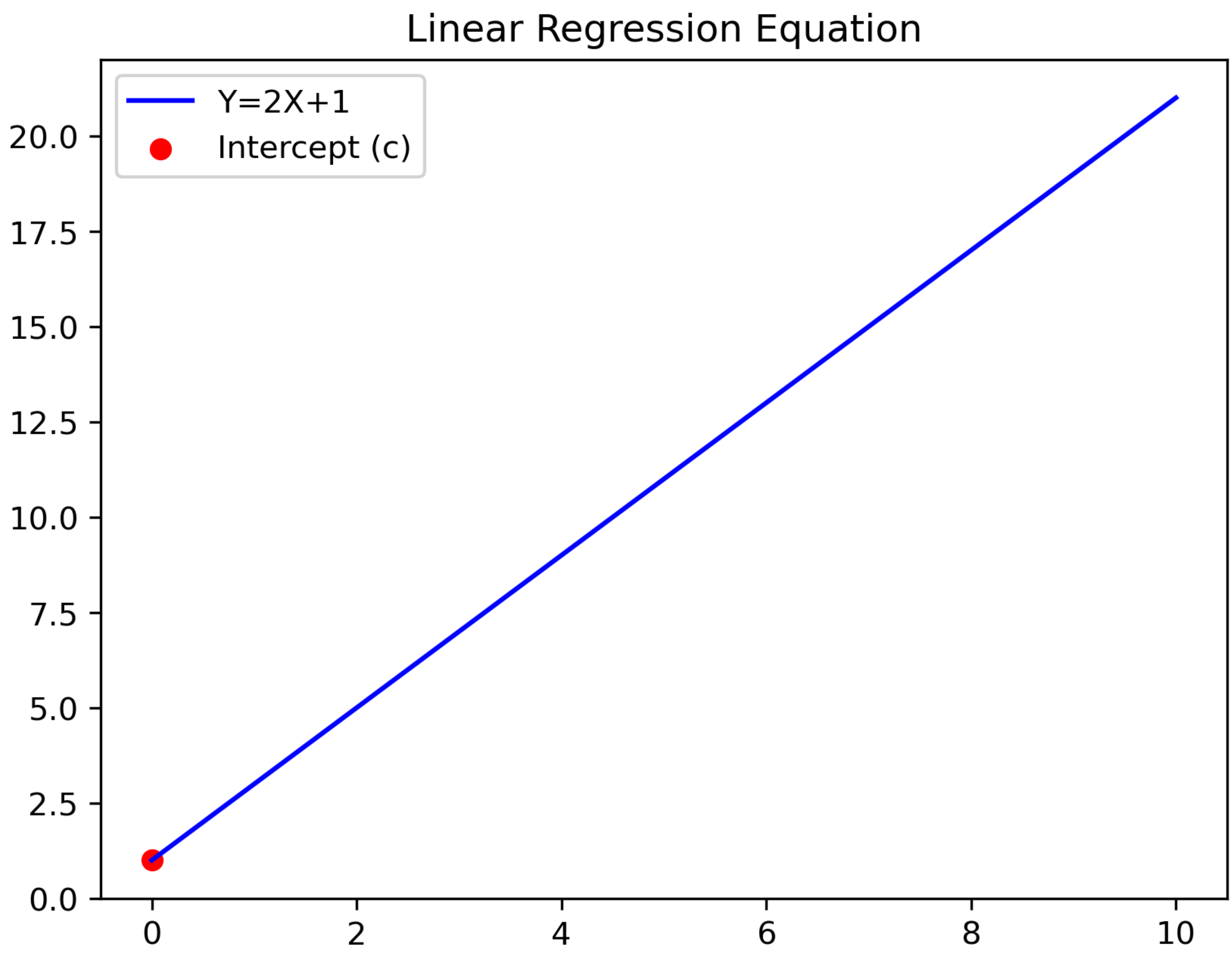
🔥 Key Differences: Linear vs Logistic Regression

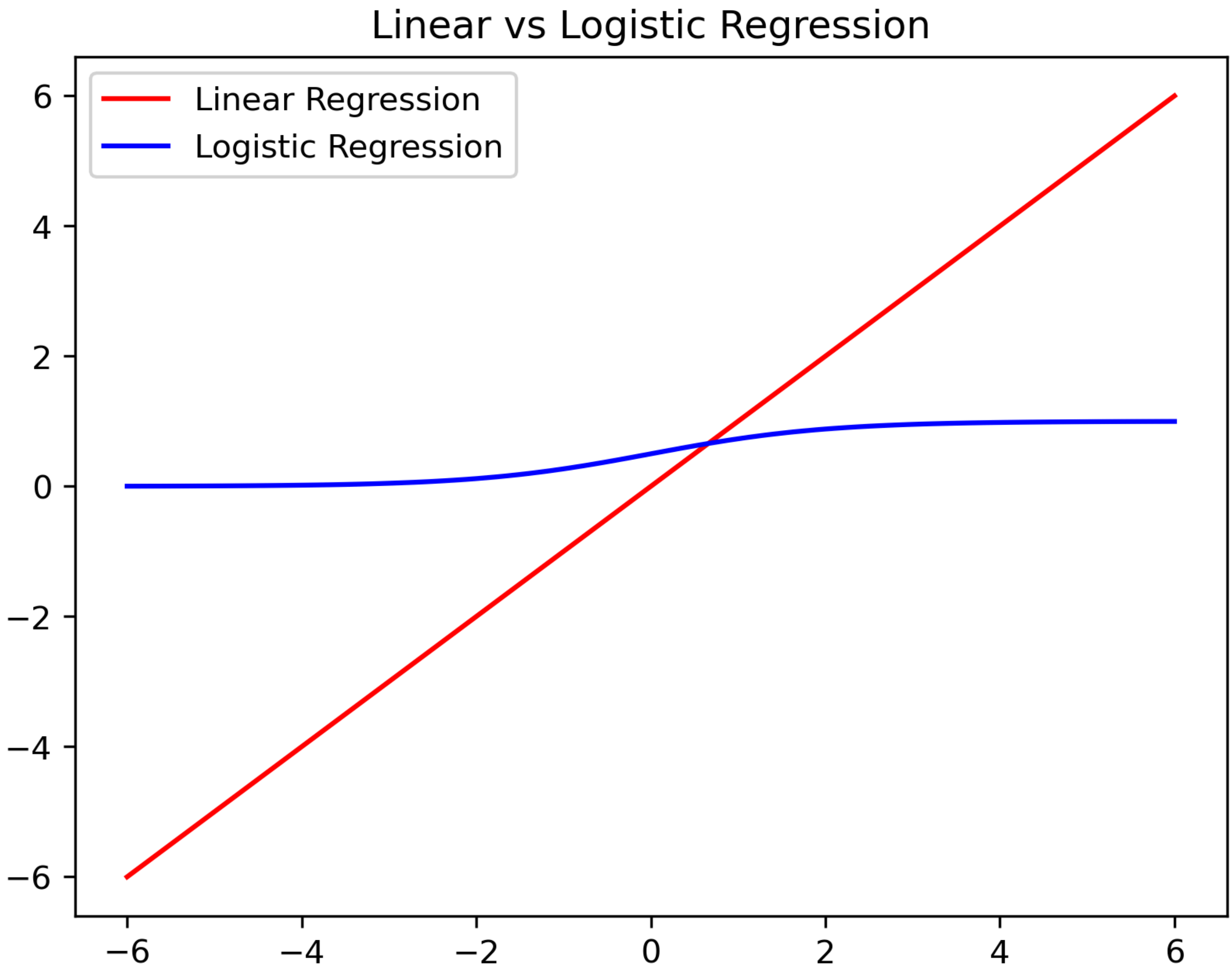
Feature	Linear Regression	Logistic Regression
Output Type	Continuous (Real values)	Probability (0–1)
Equation	`Y = mX + c`	Sigmoid Function
Problem Type	Regression	Classification
Cost Function	MSE	Log Loss

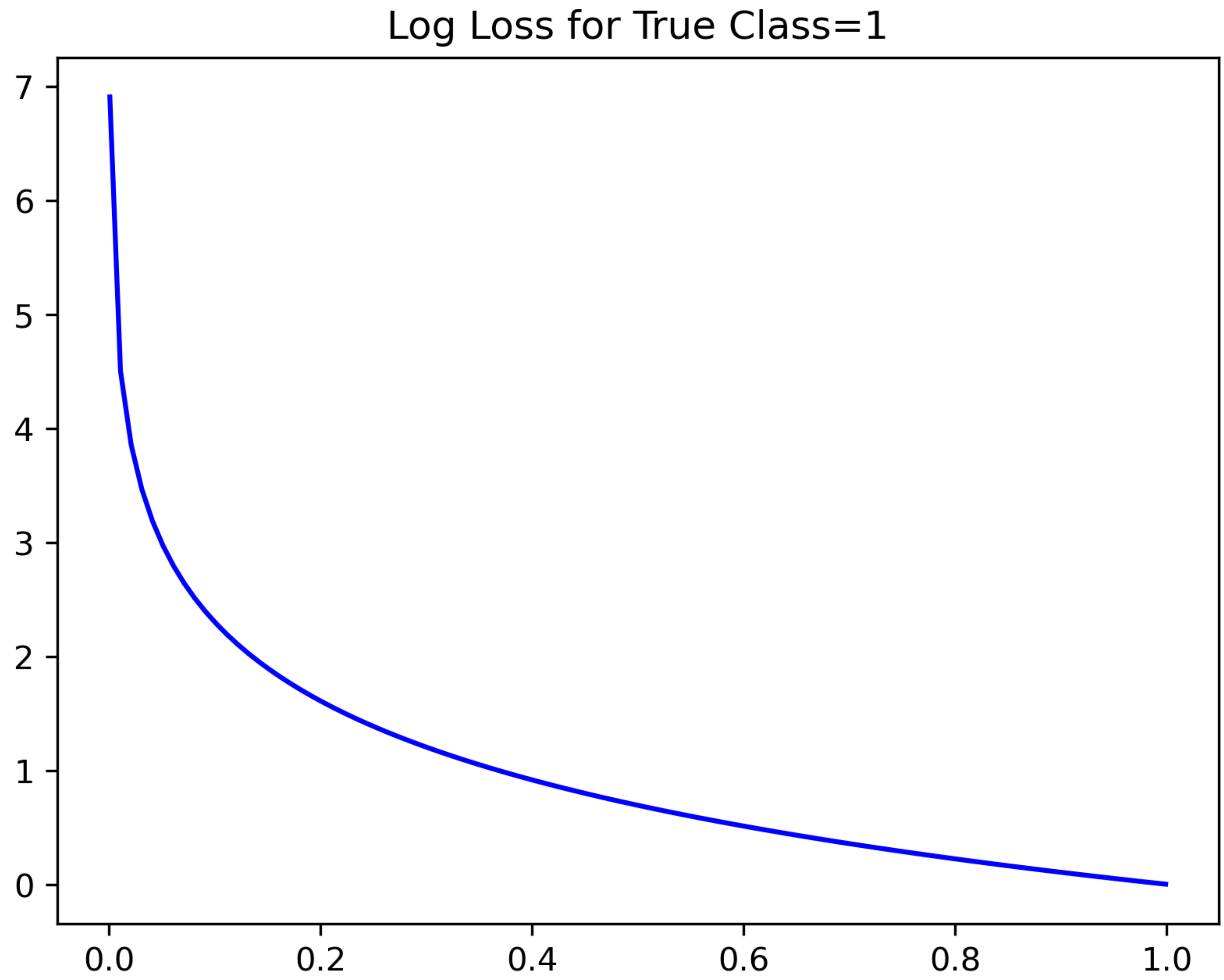
Now the notes include:
Core theory
Advanced concepts (Overfitting, Bias-Variance, Metrics, Regularization)
Equations, assumptions, examples

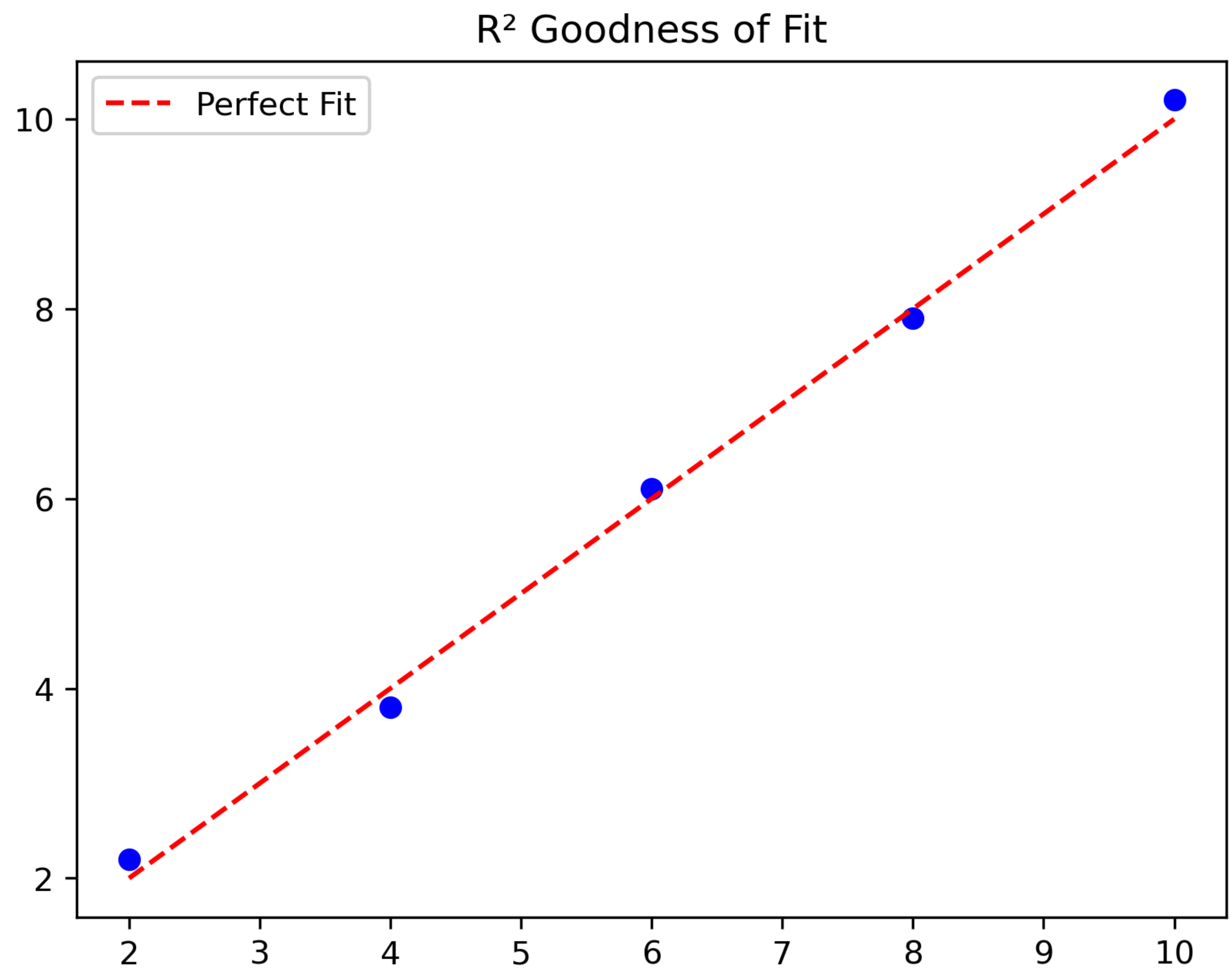


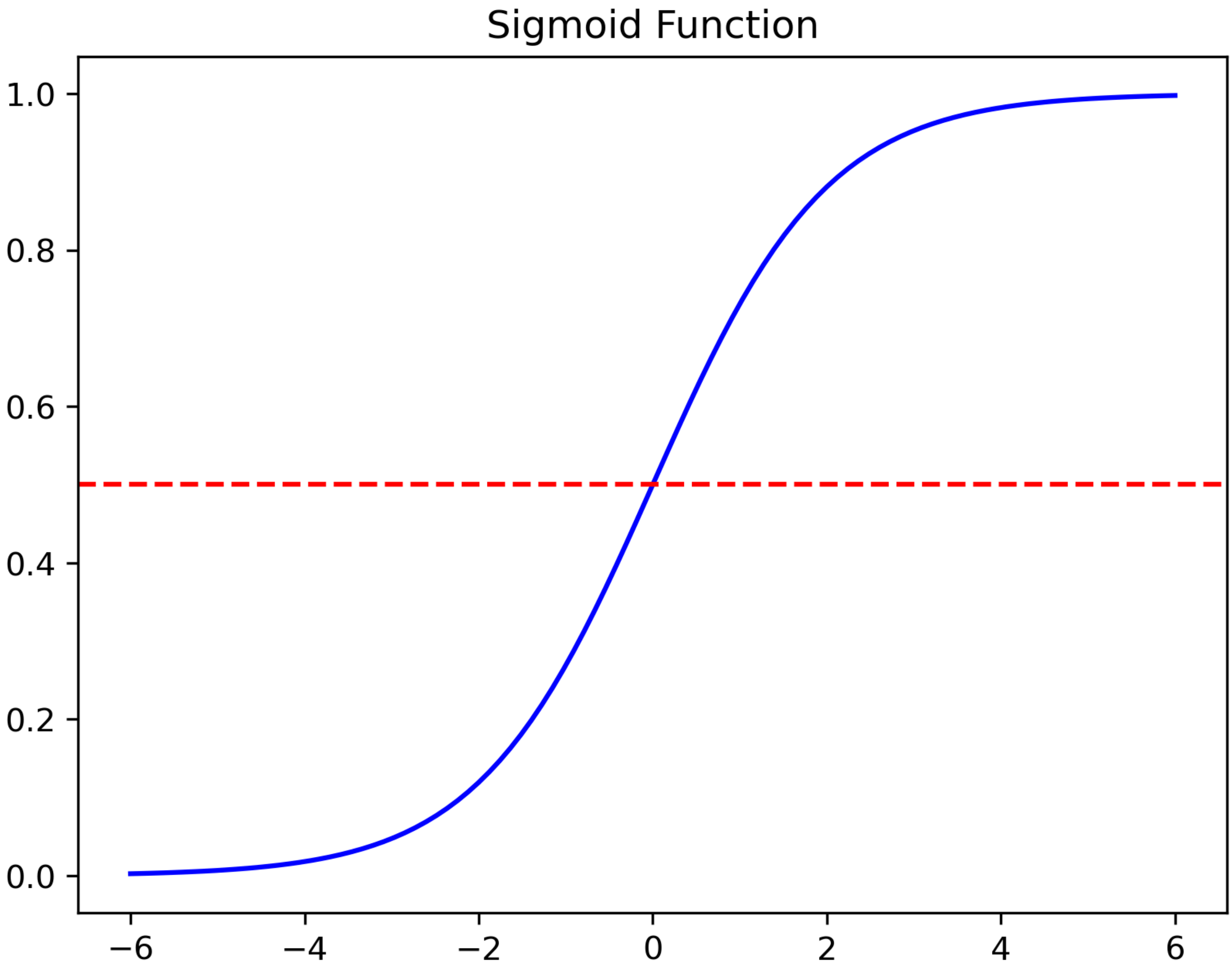
Gradient Descent
Steps of Gradient Descent
8
6
4
2
0
−3
−2
−1
0
1
2
3


Linear Regression Equation
Y=2X+1
Intercept (c)
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
2
4
6
8
10


Linear vs Logistic Regression
Linear Regression
Logistic Regression
6
4
2
0
−2
−4
−6
−6
−4
−2
0
2
4
6


Log Loss for True Class=1
7
6
5
4
3
2
1
0
0.0
0.2
0.4
0.6
0.8
1.0


R² Goodness of Fit
Perfect Fit
10
8
6
4
2
2
3
4
5
6
7
8
9
10


Sigmoid Function
1.0
0.8
0.6
0.4
0.2
0.0
−6
−4
−2
0
2
4
6