

# Logistic Regression Answer

1. What is Logistic Regression, and how does it differ from Linear Regression?

- **Logistic Regression** is a statistical and machine learning model used for **classification problems**, especially when the output (dependent variable) is **categorical** — most often **binary** (e.g., Yes/No, Spam/Not Spam, 0/1).
- Instead of predicting a continuous value like linear regression, logistic regression predicts the **probability** that a given input belongs to a certain class.

- Key Differences: Logistic vs. Linear Regression

Aspect	Linear Regression	Logistic Regression
<b>Purpose</b>	Predicts continuous numerical values	Predicts probabilities for classification
<b>Output Range</b>	$(-\infty, +\infty)$ $(-\infty, +\infty)$	00 to 11 (probabilities)
<b>Activation Function</b>	None (direct output)	Sigmoid (logistic) or other link functions
<b>Loss Function</b>	Mean Squared Error (MSE)	Log Loss / Binary Cross-Entropy
<b>Best Use Case</b>	Regression problems (e.g., predicting price)	Classification problems (e.g., spam detection)
<b>Assumption on Residuals</b>	Errors are normally distributed	Follows Bernoulli distribution

2. Explain the role of the Sigmoid function in Logistic Regression.

- The **role of the Sigmoid function in Logistic Regression** is to **convert the raw linear output into a probability between 0 and 1**.

- **Step-by-step role in Logistic Regression:**

1. **Compute a Linear Score**

Logistic regression first calculates:

$$z = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n$$

$$b_nx_n = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n$$

Here,  $z$  can be any real number (negative, zero, or positive).

2. **Transform to Probability**

The **sigmoid function**:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad \sigma(z) = \frac{1}{1 + e^{-z}}$$

maps  $z$  into the range  $(0, 1)$   $(0, 1)$   $(0, 1)$ , making it interpretable as a probability.

### 3. Decision Making

Once we have a probability:

- If  $p \geq 0.5$  → predict **class 1**
- If  $p < 0.5$  → predict **class 0**

### 4. Smooth and Differentiable

The sigmoid function is smooth and differentiable, which allows **gradient descent** to optimize the model efficiently.

## 3. What is Regularization in Logistic Regression and why is it needed?

- **Regularization in Logistic Regression** is a technique used to **prevent overfitting** by adding a penalty to the model's loss function for having large coefficient values (weights).

### Why It's Needed

- In logistic regression, if the model learns **very large weights**, it can become **too sensitive** to small changes in input data.
- This leads to **overfitting** — the model performs well on training data but poorly on unseen data.
- Regularization **controls model complexity**, encouraging simpler models that generalize better.

## 4. What are some common evaluation metrics for classification models, and why are they important.?

- **classification models** (like logistic regression, decision trees, etc.), we need metrics that tell us **how well the model predicts classes** — not just overall accuracy. Different metrics are important because classification tasks often have **imbalanced classes** or different costs for false positives vs. false negatives.

Common Evaluation Metrics

### 1. Accuracy

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}}$$

- **Meaning:** Percentage of correctly classified samples.
  - **Good when:** Classes are balanced.
  - **Limitation:** Misleading if data is imbalanced (e.g., predicting “not spam” for all emails in a 99% non-spam dataset still gives 99% accuracy).
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## 2. Precision

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- **Meaning:** Of all predicted positives, how many are actually positive.
  - **Good when:** Cost of false positives is high (e.g., predicting cancer when not present).
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## 3. Recall (Sensitivity / True Positive Rate)

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- **Meaning:** Of all actual positives, how many the model correctly identified.
  - **Good when:** Cost of false negatives is high (e.g., missing a fraud transaction).
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## 4. F1 Score

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Meaning:** Harmonic mean of precision and recall.
  - **Good when:** You want a balance between precision and recall.
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## 5. ROC-AUC (Receiver Operating Characteristic – Area Under Curve)

- **Meaning:** Measures the model's ability to distinguish between classes across all thresholds.
  - **Good when:** You want a threshold-independent performance measure.
  - **AUC close to 1:** Very good separation of classes.
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## 6. Confusion Matrix

- A table showing **True Positives, True Negatives, False Positives, False Negatives**.
- **Meaning:** Gives detailed insight into exactly where the model is making mistakes.

### Why They're Important

- **Different problems need different priorities** (e.g., in spam detection, false negatives may be fine, but in cancer detection, they're dangerous).
- **One metric alone can mislead** — especially with imbalanced datasets.
- **Helps choose the right threshold** and model for the business objective.

5. Write a Python program that loads a CSV file into a Pandas DataFrame, splits into train/test sets, trains a Logistic Regression model, and prints its accuracy. (Use Dataset from sklearn package) (Include your Python code and output in the code box below)

```
import pandas as pd

from sklearn.datasets import load_Lungs_cancer

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score

data = load_Lungs_cancer()
```

```

df = pd.DataFrame(data.data, columns=data.feature_names)

df['target'] = data.target


# Display first 5 rows

print("First 5 rows of the dataset:")

print(df.head())


# Split into features and target

X = df.drop('target', axis=1)

y = df['target']

# Split into training and testing sets (80% train, 20% test)

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# Create and train the Logistic Regression model

model = LogisticRegression(max_iter=10000) # Increased iterations for convergence

model.fit(X_train, y_train)

# Make predictions on the test set

y_pred = model.predict(X_test)

# Calculate and print accuracy

accuracy = accuracy_score(y_test, y_pred)

print(f"\nLogistic Regression Model Accuracy: {accuracy:.4f}")

```

First 5 rows of the dataset:

```

    mean radius  mean texture  mean perimeter  mean area  mean
smoothness  \

```

0	17.99	10.38	122.80	1001.0
0.11840				
1	20.57	17.77	132.90	1326.0
0.08474				
2	19.69	21.25	130.00	1203.0
0.10960				
3	11.42	20.38	77.58	386.1
0.14250				
4	20.29	14.34	135.10	1297.0
0.10030				

	mean compactness	mean concavity	mean concave points	mean symmetry
0	0.27760	0.3001	0.14710	0.2419
1	0.07864	0.0869	0.07017	0.1812
2	0.15990	0.1974	0.12790	0.2069
3	0.28390	0.2414	0.10520	0.2597
4	0.13280	0.1980	0.10430	0.1809

	mean fractal dimension	... worst texture	worst perimeter	worst area
0	0.07871	...	17.33	184.60
2019.0				
1	0.05667	...	23.41	158.80
1956.0				
2	0.05999	...	25.53	152.50
1709.0				
3	0.09744	...	26.50	98.87
567.7				
4	0.05883	...	16.67	152.20
1575.0				

	worst smoothness points \	worst compactness	worst concavity	worst concave
0	0.1622	0.6656	0.7119	
0.2654				
1	0.1238	0.1866	0.2416	
0.1860				
2	0.1444	0.4245	0.4504	
0.2430				
3	0.2098	0.8663	0.6869	
0.2575				
4	0.1374	0.2050	0.4000	
0.1625				

	worst symmetry	worst fractal dimension	target
0	0.4601	0.11890	0
1	0.2750	0.08902	0
2	0.3613	0.08758	0
3	0.6638	0.17300	0
4	0.2364	0.07678	0

[5 rows x 31 columns]

Logistic Regression Model Accuracy: 0.9561