12-Logistical_Regression

October 20, 2024

1 Logistic Regression

Logistic Regression is a supervised learning algorithm used for classification tasks, not regression, despite its name. It estimates the probability that a given input point belongs to a certain class by applying a logistic (sigmoid) function to a linear combination of input features. The output is a probability between 0 and 1, making it ideal for binary classification problems (two possible outcomes, like yes/no, spam/not spam).

Logistic regression predicts a binary outcome based on one or more predictor variables (features) and is one of the foundational techniques in machine learning and statistics.

When to Use Logistic Regression? Logistic Regression is commonly used when:

- **The dependent variable is binary**: For example, a classification problem where the output is either "1" or "0" (e.g., true/false, success/failure).
- **You need probabilistic interpretations**: Logistic regression outputs probabilities that a data point belongs to a certain class, which makes it useful in areas where you need both the prediction and the confidence of that prediction.
- **When interpretability is important**: It provides clear and interpretable coefficients, which can explain the impact of each feature on the prediction.
- **The relationship between features and the target is linear in the log-odds**: While logistic regression assumes a linear relationship between the features and the log-odds of the outcome, it can still handle non-linear relationships by transforming the input features (e.g., polynomial or interaction terms).

Typical use cases include:

- **Medical Diagnosis**: Predicting whether a patient has a disease or not.
- **Email Classification**: Determining whether an email is spam or not.
- **Customer Churn**: Predicting whether a customer will leave a service or remain.
- **Credit Scoring**: Estimating the probability of a customer defaulting on a loan.

Who Should Use Logistic Regression? Logistic Regression is ideal for:

- **Data scientists and machine learning practitioners** who need a simple, interpretable model for binary classification tasks.

- **Business analysts and researchers** looking for an explainable model where they can interpret the effect of each feature on the outcome.
- **Medical professionals** making decisions based on classification problems like disease detection.
- **Beginner machine learning students** since logistic regression is one of the simplest and easiest algorithms to learn and apply.

Advantages of Logistic Regression:

- **Simplicity and Interpretability**: It is easy to implement and interpret, making it a popular choice for binary classification problems.
- **Probabilistic Output**: Logistic regression provides probabilities for class membership, which can be useful for understanding the confidence of predictions.
- **Fast and Efficient**: It performs well on relatively small datasets and is computationally efficient.
- **No Feature Scaling Required**: While performance can be improved by scaling features, logistic regression does not require it.
- **Linear Decision Boundary**: The decision boundary is linear, which makes it suitable for linearly separable datasets.

Disadvantages of Logistic Regression:

- **Limited to Linear Boundaries**: Logistic regression assumes a linear relationship between the features and the log-odds, making it unsuitable for complex or highly non-linear problems.
- **Assumes Independence of Features**: Like Naive Bayes, logistic regression assumes that the features are independent of each other, which may not hold true in many cases. Cannot Handle Multiclass Problems Directly: Logistic regression is a binary classifier by default, but techniques like One-vs-Rest or Softmax Regression can extend it to multiclass problems.
- **Sensitive to Outliers**: Logistic regression can be sensitive to outliers, which can skew the decision boundary.

Real-World Applications of Logistic Regression:

1. **Credit Scoring**: Predicting the probability of a customer defaulting on a loan.
2. **Medical Diagnosis**: Predicting the likelihood of a disease based on symptoms.
3. **Customer Retention**: Estimating the probability that a customer will churn or stay with the company.
4. **Marketing Campaigns**: Predicting whether a customer will respond to an advertisement or not.
5. **Email Classification**: Classifying emails as spam or non-spam.

[1]:
```python
import pandas as pd

d = {
        'miles_per_week':␣
 ↪[37,39,46,51,88,17,18,20,21,22,23,24,25,27,28,29,30,31,32,33,34,38,40,42,57,68,35,36,41,43,
        'completed_50m_ultra':␣
 ↪['no','no','no','no','no','no','no','no','no','no','no','no','no','no','no','no','no','no',
    }

df = pd.DataFrame(data=d)
df
```

[1]:
```
     miles_per_week completed_50m_ultra
0                37                  no
1                39                  no
2                46                  no
3                51                  no
4                88                  no
..              …                   …
96               67                 yes
97               74                 yes
98               79                 yes
99               90                 yes
100             112                 yes

[101 rows x 2 columns]
```

[2]:
```python
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.preprocessing import OrdinalEncoder
from sklearn.linear_model import LogisticRegression
from matplotlib import pyplot as plt

import seaborn as sns

finished_race = ['no', 'yes']
enc = OrdinalEncoder(categories=[finished_race])
df['completed_50m_ultra'] = enc.fit_transform(df[['completed_50m_ultra']])

df
```

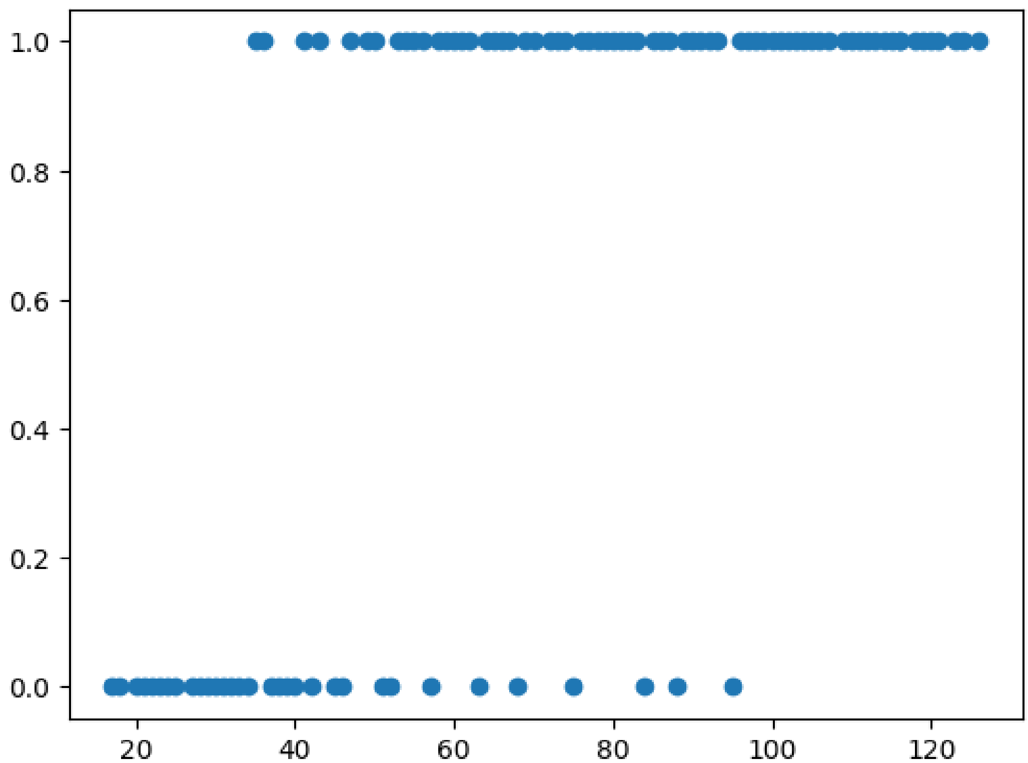
[2]:
```
     miles_per_week  completed_50m_ultra
0                37                  0.0
1                39                  0.0
2                46                  0.0
3                51                  0.0
4                88                  0.0
```

```
..                …                   …
96                67                1.0
97                74                1.0
98                79                1.0
99                90                1.0
100              112                1.0

[101 rows x 2 columns]
```

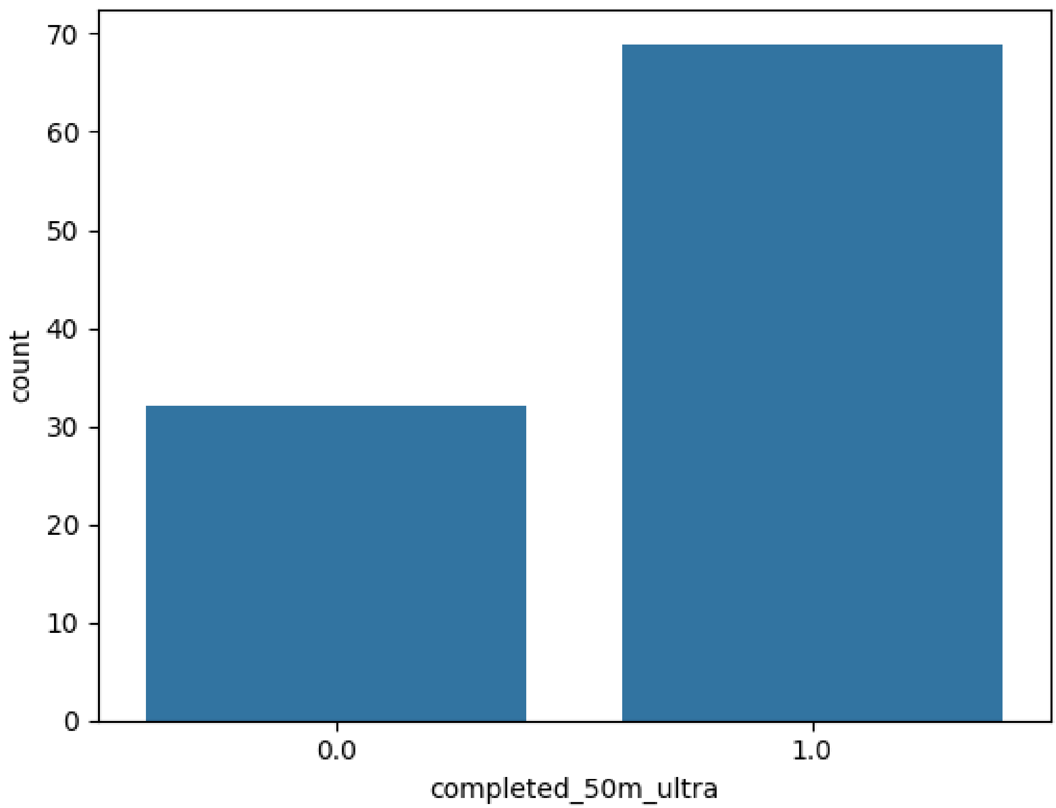
[3]:
```python
plt.scatter(df['miles_per_week'], df['completed_50m_ultra'])
```

[3]:
```
<matplotlib.collections.PathCollection at 0x1f0ce21e410>
```



[4]:
```python
sns.countplot(x='completed_50m_ultra', data=df)
```

[4]:
```
<Axes: xlabel='completed_50m_ultra', ylabel='count'>
```



[5]:
```
X = df.iloc[:,0:1]
y = df.iloc[:,1]

X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.8,␣
↪random_state=11)

model = LogisticRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
model.score(X_test, y_test)
```

[5]: 0.9047619047619048

[6]:
```
print(confusion_matrix(y_test, y_pred))
```

```
[[ 5  1]
 [ 1 14]]
```

[7]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support
```

```
         0.0       0.83      0.83      0.83         6
         1.0       0.93      0.93      0.93        15

    accuracy                           0.90        21
   macro avg       0.88      0.88      0.88        21
weighted avg       0.90      0.90      0.90        21
```