

Comprehensive Guide to Linear Regression

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1 Introduction

Linear regression is a fundamental algorithm in machine learning used for predicting a continuous target variable based on one or more input features. It is widely used due to its simplicity and interpretability.

2 Understanding Linear Regression

Linear regression models the relationship between a dependent variable (y) and one or more independent variables (X) by fitting a linear equation to the observed data.

3 Mathematical Foundations

3.1 Equation of a Line

The equation for a simple linear regression line is:

$$y = \beta_0 + \beta_1 X$$

Where:

- y is the dependent variable.
- X is the independent variable.
- β_0 is the intercept.
- β_1 is the slope.

3.2 Cost Function

The cost function (Mean Squared Error) measures the accuracy of the model:

$$J(\beta_0, \beta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

3.3 Normal Equation

The normal equation provides a closed-form solution:

$$\theta = (X^T X)^{-1} X^T y$$

4 Methods for Solving Linear Regression

4.1 Normal Equation

A direct method to solve for coefficients:

$$\theta = (X^T X)^{-1} X^T y$$

4.2 Gradient Descent

An iterative optimization algorithm:

$$\theta := \theta - \alpha \frac{1}{m} \sum (h_{\theta}(x^{(i)}) - y^{(i)}) x^{(i)}$$

4.3 QR Decomposition

Decomposes matrix X into Q and R :

$$X = QR$$

$$\theta = R^{-1} Q^T y$$

4.4 Singular Value Decomposition (SVD)

Factorizes matrix X into U , Σ , and V^T :

$$X = U \Sigma V^T$$

$$\theta = V \Sigma^{-1} U^T y$$

5 Practical Implementation in Python

5.1 Using NumPy

```
1 import numpy as np
2
3 # Preparing data
4 X = np.array([2, 3, 5]).reshape(-1, 1)
5 y = np.array([4, 5, 7])
6 X_b = np.c_[np.ones((X.shape[0], 1)), X]
7
```

```
8 # Calculating coefficients
9 theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T
    ).dot(y)
10 print(f"Intercept: {theta_best[0]}, Slope: {
    theta_best[1]}")
```

Listing 1: Linear Regression using NumPy

5.2 Using scikit-learn

```
1 from sklearn.linear_model import LinearRegression
2
3 model = LinearRegression()
4 model.fit(X, y)
5 print(f"Intercept: {model.intercept_}, Slope: {model
    .coef_[0]}")
```

Listing 2: Linear Regression using scikit-learn

5.3 Using statsmodels

```
1 import statsmodels.api as sm
2
3 X_b = sm.add_constant(X)
4 model = sm.OLS(y, X_b).fit()
5 print(model.summary())
```

Listing 3: Linear Regression using statsmodels

5.4 Using TensorFlow

```
1 import tensorflow as tf
2
3 X = tf.constant([[2.0], [3.0], [5.0]], dtype=tf.
    float32)
4 y = tf.constant([4.0, 5.0, 7.0], dtype=tf.float32)
5
6 model = tf.keras.Sequential([tf.keras.layers.Dense
    (1, input_shape=(1,))])
```

```
7 model.compile(optimizer='sgd', loss='mse')
8 model.fit(X, y, epochs=100)
9 print(f"Intercept and Slope: {model.layers[0].
    weights}")
```

Listing 4: Linear Regression using TensorFlow

6 Sample Projects

6.1 Simple Linear Regression with NumPy

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 # Data
5 X = np.array([1, 2, 4, 3, 5])
6 y = np.array([1, 3, 3, 2, 5])
7 X_b = np.c_[np.ones((X.shape[0], 1)), X]
8
9 # Linear Regression using Normal Equation
10 theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T
    ).dot(y)
11
12 # Prediction
13 X_new = np.array([[0], [6]])
14 X_new_b = np.c_[np.ones((2, 1)), X_new]
15 y_predict = X_new_b.dot(theta_best)
16
17 # Plot
18 plt.plot(X, y, "b.")
19 plt.plot(X_new, y_predict, "r-")
20 plt.xlabel("X")
21 plt.ylabel("y")
22 plt.show()
```

Listing 5: Simple Linear Regression with NumPy

6.2 Multiple Linear Regression with scikit-learn

```
1 from sklearn.linear_model import LinearRegression
2 import numpy as np
3
4 # Data
5 X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])
6 y = np.dot(X, np.array([1, 2])) + 3
7
8 # Model
9 model = LinearRegression().fit(X, y)
10 print(f"Intercept: {model.intercept_}, Coefficients:
      {model.coef_}")
```

Listing 6: Multiple Linear Regression with scikit-learn

6.3 Linear Regression with TensorFlow

```
1 import tensorflow as tf
2
3 # Data
4 X = tf.constant([[1.0], [2.0], [4.0], [3.0], [5.0]],
5                  dtype=tf.float32)
6 y = tf.constant([1.0, 3.0, 3.0, 2.0, 5.0], dtype=tf.float32)
7
8 # Model
9 model = tf.keras.Sequential([tf.keras.layers.Dense
10                               (1, input_shape=(1,))])
11 model.compile(optimizer='sgd', loss='mse')
12 model.fit(X, y, epochs=100)
```

Listing 7: Linear Regression with TensorFlow