```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

```
df = pd.read_csv('/content/auto-mpg.csv')
df.head(10)
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino
5	15.0	8	429.0	198	4341	10.0	70	1	ford galaxie 500
6	14.0	8	454.0	220	4354	9.0	70	1	chevrolet impala
7	14.0	8	440.0	215	4312	8.5	70	1	plymouth fury iii
8	14.0	8	455.0	225	4425	10.0	70	1	pontiac catalina

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.dtypes
```

	0
mpg	float64
cylinders	int64
displacement	float64
horsepower	object
weight	int64
acceleration	float64
model year	int64
origin	int64
car name	object

dtype: object

```
df['horsepower'] = pd.to_numeric(df['horsepower'], errors='coerce').astype('Int64')
df.dtypes
```

	0
mpg	float64
cylinders	int64
displacement	float64
horsepower	Int64
weight	int64
acceleration	float64
model year	int64
origin	int64
car name	object

dtype: object

```
df.notnull().sum()
```

	0
mpg	398
cylinders	398
displacement	398
horsepower	392
weight	398
acceleration	398
model year	398
origin	398
car name	398

dtype: int64

```
df = df.dropna()
df.notnull().sum()
```

	0
mpg	392
cylinders	392
displacement	392
horsepower	392
weight	392
acceleration	392
model year	392
origin	392
car name	392

dtype: int64

```
count = {}

for i in df.columns:
  if i == 'car name':
    continue
  count[i] = len(df[i].unique())
```

```
count
```

```
{'mpg': 127,
 'cylinders': 5,
 'displacement': 81,
 'horsepower': 93,
 'weight': 346,
 'acceleration': 95,
 'model year': 13,
 'origin': 3}
```

```
X = df.drop(['car name', 'mpg'], axis=1)
y = df['mpg']
```

```
X.shape, y.shape
```

```
((392, 7), (392,))
```

```
transform = StandardScaler()
X = transform.fit_transform(X)
y = transform.fit_transform(y.values.reshape(-1, 1))
```

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

```
print(X_train.shape, X_test.shape)
print(y_train.shape, y_test.shape)
```

```
(313, 7) (79, 7)
(313, 1) (79, 1)
```

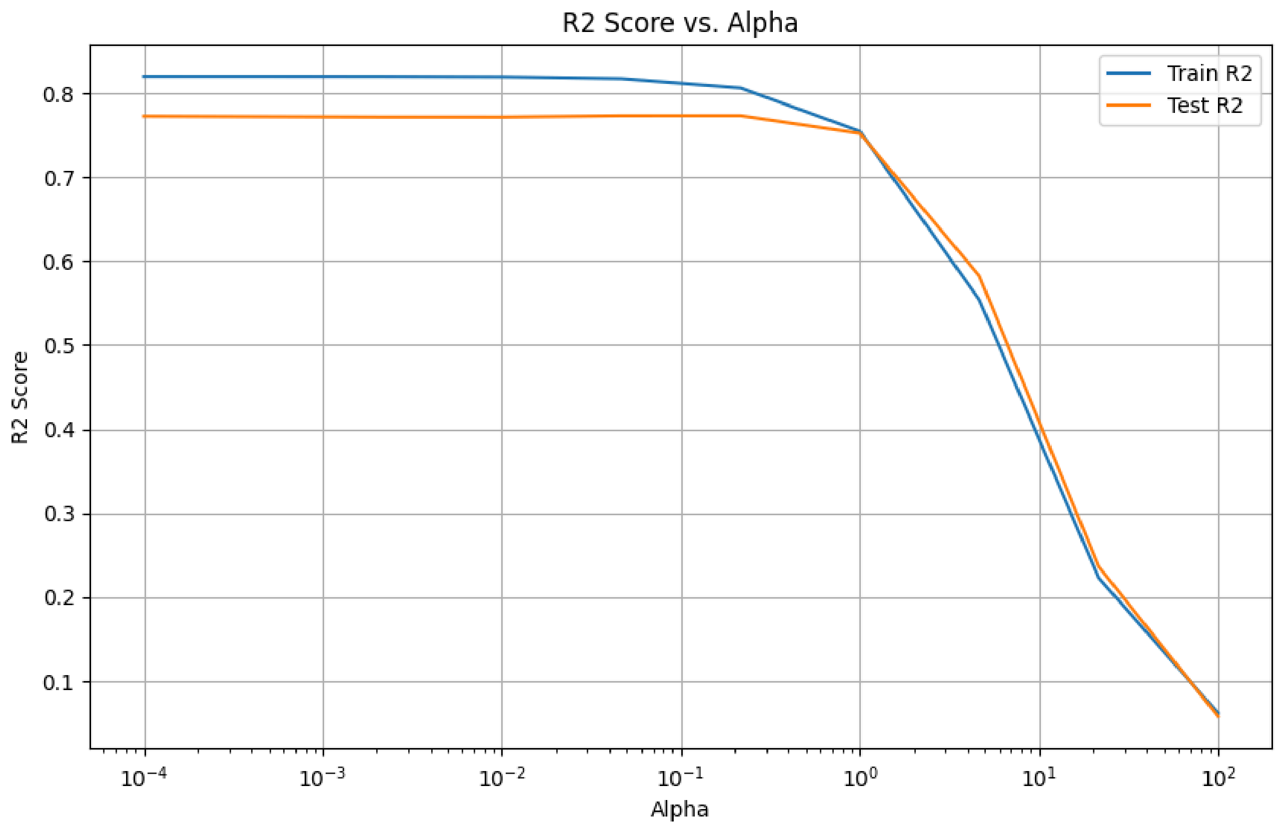
```
def train(X, y, batch_size=32, learning_rate=0.01, epochs=100, alpha=0.0):
    n_samples, n_features = X.shape
    weights = np.zeros((n_features, 1))
    bias = 0

    for epoch in range(epochs):
        indices = np.arange(n_samples)
        np.random.shuffle(indices)
        X_shuffled = X[indices]
        y_shuffled = y[indices]

        for i in range(0, n_samples, batch_size):
            X_batch = X_shuffled[i:i + batch_size]
            y_batch = y_shuffled[i:i + batch_size]

            y_batch = y_batch.reshape(-1, 1)

            y_predicted = np.dot(X_batch, weights) + bias
            error = y_predicted - y_batch

            dw = (1 / batch_size) * np.dot(X_batch.T, error) + alpha * weights
            db = (1 / batch_size) * np.sum(error)

            weights -= learning_rate * dw
            bias -= learning_rate * db

    return weights, bias
```

```
def evaluate_model(y_true, y_pred):
    mae = mean_absolute_error(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    r2 = r2_score(y_true, y_pred)
    return {'mae': mae, 'rmse': rmse, 'r2': r2}
```

```
alpha_list = np.logspace(-4, 2, 10)

train_r2_scores = []
```

```
test_r2_scores = []
alpha_values = []
weights_list = []
bias_list = []

for alpha in alpha_list:
    weights, bias = train(X_train, y_train, alpha=alpha)

    y_train_pred = np.dot(X_train, weights) + bias
    y_test_pred = np.dot(X_test, weights) + bias

    train_r2 = r2_score(y_train, y_train_pred)
    test_r2 = r2_score(y_test, y_test_pred)

    train_r2_scores.append(train_r2)
    test_r2_scores.append(test_r2)
    alpha_values.append(alpha)
    weights_list.append(weights)
    bias_list.append(bias)
```

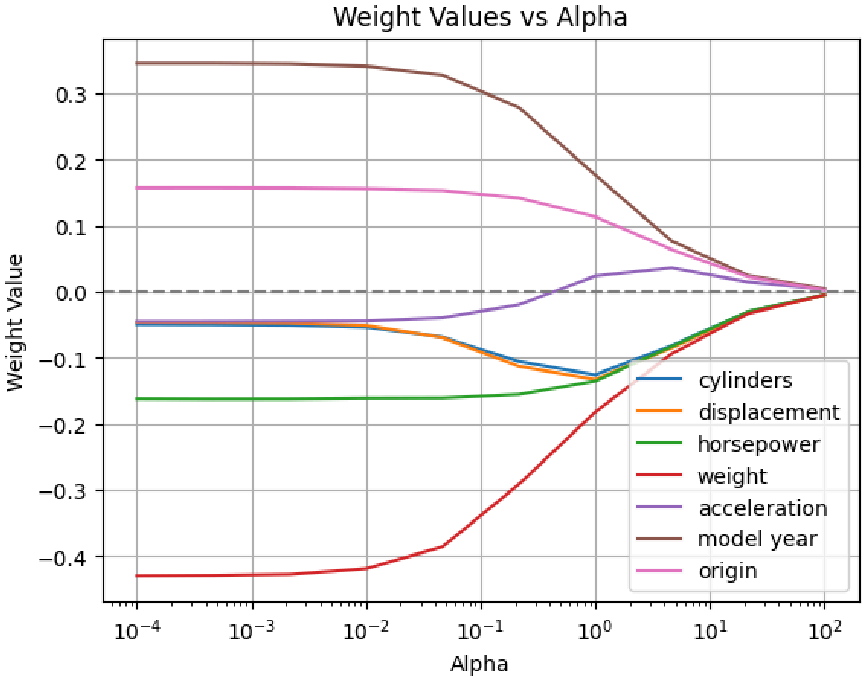
```
plt.figure(figsize=(10, 6))
plt.plot(alpha_values, train_r2_scores, label='Train R2')
plt.plot(alpha_values, test_r2_scores, label='Test R2')
plt.xscale('log')
plt.xlabel('Alpha')
plt.ylabel('R2 Score')
plt.title('R2 Score vs. Alpha')
plt.legend()
plt.grid(True)
plt.show()

best_alpha_index = np.argmax(test_r2_scores)
best_alpha = alpha_values[best_alpha_index]
print(f"Best Alpha: {best_alpha}")
```




```
Best Alpha: 0.21544346900318823
```

```
labels = ['cylinders', 'displacement', 'horsepower', 'weight', 'acceleration', 'model year', 'origin']

for i in range(len(labels)):
    weights_for_feature = [w[i, 0] for w in weights_list]
    plt.plot(alpha_values, weights_for_feature, label=labels[i])
```

```
plt.axhline(y=0, color='gray', linestyle='--')
plt.xlabel('Alpha')
plt.ylabel('Weight Value')
plt.title('Weight Values vs Alpha')
plt.legend()
plt.xscale('log')
plt.grid(True)
plt.show()
```



- Các trọng số có vai trò nhỏ dần khi α tăng lên.
- Mô hình trở nên đơn giản hơn khi α tăng lên.
- Khi λ lớn dần lên kết quả dự đoán sẽ giảm dần sử phụ thuộc vào các đặc trưng đầu vào. Như vạy sẽ giảm bớt tình trạng overfitting. Nhưng λ quá lớn sẽ làm cho kết quả dự đoán bị underfitting.