

```
In [19]: # Logistic Regression on SUV dataset
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.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

```
In [20]: data = pd.read_csv(r"C:\Users\Admin\Downloads\archive\suv_data.csv")
data.head()
data.shape
data['Age'].unique()
```

```
Out[20]: array([19, 35, 26, 27, 32, 25, 20, 18, 29, 47, 45, 46, 48, 49, 31, 21, 28,
       33, 30, 23, 24, 22, 59, 34, 39, 38, 37, 42, 40, 36, 41, 58, 55, 52,
       60, 56, 53, 50, 51, 57, 44, 43, 54])
```

```
In [21]: data.shape
```

```
Out[21]: (400, 5)
```

```
In [22]: data['Age'].unique()
```

```
Out[22]: array([19, 35, 26, 27, 32, 25, 20, 18, 29, 47, 45, 46, 48, 49, 31, 21, 28,
       33, 30, 23, 24, 22, 59, 34, 39, 38, 37, 42, 40, 36, 41, 58, 55, 52,
       60, 56, 53, 50, 51, 57, 44, 43, 54])
```

```
In [23]: for col in data.columns:
    print(f"Unique values in '{col}': {data[col].unique()}")
```

Unique values in 'User ID': [15624510 15810944 15668575 15603246 15804002 15728773 15598044 15694829]

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15748589 15635893 15757632 15691863 15706071 15654296 15755018 15594041]

Unique values in 'Gender': ['Male' 'Female']

Unique values in 'Age': [19 35 26 27 32 25 20 18 29 47 45 46 48 49 31 21 28 33 30 23 24 22 59 34

39 38 37 42 40 36 41 58 55 52 60 56 53 50 51 57 44 43 54]

Unique values in 'EstimatedSalary': [19000 20000 43000 57000 76000 58000 84000 150000 33000 65000

80000 52000 86000 18000 82000 25000 26000 28000 29000 22000
49000 41000 23000 30000 74000 137000 16000 44000 90000 27000
72000 31000 17000 51000 108000 15000 79000 54000 135000 89000
32000 83000 55000 48000 117000 87000 66000 120000 63000 68000
113000 112000 42000 88000 62000 118000 85000 81000 50000 116000
123000 73000 37000 59000 149000 21000 35000 71000 61000 75000

```
53000 107000 96000 45000 47000 100000 38000 69000 148000 115000
34000 60000 70000 36000 39000 134000 101000 130000 114000 142000
78000 143000 91000 144000 102000 126000 133000 147000 104000 146000
122000 97000 95000 131000 77000 125000 106000 141000 93000 138000
119000 105000 99000 129000 46000 64000 139000]
Unique values in 'Purchased': [0 1]
```

```
In [24]: data.isnull().sum()
```

```
Out[24]: User ID      0
Gender        0
Age          0
EstimatedSalary 0
Purchased     0
dtype: int64
```

```
In [25]: data.duplicated().sum()
```

```
Out[25]: np.int64(0)
```

```
In [26]: data.describe()
```

```
Out[26]:
```

	User ID	Age	EstimatedSalary	Purchased
count	4.000000e+02	400.000000	400.000000	400.000000
mean	1.569154e+07	37.655000	69742.500000	0.357500
std	7.165832e+04	10.482877	34096.960282	0.479864
min	1.556669e+07	18.000000	15000.000000	0.000000
25%	1.562676e+07	29.750000	43000.000000	0.000000
50%	1.569434e+07	37.000000	70000.000000	0.000000
75%	1.575036e+07	46.000000	88000.000000	1.000000
max	1.581524e+07	60.000000	150000.000000	1.000000

```
In [27]: # ---- STEP 2: Select Features and Target ----
X = data[['Age', 'EstimatedSalary']] # Features
y = data['Purchased'] # Target (0 = No, 1 = Yes)
```

```
In [28]: # ---- STEP 3: Split Dataset ----
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.25, random_state=42
)
```

```
In [29]: # ---- STEP 4: Feature Scaling ----
# -3 to +3
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
In [30]: X_train_scaled
```

```
Out[30]: array([[ 1.8925893 ,  1.52189404],  
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```

```
In [31]: # ---- STEP 5: Train Logistic Regression Model ----  
model = LogisticRegression()  
model.fit(X_train_scaled, y_train)
```

```
Out[31]: ▾ LogisticRegression ⓘ ?  
LogisticRegression()
```

```
In [32]: # ---- STEP 6: Predictions ----  
y_pred = model.predict(X_test_scaled)
```

```
In [33]: # ---- STEP 7: Evaluation ----  
cm = confusion_matrix(y_test, y_pred)
```

```

print("Confusion Matrix:\n", cm)
print("\nClassification Report:\n", classification_report(y_test, y_pred))
accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy: {accuracy:.2f}")

```

Confusion Matrix:

```

[[61  2]
 [12 25]]

```

Classification Report:

	precision	recall	f1-score	support
0	0.84	0.97	0.90	63
1	0.93	0.68	0.78	37
accuracy			0.86	100
macro avg	0.88	0.82	0.84	100
weighted avg	0.87	0.86	0.85	100

Accuracy: 0.86

```

In [34]: import matplotlib.pyplot as plt
import numpy as np

# Use test set features
X_set, y_set = X_test_scaled, y_test

# Create mesh grid directly from feature values
X1, X2 = np.meshgrid(
    np.arange(start=X_set[:, 0].min(), stop=X_set[:, 0].max(), step=0.01),
    np.arange(start=X_set[:, 1].min(), stop=X_set[:, 1].max(), step=0.01)
)

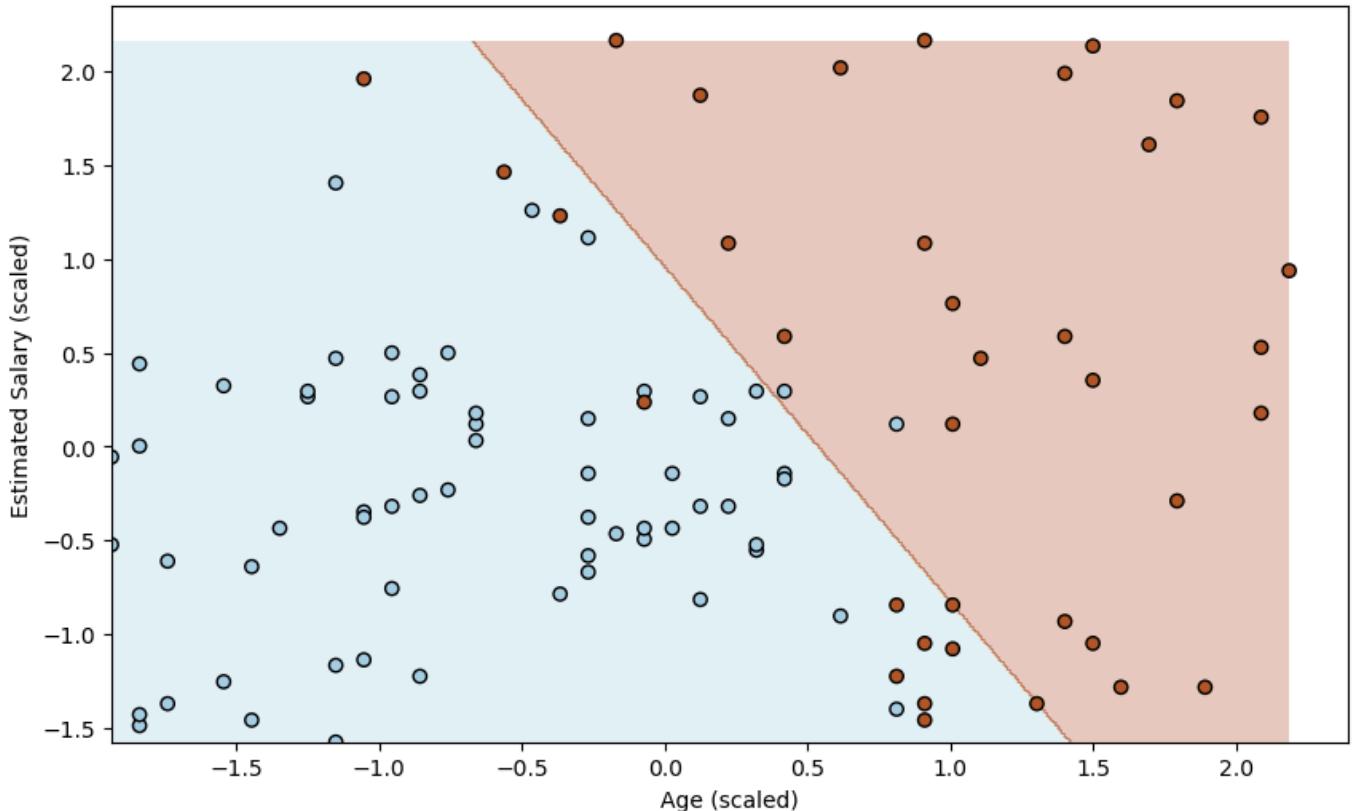
# Predict on the grid
Z = model.predict(np.array([X1.ravel(), X2.ravel()]).T)
Z = Z.reshape(X1.shape)

# Plot decision boundary
plt.figure(figsize=(10, 6))
plt.contourf(X1, X2, Z, alpha=0.3, cmap=plt.cm.Paired)

# Plot test points
plt.scatter(X_set[:, 0], X_set[:, 1], c=y_set, cmap=plt.cm.Paired, edgecolors='k')
plt.title("Logistic Regression - SUV Purchase Prediction")
plt.xlabel("Age (scaled)")
plt.ylabel("Estimated Salary (scaled)")
plt.show()

```

Logistic Regression - SUV Purchase Prediction



```
In [35]: test_data = pd.DataFrame({
    "Age": [25, 40, 50],
    "EstimatedSalary": [30000, 70000, 90000]
})
```

```
In [36]: # Scale and predict
test_scaled = scaler.transform(test_data)
predictions = model.predict(test_scaled)
probs = model.predict_proba(test_scaled)
```

```
In [37]: print("\n--- Test Data Predictions ---")
for i, row in test_data.iterrows():
    print(f"Age: {row['Age']}, Salary: {row['EstimatedSalary']} -> "
          f"{'Buys SUV' if predictions[i] else 'No Purchase'} "
          f"(Prob: {probs[i][1]*100:.1f}%)")
```

--- Test Data Predictions ---
Age: 25, Salary: 30000 -> No Purchase (Prob: 0.9%)
Age: 40, Salary: 70000 -> No Purchase (Prob: 35.5%)
Age: 50, Salary: 90000 -> Buys SUV (Prob: 87.2%)

```
In [38]: # Simple plot with legend + probability annotations (on top)
plt.figure(figsize=(8, 5))

# Decision boundary
plt.contourf(
    X1, X2,
    model.predict(np.c_[X1.ravel(), X2.ravel()]).reshape(X1.shape),
    alpha=0.3, cmap=plt.cm.Paired
)

# Original test set points
plt.scatter(X_set[:, 0], X_set[:, 1], c=y_set, cmap=plt.cm.Paired, alpha=0.5, label="Test set")

# Test points (new data)
plt.scatter(
```

```

    test_scaled[:, 0], test_scaled[:, 1], c=predictions,
    cmap=plt.cm.coolwarm, marker='X', s=200, edgecolors='black', label="New test data"
)

plt.title("Logistic Regression - Test Data with Probabilities")
plt.xlabel("Age (scaled)")
plt.ylabel("Salary (scaled)")
plt.legend()
plt.show()

```

