🧠 Predict Heart Disease Using Logistic Regression

Import Libraries

In [1]:
```
import joblib
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
```

In [2]:
```
df = pd.read_csv("heart.csv")
df.head()
```

Out[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

🔍 Step 1: Explore the Dataset

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1025 non-null   int64  
 1   sex       1025 non-null   int64  
 2   cp        1025 non-null   int64  
 3   trestbps  1025 non-null   int64  
 4   chol      1025 non-null   int64  
 5   fbs       1025 non-null   int64  
 6   restecg   1025 non-null   int64  
 7   thalach   1025 non-null   int64  
 8   exang     1025 non-null   int64  
 9   oldpeak   1025 non-null   float64
 10  slope     1025 non-null   int64  
 11  ca        1025 non-null   int64  
 12  thal      1025 non-null   int64  
 13  target    1025 non-null   int64  
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
```

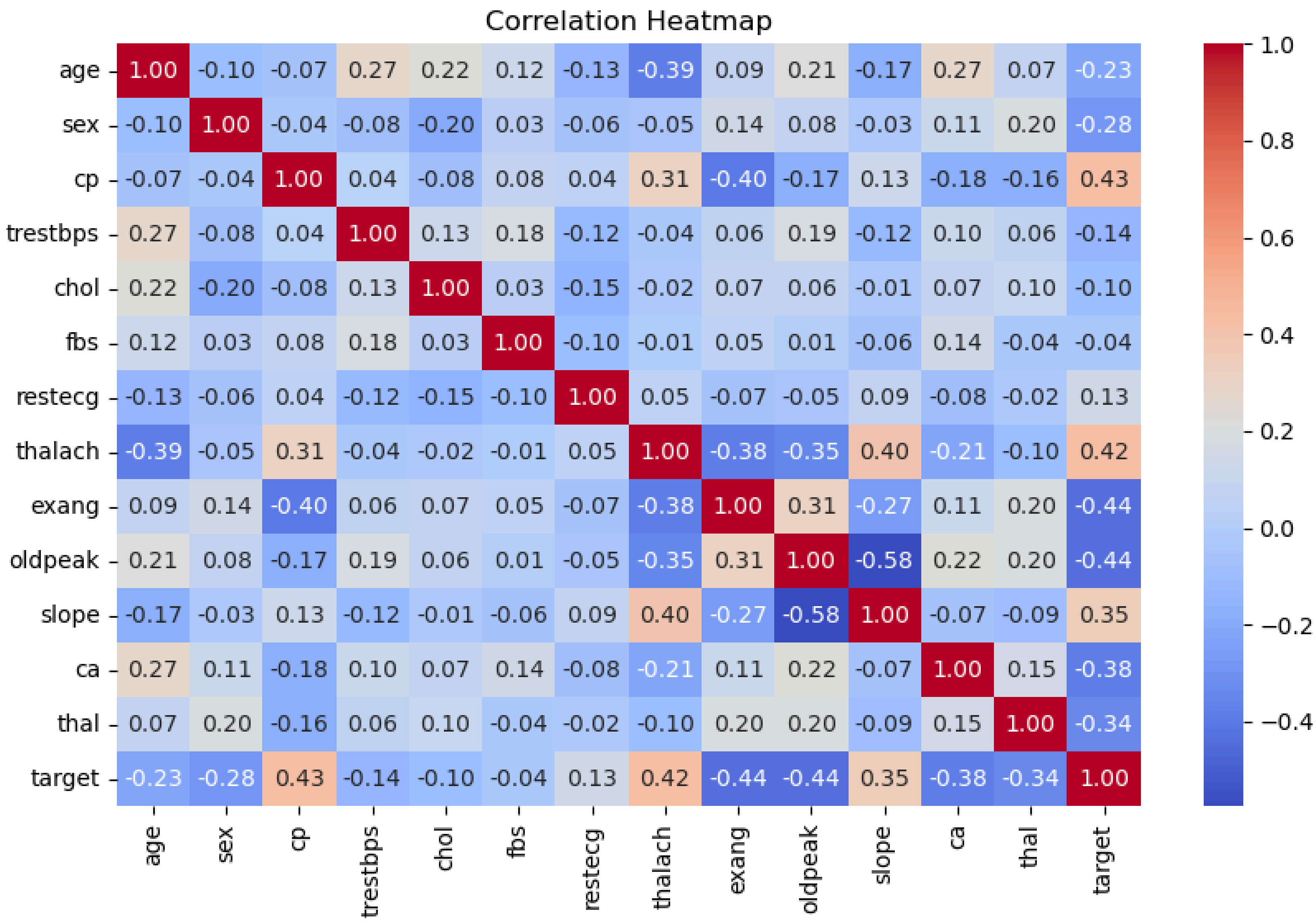
In [4]:
```python
df.describe()
```

Out[4]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	
count	1025.000000	1025.000000	1025.000000	1025.000000	1025.00000	1025.000000	1025.000000	1025.000000	1025.000000	102
mean	54.434146	0.695610	0.942439	131.611707	246.00000	0.149268	0.529756	149.114146	0.336585	
std	9.072290	0.460373	1.029641	17.516718	51.59251	0.356527	0.527878	23.005724	0.472772	
min	29.000000	0.000000	0.000000	94.000000	126.00000	0.000000	0.000000	71.000000	0.000000	
25%	48.000000	0.000000	0.000000	120.000000	211.00000	0.000000	0.000000	132.000000	0.000000	
50%	56.000000	1.000000	1.000000	130.000000	240.00000	0.000000	1.000000	152.000000	0.000000	
75%	61.000000	1.000000	2.000000	140.000000	275.00000	0.000000	1.000000	166.000000	1.000000	
max	77.000000	1.000000	3.000000	200.000000	564.00000	1.000000	2.000000	202.000000	1.000000	

⚙️ Step 2: Exploratory Data Analysis

In [5]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```



Most Positively Correlated Features

In [6]:
```
corr_matrix = df.corr()

target = 'target'

corr_with_target = corr_matrix[target].sort_values(ascending=False)

print("Most Positively Correlated Features:")
print(corr_with_target.head(6))
```

```
Most Positively Correlated Features:
target     1.000000
cp         0.434854
thalach    0.422895
slope      0.345512
restecg    0.134468
fbs       -0.041164
Name: target, dtype: float64
```

Most Negatively Correlated Features

In [7]:
```
print("Most Positively Correlated Features:")
print(corr_with_target.tail(5))
```

```
Most Positively Correlated Features:
sex       -0.279501
thal      -0.337838
ca        -0.382085
exang     -0.438029
oldpeak   -0.438441
Name: target, dtype: float64
```

⚙️ Step 3: Prepare the Data

In [8]:
```
# Split features and target
X = df[["cp","thalach","slope","restecg","fbs","sex","thal","ca","exang","oldpeak"]]
y = df["target"]
```

In [9]:
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [10]:
```
# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

🤖 Step 4: Train the Model

In [11]:
```
# Train logistic regression
model = LogisticRegression()
model.fit(X_train_scaled, y_train)
```

Out[11]:
```
▾ LogisticRegression
LogisticRegression()
```

📊 Step 5: Evaluate the Model

In [12]:
```
# Predict
y_pred = model.predict(X_test_scaled)
```

In [13]:
```
# Evaluate
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
```

In [14]:
```
print("Accuracy:", accuracy)
print("\nClassification Report:\n", report)
```

```
Accuracy: 0.824390243902439

Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.74      0.81       102
           1       0.78      0.91      0.84       103

    accuracy                           0.82       205
   macro avg       0.83      0.82      0.82       205
weighted avg       0.83      0.82      0.82       205
```

📊 Step 6: Save the Model

In [15]:
```
joblib.dump(model, 'heart_model.joblib')
```

Out[15]:
```
['heart_model.joblib']
```

✅ Done! You've built a working heart disease predictor!