

adaboost

January 23, 2025

```
[1]: import pandas as pd
import numpy
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import accuracy_score, classification_report, \
    ↪confusion_matrix, mean_squared_error, mean_absolute_error, r2_score
from sklearn.ensemble import HistGradientBoostingRegressor

[2]: # Load Titanic dataset
data = pd.read_csv("C:/Users/91703/OneDrive/Desktop/TITANIC.csv")

[3]: # Select relevant columns and convert categorical variables
data = data[['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']]
data['Sex'] = data['Sex'].map({'male': 0, 'female': 1})

[4]: # Handle missing Age values
data['Age'] = pd.to_numeric(data['Age'], errors='coerce')
data['Age'] = data['Age'].fillna(data['Age'].mean())

[5]: # Define target variable (y) and feature variables (X)
y = data['Survived']
X = data[['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']]

[6]: # Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, \
    ↪random_state=42)

[7]: # Create and train AdaBoost Classifier model
model = AdaBoostClassifier(DecisionTreeClassifier(max_depth=1), \
    ↪n_estimators=100, random_state=42, algorithm="SAMME")
model.fit(X_train, y_train)
```

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[7]: AdaBoostClassifier(algorithm='SAMME',
                        estimator=DecisionTreeClassifier(max_depth=1),
                        n_estimators=100, random_state=42)
```

```
[8]: # Make predictions on test data
y_pred = model.predict(X_test)
print(y_pred)
```

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[0 0 0 1 1 1 1 0 1 1 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 1 0 1 0 1 0 0 0
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```

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[9]: # Evaluate model performance
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
```

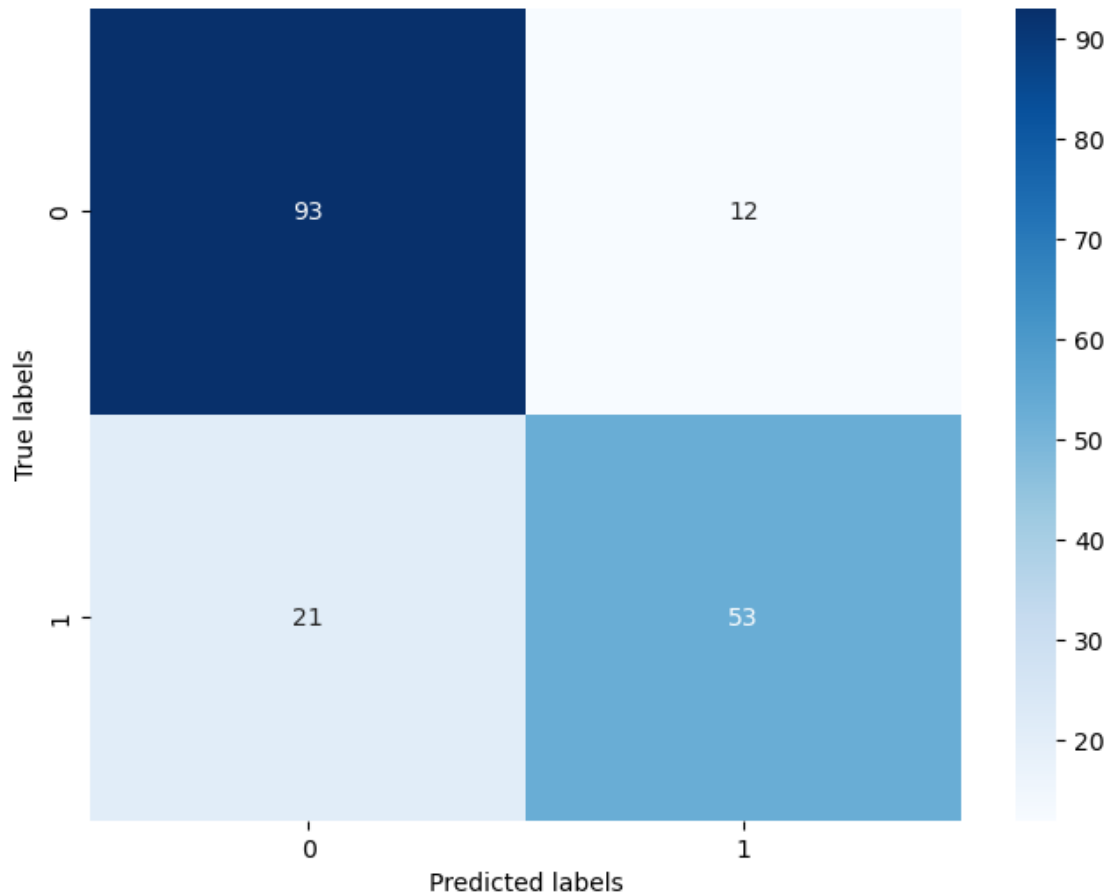
Accuracy: 0.8156424581005587

Classification Report:

	precision	recall	f1-score	support
0	0.82	0.89	0.85	105
1	0.82	0.72	0.76	74
accuracy			0.82	179
macro avg	0.82	0.80	0.81	179
weighted avg	0.82	0.82	0.81	179

Confusion Matrix: [[93 12]
[21 53]]

```
[10]: # Plot Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap='Blues')
plt.xlabel("Predicted labels")
plt.ylabel("True labels")
plt.show()
```



```
[11]: # Select relevant columns and convert categorical variables
data = data[['Age', 'Pclass', 'Sex', 'SibSp', 'Parch', 'Fare']]
data['Sex'] = data['Sex'].map({'male': 0, 'female': 1})
```

```
[12]: # Handle missing values
data['Age'] = pd.to_numeric(data['Age'], errors='coerce')
data['Age'] = data['Age'].fillna(data['Age'].mean())
```

```
[13]: # Define target variable (y) and feature variables (X)
y = data['Age']
X = data[['Pclass', 'Sex', 'SibSp', 'Parch', 'Fare']]
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='mean')
data[['Pclass', 'SibSp', 'Parch', 'Fare']] = imputer.
    ↪fit_transform(data[['Pclass', 'SibSp', 'Parch', 'Fare']])
```

```
[14]: # Split data into training and testing sets
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X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)
```

```
[15]: # Create and train AdaBoost Regressor model
model = AdaBoostRegressor(DecisionTreeRegressor(max_depth=1), n_estimators=100,
↳random_state=42)
model = HistGradientBoostingRegressor()
model.fit(X_train, y_train)
```

```
[15]: HistGradientBoostingRegressor()
```

```
[16]: # Make predictions on test data
y_pred = model.predict(X_test)
print(y_pred)
```

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[20.37925076 33.03821441 29.79172696 27.6594605 16.49529091 34.31836463
32.24422894 24.67750644 32.24422894 33.51014658 32.93673764 29.68526189
23.38691519 28.9880119 32.1189735 34.09219567 38.02548303 26.38266897
32.1189735 32.86371629 29.34245504 49.00648239 24.08712432 26.77258367
28.22043433 13.29237003 38.58744356 32.1189735 13.29237003 26.38266897
29.34245504 32.24422894 39.12397318 27.05475416 29.68526189 27.60067185
40.68438883 32.24422894 40.14277115 29.34245504 30.16371881 23.57538821
29.68526189 32.24422894 20.65461021 29.80447322 29.68526189 26.77258367
27.35841301 25.68450682 7.33325263 40.54374157 31.78761847 28.48274527
32.24422894 36.39211919 33.03821441 35.07391897 34.20581694 28.48425678
28.12148944 25.9826291 30.70754768 44.37444736 32.24422894 33.03821441
29.8548642 28.48425678 14.08292954 45.03929936 22.48865568 27.78672487
39.58705861 41.12819225 26.38266897 31.1238285 32.24422894 27.31506529
32.1189735 26.28073497 7.80596643 33.03821441 35.68660461 27.23891341
39.12397318 32.65912497 31.96873732 29.84631218 36.72753822 29.88810389
26.28073497 5.79743052 42.56761717 26.34420585 29.34245504 26.38266897
38.02548303 29.68526189 32.1189735 29.34245504 39.27928969 31.13661898
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32.1189735 32.41152836 32.82653263 39.79139979 33.03821441 43.20984628
29.34245504 27.35841301 39.46216674 21.96621512 43.954191 20.37925076
31.13661898 28.9880119 32.49929883 33.03821441 18.62755246]
```

```
[17]: # Evaluate model performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse)
print("Mean Absolute Error:", mae)
print("R-squared:", r2)
```

Mean Squared Error: 127.75959541084642
Mean Absolute Error: 8.550550712237309
R-squared: 0.24541436874490408

```
[18]: # Plot predicted vs actual values
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred)
plt.xlabel("Actual Age")
plt.ylabel("Predicted Age")
plt.show()
```

