

mubx98vlp

January 23, 2025

```
[29]: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, \
    confusion_matrix
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns
```

```
[30]: # Load Titanic dataset
data = pd.read_csv(r"C:\Users\91703\OneDrive\Desktop\TITANIC.csv")
```

```
[31]: data.head()
```

```
[31]:
```

	PassengerId	Survived	Pclass	\
0	1	0	3	
1	2	1	1	
2	3	1	3	
3	4	1	1	
4	5	0	3	

	Name	Sex	Age	SibSp	\
0	Braund, Mr. Owen Harris	male	22.0	1	
1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	
2	Heikkinen, Miss. Laina	female	26.0	0	
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	
4	Allen, Mr. William Henry	male	35.0	0	

	Parch	Ticket	Fare	Cabin	Embarked
0	0	A/5 21171	7.2500	NaN	S
1	0	PC 17599	71.2833	C85	C
2	0	STON/O2. 3101282	7.9250	NaN	S
3	0	113803	53.1000	C123	S
4	0	373450	8.0500	NaN	S

```
[32]: # 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})
```

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

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

```
[35]: # 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)
```

```
[36]: # Create and train SVM Classifier model
model = SVC(kernel='rbf', C=1, random_state=42)
model.fit(X_train, y_train)
```

```
[36]: SVC(C=1, random_state=42)
```

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

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

```
[38]: # 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))
```

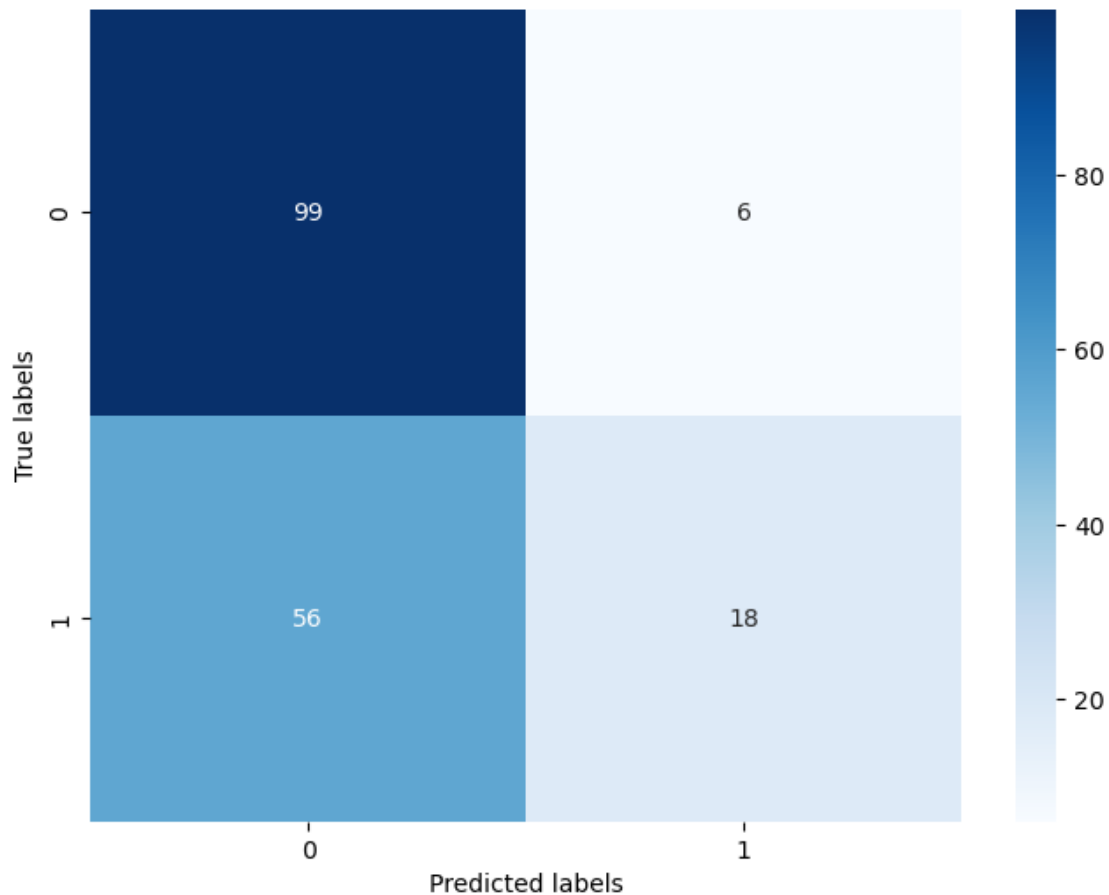
Accuracy: 0.6536312849162011

Classification Report:

	precision	recall	f1-score	support
0	0.64	0.94	0.76	105
1	0.75	0.24	0.37	74
accuracy			0.65	179
macro avg	0.69	0.59	0.56	179
weighted avg	0.68	0.65	0.60	179

Confusion Matrix: $\begin{bmatrix} 99 & 6 \\ 56 & 18 \end{bmatrix}$

```
[39]: # 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()
```



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

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

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

```
[43]: # Create and train SVM Regressor model
from sklearn.svm import SVR
model = SVR(kernel='linear', C=1, epsilon=0.1) #we can use all these
↳("linear", "rbf", 'poly', 'sigmoid')
model.fit(X_train, y_train)
```

```
[43]: SVR(C=1, kernel='linear')
```

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

```
[25.92974974 32.23856492 29.59949925 29.7741793 26.44052654 33.99114561
28.60763877 25.27021458 28.60763877 30.88964316 32.7688916 29.59969898
20.60911733 29.59838079 32.24255945 32.41935659 32.76801952 28.60776531
32.24255945 34.93982531 29.5994526 34.89916107 26.43511396 29.6015764
29.61000485 20.09583069 34.90103179 32.24255945 20.09583069 28.60780526
29.5994526 28.60763877 34.90578527 28.60731921 29.59969898 27.43724037
34.91346146 28.60763877 33.91469045 29.5994526 27.99384429 27.42540316
29.59969898 29.59921964 27.10959534 22.94280364 29.59987202 29.6015764
29.59810117 32.02022014 22.77188879 30.33310676 21.42370238 29.85827411
29.59921964 30.97491295 32.23856492 32.75189387 31.26376105 28.6078452
29.59925958 29.75260888 29.0990588 34.89816244 29.59921964 31.24698405
32.33922689 29.59941936 25.91694075 31.81752231 27.59030334 26.92148999
34.90467351 30.3165827 29.59938613 27.43899125 28.60763877 30.92673901
31.25097858 25.61004056 19.45072902 31.24698405 30.39861693 29.59919966
34.90578527 34.9358375 31.87345888 33.95612036 34.85673924 29.59842073
26.60212074 16.93695113 34.90838171 29.5991864 29.5994526 29.59938613
32.76713401 29.59969898 31.25097858 29.5994526 34.89828228 29.59822101
31.83799424 29.59810117 29.59969898 27.42656828 27.61107486 34.91825489
29.6020158 34.90627132 31.77555314 29.59842073 31.83483856 34.89874165
35.21110003 29.60256832 34.91211003 32.24235972 27.59509677 21.95122277
26.38602469 33.98705793 31.81702955 29.25061348 29.59842073 34.89916107
33.90658828 34.98328571 26.44566605 29.59969898 28.6078452 25.92974974
32.22178793 28.61518841 32.77500993 26.4456595 34.0423287 29.59925958
29.59890007 26.45100545 29.60031142 29.0990588 32.24255945 30.09063967
21.09801467 27.6006891 32.24255945 32.23856492 31.92657932 29.59969898
29.60075753 29.59881347 29.59929282 26.46115154 29.59969898 29.59810117
29.67710611 28.60769868 29.0990588 24.93857504 29.5983875 34.89916107
32.24255945 31.82376032 29.60035136 33.44701471 32.23856492 31.77533344
29.5994526 29.59810117 33.44921825 28.23346767 34.89890143 24.93816887
29.59822101 29.59838079 18.92893841 31.24698405 24.94049241]
```

```
[46]: # Evaluate model performance
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
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: 144.6838854003675
Mean Absolute Error: 8.772704271747479
R-squared: 0.14545454964701998

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

