

titanic

June 21, 2024

```
[6]: # Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix

# Load dataset
df = sns.load_dataset('titanic')

# EDA: Data Overview
print(df.head())
print(df.info())
print(df.describe())

# EDA: Missing Values
plt.figure(figsize=(10, 6))
sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
plt.title('Missing Values in Titanic Dataset')
plt.show()

# EDA: Categorical Variables
plt.figure(figsize=(12, 6))
sns.countplot(x='survived', data=df)
plt.title('Count of Survived vs. Not Survived')
plt.show()

plt.figure(figsize=(12, 6))
sns.countplot(x='pclass', hue='survived', data=df)
plt.title('Survival Count by Passenger Class')
plt.show()

plt.figure(figsize=(12, 6))
sns.countplot(x='sex', hue='survived', data=df)
plt.title('Survival Count by Gender')
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plt.show()

plt.figure(figsize=(12, 6))
sns.boxplot(x='survived', y='age', data=df)
plt.title('Age Distribution by Survival')
plt.show()

# EDA: Pair Plot
sns.pairplot(df.dropna(), hue='survived', vars=['age', 'fare', 'pclass', 'sibsp', 'parch'])
plt.show()

# Feature Engineering
# Fill missing values
df['age'].fillna(df['age'].median(), inplace=True)
df['embarked'].fillna(df['embarked'].mode()[0], inplace=True)

# Add 'Unknown' category to 'deck' and fill missing values
df['deck'] = df['deck'].cat.add_categories('Unknown')
df['deck'].fillna('Unknown', inplace=True)

# Convert categorical variables to numerical
df = pd.get_dummies(df, columns=['sex', 'embarked', 'deck', 'class', 'who', 'adult_male', 'embark_town', 'alive', 'alone'], drop_first=True)

# Drop irrelevant columns
df.drop(columns=['passenger_id', 'name', 'ticket', 'fare'], inplace=True)

# Split dataset into features and target variable
X = df.drop(columns=['survived'])
y = df['survived']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Hyperparameter tuning using GridSearchCV
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth': [4, 6, 8],
    'criterion': ['gini', 'entropy']
}

rf = RandomForestClassifier(random_state=42)
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1, verbose=2)

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grid_search.fit(X_train, y_train)

print(f'Best Parameters: {grid_search.best_params_}')

# Train model with best parameters
best_rf = grid_search.best_estimator_
best_rf.fit(X_train, y_train)

# Predict and evaluate
y_pred = best_rf.predict(X_test)
print(classification_report(y_test, y_pred))

# Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

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	survived	pclass	sex	age	sibsp	parch	fare	embarked	class \
0	0	3	male	22.0	1	0	7.2500	S	Third
1	1	1	female	38.0	1	0	71.2833	C	First
2	1	3	female	26.0	0	0	7.9250	S	Third
3	1	1	female	35.0	1	0	53.1000	S	First
4	0	3	male	35.0	0	0	8.0500	S	Third

	who	adult_male	deck	embark_town	alive	alone
0	man	True	NaN	Southampton	no	False
1	woman	False	C	Cherbourg	yes	False
2	woman	False	NaN	Southampton	yes	True
3	woman	False	C	Southampton	yes	False
4	man	True	NaN	Southampton	no	True

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 891 entries, 0 to 890

Data columns (total 15 columns):

#	Column	Non-Null Count	Dtype
0	survived	891 non-null	int64
1	pclass	891 non-null	int64
2	sex	891 non-null	object
3	age	714 non-null	float64
4	sibsp	891 non-null	int64
5	parch	891 non-null	int64
6	fare	891 non-null	float64
7	embarked	889 non-null	object
8	class	891 non-null	category

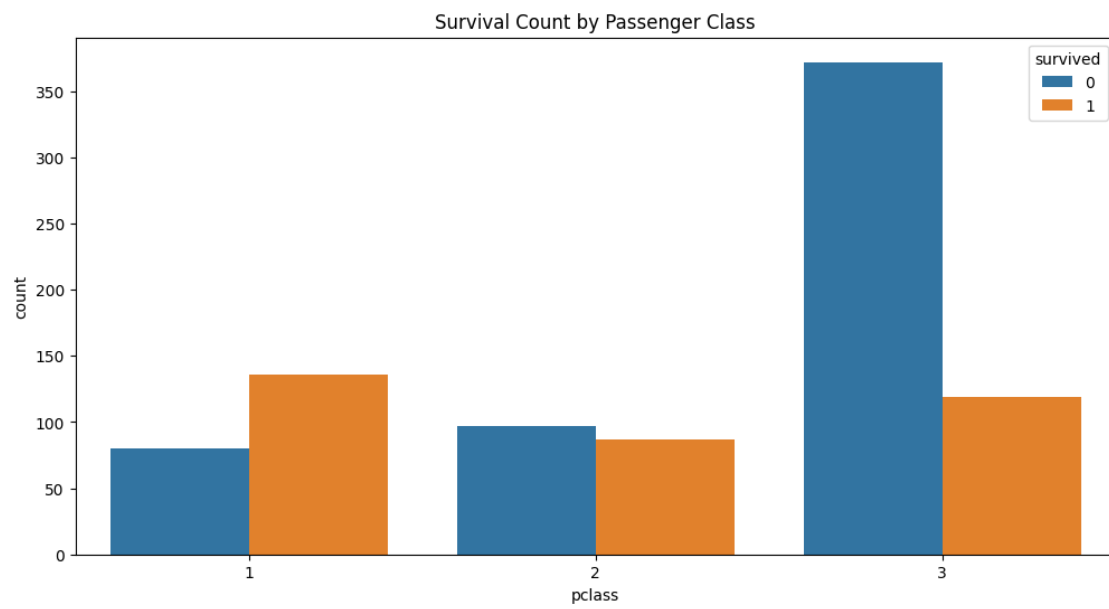
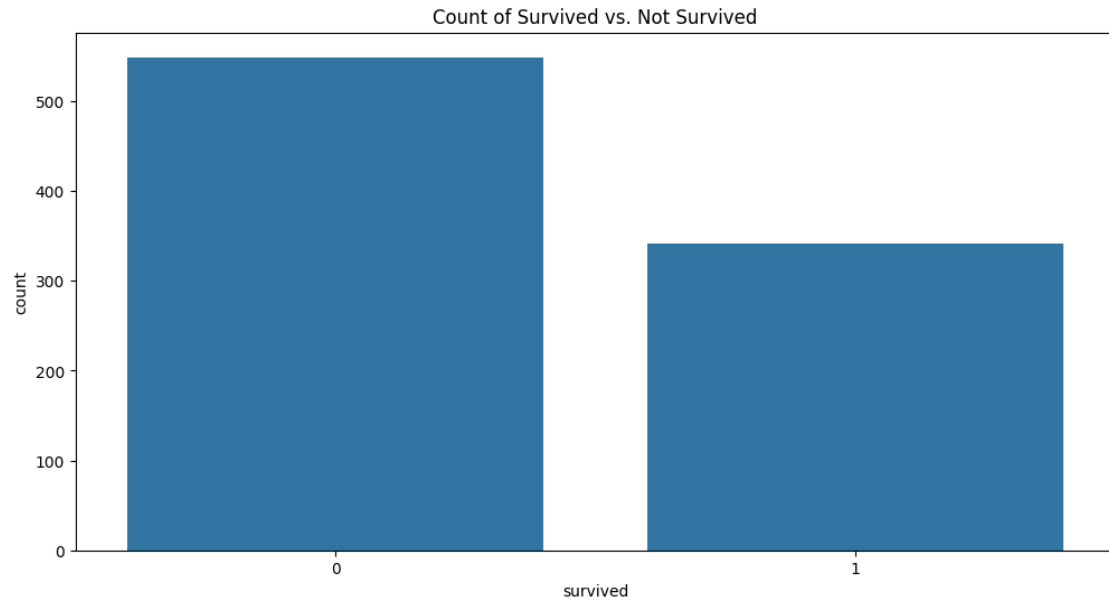
```

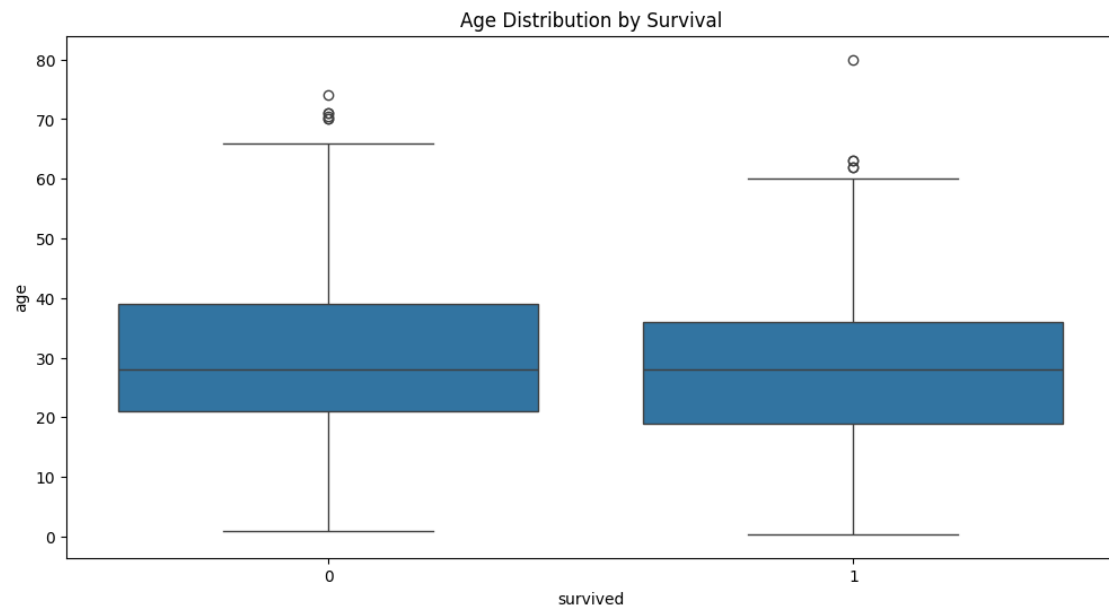
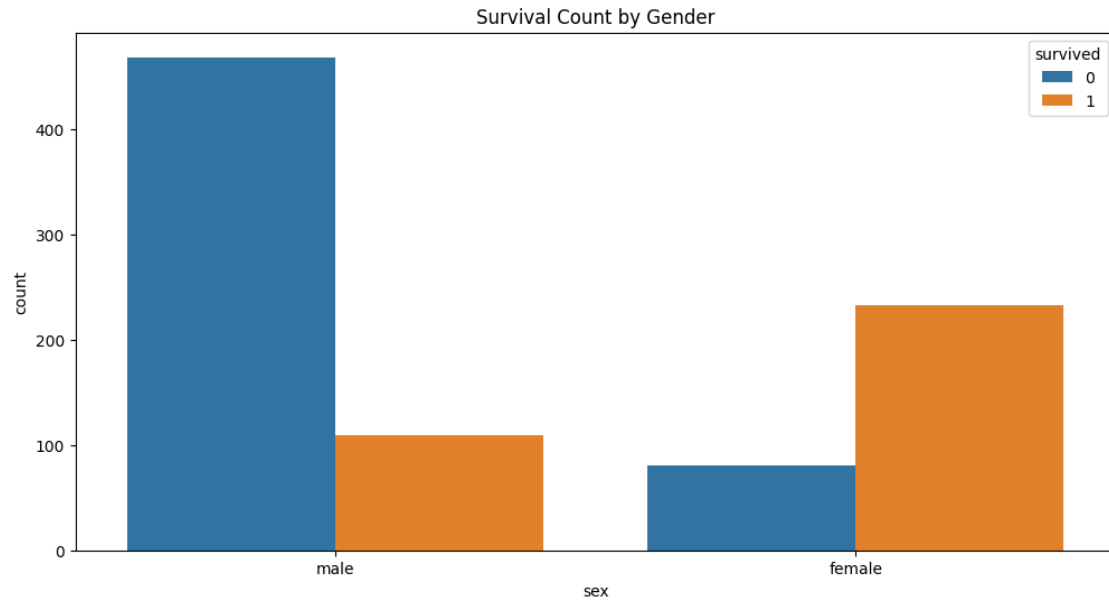
9   who          891 non-null   object
10  adult_male    891 non-null   bool
11  deck          203 non-null   category
12  embark_town   889 non-null   object
13  alive         891 non-null   object
14  alone         891 non-null   bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
None

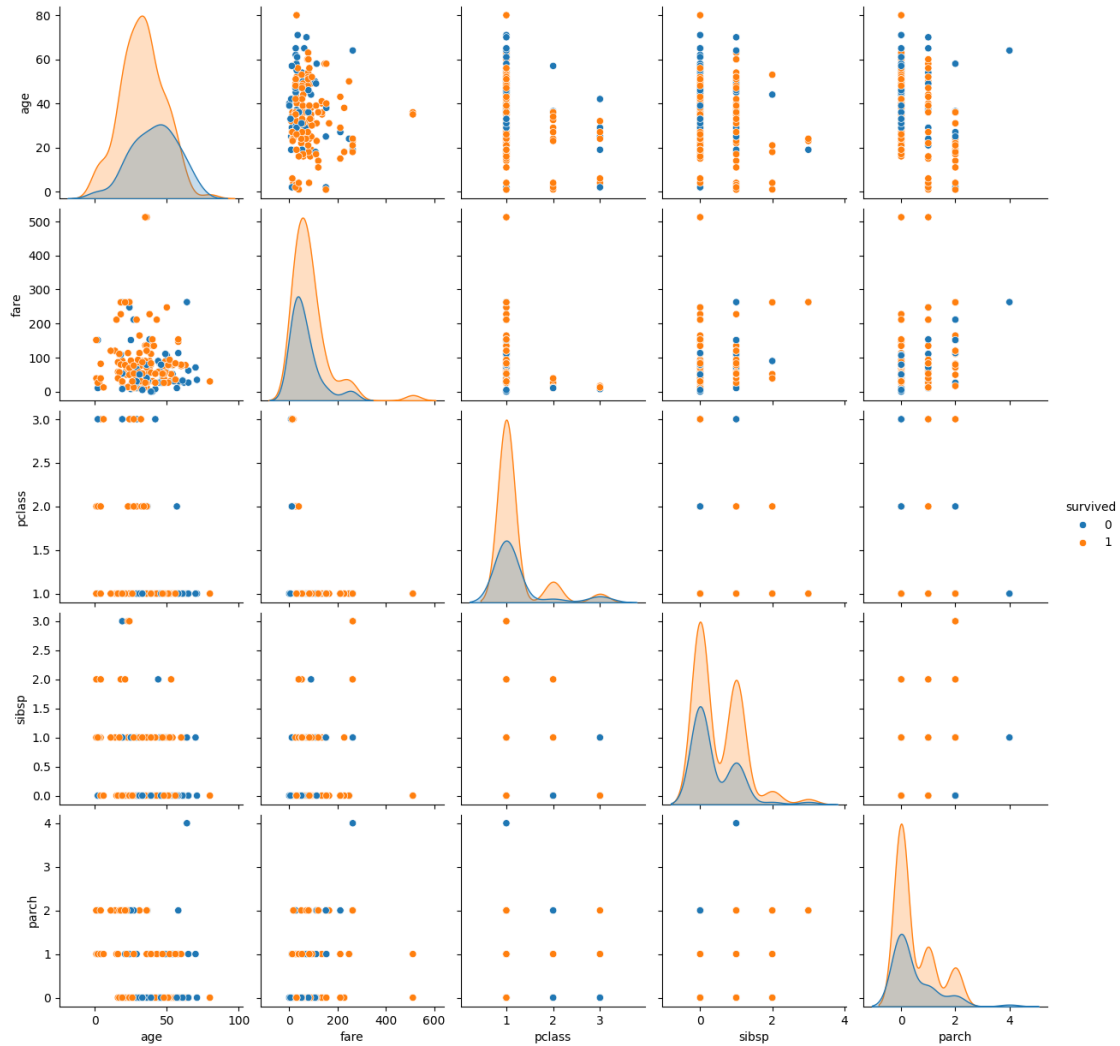
```

	survived	pclass	age	sibsp	parch	fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200









Fitting 5 folds for each of 54 candidates, totalling 270 fits

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_forest.py:424:
FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be
removed in 1.3. To keep the past behaviour, explicitly set `max_features='sqrt'`
or remove this parameter as it is also the default value for
RandomForestClassifiers and ExtraTreesClassifiers.
warn(
```

```
Best Parameters: {'criterion': 'gini', 'max_depth': 8, 'max_features': 'auto',
'n_estimators': 200}
```

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```

```
warn(
      precision    recall  f1-score   support

     0       1.00      1.00      1.00     105
     1       1.00      1.00      1.00      74

 accuracy              1.00         179
 macro avg           1.00         179
 weighted avg        1.00         179
```

