eda

April 14, 2025

[10]:
```python
import pandas as pd

df = pd.read_csv('task5.csv')  # assuming Titanic dataset
```

[12]:
```python
df.info()
df.describe()
df.isnull().sum()
df.nunique()
df['Survived'].value_counts()
```

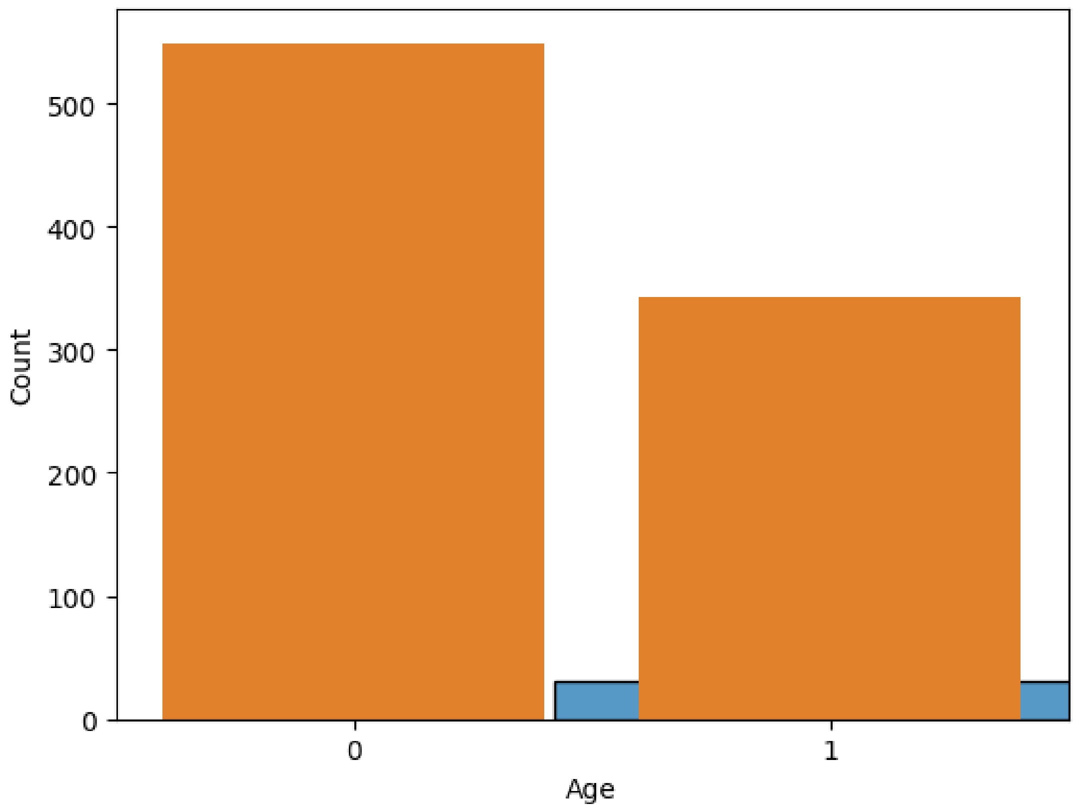
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[12]:
```
Survived
0    549
1    342
Name: count, dtype: int64
```

[16]:
```python
df['Age'] = df['Age'].fillna(df['Age'].median())
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])
```

[18]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

sns.histplot(df['Age'])
sns.countplot(x='Survived', data=df)

#Observation:
#The number of passengers who did not survive is higher than those who did.␣
↪This indicates a survival rate of less than 50%.
```

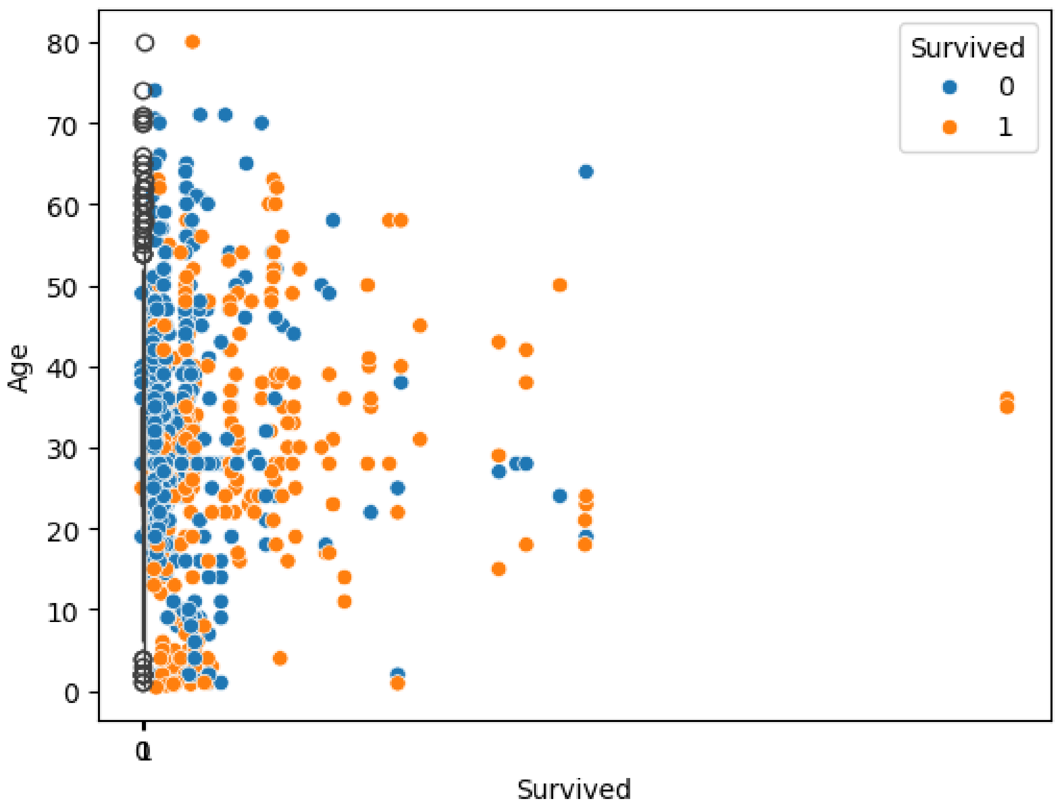
[18]: <Axes: xlabel='Age', ylabel='Count'>



[19]:
```python
sns.boxplot(x='Survived', y='Age', data=df)
sns.scatterplot(x='Fare', y='Age', hue='Survived', data=df)

#"Observation:

#The median age of survivors and non-survivors appears fairly similar,␣
↪suggesting that age alone was not a strong determinant of survival.
```

```
#However, non-survivors have a slightly wider age spread, with more elderly␣
↪individuals compared to survivors.

#There are more outliers among the survivors in the lower age range, indicating␣
↪that several young children managed to survive.

#Overall, younger passengers (especially children) had a relatively better␣
↪chance of survival, though the trend isn't very strong.
```

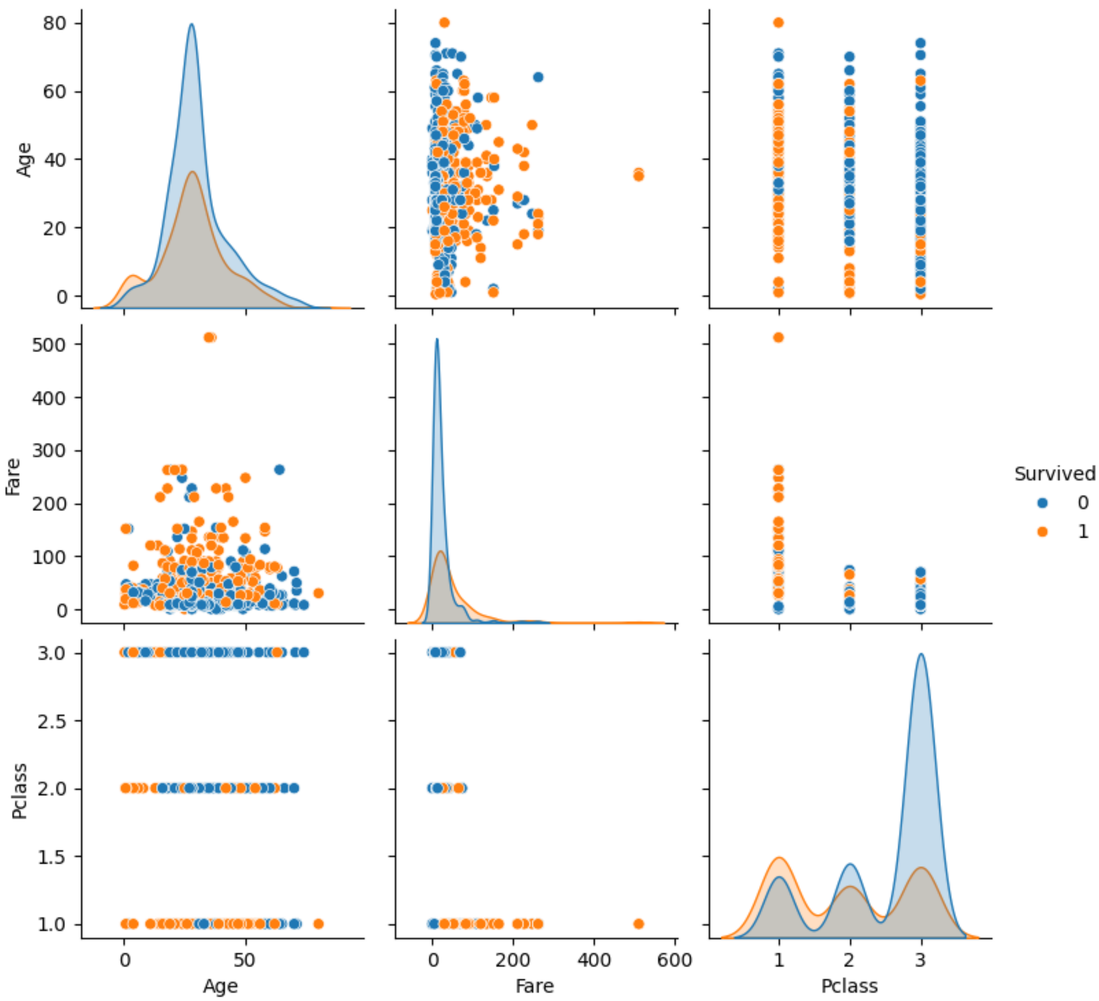
[19]: <Axes: xlabel='Survived', ylabel='Age'>



[22]:
```
sns.pairplot(df[['Survived', 'Age', 'Fare', 'Pclass']], hue='Survived')

##Observation:

#Distribution and Clustering:
```

```
#The pairplot clearly shows that survivors and non-survivors tend to occupy
 ↪different regions in the feature space. For instance, when looking at the
 ↪scatter plots, there are noticeable clusters where survivors tend to have
 ↪lower values for Pclass (indicating higher classes) and often higher fares,
 ↪whereas non-survivors are more prevalent in the higher Pclass (lower
 ↪classes) with relatively lower fares.

#Age Impact:
#The distribution of Age across survivors and non-survivors shows a significant
 ↪overlap, meaning that while age plays some role, it is not as distinctive a
 ↪feature for survival as class or fare. However, in some plots you might
 ↪notice survivors having a slightly higher density at younger ages, which
 ↪could hint at a survival benefit for children.

#Inter-feature Relationships:
#The diagonal plots (i.e., the histograms) provide insight into the individual
 ↪distributions of each variable. You can see that Fare is particularly
 ↪skewed, which supports the need for additional steps like log transformation
 ↪if you wish to conduct more rigorous analyses later on. The scatter plot
 ↪between Fare and Pclass reinforces the idea of a relationship where higher
 ↪fares often correspond to lower Pclass values (higher socio-economic status).

#Overall Insights:
#The multivariate analysis indicates that socio-economic status (as reflected
 ↪by Pclass and Fare) is more strongly linked to survival outcomes than age
 ↪alone. This observation aligns with historical context about the Titanic,
 ↪where higher-class passengers had better access to lifeboats and safer
 ↪quarters.
```

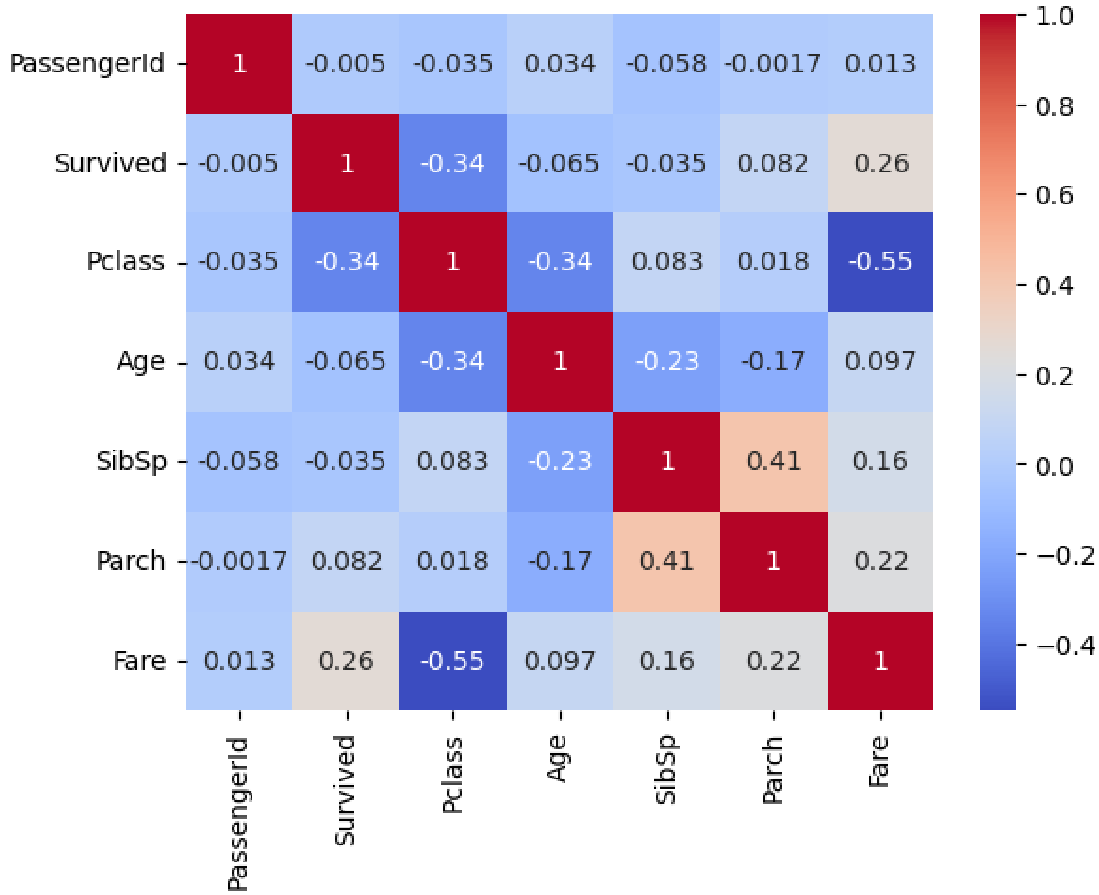
[22]: <seaborn.axisgrid.PairGrid at 0x1d541cd6de0>



[26]:
```
corr = df.select_dtypes(include='number').corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')

#Observation:

#Correlation Strengths:
#The heatmap reveals that some numerical variables are strongly correlated with each other, while others have a weak or negligible relationship. For example, there is a notable negative correlation between Pclass and Survived, suggesting that higher-class passengers (lower Pclass values) had a higher chance of survival.

#Fare and Survival:
```

```
#The correlation between Fare and Survived is positive, indicating that
↪passengers who paid higher fares (likely from higher classes) were more
↪likely to survive. However, the correlation strength may not be as high as
↪the relationship between Pclass and Survived.

#Age Factor:
#Age shows a relatively weak correlation with Survived, implying that while age
↪might have some influence on survival outcomes, it is less definitive
↪compared to socio-economic indicators like Pclass and Fare.

#Other Relationships:
# how some numeric features, such as Fare and Pclass, are inversely related.
↪This reinforces the idea that passengers in the first class (with lower
↪Pclass values) paid higher fares, which aligns with historical observations
↪from the Titanic dataset.
```

[26]: <Axes: >



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[ ]:
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