In [6]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from warnings import filterwarnings
filterwarnings('ignore')
```

In [7]:
```python
titanic = sns.load_dataset('titanic')
```

In [8]:
```python
titanic
```

Out[8]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	Fal
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	Fal
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	Tr
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	Fal
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	Tr
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True	NaN	Southampton	no	Tr
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False	B	Southampton	yes	Tr
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False	NaN	Southampton	no	Fal
889	1	1	male	26.0	0	0	30.0000	C	First	man	True	C	Cherbourg	yes	Tr
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True	NaN	Queenstown	no	Tr

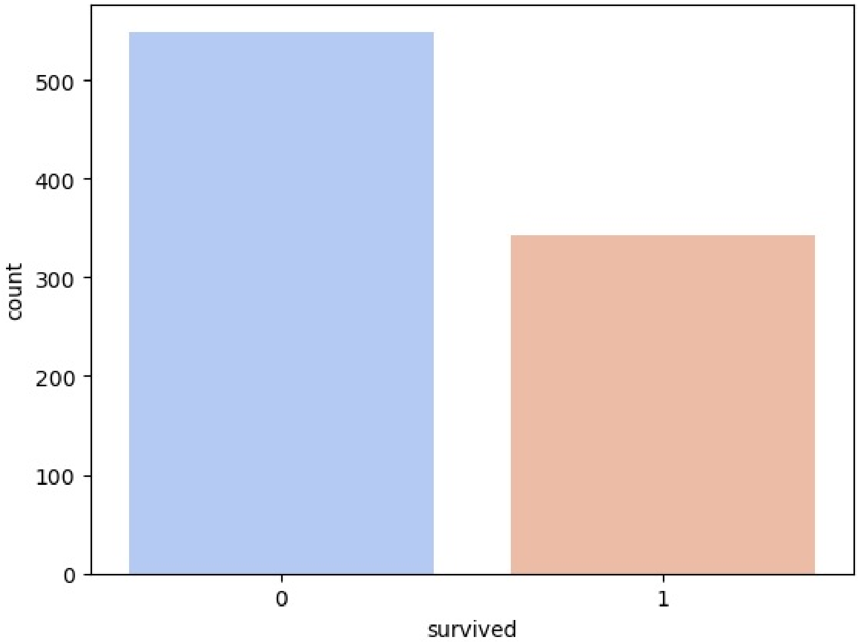
891 rows × 15 columns

In [51]:
```python
titanic.survived.value_counts(normalize=True)*100
```

Out[51]:
```
survived
0    61.616162
1    38.383838
Name: proportion, dtype: float64
```

In [160…
```python
sns.countplot(x='survived', data=titanic, palette='coolwarm')
```

Out[160…
```
<Axes: xlabel='survived', ylabel='count'>
```



In [9]:
```python
titanic.info()
```

```
<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
```

In [98]:
```
titanic.shape
```

Out[98]:
```
(891, 15)
```

In [46]:
```
titanic.describe()
```

Out[46]:

	survived	pclass	age	sibsp	parch	fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.361582	0.523008	0.381594	32.204208
std	0.486592	0.836071	13.019697	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	22.000000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	35.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [11]:
```
titanic.isnull().sum()
```

Out[11]:
```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [13]:
```
titanic[titanic.age.isnull()]
```

Out[13]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo
5	0	3	male	NaN	0	0	8.4583	Q	Third	man	True	NaN	Queenstown	no	Tr
17	1	2	male	NaN	0	0	13.0000	S	Second	man	True	NaN	Southampton	yes	Tr
19	1	3	female	NaN	0	0	7.2250	C	Third	woman	False	NaN	Cherbourg	yes	Tr
26	0	3	male	NaN	0	0	7.2250	C	Third	man	True	NaN	Cherbourg	no	Tr
28	1	3	female	NaN	0	0	7.8792	Q	Third	woman	False	NaN	Queenstown	yes	Tr
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
859	0	3	male	NaN	0	0	7.2292	C	Third	man	True	NaN	Cherbourg	no	Tr
863	0	3	female	NaN	8	2	69.5500	S	Third	woman	False	NaN	Southampton	no	Fal
868	0	3	male	NaN	0	0	9.5000	S	Third	man	True	NaN	Southampton	no	Tr
878	0	3	male	NaN	0	0	7.8958	S	Third	man	True	NaN	Southampton	no	Tr
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False	NaN	Southampton	no	Fal

177 rows × 15 columns

In [18]:

```
titanic.age.fillna(titanic.age.median(),inplace=True)
```

In [19]:

```
titanic.isnull().sum()
```

Out[19]:

```
survived         0
pclass           0
sex              0
age              0
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

Deck Nan

In [21]:

```
titanic[titanic.deck.isnull()]
```

Out[21]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	Fal
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	Tr
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	Tr
5	0	3	male	28.0	0	0	8.4583	Q	Third	man	True	NaN	Queenstown	no	Tr
7	0	3	male	2.0	3	1	21.0750	S	Third	child	False	NaN	Southampton	no	Fal
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
884	0	3	male	25.0	0	0	7.0500	S	Third	man	True	NaN	Southampton	no	Tr
885	0	3	female	39.0	0	5	29.1250	Q	Third	woman	False	NaN	Queenstown	no	Fal
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True	NaN	Southampton	no	Tr
888	0	3	female	28.0	1	2	23.4500	S	Third	woman	False	NaN	Southampton	no	Fal
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True	NaN	Queenstown	no	Tr

688 rows × 15 columns

In [31]:

```
titanic['deck'].fillna(titanic['deck'].mode()[0], inplace=True)
```

In [32]:

```
titanic.isnull().sum()
```

Out[32]:
```
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       2
class          0
who            0
adult_male     0
deck           0
embark_town    2
alive          0
alone          0
dtype: int64
```

embarked NaN

In [38]:
```
titanic[titanic.embarked.isnull()]
```

Out[38]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
61	1	1	female	38.0	0	0	80.0	NaN	First	woman	False	B	NaN	yes	True
829	1	1	female	62.0	0	0	80.0	NaN	First	woman	False	B	NaN	yes	True

In [40]:
```
titanic.embarked.fillna(titanic.embarked.mode()[0],inplace=True)
```

In [41]:
```
titanic.isnull().sum()
```

Out[41]:
```
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       0
class          0
who            0
adult_male     0
deck           0
embark_town    2
alive          0
alone          0
dtype: int64
```

embark_town NaN

In [43]:
```
titanic[titanic.embark_town.isnull()]
```

Out[43]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
61	1	1	female	38.0	0	0	80.0	S	First	woman	False	B	NaN	yes	True
829	1	1	female	62.0	0	0	80.0	S	First	woman	False	B	NaN	yes	True

In [44]:
```
titanic.embark_town.fillna(titanic.embark_town.mode()[0],inplace=True)
```

In [45]:
```
titanic.isnull().sum()
```

Out[45]:
```
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       0
class          0
who            0
adult_male     0
deck           0
embark_town    0
alive          0
alone          0
dtype: int64
```

Encoding categorical variable 'sex'

In [58]:
```
titanic
```

Out[58]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	C	Southampton	no	Fal
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	Fal
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	C	Southampton	yes	Tr
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	Fal
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	C	Southampton	no	Tr
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True	C	Southampton	no	Tr
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False	B	Southampton	yes	Tr
888	0	3	female	28.0	1	2	23.4500	S	Third	woman	False	C	Southampton	no	Fal
889	1	1	male	26.0	0	0	30.0000	C	First	man	True	C	Cherbourg	yes	Tr
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True	C	Queenstown	no	Tr

891 rows × 15 columns

In [57]:
```
from sklearn.preprocessing import OneHotEncoder
```

In [66]:
```
titanic.columns
```

Out[66]:
```
Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
       'embarked', 'class', 'who', 'adult_male', 'deck', 'embark_town',
       'alive', 'alone'],
      dtype='object')
```

In [114...

Data Split

In [135...
```
X = titanic[['pclass','sex','age','fare']]
y = titanic['survived']
 # Encoding categorical variable 'sex'
encoder = OneHotEncoder(drop='first', sparse_output=False)
X_encoded = encoder.fit_transform(X[['sex']])
X_final = np.concatenate([X[['pclass','age','fare']].values, X_encoded], axis=1)
```

In [137...
```
from sklearn.model_selection import train_test_split
```

In [138...
```
X_train,X_test,y_train,y_test = train_test_split(X_final,y,test_size=0.2,random_state=42)
```

In [139...
```
print("X_train shape :",X_train.shape)
print("y_train shape :",y_train.shape)

print('-'*30)

print("X_test shape :",X_test.shape)
print("y_test shape :",y_test.shape)
```

```
X_train shape : (712, 4)
y_train shape : (712,)
------------------------------
X_test shape : (179, 4)
y_test shape : (179,)
```

Model Buliding

In [140...
```
from sklearn.linear_model import LogisticRegression
```

In [141...
```
lr =LogisticRegression()
lr
```

Out[141...

▾ LogisticRegression

```
LogisticRegression()
```

In [142…
```
lr.fit(X_train,y_train)
```

Out[142…

▾ LogisticRegression

```
LogisticRegression()
```

In [143…
```
y_pred_lr =lr.predict(X_test)
```

In [144…
```
pd.DataFrame(y_pred_lr,columns=['Predicted'])
```

Out[144…

	Predicted
0	0
1	0
2	0
3	1
4	1
...	...
174	0
175	0
176	1
177	1
178	1

179 rows × 1 columns

In [145…
```
pd.DataFrame(y_test)
```

Out[145…

	survived
709	1
439	0
840	0
720	1
39	1
...	...
433	0
773	0
25	1
84	1
10	1

179 rows × 1 columns

In [146…
```
from sklearn.tree import DecisionTreeClassifier
```

In [147…
```
dt = DecisionTreeClassifier(max_depth=3,random_state=42)
```

In [148…
```
dt.fit(X_train,y_train)
```

Out[148…

▾ DecisionTreeClassifier

```
DecisionTreeClassifier(max_depth=3, random_state=42)
```

In [149…
```
y_pred_dt = dt.predict(X_test)
```

In [150…
```
pd.DataFrame(y_pred_dt,columns=['Predicted'])
```

Out[150…

	Predicted
0	0
1	0
2	0
3	1
4	1
...	...
174	0
175	0
176	0
177	1
178	1

179 rows × 1 columns

In [151…

```
pd.DataFrame(y_test)
```

Out[151…

	survived
709	1
439	0
840	0
720	1
39	1
...	...
433	0
773	0
25	1
84	1
10	1

179 rows × 1 columns

Evaluate Model

In [152…

```
from sklearn.metrics import confusion_matrix,accuracy_score,recall_score,f1_score
```

In [156…

```
print("Logistic Regression accuracy_score : ",accuracy_score(y_test,y_pred_lr))
print("Decision Tree accuracy_score : ",accuracy_score(y_test,y_pred_dt))
print('-'*80)
print("Logistic Regression f1_score : ",f1_score(y_test,y_pred_lr))
```

```
Logistic Regression accuracy_score :  0.8044692737430168
Decision Tree accuracy_score :  0.7988826815642458
--------------------------------------------------------------------------------
Logistic Regression f1_score :  0.7552447552447552
```

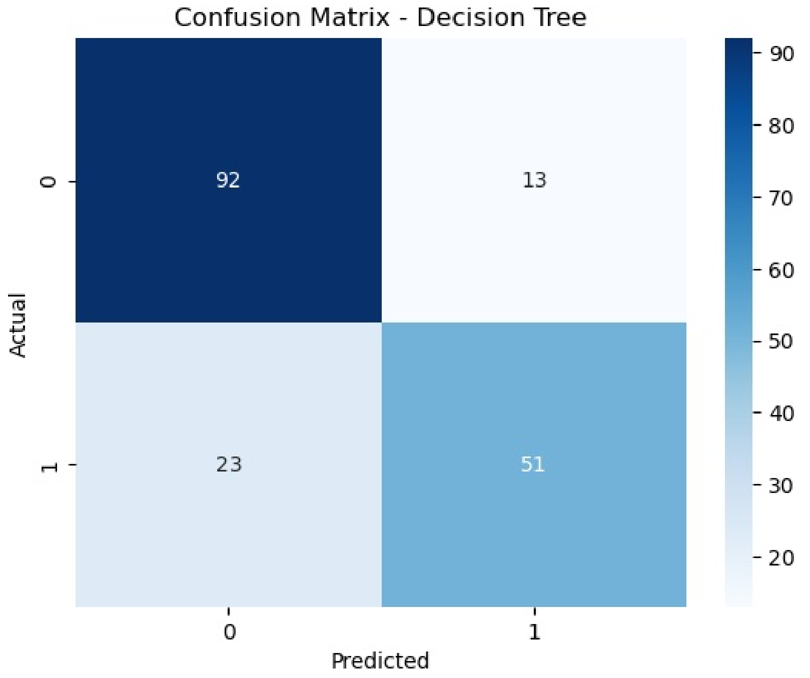
In [157…

```
print("Confusion Metrix :\n ",confusion_matrix(y_test,y_pred_dt))
```

```
Confusion Metrix :
  [[92 13]
 [23 51]]
```

In [155…

```
#Confusion Matrix Heatmap for Decision Tree
cm = confusion_matrix(y_test, y_pred_dt)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Decision Tree')
plt.show()
```


Confusion Matrix - Decision Tree
92
13
23
51
Actual
Predicted
0
1
0
1
90
80
70
60
50
40
30
20

In [ ]:

In [ ]: