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SECURITE RESEAU

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn

data = pd.read_csv('Titanic-Dataset - Titanic-Dataset.csv')

data.head()
```

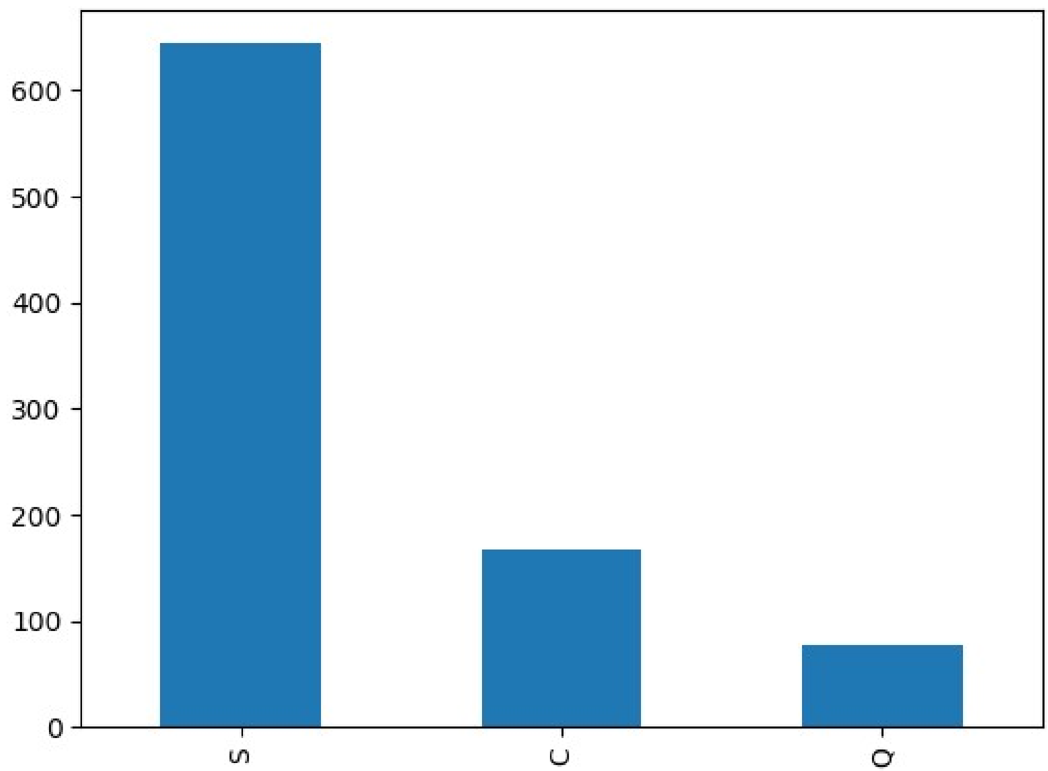
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                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
```

```
data.shape
```

```
(891, 12)
```

```
data.Embarked.value_counts().plot(kind='bar')
```

```
<Axes: >
```




```
#  2: Nettoyage des données

# Supprimez les colonnes non nécessaires, encodez les variables
catégoriques, et supprimez les valeurs manquantes
data = data.drop(['Name', 'Ticket', 'Cabin', 'PassengerId'], axis=1)
data = pd.get_dummies(data, columns=['Sex', 'Embarked'],
drop_first=True)
data = data.dropna()

data.head()
```

```
   Survived  Pclass   Age  SibSp  Parch     Fare  Sex_male  Embarked_Q
\
0         0       3  22.0      1      0   7.2500         1           0

1         1       1  38.0      1      0  71.2833         0           0

2         1       3  26.0      0      0   7.9250         0           0

3         1       1  35.0      1      0  53.1000         0           0

4         0       3  35.0      0      0   8.0500         1           0


   Embarked_S
0           1
```

```
1           0
2           1
3           1
4           1
```

```python
data.isnull().values.any()
```

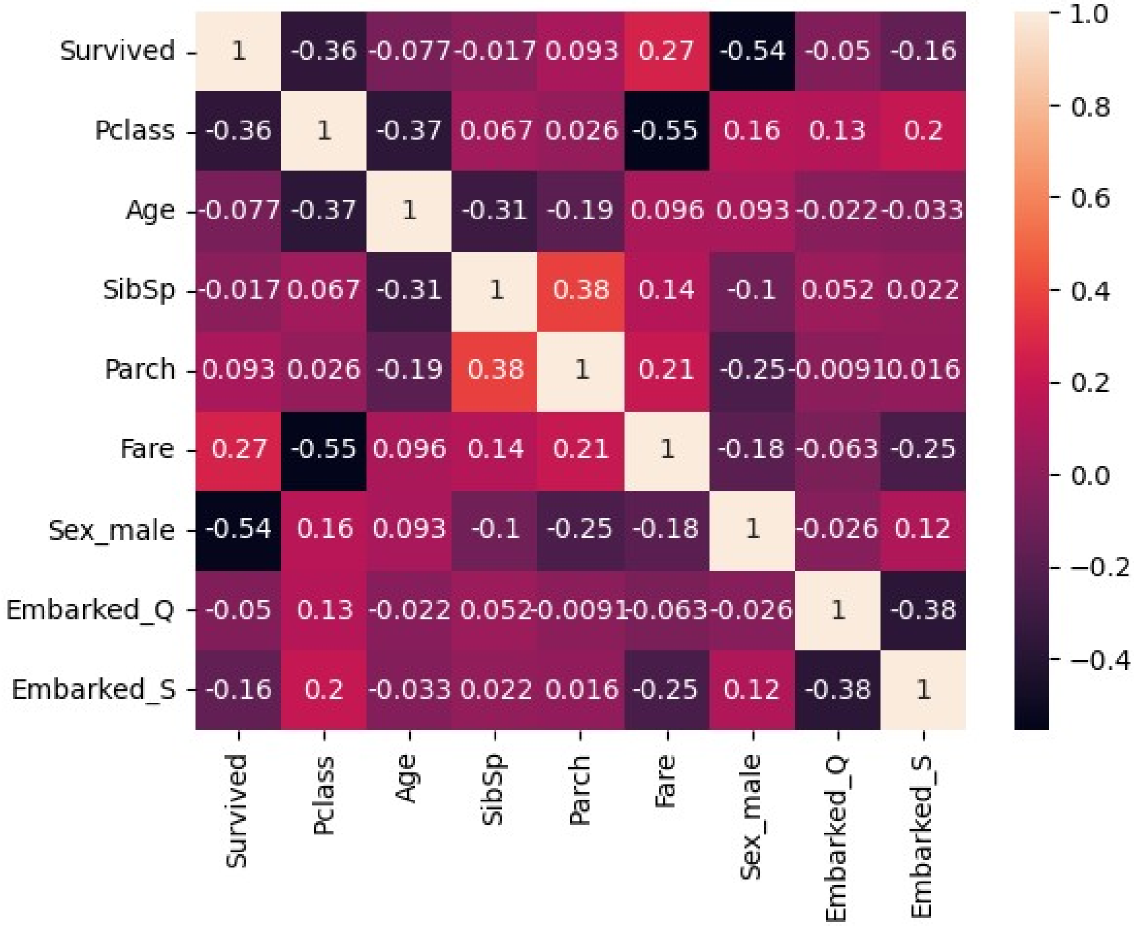
```
False
```

```python
data.corr()
```

```
            Survived    Pclass       Age     SibSp     Parch      Fare  \
Survived    1.000000 -0.359653 -0.077221 -0.017358  0.093317  0.268189   
Pclass     -0.359653  1.000000 -0.369226  0.067247  0.025683 -0.554182   
Age        -0.077221 -0.369226  1.000000 -0.308247 -0.189119  0.096067   
SibSp      -0.017358  0.067247 -0.308247  1.000000  0.383820  0.138329   
Parch       0.093317  0.025683 -0.189119  0.383820  1.000000  0.205119   
Fare        0.268189 -0.554182  0.096067  0.138329  0.205119  1.000000   
Sex_male   -0.538826  0.155460  0.093254 -0.103950 -0.246972 -0.184994   
Embarked_Q -0.049549  0.132415 -0.022405  0.051619 -0.009126 -0.062765   
Embarked_S -0.164235  0.203980 -0.032523  0.021751  0.015833 -0.253991   

            Sex_male  Embarked_Q  Embarked_S  
Survived   -0.538826   -0.049549   -0.164235  
Pclass      0.155460    0.132415    0.203980  
Age         0.093254   -0.022405   -0.032523  
SibSp      -0.103950    0.051619    0.021751  
Parch      -0.246972   -0.009126    0.015833  
Fare       -0.184994   -0.062765   -0.253991  
Sex_male    1.000000   -0.026440    0.115167  
Embarked_Q -0.026440    1.000000   -0.375934  
Embarked_S  0.115167   -0.375934    1.000000  
```

```python
sns.heatmap(data.corr(), annot=True)
```

```
<Axes: >
```




```
print(data.head(10))

   Survived  Pclass   Age  SibSp  Parch     Fare  Sex_male
Embarked_Q  \
0         0       3  22.0      1      0   7.2500         1
0
1         1       1  38.0      1      0  71.2833         0
0
2         1       3  26.0      0      0   7.9250         0
0
3         1       1  35.0      1      0  53.1000         0
0
4         0       3  35.0      0      0   8.0500         1
0
6         0       1  54.0      0      0  51.8625         1
0
7         0       3   2.0      3      1  21.0750         1
0
8         1       3  27.0      0      2  11.1333         0
0
9         1       2  14.0      1      0  30.0708         0
```

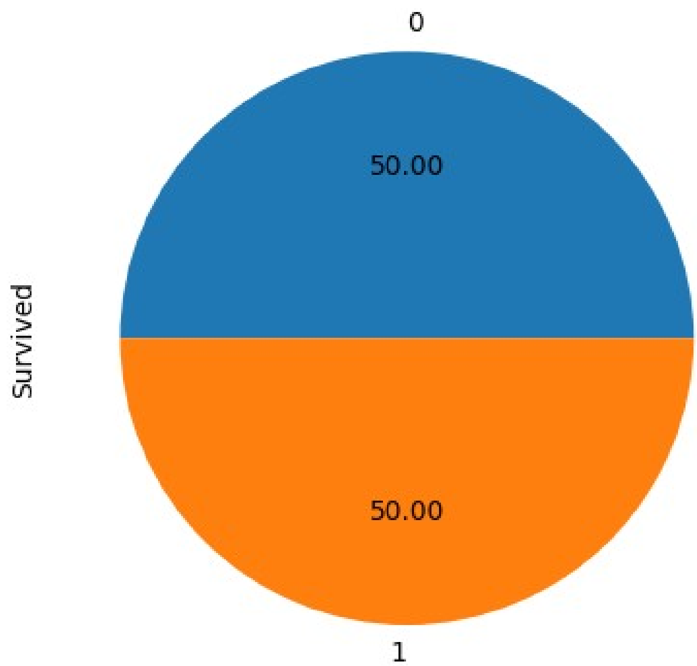
```
0
10          1       3   4.0      1      1  16.7000         0
0

    Embarked_S
0            1
1            0
2            1
3            1
4            1
6            1
7            1
8            1
9            0
10           1
```

```
#  3: Équilibrage de l'ensemble de données par sous-échantillonnage

from sklearn.utils import resample

# Séparez les classes majoritaires et minoritaires
majority_class = data[data['Survived'] == 0]
minority_class = data[data['Survived'] == 1]

# Sous-échantillonnage de la classe majoritaire
majority_downsampled = resample(majority_class, replace=False,
n_samples=len(minority_class), random_state=42)


# Fusionnez les classes équilibrées
data_balanced = pd.concat([majority_downsampled, minority_class])

# Vérifiez la distribution des classes après l'équilibrage
print(data_balanced['Survived'].value_counts())
```

```
0    290
1    290
Name: Survived, dtype: int64
```

```
print(data_balanced['Survived'].value_counts().plot.pie(autopct="%.2f"
))
```

```
Axes(0.22375,0.11;0.5775x0.77)
```

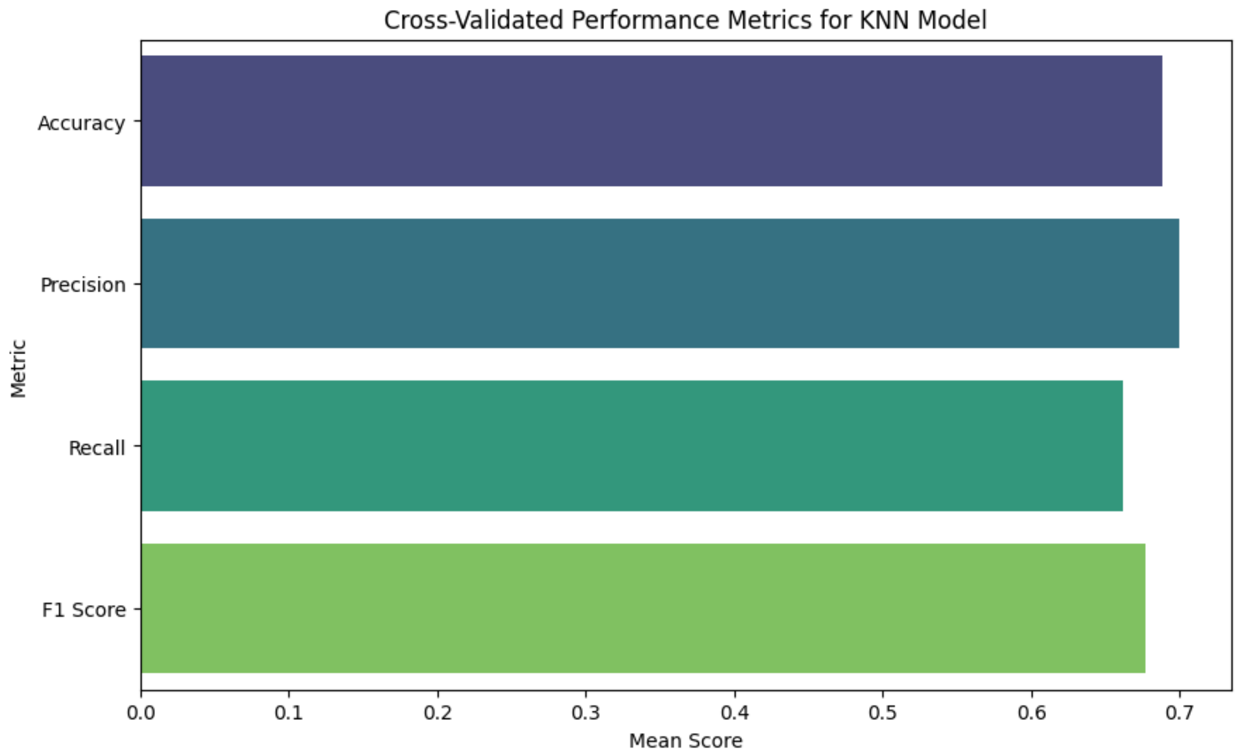



```
# 4: Créez un modèle KNN

from sklearn.neighbors import KNeighborsClassifier

X = data_balanced.drop('Survived', axis=1)
y = data_balanced['Survived']

# Initialisez le modèle KNN
knn_model = KNeighborsClassifier()

# 5: Évaluez le modèle avec la validation croisée

from sklearn.model_selection import cross_validate
from sklearn.metrics import precision_score, recall_score, f1_score,
accuracy_score
import numpy as np

# Définissez les métriques à évaluer
scoring = {'accuracy': 'accuracy',
           'precision': 'precision',
           'recall': 'recall',
           'f1': 'f1'}

# Effectuez la validation croisée
cv_results = cross_validate(knn_model, X, y, cv=5, scoring=scoring)

# Calculez les moyennes des métriques
```

```
accuracy_mean = np.mean(cv_results['test_accuracy'])
precision_mean = np.mean(cv_results['test_precision'])
recall_mean = np.mean(cv_results['test_recall'])
f1_mean = np.mean(cv_results['test_f1'])

# Affichez les résultats
print(f'Accuracy: {accuracy_mean}')
print(f'Precision: {precision_mean}')
print(f'Recall: {recall_mean}')
print(f'F1 Score: {f1_mean}')
```

```
Accuracy: 0.6879310344827586
Precision: 0.6995931307403759
Recall: 0.6620689655172414
F1 Score: 0.6774384121774
```

```
# 6: Visualisez les résultats de précision à l’aide d’un graphique

import matplotlib.pyplot as plt
import seaborn as sns

# Créez un DataFrame avec les résultats
results_df = pd.DataFrame({'Metric': ['Accuracy', 'Precision',
'Recall', 'F1 Score'],
                           'Mean Score': [accuracy_mean,
precision_mean, recall_mean, f1_mean]})

# Visualisez les résultats
plt.figure(figsize=(10, 6))
sns.barplot(x='Mean Score', y='Metric', data=results_df,
palette='viridis')
plt.title('Cross-Validated Performance Metrics for KNN Model')
plt.show()
```


Cross-Validated Performance Metrics for KNN Model
Accuracy
Precision
Recall
F1 Score
Metric
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Mean Score