Topic 2. Visual data analysis

Practice. Analyzing "Titanic" passengers

Fill in the missing code ("You code here").

Competition Kaggle "Titanic: Machine Learning from Disaster".

```
In [1]:
        import numpy as np
         import pandas as pd
         import seaborn as sns
         sns.set()
         import matplotlib.pyplot as plt
         Read data
In [2]:
        train df = pd.read csv("titanic train.csv", index col="PassengerId")
In [3]:
        train df.head(2)
                     Survived Pclass
Out[3]:
                                        Name
                                                 Sex Age SibSp Parch Ticket
                                                                                  Fare
         PassengerId
                                      Braund,
                                  3
                                                                                7.2500
                                                male 22.0
                                        Owen
                                        Harris
                                      Cumings,
                                         Mrs.
                                         John
                  2
                                                                               71.2833
                                       Bradley female 38.0
                                     (Florence
                                        Briggs
                                         Th...
        train_df.describe(include="all")
In [4]:
```

```
Out[4]:
                   Survived
                                Pclass
                                                                      SibSp
                                                                                 Parch
                                         Name
                                                Sex
                                                            Age
          count 891.000000 891.000000
                                                891 714.000000 891.000000 891.000000
                                           891
         unique
                       NaN
                                  NaN
                                           891
                                                           NaN
                                                                       NaN
                                                                                  NaN
                                        Dooley,
            top
                       NaN
                                  NaN
                                           Mг.
                                               male
                                                           NaN
                                                                       NaN
                                                                                  NaN 3
                                        Patrick
                                                                                  NaN
           freq
                       NaN
                                  NaN
                                            1
                                                577
                                                           NaN
                                                                       NaN
                   0.383838
                              2.308642
                                                      29.699118
                                                                   0.523008
                                                                              0.381594
          mean
                                          NaN
                                                NaN
                   0.486592
                                                                              0.806057
            std
                              0.836071
                                          NaN
                                                NaN
                                                      14.526497
                                                                   1.102743
            min
                   0.000000
                              1.000000
                                          NaN
                                                NaN
                                                       0.420000
                                                                   0.000000
                                                                              0.000000
           25%
                   0.000000
                              2.000000
                                                      20.125000
                                                                   0.000000
                                                                              0.000000
                                          NaN
                                                NaN
           50%
                   0.000000
                              3.000000
                                          NaN
                                                NaN
                                                      28.000000
                                                                   0.000000
                                                                              0.000000
           75%
                   1.000000
                              3.000000
                                                      38.000000
                                                                   1.000000
                                                                              0.000000
                                          NaN
                                                NaN
           max
                   1.000000
                              3.000000
                                          NaN
                                                NaN
                                                      80.000000
                                                                   8.000000
                                                                              6.000000
In [5]: train df.info()
        <class 'pandas.core.frame.DataFrame'>
        Index: 891 entries, 1 to 891
       Data columns (total 11 columns):
        #
             Column
                        Non-Null Count
                                         Dtype
             -----
                        _____
        - - -
                                         ----
             Survived 891 non-null
                                         int64
         0
                        891 non-null
         1
             Pclass
                                         int64
         2
             Name
                        891 non-null
                                         object
         3
             Sex
                        891 non-null
                                         object
         4
             Age
                        714 non-null
                                         float64
                        891 non-null
         5
             SibSp
                                         int64
                        891 non-null
                                         int64
         6
             Parch
         7
             Ticket
                        891 non-null
                                         object
         8
             Fare
                        891 non-null
                                         float64
         9
             Cabin
                        204 non-null
                                         object
         10 Embarked 889 non-null
                                         object
        dtypes: float64(2), int64(4), object(5)
        memory usage: 83.5+ KB
         Let's drop Cabin, and then – all rows with missing values.
In [6]: train df = train df.drop("Cabin", axis=1).dropna()
In [7]: train_df.shape
Out[7]: (712, 10)
         1. Build a picture to visualize all scatter plots for each pair of features Age, Fare,
```

SibSp, Parch and Survived. (scatter matrix from Pandas or

pairplot from Seaborn)

```
In [8]: from pandas.plotting import scatter_matrix

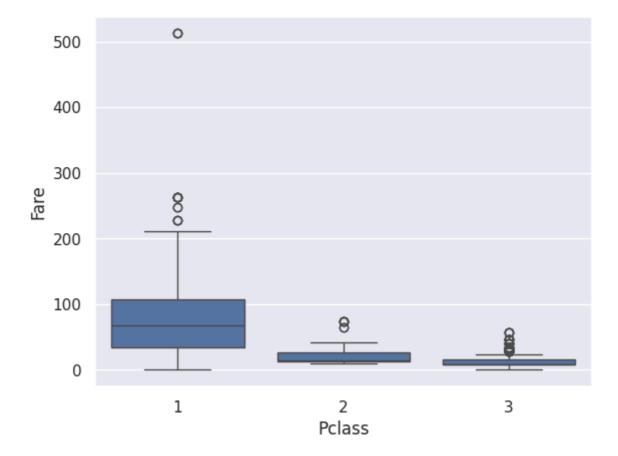
features = ['Age', 'Fare', 'SibSp', 'Parch', 'Survived']
    scatter_matrix(train_df[features])
    plt.show()
```



2. How does ticket price (Fare) depend on Pclass? Build a boxplot.

```
In [9]: sns.boxplot(x="Pclass", y="Fare", data=train_df)
```

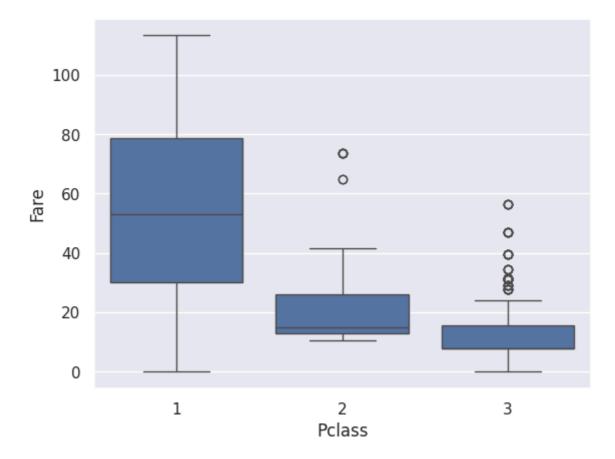
Out[9]: <Axes: xlabel='Pclass', ylabel='Fare'>



3. Let's build the same plot but restricting values of Fare to be less than 95% quantile of the initial vector (to drop outliers that make the plot less clear).

```
In [10]: train_df_95_quantile = train_df[train_df["Fare"] < train_df["Fare"].quant
    sns.boxplot(x="Pclass", y="Fare", data=train_df_95_quantile)</pre>
```

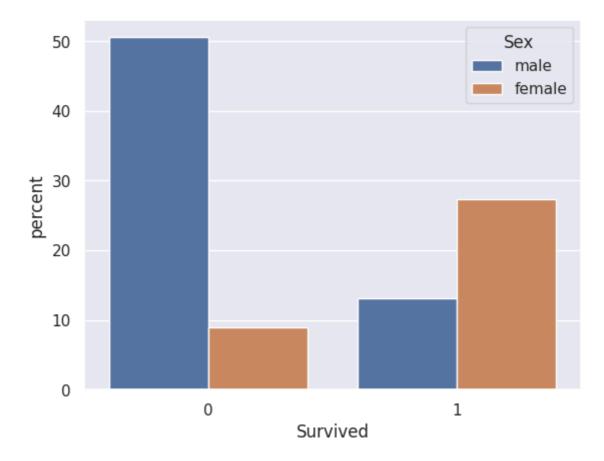
Out[10]: <Axes: xlabel='Pclass', ylabel='Fare'>



4. How is the percentage of surviving passengers dependent on passengers' gender? Depict it with Seaborn.countplot using the hue argument.

```
In [11]: sns.countplot(train_df, x="Survived", hue="Sex", stat="percent")
```

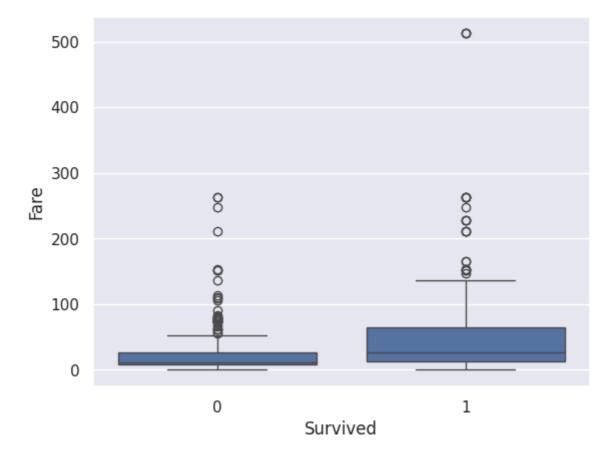
Out[11]: <Axes: xlabel='Survived', ylabel='percent'>



5. How does the distribution of ticket prices differ for those who survived and those who didn't. Depict it with Seaborn.boxplot

```
In [12]: sns.boxplot(x="Survived", y="Fare", data=train_df)
```

Out[12]: <Axes: xlabel='Survived', ylabel='Fare'>



6. How does survival depend on passengers' age? Verify (graphically) an assumption that youngsters (< 30 y.o.) survived more frequently than old people (> 55 y.o.).

```
In [13]: def get_age_category(age: int) -> str:
    if age < 30:
        return "<30"
    elif age > 55:
        return ">55"

    else:
        return "30-55"

In [14]: age_category = [get_age_category(age) for age in train_df.Age]
    train_df["Age category"] = age_category

In [15]: sns.countplot(train_df, x="Survived", hue="Age category")

Out[15]: <Axes: xlabel='Survived', ylabel='count'>
```

