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ЗВІТ
про виконання лабораторної роботи №6
з дисципліни
" Аналіз даних в інформаційно-управляючих системах"

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Lab Six

Main Assignment

In [39]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import missingno as msno
from kneed import KneeLocator
from sklearn.cluster import KMeans, AgglomerativeClustering
import math
```

Correct File

In [40]:
```
with open('data/titanic.csv') as input_file:
    with open('data/data_titanic.csv', 'w') as output_file:
        lines = []
        statuses = []
        for index, line in enumerate(input_file):
            if index == 0:
                lines.append(line.replace(',', ';'))
                continue
            parts = line.split('"')
            parts[0] = parts[0].replace(',', ';')
            parts[2] = parts[2].replace(',', ';')
            statuses.append(parts[1].split(',')[1].split('.')[0].lstrip())
            lines.append(''.join(parts))
        statuses = list(set(statuses))
        output_file.writelines(lines)
```

Status-Gender Pairs

In [41]:
```
status_gender_pairs = {
    'Rev': 'male',
    'Miss': 'female',
    'Ms': 'male',
    'Dr': 'male',
    'Mlle': 'female',
    'Col': 'male',
    'the Countess': 'female',
    'Jonkheer': 'male',
    'Don': 'male',
    'Capt': 'male',
    'Master': 'male',
    'Mme': 'female',
    'Mrs': 'female',
    'Mr': 'male',
    'Lady': 'female',
    'Sir': 'male',
    'Major': 'male'
}
```

Load Dataframe

In [42]:
```
df = pd.read_csv('data/data_titanic.csv', delimiter=';', decimal='.')
```

Drop unnecessary columns

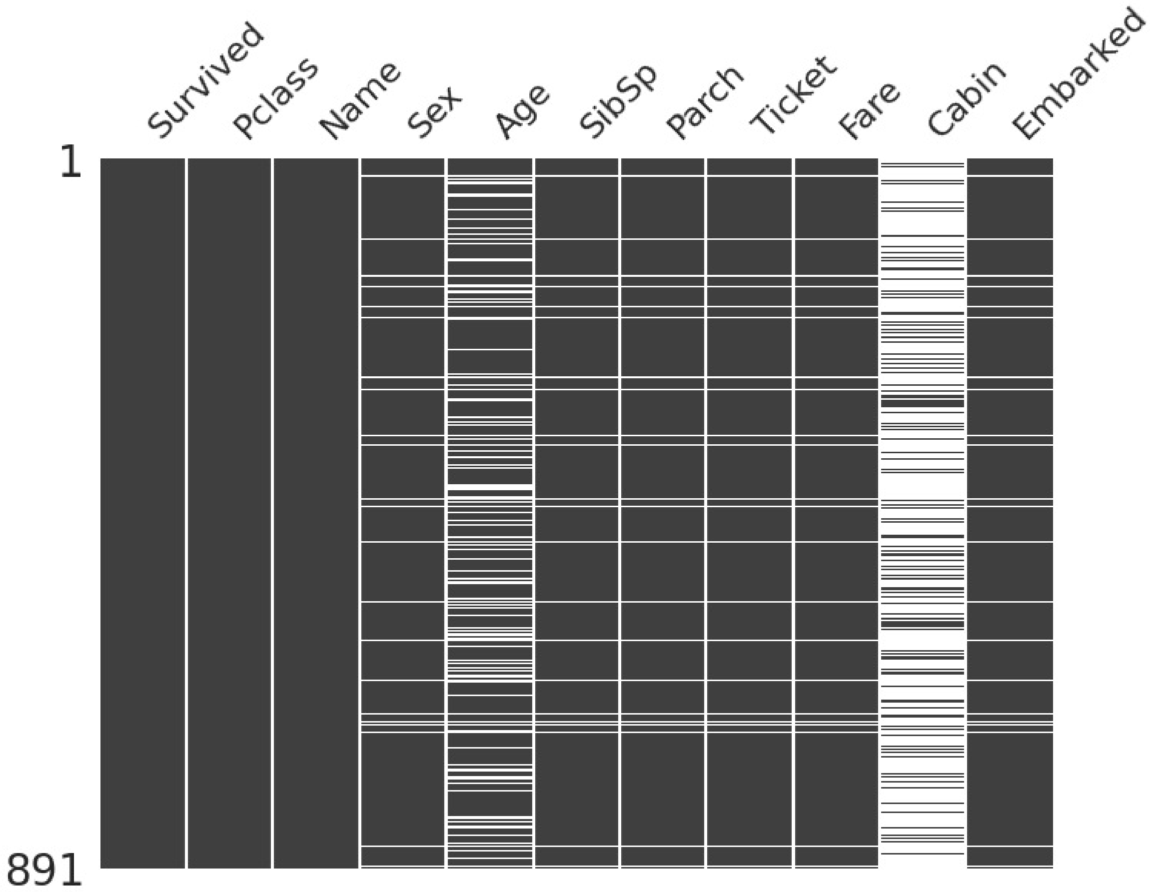
In [43]:
```
df = df.drop(['PassengerId'], axis=1)
```

Take a look on what data is missing

In [44]:
```
percent_1 = df.isnull().sum() / df.isnull().count() * 100
percent_2 = (round(percent_1, 1)).sort_values(ascending=False)
missing_data = pd.concat([percent_2], axis=1, keys=['%'])
plot_rows = 1
plot_cols = 1
fig, axis = plt.subplots(plot_rows, plot_cols, figsize=(8, 6))
msno.matrix(df, ax=axis)
```

```
/usr/local/lib/python3.10/dist-packages/missingno/missingno.py:61: UserWarning:

Plotting a sparkline on an existing axis is not currently supported. To remove this warning, set sparkline=Fals
e.
```

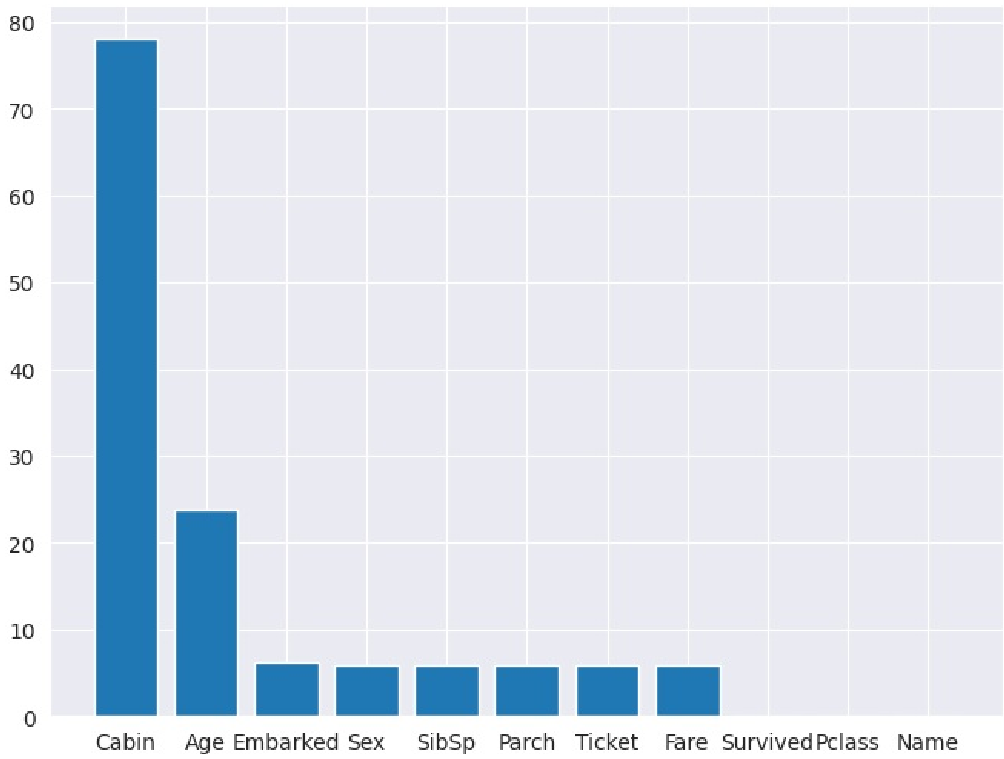
Out[44]: <AxesSubplot: >



Empty values by percentage in column

In [45]:
```python
fig, axis = plt.subplots(plot_rows, plot_cols, figsize=(8, 6))
axis.bar(missing_data.index, missing_data.iloc[:, 0])
```

Out[45]: <BarContainer object of 11 artists>



Drop "Cabin" due to large number of missing data

In [46]:
```
df = df.drop(['Cabin'], axis=1)
```

Fill Nan "Age"-values with mean

In [47]:
```
df_sex_mean_age = pd.pivot_table(df, index='Sex', values='Age', aggfunc='mean')
mean_age_female, mean_age_male = df_sex_mean_age.iloc[0, 0], df_sex_mean_age.iloc[1, 0]
df_sex_mean_age
```

Out[47]:

Sex	Age
female	28.445833
male	30.863713

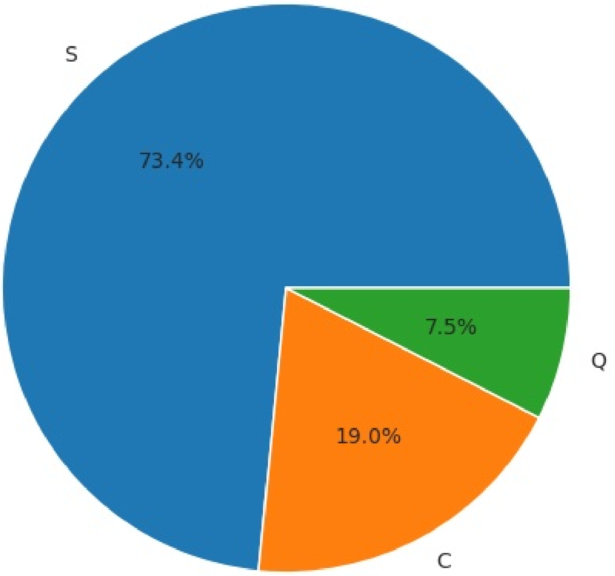
Fill gender

In [48]:
```
df['Sex'] = df.apply(lambda x: status_gender_pairs[x['Name'].split(',')[1].split('.')[0].lstrip()], axis=1)
df['Gender'] = df.apply(lambda x: x['Sex'] == 'male', axis=1)

def mean_age_functor(row):
    if str(row['Age']) != 'nan':
        return row['Age']
    if row['Sex'] == 'male':
        return mean_age_male
    return mean_age_female


df['Age'] = df.apply(mean_age_functor, axis=1)
```

Fill "Embarked" with the most frequent value

In [49]:
```
fig, axis = plt.subplots(figsize=(8, 6))
embarked_counts = df['Embarked'].value_counts()
axis.pie(embarked_counts, labels=embarked_counts.index, autopct='%1.1f%%')
```

Out[49]:
```
([<matplotlib.patches.Wedge at 0x7f84b44872b0>,
  <matplotlib.patches.Wedge at 0x7f84b4486e30>,
  <matplotlib.patches.Wedge at 0x7f84b44859c0>],
 [Text(-0.7389062157855284, 0.8148727534244291, 'S'),
  Text(0.5271737867829742, -0.9654469423686107, 'C'),
  Text(1.069316711618934, -0.2579956787476679, 'Q')],
 [Text(-0.4030397540648336, 0.4444760473224158, '73.4%'),
  Text(0.28754933824525863, -0.5266074231101512, '19.0%'),
  Text(0.5832636608830548, -0.1407249156805461, '7.5%')])
```



Fill empty embarked with "S"

In [50]:
```
df['Embarked'].fillna('S', inplace=True)
```

```
df['EmbarkedValue'] = df.apply(lambda x: ['S', 'Q', 'C'].index(x['Embarked']), axis=1)
```

Fill "Fare" with mean

In [51]:
```
df['Fare'].fillna(value=df['Fare'].mean(), inplace=True)
df['SibSp'].fillna(value=0, inplace=True)
df['Parch'].fillna(value=0, inplace=True)
df['Relatives'] = df['SibSp'] + df['Parch']
df = df.drop(['Parch', 'SibSp'], axis=1)
```

Since the Ticket attribute has 681 unique tickets, it is fair to drop that column

In [52]:
```
df['Ticket'].describe()
```

Out[52]:
```
count      838
unique     647
top       1601
freq         7
Name: Ticket, dtype: object
```

In [53]:
```
df = df.drop(['Ticket'], axis=1)
```

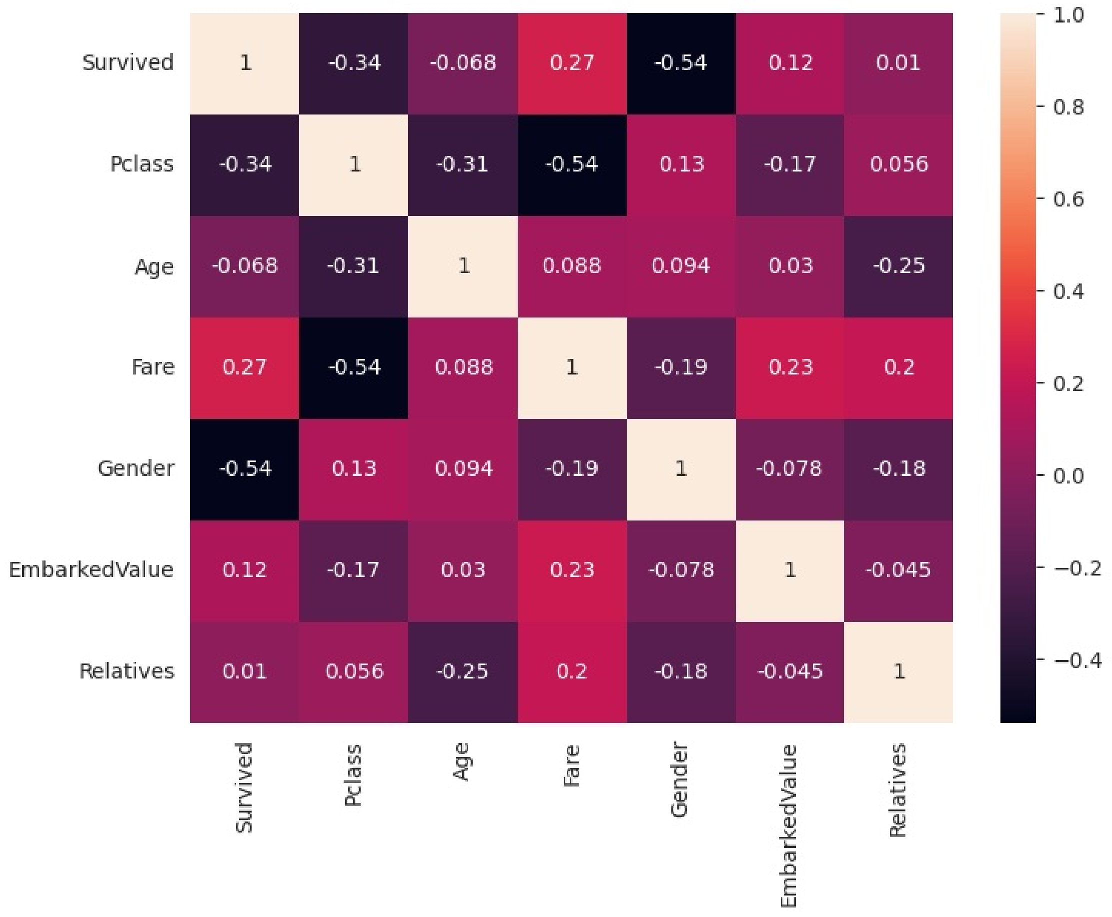
Change column types

In [54]:
```
for row in df.columns:
    if df[row].dtype == bool:
        df[row] = df[row].astype(int)
```

Plot correlation matrix

In [55]:
```
fig, axis = plt.subplots(figsize=(8, 6))
sns.heatmap(df.corr(numeric_only=True), ax=axis, annot=True)
```

Out[55]: <AxesSubplot: >

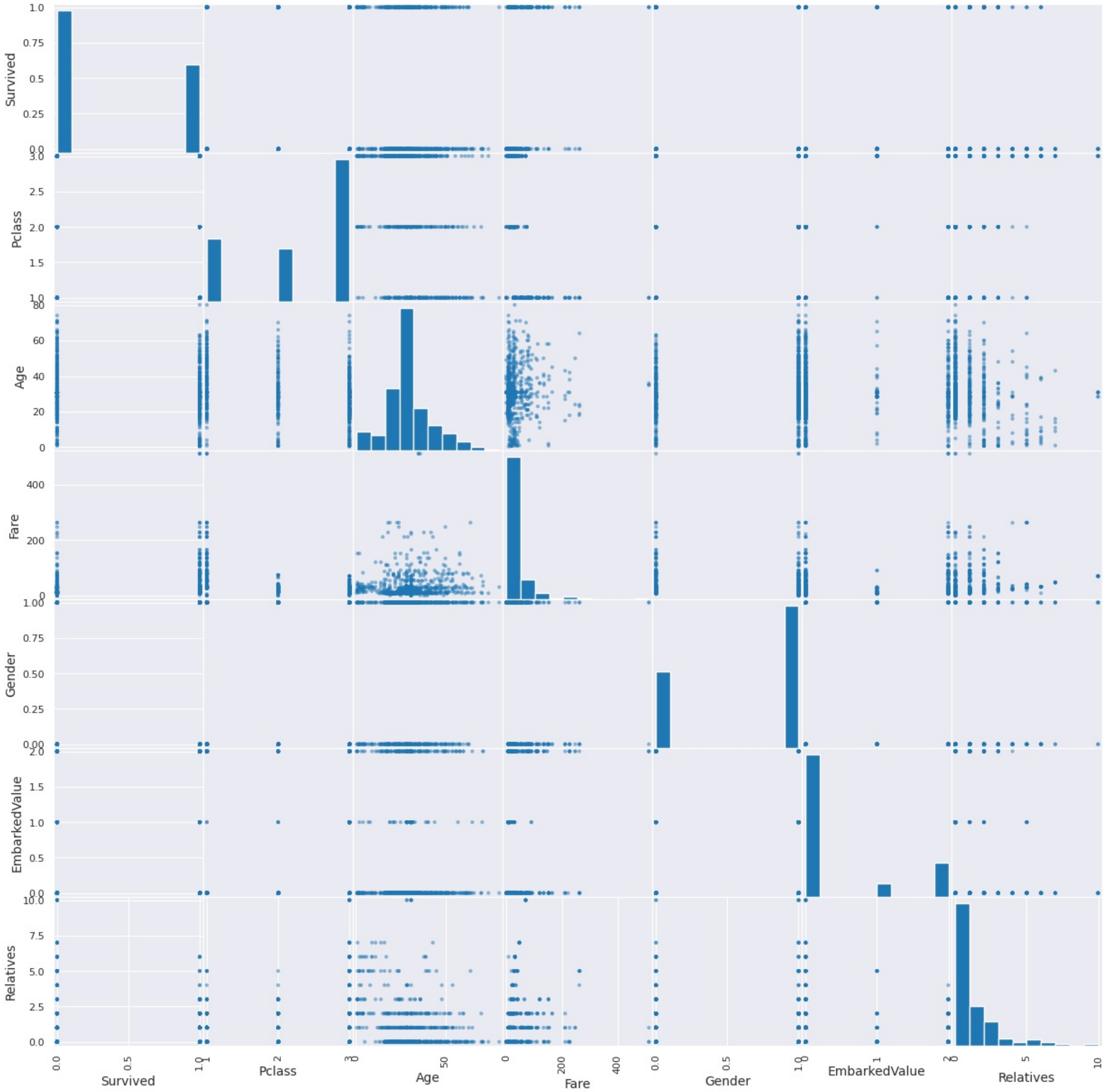


Plot all correlations

In [56]:
```
fig, axis = plt.subplots(figsize=(15, 15))
pd.plotting.scatter_matrix(df, ax=axis)
```

```
/tmp/ipykernel_90859/2677134439.py:2: UserWarning:

To output multiple subplots, the figure containing the passed axes is being cleared.
```

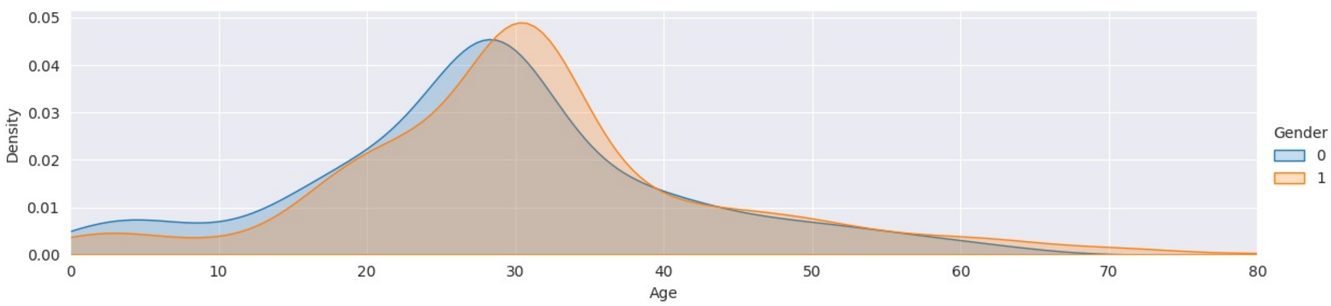
Out[56]:
```
array([[<AxesSubplot: xlabel='Survived', ylabel='Survived'>,
        <AxesSubplot: xlabel='Pclass', ylabel='Survived'>,
        <AxesSubplot: xlabel='Age', ylabel='Survived'>,
        <AxesSubplot: xlabel='Fare', ylabel='Survived'>,
        <AxesSubplot: xlabel='Gender', ylabel='Survived'>,
        <AxesSubplot: xlabel='EmbarkedValue', ylabel='Survived'>,
        <AxesSubplot: xlabel='Relatives', ylabel='Survived'>],
       [<AxesSubplot: xlabel='Survived', ylabel='Pclass'>,
        <AxesSubplot: xlabel='Pclass', ylabel='Pclass'>,
        <AxesSubplot: xlabel='Age', ylabel='Pclass'>,
        <AxesSubplot: xlabel='Fare', ylabel='Pclass'>,
        <AxesSubplot: xlabel='Gender', ylabel='Pclass'>,
        <AxesSubplot: xlabel='EmbarkedValue', ylabel='Pclass'>,
        <AxesSubplot: xlabel='Relatives', ylabel='Pclass'>],
       [<AxesSubplot: xlabel='Survived', ylabel='Age'>,
        <AxesSubplot: xlabel='Pclass', ylabel='Age'>,
        <AxesSubplot: xlabel='Age', ylabel='Age'>,
        <AxesSubplot: xlabel='Fare', ylabel='Age'>,
        <AxesSubplot: xlabel='Gender', ylabel='Age'>,
        <AxesSubplot: xlabel='EmbarkedValue', ylabel='Age'>,
        <AxesSubplot: xlabel='Relatives', ylabel='Age'>],
       [<AxesSubplot: xlabel='Survived', ylabel='Fare'>,
        <AxesSubplot: xlabel='Pclass', ylabel='Fare'>,
        <AxesSubplot: xlabel='Age', ylabel='Fare'>,
        <AxesSubplot: xlabel='Fare', ylabel='Fare'>,
        <AxesSubplot: xlabel='Gender', ylabel='Fare'>,
        <AxesSubplot: xlabel='EmbarkedValue', ylabel='Fare'>,
        <AxesSubplot: xlabel='Relatives', ylabel='Fare'>],
       [<AxesSubplot: xlabel='Survived', ylabel='Gender'>,
        <AxesSubplot: xlabel='Pclass', ylabel='Gender'>,
        <AxesSubplot: xlabel='Age', ylabel='Gender'>,
        <AxesSubplot: xlabel='Fare', ylabel='Gender'>,
        <AxesSubplot: xlabel='Gender', ylabel='Gender'>,
        <AxesSubplot: xlabel='EmbarkedValue', ylabel='Gender'>,
        <AxesSubplot: xlabel='Relatives', ylabel='Gender'>],
       [<AxesSubplot: xlabel='Survived', ylabel='EmbarkedValue'>,
        <AxesSubplot: xlabel='Pclass', ylabel='EmbarkedValue'>,
        <AxesSubplot: xlabel='Age', ylabel='EmbarkedValue'>,
        <AxesSubplot: xlabel='Fare', ylabel='EmbarkedValue'>,
        <AxesSubplot: xlabel='Gender', ylabel='EmbarkedValue'>,
        <AxesSubplot: xlabel='EmbarkedValue', ylabel='EmbarkedValue'>,
        <AxesSubplot: xlabel='Relatives', ylabel='EmbarkedValue'>],
       [<AxesSubplot: xlabel='Survived', ylabel='Relatives'>,
        <AxesSubplot: xlabel='Pclass', ylabel='Relatives'>,
        <AxesSubplot: xlabel='Age', ylabel='Relatives'>,
        <AxesSubplot: xlabel='Fare', ylabel='Relatives'>,
        <AxesSubplot: xlabel='Gender', ylabel='Relatives'>,
        <AxesSubplot: xlabel='EmbarkedValue', ylabel='Relatives'>,
        <AxesSubplot: xlabel='Relatives', ylabel='Relatives'>]],
      dtype=object)
```



Plot male-female Age statistic

In [57]:
```
fig = sns.FacetGrid(df, hue='Gender', aspect=4)
fig.map(sns.kdeplot, 'Age', fill=True)
oldest = df['Age'].max()
fig.set(xlim=(0, oldest))
fig.add_legend()
```

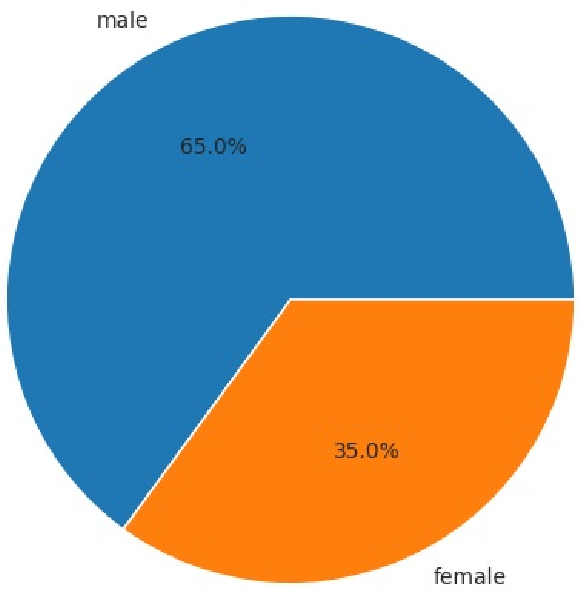
Out[57]: <seaborn.axisgrid.FacetGrid at 0x7f849d833130>



Plot male-female Count statistic

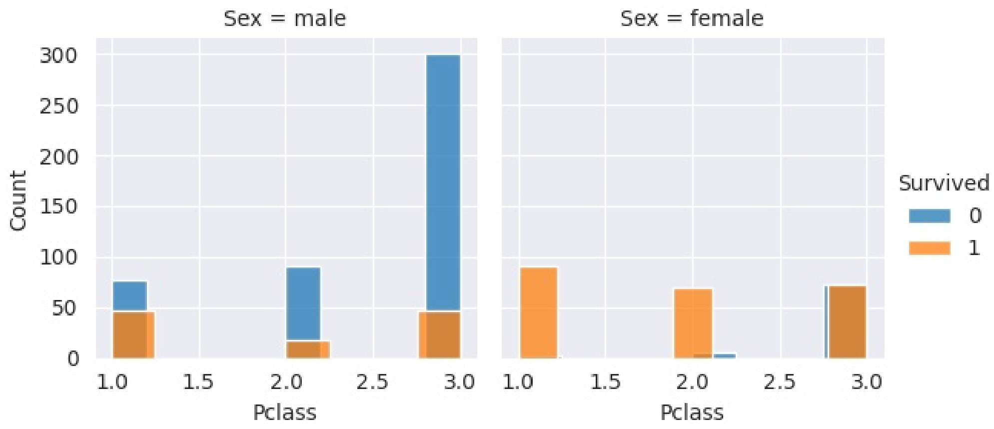
In [58]:
```
fig, axis = plt.subplots(figsize=(8, 6))
male_female_counts = df['Sex'].value_counts()
axis.pie(male_female_counts, labels=male_female_counts.index, autopct='%1.1f%%')
```

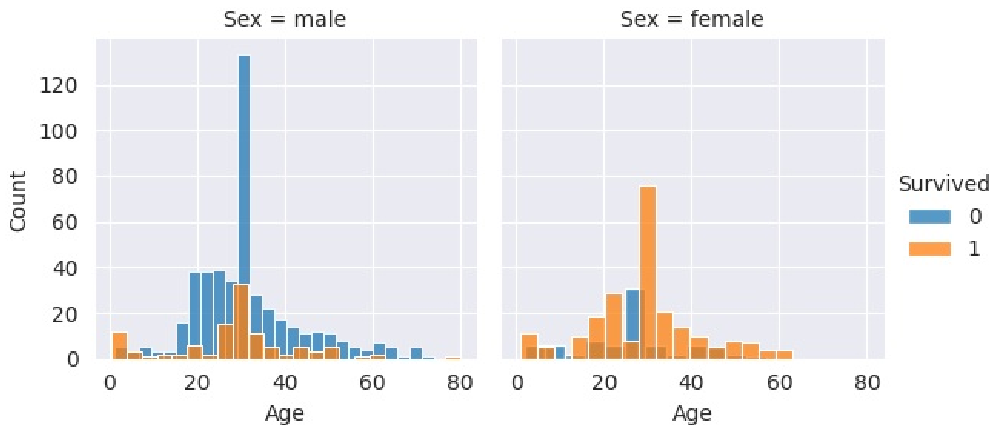
```
factors = df.columns.values.tolist()
factors = [f for f in factors if f not in ['Sex', 'Survived', 'Gender', 'Name', 'EmbarkedValue']]
```

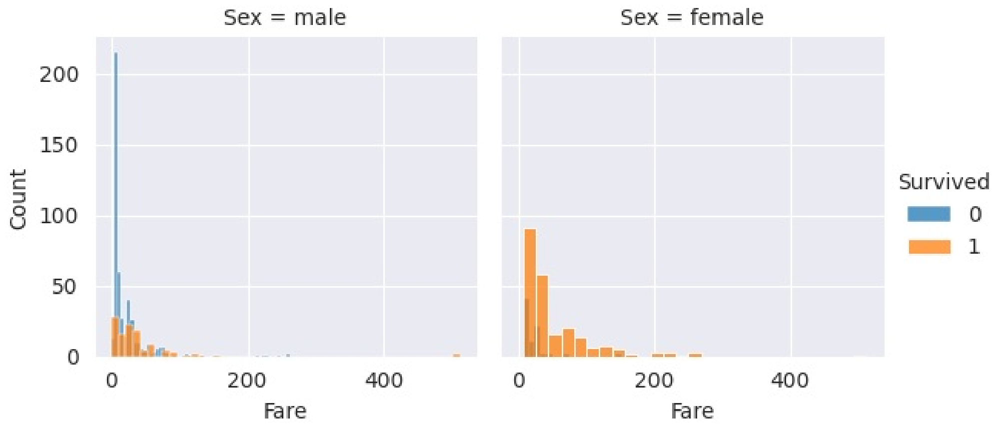


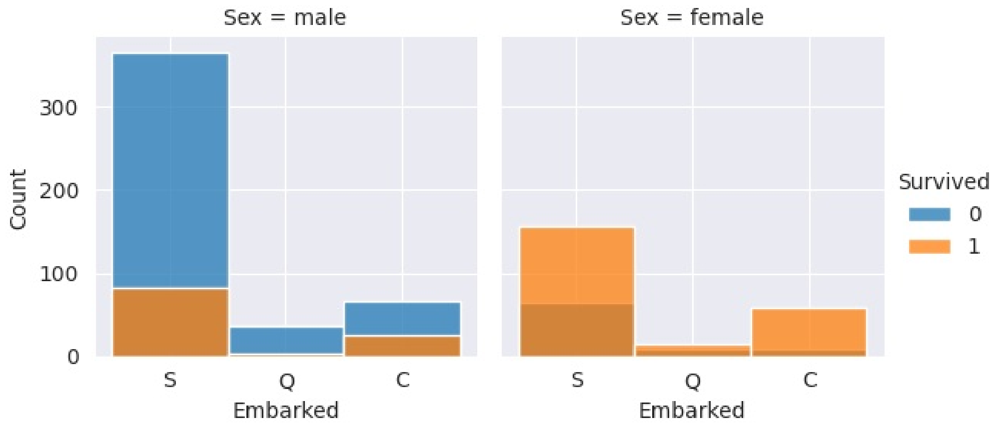
Plot male-female Survival Rate based on Age statistic

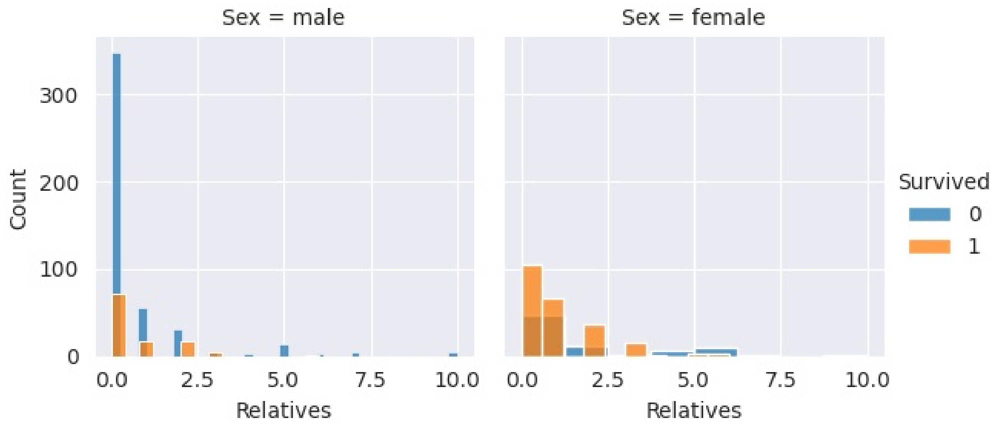
In [59]:
```
for row, factor in enumerate(factors):
    g = sns.FacetGrid(df[['Sex', 'Survived'] + [factor]], col='Sex', hue='Survived')
    g.map(sns.histplot, factor)
    g.add_legend()
```









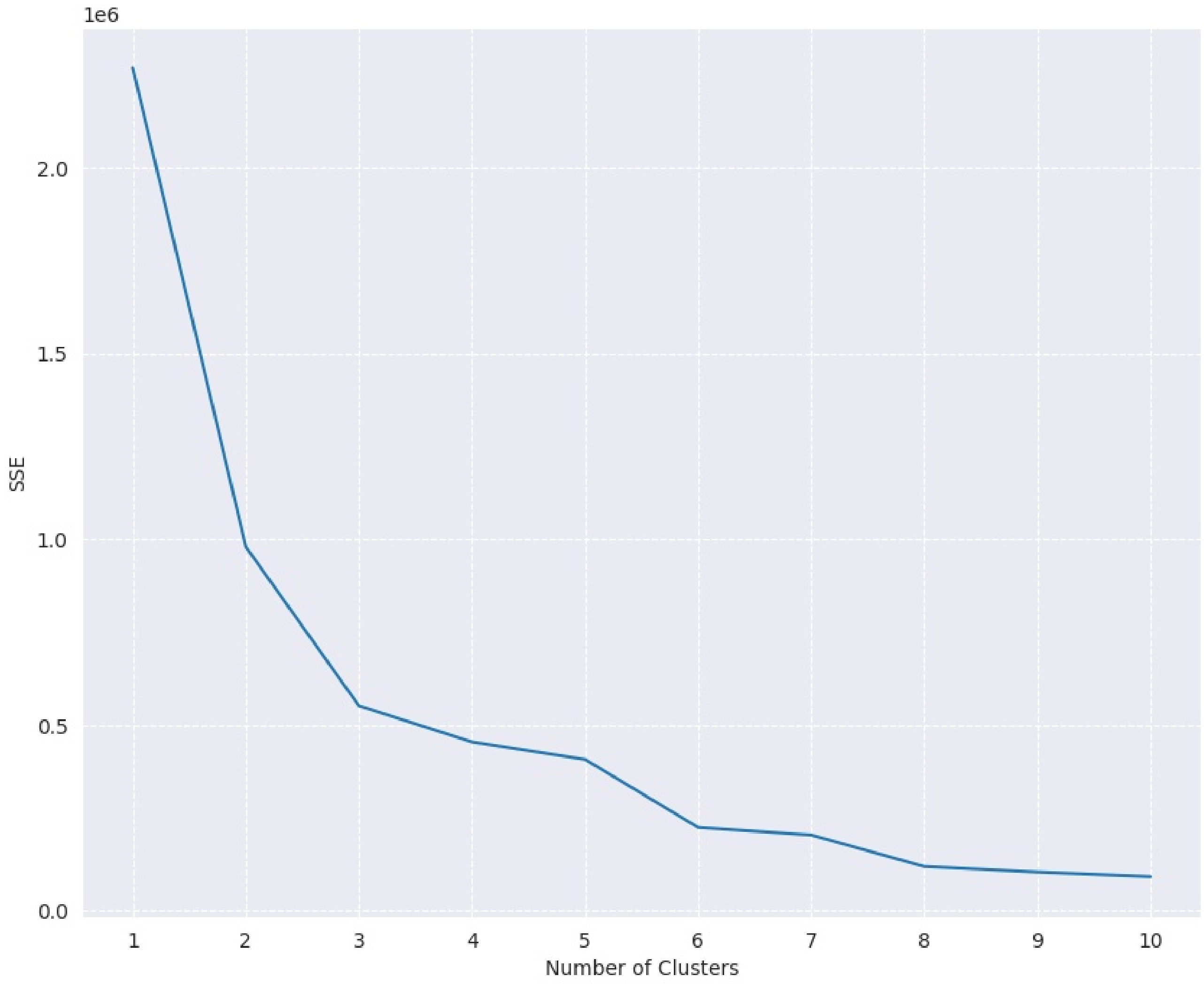


KMeans without PCA

In [60]:

```
factors.remove('Embarked')
factors.append('EmbarkedValue')
kmeans_kwargs = {
    'init': 'random',
    'n_init': 10,
    'max_iter': 300,
    'random_state': 0,
}
sse = []
max_kernels = 10
features = df[['Survived'] + factors]
for k in range(1, max_kernels + 1):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(features)
    sse.append(kmeans.inertia_)

plt.figure(figsize=(10, 8))
plt.plot(range(1, max_kernels + 1), sse)
```

```
plt.xticks(range(1, max_kernels + 1))
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.grid(linestyle='--')
```



Elbow point

In [61]:
```
kl = KneeLocator(range(1, max_kernels + 1), sse, curve='convex', direction='decreasing')
kl.elbow
```

Out[61]: 3

Set number of clusters to elbow point

In [62]:
```
kmeans = KMeans(
    init='random',
    n_clusters=kl.elbow,
    n_init=10,
    max_iter=300,
    random_state=0
)
kmeans.fit(features)
```

Out[62]:
```
▾                         KMeans
KMeans(init='random', n_clusters=3, n_init=10, random_state=0)
```

In [63]:
```
kmeans.cluster_centers_
```

Out[63]:
```
array([[  0.67391304,   1.23913043,  34.96908602,  83.96026449,
          1.41304348,   0.72463768],
       [  0.32152589,   2.54359673,  29.03663864,  16.70048021,
          0.72752044,   0.35286104],
       [  0.68421053,   1.        ,  31.66986452, 280.19978421,
          1.68421053,   1.15789474]])
```

In [64]:
```
fig = px.scatter_3d(
    df, x='Survived', y='Fare', z='Relatives',
    color=kmeans.labels_, hover_data=['Sex', 'Age', 'EmbarkedValue'],
```

```
    width=1000, height=800,
    title='Survived-Fare-Relatives KMeans Plot Clusters'
)
fig.update(layout_coloraxis_showscale=False)
fig.show()
```

Agglomerate Clustering

In [65]:
```
model = AgglomerativeClustering(n_clusters=kl.elbow, affinity='euclidean', linkage='ward')
clust_labels = model.fit_predict(features)
agglomerative = pd.DataFrame(clust_labels)
agglomerative
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_agglomerative.py:983: FutureWarning:

Attribute `affinity` was deprecated in version 1.2 and will be removed in 1.4. Use `metric` instead
```

Out[65]:

	0
0	1
1	2
2	1
3	1
4	1
...	...
886	1
887	1
888	1
889	1
890	1

891 rows × 1 columns

In [66]:

```
df.insert((df.shape[1]), 'agglomerative', agglomerative)
fig = px.scatter_3d(
    df, x='Survived', y='Fare', z='Relatives',
    color=df['agglomerative'], hover_data=['Sex', 'Age', 'EmbarkedValue'],
    width=1000, height=800,
    title='Survived-Fare-Relatives Agglomerative Plot Clusters'
)
fig.update(layout_coloraxis_showscale=False)
fig.show()
```

Results

Results

Результати кластеризації показують невелику різницю у двох методах на даному наборі даних. Можливо, що інформації замало, тому не показується різниця

Additional Assignment

Useful Funcs

In [67]:
```
def read_dataset(path: str, sep: str = ';') -> pd.DataFrame:
    data = pd.read_csv(path, sep=sep)
    return data


def replace_comma_with_dots(dataset: pd.DataFrame, column_name: str) -> None:
    dataset[column_name] = dataset[column_name].astype(str)
    dataset[column_name] = dataset[column_name].str.replace(',', '.')


def convert_column_to_float(dataset: pd.DataFrame, column_name: str) -> None:
    dataset[column_name] = dataset[column_name].astype(float)


def replace_nan_with_mean(dataset: pd.DataFrame, column_name: str):
    mean_value = dataset[column_name].mean()
    dataset[column_name].fillna(value=mean_value, inplace=True)


def convert_float_with_positive(dataset: pd.DataFrame, column_name: str):
    dataset[column_name] = dataset[column_name].abs()
```

Read Dataset and filter it

In [68]:
```
data_path = 'data/Data2.csv'
df = read_dataset(data_path, sep=';')

df['Population'] = df['Populatiion']
df = df.drop(['Populatiion'], axis=1)

numeric_cols = df.columns[2:]

for column_name in numeric_cols:
    replace_comma_with_dots(df, column_name)
    convert_column_to_float(df, column_name)
    replace_nan_with_mean(df, column_name)
    convert_float_with_positive(df, column_name)
    print(column_name, df[column_name].dtype)

## density column
df['GDP'] = df['GDP per capita'] * df['Population']

df['Density'] = df['Population'] / df['Area']
df.head(10)
```

```
GDP per capita float64
CO2 emission float64
Area float64
Population float64
```

Out[68]:

	Country Name	Region	GDP per capita	CO2 emission	Area	Population	GDP	Density
0	Afghanistan	South Asia	561.778746	9809.225000	652860.0	34656032.0	1.946902e+10	53.083405
1	Albania	Europe & Central Asia	4124.982390	5716.853000	28750.0	2876101.0	1.186387e+10	100.038296
2	Algeria	Middle East & North Africa	3916.881571	145400.217000	2381740.0	40606052.0	1.590491e+11	17.048902
3	American Samoa	East Asia & Pacific	11834.745230	165114.116337	200.0	55599.0	6.580000e+08	277.995000
4	Andorra	Europe & Central Asia	36988.622030	462.042000	470.0	77281.0	2.858518e+09	164.427660
5	Angola	Sub-Saharan Africa	3308.700233	34763.160000	1246700.0	28813463.0	9.533511e+10	23.111786
6	Antigua and Barbuda	Latin America & Caribbean	14462.176280	531.715000	440.0	100963.0	1.460145e+09	229.461364
7	Argentina	Latin America & Caribbean	12440.320980	204024.546000	2780400.0	43847430.0	5.454761e+11	15.770188
8	Armenia	Europe & Central Asia	3614.688357	5529.836000	29740.0	2924816.0	1.057230e+10	98.346200
9	Aruba	Latin America & Caribbean	13374.833168	872.746000	180.0	104822.0	1.401977e+09	582.344444

Factors

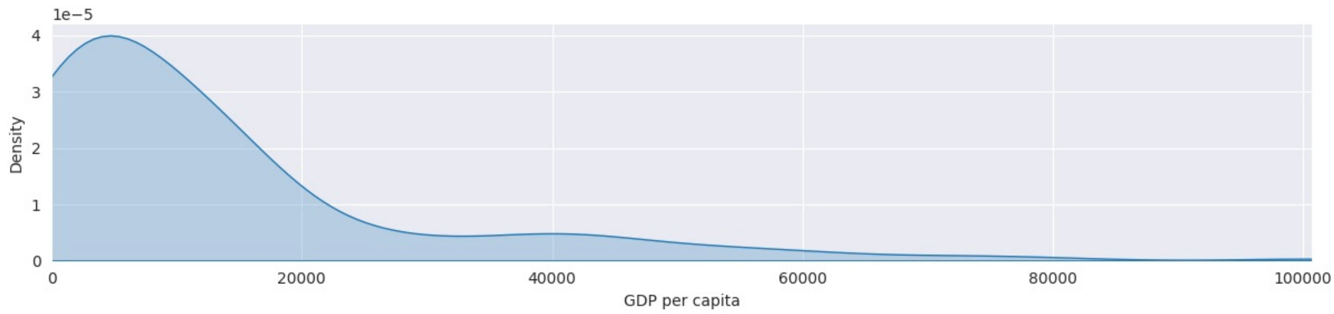
In [69]:

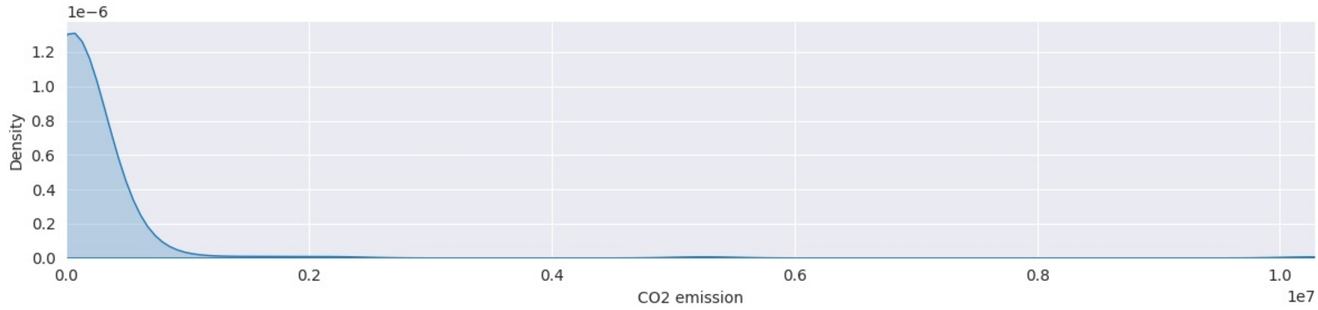
```
factors = df.columns.values.tolist()
factors = [f for f in factors if f not in ['Region', 'Country Name']]
```

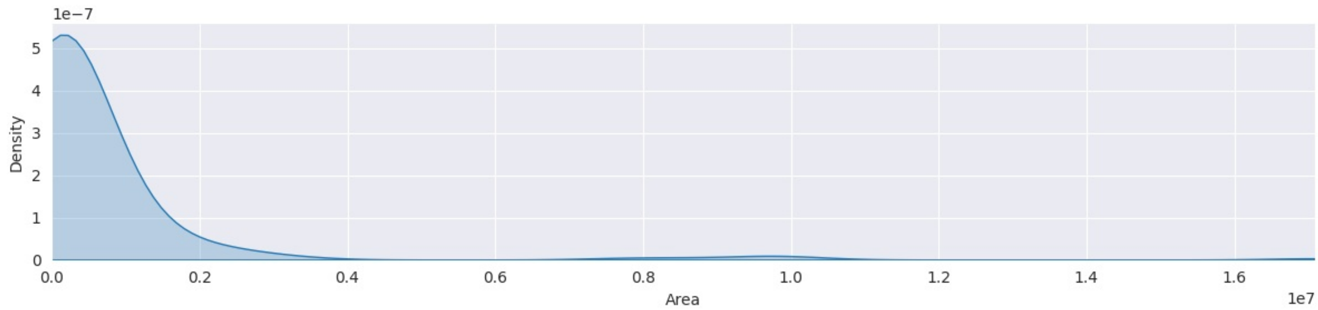
Frequency diagrams

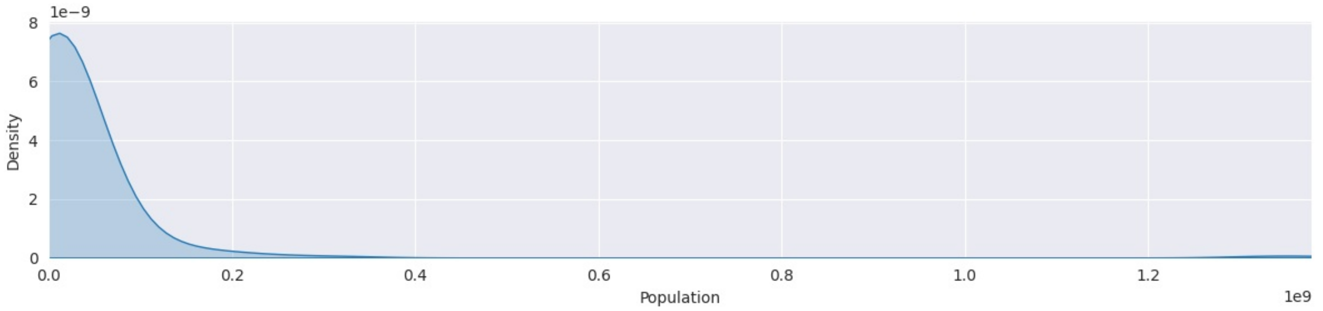
In [70]:

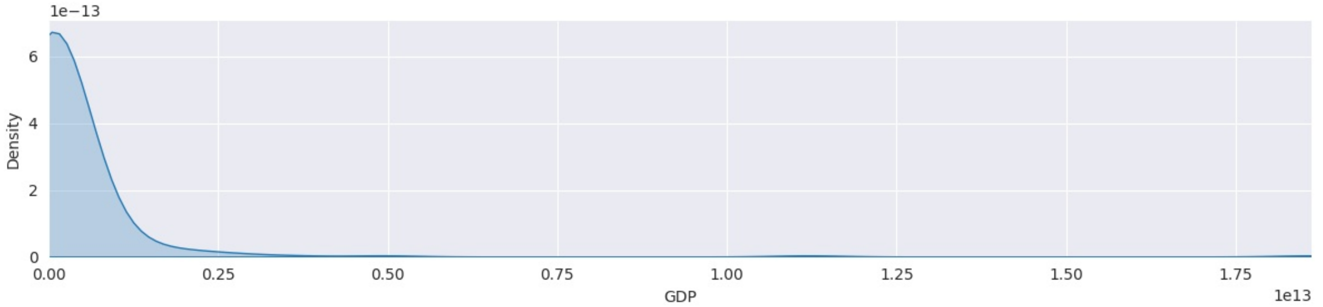
```
for column_name in factors:
    fig = sns.FacetGrid(df, aspect=4)
    fig.map(sns.kdeplot, column_name, fill=True)
    oldest = df[column_name].max()
    fig.set(xlim=(0, oldest))
    fig.add_legend()
```

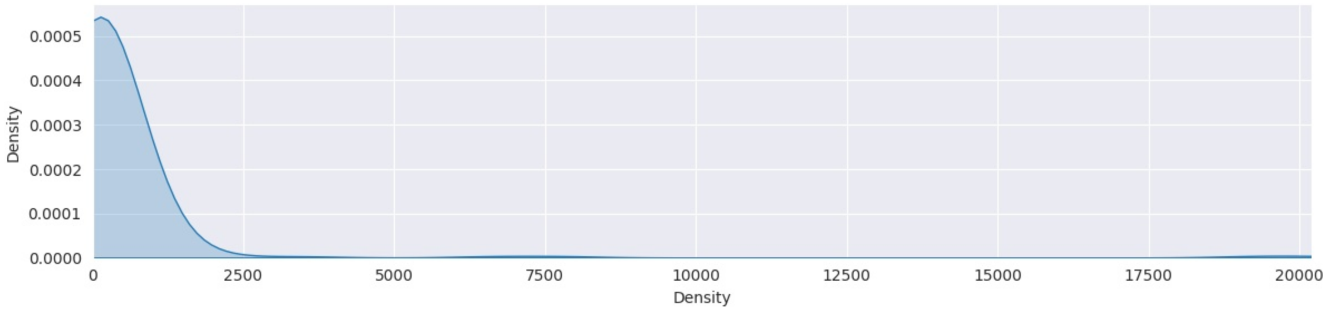








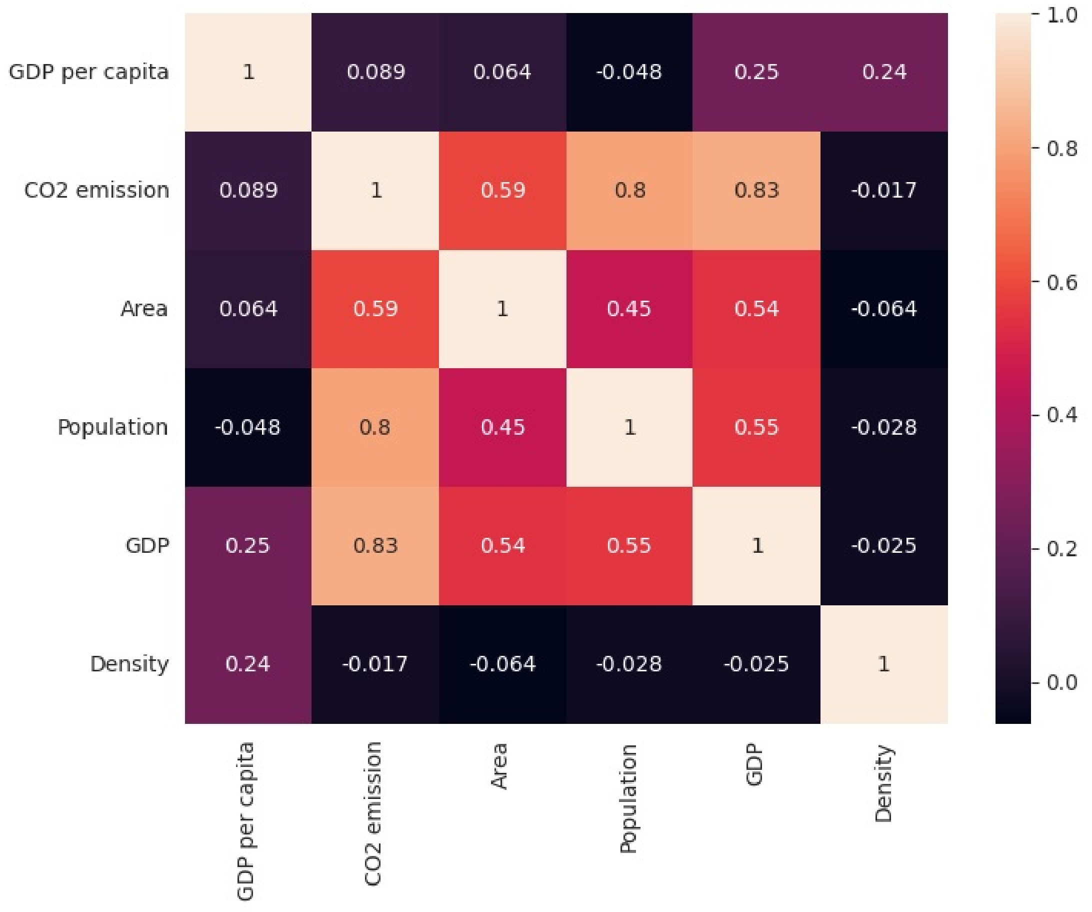




Check for linear correlation

In [71]:
```
df_nums = df[factors]
fig, axis = plt.subplots(figsize=(8, 6))
sns.heatmap(df_nums.corr(numeric_only=True), ax=axis, annot=True)
```

Out[71]: <AxesSubplot: >



Linear Func

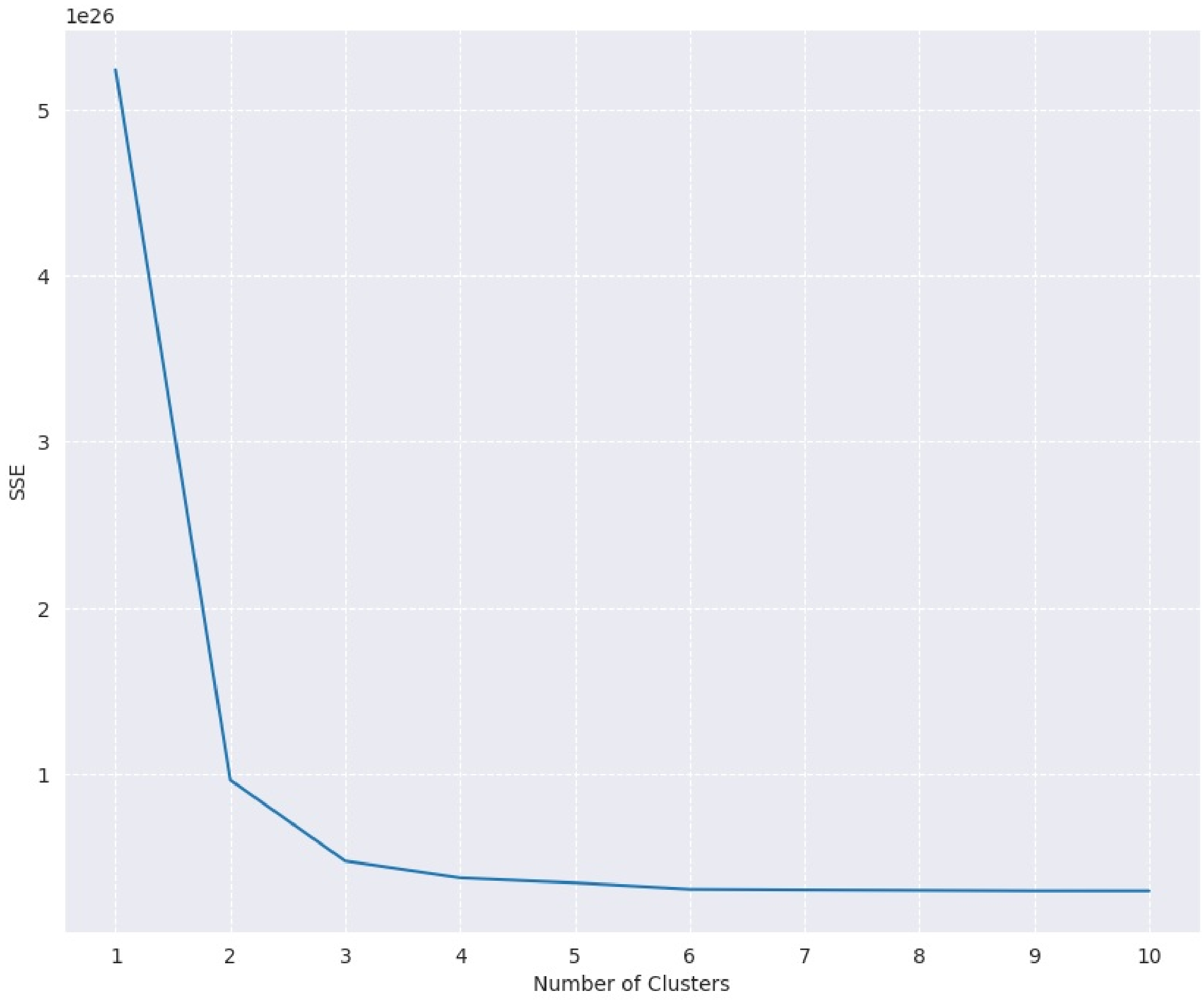
In [72]:

```
def is_linear(series_one: pd.Series, series_two: pd.Series) -> bool:
    return math.fabs(series_one.corr(series_two)) >= 0.8

rows = []
for c_one in factors:
    corrs_row = [{c: is_linear(df[c_one], df[c])} for c in factors]
    pairs = {}
    for cc in corrs_row:
        pairs.update(cc)
    row = {c_one: pairs}
    rows.append(row)
rows
```

Out[72]:
```
[{'GDP per capita': {'GDP per capita': True,
   'CO2 emission': False,
   'Area': False,
   'Population': False,
   'GDP': False,
   'Density': False}},
 {'CO2 emission': {'GDP per capita': False,
   'CO2 emission': True,
   'Area': False,
   'Population': True,
   'GDP': True,
   'Density': False}},
 {'Area': {'GDP per capita': False,
   'CO2 emission': False,
   'Area': True,
   'Population': False,
   'GDP': False,
   'Density': False}},
 {'Population': {'GDP per capita': False,
   'CO2 emission': True,
   'Area': False,
   'Population': True,
   'GDP': False,
   'Density': False}},
 {'GDP': {'GDP per capita': False,
   'CO2 emission': True,
   'Area': False,
   'Population': False,
   'GDP': True,
   'Density': False}},
 {'Density': {'GDP per capita': False,
   'CO2 emission': False,
   'Area': False,
   'Population': False,
   'GDP': False,
   'Density': True}}]
```

Clusterization

In [73]:
```
kmeans_kwargs = {
    'init': 'random',
    'n_init': 10,
    'max_iter': 300,
    'random_state': 0,
}
sse = []
max_kernels = 10
features = df[factors]
for k in range(1, max_kernels + 1):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(features)
    sse.append(kmeans.inertia_)

plt.figure(figsize=(10, 8))
plt.plot(range(1, max_kernels + 1), sse)
plt.xticks(range(1, max_kernels + 1))
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.grid(linestyle='--')
```



Elbow Point

In [74]:
```
kl = KneeLocator(range(1, max_kernels + 1), sse, curve='convex', direction='decreasing')
kl.elbow
```

Out[74]: 2

Plot clusterizations with different number of clusters and region statistic in them

In [75]:
```
n_clusters_list = [kl.elbow, 3, 4, 5]
for n in n_clusters_list:
    kmeans = KMeans(
        init='random',
        n_clusters=n,
        n_init=10,
        max_iter=300,
        random_state=0
    )
    kmeans.fit(features)
    name = f'N-Clusters {n}'
    df[name] = kmeans.labels_

    print(name)
    for i in range(n):
        t = df[df[name] == i]
        table = pd.pivot_table(
            t, values=['GDP', 'Population', 'Area'], index=['Region'], aggfunc=np.sum
        )
        table['Density'] = table['Population'] / table['Area']
        table['GDP per capita'] = table['GDP'] / table['Population']
        max_gdp = table['GDP per capita'].max()
        max_density = table['Density'].max()
        max_gdp_region = table[table['GDP per capita'] == max_gdp].index[0]
        max_density_region = table[table['Density'] == max_density].index[0]
        print(f'\tCluster {i}')
        print(f'\t\tMax GDP: {max_gdp}\tRegion: {max_gdp_region}')
        print(f'\t\tMax Density: {max_density}\tRegion: {max_density_region}')
```

```python
    fig = px.scatter_3d(
        df, x='GDP per capita', y='Area', z='Population',
        color=kmeans.labels_, hover_data=['Country Name', 'Region', 'CO2 emission', 'Density'],
        width=1000, height=800,
        title=f'N-Clusters {n}'
    )
    fig.update(layout_coloraxis_showscale=False)
    fig.show()
```

```
N-Clusters 2
        Cluster 0
                Max GDP: 42131.52083010065      Region: North America
                Max Density: 343.9666814206596  Region: South Asia
        Cluster 1
                Max GDP: 57638.15909    Region: North America
                Max Density: 144.1679212532669  Region: East Asia & Pacific
```

```
N-Clusters 3
        Cluster 0
                Max GDP: 16366.379137353946     Region: Europe & Central Asia
                Max Density: 1306.62    Region: North America
        Cluster 1
                Max GDP: 42183.2951     Region: North America
                Max Density: 402.8192953460619  Region: South Asia
        Cluster 2
                Max GDP: 57638.15909    Region: North America
                Max Density: 144.1679212532669  Region: East Asia & Pacific
```

```
N-Clusters 4
	Cluster 0
		Max GDP: 14626.78085289752	Region: Europe & Central Asia
		Max Density: 1306.62	Region: North America
	Cluster 1
		Max GDP: 42183.2951	Region: North America
		Max Density: 34.50302001624005	Region: East Asia & Pacific
	Cluster 2
		Max GDP: 39965.22390624113	Region: Europe & Central Asia
		Max Density: 402.8192953460619	Region: South Asia
	Cluster 3
		Max GDP: 57638.15909	Region: North America
		Max Density: 144.1679212532669	Region: East Asia & Pacific
```

```
N-Clusters 5
        Cluster 0
                Max GDP: 37771.51075860539      Region: Europe & Central Asia
                Max Density: 377.3908172888432  Region: South Asia
        Cluster 1
                Max GDP: 42183.2951     Region: North America
                Max Density: 34.50302001624005  Region: East Asia & Pacific
        Cluster 2
                Max GDP: 39965.22390624113      Region: Europe & Central Asia
                Max Density: 402.8192953460619  Region: South Asia
        Cluster 3
                Max GDP: 57638.15909    Region: North America
                Max Density: 144.1679212532669  Region: East Asia & Pacific
        Cluster 4
                Max GDP: 13374.83316831 Region: North America
                Max Density: 1306.62    Region: North America
```

Results

Проаналізували корельованість параметрів, статистику решіонів в кластерах та намалювали частотні діаграми