In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from itertools import product

import plotly as py
import plotly.graph_objs as go

from sklearn.cluster import KMeans, DBSCAN, HDBSCAN, OPTICS, estimate_bandwidth, MeanShift, A
from scipy.cluster.hierarchy import dendrogram, linkage

from yellowbrick.cluster import KElbowVisualizer

from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import umap.umap_ as umap

import warnings
warnings.filterwarnings('ignore')
```

```
c:\coding\python\MTS\ML\venv\lib\site-packages\tqdm\auto.py:21: TqdmWarning: IProgress not fou
nd. Please update jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user
_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

In [ ]:
```
df = pd.read_csv('onlinefoods.csv')

print('There are {} rows and {} columns in our dataset.'.format(df.shape[0],df.shape[1]))
```

```
There are 388 rows and 13 columns in our dataset.
```

In [ ]:
```
df.sample(10)
```

Out[ ]:

	Age	Gender	Marital Status	Occupation	Monthly Income	Educational Qualifications	Family size	latitude	longitude	Pin code
100	24	Female	Single	Student	10001 to 25000	Post Graduate	3	12.9335	77.5691	560028
224	25	Female	Married	Student	No Income	Post Graduate	2	12.8834	77.5486	560062
275	23	Female	Single	Student	No Income	Post Graduate	4	13.0487	77.5923	560024
12	23	Male	Single	Student	No Income	Post Graduate	5	12.8988	77.5764	560078
325	27	Male	Married	Employee	25001 to 50000	Graduate	2	12.8845	77.6036	560076
346	26	Male	Married	Employee	More than 50000	Graduate	4	12.9048	77.6821	560036
153	21	Male	Single	Student	No Income	Graduate	2	12.9579	77.6309	560007
113	23	Female	Single	Student	No Income	Graduate	5	13.0206	77.6479	560043
365	22	Male	Single	Student	No Income	Graduate	3	13.0158	77.5390	560096
371	28	Male	Married	Employee	25001 to 50000	Graduate	3	12.9369	77.6407	560095

In [ ]:
```
df.info()
```

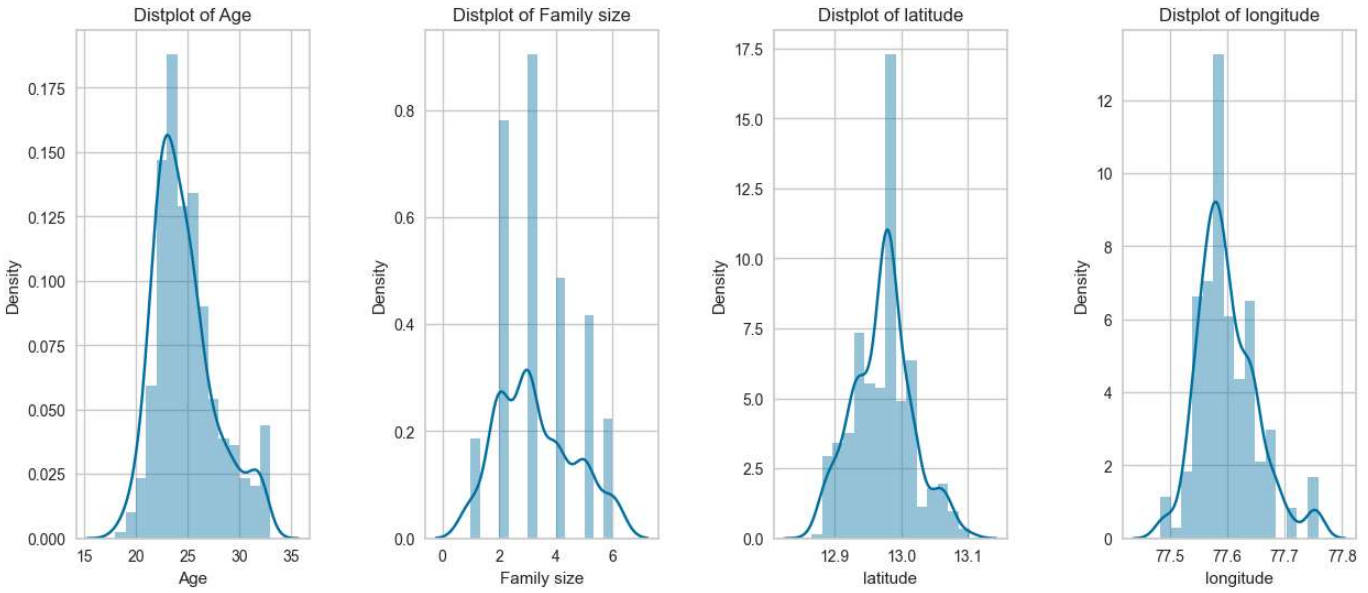
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 388 entries, 0 to 387
Data columns (total 13 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Age                          388 non-null    int64  
 1   Gender                       388 non-null    object 
 2   Marital Status               388 non-null    object 
 3   Occupation                   388 non-null    object 
 4   Monthly Income               388 non-null    object 
 5   Educational Qualifications   388 non-null    object 
 6   Family size                  388 non-null    int64  
 7   latitude                     388 non-null    float64
 8   longitude                    388 non-null    float64
 9   Pin code                     388 non-null    int64  
 10  Output                       388 non-null    object 
 11  Feedback                     388 non-null    object 
 12  Unnamed: 12                  388 non-null    object 
dtypes: float64(2), int64(3), object(8)
memory usage: 39.5+ KB
```

In [ ]:
```
df.describe()
```

Out[ ]:

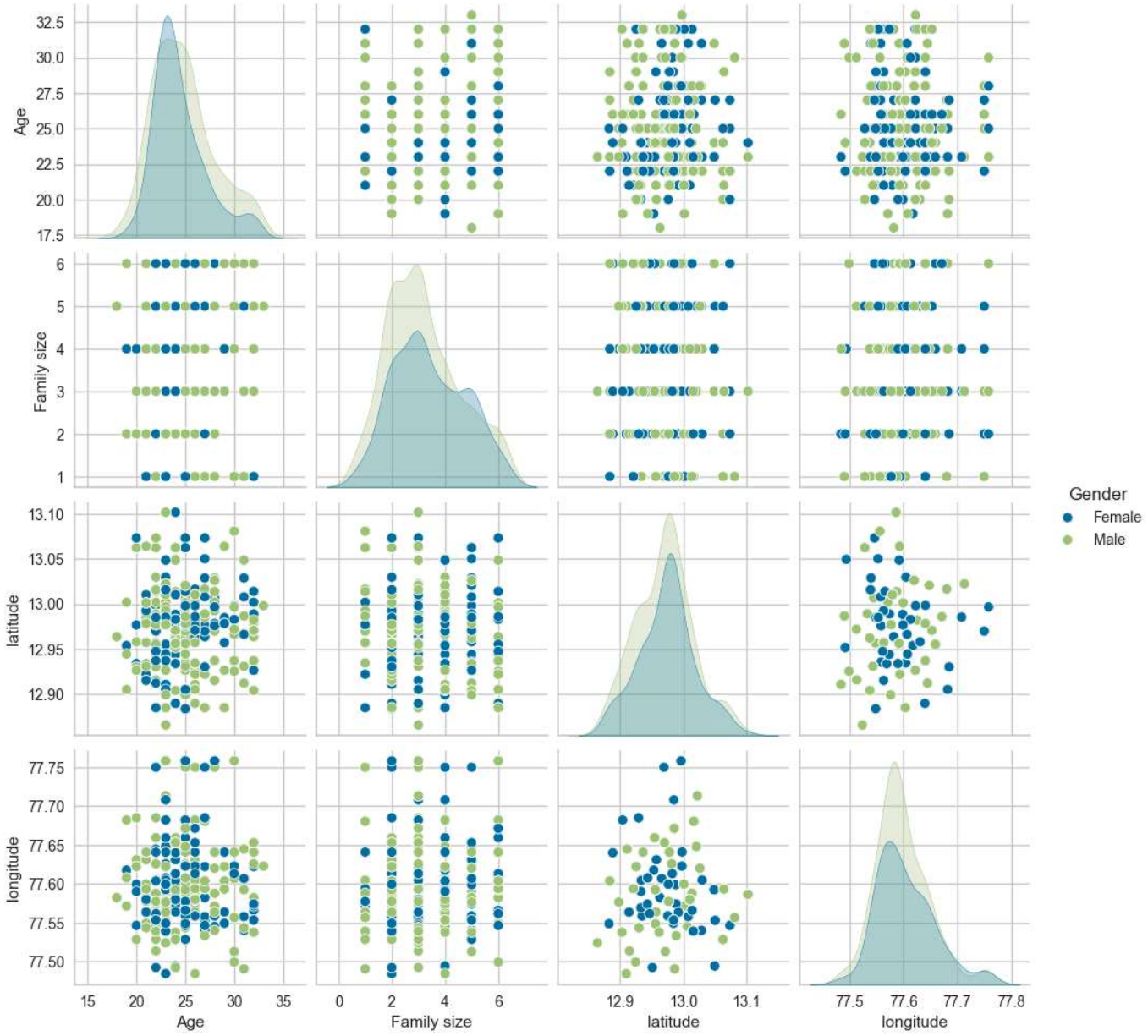
	Age	Family size	latitude	longitude	Pin code
count	388.000000	388.000000	388.000000	388.000000	388.000000
mean	24.628866	3.280928	12.972058	77.600160	560040.113402
std	2.975593	1.351025	0.044489	0.051354	31.399609
min	18.000000	1.000000	12.865200	77.484200	560001.000000
25%	23.000000	2.000000	12.936900	77.565275	560010.750000
50%	24.000000	3.000000	12.977000	77.592100	560033.500000
75%	26.000000	4.000000	12.997025	77.630900	560068.000000
max	33.000000	6.000000	13.102000	77.758200	560109.000000

In [ ]:
```
plt.figure(1, figsize=(15 , 6))
n = 0
for x in ['Age', 'Family size', 'latitude' , 'longitude']:
    n += 1
    plt.subplot(1 , 4 , n)
    plt.subplots_adjust(hspace=0.5 , wspace=0.5)
    sns.distplot(df[x] , bins=15)
    plt.title('Distplot of {}'.format(x))
plt.show()
```



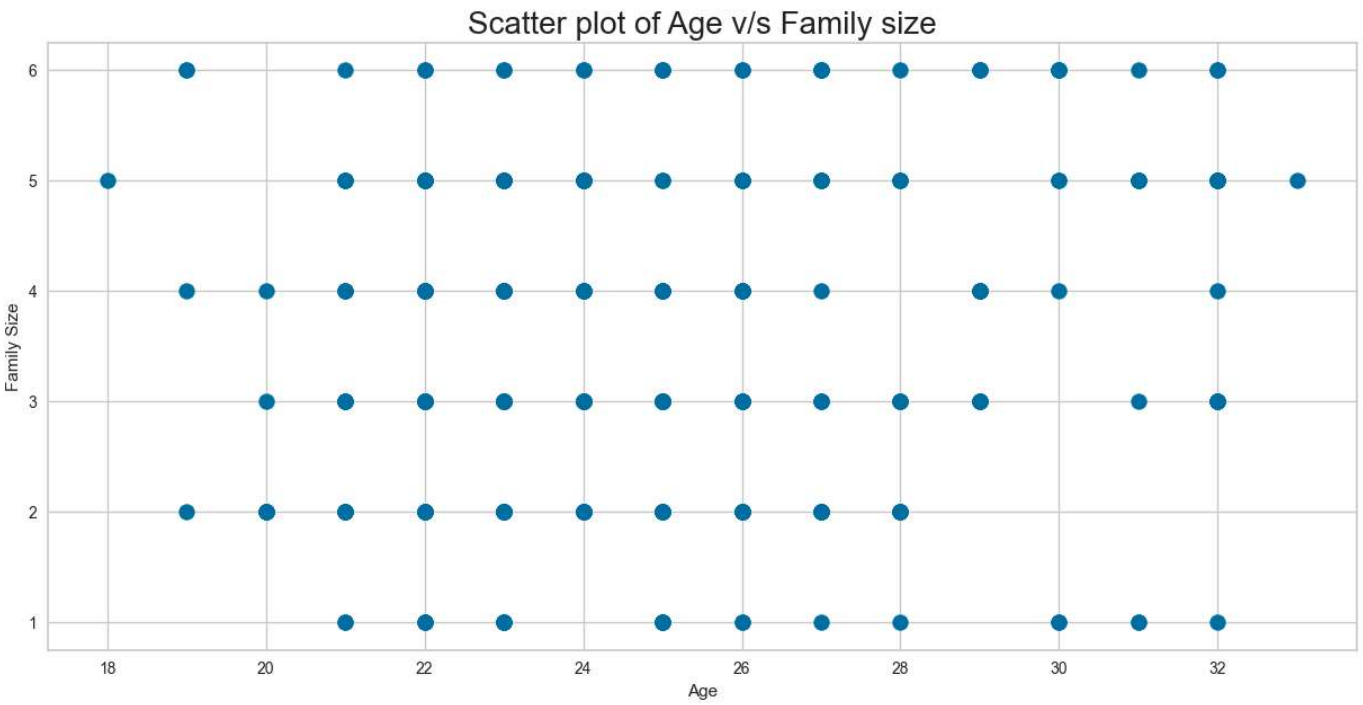
In [ ]:
```
sns.pairplot(df, vars=['Age', 'Family size', 'latitude' , 'longitude'], hue="Gender")
```

Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x28826fae950>
```



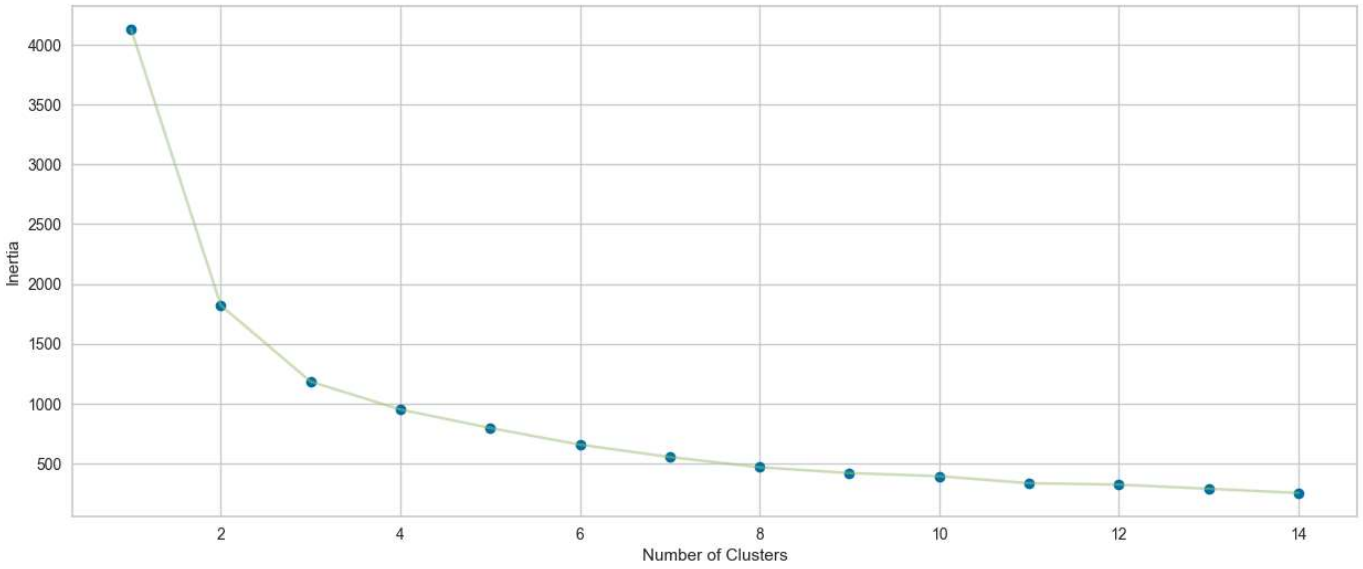
In [ ]:
```
# технические параметры k-means, которые мы будем использовать дальше
kmeans_params = {
    'init': 'k-means++',
    'n_init': 6,
    'max_iter': 300,
    'tol': 0.0001,
    'random_state': 42,
    'algorithm': 'elkan'
}
```

In [ ]:
```
plt.figure(1, figsize=(15 , 7))
plt.title('Scatter plot of Age v/s Family size', fontsize=20)
plt.xlabel('Age')
plt.ylabel('Family Size')
plt.scatter(x='Age', y='Family size', data=df, s=100)
plt.show()
```

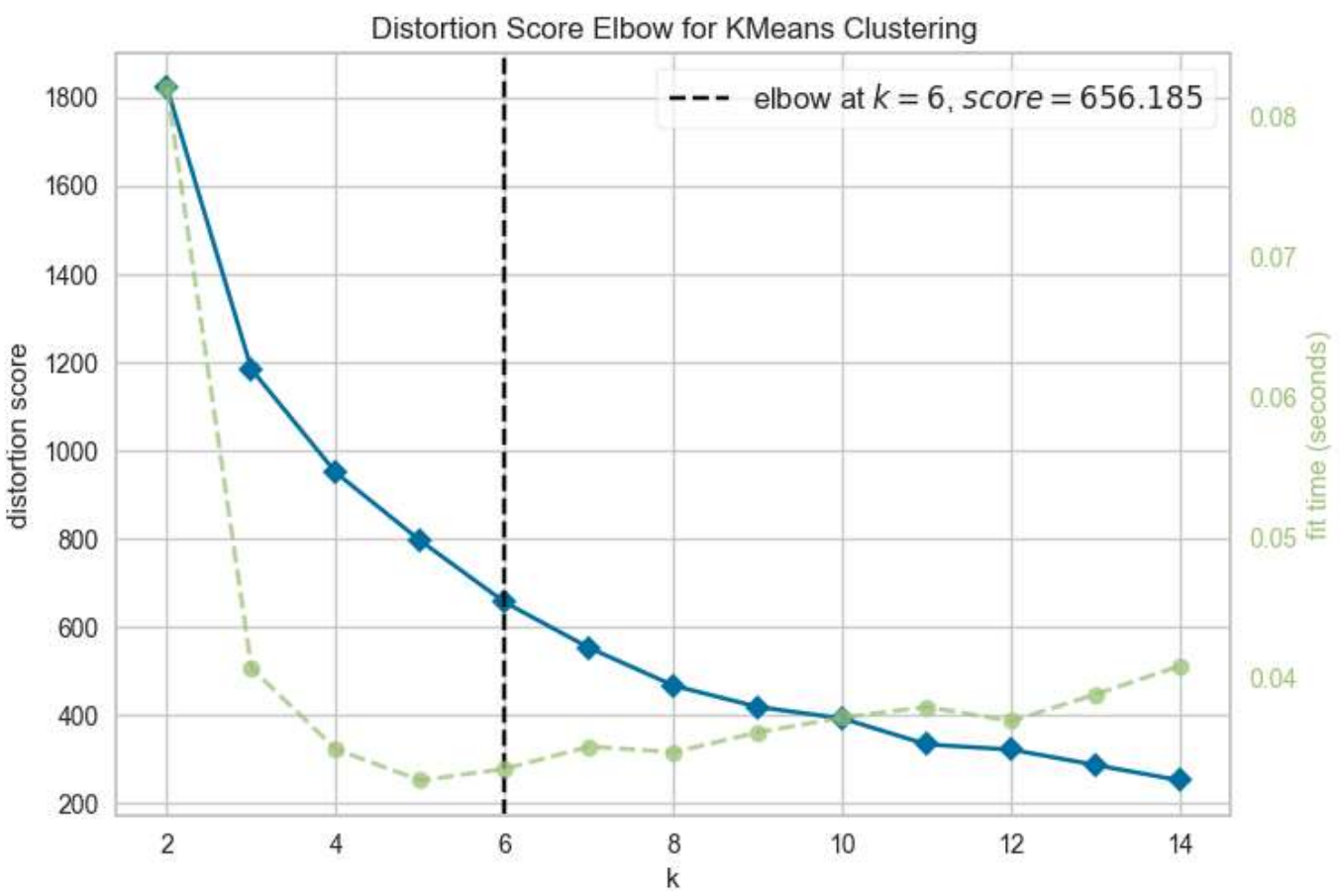


In [ ]:
```
X = df[['Age' , 'Family size']].iloc[: , :].values
inertia = []
for n in range(1 , 15):
    algorithm = KMeans(n_clusters=n, **kmeans_params)
    algorithm.fit(X)
    inertia.append(algorithm.inertia_)
```

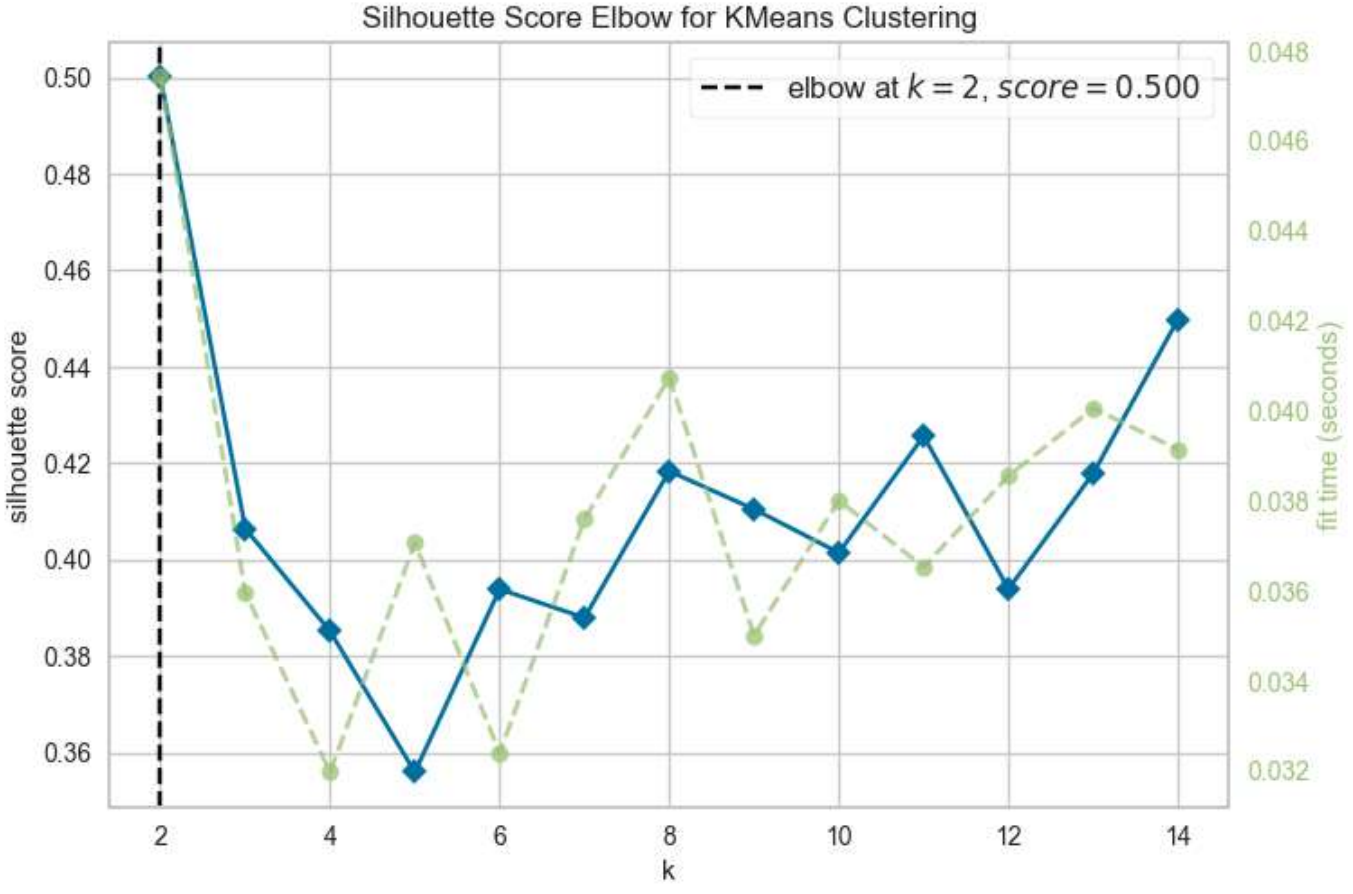
In [ ]:
```
plt.figure(1 , figsize = (15 ,6))
plt.plot(np.arange(1 , 15) , inertia , 'o')
plt.plot(np.arange(1 , 15) , inertia , '-' , alpha = 0.5)
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia')
plt.show()
```



In [ ]:
```
model = KMeans(**kmeans_params)
visualizer = KElbowVisualizer(model, k=(2, 15))

visualizer.fit(X)
visualizer.show()
plt.show()
```



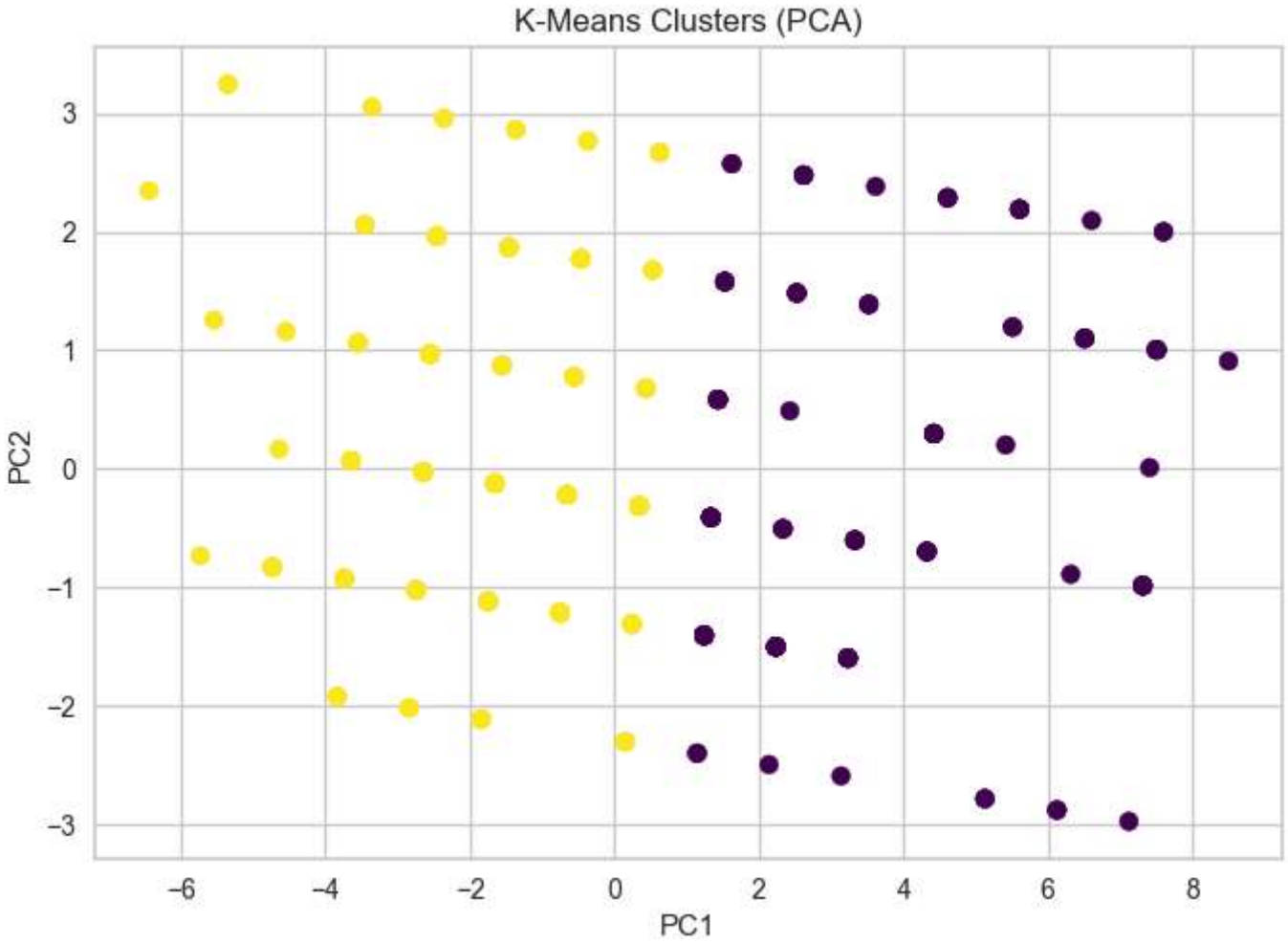
In [ ]:
```
model = KMeans(**kmeans_params)
visualizer = KElbowVisualizer(model, k=(2, 15), metric='silhouette')

visualizer.fit(X)
visualizer.show()
plt.show()
```



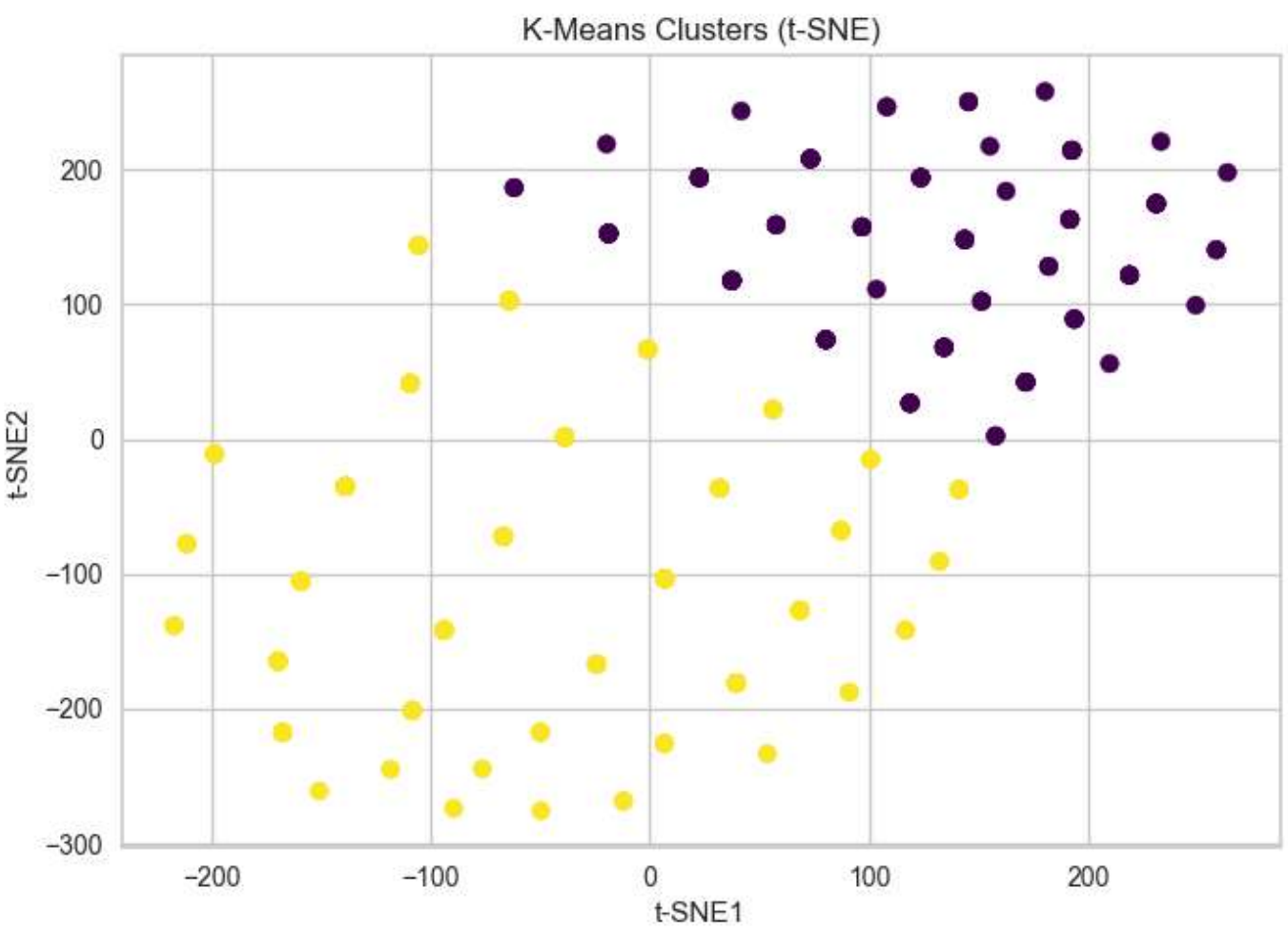
In [ ]:
```
kmeans = KMeans(n_clusters=2, **kmeans_params)
```

```
clusters = kmeans.fit_predict(X)
```

In [ ]:
```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Plot the clusters
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=clusters, cmap='viridis')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('K-Means Clusters (PCA)')
plt.show()
```

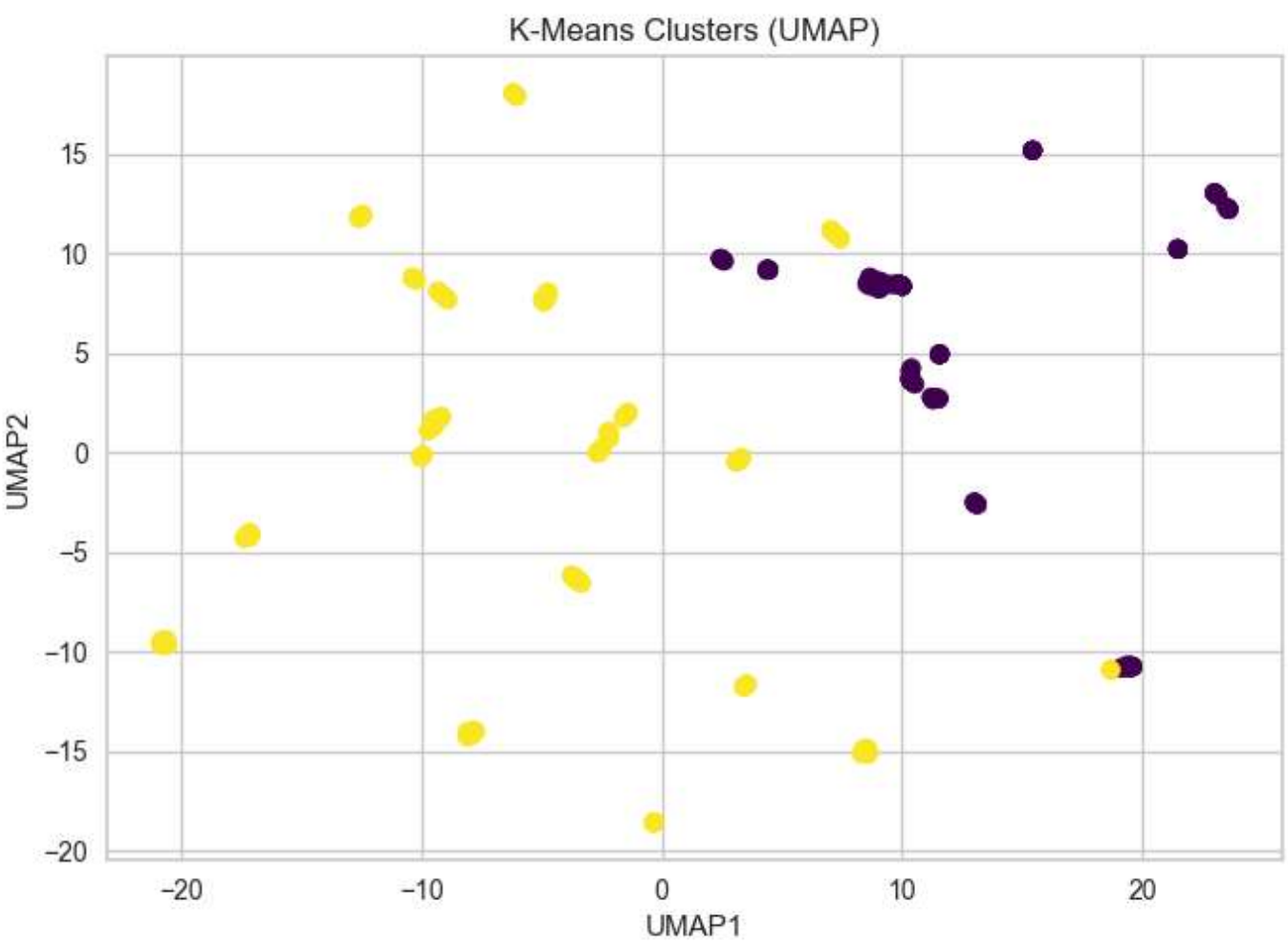


In [ ]:
```
tsne = TSNE(n_components=2, random_state=42, perplexity=150)
X_tsne = tsne.fit_transform(X)

# Plot the clusters
plt.scatter(X_tsne[:, 0], X_tsne[:, 1], c=clusters, cmap='viridis')
plt.xlabel('t-SNE1')
plt.ylabel('t-SNE2')
plt.title('K-Means Clusters (t-SNE)')
plt.show()
```



In [ ]:

```
umap_ = umap.UMAP(n_components=2, random_state=42, n_neighbors=5|0, min_dist=0.05)
X_umap = umap_.fit_transform(X)

# Plot the clusters
plt.scatter(X_umap[:, 0], X_umap[:, 1], c=clusters, cmap='viridis')
plt.xlabel('UMAP1')
plt.ylabel('UMAP2')
plt.title('K-Means Clusters (UMAP)')
plt.show()
```



Выводы: Для данного датасета метод понижения размерности PCA оказался наиболее информативным для визуализации кластеров, полученных с помощью метода k-Means.

PCA четко разделил кластеры и сохранил их форму, в то время как другие методы (t-SNE и UMAP) не смогли этого сделать так же эффективно.