Loading Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

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

Loading Dataset

In [2]:
```
players_df = pd.read_csv(r"E:\Data Science Projects\Project Files\Unsupervised
```

In [3]:
```
players_df.head()
```

Out[3]:

	sofifa_id	player_url	short_name	long_name	player_positions	o
0	158023	https://sofifa.com/player/158023/lionel-messi/...	L. Messi	Lionel Andrés Messi Cuccittini	RW, ST, CF	
1	188545	https://sofifa.com/player/188545/robert-lewand...	R. Lewandowski	Robert Lewandowski	ST	
2	20801	https://sofifa.com/player/20801/c-ronaldo-dos-...	Cristiano Ronaldo	Cristiano Ronaldo dos Santos Aveiro	ST, LW	
3	190871	https://sofifa.com/player/190871/neymar-da-sil...	Neymar Jr	Neymar da Silva Santos Júnior	LW, CAM	
4	192985	https://sofifa.com/player/192985/kevin-de-bruy...	K. De Bruyne	Kevin De Bruyne	CM, CAM	

5 rows × 110 columns

EDA and Visualization

In [4]:
```
players_df.shape
```

Out[4]:
```
(19239, 110)
```

In [5]:
```
features=['overall','potential','wage_eur','value_eur','age']
```

In [6]:
```
players_df=players_df.dropna(subset=features)
```

In [7]:
```
data=players_df[features].copy()
```

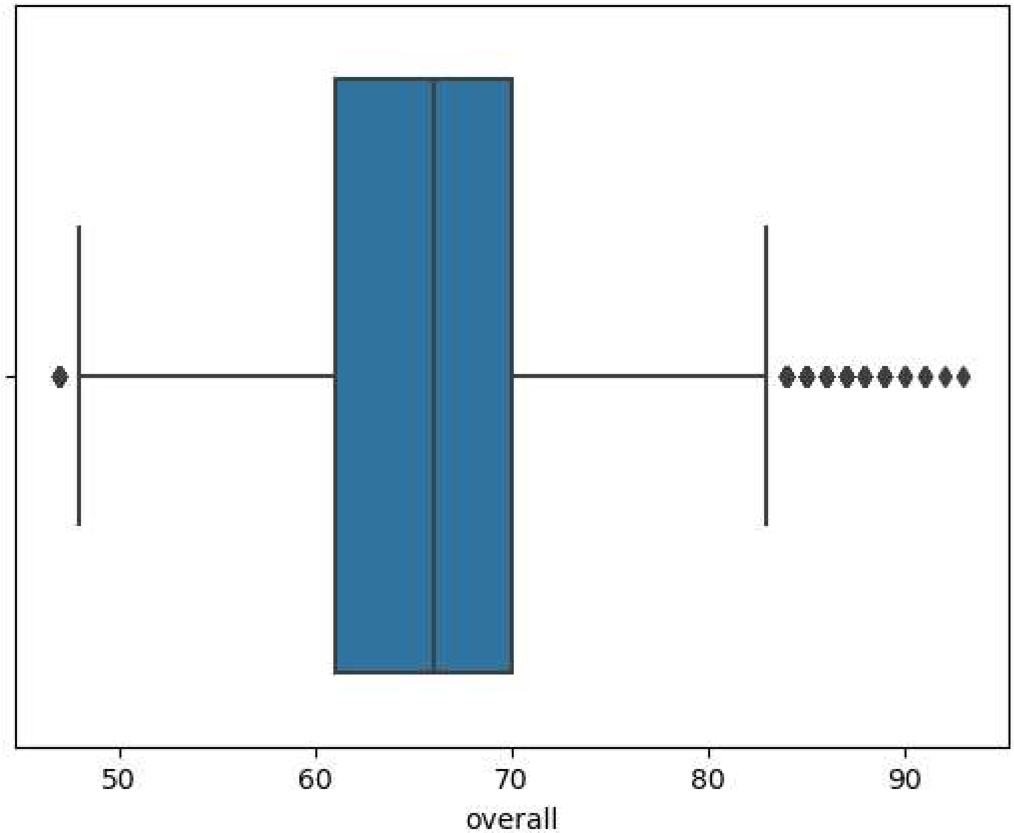
In [8]:
```
data
```

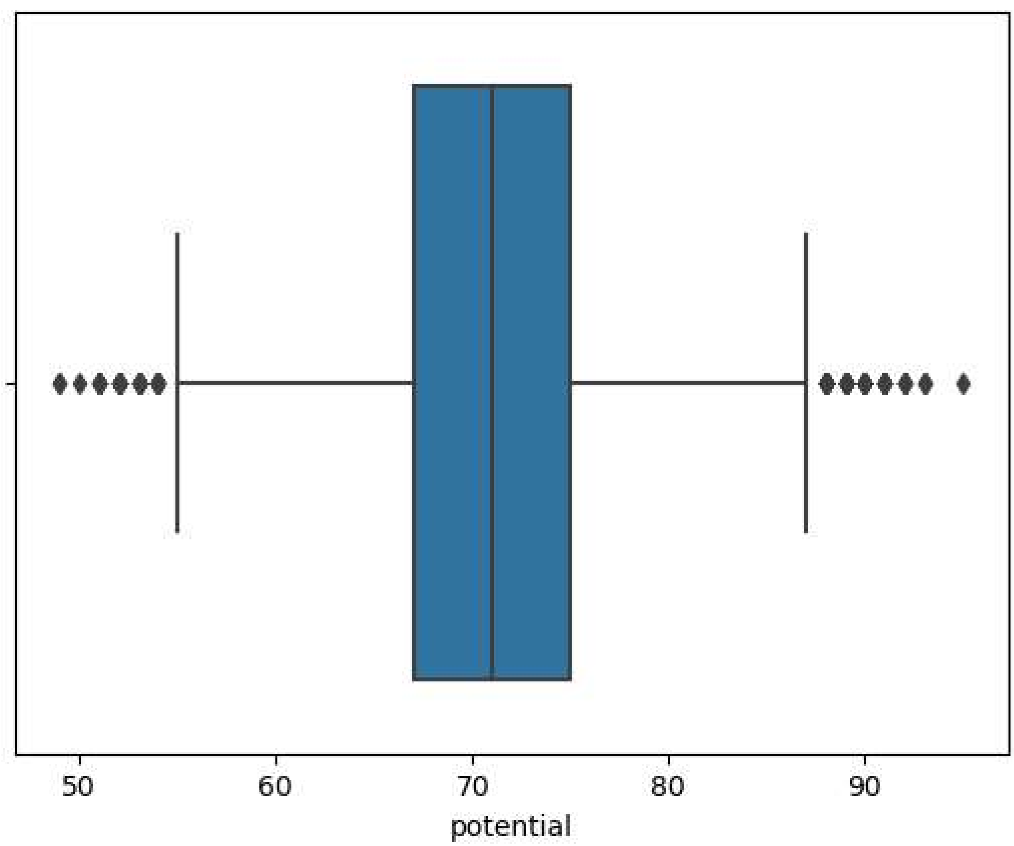
Out[8]:

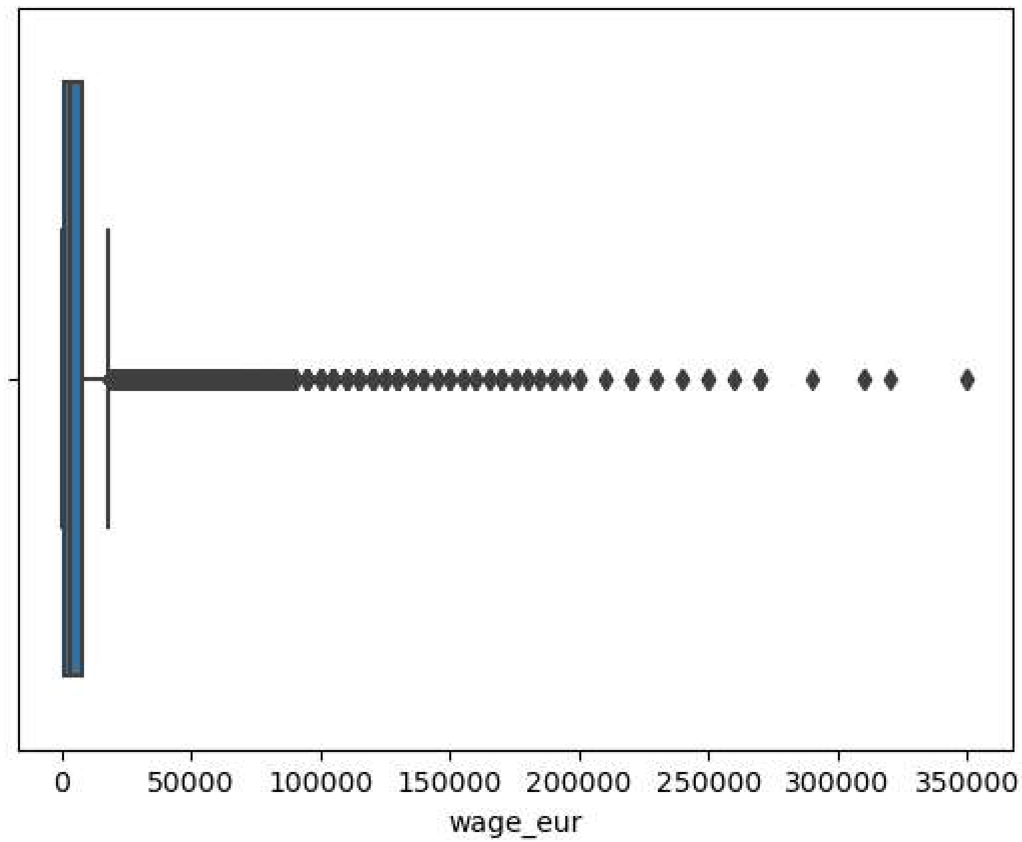
	overall	potential	wage_eur	value_eur	age
0	93	93	320000.0	78000000.0	34
1	92	92	270000.0	119500000.0	32
2	91	91	270000.0	45000000.0	36
3	91	91	270000.0	129000000.0	29
4	91	91	350000.0	125500000.0	30
...	...	...	...	...	...
19234	47	52	1000.0	70000.0	22
19235	47	59	500.0	110000.0	19
19236	47	55	500.0	100000.0	21
19237	47	60	500.0	110000.0	19
19238	47	60	500.0	110000.0	19

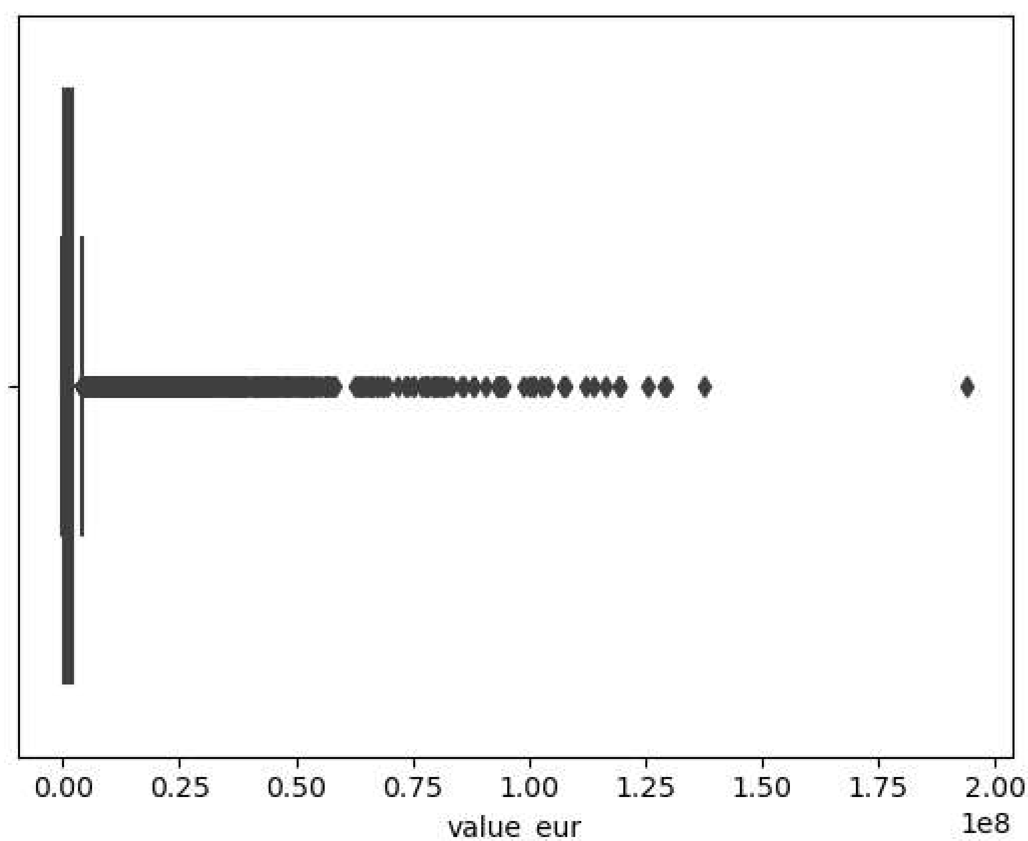
19165 rows × 5 columns

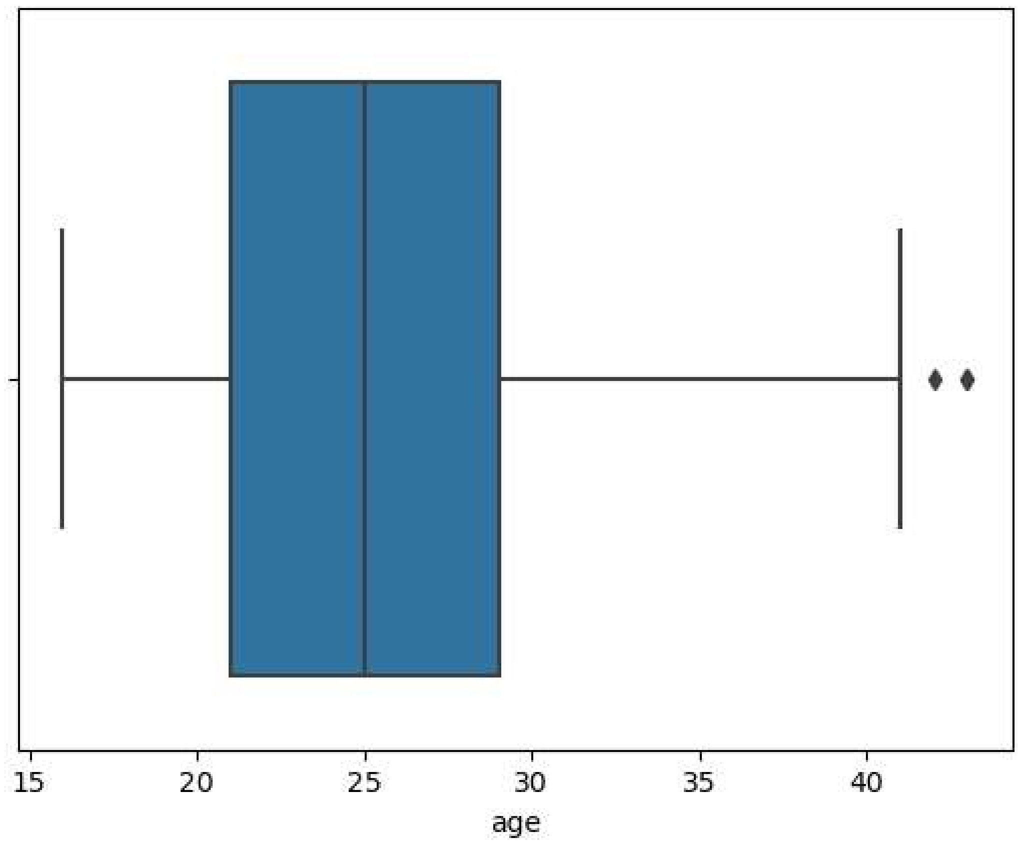
In [9]:
```
for i in data.columns:
    sns.boxplot(x=data[i])
    plt.show()
```





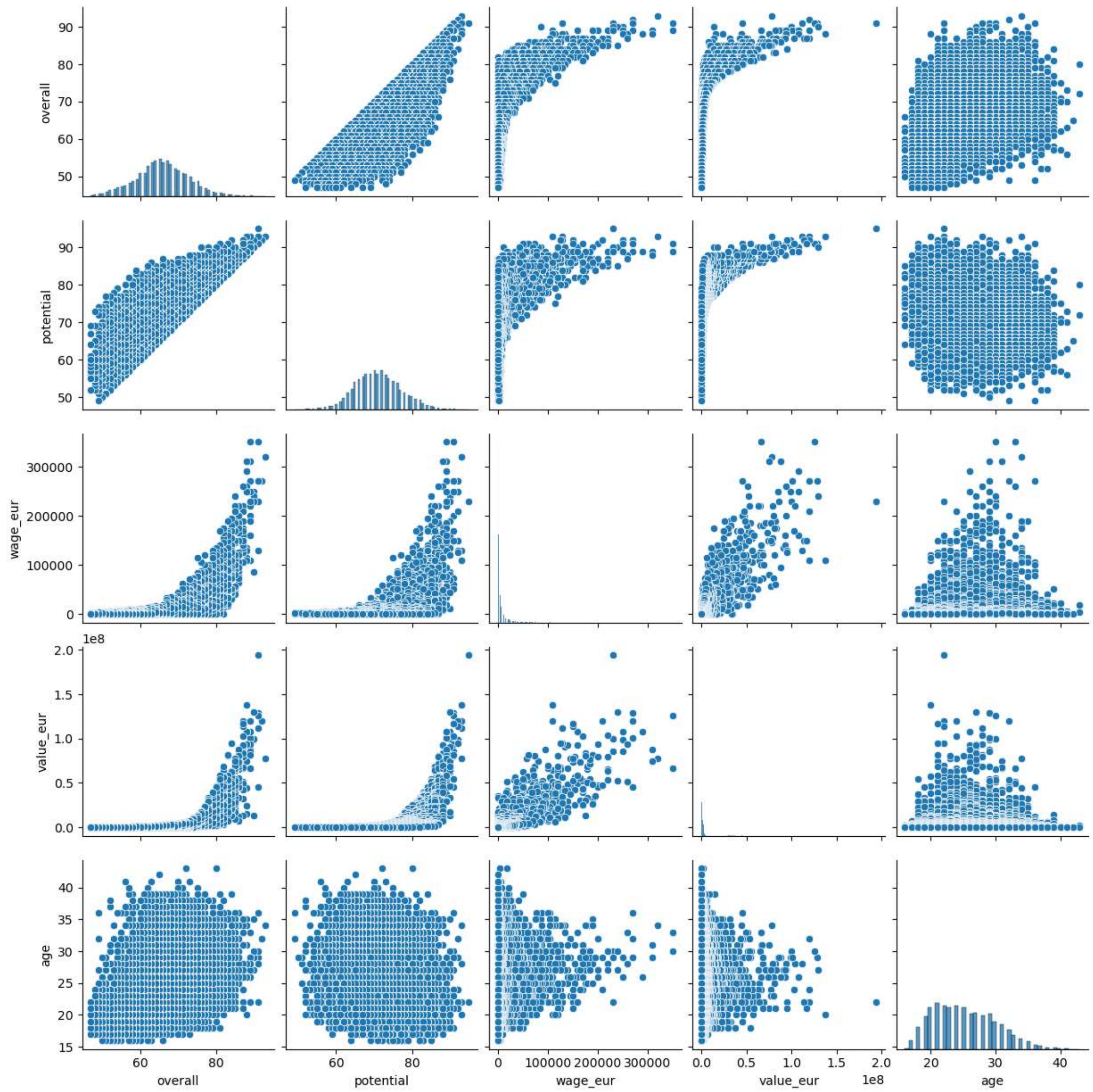

0
50000
100000
150000
200000
250000
300000
350000
wage_eur


0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
1e8
value_eur

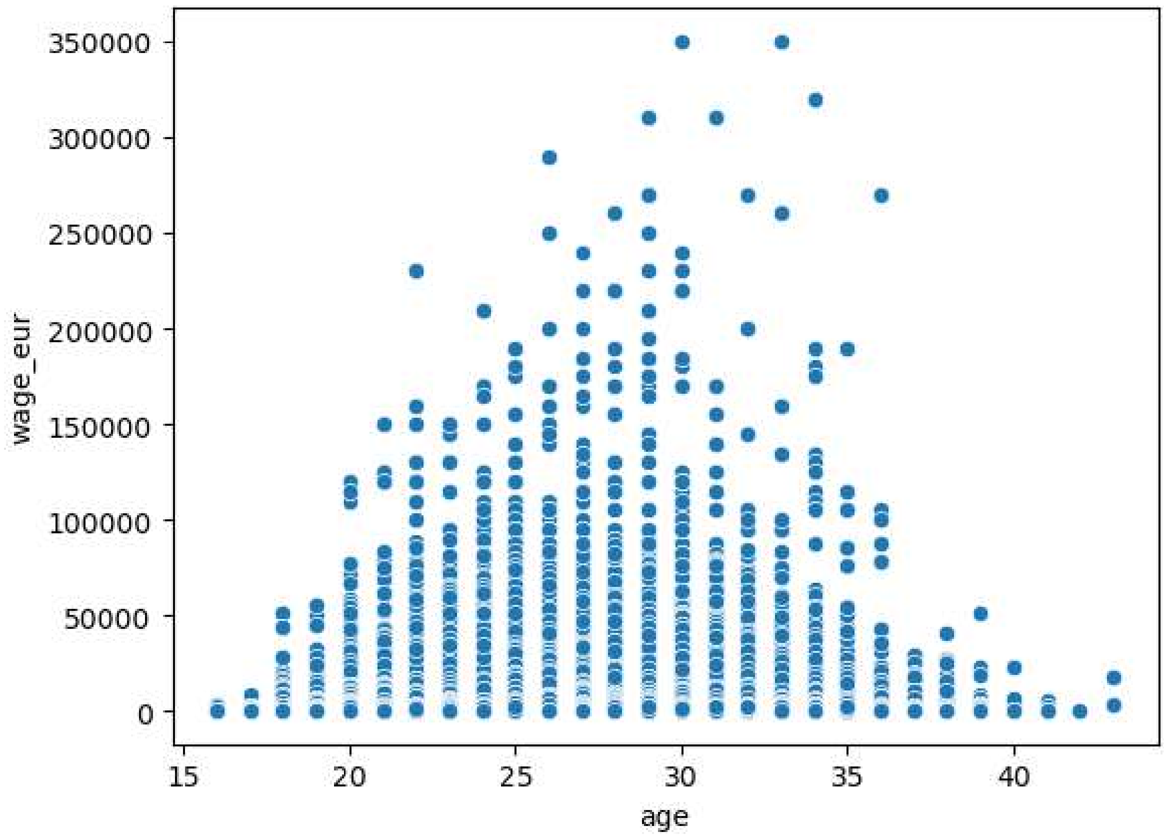

15
20
25
30
35
40
age

In [10]:
```
sns.pairplot(data)
```

Out[10]: <seaborn.axisgrid.PairGrid at 0x1e681653790>

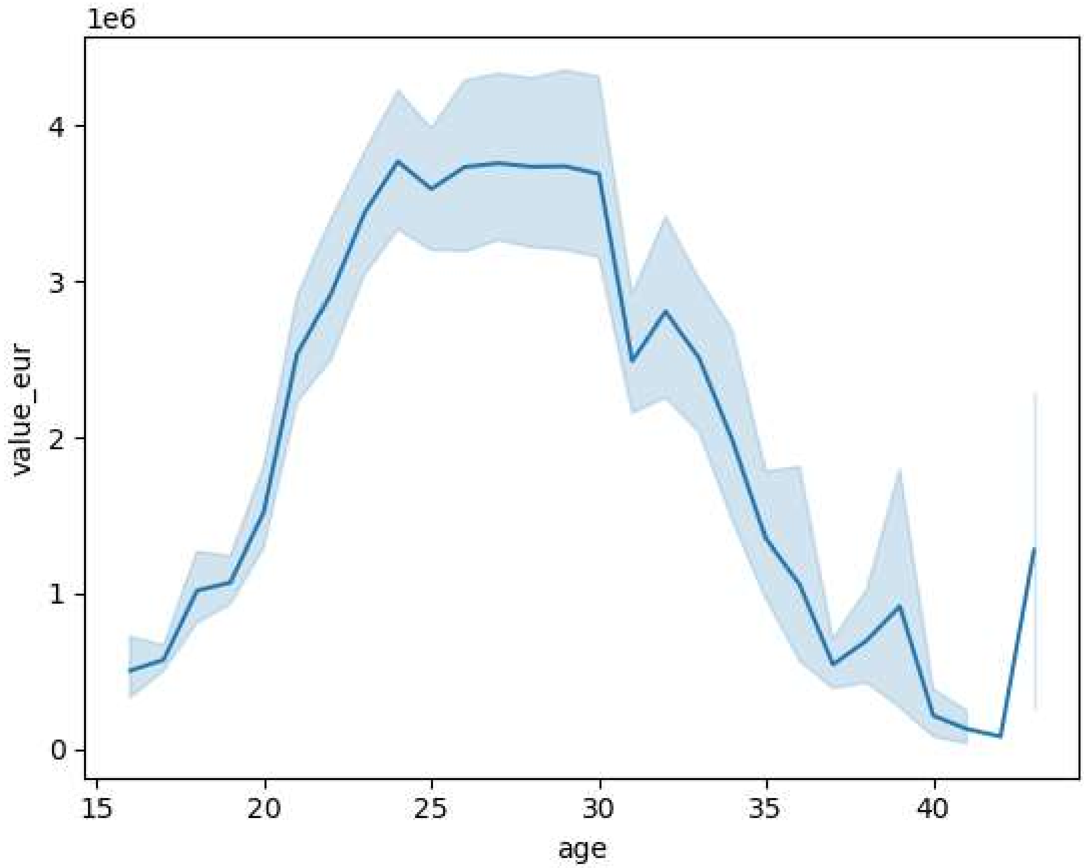


In [11]:
```
sns.scatterplot(x='age',y='wage_eur',data=data)
plt.show()
```

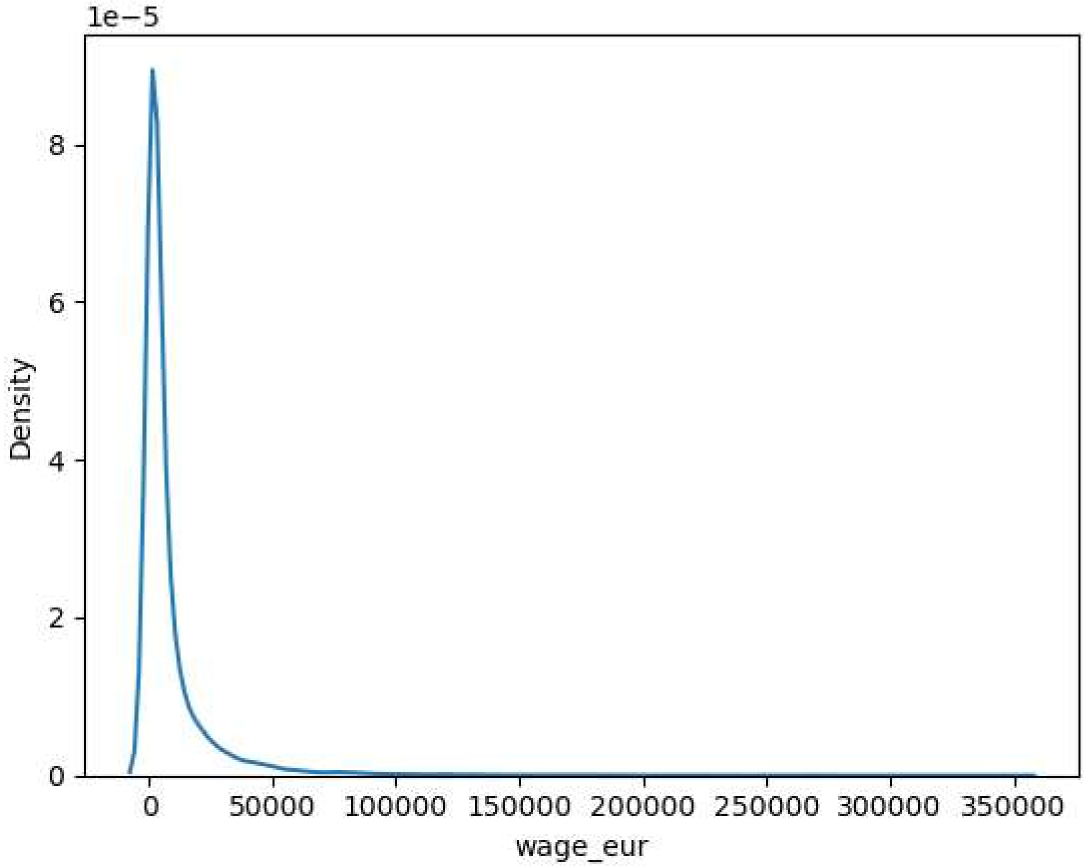


In [12]:
```
sns.lineplot(x='age',y='value_eur',data=data)
```

Out[12]: <Axes: xlabel='age', ylabel='value_eur'>

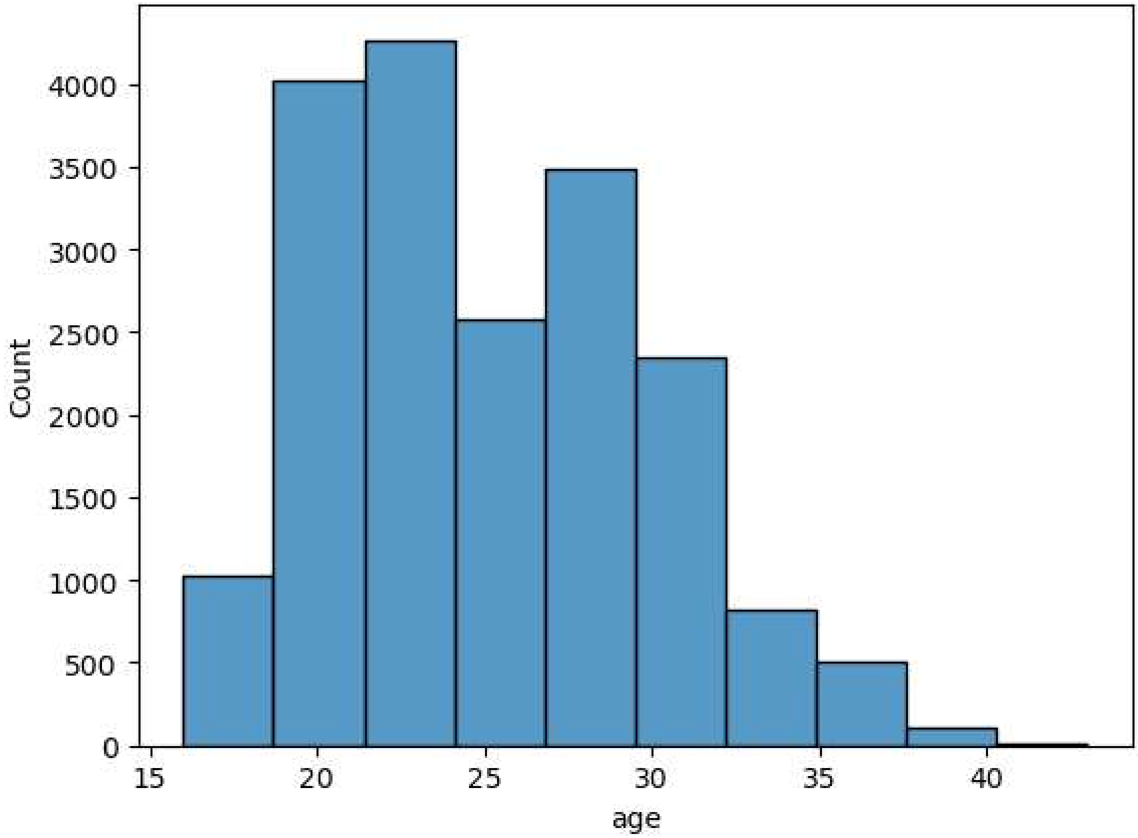


In [13]:
```
sns.kdeplot(x='wage_eur',data=data)
plt.show()
```



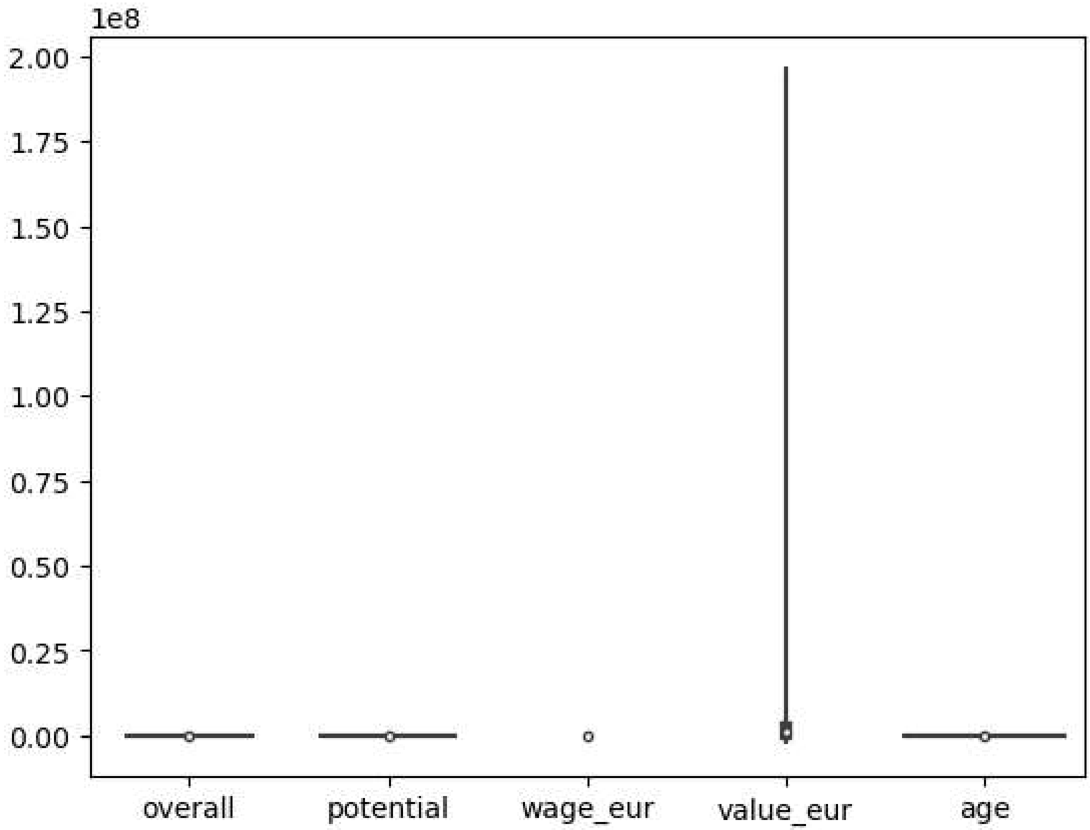
In [14]:
```
sns.histplot(x='age',bins=10,data=data)
```

Out[14]: <Axes: xlabel='age', ylabel='Count'>

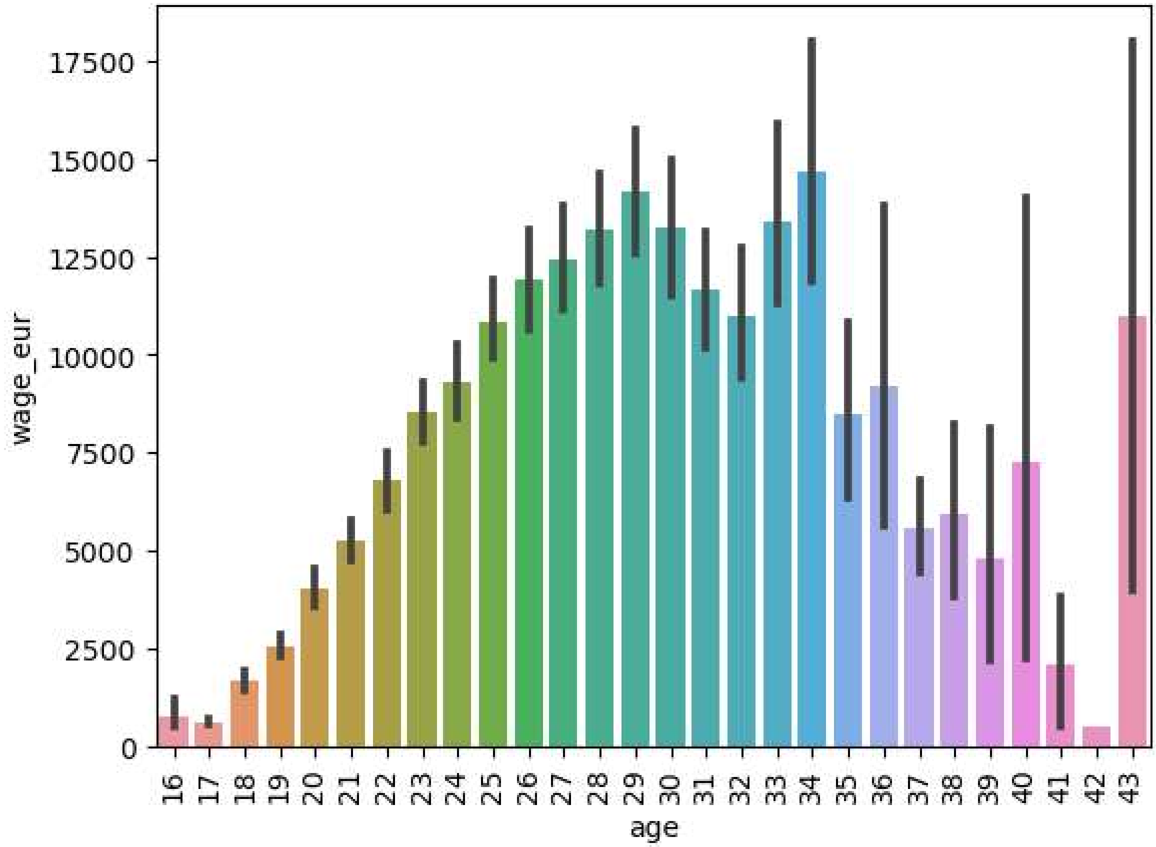


In [15]:
```
sns.violinplot( data=data)
```

Out[15]: <Axes: >



In [16]:
```
sns.barplot(x="age",y="wage_eur",data=data)
plt.xticks(rotation=90)
plt.show()
```



Scaling Data

In [17]:
```
data=((data - data.min()) / (data.max() - data.min())) * 9 + 1
```

In [18]:
```
data.describe()
```

Out[18]:

	overall	potential	wage_eur	value_eur	age
count	19165.000000	19165.000000	19165.000000	19165.000000	19165.000000
mean	4.670472	5.319998	1.219443	1.131826	4.063345
std	1.346635	1.191076	0.501528	0.353229	1.575838
min	1.000000	1.000000	1.000000	1.000000	1.000000
25%	3.739130	4.521739	1.012876	1.021620	2.666667
50%	4.717391	5.304348	1.064378	1.044817	4.000000
75%	5.500000	6.086957	1.193133	1.092370	5.333333
max	10.000000	10.000000	10.000000	10.000000	10.000000

In [19]:
```
def random_centroids(data,k):
    centroids = []
    for i in range(k):
        centroid = data.apply(lambda x: float(x.sample()))
        centroids.append(centroid)
    return pd.concat(centroids,axis=1)
```

In [20]:
```
centroids=random_centroids(data,5)
```

In [21]:
```
centroids
```

Out[21]:

	0	1	2	3	4
overall	3.739130	7.652174	3.347826	4.521739	4.913043
potential	2.173913	4.521739	4.521739	4.913043	3.934783
wage_eur	1.399142	1.218884	1.007725	1.000000	1.141631
value_eur	1.180519	1.034378	1.175879	1.029738	1.101649
age	3.333333	1.666667	5.333333	3.666667	2.333333

In [22]:
```
def get_labels(data,centroids):
    distances = centroids.apply(lambda x: np.sqrt(((data - x)**2).sum(axis=1)))
    return distances.idxmin(axis=1)
```

In [23]:
```
labels = get_labels(data,centroids)
```

In [24]:
```
labels.value_counts()
```

Out[24]:
```
3    12848
2     4212
0      818
4      770
1      517
Name: count, dtype: int64
```

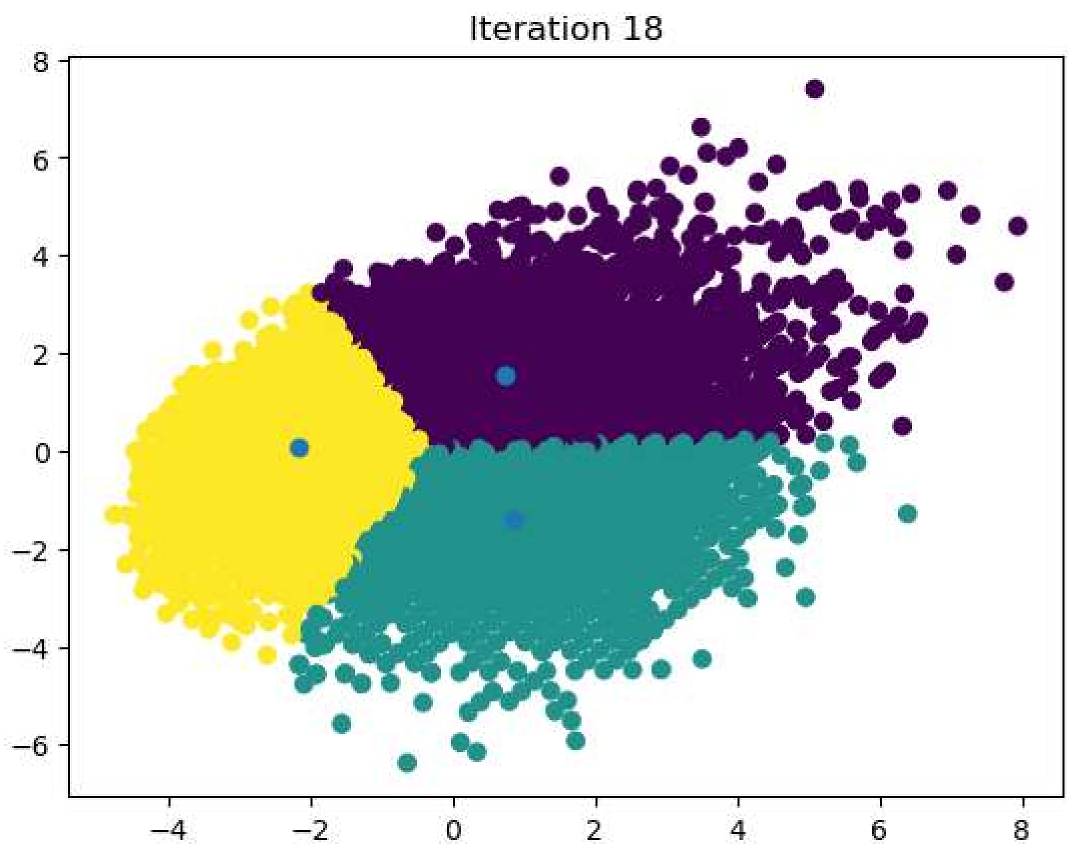
In [25]:
```
def new_centroids(data,labels,k):
    return data.groupby(labels).apply(lambda x: np.exp(np.log(x).mean())).T
```

PCA

In [26]:
```
from sklearn.decomposition import PCA
from IPython.display import clear_output
```

In [27]:
```
def plot_cluster(data, labels, centroids, iteration):
    pca = PCA(n_components=2)
    data_2d = pca.fit_transform(data)
    centroids_2d = pca.transform(centroids.T)
    clear_output(wait=True)
    plt.title(f'Iteration {iteration}')
    plt.scatter(x=data_2d[:,0], y=data_2d[:,1], c=labels)
    plt.scatter(x=centroids_2d[:,0],y=centroids_2d[:,1])
    plt.show()
```

In [28]:
```
max_iterations = 100
k=3

centroids = random_centroids(data,k)
old_centroids=pd.DataFrame()
iteration =1

while iteration<max_iterations and not centroids.equals(old_centroids):
    old_centroids=centroids

    labels=get_labels(data,centroids)
    centroids = new_centroids(data,labels, k)
    plot_cluster(data, labels, centroids, iteration)
    iteration += 1
```



In [29]:
```
centroids
```

Out[29]:

	0	1	2
overall	5.807503	4.781960	3.205672
potential	6.497870	4.506813	4.930905
wage_eur	1.420500	1.118498	1.028564
value_eur	1.285685	1.044909	1.026655
age	3.598215	5.467648	2.514741

In [30]:
```
players_df[labels ==1][["short_name"] + features]
```

Out[30]:

	short_name	overall	potential	wage_eur	value_eur	age
199	Pepe	82	82	14000.0	5500000.0	38
284	Joaquín	81	81	23000.0	8500000.0	39
292	José Fonte	81	81	30000.0	4600000.0	37
388	G. Buffon	80	80	18000.0	2300000.0	43
509	Iniesta	79	79	10000.0	5500000.0	37
...	...	...	...	...	...	...
18890	S. Haokip	51	51	500.0	60000.0	28
18971	Lalkhawpuimawia	51	51	500.0	60000.0	29
19032	Song Yue	50	50	2000.0	40000.0	29
19100	J. Russell	49	49	500.0	15000.0	36
19118	Gao Xiang	49	49	2000.0	35000.0	32

7191 rows × 6 columns

KMeans

In [31]:
```
from sklearn.cluster import KMeans
```

In [32]:
```
kmeans = KMeans(3)
```

In [33]:
```
kmeans.fit(data)
```

Out[33]:
```
KMeans(n_clusters=3)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [34]:
```
centroids=kmeans.cluster_centers_
```

In [35]:
```
pd.DataFrame(centroids, columns=features).T
```

Out[35]:

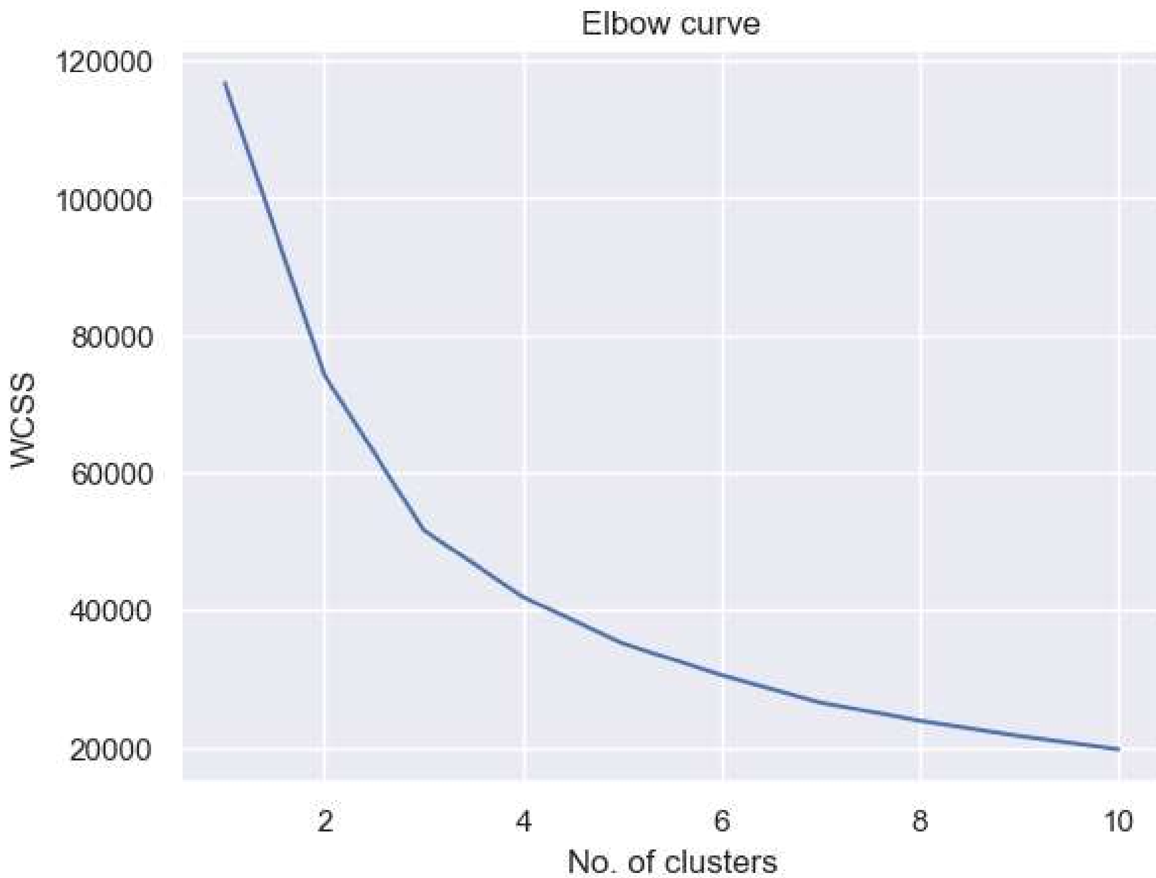
	0	1	2
overall	4.800460	6.210055	3.587122
potential	4.501645	6.607522	5.198413
wage_eur	1.112823	1.646976	1.039359
value_eur	1.039900	1.407513	1.035310
age	5.616384	4.126952	2.709082

In [36]:
```
#Elbow method

wcss = []

for i in range(1,11):
    kmeans=KMeans(n_clusters=i,init='k-means++',random_state=25)
    kmeans.fit(data)

    wcss.append(kmeans.inertia_)
```

In [37]:
```
wcss
```

Out[37]:
```
[116740.5025497065,
 74273.1381008405,
 51663.985688553716,
 41921.112070456285,
 35179.88728999961,
 30518.54500695888,
 26527.552088666842,
 23852.320933146504,
 21651.118307793884,
 19727.519439476724]
```

In [38]:
```
sns.set()
plt.plot(range(1,11),wcss)
plt.title('Elbow curve')
plt.xlabel('No. of clusters')
plt.ylabel('WCSS')
plt.show()
```



In [39]:
```
kmeans=KMeans(n_clusters=4,init='k-means++',random_state=0)
y=kmeans.fit_predict(data)
```

In [40]:
```
print(y)
```

```
[2 2 2 ... 0 0 0]
```

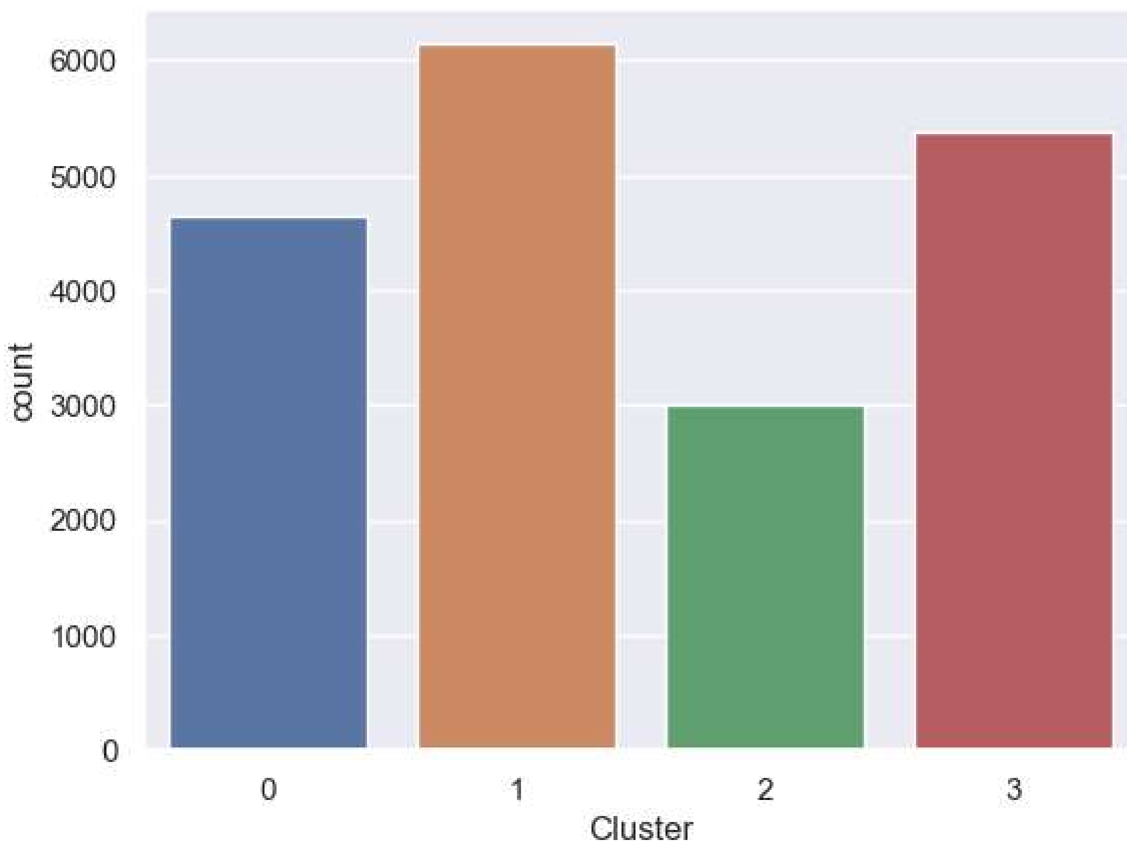
In [41]:
```
data_output = data.copy(deep = True)
data_output['Cluster'] = kmeans.labels_
data_output.head()
```

Out[41]:

	overall	potential	wage_eur	value_eur	age	Cluster
0	10.000000	9.608696	9.227468	4.618307	7.000000	2
1	9.804348	9.413043	7.939914	6.543654	6.333333	2
2	9.608696	9.217391	7.939914	3.087308	7.666667	2
3	9.608696	9.217391	7.939914	6.984396	5.333333	2
4	9.608696	9.217391	10.000000	6.822018	5.666667	2

In [42]:
```
sns.countplot(x='Cluster',data=data_output)
```

Out[42]: <Axes: xlabel='Cluster', ylabel='count'>



In [43]:
```
np.unique(kmeans.labels_, return_counts=True)
```

Out[43]: (array([0, 1, 2, 3]), array([4651, 6142, 2998, 5374], dtype=int64))

In [44]:
```
from sklearn.metrics import silhouette_score, calinski_harabasz_score,davies_b
silhouette_avg = silhouette_score(data, y)
print(f"Silhouette Score: {silhouette_avg}")
```

Silhouette Score: 0.3306415427738189

In [45]:
```
calinski_harabasz_index = calinski_harabasz_score(data, y)
print(f"Calinski-Harabasz Index: {calinski_harabasz_index}")
```

```
Calinski-Harabasz Index: 11399.358190897265
```

In [46]:
```
davies_bouldin_index = davies_bouldin_score(data, y)
print(f"Davies-Bouldin Index: {davies_bouldin_index}")
```

```
Davies-Bouldin Index: 0.9890325845696226
```

Hierarchical Clustering

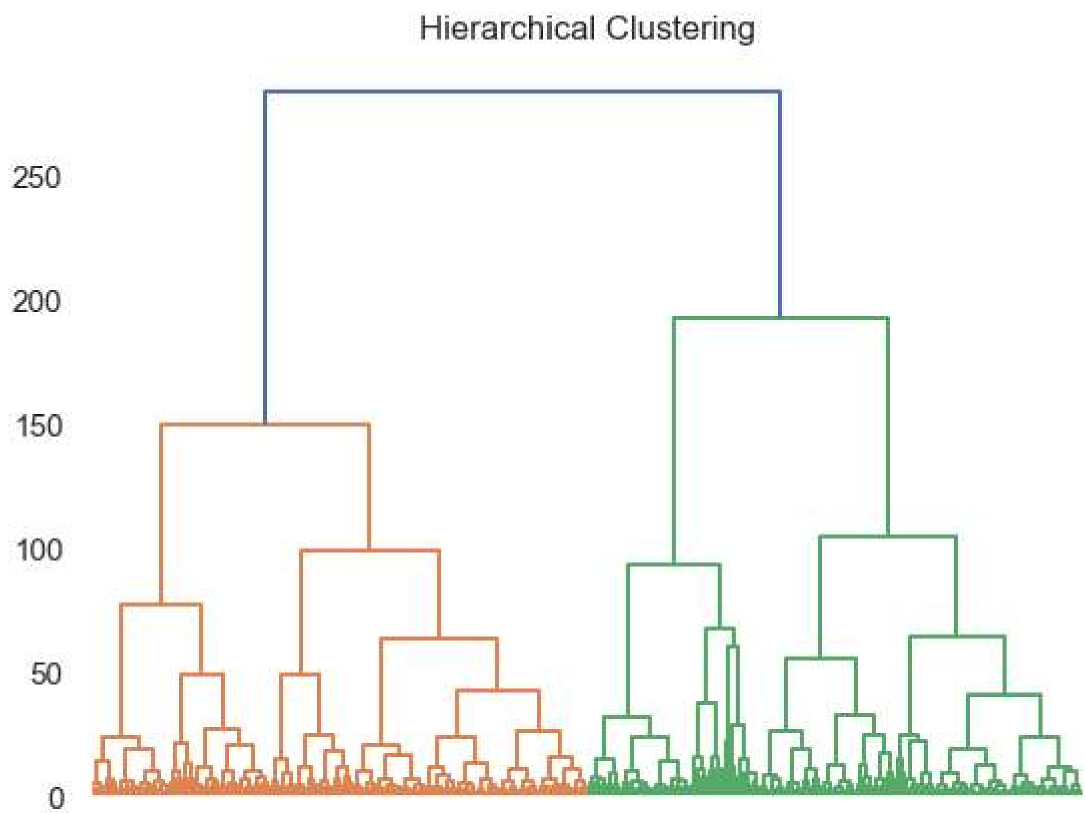
In [47]:
```
import scipy.cluster.hierarchy as sch
from sklearn.preprocessing import scale as s
from scipy.cluster.hierarchy import dendrogram, linkage
```

In [48]:
```
Z = sch.linkage(data,method='ward')
Z
```

Out[48]:
```
array([[1.60000000e+01, 1.70000000e+01, 0.00000000e+00, 2.00000000e+00],
       [2.54000000e+02, 2.70000000e+02, 0.00000000e+00, 2.00000000e+00],
       [3.73000000e+02, 3.76000000e+02, 0.00000000e+00, 2.00000000e+00],
       ...,
       [3.83220000e+04, 3.83240000e+04, 1.50062967e+02, 9.62000000e+03],
       [3.83230000e+04, 3.83250000e+04, 1.92818967e+02, 9.54500000e+03],
       [3.83260000e+04, 3.83270000e+04, 2.84734519e+02, 1.91650000e+04]])
```

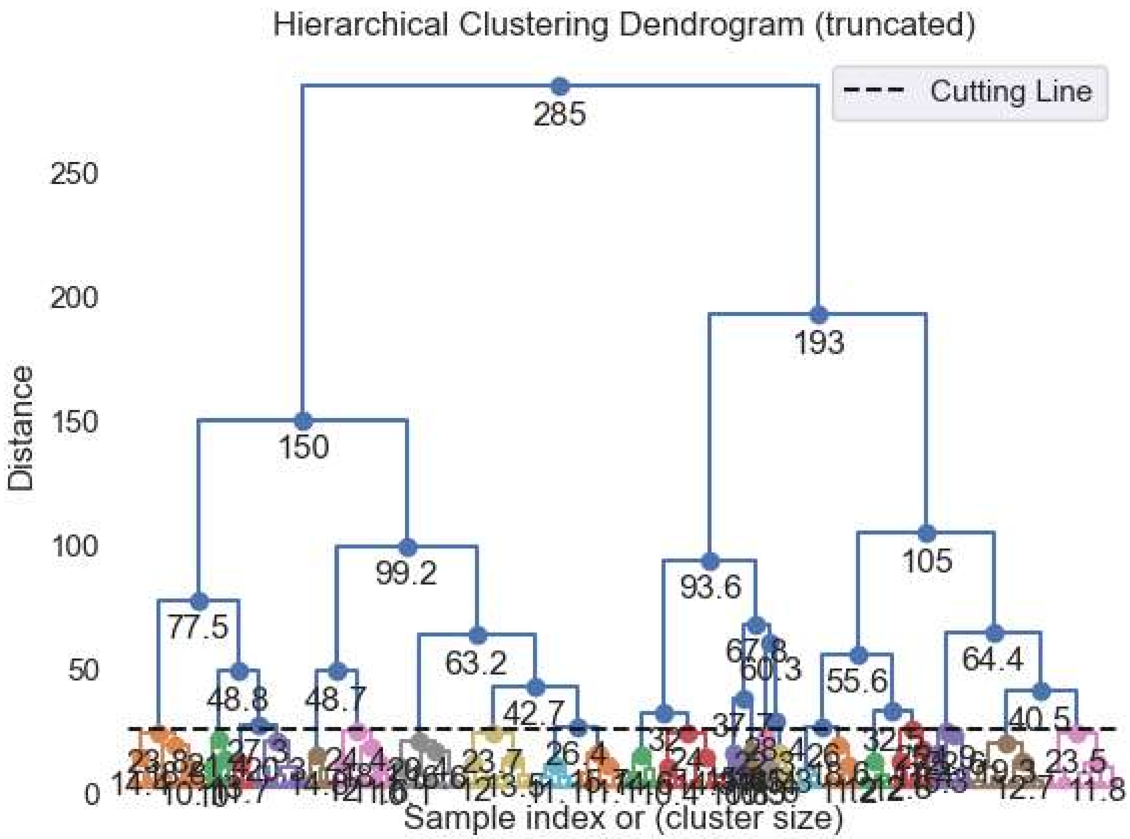
In [49]:
```
den = sch.dendrogram(Z)
plt.tick_params(
    axis='x',
    which='both',
    bottom=False,
    top=False,
    labelbottom=False)
plt.title('Hierarchical Clustering')
```

Out[49]:
```
Text(0.5, 1.0, 'Hierarchical Clustering')
```



In [50]:
```
def fd(*args, **kwargs):
    max_d = kwargs.pop('max_d', None)
    if max_d and 'color_threshold' not in kwargs:
        kwargs['color_threshold'] = max_d
    annotate_above = kwargs.pop('annotate_above', 0)

    ddata = dendrogram(*args, **kwargs)

    if not kwargs.get('no_plot', False):
        plt.title('Hierarchical Clustering Dendrogram (truncated)')
        plt.xlabel('Sample index or (cluster size)')
        plt.ylabel('Distance')
        for i, d, c in zip(ddata['icoord'], ddata['dcoord'], ddata['color_list
            x = 0.5 * sum(i[1:3])
            y = d[1]
            if y > annotate_above:
                plt.plot(x, y, 'o', c=c)
                plt.annotate("%.3g" % y, (x,y), xytext=(0, -5),
                             textcoords='offset points',
                             va='top', ha='center')

        if max_d:
            plt.axhline(y=max_d, c='k', linestyle='--', label='Cutting Line')
            plt.legend()
    return ddata
```

In [51]:
```
fd(Z, leaf_rotation=90., show_contracted=True, annotate_above=10, max_d=25)
plt.tick_params(
    axis='x',
    which='both',
    bottom=False,
    top=False,
    labelbottom=False)
```



Agglomerative Clustering

In [52]:
```
from sklearn.cluster import AgglomerativeClustering
```

In [53]:
```
hc_model = AgglomerativeClustering(n_clusters = 2, affinity = 'euclidean', lin
```

In [54]:
```
y_cluster = hc_model.fit_predict(data)
```

In [55]:
```
y_cluster
```

Out[55]:
```
array([0, 0, 0, ..., 1, 1, 1], dtype=int64)
```

In [56]:
```
data_out = data.copy(deep = True)
data_out['Cluster'] = hc_model.labels_
data_out.head()
```

Out[56]:

	overall	potential	wage_eur	value_eur	age	Cluster
0	10.000000	9.608696	9.227468	4.618307	7.000000	0
1	9.804348	9.413043	7.939914	6.543654	6.333333	0
2	9.608696	9.217391	7.939914	3.087308	7.666667	0
3	9.608696	9.217391	7.939914	6.984396	5.333333	0
4	9.608696	9.217391	10.000000	6.822018	5.666667	0

In [57]:
```
np.unique(hc_model.labels_, return_counts=True)
```

Out[57]:
```
(array([0, 1], dtype=int64), array([9545, 9620], dtype=int64))
```

In [60]:
```
silhouette_avg = silhouette_score(data, y_cluster)
print(f"Silhouette Score: {silhouette_avg}")
```

```
Silhouette Score: 0.33823622989676916
```

In [59]:
```
calinski_harabasz_index = calinski_harabasz_score(data, y_cluster)
print(f"Calinski-Harabasz Index: {calinski_harabasz_index}")
```

```
Calinski-Harabasz Index: 10193.846463007581
```

In [61]:
```
davies_bouldin_index = davies_bouldin_score(data, y_cluster)
print(f"Davies-Bouldin Index: {davies_bouldin_index}")
```

```
Davies-Bouldin Index: 1.1793518853344636
```

In [ ]: