Biblioteke

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.cluster import MeanShift,BisectingKMeans
from sklearn.cluster import DBSCAN
import plotly as py
import plotly.graph_objs as go
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
from sklearn.metrics import silhouette_score, calinski_harabasz_score,davies_bouldin_score
from sklearn.metrics import  adjusted_rand_score
import warnings
warnings.filterwarnings('ignore')
```

Ucitavanje

```
url = "https://raw.githubusercontent.com/aleksicmilica/ml-projekat2/main/bank_marketing_dataset.csv"
dataset= pd.read_csv(url)
```

```
dataset.head()
```

	age	job	marital	education	default	housing	loan	contact	month	day_of_w
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	
1	57	services	married	high.school	unknown	no	no	telephone	may	
2	37	services	married	high.school	no	yes	no	telephone	may	
3	40	admin.	married	basic.6y	no	no	no	telephone	may	
4	56	services	married	high.school	no	no	yes	telephone	may	

5 rows × 21 columns

```
dataset.columns
```

```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'subscribed'],
      dtype='object')
```

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
```

```
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  subscribed      41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

Predobrada

Provera prisustva missing values

```
total_missing = dataset.isnull().sum()
print(total_missing)
if (total_missing == 0).all():
  print("Sve vrednosti su prisutne u dataset-u")
```

```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
subscribed        0
dtype: int64
Sve vrednosti su prisutne u dataset-u
```

Provera da li su svi podaci odgovarajuceg tipa

```
irregular_values =  (dataset["duration"] < 0).sum() + (dataset["campaign"] < 0).sum() + (dataset["pdays"] < 0).sum() + (dataset["previou
print(irregular_values)
```

```
0
```

```
numerical_type = pd.api.types.is_numeric_dtype(dataset["age"].dtype) and pd.api.types.is_numeric_dtype(dataset["duration"].dtype) and pd
print(numerical_type)
```

```
True
```

```
if irregular_values == 0 and numerical_type :
  print("Svi podaci su odgovarajuceg tipa")
else:
  print("Podaci nisu odgovarajuceg tipa")
```

```
Svi podaci su odgovarajuceg tipa
```

Vizuelizacija podataka

```
columns = dataset.columns
n = len(columns)
```

```
fig, axes = plt.subplots(n//4+1, 4, figsize=(20, 20))
axes = axes.flatten()
for i, column_name in enumerate(columns):
    sns.histplot(x=column_name, data=dataset, ax=axes[i])
    axes[i].set_title(column_name)
    axes[i].set_xlabel('')
    axes[i].set_ylabel('')

plt.tight_layout()
plt.show()
```


```
dataset_2 = dataset.copy()
```

Labeliranje kategorickih tipova

```
lista = ["job","marital", "education", "default", "housing", "loan", "contact", "month", "day_of_week", "poutcome", "subscribed"]
for el in lista:
  possible_location = dataset[el].unique().tolist()
  # possible_location.insert(0,'nan')
  dict_help ={}
  for i in range(len(possible_location)):
    dict_help[possible_location[i]] = i
  print(dict_help)
  dataset.replace({el:dict_help},inplace = True)
dataset
```

```
{'housemaid': 0, 'services': 1, 'admin.': 2, 'blue-collar': 3, 'technician': 4, 'retire
{'married': 0, 'single': 1, 'divorced': 2, 'unknown': 3}
{'basic.4y': 0, 'high.school': 1, 'basic.6y': 2, 'basic.9y': 3, 'professional.course':
{'no': 0, 'unknown': 1, 'yes': 2}
{'no': 0, 'yes': 1, 'unknown': 2}
{'no': 0, 'yes': 1, 'unknown': 2}
{'telephone': 0, 'cellular': 1}
{'may': 0, 'jun': 1, 'jul': 2, 'aug': 3, 'oct': 4, 'nov': 5, 'dec': 6, 'mar': 7, 'apr':
{'mon': 0, 'tue': 1, 'wed': 2, 'thu': 3, 'fri': 4}
{'nonexistent': 0, 'failure': 1, 'success': 2}
{'no': 0, 'yes': 1}
```

	age	job	marital	education	default	housing	loan	contact	month	day_of_week
0	56	0	0	0	0	0	0	0	0	0
1	57	1	0	1	1	0	0	0	0	0
2	37	1	0	1	0	1	0	0	0	0
3	40	2	0	2	0	0	0	0	0	0
4	56	1	0	1	0	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...
41183	73	5	0	4	0	1	0	1	5	4
41184	46	3	0	4	0	0	0	1	5	4
41185	56	5	0	6	0	1	0	1	5	4
41186	44	4	0	4	0	0	0	1	5	4
41187	74	5	0	4	0	1	0	1	5	4

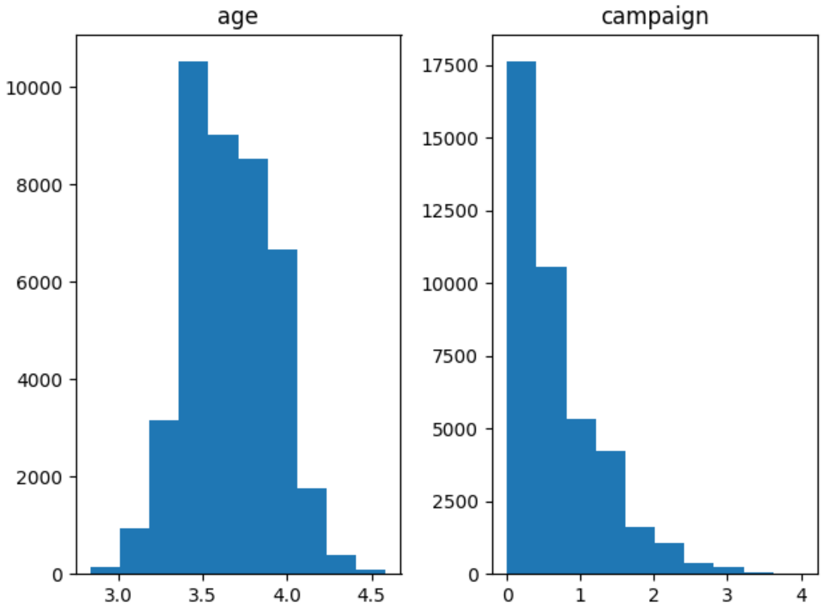
41188 rows × 21 columns

```
dataset_bckup = dataset.copy()
```

```
dataset = dataset_bckup.copy()
```

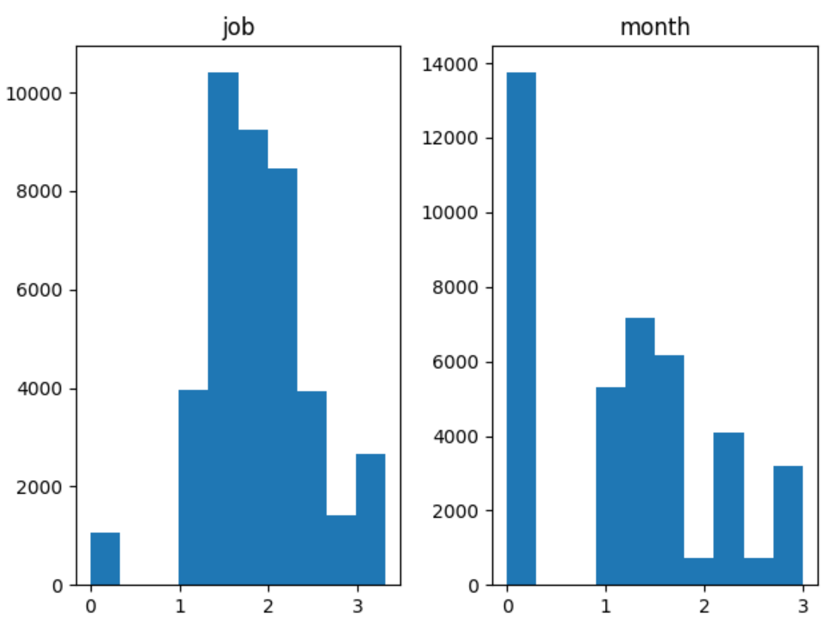
Iskoseni podaci normalizuju se primenom logaritma

```
skewed_columns = ["age","campaign"]
fig, axes = plt.subplots(1,2)

for ind,col in enumerate(skewed_columns):
  dataset[col] = np.log(dataset[col])

  axes[ind].hist(dataset[col])
  axes[ind].set_title(col)
  axes[ind].set_xlabel('')
  axes[ind].set_ylabel('')

plt.tight_layout()
plt.show()

```



Umereno iskoseni podaci normalizuju se primenom korena

```
moderate_skewed_columns = ["job","month"]
fig, axes = plt.subplots(1,2)

for ind,col in enumerate(moderate_skewed_columns):
  dataset[col] = np.sqrt(dataset[col])

  axes[ind].hist(dataset[col])
  axes[ind].set_title(col)
  axes[ind].set_xlabel('')
  axes[ind].set_ylabel('')

plt.tight_layout()
plt.show()

```



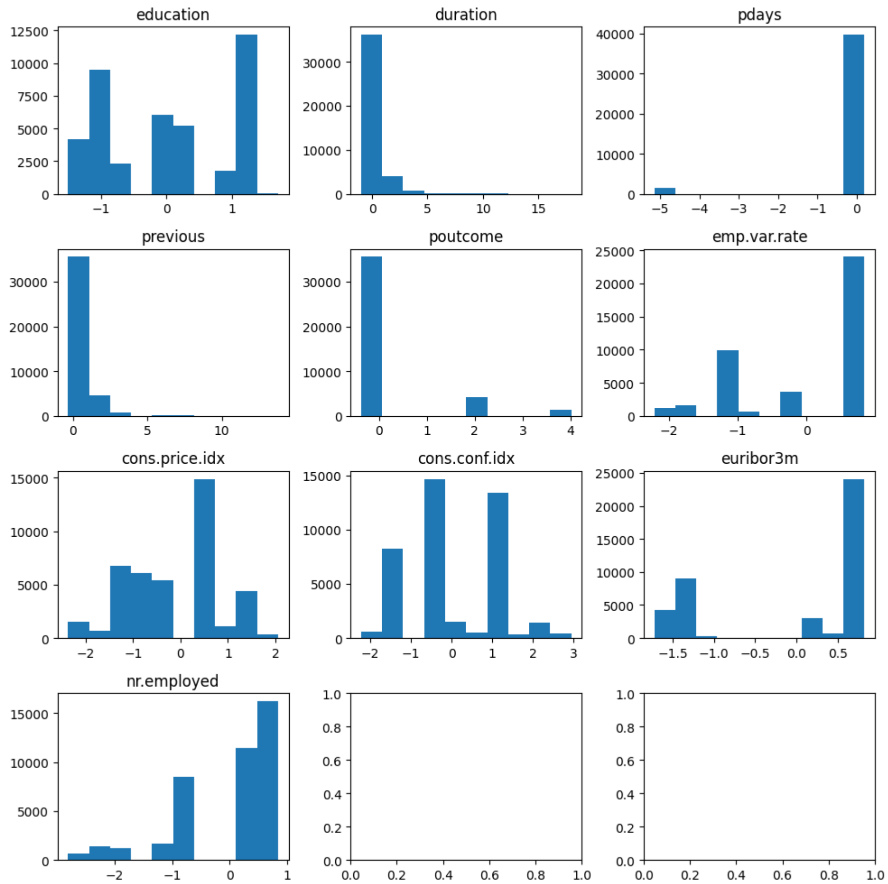
Ostali numericki podaci standardizuju se

```
scaler = StandardScaler()
normalize_columns = ["education" , "duration", "pdays", "previous", "poutcome", "emp.var.rate", "cons.price.idx", "cons.conf.idx", "euribc
# normalize_columns = ["education","duration"]
```

```
normalized_data= scaler.fit_transform(dataset[normalize_columns])
dataset[normalize_columns] = normalized_data

```

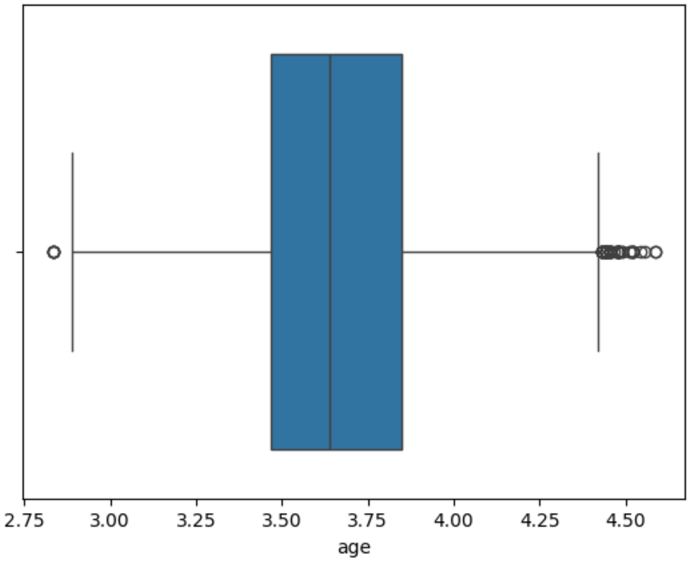
```

```

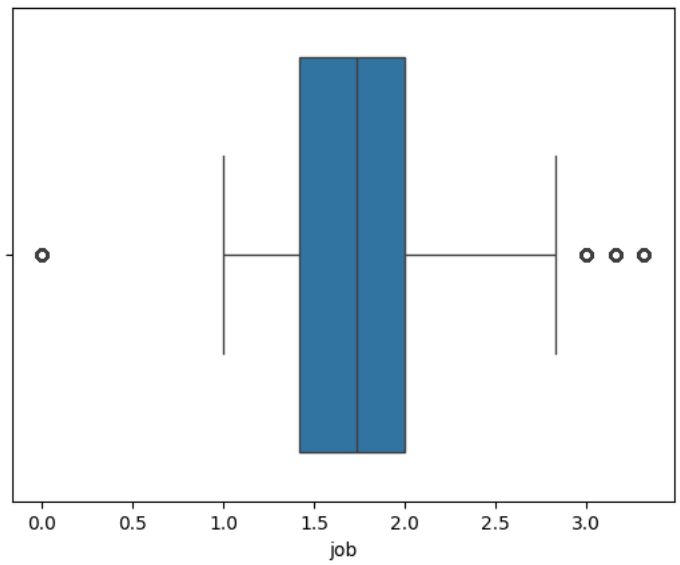
```
fig, axes = plt.subplots(4,3,figsize=(10,10))
axes = axes.flatten()
for ind,col in enumerate(normalize_columns):
  axes[ind].hist(dataset[col])
  axes[ind].set_title(col)
  axes[ind].set_xlabel('')
  axes[ind].set_ylabel('')

plt.tight_layout()
plt.show()

```

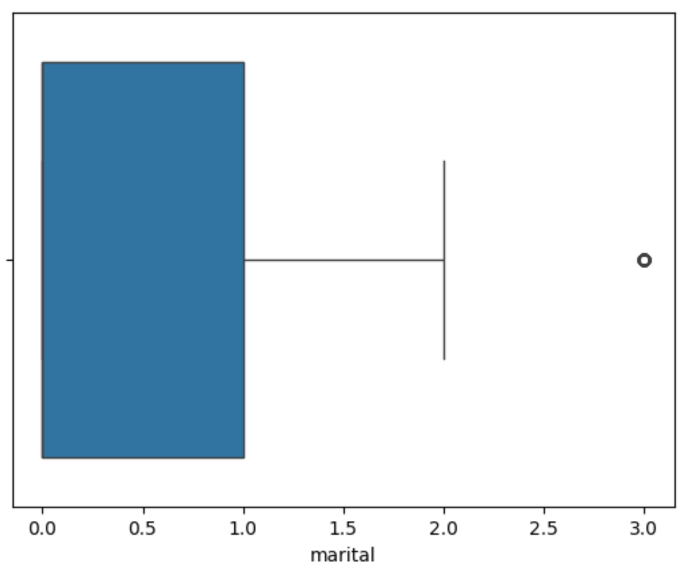


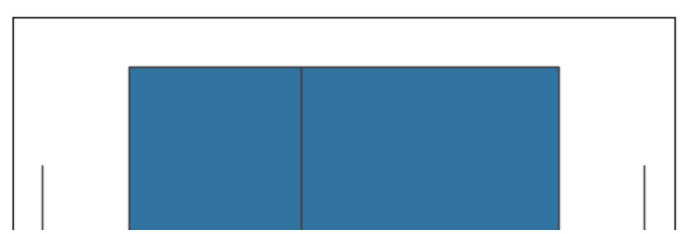
Detekcija i otklanjanje outlier-a, normalizacija podataka

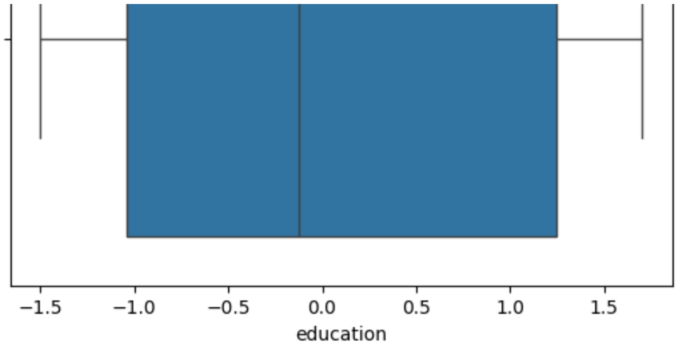
```
lista = ["age", "job","marital", "education", "default", "housing", "loan", "contact", "month", "day_of_week", "duration", "campaign", "
for el in lista:
  sns.boxplot(x = dataset[el])
  plt.show()
```

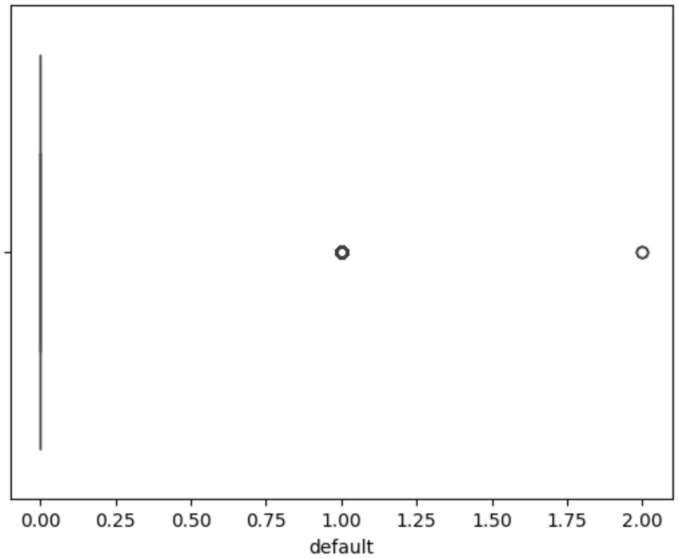

2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50
age

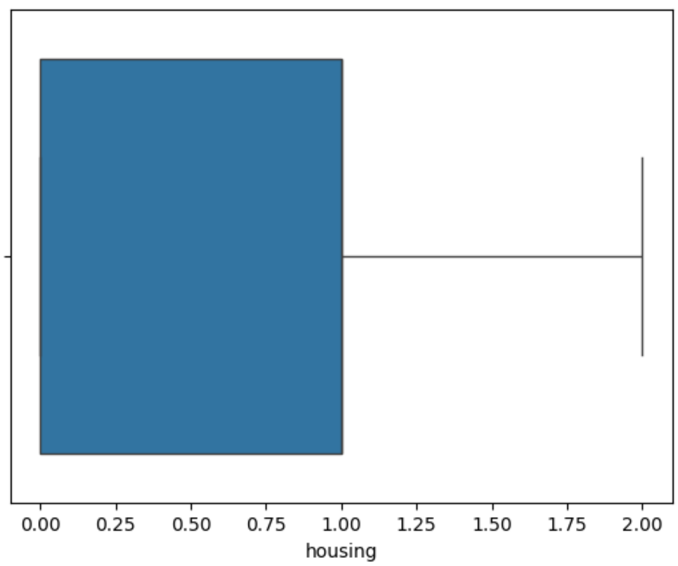

0.0
0.5
1.0
1.5
2.0
2.5
3.0
job

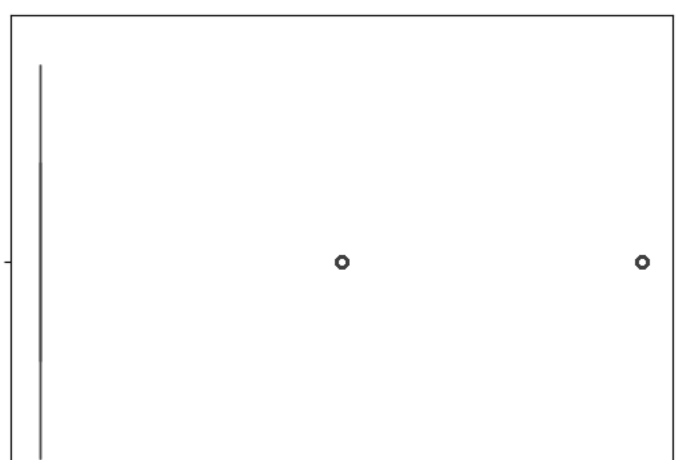

0.0
0.5
1.0
1.5
2.0
2.5
3.0
marital

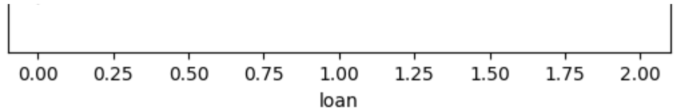


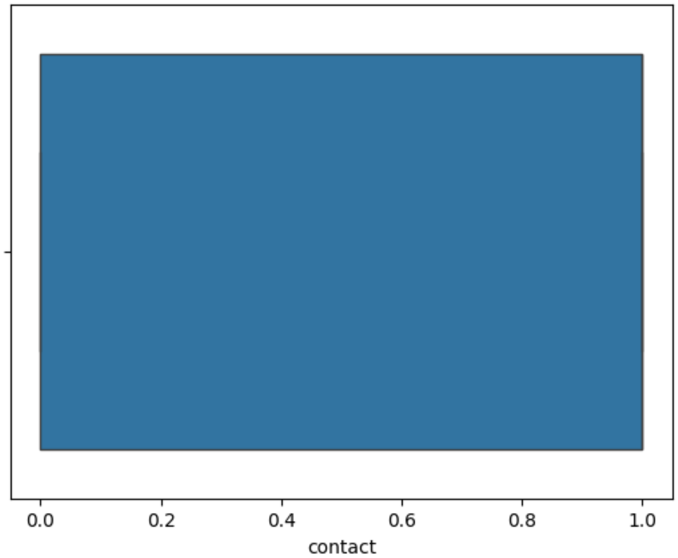

−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
education

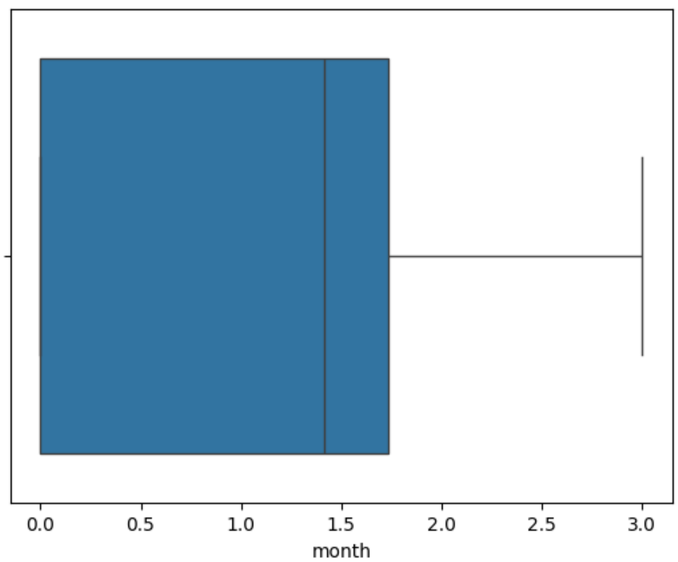

0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
default

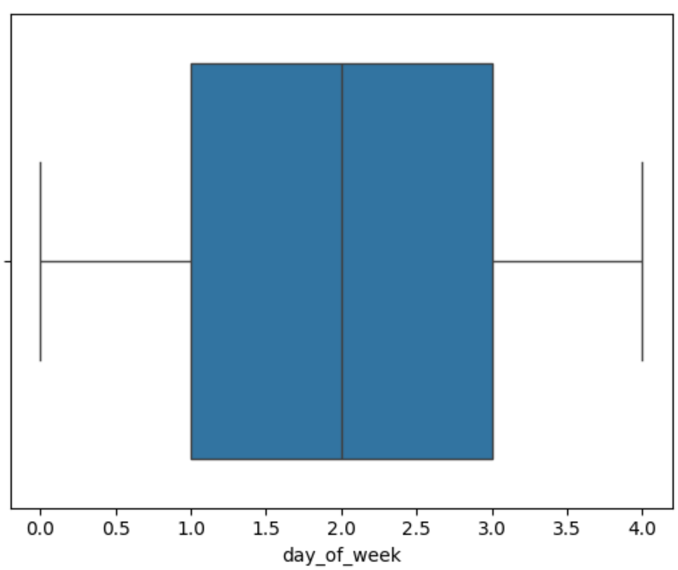

0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
housing

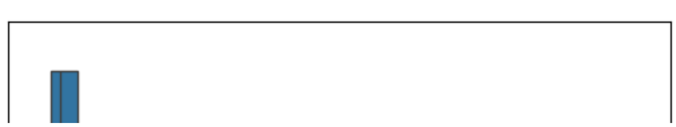


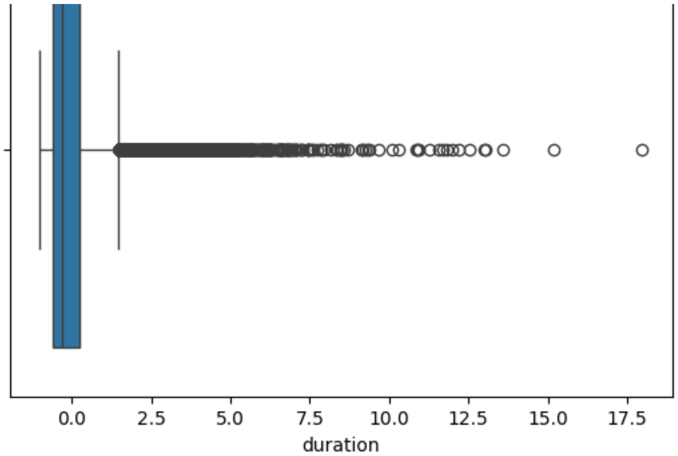

0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
loan

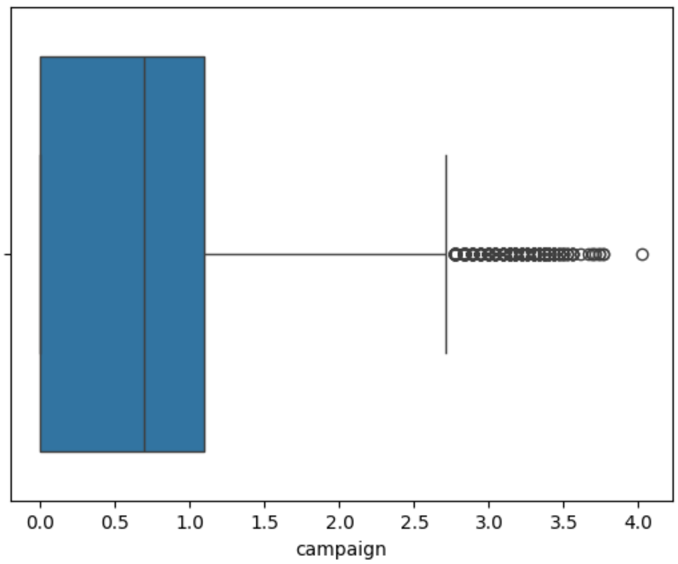

0.0
0.2
0.4
0.6
0.8
1.0
contact

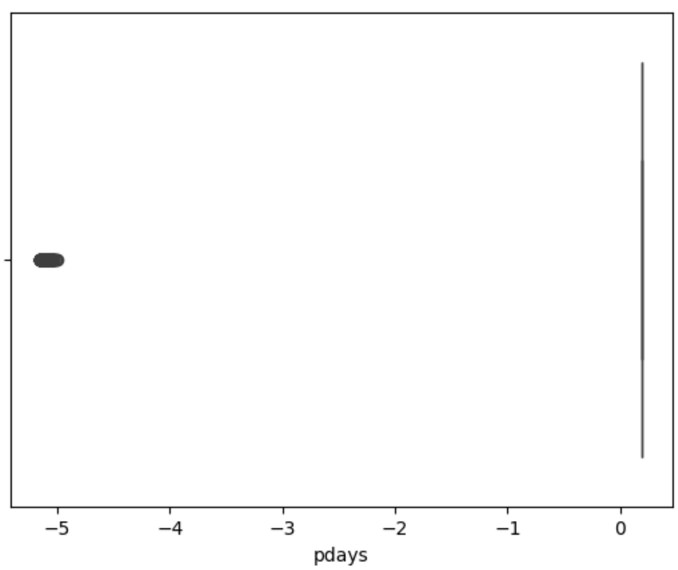

0.0
0.5
1.0
1.5
2.0
2.5
3.0
month

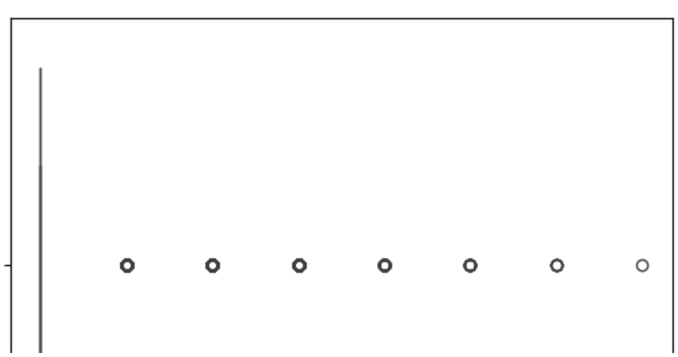

0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
day_of_week

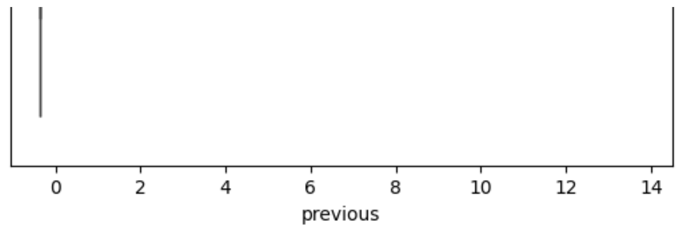


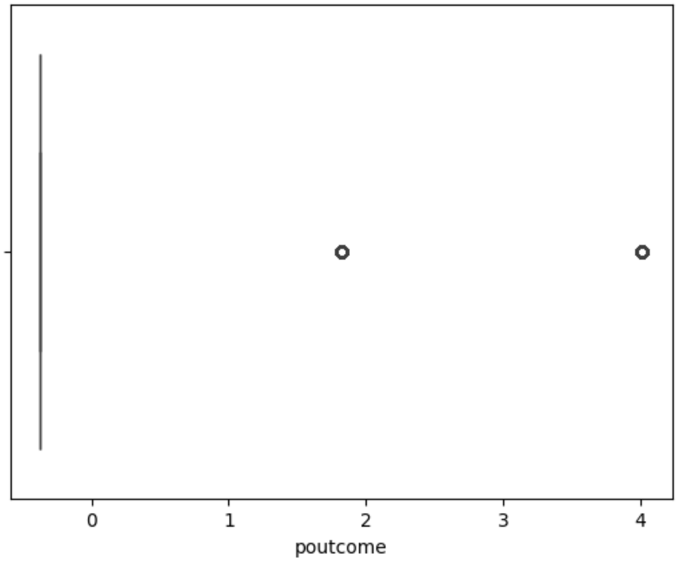

0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
duration

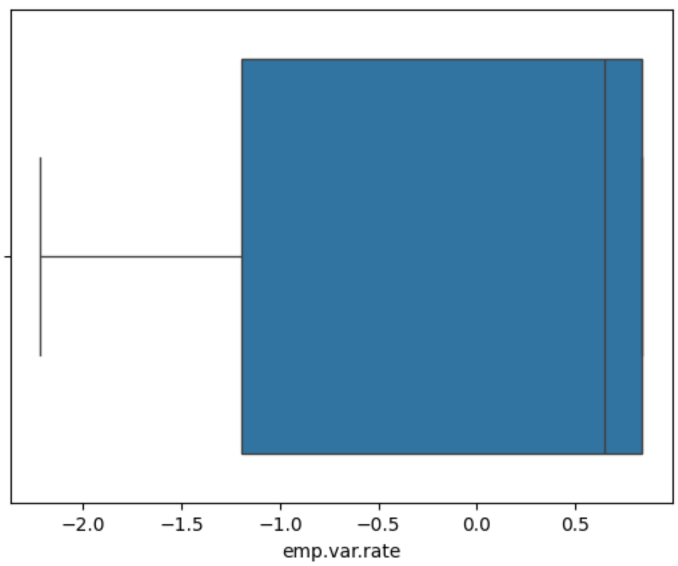

0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
campaign

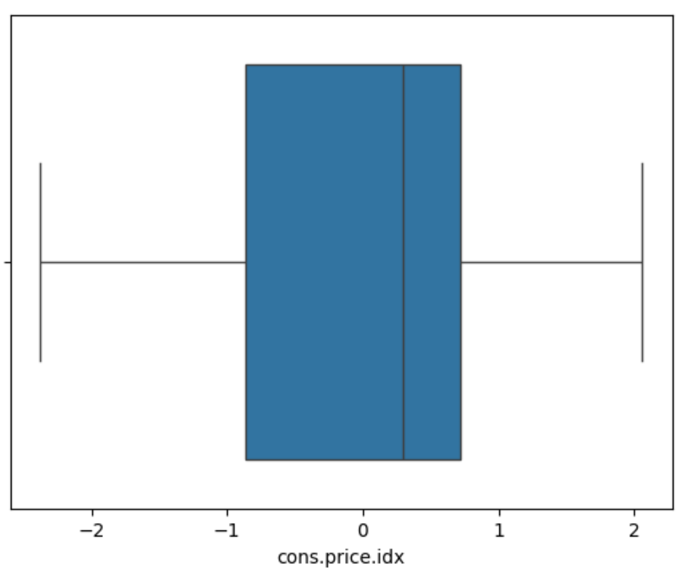

−5
−4
−3
−2
−1
0
pdays

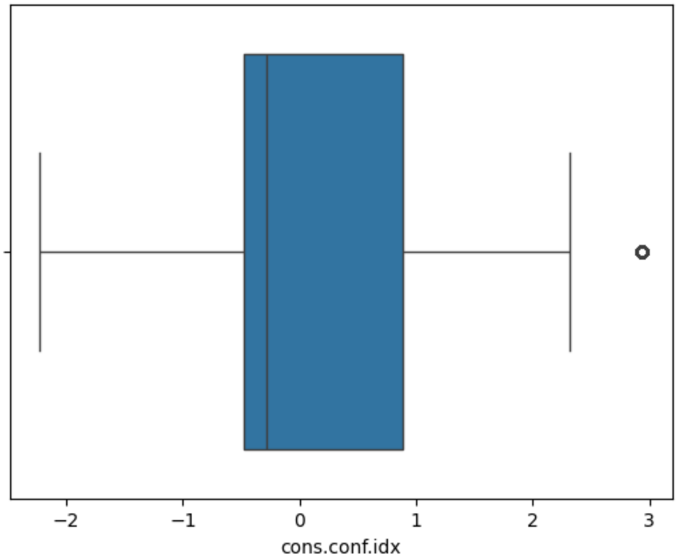


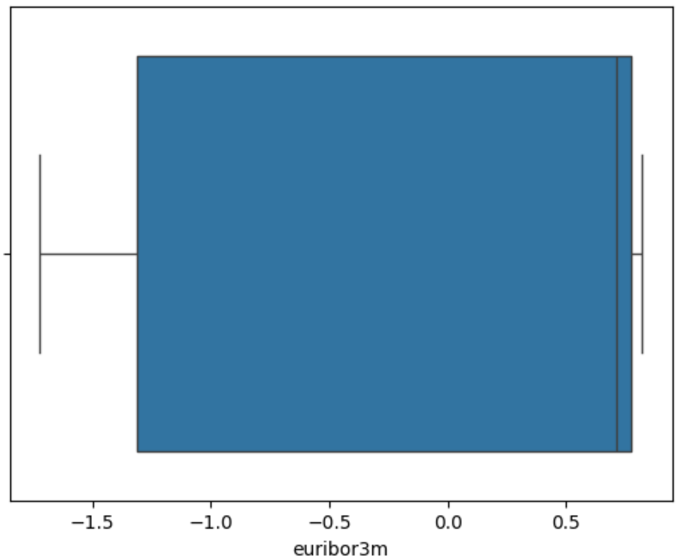

0
2
4
6
8
10
12
14
previous

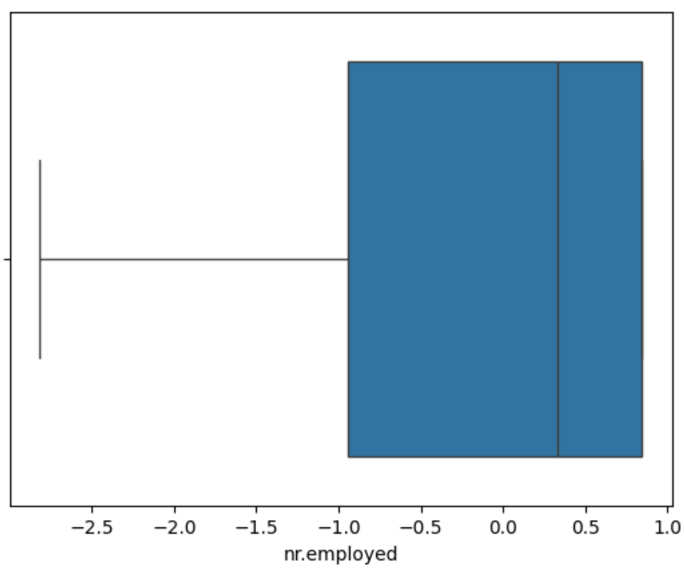

0
1
2
3
4
poutcome

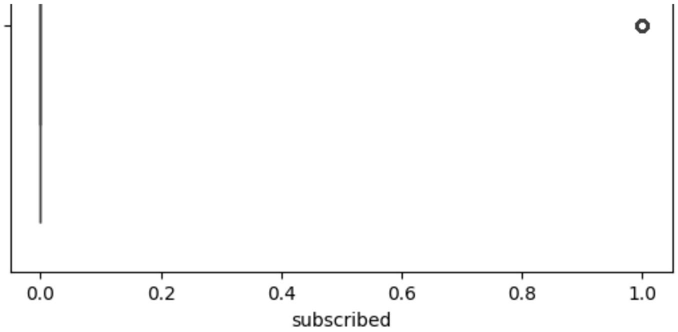

−2.0
−1.5
−1.0
−0.5
0.0
0.5
emp.var.rate


−2
−1
0
1
2
cons.price.idx


−2
−1
0
1
2
3
cons.conf.idx


−1.5
−1.0
−0.5
0.0
0.5
euribor3m


−2.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
nr.employed



Druga varijanta dataseta

Kategoricki podaci kod kojih je jasno zastoupljenija jedna kategorija u odnosu na sve ostale transformisu se tako da imaju samo 2 moguce vrednosti

```
lista = ["marital", "default", "loan","poutcome"]
dataset_2 = dataset.copy()
for ind,el in enumerate(lista):
  dataset_2[el] = np.where(dataset_2[el] == 0, 0, 1)
dataset_2
```

	age	job	marital	education	default	housing	loan	contact	month
0	4.025352	0.000000	0	-1.499673	0	0	0	0	0.000000
1	4.043051	1.000000	0	-1.042111	1	0	0	0	0.000000
2	3.610918	1.000000	0	-1.042111	0	1	0	0	0.000000
3	3.688879	1.414214	0	-0.584550	0	0	0	0	0.000000
4	4.025352	1.000000	0	-1.042111	0	0	1	0	0.000000
...	...	...	...	...	...	...	...	...	...
41183	4.290459	2.236068	0	0.330573	0	1	0	1	2.236068
41184	3.828641	1.732051	0	0.330573	0	0	0	1	2.236068
41185	4.025352	2.236068	0	1.245696	0	1	0	1	2.236068
41186	3.784190	2.000000	0	0.330573	0	0	0	1	2.236068
41187	4.304065	2.236068	0	0.330573	0	1	0	1	2.236068

41188 rows × 21 columns

ALGORITMI

```
def eval_metrics(X,labels):
  silhouette = silhouette_score(X, labels)
  ch_index = calinski_harabasz_score(X,labels)
  db_index = davies_bouldin_score(X, labels)
  return (silhouette,db_index,ch_index)
```

```
def visualise_3d_data( datas, cluster_labels, n_clusters):
  pca = PCA(n_components=3)
  PCs = pd.DataFrame(pca.fit_transform(datas))
  PCs.columns = ["PC1","PC2","PC3"]
  PCs["cluster"] = cluster_labels
  cluster = []
  trace = []
  for i in range(n_clusters):
    cluster.append(PCs[PCs["cluster"]==i])
    trace.append (go.Scatter3d(
                    x = cluster[i]["PC1"],
                    y = cluster[i]["PC2"],
                    z = cluster[i]["PC3"],
                    mode = "markers",
                    name = "Cluster "+str(i),
                    # marker = dict(color = 'rgba(255, 128, 255, 0.8)'),
                    text = None))


  title = "Vizuelizacija klastera u 3D pomocu 3 PCA komponente"

  layout = dict(title = title,
              xaxis= dict(title= 'PC1',ticklen= 5,zeroline= False),
              yaxis= dict(title= 'PC2',ticklen= 5,zeroline= False)
             )

  fig = dict(data = trace, layout = layout)

  iplot(fig)
```

```
def visualise_2d_data(datas, cluster_labels, n_clusters):
  pcas=PCA(n_components=2).fit_transform(datas)
  df2=pd.DataFrame(pcas,columns=['PC1','PC2'])
  sns.scatterplot(data=df2, x="PC1", y="PC2", hue=cluster_labels)
  plt.title("Vizuelizacija klastera u 2d pomocu 2 PCA komponente")
  plt.show()
```

```
pcas=PCA(n_components=2).fit_transform(dataset)
df2=pd.DataFrame(pcas,columns=['PC1','PC2'])
```

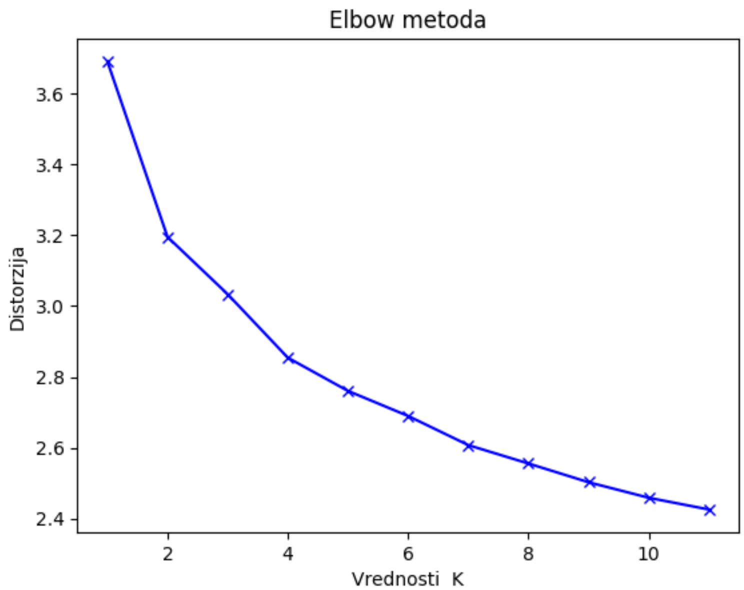
Kmeans

```
from scipy.spatial.distance import cdist
inertias = []
mapping2 = {}
K = range(1, 12)
distortions = []
mapping1 = {}
for k in K:
    kmeanModel = KMeans(n_clusters=k).fit(dataset)
    kmeanModel.fit(dataset)
    distortions.append(sum(np.min(cdist(dataset, kmeanModel.cluster_centers_,
                                        'euclidean'), axis=1)) / dataset.shape[0])
    mapping1[k] = sum(np.min(cdist(dataset, kmeanModel.cluster_centers_,'euclidean'), axis=1)) / dataset.shape[0]
    inertias.append(kmeanModel.inertia_)
    mapping2[k] = kmeanModel.inertia_
```

```
print("Vrednosti distrozije po broj klastera")
for key, val in mapping1.items():
    print(f'{key} : {val}')
```

```
Vrednosti distrozije po broj klastera
1 : 3.6913650287156656
2 : 3.195397659473886
3 : 3.0337668694656728
4 : 2.854440107706939
5 : 2.7606542867947423
6 : 2.6898759944248862
7 : 2.6076150932171145
8 : 2.5556592662526554
9 : 2.5027815746300863
10 : 2.4589177197818985
11 : 2.425843796089128
```

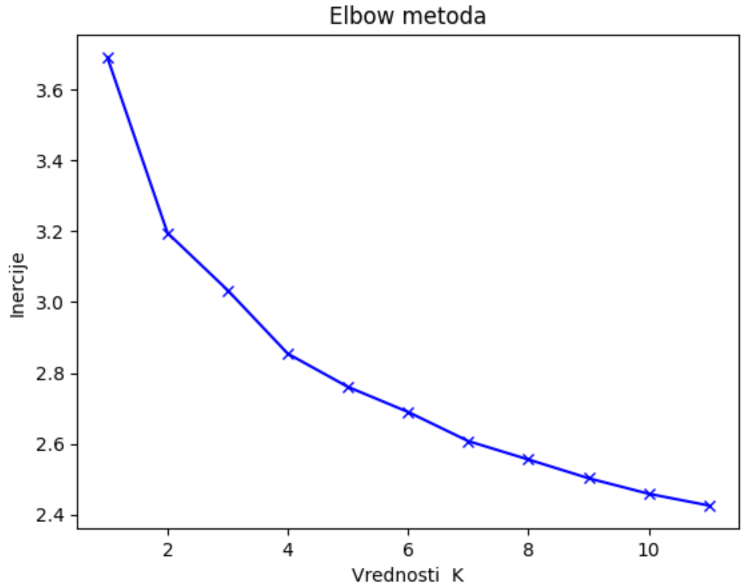
```
plt.plot(K, distortions, 'bx-')
plt.xlabel('Vrednosti  K')
plt.ylabel('Distorzija')
plt.title('Elbow metoda')
plt.show()
```




```
print("Vrednosti inercije po broj klastera")
for key, val in mapping2.items():
    print(f'{key} : {val}')
```

```
Vrednosti inercije po broj klastera
1 : 631425.3405406944
2 : 474669.1279857573
3 : 407115.17265450803
4 : 367195.09307091916
5 : 340396.85283842846
6 : 321577.40636241285
7 : 305634.37154894805
8 : 293727.4616294227
9 : 283660.95170666
10 : 270095.10949484084
11 : 264163.24255030265
```

```
plt.plot(K, distortions, 'bx-')
plt.xlabel('Vrednosti  K')
plt.ylabel('Inercije')
plt.title('Elbow metoda')
plt.show()
```

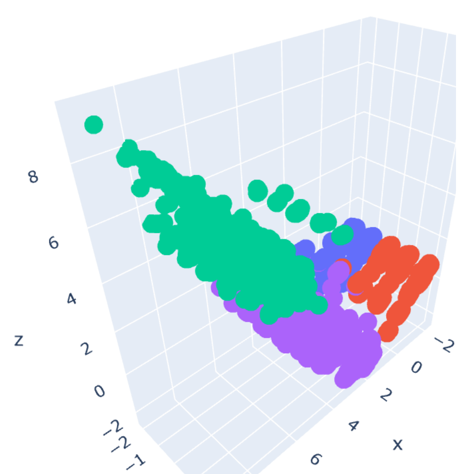



```
1 kmeans = KMeans(n_clusters =4)
2 cluster_labels = kmeans.fit_predict(dataset)
3 results = eval_metrics(dataset,cluster_labels)
4 print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
5 results_df = pd.DataFrame()
6 results_df.loc[1,"KMeans"] = results[0]
```

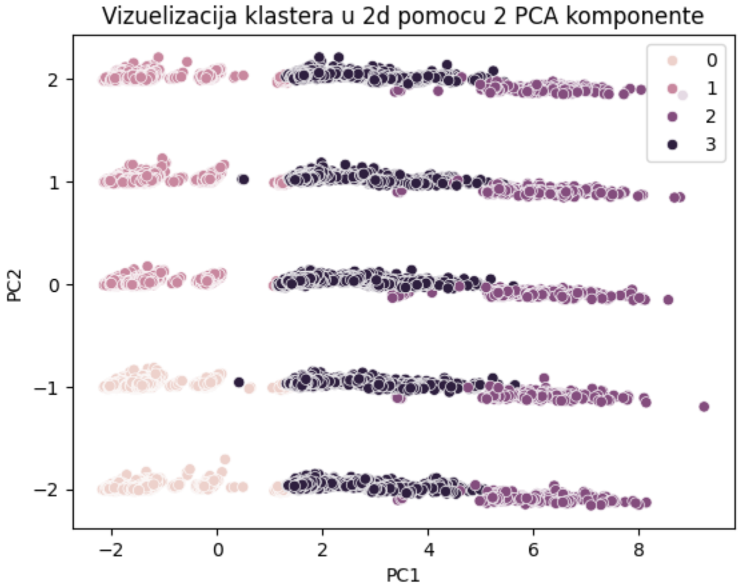
```
Silhouette Score : 0.16992386604518878 Davies-Bouldin Index: 1.6498489644815606Calinski-Harabasz Index: 9878.544076019489
```

```
1 visualise_3d_data(dataset,cluster_labels,4)
```

Vizuelizacija klastera u 3D pomocu 3 PCA komponente




```
1 visualise_2d_data(dataset,cluster_labels,4)
```




```
1 unique_values, counts = np.unique(cluster_labels, return_counts=True)
```

```
1 clustering_dataframe = pd.DataFrame(counts)
```

```
1 clustering_dataframe.columns = ["KMeans"]
```

```
1 results_df
```

	KMeans
1	0.169924

```
1 clustering_dataframe
```

	KMeans
0	11101
1	16398
2	1537
3	12152

```
1 kmeans = KMeans(n_clusters =4)
2 cluster_labels = kmeans.fit_predict(df2)
3 results = eval_metrics(df2,cluster_labels)
4 print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
5 results_df.loc[1,"PCA_KMeans"] = results[0]
```

```
Silhouette Score : 0.516524642626481 Davies-Bouldin Index: 0.8108890221200817Calinski-Harabasz Index: 52734.52377635431
```

```
1 unique_values, counts = np.unique(cluster_labels, return_counts=True)
2 clustering_dataframe["PCA_Kmeans"] = counts
```

```
1 results_df
```

	KMeans	PCA_KMeans
1	0.169924	0.516525

```
1 clustering_dataframe
```

	KMeans	PCA_Kmeans
0	11101	16136
1	16398	5783
2	1537	8448
3	12152	10821

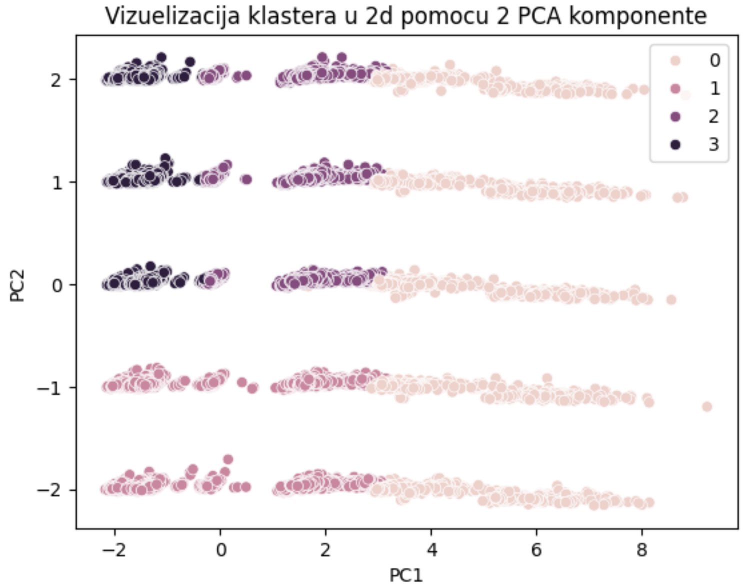
Next steps: View recommended plots

Bisecting K-means

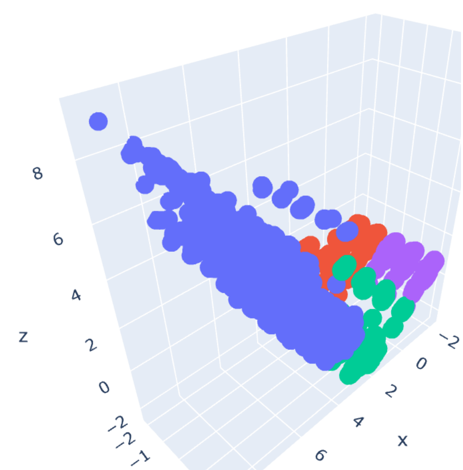
```
bisectingkmeans = BisectingKMeans(n_clusters =4)
cluster_labels = bisectingkmeans.fit_predict(dataset)
results = eval_metrics(dataset,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc[1,"BisectingKMeans"] = results[0]
```

```
Silhouette Score : 0.13733267375248376 Davies-Bouldin Index: 1.8845460378968608Calinski-Harabasz Index: 7462.77928516293
```

```
visualise_2d_data(dataset,cluster_labels,4)
visualise_3d_data(dataset,cluster_labels,4)
```



Vizuelizacija klastera u 3D pomocu 3 PCA komponente




```
1 unique_values, counts = np.unique(cluster_labels, return_counts=True)
2 clustering_dataframe["Bisecting Kmeans"] = counts
```

```
1 results_df
```

	KMeans	PCA_KMeans	BisectingKMeans
1	0.169924	0.516525	0.137333

```
1 clustering_dataframe
```

	KMeans	PCA_Kmeans	Bisecting Kmeans
0	11101	16136	4927
1	16398	5783	14641
2	1537	8448	7285
3	12152	10821	14335

Next steps: View recommended plots

```
bisectingkmeans = BisectingKMeans(n_clusters =4)
cluster_labels = bisectingkmeans.fit_predict(df2)
results = eval_metrics(df2,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc[1,"PCA_BisectingKMeans"] = results[0]
```

```
Silhouette Score : 0.5105757848760489 Davies-Bouldin Index: 0.7468223050428169Calinski-Harabasz Index: 50709.23961838911
```

```
unique_values, counts = np.unique(cluster_labels, return_counts=True)
clustering_dataframe["PCA_BisectingKMeans"] = counts
```

Gaussian Mixture

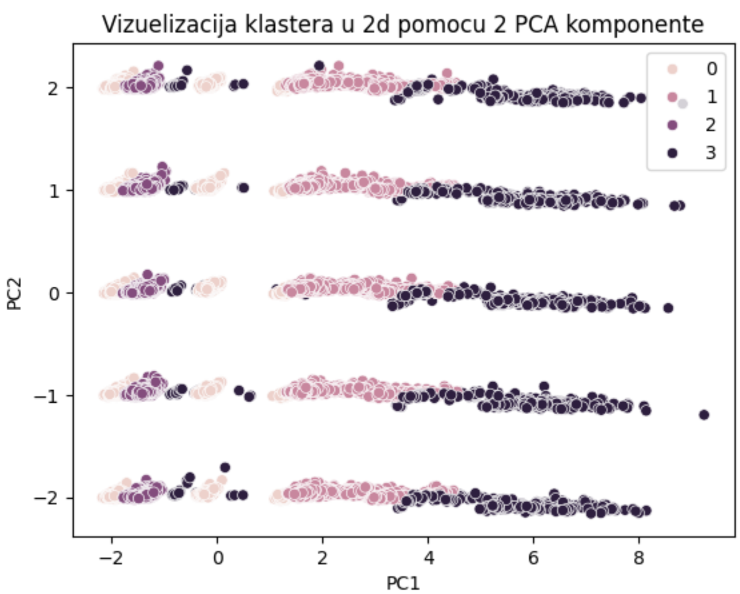
```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components = 4,random_state=42)
```

```
cluster_labels = gmm.fit_predict(dataset)
results = eval_metrics(dataset,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc[1,"Gaussian Mixture"] = results[0]
```

```
Silhouette Score : 0.09975477726149581 Davies-Bouldin Index: 3.3015872624880185Calinski-Harabasz Index: 7460.016926791017
```

```
unique_values, counts = np.unique(cluster_labels, return_counts=True)
clustering_dataframe["Gaussian Mixture"] = counts
```

```
visualise_2d_data(dataset,cluster_labels,4)
```




```
cluster_labels = gmm.fit_predict(df2)
results = eval_metrics(df2,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc[1,"PCA_Gaussian Mixture"] = results[0]
```

```
Silhouette Score : 0.4654669162073473 Davies-Bouldin Index: 0.8838660347437242Calinski-Harabasz Index: 38707.1393547403
```

```
unique_values, counts = np.unique(cluster_labels, return_counts=True)
clustering_dataframe["PCA_Gaussian Mixture"] = counts
```

```
results_df
```

KMeans	PCA_KMeans	BisectingKMeans	PCA_BisectingKMeans	Gaussian Mixture	PCA_Gaussian Mixture

```
clustering_dataframe
```

	KMeans	PCA_Kmeans	Bisecting Kmeans	PCA_BisectingKMeans	Gaussian Mixture	PCA_Gaussian Mixture
0	11101	16136	4927	12223	7931	9756
1	16398	5783	14641	2008	11603	7315
2	1537	8448	7285	16136	19623	14241
3	12152	10821	14335	10821	2031	9876

Next steps: View recommended plots

Hierarchical Clustering

```
from sklearn.cluster import AgglomerativeClustering

```

```
from scipy.cluster.hierarchy import dendrogram,linkage
```

```
# linkage_data = linkage(df2,method = "ward",metric = "euclidean")
```

```
# dendrogram(linkage_data)
# plt.show()
```

```
# hierarchical_cluster = AgglomerativeClustering(n_clusters = 4, affinity = "euclidean",linkage = "ward")
# cluster_labels = hierarchical_cluster.fit_predict(df2)
```

```
# results = eval_metrics(df2,cluster_labels)
# print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
# results_df.loc[1,"Hierarchical Clustering(ward)"] = results[0]
```

```
# visualise_2d_data(dataset,cluster_labels,4)
```