## 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 | r |
| **1** | 57 | services | married | high.school | unknown | no | no | telephone | may | r |
| **2** | 37 | services | married | high.school | no | yes | no | telephone | may | r |
| **3** | 40 | admin. | married | basic.6y | no | no | no | telephone | may | r |
| **4** | 56 | services | married | high.school | no | no | yes | telephone | may | r |

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["previous
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, 'retired': 5, 'management': 6, 'unemployed': 7, 'self-em
{'married': 0, 'single': 1, 'divorced': 2, 'unknown': 3}
{'basic.4y': 0, 'high.school': 1, 'basic.6y': 2, 'basic.9y': 3, 'professional.course': 4, 'unknown': 5, 'university.degree': 6, 'illiter
{'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': 8, 'sep': 9}
{'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 | ... | campaign | pdays | previous | poutcome | emp.va |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 56 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 1 | 999 | 0 | 0 | |
| **1** | 57 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | ... | 1 | 999 | 0 | 0 | |
| **2** | 37 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | ... | 1 | 999 | 0 | 0 | |
| **3** | 40 | 2 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 1 | 999 | 0 | 0 | |
| **4** | 56 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | ... | 1 | 999 | 0 | 0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **41183** | 73 | 5 | 0 | 4 | 0 | 1 | 0 | 1 | 5 | 4 | ... | 1 | 999 | 0 | 0 | |
| **41184** | 46 | 3 | 0 | 4 | 0 | 0 | 0 | 1 | 5 | 4 | ... | 1 | 999 | 0 | 0 | |
| **41185** | 56 | 5 | 0 | 6 | 0 | 1 | 0 | 1 | 5 | 4 | ... | 2 | 999 | 0 | 0 | |
| **41186** | 44 | 4 | 0 | 4 | 0 | 0 | 0 | 1 | 5 | 4 | ... | 1 | 999 | 0 | 0 | |
| **41187** | 74 | 5 | 0 | 4 | 0 | 1 | 0 | 1 | 5 | 4 | ... | 3 | 999 | 1 | 1 | |

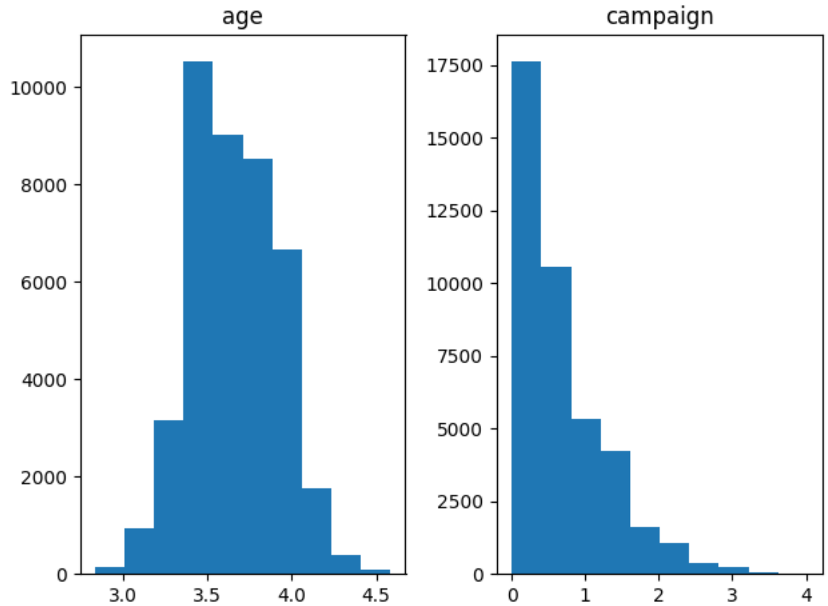
41188 rows × 21 columns

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

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

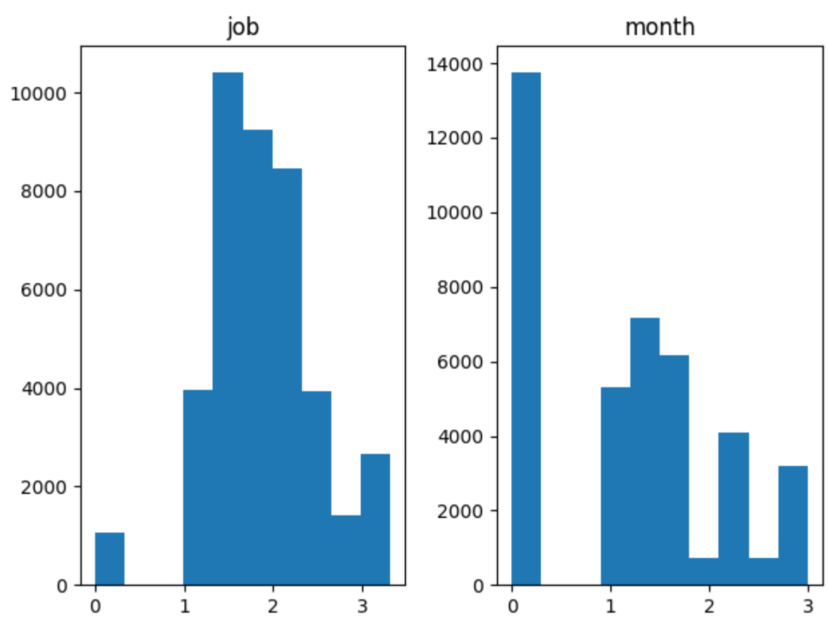
Iskoseni podaci normalizuju se primenom logaritma

```
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()

```

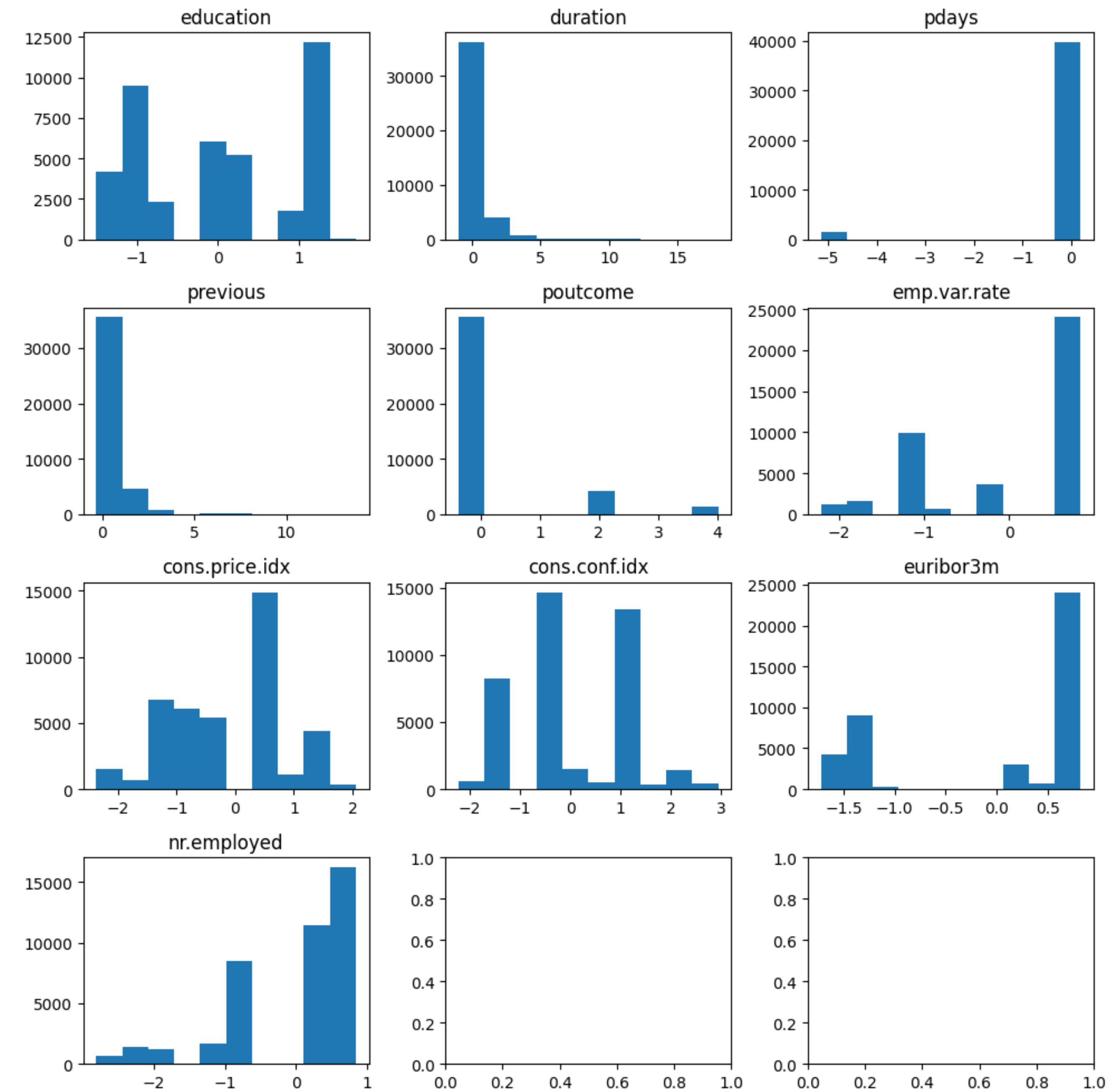



Ostali numericki podaci standardizuju se

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

```

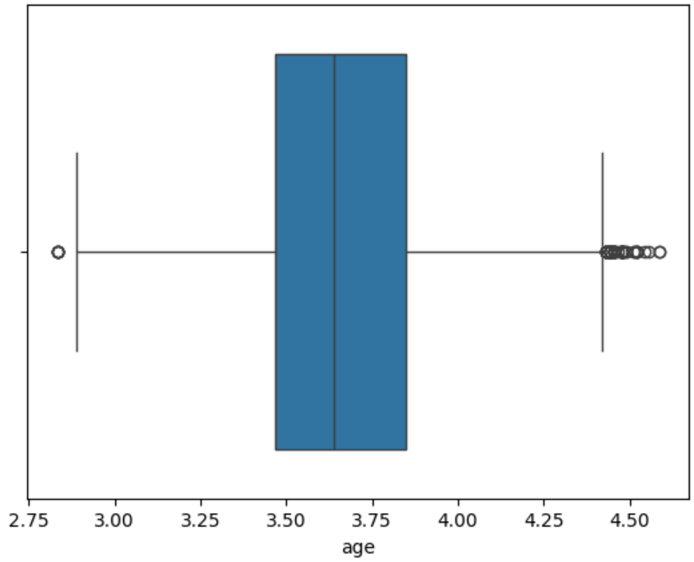
```

```

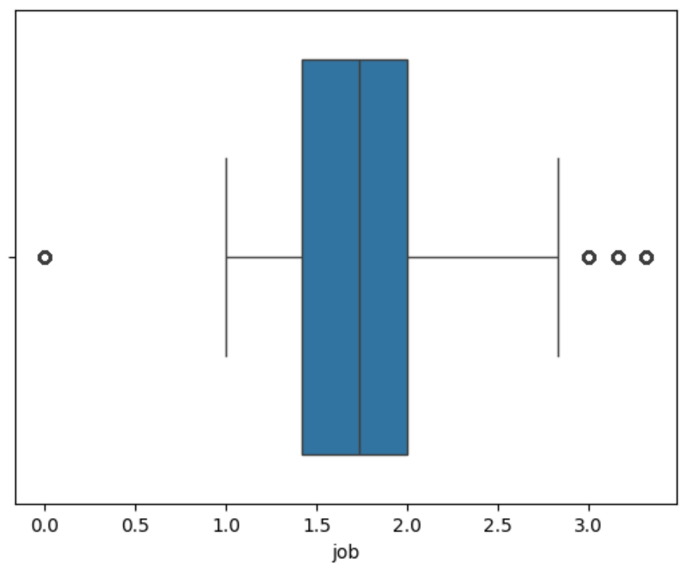
```
fig, axes = plt.subplots(4,3,figsize=(10,10))
axes = axes.flatten()
for ind,col in enumerate(normalize_columns):
  axes[ind].hist(dataset[col])
  axes[ind].set_title(col)
  axes[ind].set_xlabel('')
  axes[ind].set_ylabel('')

plt.tight_layout()
plt.show()

```

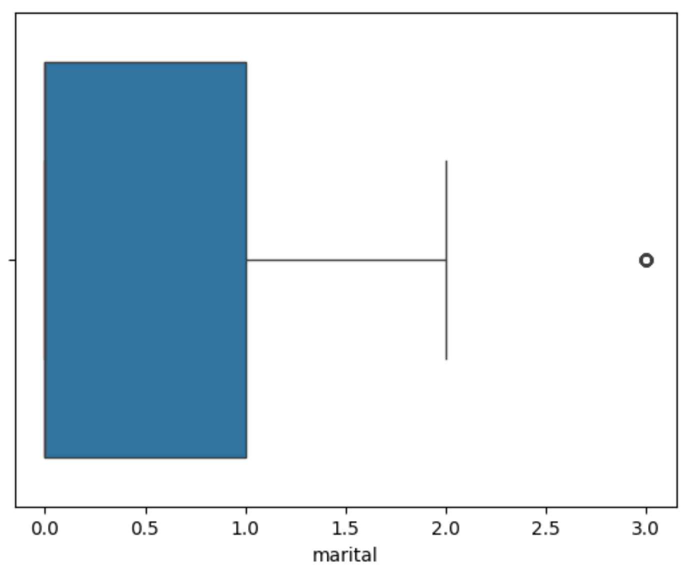


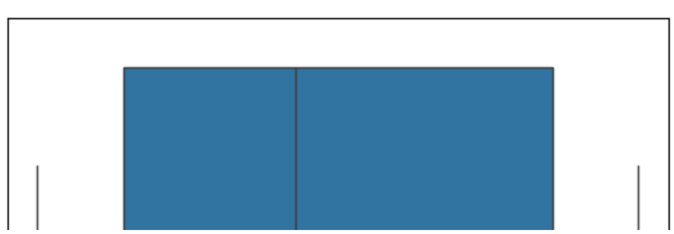
## Detekcija i otklanjanje outlier-a, normalizacija podataka

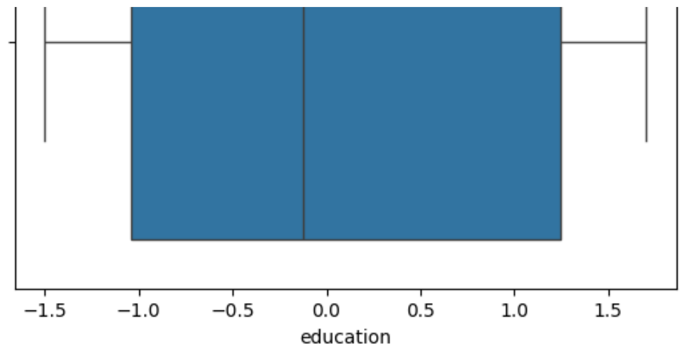
```
lista = ["age", "job","marital", "education", "default", "housing", "loan", "contact", "month", "day_of_week", "duration", "campaign", "p
for el in lista:
  sns.boxplot(x = dataset[el])
  plt.show()
```

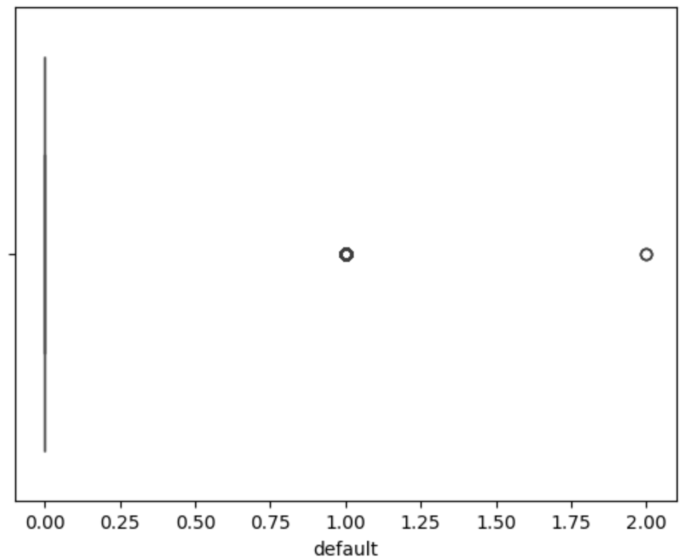

2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50
age

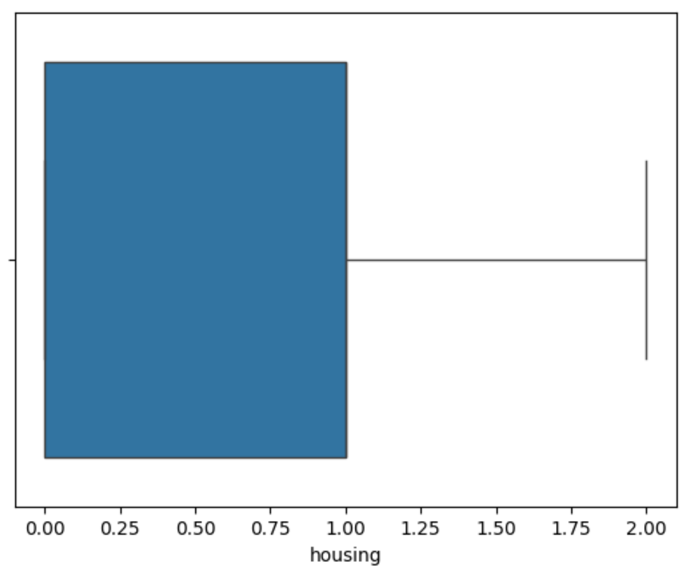

0.0
0.5
1.0
1.5
2.0
2.5
3.0
job

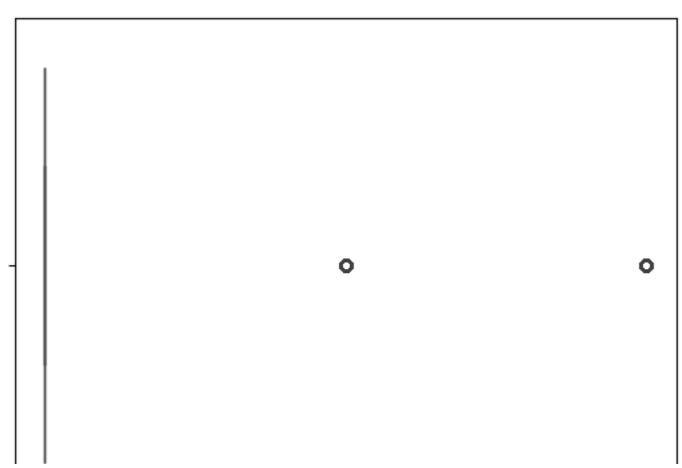

0.0
0.5
1.0
1.5
2.0
2.5
3.0
marital

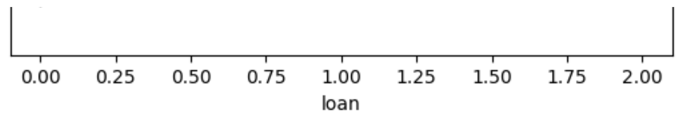


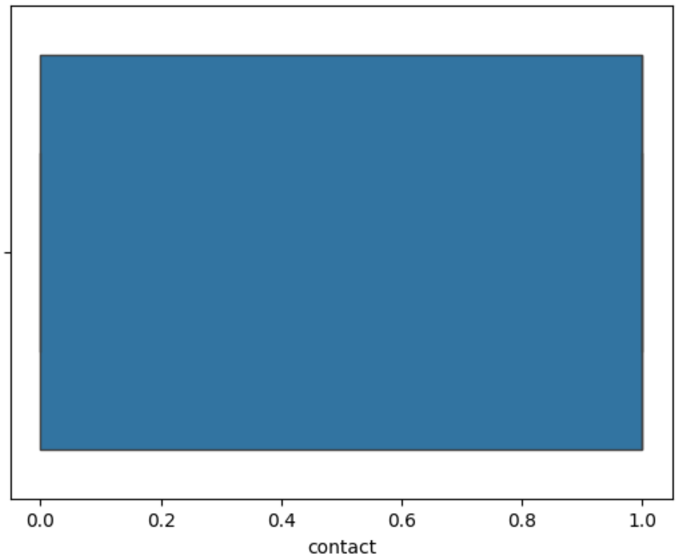

−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
education

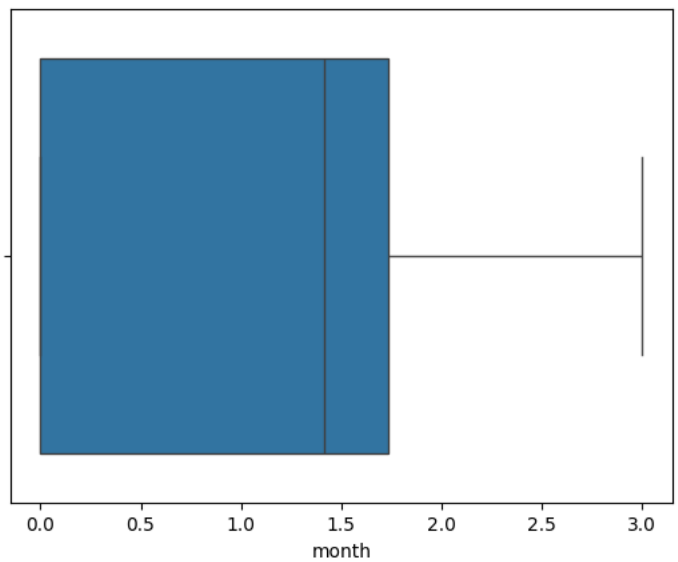

0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
default

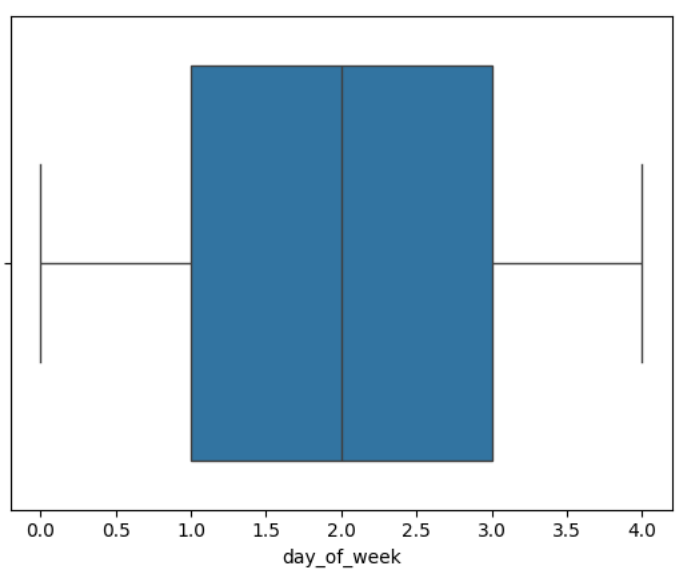

0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
housing

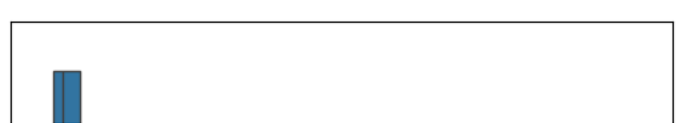


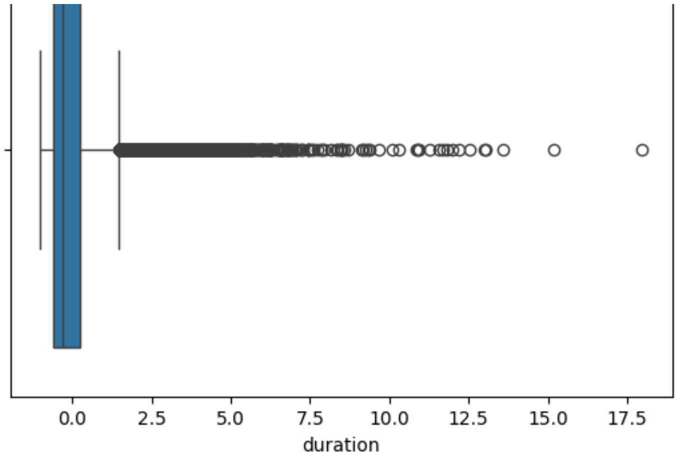

0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
loan

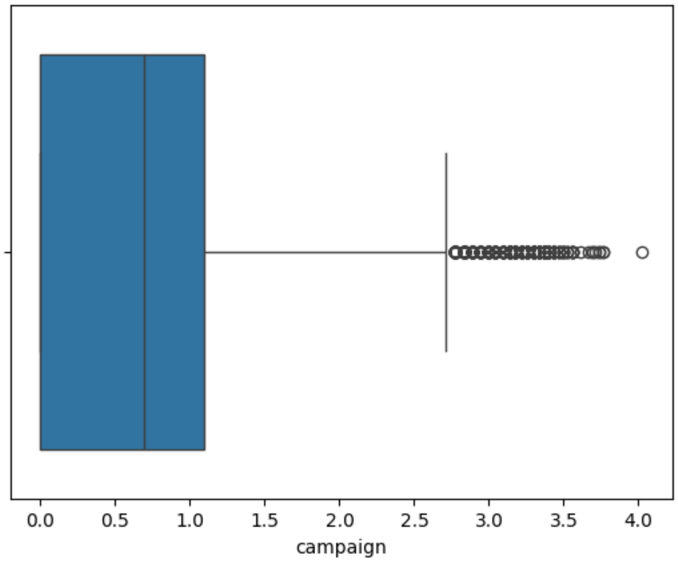

0.0
0.2
0.4
0.6
0.8
1.0
contact

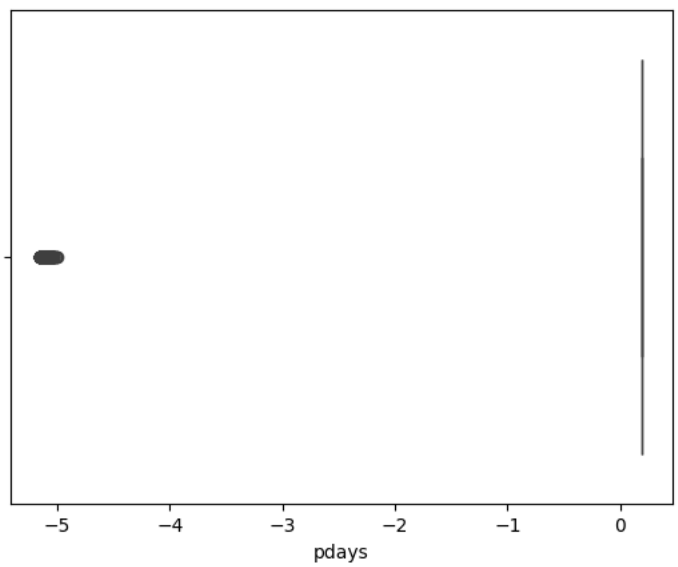

0.0
0.5
1.0
1.5
2.0
2.5
3.0
month

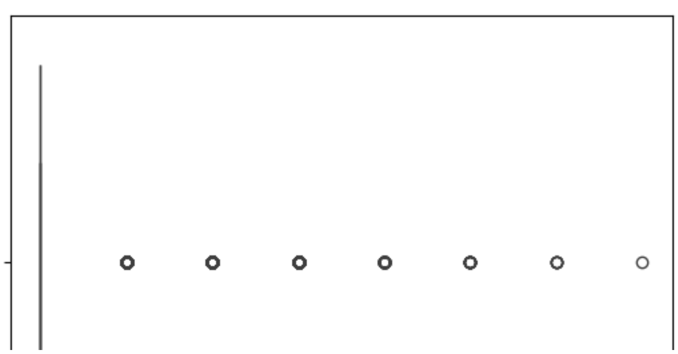

0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
day_of_week

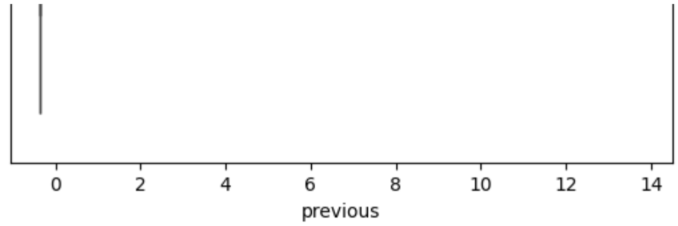


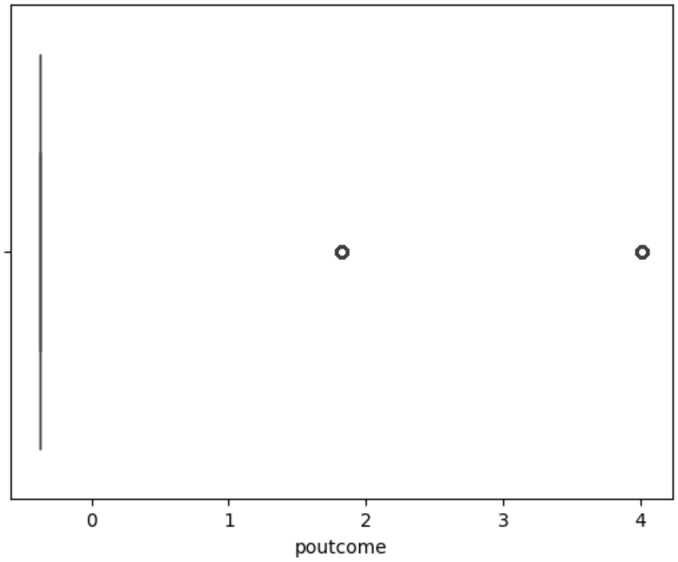

0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
duration

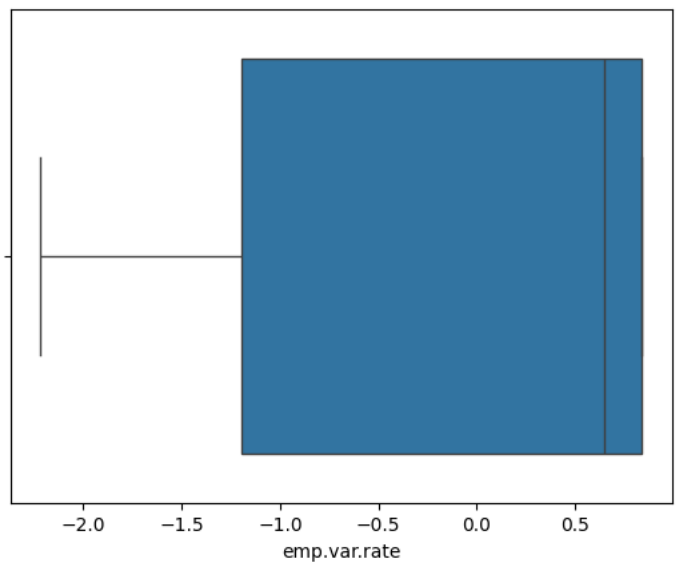

0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
campaign

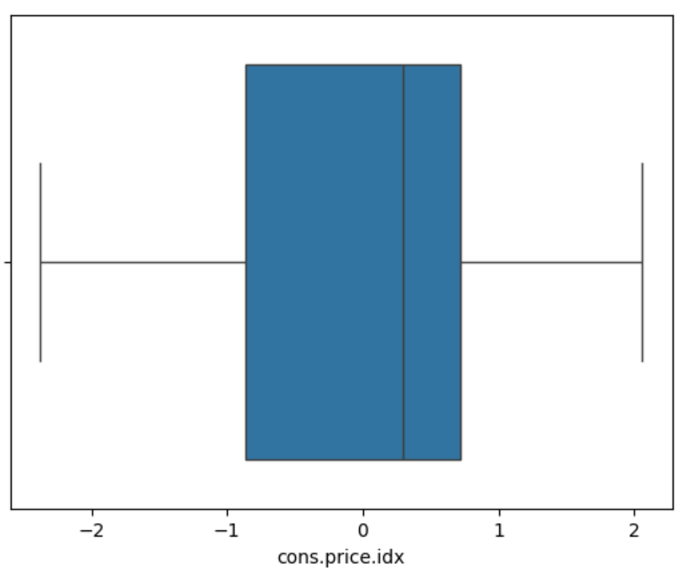

−5
−4
−3
−2
−1
0
pdays

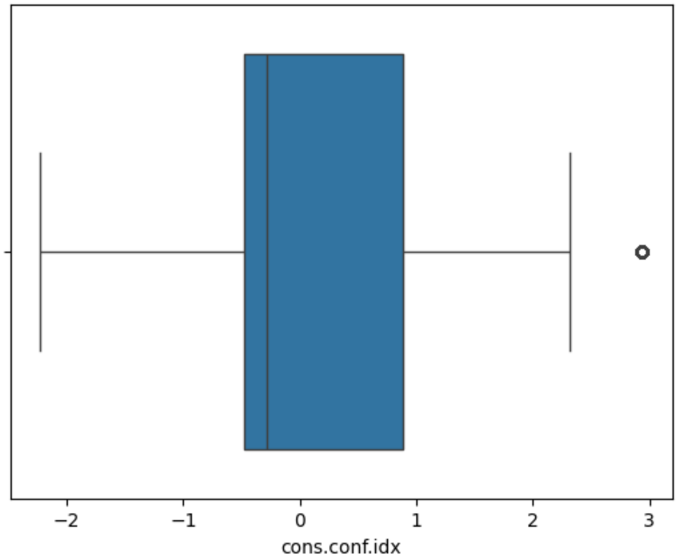


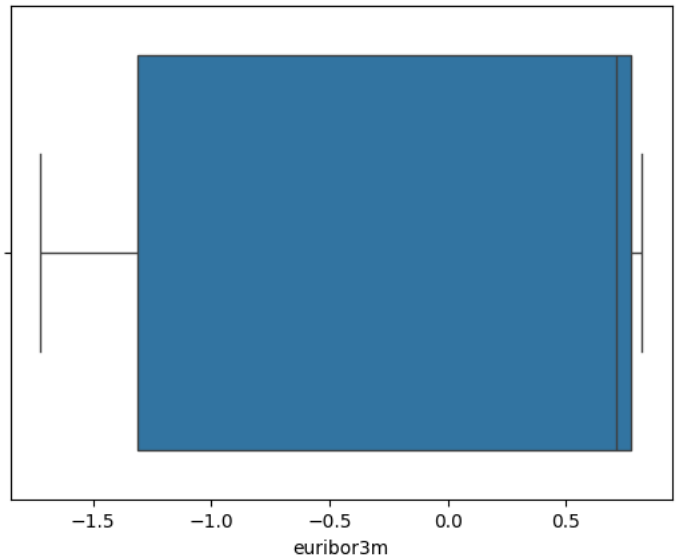

0
2
4
6
8
10
12
14
previous

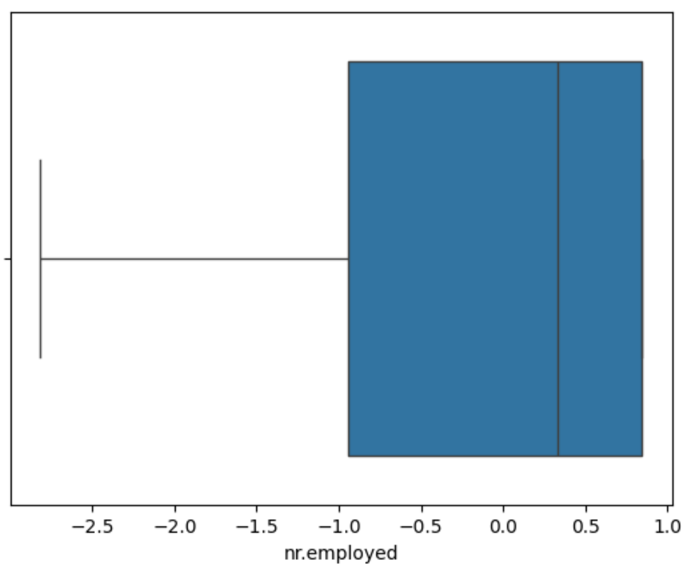

0
1
2
3
4
poutcome

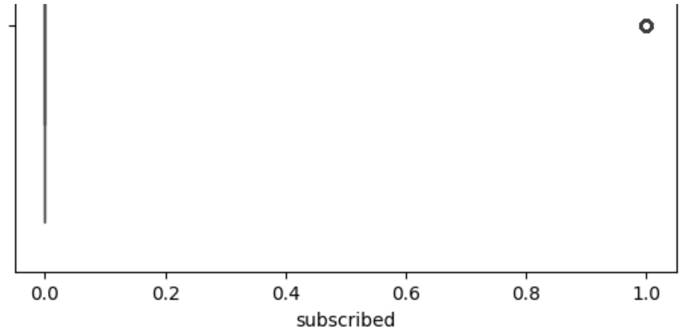

−2.0
−1.5
−1.0
−0.5
0.0
0.5
emp.var.rate


−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 | day_of_week | ... | campaign | pdays | previous | p |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 4.025352 | 0.000000 | 0 | -1.499673 | 0 | 0 | 0 | 0 | 0.000000 | 0 | ... | 0.000000 | 0.195414 | -0.349494 | |
| **1** | 4.043051 | 1.000000 | 0 | -1.042111 | 1 | 0 | 0 | 0 | 0.000000 | 0 | ... | 0.000000 | 0.195414 | -0.349494 | |
| **2** | 3.610918 | 1.000000 | 0 | -1.042111 | 0 | 1 | 0 | 0 | 0.000000 | 0 | ... | 0.000000 | 0.195414 | -0.349494 | |
| **3** | 3.688879 | 1.414214 | 0 | -0.584550 | 0 | 0 | 0 | 0 | 0.000000 | 0 | ... | 0.000000 | 0.195414 | -0.349494 | |
| **4** | 4.025352 | 1.000000 | 0 | -1.042111 | 0 | 0 | 1 | 0 | 0.000000 | 0 | ... | 0.000000 | 0.195414 | -0.349494 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **41183** | 4.290459 | 2.236068 | 0 | 0.330573 | 0 | 1 | 0 | 1 | 2.236068 | 4 | ... | 0.000000 | 0.195414 | -0.349494 | |
| **41184** | 3.828641 | 1.732051 | 0 | 0.330573 | 0 | 0 | 0 | 1 | 2.236068 | 4 | ... | 0.000000 | 0.195414 | -0.349494 | |
| **41185** | 4.025352 | 2.236068 | 0 | 1.245696 | 0 | 1 | 0 | 1 | 2.236068 | 4 | ... | 0.693147 | 0.195414 | -0.349494 | |
| **41186** | 3.784190 | 2.000000 | 0 | 0.330573 | 0 | 0 | 0 | 1 | 2.236068 | 4 | ... | 0.000000 | 0.195414 | -0.349494 | |
| **41187** | 4.304065 | 2.236068 | 0 | 0.330573 | 0 | 1 | 0 | 1 | 2.236068 | 4 | ... | 1.098612 | 0.195414 | 1.671136 | |

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+1))
  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'])
```

```
def printFeatureImportance(df, pred, centers = None):

    if centers is None:
        cluster_means = df.groupby(pred).mean()
    else:
        cluster_means = centers

    fig, ax = plt.subplots(figsize=(16, 6))
    cluster_means.T.plot(kind='bar', ax=ax, cmap='plasma')
    plt.title('Feature importance')
    plt.show()
```

## Kmeans

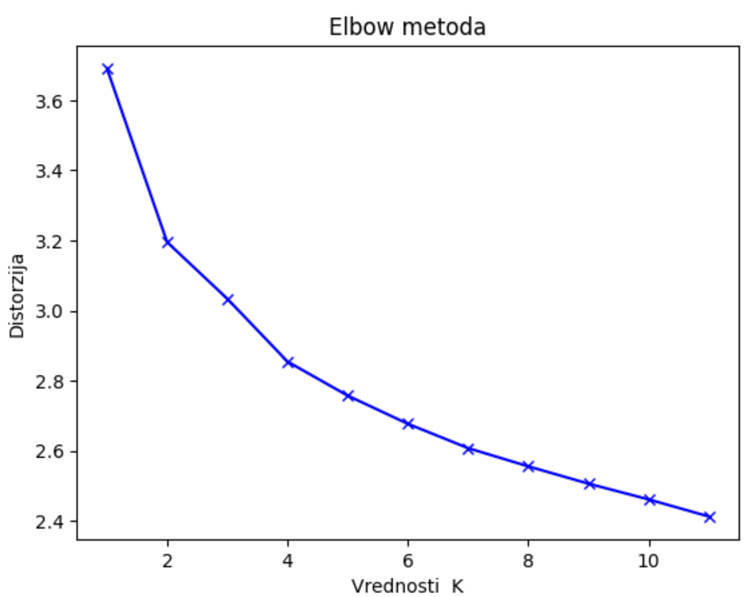
### Odredjivanje broja klastera

```
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 : 2.7573355324683564
6 : 2.6768714773642075
7 : 2.6076204759999184
8 : 2.5555242327853667
9 : 2.506167610990432
10 : 2.4612022069180175
11 : 2.4125094232084505
```

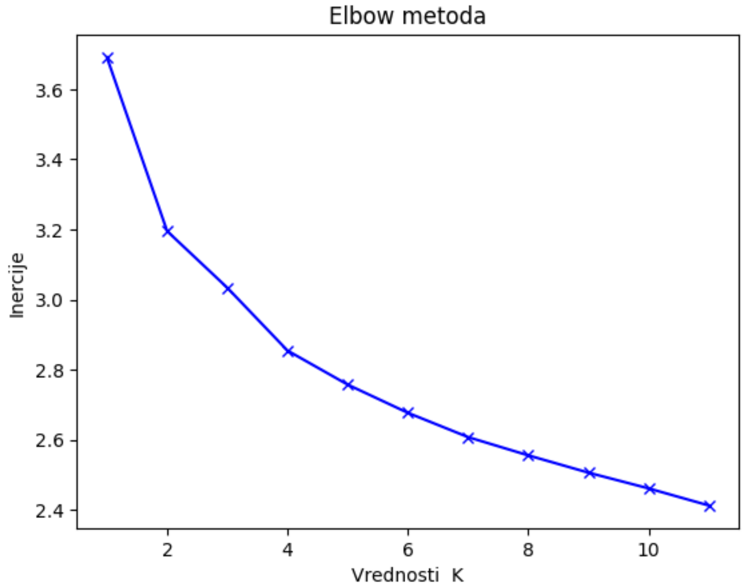
```
plt.plot(K, distortions, 'bx-')
plt.xlabel('Vrednosti  K')
plt.ylabel('Distorzija')
plt.title('Elbow metoda')
plt.show()
```




```
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 : 339662.1240076279
6 : 324003.9517890938
7 : 305634.40413226635
8 : 293676.15158675454
9 : 281434.2349200344
10 : 271443.97278337204
11 : 262839.81831405795
```

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




## Klasterovanje

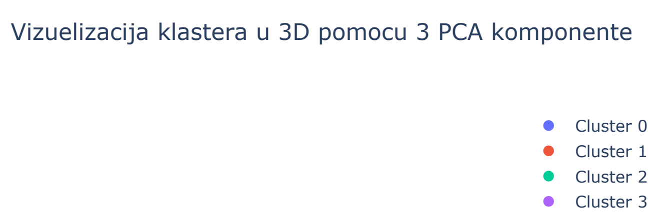
Prvo se vrsi klasterovanje neredukovanog seta podataka u 4 klastera

```
kmeans = KMeans(n_clusters =4)
cluster_labels = kmeans.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 = pd.DataFrame()


```

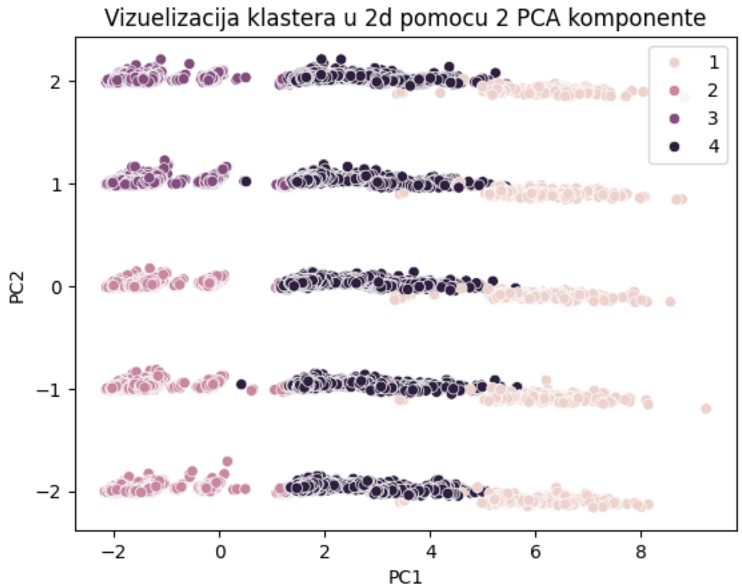
```
Silhouette Score : 0.17114653033315932 Davies-Bouldin Index: 1.650009374118620Calinski-Harabasz Index: 9862.011660070055
```

```
results_df.loc["KMeans","Silhouette Score"] = results[0]
```

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



```
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"]
```

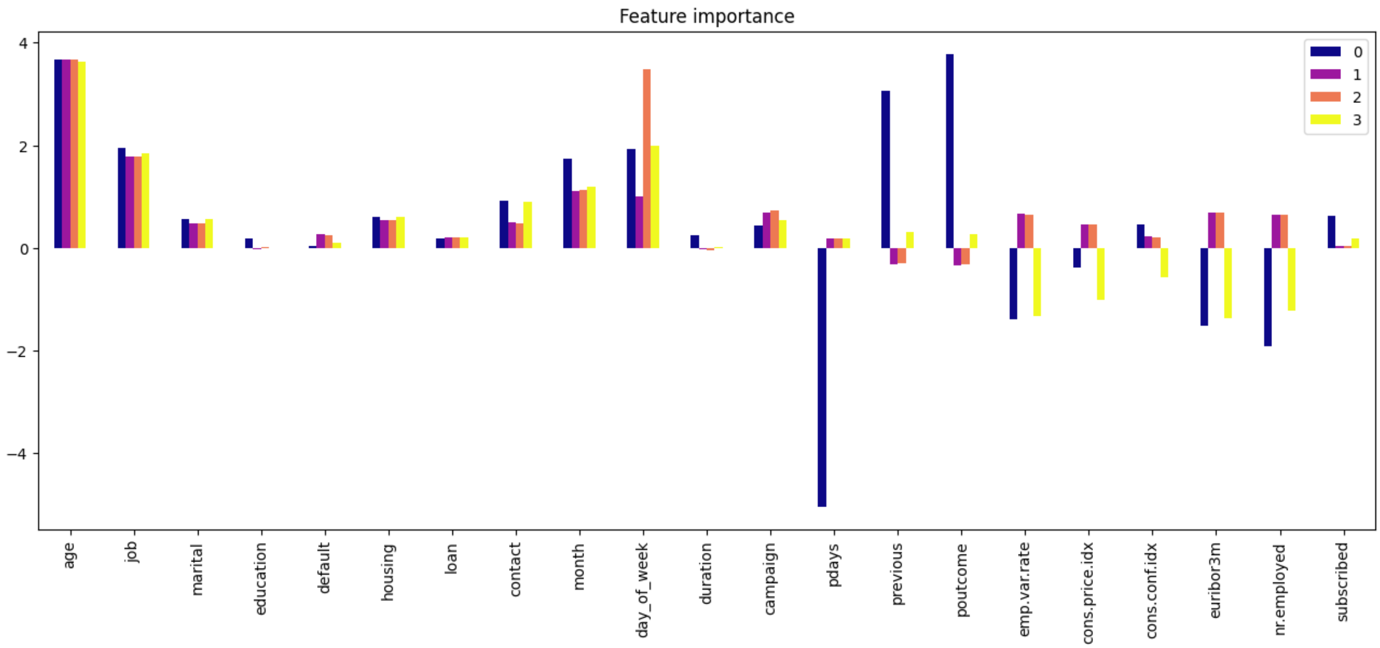
```
1 results_df
```

| | Silhouette Score |
|---|---|
| **KMeans** | 0.171147 |

```
1 clustering_dataframe
```

| | KMeans |
|---|---|
| **0** | 1537 |
| **1** | 16652 |
| **2** | 10845 |
| **3** | 12154 |

```
1 printFeatureImportance(dataset, cluster_labels)
```




Na osnovu uticaja svakog ficera za svaki klaster, odbacuju se kolone **education**,**default**,**loan**,**duration**,**subscribed**, i vrsi klasterovanje u 4 klastera

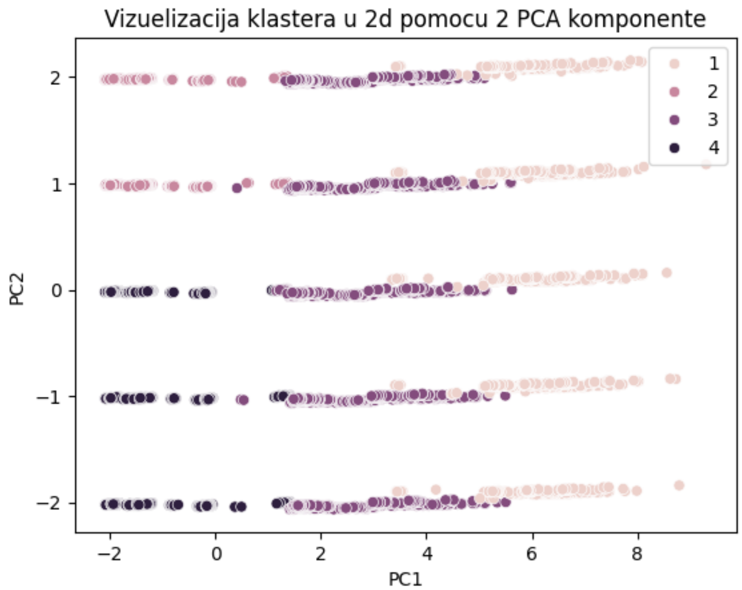
```
dataset_3 = dataset.copy()
delete_columns = ["education","default","loan","duration","subscribed"]
dataset_3.drop(delete_columns,axis=1,inplace=True)

```

```
kmeans = KMeans(n_clusters =4)
cluster_labels = kmeans.fit_predict(dataset_3)
results = eval_metrics(dataset_3,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc["Najbitnije_kolone_KMeans",:] = results[0]
```

```
Silhouette Score : 0.21905577735050674 Davies-Bouldin Index: 1.3776859463120819Calinski-Harabasz Index: 13567.142893603963
```

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

```
pcas=PCA(n_components=2).fit_transform(dataset_3)
dataset_3_pca=pd.DataFrame(pcas,columns=['PC1','PC2'])
visualise_2d_data(dataset_3_pca,cluster_labels,4)
```




Izvrsena je PCA redukcija za redukovani set podataka, nakon cega se vrsi klasterovanje podataka u 4 grupe.

```
kmeans = KMeans(n_clusters =4)
cluster_labels = kmeans.fit_predict(dataset_3_pca)
results = eval_metrics(dataset_3_pca,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc["Najbitnije_PCA_KMeans",:] = results[0]
```

```
Silhouette Score : 0.5198752896108609 Davies-Bouldin Index: 0.8075172260055952Calinski-Harabasz Index: 53202.08871939428
```

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

Na kraju je istim algoritmom klasterovan polazni set podataka nakon PCA redukcije u 4 klastera.

```
kmeans = KMeans(n_clusters =4)
cluster_labels = kmeans.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["PCA_KMeans",:] = results[0]
```

```
Silhouette Score : 0.5172239943083106 Davies-Bouldin Index: 0.8238340653763321Calinski-Harabasz Index: 52865.5266060788
```

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

```
results_df
```

| | Silhouette Score |
|---|---|
| **KMeans** | 0.171147 |
| **Najbitnije_kolone_KMeans** | 0.219056 |
| **Najbitnije_PCA_KMeans** | 0.519875 |
| **PCA_KMeans** | 0.517224 |

```
clustering_dataframe
```

| | KMeans | Najbitnije_Kmeans | Najbitnije_PCA_Kmeans | PCA_Kmeans |
|---|---|---|---|---|
| **0** | 1537 | 1541 | 10821 | 10822 |
| **1** | 16652 | 11102 | 5783 | 6143 |
| **2** | 10845 | 12146 | 16136 | 16136 |
| **3** | 12154 | 16399 | 8448 | 8087 |

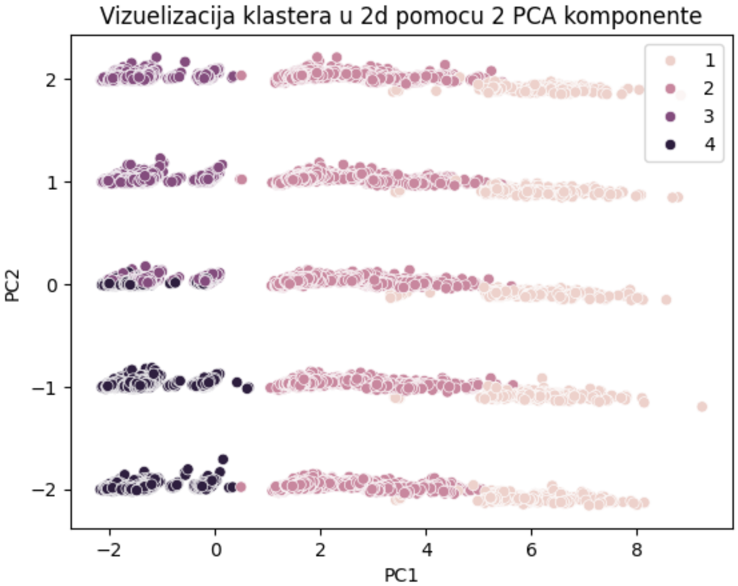
Next steps: View recommended plots

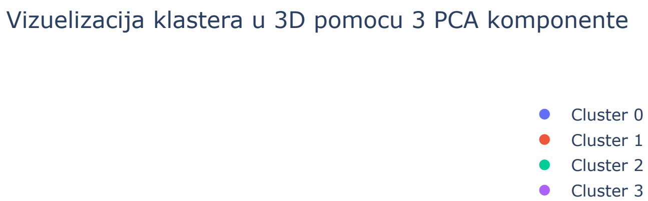
## Bisecting K-means

```
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["BisectingKMeans",:] = results[0]
```

```
Silhouette Score : 0.1635755840390671 Davies-Bouldin Index: 1.6770112397349854Calinski-Harabasz Index: 9796.98105156303
```

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




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

```
results_df
```

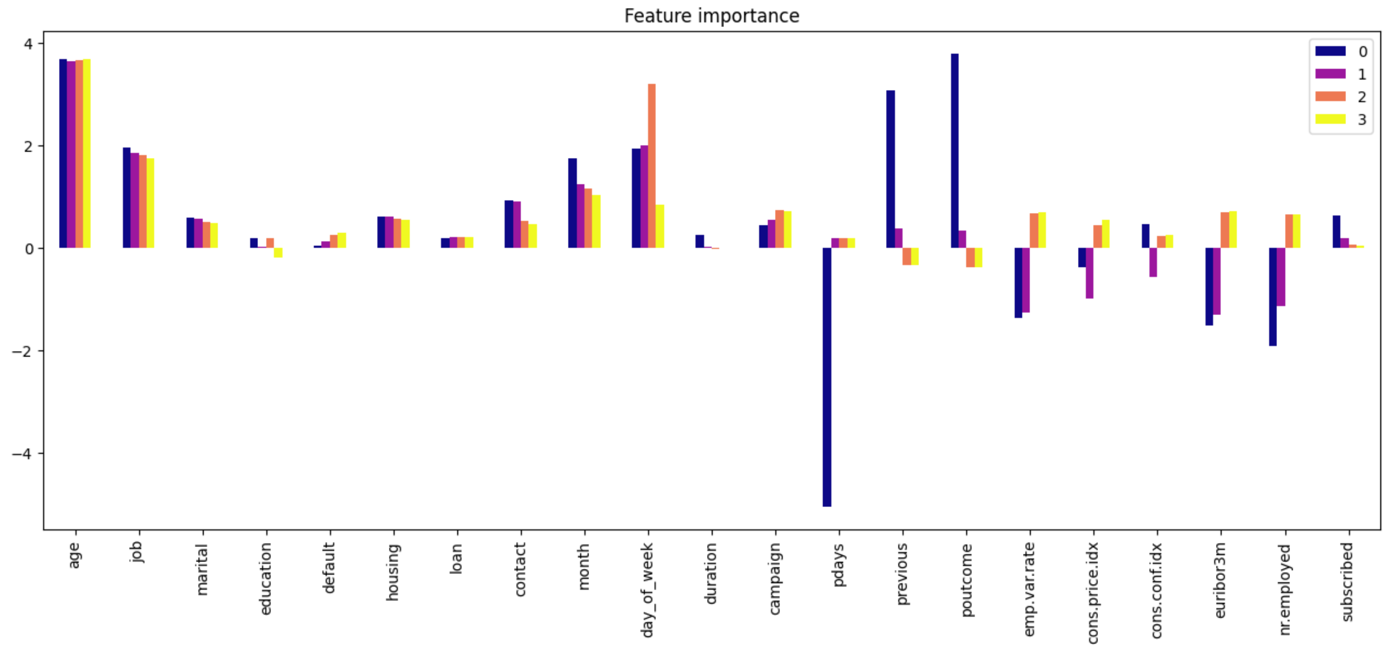
| | Silhouette Score |
|---|---|
| **KMeans** | 0.171147 |
| **Najbitnije_kolone_KMeans** | 0.219056 |
| **Najbitnije_PCA_KMeans** | 0.519875 |
| **PCA_KMeans** | 0.517224 |
| **BisectingKMeans** | 0.163576 |

```
clustering_dataframe
```

| | KMeans | Najbitnije_Kmeans | Najbitnije_PCA_Kmeans | PCA_Kmeans | Bisecting Kmeans |
|---|---|---|---|---|---|
| 0 | 1537 | 1541 | 10821 | 10822 | 1534 |
| 1 | 16652 | 11102 | 5783 | 6143 | 12700 |
| 2 | 10845 | 12146 | 16136 | 16136 | 13013 |
| 3 | 12154 | 16399 | 8448 | 8087 | 13941 |

Next steps: View recommended plots

```
printFeatureImportance(dataset, cluster_labels)
```

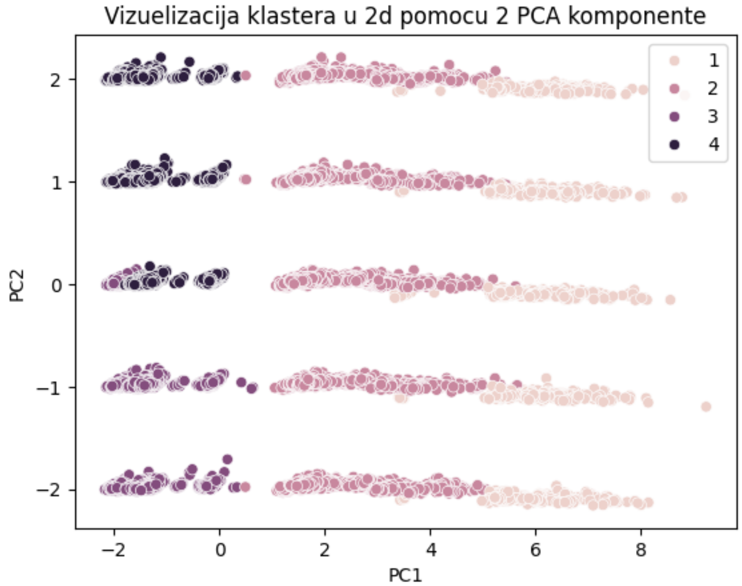



Na osnovu prikaza uticaja svakog ficera za svaki klaster izbacuju se kolone **education**, **default**, **loan** i **duration**, pa se vrsi klasterovanje za dobijeni set podataka

```
dataset_4 = dataset.copy()
dataset_4.drop(["education","default","loan","duration"],axis =1,inplace = True)
bisectingkmeans = BisectingKMeans(n_clusters =4)
cluster_labels = bisectingkmeans.fit_predict(dataset_4)
results = eval_metrics(dataset_4,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc["Najbitnije_BisectingKMeans",:] = results[0]
unique_values, counts = np.unique(cluster_labels, return_counts=True)
clustering_dataframe["Najbitnije_BisectingKMeans"] = counts
```

```
Silhouette Score : 0.20844716771499355 Davies-Bouldin Index: 1.4080440435805721Calinski-Harabasz Index: 13286.495522703544
```

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




Izvrsena je redukcija novodobijenog seta podataka na 2 glavne komponenete PCA metodom.

```
pcas=PCA(n_components=2).fit_transform(dataset_4)
dataset_4_pca=pd.DataFrame(pcas,columns=['PC1','PC2'])
bisectingkmeans = BisectingKMeans(n_clusters =4)
cluster_labels = bisectingkmeans.fit_predict(dataset_4_pca)
results = eval_metrics(dataset_4_pca,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc["Najbitnije_PCA_BisectingKMeans",:] = results[0]
unique_values, counts = np.unique(cluster_labels, return_counts=True)
clustering_dataframe["Najbitnije_PCA_BisectingKMeans"] = counts
```

```
Silhouette Score : 0.5158424202482829 Davies-Bouldin Index: 0.8319366775858243Calinski-Harabasz Index: 52415.54121833599
```

Izvrseno je klasterovanje nakon originalong redukcije primenom PCA metode na 2 komponente.

```
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["PCA_BisectingKMeans",:] = results[0]
```

```
Silhouette Score : 0.512936777229905 Davies-Bouldin Index: 0.8340137361907445Calinski-Harabasz Index: 52175.537242845814
```

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

```
results_df
```

| | Silhouette Score |
|---|---|
| **KMeans** | 0.171147 |
| **Najbitnije_kolone_KMeans** | 0.219056 |
| **Najbitnije_PCA_KMeans** | 0.519875 |
| **PCA_KMeans** | 0.517224 |
| **BisectingKMeans** | 0.163576 |
| **Najbitnije_BisectingKMeans** | 0.208447 |
| **Najbitnije_PCA_BisectingKMeans** | 0.515842 |
| **PCA_BisectingKMeans** | 0.512937 |

## Gaussian Mixture

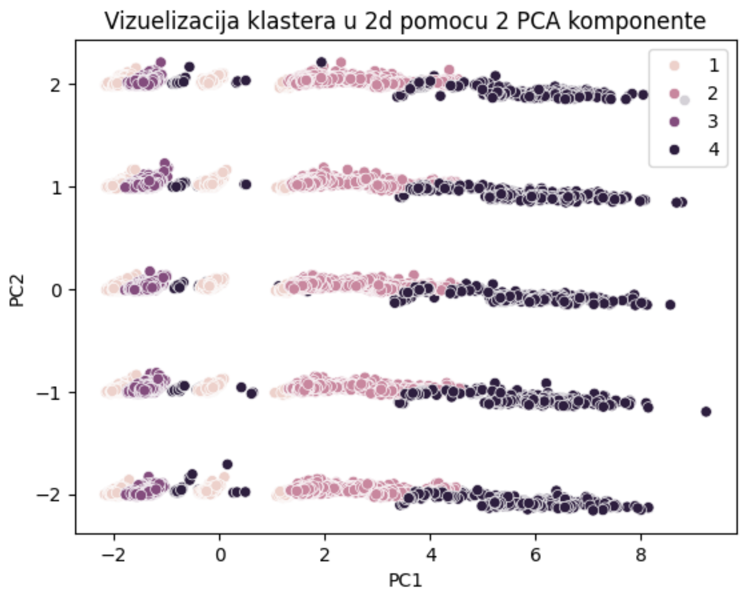
```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components = 4,random_state=42)
```

```
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["Gaussian Mixture",:] = results[0]
```

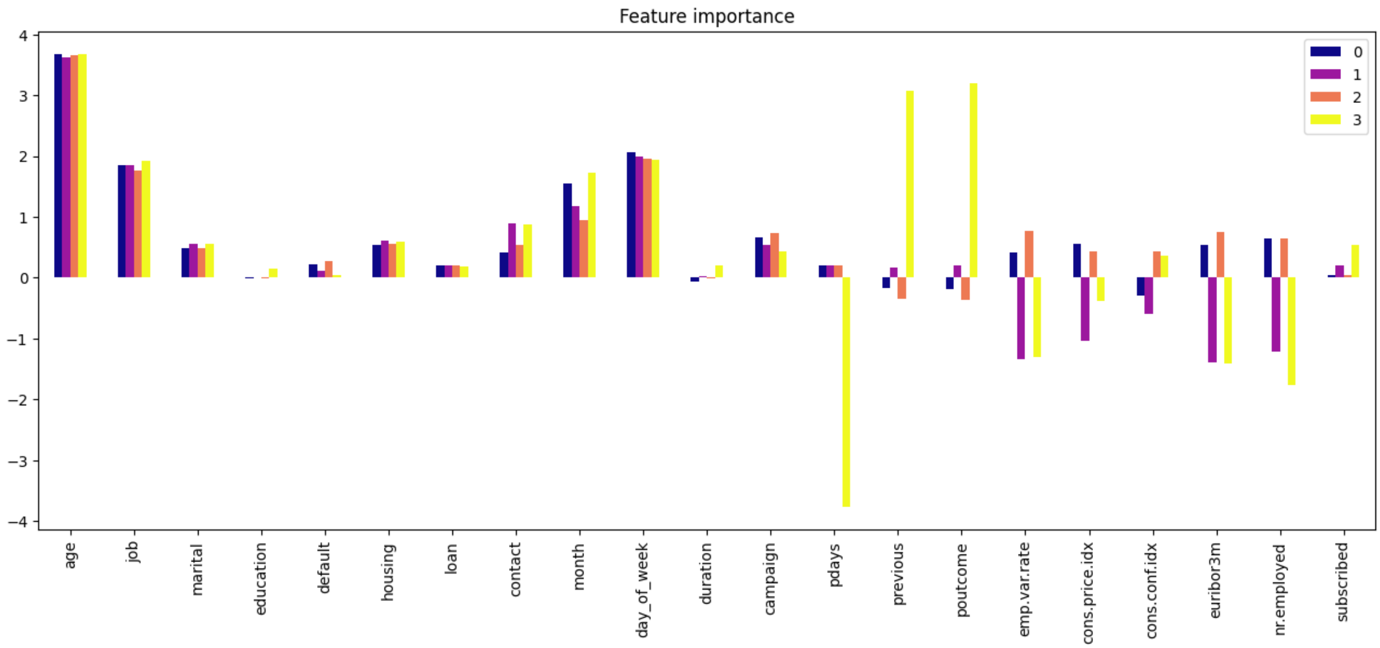
```
Silhouette Score : 0.09975477726149581 Davies-Bouldin Index: 3.3015872624880185Calinski-Harabasz Index: 7460.016926791017
```

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

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




```
printFeatureImportance(dataset, cluster_labels)
```




Na osnovu prikazanog uticaja ficera na klastere izbacuju se **education**, **default**, **loan**, **duration**. Vrsi se klasterovanje novodobijenog dataseta.

```
dataset_5 = dataset.copy()
dataset_5.drop(["education","default","loan","duration"],axis =1, inplace = True)
cluster_labels = gmm.fit_predict(dataset_5)
results = eval_metrics(dataset_5,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc["Najbitnije_Gaussian_Mixture",:] = results[0]
```

```
Silhouette Score : 0.12713395035214892 Davies-Bouldin Index: 2.329832381913431Calinski-Harabasz Index: 10306.446779961354
```

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

Nakon toga se vrsi redukcija dimenzionalnosti PCA metodom na 2 komponente i klasterizacija

```
pcas=PCA(n_components=2).fit_transform(dataset_5)
dataset_5_pca=pd.DataFrame(pcas,columns=['PC1','PC2'])
cluster_labels = gmm.fit_predict(dataset_5_pca)
results = eval_metrics(dataset_5_pca,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc["Najbitnije_PCA_Gaussian_Mixture",:] = results[0]
unique_values, counts = np.unique(cluster_labels, return_counts=True)
clustering_dataframe["Najbitnije_PCA_Gaussian_Mixture"] = counts
```

```
Silhouette Score : 0.46328132173778425 Davies-Bouldin Index: 0.6972159159809895Calinski-Harabasz Index: 38306.47305693685
```

Na kraju se izvrsava klasterizacija ovom metodom za polazni dataset koji je redukovan na dve glavne komponente PCA metodom

```
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["PCA_Gaussian Mixture",:] = results[0]
```

```
Silhouette Score : 0.46546688598306035 Davies-Bouldin Index: 0.8838661416398568Calinski-Harabasz Index: 38707.137751568815
```

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

```
results_df
```

| | Silhouette Score |
|---|---|
| **KMeans** | 0.171147 |
| **Najbitnije_kolone_KMeans** | 0.219056 |
| **Najbitnije_PCA_KMeans** | 0.519875 |
| **PCA_KMeans** | 0.517224 |
| **BisectingKMeans** | 0.163576 |
| **Najbitnije_BisectingKMeans** | 0.208447 |
| **Najbitnije_PCA_BisectingKMeans** | 0.515842 |
| **PCA_BisectingKMeans** | 0.512937 |
| **Gaussian Mixture** | 0.099755 |
| **Najbitnije_Gaussian_Mixture** | 0.127134 |
| **Najbitnije_PCA_Gaussian_Mixture** | 0.463281 |
| **PCA_Gaussian Mixture** | 0.465467 |

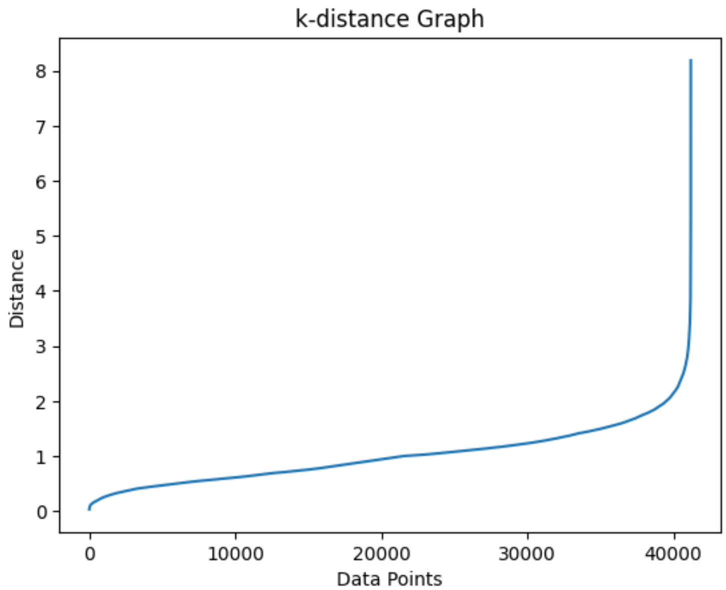
```
clustering_dataframe
```

| | KMeans | Najbitnije_Kmeans | Najbitnije_PCA_Kmeans | PCA_Kmeans | Bisecting Kmeans | Najbitnije_BisectingKMeans | Najbitnije_PCA_BisectingKMeans |
|---|---|---|---|---|---|---|---|
| **0** | 1537 | 1541 | 10821 | 10822 | 1534 | 1530 | 6246 |
| **1** | 16652 | 11102 | 5783 | 6143 | 12700 | 12704 | 7986 |
| **2** | 10845 | 12146 | 16136 | 16136 | 13013 | 13326 | 10820 |
| **3** | 12154 | 16399 | 8448 | 8087 | 13941 | 13628 | 16136 |

Next steps: View recommended plots

## DBSCAN

```
from sklearn.neighbors import NearestNeighbors
neigh = NearestNeighbors(n_neighbors=4)
distances, indices = neigh.fit(dataset).kneighbors(dataset)
distances = np.sort(distances[:, -1])
plt.plot(distances)
plt.xlabel('Data Points')
plt.ylabel('Distance')
plt.title('k-distance Graph')
plt.show()
```




```
1 dbscan = DBSCAN(eps = 2.75, n_jobs=-1)
2 cluster_labels = dbscan.fit_predict(dataset)
3 max(cluster_labels)
```

```
3
```

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

```
Silhouette Score : 0.2389458490253637 Davies-Bouldin Index: 1.968267519982127Calinski-Harabasz Index: 3303.7085306796844
```

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

```
array([-1,  0,  1,  2,  3])
```

```
1 clustering_dataframe["DBSCAN"] = counts[1:5]
```

```
1 results_df
```

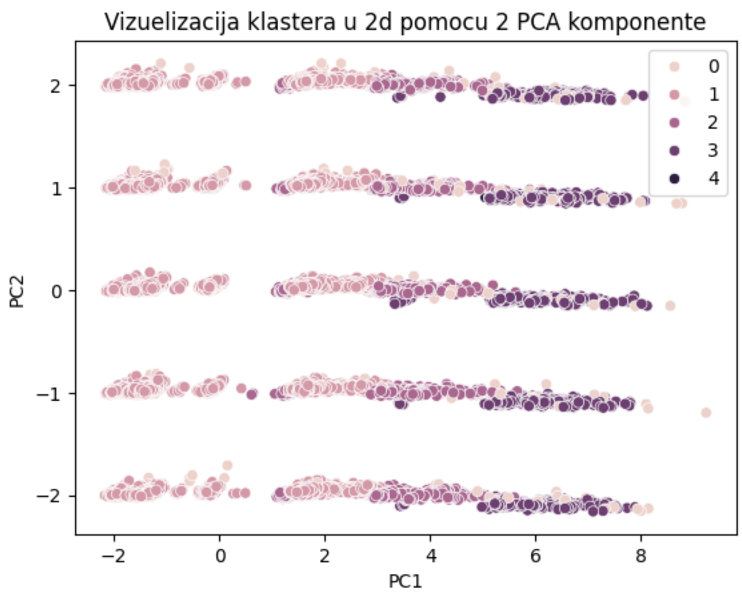
| | Silhouette Score |
|---|---|
| **KMeans** | 0.171147 |
| **Najbitnije_kolone_KMeans** | 0.219056 |
| **Najbitnije_PCA_KMeans** | 0.519875 |
| **PCA_KMeans** | 0.517224 |
| **BisectingKMeans** | 0.163576 |
| **Najbitnije_BisectingKMeans** | 0.208447 |
| **Najbitnije_PCA_BisectingKMeans** | 0.515842 |
| **PCA_BisectingKMeans** | 0.512937 |
| **Gaussian Mixture** | 0.099755 |
| **Najbitnije_Gaussian_Mixture** | 0.127134 |
| **Najbitnije_PCA_Gaussian_Mixture** | 0.463281 |
| **PCA_Gaussian Mixture** | 0.465467 |
| **DBSCAN** | 0.238946 |

```
1 clustering_dataframe
```

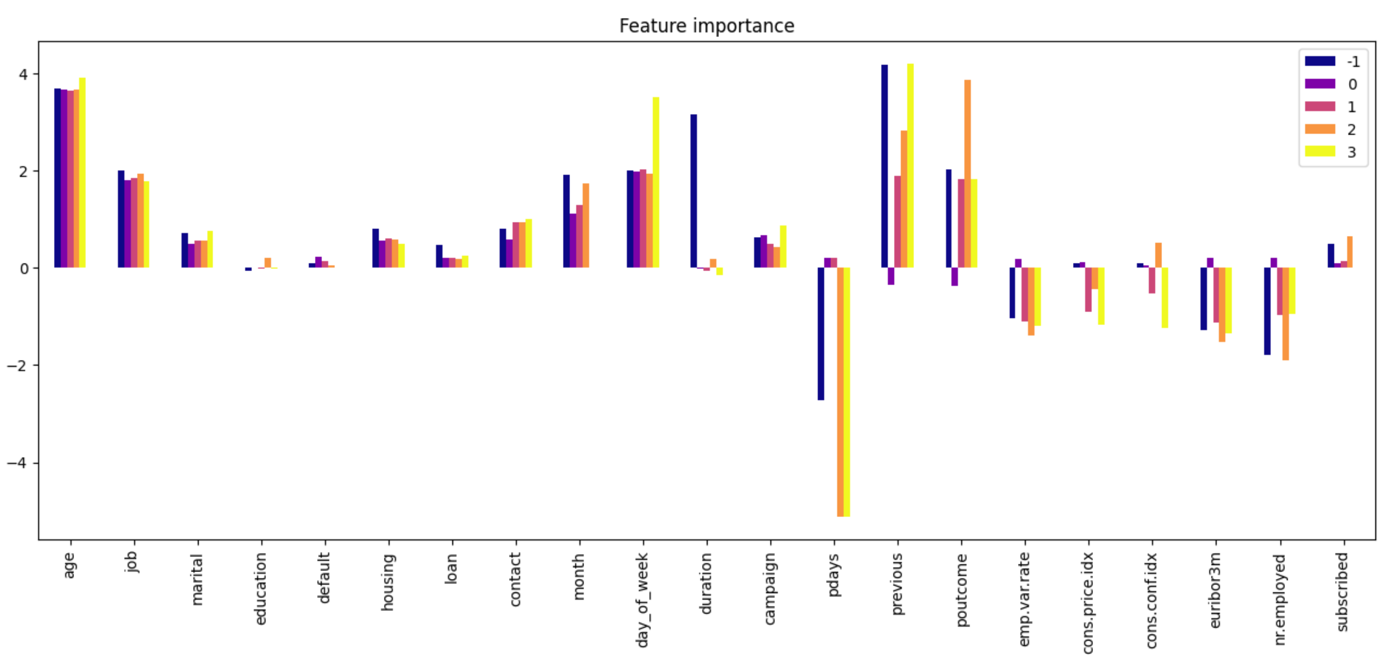
| | KMeans | Najbitnije_Kmeans | Najbitnije_PCA_Kmeans | PCA_Kmeans | Bisecting Kmeans | Najbitnije_BisectingKMeans | Najbitnije_PCA_BisectingKMeans |
|---|---|---|---|---|---|---|---|
| **0** | 1537 | 1541 | 10821 | 10822 | 1534 | 1530 | 6246 |
| **1** | 16652 | 11102 | 5783 | 6143 | 12700 | 12704 | 7986 |
| **2** | 10845 | 12146 | 16136 | 16136 | 13013 | 13326 | 10820 |
| **3** | 12154 | 16399 | 8448 | 8087 | 13941 | 13628 | 16136 |

Next steps: View recommended plots

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




```
1 printFeatureImportance(dataset, cluster_labels)
```



```
dataset_6 = dataset.copy()
dataset_6.drop(["education","default"],axis =1, inplace = True)
dbscan = DBSCAN(eps = 2.75, n_jobs=-1)
cluster_labels = dbscan.fit_predict(dataset_6)
results = eval_metrics(dataset_6,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df.loc["Najbitnije_DBSCAN",:] = results[0]
```

```
Silhouette Score : 0.26144058353883676 Davies-Bouldin Index: 1.719416723737258Calinski-Harabasz Index: 3683.1650027445903
```

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

```
array([-1,  0,  1,  2,  3])
```

```
clustering_dataframe["DBSCAN"] = counts[1:5]
```

```
results_df
```

| | Silhouette Score |
|---|---|
| **KMeans** | 0.171147 |
| **Najbitnije_kolone_KMeans** | 0.219056 |
| **Najbitnije_PCA_KMeans** | 0.519875 |
| **PCA_KMeans** | 0.517224 |
| **BisectingKMeans** | 0.163576 |
| **Najbitnije_BisectingKMeans** | 0.208447 |
| **Najbitnije_PCA_BisectingKMeans** | 0.515842 |
| **PCA_BisectingKMeans** | 0.512937 |
| **Gaussian Mixture** | 0.099755 |
| **Najbitnije_Gaussian_Mixture** | 0.127134 |
| **Najbitnije_PCA_Gaussian_Mixture** | 0.463281 |
| **PCA_Gaussian Mixture** | 0.465467 |
| **DBSCAN** | 0.238946 |
| **Najbitnije_DBSCAN** | 0.261441 |

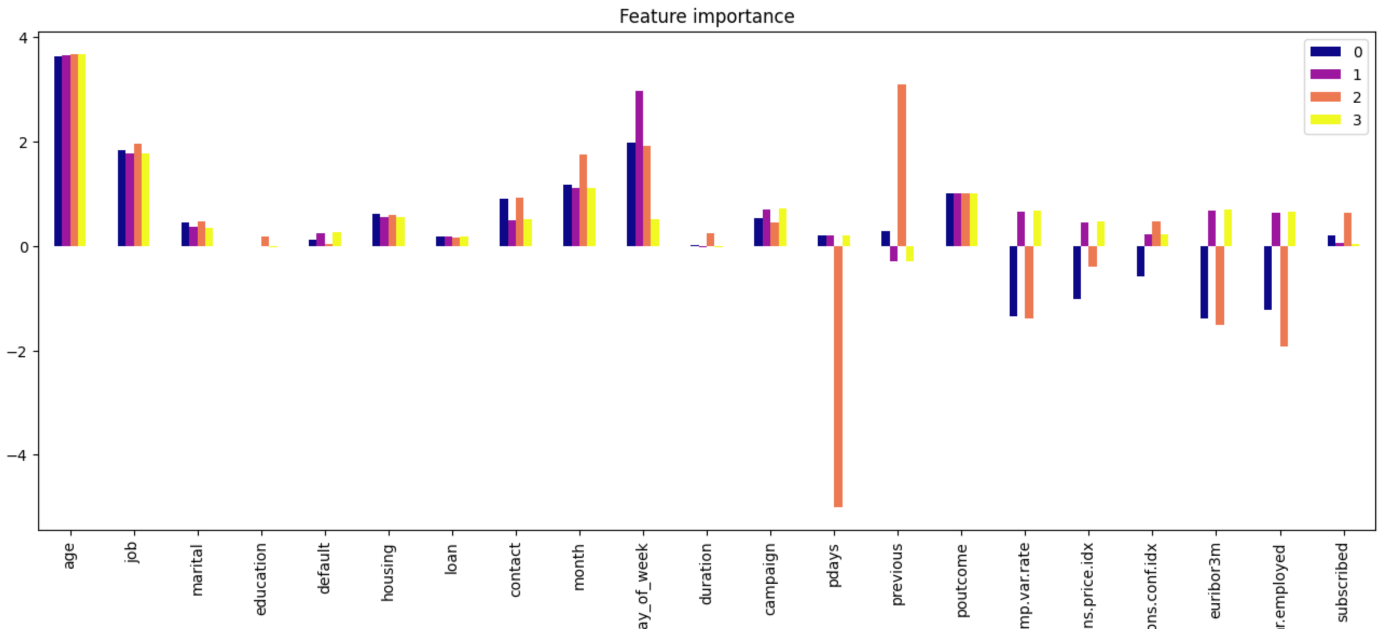
Na osnovu dobijenih tabela zakljucuje se da primena KMeans algoritma za klasterovanje u 4 klastera, daje najbolje rezultate, sa malom razlikom u odnosu na Bisecting KMeans i Gaussian Mixture, sve nad podacima redukovane dimenzionalnosti. KMeans i Gaussian Mixture bice testirani i na drugoj varijanti dataseta.

## Druga varijanta

```
kmeans = KMeans(n_clusters =4)
cluster_labels = kmeans.fit_predict(dataset_2)
results = eval_metrics(dataset_2,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))
results_df_2 = pd.DataFrame()
results_df_2.loc["KMeans","Silhouette Score"] = results[0]
```

```
Silhouette Score : 0.17896779164819634 Davies-Bouldin Index: 1.6419446085231888Calinski-Harabasz Index: 9668.543718253422
```

```
printFeatureImportance(dataset_2, cluster_labels)
```




```
results_df_2
```

| | Silhouette Score |
|---|---|
| **KMeans** | 0.178968 |

```
dataset_7 = dataset_2.copy()
dataset_7.drop(["education","default","loan","duration"],axis=1,inplace=True)
cluster_labels = kmeans.fit_predict(dataset_7)
results = eval_metrics(dataset_7,cluster_labels)
print("Silhouette Score : "+str(results[0])+" Davies-Bouldin Index: "+str(results[1])+"Calinski-Harabasz Index: "+str(results[2]))

results_df_2.loc["Najbitniji_KMeans","Silhouette Score"] = results[0]
```

```
Silhouette Score : 0.22921389181397597 Davies-Bouldin Index: 1.3724886463730646Calinski-Harabasz Index: 13398.876434245802
```

Nakon toga odredjuju se dva glavne komponente sa PCA metodom i vrsi klasterovanje

```
pcas=PCA(n_components=2).fit_transform(dataset_7)
dataset_7_pca = pd.DataFrame(pcas,columns=['PC1','PC2'])
cluster_labels = kmeans.fit_predict(dataset_7_pca)
```