Data Science com Python

Módulo 5 - Modelagem Clustering

Professor: Lucas Roberto Correa

LEMBRETE: Fazer o import dos datasets usados no ambiente do colab antes de executar os comandos.

Import dos pacotes

```
# Manipulação dados
import pandas as pd

# Visualização de dados
import seaborn as sns
import matplotlib.pyplot as plt

# Pre processamento
from sklearn.preprocessing import StandardScaler

# Modelos de agrupamento
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import DBSCAN

#Métricas
from sklearn.metrics import silhouette_score

# Limpeza de memória
import gc
```

```
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', None)
```

Import dos metadados

link da base: https://www.kaggle.com/rashmiranu/banking-dataset-classification?select=new_train.csv

```
meta = pd.read_excel('metadata.xlsx')
```

```
meta
```

	Feature	Feature_Type	
0	age	numeric	
1	job	Categorical,nominal	type of job ('admin.','blue-collar','entrepreneur','l employed','services','stude
2	marital	categorical,nominal	marital status ('divorced','married','single','unknown'; note:
3	education	categorical,nominal	('basic.4y','basic.6y','basic.9y','high.school','illiterate','professiona
4	default	categorical,nominal	ha
5	housing	categorical,nominal	l
6	loan	categorical,nominal	h
7	contact	categorical,nominal	contact co
8	month	categorical,ordinal	last contact month
9	dayofweek	categorical,ordinal	last contact da
10	duration	numeric	last contact duration, in seconds . Important note: this attribute
11	campaign	numeric	number of contacts performed during this campaign a
12	pdays	numeric	number of days that passed by after the client was last co mea
13	previous	numeric	number of contacts performed

Import da base

```
df = pd.read_csv('new_train.csv', sep=',')
```

```
df.head()
```

	age	job	marital	education	default	housing	loan	contact	month
0	49	blue-collar	married	basic.9y	unknown	no	no	cellular	nov
1	37	entrepreneur	married	university.degree	no	no	no	telephone	nov
2	78	retired	married	basic.4y	no	no	no	cellular	jul
3	36	admin.	married	university.degree	no	yes	no	telephone	may
4	59	retired	divorced	university.degree	no	no	no	cellular	jun

Retirando a target, pois o conjunto de dados será usado para uma análise não supervionada

```
expl = df.drop(columns=['y'], axis=1)
expl.head()
```

	age	job	marital	education	default	housing	loan	contact	month
0	49	blue-collar	married	basic.9y	unknown	no	no	cellular	nov
1	37	entrepreneur	married	university.degree	no	no	no	telephone	nov
2	78	retired	married	basic.4y	no	no	no	cellular	jul
3	36	admin.	married	university.degree	no	yes	no	telephone	may
4	59	retired	divorced	university.degree	no	no	no	cellular	jun

```
expl_cat = expl[['job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month','poutcome']]
```

```
expl_num = expl[['duration', 'campaign', 'pdays', 'previous']]
```

Resultado a ser considerado na modelagem

```
expl_num.head()
```

	duration	campaign	pdays	previous
0	227	4	999	0
1	202	2	999	1
2	1148	1	999	0
3	120	2	999	0
4	368	2	999	0

Checagem de nulos

```
expl_num.isnull().sum()
```

```
duration    0
campaign    0
pdays       0
previous    0
dtype: int64
```

Transformação dos dados com Padronização

```
'''
z = (x - u) / s
onde `u` é a média na amostra de train,`s` é o desvio padrão da amostra.
'''
```

```
scale = StandardScaler()
```

```
expl_num_scale = scale.fit_transform(expl_num)
```

```
expl_num_scale
```

```
array([[-0.12019627,  0.52298128,  0.19658384, -0.35012691],
       [-0.2167318 , -0.20368791,  0.19658384,  1.65381294],
       [ 3.43617293, -0.56702251,  0.19658384, -0.35012691],
       ...,
       [-0.49089273,  0.52298128,  0.19658384, -0.35012691],
       [-0.3596044 , -0.56702251,  0.19658384, -0.35012691],
       [ 1.10387435,  0.15964669,  0.19658384, -0.35012691]])
```

```
del df
```

```
gc.collect()
```

```
756
```

O algoritmo

```
km = KMeans(n_clusters=5, random_state=42)
km
```

```
KMeans(n_clusters=5, random_state=42)
```

```
agg = AgglomerativeClustering(n_clusters=5)
agg
```

```
AgglomerativeClustering(n_clusters=5)
```

Aplicando no conjunto de dados

```
expl['km_05'] = km.fit_predict(expl_num_scale)
```

```
expl['agg_05'] = agg.fit_predict(expl_num_scale)
```

```
gc.collect()
```

```
253
```

Avaliação de métrica

```
# Kmeans

centroides = [2,3,4,5,6,7,8,9,10]

for num_centroide in centroides:
    clusters = KMeans(n_clusters=num_centroide)
    predicao = clusters.fit_predict(expl_num_scale)

    score = silhouette_score(expl_num_scale, predicao)
    print('O valor de silhouette_score é {}, para n_clusters igual a {}'.format(score, num
```

```
O valor de silhouette_score é 0.7402315385741535, para n_clusters igual a 2
O valor de silhouette_score é 0.49370005842359754, para n_clusters igual a 3
O valor de silhouette_score é 0.5351424511751384, para n_clusters igual a 4
O valor de silhouette_score é 0.5835357761705634, para n_clusters igual a 5
O valor de silhouette_score é 0.5097146809826781, para n_clusters igual a 6
O valor de silhouette_score é 0.4984423997440828, para n_clusters igual a 7
O valor de silhouette_score é 0.4993336457007373, para n_clusters igual a 8
O valor de silhouette_score é 0.4847810948605838, para n_clusters igual a 9
O valor de silhouette_score é 0.4583793318818555, para n_clusters igual a 10
```

```
# Aglomerativo
n_clusters = [2,3,4,5,6,7,8,9,10]

for num_cluster in n_clusters:
    clusters = AgglomerativeClustering(n_clusters=num_cluster)
    predicao = clusters.fit_predict(expl_num_scale)

    score = silhouette_score(expl_num_scale, predicao)

    print('O valor de silhouette_score é {}, para n_clusters igual a {}'.format(score, num
```

```
O valor de silhouette_score é 0.7400764067995907, para n_clusters igual a 2
O valor de silhouette_score é 0.46001091987589987, para n_clusters igual a 3
O valor de silhouette_score é 0.5182638090537325, para n_clusters igual a 4
O valor de silhouette_score é 0.5438837083028822, para n_clusters igual a 5
O valor de silhouette_score é 0.4623811376016544, para n_clusters igual a 6
O valor de silhouette_score é 0.4437816163884292, para n_clusters igual a 7
O valor de silhouette_score é 0.41209524550135684, para n_clusters igual a 8
O valor de silhouette_score é 0.41165993887296853, para n_clusters igual a 9
O valor de silhouette_score é 0.3859081975419649, para n_clusters igual a 10
```

```
gc.collect()
```

```
150
```

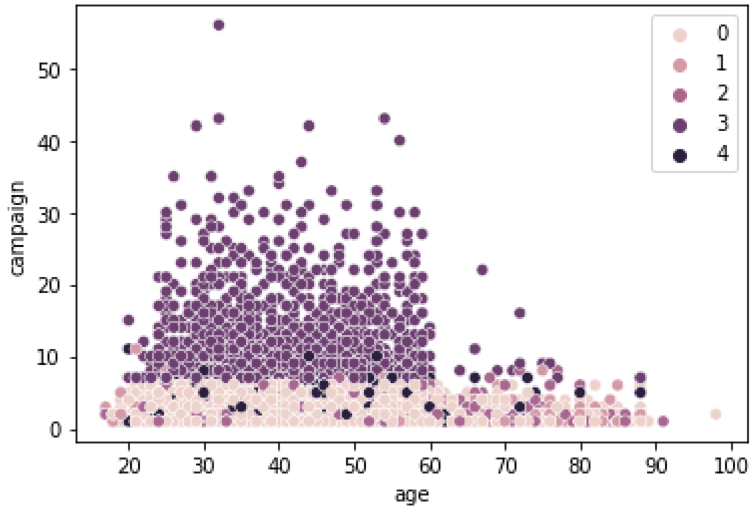
Avaliação dos resultados considerando os dados de explicativas categóricas

```
expl.head()
```

	age	job	marital	education	default	housing	loan	contact	month
0	49	blue-collar	married	basic.9y	unknown	no	no	cellular	nov
1	37	entrepreneur	married	university.degree	no	no	no	telephone	nov
2	78	retired	married	basic.4y	no	no	no	cellular	jul
3	36	admin.	married	university.degree	no	yes	no	telephone	may
4	59	retired	divorced	university.degree	no	no	no	cellular	jun

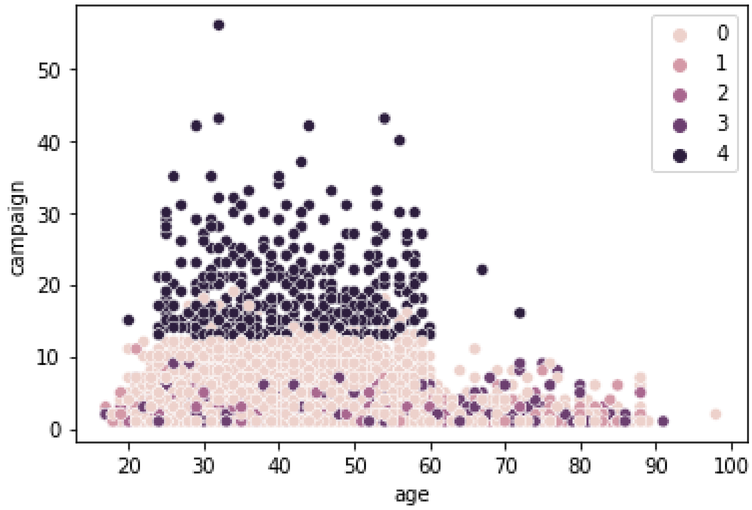
```
sns.scatterplot(data=expl, x="age", y="campaign", hue=km.labels_)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd2c748a6d0>
```



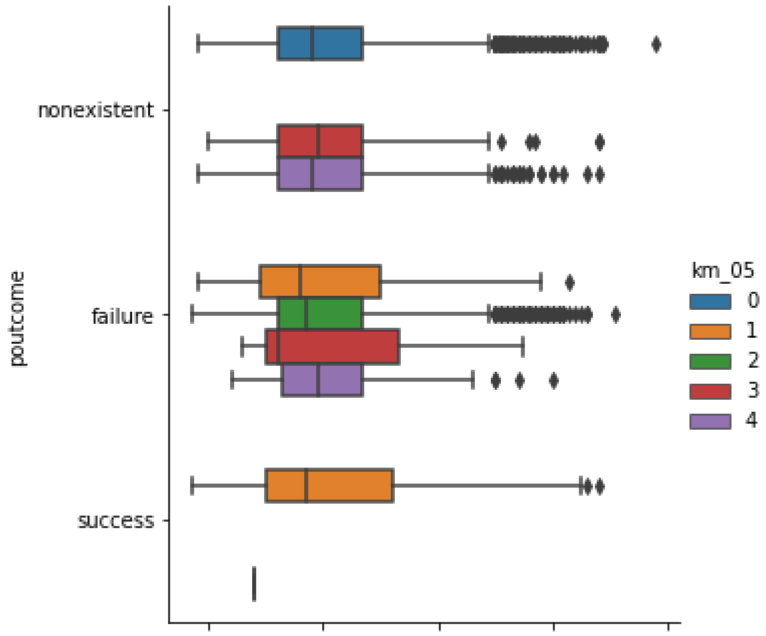

```
sns.scatterplot(data=expl, x="age", y="campaign", hue=agg.labels_)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd2c74a7690>
```




```
sns.catplot(x="age", y="poutcome", hue="km_05", kind="box", data=expl)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd2c91996d0>
```




```
sns.catplot(x="age", y="poutcome", hue="agg_05", kind="box", data=expl)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd2c70b5290>
```