# Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy
%matplotlib inline
plt.style.use('fivethirtyeight')
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)
```

# Loading the Dataset :

In [2]:
```
data = pd.read_csv('ml_project1_data_pt.csv',delimiter =',')
data.head(3)
```

Out[2]:

| | ID | ano_nasc | educacao | estado_civil | renda_ano | crianca_casa | adoles_casa | dt_primcomp | recencia_dias | vinho_montante | frutas_montante | carne_mon |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 5524 | 1957 | Graduation | Single | 58138.0 | 0 | 0 | 9/4/2012 | 58 | 635 | 88 | |
| **1** | 2174 | 1954 | Graduation | Single | 46344.0 | 1 | 1 | 3/8/2014 | 38 | 11 | 1 | |
| **2** | 4141 | 1965 | Graduation | Together | 71613.0 | 0 | 0 | 8/21/2013 | 26 | 426 | 49 | |

In [3]:
```
data.shape
```

Out[3]:
```
(2240, 27)
```

In [4]:
```
data.columns
```

Out[4]:
```
Index(['ID', 'ano_nasc', 'educacao', 'estado_civil', 'renda_ano', 'crianca_casa', 'adoles_casa', 'dt_primcomp', 'recencia_dia
s', 'vinho_montante', 'frutas_montante', 'carne_montante', 'peixe_montante', 'doces_montante', 'ouro_montante', 'promocoes_desc
onto', 'promocoes_web', 'promocoes_catalogo', 'promocoes_store', 'num_visit_web_ult_mes', 'Cmp3', 'Cmp4', 'Cmp5', 'Cmp1', 'Cmp
2', 'reclamacoes', 'target'], dtype='object')
```

# Data Preprocessing

In [4]:
```
# Checking for null values.
info = pd.DataFrame(data=data.isnull().sum()).T.rename(index={0:'Null values'})
info = info.append(pd.DataFrame(data=data.isnull().sum()/data.shape[0] * 100).T.rename(index={0:'% Null values'}))
info
```

Out[4]:

| | ID | ano_nasc | educacao | estado_civil | renda_ano | crianca_casa | adoles_casa | dt_primcomp | recencia_dias | vinho_montante | frutas_montante | carne_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Null values** | 0.0 | 0.0 | 0.0 | 0.0 | 24.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **% Null values** | 0.0 | 0.0 | 0.0 | 0.0 | 1.071429 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |

In [5]:
```
# Checking for Duplicates :
data.duplicated().sum()
```

Out[5]: 0

In [6]:
```
data.describe()
```

Out[6]:

| | ID | ano_nasc | renda_ano | crianca_casa | adoles_casa | recencia_dias | vinho_montante | frutas_montante | carne_montante | peixe_montante |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 2240.000000 | 2240.000000 | 2216.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 |
| **mean** | 5592.159821 | 1968.805804 | 52247.251354 | 0.444196 | 0.506250 | 49.109375 | 303.935714 | 26.302232 | 166.950000 | 37.525446 |
| **std** | 3246.662198 | 11.984069 | 25173.076661 | 0.538398 | 0.544538 | 28.962453 | 336.597393 | 39.773434 | 225.715373 | 54.628979 |
| **min** | 0.000000 | 1893.000000 | 1730.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| **25%** | 2828.250000 | 1959.000000 | 35303.000000 | 0.000000 | 0.000000 | 24.000000 | 23.750000 | 1.000000 | 16.000000 | 3.000000 |
| **50%** | 5458.500000 | 1970.000000 | 51381.500000 | 0.000000 | 0.000000 | 49.000000 | 173.500000 | 8.000000 | 67.000000 | 12.000000 |
| **75%** | 8427.750000 | 1977.000000 | 68522.000000 | 1.000000 | 1.000000 | 74.000000 | 504.250000 | 33.000000 | 232.000000 | 50.000000 |
| **max** | 11191.000000 | 1996.000000 | 666666.000000 | 2.000000 | 2.000000 | 99.000000 | 1493.000000 | 199.000000 | 1725.000000 | 259.000000 |

In [7]:
```
data['dt_primcomp'] = pd.to_datetime(data['dt_primcomp'], errors='coerce')
data['dt_primcomp'] = data['dt_primcomp'].dt.strftime('%m/%Y')
```

In [8]:
```
data['age']= 2020 - data['ano_nasc']
```

In [9]:
```
data['renda_mes_media']= data['renda_ano']/12
```

In [10]:
```
data['campaing_engagement'] =( data['Cmp1']+data['Cmp2']+data['Cmp3']+data['Cmp4']+data['Cmp5']) /5
```

In [11]:
```
data['target'] = data['target'].astype(str)
data['Cmp1'] = data['Cmp1'].astype(str)
data['Cmp2'] = data['Cmp2'].astype(str)
data['Cmp3'] = data['Cmp3'].astype(str)
data['Cmp4'] = data['Cmp4'].astype(str)
data['Cmp5'] = data['Cmp5'].astype(str)
data['reclamacoes'] = data['reclamacoes'].astype(str)
data['digital_profile'] = '0'
data['digital_profile'][(data['num_visit_web_ult_mes']< 5) & (data['promocoes_web']<3)]='1'
```

## Exploratory Data Analysis :

In [13]:
```
data.dtypes.groupby(data.dtypes).size()
```

Out[13]:
```
int64      17
float64     3
object     11
dtype: int64
```

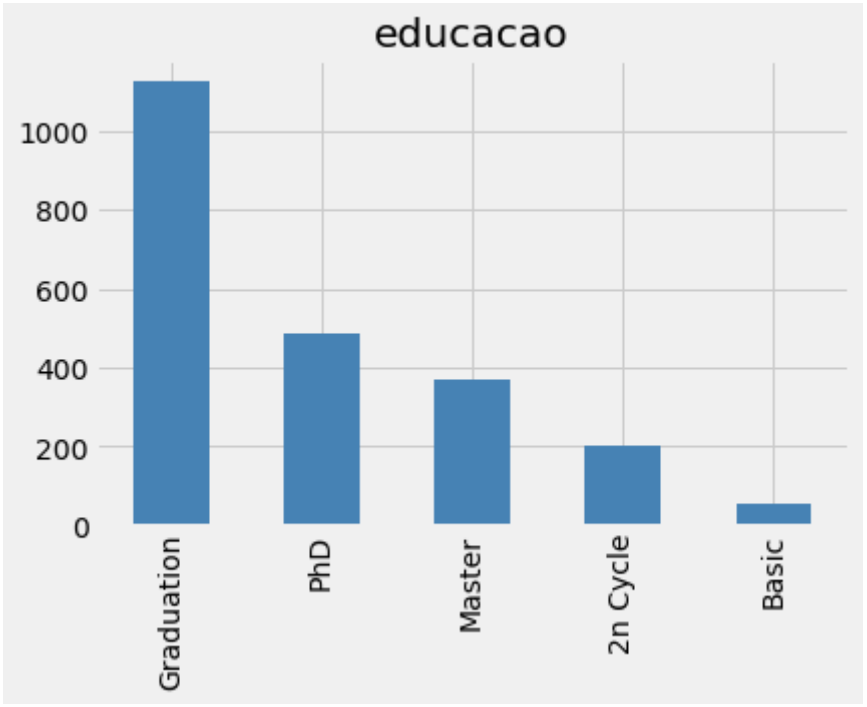
In [15]:
```
dtypes = pd.DataFrame(data.dtypes.rename('type')).reset_index().astype('str')
dtypes = dtypes.query('index != "dt_primcomp"',)
dtypes = dtypes.query('index != "ID"')
dtypes = dtypes.query('index != "target"')
numeric = dtypes[(dtypes.type.isin(['int64', 'float64']))]['index'].values
categorical = dtypes[~(dtypes['index'].isin(numeric)) & (dtypes['index'] != 'target')]['index'].values

print('Numeric:\n', numeric)
print('Categorical:\n', categorical)
```

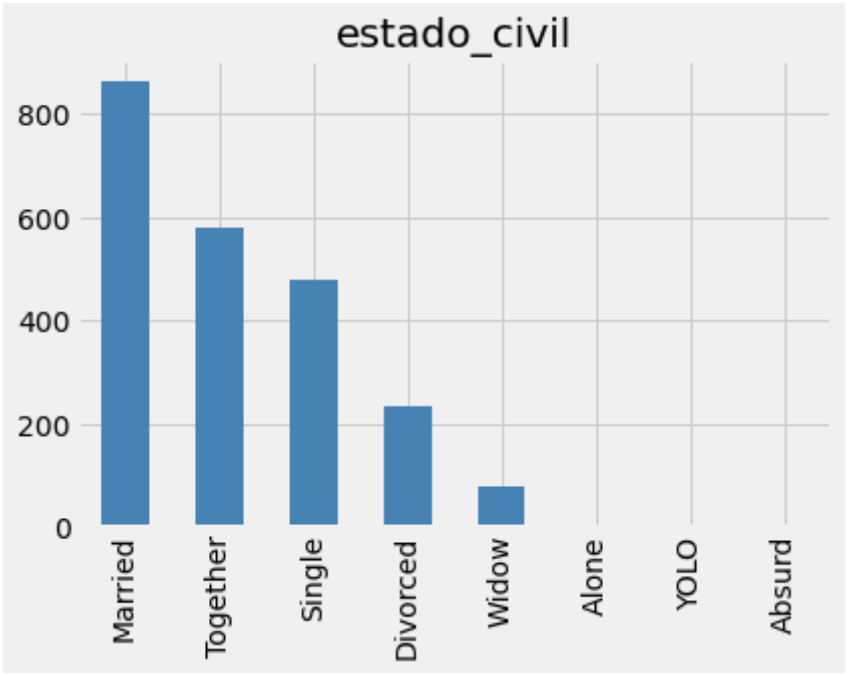
```
Numeric:
 ['ano_nasc' 'renda_ano' 'crianca_casa' 'adoles_casa' 'recencia_dias'
 'vinho_montante' 'frutas_montante' 'carne_montante' 'peixe_montante'
 'doces_montante' 'ouro_montante' 'promocoes_desconto' 'promocoes_web'
 'promocoes_catalogo' 'promocoes_store' 'num_visit_web_ult_mes' 'age'
 'renda_mes_media' 'campaing_engagement']
Categorical:
 ['educacao' 'estado_civil' 'Cmp3' 'Cmp4' 'Cmp5' 'Cmp1' 'Cmp2'
 'reclamacoes' 'digital_profile']
```

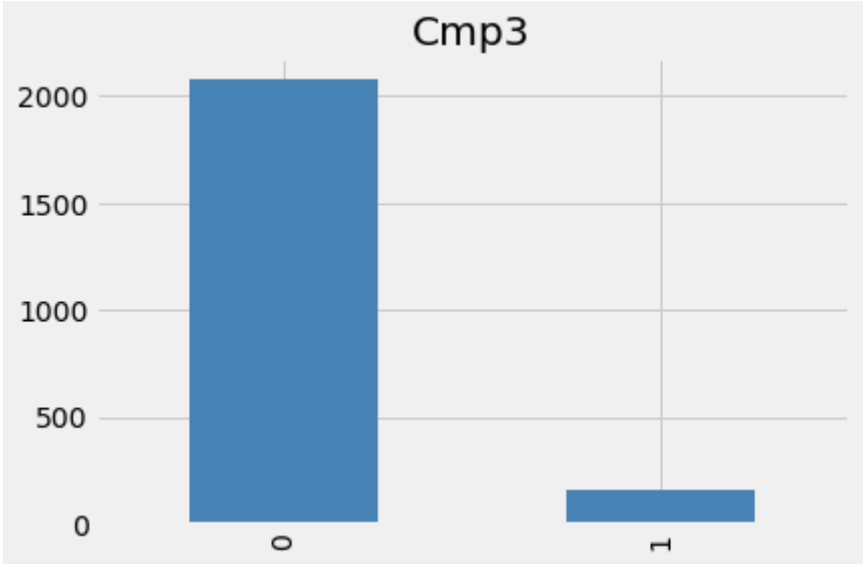
### Categorical Data Analysis

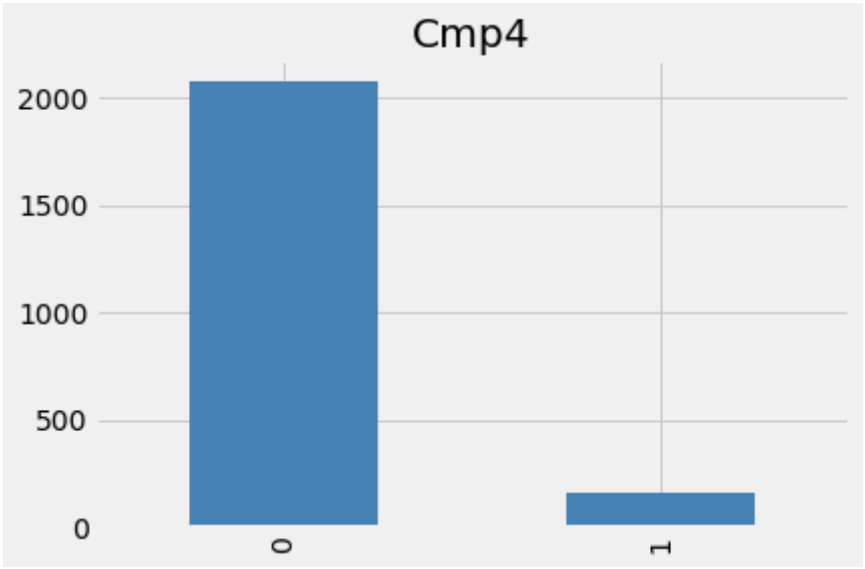
In [830]:
```
pylab.rcParams['figure.figsize'] = (6.0, 4.0)
```

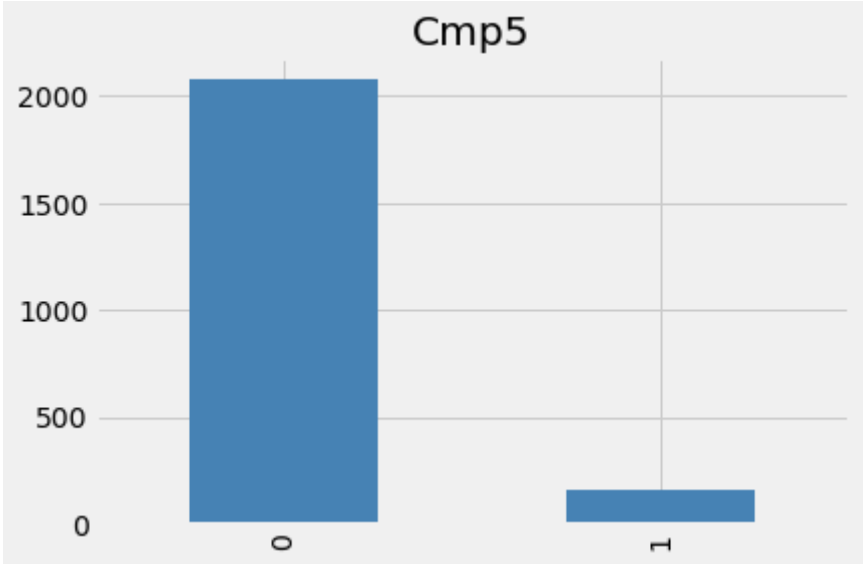
In [16]:
```
for attr in categorical:
  figsize=(8,4)
  plt.figure()
  data[attr].value_counts().plot(kind='bar', color='steelblue');
  plt.title(attr);
```

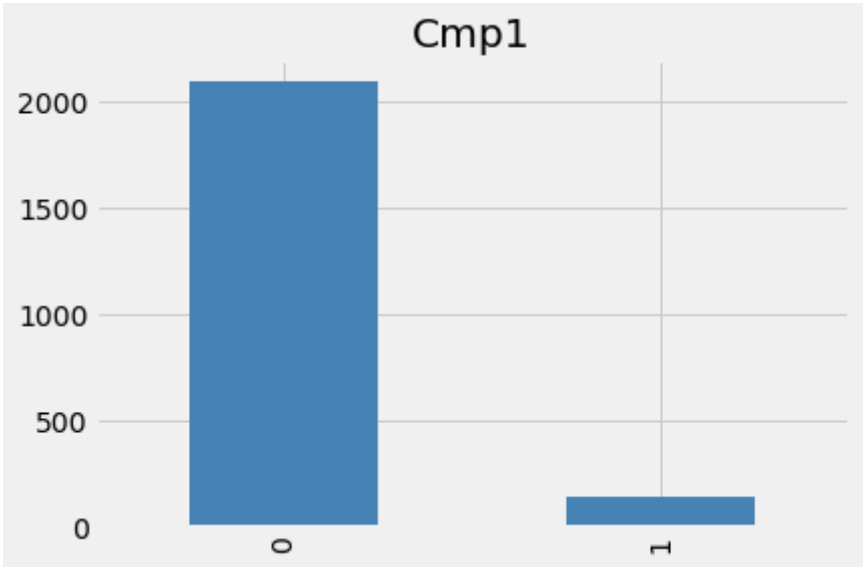

educacao
1000
800
600
400
200
0
Graduation
PhD
Master
2n Cycle
Basic

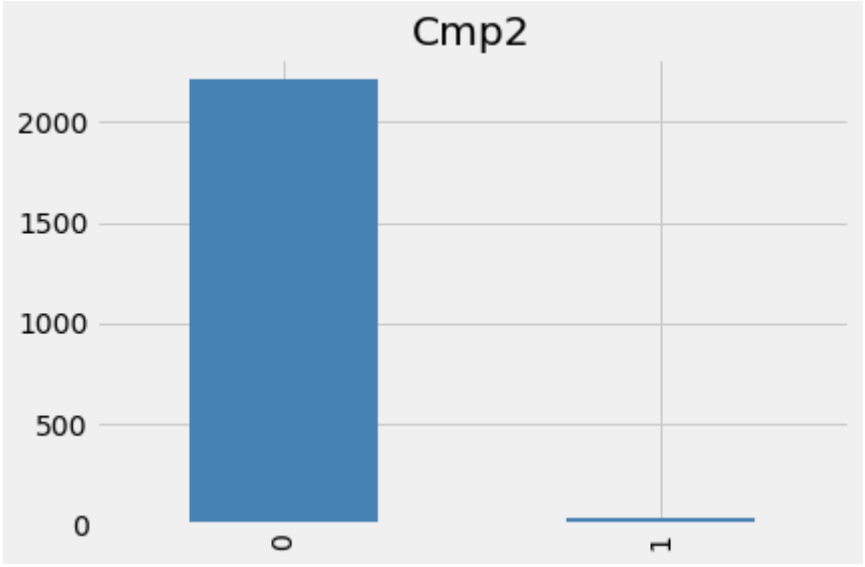

estado_civil
800
600
400
200
0
Married
Together
Single
Divorced
Widow
Alone
YOLO
Absurd

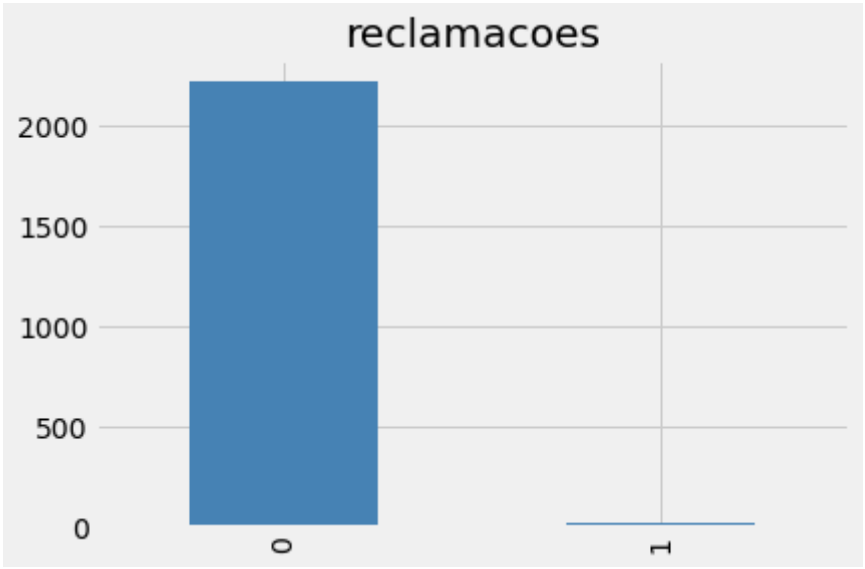

Cmp3
2000
1500
1000
500
0
0
1

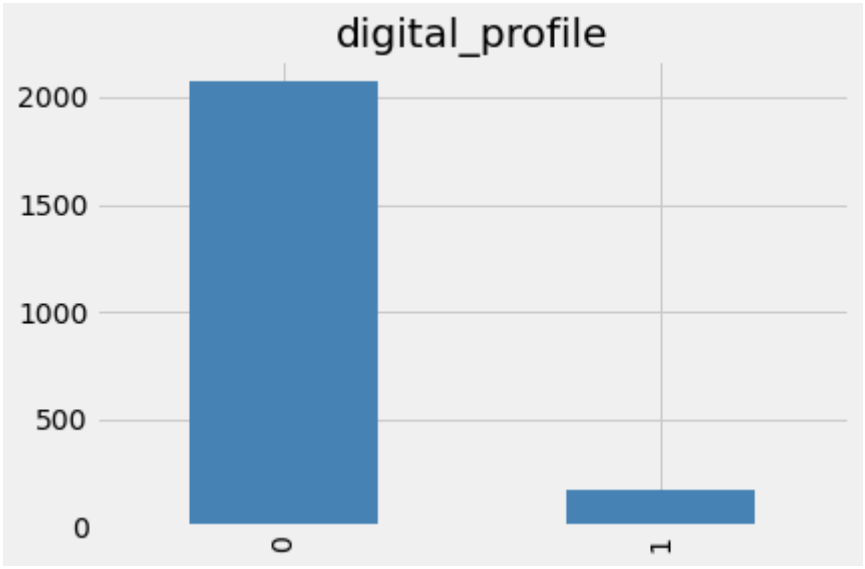

Cmp4
2000
1500
1000
500
0
0
1


Cmp5
2000
1500
1000
500
0
0
1


Cmp1
2000
1500
1000
500
0
0
1


Cmp2
2000
1500
1000
500
0
0
1


reclamacoes
2000
1500
1000
500
0
0
1

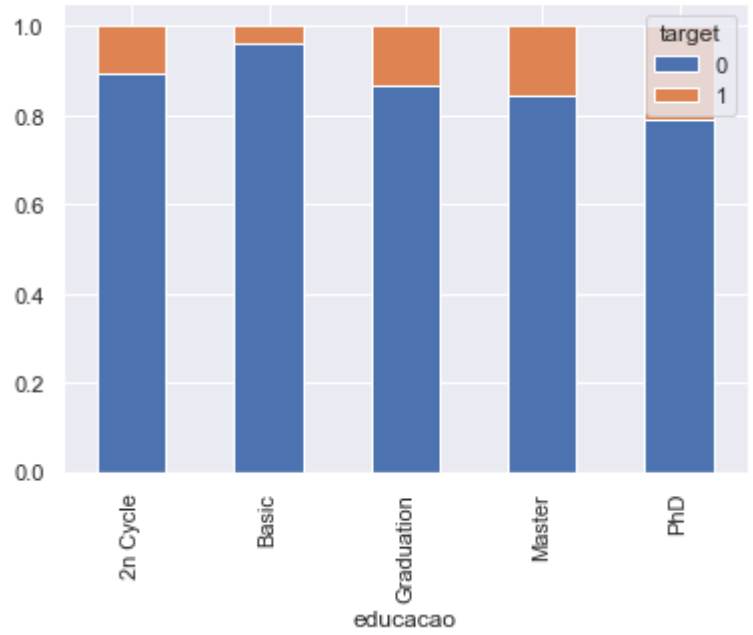

digital_profile
2000
1500
1000
500
0
0
1

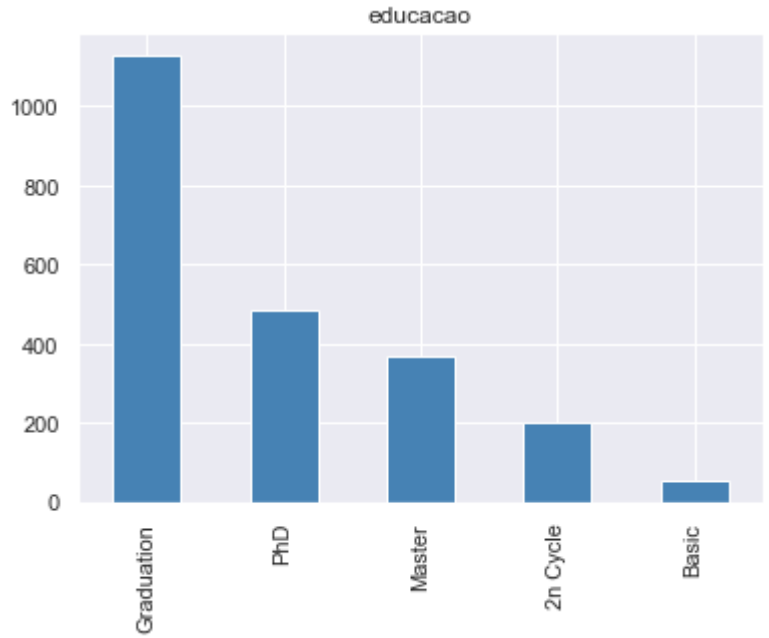
In [56]:

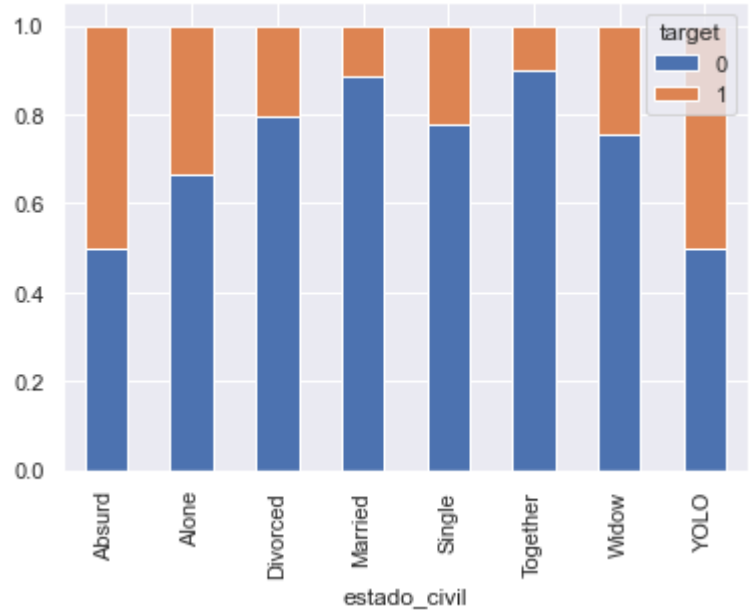
```
for attr in categorical:
  fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12,4))
  outcome_counts = data.groupby([attr, 'target']).size().rename('count').reset_index()
  by_outcome = outcome_counts.pivot(columns='target', values='count', index=attr)
  # Plot the proportions
  by_outcome.div(by_outcome.sum(1), axis=0).plot.bar(stacked=True, ax=ax1);
  # Plot the counts
  data[attr].value_counts().plot.bar(ax=ax2, legend=False,color='steelblue');
  print('Support (%s)\n' % attr)
  print(data[attr].value_counts(), '\n')
  plt.title(attr);
```

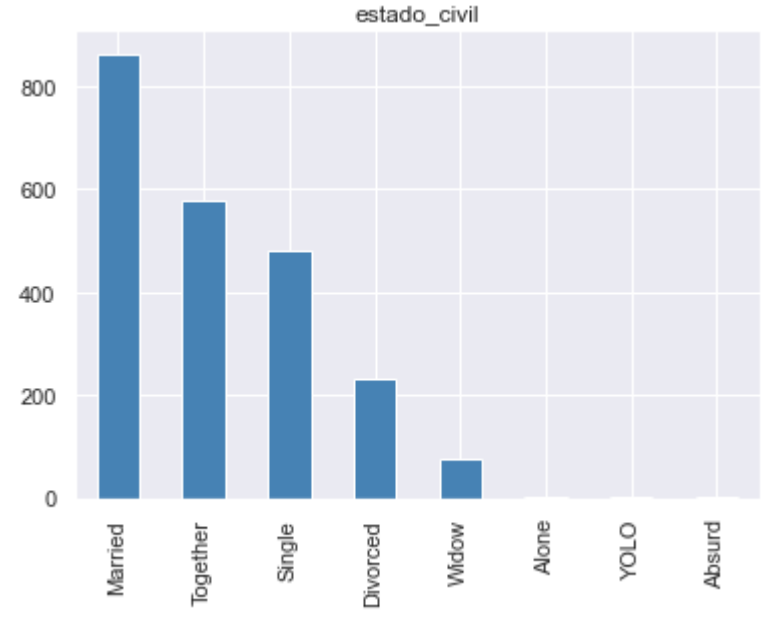
```
Support (educacao)

Graduation    1127
PhD            486
Master         370
2n Cycle       203
Basic           54
Name: educacao, dtype: int64

Support (estado_civil)

Married     864
Together    580
Single      480
Divorced    232
Widow        77
Alone         3
YOLO          2
Absurd        2
Name: estado_civil, dtype: int64

Support (Cmp3)

0    2077
1     163
Name: Cmp3, dtype: int64

Support (Cmp4)

0    2073
1     167
Name: Cmp4, dtype: int64

Support (Cmp5)

0    2077
1     163
Name: Cmp5, dtype: int64

Support (Cmp1)

0    2096
1     144
Name: Cmp1, dtype: int64

Support (Cmp2)
```

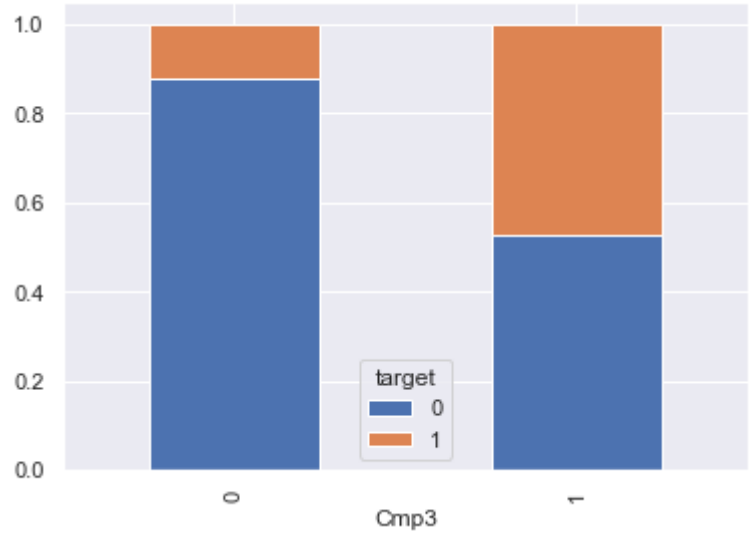
```
0    2210
1      30
Name: Cmp2, dtype: int64

Support (reclamacoes)

0    2219
1      21
Name: reclamacoes, dtype: int64

Support (digital_profile)

0    2071
1     169
Name: digital_profile, dtype: int64
```

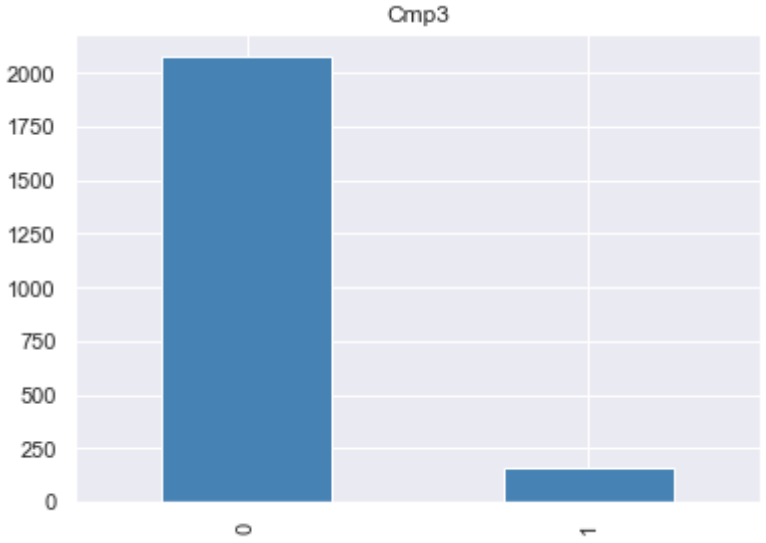


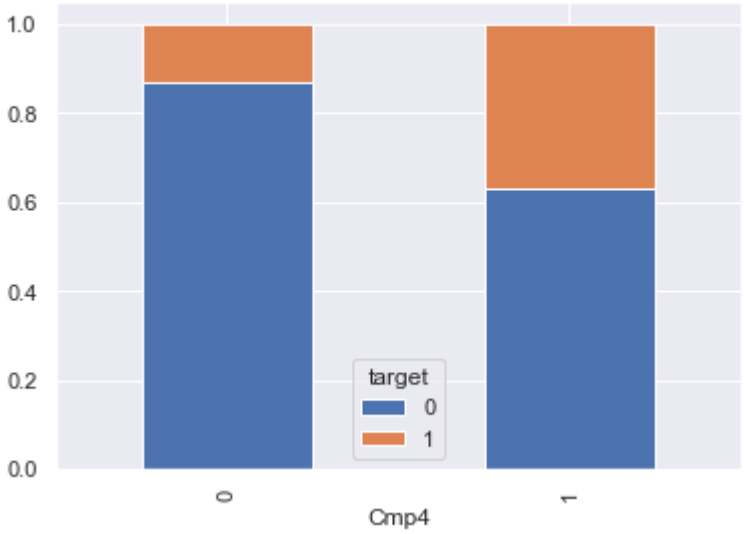



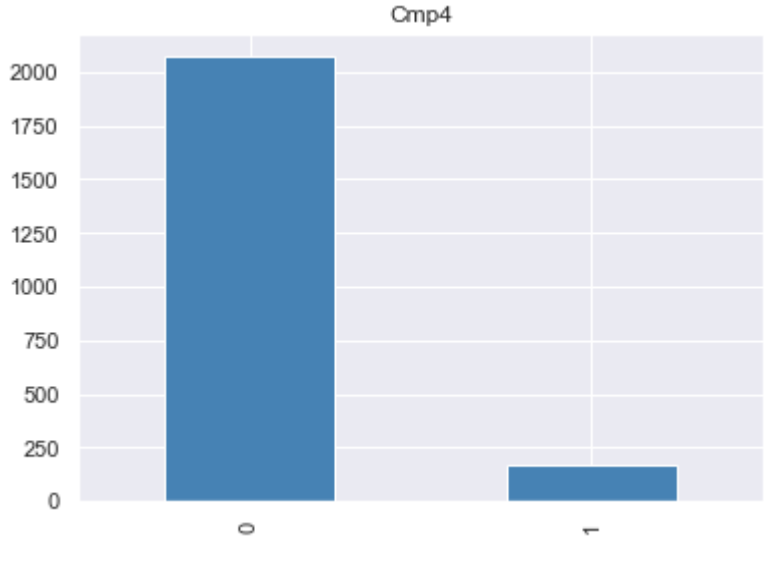

target
0
1
1.0
0.8
0.6
0.4
0.2
0.0
Absurd
Alone
Divorced
Married
Single
Together
Widow
YOLO
estado_civil

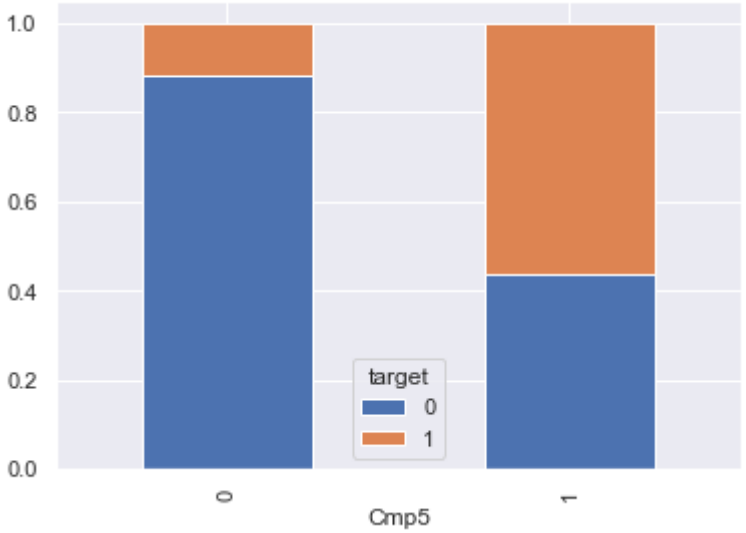

estado_civil
800
600
400
200
0
Married
Together
Single
Divorced
Widow
Alone
YOLO
Absurd

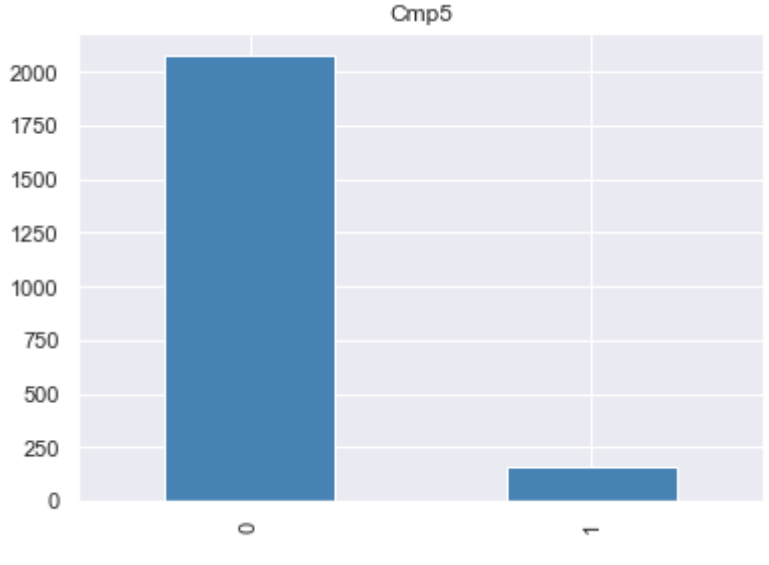

target
0
1
1.0
0.8
0.6
0.4
0.2
0.0
0
1
Cmp3

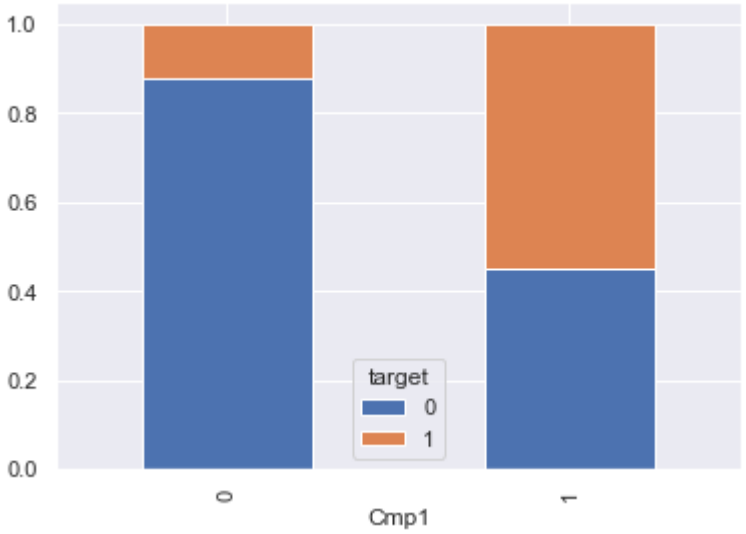

Cmp3
2000
1750
1500
1250
1000
750
500
250
0
0
1

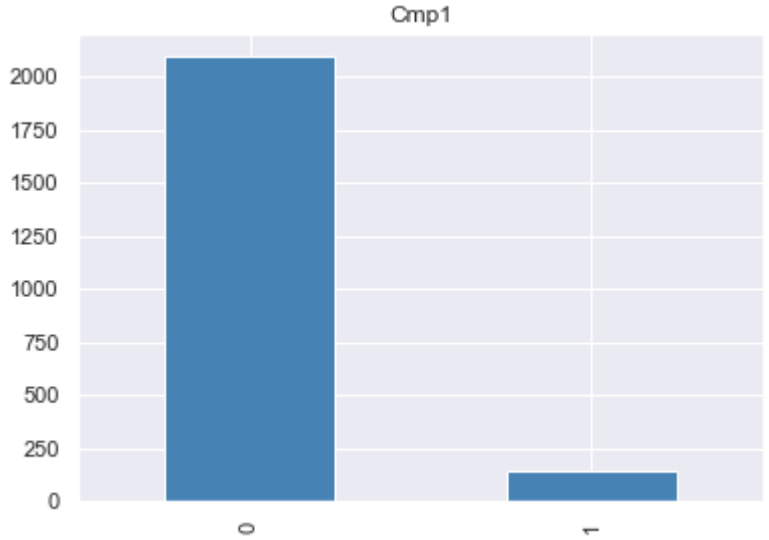

1.0
0.8
0.6
0.4
0.2
0.0
target
0
1
0
1
Cmp4

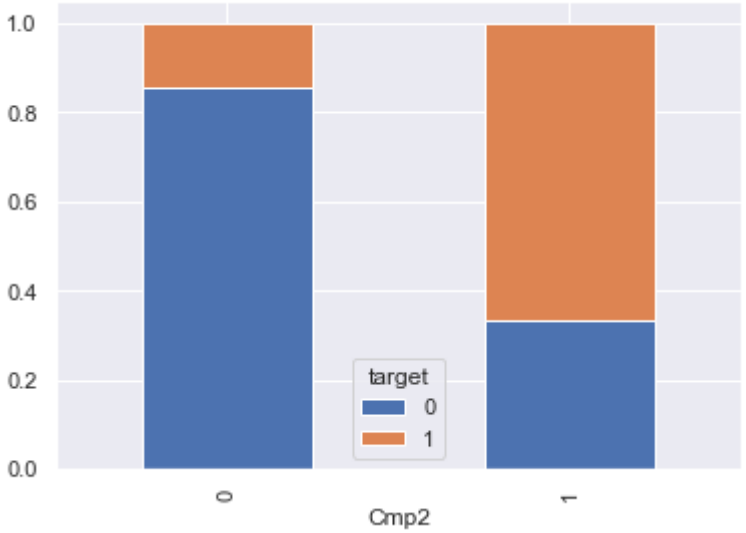

Cmp4
2000
1750
1500
1250
1000
750
500
250
0
0
1

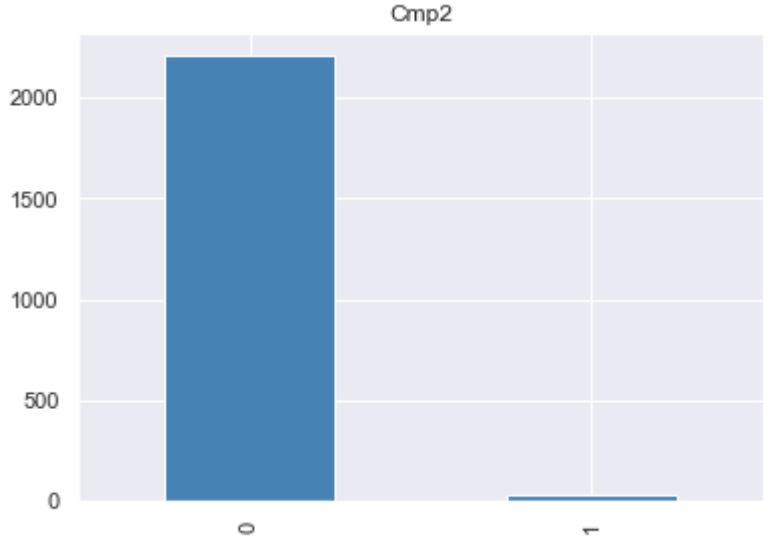

1.0
0.8
0.6
0.4
0.2
0.0
target
0
1
0
1
Cmp5

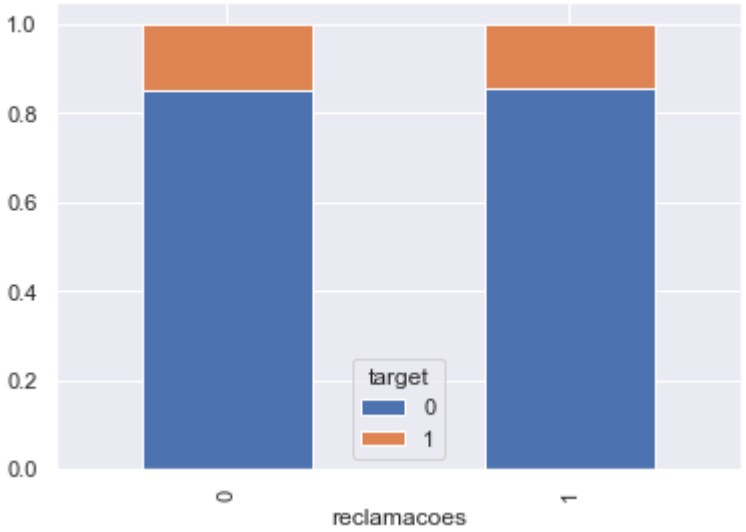

Cmp5
2000
1750
1500
1250
1000
750
500
250
0
0
1

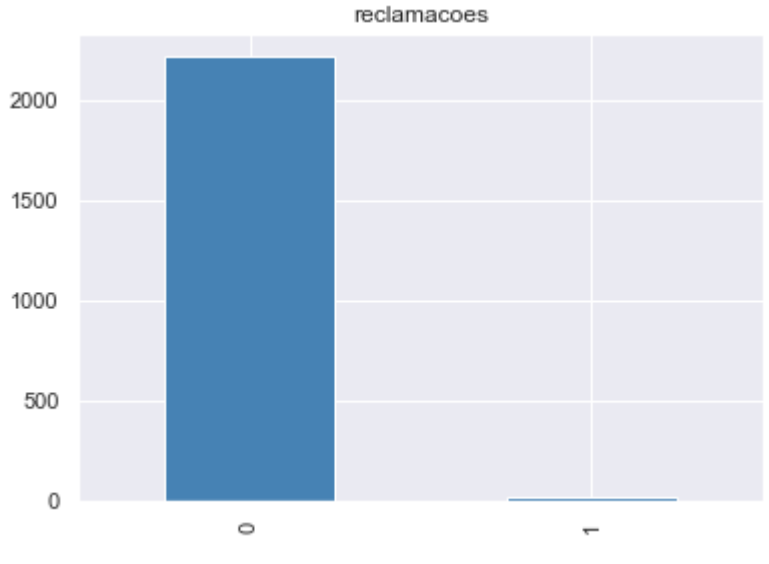

1.0
0.8
0.6
0.4
0.2
0.0
target
0
1
0
1
Cmp1

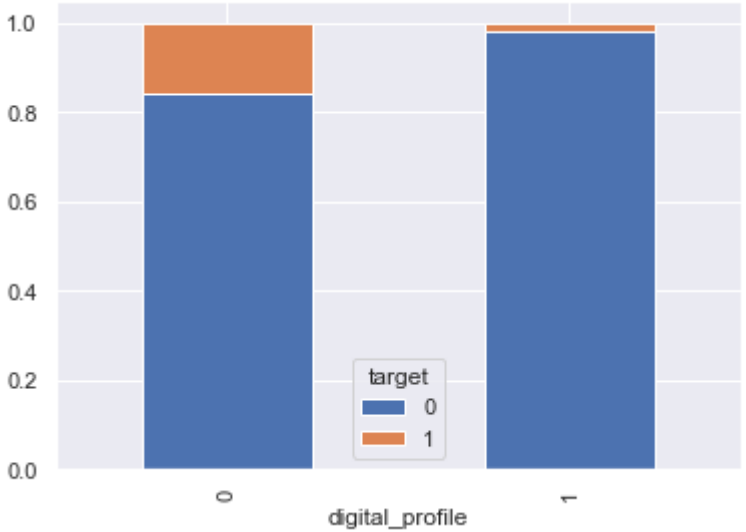

Cmp1
2000
1750
1500
1250
1000
750
500
250
0
0
1

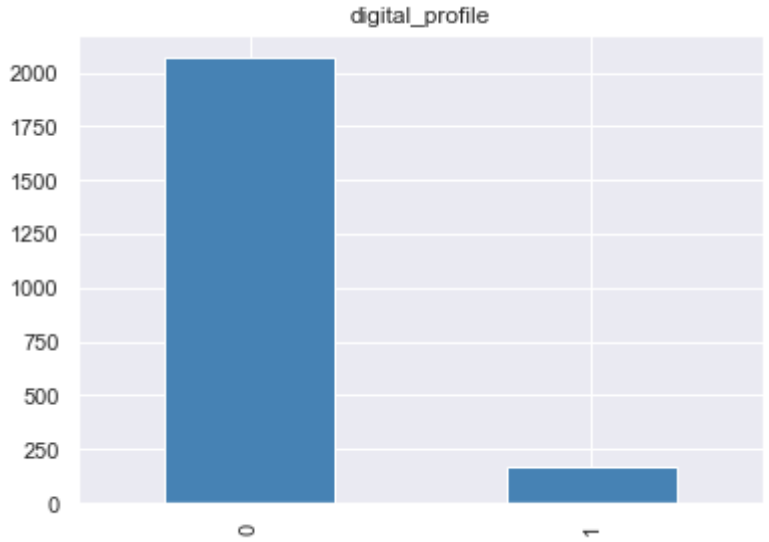

1.0
0.8
0.6
0.4
0.2
0.0
target
0
1
0
1
Cmp2


Cmp2
2000
1500
1000
500
0
0
1



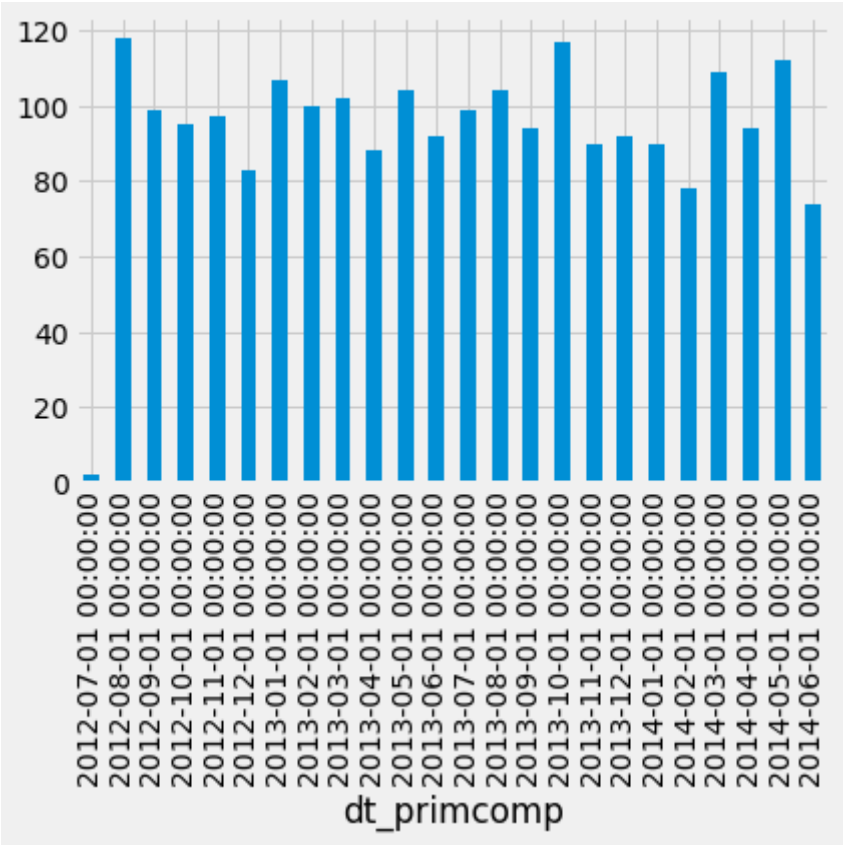



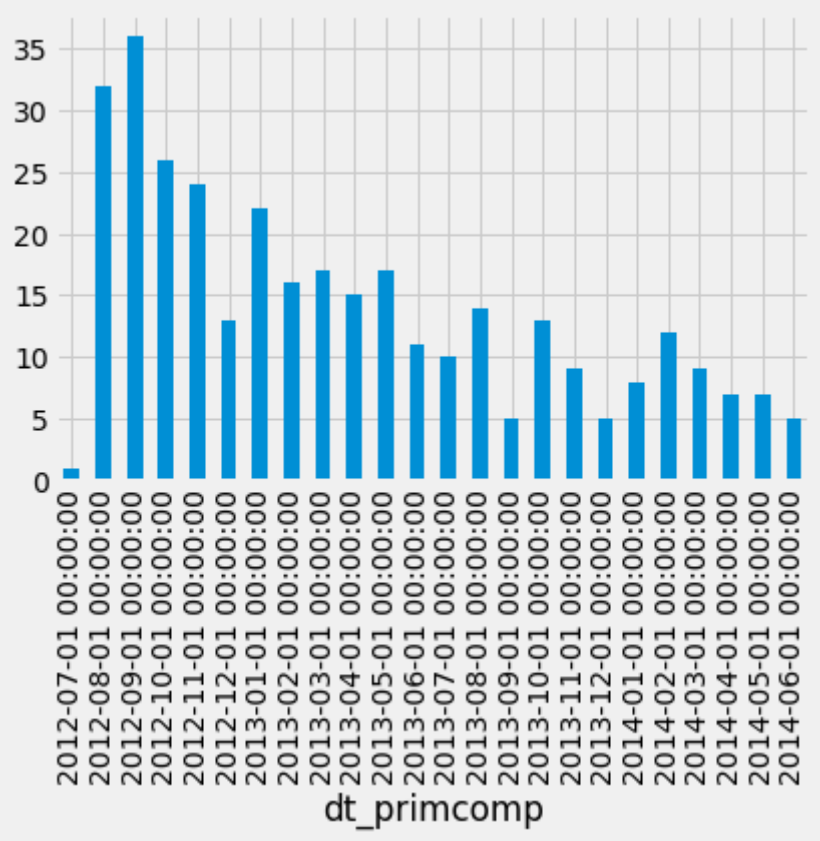




**Date Analysis**

In [18]:
```
data['dt_primcomp'] = pd.to_datetime(data['dt_primcomp'], infer_datetime_format=True)
data.groupby('dt_primcomp')['ID'].nunique().plot(kind='bar')
plt.show()
```

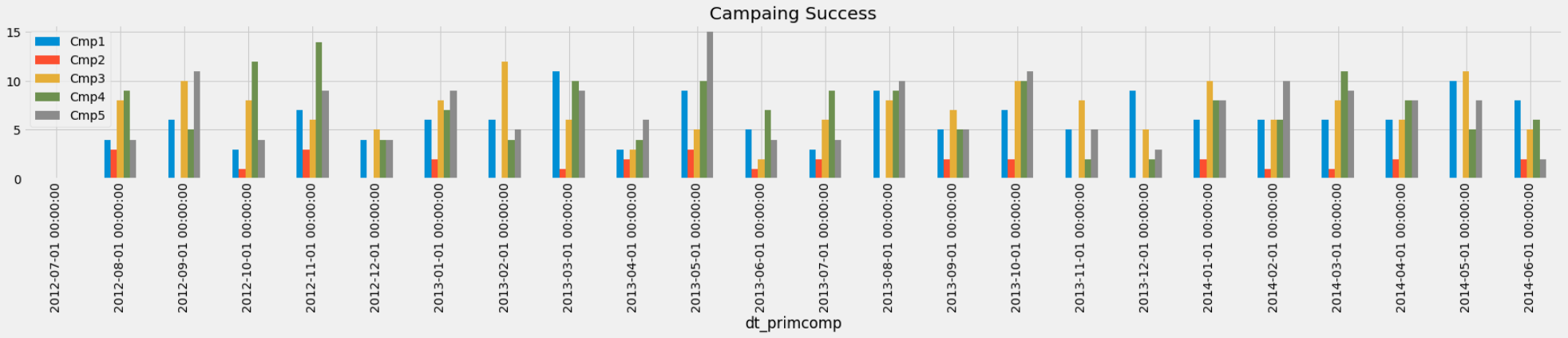


In [21]:
```
data['target'] = data['target'].astype(int)
data.groupby('dt_primcomp')['target'].sum().plot(kind='bar')
plt.show()
```



In [280]:
```
# campaing
pylab.rcParams['figure.figsize'] = (28, 3)
data.groupby(('dt_primcomp'))['Cmp1','Cmp2','Cmp3','Cmp4','Cmp5'].sum().plot(kind='bar')
plt.title("Campaing Success")
plt.figure( figsize=(20, 18))
plt.show()
```

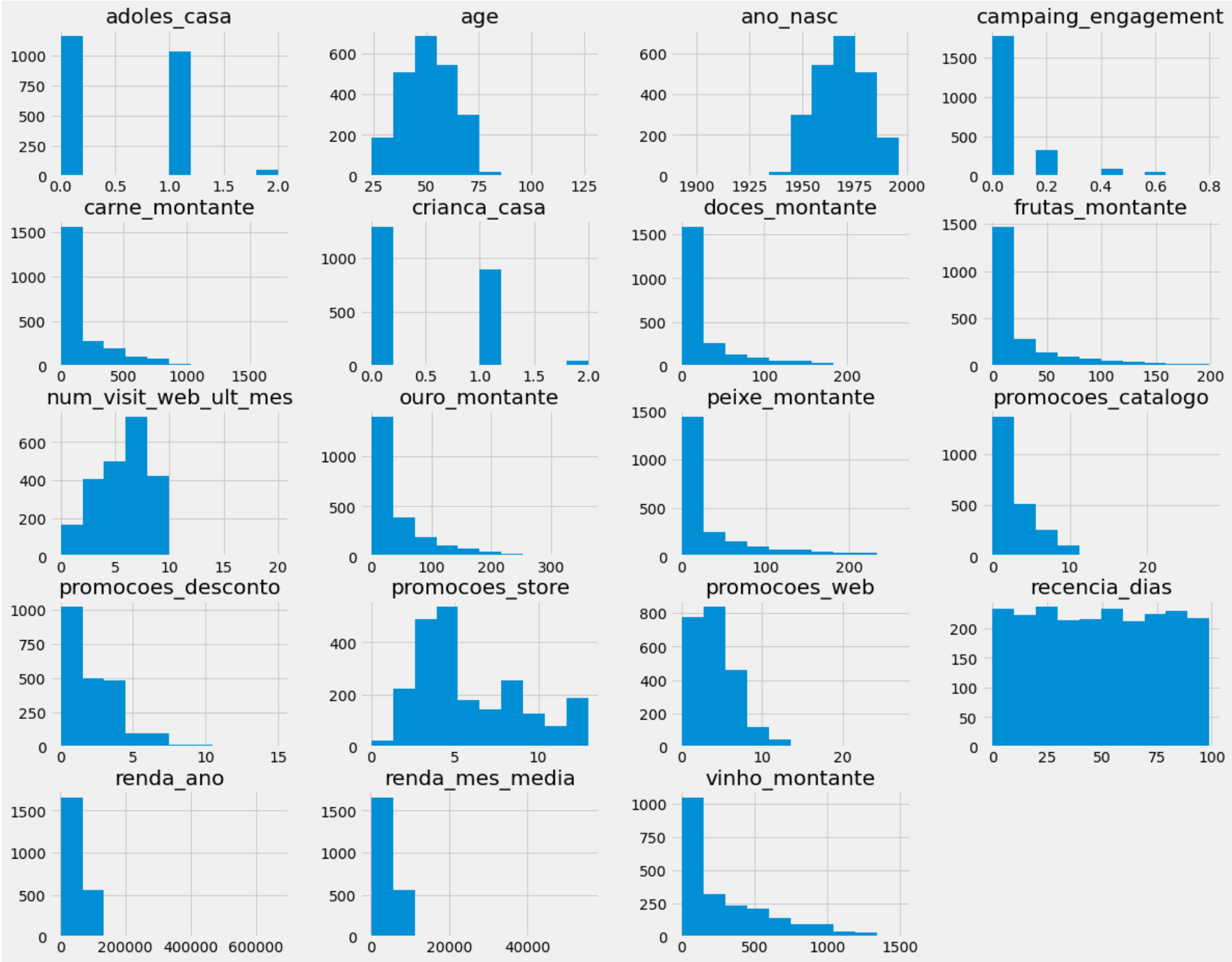
```
C:\Users\patri\anaconda3\lib\site-packages\ipykernel_launcher.py:3: FutureWarning: Indexing with multiple keys (implicitly conv
erted to a tuple of keys) will be deprecated, use a list instead.
  This is separate from the ipykernel package so we can avoid doing imports until
```




```
<Figure size 1440x1296 with 0 Axes>
```

**Numerical Data Analysis**

In [22]:
```
data[numeric].hist(figsize=(18,15));
```

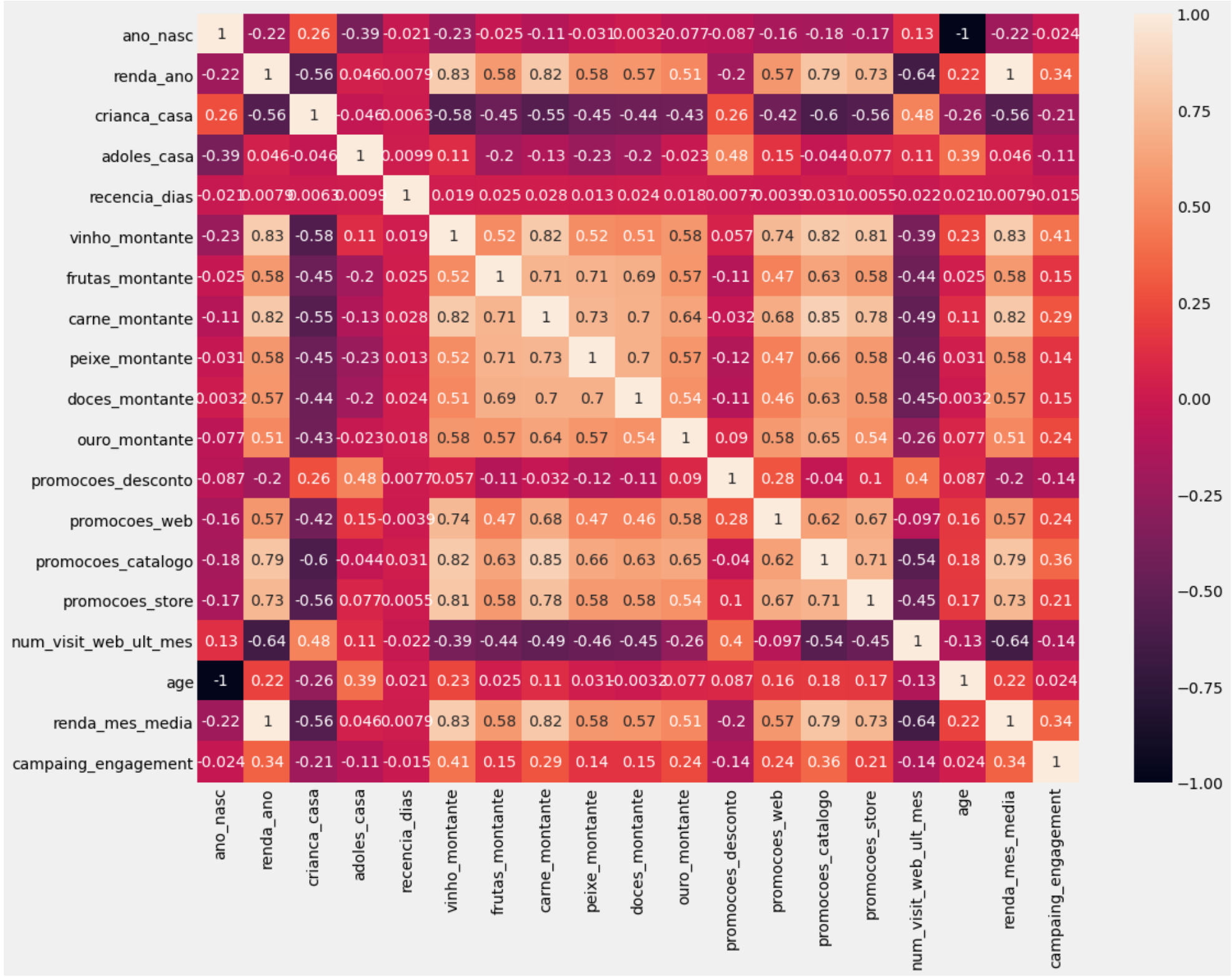

adoles_casa
age
ano_nasc
campaing_engagement
carne_montante
crianca_casa
doces_montante
frutas_montante
num_visit_web_ult_mes
ouro_montante
peixe_montante
promocoes_catalogo
promocoes_desconto
promocoes_store
promocoes_web
recencia_dias
renda_ano
renda_mes_media
vinho_montante

In [23]:
```
data[numeric].describe()
```

Out[23]:

| | ano_nasc | renda_ano | crianca_casa | adoles_casa | recencia_dias | vinho_montante | frutas_montante | carne_montante | peixe_montante | doces_mont |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 2240.000000 | 2216.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.00( |
| **mean** | 1968.805804 | 52247.251354 | 0.444196 | 0.506250 | 49.109375 | 303.935714 | 26.302232 | 166.950000 | 37.525446 | 27.06 |
| **std** | 11.984069 | 25173.076661 | 0.538398 | 0.544538 | 28.962453 | 336.597393 | 39.773434 | 225.715373 | 54.628979 | 41.28( |
| **min** | 1893.000000 | 1730.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00( |
| **25%** | 1959.000000 | 35303.000000 | 0.000000 | 0.000000 | 24.000000 | 23.750000 | 1.000000 | 16.000000 | 3.000000 | 1.00( |
| **50%** | 1970.000000 | 51381.500000 | 0.000000 | 0.000000 | 49.000000 | 173.500000 | 8.000000 | 67.000000 | 12.000000 | 8.00( |
| **75%** | 1977.000000 | 68522.000000 | 1.000000 | 1.000000 | 74.000000 | 504.250000 | 33.000000 | 232.000000 | 50.000000 | 33.00( |
| **max** | 1996.000000 | 666666.000000 | 2.000000 | 2.000000 | 99.000000 | 1493.000000 | 199.000000 | 1725.000000 | 259.000000 | 263.00( |

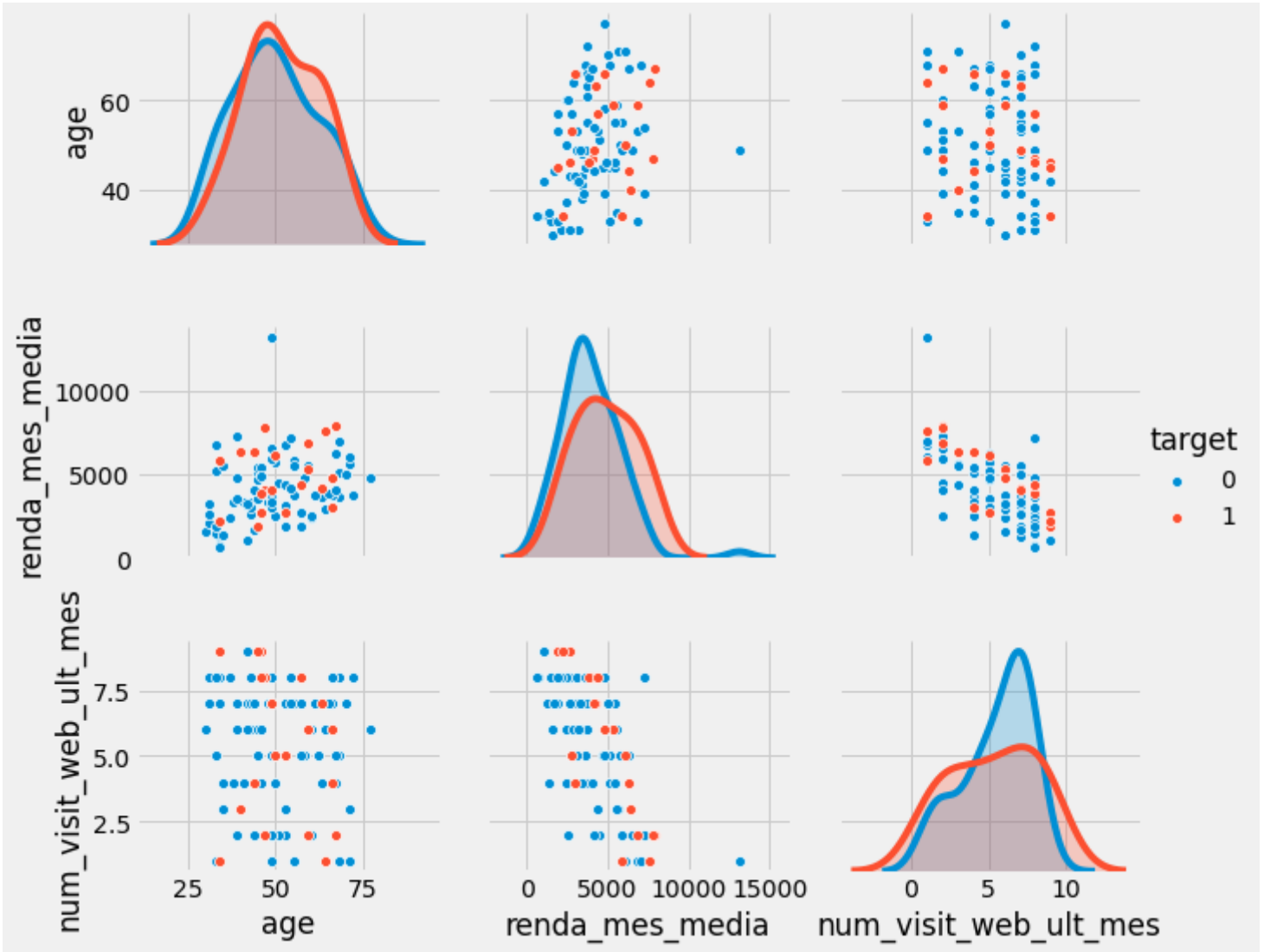
In [24]:
```
plt.figure(figsize=(16,12));
sns.heatmap(data[numeric].corr('spearman'), annot=True);
```


ano_nasc 1 -0.22 0.26 -0.39 -0.021 -0.23 -0.025 -0.11 -0.031 0.0032 -0.077 -0.087 -0.16 -0.18 -0.17 0.13 -1 -0.22 -0.024
renda_ano -0.22 1 -0.56 0.046 0.0079 0.83 0.58 0.82 0.58 0.57 0.51 -0.2 0.57 0.79 0.73 -0.64 0.22 1 0.34
crianca_casa 0.26 -0.56 1 -0.046 0.0063 -0.58 -0.45 -0.55 -0.45 -0.44 -0.43 0.26 -0.42 -0.6 -0.56 0.48 -0.26 -0.56 -0.21
adoles_casa -0.39 0.046 -0.046 1 0.0099 0.11 -0.2 -0.13 -0.23 -0.2 -0.023 0.48 0.15 -0.044 0.077 0.11 0.39 0.046 -0.11
recencia_dias -0.021 0.0079 0.0063 0.0099 1 0.019 0.025 0.028 0.013 0.024 0.018 0.0077 -0.0039 0.031 0.0055 -0.022 0.021 0.0079 -0.015
vinho_montante -0.23 0.83 -0.58 0.11 0.019 1 0.52 0.82 0.52 0.51 0.58 0.057 0.74 0.82 0.81 -0.39 0.23 0.83 0.41
frutas_montante -0.025 0.58 -0.45 -0.2 0.025 0.52 1 0.71 0.71 0.69 0.57 -0.11 0.47 0.63 0.58 -0.44 0.025 0.58 0.15
carne_montante -0.11 0.82 -0.55 -0.13 0.028 0.82 0.71 1 0.73 0.7 0.64 -0.032 0.68 0.85 0.78 -0.49 0.11 0.82 0.29
peixe_montante -0.031 0.58 -0.45 -0.23 0.013 0.52 0.71 0.73 1 0.7 0.57 -0.12 0.47 0.66 0.58 -0.46 0.031 0.58 0.14
doces_montante 0.0032 0.57 -0.44 -0.2 0.024 0.51 0.69 0.7 0.7 1 0.54 -0.11 0.46 0.63 0.58 -0.45 -0.0032 0.57 0.15
ouro_montante -0.077 0.51 -0.43 -0.023 0.018 0.58 0.57 0.64 0.57 0.54 1 0.09 0.58 0.65 0.54 -0.26 0.077 0.51 0.24
promocoes_desconto -0.087 -0.2 0.26 0.48 0.0077 0.057 -0.11 -0.032 -0.12 -0.11 0.09 1 0.28 -0.04 0.1 0.4 0.087 -0.2 -0.14
promocoes_web -0.16 0.57 -0.42 0.15 -0.0039 0.74 0.47 0.68 0.47 0.46 0.58 0.28 1 0.62 0.67 -0.097 0.16 0.57 0.24
promocoes_catalogo -0.18 0.79 -0.6 -0.044 0.031 0.82 0.63 0.85 0.66 0.63 0.65 -0.04 0.62 1 0.71 -0.54 0.18 0.79 0.36
promocoes_store -0.17 0.73 -0.56 0.077 0.0055 0.81 0.58 0.78 0.58 0.58 0.54 0.1 0.67 0.71 1 -0.45 0.17 0.73 0.21
num_visit_web_ult_mes 0.13 -0.64 0.48 0.11 -0.022 -0.39 -0.44 -0.49 -0.46 -0.45 -0.26 0.4 -0.097 -0.54 -0.45 1 -0.13 -0.64 -0.14
age -1 0.22 -0.26 0.39 0.021 0.23 0.025 0.11 0.031 -0.0032 0.077 0.087 0.16 0.18 0.17 -0.13 1 0.22 0.024
renda_mes_media -0.22 1 -0.56 0.046 0.0079 0.83 0.58 0.82 0.58 0.57 0.51 -0.2 0.57 0.79 0.73 -0.64 0.22 1 0.34
campaing_engagement -0.024 0.34 -0.21 -0.11 -0.015 0.41 0.15 0.29 0.14 0.15 0.24 -0.14 0.24 0.36 0.21 -0.14 0.024 0.34 1
ano_nasc
renda_ano
crianca_casa
adoles_casa
recencia_dias
vinho_montante
frutas_montante
carne_montante
peixe_montante
doces_montante
ouro_montante
promocoes_desconto
promocoes_web
promocoes_catalogo
promocoes_store
num_visit_web_ult_mes
age
renda_mes_media
campaing_engagement
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

**Customer Attributes**

In [37]:
```
cust_attrs = ['age', 'renda_mes_media', 'num_visit_web_ult_mes','target']
```

In [38]:
```
data['target'] = data['target'].astype(str)
numeric_outcome = pd.concat([data[numeric], data['target']], axis=1)
sns.pairplot(numeric_outcome[cust_attrs].sample(n=100), hue='target', aspect=1.2);
```



## Clustering

1 . Kmeans

In [14]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
```

In [16]:
```
X=data[['renda_ano', 'crianca_casa', 'adoles_casa',  'recencia_dias', 'vinho_montante', 'frutas_montante', 'carne_montante', 'peixe_montante', 'doces_montante', 'ouro_montante', 'promocoes_desconto', 'promocoes_web', 'promocoes_catalogo', 'promocoes_store', 'num_visit_web_ult_mes','age', 'renda_mes_media','campaing_engagement']]
```

In [17]:
```
X=X.fillna(0)
```

In [48]:
```
# define standard scaler
scaler = StandardScaler()
# transform data
scaled = scaler.fit_transform(X)
print(scaled)
```

```
[[ 0.25193856 -0.82521765 -0.92989438 ...  0.98534473  0.25193856
  -0.43903713]
 [-0.20869932  1.03255877  0.90693402 ...  1.23573295 -0.20869932
  -0.43903713]
 [ 0.77823121 -0.82521765 -0.92989438 ...  0.3176428   0.77823121
  -0.43903713]
 ...
 [ 0.20674965 -0.82521765 -0.92989438 ... -1.01776106  0.20674965
   1.03539042]
 [ 0.68574431 -0.82521765  0.90693402 ...  1.06880747  0.68574431
  -0.43903713]
 [ 0.04614739  1.03255877  0.90693402 ...  1.23573295  0.04614739
  -0.43903713]]
```

In [49]:
```
for n_clusters in range(3, 10):
    kmeans = KMeans(init='k-means++', n_clusters = n_clusters, n_init = 30)
    kmeans.fit(scaled)
    clusters = kmeans.predict(scaled)
    sil_avg = silhouette_score(scaled, clusters)
    print("For n_clusters : ", n_clusters, "The average silhouette_score is : ", sil_avg)
```

```
For n_clusters :  3 The average silhouette_score is :  0.2261032879931275
For n_clusters :  4 The average silhouette_score is :  0.15081907973264772
For n_clusters :  5 The average silhouette_score is :  0.15246532108308206
For n_clusters :  6 The average silhouette_score is :  0.15273556967922475
For n_clusters :  7 The average silhouette_score is :  0.15382971566043036
For n_clusters :  8 The average silhouette_score is :  0.15351880625259764
For n_clusters :  9 The average silhouette_score is :  0.14400645664857872
```

In [54]:
```
# Choosing number of clusters as 3:
# Trying Improving the silhouette_score :
n_clusters = 3
sil_avg = -1
while sil_avg < 0.145:
    kmeans = KMeans(init = 'k-means++', n_clusters = n_clusters, n_init = 30)
    kmeans.fit(scaled)
    clusters = kmeans.predict(scaled)
    sil_avg = silhouette_score(scaled, clusters)
    print("For n_clusters : ", n_clusters, "The average silhouette_score is : ", sil_avg)
```

```
For n_clusters :  3 The average silhouette_score is :  0.22575793720918896
```

In [55]:
```
# Printing number of elements in each cluster :
pd.Series(clusters).value_counts()
```

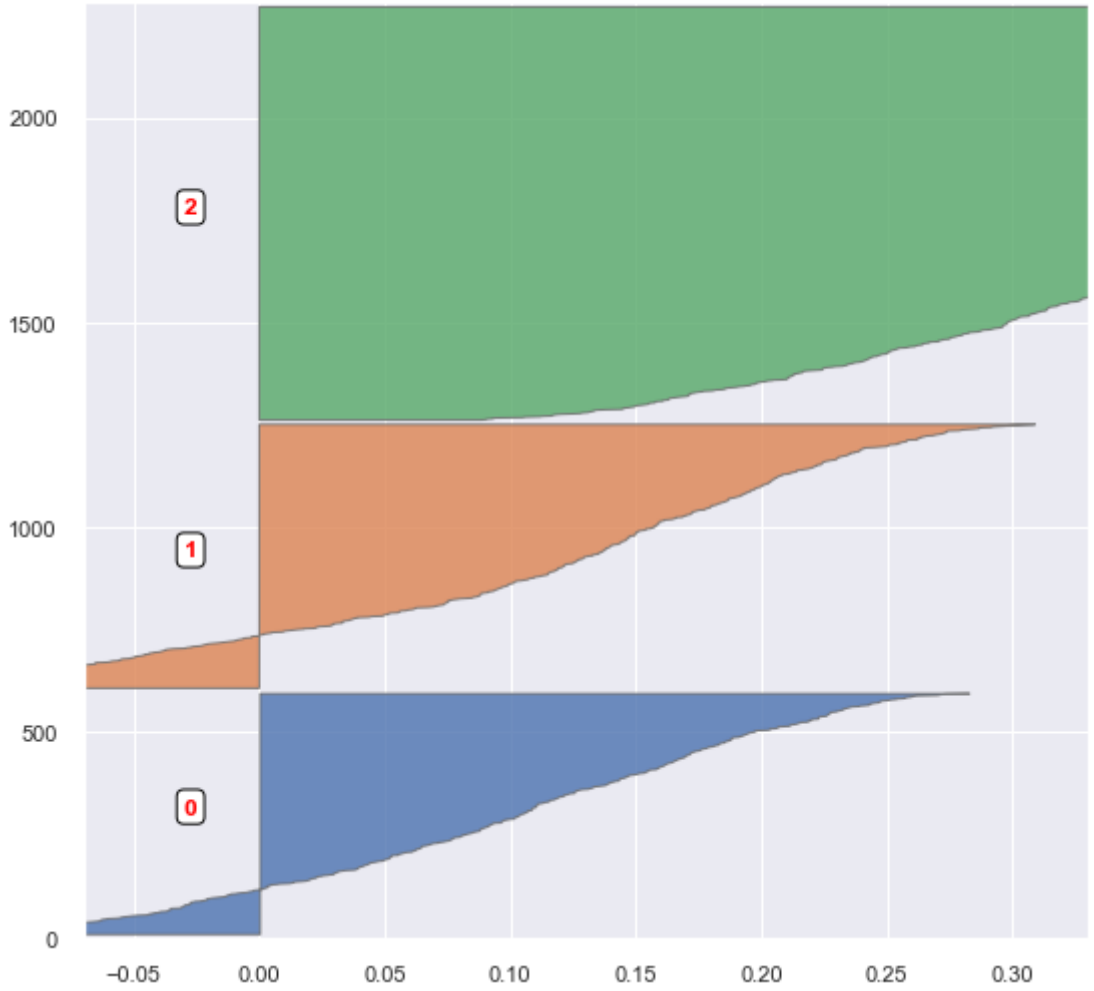
Out[55]:
```
2    1008
1     644
0     588
dtype: int64
```

**Analysing 4 Cluster**

In [56]:

```
def graph_component_silhouette(n_clusters, lim_x, mat_size, sample_silhouette_values, clusters):
    import matplotlib as mpl
    mpl.rc('patch', edgecolor = 'dimgray', linewidth = 1)

    fig, ax1 = plt.subplots(1, 1)
    fig.set_size_inches(8, 8)
    ax1.set_xlim([lim_x[0], lim_x[1]])
    ax1.set_ylim([0, mat_size + (n_clusters + 1) * 10])
    y_lower = 10

    for i in range(n_clusters):
        ith_cluster_silhoutte_values = sample_silhouette_values[clusters == i]
        ith_cluster_silhoutte_values.sort()
        size_cluster_i = ith_cluster_silhoutte_values.shape[0]
        y_upper = y_lower + size_cluster_i

        ax1.fill_betweenx(np.arange(y_lower, y_upper), 0, ith_cluster_silhoutte_values, alpha = 0.8)

        ax1.text(-0.03, y_lower + 0.5 * size_cluster_i, str(i), color = 'red', fontweight = 'bold',
                 bbox = dict(facecolor = 'white', edgecolor = 'black', boxstyle = 'round, pad = 0.3'))

        y_lower = y_upper + 10
```

In [57]:
```
# Plotting the intra cluster silhouette distances.
from sklearn.metrics import silhouette_samples
sample_silhouette_values = silhouette_samples(scaled, clusters)
graph_component_silhouette(n_clusters, [-0.07, 0.33], len(X), sample_silhouette_values, clusters)
```



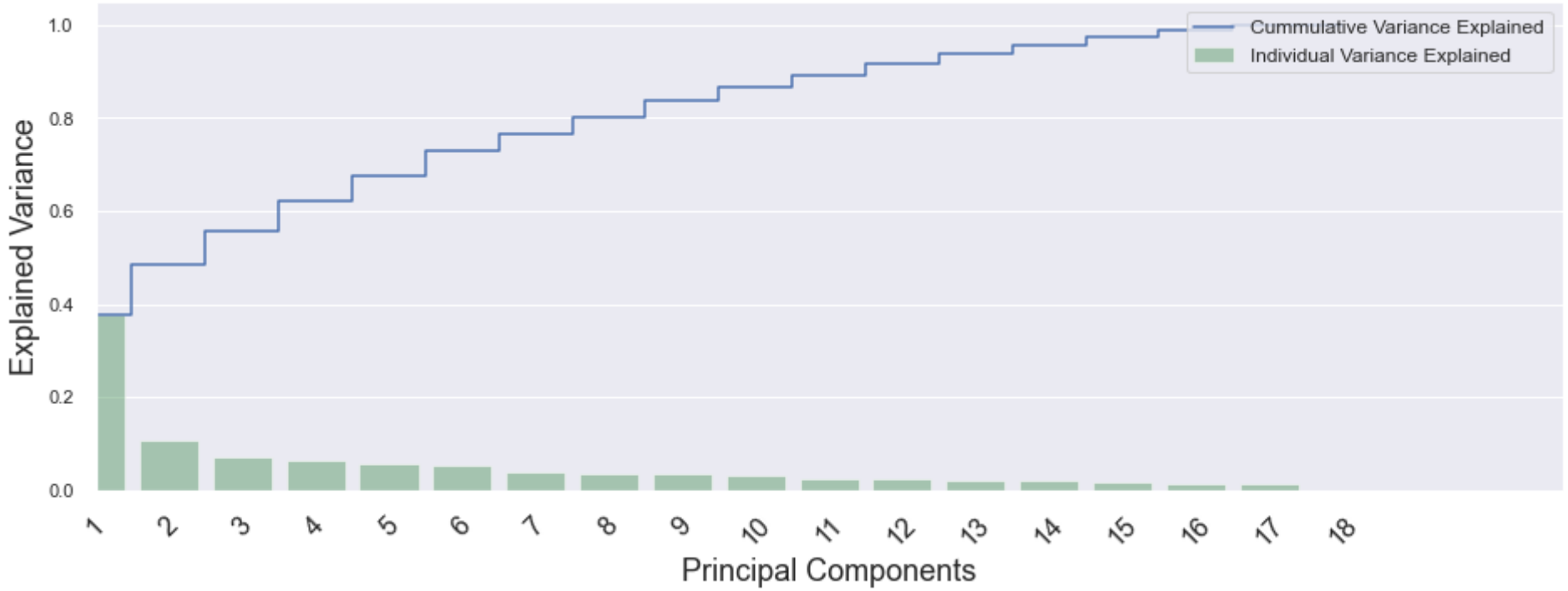

**Dimensionality Reduction**

PCA

In [58]:
```
from sklearn.decomposition import PCA
```

In [59]:
```
pca = PCA()
pca.fit(scaled)
pca_samples = pca.transform(scaled)
```

In [60]:
```
# Checking the amount of variance explained :
fig, ax = plt.subplots(figsize=(14, 5))
sns.set(font_scale=1)
plt.step(range(scaled.shape[1]), pca.explained_variance_ratio_.cumsum(), where = 'mid', label = 'Cummulative Variance Explaine
d')
sns.barplot(np.arange(1, scaled.shape[1] + 1), pca.explained_variance_ratio_, alpha = 0.5, color = 'g',
            label = 'Individual Variance Explained')
plt.xlim(0, 20)
plt.xticks(rotation = 45, fontsize = 16)
ax.set_xticklabels([s  for s in ax.get_xticklabels()])

plt.ylabel("Explained Variance", fontsize = 18)
plt.xlabel("Principal Components", fontsize = 18)
plt.legend(loc = 'upper right', fontsize = 12)
plt.show()
```




In [61]:
```
data['fit_segmentacao']= kmeans.labels_
```

In [62]:
```
data
```

Out[62]:

| | ID | ano_nasc | educacao | estado_civil | renda_ano | crianca_casa | adoles_casa | dt_primcomp | recencia_dias | vinho_montante | frutas_montante | carne_ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 5524 | 1957 | Graduation | Single | 58138.0 | 0 | 0 | 09/2012 | 58 | 635 | 88 | |
| **1** | 2174 | 1954 | Graduation | Single | 46344.0 | 1 | 1 | 03/2014 | 38 | 11 | 1 | |
| **2** | 4141 | 1965 | Graduation | Together | 71613.0 | 0 | 0 | 08/2013 | 26 | 426 | 49 | |
| **3** | 6182 | 1984 | Graduation | Together | 26646.0 | 1 | 0 | 02/2014 | 26 | 11 | 4 | |
| **4** | 5324 | 1981 | PhD | Married | 58293.0 | 1 | 0 | 01/2014 | 94 | 173 | 43 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **2235** | 10870 | 1967 | Graduation | Married | 61223.0 | 0 | 1 | 06/2013 | 46 | 709 | 43 | |
| **2236** | 4001 | 1946 | PhD | Together | 64014.0 | 2 | 1 | 06/2014 | 56 | 406 | 0 | |
| **2237** | 7270 | 1981 | Graduation | Divorced | 56981.0 | 0 | 0 | 01/2014 | 91 | 908 | 48 | |
| **2238** | 8235 | 1956 | Master | Together | 69245.0 | 0 | 1 | 01/2014 | 8 | 428 | 30 | |
| **2239** | 9405 | 1954 | PhD | Married | 52869.0 | 1 | 1 | 10/2012 | 40 | 84 | 3 | |

2240 rows × 32 columns

In [63]:
```
data['fit_segmentacao'] = data['fit_segmentacao'].astype(str)
```

### Fit Segmentação Analysis

In [64]:
```
from pandas_profiling import ProfileReport
profile = ProfileReport(data, title="Data Profile Report")
```

In [65]:
```
profile
```

# Overview

## Dataset statistics

| | |
|---|---|
| **Number of variables** | 32 |
| **Number of observations** | 2240 |
| **Missing cells** | 48 |
| **Missing cells (%)** | 0.1% |
| **Duplicate rows** | 0 |
| **Duplicate rows (%)** | 0.0% |
| **Total size in memory** | 560.1 KiB |
| **Average record size in memory** | 256.1 B |

## Variable types

| | |
|---|---|
| **NUM** | 18 |
| **CAT** | 14 |

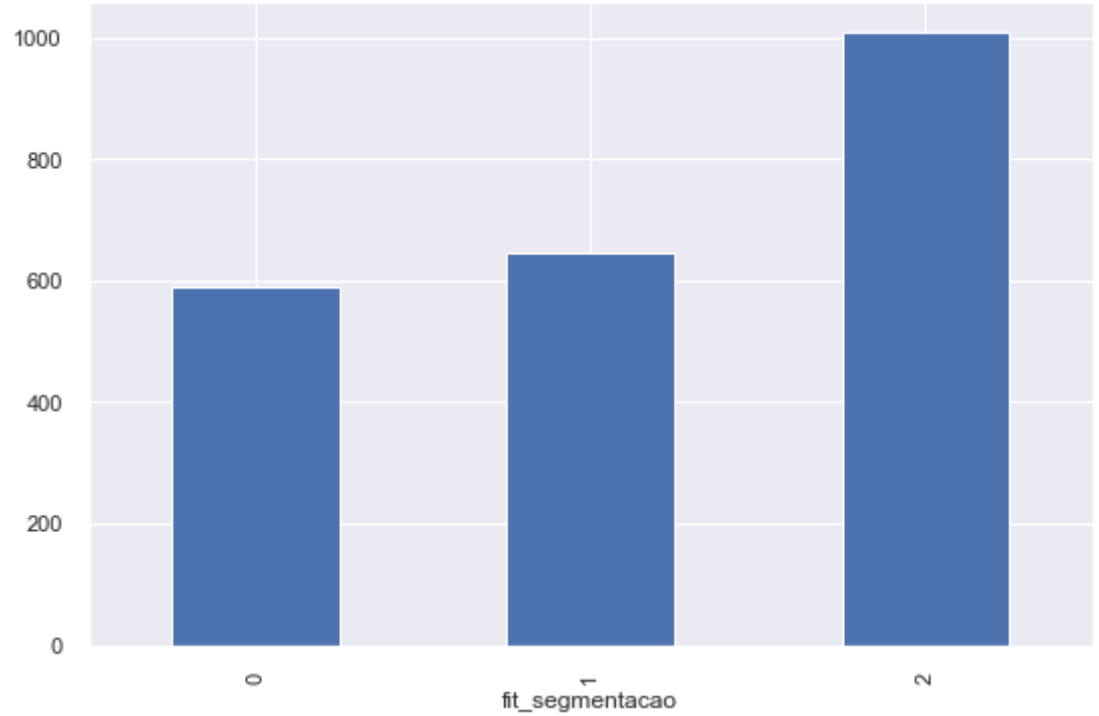
## Reproduction

| | |
|---|---|
| **Analysis started** | 2020-07-21 00:54:36.254745 |
| **Analysis finished** | 2020-07-21 00:56:00.408575 |
| **Duration** | 1 minute and 24.15 seconds |
| **Version** | pandas-profiling v2.8.0 (https://github.com/pandas-profiling/pandas-profiling) |
| **Command line** | `pandas_profiling --config_file config.yaml [YOUR_FILE.csv]` |

Out[65]:

In [188]:
```
# Customer
data.groupby(['fit_segmentacao']).fit_segmentacao.count().sort_values().plot(kind='bar')
data.groupby(['fit_segmentacao']).fit_segmentacao.count().sort_values()
```

Out[188]:
```
fit_segmentacao
0     588
1     644
2    1008
Name: fit_segmentacao, dtype: int64
```

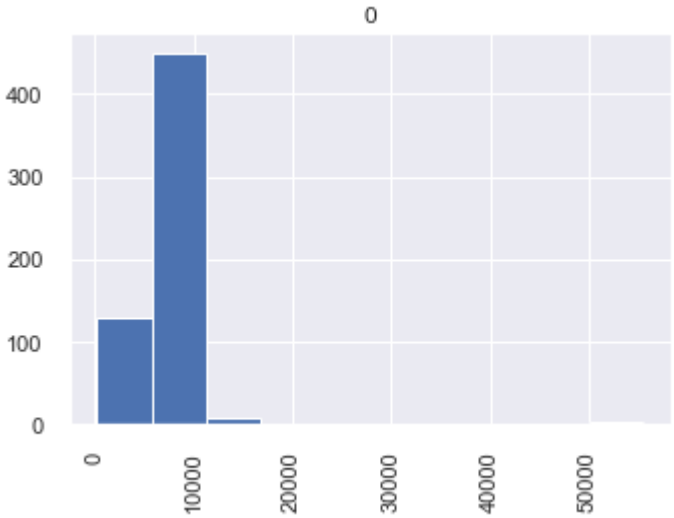


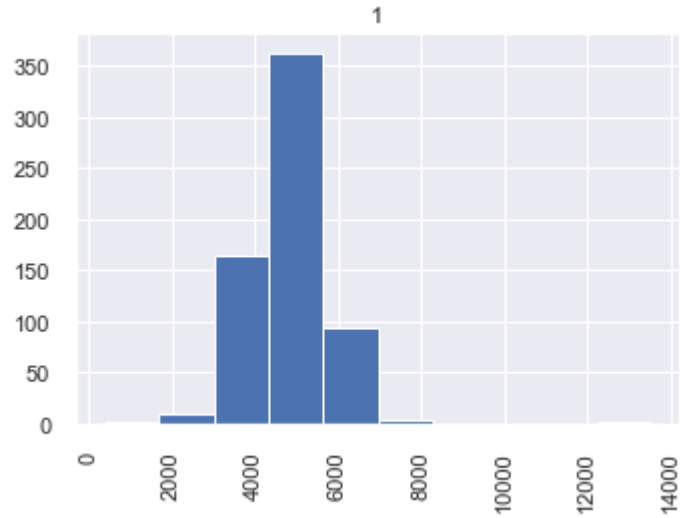

In [176]:
```
num_cluster = data[['renda_mes_media','age','crianca_casa','adoles_casa','recencia_dias','num_visit_web_ult_mes','campaing_engagement']]
```

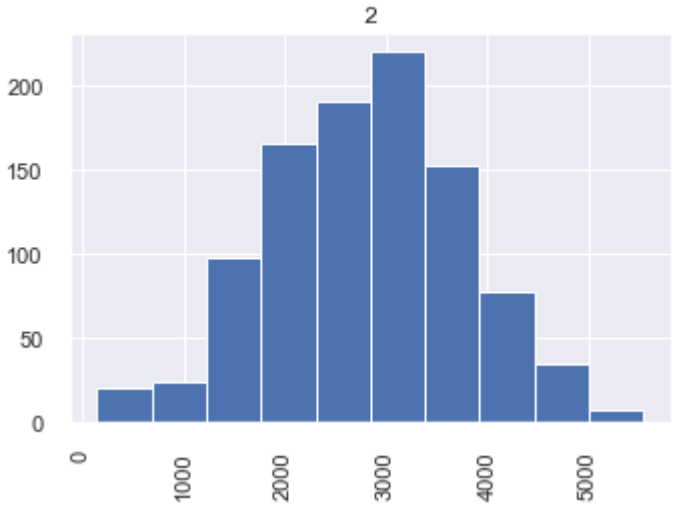
In [177]:

```
for att in num_cluster:
  figsize=(8,4)
  plt.figure()
  data[att].hist(by=data['fit_segmentacao'],figsize=(12,9))
  plt.title(att);
```

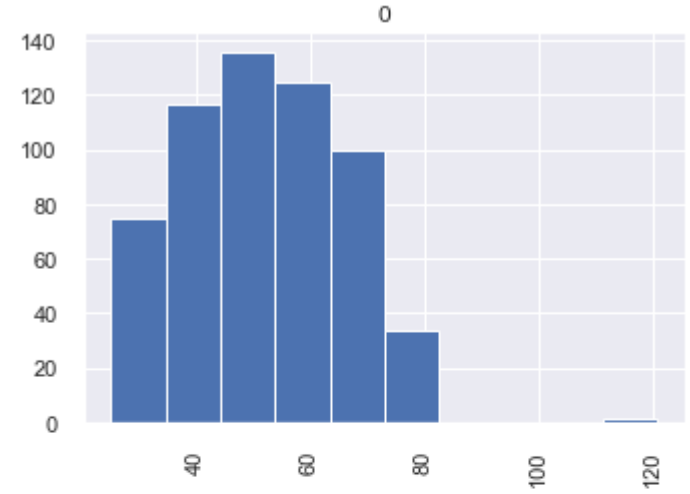
```
<Figure size 576x396 with 0 Axes>
```

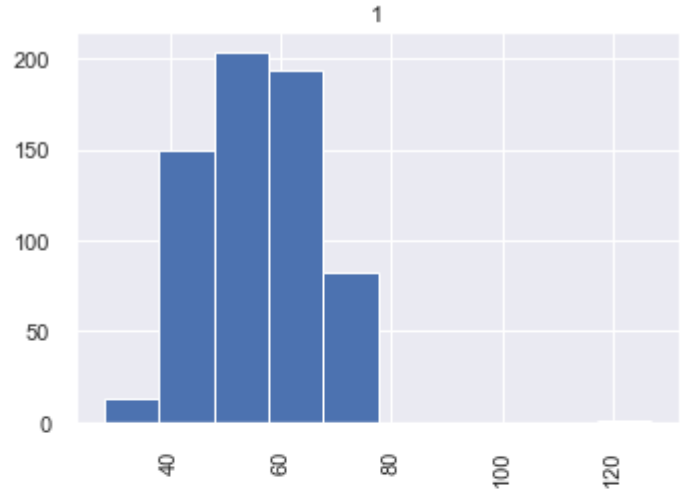


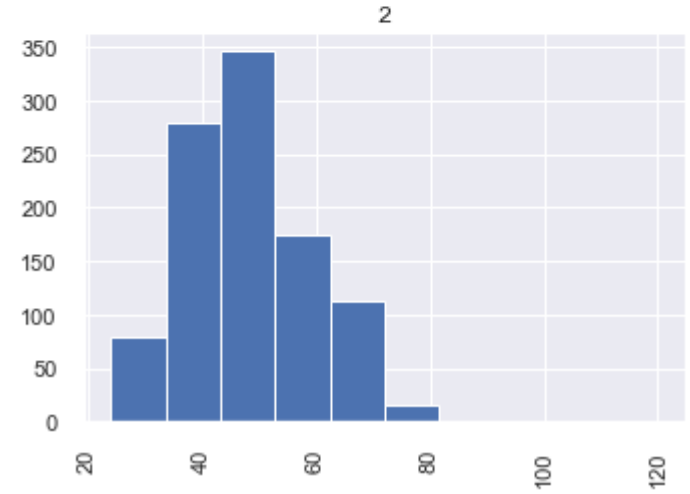



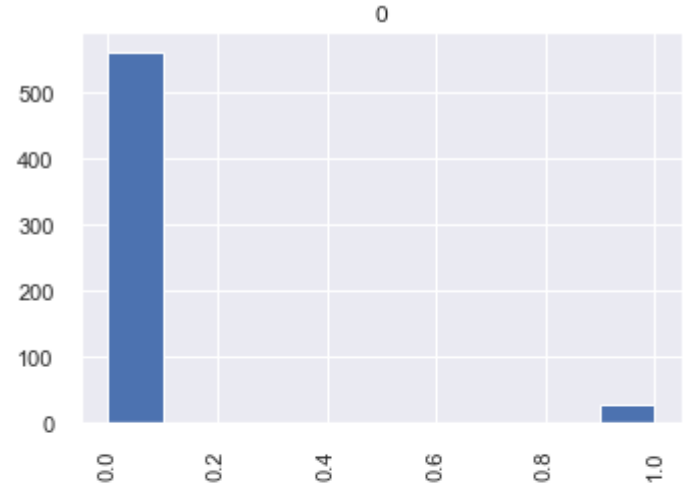

```
<Figure size 576x396 with 0 Axes>
```

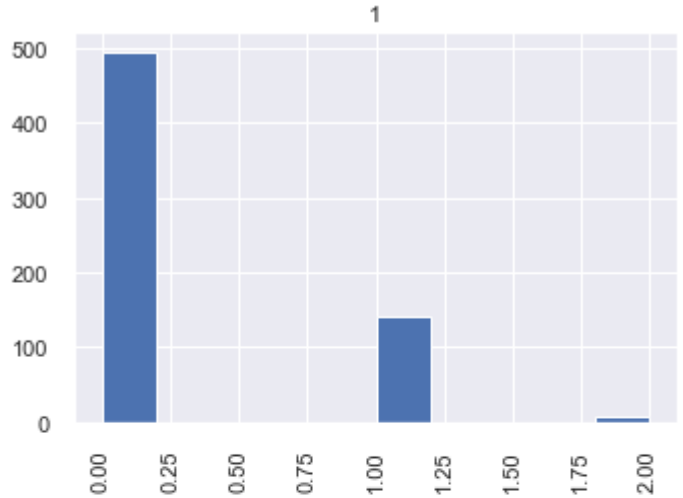


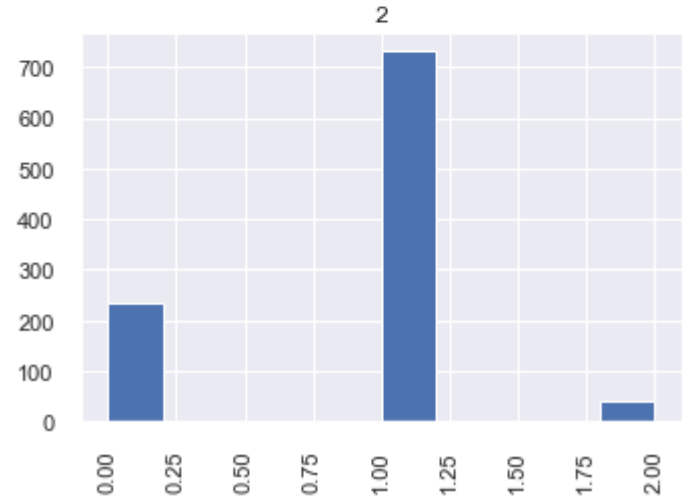



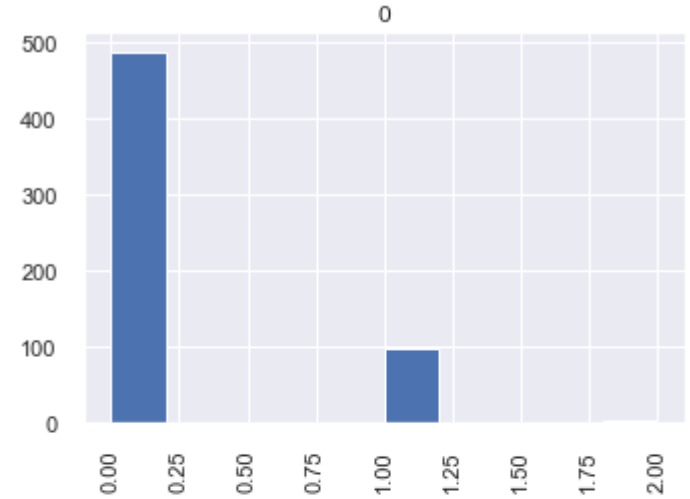

<Figure size 576x396 with 0 Axes>

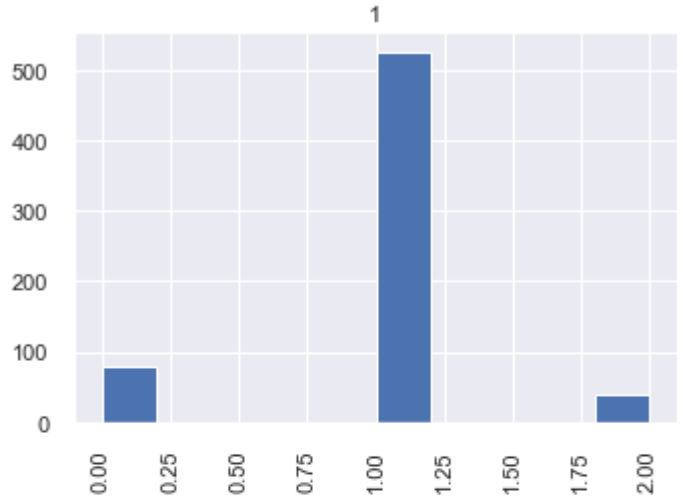


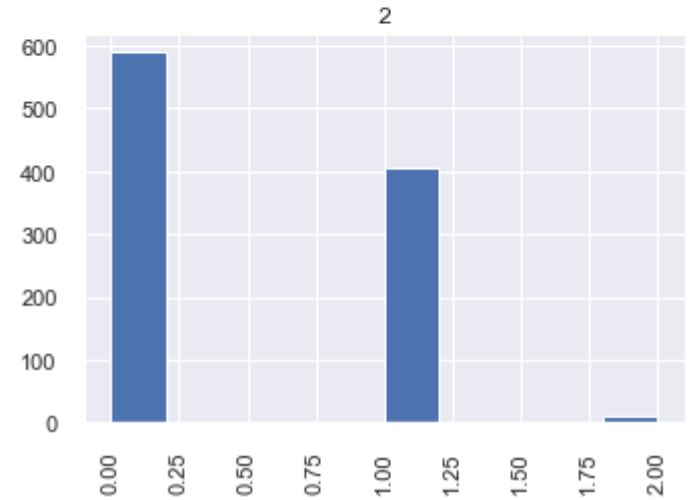



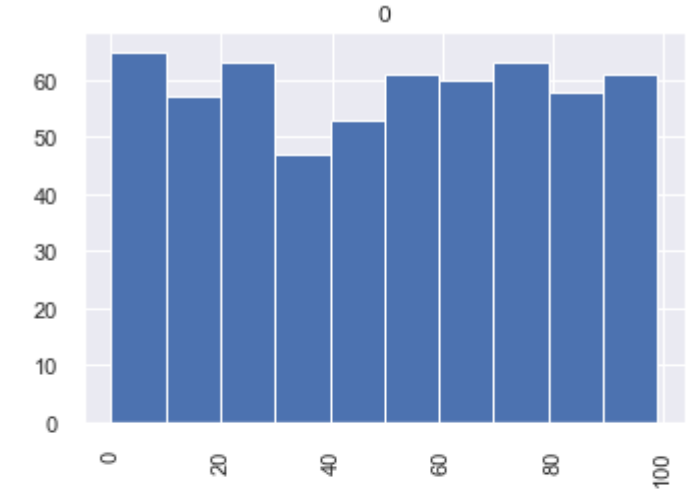

<Figure size 576x396 with 0 Axes>

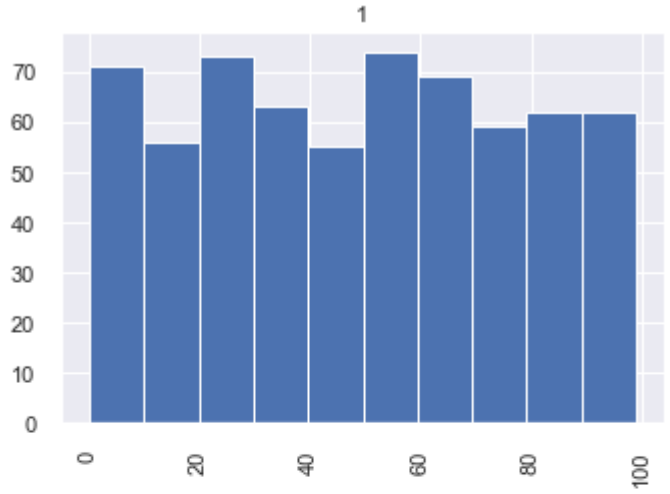


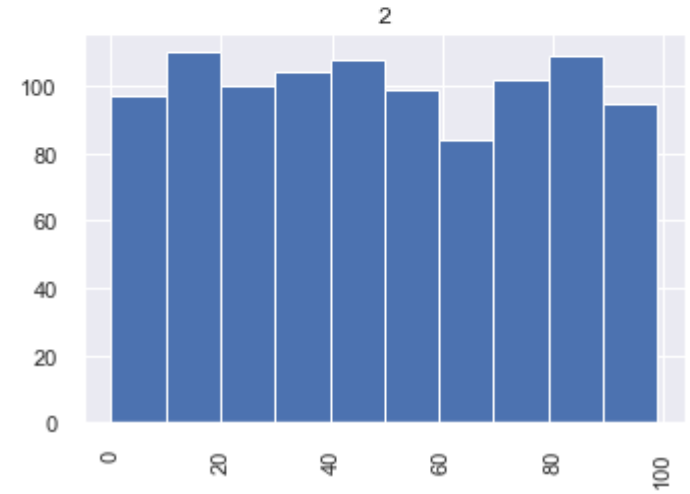



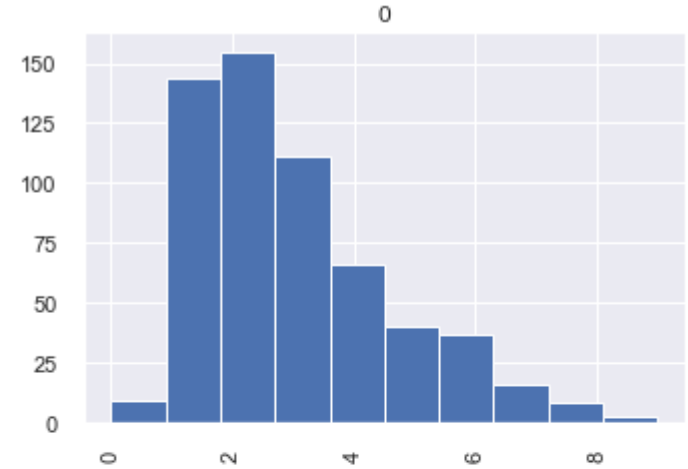

<Figure size 576x396 with 0 Axes>

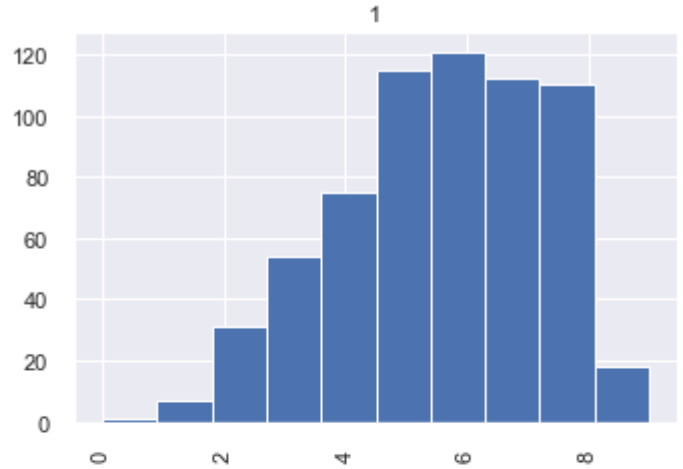


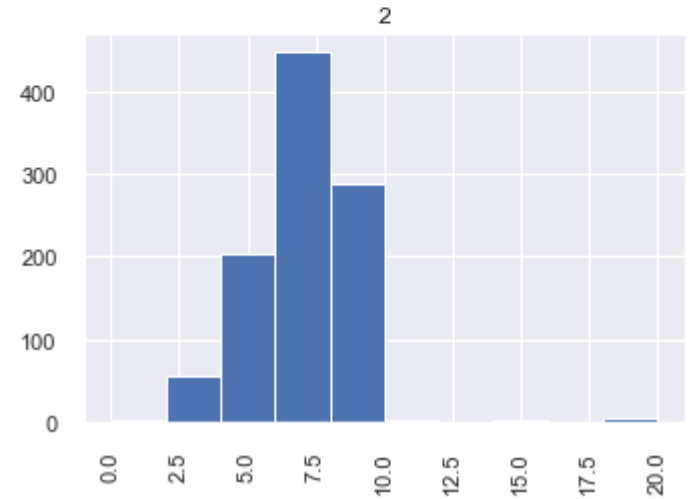



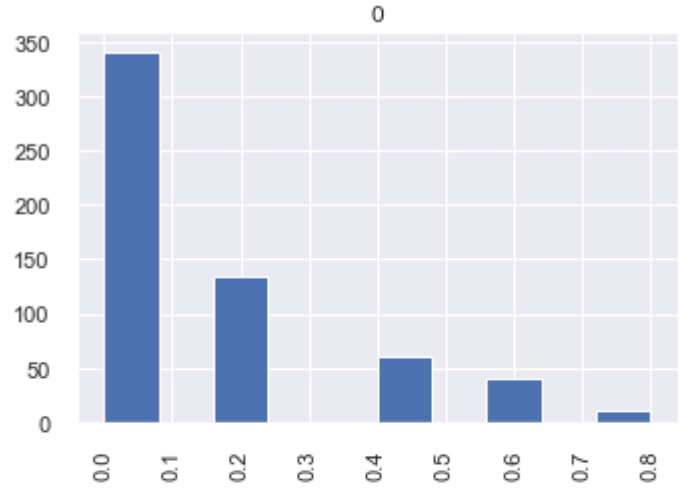

<Figure size 576x396 with 0 Axes>

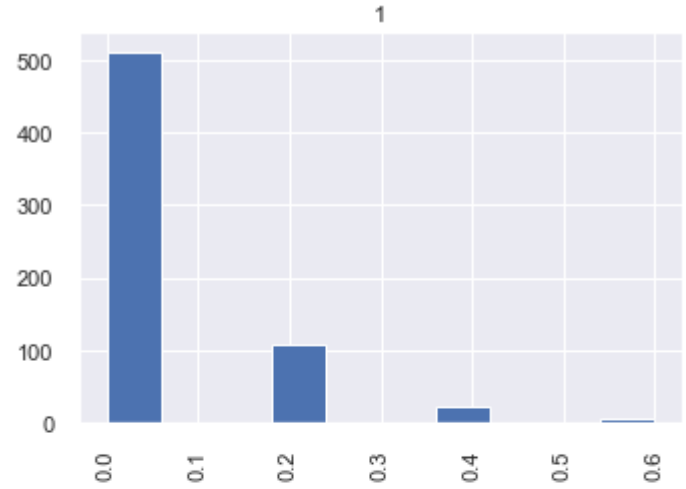


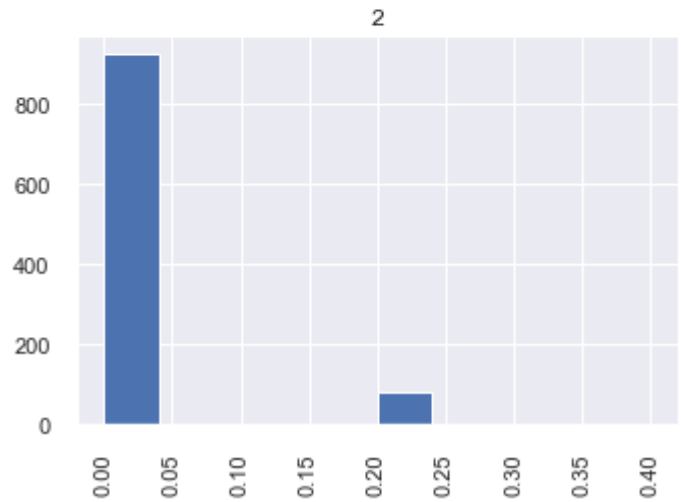




<Figure size 576x396 with 0 Axes>


0
350
300
250
200
150
100
50
0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8


1
500
400
300
200
100
0
0.0
0.1
0.2
0.3
0.4
0.5
0.6


2
800
600
400
200
0
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40

In [178]:

```
for att in num_cluster:
    print (att)

    print( data.groupby('fit_segmentacao', as_index=True)[att].describe())
```

renda_mes_media

| fit_segmentacao | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| 0 | 586.0 | 6465.720563 | 2308.773067 | 203.916667 | 5836.500000 | 6369.041667 | 6860.8750 | 55555.500000 |
| 1 | 638.0 | 4823.648119 | 946.464420 | 369.000000 | 4230.937500 | 4837.958333 | 5417.5625 | 13533.083333 |
| 2 | 992.0 | 2804.360887 | 964.706871 | 144.166667 | 2116.416667 | 2836.208333 | 3470.6250 | 5541.916667 |

age

| fit_segmentacao | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| 0 | 588.0 | 51.661565 | 13.646152 | 25.0 | 41.0 | 51.0 | 63.0 | 121.0 |
| 1 | 644.0 | 55.582298 | 10.127234 | 28.0 | 47.0 | 55.0 | 64.0 | 127.0 |
| 2 | 1008.0 | 48.118056 | 11.107355 | 24.0 | 40.0 | 47.0 | 55.0 | 120.0 |

crianca_casa

| fit_segmentacao | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| 0 | 588.0 | 0.044218 | 0.205753 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| 1 | 644.0 | 0.240683 | 0.452562 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 |
| 2 | 1008.0 | 0.807540 | 0.486830 | 0.0 | 1.0 | 1.0 | 1.0 | 2.0 |

adoles_casa

| fit_segmentacao | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| 0 | 588.0 | 0.171769 | 0.386421 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 |
| 1 | 644.0 | 0.936335 | 0.421782 | 0.0 | 1.0 | 1.0 | 1.0 | 2.0 |
| 2 | 1008.0 | 0.426587 | 0.518350 | 0.0 | 0.0 | 0.0 | 1.0 | 2.0 |

recencia_dias

| fit_segmentacao | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| 0 | 588.0 | 49.642857 | 29.420786 | 0.0 | 24.00 | 52.0 | 74.25 | 99.0 |
| 1 | 644.0 | 48.785714 | 28.658998 | 0.0 | 24.75 | 50.0 | 72.00 | 99.0 |
| 2 | 1008.0 | 49.004960 | 28.910418 | 0.0 | 24.00 | 49.0 | 75.00 | 99.0 |

num_visit_web_ult_mes

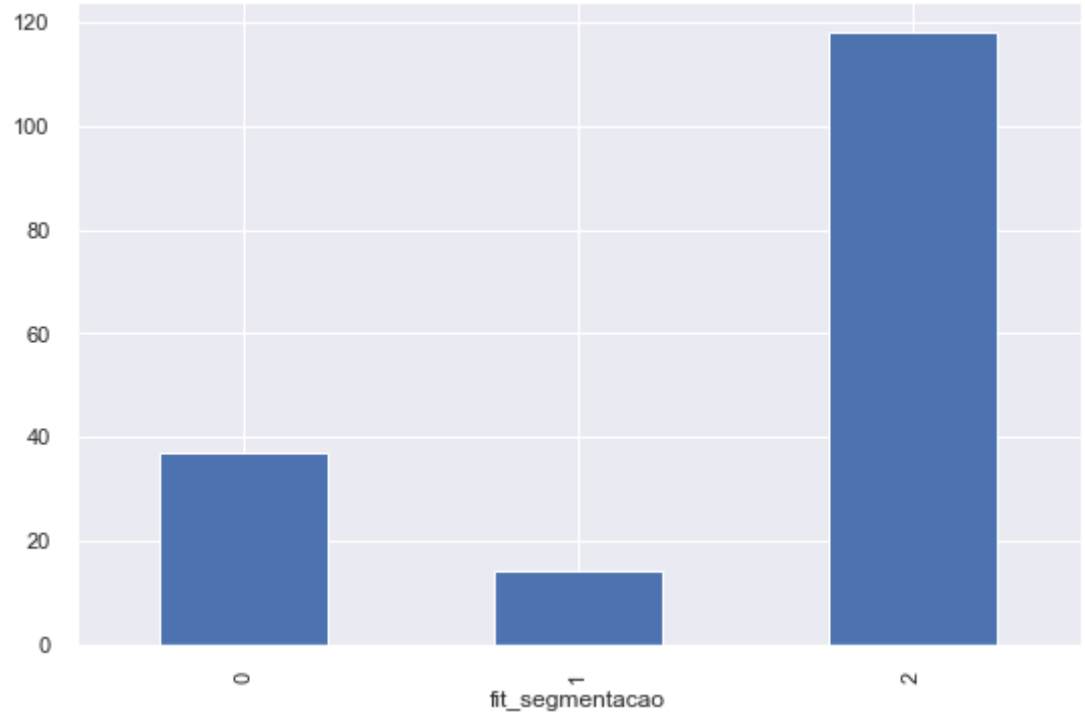
| fit_segmentacao | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| 0 | 588.0 | 2.835034 | 1.791043 | 0.0 | 1.0 | 2.0 | 4.0 | 9.0 |
| 1 | 644.0 | 5.680124 | 1.873157 | 0.0 | 4.0 | 6.0 | 7.0 | 9.0 |
| 2 | 1008.0 | 6.531746 | 1.955560 | 0.0 | 5.0 | 7.0 | 8.0 | 20.0 |

campaing_engagement

| fit_segmentacao | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| 0 | 588.0 | 0.142517 | 0.204286 | 0.0 | 0.0 | 0.0 | 0.2 | 0.8 |
| 1 | 644.0 | 0.049379 | 0.106913 | 0.0 | 0.0 | 0.0 | 0.0 | 0.6 |
| 2 | 1008.0 | 0.017659 | 0.058834 | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 |

In [187]:
```
data['digital_profile'] = data['digital_profile'].astype(int)
data.groupby(['fit_segmentacao'])['digital_profile'].sum().plot.bar()
data.groupby(['fit_segmentacao'])['digital_profile'].sum()
```

Out[187]:
```
fit_segmentacao
0     37
1     14
2    118
Name: digital_profile, dtype: int32
```




## Classifying the Customers :

In [198]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
class Class_Fit(object):
    def __init__(self, clf, params = None):
        if params:
            self.clf = clf(**params)
        else:
            self.clf = clf()

    def train(self, x_train, y_train):
        self.clf.fit(x_train, y_train)

    def predict(self, x):
        return self.clf.predict(x)

    def grid_search(self, parameters, Kfold):
        self.grid = GridSearchCV(estimator = self.clf, param_grid = parameters, cv = Kfold)

    def grid_fit(self, X, Y):
        self.grid.fit(X, Y)

    def grid_predict(self, X, Y):
        self.predictions = self.grid.predict(X)
        print("Precision: {:.2f} %".format(100 * accuracy_score(Y, self.predictions)))
```

In [197]:
```
data['target'].dtypes
```

Out[197]:
```
dtype('O')
```

In [206]:
```
data['target'] = data['target'].astype(str)
```

In [210]:
```
columns = ['renda_mes_media', 'age','recencia_dias','vinho_montante','frutas_montante','carne_montante','peixe_montante','doces
_montante','ouro_montante','promocoes_desconto','promocoes_web','promocoes_catalogo','promocoes_store','num_visit_web_ult_mes',
'Cmp3','Cmp4','Cmp5','Cmp1','Cmp2','reclamacoes','fit_segmentacao','campaing_engagement']
X = data[columns]
Y = data['target']
```

In [72]:
```
Y=Y.astype(int)
n_instances = len(X)
p_instances = Y.sum() / len(Y)
p_targeted = 0.15
n_targeted = int(n_instances*p_targeted)

print('Number of instances: {:,}'.format(n_instances))
print('Number of conversions {:,}'.format(Y.sum()))
print('Conversion rate: {:.2f}%'.format(p_instances*100.))
print('15% of the population {:,}'.format(n_targeted))
print('Expected number of conversions targetting {:,} @ {:.2f}%: {:,}'.format(n_targeted, p_instances*100., int(p_instances * n
_targeted)))
```

```
Number of instances: 2,240
Number of conversions 334
Conversion rate: 14.91%
15% of the population 336
Expected number of conversions targetting 336 @ 14.91%: 50
```

**Train, Test Splitting**

In [208]:
```
from sklearn.model_selection import train_test_split
```

In [213]:
```
X=X.fillna(0)
X=X.astype(int)
Y=Y.astype(str)
```

In [214]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, train_size = 0.8)
```

# Training Models :

In [215]:
```
from sklearn.svm import LinearSVC
from warnings import simplefilter
from sklearn.exceptions import ConvergenceWarning
simplefilter("ignore", category=ConvergenceWarning)
```

In [216]:
```
svc = Class_Fit(clf=LinearSVC)
svc.grid_search(parameters = [{'C':np.logspace(-2,2,10)}], Kfold = 5)
```

In [217]:
```
svc.grid_fit(X=X_train, Y=Y_train)
```

In [218]:
```
svc.grid_predict(X_test, Y_test)
```

```
Precision: 85.04 %
```

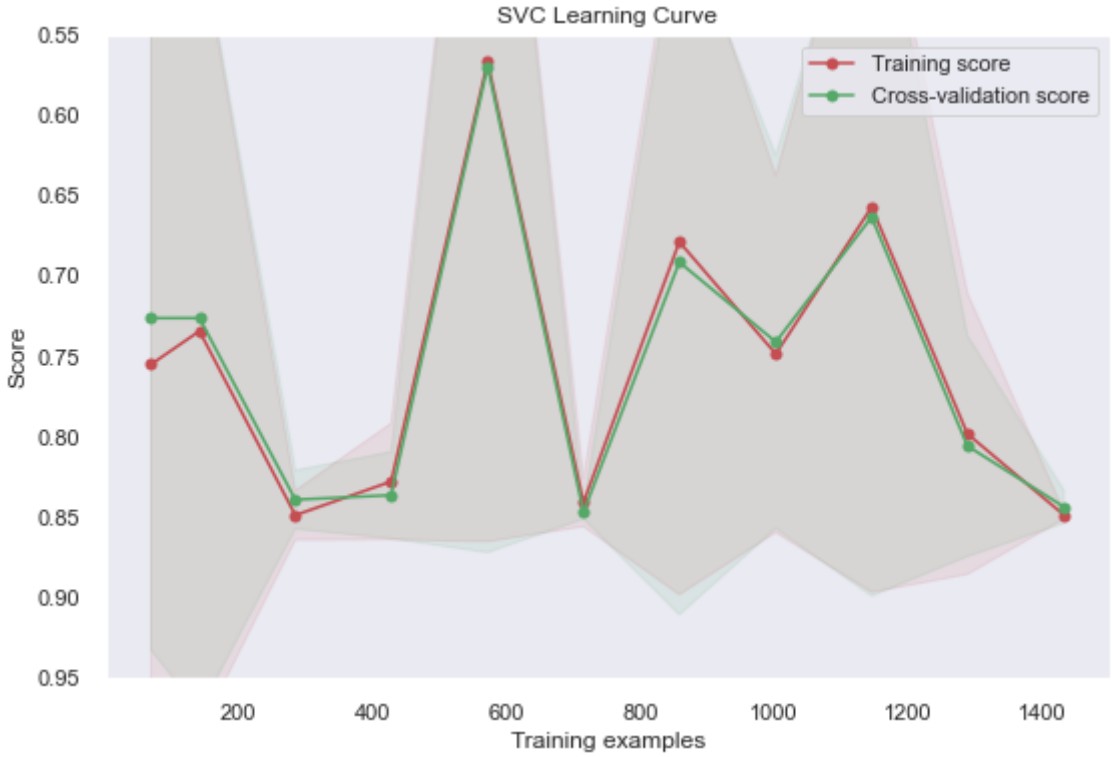
In [219]:
```
from sklearn.metrics import confusion_matrix
```

In [220]:
```
class_names = [i for i in range(1,11)]
cnf = confusion_matrix(Y_test, svc.predictions)
cnf
```

Out[220]:
```
array([[380,   1],
       [ 66,   1]], dtype=int64)
```

In [221]:
```
# Code from sklearn documentation.
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):
    """
    Generate a simple plot of the test and training learning curve.
    """
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

    plt.legend(loc="best")
    return plt
```

In [226]:
```
g = plot_learning_curve(svc.grid.best_estimator_, "SVC Learning Curve", X_train, Y_train, ylim=[0.95, 0.55], cv = 5,
                        train_sizes = [0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1])
```




**Logistic Regression**

In [227]:
```
from sklearn.linear_model import LogisticRegression
```

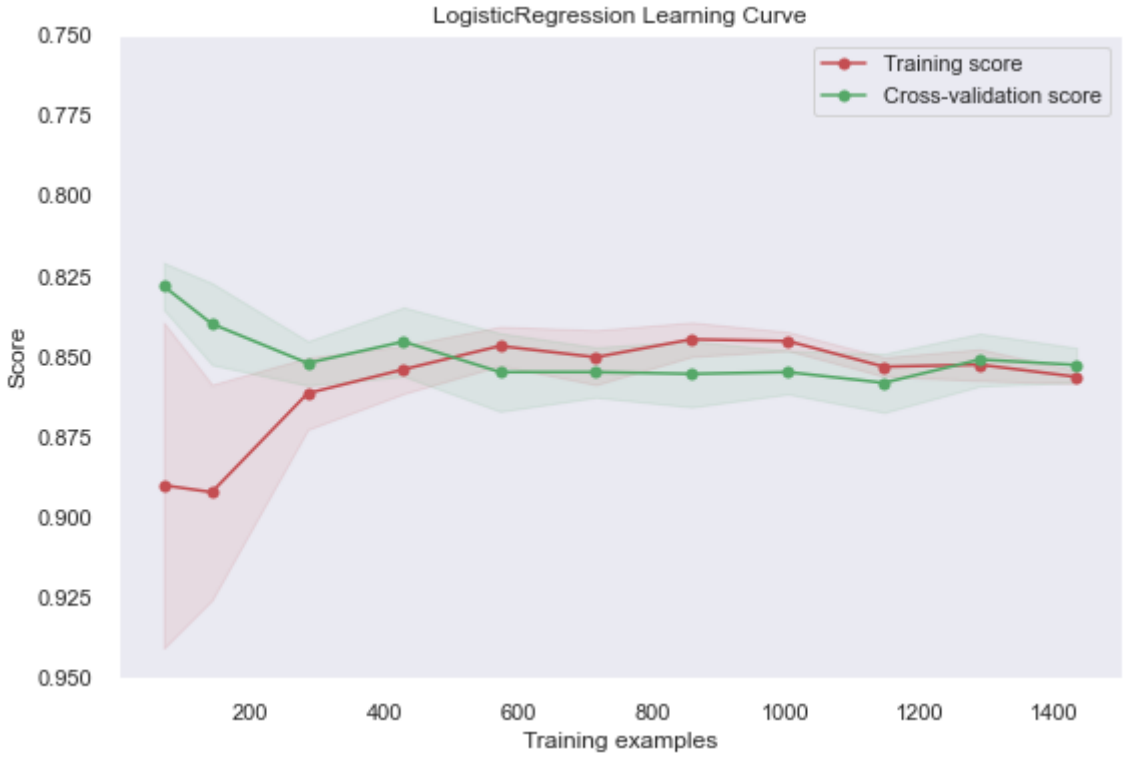
In [228]:
```
lr = Class_Fit(clf = LogisticRegression)
lr.grid_search(parameters = [{'C':np.logspace(-4,6,16)}], Kfold = 17)
lr.grid_fit(X_train, Y_train)
lr.grid_predict(X_test, Y_test)
```

```
Precision: 85.04 %
```

In [229]:
```
cnf = confusion_matrix(Y_test, lr.predictions)
cnf
```

Out[229]:
```
array([[369,  12],
       [ 55,  12]], dtype=int64)
```

In [230]:
```
g = plot_learning_curve(lr.grid.best_estimator_, "LogisticRegression Learning Curve", X_train, Y_train, ylim=[.95, 0.75], cv = 5,
                        train_sizes = [0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1])
```




**K-Nearest Neighbours :**

In [231]:
```
from sklearn.neighbors import KNeighborsClassifier
```

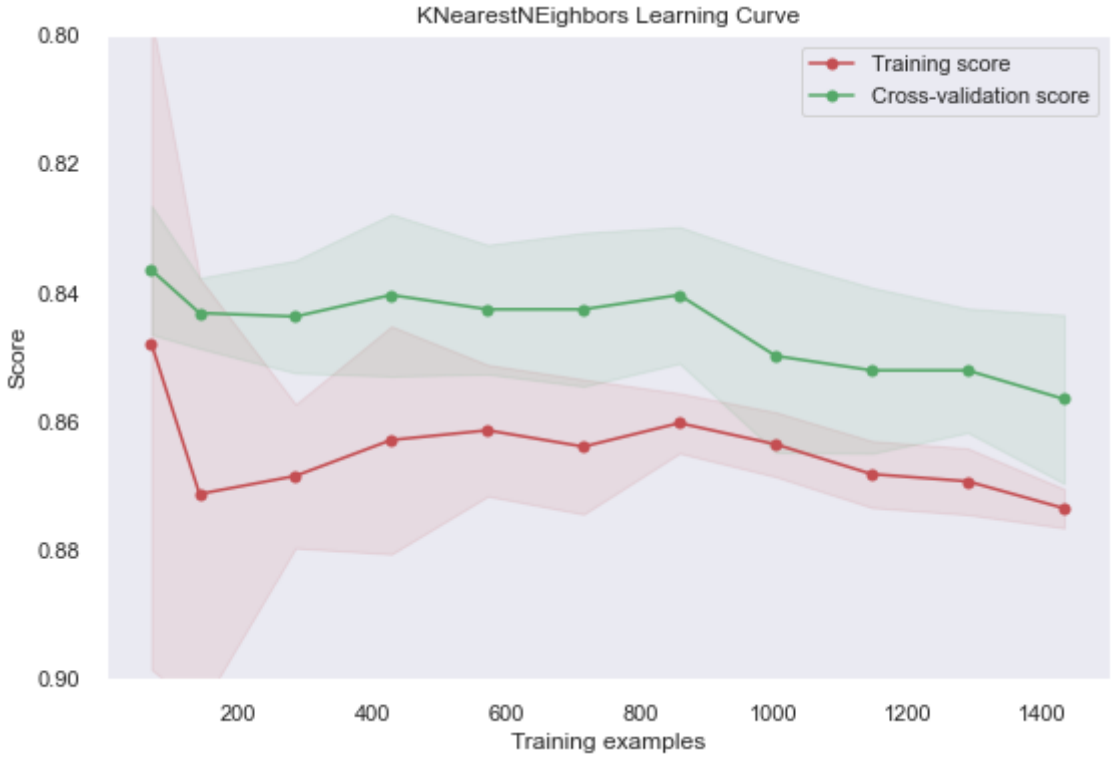
In [232]:
```
knn = Class_Fit(clf = KNeighborsClassifier)
knn.grid_search(parameters = [{'n_neighbors':np.arange(1,50,1)}], Kfold = 10)
knn.grid_fit(X_train, Y_train)
knn.grid_predict(X_test, Y_test)
```

```
Precision: 83.93 %
```

In [233]:
```
cnf = confusion_matrix(Y_test, knn.predictions)
cnf
```

Out[233]:
```
array([[369,  12],
       [ 60,   7]], dtype=int64)
```

In [234]:
```
g = plot_learning_curve(knn.grid.best_estimator_, "KNearestNEighbors Learning Curve", X_train, Y_train, ylim=[.9, 0.8], cv = 5,
                        train_sizes = [0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1])
```




**Decision Trees :**

In [235]:
```
from sklearn.tree import DecisionTreeClassifier
```

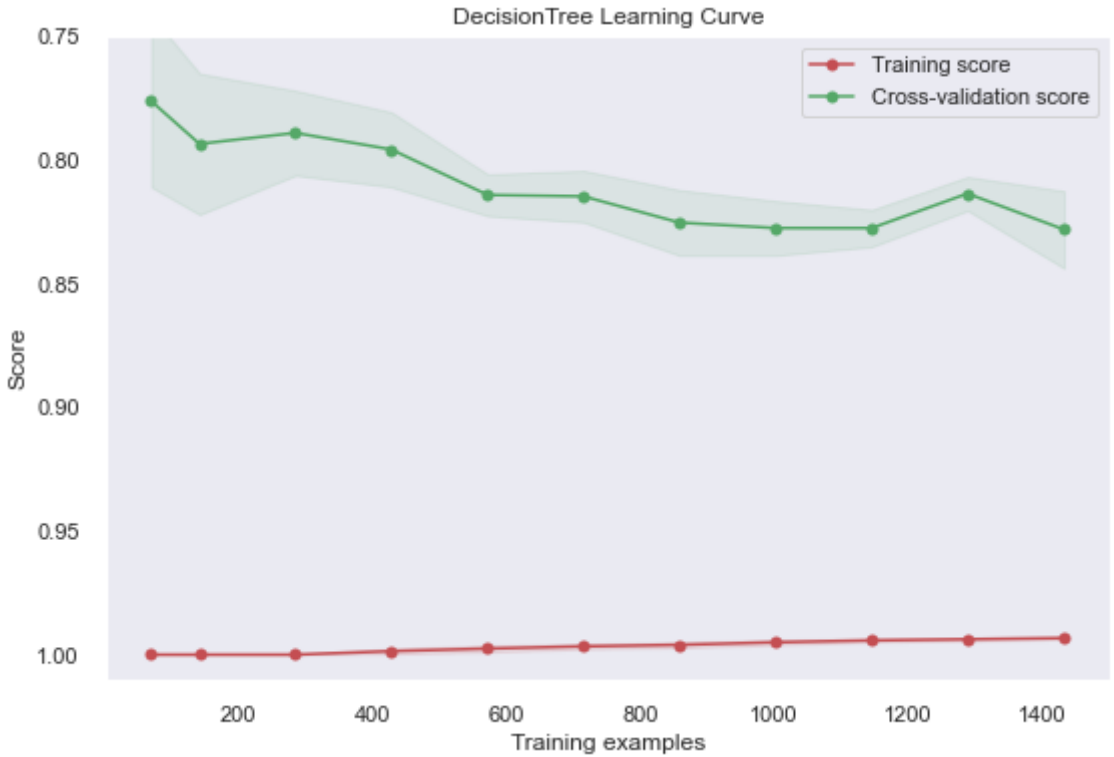
In [236]:
```
tr = Class_Fit(clf = DecisionTreeClassifier)
tr.grid_search(parameters = [{'criterion':['entropy', 'gini'], 'max_features':['sqrt', 'log2']}], Kfold = 3)
tr.grid_fit(X_train, Y_train)
tr.grid_predict(X_test, Y_test)
```

```
Precision: 81.03 %
```

In [237]:
```
cnf = confusion_matrix(Y_test, tr.predictions)
cnf
```

Out[237]:
```
array([[341,  40],
       [ 45,  22]], dtype=int64)
```

In [238]:
```
g = plot_learning_curve(tr.grid.best_estimator_, "DecisionTree Learning Curve", X_train, Y_train, ylim=[1.01, 0.75], cv = 5,
                        train_sizes = [0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1])
```



**Random Forests:**

In [239]:
```
from sklearn.ensemble import RandomForestClassifier
```

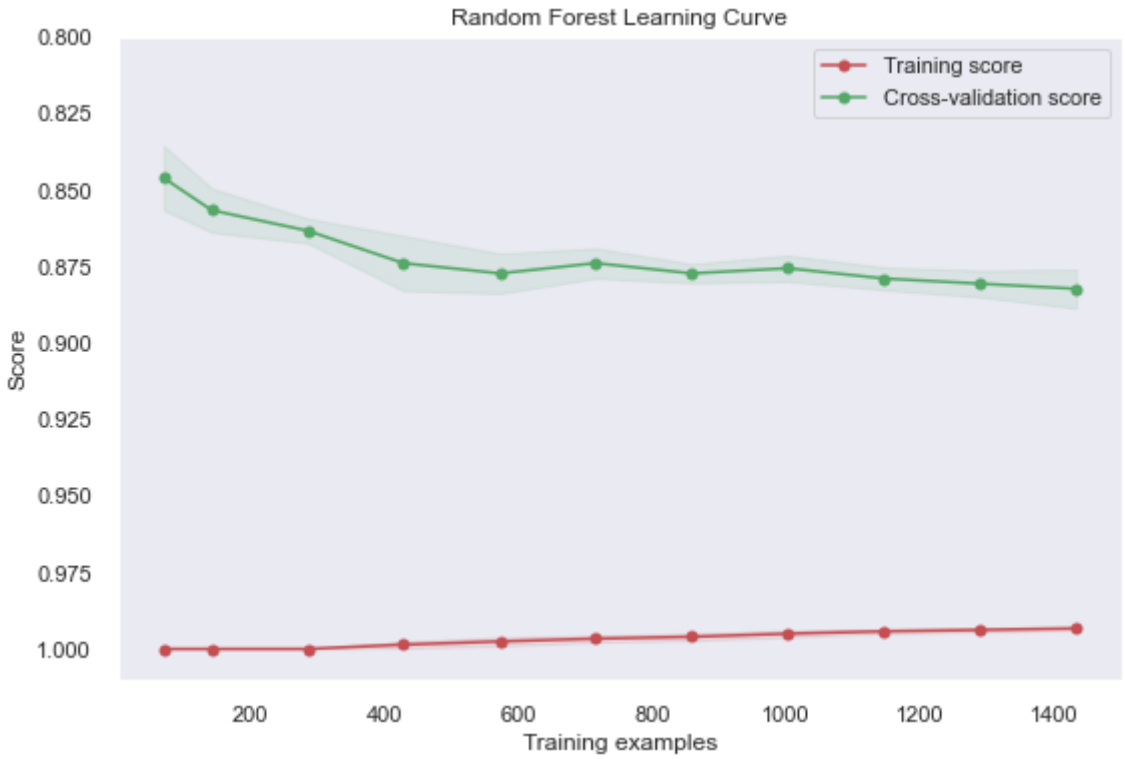
In [240]:
```
rf = Class_Fit(clf = RandomForestClassifier)
rf.grid_search(parameters = [{'criterion':['entropy', 'gini'],
                              'max_features':['sqrt', 'log2'], 'n_estimators':[40, 60, 80, 100, 140]}], Kfold = 5)
rf.grid_fit(X_train, Y_train)
rf.grid_predict(X_test, Y_test)
```

```
Precision: 86.61 %
```

In [258]:
```
cnf = confusion_matrix(Y_test, rf.predictions)
cnf
```

Out[258]:
```
array([[385,   5],
       [ 42,  16]], dtype=int64)
```

In [241]:
```
g = plot_learning_curve(rf.grid.best_estimator_, "Random Forest Learning Curve", X_train, Y_train, ylim=[1.01, 0.8], cv = 5,
                        train_sizes = [0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1])
```




In [242]:
```
from sklearn.ensemble import AdaBoostClassifier
```

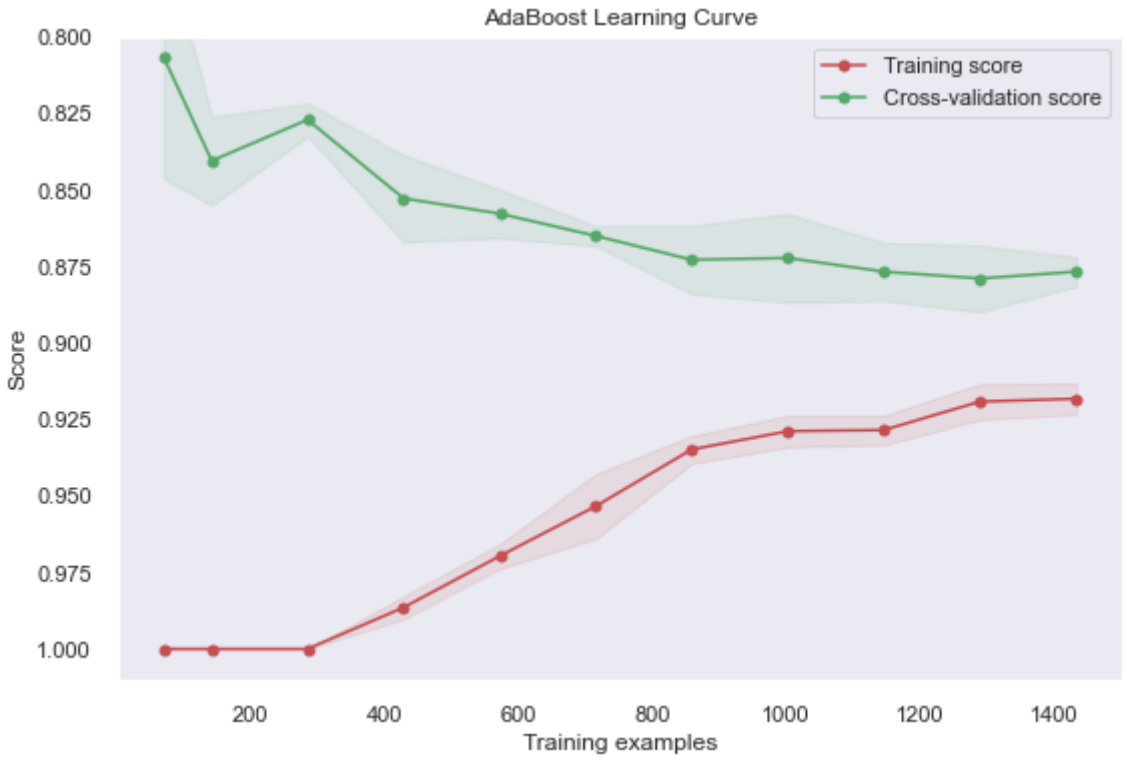
In [244]:
```
ada = Class_Fit(clf = AdaBoostClassifier)
ada.grid_search(parameters = [{'n_estimators':[20, 30, 40, 50, 60, 70, 80, 90, 100, 120, 130]}], Kfold = 8)
ada.grid_fit(X_train, Y_train)
ada.grid_predict(X_test, Y_test)
```

```
Precision: 86.16 %
```

In [245]:
```
cnf = confusion_matrix(Y_test, ada.predictions)
cnf
```

Out[245]:
```
array([[358,  23],
       [ 39,  28]], dtype=int64)
```

In [246]:
```
g = plot_learning_curve(ada.grid.best_estimator_, "AdaBoost Learning Curve", X_train, Y_train, ylim=[1.01, 0.8], cv = 5,
                        train_sizes = [0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1])
```




**Gradient Boosted Decision Trees :**

In [248]:
```
import xgboost
```

In [249]:
```
gbdt = Class_Fit(clf = xgboost.XGBClassifier)
gbdt.grid_search(parameters = [{'n_estimators':[20, 30, 40, 50, 60, 70, 80, 90, 100, 120]}], Kfold = 5)
gbdt.grid_fit(X_train, Y_train)
gbdt.grid_predict(X_test, Y_test)
```

```
Precision: 85.71 %
```

In [250]:
```
cnf = confusion_matrix(Y_test, gbdt.predictions)
cnf
```

Out[250]:
```
array([[363,  18],
       [ 46,  21]], dtype=int64)
```

In [251]:
```
g = plot_learning_curve(gbdt.grid.best_estimator_, "GBDT Learning Curve", X_train, Y_train, ylim=[1.01, 0.8], cv = 5,
                        train_sizes = [0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1])
```


**Voting Classifier :**

In [252]:
```
rf_best = RandomForestClassifier(**rf.grid.best_params_)
gbdt_best = xgboost.XGBClassifier(**gbdt.grid.best_params_)
svc_best = LinearSVC(**svc.grid.best_params_)
tr_best = DecisionTreeClassifier(**tr.grid.best_params_)
knn_best = KNeighborsClassifier(**knn.grid.best_params_)
lr_best = LogisticRegression(**lr.grid.best_params_)
```

In [253]:
```
from sklearn.ensemble import VotingClassifier
```

In [263]:
```
votingC = VotingClassifier(estimators=[('rf', rf_best), ('gb', gbdt_best), ('knn', knn_best), ('lr', lr_best),('svc', svc_best
),('tr', tr_best)])
```

In [264]:
```
votingC = votingC.fit(X_train, Y_train)
```

In [265]:
```
predictions = votingC.predict(X_test)
```

In [266]:
```
print("Precision : {:.2f}%".format(100 * accuracy_score(Y_test, predictions)))
```

```
Precision : 85.71%
```

In [267]:
```
from sklearn.metrics import classification_report
print(classification_report(Y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.87      0.98      0.92       381
           1       0.59      0.15      0.24        67

    accuracy                           0.86       448
   macro avg       0.73      0.57      0.58       448
weighted avg       0.83      0.86      0.82       448
```

**Testing Model**

In [268]:
```
X
```

Out[268]:

| | renda_mes_media | age | recencia_dias | vinho_montante | frutas_montante | carne_montante | peixe_montante | doces_montante | ouro_montante | promocoes_ |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 4844 | 63 | 58 | 635 | 88 | 546 | 172 | 88 | 88 | |
| **1** | 3862 | 66 | 38 | 11 | 1 | 6 | 2 | 1 | 6 | |
| **2** | 5967 | 55 | 26 | 426 | 49 | 127 | 111 | 21 | 42 | |
| **3** | 2220 | 36 | 26 | 11 | 4 | 20 | 10 | 3 | 5 | |
| **4** | 4857 | 39 | 94 | 173 | 43 | 118 | 46 | 27 | 15 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **2235** | 5101 | 53 | 46 | 709 | 43 | 182 | 42 | 118 | 247 | |
| **2236** | 5334 | 74 | 56 | 406 | 0 | 30 | 0 | 0 | 8 | |
| **2237** | 4748 | 39 | 91 | 908 | 48 | 217 | 32 | 12 | 24 | |
| **2238** | 5770 | 64 | 8 | 428 | 30 | 214 | 80 | 30 | 61 | |
| **2239** | 4405 | 66 | 40 | 84 | 3 | 61 | 2 | 1 | 21 | |

2240 rows × 22 columns

In [269]:
```
# define standard scaler
scaler = StandardScaler()
# transform data
scaled = scaler.fit_transform(X)
```

In [270]:
```
predictions = votingC.predict(X)
```

In [271]:
```
print("Precision : {:.2f}%".format(100 * accuracy_score(Y, predictions)))
```

```
Precision : 91.83%
```