```
In [1]:
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
from sklearn.cluster import KMeans
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import scale

import sklearn.metrics as sm
from sklearn import datasets
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
from sklearn.decomposition import PCA
```

Introdução

Tentamos identificar além das principais features, quais clusters foram responsáveis por mais empresas falidas integrantes do grupo

- Luis Gabriel Maximo - 11721BCC027
- Victor Hugo Eustáquio Lopes - 11721BCC011
- Pedro Henrique Bufulin - 11711BCC028


```
In [2]:
df = pd.read_csv('taiwan_data.csv')

#separando o dataframe de testes e o de treinamento
X = df.loc[:, df.columns != 'Bankrupt']
y =  df['Bankrupt']
X.head()
```

Out[2]:

	Cost of Interest-bearing Debt	Cash Reinvestment Ratio	Current Ratio	Acid Test	Interest Expenses/Total Revenue	Total Liability/Equity Ratio.	Liability/Total Assets	Interest-bearing Debt/Equity	Contingent Liability/Equity	Operating Income/Capital
0	0.370594	0.424389	0.405750	0.601457	0.601457	0.998969	0.796887	0.808809	0.302646	0.780985
1	0.464291	0.538214	0.516730	0.610235	0.610235	0.998946	0.797380	0.809301	0.303556	0.781506
2	0.426071	0.499019	0.472295	0.601450	0.601364	0.998857	0.796403	0.808388	0.302035	0.780284
3	0.399844	0.451265	0.457733	0.583541	0.583541	0.998700	0.796967	0.808966	0.303350	0.781241
4	0.465022	0.538432	0.522298	0.598783	0.598783	0.998973	0.797366	0.809304	0.303475	0.781550

5 rows × 95 columns

criando o modelo e definindo K pelo método do cotovelo

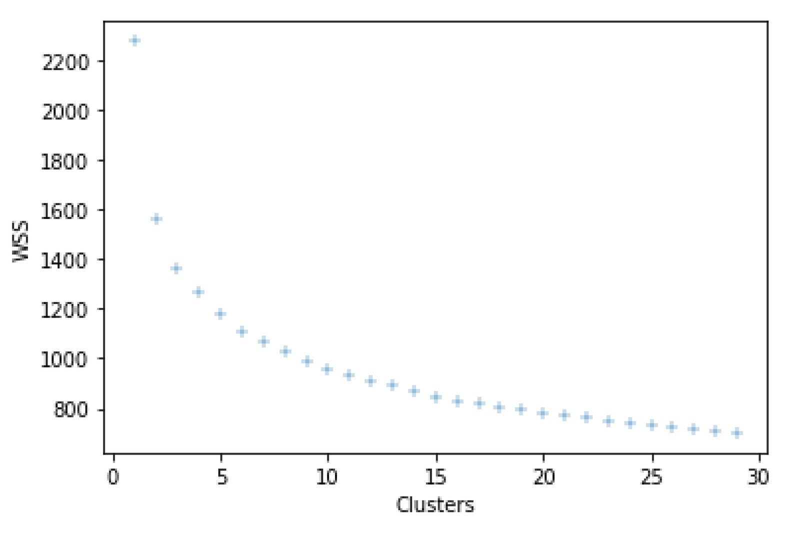
Neste caso, a distância ao quadrado entre centroids e data points deve ser a menor possível.

```
In [3]:
K=range(1,30)
wss = []
for k in K:
    kmeans= KMeans(n_clusters=k,init="k-means++",  n_init = 10 ,max_iter=300 )
    kmeans=kmeans.fit(X)
    wss_iter = kmeans.inertia_
    wss.append(wss_iter)
```

```
In [4]:
centers = pd.DataFrame({'Clusters' : K, 'WSS' : wss})
```

```
In [5]:
sns.scatterplot(x = 'Clusters', y = 'WSS', data = centers, marker="+")
```

Out[5]: <AxesSubplot:xlabel='Clusters', ylabel='WSS'>



Dá pra ver que depois de 4 clusters não desce tão rápido, então vamos usar 4, por praticidade também

```
In [6]:
clustering_kmeans = KMeans(n_clusters=4, random_state=5)
df['clusters'] = clustering_kmeans.fit_predict(X)
df.head()
```

Out[6]:

	Bankrupt	Cost of Interest-bearing Debt	Cash Reinvestment Ratio	Current Ratio	Acid Test	Interest Expenses/Total Revenue	Total Liability/Equity Ratio.	Liability/Total Assets	Interest-bearing Debt/Equity	Contingent Liability/Equity	...
0	1	0.370594	0.424389	0.405750	0.601457	0.601457	0.998969	0.796887	0.808809	0.302646	...
1	1	0.464291	0.538214	0.516730	0.610235	0.610235	0.998946	0.797380	0.809301	0.303556	...
2	1	0.426071	0.499019	0.472295	0.601450	0.601364	0.998857	0.796403	0.808388	0.302035	...
3	1	0.399844	0.451265	0.457733	0.583541	0.583541	0.998700	0.796967	0.808966	0.303350	...
4	1	0.465022	0.538432	0.522298	0.598783	0.598783	0.998973	0.797366	0.809304	0.303475	...

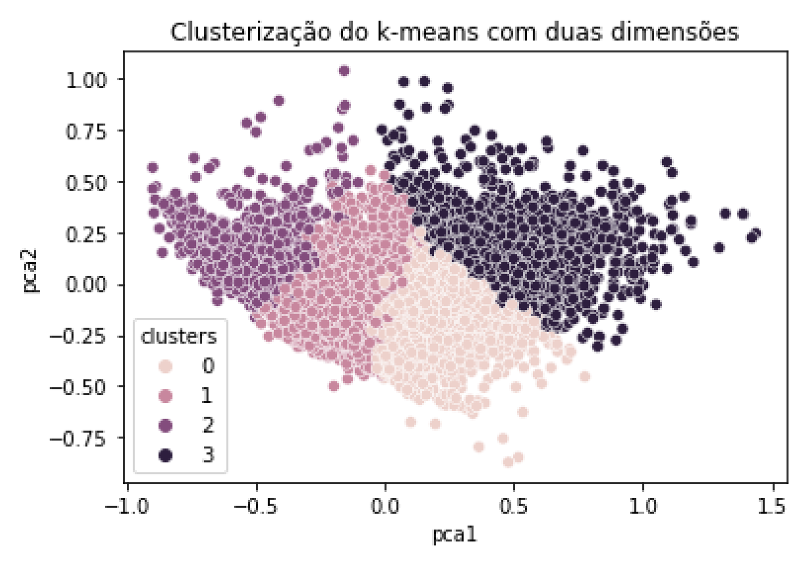
5 rows × 97 columns

Resultados, plot das saídas do modelo e análises

Vou usar análise de componentes principais, pelo menos para ver o que acontece com os dados.

```
In [7]:
### Run PCA on the data and reduce the dimensions in pca_num_components dimensions
reduced_data = PCA(n_components=2).fit_transform(X)
results = pd.DataFrame(reduced_data,columns=['pca1','pca2'])

sns.scatterplot(x="pca1", y="pca2", hue=df['clusters'], data=results)
plt.title('Clusterização do k-means com duas dimensões')
plt.show()
```

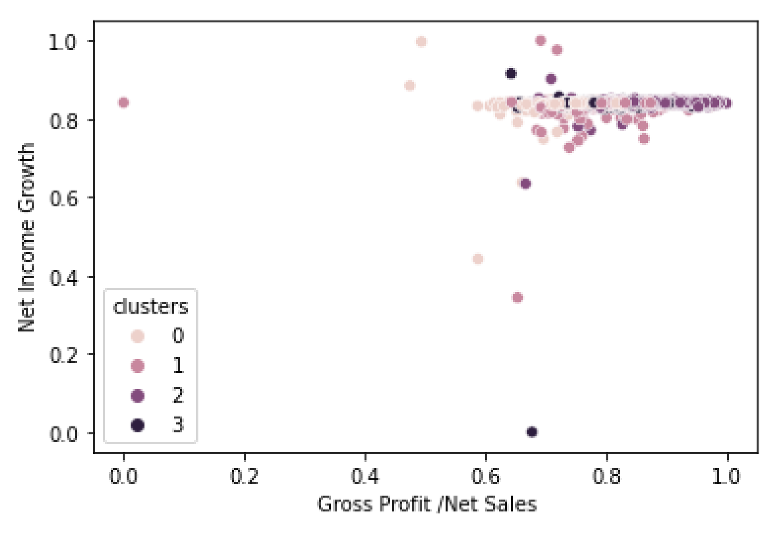



```
In [17]:
sns.scatterplot(y=' Net Income Growth', x=' Cash Reinvestment Ratio',hue = 'clusters',  data=df)
```

Out[17]: <AxesSubplot:xlabel=' Cash Reinvestment Ratio', ylabel=' Net Income Growth'>


```
In [18]:
sns.scatterplot(y=' Net Income Growth', x= ' Gross Profit /Net Sales',hue = 'clusters',  data=df)
```

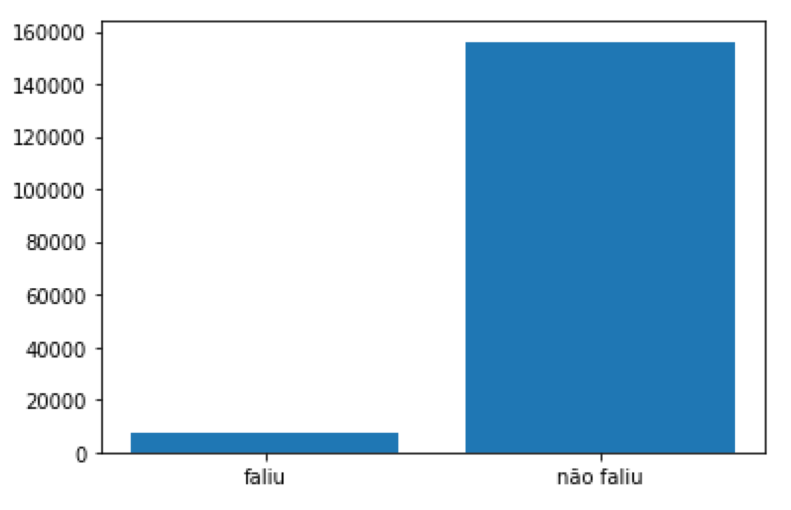
Out[18]: <AxesSubplot:xlabel=' Gross Profit /Net Sales', ylabel=' Net Income Growth'>




```
In [11]:
#bar chart do cluster 0

cluster0 = df.loc[df['clusters'] == 0]
bankrupt = cluster0.loc[cluster0['Bankrupt'] == 1].size
noBankrupt =  cluster0.loc[cluster0['Bankrupt'] == 0].size
status = ['faliu', 'não faliu']
empresas = [bankrupt, noBankrupt]
plt.bar(status, empresas)
```

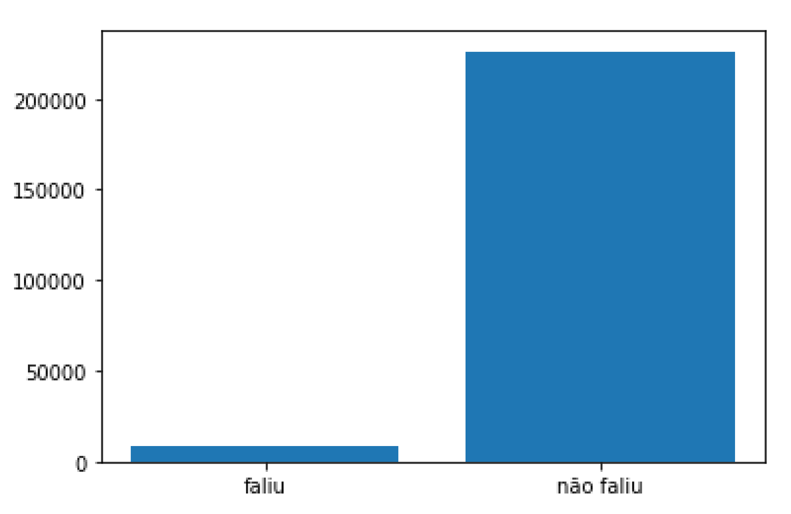
Out[11]: <BarContainer object of 2 artists>




```
In [12]:
#bar chart do cluster 1


cluster1 = df.loc[df['clusters'] == 1]
bankrupt = cluster1.loc[cluster1['Bankrupt'] == 1].size
noBankrupt =  cluster1.loc[cluster1['Bankrupt'] == 0].size
status = ['faliu', 'não faliu']
empresas = [bankrupt, noBankrupt]
plt.bar(status, empresas)
```

Out[12]: <BarContainer object of 2 artists>

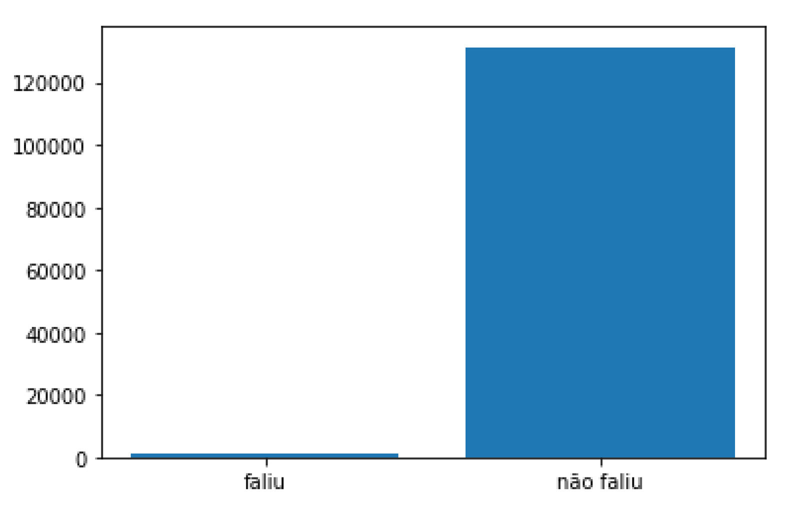



```
In [13]:
#bar chart do cluster 2

cluster2 = df.loc[df['clusters'] == 2]
bankrupt = cluster2.loc[cluster2['Bankrupt'] == 1].size
noBankrupt =  cluster2.loc[cluster2['Bankrupt'] == 0].size
status = ['faliu', 'não faliu']
empresas = [bankrupt, noBankrupt]

plt.bar(status, empresas)
```

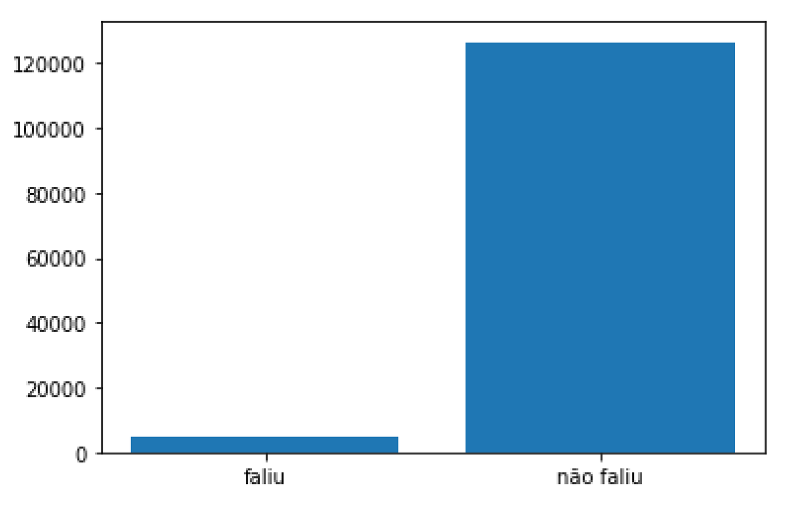
Out[13]: <BarContainer object of 2 artists>




```
In [14]:
#bar chart do cluster 3

cluster3 = df.loc[df['clusters'] == 3]
bankrupt = cluster3.loc[cluster3['Bankrupt'] == 1].size
noBankrupt =  cluster3.loc[cluster3['Bankrupt'] == 0].size
status = ['faliu', 'não faliu']
empresas = [bankrupt, noBankrupt]
plt.bar(status, empresas)
```

Out[14]: <BarContainer object of 2 artists>



sobre os bar charts

podemos ver que pelos clusters criados, o que menos teve falências foi o cluster 2, enquanto que mais teve falências foi o 0.