questaoquatro

October 17, 2018

1 Questão 4 - Prova 2 de Inteligência Artificial

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Enunciado: utilizando a base de clusterização encontrada nesse link (https://drive.google.com/file/d/1_702eOQbimT1HhTuozwMEKV6HHOykLaJ/view), execute os algoritmos de clusterização citados a seguir e compare os resultados.

- Execute os algoritmos de agrupamento K-means e Hierárquico com os seguintes valores de K: 2, 5, 10 e 100. Compare os agrupamento resultantes dos 2 algoritmos.
- Escolha um número fixo de K e altere o parâmetro do K-Means referente ao número máximo de iterações: 1, 10 e 100 e o parâmetro de Linkage do Hierárquico, quais diferenças puderam ser observadas?
- Faça uma comparação entre os 2 algoritmos, qual você acha que teve o melhor desempenho e por quê?

2 Pré-processamento de dados

2.0.1 Importando o dataset da questão

```
In [1]: import scipy.io.arff as io
        import pandas as pd
        import matplotlib.pyplot as plt

        %matplotlib inline

        import numpy as np

        # Aumentar o tamanho do plot na proporção 8/13
        x_size = 17
        y_size = x_size * (8/13)
        plt.figure(figsize=(x_size, y_size))
        # Aumentar o tamanho do plot na proporção 8/13

        # Read arff data
        with open("Genes_Atividade_IA.arff") as f:
            values = io.loadarff(f)
```

```
        f.close()

    dataset = pd.DataFrame(data=values[0])
    #X = dataset.iloc[:, :-1].values
    #y = dataset.iloc[:, 20].values
```

```
<Figure size 1224x753.231 with 0 Axes>
```

2.0.2 Melhorando a visualização da tabela do dataset

```
In [2]: print(pd.options.display.max_columns, pd.options.display.max_rows)
        pd.options.display.max_columns = 50
        print(pd.options.display.max_columns, pd.options.display.max_rows)
        #pd.options.display.max_rows =
```

```
20 60
50 60
```

```
In [3]: dataset.describe()
```

```
Out[3]:        adipose_tissue  adrenal_gland  animal_ovary     appendix      bladder  \
        count     2000.000000    2000.000000   2000.000000  2000.000000  2000.000000
        mean        39.040157      41.486336     51.338392    52.555181    48.932735
        std        195.264717     181.466441    210.726346   252.295704   221.732356
        min          0.000003       0.000003      0.000004     0.000004     0.000004
        25%          3.173068       3.105311      3.140023     7.117802     7.087438
        50%         12.692271      15.526556     19.625143    21.353406    21.262314
        75%         31.730678      34.158423     43.175314    46.265713    42.524627
        max       7377.382624    5216.922745   4827.785071  7644.519332  7548.121360

         bone_marrow  cerebral_cortex        colon     duodenum  endometrium  \
        count  2000.000000      2000.000000  2000.000000  2000.000000  2000.000000
        mean     53.852077        45.797667    40.663197    39.632611    52.066032
        std     393.758129       123.183344   157.028175   185.991398   186.169270
        min       0.000003         0.000004     0.000003     0.000003     0.000004
        25%       1.257345         7.631545     3.071134     2.765053     7.428423
        50%       9.430086        19.078863    15.355670    13.825265    21.224067
        75%      34.576981        41.973499    33.782474    30.415583    50.937760
        max   12623.741610      2663.409328  3528.732999  5275.721159  6460.605882

          esophagus  fallopian_tube  gallbladder        heart       kidney  \
        count  2000.000000     2000.000000  2000.000000  2000.000000  2000.000000
        mean     41.493874       53.691974    57.023709    21.915492    27.728612
        std     139.247221      261.725555   314.203534   116.726607   136.411996
        min       0.000004        0.000004     0.000004     0.000002     0.000002
        25%       3.506638        7.896982     8.147757     1.569051     2.492157
        50%      14.026553       23.690945    20.369393     6.724503     9.968628
```

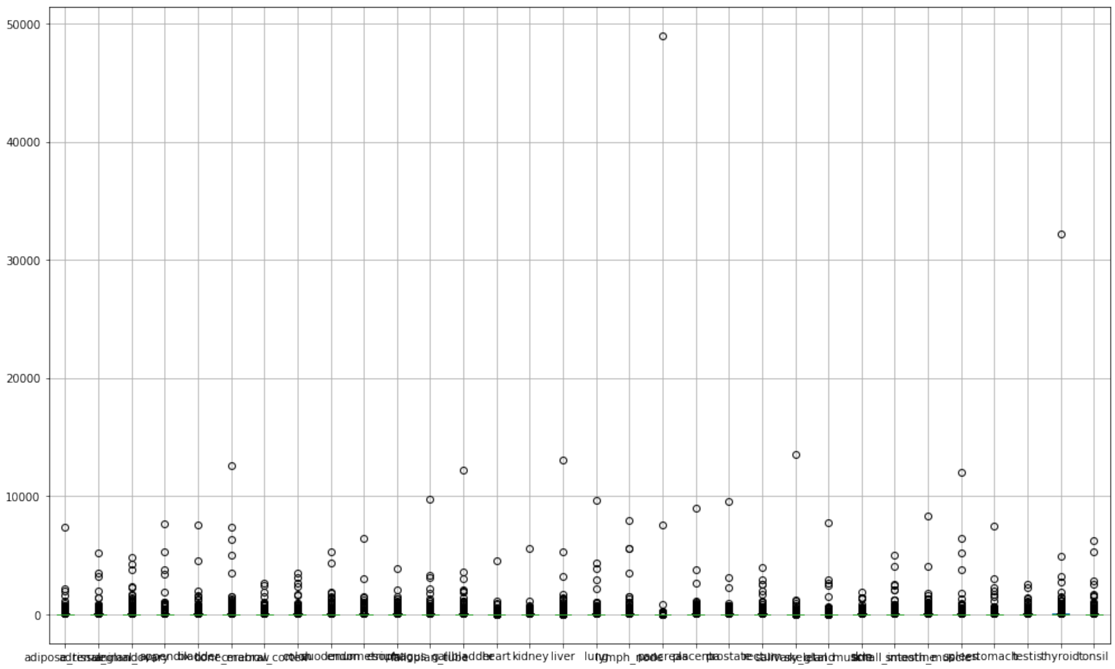
```
75%      35.066382      47.381890     48.886544    15.690507    24.921571
max    3857.301972    9733.029992  12201.266550  4512.141526  5587.416115

              liver         lung   lymph_node      pancreas     placenta  \
count   2000.000000  2000.000000  2000.000000   2000.000000  2000.000000
mean      35.790131    54.864549    54.294117     35.087462    52.105545
std      336.523288   277.654367   277.993904   1108.114405   242.242244
min        0.000003     0.000004     0.000004      0.000002     0.000004
25%        1.170095     7.812597     3.751913      0.602562     4.128284
50%        5.850474    23.437791    18.759564      2.008539    20.641418
75%       17.551423    46.875582    48.774865      6.025616    45.411120
max    13058.258680  9707.151804  7931.543465  48970.179710  9032.684565

           prostate       rectum  salivary_gland  skeletal_muscle         skin  \
count  2000.000000  2000.000000     2000.000000      2000.000000  2000.000000
mean     46.389605    42.376928       27.628763        22.053380    35.257338
std     241.613858   165.470468      308.543568       208.651352    95.223057
min       0.000004     0.000003        0.000003         0.000002     0.000003
25%       7.150531     3.094211        2.414023         0.427236     3.304699
50%      17.876327    15.471057        8.046744         2.136179    16.523495
75%      42.903184    34.036326       18.775735         8.544717    36.351689
max    9585.286431  3945.119614    13529.258260      7732.968610  1939.858329

       small_intestine  smooth_muscle        spleen      stomach       testis  \
count      2000.000000    2000.000000   2000.000000  2000.000000  2000.000000
mean         43.396844      52.185982     56.164531    37.587312    44.472439
std         193.638153     233.848790    347.561819   207.009834   114.878046
min           0.000003       0.000004      0.000004     0.000003     0.000003
25%           5.983976       4.248427      3.678518     5.874027     6.997996
50%          14.959941      21.242137     22.071107    14.685068    20.993988
75%          32.911870      42.484273     47.820732    29.370135    45.486973
max        5032.524122    8322.669088  12036.110500  7486.447452  2554.268510

            thyroid       tonsil
count   2000.000000  2000.000000
mean      72.736881    46.143284
std      742.846516   222.768691
min        0.000005     0.000003
25%        4.580134     3.174720
50%       22.900670    15.873599
75%       54.961609    38.096639
max    32253.304180  6231.975147
```

2.0.3 Visualizando o dataset através de um box plot, a fim de encontrar possíveis *outliers*

In [4]:
```
# Aumentar o tamanho do plot na proporção 8/13
x_size = 17
y_size = x_size * (8/13)
```

```
plt.figure(figsize=(x_size, y_size))
# Aumentar o tamanho do plot na proporção 8/13
dataset.boxplot()
```

Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7efced3770b8>



2.0.4 Detectamos *outliers*, logo faz-se necessário um ajuste na escala

In [5]:
```
from sklearn.preprocessing import RobustScaler
transformer = RobustScaler().fit(dataset[dataset.columns[:-1]])
```

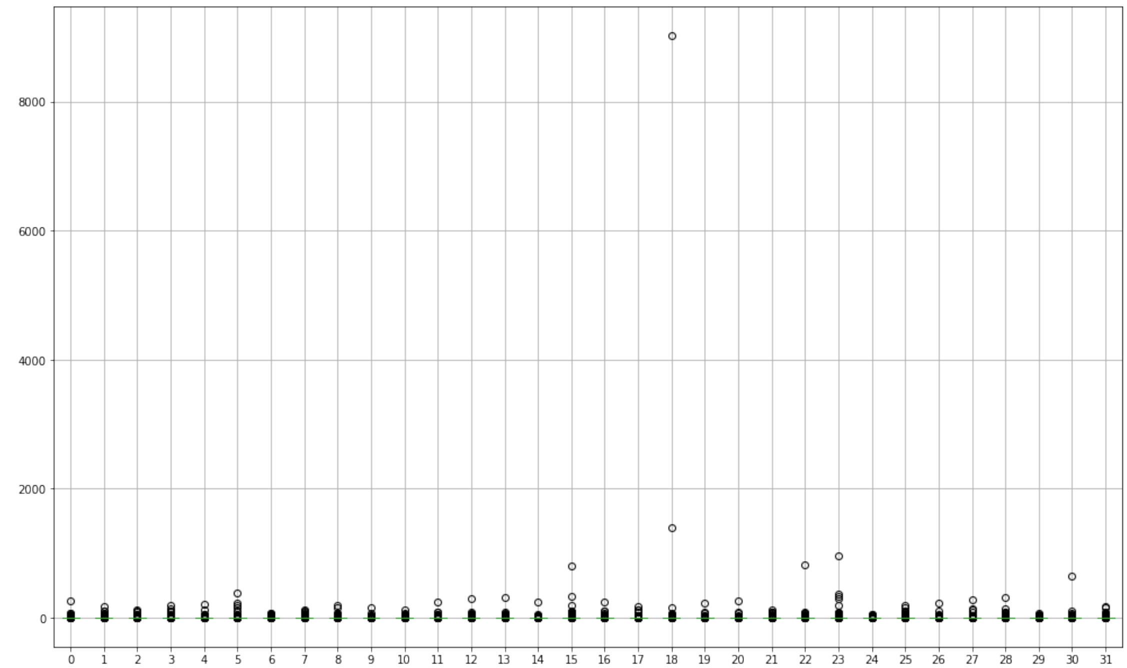
In [6]:
```
import numpy as np
a = np.array(dataset[dataset.columns[:-1]])
```

In [7]:
```
df = pd.DataFrame(transformer.transform(a))
```

2.0.5 Visualizando o boxplot depois de ter sua escala reajustada, percebe-se a presença de um *outlier* na coluna 18...

In [8]:
```
# Aumentar o tamanho do plot na proporção 8/13
x_size = 17
y_size = x_size * (8/13)
plt.figure(figsize=(x_size, y_size))
# Aumentar o tamanho do plot na proporção 8/13
df.boxplot()
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7efce959b080>



2.0.6 Tentando localizar a instância com um valor acima de 9000

```
In [9]: a = df.loc[df[18] > 9000]
```

```
In [10]: a
```

```
Out[10]:              0    1         2    3     4         5         6     7    8   \
        1940 -0.377778 -0.5  0.490196 -0.5 -0.59 -0.283019 -0.555555 -0.49  0.2

                     9         10     11   12       13        14        15     16  \
        1940 -0.478049 -0.444444 -0.58 -0.5  0.15873 -0.444444 -0.357143 -0.58

                    17            18   19     20   21        22        23    24  \
        1940 -0.408333  9029.629629  0.4 -0.49 -0.5  0.655738 -0.236842 -0.45

                    25        26        27     28        29        30        31
        1940 -0.111111 -0.544444 -0.416667 -0.375 -0.472727 -0.454545 -0.454545
```

```
In [11]: aux = np.array(df[18])
```

2.0.7 Substituindo o valor desse *outlier* pela mediana da coluna 18 do dataset

```
In [12]: df[18] = df[18].replace(9029.629629, np.nanmedian(aux))
```

3 Identificando o número de classes

```
In [13]: class_array = dataset.iloc[:, 32]
```

3.0.1 Significa que existem 2000 classes, ou seja, uma para cada instância.

```
In [14]: class_array.describe()
```

```
Out[14]: count                    2000
         unique                   2000
         top       b'ENSG00000008226'
         freq                        1
         Name: class, dtype: object
```

```
In [15]: a = np.array(class_array.value_counts())
```

```
In [16]: a.sum()
```

```
Out[16]: 2000
```

4 1. Execução dos algoritmos de aprendizagem de máquina K-means e Hierárquico para resolver um problema de agrupamento

Execute os algoritmos de agrupamento K-means e Hierárquico com os seguintes valores de K: 2, 5, 10 e 100. Compare os agrupamentos resultantes dos 2 algoritmos.

4.0.1 Separando as entradas do problema na variável X e a saída esperada do problema na variável y

```
In [17]: X = dataset.iloc[:, :-1].values
         y = dataset.iloc[:, 32].values
```

4.1 K-means, K = 2

```
In [18]: from sklearn.cluster import KMeans
         kmeans = KMeans(n_clusters=2, random_state=0).fit(X)
```

```
In [19]: a = np.array(kmeans.labels_)
         a.sum()
```

```
Out[19]: 1
```

4.1.1 Perceba que a soma da quantidade de rótulos foi igual a 1 devido ao *outlier* na coluna "pancreas" que causou um desbalanceamento nas classes

```
In [20]: unique, counts = np.unique(a, return_counts=True)
         dicionario = dict(zip(unique, counts))
         print(dicionario)
         lista = list(dicionario.items())
         class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
         class_instances
```

```
{0: 1999, 1: 1}
```

```
Out[20]:    Classe  Nž Instancias
        0       0           1999
        1       1              1
```

```
In [21]: kmeans.cluster_centers_[0]
```

```
Out[21]: array([39.05873463, 41.50708976, 51.34443912, 52.58058144, 48.95703592,
                53.87901696, 45.82057733, 40.68338489, 39.64275479, 52.09186528,
                41.51463154, 53.7184383 , 57.05223534, 21.9219698 , 27.74248304,
                35.80803475, 54.89160398, 54.32108966, 10.60767637, 52.11302411,
                46.41263207, 42.39812701, 27.63319137, 22.06430544, 35.27414936,
                43.41256626, 52.21187541, 56.19078705, 37.60317633, 44.49328609,
                72.77326733, 46.16636715])
```

4.1.2 Isso é confirmado pois é possível ver que ele foi capturado no `kmeans.cluster_centers_[1]` (valor 4.89e+4)

```
In [22]: kmeans.cluster_centers_[1]
```

```
Out[22]: array([1.90384068e+00, 3.10531000e-06, 3.92502851e+01, 1.77945050e+00,
                3.54371895e-01, 3.14336000e-06, 3.81577000e-06, 3.07113403e-01,
                1.93553711e+01, 4.24481333e-01, 3.50664000e-06, 7.89698174e-01,
                4.07388000e-06, 8.96600403e+00, 2.49216000e-06, 2.92524000e-06,
                7.81259703e-01, 3.75191271e-01, 4.89701797e+04, 3.71545526e+01,
                3.57526536e-01, 3.09421000e-06, 1.87757351e+01, 2.13617917e-01,
                1.65234951e+00, 1.19679527e+01, 4.24842730e-01, 3.67851788e+00,
                5.87402703e+00, 2.79919837e+00, 4.58013000e-06, 3.17472000e-06])
```

4.1.3 Adicionando a coluna calculada `kmeans.label_` ao conjunto de dados

```
In [23]: dataset["K-classes"] = kmeans.labels_
```

4.1.4 Provado que a única instância da classe 1 que contém o valor com *outlier*, ou seja, o *outilier* interfere diretamente na análise de dados.

```
In [24]: dataset.loc[ dataset["pancreas"] > 40000]
```

```
Out[24]:      adipose_tissue  adrenal_gland  animal_ovary  appendix   bladder  \
        1940        1.903841       0.000003     39.250285   1.77945  0.354372

              bone_marrow  cerebral_cortex     colon   duodenum  endometrium  \
        1940     0.000003         0.000004  0.307113  19.355371     0.424481

              esophagus  fallopian_tube  gallbladder     heart    kidney     liver  \
        1940   0.000004        0.789698     0.000004  8.966004  0.000002  0.000003

                 lung  lymph_node     pancreas   placenta  prostate    rectum  \
        1940  0.78126    0.375191  48970.17971  37.154553  0.357527  0.000003
```

```
      salivary_gland  skeletal_muscle     skin  small_intestine  \
1940       18.775735         0.213618  1.65235        11.967953

      smooth_muscle    spleen   stomach    testis   thyroid   tonsil  \
1940       0.424843  3.678518  5.874027  2.799198  0.000005  0.000003

                  class  K-classes
1940  b'ENSG00000091704'          1
```

4.2 K-means, K = 5

```
In [25]: from sklearn.cluster import KMeans
         kmeans = KMeans(n_clusters=5, random_state=0).fit(X)

In [26]: a = np.array(kmeans.labels_)
```

4.2.1 Analisando os rótulos de saída do algoritmo, percebe-se que temos 3 classes, de forma que a classe 0 é afetada pelo desbalanceamento das classes devido ao *outlier* presente na coluna "pancreas"

```
In [27]: unique, counts = np.unique(a, return_counts=True)
         dicionario = dict(zip(unique, counts))
         print(dicionario)
         lista = list(dicionario.items())
         class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
         class_instances

{0: 1995, 1: 1, 2: 2, 3: 1, 4: 1}
```

Out[27]:

	Classe	Nž Instancias
0	0	1995
1	1	1
2	2	2
3	3	1
4	4	1

4.2.2 A quantidade de instâncias de cada classe afetou diretamente na classificação das classes, devido ao número de *outliers* nas amostras.

4.2.3 Adicionando a coluna calculada `kmeans.label_` ao conjunto de dados

```
In [28]: dataset["K-classes"] = kmeans.labels_

In [29]: dataset.loc[dataset["K-classes"] > 0]
```

Out[29]:

	adipose_tissue	adrenal_gland	animal_ovary	appendix	bladder	\
591	0.317307	1.863187	0.000004	0.711780	0.708744	
1315	2027.590321	1400.495332	2296.141680	7644.519332	4514.697940	
1718	7377.382624	3490.369741	4827.785071	5295.644677	7548.121360	

```
1874     28.557610     46.579667    54.950399  1854.187417   836.317672
1940      1.903841      0.000003    39.250285     1.779450     0.354372

       bone_marrow  cerebral_cortex        colon     duodenum  endometrium  \
591       0.628672         0.381577     0.307113     0.000003     0.000004
1315   3463.984873      2430.647195  2346.346398  1800.049515  6460.605882
1718   6349.591147      1938.412520  3095.703101  4330.073027  2996.838208
1874  12623.741610        19.078863   546.661857  5275.721159   114.609960
1940      0.000003         0.000004     0.307113    19.355371     0.424481

        esophagus  fallopian_tube   gallbladder        heart       kidney  \
591      0.350664        0.394849      0.814776     6.724503     1.246079
1315  3857.301972     3293.041385   3637.973632   428.126692   799.982414
1718  2114.502808     3158.792695  12201.266550  1187.995534  5587.416115
1874   199.878375      110.557744   3055.408986    26.898012    32.398042
1940     0.000004        0.789698      0.000004     8.966004     0.000002

            liver         lung   lymph_node      pancreas     placenta  \
591      0.000003     0.390630    26.263389      0.000002     0.412828
1315  1292.954824  4394.585827  7931.543465    188.802629  3798.020932
1718  5344.408289  9707.151804  5612.861412    843.586214  9032.684565
1874   125.785198  2179.714570  1485.757432     18.076847   202.285898
1940     0.000003     0.781260     0.375191  48970.179710    37.154553

         prostate       rectum  salivary_gland  skeletal_muscle         skin  \
591      0.715053     0.309421        1.341124         0.000002     2.313289
1315  3128.357190  2558.912879      992.431712       183.711409  1391.278291
1718  2288.169831  3945.119614     1166.777824       324.699234  1311.965514
1874    60.779511   519.827526    13529.258260         2.136179    99.140971
1940     0.357527     0.000003       18.775735         0.213618     1.652350

      small_intestine  smooth_muscle        spleen      stomach       testis  \
591          0.000003       0.424843      0.367852     0.000003     2.449299
1315      2600.037730    8322.669088   5201.424283  2232.130272  1137.174337
1718      5032.524122    4112.477630  12036.110500  3072.116138  1445.086157
1874      2058.487869     195.427656   1364.730134  7486.447452    24.492986
1940        11.967953       0.424843      3.678518     5.874027     2.799198

          thyroid       tonsil               class  K-classes
591   32253.304180     0.952416  b'ENSG00000042832'          3
1315   2729.759911  6231.975147  b'ENSG00000075624'          2
1718   4919.064000  2809.627104  b'ENSG00000087086'          2
1874     87.022547  1561.962187  b'ENSG00000090382'          4
1940      0.000005     0.000003  b'ENSG00000091704'          1
```

4.2.4 Acima podemos ver as instâncias que pertencem às demais classes. Em cada uma delas existe um *outlier* que altera o comportamento do algoritmo.

4.3 K-means, K = 10

```
In [30]: from sklearn.cluster import KMeans
         kmeans = KMeans(n_clusters=10, random_state=0).fit(X)
```

```
In [31]: a = np.array(kmeans.labels_)
```

4.4 Analisando os rótulos de saída do algoritmo, percebem-se 3 classes, de forma que a classe 1 continua sendo afetada pelo desbalanceamento de classes causado pelo *outlier* presente na coluna "pancreas"

```
In [32]: unique, counts = np.unique(a, return_counts=True)
         dicionario = dict(zip(unique, counts))
         print(dicionario)
         lista = list(dicionario.items())
         class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
         class_instances
```

```
{0: 1925, 1: 1, 2: 1, 3: 1, 4: 1, 5: 1, 6: 66, 7: 1, 8: 2, 9: 1}
```

Out[32]:

	Classe	Nž Instancias
0	0	1925
1	1	1
2	2	1
3	3	1
4	4	1
5	5	1
6	6	66
7	7	1
8	8	2
9	9	1

4.4.1 Podemos perceber uma melhoria, com a classe 6 possuindo 66 instâncias, mas pode ser que todas elas sejam *outliers*.

4.4.2 Adicionando a coluna calculada `kmeans.label_` ao conjunto de dados

```
In [33]: dataset["K-classes"] = kmeans.labels_
```

```
In [34]: dataset.loc[(dataset["K-classes"] > 0) & (dataset["K-classes"] != 6)]
```

Out[34]:

	adipose_tissue	adrenal_gland	animal_ovary	appendix	bladder \
393	621.921288	586.903809	726.130275	3459.251765	1998.657487
510	2138.647694	794.959656	3768.027372	3800.906260	1587.586089
591	0.317307	1.863187	0.000004	0.711780	0.708744
1315	2027.590321	1400.495332	2296.141680	7644.519332	4514.697940

1657	1.903841	1.552656	3.925029	2.847121	3.543719
1718	7377.382624	3490.369741	4827.785071	5295.644677	7548.121360
1874	28.557610	46.579667	54.950399	1854.187417	836.317672
1933	0.317307	0.000003	0.000004	0.000004	0.000004
1940	1.903841	0.000003	39.250285	1.779450	0.354372

	bone_marrow	cerebral_cortex	colon	duodenum	endometrium	\
393	644.389201	450.261176	786.210311	1476.538312	827.738599	
510	1518.243824	2663.409328	3528.732999	1139.201844	1073.937771	
591	0.628672	0.381577	0.307113	0.000003	0.000004	
1315	3463.984873	2430.647195	2346.346398	1800.049515	6460.605882	
1657	3.143362	3.815773	2.764021	2.488548	16.979253	
1718	6349.591147	1938.412520	3095.703101	4330.073027	2996.838208	
1874	12623.741610	19.078863	546.661857	5275.721159	114.609960	
1933	0.000003	0.000004	1.228454	2.765053	0.000004	
1940	0.000003	0.000004	0.307113	19.355371	0.424481	

	esophagus	fallopian_tube	gallbladder	heart	kidney	\
393	511.969171	1772.872400	2049.160960	179.320080	453.572584	
510	999.391875	1113.474425	1861.762542	342.949654	495.939254	
591	0.350664	0.394849	0.814776	6.724503	1.246079	
1315	3857.301972	3293.041385	3637.973632	428.126692	799.982414	
1657	2.805311	9733.029992	4.073879	0.672450	2.492157	
1718	2114.502808	3158.792695	12201.266550	1187.995534	5587.416115	
1874	199.878375	110.557744	3055.408986	26.898012	32.398042	
1933	0.000004	0.789698	8.147757	0.000002	34.890199	
1940	0.000004	0.789698	0.000004	8.966004	0.000002	

	liver	lung	lymph_node	pancreas	placenta	\
393	532.393163	3921.923707	5612.861412	70.298851	346.775824	
510	476.813657	2925.817586	3549.309422	148.631857	2613.203533	
591	0.000003	0.390630	26.263389	0.000002	0.412828	
1315	1292.954824	4394.585827	7931.543465	188.802629	3798.020932	
1657	5.850474	3.906299	7.503825	0.200854	8.256567	
1718	5344.408289	9707.151804	5612.861412	843.586214	9032.684565	
1874	125.785198	2179.714570	1485.757432	18.076847	202.285898	
1933	13058.258680	15.625194	0.000004	4.017077	0.000004	
1940	0.000003	0.781260	0.375191	48970.179710	37.154553	

	prostate	rectum	salivary_gland	skeletal_muscle	skin	\
393	507.687681	1079.879800	565.954301	66.221554	591.541126	
510	793.708910	2558.912879	482.804617	123.898392	343.688699	
591	0.715053	0.309421	1.341124	0.000002	2.313289	
1315	3128.357190	2558.912879	992.431712	183.711409	1391.278291	
1657	7.150531	6.188423	2.145798	1.068090	9.914097	
1718	2288.169831	3945.119614	1166.777824	324.699234	1311.965514	
1874	60.779511	519.827526	13529.258260	2.136179	99.140971	
1933	0.000004	0.928263	0.000003	0.000002	0.000003	

```
1940     0.357527     0.000003       18.775735          0.213618     1.652350

      small_intestine  smooth_muscle         spleen        stomach       testis  \
393       2133.287574    1291.521900    6463.155915    1527.247028   199.442884
510       2456.422297    1797.084749    3833.015631    1715.215893  1091.687363
591          0.000003       0.424843       0.367852       0.000003     2.449299
1315      2600.037730    8322.669088    5201.424283    2232.130272  1137.174337
1657         2.094392       4.248427       3.678518       2.643312    17.494990
1718      5032.524122    4112.477630   12036.110500    3072.116138  1445.086157
1874      2058.487869     195.427656    1364.730134    7486.447452    24.492986
1933         1.196795       0.000004       0.000004       5.874027     0.349900
1940        11.967953       0.424843       3.678518       5.874027     2.799198

           thyroid       tonsil                 class  K-classes
393     609.157832  5352.577737  b'ENSG00000019582'          8
510     751.141989  2533.426473  b'ENSG00000034510'          8
591   32253.304180     0.952416  b'ENSG00000042832'          4
1315   2729.759911  6231.975147  b'ENSG00000075624'          5
1657      1.832054     3.174720  b'ENSG00000085465'          7
1718   4919.064000  2809.627104  b'ENSG00000087086'          2
1874     87.022547  1561.962187  b'ENSG00000090382'          3
1933      0.000005     0.000003  b'ENSG00000091583'          9
1940      0.000005     0.000003  b'ENSG00000091704'          1
```

4.5 K-means, K = 100

```
In [35]: from sklearn.cluster import KMeans
         kmeans = KMeans(n_clusters=100, random_state=0).fit(X)
```

```
In [36]: a = np.array(kmeans.labels_)
```

```
In [37]: unique, counts = np.unique(a, return_counts=True)
         dicionario = dict(zip(unique, counts))
         print(dicionario)
         lista = list(dicionario.items())
         class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
         class_instances
```

```
{0: 38, 1: 1, 2: 1, 3: 1, 4: 1, 5: 1, 6: 1, 7: 1, 8: 1, 9: 1, 10: 1, 11: 1, 12: 1, 13: 1, 14: 1
```

Out[37]:

	Classe	Nž Instancias
0	0	38
1	1	1
2	2	1
3	3	1
4	4	1
5	5	1
6	6	1

7	7	1
8	8	1
9	9	1
10	10	1
11	11	1
12	12	1
13	13	1
14	14	1
15	15	1
16	16	86
17	17	1
18	18	1
19	19	1
20	20	1
21	21	1
22	22	13
23	23	1
24	24	2
25	25	1
26	26	1
27	27	1
28	28	1
29	29	4
..	...	...
70	70	2
71	71	1
72	72	47
73	73	12
74	74	4
75	75	1
76	76	8
77	77	2
78	78	1
79	79	160
80	80	1
81	81	15
82	82	8
83	83	1
84	84	1
85	85	1
86	86	1
87	87	1
88	88	5
89	89	25
90	90	7
91	91	300
92	92	13
93	93	1

```
94      94              1
95      95             28
96      96              1
97      97              1
98      98              3
99      99              1

[100 rows x 2 columns]
```

4.5.1 Observando quais classes possuem mais de 10 instâncias...

```
In [38]: class_instances.loc[class_instances["Nž Instancias"] > 10]
```

```
Out[38]:     Classe  Nž Instancias
        0        0             38
        16      16             86
        22      22             13
        30      30             24
        38      38            448
        43      43             73
        55      55            519
        60      60             22
        72      72             47
        73      73             12
        79      79            160
        81      81             15
        89      89             25
        91      91            300
        92      92             13
        95      95             28
```

É possível perceber que o número de instâncias em algumas classes aumentou consideravelmente. Isso pode ser explicado pelo fato de que existem mais classes a serem alocadas, logo, os *outliers* podem ficar em classes individuais sem atrapalhar tanto o algoritmo como acontecia com as outras classes para um k menor.

4.5.2 Adicionando a coluna calculada `kmeans.label_` ao conjunto de dados

```
In [39]: dataset["K-classes"] = kmeans.labels_
```

```
In [40]: dataset.loc[ dataset["pancreas"] > 40000]
```

```
Out[40]:       adipose_tissue  adrenal_gland  animal_ovary  appendix   bladder  \
        1940        1.903841       0.000003     39.250285   1.77945  0.354372

              bone_marrow  cerebral_cortex     colon   duodenum  endometrium  \
        1940     0.000003         0.000004  0.307113  19.355371     0.424481
```

```
      esophagus  fallopian_tube  gallbladder     heart    kidney     liver  \
1940   0.000004        0.789698     0.000004  8.966004  0.000002  0.000003

         lung  lymph_node     pancreas   placenta  prostate    rectum  \
1940  0.78126    0.375191  48970.17971  37.154553  0.357527  0.000003

      salivary_gland  skeletal_muscle     skin  small_intestine  \
1940       18.775735         0.213618  1.65235        11.967953

      smooth_muscle    spleen   stomach    testis   thyroid    tonsil  \
1940       0.424843  3.678518  5.874027  2.799198  0.000005  0.000003

                  class  K-classes
1940  b'ENSG00000091704'          1
```

4.6 Hierárquico, K = 2

```
In [41]: from sklearn.cluster import AgglomerativeClustering
         clustering = AgglomerativeClustering(n_clusters=2, affinity='euclidean', linkage="ward
```

```
In [42]: a = np.array(clustering.labels_)
```

```
In [43]: unique, counts = np.unique(a, return_counts=True)
         dicionario = dict(zip(unique, counts))
         print(dicionario)
         lista = list(dicionario.items())
         class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
         class_instances
```

```
{0: 1999, 1: 1}
```

```
Out[43]:    Classe  Nž Instancias
         0       0           1999
         1       1              1
```

```
In [44]: dataset.drop("K-classes", axis=1, inplace=True)
```

```
In [45]: dataset["K-classes-hierar"] = clustering.labels_
```

```
In [46]: dataset.loc[ dataset["pancreas"] > 40000]
```

```
Out[46]:       adipose_tissue  adrenal_gland  animal_ovary  appendix   bladder  \
         1940        1.903841       0.000003     39.250285   1.77945  0.354372

               bone_marrow  cerebral_cortex     colon   duodenum  endometrium  \
         1940     0.000003         0.000004  0.307113  19.355371     0.424481

               esophagus  fallopian_tube  gallbladder     heart    kidney     liver  \
```

```
1940   0.000004        0.789698     0.000004   8.966004   0.000002   0.000003

         lung  lymph_node     pancreas   placenta  prostate    rectum  \
1940  0.78126    0.375191  48970.17971  37.154553  0.357527  0.000003

      salivary_gland  skeletal_muscle     skin  small_intestine  \
1940       18.775735         0.213618  1.65235        11.967953

      smooth_muscle    spleen   stomach    testis   thyroid    tonsil  \
1940       0.424843  3.678518  5.874027  2.799198  0.000005  0.000003

                  class  K-classes-hierar
1940  b'ENSG00000091704'                 1
```

4.7 Hierárquico, K = 5

```
In [47]: from sklearn.cluster import AgglomerativeClustering
         clustering = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage="ward
```

```
In [48]: a = np.array(clustering.labels_)
```

4.7.1 Percebemos que a classe 2 possui muitas instâncias quando comparamos com as outras classes, o que caracteriza um desbalanceamento de classes. Com o desbalanceamento, isto prejudica significativamente a classificação do algoritmo e separação em grupos.

```
In [49]: unique, counts = np.unique(a, return_counts=True)
         dicionario = dict(zip(unique, counts))
         print(dicionario)
         lista = list(dicionario.items())
         class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
         class_instances
```

```
{0: 4, 1: 1, 2: 1993, 3: 1, 4: 1}
```

```
Out[49]:    Classe  Nž Instancias
         0       0              4
         1       1              1
         2       2           1993
         3       3              1
         4       4              1
```

```
In [50]: dataset["K-classes-hierar"] = clustering.labels_
```

```
In [51]: dataset.loc[dataset["K-classes-hierar"] != 2]
```

```
Out[51]:      adipose_tissue  adrenal_gland  animal_ovary     appendix      bladder  \
         393      621.921288     586.903809    726.130275  3459.251765  1998.657487
         510     2138.647694     794.959656   3768.027372  3800.906260  1587.586089
```

591	0.317307	1.863187	0.000004	0.711780	0.708744
1315	2027.590321	1400.495332	2296.141680	7644.519332	4514.697940
1718	7377.382624	3490.369741	4827.785071	5295.644677	7548.121360
1874	28.557610	46.579667	54.950399	1854.187417	836.317672
1940	1.903841	0.000003	39.250285	1.779450	0.354372

	bone_marrow	cerebral_cortex	colon	duodenum	endometrium \
393	644.389201	450.261176	786.210311	1476.538312	827.738599
510	1518.243824	2663.409328	3528.732999	1139.201844	1073.937771
591	0.628672	0.381577	0.307113	0.000003	0.000004
1315	3463.984873	2430.647195	2346.346398	1800.049515	6460.605882
1718	6349.591147	1938.412520	3095.703101	4330.073027	2996.838208
1874	12623.741610	19.078863	546.661857	5275.721159	114.609960
1940	0.000003	0.000004	0.307113	19.355371	0.424481

	esophagus	fallopian_tube	gallbladder	heart	kidney \
393	511.969171	1772.872400	2049.160960	179.320080	453.572584
510	999.391875	1113.474425	1861.762542	342.949654	495.939254
591	0.350664	0.394849	0.814776	6.724503	1.246079
1315	3857.301972	3293.041385	3637.973632	428.126692	799.982414
1718	2114.502808	3158.792695	12201.266550	1187.995534	5587.416115
1874	199.878375	110.557744	3055.408986	26.898012	32.398042
1940	0.000004	0.789698	0.000004	8.966004	0.000002

	liver	lung	lymph_node	pancreas	placenta \
393	532.393163	3921.923707	5612.861412	70.298851	346.775824
510	476.813657	2925.817586	3549.309422	148.631857	2613.203533
591	0.000003	0.390630	26.263389	0.000002	0.412828
1315	1292.954824	4394.585827	7931.543465	188.802629	3798.020932
1718	5344.408289	9707.151804	5612.861412	843.586214	9032.684565
1874	125.785198	2179.714570	1485.757432	18.076847	202.285898
1940	0.000003	0.781260	0.375191	48970.179710	37.154553

	prostate	rectum	salivary_gland	skeletal_muscle	skin \
393	507.687681	1079.879800	565.954301	66.221554	591.541126
510	793.708910	2558.912879	482.804617	123.898392	343.688699
591	0.715053	0.309421	1.341124	0.000002	2.313289
1315	3128.357190	2558.912879	992.431712	183.711409	1391.278291
1718	2288.169831	3945.119614	1166.777824	324.699234	1311.965514
1874	60.779511	519.827526	13529.258260	2.136179	99.140971
1940	0.357527	0.000003	18.775735	0.213618	1.652350

	small_intestine	smooth_muscle	spleen	stomach	testis \
393	2133.287574	1291.521900	6463.155915	1527.247028	199.442884
510	2456.422297	1797.084749	3833.015631	1715.215893	1091.687363
591	0.000003	0.424843	0.367852	0.000003	2.449299
1315	2600.037730	8322.669088	5201.424283	2232.130272	1137.174337
1718	5032.524122	4112.477630	12036.110500	3072.116138	1445.086157

```
1874      2058.487869     195.427656   1364.730134  7486.447452    24.492986
1940        11.967953       0.424843      3.678518     5.874027     2.799198

           thyroid       tonsil               class  K-classes-hierar
393     609.157832  5352.577737  b'ENSG00000019582'                 0
510     751.141989  2533.426473  b'ENSG00000034510'                 0
591   32253.304180     0.952416  b'ENSG00000042832'                 3
1315   2729.759911  6231.975147  b'ENSG00000075624'                 0
1718   4919.064000  2809.627104  b'ENSG00000087086'                 0
1874     87.022547  1561.962187  b'ENSG00000090382'                 4
1940      0.000005     0.000003  b'ENSG00000091704'                 1
```

4.8 Hierárquico, K = 10

In [52]:
```
from sklearn.cluster import AgglomerativeClustering
clustering = AgglomerativeClustering(n_clusters=10, affinity='euclidean', linkage="wa
```

In [53]:
```
a = np.array(clustering.labels_)
```

In [54]:
```
unique, counts = np.unique(a, return_counts=True)
dicionario = dict(zip(unique, counts))
print(dicionario)
lista = list(dicionario.items())
class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
class_instances
```

```
{0: 60, 1: 1, 2: 1931, 3: 1, 4: 1, 5: 1, 6: 2, 7: 1, 8: 1, 9: 1}
```

Out[54]:

	Classe	Nž Instancias
0	0	60
1	1	1
2	2	1931
3	3	1
4	4	1
5	5	1
6	6	2
7	7	1
8	8	1
9	9	1

In [55]:
```
dataset["K-classes-hierar"] = clustering.labels_
```

In [56]:
```
dataset.loc[(dataset["K-classes-hierar"] != 2) & (dataset["K-classes-hierar"] != 0)]
```

Out[56]:

```
      adipose_tissue  adrenal_gland  animal_ovary    appendix      bladder  \
393       621.921288     586.903809    726.130275  3459.251765  1998.657487
510      2138.647694     794.959656   3768.027372  3800.906260  1587.586089
591         0.317307       1.863187      0.000004     0.711780     0.708744
```

```
1315    2027.590321    1400.495332   2296.141680  7644.519332  4514.697940
1657       1.903841       1.552656      3.925029     2.847121     3.543719
1718    7377.382624    3490.369741   4827.785071  5295.644677  7548.121360
1874      28.557610      46.579667     54.950399  1854.187417   836.317672
1933       0.317307       0.000003      0.000004     0.000004     0.000004
1940       1.903841       0.000003     39.250285     1.779450     0.354372

       bone_marrow  cerebral_cortex        colon     duodenum  endometrium  \
393     644.389201       450.261176   786.210311  1476.538312   827.738599
510    1518.243824      2663.409328  3528.732999  1139.201844  1073.937771
591       0.628672         0.381577     0.307113     0.000003     0.000004
1315   3463.984873      2430.647195  2346.346398  1800.049515  6460.605882
1657      3.143362         3.815773     2.764021     2.488548    16.979253
1718   6349.591147      1938.412520  3095.703101  4330.073027  2996.838208
1874  12623.741610        19.078863   546.661857  5275.721159   114.609960
1933      0.000003         0.000004     1.228454     2.765053     0.000004
1940      0.000003         0.000004     0.307113    19.355371     0.424481

        esophagus  fallopian_tube   gallbladder        heart       kidney  \
393    511.969171     1772.872400   2049.160960   179.320080   453.572584
510    999.391875     1113.474425   1861.762542   342.949654   495.939254
591      0.350664        0.394849      0.814776     6.724503     1.246079
1315  3857.301972     3293.041385   3637.973632   428.126692   799.982414
1657     2.805311     9733.029992      4.073879     0.672450     2.492157
1718  2114.502808     3158.792695  12201.266550  1187.995534  5587.416115
1874   199.878375      110.557744   3055.408986    26.898012    32.398042
1933     0.000004        0.789698      8.147757     0.000002    34.890199
1940     0.000004        0.789698      0.000004     8.966004     0.000002

             liver         lung   lymph_node      pancreas     placenta  \
393     532.393163  3921.923707  5612.861412     70.298851   346.775824
510     476.813657  2925.817586  3549.309422    148.631857  2613.203533
591       0.000003     0.390630    26.263389      0.000002     0.412828
1315   1292.954824  4394.585827  7931.543465    188.802629  3798.020932
1657      5.850474     3.906299     7.503825      0.200854     8.256567
1718   5344.408289  9707.151804  5612.861412    843.586214  9032.684565
1874    125.785198  2179.714570  1485.757432     18.076847   202.285898
1933  13058.258680    15.625194     0.000004      4.017077     0.000004
1940      0.000003     0.781260     0.375191  48970.179710    37.154553

        prostate       rectum  salivary_gland  skeletal_muscle         skin  \
393   507.687681  1079.879800      565.954301        66.221554   591.541126
510   793.708910  2558.912879      482.804617       123.898392   343.688699
591     0.715053     0.309421        1.341124         0.000002     2.313289
1315 3128.357190  2558.912879      992.431712       183.711409  1391.278291
1657    7.150531     6.188423        2.145798         1.068090     9.914097
1718 2288.169831  3945.119614     1166.777824       324.699234  1311.965514
1874   60.779511   519.827526    13529.258260         2.136179    99.140971
```

```
1933      0.000004      0.928263       0.000003         0.000002      0.000003
1940      0.357527      0.000003      18.775735         0.213618      1.652350

      small_intestine  smooth_muscle        spleen      stomach       testis  \
393       2133.287574    1291.521900   6463.155915  1527.247028   199.442884
510       2456.422297    1797.084749   3833.015631  1715.215893  1091.687363
591          0.000003       0.424843      0.367852     0.000003     2.449299
1315      2600.037730    8322.669088   5201.424283  2232.130272  1137.174337
1657         2.094392       4.248427      3.678518     2.643312    17.494990
1718      5032.524122    4112.477630  12036.110500  3072.116138  1445.086157
1874      2058.487869     195.427656   1364.730134  7486.447452    24.492986
1933         1.196795       0.000004      0.000004     5.874027     0.349900
1940        11.967953       0.424843      3.678518     5.874027     2.799198

          thyroid       tonsil                class  K-classes-hierar
393    609.157832  5352.577737  b'ENSG00000019582'                 6
510    751.141989  2533.426473  b'ENSG00000034510'                 6
591  32253.304180     0.952416  b'ENSG00000042832'                 7
1315  2729.759911  6231.975147  b'ENSG00000075624'                 8
1657     1.832054     3.174720  b'ENSG00000085465'                 9
1718  4919.064000  2809.627104  b'ENSG00000087086'                 5
1874    87.022547  1561.962187  b'ENSG00000090382'                 4
1933     0.000005     0.000003  b'ENSG00000091583'                 3
1940     0.000005     0.000003  b'ENSG00000091704'                 1
```

4.9 Hierárquico, K = 100

In [57]:
```python
from sklearn.cluster import AgglomerativeClustering
clustering = AgglomerativeClustering(n_clusters=100, affinity='euclidean', linkage="wa
```

In [58]:
```python
a = np.array(clustering.labels_)
```

In [59]:
```python
unique, counts = np.unique(a, return_counts=True)
dicionario = dict(zip(unique, counts))
print(dicionario)
lista = list(dicionario.items())
class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
class_instances
```

```
{0: 564, 1: 2, 2: 10, 3: 28, 4: 10, 5: 12, 6: 8, 7: 6, 8: 4, 9: 69, 10: 9, 11: 34, 12: 5, 13: :
```

Out[59]:

	Classe	Nž Instancias
0	0	564
1	1	2
2	2	10
3	3	28
4	4	10
5	5	12

6	6	8
7	7	6
8	8	4
9	9	69
10	10	9
11	11	34
12	12	5
13	13	2
14	14	2
15	15	2
16	16	15
17	17	3
18	18	13
19	19	17
20	20	333
21	21	8
22	22	2
23	23	320
24	24	2
25	25	1
26	26	1
27	27	2
28	28	2
29	29	60
..	...	...
70	70	1
71	71	1
72	72	1
73	73	1
74	74	3
75	75	1
76	76	1
77	77	1
78	78	1
79	79	1
80	80	1
81	81	1
82	82	1
83	83	1
84	84	1
85	85	1
86	86	1
87	87	1
88	88	8
89	89	1
90	90	4
91	91	1
92	92	1

```
93      93              1
94      94              1
95      95              1
96      96              1
97      97              1
98      98              1
99      99              1

[100 rows x 2 columns]
```

4.9.1 Com k = 100 percebemos que há uma diversidade maior de classes com mais de dez instâncias

In [60]:
```
class_instances.loc[class_instances["Nž Instancias"] > 10]
```

Out[60]:
```
    Classe  Nž Instancias
0        0            564
3        3             28
5        5             12
9        9             69
11      11             34
16      16             15
18      18             13
19      19             17
20      20            333
23      23            320
29      29             60
34      34             20
40      40             19
44      44            203
48      48             33
49      49             79
```

In [61]:
```
dataset["K-classes-hierar"] = clustering.labels_
```

In [62]:
```
dataset.describe()
```

Out[62]:
```
       adipose_tissue  adrenal_gland  animal_ovary    appendix     bladder  \
count     2000.000000    2000.000000   2000.000000 2000.000000 2000.000000
mean        39.040157      41.486336     51.338392   52.555181   48.932735
std        195.264717     181.466441    210.726346  252.295704  221.732356
min          0.000003       0.000003      0.000004    0.000004    0.000004
25%          3.173068       3.105311      3.140023    7.117802    7.087438
50%         12.692271      15.526556     19.625143   21.353406   21.262314
75%         31.730678      34.158423     43.175314   46.265713   42.524627
max       7377.382624    5216.922745   4827.785071 7644.519332 7548.121360

       bone_marrow  cerebral_cortex       colon    duodenum  endometrium  \
count  2000.000000      2000.000000 2000.000000 2000.000000  2000.000000
```

mean	53.852077	45.797667	40.663197	39.632611	52.066032
std	393.758129	123.183344	157.028175	185.991398	186.169270
min	0.000003	0.000004	0.000003	0.000003	0.000004
25%	1.257345	7.631545	3.071134	2.765053	7.428423
50%	9.430086	19.078863	15.355670	13.825265	21.224067
75%	34.576981	41.973499	33.782474	30.415583	50.937760
max	12623.741610	2663.409328	3528.732999	5275.721159	6460.605882

	esophagus	fallopian_tube	gallbladder	heart	kidney \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	41.493874	53.691974	57.023709	21.915492	27.728612
std	139.247221	261.725555	314.203534	116.726607	136.411996
min	0.000004	0.000004	0.000004	0.000002	0.000002
25%	3.506638	7.896982	8.147757	1.569051	2.492157
50%	14.026553	23.690945	20.369393	6.724503	9.968628
75%	35.066382	47.381890	48.886544	15.690507	24.921571
max	3857.301972	9733.029992	12201.266550	4512.141526	5587.416115

	liver	lung	lymph_node	pancreas	placenta \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	35.790131	54.864549	54.294117	35.087462	52.105545
std	336.523288	277.654367	277.993904	1108.114405	242.242244
min	0.000003	0.000004	0.000004	0.000002	0.000004
25%	1.170095	7.812597	3.751913	0.602562	4.128284
50%	5.850474	23.437791	18.759564	2.008539	20.641418
75%	17.551423	46.875582	48.774865	6.025616	45.411120
max	13058.258680	9707.151804	7931.543465	48970.179710	9032.684565

	prostate	rectum	salivary_gland	skeletal_muscle	skin \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	46.389605	42.376928	27.628763	22.053380	35.257338
std	241.613858	165.470468	308.543568	208.651352	95.223057
min	0.000004	0.000003	0.000003	0.000002	0.000003
25%	7.150531	3.094211	2.414023	0.427236	3.304699
50%	17.876327	15.471057	8.046744	2.136179	16.523495
75%	42.903184	34.036326	18.775735	8.544717	36.351689
max	9585.286431	3945.119614	13529.258260	7732.968610	1939.858329

	small_intestine	smooth_muscle	spleen	stomach	testis \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	43.396844	52.185982	56.164531	37.587312	44.472439
std	193.638153	233.848790	347.561819	207.009834	114.878046
min	0.000003	0.000004	0.000004	0.000003	0.000003
25%	5.983976	4.248427	3.678518	5.874027	6.997996
50%	14.959941	21.242137	22.071107	14.685068	20.993988
75%	32.911870	42.484273	47.820732	29.370135	45.486973
max	5032.524122	8322.669088	12036.110500	7486.447452	2554.268510

	thyroid	tonsil	K-classes-hierar
count	2000.000000	2000.000000	2000.000000
mean	72.736881	46.143284	20.402500
std	742.846516	222.768691	19.007371
min	0.000005	0.000003	0.000000
25%	4.580134	3.174720	0.000000
50%	22.900670	15.873599	20.000000
75%	54.961609	38.096639	29.000000
max	32253.304180	6231.975147	99.000000

Para k = 100, percebeu-se que as classes com maior quantidade de instâncias foram as iniciais no Hierárquico. Já no K-Means, as classes intermediárias apresentaram a maior quantidade de instâncias.

5 2.1. Fixar K no K-means e alterar o parâmetro de quantidade máxima de iterações

Escolha um número fixo de K e altere o parâmetro do K-Means referente ao número máximo de iterações: 1, 10 e 100.

5.1 K-means com K = 50, max_iter = 1

```
In [63]: from sklearn.cluster import KMeans
         kmeans = KMeans(n_clusters=50, max_iter=1, random_state=0).fit(X)

In [64]: a = np.array(kmeans.labels_)

In [65]: unique, counts = np.unique(a, return_counts=True)
         dicionario = dict(zip(unique, counts))
         print(dicionario)
         lista = list(dicionario.items())
         class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
         class_instances
```

```
{0: 238, 1: 1, 2: 1, 3: 1, 4: 1, 5: 1, 6: 1, 7: 1, 8: 1, 9: 1, 10: 1, 11: 1, 12: 1, 13: 1, 14:
```

Out[65]:

	Classe	Nž Instancias
0	0	238
1	1	1
2	2	1
3	3	1
4	4	1
5	5	1
6	6	1
7	7	1
8	8	1
9	9	1

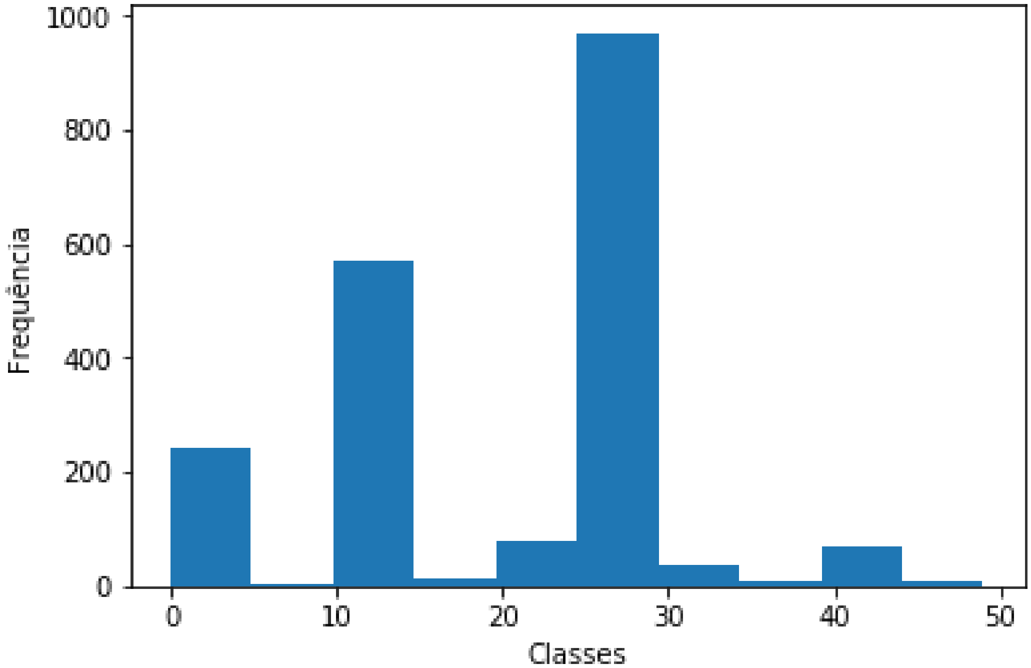
```
10    10      1
11    11      1
12    12      1
13    13      1
14    14    568
15    15      2
16    16      1
17    17      6
18    18      1
19    19      1
20    20      2
21    21     72
22    22      1
23    23      1
24    24      1
25    25     11
26    26      4
27    27      2
28    28    952
29    29      1
30    30      1
31    31     31
32    32      1
33    33      2
34    34      3
35    35      1
36    36      1
37    37      1
38    38      2
39    39      3
40    40     35
41    41      2
42    42      2
43    43     27
44    44      1
45    45      2
46    46      5
47    47      1
48    48      1
49    49      1
```

5.1.1 Adicionando a coluna calculada `kmeans.label_` ao conjunto de dados

```
In [66]: dataset["K-classes"] = kmeans.labels_
```

```
In [67]: dataset['K-classes'].plot(kind='hist')
         plt.xlabel('Classes')
         plt.ylabel('Frequência')
```

Out[67]: Text(0,0.5,'Frequência')




```
In [68]: class_instances.loc[class_instances["Nž Instancias"] > 10]
```

Out[68]:

	Classe	Nž Instancias
0	0	238
14	14	568
21	21	72
25	25	11
28	28	952
31	31	31
40	40	35
43	43	27

5.2 K-means com K = 50, max_iter = 10

```
In [69]: from sklearn.cluster import KMeans
         kmeans = KMeans(n_clusters=50, max_iter=10, random_state=0).fit(X)

In [70]: a = np.array(kmeans.labels_)

In [71]: unique, counts = np.unique(a, return_counts=True)
         dicionario = dict(zip(unique, counts))
         print(dicionario)
         lista = list(dicionario.items())
         class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
         class_instances
```

```
{0: 207, 1: 1, 2: 1, 3: 1, 4: 1, 5: 1, 6: 1, 7: 1, 8: 1, 9: 1, 10: 1, 11: 1, 12: 1, 13: 1, 14:
```

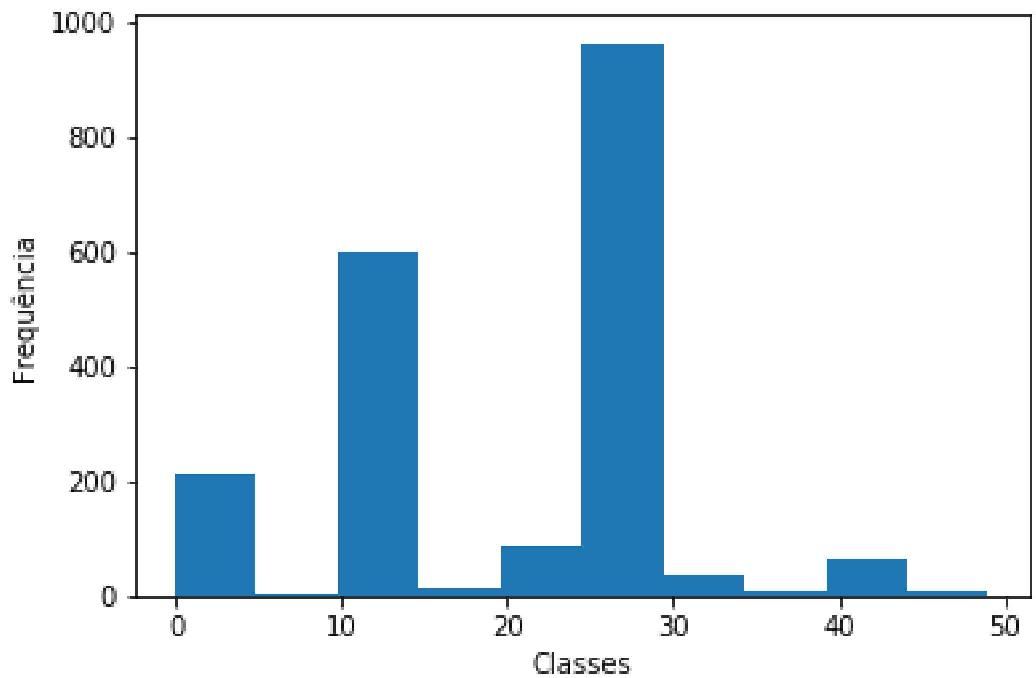
Out[71]:

	Classe	Nž Instancias
0	0	207
1	1	1
2	2	1
3	3	1
4	4	1
5	5	1
6	6	1
7	7	1
8	8	1
9	9	1
10	10	1
11	11	1
12	12	1
13	13	1
14	14	596
15	15	2
16	16	1
17	17	6
18	18	1
19	19	1
20	20	2
21	21	83
22	22	1
23	23	1
24	24	1
25	25	11
26	26	4
27	27	2
28	28	945
29	29	1
30	30	1
31	31	31
32	32	1
33	33	2
34	34	3
35	35	1
36	36	1
37	37	1
38	38	2
39	39	3
40	40	35
41	41	2
42	42	2
43	43	26

```
44        44                1
45        45                2
46        46                5
47        47                1
48        48                1
49        49                1
```

5.2.1 Adicionando a coluna calculada kmeans.label_ ao conjunto de dados

```
In [72]: dataset["K-classes"] = kmeans.labels_

In [73]: dataset['K-classes'].plot(kind='hist')
         plt.xlabel('Classes')
         plt.ylabel('Frequência')

Out[73]: Text(0,0.5,'Frequência')
```




```
In [74]: class_instances.loc[class_instances["Nž Instancias"] > 10]

Out[74]:     Classe  Nž Instancias
         0        0            207
         14      14            596
         21      21             83
         25      25             11
         28      28            945
```

31	31	31
40	40	35
43	43	26

5.3 K-means com K = 50, max_iter = 100

```
In [99]: from sklearn.cluster import KMeans
         kmeans = KMeans(n_clusters=50, max_iter=100, random_state=0).fit(X)
         y_kmeans = kmeans.fit_predict(X)
```

```
In [100]: a = np.array(kmeans.labels_)
```

```
In [101]: unique, counts = np.unique(a, return_counts=True)
          dicionario = dict(zip(unique, counts))
          print(dicionario)
          lista = list(dicionario.items())
          class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
          class_instances
```

```
{0: 207, 1: 1, 2: 1, 3: 1, 4: 1, 5: 1, 6: 1, 7: 1, 8: 1, 9: 1, 10: 1, 11: 1, 12: 1, 13: 1, 14:
```

Out[101]:

	Classe	Nž Instancias
0	0	207
1	1	1
2	2	1
3	3	1
4	4	1
5	5	1
6	6	1
7	7	1
8	8	1
9	9	1
10	10	1
11	11	1
12	12	1
13	13	1
14	14	596
15	15	2
16	16	1
17	17	6
18	18	1
19	19	1
20	20	2
21	21	83
22	22	1
23	23	1
24	24	1
25	25	11

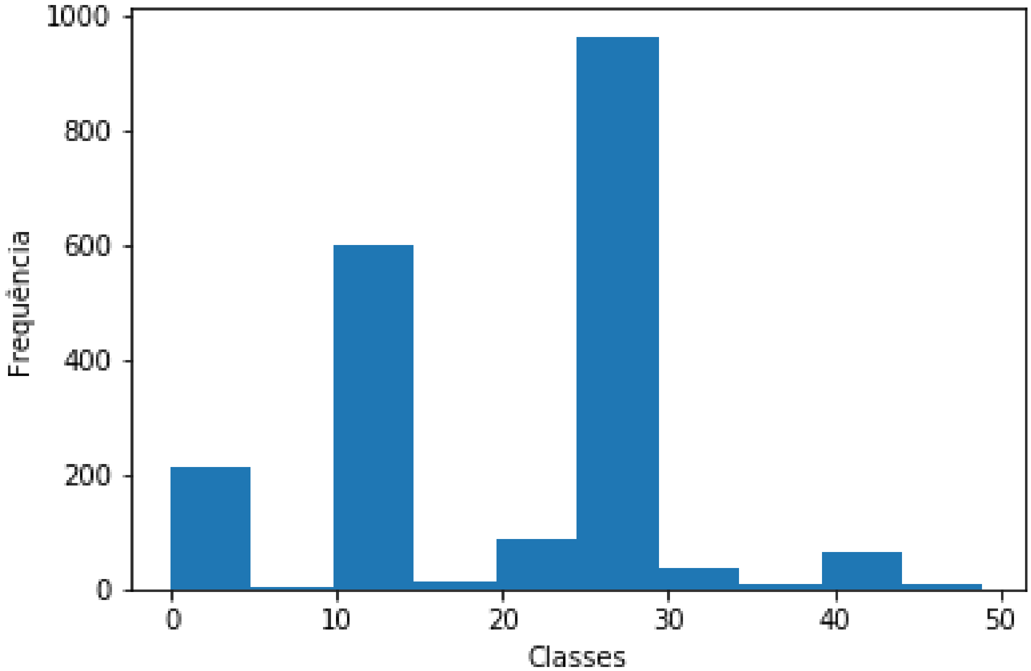
```
26         26                4
27         27                2
28         28              945
29         29                1
30         30                1
31         31               31
32         32                1
33         33                2
34         34                3
35         35                1
36         36                1
37         37                1
38         38                2
39         39                3
40         40               35
41         41                2
42         42                2
43         43               26
44         44                1
45         45                2
46         46                5
47         47                1
48         48                1
49         49                1
```

5.3.1 Adicionando a coluna calculada kmeans.label_ ao conjunto de dados

```
In [102]: dataset["K-classes"] = kmeans.labels_
```

```
In [103]: dataset['K-classes'].plot(kind='hist')
          plt.xlabel('Classes')
          plt.ylabel('Frequência')
```

```
Out[103]: Text(0,0.5,'Frequência')
```




```
In [104]: class_instances.loc[class_instances["Nž Instancias"] > 10]

Out[104]:     Classe  Nž Instancias
          0        0            207
          14      14            596
          21      21             83
          25      25             11
          28      28            945
          31      31             31
          40      40             35
          43      43             26
```

6 2.2. Alterar o parâmetro linkage do Hierárquico

Linkage : {"ward", "complete", "average", "single"}, optional (default="ward") Which linkage criterion to use. The linkage criterion determines which distance to use between sets of observation. The algorithm will merge the pairs of cluster that minimize this criterion.

ward minimizes the variance of the clusters being merged. average uses the average of the distances of each observation of the two sets. complete or maximum linkage uses the maximum distances between all observations of the two sets. single uses the minimum of the distances between all observations of the two sets.

Referência: http://scikit-learn.org/stable/modules/generated/sklearn.cluster.AgglomerativeClustering.htm

6.1 Hierárquico, K = 100

In [88]:
```
from sklearn.cluster import AgglomerativeClustering
clustering = AgglomerativeClustering(n_clusters=100, affinity='euclidean', linkage="a
```

In [89]:
```
a = np.array(clustering.labels_)
```

In [90]:
```
unique, counts = np.unique(a, return_counts=True)
dicionario = dict(zip(unique, counts))
print(dicionario)
lista = list(dicionario.items())
class_instances = pd.DataFrame(lista, columns=["Classe", "Nž Instancias"])
class_instances
```

```
{0: 1824, 1: 21, 2: 2, 3: 6, 4: 16, 5: 3, 6: 4, 7: 1, 8: 3, 9: 2, 10: 2, 11: 3, 12: 2, 13: 1,
```

Out[90]:

	Classe	Nž Instancias
0	0	1824
1	1	21
2	2	2
3	3	6
4	4	16
5	5	3
6	6	4
7	7	1
8	8	3
9	9	2
10	10	2
11	11	3
12	12	2
13	13	1
14	14	4
15	15	1
16	16	1
17	17	1
18	18	1
19	19	1
20	20	5
21	21	1
22	22	1
23	23	3
24	24	2
25	25	1
26	26	1
27	27	1
28	28	1
29	29	1
..	...	...

```
70      70               1
71      71               1
72      72               1
73      73               1
74      74               1
75      75               1
76      76               1
77      77               1
78      78               1
79      79               1
80      80               1
81      81               1
82      82               1
83      83               1
84      84               1
85      85               1
86      86               1
87      87               1
88      88               1
89      89               1
90      90               1
91      91               1
92      92               1
93      93               1
94      94               1
95      95               1
96      96               1
97      97               1
98      98               9
99      99               1

[100 rows x 2 columns]
```

```
In [91]: class_instances.loc[class_instances["Nž Instancias"] > 10]
```

```
Out[91]:    Classe  Nž Instancias
        0       0           1824
        1       1             21
        4       4             16
```

```
In [92]: dataset['K-classes-hierar'] = clustering.labels_
```

```
In [93]: dataset.describe()
```

```
Out[93]:        adipose_tissue  adrenal_gland  animal_ovary     appendix      bladder  \
        count      2000.000000    2000.000000   2000.000000  2000.000000  2000.000000
        mean         39.040157      41.486336     51.338392    52.555181    48.932735
        std         195.264717     181.466441    210.726346   252.295704   221.732356
        min           0.000003       0.000003      0.000004     0.000004     0.000004
```

25%	3.173068	3.105311	3.140023	7.117802	7.087438
50%	12.692271	15.526556	19.625143	21.353406	21.262314
75%	31.730678	34.158423	43.175314	46.265713	42.524627
max	7377.382624	5216.922745	4827.785071	7644.519332	7548.121360

	bone_marrow	cerebral_cortex	colon	duodenum	endometrium \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	53.852077	45.797667	40.663197	39.632611	52.066032
std	393.758129	123.183344	157.028175	185.991398	186.169270
min	0.000003	0.000004	0.000003	0.000003	0.000004
25%	1.257345	7.631545	3.071134	2.765053	7.428423
50%	9.430086	19.078863	15.355670	13.825265	21.224067
75%	34.576981	41.973499	33.782474	30.415583	50.937760
max	12623.741610	2663.409328	3528.732999	5275.721159	6460.605882

	esophagus	fallopian_tube	gallbladder	heart	kidney \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	41.493874	53.691974	57.023709	21.915492	27.728612
std	139.247221	261.725555	314.203534	116.726607	136.411996
min	0.000004	0.000004	0.000004	0.000002	0.000002
25%	3.506638	7.896982	8.147757	1.569051	2.492157
50%	14.026553	23.690945	20.369393	6.724503	9.968628
75%	35.066382	47.381890	48.886544	15.690507	24.921571
max	3857.301972	9733.029992	12201.266550	4512.141526	5587.416115

	liver	lung	lymph_node	pancreas	placenta \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	35.790131	54.864549	54.294117	35.087462	52.105545
std	336.523288	277.654367	277.993904	1108.114405	242.242244
min	0.000003	0.000004	0.000004	0.000002	0.000004
25%	1.170095	7.812597	3.751913	0.602562	4.128284
50%	5.850474	23.437791	18.759564	2.008539	20.641418
75%	17.551423	46.875582	48.774865	6.025616	45.411120
max	13058.258680	9707.151804	7931.543465	48970.179710	9032.684565

	prostate	rectum	salivary_gland	skeletal_muscle	skin \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	46.389605	42.376928	27.628763	22.053380	35.257338
std	241.613858	165.470468	308.543568	208.651352	95.223057
min	0.000004	0.000003	0.000003	0.000002	0.000003
25%	7.150531	3.094211	2.414023	0.427236	3.304699
50%	17.876327	15.471057	8.046744	2.136179	16.523495
75%	42.903184	34.036326	18.775735	8.544717	36.351689
max	9585.286431	3945.119614	13529.258260	7732.968610	1939.858329

	small_intestine	smooth_muscle	spleen	stomach	testis \
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	43.396844	52.185982	56.164531	37.587312	44.472439

std	193.638153	233.848790	347.561819	207.009834	114.878046
min	0.000003	0.000004	0.000004	0.000003	0.000003
25%	5.983976	4.248427	3.678518	5.874027	6.997996
50%	14.959941	21.242137	22.071107	14.685068	20.993988
75%	32.911870	42.484273	47.820732	29.370135	45.486973
max	5032.524122	8322.669088	12036.110500	7486.447452	2554.268510

	thyroid	tonsil	K-classes-hierar	K-classes
count	2000.000000	2000.000000	2000.00000	2000.000000
mean	72.736881	46.143284	3.20350	21.039000
std	742.846516	222.768691	14.20521	10.258708
min	0.000005	0.000003	0.00000	0.000000
25%	4.580134	3.174720	0.00000	14.000000
50%	22.900670	15.873599	0.00000	28.000000
75%	54.961609	38.096639	0.00000	28.000000
max	32253.304180	6231.975147	99.00000	49.000000

```
In [94]: dataset['K-classes-hierar'].plot(kind='hist')
         plt.xlabel('Classes')
         plt.ylabel('Frequência')

Out[94]: Text(0,0.5,'Frequência')
```