DIABETES-definitivo

March 25, 2020

COVID-19: ULAs

Rodrigo Carrillo-Larco, Manuel Castillo-Cara Universidad Peruana Cayetano Heredia Universidad Nacional de Ingeniería

---

Índice

---

1. Introducción

[2]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pylab as pl
import pandas as pd
import os
```

0.0.1 Lectura de datos

[3]:
```
df_original = pd.read_csv('dataset/data_2020-03-22.csv', parse_dates=[2])
df_original.head(1)
```

[3]:
```
       Country  Speed.Number first_date  order  total_deaths      p.db  \
0  Afghanistan      0.888889 2020-02-24     34             0  0.105599
```

```
    ylds.db   p.copd  ylds.copd     p.hiv  ylds.hiv     p.tbc  ylds.tbc  \
0  0.052702  0.05014   0.030484  0.000186  0.000165  0.261146  0.001078

     GDP_2017       pop_men     pop_women  prop_men  pm2.5  UHC_index_2017
0  556.302138  1.674320e+07  1.611156e+07  0.509613   53.2              37
```

[5]:
```
df = pd.read_csv('dataset/data_2020-03-22.csv', parse_dates=[2])
df.drop(['pop_men'], axis=1, inplace=True)
df.drop(['pop_women'], axis=1, inplace=True)
#df.drop(['p.db'], axis=1, inplace=True)
#df.drop(['p.copd'], axis=1, inplace=True)
#df.drop(['p.hiv'], axis=1, inplace=True)
#df.drop(['p.tbc'], axis=1, inplace=True)
df.drop(['ylds.db'], axis=1, inplace=True)
df.drop(['ylds.copd'], axis=1, inplace=True)
df.drop(['ylds.hiv'], axis=1, inplace=True)
df.drop(['ylds.tbc'], axis=1, inplace=True)
df.drop(['Country'], axis=1, inplace=True)
df.drop(['Speed.Number'], axis=1, inplace=True)
df.drop(['first_date'], axis=1, inplace=True)
df.drop(['order'], axis=1, inplace=True)
df.drop(['total_deaths'], axis=1, inplace=True)
```

---

2. Análisis Exploratorio de Datos

[6]:
```
df.dtypes
```

[6]:
```
p.db              float64
p.copd            float64
p.hiv             float64
p.tbc             float64
GDP_2017          float64
prop_men          float64
pm2.5             float64
UHC_index_2017      int64
dtype: object
```

[7]:
```
df.describe().transpose()
```

[7]:
```
                count      mean       std       min       25%  \
p.db            155.0  0.075416  0.024032  0.040218  0.058969
p.copd          155.0  0.035794  0.010533  0.015853  0.028062
p.hiv           155.0  0.007677  0.018914  0.000011  0.000456
```

```
p.tbc           155.0       0.204458      0.101806    0.051712     0.122820
GDP_2017        155.0   14913.661431  19415.536446  309.055355  2403.065919
prop_men        155.0       0.501432      0.036320    0.459118     0.487198
pm2.5           155.0      25.774194     17.370791    5.700000    14.150000
UHC_index_2017  155.0      66.045161     15.452206   25.000000    55.000000

                        50%           75%            max
p.db               0.069308      0.089140       0.222176
p.copd             0.034655      0.041736       0.082202
p.hiv              0.001715      0.005737       0.119882
p.tbc              0.195166      0.270030       0.519770
GDP_2017        6284.192672  17470.845955  107361.306900
prop_men           0.495217      0.502629       0.754109
pm2.5             20.200000     32.900000      94.300000
UHC_index_2017    71.000000     77.000000      89.000000
```

[8]:
```
df.shape
```

[8]:
```
(155, 8)
```

[9]:
```
list_columns = df.columns
```

2.1. Data Cleaning: Handling missing data

[10]:
```
df.isnull().any().any(), df.shape
```

[10]:
```
(False, (155, 8))
```

[11]:
```
df.isnull().sum(axis=0)
```

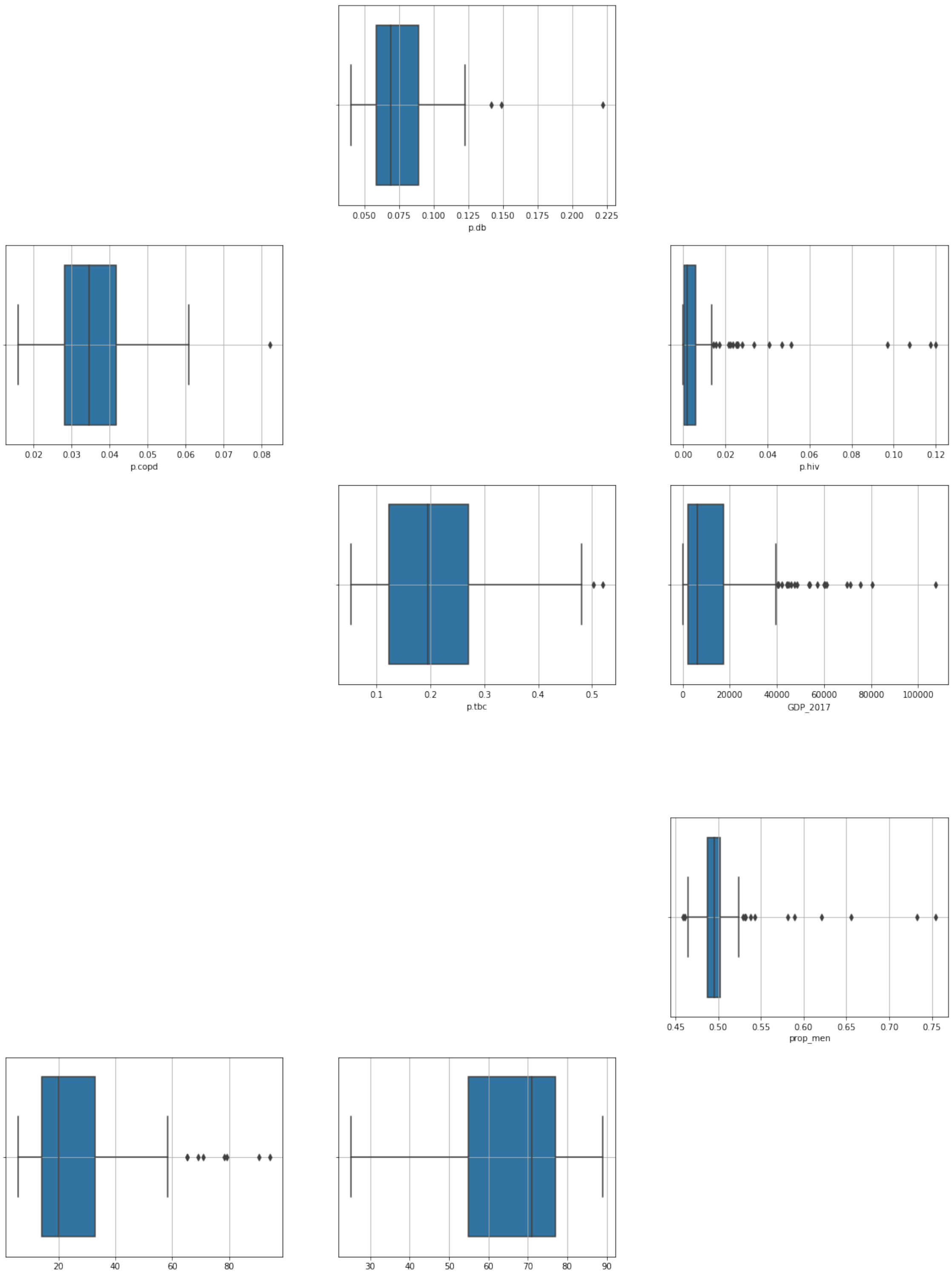
[11]:
```
p.db              0
p.copd            0
p.hiv             0
p.tbc             0
GDP_2017          0
prop_men          0
pm2.5             0
UHC_index_2017    0
dtype: int64
```

2.2. Boxplots

[15]:
```
pl.figure(1)
plt.subplots(figsize=(20,20))
#pl.subplot(431)
```

```python
#sns.boxplot(df["Speed.Number"])
#pl.grid(True)
pl.subplot(432)
sns.boxplot(df["p.db"])
pl.grid(True)
#pl.subplot(433)
#sns.boxplot(df["ylds.db"])
#pl.grid(True)
pl.subplot(434)
sns.boxplot(df["p.copd"])
pl.grid(True)
#pl.subplot(435)
#sns.boxplot(df["ylds.copd"])
#pl.grid(True)
pl.subplot(436)
sns.boxplot(df["p.hiv"])
pl.grid(True)
#pl.subplot(437)
#sns.boxplot(df["ylds.hiv"])
#pl.grid(True)
pl.subplot(438)
sns.boxplot(df["p.tbc"])
pl.grid(True)
pl.subplot(439)
sns.boxplot(df["GDP_2017"])
pl.grid(True)
#=======================
pl.figure(2)
plt.subplots(figsize=(20,20))
#pl.subplot(431)
#sns.boxplot(df["pop_men"])
pl.grid(True)
#pl.subplot(432)
#sns.boxplot(df["pop_women"])
#pl.grid(True)
pl.subplot(433)
sns.boxplot(df["prop_men"])
pl.grid(True)
pl.subplot(434)
sns.boxplot(df["pm2.5"])
pl.grid(True)
pl.subplot(435)
sns.boxplot(df["UHC_index_2017"])
pl.grid(True)


pl.show()
```

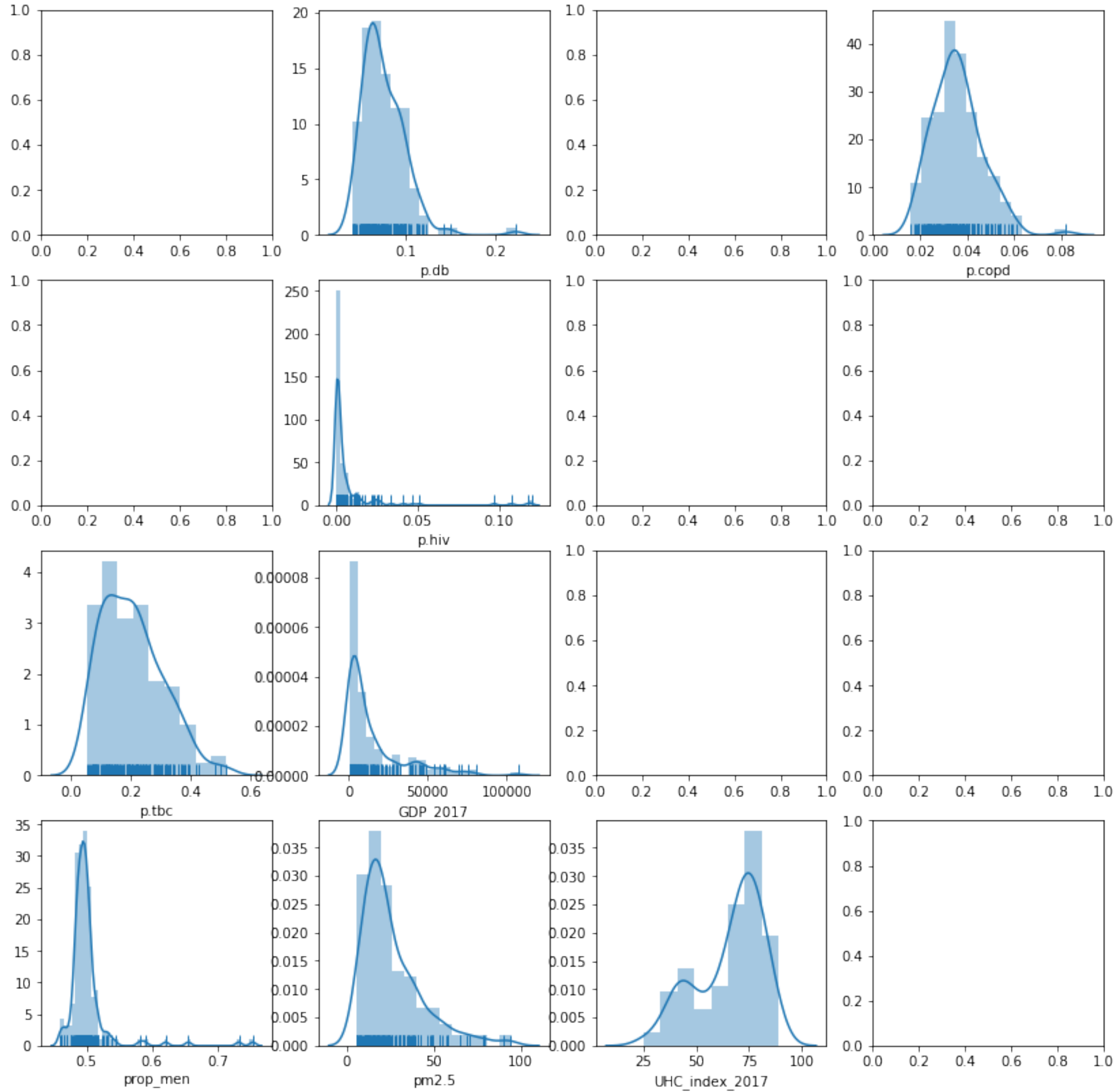
<Figure size 432x288 with 0 Axes>



2.3. Histogramas

[17]:
```
%matplotlib inline
# Univariate Histograms
f, axes = plt.subplots(4, 4, figsize=(14, 14))
#sns.distplot(df["Speed.Number"], rug=True, ax=axes[0, 0])
sns.distplot(df["p.db"], rug=True, ax=axes[0, 1])
#sns.distplot(df["ylds.db"], rug=True, ax=axes[0, 2])
sns.distplot(df["p.copd"], rug=True, ax=axes[0, 3])
#sns.distplot(df["ylds.copd"], rug=True, ax=axes[1, 0])
sns.distplot(df["p.hiv"], rug=True, ax=axes[1, 1])
#sns.distplot(df["ylds.hiv"], rug=True, ax=axes[1, 2])
sns.distplot(df["p.tbc"], rug=True, ax=axes[2, 0])
sns.distplot(df["GDP_2017"], rug=True, ax=axes[2, 1])
#sns.distplot(df["pop_men"], rug=True, ax=axes[2, 2])
#sns.distplot(df["pop_women"], rug=True, ax=axes[2, 3])
sns.distplot(df["prop_men"], rug=True, ax=axes[3, 0])
sns.distplot(df["pm2.5"], rug=True, ax=axes[3, 1])
sns.distplot(df["UHC_index_2017"], ax=axes[3, 2])
```

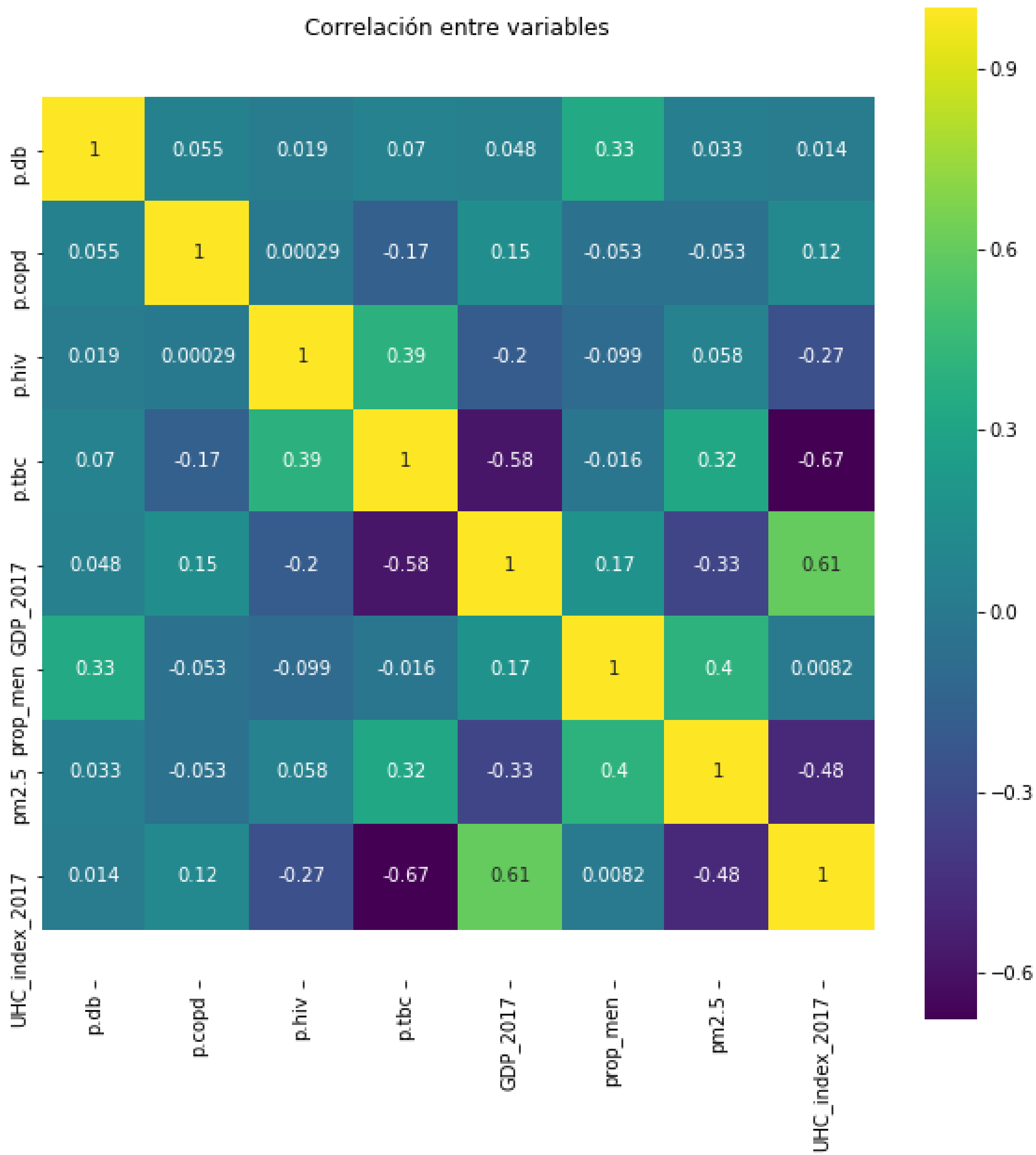
[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2a3001a2b0>
```



2.4. Matriz de correlación

[18]:
```
correlation = df.corr()
plt.figure(figsize=(10,10))
ax = sns.heatmap(correlation, vmax=1, square=True, annot = True, cmap =␣
 ↪'viridis')
# Esto se ponde debido al bug de Matplotlib 3.1.1 (quitarlo en versiones␣
 ↪diferentes)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
# ----------
plt.title('Correlación entre variables')
```

```
plt.show()
```

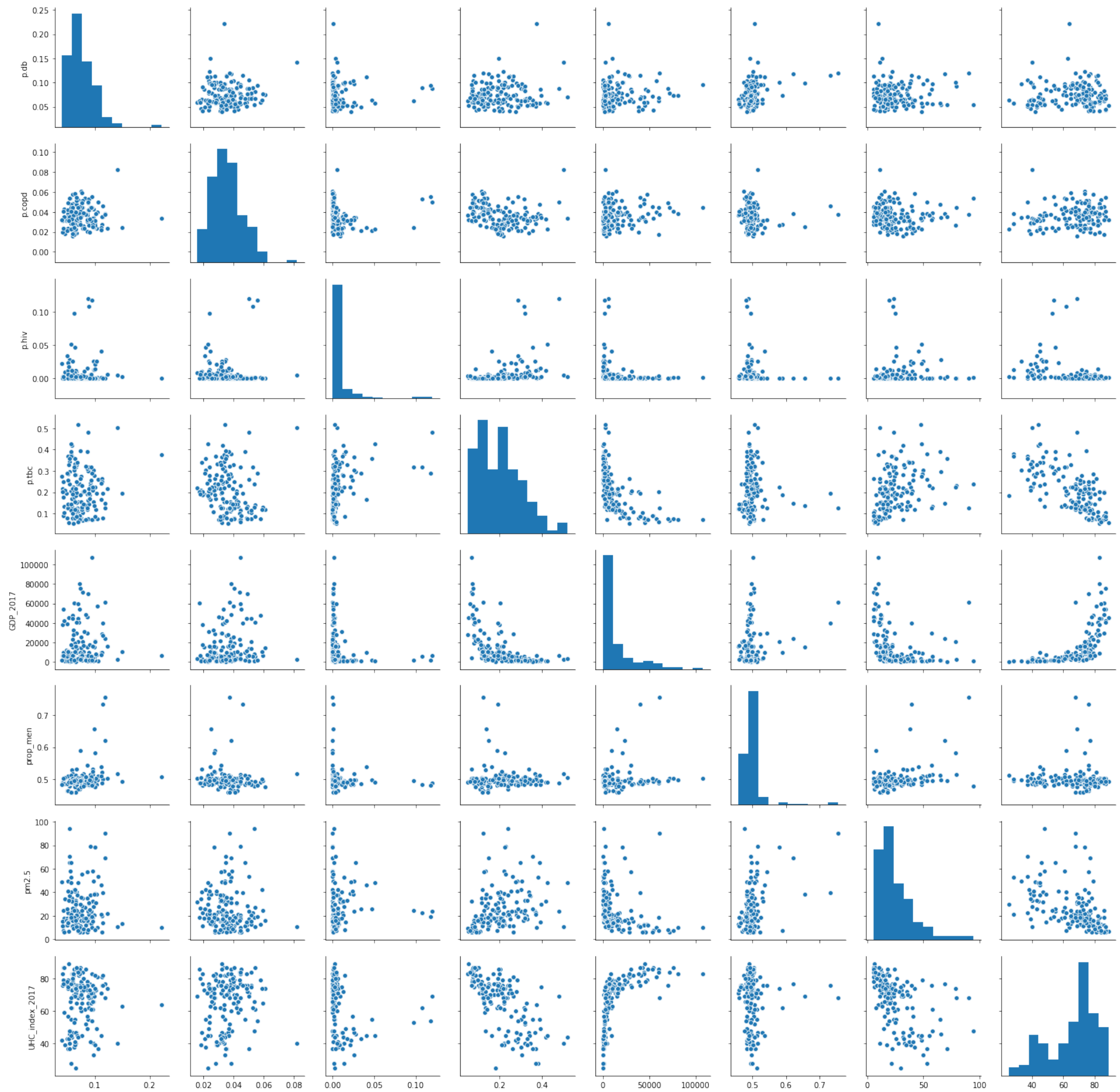


2.5. Matriz de dispersión

Al igual que el diagrama de matriz de correlación anterior, la matriz de diagrama de dispersión es simétrica. Esto es útil para mirar las relaciones por pares desde diferentes perspectivas. Debido a que no tiene mucho sentido dibujar un diagrama de dispersión de cada variable consigo mismo, la diagonal muestra histogramas de cada atributo.

Aquí es importante ver el comportamiento entre variables, es decir, si tienen un comportamiento clusterizado entre ambas o tiene un comportamiento lineal

[19]:
```
sns.pairplot(df);
```



3. Transformaciones categórico a dummy

[12]:
```
cat_features = ['Country', 'first_date']
```

```
#num_features = ['Speed.Number', 'order', 'total_deaths', 'p.db', 'ylds.db', 'p.
↪copd', 'ylds.copd', 'p.hiv', 'ylds.hiv', 'p.tbc', 'ylds.tbc', 'GDP_2017',␣
↪'prop_men', 'pm2.5', 'UHC_index_2017']
num_features = ['Speed.Number', 'order', 'total_deaths', 'p.db', 'p.copd', 'p.
↪hiv', 'p.tbc', 'GDP_2017', 'prop_men', 'pm2.5', 'UHC_index_2017']
#num_features = ['Speed.Number', 'order', 'total_deaths', 'ylds.db', 'ylds.
↪copd', 'ylds.hiv', 'ylds.tbc', 'GDP_2017', 'prop_men', 'pm2.5',␣
↪'UHC_index_2017']


def generateonlyDummies2(X):
    outd_X = pd.DataFrame()
    categories = {}
    for c in cat_features:
        categories[c] = X[c].dropna().unique().tolist()

    for c in cat_features:
            # Cambiamos las variables object a categorical para que las␣
↪categorias tengan siempre el mismo orden
            c_df = X[c].astype(pd.api.types.CategoricalDtype(categories =␣
↪categories[c]))
            #c_df.reset_index(drop=True, inplace=True)
            # One-hot encoding. Utilizamos get_dummies de pandas!
            c_dummies = pd.get_dummies(c_df, prefix=c)
            outd_X = pd.concat([outd_X, c_dummies], axis=1)
    outc_X = pd.DataFrame(X[num_features],columns=num_features)

    for c in num_features:
        outd_X[c] = outc_X[c].values
    return outd_X
```

4.PCA + k-Means

Se generan las variables dummies correspondientes y con ello ya se tiene listo el dataset para aplicar k-means. El código en comentario es dependiendo las variables a analizar, también si hay que pasar a dummy o no.

Cambiar los componentes de PCA

O si no se utiliza PCA comentar el bloque correspondiente

[20]:
```
df_original = pd.read_csv('dataset/data_2020-03-22.csv', parse_dates=[2])
df_original.head(1)
```

[20]:
```
       Country  Speed.Number first_date  order  total_deaths      p.db  \
0  Afghanistan      0.888889 2020-02-24     34             0  0.105599

    ylds.db   p.copd  ylds.copd     p.hiv  ylds.hiv     p.tbc  ylds.tbc  \
```

```
0  0.052702  0.05014   0.030484  0.000186  0.000165  0.261146  0.001078

     GDP_2017       pop_men     pop_women  prop_men  pm2.5  UHC_index_2017
0  556.302138  1.674320e+07  1.611156e+07  0.509613   53.2              37
```

[21]:
```
df = pd.read_csv('dataset/data_2020-03-22.csv', parse_dates=[2])
df.drop(['pop_men'], axis=1, inplace=True)
df.drop(['pop_women'], axis=1, inplace=True)
#df.drop(['p.db'], axis=1, inplace=True)
#df.drop(['p.copd'], axis=1, inplace=True)
#df.drop(['p.hiv'], axis=1, inplace=True)
#df.drop(['p.tbc'], axis=1, inplace=True)
df.drop(['ylds.db'], axis=1, inplace=True)
df.drop(['ylds.copd'], axis=1, inplace=True)
df.drop(['ylds.hiv'], axis=1, inplace=True)
df.drop(['ylds.tbc'], axis=1, inplace=True)
df.drop(['Country'], axis=1, inplace=True)
df.drop(['Speed.Number'], axis=1, inplace=True)
df.drop(['first_date'], axis=1, inplace=True)
df.drop(['order'], axis=1, inplace=True)
df.drop(['total_deaths'], axis=1, inplace=True)
```

[22]:
```
df.head(1)
```

[22]:
```
       p.db   p.copd     p.hiv     p.tbc    GDP_2017  prop_men  pm2.5  \
0  0.105599  0.05014  0.000186  0.261146  556.302138  0.509613   53.2

   UHC_index_2017
0              37
```

[23]:
```
df_dummy = df.copy()
#df_dummy= generateonlyDummies2(df)
```

[24]:
```
df_dummy.head(1)
```

[24]:
```
       p.db   p.copd     p.hiv     p.tbc    GDP_2017  prop_men  pm2.5  \
0  0.105599  0.05014  0.000186  0.261146  556.302138  0.509613   53.2

   UHC_index_2017
0              37
```

[25]:
```
from sklearn.decomposition import PCA
n_components = 3 # reducir de 67 a 40 variables
pca = PCA(n_components=n_components, iterated_power='auto', svd_solver='auto',␣
 ↪whiten=True).fit(df_dummy)
```

[26]:
```
pca_trans = pca.transform(df_dummy)
```

[27]:
```
total_variance = np.cumsum(pca.explained_variance_ratio_)
total_variance[:5] # Cinco primeros...
```

[27]:
```
array([0.99999889, 0.9999997 , 1.        ])
```

[28]:
```
df_pca = pd.DataFrame(pca_trans)
```

[29]:
```
df_dummyo = df_pca.copy()
#df_dummyo = df_dummy.copy()
```

[30]:
```
df_dummyo.head(1)
```

[30]:

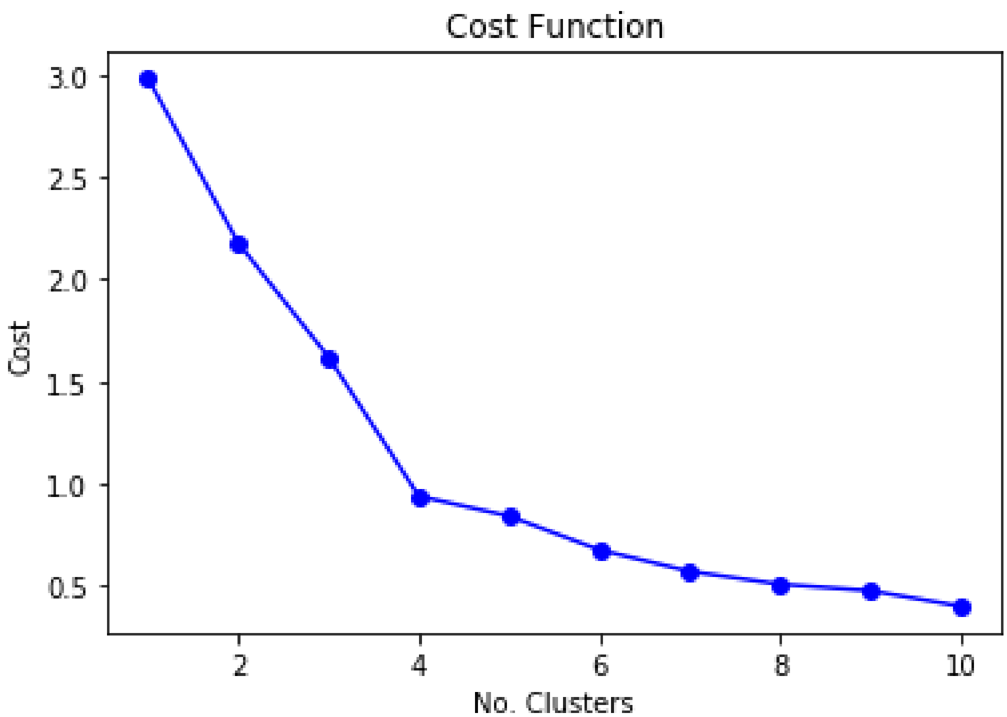
	0	1	2
0	-0.739479	1.74627	0.907929

[31]:
```
from sklearn.metrics import pairwise_distances

def cost(data, k, centroids, clusters):
    cost = 0.0
    for c in range(k):
        points_cluster = data[clusters==c, :]
        if points_cluster.shape[0] > 0:
            distances = pairwise_distances(points_cluster, [centroids[c]],␣
↪metric='euclidean')
            cost += np.sum(distances**2)
    return cost/len(clusters)
```

[32]:
```
from sklearn.cluster import MiniBatchKMeans

# Arrat que guardará los costes
costsD = np.zeros(10,)
# Valores de k de 1 a 64
ks = 1+np.arange(10)
# Guarda los costes
#costs = np.zeros(20,)
# Valores de k de 5 a 125
#ks = np.linspace(1,20,20).astype(int)

# Ejecuta k-means para cada valor de k, y guarda el coste asociado
for i,k in enumerate(ks):
    kmeans = MiniBatchKMeans(n_clusters=k, init='k-means++', max_iter=500)
    kmeans.fit(df_dummyo.values)
    centroidsD = kmeans.cluster_centers_
    clustersD = kmeans.labels_
    costsD[i] = cost(df_dummyo.values, k, centroidsD, clustersD)
    print(i,end=',')
```

```
plt.xlabel('No. Clusters')
plt.ylabel('Cost')
plt.title('Cost Function')
plt.plot(ks,costsD, 'bo-');
plt.savefig('coste.eps', format='eps', dpi=400)
```

```
0,1,2,3,4,5,6,7,8,9,
```



[33]:
```
for i in range(10):
    print(costsD[i])
```

```
2.982003796388678
2.177583050237878
1.6203241893674032
0.939629902780109
0.8420055700486618
0.6767450900331292
0.5713868959553393
0.5084328313116632
0.47695589796201515
0.40100944597848864
```

[34]:
```
np.mean(costsD)
```

[34]: 1.1196076670063364

La gráfica muestra claramente que existe un punto a partir del cual la disminución del coste es significativamente más lenta. En concreto, hasta 2-4 clusters, la disminución del coste es considerable. A partir de ese punto, es mucho más lenta.

0.0.2 Con 2 clústers

[35]:
```
from sklearn.cluster import KMeans
# Elegimos con 2 clusters
km_2 = KMeans(n_clusters=2, init='k-means++', max_iter=500, random_state=0)
df_dummy = df_dummyo.copy()
km_2.fit(df_dummy)
df_dummy_2 = df_dummy.copy()
df_dummy_2['label'] = km_2.labels_
df_dummy_2['Country'] = df_original['Country']
df_dummy_2.to_csv(r'Dataset_2_clusters.csv', index = False)
#df_dummy.drop(['Country'], axis=1, inplace=True)
#df_dummy.drop(['label'], axis=1, inplace=True)
```

[36]:
```
df_dummy_2.head(1)
```

[36]:

	0	1	2	label	Country
0	-0.739479	1.74627	0.907929	0	Afghanistan

0.0.3 Con 3 clústers

[37]:
```
from sklearn.cluster import KMeans
# Elegimos con 2 clusters
km_3 = KMeans(n_clusters=3, init='k-means++', max_iter=500, random_state=0)
df_dummy = df_dummyo.copy()
km_3.fit(df_dummy)
df_dummy_3 = df_dummy.copy()
df_dummy_3['label'] = km_3.labels_
df_dummy_3['Country'] = df_original['Country']
df_dummy_3.to_csv(r'Dataset_3_clusters.csv', index = False)
#df_dummy.drop(['Country'], axis=1, inplace=True)
#df_dummy.drop(['label'], axis=1, inplace=True)
```

0.0.4 Con 4 clústers

[38]:
```
from sklearn.cluster import KMeans
# Elegimos con 2 clusters
km_4 = KMeans(n_clusters=4, init='k-means++', max_iter=500, random_state=0)
df_dummy = df_dummyo.copy()
km_4.fit(df_dummy)
df_dummy_4 = df_dummy.copy()
df_dummy_4['label'] = km_4.labels_
df_dummy_4['Country'] = df_original['Country']
df_dummy_4.to_csv(r'Dataset_4_clusters.csv', index = False)
```

0.0.5 Con 5 clústers

[39]:
```
from sklearn.cluster import KMeans
# Elegimos con 2 clusters
km_5 = KMeans(n_clusters=5, init='k-means++', max_iter=500, random_state=0)
df_dummy = df_dummyo.copy()
km_5.fit(df_dummy)
df_dummy_5 = df_dummy.copy()
df_dummy_5['label'] = km_5.labels_
df_dummy_5['Country'] = df_original['Country']
df_dummy_5.to_csv(r'Dataset_5_clusters.csv', index = False)
```

0.0.6 Con 6 clústers

[40]:
```
from sklearn.cluster import KMeans
# Elegimos con 2 clusters
km_6 = KMeans(n_clusters=6, init='k-means++', max_iter=500, random_state=0)
df_dummy = df_dummyo.copy()
km_6.fit(df_dummy)
df_dummy_6 = df_dummy.copy()
df_dummy_6['label'] = km_6.labels_
df_dummy_6['Country'] = df_original['Country']
df_dummy_6.to_csv(r'Dataset_6_clusters.csv', index = False)
```

0.0.7 Con 7 clústers

[41]:
```
from sklearn.cluster import KMeans
# Elegimos con 2 clusters
km_7 = KMeans(n_clusters=7, init='k-means++', max_iter=500, random_state=0)
df_dummy = df_dummyo.copy()
km_7.fit(df_dummy)
df_dummy_7 = df_dummy.copy()
```

```
df_dummy_7['label'] = km_7.labels_
df_dummy_7['Country'] = df_original['Country']
df_dummy_7.to_csv(r'Dataset_7_clusters.csv', index = False)
```

0.0.8 Con 8 clústers

[42]:
```
from sklearn.cluster import KMeans
# Elegimos con 2 clusters
km_8 = KMeans(n_clusters=8, init='k-means++', max_iter=500, random_state=0)
df_dummy = df_dummyo.copy()
km_8.fit(df_dummy)
df_dummy_8 = df_dummy.copy()
df_dummy_8['label'] = km_8.labels_
df_dummy_8['Country'] = df_original['Country']
df_dummy_8.to_csv(r'Dataset_8_clusters.csv', index = False)
```

[59]:
```
df_dummy
```

[59]:
```
            0         1         2
0   -0.739479  1.746270  0.907929
1   -0.534663 -0.510141  0.620321
2   -0.559828 -0.111373 -1.703967
3   -0.557175  0.467979  1.796219
4    0.024195 -0.566016 -0.248403
..        …         …         …
150 -0.674052 -0.554764 -0.939502
151  0.040110 -0.690534 -0.237444
152 -0.646288 -0.364258 -1.273233
153 -0.689077 -0.092000  0.760386
154 -0.685598 -0.387436  0.895953

[155 rows x 3 columns]
```

5. Análisis clustering

5.1. Tamaño/Densidad de clústers

[46]:
```
print(90*'_')
print("\nNumero de paises en cada cluster 2")
print(90*'_')

pd.value_counts(km_2.labels_, sort=False)
```

```
__________________________________________________________________________________
__________

Numero de paises en cada cluster 2
```

```
------------------------------------------------------------------------------------
----------
```

[46]:
```
0     43
1    112
dtype: int64
```

[47]:
```
print(90*'_')
print("\nNumero de paises en cada cluster 3")
print(90*'_')

pd.value_counts(km_3.labels_, sort=False)
```

```
------------------------------------------------------------------------------------
----------

Numero de paises en cada cluster 3
------------------------------------------------------------------------------------
----------
```

[47]:
```
0    40
1    92
2    23
dtype: int64
```

[48]:
```
print(90*'_')
print("\nNumero de paises en cada cluster 4")
print(90*'_')

pd.value_counts(km_4.labels_, sort=False)
```

```
------------------------------------------------------------------------------------
----------

Numero de paises en cada cluster 4
------------------------------------------------------------------------------------
----------
```

[48]:
```
0    36
1    85
2    22
3    12
dtype: int64
```

[49]:
```
print(90*'_')
print("\nNumero de paises en cada cluster 5")
print(90*'_')
```

```
pd.value_counts(km_5.labels_, sort=False)
```

```
------------------------------------------------------------------------------------------

Numero de paises en cada cluster 5
------------------------------------------------------------------------------------------
```

[49]:
```
0    83
1    12
2    36
3     5
4    19
dtype: int64
```

[50]:
```
print(90*'_')
print("\nNumero de paises en cada cluster 6")
print(90*'_')

pd.value_counts(km_6.labels_, sort=False)
```

```
------------------------------------------------------------------------------------------

Numero de paises en cada cluster 6
------------------------------------------------------------------------------------------
```

[50]:
```
0    80
1    20
2    22
3     5
4    19
5     9
dtype: int64
```

[51]:
```
print(90*'_')
print("\nNumero de paises en cada cluster 7")
print(90*'_')

pd.value_counts(km_7.labels_, sort=False)
```

```
------------------------------------------------------------------------------------------

Numero de paises en cada cluster 7
--------------------------------------------------------------------------------
```

```
----------
```

[51]:
```
0    62
1    18
2    21
3     5
4    19
5     7
6    23
dtype: int64
```

[52]:
```
print(90*'_')
print("\nNumero de paises en cada cluster 8")
print(90*'_')

pd.value_counts(km_8.labels_, sort=False)
```

```
--------------------------------------------------------------------------------
----------

Numero de paises en cada cluster 8
--------------------------------------------------------------------------------
----------
```

[52]:
```
0    22
1    18
2     5
3     7
4    22
5    19
6    15
7    47
dtype: int64
```

5.2. Centroides de clústers (Formas)

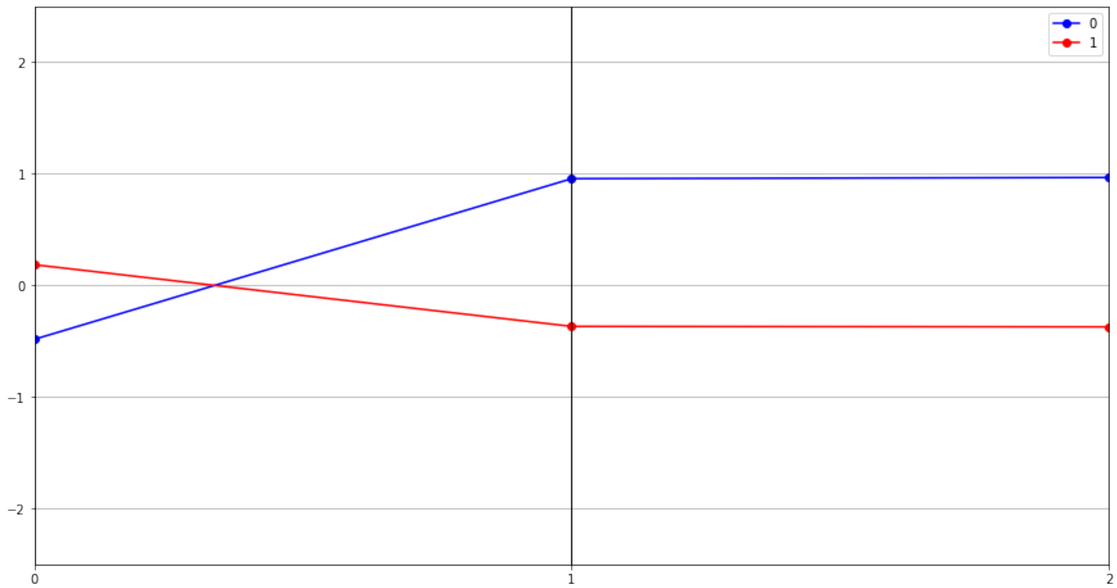
[54]:
```
def pd_centers(featuresUsed, centers):
        from itertools import cycle, islice
        from pandas.plotting import parallel_coordinates
        import matplotlib.pyplot as plt
        import pandas as pd
        import numpy as np

        colNames = list(featuresUsed)
        colNames.append('prediction')

        # Zip with a column called 'prediction' (index)
        Z = [np.append(A, index) for index, A in enumerate(centers)]
```

```
        # Convert to pandas for plotting
        P = pd.DataFrame(Z, columns=colNames)
        P['prediction'] = P['prediction'].astype(int)
        return P

def parallel_plot(data):
        from itertools import cycle, islice
        from pandas.plotting import parallel_coordinates
        import matplotlib.pyplot as plt

        my_colors = list(islice(cycle(['b', 'r', 'g', 'y', 'k']), None,␣
 ↪len(data)))
        plt.figure(figsize=(15,8)).gca().axes.set_ylim([-2.5,+2.5])
        parallel_coordinates(data, 'prediction', color = my_colors, marker='o')

#
# First, let us create some utility functions for Plotting
#


def pd_centers(featuresUsed, centers):
        from itertools import cycle, islice
        from pandas.plotting import parallel_coordinates
        import matplotlib.pyplot as plt
        import pandas as pd
        import numpy as np

        colNames = list(featuresUsed)
        colNames.append('prediction')

        # Zip with a column called 'prediction' (index)
        Z = [np.append(A, index) for index, A in enumerate(centers)]

        # Convert to pandas for plotting
        P = pd.DataFrame(Z, columns=colNames)
        P['prediction'] = P['prediction'].astype(int)
        return P

def parallel_plot(data):
        from itertools import cycle, islice
        from pandas.plotting import parallel_coordinates
        import matplotlib.pyplot as plt

        my_colors = list(islice(cycle(['b', 'r', 'g', 'y', 'k']), None,␣
 ↪len(data)))
        plt.figure(figsize=(15,8)).gca().axes.set_ylim([-2.5,+2.5])
```

```
parallel_coordinates(data, 'prediction', color = my_colors, marker='o')
```

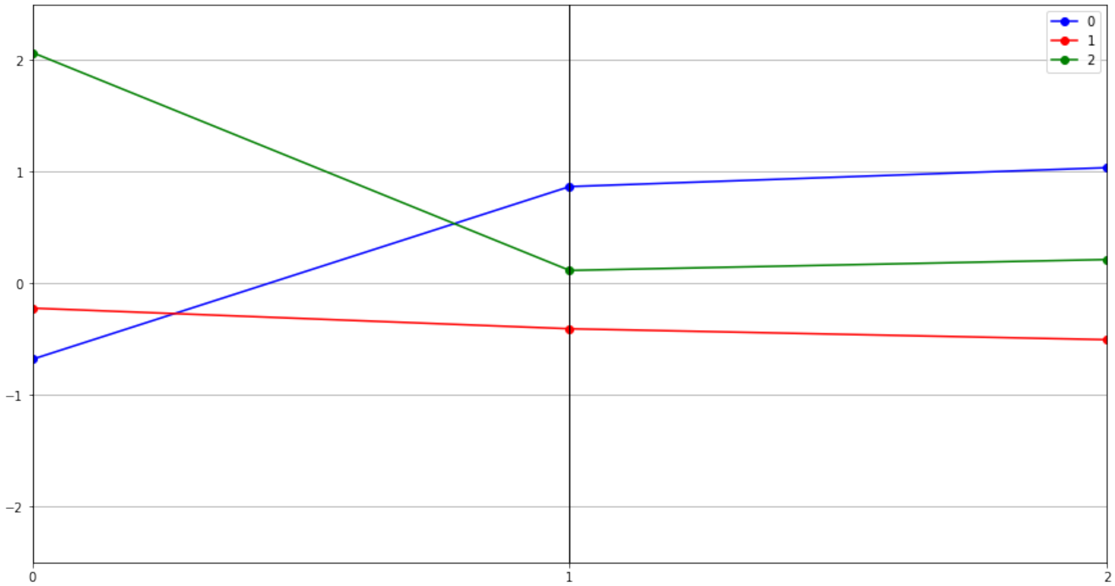
0.0.9 2 Clusters

[60]:
```
%matplotlib inline
P1 = pd_centers(featuresUsed=df_dummy, centers=km_2.cluster_centers_)
P1.head(3)
parallel_plot(P1)
```



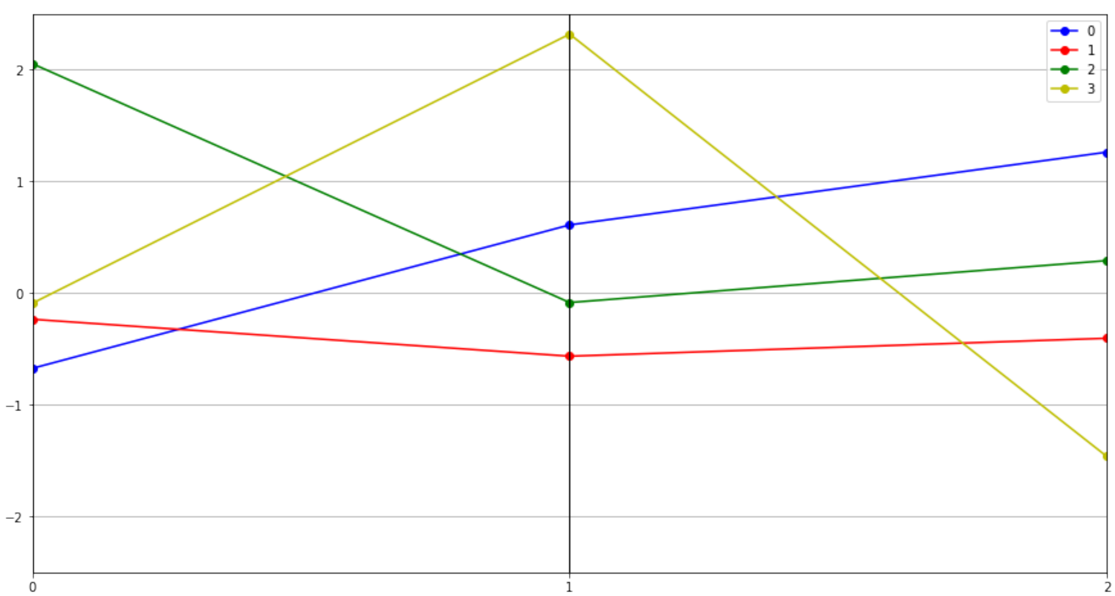
0.0.10 3 Clusters

[61]:
```
%matplotlib inline
P1 = pd_centers(featuresUsed=df_dummy, centers=km_3.cluster_centers_)
P1.head(3)
parallel_plot(P1)
```



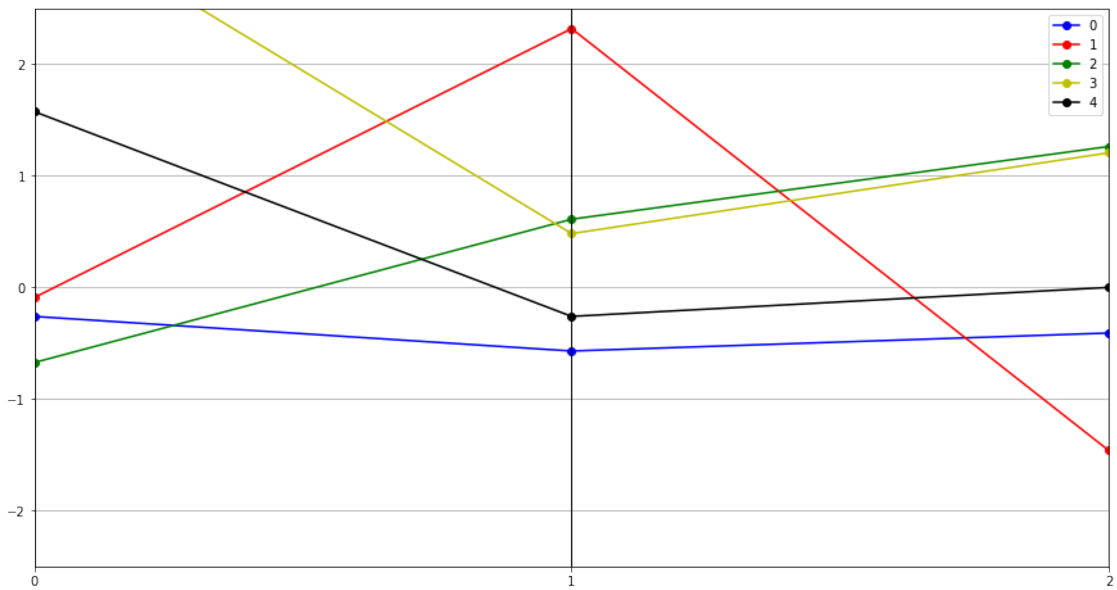
0.0.11 4 Clusters

[62]:
```
%matplotlib inline
P1 = pd_centers(featuresUsed=df_dummy, centers=km_4.cluster_centers_)
P1.head(3)
parallel_plot(P1)
```



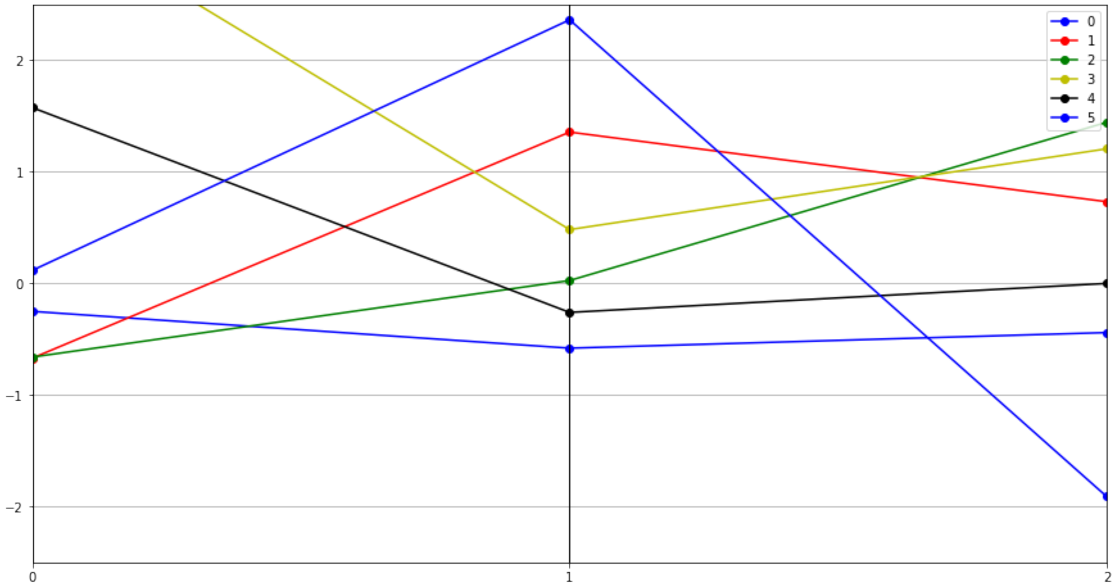
0.0.12 5 Clusters

[63]:
```
%matplotlib inline
P1 = pd_centers(featuresUsed=df_dummy, centers=km_5.cluster_centers_)
P1.head(3)
parallel_plot(P1)
```



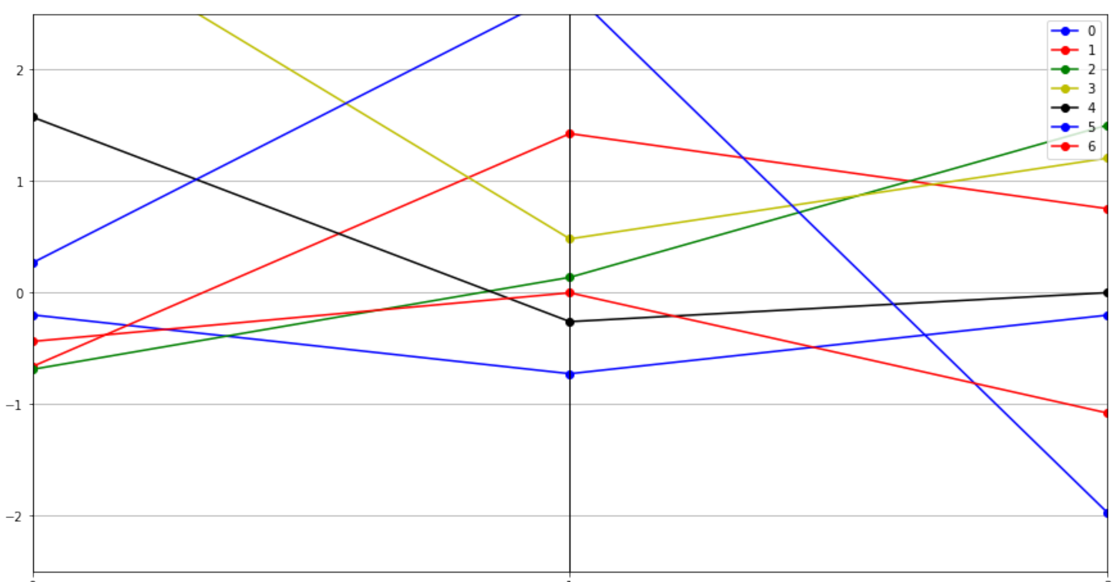
0.0.13 6 Clusters

[64]:
```
%matplotlib inline
P1 = pd_centers(featuresUsed=df_dummy, centers=km_6.cluster_centers_)
P1.head(3)
parallel_plot(P1)
```



0.0.14 7 Clusters

[65]:
```
%matplotlib inline
P1 = pd_centers(featuresUsed=df_dummy, centers=km_7.cluster_centers_)
P1.head(3)
parallel_plot(P1)
```



0.0.15 8 Clusters

[66]:
```
%matplotlib inline
P1 = pd_centers(featuresUsed=df_dummy, centers=km_8.cluster_centers_)
P1.head(3)
parallel_plot(P1)
```