### TP FINAL - ALGORITHMES D'APPRENTISSAGE SUPERVISÉ

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### 1. LOAD DATA

```
In [1]:
         import pandas as pd
         import matplotlib.pyplot as plt
         import statistics
         import numpy as np
         import scipy.stats
         import seaborn as sns
         dataOriginal = pd.read_csv("covid.csv")
         pd.set_option('display.max_rows', None)
         dataOriginal.head(5)
Out[1]:
                 id sex patient_type entry_date date_symptoms date_died intubed pneumonia age pregnancy ... inmsupr hypertension other_
                                                                 9999-99-
          0 16169f
                                                                                              27
                                                                                                        97 ...
                      2
                                                     02-05-2020
                                                                                          2
                                           2020
                                         19-03-
                                                                 9999-99-
                                                                                                                                  2
             1009bf
                      2
                                  1
                                                     17-03-2020
                                                                              97
                                                                                          2
                                                                                             24
                                                                                                        97 ...
                                                                                                                     2
          1
                                           2020
                                                                      99
                                         06-04-
                                                                9999-99-
                                                    01-04-2020
                                  2
                                                                                          2 54
                                                                                                         2 ...
                                                                                                                                  2
          2 167386
                       1
                                                                                                                     2
                                           2020
                                         17-04-
                                                                 9999-99-
          3 0b5948
                      2
                                  2
                                                     10-04-2020
                                                                                          1
                                                                                              30
                                                                                                        97 ...
                                                                                                                     2
                                                                                                                                  2
                                         13-04-
                                                                   22-04-
          4 0d01b5
                                   2
                                                     13-04-2020
                                                                               2
                                                                                          2
                                                                                             60
                                                                                                         2 ...
                                                                                                                     2
                                                                                                                                  1
                                          2020
                                                                    2020
```

### 1.1. LOAD METADA

5 rows × 23 columns

```
In [2]: cat_si_no = pd.read_excel("Catalogs.xlsx", 'Catálogo SI_NO')
    pd.set_option('display.max_rows', None)
             cat_si_no.head(5)
```

Out[2]:

	CLAVE	DESCRIPCIÓN
0	1	SI
1	2	NO
2	97	NO APLICA
3	98	SE IGNORA
4	99	NO ESPECIFICADO

```
cat_pacient_type = pd.read_excel("Catalogs.xlsx", 'Catálogo TIPO_PACIENTE')
In [3]:
        pd.set_option('display.max_rows', None)
        cat_pacient_type.head(5)
```

Out[3]:

	CLAVE	DESCRIPCIÓN
0	1	AMBULATORIO
1	2	HOSPITALIZADO
2	00	NO ESDECIFICADO

```
In [4]: cat_sex = pd.read_excel("Catalogs.xlsx", 'Catálogo SEXO')
        pd.set_option('display.max_rows', None)
        cat_sex.head(5)
```

Out[4]:

	CLAVE	DESCRIPCIÓN
0	1	MUJER
1	2	HOMBRE
2	99	NO ESPECIFICADO

```
In [5]: cat_result = pd.read_excel("Catalogs.xlsx", 'Catálogo RESULTADO')
   pd.set_option('display.max_rows', None)
   cat_sex.head(5)
```

#### Out[5]:

	CLAVE	DESCRIPCIÓN
0	1	MUJER
1	2	HOMBRE
2	99	NO ESPECIFICADO

#### 2. IDENTIFYING MODEL VARIABLES

We are gooing to predict if the pacient needs ICU

```
In [6]: dataInfo = pd.read_excel("covidInfo.xlsx", "DataTypes")
    pd.set_option('display.max_rows', None)
    dataInfo
```

#### Out[6]:

```
DB Type
                                                                                                    CATALOG
         Variable Name
                                                                       Model Type
 0
 1
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                               Catálogo SEXO
                    sex
 2
                         String / Date Categorical, Numerical, Non-ordinal, Nominal Catálogo TIPO PACIENTE
            patient type
 3
                         String / Date
             entry_date
 4
        date_symptoms
                         String / Date
                                                                             Date
                                                                                                          N.A
 5
              date died String / Date
                                                                              Date
                                                                                                          N.A
 6
                intubed
                                   int Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI_NO
 7
             pneumonia
                                   int Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI_NO
 8
                                   int Categorical, Numerical, Non-ordinal, Nominal
                                                                                                          N.A
                    age
 9
             pregnancy
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI_NO
10
               diabetes
                                   int
                                      Categorical Numerical Non-ordinal Nominal
                                                                                              Catálogo SI NO
11
                                   int
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI NO
                   copd
12
                asthma
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI_NO
13
               inmsupr
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI NO
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI_NO
           hypertension
14
                                   int
15
          other_disease
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI_NO
16
         cardiovascular
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI NO
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI_NO
                obesity
                                   int
18
           renal_chronic
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI_NO
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI NO
19
               tobacco
20
    contact_other_covid
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                              Catálogo SI NO
21
              covid_res
                                       Categorical, Numerical, Non-ordinal, Nominal
                                                                                        Catálogo RESULTADO
22
                                                                                              Catálogo SI NO
                    icu
                                   int Categorical, Numerical, Non-ordinal, Nominal
```

### 3. DATA EXPLORATION

### 3.1. Applying Catalogs

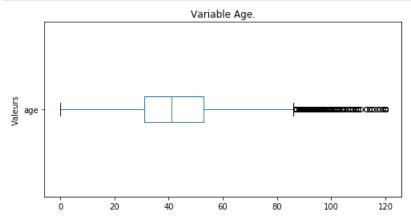
### 3.1. Inspecting for types and Null values detection

```
In [8]: dataOriginal.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 566602 entries, 0 to 566601
        Data columns (total 23 columns):
            Column
                                 Non-Null Count
        #
                                                  Dtype
         0
                                 566602 non-null object
            id
                                 566602 non-null
                                                  int64
         1
             sex
         2
             patient_type
                                                  int64
                                 566602 non-null
                                 566602 non-null
         3
             entry_date
                                                  object
         4
            date_symptoms
                                 566602 non-null
                                                  object
         5
                                 566602 non-null
             date died
                                                  object
         6
            intubed
                                 566602 non-null
                                                  int64
         7
             pneumonia
                                 566602 non-null
                                                  int64
         8
             age
                                 566602 non-null
                                                  int64
         9
             pregnancy
                                 566602 non-null
                                                  int64
         10 diabetes
                                  566602 non-null
                                                  int64
         11 copd
                                 566602 non-null
         12
             asthma
                                  566602 non-null
                                                  int64
         13 inmsupr
                                 566602 non-null
         14 hypertension
                                 566602 non-null
         15 other_disease
                                 566602 non-null int64
                                  566602 non-null
         16
            cardiovascular
                                  566602 non-null int64
         17 obesity
         18
                                  566602 non-null
           renal_chronic
                                  566602 non-null
         19 tobacco
         20
            contact_other_covid 566602 non-null
                                                  int64
                                 566602 non-null
                                                  int64
         21 covid res
                                  566602 non-null int64
         22
            icu
        dtypes: int64(19), object(4)
        memory usage: 99.4+ MB
In [9]: dataOriginal.isnull().values.sum()
Out[9]: 0
```

# 3.1.1. Searching odd information in numerical descriptor - AGE

```
In [10]: #Diagram de moustache

dataOriginal.boxplot(column='age', figsize=(8,4), vert=False)
plt.ylabel("Valeurs")
plt.title("Variable Age." )
plt.grid()
plt.show()
```



There are 2944 samples with age greater than 100 ans.. to DO ???

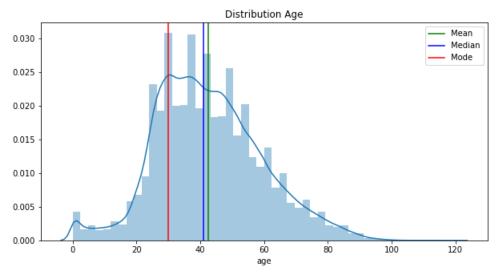
### 3.2. Inspecting variables quantitatives - Age

```
In [11]: import seaborn as sns

mean=dataOriginal['age'].mean();
    median=dataOriginal['age'].median();
    mode=dataOriginal['age'].mode();
    fig, ax = plt.subplots(figsize=(10,5));

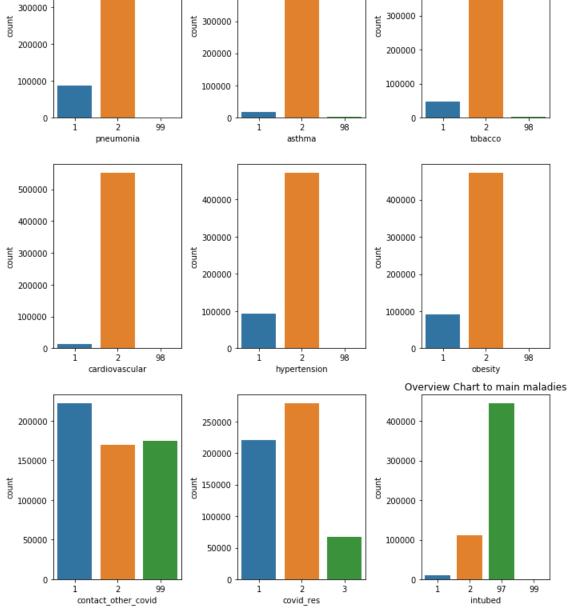
sns.distplot(dataOriginal['age']);
    plt.title('Distribution Age');
    plt.axvline(mean,color='green',label='Mean');
    plt.axvline(median,color='blue',label='Median');
    plt.axvline(mode[0],color='red',label='Mode')

plt.legend();
```



# 2.3. Inspecting categorical variables

```
In [14]: import matplotlib.pyplot as plt
           fig, ax =plt.subplots(3,3)
           fig.set_size_inches(10, 12, forward=True)
           plt.title("Overview Chart to main maladies")
           sns.countplot(x='pneumonia', data=dataOriginal, ax=ax[0,0])
           \label{eq:sns_countplot} $$ sns.countplot(x='asthma', data=dataOriginal, ax=ax[0,1]) $$ sns.countplot(x='tobacco', data=dataOriginal, ax=ax[0,2]) $$
           \verb|sns.countplot(x='cardiovascular', data=dataOriginal, ax=ax[1,0])| \\
           sns.countplot(x='hypertension', data=dataOriginal, ax=ax[1,1])
           sns.countplot(x='obesity', data=dataOriginal, ax=ax[1,2])
           sns.countplot(x=\contact\_other\_covid',\ data=dataOriginal,\ ax=ax[2,0])
           sns.countplot(x='covid_res', data=dataOriginal, ax=ax[2,1])
           sns.countplot(x='intubed', data=dataOriginal, ax=ax[2,2])
           #fig.legend() use handles
           fig.tight_layout()
              500000
                                                                                      500000
                                                  500000
              400000
                                                                                      400000
                                                  400000
              300000
                                                                                     300000
                                                  300000
              200000
                                                                                      200000
                                                  200000
              100000
                                                                                     100000
                                                  100000
                   0
                                                                                          0
                                 2
                                                                            98
                                         99
                                                                                                        ż
                                                                                                                98
```



### Calculate numerical values

```
In [16]: pd.DataFrame(dataOriginal['asthma'].value_counts())
```

Out[16]:

```
    asthma

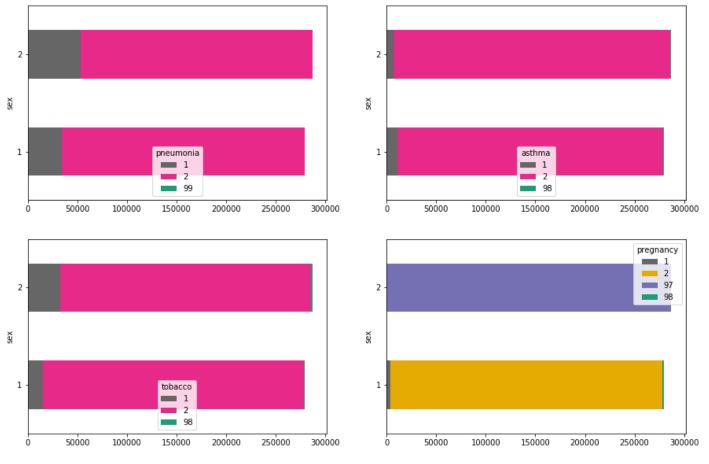
    2
    546824

    1
    18026

    98
    1752
```

```
pd.DataFrame(dataOriginal['tobacco'].value_counts())
In [17]:
Out[17]:
              tobacco
               516678
            1
                48017
                 1907
           98
In [18]:
          pd.DataFrame(dataOriginal['pregnancy'].value_counts())
Out[18]:
               pregnancy
           97
                 287112
            2
                 273840
            1
                   4063
                   1587
           98
```

### 2.3.1. Inspecting categorical variables using bivariable relatioships with sex of patients.



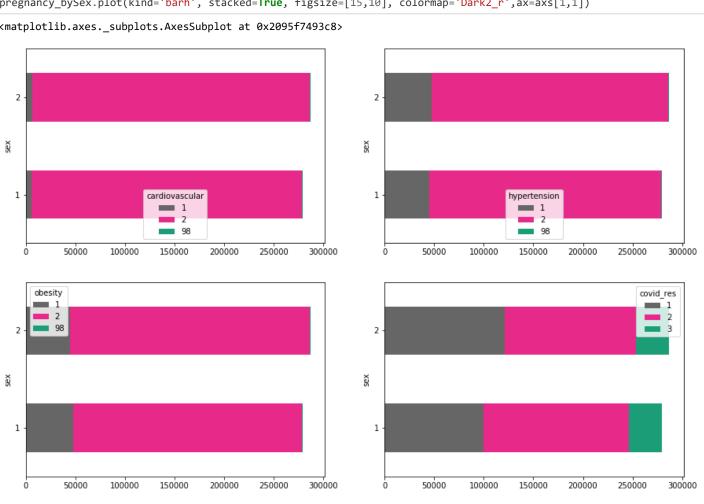
#### Calculate numerical values

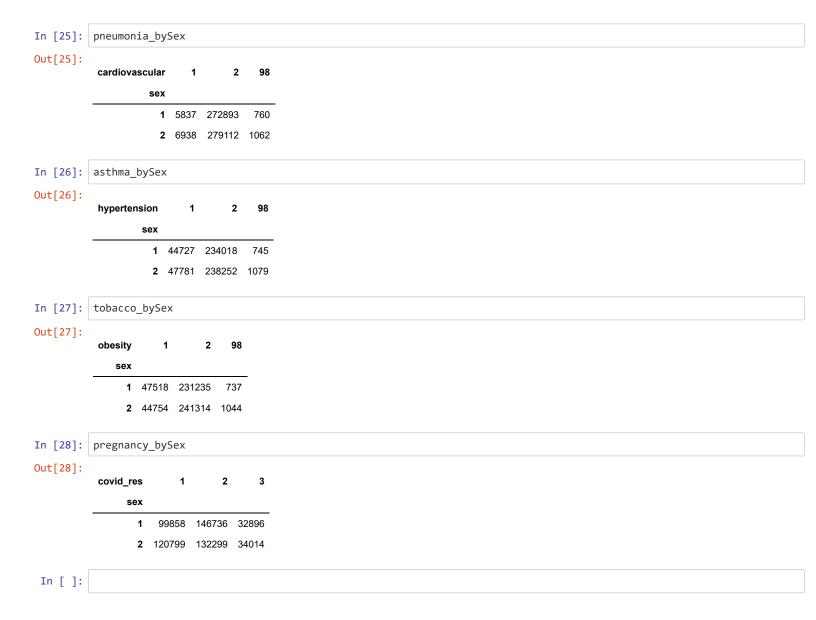
```
In [21]: tobacco_bySex
Out[21]:
           tobacco
                                   98
                1 15545 263171
                                  774
                2 32472 253507 1133
In [22]: asthma bySex
Out[22]:
           asthma
                              2
                                  98
                   11203 267558
                   6823 279266 1023
In [23]: pregnancy_bySex
Out[23]:
           pregnancy
                                                 98
                            273840.0
                     4063.0
                                         NaN
                                              1587.0
                       NaN
                                NaN 287112.0
                                               NaN
```

### 2.3.2. Inspecting categorical variables using bivariable relatioships with ICU (Intensive Care Medical Unit) reference

```
In [24]: fig, axs = plt.subplots(2,2)
           pneumonia_bySex= dataOriginal.pivot_table(index='sex', columns='cardiovascular', values='icu', aggfunc='count')
           pneumonia\_by Sex.plot(kind='barh', stacked=True, figsize=[15,10], colormap='Dark2\_r', ax=axs[0,0])
           asthma_bySex= dataOriginal.pivot_table(index='sex', columns='hypertension', values='icu', aggfunc='count')
           asthma_bySex.plot(kind='barh', stacked=True, figsize=[15,10], colormap='Dark2_r',ax=axs[0,1])
           tobacco_bySex= dataOriginal.pivot_table(index='sex', columns='obesity', values='icu', aggfunc='count')
           tobacco_bySex.plot(kind='barh', stacked=True, figsize=[15,10], colormap='Dark2_r',ax=axs[1,0])
           pregnancy_bySex= dataOriginal.pivot_table(index='sex', columns='covid_res', values='icu', aggfunc='count')
pregnancy_bySex.plot(kind='barh', stacked=True, figsize=[15,10], colormap='Dark2_r',ax=axs[1,1])
```

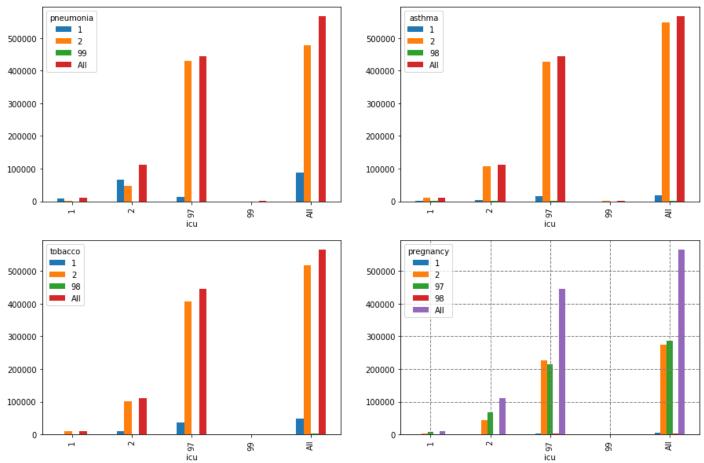
Out[24]: <matplotlib.axes.\_subplots.AxesSubplot at 0x2095f7493c8>





Inspecting relationship between categorical variables - Diseases vs ICU assignation - Overview respiratory diseases

```
In [29]: fig, axs = plt.subplots(2,2)
          pneumonia_byICU = pd.crosstab(index=dataOriginal['icu'],
                        columns=dataOriginal['pneumonia'],
                        margins=True)
          pneumonia_byICU.plot(kind='bar',ax=axs[0,0], figsize=[15,10])
          plt.grid(color='gray', linestyle='--', linewidth=1)
#plt.ylabel("Frequency")
          #plt.title('Relationship between Asthma diagnostic and ICU assignation COVID')
          asthma_byICU = pd.crosstab(index=dataOriginal['icu'],
                        columns=dataOriginal['asthma'],
                        margins=True)
          asthma_byICU.plot(kind='bar',ax=axs[0,1])
          plt.grid(color='gray', linestyle='--', linewidth=1)
#plt.ylabel("Frequency")
#plt.title('Relationship between Tobacco diagnostic and ICU assignation COVID')
          tobacco_byICU = pd.crosstab(index=dataOriginal['icu'],
                        columns=dataOriginal['tobacco'],
                        margins=True)
          tobacco_byICU.plot(kind='bar',ax=axs[1,0])
          plt.grid(color='gray', linestyle='--', linewidth=1)
#plt.ylabel("Frequency")
          #plt.title('Relationship between Pregnancy diagnostic and ICU assignation COVID')
          pregnancy_byICU = pd.crosstab(index=dataOriginal['icu'],
                        columns=dataOriginal['pregnancy'],
                        margins=True)
          pregnancy_byICU.plot(kind='bar',ax=axs[1,1])
          plt.grid(color='gray', linestyle='--', linewidth=1)
          #plt.ylabel("Frequency")
          #plt.title('Relationship between Pneumonia diagnostic and ICU assignation COVID')
```



```
In [30]: pneumonia_byICU
```

#### Out[30]:

pneumonia	1	2	99	All
icu				
1	8393	1719	0	10112
2	65295	46381	0	111676
97	14428	430251	10	444689
99	59	65	1	125
All	88175	478416	11	566602

#### In [31]: asthma\_byICU

#### Out[31]:

asthma	1	2	98	All
icu				
1	247	9751	114	10112
2	2894	108311	471	111676
97	14882	428640	1167	444689
99	3	122	0	125
All	18026	546824	1752	566602

```
In [32]: tobacco_byICU
Out[32]:
        tobacco 1 2 98 All
            1 871 9128 113 10112
            2 9865 101285 526 111676
           97 37272 406149 1268 444689
            99 9 116 0 125
           All 48017 516678 1907 566602
In [33]: pregnancy_byICU
Out[33]:
        pregnancy 1 2 97 98 All
              1 74 3519 6500 19 10112
             2 995 44035 66499 147 111676
             97 2992 226235 214041 1421 444689
             99
                  2
                       51
                          72 0
                                      125
             All 4063 273840 287112 1587 566602
```

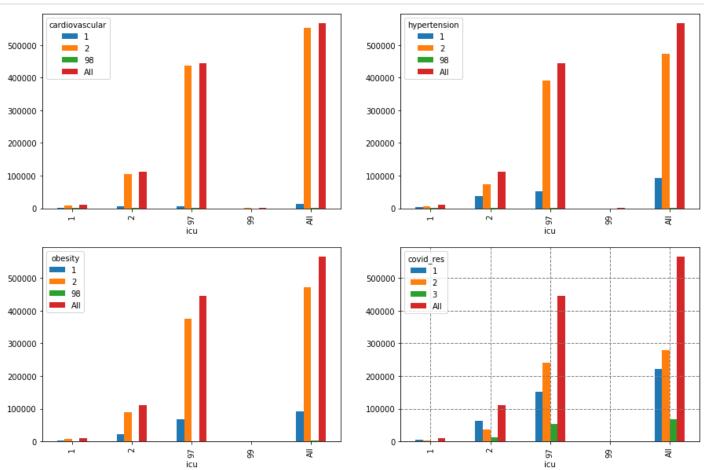
Inspecting relationship between diseases and ICU assignation - Overview General diseases

```
In [34]:
          fig, axs = plt.subplots(2,2)
           pneumonia_byICU = pd.crosstab(index=dataOriginal['icu'],
                        columns=dataOriginal['cardiovascular'],
                        margins=True)
           pneumonia_byICU.plot(kind='bar',ax=axs[0,0], figsize=[15,10])
           plt.grid(color='gray', linestyle='--', linewidth=1)
#plt.ylabel("Frequency")
           #plt.title('Relationship between Asthma diagnostic and ICU assignation COVID')
           margins=True)
           asthma_byICU.plot(kind='bar',ax=axs[0,1])
          plt.grid(color='gray', linestyle='--', linewidth=1)

#plt.ylabel("Frequency")

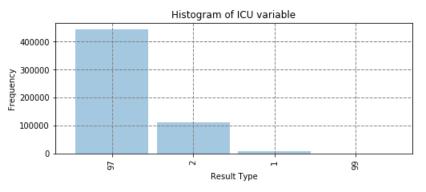
#plt.title('Relationship between Tobacco diagnostic and ICU assignation COVID')

tobacco_byICU = pd.crosstab(index=dataOriginal['icu'],
                        columns=dataOriginal['obesity'],
                        margins=True)
           tobacco_byICU.plot(kind='bar',ax=axs[1,0])
           plt.grid(color='gray', linestyle='--', linewidth=1)
#plt.ylabel("Frequency")
           #plt.title('Relationship between Pregnancy diagnostic and ICU assignation COVID')
           pregnancy_byICU = pd.crosstab(index=dataOriginal['icu'],
                        columns=dataOriginal['covid_res'],
                        margins=True)
           pregnancy_byICU.plot(kind='bar',ax=axs[1,1])
           plt.grid(color='gray', linestyle='--', linewidth=1)
           #plt.ylabel("Frequency")
           #plt.title('Relationship between Pneumonia diagnostic and ICU assignation COVID')
                    cardiovascular
                                                                                      hypertension
                      ___1
                                                                                        ___1
            500000
                                                                              500000
                                                                                          2
                          2
```



3.1. Classes identification

In [ ]:



```
In [36]: cat_si_no
```

Out[36]:

	CLAVE	DESCRIPCIÓN
0	1	SI
1	2	NO
2	97	NO APLICA
3	98	SE IGNORA
4	99	NO ESPECIFICADO

125

99 0.022061

## 3.2. Check the distribution or instances of any class

```
In [38]: pd.DataFrame(targetOriginal.value_counts(normalize=True) * 100)
```

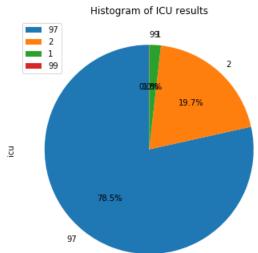
Out[38]:

```
icu

97 78.483486

2 19.709779

1 1.784674
```



### 4. Splitting DATA to create Training and Test sets.

```
In [3]: # Labels for descriptors
      on',
                'other_disease','cardiovascular','obesity','renal_chronic','tobacco','contact_other_covid'
                ,'covid_res','icu']
      # Ignored: id, entrydate, date_symptons, date_died, icu
      'other_disease','cardiovascular','obesity','renal_chronic','tobacco',
'contact_other_covid','covid_res']
      target_column= 'icu'
      In [4]: # Split in traning and test sets
      from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test =train_test_split(dataOriginal[predictors],
                                          dataOriginal[target_column],
                                          test_size=0.20, random_state=44)
      print("Size training set: ", X_train.shape)
print("Size test set: ", X_test.shape)
```

### 4. IMPUTATION AND DETECTION OF NULL AND ODD VALUES.

### Make transformations with mocked data in order to show competences???

```
I didnt find odd values.
```

In [ ]:

```
In [42]: print(model_columns)
    ['sex', 'patient_type', 'intubed', 'pneumonia', 'age', 'pregnancy', 'diabetes', 'copd', 'asthma', 'inmsupr', 'hype rtension', 'other_disease', 'cardiovascular', 'obesity', 'renal_chronic', 'tobacco', 'contact_other_covid', 'covid _res', 'icu']
```

#### Check for null values in the dataset

Size training set: (453281, 18) Size test set: (113321, 18)

```
In [43]: X_train[predictors].isnull().values.sum()
Out[43]: 0
In [44]: y_train.isnull().values.sum()
Out[44]: 0
```

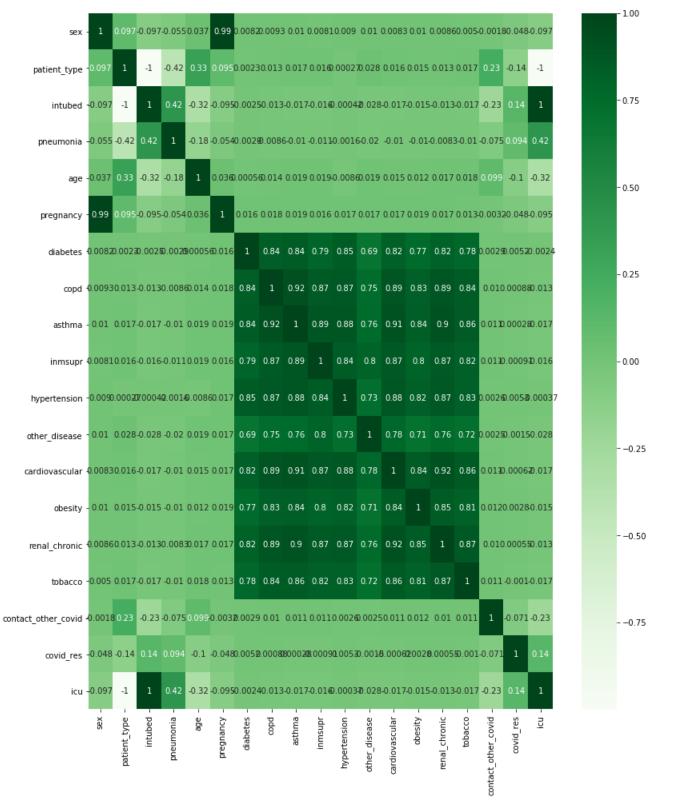
### 5. CORRELATION ANALYSIS

### 5.1 Correlation Matrix

```
In [37]: import seaborn as sn

#The default correlation Algorithme user is Pearson, which its not appropriate for categorical
#variables but its interesting to see its able to detect dependent variables detected with Chi-squared too.

df = pd.DataFrame(dataOriginal[model_columns], columns=model_columns)
plt.figure(figsize=(13,16))
corrMatrix = df.corr()
sn.heatmap(corrMatrix, annot=True, cmap="Greens")
plt.show()
```



All the maladies are really corelated, for example: - Renal\_chronic vs Tobacco - Asthma et tobaccon are highly corelated to all diseases. - Sex correlated with age?

```
intubed
                                                                                             diabetes
                                                                                                                   asthma
                          sex patient_type
                                                        pneumonia
                                                                          age
                                                                               pregnancy
                                                                                                           copd
                                                                                                                             inmsupr hyperter
                                   0.097025
                                                                                                       0.009339
               sex
                     1.000000
                                             -0.097029
                                                          -0.054758
                                                                     0.036709
                                                                                 0.994293
                                                                                             0.008153
                                                                                                                  0.010119
                                                                                                                             0.008096
       patient_type
                     0.097025
                                   1.000000
                                             -0.999319
                                                          -0.420400
                                                                     0.325059
                                                                                 0.095472
                                                                                            0.002315
                                                                                                       0.013227
                                                                                                                  0.016670
                                                                                                                             0.016359
                                                                                                                                            0.00
                     -0.097029
                                  -0.999319
                                              1.000000
                                                          0.421256 -0.324869
                                                                                 -0.095481
                                                                                            -0.002456
                                                                                                       -0.013363
                                                                                                                  -0.016807
                                                                                                                            -0.016424
                                                                                                                                           -0.00
            intubed
                     -0.054758
                                                                                                                  -0.010370
                                                                                                                            -0.010979
        pneumonia
                                  -0.420400
                                              0.421256
                                                           1.000000
                                                                    -0.183492
                                                                                 -0.054031
                                                                                            -0.002875
                                                                                                       -0.008592
                                                                                                                                           -0.00
                     0.036709
                                   0.325059 -0.324869
                                                          -0.183492
                                                                     1.000000
                                                                                 0.036239
                                                                                            0.000556
                                                                                                       0.014440
                                                                                                                  0.018668
                                                                                                                             0.018625
                                                                                                                                           -0.00
               age
                     0.994293
                                   0.095472 -0.095481
                                                          -0.054031
                                                                     0.036239
                                                                                 1.000000
                                                                                            0.016239
                                                                                                       0.018035
                                                                                                                  0.018931
                                                                                                                             0.016412
                                                                                                                                            0.01
         pregnancy
                     0.008153
                                   0.002315 -0.002456
                                                          -0.002875
                                                                     0.000556
                                                                                 0.016239
                                                                                             1.000000
                                                                                                       0.838368
                                                                                                                  0.843817
                                                                                                                             0.794140
           diabetes
                                                                                                                                            0.84
                                   0.013227 -0.013363
                                                                     0.014440
                                                                                            0.838368
              copd
                     0.009339
                                                          -0.008592
                                                                                 0.018035
                                                                                                       1.000000
                                                                                                                  0.922057
                                                                                                                             0.866870
                                                                                                                                            0.87
                     0.010119
                                   0.016670 -0.016807
                                                          -0.010370
                                                                     0.018668
                                                                                 0.018931
                                                                                            0.843817
                                                                                                       0.922057
                                                                                                                  1.000000
                                                                                                                             0.886307
            asthma
                                                                                                                                            38.0
                                                                                                                             1.000000
                     0.008096
                                   0.016359 -0.016424
                                                          -0.010979
                                                                     0.018625
                                                                                 0.016412
                                                                                            0.794140
                                                                                                       0.866870
                                                                                                                  0.886307
           inmsupr
                                                                                                                                            0.84
                     0.009019
                                   0.000274 -0.000419
                                                          -0.001568 -0.008617
                                                                                 0.017474
                                                                                            0.845727
                                                                                                       0.872321
                                                                                                                  0.883549
                                                                                                                             0.844534
      hypertension
                                                                                                                                            1.00
      other_disease
                     0.010155
                                   0.028232
                                             -0.028389
                                                          -0.019541
                                                                     0.018627
                                                                                 0.017392
                                                                                            0.688245
                                                                                                       0.748066
                                                                                                                  0.756712
                                                                                                                             0.800965
     cardiovascular
                     0.008344
                                   0.016446 -0.016587
                                                          -0.010392
                                                                     0.015049
                                                                                 0.016854
                                                                                            0.821716
                                                                                                       0.893562
                                                                                                                  0.906039
                                                                                                                             0.872862
                                                                                                                                            0.87
            obesity
                     0.010199
                                   0.014967 -0.015101
                                                          -0.010070
                                                                     0.012068
                                                                                 0.018692
                                                                                            0.765574
                                                                                                       0.827598
                                                                                                                  0.839128
                                                                                                                             0.804051
                                                                                                                                            0.82
      renal_chronic
                     0.008577
                                   0.013240
                                             -0.013384
                                                          -0.008296
                                                                     0.016643
                                                                                 0.016970
                                                                                            0.817052
                                                                                                       0.889774
                                                                                                                  0.901793
           tobacco 0.004980
                                   0.016603 -0.016738
                                                          -0.009996
                                                                     0.017531
                                                                                 0.013060
                                                                                            0.777978
                                                                                                       0.844021
                                                                                                                  0.855136
                                                                                                                             0.821285
                                                                                                                                            0.82
                                   0.228929 -0.228811
                                                                     0.099339
                                                                                                                  0.010714
                                                                                                                             0.010554
contact other covid -0.001791
                                                          -0.074756
                                                                                 -0.003185
                                                                                            0.002895
                                                                                                       0.010322
                                                                                                                                            0.00
         covid_res
                    -0.047575
                                  -0.135931
                                              0.135738
                                                          0.093832
                                                                     -0.102643
                                                                                 -0.047589
                                                                                            0.005156
                                                                                                       0.000882
                                                                                                                  0.000276
                                                                                                                             -0.000914
                                                                                                                                            0.00
                icu -0.097024
                                  -0.999314
                                             0.999989
                                                          0.421182 -0.324791
                                                                                 -0.095474 -0.002429 -0.013308
                                                                                                                 -0.016759 -0.016299
                                                                                                                                           -0.00
```

# 5.2. Correlation between numerique and categorical information - Age vs diseases.

```
In [46]: #ANOVA
In [ ]:
```

### 6. VARIABLE REDUCTION

In [38]: df.corr()

Out[38]:

https://machinelearningmastery.com/feature-selection-with-real-and-categorical-data/ (https://machinelearningmastery.com/feature-selection-with-real-and-categorical-data/)

Jai essaie Variance Tresholding, normalisation et standarisation, mais ca marche pas pour notre cas.

### 6.1. Based on exploration info

```
In [72]: # Reduce variables based on correlation

# Patient_type and intubed are the same information of icu. We have to eliminate from dataModel.

predictors.remove('intubed')
predictors.remove('patient_type')
```

### 6.2. Variances Tresholding

Normalisation, Variance Tresholding and Standarisation doesnt apply for most of our model descriptors, variance its important in descriptors where means, mode distribution has significant information value.

the degree of association between predictor and outcome can be measured with statistics such as X2 (chi-squared) tests.

i did it but doesnt work well with categorical

### 6.2. Chi-Squared Feature Selection

Pearson's chi-squared statistical hypothesis test is an example of a test for independence between categorical variables

The degree of association between predictor and outcome can be measured with statistics such as X2 (chi-squared) tests.

1.Define Hypothesis Null Hypothesis (H0): Two variables are independent. Alternate Hypothesis (H1): Two variables are not independent.

https://towardsdatascience.com/the-search-for-categorical-correlation-a1cf7f1888c9 https://towardsdatascience.com/categorical-feature-selection-via-chi-square-fc558b09de43 https://towardsdatascience.com/feature-selection-with-pandas-e3690ad8504b https://towardsdatascience.com/the-search-for-categorical-correlation-a1cf7f1888c9

```
In [73]: # Labels for descriptors
         In [75]: import scipy.stats as ss #import chi2_contingency
         def cramers_v(x, y):
             confusion_matrix = pd.crosstab(x,y)
             chi2 = ss.chi2_contingency(confusion_matrix)[0]
             n = confusion_matrix.sum().sum()
             phi2 = chi2/n
             r,k = confusion_matrix.shape
             phi2corr = \max(0, \text{ phi2-}((k-1)*(r-1))/(n-1))

rcorr = r-((r-1)**2)/(n-1)

kcorr = k-((k-1)**2)/(n-1)
             return round(np.sqrt(phi2corr/min((kcorr-1),(rcorr-1))),3)
         cramers_v(X_train['pneumonia'], X_train['sex'])
Out[75]: 0.085
In [76]: cramers_v(X_train['hypertension'], X_train['obesity'])
Out[76]: 0.593
In [77]: model_columns
Out[77]: ['sex',
           'pneumonia',
           'age',
           'pregnancy',
          'diabetes',
          'copd',
           'asthma'
          'inmsupr'
          'hypertension',
'other_disease'
          'cardiovascular',
          'obesity',
'renal_chronic',
           'tobacco',
          'contact_other_covid',
           'covid_res',
```

'icu']

```
In [78]: XY = X_train
   XY['icu'] = y_train

df2 = pd.DataFrame(columns=model_columns, index=model_columns)
   for i in range(len(model_columns)):
        for j in range(len(model_columns)):
            # print("f: " + fname + " c: "+ cname)
            fname = model_columns[i]
            cname = model_columns[j]
            df2.loc[fname, cname] = cramers_v(X_train[fname], X_train[cname])

display(df2)
```

	sex	pneumonia	age	pregnancy	diabetes	copd	asthma	inmsupr	hypertension	other_disease	cardiovascular	ob
sex	1	0.085	0.054	1	0.017	0.011	0.047	0.01	0.013	0.027	0.014	(
pneumonia	0.085	1	0.227	0.061	0.153	0.068	0.015	0.048	0.135	0.041	0.057	
age	0.054	0.227	1	0.067	0.255	0.157	0.03	0.054	0.294	0.058	0.123	(
pregnancy	1	0.061	0.067	1	0.056	0.056	0.065	0.053	0.058	0.051	0.055	(
diabetes	0.017	0.153	0.255	0.056	1	0.597	0.599	0.565	0.657	0.488	0.588	(
copd	0.011	0.068	0.157	0.056	0.597	1	0.652	0.614	0.621	0.529	0.634	(
asthma	0.047	0.015	0.03	0.065	0.599	0.652	1	0.628	0.626	0.535	0.642	(
inmsupr	0.01	0.048	0.054	0.053	0.565	0.614	0.628	1	0.599	0.576	0.618	
hypertension	0.013	0.135	0.294	0.058	0.657	0.621	0.626	0.599	1	0.52	0.633	(
other_disease	0.027	0.041	0.058	0.051	0.488	0.529	0.535	0.576	0.52	1	0.55	
cardiovascular	0.014	0.057	0.123	0.055	0.588	0.634	0.642	0.618	0.633	0.55	1	(
obesity	0.021	0.05	0.092	0.057	0.549	0.585	0.596	0.57	0.593	0.5	0.599	
renal_chronic	0.018	0.074	0.086	0.055	0.593	0.63	0.641	0.619	0.632	0.541	0.654	(
tobacco	0.105	0.013	0.051	0.091	0.554	0.601	0.61	0.584	0.59	0.513	0.614	(
contact_other_covid	0.049	0.131	0.123	0.042	0.078	0.041	0.016	0.034	0.081	0.091	0.029	(
covid_res	0.069	0.135	0.118	0.05	0.071	0.012	0.021	0.015	0.062	0.013	0.011	(
icu	0.098	0.464	0.24	0.058	0.187	0.088	0.02	0.07	0.168	0.068	0.075	(
4												•

In [79]: X\_train.head(5)

Out[79]:

	sex	patient_type	intubed	pneumonia	age	pregnancy	diabetes	copd	asthma	inmsupr	hypertension	other_disease	cardiovascul
380621	1	1	97	2	42	2	2	2	2	2	2	2	_
215435	2	2	1	1	60	97	2	2	2	2	2	2	
81577	2	1	97	2	25	97	2	2	2	2	2	2	
508482	1	1	97	2	29	2	2	2	2	2	2	2	
430578	1	1	97	2	41	2	2	2	2	2	2	2	
4													<b>&gt;</b>

In [80]: df2.shape

Out[80]: (17, 17)

```
In [81]: | #df = pd.DataFrame(index=predictors, columns=predictors)
           import seaborn as sns
           df2 = df2.astype('float') # !! Neccessary for Heatmap
           plt.figure(figsize=(12,10))
           sns.heatmap(df2, annot=True, cmap="Greens")
           plt.show()
                                                                                                                            1.0
                              1 0.085 0.054 1 0.017 0.011 0.047 0.01 0.013 0.027 0.014 0.021 0.018 0.1 0.049 0.069 0.098
                                   0.23 0.061 0.15 0.068 0.015 0.048 0.14 0.041 0.057 0.05 0.074 0.013 0.13 0.14 0.46
                   pneumonia -0.085
                                            0.067 0.26 0.16 0.03 0.054 0.29 0.058 0.12 0.092 0.086 0.051 0.12 0.12 0.24
                               0.061 0.067
                                             1 0.056 0.056 0.065 0.053 0.058 0.051 0.055 0.057 0.055 0.091 0.042 0.05 0.058
                                                                                                                            - 0.8
                     diabetes -0.017 0.15 0.26 0.056 1 0.6 0.6 0.56 0.66 0.49 0.59 0.55 0.59 0.55 0.078 0.071 0.19
                        copd -0.011 0.068 0.16 0.056
                                                           0.6 0.65 1 0.63 0.63 <mark>0.54</mark> 0.64 0.6 0.64 0.61 0.016 0.021 0.02
                      asthma -0.047 0.015 0.03 0.065
                                                                                                                            0.6
                      inmsupr - 0.01 0.048 0.054 0.053 0.56 0.61 0.63
                                                                 1 0.6 0.58 0.62 0.57 0.62 0.58 0.034 0.015 0.07
                  hypertension -0.013 0.14 0.29 0.058 0.66 0.62 0.63 0.6
                                                                      1 0.52 0.63 0.59 0.63 0.59 0.081 0.062 0.17
                 other disease -0.027 0.041 0.058 0.051 0.49 0.53 0.54 0.58 0.52
                                                                           1 0.55 0.5 0.54 0.51 0.091 0.013 0.068
                                                                                                                            - 0.4
                 cardiovascular -0.014 0.057 0.12 0.055 0.59 0.63 0.64 0.62 0.63 0.55
                                                                                     0.6 0.65 0.61 0.029 0.011 0.075
                      obesity -0.021 0.05 0.092 0.057 0.55 0.58 0.6 0.57 0.59 0.5 0.6
                                                                                          0.6 0.58 0.019 0.053 0.048
                 renal chronic -0.018 0.074 0.086 0.055 0.59 0.63 0.64 0.62 0.63 0.54 0.65 0.6
                                                                                              0.62 0.051 0.012 0.11
                      tobacco - 0.1 0.013 0.051 0.091 0.55 0.6 0.61 0.58 0.59 0.51 0.61 0.58 0.62
                                                                                                                           - 0.2
            contact_other_covid -0.049 0.13 0.12 0.042 0.078 0.041 0.016 0.034 0.081 0.091 0.029 0.019 0.051 0.012 1 0.084 0.21
                     covid_res -0.069 0.14 0.12 0.05 0.071 0.012 0.021 0.015 0.062 0.013 0.011 0.053 0.012 0.022 0.084
                          icu -0.098 0.46 0.24 0.058 0.19 0.088 0.02 0.07 0.17 0.068 0.075 0.048 0.11 0.016 0.21 0.14
In [67]: # TODO UTIL?
 In [9]:
           contigency= pd.crosstab(X_train['pneumonia'], y_train)
           contigency
           plt.figure(figsize=(12,8))
           sns.heatmap(contigency, annot=True, cmap="YlGnBu")
 Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x16aeee32e08>
                                                                                                               300000
                                                                   1.2e+04
                        6.7e+03
                                             5.2e+04
                                                                                                               250000
                                                                                                                200000
                         1.4e+03
                                             3.7e+04
                                                                   3.4e+05
                                                                                                               150000
                                                                                                               100000
              නු -
                                                                                                               50000
```

### 6.3. Componenent Analysis

icu

### 7. MODELISATION & PREDICTION

#### **7.1 KNN**

#### 7.1.1 Model Evaluation

```
In [7]: # METRIQUES

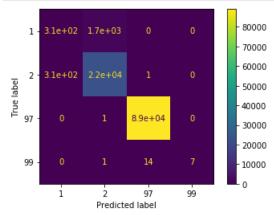
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix

y_predicted_train = model1.predict(X_train)
y_predicted_test = model1.predict(X_test)

print("Accuracy:", metrics.accuracy_score(y_predicted_test, y_test))
```

Accuracy: 0.9822716001447216

```
In [12]: from sklearn.metrics import plot_confusion_matrix
    plot_confusion_matrix(model1, X_test, y_test)
    plt.show()
```



Precision: 0.9770914170233116

```
In [11]: print ("F1 score:", metrics.f1_score(y_test, y_predicted_test, average='macro'))
```

F1 score: 0.6694207066190329

7.1.1. Wodei			
In [ ]:			
In [ ]:			
III [ ].			
In [ ]:			
In [ ]:			
7.1.2. Predicti	on		
. I.Z. I ICAICH			
In [ ]:			
7.2. Desicio	n Tree		
In [ ]:			
7.2 November	Daves		
7.3. Nayve I	sayes		

# 8. CONCLUSIONS

In [ ]: