analyse

October 14, 2023

[ ]:
```
print("hello")
```

```
hello
```

0.1 # Analyse simple sur la stat-desc

0.1.1 Importation des packages

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
```

0.1.2 Data importation

[ ]:
```
try:
    df = pd.read_excel('data.xlsx')
except:
    print('erreur :')
    %pip install openpyxl
```

0.1.3 Basic manipulation

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

[ ]:

	annee	mois	rec_douane	rec_connexe
0	2018	janvier	46951137555	19.549.999.674
1	2018	février	47313934748	5.248.767.786
2	2018	mars	50398861182	6.547.525.686
3	2018	avril	58775911887	7.220.072.918
4	2018	mai	58775911887	6.938.560.710

0.2 ### Data manipulation

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60 entries, 0 to 59
```

```
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   annee        60 non-null     int64
 1   mois         60 non-null     object
 2   rec_douane   48 non-null     object
 3   rec_connexe  60 non-null     object
dtypes: int64(1), object(3)
memory usage: 2.0+ KB
```

[ ]:
```python
print(df.isnull().sum())
```

```
annee           0
mois            0
rec_douane     12
rec_connexe     0
dtype: int64
```

[ ]:
```python
df_copy = df.copy()
```

[ ]:
```python
df_copy.head()
```

[ ]:

	annee	mois	rec_douane	rec_connexe
0	2018	janvier	46951137555	19.549.999.674
1	2018	février	47313934748	5.248.767.786
2	2018	mars	50398861182	6.547.525.686
3	2018	avril	58775911887	7.220.072.918
4	2018	mai	58775911887	6.938.560.710

[ ]:
```python
df_copy.rec_douane.unique()
```

[ ]:
```
array([46951137555, 47313934748, 50398861182, 58775911887, 68656726875,
       67199882580, 91744270326, 81660584134, 86950027364, 77933324364,
       77055520300, 79921904201, 80077845319, 92707936942, 83347546877,
       90188111899, 82674828124, 86585709871, 74503183149, 71673553416,
       72467971836, 67422443268, 64175523691, '605 672 967 11',
       '674 329 875 42', '598 034 911 26', '572 341 506 44',
       '508 469 326 05', '547 063 519 15', '683 389 565 01',
       '868 370 554 60', '886 483 694 70', '766 505 408 72',
       '721 957 331 65', '636 420 776 89', '660 550 884 82',
       '717 241 756 94', '757 398 038 44', '796 947 998 13',
       '924 727 438 60', '976 677 455 15', '971 394 666 03', 220499157780,
       '127 1200 116 74', 118926586673, 122463353583, 127929318831, nan],
      dtype=object)
```

[ ]:
```python
df_copy.rec_connexe.unique()
```

```
[ ]: array(['19.549.999.674', '  5.248.767.786', '  6.547.525.686',
        '  7.220.072.918', '  6.938.560.710', '10.087.033.209',
        '13.747.618.364', '18.154.441.800', '22.319.200.107',
        '18.872.341.724', '17.499.907.474', '20.518.021.342',
        '20.456.591.937', '16.382.282.808', '20.163.096.373',
        '22.212.658.797', '19.504.046.902', '16.797.307.841',
        '18.382.897.338', '28.529.563.557', '25.723.259.339',
        '27.152.511.693', '23.529.903.715', '24.667.260.047',
        '17.818.736.907', '17.921.237.425', '18.428.901.188',
        '14.310.096.310', '14.515.819.753', '17.726.283.703',
        '18.939.079.682', '18.318.468.473', '17.534.840.664',
        '19.586.626.410', '15.957.368.731', '17.014.737.376',
        '23.049.066.917', '16.036.148.675', '17.654.667.381',
        '18.520.275.640', '18.661.258.606', '33.011.803.549',
        '22.590.445.106', '23.409.205.473', '21.840.804.138',
        '23.273.983.165', '23.917.713.477', '20,720,485,819',
        '21,390,075,497', '27,574,121,734', '26,861,850,903',
        '34,393,431,285', '36,360,766,011', '40,254,144,158',
        '46,817,361,628', '45,234,266,283', '42,991,169,158',
        '41,916,221,297', '47,684,200,972'], dtype=object)
```

Deleting all empties str inside the value (suppression des vides dans une chaine)

```
[ ]: def str_with_point_or_comma(v):
         try:
             k = str(v).strip()

             if ' ' in k:
                 l = k.split(' ')

                 # On supprime les valeurs vide de la liste
                 for i in range(len(l)-1, -1, -1):
                     if l[i] == "":
                         del l[i]

                 if len(l)==1:
                     return int(l[0])
                 else:
                     concatenation = ''.join(str(element) for element in l) # On␣
      ↪fait la concaténation des entiers converti en str

                     if '.' in concatenation:
                         l = concatenation.split('.')
                         concatenation = ''.join(str(element) for element in l)

                         if ',' in concatenation:
                             l = concatenation.split(',')
                             concatenation = ''.join(str(element) for element in l)
```

```
                        return int(concatenation)
                    return int(concatenation)
                return int(concatenation)

        elif '.' in k:
            l = k.split('.')
            concatenation = ''.join(str(element) for element in l)
            return int(concatenation)

        elif ',' in k:
            l = k.split(',')
            concatenation = ''.join(str(element) for element in l)
            return int(concatenation)

        return int(k)
    except:
        return v
```

Converti un objet en un int

[ ]:
```
str_with_point_or_comma(' 7170.24175.694 ')
```

[ ]: 717024175694

[ ]:
```
# Applying converte_to_number function to df_copy
df_copy.rec_douane = df_copy.rec_douane.apply(str_with_point_or_comma)
```

[ ]:
```
df_copy.head()
```

[ ]:

	annee	mois	rec_douane	rec_connexe
0	2018	janvier	4.695114e+10	19.549.999.674
1	2018	février	4.731393e+10	5.248.767.786
2	2018	mars	5.039886e+10	6.547.525.686
3	2018	avril	5.877591e+10	7.220.072.918
4	2018	mai	5.877591e+10	6.938.560.710

[ ]:
```
df_copy.rec_connexe.unique()
```

[ ]:
```
array(['19.549.999.674', '  5.248.767.786', '  6.547.525.686',
       '  7.220.072.918', '  6.938.560.710', '10.087.033.209',
       '13.747.618.364', '18.154.441.800', '22.319.200.107',
       '18.872.341.724', '17.499.907.474', '20.518.021.342',
       '20.456.591.937', '16.382.282.808', '20.163.096.373',
       '22.212.658.797', '19.504.046.902', '16.797.307.841',
       '18.382.897.338', '28.529.563.557', '25.723.259.339',
       '27.152.511.693', '23.529.903.715', '24.667.260.047',
       '17.818.736.907', '17.921.237.425', '18.428.901.188',
       '14.310.096.310', '14.515.819.753', '17.726.283.703',
```

```
'18.939.079.682', '18.318.468.473', '17.534.840.664',
'19.586.626.410', '15.957.368.731', '17.014.737.376',
'23.049.066.917', '16.036.148.675', '17.654.667.381',
'18.520.275.640', '18.661.258.606', '33.011.803.549',
'22.590.445.106', '23.409.205.473', '21.840.804.138',
'23.273.983.165', '23.917.713.477', '20,720,485,819',
'21,390,075,497', '27,574,121,734', '26,861,850,903',
'34,393,431,285', '36,360,766,011', '40,254,144,158',
'46,817,361,628', '45,234,266,283', '42,991,169,158',
'41,916,221,297', '47,684,200,972'], dtype=object)
```

[ ]:
```
str_with_point_or_comma('5.248, 767 .786 ')
```

[ ]:
```
5248767786
```

[ ]:
```
df_copy.rec_connexe = df_copy.rec_connexe.apply(str_with_point_or_comma)
```

[ ]:
```
df_copy.head()
```

[ ]:

	annee	mois	rec_douane	rec_connexe
0	2018	janvier	4.695114e+10	19549999674
1	2018	février	4.731393e+10	5248767786
2	2018	mars	5.039886e+10	6547525686
3	2018	avril	5.877591e+10	7220072918
4	2018	mai	5.877591e+10	6938560710

[ ]:
```
df_copy.rec_connexe.unique()
```

[ ]:
```
array([19549999674,  5248767786,  6547525686,  7220072918,  6938560710,
       10087033209, 13747618364, 18154441800, 22319200107, 18872341724,
       17499907474, 20518021342, 20456591937, 16382282808, 20163096373,
       22212658797, 19504046902, 16797307841, 18382897338, 28529563557,
       25723259339, 27152511693, 23529903715, 24667260047, 17818736907,
       17921237425, 18428901188, 14310096310, 14515819753, 17726283703,
       18939079682, 18318468473, 17534840664, 19586626410, 15957368731,
       17014737376, 23049066917, 16036148675, 17654667381, 18520275640,
       18661258606, 33011803549, 22590445106, 23409205473, 21840804138,
       23273983165, 23917713477, 20720485819, 21390075497, 27574121734,
       26861850903, 34393431285, 36360766011, 40254144158, 46817361628,
       45234266283, 42991169158, 41916221297, 47684200972], dtype=int64)
```

[ ]:
```
df_copy.rec_douane.unique()
```

[ ]:
```
array([4.69511376e+10, 4.73139347e+10, 5.03988612e+10, 5.87759119e+10,
       6.86567269e+10, 6.71998826e+10, 9.17442703e+10, 8.16605841e+10,
       8.69500274e+10, 7.79333244e+10, 7.70555203e+10, 7.99219042e+10,
       8.00778453e+10, 9.27079369e+10, 8.33475469e+10, 9.01881119e+10,
       8.26748281e+10, 8.65857099e+10, 7.45031831e+10, 7.16735534e+10,
```

```
        7.24679718e+10, 6.74224433e+10, 6.41755237e+10, 6.05672967e+10,
        6.74329875e+10, 5.98034911e+10, 5.72341506e+10, 5.08469326e+10,
        5.47063519e+10, 6.83389565e+10, 8.68370555e+10, 8.86483695e+10,
        7.66505409e+10, 7.21957332e+10, 6.36420777e+10, 6.60550885e+10,
        7.17241757e+10, 7.57398038e+10, 7.96947998e+10, 9.24727439e+10,
        9.76677455e+10, 9.71394666e+10, 2.20499158e+11, 1.27120012e+11,
        1.18926587e+11, 1.22463354e+11, 1.27929319e+11,            nan])
```

0.2.1 Missing data Manipulation

There are a lot of technics for filling missing data, in our case, we will use KNNImputer. Such as :

- Next or Previous Value
- K Nearest Neighbors
- Maximum or Minimum Value
- Missing Value Prediction
- Most Frequent Value
- Average or Linear Interpolation
- (Rounded) Mean or Moving Average or Median Value
- Fixed Value

[ ]:
```
df_copy.isnull().sum()
```

[ ]:
```
annee          0
mois           0
rec_douane    12
rec_connexe    0
dtype: int64
```

[ ]:
```
df_copy.tail(13)
```

[ ]:

	annee	mois	rec_douane	rec_connexe
47	2021	décembre	1.279293e+11	23917713477
48	2022	janvier	NaN	20720485819
49	2022	février	NaN	21390075497
50	2022	mars	NaN	27574121734
51	2022	avril	NaN	26861850903
52	2022	mai	NaN	34393431285
53	2022	juin	NaN	36360766011
54	2022	juillet	NaN	40254144158
55	2022	août	NaN	46817361628
56	2022	septembre	NaN	45234266283
57	2022	octobre	NaN	42991169158
58	2022	novembre	NaN	41916221297
59	2022	décembre	NaN	47684200972

visualling missing data

[ ]:
```
%pip install missingno
%pip install datatile
```

```
Requirement already satisfied: missingno in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (0.5.2)
Requirement already satisfied: numpy in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
missingno) (1.24.3)
Requirement already satisfied: matplotlib in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
missingno) (3.8.0)
Requirement already satisfied: scipy in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
missingno) (1.11.3)
Requirement already satisfied: seaborn in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
missingno) (0.13.0)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
matplotlib->missingno) (1.1.1)
Requirement already satisfied: cycler>=0.10 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
matplotlib->missingno) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
matplotlib->missingno) (4.43.1)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
matplotlib->missingno) (1.4.5)
Requirement already satisfied: packaging>=20.0 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
matplotlib->missingno) (23.1)
Requirement already satisfied: pillow>=6.2.0 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
matplotlib->missingno) (10.0.1)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
matplotlib->missingno) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
matplotlib->missingno) (2.8.2)
Requirement already satisfied: pandas>=1.2 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
seaborn->missingno) (2.1.1)
Requirement already satisfied: pytz>=2020.1 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from
pandas>=1.2->seaborn->missingno) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in c:\users\pinto
```

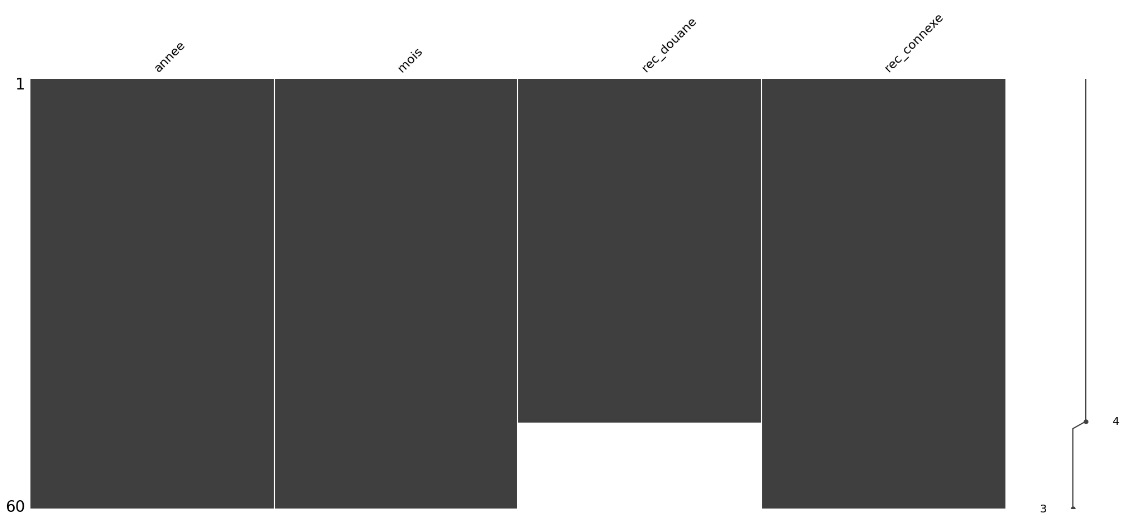
```
katende\appdata\local\programs\python\python311\lib\site-packages (from
pandas>=1.2->seaborn->missingno) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\pinto
katende\appdata\local\programs\python\python311\lib\site-packages (from python-
dateutil>=2.7->matplotlib->missingno) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
Collecting datatile
  Downloading datatile-1.0.3-py3-none-any.whl (6.0 kB)
Collecting traceml<1.1 (from datatile)
  Downloading traceml-1.0.8-py3-none-any.whl (144 kB)
     ---------------------------------------- 0.0/144.5 kB ? eta -:--:--
     ---------------------------------------- 0.0/144.5 kB ? eta -:--:--
     ---------------------------------------- 0.0/144.5 kB ? eta -:--:--
     ---------------------------------------- 0.0/144.5 kB ? eta -:--:--
     -- ------------------------------------- 10.2/144.5 kB ? eta -:--:--
     -- ------------------------------------- 10.2/144.5 kB ? eta -:--:--
     -- ------------------------------------- 10.2/144.5 kB ? eta -:--:--
     -- ------------------------------------- 10.2/144.5 kB ? eta -:--:--
     -- ------------------------------------- 10.2/144.5 kB ? eta -:--:--
     -- ------------------------------------- 10.2/144.5 kB ? eta -:--:--
     -- ------------------------------------- 10.2/144.5 kB ? eta -:--:--
     -------- ----------------------------- 30.7/144.5 kB 59.5 kB/s eta 0:00:02
     -------- ----------------------------- 30.7/144.5 kB 59.5 kB/s eta 0:00:02
     -------- ----------------------------- 30.7/144.5 kB 59.5 kB/s eta 0:00:02
     -------- ----------------------------- 30.7/144.5 kB 59.5 kB/s eta 0:00:02
     -------- ----------------------------- 30.7/144.5 kB 59.5 kB/s eta 0:00:02
     -------- ----------------------------- 30.7/144.5 kB 59.5 kB/s eta 0:00:02
     -------- ----------------------------- 30.7/144.5 kB 59.5 kB/s eta 0:00:02
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
     ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
```

```
   ---------- --------------------------- 41.0/144.5 kB 43.7 kB/s eta 0:00:03
   ---------------- --------------------- 61.4/144.5 kB 29.5 kB/s eta 0:00:03
   ---------------- --------------------- 61.4/144.5 kB 29.5 kB/s eta 0:00:03
   ------------------ ------------------- 71.7/144.5 kB 33.3 kB/s eta 0:00:03
   ---------------------------- -------- 112.6/144.5 kB 54.2 kB/s eta 0:00:01
   ---------------------------- -------- 112.6/144.5 kB 54.2 kB/s eta 0:00:01
   ------------------------------- ----- 122.9/144.5 kB 57.2 kB/s eta 0:00:01
   ------------------------------- ----- 122.9/144.5 kB 57.2 kB/s eta 0:00:01
   ------------------------------- ----- 122.9/144.5 kB 57.2 kB/s eta 0:00:01
   ------------------------------- ----- 122.9/144.5 kB 57.2 kB/s eta 0:00:01
   ------------------------------- ----- 122.9/144.5 kB 57.2 kB/s eta 0:00:01
   ------------------------------------  143.4/144.5 kB 59.6 kB/s eta 0:00:01
   ------------------------------------- 144.5/144.5 kB 58.9 kB/s eta 0:00:00
Installing collected packages: traceml, datatile
Successfully installed datatile-1.0.3 traceml-1.0.8
Note: you may need to restart the kernel to use updated packages.
```

[ ]:
```python
import missingno as msno # to visualize missing value
```

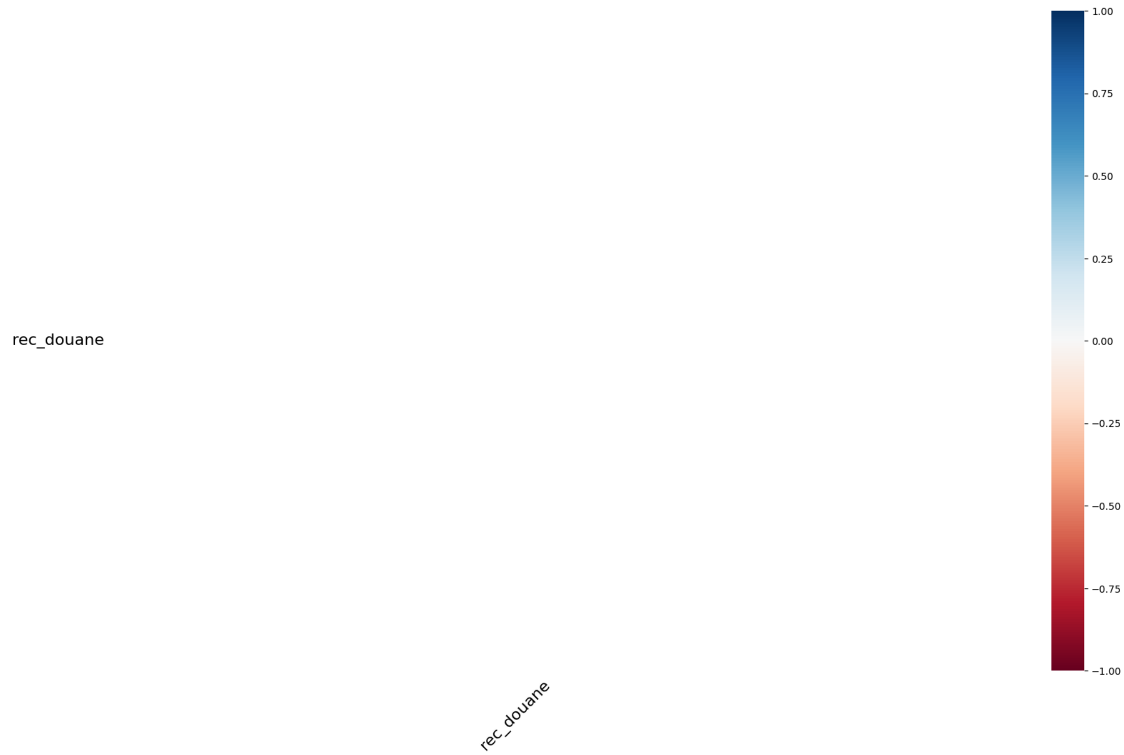
[ ]:
```python
# visualize missing data
msno.matrix(df_copy)
```

[ ]: <Axes: >



[ ]:
```python
msno.heatmap(df_copy)
```

[ ]: <Axes: >



Missing data summary

[ ]:
```
# Exhaustive Summary of dataframe
from datatile.summary.df import DataFrameSummary
dfs = DataFrameSummary(df_copy.iloc[:,2:])
dfs.columns_stats
```

[ ]:

	rec_douane	rec_connexe
counts	48	60
uniques	47	59
missing	12	0
missing_perc	20%	0%
types	numeric	numeric

Imputation with KNNImputer

[ ]:
```
# import the KNNimputer class
from sklearn.impute import KNNImputer
```

[ ]:
```
# create an object for KNNImputer
imputer = KNNImputer(n_neighbors=6)

# Sélection de la colonne "rec_douane"
rec_douane = df_copy.rec_douane
```

```
# Réorganiser les données pour correspondre à la forme requise
rec_douane = rec_douane.values.reshape(-1, 1)

# Appliquer l'imputation
imputed_rec_douane = imputer.fit_transform(rec_douane)

# Mise à jour de la colonne "rec_douane"
df_copy["rec_douane"] = imputed_rec_douane
```

[ ]:
```
# Exhaustive Summary of dataframe
from datatile.summary.df import DataFrameSummary
dfs = DataFrameSummary(df_copy.iloc[:,2:])
dfs.columns_stats
```

[ ]:

	rec_douane	rec_connexe
counts	60	60
uniques	48	59
missing	0	0
missing_perc	0%	0%
types	numeric	numeric

[ ]:
```
df_copy.tail(12)
```

[ ]:

	annee	mois	rec_douane	rec_connexe
48	2022	janvier	8.048956e+10	20720485819
49	2022	février	8.048956e+10	21390075497
50	2022	mars	8.048956e+10	27574121734
51	2022	avril	8.048956e+10	26861850903
52	2022	mai	8.048956e+10	34393431285
53	2022	juin	8.048956e+10	36360766011
54	2022	juillet	8.048956e+10	40254144158
55	2022	août	8.048956e+10	46817361628
56	2022	septembre	8.048956e+10	45234266283
57	2022	octobre	8.048956e+10	42991169158
58	2022	novembre	8.048956e+10	41916221297
59	2022	décembre	8.048956e+10	47684200972

Imputation with Means of previous months KNNImputer doesn't work well, we choose an others custom technic

In this case, we will impute using the means of the previous months, except for the last month where we have missing data.

[ ]:
```
# Iterate over each month in the last year
last_year = df_copy[df_copy["annee"] == df_copy["annee"].max()]

previous_year = df_copy[df_copy["annee"] < df_copy["annee"].max()]
```

[ ]:
```
last_year.head()
```

[ ]:
```
    annee      mois    rec_douane  rec_connexe
48   2022   janvier  8.048956e+10  20720485819
49   2022   février  8.048956e+10  21390075497
50   2022      mars  8.048956e+10  27574121734
51   2022     avril  8.048956e+10  26861850903
52   2022       mai  8.048956e+10  34393431285
```

[ ]:
```
previous_year.head(13)
```

[ ]:
```
    annee       mois    rec_douane  rec_connexe
0    2018    janvier  4.695114e+10  19549999674
1    2018    février  4.731393e+10   5248767786
2    2018       mars  5.039886e+10   6547525686
3    2018      avril  5.877591e+10   7220072918
4    2018        mai  5.877591e+10   6938560710
5    2018       juin  6.865673e+10  10087033209
6    2018    juillet  6.719988e+10  13747618364
7    2018       août  9.174427e+10  18154441800
8    2018  septembre  8.166058e+10  22319200107
9    2018    octobre  8.695003e+10  18872341724
10   2018   novembre  7.793332e+10  17499907474
11   2018   décembre  7.705552e+10  20518021342
12   2019    janvier  7.992190e+10  20456591937
```

[ ]:
```
month = previous_year.groupby('mois').rec_douane.mean()
```

[ ]:
```
month
```

[ ]:
```
mois
août         1.183959e+11
avril        6.976310e+10
décembre     8.320061e+10
février      6.663724e+10
janvier      6.337386e+10
juillet      7.981600e+10
juin         7.592641e+10
mai          7.307093e+10
mars         6.966252e+10
novembre     8.500371e+10
octobre      8.874878e+10
septembre    9.227563e+10
Name: rec_douane, dtype: float64
```

[ ]:
```
# Replace the values in the last year with the monthly means
for month_name, mean_value in month.items():
    last_year.loc[last_year["mois"] == month_name, "rec_douane"] = mean_value
```

```
# Update the original DataFrame with the imputed values
df_copy.update(last_year)
```

[ ]:
```
df_copy.tail(12)
```

[ ]:

	annee	mois	rec_douane	rec_connexe
48	2022	janvier	6.337386e+10	20720485819
49	2022	février	6.663724e+10	21390075497
50	2022	mars	6.966252e+10	27574121734
51	2022	avril	6.976310e+10	26861850903
52	2022	mai	7.307093e+10	34393431285
53	2022	juin	7.592641e+10	36360766011
54	2022	juillet	7.981600e+10	40254144158
55	2022	août	1.183959e+11	46817361628
56	2022	septembre	9.227563e+10	45234266283
57	2022	octobre	8.874878e+10	42991169158
58	2022	novembre	8.500371e+10	41916221297
59	2022	décembre	8.320061e+10	47684200972

In this case, the type of rec_douane changes the type beacause we are using means, the have to change rec_douane to int value

[ ]:
```
df_copy.rec_douane = df_copy.rec_douane.apply(lambda x: int(x))
```

[ ]:
```
df_copy.tail(12)
```

[ ]:

	annee	mois	rec_douane	rec_connexe
48	2022	janvier	63373856737	20720485819
49	2022	février	66637235825	21390075497
50	2022	mars	69662523273	27574121734
51	2022	avril	69763102305	26861850903
52	2022	mai	73070925062	34393431285
53	2022	juin	75926413107	36360766011
54	2022	juillet	79816003888	40254144158
55	2022	août	118395916678	46817361628
56	2022	septembre	92275629673	45234266283
57	2022	octobre	88748781686	42991169158
58	2022	novembre	85003713595	41916221297
59	2022	décembre	83200610127	47684200972

Now we are abble to analyse

0.3 ### Descriptive analysis

Descriptive stat

[ ]:
```
df_copy.iloc[:,2:].describe()
```

[ ]:
```
         rec_douane   rec_connexe
count  6.000000e+01  6.000000e+01
mean   8.048956e+10  2.221495e+10
std    2.601989e+10  9.481640e+09
min    4.695114e+10  5.248768e+09
25%    6.705922e+10  1.762471e+10
50%    7.628848e+10  1.987486e+10
75%    8.737461e+10  2.410510e+10
max    2.204992e+11  4.768420e+10
```

[ ]:
```python
# Calculate the coefficient of variation (CV) for the columns "rec_douane" and␣
↪"rec_connexe"
cv_rec_douane = (df_copy["rec_douane"].std() / df_copy["rec_douane"].mean()) *␣
↪100
cv_rec_connexe = (df_copy["rec_connexe"].std() / df_copy["rec_connexe"].mean())␣
↪* 100

# Print the descriptive statistics and CV values
print("Descriptive Statistics:")
print(df_copy.iloc[:, 2:].describe())

print("\nCoefficient of Variation (CV):")
print("rec_douane: {:.2f}%".format(cv_rec_douane))
print("rec_connexe: {:.2f}%".format(cv_rec_connexe))
```

```
Descriptive Statistics:
         rec_douane   rec_connexe
count  6.000000e+01  6.000000e+01
mean   8.048956e+10  2.221495e+10
std    2.601989e+10  9.481640e+09
min    4.695114e+10  5.248768e+09
25%    6.705922e+10  1.762471e+10
50%    7.628848e+10  1.987486e+10
75%    8.737461e+10  2.410510e+10
max    2.204992e+11  4.768420e+10

Coefficient of Variation (CV):
rec_douane: 32.33%
rec_connexe: 42.68%
```

Correlation

[ ]:
```python
df_copy.iloc[:, 2:].corr()
```

[ ]:
```
             rec_douane  rec_connexe
rec_douane      1.00000      0.29391
rec_connexe     0.29391      1.00000
```

Working scalling data (on usd currency : 1 usd = 2500 FC)

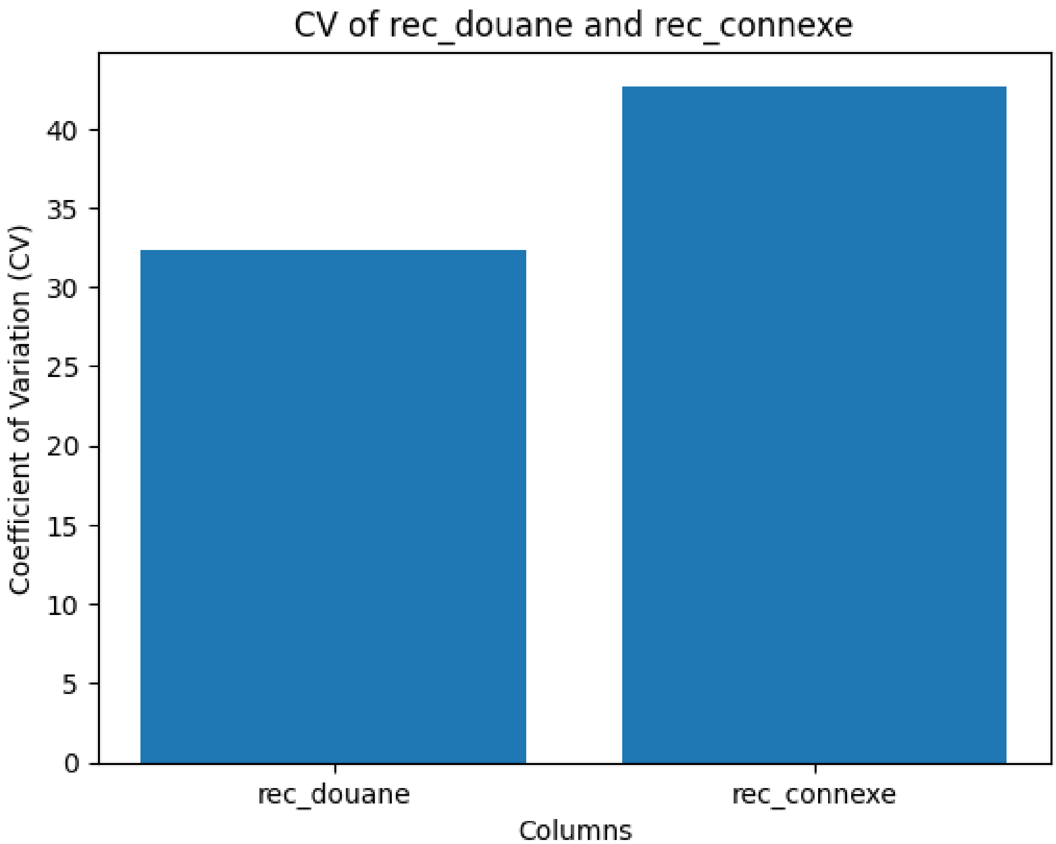
[ ]:
```python
df_copy.rec_douane = df_copy.rec_douane.apply(lambda x: int(x/2500))
df_copy.rec_connexe = df_copy.rec_connexe.apply(lambda x: int(x/2500))
```

[ ]:
```python
# Calculate the coefficient of variation (CV) for the columns "rec_douane" and␣
↪"rec_connexe"
cv_rec_douane = (df_copy["rec_douane"].std() / df_copy["rec_douane"].mean()) *␣
↪100
cv_rec_connexe = (df_copy["rec_connexe"].std() / df_copy["rec_connexe"].mean())␣
↪* 100

# Print the descriptive statistics and CV values
print("Descriptive Statistics:")
print(df_copy.iloc[:, 2:].describe())

print("\nCoefficient of Variation (CV):")
print("rec_douane: {:.2f}%".format(cv_rec_douane))
print("rec_connexe: {:.2f}%".format(cv_rec_connexe))
```

```
Descriptive Statistics:
          rec_douane   rec_connexe
count  6.000000e+01  6.000000e+01
mean   3.219582e+07  8.885980e+06
std    1.040796e+07  3.792656e+06
min    1.878046e+07  2.099507e+06
25%    2.682369e+07  7.049884e+06
50%    3.051539e+07  7.949944e+06
75%    3.494984e+07  9.642040e+06
max    8.819966e+07  1.907368e+07

Coefficient of Variation (CV):
rec_douane: 32.33%
rec_connexe: 42.68%
```

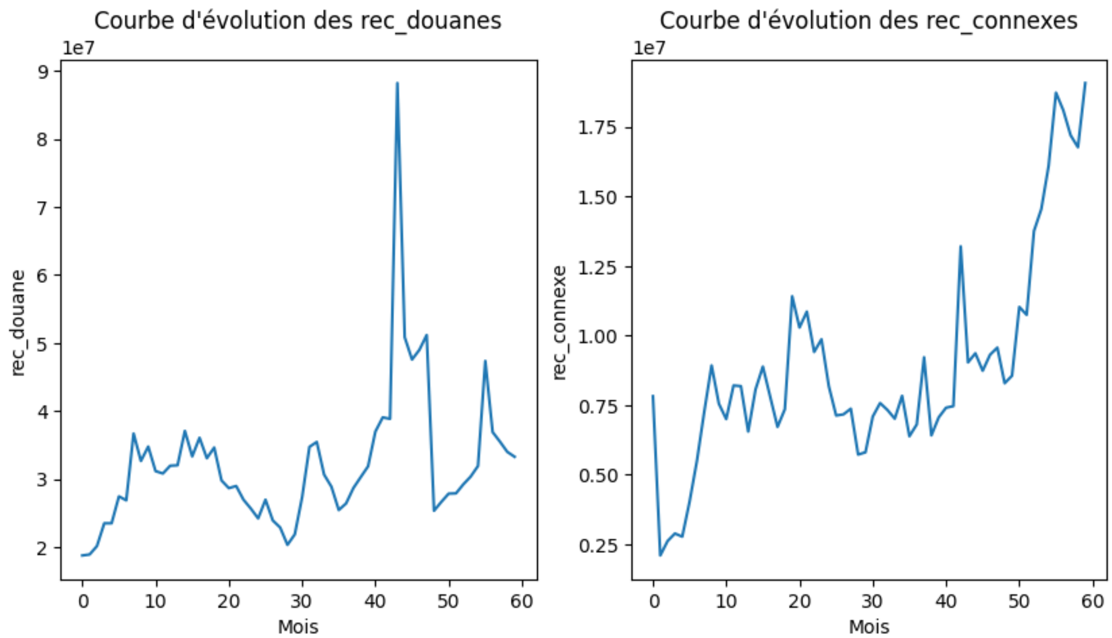
Visualisation

[ ]:
```python
# Create a bar plot of the CV values
columns = ["rec_douane", "rec_connexe"]
cv_values = [cv_rec_douane, cv_rec_connexe]

plt.bar(columns, cv_values)
plt.xlabel("Columns")
plt.ylabel("Coefficient of Variation (CV)")
plt.title("CV of rec_douane and rec_connexe")

plt.show()
```



[ ]:
```python
# Get the values for rec_douane and rec_connexe
rec_douane_values = df_copy["rec_douane"].values
rec_connexe_values = df_copy["rec_connexe"].values

# Create separate bar plots for rec_douane and rec_connexe
plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.plot(range(len(rec_douane_values)), rec_douane_values)
plt.xlabel("Mois")
plt.ylabel("rec_douane")
plt.title("Courbe d'évolution des rec_douanes")

plt.subplot(1, 2, 2)
plt.plot(range(len(rec_connexe_values)), rec_connexe_values)
plt.xlabel("Mois")
plt.ylabel("rec_connexe")
plt.title("Courbe d'évolution des rec_connexes")
```

[ ]:
```
Text(0.5, 1.0, "Courbe d'évolution des rec_connexes")
```



[ ]:
```
df_copy.iloc[:, 2:].corr()
```

[ ]:

	rec_douane	rec_connexe
rec_douane	1.00000	0.29391
rec_connexe	0.29391	1.00000

[ ]:
```
df_copy.shape
```

[ ]: (60, 4)

[ ]: