analyse

October 18, 2023

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

```
hello
```

Github link : https://github.com/Pinto-Katende-Jonathan/SimpleDescriptiveStat.git

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
```

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

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

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

```
[ ]: 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
```

```
[ ]: 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)
```

[ ]:
```
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)

[ ]:
```
#Cette fonction supprime tous les points, les espaces et vigules dans un␣
 ↪montant (car nos valeurs sont entières)
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
```

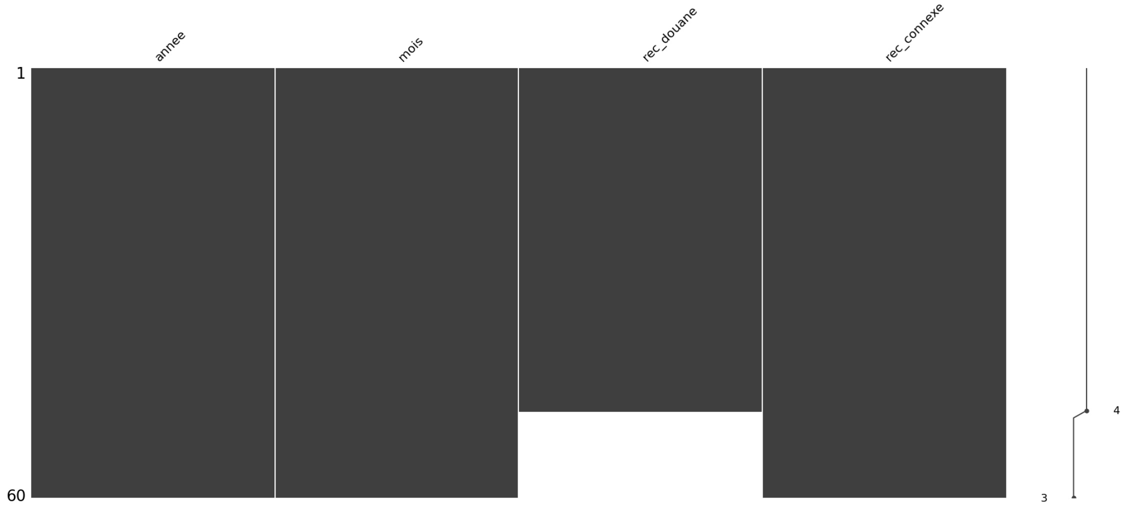
```
58   2022   novembre          NaN  41916221297
59   2022   décembre          NaN  47684200972
```

visualling missing data

```
[ ]: try:
         import missingno as msno # to visualize missing value
     except:
         %pip install missingno
         %pip install datatile
```

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

```
[ ]: <Axes: >
```



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

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
```

```
[ ]: # 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

[ ]:

```
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)

[ ]:

```
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))
```

[ ]:

```
# 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))
```

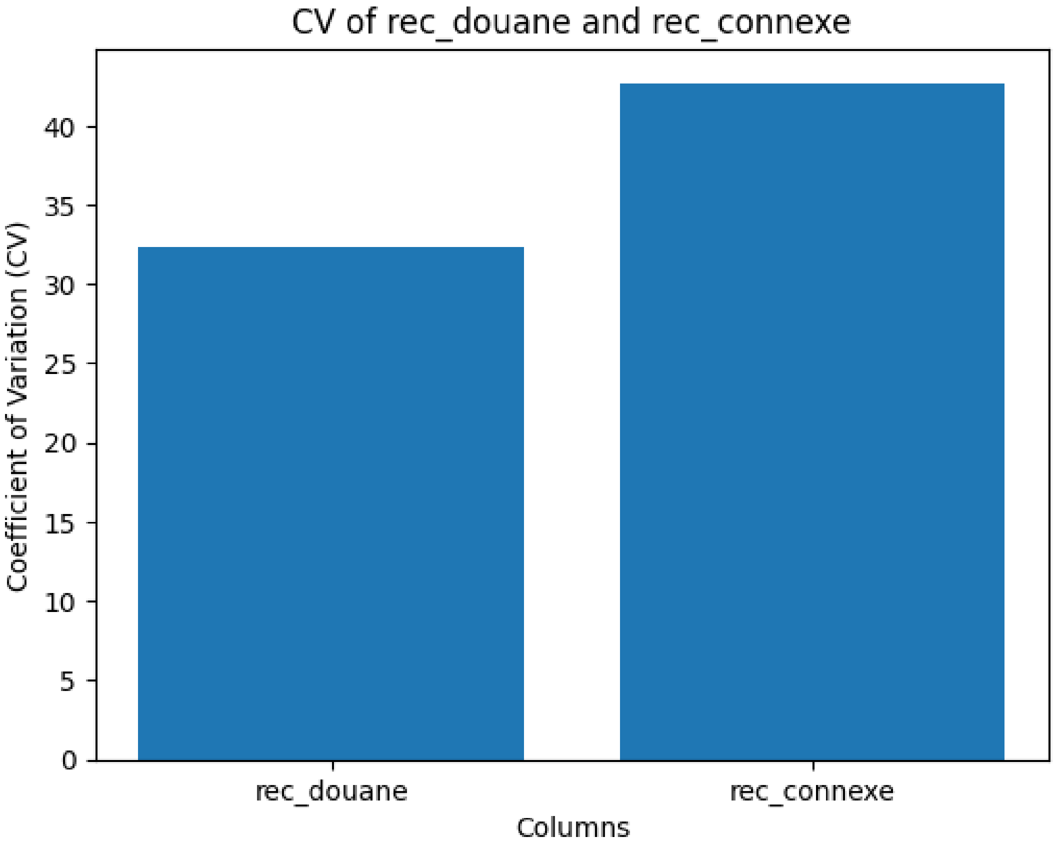
```
Descriptive Statistics:
         rec_douane   rec_connexe
count  6.000000e+01  6.000000e+01
mean   3.219582e+07  8.885980e+06
std    1.040796e+07  3.792656e+06
min    1.878046e+07  2.099507e+06
25%    2.682369e+07  7.049884e+06
50%    3.051539e+07  7.949944e+06
75%    3.494984e+07  9.642040e+06
max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

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

Visualisation

[ ]:

```
# 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()
```

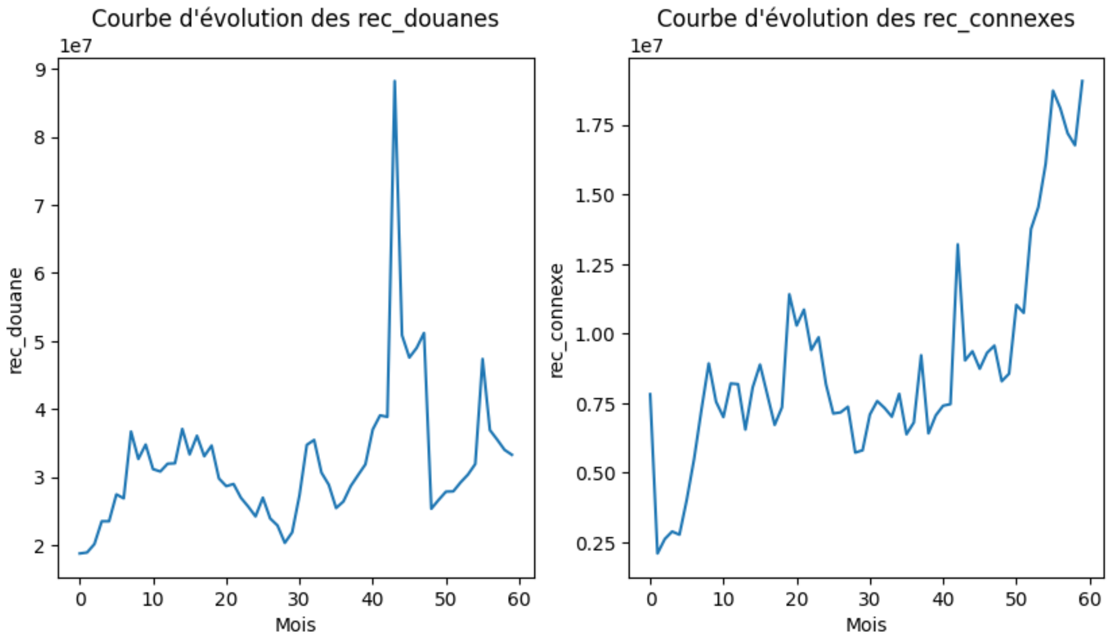


[ ]:

```
# 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
```

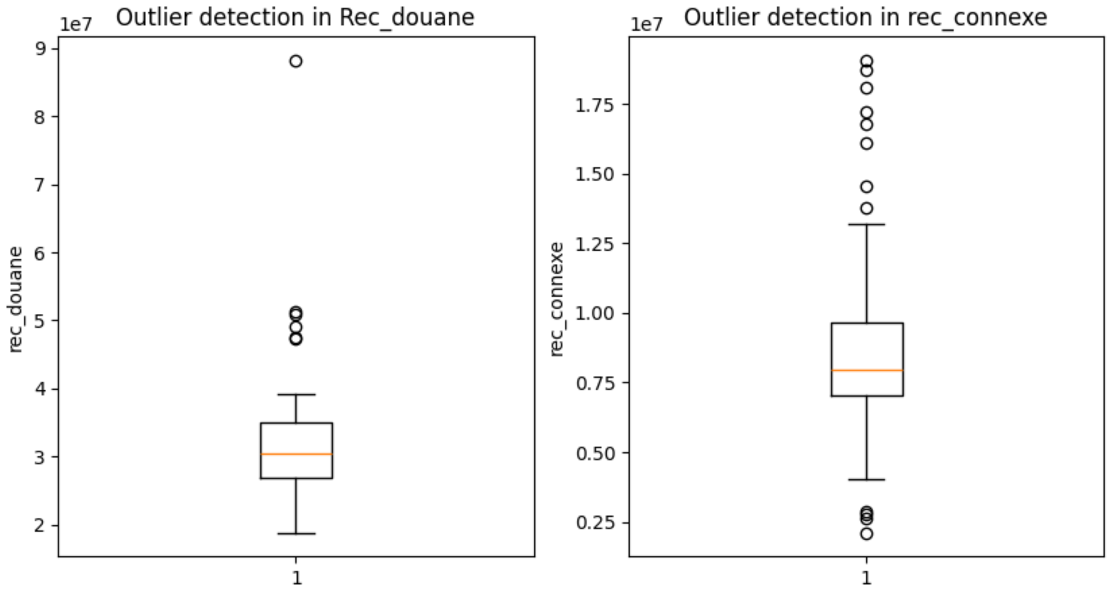
[ ]:

```
(60, 4)
```

[ ]:

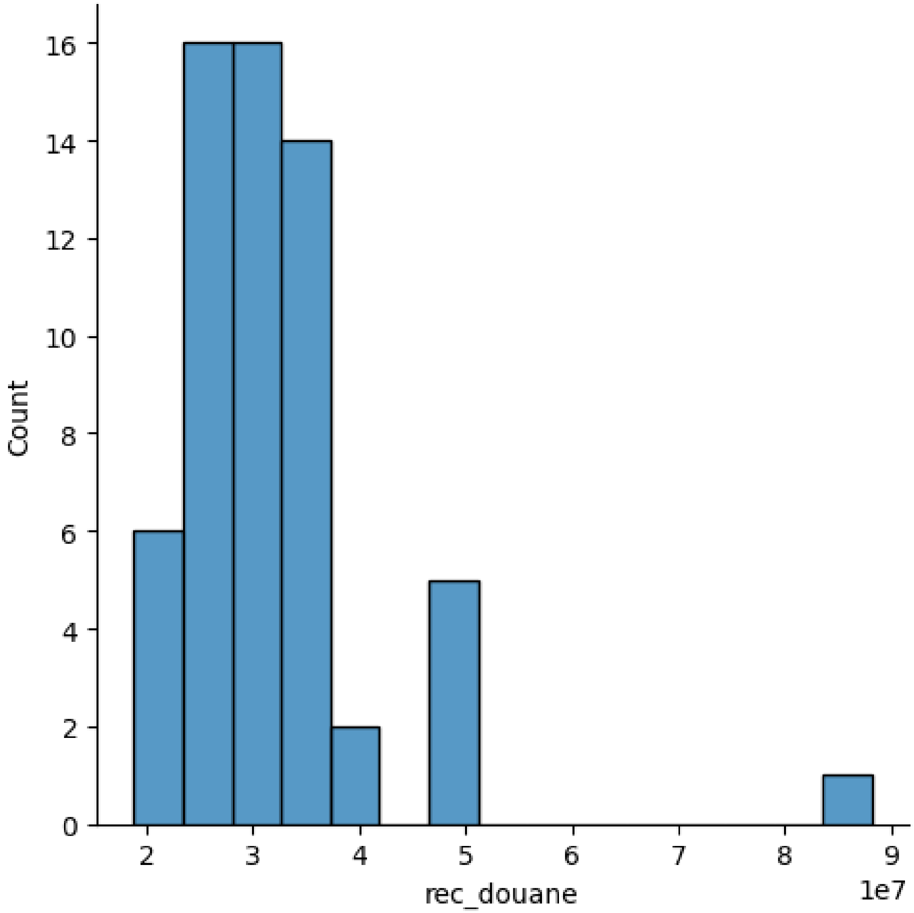
```
plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.boxplot(df_copy.rec_douane)
plt.ylabel("rec_douane")
plt.title('Outlier detection in Rec_douane')

plt.subplot(1, 2, 2)
plt.boxplot(df_copy.rec_connexe)
plt.ylabel("rec_connexe")
plt.title('Outlier detection in rec_connexe')
```

```
[ ]: Text(0.5, 1.0, 'Outlier detection in rec_connexe')
```



```
[ ]: # plt.subplot(1, 2, 1)
     # sns.boxplot(x=df_copy.rec_douane)

     # plt.subplot(1, 2, 2)
     # sns.boxplot(x=df_copy.rec_connexe)

     sns.displot(x = df_copy.rec_douane, bins = 15, kde = False)
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x1d746db42d0>
```



0.3.1 Outlier Imputation

Lower Bound = Q1 - 1.5*EIQ

Upper Bound = Q3 + 1.5*EIQ

EIQ = Q3 - Q1

[ ]:
```
# def remove_outlier(col):
#     sorted(col)
#     Q1,Q3 = col.quantile([.25, .75])
#     EIQ = Q3 -Q1
#     return Q1 - (1.5 * EIQ), Q3 + (1.5 * EIQ)
```

[ ]:
```
# for val in df.columns[2:]:
#     lower_bound, upper_bound = remove_outlier(df_copy[val])

#     df[val] = np.where(df_copy[val] > upper_bound, upper_bound, df_copy[val])
#     df[val] = np.where(df_copy[val] < lower_bound, lower_bound, df_copy[val])
```

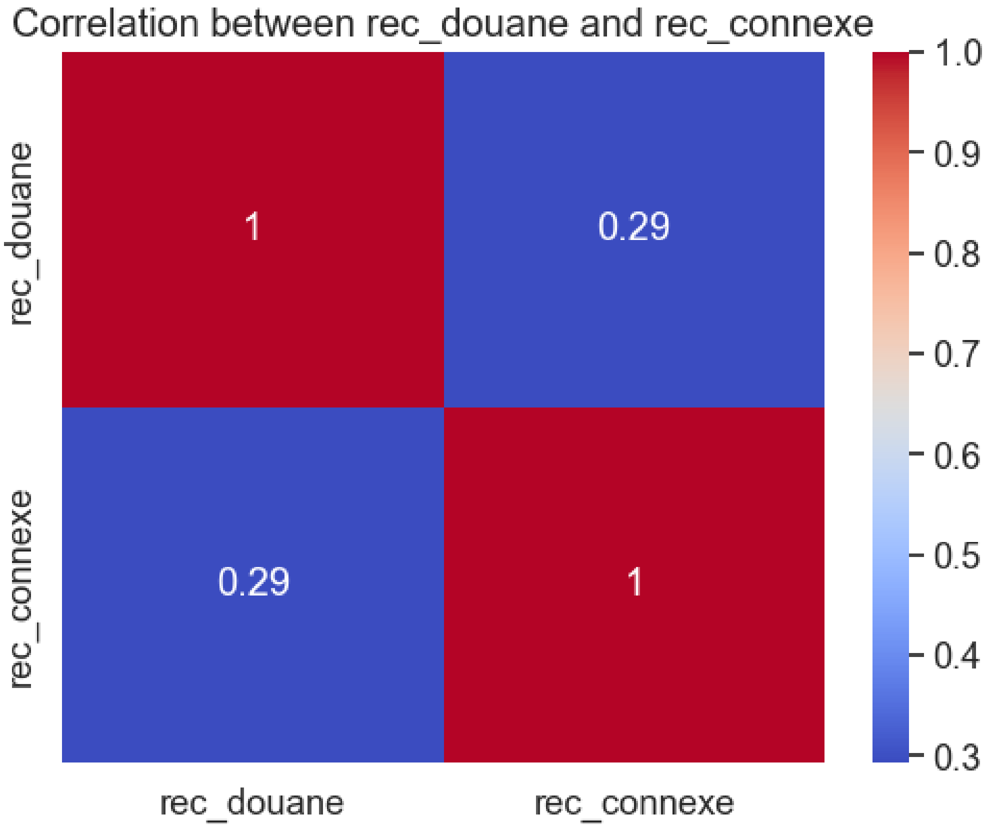
[ ]:
```
df_copy.shape
```

[ ]:
```
(60, 4)
```

[ ]:
```
# #Check Outliers
# recettes = df_copy.select_dtypes(include=['int64', 'float64']).iloc[:,1:]
# plt.figure(figsize=(15,6))

# sns.boxplot(data = recettes)
# plt.show()
```

[ ]:
```
sns.heatmap(df_copy.iloc[:,2:].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation between rec_douane and rec_connexe')
```

[ ]:
```
Text(0.5, 1.0, 'Correlation between rec_douane and rec_connexe')
```



0.3.2 Correlation test

[ ]:
```
import pingouin as pg
```

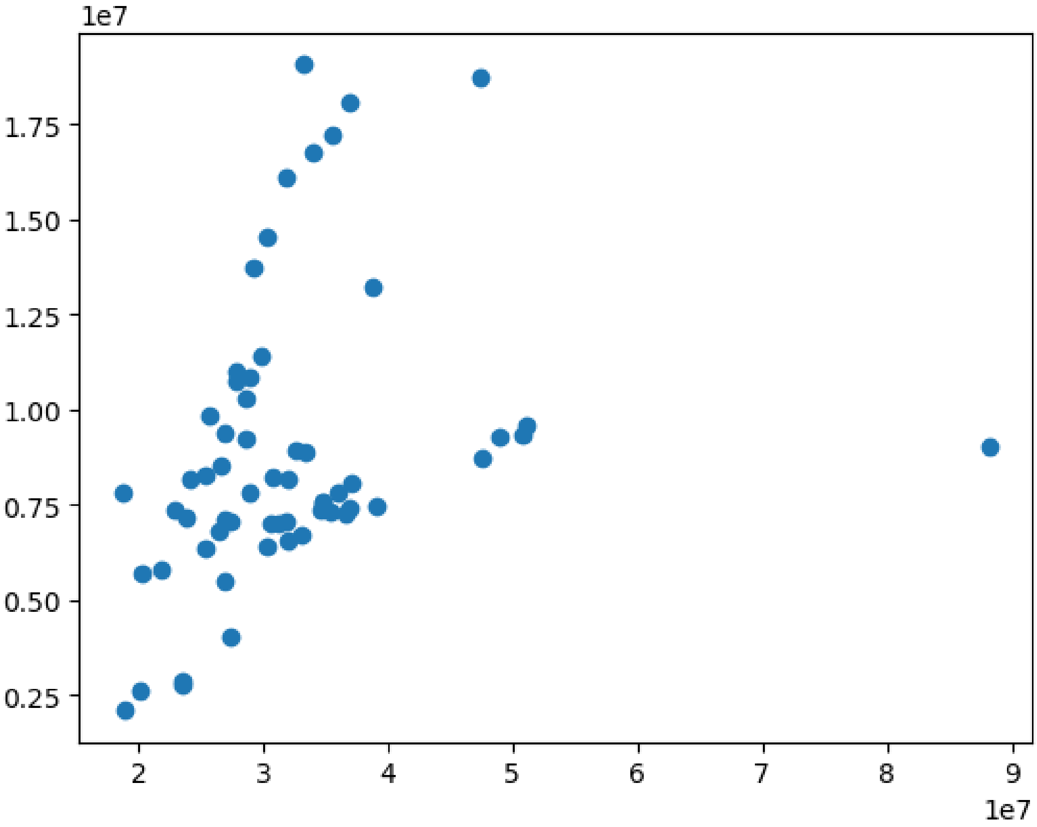
```
[ ]: pg.corr(x=df_copy.rec_douane, y=df_copy.rec_connexe)
```

```
[ ]:            n        r          CI95%     p-val   BF10     power
     pearson   60  0.29391  [0.04, 0.51]  0.022648  2.035  0.634204
```

```
[ ]: r = round(pg.corr(x=df_copy.rec_douane, y=df_copy.rec_connexe).r['pearson'], 2)
```

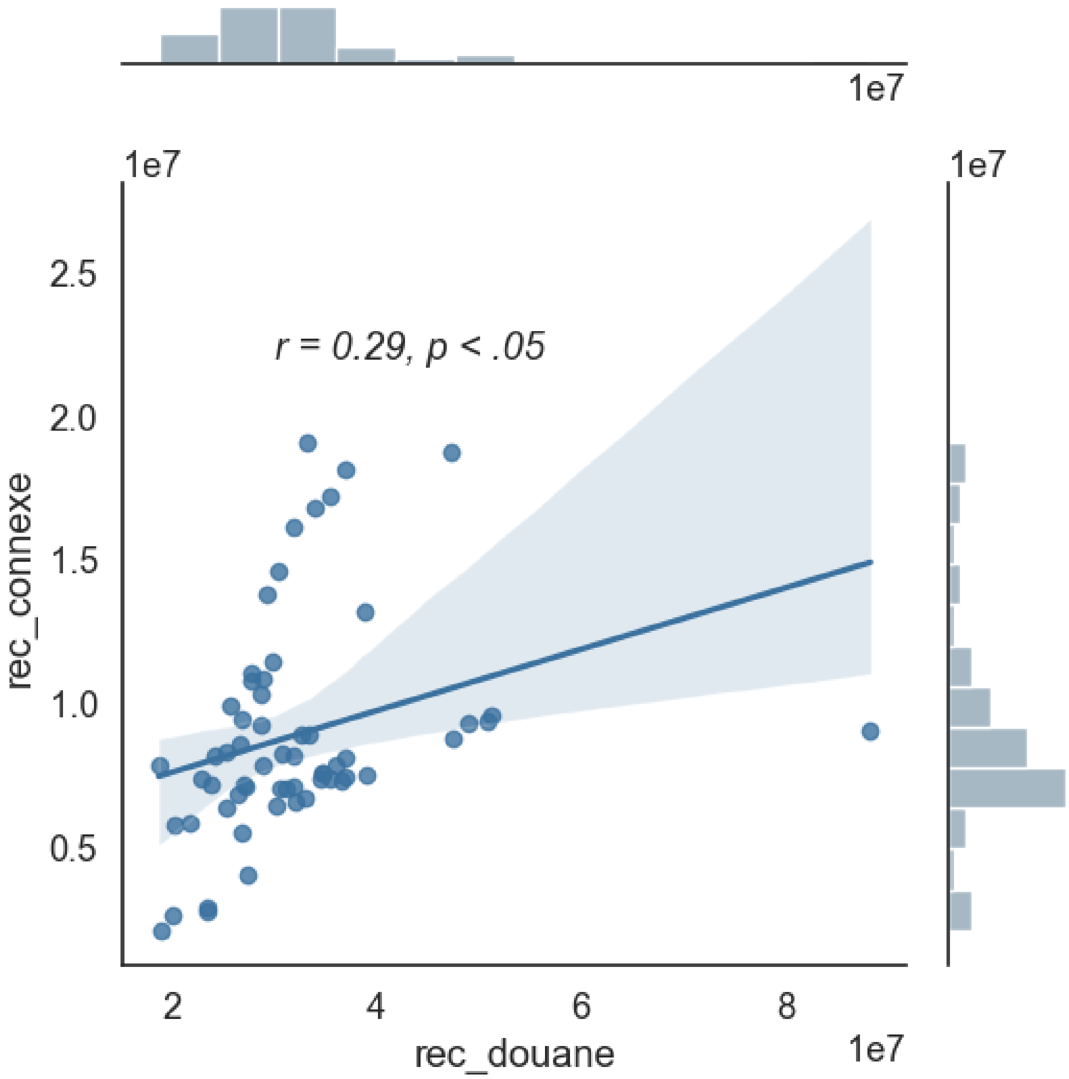
```
[ ]: plt.scatter(df_copy.rec_douane, df_copy.rec_connexe)
```

```
[ ]: <matplotlib.collections.PathCollection at 0x1d74764a250>
```



```
[ ]: # from scipy.stats import pearsonr
     # sns.set(style='white', font_scale=1.2)

     # g = sns.JointGrid(data=df_copy, x='rec_douane', y='rec_connexe')
     # g = g.plot_joint(sns.regplot, color="xkcd:muted blue")
     # g = g.plot_marginals(sns.displot, kde=False, bins=12, color="xkcd:bluey grey")
     # g.ax_joint.text(3e7, 2.2e7, f'r = {r}, p < .05', fontstyle='italic')
     # plt.tight_layout()
```

```
from scipy.stats import pearsonr
import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style='white', font_scale=1.2)

g = sns.JointGrid(data=df_copy, x='rec_douane', y='rec_connexe')
g = g.plot_joint(sns.regplot, color="xkcd:muted blue")
g = g.plot_marginals(sns.histplot, kde=False, bins=12, color="xkcd:bluey grey")
g.ax_joint.text(3e7, 2.2e7, f'r = {r}, p < .05', fontstyle='italic')
plt.tight_layout()
```



```
[ ]:
```