TP_Final_Collecte de Donnes_Yulia_Ricardo_2021_01_01

January 2, 2021

0.1 TP FINAL - Stockage de donnes

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1 Python (Importation et Manipulation de données)

1.1 1.1. Aller sur le site data.gov https://www.data.gov/ , charger et fusionner les jeux de données

- Chicago Park District: Movies in the Parks 2015
- Chicago Park District: Movies in the Parks 2016
- Chicago Park District: Movies in the Parks 2017 ### Calculer le nombre de lignes de votre table de données résultante (dataframe) (avec les fichiers fusionnés) sans et avec redondances des données (doublons s ils existent). Afficher des statistiques sur ces données. Préciser toutes les vérifications que vous avez effectuées sans faire de nettoyage sur les données.

1.1.1 Chargement des jeux de donnees

[2]:
```
import pandas as pd
import numpy as np
import requests

df1 = pd.read_csv("data_projet/Chicago_Park_District__Movies_in_the_Parks_2015.
↪csv",header =0) #Reading the data from sheet cars
df1.head(2)
```

[2]:
```
                                    EventName             MovieName  \
0  Night Out: Movies in the Parks at Lindblom           Annie (2014)
1    Night Out: Movies in the Parks at Wicker  Night at the Museum

        ParkName   ZipCode            Phone              StartDate  \
0  Lindblom Park   60636.0  (312) 747-6443  08/06/2015 08:30:00 PM
1    Wicker Park   60622.0  (312) 742-7553  06/18/2015 08:00:00 PM

                 EndDate                  ContactName  \
0  08/06/2015 10:30:00 PM                Maceo Johnson
1  06/18/2015 09:48:00 PM  Claribel "Clare" Rodriguez
```

```
                                    ContactEmail  \
0      maceo.johnson@chicagoparkdistrict.com
1  claribel.rodriguez@chicagoparkdistrict.com

                                             EventUrl  \
0  http://www.chicagoparkdistrict.com/events/Nigh…
1  http://www.chicagoparkdistrict.com/events/Nigh…

                                              ParkUrl  \
0  http://www.chicagoparkdistrict.com/parks/Lindb…
1  http://www.chicagoparkdistrict.com/parks/Wicke…

                Community  MovieClosedCaption  MovieRating  \
0  Englewood, West Englewood                NaN           PG
1                West Town                Yes           PG

                                          Location 1
0  6054 S. Damen Ave. Chicago IL 60636\nChicago, …
1  1425 N. Damen Avenue Chicago IL 60622\nChicago…
```

```
[3]: df1.shape
```

```
[3]: (237, 15)
```

```
[4]: df2 = pd.read_csv("data_projet/Chicago_Park_District__Movies_in_the_Parks_2016.
      ↪csv",header =0) #Reading the data from sheet cars
     df2.head(2)
```

```
[4]:                                 EventName         MovieName  \
0         Movies in the Parks at Rosenblum  The Color Purple
1  Movies in the Parks at Rutherford Sayre        Inside Out

  MovieClosedCaption MovieRating               Location Location Notes  \
0                Yes       PG-13          Rosenblum Park            NaN
1                NaN          PG  Rutherford Sayre Park            NaN

   StartDate  EndDate  Zipcode           Phone   ContactName ContactEmail  \
0        NaN      NaN    60649  (312) 747-7661           TBD          NaN
1        NaN      NaN    60635  (312) 746-5368  Kim Gapinski          NaN

   EventUrl  ParkUrl                                    Location 1
0       NaN      NaN                    7547 S. Euclid Ave.\nChicago, IL
1       NaN      NaN  6871 W. Belden Ave.\nChicago, IL\n(41.921134, …
```

```
[5]: df2.shape
```

```
[5]: (243, 15)
```

```
[6]: df3 = pd.read_csv("data_projet/Chicago_Park_District__Movies_in_the_Parks_2017.
      ↪csv",header =0) #Reading the data from sheet cars
     df3.head(2)
```

```
[6]:    Day        Date           Park      Park Phone       Title CC Rating  \
     0  Mon  08/07/2017  Oakwood Beach  (312) 742-1134  Home Alone  Y     PG
     1  Tue  06/13/2017     Grant Park  (312) 742-3918     Jumanji  Y     PG

                                              Underwriter           Park Address  \
     0                                                NaN  3900 S. Lake Shore Dr.
     1  Underwritten by the Greater South Loop Associa…         Columbus Drive

                                   Location
     0  3900 S. Lake Shore Dr.\nChicago, IL
     1          Columbus Drive\nChicago, IL
```

```
[7]: df3.shape
```

```
[7]: (237, 10)
```

1.2 Analysis preliminaire

A cause que tous les tables ont de differentes columns, mais avec information common, on dois identifier les labels que partage information differente et unifier le nom de label. Pour faciliter le travail on enleve les espaces de nom de Labels.

1.2.1 Affichage des noms de colognes

```
[8]: #df1.columns
     df1.columns.sort_values()
```

```
[8]: Index([' Community', ' ContactEmail', ' ContactName', ' EndDate',
            ' EventName ', ' EventUrl', ' MovieClosedCaption', ' MovieName',
            ' MovieRating', ' ParkUrl', ' Phone', ' StartDate', ' ZipCode',
            'Location 1', 'ParkName'],
           dtype='object')
```

```
[9]: df2.columns.sort_values()
```

```
[9]: Index(['ContactEmail', 'ContactName', 'EndDate', 'EventName', 'EventUrl',
            'Location', 'Location 1', 'Location Notes', 'MovieClosedCaption',
            'MovieName', 'MovieRating', 'ParkUrl', 'Phone', 'StartDate', 'Zipcode'],
           dtype='object')
```

```
[10]: df3.columns.sort_values()
```

```
[10]: Index(['CC', 'Date', 'Day', 'Location', 'Park', 'Park Address', 'Park Phone',
             'Rating', 'Title', 'Underwriter'],
            dtype='object')
```

1.3 Modification et unification de labels

```
[11]: df1.columns = df1.columns.str.replace(' ', '')
      print(df1.columns)
```

```
Index(['EventName', 'MovieName', 'ParkName', 'ZipCode', 'Phone', 'StartDate',
       'EndDate', 'ContactName', 'ContactEmail', 'EventUrl', 'ParkUrl',
       'Community', 'MovieClosedCaption', 'MovieRating', 'Location1'],
      dtype='object')
```

```
[12]: df2.columns = df2.columns.str.replace(' ', '')
      df2.rename(columns={   'Location':  'ParkName',
                             'Zipcode':  'ZipCode'}, inplace=True)
      print(df2.columns)
```

```
Index(['EventName', 'MovieName', 'MovieClosedCaption', 'MovieRating',
       'ParkName', 'LocationNotes', 'StartDate', 'EndDate', 'ZipCode', 'Phone',
       'ContactName', 'ContactEmail', 'EventUrl', 'ParkUrl', 'Location1'],
      dtype='object')
```

```
[13]: df3.columns = df3.columns.str.replace(' ', '')
      df3.rename(columns={'Park'      :'ParkName',
                          'Title'     :'MovieName',
                          'CC'        :'MovieClosedCaption',
                          'ParkPhone' :'Phone',
                          'Rating'    :'MovieRating',
                          'Location'  :'Location1',
                          'Date'      :'StartDate'},
                           inplace=True)

      print(df3.columns)
```

```
Index(['Day', 'StartDate', 'ParkName', 'Phone', 'MovieName',
       'MovieClosedCaption', 'MovieRating', 'Underwriter', 'ParkAddress',
       'Location1'],
      dtype='object')
```

```
[14]: finalColumnsx = np.concatenate((df1.columns, df2.columns, df3.columns))
      finalColumns = list(set(finalColumnsx))
      print(finalColumns)
```

```
['MovieClosedCaption', 'ParkAddress', 'ContactEmail', 'EndDate', 'ZipCode',
'LocationNotes', 'Location1', 'Phone', 'EventUrl', 'Day', 'MovieRating',
'ContactName', 'EventName', 'MovieName', 'StartDate', 'ParkName', 'ParkUrl',
'Underwriter', 'Community']
```

1.3.1 Maintenant on fait la fusion avec la fonction .concat

```
[15]: FUSIONA = pd.concat([df1, df2, df3])
      FUSIONA.head(3)
```

```
[15]:                                          EventName           MovieName  \
      0       Night Out: Movies in the Parks at Lindblom        Annie (2014)
      1         Night Out: Movies in the Parks at Wicker  Night at the Museum
      2  Night Out: Movies in the Parks at Belmont Harbor     Dial M for Murder

             ParkName  ZipCode           Phone              StartDate  \
      0  Lindblom Park  60636.0   (312) 747-6443  08/06/2015 08:30:00 PM
      1    Wicker Park  60622.0   (312) 742-7553  06/18/2015 08:00:00 PM
      2   Lincoln Park  60614.0  (312) 742-7726   06/15/2015 08:30:00 PM

                        EndDate                ContactName  \
      0  08/06/2015 10:30:00 PM              Maceo Johnson
      1  06/18/2015 09:48:00 PM  Claribel "Clare" Rodriguez
      2  06/15/2015 10:15:00 PM               Lauren Quinn

                                     ContactEmail  \
      0      maceo.johnson@chicagoparkdistrict.com
      1  claribel.rodriguez@chicagoparkdistrict.com
      2                                        NaN

                                                  EventUrl  \
      0  http://www.chicagoparkdistrict.com/events/Nigh…
      1  http://www.chicagoparkdistrict.com/events/Nigh…
      2  http://www.chicagoparkdistrict.com/events/Nigh…

                                                   ParkUrl  \
      0  http://www.chicagoparkdistrict.com/parks/Lindb…
      1  http://www.chicagoparkdistrict.com/parks/Wicke…
      2  http://www.chicagoparkdistrict.com/parks/linco…

                        Community MovieClosedCaption MovieRating  \
      0  Englewood, West Englewood                NaN          PG
      1                  West Town                Yes          PG
      2               Lincoln Park                Yes          PG

                                                Location1 LocationNotes  Day  \
      0  6054 S. Damen Ave. Chicago IL 60636\nChicago, …           NaN  NaN
      1  1425 N. Damen Avenue Chicago IL 60622\nChicago…           NaN  NaN
      2  2045 N Lincoln Park West Chicago IL 60614\nChi…           NaN  NaN
```

```
  Underwriter ParkAddress
0         NaN         NaN
1         NaN         NaN
2         NaN         NaN
```

```
[16]: FUSIONA.shape
```

```
[16]: (717, 19)
```

1.3.2 Le resultat sans doublons

```
[17]: result2 = FUSIONA.drop_duplicates()
```

1.3.3 Affichage de dimensions de data frame resultante (sans doublons)

```
[18]: result2.shape
```

```
[18]: (717, 19)
```

```
[19]: result2.columns
```

```
[19]: Index(['EventName', 'MovieName', 'ParkName', 'ZipCode', 'Phone', 'StartDate',
              'EndDate', 'ContactName', 'ContactEmail', 'EventUrl', 'ParkUrl',
              'Community', 'MovieClosedCaption', 'MovieRating', 'Location1',
              'LocationNotes', 'Day', 'Underwriter', 'ParkAddress'],
             dtype='object')
```

```
[20]: print('Le nombre des lignes de data frame resultante', result2.shape[0])
```

```
Le nombre des lignes de data frame resultante 717
```

1.3.4 Il y a pas de doublons dans le data frame resultante. Le nombre des lignes avec et sans "drop_duplicates()" est pareil. Sans le nettoyage des donnees, on peut pas faire beaucoup de choses pour statistique, suelement ".shape" pour afficher les dimension de data frame.

```
[21]: result2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 717 entries, 0 to 236
Data columns (total 19 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   EventName           480 non-null    object
 1   MovieName           717 non-null    object
 2   ParkName            717 non-null    object
 3   ZipCode            477 non-null    float64
 4   Phone              715 non-null    object
 5   StartDate          474 non-null    object
 6   EndDate            237 non-null    object
 7   ContactName        474 non-null    object
 8   ContactEmail       367 non-null    object
 9   EventUrl           237 non-null    object
 10  ParkUrl            237 non-null    object
 11  Community          237 non-null    object
 12  MovieClosedCaption 605 non-null    object
 13  MovieRating        704 non-null    object
 14  Location1          717 non-null    object
 15  LocationNotes      33 non-null     object
 16  Day                237 non-null    object
 17  Underwriter        86 non-null     object
 18  ParkAddress        237 non-null    object
dtypes: float64(1), object(18)
memory usage: 112.0+ KB
```

1.4 1.2 Charger le jeu de données movies (movies.csv) dans une table de données (dataframe) et répondre aux questions suivantes

- Qui est l'acteur principal ayant été dans le film le plus couteux de la table de données? Quel est le montant du budget de ce film?
- Quels sont les 2 films ayant eu la plus grande rentabilité de notre table de données?
- Lister des titres de films dans lesquelles ont tourné votre acteur (actrice) préféré(e)?

[22]:
```
df = pd.read_csv("data_projet/movies.csv",header =0) #Chargement de donnees␣
 ↪dans data frame df1
df.head(2)
```

[22]:
```
     color   director_name  num_critic_for_reviews duration  \
0  Colores   James Cameron                   723.0  178 min
1  Colores  Gore Verbinski                   302.0  169 min

   director_facebook_likes  actor_3_facebook_likes      actor_2_name  \
0                      0.0                   855.0  Joel David Moore
1                    563.0                  1000.0     ORLANDO BLOOM

   actor_1_facebook_likes        gross                           genres  …  \
0                  1000.0  760505847 $  Action|Adventure|Fantasy|Sci-Fi  …
1                 40000.0  309404152 $         Action|Adventure|Fantasy  …

  num_user_for_reviews language  country  content_rating      budget  \
0                 3054  English      USA           PG-13  2.37e+08 $
1                 1238  English      USA           PG-13     3e+08 $

   title_year actor_2_facebook_likes imdb_score aspect_ratio  \
0      2009.0                     936      7.9 #         1.78
1      2007.0                    5000      7.1 #         2.35

  movie_facebook_likes
0                 4834
1                48350

[2 rows x 28 columns]
```

[23]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7410 entries, 0 to 7409
Data columns (total 28 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   color                      7386 non-null   object
 1   director_name              7263 non-null   object
 2   num_critic_for_reviews     7338 non-null   float64
 3   duration                   7410 non-null   object
 4   director_facebook_likes    7263 non-null   float64
 5   actor_3_facebook_likes     7373 non-null   float64
 6   actor_2_name               7391 non-null   object
 7   actor_1_facebook_likes     7400 non-null   float64
 8   gross                      7410 non-null   object
 9   genres                     7410 non-null   object
 10  actor_1_name               7400 non-null   object
 11  movie_title                7410 non-null   object
 12  num_voted_users            7410 non-null   int64
 13  cast_total_facebook_likes  7410 non-null   int64
 14  actor_3_name               7373 non-null   object
 15  facenumber_in_poster       7388 non-null   float64
 16  plot_keywords              7189 non-null   object
 17  movie_imdb_link            7410 non-null   object
 18  num_user_for_reviews       7410 non-null   object
 19  language                   7394 non-null   object
 20  country                    7403 non-null   object
 21  content_rating             6973 non-null   object
 22  budget                     7410 non-null   object
 23  title_year                 7258 non-null   float64
 24  actor_2_facebook_likes     7410 non-null   object
 25  imdb_score                 7410 non-null   object
 26  aspect_ratio               6944 non-null   float64
 27  movie_facebook_likes       7410 non-null   int64
dtypes: float64(7), int64(3), object(18)
memory usage: 1.6+ MB
```

1.4.1 1.2.a Le film le plus couteux -> 'budget' doit etre maximale

```
[24]: df['budget'].max()
```

```
[24]: 'NA $'
```

Data frame n'est pas formattee, dans le 'budget' on doit enlever 2 dernieres strings " $". Apres, on replace 'NA' par np.nan. On convert en float et cherche le max. On fait pas les modifications au tableau.

```
[25]: print('le budget maximal = ',df['budget'].str.rstrip(' $').replace('NA', np.
       ↪nan).astype(float).max())
```

```
le budget maximal =  12215500000.0
```

```
[26]: indm=df['budget'].str.rstrip(' $').replace('NA', np.nan).astype(float).idxmax()
      print('index de la valuer maximal du budget = ',indm)
```

```
index de la valuer maximal du budget =  2988
```

1.4.2 Affichage de ligne 2988

```
[27]: df.iloc[indm]
```

```
[27]: color                                                            Colores
      director_name                                               Joon-ho Bong
      num_critic_for_reviews                                               363
      duration                                                         110 min
      director_facebook_likes                                              584
      actor_3_facebook_likes                                                74
      actor_2_name                                                KANG-HO SONG
      actor_1_facebook_likes                                               629
      gross                                                          2201412 $
      genres                                        Comedy|Drama|Horror|Sci-Fi
      actor_1_name                                                   DOONA BAE
      movie_title                                                    The Host
      num_voted_users                                                    68883
      cast_total_facebook_likes                                           1173
      actor_3_name                                                 Ah-sung Ko
      facenumber_in_poster                                                   0
      plot_keywords                             daughter|han river|monster|river|seoul
      movie_imdb_link                 http://www.imdb.com/title/tt0468492/?ref_=fn_t…
      num_user_for_reviews                                                 279
      language                                                          Korean
      country                                                      South Korea
      content_rating                                                         R
      budget                                                     12215500000 $
      title_year                                                          2006
```

```
actor_2_facebook_likes                                                        398
imdb_score                                                                    7 #
aspect_ratio                                                                 1.85
movie_facebook_likes                                                         1173
Name: 2988, dtype: object
```

1.4.3 1.2.b. Comme on peut voir de le tableau, “actor_1_facebook_likes” a obtenu le plus de facebook likes (629). Donc, on a choisi “actor_1_name” comme acteur principal

```
[28]: print("l'acteur principal du film le plus couteaux:" ,df['actor_1_name'].
       ↪iloc[indm])
```

```
l'acteur principal du film le plus couteaux: DOONA BAE
```

```
[29]: df1=df.copy()
      df1['gross']=df['gross'].str.rstrip(' $').replace('NA', np.nan).astype(float)
```

1.4.4 1.2.c. Quels sont les 2 films ayant eu la plus grande rentabilité

```
[30]: print('les 2 films ayant eu la plus grande rentabilité:\n',df1.
       ↪sort_values(by='gross',ascending=[False])['movie_title'][0:2])
```

```
les 2 films ayant eu la plus grande rentabilité:
 0      Avatar
26    Titanic
Name: movie_title, dtype: object
```

1.4.5 Notre acteur prefere est Orlando Bloom. Pour eviter les repititions, on a enleve les doublicats. On cherche dans les colognes ‘actor_1_name’,‘actor_2_name’,‘actor_3_name’. On compare les strings, donc, on a fait ces colognes upper case et enleve les espaces vides avant et apres les noms.

```
[31]: a=['actor_1_name','actor_2_name','actor_3_name']
      df2=df.drop_duplicates()

      for col in list(a):
          print(df2[df2[col].str.upper().str.strip()=='ORLANDO BLOOM']['movie_title'])
          #None
```

```
339     The Lord of the Rings: The Return of the King
896                                   Elizabethtown
2591                                           Zulu
Name: movie_title, dtype: object
1             Pirates of the Caribbean: At World's End
13           Pirates of the Caribbean: Dead Man's Chest
```

```
147                                                   Troy
205    Pirates of the Caribbean: The Curse of the Bla…
270    The Lord of the Rings: The Fellowship of the R…
275                                      Kingdom of Heaven
340                 The Lord of the Rings: The Two Towers
Name: movie_title, dtype: object
401    The Three Musketeers
Name: movie_title, dtype: object
```

1.5 1.3. Charger le jeu de données Film Locations in San Francisco du site data.gov https://www.data.gov/ .Transposer l'affichage de la table de données et donner le nombre et les endroits de tournage (location) par film. Créer une nouvelle table de données n'ayant que ces trois attributs et afficher les 10 premiers enregistrements:

- Titre (title)
- Release year
- Production

1.5.1 Chargement de fichier csv dans la dataframe df. Affichage de 5 premieres lignes

[32]:
```python
df = pd.read_csv("data_projet/Film_Locations_in_San_Francisco.csv",header =0)␣
↪#Chargement de donnees dans data frame df
df.head(5)
```

[32]:
```
  Title  Release Year                              Locations Fun Facts  \
0   180          2011      Epic Roasthouse (399 Embarcadero)       NaN
1   180          2011  Mason & California Streets (Nob Hill)       NaN
2   180          2011                    Justin Herman Plaza       NaN
3   180          2011                   200 block Market Street       NaN
4   180          2011                              City Hall       NaN

  Production Company Distributor  Director  \
0        SPI Cinemas         NaN  Jayendra
1        SPI Cinemas         NaN  Jayendra
2        SPI Cinemas         NaN  Jayendra
3        SPI Cinemas         NaN  Jayendra
4        SPI Cinemas         NaN  Jayendra

                                          Writer   Actor 1       Actor 2  \
0  Umarji Anuradha, Jayendra, Aarthi Sriram, & Suba  Siddarth  Nithya Menon
1  Umarji Anuradha, Jayendra, Aarthi Sriram, & Suba  Siddarth  Nithya Menon
2  Umarji Anuradha, Jayendra, Aarthi Sriram, & Suba  Siddarth  Nithya Menon
3  Umarji Anuradha, Jayendra, Aarthi Sriram, & Suba  Siddarth  Nithya Menon
4  Umarji Anuradha, Jayendra, Aarthi Sriram, & Suba  Siddarth  Nithya Menon

      Actor 3
```

```
0   Priya Anand
1   Priya Anand
2   Priya Anand
3   Priya Anand
4   Priya Anand
```

[33]:
```
df.shape
```

[33]:
```
(3414, 11)
```

1.5.2 Affichage de dataFrame transposee

[34]:
```
df.T.head(5)
```

[34]:
```
                                                 0     \
Title                                          180
Release Year                                  2011
Locations           Epic Roasthouse (399 Embarcadero)
Fun Facts                                      NaN
Production Company                     SPI Cinemas

                                                     1     \
Title                                                180
Release Year                                        2011
Locations           Mason & California Streets (Nob Hill)
Fun Facts                                            NaN
Production Company                           SPI Cinemas

                                      2                        3            4     \
Title                               180                      180          180
Release Year                       2011                     2011         2011
Locations           Justin Herman Plaza  200 block Market Street    City Hall
Fun Facts                           NaN                      NaN          NaN
Production Company          SPI Cinemas              SPI Cinemas  SPI Cinemas

                                        5               6                7     \
Title                                 180             180              180
Release Year                         2011            2011             2011
Locations           Polk & Larkin Streets  Randall Museum  555 Market St.
Fun Facts                             NaN             NaN              NaN
Production Company            SPI Cinemas     SPI Cinemas      SPI Cinemas

                                        8     \
Title                 24 Hours on Craigslist
Release Year                            2005
Locations                                NaN
Fun Facts                                NaN
```

```
Production Company  Yerba Buena Productions

                                                   9     …  \
Title                                     Summertime  …
Release Year                                    2015  …
Locations                              Alamo Square   …
Fun Facts                                        NaN  …
Production Company  Creative Monster Productions, Inc.  …

                                        3404  \
Title                         Basic Instinct
Release Year                            1992
Locations           Gibb Street (Chinatown)
Fun Facts                                NaN
Production Company         Carolco Pictures

                                                   3405                   3406  \
Title                                          GirlBoss                Burglar
Release Year                                       2017                   1987
Locations           Fillmore between Haight and Waller       1400 18th Street
Fun Facts                                           NaN                    NaN
Production Company         Hippolyta Productions, LLC  Warner Bros. Pictures

                                              3407                     3408  \
Title                                     The Game        Tales of the City
Release Year                                  1997                     2019
Locations              Merchant Exchange Building         Mission District
Fun Facts                                      NaN                      NaN
Production Company  Polygram Filmed Entertainment  Universal Television LLC

                                              3409  \
Title                                   Quicksilver
Release Year                                  1986
Locations                    Pacific Stock Exchange
Fun Facts                                      NaN
Production Company  Columbia Pictures Corporation

                                               3410  \
Title                   Murder in the First, Season 1
Release Year                                   2014
Locations                         50 California Street
Fun Facts                                       NaN
Production Company  Turner North Center Productions

                                                              3411  \
Title                                Murder in the First, Season 3
Release Year                                                  2016
```

```
Locations           Linden Alley between Octavia and Gough Streets
Fun Facts                                                      NaN
Production Company                  Turner North Center Productions

                                  3412                                 3413
Title               George of the Jungle                             Alcatraz
Release Year                      1997                                 2012
Locations             755 Vallejo Street  Chestnut St. from Larkin to Columbus
Fun Facts                          NaN                                  NaN
Production Company  Walt Disney Pictures          Bonanza Productions Inc.

[5 rows x 3414 columns]
```

[35]:
```python
df.columns
```

[35]:
```
Index(['Title', 'Release Year', 'Locations', 'Fun Facts', 'Production Company',
       'Distributor', 'Director', 'Writer', 'Actor 1', 'Actor 2', 'Actor 3'],
      dtype='object')
```

1.5.3 Donner le nombre et les endroits de tournage (location) par film.

[36]:
```python
df['Title'].value_counts().to_frame().head(5)
```

[36]:
```
                 Title
Looking             82
Chance Season 2     60
The Dead Pool       58
Blue Jasmine        56
Etruscan Smile      56
```

1.5.4 On souvegarde les valeurs unique dans une liste

[37]:
```python
uniqueValues = (df['Title']).unique()
# print(uniqueValues)
```

[38]:
```python
uniqueValues.size
```

[38]:
```
316
```

Il y a 316 films

1.5.5 We create an empty data frame dfn with column names: 'Title' and'Locations'. Then, we search in df dataframe unique values (Title) and append all the Locations corresponding to the Title to dfn dataframe.

```
[39]: dfn = pd.DataFrame(columns=['Title','Locations'])
      for i in (uniqueValues):
          dfn = dfn.append({'Title':i,'Locations': df[df['Title']==i]['Locations']},␣
       ↪ignore_index=True)
      dfn.to_csv('movies_Locations.csv', index = False)
```

1.5.6 Example: on va meintenant afficher le nombre des tournages et tout les locations pour le deuxieme Film dans une dataframe dfn

```
[40]: k=2

      print('Title :',dfn['Title'][k],'\n Nombre des tournages: ',dfn['Locations'][k].
       ↪shape[0], '\n  Locations:\n',str(dfn['Locations'][k]))
```

```
Title : Summertime
 Nombre des tournages:  28
  Locations:
 9                                              Alamo Square
21      Chinatown (Stockton @ Jackson & Jackson toward…
22                    Broadway and Taylor St Intersection
24      Buena Vista East & Duboce; Buena Vista East & …
26      Love Street Vintage (1506 Haight & adjacent Ha…
27                 Montgomery between California and Pine
51      Sansome (Washington to Bush) Pine (Davis to Ke…
52                                       Stanyan & Belgrave
65                                               Duboce Park
180                        20th St and Church (3885 20th St)
187                        Turk St between Lyon and Baker St
189                                            53 Potomac St
194                            Oasis Nightclub (298 11th St)
200     Fisherman's Wharf pier near Chapel (Port Walk …
650     Chinatown (Stockton @ Jackson & Jackson toward…
715                   Broadway and Taylor St Intersection
829     Buena Vista East & Duboce; Buena Vista East & …
909     Love Street Vintage (1506 Haight & adjacent Ha…
1011               Montgomery between California and Pine
2437    Sansome (Washington to Bush) Pine (Davis to Ke…
2450                                     Stanyan & Belgrave
2511                                           Alamo Square
2546                                            Duboce Park
2841                       20th St and Church (3885 20th St)
3072                       Turk St between Lyon and Baker St
3097                                          53 Potomac St
```

```
3217                        Oasis Nightclub (298 11th St)
3388    Fisherman's Wharf pier near Chapel (Port Walk …
Name: Locations, dtype: object
```

1.5.7 Création de nouvelle table de données n'ayant que ces trois attributs et afficher les 10 premiers enregistrements: Title, Release Year et Production

[41]:
```
df1=df[['Title','Release Year', 'Production Company']]
result = df1.drop_duplicates()
print(result.shape)
result.reset_index(inplace=True)
result_movie=result.drop('index',axis=1)

result_movie.head(10)
```

```
(319, 3)
```

[41]:
```
                     Title  Release Year                 Production Company
0                      180          2011                        SPI Cinemas
1  24 Hours on Craigslist          2005           Yerba Buena Productions
2               Summertime          2015  Creative Monster Productions, Inc.
3          Ballers Season 3          2017       Chori Perros Productions, LLC
4           Chance Season 2          2017                TVM Productions Inc.
5        A Night Full of Rain          1978                       Liberty Film
6           Vegas in Space          1992                Troma Entertainment
7              Nine Months          1995                      1492 Pictures
8            Beautiful Boy          2018                 Big Indie Pictures
9              About a Boy          2014                        NBC Studios
```

[42]:
```
result_movie.to_csv('RESULT_moviesx.csv', index = False)
```

1.6 1.4. Charger le jeu de données « data_employe.profiles.txt ».

- Déterminer la classe des travailleurs qui ont un capital gain (gain capital) le plus élevé et afficher uniquement l'âge, genre, classe de travail (class work) et le salaire ?
- Déterminer les employés qui sont susceptibles d'avoir un capital perte (capital loss) élevé (choisir les attributs qui vous semblent pertinents pour faire cette investigation et dites pourquoi ?
- Selon vous quelles sont les facteurs (combinaison d'attributs) ou le capital gain est au maximum et la perte en capitale (capital loss) est au minimum avec un salaire moyen par rapport à tous les employés ?

1.6.1 Chargement de jeu de données « data_person_profiles.txt »

[43]:
```
df = pd.read_csv('data_projet/data_employe_profiles.csv', delimiter=",")␣
 ↪#Chargement de donnees dans data frame df
df.head(5)
```

```
[43]:    age         work_class  salary  education  education_num  \
      0   39          State-gov   77516  BACHELORS           13.0
      1   50   Self-emp-not-inc   83311  BACHELORS           13.0
      2   38            PRIvate  215646    HS-grad            9.0
      3   53            PRIvate  234721       11th            7.0
      4   28            PRIvate  338409  BACHELORS           13.0

             marital_status         occupation   relationship   race  gender  \
      0       NEVER-MARRIED       Adm-clerical  Not-in-family  white    Male
      1  Married-civ-spouse    Exec-managerial        husband  white    Male
      2            Divorced  Handlers-cleaners  Not-in-family  white    Male
      3  Married-civ-spouse  Handlers-cleaners        husband  Black    Male
      4  Married-civ-spouse     Prof-specialty           Wife  Black  Female

         capital_gain  capital_loss  hours_per_week        country target
      0        2174.0           NaN            40.0  United-States  <=50K
      1           NaN           NaN            13.0  United-States  <=50K
      2           NaN           NaN            40.0  United-States  <=50K
      3           NaN           NaN            40.0  United-States  <=50K
      4           NaN           NaN            40.0           Cuba  <=50K
```

```
[44]: df.shape
```

```
[44]: (5730, 15)
```

```
[45]: df.columns
```

```
[45]: Index(['age', 'work_class', 'salary', 'education', 'education_num',
              'marital_status', 'occupation', 'relationship', 'race', 'gender',
              'capital_gain', 'capital_loss', 'hours_per_week', 'country', 'target'],
             dtype='object')
```

1.6.2 1.4.a. On cherche le 'capital_gain' moyen par classe le plus eleve.

```
[46]: df2 = df[['age', 'gender', 'work_class', 'salary', 'capital_gain', 'gender']]
      df2.groupby('work_class').mean().sort_values(by='capital_gain',ascending=False)
```

```
[46]:                         age         salary  capital_gain
      work_class
      Self-emp-inc      45.373786  172596.470874   8928.105263
      PRIvate           36.586047  191583.953488   7291.619048
      Self-emp-not-inc  44.890661  184634.865604   3134.097959
      Private           36.981745  193673.559732   1453.709648
      Local-gov         41.808511  187465.561170   1179.922330
      Federal-gov       42.503030  187870.787879   1106.621053
      State-gov         38.926724  179988.715517    970.074074
      ?                 39.667568  192141.686486    642.689320
```

```
Never-worked      18.000000  206359.000000      0.000000
Without-pay       65.000000   27012.000000           NaN
```

1.6.3 La classe de travaillurs avec le capital_gain plus eleve est "Self-emp-inc"

[49]:
```
df1=df.groupby('work_class').mean().
 ↪sort_values(by='capital_gain',ascending=False).head(1).idxmax()[1]
df1
```

[49]:
```
'Self-emp-inc'
```

[50]:
```
dfx = df[df.work_class == 'Self-emp-inc'][['age', 'gender', 'work_class',␣
 ↪'salary']]
dfx.head(5)
```

[50]:
```
     age gender    work_class  salary
54    47   Male  Self-emp-inc  109832
68    49   Male  Self-emp-inc  191681
105   32   Male  Self-emp-inc  317660
116   56   Male  Self-emp-inc  303090
140   61   Male  Self-emp-inc   66614
```

[51]:
```
print('La classe de travail avec le capital gain le plus eleve: ',df1)
print('age moyen ',df.groupby('work_class').mean().loc['Self-emp-inc']['age'])
print('le genre plus courant: ',df[df['work_class']=='Self-emp-inc']['gender'].
 ↪value_counts().idxmax())
print('le salaire moyen ',df.groupby('work_class').mean().
 ↪loc['Self-emp-inc']['salary'])
```

```
La classe de travail avec le capital gain le plus eleve:  Self-emp-inc
age moyen  45.37378640776699
le genre plus courant:  Male
le salaire moyen  172596.4708737864
```

Pour savoir le genre le plus courant dans la class 'Self-emp-inc' on applique .value_counts().idxmax() pour les autres caracteristiques on cherche le moyenne

[52]:
```
print(df[df['work_class']=='Self-emp-inc']['gender'].value_counts())
```

```
Male      177
Female     29
Name: gender, dtype: int64
```

[53]:
```
df[df['work_class']=='Self-emp-inc']['gender'].value_counts().idxmax()
```

[53]:
```
'Male'
```

1.6.4 Déterminer les employés qui sont susceptibles d'avoir un capital perte (capital loss) élevé

[54]:
```
df.sort_values(by='capital_loss',ascending=False).head(5)
```

[54]:
```
      age        work_class  salary     education  education_num  \
5309   41           Private   70037  Some-college           10.0
5713   38  Self-emp-not-inc  164526   Prof-school           15.0
2414   44           Private  326232     BACHELORS           13.0
2859   40  Self-emp-not-inc  335549   Prof-school           15.0
387    44           Private  162028  Some-college           10.0

          marital_status        occupation   relationship   race  gender  \
5309       Never-married      Craft-repair      Unmarried  White    Male
5713       Never-married    Prof-specialty  Not-in-family  White    Male
2414            Divorced   Exec-managerial      Unmarried  white    Male
2859       Never-married    Prof-specialty  Not-in-family  White    Male
387   Married-civ-spouse      Adm-clerical           Wife  white  Female

      capital_gain  capital_loss  hours_per_week        country target
5309           0.0        3004.0            60.0              ?   >50K
5713           0.0        2824.0            45.0  United-States   >50K
2414           NaN        2547.0            50.0  United-States   >50K
2859           0.0        2444.0            45.0  United-States   >50K
387            NaN        2415.0             6.0  United-States   >50K
```

Le personnes le plus susceptible a capital perte sont dans le work_class privee et self-empl-not-inc, ils ont capital_gain=0, genre "Male" et ils sont never-married or divorced. On a choisi ces attributs parce que il sont plus courant pour les personnes concernees

1.6.5 Selon vous quelles sont les facteurs (combinaison d'attributs) ou le capital gain est au maximum et la perte en capitale (capital loss) est au minimum avec un salaire moyen par rapport à tous les employés?

1.6.6 On cherche les salaires qui sont plus proches a la moyenne

[55]:
```
idx = np.where((df['capital_loss']==df['capital_loss'].min()) &␣
 ↪(df['capital_gain']==df['capital_gain'].max()) & (df['salary']>0.
 ↪9*df['salary'].mean())&  (df['salary']<=1.1*df['salary'].mean()))
print(idx)
```

```
(array([3105, 3175], dtype=int64),)
```

[56]:
```
df.loc[idx]
```

```
[56]:       age work_class  salary    education  education_num      marital_status  \
      3105   46    Private  176814  Prof-school           15.0  Married-civ-spouse
      3175   36    Private  208358  Prof-school           15.0            Divorced

                occupation   relationship   race gender  capital_gain  capital_loss  \
      3105  Prof-specialty        Husband  White   Male       99999.0           0.0
      3175  Prof-specialty  Not-in-family  White   Male       99999.0           0.0

            hours_per_week        country target
      3105            50.0  United-States   >50K
      3175            45.0  United-States   >50K
```

```
[57]: df['age'].mean()
```

```
[57]: 38.60401396160559
```

```
[58]: df['education_num'].mean()
```

```
[58]: 10.20142774454949
```

```
[59]: df['salary'].mean()
```

```
[59]: 190890.58411867364
```

```
[60]: df['hours_per_week'].mean()
```

```
[60]: 40.49607261302147
```

1.6.7 Si on regarde sur 2 ligne on peut dire que c'est un homme qui travail beaucoup (5-10 h en plus que moyen) dans le secteur prive avec l'education Prof-school (15 points education_num) et occupation Prof-specialty.

1.6.8 Donc, work_class, education, eduction_num, occupation et gender sont les attributs le plus important

```
[61]: df['race'].value_counts()
```

```
[61]: White                 2582
      white                 2300
      Black                  576
      Asian-Pac-Islander     174
      Amer-Indian-Eskimo      58
      Other                   40
      Name: race, dtype: int64
```

1.6.9 Je doit noter que la majorite des tout les employees sont ‘white’, donc on ne peut pas dire que race est important.

2 SQL & Python

2.1 Running code example for SQL:

[63]:
```
import sqlite3

conn = sqlite3.connect('testYuliaRicardo_example.db')

conn.execute('''CREATE TABLE COMPANY
    (ID INT PRIMARY KEY NOT NULL,
    NAME TEXT NOT NULL,
    AGE INT NOT NULL,
    ADDRESS CHAR(50),
    SALARY REAL);''')

print("Table created successfully")
conn.execute("INSERT INTO COMPANY (ID,NAME,AGE,ADDRESS,SALARY) \
VALUES (1, 'Paul', 32, 'California', 20000.00 )")

conn.commit()
cursor = conn.execute("SELECT id, name, address, salary from COMPANY")

for row in cursor:
    print ("ID = ", row[0])
    print ("NAME = ", row[1])
    print ("ADDRESS = ", row[2])
    print ("SALARY = ", row[3], "\n")

conn.close() #Run example
```

```
Table created successfully
ID =  1
NAME =  Paul
ADDRESS =  California
SALARY =  20000.0
```

2.1.1 Notes:

- Adding parenthesis to prints
- Database created automatically in folder of jupyter file
- Execute 2nd time doesnt work second time because its already created the table or the database.
- To Erase database, i have to close jupyther (Windows show file already in use)

2.2 1.5. Importer le jeu de données movies (movies.csv) dans une table de données qui se nommera data_movies en gardant seulement les variables suivantes :

- num_voted_users,
- country,
- movie_facebook_likes,
- director_facebook_likes,
- aspect_ratio,
- movie_title,
- actor_1_name,
- imdb_score,
- duration

Cette table de données comprendra seulement les films qui ont plus de 52000 personnes ayant voté

[64]:
```
import pandas as pd

data= pd.read_csv("data_projet/movies.csv")
pd.set_option('display.max_rows', None)
data.head()
```

[64]:
```
     color      director_name  num_critic_for_reviews duration  \
0  Colores      James Cameron                   723.0  178 min
1  Colores     Gore Verbinski                   302.0  169 min
2  Colores         Sam Mendes                   602.0  148 min
3  Colores  Christopher Nolan                   813.0  164 min
4      NaN        Doug Walker                     NaN   NA min

   director_facebook_likes  actor_3_facebook_likes      actor_2_name  \
0                      0.0                   855.0  Joel David Moore
1                    563.0                  1000.0     ORLANDO BLOOM
2                      0.0                   161.0      Rory Kinnear
3                  22000.0                 23000.0    Christian Bale
4                    131.0                     NaN        ROB WALKER

   actor_1_facebook_likes        gross                           genres  …  \
0                  1000.0  760505847 $  Action|Adventure|Fantasy|Sci-Fi  …
1                 40000.0  309404152 $         Action|Adventure|Fantasy  …
2                 11000.0  200074175 $        Action|Adventure|Thriller  …
3                 27000.0  448130642 $                  Action|Thriller  …
4                   131.0         NA $                      Documentary  …

  num_user_for_reviews language  country  content_rating       budget  \
0                 3054  English      USA           PG-13  2.37e+08 $
1                 1238  English      USA           PG-13     3e+08 $
2                  994  English       UK           PG-13  2.45e+08 $
3                 2701  English      USA           PG-13   2.5e+08 $
```

```
4                 NA        NaN      NaN             NaN        NA $

   title_year actor_2_facebook_likes imdb_score aspect_ratio  \
0      2009.0                    936      7.9 #         1.78
1      2007.0                   5000      7.1 #         2.35
2      2015.0                    393      6.8 #         2.35
3      2012.0                  23000      8.5 #         2.35
4         NaN                     12      7.1 #          NaN

  movie_facebook_likes
0                 4834
1                48350
2                11700
3               106759
4                  143

[5 rows x 28 columns]
```

[65]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7410 entries, 0 to 7409
Data columns (total 28 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   color                      7386 non-null   object
 1   director_name              7263 non-null   object
 2   num_critic_for_reviews     7338 non-null   float64
 3   duration                   7410 non-null   object
 4   director_facebook_likes    7263 non-null   float64
 5   actor_3_facebook_likes     7373 non-null   float64
 6   actor_2_name               7391 non-null   object
 7   actor_1_facebook_likes     7400 non-null   float64
 8   gross                      7410 non-null   object
 9   genres                     7410 non-null   object
 10  actor_1_name               7400 non-null   object
 11  movie_title                7410 non-null   object
 12  num_voted_users            7410 non-null   int64
 13  cast_total_facebook_likes  7410 non-null   int64
 14  actor_3_name               7373 non-null   object
 15  facenumber_in_poster       7388 non-null   float64
 16  plot_keywords              7189 non-null   object
 17  movie_imdb_link            7410 non-null   object
 18  num_user_for_reviews       7410 non-null   object
 19  language                   7394 non-null   object
 20  country                    7403 non-null   object
 21  content_rating             6973 non-null   object
 22  budget                      7410 non-null   object
 23  title_year                  7258 non-null   float64
 24  actor_2_facebook_likes      7410 non-null   object
 25  imdb_score                  7410 non-null   object
 26  aspect_ratio                6944 non-null   float64
 27  movie_facebook_likes        7410 non-null   int64
dtypes: float64(7), int64(3), object(18)
memory usage: 1.6+ MB
```

2.2.1 Response

[66]:
```
# Obtention de certaines characteristiques.

dataMovies = data␣
 ↪[['num_voted_users','country','movie_facebook_likes','director_facebook_likes',
                  ␣
 ↪'aspect_ratio','movie_title','actor_1_name','imdb_score','duration']]

dataMovies_filtered =  dataMovies[data.num_voted_users>52000]

dataMovies_filtered.head()
```

[66]:
```
   num_voted_users country  movie_facebook_likes  director_facebook_likes  \
0           886204     USA                  4834                      0.0
1           471220     USA                 48350                    563.0
2           275868      UK                 11700                      0.0
3          1144337     USA                106759                  22000.0
5           212204     USA                  1873                    475.0

   aspect_ratio                               movie_title     actor_1_name  \
0          1.78                                    Avatar       CCH POUNDER
1          2.35  Pirates of the Caribbean: At World's End       JOHNNY DEPP
2          2.35                                   Spectre  Christoph Waltz
3          2.35                     The Dark Knight Rises        Tom Hardy
5          2.35                               John Carter      DARYL SABARA

  imdb_score duration
0      7.9 #  178 min
1      7.1 #  169 min
2      6.8 #  148 min
3      8.5 #  164 min
5      6.6 #  132 min
```

2.2.2 Verification

[67]:
```
dataMovies.info() #Data not filtered
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7410 entries, 0 to 7409
Data columns (total 9 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   num_voted_users          7410 non-null   int64
 1   country                  7403 non-null   object
 2   movie_facebook_likes     7410 non-null   int64
 3   director_facebook_likes  7263 non-null   float64
 4   aspect_ratio             6944 non-null   float64
 5   movie_title              7410 non-null   object
 6   actor_1_name             7400 non-null   object
 7   imdb_score               7410 non-null   object
 8   duration                 7410 non-null   object
dtypes: float64(2), int64(2), object(5)
memory usage: 521.1+ KB
```

[68]:
```
dataMovies_filtered.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3033 entries, 0 to 7407
Data columns (total 9 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   num_voted_users          3033 non-null   int64
 1   country                  3033 non-null   object
 2   movie_facebook_likes     3033 non-null   int64
 3   director_facebook_likes  3009 non-null   float64
 4   aspect_ratio             3033 non-null   float64
 5   movie_title              3033 non-null   object
 6   actor_1_name             3033 non-null   object
 7   imdb_score               3033 non-null   object
 8   duration                 3033 non-null   object
dtypes: float64(2), int64(2), object(5)
memory usage: 237.0+ KB
```

Ilya 3033 films.

2.3 1.6 Créer la variable « popularite » qui prendra les valeurs suivantes :

- Faible - Si le nombre de « Likes » sur FACEBOOK du film est en-dessous de 5000.
- Moyenne- Si le nombre de « Likes » sur FACEBOOK du film est compris entre 5000 et 24999.
- Forte- Si le nombre de « Likes » sur FACEBOOK du film est supérieur ou égale à 25000

2.3.1 Metode 1 - np.select

[69]:
```
# create a list of our conditions
#df = dataMovies
conditions = [
    (dataMovies['movie_facebook_likes'] <= 5000),
    (dataMovies['movie_facebook_likes'] > 5000) &␣
 ↪(dataMovies['movie_facebook_likes'] <= 24999),
    (dataMovies['movie_facebook_likes'] >= 25000)
    ]

# create a list of the values we want to assign for each condition
condition_values = ['Faible', 'Moyenne', 'Forte']

# create a new column and use np.select to assign values to it using our lists␣
 ↪as arguments
dataMovies['popularite'] = np.select(conditions, condition_values)
dataMovies.head()
```

```
<ipython-input-69-295e12a84965>:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dataMovies['popularite'] = np.select(conditions, condition_values)
```

[69]:
```
   num_voted_users country  movie_facebook_likes  director_facebook_likes  \
0           886204     USA                  4834                      0.0
1           471220     USA                 48350                    563.0
2           275868      UK                 11700                      0.0
3          1144337     USA                106759                  22000.0
4                8     NaN                   143                    131.0

   aspect_ratio                                       movie_title  \
0          1.78                                           Avatar
1          2.35         Pirates of the Caribbean: At World's End
2          2.35                                          Spectre
3          2.35                            The Dark Knight Rises
4           NaN  Star Wars: Episode VII - The Force Awakens    …

      actor_1_name imdb_score duration popularite
0      CCH POUNDER      7.9 #  178 min     Faible
1      JOHNNY DEPP      7.1 #  169 min      Forte
2  Christoph Waltz      6.8 #  148 min    Moyenne
3        Tom Hardy      8.5 #  164 min      Forte
```

```
4      Doug Walker      7.1 #   NA min     Faible
```

2.3.2 Metode 2 - custom algorithme

[76]:
```
populariteX = []
for row in dataMovies['movie_facebook_likes']:
    if row <= 5000 : populariteX.append('FIABLE')
    elif ((row > 5000) & (row <= 24999)): populariteX.append('MOYENNE')
    elif (row >= 25000) :  populariteX.append('FORTE')
    else: populariteX.append('Not_Rated')

dataMovies['popularite'] =  populariteX
```

```
<ipython-input-76-e508149c68a6>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dataMovies['popularite'] =  populariteX
```

[77]:
```
dataMovies.head()
```

[77]:
```
   num_voted_users country  movie_facebook_likes  director_facebook_likes  \
0           886204     USA                  4834                      0.0
1           471220     USA                 48350                    563.0
2           275868      UK                 11700                      0.0
3          1144337     USA                106759                  22000.0
4                8     NaN                   143                    131.0

   aspect_ratio                                        movie_title  \
0          1.78                                            Avatar
1          2.35          Pirates of the Caribbean: At World's End
2          2.35                                           Spectre
3          2.35                             The Dark Knight Rises
4           NaN  Star Wars: Episode VII - The Force Awakens    …

      actor_1_name imdb_score duration popularite
0      CCH POUNDER      7.9 #  178 min     FIABLE
1      JOHNNY DEPP      7.1 #  169 min      FORTE
2  Christoph Waltz      6.8 #  148 min    MOYENNE
3        Tom Hardy      8.5 #  164 min      FORTE
4      Doug Walker      7.1 #   NA min     FIABLE
```

2.3.3 1.7. Renommer la variable « duration » en « temps » et la variable « movie_title » en « titre »

[78]:
```
dataMovies_new = dataMovies.rename(columns={'duration': 'temps', 'movie_title':␣
↪'tittre'})
dataMovies_new.head()
```

[78]:
```
   num_voted_users country  movie_facebook_likes  director_facebook_likes  \
0           886204     USA                  4834                      0.0
1           471220     USA                 48350                    563.0
2           275868      UK                 11700                      0.0
3          1144337     USA                106759                  22000.0
4                8     NaN                   143                    131.0

   aspect_ratio                                       tittre  \
0          1.78                                       Avatar
1          2.35     Pirates of the Caribbean: At World's End
2          2.35                                      Spectre
3          2.35                        The Dark Knight Rises
4           NaN  Star Wars: Episode VII - The Force Awakens    …

      actor_1_name imdb_score    temps popularite
0      CCH POUNDER      7.9 #  178 min     FIABLE
1      JOHNNY DEPP      7.1 #  169 min      FORTE
2  Christoph Waltz      6.8 #  148 min    MOYENNE
3        Tom Hardy      8.5 #  164 min      FORTE
4      Doug Walker      7.1 #   NA min     FIABLE
```

3 SQL & Python- Partie 2:

3.1 2.1. Charger les 6 fichiers (data_credit*_infos et data_credit*_socio) dans 6 tables

3.1.1 data_credit_mtl_infos.xlsx

[79]:
```
import pandas as pd

data1= pd.read_excel("data_projet/data_credit_mtl_infos.xlsx")
pd.set_option('display.max_rows', None)
data1.head()
```

[79]:
```
   ClientID checking_status   duration           credit_history   purpose  \
0   1215693              <0  1_2_years            existing paid  radio/tv
1   1215693              <0  1_2_years            existing paid  radio/tv
2   1215696       0<=X<200  lo_1_year  critical/other existing  used car
3   1215696       0<=X<200  lo_1_year  critical/other existing  used car
4   1215699     no checking  lo_1_year  critical/other existing  radio/tv
```

```
     amount    savings_status other_parties property_magnitude  \
0  1000_2000              <100          none        real estate
1  1000_2000              <100          none        real estate
2  1000_2000              <100          none                car
3  1000_2000              <100          none                car
4  1000_2000  no known savings          none        real estate

  other_payment_plans existing_credits class  number_product
0                none              two   bad               5
1                none              two   bad               5
2                none              two  good               5
3                none              two  good               5
4                none              two  good               5
```

3.1.2 data_credit_mtl_socio.xlsx

```
[80]: data2= pd.read_excel("data_projet/data_credit_mtl_socio.xlsx")
      pd.set_option('display.max_rows', None)
      data2.head()
```

```
[80]:    ClientID     personal_status  employment                        job  \
      0   1218528         male single  unemployed  high qualif/self emp/mgm
      1   1218459         male single         >=7                   skilled
      2   1218507         male single         >=7  high qualif/self emp/mgm
      3   1218450  female div/dep/mar          <1                   skilled
      4   1218360  female div/dep/mar         >=7                   skilled

        own_telephone foreign_worker      City housing  age
      0           yes            yes  Montreal    rent   15
      1           yes            yes  Montreal    rent   17
      2           yes            yes  Montreal    rent   19
      3          none            yes  Montreal    rent   22
      4           yes            yes  Montreal    rent   22
```

3.1.3 data_credit_que_infos.xlsx

```
[81]: data3= pd.read_excel("data_projet/data_credit_que_infos.xlsx")
      pd.set_option('display.max_rows', None)
      data3.head()
```

```
[81]:    ClientID checking_status   duration      credit_history  \
      0   1216377              <0  1_2_years       existing paid
      1   1216371              <0  1_2_years  delayed previously
      2   1216380     no checking  lo_1_year  delayed previously
      3   1216374     no checking  lo_1_year       existing paid
```

```
4   1216104        0<=X<200  lo_1_year  delayed previously

              purpose     amount savings_status other_parties  \
0             new car  1000_2000           <100          none
1            radio/tv  1000_2000           <100          none
2            used car  1000_2000           <100          none
3             new car  1000_2000     100<=X<500          none
4  furniture/equipment  1000_2000           <100          none

  property_magnitude other_payment_plans existing_credits class  \
0     life insurance                none              one   bad
1                car                none              one   bad
2        real estate                none              one  good
3        real estate                none              one  good
4     life insurance              stores              two  good

   number_product
0               5
1               5
2               2
3               6
4               3
```

3.1.4 data_credit_que_socio.xlsx

[82]:
```
data4 = pd.read_excel("data_projet/data_credit_que_socio.xlsx")
pd.set_option('display.max_rows', None)
data4.head()
```

[82]:
```
   ClientID     personal_status  employment                        job  \
0   1216377  female div/dep/mar          <1                    skilled
1   1216371  female div/dep/mar          <1         unskilled resident
2   1216380        male mar/wid      1<=X<4                    skilled
3   1216374         male single      1<=X<4         unskilled resident
4   1216104         male single  unemployed  high qualif/self emp/mgmt

  own_telephone foreign_worker    City housing  age
0          none            yes  Quebec    rent   25
1           yes            yes  Quebec    rent   28
2          none            yes  Quebec    rent   29
3          none             no  Quebec    rent   29
4           yes            yes  Quebec     own   33
```

3.1.5 data_credit_tor_infos.xlsx

[83]:
```
data5= pd.read_excel("data_projet/data_credit_tor_infos.xlsx")
pd.set_option('display.max_rows', None)
data5.head()
```

[83]:
```
   ClientID checking_status    duration      credit_history   purpose  \
0   1216830              <0   1_2_years  delayed previously   new car
1   1217052              <0   1_2_years       existing paid  used car
2   1216386              <0   1_2_years            all paid  radio/tv
3   1216836        0<=X<200   1_2_years       existing paid  used car
4   1216902        0<=X<200  up_2_years       existing paid     other

      amount    savings_status other_parties property_magnitude  \
0    up_2000              <100          none  no known property
1    up_2000              <100          none  no known property
2  1000_2000              <100     guarantor                car
3    up_2000              <100          none  no known property
4    up_2000  no known savings          none  no known property

  other_payment_plans existing_credits class  number_product
0                none              two   bad               3
1                none              one  good               4
2                bank              one   bad               6
3                none              one   bad               7
4                bank              one  good               1
```

3.1.6 data_credit_tor_socio.xlsx

[84]:
```
data6= pd.read_excel("data_projet/data_credit_tor_socio.xlsx")
pd.set_option('display.max_rows', None)
data6.head()
```

[84]:
```
   ClientID     personal_status  employment                          job  \
0   1216830         male single      1<=X<4                      skilled
1   1217052         male single  unemployed  high qualif/self emp/mgm
2   1216386         male single      4<=X<7           unskilled resident
3   1216836  female div/dep/mar         >=7  high qualif/self emp/mgm
4   1216902         male single  unemployed   unemp/unskilled non res

  own_telephone foreign_worker     City   housing  age
0          none            yes  Toronto  for free   15
1           yes            yes  Toronto  for free   15
2          none            yes  Toronto      rent   15
3           yes            yes  Toronto  for free   15
4           yes            yes  Toronto  for free   16
```

3.2 2.2. Fusionner les de façon à avoir toutes ces données toutes ensembles dans une table de base de données. Cette nouvelle table a comme nom data_credit

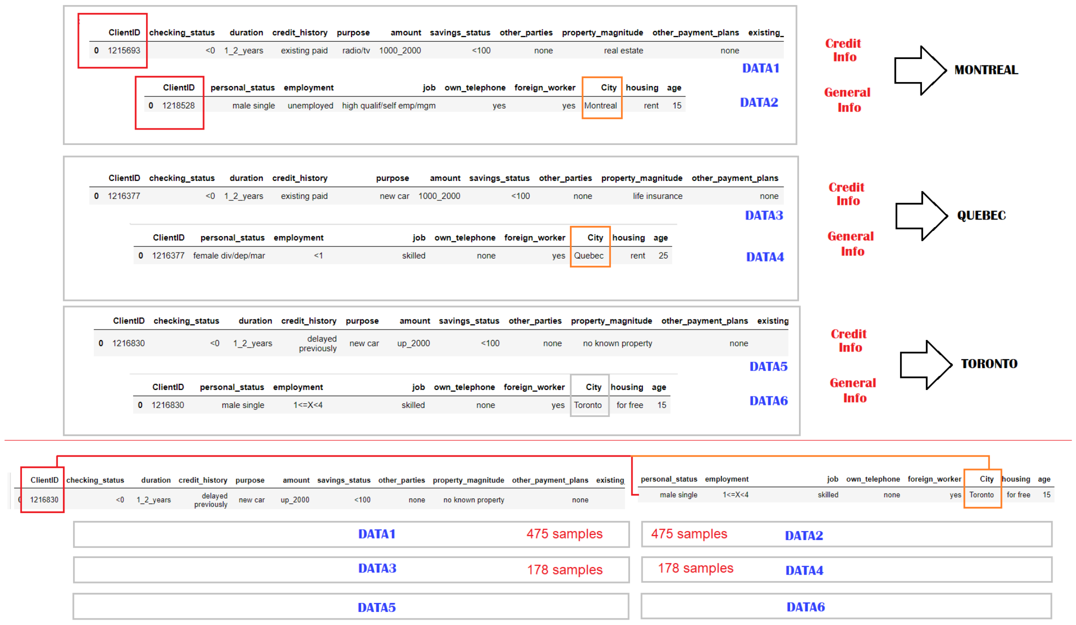
Aucun enregistrement (donnée) provenant des fichiers ne doit être perdu lors de la fusion et assurer qu'il n'y a aucun doublon dans cette nouvelle table (par doublons, nous voulons dire qu'aucune ligne de données ne se retrouve plus d'une fois dans la nouvelle table) ?

3.3 Analysis preliminaire:

- On a besoin de preserver tous les donnes, effacer pas de variables et conserver la structuture adequate pour profiter de la functionalite de pandas dataframes.
- Les 6 tables de data sont de 2 types:
  - Information general socio.
  - Information credit socio.
- Ilya deux champs importantes pour la fussion, City pour identifier le set de donnes et ClientId pour indexer des donnes.
- Les donnes ont de deux types: **DATACREDIT et DATAINFOUSER**
- Le numero de set de donnes est 3, **MONTREAL, TORONTO, QUEBEC**
- Chaque set de donnes est composse de deux fichiers chaque excell.
- Selon l'information generale de datasets:
  - On a pas des valeurs null comme valeurs des donnes des datasets.
  - On va reduire les donnes a un dataset de 21 labels.
- Pour chaque Ville ou set donnes on va faire un **fusion preliminaire** de donnes de credit et info general basse sur le **ClientId**.
- La image suivant explique le methodologie de fussion.

```
[85]: from IPython.display import Image
      Image(filename = "data_projet/strategieFusionData.png", width = 1600, height =␣
       ↪1200)
```

```
[85]:
```



	ClientID	checking_status	duration	credit_history	purpose	amount	savings_status	other_parties	property_magnitude	other_payment_plans	existing_
0	1215693	<0	1_2_years	existing paid	radio/tv	1000_2000	<100	none	real estate	none	

	ClientID	personal_status	employment	job	own_telephone	foreign_worker	City	housing	age
0	1218528	male single	unemployed	high qualif/self emp/mgm	yes	yes	Montreal	rent	15

	ClientID	checking_status	duration	credit_history	purpose	amount	savings_status	other_parties	property_magnitude	other_payment_plans
0	1216377	<0	1_2_years	existing paid	new car	1000_2000	<100	none	life insurance	none

	ClientID	personal_status	employment	job	own_telephone	foreign_worker	City	housing	age
0	1216377	female div/dep/mar	<1	skilled	none	yes	Quebec	rent	25

	ClientID	checking_status	duration	credit_history	purpose	amount	savings_status	other_parties	property_magnitude	other_payment_plans	existing
0	1216830	<0	1_2_years	delayed previously	new car	up_2000	<100	none	no known property	none	

	ClientID	personal_status	employment	job	own_telephone	foreign_worker	City	housing	age
0	1216830	male single	1<=X<4	skilled	none	yes	Toronto	for free	15

	ClientID	checking_status	duration	credit_history	purpose	amount	savings_status	other_parties	property_magnitude	other_payment_plans	existing	personal_status	employment	job	own_telephone	foreign_worker	City	housing	age
0	1216830	<0	1_2_years	delayed previously	new car	up_2000	<100	none	no known property	none		male single	1<=X<4	skilled	none	yes	Toronto	for free	15

[86]:
```python
# Numero de columns dataset resultat

ncols_merged = data1.shape[1] + data2.shape[1] - 1 #No repeter clientId
print("No. Columns merged dataSet: ", ncols_merged)
```

```
No. Columns merged dataSet:  21
```

[87]:
```python
data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 475 entries, 0 to 474
Data columns (total 13 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   ClientID             475 non-null    int64 
 1   checking_status      475 non-null    object
 2   duration             475 non-null    object
 3   credit_history       475 non-null    object
 4   purpose              475 non-null    object
 5   amount               475 non-null    object
 6   savings_status       475 non-null    object
 7   other_parties        475 non-null    object
 8   property_magnitude   475 non-null    object
 9   other_payment_plans  475 non-null    object
 10  existing_credits     475 non-null    object
 11  class                475 non-null    object
 12  number_product       475 non-null    int64 
```

```
dtypes: int64(2), object(11)
memory usage: 48.4+ KB
```

[88]:
```
data2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 475 entries, 0 to 474
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ClientID         475 non-null    int64
 1   personal_status  475 non-null    object
 2   employment       475 non-null    object
 3   job              475 non-null    object
 4   own_telephone    475 non-null    object
 5   foreign_worker   475 non-null    object
 6   City             475 non-null    object
 7   housing          475 non-null    object
 8   age              475 non-null    int64
dtypes: int64(2), object(7)
memory usage: 33.5+ KB
```

3.4 Analysis de relation entre tables - ClientID

- Dans les tables de type DATACREDIT (Data 1,3,5) on repete des ClientIDs, apres de explorer les donnes on arrive a la conclusion que pour les cases ou les socios sont enregistres plus d'une fois, sont des doublons, mais pas tout les socios sont en doublon.
- On va enlever les donnes doublons sur tables DATA 1,3,5 avant le merge preliminaire

[89]:
```
data1['ClientID'].count()
```

[89]:
```
475
```

[90]:
```
data1['ClientID'].nunique()
```

[90]:
```
241
```

[91]:
```
data1.sort_values('ClientID').head(6)
```

[91]:
```
   ClientID checking_status   duration            credit_history   purpose  \
0   1215693              <0  1_2_years             existing paid  radio/tv
1   1215693              <0  1_2_years             existing paid  radio/tv
2   1215696        0<=X<200  lo_1_year  critical/other existing  used car
3   1215696        0<=X<200  lo_1_year  critical/other existing  used car
4   1215699     no checking  lo_1_year  critical/other existing  radio/tv
5   1215699     no checking  lo_1_year  critical/other existing  radio/tv
```

```
      amount    savings_status other_parties property_magnitude  \
0  1000_2000              <100          none        real estate
1  1000_2000              <100          none        real estate
2  1000_2000              <100          none                car
3  1000_2000              <100          none                car
4  1000_2000  no known savings          none        real estate
5  1000_2000  no known savings          none        real estate

  other_payment_plans existing_credits class  number_product
0                none              two   bad               5
1                none              two   bad               5
2                none              two  good               5
3                none              two  good               5
4                none              two  good               5
5                none              two  good               5
```

- Dans les tables de type DATAINFOUSER on repete les ClientIDs, donc ilya une plus de une credit pour usager, il faut tenir en compte un relation many to many or one to many entre les deux tables.
- On va enlever les donnes doublons sur tables DATA 2,4,6 avant de merge preliminaire

[92]:
```
data2['ClientID'].count() # Numero de ClientIDs des clients dans le dataset
```

[92]:
```
475
```

[93]:
```
data2['ClientID'].nunique() # Numero de ClientIDs uniques dans le dataset
```

[93]:
```
241
```

[94]:
```
data2.sort_values('ClientID').head(10) # Pour regarder les valeurs␣
 ↪repetetitives.
```

[94]:
```
     ClientID     personal_status  employment                          job  \
375   1215693  female div/dep/mar      1<=X<4                      skilled
134   1215693  female div/dep/mar      1<=X<4                      skilled
355   1215696         male single  unemployed  high qualif/self emp/mgm
114   1215696         male single  unemployed  high qualif/self emp/mgm
376   1215699  female div/dep/mar         >=7                      skilled
135   1215699  female div/dep/mar         >=7                      skilled
51    1215702         male single         >=7                      skilled
292   1215702         male single         >=7                      skilled
397   1215705         male single      1<=X<4                      skilled
156   1215705         male single      1<=X<4                      skilled

    own_telephone foreign_worker      City housing  age
```

```
375           yes           yes  Montreal     own   49
134           yes           yes  Montreal     own   49
355           yes           yes  Montreal     own   46
114           yes           yes  Montreal     own   46
376           yes           yes  Montreal     own   49
135           yes           yes  Montreal     own   49
51           none           yes  Montreal     own   35
292          none           yes  Montreal     own   35
397           yes            no  Montreal     own   52
156           yes            no  Montreal     own   52
```

[95]:
```
# All the ClientIDs of DATA1 are in DATA2, in order to evaluate if the inner␣
 ↪join its valid.
```

[96]:
```
res = data1.isin(data2['ClientID']).any().any()
print(res)
```

```
True
```

3.4.1 Procedure de fussion:

[97]:
```
DATACLIENTS = pd.concat([data1, data3, data5]).drop_duplicates()
DATACLIENTS.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 946 entries, 0 to 600
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   ClientID            946 non-null    int64
 1   checking_status     946 non-null    object
 2   duration            946 non-null    object
 3   credit_history      946 non-null    object
 4   purpose             946 non-null    object
 5   amount              946 non-null    object
 6   savings_status      946 non-null    object
 7   other_parties       946 non-null    object
 8   property_magnitude  946 non-null    object
 9   other_payment_plans 946 non-null    object
 10  existing_credits    946 non-null    object
 11  class               946 non-null    object
 12  number_product      946 non-null    int64
dtypes: int64(2), object(11)
memory usage: 103.5+ KB
```

[98]:
```
DATACREDITS = pd.concat([data2, data4, data6]).drop_duplicates()
DATACREDITS.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 946 entries, 0 to 600
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ClientID         946 non-null    int64
 1   personal_status  946 non-null    object
 2   employment       946 non-null    object
 3   job              946 non-null    object
 4   own_telephone    946 non-null    object
 5   foreign_worker   946 non-null    object
 6   City             946 non-null    object
 7   housing          946 non-null    object
 8   age              946 non-null    int64
dtypes: int64(2), object(7)
memory usage: 73.9+ KB
```

```
[99]: FUSION = pd.merge(DATACLIENTS, DATACREDITS, on=["ClientID"], how = 'inner')
      FUSION.sort_values('ClientID').head()
```

```
[99]:    ClientID checking_status   duration           credit_history   purpose  \
      0   1215693              <0  1_2_years            existing paid  radio/tv
      1   1215696        0<=X<200  lo_1_year  critical/other existing  used car
      2   1215699     no checking  lo_1_year  critical/other existing  radio/tv
      3   1215702     no checking  1_2_years  critical/other existing  radio/tv
      4   1215705     no checking  lo_1_year            existing paid  radio/tv

            amount    savings_status other_parties property_magnitude  \
      0  1000_2000              <100          none        real estate
      1  1000_2000              <100          none                car
      2  1000_2000  no known savings          none        real estate
      3  1000_2000             >=1000         none                car
      4  1000_2000              <100          none     life insurance

        other_payment_plans  … class number_product     personal_status  \
      0                none  …   bad              5  female div/dep/mar
      1                none  …  good              5         male single
      2                none  …  good              5  female div/dep/mar
      3                none  …  good              5         male single
      4                none  …  good              5         male single

         employment                         job own_telephone foreign_worker  \
      0      1<=X<4                     skilled           yes            yes
      1  unemployed  high qualif/self emp/mgm           yes            yes
      2         >=7                     skilled           yes            yes
      3         >=7                     skilled          none            yes
      4      1<=X<4                     skilled           yes             no
```

```
       City housing age
0  Montreal     own  49
1  Montreal     own  46
2  Montreal     own  49
3  Montreal     own  35
4  Montreal     own  52

[5 rows x 21 columns]
```

[100]:
```
FUSION.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 946 entries, 0 to 945
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   ClientID              946 non-null    int64
 1   checking_status       946 non-null    object
 2   duration              946 non-null    object
 3   credit_history        946 non-null    object
 4   purpose               946 non-null    object
 5   amount                946 non-null    object
 6   savings_status        946 non-null    object
 7   other_parties         946 non-null    object
 8   property_magnitude    946 non-null    object
 9   other_payment_plans   946 non-null    object
 10  existing_credits      946 non-null    object
 11  class                 946 non-null    object
 12  number_product        946 non-null    int64
 13  personal_status       946 non-null    object
 14  employment            946 non-null    object
 15  job                   946 non-null    object
 16  own_telephone         946 non-null    object
 17  foreign_worker        946 non-null    object
 18  City                  946 non-null    object
 19  housing               946 non-null    object
 20  age                   946 non-null    int64
dtypes: int64(3), object(18)
memory usage: 162.6+ KB
```

3.5 2.3. Afficher le nombre de clients qu'il y a dans la région de Toronto et après de Québec ainsi que l'âge moyen des clients de chaque région ?

[101]:
```
respTor = FUSION[FUSION.City=="Toronto"]
print("nombre de clients qu'il y a dans la région de Toronto: ", respTor.
 ↪shape[0])

respQc = FUSION[FUSION.City=="Quebec"]
print("nombre de clients qu'il y a dans la région de Quebec: ", respQc.shape[0])

respMtl = FUSION[FUSION.City=="Montreal"]
print("nombre de clients qu'il y a dans la région de Montreal: ", respMtl.
 ↪shape[0])
```

```
nombre de clients qu'il y a dans la région de Toronto:  582
nombre de clients qu'il y a dans la région de Quebec:  104
nombre de clients qu'il y a dans la région de Montreal:  241
```

[102]:
```
FUSION.groupby('City').size().to_frame()
```

[102]:
```
            0
City
Montreal  241
Quebec    104
Toronto   582
Totonto    19
```

- Ca dois etre corrige l'erreur de typo ``Totonto'' dans les donnes, en total Toronto 582 + 19 = 601
- **On le fait pas la modification pour respecter les donnes original dans l'analysis de projet**

[103]:
```
print("Age moyene Toronto", respTor['age'].mean())
```

```
Age moyene Toronto 42.94329896907217
```

3.5.1 Age moyenne pour chaque region

[104]:
```
FUSION.groupby('City').mean()['age'].to_frame()
```

[104]:
```
                age
City
Montreal  47.742739
Quebec    55.317308
Toronto   42.943299
Totonto   46.947368
```

3.6 2.4. Dans cette nouvelle table, veuillez afficher le nombre de produits moyen, le minimum du nombre de produit, le maximum du nombre de produits et cela grouper par ville. Nous voulons seulement la ville de Montréal et de Québec. Quelle est la ville qui a la plus petite moyenne ? Est-ce une grande différence?

[105]:
```
f2 = FUSION[(FUSION.City == "Montreal") | (FUSION.City == "Quebec")]
f2.groupby('City').describe()['number_product']
```

[105]:
```
          count      mean       std  min  25%  50%  75%   max
City
Montreal  241.0  5.049793  1.164407  1.0  5.0  5.0  5.0  12.0
Quebec    104.0  4.942308  2.198088  1.0  3.0  5.0  6.0  12.0
```

```
La Ville avec plut petite moyenne cest Quebec, et il n'as pas bcp de difference.
```

[106]:
```
difference = FUSION[(FUSION.City == "Montreal")].mean()['number_product'] -␣
 ↪FUSION[(FUSION.City == "Quebec")].mean()['number_product']
print("Differences entre moyennes number_product de Montreal et Quebec: ",␣
 ↪difference)
```

```
Differences entre moyennes number_product de Montreal et Quebec:
0.10748483881263926
```

3.7 2.5. Créer deux nouvelles variables pour grouper la variable « âge » avec un pas de 5 et après un pas de 10 en commençant par la valeur 10 (des groupes 10-15 pour les pas de 5) et (des groupes 10-20 pour les pas de 10, etc.) jusqu'à atteindre l'âge maximum de la table de données. Vous nommerez ces variables «age_group_5 et age_group_10 » (4 requêtes maximum).

[107]:
```
FUSION['age'].describe()
```

[107]:
```
count    946.000000
mean      45.606765
std       13.585150
min       15.000000
25%       37.000000
50%       46.000000
75%       53.000000
max       79.000000
Name: age, dtype: float64
```

3.7.1 Version 1.

[108]:
```
bins5 = np.arange(start=10, stop=100, step=5)
print(bins5)
print("No de bins de 5: ", len(bins5))
```

```
labels5 = ['11-15', '16-20', '21-25', '26-30', '31-35', '36-40','41-45',␣
↪'46-50','51-55', '56-60', '61-65', '66-70', '71-75', '76-80', '81-85',␣
↪'86-90', '91-95']
print("No de labels de 5: ", len(labels5))

FUSION['age_group_5']  =  pd.cut(FUSION['age'], bins5, labels = labels5,␣
↪include_lowest = True)


bins10 = np.arange(start=10, stop=100, step=10)
print(bins10)
print("No de bins de 10: ", len(bins5))
labels10 = ['11-20', '21-30', '31-40', '41-50', '51-60', '61-70','71-80',␣
↪'81-90']
print("No de labels de 10: ", len(labels5))

FUSION['age_group_10']  =  pd.cut(FUSION['age'], bins10, labels = labels10,␣
↪include_lowest = True)
FUSION.head(10)
```

```
[10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95]
No de bins de 5:  18
No de labels de 5:  17
[10 20 30 40 50 60 70 80 90]
No de bins de 10:  18
No de labels de 10:  17
```

```
[108]:   ClientID checking_status   duration          credit_history  \
0   1215693              <0  1_2_years           existing paid
1   1215696        0<=X<200  lo_1_year  critical/other existing
2   1215699     no checking  lo_1_year  critical/other existing
3   1215702     no checking  1_2_years  critical/other existing
4   1215705     no checking  lo_1_year           existing paid
5   1215708              <0  lo_1_year  critical/other existing
6   1215711     no checking  lo_1_year  critical/other existing
7   1215714     no checking  1_2_years  critical/other existing
8   1215717     no checking  1_2_years           existing paid
9   1215720              <0  1_2_years           existing paid

             purpose     amount    savings_status other_parties  \
0           radio/tv  1000_2000              <100          none
1           used car  1000_2000              <100          none
2           radio/tv  1000_2000  no known savings          none
3           radio/tv  1000_2000             >=1000          none
4           radio/tv  1000_2000              <100          none
5            repairs  1000_2000        100<=X<500     guarantor
6           radio/tv  1000_2000  no known savings          none
```

```
7              new car  1000_2000             <100          none
8   domestic appliance  1000_2000       500<=X<1000          none
9  furniture/equipment  1000_2000             <100          none

  property_magnitude other_payment_plans  …     personal_status  employment  \
0        real estate                none  …  female div/dep/mar      1<=X<4
1                car                none  …         male single  unemployed
2        real estate                none  …  female div/dep/mar         >=7
3                car                none  …         male single         >=7
4     life insurance                none  …         male single      1<=X<4
5        real estate                none  …         male single         >=7
6        real estate                none  …         male single      1<=X<4
7     life insurance                none  …  female div/dep/mar          <1
8     life insurance                none  …         male single      4<=X<7
9                car                none  …  female div/dep/mar  unemployed

                       job own_telephone foreign_worker      City housing  \
0                  skilled           yes            yes  Montreal     own
1  high qualif/self emp/mgm           yes            yes  Montreal     own
2                  skilled           yes            yes  Montreal     own
3                  skilled          none            yes  Montreal     own
4                  skilled           yes             no  Montreal     own
5                  skilled          none             no  Montreal     own
6       unskilled resident          none            yes  Montreal     own
7                  skilled          none            yes  Montreal     own
8                  skilled           yes            yes  Montreal     own
9                  skilled          none            yes  Montreal     own

  age age_group_5 age_group_10
0  49       46-50        41-50
1  46       46-50        41-50
2  49       46-50        41-50
3  35       31-35        31-40
4  52       51-55        51-60
5  38       36-40        31-40
6  58       56-60        51-60
7  51       51-55        51-60
8  54       51-55        51-60
9  39       36-40        31-40

[10 rows x 23 columns]
```

3.7.2 Version 2

[109]:
```python
def age_gr10(x):
    if   x < 20: return '10-19'
    elif x < 30: return '20-29'
    elif x < 40: return '30-39'
    elif x < 50: return '40-49'
    elif x < 60: return '50-59'
    elif x < 70: return '60-69'
    elif x < 80: return '70-79'
    elif x <=90: return '80-90'
    else: return 'other'


def age_gr5(x):
    if   x < 10: return '<10'
    elif x < 15: return '10-14'
    elif x < 20: return '15-19'
    elif x < 25: return '20-24'
    elif x < 30: return '25-29'
    elif x < 35: return '30-34'
    elif x < 40: return '35-39'
    elif x < 45: return '40-44'
    elif x < 50: return '45-49'
    elif x < 55: return '50-54'
    elif x < 60: return '55-59'
    elif x < 65: return '60-64'
    elif x < 70: return '65-69'
    elif x < 75: return '70-74'
    elif x < 80: return '75-79'
    elif x < 85: return '80-84'
    elif x < 90: return '85-89'
    else: return 'other'



#FUSION['age_group_10'] = FUSION.age.apply(age_gr10)
#FUSION['age_group_5']  = FUSION.age.apply(age_gr5)
#FUSION.head(2)
```

3.8 2.6. Afficher la proportion totale de clients qui possèdent soit un mauvais crédit ou un bon crédit. Quelle est la catégorie où il l'y a le plus de mauvais crédit ?

[110]:
```python
FUSION.groupby(['other_parties', 'class'])['ClientID'].count().to_frame()␣
 ↪#nested Groupby Housing -- Categorie assumed
```

```
[110]:                        ClientID
        other_parties class
        co applicant  bad           18
                      good          22
        guarantor     bad           10
                      good          39
        none          bad          255
                      good         602
```

La categorie avec le plus mauvaise credit est pour les socios lequelles ont pas ni guarantor ni co applicant.

3.9 2.7. Y a-t-il une préférence par territoire pour ce qui est des montants prêtés à la clientèle. Pour cela, vous devez exclure les personnes ayant entre 10 et 24 ans et les personnes de plus de 70 ans. Veuillez ordonner (ordre décroissant) cette sortie par le nombre de clients qu'il y a dans chacun des groupes

```
[111]: #Filtrer les donnees
subFusion = FUSION[(FUSION.age < 10) | ((FUSION.age > 24) & (FUSION.age < 70)) ]
subFusion.groupby(['City', 'amount'])['ClientID'].count().
 ↪sort_values(ascending=False).to_frame()
```

```
[111]:                     ClientID
        City     amount
        Toronto  up_2000         371
        Montreal 1000_2000       107
                 up_2000         105
        Toronto  lo_1000         103
        Quebec   1000_2000        90
        Toronto  1000_2000        27
        Totonto  1000_2000        19
```

Oui, il y a une preference. Par exemple, a Toronto la preference pour les montantes pretes a la clientele : 2000+ CAD. A Montreal les pretes 1000-2000 CAD et 2000+ CAD sont egales (en preference), parcontre il y a pas des pretes de <1000 CAD. A Quebec il y a que des pretes de 1000-2000 CAD.

4 THE END

```
[ ]:
```