mooc_mertes

June 15, 2023

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.graphics.mosaicplot import mosaic
from statsmodels.formula.api import ols
from statsmodels.formula.api import logit
from statsmodels.formula.api import glm
from statsmodels.api import qqplot
from scipy.stats import ttest_ind as t_student
from scipy.stats import mannwhitneyu
from scipy.stats import chi2_contingency
from scipy.stats import pearsonr
from scipy.stats import spearmanr
from scipy.stats import kstest
from scipy.stats import norm
from matplotlib.patches import Rectangle
```

[ ]:
```
# Chargement des données
effec1 = pd.read_csv("../csv/effec1.quest.compil.csv", encoding="ISO-8859-1")
effec2 = pd.read_csv("../csv/effec2.quest.compil.csv", encoding="ISO-8859-1")
effec3 = pd.read_csv("../csv/effec3.quest.compil.csv", encoding="ISO-8859-1")
#
usage1 = pd.read_csv("../csv/usages.effec1.csv", encoding="ISO-8859-1")
usage2 = pd.read_csv("../csv/usages.effec2.csv", encoding="ISO-8859-1")
usage3 = pd.read_csv("../csv/usages.effec3.csv", encoding="ISO-8859-1")
```

[ ]:
```
usage3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 76 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Student_ID            3883 non-null   int64
 1   Exam.score            843 non-null    float64
 2   Exam.bin              3883 non-null   int64
```

```
3   Assignment.score       838 non-null    float64
4   Assignment.bin         3883 non-null   int64
5   Quizz.1.score          1774 non-null   float64
6   Quizz.1.bin            3883 non-null   int64
7   Quizz.2.score          1295 non-null   float64
8   Quizz.2.bin            3883 non-null   int64
9   Quizz.3.score          1069 non-null   float64
10  Quizz.3.bin            3883 non-null   int64
11  Quizz.4.bin            3883 non-null   int64
12  Quizz.4.score          973 non-null    float64
13  Quizz.5.bin            3883 non-null   int64
14  Quizz.5.score          911 non-null    float64
15  Intro.MOOC             0 non-null      float64
16  Prez.sem.1             3883 non-null   int64
17  S1.L1                  3883 non-null   int64
18  S1.L2                  3883 non-null   int64
19  S1.L3                  3883 non-null   int64
20  S1.L4                  3883 non-null   int64
21  S1.L5                  3883 non-null   int64
22  S1.L6                  3883 non-null   int64
23  Prez.sem.2             3883 non-null   int64
24  S2.L1                  3883 non-null   int64
25  S2.L2                  3883 non-null   int64
26  S2.L3                  3883 non-null   int64
27  S2.L4                  3883 non-null   int64
28  S2.L5                  3883 non-null   int64
29  S2.L6                  3883 non-null   int64
30  Prez.sem.3             3883 non-null   int64
31  S3.L1.1                3883 non-null   int64
32  S3.L1.2                3883 non-null   int64
33  S3.L2                  3883 non-null   int64
34  S3.L3                  3883 non-null   int64
35  S3.L4                  3883 non-null   int64
36  S3.L5                  3883 non-null   int64
37  Prez.sem.4             3883 non-null   int64
38  S4.L1.1                3883 non-null   int64
39  S4.L1.2                3883 non-null   int64
40  S4.L2                  3883 non-null   int64
41  S4.L3                  3883 non-null   int64
42  S4.L4                  3883 non-null   int64
43  S4.L5                  3883 non-null   int64
44  Prez.sem.5             3883 non-null   int64
45  S5.L1.1                3883 non-null   int64
46  S5.L1.2                3883 non-null   int64
47  S5.L2                  3883 non-null   int64
48  S5.L3                  3883 non-null   int64
49  S5.L4                  3883 non-null   int64
50  S5.L5                  3883 non-null   int64
```

```
 51  Post.forum.0           3883 non-null   int64
 52  view.forum.0           3883 non-null   int64
 53  Post.forum.1           3883 non-null   int64
 54  Post.forum.1.2         3883 non-null   int64
 55  view.forum.1           3883 non-null   int64
 56  view.forum.1.2         3883 non-null   int64
 57  Post.forum.2           3883 non-null   int64
 58  Post.forum.2.2         3883 non-null   int64
 59  view.forum.2           3883 non-null   int64
 60  view.forum.2.2         3883 non-null   int64
 61  Post.forum.3           3883 non-null   int64
 62  view.forum.3           3883 non-null   int64
 63  Post.forum.4           3883 non-null   int64
 64  Post.forum.4.2         3883 non-null   int64
 65  view.forum.4           3883 non-null   int64
 66  view.forum.4.2         3883 non-null   int64
 67  Post.forum.5           3883 non-null   int64
 68  Post.forum.5.2         3883 non-null   int64
 69  view.forum.5           3883 non-null   int64
 70  view.forum.5.2         3883 non-null   int64
 71  last.video             3883 non-null   int64
 72  last.quizz             3883 non-null   int64
 73  Assignment.choice      3883 non-null   int64
 74  Post.forum.fonc.cours  3883 non-null   int64
 75  view.forum.fonc.cours  3883 non-null   int64
dtypes: float64(8), int64(68)
memory usage: 2.3 MB
```

[ ]:
```
effec3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4233 entries, 0 to 4232
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Student_ID        3883 non-null   float64
 1   Certif.bin        3883 non-null   float64
 2   Section           1587 non-null   object
 3   Gender            1577 non-null   object
 4   birth.year        1543 non-null   float64
 5   Country           1575 non-null   object
 6   Diploma           1574 non-null   object
 7   EMLYON.et         1567 non-null   object
 8   Formation         1562 non-null   object
 9   CSP               1572 non-null   object
 10  How.heard         1571 non-null   object
 11  Exp.crea          1570 non-null   object
 12  Curiosity.MOOC    1569 non-null   object
```

```
 13  Certif.self.sat   1561 non-null   float64
 14  Rencontres        1551 non-null   object
 15  Certif.work       1562 non-null   float64
 16  Incitation        1564 non-null   float64
 17  Temps.Dispo       1561 non-null   object
 18  Exp.MOOC          1556 non-null   object
 19  Completion.proba  1559 non-null   float64
 20  EMLyon            1567 non-null   object
 21  Country_HDI       1562 non-null   object
 22  Country_HDI.fin   1562 non-null   object
 23  age               1543 non-null   float64
 24  CSP.fin           1572 non-null   object
 25  Temps.dispo.fin   1561 non-null   object
dtypes: float64(8), object(18)
memory usage: 860.0+ KB
```

[ ]:
```
usage1.head()
```

[ ]:

	Student_ID	Exam.score	Exam.bin	Assignment.score	Assignment.bin	\
0	28	NaN	0	NaN	0	
1	36	NaN	0	NaN	0	
2	45	NaN	0	NaN	0	
3	83	NaN	0	60.0	1	
4	84	NaN	0	NaN	0	

	Quizz.1.score	Quizz.1.bin	Quizz.2.score	Quizz.2.bin	Quizz.3.score	…	\
0	NaN	0	NaN	0	NaN	…	
1	NaN	0	NaN	0	NaN	…	
2	16.0	1	20.0	1	18.0	…	
3	13.0	1	20.0	1	18.0	…	
4	18.0	1	20.0	1	NaN	…	

	Post.forum.4	Post.forum.4.2	view.forum.4	view.forum.4.2	Post.forum.5	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	1	1	0	
3	0	0	1	0	0	
4	0	0	0	0	0	

	Post.forum.5.2	view.forum.5	view.forum.5.2	last.video	last.quizz
0	0	0	0	1	0
1	0	0	0	0	0
2	0	1	1	34	5
3	0	1	0	29	5
4	0	0	0	23	2

[5 rows x 73 columns]

[ ]:
```
# Fusion des tables effec[n] et usage[n] dans des bases intermédiaires selon␣
 ↪les identifiants des étudiants
bases_inter = []
for tabs in [(effec1, usage1), (effec2, usage2), (effec3, usage3)]:
    bases_inter.append(tabs[0].merge(tabs[1], on="Student_ID"))
```

[ ]:
```
# Concaténation des tables intermédiaires afin de créer une seule base commune
base = pd.concat(bases_inter, join="outer",
                 axis=0, ignore_index=False,
                 keys=[1, 2, 3])
```

[ ]:
```
base["Certif.bin"].fillna(0, inplace=True)
base = base.astype({"Exam.bin": bool, "Certif.bin": bool, "Student_ID": int})
```

[ ]:
```
base = base.copy()
# Map des modalités M et H de la variable Country_HDI
base["New_HDI"] = np.select([base["Country_HDI"] == "M",
                             base["Country_HDI"] == "H"],
                            ["I", "I"], default=base["Country_HDI"])
```

[ ]:
```
HDI = base.groupby(["New_HDI"])[["New_HDI"]].count().rename({"New_HDI":␣
 ↪"count"}, axis=1)
```

[ ]:
```
HDI
```

[ ]:
```
          count
New_HDI
B          1032
I           667
TH         7264
```

[ ]:
```
base = base.reset_index(level=0).rename({"level_0": "Itération"}, axis=1)
```

[ ]:
```
# Nombre de catégories (videos, quiz, exam...) par apprenant par place de␣
 ↪séquence dans la semaine pour les différentes itérations
groups = base.groupby(["Student_ID", "Itération"]).sum()

# Nombre de passages à l'examen
exam = groups[["Exam.bin"]]

# Nombre de Certifications
certif = groups[["Certif.bin"]]

# Nombre de devoirs par apprenant
devoir = groups[["Assignment.bin"]]

# Nombre de videos par apprenant par semaine pour chaque itération
```

```
week_video = [pd.DataFrame(groups.loc[:, 'S1.L1':'S1.L6'].sum(axis=1),␣
 ↪columns=["video.S1"]),
              pd.DataFrame(groups.loc[:, 'S2.L1':'S2.L6'].sum(axis=1),␣
 ↪columns=["video.S2"]),
              pd.DataFrame(groups.loc[:, 'S3.L1.1':'S3.L5'].sum(axis=1),␣
 ↪columns=["video.S3"]),
              pd.DataFrame(groups.loc[:, 'S4.L1.1':'S4.L5'].sum(axis=1),␣
 ↪columns=["video.S4"]),
              pd.DataFrame(groups.loc[:, 'S5.L1.1':'S5.L5'].sum(axis=1),␣
 ↪columns=["video.S5"])]

# Nombre de quiz par apprenant par semaine pour chaque itération
week_quiz = [groups[["Quizz.1.bin"]],
             groups[["Quizz.2.bin"]],
             groups[["Quizz.3.bin"]],
             groups[["Quizz.4.bin"]],
             groups[["Quizz.5.bin"]]]
```

[ ]:
```
# Concaténation des videos et des questionnaires de l'ensemble des semaines
compil_week_video = pd.concat(week_video, axis=1)
compil_week_quiz = pd.concat(week_quiz, axis=1)
```

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

[ ]:

Student_ID	Itération	video.S1	video.S2	video.S3	video.S4	video.S5
15	2	2	0	0	0	0
	3	1	0	0	0	0
28	1	0	0	0	0	0
34	3	0	0	0	0	0
36	1	0	0	0	0	0

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

[ ]:

Student_ID	Itération	Quizz.1.bin	Quizz.2.bin	Quizz.3.bin	Quizz.4.bin	\
15	2	0	0	0	0	
	3	0	0	0	0	
28	1	0	0	0	0	
34	3	0	0	0	0	
36	1	0	0	0	0	

Student_ID	Itération	Quizz.5.bin
15	2	0
	3	0
28	1	0

```
34          3                     0
36          1                     0
```

[ ]:
```
# Nombre de videos et questionnaires par itération par apprenant pour␣
↪l'ensemble du MOOC.
total_video = pd.DataFrame(compil_week_video.sum(axis=1), columns=["video"])

# Nombre de questionnaires par itération par apprenant pour l'ensemble du MOOC.
total_quiz = pd.DataFrame(compil_week_quiz.sum(axis=1), columns=["quiz"])
```

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

[ ]:
```
                      video
Student_ID Itération
15         2              2
           3              1
28         1              0
34         3              0
36         1              0
```

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

[ ]:
```
                      quiz
Student_ID Itération
15         2             0
           3             0
28         1             0
34         3             0
36         1             0
```

[ ]:
```
# Création de la table regroupant toutes la variables pour mesurer l'engagement␣
↪de chaque apprenant pour chaque itération
total_student = pd.concat([total_video, total_quiz, devoir, exam, certif],␣
↪axis=1)
```

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

[ ]:
```
                      video  quiz  Assignment.bin  Exam.bin  Certif.bin
Student_ID Itération
15         2              2     0               0         0           0
           3              1     0               0         0           0
28         1              0     0               0         0           0
34         3              0     0               0         0           0
36         1              0     0               0         0           0
```

[ ]:
```
# Sélection des itérations
#total_student.xs(1, level=1)
```

[ ]:
```
# selection des types d'apprenant
def student_type(col):
    video, quiz, devoir, exam, certif = col
    if (exam >= 1 or certif >= 1):
        return "Completer"
    elif quiz > 0 and devoir > 0:
        return "Disengaging"
    elif video > 6:
        return "Auditing"
    else:
        return "Bystander"
```

[ ]:
```
total_student["Type"] = total_student.apply(student_type, axis=1)
```

[ ]:
```
total_student.head(10)
```

[ ]:
```
                      video  quiz  Assignment.bin  Exam.bin  Certif.bin  \
Student_ID Itération
15         2              2     0               0         0           0
           3              1     0               0         0           0
28         1              0     0               0         0           0
34         3              0     0               0         0           0
36         1              0     0               0         0           0
45         1             25     5               0         0           0
83         1             22     5               1         0           0
84         1              8     2               0         0           0
87         1              1     0               0         0           0
88         3              1     0               0         0           0

                             Type
Student_ID Itération
15         2            Bystander
           3            Bystander
28         1            Bystander
34         3            Bystander
36         1            Bystander
45         1             Auditing
83         1          Disengaging
84         1             Auditing
87         1            Bystander
88         3            Bystander
```

[ ]:
```
student = total_student.reset_index()[["Student_ID", "Type", "Itération"]]
```

[ ]:
```
student["Type"].value_counts()
```

[ ]:
```
Bystander      8691
Disengaging    2643
Auditing       2120
Completer      1728
Name: Type, dtype: int64
```

[ ]:
```
# Calcul du nombre d'apprenants par type et par itération
df_type = student.groupby(["Itération", "Type"])[["Type"]].count().
 ↪rename({'Type': 'total'}, axis=1)
```

[ ]:
```
df_type
```

[ ]:
```
                      total
Itération Type
1         Auditing      1207
          Bystander     4285
          Completer       20
          Disengaging   2453
2         Auditing       538
          Bystander     2168
          Completer      876
          Disengaging    120
3         Auditing       375
          Bystander     2238
          Completer      832
          Disengaging     70
```

[ ]:
```
df_type.reset_index("Type", inplace=True)
```

[ ]:
```
# Nombre total d'apprenants par itération
df_iter = df_type.groupby("Itération").sum()
```

[ ]:
```
df_iter
```

[ ]:
```
           total
Itération
1           7965
2           3702
3           3515
```

[ ]:
```
total_iter = df_type.merge(df_iter, on="Itération", suffixes=["_type", "_iter"])
```

[ ]:
```
total_iter
```

[ ]:
```
                 Type  total_type  total_iter
Itération
1             Auditing        1207        7965
1            Bystander        4285        7965
```

```
1            Completer          20        7965
1          Disengaging        2453        7965
2             Auditing         538        3702
2           Bystander         2168        3702
2           Completer          876        3702
2          Disengaging         120        3702
3             Auditing         375        3515
3           Bystander         2238        3515
3           Completer          832        3515
3          Disengaging          70        3515
```

[ ]:
```
# Proportion d'apprenants par types d'apprenants et par itération
total_iter["proportion/iter"] = round(total_iter["total_type"] /␣
 ↪total_iter["total_iter"] * 100, 1)
```

[ ]:
```
total_iter
```

[ ]:
```
                  Type  total_type  total_iter  proportion/iter
Itération
1             Auditing        1207        7965             15.2
1           Bystander         4285        7965             53.8
1           Completer           20        7965              0.3
1          Disengaging        2453        7965             30.8
2             Auditing         538        3702             14.5
2           Bystander         2168        3702             58.6
2           Completer          876        3702             23.7
2          Disengaging         120        3702              3.2
3             Auditing         375        3515             10.7
3           Bystander         2238        3515             63.7
3           Completer          832        3515             23.7
3          Disengaging          70        3515              2.0
```

[ ]:
```
base["Genre"] = base["Gender"].map({"un homme": "Homme", "une femme": "Femme"})
```

[ ]:
```
# Tableau de contingence (croisement des 2 variables catégorielles)
tab_obs = pd.crosstab(index=base["Genre"], columns=base["New_HDI"])
```

[ ]:
```
tab_obs.rename(columns={"un homme": "H", "une femme": "F"}, inplace=True)
```

[ ]:
```
tab_obs
```

[ ]:
```
New_HDI    B    I    TH
Genre
Femme    147  233  2545
Homme    883  432  4711
```

[ ]:
```
#tab_obs = tab_HDI_gender.melt(value_vars=["H", "F"], var_name="genre",␣
 ↪value_name="residus", ignore_index=False).reset_index()
```

[ ]:
```
#tab_obs
```

[ ]:
```
# Test d'indépendance (chi2)
chi2, p_value, degres_liberte, tableau_attendu = chi2_contingency(tab_obs)
```

[ ]:
```
tableau_attendu
```

[ ]:
```
array([[ 336.58250475,  217.308122  , 2371.10937325],
       [ 693.41749525,  447.691878  , 4884.89062675]])
```

[ ]:
```
chi2
```

[ ]:
```
179.2420322171424
```

[ ]:
```
p_value
```

[ ]:
```
1.196980957821505e-39
```

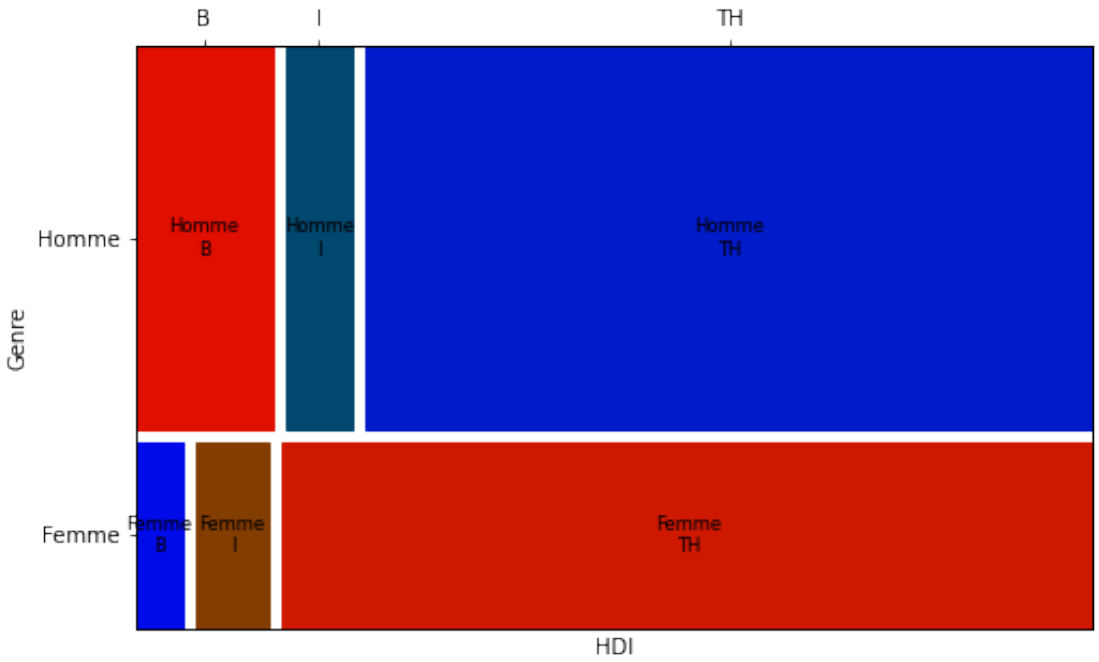
La p value est $< 5\%$ indiquerait que l'index HDI serait significativement lié au genre puisqu'il y a moins de 5 % de chance que les 2 variables soient indépendantes.

[ ]:
```
#residus = (tab_HDI_gender - tableau_attendu) / tableau_attendu
residus = tab_obs - tableau_attendu
```

[ ]:
```
residus
```

[ ]:
```
New_HDI           B          I          TH
Genre
Femme   -189.582505  15.691878  173.890627
Homme    189.582505 -15.691878 -173.890627
```

[ ]:
```
# Mosaic du tableau de contingence
#props = lambda key: {'color': 'red' if residus(key[0]) > 0 else 'blue'},
fig, ax = plt.subplots(figsize=(8,5))
mosaic(tab_obs.stack(), statistic=True, gap=0.02, horizontal=False, ax=ax)
ax.set_xlabel("HDI")
ax.set_ylabel("Genre")
plt.savefig("../graph/mosaic_contingence.png")
plt.show()
```



[ ]:
```
# valeurs attendues sous l'hypothèse nulle (H0).
x = tableau_attendu.flatten()
```

[ ]:
```
x
```

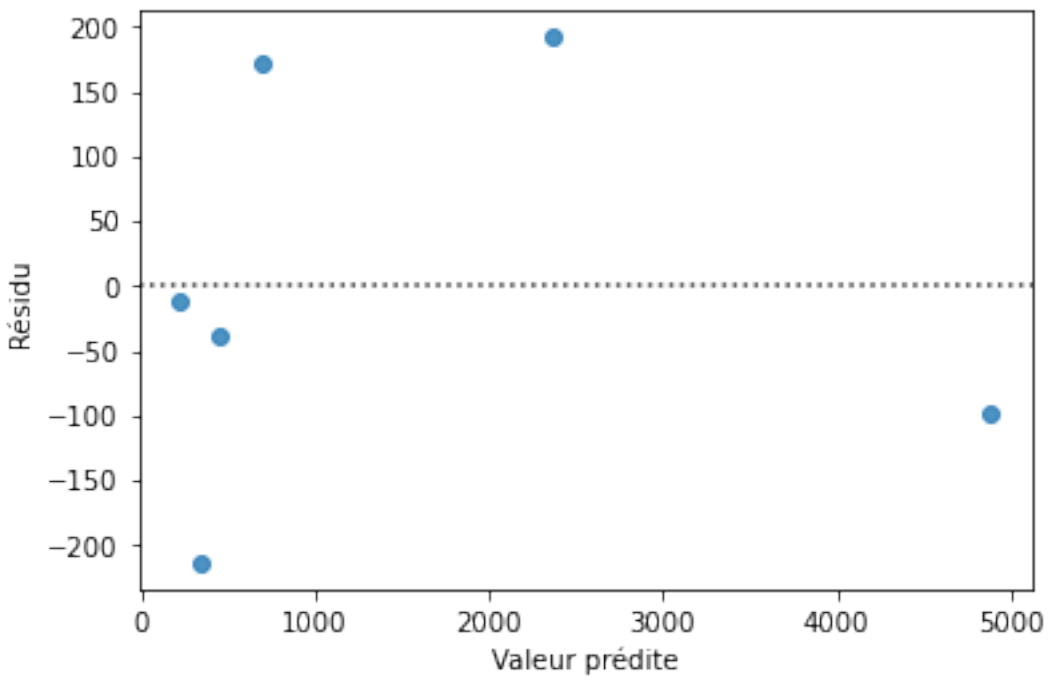
[ ]:
```
array([ 336.58250475,  217.308122  , 2371.10937325,  693.41749525,
        447.691878  , 4884.89062675])
```

[ ]:
```
# valeurs observées
y = tab_obs.stack().values
```

[ ]:
```
y
```

[ ]:
```
array([ 147,  233, 2545,  883,  432, 4711])
```

[ ]:
```
# Résidus du modèle de prédiction
fig, ax = plt.subplots()
sns.residplot(x=x, y=y, ax=ax)
#ax.set_title("Résidus du modèle observé")
ax.set_ylabel("Résidu")
ax.set_xlabel("Valeur prédite")
plt.savefig("../graph/residus_chi2.png")
plt.show()
```



fig, ax = plt.subplots() sns.heatmap(residus, annot=True, cmap='coolwarm', cbar=True, ax=ax) ax.set_ylabel("Genre") ax.set_ylabel("HDI") plt.show()

formule du V de Cramer :

V = √(² / (n * (min(r, c) - 1)))

Dans cette formule :

V représente le coefficient de Cramer. ² est la statistique du chi carré. n est la taille de l'échantillon. r est le nombre de niveaux ou de catégories de la première variable. c est le nombre de niveaux ou de catégories de la deuxième variable.

[ ]:
```
# Fonction de calcul du V de Cramer
# data = tab ndarray
def V_Cramer(data):
    # somme de chaque colonne
    n = np.sum(data)
    # taille du tableau de contingence des variables catégorielles (taille de␣
 ↪chaque échantillon pour chaque variable)
    row, col = tab_obs.shape
    # Formule du V de Cramer
    V = np.sqrt(chi2 / (n * (min([row, col]) - 1)))
    return V
```

[ ]:
```
V_Cramer(np.array(tab_obs))
```

[ ]: 0.14150902903141144

[ ]:
```
V_Cramer(tableau_attendu)
```

[ ]: 0.14150902903141144

La valeur V de Cramer étant faible il y a aurait une faible dépendance entre l'index HDI et le genre. Il y aurait donc statistiquement une association entre ses deux variables catégorielles, indiquée par la p-value du chi2, mais la valeur du V de Cramer indiquerait que cette dépendance serait faible.

[ ]:
```
# tableau du genre par étudiant
genre_etu = base[["Student_ID", "Genre"]].drop_duplicates(subset="Student_ID").
 ↪dropna()
```

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

[ ]:
```
   Student_ID  Genre
1       19178  Femme
2        1086  Femme
3        1948  Femme
4       16209  Femme
5        6685  Homme
```

[ ]:
```
# Nombre total de videos par étudiant
total_video_etu = total_video.groupby("Student_ID").sum()
```

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

[ ]:
```
            video
Student_ID
15              3
28              0
34              0
36              0
45             25
```

[ ]:
```
# tableau du genre et du nombre total de videos visionnées par étudiant
etu_genre_video = total_video_etu.merge(genre_etu, on='Student_ID')
```

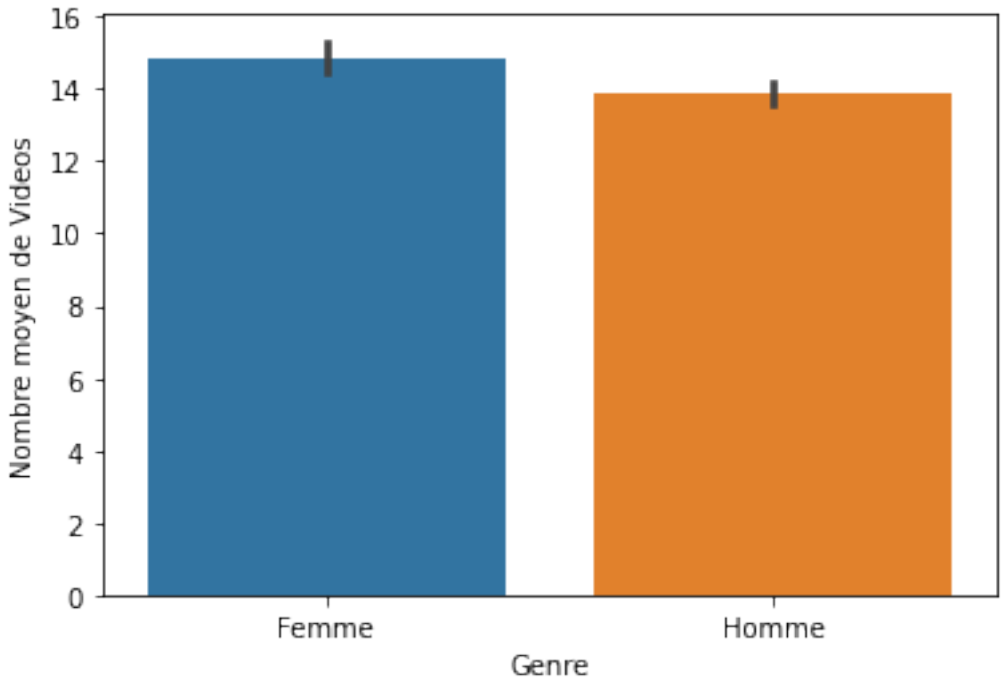
[ ]:
```
etu_genre_video.head()
```

[ ]:
```
   Student_ID  video  Genre
0          45     25  Femme
1          83     22  Homme
2          84      8  Homme
3          87      1  Homme
4          94      2  Homme
```

[ ]:
```
# moyenne du nombre de videos visionnées par genre
total_video_etu.merge(genre_etu, on="Student_ID").groupby("Genre")[["video"]].
↪mean()
```

[ ]:
```
            video
Genre
Femme  14.855376
Homme  13.867276
```

[ ]:
```
# Figure de la distribution du nombre de video par rapport au genre
fig, ax = plt.subplots()
sns.barplot(data=etu_genre_video, x="Genre", y="video", ax=ax)
ax.set_xlabel("Genre")
ax.set_ylabel("Nombre moyen de Videos")
plt.savefig("../graph/mean_video.png")
plt.show()
```



H0 (Hypothèse nulle) : il n'y a pas de différence sur le nombre de video visionnées entre les hommes et les femmes

[ ]:
```
tab_stat = etu_genre_video.pivot_table(columns="Genre", index="Student_ID",␣
↪values="video").fillna(0)
```

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

[ ]:
```
Genre       Femme  Homme
Student_ID
45           25.0    0.0
83            0.0   22.0
84            0.0    8.0
87            0.0    1.0
94            0.0    2.0
```

[ ]:
```
# Test de Student
statistique, p_value = t_student(tab_stat["Homme"], tab_stat["Femme"])
```

[ ]:
```
statistique
```

[ ]:
```
26.98492395204523
```

[ ]:
```
p_value
```

[ ]:
```
3.4121378553908065e-157
```

Il y a moins de 5% de chance qu'il n'y ait pas de différence du nombre de visionnages entre les femmes et les hommes. Il y aurait significativement un lien entre le nombre de visionnages et le genre.

[ ]:
```
# Sélection par genre
df_hom = etu_genre_video[etu_genre_video["Genre"] == "Homme"]
df_fem = etu_genre_video[etu_genre_video["Genre"] == "Femme"]
```

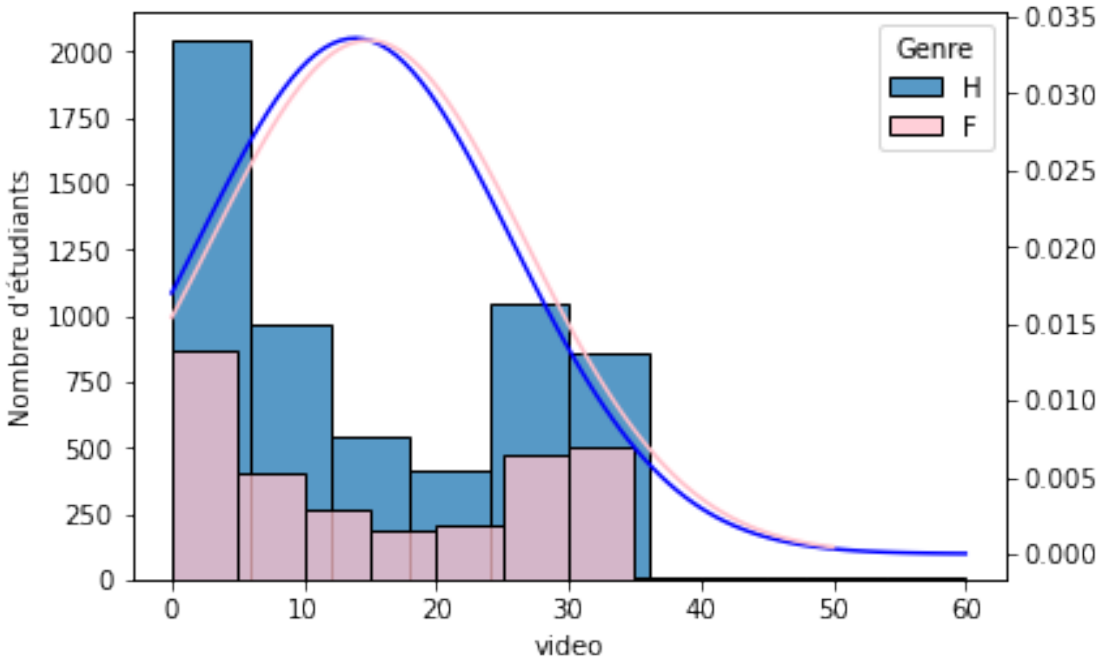
[ ]:
```
df_hom
```

[ ]:
```
      Student_ID  video  Genre
1             83     22  Homme
2             84      8  Homme
3             87      1  Homme
4             94      2  Homme
5             98     23  Homme
…          …    …    …
8807       68205     30  Homme
8808       68220     30  Homme
8809       68223      0  Homme
8811       68265     14  Homme
8813       68282      1  Homme

[5907 rows x 3 columns]
```

[ ]:
```
# Calcul des paramètres de la distribution normale pour chaque groupe
mu_hommes, std_hommes = np.mean(df_hom["video"]), np.std(df_hom["video"])
mu_femmes, std_femmes = np.mean(df_fem["video"]), np.std(df_fem["video"])
```

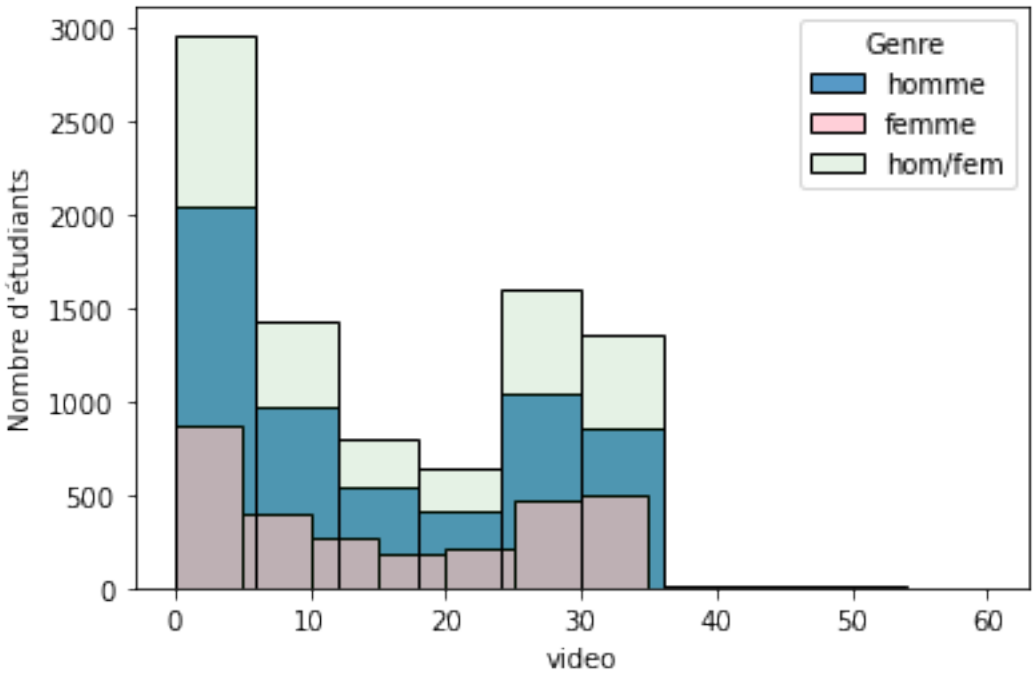
```
# Création des valeurs x pour tracer la courbe théorique
x_hommes = np.linspace(min(df_hom["video"]), max(df_hom["video"]), 100)
x_femmes = np.linspace(min(df_fem["video"]), max(df_fem["video"]), 100)

# Calcul des valeurs y correspondantes en utilisant la PDF de la distribution␣
 ↪normale
y_hommes = norm.pdf(x_hommes, mu_hommes, std_hommes)
y_femmes = norm.pdf(x_femmes, mu_femmes, std_femmes)
```

[ ]:
```
figure, ax1 = plt.subplots()
sns.histplot(data=df_hom, x="video", bins=10, color="tab:blue", ax=ax1,␣
 ↪label="H")
sns.histplot(data=df_fem, x="video", bins=10, color="pink", ax=ax1, label="F")
ax1.set_xlabel("video")
ax1.set_ylabel("Nombre d'étudiants")
ax1.legend(title="Genre")
ax2 = ax1.twinx()
ax2.plot(x_hommes, y_hommes, color='blue')
ax2.plot(x_femmes, y_femmes, color='pink')
plt.savefig("../graph/distribution_video.png")
plt.show()
```



[ ]:
```
# visualisation de la normalité de la distribution des données (histogramme de␣
 ↪distribution)
```

```
data = pd.concat([df_hom["video"], df_fem["video"]])
figure, ax = plt.subplots()
sns.histplot(data=df_hom, x="video", bins=10, color="tab:blue", ax=ax,␣
 ↪label="homme")
sns.histplot(data=df_fem, x="video", bins=10, color="pink", ax=ax,␣
 ↪label="femme")
sns.histplot(data=data, bins=10, color="green", ax=ax, label="hom/fem", alpha=0.
 ↪1)
ax.set_xlabel("video")
ax.set_ylabel("Nombre d'étudiants")
ax.legend(title="Genre")
plt.savefig("../graph/distribution_video2.png")
plt.show()
```



La distribution des données ne suit pas une loi normale. Ce qui ne permet pas de faire un test t-Student puisque la condition première est que les données doivent être normalement distribuées.

[ ]:
```
# Models de regression du nombre de video selon le genre
mdl_video_vs_genre = ols("video ~ Genre", data=etu_genre_video).fit()
```

[ ]:
```
mdl_video_vs_genre.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
```

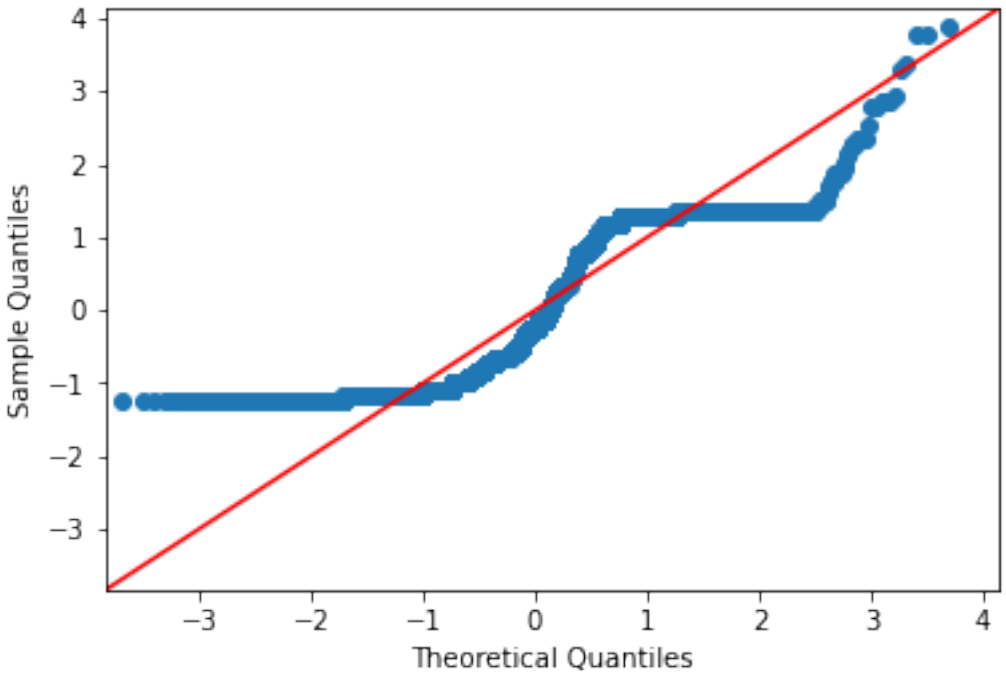
```
==============================================================================
Dep. Variable:                  video   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     13.45
Date:                Thu, 15 Jun 2023   Prob (F-statistic):           0.000247
Time:                        15:25:02   Log-Likelihood:                -34348.
No. Observations:                8818   AIC:                         6.870e+04
Df Residuals:                    8816   BIC:                         6.871e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     14.8554      0.221     67.365      0.000      14.423      15.288
Genre[T.Homme]    -0.9881      0.269     -3.667      0.000      -1.516      -0.460
==============================================================================
Omnibus:                    59307.238   Durbin-Watson:                   1.962
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              878.417
Skew:                           0.240   Prob(JB):                    1.80e-191
Kurtosis:                       1.530   Cond. No.                         3.24
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
"""
```

Le coefficient R^2 étant proche de 0, le model de régression est peu fidèle à l'observation des données.

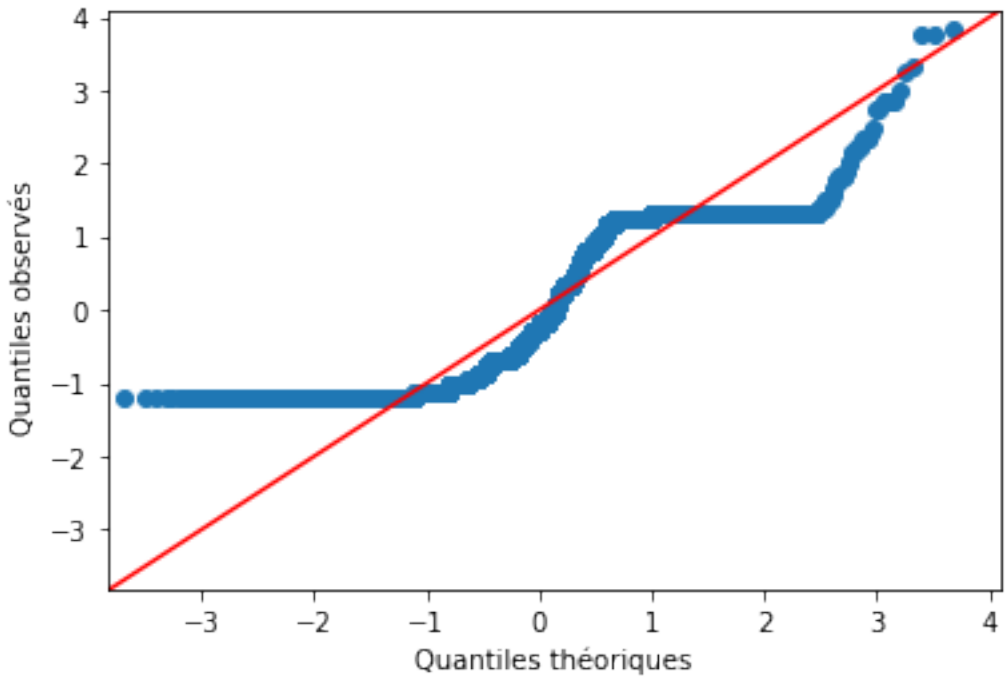
[ ]:
```
mdl_video_vs_genre.params
```

[ ]:
```
Intercept         14.855376
Genre[T.Homme]    -0.988100
dtype: float64
```

[ ]:
```
# Test de normalité de la distribution des données (Q-Q plot)
qqplot(data=mdl_video_vs_genre.resid, fit=True, line="45")
plt.show()
```



[ ]:
```
qqplot(data=data, fit=True, line="45")
plt.xlabel("Quantiles théoriques")
plt.ylabel("Quantiles observés ")
plt.savefig("../graph/distribution_video3.png")
plt.show()
```



[ ]:
```
# Test de  Kolmogrov-Smirnov
stat, p = kstest(data, 'norm')
```

[ ]:
```
stat, p
```

[ ]:
```
(0.7626887430801719, 0.0)
```

[ ]:
```
# Test non paramétrique de Mann-Whitney U
mannwhitneyu(df_hom["video"], df_fem["video"])
```

[ ]:
```
MannwhitneyuResult(statistic=8200580.5, pvalue=0.0003907509304995919)
```

[ ]:
```
# Nombre de quiz par étudiant
total_quiz_etu = total_quiz.groupby("Student_ID").sum()
```

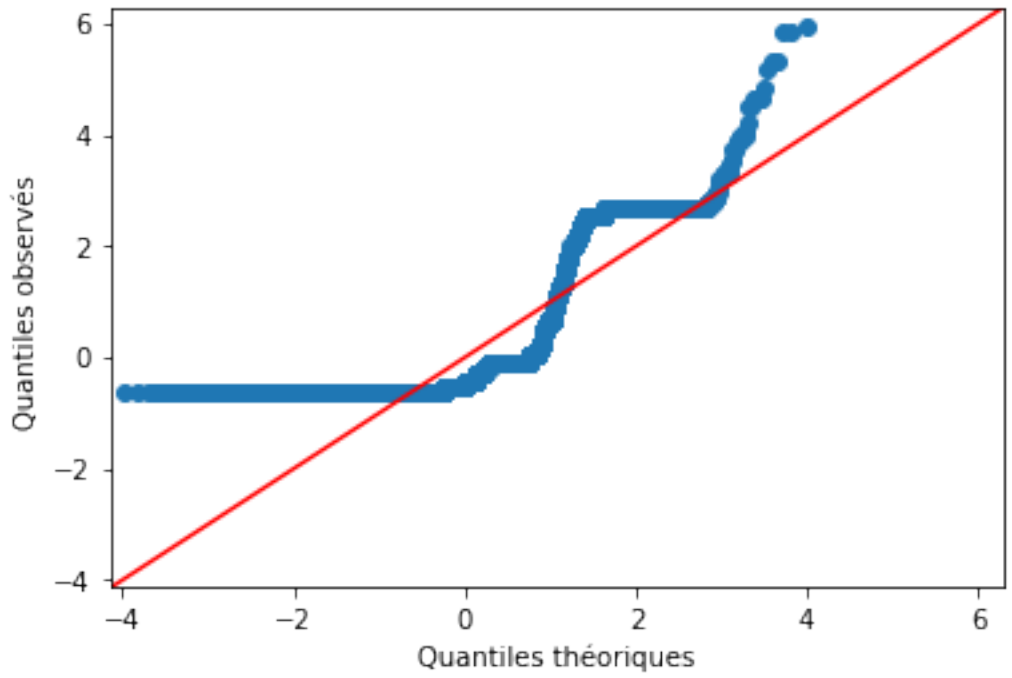
[ ]:
```
# Nombre de Quiz et vidéos par étudiants
video_quiz_etu = total_video_etu.merge(total_quiz_etu, on="Student_ID")
```

[ ]:
```
video_quiz_etu.loc[3139]
```

[ ]:
```
video    48
quiz     10
Name: 3139, dtype: int64
```

[ ]:
```
data = pd.concat([video_quiz_etu["quiz"], video_quiz_etu["video"]])
```

[ ]:
```
qqplot(data=data, fit=True, line="45")
plt.xlabel("Quantiles théoriques")
plt.ylabel("Quantiles observés ")
plt.savefig("../graph/distribution_video4.png")
plt.show()
```



[ ]:
```
# Test de Pearson
correlation, p_value = pearsonr(video_quiz_etu["quiz"], video_quiz_etu["video"])
```

[ ]:
```
correlation, p_value
```

[ ]:
```
(0.8036026075037674, 0.0)
```

[ ]:
```
# Test de Spearman
correlation, p_value = spearmanr(video_quiz_etu["quiz"],␣
 ↪video_quiz_etu["video"])
```

[ ]:
```
correlation, p_value
```

[ ]:
```
(0.804511796629543, 0.0)
```

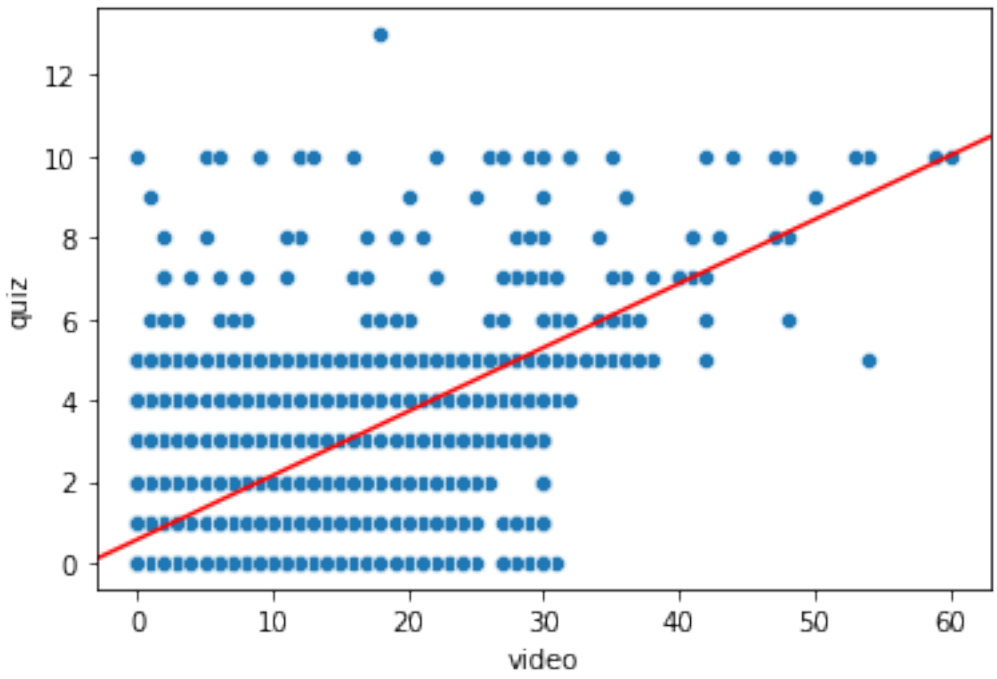
Il y a une forte corrélation (0.8) entre le nombre de videos vues et le nombre de quiz réalisés par un étudiant. La corrélation observée est statistiquement significative (p-value=0).

[ ]:
```
# Modèle de regression sur le nombre de vidéos selon le nombre de quiz
mdl_video_vs_quiz = ols("quiz ~ video", data=video_quiz_etu).fit()
```

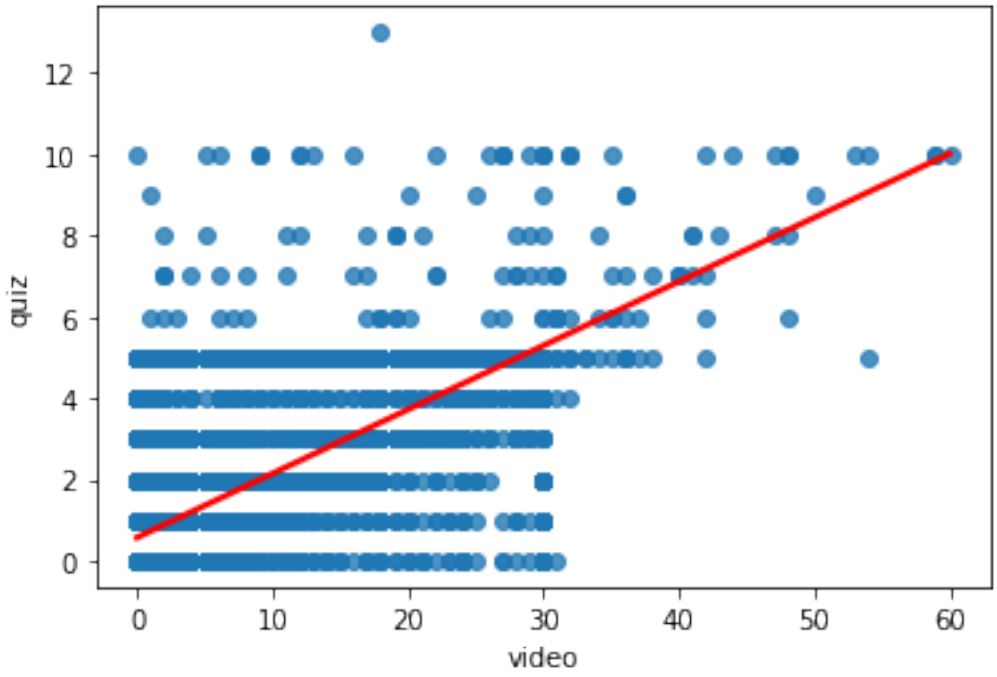
[ ]:
```
mdl_video_vs_quiz.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                   quiz   R-squared:                       0.646
Model:                            OLS   Adj. R-squared:                  0.646
Method:                 Least Squares   F-statistic:                 2.653e+04
Date:                Thu, 15 Jun 2023   Prob (F-statistic):               0.00
Time:                        15:25:03   Log-Likelihood:                -24981.
No. Observations:               14557   AIC:                            4.997e+04
Df Residuals:                   14555   BIC:                            4.998e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.5652      0.014     39.183      0.000       0.537       0.594
video          0.1575      0.001    162.896      0.000       0.156       0.159
==============================================================================
Omnibus:                     5315.454   Durbin-Watson:                   1.939
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            20116.783
Skew:                           1.821   Prob(JB):                         0.00
Kurtosis:                       7.461   Cond. No.                         19.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

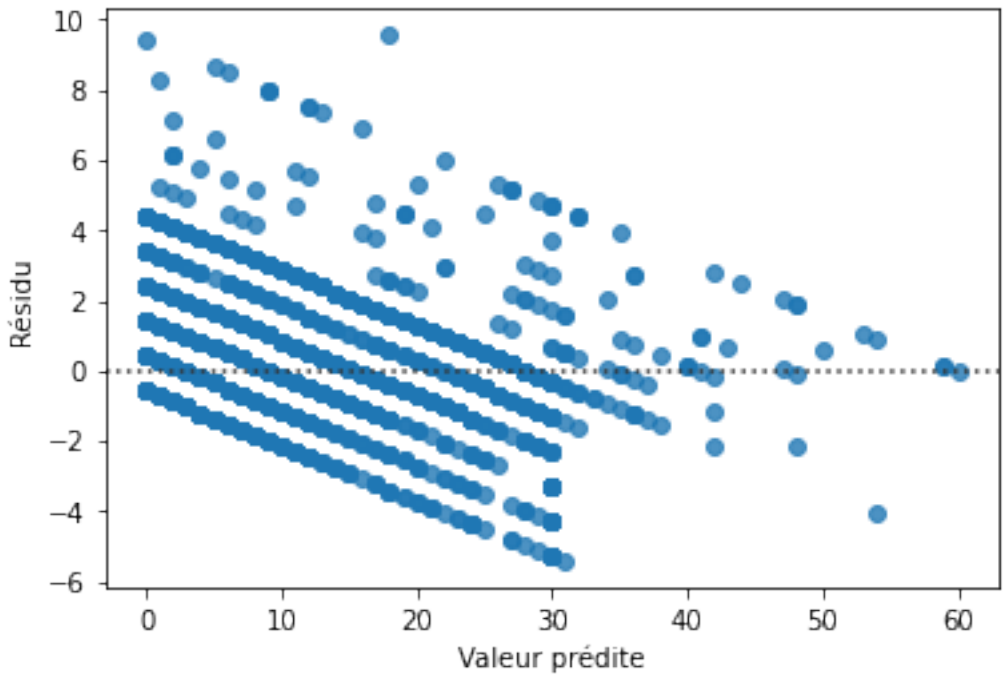
[ ]:
```
intercept, coef = mdl_video_vs_quiz.params
sns.scatterplot(data=video_quiz_etu, x="video", y="quiz")
plt.axline(xy1=(0,intercept), slope=coef, color="red")
plt.savefig("../graph/scatter_regression.png")
plt.show()
```



[ ]:
```
fig, ax = plt.subplots()
sns.regplot(data=video_quiz_etu, x=video_quiz_etu["video"],␣
 ↪y=video_quiz_etu["quiz"], line_kws={"color": "red"}, ax=ax)
#plt.savefig("../graph/scatter_regression.png")
plt.show()
```



[ ]:
```
# Résidus du modèle de prédiction
fig, ax = plt.subplots()
sns.residplot(data=video_quiz_etu, x="video", y="quiz", ax=ax)
#ax.set_title("Résidus du modèle observé")
ax.set_ylabel("Résidu")
ax.set_xlabel("Valeur prédite")
plt.savefig("../graph/residus_regression.png")
plt.show()
```



[ ]:
```
# HDI des apprenants
student_hdi = base[["Student_ID", "New_HDI"]].dropna().set_index("Student_ID")
student_hdi.sort_values("Student_ID", inplace=True)
```

[ ]:
```
student_hdi
```

[ ]:
```
            New_HDI
Student_ID
45               TH
83                I
84                B
87               TH
94               TH
…                …
68282             B
68326            TH
68332             I
68365            TH
69565            TH

[8963 rows x 1 columns]
```

[ ]:
```
# Tableau des 3 variables dont 2 catégorielles et 1 continue
video_genre_hdi = etu_genre_video.merge(student_hdi, on="Student_ID")
```

[ ]:
```
video_genre_hdi
```

[ ]:
```
      Student_ID  video  Genre New_HDI
0             45     25  Femme      TH
1             83     22  Homme       I
2             84      8  Homme       B
3             87      1  Homme      TH
4             94      2  Homme      TH
…            …    …     …        …
8860       68282      1  Homme       B
8861       68326     30  Femme      TH
8862       68332      4  Femme       I
8863       68365      0  Femme      TH
8864       69565      9  Femme      TH

[8865 rows x 4 columns]
```

[ ]:
```
# Modèle linéaire sans interaction(genre, HDI, video)
mdl1 = ols("video ~ C(Genre) + C(New_HDI)", data=video_genre_hdi).fit()
```

[ ]:
```
mdl1.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  video   R-squared:                       0.057
Model:                            OLS   Adj. R-squared:                  0.056
Method:                 Least Squares   F-statistic:                     177.2
Date:                Thu, 15 Jun 2023   Prob (F-statistic):          1.41e-111
Time:                        15:25:04   Log-Likelihood:                -34351.
No. Observations:                8865   AIC:                         6.871e+04
Df Residuals:                    8861   BIC:                         6.874e+04
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
=====
                         coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----
Intercept              7.0011      0.432     16.211      0.000       6.155
7.848
C(Genre)[T.Homme]     -0.0959      0.267     -0.360      0.719      -0.618
0.427
C(New_HDI)[T.I]        4.6774      0.586      7.979      0.000       3.528
5.826
```

```
C(New_HDI)[T.TH]      8.6728      0.395     21.937      0.000       7.898
9.448
==============================================================================
Omnibus:                    11867.785   Durbin-Watson:                   1.891
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              639.581
Skew:                           0.218   Prob(JB):                    1.31e-139
Kurtosis:                       1.759   Cond. No.                         8.79
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[ ]:
```
# ANOVA sans interaction
anova_table = sm.stats.anova_lm(mdl1, typ=1)
```

[ ]:
```
anova_table
```

[ ]:
```
                 df        sum_sq       mean_sq           F         PR(>F)
C(Genre)        1.0  1.554895e+03   1554.895102   11.437356   7.229351e-04
C(New_HDI)      2.0  7.071483e+04  35357.416782  260.078874  1.738249e-110
Residual     8861.0  1.204643e+06    135.948823         NaN            NaN
```

[ ]:
```
# Modèle de regression avec interaction
mdl2 = ols("video ~ C(Genre)*C(New_HDI)", data=video_genre_hdi).fit()
```

[ ]:
```
mdl2.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  video   R-squared:                       0.057
Model:                            OLS   Adj. R-squared:                  0.057
Method:                 Least Squares   F-statistic:                     107.8
Date:                Thu, 15 Jun 2023   Prob (F-statistic):          7.64e-111
Time:                        15:25:04   Log-Likelihood:                -34347.
No. Observations:                8865   AIC:                         6.871e+04
Df Residuals:                    8859   BIC:                         6.875e+04
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
======================
                                 coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
```

```
----------------------
Intercept                                 7.3310      0.968      7.573      0.000
5.434       9.229
C(Genre)[T.Homme]                        -0.4810      1.046     -0.460      0.646
-2.531       1.569
C(New_HDI)[T.I]                           2.7733      1.236      2.244      0.025
0.350       5.196
C(New_HDI)[T.TH]                          8.4673      0.995      8.506      0.000
6.516      10.419
C(Genre)[T.Homme]:C(New_HDI)[T.I]         2.8032      1.415      1.982      0.048
0.030       5.576
C(Genre)[T.Homme]:C(New_HDI)[T.TH]        0.1933      1.085      0.178      0.859
-1.933       2.320
==============================================================================
Omnibus:                    11724.976   Durbin-Watson:                   1.891
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              637.561
Skew:                           0.217   Prob(JB):                    3.59e-139
Kurtosis:                       1.760   Cond. No.                         33.0
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[ ]:
```
# ANOVA avec interaction
anova_table = sm.stats.anova_lm(mdl2, typ=1)
```

[ ]:
```
anova_table
```

[ ]:
```
                          df        sum_sq       mean_sq           F  \
C(Genre)                 1.0  1.554895e+03   1554.895102   11.443839
C(New_HDI)               2.0  7.071483e+04  35357.416782  260.226287
C(Genre):C(New_HDI)      2.0  9.541531e+02    477.076535    3.511225
Residual              8859.0  1.203688e+06    135.871810         NaN

                            PR(>F)
C(Genre)                7.204212e-04
C(New_HDI)             1.514733e-110
C(Genre):C(New_HDI)     2.990187e-02
Residual                         NaN
```

[ ]:
```
# obtention de l'examen /certification par étudiant par session, selon le genre␣
 ↪et l'HDI
df_exam = base.groupby(["Student_ID", "Itération", "Gender", "New_HDI"])[["Exam.
 ↪bin", "Certif.bin"]].sum().reset_index(["Gender", "New_HDI"])
```

```
[ ]: df_exam.rename(columns={"Exam.bin": "Exam", "Certif.bin": "Certif"},␣
      ↪inplace=True)
```

```
[ ]: df_exam
```

```
[ ]:                          Gender New_HDI  Exam  Certif
     Student_ID Itération
     45         1          une femme      TH     0       0
     83         1           un homme       I     0       0
     84         1           un homme       B     0       0
     87         1           un homme      TH     0       0
     94         1           un homme      TH     0       0
     …                          …      …    …     …
     68282      3           un homme       B     0       0
     68326      3          une femme      TH     1       0
     68332      3          une femme       I     1       1
     68365      3          une femme      TH     0       0
     69565      3          une femme      TH     0       0

     [8951 rows x 4 columns]
```

```
[ ]: # Obtention de l'examen et/ou de la certifcation
     df_exam["Exam_Certif"] = df_exam["Exam"] | df_exam["Certif"]
```

```
[ ]: # Generalized Linear Models (Formula)
     formula = "Exam_Certif ~ Gender + New_HDI"
```

```
[ ]: # Modèle logistic de type binomial (variable dépendante binaire)
     model = glm(formula=formula, data=df_exam, family=sm.families.Binomial())
```

```
[ ]: result = model.fit()
```

```
[ ]: odds_ratios = np.exp(result.params)
```

```
[ ]: odds_ratios
```

```
[ ]: Intercept              0.166282
     Gender[T.une femme]    1.121606
     New_HDI[T.I]           1.118971
     New_HDI[T.TH]          1.372423
     dtype: float64
```

```
[ ]: result.summary()
```

```
[ ]: <class 'statsmodels.iolib.summary.Summary'>
     """
                      Generalized Linear Model Regression Results
     ==============================================================================
```

```
Dep. Variable:            Exam_Certif   No. Observations:                 8951
Model:                            GLM   Df Residuals:                     8947
Model Family:                Binomial   Df Model:                            3
Link Function:                  Logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -4269.0
Date:                Thu, 15 Jun 2023   Deviance:                       8538.0
Time:                        15:25:19   Pearson chi2:                 8.95e+03
No. Iterations:                     4   Pseudo R-squ. (CS):          0.002283
Covariance Type:            nonrobust
==============================================================================
=======
                             coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept                -1.7941      0.089    -20.151      0.000      -1.969
-1.620
Gender[T.une femme]       0.1148      0.058      1.984      0.047       0.001
0.228
New_HDI[T.I]              0.1124      0.138      0.814      0.416      -0.158
0.383
New_HDI[T.TH]             0.3166      0.094      3.358      0.001       0.132
0.501
==============================================================================
=======
"""
```