

H4212

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30 Avril, 2023

Lien vers les datasets

```
[128]: path_mat = "/content/content/student-mat.csv"
      path_por = "/content/content/student-por.csv"
```

0.1 Imports

Afin de l'analyse du modèle, nous introduisons le cadre de shap. SHAP peut être utilisé pour expliquer les causes des prédictions individuelles, ainsi que le comportement du modèle dans son ensemble.

```
[129]: pip install shap
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: shap in /usr/local/lib/python3.10/dist-packages
(0.41.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from shap) (1.22.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from shap) (1.10.1)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-
packages (from shap) (1.2.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages
(from shap) (1.5.3)
Requirement already satisfied: tqdm>4.25.0 in /usr/local/lib/python3.10/dist-
packages (from shap) (4.65.0)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.10/dist-
packages (from shap) (23.1)
Requirement already satisfied: slicer==0.0.7 in /usr/local/lib/python3.10/dist-
packages (from shap) (0.0.7)
Requirement already satisfied: numba in /usr/local/lib/python3.10/dist-packages
(from shap) (0.56.4)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.10/dist-
packages (from shap) (2.2.1)
Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba->shap) (0.39.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-
packages (from numba->shap) (67.7.2)
```

Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas->shap) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->shap) (2022.7.1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->shap) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->shap) (3.1.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas->shap) (1.16.0)

```
[130]: import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import KFold, cross_val_score, train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.metrics import mean_squared_error, r2_score
import seaborn as sns
import shap

pd.set_option('display.max_columns', None)
```

0.2 Lecture des données

```
[131]: data_mat = pd.read_csv(path_mat, sep=';')
data_por = pd.read_csv(path_por, sep=';')
```

0.3 Visualisation et exploration des données

Explorer la forme des ensembles de données

```
[133]: data_mat.shape
```

```
[133]: (395, 33)
```

```
[134]: data_por.shape
```

```
[134]: (649, 33)
```

```
[135]: data_mat.columns
```

```
[135]: Index(['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fedu',
            'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime',
            'failures', 'schoolsup', 'famsup', 'paid', 'activities', 'nursery',
            'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout', 'Dalc',
            'Walc', 'health', 'absences', 'G1', 'G2', 'G3'],
            dtype='object')
```

```
[136]: data_por.columns
```

```
[136]: Index(['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fedu',
            'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime',
            'failures', 'schoolsup', 'famsup', 'paid', 'activities', 'nursery',
            'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout', 'Dalc',
            'Walc', 'health', 'absences', 'G1', 'G2', 'G3'],
            dtype='object')
```

On remarque que les colonnes des 2 datasets sont les mêmes. En effet, on possède 2 datasets de la même structure : une pour les notes de Mathématiques et l'autre pour les notes de Portugais. On explore encore les 2 datasets en utilisant 'head' pour les 5 premiers lignes, et 'tail' pour les 5 derniers lignes.

```
[137]: data_mat.head()
```

```
[137]:  school sex  age address famsize Pstatus  Medu  Fedu   Mjob   Fjob \
0      GP   F   18      U      GT3        A     4    4  at_home teacher
1      GP   F   17      U      GT3        T     1    1  at_home  other
2      GP   F   15      U      LE3        T     1    1  at_home  other
3      GP   F   15      U      GT3        T     4    2  health services
4      GP   F   16      U      GT3        T     3    3   other   other

      reason guardian  traveltime  studytime  failures  schoolsup  famsup  paid \
0  course   mother         2         2         0         yes     no    no
1  course   father         1         2         0         no     yes    no
2   other   mother         1         2         3         yes     no    yes
3   home   mother         1         3         0         no     yes    yes
4   home   father         1         2         0         no     yes    yes

      activities  nursery  higher  internet  romantic  famrel  freetime  goout  Dalc \
0           no     yes     yes       no       no       4         3       4       1
1           no     no     yes     yes       no       5         3       3       1
2           no     yes     yes     yes       no       4         3       2       2
3          yes     yes     yes     yes     yes       3         2       2       1
4           no     yes     yes     no       no       4         3       2       1

      Walc  health  absences  G1  G2  G3
0       1       3         6   5   6   6
1       1       3         4   5   5   6
```

2	3	3	10	7	8	10
3	1	5	2	15	14	15
4	2	5	4	6	10	10

```
[138]: data_por.head()
```

```
[138]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	
1	GP	F	17	U	GT3	T	1	1	at_home	other	
2	GP	F	15	U	LE3	T	1	1	at_home	other	
3	GP	F	15	U	GT3	T	4	2	health	services	
4	GP	F	16	U	GT3	T	3	3	other	other	

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	paid	\
0	course	mother	2	2	0	yes	no	no	
1	course	father	1	2	0	no	yes	no	
2	other	mother	1	2	0	yes	no	no	
3	home	mother	1	3	0	no	yes	no	
4	home	father	1	2	0	no	yes	no	

	activities	nursery	higher	internet	romantic	famrel	freetime	goout	Dalc	\
0	no	yes	yes	no	no	4	3	4	1	
1	no	no	yes	yes	no	5	3	3	1	
2	no	yes	yes	yes	no	4	3	2	2	
3	yes	yes	yes	yes	yes	3	2	2	1	
4	no	yes	yes	no	no	4	3	2	1	

	Walc	health	absences	G1	G2	G3
0	1	3	4	0	11	11
1	1	3	2	9	11	11
2	3	3	6	12	13	12
3	1	5	0	14	14	14
4	2	5	0	11	13	13

```
[139]: data_mat.tail()
```

```
[139]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
390	MS	M	20	U	LE3	A	2	2	services	services	
391	MS	M	17	U	LE3	T	3	1	services	services	
392	MS	M	21	R	GT3	T	1	1	other	other	
393	MS	M	18	R	LE3	T	3	2	services	other	
394	MS	M	19	U	LE3	T	1	1	other	at_home	

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	paid	\
390	course	other	1	2	2	no	yes	yes	
391	course	mother	2	1	0	no	no	no	
392	course	other	1	1	3	no	no	no	

393	course	mother	3	1	0	no	no	no
394	course	father	1	1	0	no	no	no

	activities	nursery	higher	internet	romantic	famrel	freetime	goout	\
390	no	yes	yes	no	no	5	5	4	
391	no	no	yes	yes	no	2	4	5	
392	no	no	yes	no	no	5	5	3	
393	no	no	yes	yes	no	4	4	1	
394	no	yes	yes	yes	no	3	2	3	

	Dalc	Walc	health	absences	G1	G2	G3
390	4	5	4	11	9	9	9
391	3	4	2	3	14	16	16
392	3	3	3	3	10	8	7
393	3	4	5	0	11	12	10
394	3	3	5	5	8	9	9

```
[140]: data_por.tail()
```

```
[140]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
644	MS	F	19	R	GT3	T	2	3	services	other	
645	MS	F	18	U	LE3	T	3	1	teacher	services	
646	MS	F	18	U	GT3	T	1	1	other	other	
647	MS	M	17	U	LE3	T	3	1	services	services	
648	MS	M	18	R	LE3	T	3	2	services	other	

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	paid	\
644	course	mother	1	3	1	no	no	no	
645	course	mother	1	2	0	no	yes	no	
646	course	mother	2	2	0	no	no	no	
647	course	mother	2	1	0	no	no	no	
648	course	mother	3	1	0	no	no	no	

	activities	nursery	higher	internet	romantic	famrel	freetime	goout	\
644	yes	no	yes	yes	no	5	4	2	
645	no	yes	yes	yes	no	4	3	4	
646	yes	yes	yes	no	no	1	1	1	
647	no	no	yes	yes	no	2	4	5	
648	no	no	yes	yes	no	4	4	1	

	Dalc	Walc	health	absences	G1	G2	G3
644	1	2	5	4	10	11	10
645	1	1	1	4	15	15	16
646	1	1	5	6	11	12	9
647	3	4	2	6	10	10	10
648	3	4	5	4	10	11	11

Vérifier si les colonnes des deux fichiers correspondent

```
[141]: sum(list(data_mat.columns != data_por.columns))
```

```
[141]: 0
```

On prend un échantillon aléatoire de chaque dataset:

```
[142]: data_mat.sample()
```

```
[142]:   school sex  age address famsize Pstatus  Medu  Fedu    Mjob    Fjob \
38     GP   F   15      R    GT3      T     3    4  services  health

   reason guardian  traveltime  studytime  failures schoolsup famsup paid \
38  course   mother          1          3          0      yes    yes  yes

   activities nursery higher internet romantic  famrel  freetime  goout  Dalc \
38         yes     yes     yes     yes      no      4          3      2    1

   Walc  health  absences  G1  G2  G3
38     1        5         2  12  12  11
```

```
[143]: data_por.sample()
```

```
[143]:   school sex  age address famsize Pstatus  Medu  Fedu    Mjob    Fjob  reason \
355     GP   F   17      U    GT3      T     2    3   other   other  course

   guardian  traveltime  studytime  failures schoolsup famsup paid \
355  father          2          2          0      no    no    no

   activities nursery higher internet romantic  famrel  freetime  goout  \
355         yes     yes     yes     yes     yes      4          2    1

   Dalc  Walc  health  absences  G1  G2  G3
355     1     1        3         2  11  12  14
```

Avec le `.info()` on peut voir un sommaire de type data de chaque colonnes, le nombre de valeurs non nulles, et l'utilisation de la mémoire. Il y a des objets dans le dataset, ce qui signifie que nous avons des catégories que nous devons transformer en int.

```
[144]: data_mat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 33 columns):
#   Column      Non-Null Count  Dtype
---  -
0   school      395 non-null   object
1   sex         395 non-null   object
```

```

2   age          395 non-null   int64
3   address      395 non-null   object
4   famsize      395 non-null   object
5   Pstatus      395 non-null   object
6   Medu         395 non-null   int64
7   Fedu         395 non-null   int64
8   Mjob         395 non-null   object
9   Fjob         395 non-null   object
10  reason       395 non-null   object
11  guardian     395 non-null   object
12  traveltime   395 non-null   int64
13  studytime    395 non-null   int64
14  failures     395 non-null   int64
15  schoolsup    395 non-null   object
16  famsup       395 non-null   object
17  paid         395 non-null   object
18  activities   395 non-null   object
19  nursery      395 non-null   object
20  higher       395 non-null   object
21  internet     395 non-null   object
22  romantic     395 non-null   object
23  famrel       395 non-null   int64
24  freetime     395 non-null   int64
25  goout        395 non-null   int64
26  Dalc         395 non-null   int64
27  Walc         395 non-null   int64
28  health       395 non-null   int64
29  absences     395 non-null   int64
30  G1           395 non-null   int64
31  G2           395 non-null   int64
32  G3           395 non-null   int64
dtypes: int64(16), object(17)
memory usage: 102.0+ KB

```

```
[145]: data_por.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 649 entries, 0 to 648
Data columns (total 33 columns):
#   Column      Non-Null Count  Dtype
---  -
0   school      649 non-null   object
1   sex         649 non-null   object
2   age         649 non-null   int64
3   address     649 non-null   object
4   famsize     649 non-null   object
5   Pstatus     649 non-null   object
6   Medu        649 non-null   int64

```

```

7  Fedu      649 non-null  int64
8  Mjob      649 non-null  object
9  Fjob      649 non-null  object
10 reason    649 non-null  object
11 guardian  649 non-null  object
12 traveltime 649 non-null  int64
13 studytime  649 non-null  int64
14 failures   649 non-null  int64
15 schoolsup  649 non-null  object
16 famsup     649 non-null  object
17 paid       649 non-null  object
18 activities 649 non-null  object
19 nursery    649 non-null  object
20 higher     649 non-null  object
21 internet   649 non-null  object
22 romantic   649 non-null  object
23 famrel     649 non-null  int64
24 freetime   649 non-null  int64
25 goout      649 non-null  int64
26 Dalc       649 non-null  int64
27 Walc       649 non-null  int64
28 health     649 non-null  int64
29 absences   649 non-null  int64
30 G1         649 non-null  int64
31 G2         649 non-null  int64
32 G3         649 non-null  int64

```

```
dtypes: int64(16), object(17)
```

```
memory usage: 167.4+ KB
```

Puisqu'on a vérifié que les 2 datasets ont la même structure, on peut concaténer les 2 datasets pour faciliter leurs manipulations.

```
[146]: data = pd.concat([data_mat, data_por], ignore_index=True)
data
```

```
[146]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	
1	GP	F	17	U	GT3	T	1	1	at_home	other	
2	GP	F	15	U	LE3	T	1	1	at_home	other	
3	GP	F	15	U	GT3	T	4	2	health	services	
4	GP	F	16	U	GT3	T	3	3	other	other	
...	
1039	MS	F	19	R	GT3	T	2	3	services	other	
1040	MS	F	18	U	LE3	T	3	1	teacher	services	
1041	MS	F	18	U	GT3	T	1	1	other	other	
1042	MS	M	17	U	LE3	T	3	1	services	services	
1043	MS	M	18	R	LE3	T	3	2	services	other	

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	paid	\
0	course	mother	2	2	0	yes	no	no	
1	course	father	1	2	0	no	yes	no	
2	other	mother	1	2	3	yes	no	yes	
3	home	mother	1	3	0	no	yes	yes	
4	home	father	1	2	0	no	yes	yes	
...	
1039	course	mother	1	3	1	no	no	no	
1040	course	mother	1	2	0	no	yes	no	
1041	course	mother	2	2	0	no	no	no	
1042	course	mother	2	1	0	no	no	no	
1043	course	mother	3	1	0	no	no	no	

	activities	nursery	higher	internet	romantic	famrel	freetime	goout	\
0	no	yes	yes	no	no	4	3	4	
1	no	no	yes	yes	no	5	3	3	
2	no	yes	yes	yes	no	4	3	2	
3	yes	yes	yes	yes	yes	3	2	2	
4	no	yes	yes	no	no	4	3	2	
...	
1039	yes	no	yes	yes	no	5	4	2	
1040	no	yes	yes	yes	no	4	3	4	
1041	yes	yes	yes	no	no	1	1	1	
1042	no	no	yes	yes	no	2	4	5	
1043	no	no	yes	yes	no	4	4	1	

	Dalc	Walc	health	absences	G1	G2	G3
0	1	1	3	6	5	6	6
1	1	1	3	4	5	5	6
2	2	3	3	10	7	8	10
3	1	1	5	2	15	14	15
4	1	2	5	4	6	10	10
...
1039	1	2	5	4	10	11	10
1040	1	1	1	4	15	15	16
1041	1	1	5	6	11	12	9
1042	3	4	2	6	10	10	10
1043	3	4	5	4	10	11	11

[1044 rows x 33 columns]

On affiche les domaines des valeurs du dataset:

```
[147]: for col in data.columns:
        print(col, " ", data[col].unique())
```

```
school    ['GP' 'MS']
sex       ['F' 'M']
```

```

age      [18 17 15 16 19 22 20 21]
address   ['U' 'R']
famsize   ['GT3' 'LE3']
Pstatus   ['A' 'T']
Medu      [4 1 3 2 0]
Fedu      [4 1 2 3 0]
Mjob      ['at_home' 'health' 'other' 'services' 'teacher']
Fjob      ['teacher' 'other' 'services' 'health' 'at_home']
reason    ['course' 'other' 'home' 'reputation']
guardian   ['mother' 'father' 'other']
traveltime [2 1 3 4]
studytime [2 3 1 4]
failures   [0 3 2 1]
schoolsup  ['yes' 'no']
famsup     ['no' 'yes']
paid       ['no' 'yes']
activities ['no' 'yes']
nursery    ['yes' 'no']
higher     ['yes' 'no']
internet   ['no' 'yes']
romantic   ['no' 'yes']
famrel     [4 5 3 1 2]
freetime   [3 2 4 1 5]
goout      [4 3 2 1 5]
Dalc       [1 2 5 3 4]
Walc       [1 3 2 4 5]
health     [3 5 1 2 4]
absences   [ 6  4 10  2  0 16 14  7  8 25 12 54 18 26 20 56 24 28  5 13 15 22
3 21
 1 75 30 19  9 11 38 40 23 17 32]
G1      [ 5  7 15  6 12 16 14 10 13  8 11  9 17 19 18  4  3  0]
G2      [ 6  5  8 14 10 15 12 18 16 13  9 11  7 19 17  4  0]
G3      [ 6 10 15 11 19  9 12 14 16  5  8 17 18 13 20  7  0  4  1]

```

On remarque que par rapport au fichier de renseignement fourni avec les 2 databases, la colonne de failures prend les valeurs de 0 à 3 au lieu de 1 à 4. On considère que l'erreur est fait au niveau du fichier de renseignement, et pas au niveau des datasets.

```
[148]: data.duplicated().sum()
```

```
[148]: 0
```

On remarque qu'il n'y a pas de duplication au niveau de nos données.

```
[150]: data.describe()
```

```

[150]:           age           Medu           Fedu  traveltime  studytime  \
count  1044.000000  1044.000000  1044.000000  1044.000000  1044.000000

```

mean	16.726054	2.603448	2.387931	1.522989	1.970307
std	1.239975	1.124907	1.099938	0.731727	0.834353
min	15.000000	0.000000	0.000000	1.000000	1.000000
25%	16.000000	2.000000	1.000000	1.000000	1.000000
50%	17.000000	3.000000	2.000000	1.000000	2.000000
75%	18.000000	4.000000	3.000000	2.000000	2.000000
max	22.000000	4.000000	4.000000	4.000000	4.000000

	failures	famrel	freetime	goout	Dalc \
count	1044.000000	1044.000000	1044.000000	1044.000000	1044.000000
mean	0.264368	3.935824	3.201149	3.156130	1.494253
std	0.656142	0.933401	1.031507	1.152575	0.911714
min	0.000000	1.000000	1.000000	1.000000	1.000000
25%	0.000000	4.000000	3.000000	2.000000	1.000000
50%	0.000000	4.000000	3.000000	3.000000	1.000000
75%	0.000000	5.000000	4.000000	4.000000	2.000000
max	3.000000	5.000000	5.000000	5.000000	5.000000

	Walc	health	absences	G1	G2 \
count	1044.000000	1044.000000	1044.000000	1044.000000	1044.000000
mean	2.284483	3.543103	4.434866	11.213602	11.246169
std	1.285105	1.424703	6.210017	2.983394	3.285071
min	1.000000	1.000000	0.000000	0.000000	0.000000
25%	1.000000	3.000000	0.000000	9.000000	9.000000
50%	2.000000	4.000000	2.000000	11.000000	11.000000
75%	3.000000	5.000000	6.000000	13.000000	13.000000
max	5.000000	5.000000	75.000000	19.000000	19.000000

	G3
count	1044.000000
mean	11.341954
std	3.864796
min	0.000000
25%	10.000000
50%	11.000000
75%	14.000000
max	20.000000

On remarque que le std de la colonne absences est élevé par rapport aux autres colonnes(= environ 6).

```
[151]: data.describe(include="object")
```

```
[151]:
```

	school	sex	address	famsize	Pstatus	Mjob	Fjob	reason	guardian \
count	1044	1044	1044	1044	1044	1044	1044	1044	1044
unique	2	2	2	2	2	5	5	4	3
top	GP	F	U	GT3	T	other	other	course	mother

freq	772	591	759	738	923	399	584	430	728
	schoolsup	famsup	paid	activities	nursery	higher	internet	romantic	
count	1044	1044	1044	1044	1044	1044	1044	1044	
unique	2	2	2	2	2	2	2	2	
top	no	yes	no	no	yes	yes	yes	no	
freq	925	640	824	528	835	955	827	673	

dtypes nous permet d'explorer les types de données qu'on a. Object correspond à une variable catégorique et int est une variable numérique.

```
[152]: data.dtypes
```

```
[152]: school      object
sex             object
age            int64
address        object
famsize        object
Pstatus        object
Medu          int64
Fedu          int64
Mjob          object
Fjob          object
reason        object
guardian       object
traveltime    int64
studytime     int64
failures      int64
schoolsup     object
famsup        object
paid          object
activities    object
nursery       object
higher        object
internet      object
romantic      object
famrel        int64
freetime      int64
goout         int64
Dalc          int64
Walc          int64
health        int64
absences      int64
G1            int64
G2            int64
G3            int64
dtype: object
```

```
[153]: data.isna().sum()
```

```
[153]: school      0
sex           0
age          0
address      0
famsize      0
Pstatus      0
Medu         0
Fedu         0
Mjob         0
Fjob         0
reason       0
guardian     0
traveltime   0
studytime    0
failures     0
schoolsup    0
famsup       0
paid         0
activities   0
nursery      0
higher       0
internet     0
romantic     0
famrel       0
freetime     0
goout        0
Dalc         0
Walc         0
health       0
absences     0
G1           0
G2           0
G3           0
dtype: int64
```

Chercher les valeurs nulles

```
[154]: data.isnull().sum()
```

```
[154]: school      0
sex           0
age          0
address      0
famsize      0
Pstatus      0
```

```

Medu      0
Fedu      0
Mjob      0
Fjob      0
reason    0
guardian  0
traveltime 0
studytime 0
failures  0
schoolsup 0
famsup    0
paid      0
activities 0
nursery   0
higher    0
internet  0
romantic  0
famrel    0
freetime  0
goout     0
Dalc      0
Walc      0
health    0
absences  0
G1        0
G2        0
G3        0
dtype: int64

```

```

[155]: total = data.isnull().sum().sort_values(ascending=False)
percent = (data.isnull().sum()/data.isnull().count()).
         ↪sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
f, ax = plt.subplots(figsize=(15, 6))

plt.xticks(rotation=90)

sns.barplot(x=missing_data.index, y=missing_data['Percent'])
plt.xlabel('df_cont', fontsize=15)
plt.ylabel('Percent of missing values', fontsize=15)
plt.title('Percent missing data by feature', fontsize=15)
missing_data

```

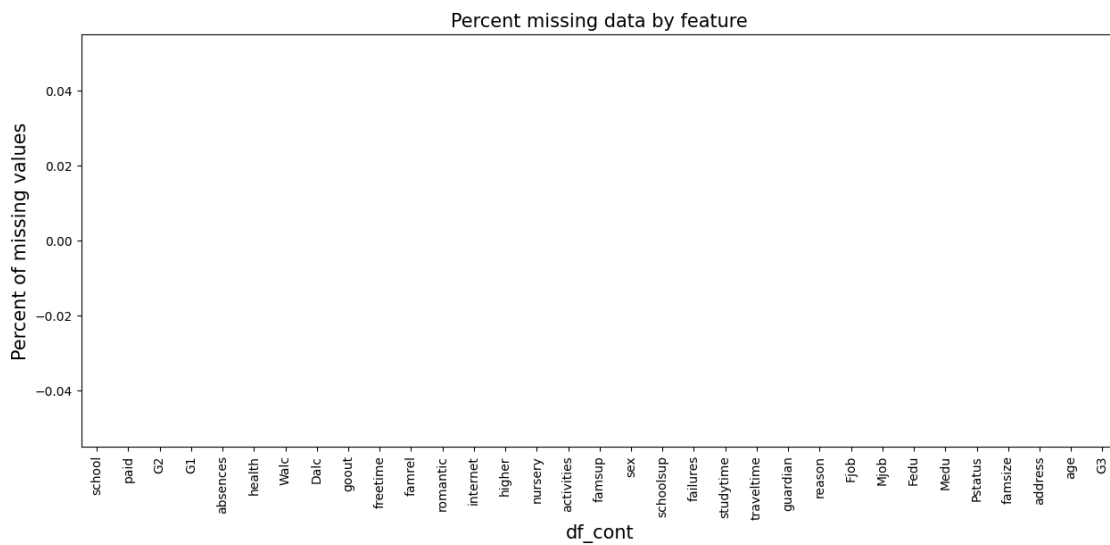
```

[155]:

```

	Total	Percent
school	0	0.0
paid	0	0.0
G2	0	0.0

G1	0	0.0
absences	0	0.0
health	0	0.0
Walc	0	0.0
Dalc	0	0.0
goout	0	0.0
freetime	0	0.0
famrel	0	0.0
romantic	0	0.0
internet	0	0.0
higher	0	0.0
nursery	0	0.0
activities	0	0.0
famsup	0	0.0
sex	0	0.0
schoolsup	0	0.0
failures	0	0.0
studytime	0	0.0
traveltime	0	0.0
guardian	0	0.0
reason	0	0.0
Fjob	0	0.0
Mjob	0	0.0
Fedu	0	0.0
Medu	0	0.0
Pstatus	0	0.0
famsize	0	0.0
address	0	0.0
age	0	0.0
G3	0	0.0



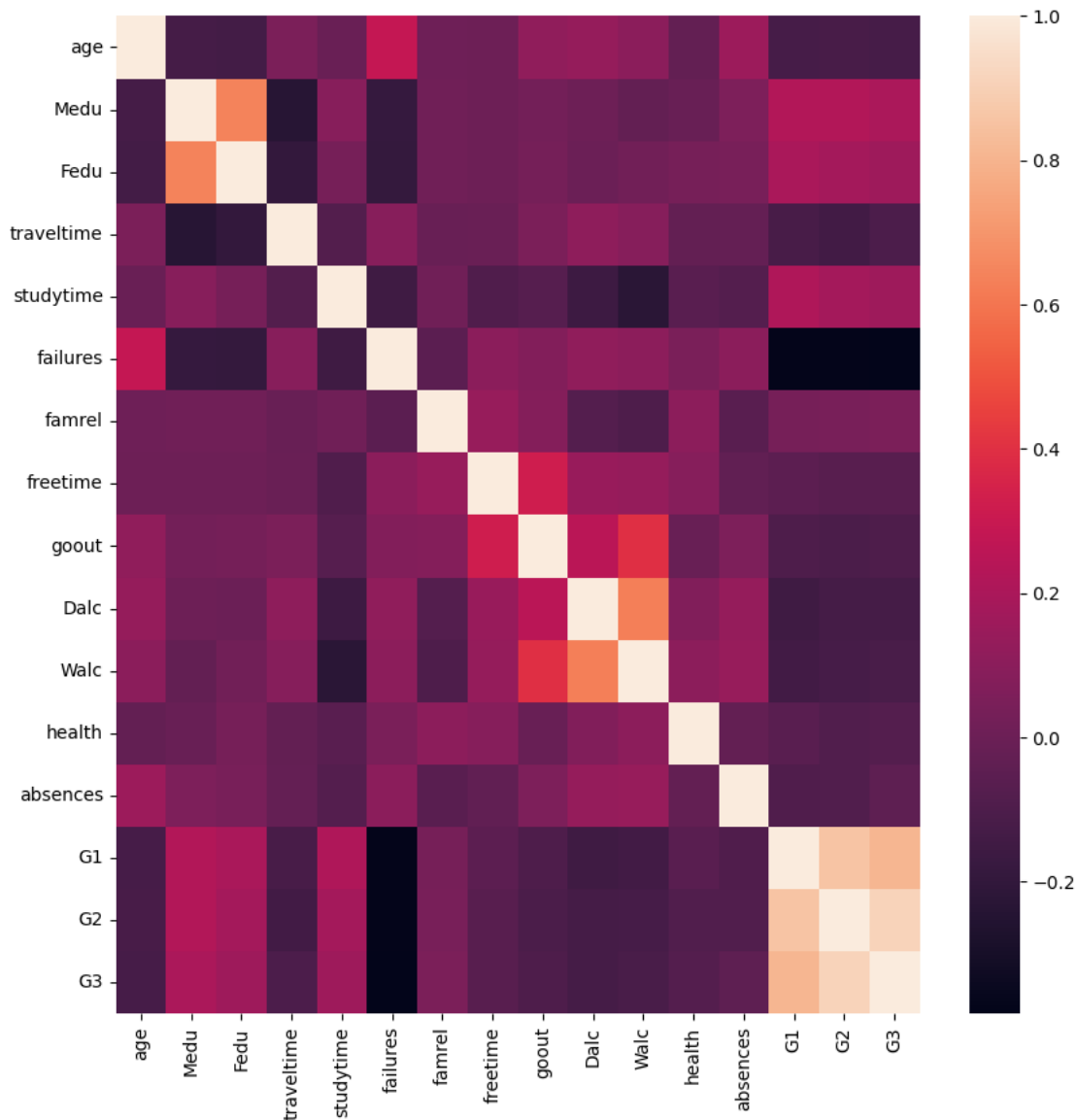
Aucune valeur manquante ou nulle dans l'ensemble de données, mais les notes = 0 pourraient être des absences, Nous traiterons les absences potentielles (note = 0 plus tard dans le processus, pour l'instant nous allons juste explorer les données et détecter les anomalies).

```
[156]: import matplotlib.pyplot as plt
import seaborn as sns

plt.figure( figsize = (10,10))
sns.heatmap(data.corr())
```

The default value of `numeric_only` in `DataFrame.corr` is deprecated. In a future version, it will default to `False`. Select only valid columns or specify the value of `numeric_only` to silence this warning.

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

On note les corrélations entre: Medu et Fedu (éducation de la mère et du père) Dalc et Walc qui correspondent à la consommation d'alcool et les niveaux scolaires G1, G2, et G3

Il existe aussi une légère corrélation entre goout et Walc, et une très faible corrélation entre les failures et G1, G2, G3.

```
[157]: data = pd.DataFrame(data)

print(data.corr())
```

	age	Medu	Fedu	traveltime	studytime	failures	\
age	1.000000	-0.130196	-0.138521	0.049216	-0.007870	0.282364	
Medu	-0.130196	1.000000	0.642063	-0.238181	0.090616	-0.187769	

Fedu	-0.138521	0.642063	1.000000	-0.196328	0.033458	-0.191390
traveltime	0.049216	-0.238181	-0.196328	1.000000	-0.081328	0.087177
studytime	-0.007870	0.090616	0.033458	-0.081328	1.000000	-0.152024
failures	0.282364	-0.187769	-0.191390	0.087177	-0.152024	1.000000
famrel	0.007162	0.015004	0.013066	-0.012578	0.012324	-0.053676
freetime	0.002645	0.001054	0.002142	-0.007403	-0.094429	0.102679
goout	0.118510	0.025614	0.030075	0.049740	-0.072941	0.074683
Dalc	0.133453	0.001515	-0.000165	0.109423	-0.159665	0.116336
Walc	0.098291	-0.029331	0.019524	0.084292	-0.229073	0.107432
health	-0.029129	-0.013254	0.034288	-0.029002	-0.063044	0.048311
absences	0.153196	0.059708	0.040829	-0.022669	-0.075594	0.099998
G1	-0.124121	0.226101	0.195898	-0.121053	0.211314	-0.374175
G2	-0.119475	0.224662	0.182634	-0.140163	0.183167	-0.377172
G3	-0.125282	0.201472	0.159796	-0.102627	0.161629	-0.383145

	famrel	freetime	goout	Dalc	Walc	health \
age	0.007162	0.002645	0.118510	0.133453	0.098291	-0.029129
Medu	0.015004	0.001054	0.025614	0.001515	-0.029331	-0.013254
Fedu	0.013066	0.002142	0.030075	-0.000165	0.019524	0.034288
traveltime	-0.012578	-0.007403	0.049740	0.109423	0.084292	-0.029002
studytime	0.012324	-0.094429	-0.072941	-0.159665	-0.229073	-0.063044
failures	-0.053676	0.102679	0.074683	0.116336	0.107432	0.048311
famrel	1.000000	0.136901	0.080619	-0.076483	-0.100663	0.104101
freetime	0.136901	1.000000	0.323556	0.144979	0.130377	0.081517
goout	0.080619	0.323556	1.000000	0.253135	0.399794	-0.013736
Dalc	-0.076483	0.144979	0.253135	1.000000	0.627814	0.065515
Walc	-0.100663	0.130377	0.399794	0.627814	1.000000	0.106669
health	0.104101	0.081517	-0.013736	0.065515	0.106669	1.000000
absences	-0.062171	-0.032079	0.056142	0.132867	0.139703	-0.027479
G1	0.036947	-0.051985	-0.101163	-0.150943	-0.142401	-0.060478
G2	0.042054	-0.068952	-0.108411	-0.131576	-0.128114	-0.088001
G3	0.054461	-0.064890	-0.097877	-0.129642	-0.115740	-0.080079

	absences	G1	G2	G3
age	0.153196	-0.124121	-0.119475	-0.125282
Medu	0.059708	0.226101	0.224662	0.201472
Fedu	0.040829	0.195898	0.182634	0.159796
traveltime	-0.022669	-0.121053	-0.140163	-0.102627
studytime	-0.075594	0.211314	0.183167	0.161629
failures	0.099998	-0.374175	-0.377172	-0.383145
famrel	-0.062171	0.036947	0.042054	0.054461
freetime	-0.032079	-0.051985	-0.068952	-0.064890
goout	0.056142	-0.101163	-0.108411	-0.097877
Dalc	0.132867	-0.150943	-0.131576	-0.129642
Walc	0.139703	-0.142401	-0.128114	-0.115740
health	-0.027479	-0.060478	-0.088001	-0.080079
absences	1.000000	-0.092425	-0.089332	-0.045671
G1	-0.092425	1.000000	0.858739	0.809142

G2	-0.089332	0.858739	1.000000	0.910743
G3	-0.045671	0.809142	0.910743	1.000000

The default value of `numeric_only` in `DataFrame.corr` is deprecated. In a future version, it will default to `False`. Select only valid columns or specify the value of `numeric_only` to silence this warning.

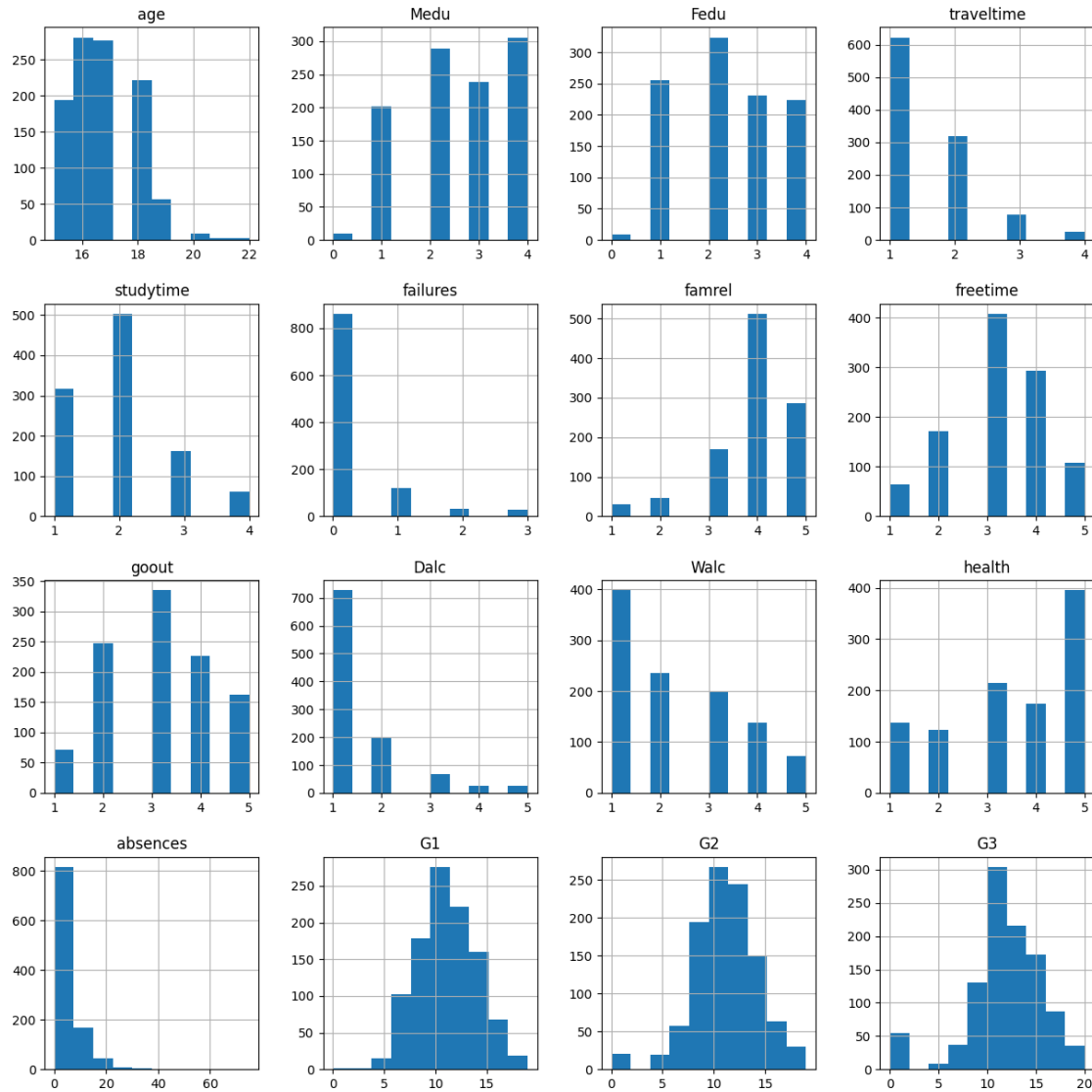
On peut voir qu'il existe une très forte corrélation entre les notes des semestres 1, 2 et la note finale. Or nous ne voulons pas entraîner un modèle qui se base principalement sur les notes de l'année pour prédire la note finale mais plutôt avoir un modèle qui s'appuie sur l'ensemble des autres données. C'est pourquoi dans la suite, nous n'inclurons pas les notes des semestres 1 et 2 comme features dans nos modèles.

1 Statistiques

1.1 Histogramme

```
[158]: data.hist(figsize = (15,15))
```

```
[158]: array([[<Axes: title={'center': 'age'}>,
               <Axes: title={'center': 'Medu'}>,
               <Axes: title={'center': 'Fedu'}>,
               <Axes: title={'center': 'traveltime'}>],
             [<Axes: title={'center': 'studytime'}>,
               <Axes: title={'center': 'failures'}>,
               <Axes: title={'center': 'famrel'}>,
               <Axes: title={'center': 'freetime'}>],
             [<Axes: title={'center': 'goout'}>,
               <Axes: title={'center': 'Dalc'}>,
               <Axes: title={'center': 'Walc'}>,
               <Axes: title={'center': 'health'}>],
             [<Axes: title={'center': 'absences'}>,
               <Axes: title={'center': 'G1'}>, <Axes: title={'center': 'G2'}>,
               <Axes: title={'center': 'G3'}>]], dtype=object)
```



Afin de pouvoir mieux analyser ces données, nous avons d'abord utilisé l'histogramme pour montrer la distribution de chaque type de manière générale. Nous remarquons par exemple que les absences possèdent des valeurs rares > 20 et que la plupart des valeurs sont < 20 , que les notes sont centrées sur 11 environ... Toutes ces colonnes vont ensuite être vues plus en détail grâce aux boxplots.

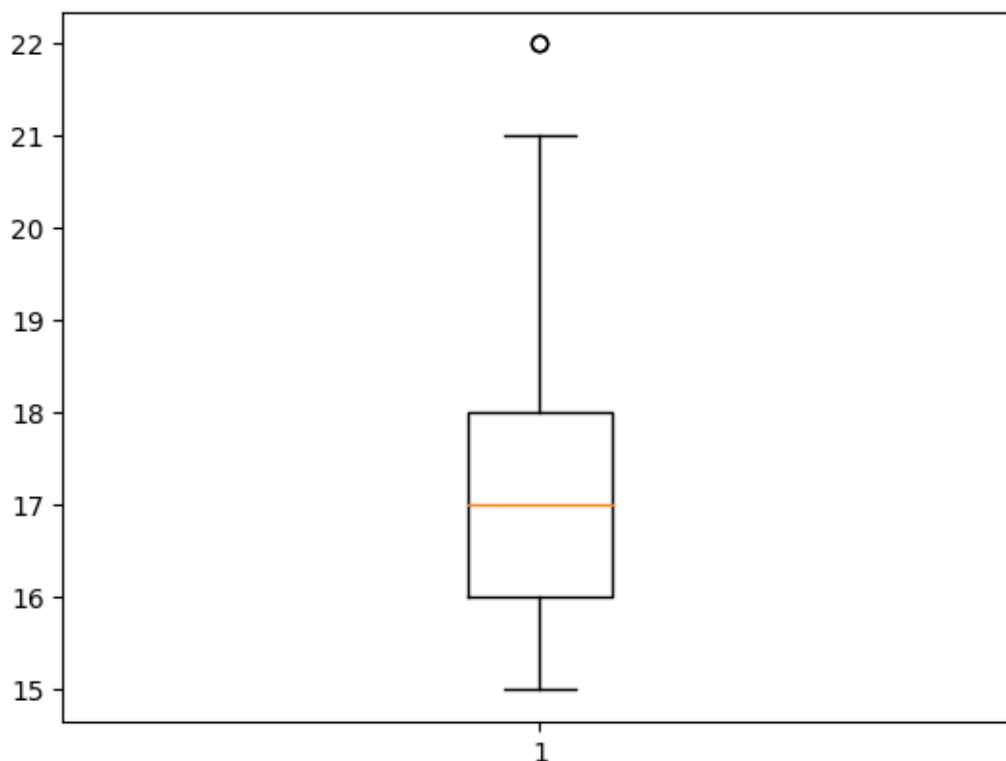
1.2 Box plot

1.2.1 Age des étudiants

```
[159]: plt.boxplot(data['age'])
```

```
[159]: {'whiskers': [<matplotlib.lines.Line2D at 0x7ff1b30bebf0>,
<matplotlib.lines.Line2D at 0x7ff1b30beec0>],
```

```
'caps': [<matplotlib.lines.Line2D at 0x7ff1b30bf160>,
<matplotlib.lines.Line2D at 0x7ff1b30bf400>],
'boxes': [<matplotlib.lines.Line2D at 0x7ff1b30bea70>],
'medians': [<matplotlib.lines.Line2D at 0x7ff1b30bf6a0>],
'fliers': [<matplotlib.lines.Line2D at 0x7ff1b30bf940>],
'means': []}
```



On observe une médiane de 17 ans, une valeur minimale de 15 ans et une valeur maximale de 21 ans, avec une valeur hors de boxplot de 22 ans. On va par la suite vérifier cette valeur pour déterminer s'il s'agit d'un outlier (bruit) .

```
[160]: data[data['age']>21]
```

```
[160]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
247	GP	M	22	U	GT3	T	3	1	services	services	
674	GP	M	22	U	GT3	T	3	1	services	services	

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	paid	\
247	other	mother		1	1	3	no	no	no
674	other	mother		1	1	3	no	no	no

	activities	nursery	higher	internet	romantic	famrel	freetime	goout	\

247	no	no	no	yes	yes	5	4	5
674	no	no	no	yes	yes	5	4	5

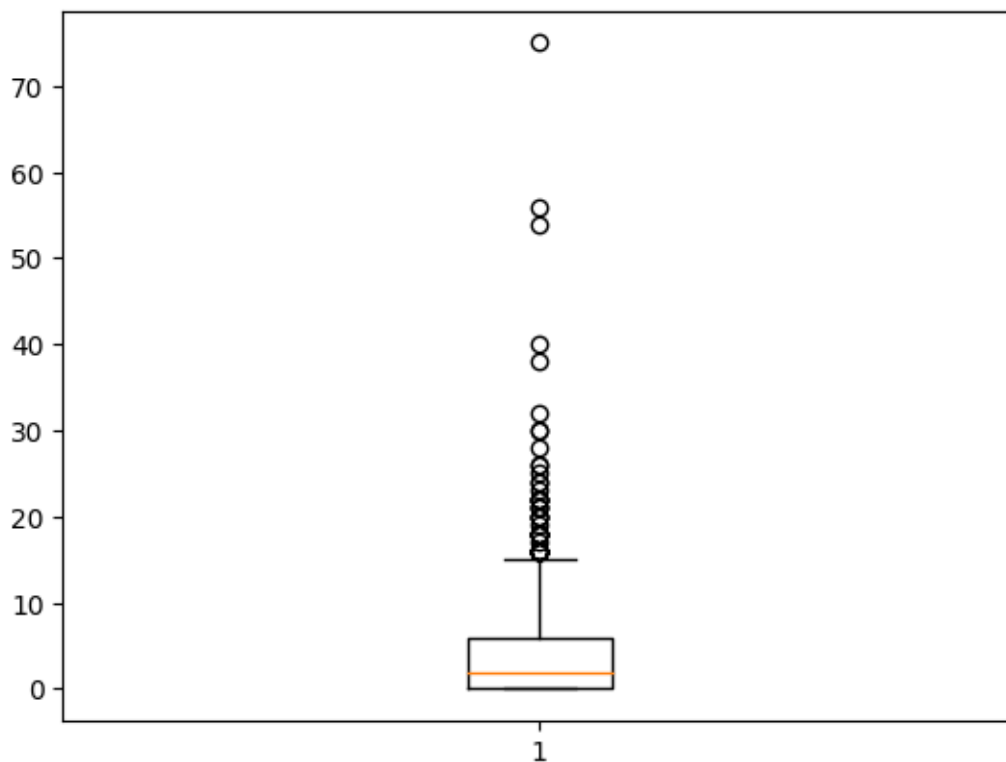
	Dalc	Walc	health	absences	G1	G2	G3
247	5	5	1	16	6	8	8
674	5	5	1	12	7	8	5

Les données correspondantes à l'âge 22 semblent pas hors la norme, donc on décide de garder ce point.

1.2.2 Nombre d'absences des étudiants

```
[161]: plt.boxplot(data['absences'])
```

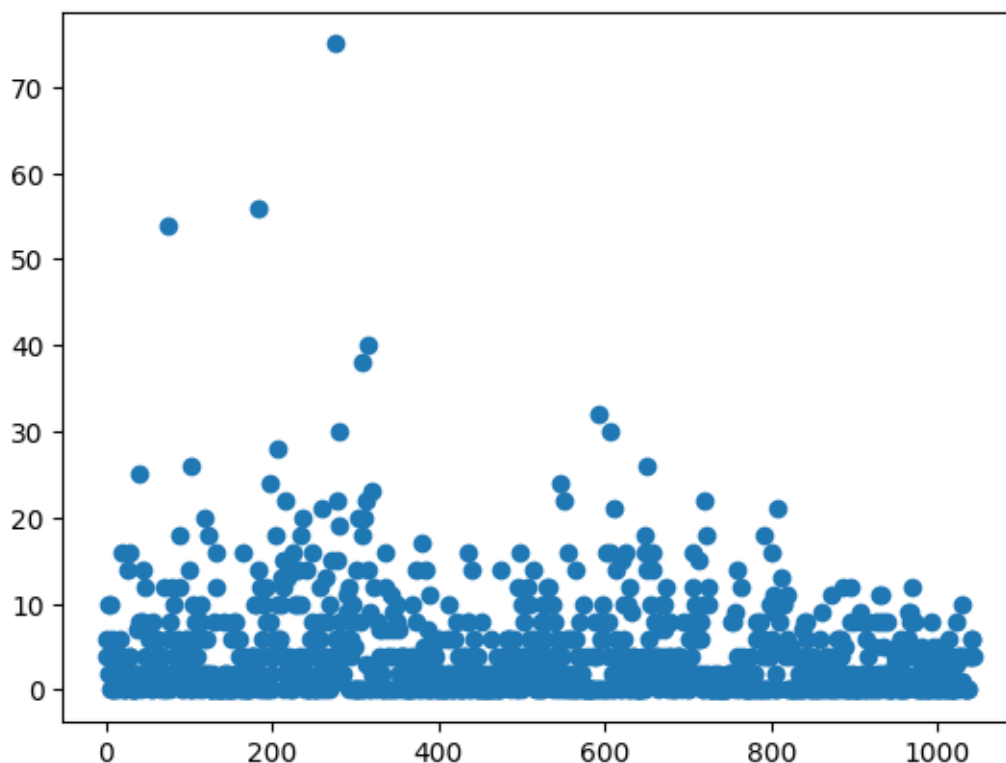
```
[161]: {'whiskers': [<matplotlib.lines.Line2D at 0x7ff1b38603d0>,
<matplotlib.lines.Line2D at 0x7ff1b3af8880>],
'caps': [<matplotlib.lines.Line2D at 0x7ff1b3afb5e0>,
<matplotlib.lines.Line2D at 0x7ff1b3afad40>],
'boxes': [<matplotlib.lines.Line2D at 0x7ff1b3862140>],
'medians': [<matplotlib.lines.Line2D at 0x7ff1b3afab90>],
'fliers': [<matplotlib.lines.Line2D at 0x7ff1b33ec310>],
'means': []}
```



On observe qu'ici il y a beaucoup de valeurs hors boxplot. On essaye de trouver s'il s'agit d'anomalies.

```
[163]: plt.plot(data['absences'], 'o')
```

```
[163]: [<matplotlib.lines.Line2D at 0x7ff1b7144c70>]
```



Les valeurs des absences sont plutôt concentrées entre 0 et 20.

```
[164]: data[data['absences'] > 20]
```

```
[164]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
40	GP	F	16	U	LE3	T	2	2	other	other	
74	GP	F	16	U	GT3	T	3	3	other	services	
103	GP	F	15	U	GT3	T	3	2	services	other	
183	GP	F	17	U	LE3	T	3	3	other	other	
198	GP	F	17	U	GT3	T	4	4	services	teacher	
205	GP	F	17	U	GT3	T	3	4	at_home	services	
216	GP	F	17	U	GT3	T	4	3	other	other	
260	GP	F	18	U	GT3	T	4	3	services	other	
276	GP	F	18	R	GT3	A	3	2	other	services	
277	GP	M	18	U	GT3	T	4	4	teacher	services	
280	GP	M	17	U	LE3	A	4	1	services	other	

307	GP	M	19	U	GT3	T	4	4	teacher	services
313	GP	F	19	U	LE3	T	3	2	services	other
315	GP	F	19	R	GT3	T	2	3	other	other
320	GP	F	17	U	GT3	A	4	3	services	services
545	GP	F	15	U	GT3	A	3	3	services	services
550	GP	M	17	U	GT3	T	2	1	other	other
592	GP	F	17	U	LE3	T	3	3	other	other
607	GP	F	17	U	GT3	T	4	4	services	teacher
612	GP	F	17	R	GT3	T	2	2	other	other
651	GP	M	18	U	GT3	T	2	2	other	at_home
720	GP	M	17	U	LE3	A	4	1	services	other
808	GP	M	21	R	LE3	T	1	1	at_home	other

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	\
40	home	mother	2	2	1	no	yes	
74	home	mother	1	2	0	yes	yes	
103	home	mother	2	2	0	yes	yes	
183	reputation	mother	1	2	0	no	yes	
198	home	mother	2	1	1	no	yes	
205	home	mother	1	3	1	no	yes	
216	reputation	mother	1	2	2	no	no	
260	home	father	1	2	0	no	yes	
276	home	mother	2	2	0	no	no	
277	home	mother	2	1	0	no	no	
280	home	mother	2	1	0	no	no	
307	reputation	other	2	1	1	no	yes	
313	reputation	other	2	2	1	no	yes	
315	reputation	other	1	3	1	no	no	
320	course	mother	1	2	0	no	yes	
545	home	mother	1	2	0	no	no	
550	home	mother	1	1	0	no	yes	
592	reputation	mother	1	2	0	no	yes	
607	home	mother	2	1	1	no	yes	
612	reputation	mother	1	1	0	no	yes	
651	course	other	1	1	1	no	yes	
720	home	mother	2	1	0	no	no	
808	course	other	2	2	2	no	yes	

	paid	activities	nursery	higher	internet	romantic	famrel	freetime	goout	\
40	no	yes	no	yes	yes	yes	3	3	3	
74	yes	yes	yes	yes	yes	no	4	3	3	
103	yes	no	yes	yes	yes	no	4	3	5	
183	no	yes	yes	yes	yes	yes	5	3	3	
198	no	no	yes	yes	yes	no	4	2	4	
205	yes	no	yes	yes	yes	yes	4	4	3	
216	yes	no	yes	yes	yes	yes	3	4	5	
260	yes	no	yes	yes	yes	yes	3	1	2	

276	no	no	no	no	yes	yes	4	1	1
277	yes	yes	yes	yes	yes	no	3	2	4
280	yes	yes	yes	yes	yes	yes	4	5	4
307	yes	no	yes	yes	yes	yes	4	3	4
313	yes	no	no	yes	yes	yes	4	2	2
315	no	no	yes	yes	yes	yes	4	1	2
320	yes	no	yes	yes	yes	yes	5	2	2
545	no	no	no	yes	no	yes	1	3	2
550	no	no	yes	yes	yes	no	5	4	5
592	no	yes	yes	yes	yes	yes	5	3	3
607	no	no	yes	yes	yes	no	4	2	4
612	no	no	yes	yes	yes	no	5	3	2
651	no	yes	no	no	yes	yes	4	4	3
720	no	yes	yes	yes	yes	yes	4	5	4
808	no	yes	yes	no	yes	yes	5	3	3

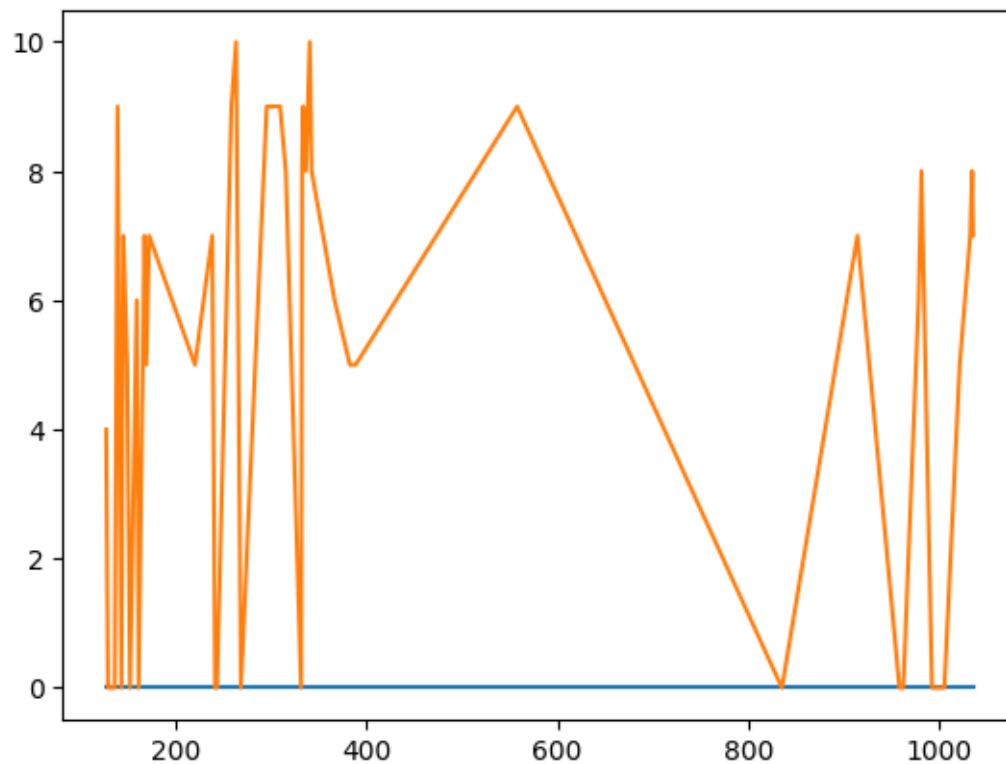
	Dalc	Walc	health	absences	G1	G2	G3
40	1	2	3	25	7	10	11
74	2	4	5	54	11	12	11
103	1	1	2	26	7	6	6
183	2	3	1	56	9	9	8
198	2	3	2	24	18	18	18
205	3	4	5	28	10	9	9
216	2	4	1	22	6	6	4
260	1	3	2	21	17	18	18
276	1	1	5	75	10	9	9
277	1	4	3	22	9	9	9
280	2	4	5	30	8	8	8
307	1	1	4	38	8	9	8
313	1	2	1	22	13	10	11
315	1	1	3	40	13	11	11
320	1	2	5	23	13	13	13
545	2	3	1	24	9	8	9
550	1	2	5	22	9	7	6
592	2	3	1	32	14	13	14
607	2	3	2	30	14	15	16
612	1	2	3	21	13	13	13
651	2	2	1	26	7	8	8
720	2	4	5	22	11	11	10
808	5	2	4	21	9	10	10

On essaye de voir si $G3 = 0$ a une relation avec les absences.

```
[162]: data[data['G3'] == 0]['absences'].plot()

data[data['G3'] == 0]['G2'].plot()
```

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



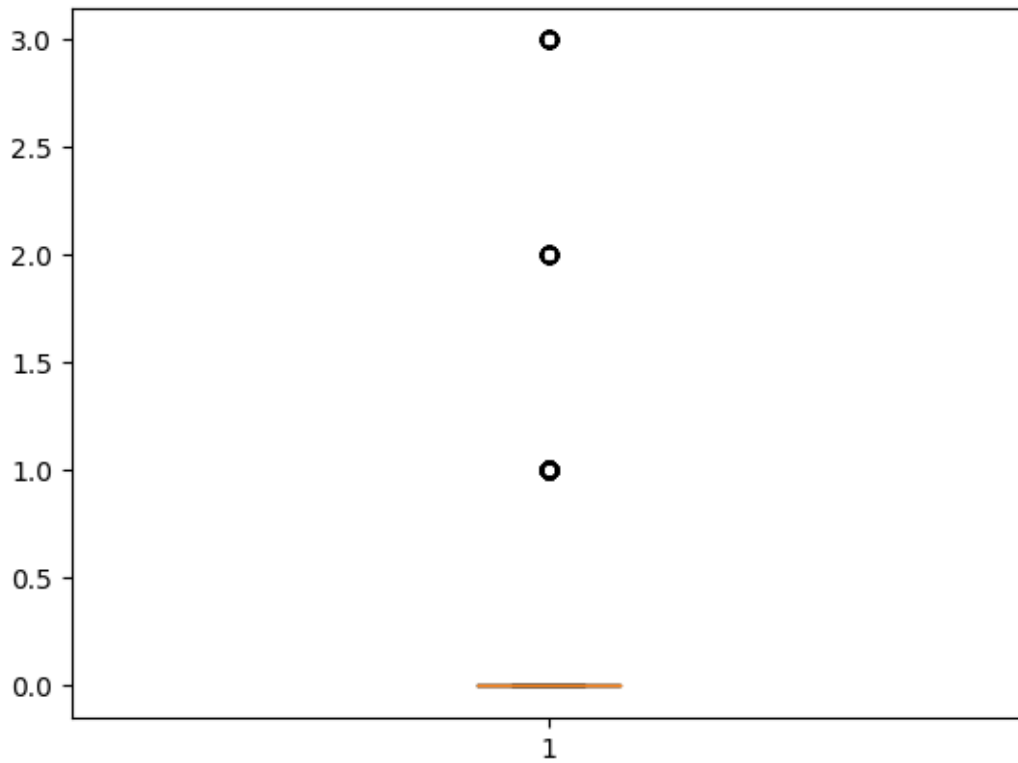
Nous ne voyons pas de relation entre les absences et le fait que G3 soit égal à 0. Nous remarquons que si $G3 = 0$, $G2 = 0$ également. Cependant, comme nous n'avons pas l'intention d'utiliser G1 et G2 comme caractéristiques, les valeurs 0 pourraient influencer négativement les prédictions. Nous décidons donc de supprimer les valeurs zéros par la suite.

Avec un nombre élevé d'absences, nous pouvons voir que G3 a des résultats variables, ce qui pourrait entraîner des erreurs dans les prédictions de nos modèles. Nous décidons d'éliminer les absences > 20 dans la partie élimination des valeurs aberrantes.

1.2.3 Nombre d'échecs

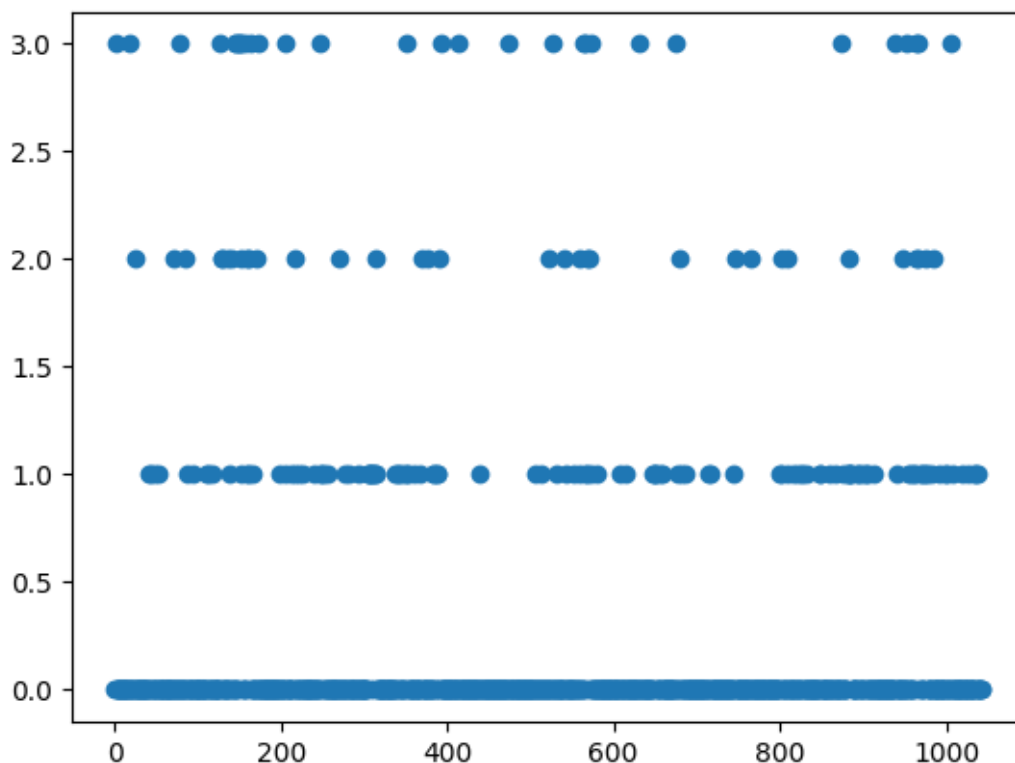
```
[165]: plt.boxplot(data['failures'])
```

```
[165]: {'whiskers': [matplotlib.lines.Line2D at 0x7ff1b45c1600>,
    <matplotlib.lines.Line2D at 0x7ff1b45c2410>],
    'caps': [matplotlib.lines.Line2D at 0x7ff1b45c1b70>,
    <matplotlib.lines.Line2D at 0x7ff1b45c2860>],
    'boxes': [matplotlib.lines.Line2D at 0x7ff1b45c16f0>],
    'medians': [matplotlib.lines.Line2D at 0x7ff1b45c2500>],
    'fliers': [matplotlib.lines.Line2D at 0x7ff1b45c2740>],
    'means': []}
```



```
[166]: plt.plot(data['failures'], 'o')
```

```
[166]: [<matplotlib.lines.Line2D at 0x7ff1b4605870>]
```



```
[167]: data[data['failures'] > 0]
```

```
[167]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
2	GP	F	15	U	LE3	T	1	1	at_home	other	
18	GP	M	17	U	GT3	T	3	2	services	services	
25	GP	F	16	U	GT3	T	2	2	services	services	
40	GP	F	16	U	LE3	T	2	2	other	other	
44	GP	F	16	U	LE3	T	2	2	other	at_home	
...	
1019	MS	F	17	R	GT3	T	1	1	other	services	
1027	MS	F	19	R	GT3	T	1	1	at_home	other	
1034	MS	M	19	R	GT3	T	1	1	other	services	
1035	MS	M	18	R	GT3	T	4	2	other	other	
1039	MS	F	19	R	GT3	T	2	3	services	other	

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	\
2	other	mother	1	2	3	yes	no	
18	course	mother	1	1	3	no	yes	
25	home	mother	1	1	2	no	yes	
40	home	mother	2	2	1	no	yes	
44	course	father	2	2	1	yes	no	
...	

1019	reputation	mother	3	1	1	no	yes
1027	course	other	2	2	1	no	yes
1034	other	mother	2	1	1	no	no
1035	home	father	2	1	1	no	no
1039	course	mother	1	3	1	no	no

	paid	activities	nursery	higher	internet	romantic	famrel	freetime	\
2	yes	no	yes	yes	yes	no	4	3	
18	no	yes	yes	yes	yes	no	5	5	
25	yes	no	no	yes	yes	no	1	2	
40	no	yes	no	yes	yes	yes	3	3	
44	no	yes	yes	yes	yes	no	4	3	
...
1019	no	no	yes	yes	yes	yes	5	2	
1027	no	no	yes	yes	yes	yes	4	3	
1034	no	no	yes	yes	no	no	4	3	
1035	yes	no	yes	yes	no	no	5	4	
1039	no	yes	no	yes	yes	no	5	4	

	goout	Dalc	Walc	health	absences	G1	G2	G3
2	2	2	3	3	10	7	8	10
18	5	2	4	5	16	6	5	5
25	2	1	3	5	14	6	9	8
40	3	1	2	3	25	7	10	11
44	3	2	2	5	14	10	10	9
...
1019	1	1	2	1	0	8	8	9
1027	3	1	1	3	4	7	8	9
1034	2	1	3	5	0	5	8	0
1035	3	4	3	3	0	7	7	0
1039	2	1	2	5	4	10	11	10

[183 rows x 33 columns]

```
[168]: data[data['failures'] == 0]
```

```
[168]:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	\
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	
1	GP	F	17	U	GT3	T	1	1	at_home	other	
3	GP	F	15	U	GT3	T	4	2	health	services	
4	GP	F	16	U	GT3	T	3	3	other	other	
5	GP	M	16	U	LE3	T	4	3	services	other	
...
1038	MS	F	18	R	GT3	T	4	4	teacher	at_home	
1040	MS	F	18	U	LE3	T	3	1	teacher	services	
1041	MS	F	18	U	GT3	T	1	1	other	other	
1042	MS	M	17	U	LE3	T	3	1	services	services	

1043	MS	M	18	R	LE3	T	3	2	services	other
------	----	---	----	---	-----	---	---	---	----------	-------

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	\
0	course	mother	2	2	0	yes	no	
1	course	father	1	2	0	no	yes	
3	home	mother	1	3	0	no	yes	
4	home	father	1	2	0	no	yes	
5	reputation	mother	1	2	0	no	yes	
...	
1038	reputation	mother	3	1	0	no	yes	
1040	course	mother	1	2	0	no	yes	
1041	course	mother	2	2	0	no	no	
1042	course	mother	2	1	0	no	no	
1043	course	mother	3	1	0	no	no	

	paid	activities	nursery	higher	internet	romantic	famrel	freetime	\
0	no	no	yes	yes	no	no	4	3	
1	no	no	no	yes	yes	no	5	3	
3	yes	yes	yes	yes	yes	yes	3	2	
4	yes	no	yes	yes	no	no	4	3	
5	yes	yes	yes	yes	yes	no	5	4	
...	
1038	no	yes	yes	yes	yes	yes	4	4	
1040	no	no	yes	yes	yes	no	4	3	
1041	no	yes	yes	yes	no	no	1	1	
1042	no	no	no	yes	yes	no	2	4	
1043	no	no	no	yes	yes	no	4	4	

	goout	Dalc	Walc	health	absences	G1	G2	G3
0	4	1	1	3	6	5	6	6
1	3	1	1	3	4	5	5	6
3	2	1	1	5	2	15	14	15
4	2	1	2	5	4	6	10	10
5	2	1	2	5	10	15	15	15
...
1038	3	2	2	5	4	7	9	10
1040	4	1	1	1	4	15	15	16
1041	1	1	1	5	6	11	12	9
1042	5	3	4	2	6	10	10	10
1043	1	3	4	5	4	10	11	11

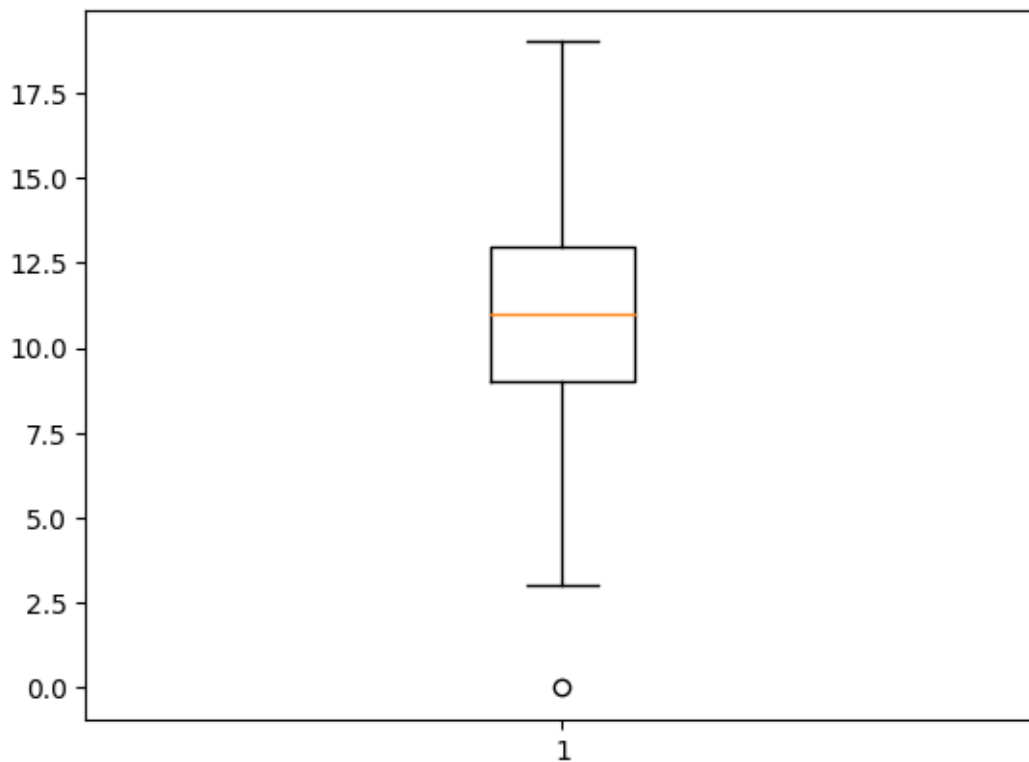
[861 rows x 33 columns]

On observe que la majorité des valeurs des failures sont = 0, par contre les autres valeurs ne représentent pas d'anomalies.

1.2.4 Note au premier trimestre

```
[169]: plt.boxplot(data['G1'])
```

```
[169]: {'whiskers': [<matplotlib.lines.Line2D at 0x7ff1b4714640>,  
                  <matplotlib.lines.Line2D at 0x7ff1b4714d90>],  
        'caps': [<matplotlib.lines.Line2D at 0x7ff1b4714f40>,  
                 <matplotlib.lines.Line2D at 0x7ff1b4714280>],  
        'boxes': [<matplotlib.lines.Line2D at 0x7ff1b4717370>],  
        'medians': [<matplotlib.lines.Line2D at 0x7ff1b4714eb0>],  
        'fliers': [<matplotlib.lines.Line2D at 0x7ff1b4b4a800>],  
        'means': []}
```



```
[170]: data[data['G1'] == 0]
```

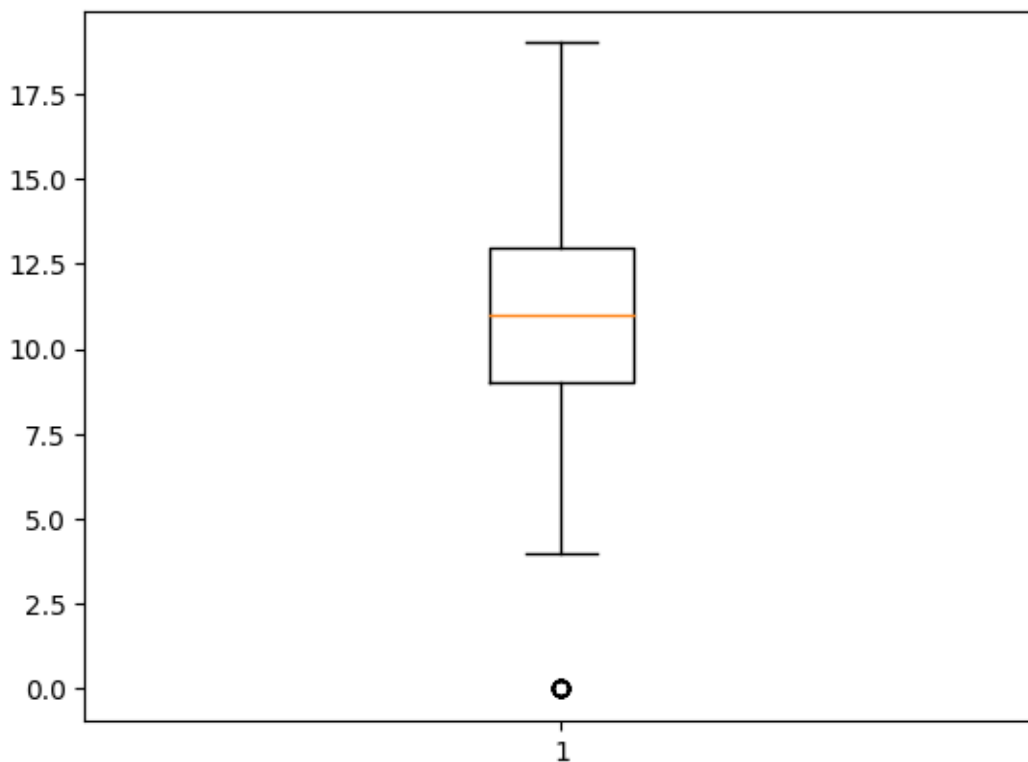
```
[170]: school sex age address famsize Pstatus Medu Fedu Mjob Fjob \  
395 GP F 18 U GT3 A 4 4 at_home teacher  
  
reason guardian traveltime studytime failures schoolsup famsup paid \  
395 course mother 2 2 0 yes no no  
  
activities nursery higher internet romantic famrel freetime goout \
```

395	no	yes	yes	no	no	4	3	4
	Dalc	Walc	health	absences	G1	G2	G3	
395	1	1	3	4	0	11	11	

1.2.5 Note au deuxième trimestre

```
[171]: plt.boxplot(data['G2'])
```

```
[171]: {'whiskers': [<matplotlib.lines.Line2D at 0x7ff1b4665f60>,
<matplotlib.lines.Line2D at 0x7ff1b4666200>],
'caps': [<matplotlib.lines.Line2D at 0x7ff1b46664a0>,
<matplotlib.lines.Line2D at 0x7ff1b4666740>],
'boxes': [<matplotlib.lines.Line2D at 0x7ff1b4665de0>],
'medians': [<matplotlib.lines.Line2D at 0x7ff1b46669e0>],
'fliers': [<matplotlib.lines.Line2D at 0x7ff1b4666c80>],
'means': []}
```



```
[207]: data[(data['G2'] == 0 )]
```

```
[207]:      school sex  age address famsize Pstatus  Medu  Fedu      Mjob      Fjob \
130      GP   F   15      R      GT3      T      3      4  services  teacher
```


131	GP	F	15	U	GT3	T	1	1	at_home	other
134	GP	M	15	R	GT3	T	3	4	at_home	teacher
135	GP	F	15	U	GT3	T	4	4	services	at_home
136	GP	M	17	R	GT3	T	3	4	at_home	other
137	GP	F	16	U	GT3	A	3	3	other	other
144	GP	M	17	U	GT3	T	2	1	other	other
153	GP	M	19	U	GT3	T	3	2	services	at_home
162	GP	M	16	U	LE3	T	1	2	other	other
242	GP	M	16	U	LE3	T	4	3	teacher	other
244	GP	F	18	U	GT3	T	2	1	other	other
269	GP	F	18	R	GT3	T	2	1	other	other
332	GP	F	18	U	GT3	T	3	3	services	services
835	MS	M	16	U	GT3	T	1	1	at_home	services
958	MS	M	17	U	GT3	T	2	2	other	other
962	MS	M	18	R	GT3	T	3	2	services	other
992	MS	F	18	R	GT3	T	2	2	at_home	other
998	MS	F	18	R	LE3	A	4	2	teacher	other
1000	MS	F	19	U	GT3	T	1	1	at_home	services
1005	MS	F	19	R	GT3	A	1	1	at_home	at_home

		reason	guardian	traveltime	studytime	failures	schoolsup	famsup	\
130		course	father	2	3	2	no	yes	
131		course	mother	3	1	0	no	yes	
134		course	mother	4	2	0	no	yes	
135		course	mother	1	3	0	no	yes	
136		course	mother	3	2	0	no	no	
137		course	other	2	1	2	no	yes	
144		home	mother	1	1	3	no	yes	
153		home	mother	1	1	3	no	yes	
162		course	mother	2	1	1	no	no	
242		course	mother	1	1	0	no	no	
244		course	other	2	3	0	no	yes	
269	reputation		mother	2	2	0	no	yes	
332		home	mother	1	2	0	no	no	
835		home	mother	2	2	0	no	yes	
958		course	mother	1	1	1	no	no	
962		course	mother	1	1	1	no	no	
992		course	mother	3	2	1	no	no	
998	reputation		mother	1	2	0	no	no	
1000		other	father	2	1	1	no	no	
1005		course	other	2	2	3	no	yes	

	paid	activities	nursery	higher	internet	romantic	famrel	freetime	\
130	no		no	yes	yes	yes	4	2	
131	no		yes	no	yes	yes	4	3	
134	no		no	yes	yes	no	5	3	
135	no		yes	yes	yes	yes	4	3	

136	no	no	yes	yes	no	no	5	4
137	no	yes	no	yes	yes	yes	4	3
144	no	no	yes	yes	yes	no	5	4
153	no	no	yes	no	yes	yes	4	5
162	no	yes	yes	yes	no	no	4	4
242	no	yes	no	yes	yes	no	5	4
244	yes	no	no	yes	yes	yes	4	4
269	no	no	yes	no	yes	yes	4	3
332	no	yes	yes	yes	yes	no	5	3
835	no	yes	yes	yes	no	yes	5	4
958	no	yes	yes	yes	no	yes	1	2
962	no	no	yes	no	yes	no	2	3
992	no	yes	yes	yes	no	yes	4	3
998	no	yes	yes	yes	yes	yes	5	3
1000	no	no	yes	no	no	no	5	5
1005	no	yes	yes	no	no	yes	3	5

	goout	Dalc	Walc	health	absences	G1	G2	G3
130	2	2	2	5	0	12	0	0
131	3	1	2	4	0	8	0	0
134	3	1	1	5	0	9	0	0
135	3	1	1	5	0	11	0	0
136	5	2	4	5	0	10	0	0
137	2	1	1	5	0	4	0	0
144	5	1	2	5	0	5	0	0
153	4	1	1	4	0	5	0	0
162	4	2	4	5	0	7	0	0
242	5	1	1	3	0	6	0	0
244	4	1	1	3	0	7	0	0
269	5	1	2	3	0	6	0	0
332	4	1	1	4	0	7	0	0
835	5	4	5	3	0	7	0	0
958	1	2	3	5	0	7	0	0
962	1	2	2	5	0	4	0	0
992	3	1	1	4	0	9	0	0
998	1	1	1	5	0	5	0	0
1000	5	2	3	2	0	5	0	0
1005	4	1	4	1	0	8	0	0

On décide de ne pas éliminer ces données car ils ne sont pas des anomalies.

1.2.6 Note finale

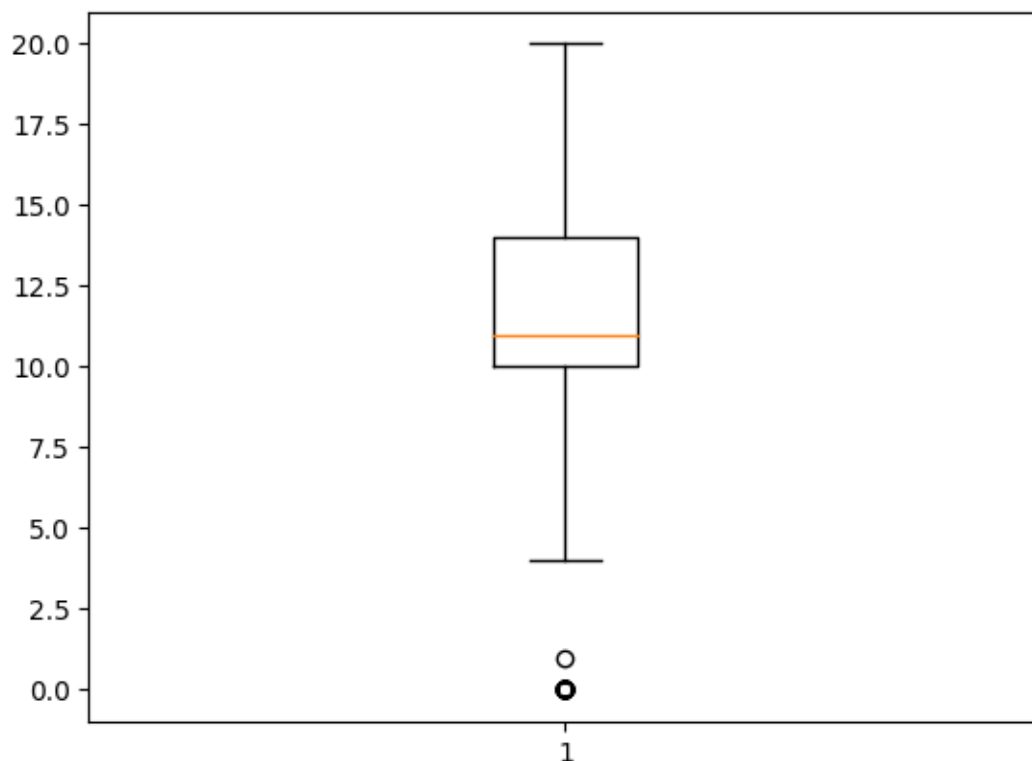
```
[173]: plt.boxplot(data['G3'])
```

```
[173]: {'whiskers': [<matplotlib.lines.Line2D at 0x7ff1b2f89db0>,
<matplotlib.lines.Line2D at 0x7ff1b2f8a050>],
```

```

'caps': [<matplotlib.lines.Line2D at 0x7ff1b2f8a2f0>,
<matplotlib.lines.Line2D at 0x7ff1b2f8a590>],
'boxes': [<matplotlib.lines.Line2D at 0x7ff1b2f89b10>],
'medians': [<matplotlib.lines.Line2D at 0x7ff1b2f8a830>],
'fliers': [<matplotlib.lines.Line2D at 0x7ff1b2f8aad0>],
'means': []}

```



```
[208]: data[data['G3'] < 2]
```

```

[208]:
   school sex  age address famsize Pstatus  Medu  Fedu  Mjob  Fjob \
128    GP   M   18      R    GT3      T    2    2  services  other
130    GP   F   15      R    GT3      T    3    4  services  teacher
131    GP   F   15      U    GT3      T    1    1   at_home  other
134    GP   M   15      R    GT3      T    3    4   at_home  teacher
135    GP   F   15      U    GT3      T    4    4  services  at_home
136    GP   M   17      R    GT3      T    3    4   at_home  other
137    GP   F   16      U    GT3      A    3    3   other    other
140    GP   M   15      U    GT3      T    4    3  teacher  services
144    GP   M   17      U    GT3      T    2    1   other    other
146    GP   F   15      U    GT3      T    3    2  health  services
148    GP   M   16      U    GT3      T    4    4  teacher  teacher
150    GP   M   18      U    LE3      T    1    1   other    other

```

153	GP	M	19	U	GT3	T	3	2	services	at_home
160	GP	M	17	R	LE3	T	2	1	at_home	other
162	GP	M	16	U	LE3	T	1	2	other	other
168	GP	F	16	U	GT3	T	2	2	other	other
170	GP	M	16	U	GT3	T	3	4	other	other
173	GP	F	16	U	GT3	T	1	3	at_home	services
221	GP	F	17	U	GT3	T	1	1	at_home	other
239	GP	M	18	U	GT3	T	2	2	other	services
242	GP	M	16	U	LE3	T	4	3	teacher	other
244	GP	F	18	U	GT3	T	2	1	other	other
259	GP	F	17	U	LE3	T	2	2	services	services
264	GP	F	18	U	GT3	T	2	2	at_home	services
269	GP	F	18	R	GT3	T	2	1	other	other
296	GP	F	19	U	GT3	T	4	4	health	other
310	GP	F	19	U	LE3	T	1	2	services	services
316	GP	F	18	U	GT3	T	2	1	services	other
332	GP	F	18	U	GT3	T	3	3	services	services
333	GP	F	18	U	LE3	T	2	2	other	other
334	GP	F	18	R	GT3	T	2	2	at_home	other
337	GP	F	17	U	GT3	T	3	2	other	other
341	GP	M	18	U	GT3	T	4	4	teacher	services
343	GP	F	17	U	GT3	A	2	2	at_home	at_home
367	MS	F	17	R	GT3	T	1	1	other	services
383	MS	M	19	R	GT3	T	1	1	other	services
387	MS	F	19	R	GT3	T	2	3	services	other
389	MS	F	18	U	GT3	T	1	1	other	other
558	GP	M	18	U	LE3	T	1	1	other	other
567	GP	M	16	U	GT3	T	3	3	other	services
835	MS	M	16	U	GT3	T	1	1	at_home	services
914	MS	M	16	R	GT3	T	2	1	other	services
958	MS	M	17	U	GT3	T	2	2	other	other
962	MS	M	18	R	GT3	T	3	2	services	other
978	MS	F	18	R	GT3	T	2	2	other	other
981	MS	F	17	U	GT3	T	4	2	teacher	services
992	MS	F	18	R	GT3	T	2	2	at_home	other
998	MS	F	18	R	LE3	A	4	2	teacher	other
1000	MS	F	19	U	GT3	T	1	1	at_home	services
1005	MS	F	19	R	GT3	A	1	1	at_home	at_home
1021	MS	F	18	R	GT3	T	4	4	other	teacher
1032	MS	M	18	R	GT3	T	2	1	other	other
1034	MS	M	19	R	GT3	T	1	1	other	services
1035	MS	M	18	R	GT3	T	4	2	other	other

	reason	guardian	traveltime	studytime	failures	schoolsup	famsup	\
128	reputation	mother	1	1	2	no	yes	
130	course	father	2	3	2	no	yes	
131	course	mother	3	1	0	no	yes	

134	course	mother	4	2	0	no	yes
135	course	mother	1	3	0	no	yes
136	course	mother	3	2	0	no	no
137	course	other	2	1	2	no	yes
140	course	father	2	4	0	yes	yes
144	home	mother	1	1	3	no	yes
146	home	father	1	2	3	no	yes
148	course	mother	1	1	0	no	yes
150	course	mother	1	1	3	no	no
153	home	mother	1	1	3	no	yes
160	course	mother	2	1	2	no	no
162	course	mother	2	1	1	no	no
168	home	mother	1	2	0	no	yes
170	course	father	3	1	2	no	yes
173	home	mother	1	2	3	no	no
221	reputation	mother	1	3	1	no	yes
239	reputation	father	1	2	1	no	no
242	course	mother	1	1	0	no	no
244	course	other	2	3	0	no	yes
259	course	father	1	4	0	no	no
264	home	mother	1	3	0	no	yes
269	reputation	mother	2	2	0	no	yes
296	reputation	other	2	2	0	no	yes
310	home	other	1	2	1	no	no
316	course	mother	2	2	0	no	yes
332	home	mother	1	2	0	no	no
333	home	other	1	2	0	no	no
334	course	mother	2	4	0	no	no
337	home	mother	1	2	0	no	yes
341	home	father	1	2	1	no	yes
343	home	father	1	2	1	no	yes
367	reputation	mother	3	1	1	no	yes
383	other	mother	2	1	1	no	no
387	course	mother	1	3	1	no	no
389	course	mother	2	2	1	no	no
558	course	mother	1	1	2	no	no
567	course	father	1	2	1	no	yes
835	home	mother	2	2	0	no	yes
914	reputation	mother	2	2	0	no	no
958	course	mother	1	1	1	no	no
962	course	mother	1	1	1	no	no
978	other	mother	2	1	1	no	no
981	home	mother	1	2	0	yes	yes
992	course	mother	3	2	1	no	no
998	reputation	mother	1	2	0	no	no
1000	other	father	2	1	1	no	no
1005	course	other	2	2	3	no	yes

1021	other	father	3	2	0	no	yes
1032	other	mother	2	1	0	no	no
1034	other	mother	2	1	1	no	no
1035	home	father	2	1	1	no	no

	paid	activities	nursery	higher	internet	romantic	famrel	freetime	\
128	no	yes	yes	yes	yes	no	3	3	
130	no	no	yes	yes	yes	yes	4	2	
131	no	yes	no	yes	yes	yes	4	3	
134	no	no	yes	yes	no	yes	5	3	
135	no	yes	yes	yes	yes	yes	4	3	
136	no	no	yes	yes	no	no	5	4	
137	no	yes	no	yes	yes	yes	4	3	
140	no	no	yes	yes	yes	no	2	2	
144	no	no	yes	yes	yes	no	5	4	
146	no	no	yes	yes	yes	no	3	3	
148	no	no	yes	no	yes	yes	3	3	
150	no	no	yes	no	yes	yes	2	3	
153	no	no	yes	no	yes	yes	4	5	
160	no	yes	yes	no	yes	yes	3	3	
162	no	yes	yes	yes	no	no	4	4	
168	yes	no	no	yes	yes	no	5	1	
170	no	yes	no	yes	yes	no	3	4	
173	no	yes	no	yes	yes	yes	4	3	
221	no	yes	yes	yes	no	yes	4	3	
239	no	no	yes	no	yes	no	5	5	
242	no	yes	no	yes	yes	no	5	4	
244	yes	no	no	yes	yes	yes	4	4	
259	yes	yes	yes	yes	yes	yes	3	4	
264	yes	yes	yes	yes	yes	yes	4	3	
269	no	no	yes	no	yes	yes	4	3	
296	yes	yes	yes	yes	yes	no	2	3	
310	no	yes	no	yes	no	yes	4	2	
316	yes	yes	yes	yes	yes	no	5	3	
332	no	yes	yes	yes	yes	no	5	3	
333	no	yes	no	yes	yes	yes	4	3	
334	no	yes	yes	yes	no	no	4	4	
337	yes	no	yes	yes	yes	yes	4	3	
341	no	yes	yes	yes	yes	no	4	3	
343	no	no	yes	yes	yes	yes	3	3	
367	yes	no	yes	yes	yes	yes	5	2	
383	no	no	yes	yes	no	no	4	3	
387	no	yes	no	yes	yes	no	5	4	
389	no	yes	yes	yes	no	no	1	1	
558	no	no	yes	no	yes	yes	2	3	
567	no	no	yes	yes	yes	yes	4	5	
835	no	yes	yes	yes	no	yes	5	4	

914	no	yes	yes	yes	yes	no	5	2
958	no	yes	yes	yes	no	yes	1	2
962	no	no	yes	no	yes	no	2	3
978	no	no	yes	no	yes	yes	5	5
981	no	yes	yes	yes	yes	no	5	5
992	no	yes	yes	yes	no	yes	4	3
998	no	yes	yes	yes	yes	yes	5	3
1000	no	no	yes	no	no	no	5	5
1005	no	yes	yes	no	no	yes	3	5
1021	no	no	no	yes	yes	yes	3	2
1032	no	yes	no	yes	yes	yes	4	4
1034	no	no	yes	yes	no	no	4	3
1035	yes	no	yes	yes	no	no	5	4

	goout	Dalc	Walc	health	absences	G1	G2	G3
128	3	1	2	4	0	7	4	0
130	2	2	2	5	0	12	0	0
131	3	1	2	4	0	8	0	0
134	3	1	1	5	0	9	0	0
135	3	1	1	5	0	11	0	0
136	5	2	4	5	0	10	0	0
137	2	1	1	5	0	4	0	0
140	2	1	1	3	0	7	9	0
144	5	1	2	5	0	5	0	0
146	2	1	1	3	0	6	7	0
148	2	2	1	5	0	7	6	0
150	5	2	5	4	0	6	5	0
153	4	1	1	4	0	5	0	0
160	2	2	2	5	0	7	6	0
162	4	2	4	5	0	7	0	0
168	5	1	1	4	0	6	7	0
170	5	2	4	2	0	6	5	0
173	5	1	1	3	0	8	7	0
221	4	1	1	5	0	6	5	0
239	4	3	5	2	0	7	7	0
242	5	1	1	3	0	6	0	0
244	4	1	1	3	0	7	0	0
259	1	1	1	2	0	10	9	0
264	3	1	1	3	0	9	10	0
269	5	1	2	3	0	6	0	0
296	4	2	3	2	0	10	9	0
310	4	2	2	3	0	9	9	0
316	3	1	2	1	0	8	8	0
332	4	1	1	4	0	7	0	0
333	3	1	1	2	0	8	8	0
334	4	1	1	4	0	10	9	0
337	2	2	3	2	0	7	8	0

341	3	2	2	2	0	10	10	0
343	1	1	2	4	0	9	8	0
367	1	1	2	1	0	7	6	0
383	2	1	3	5	0	6	5	0
387	2	1	2	5	0	7	5	0
389	1	1	1	5	0	6	5	0
558	5	2	5	4	0	11	9	0
567	5	4	4	5	0	10	10	1
835	5	4	5	3	0	7	0	0
914	1	1	1	2	0	8	7	0
958	1	2	3	5	0	7	0	0
962	1	2	2	5	0	4	0	0
978	5	1	1	3	0	8	6	0
981	5	1	3	5	0	8	8	0
992	3	1	1	4	0	9	0	0
998	1	1	1	5	0	5	0	0
1000	5	2	3	2	0	5	0	0
1005	4	1	4	1	0	8	0	0
1021	2	4	2	5	0	7	5	0
1032	3	1	3	5	0	7	7	0
1034	2	1	3	5	0	5	8	0
1035	3	4	3	3	0	7	7	0

On décide de ne pas éliminer ces données car ils ne sont pas des anomalies.

1.2.7 Tous les boxplots et filtrage initial

Sélectionner les dtypes de données

```
[175]: result = data.select_dtypes(include='number')

for i in result.columns:
    percentile25 = data[i].quantile(0.25)
    percentile75 = data[i].quantile(0.75)

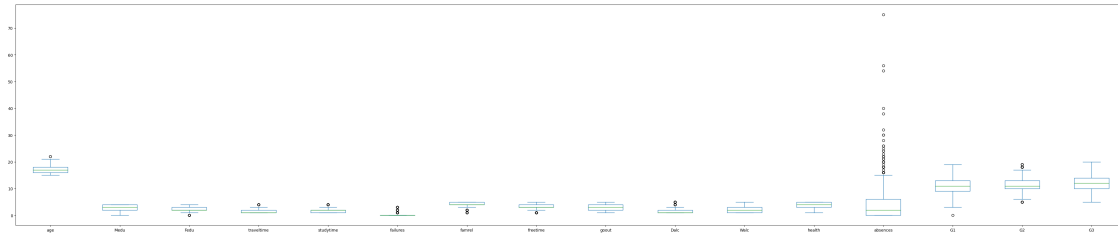
    iqr = percentile75-percentile25

    upper_limit = percentile75 + 1.5 * iqr
    lower_limit = percentile25 - 1.5 * iqr

    data[data[i] > upper_limit]
    data[data[i] < lower_limit]

    dataset_new = data[data[i] < upper_limit ]
    dataset_new = data[data[i] > lower_limit ]
dataset_new.plot(kind='box',figsize=(50,10))
```

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

On a représenté tous les boxplots ensemble et on a décidé de supprimer les outliers par la méthode d'IQR.

L'écart interquartile (IQR) est une mesure de l'étendue des données. Elle est calculée en soustrayant le 25ème percentile du 75ème percentile des données. Les points de données qui se trouvent en dehors d'une certaine plage (par exemple, 1,5 fois l'IQR) peuvent être considérés comme des valeurs aberrantes.

2 Création d'un dataset filtré

2.0.1 Filtre des zeros à G3

Nous avons remarqué dans les analyses ci dessus que de nombreux étudiants ont eu la note de 0 pour leur note finale. Cette note est dans la majorité des cas due à une absence lors de l'examen ou même encore à une valeur manquante. Nous avons donc choisi de retirer des données les étudiants qui ont eu un 0 comme note finale.

```
[176]: filtered_data = data[(data.G3 != 0) & (data.absences <=20)]
```

2.0.2 Transformation des catégories non-numériques en catégories binaire en utilisant des dummies

Plusieurs des features sont des littéraux. Il faut donc les encoder dans des feature "dummies" numériques pour pouvoir les exploiter.

```
[177]: filtered_data_with_dummies = pd.get_dummies(filtered_data,drop_first=True)
filtered_data_with_dummies.head()
```

```
[177]:
```

	age	Medu	Fedu	traveltime	studytime	failures	famrel	freetime	goout	\
0	18	4	4	2	2	0	4	3	4	
1	17	1	1	1	2	0	5	3	3	
2	15	1	1	1	2	3	4	3	2	
3	15	4	2	1	3	0	3	2	2	
4	16	3	3	1	2	0	4	3	2	

	Dalc	Walc	health	absences	G1	G2	G3	school_MS	sex_M	address_U	\
0	1	1	3	6	5	6	6	0	0	1	
1	1	1	3	4	5	5	6	0	0	1	
2	2	3	3	10	7	8	10	0	0	1	

3	1	1	5	2	15	14	15	0	0	1
4	1	2	5	4	6	10	10	0	0	1

	famsize_LE3	Pstatus_T	Mjob_health	Mjob_other	Mjob_services	\
0	0	0	0	0	0	
1	0	1	0	0	0	
2	1	1	0	0	0	
3	0	1	1	0	0	
4	0	1	0	1	0	

	Mjob_teacher	Fjob_health	Fjob_other	Fjob_services	Fjob_teacher	\
0	0	0	0	0	1	
1	0	0	1	0	0	
2	0	0	1	0	0	
3	0	0	0	1	0	
4	0	0	1	0	0	

	reason_home	reason_other	reason_reputation	guardian_mother	\
0	0	0	0	1	
1	0	0	0	0	
2	0	1	0	1	
3	1	0	0	1	
4	1	0	0	0	

	guardian_other	schoolsup_yes	famsup_yes	paid_yes	activities_yes	\
0	0	1	0	0	0	
1	0	0	1	0	0	
2	0	1	0	1	0	
3	0	0	1	1	1	
4	0	0	1	1	0	

	nursery_yes	higher_yes	internet_yes	romantic_yes
0	1	1	0	0
1	0	1	1	0
2	1	1	1	0
3	1	1	1	1
4	1	1	0	0

2.0.3 Extraction de la cible

```
[178]: y_filtered_data = filtered_data_with_dummies['G3']
y_filtered_data.head()
```

```
[178]: 0    6
      1    6
      2   10
      3   15
```

```
4    10
Name: G3, dtype: int64
```

2.0.4 Extraction des features

```
[179]: X_filtered_data = filtered_data_with_dummies.drop(['G3', 'G2', 'G1'],axis=1)
X_filtered_data.head()
```

```
[179]:
```

	age	Medu	Fedu	traveltime	studytime	failures	famrel	freetime	goout	\
0	18	4	4	2	2	0	4	3	4	
1	17	1	1	1	2	0	5	3	3	
2	15	1	1	1	2	3	4	3	2	
3	15	4	2	1	3	0	3	2	2	
4	16	3	3	1	2	0	4	3	2	

	Dalc	Walc	health	absences	school_MS	sex_M	address_U	famsize_LE3	\
0	1	1	3	6	0	0	1	0	
1	1	1	3	4	0	0	1	0	
2	2	3	3	10	0	0	1	1	
3	1	1	5	2	0	0	1	0	
4	1	2	5	4	0	0	1	0	

	Pstatus_T	Mjob_health	Mjob_other	Mjob_services	Mjob_teacher	\
0		0	0	0	0	
1		1	0	0	0	
2		1	0	0	0	
3		1	1	0	0	
4		1	0	1	0	

	Fjob_health	Fjob_other	Fjob_services	Fjob_teacher	reason_home	\
0		0	0		1	0
1		0	1	0	0	0
2		0	1	0	0	0
3		0	0	1	0	1
4		0	1	0	0	1

	reason_other	reason_reputation	guardian_mother	guardian_other	\
0		0		1	0
1		0		0	0
2		1		1	0
3		0		1	0
4		0		0	0

	schoolsup_yes	famsup_yes	paid_yes	activities_yes	nursery_yes	\
0		1	0		0	1
1		0	1		0	0
2		1	0	1		0

3	0	1	1	1	1
4	0	1	1	0	1

	higher_yes	internet_yes	romantic_yes
0	1	0	0
1	1	1	0
2	1	1	0
3	1	1	1
4	1	0	0

3 Création des jeu d'entrainement et de validation

```
[180]: X_filtered_train, X_filtered_test, y_filtered_train, y_filtered_test =
↳ train_test_split(X_filtered_data, y_filtered_data, test_size=0.
↳ 2, random_state=2023)
```

3.1 Régression linéaire simple

Nous construisons d'abord un modèle de régression linéaire car c'est le modèle le plus simple et le plus facilement interprétable.

```
[181]: regFiltered = LinearRegression().fit(X_filtered_train, y_filtered_train)
regFiltered.score(X_filtered_train, y_filtered_train)
```

```
[181]: 0.32839393127148553
```

```
[182]: regFiltered.score(X_filtered_test, y_filtered_test)
```

```
[182]: 0.29092295912393107
```

```
[183]: y_pred = regFiltered.predict(X_filtered_test)
```

```
[184]: # Calculate mean squared error and R-squared score
mse = mean_squared_error(y_filtered_test, y_pred)
r2 = r2_score(y_filtered_test, y_pred)

print("Mean squared error: ", mse)
print("Mean error", math.sqrt(mse))
print("R-squared score: ", r2)
```

```
Mean squared error: 6.211621137892372
Mean error 2.492312407763596
R-squared score: 0.29092295912393107
```

3.1.1 Validation croisée

```
[187]: kfold = KFold(n_splits=10, shuffle = True)
cv_results_filtered = cross_val_score(LinearRegression(), X_filtered_train,
    ↪ y_filtered_train, cv=kfold, scoring='neg_mean_absolute_error')
print(f"{cv_results_filtered.mean():.2f} {cv_results_filtered.std():.2f}")
```

-1.96 0.23

3.2 Regression polynomiale à régularisation Ridge

Création d'une fonction custom pour générer un modèle polynomial à régularisation Ridge. Une normalization est appliquée avant.

```
[188]: def polynomial_ridge_regression(degree, alpha):
    return make_pipeline(StandardScaler(), PolynomialFeatures(degree),
    ↪ Ridge(alpha=alpha))
```

Validation croisée

```
[189]: # Create a range of degrees and alphas for cross-validation
degrees = np.arange(1, 6)
alphas = np.logspace(-4, 4, 9)
```

```
[190]: # Initialize GridSearchCV with the custom model, hyperparameters, and the
    ↪ number of folds for cross-validation
grid_search = GridSearchCV(polynomial_ridge_regression(None, None),
    param_grid={'polynomialfeatures__degree': degrees,
    'ridge__alpha': alphas},
    scoring='neg_mean_squared_error',
    cv=5)

# Fit the grid search using the training data
grid_search.fit(X_filtered_train, y_filtered_train)

best_degree = grid_search.best_params_['polynomialfeatures__degree']
best_alpha = grid_search.best_params_['ridge__alpha']

print("Best degree: ", best_degree)
print("Best alpha: ", best_alpha)
```

Best degree: 2
Best alpha: 1000.0

```
[194]: model_polynomial_ridge = polynomial_ridge_regression(best_degree, best_alpha)
model_polynomial_ridge.fit(X_filtered_train, y_filtered_train)
```

```
[194]: Pipeline(steps=[('standardscaler', StandardScaler()),
                        ('polynomialfeatures', PolynomialFeatures()),
                        ('ridge', Ridge(alpha=1000.0))])
```

```
[195]: y_pred_polynomial_ridge = model_polynomial_ridge.predict(X_filtered_test)
```

```
[196]: # Calculate mean squared error and R-squared score
mse = mean_squared_error(y_filtered_test, y_pred_polynomial_ridge)
r2 = r2_score(y_filtered_test, y_pred_polynomial_ridge)

print("Mean squared error: ", mse)
print("Mean error", math.sqrt(mse))
print("R-squared score: ", r2)
```

```
Mean squared error:  5.343158845522805
Mean error 2.311527383684391
R-squared score:  0.39006079427445106
```

Le meilleur paramètre de degré du polynome est de 2 avec un alpha de 1000. Le modèle ainsi obtenu à un score R2 de 0.39 ce qui est mieux de 0.1 par rapport au modèle linéaire.

3.3 Regression random forest

```
[200]: n_estimators_range = [10, 25, 50, 75, 100, 200, 400]
cv_scores = []

for n_estimators in n_estimators_range:
    model = RandomForestRegressor(n_estimators=n_estimators, random_state=42)
    scores = cross_val_score(model, X_filtered_train, y_filtered_train, cv=5,
    ↪scoring='neg_mean_squared_error')
    cv_scores.append(np.mean(scores))

# Find the best n_estimators based on the highest cross-validation score
best_n_estimators = n_estimators_range[np.argmax(cv_scores)]
print("Best n_estimators: ", best_n_estimators)
```

```
Best n_estimators:  400
```

```
[201]: model_random_forest = RandomForestRegressor(n_estimators=best_n_estimators,
    ↪random_state=0)
model_random_forest.fit(X_filtered_train, y_filtered_train)
```

```
[201]: RandomForestRegressor(n_estimators=400, random_state=0)
```

```
[202]: y_pred_random_forest = model_random_forest.predict(X_filtered_test)
```

```
[203]: # Calculate mean squared error and R-squared score
mse = mean_squared_error(y_filtered_test, y_pred_random_forest)
r2 = r2_score(y_filtered_test, y_pred_random_forest)

print("Mean squared error: ", mse)
print("Mean error", math.sqrt(mse))
print("R-squared score: ", r2)
```

Mean squared error: 4.957514442076605

Mean error 2.2265476509782145

R-squared score: 0.43408337491091786

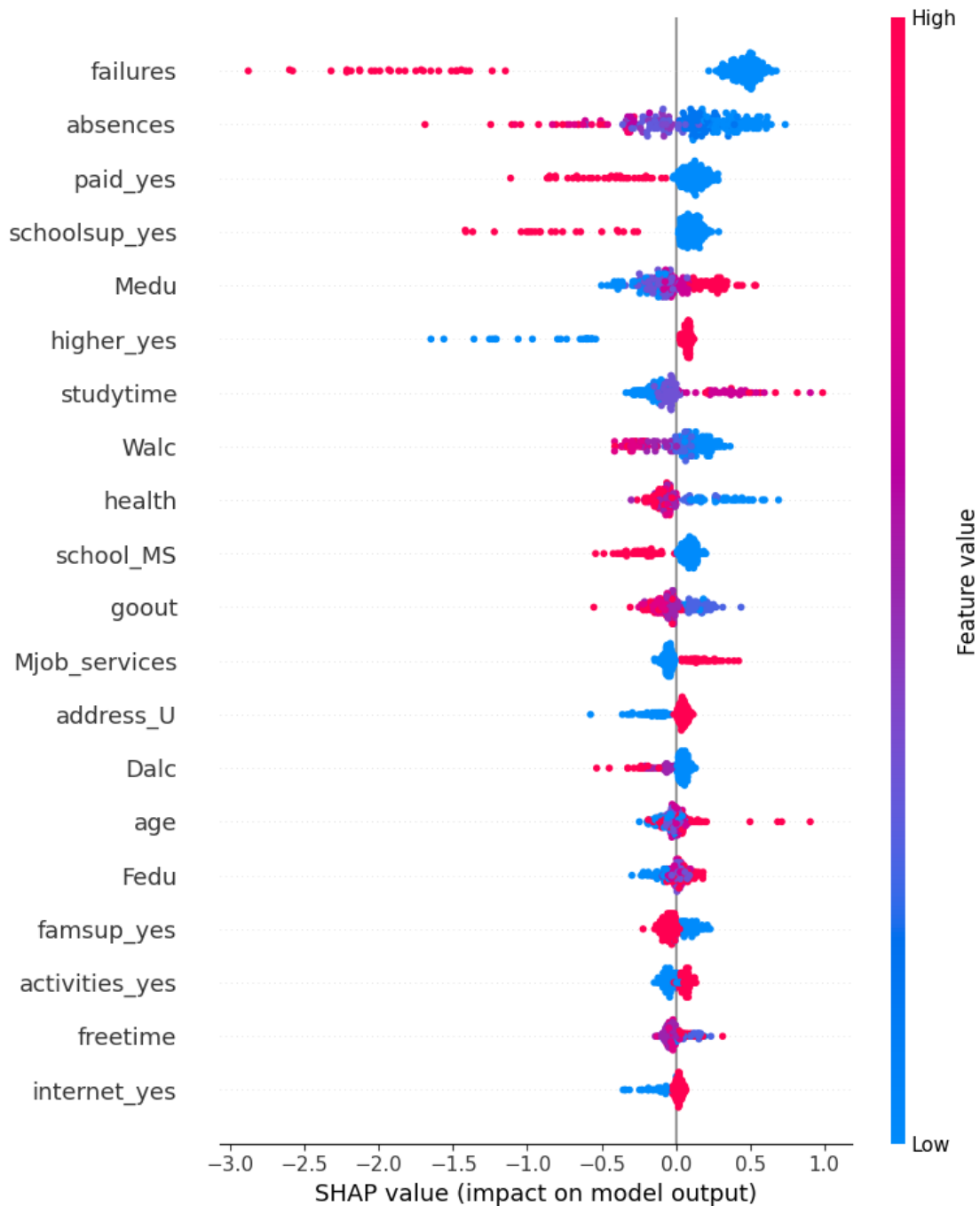
On obtien alors un modèle avec un R2 de 0.43 soit 0.04 points de plus que le modèle polynomial précédent.

4 Explication du modèle random forest en utilisant shap

```
[197]: explainer = shap.Explainer(model_random_forest)
shap_values = explainer(X_filtered_test)
```

```
[198]: shap.summary_plot(shap_values, X_filtered_test)
```

No data for colormapping provided via 'c'. Parameters 'vmin', 'vmax' will be ignored



On peut alors voir que les features les plus importantes pour décider de la note d'un étudiant sont : son nombre passé d'echecs scolaire, son nombre d'absences, les cours supplémentaires en dehors de l'école, le niveau d'éducation de la mère, le temps passé à étudier chaque semaine ou bien encore la consommation d'alcool.


```
[199]: instance_index = 0
shap.initjs()
shap.force_plot(explainer.expected_value, shap_values.values[instance_index],
↳X_filtered_test.iloc[instance_index])
```

<IPython.core.display.HTML object>

```
[199]: <shap.plots._force.AdditiveForceVisualizer at 0x7ff1b2de77c0>
```

On peut voir ici pour une prédiction individuelle les contributions individuelle de chaque paramètres sur la prédiction de sa note finale. on retrouve les features vu dans l'analyse précédente.

5 Conclusion

Pour conclure, parmi les modèles que nous avons entraînés, le modèle random forest est celui qui obtient les meilleurs résultats. Cependant le R^2 du modèle est de 0.43 ce qui signifie qu'il explique 43% de la variance des données. Ce n'est pas suffisant pour que l'on puisse utiliser le modèle pour des tâches prédictives qui ont besoin d'être fiables (Si on avait utilisé G1 et G2, on aurait bien évidemment obtenu de meilleurs résultats de prédiction) . Cependant on notera que le modèle s'explique plutôt bien comme vu grâce à l'outil shap. Cette capacité peut permettre de tout de même utiliser le modèle afin de mieux comprendre ce qui pourrai nuire à la note finale d'un étudiant (par exemple -> beaucoup d'absences -> le modèle applique une forte pénalité à la note finale -> il y a tout intérêt à réduire le nombre d'absences de l'élève). Pour continuer l'étude, on aurai pu essayer d'entraîner un modèle de réseaux de neurone simple ou analyser plus finement les données pour vérifier s'il n'y a pas des outliers restant.