CHAFIKI FATIMA ELZAHRA

l'importation des librairies

In [392…

```python
import seaborn as sns
import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix , accuracy_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import *
from sklearn.model_selection import train_test_split ,cross_val_score
from sklearn.feature_selection import VarianceThreshold
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler ,MinMaxScaler
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.svm import SVC ,SVR
from sklearn.neighbors import NearestNeighbors
from sklearn.linear_model import LogisticRegression
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LinearRegression
from sklearn.pipeline import make_pipeline
from sklearn import datasets, ensemble
```

Collecte des données

In [393…

```python
data = pd.read_csv("./zia.csv" ,delimiter=";")
data.insert(2, "teamSize",[5]*5+[7]+[5]*7+[7]+[5]*7 )
print(data.shape)
data
```

```
(21, 4)
```

Out[393…

	storyPoint	velocity	teamSize	Effort
0	156	2.7	5	63
1	202	2.5	5	92
2	173	3.3	5	56
3	331	3.8	5	86
4	124	4.2	5	32
5	339	3.6	7	91
6	97	3.4	5	35
7	257	3.0	5	93
8	84	2.4	5	36
9	211	3.2	5	62
10	131	3.2	5	45
11	112	2.9	5	37
12	101	2.9	5	32
13	74	2.9	7	30
14	62	2.9	5	21
15	289	2.8	5	112
16	113	2.8	5	39
17	141	2.8	5	52
18	213	2.8	5	80
19	137	2.7	5	56
20	91	2.7	5	35

Analyse des données

d'aprés les résultat ,le dataset contient 21 enregistrements et 3 colonnes qui décrit l'effort de développement d'un projet logiciel en fonction de 2 features : storyPoint et velocity .

In [394…

```python
data.isnull().sum()
```

Out[394…

```
storyPoint    0
velocity      0
teamSize      0
Effort        0
dtype: int64
```

On a pas de valeur manquante dans notre data set

In [395…

```python
data.describe()
```

Out[395…

	storyPoint	velocity	teamSize	Effort
count	21.000000	21.000000	21.000000	21.000000
mean	163.714286	3.023810	5.190476	56.428571
std	82.743062	0.438069	0.601585	26.177417
min	62.000000	2.400000	5.000000	21.000000
25%	101.000000	2.800000	5.000000	35.000000
50%	137.000000	2.900000	5.000000	52.000000
75%	211.000000	3.200000	5.000000	80.000000
max	339.000000	4.200000	7.000000	112.000000

In [396…

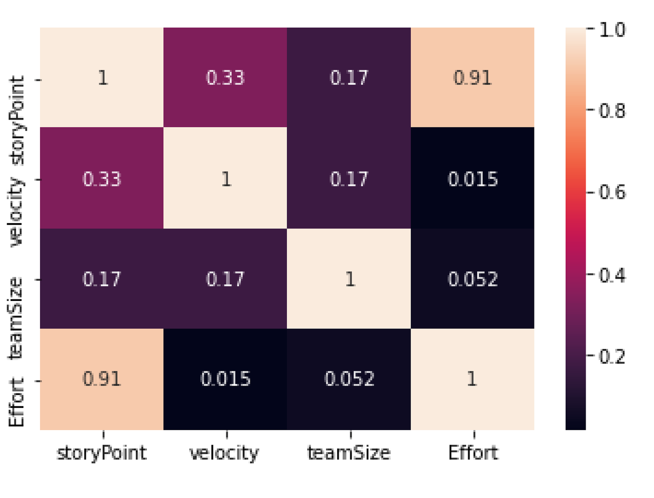
```python
corelation = data.corr()
```

In [397…

```python
sns.heatmap(corelation , xticklabels=data.columns , yticklabels=data.columns , annot=True)
```

Out[397…

```
<AxesSubplot:>
```

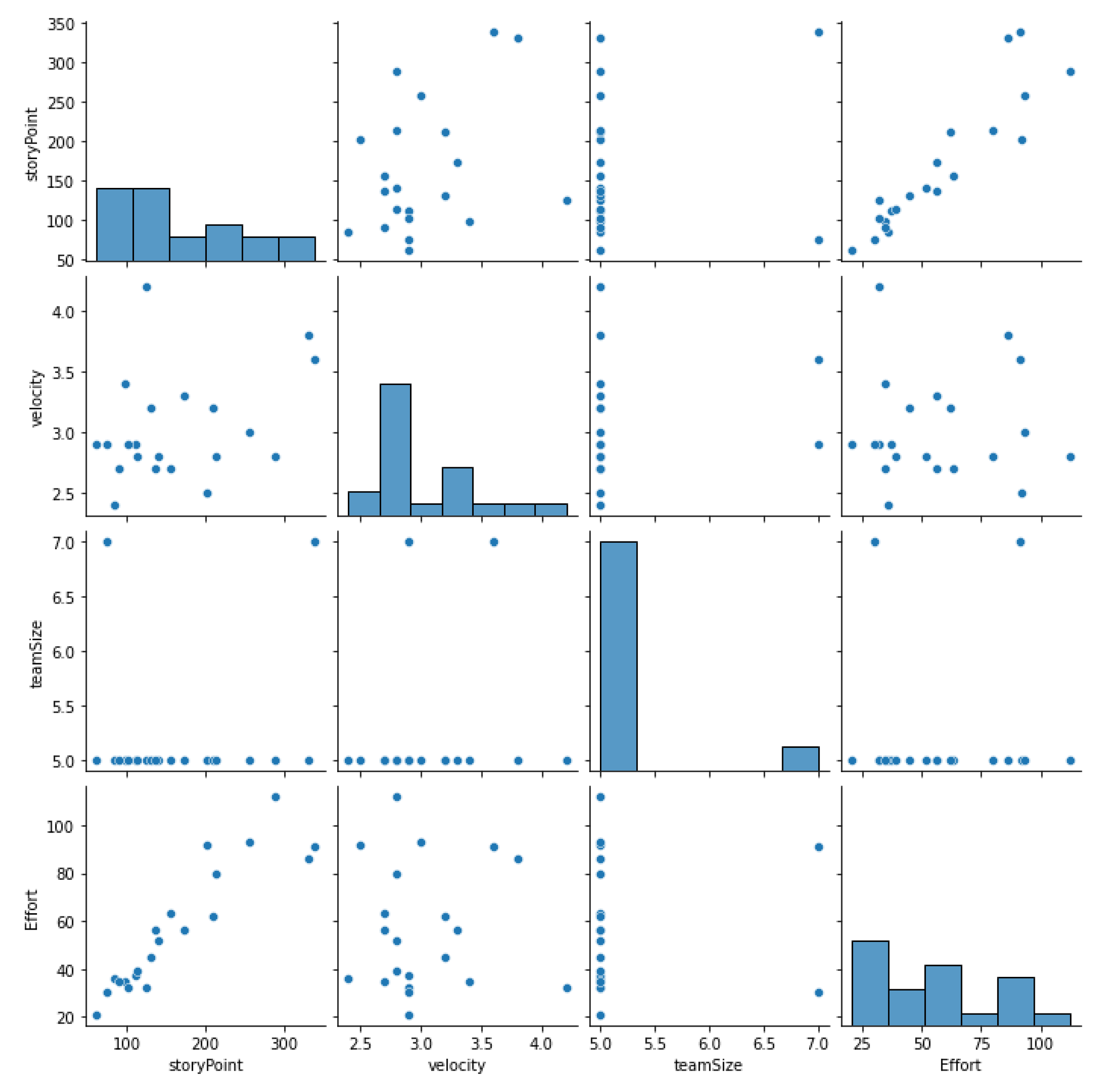


In [398…

```python
sns.pairplot(data)
```

Out[398…

```
<seaborn.axisgrid.PairGrid at 0x17090b4ed90>
```



On constate qu'on a une corrélation entre Effort et storyPoint car le coefficient de corrélation est 0.91 .

Préprocessing des données

Avant le préprocessing des données ,On doit faire la dévision des données en deux parties : training dataset et testing dataset

In [399…

```python
X = data.iloc[:,0:3]
Y = data.iloc[:,3]



X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3)
```

In [400…

```python
def trouver_donnees_importantes(X_train,TR):
    Filtre=VarianceThreshold(threshold=TR)
    Donnees_filtrees=Filtre.fit_transform(X_train)
    FS=list(Filtre.get_support())
    X=[]
    for i in range(0,len(FS)):
        if FS[i]==True:
            X += [i]
    return tuple(X)
```

In [401…

```python
trouver_donnees_importantes(X_train,0.01)
```

Out[401…

```
(0, 1, 2)
```

Don On peut désuire que les 3 features : velocity , teamSize et StoryPoint ont un impact sur l'effort

Modélisation

In [402…

```python
# On va définir une fonction qui va calculer l'erreur pour l'évaluation

# calculer MRE
def MRE(y_test,y_predict):
    y_test = np.array(y_test)
    y_predict = np.array(y_predict)
    AbEi = np.abs(y_test-y_predict)
#     print(AbEi)
    MRE = AbEi / y_test
    return MRE

# calculer pred(25)
def pred_25(y_test,y_predict):
    mre =MRE(y_test,y_predict)
    s= 0
    for i in mre :
        if i <= 0.25 :
            s += 1
    return s / len(mre)

# calculer le MMRE
def MMRE(y_test,y_predict) :
    mre =MRE(y_test,y_predict)
    return np.sum(mre) / len(mre)
```

le modéle de regression linéaire

In [403…

```python
regressor0 = LinearRegression().fit(X_train, y_train)
```

In [404…

```python
regressor0.score(X_train, y_train)
y_predict = regressor0.predict(X_test)
```

In [405…

```python
print("l'accuracy ----> ",pred_25(y_test,y_predict)*100)
print("l'erreur ------>" ,MMRE(y_test,y_predict))
```

```
l'accuracy ---->  71.42857142857143
l'erreur ------> 0.16822185375800586
```

le modéle de SVR

In [406…

```python
regressor1 = SVR(C=1000)
regressor1.fit(X_train, y_train)
```

Out[406…

```
SVR(C=1000)
```

In [407…

```python
regressor1.score(X_train, y_train)
y_predict1 = regressor1.predict(X_test)
```

In [408…

```python
print("l'accuracy ----> ",pred_25(y_test,y_predict)*100)
print("l'erreur ------>" ,MMRE(y_test,y_predict1))
```

```
l'accuracy ---->  71.42857142857143
l'erreur ------> 0.08693320168404169
```

le modéle d'arbre de décidion de régression

In [409…

```python
regressor2 = DecisionTreeRegressor(random_state=0)
regressor2.fit(X_train, y_train)
```

Out[409…

```
DecisionTreeRegressor(random_state=0)
```

In [410…

```python
regressor2.score(X_train, y_train)
y_predict2 = regressor2.predict(X_test)
```

In [411…

```python
print("l'accuracy ----> ",pred_25(y_test,y_predict2)*100)
print("l'erreur ------>" ,MMRE(y_test,y_predict2))
```

```
l'accuracy ---->  100.0
l'erreur ------> 0.09529369440083725
```

On va creer un tableau pour comparer les modéles

In [412…

```python
Tst_MMRE = [MMRE(y_test,regressor0.predict(X_test)) ,MMRE(y_test,regressor1.predict(X_test)) ,MMRE(y_test,regre
TR_MMRE = [MMRE(y_train,regressor0.predict(X_train)) ,MMRE(y_train,regressor1.predict(X_train)) ,MMRE(y_train,r
Tst_pred = [pred_25(y_test,regressor0.predict(X_test)) ,pred_25(y_test,regressor1.predict(X_test)) ,pred_25(y_t
TR_pred = [pred_25(y_train,regressor0.predict(X_train)) ,pred_25(y_train,regressor1.predict(X_train)) ,pred_25

dic ={ "TR.MMRE" : TR_MMRE  ,"TR.pred":TR_pred , "Tst.MMRE" :Tst_MMRE, "Tst.pred":Tst_pred}
pd.DataFrame(dic , index=["regression lineaire" , "SVR" ,"Decision tree regressor"])
```

Out[412…

	TR.MMRE	TR.pred	Tst.MMRE	Tst.pred
regression lineaire	0.114032	0.857143	0.168222	0.714286
SVR	0.106845	0.928571	0.086933	1.000000
Decision tree regressor	0.000000	1.000000	0.095294	1.000000

le modéle le plus performant est Decision tree regressor car les MMRE de training et testing sont petits par contre les autres

Amélioration de peformance

On peut utiliser le ENSEMBLE LEARNING exactement le boosting

In [413…

```python
params = {
    "n_estimators": 1000,
    "max_depth": 4,
    "min_samples_split": 5,
    "learning_rate": 0.01,

}
reg = ensemble.GradientBoostingRegressor(**params)
reg.fit(X_train, y_train)
```

Out[413…

```
GradientBoostingRegressor(learning_rate=0.01, max_depth=4, min_samples_split=5,
                          n_estimators=1000)
```

In [414…

```python
reg.score(X_train, y_train)
y_predict2 = regr.predict(X_test)
```

In [415…

```python
print("l'accuracy ----> ",pred_25(y_test,y_predict2)*100)
print("l'erreur ------>" ,MMRE(y_test,y_predict2))
```

```
l'accuracy ---->  42.857142857142854
l'erreur ------> 0.28550488780446165
```

le boosting ne donne aucune amélioration parce que on a pas une grande quantité de données

In [ ]:

In [ ]: