PROJET TECHNO DATA

Auteurs

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Declaration librairies

```
# imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
# show plots in the notebook
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import preprocessing
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier

import warnings
warnings.filterwarnings('ignore')
```

I - Analyse et Preparation des données

1. Etudier les données en affichants les informations correspondantes (colonnes, indice, etc) :

```
## TO DO
df_caracteristique = pd.read_csv('./bdd/caracteristiques-2017.csv', encoding ='latin1')
print(df_caracteristique.shape)
```

```
(60701, 16)
```

```
df_lieux = pd.read_csv('./bdd/lieux-2017.csv', encoding ='latin1')

print(df_lieux.shape)
```

```
(60701, 18)
```

```
df_usagers = pd.read_csv('./bdd/usagers-2017.csv', encoding ='latin1')

print(df_usagers.shape)
```

```
(136021, 12)
```

```
df_vehicules = pd.read_csv('./bdd/vehicules-2017.csv', encoding ='latin1')

print(df_vehicules.shape)
```

```
(103546, 9)
```

2. Fusionner les fichiers de donnés

```
frames = [df_caracteristique, df_lieux, df_usagers, df_vehicules]
df_total = pd.concat(frames, axis=1)

print(df_total.shape)
```

```
(136021, 55)
```

3. Nettoyer la base de données

Ex : Identifier le pourcentage de valeurs NaN dans la base et éliminez les colonnes où la majorité des valeurs sont NaN.

```
df = df_total.loc[:, df_total.isnull().mean() < .5]

#Also we remove the colums in named "num_veh" because we will not need it and it's not numerical values
df = df.loc[:,~df.columns.duplicated()]
df.drop(['num_veh'], axis=1, inplace=True)

df
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Num_Acc	place	catu	grav	sexe	trajet	secu	locp	actp	etatp	an_nais	senc	catv	occutc	obs	obsm	choc	r
0	201700000001	1.0	1	3	1	9.0	13.0	0.0	0.0	0.0	1968.0	0.0	7.0	0.0	0.0	2.0	3.0	9
1	201700000001	2.0	2	3	2	9.0	11.0	0.0	0.0	0.0	1973.0	0.0	10.0	0.0	0.0	2.0	3.0	1
2	201700000001	1.0	1	3	1	1.0	13.0	0.0	0.0	0.0	1967.0	0.0	7.0	0.0	0.0	0.0	1.0	1
3	201700000002	1.0	1	1	1	0.0	11.0	0.0	0.0	0.0	1953.0	0.0	1.0	0.0	0.0	0.0	7.0	1
4	201700000002	1.0	1	3	1	5.0	22.0	0.0	0.0	0.0	1960.0	0.0	10.0	0.0	0.0	2.0	1.0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
136016	201700060699	1.0	1	1	2	9.0	11.0	0.0	0.0	0.0	1974.0	NaN	NaN	NaN	NaN	NaN	NaN	N
136017	201700060700	1.0	1	1	2	9.0	11.0	0.0	0.0	0.0	1987.0	NaN	NaN	NaN	NaN	NaN	NaN	N
136018	201700060700	1.0	1	4	1	9.0	21.0	0.0	0.0	0.0	1991.0	NaN	NaN	NaN	NaN	NaN	NaN	N
136019	201700060700	2.0	2	4	2	9.0	21.0	0.0	0.0	0.0	1990.0	NaN	NaN	NaN	NaN	NaN	NaN	N
136020	201700060701	1.0	1	4	1	1.0	21.0	0.0	0.0	0.0	1992.0	NaN	NaN	NaN	NaN	NaN	NaN	N

136021 rows × 18 columns

4. Supprimer les variables dont la majorité des observations sont manquantes

```
# Count number of zeros in all columns of Dataframe
for column_name in df.columns:
    shape=df.shape[0]
    column = df[column_name]
    # Get the count of Zeros in column
    count = (column == 0).sum()
    pct=count/df.shape[0]
    if(isinstance(pct, pd.Series)):
        print("Can't process Series...")
    elif(pct > 0.5):
        df.drop([column_name], axis=1, inplace=True)
        print("Removing column ", column_name)

df
```

```
Removing column  locp
Removing column  actp
Removing column  etatp
Removing column  occutc
Removing column  obs
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Num_Acc	place	catu	grav	sexe	trajet	secu	an_nais	senc	catv	obsm	choc	manv
0	201700000001	1.0	1	3	1	9.0	13.0	1968.0	0.0	7.0	2.0	3.0	9.0
1	201700000001	2.0	2	3	2	9.0	11.0	1973.0	0.0	10.0	2.0	3.0	13.0
2	201700000001	1.0	1	3	1	1.0	13.0	1967.0	0.0	7.0	0.0	1.0	16.0
3	201700000002	1.0	1	1	1	0.0	11.0	1953.0	0.0	1.0	0.0	7.0	1.0
4	201700000002	1.0	1	3	1	5.0	22.0	1960.0	0.0	10.0	2.0	1.0	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
136016	201700060699	1.0	1	1	2	9.0	11.0	1974.0	NaN	NaN	NaN	NaN	NaN
136017	201700060700	1.0	1	1	2	9.0	11.0	1987.0	NaN	NaN	NaN	NaN	NaN
136018	201700060700	1.0	1	4	1	9.0	21.0	1991.0	NaN	NaN	NaN	NaN	NaN
136019	201700060700	2.0	2	4	2	9.0	21.0	1990.0	NaN	NaN	NaN	NaN	NaN
136020	201700060701	1.0	1	4	1	1.0	21.0	1992.0	NaN	NaN	NaN	NaN	NaN

136021 rows × 13 columns

5. Remplir les valeurs NaN par différentes méthodes

```
def fill_nas_by_type(df, col_name):
    """Fill null values in df according to col_name type

    Parameters
    ----------
    df : dataframe, (default=None)
        input dataframe
    col_name : str, (default=None)
        column with null values to fill

    Returns
    -------
    df with filled values in col_name
    """
    if (col_name == "trajet"):
        df[col_name] = df[col_name].fillna(value=9)
    elif (col_name == "place"):
        df[col_name] = df[col_name].fillna(df[col_name].value_counts()[:1].index.tolist()[0])
    elif (col_name == "an_nais"):
        df[col_name] = df[col_name].fillna(float(df[col_name].median()))
    elif (col_name == "catv"):
        df[col_name] = df[col_name].fillna(value=99)
    elif (col_name == "obsm"):
        df[col_name] = df[col_name].fillna(value=99)
    elif (col_name == "choc"):
        df[col_name] = df[col_name].fillna(value=9)
    elif (col_name == "manv"):
        df[col_name] = df[col_name].fillna(value=25)
    elif (col_name == "senc"):
        df[col_name] = df[col_name].fillna(df[col_name].value_counts()[:1].index.tolist()[0])
    elif (col_name == "num_veh"):
        df[col_name] = df[col_name].iloc[:, 0].fillna(pd.Series(np.random.choice(['A01', 'B01', 'C01'], p=[0.52, 0.30, 0.18],
size=len(df))))
        df[col_name] = df[col_name].iloc[:, 1].fillna(pd.Series(np.random.choice(['A01', 'B01', 'C01'], p=[0.52, 0.30, 0.18],
size=len(df))))
```

```
    elif (col_name == "Num_Acc"):
        df[col_name] = df[col_name].fillna(method='ffill')
    elif (col_name == "secu"):
        df[col_name] = df[col_name].fillna(df[col_name].value_counts()[:1].index.tolist()[0])
    return df

cols_to_fill = list(df.columns)

print(df.isnull().sum(axis = 0))

print(df.isnull().sum().sum())
for x in cols_to_fill:
    df = fill_nas_by_type(df, x)
print(df.isnull().sum().sum())
print(df.isnull().sum(axis = 0))
```

```
Num_Acc        0
place      11802
catu           0
grav           0
sexe           0
trajet        11
secu        8950
an_nais       37
senc       32543
catv       32475
obsm       32517
choc       32510
manv       32505
dtype: int64
183350
0
Num_Acc    0
place      0
catu       0
grav       0
sexe       0
trajet     0
secu       0
an_nais    0
senc       0
catv       0
obsm       0
choc       0
manv       0
dtype: int64
```

6. Analyser les données par les statistiques (min, max, médiane)

```
## TO DO

for col_name in df.columns:

    if(col_name != "Num_Acc"):
        print("Column: " + col_name)

        print(df[col_name].describe())
        print("\n \n")
```

```
Column: place
count    136021.000000
mean          1.393300
std           1.233188
min           1.000000
25%           1.000000
50%           1.000000
75%           1.000000
max           9.000000
Name: place, dtype: float64
```

```
Column: catu
count    136021.000000
mean          1.349814
std           0.639996
min           1.000000
25%           1.000000
50%           1.000000
75%           2.000000
max           4.000000
Name: catu, dtype: float64



Column: grav
count    136021.000000
mean          2.492858
std           1.330687
min           1.000000
25%           1.000000
50%           3.000000
75%           4.000000
max           4.000000
Name: grav, dtype: float64



Column: sexe
count    136021.000000
mean          1.323016
std           0.467631
min           1.000000
25%           1.000000
50%           1.000000
75%           2.000000
max           2.000000
Name: sexe, dtype: float64



Column: trajet
count    136021.000000
mean          3.476713
std           2.647390
min           0.000000
25%           1.000000
50%           4.000000
75%           5.000000
max           9.000000
Name: trajet, dtype: float64



Column: secu
count    136021.000000
mean         17.393175
std          17.277594
min           1.000000
25%          11.000000
50%          11.000000
75%          21.000000
max          93.000000
Name: secu, dtype: float64



Column: an_nais
count    136021.000000
mean       1978.317797
std          18.883170
min        1914.000000
25%        1965.000000
50%        1982.000000
75%        1993.000000
max        2017.000000
Name: an_nais, dtype: float64
```

```
Column: senc
count    136021.000000
mean          1.114401
std           0.612836
min           0.000000
25%           1.000000
50%           1.000000
75%           2.000000
max           2.000000
Name: senc, dtype: float64



Column: catv
count    136021.000000
mean         32.817205
std          38.390817
min           1.000000
25%           7.000000
50%           7.000000
75%          36.000000
max          99.000000
Name: catv, dtype: float64



Column: obsm
count    136021.000000
mean         24.930540
std          41.530365
min           0.000000
25%           2.000000
50%           2.000000
75%           9.000000
max          99.000000
Name: obsm, dtype: float64



Column: choc
count    136021.000000
mean          4.377677
std           3.353667
min           0.000000
25%           1.000000
50%           3.000000
75%           9.000000
max           9.000000
Name: choc, dtype: float64



Column: manv
count    136021.000000
mean         10.862845
std          10.156319
min           0.000000
25%           1.000000
50%           9.000000
75%          23.000000
max          25.000000
Name: manv, dtype: float64
```

7. Expliquer la gravité des accidents en fonction des autres variables (créer une nouvelle variable "mortalité" qui indique si la victime est décédée ou non suite à l'accident : tué=1 non=0)

```
tue = df.grav == 2

df['mortalite'] = np.where(tue, 1, np.where(np.logical_not(tue), 0, np.NaN))
df
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Num_Acc	place	catu	grav	sexe	trajet	secu	an_nais	senc	catv	obsm	choc	manv	mortalite
0	201700000001	1.0	1	3	1	9.0	13.0	1968.0	0.0	7.0	2.0	3.0	9.0	0.0
1	201700000001	2.0	2	3	2	9.0	11.0	1973.0	0.0	10.0	2.0	3.0	13.0	0.0
2	201700000001	1.0	1	3	1	1.0	13.0	1967.0	0.0	7.0	0.0	1.0	16.0	0.0
3	201700000002	1.0	1	1	1	0.0	11.0	1953.0	0.0	1.0	0.0	7.0	1.0	0.0
4	201700000002	1.0	1	3	1	5.0	22.0	1960.0	0.0	10.0	2.0	1.0	1.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
136016	201700060699	1.0	1	1	2	9.0	11.0	1974.0	1.0	99.0	99.0	9.0	25.0	0.0
136017	201700060700	1.0	1	1	2	9.0	11.0	1987.0	1.0	99.0	99.0	9.0	25.0	0.0
136018	201700060700	1.0	1	4	1	9.0	21.0	1991.0	1.0	99.0	99.0	9.0	25.0	0.0
136019	201700060700	2.0	2	4	2	9.0	21.0	1990.0	1.0	99.0	99.0	9.0	25.0	0.0
136020	201700060701	1.0	1	4	1	1.0	21.0	1992.0	1.0	99.0	99.0	9.0	25.0	0.0

136021 rows × 14 columns

```
df['mortalite'].value_counts(normalize=True) * 100
```

```
0.0    97.35335
1.0     2.64665
Name: mortalite, dtype: float64
```

II - Visualisation et modélisation

1. Mettre en place les modèles de machine learning pour prédire et classifier la mortalité : Régression logistique, Decision Tree, Random Forest, etc

```
y = df["mortalite"]
x = df.drop('mortalite', axis=1)

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=100)
print ("train shape", x_train.shape, y_train.shape)
print ("test shape", x_test.shape, y_train.shape)
```

```
train shape (95214, 13) (95214,)
test shape (40807, 13) (95214,)
```

Régression Logistique

```
modele_regLog = LogisticRegression(random_state = 0, solver = 'liblinear', multi_class = 'auto')
modele_regLog.fit(x_train,y_train)
precision = modele_regLog.score(x_test,y_test)
print("Precision ")
print(precision*100)
```

```
Precision
97.36074693067366
```

Decision Tree

```
clf = DecisionTreeClassifier()
clf.fit(x_train, y_train)

predictions = clf.predict(x_test)
print(metrics.accuracy_score(y_test, predictions))
```

```
1.0
```

```
from sklearn.model_selection import GridSearchCV

params = {
    'criterion':  ['gini', 'entropy'],
    'max_depth':  [None, 2, 4, 6, 8, 10],
    'max_features': [None, 'sqrt', 'log2', 0.2, 0.4, 0.6, 0.8],
    'splitter': ['best', 'random']
}

clf = GridSearchCV(
    estimator=DecisionTreeClassifier(),
    param_grid=params,
    cv=5,
    n_jobs=5,
    verbose=1,
)

clf.fit(x_train, y_train)
print(clf.best_params_)
```

```
Fitting 5 folds for each of 168 candidates, totalling 840 fits
{'criterion': 'gini', 'max_depth': None, 'max_features': None, 'splitter': 'best'}
```

```
clf = DecisionTreeClassifier(criterion='gini', splitter='best')
clf.fit(x_train, y_train)
predictions = clf.predict(x_test)

print(metrics.accuracy_score(y_test, predictions))
```

```
1.0
```

Random Forest

```
from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier(random_state=1, max_depth=2)

# your code here
n_scores = cross_val_score(clf, x, y, scoring='accuracy', cv=5)
print('Precision: %.3f (%.3f)' % (np.mean(n_scores), np.std(n_scores)))
```

```
Precision: 0.974 (0.000)
```

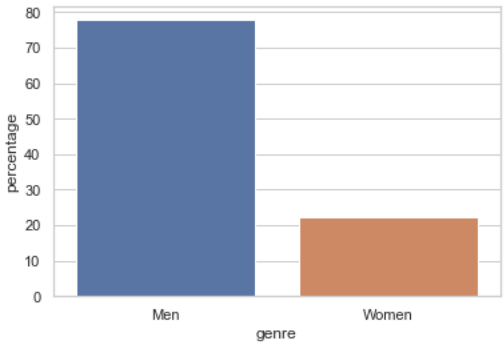
2. Visualiser et expliquer la distribution de la variable 'mortalité' selon les différentes variables (le genre des victimes, l'Age, etc)

Mortalité selon le genre des victimes

```
pct_genre = df[df['mortalite'] == 1]['sexe'].value_counts(normalize=True) * 100

sns.set_theme(style="whitegrid");
```

```
g = pd.DataFrame(columns=['percentage', 'genre'])
g['percentage'] = pct_genre
g['genre'][:1] = "Men"
g['genre'][1:2] = "Women"
sns.barplot(x="genre", y="percentage", data=g)
```

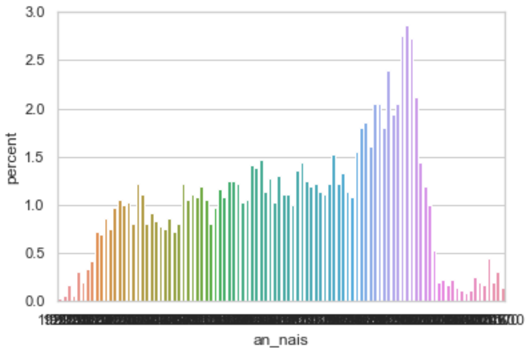
```
<AxesSubplot:xlabel='genre', ylabel='percentage'>
```



Mortalité selon l'age

```
pct_age = df_total[df['mortalite'] == 1]['an_nais'].value_counts(normalize=True) * 100
print(pct_age.to_frame())

sns.set_theme(style="whitegrid");
a = pd.DataFrame(columns=['an_nais', 'mortalite'])
a['percent'] = pct_age
a['an_nais'] = a.index
a.reset_index()
a.drop(['mortalite'], axis=1, inplace=True)
print(a.head())
sns.barplot(x="an_nais", y="percent", data=a)
```

```
         an_nais
1996.0  2.861111
1995.0  2.750000
1997.0  2.722222
1992.0  2.388889
1998.0  2.111111
...          ...
2010.0  0.111111
2009.0  0.083333
1923.0  0.055556
1921.0  0.055556
1920.0  0.027778

[98 rows x 1 columns]
        an_nais   percent
1996.0   1996.0  2.861111
1995.0   1995.0  2.750000
1997.0   1997.0  2.722222
1992.0   1992.0  2.388889
1998.0   1998.0  2.111111




<AxesSubplot:xlabel='an_nais', ylabel='percent'>
```



3. Normaliser les données et les appliquer aux modèles

```
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(df)
df_normalized = pd.DataFrame(x_scaled)
print(df.columns.tolist())
df_normalized.columns = df.columns.tolist()
df_normalized
```

```
['Num_Acc', 'place', 'catu', 'grav', 'sexe', 'trajet', 'secu', 'an_nais', 'senc', 'catv', 'obsm', 'choc', 'manv', 'mortalite']
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Num_Acc	place	catu	grav	sexe	trajet	secu	an_nais	senc	catv	obsm	choc	manv	mortalite
0	0.000000	0.000	0.000000	0.666667	0.0	1.000000	0.130435	0.524272	0.0	0.061224	0.020202	0.333333	0.36	0.0
1	0.000000	0.125	0.333333	0.666667	1.0	1.000000	0.108696	0.572816	0.0	0.091837	0.020202	0.333333	0.52	0.0
2	0.000000	0.000	0.000000	0.666667	0.0	0.111111	0.130435	0.514563	0.0	0.061224	0.000000	0.111111	0.64	0.0
3	0.000016	0.000	0.000000	0.000000	0.0	0.000000	0.108696	0.378641	0.0	0.000000	0.000000	0.777778	0.04	0.0
4	0.000016	0.000	0.000000	0.666667	0.0	0.555556	0.228261	0.446602	0.0	0.091837	0.020202	0.111111	0.04	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
136016	0.999967	0.000	0.000000	0.000000	1.0	1.000000	0.108696	0.582524	0.5	1.000000	1.000000	1.000000	1.00	0.0
136017	0.999984	0.000	0.000000	0.000000	1.0	1.000000	0.108696	0.708738	0.5	1.000000	1.000000	1.000000	1.00	0.0
136018	0.999984	0.000	0.000000	1.000000	0.0	1.000000	0.217391	0.747573	0.5	1.000000	1.000000	1.000000	1.00	0.0
136019	0.999984	0.125	0.333333	1.000000	1.0	1.000000	0.217391	0.737864	0.5	1.000000	1.000000	1.000000	1.00	0.0
136020	1.000000	0.000	0.000000	1.000000	0.0	0.111111	0.217391	0.757282	0.5	1.000000	1.000000	1.000000	1.00	0.0

136021 rows × 14 columns

Application des modèles sur les donéées normalisés

```
y = df_normalized["mortalite"]
x = df_normalized.drop('mortalite', axis=1)

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=100)
print ("train shape", x_train.shape, y_train.shape)
print ("test shape", x_test.shape, y_train.shape)
```

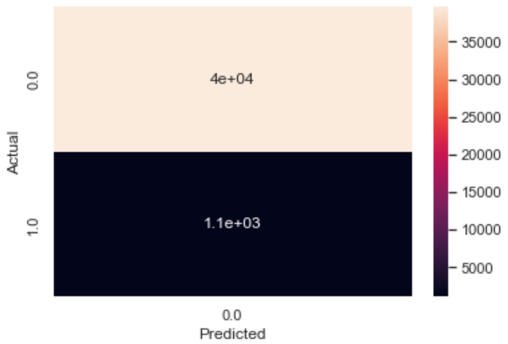
```
train shape (95214, 13) (95214,)
test shape (40807, 13) (95214,)
```

Régression Logistique

```
modele_regLog = LogisticRegression(random_state = 0, solver = 'liblinear', multi_class = 'auto')
modele_regLog.fit(x_train,y_train)
y_pred = modele_regLog.predict(x_test)
precision = modele_regLog.score(x_test,y_test)
print("Precision ")
print(precision)
```

```
Precision
0.9736074693067366
```

```
confusion_matrix = pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Predicted'])

sns.heatmap(confusion_matrix, annot=True)
plt.show()
```



Decision Tree

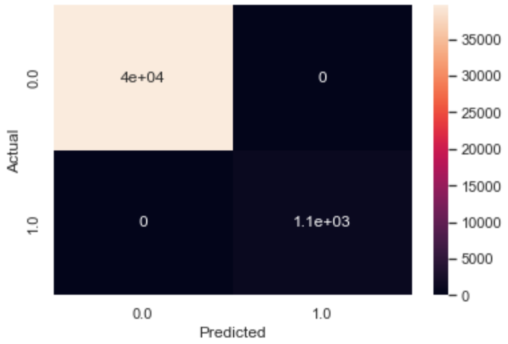
```
from sklearn.model_selection import GridSearchCV

params = {
    'criterion':  ['gini', 'entropy'],
    'max_depth':  [None, 2, 4, 6, 8, 10],
    'max_features': [None, 'sqrt', 'log2', 0.2, 0.4, 0.6, 0.8],
    'splitter': ['best', 'random']
}

clf = GridSearchCV(
    estimator=DecisionTreeClassifier(),
    param_grid=params,
    cv=5,
    n_jobs=5,
    verbose=1,
)

clf.fit(x_train, y_train)
print(clf.best_params_)
```

```
Fitting 5 folds for each of 168 candidates, totalling 840 fits
{'criterion': 'gini', 'max_depth': None, 'max_features': None, 'splitter': 'best'}
```

```
clf = DecisionTreeClassifier(criterion='gini', splitter='best')
clf.fit(x_train, y_train)
predictions = clf.predict(x_test)
print(metrics.accuracy_score(y_test, predictions))
```

```
1.0
```

```
confusion_matrix = pd.crosstab(y_test, predictions, rownames=['Actual'], colnames=['Predicted'])

sns.heatmap(confusion_matrix, annot=True)
plt.show()
```



Random Forest

```
from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier(random_state=1, max_depth=2)

n_scores = cross_val_score(clf, x, y, scoring='accuracy', cv=5)
print('Precision: %.3f (%.3f)' % (np.mean(n_scores), np.std(n_scores)))
```

```
Precision: 0.974 (0.001)
```

4. Analyser, visualiser et expliquer le niveau de corrélation entre les variables

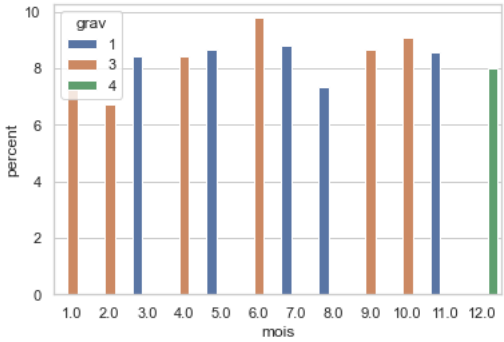
```
print(df_normalized.corr(method ='pearson')['mortalite'].sort_values(ascending=False))
```

```
mortalite    1.000000
secu         0.037220
catu         0.023449
trajet       0.020204
senc         0.001282
place       -0.005195
sexe        -0.035637
choc        -0.045022
manv        -0.049638
grav        -0.061069
obsm        -0.061198
catv        -0.061970
an_nais     -0.064513
Num_Acc     -0.093130
Name: mortalite, dtype: float64
```

5. Analyser à la base du temps : Nombre d'accidents en années, Nombre d'accidents en mois, etc

```
pct_mois = df_total['mois'].value_counts(normalize=True) * 100
mort = df_total['grav']

sns.set_theme(style="whitegrid");
d_mois = pd.DataFrame(columns=['mois', 'pct','grav'])
d_mois['percent'] = pct_mois
d_mois['mois'] = d_mois.index
d_mois['grav'] = mort
d_mois.reset_index()
d_mois.drop(['pct'], axis=1, inplace=True)
sns.barplot(x="mois", y="percent", hue="grav", data=d_mois)
```

```
<AxesSubplot:xlabel='mois', ylabel='percent'>
```



6. Trouver l'heure de la journée la plus dangereuse

```
pct_heure = df_total['hrmn'].value_counts(normalize=True) * 100
mort = df_total['grav']

sns.set_theme(style="whitegrid");
d_heure = pd.DataFrame(columns=['heure', 'pct','grav'])
d_heure['percent'] = pct_heure
d_heure['hrmn'] = d_heure.index
d_heure['grav'] = mort
d_heure.reset_index()
d_heure.drop(['pct'], axis=1, inplace=True)
sns.scatterplot(x="hrmn", y="percent", hue="grav", data=d_heure)
```

```
<AxesSubplot:xlabel='hrmn', ylabel='percent'>
```