In [ ]:

```
import pandas as pd
from google.colab import files
import numpy as np
%load_ext google.colab.data_table
import seaborn as sns
import matplotlib.pyplot as plt
```

```
The google.colab.data_table extension is already loaded. To reload it, use:
  %reload_ext google.colab.data_table
```

In [ ]:

```
uploaded = files.upload()
```

Sélect. fichiers Aucun fichier choisi Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving healthcare-dataset-stroke-data.csv to healthcare-dataset-stroke-data
(1).csv
```

In [ ]:

```
t_stroke = pd.read_csv('healthcare-dataset-stroke-data.csv')
```

Introduction

Dans notre projet, nous allons voir un domaine dans lequel le machine learning peut se réveler utile mais où il soulève également des questions éthiques : celui de la santé.

Notre but sera donc, suivant différents paramètres, de prédire le risque d'AVC chez des patients.

Pour cela, nous allons utiliser différentes méthodes et les comparer afin d'ensuite voir quel serait le meilleur choix.

Présentation de nos données

Nos données proviennent d'ici : https://www.kaggle.com/fedesoriano/stroke-prediction-dataset

Elle comprend de base plus de 5000 exemples avec 11 attributs (nous ne considèrerons pas l'id).

On cherchera donc à prédire l'étiquette 'stroke' suivant :

- Le genre
- L'âge
- L'hypertension
- Si le sujet a une maladie cardiaque
- Si il est marié
- Son secteur d'emploi
- Si il habite en milieu rural ou urbain
- Son taux de glucose
- Son indice de masse corporelle (BMI)
- Si il a fumé

Il s'agira donc d'un problème de classification binaire. (Apprentissage supervisé)

In [ ]:
```
t_stroke
```

Out[ ]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence
0	9046	Male	67.0	0	1	Yes	Private	
1	51676	Female	61.0	0	0	Yes	Self-employed	
2	31112	Male	80.0	0	1	Yes	Private	
3	60182	Female	49.0	0	0	Yes	Private	
4	1665	Female	79.0	1	0	Yes	Self-employed	
...	...	...	...	...	...	...	...	
5105	18234	Female	80.0	1	0	Yes	Private	
5106	44873	Female	81.0	0	0	Yes	Self-employed	
5107	19723	Female	35.0	0	0	Yes	Self-employed	
5108	37544	Male	51.0	0	0	Yes	Private	
5109	44679	Female	44.0	0	0	Yes	Govt_job	

5110 rows × 12 columns

In [ ]:
```
t_stroke = pd.concat([t_stroke.iloc[:249],t_stroke], ignore_index=True)
t_stroke = pd.concat([t_stroke.iloc[:249],t_stroke], ignore_index=True)
t_stroke = pd.concat([t_stroke.iloc[:249],t_stroke], ignore_index=True)
```

In [ ]:
```
t_stroke['stroke'].value_counts()
```

Out[ ]:
```
0    4861
1     996
Name: stroke, dtype: int64
```

In [ ]:
```
t_stroke['smoking_status'] = t_stroke['smoking_status'].apply(lambda x: np.Na
```

In [ ]:
```
t_stroke.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5857 entries, 0 to 5856
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5857 non-null   int64  
 1   gender             5857 non-null   object 
 2   age                5857 non-null   float64
 3   hypertension       5857 non-null   int64  
 4   heart_disease      5857 non-null   int64  
 5   ever_married       5857 non-null   object 
 6   work_type          5857 non-null   object 
 7   Residence_type     5857 non-null   object 
```

```
 8   avg_glucose_level  5857 non-null   float64
 9   bmi                5536 non-null   float64
 10  smoking_status     4172 non-null   object
 11  stroke             5857 non-null   int64
dtypes: float64(3), int64(4), object(5)
memory usage: 549.2+ KB
```

In [ ]:

```
t_stroke.isnull()
```

Out[ ]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_
0	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	
5852	False	False	False	False	False	False	False	
5853	False	False	False	False	False	False	False	
5854	False	False	False	False	False	False	False	
5855	False	False	False	False	False	False	False	
5856	False	False	False	False	False	False	False	

5857 rows × 12 columns

In [ ]:

```
t_stroke.isnull().sum()
```

Out[ ]:

```
id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  321
smoking_status      1685
stroke                 0
dtype: int64
```

On supprime les lignes avec données manquantes, on reste tout de même sur un dataset assez fourni

In [ ]:

```
t_stroke.dropna(inplace=True)
t_stroke.isnull().sum()
```

Out[ ]:

```
id                0
gender            0
age               0
hypertension      0
heart_disease     0
ever_married      0
work_type         0
```

```
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

On crée ensuite des groupes d'âges par décénies

In [ ]:

```
age_labels = ['0-9', '10-19', '20-29', '30-39', '40-49', '50-59', '60-69', '7
t_stroke['Age_group'] = pd.cut(t_stroke.age, range(0, 91, 10), right=False, l
t_stroke.head(20)
```

Out[ ]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_ty
0	9046	Male	67.0	0	1	Yes	Private	Ur
2	31112	Male	80.0	0	1	Yes	Private	Ru
3	60182	Female	49.0	0	0	Yes	Private	Ur
4	1665	Female	79.0	1	0	Yes	Self-employed	Ru
5	56669	Male	81.0	0	0	Yes	Private	Ur
6	53882	Male	74.0	1	1	Yes	Private	Ru
7	10434	Female	69.0	0	0	No	Private	Ur
10	12109	Female	81.0	1	0	Yes	Private	Ru
11	12095	Female	61.0	0	1	Yes	Govt_job	Ru
12	12175	Female	54.0	0	0	Yes	Private	Ur
14	5317	Female	79.0	0	1	Yes	Private	Ur
15	58202	Female	50.0	1	0	Yes	Self-employed	Ru
16	56112	Male	64.0	0	1	Yes	Private	Ur
17	34120	Male	75.0	1	0	Yes	Private	Ur
18	27458	Female	60.0	0	0	No	Private	Ur
20	70630	Female	71.0	0	0	Yes	Govt_job	Ru
21	13861	Female	52.0	1	0	Yes	Self-employed	Ur
22	68794	Female	79.0	0	0	Yes	Self-employed	Ur
24	4219	Male	71.0	0	0	Yes	Private	Ur
25	70822	Male	80.0	0	0	Yes	Self-employed	Ru

In [ ]:

```
t_stroke.Age_group.value_counts()
```

Out[ ]:

```
50-59    759
70-79    609
60-69    590
40-49    590
30-39    515
20-29    423
80-89    251
```

```
10-19     229
0-9         0
Name: Age_group, dtype: int64
```

In [ ]:

```
t_stroke = t_stroke.drop(columns=['age'])
```

On transforme les attributs (comme par exemple le type d'emploi) en valeur numérique.

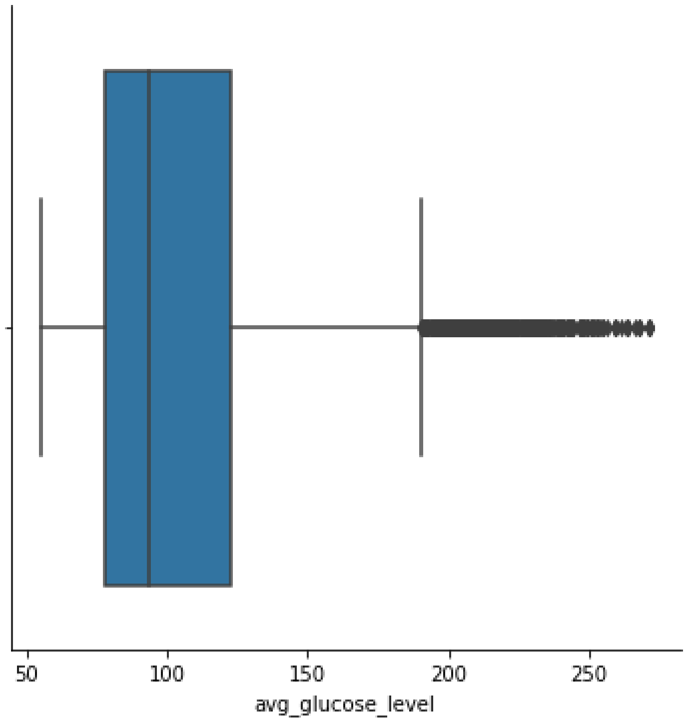
In [ ]:

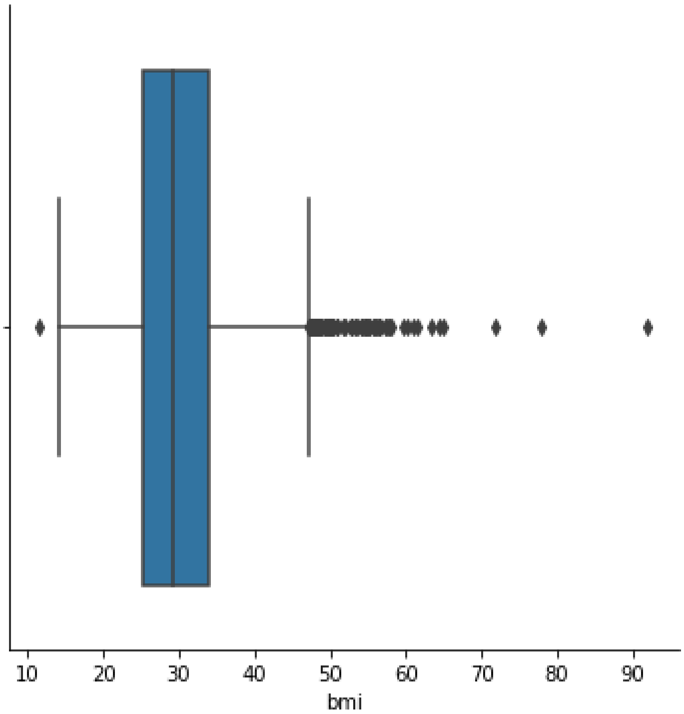
```
from sklearn.preprocessing import OrdinalEncoder
enc = OrdinalEncoder()
list_cat = ["gender","ever_married","work_type","Residence_type","smoking_sta
for el_cat in list_cat:
  t_stroke[el_cat] = enc.fit_transform(t_stroke[[el_cat]])
```

In [ ]:

```
PA = sns.factorplot(data = t_stroke , x = 'avg_glucose_level' , kind = 'box')
PA = sns.factorplot(data = t_stroke , x = 'bmi' , kind = 'box')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3714: UserWarnin
g: The `factorplot` function has been renamed to `catplot`. The original name
will be removed in a future release. Please update your code. Note that the de
fault `kind` in `factorplot` (`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3714: UserWarnin
g: The `factorplot` function has been renamed to `catplot`. The original name
will be removed in a future release. Please update your code. Note that the de
fault `kind` in `factorplot` (`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)
```





In [ ]:

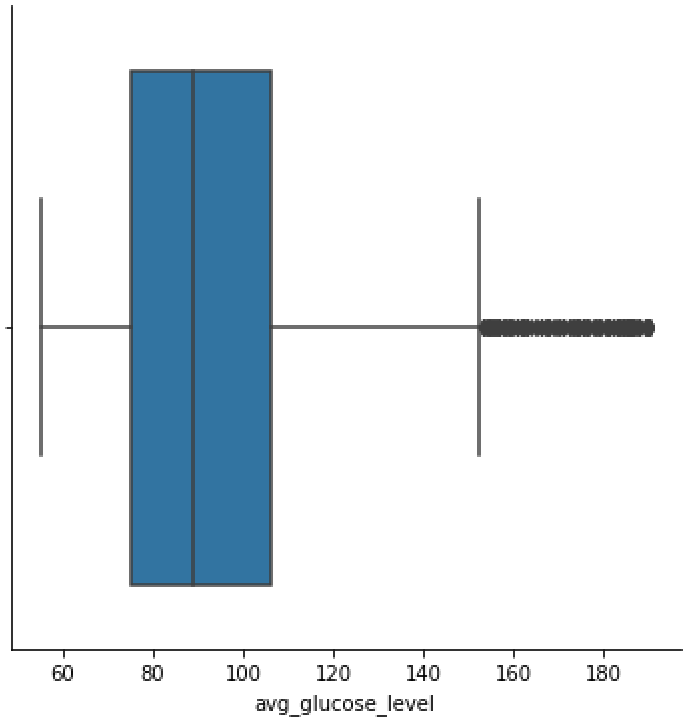
```
from collections import Counter
def detect_outliers(df,n,features):
    """
    Takes a dataframe df of features and returns a list of the indices
    corresponding to the observations containing more than n outliers accordi
    to the Tukey method.
    """
    outlier_indices = []

    # iterate over features(columns)
    for col in features:

        # 1st quartile (25%)
        Q1 = np.percentile(df[col], 25)

        # 3rd quartile (75%)
        Q3 = np.percentile(df[col],75)

        # Interquartile range (IQR)
        IQR = Q3 - Q1

        # outlier step
        outlier_step = 1.5 * IQR

        # Determine a list of indices of outliers for feature col
        outlier_list_col = df[(df[col] < Q1 - outlier_step) |
                              (df[col] > Q3 + outlier_step )].index
        # append the found outlier indices for col to the list of outlier ind
        outlier_indices.extend(outlier_list_col)
        #print(outlier_list_col)


    # select observations containing more than 2 outliers
    outlier_indices = Counter(outlier_indices)

    multiple_outliers = list( k for k, v in outlier_indices.items() if v > n
    return multiple_outliers

Outliers_to_drop = detect_outliers(t_stroke,0,["avg_glucose_level"])
t_stroke.drop(Outliers_to_drop, inplace=True)
```

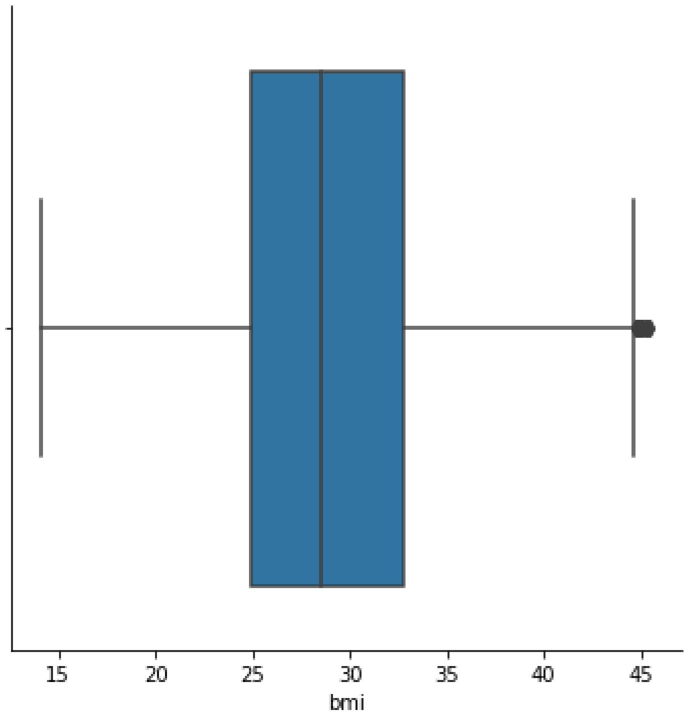
```
Outliers_to_drop = detect_outliers(t_stroke,0,["bmi"])
t_stroke.drop(Outliers_to_drop, inplace=True)
```

In [ ]:

```
PA = sns.factorplot(data = t_stroke , x = 'avg_glucose_level' , kind = 'box')
PA = sns.factorplot(data = t_stroke , x = 'bmi' , kind = 'box')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3714: UserWarnin
g: The `factorplot` function has been renamed to `catplot`. The original name
will be removed in a future release. Please update your code. Note that the de
fault `kind` in `factorplot` (`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:3714: UserWarnin
g: The `factorplot` function has been renamed to `catplot`. The original name
will be removed in a future release. Please update your code. Note that the de
fault `kind` in `factorplot` (`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)
```





In [ ]:

```
t_stroke
```

Out[ ]:

	id	gender	hypertension	heart_disease	ever_married	work_type	Residence_type
2	31112	1.0	0	1	1.0	2.0	0.0
3	60182	0.0	0	0	1.0	2.0	1.0
4	1665	0.0	1	0	1.0	3.0	0.0
5	56669	1.0	0	0	1.0	2.0	1.0
6	53882	1.0	1	1	1.0	2.0	0.0
...	...	...	...	...	...	...	...
5847	68398	1.0	1	0	1.0	3.0	0.0
5849	45010	0.0	0	0	1.0	2.0	0.0
5853	44873	0.0	0	0	1.0	3.0	1.0
5854	19723	0.0	0	0	1.0	3.0	0.0
5855	37544	1.0	0	0	1.0	2.0	0.0

3315 rows × 12 columns

In [ ]:

```
from sklearn.preprocessing import StandardScaler
numericals_list = ['avg_glucose_level']
for column in numericals_list:
    sc = StandardScaler(with_mean=True, with_std=True)
    sc.fit(t_stroke[column].values.reshape(-1,1))
    t_stroke[column] = sc.transform(t_stroke[column].values.reshape(-1,1))
numericals_list = ['bmi']
for column in numericals_list:
    sc = StandardScaler(with_mean=True, with_std=True)
    sc.fit(t_stroke[column].values.reshape(-1,1))
    t_stroke[column] = sc.transform(t_stroke[column].values.reshape(-1,1))
```

In [ ]:

```
t_stroke
```

Out[ ]:

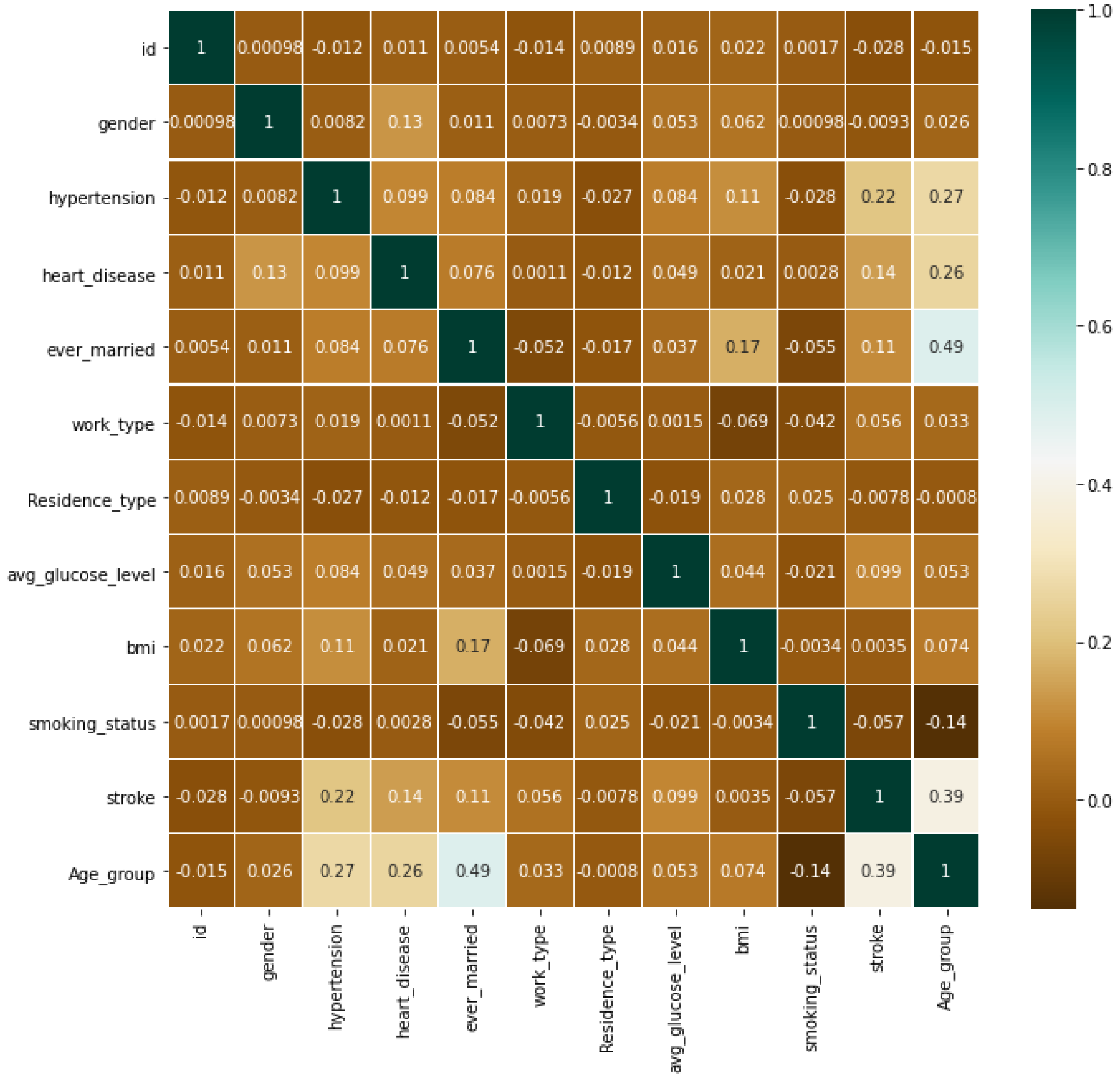
	id	gender	hypertension	heart_disease	ever_married	work_type	Residence_type
2	31112	1.0	0	1	1.0	2.0	0.0
3	60182	0.0	0	0	1.0	2.0	1.0
4	1665	0.0	1	0	1.0	3.0	0.0
5	56669	1.0	0	0	1.0	2.0	1.0
6	53882	1.0	1	1	1.0	2.0	0.0
...	...	...	...	...	...	...	...
5847	68398	1.0	1	0	1.0	3.0	0.0
5849	45010	0.0	0	0	1.0	2.0	0.0
5853	44873	0.0	0	0	1.0	3.0	1.0
5854	19723	0.0	0	0	1.0	3.0	0.0
5855	37544	1.0	0	0	1.0	2.0	0.0

3315 rows × 12 columns

In [ ]:

```
corr_matrix = t_stroke.corr()
plt.figure(figsize=(11, 10))
sns.heatmap(data = corr_matrix,cmap='BrBG', annot=True, linewidths=0.2)
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc0e5caaf10>



Pas de corrélation très importante entre les variables, il n'est pas nécessaire de faire une ACP.

In [ ]:

```
from sklearn.utils import shuffle
t_stroke = shuffle(t_stroke, n_samples=2883)
frames1 = []
frames2 = []
frames1.append(t_stroke.iloc[:3200])
frames2.append(t_stroke.iloc[3200:])
train_stroke = pd.concat(frames1)
test_stroke = pd.concat(frames2)
```

In [ ]:

```
X_train = train_stroke.drop(['stroke'],axis=1)
X_train = X_train.drop(['id'],axis=1)
y_train = train_stroke['stroke']
X_test = test_stroke.drop(['stroke'],axis=1)
```

```
X_test = X_test.drop(['id'],axis=1)
y_test = test_stroke['stroke']
```

In [ ]:

```
from sklearn.model_selection import train_test_split
X = t_stroke.drop(['stroke','id'], axis = 1)
Y = t_stroke['stroke']

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

In [ ]:

```
y_test.value_counts()
```

Out[ ]:

```
0    715
1    150
Name: stroke, dtype: int64
```

Régression logistique

Le premier choix de méthodes est une régression logistique

In [ ]:

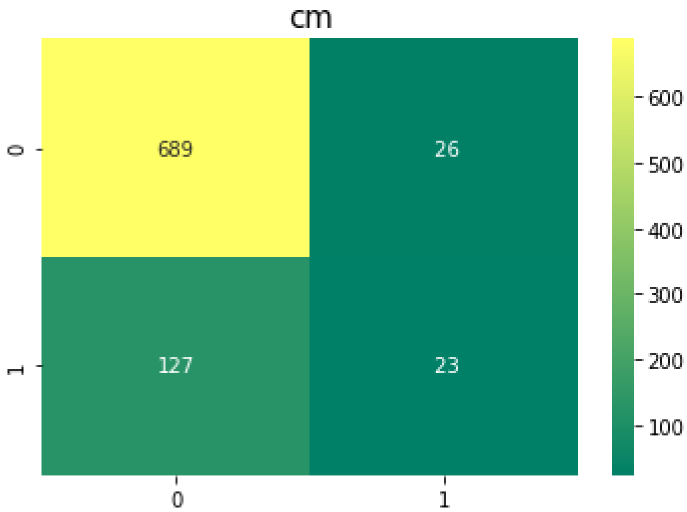
```
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)

d = logmodel.decision_function(X_test)
```

In [ ]:

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

y_pred_log = logmodel.predict(X_test)
cm = confusion_matrix(y_test,y_pred_log)
sns.heatmap(confusion_matrix(y_test,y_pred_log),annot=True,fmt='3.0f',cmap="s
plt.title('cm', y=1.05, size=15)
cm
```

Out[ ]:

```
array([[689,  26],
       [127,  23]])
```



In [ ]:

```
print(logmodel.score(X_test,y_test))
```

```
0.823121387283237
```

In [ ]:
```
print(logmodel.score(X_train,y_train))
```

```
0.8562933597621407
```

In [ ]:
```
from sklearn.model_selection import cross_validate
scores_logmodel = cross_validate(logmodel, X_train, y_train, cv=3, scoring=('
print(scores_logmodel)

print("score moyen :" + str(scores_logmodel['test_accuracy'].mean()))
print("vitesse moyenne fit_time : " + str(scores_logmodel['fit_time'].mean())
```

```
{'fit_time': array([0.02992392, 0.02305341, 0.02017617]), 'score_time': array
([0.00785208, 0.0076189 , 0.00747609]), 'test_accuracy': array([0.84992571, 0.
85586924, 0.86309524]), 'test_precision': array([0.47368421, 0.53846154, 0.575
]), 'test_recall': array([0.18181818, 0.14141414, 0.23469388]), 'test_roc_au
c': array([0.78643579, 0.83602576, 0.83723245])}
score moyen :0.8562967286964316
vitesse moyenne fit_time : 0.024384498596191406
```

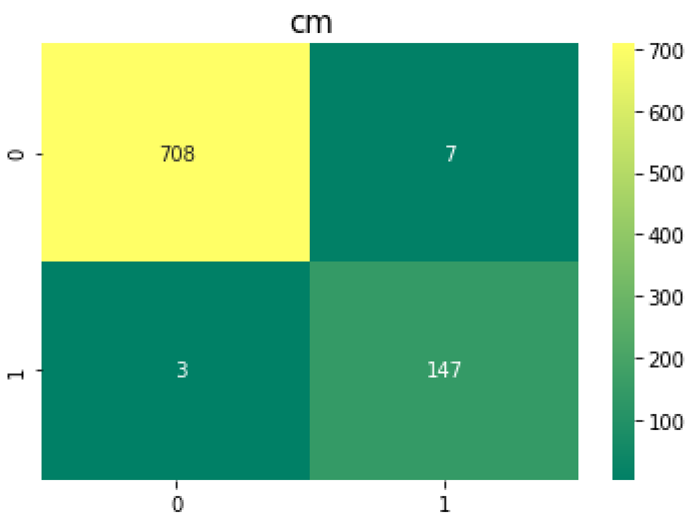
Random Forest

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators = 50, random_state = 2020, max_depth=
rf.fit(X_train,y_train)
y_test_pred = rf.predict(X_test)
print(rf.score(X_train,y_train))
print(rf.score(X_test,y_test))
```

```
1.0
0.9884393063583815
```

In [ ]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns

y_pred = rf.predict(X_test)
cm = confusion_matrix(y_test,y_pred)
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,fmt='3.0f',cmap="summe
plt.title('cm', y=1.05, size=15)
cm
```

Out[ ]:
```
array([[708,   7],
       [  3, 147]])
```



On va ensuite tuner les hyperparamètres pour avoir un modèle plus optimisé :

In [ ]:

```
from sklearn.model_selection import RandomizedSearchCV

n_estimators = [int(x) for x in np.linspace(start = 20, stop = 200, num = 10)
print(n_estimators)
```

```
[20, 40, 60, 80, 100, 120, 140, 160, 180, 200]
```

In [ ]:

```
max_depth = [int(x) for x in np.linspace(20, 100, num = 5)]
print(max_depth)
```

```
[20, 40, 60, 80, 100]
```

In [ ]:

```
random_grid = { 'n_estimators': n_estimators, 'max_depth' : max_depth}
```

In [ ]:

```
from sklearn.model_selection import RandomizedSearchCV
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_g
rf_random.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 50 candidates, totalling 150 fits
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_search.py:281:
UserWarning: The total space of parameters 50 is smaller than n_iter=100. Runn
ing 50 iterations. For exhaustive searches, use GridSearchCV.
  % (grid_size, self.n_iter, grid_size), UserWarning)
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:    8.2s
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed:   33.5s finished
```

Out[ ]:

```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=RandomForestClassifier(bootstrap=True,
                                                    ccp_alpha=0.0,
                                                    class_weight=None,
                                                    criterion='gini',
                                                    max_depth=20,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=
0.0,
                                                    n_estimators=50,
                                                    n_jobs=None,
                                                    oob_score=False,
                                                    random_state=2020,
                                                    verbose=0,
                                                    warm_start=False),
                   iid='deprecated', n_iter=100, n_jobs=-1,
                   param_distributions={'max_depth': [20, 40, 60, 80, 100],
                                        'n_estimators': [20, 40, 60, 80, 100,
                                                         120, 140, 160, 180,
                                                         200]},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring=None, verbose=2)
```

In [ ]:

```
print(rf_random.best_params_)
```

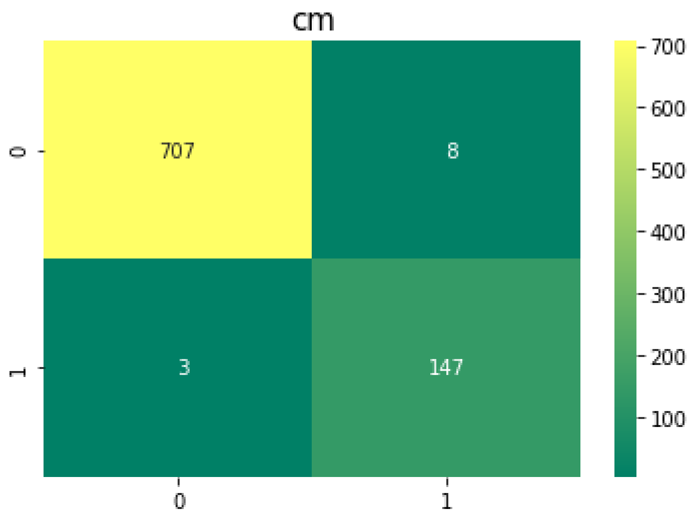
```
{'n_estimators': 160, 'max_depth': 20}
```

In [ ]:
```
rf = RandomForestClassifier(n_estimators = 160, random_state = 2020, max_dept
rf.fit(X_train,y_train)
y_pred = rf.predict(X_test)
print(rf.score(X_train,y_train))
print(rf.score(X_test,y_test))
```

```
1.0
0.9872832369942196
```

In [ ]:
```
cm = confusion_matrix(y_test,y_pred)
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,fmt='3.0f',cmap="summe
plt.title('cm', y=1.05, size=15)
cm
```

Out[ ]:
```
array([[707,   8],
       [  3, 147]])
```



In [ ]:
```
scores_rf = cross_validate(rf, X_train, y_train, cv=3, scoring=('accuracy','p
print(scores_rf)

print("Le score moyen est :" + str(scores_rf['test_accuracy'].mean()))
print("La vitesse moyenne fit_time : " + str(scores_rf['fit_time'].mean()))
```

```
{'fit_time': array([0.33340549, 0.34816742, 0.31178093]), 'score_time': array
([0.05432034, 0.05467868, 0.05903864]), 'test_accuracy': array([0.95393759, 0.
94205052, 0.94791667]), 'test_precision': array([0.88636364, 0.875     , 0.838
70968]), 'test_recall': array([0.78787879, 0.70707071, 0.79591837]), 'test_roc
_auc': array([0.93446662, 0.91918312, 0.94100654])}
Le score moyen est :0.9479682598646194
La vitesse moyenne fit_time : 0.3311179478963216
```

Conclusion

In [ ]:
```
from sklearn.metrics import roc_curve, auc, plot_roc_curve

logistic_fpr, logistic_tpr, threshold = roc_curve(y_test, d)
auc_logistic = auc(logistic_fpr, logistic_tpr)




plt.figure(figsize = (5,5), dpi = 100)
```

```
plt.plot(logistic_fpr,logistic_tpr, linestyle = "-", label="Log"%auc_logistic

plt.ylabel("taux vrai positif")
plt.xlabel("taux faux positif")

plot_roc_curve(rf, X_test, y_test)

plt.show()
```