```
import numpy as np
import spicy
import matplotlib as plt
import os
import pandas as pd
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score,confusion_matrix
from joblib import dump, load
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.inspection import permutation_importance
from joblib import load
from sklearn.compose import ColumnTransformer
from sklearn.utils import shuffle
from sklearn.pipeline import Pipeline
from sklearn.svm import SVC
from sklearn import tree
from sklearn.preprocessing import RobustScaler,OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix
```

```
dataset_name: str ="/data/notebook_files/acsincome_ca_features.csv"
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "/data/notebook_files/acsincome_ca_labels.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)


X_all, y_all = shuffle(X_all, y_all, random_state=1)
# only use the first N samples to limit training time
num_samples = int(len(X_all)*1)
X, y = X_all[:num_samples], y_all[:num_samples]
```

```
Dataset directory: /data/notebook_files/acsincome_ca_features.csv
```

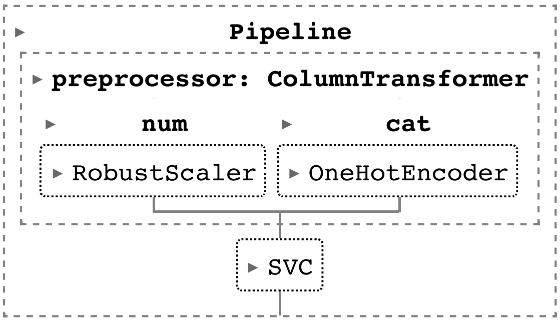
```
from sklearn.pipeline import Pipeline
from sklearn.svm import SVC
from sklearn import tree
from sklearn.preprocessing import RobustScaler,OneHotEncoder
from sklearn.compose import ColumnTransformer
from gensim.models import Word2Vec
import gensim
from sklearn.feature_extraction.text import CountVectorizer
from nltk.tokenize import word_tokenize
import nltk

numeric_feature = ["AGEP", "WKHP"]
categorical_features = ["COW", "SCHL", "MAR", "OCCP", "POBP", "RELP", "S


preprocessor = ColumnTransformer(transformers=[('num', RobustScaler(), n
                                               ('cat', OneHotEncoder(han
                                               ])




modelSVM = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', SVC())
])
modelSVM
```



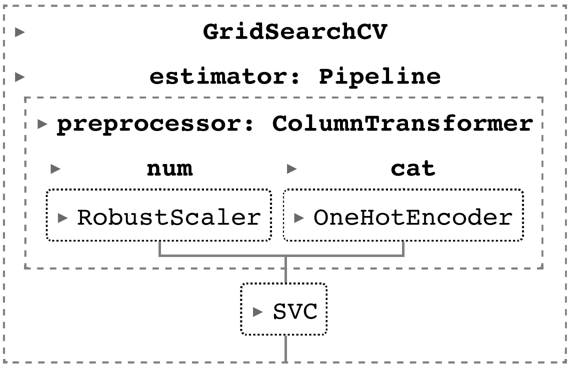

```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score



param_grid_SVM = {
    'classifier__C' : [0.01,0.1,1,10,100],
    'classifier__kernel' : ["linear", "poly", "rbf", "sigmoid"],
    'classifier__shrinking' : [True, False]
```

```
}

grid_SVM = GridSearchCV(modelSVM,param_grid_SVM,cv=5, verbose=2)
grid_SVM
```




```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix

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

```
model_SVM = load('/data/notebook_files/model_SVM.joblib')
predict = model_SVM.predict(X_test)
accuracy_score_svc = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test: ", accuracy_score_svc)
confusion_matrix_svc = confusion_matrix(y_test,predict)
print(confusion_matrix_svc)
print(classification_report(y_test["PINCP"], predict, labels=[0,1]))
print(classification_report(y_test["PINCP"], predict))
```

```
Accuracy test:  0.7846678023850086
[[28347  6253]
 [ 6387 17713]]
              precision    recall  f1-score   support

           0       0.82      0.82      0.82     34600
           1       0.74      0.73      0.74     24100

    accuracy                           0.78     58700
   macro avg       0.78      0.78      0.78     58700
weighted avg       0.78      0.78      0.78     58700

              precision    recall  f1-score   support
```

```
       False       0.82      0.82      0.82     34600
        True       0.74      0.73      0.74     24100

    accuracy                           0.78     58700
   macro avg       0.78      0.78      0.78     58700
```

```
dataset_name: str ="/data/notebook_files/acsincome_co_allfeaturesTP2.csv
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "acsincome_co_labelTP2.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)


model_SVM = load('model_SVM.joblib')
predict = model_SVM.predict(X_all)
accuracy_score_svc_co = accuracy_score(y_all["PINCP"], predict)
print("Accuracy test on colorado: ", accuracy_score_svc_co)
```

```
Dataset directory: /data/notebook_files/acsincome_co_allfeaturesTP2.cs
Accuracy test on colorado:  0.7517089375838497
```

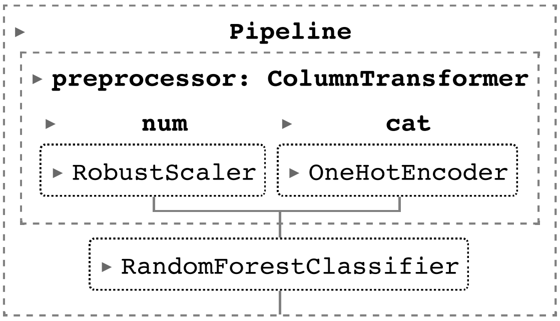
```
dataset_name: str ="/data/notebook_files/acsincome_ne_allfeaturesTP2.csv
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "acsincome_ne_labelTP2.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)


model_SVM = load('/data/notebook_files/model_SVM.joblib')
predict = model_SVM.predict(X_all)
accuracy_score_svc_ne = accuracy_score(y_all["PINCP"], predict)
print("Accuracy test on nevada: ", accuracy_score_svc_ne)
```

```
Dataset directory: /data/notebook_files/acsincome_ne_allfeaturesTP2.cs
Accuracy test on nevada:  0.7399165507649513
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
modelRF = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier())
])
modelRF
```




```
import numpy as np
param_grid_RF = {
    'classifier__max_depth' : np.arange(1,1501,300),
    'classifier__criterion' : ["gini","entropy","log_loss"],
    'classifier__min_samples_leaf' : np.arange(1,16,2),
    'classifier__min_samples_split': np.arange(2,16,2)
}

grid_RF = GridSearchCV(modelRF,param_grid_RF,cv=5, verbose=2)

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

grid_RF.fit(X_train, y_train["PINCP"])

predict = grid_RF.predict(X_test)
accuracy_score_rf = accuracy_score(y_test["PINCP"], predict)
print("Score training: ", grid_RF.best_score_)
print("Accuracy test: ", accuracy_score_rf)
print("Best parameters : ", grid_RF.best_params_)

best_model = grid_RF.best_estimator_
dump(best_model, '/data/notebook_files/model_RF.joblib')
```

```
NameError: name 'modelRF' is not defined
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
model_RF = load("/data/notebook_files/model_RF.joblib")
predict = model_RF.predict(X_test)
accuracy_score_rf = accuracy_score(y_test["PINCP"], predict)
```

```
print("Accuracy test: ", accuracy_score_rf)
confusion_matrix_rf = confusion_matrix(y_test,predict)
print(confusion_matrix_rf)
print(classification_report(y_test["PINCP"], predict, labels=[0,1]))
```

```
Accuracy test:  0.7910391822827939
[[29803  4809]
 [ 7457 16631]]
              precision    recall  f1-score   support

           0       0.80      0.86      0.83     34612
           1       0.78      0.69      0.73     24088

    accuracy                           0.79     58700
   macro avg       0.79      0.78      0.78     58700
weighted avg       0.79      0.79      0.79     58700
```

```
dataset_name: str ="/data/notebook_files/acsincome_co_allfeaturesTP2.csv
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "/data/notebook_files/acsincome_co_labelTP2.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)


model_RF = load('/data/notebook_files/model_RF.joblib')
predict = model_RF.predict(X_all)
accuracy_score_rf_co = accuracy_score(y_all["PINCP"], predict)
print("Accuracy test on colorado: ", accuracy_score_rf_co)
```

```
Dataset directory: /data/notebook_files/acsincome_co_allfeaturesTP2.cs
Accuracy test on colorado:  0.7633041589471666
```

```
dataset_name: str ="/data/notebook_files/acsincome_ne_allfeaturesTP2.csv
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "/data/notebook_files/acsincome_ne_labelTP2.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)

print(classification_report(y_test["PINCP"], predict, labels=[0,1]))
```

```
model_RF = load('/data/notebook_files/model_RF.joblib')
predict = model_RF.predict(X_all)
accuracy_score_rf_ne = accuracy_score(y_all["PINCP"], predict)
print("Accuracy test on nevada: ", accuracy_score_rf_ne)
```

```
Dataset directory: /data/notebook_files/acsincome_ne_allfeaturesTP2.cs
              precision    recall  f1-score   support

           0       0.81      0.84      0.82     34612
           1       0.76      0.72      0.74     24088

    accuracy                           0.79     58700
   macro avg       0.78      0.78      0.78     58700
weighted avg       0.79      0.79      0.79     58700

Accuracy test on nevada:  0.7523412146499768
```

```
from sklearn.ensemble import AdaBoostClassifier



modelADA = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', AdaBoostClassifier())
])

modelADA
```

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression

param_grid_ADA = {
    'classifier__n_estimators' : np.arange(1,91,30),
    'classifier__learning_rate' : np.arange(0,3, 1),
    'classifier__algorithm' : ['SAMME', 'SAMME.R'],
    'classifier__estimator' : [SVC(), RandomForestClassifier(), KNeighbo
}

grid_ADA = GridSearchCV(modelADA,param_grid_ADA,cv=5, verbose=2)


grid_ADA.fit(X_train, y_train["PINCP"])
```

```
best_model = grid_RF.best_estimator_
dump(best_model, '/data/notebook_files/model_ADA.joblib')
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression

model_ADA = load("/data/notebook_files/model_ADA.joblib")
predict = model_ADA.predict(X_test)
accuracy_score_ada = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test: ", accuracy_score_ada)
confusion_matrix_ada = confusion_matrix(y_test,predict)
print(confusion_matrix_ada)
print(classification_report(y_test["PINCP"], predict, labels=[0,1]))
```

```
Accuracy test:  0.778756388415673
[[29114  5498]
 [ 7489 16599]]
              precision    recall  f1-score   support

           0       0.80      0.84      0.82     34612
           1       0.75      0.69      0.72     24088

    accuracy                           0.78     58700
   macro avg       0.77      0.77      0.77     58700
weighted avg       0.78      0.78      0.78     58700
```

```
dataset_name: str ="/data/notebook_files/acsincome_co_allfeaturesTP2.csv
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "/data/notebook_files/acsincome_co_labelTP2.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)


model_ADA = load('/data/notebook_files/model_ADA.joblib')
predict = model_ADA.predict(X_all)
accuracy_score_ada_co = accuracy_score(y_all["PINCP"], predict)
print("Accuracy test on colorado: ", accuracy_score_ada_co)
```

```
Dataset directory: /data/notebook_files/acsincome_co_allfeaturesTP2.cs
Accuracy test on colorado:  0.7534019037884112
```

```
dataset_name: str ="/data/notebook_files/acsincome_ne_allfeaturesTP2.csv
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "/data/notebook_files/acsincome_ne_labelTP2.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)


model_ADA = load('/data/notebook_files/model_ADA.joblib')
predict = model_ADA.predict(X_all)
accuracy_score_ada_ne = accuracy_score(y_all["PINCP"], predict)
print("Accuracy test on nevada: ", accuracy_score_ada_ne)
```

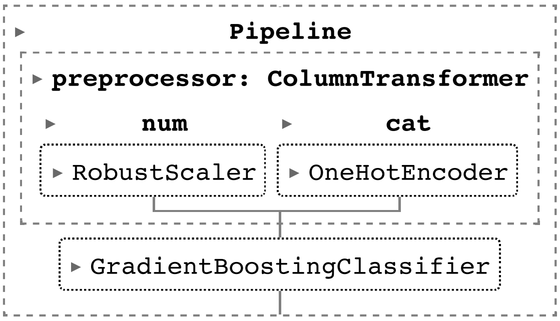
```
Dataset directory: /data/notebook_files/acsincome_ne_allfeaturesTP2.cs
Accuracy test on nevada:  0.7387111729253593
```

```
from sklearn.ensemble import GradientBoostingClassifier



modelGBC = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', GradientBoostingClassifier())
])

modelGBC
```




```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression


param_grid_GBC = {
    'classifier__n_estimators' : np.arange(1,401,50),
```

```
    'classifier__learning_rate' : np.arange(0.0,2.0, 0.2),
    'classifier__min_samples_split' : np.arange(2,22, 5),
    'classifier__criterion' : ['friedman_mse', 'squared_error']
}

grid_GBC = GridSearchCV(modelGBC,param_grid_GBC,cv=5, verbose=2)


grid_GBC.fit(X_train, y_train["PINCP"])

predict = grid_GBC.predict(X_test)
accuracy_score_gbc = accuracy_score(y_test["PINCP"], predict)
print("Score training: ", grid_GBC.best_score_)
print("Accuracy test: ", accuracy_score_gbc)
print("Best parameters : ", grid_GBC.best_params_)

best_model = grid_GBC.best_estimator_
dump(best_model, 'model_GBC.joblib')
```

```
model_GBC = load("/data/notebook_files/model_GBC.joblib")
predict = model_GBC.predict(X_test)
accuracy_score_gbc = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test: ", accuracy_score_gbc)
confusion_matrix_gbc = confusion_matrix(y_test,predict)
print(confusion_matrix_gbc)
print(classification_report(y_test["PINCP"], predict, labels=[0,1]))
```

```
Accuracy test:  0.7897955706984667
[[29030  5582]
 [ 6757 17331]]
              precision    recall  f1-score   support

           0       0.81      0.84      0.82     34612
           1       0.76      0.72      0.74     24088

    accuracy                           0.79     58700
   macro avg       0.78      0.78      0.78     58700
weighted avg       0.79      0.79      0.79     58700
```

```
dataset_name: str ="/data/notebook_files/acsincome_co_allfeaturesTP2.csv
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "/data/notebook_files/acsincome_co_labelTP2.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)
```

```
model_GBC = load('/data/notebook_files/model_GBC.joblib')
predict = model_GBC.predict(X_all)
accuracy_score_gbc_co = accuracy_score(y_all["PINCP"], predict)
print("Accuracy test on colorado: ", accuracy_score_gbc_co)
```

```
Dataset directory: /data/notebook_files/acsincome_co_allfeaturesTP2.cs
Accuracy test on colorado:  0.6835430907813199
```

```
dataset_name: str ="/data/notebook_files/acsincome_ne_allfeaturesTP2.csv
dataset_path: str = os.path.join(dataset_name)
print(f"Dataset directory: {dataset_path}")
X_all : pd.DataFrame = pd.read_csv(dataset_path)
output_name = "/data/notebook_files/acsincome_ne_labelTP2.csv"
output_path = os.path.join(output_name)
y_all : pd.DataFrame = pd.read_csv(output_path)


model_GBC = load('/data/notebook_files/model_GBC.joblib')
predict = model_GBC.predict(X_all)
accuracy_score_gbc_ne = accuracy_score(y_all["PINCP"], predict)
print("Accuracy test on nevada: ", accuracy_score_gbc_ne)
```

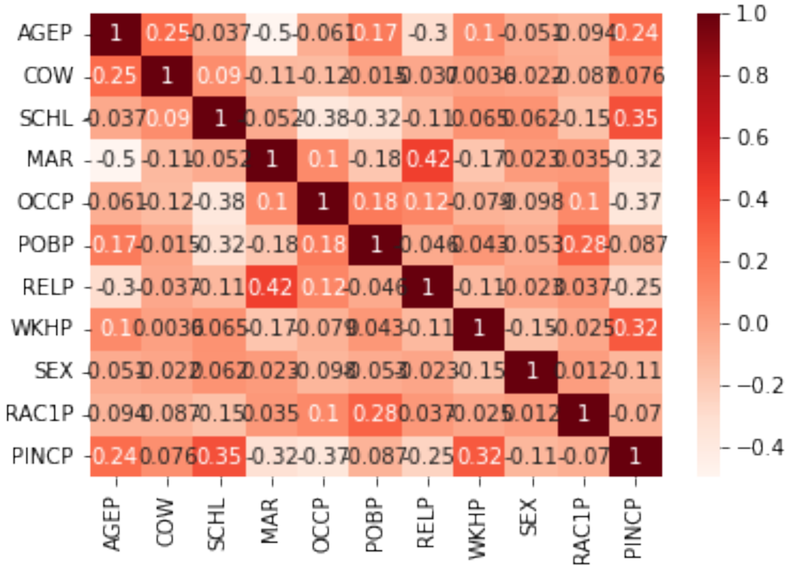
```
Dataset directory: /data/notebook_files/acsincome_ne_allfeaturesTP2.cs
Accuracy test on nevada:  0.7353732035234122
```

```
import seaborn as sns
merged_data = pd.concat([X_train, y_train], axis=1)
print(y_train.shape)
cor = merged_data.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
```

```
(1369, 1)
```

```
<Axes: >
```

Download




```
#On observe que que les features que sont le plus corrélé avec le label
#Ces features correspondent à l'occupation, leur graduation scolaire, et
```

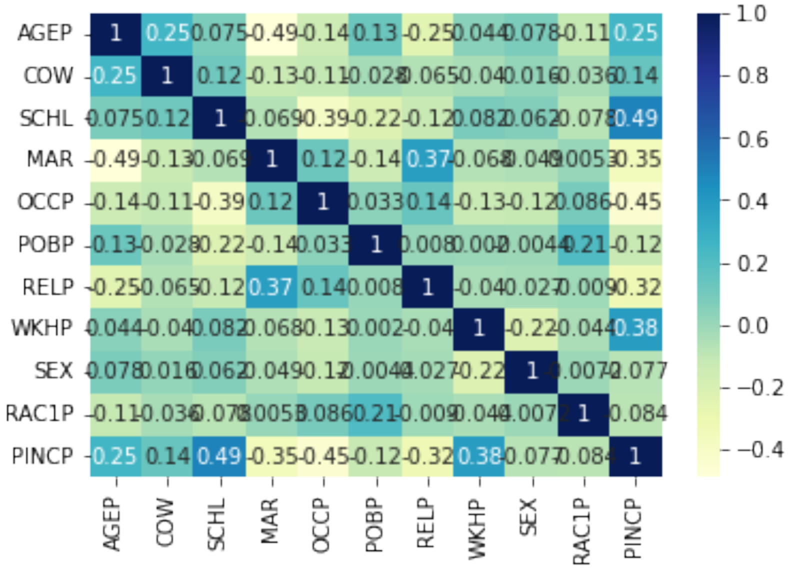
```
from joblib import load

model_SVM = load("/data/notebook_files/model_SVM.joblib")

testSVM = pd.DataFrame(X_test)
predictSVM = model_SVM.predict(X_test)
testSVM['PINCP'] = predictSVM
cor = testSVM.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.YlGnBu)
```

<Axes: >

Download



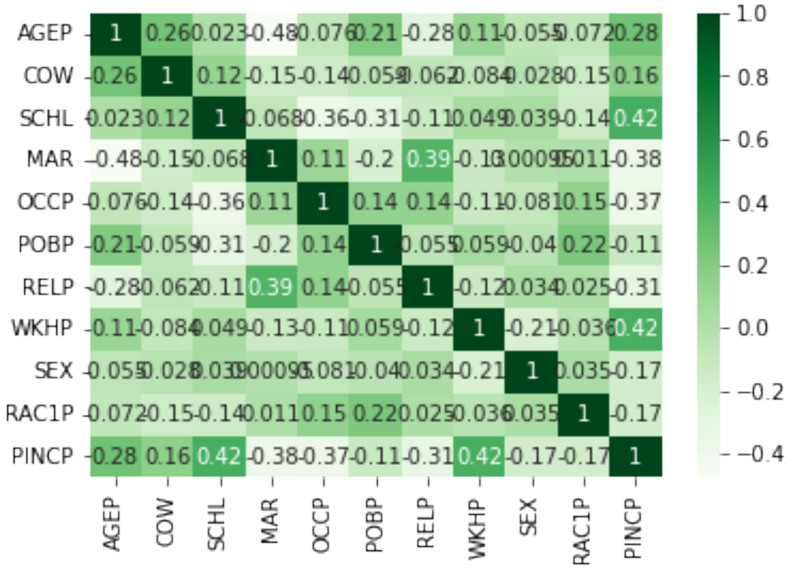

```
#On observe une similarité pour les features importantes
```

```
from joblib import load

model_ADA = load("/data/notebook_files/model_ADA.joblib")
testADA = pd.DataFrame(X_test)
predictAda = model_ADA.predict(X_test)
testADA['PINCP'] = predictAda
cor = testADA.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Greens)
```

```
<Axes: >
```

Download



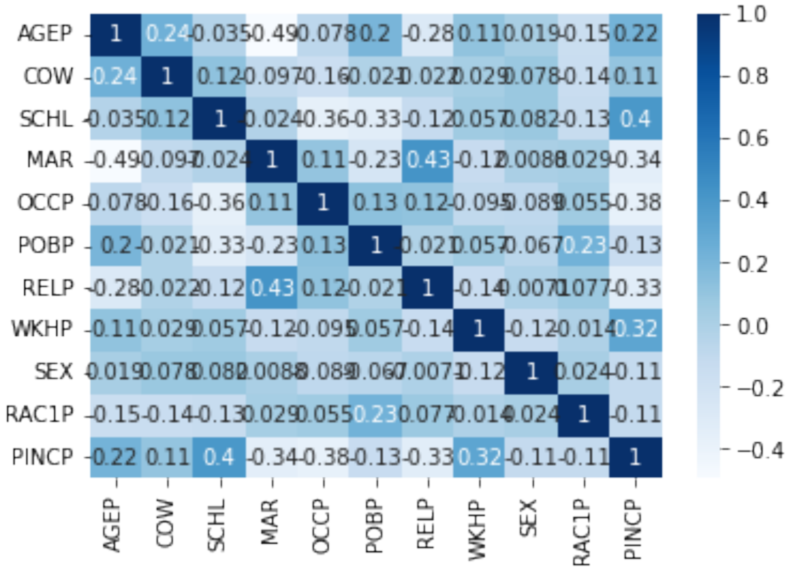

```
#Ici, on observe qye MAR a une grande importance, c'est celle correspond
```

```
model_RF = load("/data/notebook_files/model_RF.joblib")

predictRf = model_RF.predict(X_test)
testRF = pd.DataFrame(X_test)
testRF['PINCP'] = predictRf
cor = pd.DataFrame(testRF).corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Blues)
```

```
<Axes: >
```

Download



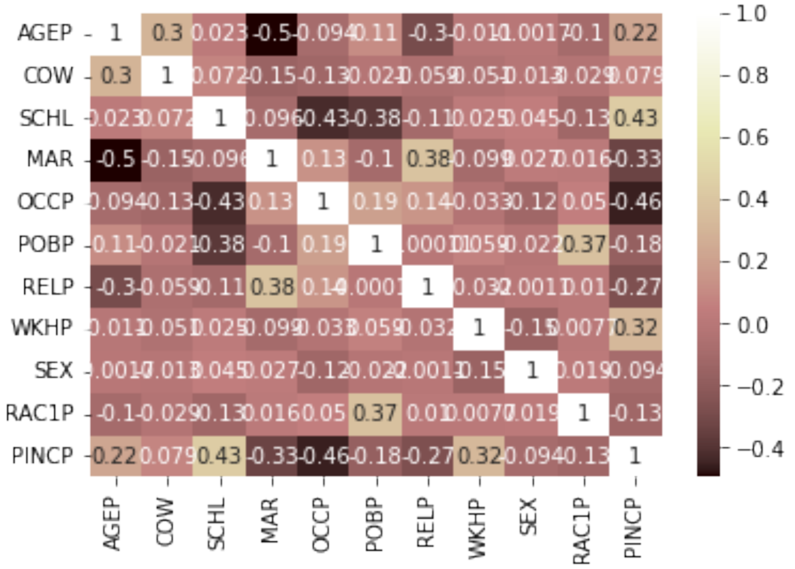
```
#Comme celle initiale
```

```
model_GBC = load("/data/notebook_files/model_GBC.joblib")

testGBC = pd.DataFrame(X_test)
predictGBC = model_GBC.predict(X_test)
pdPredictGBC = pd.DataFrame(predictGBC)
testGBC['PINCP'] = predictGBC
cor = testGBC.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.pink)
```

```
<Axes: >
```

Download




```
#Comme celle initiale
```

```
from sklearn.inspection import permutation_importance
```

```
r = permutation_importance(model_ADA, X_test, y_test,n_repeats=30,random
for i in r.importances_mean.argsort()[::-1]:
     if r.importances_mean[i] - 2 * r.importances_std[i] > 0:
         print(f"{X.columns[i]:<8}" f"{r.importances_mean[i]:.3f}" f" +/
```

```
#Ici, on observe que la feature la plus importante vient de l'éducation,
```

```
SCHL    0.074 +/- 0.013
WKHP    0.050 +/- 0.011
RELP    0.029 +/- 0.010
POBP    0.029 +/- 0.009
MAR     0.025 +/- 0.009
SEX     0.016 +/- 0.007
```

```
r = permutation_importance(model_GBC, X_test, y_test,n_repeats=30,random
for i in r.importances_mean.argsort()[::-1]:
     if r.importances_mean[i] - 2 * r.importances_std[i] > 0:
         print(f"{X.columns[i]:<8}" f"{r.importances_mean[i]:.3f}" f" +/
#Ici, le plus important semble être l'occupation, puis l'éducation.
```

```
OCCP    0.111 +/- 0.010
SCHL    0.089 +/- 0.010
WKHP    0.061 +/- 0.008
POBP    0.039 +/- 0.009
AGEP    0.027 +/- 0.008
RELP    0.024 +/- 0.005
COW     0.020 +/- 0.005
MAR     0.019 +/- 0.007
```

```
r = permutation_importance(model_RF, X_test, y_test,n_repeats=30,random_
for i in r.importances_mean.argsort()[::-1]:
     if r.importances_mean[i] - 2 * r.importances_std[i] > 0:
         print(f"{X.columns[i]:<8}" f"{r.importances_mean[i]:.3f}" f" +/
#Education, occupation, sex et race sont aussi important
```

```
SCHL    0.104 +/- 0.009
OCCP    0.064 +/- 0.005
WKHP    0.064 +/- 0.008
MAR     0.059 +/- 0.009
RELP    0.055 +/- 0.007
POBP    0.038 +/- 0.007
AGEP    0.035 +/- 0.008
SEX     0.032 +/- 0.007
RAC1P   0.024 +/- 0.007
COW     0.016 +/- 0.005
```

```
r = permutation_importance(model_SVM, X_test, y_test,n_repeats=30,random
for i in r.importances_mean.argsort()[::-1]:
     if r.importances_mean[i] - 2 * r.importances_std[i] > 0:
```

```
        print(f"{X.columns[i]:<8}" f"{r.importances_mean[i]:.3f}" f" +/
#Education beaucoup, et Taux de travail.
```

```
SCHL    0.072 +/- 0.012
WKHP    0.034 +/- 0.009
OCCP    0.028 +/- 0.008
RELP    0.023 +/- 0.009
POBP    0.020 +/- 0.007
```

```
#Equité :
```

```
model_SVM = load("/data/notebook_files/model_SVM.joblib")

def sex_confusion_matrix(model) :
    X_test_homme = X_test[X_test['SEX']==1]
    y_pred = model.predict(X_test_homme)

    y_test_homme = y_test[X_test['SEX']==1]

    conf_matrix_homme = confusion_matrix(y_test_homme, y_pred)

    print("Matrice de confusion homme : \n", conf_matrix_homme)

    X_test_femme = X_test[X_test['SEX']==2]
    y_pred = model.predict(X_test_femme)

    y_test_femme = y_test[X_test['SEX']==2]

    conf_matrix_femme = confusion_matrix(y_test_femme, y_pred)

    print("Matrice de confusion femme : \n", conf_matrix_femme)
    return conf_matrix_homme, conf_matrix_femme
```

```
model_SVM = load("/data/notebook_files/model_SVM.joblib")

sex_confusion_matrix(model_SVM)
```

```
Matrice de confusion homme :
 [[146  32]
 [ 33 117]]
Matrice de confusion femme :
 [[149  22]
```

```
 [ 22  66]]
```

```
model_ADA = load("/data/notebook_files/model_ADA.joblib")
sex_confusion_matrix(model_ADA)
```

```
Matrice de confusion homme :
 [[149  29]
 [ 35 115]]
Matrice de confusion femme :
 [[155  16]
 [ 32  56]]
```

```
model_RF = load("/data/notebook_files/model_RF.joblib")
sex_confusion_matrix(model_RF)
```

```
Matrice de confusion homme :
 [[160  18]
 [ 19 131]]
Matrice de confusion femme :
 [[160  11]
 [ 19  69]]
```

```
model_GBC = load('/data/notebook_files/model_GBC.joblib')
sex_confusion_matrix(model_GBC)
```

```
Matrice de confusion homme :
 [[158  14]
 [ 18 127]]
Matrice de confusion femme :
 [[166  11]
 [ 14  79]]
```

```
#On observe que le biais de sex est plus important pour ADA,a plus de fa
```

```
X_test['SEX'] = 1

model_GBC = load('/data/notebook_files/model_GBC.joblib')
predict = model_GBC.predict(X_test)
accuracy_score_gbc_ne = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test en disant que c'est des hommes: ", accuracy_score_g
```

```
X_test['SEX'] = 2
predict = model_GBC.predict(X_test)
accuracy_score_gbc_ne = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test en disant que c'est des femmes: ", accuracy_score_g

#Accuracy avant : 0.89437
#Score tres legerement plus faible pour les femmes
```

```
Accuracy test en disant que c'est des hommes:  0.9045996592844975
Accuracy test en disant que c'est des femmes:  0.9011925042589438
```

```
X_test['SEX'] = 1

model_SVM = load("/data/notebook_files/model_SVM.joblib")
predict = model_SVM.predict(X_test)
accuracy_score_hommes = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test en disant que c'est des hommes: ", accuracy_score_h

X_test['SEX'] = 2
predict = model_SVM.predict(X_test)
accuracy_score_femmes = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test en disant que c'est des femmes: ", accuracy_score_f

#Accuracy avant : 0.804088
```

```
Accuracy test en disant que c'est des hommes:  0.8126064735945485
Accuracy test en disant que c'est des femmes:  0.8245315161839863
```

```
X_test['SEX'] = 1

model_ADA = load("/data/notebook_files/model_ADA.joblib")
predict = model_ADA.predict(X_test)
accuracy_score_hommes = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test en disant que c'est des hommes: ", accuracy_score_h

X_test['SEX'] = 2
predict = model_ADA.predict(X_test)
accuracy_score_femmes = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test en disant que c'est des femmes: ", accuracy_score_f

#0.79557069846 avant
```

```
Accuracy test en disant que c'est des hommes:  0.7904599659284497
Accuracy test en disant que c'est des femmes:  0.8040885860306644
```

```
X_test['SEX'] = 1

model_RF = load("/data/notebook_files/model_RF.joblib")
predict = model_RF.predict(X_test)
accuracy_score_hommes = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test en disant que c'est des hommes: ", accuracy_score_h

X_test['SEX'] = 2
predict = model_RF.predict(X_test)
accuracy_score_femmes = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test en disant que c'est des femmes: ", accuracy_score_f

#Accuracy avant : 0.89097
```

```
Accuracy test en disant que c'est des hommes:  0.8722316865417377
Accuracy test en disant que c'est des femmes:  0.8705281090289608
```

```
#Il faudra regarder a quel point on a perdu d accuracy en utilisant ces
```

```
model_RF = load("/data/notebook_files/model_RF.joblib")


def biais_race(model) :
    X_new = X_test
    for i in range(1,10) :
        print(i)
        X_test['RAC1P'] = i
        predict = model.predict(X_new)
        accuracy_score_race = accuracy_score(y_test["PINCP"], predict)
        print("Accuracy test : ", accuracy_score_race)


biais_race(model_RF)
```

```
1
Accuracy test :  0.8875638841567292
2
Accuracy test :  0.879045996592845
3
Accuracy test :  0.8909710391822828
4
Accuracy test :  0.8858603066439523
5
```

```
Accuracy test :  0.8858603066439523
6
Accuracy test :  0.8875638841567292
7
Accuracy test :  0.889267461669506
8
Accuracy test :  0.7904599659284497
9
Accuracy test :  0.8875638841567292
```

```
model_ADA = load("/data/notebook_files/model_ADA.joblib")
biais_race(model_ADA)
```

```
1
Accuracy test :  0.8143100511073254
2
Accuracy test :  0.8143100511073254
3
Accuracy test :  0.8109028960817717
4
Accuracy test :  0.8143100511073254
5
Accuracy test :  0.8143100511073254
6
Accuracy test :  0.8109028960817717
7
Accuracy test :  0.807495741056218
8
Accuracy test :  0.7938671209540034
9
Accuracy test :  0.8109028960817717
```

```
model_SVM = load("/data/notebook_files/model_SVM.joblib")
biais_race(model_SVM)
```

```
1
Accuracy test :  0.8347529812606473
2
Accuracy test :  0.8347529812606473
3
Accuracy test :  0.8347529812606473
4
Accuracy test :  0.8364565587734242
5
Accuracy test :  0.8364565587734242
6
```

```
Accuracy test :  0.82793867120954
7
Accuracy test :  0.838160136286201
8
Accuracy test :  0.8330494037478705
9
Accuracy test :  0.82793867120954
```

```
model_GBC = load('/data/notebook_files/model_GBC.joblib')
biais_race(model_GBC)
```

```
1
Accuracy test :  0.8943781942078365
2
Accuracy test :  0.9011925042589438
3
Accuracy test :  0.8977853492333902
4
Accuracy test :  0.8977853492333902
5
Accuracy test :  0.8977853492333902
6
Accuracy test :  0.8926746166950597
7
Accuracy test :  0.7734241908006815
8
Accuracy test :  0.9080068143100511
9
Accuracy test :  0.8841567291311755
```

```
def race_confusion_matrix(model) :
    X_test_hawai = X_test[X_test['RAC1P']==7]
    y_pred = model.predict(X_test_hawai)

    y_test_hawai = y_test[X_test['RAC1P']==7]

    conf_matrix_hawai = confusion_matrix(y_test_hawai, y_pred)

    print("Matrice de confusion hawai : \n", conf_matrix_hawai)

    X_test_twormore = X_test[X_test['RAC1P']==9]
    y_pred = model.predict(X_test_twormore)

    y_test_twormore = y_test[X_test['RAC1P']==9]

    conf_matrix_twormore = confusion_matrix(y_test_twormore, y_pred)
```

```
    print("Matrice de confusion other race alone : \n", conf_matrix_twor
    return conf_matrix_hawai, conf_matrix_twormore

model_GBC = load('/data/notebook_files/model_GBC.joblib')
mat = race_confusion_matrix(model_GBC)
```

```
Matrice de confusion hawai :
 [[126   5]
 [ 41   8]]
Matrice de confusion other race alone :
 [[1268  300]
 [ 196  664]]
```

```
#Pour hawai on observe que l'on croit systématiquement que le salaire es
```

```
model_SVM = load("/data/notebook_files/model_SVM.joblib")
race_confusion_matrix(model_SVM)
```

```
Matrice de confusion hawai :
 [[4 0]
 [1 0]]
Matrice de confusion two or more :
 [[16  1]
 [ 0  6]]
```

```
model_ADA = load("/data/notebook_files/model_ADA.joblib")
race_confusion_matrix(model_ADA)
```

```
Matrice de confusion hawai :
 [[4 0]
 [1 0]]
Matrice de confusion two or more :
 [[16  1]
 [ 0  6]]
```

```
model_RF = load("/data/notebook_files/model_RF.joblib")
race_confusion_matrix(model_RF)
```

```
Matrice de confusion hawai :
 [[3 1]
 [1 0]]
```

```
Matrice de confusion two or more :
 [[17  0]
 [ 0  6]]
```

```
#RF est le seul avec des résultats différents.
```

```
def statistical_parity(matrice1, matrice2) :
    print("Taux de prédiction négative pour hommes : ", (matrice1[0][0]+
    print("Taux de négatif détecté : ",matrice1[0][0]/np.sum(matrice1[0]
    print("Taux de positive détecté : ",matrice1[1][1]/np.sum(matrice1[1
    print("Taux de prédiction négative pour femmes : ", (matrice2[0][0]+
    print("Taux de négatif détecté : ",matrice2[0][0]/np.sum(matrice2[0]
    print("Taux de positive détecté : ",matrice2[1][1]/np.sum(matrice2[1
```

```
model_GBC = load('/data/notebook_files/model_GBC.joblib')
conf = sex_confusion_matrix(model_GBC)
statistical_parity(conf[0], conf[1])
```

```
Matrice de confusion homme :
 [[13506  3078]
 [ 3738 10770]]
Matrice de confusion femme :
 [[15347  2509]
 [ 3112  6640]]
Taux de prédiction négative pour hommes :  0.554612118873022
Taux de négatif détecté :  0.8143994211287988
Taux de positive détecté :  0.7423490488006617
Taux de prédiction négative pour femmes :  0.6686105476673428
Taux de négatif détecté :  0.8594870071684588
Taux de positive détecté :  0.6808859721082855
```

```
model_ADA = load('/data/notebook_files/model_ADA.joblib')
conf = sex_confusion_matrix(model_ADA)
statistical_parity(conf[0], conf[1])
```

```
Matrice de confusion homme :
 [[13327  3257]
 [ 3672 10836]]
Matrice de confusion femme :
 [[15656  2200]
 [ 3906  5846]]
Taux de prédiction négative pour hommes :  0.5467322783995883
Taux de négatif détecté :  0.8036058851905451
```

```
Taux de positive détecté :  0.7468982630272953
Taux de prédiction négative pour femmes :  0.7085627354390032
Taux de négatif détecté :  0.8767921146953405
Taux de positive détecté :  0.5994667760459393
```

```
model_RF = load('/data/notebook_files/model_RF.joblib')
conf = sex_confusion_matrix(model_RF)
statistical_parity(conf[0], conf[1])
```

```
Matrice de confusion homme :
 [[13750  2834]
 [ 3838 10670]]
Matrice de confusion femme :
 [[15899  1957]
 [ 3637  6115]]
Taux de prédiction négative pour hommes :  0.5656760581500064
Taux de négatif détecté :  0.8291123974915581
Taux de positive détecté :  0.735456299972429
Taux de prédiction négative pour femmes :  0.7076209794262532
Taux de négatif détecté :  0.8904009856630825
Taux de positive détecté :  0.6270508613617719
```

```
model_SVM = load('/data/notebook_files/model_SVM.joblib')
conf = sex_confusion_matrix(model_SVM)
statistical_parity(conf[0], conf[1])
```

```
Matrice de confusion homme :
 [[13713  2871]
 [ 3957 10551]]
Matrice de confusion femme :
 [[14439  3417]
 [ 2456  7296]]
Taux de prédiction négative pour hommes :  0.5683133925125434
Taux de négatif détecté :  0.8268813314037626
Taux de positive détecté :  0.727253928866832
Taux de prédiction négative pour femmes :  0.611960301361924
Taux de négatif détecté :  0.808635752688172
Taux de positive détecté :  0.7481542247744053
```

```
#On observe bien que notre modèle considère que les femmes auront un plu
```

```
def statistical_parity_race(matrice1, matrice2) :
    print("Taux de prédiction négative pour hawai : ", (matrice1[0][0]+m
    print("Taux de négatif détecté : ",matrice1[0][0]/np.sum(matrice1[0]
    print("Taux de positif détecté : ",matrice1[1][1]/np.sum(matrice1[1]
    print("Taux de prédiction négative pour other race alone : ", (matri
    print("Taux de négatif détecté : ",matrice2[0][0]/np.sum(matrice2[0]
    print("Taux de positif détecté : ",matrice2[1][1]/np.sum(matrice2[1]
```

```
model_SVM = load('/data/notebook_files/model_SVM.joblib')
conf = race_confusion_matrix(model_SVM)
statistical_parity_race(conf[0], conf[1])
```

```
Matrice de confusion hawai :
 [[110  21]
 [ 27  22]]
Matrice de confusion other race alone :
 [[1222  346]
 [ 177  683]]
Taux de prédiction négative pour hawai :  0.7611111111111111
Taux de négatif détecté :  0.8396946564885496
Taux de positif détecté :  0.4489795918367347
Taux de prédiction négative pour other race alone :  0.576194398682042
Taux de négatif détecté :  0.7793367346938775
Taux de positif détecté :  0.7941860465116279
```

```
model_ADA = load('/data/notebook_files/model_ADA.joblib')
conf = race_confusion_matrix(model_ADA)
statistical_parity_race(conf[0], conf[1])
```

```
Matrice de confusion hawai :
 [[114  17]
 [ 29  20]]
Matrice de confusion other race alone :
 [[1319  249]
 [ 262  598]]
Taux de prédiction négative pour hawai :  0.7944444444444444
Taux de négatif détecté :  0.8702290076335878
Taux de positif détecté :  0.40816326530612246
Taux de prédiction négative pour other race alone :  0.651153212520593
Taux de négatif détecté :  0.8411989795918368
Taux de positif détecté :  0.6953488372093023
```

```
model_RF = load('/data/notebook_files/model_RF.joblib')
conf = race_confusion_matrix(model_RF)
```

```
statistical_parity_race(conf[0], conf[1])
```

```
Matrice de confusion hawai :
 [[118  13]
 [ 29  20]]
Matrice de confusion other race alone :
 [[1328  240]
 [ 255  605]]
Taux de prédiction négative pour hawai :  0.8166666666666667
Taux de négatif détecté :  0.9007633587786259
Taux de positif détecté :  0.40816326530612246
Taux de prédiction négative pour other race alone :  0.651976935749588
Taux de négatif détecté :  0.8469387755102041
Taux de positif détecté :  0.7034883720930233
```

```
model_GBC = load('/data/notebook_files/model_GBC.joblib')
conf = race_confusion_matrix(model_GBC)
statistical_parity_race(conf[0], conf[1])
```

```
Matrice de confusion hawai :
 [[126   5]
 [ 41   8]]
Matrice de confusion other race alone :
 [[1268  300]
 [ 196  664]]
Taux de prédiction négative pour hawai :  0.9277777777777778
Taux de négatif détecté :  0.9618320610687023
Taux de positif détecté :  0.16326530612244897
Taux de prédiction négative pour other race alone :  0.602965403624382
Taux de négatif détecté :  0.8086734693877551
Taux de positif détecté :  0.772093023255814
```

```
#On définit les même choses avec le train

def race_confusion_matrix_train(model) :
    X_train_hawai = X_train[X_train['RAC1P']==7]
    y_pred = model.predict(X_train_hawai)

    y_train_hawai = y_train[X_train['RAC1P']==7]

    conf_matrix_hawai = confusion_matrix(y_train_hawai, y_pred)

    print("Matrice de confusion hawai : \n", conf_matrix_hawai)

    X_train_twormore = X_train[X_train['RAC1P']==8]
    y_pred = model.predict(X_train_twormore)
```

```
    y_train_twormore = y_train[X_train['RAC1P']==8]

    conf_matrix_twormore = confusion_matrix(y_train_twormore, y_pred)

    print("Matrice de confusion other race alone : \n", conf_matrix_twor
    return conf_matrix_hawai, conf_matrix_twormore

def sexe_confusion_matrix_train(model) :
    X_train_homme = X_train[X_train['SEX']==1]
    y_pred = model.predict(X_train_homme)

    y_train_homme = y_train[X_train['SEX']==1]

    conf_matrix_homme = confusion_matrix(y_train_homme, y_pred)

    print("Matrice de confusion homme : \n", conf_matrix_homme)

    X_train_femme = X_train[X_train['SEX']==2]
    y_pred = model.predict(X_train_femme)

    y_train_femme = y_train[X_train['SEX']==2]

    conf_matrix_femme = confusion_matrix(y_train_femme, y_pred)

    print("Matrice de confusion femme : \n", conf_matrix_femme)
    return conf_matrix_homme, conf_matrix_femme
```

```
model_SVM = load('/data/notebook_files/model_SVM.joblib')
conf = race_confusion_matrix_train(model_SVM)
statistical_parity_race(conf[0], conf[1])
conf2 = sexe_confusion_matrix_train(model_SVM)
statistical_parity(conf2[0], conf2[1])
```

```
Matrice de confusion hawai :
 [[271  45]
 [ 62  79]]
Matrice de confusion other race alone :
 [[12156   680]
 [ 2023  1074]]
Taux de prédiction négative pour hawai :  0.7286652078774617
Taux de négatif détecté :  0.8575949367088608
Taux de positif détecté :  0.5602836879432624
Taux de prédiction négative pour other race alone :  0.88991401493755
Taux de négatif détecté :  0.947023995014023
Taux de positif détecté :  0.3467872134323539
Matrice de confusion homme :
 [[31965  6665]
```

```
 [ 9187 24402]]
Matrice de confusion femme :
 [[34219  8041]
 [ 5764 16722]]
Taux de prédiction négative pour hommes :  0.5698223459200488
```

```
#L'erreur est normal, on découvre que le modèle est biaisé simplement pa
```

```
conf2 = sexe_confusion_matrix_train(model_SVM)
statistical_parity(conf2[0], conf2[1])
```

```
Matrice de confusion homme :
 [[31965  6665]
 [ 9187 24402]]
Matrice de confusion femme :
 [[34219  8041]
 [ 5764 16722]]
Taux de prédiction négative pour hommes :  0.5698223459200488
Taux de négatif détecté :  0.8274657002329795
Taux de positive détecté :  0.7264878382803894
Taux de prédiction négative pour femmes :  0.6175362184536497
Taux de négatif détecté :  0.8097255087553242
Taux de positive détecté :  0.7436627234723828
```

```
model_ADA = load('/data/notebook_files/model_ADA.joblib')
conf = race_confusion_matrix_train(model_ADA)
statistical_parity_race(conf[0], conf[1])
conf2 = sexe_confusion_matrix_train(model_ADA)
statistical_parity(conf2[0], conf2[1])
```

```
Matrice de confusion hawai :
 [[281  35]
 [ 75  66]]
Matrice de confusion other race alone :
 [[12346   490]
 [ 2231   866]]
Taux de prédiction négative pour hawai :  0.7789934354485777
Taux de négatif détecté :  0.8892405063291139
Taux de positif détecté :  0.46808510638297873
Taux de prédiction négative pour other race alone :  0.91489361702127
Taux de négatif détecté :  0.9618261140542225
Taux de positif détecté :  0.2796254439780433
Matrice de confusion homme :
 [[31117  7513]
```

```
 [ 8582 25007]]
Matrice de confusion femme :
 [[36963  5297]
 [ 8970 13516]]
Taux de prédiction négative pour hommes :  0.5497029867486396
```

```python
model_GBC = load('/data/notebook_files/model_GBC.joblib')
conf = race_confusion_matrix_train(model_GBC)
statistical_parity_race(conf[0], conf[1])
conf2 = sexe_confusion_matrix_train(model_GBC)
statistical_parity(conf2[0], conf2[1])
```

```
Matrice de confusion hawai :
 [[306  10]
 [115  26]]
Matrice de confusion other race alone :
 [[12099   737]
 [ 1909  1188]]
Taux de prédiction négative pour hawai :  0.9212253829321663
Taux de négatif détecté :  0.9683544303797469
Taux de positif détecté :  0.18439716312056736
Taux de prédiction négative pour other race alone :  0.87918157283625
Taux de négatif détecté :  0.9425833593019632
Taux de positif détecté :  0.3835970293832741
Matrice de confusion homme :
 [[31483  7147]
 [ 8728 24861]]
Matrice de confusion femme :
 [[36385  5875]
 [ 7219 15267]]
Taux de prédiction négative pour hommes :  0.5567925338207397
Taux de négatif détecté :  0.8149883510225213
```

```python
model_RF = load('/data/notebook_files/model_RF.joblib')
conf = race_confusion_matrix_train(model_RF)
statistical_parity_race(conf[0], conf[1])
conf2 = sexe_confusion_matrix_train(model_RF)
statistical_parity(conf2[0], conf2[1])
```

```
Matrice de confusion hawai :
 [[285  31]
 [ 74  67]]
Matrice de confusion other race alone :
 [[12634   202]
 [ 2530   567]]
Taux de prédiction négative pour hawai :  0.7855579868708972
```

```
Taux de négatif détecté :  0.9018987341772152
Taux de positif détecté :  0.475177304964539
Taux de prédiction négative pour other race alone :  0.95173539195380
Taux de négatif détecté :  0.9842630102835774
Taux de positif détecté :  0.18308040038747175
Matrice de confusion homme :
 [[32083  6547]
 [ 9046 24543]]
Matrice de confusion femme :
 [[37706  4554]
 [ 8342 14144]]
Taux de prédiction négative pour hommes :  0.5695038701726692
```

```
X_train_SEX = X_train.drop(['SEX'], axis=1)
X_test_SEX = X_test.drop(['SEX'], axis=1)
```

```
model_SVM = load('/data/notebook_files/model_SVM.joblib')

model_SVM.get_params()
```

```
{'memory': None,
 'steps': [('preprocessor',
   ColumnTransformer(transformers=[('num', RobustScaler(), ['AGEP', '
                                    ('cat', OneHotEncoder(handle_unkno
                                     ['COW', 'SCHL', 'MAR', 'OCCP', 'P
                                      'RAC1P'])])),
  ('classifier', SVC(C=0.1, kernel='linear'))],
 'verbose': False,
 'preprocessor': ColumnTransformer(transformers=[('num', RobustScaler
                                ('cat', OneHotEncoder(handle_unknown
                                 ['COW', 'SCHL', 'MAR', 'OCCP', 'POB
                                  'RAC1P'])]),
 'classifier': SVC(C=0.1, kernel='linear'),
 'preprocessor__n_jobs': None,
 'preprocessor__remainder': 'drop',
 'preprocessor__sparse_threshold': 0.3,
 'preprocessor__transformer_weights': None,
 'preprocessor__transformers': [('num', RobustScaler(), ['AGEP', 'WKH
  ('cat',
   OneHotEncoder(handle_unknown='ignore')
```

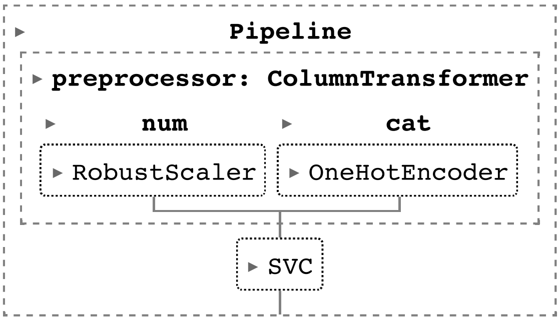
```
#Nouveau training sans SEX
from sklearn.compose import ColumnTransformer
numeric_feature = ["AGEP", "WKHP"]
```

```
categorical_features = ["COW", "SCHL", "MAR", "OCCP", "POBP", "RELP", "R


preprocessor = ColumnTransformer(transformers=[('num', RobustScaler(), n
                                               ('cat', OneHotEncoder(han
                                               ])




modelSVM = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', SVC())
])
modelSVM
```




```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score



param_grid_SVM = {
    'classifier__C' : [0.1],
    'classifier__kernel' : ["linear"],
    'classifier__shrinking' : [True]
}

grid_SVM = GridSearchCV(modelSVM,param_grid_SVM,cv=5, verbose=2)
```

```
NameError: name 'modelSVM' is not defined
```

```
X_train_SEX = X_train.drop(['SEX'], axis=1)
X_test_SEX = X_test.drop(['SEX'], axis=1)
grid_SVM.fit(X_train, y_train["PINCP"])
best_model = grid_SVM.best_estimator_
dump(best_model, '/data/notebook_files/model_SVM_SEX.joblib')
```

```
NameError: name 'grid_SVM' is not defined
```

```
model_SVM_SEX = load('/data/notebook_files/model_SVM_SEX.joblib')
predict = model_SVM_SEX.predict(X_test_SEX)
accuracy_score(y_test["PINCP"], predict)
#Accuracy avant : 0.804088
```

```
0.8194207836456558
```

```
model_GBC = load('/data/notebook_files/model_GBC.joblib')

model_GBC.get_params()
```

```
{'memory': None,
 'steps': [('preprocessor',
   ColumnTransformer(transformers=[('num', RobustScaler(), ['AGEP', '
                                    ('cat', OneHotEncoder(handle_unkno
                                     ['COW', 'SCHL', 'MAR', 'OCCP', 'P
                                      'SEX', 'RAC1P'])])),
  ('classifier',
   GradientBoostingClassifier(learning_rate=0.2, min_samples_split=12
                              n_estimators=351))],
 'verbose': False,
 'preprocessor': ColumnTransformer(transformers=[('num', RobustScaler
                                  ('cat', OneHotEncoder(handle_unknown
                                   ['COW', 'SCHL', 'MAR', 'OCCP', 'POB
                                    'SEX', 'RAC1P'])]),
 'classifier': GradientBoostingClassifier(learning_rate=0.2, min_samp
                                    n_estimators=351),
 'preprocessor__n_jobs': None,
 'preprocessor__remainder': 'drop',
 'preprocessor__sparse_threshold': 0.3,
 'preprocessor__transformer_weights': None
```

```
modelGBC = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', GradientBoostingClassifier())
])


param_grid_GBC = {
    'classifier__n_estimators' : [351],
    'classifier__learning_rate' : [0.2],
    'classifier__min_samples_split' : [12],
    'classifier__criterion' : ['friedman_mse']
}
```

```
grid_GBC = GridSearchCV(modelGBC,param_grid_GBC,cv=5, verbose=2)


grid_GBC.fit(X_train_SEX, y_train["PINCP"])

predict = grid_GBC.predict(X_test_SEX)
accuracy_score_gbc = accuracy_score(y_test["PINCP"], predict)
print("Score training: ", grid_GBC.best_score_)
print("Accuracy test: ", accuracy_score_gbc)

best_model = grid_GBC.best_estimator_
dump(best_model, 'model_GBC_SEX.joblib')

#Acuracy avant 0.89437
```

```
NameError: name 'GradientBoostingClassifier' is not defined
```

```
model_GBC = load('/data/notebook_files/model_GBC_SEX.joblib')
X_test_SEX = X_test.drop(['SEX'], axis=1)
conf2 = sexe_confusion_matrix_train(model_GBC)
statistical_parity(conf2[0], conf2[1])

predict = model_GBC.predict(X_test_SEX)
accuracy_score_gbc = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test: ", accuracy_score_gbc)
```

```
Matrice de confusion homme :
 [[31952  6620]
 [ 9388 24435]]
Matrice de confusion femme :
 [[35033  6903]
 [ 6251 16383]]
Taux de prédiction négative pour hommes :  0.5710339111817114
Taux de négatif détecté :  0.8283729129938816
Taux de positive détecté :  0.7224373946722644
Taux de prédiction négative pour femmes :  0.6393681276134427
Taux de négatif détecté :  0.8353920259442961
Taux de positive détecté :  0.7238225678183264
Accuracy test:  0.7841396933560477
```

```
model_GBC = load('/data/notebook_files/model_GBC.joblib')


predict = model_GBC.predict(X_test)
accuracy_score_gbc = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test: ", accuracy_score_gbc)
```

```
Accuracy test:  0.7872572402044293
```

```
from sklearn.ensemble import RandomForestClassifier

X_train_RACE = X_train.drop(['SEX'], axis=1)
X_test_RACE = X_test.drop(['SEX'], axis=1)
modelRF = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier())
])


param_grid_RF = {
    'classifier__max_depth' : [100],
    'classifier__criterion' : ['entropy'],
    'classifier__min_samples_leaf' : [1],
    'classifier__min_samples_split': [12]
}

grid_RF = GridSearchCV(modelRF,param_grid_RF,cv=5, verbose=2)


grid_RF.fit(X_train_RACE, y_train["PINCP"])

predict = grid_RF.predict(X_test_RACE)
accuracy_score_RF = accuracy_score(y_test["PINCP"], predict)
print("Score training: ", grid_RF.best_score_)
print("Accuracy test: ", accuracy_score_RF)

best_model = grid_RF.best_estimator_
dump(best_model, 'model_RF_SEX.joblib')
```

```
Fitting 5 folds for each of 1 candidates, totalling 5 fits
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
Score training:  0.7982831716828317
Accuracy test:  0.8100511073253833

['model_RF_SEX.joblib']
```

```
model_RF = load('/data/notebook_files/model_RF_SEX.joblib')
X_test_SEX = X_test.drop(['SEX'], axis=1)
conf2 = sexe_confusion_matrix_train(model_RF)
```

```
statistical_parity(conf2[0], conf2[1])

predict = model_RF.predict(X_test_SEX)
accuracy_score_rf = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test: ", accuracy_score_rf)
```

```
Matrice de confusion homme :
 [[33529  5153]
 [ 9580 24025]]
Matrice de confusion femme :
 [[36415  5658]
 [ 6465 16140]]
Taux de prédiction négative pour hommes :  0.5963589580422483
Taux de négatif détecté :  0.8667855850266274
Taux de positive détecté :  0.7149233744978426
Taux de prédiction négative pour femmes :  0.662976591731346
Taux de négatif détecté :  0.8655194542818435
Taux de positive détecté :  0.7140013271400133
Accuracy test:  0.8050596252129472
```

```
#On dirait que c'est pas un biais du modèle du coup ?
model_RF = load('/data/notebook_files/model_RF.joblib')

model_RF.get_params()
```

```
{'memory': None,
 'steps': [('preprocessor',
   ColumnTransformer(transformers=[('num', RobustScaler(), ['AGEP', '
                                   ('cat', OneHotEncoder(handle_unkno
                                    ['COW', 'SCHL', 'MAR', 'OCCP', 'P
                                     'SEX', 'RAC1P'])])),
  ('classifier',
   RandomForestClassifier(criterion='entropy', max_depth=901, min_sam
 'verbose': False,
 'preprocessor': ColumnTransformer(transformers=[('num', RobustScaler
                                 ('cat', OneHotEncoder(handle_unknown
                                  ['COW', 'SCHL', 'MAR', 'OCCP', 'POB
                                   'SEX', 'RAC1P'])]),
 'classifier': RandomForestClassifier(criterion='entropy', max_depth=
 'preprocessor__n_jobs': None,
 'preprocessor__remainder': 'drop',
 'preprocessor__sparse_threshold': 0.3,
 'preprocessor__transformer_weights': None,
 'preprocessor__transformers': [('num', RobustScaler(), ['AGEP', 'WKH
  ('cat'
```

```
numeric_feature = ["AGEP", "WKHP"]
```

```
categorical_features = ["COW", "SCHL", "MAR", "OCCP", "POBP","SEX", "REL


preprocessor = ColumnTransformer(transformers=[('num', RobustScaler(), n
                                               ('cat', OneHotEncoder(han
                                               ])
```

```
X_train_RACE = X_train.drop(['RAC1P'], axis=1)
X_test_RACE = X_test.drop(['RAC1P'], axis=1)
modelGBC = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', GradientBoostingClassifier())
])


param_grid_GBC = {
    'classifier__n_estimators' : [351],
    'classifier__learning_rate' : [0.2],
    'classifier__min_samples_split' : [12],
    'classifier__criterion' : ['friedman_mse']
}

grid_GBC = GridSearchCV(modelGBC,param_grid_GBC,cv=5, verbose=2)


grid_GBC.fit(X_train_RACE, y_train["PINCP"])

predict = grid_GBC.predict(X_test_RACE)
accuracy_score_gbc = accuracy_score(y_test["PINCP"], predict)
print("Score training: ", grid_GBC.best_score_)
print("Accuracy test: ", accuracy_score_gbc)

best_model = grid_GBC.best_estimator_
dump(best_model, 'model_GBC_RACE.joblib')
```

```
NameError: name 'GradientBoostingClassifier' is not defined
```

```
model_GBC = load('/data/notebook_files/model_GBC_RACE.joblib')
conf = race_confusion_matrix(model_GBC)
statistical_parity_race(conf[0], conf[1])
X_train_RACE = X_train.drop(['RAC1P'], axis=1)
X_test_RACE = X_test.drop(['RAC1P'], axis=1)
predict = model_GBC.predict(X_test_RACE)
accuracy_score_gbc = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test: ", accuracy_score_gbc)
```

```
Matrice de confusion hawai :
```

```
Matrice de confusion hawai :
 [[128  16]
 [ 17  35]]
Matrice de confusion other race alone :
 [[1336  242]
 [ 274  640]]
Taux de prédiction négative pour hawai :  0.7397959183673469
Taux de négatif détecté :  0.8888888888888888
Taux de positif détecté :  0.6730769230769231
Taux de prédiction négative pour other race alone :  0.6460674157303337
Taux de négatif détecté :  0.8466413181242078
Taux de positif détecté :  0.700218818380744
Accuracy test:  0.7878023850085178
```

```
#Voilà on remarque des différences
```

```
from sklearn.ensemble import RandomForestClassifier

X_train_RACE = X_train.drop(['RAC1P'], axis=1)
X_test_RACE = X_test.drop(['RAC1P'], axis=1)
modelRF = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier())
])


param_grid_RF = {
    'classifier__max_depth' : [100],
    'classifier__criterion' : ['entropy'],
    'classifier__min_samples_leaf' : [1],
    'classifier__min_samples_split': [12]
}

grid_RF = GridSearchCV(modelRF,param_grid_RF,cv=5, verbose=2)


grid_RF.fit(X_train_RACE, y_train["PINCP"])

predict = grid_RF.predict(X_test_RACE)
accuracy_score_RF = accuracy_score(y_test["PINCP"], predict)
print("Score training: ", grid_RF.best_score_)
print("Accuracy test: ", accuracy_score_RF)

best_model = grid_RF.best_estimator_
dump(best_model, 'model_RF_RACE.joblib')
```

```
Fitting 5 folds for each of 1 candidates, totalling 5 fits
```

```
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
[CV] END classifier__criterion=entropy, classifier__max_depth=100, cla
Score training:  0.7977367263273673
Accuracy test:  0.8160136286201022

['model_RF_RACE.joblib']
```

```
model_RF= load('/data/notebook_files/model_RF_RACE.joblib')
conf = race_confusion_matrix(model_RF)
statistical_parity_race(conf[0], conf[1])
X_train_RACE = X_train.drop(['RAC1P'], axis=1)
X_test_RACE = X_test.drop(['RAC1P'], axis=1)
predict = model_RF.predict(X_test_RACE)
accuracy_score_rf = accuracy_score(y_test["PINCP"], predict)
print("Accuracy test: ", accuracy_score_rf)
```

```
Matrice de confusion hawai :
 [[106  20]
 [ 22  32]]
Matrice de confusion other race alone :
 [[1471  169]
 [ 277  619]]
Taux de prédiction négative pour hawai :  0.7111111111111111
Taux de négatif détecté :  0.8412698412698413
Taux de positif détecté :  0.5925925925925926
Taux de prédiction négative pour other race alone :  0.689274447949526
Taux de négatif détecté :  0.8969512195121951
Taux de positif détecté :  0.6908482142857143
Accuracy test:  0.8068143100511074
```

```
percentage_sex_1 = (X_test['SEX'].eq(1).sum() / len(X_test['SEX'])) * 10

print(f"Pourcentage de SEX=1 dans X_test : {percentage_sex_1:.2f}%")
```

```
Pourcentage de SEX=1 dans X_test : 54.34%
```

```
for i in range(1, 10):
    percentage_race = (X['RAC1P'].eq(i).sum() / len(X['RAC1P'])) * 100
    print(f"Pourcentage de RAC1P={i} dans X_test : {percentage_race:.2f}
```

```
Pourcentage de RAC1P=1 dans X_test : 61.84%
```

```
Pourcentage de RAC1P=2 dans X_test : 4.37%
Pourcentage de RAC1P=3 dans X_test : 0.66%
Pourcentage de RAC1P=4 dans X_test : 0.01%
Pourcentage de RAC1P=5 dans X_test : 0.23%
Pourcentage de RAC1P=6 dans X_test : 16.72%
Pourcentage de RAC1P=7 dans X_test : 0.33%
Pourcentage de RAC1P=8 dans X_test : 11.65%
Pourcentage de RAC1P=9 dans X_test : 4.19%
```