# ESILV_PFDS_Online_Shoppers_Purchasing_Intention_Analysis

January 10, 2021

## 1 ESILV Python for Data Analysis Final Project - Online Shoppers Purchasing Intention Dataset

### 1.1 STEP 0 : Importing libraries and files

[103]:
```
# Importing the libraries
import pickle
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

from sklearn.compose import make_column_transformer
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.utils import resample
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.decomposition import PCA
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
 ↪accuracy_score, f1_score
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,␣
 ↪GradientBoostingClassifier, VotingClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

# Importing the dataset (Link - https://archive.ics.uci.edu/ml/datasets/
 ↪Online+Shoppers+Purchasing+Intention+Dataset)
data = pd.read_csv("online_shoppers_intention.csv", header = 0)
```

### 1.2 STEP 1 : Data Cleaning (if necessary)

**We can have a quick look at the data type in each column of our dataset to make sure if there are any missing values.**

[92]:
```
data.dtypes
```

[92]:
```
Administrative               int64
Administrative_Duration    float64
Informational                int64
Informational_Duration     float64
ProductRelated               int64
ProductRelated_Duration    float64
BounceRates                float64
ExitRates                  float64
PageValues                 float64
SpecialDay                 float64
Month                       object
OperatingSystems             int64
Browser                      int64
Region                       int64
TrafficType                  int64
VisitorType                 object
Weekend                       bool
Revenue                       bool
dtype: object
```

**Month and VisitorType are object type, we can quickly check if there is any missing values by counting the values.**

[93]:
```
print(data['Month'].value_counts())
print(data['VisitorType'].value_counts())
```

```
May     3364
Nov     2998
Mar     1907
Dec     1727
Oct      549
Sep      448
Aug      433
Jul      432
June     288
Feb      184
Name: Month, dtype: int64
Returning_Visitor    10551
New_Visitor           1694
Other                   85
Name: VisitorType, dtype: int64
```

### 1.3 STEP 2 : Data preprocessing

**As we have categorical features in our dataset, we need to encode them before so we can use them in our analysis later.**

[94]:
```
column_trans =␣
↪make_column_transformer((OneHotEncoder(),['Month','OperatingSystems','Browser','VisitorType

# Scaler
scalar = MinMaxScaler()

# Purchased
dataset_p = data[data.Revenue==True]
# Not Purchased
dataset_np = data[data.Revenue==False]

# Downsampled Dataset
dataset_p_down = resample(dataset_p,replace=False,n_samples=1000)
dataset_np_down = resample(dataset_np,replace=False,n_samples=5000)
dataset = pd.concat([dataset_p_down,dataset_np_down])

# Identifying the class label
X = dataset.drop(columns=['Revenue'])
y = dataset['Revenue']

# Encoding categorical features
column_trans.fit(X)
X = column_trans.transform(X)

# Creating training and testing set
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.
↪25,random_state=0)

# Center and normalize the data
scalar.fit(X)
X_train = scalar.transform(X_train)
X_test = scalar.transform(X_test)
```

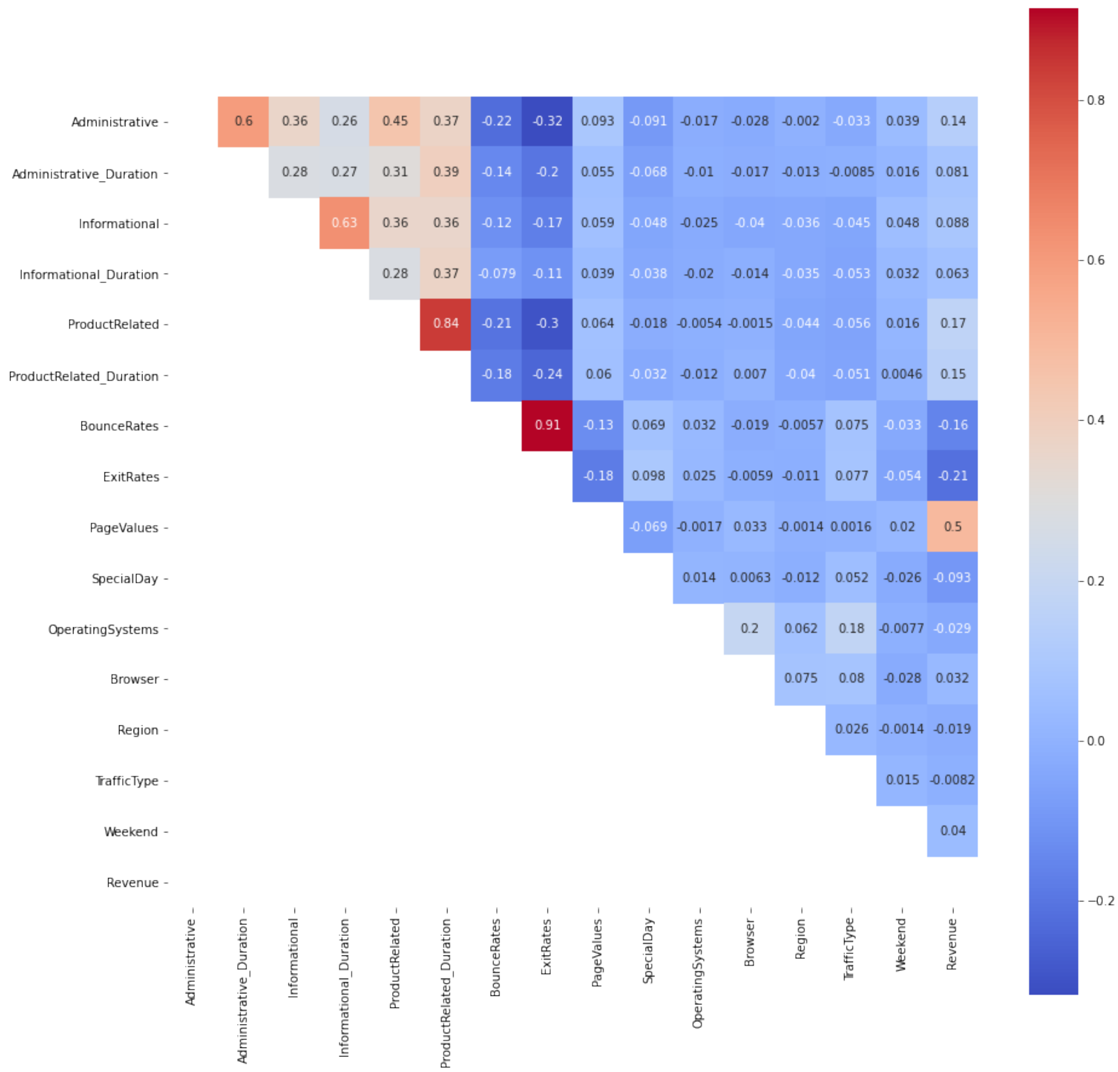
## 1.4 STEP 3 : Data Visualisation

## 1.5 Features correlation matrix

**To have an idea of correlation between our variables we can plot the correlation matrix.**

[95]:
```
plt.subplots(figsize=(15,15))
matrix = np.tril(data.corr())
sns.heatmap(dataset.corr(), annot = True, cmap= 'coolwarm',square=True,mask =␣
↪matrix)
```

[95]: <matplotlib.axes._subplots.AxesSubplot at 0x19a3ca1a0d0>



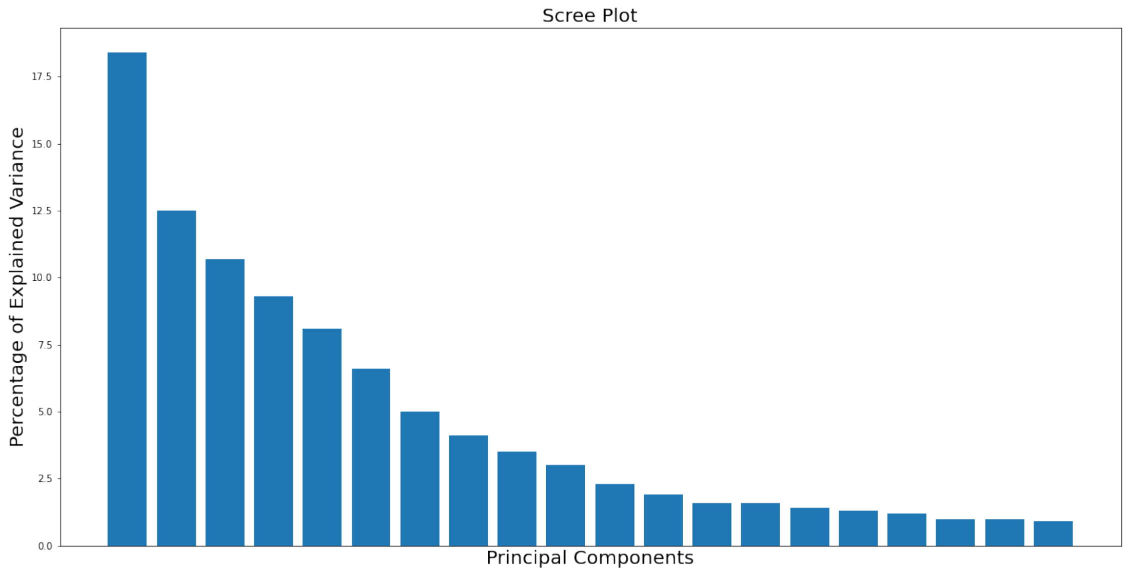

**We see in the last column that the target is only correlated to a small number of variables in this dataset.**

## 1.6 Principal Component Analysis

**We can use principal component analysis to see if we can have a good representation of our dataset in two or three dimensions.**

[107]:
```
pca = PCA(n_components=20)
X_train_pca = pca.fit_transform(X_train)
per_var = np.round(pca.explained_variance_ratio_*100,decimals=1)
labels = [str(x) for x in range(1,len(per_var)+1)]
plt.rcParams['figure.figsize'] = (20, 10)
font=20
plt.bar(x=range(1,len(per_var)+1),height=per_var)
```

```
plt.tick_params(axis='x',which='both',bottom=False,top=False,labelbottom=False)
plt.ylabel('Percentage of Explained Variance', fontsize = font)
plt.xlabel('Principal Components', fontsize = font)
plt.title('Scree Plot', fontsize = font)
plt.show()
```



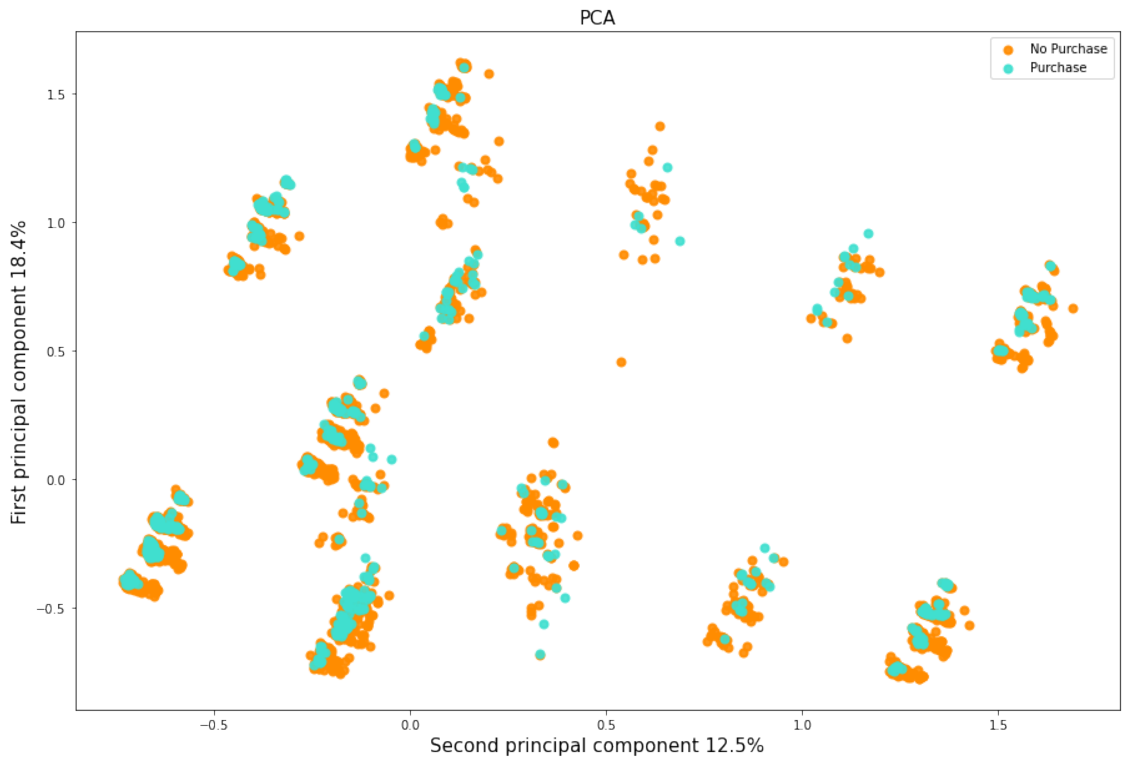

**Because the percentage of explained variance decay slowly, it is not possible to represent well our dataset in two or three dimensions.**

## 1.7 2D PCA Plot

**We can have a look at our dataset in a 2D Plot.**

[99]:
```
X_r = pca.fit(X_train).transform(X_train)
plt.figure()
colors = ['darkorange', 'turquoise']
lw = 2
target_names= ["No Purchase","Purchase"]

for color, i, target_name in zip(colors, [0, 1], target_names):
    plt.scatter(X_r[y_train == i, 0], X_r[y_train == i, 1], color=color, alpha=.
 ↪9, lw=lw,
                label=target_name)

font=15
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.title('PCA',fontsize=font)
pca100 = pca.explained_variance_ratio_
D1 = "First principal component " + str(round(pca100[0] * 100,1)) + "%"
```

```
D2 = "Second principal component " + str(round(pca100[1] * 100,1)) + "%"
plt.ylabel(D1,fontsize=font)
plt.xlabel(D2,fontsize=font)
plt.rcParams['figure.figsize'] = (15, 10)
plt.show()
```



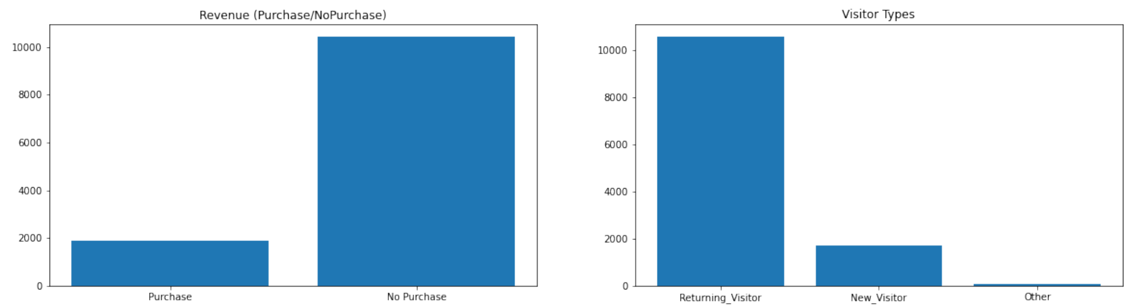

There are 12 clusters that may correspond to the 12 months.

## 1.8 Univariate Analysis

We can look at the dataset balance with a few bar plots.

[83]:
```
fig, axs = plt.subplots(1,2)
fig.set_size_inches(20,5)

#Visitor Types
axs[1].set_title("Visitor Types")
Vtype = ['Returning_Visitor','New_Visitor','Other']
count_vtype = [data['VisitorType'].value_counts()['Returning_Visitor'],
               data['VisitorType'].value_counts()['New_Visitor'],
               data['VisitorType'].value_counts()['Other']]
axs[1].bar(Vtype,count_vtype)

#Number of Purchased
```

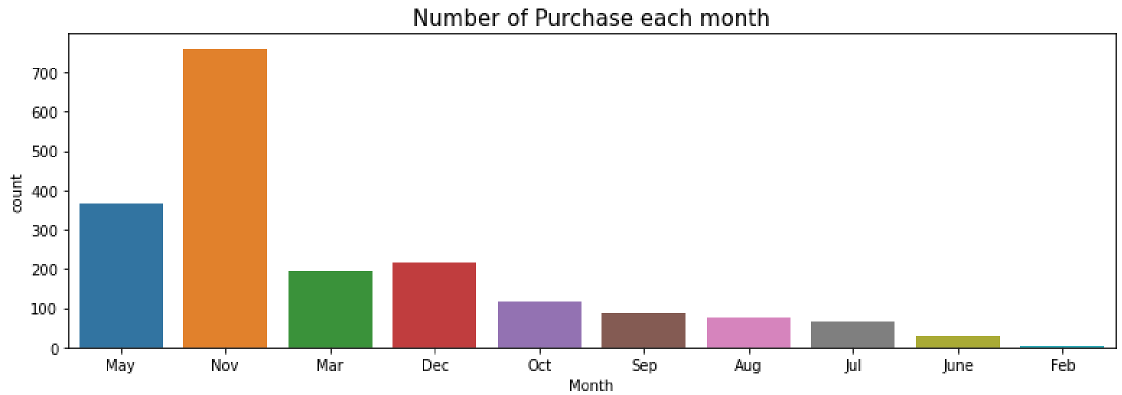
```
axs[0].set_title("Revenue (Purchase/NoPurchase)")
TF = ["Purchase","No Purchase"]
TF_count = [data['Revenue'].value_counts()[True],data['Revenue'].
 ↪value_counts()[False]]
axs[0].bar(TF,TF_count)

plt.show()
```




**We have approximately 5 times more negative entries and most of our dataset is composed of Returning_Visitors**

[84]:
```
plt.figure(figsize=(13, 4))
sns.countplot(dataset_p.Month.dropna(), order = data.Month.value_counts().
 ↪index);
plt.title('Number of Purchase each month', fontsize = 15)
```

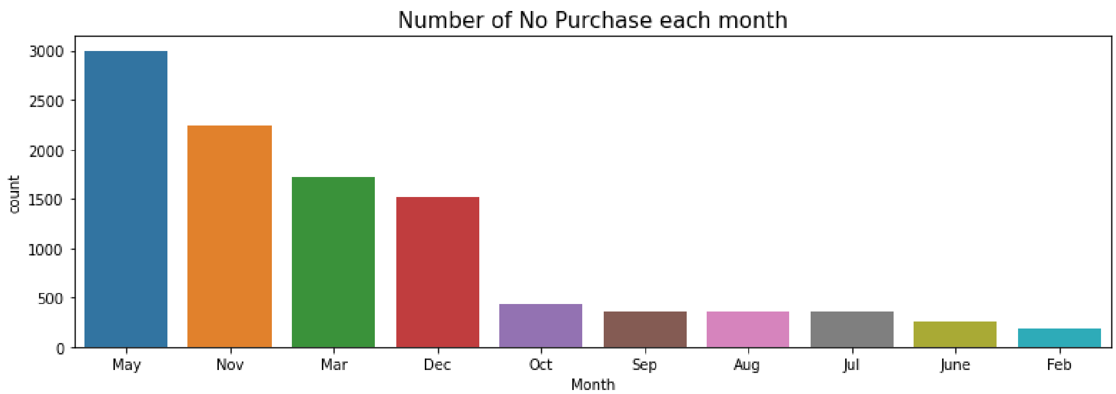
[84]: Text(0.5, 1.0, 'Number of Purchase each month')




**The number of 'purchase' is very important in November, maybe it is because of Black Friday ? ;)**

[85]:
```
plt.figure(figsize=(13, 4))
sns.countplot(dataset_np.Month.dropna(), order = data.Month.value_counts().
↪index);
plt.title('Number of No Purchase each month', fontsize = 15)
```

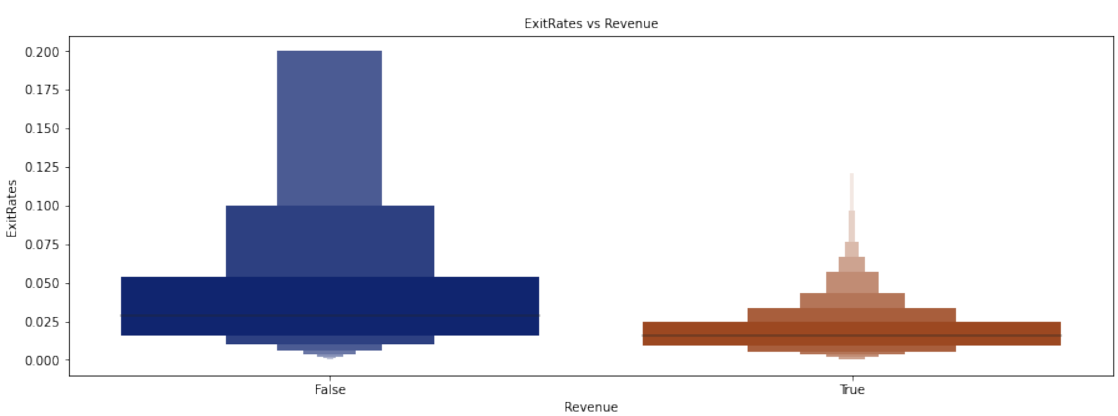
[85]: Text(0.5, 1.0, 'Number of No Purchase each month')




**The number of "no purchase" sessions is more important in May, November, March and December, showing that there are more visits to the site these months.**

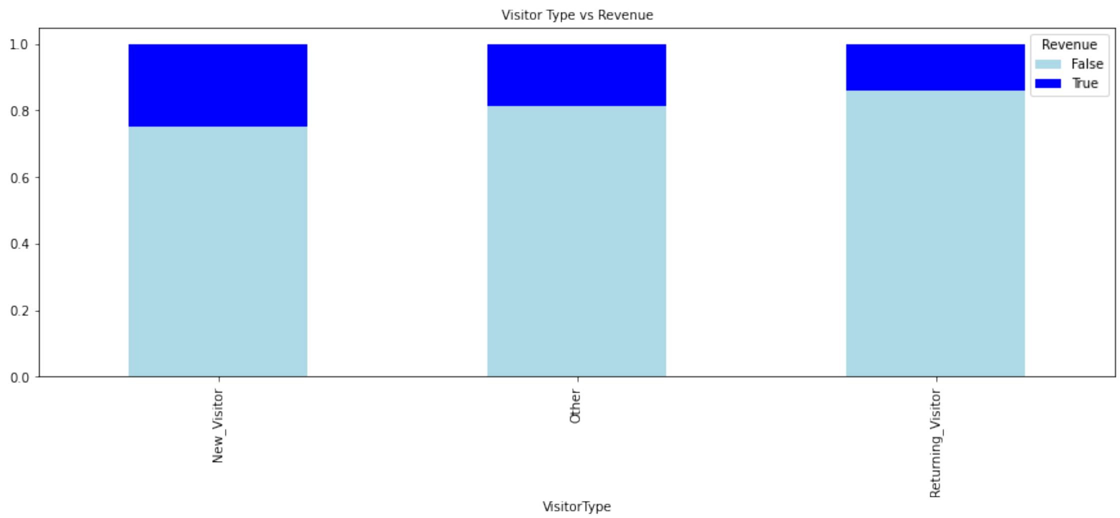
## 1.9 Bivariate analysis

[100]:
```
plt.rcParams['figure.figsize'] = (15, 5)
# exit rate vs raevenue
sns.boxenplot(data['Revenue'], data['ExitRates'], palette = 'dark')
plt.title('ExitRates vs Revenue', fontsize = 10)
plt.xlabel('Revenue', fontsize = 10)
plt.ylabel('ExitRates', fontsize = 10)

plt.show()
```



Differences in ExitRates are not that significant by Revenue. We can note that the ExitRates are a little lower when there is a 'Purchase'.

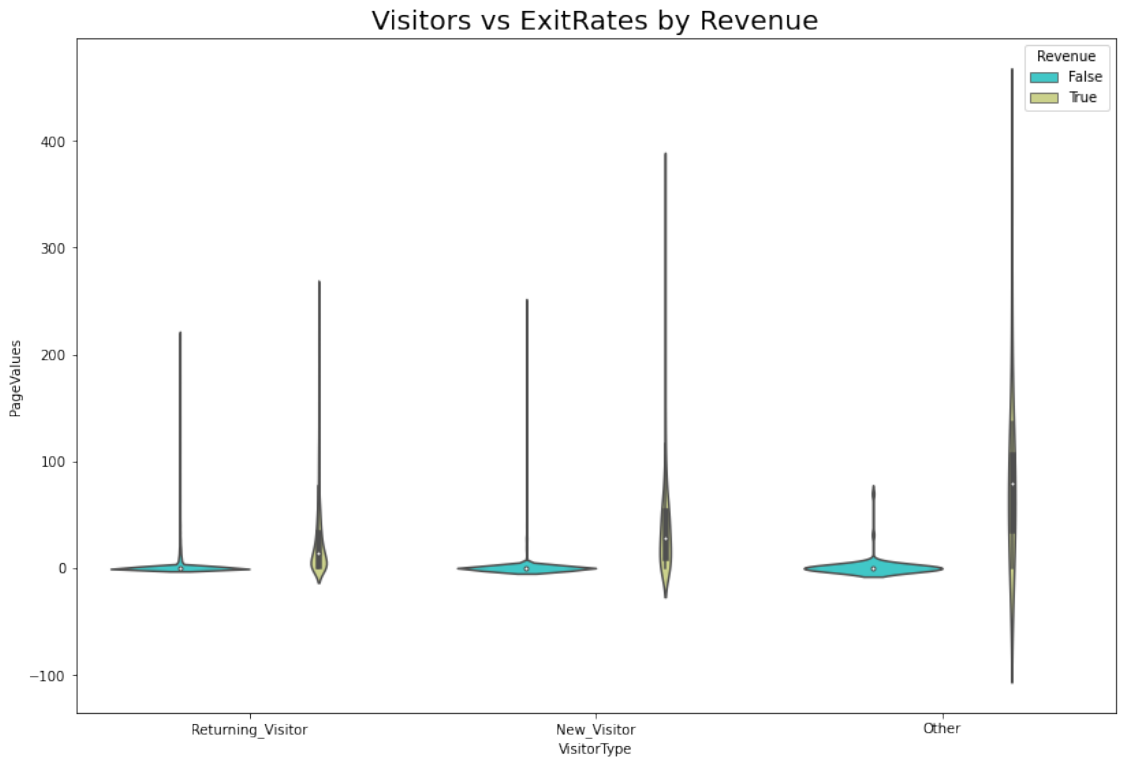
[102]:
```
df = pd.crosstab(data['VisitorType'], data['Revenue'])
df.div(df.sum(1).astype(float), axis = 0).plot(kind = 'bar', stacked = True,␣
↪figsize = (15, 5), color = ['lightblue', 'blue'])
plt.title('Visitor Type vs Revenue', fontsize = 10)
plt.show()
```




This crosstab shows us that the Visitor_Type has almost no influence on the number of Purchases.

### 1.10 Multivariate analysis

[88]:
```
plt.rcParams['figure.figsize'] = (30, 20)
plt.subplot(2, 2, 1)
sns.violinplot(x = data['VisitorType'], y = data['PageValues'], hue =␣
↪data['Revenue'], palette = 'rainbow')
plt.title('Visitors vs ExitRates by Revenue', fontsize = 20)
plt.show()
```




**The violin plot is showing us the same pattern for each visitor type. Page Value for most of the entries are close to 0 when the Revenue is False. But the values are spread out when Revenue is True. This may come from the definition of the PageValue, which gives a value close to 0 to pages which did not generate a lot of revenue.**

## 1.11 STEP 4: Building ML Model

## 1.12 Overview of a few model's performance

**Let's compare a few algorithms that can be used for classification to see the performance of each ones.**

[105]:
```
classifiers = {
    "Naive Bayes": GaussianNB(),
    "Logistic Regression": LogisticRegression(),
    "K Nearest Neighbour": KNeighborsClassifier(),
    "Support Vector Classification": SVC(),
    "Decision Tree Classification": DecisionTreeClassifier(),
    "Stochastic Gradient Descent": SGDClassifier(),
    "Linear Discriminant Analysis": LinearDiscriminantAnalysis(),
    "Gradient Boosting Classification ": GradientBoostingClassifier(),
    "Random Forest Classification": RandomForestClassifier()
    }
```

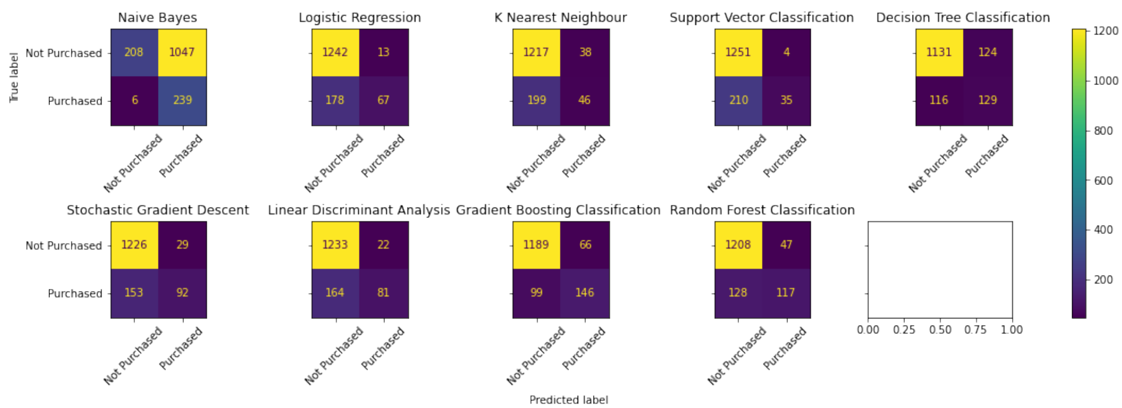
```python
f, axes = plt.subplots(2, 5, figsize=(20, 5), sharey='row')

for i, (key, classifier) in enumerate(classifiers.items()):
    j = 0
    k = i
    if i>4:
        k = i-5
        j+=1

    y_pred = classifier.fit(X_train, y_train).predict(X_test)
    cf_matrix = confusion_matrix(y_test, y_pred)
    print(key, "\n Accuracy:",accuracy_score(y_test,y_pred),"\n␣
↪F-score",f1_score(y_test,y_pred))
    disp = ConfusionMatrixDisplay(cf_matrix,
                                  display_labels=["Not Purchased","Purchased"])
    disp.plot(ax=axes[j][k], xticks_rotation=45)
    disp.ax_.set_title(key)
    disp.im_.colorbar.remove()
    disp.ax_.set_xlabel('')
    if i!=0:
        disp.ax_.set_ylabel('')

f.text(0.43, -0.1, 'Predicted label', ha='left')
plt.subplots_adjust(wspace=0.40, hspace=1)


f.colorbar(disp.im_, ax=axes)
plt.show()
```

```
Naive Bayes
 Accuracy: 0.298
 F-score 0.3122142390594383
Logistic Regression
 Accuracy: 0.8726666666666667
 F-score 0.41230769230769226
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\linear_model\_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
K Nearest Neighbour
```

```
 Accuracy: 0.842
 F-score 0.2796352583586626
Support Vector Classification
 Accuracy: 0.8573333333333333
 F-score 0.24647887323943657
Decision Tree Classification
 Accuracy: 0.84
 F-score 0.5180722891566265
Stochastic Gradient Descent
 Accuracy: 0.8786666666666667
 F-score 0.5027322404371585
Linear Discriminant Analysis
 Accuracy: 0.876
 F-score 0.4655172413793104
Gradient Boosting Classification
 Accuracy: 0.89
 F-score 0.6389496717724289
Random Forest Classification
 Accuracy: 0.8833333333333333
 F-score 0.5721271393643031
```




**The four best performing ones are Random Forest, Gradient Boosting, Stochastic Gradient Descent and Decision Tree.**

### 1.13 STEP 5 : Model Tuning (Grid Search)

**We will tune the hyperparameters of our four best performing algorithms to see if we can improve the accuracy and f-score. We have to tune our parameters by the F-score because our dataset is unbalanced.**

### 1.14 Gradient Boosting

[15]:
```
parameters = [{
    "loss":["deviance"],
    "learning_rate": [0.2,0.3,0.4],
    "min_samples_split": [0.01,0.1, 0.5],
    "min_samples_leaf": [0.0001,0.001, 0.01],
    "max_depth":[8,10,15],
    "max_features":["log2","sqrt"],
    "criterion": ["friedman_mse",  "mae"],
    "subsample":[0.7,0.8,0.9],
    "n_estimators":[10,20,30]
    }]
gbm = GridSearchCV(GradientBoostingClassifier(), parameters, cv=5,␣
↪n_jobs=-1,scoring='f1', verbose=True)
gbm.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 2916 candidates, totalling 14580 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:    2.3s
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed:    4.8s
[Parallel(n_jobs=-1)]: Done 576 tasks      | elapsed:    8.8s
[Parallel(n_jobs=-1)]: Done 1276 tasks      | elapsed:   16.9s
[Parallel(n_jobs=-1)]: Done 2176 tasks      | elapsed:   30.9s
[Parallel(n_jobs=-1)]: Done 3276 tasks      | elapsed:   42.8s
[Parallel(n_jobs=-1)]: Done 4576 tasks      | elapsed:   59.3s
[Parallel(n_jobs=-1)]: Done 6076 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 7566 tasks      | elapsed:  3.7min
[Parallel(n_jobs=-1)]: Done 8516 tasks      | elapsed: 10.9min
[Parallel(n_jobs=-1)]: Done 9566 tasks      | elapsed: 19.9min
[Parallel(n_jobs=-1)]: Done 10716 tasks      | elapsed: 29.2min
[Parallel(n_jobs=-1)]: Done 11966 tasks      | elapsed: 39.6min
[Parallel(n_jobs=-1)]: Done 13316 tasks      | elapsed: 50.2min
[Parallel(n_jobs=-1)]: Done 14580 out of 14580 | elapsed: 60.3min finished
```

[15]:
```
GridSearchCV(cv=5, estimator=GradientBoostingClassifier(), n_jobs=-1,
             param_grid=[{'criterion': ['friedman_mse', 'mae'],
                          'learning_rate': [0.2, 0.3, 0.4],
                          'loss': ['deviance'], 'max_depth': [8, 10, 15],
                          'max_features': ['log2', 'sqrt'],
                          'min_samples_leaf': [0.0001, 0.001, 0.01],
                          'min_samples_split': [0.01, 0.1, 0.5],
                          'n_estimators': [10, 20, 30],
                          'subsample': [0.7, 0.8, 0.9]}],
             scoring='f1', verbose=True)
```

[16]:
```
print(gbm.best_params_)
```

```
{'criterion': 'friedman_mse', 'learning_rate': 0.2, 'loss': 'deviance',
'max_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf': 0.0001,
'min_samples_split': 0.1, 'n_estimators': 30, 'subsample': 0.7}
```

[18]:
```
# Gradient boosting with best parameters
gs_gbm = GradientBoostingClassifier(
    criterion='friedman_mse',
    learning_rate=0.2,
    loss='deviance',
    max_depth=10,
    max_features='sqrt',
    min_samples_leaf= 0.0001,
    min_samples_split= 0.1,
    n_estimators = 30,
    subsample = 0.7
)
gs_gbm.fit(X_train, y_train)
gs_gbm.score(X_test,y_test)
```

[18]: 0.8926666666666667

### 1.15 Stochastic gradient descent

[18]:
```
parameters = [{
    "max_iter": [100,200,300],
    "loss": ["hinge","log","squared_hinge","perceptron"],
    "penalty": ["elasticnet", "l1", "l2"],
    "alpha": [0.0001, 0.001, 0.01, 0.1],
    "learning_rate": ['constant', 'optimal', 'invscaling', 'adaptive'],
    "class_weight": [{1:0.5, 0:0.5}, {1:0.4, 0:0.6}, {1:0.6, 0:0.4}, {1:0.7, 0:
 ↪0.3}],
    "eta0": [1, 10]
             }]
sgd = GridSearchCV(SGDClassifier(), parameters, cv=5, n_jobs=-1,scoring='f1',␣
 ↪verbose=True)
sgd.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 4608 candidates, totalling 23040 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed:    0.2s
[Parallel(n_jobs=-1)]: Done 952 tasks      | elapsed:    5.7s
[Parallel(n_jobs=-1)]: Done 1828 tasks      | elapsed:   13.3s
[Parallel(n_jobs=-1)]: Done 3224 tasks      | elapsed:   24.6s
[Parallel(n_jobs=-1)]: Done 5024 tasks      | elapsed:   39.9s
[Parallel(n_jobs=-1)]: Done 7292 tasks      | elapsed:   56.8s
[Parallel(n_jobs=-1)]: Done 9848 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 13368 tasks      | elapsed:  1.6min
```

```
[Parallel(n_jobs=-1)]: Done 16992 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done 23040 out of 23040 | elapsed:  2.5min finished
```

[18]:
```
GridSearchCV(cv=5, estimator=SGDClassifier(), n_jobs=-1,
             param_grid=[{'alpha': [0.0001, 0.001, 0.01, 0.1],
                          'class_weight': [{0: 0.5, 1: 0.5}, {0: 0.6, 1: 0.4},
                                           {0: 0.4, 1: 0.6}, {0: 0.3, 1: 0.7}],
                          'eta0': [1, 10],
                          'learning_rate': ['constant', 'optimal', 'invscaling',
                                            'adaptive'],
                          'loss': ['hinge', 'log', 'squared_hinge',
                                   'perceptron'],
                          'max_iter': [100, 200, 300],
                          'penalty': ['elasticnet', 'l1', 'l2']}],
             scoring='f1', verbose=True)
```

[35]:
```python
print(sgd.best_params_)
```

```
{'alpha': 0.001, 'class_weight': {1: 0.7, 0: 0.3}, 'eta0': 10, 'learning_rate':
'adaptive', 'loss': 'perceptron', 'max_iter': 300, 'penalty': 'elasticnet'}
```

[19]:
```python
# Stochastic gradient descent with best parameters
gs_sgd = SGDClassifier(alpha =0.001,
                       class_weight ={1: 0.7, 0: 0.3},
                       eta0 =10,
                       learning_rate = 'adaptive',
                       loss= 'perceptron',
                       max_iter=300,
                       penalty= 'elasticnet')
gs_sgd.fit(X_train, y_train)
gs_sgd.score(X_test,y_test)
```

[19]:
```
0.8846666666666667
```

### 1.16 Random Forest

[21]:
```python
parameters = [{
    "criterion": ["gini",  "entropy"],
    "n_estimators": [200,400,600,800,1000],
    "max_features": ['auto', 'sqrt'],
    "max_depth": [5, 50, 100],
    "min_samples_split": [5,10,15,20,25,30],
    "min_samples_leaf": [1,5,10,15,20],
    "bootstrap": [True, False]
             }]

rf = GridSearchCV(RandomForestClassifier(),
                  parameters,
```

```
                    cv=5,
                    n_jobs=-1,
                    scoring='f1',
                    verbose=True)

rf.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 3600 candidates, totalling 18000 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:    7.0s
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed:   47.5s
[Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 776 tasks      | elapsed:  3.7min
[Parallel(n_jobs=-1)]: Done 1226 tasks      | elapsed:  6.0min
[Parallel(n_jobs=-1)]: Done 1776 tasks      | elapsed:  9.1min
[Parallel(n_jobs=-1)]: Done 2426 tasks      | elapsed: 13.1min
[Parallel(n_jobs=-1)]: Done 3176 tasks      | elapsed: 17.5min
[Parallel(n_jobs=-1)]: Done 4026 tasks      | elapsed: 23.2min
[Parallel(n_jobs=-1)]: Done 4976 tasks      | elapsed: 28.4min
[Parallel(n_jobs=-1)]: Done 6026 tasks      | elapsed: 34.0min
[Parallel(n_jobs=-1)]: Done 7176 tasks      | elapsed: 41.6min
[Parallel(n_jobs=-1)]: Done 8426 tasks      | elapsed: 49.7min
[Parallel(n_jobs=-1)]: Done 9776 tasks      | elapsed: 57.3min
[Parallel(n_jobs=-1)]: Done 11226 tasks      | elapsed: 66.1min
[Parallel(n_jobs=-1)]: Done 12776 tasks      | elapsed: 77.0min
[Parallel(n_jobs=-1)]: Done 14426 tasks      | elapsed: 86.8min
[Parallel(n_jobs=-1)]: Done 16176 tasks      | elapsed: 98.8min
[Parallel(n_jobs=-1)]: Done 18000 out of 18000 | elapsed: 117.3min finished
```

[21]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid=[{'bootstrap': [True, False],
                          'criterion': ['gini', 'entropy'],
                          'max_depth': [5, 50, 100],
                          'max_features': ['auto', 'sqrt'],
                          'min_samples_leaf': [1, 5, 10, 15, 20],
                          'min_samples_split': [5, 10, 15, 20, 25, 30],
                          'n_estimators': [200, 400, 600, 800, 1000]}],
             scoring='f1', verbose=True)
```

[40]:
```
print(rf.best_params_)
```

```
{'bootstrap': False, 'criterion': 'entropy', 'max_depth': 100, 'max_features':
'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 25, 'n_estimators': 800}
```

[20]:
```
# Random forest with best parameters
gs_rf = RandomForestClassifier(bootstrap=False,
                               criterion='entropy',
                               max_depth= 100,
```

```
                                max_features='sqrt',
                                min_samples_leaf=1,
                                min_samples_split=25,
                                n_estimators=800)
gs_rf.fit(X_train, y_train)
gs_rf.score(X_test,y_test)
```

[20]: 0.9

### 1.17 Decision Tree

[24]:
```
parameters = [{
    "criterion": ['gini','entropy'],
    "max_depth": range(1,10),
    "min_samples_split": range(1,10),
    "min_samples_leaf": [1,2,5,10],
             }]

dt = GridSearchCV(DecisionTreeClassifier(),
                  parameters,
                  cv=5, n_jobs=-1,
                  scoring='f1',
                  verbose=True)

dt.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 648 candidates, totalling 3240 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed:    0.2s
[Parallel(n_jobs=-1)]: Done 1640 tasks      | elapsed:    3.2s
[Parallel(n_jobs=-1)]: Done 3240 out of 3240 | elapsed:    6.2s finished
```

[24]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid=[{'criterion': ['gini', 'entropy'],
                          'max_depth': range(1, 10),
                          'min_samples_leaf': [1, 2, 5, 10],
                          'min_samples_split': range(1, 10)}],
             scoring='f1', verbose=True)
```

[43]:
```
print(dt.best_params_)
```

```
{'criterion': 'gini', 'max_depth': 1, 'min_samples_leaf': 1,
'min_samples_split': 2}
```

[21]:
```
# Decision Tree with best parameters
gs_dt = DecisionTreeClassifier(criterion='gini',
                                max_depth= 6,
                                min_samples_leaf=1,
```

```
                                    min_samples_split=2,)
gs_dt.fit(X_train, y_train)
gs_dt.score(X_test,y_test)
```

[21]: 0.8913333333333333

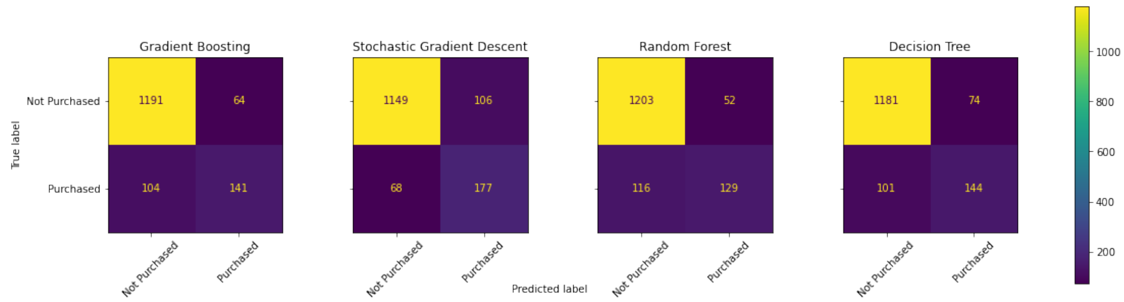
## 1.18 STEP 6 : Ensemble Model Building

**We will now compare our four model's performance.**

[104]:
```
classifiers = {
    "Gradient Boosting": gs_gbm,
    "Stochastic Gradient Descent": gs_sgd,
    "Random Forest": gs_rf,
    "Decision Tree": gs_dt
}

f, axes = plt.subplots(1, 4, figsize=(20, 5), sharey='row')

for i, (key, classifier) in enumerate(classifiers.items()):
    y_pred = classifier.fit(X_train, y_train).predict(X_test)
    cf_matrix = confusion_matrix(y_test, y_pred)
    print(key, " \n Accuracy:",accuracy_score(y_test,y_pred),"\n␣
↪F-score",f1_score(y_test,y_pred))
    disp = ConfusionMatrixDisplay(cf_matrix,
                                  display_labels=["Not Purchased","Purchased"])
    disp.plot(ax=axes[i], xticks_rotation=45)
    disp.ax_.set_title(key)
    disp.im_.colorbar.remove()
    disp.ax_.set_xlabel('')
    if i!=0:
        disp.ax_.set_ylabel('')

f.text(0.4, 0.1, 'Predicted label', ha='left')
plt.subplots_adjust(wspace=0.40, hspace=0.1)


f.colorbar(disp.im_, ax=axes)
plt.show()
```

```
Gradient Boosting
 Accuracy: 0.888
 F-score 0.6266666666666667
Stochastic Gradient Descent
 Accuracy: 0.884
 F-score 0.6704545454545454
Random Forest
 Accuracy: 0.888
 F-score 0.6056338028169014
```

```
Decision Tree
 Accuracy: 0.8833333333333333
 F-score 0.6220302375809936
```




**Now we will make a model out of our three best performing ones.**

[106]:
```python
# Combination of the three best models
estimators=[('Random Forest',gs_rf),('Decision Tree',gs_dt),('Stochastic␣
↪Gradient Descent',gs_sgd)]
ensemble = VotingClassifier(estimators, voting='hard')
ensemble.fit(X_train, y_train)
y_pred = ensemble.fit(X_train, y_train).predict(X_test)
print(" Accuracy : ",accuracy_score(y_test,y_pred),"\n␣
↪F-score",f1_score(y_test,y_pred))
```

```
 Accuracy :  0.8926666666666667
 F-score 0.6567164179104478
```

## 1.19 STEP 7 : Export

### 1.19.1 Exporting files for the API

**In order to make our API we need to export all the processing our model. This will allow us to process our new data and make a prediction.**

[82]:
```python
pickle.dump(ensemble, open('Flask_restful_api/model.pickle', 'wb'))
pickle.dump(scalar, open('Flask_restful_api/scaler.pickle','wb'))
pickle.dump(column_trans, open('Flask_restful_api/column_trans.pickle','wb'))
```