Lab 4: Scikit Tutorial (Week 2.2)

1 – Objectives

With this assignment the student should be able to learn how to work with Scikit.

2 – Scikit Tutorial

Scikit-learn (`https://scikit-learn.org/`) is a free machine learning (ML) library for Python. It supports Python numerical and scientific libraries like NumPy and SciPy. It features various ML and CI algorithms, and most important from the CI point of view, it presents many useful modules that simplify the implementation of data experimental setup. A good example is the function

`sklearn.model_selection.`**`train_test_split()`**

that automatically splits arrays or matrices into random train and test subsets.

In order to learn how to work with Scikit I suggest following the DataQuest Scikitlearn tutorial, by Satyabrata Pal:

`https://www.dataquest.io/blog/sci-kit-learn-tutorial/`

By now you should be familiar with most terms used during the tutorial and be able to understand any new concepts. The ML algorithms mentioned and used in the tutorial are a good complement to the algorithms you will learn in CI4IoT and can be further used as comparison.

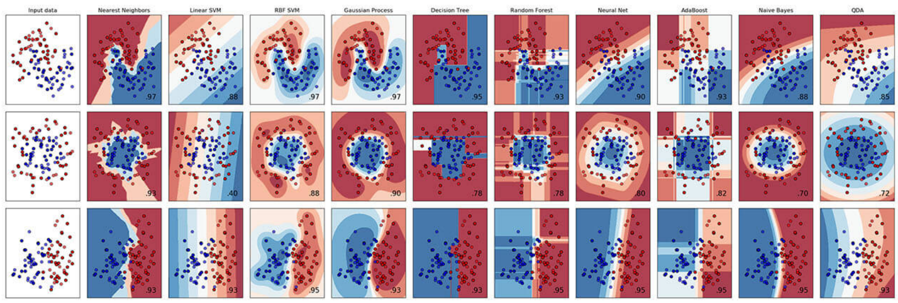
The following ANNEX contains an edited version of the online tutorial.

The dataset used in the tutorial is included within the .zip datasets file for this lab class.

ANNEX A

Scikit-learn Tutorial: Machine Learning in Python

Satyabrata Pal



Scikit-learn is a free machine learning library for Python. It features various algorithms like support vector machine, random forests, and k-neighbours, and it also supports Python numerical and scientific libraries like `NumPy` and `SciPy`.

In this tutorial we will learn to code python and apply Machine Learning with the help of the scikit-learn library, which was created to make doing machine learning in Python easier and more robust.

To do this, we'll be using the Sales_Win_Loss data set from IBM's Watson repository. We will import the data set using pandas, explore the data using pandas methods like `head()`, `tail()`, `dtypes()`, and then try our hand at using plotting techniques from `Seaborn` to visualize our data.

Then we'll dive into scikit-learn and use `preprocessing.LabelEncoder()` in scikit-learn to process the data, and `train_test_split()` to split the data set into test and train samples. We will also use a cheat sheet to help us decide which algorithms to use for the data set. Finally we will use three different algorithms (Naive-Bayes, LinearSVC, K-Neighbors Classifier) to make predictions and compare their performance using methods like `accuracy_score()` provided by the scikit-learn library. We will also visualize the performance score of different models using scikit-learn and Yellowbrick visualization.

To get the most out of this post, you should probably already be comfortable with:

- pandas fundamentals
- Seaborn and matplotlib basics

If you need to brush up on these topics, check out these [pandas]() and [data visualization]() blog posts.

The data set

For this tutorial, we will use the [Sales-Win-Loss data set]() available on the IBM Watson website. This data set contains the sales campaign data of an automotive parts wholesale supplier.

We will use scikit-learn to build a predictive model to tell us which sales campaign will result in a loss and which will result in a win.

Let's begin by importing the data set.

Importing the data set

First we will import the pandas module and use a variable `url` to store the url from which the data set is to be downloaded.

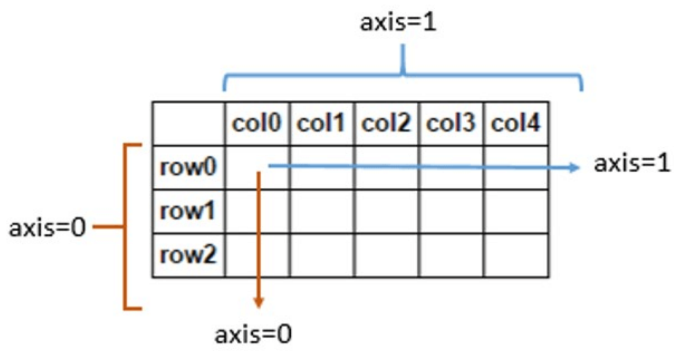
```
#import necessary modules

import pandas as pd

#store the url in a variable

url = "https://community.watsonanalytics.com/wp-content/uploads/2015/04/WA_Fn-UseC_-Sales-Win-Loss.csv"
```

Next, we will use the `read_csv()` method provided by the pandas module to read the `csv` file which contains comma separated values and convert that into a pandas DataFrame.

```
# Read in the data with `read_csv()`

sales_data = pd.read_csv(url)
```

The code snippet above returns a variable `sales_data` where the dataframe is now stored.

For those who are new to pandas, the `pd.read_csv()` method in the above code creates a tabular data-structure known as a `Dataframe`, where the first column contains the index which marks each row of data uniquely and the first row contains a label/name for each column, which are the original column names retained from the data set. The `sales_data` variable in the above code snippet will have a structure similar to the diagram represented below.



Source: [Stack Overflow]

In the above diagram the row0, row1, row2 are the index for each record in the data set and the col0, col1, col2 etc are the column names for each columns(features) of the data set.

Now that we have downloaded the data set from its source and converted that into a pandas Dataframe, let's display a few records from this dataframe. For this we will use the `head()` method.

```
# Using .head() method to view the first few records of the data set

sales_data.head()
```

	Opportunity Number	Supplies Subgroup	Supplies Group	Region	Route To Market	Elapsed Days In Sales Stage	Opportunity Result	Sales Stage Change Count	Total Days Identified Through Closing
0	1641984	Exterior Accessories	Car Accessories	Northwest	Fields Sales	76	Won	13	104
1	1658010	Exterior Accessories	Car Accessories	Pacific	Reseller	63	Loss	2	163
2	1674737	Motorcycle Parts	Performance & Non-auto	Pacific	Reseller	24	Won	7	82
3	1675224	Shelters & RV	Performance & Non-auto	Midwest	Reseller	16	Loss	5	124
4	1689785	Exterior Accessories	Car Accessories	Pacific	Reseller	69	Loss	11	91

As can be seen from the above display, the `head()` method shows us the first few records from the data set. The `head()` method is a very nifty tool provided by pandas that helps us to get a feel of the content of a data set. We will talk more about the `head()` method in the next section.

Data Exploration

Now that we have got the data set downloaded and converted into a pandas dataframe, lets do a quick exploration of the data see what stories the data can tell us so that we can plan our course of action.

Data exploration is a very important step in any Data Science or Machine Learning project. Even a quick exploration of the data set can give us important information that we might otherwise miss, and that information can suggest important questions we can try to answer through our project.

For exploring the data set, we will use some third party Python libraries to help us process the data so that it can be effectively used with scikit-learn's powerful algorithms. But we can start with the same `head()` method we used in the previous section to view the first few records of the imported data set, because `head()` is actually capable of doing much more than that! We can customize the `head()` method to show only a specific number of records as well:

```
# Using head() method with an argument which helps us to restrict the number of initial records that should be displayed

sales_data.head(n=2)
```

	Opportunity Number	Supplies Subgroup	Supplies Group	Region	Route To Market	Elapsed Days In Sales Stage	Opportunity Result	Sales Stage Change Count	Total Days Identified Through Closing
0	1641984	Exterior Accessories	Car Accessories	Northwest	Fields Sales	76	Won	13	104
1	1658010	Exterior Accessories	Car Accessories	Pacific	Reseller	63	Loss	2	163

In the code snippet above, we used an argument inside the `head()` method to display only the first two records from our data set. The integer '2' in the argument `n=2` actually denotes the second `index` of the Dataframe `Sales_data`. Using this we can get a quick look into the kind of data we have to work with. For example, we can see that columns like 'Supplies Group' and 'Region' contain string data, while columns like Opportunity Result, Opportunity Number etc. contain integers. Also, we can see that the 'Opportunity Number' column contains unique identifiers for each record.

Now that we have viewed the initial records of our dataframe, let's try to view the last few records in the data set. This can be done using the `tail()` method, which has similar syntax as the `head()` method. Let's see what the `tail()` method can do:

```
# Using .tail() method to view the last few records from the dataframe

sales_data.tail()
```

	Opportunity Number	Supplies Subgroup	Supplies Group	Region	Route To Market	Elapsed Days In Sales Stage	Opportunity Result	Sales Stage Change Count	Total Days Identifi Throug Closin
78020	10089932	Batteries & Accessories	Car Accessories	Southeast	Reseller	0	Loss	2	0
78021	10089961	Shelters & RV	Performance & Non-auto	Northeast	Reseller	0	Won	1	0
78022	10090145	Exterior Accessories	Car Accessories	Southeast	Reseller	0	Loss	2	0
78023	10090430	Exterior Accessories	Car Accessories	Southeast	Fields Sales	0	Loss	2	0
78024	10094255	Interior Accessories	Car Accessories	Mid-Atlantic	Reseller	0	Loss	1	0

The `tail()` method in the code snippet above returns us the last few records from the dataframe `sales_data`. We can pass an argument to the `tail()` method to view only a limited number of records from our dataframe, too:

```
# Using .tail() method with an argument which helps us to restrict the number of initial records that should be displayed

sales_data.tail(n=2)
```

Opportunity Number	Supplies Subgroup	Supplies Group	Region	Route To Market	Elapsed Days In Sales Stage	Opportunity Result	Sales Stage Change Count	Total Days Identified Through Closing
78023	10090430	Exterior Accessories	Car Accessories	Southeast	Fields Sales	0	Loss	2
78024	10094255	Interior Accessories	Car Accessories	Mid-Atlantic	Reseller	0	Loss	1

We can now view only the last two records from the dataframe, as indicated by the argument `n=2` inside the `tail()` method. Similar to the `head()` method, the integer ‘2’ in the argument `n=2` in the `tail()` method points to the second index from the last two records in the data set `sales_data`.

What story do these last two records tell us? Looking at the ‘Opportunity Number’ column of the trailer records from the dataframe, it becomes clear to us that a total of 78,024 records are available. This is evident from the 'index' number of the records displayed with the `tail()` method.

Now, it would be good if we could see the different datatypes that are available in this data set; this information can be handy in case we need to do some conversion later on. We can do that with the `dtypes()` method in pandas:

```
# using the dtypes() method to display the different datatypes available

sales_data.dtypes

Opportunity Number int64

Supplies Subgroup object

Supplies Group object

Region object

Route To Market object

Elapsed Days In Sales Stage int64

Opportunity Result object

Sales Stage Change Count int64

Total Days Identified Through Closing int64

Total Days Identified Through Qualified int64

Opportunity Amount USD int64

Client Size By Revenue int64

Client Size By Employee Count int64

Revenue From Client Past Two Years int64

Competitor Type object
```

```
Ratio Days Identified To Total Days float64

Ratio Days Validated To Total Days float64

Ratio Days Qualified To Total Days float64

Deal Size Category int64

dtype: object
```

As we can see in the code snippet above, using the `dtypes` method, we can list the different columns available in the Dataframe along with their respective datatypes. For example, we can see that the Supplies Subgroup column is an `object` datatype and the 'Client Size By Revenue' column is an `integer` datatype. So, now we know which columns have integers in them and which columns have string data in them.

Data Visualization

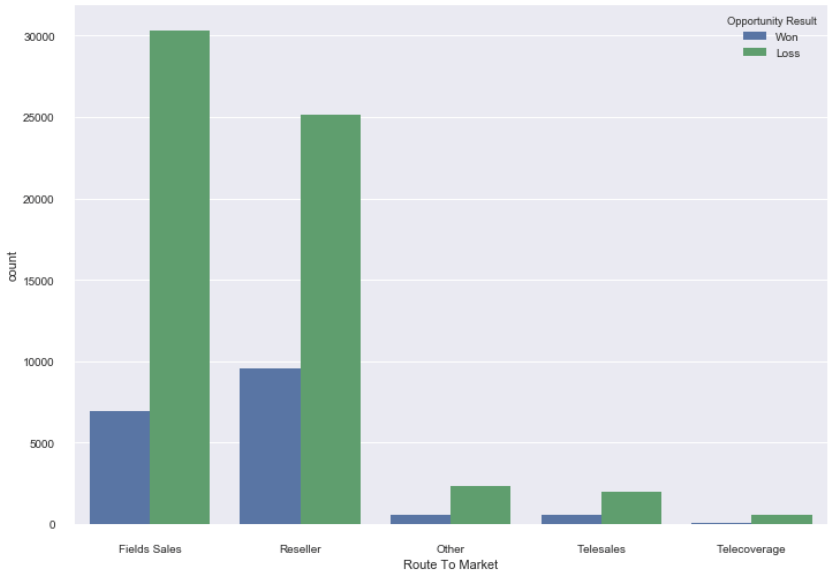
Now that we've done some basic data exploration, let's try to create some nice plots to visually represent the data and uncover more stories hidden in the data set.

There are many python libraries that provide functions for doing data visualization; one such library is `Seaborn`. To use Seaborn plots, we should make sure that this python module is downloaded and installed.

Let's set up the code to use the `Seaborn` module:

```
# import the seaborn module

import seaborn as sns

# import the matplotlib module

import matplotlib.pyplot as plt

# set the background colour of the plot to white

sns.set(style="whitegrid", color_codes=True)
```

```
# setting the plot size for all plots

sns.set(rc={'figure.figsize':(11.7,8.27)})

# create a countplot

sns.countplot('Route  To  Market',data=sales_data,hue  =  'Opportunity
Result')

# Remove the top and down margin

sns.despine(offset=10, trim=True)

# display the plotplt.show()
```



Now that we've got Seaborn set up, let's take a deeper look at what we just did.

First we imported the Seaborn module and the matplotlib module. The `set()` method in the next line helps to set different properties for our plot, like 'styles', 'color' etc. Using the `sns.set(style="whitegrid", color_codes=True)` code snippet we set the background of the plot to a light color. Then we set the plot size with the `sns.set(rc={'figure.figsize':(11.7,8.27)})` code snippet, which defines the plot figure size to be 11.7px and 8.27px.

Next, we create the plot using `sns.countplot('Route To Market',data=sales_data,hue = 'Opportunity Result')`.

The `countplot()` method helps us to create a countplot and it exposes several arguments to customize the countplot per our needs. Here, in the first argument of the `countplot()` method, we defined the X-axis as the column 'Route To Market' from our data set. The second argument is the data source, which in this case is the dataframe `sales_data` that we created in the first section of this tutorial. The third argument is the color of the barplots which we assigned to 'blue' for the label 'won' and 'green' for the label 'loss' from the 'Opportunity Result' column of the `sales_data` dataframe.

More details about Seaborn countplots can be found here.

So, what does the countplot tell us about the data? The first thing is that the data set has more records of the type 'loss' than records of the type 'won', as we can see from the size of the bars. Looking at the x axis and the corresponding bars for each label on the x axis, we can see that most of the data from our data set is concentrated towards the left side of the plot: towards the 'Field Sales' and 'Reseller' categories. Another thing to notice is that the category 'Field Sales' has more losses than the category 'Reseller'.

We selected the Route To Market column for our plot because it seemed like it would provide helpful information after our initial study of the `head()` and `tail()` methods' output. But other fields like 'Region' , 'Supplies Group' etc. can also be used to make plots in the same manner.

Now that we have got a pretty good visualization of what our overall data looks like, let's see what more information can we dig out with the help of other Seaborn plots. Another popular option is `violinplots`, so let's create a violin plot and see what that style of plot can tell us.

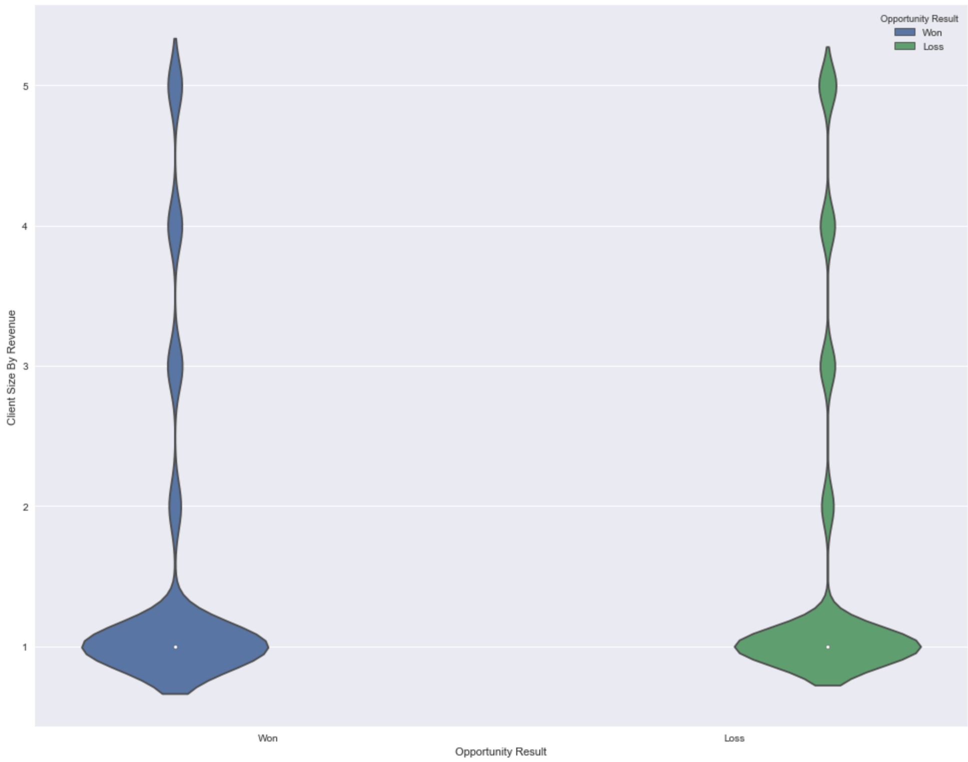
We will use the `violinplot()` method provided by the Seaborn module to create the violin plot. Let's first import the `seaborn` module and use the `set()` method to customize the size of our plot. We will seet the size of the plot as 16.7px by 13.27px:

```
# import the seaborn module

import seaborn as sns

# import the matplotlib module

```

```
import matplotlib.pyplot as plt

# setting the plot size for all plots

sns.set(rc={'figure.figsize':(16.7,13.27)})
```

Next, we will use the `violinplot()` method to create the violinplot and then use the `show()` mehtod to display the plot –

```
# plotting the violinplot

sns.violinplot(x="Opportunity Result",y="Client Size By Revenue", hue="Opportunity Result", data=sales_data);

plt.show()
```



Now, that our plot is created, let's see what it tells us. In its simplest form, a violin plot displays the distribution of data across labels. In the above plot we have labels 'won' and 'loss' on the x-axis and the values of 'Client Size By Revenue' in the y-axis. The violin plot shows us that the largest distribution of data is in the client size '1', and the rest of the client size labels have less data.

This violin plot gives us very valuable insight into how the data is distributed and which features and labels have the largest concentration of data, but there is more than what meets the eye in case of violin plots. You can dig deeper into the additional uses of violin plots via the official documentation of the `Seaborn` module

Preprocessing Data

Now that we have a good understanding of what our data looks like, we can move towards preparing it to build prediction models using scikit-learn.

We saw in our initial exploration that most of the columns in our data set are strings, but the algorithms in scikit-learn understand only numeric data. Luckily, the scikit-learn library provides us with many methods for converting string data into numerical data. One such method is the `LabelEncoder()` method. We will use this method to convert the categorical labels in our data set like 'won' and 'loss' into numerical labels. To visualize what we are trying to to achieve with the `LabelEncoder()` method let's consider the images below.

The image below represents a dataframe that has one column named 'color' and three records 'Red', 'Green' and 'Blue'.

	Color
0	Red
1	Green
2	Blue

Since the machine learning algorithms in scikit-learn understand only numeric inputs, we would like to convert the categorical labels like 'Red, 'Green' and 'Blue' into numeric labels. When we are done converting the categorical labels in the original dataframe, we would get something like this:

	Color
0	1
1	2
2	3

Now, let's start the actual conversion process. We will use the `fit_transform()` method provided by `LabelEncoder()` to encode the labels in the categorical column such as 'Route To Market' in the `sales_data` dataframe and convert them into numeric labels similar to what we visualized in the above diagrams. The `fit_transform()` function takes user defined labels as input and then returns encoded labels. Let's go through a quick example to understand how the encoding is done. In the code example below we have a list of cities i.e. `["paris", "paris", "tokyo", "amsterdam"]` and we will try to encode these string labels into something similar to this – `[2, 2, 1,3]`.

```
#import the necessary module

from sklearn import preprocessing

# create the Labelencoder object

le = preprocessing.LabelEncoder()

#convert the categorical columns into numeric

encoded_value = le.fit_transform(["paris", "paris", "tokyo",
"amsterdam"])

print(encoded_value)

[1 1 2 0]
```

Voila! We have successfully converted the string labels into numeric labels. How'd we do that? First we imported the `preprocessing` module which provides the `LabelEncoder()` method. Then we created an object which represents the `LabelEncoder()` type. Next we used this object's `fit_transform()` function to differentiate between different unique classes of the list `["paris", "paris", "tokyo", "amsterdam"]` and then return a list with the respective encoded values, i.e. `[1 1 2 0]`.

Notice how the `LabelEncoder()` method assigns the numeric values to the classes in the order of the first letter of the classes from the original list: "(a)msterdam" gets an encoding of '0' , "(p)aris gets an encoding of 1" and "(t)okyo" gets an encoding of 2.

There are many more functions provided by `LabelEncoder()` that are handy under a variety of encoding requirements. We won't need them here, but to learn more, a good place to start is [the official page of scikit-learn]() where the `LabelEncoder()` and its related functions are described in detail.

Since, we now have a good idea of how the `LabelEncoder()` works, we can move forward with using this method to encode the categorical labels from the `sales_data` dataframe and convert them into numeric labels. In the previous sections during the initial exploration of the data set we saw that the following columns contain string values: 'Supplies Subgroup', 'Region', 'Route To Market', 'Opportunity Result', 'Competitor Type', and 'Supplies Group'. Before we start encoding these string labels, let's take a quick look into the different labels that these columns contain:-

```
print("Supplies Subgroup' : ",sales_data['Supplies Subgroup'].unique())

print("Region : ",sales_data['Region'].unique())

print("Route To Market : ",sales_data['Route To Market'].unique())

print("Opportunity       Result       :       ",sales_data['Opportunity
Result'].unique())

print("Competitor Type : ",sales_data['Competitor Type'].unique())

print("'Supplies Group : ",sales_data['Supplies Group'].unique())

Supplies  Subgroup'  :  ['Exterior  Accessories'  'Motorcycle  Parts'
'Shelters & RV'

'Garage & Car Care' 'Batteries & Accessories' 'Performance Parts'

'Towing & Hitches' 'Replacement Parts' 'Tires & Wheels'

'Interior Accessories' 'Car Electronics']

Region  :  ['Northwest'  'Pacific'  'Midwest'  'Southwest'  'Mid-Atlantic'
'Northeast'

'Southeast']
```

```
Route To Market : ['Fields Sales' 'Reseller' 'Other' 'Telesales'
'Telecoverage']

Opportunity Result : ['Won' 'Loss']

Competitor Type : ['Unknown' 'Known' 'None']

'Supplies Group : ['Car Accessories' 'Performance & Non-auto' 'Tires &
Wheels'

'Car Electronics']
```

We have now laid out the different categorical columns from the `sales_data` dataframe and the unique classes under each of these columns. Now, it's time to encode these strings into numeric labels. To do this, we will run the code below and then do a deep dive to understand how it works:

```
#import the necessary module

from sklearn import preprocessing

# create the Labelencoder object

le = preprocessing.LabelEncoder()

#convert the categorical columns into numeric

sales_data['Supplies Subgroup'] = le.fit_transform(sales_data['Supplies
Subgroup'])

sales_data['Region'] = le.fit_transform(sales_data['Region'])

sales_data['Route To Market'] = le.fit_transform(sales_data['Route To
Market'])

sales_data['Opportunity                   Result']                  =
le.fit_transform(sales_data['Opportunity Result'])

sales_data['Competitor Type'] = le.fit_transform(sales_data['Competitor
Type'])
```

```
sales_data['Supplies Group'] = le.fit_transform(sales_data['Supplies Group'])

#display the initial records

sales_data.head()
```

	Opportunity Number	Supplies Subgroup	Supplies Group	Region	Route To Market	Elapsed Days In Sales Stage	Opportunity Result	Sales Stage Change Count	Total Days Identified Through Closing	To Id Th Q
0	1641984	2	0	3	0	76	1	13	104	10
1	1658010	2	0	4	2	63	0	2	163	16
2	1674737	5	2	4	2	24	1	7	82	82
3	1675224	8	2	1	2	16	0	5	124	12
4	1689785	2	0	4	2	69	0	11	91	13

So what did we just do? First we imported the `preprocessing` module which provides the `LabelEncoder()` method. Then we created an object `le` of the type `labelEncoder()`. In the next couple of lines we used the `fit_transform()` function provided by `LabelEncoder()` and converted the categorical labels of different columns like 'Supplies Subgroup', 'Region', Route To Market' into numeric labels. In doing this, we successfully converted all the categorical (string) columns into numeric values.

Now that we have our data prepared and converted it is *almost* ready to be used for building our predictive model. But we still need to do one critical thing:

Training Set & Test Set

A Machine Learning algorithm needs to be trained on a set of data to learn the relationships between different features and how these features affect the target variable. For this we need to divide the entire data set into two sets. One is the training set on which we are going to train our algorithm to build a model. The other is the testing set on which we will test our model to see how accurate its predictions are.

But before doing all this splitting, let's first separate our features and target variables. As before in this tutorial, we will first run the code below, and then take a closer look at what it does:

```
# select columns other than 'Opportunity Number','Opportunity
Result'cols = [col for col in sales_data.columns if col not in
['Opportunity Number','Opportunity Result']]

# dropping the 'Opportunity Number'and 'Opportunity Result' columns

data = sales_data[cols]

#assigning the Oppurtunity Result column as target

target = sales_data['Opportunity Result']

data.head(n=2)
```

	Supplies Subgroup	Supplies Group	Region	Route To Market	Elapsed Days In Sales Stage	Sales Stage Change Count	Total Days Identified Through Closing	Total Days Identified Through Qualified	Opp Amo
0	2	0	3	0	76	13	104	101	0
1	2	0	4	2	63	2	163	163	0

OK, so what did we just do? First, we don't need the 'Opportunity Number' column as it is just a unique identifier for each record. Also, we want to predict the 'Opportunity Result', so it should be our 'target' rather than part of 'data'. So, in the first line of the code above, we selected only the columns which didn't match 'Opportunity Number'and 'Opportunity Result' and assigned them to a variable `cols`. Next, we created a new dataframe `data` with the columns in the list `cols`. This will serve as our feature set. Then we took the 'Opportunity Result' column from the dataframe `sales_data` and created a new dataframe `target`.

That's it! We are all set with defining our features and target into two separate dataframes. Next we will divide the dataframes `data` and `target` into training sets and testing sets. When splitting the data set we will keep 30% of the data as the test data and the remaining 70% as the training data. But keep in mind that those numbers are arbitrary and the best split will depend on the specific data you're working with. If you're not sure how to split your data, the 80/20 principle where you keep 80% of the data as training data and use the remaining 20% as test data is a decent default. However, for this tutorial, we are going to stick with our earlier decision of keeping aside 30% of the data as test data. The `train_test_split()` method in scikit-learn can be used to split the data:

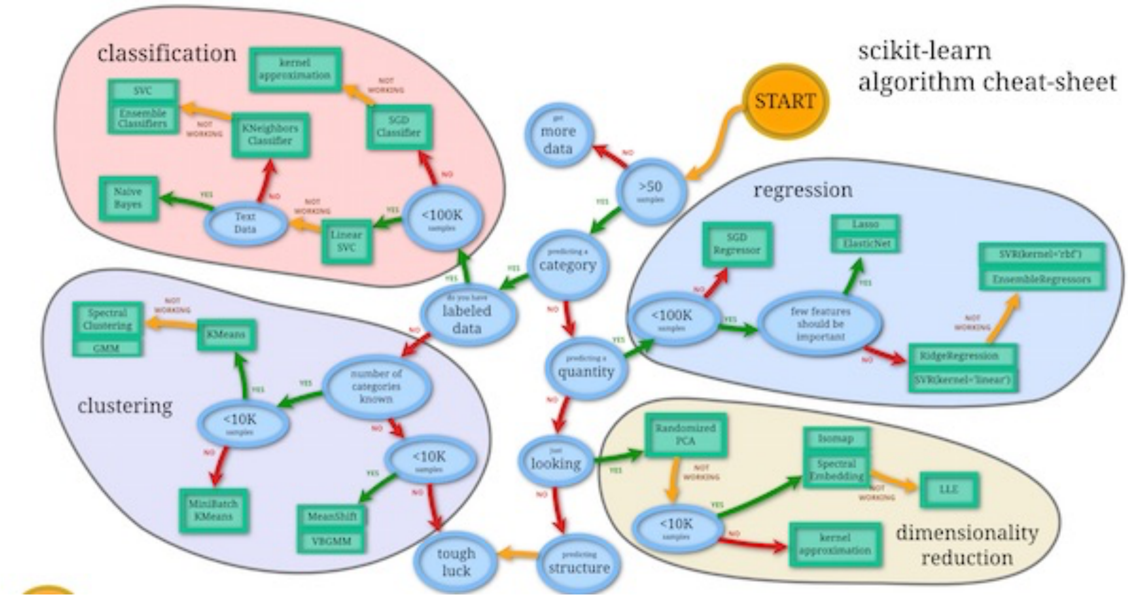
```
#import the necessary module

from sklearn.model_selection import train_test_split

#split data set into train and test setsdata_train, data_test,
target_train, target_test = train_test_split(data,target, test_size =
0.30, random_state = 10)
```

With this, we have now successfully prepared a testing set and a training set. In the above code first we imported the train_test_split module. Next we used the `train_test_split()` method to divide the data into a training set (data_train,target_train) and a test set (data_test,data_train). The first argument of the `train_test_split()` method are the features that we separated out in the previous section, the second argument is the target('Opportunity Result'). The third argument 'test_size' is the percentage of the data that we want to separate out as training data . In our case it's 30% , although this can be any number. The fourth argument 'random_state' just ensures that we get reproducible results every time.

Now, we have everything ready and here comes the most important and interesting part of this tutorial: building a prediction model using the vast library of algorithms available through scikit-learn.

Building The Model

There's a `machine_learning_map` available on scikit learn's website that we can use as a quick reference when choosing an algorithm. It looks something like this:



We can use this map as a cheat sheet to shortlist the algorithms that we can try out to build our prediction model. Using the checklist let's see under which category we fall:

- More than 50 samples – Check
- Are we predicting a category – Check
- We have labeled data? (*data with clear names like opportunity amount etc.*) – Check
- Less than 100k samples – Check

Based on the checklist that we prepared above and going by the `machine_learning_map` we can try out the below mentioned algorithms.

- Naive Bayes
- Linear SVC
- K-Neighbours Classifier

The real beauty of the scikit-learn library is that it exposes high level APIs for different algorithms, making it easier for us to try out different algorithms and compare the accuracy of the models to see what works best for our data set.

Let's begin trying out the different algorithms one by one.

Naive-Bayes

Scikit-learn provides a set of classification algorithms which "naively" assumes that in a data set every pair of features are independent. This assumption is the underlying principle of Bayes theorem. The algorithms based on this principle are known as Naive-Bayes algorithms.

On a very high level a Naive-Bayes algorithm calculates the probability of the connection of a feature with a target variable and then it selects the feature with the highest probability. Let's try to understand this with a very simple problem statement: Will it rain today? Suppose we have a set of weather data with us that will be our feature set, and the probability of 'Rain' will be our target. Based on this feature set we can create a table to show us the number of times a particular feature/target pair occur. It would look something like this:

Weather	Rain
Partially Cloudy	No
Cloudy	Yes
Partially Cloudy	No
Partially Cloudy	Yes
Partially Cloudy	Yes
Cloudy	Yes
Total	6

In the table above the feature (column) 'Weather' contains the labels ('Partially Cloudy' and 'Cloudy') and the column 'Rain' contains the occurrence of rain coinciding with the feature 'Weather' (Yes/No). Whenever a feature lcoincides with rain, it's recorded as a 'Yes' and when the feature didn't lead to rain it is recorded as a 'No'. We can now use the data from the occurrence table to create another table known as the 'Frequency table' where we can record the number of 'Yes' and the number of 'No' answers that each feature relates to:

Frequency		
Weater	No	Yes
Partially Cloudy	2	2
Cloudy	0	2
Total	2	4

Finally, we combine the data from the 'occurrence table' and the 'frequency table' and create a 'likelihood table'. This table lists the amount of 'Yes' and 'No' for each feature and then uses this data to calculate the probability of contibution of each feature towards the occurrence of rain:

Likelihood				
Weather	No	Yes	Individual Probability	
Partially Clody	2	2	4/6	0.6666666667
Cloudy	0	2	2/6	0.3333333333
Total	2	4		
Total Probability	2/6	4/6		
	0.3333333333	0.6666666667		

Notice the 'Individual Probability' column in the table above. We had 6 occurrences of the features 'Partially Cloudy' and 'Cloudy' from the 'Occurrence table' and from the 'Likelihood table' it was clear that the feature 'Partially Cloudy' had 4 occurrences (2 for 'No' and 2 for 'yes'). When we divide the number of occurrences of 'No' and 'Yes' of a particular feature with the 'total' of the 'occurrence table', we get the probability of that particular feature. In our case if we need to find out that which feature has the strongest probability of contributing to the occurrence of Rain then we take the total number of 'No' of each feature and add it to their respective number of 'Yes' from the 'frequency table' and then divide the sum with the 'Total' from the óccurances table'. This gives us the probability of each of these features coinciding with rain.

The algorithm that we are going to use for our sales data is the `Gaussian Naive Bayes` and it is based on a concept similar to the weather example we just explored above, although significantly more mathematically complicated. A more detailed explanation of 'Naive-Bayes' algorithms can be found here for those who wish to delve deeper.

Now let's implement the Gaussian Naive Bayes or `GaussianNB` algorithm from scikit-learn to create our prediction model:

```
# import the necessary module

from sklearn.naive_bayes import GaussianNB

from sklearn.metrics import accuracy_score

#create an object of the type GaussianNB

gnb = GaussianNB()

#train the algorithm on training data and predict using the testing data
```

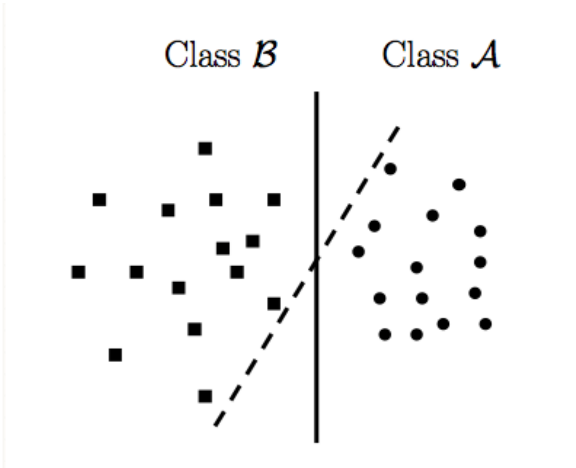
```
pred = gnb.fit(data_train, target_train).predict(data_test)

#print(pred.tolist())

#print the accuracy score of the model

print("Naive-Bayes accuracy : ",accuracy_score(target_test, pred, normalize = True))

Naive-Bayes accuracy : 0.759056732741
```

Now let's take a closer look at what we just did. First, we imported the `GaussianNB` method and the `accuracy_score` method. Then we created an object `gnb` of the type `GaussianNB`. After this, we trained the algorithm on the testing data(data_train) and testing target(target_train) using the `fit()` method, and then predicted the targets in the test data using the `predict()` method. Finally we printed the score using the `accuracy_score()` method and with this we have successfully applied the `Naive-Bayes` algorithm to build a prediction model.

Now lets see how the other algorithms in our list perform as compared to the Naive-Bayes algorithm.

LinearSVC

LinearSVC or Linear Support Vector Classification is a subclass of the `SVM` (Support Vector Machine) class. We won't go into the intricacies of the mathematics involved in this class of algorithms, but on a very basic level LinearSVC tries to divide the data into different planes so that it can find a best possible grouping of different classes. To get a clear understanding of this concept let's imagine a data set of 'dots' and 'squares' divided into a two dimensional space along two axis, as shown in the image below:



Source:[StackOverflow]

In the image above a `LinearSVC` implementation tries to divide the two-dimensional space in such a way that the two classes of data i.e the `dots` and `squares` are clearly divided. Here the two lines visually represent the various division that the `LinearSVC` tries to implement to separate out the two available classes.

A very good writeup explaining a `Support Vector Machine(SVM)` can be found here for those who'd like more detail, but for now, let's just dive in and get our hands dirty:

```
#import the necessary modules

from sklearn.svm import LinearSVC

from sklearn.metrics import accuracy_score

#create an object of type LinearSVC

svc_model = LinearSVC(random_state=0)

#train the algorithm on training data and predict using the testing data

pred = svc_model.fit(data_train, target_train).predict(data_test)

#print the accuracy score of the model

print("LinearSVC accuracy : ",accuracy_score(target_test, pred, normalize = True))
```

```
LinearSVC accuracy : 0.777811004785
```

Similar to what we did during the implementation of GaussianNB, we imported the required modules in the first two lines. Then we created an object `svc_model` of type LinearSVC with random_state as ‘0’. Hold on! What is a “random_state” ? Simply put the `random_state` is an instruction to the built-in random number generator to shuffle the data in a specific order.

Next, we trained the LinearSVC on the training data and then predicted the target using the test data. Finally, we checked the accuracy score using the `accuracy_score()` method.

Now that we have tried out the `GaussianNB` and `LinearSVC` algorithms we will try out the last algorithm in our list and that’s the `K-nearest neighbours classifier`

K-Neighbors Classifier

Compared to the previous two algorithms we’ve worked with, this classifier is a bit more complex. For the purposes of this tutorial we are better off using the `KNeighborsClassifier` class provided by scikit-learn without worrying much about how the algorithm works. (But if you’re interested, a very detailed explanation of this class of algorithms can be found here)

Now, let’s implement the K-Neighbors Classifier and see how it scores:

```
#import necessary modules

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score

#create object of the lassifier

neigh = KNeighborsClassifier(n_neighbors=3)

#Train the algorithm

neigh.fit(data_train, target_train)
```

```
# predict the response

pred = neigh.predict(data_test)

# evaluate accuracy

print ("KNeighbors accuracy score : ",accuracy_score(target_test,
pred))

KNeighbors accuracy score : 0.814550580998
```

The above code can be explained just like the previous implementations. First we imported the necessary modules, then we created the object `neigh` of type KNeighborsClassifier with the number of neighbors being `n_neighbors=3`. Then we used the `fit()` method to train our algorithm on the training set, then we tested the model on the test data. Finally, we printed out the accuracy score.

Now that we have implemented all the algorithms in our list, we can simply compare the scores of all the models to select the model with the highest score. But wouldn't it be nice if we had a way to visually compare the performance of the different models? We can use the `yellowbrick` library in scikit-learn, which provides methods for visually representing different scoring methods.

Performance Comparison

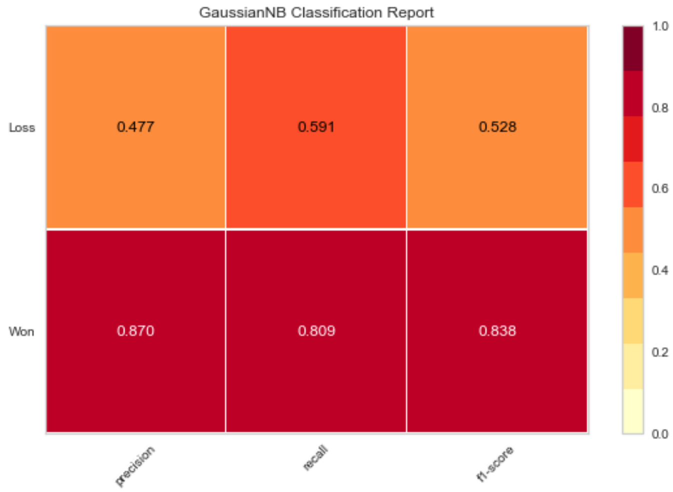
In the previous sections we have used the `accuracy_score()` method to measure the accuracy of the different algorithms. Now, we will use the `ClassificationReport` class provided by the `Yellowbrick` library to give us a visual report of how our models perform.

GaussianNB

Let's start off with the `GaussianNB` model:

```
from yellowbrick.classifier import ClassificationReport

# Instantiate the classification model and visualizer
```

```
visualizer = ClassificationReport(gnb, classes=['Won','Loss'])

visualizer.fit(data_train, target_train) # Fit the training data to the visualizer

visualizer.score(data_test, target_test) # Evaluate the model on the test data

g = visualizer.poof() # Draw/show/poof the data
```



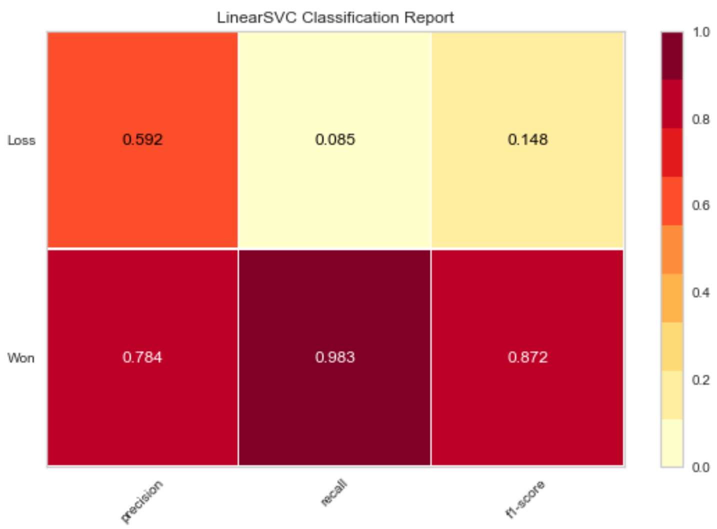
In the code above, first we import the `ClassificationReport` class provided by the `yellowbrick.classifier` module. Next, an object `visualizer` of the type `ClassificationReport` is created. Here the first argument is the `GaussianNB` object `gnb` that was created while implementing the `Naive-Bayes` algorithm in the 'Naive-Bayes' section. The second argument contains the labels 'Won' and 'Loss' from the 'Opportunity Result' column from the `sales_data` dataframe.

Next, we use the `fit()` method to train the `visualizer` object. This is followed by the `score()` method, which uses `gnb` object to carry out predictions as per the `GaussianNB` algorithm and then calculate the accuracy score of the predictions made by this algorithm. Finally, we use the `poof()` method to draw a plot of the different scores for the `GaussianNB` algorithm. Notice how the different scores are laid out against each of the labels 'Won' and 'Loss'; this enables us to visualize the scores across the different target classes.

LinearSVC

Similar to what we just did in the previous section, we can also plot the accuracy scores of the `LinearSVC` algorithm:

```
from yellowbrick.classifier import ClassificationReport

# Instantiate the classification model and visualizer

visualizer = ClassificationReport(svc_model, classes=['Won','Loss'])

visualizer.fit(data_train, target_train) # Fit the training data to the visualizer

visualizer.score(data_test, target_test) # Evaluate the model on the test data

g = visualizer.poof() # Draw/show/poof the data
```



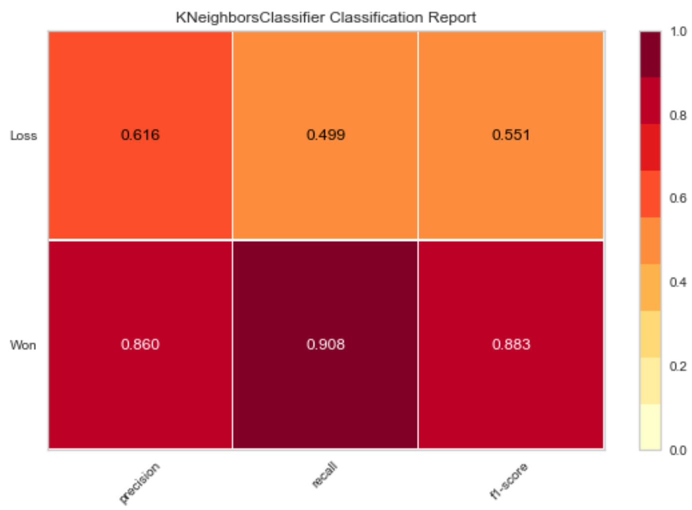
In the code above, first we imported the `ClassificationReport` class provided by the `yellowbrick.classifier` module. Next, an object `visualizer` of the type `ClassificationReport` was created. Here the first argument is the `LinearSVC` object `svc_model`, that was created while implementing the `LinearSVC` algorithm in the 'LinearSVC' section. The second argument contains the labels 'Won' and 'Loss' from the 'Opportunity Result' column from the `sales_data` dataframe.

Next, we used the `fit()` method to train the 'svc_model' object. This is followed by the `score()` method which uses the `svc_model` object to carry out predictions according to the `LinearSVC` algorithm and then calculate the accuracy score of the predictions made by this algorithm. Finally, we used the `poof()` method to draw a plot of the different scores for the `LinearSVC` algorithm.

KNeighborsClassifier

Now, let's do the same thing for the K-Neighbors Classifier scores.

```
from yellowbrick.classifier import ClassificationReport

# Instantiate the classification model and visualizer

visualizer = ClassificationReport(neigh, classes=['Won','Loss'])

visualizer.fit(data_train, target_train) # Fit the training data to the visualizer

visualizer.score(data_test, target_test) # Evaluate the model on the test data

g = visualizer.poof() # Draw/show/poof the data
```



Once again, we first import the `ClassificationReport` class provided by the `yellowbrick.classifier` module. Next, an object `visualizer` of the type `ClassificationReport` is created. Here the first argument is the `KNeighborsClassifier` object `neigh`, that was created while implementing the `KNeighborsClassifier` algorithm in the 'KNeighborsClassifier' section. The second argument contains the labels 'Won' and 'Loss' from the 'Opportunity Result' column from the `sales_data` dataframe.

Next, we use the `fit()` method to train the 'neigh' object. This is followed by the `score()` method which uses the `neigh` object to carry out predictions according to the `KNeighborsClassifier` algorithm and then calculate the accuracy score of the predictions made by this algorithm. Finally we use the `poof()` method to draw a plot of the different scores for the `KNeighborsClassifier` algorithm.

Now that we've visualized the results, it's much easier for us to compare the scores and choose the algorithm that's going to work best for our needs.

Conclusion

The scikit-learn library provides many different algorithms which can be imported into the code and then used to build models just like we would import any other Python library. This makes it easier to quickly build different models and compare these models to select the highest scoring one.

In this tutorial, we have only scratched the surface of what is possible with the scikit-learn library. To use this Machine Learning library to the fullest, there are many resources available on the official page of scikit-learn with detailed documentation that you can dive into. The quick start guide for scikit-learn can be found here, and that's a good entry point for beginners who have just started exploring the world of Machine Learning.

But to really appreciate the true power of the scikit-learn library, what you really need to do is start using it on different open data sets and building predictive models using these data sets. Sources for open data sets include Kaggle and Data.world. Both contain many interesting data sets on which one can practice building predictive models by using the algorithms provided by the scikit-learn library.