Project Report IDS

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Problem Statement:-

Data Preprocessing and Preliminary Analysis and get inferences from the data.

Data Sources:-

https://archive.ics.uci.edu/ml/datasets.php

Dataset description

This is a Glass Identification Data Set from UCI. It contains 10 attributes including id. The response is glass type(discrete 7 values)

1. The study of the classification of types of glass was motivated by the criminological investigation. At the scene of the crime, the glass left can be used as evidence...if it is correctly identified!
2. Number of Instances: 214
3. Number of Attributes: 10 (including an Id#) plus the class attribute -- all attributes are continuously valued

Goal:-

The goal of the project is to find the type of glass based on the characteristics of the new glass. To perform preprocessing of the dataset provided for the glass type and get inferences from it Through Data analysis and Visualization Then Train Machine Learning Models/Algorithms.

Importing Libraries

```
import pandas as pd
 # read and wrangle dataframes
import matplotlib.pyplot as plt
 # visualization
import seaborn as sns
# statistical visualizations and aesthetics
from sklearn.base import TransformerMixin
# To create new classes for transformations
from sklearn.preprocessing import (FunctionTransformer,
StandardScaler)
# preprocessing
from sklearn.decomposition import PCA
# dimensionality reduction
from sklearn.discriminant_analysis import
LinearDiscriminantAnalysis as LDA
from scipy.stats import boxcox
# data transform
from sklearn.model_selection import (train_test_split, KFold ,
StratifiedKFold,
cross_val_score, GridSearchCV,
learning_curve, validation_curve)
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
# model selection modules
from sklearn.pipeline import Pipeline # streaming pipelines
from sklearn.base import BaseEstimator, TransformerMixin
# To create a box-cox transformation class
from collections import Counter
import warnings
```

Importing Dataset

```
url =
'https://archive.ics.uci.edu/ml/machine-learning-databases/glass/glass.dat
a'
data = pd.read_csv(url, header=None)
data.head()
```

	0	1	2	3	4	5	6	7	8	9	10
0	1	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.0	0.0	1
1	2	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.0	0.0	1
2	3	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	1
3	4	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.0	0.0	1
4	5	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.0	0.0	1

Exploring Dataset

1.Count of Null values

2.Shape of dataset

3.Uniques values

```
#Calculating number of null Values Belonging to each Column

data.isnull().sum()
```

```
0     0
1     0
2     0
3     0
4     0
5     0
6     0
7     0
8     0
9     0
10    0
dtype: int64
```

#Shape of Data

```
Data.shape
```

The dataset consists of 214 observations

```
data[10].unique()
```

Checking Data type of Columns

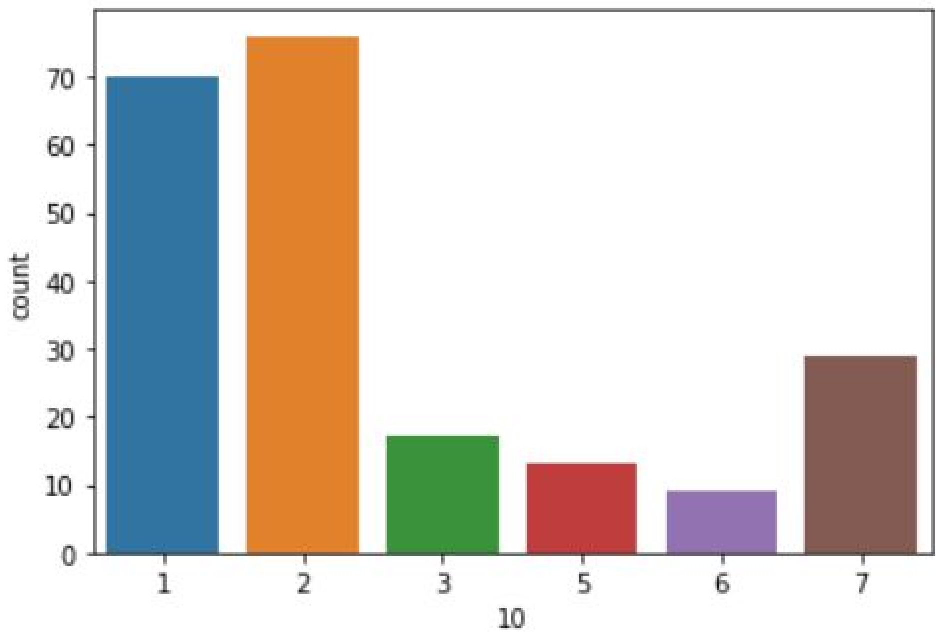
```
data.dtypes
```

```
0       int64
1     float64
2     float64
3     float64
4     float64
5     float64
6     float64
7     float64
8     float64
9     float64
10      int64
dtype: object
```

```
#Counting Number of Values Belonging to each class

data[10].value_counts()
sns.countplot(x=10, data=data)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f2defd78908>



As we can see The dataset is very very unbalanced.

The occurrences of types 1 and 2 constitute more than 67 % of the glass types.

Preprocessing of the dataset:

Data **preprocessing** is an integral step in Machine Learning as the quality of data and the useful information that can be derived from it directly affects the ability of our model to learn; therefore, it is extremely **important** that we **preprocess** our data before feeding it into our model.

Attribute Information(Features):

Id number: 1 to 214 (removed from CSV file)

* RI: refractive index
* Na: Sodium (unit measurement: weight percent in corresponding oxide, as attributes 4-10)
* Mg: Magnesium
* Al: Aluminum
* K: Potassium
* Ca: Calcium
* Ba: Barium
* Fe: Iron
* Type of glass: (class attribute) [1-7]
  1. Building_windows_float_processed
  2. Building_windows_non_float_processed
  3. Vehicle_windows_float_processed
  4. Vehicle_windows_non_float_processed
  5. Containers
  6. Tableware
  7. Headlamps

1. Adding meaningful column/attribute names

WHY?
The columns in our dataset are named from 0 to 10 which is ambiguous and difficult to read and interpret.

```
names =
['Id','RI','Na','Mg','Al','Si','K','Ca','Ba','Fe','glass_type']
data.columns = names
data.head()
```

	Id	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	glass_type
0	1	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.0	0.0	1
1	2	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.0	0.0	1
2	3	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	1
3	4	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.0	0.0	1
4	5	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.0	0.0	1

2.Removing unnecessary columns

WHY?
Because our Dataset has columns which are not required and are not important.

```
data = data.drop('Id',1)
data.head(3)
```

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	glass_type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.0	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.0	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	1

Statistics of Dataset

Descriptive statistics

Summarizing the distribution of the numerical variables.

```
data.describe()
```

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	glass_type
count	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000
mean	1.518365	13.407850	2.684533	1.444907	72.650935	0.497056	8.956963	0.175047	0.057009	2.780374
std	0.003037	0.816604	1.442408	0.499270	0.774546	0.652192	1.423153	0.497219	0.097439	2.103739
min	1.511150	10.730000	0.000000	0.290000	69.810000	0.000000	5.430000	0.000000	0.000000	1.000000
25%	1.516523	12.907500	2.115000	1.190000	72.280000	0.122500	8.240000	0.000000	0.000000	1.000000
50%	1.517680	13.300000	3.480000	1.360000	72.790000	0.555000	8.600000	0.000000	0.000000	2.000000
75%	1.519157	13.825000	3.600000	1.630000	73.087500	0.610000	9.172500	0.000000	0.100000	3.000000
max	1.533930	17.380000	4.490000	3.500000	75.410000	6.210000	16.190000	3.150000	0.510000	7.000000

OUTCOMES

Above statistics shows that data is across all attributes is not in the same range, so we will have to normalize the data first

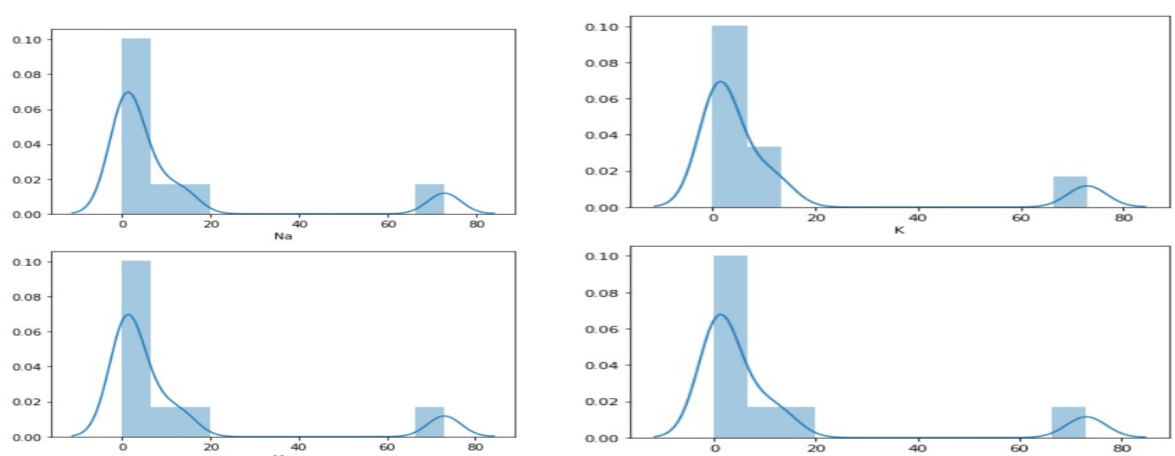
The features are not on the same scale. I.e. Si has a mean of 72.65 while Fe has a mean value of 0.057. Features should be on the same scale for algorithms such as logistic regression (gradient descent) to converge smoothly. Let's go ahead and check the distribution of the glass types.

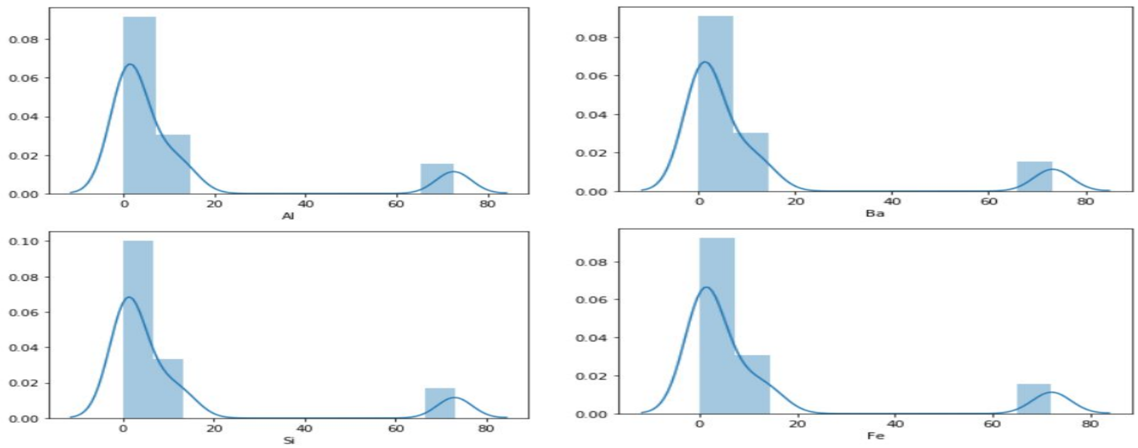
Data Visualization

1. Using Univariate Plots

```
# Separating Class labels and Features
features = ['RI','Na','Mg','Al','Si','K','Ca','Ba','Fe']
label = ['glass_type']
X = data[features]
y = data[label]

x2 = X.values
from matplotlib import pyplot as plt
import seaborn as sns
for i in range(1,9):
        sns.distplot(x2[i])
        plt.xlabel(features[i])
        plt.show()
```

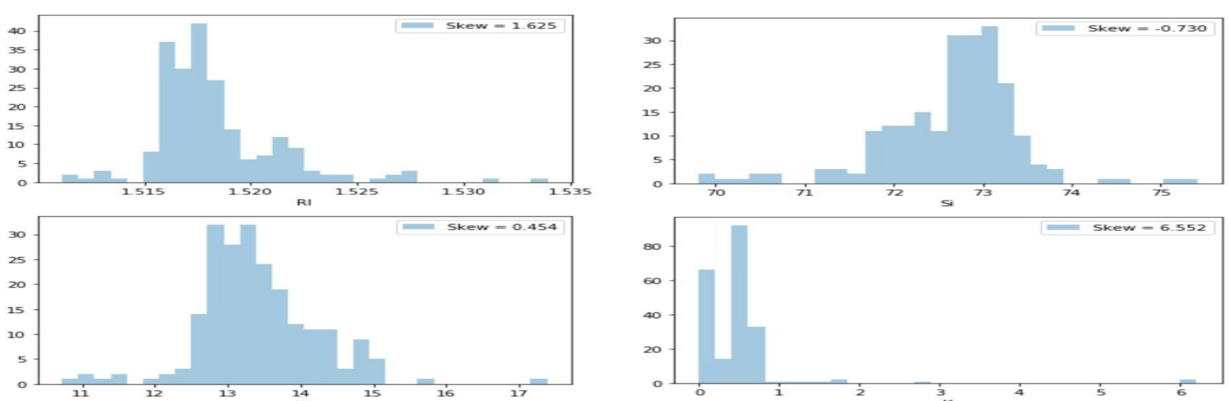


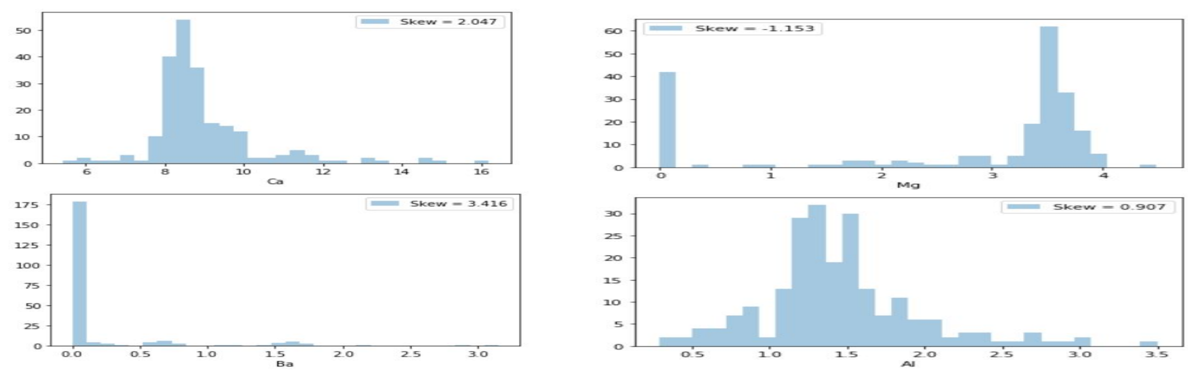


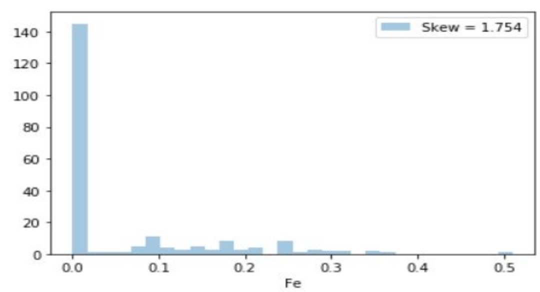
Outcomes

1. Our dataset is skewed either on the positive side or negative side and data is not normalized

```
#Trying to gain more Insights about the data
for feat in features:
    skew = data[feat].skew()
    sns.distplot(data[feat], kde= False, label='Skew = %.3f'
%(skew), bins=30)
  plt.legend(loc='best')
    plt.show()
```





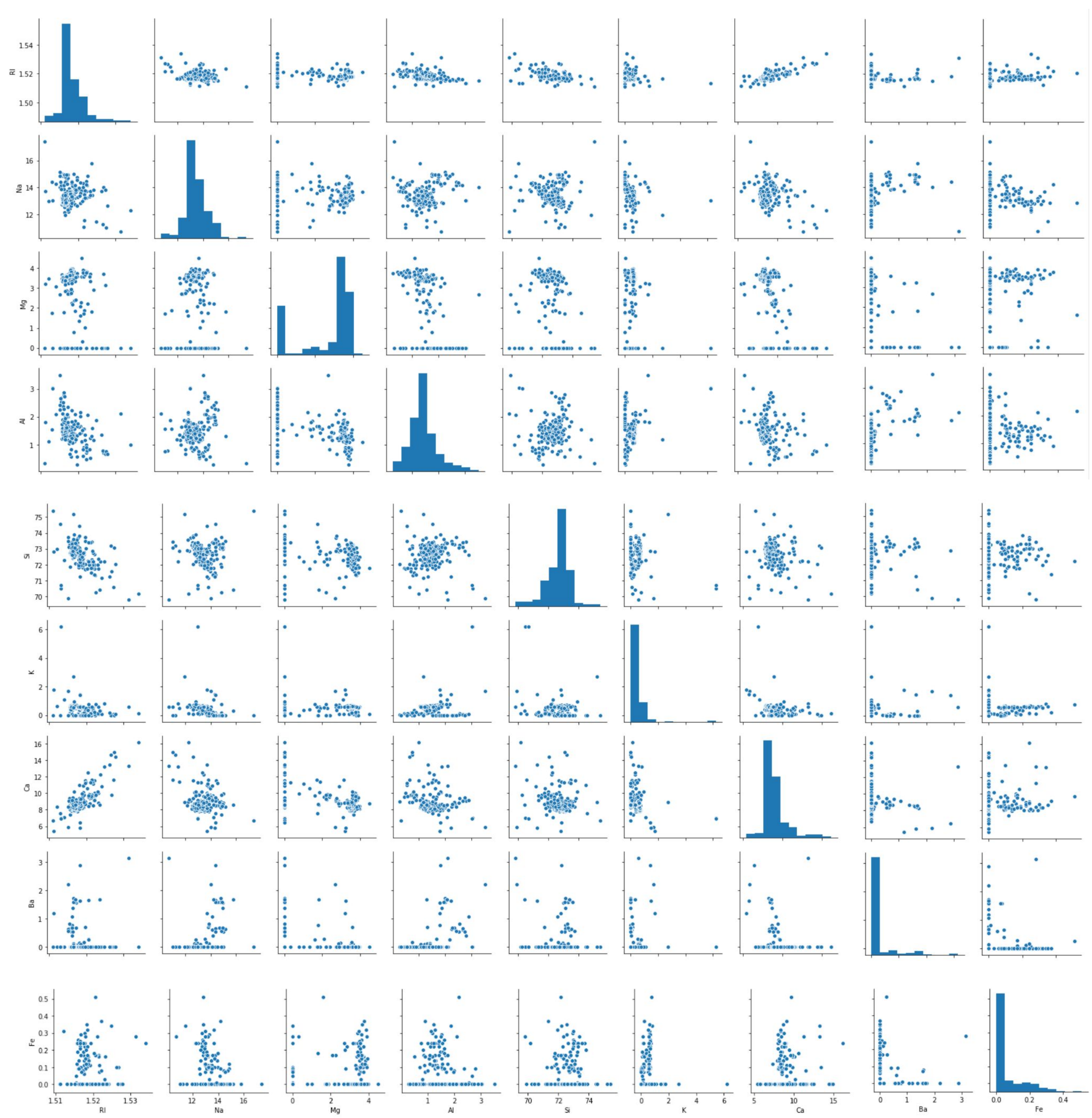


Outcomes

1. The distribution of potassium (K) and Barium (Ba) seem to contain many outliers.
2. The features Fe, Ba, Ca and K are Highly Skewed (They have High skew coefficients).
3. None of the features follow Normal Distribution (are not normally distributed).

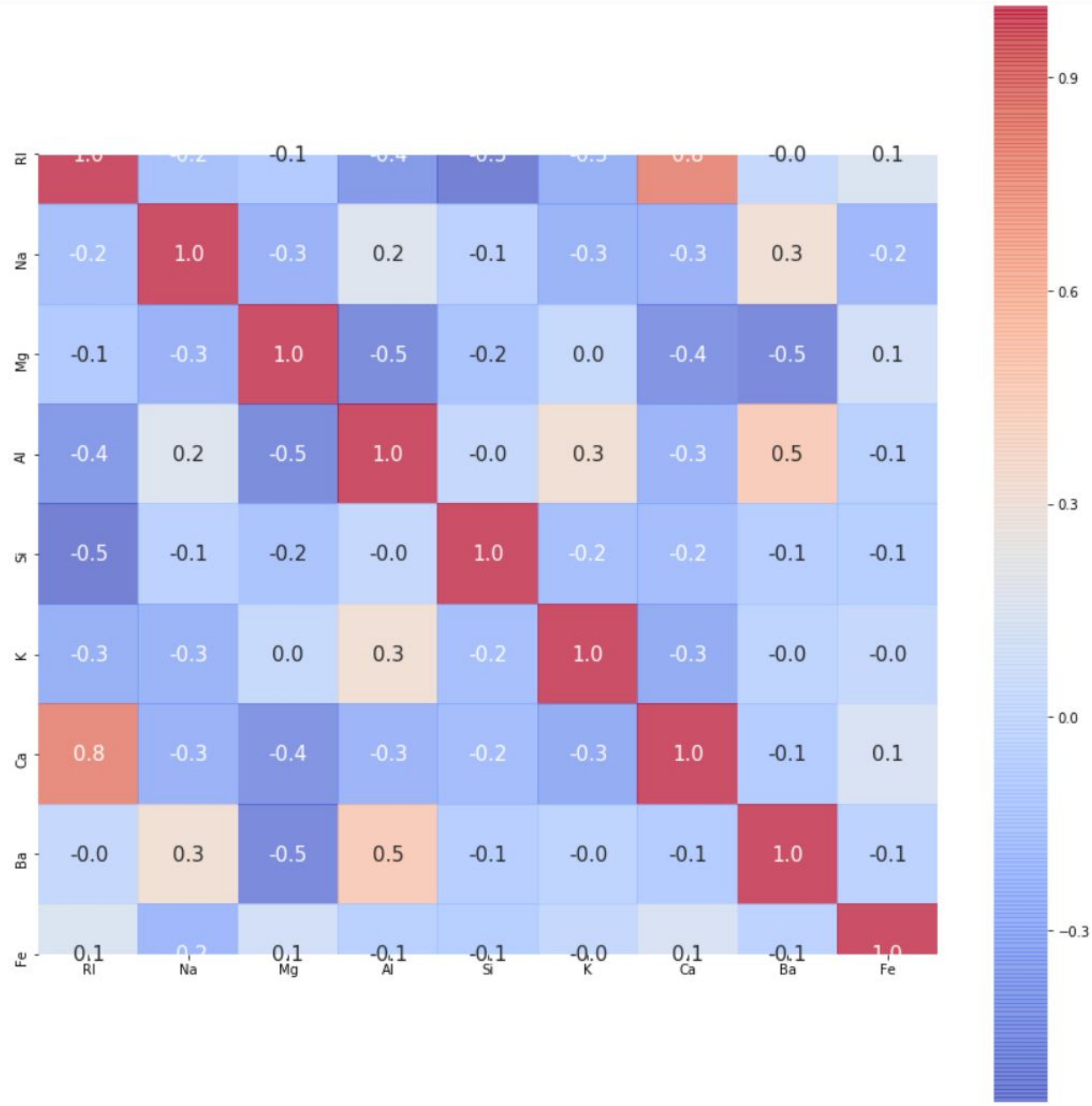
2. Using Multivariate Plots

```
x2 = pd.DataFrame(X)
plt.figure(figsize=(8,8))
sns.pairplot(data=x2)
plt.show()
```



3. Using Correlation Matrix

```
coreleation= X.corr()
plt.figure(figsize=(15,15))
sns.heatmap(coreleation,cbar=True,square=True,annot=True,fmt='.1f',annot_kws={'size':15},xticklabels=features,yticklabels=features,alpha=0.7,cmap='coolwarm')
plt.show()
```



Outcomes(Analysis)

1. Al and Ba have an intermediate correlation between each other.
2. RI and Ca have a strong correlation between each other. (This could be a sign to perform Principal component analysis in order to decorrelate some of the input features.)

Outlier Detection

Why?
To Get inference about the no. of outliers present in our dataset.

```
# Detect observations with more than one outlier

def outlier_hunt(data):
    """
    Takes a data frame df of features and returns a list of the indices
    corresponding to the observations containing more than 2 outliers.
    """
    outlier_indices = []

    for col in data.columns.tolist():
        Q1 = np.percentile(data[col], 25)
        Q3 = np.percentile(data[col],75)

        IQR = Q3 - Q1
        outlier_step = 1.5 * IQR

        outlier_list_col = data[(data[col] < Q1 - outlier_step) |
(data[col] > Q3 + outlier_step )].index

        outlier_indices.extend(outlier_list_col)

    outlier_indices = Counter(outlier_indices)
    multiple_outliers = list( k for k, v in outlier_indices.items() if v >
2 )
    return multiple_outliers
print('The dataset contains %d observations with more than 2 outliers'
%(len(outlier_hunt(data[features]))))
```

Outcomes

1. In our data, There exist around 14 observations with multiple outliers.
2. These could harm the efficiency of our learning algorithms. We'll remove them now.

Data Treatment

Why?
To Clean our data and process it so that our Models & Algorithms Train better and make better predictions.

```
#Information about data in hand

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 214 entries, 0 to 213
Data columns (total 10 columns):
RI             214 non-null float64
Na             214 non-null float64
Mg             214 non-null float64
Al             214 non-null float64
Si             214 non-null float64
K              214 non-null float64
Ca             214 non-null float64
Ba             214 non-null float64
Fe             214 non-null float64
glass_type     214 non-null int64
dtypes: float64(9), int64(1)
memory usage: 16.8 KB
```

Outcomes

1. This dataset is clean; there aren't any missing values in it.

1. Removing Outliers

Why?
The outlier affects both results and assumptions. And are generally not the best representatives of the dataset.

```
outlier_indices = outlier_hunt(data[features])
df = data.drop(outlier_indices).reset_index(drop=True)

print(data.shape)
```

Outcomes

1. Removing observations with multiple outliers (more than 2) left us with 200 observations to train from

2. Normalizing the Data

Why?
to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values (Features also have different Ranges)

```
## normalizing/Scaling the data in [0,1] Range


from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X.head(2)
```

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.0	0.0
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.0	0.0

	glass_type
0	1
1	1

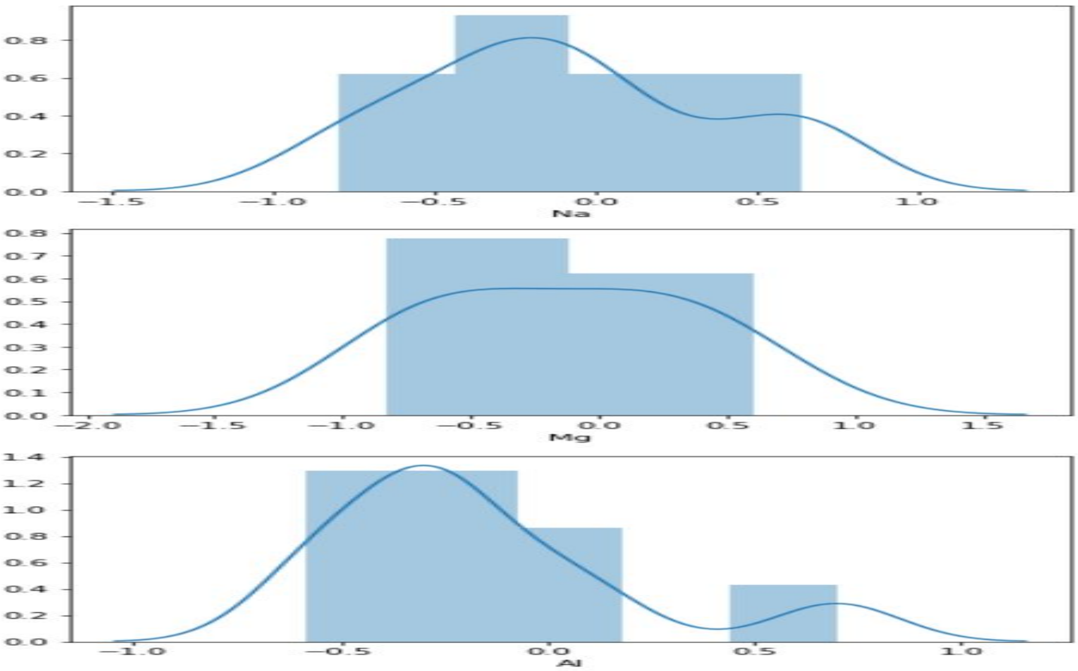
3. Scaling The Features

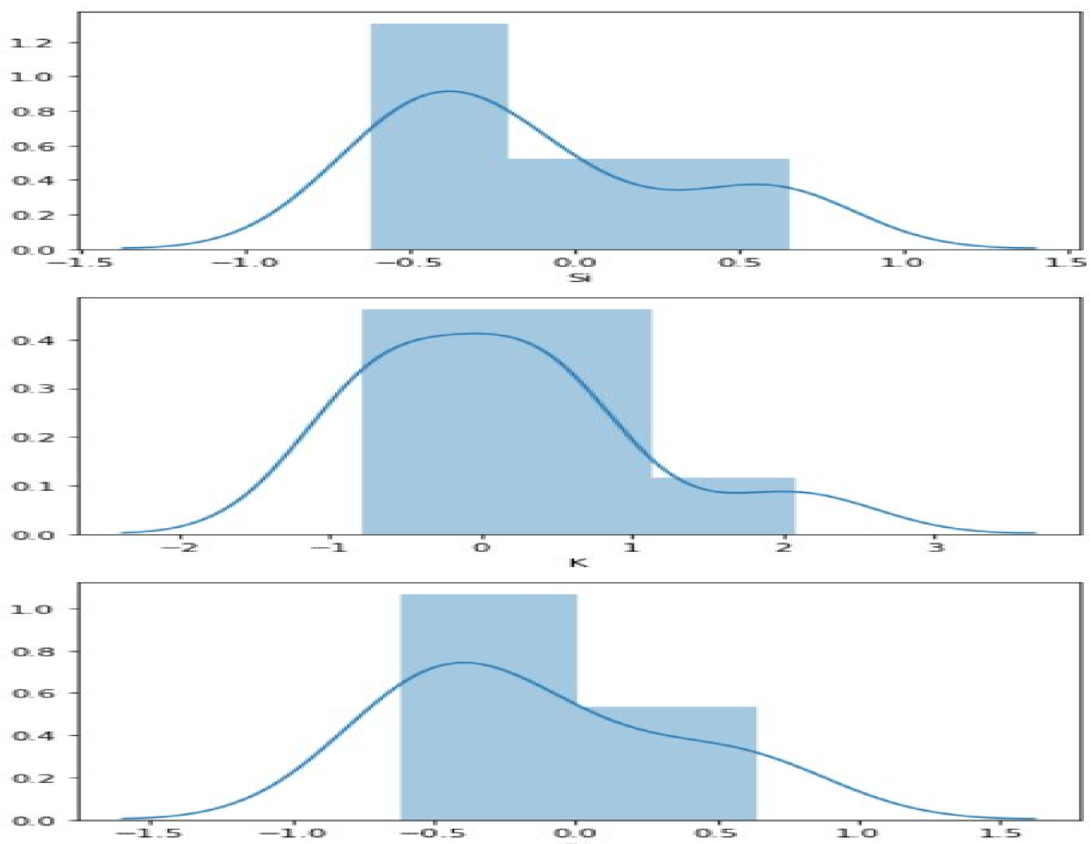
```
from sklearn import preprocessing
X=preprocessing.scale(X)
```

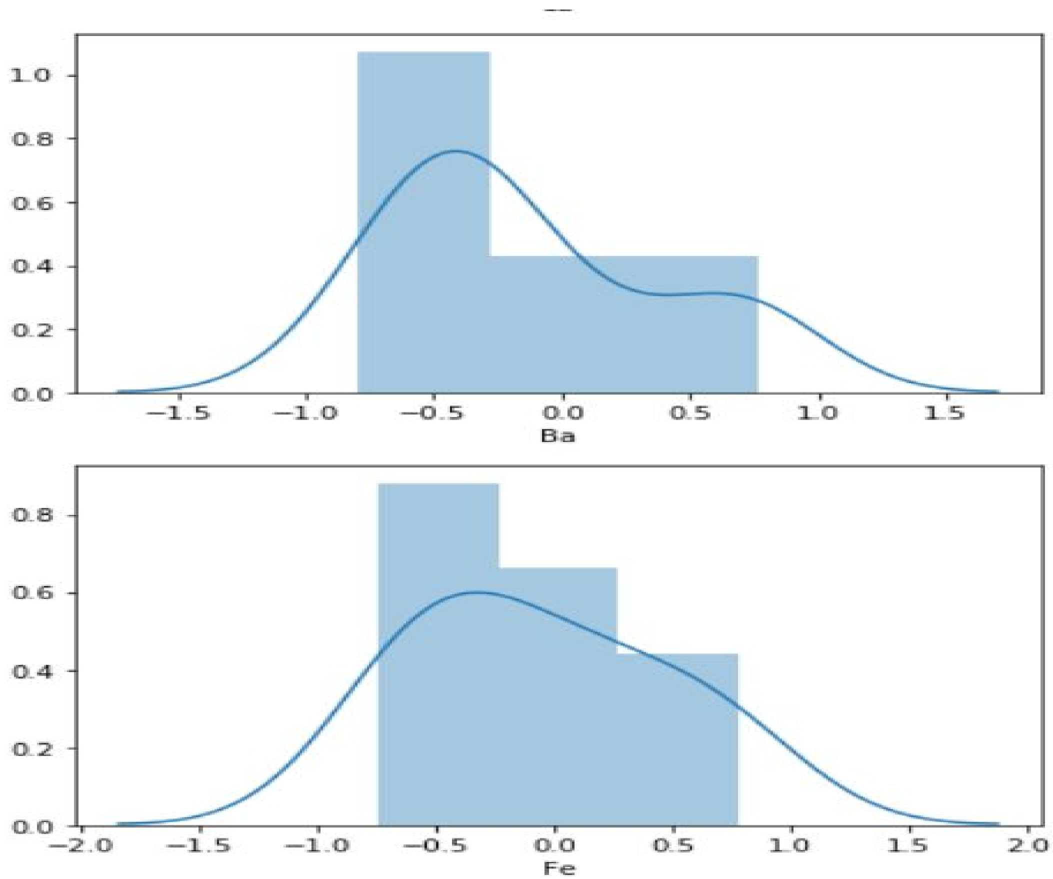
Visualization of Data after Being Preprocessed

```
x2 = X

for i in range(1,9):
        sns.distplot(x2[i])
        plt.xlabel(features[i])
        plt.show()
```


Na
Mg
Al


Si
K
Ca



Outcomes

According to the Diagrams above, After preprocessing,

1. Skewness is reduced.
2. Data is more normalized.

Training set - Test set Split

WHY?

Testing is a way to assess our model performance. To incorporate Cross Validation and to know how our model is performing.

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.25, random_state=0,stratify=y)


y_train = y_train.values.ravel()
```

```python
y_test = y_test.values.ravel()

print('Shape of X_train = ' + str(X_train.shape))
print('Shape of X_test = ' + str(X_test.shape))
print('Shape of y_train = ' + str(y_train.shape))
print('Shape of y_test = ' + str(y_test.shape))
```

```
Shape of X_train = (160, 9)
Shape of X_test = (54, 9)
Shape of y_train = (160,)
Shape of y_test = (54,)
```

Training Different Machine learning Models

1. K-Nearest Neighbors

```python
Scores = []
for i in range (2,11):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train, y_train)
    score = knn.score(X_test,y_test)
    Scores.append(score)
print(knn.score(X_train,y_train))
print(Scores)
```

Training accuracy `0.65625`

Testing accuracy `[0.6666666666666666, 0.6296296296296297, 0.6851851851851852, 0.6851851851851852, 0.6851851851851852, 0.7222222222222222, 0.7407407407407407, 0.7222222222222222, 0.7407407407407407]`

2. Decision Tree

```
Scores = []

for i in range(1):
    tree = DecisionTreeClassifier(random_state=0)
    tree.fit(X_train, y_train)
    score = tree.score(X_test,y_test)
    Scores.append(score)

print(tree.score(X_train,y_train))
print(Scores)
```

Training accuracy `1.0`
Testing accuracy: `[0.7037037037037037]`

3. Logistic Regression

```
Scores = []

for i in range(1):
    logistic = LogisticRegression(random_state=0,
solver='lbfgs',multi_class='multinomial',max_iter=100)
    logistic.fit(X_train, y_train)
    score = logistic.score(X_test,y_test)
    Scores.append(score)

print(logistic.score(X_train,y_train))
print(Scores)
```

Training accuracy `0.65`
Testing accuracy `[0.6296296296296297]`

4. SVM Classifier (Non-Linear)

```
Scores = []

for i in range(1):
    svc = SVC(gamma='auto')
    svc.fit(X_train, y_train)
    score = svc.score(X_test,y_test)
    Scores.append(score)

print(svc.score(X_train,y_train))
print(Scores)
```

Training accuracy : `0.76875`
Testing accuracy `[0.7407407407407407]`

Summary

Out of all above models:

Decision Tree

Decision tree is overfitting with **:->**

Training accuracy: 1.0

Testing accuracy: 0.7037037037037037

SVM (Non Linear Kernel)

SVM (Non Linear Kernel) is giving best result with:

Training accuracy: 0.76875

Testing accuracy: 0.7407407407407407