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Requirement

For the given anonymous dataset of size 199x35 perform the following task:

1. Exploratory Data analysis to study the nature of the data and to decide whether to follow a parametric approach or non parametric approach for predicting the target.
2. Preprocessing
3. Dimensionality reduction
4. Model building
5. Model Evaluation

NOTE: Register Number 1 to 20 will perform prediction on column named predictLabel2(continuous value)

In [1]:
```
#Importing libraries
import numpy as np
import pandas as pd
from sklearn.impute import KNNImputer

#Importing the visualisation libraries
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
#Reading the data
MainDataset = pd.read_csv('AnonymousDataset.csv')
MainDataset.head(4)
```

Out[2]:

	col1	classLabel	col3	col4	col5	col6	col7	col8	col9	col10	...	col26	col27	col28	col29	col30	col31	col32	col33	PredictLabel1	PredictLabel2
0	119513	0	31	18.02	27.60	117.50	1013.0	0.09489	0.1036	0.1086	...	139.70	1436.0	0.1195	0.1926	0.3140	0.1170	0.2677	0.08113	5.0	5
1	8423	0	61	17.99	10.38	122.80	1001.0	0.11840	0.2776	0.3001	...	184.60	2019.0	0.1622	0.6656	0.7119	0.2654	0.4601	0.11890	3.0	2
2	842517	0	116	21.37	17.44	137.50	1373.0	0.08836	0.1189	0.1255	...	159.10	1949.0	0.1188	0.3449	0.3414	0.2032	0.4334	0.09067	2.5	0
3	843483	0	123	11.42	20.38	77.58	386.1	0.14250	0.2839	0.2414	...	98.87	567.7	0.2098	0.8663	0.6869	0.2575	0.6638	0.17300	2.0	0

4 rows × 35 columns

Regression predictive modeling problem

Perform Exploratory data analysis

In [3]:
```
MainDataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 198 entries, 0 to 197
Data columns (total 35 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   col1           198 non-null    int64  
 1   classLabel     198 non-null    int64  
 2   col3           198 non-null    int64  
 3   col4           198 non-null    float64
 4   col5           198 non-null    float64
 5   col6           198 non-null    float64
 6   col7           198 non-null    float64
 7   col8           198 non-null    float64
 8   col9           198 non-null    float64
 9   col10          198 non-null    float64
 10  col11          198 non-null    float64
 11  col12          198 non-null    float64
 12  col13          198 non-null    float64
 13  col14          198 non-null    float64
 14  col15          198 non-null    float64
 15  col16          198 non-null    float64
 16  col17          198 non-null    float64
 17  col18          198 non-null    float64
 18  col19          198 non-null    float64
 19  col20          198 non-null    float64
 20  col21          198 non-null    float64
 21  col22          198 non-null    float64
 22  col23          198 non-null    float64
 23  col24          198 non-null    float64
 24  col25          198 non-null    float64
 25  col26          198 non-null    float64
 26  col27          198 non-null    float64
 27  col28          198 non-null    float64
 28  col29          198 non-null    float64
 29  col30          198 non-null    float64
 30  col31          198 non-null    float64
 31  col32          198 non-null    float64
 32  col33          198 non-null    float64
 33  PredictLabel1  198 non-null    float64
 34  PredictLabel2  198 non-null    object 
dtypes: float64(31), int64(3), object(1)
memory usage: 54.3+ KB
```

```
Data columns (total 35 columns)  : Hidden column labels
Non-Null Count                   : 35 columns having non-null entry
dtypes                           : float64(31), int64(3), object(1)
RangeIndex                       : 198 entries, 0 to 197
memory usage                     : 54.3+ KB
```

In [4]:
```
print(f"Totally AnonymousDataset contains, {MainDataset.shape[1]} columns and {MainDataset.shape[0]} Rows")
```

```
Totally AnonymousDataset contains, 35 columns and 198 Rows
```

In [5]:
```
MainDataset.iloc[:,-1].unique()
```

Out[5]:
```
array(['5', '2', '0', '?', '10', '1', '20', '6', '13', '4', '17', '15',
       '11', '9', '8', '7', '3', '14', '27', '24', '18', '16', '21'],
      dtype=object)
```

- They provided a dataset with only 1 column under Object data type, which is a continuous value as per the requirement.
- Drilling PredictLabel2 values with unique() Predefined function and found PredictLabel2 contains Integer and some special characters ?
- We assume it's a data acquisition Errors.

Missing values must be marked with NaN values and can be replaced with nearest neighbor estimated values.

In [6]:
```
Dataset=MainDataset.iloc[:,-1]
MainDataset.iloc[:,-1]=Dataset.replace('?',np.nan)
MainDataset.iloc[:,-1].unique()
```

Out[6]:
```
array(['5', '2', '0', nan, '10', '1', '20', '6', '13', '4', '17', '15',
       '11', '9', '8', '7', '3', '14', '27', '24', '18', '16', '21'],
      dtype=object)
```

- Missing numerical data are replaced and represented by numpy 'nan'

In [7]:
```
MainDataset.isnull().sum().sort_values(ascending=False)
```

Out[7]:
```
PredictLabel2    4
col9             0
col15            0
col14            0
col13            0
col12            0
col11            0
col10            0
col8             0
col17            0
col7             0
col6             0
col5             0
col4             0
col3             0
classLabel       0
col16            0
col18            0
PredictLabel1    0
col27            0
col33            0
col32            0
col31            0
col30            0
col29            0
col28            0
col26            0
col19            0
col25            0
col24            0
col23            0
col22            0
col21            0
col20            0
col1             0
dtype: int64
```

- Checking null values after replacing '?' by NaN (NaN : Missing numerical data)
- There are 4 NaN values in the PredictLabel2 column, which perform prediction.

In [8]:
```
knn_impute=KNNImputer()
MainDataset['PredictLabel2']=np.around(knn_impute.fit_transform(MainDataset[['PredictLabel2']]))
MainDataset.iloc[:,-1]=MainDataset.iloc[:,-1].astype('int64')
```

In [9]:
```
MainDataset.head(9).T
```

Out[9]:

	0	1	2	3	4	5	6	7	8
col1	119513.000000	8423.000000	842517.000000	843483.000000	843584.000000	843786.000000	844359.000000	844582.000000	844981.000000
classLabel	0.000000	0.000000	0.000000	0.000000	1.000000	1.000000	0.000000	1.000000	0.000000
col3	31.000000	61.000000	116.000000	123.000000	27.000000	77.000000	60.000000	77.000000	119.000000
col4	18.020000	17.990000	21.370000	11.420000	20.290000	12.750000	18.980000	13.710000	13.000000
col5	27.600000	10.380000	17.440000	20.380000	14.340000	15.290000	19.610000	20.830000	21.820000
col6	117.500000	122.800000	137.500000	77.580000	135.100000	84.600000	124.400000	90.200000	87.500000
col7	1013.000000	1001.000000	1373.000000	386.100000	1297.000000	502.700000	1112.000000	577.900000	519.800000
col8	0.094890	0.118400	0.088360	0.142500	0.100300	0.118900	0.090870	0.118900	0.127300
col9	0.103600	0.277600	0.118900	0.283900	0.132800	0.156900	0.123700	0.164500	0.193200
col10	0.108600	0.300100	0.125500	0.241400	0.198000	0.166400	0.121300	0.093660	0.185900
col11	0.070550	0.147100	0.081800	0.105200	0.104300	0.076660	0.089100	0.059850	0.093530
col12	0.186500	0.241900	0.233300	0.259700	0.180900	0.199500	0.172700	0.219600	0.235000
col13	0.063330	0.078710	0.060100	0.097440	0.058830	0.071640	0.057670	0.074510	0.073890
col14	0.624900	1.095000	0.585400	0.495600	0.757200	0.387700	0.528500	0.583500	0.306300
col15	1.890000	0.905300	0.610500	1.156000	0.781300	0.740200	0.843400	1.377000	1.002000
col16	3.972000	8.589000	3.928000	3.445000	5.438000	2.999000	3.592000	3.856000	2.406000
col17	71.550000	153.400000	82.150000	27.230000	94.440000	30.850000	61.210000	50.960000	24.320000
col18	0.004433	0.006399	0.006167	0.009110	0.011490	0.007775	0.003703	0.008805	0.005731
col19	0.014210	0.049040	0.034490	0.074580	0.024610	0.029870	0.023540	0.030290	0.035020
col20	0.032330	0.053730	0.033000	0.056610	0.056880	0.045610	0.022220	0.024880	0.035530
col21	0.009854	0.015870	0.018050	0.018670	0.018850	0.013570	0.013320	0.014480	0.012260
col22	0.016940	0.030030	0.030940	0.059630	0.017560	0.017740	0.013780	0.014860	0.021430
col23	0.003495	0.006193	0.005039	0.009208	0.005115	0.005114	0.003926	0.005412	0.003749
col24	21.630000	25.380000	24.900000	14.910000	22.540000	15.510000	23.390000	17.060000	15.490000
col25	37.080000	17.330000	20.980000	26.500000	16.670000	20.370000	25.450000	28.140000	30.730000
col26	139.700000	184.600000	159.100000	98.870000	152.200000	107.300000	152.600000	110.600000	106.200000
col27	1436.000000	2019.000000	1949.000000	567.700000	1575.000000	733.200000	1593.000000	897.000000	739.300000
col28	0.119500	0.162200	0.118800	0.209800	0.137400	0.170600	0.114400	0.165400	0.170300
col29	0.192600	0.665600	0.344900	0.866300	0.205000	0.419600	0.337100	0.368200	0.540100
col30	0.314000	0.711900	0.341400	0.686900	0.400000	0.599900	0.299000	0.267800	0.539000
col31	0.117000	0.265400	0.203200	0.257500	0.162500	0.170900	0.192200	0.155600	0.206000
col32	0.267700	0.460100	0.433400	0.663800	0.236400	0.348500	0.272600	0.319600	0.437800
col33	0.081130	0.118900	0.090670	0.173000	0.076780	0.117900	0.095810	0.115100	0.107200
PredictLabel1	5.000000	3.000000	2.500000	2.000000	3.500000	2.500000	1.500000	4.000000	2.000000
PredictLabel2	5.000000	2.000000	0.000000	0.000000	0.000000	0.000000	3.000000	10.000000	1.000000

The use of a KNN model to predict or fill missing values is referred to as “Nearest Neighbor Imputation”.

- “KNN imputation” implemented in PredictLabel2 to handle missing values.
- PredictLabel2 data types are converted to int64.

In [10]:
```python
dataset = MainDataset
dataset = dataset.drop(['col1','PredictLabel1'], axis=1)
dataset.describe().T
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
classLabel	198.0	0.237374	0.426552	0.000000	0.000000	0.000000	0.000000	1.00000
col3	198.0	46.732323	34.462870	1.000000	14.000000	39.500000	72.750000	125.00000
col4	198.0	17.412323	3.161676	10.950000	15.052500	17.290000	19.580000	27.22000
col5	198.0	22.276010	4.298290	10.380000	19.412500	21.750000	24.655000	39.28000
col6	198.0	114.856566	21.383402	71.900000	98.160000	113.700000	129.650000	182.10000
col7	198.0	970.040909	352.149215	361.600000	702.525000	929.100000	1193.500000	2250.00000
col8	198.0	0.102681	0.012522	0.074970	0.093900	0.101900	0.110975	0.14470
col9	198.0	0.142648	0.049898	0.046050	0.110200	0.131750	0.172200	0.31140
col10	198.0	0.156243	0.070572	0.023980	0.106850	0.151350	0.200500	0.42680
col11	198.0	0.086776	0.033877	0.020310	0.063670	0.086075	0.103925	0.20120
col12	198.0	0.192754	0.027437	0.130800	0.174075	0.189350	0.209325	0.30400
col13	198.0	0.062706	0.007240	0.050250	0.056718	0.061715	0.066715	0.09744
col14	198.0	0.603346	0.310112	0.193800	0.388200	0.533250	0.750900	1.81900
col15	198.0	1.264450	0.526467	0.362100	0.921300	1.168500	1.463250	3.50300
col16	198.0	4.255394	2.194128	1.153000	2.742500	3.767000	5.212750	13.28000
col17	198.0	70.228737	47.982255	13.990000	35.365000	58.455000	92.477500	316.00000
col18	198.0	0.006762	0.002974	0.002667	0.005001	0.006193	0.007973	0.03113
col19	198.0	0.031199	0.017613	0.007347	0.019803	0.027880	0.038335	0.13540
col20	198.0	0.040750	0.020869	0.010940	0.026810	0.036910	0.048970	0.14380
col21	198.0	0.015099	0.005504	0.005174	0.011422	0.014175	0.017665	0.03927
col22	198.0	0.020555	0.009578	0.007882	0.014795	0.017905	0.022880	0.06041
col23	198.0	0.003987	0.001938	0.001087	0.002748	0.003719	0.004630	0.01256
col24	198.0	21.021818	4.242997	12.840000	17.632500	20.525000	23.730000	35.13000
col25	198.0	30.139091	6.017777	16.670000	26.210000	30.135000	33.555000	49.54000
col26	198.0	140.347778	28.892279	85.100000	118.075000	136.500000	159.875000	232.20000
col27	198.0	1404.958586	586.006972	508.100000	947.275000	1295.000000	1694.250000	3903.00000
col28	198.0	0.143921	0.022004	0.081910	0.129325	0.141850	0.154875	0.22260
col29	198.0	0.365102	0.163965	0.051310	0.248700	0.351300	0.423675	1.05800
col30	198.0	0.436685	0.173625	0.023980	0.322150	0.402350	0.541050	1.17000
col31	198.0	0.178778	0.045181	0.028990	0.152650	0.179250	0.207125	0.29030
col32	198.0	0.323404	0.075161	0.156500	0.275950	0.310300	0.358800	0.66380
col33	198.0	0.090828	0.021172	0.055040	0.076578	0.086890	0.101375	0.20750
PredictLabel2	198.0	3.207071	5.423445	0.000000	0.000000	1.000000	4.000000	27.00000

- Since col1, PredictLabel1 are unique and unwanted columns for our prediction process.
- Dropping col1 & PredictLabel1 from the dataset.

In [11]:
```python
for i in dataset.columns:
    print(f'{i} \t \t \t : \t {dataset[i].nunique()} values')
```

```
classLabel                        :        2 values
col3                     :       95 values
col4                     :       177 values
col5                     :       193 values
col6                     :       181 values
col7                     :       192 values
col8                     :       179 values
col9                     :       192 values
col10                    :       196 values
col11                    :       189 values
col12                    :       175 values
col13                    :       194 values
col14                    :       196 values
col15                    :       191 values
col16                    :       192 values
col17                    :       196 values
col18                    :       196 values
col19                    :       193 values
col20                    :       192 values
col21                    :       187 values
col22                    :       189 values
col23                    :       195 values
col24                    :       182 values
col25                    :       187 values
col26                    :       183 values
col27                    :       191 values
col28                    :       172 values
col29                    :       191 values
col30                    :       197 values
col31                    :       185 values
col32                    :       192 values
col33                    :       189 values
PredictLabel2                     :        22 values
```

We are finding unique values for the rest of the columns in the dataset.

- ClassLabel and PredictLabel2 contain the lowest unique values.
- Rest of the columns own float data, so there exists higher uniqueness in those columns.

In [12]:
```python
numerical_features = []
categorical_features = []

for i in dataset.columns:
    if dataset[i].nunique()>7:
        numerical_features.append(i)
    else:
        categorical_features.append(i)


print(len(numerical_features))
print(len(categorical_features))
```

```
32
1
```

In [13]:
```python
# Numerical features:
print("Numerical features : ",numerical_features)

# Categorical features:
print("\n Categorical features : ",categorical_features)
```

```
Numerical features :  ['col3', 'col4', 'col5', 'col6', 'col7', 'col8', 'col9', 'col10', 'col11', 'col12', 'col13', 'col14', 'col15', 'col16', 'col17', 'col18', 'col1
9', 'col20', 'col21', 'col22', 'col23', 'col24', 'col25', 'col26', 'col27', 'col28', 'col29', 'col30', 'col31', 'col32', 'col33', 'PredictLabel2']

 Categorical features :  ['classLabel']
```

Numerical features and Categorical features are identified and stored in a separate python list.

- numerical_features = 32 columns
- categorical_features = 1 column

In [14]:
```python
# checking for unique values in categorical features:

for feats in categorical_features:
    print(f'{feats} has {dataset[feats].unique()} categories.\n')
```

```
classLabel has [0 1] categories.
```

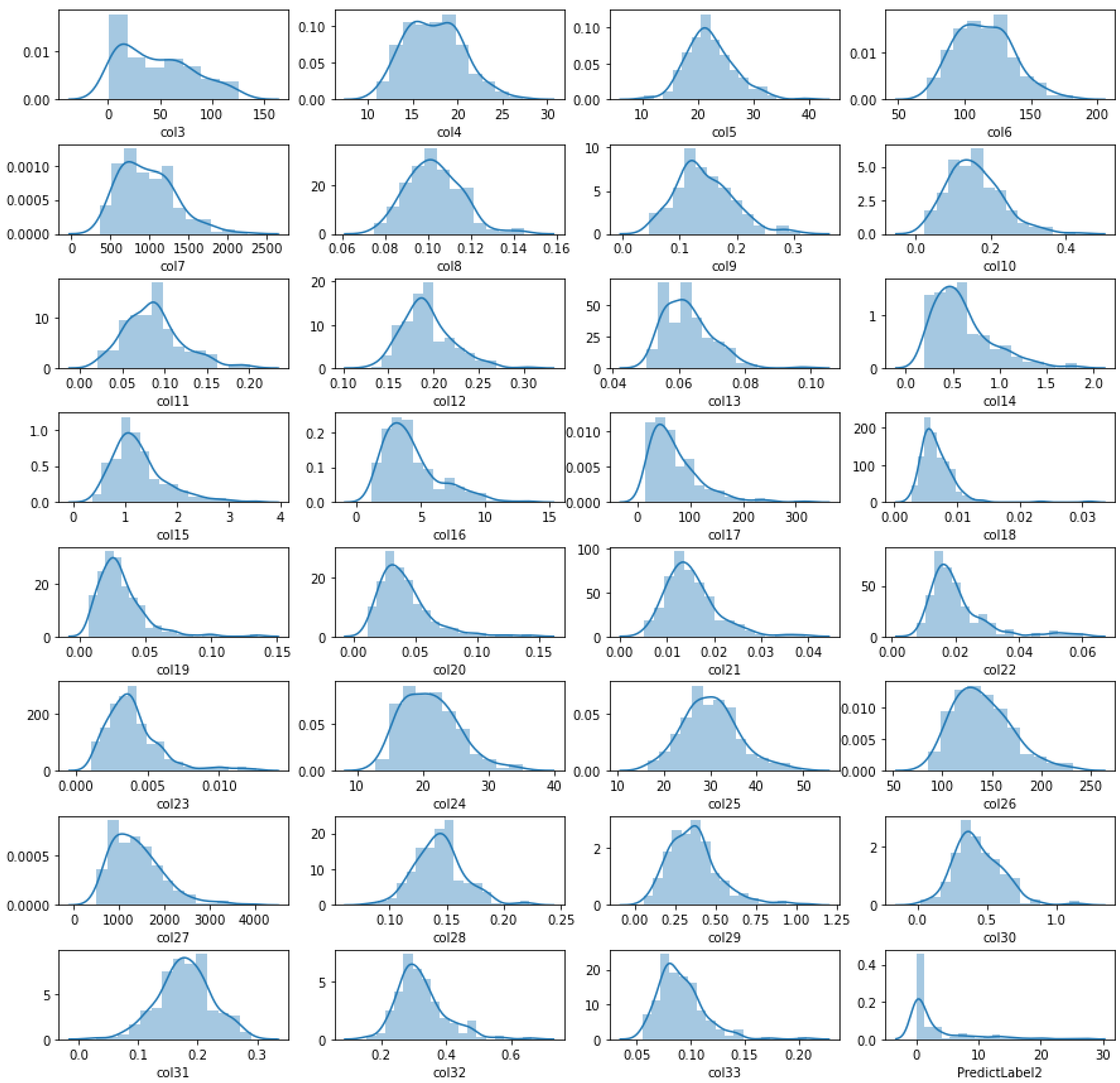
Perform Data cleaning & Pre-processing

In [15]:
```python
# Checking distribution of the numerical features:

fig, axes = plt.subplots(nrows=8, ncols=4, figsize=(15,15))
fig.subplots_adjust(hspace=0.5)
fig.suptitle('Distributions of numerical Features')


for ax, feats in zip(axes.flatten(), numerical_features):
    sns.distplot(a=dataset[feats], ax=ax)
```

Distributions of numerical Features

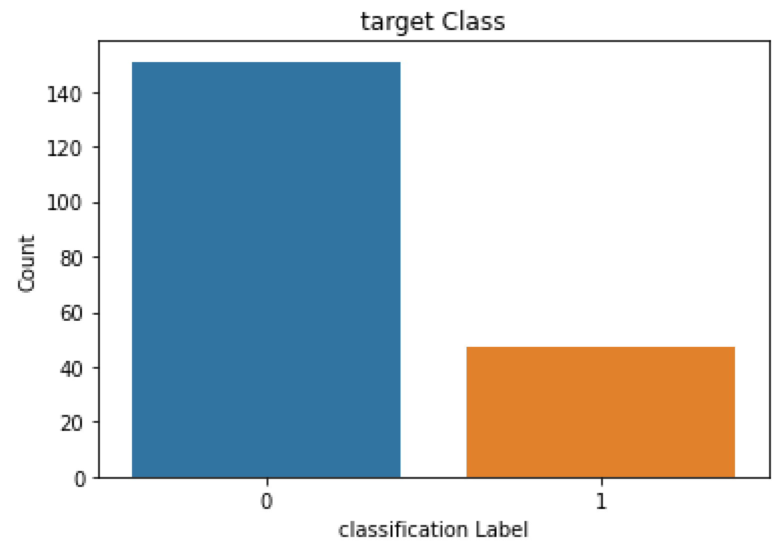


Distributions of numerical Features

- In general, Row no. 1, 2, 6, 8 are appropriately distubuted normally.
- Also, Row no. 3, 4, 5 and 7 are right skewed. (Positive skewed data)
- PredictLabel2 does not consider to picture.

In [16]:
```python
# Checking the label distribution for categorical data:

sns.countplot(x='classLabel',data=dataset)
plt.xlabel("classification Label")
plt.ylabel("Count")
plt.title("target Class")
plt.show()
```



Distributions of categorical Features

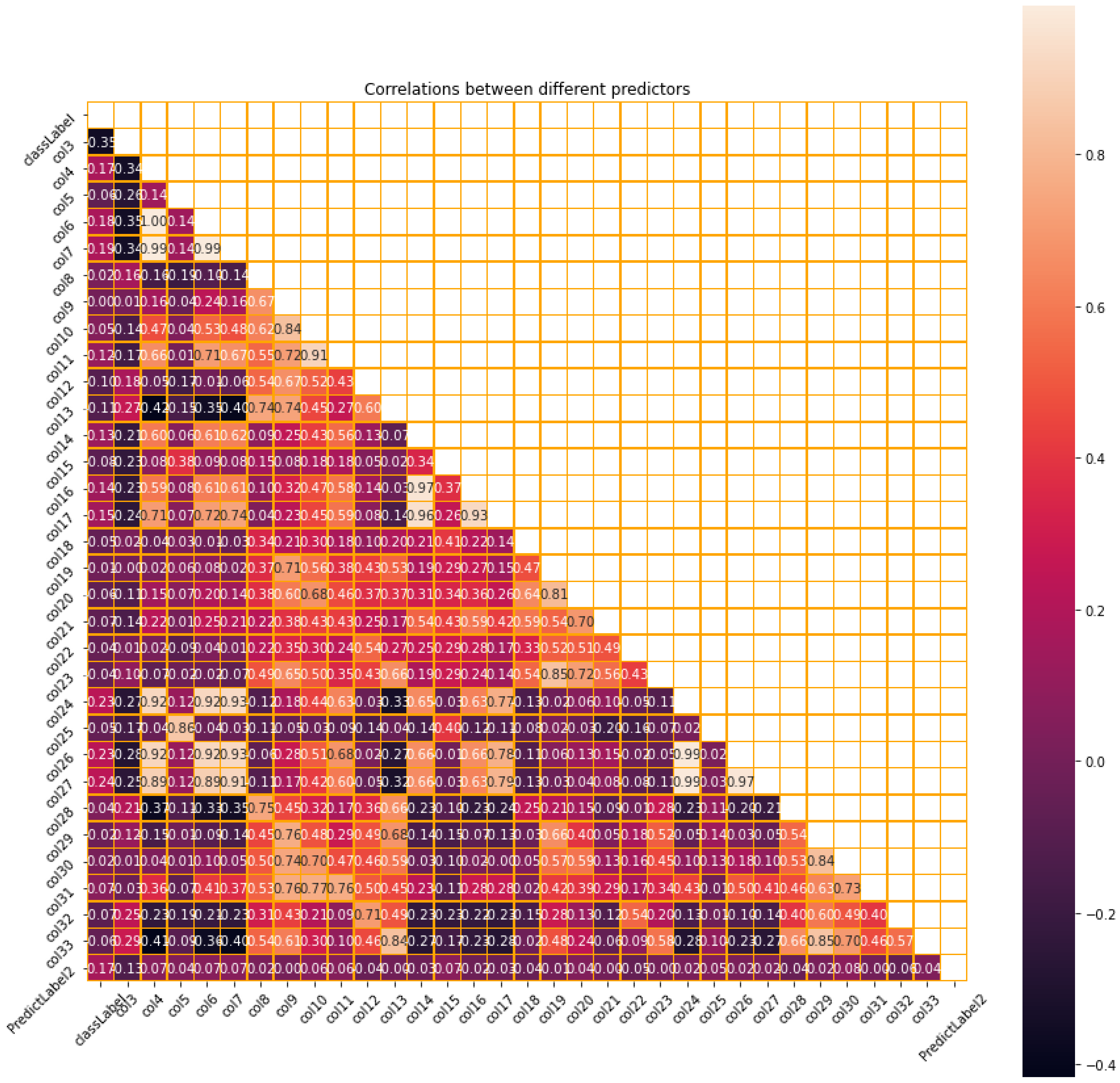
- We have only one categorical feature named 'classLabel'
- 0 and 1 are the classification Label contain in the classLabel feature.
- 3/4th of the values dominates 0.
- One is holding 1/4 of the values.

In [17]:
```python
# Correlations between different predictors

corr_df = dataset.corr()

f,ax=plt.subplots(figsize=(15,15))
mask = np.zeros_like(corr_df)
mask[np.triu_indices_from(mask)] = True

sns.heatmap(corr_df,annot=True,fmt=".2f",ax=ax,linewidths=0.5,linecolor="orange", mask = mask, square=True)
plt.xticks(rotation=45)
plt.yticks(rotation=45)
plt.title('Correlations between different predictors')
plt.show()
```



Correlations between different predictors are not clear to the understanding. So, converting into understandable matrix format.

In [18]:
```
corr_df = dataset.corr()
corr_df
cm = sns.light_palette("black", as_cmap=True)
corr_df.style.background_gradient(cmap=cm)
```

Out[18]:

	classLabel	col3	col4	col5	col6	col7	col8	col9	col10	col11	col12	col13	col14	col15	col16	col17	col18	col19	col20	
classLabel	1.000000	-0.351326	0.174124	-0.064295	0.176486	0.189893	0.020778	0.000798	0.054893	0.118224	-0.099777	-0.112352	0.132512	-0.076212	0.141633	0.151826	-0.052213	-0.009537	-0.060379	-0.
col3	-0.351326	1.000000	-0.344722	-0.264671	-0.346080	-0.344031	0.164793	0.010000	-0.139475	-0.171841	0.177311	0.269992	-0.214543	-0.230477	-0.231621	-0.244159	0.019775	-0.002386	-0.108648	-0.
col4	0.174124	-0.344722	1.000000	0.143456	0.995933	0.992855	-0.158239	0.159017	0.469518	0.664010	-0.051610	-0.416674	0.602035	0.079693	0.588927	0.710586	-0.036419	0.023647	0.154254	0.
col5	-0.064295	-0.264671	0.143456	1.000000	0.142033	0.140440	-0.192262	-0.039803	0.037165	0.006687	-0.165166	-0.145572	0.059168	0.382533	0.075025	0.068517	0.027119	0.063988	0.071920	0.
col6	0.176486	-0.346080	0.995933	0.142033	1.000000	0.990699	-0.102912	0.236721	0.533194	0.712766	-0.006512	-0.353560	0.612708	0.092256	0.609964	0.718581	-0.011788	0.080725	0.202027	0.
col7	0.189893	-0.344031	0.992855	0.140440	0.990699	1.000000	-0.141470	0.163176	0.475862	0.667530	-0.060785	-0.397733	0.623019	0.084288	0.609887	0.740830	-0.032969	0.020395	0.144443	0.
col8	0.020778	0.164793	-0.158239	-0.192262	-0.102912	-0.141470	1.000000	0.666559	0.623867	0.545734	0.540761	0.744890	0.094728	0.153848	0.099518	0.037955	0.344678	0.372393	0.375011	0.
col9	0.000798	0.010000	0.159017	-0.039803	0.236721	0.163176	0.666559	1.000000	0.836015	0.716438	0.666822	0.735474	0.251568	0.082994	0.318684	0.233326	0.212552	0.714122	0.599020	0.
col10	0.054893	-0.139475	0.469518	0.037165	0.533194	0.475862	0.623867	0.836015	1.000000	0.909990	0.524861	0.449928	0.427031	0.181984	0.468426	0.449059	0.297014	0.564196	0.676804	0.
col11	0.118224	-0.171841	0.664010	0.006687	0.712766	0.667530	0.545734	0.716438	0.909990	1.000000	0.429968	0.268210	0.555034	0.179486	0.580562	0.586508	0.177402	0.376339	0.463710	0.
col12	-0.099777	0.177311	-0.051610	-0.165166	-0.006512	-0.060785	0.540761	0.666822	0.524861	0.429968	1.000000	0.604104	0.130985	0.049953	0.143176	0.079773	0.104636	0.426781	0.374679	0.
col13	-0.112352	0.269992	-0.416674	-0.145572	-0.353560	-0.397733	0.744890	0.735474	0.449928	0.268210	0.604104	1.000000	-0.071115	0.019497	-0.027045	-0.142039	0.197743	0.528359	0.374871	0.
col14	0.132512	-0.214543	0.602035	0.059168	0.612708	0.623019	0.094728	0.251568	0.427031	0.555034	0.130985	-0.071115	1.000000	0.341365	0.973267	0.956929	0.212261	0.186815	0.310532	0.
col15	-0.076212	-0.230477	0.079693	0.382533	0.092256	0.084288	0.153848	0.082994	0.181984	0.179486	0.049953	0.019497	0.341365	1.000000	0.374428	0.261746	0.407036	0.285564	0.339956	0.
col16	0.141633	-0.231621	0.588927	0.075025	0.609964	0.609887	0.099518	0.318684	0.468426	0.580562	0.143176	-0.027045	0.973267	0.374428	1.000000	0.929603	0.220245	0.267606	0.363244	0.
col17	0.151826	-0.244159	0.710586	0.068517	0.718581	0.740830	0.037955	0.233326	0.449059	0.586508	0.079773	-0.142039	0.956929	0.261746	0.929603	1.000000	0.138948	0.145281	0.260979	0.
col18	-0.052213	0.019775	-0.036419	0.027119	-0.011788	-0.032969	0.344678	0.212552	0.297014	0.177402	0.104636	0.197743	0.212261	0.407036	0.220245	0.138948	1.000000	0.474982	0.643395	0.
col19	-0.009537	-0.002386	0.023647	0.063988	0.080725	0.020395	0.372393	0.714122	0.564196	0.376339	0.426781	0.528359	0.186815	0.285564	0.267606	0.145281	0.474982	1.000000	0.813994	0.
col20	-0.060379	-0.108648	0.154254	0.071920	0.202027	0.144443	0.375011	0.599020	0.676804	0.463710	0.374679	0.374871	0.310532	0.339956	0.363244	0.260979	0.643395	0.813994	1.000000	0.
col21	-0.065570	-0.140754	0.224771	0.010470	0.254473	0.213582	0.223510	0.384747	0.434928	0.426638	0.251257	0.174633	0.537011	0.427772	0.592707	0.423337	0.589114	0.537276	0.695257	1.
col22	-0.044325	0.011156	0.019146	-0.094843	0.038613	0.009121	0.223723	0.350009	0.304383	0.238520	0.541034	0.268176	0.253774	0.293346	0.276477	0.165206	0.328773	0.516171	0.514692	0.
col23	-0.042751	0.099203	-0.072618	-0.020673	-0.019514	-0.071906	0.486112	0.648248	0.504069	0.350050	0.432752	0.662116	0.188546	0.287900	0.239101	0.135502	0.538804	0.845176	0.716976	0.
col24	0.233225	-0.265115	0.924183	0.123028	0.921552	0.932381	-0.115092	0.183277	0.437961	0.630309	-0.030809	-0.334231	0.653635	-0.033230	0.625588	0.772286	-0.133839	-0.016804	0.057881	0.
col25	-0.051134	-0.171125	-0.039439	0.862050	-0.039728	-0.032122	-0.106172	-0.047665	-0.032081	-0.094163	-0.137598	-0.039644	-0.143369	0.401277	-0.122254	-0.106107	-0.082080	0.019361	-0.034301	-0.
col26	0.231998	-0.280596	0.915053	0.123674	0.923659	0.925335	-0.064664	0.276994	0.514336	0.682749	0.019708	-0.265607	0.660942	-0.012545	0.663958	0.776267	-0.107891	0.062830	0.128143	0.
col27	0.235310	-0.253930	0.891489	0.117467	0.889344	0.914166	-0.106691	0.168275	0.421021	0.604029	-0.050522	-0.318351	0.656442	-0.031464	0.627129	0.793467	-0.134124	-0.029747	0.035591	0.
col28	0.038520	0.212769	-0.372894	-0.113308	-0.331667	-0.345111	0.745400	0.452067	0.319247	0.174917	0.355244	0.660332	-0.228740	-0.101748	-0.229088	-0.241462	0.251764	0.212309	0.146979	-0.
col29	-0.020067	0.120516	-0.150712	-0.006467	-0.092041	-0.141358	0.447849	0.764824	0.483300	0.286599	0.488231	0.683414	-0.140472	-0.146005	-0.073668	-0.126673	-0.028113	0.664129	0.395843	0.
col30	0.017621	0.009546	0.038952	0.013635	0.096790	0.046641	0.499438	0.743333	0.702673	0.471429	0.458280	0.585507	-0.034290	-0.103871	0.019657	-0.001336	0.045155	0.568806	0.585400	0.
col31	0.074345	-0.026541	0.357869	-0.069921	0.410000	0.365026	0.531015	0.761044	0.767571	0.764803	0.501957	0.453304	0.229593	-0.109804	0.275071	0.275015	0.024474	0.420393	0.393513	0.
col32	-0.074731	0.247678	-0.232142	-0.186850	-0.206949	-0.234294	0.308964	0.429953	0.212976	0.089804	0.705076	0.493337	-0.227902	-0.228037	-0.215541	-0.232644	-0.146274	0.284148	0.125586	-0.
col33	-0.055170	0.288715	-0.414340	-0.085847	-0.364022	-0.395026	0.535751	0.611315	0.302868	0.101327	0.458548	0.838737	-0.265243	-0.173675	-0.231810	-0.276872	-0.017428	0.479000	0.241911	-0.
PredictLabel2	0.167351	-0.125745	0.066319	0.042661	0.067565	0.067452	0.024576	0.002737	0.059703	0.056019	-0.040554	-0.004518	-0.028926	0.070519	-0.020855	-0.026482	-0.036508	-0.011709	0.041702	-0.

PredictLabel2 feature Observations

- col4, col6, col7, col15, col30
  - Columns having highest Correlations values among all the values features compared with PredictLabel2

Positive Correlations
Other feature Observations based on Correlations Matrix

- col4 col6 col7 (Having Strong positive correlations value ~ 0.99XX)
- col8 col9 col10 col11 col12 col13 (Having positive correlations value between (0.50 and 0.85))
- col28 col29 col30 col31 col32 col33 (Having positive correlations value between (0.35 and 0.80))

Perform Feature Selection Techniques

Numerical Input, Numerical Output

1. pearson's correlation / Filter methods
   - Filter methods pick up the intrinsic properties of the features measured via univariate statistics instead of cross-validation performance. These methods are faster and less computationally expensive than wrapper methods. When dealing with high-dimensional data, it is computationally cheaper to use filter methods.

In [19]:
```
# pearson's correlation feature selection for numeric input and numeric output

from sklearn.datasets import make_regression
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_regression

# generate dataset
X = dataset.iloc[:,:-1].values
y = dataset.iloc[:,-1].values

# define feature selection
fs = SelectKBest(score_func=f_regression, k=10)
# apply feature selection

X_selected = fs.fit_transform(X, y)
print(X_selected.shape)
```

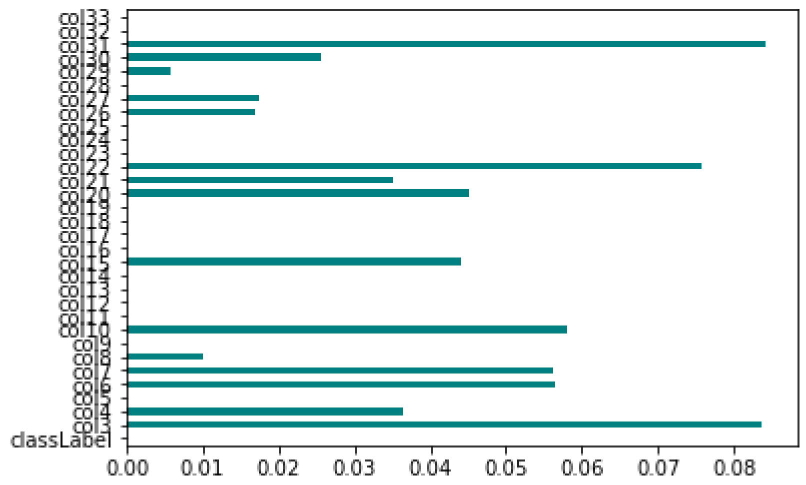
```
(198, 10)
```

In [20]:
```
# Filter methods

from sklearn.feature_selection import mutual_info_classif

# generate dataset
X = dataset.iloc[:,:-1].values
Y = dataset.iloc[:,-1].values
```

In [21]:
```
importanes = mutual_info_classif(X,Y)
feat_importanes = pd.Series(importanes, dataset.columns[0:len(dataset.columns)-1])
feat_importanes.plot(kind='barh', color='teal')
plt.show()
```



- Here got some of the best suggested features by Filter methods.
- 1/3th of the features can be easily filtered from our dataset, which will be added value in terms of most appropriate regression model selection.

In [22]:
```
df = pd.DataFrame(feat_importanes)
df.columns = ['Values']
df = df.sort_values(by = 'Values', ascending = False)
cm = sns.light_palette("black", as_cmap=True)
df.style.background_gradient(cmap=cm)
```

Out[22]:

	Values
col31	0.084185
col3	0.083746
col22	0.075695
col10	0.058156
col6	0.056430
col7	0.056210
col20	0.045152
col15	0.044103
col4	0.036287
col21	0.035175
col30	0.025541
col27	0.017350
col26	0.016804
col8	0.009985
col29	0.005730
col25	0.000000
col28	0.000000
col24	0.000000
col23	0.000000
col32	0.000000
classLabel	0.000000
col18	0.000000
col19	0.000000
col17	0.000000
col16	0.000000
col14	0.000000
col13	0.000000
col12	0.000000
col11	0.000000
col9	0.000000
col5	0.000000
col33	0.000000

- Suggested features based on their weightage are arranged descendingly.

In [23]:
```
df.describe().T
```

Out[23]:

	count	mean	std	min	25%	50%	75%	max
Values	32.0	0.02033	0.027961	0.0	0.0	0.0	0.038241	0.084185

- Mean value (0.02XX)
- 75% value (0.04XX)

Here our threshold could be in-between mean and 75% of suggested values

- threshold - 0.03

In [24]:
```
df = df[df['Values'] > 0.03]
df = df.sort_values(by = 'Values', ascending = False)
cm = sns.light_palette("green", as_cmap=True)
df.style.background_gradient(cmap=cm)
```

Out[24]:

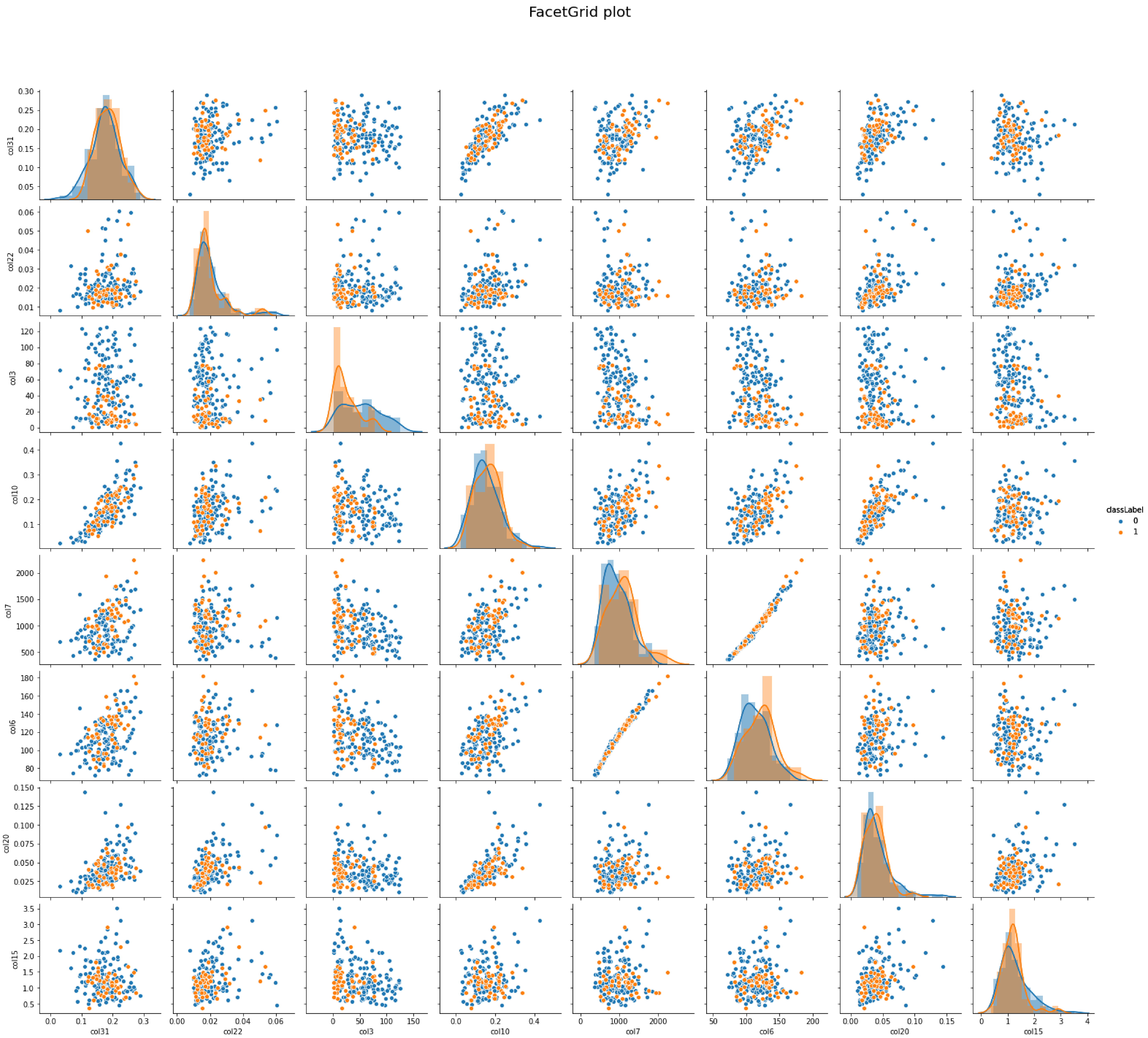
	Values
col31	0.084185
col3	0.083746
col22	0.075695
col10	0.058156
col6	0.056430
col7	0.056210
col20	0.045152
col15	0.044103
col4	0.036287
col21	0.035175

3 - 0.75 above
4 - 0.50 above and 0.75 below
2 - 0.04 above and 0.50 below

In [25]:
```
selected_feat = ['col31','col22','col3','col10','col7','col6','col20','col15']
len(selected_feat)
```

Out[25]: 8

In [26]:
```
g = sns.pairplot(dataset, vars = selected_feat ,hue = 'classLabel')
g.map_diag(sns.distplot)
g.add_legend()
g.fig.suptitle('FacetGrid plot', fontsize = 20)
g.fig.subplots_adjust(top= 0.9);
```



Perform Model building

In [27]:
```
selected_feat
# preferred by correlation matrix [4, 6, 7, 15, 30]
```

Out[27]: ['col31', 'col22', 'col3', 'col10', 'col7', 'col6', 'col20', 'col15']

Regression

- Simple Linear Regression
- Multiple Linear Regression
- Polynomial Linear Regression
- Support Vector Regression (SVR)
- Decision Tree Regression
- Random Forest Regression

Multiple Linear Regression

Case 1

In [28]:
```
#Splitting into Training and Testing Data

X=dataset[selected_feat]
#X=dataset[["col4","col6", "col7" , "col15", "col30"]]
y=dataset[["PredictLabel2"]]
```

In [29]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=101)
```

In [30]:
```
from sklearn.linear_model import LinearRegression

multi_lr=LinearRegression()
multi_lr.fit(X_train,y_train)
```

Out[30]:
```
LinearRegression()
```

In [31]:
```
#Prediction
prediction=multi_lr.predict(X_test)
```

In [32]:
```
from sklearn import metrics
print("MAE: ",metrics.mean_absolute_error(y_test,prediction))
print("MSE: ",metrics.mean_squared_error(y_test,prediction))
print("RMSE: ",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
MAE:  4.089827655203477
MSE:  37.87414406082943
RMSE:  6.1541972718486555
```

In [33]:
```
#Training Accuracy
multi_lr.score(X_train,y_train)
```

Out[33]:
```
0.04575202461006067
```

Case 2

In [34]:
```
X=dataset[["col4","col6", "col7" , "col15", "col30"]]
y=dataset[["PredictLabel2"]]

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=101)
```

In [35]:
```
from sklearn.linear_model import LinearRegression

multi_lr=LinearRegression()
multi_lr.fit(X_train,y_train)
```

Out[35]:
```
LinearRegression()
```

In [36]:
```
#Prediction
prediction=multi_lr.predict(X_test)
```

In [37]:
```
from sklearn import metrics
print("MAE: ",metrics.mean_absolute_error(y_test,prediction))
print("MSE: ",metrics.mean_squared_error(y_test,prediction))
print("RMSE: ",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
MAE:  4.094545812604858
MSE:  38.09620959608881
RMSE:  6.172212698545701
```

In [38]:
```
#Training Accuracy
multi_lr.score(X_train,y_train)
```

Out[38]:
```
0.03536624222620932
```

Decision Tree Regression Model

In [39]:
```
#Splitting into Training and Testing Data

#X=dataset[["col4","col6", "col7" , "col15", "col30"]]
X = dataset[selected_feat]
Y = dataset[["PredictLabel2"]]

# Fitting the Regression model to the dataset
from sklearn.tree import DecisionTreeRegressor
X_train, X_test, y_train, y_test = train_test_split(X, Y) #, test_size=0.3, random_state=101)
regressor = DecisionTreeRegressor(random_state = 0)
regressor.fit(X,Y)
```

Out[39]:
```
DecisionTreeRegressor(random_state=0)
```

In [40]:
```
# Predicting a new result with the Decision Tree Regression
Y_Pred = regressor.predict(X_test)
```

In [41]:
```
regressor.score(X_test,y_test)
```

Out[41]:
```
1.0
```

In [42]:
```
X=dataset[["col4"]]
Y = dataset[["PredictLabel2"]]

# Fitting the Regression model to the dataset
from sklearn.tree import DecisionTreeRegressor
X_train, X_test, y_train, y_test = train_test_split(X, Y) #, test_size=0.3, random_state=101)
regressor = DecisionTreeRegressor(random_state = 0)
regressor.fit(X,Y)

# Predicting a new result with the Decision Tree Regression
Y_Pred = regressor.predict(X_test)

regressor.score(X_test,y_test)
```

Out[42]:
```
0.9736932731307875
```

In [43]:
```
#Splitting into Training and Testing Data

X=dataset[["col6"]]
Y = dataset[["PredictLabel2"]]

# Fitting the Regression model to the dataset
from sklearn.tree import DecisionTreeRegressor
X_train, X_test, y_train, y_test = train_test_split(X, Y) #, test_size=0.3, random_state=101)
regressor = DecisionTreeRegressor(random_state = 0)
regressor.fit(X,Y)

# Predicting a new result with the Decision Tree Regression
Y_Pred = regressor.predict(X_test)

regressor.score(X_test,y_test)
```
Out[43]: 0.9639099081840697

In [44]:
```
X=dataset[["col7"]]
Y = dataset[["PredictLabel2"]]

# Fitting the Regression model to the dataset
from sklearn.tree import DecisionTreeRegressor
X_train, X_test, y_train, y_test = train_test_split(X, Y) #, test_size=0.3, random_state=101)
regressor = DecisionTreeRegressor(random_state = 0)
regressor.fit(X,Y)

# Predicting a new result with the Decision Tree Regression
Y_Pred = regressor.predict(X_test)

regressor.score(X_test,y_test)
```
Out[44]: 0.9754762540485947

In [45]:
```
X=dataset[["col15"]]
Y = dataset[["PredictLabel2"]]

# Fitting the Regression model to the dataset
from sklearn.tree import DecisionTreeRegressor
X_train, X_test, y_train, y_test = train_test_split(X, Y) #, test_size=0.3, random_state=101)
regressor = DecisionTreeRegressor(random_state = 0)
regressor.fit(X,Y)

# Predicting a new result with the Decision Tree Regression
Y_Pred = regressor.predict(X_test)

regressor.score(X_test,y_test)
```
Out[45]: 0.993990846857934

In [46]:
```
X=dataset[["col30"]]
Y = dataset[["PredictLabel2"]]

# Fitting the Regression model to the dataset
from sklearn.tree import DecisionTreeRegressor
X_train, X_test, y_train, y_test = train_test_split(X, Y) #, test_size=0.3, random_state=101)
regressor = DecisionTreeRegressor(random_state = 0)
regressor.fit(X,Y)

# Predicting a new result with the Decision Tree Regression
Y_Pred = regressor.predict(X_test)

regressor.score(X_test,y_test)
```
Out[46]: 0.9998508993749702

Simple Linear Regression

In [47]:
```
#Splitting into Training and Testing Data

X = dataset[["col7"]]
Y = dataset[['PredictLabel2']]
```

In [48]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y) #, test_size=0.3, random_state=101)

from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
linreg.fit(X_train, y_train)
```
Out[48]: LinearRegression()

In [49]:
```
#Training Accuracy
linreg.score(X_train,y_train)

#Prediction
prediction=linreg.predict(X_test)
```

In [50]:
```
from sklearn import metrics
print("MAE: ",metrics.mean_absolute_error(y_test,prediction))
print("MSE: ",metrics.mean_squared_error(y_test,prediction))
print("RMSE: ",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
MAE:  3.8652010762382543
MSE:  29.256258591045363
RMSE:  5.408905489195145
```

In [51]:
```
coef=pd.DataFrame()
coef['Features'] = X.columns.values
coef['Coefficients'] = linreg.coef_
coef
```
Out[51]:

	Features	Coefficients
0	col7	0.000818

In [52]:
```
#Testing Accuracy
linreg.score(X_test,y_test)
```
Out[52]: 0.007064165873211015

Perform Model Evaluation

Based on the above observations, we evidenced that

- Performance, Accuracy score, Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error are significantly different while compared with other Regression models.
- Some of the individual column likely to have some kind of inter connections with our predict Label2.
- Features selection methods and our observations might differ based on taked Domain or dataset.

Model Evaluation

- Simple Linear Regression
    1. Accuracy level 0.007 (Too poor)

- Multiple Linear Regression
    1. Accuracy level 0.045 (Too poor)
    2. Accuracy level 0.035 (Too poor)

- Decision Tree Regression Model
    1. Accuracy level 1.0 (Recommended and overfitting)

Top suggested columns for predicting predictLabel2 are listed with their score.

1. col30 - 0.99987
2. col7 - 0.99337
3. col6 - 0.90921
4. col15 - 0.83125

col30, col7, col6, and col15 can be used for predicting predictLabel2

In [ ]:
```

```