In [2]:
```python
# Importing necessary modules for analysis
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

#pd.set_option('display.max_columns',400)
```

In [3]:
```python
# Load Train and Test data set
data_train = pd.read_csv("train.csv")
data_test = pd.read_csv("test.csv")
```

In [4]:
```python
# Describing the data to see different statistical parameters
data_train.describe(include='all')
```

Out[4]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	
count	4209.000000	4209.000000	4209	4209	4209	4209	4209	4209	4209	4209	...	4209.000000	4209.000000	4209.000000	4209.000000	4209.00
unique	NaN	NaN	47	27	44	7	4	29	12	25	...	NaN	NaN	NaN	NaN	
top	NaN	NaN	z	aa	as	c	d	v	g	j	...	NaN	NaN	NaN	NaN	
freq	NaN	NaN	360	833	1659	1942	4205	231	1042	277	...	NaN	NaN	NaN	NaN	
mean	4205.960798	100.669318	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	0.318841	0.057258	0.314802	0.020670	0.00
std	2437.608688	12.679381	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	0.466082	0.232363	0.464492	0.142294	0.09
min	0.000000	72.110000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	0.000000	0.000000	0.000000	0.000000	0.00
25%	2095.000000	90.820000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	0.000000	0.000000	0.000000	0.000000	0.00
50%	4220.000000	99.150000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	0.000000	0.000000	0.000000	0.000000	0.00
75%	6314.000000	109.010000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	1.000000	0.000000	1.000000	0.000000	0.00
max	8417.000000	265.320000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	1.000000	1.000000	1.000000	1.000000	1.00

11 rows × 378 columns

In [5]:
```python
# Droping duplicate rows from train data set
data_train.drop_duplicates(subset = data_train.drop(['ID'],axis=1).columns,inplace=True)
```

In [8]:
```python
# Checking if any column in train data has got null values
print(data_train.isna().sum()[data_train.isna().sum() > 0])
print(data_test.isna().sum()[data_test.isna().sum() > 0])
```

```
Series([], dtype: int64)
Series([], dtype: int64)
```

In [6]:
```python
# No of unique values in each column in train data
pd.DataFrame(data_train.nunique()).transpose()
```

Out[6]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	4208	2545	47	27	44	7	4	29	12	25	...	2	2	2	2	2	2	2	2	2	2

1 rows × 378 columns

In [7]:
```python
# Getting index having zero variance in train set
data_train_zero_var = data_train.std()[data_train.std() == 0].index
print(data_train_zero_var)
```

```
Index(['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293',
       'X297', 'X330', 'X347'],
      dtype='object')
```

In [8]:
```python
# Drop the columns with zero variance in train and test data sets
data_train.drop(data_train_zero_var,axis=1,inplace=True)
data_train.drop(['ID'],axis=1,inplace=True)

data_test.drop(data_train_zero_var,axis=1,inplace=True)
data_test.drop(['ID'],axis=1,inplace=True)
```

In [9]:
```python
# Splitting train data into dependent and independent variables
data_train_X = data_train[data_train.columns.drop('y')]
data_train_y = data_train['y']
```

In [10]:
```python
# Concatenating test and train data set do perform Label Encoding.
concat_train_test = pd.concat([data_train_X,data_test],ignore_index=True)
```

Applying Label Encoder

In [11]:
```
# Import module to perform Label Encoding
from sklearn.preprocessing import LabelEncoder
```

In [12]:
```
# Encode categorical data to numerical
encoder = LabelEncoder()
concat_train_test = concat_train_test.apply(encoder.fit_transform)
```

In [13]:
```
# Splitting test and train data set
data_train_X = concat_train_test[0:data_train_y.shape[0]]
data_test_X = concat_train_test[data_train_y.shape[0]:]
```

Scaling and Dimensionality Reduction on Train data set

In [14]:
```
# Import module to scale the data in the same range to perform PCA
from sklearn.preprocessing import MinMaxScaler
```

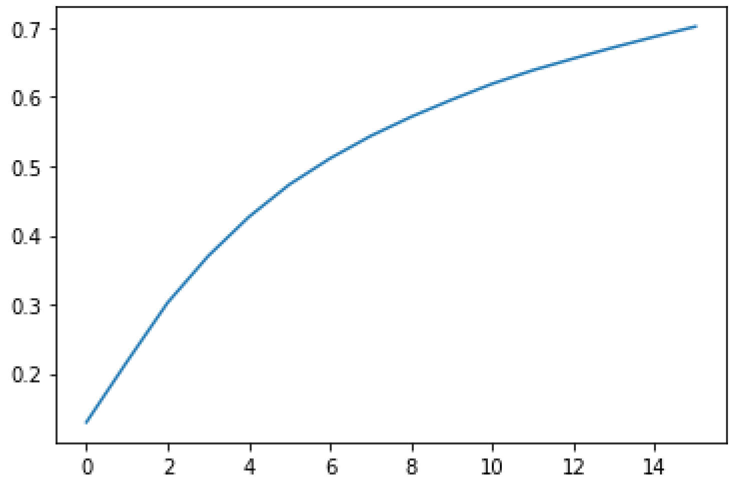
In [15]:
```
# Scaling the train data
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(data_train_X)
```

In [16]:
```
# Import module to perform PCA
from sklearn.decomposition import PCA
```

In [17]:
```
# Perform dimensionality recudtion on train data.
# It will choose no of components for which it achieves 70% variability
pca = PCA(0.7)
X_pca = pca.fit_transform(scaled_data)
pca.explained_variance_ratio_
```

Out[17]:
```
array([0.12978678, 0.08757254, 0.08519355, 0.06744382, 0.05641114,
       0.04697422, 0.03764255, 0.03240446, 0.02777835, 0.02473192,
       0.02307844, 0.0194863 , 0.01692304, 0.0162795 , 0.01522939,
       0.0146443 ])
```

In [18]:
```
# Plotting Explained variance against no of components.
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.show()
```



Model Building

In [19]:
```
# Import XGB regressor to build the model
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split
```

In [20]:
```
# Splitting train data set into : Train and test
X_train,X_test,y_train,y_test = train_test_split(X_pca,data_train_y,test_size=0.3,random_state=101)
```

In [21]:
```
# Fit the model using learing rate as 0.05
xgb = XGBRegressor(learning_rate=0.05)
xgb.fit(X_train,y_train)
```

Out[21]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.05, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=2, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

In [22]:
```
# Predict test data output to check accuracy of model
X_test_pred = xgb.predict(X_test)
```

In [23]:
```
# Check accuracy of model
from sklearn.metrics import r2_score
r2_score(y_test,X_test_pred)
```

Out[23]:
```
0.557054705719338
```

Predicting values for test data set

In [25]:
```
# Scale the test data set
data_test_scaled = scaler.transform(data_test_X)
```

In [26]:
```
# Do PCA on test data using same transformation as train data set
data_test_PCA = pca.transform(data_test_scaled)
```

In [27]:
```
# Predict output for the test data set
y_pred = xgb.predict(data_test_PCA)
```

In [28]:
```
# Adding predicted value to original train data set
data_test['y']=y_pred
```

In [29]:
```
data_test.head()
```

Out[29]:

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	...	X376	X377	X378	X379	X380	X382	X383	X384	X385	y
0	az	v	n	f	d	t	a	w	0	0	...	0	0	1	0	0	0	0	0	0	77.194572
1	t	b	ai	a	d	b	g	y	0	0	...	0	1	0	0	0	0	0	0	0	93.804947
2	az	v	as	f	d	a	j	j	0	0	...	0	0	1	0	0	0	0	0	0	77.667870
3	az	l	n	f	d	z	l	n	0	0	...	0	0	1	0	0	0	0	0	0	77.153069
4	w	s	as	c	d	y	i	m	0	0	...	0	0	0	0	0	0	0	0	0	111.298172

5 rows × 365 columns