Mercedes-Benz Greener Manufacturing

DESCRIPTION

Reduce the time a Mercedes-Benz spends on the test bench.

Problem Statement Scenario: Since the first automobile, the Benz Patent Motor Car in 1886, Mercedes-Benz has stood for important automotive innovations. These include the passenger safety cell with a crumple zone, the airbag, and intelligent assistance systems. Mercedes-Benz applies for nearly 2000 patents per year, making the brand the European leader among premium carmakers. Mercedes-Benz is the leader in the premium car industry. With a huge selection of features and options, customers can choose the customized Mercedes-Benz of their dreams.To ensure the safety and reliability of every unique car configuration before they hit the road, the company's engineers have developed a robust testing system. As one of the world's biggest manufacturers of premium cars, safety and efficiency are paramount on Mercedes-Benz's production lines. However, optimizing the speed of their testing system for many possible feature combinations is complex and time-consuming without a powerful algorithmic approach. You are required to reduce the time that cars spend on the test bench. Others will work with a dataset representing different permutations of features in a Mercedes-Benz car to predict the time it takes to pass testing. Optimal algorithms will contribute to faster testing, resulting in lower carbon dioxide emissions without reducing Mercedes-Benz's standards.

Following actions should be performed:

1. If for any column(s), the variance is equal to zero, then you need to remove those variable(s).
2. Check for null and unique values for test and train sets.
3. Apply label encoder.
4. Perform dimensionality reduction.
5. Predict your test_df values using XGBoost.

Step 1: Importing Data

In [ ]:

```
#Importing Necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE
from sklearn import metrics
from sklearn.metrics import r2_score
import statsmodels.api as sm
%matplotlib inline
```

In [ ]:

```
#Importing the train and test data
cars_train = pd.read_csv("/content/drive/MyDrive/Python/Projects_ML/Mercedes/train.csv")
cars_test = pd.read_csv("/content/drive/MyDrive/Python/Projects_ML/Mercedes/test.csv")
```

Step 2: Inspecting the Dataframe

In [ ]:

```
#Printing the shape of the df
print(cars_train.shape)
print(cars_test.shape)
```

```
(4209, 378)
(4209, 377)
```

In [ ]:

```
#Viewing the first 5 rows of the Train data
cars_train.head()
```

Out[ ]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23	X24	X26	X
0	0	130.81	k	v	at	a	d	u	j	o	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	
1	6	88.53	k	t	av	e	d	y	l	o	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	
2	7	76.26	az	w	n	c	d	x	j	x	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	
3	9	80.62	az	t	n	f	d	x	l	e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	13	78.02	az	v	n	f	d	h	d	n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

5 rows × 378 columns

In [ ]:

```
pd.set_option("display.max_columns", 340)
pd.set_option("display.max_columns", None)
```

In [ ]:

```
#Describing the data
cars_train.describe()
```

Out[ ]:

	ID	y	X10	X11	X12	X13	X14	X15	X16	X17
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	4205.960798	100.669318	0.013305	0.0	0.075077	0.057971	0.428130	0.000475	0.002613	0.007603
std	2437.608688	12.679381	0.114590	0.0	0.263547	0.233716	0.494867	0.021796	0.051061	0.086872
min	0.000000	72.110000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	2095.000000	90.820000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	4220.000000	99.150000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	6314.000000	109.010000	0.000000	0.0	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000
max	8417.000000	265.320000	1.000000	0.0	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

Step 3: Data Preprocessing

1. If for any column(s), the variance is equal to zero, then you need to remove those variable(s).

In [ ]:

```
#Displaying the Variance of all the columns
x=cars_train.var().sort_values()
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(x)
```

```
X289    0.000000e+00
X330    0.000000e+00
X268    0.000000e+00
X347    0.000000e+00
X107    0.000000e+00
X235    0.000000e+00
X233    0.000000e+00
X290    0.000000e+00
X11     0.000000e+00
X297    0.000000e+00
X293    0.000000e+00
X93     0.000000e+00
X257    2.375861e-04
X207    2.375861e-04
X280    2.375861e-04
X288    2.375861e-04
X33     2.375861e-04
X39     2.375861e-04
X190    2.375861e-04
X270    2.375861e-04
```

X295	2.375861e-04
X296	2.375861e-04
X95	2.375861e-04
X260	2.375861e-04
X210	2.375861e-04
X259	2.375861e-04
X339	2.375861e-04
X42	2.375861e-04
X204	2.375861e-04
X205	2.375861e-04
X372	4.750593e-04
X384	4.750593e-04
X236	4.750593e-04
X369	4.750593e-04
X15	4.750593e-04
X269	4.750593e-04
X319	4.750593e-04
X124	4.750593e-04
X278	4.750593e-04
X40	7.124196e-04
X332	7.124196e-04
X245	7.124196e-04
X89	7.124196e-04
X318	7.124196e-04
X74	7.124196e-04
X153	7.124196e-04
X59	7.124196e-04
X252	7.124196e-04
X110	9.496670e-04
X87	9.496670e-04
X167	9.496670e-04
X92	9.496670e-04
X160	1.186801e-03
X357	1.186801e-03
X366	1.186801e-03
X83	1.186801e-03
X266	1.423823e-03
X262	1.423823e-03
X184	1.423823e-03
X86	1.423823e-03
X145	1.423823e-03
X277	1.423823e-03
X253	1.423823e-03
X248	1.423823e-03
X60	1.423823e-03
X385	1.423823e-03
X383	1.660732e-03
X91	1.660732e-03
X104	1.897527e-03
X24	1.897527e-03
X67	1.897527e-03
X213	1.897527e-03
X271	2.134210e-03
X353	2.134210e-03
X65	2.134210e-03
X307	2.134210e-03
X105	2.370780e-03
X192	2.370780e-03
X258	2.370780e-03
X281	2.607237e-03
X310	2.607237e-03
X123	2.607237e-03
X21	2.607237e-03
X16	2.607237e-03
X112	2.843581e-03
X199	2.843581e-03
X365	2.843581e-03
X364	2.843581e-03
X240	2.843581e-03
X227	3.079812e-03
X125	3.079812e-03
X335	3.551935e-03
X282	4.023607e-03
X183	4.023607e-03
X312	4.259273e-03
X97	4.259273e-03
X36	4.494827e-03
X30	4.494827e-03
X165	4.494827e-03
X298	4.494827e-03
X299	4.494827e-03
X26	4.965595e-03
X254	5.200810e-03

X230	5.200810e-03
X55	5.200810e-03
X34	5.435912e-03
X212	5.435912e-03
X78	5.670901e-03
X325	5.670901e-03
X216	5.905777e-03
X62	5.905777e-03
X172	5.905777e-03
X237	6.609727e-03
X169	6.609727e-03
X200	6.609727e-03
X370	6.609727e-03
X239	6.844152e-03
X214	6.844152e-03
X53	6.844152e-03
X102	6.844152e-03
X338	6.844152e-03
X243	7.078463e-03
X88	7.078463e-03
X320	7.078463e-03
X122	7.078463e-03
X309	7.078463e-03
X242	7.312662e-03
X90	7.312662e-03
X94	7.312662e-03
X217	7.312662e-03
X382	7.546747e-03
X17	7.546747e-03
X317	7.546747e-03
X249	7.546747e-03
X18	7.780720e-03
X380	8.014579e-03
X221	8.014579e-03
X341	8.014579e-03
X344	8.481960e-03
X99	8.481960e-03
X292	8.948889e-03
X267	8.948889e-03
X323	9.182184e-03
X379	9.415366e-03
X308	9.415366e-03
X173	9.648436e-03
X274	9.881392e-03
X196	1.011424e-02
X291	1.034697e-02
X32	1.104448e-02
X44	1.127676e-02
X302	1.127676e-02
X41	1.127676e-02
X63	1.127676e-02
X195	1.150892e-02
X77	1.243646e-02
X47	1.266806e-02
X106	1.289955e-02
X305	1.313092e-02
X10	1.313092e-02
X57	1.313092e-02
X159	1.336219e-02
X371	1.405530e-02
X141	1.405530e-02
X108	1.451681e-02
X211	1.474739e-02
X287	1.566860e-02
X231	1.589862e-02
X203	1.658801e-02
X82	1.681757e-02
X176	1.681757e-02
X174	1.704703e-02
X185	1.842139e-02
X373	1.887861e-02
X206	1.887861e-02
X255	1.910705e-02
X73	1.956359e-02
X378	2.024755e-02
X23	2.024755e-02
X56	2.070297e-02
X322	2.138524e-02
X175	2.183952e-02
X342	2.183952e-02
X345	2.183952e-02
X134	2.183952e-02
X147	2.183952e-02

X222	2.183952e-02
X113	2.183952e-02
X48	2.183952e-02
X340	2.183952e-02
X198	2.252009e-02
X333	2.342595e-02
X170	2.365213e-02
X79	2.455572e-02
X111	2.455572e-02
X131	2.590773e-02
X135	2.635749e-02
X66	2.635749e-02
X315	2.792811e-02
X69	2.904660e-02
X359	3.083030e-02
X197	3.127510e-02
X152	3.127510e-02
X326	3.127510e-02
X226	3.127510e-02
X28	3.149733e-02
X166	3.216333e-02
X38	3.216333e-02
X361	3.282833e-02
X75	3.481721e-02
X272	3.613805e-02
X143	3.679694e-02
X276	3.701635e-02
X228	3.745482e-02
X126	3.745482e-02
X264	3.789284e-02
X229	3.833041e-02
X328	3.854903e-02
X109	3.876753e-02
X140	3.876753e-02
X162	3.920419e-02
X146	3.920419e-02
X138	3.920419e-02
X284	3.942236e-02
X130	3.985835e-02
X128	3.985835e-02
X52	4.051148e-02
X120	4.051148e-02
X29	4.116360e-02
X279	4.116360e-02
X232	4.116360e-02
X263	4.116360e-02
X54	4.159778e-02
X76	4.159778e-02
X136	4.159778e-02
X306	4.181471e-02
X148	4.289762e-02
X349	4.289762e-02
X61	4.397771e-02
X301	4.462441e-02
X346	4.527009e-02
X179	4.569998e-02
X117	4.677274e-02
X177	4.762890e-02
X367	4.912285e-02
X348	4.997405e-02
X80	5.018657e-02
X352	5.124746e-02
X286	5.167103e-02
X331	5.293902e-02
X376	5.399258e-02
X98	5.420295e-02
X13	5.462335e-02
X164	5.859468e-02
X368	5.880257e-02
X208	5.901034e-02
X101	6.025462e-02
X219	6.293661e-02
X43	6.702548e-02
X256	6.783784e-02
X68	6.804065e-02
X12	6.945713e-02
X304	7.006250e-02
X155	7.066685e-02
X360	7.066685e-02
X343	7.227350e-02
X70	7.367338e-02
X238	7.685234e-02
X189	7.744517e-02

X151	7.823404e-02
X22	7.941395e-02
X139	8.234595e-02
X181	8.505956e-02
X265	8.563817e-02
X225	8.755952e-02
X241	8.775104e-02
X215	8.889775e-02
X19	8.965997e-02
X209	9.117898e-02
X84	9.287924e-02
X244	9.287924e-02
X71	9.287924e-02
X182	9.494490e-02
X49	1.072316e-01
X129	1.075906e-01
X133	1.088435e-01
X294	1.093787e-01
X336	1.111555e-01
X327	1.118631e-01
X283	1.208970e-01
X20	1.224296e-01
X114	1.247954e-01
X180	1.330640e-01
X201	1.461667e-01
X356	1.475408e-01
X144	1.551541e-01
X316	1.573375e-01
X116	1.580596e-01
X161	1.586353e-01
X234	1.610617e-01
X354	1.617692e-01
X285	1.634555e-01
X300	1.641534e-01
X150	1.645707e-01
X154	1.652641e-01
X50	1.682812e-01
X103	1.690946e-01
X374	1.757146e-01
X81	1.766189e-01
X158	1.770047e-01
X142	1.770047e-01
X37	1.784108e-01
X35	1.784108e-01
X31	1.784108e-01
X321	1.818042e-01
X202	1.831631e-01
X247	1.831631e-01
X96	1.834087e-01
X363	1.855988e-01
X45	1.891677e-01
X168	1.975364e-01
X275	1.986199e-01
X51	2.008584e-01
X273	2.015935e-01
X156	2.028408e-01
X157	2.028408e-01
X115	2.040719e-01
X351	2.089300e-01
X313	2.104576e-01
X163	2.113977e-01
X100	2.138795e-01
X132	2.145094e-01
X218	2.148670e-01
X377	2.157528e-01
X224	2.167142e-01
X27	2.167142e-01
X375	2.172329e-01
X350	2.240671e-01
X171	2.252785e-01
X64	2.344678e-01
X119	2.351137e-01
X118	2.351137e-01
X355	2.357460e-01
X251	2.388537e-01
X311	2.403589e-01
X46	2.405915e-01
X85	2.416252e-01
X246	2.418420e-01
X137	2.433587e-01
X261	2.435900e-01
X187	2.437420e-01
X324	2.444393e-01

```
X58      2.444393e-01
X358     2.447207e-01
X14      2.448929e-01
X314     2.453926e-01
X329     2.458669e-01
X220     2.463157e-01
X178     2.467665e-01
X223     2.470074e-01
X250     2.472643e-01
X334     2.486588e-01
X186     2.487635e-01
X194     2.487635e-01
X191     2.492121e-01
X362     2.496467e-01
X337     2.497867e-01
X127     2.500357e-01
y        1.607667e+02
ID       5.941936e+06
dtype: float64
```

In [ ]:

```
#Removing columns with variance =0 from train and test data
cars_train = cars_train.drop((["X289","X330","X268","X347","X107","X235","X233","X290","X11","X297","X293","X93"]
),axis=1)
cars_test = cars_test.drop((["X289","X330","X268","X347","X107","X235","X233","X290","X11","X297","X293","X93"]),
axis=1)
```

In [ ]:

```
#Printing the shape of the df
print(cars_train.shape)
print(cars_test.shape)
```

```
(4209, 366)
(4209, 365)
```

2. Check for null and unique values for test and train sets.

In [ ]:

```
#Checking for missing values in train data
cars_train.isnull().sum().sort_values(ascending = False)
```

Out[ ]:

```
X385    0
X119    0
X122    0
X123    0
X124    0
       ..
X256    0
X257    0
X258    0
X259    0
ID      0
Length: 366, dtype: int64
```

In [ ]:

```
#Checking for missing values in test data
cars_test.isnull().sum().sort_values(ascending = False)
```

Out[ ]:

```
X385    0
X119    0
X122    0
X123    0
X124    0
       ..
X256    0
X257    0
X258    0
X259    0
ID      0
Length: 365, dtype: int64
```

There are no missing values in Train and test data.

In [ ]:

```
#Checking for unique values in train dataset
x= cars_train.drop(('y'),axis=1)
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(x.nunique()) #Gets the count of unique values
```

```
ID      4209
X0        47
X1        27
X2        44
X3         7
X4         4
X5        29
X6        12
X8        25
X10        2
X12        2
X13        2
X14        2
X15        2
X16        2
X17        2
X18        2
X19        2
X20        2
X21        2
X22        2
X23        2
X24        2
X26        2
X27        2
X28        2
X29        2
X30        2
X31        2
X32        2
X33        2
X34        2
X35        2
X36        2
X37        2
X38        2
X39        2
X40        2
X41        2
X42        2
X43        2
X44        2
X45        2
X46        2
X47        2
X48        2
X49        2
X50        2
X51        2
X52        2
X53        2
X54        2
X55        2
X56        2
X57        2
X58        2
X59        2
X60        2
X61        2
X62        2
X63        2
X64        2
X65        2
X66        2
X67        2
X68        2
X69        2
X70        2
X71        2
X73        2
X74        2
X75        2
```

X76	2
X77	2
X78	2
X79	2
X80	2
X81	2
X82	2
X83	2
X84	2
X85	2
X86	2
X87	2
X88	2
X89	2
X90	2
X91	2
X92	2
X94	2
X95	2
X96	2
X97	2
X98	2
X99	2
X100	2
X101	2
X102	2
X103	2
X104	2
X105	2
X106	2
X108	2
X109	2
X110	2
X111	2
X112	2
X113	2
X114	2
X115	2
X116	2
X117	2
X118	2
X119	2
X120	2
X122	2
X123	2
X124	2
X125	2
X126	2
X127	2
X128	2
X129	2
X130	2
X131	2
X132	2
X133	2
X134	2
X135	2
X136	2
X137	2
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X139	2
X140	2
X141	2
X142	2
X143	2
X144	2
X145	2
X146	2
X147	2
X148	2
X150	2
X151	2
X152	2
X153	2
X154	2
X155	2
X156	2
X157	2
X158	2
X159	2
X160	2
X161	2
X162	2

X163	2
X164	2
X165	2
X166	2
X167	2
X168	2
X169	2
X170	2
X171	2
X172	2
X173	2
X174	2
X175	2
X176	2
X177	2
X178	2
X179	2
X180	2
X181	2
X182	2
X183	2
X184	2
X185	2
X186	2
X187	2
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X194	2
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X197	2
X198	2
X199	2
X200	2
X201	2
X202	2
X203	2
X204	2
X205	2
X206	2
X207	2
X208	2
X209	2
X210	2
X211	2
X212	2
X213	2
X214	2
X215	2
X216	2
X217	2
X218	2
X219	2
X220	2
X221	2
X222	2
X223	2
X224	2
X225	2
X226	2
X227	2
X228	2
X229	2
X230	2
X231	2
X232	2
X234	2
X236	2
X237	2
X238	2
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X240	2
X241	2
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X243	2
X244	2
X245	2
X246	2
X247	2
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X250	2
X251	2
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X257	2
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X272	2
X273	2
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X300	2
X301	2
X302	2
X304	2
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X319	2
X320	2
X321	2
X322	2
X323	2
X324	2
X325	2
X326	2
X327	2
X328	2
X329	2
X331	2
X332	2
X333	2
X334	2
X335	2
X336	2
X337	2
X338	2
X339	2

```
X340       2
X341       2
X342       2
X343       2
X344       2
X345       2
X346       2
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X349       2
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X351       2
X352       2
X353       2
X354       2
X355       2
X356       2
X357       2
X358       2
X359       2
X360       2
X361       2
X362       2
X363       2
X364       2
X365       2
X366       2
X367       2
X368       2
X369       2
X370       2
X371       2
X372       2
X373       2
X374       2
X375       2
X376       2
X377       2
X378       2
X379       2
X380       2
X382       2
X383       2
X384       2
X385       2
dtype: int64
```

In [ ]:

```
#Displaying the unique values in the train data
unique_values=[]
unique_count =[]
for col in cars_train.columns :
        unique_values.append(cars_train[col].unique())
        unique_count.append(len(cars_train[col].unique()))

train_uniques = pd.concat([pd.DataFrame(cars_train.columns),pd.Series(unique_values),pd.Series(unique_count)],axi
s=1)
train_uniques.columns=['Feature','Unique Values','Count']
train_uniques=train_uniques.set_index('Feature')
train_uniques.head(12)
```

Out[ ]:

Feature	Unique Values	Count
ID	[0, 6, 7, 9, 13, 18, 24, 25, 27, 30, 31, 32, 3...	4209
y	[130.81, 88.53, 76.26, 80.62, 78.02, 92.93, 12...	2545
X0	[k, az, t, al, o, w, j, h, s, n, ay, f, x, y, ...	47
X1	[v, t, w, b, r, l, s, aa, c, a, e, h, z, j, o,...	27
X2	[at, av, n, e, as, aq, r, ai, ak, m, a, k, ae,...	44
X3	[a, e, c, f, d, b, g]	7
X4	[d, b, c, a]	4
X5	[u, y, x, h, g, f, j, i, d, c, af, ag, ab, ac,...	29
X6	[j, l, d, h, i, a, g, c, k, e, f, b]	12
X8	[o, x, e, n, s, a, h, p, m, k, d, i, v, j, b, ...	25
X10	[0, 1]	2
X12	[0, 1]	2

In [ ]:

```
#Displaying the last 5 rows of the unique values dataframe in train data
train_uniques.tail()
```

Out[ ]:

Feature	Unique Values	Count
X380	[0, 1]	2
X382	[0, 1]	2
X383	[0, 1]	2
X384	[0, 1]	2
X385	[0, 1]	2

In [ ]:

```
#Checking for unique values in test dataset

with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(cars_test.nunique()) #Gets the count of unique values
```

```
ID      4209
X0        49
X1        27
X2        45
X3         7
X4         4
X5        32
X6        12
X8        25
X10        2
X12        2
X13        2
X14        2
X15        2
X16        2
X17        2
X18        2
```

X19	2
X20	2
X21	2
X22	2
X23	2
X24	2
X26	2
X27	2
X28	2
X29	2
X30	2
X31	2
X32	2
X33	2
X34	2
X35	2
X36	2
X37	2
X38	2
X39	2
X40	2
X41	2
X42	2
X43	2
X44	2
X45	2
X46	2
X47	2
X48	2
X49	2
X50	2
X51	2
X52	2
X53	2
X54	2
X55	2
X56	2
X57	2
X58	2
X59	2
X60	2
X61	2
X62	2
X63	2
X64	2
X65	2
X66	2
X67	2
X68	2
X69	2
X70	2
X71	2
X73	2
X74	2
X75	2
X76	2
X77	2
X78	2
X79	2
X80	2
X81	2
X82	2
X83	2
X84	2
X85	2
X86	2
X87	2
X88	2
X89	2
X90	2
X91	2
X92	2
X94	2
X95	2
X96	2
X97	2
X98	2
X99	2
X100	2
X101	2
X102	2
X103	2
X104	2

X105	2
X106	2
X108	2
X109	2
X110	2
X111	2
X112	2
X113	2
X114	2
X115	2
X116	2
X117	2
X118	2
X119	2
X120	2
X122	2
X123	2
X124	2
X125	2
X126	2
X127	2
X128	2
X129	2
X130	2
X131	2
X132	2
X133	2
X134	2
X135	2
X136	2
X137	2
X138	2
X139	2
X140	2
X141	2
X142	2
X143	2
X144	2
X145	2
X146	2
X147	2
X148	2
X150	2
X151	2
X152	2
X153	2
X154	2
X155	2
X156	2
X157	2
X158	2
X159	2
X160	2
X161	2
X162	2
X163	2
X164	2
X165	2
X166	2
X167	2
X168	2
X169	2
X170	2
X171	2
X172	2
X173	2
X174	2
X175	2
X176	2
X177	2
X178	2
X179	2
X180	2
X181	2
X182	2
X183	2
X184	2
X185	2
X186	2
X187	2
X189	2
X190	2
X191	2

X192	2
X194	2
X195	2
X196	2
X197	2
X198	2
X199	2
X200	2
X201	2
X202	2
X203	2
X204	2
X205	2
X206	2
X207	2
X208	2
X209	2
X210	2
X211	2
X212	2
X213	2
X214	2
X215	2
X216	2
X217	2
X218	2
X219	2
X220	2
X221	2
X222	2
X223	2
X224	2
X225	2
X226	2
X227	2
X228	2
X229	2
X230	2
X231	2
X232	2
X234	2
X236	2
X237	2
X238	2
X239	2
X240	2
X241	2
X242	2
X243	2
X244	2
X245	2
X246	2
X247	2
X248	2
X249	2
X250	2
X251	2
X252	2
X253	2
X254	2
X255	2
X256	2
X257	1
X258	1
X259	2
X260	2
X261	2
X262	2
X263	2
X264	2
X265	2
X266	2
X267	2
X269	2
X270	2
X271	2
X272	2
X273	2
X274	2
X275	2
X276	2
X277	2
X278	2

X279	2
X280	2
X281	2
X282	2
X283	2
X284	2
X285	2
X286	2
X287	2
X288	2
X291	2
X292	2
X294	2
X295	1
X296	1
X298	2
X299	2
X300	2
X301	2
X302	2
X304	2
X305	2
X306	2
X307	2
X308	2
X309	2
X310	2
X311	2
X312	2
X313	2
X314	2
X315	2
X316	2
X317	2
X318	2
X319	2
X320	2
X321	2
X322	2
X323	2
X324	2
X325	2
X326	2
X327	2
X328	2
X329	2
X331	2
X332	2
X333	2
X334	2
X335	2
X336	2
X337	2
X338	2
X339	2
X340	2
X341	2
X342	2
X343	2
X344	2
X345	2
X346	2
X348	2
X349	2
X350	2
X351	2
X352	2
X353	2
X354	2
X355	2
X356	2
X357	2
X358	2
X359	2
X360	2
X361	2
X362	2
X363	2
X364	2
X365	2
X366	2
X367	2
X368	2

```
X369       1
X370       2
X371       2
X372       2
X373       2
X374       2
X375       2
X376       2
X377       2
X378       2
X379       2
X380       2
X382       2
X383       2
X384       2
X385       2
dtype: int64
```

In [ ]:

```
#Displaying the unique values in the test data
unique_values=[]
unique_count =[]
for col in cars_test.columns :
        unique_values.append(cars_test[col].unique())
        unique_count.append(len(cars_test[col].unique()))

test_uniques = pd.concat([pd.DataFrame(cars_test.columns),pd.Series(unique_values),pd.Series(unique_count)],axis=
1)
test_uniques.columns=['Feature','Unique Values','Count']
test_uniques=test_uniques.set_index('Feature')
test_uniques.head(12)
```

Out[ ]:

Feature	Unique Values	Count
ID	[1, 2, 3, 4, 5, 8, 10, 11, 12, 14, 15, 16, 17,...	4209
X0	[az, t, w, y, x, f, ap, o, ay, al, h, z, aj, d...	49
X1	[v, b, l, s, aa, r, a, i, p, c, o, m, z, e, h,...	27
X2	[n, ai, as, ae, s, b, e, ak, m, a, aq, ag, r, ...	45
X3	[f, a, c, e, d, g, b]	7
X4	[d, b, a, c]	4
X5	[t, b, a, z, y, x, h, g, f, j, i, d, c, af, ag...	32
X6	[a, g, j, l, i, d, f, h, c, k, e, b]	12
X8	[w, y, j, n, m, s, a, v, r, o, t, h, c, k, p, ...	25
X10	[0, 1]	2
X12	[0, 1]	2
X13	[0, 1]	2

In [ ]:

```
#Displaying the last 5 rows of the unique values dataframe in test data
test_uniques.tail()
```

Out[ ]:

Feature	Unique Values	Count
X380	[0, 1]	2
X382	[0, 1]	2
X383	[0, 1]	2
X384	[0, 1]	2
X385	[0, 1]	2

In [ ]:

```
#Checking the datatype of the columns in the train data
cars_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4209 entries, 0 to 4208
Columns: 366 entries, ID to X385
dtypes: float64(1), int64(357), object(8)
memory usage: 11.8+ MB
```

In [ ]:

```
dt = cars_train.dtypes
with pd.option_context('display.max_rows', None) :
  display(dt)
```

```
ID        int64
y       float64
X0       object
X1       object
X2       object
X3       object
X4       object
X5       object
X6       object
X8       object
X10       int64
X12       int64
X13       int64
X14       int64
X15       int64
X16       int64
X17       int64
X18       int64
X19       int64
X20       int64
X21       int64
X22       int64
X23       int64
X24       int64
X26       int64
X27       int64
X28       int64
X29       int64
X30       int64
X31       int64
X32       int64
X33       int64
X34       int64
X35       int64
X36       int64
X37       int64
X38       int64
X39       int64
X40       int64
X41       int64
X42       int64
X43       int64
X44       int64
X45       int64
X46       int64
X47       int64
X48       int64
X49       int64
X50       int64
X51       int64
X52       int64
X53       int64
X54       int64
X55       int64
X56       int64
X57       int64
X58       int64
X59       int64
X60       int64
X61       int64
X62       int64
X63       int64
X64       int64
X65       int64
X66       int64
X67       int64
```

```
X68       int64
X69       int64
X70       int64
X71       int64
X73       int64
X74       int64
X75       int64
X76       int64
X77       int64
X78       int64
X79       int64
X80       int64
X81       int64
X82       int64
X83       int64
X84       int64
X85       int64
X86       int64
X87       int64
X88       int64
X89       int64
X90       int64
X91       int64
X92       int64
X94       int64
X95       int64
X96       int64
X97       int64
X98       int64
X99       int64
X100      int64
X101      int64
X102      int64
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X141      int64
X142      int64
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X150      int64
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X155      int64
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```
X156     int64
X157     int64
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X165     int64
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X226     int64
X227     int64
X228     int64
X229     int64
X230     int64
X231     int64
X232     int64
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X240     int64
X241     int64
X242     int64
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X243      int64
X244      int64
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X263      int64
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X266      int64
X267      int64
X269      int64
X270      int64
X271      int64
X272      int64
X273      int64
X274      int64
X275      int64
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X277      int64
X278      int64
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X295      int64
X296      int64
X298      int64
X299      int64
X300      int64
X301      int64
X302      int64
X304      int64
X305      int64
X306      int64
X307      int64
X308      int64
X309      int64
X310      int64
X311      int64
X312      int64
X313      int64
X314      int64
X315      int64
X316      int64
X317      int64
X318      int64
X319      int64
X320      int64
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X322      int64
X323      int64
X324      int64
X325      int64
X326      int64
X327      int64
X328      int64
X329      int64
X331      int64
X332      int64
```

```
X333      int64
X334      int64
X335      int64
X336      int64
X337      int64
X338      int64
X339      int64
X340      int64
X341      int64
X342      int64
X343      int64
X344      int64
X345      int64
X346      int64
X348      int64
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X357      int64
X358      int64
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X363      int64
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X368      int64
X369      int64
X370      int64
X371      int64
X372      int64
X373      int64
X374      int64
X375      int64
X376      int64
X377      int64
X378      int64
X379      int64
X380      int64
X382      int64
X383      int64
X384      int64
X385      int64
dtype: object
```

3. Apply label encoder.

In [ ]:

```
#Importing library
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

In [ ]:

```
#Setting up X and y(features and target variable)
X_train= cars_train.drop(('y'),axis=1) #Dropping 'y' as its the target
y_train= cars_train['y']
```

In [ ]:

```
#Identifying the object columns and Applying label encoding to it
Object_cols = X_train.select_dtypes(include=np.object_)
Object_cols = Object_cols.apply(le.fit_transform)
Object_cols.head()
```

Out[ ]:

	X0	X1	X2	X3	X4	X5	X6	X8
0	32	23	17	0	3	24	9	14
1	32	21	19	4	3	28	11	14
2	20	24	34	2	3	27	9	23
3	20	21	34	5	3	27	11	4
4	20	23	34	5	3	12	3	13

In [ ]:

```
#Dropping the original object columns from the train and concatenating label encoded data.
X_train_new = X_train.drop(Object_cols.columns,axis=1)
X_train_new = pd.concat([Object_cols,X_train_new],axis=1)
X_train_new.head()
```

Out[ ]:

	X0	X1	X2	X3	X4	X5	X6	X8	ID	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23	X24	X26	X27	X28	X
0	32	23	17	0	3	24	9	14	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	
1	32	21	19	4	3	28	11	14	6	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	
2	20	24	34	2	3	27	9	23	7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	
3	20	21	34	5	3	27	11	4	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	
4	20	23	34	5	3	12	3	13	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	

4.Perform dimensionality reduction

In [ ]:

```
#Dropping 'ID' in train data as it plays no value in the model
X_train_new.drop(('ID'),axis=1,inplace=True)
```

In [ ]:

```
#Dropping 'ID' in test data as it plays no value in the model
cars_test.drop(('ID'),axis=1,inplace=True)
```

In [ ]:

```
X_train_new.shape
```

Out[ ]:

```
(4209, 364)
```

In [ ]:

```
#Checking correlation between variables
correlation_X = X_train_new.corr()
with pd.option_context('display.max_rows',None):
  display(correlation_X)
```

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14
X0	1.000000	-0.271123	-0.139904	-0.070645	0.017988	0.012293	0.037549	0.047735	0.081122	-0.134577	-0.130529	-0.138310
X1	-0.271123	1.000000	0.088266	0.205657	-0.020724	0.046417	-0.079119	-0.000306	-0.137193	0.112263	0.286683	0.079784
X2	-0.139904	0.088266	1.000000	-0.093546	0.002289	-0.017722	0.065778	-0.069932	0.042398	0.131464	0.222132	-0.079183
X3	-0.070645	0.205657	-0.093546	1.000000	0.015298	-0.008161	-0.048468	-0.001249	0.019663	0.056166	-0.216464	0.045183
X4	0.017988	-0.020724	0.002289	0.015298	1.000000	0.039778	0.027854	-0.008909	0.003360	0.008245	0.007179	0.005544
X5	0.012293	0.046417	-0.017722	-0.008161	0.039778	1.000000	-0.019917	0.012746	-0.006800	0.060161	-0.003452	-0.003439
X6	0.037549	-0.079119	0.065778	-0.048468	0.027854	-0.019917	1.000000	0.018565	0.092986	-0.099264	-0.041825	0.028516
X8	0.047735	-0.000306	-0.069932	-0.001249	-0.008909	0.012746	0.018565	1.000000	0.014075	-0.061136	-0.038309	0.026162
X10	0.081122	-0.137193	0.042398	0.019663	0.003360	-0.006800	0.092986	0.014075	1.000000	-0.033084	-0.028806	-0.100474

X12	-0.134577	0.112263	0.131464	0.056166	0.008245	0.060161	-0.099264	-0.061136	-0.033084	1.000000	0.214825	-0.246513
X13	-0.130529	0.286683	0.222132	-0.216464	0.007179	-0.003452	-0.041825	-0.038309	-0.028806	0.214825	1.000000	-0.083141
X14	-0.138310	0.079784	-0.079183	0.045183	0.005544	-0.003439	0.028516	0.026162	-0.100474	-0.246513	-0.083141	1.000000
X15	0.011491	-0.023295	-0.001613	-0.024059	0.000631	-0.003542	-0.002297	-0.006542	-0.002532	-0.006212	-0.005409	-0.018865
X16	0.003940	-0.005591	-0.020227	-0.008337	-0.061497	-0.032571	0.035292	0.030602	-0.005944	-0.014584	-0.012698	-0.044291
X17	-0.060401	0.120044	0.024392	-0.046271	0.002533	-0.031128	0.054548	-0.000996	-0.010164	-0.024937	-0.021713	0.012713
X18	-0.036495	0.068924	-0.060337	-0.028413	0.002572	-0.004646	-0.019988	0.044339	-0.010323	-0.025327	-0.010525	-0.076916
X19	0.203244	-0.207605	-0.312393	-0.068126	0.009622	0.009854	0.048629	0.031221	-0.038610	-0.094730	-0.082482	-0.287691
X20	0.030838	0.030153	-0.494692	0.073098	-0.015761	0.008522	-0.122983	0.011349	-0.047393	-0.116280	-0.043126	-0.353137
X21	-0.025532	0.069149	-0.018519	-0.032411	0.001481	-0.029751	0.003382	0.053085	-0.005944	-0.014584	0.007215	-0.044291
X22	0.147904	-0.129648	0.444380	-0.188833	0.008931	-0.050032	0.035421	-0.051851	-0.035836	-0.087924	0.226530	-0.267021
X23	0.115098	-0.011723	0.115886	0.055659	0.004204	-0.033924	0.026774	0.062841	-0.016870	-0.041391	-0.036040	-0.125703
X24	0.001554	-0.022323	-0.008234	-0.048153	0.001263	0.008780	-0.000858	0.002410	-0.005067	-0.012433	-0.010825	-0.004686
X26	-0.006131	-0.004501	0.030495	-0.041311	0.002049	-0.024992	0.026645	0.020203	-0.008223	-0.020175	-0.017566	-0.061270
X27	0.050622	-0.048785	0.137151	-0.049081	0.021713	0.037836	-0.062026	0.031821	0.070276	0.184599	0.110191	0.126863
X28	-0.100412	0.127520	0.280952	0.162385	0.005308	0.026029	-0.003490	0.004614	-0.021300	-0.052259	-0.039773	-0.158707
X29	-0.149090	0.202989	0.209387	0.188854	0.006134	0.006306	0.013201	0.004552	-0.024615	-0.042617	-0.052586	-0.076904
X30	0.062321	0.035667	-0.076038	0.078486	0.001949	0.010111	0.006879	-0.032543	-0.007820	-0.019185	-0.016705	-0.058265
X31	0.120973	-0.092994	0.110163	-0.080666	0.000695	-0.040828	0.019952	0.059488	-0.044248	-0.126861	-0.095558	-0.313459
X32	0.094024	-0.004861	-0.168747	-0.082171	0.003075	0.025765	0.058184	-0.035257	-0.012340	-0.030276	-0.026362	-0.091947
X33	0.012613	0.021482	-0.001848	-0.008149	0.000446	0.018050	0.022160	0.027139	-0.001790	-0.004392	-0.003824	0.017817
X34	0.037187	-0.051615	0.079531	-0.020661	0.002145	-0.010089	0.056831	-0.019721	-0.008608	-0.021119	-0.018388	-0.064136
X35	0.120973	-0.092994	0.110163	-0.080666	0.000695	-0.040828	0.019952	0.059488	-0.044248	-0.126861	-0.095558	-0.313459
X36	0.044776	-0.024995	0.158753	0.001071	0.001949	-0.027694	0.042119	-0.006353	-0.007820	-0.019185	-0.016705	-0.058265
X37	0.120973	-0.092994	0.110163	-0.080666	0.000695	-0.040828	0.019952	0.059488	-0.044248	-0.126861	-0.095558	-0.313459
X38	-0.010562	0.078145	0.003780	0.023032	0.005368	0.120028	-0.019545	0.002714	-0.021539	0.017543	-0.029005	0.061752
X39	0.012613	0.021482	-0.001848	-0.008149	0.000446	0.018050	0.022160	0.027139	-0.001790	-0.004392	-0.003824	0.017817
X40	-0.010552	-0.021229	-0.003202	0.021701	0.000773	0.012927	0.020078	0.020451	-0.003101	-0.007609	-0.006625	0.030866
X41	-0.008554	0.018769	-0.012875	0.055119	0.003108	0.011844	0.032413	0.015790	-0.012472	-0.030600	-0.026644	0.124132
X42	-0.026665	-0.018278	0.005224	0.027295	0.000446	-0.000636	-0.004267	-0.005720	0.132754	-0.004392	-0.003824	-0.013338
X43	-0.028147	0.082471	0.266184	0.119448	-0.004347	0.019644	0.070355	0.030802	0.400164	-0.079493	-0.065287	-0.091170
X44	-0.009858	-0.090357	0.052208	-0.038773	0.003108	-0.054607	-0.013618	-0.035086	-0.012472	-0.030600	-0.026644	-0.092931
X45	0.125718	-0.342465	-0.005299	-0.394862	0.009459	0.011412	0.073876	-0.029552	-0.062859	0.033104	-0.128106	-0.088756
X46	0.074638	0.018940	-0.081631	-0.033725	-0.023761	0.004737	-0.043615	0.029131	-0.124508	-0.054680	-0.030554	-0.471226
X47	-0.043813	0.004175	-0.000881	-0.034783	0.003299	-0.013146	-0.020698	0.007797	0.005188	-0.032480	0.007856	0.114690
X48	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X49	0.072314	-0.149410	-0.085257	-0.147537	-0.008847	-0.002188	0.017425	0.036893	-0.036977	-0.086986	-0.055262	-0.171664
X50	0.009891	-0.022295	-0.123523	-0.133728	-0.024093	0.042159	-0.022520	0.043807	-0.055547	-0.106926	0.004383	0.030734
X51	-0.092869	0.063273	-0.049236	-0.078943	-0.010791	0.022005	-0.094822	-0.021560	0.067466	-0.018278	-0.043370	0.415034
X52	-0.157480	0.021976	0.210407	-0.077838	-0.025873	0.006646	-0.010808	0.032074	0.037420	-0.046429	-0.042025	-0.043440
X53	0.045359	0.096876	0.173437	-0.012665	0.002410	0.010491	0.031107	-0.065193	-0.009672	-0.023731	-0.020663	-0.072069
X54	-0.153188	0.203808	0.206302	0.190653	0.006170	0.006177	0.011289	0.004657	-0.024757	-0.034216	-0.052889	-0.078518
X55	-0.068057	0.019507	0.025473	-0.049684	0.002098	0.002602	-0.003119	0.021796	-0.008417	-0.020652	-0.017982	-0.062719
X56	-0.021364	0.003464	-0.067319	-0.059663	0.004253	0.014357	-0.058235	-0.022389	-0.017067	-0.016807	-0.022327	0.023017
X57	-0.068020	0.161085	0.046964	0.017279	0.003360	0.013057	-0.011524	-0.055761	-0.013484	-0.033084	-0.028806	0.037820
X58	0.049016	-0.030810	-0.154328	-0.183065	-0.018377	-0.029963	-0.078223	0.039177	-0.051164	-0.205520	0.026140	-0.160336
X59	-0.024162	0.017387	0.001699	-0.014119	0.000773	-0.012971	0.020078	0.020451	-0.003101	-0.007609	-0.006625	-0.023108
X60	0.011660	0.008356	-0.004529	0.045180	0.001093	0.032027	-0.021254	0.045040	-0.004387	-0.010765	-0.009373	0.043667
X61	0.151655	-0.027227	-0.200188	0.084943	0.024308	0.011949	0.006068	-0.034684	-0.033810	0.049727	0.039984	0.057379
X62	-0.139559	0.100466	0.097122	-0.058637	0.002237	0.032042	0.007227	-0.077016	-0.008976	-0.022023	-0.019176	-0.066883
X63	0.063444	0.074118	0.044406	-0.002759	0.003108	0.036255	-0.041237	0.069209	-0.012472	-0.022109	-0.026644	0.096999
X64	-0.052449	0.062860	-0.012785	0.065384	0.002499	-0.017143	-0.070623	-0.046321	-0.081410	-0.086679	0.055571	0.434361
X65	0.009418	-0.016294	-0.015460	-0.030385	0.001340	0.000585	0.036564	0.010597	-0.005375	-0.013189	-0.011483	0.032711
X66	-0.171936	0.014937	0.292361	-0.086523	-0.034787	-0.006171	-0.004533	0.038750	-0.019375	-0.047536	-0.041390	-0.144366

X67	0.016247	0.043543	0.010785	-0.007392	0.001263	0.000845	0.001013	0.039618	-0.005067	-0.012433	-0.010825	-0.037758
X68	-0.139264	0.068230	0.050007	-0.099061	-0.016511	-0.006419	-0.050428	0.004027	-0.024735	-0.038713	-0.038642	0.006826
X69	-0.040786	-0.032086	-0.042678	-0.150568	0.005084	0.038554	0.177478	0.011090	-0.020399	-0.050049	-0.043578	0.166399
X70	0.055022	-0.045026	0.068539	-0.039784	-0.008537	-0.011815	-0.162361	-0.058965	0.034258	0.067442	0.069439	-0.194119
X71	-0.240184	0.218500	0.134877	-0.125480	-0.011266	0.010647	-0.070837	-0.015681	-0.039474	0.201982	0.199264	0.011558
X73	-0.040799	0.055060	-0.037526	0.001705	0.004130	-0.005267	-0.027850	0.010296	-0.016571	0.036705	-0.013591	0.096260
X74	-0.016667	0.032709	-0.016402	0.014119	-0.000773	0.020525	-0.001764	0.004850	0.003101	0.007609	0.006625	0.023108
X75	-0.179995	0.044748	0.233268	-0.081831	-0.028866	0.001588	0.006675	0.046703	-0.022477	-0.055147	-0.037118	-0.046520
X76	-0.153188	0.203808	0.206302	0.190653	0.006170	0.006177	0.011289	0.004657	-0.024757	-0.034216	-0.052889	-0.078518
X77	-0.032468	0.016481	-0.013537	-0.024181	0.003268	-0.018862	0.000886	0.007751	-0.013113	-0.032174	-0.000661	0.130515
X78	0.078499	0.105526	0.053458	-0.040034	0.002191	0.040479	-0.020961	0.070545	-0.008794	-0.021575	-0.018786	0.087522
X79	-0.222609	0.060967	-0.041946	0.164309	0.004651	0.018368	-0.036692	0.018575	-0.018664	-0.034285	-0.039873	0.139797
X80	0.169303	-0.059024	-0.319569	0.116505	0.021864	0.024154	-0.007262	0.027330	0.027466	0.067388	0.054137	0.204655
X81	0.115520	-0.031052	-0.300293	-0.082740	-0.007183	-0.014185	-0.084957	-0.020914	-0.063291	-0.116665	0.075283	-0.287628
X82	-0.032383	-0.030540	0.082031	-0.048677	0.003818	-0.005218	0.021908	-0.034634	0.304515	-0.037586	-0.032726	-0.051195
X83	0.008634	0.000349	0.062317	0.029345	0.000998	0.016135	0.007008	-0.025539	-0.004005	-0.009826	-0.008555	-0.029840
X84	-0.240184	0.218500	0.134877	-0.125480	-0.011266	0.010647	-0.070837	-0.015681	-0.039474	0.201982	0.199264	0.011558
X85	-0.392543	0.541306	0.060696	0.113356	-0.015220	-0.016026	-0.108553	-0.048375	-0.096436	0.078911	0.296641	0.139186
X86	-0.016303	0.013523	0.037072	0.005364	0.001093	0.009128	-0.036367	-0.002387	-0.004387	-0.010765	-0.009373	-0.032692
X87	0.014009	0.042978	-0.003697	0.036881	0.000893	-0.019030	0.012612	-0.028976	-0.003581	-0.008787	-0.007651	0.035646
X88	0.040334	0.117073	-0.010157	0.068847	0.002452	-0.007260	-0.001181	-0.014183	-0.009839	-0.024139	-0.021018	0.097923
X89	0.012130	0.037216	-0.003202	0.031936	0.000773	-0.012971	0.020078	-0.023826	-0.003101	-0.007609	-0.006625	0.030866
X90	0.037708	0.115798	-0.010326	0.071058	0.002493	-0.010625	0.002833	-0.014195	-0.010003	-0.024541	-0.021368	0.099554
X91	0.020661	0.056192	-0.004893	0.032048	0.001181	-0.030661	-0.005300	0.017997	-0.004740	-0.011628	-0.010125	0.047172
X92	0.005028	-0.025721	0.052901	0.019152	0.000893	0.021159	0.023187	0.012661	-0.003581	-0.008787	-0.007651	-0.026686
X94	0.037708	0.115798	-0.010326	0.071058	0.002493	-0.010625	0.002833	-0.014195	-0.010003	-0.024541	-0.021368	0.099554
X95	0.007002	0.021482	0.023612	0.018434	0.000446	-0.017453	-0.020123	0.020567	-0.001790	-0.004392	-0.003824	-0.013338
X96	-0.228835	0.224250	-0.066181	0.030378	-0.008836	0.033987	-0.094574	-0.003996	0.055903	0.091439	0.054642	0.220715
X97	0.056271	0.023030	0.040249	0.055345	0.001896	-0.000055	-0.015644	0.049667	-0.007610	-0.018671	-0.016257	-0.056704
X98	0.142066	-0.036675	-0.250019	0.064865	0.020477	0.020330	0.001879	-0.001169	0.028681	0.070368	0.056903	0.213706
X99	0.041623	0.110373	-0.011134	0.081405	0.002688	0.006490	-0.009787	0.005497	-0.010785	-0.026462	-0.023041	0.107346
X100	0.040508	-0.002524	-0.192736	-0.042740	0.001472	0.053974	-0.140445	-0.012182	-0.168835	0.114842	0.106840	0.310765
X101	0.119456	-0.067434	-0.295585	0.065790	0.018609	0.015747	-0.008701	0.020863	0.030462	0.074739	0.060934	0.226979
X102	0.045359	0.096876	0.173437	-0.012665	0.002410	0.010491	0.031107	-0.065193	-0.009672	-0.023731	-0.020663	-0.072069
X103	0.078831	-0.074652	-0.339114	-0.038475	0.008294	0.071694	-0.123580	0.010630	0.050773	0.147127	0.078087	0.291151
X104	0.006716	0.033951	-0.009736	-0.007392	0.001263	0.011424	-0.002728	0.011712	-0.005067	-0.012433	0.035859	0.017362
X105	-0.011229	0.004499	0.106093	0.024694	0.001412	0.008635	0.021629	-0.003546	-0.005667	-0.013904	-0.012106	-0.042225
X106	0.023631	0.021523	-0.015329	0.088289	0.003330	-0.048110	-0.034719	-0.111375	-0.013362	-0.032783	-0.010639	0.132987
X108	-0.086882	0.083685	0.179143	0.146211	0.003538	-0.001935	0.018896	0.020766	-0.014198	-0.034836	-0.030332	-0.093839
X109	-0.020762	-0.013342	-0.024594	0.043461	0.005937	-0.002463	-0.013755	-0.007018	-0.023823	-0.058451	-0.045729	0.237109
X110	-0.021915	0.023996	-0.003697	0.010288	0.000893	-0.016226	0.033762	-0.011445	-0.003581	-0.008787	-0.007651	0.035646
X111	0.182649	-0.003371	-0.299899	0.087586	0.036391	0.006629	0.004978	-0.029133	0.018664	0.045793	0.039873	0.139073
X112	0.004824	-0.037279	0.047559	-0.010338	0.001547	0.000495	-0.002579	0.003587	-0.006209	-0.015234	-0.013265	-0.046266
X113	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X114	-0.254859	0.281680	0.264240	-0.044313	-0.006235	0.034061	-0.080832	0.016636	-0.048035	0.139947	0.231265	-0.077892
X115	-0.096472	-0.100667	-0.135202	0.045813	-0.003059	-0.008859	0.059081	0.056972	0.009216	-0.090308	-0.100570	0.135416
X116	0.077929	-0.128996	-0.068701	-0.249933	-0.001856	0.004078	-0.015668	-0.023455	-0.041816	-0.077486	-0.015345	-0.182985
X117	0.036194	-0.044889	-0.057809	0.205644	0.006581	0.031240	-0.016995	-0.018196	-0.016820	0.402172	-0.051717	-0.152373
X118	0.136117	0.028872	0.064132	-0.213425	-0.002652	-0.008319	-0.052987	-0.046867	0.009215	-0.077411	0.138766	-0.026020
X119	0.136117	0.028872	0.064132	-0.213425	-0.002652	-0.008319	-0.052987	-0.046867	0.009215	-0.077411	0.138766	-0.026020
X120	0.157480	-0.021976	-0.210407	0.077838	0.025873	-0.006646	0.010808	-0.032074	-0.037420	0.046429	0.042025	0.043440
X122	0.040334	0.117073	-0.010157	0.068847	0.002452	-0.007260	-0.001181	-0.014183	-0.009839	-0.024139	-0.021018	0.097923
X123	-0.041115	-0.029596	-0.026632	-0.029736	0.001481	-0.019597	0.000191	-0.000479	-0.005944	-0.014584	-0.012698	0.021542
X124	-0.013906	0.022715	0.009390	-0.024059	0.000631	0.007030	-0.017249	0.010500	-0.002532	-0.006212	-0.005409	0.003167
X125	-0.018667	0.033894	-0.078173	-0.004814	0.001611	0.004451	-0.030087	-0.001793	-0.006463	-0.015858	-0.013808	-0.048161

X126	-0.192859	0.114483	0.340411	-0.107152	-0.027405	0.008216	0.015407	-0.016096	-0.023382	-0.057367	-0.049950	-0.174222
X127	0.473392	-0.122318	-0.237877	0.052541	0.009365	0.002015	-0.034614	-0.010330	0.055047	-0.085586	0.000383	-0.304649
X128	0.135520	-0.005878	-0.320774	0.094373	0.026187	0.030662	-0.003150	0.020800	0.024186	0.059341	0.051668	0.180215
X129	0.070162	-0.150708	-0.085887	-0.148056	-0.008791	-0.002595	0.018485	0.037735	-0.037083	-0.087254	-0.055529	-0.171167
X130	-0.135520	0.005878	0.320774	-0.094373	-0.026187	-0.030662	0.003150	-0.020800	-0.024186	-0.059341	-0.051668	-0.180215
X131	-0.044406	0.078793	-0.057341	0.004238	0.004785	-0.044038	-0.014891	-0.001357	-0.019199	-0.041504	0.009521	0.047883
X132	-0.056980	0.295066	-0.036585	0.359400	0.001366	0.002738	-0.047600	0.026058	0.073625	-0.045896	0.133919	0.119526
X133	0.184564	-0.325615	0.081463	-0.308841	0.010900	-0.024701	0.031552	-0.032415	-0.037455	-0.071787	-0.093443	-0.146885
X134	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X135	0.082176	-0.014918	-0.037325	0.199515	0.004828	0.031617	-0.077798	-0.034253	-0.019375	0.363467	-0.041390	-0.126619
X136	0.153188	-0.203808	-0.206302	-0.190653	-0.006170	-0.006177	-0.011289	-0.004657	0.024757	0.034216	0.052889	0.078518
X137	0.056731	-0.014632	-0.125585	-0.185595	-0.018013	-0.028271	-0.073180	0.028331	-0.052900	-0.209955	0.022733	-0.172778
X138	0.046140	-0.079142	-0.119220	-0.123606	0.005973	0.004870	0.009522	0.052671	-0.023969	-0.045146	-0.030663	-0.011250
X139	0.007966	0.001915	0.126291	0.034077	-0.002077	-0.091701	0.081313	0.019897	-0.036634	-0.089883	-0.010938	-0.212726
X140	0.046182	-0.077291	-0.122036	-0.124411	0.005937	0.005290	0.008174	0.051461	-0.023823	-0.044712	-0.030237	-0.009224
X141	-0.030442	-0.007240	-0.027473	-0.027859	0.003480	-0.001315	-0.003738	0.005788	-0.013964	-0.026656	-0.012678	0.074175
X142	0.110379	-0.166666	0.027640	-0.353098	0.007126	-0.009448	0.031888	-0.064276	0.058490	-0.140169	0.116147	-0.061634
X143	-0.038818	-0.017758	-0.015610	-0.015715	0.005771	-0.049665	0.096417	-0.054114	-0.001536	-0.052118	-0.049473	0.085293
X144	0.063223	0.040647	-0.137344	0.078405	0.010387	0.091248	-0.109348	-0.025722	0.046070	0.129712	0.061542	0.168155
X145	-0.000717	-0.005671	0.017427	-0.019974	0.001093	0.001495	-0.032049	-0.018495	-0.004387	0.013132	-0.009373	-0.019965
X146	0.046140	-0.079142	-0.119220	-0.123606	0.005973	0.004870	0.009522	0.052671	-0.023969	-0.045146	-0.030663	-0.011250
X147	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X148	-0.104378	0.113990	0.224644	0.122115	0.006275	0.026658	0.000164	0.008227	-0.025179	-0.040008	-0.039061	-0.097186
X150	-0.273111	0.297895	-0.048967	0.044043	-0.014814	0.022887	-0.091456	-0.006219	0.049222	0.076946	0.126993	0.260645
X151	-0.112547	0.155177	-0.041494	0.079551	0.008850	-0.005713	-0.007175	0.017134	-0.035513	0.003134	0.007745	0.252163
X152	0.036243	-0.013459	0.012737	0.042417	0.005288	-0.030337	-0.032153	-0.072772	0.002234	0.009124	-0.039580	-0.014190
X153	-0.025458	0.016343	-0.022806	0.021701	0.000773	0.020480	0.010921	0.012861	-0.003101	0.093740	-0.006625	-0.023108
X154	-0.154785	0.239910	-0.009085	0.450741	-0.000953	-0.020550	-0.010948	-0.034498	-0.059660	0.055468	-0.127452	0.018515
X155	-0.212191	0.240327	0.185954	-0.117218	-0.015865	0.037645	-0.078442	0.010690	-0.033422	0.236848	0.341697	0.005676
X156	0.075635	-0.140393	0.015380	0.034705	0.003252	0.002486	0.083699	0.044793	-0.175748	0.090779	-0.083566	0.178570
X157	-0.075635	0.140393	-0.015380	-0.034705	-0.003252	-0.002486	-0.083699	-0.044793	0.175748	-0.090779	0.083566	-0.178570
X158	-0.110379	0.166666	-0.027640	0.353098	-0.007126	0.009448	-0.031888	0.064276	-0.058490	0.140169	-0.116147	0.061634
X159	-0.081908	0.122546	0.022356	0.058579	0.003391	-0.017539	0.025360	0.012022	-0.013606	-0.009980	-0.029066	0.064793
X160	-0.018480	-0.026334	-0.004134	-0.022196	0.000998	-0.021488	0.004643	0.001905	-0.004005	-0.009826	-0.008555	0.039858
X161	0.148924	-0.353580	-0.011057	-0.421517	0.014364	0.024365	0.113792	-0.034048	-0.052431	-0.082553	-0.123132	-0.070176
X162	-0.148939	0.196889	0.216622	0.184740	0.005973	0.008507	0.012402	0.002704	-0.023969	-0.036038	-0.051205	-0.084009
X163	0.041554	-0.056650	-0.082432	-0.109156	-0.015872	0.008553	0.011173	0.020516	0.013575	-0.188025	-0.046505	0.242602
X164	0.038654	-0.189059	-0.135247	-0.205882	0.007471	-0.001247	-0.040833	0.039648	-0.029979	-0.028852	-0.064043	-0.094427
X165	-0.068231	0.048132	0.059893	-0.007078	0.001949	0.013118	-0.007703	0.067683	-0.007820	-0.019185	-0.016705	-0.058265
X166	-0.131802	0.165593	0.235124	0.201242	0.005368	0.009695	0.002714	-0.002557	-0.021539	-0.037763	-0.046014	-0.098908
X167	-0.015180	0.048402	-0.043316	-0.003008	0.000893	-0.001272	0.023187	0.003895	-0.003581	-0.008787	-0.007651	-0.026686
X168	-0.036166	0.070795	-0.158563	0.375698	-0.004069	0.001824	-0.031224	0.024927	0.087874	0.059671	-0.148904	0.067996
X169	-0.066234	0.095876	0.025320	0.007137	0.002368	-0.000186	0.015427	0.010750	-0.009503	-0.001133	-0.020301	0.023700
X170	-0.179464	0.032135	0.238552	-0.095745	-0.037259	-0.021107	-0.011838	0.024513	-0.018300	-0.044899	-0.032483	-0.136357
X171	0.166988	-0.169628	-0.027333	-0.400510	0.012985	0.001796	0.026974	-0.042649	-0.064729	-0.024201	0.174797	0.021615
X172	-0.139559	0.100466	0.097122	-0.058637	0.002237	0.032042	0.007227	-0.077016	-0.008976	-0.022023	-0.019176	-0.066883
X173	0.019690	-0.003873	0.000984	0.024045	0.002870	0.013503	-0.002571	0.069417	-0.011517	-0.000718	-0.024604	0.085294
X174	0.042192	0.075252	0.025987	-0.032573	0.003845	0.026949	-0.009943	0.053113	-0.015427	-0.037851	-0.032957	0.098374
X175	0.005090	-0.111340	-0.047919	-0.121490	0.004374	-0.030790	-0.023092	-0.003762	-0.017551	0.005752	-0.037493	0.012204
X176	-0.032649	-0.003475	-0.015815	-0.017081	0.003818	-0.035424	-0.005105	0.013015	-0.015319	-0.037586	-0.032726	0.152470
X177	-0.027386	0.004217	-0.027539	0.064426	0.006648	0.010850	0.014804	-0.001236	-0.026677	-0.065452	-0.038353	0.265510
X178	0.205178	-0.099616	-0.035288	-0.000992	0.006580	0.030082	-0.037715	-0.012652	0.103480	0.253889	0.088016	-0.832712
X179	-0.164475	0.090441	0.302603	-0.105278	-0.023588	-0.026370	0.011403	-0.028192	-0.026072	-0.063969	-0.050942	-0.194270
X180	-0.069228	-0.110769	0.001804	-0.174707	-0.013911	0.041039	0.038444	-0.003103	-0.050301	0.143554	-0.087946	-0.043057
X181	0.141662	-0.287863	0.157504	-0.271752	0.009313	0.011022	0.030478	-0.068015	-0.030259	-0.032944	-0.079833	-0.156606

X182	0.045356	-0.033338	-0.218000	0.112099	0.009975	0.034952	-0.069502	0.010163	-0.026567	0.384644	-0.065711	-0.162665
X183	-0.020161	-0.006996	0.025706	-0.029359	0.001843	-0.005351	-0.003499	0.027472	-0.007395	-0.018143	-0.015797	-0.055100
X184	0.006159	0.052650	-0.001063	-0.009115	0.001093	-0.030564	0.006814	0.030722	-0.004387	-0.010765	0.017574	-0.032692
X185	-0.097127	0.144906	0.127671	0.165383	0.004002	0.027401	-0.021476	-0.015498	-0.016060	-0.019473	-0.034309	-0.041829
X186	0.421405	-0.570809	-0.098067	-0.218208	0.011760	0.022144	0.103509	0.039123	0.108042	-0.092879	-0.266619	-0.135624
X187	-0.362440	0.492463	0.013845	0.141683	-0.014429	-0.024922	-0.109233	-0.041448	-0.098922	0.107966	0.291201	0.169451
X189	0.205917	-0.152207	-0.382779	-0.069982	0.014314	0.017400	-0.011884	0.011603	0.035297	0.073641	0.075405	0.185354
X190	-0.012076	-0.014663	-0.001848	-0.008149	0.000446	0.008707	-0.020123	0.009614	-0.001790	-0.004392	-0.003824	0.017817
X191	-0.144415	0.040339	-0.200524	0.104832	0.007975	-0.007519	-0.025639	0.037498	-0.109548	0.022031	-0.093487	0.819047
X192	-0.008742	0.006788	0.008479	-0.020188	0.001412	0.005086	-0.016854	-0.010481	-0.005667	-0.013904	-0.012106	0.016951
X194	-0.421405	0.570809	0.098067	0.218208	-0.011760	-0.022144	-0.103509	-0.039123	-0.108042	0.092879	0.266619	0.135624
X195	-0.073731	0.069443	0.017677	0.027926	0.003141	0.005189	-0.031560	0.009142	-0.012603	0.053131	-0.026923	0.031431
X196	-0.019902	0.075096	-0.021934	0.008764	0.002940	-0.002185	-0.003819	0.038179	-0.011797	-0.002047	0.065791	0.055344
X197	-0.063329	-0.023855	-0.020672	-0.161476	0.005288	0.040021	0.213847	-0.009764	-0.021219	-0.052061	-0.045330	0.208474
X198	-0.196737	0.019859	0.296563	-0.090296	-0.038413	-0.009405	-0.000711	0.032784	-0.017835	-0.043758	-0.038101	-0.132892
X199	0.004824	-0.037279	0.047559	-0.010338	0.001547	0.000495	-0.002579	0.003587	-0.006209	-0.015234	-0.013265	-0.046266
X200	0.058446	-0.076127	-0.129950	-0.061742	0.002368	0.020716	0.038475	-0.041581	-0.009503	-0.023315	-0.020301	-0.070807
X201	0.257258	-0.423469	-0.033318	-0.013551	0.013453	-0.030020	-0.001678	0.016758	0.211812	-0.125374	-0.115325	0.004721
X202	0.101290	-0.391924	0.001916	-0.477880	0.008810	0.020683	0.097609	-0.033617	-0.060657	-0.076436	-0.139933	-0.080766
X203	-0.009000	-0.090421	0.094498	-0.113787	0.003791	-0.021503	-0.019179	0.005400	-0.015211	-0.030318	-0.032494	-0.049952
X204	0.002513	0.021482	-0.000434	-0.025872	0.000446	0.019919	0.011589	0.005233	-0.001790	-0.004392	0.062143	-0.013338
X205	-0.002513	-0.021482	0.000434	0.025872	-0.000446	-0.019919	-0.011589	-0.005233	0.001790	0.004392	-0.062143	0.013338
X206	-0.047037	0.007664	-0.000607	-0.036279	0.004054	0.016863	-0.031065	0.040176	-0.016266	-0.000533	-0.005148	0.067529
X207	-0.018809	0.001602	-0.001848	-0.008149	0.000446	0.023656	0.001018	-0.010102	-0.001790	-0.004392	-0.003824	0.017817
X208	-0.080080	-0.054251	0.085961	-0.154462	-0.018974	-0.001916	0.005051	0.061578	-0.030100	-0.062715	-0.047560	-0.089856
X209	0.090043	0.054843	-0.059143	0.134661	0.011576	0.031885	-0.065366	-0.014646	0.025282	0.083787	0.069885	0.017194
X210	-0.005343	-0.007434	-0.017407	0.018434	0.000446	-0.023059	-0.004267	-0.021055	-0.001790	-0.004392	-0.003824	-0.013338
X211	-0.026911	-0.080779	-0.037398	-0.060668	0.003567	0.016974	-0.028754	-0.022387	-0.014314	-0.035120	-0.030579	0.063380
X212	0.038829	-0.053882	0.044933	0.012684	0.002145	-0.006573	0.017052	0.002720	0.441442	-0.021119	-0.018388	-0.064136
X213	0.016247	0.043543	0.010785	-0.007392	0.001263	0.000845	0.001013	0.039618	-0.005067	-0.012433	-0.010825	-0.037758
X214	0.045359	0.096876	0.173437	-0.012665	0.002410	0.010491	0.031107	-0.065193	-0.009672	-0.023731	-0.020663	-0.072069
X215	0.203709	-0.204714	-0.312762	-0.066274	0.009571	0.009448	0.048627	0.033217	-0.038405	-0.094227	-0.082044	-0.286164
X216	-0.139559	0.100466	0.097122	-0.058637	0.002237	0.032042	0.007227	-0.077016	-0.008976	-0.022023	-0.019176	-0.066883
X217	0.040945	0.119056	-0.005737	0.071058	0.002493	-0.010289	-0.004789	-0.010247	-0.010003	-0.024541	-0.021368	0.093938
X218	-0.144207	0.071733	0.193593	-0.262360	-0.001305	-0.019224	-0.076563	-0.013977	-0.078276	0.072507	0.339494	-0.130524
X219	-0.181137	0.262799	0.133223	-0.088848	0.007784	0.040686	-0.076405	0.017280	-0.031236	0.264821	0.371002	0.048641
X220	-0.118393	0.051007	0.266040	-0.161081	0.032725	0.021669	0.010689	-0.093747	-0.118781	-0.007871	0.176341	0.224245
X221	-0.157834	0.054496	0.059564	-0.061438	0.002611	0.007861	-0.008599	-0.055740	-0.010479	-0.025711	-0.022386	-0.045897
X222	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X223	-0.225250	0.129003	0.141726	0.039483	-0.006489	0.000458	0.019556	0.027881	0.095583	-0.147785	-0.129869	0.727050
X224	-0.104389	0.049084	-0.078562	0.051135	-0.000990	0.002751	-0.036152	0.013730	-0.079186	-0.194284	-0.053402	0.779874
X225	-0.015105	-0.003985	-0.018497	-0.157507	0.009481	0.029901	0.009805	0.062828	-0.031036	-0.020208	-0.019422	0.091405
X226	0.036243	-0.013459	0.012737	0.042417	0.005288	-0.030337	-0.032153	-0.072772	0.002234	0.009124	-0.039580	-0.014190
X227	-0.018667	0.033894	-0.078173	-0.004814	0.001611	0.004451	-0.030087	-0.001793	-0.006463	-0.015858	-0.013808	-0.048161
X228	-0.150940	-0.004984	0.152279	-0.096566	-0.027405	-0.005327	-0.023321	0.031710	-0.023382	-0.038730	-0.044696	-0.092338
X229	0.147355	-0.001838	-0.150059	0.093140	0.026950	0.005466	0.019403	-0.028509	0.023677	0.039669	0.040193	0.088119
X230	-0.045030	0.043842	-0.008689	0.005240	0.002098	-0.038535	0.012697	0.005877	-0.008417	-0.020652	-0.017982	0.083776
X231	-0.091055	-0.011648	-0.073114	-0.031998	0.003708	0.007964	-0.037409	0.029305	0.001567	-0.036509	-0.007597	0.026230
X232	-0.149090	0.202989	0.209387	0.188854	0.006134	0.006306	0.013201	0.004552	-0.024615	-0.042617	-0.052586	-0.076904
X234	0.325250	-0.206457	0.041494	-0.143218	0.014546	-0.025682	0.066297	-0.007404	-0.058371	-0.143214	0.083058	-0.434934
X236	-0.045651	0.017603	-0.018618	0.026072	0.000631	-0.000899	-0.017249	0.001204	-0.002532	0.076529	-0.005409	-0.018865
X237	-0.006021	-0.021648	-0.020269	-0.041582	0.002368	-0.066435	-0.003612	-0.015416	-0.009503	-0.023315	-0.007794	-0.070807
X238	0.240511	-0.205279	-0.382044	-0.058801	0.014444	0.008634	-0.015286	0.025309	0.035134	0.073192	0.071389	0.183842
X239	0.045359	0.096876	0.173437	-0.012665	0.002410	0.010491	0.031107	-0.065193	-0.009672	-0.023731	-0.020663	-0.072069
X240	-0.040265	0.026452	0.018530	0.048572	0.001547	-0.002205	0.027977	0.021317	-0.006209	-0.015234	0.005803	0.061799

X241	-0.219042	0.227151	0.166088	-0.110730	-0.012217	0.020404	-0.053407	-0.032261	-0.038096	0.147004	0.203512	0.050084
X242	0.037708	0.115798	-0.010326	0.071058	0.002493	-0.010625	0.002833	-0.014195	-0.010003	-0.024541	-0.021368	0.099554
X243	0.040334	0.117073	-0.010157	0.068847	0.002452	-0.007260	-0.001181	-0.014183	-0.009839	-0.024139	-0.021018	0.097923
X244	-0.240184	0.218500	0.134877	-0.125480	-0.011266	0.010647	-0.070837	-0.015681	-0.039474	0.201982	0.199264	0.011558
X245	0.012130	0.037216	-0.003202	0.031936	0.000773	-0.012971	0.020078	-0.023826	-0.003101	-0.007609	-0.006625	0.030866
X246	-0.341428	0.522338	-0.006343	0.215346	-0.015143	-0.011843	-0.118948	-0.028514	-0.096673	0.091023	0.293841	0.154610
X247	0.101290	-0.391924	0.001916	-0.477880	0.008810	0.020683	0.097609	-0.033617	-0.060657	-0.076436	-0.139933	-0.080766
X248	0.011660	0.008356	-0.004529	0.045180	0.001093	0.032027	-0.021254	0.045040	-0.004387	-0.010765	-0.009373	0.043667
X249	0.038361	0.117799	-0.005975	0.073218	0.002533	-0.013556	-0.000782	-0.010324	-0.010164	-0.024937	-0.021713	0.095631
X250	0.210866	-0.088023	-0.048940	0.007105	0.006310	0.028457	-0.035492	-0.013277	0.104430	0.256220	0.090179	-0.824017
X251	-0.136941	0.062503	-0.096691	0.046175	0.003602	-0.017882	0.032782	0.026036	-0.093663	-0.229802	-0.066938	0.932210
X252	-0.018977	0.036172	0.040907	0.016584	0.000773	0.028034	0.007869	0.006535	-0.003101	-0.007609	-0.006625	-0.023108
X253	0.011660	0.008356	-0.004529	0.045180	0.001093	0.032027	-0.021254	0.045040	-0.004387	-0.010765	-0.009373	0.043667
X254	-0.045030	0.043842	-0.008689	0.005240	0.002098	-0.038535	0.012697	0.005877	-0.008417	-0.020652	-0.017982	0.083776
X255	-0.052481	0.071881	0.214645	-0.051791	0.004079	0.010856	0.016974	-0.095300	-0.016368	-0.040160	-0.034967	-0.121963
X256	0.016251	0.049735	0.177008	0.050727	0.008131	0.025679	0.072363	-0.014427	0.397338	-0.080055	-0.065801	-0.243123
X257	0.001391	0.023289	0.025027	-0.017011	0.000446	-0.024928	0.011589	-0.012292	-0.001790	-0.004392	-0.003824	-0.013338
X258	-0.016913	-0.057861	0.110570	-0.000552	0.001412	-0.001421	-0.008488	-0.025044	-0.005667	-0.013904	-0.012106	-0.042225
X259	0.011491	-0.014663	0.034928	0.000712	0.000446	-0.008110	0.011589	0.007423	-0.001790	-0.004392	-0.003824	-0.013338
X260	0.015980	-0.018278	-0.010335	-0.008149	0.000446	-0.023059	-0.014838	0.013995	-0.001790	-0.004392	-0.003824	-0.013338
X261	-0.346534	0.014135	0.121778	-0.093864	-0.014489	0.007013	0.036361	0.019528	-0.035701	0.119510	0.028066	0.341442
X262	0.006159	0.052650	-0.001063	-0.009115	0.001093	-0.030564	0.006814	0.030722	-0.004387	-0.010765	0.017574	-0.032692
X263	0.149090	-0.202989	-0.209387	-0.188854	-0.006134	-0.006306	-0.013201	-0.004552	0.024615	0.042617	0.052586	0.076904
X264	-0.192854	0.111068	0.338257	-0.108523	-0.027176	0.009843	0.012968	-0.017602	-0.023530	-0.057730	-0.050266	-0.175324
X265	0.227735	-0.181413	-0.392478	-0.047588	0.012626	0.013819	-0.014389	0.021842	0.037526	0.079746	0.076692	0.205772
X266	0.006159	0.052650	-0.001063	-0.009115	0.001093	-0.030564	0.006814	0.030722	-0.004387	-0.010765	0.017574	-0.032692
X267	-0.032166	-0.010105	-0.000379	-0.025914	0.002762	-0.020987	-0.016086	-0.000796	0.010839	-0.027194	-0.012929	0.095085
X269	-0.015493	0.013768	0.009390	0.007273	0.000631	-0.029971	-0.013511	-0.011189	-0.002532	-0.006212	-0.005409	0.003167
X270	-0.010954	0.016060	-0.001848	0.018434	0.000446	0.004970	-0.035980	0.007423	-0.001790	-0.004392	-0.003824	0.017817
X271	-0.032893	0.035563	0.021351	0.028745	0.001340	-0.010014	-0.000469	0.026677	-0.005375	0.006330	-0.011483	0.032711
X272	-0.139510	0.185082	0.225772	0.180114	0.005715	0.013067	0.015618	0.005935	-0.022933	-0.056266	-0.048992	-0.082464
X273	0.050051	-0.025389	-0.046565	0.171387	-0.018041	-0.027983	-0.107958	0.019638	-0.181647	-0.009156	-0.071812	-0.276651
X274	-0.069771	0.116640	0.031611	0.033488	0.002905	-0.006169	0.028761	0.008602	-0.011658	-0.019532	-0.024905	0.033906
X275	0.142594	-0.066217	0.057895	-0.355917	0.003903	-0.013814	0.032249	-0.070613	-0.017215	-0.096432	0.115597	-0.003933
X276	-0.142165	0.188599	0.225772	0.190261	0.005790	0.008216	0.015758	-0.001761	-0.023233	-0.042942	-0.049632	-0.085754
X277	-0.018596	0.057818	-0.053064	0.012603	0.001093	0.013708	-0.010458	0.005666	-0.004387	-0.010765	-0.009373	-0.032692
X278	-0.015493	0.035495	-0.006615	-0.011526	0.000631	0.013637	0.016392	0.002754	-0.002532	-0.006212	-0.005409	0.025199
X279	-0.149090	0.202989	0.209387	0.188854	0.006134	0.006306	0.013201	0.004552	-0.024615	-0.042617	-0.052586	-0.076904
X280	-0.024420	0.003409	0.032099	-0.017011	0.000446	0.016182	0.011589	-0.003530	-0.001790	-0.004392	-0.003824	-0.013338
X281	0.004618	0.045690	0.106587	-0.005662	0.001481	-0.029187	0.025719	-0.033544	-0.005944	-0.014584	-0.012698	-0.044291
X282	0.061375	0.088740	0.132600	-0.007827	0.001843	0.033245	0.017051	-0.057167	-0.007395	-0.018143	-0.015797	-0.055100
X283	-0.235678	0.144991	-0.044422	0.327428	-0.006790	-0.046588	-0.036302	-0.059325	-0.046979	-0.021903	-0.076965	0.080860
X284	-0.076545	-0.135900	0.025692	-0.176176	-0.010205	0.002777	-0.016686	-0.005060	-0.024041	-0.004489	-0.051360	-0.036440
X285	-0.205316	0.585840	0.100820	-0.069071	-0.009133	0.010926	-0.075996	-0.021330	-0.059102	0.095866	0.444642	0.130940
X286	-0.088499	0.041406	0.082726	0.237622	0.006957	-0.000665	-0.005262	0.026055	-0.027918	0.046540	-0.059642	-0.066483
X287	0.055418	-0.016604	-0.053913	-0.113064	0.003680	0.023517	0.063724	0.035619	-0.014769	-0.036235	-0.031550	0.035737
X288	0.014857	0.021482	0.032099	-0.008149	0.000446	0.016182	-0.004267	0.005233	-0.001790	-0.004392	-0.003824	-0.013338
X291	-0.036472	0.027112	0.042120	0.026228	0.002974	-0.007070	0.002786	0.026258	-0.011935	-0.011554	-0.015501	-0.060606
X292	-0.027411	0.029060	0.015293	0.023176	0.002762	-0.016115	-0.051395	-0.007221	-0.011084	0.001402	0.008568	-0.047052
X294	0.158783	-0.272456	-0.065739	-0.244799	0.010936	-0.004873	-0.011245	-0.018331	-0.025072	-0.072226	-0.093749	-0.194855
X295	0.005880	0.016060	-0.001848	0.000712	0.000446	-0.017453	-0.004267	0.013995	-0.001790	-0.004392	-0.003824	0.017817
X296	0.005880	0.016060	-0.001848	0.000712	0.000446	-0.017453	-0.004267	0.013995	-0.001790	-0.004392	-0.003824	0.017817
X298	0.059225	-0.040784	-0.000918	-0.000966	0.001949	0.035887	-0.002842	-0.021966	-0.007820	-0.019185	-0.016705	0.020525
X299	0.059225	-0.040784	-0.000918	-0.000966	0.001949	0.035887	-0.002842	-0.021966	-0.007820	-0.019185	-0.016705	0.020525

X300	-0.178401	0.076323	-0.061827	0.110216	0.014782	-0.033791	-0.051109	0.003046	-0.059317	-0.145535	-0.058958	0.589188
X301	0.145602	-0.024840	-0.068673	0.072945	0.006412	0.145477	0.035465	0.054918	0.042989	0.060655	-0.054970	-0.128079
X302	-0.009858	-0.090357	0.052208	-0.038773	0.003108	-0.054607	-0.013618	-0.035086	-0.012472	-0.030600	-0.026644	-0.092931
X304	0.079118	-0.035021	-0.242346	0.121975	0.016011	0.010504	-0.042926	0.025514	0.017583	0.081587	0.067197	0.247776
X305	0.061800	-0.041171	0.104233	0.013704	0.003360	-0.000265	0.024734	0.024978	0.022712	-0.033084	-0.028806	-0.100474
X306	-0.149048	0.058455	0.167671	-0.137076	-0.025265	0.011324	0.032053	-0.011143	-0.024828	-0.060915	-0.048067	-0.184997
X307	-0.008180	-0.025339	-0.011684	-0.033341	0.001340	-0.035576	0.010112	-0.012061	-0.005375	-0.013189	-0.011483	-0.040053
X308	0.032011	0.051232	0.208903	-0.010962	0.002835	0.006943	0.024103	-0.066971	-0.011374	-0.027907	-0.024299	-0.084753
X309	-0.003253	-0.020994	-0.021559	-0.038298	0.002452	-0.048683	-0.009896	-0.003347	-0.009839	-0.024139	-0.021018	-0.073310
X310	-0.034340	0.050600	-0.015957	0.045161	0.001481	-0.008316	-0.003000	0.008118	-0.005944	0.003075	-0.012698	0.012137
X311	0.193054	0.019371	-0.027173	-0.183512	0.009093	-0.003702	-0.051619	-0.057639	0.014742	-0.062754	0.147193	0.016201
X312	0.001937	-0.076849	-0.035584	-0.034645	0.001896	-0.047718	-0.018140	-0.028975	-0.007610	-0.018671	-0.016257	-0.056704
X313	0.429398	-0.029443	-0.244862	0.164566	-0.002038	-0.032840	-0.026615	-0.009387	0.036810	0.011552	-0.040891	-0.205630
X314	-0.339141	0.022699	0.147049	-0.101764	-0.013728	0.000164	0.040310	0.003698	-0.038410	0.112101	0.021894	0.319019
X315	-0.231550	0.040382	0.021906	-0.082778	0.004979	-0.007267	-0.033484	0.007482	-0.019978	-0.022038	-0.006173	0.066655
X316	0.100732	-0.115136	-0.016777	-0.124962	0.014267	0.037613	-0.012205	0.000757	0.026404	-0.122276	0.049448	-0.149336
X317	-0.005843	-0.066580	0.002558	-0.035266	0.002533	-0.045385	-0.009223	-0.019264	-0.010164	-0.024937	-0.021713	-0.075732
X318	-0.017681	-0.005574	0.032739	-0.009002	0.000773	0.028034	0.004817	-0.008645	-0.003101	0.026174	-0.006625	-0.005117
X319	-0.025810	-0.014349	-0.002614	-0.011526	0.000631	0.008351	0.020130	0.027541	-0.002532	-0.006212	-0.005409	-0.018865
X320	0.040334	0.117073	-0.010157	0.068847	0.002452	-0.007260	-0.001181	-0.014183	-0.009839	-0.024139	-0.021018	0.097923
X321	-0.141728	0.321879	-0.051798	0.434591	-0.021502	-0.022692	-0.017264	-0.027350	-0.065035	0.020191	-0.119857	-0.017199
X322	-0.063873	0.024107	-0.009124	-0.017383	0.004326	0.007622	-0.042492	0.026267	-0.017359	0.031403	-0.030130	0.002010
X323	-0.042542	0.003654	0.000011	-0.078207	0.002799	-0.009098	-0.025919	-0.005230	-0.011230	0.028908	-0.023990	-0.013516
X324	0.049016	-0.030810	-0.154328	-0.183065	-0.018377	-0.029963	-0.078223	0.039177	-0.051164	-0.205520	0.026140	-0.160336
X325	-0.051742	0.119213	0.015531	-0.040034	0.002191	-0.039075	0.056932	-0.000749	-0.008794	-0.021575	-0.018786	0.004622
X326	0.036243	-0.013459	0.012737	0.042417	0.005288	-0.030337	-0.032153	-0.072772	0.002234	0.009124	-0.039580	-0.014190
X327	0.004613	-0.121544	-0.117760	-0.319196	0.001487	-0.018663	-0.041885	0.034012	-0.044549	0.049764	0.242285	-0.056269
X328	-0.144536	0.193212	0.220778	0.188223	0.005919	0.007115	0.012267	0.007858	-0.023750	-0.044493	-0.050737	-0.079133
X329	0.071595	0.076906	0.022667	-0.116484	0.005949	-0.007800	-0.084452	0.020231	0.128089	-0.031899	0.266164	0.142041
X331	-0.036578	-0.047799	-0.049874	-0.208983	-0.006923	0.032385	0.210492	0.025202	-0.028302	-0.069438	-0.060460	0.214893
X332	0.018611	0.027823	-0.003202	0.026819	0.000773	0.034509	-0.019602	0.002740	-0.003101	-0.007609	-0.006625	0.030866
X333	-0.002468	-0.128397	-0.094721	0.180359	0.004537	0.004448	-0.014659	0.013294	-0.018208	0.155634	-0.038897	-0.041544
X334	-0.061232	-0.159830	0.276947	-0.558937	0.007501	-0.030001	0.062598	-0.032585	-0.103574	-0.043716	0.267385	-0.137297
X335	0.022810	0.013226	-0.007169	-0.065992	0.001731	-0.038229	-0.016554	0.062793	-0.006945	-0.017039	-0.014836	0.069118
X336	-0.100537	0.420864	-0.073259	0.065564	-0.017881	0.027354	-0.062243	0.017454	-0.044359	-0.014176	-0.094764	0.225448
X337	0.047351	0.138232	-0.282255	0.574053	-0.008695	0.027452	-0.057885	0.011149	0.108199	0.055537	-0.256402	0.103045
X338	0.024660	0.017410	-0.011039	-0.017618	0.002410	0.011535	-0.008284	0.024192	0.015396	-0.001932	-0.020663	-0.002413
X339	-0.032276	0.003409	-0.013164	0.018434	0.000446	-0.000636	-0.025409	-0.018864	-0.001790	0.054108	-0.003824	-0.013338
X340	0.057060	-0.129059	-0.043493	-0.127035	0.004374	0.003707	0.024869	0.039194	-0.017551	-0.030857	-0.037493	0.008955
X341	-0.031662	0.069743	-0.011792	-0.008040	0.002611	-0.005008	-0.008599	-0.001805	-0.010479	0.004506	-0.022386	0.072112
X342	0.055305	0.013067	-0.135847	-0.029992	-0.060906	-0.039171	-0.025297	-0.010388	0.052615	-0.043061	-0.037493	-0.111276
X343	0.050892	-0.067608	0.003962	-0.112025	0.008440	-0.057990	-0.013460	-0.038023	-0.033870	-0.076391	-0.057226	0.031647
X344	-0.122156	0.107954	0.060595	-0.062449	0.002688	-0.002579	-0.014210	-0.046565	-0.010785	-0.006881	-0.023041	-0.054294
X345	0.004856	0.007790	-0.137912	0.178881	0.004374	0.027874	0.008882	0.049704	-0.017551	0.085073	-0.037493	-0.101528
X346	-0.049686	-0.039632	-0.034358	-0.202812	-0.008650	0.039522	0.212715	-0.002105	-0.025936	-0.063635	-0.055408	0.222029
X348	0.170687	-0.060908	-0.320180	0.116191	0.021941	0.025579	-0.008300	0.026540	0.027401	0.067229	0.053988	0.204170
X349	-0.023534	-0.035300	-0.046940	-0.197058	0.006275	0.056139	0.201164	0.020943	-0.025179	-0.061776	-0.053789	0.204227
X350	-0.106772	0.152362	-0.230941	0.143553	-0.006459	-0.055928	-0.100208	0.016212	-0.083122	-0.194416	-0.076614	0.108029
X351	-0.144929	0.157290	0.065231	0.077231	0.018819	-0.032679	-0.019419	-0.005965	-0.070980	-0.151745	0.150106	0.340823
X352	-0.037934	-0.046500	-0.048432	-0.207965	-0.007280	0.033643	0.207265	0.023063	-0.027790	-0.068182	-0.059367	0.210827
X353	-0.042253	-0.010867	-0.005549	-0.024472	0.001340	-0.026847	0.034801	-0.006214	-0.005375	-0.013189	-0.011483	0.053500
X354	-0.182165	0.177373	0.099700	-0.071795	-0.001390	0.005689	-0.096507	-0.058520	-0.053430	0.255318	0.130177	0.020747
X355	0.132281	-0.332577	-0.065141	-0.189158	-0.010442	0.022560	0.026425	0.050301	0.139665	-0.037512	-0.192270	0.056933
X356	0.159288	-0.407207	0.017311	-0.392994	0.013551	-0.002591	-0.003423	-0.048943	-0.048979	-0.046559	-0.116168	-0.208902
X357	0.015664	0.048057	-0.004134	0.041239	0.000998	-0.023996	0.007008	-0.033381	-0.004005	-0.009826	-0.008555	0.039858

X358	-0.331767	0.492712	-0.020174	0.196666	-0.014025	-0.018653	-0.129731	-0.027884	-0.100230	0.085827	0.283290	0.161773
X359	-0.024918	0.124822	-0.015778	0.037152	0.005248	-0.022078	-0.004724	-0.046906	-0.021057	-0.051664	0.007134	0.168556
X360	-0.212191	0.240327	0.185954	-0.117218	-0.015865	0.037645	-0.078442	0.010690	-0.033422	0.236848	0.341697	0.005676
X361	-0.021215	0.244337	0.095281	-0.209929	-0.005427	-0.028669	-0.030375	-0.023963	0.021777	-0.210335	0.046522	0.085403
X362	0.417100	-0.553714	-0.121228	-0.208063	0.010831	0.035216	0.104187	0.046646	0.111496	-0.083772	-0.258361	-0.108226
X363	-0.235644	0.209735	-0.086462	0.031959	-0.009071	0.028312	-0.096939	0.004571	0.056725	0.093726	0.056781	0.227999
X364	-0.040265	0.026452	0.018530	0.048572	0.001547	-0.002205	0.027977	0.021317	-0.006209	-0.015234	0.005803	0.061799
X365	-0.040265	0.026452	0.018530	0.048572	0.001547	-0.002205	0.027977	0.021317	-0.006209	-0.015234	0.005803	0.061799
X366	0.010643	-0.003694	-0.005400	0.017451	0.000998	-0.000586	0.040116	0.012687	-0.004005	-0.009826	0.020960	0.039858
X367	-0.054229	-0.045593	-0.044346	-0.203050	-0.007746	0.040783	0.205846	0.014585	-0.027139	-0.066587	-0.057978	0.226781
X368	-0.081594	-0.052381	0.084253	-0.155343	-0.019036	-0.000097	0.003987	0.059822	-0.030039	-0.062547	-0.047400	-0.087187
X369	0.001967	-0.020739	0.019393	0.001006	0.000631	-0.003542	0.012654	0.013598	-0.002532	-0.006212	-0.005409	-0.018865
X370	0.050787	0.097932	0.170400	-0.009662	0.002368	0.007608	0.029456	-0.065670	-0.009503	-0.023315	-0.020301	-0.070807
X371	-0.085449	0.079697	0.175921	0.143799	0.003480	-0.003016	0.015503	0.022877	-0.013964	-0.034261	-0.029832	-0.091899
X372	-0.015493	0.029105	0.033397	0.026072	0.000631	0.005708	0.020130	-0.009640	-0.002532	-0.006212	-0.005409	-0.018865
X373	0.021198	-0.123914	-0.102637	0.161539	0.004054	-0.007035	-0.040552	0.004788	-0.016266	0.176659	-0.034749	-0.054797
X374	-0.161102	0.202307	-0.036632	0.518349	0.000355	0.002639	-0.007503	-0.004513	-0.062993	0.097125	-0.134572	-0.008845
X375	0.113272	0.056874	-0.174308	0.051801	-0.021598	0.012756	-0.036780	0.044093	0.165277	-0.107864	-0.169721	0.118950
X376	0.070546	-0.102424	0.033697	-0.105009	0.007132	-0.062472	-0.021234	-0.054105	-0.028618	-0.070214	-0.061136	0.026496
X377	0.045173	-0.248791	0.122503	-0.588272	0.012692	0.005345	0.069685	-0.033075	-0.074244	0.030134	0.357229	-0.097464
X378	-0.102136	0.145282	0.131974	0.173723	0.004204	0.029634	-0.030480	-0.010485	-0.016870	-0.016043	-0.036040	-0.037958
X379	0.083352	0.070753	0.033645	-0.026446	0.002835	0.034548	-0.030471	0.069440	-0.011374	-0.027907	-0.024299	0.103309
X380	-0.038618	-0.022360	0.006473	0.004166	0.002611	0.010434	-0.014059	0.009511	-0.010479	-0.005566	0.023045	0.007743
X382	-0.060401	0.120044	0.024392	-0.046271	0.002533	-0.031128	0.054548	-0.000996	-0.010164	-0.024937	-0.021713	0.012713
X383	-0.011174	-0.029253	-0.019873	-0.028280	0.001181	-0.007337	-0.021293	0.038712	-0.004740	-0.011628	-0.010125	0.023604
X384	0.009110	0.017603	-0.002614	0.007273	0.000631	0.007030	0.023867	0.008950	-0.002532	-0.006212	0.041242	0.025199
X385	0.011660	0.008356	-0.004529	0.045180	0.001093	0.032027	-0.021254	0.045040	-0.004387	-0.010765	-0.009373	0.043667

In [ ]:

```
#Choosing the upper part of the correlation matrix as it will be same as the lower half
Corr_upper = correlation_X.where(np.triu(np.ones_like(correlation_X),k=1).astype(np.bool))
Corr_upper
with pd.option_context('display.max_rows',None):
  display(Corr_upper)
```

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14	
X0	NaN	-0.271123	-0.139904	-0.070645	0.017988	0.012293	0.037549	0.047735	0.081122	-0.134577	-0.130529	-0.138310	0.01
X1	NaN	NaN	0.088266	0.205657	-0.020724	0.046417	-0.079119	-0.000306	-0.137193	0.112263	0.286683	0.079784	-0.02
X2	NaN	NaN	NaN	-0.093546	0.002289	-0.017722	0.065778	-0.069932	0.042398	0.131464	0.222132	-0.079183	-0.00
X3	NaN	NaN	NaN	NaN	0.015298	-0.008161	-0.048468	-0.001249	0.019663	0.056166	-0.216464	0.045183	-0.02
X4	NaN	NaN	NaN	NaN	NaN	0.039778	0.027854	-0.008909	0.003360	0.008245	0.007179	0.005544	0.00
X5	NaN	NaN	NaN	NaN	NaN	NaN	-0.019917	0.012746	-0.006800	0.060161	-0.003452	-0.003439	-0.00
X6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.018565	0.092986	-0.099264	-0.041825	0.028516	-0.00
X8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.014075	-0.061136	-0.038309	0.026162	-0.00
X10	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-0.033084	-0.028806	-0.100474	-0.00
X12	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.214825	-0.246513	-0.00
X13	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-0.083141	-0.00
X14	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-0.01
X15	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X16	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X17	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X18	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X19	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X20	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X21	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X22	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

X23	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X24	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X26	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X27	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X28	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X29	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X30	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X32	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X33	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X34	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X35	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X36	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X37	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X38	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X39	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X40	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X41	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X42	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X43	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X44	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X45	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X46	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X47	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X48	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X49	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X50	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X51	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X52	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X53	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X54	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X55	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X56	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X57	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X58	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X59	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X60	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X61	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X62	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X63	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X64	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X65	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X66	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X67	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X68	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X69	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X70	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X71	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X73	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X74	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X75	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X76	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X77	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X78	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X79	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

X80	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X81	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X82	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X83	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X84	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X85	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X86	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X87	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X88	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X89	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X90	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X91	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X92	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X94	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X95	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X96	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X97	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X98	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X99	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X100	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X101	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X102	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X103	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X104	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X105	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X106	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X108	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X109	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X110	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X111	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X112	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X113	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X114	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X115	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X116	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X117	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X118	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X119	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X120	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X122	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X123	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X124	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X125	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X126	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X127	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X128	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X129	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X130	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X131	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X132	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X133	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X134	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X135	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X136	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X137	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

X138	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X139	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X140	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X141	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X142	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X143	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X144	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X145	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X146	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X147	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X148	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X150	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X151	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X152	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X153	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X154	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X155	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X156	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X157	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X158	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X159	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X160	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X161	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X162	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X163	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X164	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X165	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X166	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X167	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X168	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X169	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X170	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X171	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X172	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X173	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X174	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X175	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X176	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X177	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X178	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X179	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X180	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X181	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X182	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X183	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X184	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X185	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X186	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X187	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X189	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X190	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X191	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X192	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X194	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X195	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

X196	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X197	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X198	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X199	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X200	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X201	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X202	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X203	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X204	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X205	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X206	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X207	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X208	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X209	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X210	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X211	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X212	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X213	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X214	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X215	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X216	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X217	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X218	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X219	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X220	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X221	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X222	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X223	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X224	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X225	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X226	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X227	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X228	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X229	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X230	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X231	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X232	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X234	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X236	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X237	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X238	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X239	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X240	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X241	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X242	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X243	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X244	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X245	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X246	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X247	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X248	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X249	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X250	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X251	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

X252	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X253	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X254	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X255	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X256	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X257	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X258	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X259	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X260	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X261	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X262	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X263	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X264	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X265	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X266	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X267	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X269	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X270	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X271	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X272	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X273	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X274	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X275	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X276	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X277	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X278	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X279	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X280	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X281	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X282	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X283	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X284	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X285	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X286	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X287	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X288	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X291	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X292	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X294	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X295	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X296	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X298	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X299	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X300	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X301	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X302	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X304	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X305	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X306	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X307	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X308	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X309	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X310	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X311	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X312	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

X313	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X314	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X315	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X316	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X317	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X318	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X319	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X320	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X321	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X322	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X323	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X324	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X325	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X326	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X327	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X328	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X329	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X331	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X332	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X333	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X334	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X335	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X336	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X337	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X338	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X339	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X340	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X341	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X342	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X343	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X344	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X345	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X346	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X348	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X349	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X350	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X351	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X352	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X353	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X354	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X355	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X356	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X357	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X358	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X359	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X360	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X361	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X362	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X363	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X364	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X365	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X366	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X367	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X368	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X369	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

X370	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X371	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X372	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X373	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X374	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X375	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X376	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X377	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X378	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X379	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X380	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X382	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X383	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X384	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X385	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [ ]:

```
#Finding the columns with correlation > .95
droppables = [col for col in Corr_upper.columns if any(abs(Corr_upper[col])>.95)]
droppables
```

Out[ ]:

```
['X35',
 'X37',
 'X39',
 'X54',
 'X61',
 'X76',
 'X84',
 'X90',
 'X94',
 'X102',
 'X111',
 'X113',
 'X119',
 'X120',
 'X122',
 'X129',
 'X130',
 'X134',
 'X136',
 'X137',
 'X140',
 'X146',
 'X147',
 'X157',
 'X158',
 'X162',
 'X172',
 'X194',
 'X198',
 'X199',
 'X205',
 'X213',
 'X214',
 'X215',
 'X216',
 'X217',
 'X222',
 'X226',
 'X227',
 'X229',
 'X232',
 'X239',
 'X242',
 'X243',
 'X244',
 'X245',
 'X247',
 'X248',
 'X249',
 'X250',
 'X253',
 'X254',
```

```
 'X262',
 'X263',
 'X264',
 'X266',
 'X279',
 'X296',
 'X299',
 'X302',
 'X311',
 'X314',
 'X320',
 'X324',
 'X326',
 'X328',
 'X337',
 'X348',
 'X352',
 'X358',
 'X360',
 'X362',
 'X363',
 'X364',
 'X365',
 'X367',
 'X368',
 'X370',
 'X371',
 'X378',
 'X382',
 'X385']
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X385'] > 0.9, correlation_X['X385'] > 0.9]
```

Out[ ]:

	X60	X248	X253	X385
X60	1.0	1.0	1.0	1.0
X248	1.0	1.0	1.0	1.0
X253	1.0	1.0	1.0	1.0
X385	1.0	1.0	1.0	1.0

In [ ]:

```
#Dropping all 4 columns since they are highly correlated.
X_train_1=X_train_new.drop((['X60','X248','X253','X385']),axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X382'] > 0.9, correlation_X['X382'] > 0.9]
```

Out[ ]:

	X17	X382
X17	1.0	1.0
X382	1.0	1.0

In [ ]:

```
#Dropping X382
X_train_2 = X_train_1.drop('X382',axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X378'] > 0.9, correlation_X['X378'] > 0.9]
```

Out[ ]:

	X185	X378
X185	1.000000	0.951991
X378	0.951991	1.000000

In [ ]:

```
#Dropping X378
X_train_3 = X_train_2.drop('X378',axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X371'] > 0.9, correlation_X['X371'] > 0.9]
```

Out[ ]:

	X108	X371
X108	1.000000	0.983502
X371	0.983502	1.000000

In [ ]:

```
#Dropping X371
X_train_4 = X_train_2.drop('X371',axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X370'] > 0.9, correlation_X['X370'] > 0.9]
```

Out[ ]:

	X53	X102	X214	X239	X370
X53	1.00000	1.00000	1.00000	1.00000	0.98249
X102	1.00000	1.00000	1.00000	1.00000	0.98249
X214	1.00000	1.00000	1.00000	1.00000	0.98249
X239	1.00000	1.00000	1.00000	1.00000	0.98249
X370	0.98249	0.98249	0.98249	0.98249	1.00000

In [ ]:

```
#Dropping 4 columns since they are highly correlated.
X_train_5=X_train_4.drop((['X53','X102','X214','X239']),axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X368'] > 0.9, correlation_X['X368'] > 0.9]
```

Out[ ]:

	X208	X368
X208	1.000000	0.993951
X368	0.993951	1.000000

In [ ]:

```
#Dropping X368
X_train_6 = X_train_5.drop('X368',axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X367'] > 0.9, correlation_X['X367'] > 0.9]
```

Out[ ]:

	X331	X346	X352	X367
X331	1.000000	0.916432	0.981917	0.958938
X346	0.916432	1.000000	0.923442	0.940555
X352	0.981917	0.923442	1.000000	0.948180
X367	0.958938	0.940555	0.948180	1.000000

In [ ]:

```
#Dropping 3 columns since they are highly correlated.
X_train_7=X_train_6.drop((['X331','X346','X352']),axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X365'] > 0.9, correlation_X['X365'] > 0.9]
```

Out[ ]:

	X240	X364	X365
X240	1.0	1.0	1.0
X364	1.0	1.0	1.0
X365	1.0	1.0	1.0

In [ ]:

```
#Dropping 2 columns since they are highly correlated.
X_train_8=X_train_7.drop((['X240','X364']),axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X363'] > 0.9, correlation_X['X363'] > 0.9]
```

Out[ ]:

	X96	X363
X96	1.000000	0.988475
X363	0.988475	1.000000

In [ ]:

```
#Dropping X363
X_train_9 = X_train_8.drop('X363',axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X362'] > 0.9, correlation_X['X362'] > 0.9]
```

Out[ ]:

	X186	X362
X186	1.000000	0.969026
X362	0.969026	1.000000

In [ ]:

```
#Dropping X362
X_train_9 = X_train_9.drop('X362',axis=1)
```

In [ ]:

```
#These show one out of each pair of correlated variables. To find the other pair, we can subset the correlation_X
.
  correlation_X.loc[correlation_X['X360'] > 0.9, correlation_X['X360'] > 0.9]
```

Out[ ]:

	X155	X219	X360
X155	1.000000	0.906078	1.000000
X219	0.906078	1.000000	0.906078
X360	1.000000	0.906078	1.000000

In [ ]:

```
#Dropping 2 columns since they are highly correlated.
X_train_10=X_train_9.drop((['X360','X155']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X358'] > 0.9, correlation_X['X358'] > 0.9]
```

Out[ ]:

	X246	X358
X246	1.00000	0.96451
X358	0.96451	1.00000

In [ ]:

```
#Dropping X358
X_train_10=X_train_10.drop((['X358']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X348'] > 0.9, correlation_X['X348'] > 0.9]
```

Out[ ]:

	X80	X348
X80	1.000000	0.992885
X348	0.992885	1.000000

In [ ]:

```
#Dropping X348
X_train_10=X_train_10.drop((['X348']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X337'] > 0.9, correlation_X['X337'] > 0.9]
```

Out[ ]:

	X337
X337	1.0

In [ ]:

```
#X337 is good to keep , so we will move onto the next one
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X328'] > 0.9, correlation_X['X328'] > 0.9]
```

Out[ ]:

	X29	X54	X76	X162	X232	X272	X276	X279	X328
X29	1.000000	0.994274	0.994274	0.961903	1.000000	0.931650	0.943836	1.000000	0.964846
X54	0.994274	1.000000	1.000000	0.968158	0.994274	0.926315	0.938431	0.994274	0.959321
X76	0.994274	1.000000	1.000000	0.968158	0.994274	0.926315	0.938431	0.994274	0.959321
X162	0.961903	0.968158	0.968158	1.000000	0.961903	0.944154	0.919389	0.961903	0.954195
X232	1.000000	0.994274	0.994274	0.961903	1.000000	0.931650	0.943836	1.000000	0.964846
X272	0.931650	0.926315	0.926315	0.944154	0.931650	1.000000	0.915617	0.931650	0.946493
X276	0.943836	0.938431	0.938431	0.919389	0.943836	0.915617	1.000000	0.943836	0.940478
X279	1.000000	0.994274	0.994274	0.961903	1.000000	0.931650	0.943836	1.000000	0.964846
X328	0.964846	0.959321	0.959321	0.954195	0.964846	0.946493	0.940478	0.964846	1.000000

In [ ]:

```
#Dropping  columns which are highly correlated.
X_train_11=X_train_10.drop((['X328','X279','X276','X272','X162','X76','X54']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X326'] > 0.9, correlation_X['X326'] > 0.9]
```

Out[ ]:

	X152	X226	X326
X152	1.0	1.0	1.0
X226	1.0	1.0	1.0
X326	1.0	1.0	1.0

In [ ]:

```
#Dropping X326, X226
X_train_11=X_train_11.drop((['X326','X226']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X324'] > 0.9, correlation_X['X324'] > 0.9]
```

Out[ ]:

	X58	X137	X324
X58	1.000000	0.985972	1.000000
X137	0.985972	1.000000	0.985972
X324	1.000000	0.985972	1.000000

In [ ]:

```
#Dropping X324, X137
X_train_11=X_train_11.drop((['X324','X137']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X320'] > 0.9, correlation_X['X320'] > 0.9]
```

Out[ ]:

	X88	X90	X94	X99	X122	X217	X242	X243	X249	X320
X88	1.000000	0.983621	0.983621	0.912215	1.000000	0.983621	0.983621	1.000000	0.968014	1.000000
X90	0.983621	1.000000	1.000000	0.897231	0.983621	0.967503	1.000000	0.983621	0.984133	0.983621
X94	0.983621	1.000000	1.000000	0.897231	0.983621	0.967503	1.000000	0.983621	0.984133	0.983621
X99	0.912215	0.897231	0.897231	1.000000	0.912215	0.897231	0.897231	0.912215	0.882952	0.912215
X122	1.000000	0.983621	0.983621	0.912215	1.000000	0.983621	0.983621	1.000000	0.968014	1.000000
X217	0.983621	0.967503	0.967503	0.897231	0.983621	1.000000	0.967503	0.983621	0.984133	0.983621
X242	0.983621	1.000000	1.000000	0.897231	0.983621	0.967503	1.000000	0.983621	0.984133	0.983621
X243	1.000000	0.983621	0.983621	0.912215	1.000000	0.983621	0.983621	1.000000	0.968014	1.000000
X249	0.968014	0.984133	0.984133	0.882952	0.968014	0.984133	0.984133	0.968014	1.000000	0.968014
X320	1.000000	0.983621	0.983621	0.912215	1.000000	0.983621	0.983621	1.000000	0.968014	1.000000

In [ ]:

```
#Dropping 9 columns since they are highly correlated.
X_train_12=X_train_11.drop((['X320','X249','X243','X242','X217','X122','X99','X94','X90']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X314'] > 0.9, correlation_X['X314'] > 0.9]
```

Out[ ]:

	X261	X314
X261	1.000000	0.975521
X314	0.975521	1.000000

In [ ]:

```
#Dropping X314
X_train_13=X_train_12.drop((['X314']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X311'] > 0.9, correlation_X['X311'] > 0.9]
```

Out[ ]:

	X118	X119	X311
X118	1.000000	1.000000	0.951265
X119	1.000000	1.000000	0.951265
X311	0.951265	0.951265	1.000000

In [ ]:

```
#Dropping X311,x119
X_train_13=X_train_13.drop((['X311','X119']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X302'] > 0.9, correlation_X['X302'] > 0.9]
```

Out[ ]:

	X44	X302
X44	1.0	1.0
X302	1.0	1.0

In [ ]:

```
#Dropping X302
X_train_13=X_train_13.drop((['X302']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X299'] > 0.9, correlation_X['X299'] > 0.9]
```

Out[ ]:

	X298	X299
X298	1.0	1.0
X299	1.0	1.0

In [ ]:

```
#Dropping X299
X_train_13=X_train_13.drop((['X299']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X296'] > 0.9, correlation_X['X296'] > 0.9]
```

Out[ ]:

	X295	X296
X295	1.0	1.0
X296	1.0	1.0

In [ ]:

```
#Dropping X296
X_train_13=X_train_13.drop((['X296']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X266'] > 0.9, correlation_X['X266'] > 0.9]
```

Out[ ]:

	X184	X262	X266
X184	1.0	1.0	1.0
X262	1.0	1.0	1.0
X266	1.0	1.0	1.0

In [ ]:

```
#Dropping X266,X262
X_train_13=X_train_13.drop((['X266','X262']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X264'] > 0.9, correlation_X['X264'] > 0.9]
```

Out[ ]:

	X126	X264
X126	1.000000	0.993712
X264	0.993712	1.000000

In [ ]:

```
#Dropping X264
X_train_13=X_train_13.drop((['X264']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X263'] > 0.9, correlation_X['X263'] > 0.9]
```

Out[ ]:

	X136	X263
X136	1.000000	0.994274
X263	0.994274	1.000000

In [ ]:

```
#Dropping X263
X_train_13=X_train_13.drop((['X263']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X254'] > 0.9, correlation_X['X254'] > 0.9]
```

Out[ ]:

	X230	X254
X230	1.0	1.0
X254	1.0	1.0

In [ ]:

```
#Dropping X254
X_train_13=X_train_13.drop((['X254']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X250'] > 0.9, correlation_X['X250'] > 0.9]
```

Out[ ]:

	X178	X250
X178	1.000000	0.984168
X250	0.984168	1.000000

In [ ]:

```
#Dropping X250
X_train_13=X_train_13.drop((['X250']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X247'] > 0.9, correlation_X['X247'] > 0.9]
```

Out[ ]:

	X202	X247
X202	1.0	1.0
X247	1.0	1.0

In [ ]:

```
#Dropping X247
X_train_13=X_train_13.drop((['X247']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X245'] > 0.9, correlation_X['X245'] > 0.9]
```

Out[ ]:

	X89	X245
X89	1.0	1.0
X245	1.0	1.0

In [ ]:

```
#Dropping X245
X_train_13=X_train_13.drop((['X245']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X244'] > 0.9, correlation_X['X244'] > 0.9]
```

Out[ ]:

	X71	X84	X244
X71	1.0	1.0	1.0
X84	1.0	1.0	1.0
X244	1.0	1.0	1.0

In [ ]:

```
#Dropping X244 and X84
X_train_14=X_train_13.drop((['X244','X84']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X232'] > 0.9, correlation_X['X232'] > 0.9]
```

Out[ ]:

	X29	X54	X76	X162	X232	X272	X276	X279	X328
X29	1.000000	0.994274	0.994274	0.961903	1.000000	0.931650	0.943836	1.000000	0.964846
X54	0.994274	1.000000	1.000000	0.968158	0.994274	0.926315	0.938431	0.994274	0.959321
X76	0.994274	1.000000	1.000000	0.968158	0.994274	0.926315	0.938431	0.994274	0.959321
X162	0.961903	0.968158	0.968158	1.000000	0.961903	0.944154	0.919389	0.961903	0.954195
X232	1.000000	0.994274	0.994274	0.961903	1.000000	0.931650	0.943836	1.000000	0.964846
X272	0.931650	0.926315	0.926315	0.944154	0.931650	1.000000	0.915617	0.931650	0.946493
X276	0.943836	0.938431	0.938431	0.919389	0.943836	0.915617	1.000000	0.943836	0.940478
X279	1.000000	0.994274	0.994274	0.961903	1.000000	0.931650	0.943836	1.000000	0.964846
X328	0.964846	0.959321	0.959321	0.954195	0.964846	0.946493	0.940478	0.964846	1.000000

In [ ]:

```
#Checking correlation between variables
correlation_X = X_train_14.corr()
with pd.option_context('display.max_rows',None):
  display(correlation_X)
```

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14
X0	1.000000	-0.271123	-0.139904	-0.070645	0.017988	0.012293	0.037549	0.047735	0.081122	-0.134577	-0.130529	-0.138310
X1	-0.271123	1.000000	0.088266	0.205657	-0.020724	0.046417	-0.079119	-0.000306	-0.137193	0.112263	0.286683	0.079784
X2	-0.139904	0.088266	1.000000	-0.093546	0.002289	-0.017722	0.065778	-0.069932	0.042398	0.131464	0.222132	-0.079183
X3	-0.070645	0.205657	-0.093546	1.000000	0.015298	-0.008161	-0.048468	-0.001249	0.019663	0.056166	-0.216464	0.045183
X4	0.017988	-0.020724	0.002289	0.015298	1.000000	0.039778	0.027854	-0.008909	0.003360	0.008245	0.007179	0.005544
X5	0.012293	0.046417	-0.017722	-0.008161	0.039778	1.000000	-0.019917	0.012746	-0.006800	0.060161	-0.003452	-0.003439
X6	0.037549	-0.079119	0.065778	-0.048468	0.027854	-0.019917	1.000000	0.018565	0.092986	-0.099264	-0.041825	0.028516
X8	0.047735	-0.000306	-0.069932	-0.001249	-0.008909	0.012746	0.018565	1.000000	0.014075	-0.061136	-0.038309	0.026162

X10	0.081122	-0.137193	0.042398	0.019663	0.003360	-0.006800	0.092986	0.014075	1.000000	-0.033084	-0.028806	-0.100474
X12	-0.134577	0.112263	0.131464	0.056166	0.008245	0.060161	-0.099264	-0.061136	-0.033084	1.000000	0.214825	-0.246513
X13	-0.130529	0.286683	0.222132	-0.216464	0.007179	-0.003452	-0.041825	-0.038309	-0.028806	0.214825	1.000000	-0.083141
X14	-0.138310	0.079784	-0.079183	0.045183	0.005544	-0.003439	0.028516	0.026162	-0.100474	-0.246513	-0.083141	1.000000
X15	0.011491	-0.023295	-0.001613	-0.024059	0.000631	-0.003542	-0.002297	-0.006542	-0.002532	-0.006212	-0.005409	-0.018865
X16	0.003940	-0.005591	-0.020227	-0.008337	-0.061497	-0.032571	0.035292	0.030602	-0.005944	-0.014584	-0.012698	-0.044291
X17	-0.060401	0.120044	0.024392	-0.046271	0.002533	-0.031128	0.054548	-0.000996	-0.010164	-0.024937	-0.021713	0.012713
X18	-0.036495	0.068924	-0.060337	-0.028413	0.002572	-0.004646	-0.019988	0.044339	-0.010323	-0.025327	-0.010525	-0.076916
X19	0.203244	-0.207605	-0.312393	-0.068126	0.009622	0.009854	0.048629	0.031221	-0.038610	-0.094730	-0.082482	-0.287691
X20	0.030838	0.030153	-0.494692	0.073098	-0.015761	0.008522	-0.122983	0.011349	-0.047393	-0.116280	-0.043126	-0.353137
X21	-0.025532	0.069149	-0.018519	-0.032411	0.001481	-0.029751	0.003382	0.053085	-0.005944	-0.014584	0.007215	-0.044291
X22	0.147904	-0.129648	0.444380	-0.188833	0.008931	-0.050032	0.035421	-0.051851	-0.035836	-0.087924	0.226530	-0.267021
X23	0.115098	-0.011723	0.115886	0.055659	0.004204	-0.033924	0.026774	0.062841	-0.016870	-0.041391	-0.036040	-0.125703
X24	0.001554	-0.022323	-0.008234	-0.048153	0.001263	0.008780	-0.000858	0.002410	-0.005067	-0.012433	-0.010825	-0.004686
X26	-0.006131	-0.004501	0.030495	-0.041311	0.002049	-0.024992	0.026645	0.020203	-0.008223	-0.020175	-0.017566	-0.061270
X27	0.050622	-0.048785	0.137151	-0.049081	0.021713	0.037836	-0.062026	0.031821	0.070276	0.184599	0.110191	0.126863
X28	-0.100412	0.127520	0.280952	0.162385	0.005308	0.026029	-0.003490	0.004614	-0.021300	-0.052259	-0.039773	-0.158707
X29	-0.149090	0.202989	0.209387	0.188854	0.006134	0.006306	0.013201	0.004552	-0.024615	-0.042617	-0.052586	-0.076904
X30	0.062321	0.035667	-0.076038	0.078486	0.001949	0.010111	0.006879	-0.032543	-0.007820	-0.019185	-0.016705	-0.058265
X31	0.120973	-0.092994	0.110163	-0.080666	0.000695	-0.040828	0.019952	0.059488	-0.044248	-0.126861	-0.095558	-0.313459
X32	0.094024	-0.004861	-0.168747	-0.082171	0.003075	0.025765	0.058184	-0.035257	-0.012340	-0.030276	-0.026362	-0.091947
X33	0.012613	0.021482	-0.001848	-0.008149	0.000446	0.018050	0.022160	0.027139	-0.001790	-0.004392	-0.003824	0.017817
X34	0.037187	-0.051615	0.079531	-0.020661	0.002145	-0.010089	0.056831	-0.019721	-0.008608	-0.021119	-0.018388	-0.064136
X35	0.120973	-0.092994	0.110163	-0.080666	0.000695	-0.040828	0.019952	0.059488	-0.044248	-0.126861	-0.095558	-0.313459
X36	0.044776	-0.024995	0.158753	0.001071	0.001949	-0.027694	0.042119	-0.006353	-0.007820	-0.019185	-0.016705	-0.058265
X37	0.120973	-0.092994	0.110163	-0.080666	0.000695	-0.040828	0.019952	0.059488	-0.044248	-0.126861	-0.095558	-0.313459
X38	-0.010562	0.078145	0.003780	0.023032	0.005368	0.120028	-0.019545	0.002714	-0.021539	0.017543	-0.029005	0.061752
X39	0.012613	0.021482	-0.001848	-0.008149	0.000446	0.018050	0.022160	0.027139	-0.001790	-0.004392	-0.003824	0.017817
X40	-0.010552	-0.021229	-0.003202	0.021701	0.000773	0.012927	0.020078	0.020451	-0.003101	-0.007609	-0.006625	0.030866
X41	-0.008554	0.018769	-0.012875	0.055119	0.003108	0.011844	0.032413	0.015790	-0.012472	-0.030600	-0.026644	0.124132
X42	-0.026665	-0.018278	0.005224	0.027295	0.000446	-0.000636	-0.004267	-0.005720	0.132754	-0.004392	-0.003824	-0.013338
X43	-0.028147	0.082471	0.266184	0.119448	-0.004347	0.019644	0.070355	0.030802	0.400164	-0.079493	-0.065287	-0.091170
X44	-0.009858	-0.090357	0.052208	-0.038773	0.003108	-0.054607	-0.013618	-0.035086	-0.012472	-0.030600	-0.026644	-0.092931
X45	0.125718	-0.342465	-0.005299	-0.394862	0.009459	0.011412	0.073876	-0.029552	-0.062859	0.033104	-0.128106	-0.088756
X46	0.074638	0.018940	-0.081631	-0.033725	-0.023761	0.004737	-0.043615	0.029131	-0.124508	-0.054680	-0.030554	-0.471226
X47	-0.043813	0.004175	-0.000881	-0.034783	0.003299	-0.013146	-0.020698	0.007797	0.005188	-0.032480	0.007856	0.114690
X48	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X49	0.072314	-0.149410	-0.085257	-0.147537	-0.008847	-0.002188	0.017425	0.036893	-0.036977	-0.086986	-0.055262	-0.171664
X50	0.009891	-0.022295	-0.123523	-0.133728	-0.024093	0.042159	-0.022520	0.043807	-0.055547	-0.106926	0.004383	0.030734
X51	-0.092869	0.063273	-0.049236	-0.078943	-0.010791	0.022005	-0.094822	-0.021560	0.067466	-0.018278	-0.043370	0.415034
X52	-0.157480	0.021976	0.210407	-0.077838	-0.025873	0.006646	-0.010808	0.032074	0.037420	-0.046429	-0.042025	-0.043440
X55	-0.068057	0.019507	0.025473	-0.049684	0.002098	0.002602	-0.003119	0.021796	-0.008417	-0.020652	-0.017982	-0.062719
X56	-0.021364	0.003464	-0.067319	-0.059663	0.004253	0.014357	-0.058235	-0.022389	-0.017067	-0.016807	-0.022327	0.023017
X57	-0.068020	0.161085	0.046964	0.017279	0.003360	0.013057	-0.011524	-0.055761	-0.013484	-0.033084	-0.028806	0.037820
X58	0.049016	-0.030810	-0.154328	-0.183065	-0.018377	-0.029963	-0.078223	0.039177	-0.051164	-0.205520	0.026140	-0.160336
X59	-0.024162	0.017387	0.001699	-0.014119	0.000773	-0.012971	0.020078	0.020451	-0.003101	-0.007609	-0.006625	-0.023108
X61	0.151655	-0.027227	-0.200188	0.084943	0.024308	0.011949	0.006068	-0.034684	-0.033810	0.049727	0.039984	0.057379
X62	-0.139559	0.100466	0.097122	-0.058637	0.002237	0.032042	0.007227	-0.077016	-0.008976	-0.022023	-0.019176	-0.066883
X63	0.063444	0.074118	0.044406	-0.002759	0.003108	0.036255	-0.041237	0.069209	-0.012472	-0.022109	-0.026644	0.096999
X64	-0.052449	0.062860	-0.012785	0.065384	0.002499	-0.017143	-0.070623	-0.046321	-0.081410	-0.086679	0.055571	0.434361
X65	0.009418	-0.016294	-0.015460	-0.030385	0.001340	0.000585	0.036564	0.010597	-0.005375	-0.013189	-0.011483	0.032711
X66	-0.171936	0.014937	0.292361	-0.086523	-0.034787	-0.006171	-0.004533	0.038750	-0.019375	-0.047536	-0.041390	-0.144366
X67	0.016247	0.043543	0.010785	-0.007392	0.001263	0.000845	0.001013	0.039618	-0.005067	-0.012433	-0.010825	-0.037758
X68	-0.139264	0.068230	0.050007	-0.099061	-0.016511	-0.006419	-0.050428	0.004027	-0.024735	-0.038713	-0.038642	0.006826
X69	-0.040786	-0.032086	-0.042678	-0.150568	0.005084	0.038554	0.177478	0.011090	-0.020399	-0.050049	-0.043578	0.166399

X70	0.055022	-0.045026	0.068539	-0.039784	-0.008537	-0.011815	-0.162361	-0.058965	0.034258	0.067442	0.069439	-0.194119
X71	-0.240184	0.218500	0.134877	-0.125480	-0.011266	0.010647	-0.070837	-0.015681	-0.039474	0.201982	0.199264	0.011558
X73	-0.040799	0.055060	-0.037526	0.001705	0.004130	-0.005267	-0.027850	0.010296	-0.016571	0.036705	-0.013591	0.096260
X74	-0.016667	0.032709	-0.016402	0.014119	-0.000773	0.020525	-0.001764	0.004850	0.003101	0.007609	0.006625	0.023108
X75	-0.179995	0.044748	0.233268	-0.081831	-0.028866	0.001588	0.006675	0.046703	-0.022477	-0.055147	-0.037118	-0.046520
X77	-0.032468	0.016481	-0.013537	-0.024181	0.003268	-0.018862	0.000886	0.007751	-0.013113	-0.032174	-0.000661	0.130515
X78	0.078499	0.105526	0.053458	-0.040034	0.002191	0.040479	-0.020961	0.070545	-0.008794	-0.021575	-0.018786	0.087522
X79	-0.222609	0.060967	-0.041946	0.164309	0.004651	0.018368	-0.036692	0.018575	-0.018664	-0.034285	-0.039873	0.139797
X80	0.169303	-0.059024	-0.319569	0.116505	0.021864	0.024154	-0.007262	0.027330	0.027466	0.067388	0.054137	0.204655
X81	0.115520	-0.031052	-0.300293	-0.082740	-0.007183	-0.014185	-0.084957	-0.020914	-0.063291	-0.116665	0.075283	-0.287628
X82	-0.032383	-0.030540	0.082031	-0.048677	0.003818	-0.005218	0.021908	-0.034634	0.304515	-0.037586	-0.032726	-0.051195
X83	0.008634	0.000349	0.062317	0.029345	0.000998	0.016135	0.007008	-0.025539	-0.004005	-0.009826	-0.008555	-0.029840
X85	-0.392543	0.541306	0.060696	0.113356	-0.015220	-0.016026	-0.108553	-0.048375	-0.096436	0.078911	0.296641	0.139186
X86	-0.016303	0.013523	0.037072	0.005364	0.001093	0.009128	-0.036367	-0.002387	-0.004387	-0.010765	-0.009373	-0.032692
X87	0.014009	0.042978	-0.003697	0.036881	0.000893	-0.019030	0.012612	-0.028976	-0.003581	-0.008787	-0.007651	0.035646
X88	0.040334	0.117073	-0.010157	0.068847	0.002452	-0.007260	-0.001181	-0.014183	-0.009839	-0.024139	-0.021018	0.097923
X89	0.012130	0.037216	-0.003202	0.031936	0.000773	-0.012971	0.020078	-0.023826	-0.003101	-0.007609	-0.006625	0.030866
X91	0.020661	0.056192	-0.004893	0.032048	0.001181	-0.030661	-0.005300	0.017997	-0.004740	-0.011628	-0.010125	0.047172
X92	0.005028	-0.025721	0.052901	0.019152	0.000893	0.021159	0.023187	0.012661	-0.003581	-0.008787	-0.007651	-0.026686
X95	0.007002	0.021482	0.023612	0.018434	0.000446	-0.017453	-0.020123	0.020567	-0.001790	-0.004392	-0.003824	-0.013338
X96	-0.228835	0.224250	-0.066181	0.030378	-0.008836	0.033987	-0.094574	-0.003996	0.055903	0.091439	0.054642	0.220715
X97	0.056271	0.023030	0.040249	0.055345	0.001896	-0.000055	-0.015644	0.049667	-0.007610	-0.018671	-0.016257	-0.056704
X98	0.142066	-0.036675	-0.250019	0.064865	0.020477	0.020330	0.001879	-0.001169	0.028681	0.070368	0.056903	0.213706
X100	0.040508	-0.002524	-0.192736	-0.042740	0.001472	0.053974	-0.140445	-0.012182	-0.168835	0.114842	0.106840	0.310765
X101	0.119456	-0.067434	-0.295585	0.065790	0.018609	0.015747	-0.008701	0.020863	0.030462	0.074739	0.060934	0.226979
X103	0.078831	-0.074652	-0.339114	-0.038475	0.008294	0.071694	-0.123580	0.010630	0.050773	0.147127	0.078087	0.291151
X104	0.006716	0.033951	-0.009736	-0.007392	0.001263	0.011424	-0.002728	0.011712	-0.005067	-0.012433	0.035859	0.017362
X105	-0.011229	0.004499	0.106093	0.024694	0.001412	0.008635	0.021629	-0.003546	-0.005667	-0.013904	-0.012106	-0.042225
X106	0.023631	0.021523	-0.015329	0.088289	0.003330	-0.048110	-0.034719	-0.111375	-0.013362	-0.032783	-0.010639	0.132987
X108	-0.086882	0.083685	0.179143	0.146211	0.003538	-0.001935	0.018896	0.020766	-0.014198	-0.034836	-0.030332	-0.093839
X109	-0.020762	-0.013342	-0.024594	0.043461	0.005937	-0.002463	-0.013755	-0.007018	-0.023823	-0.058451	-0.045729	0.237109
X110	-0.021915	0.023996	-0.003697	0.010288	0.000893	-0.016226	0.033762	-0.011445	-0.003581	-0.008787	-0.007651	0.035646
X111	0.182649	-0.003371	-0.299899	0.087586	0.036391	0.006629	0.004978	-0.029133	0.018664	0.045793	0.039873	0.139073
X112	0.004824	-0.037279	0.047559	-0.010338	0.001547	0.000495	-0.002579	0.003587	-0.006209	-0.015234	-0.013265	-0.046266
X113	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X114	-0.254859	0.281680	0.264240	-0.044313	-0.006235	0.034061	-0.080832	0.016636	-0.048035	0.139947	0.231265	-0.077892
X115	-0.096472	-0.100667	-0.135202	0.045813	-0.003059	-0.008859	0.059081	0.056972	0.009216	-0.090308	-0.100570	0.135416
X116	0.077929	-0.128996	-0.068701	-0.249933	-0.001856	0.004078	-0.015668	-0.023455	-0.041816	-0.077486	-0.015345	-0.182985
X117	0.036194	-0.044889	-0.057809	0.205644	0.006581	0.031240	-0.016995	-0.018196	-0.016820	0.402172	-0.051717	-0.152373
X118	0.136117	0.028872	0.064132	-0.213425	-0.002652	-0.008319	-0.052987	-0.046867	0.009215	-0.077411	0.138766	-0.026020
X120	0.157480	-0.021976	-0.210407	0.077838	0.025873	-0.006646	0.010808	-0.032074	-0.037420	0.046429	0.042025	0.043440
X123	-0.041115	-0.029596	-0.026632	-0.029736	0.001481	-0.019597	0.000191	-0.000479	-0.005944	-0.014584	-0.012698	0.021542
X124	-0.013906	0.022715	0.009390	-0.024059	0.000631	0.007030	-0.017249	0.010500	-0.002532	-0.006212	-0.005409	0.003167
X125	-0.018667	0.033894	-0.078173	-0.004814	0.001611	0.004451	-0.030087	-0.001793	-0.006463	-0.015858	-0.013808	-0.048161
X126	-0.192859	0.114483	0.340411	-0.107152	-0.027405	0.008216	0.015407	-0.016096	-0.023382	-0.057367	-0.049950	-0.174222
X127	0.473392	-0.122318	-0.237877	0.052541	0.009365	0.002015	-0.034614	-0.010330	0.055047	-0.085586	0.000383	-0.304649
X128	0.135520	-0.005878	-0.320774	0.094373	0.026187	0.030662	-0.003150	0.020800	0.024186	0.059341	0.051668	0.180215
X129	0.070162	-0.150708	-0.085887	-0.148056	-0.008791	-0.002595	0.018485	0.037735	-0.037083	-0.087254	-0.055529	-0.171167
X130	-0.135520	0.005878	0.320774	-0.094373	-0.026187	-0.030662	0.003150	-0.020800	-0.024186	-0.059341	-0.051668	-0.180215
X131	-0.044406	0.078793	-0.057341	0.004238	0.004785	-0.044038	-0.014891	-0.001357	-0.019199	-0.041504	0.009521	0.047883
X132	-0.056980	0.295066	-0.036585	0.359400	0.001366	0.002738	-0.047600	0.026058	0.073625	-0.045896	0.133919	0.119526
X133	0.184564	-0.325615	0.081463	-0.308841	0.010900	-0.024701	0.031552	-0.032415	-0.037455	-0.071787	-0.093443	-0.146885
X134	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X135	0.082176	-0.014918	-0.037325	0.199515	0.004828	0.031617	-0.077798	-0.034253	-0.019375	0.363467	-0.041390	-0.126619
X136	0.153188	-0.203808	-0.206302	-0.190653	-0.006170	-0.006177	-0.011289	-0.004657	0.024757	0.034216	0.052889	0.078518

X138	0.046140	-0.079142	-0.119220	-0.123606	0.005973	0.004870	0.009522	0.052671	-0.023969	-0.045146	-0.030663	-0.011250
X139	0.007966	0.001915	0.126291	0.034077	-0.002077	-0.091701	0.081313	0.019897	-0.036634	-0.089883	-0.010938	-0.212726
X140	0.046182	-0.077291	-0.122036	-0.124411	0.005937	0.005290	0.008174	0.051461	-0.023823	-0.044712	-0.030237	-0.009224
X141	-0.030442	-0.007240	-0.027473	-0.027859	0.003480	-0.001315	-0.003738	0.005788	-0.013964	-0.026656	-0.012678	0.074175
X142	0.110379	-0.166666	0.027640	-0.353098	0.007126	-0.009448	0.031888	-0.064276	0.058490	-0.140169	0.116147	-0.061634
X143	-0.038818	-0.017758	-0.015610	-0.015715	0.005771	-0.049665	0.096417	-0.054114	-0.001536	-0.052118	-0.049473	0.085293
X144	0.063223	0.040647	-0.137344	0.078405	0.010387	0.091248	-0.109348	-0.025722	0.046070	0.129712	0.061542	0.168155
X145	-0.000717	-0.005671	0.017427	-0.019974	0.001093	0.001495	-0.032049	-0.018495	-0.004387	0.013132	-0.009373	-0.019965
X146	0.046140	-0.079142	-0.119220	-0.123606	0.005973	0.004870	0.009522	0.052671	-0.023969	-0.045146	-0.030663	-0.011250
X147	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X148	-0.104378	0.113990	0.224644	0.122115	0.006275	0.026658	0.000164	0.008227	-0.025179	-0.040008	-0.039061	-0.097186
X150	-0.273111	0.297895	-0.048967	0.044043	-0.014814	0.022887	-0.091456	-0.006219	0.049222	0.076946	0.126993	0.260645
X151	-0.112547	0.155177	-0.041494	0.079551	0.008850	-0.005713	-0.007175	0.017134	-0.035513	0.003134	0.007745	0.252163
X152	0.036243	-0.013459	0.012737	0.042417	0.005288	-0.030337	-0.032153	-0.072772	0.002234	0.009124	-0.039580	-0.014190
X153	-0.025458	0.016343	-0.022806	0.021701	0.000773	0.020480	0.010921	0.012861	-0.003101	0.093740	-0.006625	-0.023108
X154	-0.154785	0.239910	-0.009085	0.450741	-0.000953	-0.020550	-0.010948	-0.034498	-0.059660	0.055468	-0.127452	0.018515
X156	0.075635	-0.140393	0.015380	0.034705	0.003252	0.002486	0.083699	0.044793	-0.175748	0.090779	-0.083566	0.178570
X157	-0.075635	0.140393	-0.015380	-0.034705	-0.003252	-0.002486	-0.083699	-0.044793	0.175748	-0.090779	0.083566	-0.178570
X158	-0.110379	0.166666	-0.027640	0.353098	-0.007126	0.009448	-0.031888	0.064276	-0.058490	0.140169	-0.116147	0.061634
X159	-0.081908	0.122546	0.022356	0.058579	0.003391	-0.017539	0.025360	0.012022	-0.013606	-0.009980	-0.029066	0.064793
X160	-0.018480	-0.026334	-0.004134	-0.022196	0.000998	-0.021488	0.004643	0.001905	-0.004005	-0.009826	-0.008555	0.039858
X161	0.148924	-0.353580	-0.011057	-0.421517	0.014364	0.024365	0.113792	-0.034048	-0.052431	-0.082553	-0.123132	-0.070176
X163	0.041554	-0.056650	-0.082432	-0.109156	-0.015872	0.008553	0.011173	0.020516	0.013575	-0.188025	-0.046505	0.242602
X164	0.038654	-0.189059	-0.135247	-0.205882	0.007471	-0.001247	-0.040833	0.039648	-0.029979	-0.028852	-0.064043	-0.094427
X165	-0.068231	0.048132	0.059893	-0.007078	0.001949	0.013118	-0.007703	0.067683	-0.007820	-0.019185	-0.016705	-0.058265
X166	-0.131802	0.165593	0.235124	0.201242	0.005368	0.009695	0.002714	-0.002557	-0.021539	-0.037763	-0.046014	-0.098908
X167	-0.015180	0.048402	-0.043316	-0.003008	0.000893	-0.001272	0.023187	0.003895	-0.003581	-0.008787	-0.007651	-0.026686
X168	-0.036166	0.070795	-0.158563	0.375698	-0.004069	0.001824	-0.031224	0.024927	0.087874	0.059671	-0.148904	0.067996
X169	-0.066234	0.095876	0.025320	0.007137	0.002368	-0.000186	0.015427	0.010750	-0.009503	-0.001133	-0.020301	0.023700
X170	-0.179464	0.032135	0.238552	-0.095745	-0.037259	-0.021107	-0.011838	0.024513	-0.018300	-0.044899	-0.032483	-0.136357
X171	0.166988	-0.169628	-0.027333	-0.400510	0.012985	0.001796	0.026974	-0.042649	-0.064729	-0.024201	0.174797	0.021615
X172	-0.139559	0.100466	0.097122	-0.058637	0.002237	0.032042	0.007227	-0.077016	-0.008976	-0.022023	-0.019176	-0.066883
X173	0.019690	-0.003873	0.000984	0.024045	0.002870	0.013503	-0.002571	0.069417	-0.011517	-0.000718	-0.024604	0.085294
X174	0.042192	0.075252	0.025987	-0.032573	0.003845	0.026949	-0.009943	0.053113	-0.015427	-0.037851	-0.032957	0.098374
X175	0.005090	-0.111340	-0.047919	-0.121490	0.004374	-0.030790	-0.023092	-0.003762	-0.017551	0.005752	-0.037493	0.012204
X176	-0.032649	-0.003475	-0.015815	-0.017081	0.003818	-0.035424	-0.005105	0.013015	-0.015319	-0.037586	-0.032726	0.152470
X177	-0.027386	0.004217	-0.027539	0.064426	0.006648	0.010850	0.014804	-0.001236	-0.026677	-0.065452	-0.038353	0.265510
X178	0.205178	-0.099616	-0.035288	-0.000992	0.006580	0.030082	-0.037715	-0.012652	0.103480	0.253889	0.088016	-0.832712
X179	-0.164475	0.090441	0.302603	-0.105278	-0.023588	-0.026370	0.011403	-0.028192	-0.026072	-0.063969	-0.050942	-0.194270
X180	-0.069228	-0.110769	0.001804	-0.174707	-0.013911	0.041039	0.038444	-0.003103	-0.050301	0.143554	-0.087946	-0.043057
X181	0.141662	-0.287863	0.157504	-0.271752	0.009313	0.011022	0.030478	-0.068015	-0.030259	-0.032944	-0.079833	-0.156606
X182	0.045356	-0.033338	-0.218000	0.112099	0.009975	0.034952	-0.069502	0.010163	-0.026567	0.384644	-0.065711	-0.162665
X183	-0.020161	-0.006996	0.025706	-0.029359	0.001843	-0.005351	-0.003499	0.027472	-0.007395	-0.018143	-0.015797	-0.055100
X184	0.006159	0.052650	-0.001063	-0.009115	0.001093	-0.030564	0.006814	0.030722	-0.004387	-0.010765	0.017574	-0.032692
X185	-0.097127	0.144906	0.127671	0.165383	0.004002	0.027401	-0.021476	-0.015498	-0.016060	-0.019473	-0.034309	-0.041829
X186	0.421405	-0.570809	-0.098067	-0.218208	0.011760	0.022144	0.103509	0.039123	0.108042	-0.092879	-0.266619	-0.135624
X187	-0.362440	0.492463	0.013845	0.141683	-0.014429	-0.024922	-0.109233	-0.041448	-0.098922	0.107966	0.291201	0.169451
X189	0.205917	-0.152207	-0.382779	-0.069982	0.014314	0.017400	-0.011884	0.011603	0.035297	0.073641	0.075405	0.185354
X190	-0.012076	-0.014663	-0.001848	-0.008149	0.000446	0.008707	-0.020123	0.009614	-0.001790	-0.004392	-0.003824	0.017817
X191	-0.144415	0.040339	-0.200524	0.104832	0.007975	-0.007519	-0.025639	0.037498	-0.109548	0.022031	-0.093487	0.819047
X192	-0.008742	0.006788	0.008479	-0.020188	0.001412	0.005086	-0.016854	-0.010481	-0.005667	-0.013904	-0.012106	0.016951
X194	-0.421405	0.570809	0.098067	0.218208	-0.011760	-0.022144	-0.103509	-0.039123	-0.108042	0.092879	0.266619	0.135624
X195	-0.073731	0.069443	0.017677	0.027926	0.003141	0.005189	-0.031560	0.009142	-0.012603	0.053131	-0.026923	0.031431
X196	-0.019902	0.075096	-0.021934	0.008764	0.002940	-0.002185	-0.003819	0.038179	-0.011797	-0.002047	0.065791	0.055344
X197	-0.063329	-0.023855	-0.020672	-0.161476	0.005288	0.040021	0.213847	-0.009764	-0.021219	-0.052061	-0.045330	0.208474

X198	-0.196737	0.019859	0.296563	-0.090296	-0.038413	-0.009405	-0.000711	0.032784	-0.017835	-0.043758	-0.038101	-0.132892
X199	0.004824	-0.037279	0.047559	-0.010338	0.001547	0.000495	-0.002579	0.003587	-0.006209	-0.015234	-0.013265	-0.046266
X200	0.058446	-0.076127	-0.129950	-0.061742	0.002368	0.020716	0.038475	-0.041581	-0.009503	-0.023315	-0.020301	-0.070807
X201	0.257258	-0.423469	-0.033318	-0.013551	0.013453	-0.030020	-0.001678	0.016758	0.211812	-0.125374	-0.115325	0.004721
X202	0.101290	-0.391924	0.001916	-0.477880	0.008810	0.020683	0.097609	-0.033617	-0.060657	-0.076436	-0.139933	-0.080766
X203	-0.009000	-0.090421	0.094498	-0.113787	0.003791	-0.021503	-0.019179	0.005400	-0.015211	-0.030318	-0.032494	-0.049952
X204	0.002513	0.021482	-0.000434	-0.025872	0.000446	0.019919	0.011589	0.005233	-0.001790	-0.004392	0.062143	-0.013338
X205	-0.002513	-0.021482	0.000434	0.025872	-0.000446	-0.019919	-0.011589	-0.005233	0.001790	0.004392	-0.062143	0.013338
X206	-0.047037	0.007664	-0.000607	-0.036279	0.004054	0.016863	-0.031065	0.040176	-0.016266	-0.000533	-0.005148	0.067529
X207	-0.018809	0.001602	-0.001848	-0.008149	0.000446	0.023656	0.001018	-0.010102	-0.001790	-0.004392	-0.003824	0.017817
X208	-0.080080	-0.054251	0.085961	-0.154462	-0.018974	-0.001916	0.005051	0.061578	-0.030100	-0.062715	-0.047560	-0.089856
X209	0.090043	0.054843	-0.059143	0.134661	0.011576	0.031885	-0.065366	-0.014646	0.025282	0.083787	0.069885	0.017194
X210	-0.005343	-0.007434	-0.017407	0.018434	0.000446	-0.023059	-0.004267	-0.021055	-0.001790	-0.004392	-0.003824	-0.013338
X211	-0.026911	-0.080779	-0.037398	-0.060668	0.003567	0.016974	-0.028754	-0.022387	-0.014314	-0.035120	-0.030579	0.063380
X212	0.038829	-0.053882	0.044933	0.012684	0.002145	-0.006573	0.017052	0.002720	0.441442	-0.021119	-0.018388	-0.064136
X213	0.016247	0.043543	0.010785	-0.007392	0.001263	0.000845	0.001013	0.039618	-0.005067	-0.012433	-0.010825	-0.037758
X215	0.203709	-0.204714	-0.312762	-0.066274	0.009571	0.009448	0.048627	0.033217	-0.038405	-0.094227	-0.082044	-0.286164
X216	-0.139559	0.100466	0.097122	-0.058637	0.002237	0.032042	0.007227	-0.077016	-0.008976	-0.022023	-0.019176	-0.066883
X218	-0.144207	0.071733	0.193593	-0.262360	-0.001305	-0.019224	-0.076563	-0.013977	-0.078276	0.072507	0.339494	-0.130524
X219	-0.181137	0.262799	0.133223	-0.088848	0.007784	0.040686	-0.076405	0.017280	-0.031236	0.264821	0.371002	0.048641
X220	-0.118393	0.051007	0.266040	-0.161081	0.032725	0.021669	0.010689	-0.093747	-0.118781	-0.007871	0.176341	0.224245
X221	-0.157834	0.054496	0.059564	-0.061438	0.002611	0.007861	-0.008599	-0.055740	-0.010479	-0.025711	-0.022386	-0.045897
X222	-0.195415	0.017026	0.300841	-0.089142	-0.039146	-0.007207	-0.004348	0.029597	-0.017551	-0.043061	-0.037493	-0.130773
X223	-0.225250	0.129003	0.141726	0.039483	-0.006489	0.000458	0.019556	0.027881	0.095583	-0.147785	-0.129869	0.727050
X224	-0.104389	0.049084	-0.078562	0.051135	-0.000990	0.002751	-0.036152	0.013730	-0.079186	-0.194284	-0.053402	0.779874
X225	-0.015105	-0.003985	-0.018497	-0.157507	0.009481	0.029901	0.009805	0.062828	-0.031036	-0.020208	-0.019422	0.091405
X227	-0.018667	0.033894	-0.078173	-0.004814	0.001611	0.004451	-0.030087	-0.001793	-0.006463	-0.015858	-0.013808	-0.048161
X228	-0.150940	-0.004984	0.152279	-0.096566	-0.027405	-0.005327	-0.023321	0.031710	-0.023382	-0.038730	-0.044696	-0.092338
X229	0.147355	-0.001838	-0.150059	0.093140	0.026950	0.005466	0.019403	-0.028509	0.023677	0.039669	0.040193	0.088119
X230	-0.045030	0.043842	-0.008689	0.005240	0.002098	-0.038535	0.012697	0.005877	-0.008417	-0.020652	-0.017982	0.083776
X231	-0.091055	-0.011648	-0.073114	-0.031998	0.003708	0.007964	-0.037409	0.029305	0.001567	-0.036509	-0.007597	0.026230
X232	-0.149090	0.202989	0.209387	0.188854	0.006134	0.006306	0.013201	0.004552	-0.024615	-0.042617	-0.052586	-0.076904
X234	0.325250	-0.206457	0.041494	-0.143218	0.014546	-0.025682	0.066297	-0.007404	-0.058371	-0.143214	0.083058	-0.434934
X236	-0.045651	0.017603	-0.018618	0.026072	0.000631	-0.000899	-0.017249	0.001204	-0.002532	0.076529	-0.005409	-0.018865
X237	-0.006021	-0.021648	-0.020269	-0.041582	0.002368	-0.066435	-0.003612	-0.015416	-0.009503	-0.023315	-0.007794	-0.070807
X238	0.240511	-0.205279	-0.382044	-0.058801	0.014444	0.008634	-0.015286	0.025309	0.035134	0.073192	0.071389	0.183842
X241	-0.219042	0.227151	0.166088	-0.110730	-0.012217	0.020404	-0.053407	-0.032261	-0.038096	0.147004	0.203512	0.050084
X246	-0.341428	0.522338	-0.006343	0.215346	-0.015143	-0.011843	-0.118948	-0.028514	-0.096673	0.091023	0.293841	0.154610
X251	-0.136941	0.062503	-0.096691	0.046175	0.003602	-0.017882	0.032782	0.026036	-0.093663	-0.229802	-0.066938	0.932210
X252	-0.018977	0.036172	0.040907	0.016584	0.000773	0.028034	0.007869	0.006535	-0.003101	-0.007609	-0.006625	-0.023108
X255	-0.052481	0.071881	0.214645	-0.051791	0.004079	0.010856	0.016974	-0.095300	-0.016368	-0.040160	-0.034967	-0.121963
X256	0.016251	0.049735	0.177008	0.050727	0.008131	0.025679	0.072363	-0.014427	0.397338	-0.080055	-0.065801	-0.243123
X257	0.001391	0.023289	0.025027	-0.017011	0.000446	-0.024928	0.011589	-0.012292	-0.001790	-0.004392	-0.003824	-0.013338
X258	-0.016913	-0.057861	0.110570	-0.000552	0.001412	-0.001421	-0.008488	-0.025044	-0.005667	-0.013904	-0.012106	-0.042225
X259	0.011491	-0.014663	0.034928	0.000712	0.000446	-0.008110	0.011589	0.007423	-0.001790	-0.004392	-0.003824	-0.013338
X260	0.015980	-0.018278	-0.010335	-0.008149	0.000446	-0.023059	-0.014838	0.013995	-0.001790	-0.004392	-0.003824	-0.013338
X261	-0.346534	0.014135	0.121778	-0.093864	-0.014489	0.007013	0.036361	0.019528	-0.035701	0.119510	0.028066	0.341442
X265	0.227735	-0.181413	-0.392478	-0.047588	0.012626	0.013819	-0.014389	0.021842	0.037526	0.079746	0.076692	0.205772
X267	-0.032166	-0.010105	-0.000379	-0.025914	0.002762	-0.020987	-0.016086	-0.000796	0.010839	-0.027194	-0.012929	0.095085
X269	-0.015493	0.013768	0.009390	0.007273	0.000631	-0.029971	-0.013511	-0.011189	-0.002532	-0.006212	-0.005409	0.003167
X270	-0.010954	0.016060	-0.001848	0.018434	0.000446	0.004970	-0.035980	0.007423	-0.001790	-0.004392	-0.003824	0.017817
X271	-0.032893	0.035563	0.021351	0.028745	0.001340	-0.010014	-0.000469	0.026677	-0.005375	0.006330	-0.011483	0.032711
X273	0.050051	-0.025389	-0.046565	0.171387	-0.018041	-0.027983	-0.107958	0.019638	-0.181647	-0.009156	-0.071812	-0.276651
X274	-0.069771	0.116640	0.031611	0.033488	0.002905	-0.006169	0.028761	0.008602	-0.011658	-0.019532	-0.024905	0.033906

X275	0.142594	-0.066217	0.057895	-0.355917	0.003903	-0.013814	0.032249	-0.070613	-0.017215	-0.096432	0.115597	-0.003933
X277	-0.018596	0.057818	-0.053064	0.012603	0.001093	0.013708	-0.010458	0.005666	-0.004387	-0.010765	-0.009373	-0.032692
X278	-0.015493	0.035495	-0.006615	-0.011526	0.000631	0.013637	0.016392	0.002754	-0.002532	-0.006212	-0.005409	0.025199
X280	-0.024420	0.003409	0.032099	-0.017011	0.000446	0.016182	0.011589	-0.003530	-0.001790	-0.004392	-0.003824	-0.013338
X281	0.004618	0.045690	0.106587	-0.005662	0.001481	-0.029187	0.025719	-0.033544	-0.005944	-0.014584	-0.012698	-0.044291
X282	0.061375	0.088740	0.132600	-0.007827	0.001843	0.033245	0.017051	-0.057167	-0.007395	-0.018143	-0.015797	-0.055100
X283	-0.235678	0.144991	-0.044422	0.327428	-0.006790	-0.046588	-0.036302	-0.059325	-0.046979	-0.021903	-0.076965	0.080860
X284	-0.076545	-0.135900	0.025692	-0.176176	-0.010205	0.002777	-0.016686	-0.005060	-0.024041	-0.004489	-0.051360	-0.036440
X285	-0.205316	0.585840	0.100820	-0.069071	-0.009133	0.010926	-0.075996	-0.021330	-0.059102	0.095866	0.444642	0.130940
X286	-0.088499	0.041406	0.082726	0.237622	0.006957	-0.000665	-0.005262	0.026055	-0.027918	0.046540	-0.059642	-0.066483
X287	0.055418	-0.016604	-0.053913	-0.113064	0.003680	0.023517	0.063724	0.035619	-0.014769	-0.036235	-0.031550	0.035737
X288	0.014857	0.021482	0.032099	-0.008149	0.000446	0.016182	-0.004267	0.005233	-0.001790	-0.004392	-0.003824	-0.013338
X291	-0.036472	0.027112	0.042120	0.026228	0.002974	-0.007070	0.002786	0.026258	-0.011935	-0.011554	-0.015501	-0.060606
X292	-0.027411	0.029060	0.015293	0.023176	0.002762	-0.016115	-0.051395	-0.007221	-0.011084	0.001402	0.008568	-0.047052
X294	0.158783	-0.272456	-0.065739	-0.244799	0.010936	-0.004873	-0.011245	-0.018331	-0.025072	-0.072226	-0.093749	-0.194855
X295	0.005880	0.016060	-0.001848	0.000712	0.000446	-0.017453	-0.004267	0.013995	-0.001790	-0.004392	-0.003824	0.017817
X298	0.059225	-0.040784	-0.000918	-0.000966	0.001949	0.035887	-0.002842	-0.021966	-0.007820	-0.019185	-0.016705	0.020525
X300	-0.178401	0.076323	-0.061827	0.110216	0.014782	-0.033791	-0.051109	0.003046	-0.059317	-0.145535	-0.058958	0.589188
X301	0.145602	-0.024840	-0.068673	0.072945	0.006412	0.145477	0.035465	0.054918	0.042989	0.060655	-0.054970	-0.128079
X304	0.079118	-0.035021	-0.242346	0.121975	0.016011	0.010504	-0.042926	0.025514	0.017583	0.081587	0.067197	0.247776
X305	0.061800	-0.041171	0.104233	0.013704	0.003360	-0.000265	0.024734	0.024978	0.022712	-0.033084	-0.028806	-0.100474
X306	-0.149048	0.058455	0.167671	-0.137076	-0.025265	0.011324	0.032053	-0.011143	-0.024828	-0.060915	-0.048067	-0.184997
X307	-0.008180	-0.025339	-0.011684	-0.033341	0.001340	-0.035576	0.010112	-0.012061	-0.005375	-0.013189	-0.011483	-0.040053
X308	0.032011	0.051232	0.208903	-0.010962	0.002835	0.006943	0.024103	-0.066971	-0.011374	-0.027907	-0.024299	-0.084753
X309	-0.003253	-0.020994	-0.021559	-0.038298	0.002452	-0.048683	-0.009896	-0.003347	-0.009839	-0.024139	-0.021018	-0.073310
X310	-0.034340	0.050600	-0.015957	0.045161	0.001481	-0.008316	-0.003000	0.008118	-0.005944	0.003075	-0.012698	0.012137
X312	0.001937	-0.076849	-0.035584	-0.034645	0.001896	-0.047718	-0.018140	-0.028975	-0.007610	-0.018671	-0.016257	-0.056704
X313	0.429398	-0.029443	-0.244862	0.164566	-0.002038	-0.032840	-0.026615	-0.009387	0.036810	0.011552	-0.040891	-0.205630
X315	-0.231550	0.040382	0.021906	-0.082778	0.004979	-0.007267	-0.033484	0.007482	-0.019978	-0.022038	-0.006173	0.066655
X316	0.100732	-0.115136	-0.016777	-0.124962	0.014267	0.037613	-0.012205	0.000757	0.026404	-0.122276	0.049448	-0.149336
X317	-0.005843	-0.066580	0.002558	-0.035266	0.002533	-0.045385	-0.009223	-0.019264	-0.010164	-0.024937	-0.021713	-0.075732
X318	-0.017681	-0.005574	0.032739	-0.009002	0.000773	0.028034	0.004817	-0.008645	-0.003101	0.026174	-0.006625	-0.005117
X319	-0.025810	-0.014349	-0.002614	-0.011526	0.000631	0.008351	0.020130	0.027541	-0.002532	-0.006212	-0.005409	-0.018865
X321	-0.141728	0.321879	-0.051798	0.434591	-0.021502	-0.022692	-0.017264	-0.027350	-0.065035	0.020191	-0.119857	-0.017199
X322	-0.063873	0.024107	-0.009124	-0.017383	0.004326	0.007622	-0.042492	0.026267	-0.017359	0.031403	-0.030130	0.002010
X323	-0.042542	0.003654	0.000011	-0.078207	0.002799	-0.009098	-0.025919	-0.005230	-0.011230	0.028908	-0.023990	-0.013516
X325	-0.051742	0.119213	0.015531	-0.040034	0.002191	-0.039075	0.056932	-0.000749	-0.008794	-0.021575	-0.018786	0.004622
X327	0.004613	-0.121544	-0.117760	-0.319196	0.001487	-0.018663	-0.041885	0.034012	-0.044549	0.049764	0.242285	-0.056269
X329	0.071595	0.076906	0.022667	-0.116484	0.005949	-0.007800	-0.084452	0.020231	0.128089	-0.031899	0.266164	0.142041
X332	0.018611	0.027823	-0.003202	0.026819	0.000773	0.034509	-0.019602	0.002740	-0.003101	-0.007609	-0.006625	0.030866
X333	-0.002468	-0.128397	-0.094721	0.180359	0.004537	0.004448	-0.014659	0.013294	-0.018208	0.155634	-0.038897	-0.041544
X334	-0.061232	-0.159830	0.276947	-0.558937	0.007501	-0.030001	0.062598	-0.032585	-0.103574	-0.043716	0.267385	-0.137297
X335	0.022810	0.013226	-0.007169	-0.065992	0.001731	-0.038229	-0.016554	0.062793	-0.006945	-0.017039	-0.014836	0.069118
X336	-0.100537	0.420864	-0.073259	0.065564	-0.017881	0.027354	-0.062243	0.017454	-0.044359	-0.014176	-0.094764	0.225448
X337	0.047351	0.138232	-0.282255	0.574053	-0.008695	0.027452	-0.057885	0.011149	0.108199	0.055537	-0.256402	0.103045
X338	0.024660	0.017410	-0.011039	-0.017618	0.002410	0.011535	-0.008284	0.024192	0.015396	-0.001932	-0.020663	-0.002413
X339	-0.032276	0.003409	-0.013164	0.018434	0.000446	-0.000636	-0.025409	-0.018864	-0.001790	0.054108	-0.003824	-0.013338
X340	0.057060	-0.129059	-0.043493	-0.127035	0.004374	0.003707	0.024869	0.039194	-0.017551	-0.030857	-0.037493	0.008955
X341	-0.031662	0.069743	-0.011792	-0.008040	0.002611	-0.005008	-0.008599	-0.001805	-0.010479	0.004506	-0.022386	0.072112
X342	0.055305	0.013067	-0.135847	-0.029992	-0.060906	-0.039171	-0.025297	-0.010388	0.052615	-0.043061	-0.037493	-0.111276
X343	0.050892	-0.067608	0.003962	-0.112025	0.008440	-0.057990	-0.013460	-0.038023	-0.033870	-0.076391	-0.057226	0.031647
X344	-0.122156	0.107954	0.060595	-0.062449	0.002688	-0.002579	-0.014210	-0.046565	-0.010785	-0.006881	-0.023041	-0.054294
X345	0.004856	0.007790	-0.137912	0.178881	0.004374	0.027874	0.008882	0.049704	-0.017551	0.085073	-0.037493	-0.101528
X349	-0.023534	-0.035300	-0.046940	-0.197058	0.006275	0.056139	0.201164	0.020943	-0.025179	-0.061776	-0.053789	0.204227
X350	-0.106772	0.152362	-0.230941	0.143553	-0.006459	-0.055928	-0.100208	0.016212	-0.083122	-0.194416	-0.076614	0.108029

X351	-0.144929	0.157290	0.065231	0.077231	0.018819	-0.032679	-0.019419	-0.005965	-0.070980	-0.151745	0.150106	0.340823
X353	-0.042253	-0.010867	-0.005549	-0.024472	0.001340	-0.026847	0.034801	-0.006214	-0.005375	-0.013189	-0.011483	0.053500
X354	-0.182165	0.177373	0.099700	-0.071795	-0.001390	0.005689	-0.096507	-0.058520	-0.053430	0.255318	0.130177	0.020747
X355	0.132281	-0.332577	-0.065141	-0.189158	-0.010442	0.022560	0.026425	0.050301	0.139665	-0.037512	-0.192270	0.056933
X356	0.159288	-0.407207	0.017311	-0.392994	0.013551	-0.002591	-0.003423	-0.048943	-0.048979	-0.046559	-0.116168	-0.208902
X357	0.015664	0.048057	-0.004134	0.041239	0.000998	-0.023996	0.007008	-0.033381	-0.004005	-0.009826	-0.008555	0.039858
X359	-0.024918	0.124822	-0.015778	0.037152	0.005248	-0.022078	-0.004724	-0.046906	-0.021057	-0.051664	0.007134	0.168556
X361	-0.021215	0.244337	0.095281	-0.209929	-0.005427	-0.028669	-0.030375	-0.023963	0.021777	-0.210335	0.046522	0.085403
X365	-0.040265	0.026452	0.018530	0.048572	0.001547	-0.002205	0.027977	0.021317	-0.006209	-0.015234	0.005803	0.061799
X366	0.010643	-0.003694	-0.005400	0.017451	0.000998	-0.000586	0.040116	0.012687	-0.004005	-0.009826	0.020960	0.039858
X367	-0.054229	-0.045593	-0.044346	-0.203050	-0.007746	0.040783	0.205846	0.014585	-0.027139	-0.066587	-0.057978	0.226781
X369	0.001967	-0.020739	0.019393	0.001006	0.000631	-0.003542	0.012654	0.013598	-0.002532	-0.006212	-0.005409	-0.018865
X370	0.050787	0.097932	0.170400	-0.009662	0.002368	0.007608	0.029456	-0.065670	-0.009503	-0.023315	-0.020301	-0.070807
X372	-0.015493	0.029105	0.033397	0.026072	0.000631	0.005708	0.020130	-0.009640	-0.002532	-0.006212	-0.005409	-0.018865
X373	0.021198	-0.123914	-0.102637	0.161539	0.004054	-0.007035	-0.040552	0.004788	-0.016266	0.176659	-0.034749	-0.054797
X374	-0.161102	0.202307	-0.036632	0.518349	0.000355	0.002639	-0.007503	-0.004513	-0.062993	0.097125	-0.134572	-0.008845
X375	0.113272	0.056874	-0.174308	0.051801	-0.021598	0.012756	-0.036780	0.044093	0.165277	-0.107864	-0.169721	0.118950
X376	0.070546	-0.102424	0.033697	-0.105009	0.007132	-0.062472	-0.021234	-0.054105	-0.028618	-0.070214	-0.061136	0.026496
X377	0.045173	-0.248791	0.122503	-0.588272	0.012692	0.005345	0.069685	-0.033075	-0.074244	0.030134	0.357229	-0.097464
X378	-0.102136	0.145282	0.131974	0.173723	0.004204	0.029634	-0.030480	-0.010485	-0.016870	-0.016043	-0.036040	-0.037958
X379	0.083352	0.070753	0.033645	-0.026446	0.002835	0.034548	-0.030471	0.069440	-0.011374	-0.027907	-0.024299	0.103309
X380	-0.038618	-0.022360	0.006473	0.004166	0.002611	0.010434	-0.014059	0.009511	-0.010479	-0.005566	0.023045	0.007743
X383	-0.011174	-0.029253	-0.019873	-0.028280	0.001181	-0.007337	-0.021293	0.038712	-0.004740	-0.011628	-0.010125	0.023604
X384	0.009110	0.017603	-0.002614	0.007273	0.000631	0.007030	0.023867	0.008950	-0.002532	-0.006212	0.041242	0.025199

In [ ]:

```
#Choosing the upper part of the correlation matrix as it will be same as the lower half
Corr_upper = correlation_X.where(np.triu(np.ones_like(correlation_X),k=1).astype(np.bool))
Corr_upper
```

Out[ ]:

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14	
X0	NaN	-0.271123	-0.139904	-0.070645	0.017988	0.012293	0.037549	0.047735	0.081122	-0.134577	-0.130529	-0.138310	0.01
X1	NaN	NaN	0.088266	0.205657	-0.020724	0.046417	-0.079119	-0.000306	-0.137193	0.112263	0.286683	0.079784	-0.02
X2	NaN	NaN	NaN	-0.093546	0.002289	-0.017722	0.065778	-0.069932	0.042398	0.131464	0.222132	-0.079183	-0.00
X3	NaN	NaN	NaN	NaN	0.015298	-0.008161	-0.048468	-0.001249	0.019663	0.056166	-0.216464	0.045183	-0.02
X4	NaN	NaN	NaN	NaN	NaN	0.039778	0.027854	-0.008909	0.003360	0.008245	0.007179	0.005544	0.00
...	...	...	...	...	...	...	...	...	...	...	...	...	
X378	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X379	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X380	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X383	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
X384	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

306 rows × 306 columns

In [ ]:

```
#Finding the columns with correlation > .95
droppables = [col for col in Corr_upper.columns if any(abs(Corr_upper[col])>.95)]
droppables
```

Out[ ]:

```
['X35',
 'X37',
 'X39',
 'X61',
 'X111',
 'X113',
 'X120',
 'X129',
 'X130',
 'X134',
 'X136',
 'X140',
 'X146',
 'X147',
 'X157',
 'X158',
 'X172',
 'X194',
 'X198',
 'X199',
 'X205',
 'X213',
 'X215',
 'X216',
 'X222',
 'X227',
 'X229',
 'X232',
 'X337',
 'X378']
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X378'] > 0.9, correlation_X['X378'] > 0.9]
```

Out[ ]:

	X185	X378
X185	1.000000	0.951991
X378	0.951991	1.000000

In [ ]:

```
#Dropping X378
X_train_15=X_train_14.drop((['X378']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X232'] > 0.9, correlation_X['X232'] > 0.9]
```

Out[ ]:

	X29	X232
X29	1.0	1.0
X232	1.0	1.0

In [ ]:

```
#Dropping X232
X_train_15=X_train_15.drop((['X232']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X227'] > 0.9, correlation_X['X227'] > 0.9]
```

Out[ ]:

	X125	X227
X125	1.0	1.0
X227	1.0	1.0

In [ ]:

```
#Dropping X227
X_train_15=X_train_15.drop((['X227']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X222'] > 0.9, correlation_X['X222'] > 0.9]
```

Out[ ]:

	X48	X66	X113	X134	X147	X198	X222
X48	1.000000	0.905844	1.000000	1.000000	1.000000	0.984056	1.000000
X66	0.905844	1.000000	0.905844	0.905844	0.905844	0.891259	0.905844
X113	1.000000	0.905844	1.000000	1.000000	1.000000	0.984056	1.000000
X134	1.000000	0.905844	1.000000	1.000000	1.000000	0.984056	1.000000
X147	1.000000	0.905844	1.000000	1.000000	1.000000	0.984056	1.000000
X198	0.984056	0.891259	0.984056	0.984056	0.984056	1.000000	0.984056
X222	1.000000	0.905844	1.000000	1.000000	1.000000	0.984056	1.000000

In [ ]:

```
#Dropping X66,  X113,   X134,   X147,   X198,   X222
X_train_15=X_train_15.drop((['X66',     'X113', 'X134', 'X147', 'X198'  ,'X222']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X216'] > 0.9, correlation_X['X216'] > 0.9]
```

Out[ ]:

	X62	X172	X216
X62	1.0	1.0	1.0
X172	1.0	1.0	1.0
X216	1.0	1.0	1.0

In [ ]:

```
#Dropping X216,X172
X_train_15=X_train_15.drop((['X216',    'X172']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X215'] > 0.9, correlation_X['X215'] > 0.9]
```

Out[ ]:

	X19	X215
X19	1.000000	0.994691
X215	0.994691	1.000000

In [ ]:

```
#Dropping X215
X_train_16=X_train_15.drop((['X215']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X213'] > 0.9, correlation_X['X213'] > 0.9]
```

Out[ ]:

	X67	X213
X67	1.0	1.0
X213	1.0	1.0

In [ ]:

```
#Dropping X213
X_train_16=X_train_16.drop((['X213']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X199'] > 0.9, correlation_X['X199'] > 0.9]
```

Out[ ]:

	X112	X199
X112	1.0	1.0
X199	1.0	1.0

In [ ]:

```
#Dropping X199
X_train_16=X_train_16.drop((['X199']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X194'] > 0.9, correlation_X['X194'] > 0.9]
```

Out[ ]:

	X187	X194
X187	1.000000	0.915586
X194	0.915586	1.000000

In [ ]:

```
#Dropping X194
X_train_16=X_train_16.drop((['X194']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X146'] > 0.9, correlation_X['X146'] > 0.9]
```

Out[ ]:

	X138	X140	X146
X138	1.000000	0.993923	1.000000
X140	0.993923	1.000000	0.993923
X146	1.000000	0.993923	1.000000

In [ ]:

```
#Dropping X146,X140
X_train_16=X_train_16.drop((['X146','X140']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X129'] > 0.9, correlation_X['X129'] > 0.9]
```

Out[ ]:

	X49	X129
X49	1.00000	0.99779
X129	0.99779	1.00000

In [ ]:

```
#Dropping X129
X_train_16=X_train_16.drop((['X129']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X120'] > 0.9, correlation_X['X120'] > 0.9]
```

Out[ ]:

	X61	X120
X61	1.000000	0.955973
X120	0.955973	1.000000

In [ ]:

```
#Dropping X120
X_train_16=X_train_16.drop((['X120']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X39'] > 0.9, correlation_X['X39'] > 0.9]
```

Out[ ]:

	X33	X39
X33	1.0	1.0
X39	1.0	1.0

In [ ]:

```
#Dropping X39
X_train_16=X_train_16.drop((['X39']),axis=1)
```

In [ ]:

```
#To find the next pair, we can subset the correlation_X.
correlation_X.loc[correlation_X['X37'] > 0.9, correlation_X['X37'] > 0.9]
```

Out[ ]:

	X31	X35	X37
X31	1.0	1.0	1.0
X35	1.0	1.0	1.0
X37	1.0	1.0	1.0

In [ ]:

```
#Dropping X37,X35
X_train_17=X_train_16.drop((['X37','X35']),axis=1)
```

In [ ]:

```
#Thus we have deleted all the variables that are highly correlated.
```

In [ ]:

```
#Dropping all these columns from the test data as well
droppables = ['X60','X248','X253','X385','X382','X378','X371','X53','X102','X214','X239','X368','X331','X346','X3
52','X240','X364','X363','X362','X360','X155','X358','X348',
'X328','X279','X276','X272','X162','X76','X54','X326','X226','X324','X137','X320','X249','X243','X242','X217','X1
22','X99','X94','X90','X314','X311','X119',
'X302','X299','X296','X266','X262','X264','X263','X254','X250','X247','X245','X244','X84','X378','X232','X227','X
66',    'X113', 'X134', 'X147', 'X198'  ,'X222',
'X216', 'X172','X215','X213','X199','X194','X146','X140','X129','X120','X39','X37','X35']

X_test = cars_test.drop((droppables),axis=1)
```

In [ ]:

```
print(X_train_17.shape)
print(y_train.shape)
```

```
(4209, 284)
(4209,)
```

In [ ]:

```
#Performing Linear Regression
lm=LinearRegression()
lm.fit(X_train_17,y_train)
```

Out[ ]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [ ]:

```
#Finding the RFE for 280 features
rfe =RFE(lm,280)
rfe=rfe.fit(X_train_17,y_train)
```

In [ ]:

```
#Listing the features, Support and Ranking.
list(zip(X_train_17.columns,rfe.support_,rfe.ranking_))
```

Out[ ]:

```
[('X0', True, 1),
 ('X1', True, 1),
 ('X2', False, 2),
 ('X3', True, 1),
 ('X4', True, 1),
 ('X5', True, 1),
 ('X6', True, 1),
 ('X8', False, 5),
 ('X10', True, 1),
 ('X12', True, 1),
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 ('X45', True, 1),
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```

```
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```
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('X379', True, 1),
('X380', True, 1),
('X383', True, 1),
('X384', True, 1)]
```

In [ ]:

```
X_train_17.columns[~rfe.support_]
```

Out[ ]:

```
Index(['X2', 'X8', 'X50', 'X225'], dtype='object')
```

In [ ]:

```
#Since RFE Support is 'False' for 'X1', 'X2', 'X5', 'X6', 'X8', 'X27', 'X275', 'X351', 'X361', we can eliminate t
hat as well
X_train_rfe = X_train_17.drop(['X1', 'X2', 'X5', 'X6', 'X8', 'X27', 'X275', 'X351', 'X361'],axis=1)
```

In [ ]:

```
# Adding a constant variable
X_train_lm= sm.add_constant(X_train_rfe)
```

In [ ]:

```
# Running the linear model
lm = sm.OLS(y_train, X_train_lm).fit()
```

In [ ]:

```
#Let's see the summary of our linear model
lm.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.590
Model:	OLS	**Adj. R-squared:**	0.565
Method:	Least Squares	**F-statistic:**	23.87
Date:	Thu, 14 Oct 2021	**Prob (F-statistic):**	0.00
Time:	20:45:32	**Log-Likelihood:**	-14788.
No. Observations:	4209	**AIC:**	3.006e+04
Df Residuals:	3969	**BIC:**	3.158e+04
Df Model:	239		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	29.1053	3.402	8.556	0.000	22.436	35.775
X0	0.0642	0.015	4.221	0.000	0.034	0.094
X3	-0.1029	0.125	-0.821	0.412	-0.349	0.143
X4	-0.4266	1.767	-0.241	0.809	-3.891	3.038
X10	5.3341	4.286	1.245	0.213	-3.069	13.737
X12	4.1357	2.980	1.388	0.165	-1.706	9.977
X13	1.7067	3.011	0.567	0.571	-4.196	7.609
X14	3.3535	3.131	1.071	0.284	-2.786	9.493
X15	9.2840	8.937	1.039	0.299	-8.237	26.805
X16	6.2089	4.328	1.435	0.151	-2.276	14.693
X17	0.9413	3.423	0.275	0.783	-5.770	7.653
X18	6.7927	4.783	1.420	0.156	-2.584	16.170
X19	2.5657	3.099	0.828	0.408	-3.511	8.642
X20	3.0069	2.960	1.016	0.310	-2.797	8.811
X21	-15.4570	7.448	-2.075	0.038	-30.060	-0.854
X22	2.6498	3.074	0.862	0.389	-3.376	8.676
X23	1.0570	3.215	0.329	0.742	-5.247	7.361
X24	-1.2170	3.597	-0.338	0.735	-8.268	5.834
X26	4.6841	4.716	0.993	0.321	-4.562	13.930
X28	4.8496	5.141	0.943	0.346	-5.230	14.929
X29	-0.7628	3.600	-0.212	0.832	-7.821	6.295
X30	-17.5868	14.854	-1.184	0.236	-46.709	11.535
X31	0.8946	0.559	1.600	0.110	-0.202	1.991

X32	7.2866	14.791	0.493	0.622	-21.712	36.285
X33	-8.5644	8.915	-0.961	0.337	-26.042	8.913
X34	8.8138	7.695	1.145	0.252	-6.273	23.901
X36	1.5839	4.000	0.396	0.692	-6.258	9.425
X38	-1.7299	0.792	-2.183	0.029	-3.284	-0.176
X40	-0.4995	4.560	-0.110	0.913	-9.439	8.440
X41	-0.0182	1.575	-0.012	0.991	-3.106	3.069
X42	3.9444	8.724	0.452	0.651	-13.160	21.048
X43	-0.0570	2.178	-0.026	0.979	-4.328	4.214
X44	-8.5224	7.439	-1.146	0.252	-23.106	6.062
X45	-4.7684	1.804	-2.644	0.008	-8.305	-1.232
X46	0.2739	0.402	0.682	0.496	-0.514	1.062
X47	5.6304	2.319	2.428	0.015	1.083	10.178
X48	9.3237	5.809	1.605	0.109	-2.065	20.713
X49	-0.0890	0.841	-0.106	0.916	-1.737	1.559
X50	-0.1401	0.580	-0.242	0.809	-1.277	0.996
X51	0.1859	0.470	0.395	0.693	-0.736	1.108
X52	-13.5232	13.837	-0.977	0.328	-40.652	13.606
X55	-2.8719	2.879	-0.998	0.319	-8.516	2.772
X56	-0.2244	1.298	-0.173	0.863	-2.770	2.321
X57	-2.7957	4.320	-0.647	0.518	-11.265	5.673
X58	0.9720	0.401	2.426	0.015	0.187	1.757
X59	-11.0739	7.245	-1.528	0.126	-25.279	3.131
X61	-14.4382	13.802	-1.046	0.296	-41.498	12.621
X62	-2.8461	5.518	-0.516	0.606	-13.664	7.972
X63	-0.7377	2.504	-0.295	0.768	-5.646	4.171
X64	-0.3540	0.429	-0.825	0.410	-1.195	0.487
X65	2.6518	3.095	0.857	0.392	-3.415	8.719
X67	2.2489	6.901	0.326	0.745	-11.282	15.779
X68	-0.1480	0.916	-0.162	0.872	-1.944	1.648
X69	-0.9268	1.563	-0.593	0.553	-3.992	2.138
X70	-0.9500	0.915	-1.039	0.299	-2.743	0.843
X71	2.2760	1.455	1.565	0.118	-0.576	5.128
X73	1.2222	1.062	1.151	0.250	-0.860	3.305
X74	9.9503	5.585	1.782	0.075	-0.999	20.900
X75	-3.3449	1.452	-2.304	0.021	-6.192	-0.498
X77	1.3741	1.490	0.922	0.356	-1.547	4.295
X78	-0.5908	3.521	-0.168	0.867	-7.495	6.313
X79	-3.6538	0.985	-3.708	0.000	-5.586	-1.722
X80	-2.9603	11.457	-0.258	0.796	-25.423	19.503
X81	-0.8254	0.593	-1.392	0.164	-1.988	0.337
X82	0.0735	1.401	0.052	0.958	-2.674	2.821
X83	-13.8744	15.227	-0.911	0.362	-43.727	15.978
X85	-1.2351	1.647	-0.750	0.453	-4.464	1.994
X86	7.2853	4.865	1.497	0.134	-2.254	16.824
X87	-0.7451	11.894	-0.063	0.950	-24.064	22.574
X88	2.2417	5.487	0.409	0.683	-8.516	12.999
X89	4.1471	7.085	0.585	0.558	-9.743	18.037
X91	-4.3168	3.855	-1.120	0.263	-11.874	3.241
X92	-12.3486	9.771	-1.264	0.206	-31.506	6.809
X95	28.1507	9.620	2.926	0.003	9.290	47.011
X96	0.8088	0.920	0.879	0.380	-0.996	2.613
X97	-9.6154	12.771	-0.753	0.452	-34.653	15.423
X98	-5.3410	6.715	-0.795	0.426	-18.507	7.825
X100	-0.8292	0.722	-1.149	0.251	-2.244	0.586

X100	-0.8292	0.722	-1.149	0.251	-2.244	0.586
X101	-13.3040	10.684	-1.245	0.213	-34.250	7.642
X103	-0.4278	3.185	-0.134	0.893	-6.673	5.817
X104	6.7796	3.097	2.189	0.029	0.707	12.852
X105	6.5458	3.988	1.641	0.101	-1.274	14.365
X106	-0.7815	1.712	-0.457	0.648	-4.138	2.575
X108	1.9937	2.027	0.984	0.325	-1.980	5.967
X109	0.7225	1.225	0.590	0.555	-1.678	3.123
X110	1.4295	4.601	0.311	0.756	-7.591	10.450
X111	16.8881	4.930	3.426	0.001	7.223	26.553
X112	2.8935	4.893	0.591	0.554	-6.699	12.486
X114	-0.4613	0.802	-0.575	0.565	-2.033	1.111
X115	10.0749	1.265	7.966	0.000	7.595	12.554
X116	-0.1817	0.673	-0.270	0.787	-1.502	1.139
X117	5.9489	1.385	4.294	0.000	3.233	8.665
X118	13.8444	1.257	11.017	0.000	11.381	16.308
X123	9.0170	2.425	3.718	0.000	4.262	13.772
X124	0.2766	6.639	0.042	0.967	-12.739	13.292
X125	-2.0459	6.811	-0.300	0.764	-15.400	11.308
X126	3.9401	7.228	0.545	0.586	-10.231	18.111
X127	-1.4718	3.563	-0.413	0.680	-8.457	5.513
X128	5.8745	3.368	1.744	0.081	-0.728	12.477
X130	23.2308	3.481	6.674	0.000	16.406	30.055
X131	2.7223	1.687	1.614	0.107	-0.585	6.030
X132	2.3407	1.474	1.587	0.112	-0.550	5.231
X133	7.5895	1.388	5.469	0.000	4.869	10.310
X135	2.2042	1.842	1.197	0.231	-1.407	5.815
X136	5.5233	3.153	1.752	0.080	-0.658	11.705
X138	6.4431	3.484	1.849	0.064	-0.388	13.274
X139	2.5782	1.810	1.424	0.154	-0.970	6.127
X141	0.2619	1.263	0.207	0.836	-2.215	2.739
X142	14.4287	1.713	8.425	0.000	11.071	17.786
X143	7.2847	2.850	2.556	0.011	1.697	12.872
X144	3.4757	1.762	1.973	0.049	0.022	6.929
X145	2.3057	4.545	0.507	0.612	-6.604	11.216
X148	-2.2273	1.356	-1.642	0.101	-4.886	0.431
X150	-0.5426	1.458	-0.372	0.710	-3.401	2.316
X151	0.6213	0.542	1.146	0.252	-0.442	1.684
X152	3.2567	1.328	2.452	0.014	0.652	5.861
X153	-1.1386	6.446	-0.177	0.860	-13.777	11.500
X154	0.7381	1.709	0.432	0.666	-2.612	4.088
X156	14.8194	1.710	8.669	0.000	11.468	18.171
X157	14.2859	1.724	8.287	0.000	10.906	17.666
X158	14.6766	1.720	8.532	0.000	11.304	18.049
X159	-1.5592	2.688	-0.580	0.562	-6.829	3.711
X160	-3.2693	3.578	-0.914	0.361	-10.284	3.746
X161	0.9040	3.364	0.269	0.788	-5.691	7.499
X163	-1.7883	0.541	-3.306	0.001	-2.849	-0.728
X164	-0.4295	2.184	-0.197	0.844	-4.711	3.852
X165	-1.8077	4.742	-0.381	0.703	-11.104	7.489
X166	6.2482	3.137	1.992	0.046	0.098	12.398
X167	4.9988	5.434	0.920	0.358	-5.654	15.652
X168	-1.3460	4.110	-0.328	0.743	-9.403	6.711
X169	7.1592	2.997	2.389	0.017	1.284	13.034
X170	-0.9417	5.395	-0.175	0.861	-11.518	9.635

X171	-0.3173	4.105	-0.077	0.938	-8.366	7.731
X173	0.3524	2.266	0.155	0.876	-4.091	4.796
X174	6.8436	1.852	3.694	0.000	3.212	10.475
X175	0.3024	2.414	0.125	0.900	-4.431	5.036
X176	0.0175	1.339	0.013	0.990	-2.608	2.643
X177	-0.2784	1.145	-0.243	0.808	-2.524	1.967
X178	-21.9892	8.721	-2.522	0.012	-39.086	-4.892
X179	-26.2020	9.265	-2.828	0.005	-44.367	-8.037
X180	7.4358	1.224	6.074	0.000	5.036	9.836
X181	1.0653	2.243	0.475	0.635	-3.331	5.462
X182	-1.0323	1.087	-0.949	0.342	-3.164	1.099
X183	1.2181	5.390	0.226	0.821	-9.349	11.785
X184	-13.7816	8.949	-1.540	0.124	-31.327	3.764
X185	1.7731	1.822	0.973	0.331	-1.800	5.346
X186	4.2121	1.864	2.259	0.024	0.557	7.867
X187	1.3112	1.841	0.712	0.476	-2.298	4.921
X189	6.6373	2.931	2.264	0.024	0.890	12.385
X190	-5.0114	8.574	-0.584	0.559	-21.821	11.798
X191	0.9910	1.273	0.779	0.436	-1.504	3.486
X192	-0.8056	3.004	-0.268	0.789	-6.694	5.083
X195	3.8813	1.547	2.509	0.012	0.849	6.914
X196	5.3272	1.531	3.480	0.001	2.326	8.328
X197	-1.8528	2.309	-0.802	0.422	-6.380	2.674
X200	-1.0346	3.644	-0.284	0.776	-8.178	6.109
X201	-3.8278	1.712	-2.236	0.025	-7.184	-0.472
X202	-1.1727	4.176	-0.281	0.779	-9.359	7.014
X203	-1.4501	2.467	-0.588	0.557	-6.287	3.386
X204	28.6254	5.287	5.414	0.000	18.260	38.991
X205	0.4799	4.279	0.112	0.911	-7.909	8.869
X206	-2.6611	1.129	-2.356	0.019	-4.875	-0.447
X207	13.6260	6.179	2.205	0.028	1.511	25.741
X208	2.1407	3.579	0.598	0.550	-4.876	9.158
X209	6.0539	1.570	3.855	0.000	2.975	9.133
X210	-29.1983	12.968	-2.252	0.024	-54.624	-3.773
X211	0.5854	2.028	0.289	0.773	-3.390	4.561
X212	-0.8294	2.172	-0.382	0.703	-5.088	3.429
X218	0.4866	0.534	0.911	0.362	-0.561	1.534
X219	-0.2891	1.024	-0.282	0.778	-2.296	1.718
X220	0.0126	0.469	0.027	0.978	-0.907	0.932
X221	0.0302	3.083	0.010	0.992	-6.014	6.074
X223	-1.0732	0.741	-1.449	0.148	-2.526	0.379
X224	0.0159	0.715	0.022	0.982	-1.386	1.418
X225	-0.0230	0.576	-0.040	0.968	-1.152	1.106
X228	-2.0121	3.127	-0.644	0.520	-8.142	4.118
X229	-1.6551	3.058	-0.541	0.588	-7.650	4.340
X230	0.0961	2.028	0.047	0.962	-3.880	4.072
X231	0.3341	1.212	0.276	0.783	-2.041	2.710
X234	1.1861	1.072	1.107	0.268	-0.915	3.287
X236	24.3449	5.392	4.515	0.000	13.774	34.916
X237	4.0912	7.730	0.529	0.597	-11.064	19.247
X238	-2.3134	8.005	-0.289	0.773	-18.009	13.382
X241	-1.1907	1.512	-0.787	0.431	-4.156	1.774
X246	0.3715	0.920	0.404	0.686	-1.432	2.175
X251	-21.5902	8.957	-2.410	0.016	-39.151	-4.030
X252	5.8234	6.539	0.891	0.373	-6.996	18.643

X255	-1.3642	5.149	-0.265	0.791	-11.459	8.730
X256	-0.7852	2.721	-0.289	0.773	-6.119	4.549
X257	-23.0958	15.263	-1.513	0.130	-53.021	6.829
X258	0.6793	5.732	0.119	0.906	-10.558	11.917
X259	-6.9888	7.913	-0.883	0.377	-22.503	8.526
X260	3.5499	8.992	0.395	0.693	-14.080	21.180
X261	7.7267	4.096	1.887	0.059	-0.303	15.757
X265	1.8612	4.796	0.388	0.698	-7.542	11.264
X267	2.2555	2.719	0.830	0.407	-3.075	7.586
X269	-4.6560	6.965	-0.668	0.504	-18.312	9.000
X270	-4.2700	8.876	-0.481	0.630	-21.671	13.131
X271	3.2502	3.432	0.947	0.344	-3.478	9.979
X273	-0.4816	0.559	-0.862	0.389	-1.577	0.614
X274	1.9113	2.470	0.774	0.439	-2.932	6.754
X277	-4.9372	7.070	-0.698	0.485	-18.798	8.924
X278	0.1125	6.664	0.017	0.987	-12.953	13.178
X280	8.0136	7.330	1.093	0.274	-6.358	22.385
X281	-0.8387	2.936	-0.286	0.775	-6.594	4.917
X282	0.7881	2.758	0.286	0.775	-4.620	6.196
X283	3.5714	1.251	2.854	0.004	1.118	6.025
X284	5.5497	2.619	2.119	0.034	0.415	10.684
X285	4.1286	1.200	3.439	0.001	1.775	6.482
X286	2.4351	1.695	1.437	0.151	-0.887	5.758
X287	-1.3124	1.984	-0.661	0.508	-5.202	2.578
X288	0.0607	8.750	0.007	0.994	-17.094	17.215
X291	-1.1174	1.342	-0.833	0.405	-3.749	1.514
X292	-2.8448	1.481	-1.920	0.055	-5.749	0.059
X294	0.3143	0.870	0.361	0.718	-1.391	2.019
X295	-6.9825	8.925	-0.782	0.434	-24.480	10.515
X298	-1.1599	1.997	-0.581	0.561	-5.076	2.756
X300	-0.6240	0.660	-0.946	0.344	-1.917	0.669
X301	1.6878	0.748	2.257	0.024	0.221	3.154
X304	17.7551	8.859	2.004	0.045	0.386	35.124
X305	10.4961	6.878	1.526	0.127	-2.988	23.980
X306	9.2625	6.190	1.496	0.135	-2.874	21.399
X307	-12.7141	9.338	-1.362	0.173	-31.021	5.593
X308	1.6536	6.212	0.266	0.790	-10.526	13.833
X309	2.6521	6.061	0.438	0.662	-9.231	14.535
X310	5.1758	3.138	1.649	0.099	-0.977	11.328
X312	2.5031	5.888	0.425	0.671	-9.042	14.048
X313	-7.1992	3.567	-2.018	0.044	-14.193	-0.206
X315	11.5590	4.147	2.787	0.005	3.428	19.690
X316	-8.0541	3.564	-2.260	0.024	-15.041	-1.067
X317	0.8521	8.117	0.105	0.916	-15.062	16.767
X318	-2.4840	6.827	-0.364	0.716	-15.870	10.902
X319	-2.1593	6.272	-0.344	0.731	-14.455	10.137
X321	-0.5085	1.364	-0.373	0.709	-3.183	2.166
X322	0.9762	1.538	0.635	0.526	-2.039	3.992
X323	-1.0887	1.641	-0.664	0.507	-4.305	2.128
X325	-1.2652	4.596	-0.275	0.783	-10.277	7.746
X327	1.4526	0.825	1.760	0.079	-0.166	3.071
X329	-0.8754	1.900	-0.461	0.645	-4.601	2.851
X332	-1.7136	4.914	-0.349	0.727	-11.347	7.920
X333	0.4320	2.609	0.166	0.869	-4.684	5.548
X334	6.1942	1.897	3.266	0.001	2.476	9.912

X335	7.4814	2.774	2.697	0.007	2.043	12.920
X336	-2.5815	1.681	-1.536	0.125	-5.877	0.713
X337	8.5861	1.350	6.358	0.000	5.938	11.234
X338	-4.4789	2.119	-2.113	0.035	-8.634	-0.324
X339	37.6149	12.819	2.934	0.003	12.482	62.748
X340	-0.5529	2.821	-0.196	0.845	-6.084	4.978
X341	-1.7417	2.076	-0.839	0.402	-5.812	2.328
X342	-1.9721	1.861	-1.060	0.289	-5.621	1.677
X343	1.0076	2.366	0.426	0.670	-3.632	5.647
X344	-3.2293	2.981	-1.083	0.279	-9.074	2.616
X345	0.9124	1.868	0.489	0.625	-2.749	4.574
X349	1.9571	1.895	1.033	0.302	-1.758	5.672
X350	0.5599	0.562	0.997	0.319	-0.541	1.661
X353	1.9898	3.302	0.603	0.547	-4.484	8.463
X354	0.0676	0.541	0.125	0.901	-0.994	1.129
X355	0.2823	1.237	0.228	0.820	-2.143	2.708
X356	0.2000	2.152	0.093	0.926	-4.019	4.419
X357	-2.7972	8.723	-0.321	0.748	-19.899	14.305
X359	-1.2256	0.982	-1.248	0.212	-3.152	0.701
X365	9.2111	3.704	2.487	0.013	1.949	16.473
X366	-3.9174	6.239	-0.628	0.530	-16.149	8.314
X367	-0.6584	3.021	-0.218	0.827	-6.581	5.264
X369	-4.4963	6.858	-0.656	0.512	-17.941	8.949
X370	-0.0506	4.091	-0.012	0.990	-8.072	7.970
X372	-0.9598	7.173	-0.134	0.894	-15.023	13.103
X373	3.6902	2.616	1.410	0.158	-1.439	8.820
X374	3.9733	1.848	2.150	0.032	0.351	7.596
X375	6.1861	1.449	4.269	0.000	3.345	9.027
X376	7.3344	2.459	2.983	0.003	2.514	12.155
X377	3.0509	2.440	1.251	0.211	-1.732	7.834
X379	4.7332	3.435	1.378	0.168	-2.002	11.468
X380	2.1171	2.979	0.711	0.477	-3.723	7.957
X383	9.3202	3.674	2.537	0.011	2.118	16.523
X384	-1.1200	7.861	-0.142	0.887	-16.533	14.293

Omnibus:	4020.908	**Durbin-Watson:**	1.974
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	481806.104
Skew:	4.227	**Prob(JB):**	0.00
Kurtosis:	54.728	**Cond. No.**	2.21e+17

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 9.61e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [ ]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [ ]:

```
# Calculate the VIFs for the new model
# Create a dataframe that will contain the names of all the feature variables and their respective VIFs
vif = pd.DataFrame()
X = X_train_lm
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
vif['VIF'] = round(vif['VIF'],2)
vif = vif.sort_values(by='VIF', ascending = False)


x=vif
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(x)
```

	Features	VIF
118	X156	inf
98	X128	inf
92	X118	inf
93	X123	inf
181	X237	inf
180	X236	inf
96	X126	inf
97	X127	inf
99	X130	inf
89	X115	inf
100	X131	inf
101	X132	inf
102	X133	inf
251	X344	inf
104	X136	inf
105	X138	inf
91	X117	inf
187	X255	inf
176	X229	inf
191	X259	inf
194	X265	inf
193	X261	inf
75	X97	inf
76	X98	inf
192	X260	inf
78	X101	inf
190	X258	inf
87	X112	inf
81	X105	inf
189	X257	inf
83	X108	inf
84	X109	inf
85	X110	inf
86	X111	inf
106	X139	inf
108	X142	inf
143	X183	inf
134	X174	inf
128	X167	inf
129	X168	inf
130	X169	inf
131	X170	inf
132	X171	inf

133	X173	inf
148	X189	inf
126	X165	inf
136	X176	inf
137	X177	inf
147	X187	inf
146	X186	inf
140	X180	inf
145	X185	inf
127	X166	inf
152	X195	inf
109	X143	inf
160	X205	inf
110	X144	inf
175	X228	inf
252	X345	inf
164	X209	inf
163	X208	inf
162	X207	inf
117	X154	inf
153	X196	inf
159	X204	inf
119	X157	inf
120	X158	inf
156	X201	inf
122	X160	inf
155	X200	inf
72	X92	inf
265	X370	inf
70	X89	inf
26	X36	inf
20	X29	inf
21	X30	inf
228	X315	inf
23	X32	inf
272	X379	inf
25	X34	inf
271	X377	inf
18	X26	inf
28	X40	inf
29	X41	inf
270	X376	inf
227	X313	inf
32	X44	inf
225	X310	inf
19	X28	inf
17	X24	inf
223	X308	inf
8	X15	inf
230	X317	inf
273	X380	inf
4	X10	inf
5	X12	inf
229	X316	inf

7	X14	inf
9	X16	inf
16	X23	inf
10	X17	inf
11	X18	inf
12	X19	inf
13	X20	inf
14	X21	inf
15	X22	inf
224	X309	inf
36	X48	inf
249	X342	inf
267	X373	inf
206	X283	inf
268	X374	inf
57	X74	inf
205	X282	inf
59	X77	inf
204	X281	inf
62	X80	inf
208	X285	inf
203	X280	inf
246	X339	inf
65	X83	inf
201	X277	inf
67	X86	inf
248	X341	inf
207	X284	inf
144	X184	inf
222	X307	inf
243	X336	inf
221	X306	inf
220	X305	inf
219	X304	inf
240	X333	inf
241	X334	inf
242	X335	inf
45	X59	inf
209	X286	inf
244	X337	inf
47	X62	inf
48	X63	inf
245	X338	inf
269	X375	inf
51	X67	inf
185	X251	1153.08
138	X178	1129.27
46	X61	504.12
40	X52	466.77
182	X238	296.38
139	X179	236.07
157	X202	192.17
123	X161	108.01
79	X103	103.24
238	X329	53.44

258	X356	41.12
66	X85	39.44
33	X45	37.03
188	X256	30.22
6	X13	29.79
263	X367	26.98
141	X181	25.74
250	X343	24.35
150	X191	24.29
257	X355	21.71
113	X150	21.05
233	X321	20.36
31	X43	19.14
125	X164	16.81
43	X57	14.74
69	X88	12.82
184	X246	12.32
183	X241	12.08
55	X71	11.83
179	X234	11.13
247	X340	10.46
154	X197	10.04
74	X96	9.35
253	X349	9.27
226	X312	8.89
95	X125	8.60
172	X223	8.16
68	X87	8.08
135	X175	7.66
236	X325	7.21
142	X182	6.75
77	X100	6.70
173	X224	6.67
158	X203	6.07
121	X159	5.81
259	X357	5.43
103	X135	5.38
214	X294	4.98
88	X114	4.83
112	X148	4.75
237	X327	4.59
171	X221	4.58
37	X49	4.56
58	X75	4.42
90	X116	4.31
217	X300	4.30
53	X69	4.27
254	X350	4.25
60	X78	4.23
35	X47	4.10
195	X267	3.98
169	X219	3.97
199	X273	3.79
63	X81	3.74
124	X163	3.72

210	X287	3.71
54	X70	3.71
168	X218	3.69
166	X211	3.65
200	X274	3.63
52	X68	3.44
38	X50	3.40
22	X31	3.36
115	X152	3.32
170	X220	3.26
234	X322	3.04
2	X3	2.86
256	X354	2.85
262	X366	2.78
39	X51	2.68
1	X0	2.63
49	X64	2.60
41	X55	2.59
165	X210	2.40
44	X58	2.36
261	X365	2.35
34	X46	2.34
82	X106	2.27
42	X56	2.10
231	X318	2.00
64	X82	1.99
186	X252	1.83
260	X359	1.79
116	X153	1.78
275	X384	1.77
111	X145	1.77
174	X225	1.75
167	X212	1.54
198	X271	1.51
218	X301	1.50
235	X323	1.49
71	X91	1.49
266	X372	1.47
161	X206	1.45
61	X79	1.43
178	X231	1.40
255	X353	1.40
196	X269	1.39
114	X151	1.38
107	X141	1.35
274	X383	1.35
264	X369	1.34
56	X73	1.33
73	X95	1.32
151	X192	1.29
177	X230	1.29
202	X278	1.27
94	X124	1.26
50	X65	1.23
27	X38	1.22

213	X292	1.18
24	X33	1.14
215	X295	1.14
197	X270	1.13
212	X291	1.12
232	X319	1.12
80	X104	1.10
211	X288	1.09
30	X42	1.09
216	X298	1.08
149	X190	1.05
239	X332	1.04
3	X4	1.03
0	const	0.00

In [ ]:

```
#Eliminating the columns that have high P value

P_cols = ['X3','X4','X10','X12','X13','X14','X15','X16','X17','X18','X19','X20','X22','X23','X24','X26','X28','X29','X30','X31','X32','X33','X34','X36','X40','X41',
'X42','X43','X44','X46','X48','X49','X50','X51','X52','X55','X56','X57','X59','X61','X62','X63','X64','X65','X67','X68','X69','X70','X71','X73','X74',
'X77','X78','X80','X81','X82','X83','X85','X86','X87','X88','X89','X91','X92','X96','X97','X98','X100','X101','X103','X105','X106','X108','X109',
'X110','X112','X114','X116','X124','X125','X126','X127','X128','X131','X132','X135','X136','X138','X139','X141','X145','X148','X150','X151',
'X153','X154','X159','X160','X161','X164','X165','X167','X168','X170','X171','X173','X175','X176','X177','X181','X182','X183','X184','X185','X187',
'X190','X191','X192','X197','X200','X202','X203','X205','X208','X211','X212','X218','X219','X220','X221','X223','X224','X225','X228','X229','X230',
'X231','X234','X237','X238','X241','X246','X252','X255','X256','X257','X258','X259','X260','X261','X265','X267','X269','X270','X271','X273','X274',
'X277','X278','X280','X281','X282','X286','X287','X288','X291','X292','X294','X295','X298','X300','X305','X306','X307','X308','X309','X310','X312',
'X317','X318','X319','X321','X322','X323','X325','X327','X329','X332','X333','X336','X340','X341','X342','X343','X344','X345','X349','X350','X353',
'X354','X355','X356','X357','X359','X366','X367','X369','X370','X372','X373','X377','X379','X380','X384']

X_vif_1 = X.drop(P_cols,axis=1)
```

In [ ]:

```
# Running the linear model
lm = sm.OLS(y_train, X_vif_1).fit()
```

In [ ]:

```
#Let's see the summary of our linear model
lm.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.576
Model:	OLS	**Adj. R-squared:**	0.570
Method:	Least Squares	**F-statistic:**	99.05
Date:	Thu, 14 Oct 2021	**Prob (F-statistic):**	0.00
Time:	20:46:47	**Log-Likelihood:**	-14855.
No. Observations:	4209	**AIC:**	2.983e+04
Df Residuals:	4151	**BIC:**	3.019e+04
Df Model:	57		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	44.5690	4.004	11.132	0.000	36.720	52.418
X0	0.0532	0.013	3.946	0.000	0.027	0.080
X21	2.7268	3.014	0.905	0.366	-3.183	8.637

X38	-1.9466	0.736	-2.644	0.008	-3.390	-0.503
X45	-5.1457	1.333	-3.860	0.000	-7.759	-2.532
X47	7.7150	1.199	6.433	0.000	5.364	10.066
X58	0.7471	0.319	2.345	0.019	0.123	1.372
X75	-1.6153	1.131	-1.428	0.153	-3.833	0.603
X79	-3.4706	0.929	-3.738	0.000	-5.291	-1.650
X95	24.6843	8.328	2.964	0.003	8.357	41.011
X104	7.9392	2.991	2.655	0.008	2.076	13.802
X111	-3.6825	1.987	-1.853	0.064	-7.578	0.213
X115	11.3772	0.996	11.420	0.000	9.424	13.330
X117	8.9159	1.125	7.924	0.000	6.710	11.122
X118	15.5799	0.975	15.979	0.000	13.668	17.491
X123	5.1683	2.898	1.783	0.075	-0.514	10.850
X130	17.5835	1.875	9.377	0.000	13.907	21.260
X133	5.3005	1.391	3.811	0.000	2.574	8.027
X142	22.0529	2.018	10.928	0.000	18.097	26.009
X143	-2.0283	1.027	-1.975	0.048	-4.042	-0.015
X144	-0.0111	0.491	-0.023	0.982	-0.973	0.951
X152	1.2767	0.800	1.596	0.110	-0.291	2.845
X156	22.4967	2.007	11.208	0.000	18.562	26.432
X157	22.0723	2.012	10.972	0.000	18.128	26.016
X158	22.5161	2.004	11.235	0.000	18.587	26.445
X163	-1.1973	0.352	-3.399	0.001	-1.888	-0.507
X166	1.1771	2.334	0.504	0.614	-3.399	5.753
X169	2.4865	2.760	0.901	0.368	-2.925	7.898
X174	9.7657	1.402	6.966	0.000	7.017	12.514
X178	-21.4798	8.415	-2.553	0.011	-37.977	-4.982
X179	-19.8843	8.539	-2.329	0.020	-36.625	-3.143
X180	5.3489	1.273	4.202	0.000	2.853	7.844
X186	-0.1984	0.894	-0.222	0.824	-1.950	1.554
X189	18.2896	1.390	13.157	0.000	15.564	21.015
X195	0.3131	1.428	0.219	0.827	-2.487	3.114
X196	1.9891	1.540	1.291	0.197	-1.031	5.009
X201	-1.5238	0.611	-2.492	0.013	-2.723	-0.325
X204	32.5782	8.765	3.717	0.000	15.394	49.763
X206	-2.5915	1.022	-2.537	0.011	-4.595	-0.589
X207	10.4622	8.548	1.224	0.221	-6.296	27.220
X209	-0.5362	0.845	-0.634	0.526	-2.193	1.121
X210	-29.6489	11.847	-2.503	0.012	-52.876	-6.422
X236	22.2987	8.934	2.496	0.013	4.783	39.814
X251	-21.6846	8.408	-2.579	0.010	-38.169	-5.200
X283	-0.2542	0.924	-0.275	0.783	-2.066	1.558
X284	0.3148	1.125	0.280	0.780	-1.891	2.521
X285	-0.0073	0.861	-0.008	0.993	-1.694	1.680
X301	2.0772	0.705	2.948	0.003	0.696	3.459
X304	1.1106	0.920	1.207	0.228	-0.694	2.915
X313	-16.1439	0.425	-37.982	0.000	-16.977	-15.311
X315	3.4815	0.909	3.830	0.000	1.699	5.264
X316	-17.0788	0.409	-41.791	0.000	-17.880	-16.278
X334	11.2691	1.233	9.137	0.000	8.851	13.687
X335	11.3338	2.126	5.330	0.000	7.165	15.503
X337	12.2004	1.207	10.111	0.000	9.835	14.566
X338	-1.8551	1.616	-1.148	0.251	-5.024	1.314
X339	37.4353	11.826	3.166	0.002	14.250	60.621
X365	8.2682	2.453	3.370	0.001	3.459	13.078

X374	0.1609	0.838	0.192	0.848	-1.483	1.804
X375	0.0092	0.781	0.012	0.991	-1.522	1.541
X376	0.8211	0.840	0.977	0.329	-0.827	2.469
X383	13.9656	3.222	4.334	0.000	7.649	20.282

Omnibus:	4043.688	**Durbin-Watson:**	1.966
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	486008.199
Skew:	4.268	**Prob(JB):**	0.00
Kurtosis:	54.946	**Cond. No.**	1.10e+16

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 3.76e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [ ]:

```
# Calculate the VIFs for the new model
# Create a dataframe that will contain the names of all the feature variables and their respective VIFs
vif = pd.DataFrame()
X = X_vif_1
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
vif['VIF'] = round(vif['VIF'],2)
vif = vif.sort_values(by='VIF', ascending = False)


x=vif
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(x)
```

	Features	VIF
28	X174	inf
18	X142	inf
22	X156	inf
14	X118	inf
13	X117	inf
12	X115	inf
23	X157	inf
24	X158	inf
16	X130	inf
33	X189	inf
52	X334	inf
53	X335	inf
54	X337	inf
29	X178	1064.80
43	X251	1029.05
30	X179	203.06
4	X45	20.48
31	X180	13.14
17	X133	12.83
32	X186	12.11
26	X166	10.68
59	X375	8.08
58	X374	7.52
46	X285	7.38
44	X283	6.29
11	X111	5.91
40	X209	3.97
48	X304	3.62

36	X201	3.33
27	X169	3.07
45	X284	3.04
7	X75	2.72
19	X143	2.37
49	X313	2.32
60	X376	2.32
42	X236	2.31
20	X144	2.28
1	X0	2.09
41	X210	2.03
56	X339	2.02
25	X163	1.60
51	X316	1.60
6	X58	1.51
35	X196	1.46
2	X21	1.44
34	X195	1.43
50	X315	1.41
47	X301	1.35
15	X123	1.33
8	X79	1.29
21	X152	1.22
38	X206	1.20
37	X204	1.11
5	X47	1.11
55	X338	1.09
3	X38	1.06
39	X207	1.06
61	X383	1.05
57	X365	1.04
10	X104	1.03
9	X95	1.00
0	const	0.00

In [ ]:

```
#Eliminating the columns that have vif as'inf'

P_cols = ['X174','X142','X156','X118','X117','X115','X157','X158','X130','X189','X334','X335','X337']
X_vif_2 = X_vif_1.drop(P_cols,axis=1)
```

In [ ]:

```
# Calculate the VIFs for the new model
# Create a dataframe that will contain the names of all the feature variables and their respective VIFs
vif = pd.DataFrame()
X = X_vif_2
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
vif['VIF'] = round(vif['VIF'],2)
vif = vif.sort_values(by='VIF', ascending = False)


x=vif
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(x)
```

	Features	VIF
0	const	4521.29
20	X178	1064.01
33	X251	1028.53
21	X179	200.76
4	X45	17.35
13	X133	10.91
22	X180	10.26
23	X186	9.56
36	X285	6.06
34	X283	4.95
11	X111	3.98
30	X209	3.91
38	X304	3.45
46	X375	3.29
45	X374	3.26
26	X201	3.21
7	X75	2.64
35	X284	2.61
14	X143	2.34
47	X376	2.25
15	X144	2.22
39	X313	2.16
32	X236	2.14
31	X210	2.03
43	X339	2.02
1	X0	1.92
18	X166	1.77
17	X163	1.58
41	X316	1.51
6	X58	1.47
25	X196	1.36
24	X195	1.31
12	X123	1.29
19	X169	1.27
2	X21	1.27
40	X315	1.26
37	X301	1.26
8	X79	1.21
28	X206	1.20
16	X152	1.16
27	X204	1.11
5	X47	1.10
42	X338	1.08
29	X207	1.06
3	X38	1.05
48	X383	1.04
44	X365	1.03
10	X104	1.03
9	X95	1.00

In [ ]:

```
#Eliminating the columns that have vif >11

P_cols = ['X178','X251','X179','X45']
X_vif_3 = X_vif_2.drop(P_cols,axis=1)
```

In [ ]:

```
# Calculate the VIFs for the new model
# Create a dataframe that will contain the names of all the feature variables and their respective VIFs
vif = pd.DataFrame()
X = X_vif_3
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
vif['VIF'] = round(vif['VIF'],2)
vif = vif.sort_values(by='VIF', ascending = False)


x=vif
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(x)
```

	Features	VIF
0	const	154.96
20	X186	8.43
32	X285	5.76
30	X283	4.76
27	X209	3.87
10	X111	3.46
42	X375	3.24
41	X374	3.23
23	X201	3.13
6	X75	2.55
34	X304	2.42
31	X284	2.31
13	X143	2.30
12	X133	2.23
29	X236	2.14
14	X144	2.13
43	X376	2.06
39	X339	2.02
35	X313	2.00
1	X0	1.91
19	X180	1.76
17	X166	1.67
16	X163	1.46
37	X316	1.44
5	X58	1.40
22	X196	1.34
21	X195	1.31
18	X169	1.26
36	X315	1.26
33	X301	1.25
2	X21	1.20
25	X206	1.20
7	X79	1.19
15	X152	1.13
24	X204	1.11
4	X47	1.07
11	X123	1.07
38	X338	1.07
26	X207	1.06
3	X38	1.04
44	X383	1.04
40	X365	1.03
9	X104	1.03
8	X95	1.00
28	X210	1.00

In [ ]:

```
# Running the linear model
lm = sm.OLS(y_train, X_vif_3).fit()
```

In [ ]:

```
#Let's see the summary of our linear model
lm.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.533
Model:	OLS	**Adj. R-squared:**	0.528
Method:	Least Squares	**F-statistic:**	108.0
Date:	Thu, 14 Oct 2021	**Prob (F-statistic):**	0.00
Time:	20:46:51	**Log-Likelihood:**	-15060.
No. Observations:	4209	**AIC:**	3.021e+04
Df Residuals:	4164	**BIC:**	3.050e+04
Df Model:	44		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	115.2134	1.671	68.932	0.000	111.937	118.490
X0	0.0878	0.013	6.504	0.000	0.061	0.114
X21	2.5575	2.885	0.886	0.375	-3.099	8.214
X38	-2.1624	0.764	-2.832	0.005	-3.660	-0.665
X47	8.3309	1.237	6.737	0.000	5.906	10.755
X58	0.9505	0.321	2.960	0.003	0.321	1.580
X75	-1.6544	1.150	-1.439	0.150	-3.909	0.600
X79	-5.4079	0.937	-5.774	0.000	-7.244	-3.572
X95	25.6333	8.724	2.938	0.003	8.529	42.737
X104	7.5138	3.130	2.400	0.016	1.376	13.651
X111	-7.3453	1.595	-4.605	0.000	-10.473	-4.218
X123	1.2977	2.722	0.477	0.634	-4.038	6.633
X133	0.6710	0.607	1.105	0.269	-0.520	1.862
X143	-2.3906	1.061	-2.253	0.024	-4.471	-0.310
X144	0.2509	0.497	0.504	0.614	-0.724	1.226
X152	-0.6056	0.809	-0.749	0.454	-2.191	0.980
X163	-0.8259	0.353	-2.337	0.019	-1.519	-0.133
X166	-30.5233	0.967	-31.555	0.000	-32.420	-28.627
X169	-29.4346	1.853	-15.889	0.000	-33.066	-25.803
X180	0.1937	0.488	0.397	0.691	-0.763	1.150
X186	-0.9382	0.782	-1.200	0.230	-2.471	0.595
X195	0.5972	1.430	0.418	0.676	-2.206	3.401
X196	1.5132	1.545	0.980	0.327	-1.515	4.542
X201	-1.8223	0.622	-2.930	0.003	-3.042	-0.603
X204	33.4189	9.166	3.646	0.000	15.448	51.390
X206	-2.2919	1.069	-2.143	0.032	-4.388	-0.196
X207	10.3330	8.955	1.154	0.249	-7.224	27.890
X209	-0.6494	0.875	-0.742	0.458	-2.364	1.066
X210	-10.5017	8.731	-1.203	0.229	-27.620	6.617
X236	50.8905	9.021	5.641	0.000	33.205	68.576
X283	0.5782	0.843	0.686	0.493	-1.074	2.230
X284	0.3718	1.028	0.362	0.718	-1.644	2.388
X285	-0.1717	0.797	-0.215	0.830	-1.735	1.392
X301	-0.1118	0.710	-0.157	0.875	-1.505	1.281
X304	-0.7509	0.789	-0.952	0.341	-2.297	0.795
X313	-16.1137	0.413	-38.970	0.000	-16.924	-15.303
X315	4.8492	0.902	5.376	0.000	3.081	6.618
X316	-16.2236	0.406	-39.978	0.000	-17.019	-15.428
X338	-2.0890	1.683	-1.242	0.214	-5.388	1.210
X339	34.2962	12.378	2.771	0.006	10.029	58.564
X365	6.8608	2.554	2.686	0.007	1.853	11.869
X374	0.9736	0.575	1.692	0.091	-0.155	2.102
X375	1.2564	0.518	2.424	0.015	0.240	2.273

X376	1.8805	0.829	2.268	0.023	0.255	3.506
X383	13.3895	3.357	3.988	0.000	6.808	19.971

Omnibus:	3563.208	**Durbin-Watson:**	1.985
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	316993.266
Skew:	3.530	**Prob(JB):**	0.00
Kurtosis:	44.925	**Cond. No.**	3.48e+03

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.48e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [ ]:

```
#Dropping all the columns which we dropped in train data from test data as well
#Eliminating the columns that have high P value

P_cols = ['X3','X4','X10','X12','X13','X14','X15','X16','X17','X18','X19','X20','X22','X23','X24','X26','X28','X2
9','X30','X31','X32','X33','X34','X36','X40','X41',
'X42','X43','X44','X46','X48','X49','X50','X51','X52','X55','X56','X57','X59','X61','X62','X63','X64','X65','X67'
,'X68','X69','X70','X71','X73','X74',
'X77','X78','X80','X81','X82','X83','X85','X86','X87','X88','X89','X91','X92','X96','X97','X98','X100','X101','X1
03','X105','X106','X108','X109',
'X110','X112','X114','X116','X124','X125','X126','X127','X128','X131','X132','X135','X136','X138','X139','X141','
X145','X148','X150','X151',
'X153','X154','X159','X160','X161','X164','X165','X167','X168','X170','X171','X173','X175','X176','X177','X181','
X182','X183','X184','X185','X187',
'X190','X191','X192','X197','X200','X202','X203','X205','X208','X211','X212','X218','X219','X220','X221','X223','
X224','X225','X228','X229','X230',
'X231','X234','X237','X238','X241','X246','X252','X255','X256','X257','X258','X259','X260','X261','X265','X267','
X269','X270','X271','X273','X274',
'X277','X278','X280','X281','X282','X286','X287','X288','X291','X292','X294','X295','X298','X300','X305','X306','
X307','X308','X309','X310','X312',
'X317','X318','X319','X321','X322','X323','X325','X327','X329','X332','X333','X336','X340','X341','X342','X343','
X344','X345','X349','X350','X353',
'X354','X355','X356','X357','X359','X366','X367','X369','X370','X372','X373','X377','X379','X380','X384']

X_test_1 = X_test.drop(P_cols,axis=1)
```

In [ ]:

```
P_cols = ['X174','X142','X156','X118','X117','X115','X157','X158','X130','X189','X334','X335','X337','X174','X142
','X156','X118','X117','X115','X157',
         'X158','X130','X189','X334','X335','X337', 'X178','X251','X179','X45']
X_test_2 = X_test_1.drop(P_cols,axis=1)
```

In [ ]:

```
X_test_2.columns
```

Out[ ]:

```
Index(['X0', 'X1', 'X2', 'X5', 'X6', 'X8', 'X21', 'X27', 'X38', 'X47', 'X58',
       'X75', 'X79', 'X95', 'X104', 'X111', 'X123', 'X133', 'X143', 'X144',
       'X152', 'X163', 'X166', 'X169', 'X180', 'X186', 'X195', 'X196', 'X201',
       'X204', 'X206', 'X207', 'X209', 'X210', 'X236', 'X275', 'X283', 'X284',
       'X285', 'X301', 'X304', 'X313', 'X315', 'X316', 'X338', 'X339', 'X351',
       'X361', 'X365', 'X374', 'X375', 'X376', 'X383'],
      dtype='object')
```

In [ ]:

```
#Displaying the columns in the final train data.
X_vif_3.columns
```

Out[ ]:

```
Index(['const', 'X0', 'X21', 'X38', 'X47', 'X58', 'X75', 'X79', 'X95', 'X104',
       'X111', 'X123', 'X133', 'X143', 'X144', 'X152', 'X163', 'X166', 'X169',
       'X180', 'X186', 'X195', 'X196', 'X201', 'X204', 'X206', 'X207', 'X209',
       'X210', 'X236', 'X283', 'X284', 'X285', 'X301', 'X304', 'X313', 'X315',
       'X316', 'X338', 'X339', 'X365', 'X374', 'X375', 'X376', 'X383'],
      dtype='object')
```

In [ ]:

```
P_cols = ['X1','X2','X5','X6', 'X8','X27','X361','X351', 'X275']
X_test_3 = X_test_2.drop(P_cols,axis=1)
```

In [ ]:

```
#Displaying the columns in the test data.
X_test_3.columns
```

Out[ ]:

```
Index(['X0', 'X21', 'X38', 'X47', 'X58', 'X75', 'X79', 'X95', 'X104', 'X111',
       'X123', 'X133', 'X143', 'X144', 'X152', 'X163', 'X166', 'X169', 'X180',
       'X186', 'X195', 'X196', 'X201', 'X204', 'X206', 'X207', 'X209', 'X210',
       'X236', 'X283', 'X284', 'X285', 'X301', 'X304', 'X313', 'X315', 'X316',
       'X338', 'X339', 'X365', 'X374', 'X375', 'X376', 'X383'],
      dtype='object')
```

In [ ]:

```
#Checking the datatype of test data
X_test_3.dtypes
```

Out[ ]:

```
X0      object
X21      int64
X38      int64
X47      int64
X58      int64
X75      int64
X79      int64
X95      int64
X104     int64
X111     int64
X123     int64
X133     int64
X143     int64
X144     int64
X152     int64
X163     int64
X166     int64
X169     int64
X180     int64
X186     int64
X195     int64
X196     int64
X201     int64
X204     int64
X206     int64
X207     int64
X209     int64
X210     int64
X236     int64
X283     int64
X284     int64
X285     int64
X301     int64
X304     int64
X313     int64
X315     int64
X316     int64
X338     int64
X339     int64
X365     int64
X374     int64
X375     int64
X376     int64
X383     int64
dtype: object
```

In [ ]:

```
#Converting X0 using Label Encoding
X_test_3.X0=le.fit_transform(X_test_3.X0)
```

In [ ]:

```
print(X_vif_3.shape)
print(X_test_3.shape)
```

```
(4209, 45)
(4209, 44)
```

In [ ]:

```
y_train_Y = lm.predict(X_vif_3)
y_train_Y
```

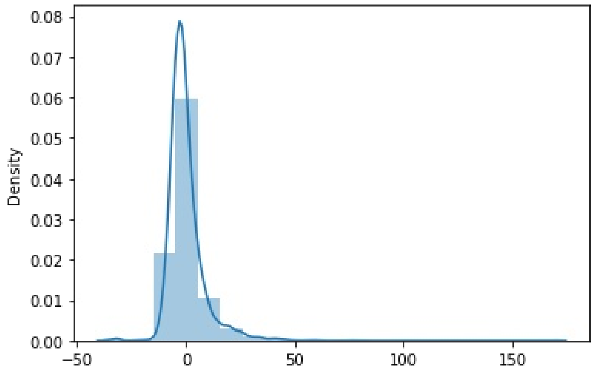
Out[ ]:

```
0       130.810000
1        94.388543
2        75.217924
3        77.950786
4        77.950786
           ...
4204    104.175752
4205    109.310615
4206    107.249076
4207     89.326500
4208     95.911372
Length: 4209, dtype: float64
```

In [ ]:

```
# Plot the histogram of the error terms

fig = plt.figure()
sns.distplot((y_train-y_train_Y), bins=20)
plt.show()
```



In [ ]:

```
#Dropping the constant from the train data
X_transformed = X_vif_3.drop('const',axis=1)
```

5. Predict your test_df values using XGBoost.

In [ ]:

```
#Importing necessary libary for XGBoost
import xgboost as xgb
```

In [ ]:

```
#fitting the model
xg = xgb.XGBRegressor()
xg.fit(X_transformed,y_train)
```

```
[21:24:30] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in
favor of reg:squarederror.
```

Out[ ]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [ ]:

```
score = xg.score(X_transformed,y_train)
score
```

Out[ ]:

```
0.5768101508292847
```

In [ ]:

```
y_pred= xg.predict(X_transformed)
```

In [ ]:

```
from sklearn.metrics import mean_absolute_error,mean_squared_error
```

In [ ]:

```
mse = mean_squared_error(y_true=y_train,y_pred=y_pred)
mse
```

Out[ ]:

```
68.01867548820672
```

In [ ]:

```
#Root mean squared error
rmse = np.sqrt(mse)
rmse
```

Out[ ]:

```
8.247343541299024
```

In [ ]:

```
#Now tying the model without dimensionality reduction

xg_1 = xgb.XGBRegressor()
xg_1.fit(X_train_new,y_train)
```

```
[21:32:41] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in
favor of reg:squarederror.
```

Out[ ]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [ ]:

```
#Finding the score
score_1 = xg_1.score(X_train_new,y_train)
score_1
```

Out[ ]:

```
0.6079199226194931
```

In [ ]:

```
#Displaying the shape of the data
print(X_train_new.shape)
print(cars_test.shape)
```

```
(4209, 364)
(4209, 364)
```

In [ ]:

```
#Performing label encoding on the object columns
Object_cols = cars_test.select_dtypes(include=np.object_)
Object_cols = Object_cols.apply(le.fit_transform)
```

In [ ]:

```
#Dropping the object columns from test data and concatenating the transformed columns
X_test_4 = cars_test.drop(Object_cols.columns,axis=1)
X_test_5 = pd.concat([Object_cols,X_test_4],axis=1)
```

In [ ]:

```
y_pred_1 = xg_1.predict(X_test_5)
```

In [ ]:

```
mse_1 = mean_squared_error(y_true=y_train,y_pred=y_pred_1)
mse_1
```

Out[ ]:

```
249.55739818916985
```

In [ ]:

```
#Root mean squared error
rmse_1 = np.sqrt(mse_1)
rmse_1
```

Out[ ]:

```
15.797385802377867
```

Conclusion: The model after feature selection and dimensionality reduction is a better model.