Business Context

Renewable energy sources play an increasingly important role in the global energy mix, as the effort to reduce the environmental impact of energy production increases.

Out of all the renewable energy alternatives, wind energy is one of the most developed technologies worldwide. The U.S Department of Energy has put together a guide to achieving operational efficiency using predictive maintenance practices.

Predictive maintenance uses sensor information and analysis methods to measure and predict degradation and future component capability. The idea behind predictive maintenance is that failure patterns are predictable and if component failure can be predicted accurately and the component is replaced before it fails, the costs of operation and maintenance will be much lower.

The sensors fitted across different machines involved in the process of energy generation collect data related to various environmental factors (temperature, humidity, wind speed, etc.) and additional features related to various parts of the wind turbine (gearbox, tower, blades, break, etc.).

Objective

"ReneWind" is a company working on improving the machinery/processes involved in the production of wind energy using machine learning and has collected data of generator failure of wind turbines using sensors. They have shared a ciphered version of the data, as the data collected through sensors is confidential (the type of data collected varies with companies). Data has 40 predictors, 20000 observations in the training set and 5000 in the test set.

The objective is to build various classification models, tune them, and find the best one that will help identify failures so that the generators could be repaired before failing/breaking to reduce the overall maintenance cost. The nature of predictions made by the classification model will translate as follows:

- True positives (TP) are failures correctly predicted by the model. These will result in repairing costs.
- False negatives (FN) are real failures where there is no detection by the model. These will result in replacement costs.
- False positives (FP) are detections where there is no failure. These will result in inspection costs. It is given that the cost of repairing a generator is much less than the cost of replacing it, and the cost of inspection is less than the cost of repair.

"1" in the target variables should be considered as "failure" and "0" represents "No failure".

Data Description

- The data provided is a transformed version of original data which was collected using sensors.
- Train.csv - To be used for training and tuning of models.
- Test.csv - To be used only for testing the performance of the final best model.
- Both the datasets consist of 40 predictor variables and 1 target variable

```
# Data manipulation and analysis libraries
import pandas as pd
import numpy as np

# Data visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns

# Preprocessing and model evaluation libraries
from sklearn import metrics
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.metrics import (
    f1_score, accuracy_score, recall_score, precision_score,
    confusion_matrix, roc_auc_score
)
from sklearn.model_selection import (
    train_test_split, StratifiedKFold, cross_val_score, RandomizedSearchCV, GridSearchCV
)

# Sampling libraries
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler

# Pipeline and transformation libraries
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer

# Model building libraries
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import (
    AdaBoostClassifier, GradientBoostingClassifier, RandomForestClassifier, BaggingClassifie
)
from xgboost import XGBClassifier
```

```python
# Settings to enhance output readability and suppress warnings
pd.set_option("display.max_columns", None)
pd.set_option("display.max_rows", None)
pd.set_option("display.float_format", lambda x: "%.3f" % x)  # Suppress scientific notation

# Suppress warnings
import warnings
warnings.filterwarnings("ignore")
```

```python
train_data = pd.read_csv('./Train.csv')
test_data = pd.read_csv('./Test.csv')
```

Data Overview

```python
# View top 5 rows of the data
train_data.head()
```

```
      V1     V2     V3     V4     V5     V6     V7     V8     V9    V10  \
0 -4.465 -4.679  3.102  0.506 -0.221 -2.033 -2.911  0.051 -1.522  3.762
1  3.366  3.653  0.910 -1.368  0.332  2.359  0.733 -4.332  0.566 -0.101
2 -3.832 -5.824  0.634 -2.419 -1.774  1.017 -2.099 -3.173 -2.082  5.393
3  1.618  1.888  7.046 -1.147  0.083 -1.530  0.207 -2.494  0.345  2.119
4 -0.111  3.872 -3.758 -2.983  3.793  0.545  0.205  4.849 -1.855 -6.220

     V11    V12    V13    V14    V15    V16    V17    V18    V19    V20  \
0 -5.715  0.736  0.981  1.418 -3.376 -3.047  0.306  2.914  2.270  4.395
1  1.914 -0.951 -1.255 -2.707  0.193 -4.769 -2.205  0.908  0.757 -5.834
2 -0.771  1.107  1.144  0.943 -3.164 -4.248 -4.039  3.689  3.311  1.059
3 -3.053  0.460  2.705 -0.636 -0.454 -3.174 -3.404 -1.282  1.582 -1.952
4  1.998  4.724  0.709 -1.989 -2.633  4.184  2.245  3.734 -6.313 -5.380

     V21    V22    V23    V24    V25    V26    V27    V28    V29    V30  \
0 -2.388  0.646 -1.191  3.133  0.665 -2.511 -0.037  0.726 -3.982 -1.073
1 -3.065  1.597 -1.757  1.766 -0.267  3.625  1.500 -0.586  0.783 -0.201
2 -2.143  1.650 -1.661  1.680 -0.451 -4.551  3.739  1.134 -2.034  0.841
3 -3.517 -1.206 -5.628 -1.818  2.124  5.295  4.748 -2.309 -3.963 -6.029
4 -0.887  2.062  9.446  4.490 -3.945  4.582 -8.780 -3.383  5.107  6.788

     V31    V32    V33     V34   V35    V36    V37    V38    V39    V40  \
0  1.667  3.060 -1.690   2.846 2.235  6.667  0.444 -2.369  2.951 -3.480
1  0.025 -1.795  3.033  -2.468 1.895 -2.298 -1.731  5.909 -0.386  0.616
2 -1.600 -0.257  0.804   4.086 2.292  5.361  0.352  2.940  3.839 -4.309
3  4.949 -3.584 -2.577   1.364 0.623  5.550 -1.527  0.139  3.101 -1.277
4  2.044  8.266  6.629 -10.069 1.223 -3.230  1.687 -2.164 -3.645  6.510

   Target
```

```
0       0
1       0
2       0
3       0
4       0
```

```
# View top 5 rows of the data
test_data.head()
```

```
      V1     V2     V3     V4     V5     V6     V7     V8     V9    V10  \
0 -0.613 -3.820  2.202  1.300 -1.185 -4.496 -1.836  4.723  1.206 -0.342
1  0.390 -0.512  0.527 -2.577 -1.017  2.235 -0.441 -4.406 -0.333  1.967
2 -0.875 -0.641  4.084 -1.590  0.526 -1.958 -0.695  1.347 -1.732  0.466
3  0.238  1.459  4.015  2.534  1.197 -3.117 -0.924  0.269  1.322  0.702
4  5.828  2.768 -1.235  2.809 -1.642 -1.407  0.569  0.965  1.918 -2.775

     V11    V12    V13    V14    V15    V16    V17    V18    V19    V20  \
0 -5.123  1.017  4.819  3.269 -2.984  1.387  2.032 -0.512 -1.023  7.339
1  1.797  0.410  0.638 -1.390 -1.883 -5.018 -3.827  2.418  1.762 -3.242
2 -4.928  3.565 -0.449 -0.656 -0.167 -1.630  2.292  2.396  0.601  1.794
3 -5.578 -0.851  2.591  0.767 -2.391 -2.342  0.572 -0.934  0.509  1.211
4 -0.530  1.375 -0.651 -1.679 -0.379 -4.443  3.894 -0.608  2.945  0.367

     V21   V22    V23    V24    V25    V26    V27    V28    V29    V30    V31  \
0 -2.242 0.155  2.054 -2.772  1.851 -1.789 -0.277 -1.255 -3.833 -1.505  1.587
1 -3.193 1.857 -1.708  0.633 -0.588  0.084  3.014 -0.182  0.224  0.865 -1.782
2 -2.120 0.482 -0.841  1.790  1.874  0.364 -0.169 -0.484 -2.119 -2.157  2.907
3 -3.260 0.105 -0.659  1.498  1.100  4.143 -0.248 -1.137 -5.356 -4.546  3.809
4 -5.789 4.598  4.450  3.225  0.397  0.248 -2.362  1.079 -0.473  2.243 -3.591

     V32    V33    V34   V35    V36    V37     V38    V39    V40  Target
0  2.291 -5.411  0.870 0.574  4.157  1.428 -10.511  0.455 -1.448       0
1 -2.475  2.494  0.315 2.059  0.684 -0.485   5.128  1.721 -1.488       0
2 -1.319 -2.997  0.460 0.620  5.632  1.324  -1.752  1.808  1.676       0
3  3.518 -3.074 -0.284 0.955  3.029 -1.367  -3.412  0.906 -2.451       0
4  1.774 -1.502 -2.227 4.777 -6.560 -0.806  -0.276 -3.858 -0.538       0
```

```
# Check the dimensions of the data
train_data.shape
```

```
(20000, 41)
```

```
# Check the dimensions of the data
test_data.shape
```

```
(5000, 41)
```

```
# Check data types
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 41 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   V1      19982 non-null  float64
 1   V2      19982 non-null  float64
 2   V3      20000 non-null  float64
 3   V4      20000 non-null  float64
 4   V5      20000 non-null  float64
 5   V6      20000 non-null  float64
 6   V7      20000 non-null  float64
 7   V8      20000 non-null  float64
 8   V9      20000 non-null  float64
 9   V10     20000 non-null  float64
 10  V11     20000 non-null  float64
 11  V12     20000 non-null  float64
 12  V13     20000 non-null  float64
 13  V14     20000 non-null  float64
 14  V15     20000 non-null  float64
 15  V16     20000 non-null  float64
 16  V17     20000 non-null  float64
 17  V18     20000 non-null  float64
 18  V19     20000 non-null  float64
 19  V20     20000 non-null  float64
 20  V21     20000 non-null  float64
 21  V22     20000 non-null  float64
 22  V23     20000 non-null  float64
 23  V24     20000 non-null  float64
 24  V25     20000 non-null  float64
 25  V26     20000 non-null  float64
 26  V27     20000 non-null  float64
 27  V28     20000 non-null  float64
 28  V29     20000 non-null  float64
 29  V30     20000 non-null  float64
 30  V31     20000 non-null  float64
 31  V32     20000 non-null  float64
 32  V33     20000 non-null  float64
 33  V34     20000 non-null  float64
 34  V35     20000 non-null  float64
 35  V36     20000 non-null  float64
 36  V37     20000 non-null  float64
 37  V38     20000 non-null  float64
 38  V39     20000 non-null  float64
 39  V40     20000 non-null  float64
 40  Target  20000 non-null  int64
```

```
dtypes: float64(40), int64(1)
memory usage: 6.3 MB
```

```python
# Check data types
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 41 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   V1      4995 non-null   float64
 1   V2      4994 non-null   float64
 2   V3      5000 non-null   float64
 3   V4      5000 non-null   float64
 4   V5      5000 non-null   float64
 5   V6      5000 non-null   float64
 6   V7      5000 non-null   float64
 7   V8      5000 non-null   float64
 8   V9      5000 non-null   float64
 9   V10     5000 non-null   float64
 10  V11     5000 non-null   float64
 11  V12     5000 non-null   float64
 12  V13     5000 non-null   float64
 13  V14     5000 non-null   float64
 14  V15     5000 non-null   float64
 15  V16     5000 non-null   float64
 16  V17     5000 non-null   float64
 17  V18     5000 non-null   float64
 18  V19     5000 non-null   float64
 19  V20     5000 non-null   float64
 20  V21     5000 non-null   float64
 21  V22     5000 non-null   float64
 22  V23     5000 non-null   float64
 23  V24     5000 non-null   float64
 24  V25     5000 non-null   float64
 25  V26     5000 non-null   float64
 26  V27     5000 non-null   float64
 27  V28     5000 non-null   float64
 28  V29     5000 non-null   float64
 29  V30     5000 non-null   float64
 30  V31     5000 non-null   float64
 31  V32     5000 non-null   float64
 32  V33     5000 non-null   float64
 33  V34     5000 non-null   float64
 34  V35     5000 non-null   float64
 35  V36     5000 non-null   float64
```

```
 36  V37     5000 non-null   float64
 37  V38     5000 non-null   float64
 38  V39     5000 non-null   float64
 39  V40     5000 non-null   float64
 40  Target  5000 non-null   int64
dtypes: float64(40), int64(1)
memory usage: 1.6 MB
```

```python
# Double check for null values per column
train_data.isnull().sum()
```

```
V1        18
V2        18
V3         0
V4         0
V5         0
V6         0
V7         0
V8         0
V9         0
V10        0
V11        0
V12        0
V13        0
V14        0
V15        0
V16        0
V17        0
V18        0
V19        0
V20        0
V21        0
V22        0
V23        0
V24        0
V25        0
V26        0
V27        0
V28        0
V29        0
V30        0
V31        0
V32        0
V33        0
V34        0
V35        0
V36        0
```

```
V37       0
V38       0
V39       0
V40       0
Target    0
dtype: int64
```

```
# Checking for null values per column
test_data.isnull().sum()
```

```
V1      5
V2      6
V3      0
V4      0
V5      0
V6      0
V7      0
V8      0
V9      0
V10     0
V11     0
V12     0
V13     0
V14     0
V15     0
V16     0
V17     0
V18     0
V19     0
V20     0
V21     0
V22     0
V23     0
V24     0
V25     0
V26     0
V27     0
V28     0
V29     0
V30     0
V31     0
V32     0
V33     0
V34     0
V35     0
V36     0
V37     0
```

```
V38       0
V39       0
V40       0
Target    0
dtype: int64
```

```python
# Check data duplicate values
train_data.duplicated().sum()
```

```
np.int64(0)
```

```python
# Check data duplicate values
test_data.duplicated().sum()
```

```
np.int64(0)
```

```python
train_data.describe().T
```

	count	mean	std	min	25%	50%	75%	max
V1	19982.000	-0.272	3.442	-11.876	-2.737	-0.748	1.840	15.493
V2	19982.000	0.440	3.151	-12.320	-1.641	0.472	2.544	13.089
V3	20000.000	2.485	3.389	-10.708	0.207	2.256	4.566	17.091
V4	20000.000	-0.083	3.432	-15.082	-2.348	-0.135	2.131	13.236
V5	20000.000	-0.054	2.105	-8.603	-1.536	-0.102	1.340	8.134
V6	20000.000	-0.995	2.041	-10.227	-2.347	-1.001	0.380	6.976
V7	20000.000	-0.879	1.762	-7.950	-2.031	-0.917	0.224	8.006
V8	20000.000	-0.548	3.296	-15.658	-2.643	-0.389	1.723	11.679
V9	20000.000	-0.017	2.161	-8.596	-1.495	-0.068	1.409	8.138
V10	20000.000	-0.013	2.193	-9.854	-1.411	0.101	1.477	8.108
V11	20000.000	-1.895	3.124	-14.832	-3.922	-1.921	0.119	11.826
V12	20000.000	1.605	2.930	-12.948	-0.397	1.508	3.571	15.081
V13	20000.000	1.580	2.875	-13.228	-0.224	1.637	3.460	15.420
V14	20000.000	-0.951	1.790	-7.739	-2.171	-0.957	0.271	5.671
V15	20000.000	-2.415	3.355	-16.417	-4.415	-2.383	-0.359	12.246
V16	20000.000	-2.925	4.222	-20.374	-5.634	-2.683	-0.095	13.583
V17	20000.000	-0.134	3.345	-14.091	-2.216	-0.015	2.069	16.756
V18	20000.000	1.189	2.592	-11.644	-0.404	0.883	2.572	13.180
V19	20000.000	1.182	3.397	-13.492	-1.050	1.279	3.493	13.238
V20	20000.000	0.024	3.669	-13.923	-2.433	0.033	2.512	16.052
V21	20000.000	-3.611	3.568	-17.956	-5.930	-3.533	-1.266	13.840
V22	20000.000	0.952	1.652	-10.122	-0.118	0.975	2.026	7.410
V23	20000.000	-0.366	4.032	-14.866	-3.099	-0.262	2.452	14.459
V24	20000.000	1.134	3.912	-16.387	-1.468	0.969	3.546	17.163
V25	20000.000	-0.002	2.017	-8.228	-1.365	0.025	1.397	8.223
V26	20000.000	1.874	3.435	-11.834	-0.338	1.951	4.130	16.836
V27	20000.000	-0.612	4.369	-14.905	-3.652	-0.885	2.189	17.560
V28	20000.000	-0.883	1.918	-9.269	-2.171	-0.891	0.376	6.528
V29	20000.000	-0.986	2.684	-12.579	-2.787	-1.176	0.630	10.722
V30	20000.000	-0.016	3.005	-14.796	-1.867	0.184	2.036	12.506

V31	20000.000	0.487	3.461	-13.723	-1.818	0.490	2.731	17.255
V32	20000.000	0.304	5.500	-19.877	-3.420	0.052	3.762	23.633
V33	20000.000	0.050	3.575	-16.898	-2.243	-0.066	2.255	16.692
V34	20000.000	-0.463	3.184	-17.985	-2.137	-0.255	1.437	14.358
V35	20000.000	2.230	2.937	-15.350	0.336	2.099	4.064	15.291
V36	20000.000	1.515	3.801	-14.833	-0.944	1.567	3.984	19.330
V37	20000.000	0.011	1.788	-5.478	-1.256	-0.128	1.176	7.467
V38	20000.000	-0.344	3.948	-17.375	-2.988	-0.317	2.279	15.290
V39	20000.000	0.891	1.753	-6.439	-0.272	0.919	2.058	7.760
V40	20000.000	-0.876	3.012	-11.024	-2.940	-0.921	1.120	10.654
Target	20000.000	0.056	0.229	0.000	0.000	0.000	0.000	1.000

```
test_data.describe().T
```

	count	mean	std	min	25%	50%	75%	max
V1	4995.000	-0.278	3.466	-12.382	-2.744	-0.765	1.831	13.504
V2	4994.000	0.398	3.140	-10.716	-1.649	0.427	2.444	14.079
V3	5000.000	2.552	3.327	-9.238	0.315	2.260	4.587	15.315
V4	5000.000	-0.049	3.414	-14.682	-2.293	-0.146	2.166	12.140
V5	5000.000	-0.080	2.111	-7.712	-1.615	-0.132	1.341	7.673
V6	5000.000	-1.042	2.005	-8.924	-2.369	-1.049	0.308	5.068
V7	5000.000	-0.908	1.769	-8.124	-2.054	-0.940	0.212	7.616
V8	5000.000	-0.575	3.332	-12.253	-2.642	-0.358	1.713	10.415
V9	5000.000	0.030	2.174	-6.785	-1.456	-0.080	1.450	8.851
V10	5000.000	0.019	2.145	-8.171	-1.353	0.166	1.511	6.599
V11	5000.000	-2.009	3.112	-13.152	-4.050	-2.043	0.044	9.956
V12	5000.000	1.576	2.907	-8.164	-0.450	1.488	3.563	12.984
V13	5000.000	1.622	2.883	-11.548	-0.126	1.719	3.465	12.620
V14	5000.000	-0.921	1.803	-7.814	-2.111	-0.896	0.272	5.734
V15	5000.000	-2.452	3.387	-15.286	-4.479	-2.417	-0.433	11.673
V16	5000.000	-3.019	4.264	-20.986	-5.648	-2.774	-0.178	13.976
V17	5000.000	-0.104	3.337	-13.418	-2.228	0.047	2.112	19.777
V18	5000.000	1.196	2.586	-12.214	-0.409	0.881	2.604	13.642
V19	5000.000	1.210	3.385	-14.170	-1.026	1.296	3.526	12.428
V20	5000.000	0.138	3.657	-13.720	-2.325	0.193	2.540	13.871
V21	5000.000	-3.664	3.578	-16.341	-5.944	-3.663	-1.330	11.047
V22	5000.000	0.962	1.640	-6.740	-0.048	0.986	2.029	7.505
V23	5000.000	-0.422	4.057	-14.422	-3.163	-0.279	2.426	13.181
V24	5000.000	1.089	3.968	-12.316	-1.623	0.913	3.537	17.806
V25	5000.000	0.061	2.010	-6.770	-1.298	0.077	1.428	6.557
V26	5000.000	1.847	3.400	-11.414	-0.242	1.917	4.156	17.528
V27	5000.000	-0.552	4.403	-13.177	-3.663	-0.872	2.247	17.290
V28	5000.000	-0.868	1.926	-7.933	-2.160	-0.931	0.421	7.416
V29	5000.000	-1.096	2.655	-9.988	-2.861	-1.341	0.522	14.039
V30	5000.000	-0.119	3.023	-12.438	-1.997	0.112	1.946	10.315
V31	5000.000	0.469	3.446	-11.263	-1.822	0.486	2.779	12.559
V32	5000.000	0.233	5.586	-17.244	-3.556	-0.077	3.752	26.539

```
V33    5000.000 -0.080 3.539 -14.904 -2.348 -0.160  2.099 13.324
V34    5000.000 -0.393 3.166 -14.700 -2.010 -0.172  1.465 12.146
V35    5000.000  2.211 2.948 -12.261  0.322  2.112  4.032 13.489
V36    5000.000  1.595 3.775 -12.736 -0.866  1.703  4.104 17.116
V37    5000.000  0.023 1.785  -5.079 -1.241 -0.110  1.238  6.810
V38    5000.000 -0.406 3.969 -15.335 -2.984 -0.381  2.288 13.065
V39    5000.000  0.939 1.717  -5.451 -0.208  0.959  2.131  7.182
V40    5000.000 -0.932 2.978 -10.076 -2.987 -1.003  1.080  8.698
Target 5000.000  0.056 0.231   0.000  0.000  0.000  0.000  1.000
```

```
# Check for class distribution of the target variable by looking at the count of observatio
class_distribution = train_data['Target'].value_counts(normalize=True) * 100
print(class_distribution)
```

```
Target
0   94.450
1    5.550
Name: proportion, dtype: float64
```

```
# Check for class distribution of the target variable by looking at the count of observatio
class_distribution = test_data['Target'].value_counts(normalize=True) * 100
print(class_distribution)
```

```
Target
0   94.360
1    5.640
Name: proportion, dtype: float64
```

Observations:

Dataset Size:

- The training set contains 20,000 observations, each with 41 columns (40 predictors and 1 target variable).
- The test set includes 5,000 observations, also with 41 columns.

Data Types:

- Both datasets primarily consist of numerical features (float64), with the target variable being an integer (int64).

Missing Values:

- In the training set, two variables (V1 and V2) have 18 missing values each.
- In the test set, V1 has 5 missing values, and V2 has 6 missing values.
- No missing values are present in the target variable of both datasets.

Data Integrity:

- There are no duplicate rows in either the training or the test dataset, indicating good data integrity.

Class Imbalance: Bot training and testing target variables have imbalanced distribution of the target variables classes where:

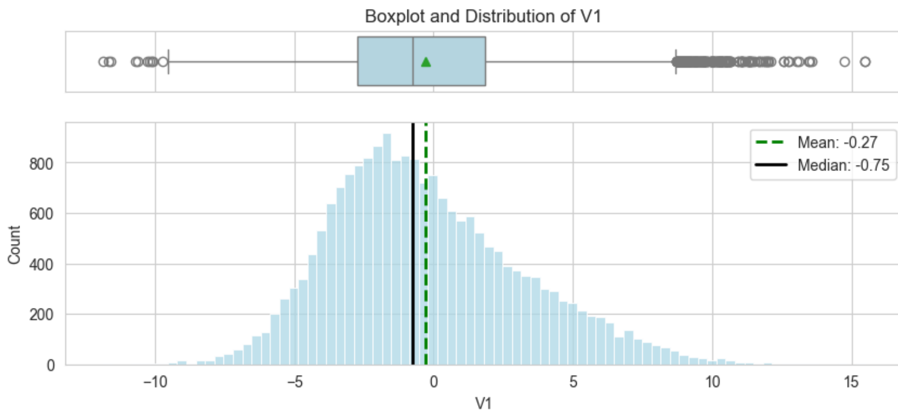
- About 94% of the observations belong to the negative class (0), which represents "Non-failure" cases.
- About 5% of the observations belong to the positive class (1), representing "Failure" cases.

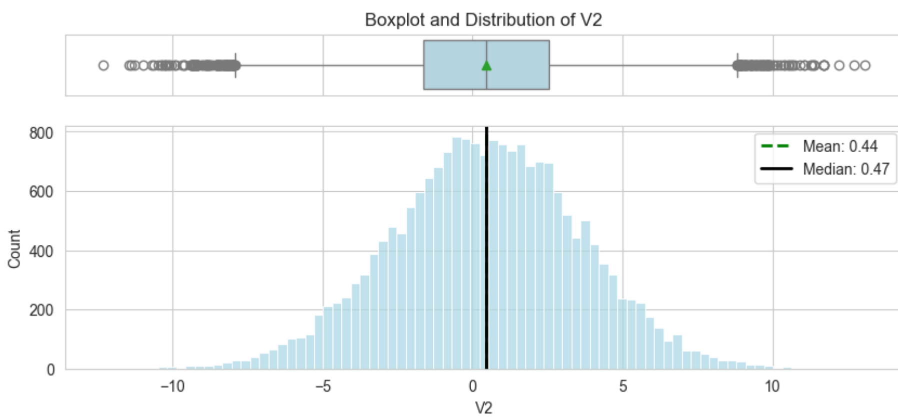
Exploratory Data analysis (EDA)

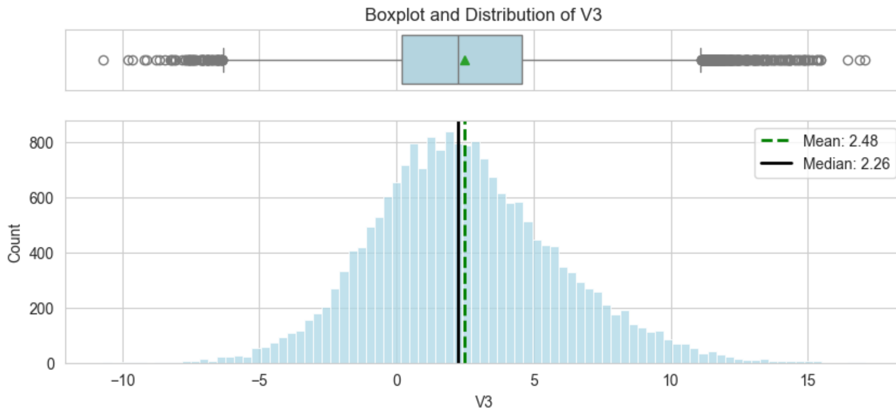
Univariate Analysis

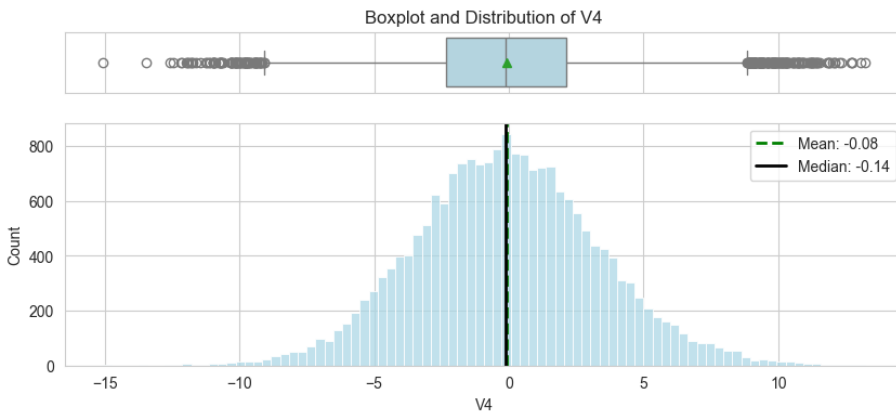
```
def hist_and_boxplot(data, variable, figsize=(12, 4), kde=False, bins=None):
    """
    Creates a plot with both a histogram and boxplot for a specified numerical variable.

    Args:
    - data: The DataFrame containing the data.
    - variable: Column name of the numerical variable (feature) to be plotted.
    - figsize: A tuple representing the size of the figure.
    - density_curve: A boolean indicating whether to overlay a density curve curve on the hi
    - bins: An integer representing the number of bins for the histogram, or None for automa

    Returns:
    None
    """
    # Set up the matplotlib figure with two rows and one column
    fig, (ax1, ax2) = plt.subplots(2, 1, figsize=figsize, sharex=True, gridspec_kw={'height_

    # Plot the boxplot on the first row
    sns.boxplot(x=variable, data=data, ax=ax1, showmeans=True, color="lightblue")
    ax1.set(xlabel='', title=f'Boxplot and Distribution of {variable}')

    # Plot the histogram on the second row
    if bins:
        sns.histplot(data[variable], kde=kde, bins=bins, ax=ax2, color="lightblue")
    else:
        sns.histplot(data[variable], kde=kde, ax=ax2, color="lightblue")

 # Draw lines for mean and median
    mean_val = data[variable].mean()
    median_val = data[variable].median()
    ax2.axvline(mean_val, color='green', linestyle='--', linewidth=2, label=f'Mean: {mean_va
    ax2.axvline(median_val, color='black', linestyle='-', linewidth=2, label=f'Median: {medi

    # Add legend to the histogram
```

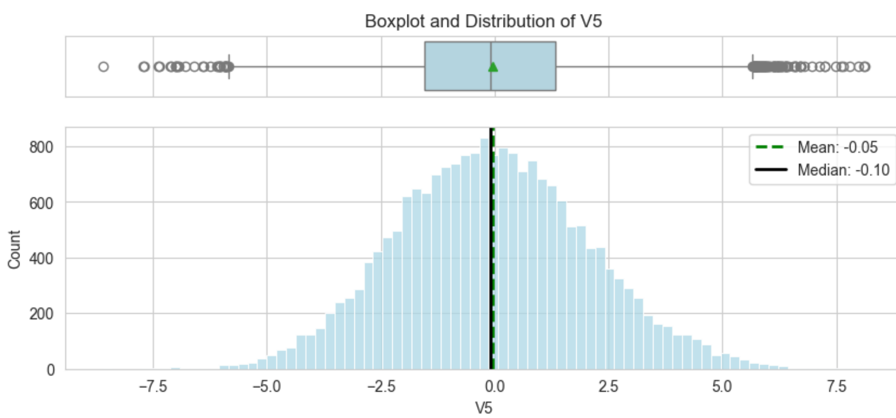
```
    ax2.legend()

    plt.show()

# Looping through the variables in the train dataset and creating a histogram and boxplot fo
for variable in train_data.columns:
    hist_and_boxplot(train_data, variable, figsize=(10, 4), kde=False, bins=None)
```

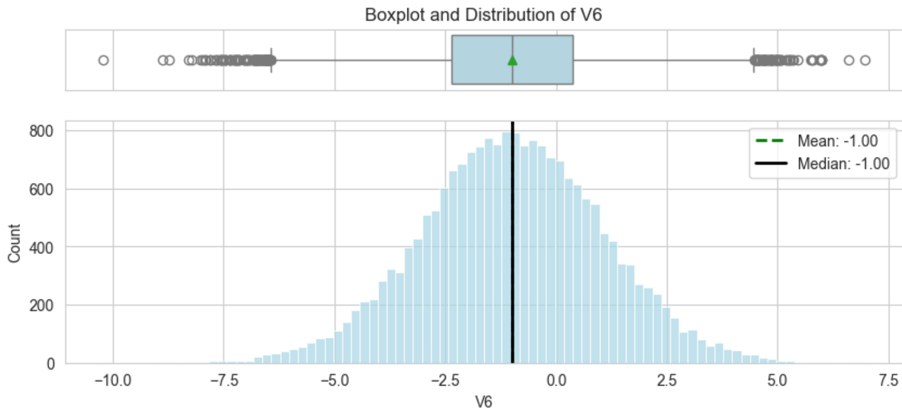


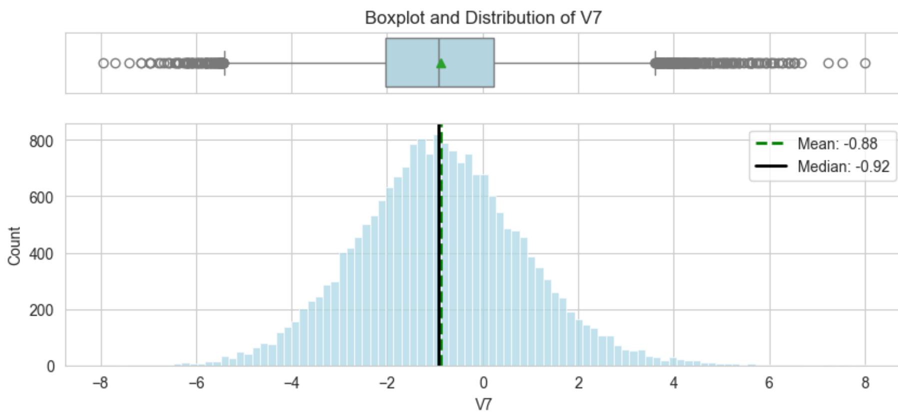


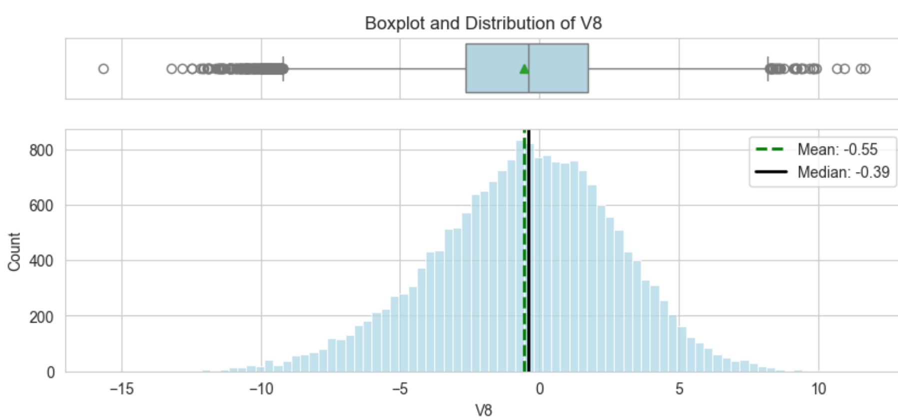

Boxplot and Distribution of V3
Mean: 2.48
Median: 2.26
Count
800
600
400
200
0
−10
−5
0
5
10
15
V3

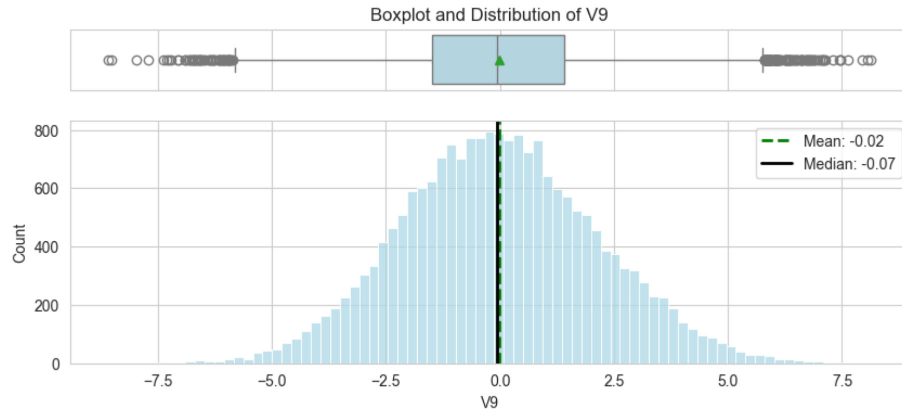

Boxplot and Distribution of V4
Mean: -0.08
Median: -0.14
Count
800
600
400
200
0
−15
−10
−5
0
5
10
V4

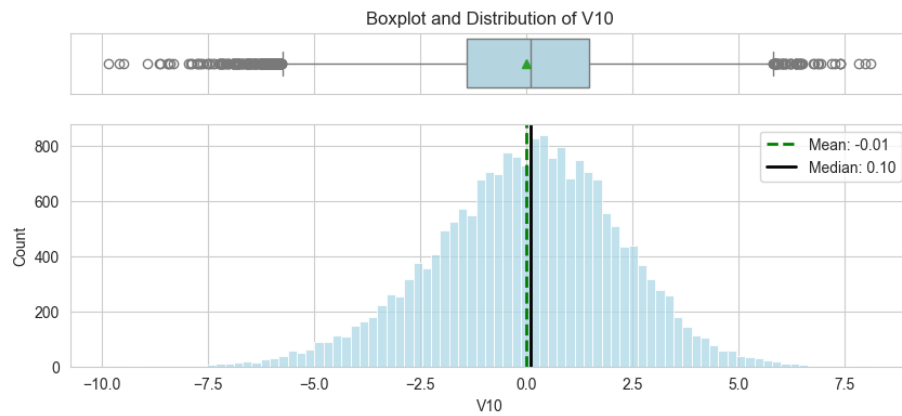

Boxplot and Distribution of V5
Mean: -0.05
Median: -0.10
Count
800
600
400
200
0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
V5

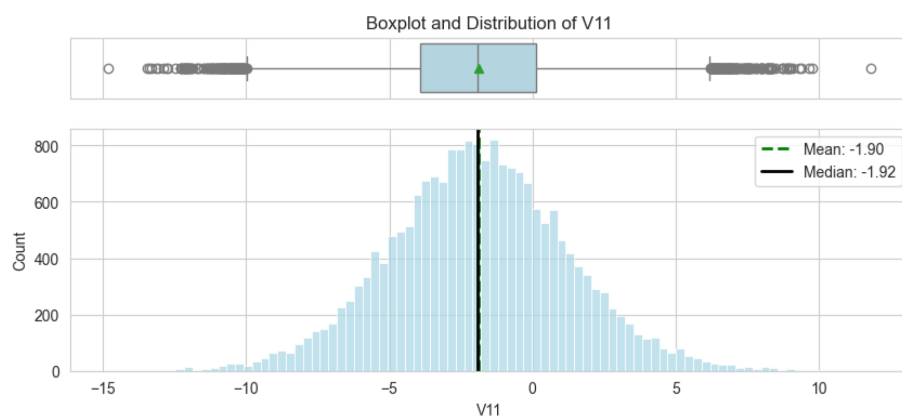

Boxplot and Distribution of V6
Mean: -1.00
Median: -1.00
Count
800
600
400
200
0
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
V6

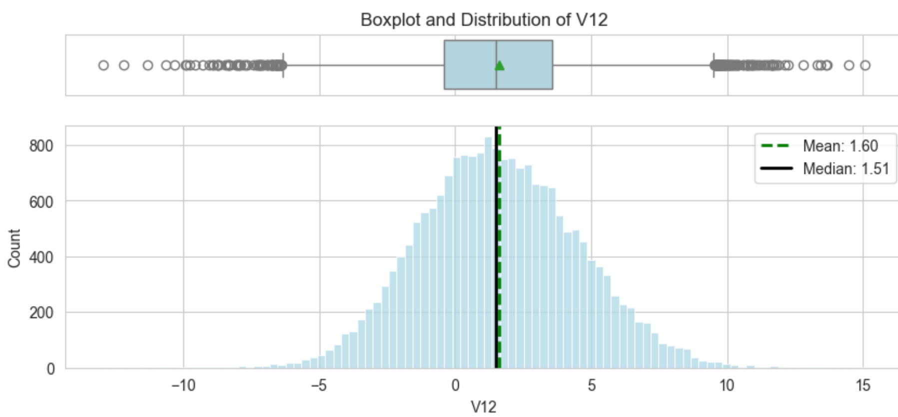

Boxplot and Distribution of V7
Mean: -0.88
Median: -0.92
Count
800
600
400
200
0
−8
−6
−4
−2
0
2
4
6
8
V7


Boxplot and Distribution of V8
Mean: -0.55
Median: -0.39
Count
800
600
400
200
0
−15
−10
−5
0
5
10
V8

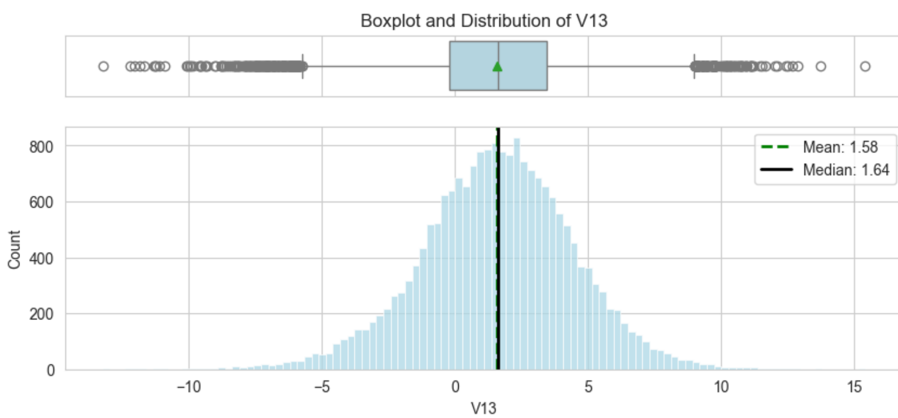

Boxplot and Distribution of V9
Mean: -0.02
Median: -0.07
Count
V9


Boxplot and Distribution of V10
Mean: -0.01
Median: 0.10
Count
V10

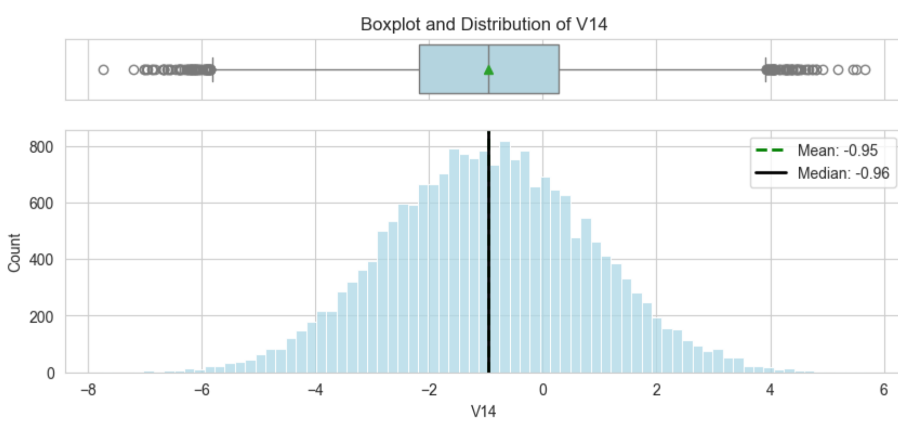

Boxplot and Distribution of V11
Mean: -1.90
Median: -1.92
Count
V11



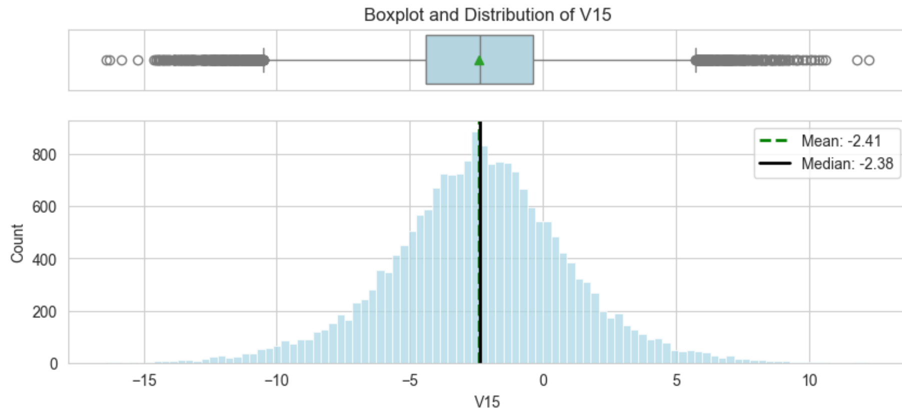
Boxplot and Distribution of V12
Mean: 1.60
Median: 1.51
Count
V12



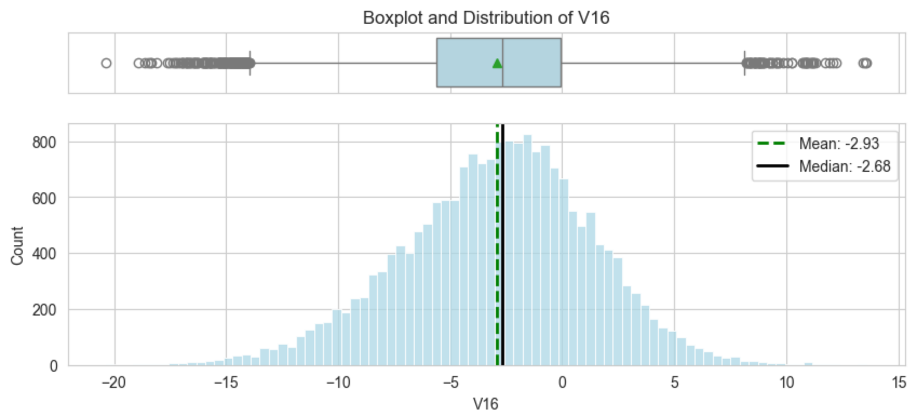
Boxplot and Distribution of V13
Mean: 1.58
Median: 1.64
Count
V13



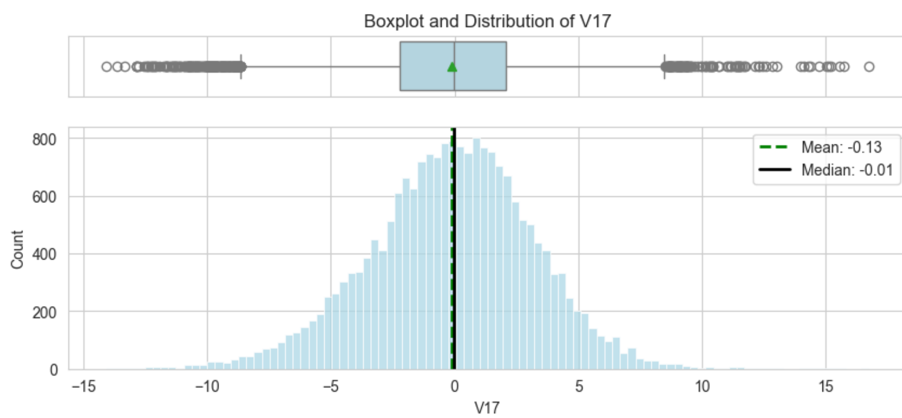
Boxplot and Distribution of V14
Mean: -0.95
Median: -0.96
Count
V14



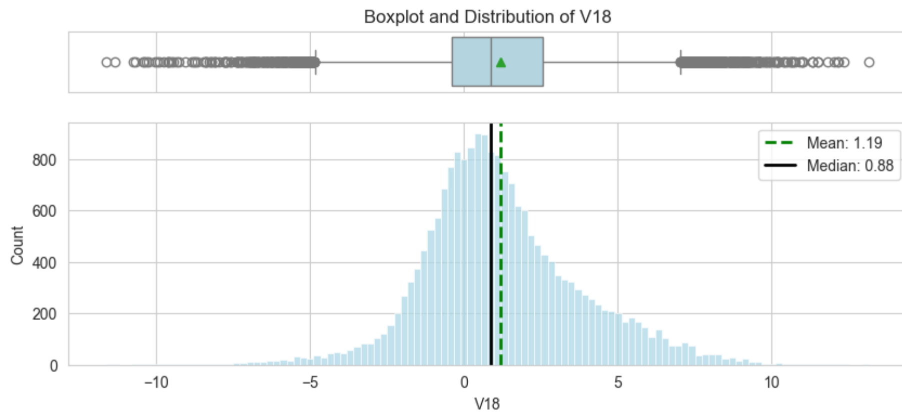
Boxplot and Distribution of V15
Mean: -2.41
Median: -2.38
Count
V15

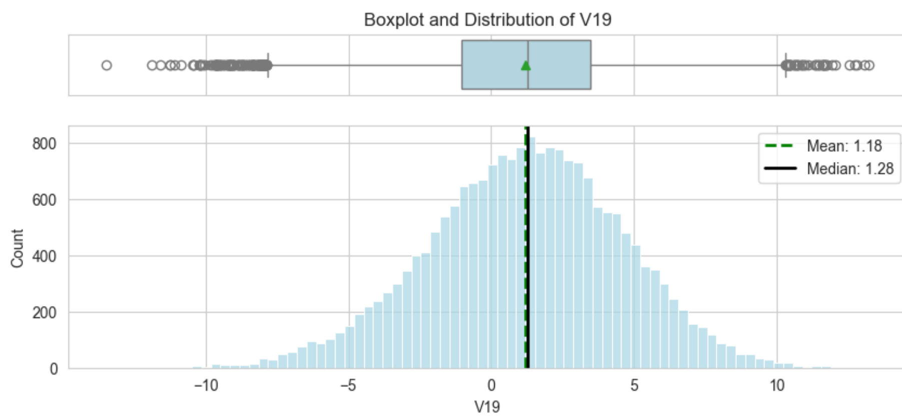


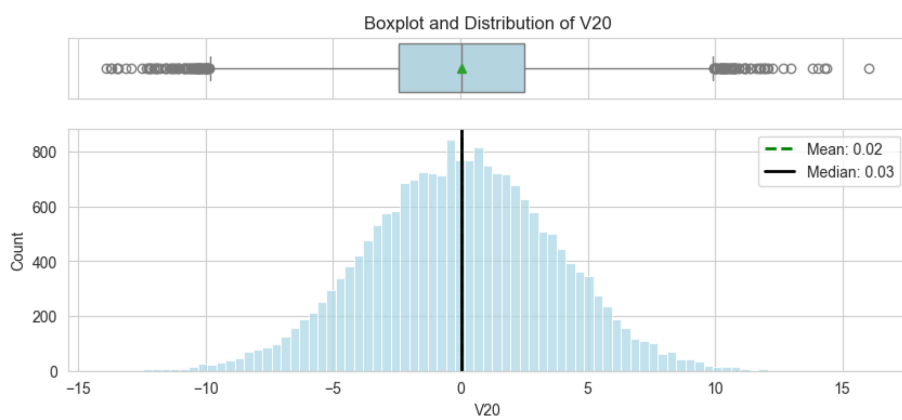
Boxplot and Distribution of V16
Mean: -2.93
Median: -2.68
Count
V16

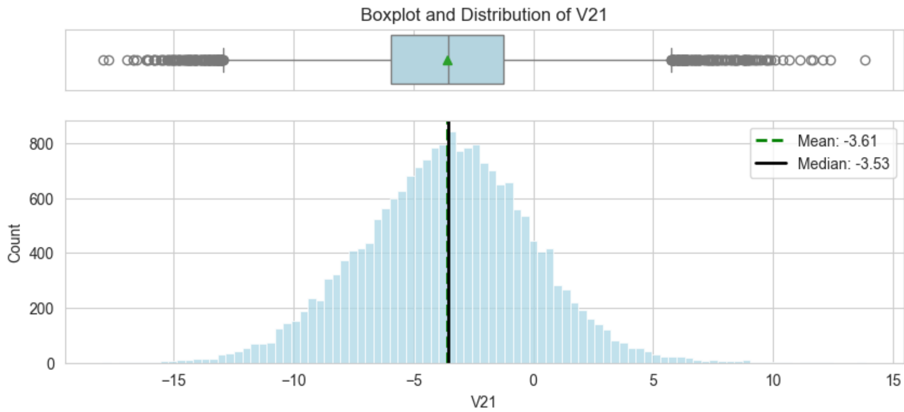


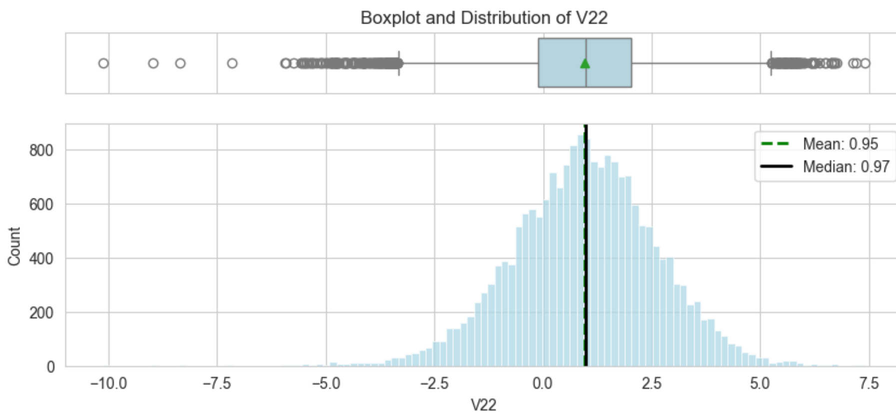
Boxplot and Distribution of V17
Mean: -0.13
Median: -0.01
Count
V17

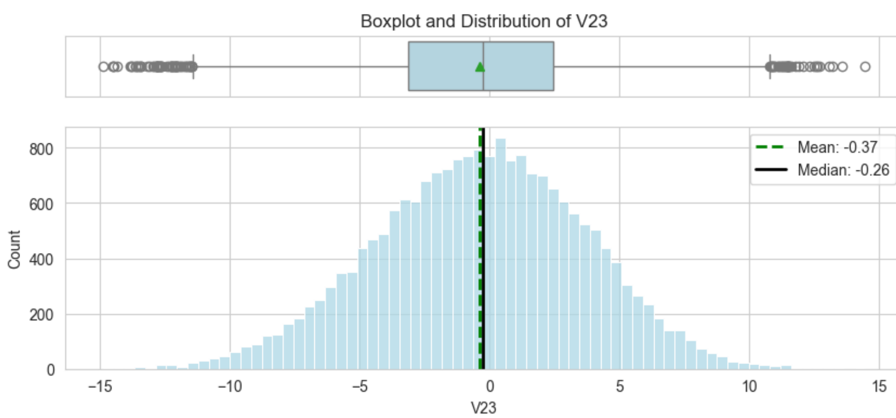

Boxplot and Distribution of V18
Mean: 1.19
Median: 0.88
Count
V18

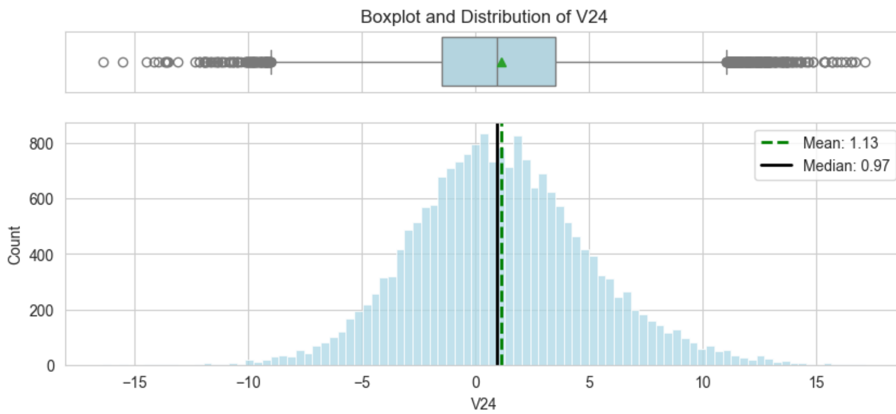

Boxplot and Distribution of V19
Mean: 1.18
Median: 1.28
Count
V19

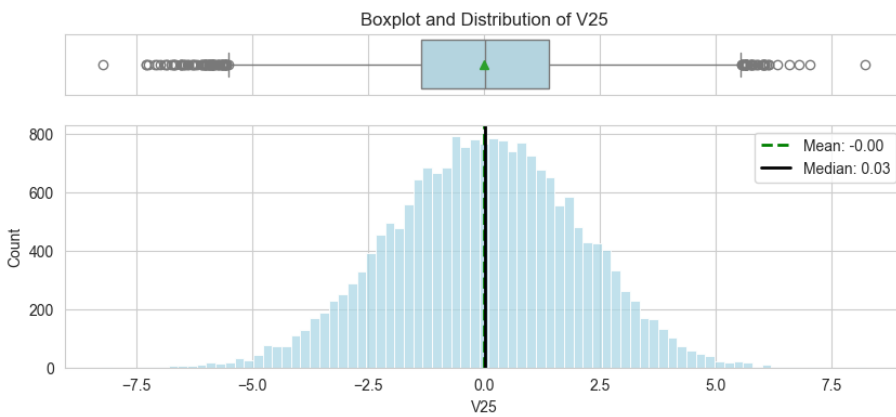

Boxplot and Distribution of V20
Mean: 0.02
Median: 0.03
Count
V20

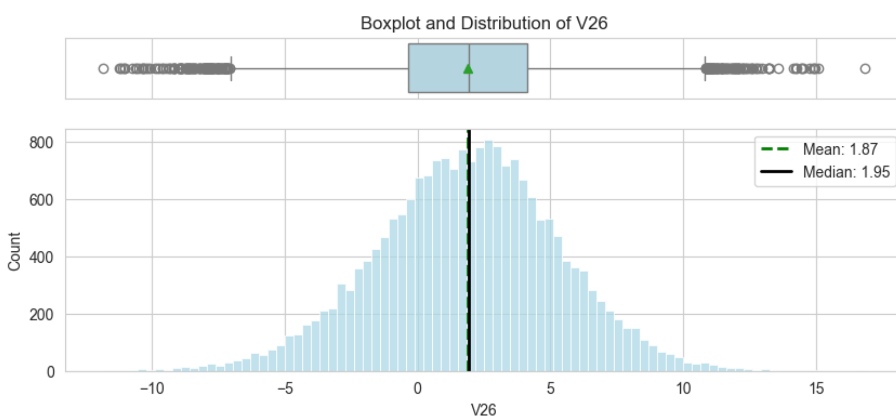

Boxplot and Distribution of V21
Mean: -3.61
Median: -3.53
Count
0
200
400
600
800
−15
−10
−5
0
5
10
15
V21

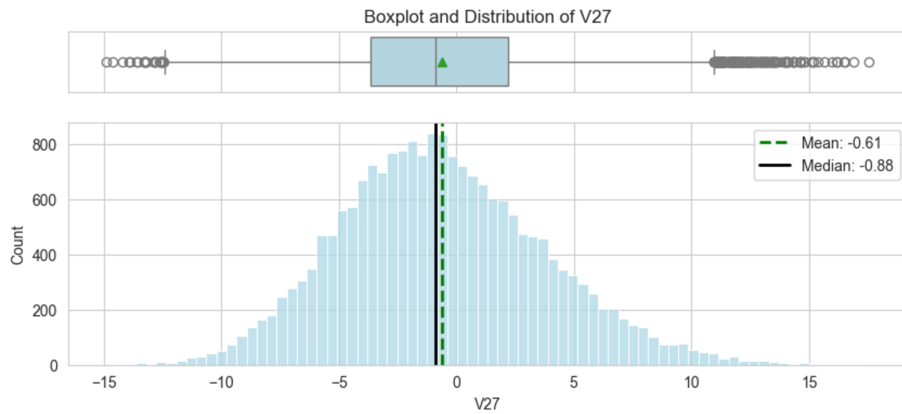

Boxplot and Distribution of V22
Mean: 0.95
Median: 0.97
Count
0
200
400
600
800
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
V22

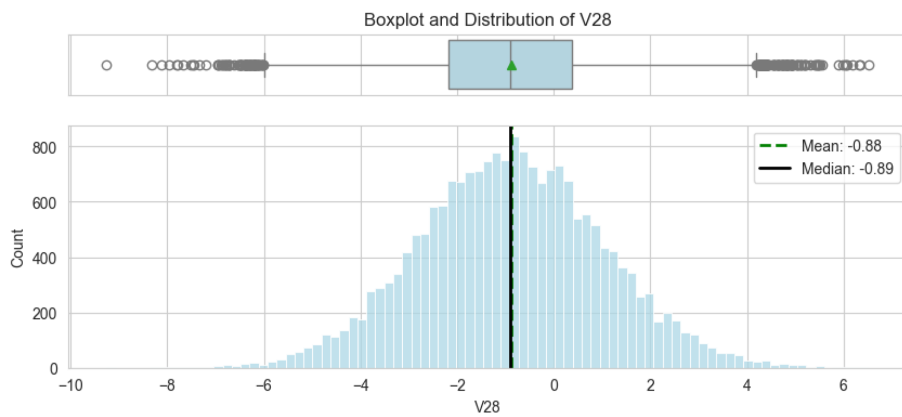

Boxplot and Distribution of V23
Mean: -0.37
Median: -0.26
Count
0
200
400
600
800
−15
−10
−5
0
5
10
15
V23

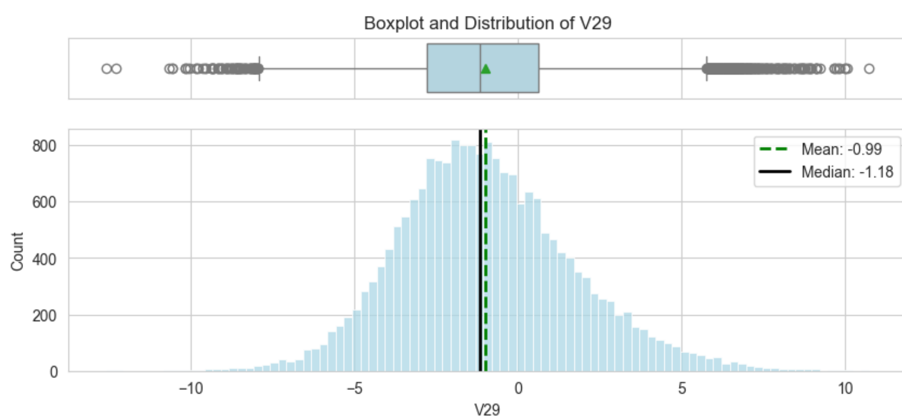

Boxplot and Distribution of V24
Mean: 1.13
Median: 0.97
Count
0
200
400
600
800
−15
−10
−5
0
5
10
15
V24

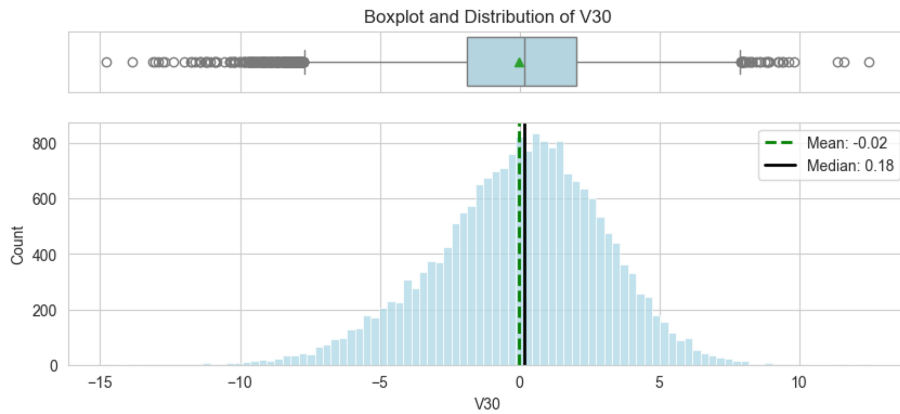

Boxplot and Distribution of V25
Mean: -0.00
Median: 0.03
Count
0
200
400
600
800
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
V25

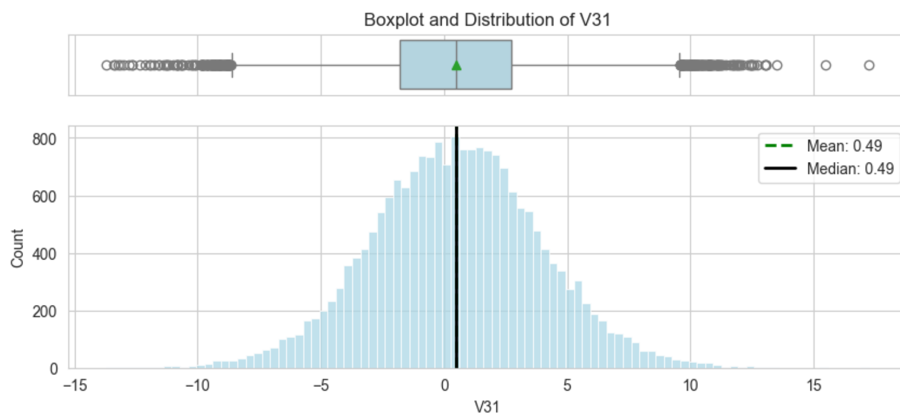

Boxplot and Distribution of V26
Mean: 1.87
Median: 1.95
Count
0
200
400
600
800
−10
−5
0
5
10
15
V26

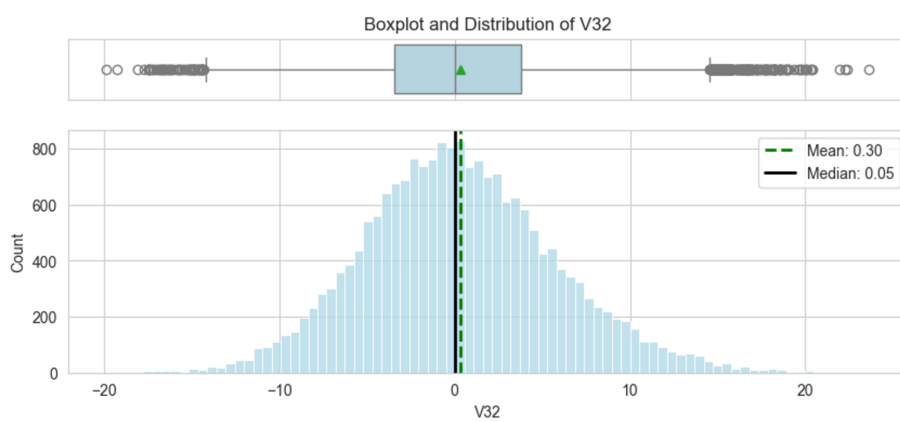

Boxplot and Distribution of V27
Mean: -0.61
Median: -0.88
Count
V27
0
200
400
600
800
−15
−10
−5
0
5
10
15

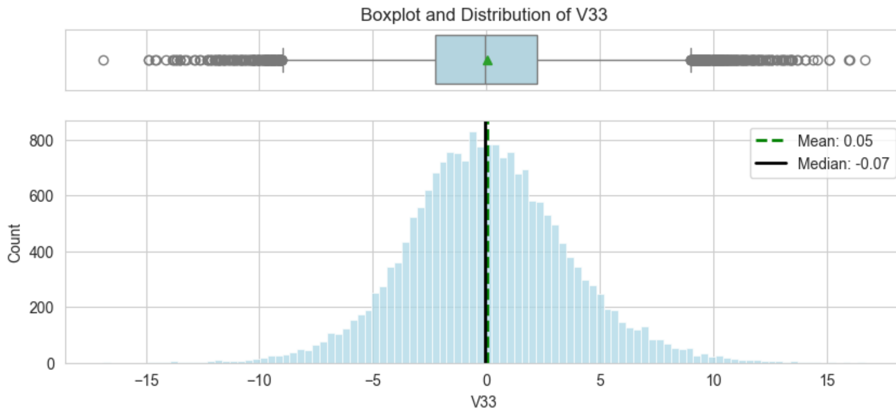

Boxplot and Distribution of V28
Mean: -0.88
Median: -0.89
Count
V28
0
200
400
600
800
−10
−8
−6
−4
−2
0
2
4
6

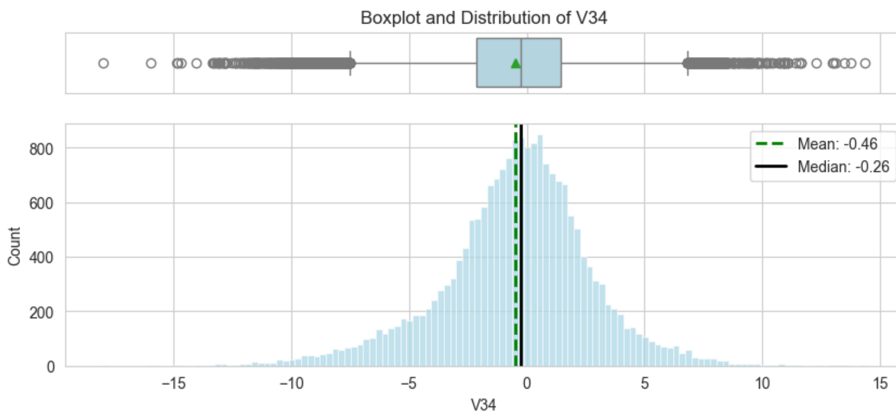

Boxplot and Distribution of V29
Mean: -0.99
Median: -1.18
Count
V29
0
200
400
600
800
−10
−5
0
5
10

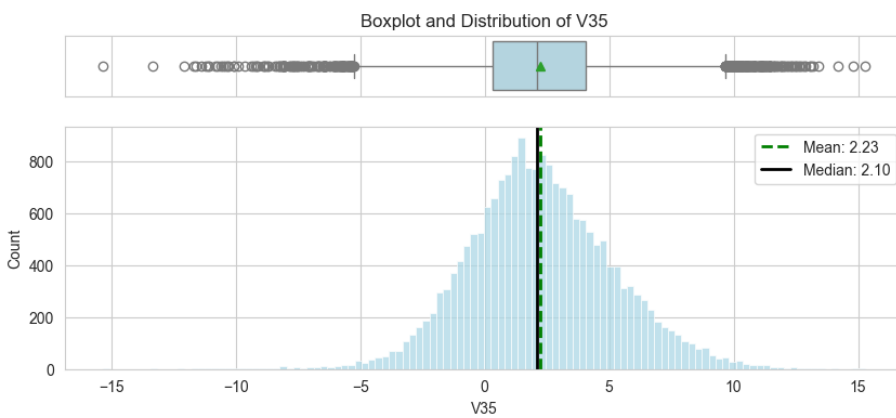

Boxplot and Distribution of V30
Mean: -0.02
Median: 0.18
Count
V30

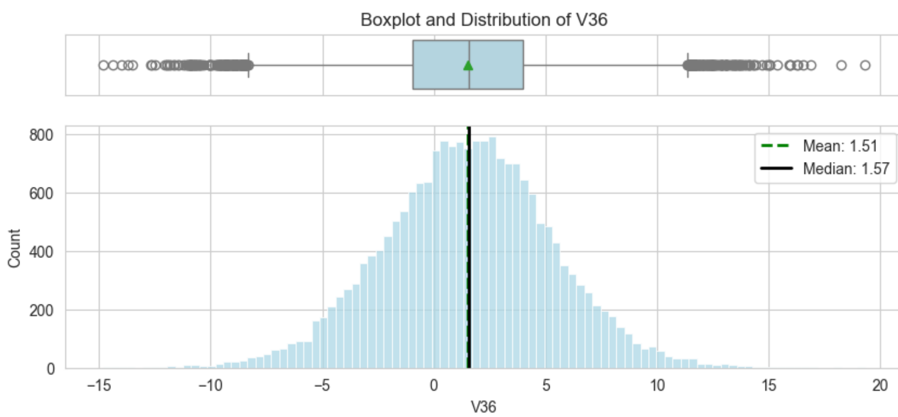

Boxplot and Distribution of V31
Mean: 0.49
Median: 0.49
Count
V31

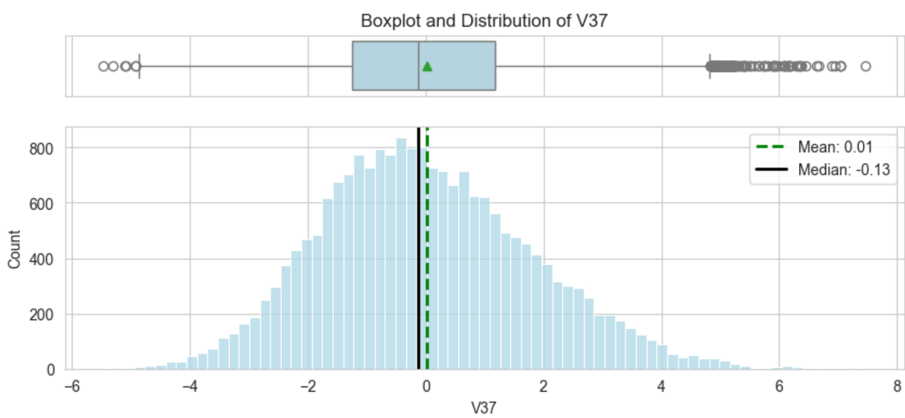

Boxplot and Distribution of V32
Mean: 0.30
Median: 0.05
Count
V32

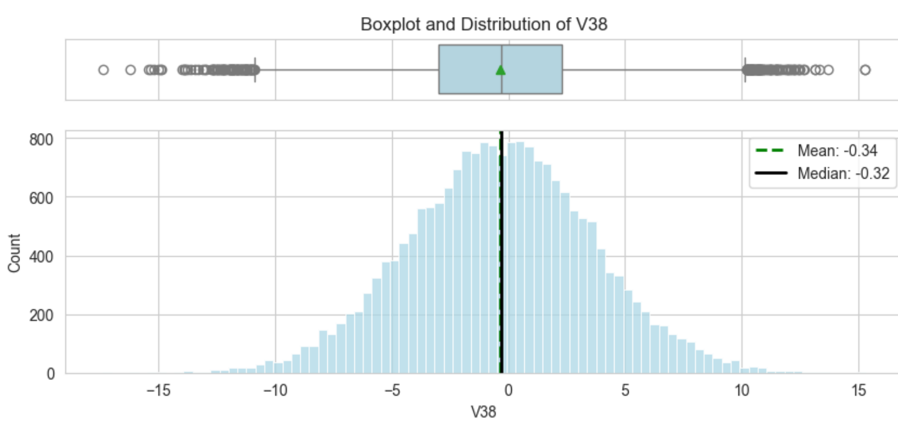

Boxplot and Distribution of V33
Mean: 0.05
Median: -0.07
Count
V33

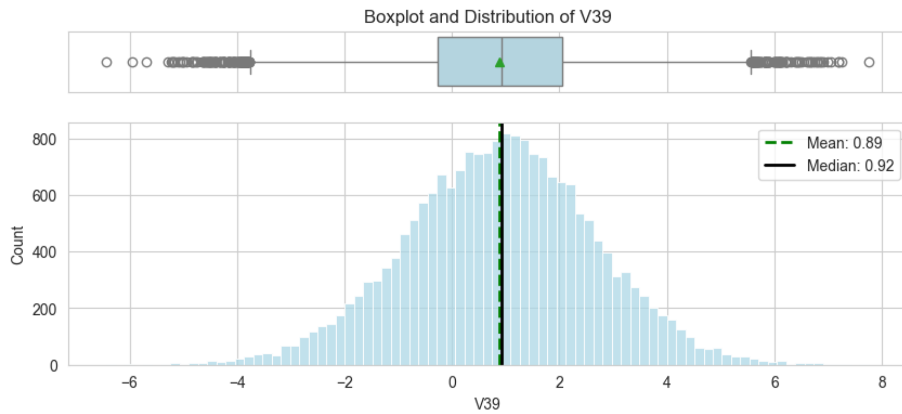

Boxplot and Distribution of V34
Mean: -0.46
Median: -0.26
Count
V34

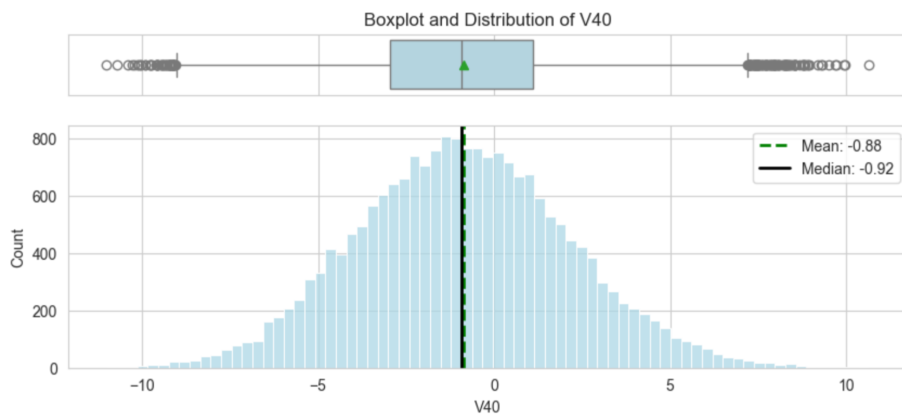

Boxplot and Distribution of V35
Mean: 2.23
Median: 2.10
Count
V35

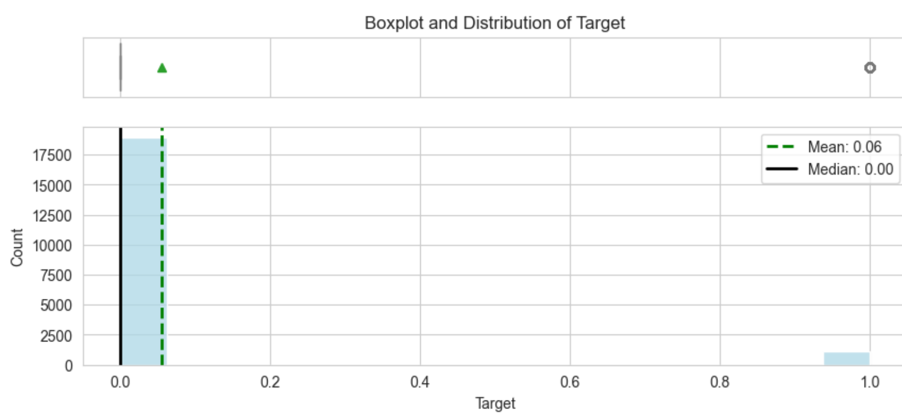

Boxplot and Distribution of V36
Mean: 1.51
Median: 1.57
Count
0
200
400
600
800
−15
−10
−5
0
5
10
15
20
V36


Boxplot and Distribution of V37
Mean: 0.01
Median: -0.13
Count
0
200
400
600
800
−6
−4
−2
0
2
4
6
8
V37


Boxplot and Distribution of V38
Mean: -0.34
Median: -0.32
Count
0
200
400
600
800
−15
−10
−5
0
5
10
15
V38







Observations:

Independent variables:

- The histograms indicate that the data for these variables is approximately

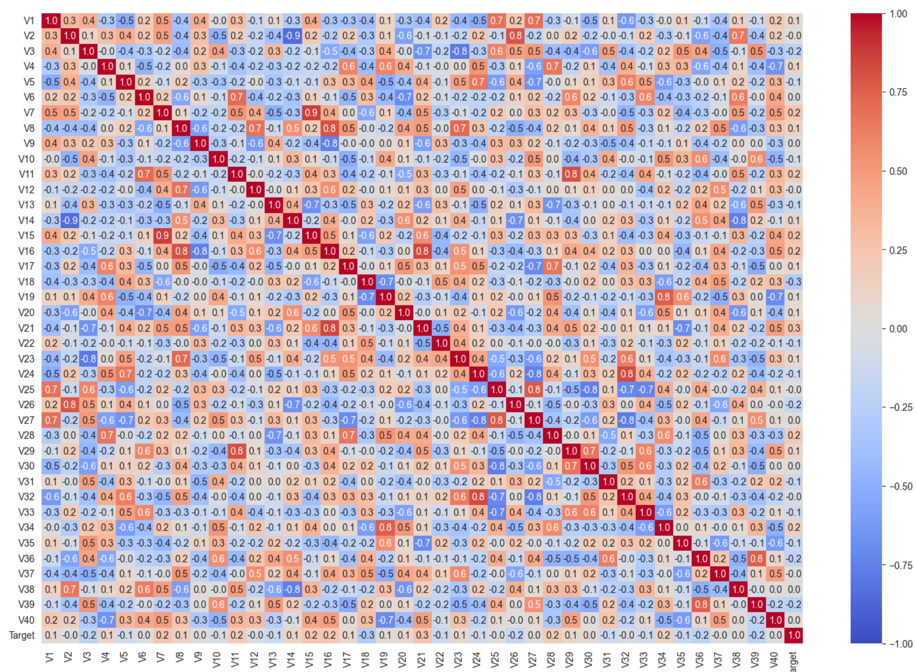
normally distributed with mean and median fairly close for most, further suggesting a normal distribution.
- The boxplots show dots outside of the whiskers, which represent outliers. These are observations that fall significantly higher or lower than the majority of the data.

The target variable:

- Highly imbalanced, with a much larger count of the 0 class compared to the 1 class consistnat with the numerical class distribution observation noted earlier.

Bivariate Analysis

```python
# Heatmap of the correlation coefficients between numerical variables in the dataset
cols_list = train_data.select_dtypes(include=np.number).columns.tolist()

plt.figure(figsize=(18, 12))
sns.heatmap(
    train_data[cols_list].corr(), annot=True, vmin=-1, vmax=1, fmt=".1f", cmap="coolwarm"
)
plt.show()
```

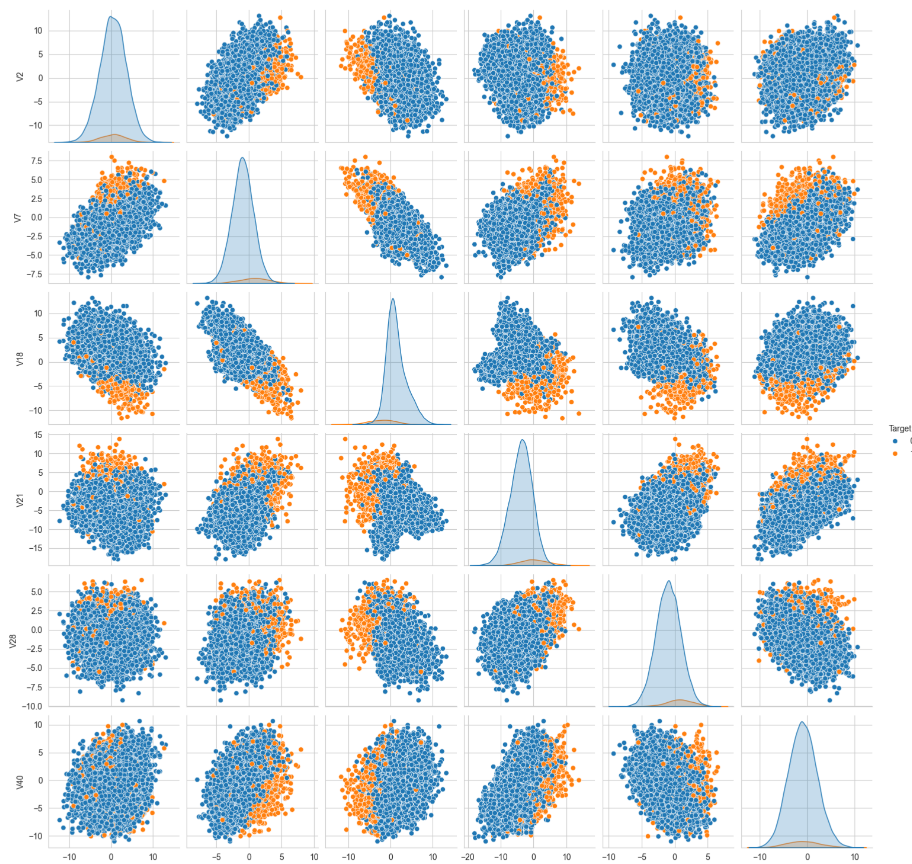


Observations:

- Highly Correlated Features:lots of them (both positive and negative). These

may represent redundancy within the dataset which means that one feature can be predicted from the other with a high degree of accuracy. In other words, these features carry similar information or signals about the data.
  - Multicollinearity in liner models
  - Overfitting the ti the training dataset due to redundant features
  - Redundant features increase computational complexity
  - Consider dimensionality reduction techniques like PCA
- Relationship with Target: features that have a stronger correlation with the target variable (V18, V21). These features may be particularly important for predicting the target and should be examined more closely in subsequent analyses.

```
# Selected a subset of features for the pair plot for better performance and clarity
selected_features = ['V2', 'V7', 'V18', 'V21', 'V28', 'V40', 'Target']

# Create the pair plot using the selected features
sns.pairplot(train_data[selected_features], hue='Target', diag_kind='kde')
plt.show()
```



```
train_df = train_data.copy()
test_df = test_data.copy()
```

Data Pre-Processing

```
# Split train data into X and y to separate the features from the target
X = train_df.drop(["Target"], axis=1)
y = train_df["Target"]
```

```
# Split the X training set into train and validate
X_train, X_val, y_train, y_val = train_test_split(
    X, y, test_size=0.25, random_state=42)
```

```
# Check the number of rows and columns in the X_train data
X_train.shape
```

```
(15000, 40)
```

```
# Check the number of rows and columns in the X_val data
X_val.shape
```

```
(5000, 40)
```

```
# Split test data into X and y to separate the features from the target
X_test = test_df.drop(["Target"], axis=1)
y_test = test_df["Target"]
```

```
# Check the number of rows and columns in the X_test data
X_test.shape
```

```
(5000, 40)
```

- X_train and y_train are now the subsets for training the model.
- X_val and y_val are for validating the model during the hyperparameter tuning and model selection process.
- X_test and y_test (from the original test dataset) are used strictly for the final evaluation of the model to assess its performance on unseen data.

Missing Value Imputation

```
# Create an instance of the imputer
imputer = SimpleImputer(strategy="median")
```

```
# Fit on the training data and transform it
X_train = pd.DataFrame(imputer.fit_transform(X_train), columns=X_train.columns)

# Transform the validation data based on the fit from the training data
X_val = pd.DataFrame(imputer.transform(X_val), columns=X_val.columns)
```

```
# Transform the test data based on the fit from the training data
X_test = pd.DataFrame(imputer.transform(X_test), columns=X_test.columns)

# Check that it worked
print(X_train.isna().sum())
print("-"*15)
print(X_val.isna().sum())
print("-"*15)
print(X_test.isna().sum())
print("-"*15)
```

```
V1     0
V2     0
V3     0
V4     0
V5     0
V6     0
V7     0
V8     0
V9     0
V10    0
V11    0
V12    0
V13    0
V14    0
V15    0
V16    0
V17    0
V18    0
V19    0
V20    0
V21    0
V22    0
V23    0
V24    0
V25    0
V26    0
V27    0
V28    0
V29    0
V30    0
V31    0
V32    0
V33    0
V34    0
V35    0
V36    0
```

```
V37    0
V38    0
V39    0
V40    0
dtype: int64
---------------
V1     0
V2     0
V3     0
V4     0
V5     0
V6     0
V7     0
V8     0
V9     0
V10    0
V11    0
V12    0
V13    0
V14    0
V15    0
V16    0
V17    0
V18    0
V19    0
V20    0
V21    0
V22    0
V23    0
V24    0
V25    0
V26    0
V27    0
V28    0
V29    0
V30    0
V31    0
V32    0
V33    0
V34    0
V35    0
V36    0
V37    0
V38    0
V39    0
V40    0
```

```
dtype: int64
---------------
V1     0
V2     0
V3     0
V4     0
V5     0
V6     0
V7     0
V8     0
V9     0
V10    0
V11    0
V12    0
V13    0
V14    0
V15    0
V16    0
V17    0
V18    0
V19    0
V20    0
V21    0
V22    0
V23    0
V24    0
V25    0
V26    0
V27    0
V28    0
V29    0
V30    0
V31    0
V32    0
V33    0
V34    0
V35    0
V36    0
V37    0
V38    0
V39    0
V40    0
dtype: int64
---------------
```

Scale/Normalize Features

```
# Create a scaler instance
scaler = StandardScaler()

# Fit on the training data and transform it
X_train = pd.DataFrame(scaler.fit_transform(X_train), columns=X_train.columns)

# Transform the validation and test data
X_val = pd.DataFrame(scaler.transform(X_val), columns=X_val.columns)

X_test = pd.DataFrame(scaler.transform(X_test), columns=X_test.columns)
```

Model Building

```
# defining a function to compute different metrics to check performance of a classification
def model_performance_classification_sklearn(model, predictors, target):
    """
    Function to compute different metrics to check classification model performance

    model: classifier
    predictors: independent variables
    target: dependent variable
    """
    TP = confusion_matrix(target, model.predict(predictors))[1,1]
    FP = confusion_matrix(target, model.predict(predictors))[0,1]
    FN = confusion_matrix(target, model.predict(predictors))[1,0]

    # predicting using the independent variables
    pred = model.predict(predictors)

    acc = accuracy_score(target, pred)  # to compute Accuracy
    recall = recall_score(target, pred)  # to compute Recall
    precision = precision_score(target, pred)  # to compute Precision
    f1 = f1_score(target, pred)  # to compute F1-score

    # creating a dataframe of metrics
    df_perf = pd.DataFrame(
        {
            "Accuracy": acc,
            "Recall": recall,
            "Precision": precision,
            "F1": f1

        },
        index=[0],
```

```
    )

    return df_perf
```

Defining scorer for cross-validation and hyperparameter tuning

- The goal heare is to reduce FN and maximize "Recall"
- So, use Recall as a scorer

```
# Defining the scorer based on recall
scorer = metrics.make_scorer(metrics.recall_score)
```

Model Building on Original Data

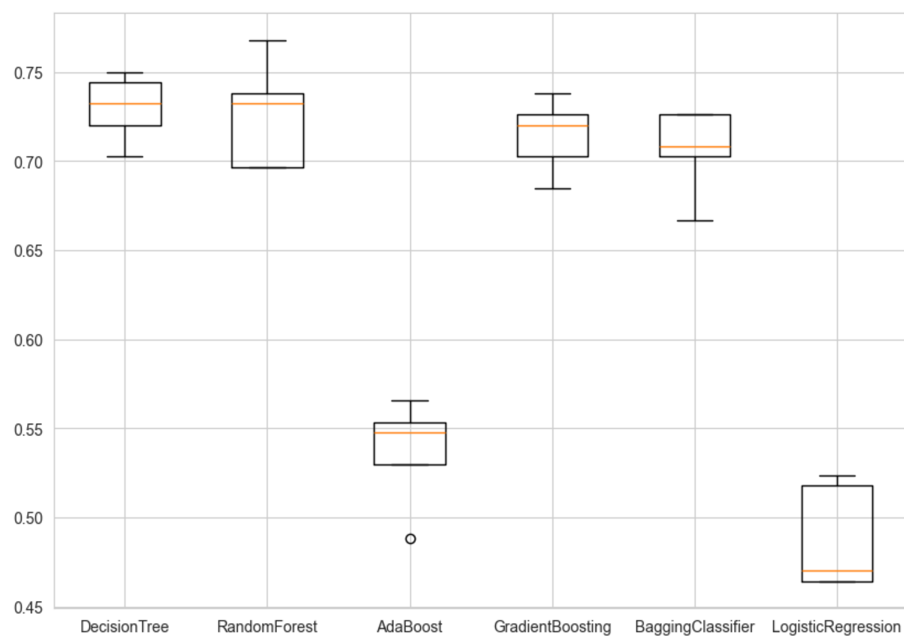
```
# Models to evaluate
models = []
models.append(("DecisionTree", DecisionTreeClassifier(random_state=1)))
models.append(("RandomForest", RandomForestClassifier(random_state=1)))
models.append(("AdaBoost", AdaBoostClassifier(random_state=1)))
models.append(("GradientBoosting", GradientBoostingClassifier(random_state=1)))
models.append(("BaggingClassifier", BaggingClassifier(random_state=1)))
models.append(("LogisticRegression", LogisticRegression(random_state=1, max_iter=10000)))  #

results_original = []  # To store cross-validation results
names_original = []  # To store model names

# Cross-validation across all models for Original Data
print("\nCross-Validation on Original Data:\n")


# StratifiedKFold setup
kfold = StratifiedKFold(n_splits=5, shuffle=True, random_state=1)

# Cross-validation across all models
for name, model in models:
    cv_result = cross_val_score(model, X_train, y_train, scoring=scorer, cv=kfold)
    results_original.append(cv_result)
    names_original.append(name)
    print(f"{name}: Mean Recall Score = {cv_result.mean()}")


print("\nValidation Performance on Original Data:\n")

# Fit models on the original training set and evaluate on the original validation set
for name, model in models:
    model.fit(X_train, y_train)  # Use the training data
```

```
    scores = recall_score(y_val, model.predict(X_val))  # Evaluate against the validation s
    print(f"{name}: Validation Recall Score = {scores}")
```

```
Cross-Validation on Original Data:

DecisionTree: Mean Recall Score = 0.7297619047619047
RandomForest: Mean Recall Score = 0.7261904761904762
AdaBoost: Mean Recall Score = 0.536904761904762
GradientBoosting: Mean Recall Score = 0.7142857142857142
BaggingClassifier: Mean Recall Score = 0.705952380952381
LogisticRegression: Mean Recall Score = 0.48809523809523814

Validation Performance on Original Data:

DecisionTree: Validation Recall Score = 0.7111111111111111
RandomForest: Validation Recall Score = 0.6962962962962963
AdaBoost: Validation Recall Score = 0.5333333333333333
GradientBoosting: Validation Recall Score = 0.6888888888888889
BaggingClassifier: Validation Recall Score = 0.7222222222222222
LogisticRegression: Validation Recall Score = 0.48148148148148145
```

```
# Plotting boxplots for CV scores of all models defined above
fig = plt.figure(figsize=(10, 7))

fig.suptitle("Algorithm Comparison of Models Trained on Original Data")
ax = fig.add_subplot(111)

plt.boxplot(results_original)
ax.set_xticklabels(names_original)

plt.show()
```

Algorithm Comparison of Models Trained on Original Data



Recall is highest for Random Forest followed by Decision Tree and Gradient Boosting.

Model Building with Oversampled Data

```
# Fit Synthetic Minority Over Sampling Technique (SMOTE) on train data, which uses kNN to g
sm = SMOTE(sampling_strategy=1, k_neighbors=5, random_state=1)
X_train_over, y_train_over = sm.fit_resample(X_train, y_train)

print("Before OverSampling, count of label '1': {}".format(sum(y_train == 1)))
print("Before OverSampling, count of label '0': {} \n".format(sum(y_train == 0)))

print("After OverSampling, count of label '1': {}".format(sum(y_train_over == 1)))
print("After OverSampling, count of label '0': {} \n".format(sum(y_train_over == 0)))

print("After OverSampling, the shape of train_X: {}".format(X_train_over.shape))
print("After OverSampling, the shape of train_y: {} \n".format(y_train_over.shape))
```

```
Before OverSampling, count of label '1': 840
Before OverSampling, count of label '0': 14160

After OverSampling, count of label '1': 14160
After OverSampling, count of label '0': 14160
```

```
After OverSampling, the shape of train_X: (28320, 40)
After OverSampling, the shape of train_y: (28320,)
```

Observations:

SMOTE has successfully balanced your dataset by generating synthetic examples of the minority class (1) using k-nearest neighbors.

Before applying SMOTE: the training dataset was significantly imbalanced with only 833 instances of the minority class (1) compared to 14,167 instances of the majority class (0). This imbalance leads to models that are biased towards the majority class and ignoring the minority class which is of greater interest to us.

After applying SMOTE: both classes now have an equal count of 14,167 instances, doubling the size of the training dataset to 28,334 instances. This balanced dataset is expected to improve model performance on the minority class by providing it with more examples to learn from, thus helping the model to generalize better and be less biased towards the majority class.

```python
# Models to evaluate on Oversampled Data
models = []
models.append(("DecisionTree", DecisionTreeClassifier(random_state=1)))
models.append(("RandomForest", RandomForestClassifier(random_state=1)))
models.append(("AdaBoost", AdaBoostClassifier(random_state=1)))
models.append(("GradientBoosting", GradientBoostingClassifier(random_state=1)))
models.append(("BaggingClassifier", BaggingClassifier(random_state=1)))
models.append(("LogisticRegression", LogisticRegression(random_state=1, max_iter=10000)))  #

# To store cross-validation results
results_oversampled = []
# To store model names
names_oversampled= []

# Cross-validation across all models for Oversampled Data
print("\nCross-Validation on Oversampled Data:\n")

# StratifiedKFold setup
kfold_oversampled = StratifiedKFold(n_splits=5, shuffle=True, random_state=1)

# Cross-validation across all models
for name, model in models:
    cv_result_oversampled = cross_val_score(model, X_train_over, y_train_over, scoring=score
    results_oversampled.append(cv_result_oversampled)
    names_oversampled.append(name)
    print(f"{name}: Mean Recall Score = {cv_result_oversampled.mean()}")
```

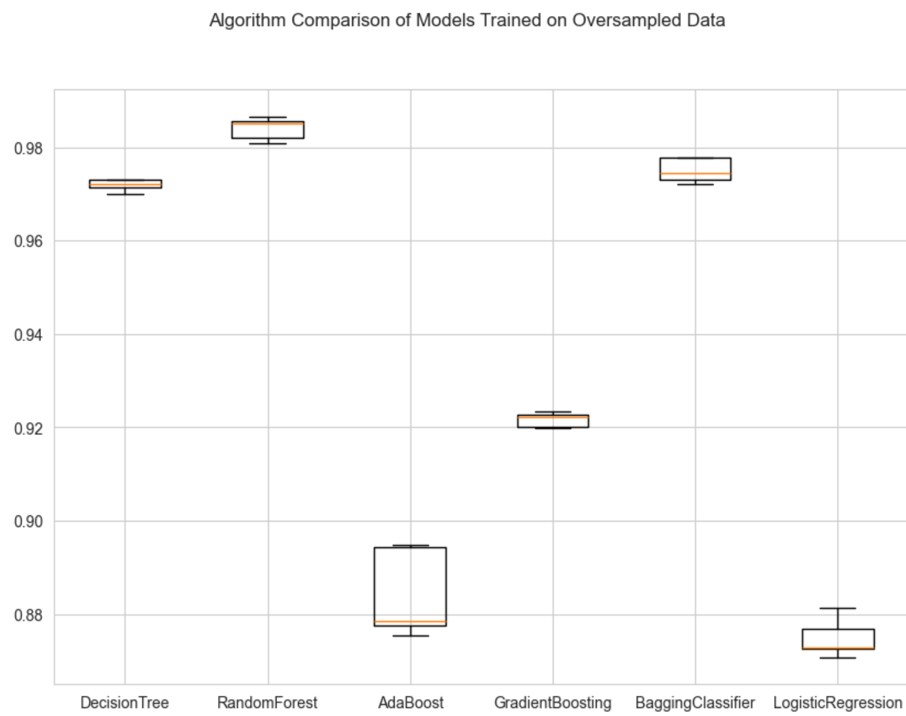
```python
print("\nValidation Performance on Oversampled Data:\n")

# Fit models on the oversampled training set and evaluate on the original validation set
for name, model in models:
    model.fit(X_train_over, y_train_over)  # Use the oversampled training data
    scores_oversampled = recall_score(y_val, model.predict(X_val))  # Evaluate against the
    print(f"{name}: Validation Recall Score = {scores_oversampled}")
```

```
Cross-Validation on Oversampled Data:

DecisionTree: Mean Recall Score = 0.9719632768361581
RandomForest: Mean Recall Score = 0.984039548022599
AdaBoost: Mean Recall Score = 0.8841101694915254
GradientBoosting: Mean Recall Score = 0.9216807909604519
BaggingClassifier: Mean Recall Score = 0.9750706214689266
LogisticRegression: Mean Recall Score = 0.8748587570621469

Validation Performance on Oversampled Data:

DecisionTree: Validation Recall Score = 0.7814814814814814
RandomForest: Validation Recall Score = 0.8296296296296296
AdaBoost: Validation Recall Score = 0.8444444444444444
GradientBoosting: Validation Recall Score = 0.8814814814814815
BaggingClassifier: Validation Recall Score = 0.8111111111111111
LogisticRegression: Validation Recall Score = 0.8518518518518519
```

Observations:

As expected, the balancing of the data with SMOTE improved model performance accross the board. However, it also introduced overfitting issues (ratio of Cross-Validation to Validation scores). Except for AdaBoost and Logistic Regression.

```python
# Plotting boxplots for CV scores of all models evaluated on oversampled data
fig = plt.figure(figsize=(10, 7))

fig.suptitle("Algorithm Comparison of Models Trained on Oversampled Data")
ax = fig.add_subplot(111)

plt.boxplot(results_oversampled)
ax.set_xticklabels(names_oversampled)

plt.show()
```



Observations:

Same trend, jsut more exagerated.

Model Building with Undersampled Data

```
# Random undersampler for under sampling the data
rus = RandomUnderSampler(random_state=1, sampling_strategy=1)
X_train_un, y_train_un = rus.fit_resample(X_train, y_train)

print("Before Under Sampling, count of label '1': {}".format(sum(y_train== 1)))
print("Before Under Sampling, count of label '0': {} \n".format(sum(y_train == 0)))

print("After Under Sampling, count of label '1': {}".format(sum(y_train_un == 1)))
print("After Under Sampling, count of label '0': {} \n".format(sum(y_train_un == 0)))

print("After Under Sampling, the shape of train_X: {}".format(X_train_un.shape))
print("After Under Sampling, the shape of train_y: {} \n".format(y_train_un.shape))
```

```
Before Under Sampling, count of label '1': 840
Before Under Sampling, count of label '0': 14160

After Under Sampling, count of label '1': 840
After Under Sampling, count of label '0': 840
```

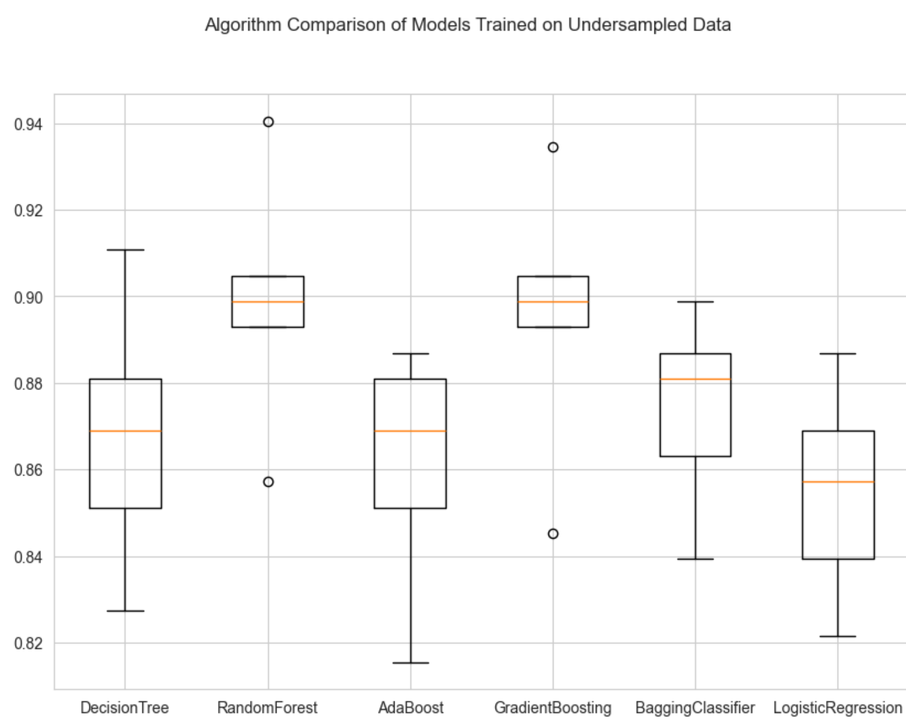
```
After Under Sampling, the shape of train_X: (1680, 40)
After Under Sampling, the shape of train_y: (1680,)
```

```
# Models to evaluate on Undersampled Data
models_undersampled = []
models_undersampled.append(("DecisionTree", DecisionTreeClassifier(random_state=1)))
models_undersampled.append(("RandomForest", RandomForestClassifier(random_state=1)))
models_undersampled.append(("AdaBoost", AdaBoostClassifier(random_state=1)))
models_undersampled.append(("GradientBoosting", GradientBoostingClassifier(random_state=1)))
models_undersampled.append(("BaggingClassifier", BaggingClassifier(random_state=1)))
models_undersampled.append(("LogisticRegression", LogisticRegression(random_state=1, max_ite

# To store cross-validation results for undersampled data
results_undersampled = []
# To store model names for undersampled data
names_undersampled = []

# Cross-validation across all models for Undersampled Data
print("\nCross-Validation on Undersampled Data:\n")

# StratifiedKFold setup for undersampled data
kfold_undersampled = StratifiedKFold(n_splits=5, shuffle=True, random_state=1)

# Cross-validation across all models
for name, model in models_undersampled:
    cv_result_undersampled = cross_val_score(model, X_train_un, y_train_un, scoring=scorer,
    results_undersampled.append(cv_result_undersampled)
    names_undersampled.append(name)
    print(f"{name}: Mean Recall Score = {cv_result_undersampled.mean()}")

print("\nValidation Performance on Undersampled Data:\n")

# Fit models on the undersampled training set and evaluate on the original validation set
for name, model in models_undersampled:
    model.fit(X_train_un, y_train_un)  # Use the undersampled training data
    scores_undersampled = recall_score(y_val, model.predict(X_val))  # Evaluate against the
    print(f"{name}: Validation Recall Score = {scores_undersampled}")
```

```
Cross-Validation on Undersampled Data:

DecisionTree: Mean Recall Score = 0.8678571428571427
RandomForest: Mean Recall Score = 0.8988095238095237
AdaBoost: Mean Recall Score = 0.8607142857142858
GradientBoosting: Mean Recall Score = 0.8952380952380953
```

```
BaggingClassifier: Mean Recall Score = 0.8738095238095237
LogisticRegression: Mean Recall Score = 0.8547619047619047

Validation Performance on Undersampled Data:

DecisionTree: Validation Recall Score = 0.837037037037037
RandomForest: Validation Recall Score = 0.8777777777777778
AdaBoost: Validation Recall Score = 0.8555555555555555
GradientBoosting: Validation Recall Score = 0.8888888888888888
BaggingClassifier: Validation Recall Score = 0.8481481481481481
LogisticRegression: Validation Recall Score = 0.8555555555555555
```

```
# Plotting boxplots for CV scores of all models evaluated on  undersampled data
fig = plt.figure(figsize=(10, 7))

fig.suptitle("Algorithm Comparison of Models Trained on Undersampled Data")
ax = fig.add_subplot(111)

plt.boxplot(results_undersampled)
ax.set_xticklabels(names_undersampled)

plt.show()
```



Observations:

Fast. Random Forest still highest performace. Less overfitting accross the board.

Hyperparameter Tuning

Model Selection for Hyperparameter Tuning

Top 3 models providing the highest Recall scores on both cross-validation and validation datasets :

1. **RandomForest**
2. **GradientBoosting**
3. **AdaBoost**

Hyperparameter Tuning of Random Forest on Original Data

```
# Defining the Random Forest model for original data
rf_model_orig = RandomForestClassifier(random_state=1)

# Parameter grid for Random Forest
param_grid_rf_orig = {
    "n_estimators": [200, 250],  # Reduced for simplicity
    "min_samples_leaf": [1, 2],  # Simplified range
    "max_features": ['sqrt'],  # Simplified choice
    "max_samples": [0.5]  # Simplified choice
}

# Setting up RandomizedSearchCV for the original data with reduced n_iter and cv
randomized_rf_orig = RandomizedSearchCV(estimator=rf_model_orig, param_distributions=param_g
                                        scoring= scorer, n_iter=10, cv=3, random_state=1)

# Fitting RandomizedSearchCV on the original data
randomized_rf_orig.fit(X_train, y_train)

# Extracting best parameters and creating a new Random Forest Classifier
best_params_rf_orig = randomized_rf_orig.best_params_
tuned_rf_orig = RandomForestClassifier(**best_params_rf_orig, random_state=1)

# Fitting the tuned model and evaluating
tuned_rf_orig.fit(X_train, y_train)
```

```
RandomForestClassifier(max_samples=0.5, n_estimators=200, random_state=1)
```

```
# Evaluating the tuned model on original data
rf_train_perf_orig = model_performance_classification_sklearn(tuned_rf_orig, X_train, y_trai
print("Performance on Train Set:")
rf_train_perf_orig
```

```
Performance on Train Set:
```

	Accuracy	Recall	Precision	F1
0	0.993	0.879	0.999	0.935

```python
rf_val_perf_orig = model_performance_classification_sklearn(tuned_rf_orig, X_val, y_val)
print("Performance on Validation Set:")
rf_val_perf_orig
```

```
Performance on Validation Set:
```

	Accuracy	Recall	Precision	F1
0	0.982	0.670	0.989	0.799

Hyperparameter Tuning of Random Forest on Oversampled Data

```python
 # Defining the Random Forest model for original data
rf_model_over = RandomForestClassifier(random_state=1)

# Parameter grid for Random Forest
param_grid_rf_orig = {
    "n_estimators": [200, 250],  # Reduced for simplicity
    "min_samples_leaf": [1, 2],  # Simplified range
    "max_features": ['sqrt'],  # Simplified choice
    "max_samples": [0.5]  # Simplified choice
}

# Setting up RandomizedSearchCV for the original data
randomized_rf_over = RandomizedSearchCV(estimator=rf_model_orig, param_distributions=param_g
                                        scoring=scorer, n_iter=50, cv=5, random_state=1)

# Fitting RandomizedSearchCV on the oversampled data
randomized_rf_over.fit(X_train_over, y_train_over)

# Extracting best parameters for oversampled data
best_params_rf_over = randomized_rf_over.best_params_

# Creating a new Random Forest Classifier with the best parameters for oversampled data
tuned_rf_over = RandomForestClassifier(**best_params_rf_over, random_state=1)

# Fitting the tuned model on the oversampled training data
tuned_rf_over.fit(X_train_over, y_train_over)
```

```
RandomForestClassifier(max_samples=0.5, n_estimators=250, random_state=1)
```

```python
# Evaluating the tuned model on oversampled train data
rf_train_perf_over = model_performance_classification_sklearn(tuned_rf_over, X_train_over, y
rf_train_perf_over
```

```
   Accuracy  Recall  Precision    F1
0     0.999   0.998      1.000 0.999
```

```
# Evaluating the tuned model on oversampled validation data
rf_val_perf_over = model_performance_classification_sklearn(tuned_rf_over, X_val, y_val)
rf_val_perf_over
```

```
   Accuracy  Recall  Precision    F1
0     0.988   0.859      0.917 0.887
```

Hyperparameter Tuning of Random Forest on Undersampled Data

```
 # Defining the Random Forest model for original data
rf_model_un = RandomForestClassifier(random_state=1)

# Parameter grid for Random Forest
param_grid_rf_orig = {
    "n_estimators": [200, 250],  # Reduced for simplicity
    "min_samples_leaf": [1, 2],  # Simplified range
    "max_features": ['sqrt'],  # Simplified choice
    "max_samples": [0.5]  # Simplified choice
}

# Setting up RandomizedSearchCV for the original data
randomized_rf_un = RandomizedSearchCV(estimator=rf_model_orig, param_distributions=param_gri
                                        scoring= scorer, n_iter=50, cv=5, random_state=1)

# Fitting RandomizedSearchCV on the undersampled data
randomized_rf_un.fit(X_train_un, y_train_un)

# Extracting best parameters for undersampled data
best_params_rf_un = randomized_rf_un.best_params_
print("Best parameters are {} with CV score={}:" .format(randomized_rf_un.best_params_,rando
```

```
Best parameters are {'n_estimators': 250, 'min_samples_leaf': 2, 'max_samples': 0.5, 'max_fe
```

```
# Creating a new Random Forest Classifier with the best parameters for undersampled data
tuned_rf_un = RandomForestClassifier(**best_params_rf_un, random_state=1)

# Fitting the tuned model on the undersampled training data
tuned_rf_un.fit(X_train_un, y_train_un)
```

```
RandomForestClassifier(max_samples=0.5, min_samples_leaf=2, n_estimators=250,
                       random_state=1)
```

```
# Evaluating the tuned model on undersampled data
rf_train_perf_un = model_performance_classification_sklearn(tuned_rf_un, X_train_un, y_trai
rf_train_perf_un
```

```
   Accuracy  Recall  Precision    F1
0     0.966   0.940      0.991 0.965
```

```
rf_val_perf_un = model_performance_classification_sklearn(tuned_rf_un, X_val, y_val)
rf_val_perf_un
```

```
   Accuracy  Recall  Precision    F1
0     0.935   0.878      0.450 0.595
```

Hyperparameter Tuning of Gradient Boost on Original Data

```
# Defining the Gradient Boosting model
gb_model_orig = GradientBoostingClassifier(random_state=1)

# Parameter grid remains the same as the oversampling case
param_grid_orig = {
    "n_estimators": np.arange(100, 150, 25),
    "learning_rate": [0.2, 0.05, 1],
    "subsample": [0.5, 0.7],
    "max_features": [0.5, 0.7]
}

# Setting up RandomizedSearchCV for the original data
randomized_cv_orig = RandomizedSearchCV(estimator=gb_model_orig, param_distributions=param_g
                                        scoring=scorer, n_iter=50, n_jobs=-1, cv=5, random_s

# Fitting RandomizedSearchCV on the original data
randomized_cv_orig.fit(X_train, y_train)

# Best parameters
# print("Best parameters for original data are {} with CV score={}:".format(randomized_cv_o

# Extracting best parameters for the original data
best_params_orig = randomized_cv_orig.best_params_

# Creating a new Gradient Boosting Classifier with the best parameters for original data
tuned_gbm_orig = GradientBoostingClassifier(
    max_features=best_params_orig['max_features'],
    random_state=1,
    learning_rate=best_params_orig['learning_rate'],
    n_estimators=best_params_orig['n_estimators'],
    subsample=best_params_orig['subsample']
)

# Fitting the tuned model on the original training data
tuned_gbm_orig.fit(X_train, y_train)
```

```
GradientBoostingClassifier(learning_rate=0.2, max_features=0.7,
                           n_estimators=np.int64(125), random_state=1,
                           subsample=0.7)
```

```
# Checking performance
gbm_train_perf_orig = model_performance_classification_sklearn(tuned_gbm_orig, X_train_over,
print("Performance on Train Set:")
gbm_train_perf_orig
```

Performance on Train Set:

	Accuracy	Recall	Precision	F1
0	0.912	0.825	1.000	0.904

```
gbm_val_perf_orig = model_performance_classification_sklearn(tuned_gbm_orig, X_val, y_val)
print("Performance on Validation Set:")
gbm_val_perf_orig
```

Performance on Validation Set:

	Accuracy	Recall	Precision	F1
0	0.979	0.715	0.869	0.785

Hyperparameter Tuning of Gradient Boost on Oversampled Data

```
# Defining the Gradient Boosting model for oversampled data
gb_model_over = GradientBoostingClassifier(random_state=1)

# Parameter grid for oversampled data (you can adjust or use the same)
param_grid_over = {
    "n_estimators": np.arange(100, 150, 25),
    "learning_rate": [0.2, 0.05, 1],
    "subsample": [0.5, 0.7],
    "max_features": [0.5, 0.7]
}

# Setting up RandomizedSearchCV for the oversampled data
randomized_cv_over = RandomizedSearchCV(estimator=gb_model_over, param_distributions=param_
                                        scoring=scorer, n_iter=50, n_jobs=-1, cv=5, random_s

# Fitting RandomizedSearchCV on the oversampled data
randomized_cv_over.fit(X_train_over, y_train_over)

# Extracting best parameters for the oversampled data
best_params_over = randomized_cv_over.best_params_

# Creating a new Gradient Boosting Classifier with the best parameters for oversampled data
tuned_gbm_over = GradientBoostingClassifier(
    max_features=best_params_over['max_features'],
```

```
    random_state=1,
    learning_rate=best_params_over['learning_rate'],
    n_estimators=best_params_over['n_estimators'],
    subsample=best_params_over['subsample']
)

# Fitting the tuned model on the oversampled training data
tuned_gbm_over.fit(X_train_over, y_train_over)
```

```
GradientBoostingClassifier(learning_rate=1, max_features=0.5,
                           n_estimators=np.int64(125), random_state=1,
                           subsample=0.7)
```

```
# Checking performance
gbm_train_perf_over = model_performance_classification_sklearn(tuned_gbm_over, X_train_over,
gbm_train_perf_over
```

	Accuracy	Recall	Precision	F1
0	0.993	0.992	0.993	0.993

```
gbm_val_perf_over = model_performance_classification_sklearn(tuned_gbm_over, X_val, y_val)
gbm_val_perf_over
```

	Accuracy	Recall	Precision	F1
0	0.968	0.867	0.657	0.748

Hyperparameter Tuning of Gradient Boost on Undersampled Data

```
# Defining the Gradient Boosting model for undersampled data
gb_model_un = GradientBoostingClassifier(random_state=1)

# Parameter grid for undersampled data (you can adjust or use the same)
param_grid_un = {
    "n_estimators": np.arange(100, 150, 25),
    "learning_rate": [0.2, 0.05, 1],
    "subsample": [0.5, 0.7],
    "max_features": [0.5, 0.7]
}

# Setting up RandomizedSearchCV for the undersampled data
randomized_cv_un = RandomizedSearchCV(estimator=gb_model_un, param_distributions=param_grid_
                                      scoring=scorer, n_iter=50, n_jobs=-1, cv=5, random_sta

# Fitting RandomizedSearchCV on the undersampled data
randomized_cv_un.fit(X_train_un, y_train_un)

# Extracting best parameters for the undersampled data
best_params_un = randomized_cv_un.best_params_
```

```python
# Creating a new Gradient Boosting Classifier with the best parameters for undersampled data
tuned_gbm_un = GradientBoostingClassifier(
    max_features=best_params_un['max_features'],
    random_state=1,
    learning_rate=best_params_un['learning_rate'],
    n_estimators=best_params_un['n_estimators'],
    subsample=best_params_un['subsample']
)

# Fitting the tuned model on the undersampled training data
tuned_gbm_un.fit(X_train_un, y_train_un)
```

```
GradientBoostingClassifier(learning_rate=0.2, max_features=0.5,
                           n_estimators=np.int64(100), random_state=1,
                           subsample=0.5)
```

```python
# Checking performance
gbm_train_perf_un = model_performance_classification_sklearn(tuned_gbm_un, X_train_un, y_tra
gbm_train_perf_un
```

	Accuracy	Recall	Precision	F1
0	0.984	0.975	0.993	0.984

```python
gbm_val_perf_un = model_performance_classification_sklearn(tuned_gbm_un, X_val, y_val)
gbm_val_perf_un
```

	Accuracy	Recall	Precision	F1
0	0.909	0.878	0.361	0.511

Hyperparameter Tuning of AdaBoost on Original Data

```python
# Defining the AdaBoost model for original data
ada_model_orig = AdaBoostClassifier(random_state=1)

# Parameter grid for AdaBoost
param_grid_ada_orig = {
    "n_estimators": [50, 100, 150],
    "learning_rate": [0.01, 0.05],
}


# Setting up RandomizedSearchCV for the original data
randomized_ada_orig = RandomizedSearchCV(estimator=ada_model_orig, param_distributions=param
                                         scoring= scorer, n_iter=10, cv=5, random_state=1)

# Fitting RandomizedSearchCV on the original data
randomized_ada_orig.fit(X_train, y_train)
```

```
# Extracting best parameters
best_params_ada_orig = randomized_ada_orig.best_params_

# Creating a new pipline of AdaBoost Classifier with the best parameters
tuned_ada_orig = AdaBoostClassifier(**best_params_ada_orig, random_state=1)

# Fitting the tuned model on the original training data
tuned_ada_orig.fit(X_train, y_train)
```

```
AdaBoostClassifier(learning_rate=0.05, n_estimators=150, random_state=1)
```

```
# Evaluating the tuned model
ada_train_perf_orig = model_performance_classification_sklearn(tuned_ada_orig, X_train, y_tr
ada_train_perf_orig
```

```
   Accuracy  Recall  Precision    F1
0     0.951   0.140      0.915 0.244
```

```
ada_val_perf_orig = model_performance_classification_sklearn(tuned_ada_orig, X_val, y_val)
ada_val_perf_orig
```

```
   Accuracy  Recall  Precision    F1
0     0.952   0.137      0.881 0.237
```

Hyperparameter Tuning of AdaBoost on Oversample Data

```
# Defining the AdaBoost model for oversampled data
ada_model_over = AdaBoostClassifier(random_state=1)

# Parameter grid for AdaBoost
param_grid_ada_over = {
    "n_estimators": [50, 100, 150],
    "learning_rate": [0.01, 0.05],
}
# Setting up RandomizedSearchCV for the oversampled data
randomized_ada_over = RandomizedSearchCV(estimator=ada_model_orig, param_distributions=param
                                         scoring=scorer, n_iter=10, cv=5, random_state=1)

# Fitting RandomizedSearchCV on the oversampled data
randomized_ada_over.fit(X_train_over, y_train_over)

# Extracting best parameters for the oversampled data
best_params_ada_over = randomized_ada_over.best_params_

# Creating a new AdaBoost Classifier with the best parameters for oversampled data
tuned_ada_over = AdaBoostClassifier(**best_params_ada_over, random_state=1)
```

```python
# Fitting the tuned model on the oversampled training data
tuned_ada_over.fit(X_train_over, y_train_over)
```

```
AdaBoostClassifier(learning_rate=0.01, random_state=1)
```

```python
print("Best parameters are {} with CV score={}:" .format(randomized_ada_over.best_params_,ra
```

```
Best parameters are {'n_estimators': 50, 'learning_rate': 0.01} with CV score=0.851694915254
```

```python
# Evaluating the tuned model on oversampled data
ada_train_perf_over = model_performance_classification_sklearn(tuned_ada_over, X_train_over,
ada_train_perf_over
```

	Accuracy	Recall	Precision	F1
0	0.759	0.864	0.714	0.782

```python
ada_val_perf_over = model_performance_classification_sklearn(tuned_ada_over, X_val, y_val)
ada_val_perf_over
```

	Accuracy	Recall	Precision	F1
0	0.664	0.804	0.118	0.205

Hyperparameter Tuning of AdaBoost on Undersampled Data

```python
# Defining the AdaBoost model for oversampled data
ada_model_un = AdaBoostClassifier(random_state=1)

# Parameter grid for AdaBoost
param_grid_ada_un = {
    "n_estimators": [50, 100, 150],
    "learning_rate": [0.01, 0.05],
}
# Setting up RandomizedSearchCV for the undersampled data
randomized_ada_un = RandomizedSearchCV(estimator=ada_model_orig, param_distributions=param_g
                                       scoring=scorer, n_iter=10, cv=5, random_state=1)

# Fitting RandomizedSearchCV on the undersampled data
randomized_ada_un.fit(X_train_un, y_train_un)

# Extracting best parameters for the undersampled data
best_params_ada_un = randomized_ada_un.best_params_

# Creating a new AdaBoost Classifier with the best parameters for undersampled data
tuned_ada_un = AdaBoostClassifier(**best_params_ada_un, random_state=1)

# Fitting the tuned model on the undersampled training data
tuned_ada_un.fit(X_train_un, y_train_un)
```

```
AdaBoostClassifier(learning_rate=0.05, n_estimators=150, random_state=1)
```

```python
# Evaluating the tuned model on undersampled data
ada_train_perf_un = model_performance_classification_sklearn(tuned_ada_un, X_train_un, y_tra
ada_train_perf_un
```

```
   Accuracy  Recall  Precision    F1
0     0.854   0.781      0.915 0.843
```

```python
ada_val_perf_un = model_performance_classification_sklearn(tuned_ada_un, X_val, y_val)
ada_val_perf_un
```

```
   Accuracy  Recall  Precision    F1
0     0.898   0.733      0.312 0.438
```

Model Performance Comparison

```python
# Training performance comparison

models_train_comp_df = pd.concat(
    [
        rf_train_perf_orig.T,
        gbm_train_perf_orig.T,
        ada_train_perf_orig.T,

        rf_train_perf_over.T,
        gbm_train_perf_over.T,
        ada_train_perf_over.T,

        rf_train_perf_un.T,
        gbm_train_perf_un.T,
        ada_train_perf_un.T,

    ],
    axis=1,
)
models_train_comp_df.columns = [
       'rf_train_perf_orig',
       'gbm_train_perf_orig',
       'ada_train_perf_orig',

       'rf_train_perf_over',
       'gbm_train_perf_over',
       'ada_train_perf_over',

       'rf_train_perf_un',
       'gbm_train_perf_un',
       'ada_train_perf_un',
```

```
]
print("Training performance comparison:")
models_train_comp_df
```

```
Training performance comparison:

           rf_train_perf_orig  gbm_train_perf_orig  ada_train_perf_orig  \
Accuracy                0.993                0.912                0.951
Recall                  0.879                0.825                0.140
Precision               0.999                1.000                0.915
F1                      0.935                0.904                0.244

           rf_train_perf_over  gbm_train_perf_over  ada_train_perf_over  \
Accuracy                0.999                0.993                0.759
Recall                  0.998                0.992                0.864
Precision               1.000                0.993                0.714
F1                      0.999                0.993                0.782

           rf_train_perf_un  gbm_train_perf_un  ada_train_perf_un
Accuracy              0.966              0.984              0.854
Recall                0.940              0.975              0.781
Precision             0.991              0.993              0.915
F1                    0.965              0.984              0.843
```

```
# Validation performance comparison

models_val_comp_df = pd.concat(
    [
        rf_val_perf_orig.T,
        gbm_val_perf_orig.T,
        ada_val_perf_orig.T,

        rf_val_perf_over.T,
        gbm_val_perf_over.T,
        ada_val_perf_over.T,

        rf_val_perf_un.T,
        gbm_val_perf_un.T,
        ada_val_perf_un.T,
    ],
    axis=1,
)
models_val_comp_df.columns = [
       'rf_val_perf_orig',
       'gbm_val_perf_orig',
       'ada_val_perf_orig',
```

```python
        'rf_val_perf_over',
        'gbm_val_perf_over',
        'ada_val_perf_over',

        'rf_val_perf_un',
        'gbm_val_perf_un',
        'ada_val_perf_un',
]
print("Validation performance comparison:")
models_val_comp_df
```

```
Validation performance comparison:

           rf_val_perf_orig  gbm_val_perf_orig  ada_val_perf_orig  \
Accuracy              0.982              0.979              0.952
Recall                0.670              0.715              0.137
Precision             0.989              0.869              0.881
F1                    0.799              0.785              0.237

           rf_val_perf_over  gbm_val_perf_over  ada_val_perf_over  \
Accuracy              0.988              0.968              0.664
Recall                0.859              0.867              0.804
Precision             0.917              0.657              0.118
F1                    0.887              0.748              0.205

           rf_val_perf_un  gbm_val_perf_un  ada_val_perf_un
Accuracy            0.935            0.909            0.898
Recall              0.878            0.878            0.733
Precision           0.450            0.361            0.312
F1                  0.595            0.511            0.438
```

```python
print("Training performance comparison:")
models_train_comp_df
```

```
Training performance comparison:

           rf_train_perf_orig  gbm_train_perf_orig  ada_train_perf_orig  \
Accuracy                0.993                0.912                0.951
Recall                  0.879                0.825                0.140
Precision               0.999                1.000                0.915
F1                      0.935                0.904                0.244

           rf_train_perf_over  gbm_train_perf_over  ada_train_perf_over  \
Accuracy                0.999                0.993                0.759
Recall                  0.998                0.992                0.864
Precision               1.000                0.993                0.714
F1                      0.999                0.993                0.782
```

```
           rf_train_perf_un  gbm_train_perf_un  ada_train_perf_un
Accuracy              0.966              0.984              0.854
Recall                0.940              0.975              0.781
Precision             0.991              0.993              0.915
F1                    0.965              0.984              0.843
```

```python
print("Validation performance comparison:")
models_val_comp_df
```

```
Validation performance comparison:

           rf_val_perf_orig  gbm_val_perf_orig  ada_val_perf_orig  \
Accuracy              0.982              0.979              0.952
Recall                0.670              0.715              0.137
Precision             0.989              0.869              0.881
F1                    0.799              0.785              0.237

           rf_val_perf_over  gbm_val_perf_over  ada_val_perf_over  \
Accuracy              0.988              0.968              0.664
Recall                0.859              0.867              0.804
Precision             0.917              0.657              0.118
F1                    0.887              0.748              0.205

           rf_val_perf_un  gbm_val_perf_un  ada_val_perf_un
Accuracy            0.935            0.909            0.898
Recall              0.878            0.878            0.733
Precision           0.450            0.361            0.312
F1                  0.595            0.511            0.438
```

AdaBoost on oversampled data emerges as a strong candidate for the final model due to its excellent performance across accuracy, **recall**, precision, and F1 score in the validation set.

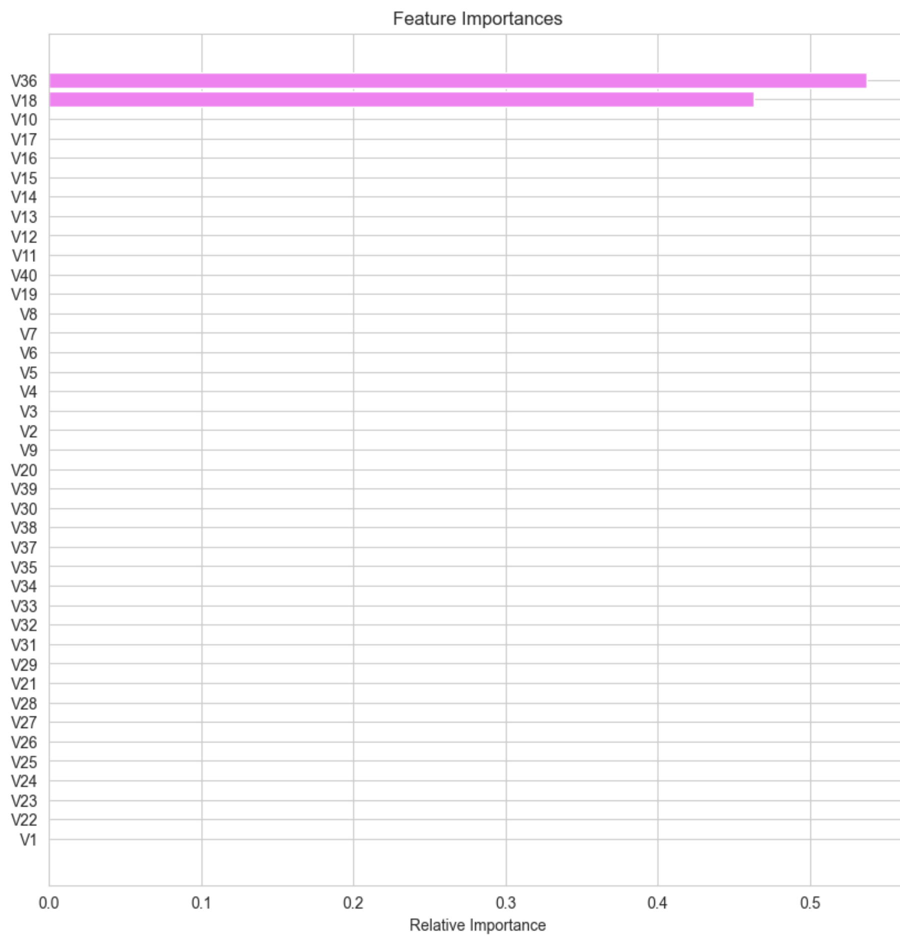
Final Model Selection

```python
# Check the performance of the final model on the test data
ada_test = model_performance_classification_sklearn(tuned_ada_over, X_test, y_test)
ada_test
```

```
   Accuracy  Recall  Precision    F1
0     0.675   0.840      0.131 0.226
```

```python
feature_names = X_train.columns
importances = tuned_ada_over.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(10, 10))
plt.title("Feature Importances")
```

```
plt.barh(range(len(indices)), importances[indices], color="violet", align="center")
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel("Relative Importance")
plt.show()
```



Pipelines to build the final model

Since we have only one datatype in the data we don't need to use column transofrmer which can be used to personalize the pipeline to perform different preprocessing steps on different columns. Note: see case study how to use this.

The steps followed in implementing a pipeline are -

- Pipeline() - A pipeline is defined as a list of tuples
- Pipeline.fit() - Pipeline is fitted on the train set
- Pipeline.score() - Pipeline objects checks the performance.

```python
pipe = Pipeline(
    steps=[
        ("imputer", SimpleImputer(strategy="median")),
        ("scaler", StandardScaler()),
        ("AdaBoost", AdaBoostClassifier
         (
               n_estimators= 50,
               learning_rate= 0.05,
            ),
        ),
    ]
)

# Check pipline steps
pipe.steps
```

```
[('imputer', SimpleImputer(strategy='median')),
 ('scaler', StandardScaler()),
 ('AdaBoost', AdaBoostClassifier(learning_rate=0.05))]
```

```python
# Fit the pipeline on training data as if it were a model since the model is included in it
pipe.fit(X_train, y_train)
# See pipeline structure below
```

```
Pipeline(steps=[('imputer', SimpleImputer(strategy='median')),
                ('scaler', StandardScaler()),
                ('AdaBoost', AdaBoostClassifier(learning_rate=0.05))])
```

The above means a model is built which becomes part of pipe

```python
# pipe object's accuracy on the train set
pipe.score(X_train, y_train)
```

```
0.944
```

Instead of model.score calling pipe.score fucntion does a predict then uses those results with the actual results to give the score.

```python
# pipe object's accuracy on the test set
pipe.score(X_test, y_test)
```

```
0.9436
```

The data called by pipe.score() undergoes transformation process in the first two steps (imputer and scaler) and the predict unction in the 3rd step ("AdaBoost").

Questions I still have:

- Am I suppose to fit the pipeline into the X_train, y_train or X and y?
- What about X_train_over, y_train_over?
- Is SMOTE incorporated into the pipeline?

Business Insights and Conclusions

Features V18, V39, and V12 have significant influence on the model's predictions.

The company can focus on further analyzing these important features to better understand their underlying relationships with the target variable.