Problem Statement:

The dataset consists of data collected from heavy scania trucks in everyday usage.

The system in focus is the air pressure system(APS) which generates pressurised air that are

utilized in various functions in a truck, such as bracking and gear changes. The datasets positive class consists of component failures for a

specific component of the APS system.

The negative class consists of trucks with failures for components not related to the APS.

The data consists of trucks with failures for components not related to the APS.

The data consists of a subset of all available data,selected by experts.

Chalange Matric

cost-metric of miss-classification

Predicted class | True Class |

| pos | neg |

---

pos | - | cost_1|

neg | Cost_2| - |

cost_1=10 and cost_2=500

The total cost of a prediction model the sum of 'Cost_1'

multiplied by the number of Instances with type 1 failure

and 'Cost_2' with the number of instances with type 2 failure,

resulting in a 'Total_cost'.

In above case cost_1 refer to the cost of an unnessecary checks

needs to be done by an mechanic at an workshop,

while cost_2 refer to the cost of missing a faulty truck, which may cause a breakdown.

Total_cost=cost_1*No_instances* + *cost_2* NO_instances

Solution: From the above problem statement we could observe that

we have to reduce false positive and false negative.

More importantly we have to reduce false negative , since cost

incurred by false negative is 50 times higher than the false positives.

In [1]:
```
# First we import imp Library
```

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [3]:
```
#Now Load Dataset
```

In [4]:
```
df_train=pd.read_csv(r"E:\C Drive Backup\Data Science Notes\DS Batch - 8\09_Supervi
```

In [5]:
```
df_train.shape
```

Out[5]:
```
(60000, 171)
```

In [7]:
```
# checking features
df_train.columns
```

Out[7]:
```
Index(['class', 'aa_000', 'ab_000', 'ac_000', 'ad_000', 'ae_000', 'af_000',
       'ag_000', 'ag_001', 'ag_002',
       ...
       'ee_002', 'ee_003', 'ee_004', 'ee_005', 'ee_006', 'ee_007', 'ee_008',
       'ee_009', 'ef_000', 'eg_000'],
      dtype='object', length=171)
```

In [8]:
```
# There is a one dependent (Target) Variables and rest 170 Independent variables.
```

In [9]:
```
# Testing Output of Dependent
df_train['class'].value_counts()
```

Out[9]:
```
class
neg    59000
pos     1000
Name: count, dtype: int64
```

In [10]:
```
# The output of dependent variables is highly imbalance. the neg output is 60 times
# now checking datatypes of all columns
df=df_train
df.dtypes
```

Out[10]:
```
class     object
aa_000     int64
ab_000    object
ac_000    object
ad_000    object
           ...
ee_007    object
ee_008    object
ee_009    object
ef_000    object
eg_000    object
Length: 171, dtype: object
```

In [11]:
```
#now we saperate numeric and categorical features
col_num =[col for col in df.columns if df[col].dtypes!='object']
col_cat=[col for col in df.columns if df[col].dtypes=='object']
```

In [12]:
```
# BY inspecting features we found that
print('There are {} Numerical Features : {}'.format(len(col_num),col_num))
```

```
There are 1 Numerical Features : ['aa_000']
```

In [15]:
```
print(f'There are {len(col_cat)} Categorical Features : {col_cat}')
```

```
There are 170 Categorical Features : ['class', 'ab_000', 'ac_000', 'ad_000', 'ae_00
0', 'af_000', 'ag_000', 'ag_001', 'ag_002', 'ag_003', 'ag_004', 'ag_005', 'ag_006',
'ag_007', 'ag_008', 'ag_009', 'ah_000', 'ai_000', 'aj_000', 'ak_000', 'al_000', 'am_
0', 'an_000', 'ao_000', 'ap_000', 'aq_000', 'ar_000', 'as_000', 'at_000', 'au_000',
'av_000', 'ax_000', 'ay_000', 'ay_001', 'ay_002', 'ay_003', 'ay_004', 'ay_005', 'ay_
006', 'ay_007', 'ay_008', 'ay_009', 'az_000', 'az_001', 'az_002', 'az_003', 'az_00
4', 'az_005', 'az_006', 'az_007', 'az_008', 'az_009', 'ba_000', 'ba_001', 'ba_002',
'ba_003', 'ba_004', 'ba_005', 'ba_006', 'ba_007', 'ba_008', 'ba_009', 'bb_000', 'bc_
000', 'bd_000', 'be_000', 'bf_000', 'bg_000', 'bh_000', 'bi_000', 'bj_000', 'bk_00
0', 'bl_000', 'bm_000', 'bn_000', 'bo_000', 'bp_000', 'bq_000', 'br_000', 'bs_000',
'bt_000', 'bu_000', 'bv_000', 'bx_000', 'by_000', 'bz_000', 'ca_000', 'cb_000', 'cc_
000', 'cd_000', 'ce_000', 'cf_000', 'cg_000', 'ch_000', 'ci_000', 'cj_000', 'ck_00
0', 'cl_000', 'cm_000', 'cn_000', 'cn_001', 'cn_002', 'cn_003', 'cn_004', 'cn_005',
'cn_006', 'cn_007', 'cn_008', 'cn_009', 'co_000', 'cp_000', 'cq_000', 'cr_000', 'cs_
000', 'cs_001', 'cs_002', 'cs_003', 'cs_004', 'cs_005', 'cs_006', 'cs_007', 'cs_00
8', 'cs_009', 'ct_000', 'cu_000', 'cv_000', 'cx_000', 'cy_000', 'cz_000', 'da_000',
'db_000', 'dc_000', 'dd_000', 'de_000', 'df_000', 'dg_000', 'dh_000', 'di_000', 'dj_
000', 'dk_000', 'dl_000', 'dm_000', 'dn_000', 'do_000', 'dp_000', 'dq_000', 'dr_00
0', 'ds_000', 'dt_000', 'du_000', 'dv_000', 'dx_000', 'dy_000', 'dz_000', 'ea_000',
'eb_000', 'ec_00', 'ed_000', 'ee_000', 'ee_001', 'ee_002', 'ee_003', 'ee_004', 'ee_0
05', 'ee_006', 'ee_007', 'ee_008', 'ee_009', 'ef_000', 'eg_000']
```

In [ ]:

In [13]:
```
# NOw checking null values
df.isnull().sum()
```

Out[13]:
```
class     0
aa_000    0
ab_000    0
ac_000    0
ad_000    0
         ..
ee_007    0
ee_008    0
ee_009    0
ef_000    0
eg_000    0
Length: 171, dtype: int64
```

In [14]:
```
# no null values
#checking values
print(df.head(15))
```

```
   class  aa_000 ab_000      ac_000 ad_000 ae_000 af_000 ag_000 ag_001 ag_002  \
0    neg   76698     na  2130706438    280      0      0      0      0      0
1    neg   33058     na           0     na      0      0      0      0      0
2    neg   41040     na         228    100      0      0      0      0      0
3    neg      12      0          70     66      0     10      0      0      0
4    neg   60874     na        1368    458      0      0      0      0      0
5    neg   38312     na  2130706432    218      0      0      0      0      0
6    neg      14      0           6     na      0      0      0      0      0
7    neg  102960     na  2130706432    116      0      0      0      0      0
8    neg   78696     na           0     na      0      0      0      0      0
9    pos  153204      0         182     na      0      0      0      0      0
10   neg   39196     na         204    170      0      0      0      0      0
11   neg   45912     na           0    454      0      0      0      0      0
12   neg    2104     na          36     26      0      0      0      0   9744
13   neg  118950     na        1390   1298      0      0      0      0      0
14   neg   24416     na           0     na      0      0      0      0      0

    ...   ee_002   ee_003   ee_004   ee_005   ee_006  ee_007  ee_008 ee_009  \
0   ...  1240520   493384   721044   469792   339156  157956   73224      0
1   ...   421400   178064   293306   245416   133654   81140   97576   1500
2   ...   277378   159812   423992   409564   320746  158022   95128    514
3   ...      240       46       58       44       10       0       0      0
4   ...   622012   229790   405298   347188   286954  311560  433954   1218
5   ...   388574   288278   900430   300412     1534     338     856      0
6   ...      168       48       60       28        0       0       0      0
7   ...   715518   384948   915978  1052166  1108672  341532  129504   7832
8   ...   699290   362510  1190028  1012704   160090   63216   41202      4
9   ...   129862    26872    34044    22472    34362       0       0      0
10  ...   198386    99614   215734   189966   219996  208724  463790  34054
11  ...   495400   278660   544710   438256   249386   73356   51344   2008
12  ...     4776     2330     4634     6534    29980   39372       0      0
13  ...  1677646  1380302  2531322   426284    17996   11734   12506    138
14  ...   190606    95674   207476   232470   154962   99406  121544   2712

   ef_000 eg_000
0       0      0
1       0      0
2       0      0
3       4     32
4       0      0
5       0      0
6       0      0
7       0      0
8       0      0
9       0      0
10      0      0
11      0      0
12      0      0
13      0      0
14      0      0

[15 rows x 171 columns]
```

In [15]:

```
# There is lots of null values are replaced by na so making it null first
df=df.replace('na',np.nan)
```

In [16]:
```
df.isnull().sum()
```

Out[16]:
```
class         0
aa_000        0
ab_000    46329
ac_000     3335
ad_000    14861
          ...
ee_007      671
ee_008      671
ee_009      671
ef_000     2724
eg_000     2723
Length: 171, dtype: int64
```

In [17]:
```
# since here data is not measurable wrt null values so we collect percentage of nul
per_null=np.round(df.isnull().sum()/df.shape[0]*100,0)
print(per_null)
```

```
class      0.0
aa_000     0.0
ab_000    77.0
ac_000     6.0
ad_000    25.0
          ...
ee_007     1.0
ee_008     1.0
ee_009     1.0
ef_000     5.0
eg_000     5.0
Length: 171, dtype: float64
```

In [18]:
```
# now checking null values greater then 90%
per_null[per_null>90]
```

Out[18]:
```
Series([], dtype: float64)
```

In [19]:
```
# Now checking null values greater then 80%
per_null[per_null>80]
```

Out[19]:
```
bq_000    81.0
br_000    82.0
dtype: float64
```

In [20]:
```
# NOw checking null values greater then 70%
per_null[per_null>70]
```

Out[20]:
```
ab_000    77.0
bn_000    73.0
bo_000    77.0
bp_000    80.0
bq_000    81.0
br_000    82.0
cr_000    77.0
dtype: float64
```

In [21]:
```
# now cheking null values greater then 60%
per_null[per_null>60]
```

Out[21]:
```
ab_000    77.0
bm_000    66.0
bn_000    73.0
bo_000    77.0
bp_000    80.0
bq_000    81.0
br_000    82.0
cr_000    77.0
dtype: float64
```

In [22]:
```
per_null[per_null>50]
```

Out[22]:
```
ab_000    77.0
bm_000    66.0
bn_000    73.0
bo_000    77.0
bp_000    80.0
bq_000    81.0
br_000    82.0
cr_000    77.0
dtype: float64
```

In [23]:
```
# By observing we found that in 8 columns more then 60% are null values
# and 7 columns has more then 70 percent missing values. so it will worth nothing t
# so it is better to remove the null in 8 columns
```

In [24]:
```
missing_col=per_null[per_null>60]
missing_col.index
```

Out[24]:
```
Index(['ab_000', 'bm_000', 'bn_000', 'bo_000', 'bp_000', 'bq_000', 'br_000',
       'cr_000'],
      dtype='object')
```

In [25]:
```
df.drop(per_null[per_null>60].index,axis=1,inplace=True)
```

In [26]:
```
# dataset shape after droping columns
df.shape
```

Out[26]:
```
(60000, 163)
```

In [27]:
```
# now checking percentage of missing values in dataset
total_missing=df.isnull().sum().sum()
total_values=np.product(df.shape)
per_missing =round(total_missing/total_values*100,2)
print('Total {} % missing values found in Dataset.'.format(per_missing))
```

```
Total 4.93 % missing values found in Dataset.
```

In [28]:
```
for col in df.columns:
    if df[col].dtype=='O' and col !='class':
        df[col]=df[col].astype(float)
```

In [ ]:

In [29]:
```
# now our cleaning is done in dataset. but before moving further we save this datas
df.to_csv('aps_failure_cleaned.csv',index=False)
```

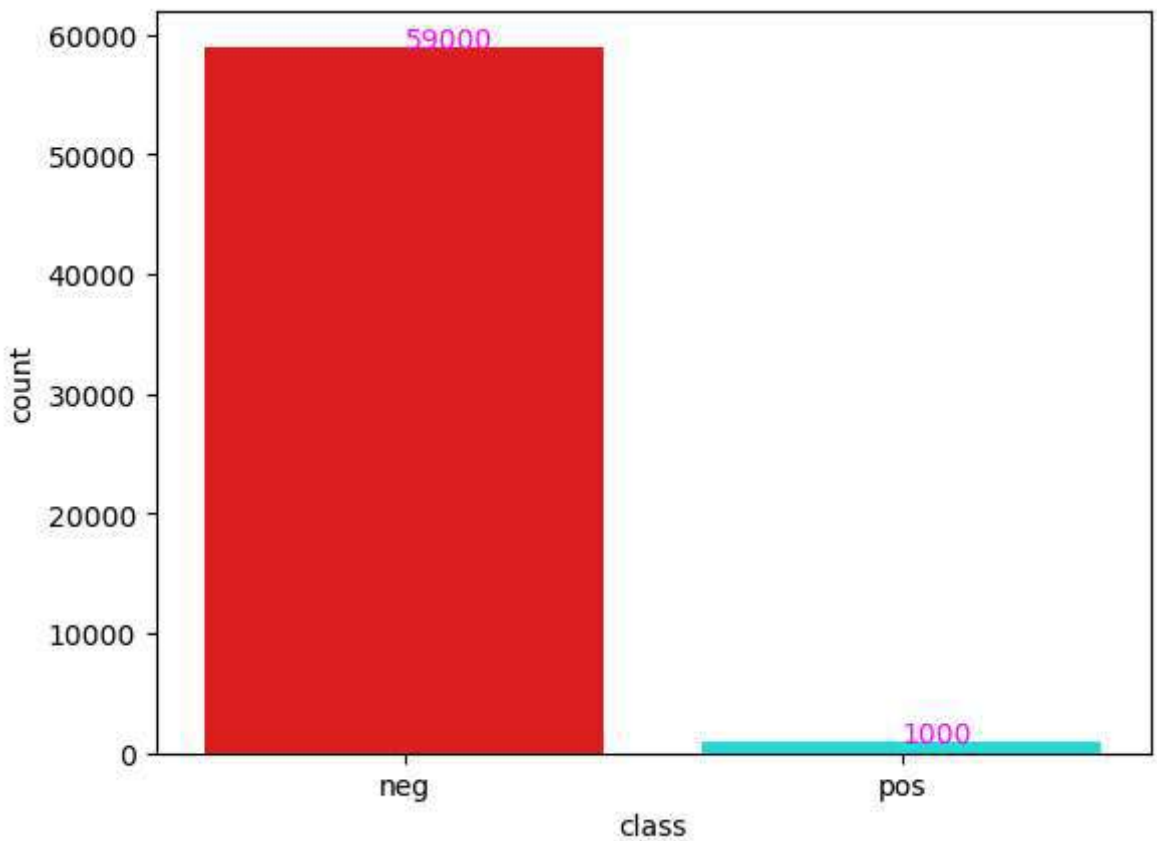
In [31]:
```
# Now we move to statistical analysis
print(df.describe())
```

```
             aa_000        ac_000        ad_000        ae_000        af_000  \
count  6.000000e+04  5.666500e+04  4.513900e+04  57500.000000  57500.000000
mean   5.933650e+04  3.560143e+08  1.906206e+05      6.819130     11.006817
std    1.454301e+05  7.948749e+08  4.040441e+07    161.543373    209.792592
min    0.000000e+00  0.000000e+00  0.000000e+00      0.000000      0.000000
25%    8.340000e+02  1.600000e+01  2.400000e+01      0.000000      0.000000
50%    3.077600e+04  1.520000e+02  1.260000e+02      0.000000      0.000000
75%    4.866800e+04  9.640000e+02  4.300000e+02      0.000000      0.000000
max    2.746564e+06  2.130707e+09  8.584298e+09  21050.000000  20070.000000

             ag_000        ag_001        ag_002        ag_003        ag_004  \
count  5.932900e+04  5.932900e+04  5.932900e+04  5.932900e+04  5.932900e+04
mean   2.216364e+02  9.757223e+02  8.606015e+03  8.859128e+04  4.370966e+05
std    2.047846e+04  3.420053e+04  1.503220e+05  7.617312e+05  2.374282e+06
min    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  3.080000e+02
50%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  3.672000e+03
75%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  4.952200e+04
max    3.376892e+06  4.109372e+06  1.055286e+07  6.340207e+07  2.288306e+08

       ...        ee_002        ee_003        ee_004        ee_005  \
count  ...  5.932900e+04  5.932900e+04  5.932900e+04  5.932900e+04
mean   ...  4.454897e+05  2.111264e+05  4.457343e+05  3.939462e+05
std    ...  1.155540e+06  5.433188e+05  1.168314e+06  1.121044e+06
min    ...  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%    ...  2.936000e+03  1.166000e+03  2.700000e+03  3.584000e+03
50%    ...  2.337960e+05  1.120860e+05  2.215180e+05  1.899880e+05
75%    ...  4.383960e+05  2.182320e+05  4.666140e+05  4.032220e+05
max    ...  7.793393e+07  3.775839e+07  9.715238e+07  5.743524e+07

             ee_006        ee_007        ee_008        ee_009        ef_000  \
count  5.932900e+04  5.932900e+04  5.932900e+04  5.932900e+04  57276.000000
mean   3.330582e+05  3.462714e+05  1.387300e+05  8.388915e+03      0.090579
std    1.069160e+06  1.728056e+06  4.495100e+05  4.747043e+04      4.368855
min    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00      0.000000
25%    5.120000e+02  1.100000e+02  0.000000e+00  0.000000e+00      0.000000
50%    9.243200e+04  4.109800e+04  3.812000e+03  0.000000e+00      0.000000
75%    2.750940e+05  1.678140e+05  1.397240e+05  2.028000e+03      0.000000
max    3.160781e+07  1.195801e+08  1.926740e+07  3.810078e+06    482.000000

             eg_000
count  57277.000000
mean       0.212756
std        8.830641
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max     1146.000000

[8 rows x 162 columns]
```

In [32]:
```
df.memory_usage()
```

Out[32]:
```
Index        132
class     480000
aa_000    480000
ac_000    480000
ad_000    480000
            ...
ee_007    480000
ee_008    480000
ee_009    480000
ef_000    480000
eg_000    480000
Length: 164, dtype: int64
```

In [33]:
```
# Visualization of Unique values in Target Variable
sns.countplot(x='class',data=df,palette=['red','cyan'])
plt.text('neg',df['class'].value_counts()[0],df['class'].value_counts()[0],color='M
plt.text('pos',df['class'].value_counts()[1],df['class'].value_counts()[1],color='M
plt.show()
```



In [34]:
```
# This clearly shows that the target output is imbalanced. i.e. negative samples ar
```

In [35]:
```
# Now checking Multicolinearity in Numerical features
# first we saprate dependent and independent variables into x and y where x is inde
```

In [36]:
```
x=df[[col for col in df.columns if col !='class']]
y=df['class']
```

In [37]:
```
x.shape
```

Out[37]: (60000, 162)

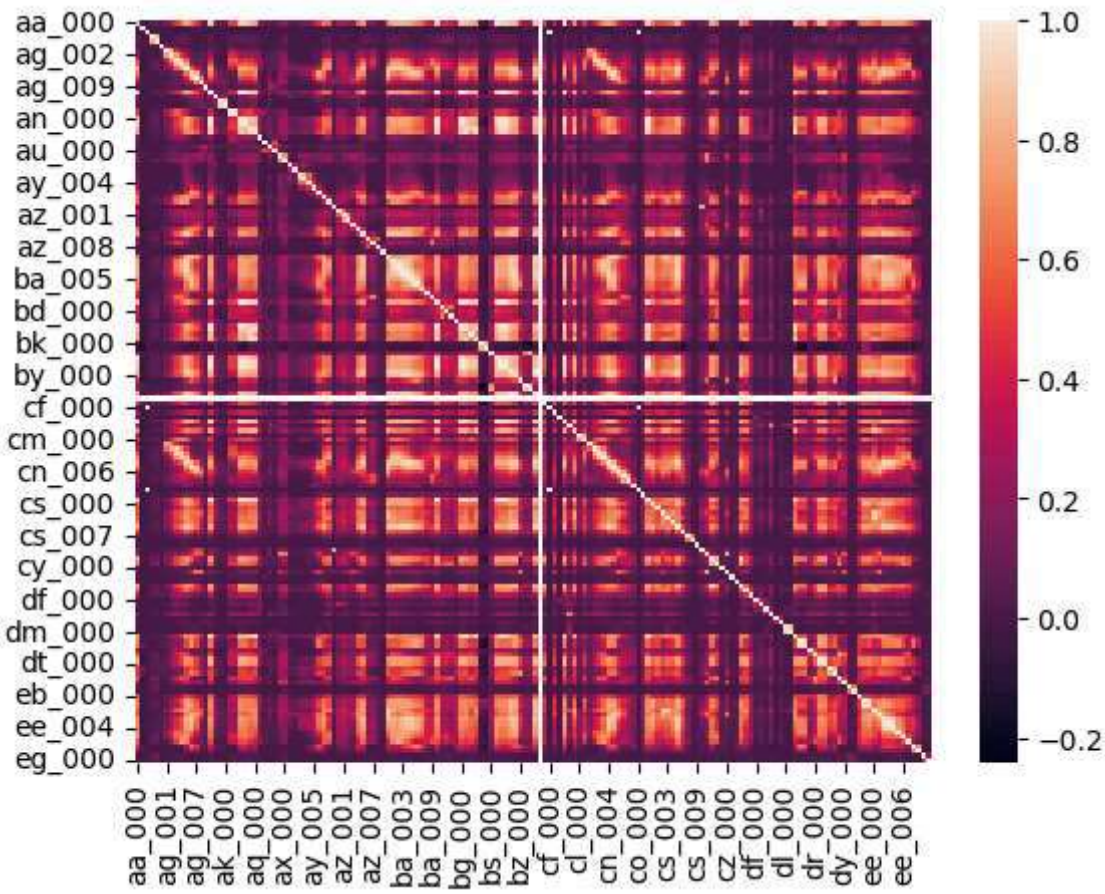
In [38]:
```
y.shape
```

Out[38]: (60000,)

In [40]:
```
print(x.corr())
```

```
          aa_000    ac_000    ad_000    ae_000    af_000    ag_000    ag_001  \
aa_000  1.000000 -0.032055 -0.001903  0.061971  0.089474  0.018610  0.143153
ac_000 -0.032055  1.000000 -0.002380 -0.004997 -0.010554  0.017620 -0.001088
ad_000 -0.001903 -0.002380  1.000000 -0.000214 -0.000269 -0.000047 -0.000131
ae_000  0.061971 -0.004997 -0.000214  1.000000  0.823108 -0.000430 -0.000832
af_000  0.089474 -0.010554 -0.000269  0.823108  1.000000 -0.000534 -0.001017
...          ...       ...       ...       ...       ...       ...       ...
ee_007  0.606232 -0.029417 -0.000829  0.052357  0.070306  0.000307  0.044186
ee_008  0.471707  0.016908 -0.002161 -0.010850 -0.013976 -0.000823  0.004878
ee_009  0.248039  0.024354 -0.001050 -0.008206 -0.010237 -0.001230 -0.004309
ef_000  0.019865 -0.006571 -0.000102  0.070886  0.106281 -0.000072  0.002875
eg_000  0.037099  0.014228 -0.000120  0.041715  0.060710  0.000244  0.010930

          ag_002    ag_003    ag_004  ...    ee_002    ee_003    ee_004  \
aa_000  0.285815  0.495529  0.607674  ...  0.735324  0.739211  0.717810
ac_000 -0.016665 -0.038680 -0.049296  ... -0.013692 -0.008111 -0.009849
ad_000 -0.000222 -0.000423 -0.000687  ... -0.002090 -0.002047 -0.001940
ae_000  0.005057  0.034163  0.064715  ...  0.017338  0.024905  0.017311
af_000  0.010518  0.052386  0.097740  ...  0.032896  0.047326  0.030789
...          ...       ...       ...  ...       ...       ...       ...
ee_007  0.182990  0.505565  0.737313  ...  0.454833  0.446803  0.437682
ee_008  0.009466  0.021151  0.056399  ...  0.453811  0.481392  0.459517
ee_009 -0.009498 -0.019311 -0.017569  ...  0.228248  0.239302  0.224638
ef_000  0.011824  0.020560  0.021319  ...  0.007118  0.017480  0.005835
eg_000  0.034202  0.024210  0.023718  ...  0.008843  0.013671  0.014528

          ee_005    ee_006    ee_007    ee_008    ee_009    ef_000    eg_000
aa_000  0.727240  0.726984  0.606232  0.471707  0.248039  0.019865  0.037099
ac_000 -0.011206 -0.021430 -0.029417  0.016908  0.024354 -0.006571  0.014228
ad_000 -0.001667 -0.001398 -0.000829 -0.002161 -0.001050 -0.000102 -0.000120
ae_000  0.039967  0.085884  0.052357 -0.010850 -0.008206  0.070886  0.041715
af_000  0.067002  0.132319  0.070306 -0.013976 -0.010237  0.106281  0.060710
...          ...       ...       ...       ...       ...       ...       ...
ee_007  0.379892  0.545929  1.000000  0.224938  0.061478 -0.000715  0.002708
ee_008  0.406920  0.373871  0.224938  1.000000  0.710056 -0.006991 -0.002833
ee_009  0.190667  0.163792  0.061478  0.710056  1.000000 -0.003942 -0.000907
ef_000  0.050270  0.008461 -0.000715 -0.006991 -0.003942  1.000000  0.282184
eg_000  0.018663  0.033091  0.002708 -0.002833 -0.000907  0.282184  1.000000

[162 rows x 162 columns]
```

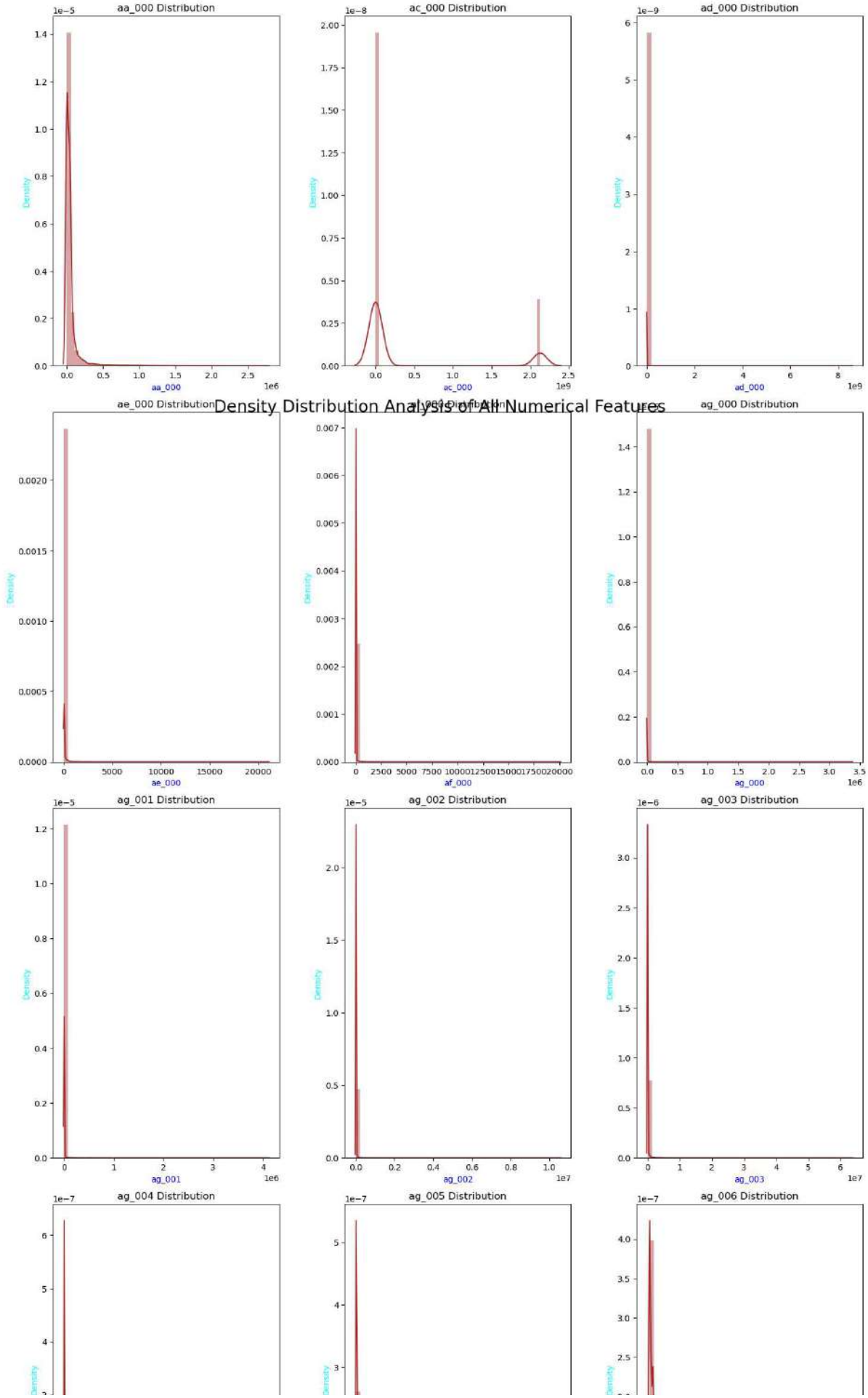
In [41]:
```
sns.heatmap(x.corr())
plt.show()
```

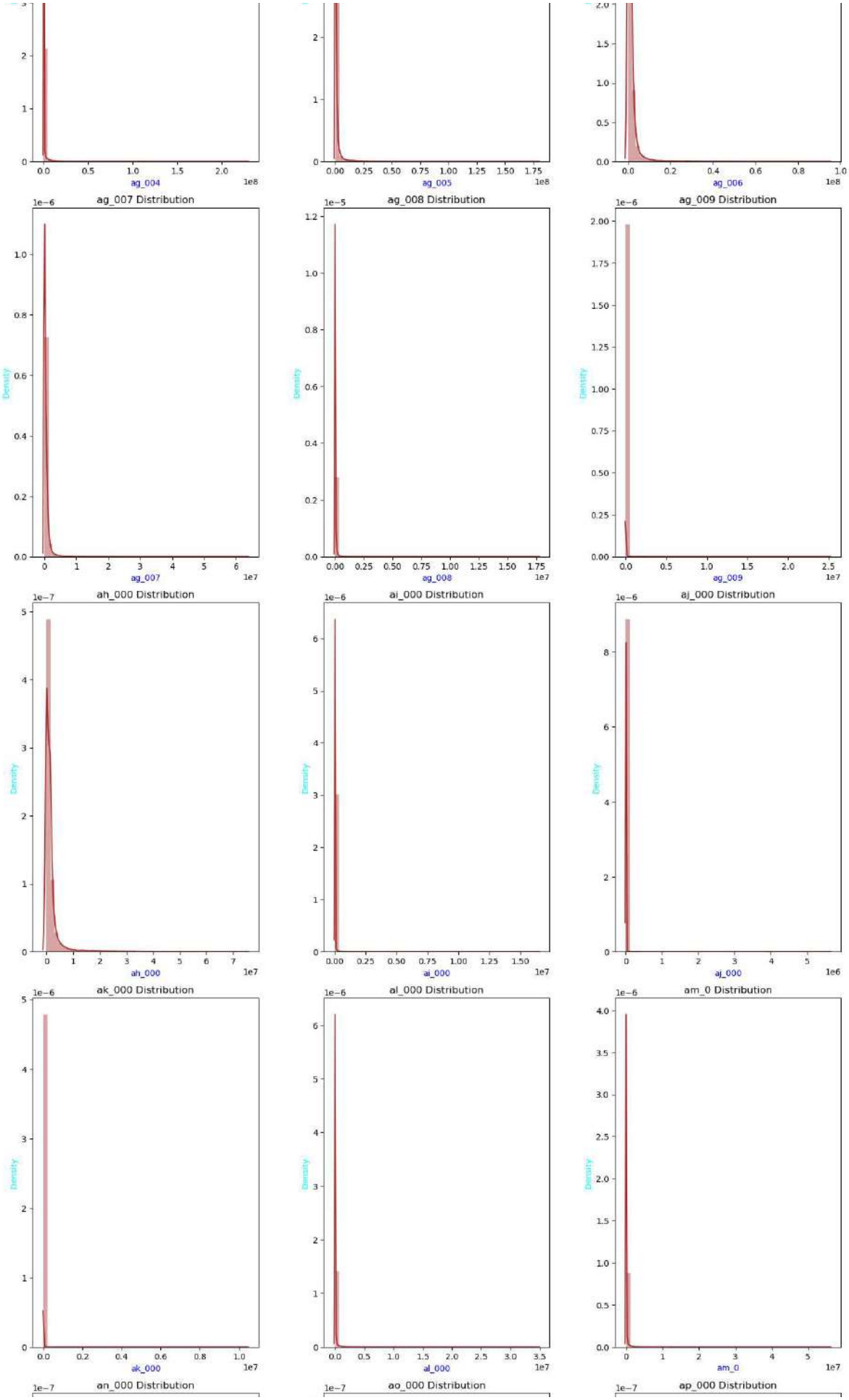


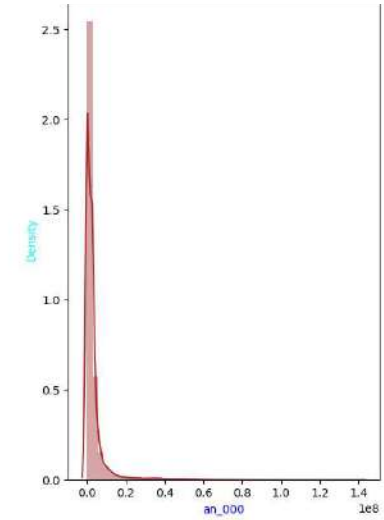
In [42]:
```
# Now we see univariate analysis
x.shape
```

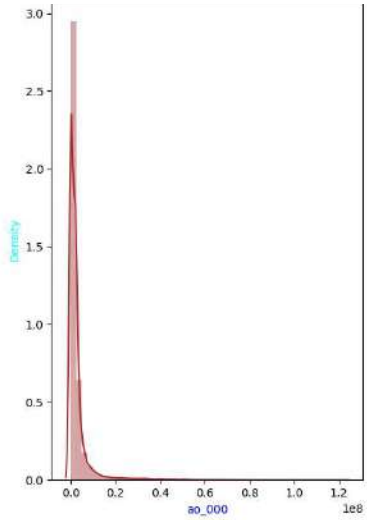
Out[42]: (60000, 162)

In [60]:
```
plt.figure(figsize=(15,360))
plt.suptitle('Density Distribution Analysis of All Numerical Features',fontsize=20)
for i,col in enumerate(x.columns):
    plt.subplot(54,3,i+1)
    sns.distplot(x=x[col],color='brown')
    plt.title('{} Distribution'.format(col))
    plt.xlabel(col,color='blue')
    plt.ylabel('Density',color='cyan')
    plt.tight_layout(pad=1.0)

print(plt.show())
```


Density Distribution Analysis of All Numerical Features
aa_000 Distribution
ac_000 Distribution
ad_000 Distribution
ae_000 Distribution
af_000 Distribution
ag_000 Distribution
ag_001 Distribution
ag_002 Distribution
ag_003 Distribution
ag_004 Distribution
ag_005 Distribution
ag_006 Distribution
Density


ag_004
ag_005
ag_006
ag_007 Distribution
ag_008 Distribution
ag_009 Distribution
ah_000 Distribution
ai_000 Distribution
aj_000 Distribution
ak_000 Distribution
al_000 Distribution
am_0 Distribution
an_000 Distribution
ao_000 Distribution
ap_000 Distribution
Density


Density
an_000
1e8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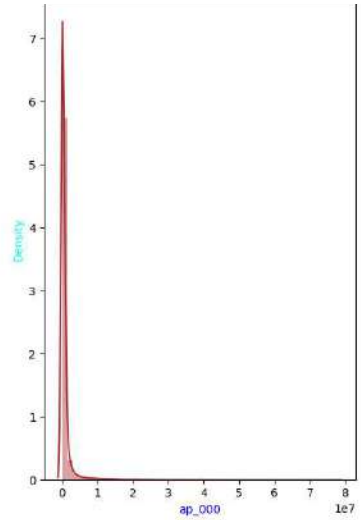
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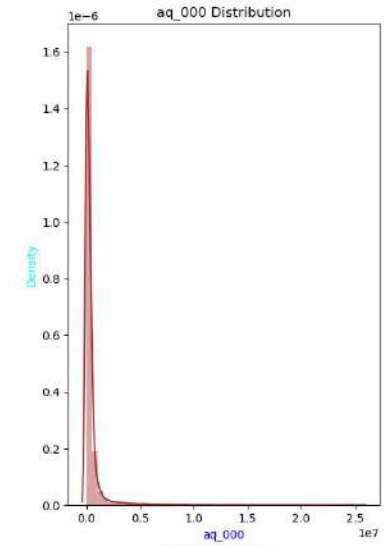
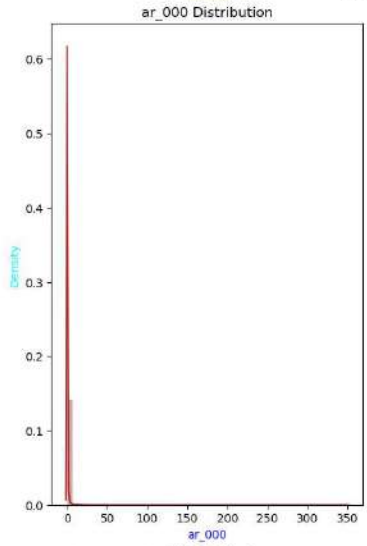
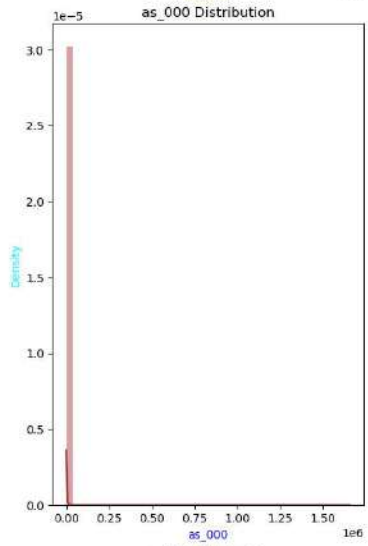

aq_000 Distribution
1e−6
Density
aq_000
1e7


ar_000 Distribution
Density
ar_000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Density
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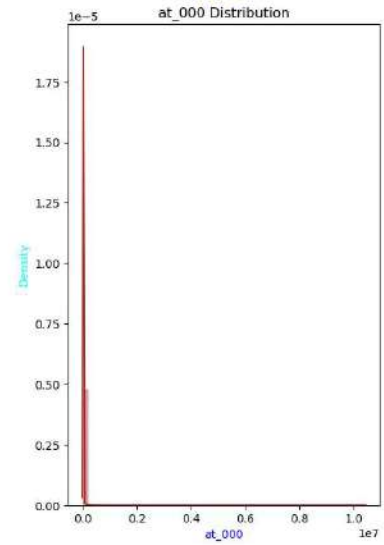
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Density
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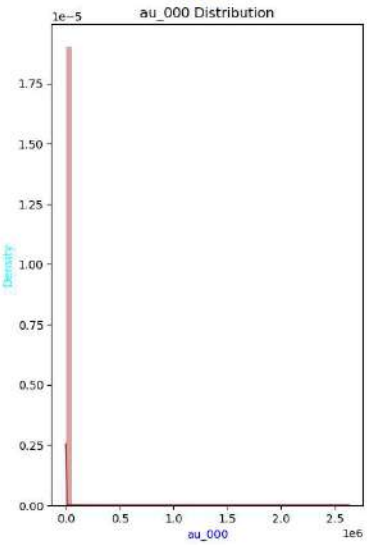
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Density
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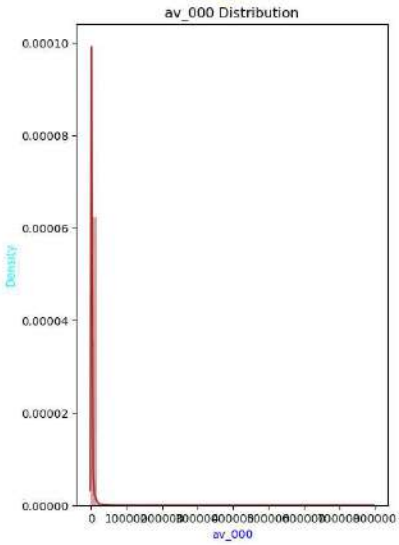
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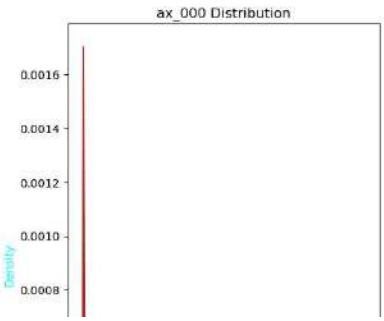
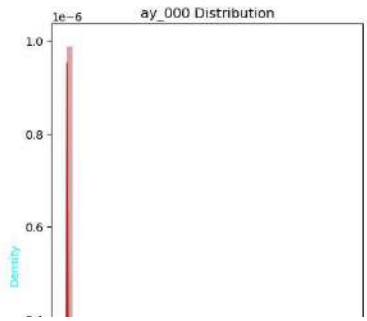
Density
av_000


ax_000 Distribution
Density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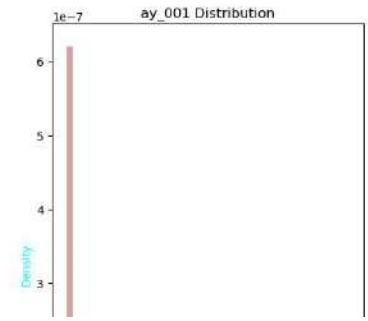
Density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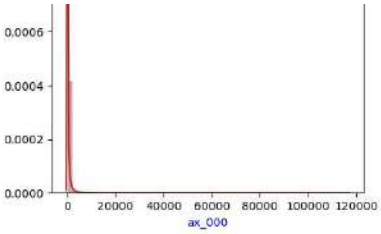
Density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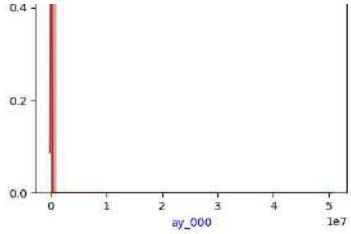
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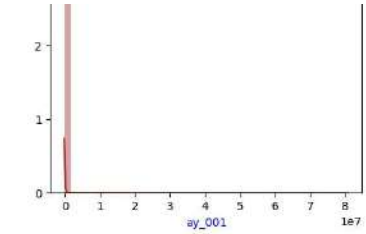
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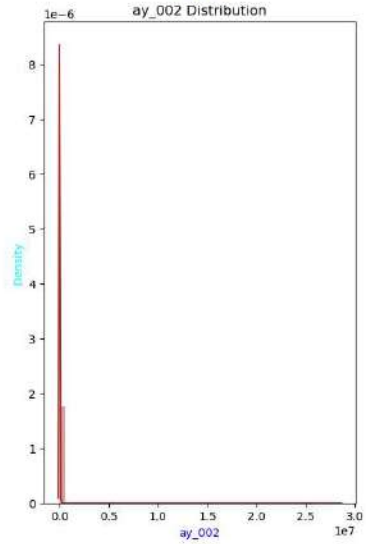
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Density
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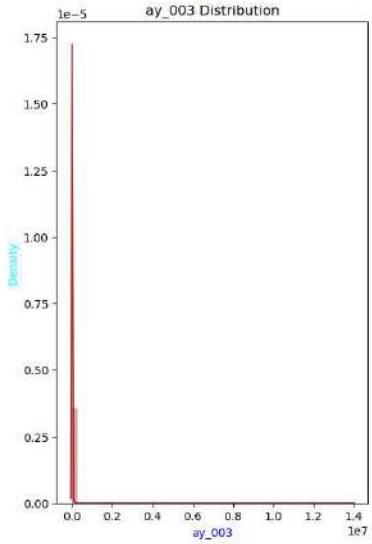
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Density
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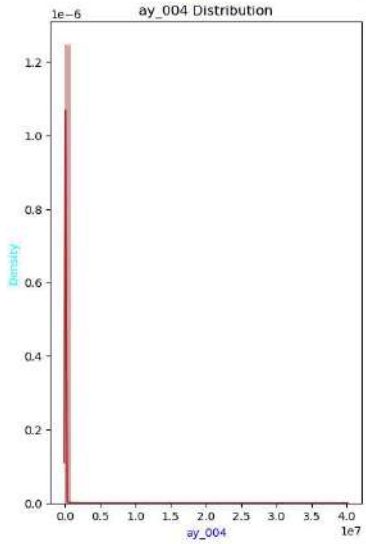
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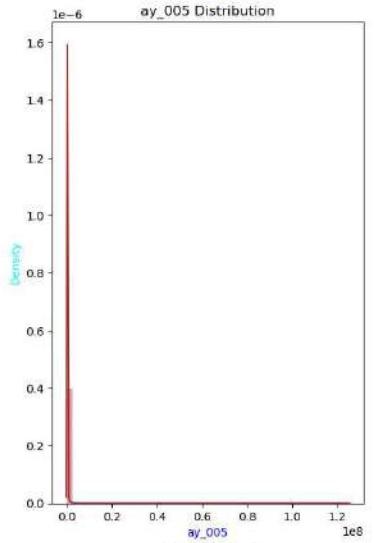
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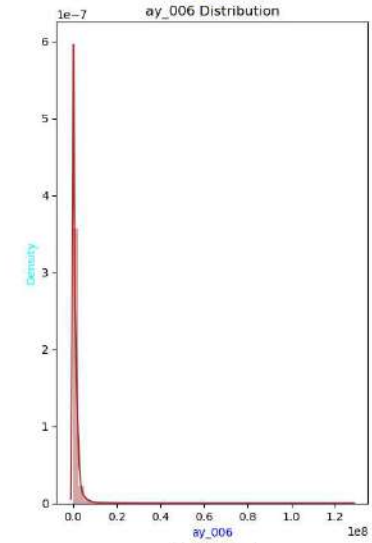
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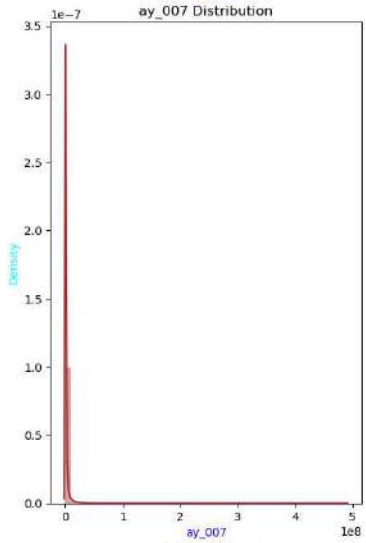
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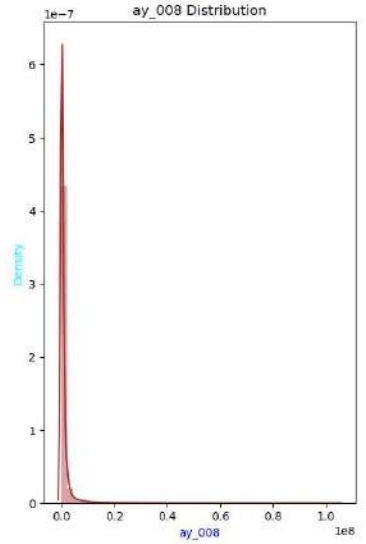
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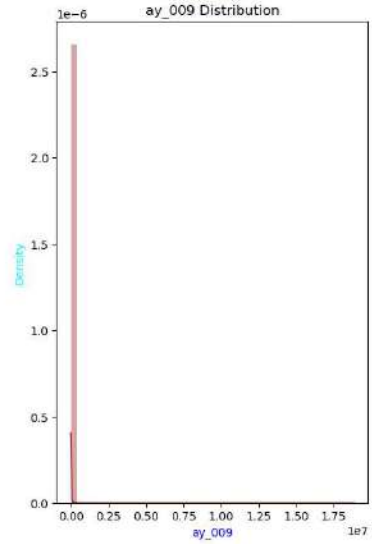
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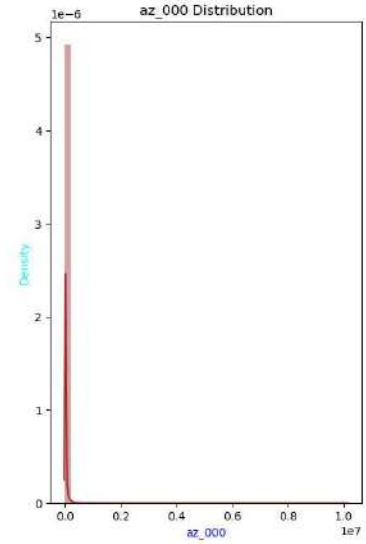
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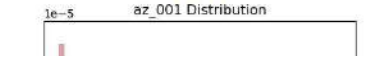
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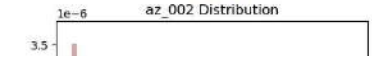
1e−5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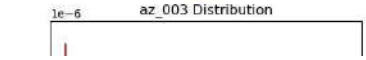
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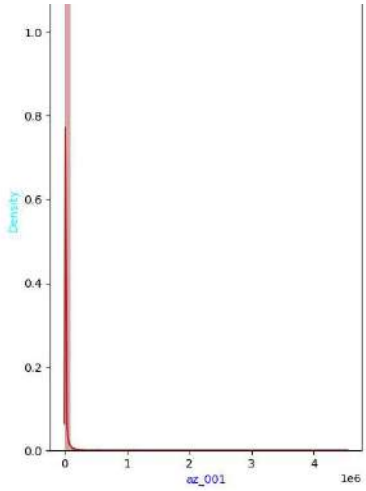
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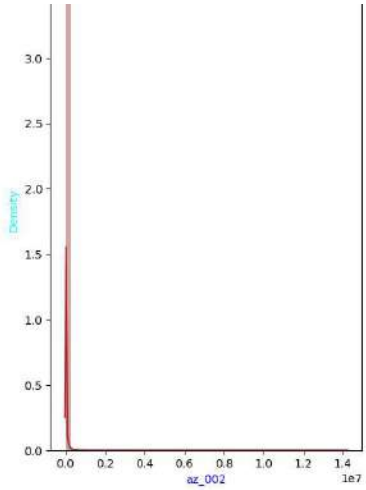
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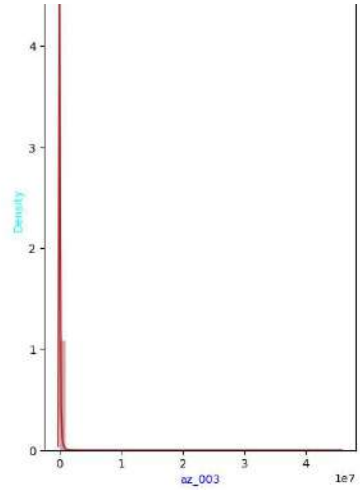
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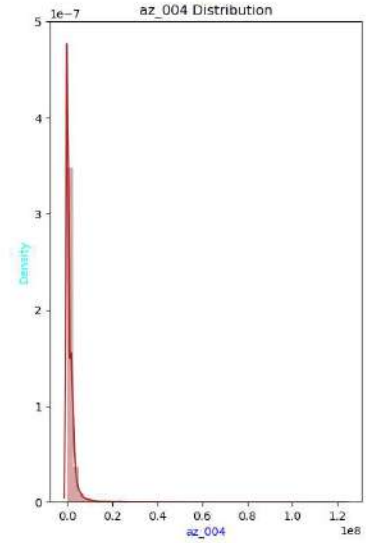
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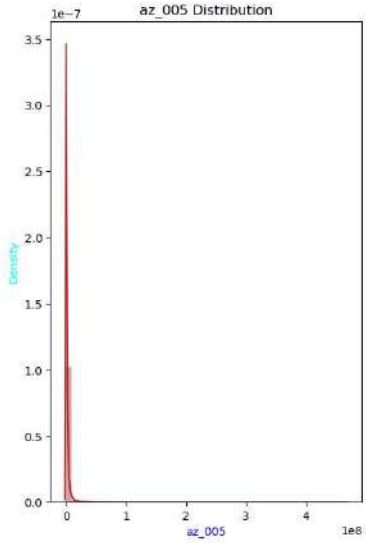
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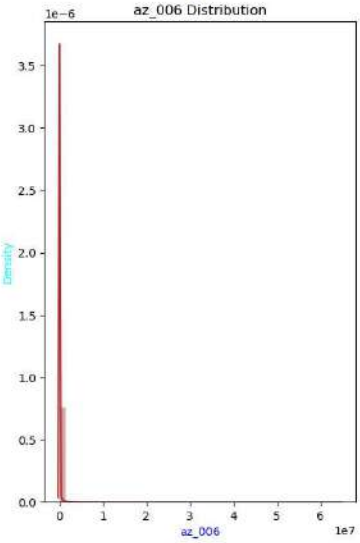
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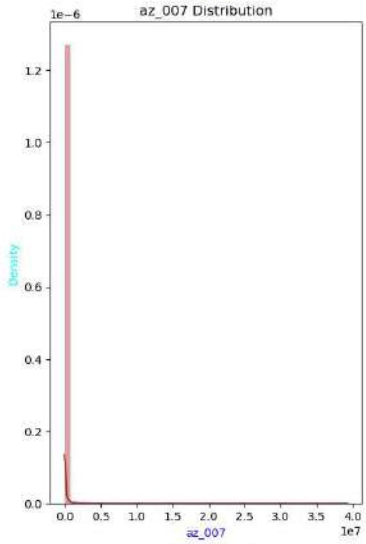
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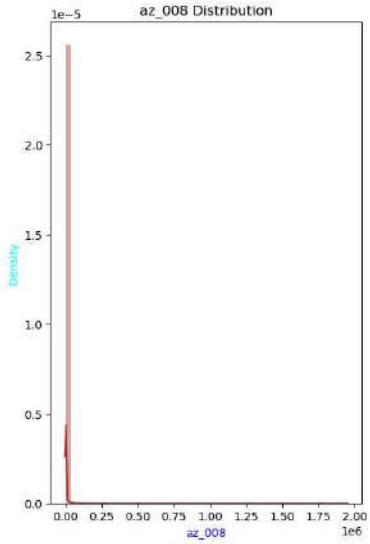
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Density
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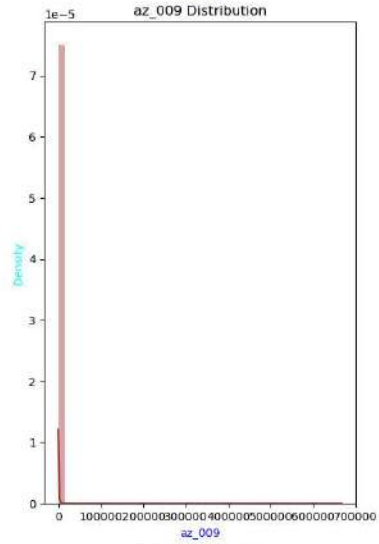
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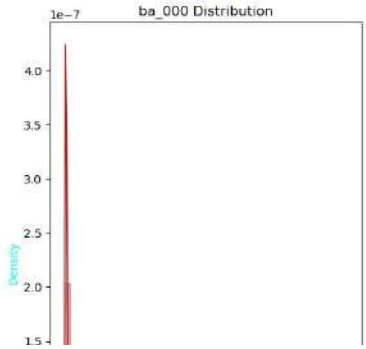
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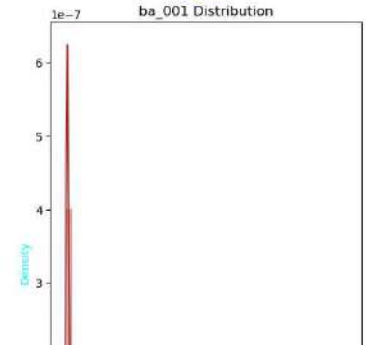
Density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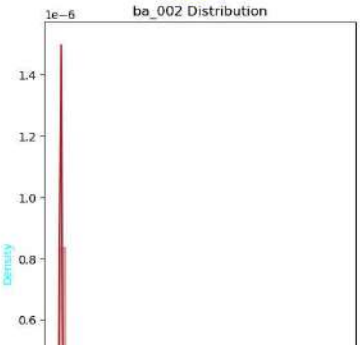
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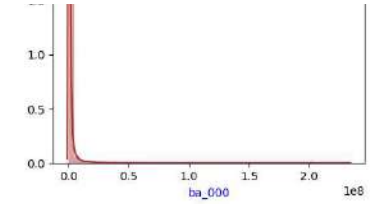
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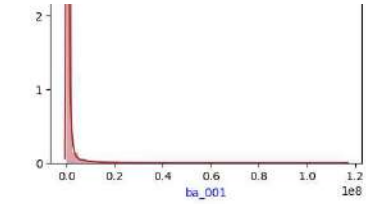
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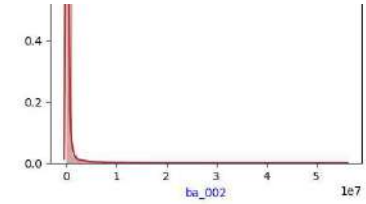
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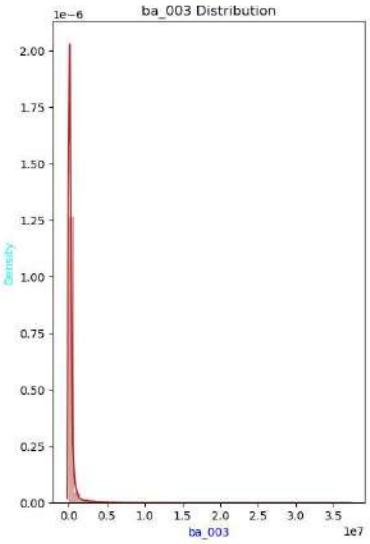
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Density
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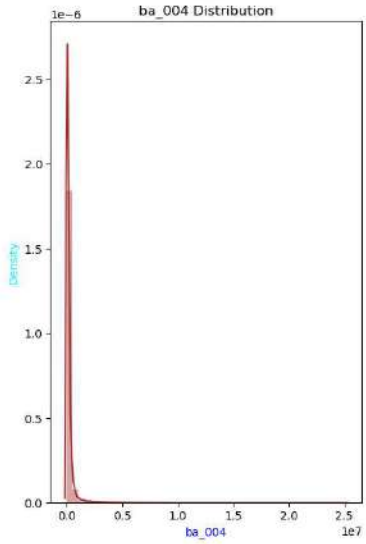
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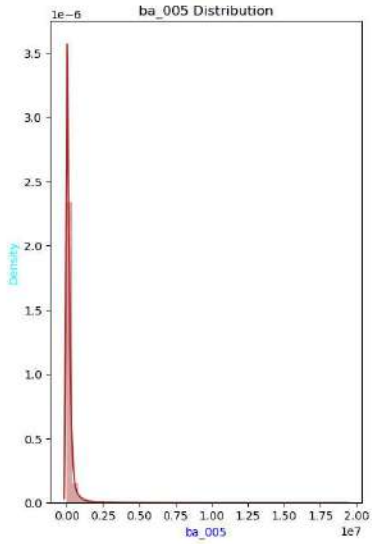
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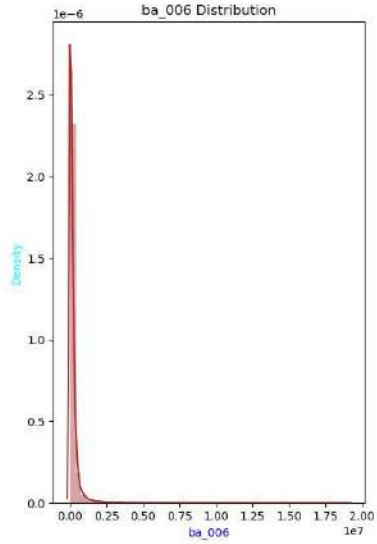
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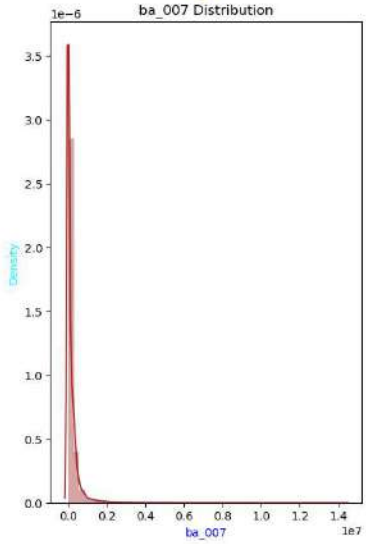
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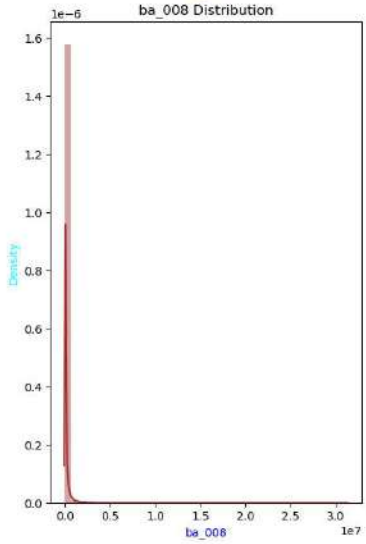
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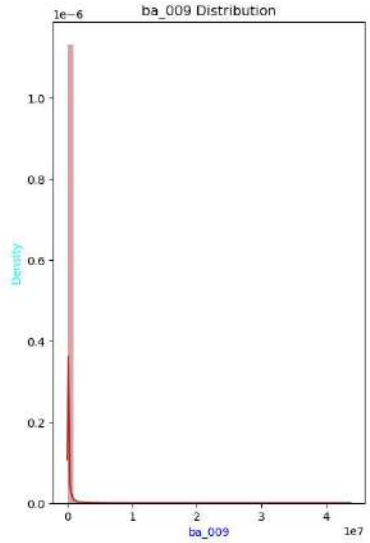
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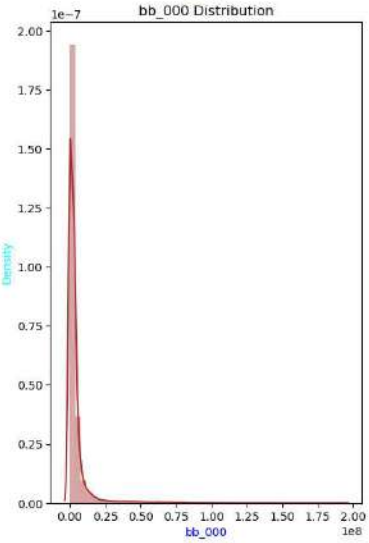
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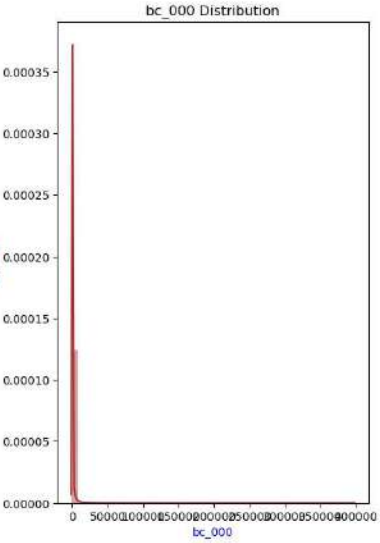
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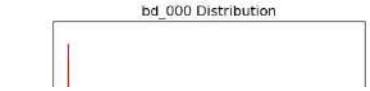
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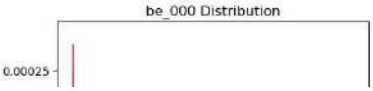
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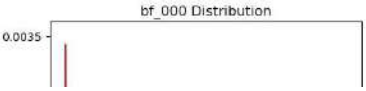
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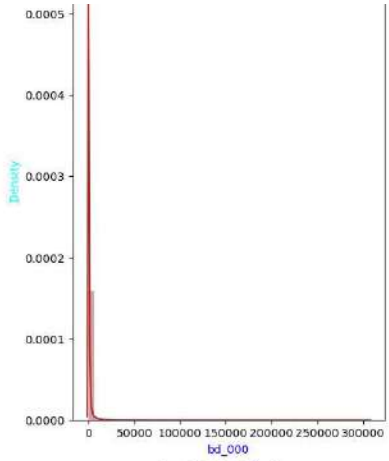
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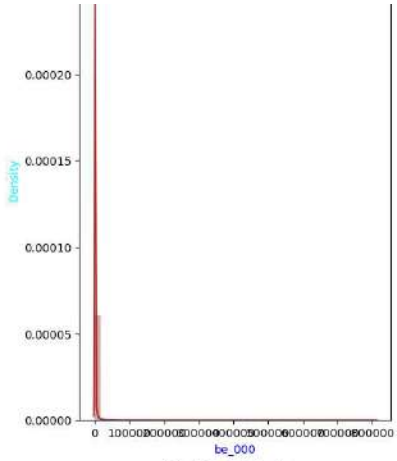
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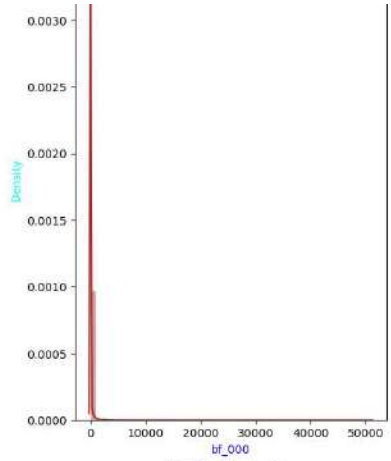
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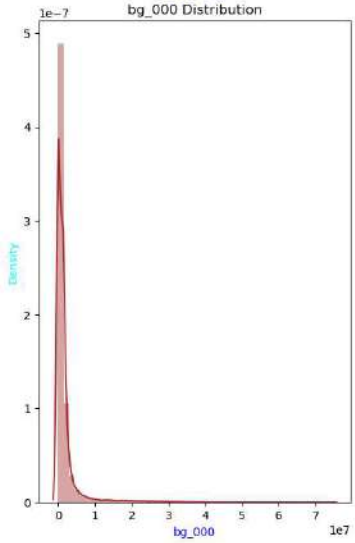
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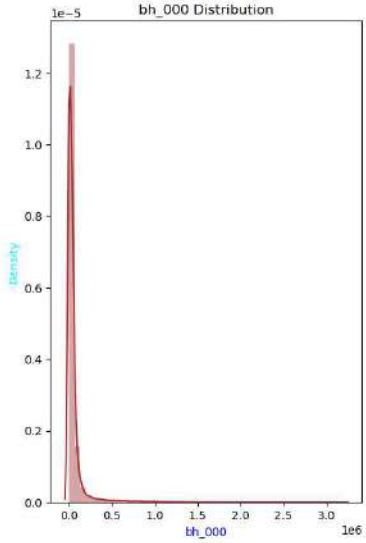
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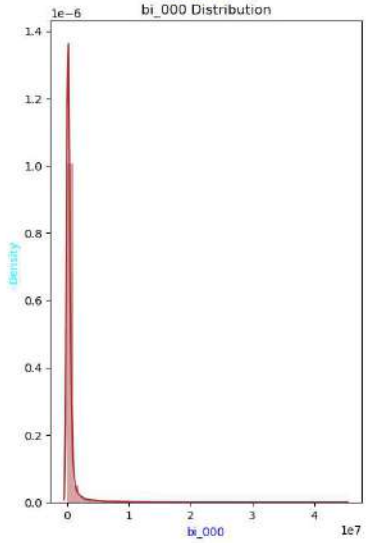
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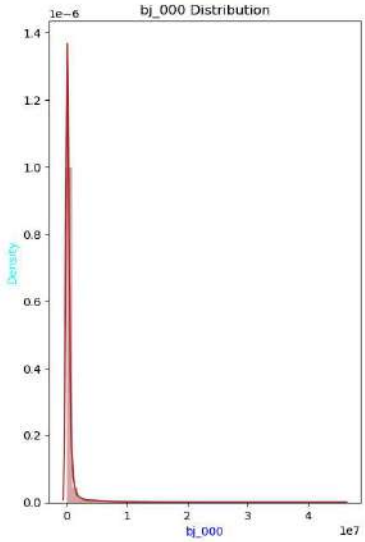
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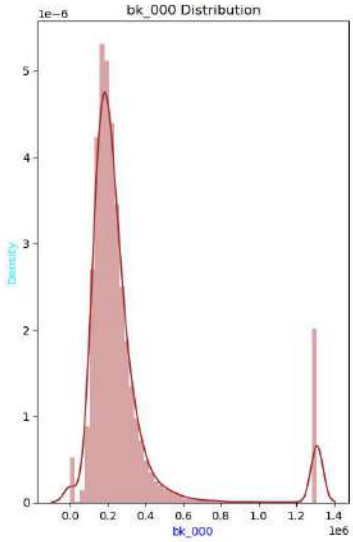
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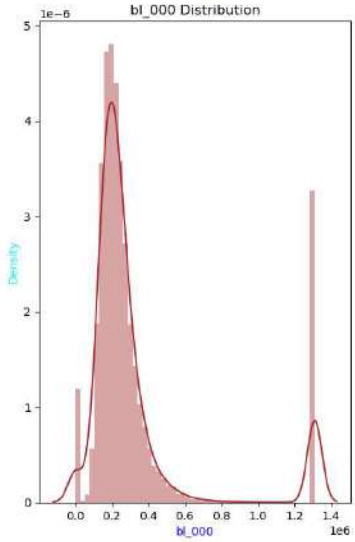
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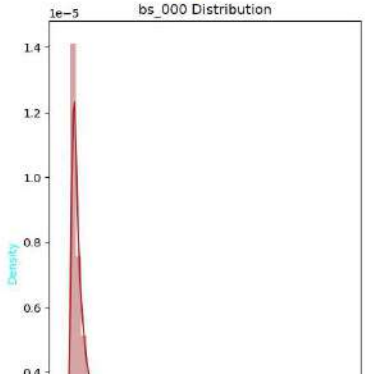
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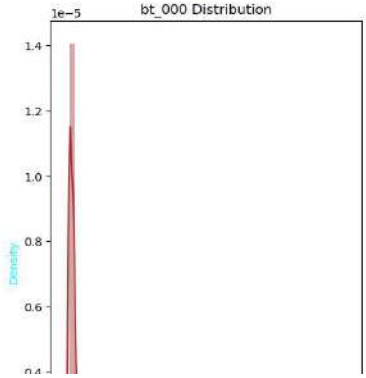
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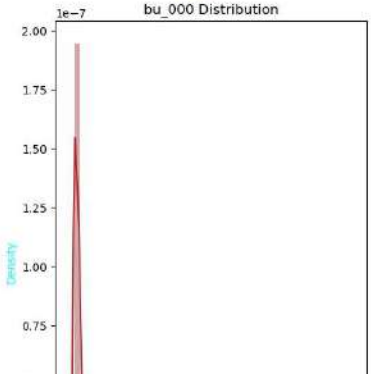
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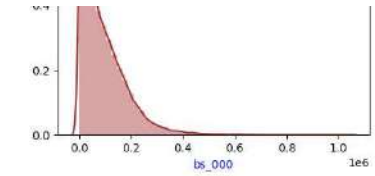
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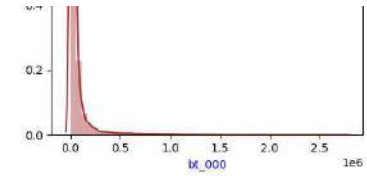
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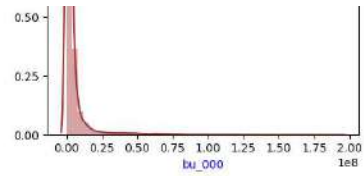
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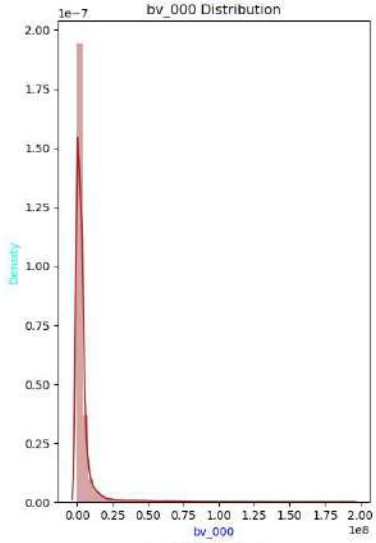
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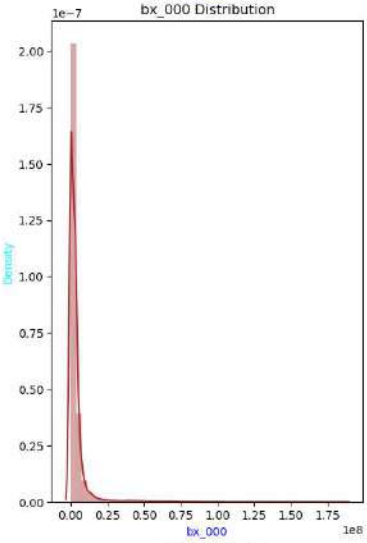
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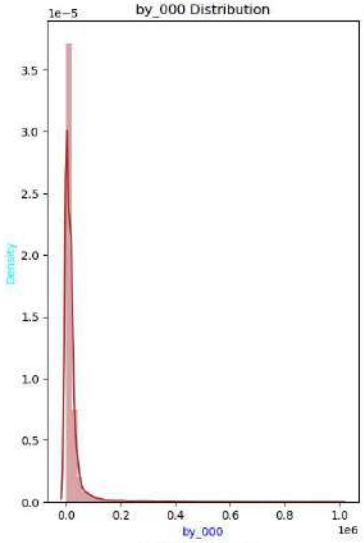
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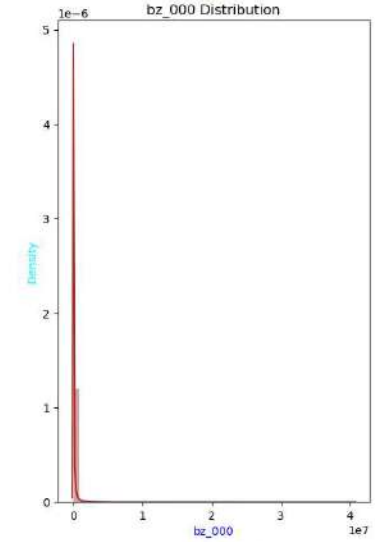
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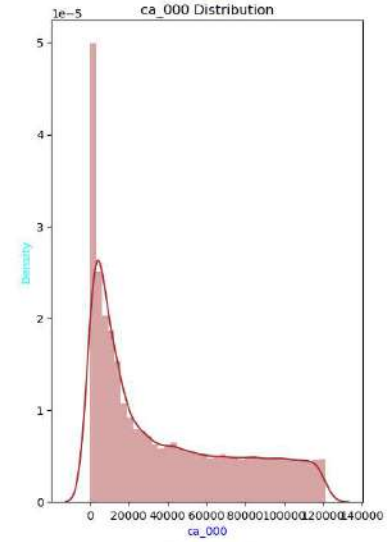
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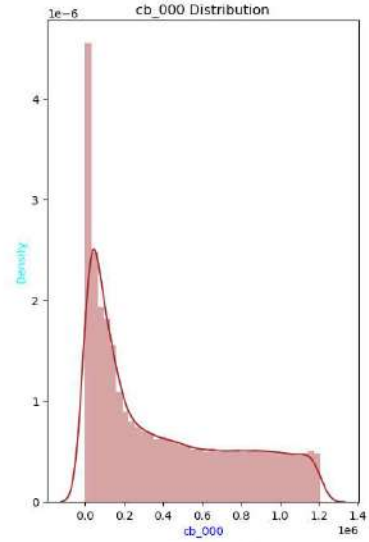
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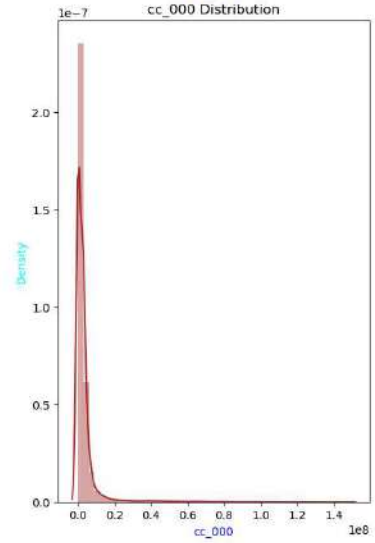
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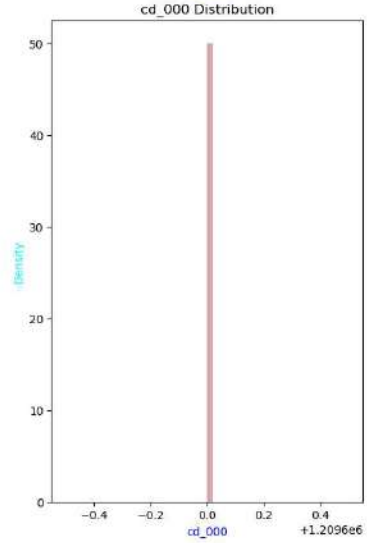
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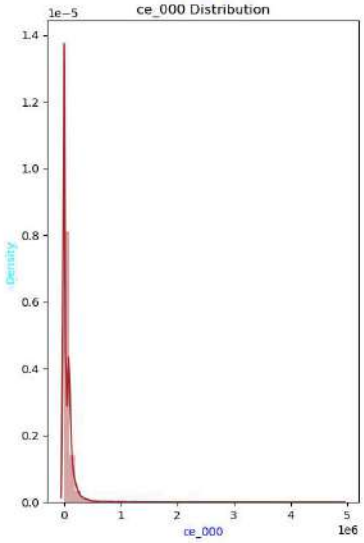
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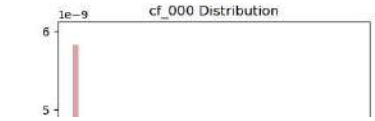
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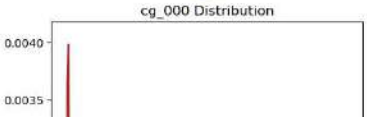
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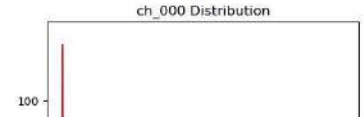
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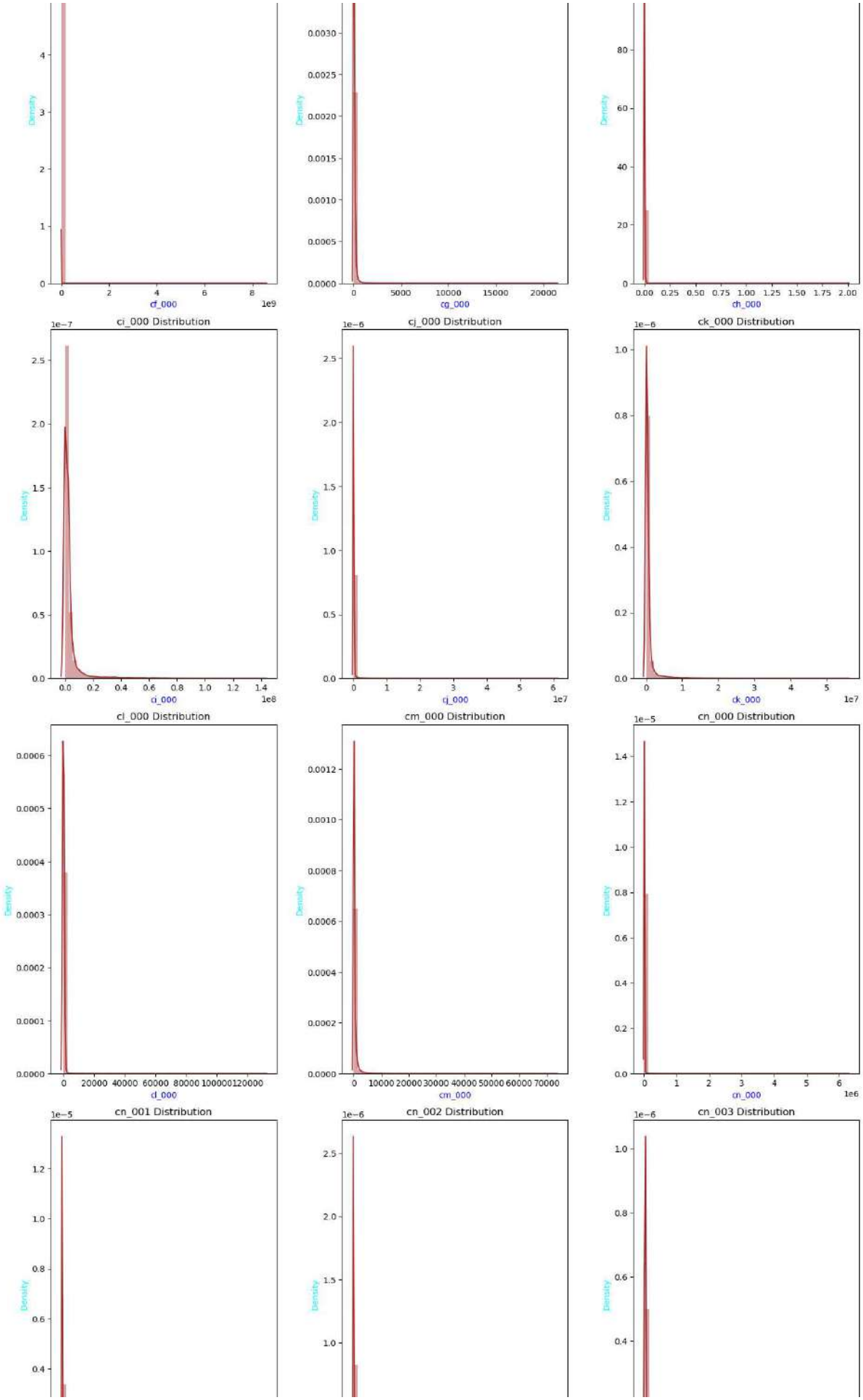
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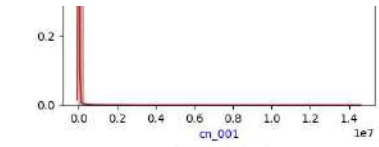
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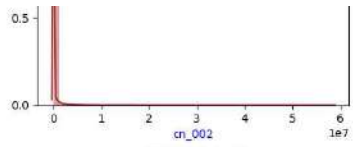
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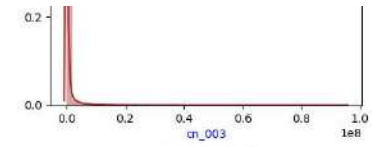
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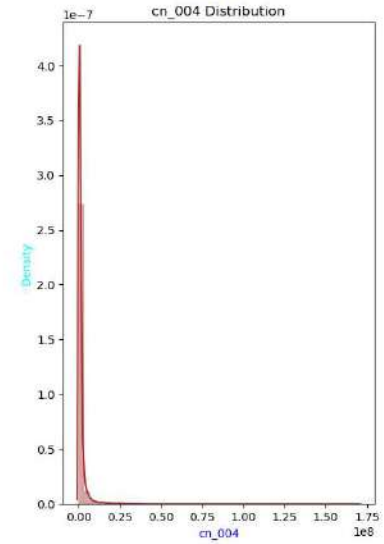
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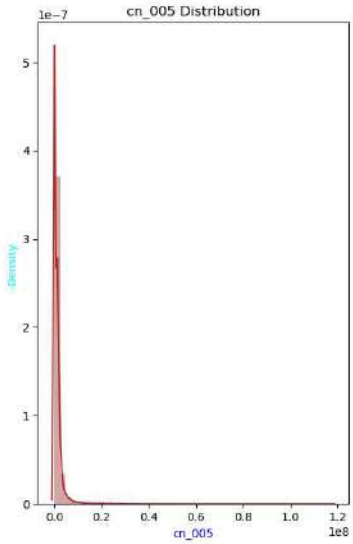
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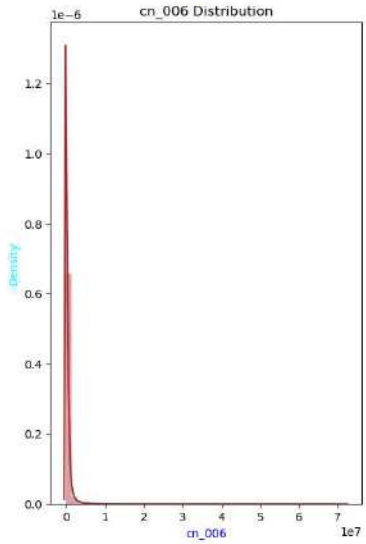
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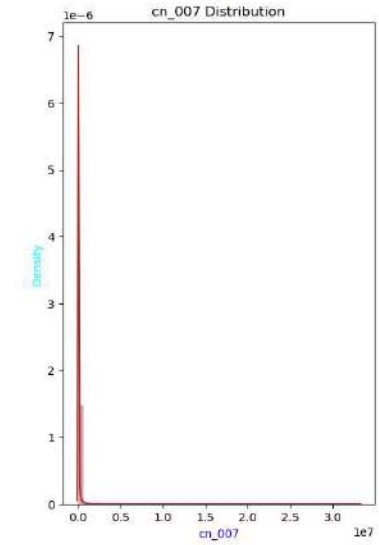
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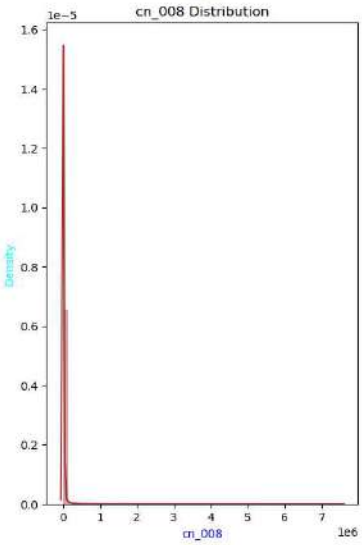
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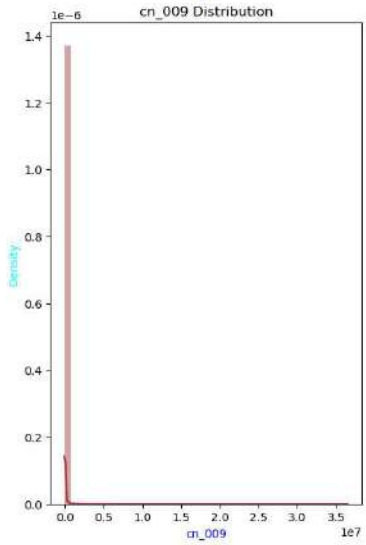
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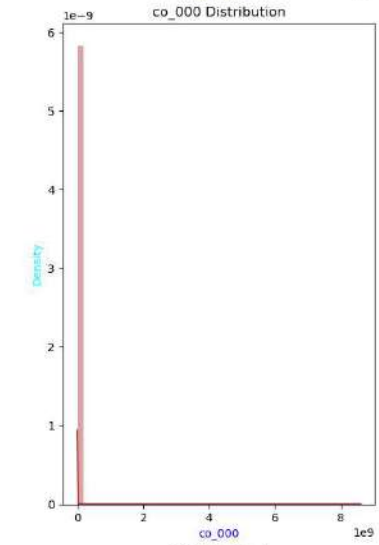
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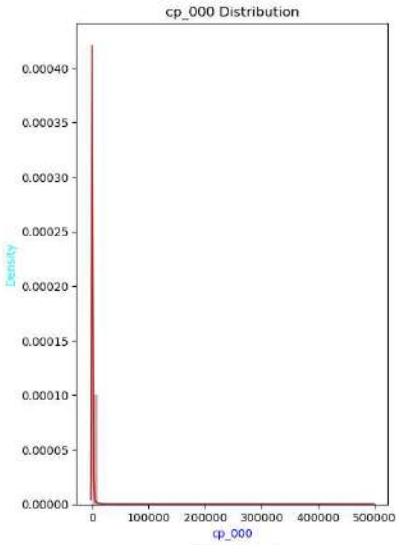
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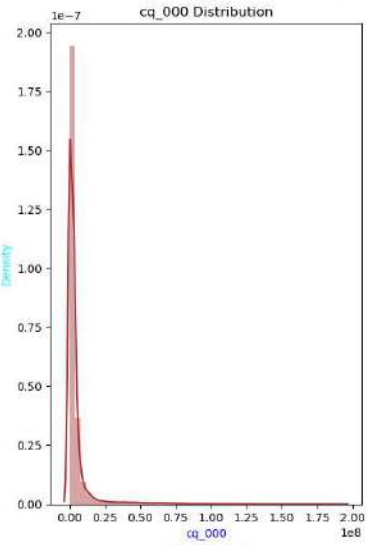
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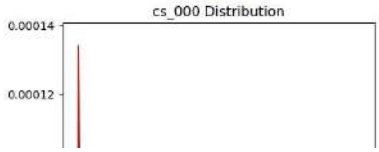
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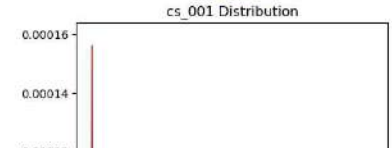
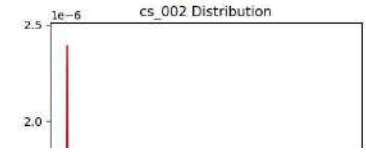
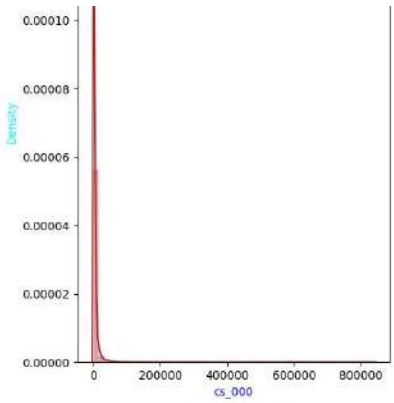
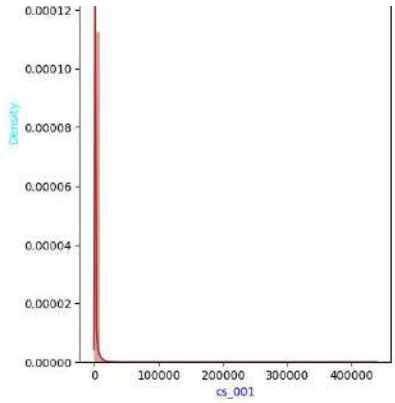
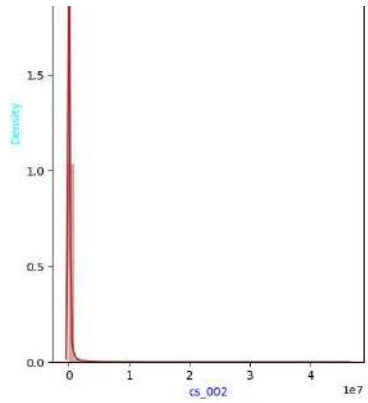
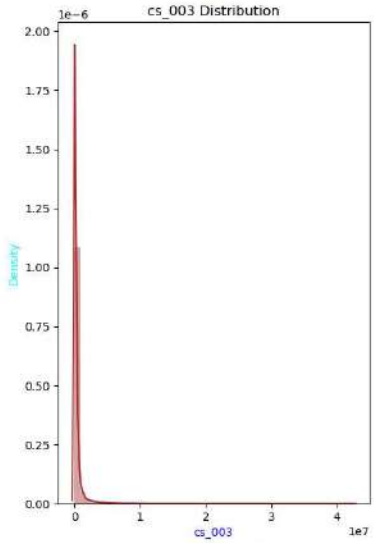

cs_001 Distribution

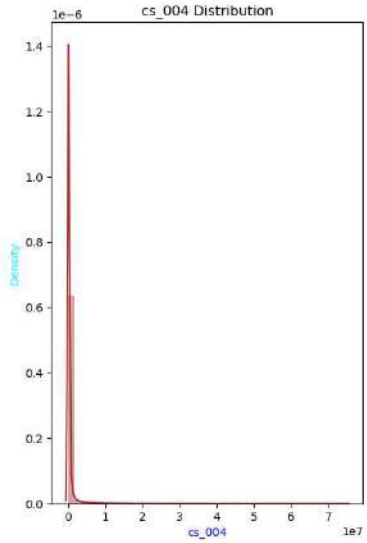

cs_002 Distribution
1e−6

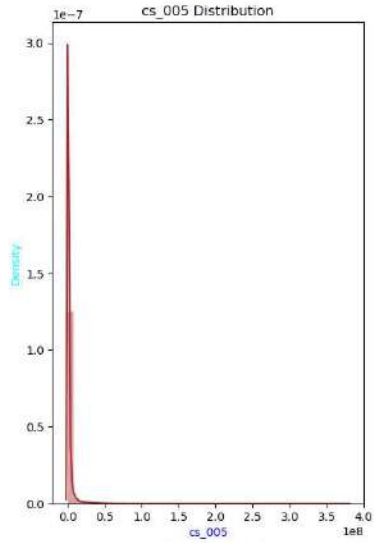

Density
cs_000

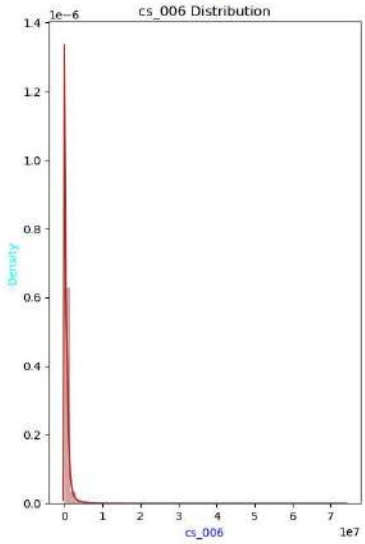

Density
cs_001

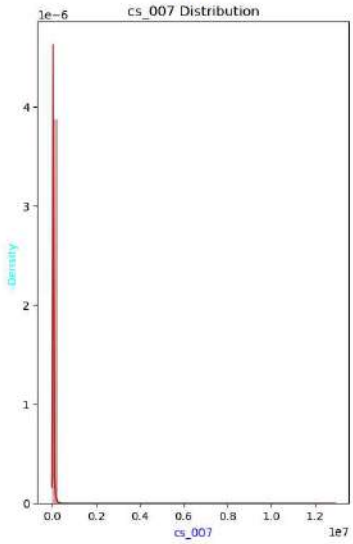

Density
cs_002
1e7

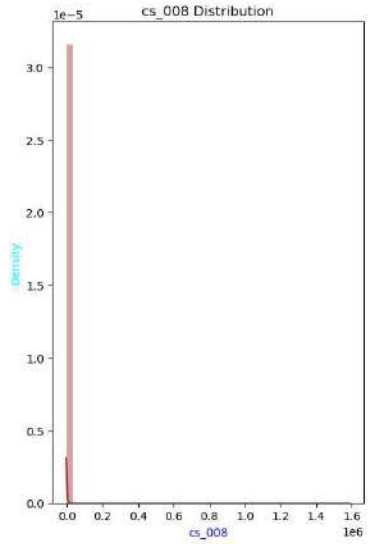

cs_003 Distribution
1e−6
Density
cs_003
1e7

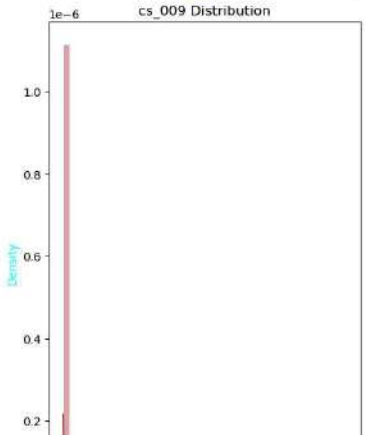

cs_004 Distribution
1e−6
Density
cs_004
1e7

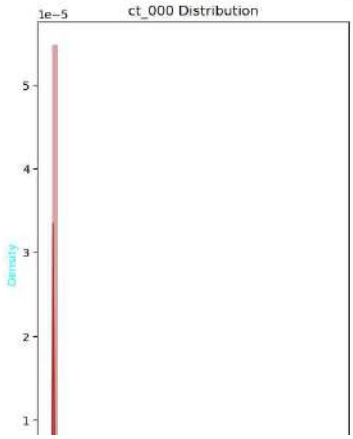

cs_005 Distribution
1e−7
Density
cs_005
1e8

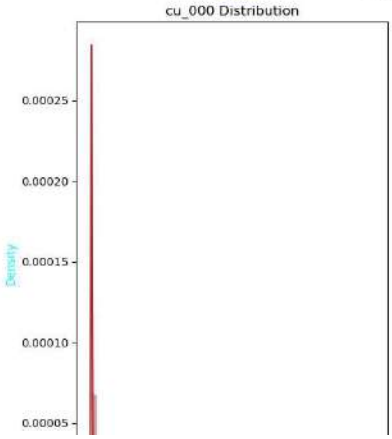

cs_006 Distribution
1e−6
Density
cs_006
1e7

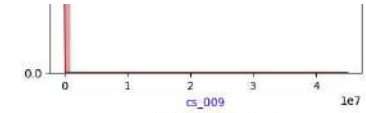

cs_007 Distribution
1e−6
Density
cs_007
1e7

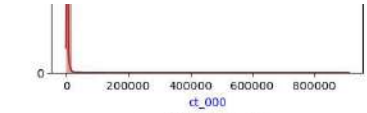

cs_008 Distribution
1e−5
Density
cs_008
1e6


cs_009 Distribution
1e−6
Density


ct_000 Distribution
1e−5
Density


cu_000 Distribution
Density


cs_009
1e7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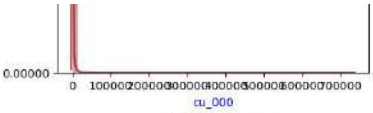
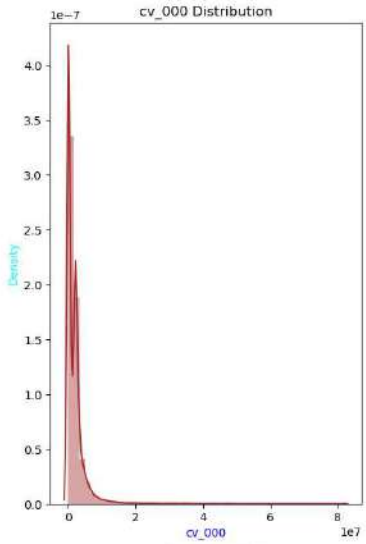
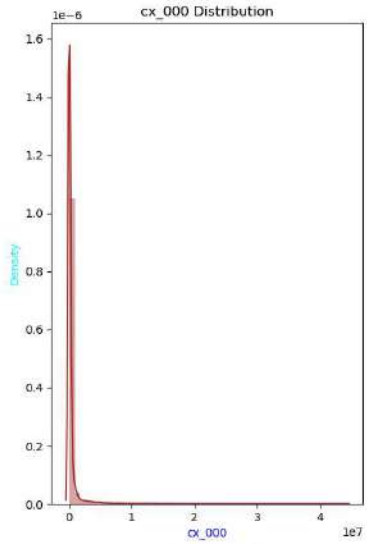
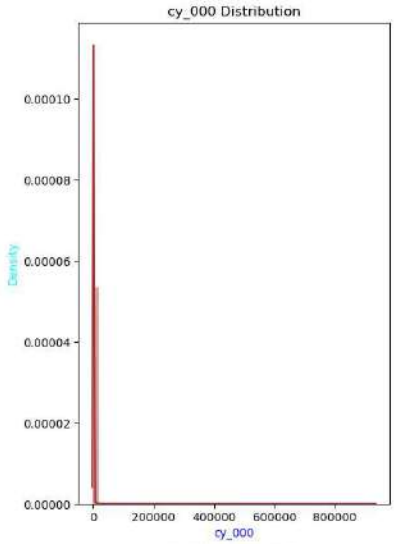
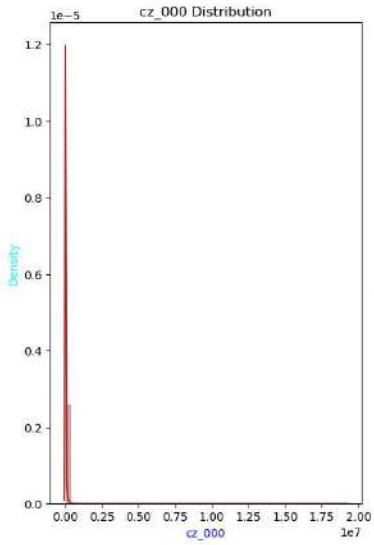
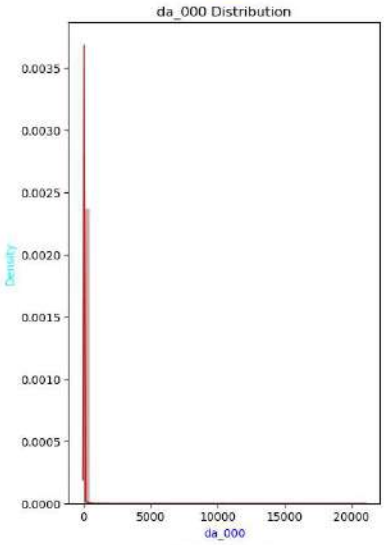

cu_000

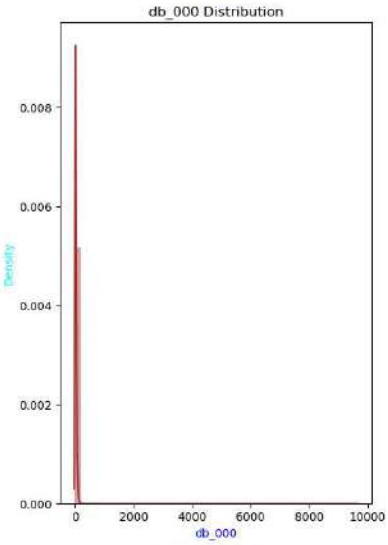

cv_000 Distribution
1e−7
Density
cv_000
1e7

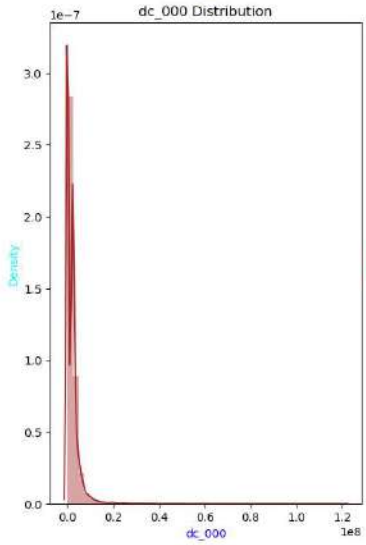

cx_000 Distribution
1e−6
Density
cx_000
1e7

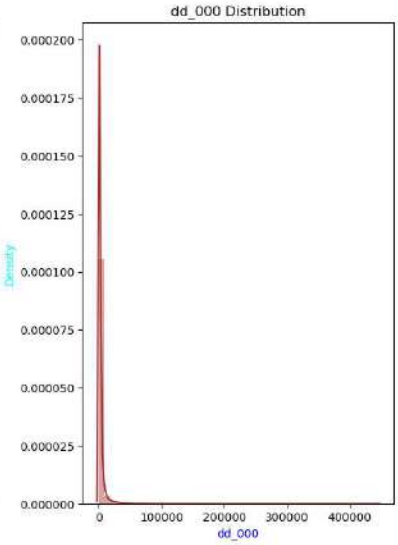

cy_000 Distribution
Density
cy_000

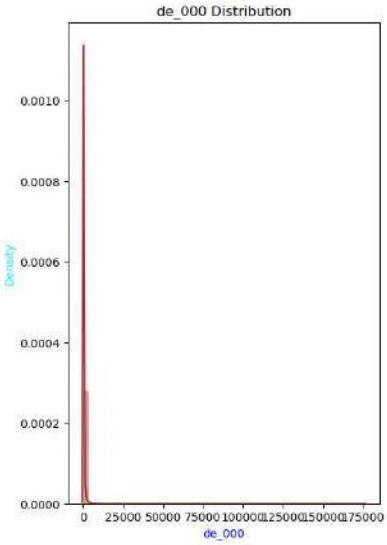

cz_000 Distribution
1e−5
Density
cz_000
1e7

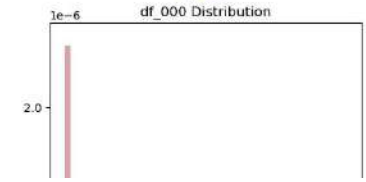

da_000 Distribution
Density
da_000

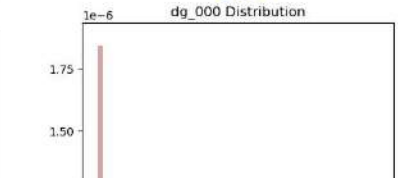

db_000 Distribution
Density
db_000

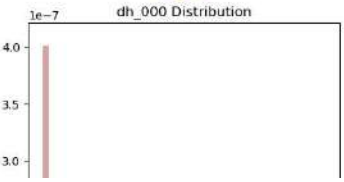

dc_000 Distribution
1e−7
Density
dc_000
1e8

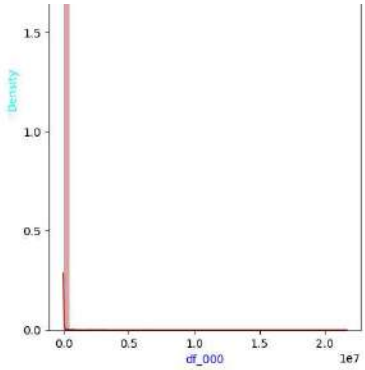

dd_000 Distribution
Density
dd_000


de_000 Distribution
Density
de_000


df_000 Distribution
1e−6


dg_000 Distribution
1e−6


dh_000 Distribution
1e−7


Density
df_000
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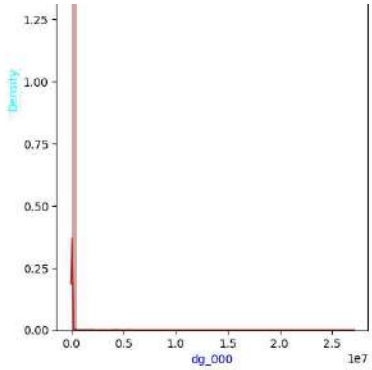
Density
dg_000
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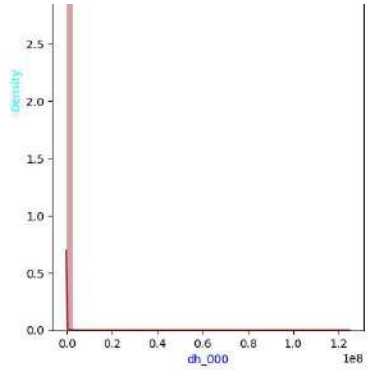
Density
dh_000
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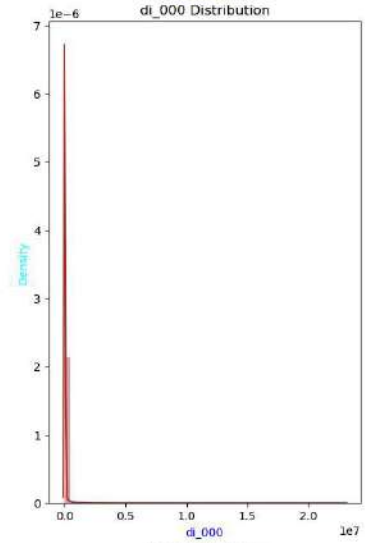
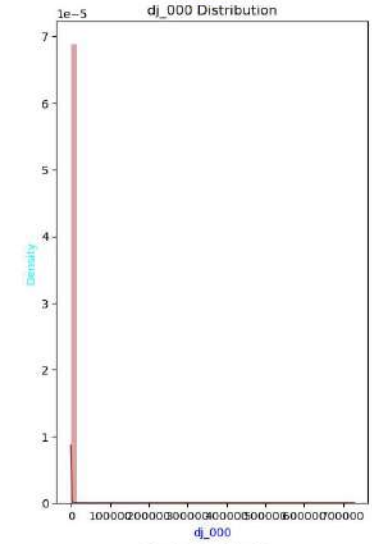
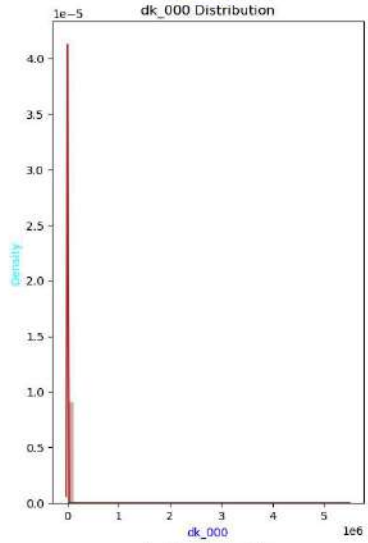
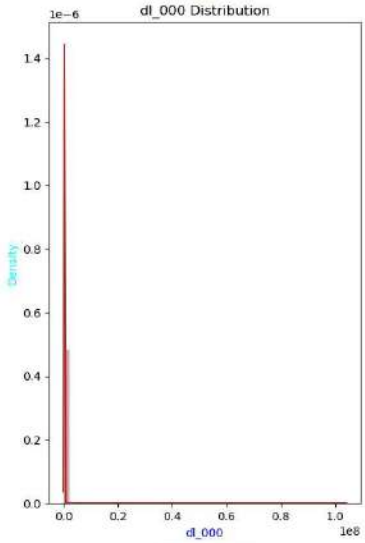

di_000 Distribution
1e−6
Density
di_000
1e7


dj_000 Distribution
1e−5
Density
dj_000


dk_000 Distribution
1e−5
Density
dk_000
1e6


dl_000 Distribution
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Density
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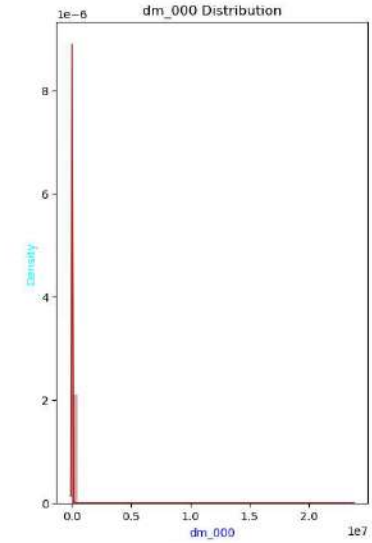
dm_000 Distribution
1e−6
Density
dm_000
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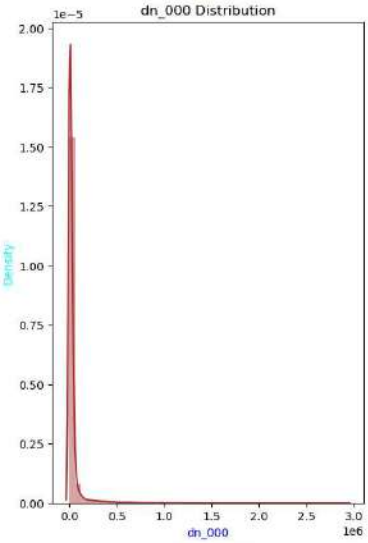
dn_000 Distribution
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Density
dn_000
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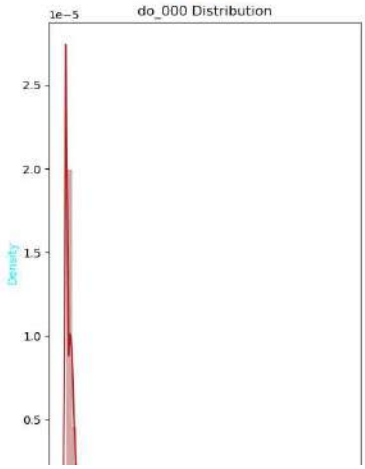
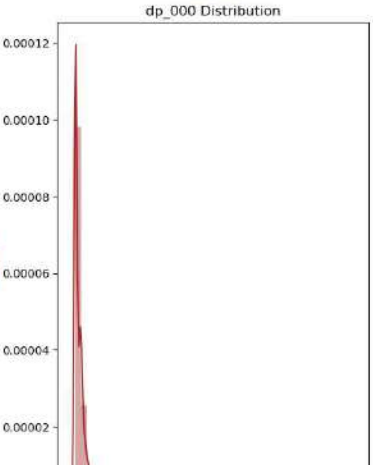
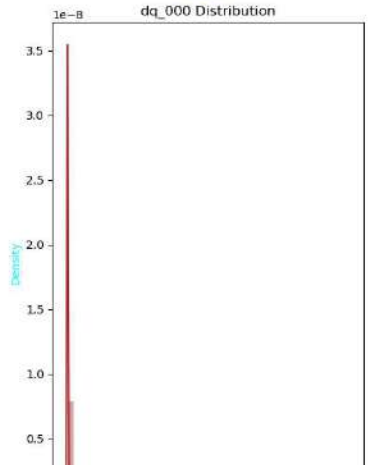

do_000 Distribution
1e−5
Density


dp_000 Distribution
Density


dq_000 Distribution
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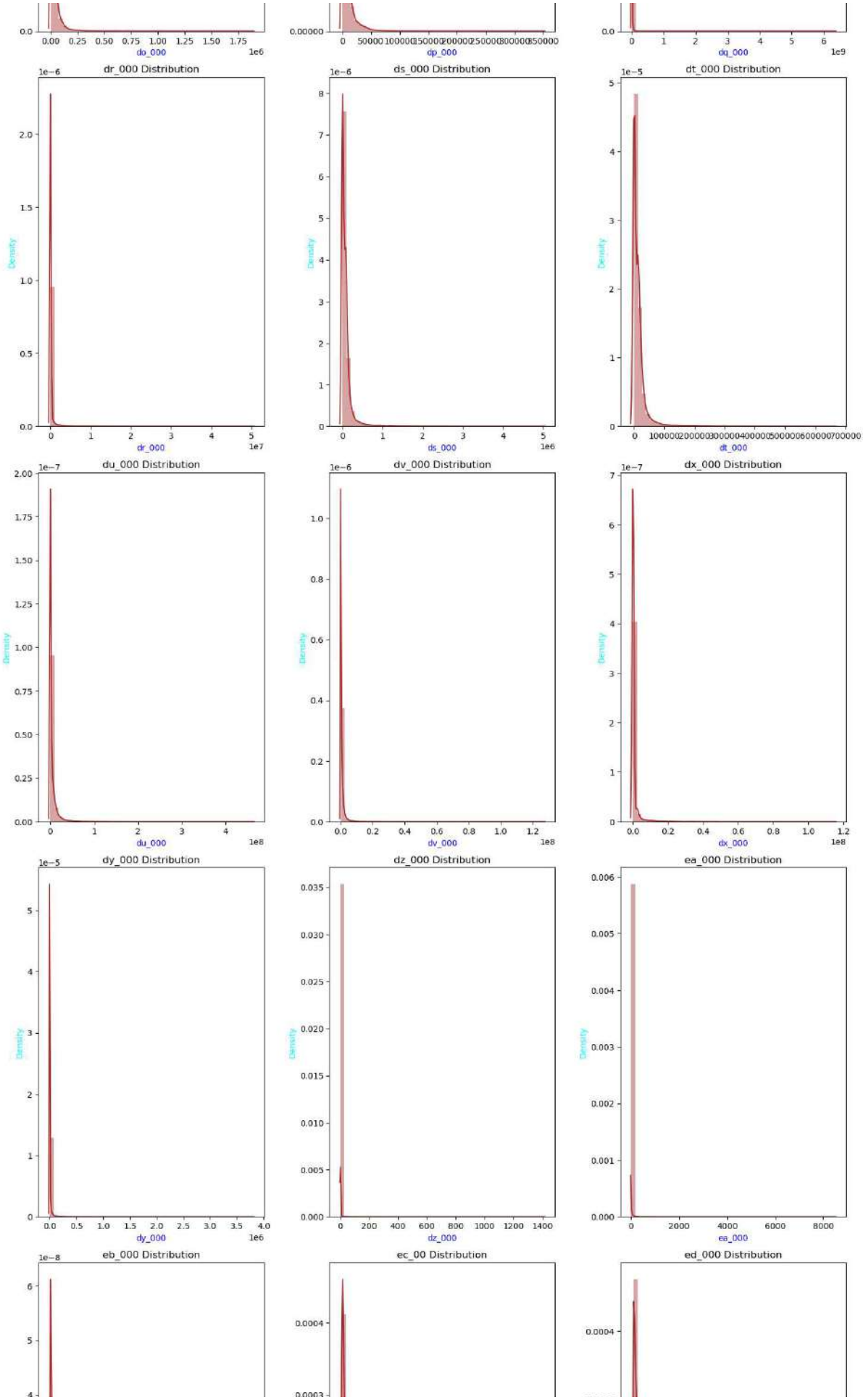
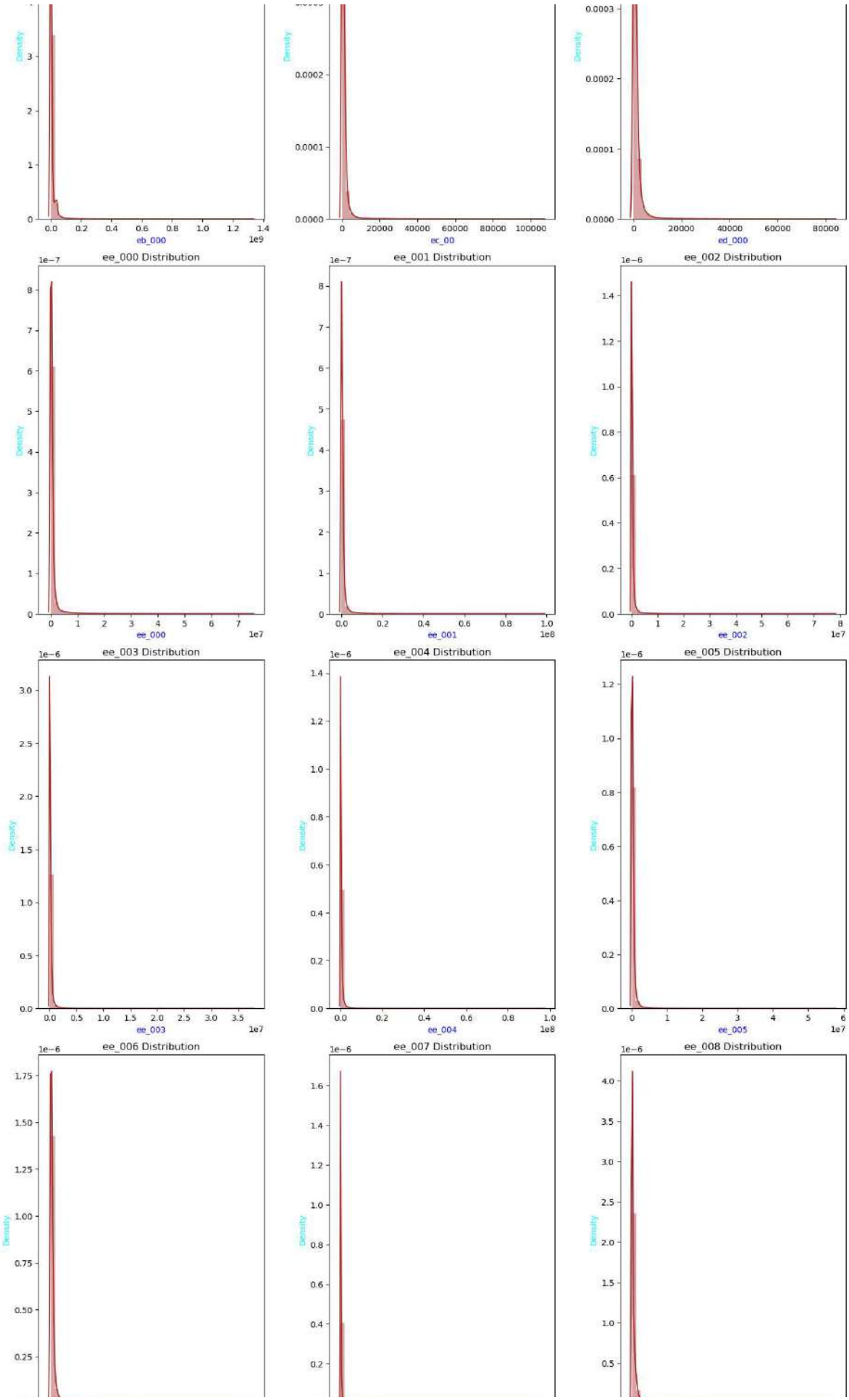
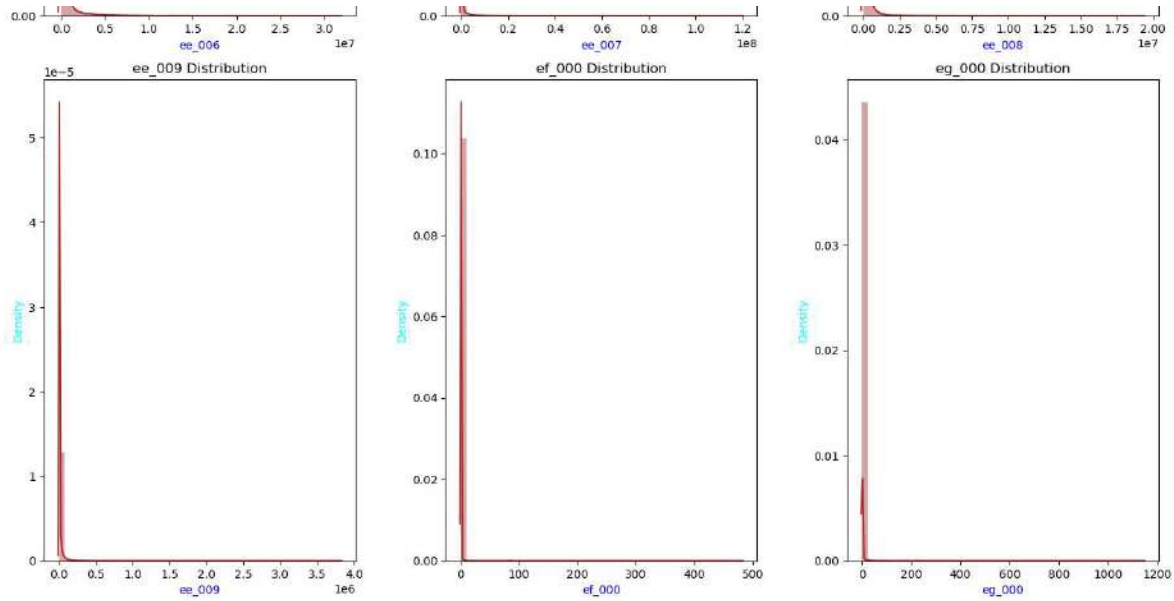
Density


do_000
dp_000
dq_000
dr_000 Distribution
ds_000 Distribution
dt_000 Distribution
du_000 Distribution
dv_000 Distribution
dx_000 Distribution
dy_000 Distribution
dz_000 Distribution
ea_000 Distribution
eb_000 Distribution
ec_00 Distribution
ed_000 Distribution
Density


Density
eb_000
1e9
ec_00
ed_000
ee_000 Distribution
1e−7
ee_000
1e7
ee_001 Distribution
1e−7
ee_001
1e8
ee_002 Distribution
1e−6
ee_002
1e7
ee_003 Distribution
1e−6
ee_003
1e7
ee_004 Distribution
1e−6
ee_004
1e8
ee_005 Distribution
1e−6
ee_005
1e7
ee_006 Distribution
1e−6
ee_007 Distribution
1e−6
ee_008 Distribution
1e−6



None

In [51]:
```
# Observation :By Observing Distribution almost all except few are not normally dis
# All the distribution is rightly skewed
# Since The problem related to classification so Transformation of Data to Normal d
# Also these data obtained by sensors so we do not need to intrepret each and every
```

In [262…
```
# Now we start training for our cleaned data
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state=12)
```

In [263…
```
x_train.shape
```

Out[263…
```
(40200, 162)
```

In [264…
```
x_test.shape
```

Out[264…
```
(19800, 162)
```

In [265…
```
y_train.shape
```

Out[265…
```
(40200,)
```

1. Model Training By Logistic Regression

In [267…
```
# since the model does not accept null values so we replace them by zeros
x_train.replace(np.nan,0,inplace=True)
x_test.replace(np.nan,0,inplace=True)
```

In [268…
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
lr =LogisticRegression()
lr.fit(x_train,y_train)
pred_test =lr.predict(x_test)
```

```
acc_score=accuracy_score(y_test,pred_test)
per_acc_score_lr=round(acc_score*100,2)
print('The Accuracy Score of Logistic regression model = {} %'.format(per_acc_score
```

```
The Accuracy Score of Logistic regression model = 98.86 %
```

In [269…

```
# Confusion Metrics for this model
from sklearn.metrics import confusion_matrix
conf_mat_lr=confusion_matrix(y_test,pred_test)
print(conf_mat_lr)
```

```
[[19393    89]
 [  136   182]]
```

In [270…

```
# saperate metrics by flatting array
tp,fp,fn,tn= conf_mat_lr.ravel()
conf_mat_lr_acc=round((tp+tn)/(tp+tn+fp+fn)*100,2)
conf_mat_lr_prec=round((tp/(tp+fp))*100,2)
conf_mat_lr_recal=round((tp/(tp+fn))*100,2)
conf_mat_lr_f1=round((2*((conf_mat_lr_prec*conf_mat_lr_recal)/(conf_mat_lr_prec+con
conf_mat_lr_errorrate=round(((fp+fn)/(fp+fn+tp+tn))*100,2)
```

In [271…

```
print(f'confusion metrics for Logistic Regression is :\n {conf_mat_lr}'+
      f'\nBased on This confusion metrics we deduce the following \n'+
      f'Accuracy  : {conf_mat_lr_acc} %'+
      f'\nPrecision : {conf_mat_lr_prec} % \nRecall    : {conf_mat_lr_recal}  % \n'+
      f'F1 Score  : {conf_mat_lr_f1} % \nError Rate : {conf_mat_lr_errorrate} %')
```

```
confusion metrics for Logistic Regression is :
 [[19393    89]
 [  136   182]]
Based on This confusion metrics we deduce the following
Accuracy  : 98.86 %
Precision : 99.54 %
Recall    : 99.3  %
F1 Score  : 99.42 %
Error Rate : 1.14 %
```

In [272…

```
# Now calculating Total cost for repairing after implementing Logistics Regression
```

In [273…

```
Total_cost_lr =10*fp+500*fn
print("The Total cost of Repairing is : {} /-".format(Total_cost_lr))
```

```
The Total cost of Repairing is : 68890 /-
```

In [ ]:

In [274…

```
# Now we store this infor to dictionary
model_details ={'Logistic Regression': {'Model_Accuracy':per_acc_score_lr,'conf_mat
                                        'Conf_Mat_Accuracy':conf_mat_lr_acc,'Precisi
                                        'Recall':conf_mat_lr_recal,'F1_Score':conf_m
                                        'Error_rate':conf_mat_lr_errorrate,'Total_co
```

In [275…

```
pd.DataFrame(model_details)
```

Out[275…

	Logistic Regression
Model_Accuracy	98.86
conf_mat	[[19393, 89], [136, 182]]
Conf_Mat_Accuracy	98.86
Precision	99.54
Recall	99.3
F1_Score	99.42
Error_rate	1.14
Total_cost	68890

2. Model Training By Decision Tree Classifier Model

In [276…

```
from sklearn.tree import DecisionTreeClassifier
dt_c=DecisionTreeClassifier()
dt_c.fit(x_train,y_train)
pred_test_dt_c =dt_c.predict(x_test)
acc_dt_c =accuracy_score(y_test,pred_test_dt_c)
per_acc_dt_c=round(acc_dt_c*100,2)
print('Accuracy of the model is : {} %'.format(per_acc_dt_c))
```

```
Accuracy of the model is : 98.9 %
```

In [277…

```
# confusion metrics
conf_mat_dt_c =confusion_matrix(y_test,pred_test_dt_c)
print(conf_mat_dt_c)
```

```
[[19377   105]
 [  113   205]]
```

In [278…

```
tp,fp,fn,tn=conf_mat_dt_c.ravel()
conf_mat_acc_dt_c=round((tp+tn)/(tp+tn+fp+fn)*100,2)
conf_mat_pre_dt_c =round(tp/(tp+fp)*100,2)
conf_mat_rec_dt_c =round((tp/(tp+fn))*100,2)
conf_mat_f1_dt_c=round(2*(conf_mat_pre_dt_c*conf_mat_rec_dt_c/(conf_mat_pre_dt_c+co
conf_mat_error_dt_c=round(((fp+fn)/(tp+tn+fp+fn))*100,2)
```

In [279…

```
print('Confusion Matrix summary')
print(f'Accuracy :{conf_mat_acc_dt_c} %')
print(f'Precision: {conf_mat_pre_dt_c} %')
print(f'Recall : {conf_mat_rec_dt_c} %')
print(f'F1-Score : {conf_mat_f1_dt_c} %')
print(f'Error Rate : {conf_mat_error_dt_c} %')
```

```
Confusion Matrix summary
Accuracy :98.9 %
Precision: 99.46 %
Recall : 99.42 %
F1-Score : 99.44 %
Error Rate : 1.1 %
```

In [280…

```
# Cost calculation for Repairing
Total_cost_dt_c =fp*10+fn*500
Total_cost_dt_c
```

Out[280…

```
57550
```

In [281…

```
# now updating this details to the model details
model_details['Decision Tree Classifier'] = {'Model_Accuracy':per_acc_dt_c,'conf_ma
                                            'Conf_Mat_Accuracy':conf_mat_acc_dt_c,'Preci
                                            'Recall':conf_mat_rec_dt_c,'F1_Score':conf_m
                                            'Error_rate':conf_mat_error_dt_c,'Total_cost
```

In [282…

```
pd.DataFrame(model_details)
```

Out[282…

	Logistic Regression	Decision Tree Classifier
Model_Accuracy	98.86	98.9
conf_mat	[[19393, 89], [136, 182]]	[[19377, 105], [113, 205]]
Conf_Mat_Accuracy	98.86	98.9
Precision	99.54	99.46
Recall	99.3	99.42
F1_Score	99.42	99.44
Error_rate	1.14	1.1
Total_cost	68890	57550

In [283…

```
# Model Training By Random Forest Classifier Model
```

In [284…

```
from sklearn.ensemble import RandomForestClassifier
rfc =RandomForestClassifier()
rfc.fit(x_train,y_train)
rfc_pred_test =rfc.predict(x_test)
rfc_acc=accuracy_score(y_test,rfc_pred_test)
rfc_per_acc=round(rfc_acc*100,2)
print('The Accuracy of the Model is : {} %'.format(rfc_per_acc))
```

```
The Accuracy of the Model is : 99.39 %
```

In [285…

```
#confusion metrics
rfc_conf_mat =confusion_matrix(y_test,rfc_pred_test)
print(rfc_conf_mat)
```

```
[[19460    22]
 [   99   219]]
```

In [286…

```
tp,fp,fn,tn=rfc_conf_mat.ravel()
rfc_conf_acc=round((tp+tn)/(tp+tn+fp+fn)*100,2)
rfc_prec =round((tp)/(tp+fp)*100,2)
rfc_recal=round((tp)/(tp+fn)*100,2)
rfc_f1_score=round( 2*(rfc_prec*rfc_recal)/(rfc_prec+rfc_recal),2)
rfc_error_rate= round((fp+fn)/(tn+tp+fp+fn)*100,2)
```

In [287…

```
print(f'Accuracy of the Random Forest Classifier : {round(rfc_per_acc,2)} %')
print(f'Confusion Precision : {rfc_prec} %')
print(f'Confusion Recall : {rfc_recal} %')
print(f'F1-Score : {rfc_f1_score} %')
print(f'Error-Rate : {rfc_error_rate} %')
```

```
Accuracy of the Random Forest Classifier : 99.39 %
Confusion Precision : 99.89 %
Confusion Recall : 99.49 %
F1-Score : 99.69 %
Error-Rate : 0.61 %
```

In [288…

```
# calculating the cost for the model
rfc_total_cost =fp*10+fn*500
```

In [289…

```
print(f'Total Cost of Repair for Random Forest Classifier is : {rfc_total_cost}')
```

```
Total Cost of Repair for Random Forest Classifier is : 49720
```

In [290…

```
# updating this details to model details
model_details['Random Forest Classifier'] ={'Model_Accuracy':rfc_per_acc,'conf_mat'
                                            'Conf_Mat_Accuracy':rfc_conf_acc,'Precision'
                                            'Recall':rfc_recal,'F1_Score':rfc_f1_score,
                                            'Error_rate':rfc_error_rate,'Total_cost':rfc
```

In [291…

```
pd.DataFrame(model_details)
```

Out[291…

	Logistic Regression	Decision Tree Classifier	Random Forest Classifier
Model_Accuracy	98.86	98.9	99.39
conf_mat	[[19393, 89], [136, 182]]	[[19377, 105], [113, 205]]	[[19460, 22], [99, 219]]
Conf_Mat_Accuracy	98.86	98.9	99.39
Precision	99.54	99.46	99.89
Recall	99.3	99.42	99.49
F1_Score	99.42	99.44	99.69
Error_rate	1.14	1.1	0.61
Total_cost	68890	57550	49720

In [292…

```
# 4. Model Training By AdaBoost Model
```

In [293…

```
from sklearn.ensemble import AdaBoostClassifier
abc=AdaBoostClassifier()
abc.fit(x_train,y_train)
abc_pred_test =abc.predict(x_test)
abc_acc =accuracy_score(y_test,abc_pred_test)
abc_per_acc=round(abc_acc*100,2)
print(f'Accuracy of the Model : {abc_per_acc} %')
```

```
Accuracy of the Model : 99.18 %
```

In [294…

```
# confusion Matrix
abc_conf_mat =confusion_matrix(y_test,abc_pred_test)
print(abc_conf_mat)
```

```
[[19427    55]
 [  107   211]]
```

In [295…

```
# separate parameter of confusion matrix
tp,fp,fn,tn =abc_conf_mat.ravel()
abc_conf_mat_acc=round((tp+tn)/(tp+tn+fp+fn)*100,2)
abc_conf_mat_prec=round(tp/(tp+fp)*100,2)
abc_conf_mat_recal=round(tp/(tp+fn)*100,2)
abc_conf_mat_f1_score =round(2*(abc_conf_mat_prec*abc_conf_mat_recal)/(abc_conf_mat
abc_conf_mat_error_rate=round((fp+fn)/(fp+fn+tp+tn)*100,2)
print(f'\nConfusion Matrics Accuracy :{abc_conf_mat_acc}'+
     f'\nPrecision : {abc_conf_mat_prec}'+
     f'\nRecall :{abc_conf_mat_recal}'+
     f'\nF1 Score : {abc_conf_mat_f1_score}'+
     f'\nError Rate : {abc_conf_mat_error_rate}')
```

```
Confusion Matrics Accuracy :99.18
Precision : 99.72
Recall :99.45
F1 Score : 99.58
Error Rate : 0.82
```

In [296…

```
# Lets check the accuracy of these parameter using default functions
from sklearn.metrics import classification_report,f1_score,recall_score,roc_auc_sco
abc_cr =classification_report(y_test,abc_pred_test)
print(abc_cr)
```

```
              precision    recall  f1-score   support

         neg       0.99      1.00      1.00     19482
         pos       0.79      0.66      0.72       318

    accuracy                           0.99     19800
   macro avg       0.89      0.83      0.86     19800
weighted avg       0.99      0.99      0.99     19800
```

In [297…

```
abc_f1_score =f1_score(y_test,abc_pred_test,average='weighted')
print(abc_f1_score)
```

```
0.9914593750981492
```

In [298…

```
abc_total_cost =fp*10+fn*500
print(f'Total Cost of Repair Using This model : {abc_total_cost} /-')
```

```
Total Cost of Repair Using This model : 54050 /-
```

In [299…

```
# now update this information to model details
model_details['AdaBoost Classifier'] ={'Model_Accuracy':abc_per_acc,'conf_mat':abc_
                                       'Conf_Mat_Accuracy':abc_conf_mat_acc,'Precis
                                       'Recall':abc_conf_mat_recal,'F1_Score':abc_c
                                       'Error_rate':abc_conf_mat_error_rate,'Total_
```

In [300…

```
pd.DataFrame(model_details)
```

Out[300…

	Logistic Regression	Decision Tree Classifier	Random Forest Classifier	AdaBoost Classifier
Model_Accuracy	98.86	98.9	99.39	99.18
conf_mat	[[19393, 89], [136, 182]]	[[19377, 105], [113, 205]]	[[19460, 22], [99, 219]]	[[19427, 55], [107, 211]]
Conf_Mat_Accuracy	98.86	98.9	99.39	99.18
Precision	99.54	99.46	99.89	99.72
Recall	99.3	99.42	99.49	99.45
F1_Score	99.42	99.44	99.69	99.58
Error_rate	1.14	1.1	0.61	0.82
Total_cost	68890	57550	49720	54050

5. Model Training Using SVM(SVC)

In [301…

```
from sklearn.svm import SVC
svc =SVC()
svc.fit(x_train,y_train)
svc_pred_test=svc.predict(x_test)
svc_acc =accuracy_score(y_test,svc_pred_test)
svc_acc_per =round(svc_acc*100,2)
print(f'The Accuracy of the model : {svc_acc_per} %')
```

```
The Accuracy of the model : 98.4 %
```

In [302…

```
# confusion matrix
svc_conf_mat =confusion_matrix(y_test,svc_pred_test)
print(svc_conf_mat)
```

```
[[19476     6]
 [  310     8]]
```

In [303…

```
#now seprating parameter of confusion matrix
tp,fp,fn,tn=svc_conf_mat.ravel()
svc_conf_mat_acc =round((tp+tn)/(tp+tn+fp+fn)*100,2)
```

```
svc_conf_mat_prec=round(tp/(tp+fp)*100,2)
svc_conf_mat_recal=round(tp/(tp+fn)*100,2)
svc_conf_mat_f1_score=round(2*(svc_conf_mat_prec*svc_conf_mat_recal)/(svc_conf_mat_
svc_conf_mat_error_rate=round((fp+fn)/(tp+tn+fp+fn)*100,2)
```

In [304…

```
print('Report of Confusion Matrix'+
     f'\nAccuracy   : {svc_conf_mat_acc}%'+
     f'\nPrecision  : {svc_conf_mat_prec}%'+
     f'\nRecall     : {svc_conf_mat_recal}%'+
     f'\nF1-Score   : {svc_conf_mat_f1_score}%'+
     f'\nError-Rate : {svc_conf_mat_error_rate}%')
```

```
Report of Confusion Matrix
Accuracy   : 98.4%
Precision  : 99.97%
Recall     : 98.43%
F1-Score   : 99.19%
Error-Rate : 1.6%
```

In [305…

```
# Cost Calculation for the model
svc_total_cost =fp*10+fn*500
print(f'Total Cost of repair for the Model :{svc_total_cost}')
```

```
Total Cost of repair for the Model :155060
```

In [306…

```
# Updating this details to the model details dict
model_details['SV Classifier'] ={'Model_Accuracy':svc_acc_per,'conf_mat':svc_conf_m
                                 'Conf_Mat_Accuracy':svc_conf_mat_acc,'Precis
                                 'Recall':svc_conf_mat_recal,'F1_Score':svc_c
                                 'Error_rate':svc_conf_mat_error_rate,'Total_
```

In [307…

```
pd.DataFrame(model_details)
```

Out[307…

	Logistic Regression	Decision Tree Classifier	Random Forest Classifier	AdaBoost Classifier	SV Classifier
Model_Accuracy	98.86	98.9	99.39	99.18	98.4
conf_mat	[[19393, 89], [136, 182]]	[[19377, 105], [113, 205]]	[[19460, 22], [99, 219]]	[[19427, 55], [107, 211]]	[[19476, 6], [310, 8]]
Conf_Mat_Accuracy	98.86	98.9	99.39	99.18	98.4
Precision	99.54	99.46	99.89	99.72	99.97
Recall	99.3	99.42	99.49	99.45	98.43
F1_Score	99.42	99.44	99.69	99.58	99.19
Error_rate	1.14	1.1	0.61	0.82	1.6
Total_cost	68890	57550	49720	54050	155060

6. Model Training by Bagging Classifier

In [308…

```
from sklearn.ensemble import BaggingClassifier
bc =BaggingClassifier()
bc.fit(x_train,y_train)
bc_pred_test =bc.predict(x_test)
bc_acc=accuracy_score(y_test,bc_pred_test)
bc_acc_per=round(bc_acc*100,2)
print(f'Accuracy of the Model : {bc_acc_per} %')
```

```
Accuracy of the Model : 99.34 %
```

In [309…

```
# Confusion Matrix
bc_conf_mat=confusion_matrix(y_test,bc_pred_test)
tp,fp,fn,tn=bc_conf_mat.ravel()
print(bc_conf_mat)
```

```
[[19457    25]
 [  106   212]]
```

In [310…

```
# calculation of Confusion Matrix Parameter
bc_conf_mat_acc=round((tp+tn)/(tp+tn+fp+fn)*100,2)
bc_conf_mat_prec=round(tp/(tp+fp)*100,2)
bc_conf_mat_recal=round(tp/(tp+fn)*100,2)
bc_conf_mat_f1_score=round(2*(bc_conf_mat_prec*bc_conf_mat_recal)/(bc_conf_mat_prec
bc_conf_mat_error_rate=round((fp+fn)/(tp+tn+fp+fn)*100,2)
```

In [311…

```
print('Confusion Matrix Report '+
     f'\nAccuracy   : {bc_conf_mat_acc}%'+
     f'\nPrecision  : {bc_conf_mat_prec}%'+
     f'\nRecall     : {bc_conf_mat_recal}%'+
     f'\nF1-Score   : {bc_conf_mat_f1_score}%'+
     f'\nError-Rate : {bc_conf_mat_error_rate}%')
```

```
Confusion Matrix Report
Accuracy   : 99.34%
Precision  : 99.87%
Recall     : 99.46%
F1-Score   : 99.66%
Error-Rate : 0.66%
```

In [312…

```
# cost Calculation
bc_total_cost =fp*10+fn*500
print(f'Total Cost of Repair using this model : {bc_total_cost} /-')
```

```
Total Cost of Repair using this model : 53250 /-
```

In [313…

```
# updating this result to model details
model_details['Bagging Classifier'] ={'Model_Accuracy':bc_acc_per,'conf_mat':bc_con
                                      'Conf_Mat_Accuracy':bc_conf_mat_acc,'Precisi
                                      'Recall':bc_conf_mat_recal,'F1_Score':bc_con
                                      'Error_rate':bc_conf_mat_error_rate,'Total_c
```

In [314…

```
print(pd.DataFrame(model_details))
```

```
                        Logistic Regression    Decision Tree Classifier  \
Model_Accuracy                        98.86                        98.9
conf_mat          [[19393, 89], [136, 182]]  [[19377, 105], [113, 205]]
Conf_Mat_Accuracy                     98.86                        98.9
Precision                             99.54                       99.46
Recall                                 99.3                       99.42
F1_Score                              99.42                       99.44
Error_rate                             1.14                         1.1
Total_cost                            68890                       57550

                   Random Forest Classifier        AdaBoost Classifier  \
Model_Accuracy                        99.39                       99.18
conf_mat          [[19460, 22], [99, 219]]  [[19427, 55], [107, 211]]
Conf_Mat_Accuracy                     99.39                       99.18
Precision                             99.89                       99.72
Recall                                99.49                       99.45
F1_Score                              99.69                       99.58
Error_rate                             0.61                        0.82
Total_cost                            49720                       54050

                           SV Classifier         Bagging Classifier
Model_Accuracy                      98.4                      99.34
conf_mat          [[19476, 6], [310, 8]]  [[19457, 25], [106, 212]]
Conf_Mat_Accuracy                   98.4                      99.34
Precision                          99.97                      99.87
Recall                             98.43                      99.46
F1_Score                           99.19                      99.66
Error_rate                           1.6                       0.66
Total_cost                        155060                      53250
```

7.Model training By Gradient Boost

In [315…

```
from sklearn.ensemble import GradientBoostingClassifier
gbc =GradientBoostingClassifier()
gbc.fit(x_train,y_train)
gbc_pred_test =gbc.predict(x_test)
gbc_acc=accuracy_score(y_test,gbc_pred_test)
gbc_acc_per=round(gbc_acc*100,2)
print(f'Accuracy of the Model :{gbc_acc_per}')
```

```
Accuracy of the Model :99.25
```

In [316…

```
# confusion matrix
gbc_conf_mat=confusion_matrix(y_test,gbc_pred_test)
tp,fp,fn,tn=gbc_conf_mat.ravel()
gbc_conf_mat_acc=round((tp+tn)/(tp+tn+fp+fn)*100,2)
gbc_conf_mat_prec=round(tp/(tp+fp)*100,2)
gbc_conf_mat_recal=round(tp/(tp+fn)*100,2)
gbc_conf_mat_f1_score=round(2*(gbc_conf_mat_prec*gbc_conf_mat_recal)/(gbc_conf_mat_
gbc_conf_mat_error_rate=round((fp+fn)/(tp+tn+fp+fn)*100,2)
```

In [317…

```
print('Confusion Matrix Report '+
     f'\nAccuracy    : {gbc_conf_mat_acc}%'+
     f'\nPrecision   : {gbc_conf_mat_prec}%'+
```

```
    f'\nRecall     : {gbc_conf_mat_recal}%'+
    f'\nF1-Score   : {gbc_conf_mat_f1_score}%'+
    f'\nError-Rate : {gbc_conf_mat_error_rate}%')
```

```
Confusion Matrix Report
Accuracy   : 99.25%
Precision  : 99.77%
Recall     : 99.47%
F1-Score   : 99.62%
Error-Rate : 0.75%
```

In [318…

```
# cost Calculation
gbc_total_cost =fp*10+fn*500
print(f'Total Cost of Repair using this model : {gbc_total_cost} /-')
```

```
Total Cost of Repair using this model : 52440 /-
```

In [319…

```
# updating this result to model details
model_details['Gradient Boost Classifier'] ={'Model_Accuracy':gbc_acc_per,'conf_mat
                                            'Conf_Mat_Accuracy':gbc_conf_mat_acc,'Precis
                                            'Recall':gbc_conf_mat_recal,'F1_Score':gbc_c
                                            'Error_rate':gbc_conf_mat_error_rate,'Total_
```

In [320…

```
print(pd.DataFrame(model_details))
```

```
                        Logistic Regression    Decision Tree Classifier  \
Model_Accuracy                        98.86                        98.9
conf_mat          [[19393, 89], [136, 182]]  [[19377, 105], [113, 205]]
Conf_Mat_Accuracy                     98.86                        98.9
Precision                             99.54                       99.46
Recall                                 99.3                       99.42
F1_Score                              99.42                       99.44
Error_rate                             1.14                         1.1
Total_cost                            68890                       57550

                   Random Forest Classifier        AdaBoost Classifier  \
Model_Accuracy                        99.39                       99.18
conf_mat          [[19460, 22], [99, 219]]  [[19427, 55], [107, 211]]
Conf_Mat_Accuracy                     99.39                       99.18
Precision                             99.89                       99.72
Recall                                99.49                       99.45
F1_Score                              99.69                       99.58
Error_rate                             0.61                        0.82
Total_cost                            49720                       54050

                           SV Classifier         Bagging Classifier  \
Model_Accuracy                      98.4                      99.34
conf_mat          [[19476, 6], [310, 8]]  [[19457, 25], [106, 212]]
Conf_Mat_Accuracy                   98.4                      99.34
Precision                          99.97                      99.87
Recall                             98.43                      99.46
F1_Score                           99.19                      99.66
Error_rate                           1.6                       0.66
Total_cost                        155060                      53250

                   Gradient Boost Classifier
Model_Accuracy                         99.25
conf_mat          [[19438, 44], [104, 214]]
Conf_Mat_Accuracy                      99.25
Precision                              99.77
Recall                                 99.47
F1_Score                               99.62
Error_rate                              0.75
Total_cost                             52440
```

8 Model Training By XG Boost Classifier

In [321…

```
# For this model we need to change the y_train parameter to binary say pos=1 and ne
y_train=y_train.replace({'pos':1,'neg':0})
y_test=y_test.replace({'pos':1,'neg':0})
```

In [322…

```
import xgboost
xgb= xgboost.XGBClassifier()
xgb.fit(x_train,y_train)
xgb_pred_test=xgb.predict(x_test)
xgb_acc=accuracy_score(y_test,xgb_pred_test)
xgb_acc_per=round(xgb_acc*100,2)
print(f'Accuracy of the Model : {xgb_acc_per} %')
```

```
Accuracy of the Model : 99.34 %
```

In [323…

```
# confusion Matrix
xgb_conf_mat=confusion_matrix(y_test,xgb_pred_test)
tp,fp,fn,tn=xgb_conf_mat.ravel()
xgb_conf_mat_acc=round((tp+tn)/(tp+tn+fp+fn)*100,2)
xgb_conf_mat_prec=round(tp/(tp+fp)*100,2)
xgb_conf_mat_recal=round(tp/(tp+fn)*100,2)
xgb_conf_mat_f1_score=round(2*(xgb_conf_mat_prec*xgb_conf_mat_recal)/(xgb_conf_mat_
xgb_conf_mat_error_rate=round((fp+fn)/(tp+tn+fp+fn)*100,2)
print('Confusion Matrix Report '+
     f'\nAccuracy   : {xgb_conf_mat_acc}%'+
     f'\nPrecision  : {xgb_conf_mat_prec}%'+
     f'\nRecall     : {xgb_conf_mat_recal}%'+
     f'\nF1-Score   : {xgb_conf_mat_f1_score}%'+
     f'\nError-Rate : {xgb_conf_mat_error_rate}%')
# cost Calculation
xgb_total_cost =fp*10+fn*500
print(f'Total Cost of Repair using this model : {xgb_total_cost} /-')
```

```
Confusion Matrix Report
Accuracy   : 99.34%
Precision  : 99.78%
Recall     : 99.55%
F1-Score   : 99.66%
Error-Rate : 0.66%
Total Cost of Repair using this model : 44420 /-
```

In [324…

```
# updating this result to model details
model_details['XG Boost Classifier'] ={'Model_Accuracy':xgb_acc_per,'conf_mat':xgb_
                                       'Conf_Mat_Accuracy':xgb_conf_mat_acc,'Precis
                                       'Recall':xgb_conf_mat_recal,'F1_Score':xgb_c
                                       'Error_rate':xgb_conf_mat_error_rate,'Total_
```

In [ ]:

Final Result of All Classifier Model

In [328…

```
final_report=pd.DataFrame(model_details)
report_col =[col for col in final_report.columns]
report_index=[ind for ind in final_report.index]
print('Accuracy of the Model :\n')
for i in range(0,8):
    print(f'{i+1}.{report_col[i]}      = {final_report[report_col[i]][report_index[
```

```
Accuracy of the Model :

1.Logistic Regression      = 98.86 %
2.Decision Tree Classifier      = 98.9 %
3.Random Forest Classifier      = 99.39 %
4.AdaBoost Classifier      = 99.18 %
5.SV Classifier      = 98.4 %
6.Bagging Classifier      = 99.34 %
7.Gradient Boost Classifier      = 99.25 %
8.XG Boost Classifier      = 99.34 %
```

In [332…

```
print('Total Cost of the Model :\n')
for i in range(0,8):
    print(f'{i+1}.{report_col[i]}          = {final_report[report_col[i]][report_in
```

```
Total Cost of the Model :

1.Logistic Regression          = 68890 Rupees
2.Decision Tree Classifier          = 57550 Rupees
3.Random Forest Classifier          = 49720 Rupees
4.AdaBoost Classifier          = 54050 Rupees
5.SV Classifier          = 155060 Rupees
6.Bagging Classifier          = 53250 Rupees
7.Gradient Boost Classifier          = 52440 Rupees
8.XG Boost Classifier          = 44420 Rupees
```

Final Report :

1. After Implementation of all classifier model , analysing accuracy score and confusion matrix and

Calculation of cost of Repair, It is observed that the XGBoost Classifier model will be the best model for our problem.

2. The Accuracy of XG Boost Model is Highest 99.34 % out of all best model.

3. The Cost of repairing is also least for XG Boost Model which is 44,420 /- Rupees only.

In [ ]: