report-1

September 30, 2019

0.1 Here is the summary of what are tried, what worked for me and what not

- My baseline score is `86.23`. I believed it was due to `over-fitting`. And as the features are unknown, so it was difficult to make an interpretation for `feature engineering`. So i followed several approach to do that

1. Handle NULL value, with two ways
   - use tree-based method
   - created an indicator variable to represent `NULL` and fill it with some number in original feature
   - used MICE(didn't help)
2. Target encoding(didn't helped)(due to target leakage, tried to handle it carefully, but failed)
3. Removed highly correlated feature
4. Used `p-test` to remove irrelavant feature(It again can create some problem, as OLS is linear model)
   - I carefully selected `p-value`, one for linear model
   - other for further feature processing
5. SVD/PCA/NMF feature on original and selected dataset.
   - use NMF, we get 2 advantage
     1. it create new feature(as we need absolute value)
     2. feature space tramnformation
6. feature interaction, (i created a list of `20000` complex feature)
   - Select a subset of 300-400 feature, prepare dataset
   - build model to evaluate those feature
     1. If score < baseline: remove them
     2. Else: calculate `oof` prediction
7. created an ensemble
   - catboost/xgboost/logistic-regression/passive-aggressive/ridge

0.2 I faced problem in final submission, so i just su

0.3 Highly suspicious feature

- These columns have very weird distribution and are highly cardinal
- Another also have high correlation
- `['Col190','Col191','Col192','Col204','Col230','Col242','Col252','Col253', 'Col912','Col347','Col384','Col387','Col388','Col389','Col401','Col427', 'Col439','Col449','Col450','Col544','Col579','Col580','Col581','Col582', 'Col583','Col584','Col585','Col586','Col587','Col597','Col603','Col623', 'Col635','Col702','Col711','Col724','Col742','Col791','Col799','Col800', 'Col813','Col831']`

0.4 I don't understand what my model is learning, following columns are garbage(1 cat is majority 99.9%, rest are single tuple)

```
- If we remove these columns `f1-score` for minority class decrease, but weighted average remain
```

```
In [9]: del_cols = ['Col635','Col427','Col242','Col230','Col439','Col623','Col597','Col401','Col
        train.drop(del_cols, axis=1, inplace=True)
        test.drop(del_cols, axis=1, inplace=True)
```

0.5 I tried to bins/groups sone rare occuring label/category for few columns, which have bincount as described below, but that doesn't helped much

```
In [ ]: # 0.000000    13890
        # 1.000000     1302
        # 0.666667      544
        # 0.333333      481
        # 1.333333       85
        # 2.000000       53
        # 1.666667       38
        # 3.000000       11
        # 2.333333        9
        # 3.333333        7
        # 4.666667        2
        # 2.666667        2
        # 5.000000        1
        # 6.333333        1
        # 4.000000        1
```

0.6 My observation on `Logistic-Regression` with `balanced` classes-weights

- choose alpha = [0.1, 1] for better `f1-score` for minority class
- logistic-regression works good on interaction based feature

0.7 observation about `PassiveAggressiveClassifier`

1. with `squared_hinge`:

- with `balanced` class-weight `alpha` of [0.0001, 0.001, 0.01], 2nd is best, it will help in ensembling as recall is high of one class as compared to others
- without `balanced`, use `alpha` = [0.001]

2. with `hinge`:

   - with `balanced`, alpha = [1, 9, 10]
   - without `balanced`, use alpha = [0.001]

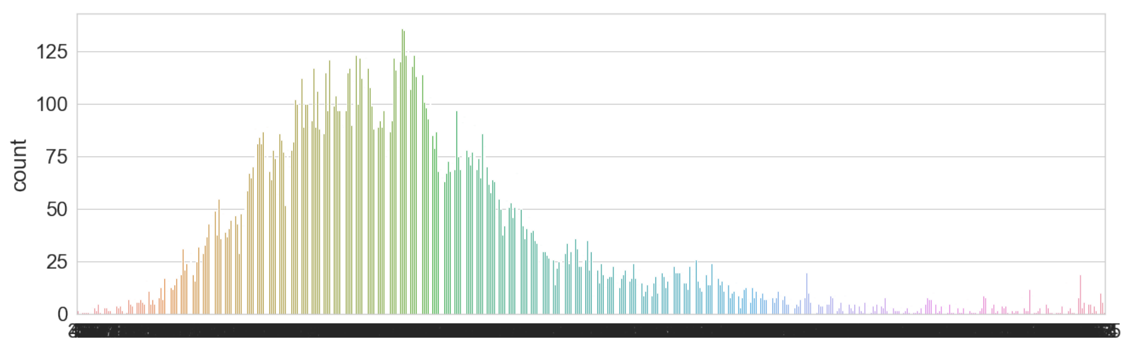
0.8 Weirdness in data(in approximately 1200 rows)

- these rows were effecting model boundary, so i dropped these columns

1 By removing these weird observation, we get following count-plot

```
In [62]: plt.figure(figsize=(20,6))
         sns.countplot(nulls1, orient='h')
```

```
Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff9e8613710>
```



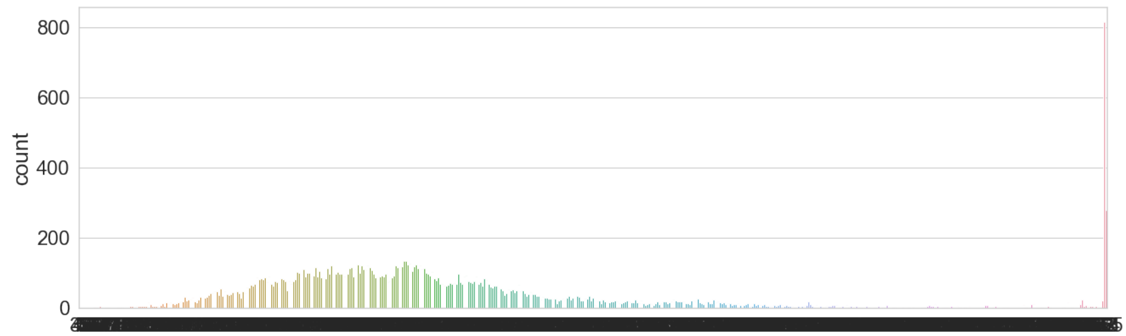

```
In [56]: train1.drop_duplicates().shape, train.shape
```

```
Out[56]: ((16405, 3171), (17521, 2391))
```

2 Countplot with weird observation

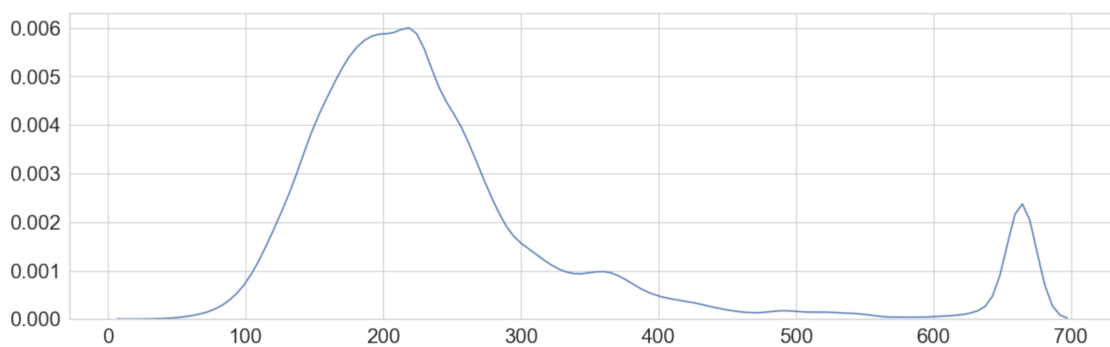
```
In [51]: plt.figure(figsize=(20,6))
         sns.countplot(train.isnull().sum(1), orient='h')
```

```
Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff9dd5e1a20>
```




```
In [52]: plt.figure(figsize=(20,6))
         sns.kdeplot(train.isnull().sum(1))
```

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff9dd0f9438>



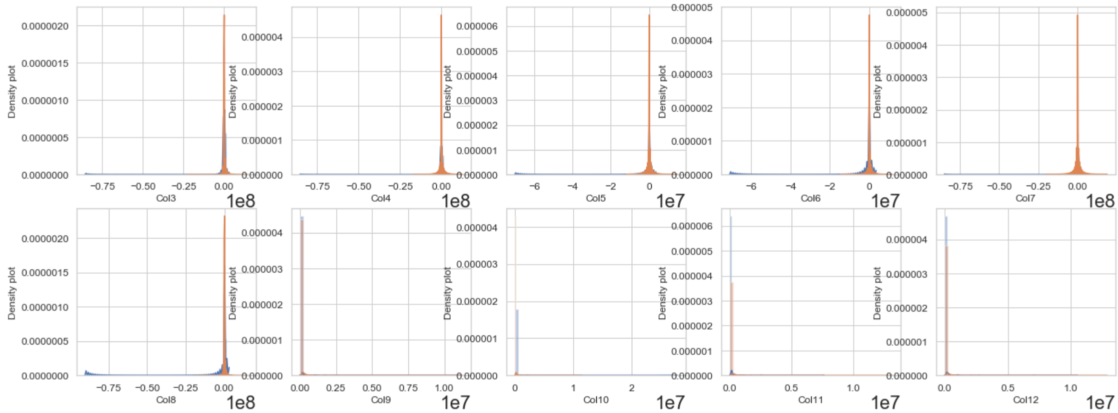
3 distribution visualization of good columns, which influence the decision

- My observation:
  - Most of them have good(normal/skewed) distribution
  - With log transformation, these are very good for linear/non-linear model
  - If we compared these with feature of less importance, these have good statistical properties

```
In [35]: for i in range(10):
             print("Printing from {} to {}".format(i*10, (i+1)*10))
             plot_distribution(good_cols[i*10:(i+1)*10])
```

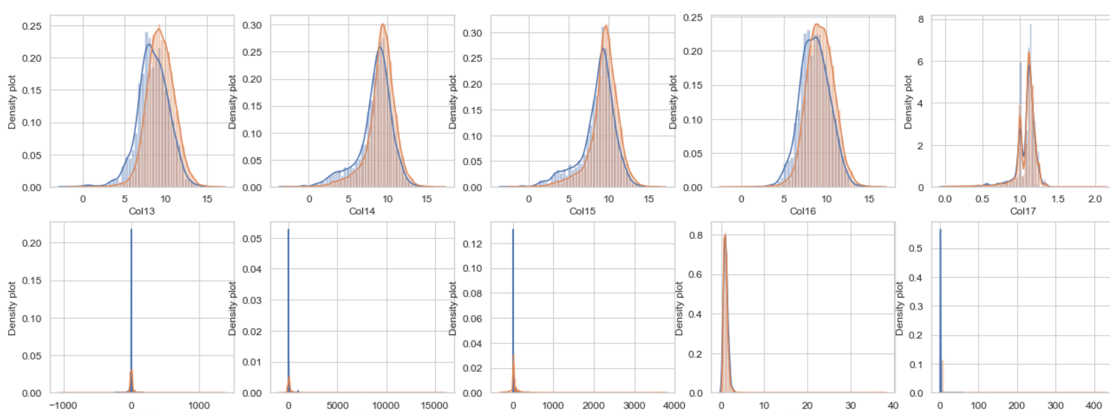
```
Printing from 0 to 10
```

<Figure size 432x288 with 0 Axes>



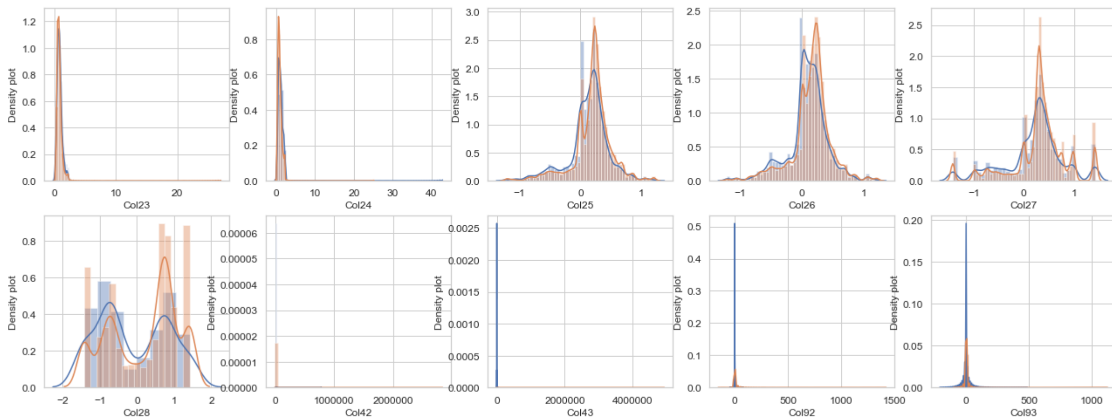
Printing from 10 to 20

<Figure size 432x288 with 0 Axes>



Printing from 20 to 30

<Figure size 432x288 with 0 Axes>



Printing from 30 to 40

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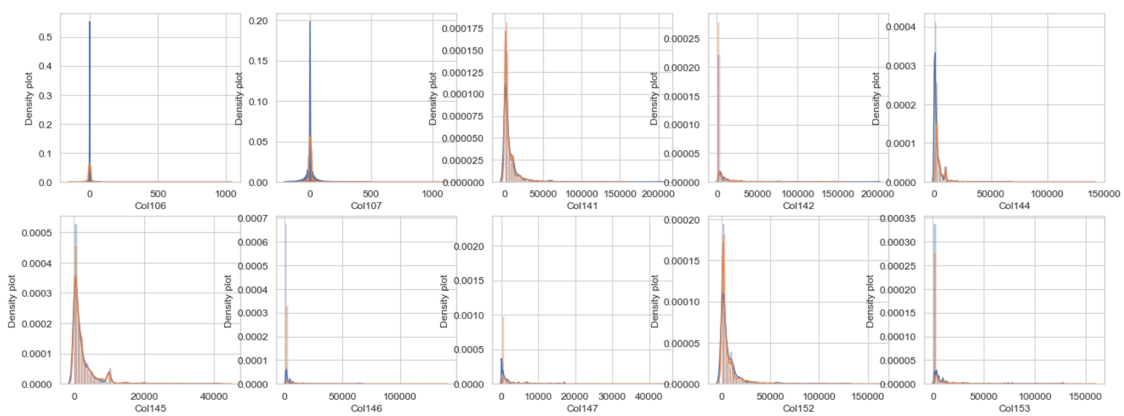
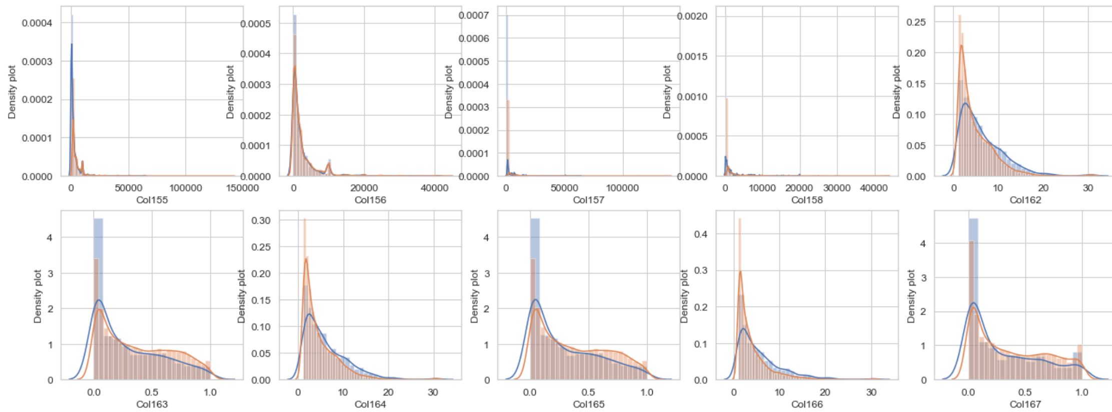


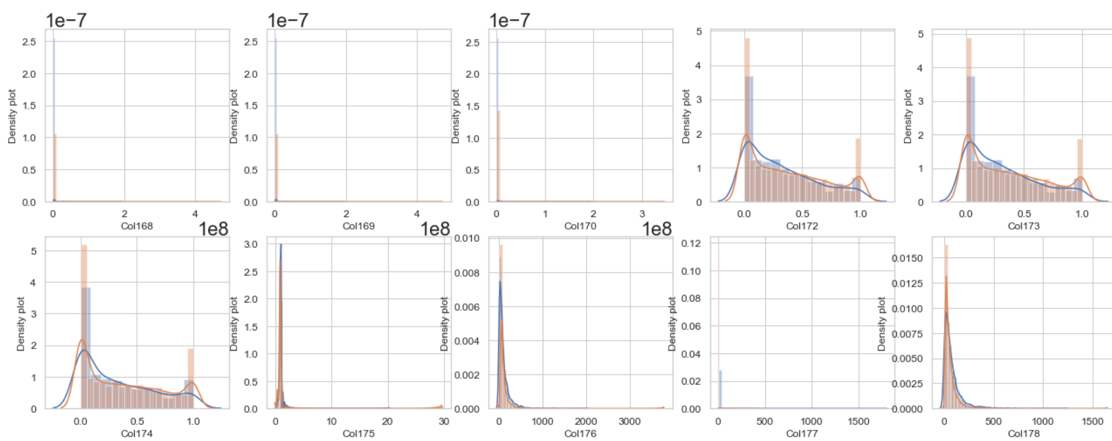
Printing from 40 to 50

<Figure size 432x288 with 0 Axes>



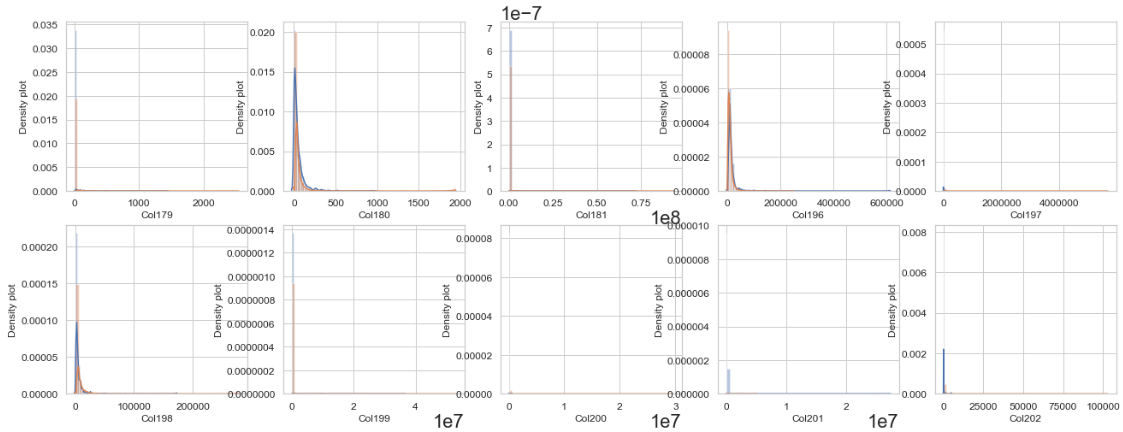
Printing from 50 to 60

<Figure size 432x288 with 0 Axes>



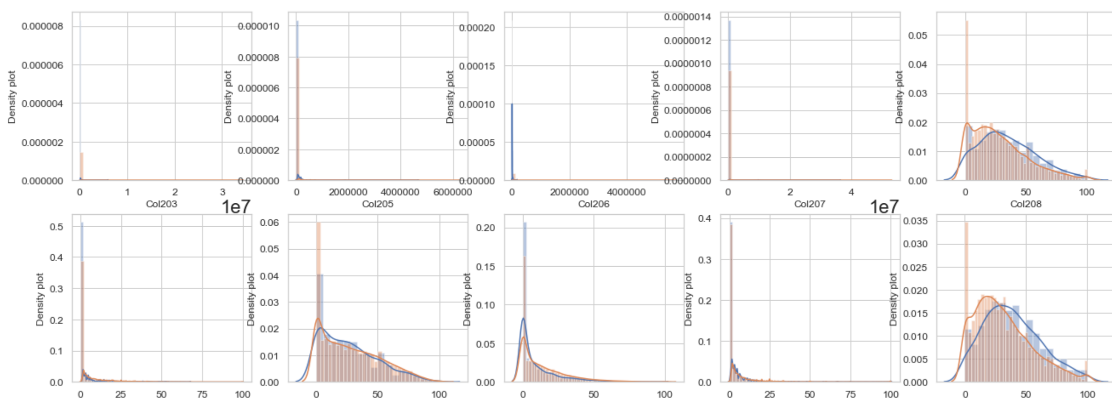
Printing from 60 to 70

<Figure size 432x288 with 0 Axes>



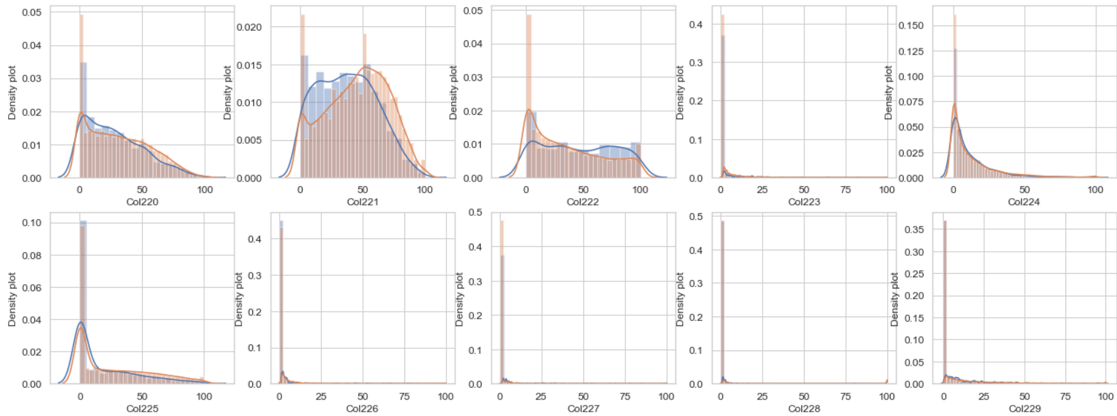
Printing from 70 to 80

<Figure size 432x288 with 0 Axes>



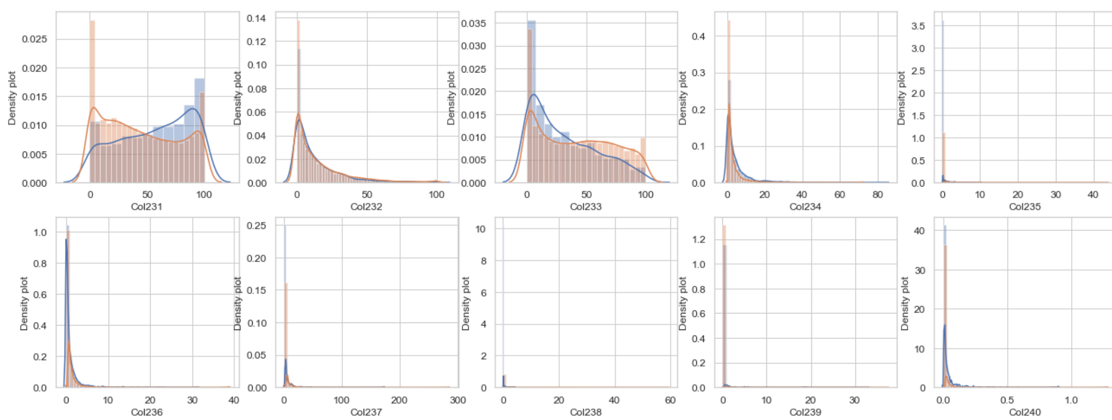
Printing from 80 to 90

<Figure size 432x288 with 0 Axes>




```
Printing from 90 to 100
```

```
<Figure size 432x288 with 0 Axes>
```

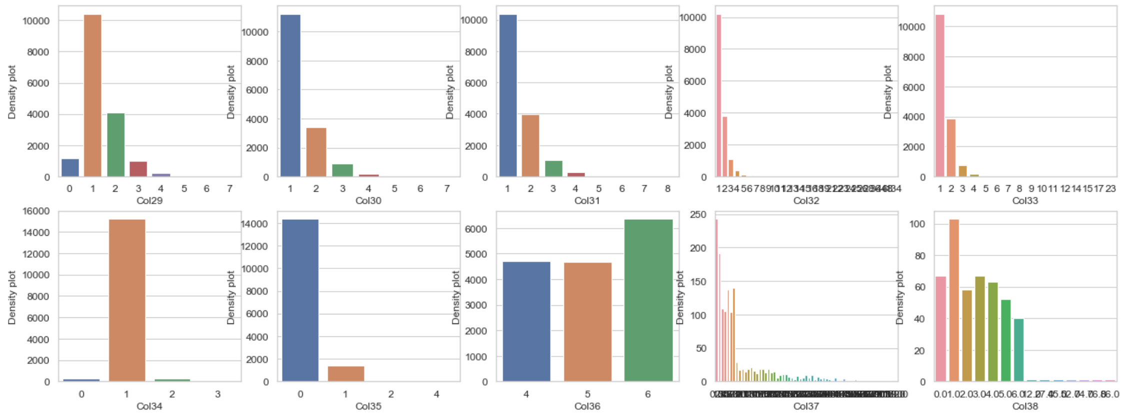


In [62]:

```python
for i in range(10):
    print("Printing from {} to {}".format(i*10, (i+1)*10))
    plot_distribution(cat_cols[i*10:(i+1)*10])
```

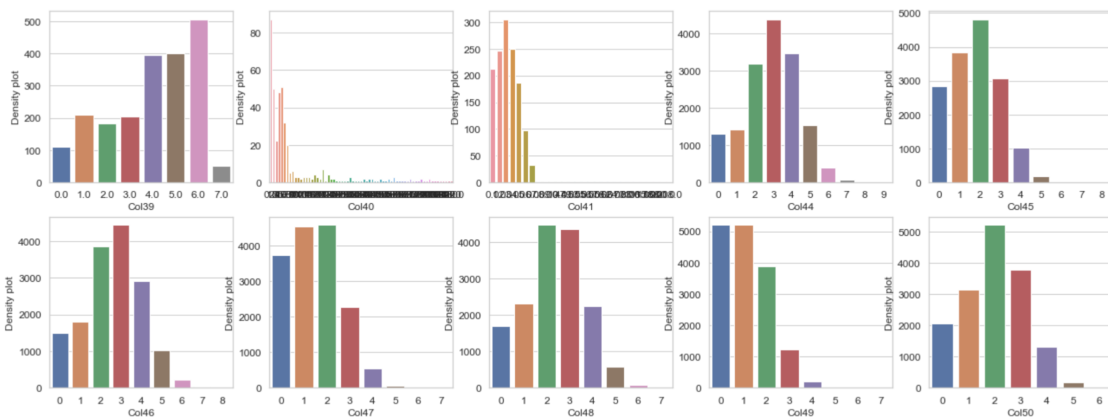
```
Printing from 0 to 10
```

```
<Figure size 432x288 with 0 Axes>
```



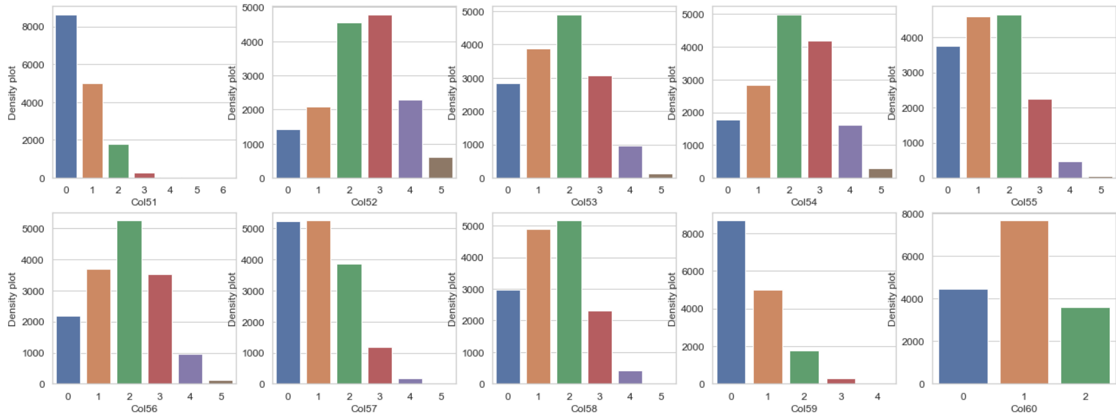

```
Printing from 10 to 20
```

```
<Figure size 432x288 with 0 Axes>
```



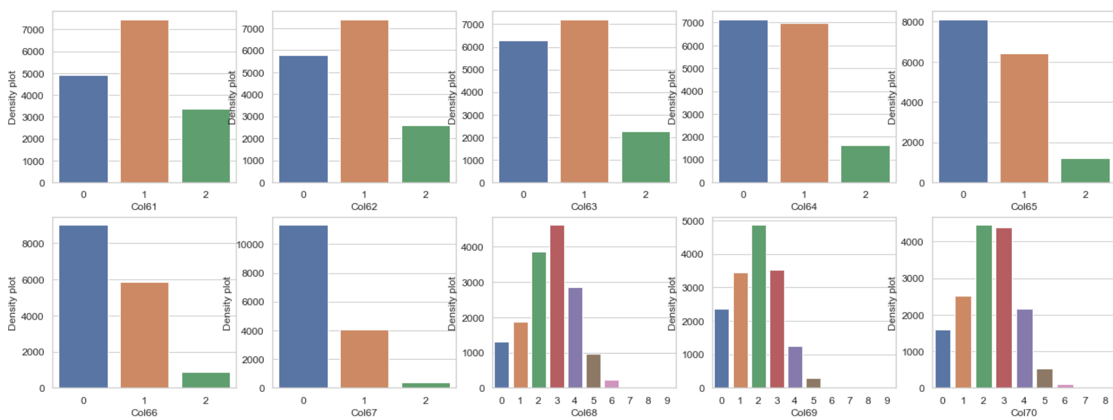

```
Printing from 20 to 30
```

```
<Figure size 432x288 with 0 Axes>
```



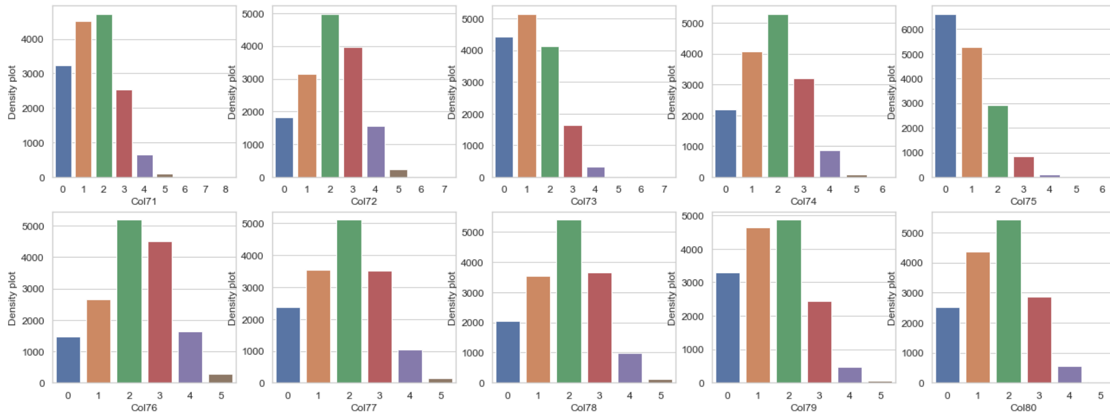
Printing from 30 to 40

<Figure size 432x288 with 0 Axes>



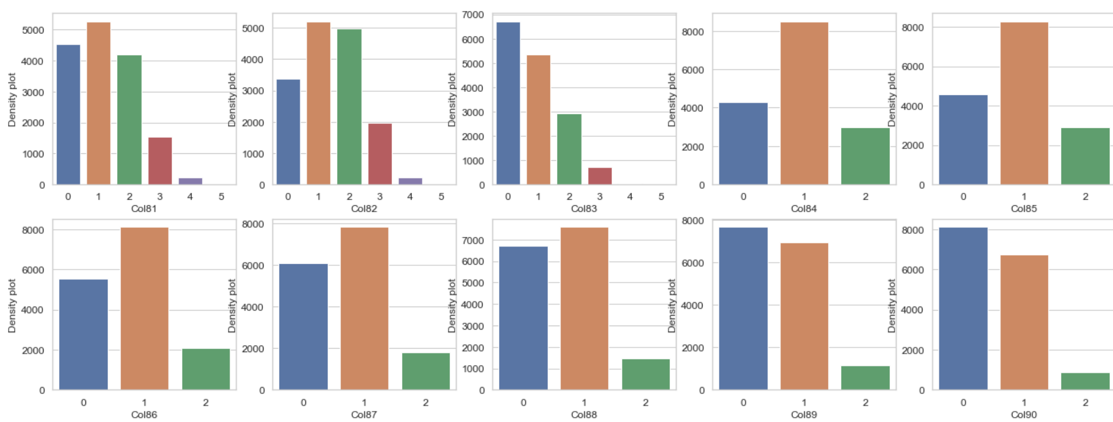
Printing from 40 to 50

<Figure size 432x288 with 0 Axes>



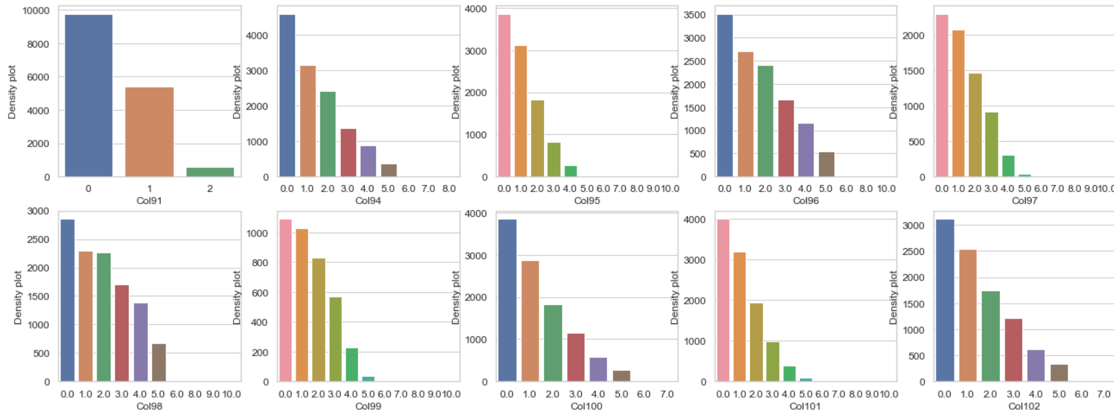
Printing from 50 to 60

<Figure size 432x288 with 0 Axes>



Printing from 60 to 70

<Figure size 432x288 with 0 Axes>



Printing from 70 to 80

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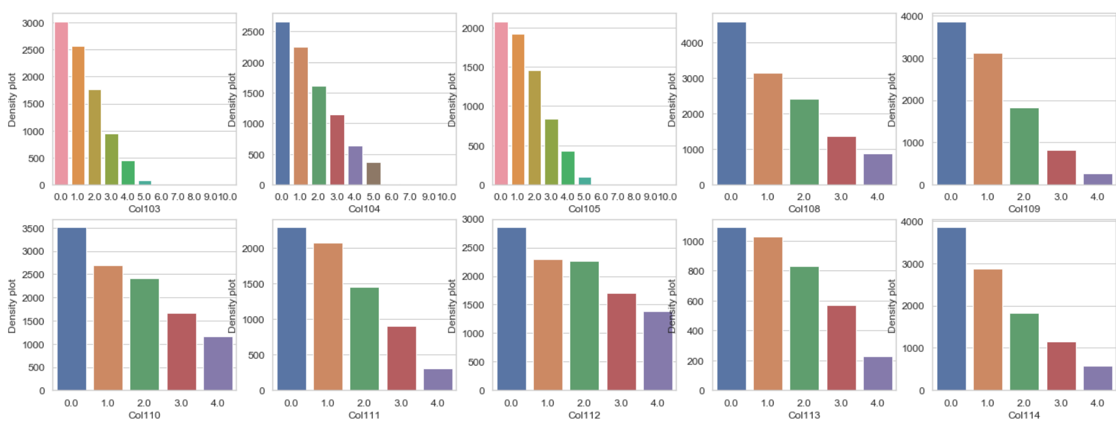
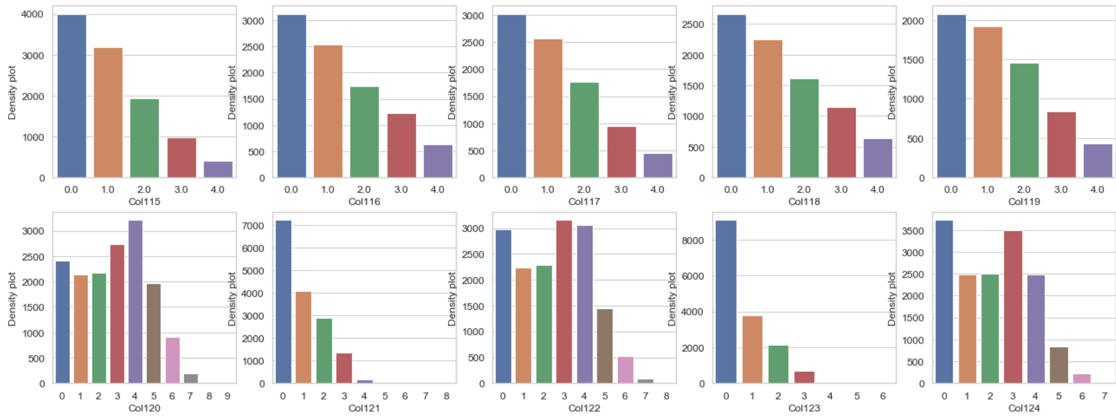


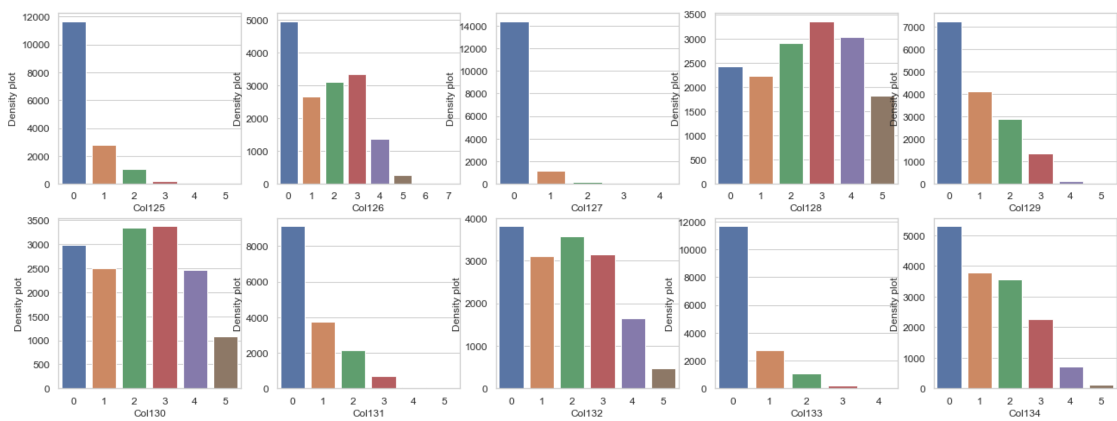
Printing from 80 to 90

<Figure size 432x288 with 0 Axes>




```
Printing from 90 to 100
```

```
<Figure size 432x288 with 0 Axes>
```



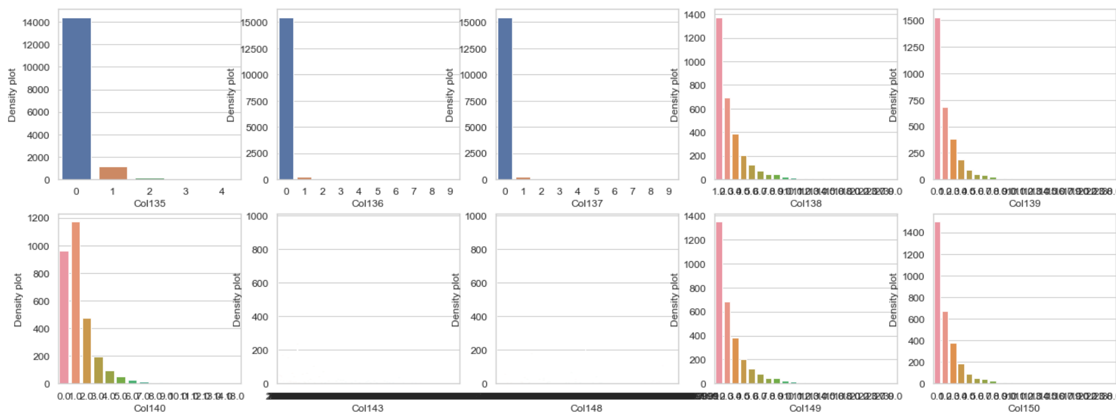
3.1 Some of those have null importance to tree-based and deep learning models

- My observation:
  - these feature looks funnier
  - their high cardinality has reduce the importance.
  - a few of them such as `[col143, col148, col186-195,...]` has majority class amount as >95%.
  - **one intersting point** that a few of them have only values/label for class `1` and null for class `0`. I removed them

```
In [67]: for i in range(10,20):
             print("Printing from {} to {}".format(i*10, (i+1)*10))
             plot_distribution(worst_cols[i*10:(i+1)*10])
```

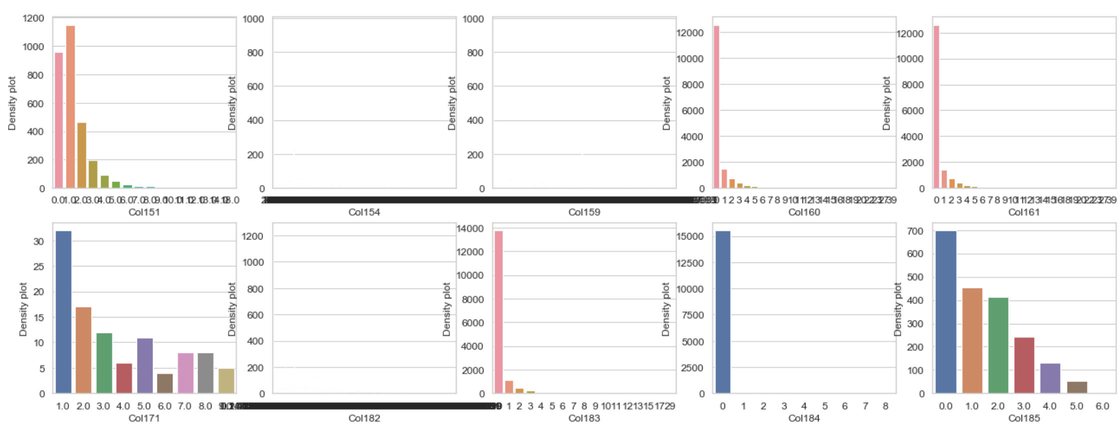
```
Printing from 100 to 110

<Figure size 432x288 with 0 Axes>
```



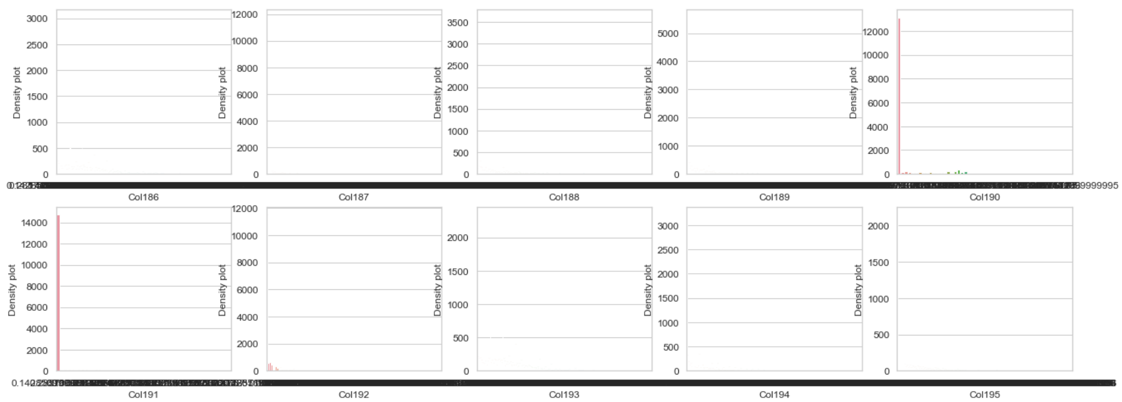

```
Printing from 110 to 120

<Figure size 432x288 with 0 Axes>
```



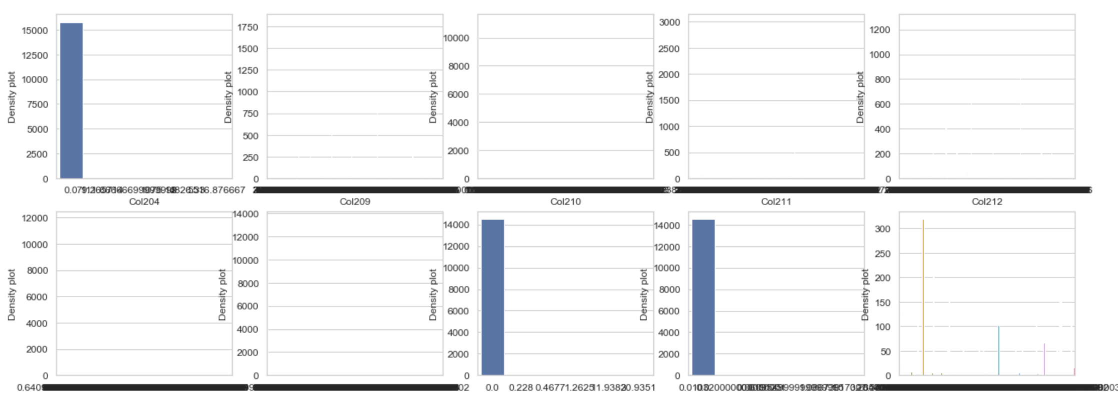

```
Printing from 120 to 130
```

<Figure size 432x288 with 0 Axes>



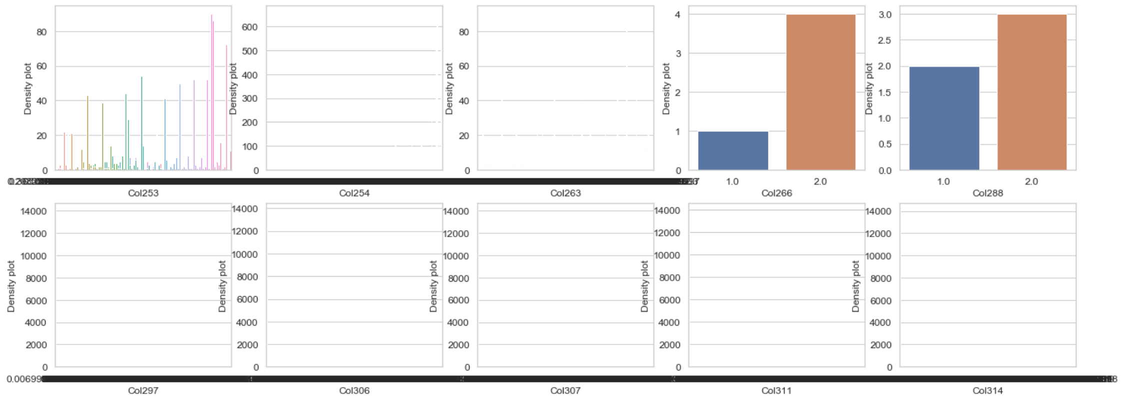
Printing from 130 to 140

<Figure size 432x288 with 0 Axes>



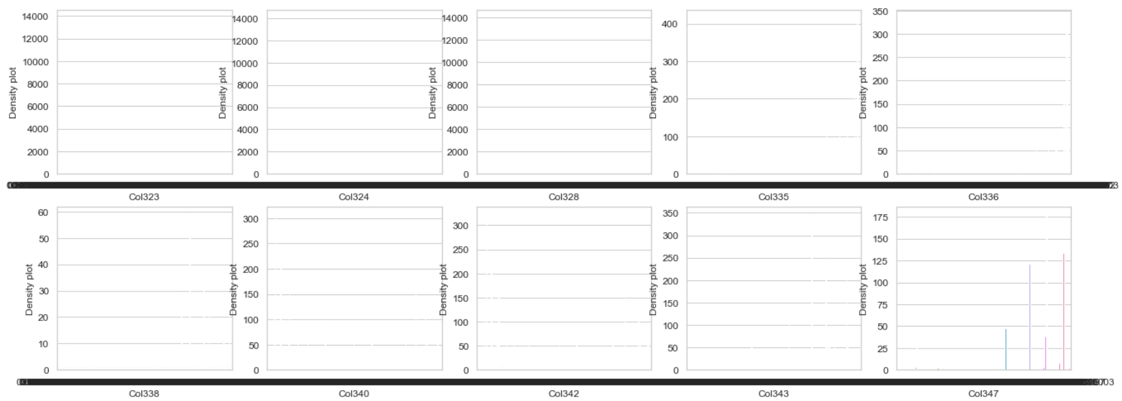
Printing from 140 to 150

<Figure size 432x288 with 0 Axes>



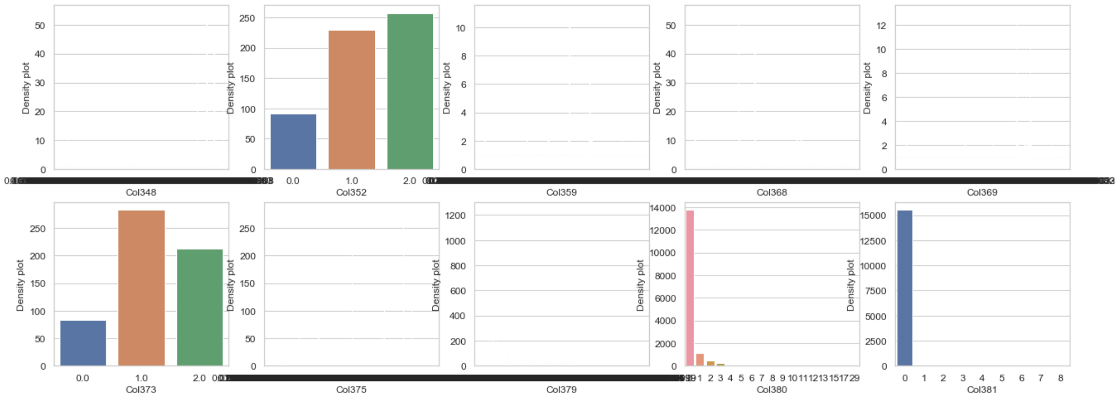
Printing from 150 to 160

<Figure size 432x288 with 0 Axes>



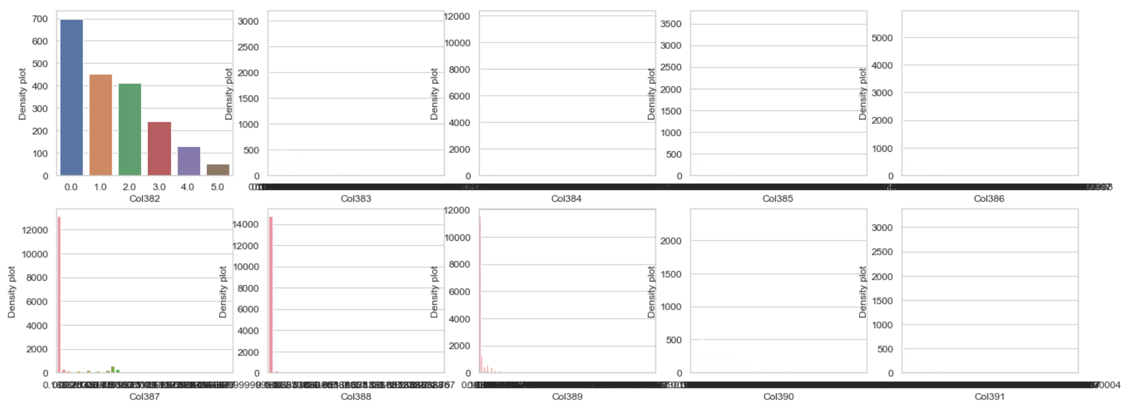
Printing from 160 to 170

<Figure size 432x288 with 0 Axes>



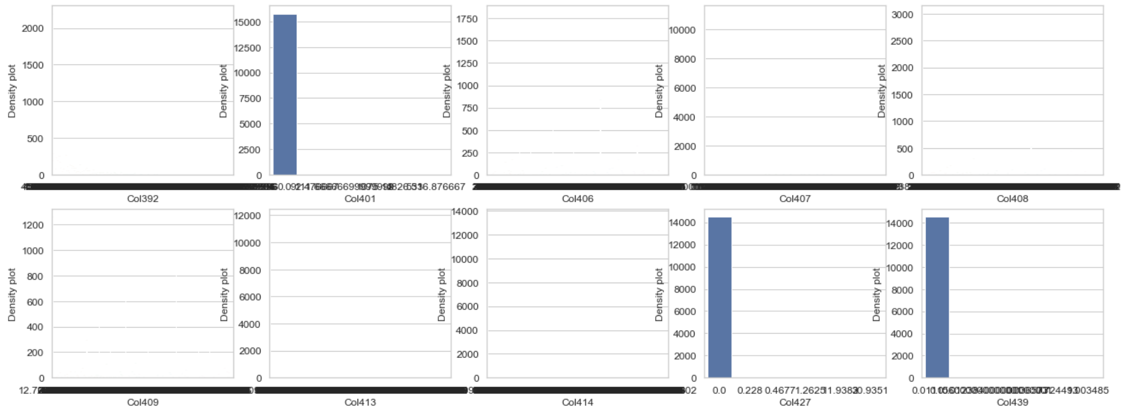
Printing from 170 to 180

<Figure size 432x288 with 0 Axes>



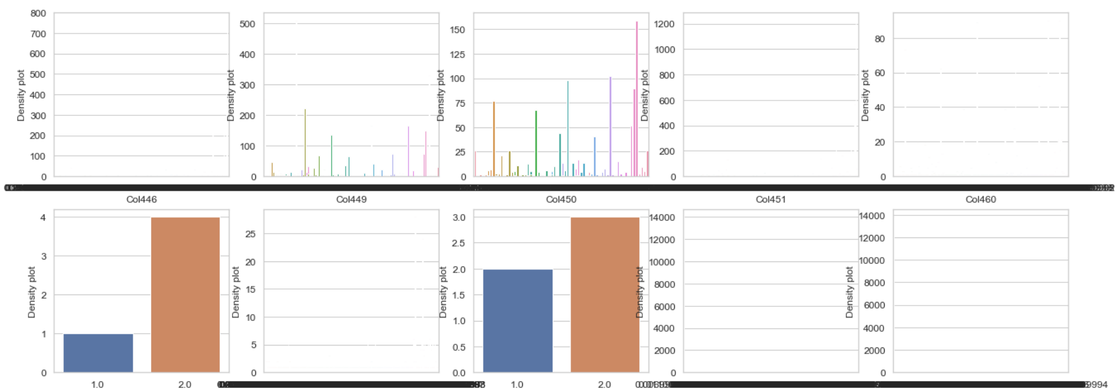
Printing from 180 to 190

<Figure size 432x288 with 0 Axes>




```
Printing from 190 to 200
```

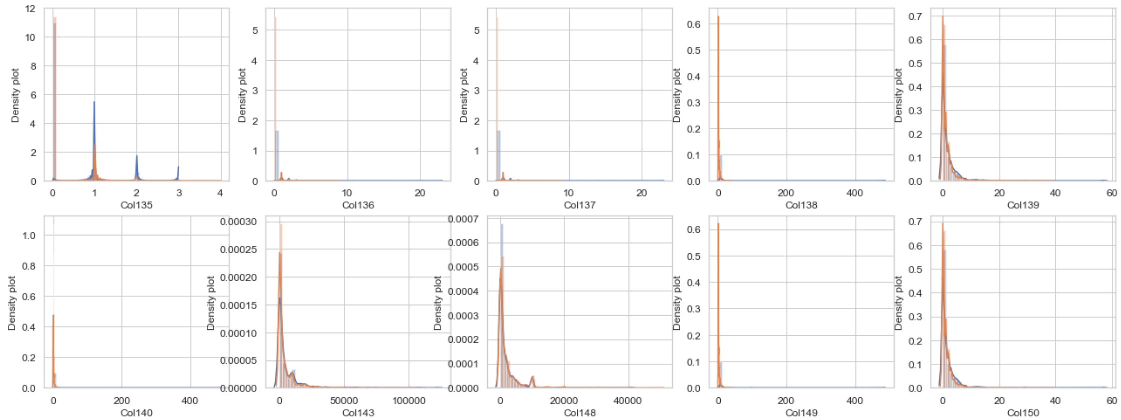
```
<Figure size 432x288 with 0 Axes>
```




```
In [70]: for i in range(10,20):
             print("Printing from {} to {}".format(i*10, (i+1)*10))
             plot_distribution(cat_cols[i*10:(i+1)*10])
```

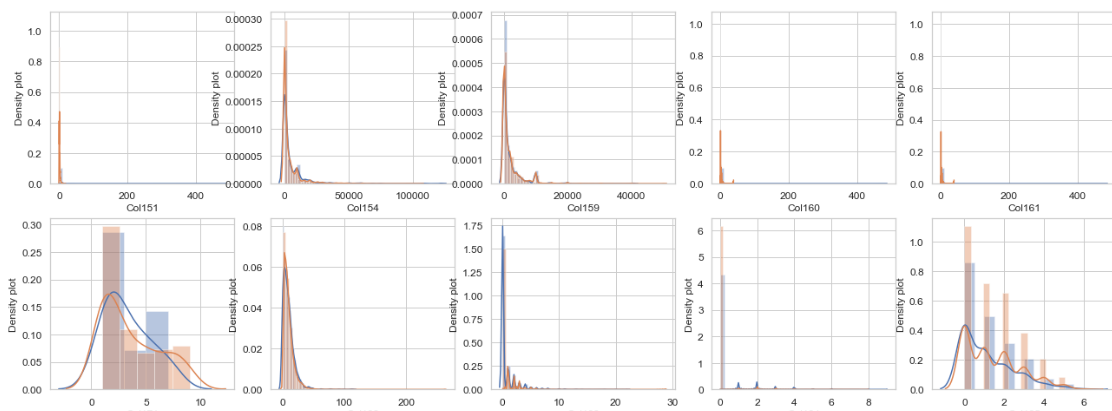
```
Printing from 100 to 110
```

```
<Figure size 432x288 with 0 Axes>
```



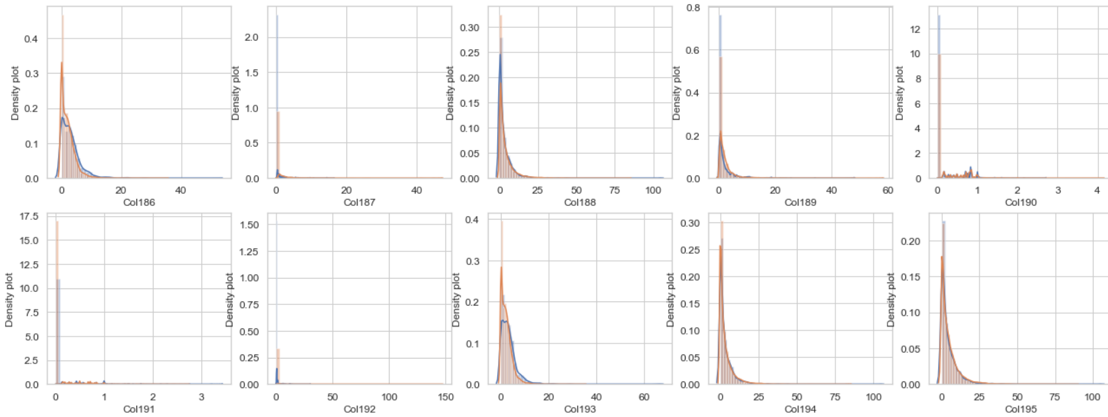

```
Printing from 110 to 120
```

```
<Figure size 432x288 with 0 Axes>
```



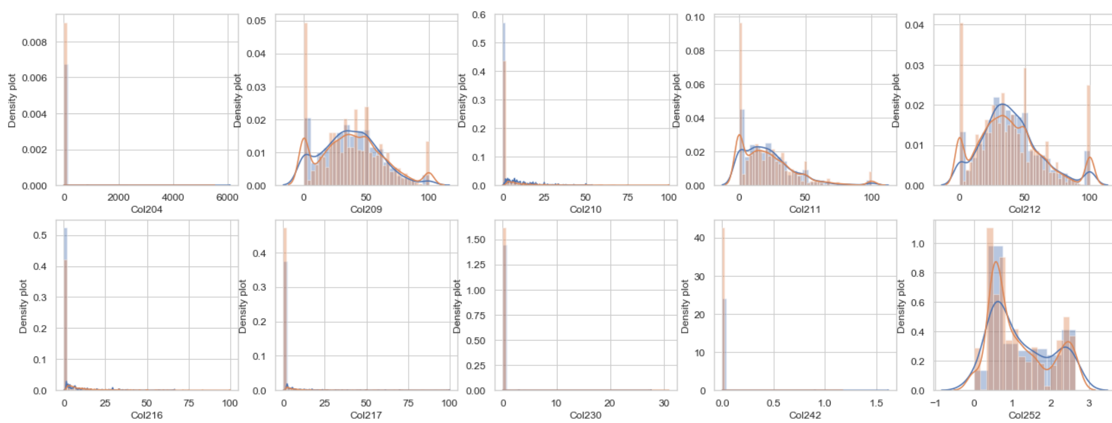

```
Printing from 120 to 130
```

```
<Figure size 432x288 with 0 Axes>
```



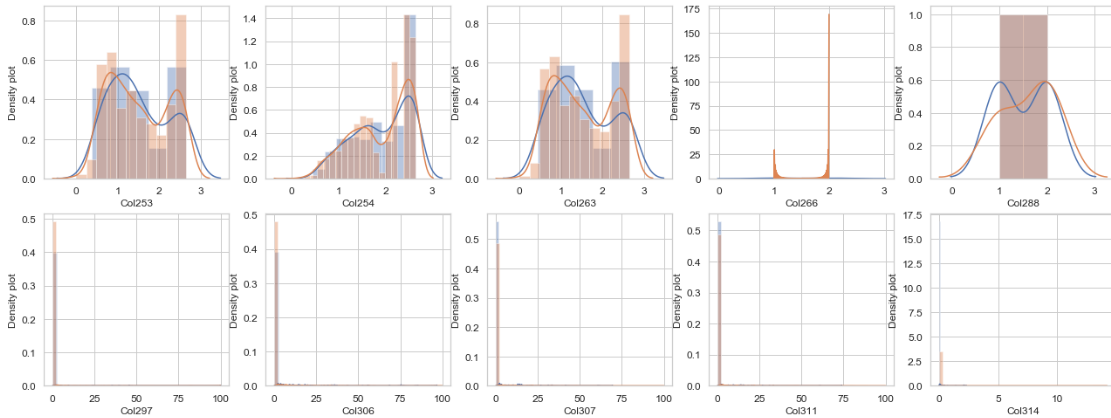
Printing from 130 to 140

<Figure size 432x288 with 0 Axes>



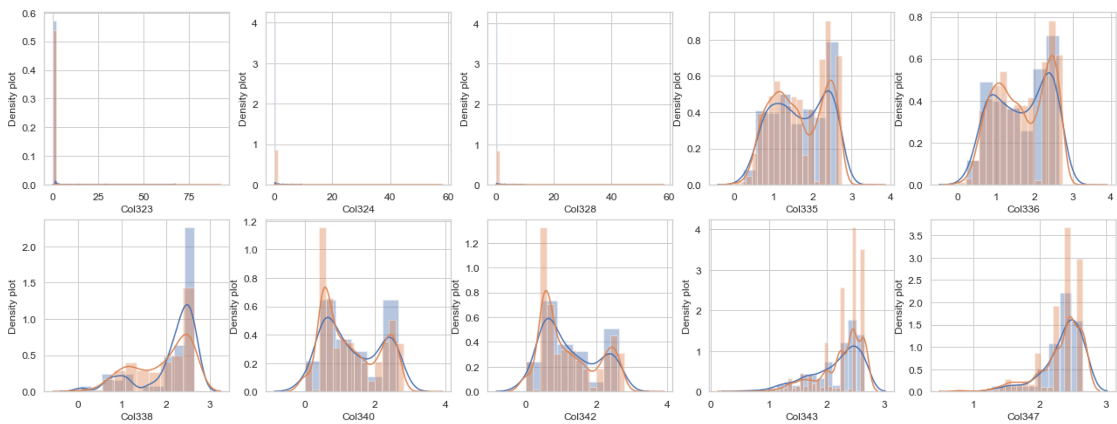
Printing from 140 to 150

<Figure size 432x288 with 0 Axes>




```
Printing from 150 to 160
```

```
<Figure size 432x288 with 0 Axes>
```




```
Printing from 160 to 170
```

```
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```

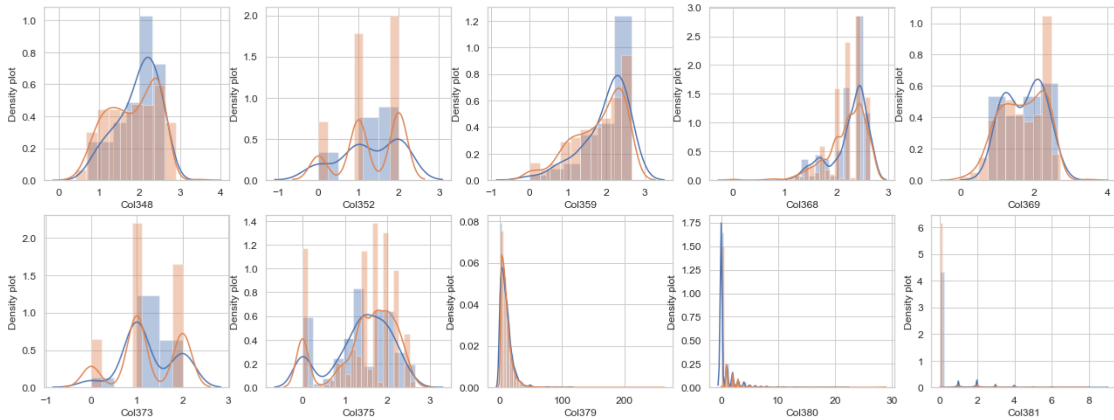


```
Printing from 170 to 180
```

```
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```
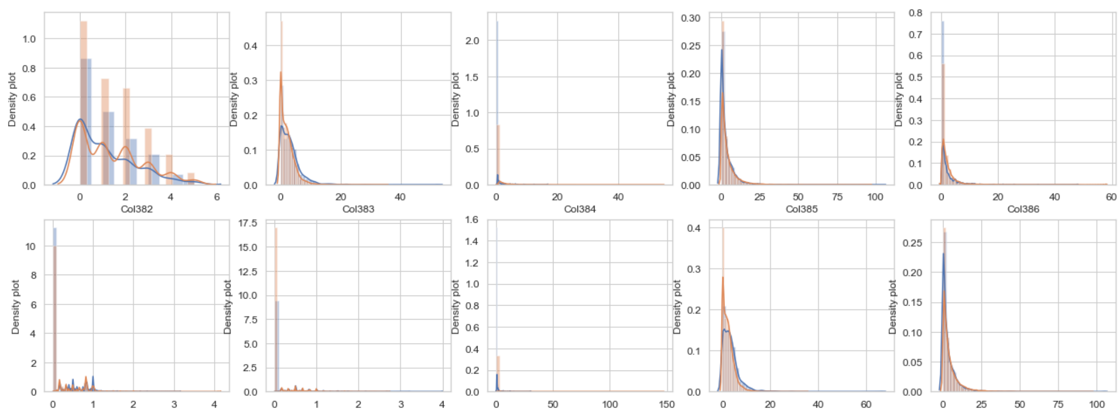
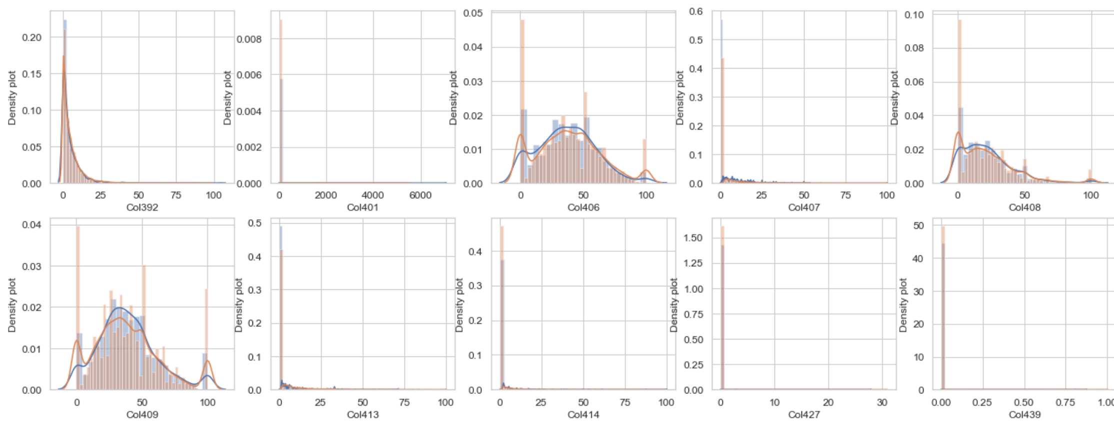



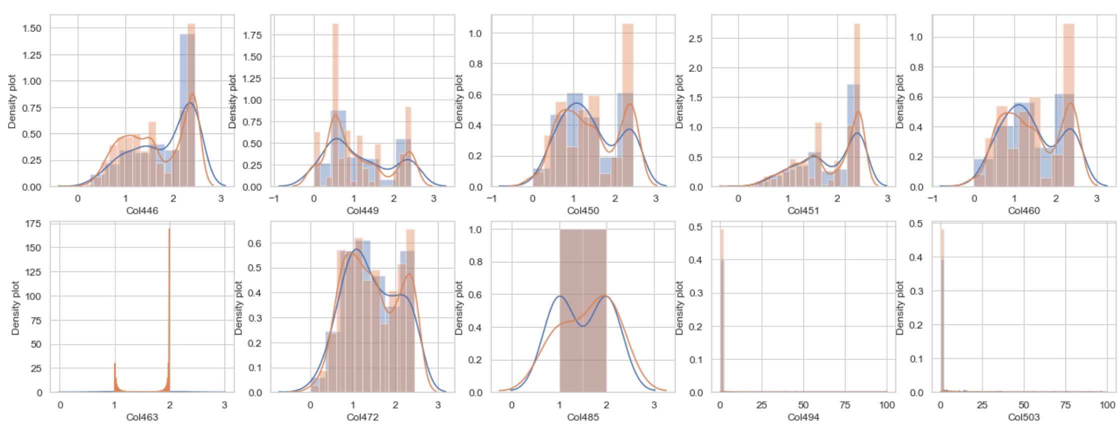

```
Printing from 180 to 190
```

```
<Figure size 432x288 with 0 Axes>
```




```
Printing from 190 to 200
```

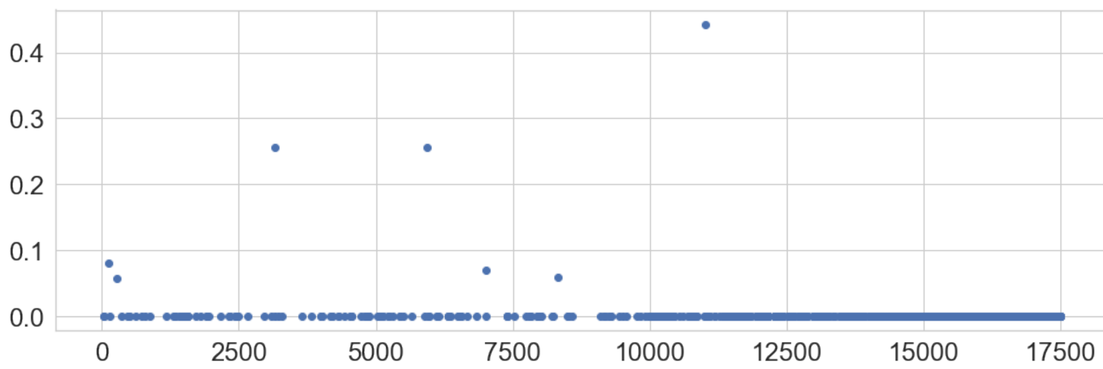
```
<Figure size 432x288 with 0 Axes>
```

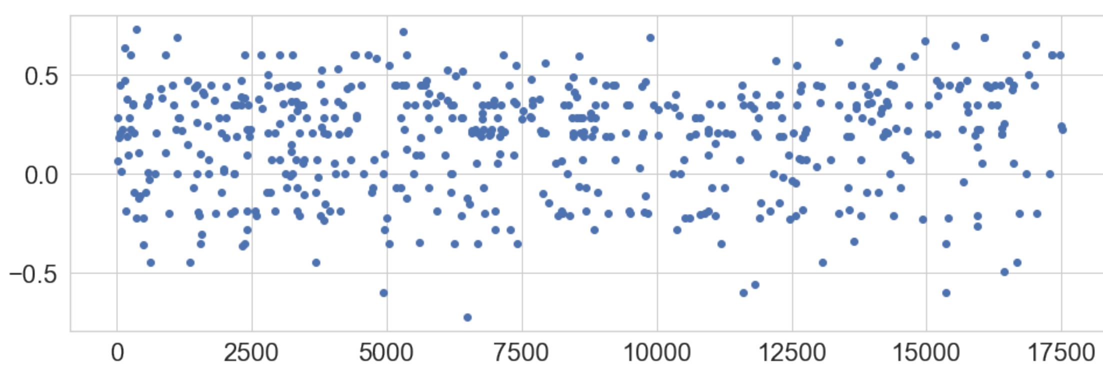


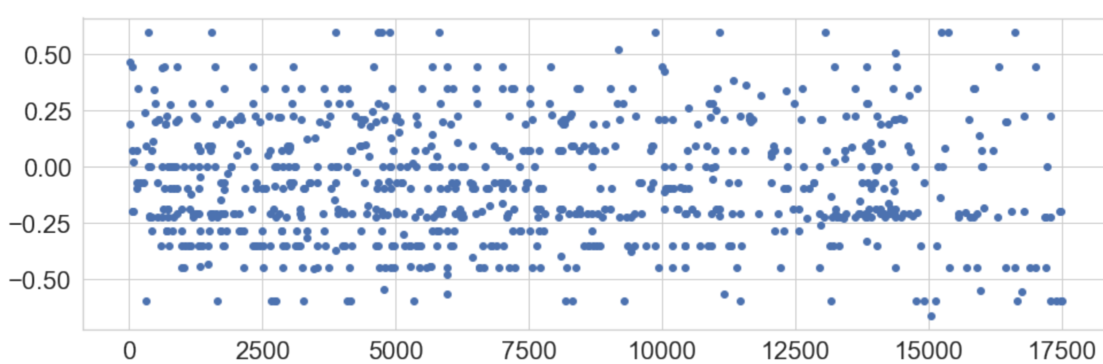
3.2 There is very high correlation among some feature

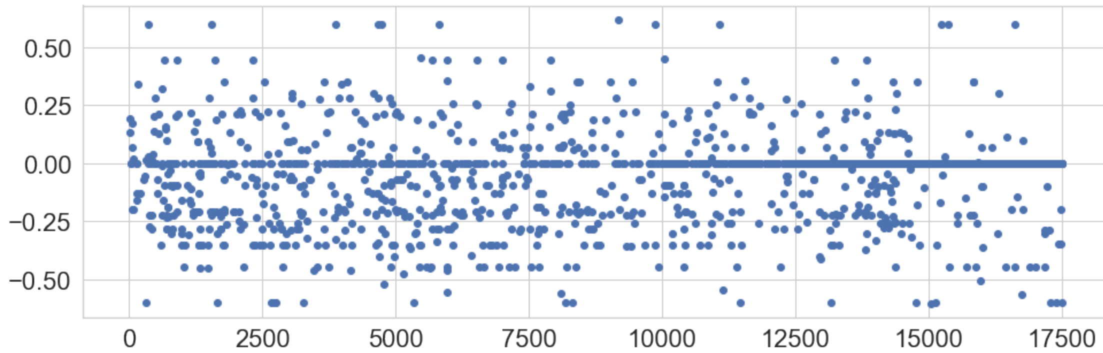
- Following is some of interesting columns, which some-time helps in decision making **with very high impotance** and other time, it has **null importance**.
- i tried to analyze them differently

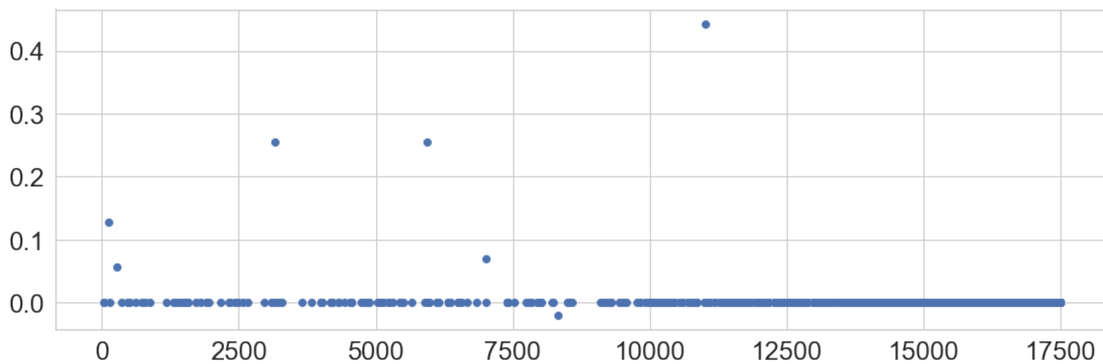
In [109]:


0.4
0.3
0.2
0.1
0.0
0
2500
5000
7500
10000
12500
15000
17500


0.5
0.0
−0.5
0
2500
5000
7500
10000
12500
15000
17500


0.50
0.25
0.00
−0.25
−0.50
0
2500
5000
7500
10000
12500
15000
17500


0.50
0.25
0.00
−0.25
−0.50
0
2500
5000
7500
10000
12500
15000
17500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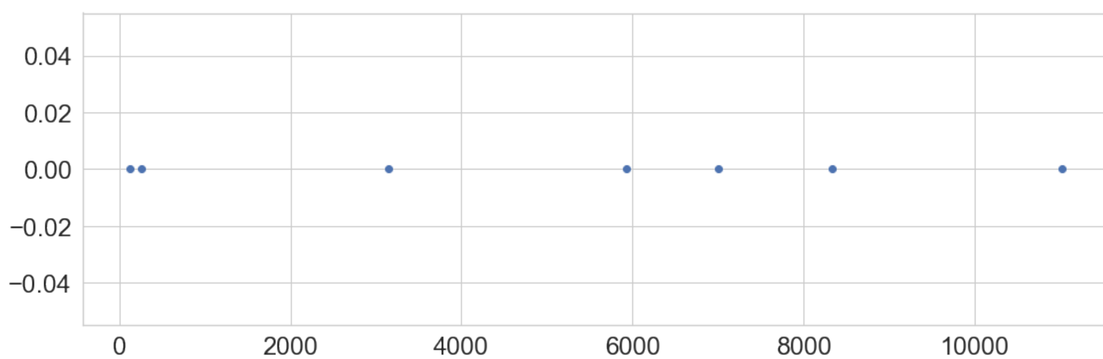
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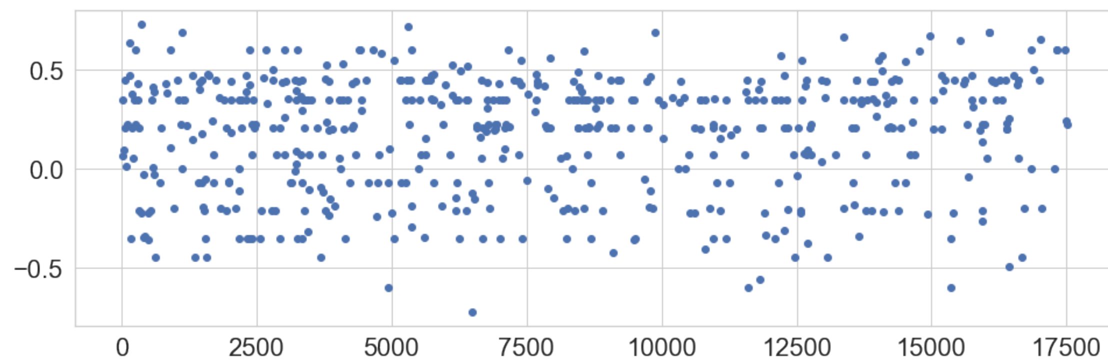
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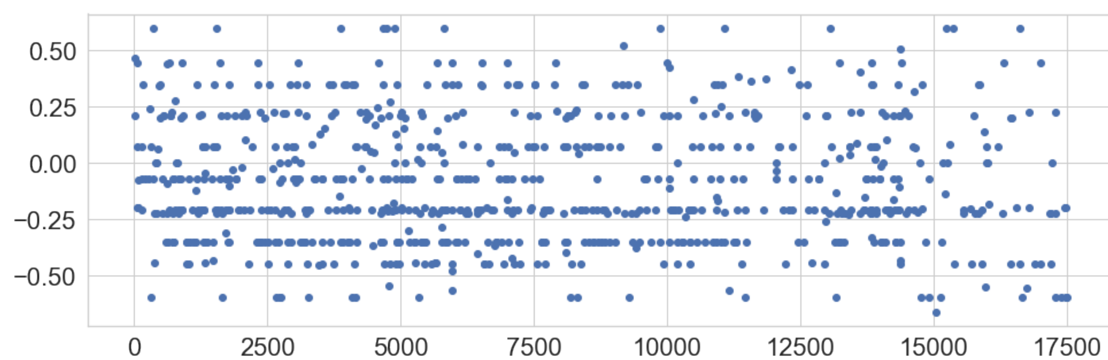
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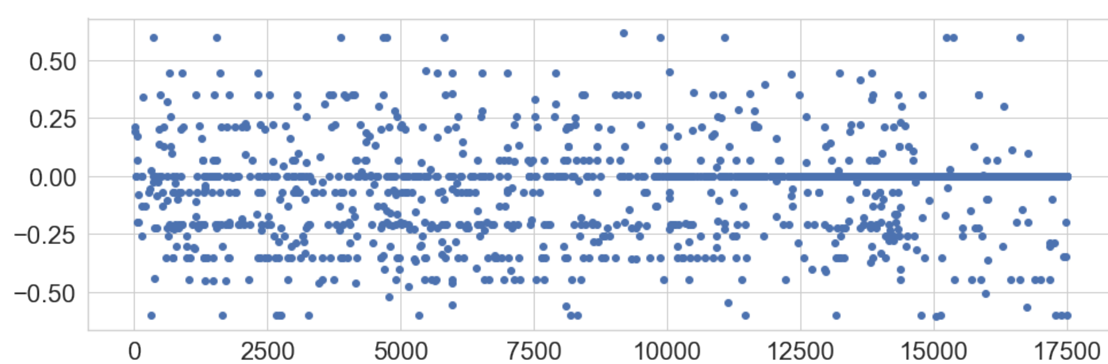
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