CS 5304: Assignment 2

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1. Partitioning the Data

Use `random.sample` to randomly sample 2 millions row ids out of 48 millions row.

Then, partition them into three parts: train(1M), validation(250K), test(750K).

In [3]:
```
selected_indice = random.sample(range(0, int(48e6)), int(2e6))

train_ids = set(selected_indice[0:int(1e6)])
validation_ids = set(selected_indice[int(1e6):int(1e6+250e3)])
test_ids = set(selected_indice[int(1e6+250e3):])
```

The following codes are used to write `train_ids, validation_ids, test_ids` into separated text files.

In [133]:
```
train_ids_file = open('train_ids.txt','w')
validation_ids_file = open('validation_ids.txt','w')
test_ids_file = open('test_ids.txt','w')

train_ids_str = [str(i) for i in train_ids]
validation_ids_str = [str(i) for i in validation_ids]
test_ids_str = [str(i) for i in test_ids]

train_ids_file.write('\n'.join(train_ids_str))
validation_ids_file.write('\n'.join(validation_ids_str))
test_ids_file.write('\n'.join(test_ids_str))

test_ids_file.close()
validation_ids_file.close()
train_ids_file.close()
```

2. Summary Statistics

The following section is used to compute histograms and display them.

Basically, I wrote two functions to compute hisograms for numerical and cetrgorical features respectively.

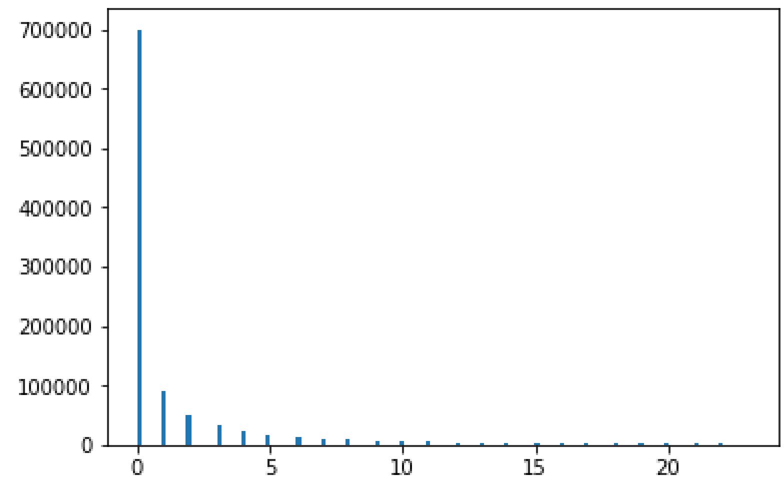
For numerical features, firstly, I drop those data points which are more than 3 times `standard variance` distance away from the `mean value`(since this kind of points are rare and likely to be outliers and would distort the histograms greatly) and use the rest data points to draw the histogram. Secondly, I use `numpy.histogram` to compute the **density** and **weights** of the histogram given certain number of bins. Then one can manually set the width of the bins of the histogram as well as the center of each bin. Finally, use `matplotlib.pyplot.bar` to draw the histogram. PS, I also calculate and display some summary statistics for the numerical features.

For categorical features, firstly, use `collections.Counter` to calculate the frequency of each categorical value of that feature. Because some features may have a very large number of unique categorical values, here I only pick the most frequent 100 categorical values to display in the histogram. After getting the frequency of each categorical value and pick the most frequent 100, we can still use `matplotlib.pyplot.bar` to draw the histogram.

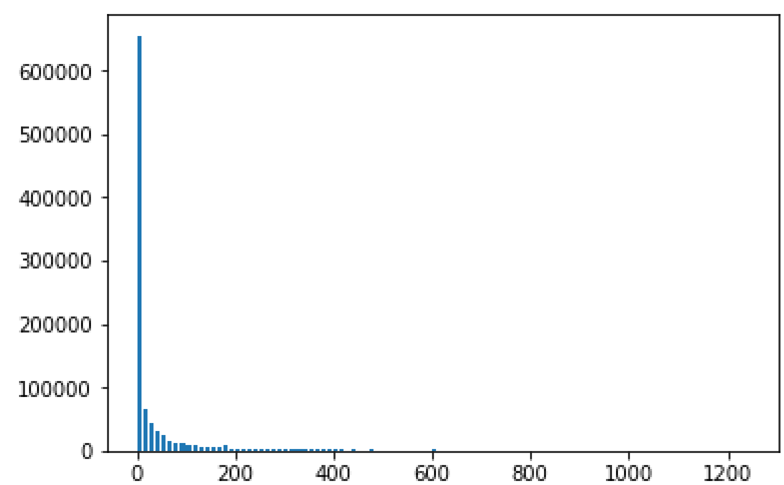
The histograms of the 39 features are shown as follow.

In [8]:
```
def showHistgram_numerical(data):
    mean = np.mean(data)
    std = np.std(data)
    filtered = list(filter(lambda x: abs(x-mean) <= 3*std, data))
    hist, bins = np.histogram(filtered, bins=100)
    width = 0.7 * (bins[1] - bins[0])
    center = (bins[:-1] + bins[1:]) / 2
    plt.bar(center, hist, align='center', width=width)
    plt.show()

def showHistgram_categorical(data):
    counter = Counter(data)
    names = [str(entry[0]) for entry in counter.most_common(100)]
    values = [entry[1] for entry in counter.most_common(100)]
    plt.bar(names,values)
    plt.show()

def calStatsData(data):
    return np.mean(data),np.std(data),skew(data),kurtosis(data)

for i in range(0,39):
    print("Feature ", i)
    if i<13:
        print("mean, standard deviation, skew, kurtosis:\n",calStatsData
(train_data[:,i]))
        showHistgram_numerical(train_data[:,i])
    else:
        showHistgram_categorical(train_data[:,i])
```

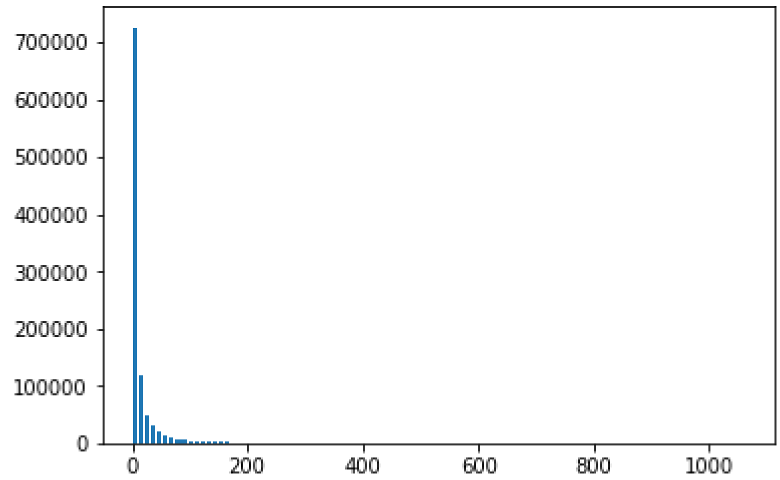
```
Feature  0
mean, standard deviation, skew, kurtosis:
 (1.8376969999999999, 7.1471233889020702, 32.84501831334796, 5536.90451
7188818)
```



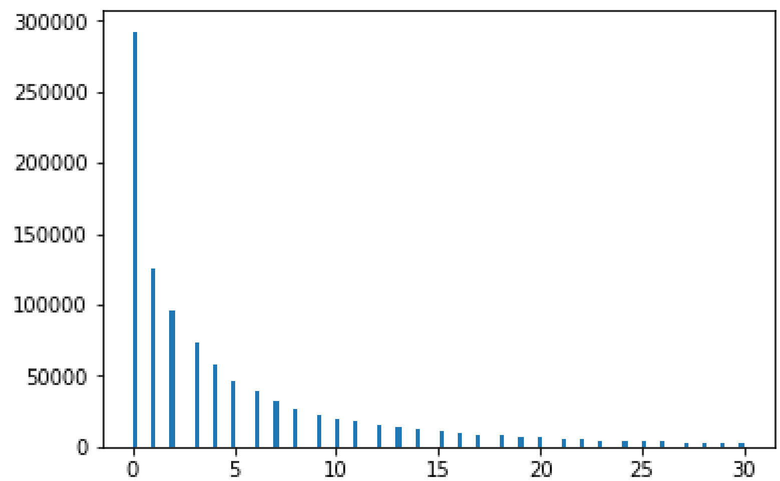
```
Feature  1
mean, standard deviation, skew, kurtosis:
 (101.127129, 380.35779217365513, 7.094944987899882, 73.99907727619193)
```



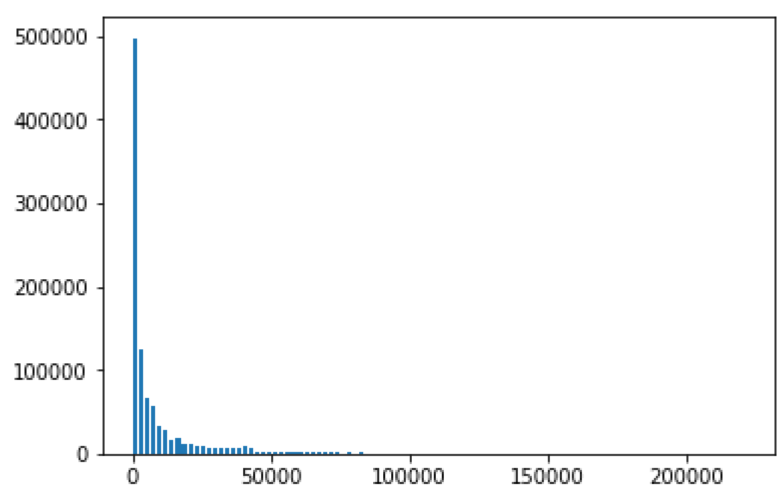
```
Feature  2
mean, standard deviation, skew, kurtosis:
 (20.443393, 347.4359542040051, 86.10120995869441, 9281.740471831203)
```



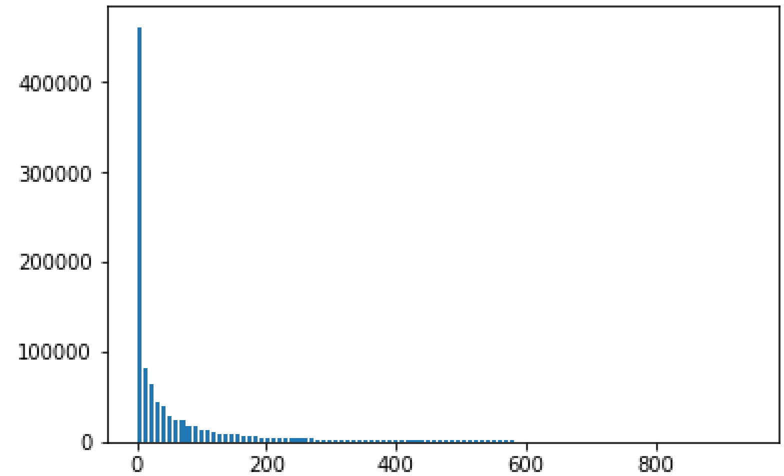

```
Feature  3
mean, standard deviation, skew, kurtosis:
 (5.4639049999999996, 8.1854045196908274, 3.7287961772607603, 63.124912
37363963)
```



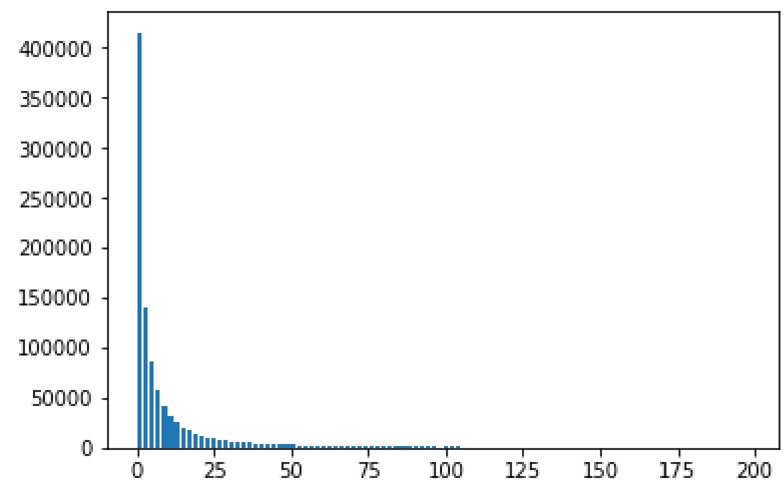

```
Feature  4
mean, standard deviation, skew, kurtosis:
 (17315.993042999999, 67974.722457699667, 9.947274606288218, 144.505734
565931)
```



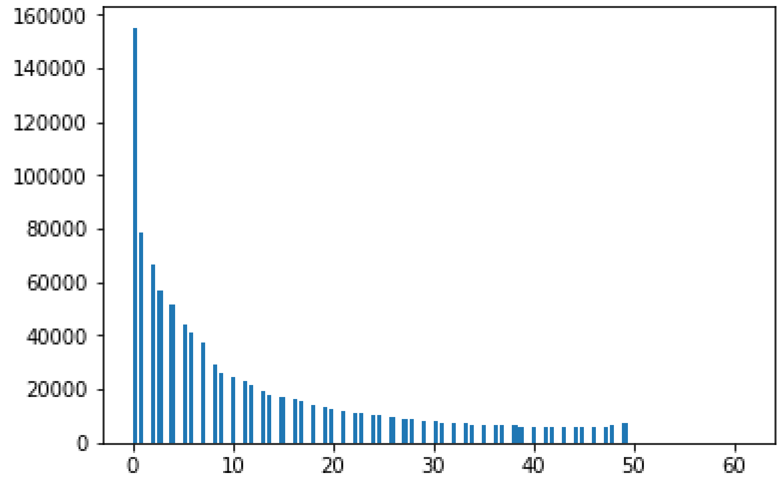
```
Feature  5
mean, standard deviation, skew, kurtosis:
 (85.72842, 285.55662329965946, 27.59700766571596, 2704.2249233261714)
```



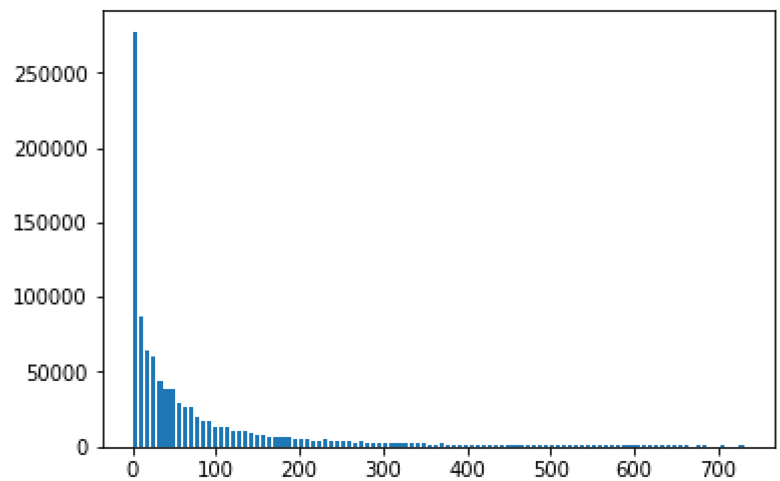

```
Feature  6
mean, standard deviation, skew, kurtosis:
 (14.940308, 61.345383435635469, 24.428309222283417, 1292.56943093399)
```



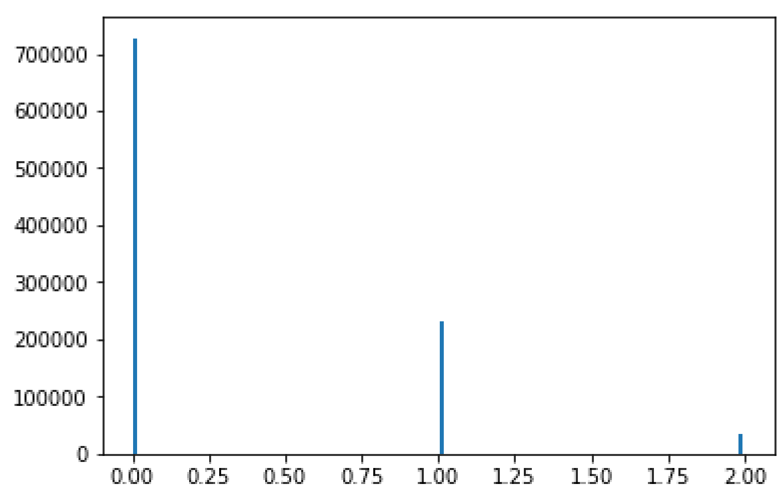

```
Feature  7
mean, standard deviation, skew, kurtosis:
 (11.938719000000001, 16.6550523757519, 72.85228710381033, 17537.658313
476113)
```



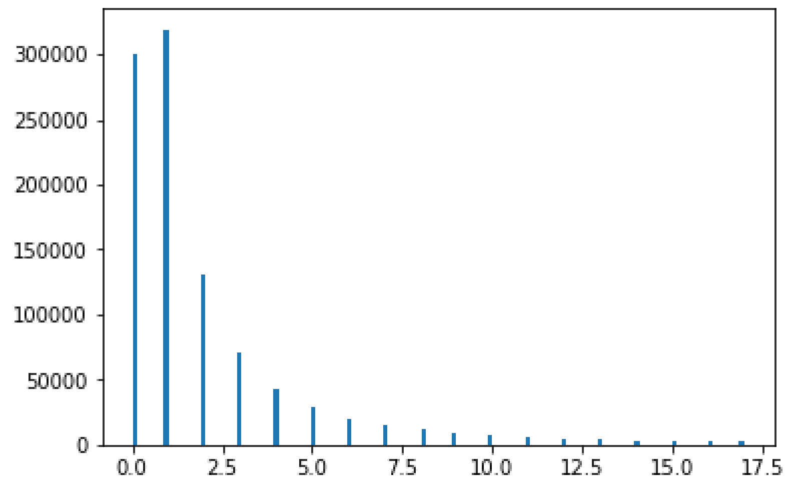

```
Feature  8
mean, standard deviation, skew, kurtosis:
 (96.87353000000002, 211.96366974870742, 8.589300282348093, 171.952336
82383932)
```



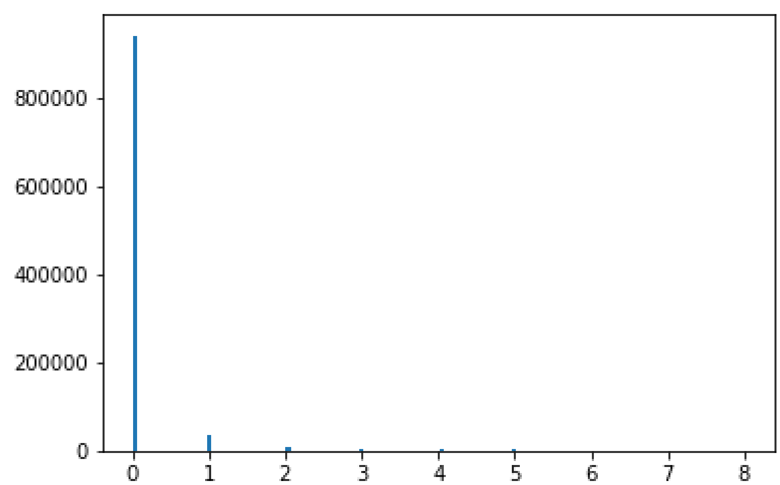

```
Feature  9
mean, standard deviation, skew, kurtosis:
 (0.32252900000000001, 0.58349125456942363, 2.0480730835089513, 5.54997
8668541556)
```



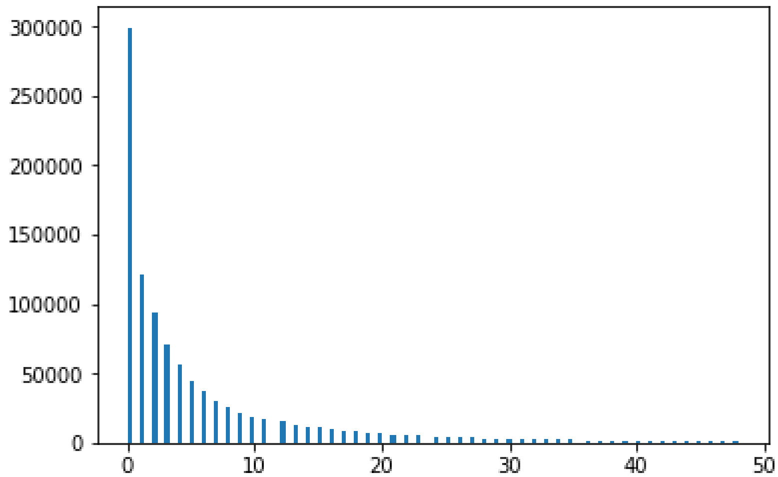
```
Feature  10
mean, standard deviation, skew, kurtosis:
 (2.5011570000000001, 5.0448546719753002, 6.268530853956374, 64.0435927
9438766)
```



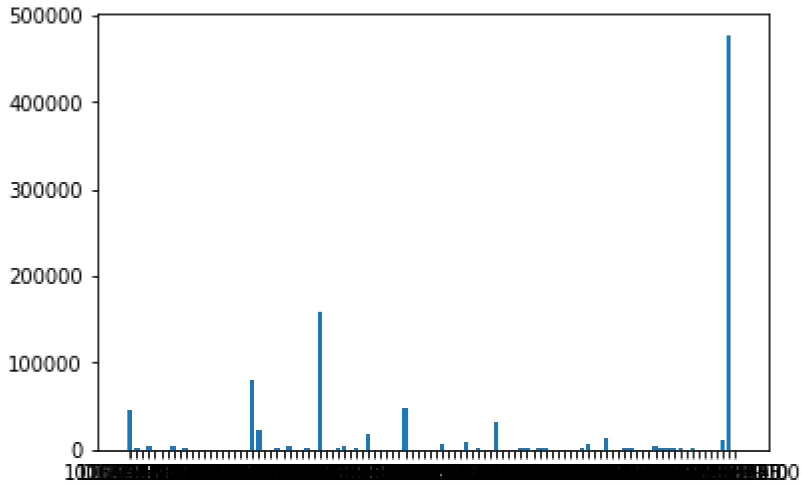

```
Feature  11
mean, standard deviation, skew, kurtosis:
 (0.22716, 2.7107221057127928, 51.61525748487304, 5537.542022626471)
```



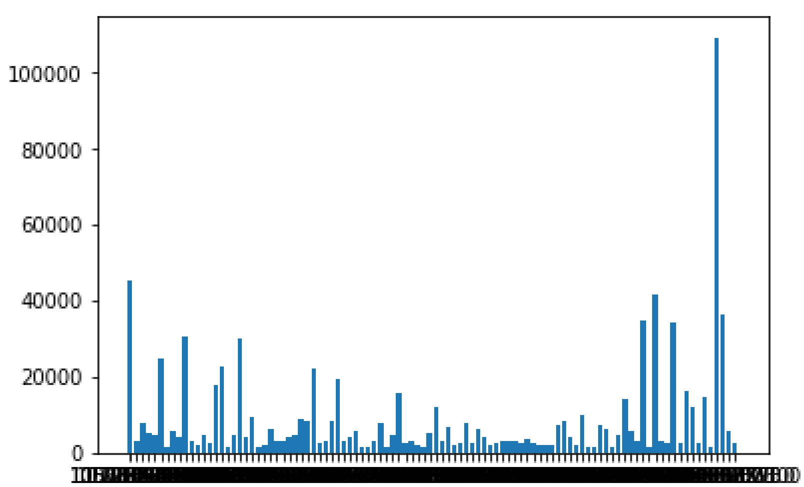

```
Feature  12
mean, standard deviation, skew, kurtosis:
 (6.134423, 14.076104981743741, 97.23930937086678, 23812.286060732826)
```



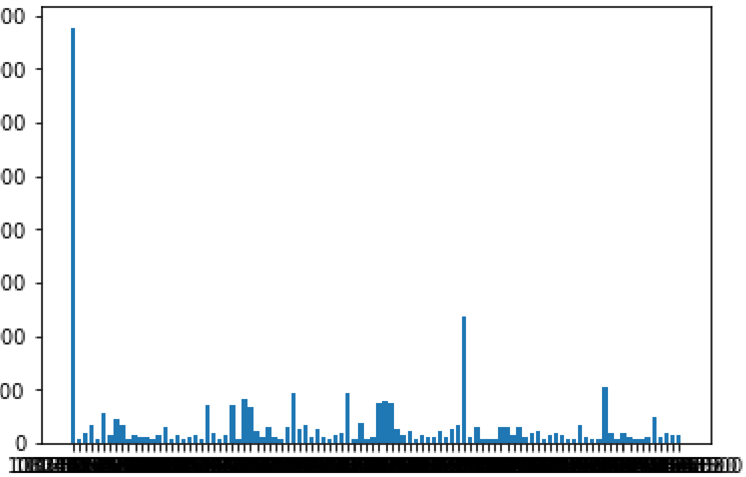
Feature 13



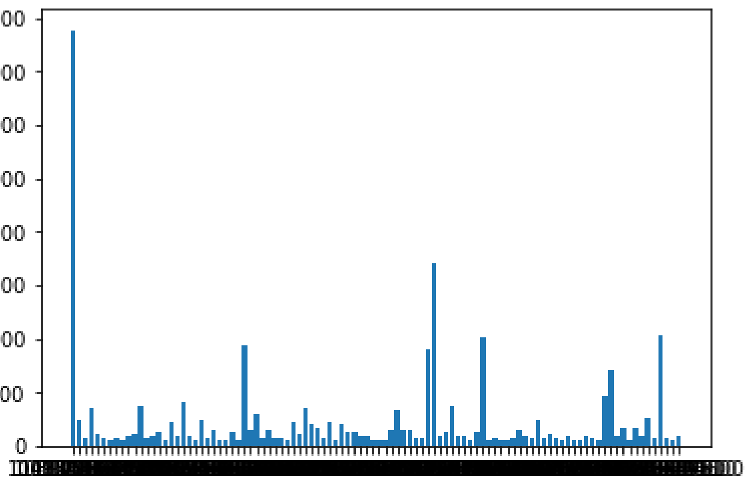
Feature 14



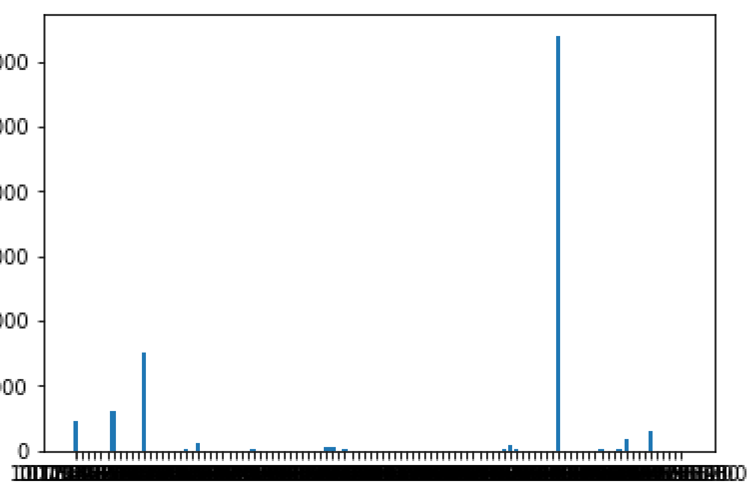
Feature 15



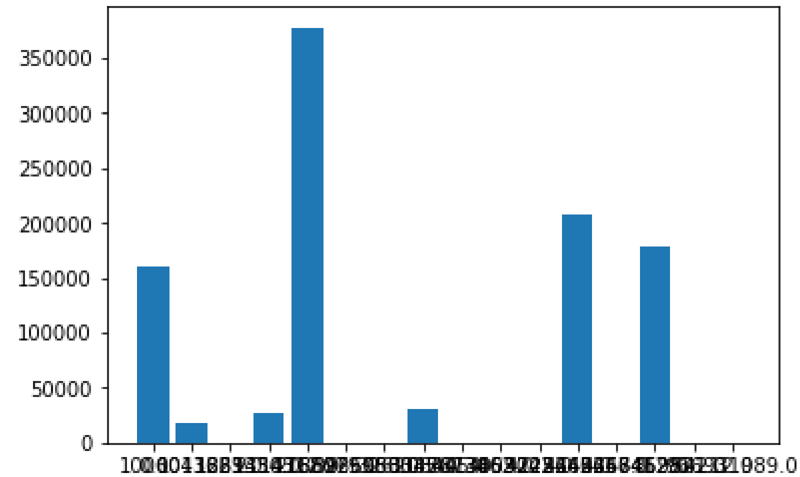
Feature 16



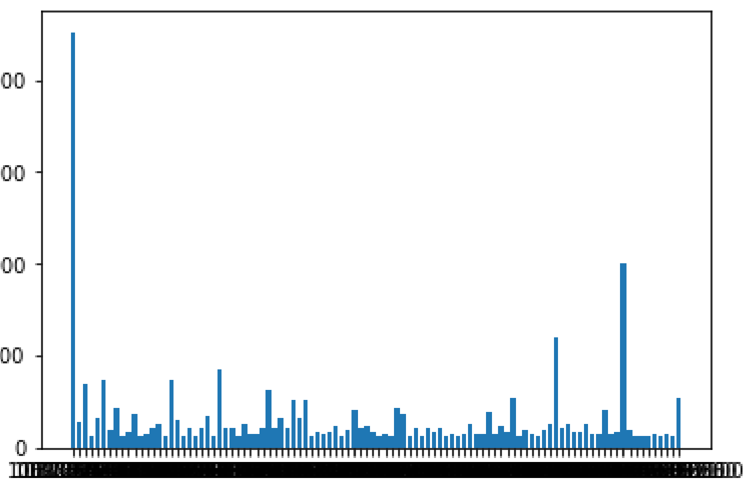
Feature 17



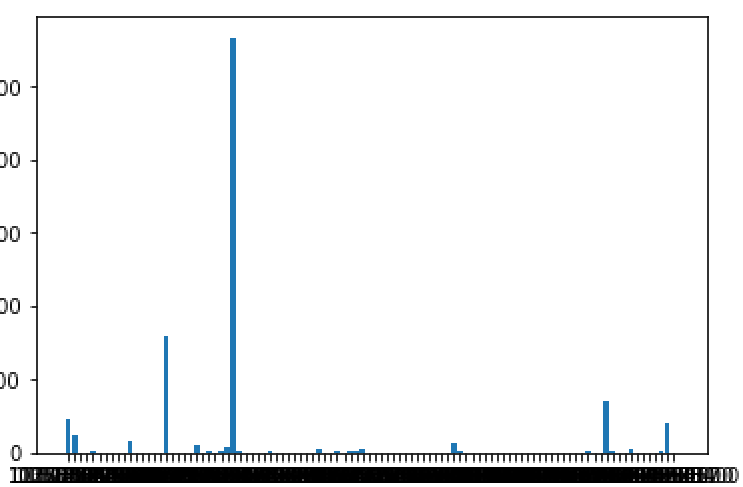
Feature 18



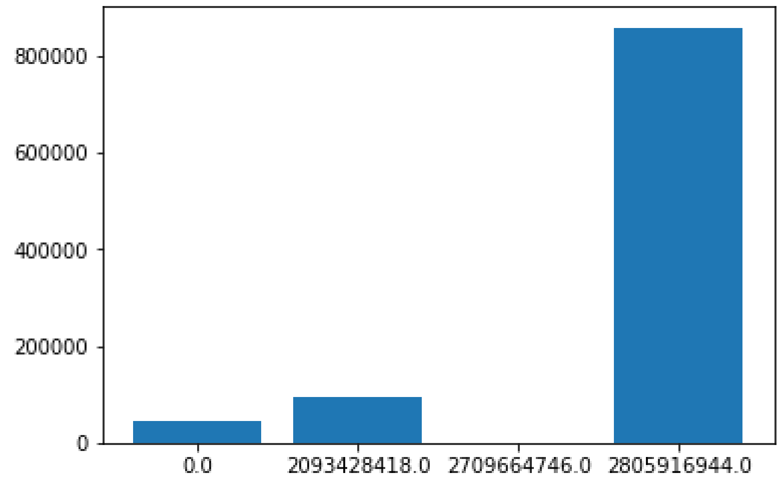

```
Feature  19
```



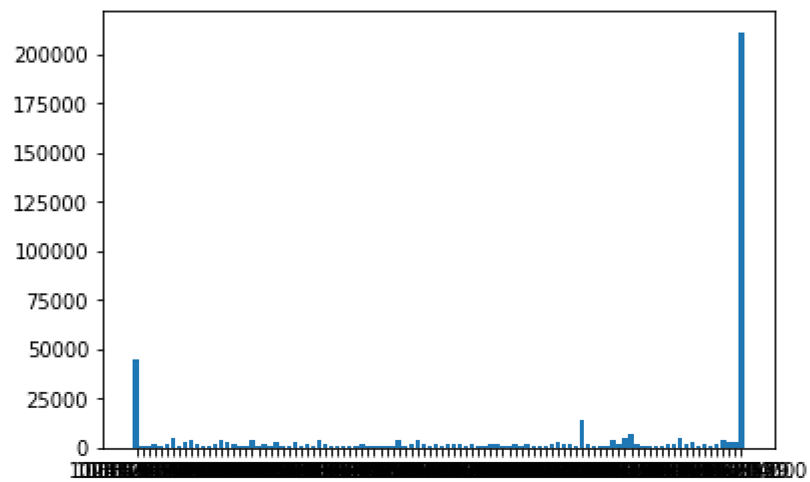

```
Feature  20
```



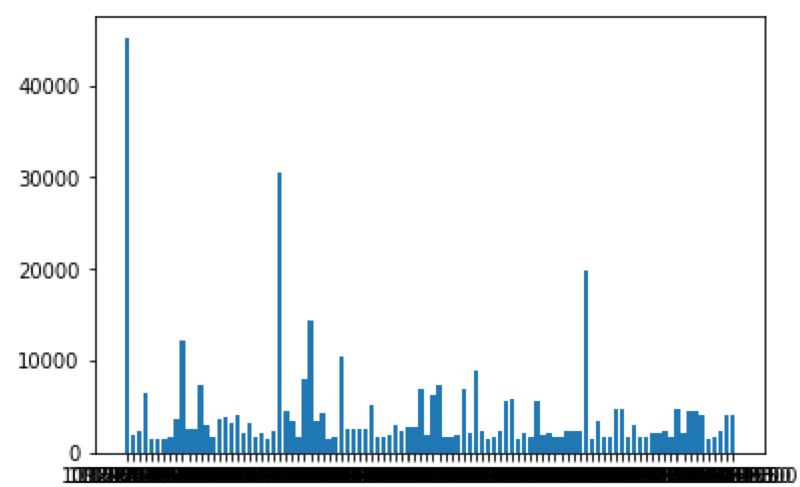

```
Feature  21
```



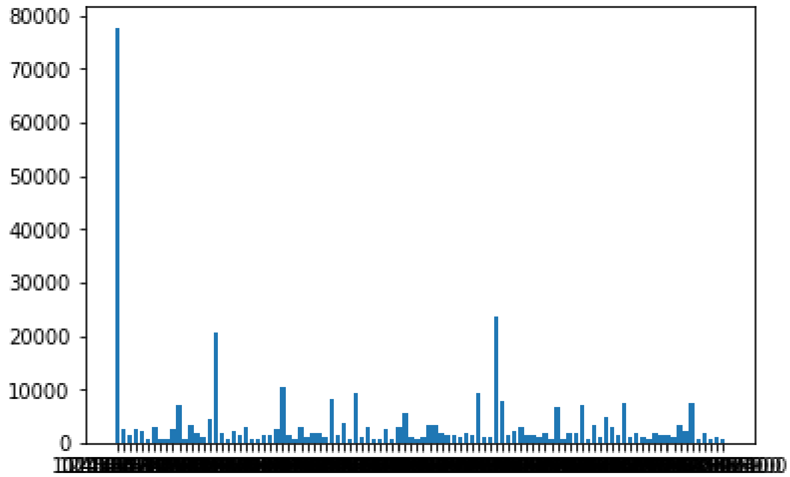

```
Feature  22
```



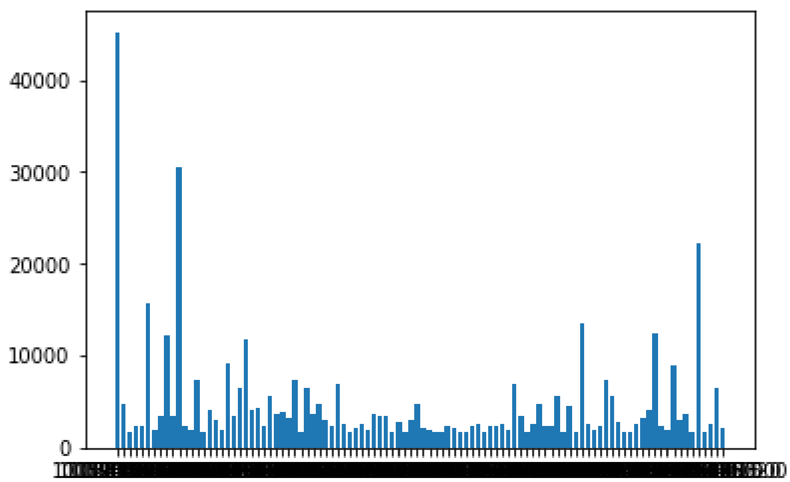

```
Feature  23
```



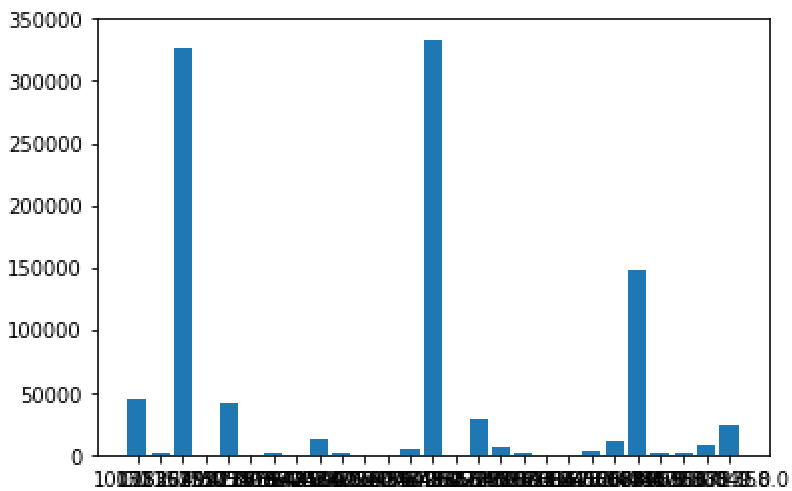

```
Feature  24
```



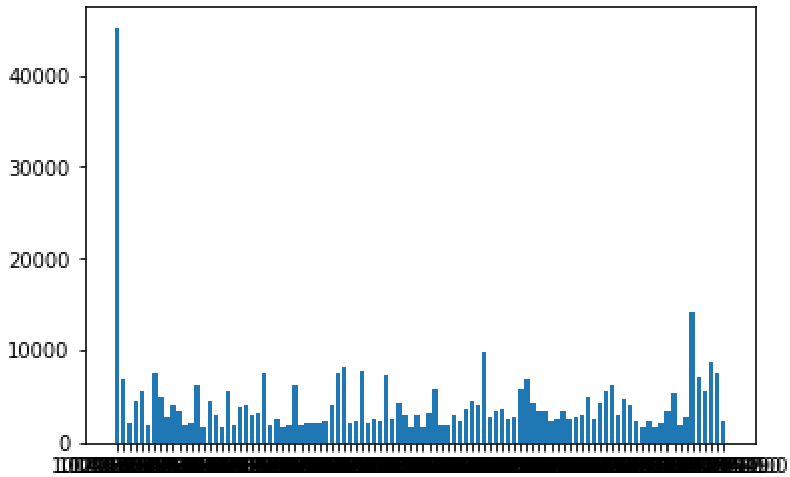
Feature 25



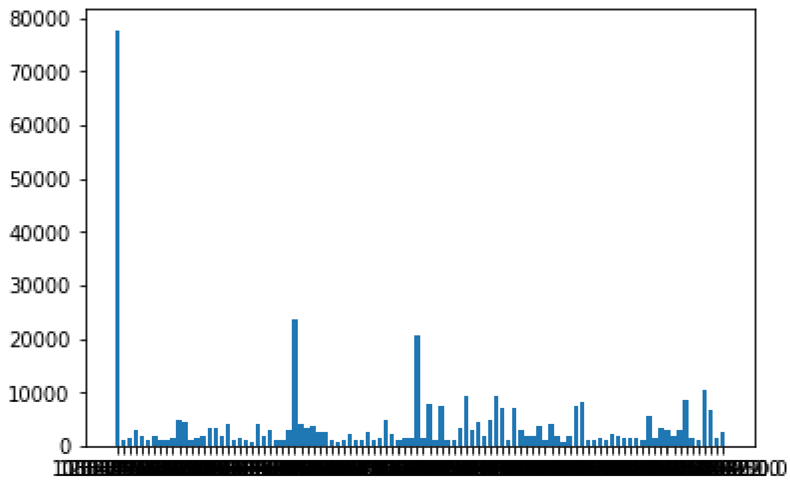
Feature 26



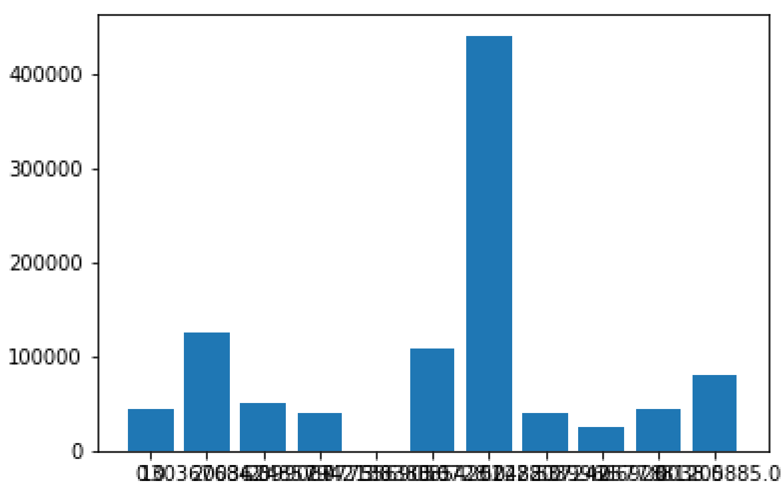
Feature 27



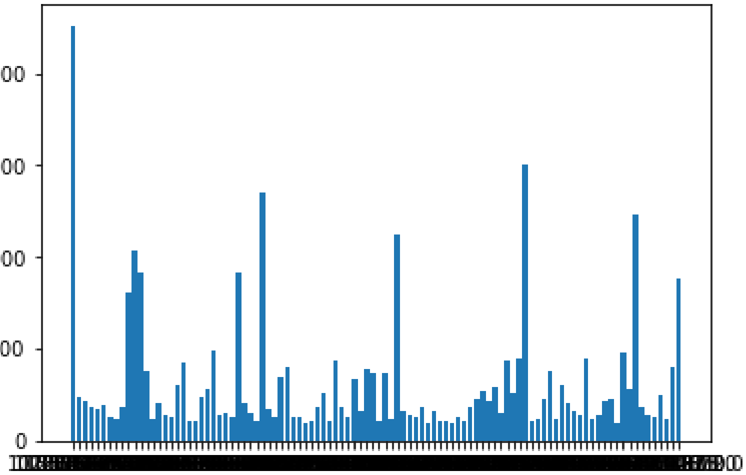
Feature 28



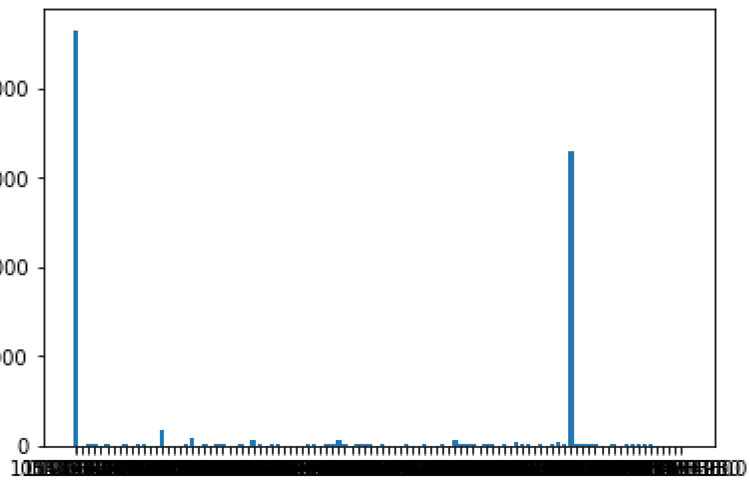
Feature 29



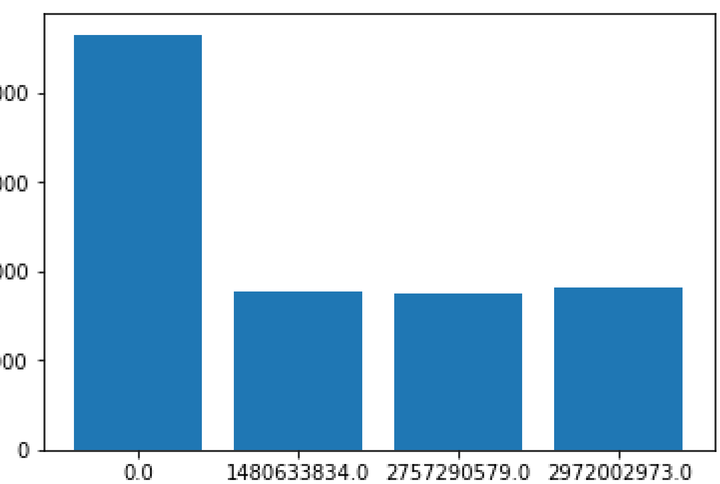
Feature 30



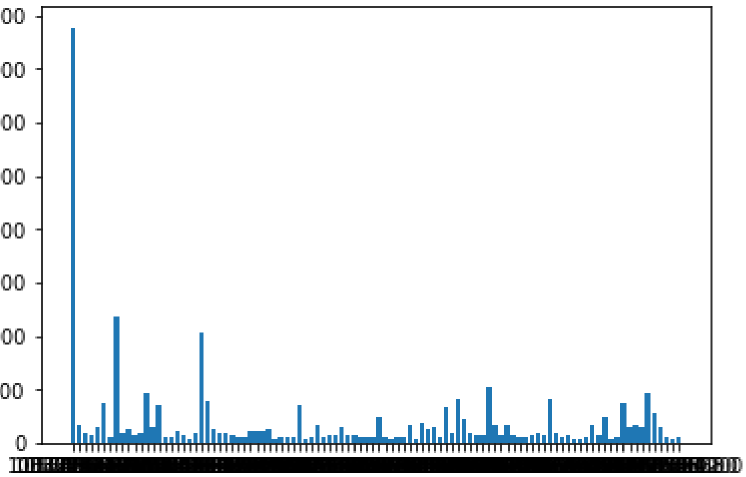
Feature 31



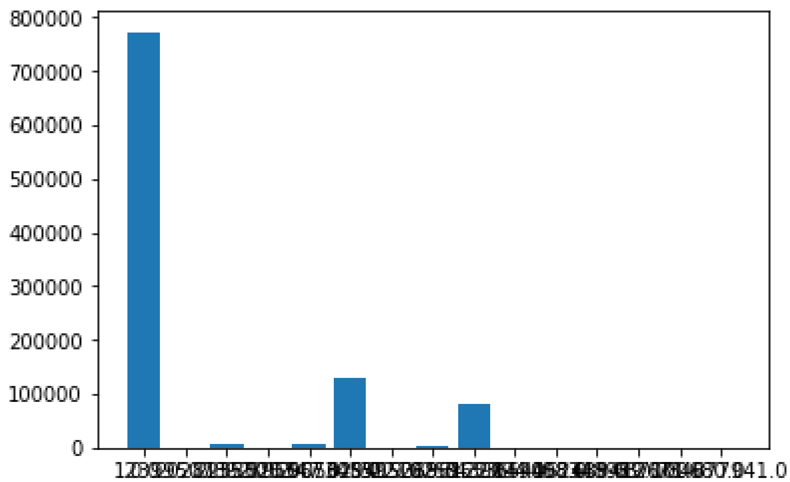
Feature 32



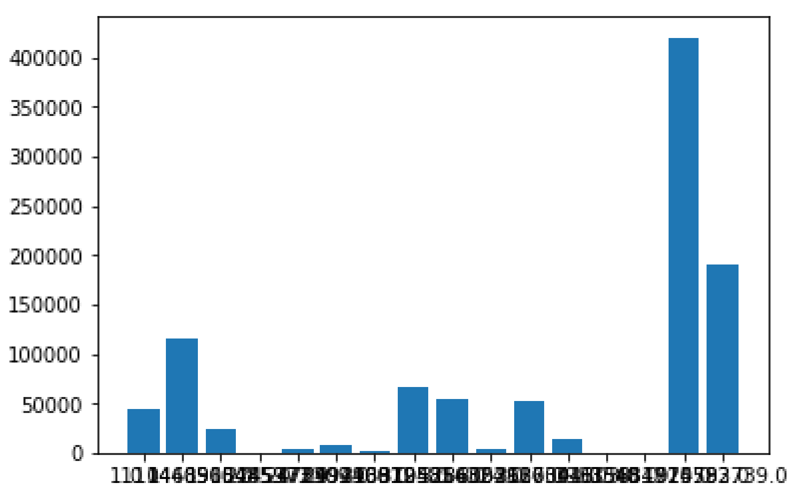
Feature 33



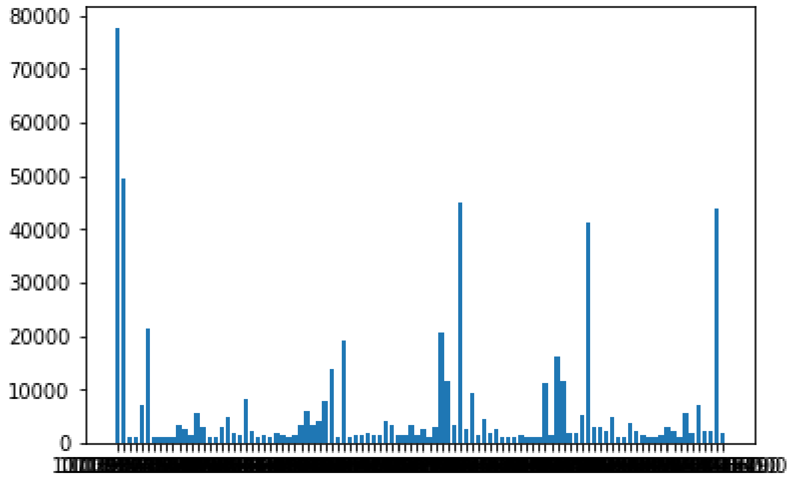
Feature 34



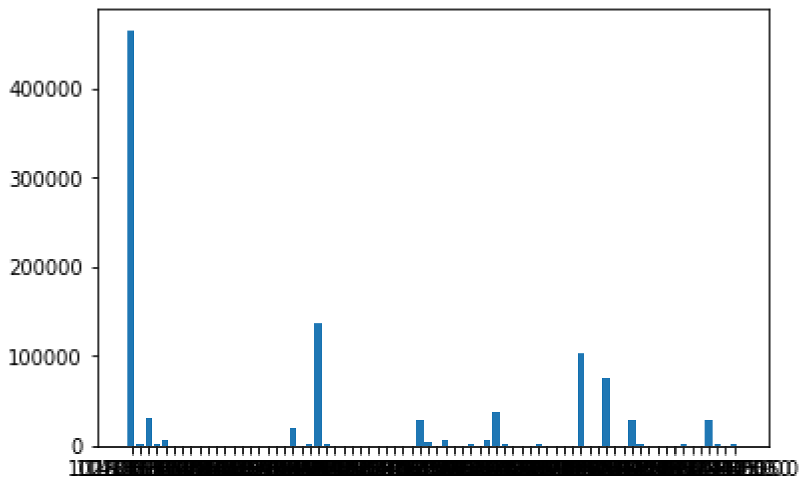
Feature 35



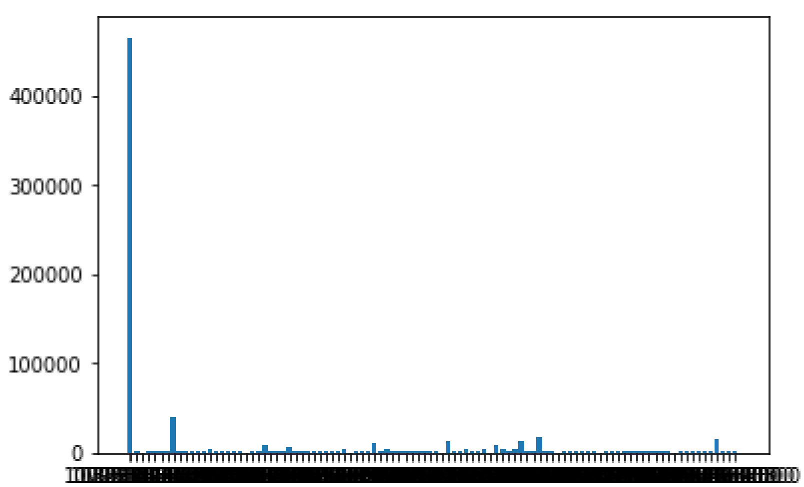
Feature 36



Feature 37



Feature 38



3. Categorical Feature Selection

For each categorical feature, I first calculate the frequency for each unique value. After this calculation, I find that some categories have a very large amount of unique values, which may result in a very sparse matrix when doing one-hot transformation.

Therefore, the next thing I do is to reduce the number of unique values for each category so as to get a better one-hot transformation. For each category, I sort its unique values descendingly according to their frequencies and select those unique values that have highest frequencies and take up more than `threshold = 90%` of the training data. These unique values form `the most common categorical value set` for each category.

In [11]:
```
import pprint
pp = pprint.PrettyPrinter(indent=4)
categorical_feature_val_sets = [getMostCommonCatVals(train_data[:,i]) fo
r i in range(13,39)]
pp.pprint([(i+13,len(j)) for i,j in enumerate(categorical_feature_val_se
ts)])
```

```
[   (13, 10),
    (14, 124),
    (15, 247291),
    (16, 36546),
    (17, 5),
    (18, 16),
    (19, 3443),
    (20, 6),
    (21, 4),
    (22, 4524),
    (23, 1494),
    (24, 209614),
    (25, 1120),
    (26, 6),
    (27, 1443),
    (28, 136769),
    (29, 11),
    (30, 542),
    (31, 44),
    (32, 4),
    (33, 179142),
    (34, 15),
    (35, 16),
    (36, 3790),
    (37, 8),
    (38, 1811)]
```

After the operation described above, one can see that some categories still have a large number of unique values in their `most common categorical value sets`. The categorical feature which has more than `threshold = 20` unique in its `most common categorical value set` is then dropped.

The reason why I do this is that a too large `most common categorical value set` will result in a very sparse feature matrix while doing one-hot transformation, which could lead to bad results in the following model training process. Additionally, if the `most common categorical value set` of a categorical feature is large, it tells us that the unique values in this feature spread quite evenly, which implies that the unique values of this feature may not be very representative. Therefore, I use this criterion to select the categorical features.

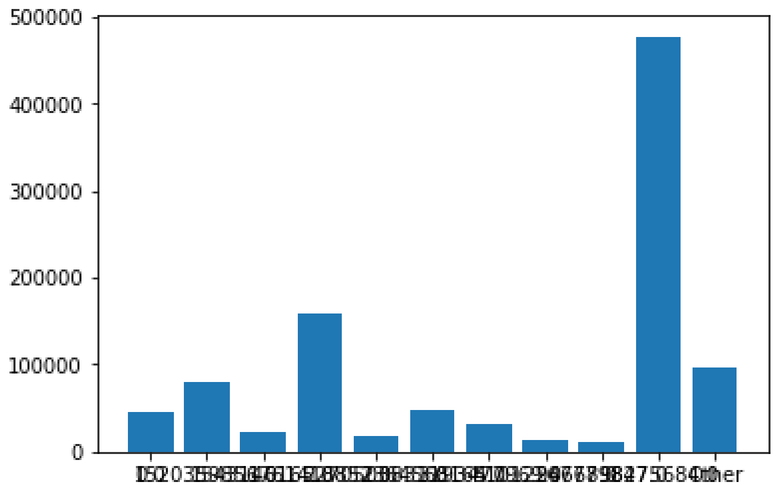
The categorical features that survive the selection are:

```
13, 17, 18, 20, 21, 26, 29, 32, 34, 35, 37
```

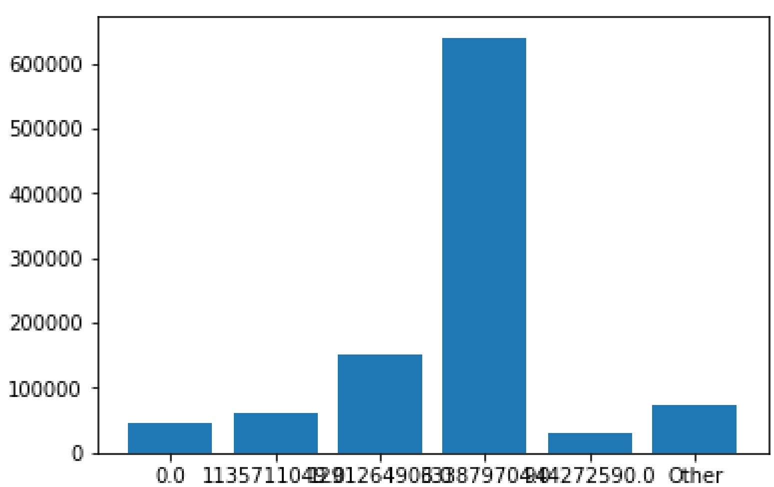
The following snippet demonstrates the histograms of the selected categorical features given the `most common categorical value sets`.

In [17]:
```
def showCatHistgramGivenValueset(data, valSet):
    counter = Counter(data)
    counter_valueSet = {'Other':0}
    for entry in counter.items():
        if entry[0] in valSet:
            counter_valueSet[str(entry[0])] = entry[1]
        else:
            counter_valueSet['Other'] += entry[1]
    pp.pprint("The frequency of each unique value is:")
    pp.pprint(counter_valueSet)
    plt.bar(counter_valueSet.keys(), counter_valueSet.values())
    plt.show()


selected_cats = [13, 17, 18, 20, 21, 26, 29, 32, 34, 35, 37]
for cat in selected_cats:
    print('categorical feature ', cat)
    showCatHistgramGivenValueset(train_data[:,cat], getMostCommonCatVals
(train_data[:,cat]))
```

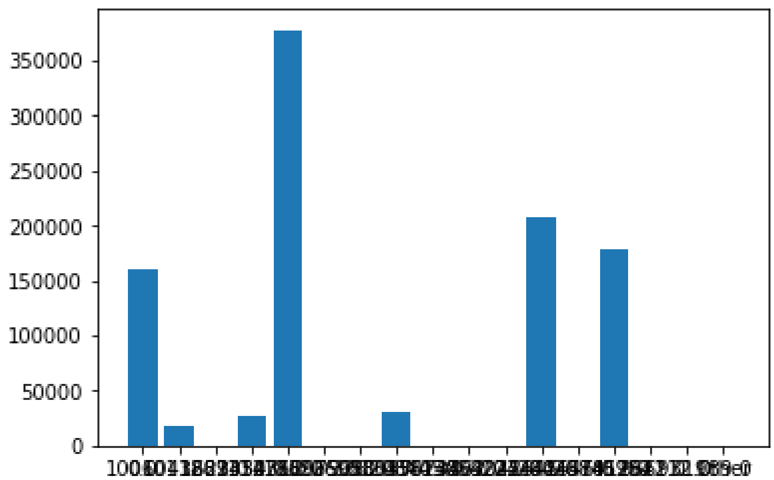
```
categorical feature  13
'The frequency of each unique value is:'
{   '0.0': 45225,
    '1520359856.0': 79676,
    '1543146165.0': 22839,
    '1761418852.0': 159315,
    '2270503831.0': 16977,
    '2364568165.0': 47217,
    '3193477969.0': 31782,
    '4101224668.0': 13521,
    '967779847.0': 10514,
    '98275684.0': 477366,
    'Other': 95568}
```



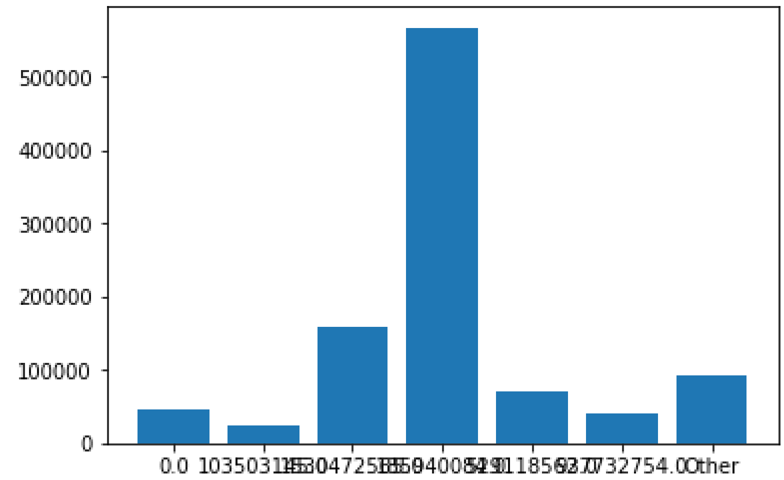

```
categorical feature  17
'The frequency of each unique value is:'
{   '0.0': 45225,
    '1135711049.0': 60687,
    '1291264903.0': 149784,
    '633879704.0': 640417,
    '944272590.0': 31254,
    'Other': 72633}
```



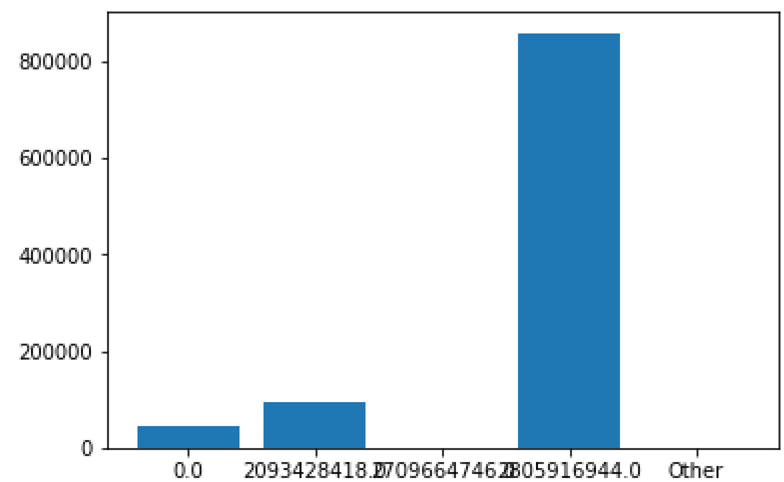
```
categorical feature  18
'The frequency of each unique value is:'
{   '0.0': 160431,
    '1006043623.0': 17237,
    '1011281330.0': 12,
    '1869454312.0': 27242,
    '2114768079.0': 378085,
    '2186965080.0': 1,
    '3226958037.0': 87,
    '326208445.0': 30394,
    '3345673462.0': 54,
    '3813803042.0': 170,
    '4059225645.0': 23,
    '4222442646.0': 208249,
    '4260457412.0': 12,
    '4268462821.0': 178000,
    '85954212.0': 2,
    '966931989.0': 1,
    'Other': 0}
```



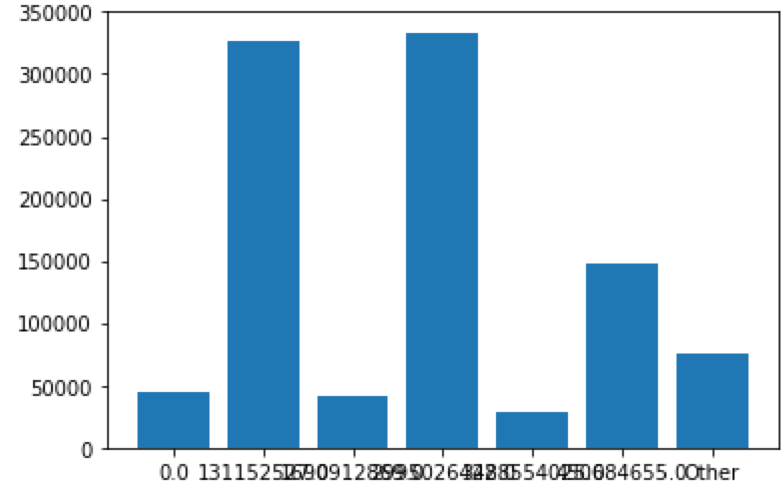

```
categorical feature  20
'The frequency of each unique value is:'
{   '0.0': 45225,
    '103503145.0': 24850,
    '1530472565.0': 158603,
    '185940084.0': 567152,
    '529118562.0': 71544,
    '937732754.0': 39729,
    'Other': 92897}
```



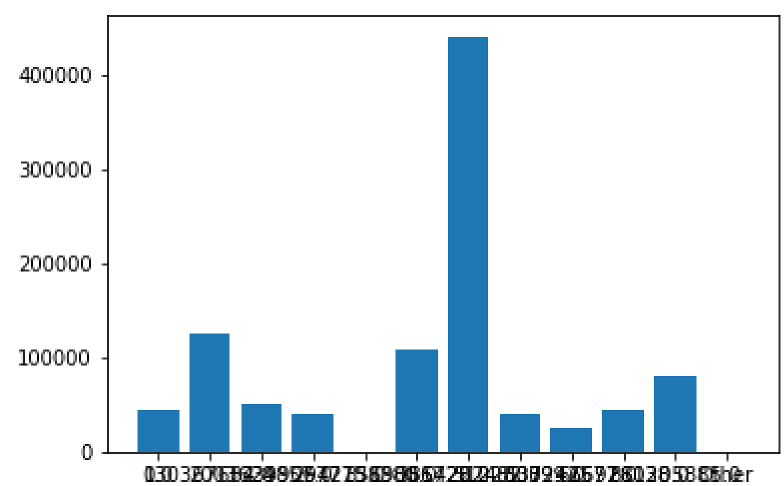

```
categorical feature  21
'The frequency of each unique value is:'
{   '0.0': 45225,
    '2093428418.0': 96423,
    '2709664746.0': 162,
    '2805916944.0': 858190,
    'Other': 0}
```



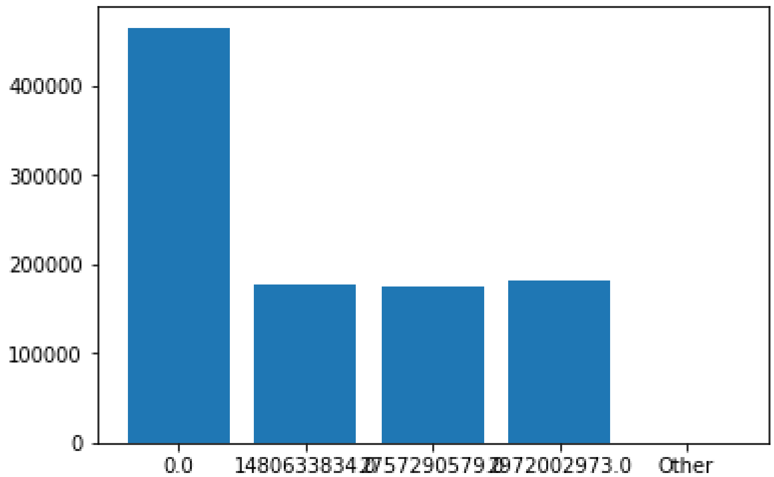

```
categorical feature  26
'The frequency of each unique value is:'
{   '0.0': 45225,
    '131152527.0': 326741,
    '1690912869.0': 42239,
    '2995026422.0': 333410,
    '3488554025.0': 29385,
    '450684655.0': 148274,
    'Other': 74726}
```



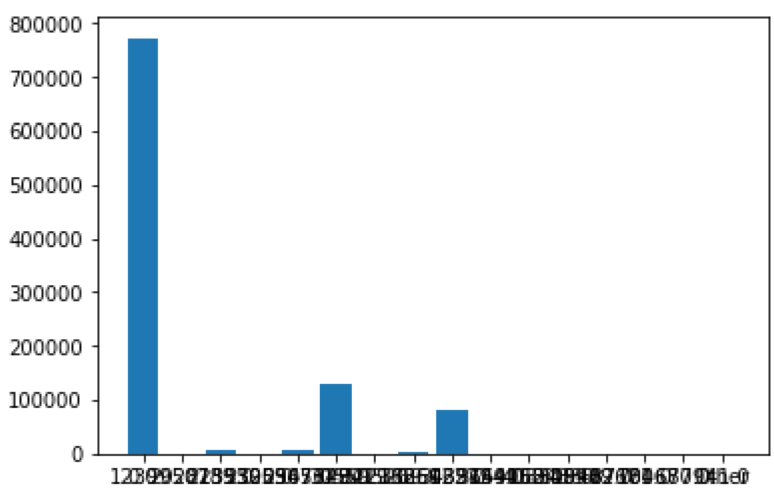

```
categorical feature  29
'The frequency of each unique value is:'
{   '0.0': 45225,
    '130367684.0': 124798,
    '2003624857.0': 50195,
    '2399067775.0': 40999,
    '2942138380.0': 33,
    '3569056728.0': 109204,
    '3854202482.0': 440871,
    '512280399.0': 40684,
    '537242577.0': 24577,
    '666926038.0': 43664,
    '881205885.0': 79750,
    'Other': 0}
```



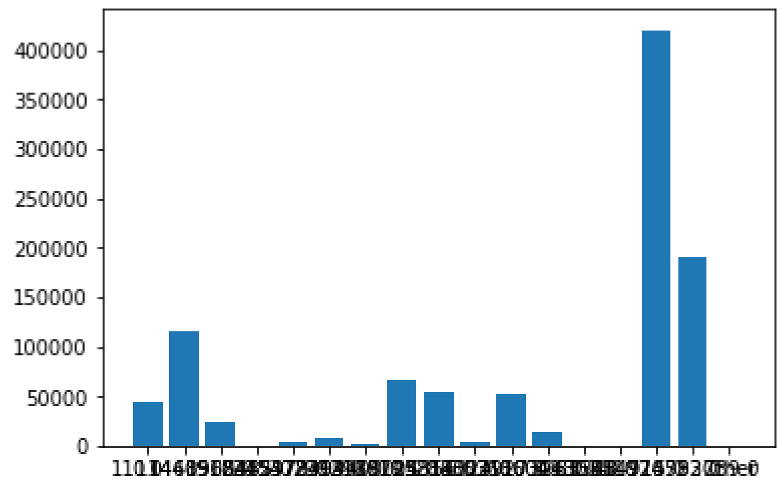

```
categorical feature  32
'The frequency of each unique value is:'
{   '0.0': 465661,
    '1480633834.0': 177934,
    '2757290579.0': 175344,
    '2972002973.0': 181061,
    'Other': 0}
```




```
categorical feature  34
'The frequency of each unique value is:'
{   '0.0': 772863,
    '1239950789.0': 110,
    '2028135305.0': 6924,
    '2253520347.0': 200,
    '2395567348.0': 5049,
    '2905629419.0': 130350,
    '305595269.0': 1,
    '3221625965.0': 3780,
    '3386122794.0': 80499,
    '3439149058.0': 205,
    '3654162488.0': 2,
    '408348989.0': 1,
    '619412671.0': 1,
    '687100680.0': 13,
    '784677941.0': 2,
    'Other': 0}
```



```
categorical feature  35
'The frequency of each unique value is:'
{   '0.0': 45225,
    '1111468905.0': 115164,
    '1440560485.0': 23075,
    '1918445973.0': 100,
    '2245372309.0': 3452,
    '2478494400.0': 8090,
    '2992939104.0': 1030,
    '3168725356.0': 66261,
    '3195814324.0': 53790,
    '3286002927.0': 4298,
    '3353110304.0': 53288,
    '3686041303.0': 14427,
    '3983348.0': 2,
    '635684715.0': 94,
    '851920782.0': 420503,
    '974593739.0': 191201,
    'Other': 0}
```




```
categorical feature  37
'The frequency of each unique value is:'
{   '0.0': 465661,
    '1146863163.0': 29958,
    '2045441.0': 136364,
    '2604566560.0': 29599,
    '3406273581.0': 37662,
    '3904386055.0': 103516,
    '3935970412.0': 76742,
    '737579441.0': 29263,
    'Other': 91235}
```