```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.linear model import LogisticRegression
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set option('display.max columns', 500)
```

```
In [2]: def analysis(col, tops = 10):
            temp = train[col].value counts()
            temp = temp.iloc[:tops].index
            #temp = train.index
            temp df = train[train[col].isin(temp)]
              prob = temp df[col].value counts(normalize=True)
              draw = np.random.choice(prob.index, p=prob, size=len(temp df))
              output = pd.Series(draw).value counts(normalize=True).rename('simu
        lated')
              zeros = set(temp df[col].dropna().unique()).difference(set(output.
        index))
              output = output.append(pd.Series([0 for i in zeros], index = zero
        s)) / (temp df[col].value counts())
            temp df['shuffle'] = temp df['HasDetections'].sample(replace=False,
        n=len(temp df)).reset index(drop=True)
            output = temp_df[temp_df['shuffle'] == 1][col].value_counts() / temp
        df[col].value_counts()
            pd.DataFrame({'train_data': temp_df[temp_df['HasDetections'] == 1][c
        ol].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}).plot(kind = 'bar', figs
        ize=(20,10))
            plt.title('Percent of Has detections by {} (most of the catogaries)'
        .format(col))
            display(pd.DataFrame({'train_data': temp_df[temp_df['HasDetections']
        == 1][col].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}))
            return stats.ks 2samp(temp df[temp df['HasDetections'] == 1][col].va
        lue counts(normalize = True),
                        output)
        #stats.chi2 contingency([temp df.groupby(col).HasDetections.mean(),
                          temp df.groupby(col).random data.mean()])
```

```
In [4]: train = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS)
```

```
In [5]: train.head()
```

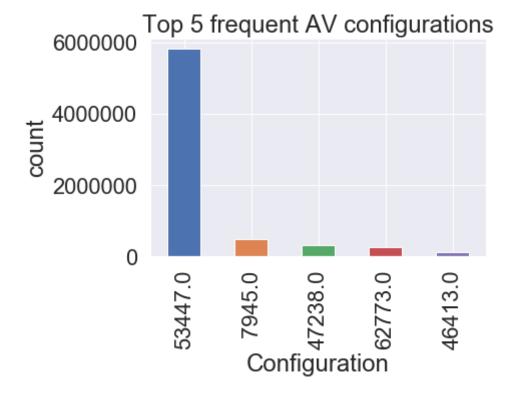
## Out[5]:

	<b>AVProductStatesIdentifier</b>	AVProductsInstalled	AVProductsEnabled	HasDetections
0	53447.0	1.0	1.0	0
1	53447.0	1.0	1.0	0
2	53447.0	1.0	1.0	0
3	53447.0	1.0	1.0	1
4	53447.0	1.0	1.0	1

```
In [6]: #General analysis
```

```
In [7]: #1.1 AVProductStatesIdentifier
#Top 20 categories detection
```

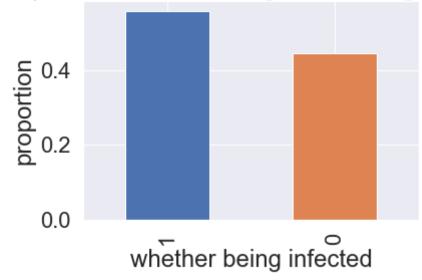
Out[8]: Text(0, 0.5, 'count')



```
In [9]: train[train[COLS[1]]==53447.0].HasDetections.value_counts(normalize=True
).plot("bar", title='Proportion of 53447 configuration being infected')
plt.xlabel("whether being infected")
plt.ylabel("proportion")
```

Out[9]: Text(0, 0.5, 'proportion')

# Proportion of 53447 configuration being infected



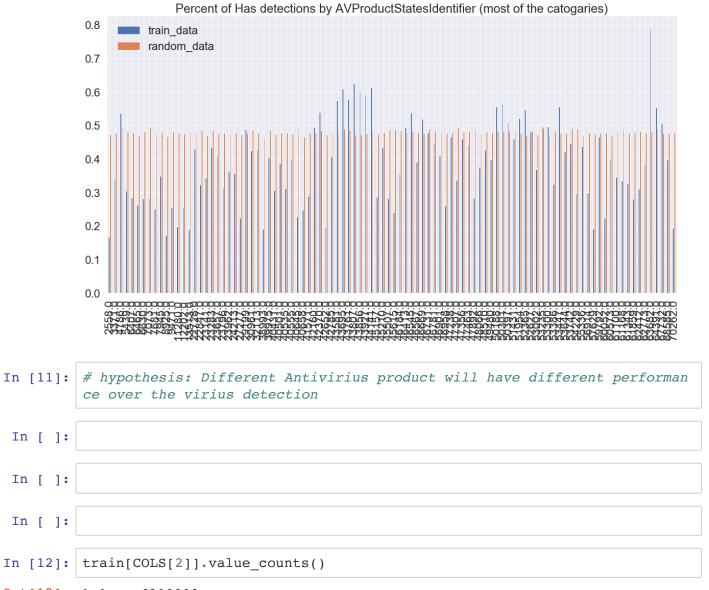
In [10]: analysis(COLS[1], 100)

	train_data	random_data
2558.0	0.168525	0.474461
3371.0	0.338305	0.477813
4786.0	0.536552	0.495636
5439.0	0.304536	0.482259
6407.0	0.285132	0.479037
6465.0	0.262006	0.471441
6630.0	0.282516	0.481675
7073.0	0.284089	0.495114
7681.0	0.252316	0.475068
7945.0	0.348334	0.479703
8925.0	0.173160	0.467787
9471.0	0.254769	0.481998
11280.0	0.198155	0.477631
12202.0	0.256114	0.475834
13513.0	0.189224	0.480837
22728.0	0.429469	0.478450
22847.0	0.322525	0.485222
23141.0	0.344138	0.470654
23283.0	0.435090	0.486606
23657.0	0.411926	0.477298
23796.0	0.313957	0.477504
23962.0	0.364146	0.474878
24213.0	0.357153	0.477913
27277.0	0.223556	0.473394
29199.0	0.489096	0.476560
30961.0	0.425086	0.487019
32113.0	0.427595	0.478979
38993.0	0.191431	0.463096
39975.0	0.403295	0.485373
40431.0	0.306254	0.474026
50397.0	0.510341	0.484150
51431.0	0.460695	0.485192
51954.0	0.521178	0.476204

	train_data	random_data
52365.0	0.546349	0.470471
52627.0	0.480683	0.484372
53002.0	0.369352	0.471840
53235.0	0.498149	0.492694
53300.0	0.496026	0.469536
53386.0	0.324058	0.484497
53447.0	0.556365	0.479063
53644.0	0.422093	0.476636
53742.0	0.446748	0.492356
54229.0	0.296696	0.491099
55336.0	0.437007	0.471176
56914.0	0.298531	0.478456
57629.0	0.192626	0.475020
59792.0	0.466745	0.476236
60052.0	0.224161	0.478859
60573.0	0.398634	0.472131
61100.0	0.345621	0.483156
61168.0	0.334874	0.490935
61343.0	0.325536	0.478360
61859.0	0.280933	0.480332
62412.0	0.311499	0.483536
62773.0	0.382132	0.478700
63682.0	0.787928	0.480876
64391.0	0.553157	0.490700
67732.0	0.507315	0.477141
68585.0	0.398314	0.477391
70262.0	0.194309	0.478992

100 rows × 2 columns

Out[10]: Ks\_2sampResult(statistic=0.99, pvalue=1.2251433537012255e-44)



Out[12]: 1.0 6208893 2.0 2459008 3.0 208103 4.0 8757 5.0 471 6.0 28 7.0 1

0.0

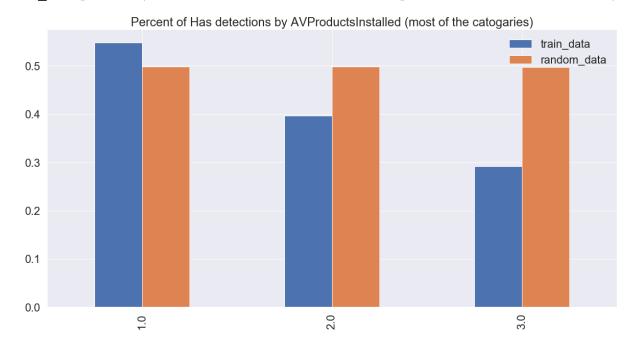
Name: AVProductsInstalled, dtype: int64

1

In [13]: # hypothesis: Different Antivirius product installed will have different performance over the virius detection

```
In [14]: analysis(COLS[2], 3)
```

	train_data	random_data
1.0	0.548581	0.498079
2.0	0.396906	0.497881
3.0	0.291596	0.497114



In [15]: #Need deep analysis

In [16]: # hypothesis: Different Antivirius product installed will have different performance over the virius detection

In [27]: train[COLS[3]].value\_counts()

Out[27]: 1.0 8654101 2.0 198652 0.0 25958 3.0 6075 4.0 453 5.0 23

Name: AVProductsEnabled, dtype: int64

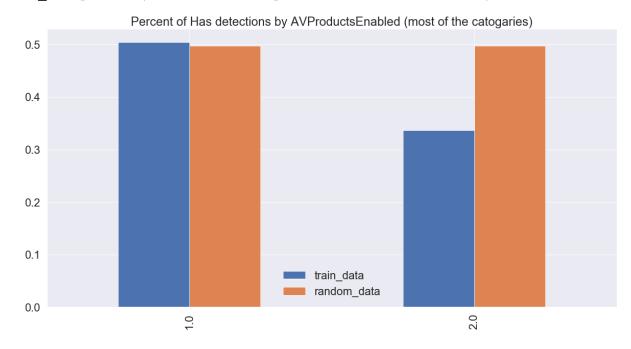
```
In [17]: analysis(COLS[3], 2)
```

	train_data	random_data
1.0	0.504636	0.496984
2.0	0.336422	0.497433

#Need deep analysis

In [18]:

Out[17]: Ks\_2sampResult(statistic=0.5, pvalue=0.8438198245415606)



```
In [ ]:
In [ ]:
In [ ]:
           trial w/ random forest
In [19]:
In [20]: def skl(col):
             nominal transformer = Pipeline(steps=[
                  ('onehot', OneHotEncoder(handle unknown='ignore'))
             preproc = ColumnTransformer(transformers=[('onehot', nominal transfo
         rmer, col)],\
                                                    remainder='drop')
             clf = RandomForestClassifier(n estimators=7, max depth=60)
             pl = Pipeline(steps=[('preprocessor', preproc),
                              ('clf', clf)
                              ])
             return pl
```

```
In [21]: X train, X test, y train, y test = train test split(train.dropna().drop(
          'HasDetections',axis = 1)\
                                                                   , train.dropna()['Ha
          sDetections'], test_size=0.25)
          N = len(y_test)
          y_random = y_test.sample(replace=False, frac = 1)
In [22]: output = pd.DataFrame(columns = ['Observation accuracy', 'Random Data ac
          curacy'], index = COLS[1:])
          for i in COLS[1:]:
              pl = skl([i])
              pl.fit(X_train, y_train)
              pred_score = pl.score(X_test, y_test)
              rand_score = pl.score(X_test, y_random)
              output.loc[i, 'Observation accuracy'] = pred_score
              output.loc[i, 'Random Data accuracy'] = rand score
          pl = skl(COLS[1:])
          pl.fit(X_train, y_train)
          pred score = pl.score(X_test, y_test)
          rand_score = pl.score(X_test, y_random)
          output.loc['combined', 'Observation accuracy'] = pred_score
output.loc['combined', 'Random_Data accuracy'] = rand_score
```

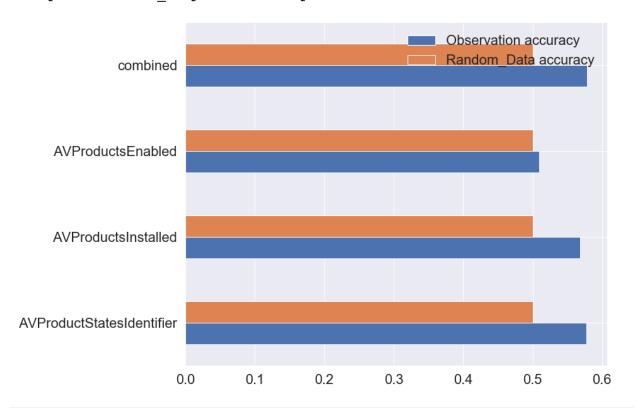
# In [23]: output

#### Out[23]:

	Observation accuracy	Random_Data accuracy
<b>AVProductStatesIdentifier</b>	0.577934	0.500461
<b>AVProductsInstalled</b>	0.568239	0.500398
<b>AVProductsEnabled</b>	0.509382	0.500699
combined	0.578303	0.500456

```
In [30]: output.plot(kind = 'barh', ylim = (0.45, 0.65), figsize=[12,10])
```

Out[30]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1a22697438>



In [25]: #Conclusion, when using random forest clustering, 'AVProductStatesIdenti fier' will dominate the performance
#of prediction, compare the comparison with random data, 'AVProductState sIdentifier' have a significant imporvement
#in identifying malware.

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.linear model import LogisticRegression
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set option('display.max columns', 500)
```

In [2]: def analysis(col, tops = 10):

```
temp = train[col].value counts()
            temp = temp.iloc[:tops].index
            #temp = train.index
            temp df = train[train[col].isin(temp)]
              prob = temp df[col].value counts(normalize=True)
              draw = np.random.choice(prob.index, p=prob, size=len(temp df))
              output = pd.Series(draw).value counts(normalize=True).rename('simu
        lated')
              zeros = set(temp df[col].dropna().unique()).difference(set(output.
        index))
              output = output.append(pd.Series([0 for i in zeros], index = zero
        s)) / (temp df[col].value counts())
            temp df['shuffle'] = temp df['HasDetections'].sample(replace=False,
        n=len(temp df)).reset index(drop=True)
            output = temp_df[temp_df['shuffle'] == 1][col].value_counts() / temp
        df[col].value_counts()
            pd.DataFrame({'train_data': temp_df[temp_df['HasDetections'] == 1][c
        ol].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}).plot(kind = 'bar', figs
        ize=(20,10))
            plt.title('Percent of Has detections by {} (most of the catogaries)'
        .format(col))
            display(pd.DataFrame({'train_data': temp_df[temp_df['HasDetections']
        == 1][col].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}))
            return stats.ks 2samp(temp df[temp df['HasDetections'] == 1][col].va
        lue counts(normalize = True),
                        output)
        #stats.chi2 contingency([temp df.groupby(col).HasDetections.mean(),
                         temp df.groupby(col).random data.mean()])
In [3]: COLS = [
            'HasDetections',
            'Platform',
```

```
'OsBuild'
```

```
In [4]: | train = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS)
```

In [5]: train.head()

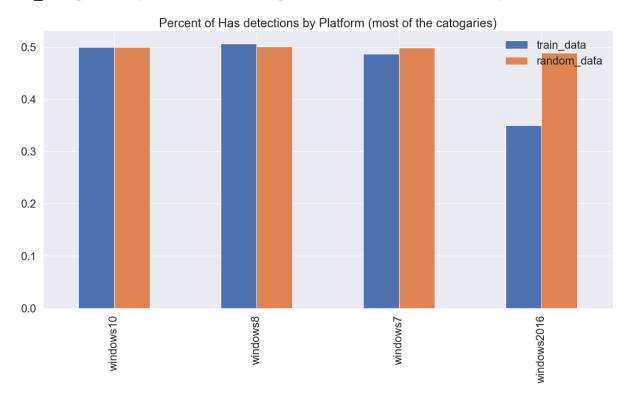
# Out[5]:

	Platform	OsBuild	HasDetections
0	windows10	17134	0
1	windows10	17134	0
2	windows10	17134	0
3	windows10	17134	1
4	windows10	17134	1

In [6]: analysis(COLS[1])

	train_data	random_data
windows10	0.500032	0.499803
windows8	0.506720	0.500540
windows7	0.486511	0.498930
windows2016	0.349593	0.489040

Out[6]: Ks\_2sampResult(statistic=0.75, pvalue=0.10749046502096637)

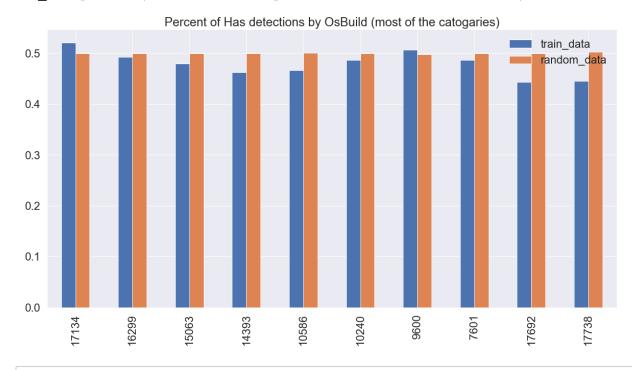


In [7]: # virius and platform is not likely revelent

In [8]: analysis(COLS[2])

	train_data	random_data
17134	0.520727	0.498950
16299	0.492128	0.498968
15063	0.478875	0.499143
14393	0.462269	0.499039
10586	0.465831	0.500046
10240	0.486584	0.499478
9600	0.506720	0.497872
7601	0.486432	0.499368
17692	0.443467	0.499058
17738	0.445117	0.502421

Out[8]: Ks\_2sampResult(statistic=1.0, pvalue=1.8879793657162556e-05)



In [9]: # We assmue malware detection may have no significant relation with oper ating system

In [ ]:

In [10]: # random forest clustering to comfirm

```
In [13]: output = pd.DataFrame(columns = ['Observation accuracy', 'Random_Data accuracy'], index = COLS[1:])
    for i in COLS[1:]:
        pl = skl([i])
        pl.fit(X_train, y_train)
        pred_score = pl.score(X_test, y_test)
        rand_score = pl.score(X_test, y_random)
        output.loc[i, 'Observation accuracy'] = pred_score
        output.loc[i, 'Random_Data accuracy'] = rand_score
    pl = skl(COLS[1:])
    pl.fit(X_train, y_train)
    pred_score = pl.score(X_test, y_test)
    rand_score = pl.score(X_test, y_random)
    output.loc['combined', 'Observation accuracy'] = pred_score
    output.loc['combined', 'Random_Data accuracy'] = rand_score
```

# In [14]: output

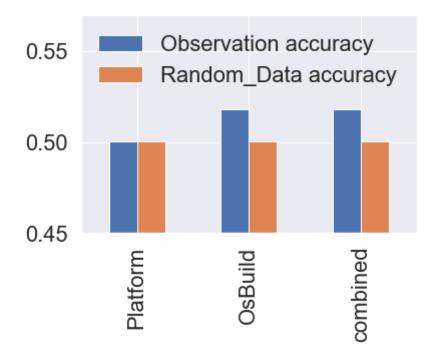
### Out[14]:

#### Observation accuracy Random\_Data accuracy

Platform	0.500503	0.500177
OsBuild	0.518036	0.500423
combined	0.518036	0.500423

```
In [15]: output.plot(kind = 'bar', ylim = (0.45, 0.57))
```

Out[15]: <matplotlib.axes.\_subplots.AxesSubplot at 0x23d8044c908>



In [16]: #Conclusion, In general, Operating system has a slightly influence to ma
 lware detection (not very significant)
 #'OSBuild' will have a more significant influence when we proceed random
 forest clustering,
 #and 'Platform' may have no affect to malware detection. When we combine
 two 'OSBuild' will dominate the
 #clf.

In [ ]:

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.linear model import LogisticRegression
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set option('display.max columns', 500)
```

```
In [2]: def analysis(col, tops = 10):
            temp = train[col].value counts()
            temp = temp.iloc[:tops].index
            #temp = train.index
            temp df = train[train[col].isin(temp)]
              prob = temp df[col].value counts(normalize=True)
              draw = np.random.choice(prob.index, p=prob, size=len(temp df))
              output = pd.Series(draw).value counts(normalize=True).rename('simu
        lated')
              zeros = set(temp df[col].dropna().unique()).difference(set(output.
        index))
              output = output.append(pd.Series([0 for i in zeros], index = zero
        s)) / (temp df[col].value counts())
            temp df['shuffle'] = temp df['HasDetections'].sample(replace=False,
        n=len(temp df)).reset index(drop=True)
            output = temp_df[temp_df['shuffle'] == 1][col].value_counts() / temp
        df[col].value_counts()
            pd.DataFrame({'train_data': temp_df[temp_df['HasDetections'] == 1][c
        ol].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}).plot(kind = 'bar', figs
        ize=(20,10))
            plt.title('Percent of Has detections by {} (most of the catogaries)'
        .format(col))
            display(pd.DataFrame({'train_data': temp_df[temp_df['HasDetections']
        == 1][col].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}))
            return stats.ks 2samp(temp df[temp df['HasDetections'] == 1][col].va
        lue counts(normalize = True),
                        output)
        #stats.chi2 contingency([temp df.groupby(col).HasDetections.mean(),
                          temp df.groupby(col).random data.mean()])
In [3]: COLS = [
            'HasDetections',
             'Census ProcessorCoreCount',
```

```
'Census PrimaryDiskTotalCapacity',
'Processor'
```

```
In [4]: train = pd.read csv("train.csv", sep=',', engine='c', usecols=COLS)
```

In [5]: train.head()

Out[5]:

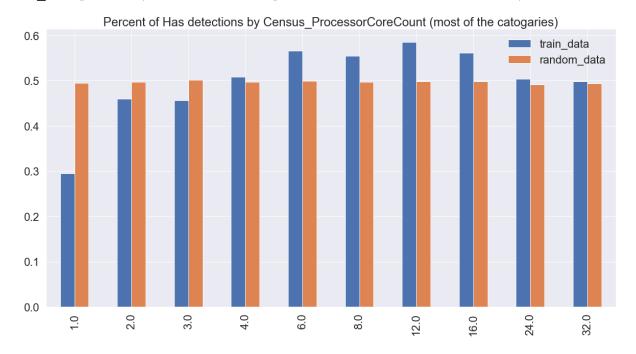
	Processor	Census_ProcessorCoreCount	Census_PrimaryDiskTotalCapacity	HasDetections
0	x64	4.0	476940.0	0
1	x64	4.0	476940.0	0
2	x64	4.0	114473.0	0
3	x64	4.0	238475.0	1
4	x64	4.0	476940.0	1

In [6]: #barplot of random\_data and chi-square test statiscs over the proportion
#only takes majority of large data to proceed analyis

In [7]: analysis(COLS[1])

	train_data	random_data
1.0	0.295042	0.494843
2.0	0.459875	0.496916
3.0	0.456038	0.501915
4.0	0.507915	0.497158
6.0	0.566400	0.498798
8.0	0.555008	0.496822
12.0	0.584691	0.497994
16.0	0.561587	0.498032
24.0	0.503519	0.491608
32.0	0.498596	0.493446

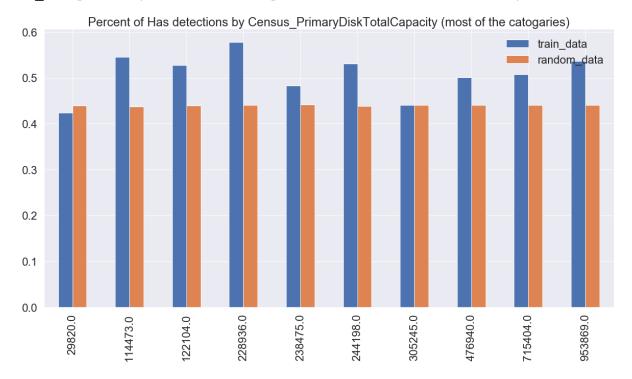
Out[7]: Ks\_2sampResult(statistic=0.9, pvalue=0.00017011925273829756)



In [8]: analysis(COLS[2])

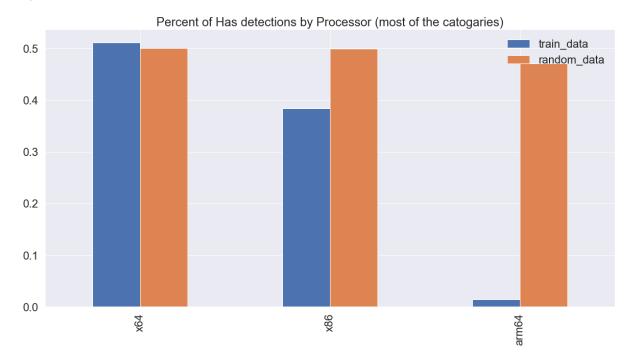
	train_data	random_data
29820.0	0.424125	0.439374
114473.0	0.545365	0.437663
122104.0	0.527792	0.439861
228936.0	0.577324	0.440526
238475.0	0.483430	0.441772
244198.0	0.530764	0.438167
305245.0	0.440135	0.440824
476940.0	0.500258	0.440021
715404.0	0.507006	0.440239
953869.0	0.536908	0.440147

Out[8]: Ks\_2sampResult(statistic=1.0, pvalue=1.8879793657162556e-05)



```
In [9]: analysis(COLS[3])
```

	train_data	random_data
x64	0.511446	0.499851
x86	0.384202	0.499226
arm64	0.014451	0.471098



```
In [10]: #First step assumption:
    #Based on plot and statistics above, we first assmue Processor > TotalDi
    skCapacity > Processor Core count
```

In [ ]:

```
In [11]: # deep study
```

```
In [13]: X train, X test, y train, y test = train test split(train.dropna().drop(
         'HasDetections',axis = 1)\
                                                              , train.dropna()['Ha
         sDetections'], test_size=0.25)
         N = len(y_test)
         y_random = y_test.sample(replace=False, frac = 1)
In [14]: output = pd.DataFrame(columns = ['Observation accuracy', 'Random Data ac
         curacy'], index = COLS[1:])
         for i in COLS[1:]:
             pl = skl([i])
             pl.fit(X_train, y_train)
             pred_score = pl.score(X_test, y_test)
             rand_score = pl.score(X_test, y_random)
             output.loc[i, 'Observation accuracy'] = pred score
             output.loc[i, 'Random_Data accuracy'] = rand_score
         pl = skl(COLS[1:])
         pl.fit(X_train, y_train)
         pred_score = pl.score(X_test, y_test)
         rand_score = pl.score(X_test, y_random)
         output.loc['combined', 'Observation accuracy'] = pred_score
         output.loc['combined', 'Random Data accuracy'] = rand_score
```

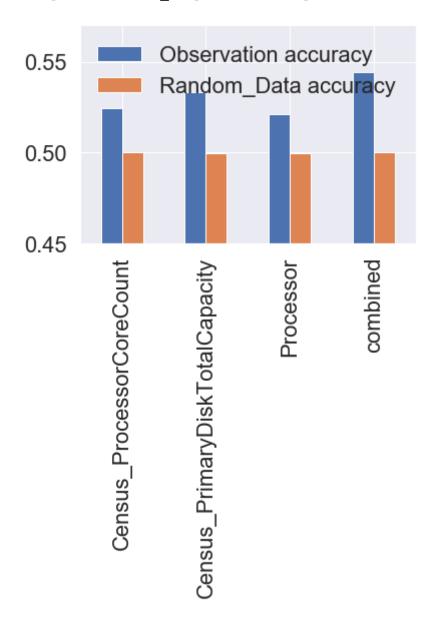
In [15]: output

#### Out[15]:

	Observation accuracy	Random_Data accuracy
Census_ProcessorCoreCount	0.524082	0.499893
Census_PrimaryDiskTotalCapacity	0.533193	0.499547
Processor	0.521055	0.49966
combined	0.543938	0.499912

```
In [16]: output.plot(kind = 'bar', ylim = (0.45, 0.57))
```

Out[16]: <matplotlib.axes.\_subplots.AxesSubplot at 0x21b00045748>



```
In [17]: # Conclusion, hardware can influence the prediction under random forest classifer of malware # The features combined has significant imporvement, which means it help
```

with malware detection

# when we combines features.

In [ ]:

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.linear model import LogisticRegression
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set option('display.max columns', 500)
```

In [2]: def analysis(col, tops = 10):

```
temp = train[col].value counts()
            temp = temp.iloc[:tops].index
            #temp = train.index
            temp df = train[train[col].isin(temp)]
              prob = temp df[col].value counts(normalize=True)
              draw = np.random.choice(prob.index, p=prob, size=len(temp df))
              output = pd.Series(draw).value counts(normalize=True).rename('simu
        lated')
              zeros = set(temp df[col].dropna().unique()).difference(set(output.
        index))
              output = output.append(pd.Series([0 for i in zeros], index = zero
        s)) / (temp df[col].value counts())
            temp df['shuffle'] = temp df['HasDetections'].sample(replace=False,
        n=len(temp df)).reset index(drop=True)
            output = temp_df[temp_df['shuffle'] == 1][col].value_counts() / temp
        df[col].value_counts()
            pd.DataFrame({'train_data': temp_df[temp_df['HasDetections'] == 1][c
        ol].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}).plot(kind = 'bar', figs
        ize=(20,10))
            plt.title('Percent of Has detections by {} (most of the catogaries)'
        .format(col))
            display(pd.DataFrame({'train_data': temp_df[temp_df['HasDetections']
        == 1][col].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}))
            return stats.ks 2samp(temp df[temp df['HasDetections'] == 1][col].va
        lue counts(normalize = True),
                        output)
        #stats.chi2 contingency([temp df.groupby(col).HasDetections.mean(),
                         temp df.groupby(col).random data.mean()])
In [3]: COLS = [
            'HasDetections',
            'IsBeta',
```

```
'ProductName'
```

```
In [4]: | train = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS)
```

```
In [5]: train.head()
```

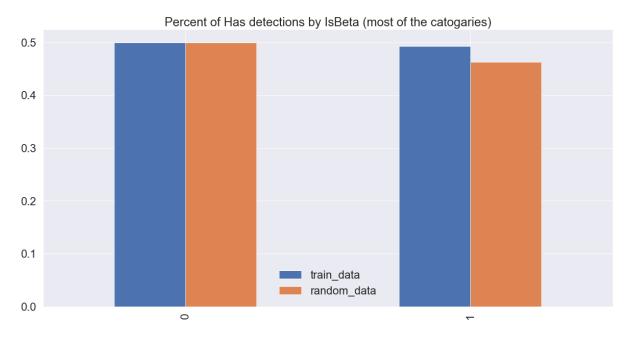
# Out[5]:

	ProductName	IsBeta	HasDetections
0	win8defender	0	0
1	win8defender	0	0
2	win8defender	0	0
3	win8defender	0	1
4	win8defender	0	1

# In [6]: analysis(COLS[1])

	train_data	random_data
0	0.499793	0.499793
1	0.492537	0.462687

Out[6]: Ks\_2sampResult(statistic=0.5, pvalue=0.8438198245415606)



In [7]: train.groupby('ProductName').HasDetections.mean()

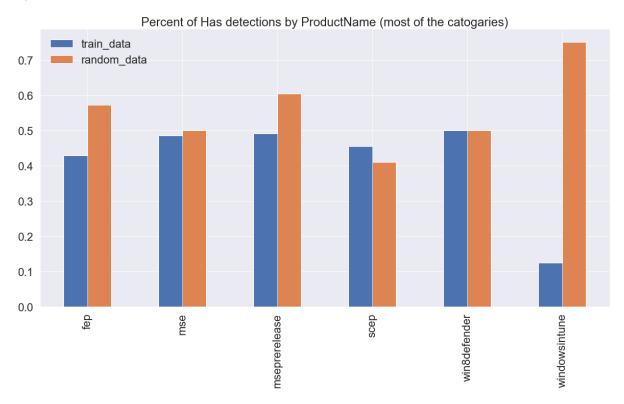
# Out[7]: ProductName

fep	0.428571
mse	0.484448
mseprerelease	0.490566
scep	0.454545
win8defender	0.499958
windowsintune	0.125000

Name: HasDetections, dtype: float64

In [8]: analysis(COLS[2])

	train_data	random_data
fep	0.428571	0.571429
mse	0.484448	0.499626
mseprerelease	0.490566	0.603774
scep	0.454545	0.409091
win8defender	0.499958	0.499794
windowsintune	0.125000	0.750000



In [9]: # We assume there has significantly difference between Defender State and Malware detection

In [ ]:

In [10]: # random forest clustering to confirm our assumption

```
In [13]: output = pd.DataFrame(columns = ['Observation accuracy', 'Random_Data accuracy'], index = COLS[1:])
    for i in COLS[1:]:
        pl = skl([i])
        pl.fit(X_train, y_train)
        pred_score = pl.score(X_test, y_test)
        rand_score = pl.score(X_test, y_random)
        output.loc[i, 'Observation accuracy'] = pred_score
        output.loc[i, 'Random_Data accuracy'] = rand_score
    pl = skl(COLS[1:])
    pl.fit(X_train, y_train)
    pred_score = pl.score(X_test, y_test)
    rand_score = pl.score(X_test, y_random)
    output.loc['combined', 'Observation accuracy'] = pred_score
    output.loc['combined', 'Random_Data accuracy'] = rand_score
```

```
In [14]: output
```

#### Out[14]:

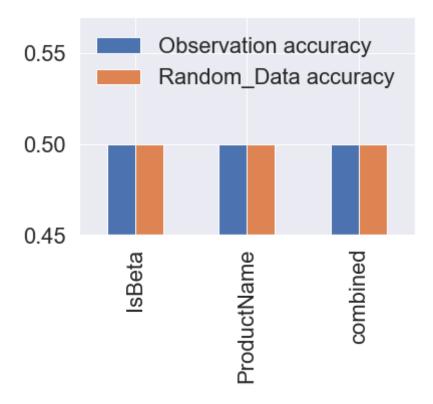
## Observation accuracy Random\_Data accuracy

IsBeta	0.500057	0.500054
ProductName	0.500058	0.500058
combined	0.500056	0.500057

3/25/2019 Scenario 4 Defender State

```
In [15]: output.plot(kind = 'bar', ylim = (0.45, 0.57))
```

Out[15]: <matplotlib.axes.\_subplots.AxesSubplot at 0x27d00074a20>



In [16]: # Conclusion: defender state has no influence to malware detection.

In [ ]:

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.linear model import LogisticRegression
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set_option('display.max columns', 500)
```

```
In [2]: def analysis(col, tops = 10):
            temp = train[col].value counts()
            temp = temp.iloc[:tops].index
            #temp = train.index
            temp df = train[train[col].isin(temp)]
              prob = temp df[col].value counts(normalize=True)
              draw = np.random.choice(prob.index, p=prob, size=len(temp df))
              output = pd.Series(draw).value counts(normalize=True).rename('simu
        lated')
              zeros = set(temp df[col].dropna().unique()).difference(set(output.
        index))
              output = output.append(pd.Series([0 for i in zeros], index = zero
        s)) / (temp df[col].value counts())
            temp df['shuffle'] = temp df['HasDetections'].sample(replace=False,
        n=len(temp df)).reset index(drop=True)
            output = temp_df[temp_df['shuffle'] == 1][col].value_counts() / temp
        _df[col].value_counts()
            pd.DataFrame({'train_data': temp_df[temp_df['HasDetections'] == 1][c
        ol].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}).plot(kind = 'bar', figs
        ize=(20,10))
            plt.title('Percent of Has detections by {} (most of the catogaries)'
        .format(col))
            display(pd.DataFrame({'train_data': temp_df[temp_df['HasDetections']
        == 1][col].value_counts()/ temp_df[col].value_counts(),
                                  'random data': output}))
            return stats.ks 2samp(temp df[temp df['HasDetections'] == 1][col].va
        lue counts(normalize = True),
                        output)
        #stats.chi2 contingency([temp df.groupby(col).HasDetections.mean(),
                          temp df.groupby(col).random data.mean()])
In [3]: COLS = [
            'HasDetections',
            'GeoNameIdentifier',
             'CountryIdentifier'
In [4]: | train = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS)
```

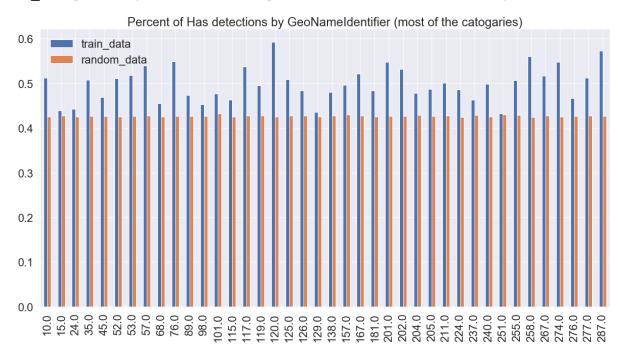
In [5]: #top 40 contries analysis

In [6]: analysis(COLS[1], 40)

	train_data	random_data
10.0	0.511848	0.425225
15.0	0.439316	0.427997
24.0	0.441928	0.424914
35.0	0.507216	0.426260
45.0	0.469069	0.425998
52.0	0.510999	0.425478
53.0	0.517883	0.426859
57.0	0.540070	0.427874
68.0	0.454544	0.425157
76.0	0.548960	0.426389
89.0	0.473733	0.426760
98.0	0.452187	0.426772
101.0	0.476334	0.431922
115.0	0.463466	0.425081
117.0	0.537920	0.427493
119.0	0.495623	0.427324
120.0	0.592210	0.425788
125.0	0.508966	0.427463
126.0	0.484070	0.427763
129.0	0.435529	0.425826
138.0	0.480256	0.428146
157.0	0.495774	0.429770
167.0	0.521564	0.427963
181.0	0.483826	0.425507
201.0	0.547603	0.426698
202.0	0.532145	0.425885
204.0	0.478396	0.429171
205.0	0.487162	0.426353
211.0	0.501151	0.427972
224.0	0.486248	0.424333
237.0	0.463296	0.428922
240.0	0.498015	0.425391
251.0	0.431757	0.429458
255.0	0.506378	0.428539

	train_data	random_data
258.0	0.559801	0.424347
267.0	0.516551	0.427381
274.0	0.547439	0.424971
276.0	0.466328	0.426719
277.0	0.511857	0.427246
287.0	0.573277	0.426770

Out[6]: Ks\_2sampResult(statistic=1.0, pvalue=6.133847783205273e-19)



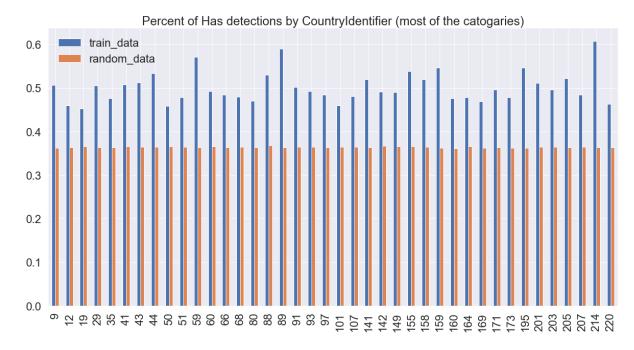
In [7]: #from the histogram, we see there is a difference in top 4 counties

In [8]: analysis(COLS[2], 40)

	train_data	random_data
9	0.506709	0.362701
12	0.459381	0.363193
19	0.452238	0.365839
29	0.505318	0.363857
35	0.476030	0.363344
41	0.507615	0.366280
43	0.512030	0.365131
44	0.533652	0.365011
50	0.458017	0.366223
51	0.478736	0.364130
59	0.570547	0.363931
60	0.492523	0.365513
66	0.484162	0.363982
68	0.479183	0.364715
80	0.469614	0.363214
88	0.530356	0.367622
89	0.589220	0.363697
91	0.501763	0.364579
93	0.492203	0.364471
97	0.483811	0.363961
101	0.459183	0.364113
107	0.481192	0.365178
141	0.519668	0.363257
142	0.490838	0.367251
149	0.490176	0.365425
155	0.538468	0.366261
158	0.519582	0.364786
159	0.546358	0.361953
160	0.475467	0.361555
164	0.477821	0.366351
169	0.468479	0.362477
171	0.496332	0.363675
173	0.477802	0.362556
195	0.546919	0.362091

	train_data	random_data
201	0.510665	0.364352
203	0.496419	0.364436
205	0.521958	0.363683
207	0.483938	0.364686
214	0.606910	0.363608
220	0.463472	0.363520

Out[8]: Ks\_2sampResult(statistic=1.0, pvalue=6.133847783205273e-19)



In [9]: # We assume there is no significant influence when malware detection

### In [10]: # random forest clustering to confirm

```
In [13]: output = pd.DataFrame(columns = ['Observation accuracy', 'Random_Data accuracy'], index = COLS[1:])
    for i in COLS[1:]:
        pl = skl([i])
        pl.fit(X_train, y_train)
        pred_score = pl.score(X_test, y_test)
        rand_score = pl.score(X_test, y_random)
        output.loc[i, 'Observation accuracy'] = pred_score
        output.loc[i, 'Random_Data accuracy'] = rand_score
    pl = skl(COLS[1:])
    pl.fit(X_train, y_train)
    pred_score = pl.score(X_test, y_test)
    rand_score = pl.score(X_test, y_random)
    output.loc['combined', 'Observation accuracy'] = pred_score
    output.loc['combined', 'Random_Data accuracy'] = rand_score
```

In [14]: output

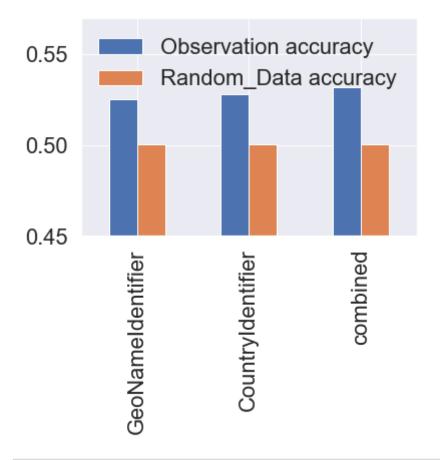
#### Out[14]:

#### Observation accuracy Random\_Data accuracy

GeoNameIdentifier	0.525165	0.500321
Countryldentifier	0.528054	0.500553
combined	0.532115	0.500415

```
In [15]: output.plot(kind = 'bar', ylim = (0.45, 0.57))
```

Out[15]: <matplotlib.axes.\_subplots.AxesSubplot at 0x17886078898>



```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.linear model import LogisticRegression
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set_option('display.max columns', 500)
```

```
In [2]: COLS1 = [
             'HasDetections',
             'AVProductStatesIdentifier','AVProductsInstalled', 'AVProductsEnable
        d'
         ]
        COLS2 = [
             'HasDetections',
             'Platform',
             'OsBuild'
         ]
        COLS3 = [
             'HasDetections',
             'Census ProcessorCoreCount',
             'Census PrimaryDiskTotalCapacity',
             'Processor'
        COLS4 = [
             'HasDetections',
             'IsBeta',
             'ProductName'
        COLS5 = [
             'HasDetections',
             'GeoNameIdentifier',
             'CountryIdentifier'
         ]
```

```
In [3]: train_1 = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS1)
    train_2 = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS2)
    train_3 = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS3)
    train_4 = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS4)
    train_5 = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS5)
```

```
In [4]: train_1.head()
```

### Out[4]:

	<b>AVProductStatesIdentifier</b>	AVProductsInstalled	AVProductsEnabled	HasDetections
0	53447.0	1.0	1.0	0
1	53447.0	1.0	1.0	0
2	53447.0	1.0	1.0	0
3	53447.0	1.0	1.0	1
4	53447.0	1.0	1.0	1

```
In [28]: train_1.describe()
```

## Out[28]:

	<b>AVProductStatesIdentifier</b>	AVProductsInstalled	AVProductsEnabled	HasDetections
count	8.885262e+06	8.885262e+06	8.885262e+06	8.921483e+06
mean	4.784001e+04	1.326779e+00	1.020967e+00	4.997927e-01
std	1.403237e+04	5.229272e-01	1.675544e-01	5.000000e-01
min	3.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	4.948000e+04	1.000000e+00	1.000000e+00	0.000000e+00
50%	5.344700e+04	1.000000e+00	1.000000e+00	0.000000e+00
75%	5.344700e+04	2.000000e+00	1.000000e+00	1.000000e+00
max	7.050700e+04	7.000000e+00	5.000000e+00	1.000000e+00

In [ ]:

In [5]: train\_2.head()

# Out[5]:

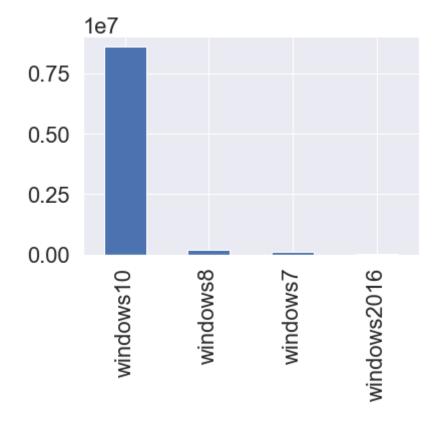
	Platform	OsBuild	HasDetections
0	windows10	17134	0
1	windows10	17134	0
2	windows10	17134	0
3	windows10	17134	1
4	windows10	17134	1

In [29]: train\_2.describe()

# Out[29]:

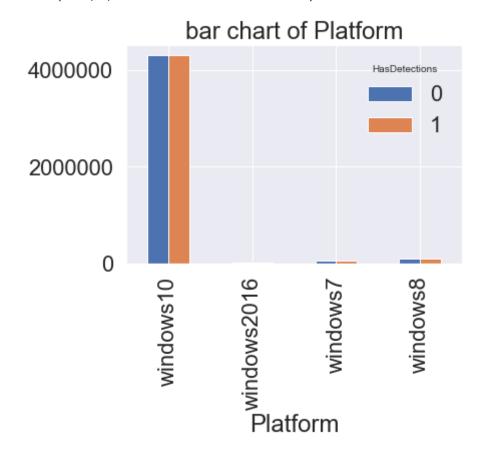
	OsBuild	HasDetections
count	8.921483e+06	8.921483e+06
mean	1.571997e+04	4.997927e-01
std	2.190685e+03	5.000000e-01
min	7.600000e+03	0.000000e+00
25%	1.506300e+04	0.000000e+00
50%	1.629900e+04	0.000000e+00
75%	1.713400e+04	1.000000e+00
max	1.824400e+04	1.000000e+00

Out[31]: <matplotlib.axes.\_subplots.AxesSubplot at 0x18391944710>



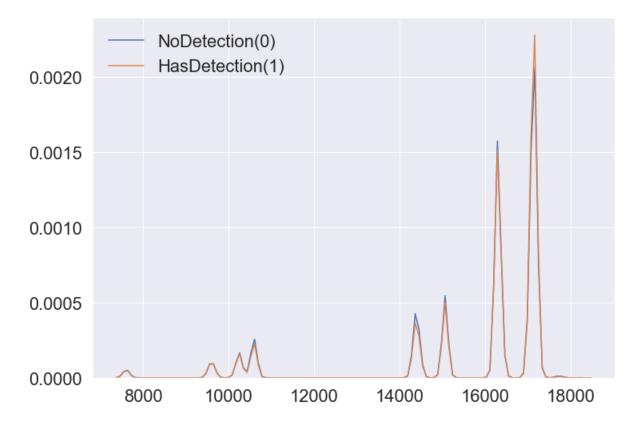
```
In [23]: train_2.pivot_table(index = 'Platform', columns = 'HasDetections', aggfu
nc = 'size').plot(kind = 'bar')
plt.title('bar chart of {}'.format('Platform'))
```

Out[23]: Text(0.5,1,'bar chart of Platform')



```
In [14]: fig, ax = plt.subplots(figsize=(11.7, 8.27))
    sns.kdeplot(train_2.loc[train_2['HasDetections'] == 0, 'OsBuild'], label
    ='NoDetection(0)')
    sns.kdeplot(train_2.loc[train_2['HasDetections'] == 1, 'OsBuild'], label
    ='HasDetection(1)')
```

Out[14]: <matplotlib.axes.\_subplots.AxesSubplot at 0x2868e0d2128>



```
In [ ]:
```

In [ ]:

In [9]: train\_3.head()

Out[9]:

	Processor	Census_ProcessorCoreCount	Census_PrimaryDiskTotalCapacity	HasDetections
0	x64	4.0	476940.0	0
1	x64	4.0	476940.0	0
2	x64	4.0	114473.0	0
3	x64	4.0	238475.0	1
4	x64	4.0	476940.0	1

In [32]: train\_3.describe()

Out[32]:

	Census_ProcessorCoreCount	Census_PrimaryDiskTotalCapacity	HasDetections
count	8.880177e+06	8.868467e+06	8.921483e+06
mean	3.989696e+00	3.089053e+06	4.997927e-01
std	2.082553e+00	4.451634e+09	5.000000e-01
min	1.000000e+00	0.000000e+00	0.000000e+00
25%	2.000000e+00	2.393720e+05	0.000000e+00
50%	4.000000e+00	4.769400e+05	0.000000e+00
75%	4.000000e+00	9.538690e+05	1.000000e+00
max	1.920000e+02	8.160437e+12	1.000000e+00

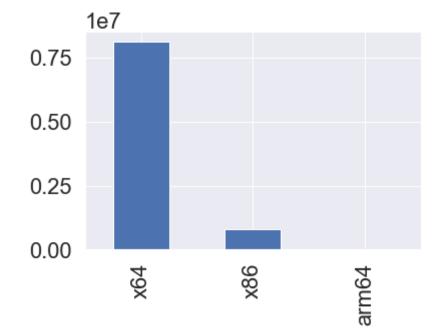
In [33]: train\_3.Processor.value\_counts()

Out[33]: x64 8105435 x86 815702 arm64 346

Name: Processor, dtype: int64

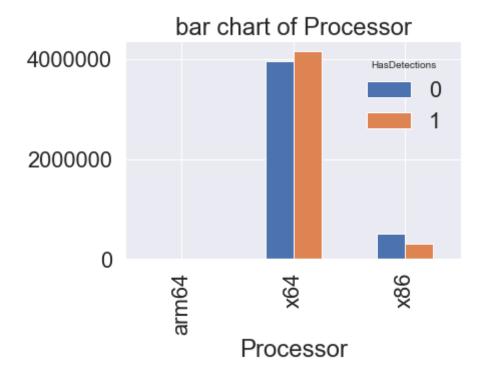
In [34]: train\_3.Processor.value\_counts().plot(kind = 'bar')

Out[34]: <matplotlib.axes.\_subplots.AxesSubplot at 0x18391999dd8>

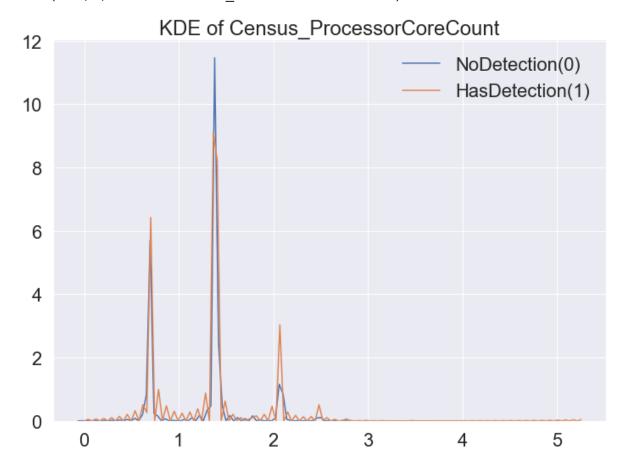


```
In [24]: train_3.pivot_table(index = 'Processor', columns = 'HasDetections', aggf
unc = 'size').plot(kind = 'bar')
plt.title('bar chart of {}'.format('Processor'))
```

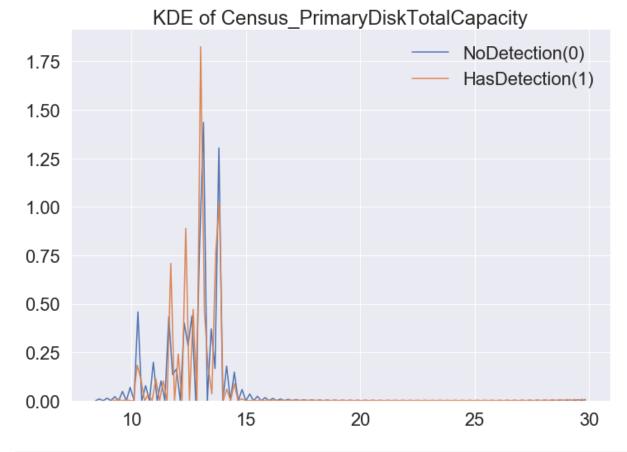
Out[24]: Text(0.5,1,'bar chart of Processor')



Out[69]: Text(0.5,1,'KDE of Census\_ProcessorCoreCount')



Out[70]: Text(0.5,1,'KDE of Census\_PrimaryDiskTotalCapacity')



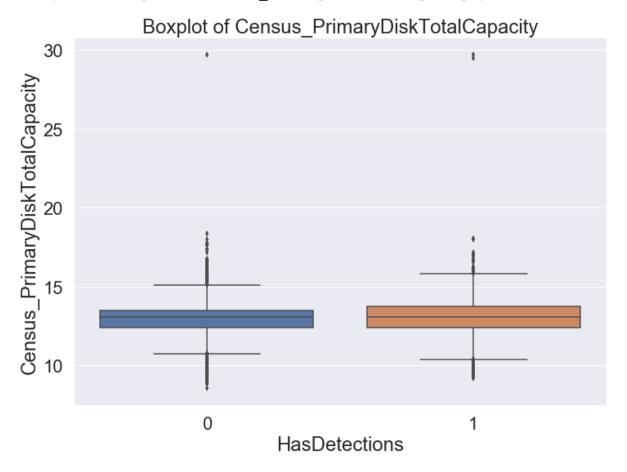
```
In [71]: log_train_3 = train_3.copy()
    log_train_3['Census_PrimaryDiskTotalCapacity'] = np.log(log_train_3['Census_PrimaryDiskTotalCapacity'])
```

```
In [72]: # 16TB = 16777216MB which is the largest capacity available, we use it a
    s the cutoff to avoid outliers
    np.log(16777216)
```

Out[72]: 16.635532333438686

```
In [74]: fig, ax = plt.subplots(figsize=(11.7, 8.27))
    ax = sns.boxplot(data=log_train_3, x='HasDetections', y='Census_PrimaryDiskTotalCapacity')
    plt.title('Boxplot of {}'.format('Census_PrimaryDiskTotalCapacity'))
```

Out[74]: Text(0.5,1,'Boxplot of Census\_PrimaryDiskTotalCapacity')



```
In [ ]:
In [ ]:
In [ ]:
In [ ]:
In [10]: train_4.head()
```

Out[10]:

	ProductName	IsBeta	HasDetections
0	win8defender	0	0
1	win8defender	0	0
2	win8defender	0	0
3	win8defender	0	1
4	win8defender	0	1

```
In [35]: train_4.describe()
```

### Out[35]:

	IsBeta	HasDetections
count	8.921483e+06	8.921483e+06
mean	7.509962e-06	4.997927e-01
std	2.740421e-03	5.000000e-01
min	0.000000e+00	0.000000e+00
25%	0.000000e+00	0.000000e+00
50%	0.000000e+00	0.000000e+00
75%	0.000000e+00	1.000000e+00
max	1.000000e+00	1.000000e+00

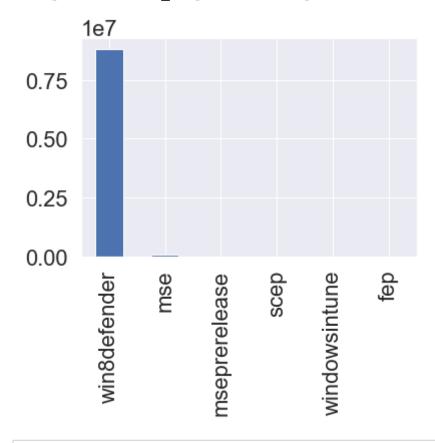
```
In [36]: train_4.ProductName.value_counts()
```

```
Out[36]: win8defender 8826520 mse 94873 mseprerelease 53 scep 22 windowsintune 8 fep 7
```

Name: ProductName, dtype: int64

```
In [38]: train_4.ProductName.value_counts().plot(kind = 'bar')
```

Out[38]: <matplotlib.axes.\_subplots.AxesSubplot at 0x18391a311d0>



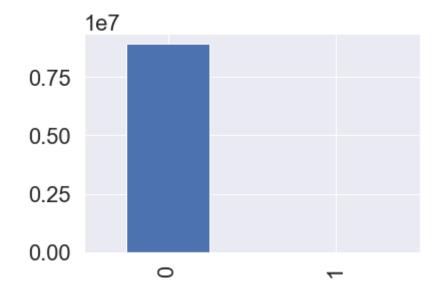
```
In [39]: train_4.IsBeta.value_counts()
```

Out[39]: 0 8921416 1 67

Name: IsBeta, dtype: int64

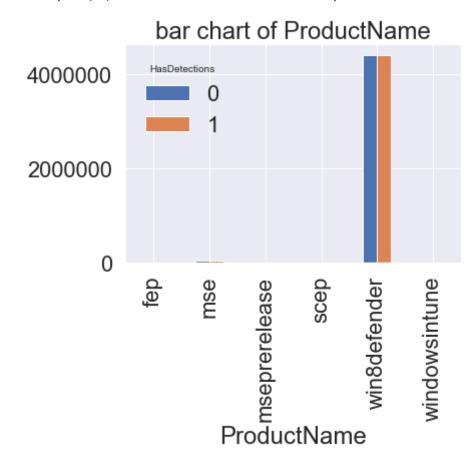
```
In [40]: train_4.IsBeta.value_counts().plot(kind = 'bar')
```

Out[40]: <matplotlib.axes.\_subplots.AxesSubplot at 0x18391a89e80>

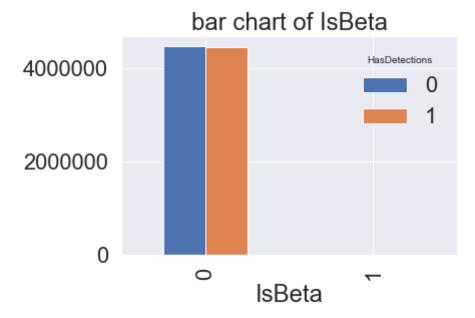


```
In [26]: train_4.pivot_table(index = 'ProductName', columns = 'HasDetections', ag
    gfunc = 'size').plot(kind = 'bar')
    plt.title('bar chart of {}'.format('ProductName'))
```

Out[26]: Text(0.5,1,'bar chart of ProductName')



```
Out[27]: Text(0.5,1,'bar chart of IsBeta')
```



```
In []: #special analysis of isbeta
In [46]: len(train_4[ (train_4.HasDetections == 1) & (train_4.IsBeta == 1)]) / (1 en(train_4[ (train_4.IsBeta == 1)]))
Out[46]: 0.4925373134328358
In [47]: len(train_4[ (train_4.HasDetections == 1) & (train_4.IsBeta == 0)]) / (1 en(train_4[ (train_4.IsBeta == 0)]))
Out[47]: 0.4997927459049102
In [48]: # same, isbeta ignored
In [11]: train_5.head()
Out[11]:
Country/deptifier GeoNameIdentifier HasDetections
```

	Countryldentifier	GeoNameIdentifier	HasDetections
0	29	35.0	0
1	93	119.0	0
2	86	64.0	0
3	88	117.0	1
4	18	277.0	1

In [49]: train\_5.CountryIdentifier.value\_counts()

2017		
Out[49]:	43	397172
046[47].		
	29	347991
	141	333411
	93	283625
	171	280572
	60	231981
	201	220622
	207	211645
	66	208579
	89	200516
	97	195161
	214	191269
	158	184766
	44	182707
	9	172594
	107	168997
	41	160533
	68	160158
	51	159940
	203	158058
	35	140027
	160	132251
	142	131907
	195	131685
	149	129578
	205	117245
	155	110779
	164	108549
	173	94129
	159	91592
	133	91392
	74	775
	192	740
	182	696
	134	689
	196	681
	198	656
	123	654
	75	643
	114	590
	126	566
	64	565
	28	553
	215	543
	105	507
	5	459
	174	449
	14	446
	79	444
	187	438
	216	379
	200	355
	10	327
	128	303
	212	299
	186	227
	165	213

 37
 212

 193
 207

 161
 206

 217
 120

Name: CountryIdentifier, Length: 222, dtype: int64

In [54]: train\_5.CountryIdentifier.nunique()

Out[54]: 222

In [55]: #222 countries

In [53]: train\_5.GeoNameIdentifier.value\_counts()

258.0 85291 129.0 84929 15.0 78629  215.0 27 231.0 19 37.0 18 95.0 14 292.0 13	129.0 84929 15.0 78629  215.0 27 231.0 19 37.0 18 95.0 14	Out[53]:	211.0 53.0 89.0 240.0 35.0 167.0 276.0 267.0 126.0 98.0 119.0 138.0 255.0 57.0 10.0 52.0 204.0 120.0 181.0 45.0 205.0 202.0 224.0 157.0 201.0 117.0	1531929 423166 408807 360798 346568 345904 339845 296774 215812 198021 184459 181876 172941 162193 155478 143023 140200 137451 128907 127368 114902 114506 112056 101510 99616 92651 89426
	259.0 11 124.0 9 249.0 7 242.0 6 280.0 6 169.0 5 116.0 5 260.0 5 290.0 4		129.0 15.0 215.0 231.0 37.0 95.0	84929 78629  27 19 18 14

1

1

```
14.0
197.0
279.0
132.0
```

Name: GeoNameIdentifier, Length: 292, dtype: int64

```
In [56]: train_5.GeoNameIdentifier.nunique()
```

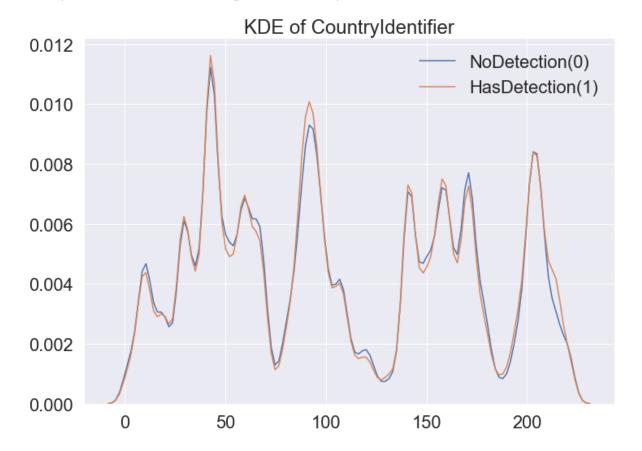
Out[56]: 292

```
In [57]: # 292 Geonames
```

```
In [75]: fig, ax = plt.subplots(figsize=(11.7, 8.27))
    sns.kdeplot(train_5.loc[train_5['HasDetections'] == 0, 'CountryIdentifie
    r'], label='NoDetection(0)')
    sns.kdeplot(train_5.loc[train_5['HasDetections'] == 1, 'CountryIdentifie
    r'], label='HasDetection(1)')

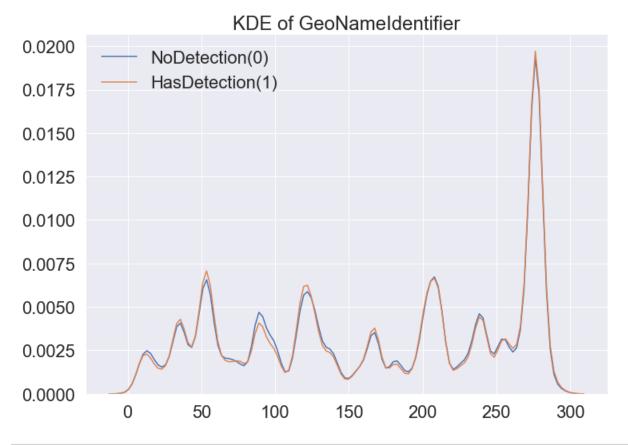
plt.title('KDE of {}'.format('CountryIdentifier'))
```

Out[75]: Text(0.5,1,'KDE of CountryIdentifier')



```
In [78]: fig, ax = plt.subplots(figsize=(11.7, 8.27))
    sns.kdeplot(train_5.loc[train_5['HasDetections'] == 0, 'GeoNameIdentifie
    r'], label='NoDetection(0)')
    sns.kdeplot(train_5.loc[train_5['HasDetections'] == 1, 'GeoNameIdentifie
    r'], label='HasDetection(1)')
    plt.title('KDE of {}'.format('GeoNameIdentifier'))
```

Out[78]: Text(0.5,1,'KDE of GeoNameIdentifier')





```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier, GradientBoostingCla
        ssifier
        from sklearn.linear model import LogisticRegression
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.linear model import SGDClassifier
        from sklearn.svm import LinearSVC
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set option('display.max columns', 500)
In [2]: COLS = [
              'HasDetections',
            'AVProductStatesIdentifier',
             'AVProductsInstalled',
            'GeoNameIdentifier',
             'CountryIdentifier',
             'OsBuild',
            'Census ProcessorCoreCount',
             'Census PrimaryDiskTotalCapacity',
            'Processor'
        ]
```

```
In [3]: train = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS)
In [4]: X train, X test, y train, y test = train test split(train.dropna().drop(
        'HasDetections',axis = 1)\
                                                              , train.dropna()['Ha
        sDetections'], test_size=0.25)
        N = len(y_test)
        y random = y test.sample(replace=False, frac = 1)
In [5]: | output = pd.DataFrame(columns = ['Observation accuracy', 'Random Data ac
        curacy'])
In [6]: def skl(col):
            nominal_transformer = Pipeline(steps=[
                ('onehot', OneHotEncoder(handle_unknown='ignore'))
            preproc = ColumnTransformer(transformers=[('onehot', nominal transfo
        rmer, col)],\
                                                   remainder='drop')
            clf = RandomForestClassifier(n_estimators=7, max_depth=60)
            pl = Pipeline(steps=[('preprocessor', preproc),
                             ('clf', clf)
                             1)
            return pl
In [ ]: | pl = skl(COLS[1:])
        pl.fit(X train, y train)
        pred score = pl.score(X test, y test)
        rand score = pl.score(X test, y random)
        output.loc['LinearSVC', 'Observation accuracy'] = pred_score
        output.loc['LinearSVC', 'Random_Data accuracy'] = rand_score
In [ ]: output
```

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier, GradientBoostingCla
        ssifier
        from sklearn.linear model import LogisticRegression
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.linear model import SGDClassifier
        from sklearn.svm import LinearSVC
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set option('display.max columns', 500)
In [2]: COLS = [
            'HasDetections',
            'AVProductStatesIdentifier',
            'AVProductsInstalled',
            'GeoNameIdentifier',
             'CountryIdentifier',
             'OsBuild',
            'Census ProcessorCoreCount',
             'Census PrimaryDiskTotalCapacity',
            'Processor'
        ]
```

```
In [3]: train = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS)
In [4]: X train, X test, y train, y test = train test split(train.dropna().drop(
        'HasDetections',axis = 1)\
                                                              , train.dropna()['Ha
        sDetections'], test_size=0.25)
        N = len(y_test)
        y random = y test.sample(replace=False, frac = 1)
In [5]: | output = pd.DataFrame(columns = ['Observation accuracy', 'Random Data ac
        curacy'])
In [6]: def skl(col):
            nominal transformer = Pipeline(steps=[
                ('onehot', OneHotEncoder(handle_unknown='ignore'))
            preproc = ColumnTransformer(transformers=[('onehot', nominal transfo
        rmer, col)],\
                                                   remainder='drop')
            clf = SGDClassifier()
            pl = Pipeline(steps=[('preprocessor', preproc),
                             ('clf', clf)
                             1)
            return pl
In [ ]: | pl = skl(COLS[1:])
        pl.fit(X train, y train)
        pred score = pl.score(X test, y test)
        rand score = pl.score(X test, y random)
        output.loc['SGDClassifier', 'Observation accuracy'] = pred_score
        output.loc['SGDClassifier', 'Random Data accuracy'] = rand score
In [ ]: output
```

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier, GradientBoostingCla
        ssifier
        from sklearn.linear model import LogisticRegression
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.linear model import SGDClassifier
        from sklearn.svm import LinearSVC
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set option('display.max columns', 500)
In [2]: COLS = [
            'HasDetections',
            'AVProductStatesIdentifier',
            'AVProductsInstalled',
            'GeoNameIdentifier',
             'CountryIdentifier',
             'OsBuild',
            'Census ProcessorCoreCount',
             'Census PrimaryDiskTotalCapacity',
            'Processor'
        ]
```

```
In [3]: train = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS)
In [4]: X train, X test, y train, y test = train test split(train.dropna().drop(
        'HasDetections',axis = 1)\
                                                              , train.dropna()['Ha
        sDetections'], test_size=0.25)
        N = len(y_test)
        y random = y test.sample(replace=False, frac = 1)
In [5]: | output = pd.DataFrame(columns = ['Observation accuracy', 'Random Data ac
        curacy'])
In [6]: def skl(col):
            nominal transformer = Pipeline(steps=[
                ('onehot', OneHotEncoder(handle_unknown='ignore'))
            preproc = ColumnTransformer(transformers=[('onehot', nominal transfo
        rmer, col)],\
                                                   remainder='drop')
            clf = SGDClassifier()
            pl = Pipeline(steps=[('preprocessor', preproc),
                             ('clf', clf)
                             1)
            return pl
In [ ]: | pl = skl(COLS[1:])
        pl.fit(X train, y train)
        pred score = pl.score(X test, y test)
        rand score = pl.score(X test, y random)
        output.loc['SGDClassifier', 'Observation accuracy'] = pred_score
        output.loc['SGDClassifier', 'Random Data accuracy'] = rand score
In [ ]: output
```

```
In [ ]: from sklearn.feature selection import RFE
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.preprocessing import LabelEncoder
        #from sklearn.impute import SimpleImputer
        import pandas as pd
        import numpy as np
        import lightgbm as lgb
In [ ]: | import numpy as np
        import pandas as pd
        import os
        import seaborn as sns
        import matplotlib.pyplot as plt
        %matplotlib inline
        plt.style.use('ggplot')
        import lightgbm as lgb
        import time
        import datetime
        from sklearn.preprocessing import LabelEncoder
        from sklearn.model selection import StratifiedKFold, KFold, TimeSeriesSp
        lit
        from sklearn.metrics import mean_squared_error, roc_auc_score
        from sklearn.linear model import LogisticRegression, LogisticRegressionC
        import qc
        from tqdm import tqdm notebook
        import warnings
        warnings.filterwarnings("ignore")
        import logging
In [ ]: #selecting columns we chosde, and ranking them in feature selection mode
        l via random forest
In [ ]: train = pd.read_csv("train.csv", sep=',', engine='c', keep_default_na =
        False)
In [ ]: train.head()
In [ ]: clf = RandomForestClassifier(n estimators=7, max depth=60)
In [ ]: selector = RFE(clf, n_features_to_select=20)
```

```
In [ ]: y = train['HasDetections']
        train = train.drop(['HasDetections', 'MachineIdentifier'], axis=1)
        test = test.drop(['MachineIdentifier'], axis=1)
        gc.collect()
        train.sort_values('AvSigVersion')
        train1 = train[:4000000]
        train = train[4000000:8000000]
        y1 = y[:4000000]
        y = y[4000000:8000000]
In [ ]: n_fold = 5
        folds = StratifiedKFold(n splits=n fold, shuffle=True, random state=15)
In [ ]: #imputer = SimpleImputer(missing values=np.nan, strategy='most frequen
        t')
        onehot = LabelEncoder()
In [ ]:
In [ ]: X = X.astype(str).apply(LabelEncoder().fit_transform)
        selector.fit(X, y)
In [ ]:
In [ ]: | selector.verbose
In [ ]:
```

3/25/2019 Additional features

```
In [ ]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        #import lightqbm as lqb
        from sklearn.model_selection import KFold
        import warnings
        import gc
        import time
        import sys
        import datetime
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import mean_squared_error
        warnings.simplefilter(action='ignore', category=FutureWarning)
        warnings.filterwarnings('ignore')
        from sklearn import metrics
        import scipy.stats as stats
        from sklearn.model_selection import permutation_test_score
        from sklearn.model selection import train test split
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.base import BaseEstimator, ClassifierMixin
        from sklearn.preprocessing import FunctionTransformer
        from sklearn.preprocessing import OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.ensemble import RandomForestClassifier, GradientBoostingCla
        ssifier
        from sklearn.linear model import LogisticRegression
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.linear model import SGDClassifier
        from sklearn.svm import LinearSVC
        plt.style.use('seaborn')
        sns.set(font scale=2)
        pd.set option('display.max columns', 500)
```

3/25/2019 Additional features

```
In [ ]: # we selecting top 20 columns from the feature selection model of Recurs
        ive feature elimination
        COLS = [
             'HasDetections',
             'CountryIdentifier',
             'Census OSVersion',
             'GeoNameIdentifier',
             'Census OSBuildRevision',
             'OsBuildLab',
             'LocaleEnglishNameIdentifier',
             'Census FirmwareManufacturerIdentifier',
             'AppVersion',
             'AVProductStatesIdentifier',
             'SmartScreen',
             'AvSigVersion',
             'Census_OEMModelIdentifier',
             'Census FirmwareVersionIdentifier',
             'Census SystemVolumeTotalCapacity',
             'CityIdentifier',
             'Census OSVersion',
             'EngineVersion',
             'Census_OEMNameIdentifier',
             'Census_ProcessorModelIdentifier',
             'Census OSInstallTypeName'
        1
In [ ]: | train = pd.read_csv("train.csv", sep=',', engine='c', usecols=COLS)
In [ ]: | X train, X test, y train, y test = train test split(train.dropna().drop(
        'HasDetections',axis = 1)\
                                                              , train.dropna()['Ha
        sDetections'], test size=0.25)
        N = len(y test)
        y_random = y_test.sample(replace=False, frac = 1)
In [ ]: output = pd.DataFrame(columns = ['Observation accuracy', 'Random Data ac
        curacy'])
In [ ]: def skl(col):
            nominal transformer = Pipeline(steps=[
                 ('onehot', OneHotEncoder(handle unknown='ignore'))
            preproc = ColumnTransformer(transformers=[('onehot', nominal transfo
        rmer, col)],\
                                                   remainder='drop')
            clf = RandomForestClassifier()
            pl = Pipeline(steps=[('preprocessor', preproc),
                             ('clf', clf)
                             ])
            return pl
```

3/25/2019 Additional features