# cse519_hw2_goutam_sanket_111463594

September 23, 2021

# 1 CSE519: HW2_Sanket_Goutam

## 1.1 Use the "Text" blocks to provide explanations wherever you find them necessary. Highlight your answers inside these text fields to ensure that we don't miss it while grading your HW.

## 1.2 Setup

- Dataset downloaded directly and saved locally

[1]:
```
import pandas as pd
import numpy as np
import random

# Display format for float values
pd.set_option('float_format', '{:f}'.format)

import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import pearsonr
from matplotlib.ticker import PercentFormatter
```

## 1.3 Section 1: Library and Data Imports (Q1)

- Import your libraries and read the data into a dataframe. Print the head of the dataframe.

[2]:
```
use_cols = ["MachineIdentifier", "SmartScreen", "AVProductsInstalled",␣
↪"AppVersion", "CountryIdentifier", "Census_OSInstallTypeName",␣
↪"Wdft_IsGamer",
            "EngineVersion", "AVProductStatesIdentifier", "Census_OSVersion",␣
↪"Census_TotalPhysicalRAM", "Census_ActivationChannel",
            "RtpStateBitfield", "Census_ProcessorModelIdentifier",␣
↪"Census_PrimaryDiskTotalCapacity",
             "Census_InternalPrimaryDiagonalDisplaySizeInInches",␣
↪"Wdft_RegionIdentifier", "LocaleEnglishNameIdentifier",
            "AvSigVersion", "IeVerIdentifier", "IsProtected",␣
↪"Census_InternalPrimaryDisplayResolutionVertical",␣
↪"Census_PrimaryDiskTypeName",
```

```
            "Census_OSWUAutoUpdateOptionsName", "Census_OSEdition",␣
↪"Census_GenuineStateName", "Census_ProcessorCoreCount",
           "Census_OEMNameIdentifier", "Census_MDC2FormFactor",␣
↪"Census_FirmwareManufacturerIdentifier", "OsBuildLab",␣
↪"Census_OSBuildRevision",
            "Census_OSBuildNumber", "Census_IsPenCapable",␣
↪"Census_IsTouchEnabled", "Census_IsAlwaysOnAlwaysConnectedCapable",␣
↪"Census_IsSecureBootEnabled",
            "Census_SystemVolumeTotalCapacity",␣
↪"Census_PrimaryDiskTotalCapacity", "HasDetections"
           ]
dtypes = {
        'MachineIdentifier':                                    'category',
        'ProductName':                                          'category',
        'EngineVersion':                                        'category',
        'AppVersion':                                           'category',
        'AvSigVersion':                                         'category',
        'IsBeta':                                               'int8',
        'RtpStateBitfield':                                     'float16',
        'IsSxsPassiveMode':                                     'int8',
        'DefaultBrowsersIdentifier':                            'float16',
        'AVProductStatesIdentifier':                            'float32',
        'AVProductsInstalled':                                  'float16',
        'AVProductsEnabled':                                    'float16',
        'HasTpm':                                               'int8',
        'CountryIdentifier':                                    'int16',
        'CityIdentifier':                                       'float32',
        'OrganizationIdentifier':                               'float16',
        'GeoNameIdentifier':                                    'float16',
        'LocaleEnglishNameIdentifier':                          'int8',
        'Platform':                                             'category',
        'Processor':                                            'category',
        'OsVer':                                                'category',
        'OsBuild':                                              'int16',
        'OsSuite':                                              'int16',
        'OsPlatformSubRelease':                                 'category',
        'OsBuildLab':                                           'category',
        'SkuEdition':                                           'category',
        'IsProtected':                                          'float16',
        'AutoSampleOptIn':                                      'int8',
        'PuaMode':                                              'category',
        'SMode':                                                'float16',
        'IeVerIdentifier':                                      'float16',
        'SmartScreen':                                          'category',
        'Firewall':                                             'float16',
        'UacLuaenable':                                         'float32',
        'Census_MDC2FormFactor':                                'category',
```

```
        'Census_DeviceFamily':                                  'category',
        'Census_OEMNameIdentifier':                             'float16',
        'Census_OEMModelIdentifier':                            'float32',
        'Census_ProcessorCoreCount':                            'float16',
        'Census_ProcessorManufacturerIdentifier':               'float16',
        'Census_ProcessorModelIdentifier':                      'float16',
        'Census_ProcessorClass':                                'category',
        'Census_PrimaryDiskTotalCapacity':                      'float32',
        'Census_PrimaryDiskTypeName':                           'category',
        'Census_SystemVolumeTotalCapacity':                     'float32',
        'Census_HasOpticalDiskDrive':                           'int8',
        'Census_TotalPhysicalRAM':                              'float32',
        'Census_ChassisTypeName':                               'category',
        'Census_InternalPrimaryDiagonalDisplaySizeInInches':    'float16',
        'Census_InternalPrimaryDisplayResolutionHorizontal':    'float16',
        'Census_InternalPrimaryDisplayResolutionVertical':      'float16',
        'Census_PowerPlatformRoleName':                         'category',
        'Census_InternalBatteryType':                           'category',
        'Census_InternalBatteryNumberOfCharges':                'float32',
        'Census_OSVersion':                                     'category',
        'Census_OSArchitecture':                                'category',
        'Census_OSBranch':                                      'category',
        'Census_OSBuildNumber':                                 'int16',
        'Census_OSBuildRevision':                               'int32',
        'Census_OSEdition':                                     'category',
        'Census_OSSkuName':                                     'category',
        'Census_OSInstallTypeName':                             'category',
        'Census_OSInstallLanguageIdentifier':                   'float16',
        'Census_OSUILocaleIdentifier':                          'int16',
        'Census_OSWUAutoUpdateOptionsName':                     'category',
        'Census_IsPortableOperatingSystem':                     'int8',
        'Census_GenuineStateName':                              'category',
        'Census_ActivationChannel':                             'category',
        'Census_IsFlightingInternal':                           'float16',
        'Census_IsFlightsDisabled':                             'float16',
        'Census_FlightRing':                                    'category',
        'Census_ThresholdOptIn':                                'float16',
        'Census_FirmwareManufacturerIdentifier':                'float16',
        'Census_FirmwareVersionIdentifier':                     'float32',
        'Census_IsSecureBootEnabled':                           'int8',
        'Census_IsWIMBootEnabled':                              'float16',
        'Census_IsVirtualDevice':                               'float16',
        'Census_IsTouchEnabled':                                'int8',
        'Census_IsPenCapable':                                  'int8',
        'Census_IsAlwaysOnAlwaysConnectedCapable':              'float16',
        'Wdft_IsGamer':                                         'float16',
        'Wdft_RegionIdentifier':                                'float16'
```

```
        }
```

Create a sample size from the data set, chosen randomly, for initial analysis. This is done so as to reduce the load on the system for processing the data.

[3]:
```
# Sampling random records from the dataset

n = 8921483 #number of records in file
s = int(n/8) #desired sample size

skip = sorted(random.sample(range(1,n+1),n-s))

# Uncomment below line to load entire dataset
skip = 0
```

[4]:
```
# Read csv file into a dataframe with the selected columns
filename = 'train.csv'
# load for select questions
data = pd.read_csv(filename, usecols = lambda x:x in use_cols, dtype = dtypes,␣
 ↪skiprows=skip)
```

Let's learn more about this dataframe. Let's look at what then dataframe looks like and how many rows have been loaded. But before, we need to set the index for the dataframe.

[5]:
```
# Set 'MachineIdentifier' as the Index for the dataframe
data.set_index('MachineIdentifier', inplace=True)
```

[8]:
```
data.shape
```

[8]: (1000000, 38)

[9]:
```
data.describe()
```

[9]:
```
       RtpStateBitfield  AVProductStatesIdentifier  AVProductsInstalled  \
count     996293.000000              995965.000000        995965.000000
mean                NaN               47777.648438                  NaN
std            0.000000               14035.049805             0.000000
min            0.000000                  16.000000             0.000000
25%            7.000000               49480.000000             1.000000
50%            7.000000               53447.000000             1.000000
75%            7.000000               53447.000000             2.000000
max           35.000000               70507.000000             6.000000

       CountryIdentifier  LocaleEnglishNameIdentifier   IsProtected  \
count     1000000.000000               1000000.000000 995987.000000
mean          108.058341                    27.854385           NaN
std            63.017084                    65.606418      0.000000
min             1.000000                  -127.000000      0.000000
```

```
25%           51.000000                          -29.000000      1.000000
50%           97.000000                           58.000000      1.000000
75%          162.000000                           75.000000      1.000000
max          222.000000                          126.000000      1.000000

       IeVerIdentifier  Census_OEMNameIdentifier  Census_ProcessorCoreCount  \
count    993302.000000             989177.000000              995353.000000
mean               NaN                       NaN                        NaN
std                NaN                       NaN                   0.000000
min           1.000000                 15.000000                   1.000000
25%         111.000000               1443.000000                   2.000000
50%         117.000000               2102.000000                   4.000000
75%         137.000000               2668.000000                   4.000000
max         429.000000               6144.000000                 112.000000

       Census_ProcessorModelIdentifier  …  Census_OSBuildNumber  \
count                    995350.000000  …        1000000.000000
mean                               NaN  …          15831.305397
std                                NaN  …           1966.159608
min                           3.000000  …           7601.000000
25%                        1998.000000  …          15063.000000
50%                        2500.000000  …          16299.000000
75%                        2874.000000  …          17134.000000
max                        4480.000000  …          18242.000000

       Census_OSBuildRevision  Census_FirmwareManufacturerIdentifier  \
count          1000000.000000                          979465.000000
mean               980.024081                                    NaN
std               2951.676927                                    NaN
min                  0.000000                               9.000000
25%                165.000000                             142.000000
50%                285.000000                             500.000000
75%                547.000000                             556.000000
max              24214.000000                            1084.000000

       Census_IsSecureBootEnabled  Census_IsTouchEnabled  Census_IsPenCapable  \
count              1000000.000000         1000000.000000       1000000.000000
mean                     0.486126               0.126244             0.038246
std                      0.499808               0.332124             0.191790
min                      0.000000               0.000000             0.000000
25%                      0.000000               0.000000             0.000000
50%                      0.000000               0.000000             0.000000
75%                      1.000000               0.000000             0.000000
max                      1.000000               1.000000             1.000000

       Census_IsAlwaysOnAlwaysConnectedCapable  Wdft_IsGamer  \
count                            991954.000000 965828.000000
```

```
mean                                0.057587       NaN
std                                 0.233154  0.000000
min                                 0.000000  0.000000
25%                                 0.000000  0.000000
50%                                 0.000000  0.000000
75%                                 0.000000  1.000000
max                                 1.000000  1.000000

       Wdft_RegionIdentifier  HasDetections
count          965828.000000 1000000.000000
mean                     NaN       0.499665
std                 0.000000       0.500000
min                 1.000000       0.000000
25%                 3.000000       0.000000
50%                10.000000       0.000000
75%                11.000000       1.000000
max                15.000000       1.000000

[8 rows x 25 columns]
```

[10]:
```
data.head(10)
```

[10]:
```
                                 EngineVersion       AppVersion  AvSigVersion  \
MachineIdentifier
000007535c3f730efa9ea0b7ef1bd645   1.1.14600.4     4.13.17134.1    1.263.48.0
00000b11598a75ea8ba1beea8459149f   1.1.15100.1  4.18.1807.18075  1.273.1527.0
000024872c81cf03fa862aa8f99e0984   1.1.15200.1  4.18.1807.18075   1.275.895.0
00003e5e679ccfe7a13e953c47dd584f   1.1.15200.1  4.18.1807.18075    1.275.26.0
000048a73fb4b6a94cc169389208032d   1.1.15200.1  4.18.1807.18075   1.275.482.0
0000714f389b8a3638597ee69b655e38   1.1.14600.4     4.9.10586.494   1.263.469.0
00007a70254b648e445a6e1937ab3efb   1.1.15200.1  4.18.1807.18075   1.275.795.0
0000870bccbcf600c7252517b1d39234   1.1.14306.0     4.13.17134.1   1.257.902.0
00008f5ffaf2a82e2ba75dd31d011c2c   1.1.15200.1       4.9.10586.0    1.275.30.0
000090720df1dd004c5cf6cd1c615643   1.1.15200.1  4.18.1807.18075    1.275.98.0

                                  RtpStateBitfield  AVProductStatesIdentifier  \
MachineIdentifier
000007535c3f730efa9ea0b7ef1bd645          7.000000               53447.000000
00000b11598a75ea8ba1beea8459149f          7.000000               53447.000000
000024872c81cf03fa862aa8f99e0984          7.000000               53447.000000
00003e5e679ccfe7a13e953c47dd584f          7.000000               53447.000000
000048a73fb4b6a94cc169389208032d          7.000000               53447.000000
0000714f389b8a3638597ee69b655e38          7.000000               53447.000000
00007a70254b648e445a6e1937ab3efb          7.000000               53447.000000
0000870bccbcf600c7252517b1d39234          7.000000                7945.000000
00008f5ffaf2a82e2ba75dd31d011c2c          7.000000               53447.000000
000090720df1dd004c5cf6cd1c615643          7.000000               53447.000000
```

```
                                 AVProductsInstalled  CountryIdentifier  \
MachineIdentifier
000007535c3f730efa9ea0b7ef1bd645            1.000000                 93
00000b11598a75ea8ba1beea8459149f            1.000000                 88
000024872c81cf03fa862aa8f99e0984            1.000000                171
00003e5e679ccfe7a13e953c47dd584f            1.000000                199
000048a73fb4b6a94cc169389208032d            1.000000                 68
0000714f389b8a3638597ee69b655e38            1.000000                 89
00007a70254b648e445a6e1937ab3efb            1.000000                100
0000870bccbcf600c7252517b1d39234            2.000000                155
00008f5ffaf2a82e2ba75dd31d011c2c            1.000000                190
000090720df1dd004c5cf6cd1c615643            1.000000                  9

                                 LocaleEnglishNameIdentifier  \
MachineIdentifier
000007535c3f730efa9ea0b7ef1bd645                           64
00000b11598a75ea8ba1beea8459149f                          115
000024872c81cf03fa862aa8f99e0984                          -74
00003e5e679ccfe7a13e953c47dd584f                           75
000048a73fb4b6a94cc169389208032d                           74
0000714f389b8a3638597ee69b655e38                          118
00007a70254b648e445a6e1937ab3efb                           75
0000870bccbcf600c7252517b1d39234                          -23
00008f5ffaf2a82e2ba75dd31d011c2c                           17
000090720df1dd004c5cf6cd1c615643                          -42

                                                                 OsBuildLab
\
MachineIdentifier
000007535c3f730efa9ea0b7ef1bd645       17134.1.amd64fre.rs4_release.180410-1804
00000b11598a75ea8ba1beea8459149f       17134.1.amd64fre.rs4_release.180410-1804
000024872c81cf03fa862aa8f99e0984       17134.1.amd64fre.rs4_release.180410-1804
00003e5e679ccfe7a13e953c47dd584f       17134.1.amd64fre.rs4_release.180410-1804
000048a73fb4b6a94cc169389208032d       17134.1.amd64fre.rs4_release.180410-1804
0000714f389b8a3638597ee69b655e38     10586.545.amd64fre.th2_release.160802-1857
00007a70254b648e445a6e1937ab3efb       17134.1.amd64fre.rs4_release.180410-1804
0000870bccbcf600c7252517b1d39234       17134.1.amd64fre.rs4_release.180410-1804
00008f5ffaf2a82e2ba75dd31d011c2c 10586.420.amd64fre.th2_release_sec.160527-1834
000090720df1dd004c5cf6cd1c615643       17134.1.amd64fre.rs4_release.180410-1804

                                 IsProtected  …  Census_GenuineStateName  \
MachineIdentifier                             …
000007535c3f730efa9ea0b7ef1bd645    1.000000  …                  OFFLINE
00000b11598a75ea8ba1beea8459149f    1.000000  …               IS_GENUINE
000024872c81cf03fa862aa8f99e0984    1.000000  …               IS_GENUINE
00003e5e679ccfe7a13e953c47dd584f    1.000000  …               IS_GENUINE
```

```
000048a73fb4b6a94cc169389208032d      1.000000  …           IS_GENUINE
0000714f389b8a3638597ee69b655e38      1.000000  …           IS_GENUINE
00007a70254b648e445a6e1937ab3efb      1.000000  …           IS_GENUINE
0000870bccbcf600c7252517b1d39234      1.000000  …       INVALID_LICENSE
00008f5ffaf2a82e2ba75dd31d011c2c      1.000000  …           IS_GENUINE
000090720df1dd004c5cf6cd1c615643      1.000000  …           IS_GENUINE

                                  Census_ActivationChannel  \
MachineIdentifier
000007535c3f730efa9ea0b7ef1bd645                    Retail
00000b11598a75ea8ba1beea8459149f                OEM:NONSLP
000024872c81cf03fa862aa8f99e0984                OEM:NONSLP
00003e5e679ccfe7a13e953c47dd584f               Volume:GVLK
000048a73fb4b6a94cc169389208032d                    Retail
0000714f389b8a3638597ee69b655e38                    Retail
00007a70254b648e445a6e1937ab3efb               Volume:GVLK
0000870bccbcf600c7252517b1d39234                    Retail
00008f5ffaf2a82e2ba75dd31d011c2c               Volume:GVLK
000090720df1dd004c5cf6cd1c615643                    Retail

                                  Census_FirmwareManufacturerIdentifier  \
MachineIdentifier
000007535c3f730efa9ea0b7ef1bd645                             628.000000
00000b11598a75ea8ba1beea8459149f                             355.000000
000024872c81cf03fa862aa8f99e0984                             142.000000
00003e5e679ccfe7a13e953c47dd584f                              93.000000
000048a73fb4b6a94cc169389208032d                             168.000000
0000714f389b8a3638597ee69b655e38                             554.000000
00007a70254b648e445a6e1937ab3efb                             554.000000
0000870bccbcf600c7252517b1d39234                             168.000000
00008f5ffaf2a82e2ba75dd31d011c2c                             355.000000
000090720df1dd004c5cf6cd1c615643                             142.000000

                                   Census_IsSecureBootEnabled  \
MachineIdentifier
000007535c3f730efa9ea0b7ef1bd645                            0
00000b11598a75ea8ba1beea8459149f                            0
000024872c81cf03fa862aa8f99e0984                            0
00003e5e679ccfe7a13e953c47dd584f                            0
000048a73fb4b6a94cc169389208032d                            0
0000714f389b8a3638597ee69b655e38                            1
00007a70254b648e445a6e1937ab3efb                            0
0000870bccbcf600c7252517b1d39234                            0
00008f5ffaf2a82e2ba75dd31d011c2c                            0
000090720df1dd004c5cf6cd1c615643                            0

                                   Census_IsTouchEnabled  Census_IsPenCapable  \
```

| MachineIdentifier | | |
|---|---|---|
| 000007535c3f730efa9ea0b7ef1bd645 | 0 | 0 |
| 00000b11598a75ea8ba1beea8459149f | 0 | 0 |
| 000024872c81cf03fa862aa8f99e0984 | 0 | 0 |
| 00003e5e679ccfe7a13e953c47dd584f | 0 | 0 |
| 000048a73fb4b6a94cc169389208032d | 1 | 0 |
| 0000714f389b8a3638597ee69b655e38 | 1 | 0 |
| 00007a70254b648e445a6e1937ab3efb | 0 | 0 |
| 0000870bccbcf600c7252517b1d39234 | 0 | 0 |
| 00008f5ffaf2a82e2ba75dd31d011c2c | 0 | 0 |
| 000090720df1dd004c5cf6cd1c615643 | 0 | 0 |

| | Census_IsAlwaysOnAlwaysConnectedCapable \ |
|---|---|
| MachineIdentifier | |
| 000007535c3f730efa9ea0b7ef1bd645 | 0.000000 |
| 00000b11598a75ea8ba1beea8459149f | 0.000000 |
| 000024872c81cf03fa862aa8f99e0984 | 0.000000 |
| 00003e5e679ccfe7a13e953c47dd584f | 0.000000 |
| 000048a73fb4b6a94cc169389208032d | 0.000000 |
| 0000714f389b8a3638597ee69b655e38 | 0.000000 |
| 00007a70254b648e445a6e1937ab3efb | 0.000000 |
| 0000870bccbcf600c7252517b1d39234 | 0.000000 |
| 00008f5ffaf2a82e2ba75dd31d011c2c | 0.000000 |
| 000090720df1dd004c5cf6cd1c615643 | 0.000000 |

| | Wdft_IsGamer | Wdft_RegionIdentifier \ |
|---|---|---|
| MachineIdentifier | | |
| 000007535c3f730efa9ea0b7ef1bd645 | 0.000000 | 8.000000 |
| 00000b11598a75ea8ba1beea8459149f | 0.000000 | 3.000000 |
| 000024872c81cf03fa862aa8f99e0984 | 0.000000 | 3.000000 |
| 00003e5e679ccfe7a13e953c47dd584f | 0.000000 | 11.000000 |
| 000048a73fb4b6a94cc169389208032d | 0.000000 | 12.000000 |
| 0000714f389b8a3638597ee69b655e38 | 0.000000 | 1.000000 |
| 00007a70254b648e445a6e1937ab3efb | 0.000000 | 11.000000 |
| 0000870bccbcf600c7252517b1d39234 | 0.000000 | 10.000000 |
| 00008f5ffaf2a82e2ba75dd31d011c2c | 1.000000 | 11.000000 |
| 000090720df1dd004c5cf6cd1c615643 | 0.000000 | 10.000000 |

| | HasDetections |
|---|---|
| MachineIdentifier | |
| 000007535c3f730efa9ea0b7ef1bd645 | 0 |
| 00000b11598a75ea8ba1beea8459149f | 1 |
| 000024872c81cf03fa862aa8f99e0984 | 0 |
| 00003e5e679ccfe7a13e953c47dd584f | 1 |
| 000048a73fb4b6a94cc169389208032d | 1 |
| 0000714f389b8a3638597ee69b655e38 | 1 |
| 00007a70254b648e445a6e1937ab3efb | 1 |

```
0000870bccbcf600c7252517b1d39234          0
00008f5ffaf2a82e2ba75dd31d011c2c          1
000090720df1dd004c5cf6cd1c615643          1

[10 rows x 38 columns]
```

### 1.4 Section 2: Measure of Power (Q2a & 2b)

***Q2a.* Define a measure of computer power as a function of RAM, processor core count and any other relevant features you find. What is the distribution of power among the machines in the dataset?**

Let's assume a simple function f(x,y) which defines the compute power of a system using > a: TotalPhysicalRAM

> b: ProcessorCoreCount.
>
> c: Wdft_IsGamer // Gaming systems are typically more powerful than an average system
>
> d: Census_PrimaryDiskTotalCapacity // Powerful systems typically tend to have higher Disk Capacity but not vice-versa

For simplicity, we assume that compute power f() is defined as > **f() = 0.3a + 0.4b + 0.2*c* + *0.1*d**

Weights are arbitrarily decided based on an understanding that CPUCoreCount and RAM contribute towards ComputePower more than other factors.

Note: We need to clean these columns first as some of them have NaN values, so we will just drop those rows with NaN values. For columns, $a$,$b$, and $d$ we will need to normalize their values to a range of 0 to 1. This is because their individual values are not on the same scale, and thus we cannot directly use them.

[209]:
```python
# Read csv file into a dataframe with the selected columns
filename = 'train.csv'

# Sampling random records from the dataset
n = 8921483 #number of records in file
s = int(n/8) #desired sample size

skip = sorted(random.sample(range(1,n+1),n-s))
# Uncomment the following line to load the entire dataset
skip = 0

data = pd.read_csv(filename, usecols = lambda x:x in use_cols, dtype = dtypes,␣
 ↪skiprows=skip)

# Set 'MachineIdentifier' as the Index for the dataframe
data.set_index('MachineIdentifier', inplace=True)
```

[210]:
```python
#Load the respective columns to the dataframe

_cols = ['Census_TotalPhysicalRAM', 'Census_ProcessorCoreCount', 'Wdft_IsGamer',
         'Census_PrimaryDiskTotalCapacity','HasDetections']

df = data[_cols]
df.shape
```

[210]: (8921483, 5)

[211]:
```python
df.head(10)
```

[211]:
```
                                  Census_TotalPhysicalRAM  \
MachineIdentifier
0000028988387b115f69f31a3bf04f09              4096.000000
000007535c3f730efa9ea0b7ef1bd645              4096.000000
000007905a28d863f6d0d597892cd692              4096.000000
00000b11598a75ea8ba1beea8459149f              4096.000000
000014a5f00daa18e76b81417eeb99fc              6144.000000
000016191b897145d069102325cab760              8192.000000
0000161e8abf8d8b89c5ab8787fd712b              4096.000000
000019515bc8f95851aff6de873405e8              4096.000000
00001a027a0ab970c408182df8484fce              4096.000000
00001a18d69bb60bda9779408dcf02ac              8192.000000

                                  Census_ProcessorCoreCount  Wdft_IsGamer  \
MachineIdentifier
0000028988387b115f69f31a3bf04f09                   4.000000      0.000000
000007535c3f730efa9ea0b7ef1bd645                   4.000000      0.000000
000007905a28d863f6d0d597892cd692                   4.000000      0.000000
00000b11598a75ea8ba1beea8459149f                   4.000000      0.000000
000014a5f00daa18e76b81417eeb99fc                   4.000000      0.000000
000016191b897145d069102325cab760                   2.000000      0.000000
0000161e8abf8d8b89c5ab8787fd712b                   2.000000      0.000000
000019515bc8f95851aff6de873405e8                   2.000000      0.000000
00001a027a0ab970c408182df8484fce                   4.000000      0.000000
00001a18d69bb60bda9779408dcf02ac                   4.000000      1.000000

                                  Census_PrimaryDiskTotalCapacity  \
MachineIdentifier
0000028988387b115f69f31a3bf04f09                    476940.000000
000007535c3f730efa9ea0b7ef1bd645                    476940.000000
000007905a28d863f6d0d597892cd692                    114473.000000
00000b11598a75ea8ba1beea8459149f                    238475.000000
000014a5f00daa18e76b81417eeb99fc                    476940.000000
000016191b897145d069102325cab760                    114473.000000
0000161e8abf8d8b89c5ab8787fd712b                    476940.000000
```

```
000019515bc8f95851aff6de873405e8                     305245.000000
00001a027a0ab970c408182df8484fce                     305245.000000
00001a18d69bb60bda9779408dcf02ac                     953869.000000

                                  HasDetections
MachineIdentifier
0000028988387b115f69f31a3bf04f09              0
000007535c3f730efa9ea0b7ef1bd645              0
000007905a28d863f6d0d597892cd692              0
00000b11598a75ea8ba1beea8459149f              1
000014a5f00daa18e76b81417eeb99fc              1
000016191b897145d069102325cab760              1
0000161e8abf8d8b89c5ab8787fd712b              1
000019515bc8f95851aff6de873405e8              0
00001a027a0ab970c408182df8484fce              0
00001a18d69bb60bda9779408dcf02ac              1
```

***Preprocessing of data*** 1. Drop rows with NaN values. 2. Normalize the columns so that everything is on the same scale of 0 to 1.

[212]:
```python
df = df.dropna(how='any')
df.shape
```

[212]:
```
(8538014, 5)
```

[213]:
```python
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

df[['Census_TotalPhysicalRAM', 'Census_ProcessorCoreCount',
         'Census_PrimaryDiskTotalCapacity']] = scaler.
 ↪fit_transform(df[['Census_TotalPhysicalRAM', 'Census_ProcessorCoreCount',
         'Census_PrimaryDiskTotalCapacity']])
```

[214]:
```python
df.head(10)
```

[214]:
```
                                  Census_TotalPhysicalRAM  \
MachineIdentifier
0000028988387b115f69f31a3bf04f09                 0.002442
000007535c3f730efa9ea0b7ef1bd645                 0.002442
000007905a28d863f6d0d597892cd692                 0.002442
00000b11598a75ea8ba1beea8459149f                 0.002442
000014a5f00daa18e76b81417eeb99fc                 0.003745
000016191b897145d069102325cab760                 0.005047
0000161e8abf8d8b89c5ab8787fd712b                 0.002442
000019515bc8f95851aff6de873405e8                 0.002442
00001a027a0ab970c408182df8484fce                 0.002442
00001a18d69bb60bda9779408dcf02ac                 0.005047
```

```
                                  Census_ProcessorCoreCount  Wdft_IsGamer  \
MachineIdentifier
0000028988387b115f69f31a3bf04f09                   0.015707      0.000000
000007535c3f730efa9ea0b7ef1bd645                   0.015707      0.000000
000007905a28d863f6d0d597892cd692                   0.015707      0.000000
00000b11598a75ea8ba1beea8459149f                   0.015707      0.000000
000014a5f00daa18e76b81417eeb99fc                   0.015707      0.000000
000016191b897145d069102325cab760                   0.005236      0.000000
0000161e8abf8d8b89c5ab8787fd712b                   0.005236      0.000000
000019515bc8f95851aff6de873405e8                   0.005236      0.000000
00001a027a0ab970c408182df8484fce                   0.015707      0.000000
00001a18d69bb60bda9779408dcf02ac                   0.015707      1.000000

                                  Census_PrimaryDiskTotalCapacity  \
MachineIdentifier
0000028988387b115f69f31a3bf04f09                         0.000000
000007535c3f730efa9ea0b7ef1bd645                         0.000000
000007905a28d863f6d0d597892cd692                         0.000000
00000b11598a75ea8ba1beea8459149f                         0.000000
000014a5f00daa18e76b81417eeb99fc                         0.000000
000016191b897145d069102325cab760                         0.000000
0000161e8abf8d8b89c5ab8787fd712b                         0.000000
000019515bc8f95851aff6de873405e8                         0.000000
00001a027a0ab970c408182df8484fce                         0.000000
00001a18d69bb60bda9779408dcf02ac                         0.000000

                                  HasDetections
MachineIdentifier
0000028988387b115f69f31a3bf04f09              0
000007535c3f730efa9ea0b7ef1bd645              0
000007905a28d863f6d0d597892cd692              0
00000b11598a75ea8ba1beea8459149f              1
000014a5f00daa18e76b81417eeb99fc              1
000016191b897145d069102325cab760              1
0000161e8abf8d8b89c5ab8787fd712b              1
000019515bc8f95851aff6de873405e8              0
00001a027a0ab970c408182df8484fce              0
00001a18d69bb60bda9779408dcf02ac              1
```

[215]:

```
df['ComputePower'] = 0.3 * df.Census_ProcessorCoreCount + 0.4 * df.
↪Census_ProcessorCoreCount + \
                     0.2 * df.Wdft_IsGamer + 0.1 * df.
↪Census_PrimaryDiskTotalCapacity
```

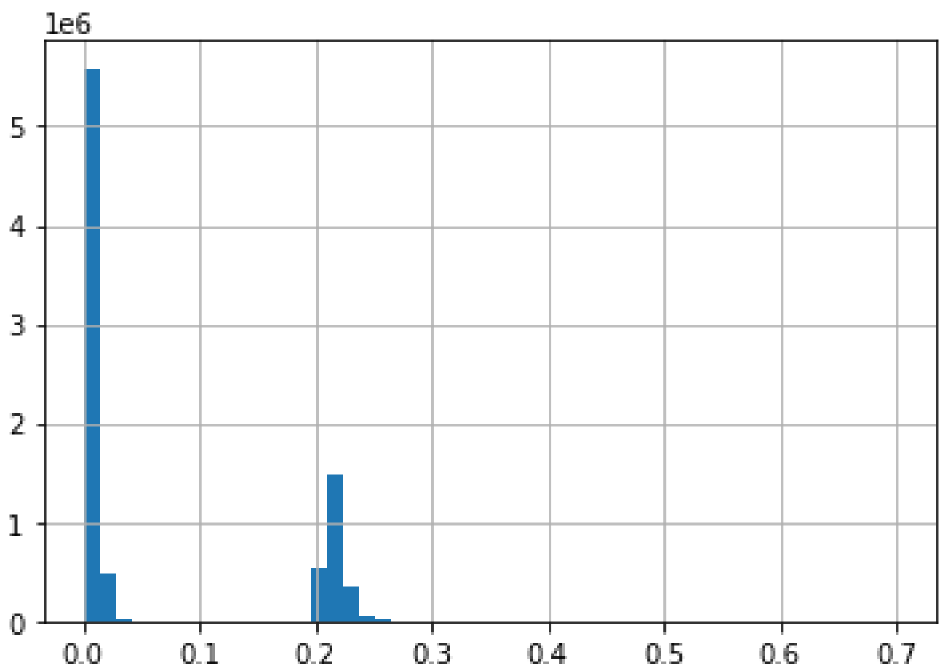
[216]:

```
df['ComputePower'].describe()
```

[216]:
```
count    8538014.000000
mean           0.067898
std            0.091635
min            0.000000
25%            0.010995
50%            0.010995
75%            0.203616
max            0.700000
Name: ComputePower, dtype: float64
```

[217]:
```
df['ComputePower'].hist(bins=50)
```

[217]:
```
<AxesSubplot:>
```




This distribution graph doesn't really provide a lot of useful information. This is happening because of the various outliers that are present in the dataset. There are some machines whose RAM and CPU values are much higher than the rest of the systems.

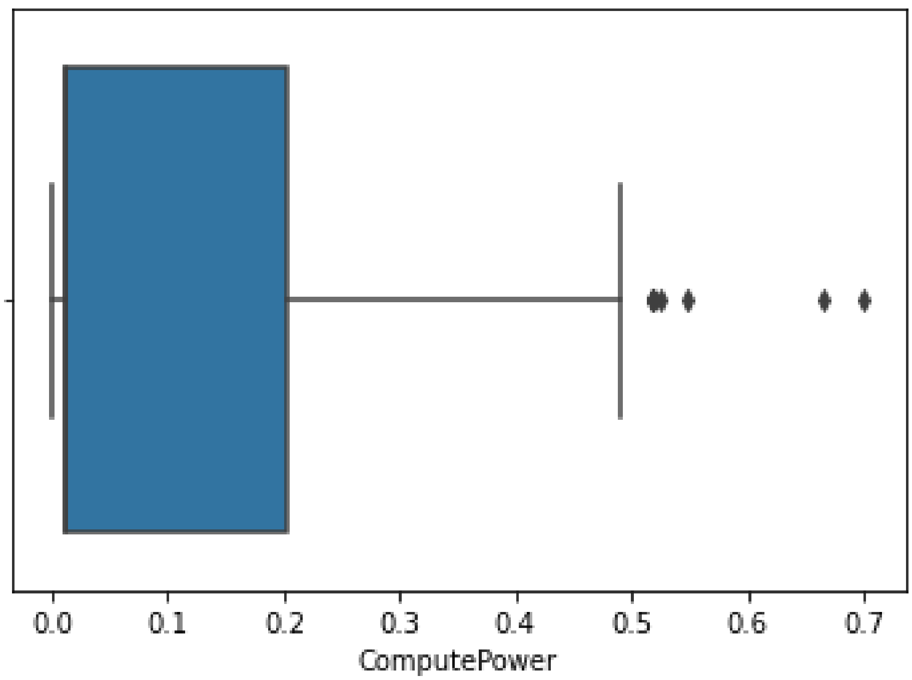
We can verify this from the statistics provided by describe(). Mean of Compute Power is at 0.07 and standard deviation is at 0.09. This implies that a majority of the points are spread around 0.1. However, if we look at the max values we see that there are outlier points at 0.7. The number of data points at that high value may be just 1 or 2 but their presence affects the distribution graph heavily.

So, for the purposes of the next question, we will remove these outliers. Now typically, removing any data point does affect the data set however in situations like this, presence of these outliers are not allowing us to understand the distribution properly.

***Q2b* Are powerful computers more or less likely to have malware than underpowered machines? Plot power vs malware detection to support your conclusion. (5 points)**

[218]:
```
# Identifying and removing the outliers from the dataset

sns.boxplot(x=df['ComputePower'])
```

[218]: <AxesSubplot:xlabel='ComputePower'>




Here we notice the outliers are present between 0.5 and 0.7. We notice most of the data points are present with ComputePower<0.5.

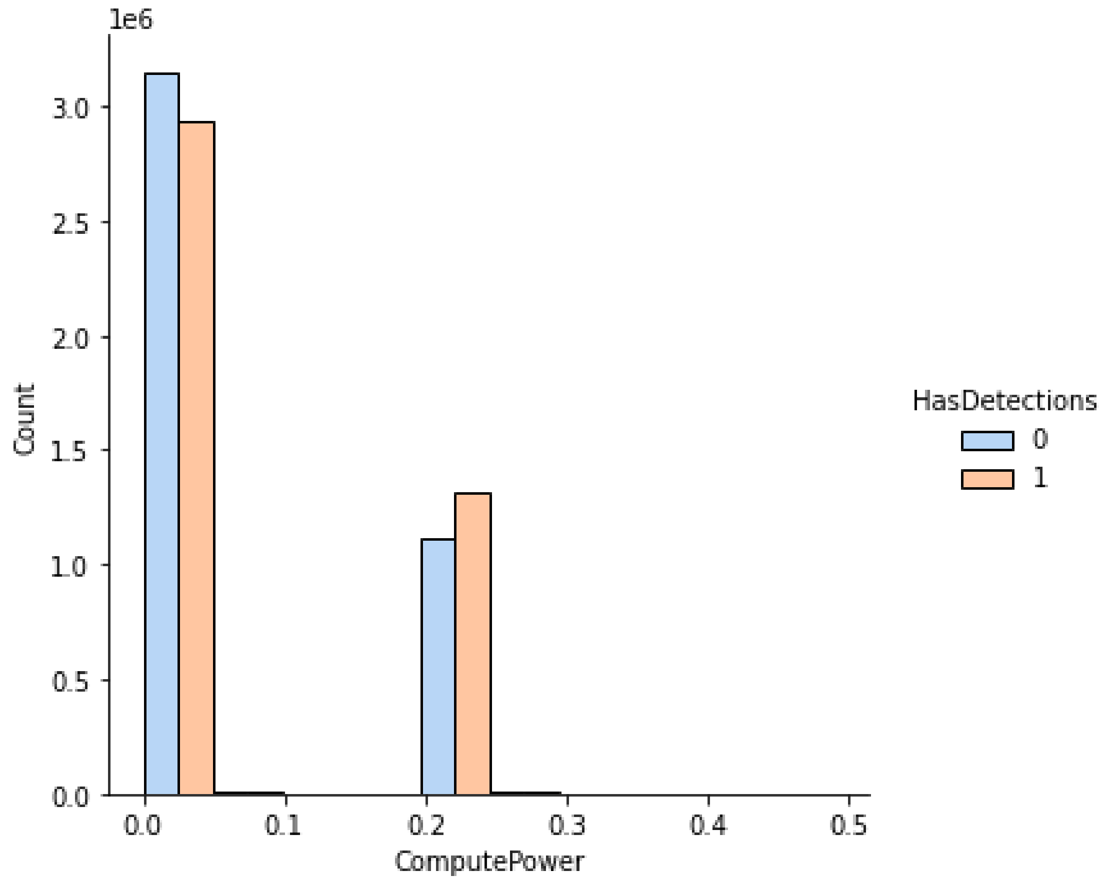
For better understanding of the distribution of data, we will only consider the points that are present in $> 0.0 <$ ComputePower $< 0.5$

[219]:
```
df = df.loc[df['ComputePower']<0.5]
df.shape
```

[219]: (8538006, 6)

[220]:
```
sns.displot(data=df, x='ComputePower', hue='HasDetections', stat='count',␣
 ↪multiple='dodge',
           palette='pastel', bins=10)
```

[220]: <seaborn.axisgrid.FacetGrid at 0x7fb0128310a0>




[221]:
```
sns.displot(data=df.loc[df['HasDetections']==1], x='ComputePower', bins=10,␣
↪stat='probability', palette='pastel')
```

[221]: <seaborn.axisgrid.FacetGrid at 0x7fb0049bfb20>

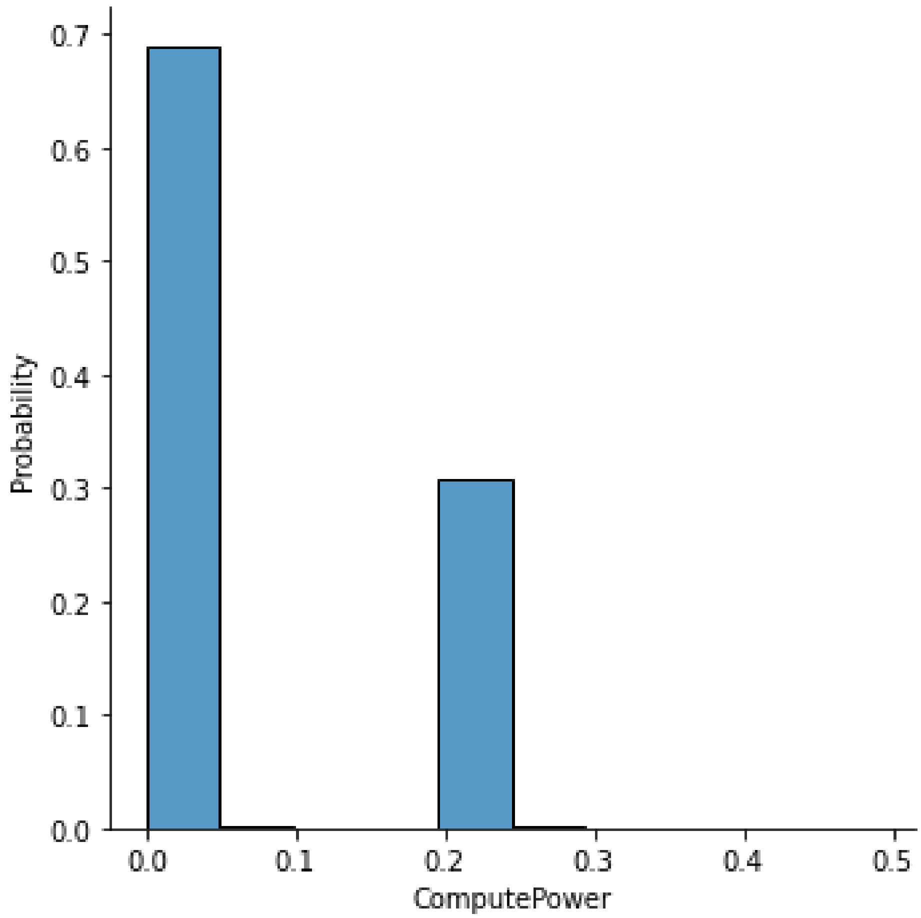



Figure above shows the distribution of ComputePower against the HasDetections.

From the figures above, there seems to be a higher ratio of low powered systems being more prone to being affected by the malware than the high powered systems. Although one thing to notice here is also the number of low-powered devices in the dataset. The dataset seems to contain a larger number of low powered systems than high-powered systems, which makes sense considering a lot of old systems are still in circulation.

So the conclusion that *low-powered systems are more vulnerable* while seems to hold true for the current dataset, it may not be very conclusive in real-world.

[222]:
```
# data['HasDetections'].corr(data['ComputePower'])

pearsonr(df['HasDetections'], df['ComputePower'])
```

[222]:
```
(0.05764713964842027, 0.0)
```

The correlation between ComputePower and HasDetections is 0.06 and the pearson coefficient of the correlation (p-value) is 0. This implies that these two features have no significant relation between them.

### 1.5 Section 3: OS version vs Malware detected (Q3)

***Q3.*** **Software is updated to fix vulnerabilities when found. But these updates can also open a can of worms. Produce plots showing the number (and %) of malware detections against Census_OSBuildNumber and also against Census_OSBuildRevision. Discuss what you find.**

[323]:
```
# Read csv file into a dataframe with the selected columns
filename = 'train.csv'

# Sampling random records from the dataset
n = 8921483 #number of records in file
s = int(n/8) #desired sample size

skip = sorted(random.sample(range(1,n+1),n-s))

# Uncomment below line to load entire dataset
skip = 0

data = pd.read_csv(filename, usecols = lambda x:x in use_cols, dtype = dtypes,␣
↪skiprows=skip)

# Set 'MachineIdentifier' as the Index for the dataframe
data.set_index('MachineIdentifier', inplace=True)
```

[324]:
```
#Load the respective columns to the dataframe

_cols = ['Census_OSBuildNumber', 'Census_OSBuildRevision', 'HasDetections']

df = data[_cols]
df.shape
```

[324]:
```
(8921483, 3)
```

[325]:
```
df = df.dropna(how='any')
df.shape
```

[325]:
```
(8921483, 3)
```

[326]:
```
df.head(10)
```

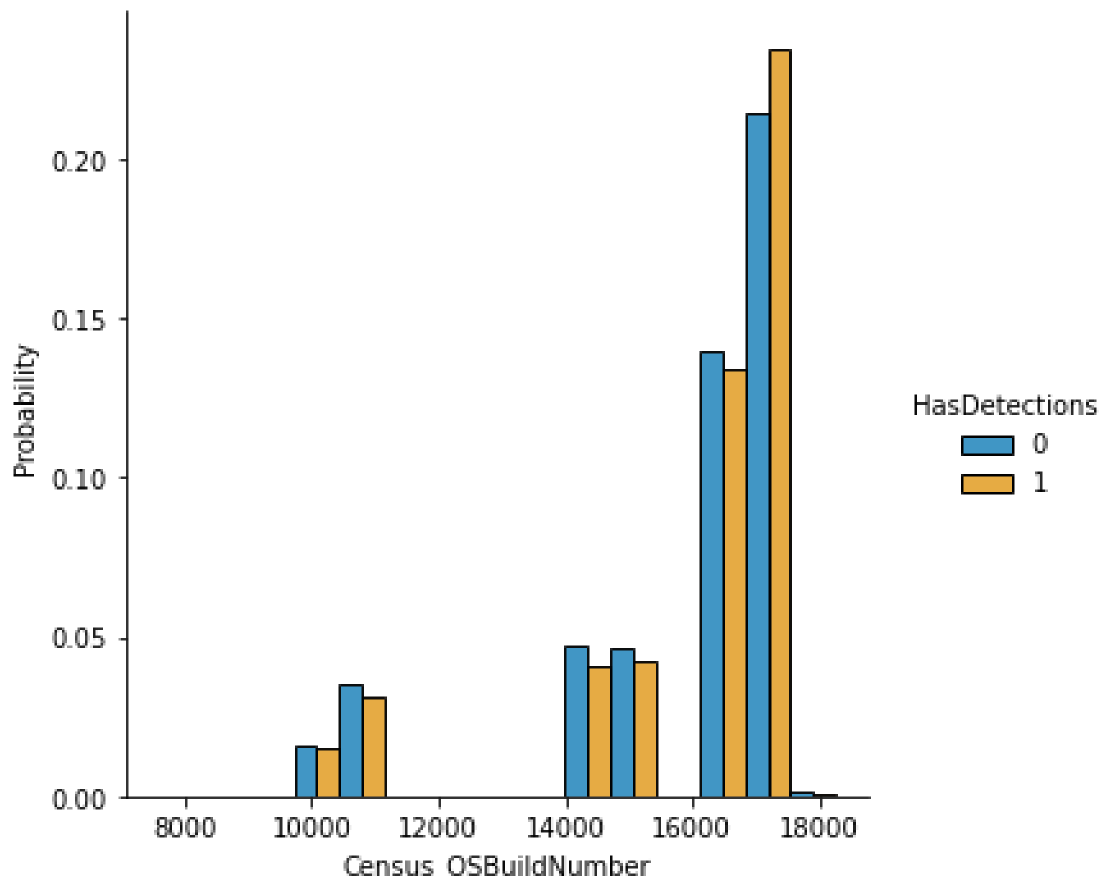
[326]:
```
                                   Census_OSBuildNumber  \
MachineIdentifier
0000028988387b115f69f31a3bf04f09                  17134
000007535c3f730efa9ea0b7ef1bd645                  17134
000007905a28d863f6d0d597892cd692                  17134
00000b11598a75ea8ba1beea8459149f                  17134
000014a5f00daa18e76b81417eeb99fc                  17134
```

```
000016191b897145d069102325cab760             17134
0000161e8abf8d8b89c5ab8787fd712b             17134
000019515bc8f95851aff6de873405e8             14393
00001a027a0ab970c408182df8484fce             17134
00001a18d69bb60bda9779408dcf02ac             16299

                                  Census_OSBuildRevision  HasDetections
MachineIdentifier
0000028988387b115f69f31a3bf04f09                     165              0
000007535c3f730efa9ea0b7ef1bd645                       1              0
000007905a28d863f6d0d597892cd692                     165              0
00000b11598a75ea8ba1beea8459149f                     228              1
000014a5f00daa18e76b81417eeb99fc                     191              1
000016191b897145d069102325cab760                     165              1
0000161e8abf8d8b89c5ab8787fd712b                     165              1
000019515bc8f95851aff6de873405e8                       0              0
00001a027a0ab970c408182df8484fce                     254              0
00001a18d69bb60bda9779408dcf02ac                     431              1
```

Let's look at how the distribution looks between different OS builds and also between OS Revisions.

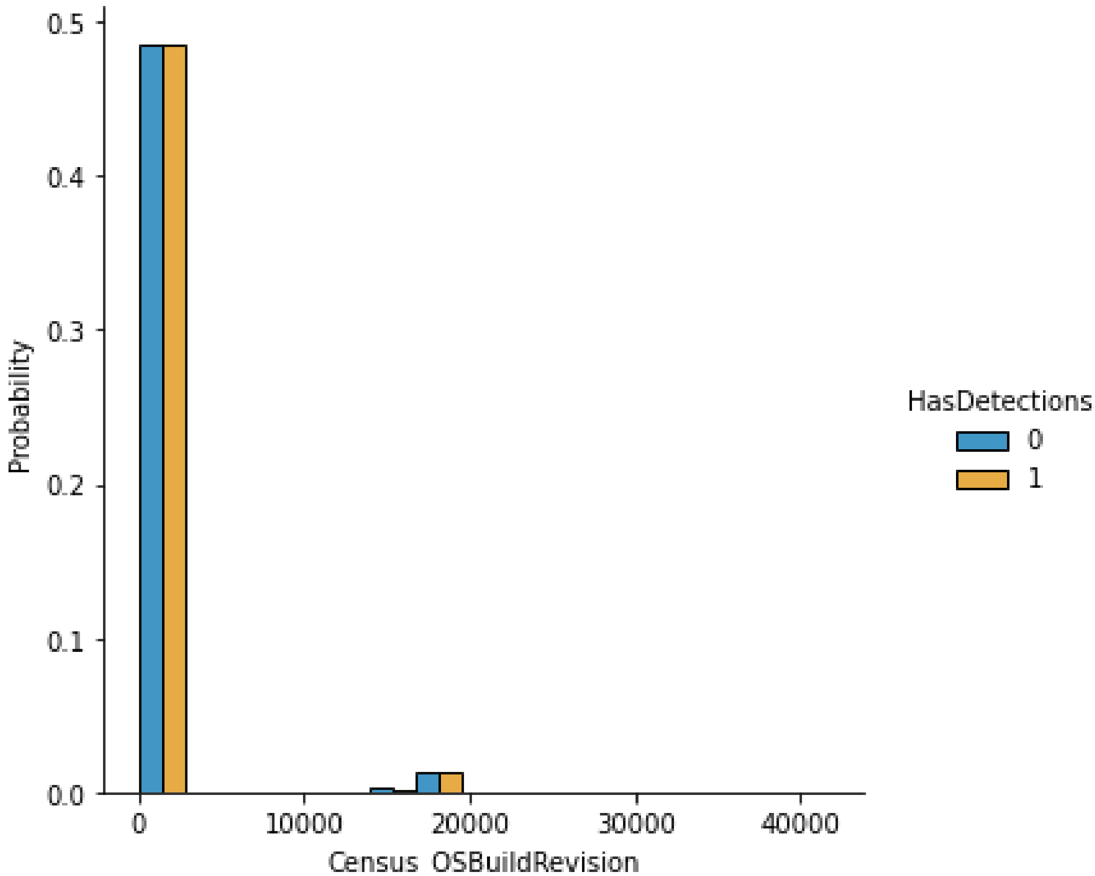
[327]:
```python
sns.displot(data=data, x='Census_OSBuildNumber', hue='HasDetections',
            stat='probability', multiple='dodge', bins=15, palette='colorblind')
```

[327]:
```
<seaborn.axisgrid.FacetGrid at 0x7faed662cb20>
```




[328]:
```
sns.displot(data=data, x='Census_OSBuildRevision', hue='HasDetections',
            stat='probability', multiple='dodge', bins=15, palette='colorblind')
```

[328]: <seaborn.axisgrid.FacetGrid at 0x7faebaf49dc0>




These graphs do not provide a lot of information other than the fact that recent OS builds seem to be more impacted by the malware and early build revisions are also more impacted by the malware. But there seems to be more information missing here.

Quite specfically, which OS versions have the most malware detected and which build revision inside each build version has the most malware detected.

So, let's zoom in on the part where we see maximum malware density.

[329]:
```
print(df.Census_OSBuildNumber.nunique(), df.Census_OSBuildRevision.nunique())
```

```
165 285
```

Let's narrow down on the revisions inside each OS release.

Let's group build revisions per OS Build. Typically each OS Build will have multiple revisions, we are interested in finding out which of these revisions inside a build is more prone to being affected.

[330]:
```
_cols = ['Census_OSBuildNumber', 'Census_OSBuildRevision', 'HasDetections']

df = data[_cols]
```

```
df = df.groupby(["Census_OSBuildNumber", 'Census_OSBuildRevision']).
 ↪agg(['count' , "sum"])
df = df[df["HasDetections"]["count"]> 1000]
df = df.sort_index()
df = df.reset_index()
df["int_percent"] = df["HasDetections"]["sum"] / df["HasDetections"]["count"] *␣
 ↪100
df.head(10)
```

[330]:

| | Census_OSBuildNumber | Census_OSBuildRevision | HasDetections | | int_percent |
|---|---|---|---|---|---|
| | | | count | sum | |
| 0 | 10240 | 16384 | 25834 | 12114 | 46.891693 |
| 1 | 10240 | 16405 | 6626 | 3070 | 46.332629 |
| 2 | 10240 | 16445 | 1003 | 443 | 44.167498 |
| 3 | 10240 | 16487 | 3770 | 1822 | 48.328912 |
| 4 | 10240 | 16520 | 1105 | 492 | 44.524887 |
| 5 | 10240 | 17071 | 1417 | 569 | 40.155258 |
| 6 | 10240 | 17146 | 1050 | 467 | 44.476190 |
| 7 | 10240 | 17236 | 1590 | 705 | 44.339623 |
| 8 | 10240 | 17319 | 1007 | 477 | 47.368421 |
| 9 | 10240 | 17394 | 1378 | 687 | 49.854862 |

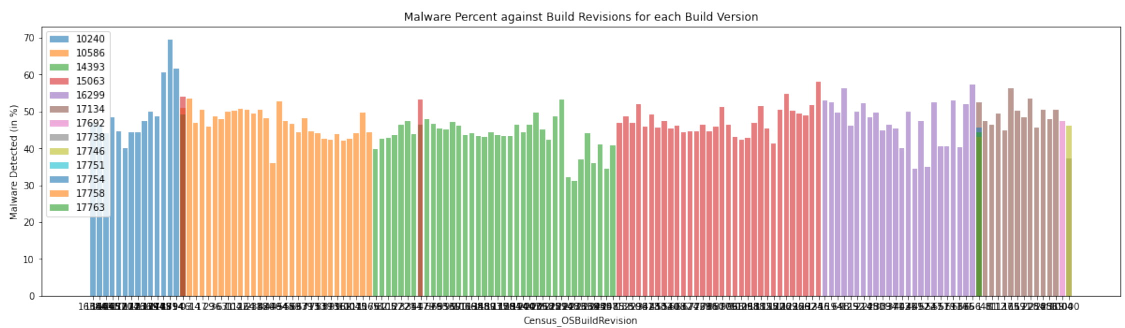
[331]:

```
x = list(str(x) for x in df["Census_OSBuildRevision"])
y1 = list(df["HasDetections"]["count"])
y2 = list(df["int_percent"])


plt.rcParams['figure.figsize'] = (16.0, 4.0)
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])

for OS in df["Census_OSBuildNumber"].unique():
  temp = df[df["Census_OSBuildNumber"] == OS]
  temp = temp.sort_values(by=['Census_OSBuildRevision'])
  x = list(str(x) for x in temp["Census_OSBuildRevision"])
  y2 = list(temp["int_percent"])
  ax.bar(x, y2, alpha=0.6, linewidth=2, label=str(OS))
  print("OS build version:",OS,"\tTotal Revisions:", len(y2), "\tMalware per␣
 ↪revision:", sum(y2)/ len(y2))

plt.legend()
ax.set_title('Malware Percent against Build Revisions for each Build Version')
ax.set_xlabel('Census_OSBuildRevision')
ax.set_ylabel('Malware Detected (in %)')
```

```
OS build version: 10240         Total Revisions: 14     Malware per revision:
49.7701849959368
OS build version: 10586         Total Revisions: 30     Malware per revision:
```

```
46.961336342943426
OS build version: 14393        Total Revisions: 39     Malware per revision:
43.66286300035224
OS build version: 15063        Total Revisions: 34     Malware per revision:
47.86627162376666
OS build version: 16299        Total Revisions: 24     Malware per revision:
47.38563590008153
OS build version: 17134        Total Revisions: 13     Malware per revision:
49.47516108087591
OS build version: 17692        Total Revisions: 1      Malware per revision:
47.44822485207101
OS build version: 17738        Total Revisions: 1      Malware per revision:
37.295885042455915
OS build version: 17746        Total Revisions: 1      Malware per revision:
46.22950819672131
OS build version: 17751        Total Revisions: 1      Malware per revision:
42.04771371769384
OS build version: 17754        Total Revisions: 1      Malware per revision:
45.564892623716155
OS build version: 17758        Total Revisions: 1      Malware per revision:
43.01439458086367
OS build version: 17763        Total Revisions: 1      Malware per revision:
44.308560677328316
```

[331]: Text(0, 0.5, 'Malware Detected (in %)')




From this analysis, we can conclusively say that OS build version 10240 has the highest number of malwares detected even between revisions. The graph also suggests that subsequent build revisions didnot see a decline in malware detection in build version 10240, where unlike other build versions the malware detection percent actually increases with subsequent revisions.

### 1.6 Section 4: Effect of Number of AV Products Installed (Q4)

***Q4.* Investigate the question of whether antivirus software(s) reduces the amount of malware. Does the number of antivirus products you use matter? What is your conclusion and what is your evidence supporting it?**

[24]:
```
# Read csv file into a dataframe with the selected columns
filename = 'train.csv'

# Sampling random records from the dataset
n = 8921483 #number of records in file
s = int(n/8) #desired sample size

skip = sorted(random.sample(range(1,n+1),n-s))

# Uncomment below line to load entire dataset
skip = 0

data = pd.read_csv(filename, usecols = lambda x:x in use_cols, dtype = dtypes,␣
↪skiprows=skip)

# Set 'MachineIdentifier' as the Index for the dataframe
data.set_index('MachineIdentifier', inplace=True)
```

[25]:
```
#Load the respective columns to the dataframe

_cols = ['AVProductStatesIdentifier','AVProductsInstalled', 'HasDetections']

df = data[_cols]
df.shape
```

[25]:
```
(8921483, 3)
```

[26]:
```
df = df.dropna(how='any')
df.shape
```

[26]:
```
(8885262, 3)
```

[28]:
```
df.AVProductStatesIdentifier.nunique()
```

[28]:
```
28970
```

[29]:
```
df.AVProductsInstalled.nunique()
```

[29]:
```
8
```

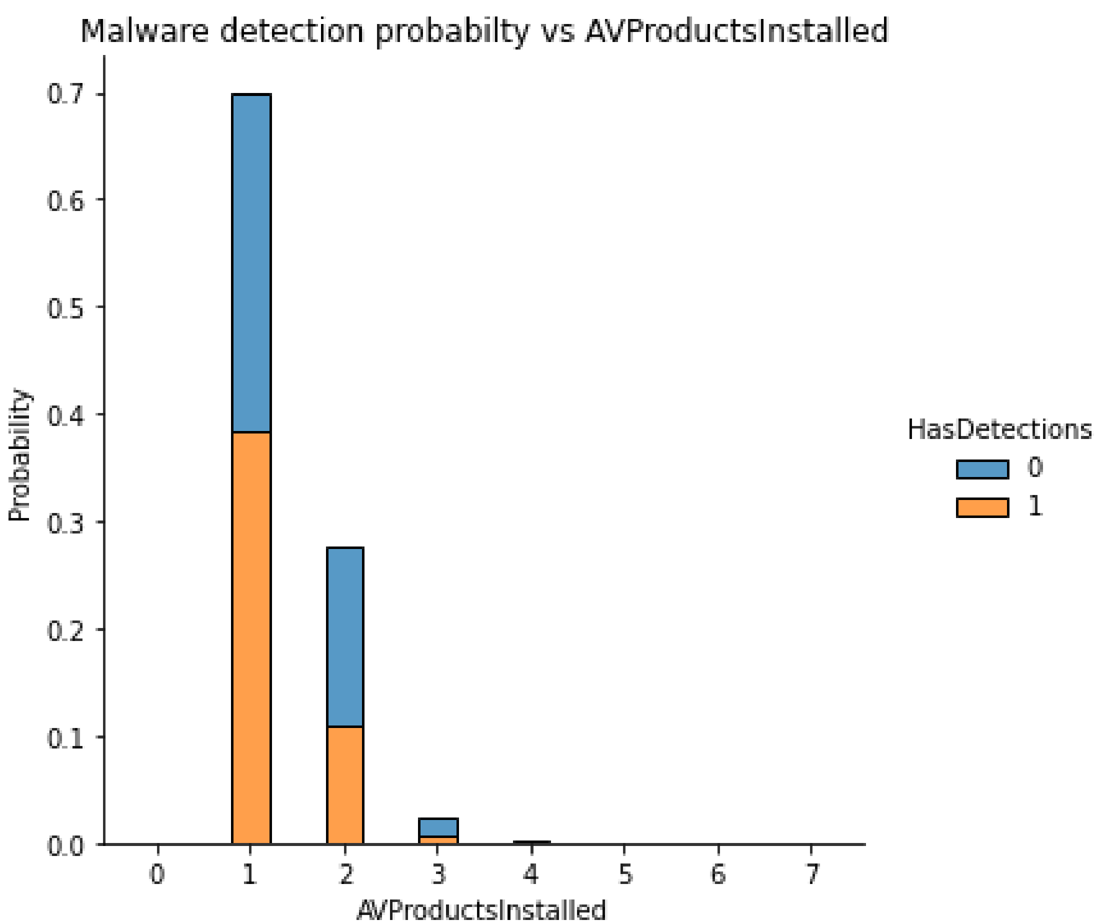
[30]:
```
df.groupby('AVProductsInstalled')['HasDetections'].value_counts()
```

[30]:
```
AVProductsInstalled  HasDetections
0.000000             0                      1
1.000000             1                3406078
                     0                2802815
2.000000             0                1483012
                     1                 975996
```

```
3.000000            0                  147421
                    1                   60682
4.000000            0                    6386
                    1                    2371
5.000000            0                     346
                    1                     125
6.000000            0                      22
                    1                       6
7.000000            1                       1
Name: HasDetections, dtype: int64
```

[31]:
```
sns.displot(data=df, x='AVProductsInstalled', hue='HasDetections',
            stat='probability', multiple='stack',
            discrete=True, shrink=0.4)
plt.title('Malware detection probabilty vs AVProductsInstalled')
```

[31]:
```
Text(0.5, 1.0, 'Malware detection probabilty vs AVProductsInstalled')
```



The plot above shows the number of systems that were installed with 1-4 different AntiVirus products and whether they were found to have the malware. From this graph, we can clearly notice that among the systems which had 2 or more AntiVirus softwares installed, the malware presence was much smaller. For systems with 2 AV softwares present, we notice that more number of systems were detected to not have the malware than ones detected to have malware.

However, with systems that had only 1 AV product installed we notice more devices were found to have the malware than did not have the malware.

So from just looking at the distribution, it does seem like having more than 1 antivirus product installed on your system reduces the chances of getting impacted by Malware.

### 1.7 Section 5: Interesting findings (Q5)

***Q5.*** **Create 3 plots of your own using the dataset that you think reveal something very interesting. Explain what it is, and anything else you learned from your exploration.**

[33]:
```
# Read csv file into a dataframe with the selected columns
filename = 'train.csv'

# Sampling random records from the dataset
n = 8921483 #number of records in file
s = int(n/8) #desired sample size

skip = sorted(random.sample(range(1,n+1),n-s))

# Uncomment below line to load entire dataset
skip = 0


data = pd.read_csv(filename, usecols = lambda x:x in use_cols, dtype = dtypes,␣
↪skiprows=skip)

# Set 'MachineIdentifier' as the Index for the dataframe
data.set_index('MachineIdentifier', inplace=True)
```

[52]:
```
#Load the respective columns to the dataframe

_cols = ['AVProductsEnabled', 'AVProductsInstalled', 'Wdft_IsGamer',
            'Census_DeviceFamily', 'Platform',
            'CountryIdentifier', 'HasTpm', 'Firewall', 'Census_MDC2FormFactor',
            'HasDetections']

#use_cols.append(_cols)

data = pd.read_csv(filename, usecols = lambda x:x in _cols, dtype = dtypes,␣
↪skiprows=skip)

df = data[_cols]
```

```
df.shape
```

[52]: (8921483, 10)

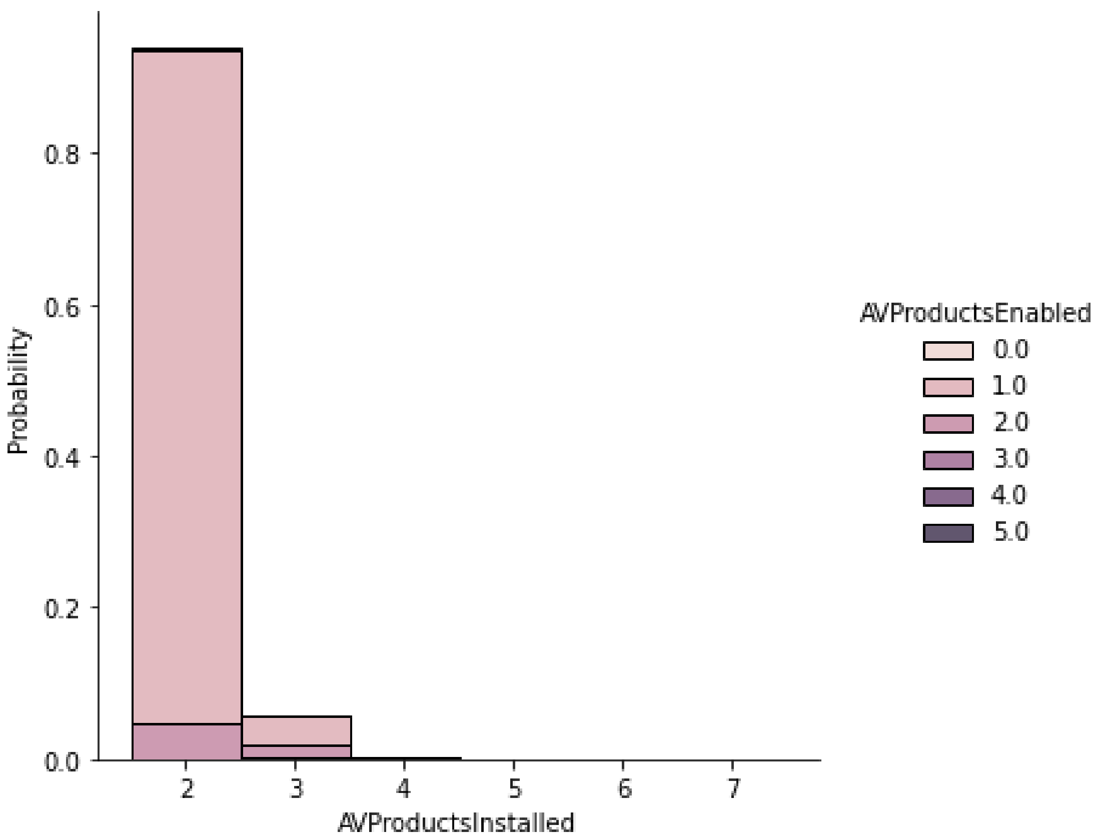
### 1.7.1 AntiVirus Products Enabled vs Installed

Continuing from the previous analysis about Malware detection against AntiVirus products installed, an interesting question arises of how many of those AntiVirus products are actually enabled on the system at a time.

AVProductsEnabled value tells us how many AVProducts are active and running on the system. Let's look the plot below.

[49]:
```
sns.displot(data=df.loc[(df['AVProductsInstalled']>1) &␣
↪(df['HasDetections']==1)], x='AVProductsInstalled', hue='AVProductsEnabled',␣
↪stat='probability',
            multiple='stack', discrete=True)
```

[49]: <seaborn.axisgrid.FacetGrid at 0x7f0fbbe50e80>




A very interesting observation here is that for most of the systems present in the dataset which have 2 or more AV Products installed, there is only 1 product which is enabled at a time.

From the graph above, we can see that there's a very small percentage (<10%) of sytems with 2 or more antivirus products enabled that were impacted with the malware.

This goes back to further bolster our previous point that having more than 1 anti virus product installed on your system does help in keeping it safe but they need to be enabled and running.

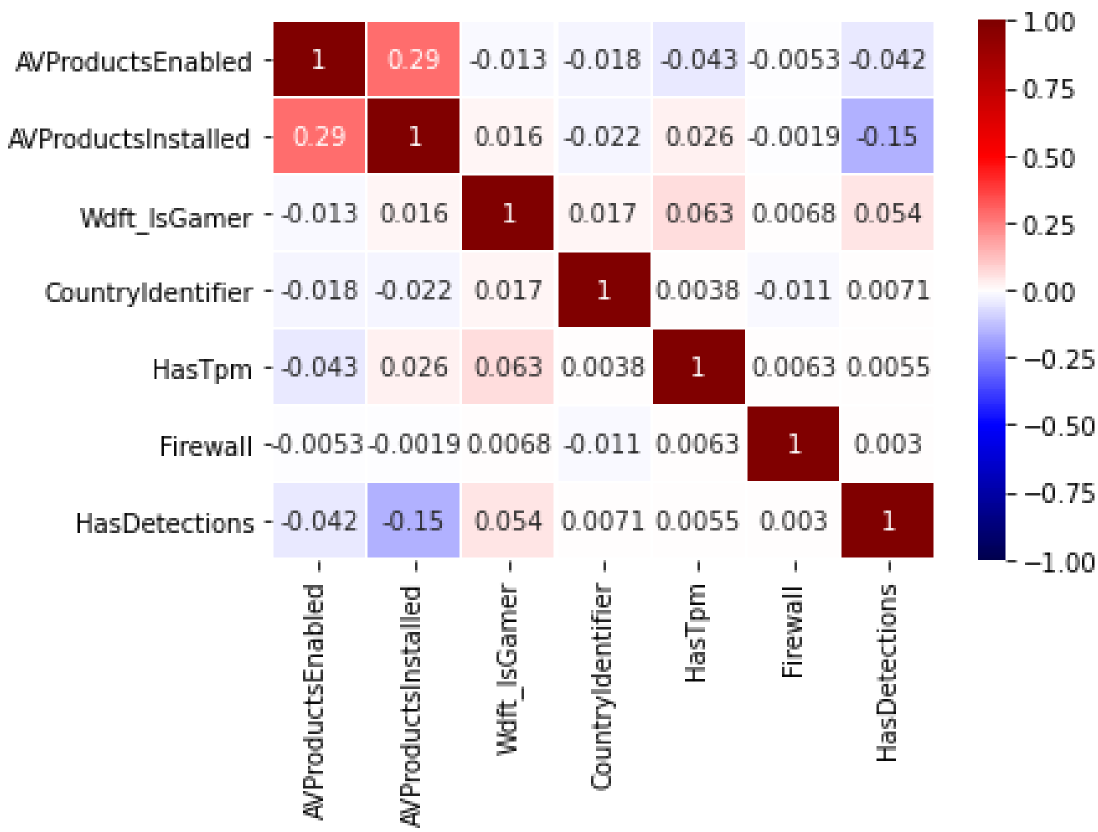
### 1.7.2 Gamer, Firewall, TPM, and other features

There are some attributes about a computer system which may provide it additional security to various kinds of malwares.

Some of these attributes are TPM (Trusted Platform Module), Firewall system, and whether the system is a Gaming system. Let's see how each of these features impact the system's chances at being affected by malware.

[53]:
```python
sns.heatmap(df.corr(), vmin=-1, vmax=1, cmap='seismic', linewidth=0.2,␣
 ↪annot=True)
```

[53]:
```
<AxesSubplot:>
```



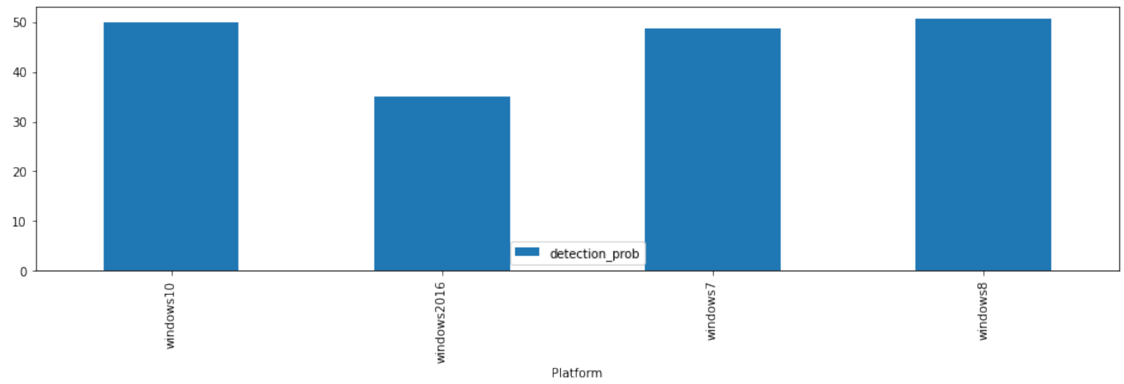

Looking at the correlation matrix between variables, features such as Firewall/Wdft__IsGamer/HasTpm do not seem to have any correlation with the system being more/less vulnerable. This is an interesting observation as during the initial analysis (Q2), I had considered Wdft_IsGamer as an impactful feature for ComputePower which we then tried to correlate with Malware detection probability.

### 1.7.3 Device Type, OS, and malware

[74]:
```
_cols = ['MachineIdentifier','HasDetections', 'SmartScreen',␣
↪'Census_OSInstallTypeName', 'Census_OSWUAutoUpdateOptionsName',␣
↪'Census_OSBranch', 'OsPlatformSubRelease', 'OsBuild',
            'Census_PrimaryDiskTypeName', 'Platform', 'Processor',␣
↪'Census_OSArchitecture', 'Census_MDC2FormFactor']

data = pd.read_csv(filename, usecols = lambda x:x in _cols, dtype = dtypes,␣
↪skiprows=skip)

df = data[_cols]
```

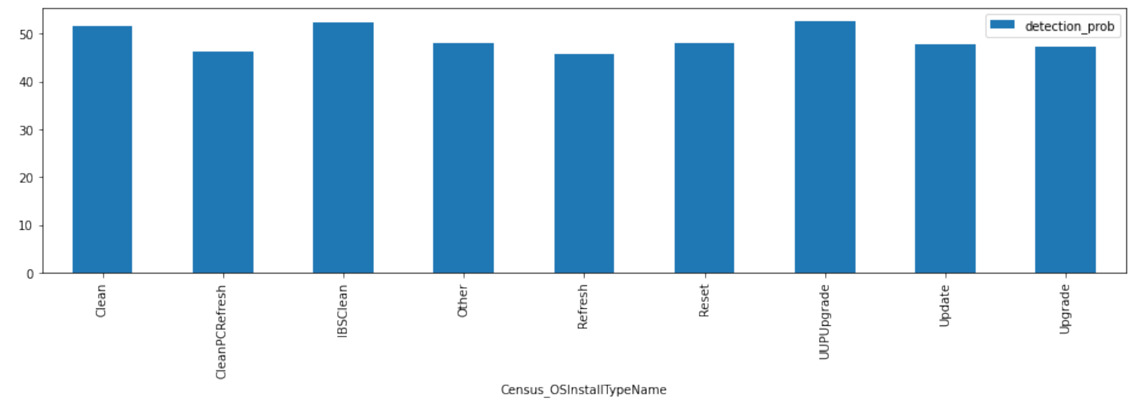
[79]:
```
d1 = df.groupby('Platform')['HasDetections'].agg(['sum','count'])
d1['detection_prob'] = d1['sum']/d1['count']*100


d1.plot.bar(y='detection_prob')
```

[79]: <AxesSubplot:xlabel='Platform'>



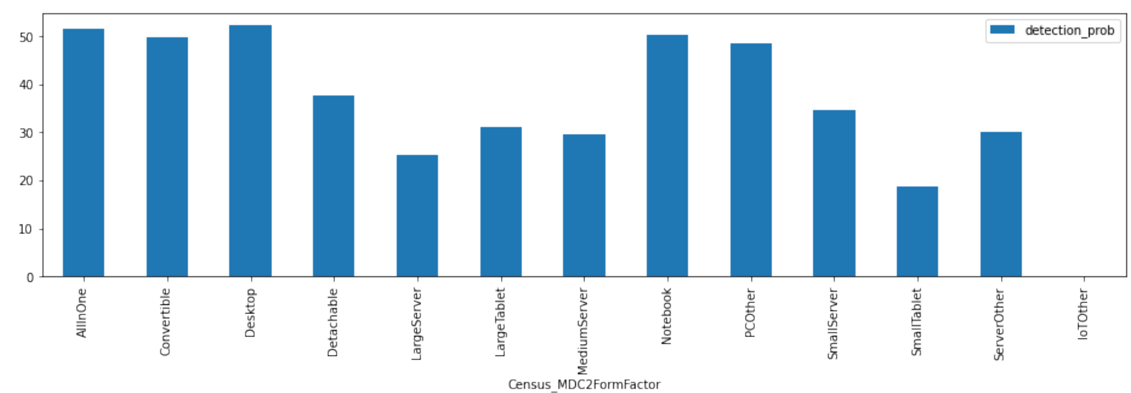

[73]:
```
d1 = df.groupby('Census_OSInstallTypeName')['HasDetections'].
↪agg(['sum','count'])
d1['detection_prob'] = d1['sum']/d1['count']*100

d1.plot.bar(y='detection_prob')
```

[73]: <AxesSubplot:xlabel='Census_OSInstallTypeName'>




[75]:
```
d1 = df.groupby('Census_MDC2FormFactor')['HasDetections'].agg(['sum','count'])
d1['detection_prob'] = d1['sum']/d1['count']*100

d1.plot.bar(y='detection_prob')
```

[75]: <AxesSubplot:xlabel='Census_MDC2FormFactor'>




The above graphs show the probability of each type of device showing up as malware in the dataset. These kind of categorical evaluations are helpful in understanding how different types of devices could get impacted to this malware. As shown, Windows2016 shows least probability of getting affected by malware, cleanPCRefresh show minimum chances of malware detection between the various upgrade types.

### 1.8 Section 6: Baseline modelling (Q6)

***Q6.* Now build a baseline model for this task. We will call this Model 0. You will train a logistic regression model on 80% of the training data and test it on the remaining 20% chosen at random. List the features used and print the error rate along with the AUC score of this model. What do you make of the error rate?**

[6]:
```
#Logistic Regression for Baseline modelling


numerical_columns =␣
↪['Census_FirmwareManufacturerIdentifier','Census_PrimaryDiskTotalCapacity','Census_OEMNameI
↪'Wdft_RegionIdentifier',
                  'Census_OSBuildRevision','LocaleEnglishNameIdentifier',␣
↪'Census_ProcessorModelIdentifier', 'Census_SystemVolumeTotalCapacity',
                  'AVProductStatesIdentifier',␣
↪'Census_InternalPrimaryDiagonalDisplaySizeInInches', 'CountryIdentifier']

categorical_columns = ['Census_ActivationChannel','OsBuildLab',
                   ␣
↪'EngineVersion','SmartScreen','AppVersion','Census_OSVersion','AvSigVersion','Census_OSInst

feature_set = numerical_columns + categorical_columns

X = data[feature_set]
y = data['HasDetections']



# split X and y into training and testing sets
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
↪20,random_state=0)
```

[7]:
```
# Create copies for this model with only numerical columns
baseline_X_train = X_train[numerical_columns].copy()
baseline_X_test = X_test[numerical_columns].copy()
```

[8]:
```
# Remove data from memory, we will use X and y for all the following questions
del data
```

[9]:
```
# Data Cleaning


#baseline_X_train = baseline_X_train.apply(pd.to_numeric, errors='coerce')


baseline_X_train.fillna(-1, inplace=True)
baseline_X_test.fillna(-1, inplace=True)
```

[10]:
```
# import LogisticRegression
from sklearn.linear_model import LogisticRegression

# instantiate the model
```

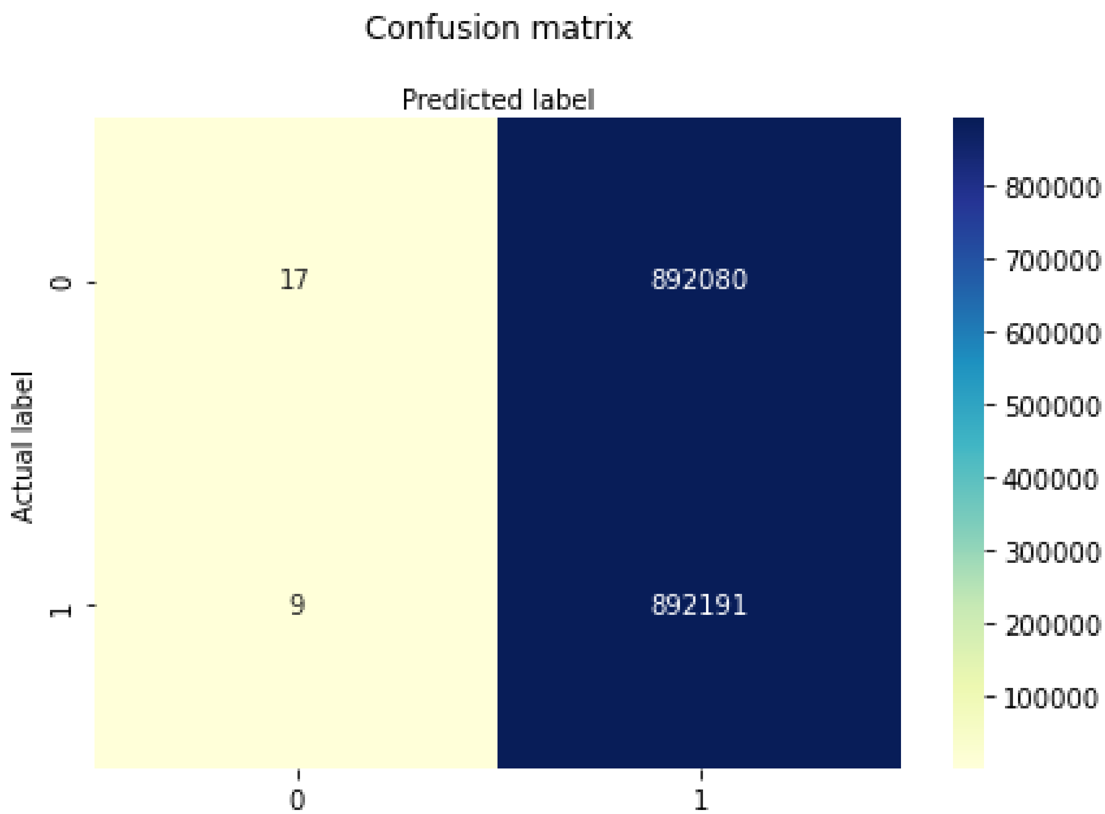
```
log_reg = LogisticRegression()

# model fit with data
log_reg.fit(baseline_X_train,y_train)

# Predict y values based on model
y_pred=log_reg.predict(baseline_X_test)
```

[11]:
```
# Test the prediction using Confusion matrix
from sklearn import metrics
cf_matrix = metrics.confusion_matrix(y_test, y_pred)
cf_matrix
```

[11]:
```
array([[    17, 892080],
       [     9, 892191]])
```

[12]:
```
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

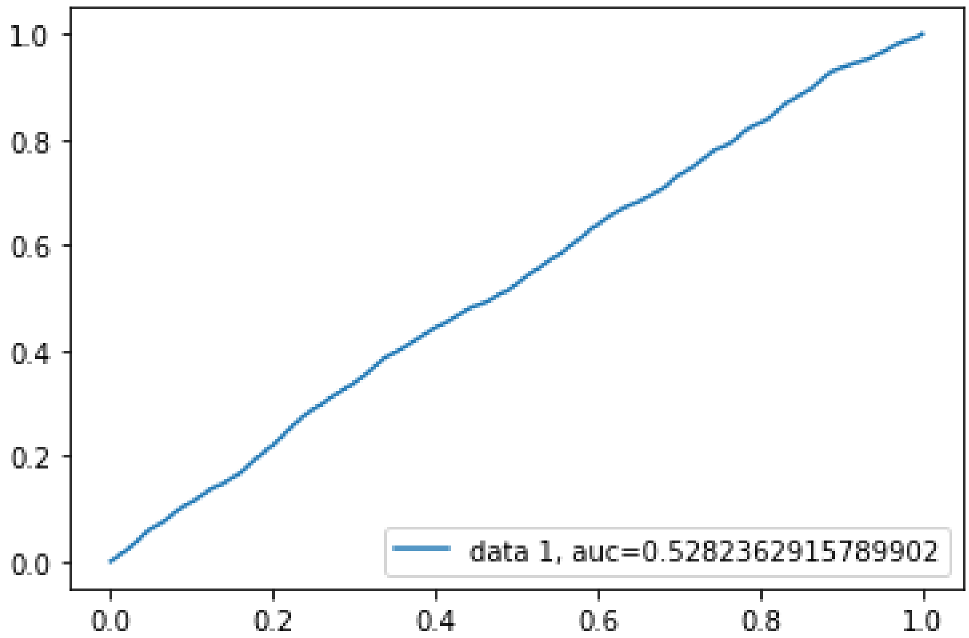
[12]:
```
Text(0.5, 257.44, 'Predicted label')
```




[13]:
```
print("Model Accuracy = ",metrics.accuracy_score(y_test, y_pred))
print("Model Precision = ",metrics.precision_score(y_test, y_pred))
print("Model Recall = ",metrics.recall_score(y_test, y_pred))
```

```
Model Accuracy =  0.5000333464664235
Model Precision =  0.5000311051404187
Model Recall =  0.9999899125756557
```

[14]:
```
y_pred_probability = log_reg.predict_proba(baseline_X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_probability)
auc = metrics.roc_auc_score(y_test, y_pred_probability)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```




[15]:
```
print('AUC Score: {}%'.format(auc*100))
print('\nError rate (Mean Squared Error) {}%\n'.format(100* metrics.
 ↪mean_squared_error(y_test, y_pred)))
```

```
AUC Score: 52.82362915789902%

Error rate (Mean Squared Error) 49.996665353357656%
```

[16]:
```
import joblib
joblib.dump(log_reg, 'log_reg_baseline.sav')
```

[16]: ['log_reg_baseline.sav']

Model accuracy is at 50% and AUC score is also ~53. This implies that the baseline model is performing the same as random guessing. It's definitely not a good model, but we can try to improve the accuracy with some data processing.

### 1.9 Section 7: Feature Cleaning and Additional models (Q7a & 7b)

***Q7.a* Cleaning Features: Features can be preprocessed to improve them before feeding into the model (e.g. normalize or scale the input vector, convert non-numerical value into float, or do a special treatment of missing values, etc). This can significantly improve the performance of your model. Do preprocessing for the features. Explain what you did.**

[8]:
```python
X_train = X_train[feature_set]
X_test = X_test[feature_set]
```

[9]:
```python
# For numerical data, fill NaN values with -1
X_train[numerical_columns] = X_train[numerical_columns].fillna(value=-1)
X_train.isnull().sum()


X_test[numerical_columns] = X_test[numerical_columns].fillna(value=-1)
X_test.isnull().sum()
```

[9]:
```
Census_FirmwareManufacturerIdentifier                  0
Census_PrimaryDiskTotalCapacity                        0
Census_OEMNameIdentifier                               0
Wdft_RegionIdentifier                                  0
Census_OSBuildRevision                                 0
LocaleEnglishNameIdentifier                            0
Census_ProcessorModelIdentifier                        0
Census_SystemVolumeTotalCapacity                       0
AVProductStatesIdentifier                              0
Census_InternalPrimaryDiagonalDisplaySizeInInches      0
CountryIdentifier                                      0
Census_ActivationChannel                               0
OsBuildLab                                             6
EngineVersion                                          0
SmartScreen                                       635267
AppVersion                                             0
Census_OSVersion                                       0
AvSigVersion                                           0
Census_OSInstallTypeName                               0
dtype: int64
```

[10]:
```python
X_train[categorical_columns].nunique()
```

[10]:
```
Census_ActivationChannel       6
OsBuildLab                   646
EngineVersion                 69
SmartScreen                   20
AppVersion                   108
Census_OSVersion             451
AvSigVersion                8474
Census_OSInstallTypeName       9
dtype: int64
```

For simplicity of model creation and feature set cleaning, we will only use 3 categorical columns [‘Census_ActivationChannel’, ‘SmartScreen’, ‘Census_OSInstallTypeName’].

We then encode each of these columns with a numerical label so that it becomes easier for our model to process them.

[11]:
```python
select_categorical_columns = ['Census_ActivationChannel', 'SmartScreen',␣
 ↪'Census_OSInstallTypeName']

print(X_train.Census_ActivationChannel.value_counts(),
      X_train.SmartScreen.value_counts(),
      X_train.Census_OSInstallTypeName.value_counts())
```

```
Retail            3781248
OEM:DM            2731351
Volume:GVLK        361133
OEM:NONSLP         254130
Volume:MAK           6466
Retail:TB:Eval       2858
Name: Census_ActivationChannel, dtype: int64 RequireAdmin    3452485
ExistsNotSet     837414
Off              149316
Warn             108179
Prompt            27543
Block             18101
off                1087
On                  594
&#x02;              342
&#x01;              253
on                  109
requireadmin          8
OFF                   2
Promt                 2
0                     2
Enabled               1
prompt                1
warn                  1
00000000              1
&#x03;                1
requireAdmin          0
Name: SmartScreen, dtype: int64 UUPUpgrade        2086177
IBSClean          1321383
Update            1274666
Upgrade           1001520
Other              671909
Reset              519243
Refresh            164367
Clean               55282
CleanPCRefresh      42639
Name: Census_OSInstallTypeName, dtype: int64
```

[12]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
for col in select_categorical_columns:
    X_train[col] = le.fit_transform(X_train[col])
    X_test[col] = le.fit_transform(X_test[col])
```

[13]:
```
X_train = X_train[numerical_columns + select_categorical_columns]
X_test = X_test[numerical_columns + select_categorical_columns]
```

[14]:
```
# Apply minmaxScalin to all column in train and test set
# This is done so that all features are now scaled 0 - 1 and thus can be
 ↪directly used in our model
from sklearn.preprocessing import MinMaxScaler

# create a scaler object
scaler = MinMaxScaler()
# fit and transform the data
X_train = pd.DataFrame(scaler.fit_transform(X_train), columns=X_train.columns)
X_test = pd.DataFrame(scaler.fit_transform(X_test), columns=X_test.columns)
```

***Q7.b.i*** **Final Model Creation: Create two models. Model 1 should use the cleaned features (All of the features do not have to be preprocessed) and logistic regression for training.**

**Model 1: Logistic Regression with pre-processed data**

[151]:
```
# import LogisticRegression
from sklearn.linear_model import LogisticRegression

# instantiate the model
log_reg = LogisticRegression()

# model fit with data
log_reg.fit(X_train,y_train)

# Predict y values based on model
y_pred=log_reg.predict(X_test)
```

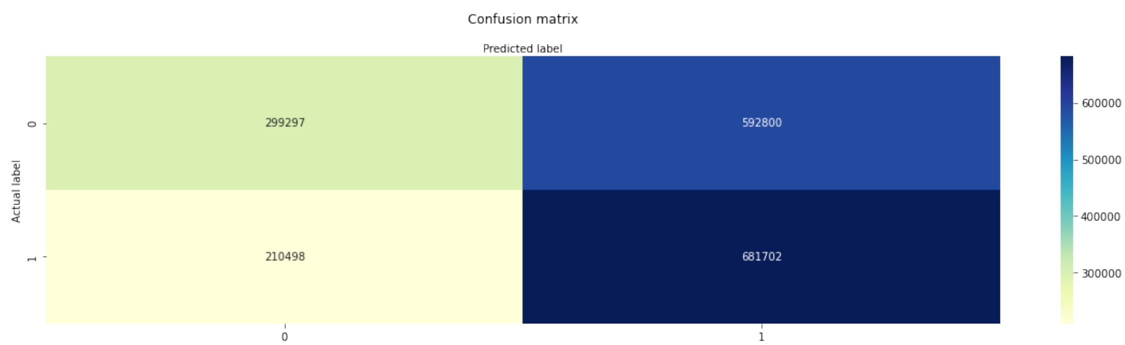
[152]:
```
# Test the prediction using Confusion matrix
from sklearn import metrics
cf_matrix = metrics.confusion_matrix(y_test, y_pred)
cf_matrix
```

[152]:
```
array([[299297, 592800],
       [210498, 681702]])
```

[153]:
```
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
```

```
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

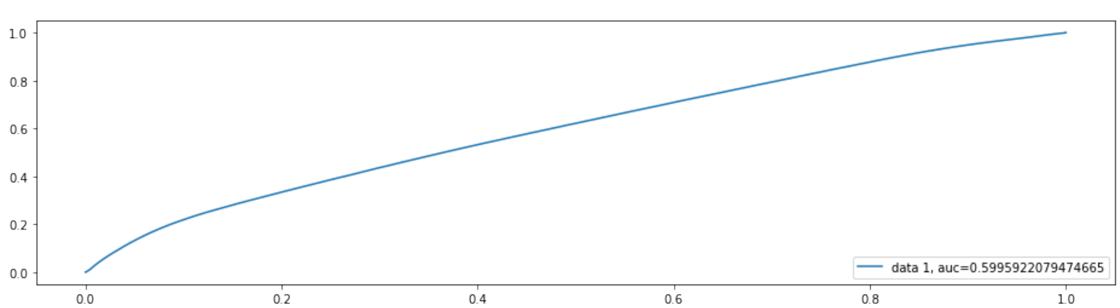
[153]: Text(0.5, 257.44, 'Predicted label')




[154]:
```
print("Model Accuracy = ",metrics.accuracy_score(y_test, y_pred))
print("Model Precision = ",metrics.precision_score(y_test, y_pred))
print("Model Recall = ",metrics.recall_score(y_test, y_pred))
```

```
Model Accuracy =  0.5497958019320774
Model Precision =  0.5348771520170231
Model Recall =  0.7640685944855413
```

[155]:
```
y_pred_probability = log_reg.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_probability)
auc = metrics.roc_auc_score(y_test, y_pred_probability)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



[157]:
```python
print('AUC Score: {}%'.format(auc*100))
print('\nError rate (Mean Squared Error) {}%\n'.format(100* metrics.
 ↪mean_squared_error(y_test, y_pred)))
```

```
AUC Score: 59.95922079474665%

Error rate (Mean Squared Error) 45.020419806792255%
```

[161]:
```python
import joblib
joblib.dump(log_reg, 'log_reg_clean_data.sav')
```

[161]:
```
['log_reg_clean_data.sav']
```

Using the same train/test split and the same Logistic Regression model, we now see that model accuracy has increased to 54% with an AUC score of ~60.

So after cleaning the feature set and doing some pre-processing, we do see an improvement in the prediction however it is still not very good.

Let's try a different model for the prediction with the same feature set and test/train split.

***Q7.b.ii.* Model 2 should use the cleaned features (All of the features do not have to be preprocessed) and an algorithm other than logistic regression (e.g. Random Forest, Nearest Neighbor, etc) for training.**

**Random Forest Classifier with Pre-processed data**

[162]:
```python
del data, log_reg, X, y
```

[15]:
```python
# Random Forest

from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=25, oob_score=True,␣
 ↪random_state=123456, verbose=3, criterion='entropy')
rf.fit(X_train, y_train)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

building tree 1 of 25

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   32.0s remaining:    0.0s

building tree 2 of 25

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:  1.0min remaining:    0.0s

building tree 3 of 25
building tree 4 of 25
building tree 5 of 25
building tree 6 of 25
```

```
building tree 7 of 25
building tree 8 of 25
building tree 9 of 25
building tree 10 of 25
building tree 11 of 25
building tree 12 of 25
building tree 13 of 25
building tree 14 of 25
building tree 15 of 25
building tree 16 of 25
building tree 17 of 25
building tree 18 of 25
building tree 19 of 25
building tree 20 of 25
building tree 21 of 25
building tree 22 of 25
building tree 23 of 25
building tree 24 of 25
building tree 25 of 25
```

```
[Parallel(n_jobs=1)]: Done  25 out of  25 | elapsed: 12.8min finished
/opt/conda/lib/python3.8/site-packages/sklearn/ensemble/_forest.py:541:
UserWarning: Some inputs do not have OOB scores. This probably means too few
trees were used to compute any reliable oob estimates.
  warn("Some inputs do not have OOB scores. "
/opt/conda/lib/python3.8/site-packages/sklearn/ensemble/_forest.py:545:
RuntimeWarning: invalid value encountered in true_divide
  decision = (predictions[k] /
```

[15]:
```
RandomForestClassifier(criterion='entropy', n_estimators=25, oob_score=True,
                       random_state=123456, verbose=3)
```

[16]:
```
from sklearn.metrics import accuracy_score
predicted = rf.predict(X_test)
accuracy = accuracy_score(y_test, predicted)
print(f'Out-of-bag score estimate: {rf.oob_score_:.3}')
print(f'Mean accuracy score: {accuracy:.3}')
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.9s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    1.9s remaining:    0.0s
```

```
Out-of-bag score estimate: 0.607
Mean accuracy score: 0.576
```

```
[Parallel(n_jobs=1)]: Done  25 out of  25 | elapsed:   21.4s finished
```

[24]:
```
print("Model Accuracy = ",metrics.accuracy_score(y_test, predicted))
print("Model Precision = ",metrics.precision_score(y_test, predicted))
print("Model Recall = ",metrics.recall_score(y_test, predicted))
```

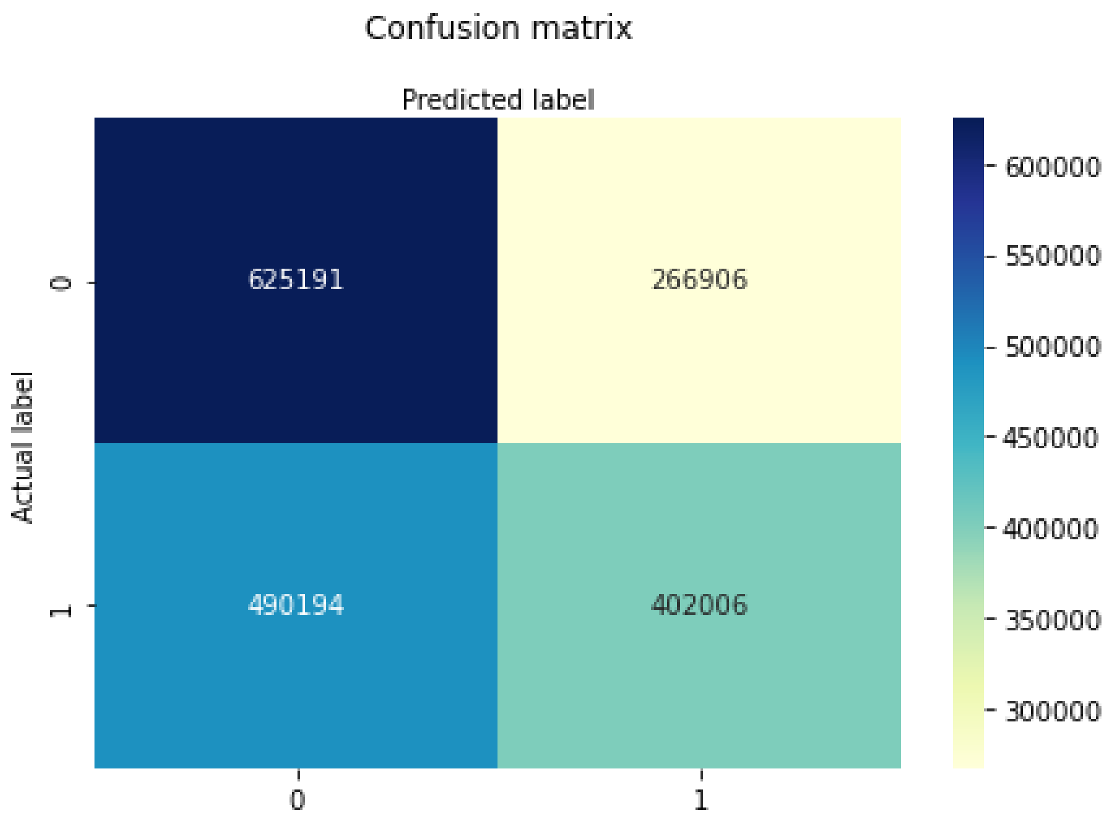
```
Model Accuracy =  0.5756872314418507
Model Precision =  0.6009848829143445
Model Recall =  0.4505783456624075
```

[18]:
```python
# Test the prediction using Confusion matrix
from sklearn import metrics
cf_matrix = metrics.confusion_matrix(y_test, predicted)
cf_matrix
```

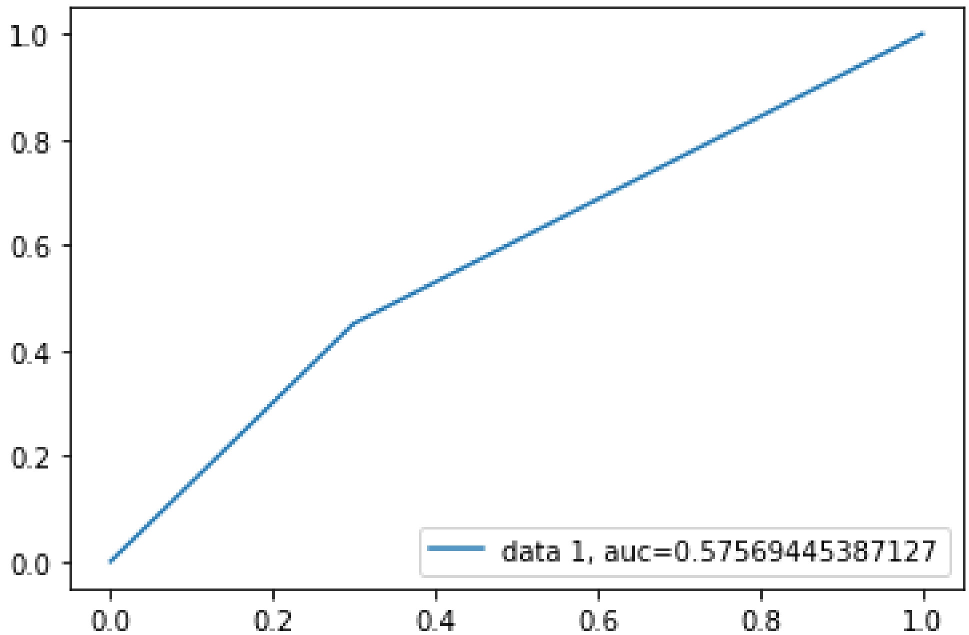
[18]:
```
array([[625191, 266906],
       [490194, 402006]])
```

[19]:
```python
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[19]:
```
Text(0.5, 257.44, 'Predicted label')
```




[20]:
```
fpr, tpr, _ = metrics.roc_curve(y_test,  predicted)

auc = metrics.roc_auc_score(y_test, predicted)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```




[22]:
```
print('AUC Score: {}%'.format(auc*100))
print('\nError rate (Mean Squared Error) {}%\n'.format(100* metrics.
 ↪mean_squared_error(y_test, predicted)))
```

```
AUC Score: 57.569445387127004%

Error rate (Mean Squared Error) 42.43127685581493%
```

Here we see model accuracy as 57% which seems to be worse than the linear regression model we used earlier. There could be multiple factors for this. One of them could be due to the number of iterations Random Forest classifier ran for.

For simiplicity, and due to memory limitations, I was not able to run the classifier for more than 25-30 iterations. But increasing the number of iterations (estimators) on the Random forest function could potentially give better results.

[26]:
```
import joblib
joblib.dump(rf, 'random_forest_clean_data.sav')
```

[26]:
```
['random_forest_clean_data.sav']
```

### 1.9.1 Error Rate Comparison between models

| Model Name | Description | AUC Score (in %) | Error (MSE) (in %) |
|---|---|---|---|
| Model 0 | Baseline Logistic Regression without Data Cleaning | 52.82% | 49.99% |
| Model 1 | Logistic Regression with Data Cleaning | 59.95% | 45.02% |

| Model Name | Description | AUC Score (in %) | Error (MSE) (in %) |
|---|---|---|---|
| Model 2 | Random Forest with Data Cleaning | 57.56% | 42.43% |

The AUC score and error rate for the three models are tabulated above.

Between all the models, we find Logistic Regression performed much better on the dataset after we cleaned the data (Model 1). Model 0 performed the worst considering that it's AUC score is only slightly better than random guessing, and that is justified since we are using only the numerical columns without any pre-processing.

An interesting observation here is that of Model 2, which uses Random Forest classifiers with clean data which did not outperform Logistic Regression. Now it is difficult to say with certainty why Model 1 is performing better than Model 2, but one of the important things to consider is the data set and the features used. Random Forests is a very versatile algorithm and generally performs better than Logistic Regression when the dataset has a lot of spare features, including categorical and numerical features. So one would expect Model 2 to be better performing here. However, we also need to consider the following points about this dataset which could have affected the outcome here:

1. Logistic Regression is much faster to train and run on large dimensional dataset compared to Random Forests. Due to the huge size of the train and test sets, I decided to not spend too much time on optimizing Random Forests.
2. Random Forests tend to give better results for a specific number (usually large) of estimators. Since creating more trees for estimation would just keep using more and more memory, I restricted the number of trees to 25. With more trial and error, it would be possible to find an estimator count which outperforms Logistic Regression. But due to interest of time and resources, I decided to stick with 25.
3. During pre-processing, I converted all categorical columns into numeric categories using Label Encoding and then normalized their distribution using MinMaxScaling. So, even though the actual column values were categorical, after pre-processing all of the columns were essentially acting as numerical features. Logistic Regression, typically, performs really well with numerical columns.

## 1.10 Section 8: Screenshots (Q8)

***Q8.* Write the probability of detection for the test instances (test.csv) into a csv file as shown in 'sample_submission.csv' at Kaggle. Submit this for every model you develop to the competition website. Report the private and public score for your best submission along with the number of submissions. Include a snapshot of your best score on the website as confirmation. Be sure to provide a link to your Kaggle profile.**

### 1.10.1 Validating results against test.csv

Pre-processing the test.csv data with the same steps as train.csv data

[19]:
```
filename = 'test.csv'
```

```
use_cols = ["MachineIdentifier", "SmartScreen", "AVProductsInstalled",␣
 ↪"AppVersion", "CountryIdentifier", "Census_OSInstallTypeName",␣
 ↪"Wdft_IsGamer",
           "EngineVersion", "AVProductStatesIdentifier", "Census_OSVersion",␣
 ↪"Census_TotalPhysicalRAM", "Census_ActivationChannel",
           "RtpStateBitfield", "Census_ProcessorModelIdentifier",␣
 ↪"Census_PrimaryDiskTotalCapacity",
            "Census_InternalPrimaryDiagonalDisplaySizeInInches",␣
 ↪"Wdft_RegionIdentifier", "LocaleEnglishNameIdentifier",
           "AvSigVersion", "IeVerIdentifier", "IsProtected",␣
 ↪"Census_InternalPrimaryDisplayResolutionVertical",␣
 ↪"Census_PrimaryDiskTypeName",
            "Census_OSWUAutoUpdateOptionsName", "Census_OSEdition",␣
 ↪"Census_GenuineStateName", "Census_ProcessorCoreCount",
           "Census_OEMNameIdentifier", "Census_MDC2FormFactor",␣
 ↪"Census_FirmwareManufacturerIdentifier", "OsBuildLab",␣
 ↪"Census_OSBuildRevision",
            "Census_OSBuildNumber", "Census_IsPenCapable",␣
 ↪"Census_IsTouchEnabled", "Census_IsAlwaysOnAlwaysConnectedCapable",␣
 ↪"Census_IsSecureBootEnabled",
            "Census_SystemVolumeTotalCapacity",␣
 ↪"Census_PrimaryDiskTotalCapacity"
           ]

skip = 0

data = pd.read_csv(filename, usecols = use_cols, dtype = dtypes, skiprows=skip)

data.set_index('MachineIdentifier', inplace=True)


numerical_columns =␣
 ↪['Census_FirmwareManufacturerIdentifier','Census_PrimaryDiskTotalCapacity','Census_OEMNameI
 ↪'Wdft_RegionIdentifier',
                  'Census_OSBuildRevision','LocaleEnglishNameIdentifier',␣
 ↪'Census_ProcessorModelIdentifier', 'Census_SystemVolumeTotalCapacity',
                  'AVProductStatesIdentifier',␣
 ↪'Census_InternalPrimaryDiagonalDisplaySizeInInches', 'CountryIdentifier']

select_categorical_columns = ['Census_ActivationChannel', 'SmartScreen',␣
 ↪'Census_OSInstallTypeName']

feature_set = numerical_columns + select_categorical_columns
```

[20]:

```
X = data[feature_set].copy()
X.head(10)
```

```
[20]:                                 Census_FirmwareManufacturerIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                                 807.000000
00000176ac758d54827acd545b6315a5                                 554.000000
0000019dcefc128c2d4387c1273dae1d                                 556.000000
0000055553dc51b1295785415f1a224d                                 628.000000
00000574cefffeca83ec8adf9285b2bf                                 556.000000
000007ffedd31948f08e6c16da31f6d1                                 168.000000
000008f31610018d898e5f315cdf1bd1                                 142.000000
00000a3c447250626dbcc628c9cbc460                                 657.000000
00000b6bf217ec9aef0f68d5c6705897                                        NaN
00000b8d3776b13e93ad83676a28e4aa                                        NaN

                                  Census_PrimaryDiskTotalCapacity  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                        488386.000000
00000176ac758d54827acd545b6315a5                       1907729.000000
0000019dcefc128c2d4387c1273dae1d                         29820.000000
0000055553dc51b1295785415f1a224d                        476940.000000
00000574cefffeca83ec8adf9285b2bf                        476940.000000
000007ffedd31948f08e6c16da31f6d1                        305244.000000
000008f31610018d898e5f315cdf1bd1                        953869.000000
00000a3c447250626dbcc628c9cbc460                        305245.000000
00000b6bf217ec9aef0f68d5c6705897                                  NaN
00000b8d3776b13e93ad83676a28e4aa                        476940.000000

                                  Census_OEMNameIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e               2688.000000
00000176ac758d54827acd545b6315a5               2206.000000
0000019dcefc128c2d4387c1273dae1d                585.000000
0000055553dc51b1295785415f1a224d               2668.000000
00000574cefffeca83ec8adf9285b2bf                585.000000
000007ffedd31948f08e6c16da31f6d1               1980.000000
000008f31610018d898e5f315cdf1bd1               4144.000000
00000a3c447250626dbcc628c9cbc460               2972.000000
00000b6bf217ec9aef0f68d5c6705897               2668.000000
00000b8d3776b13e93ad83676a28e4aa                       NaN

                                  Wdft_RegionIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e               7.000000
00000176ac758d54827acd545b6315a5              12.000000
0000019dcefc128c2d4387c1273dae1d              11.000000
0000055553dc51b1295785415f1a224d              10.000000
00000574cefffeca83ec8adf9285b2bf               3.000000
000007ffedd31948f08e6c16da31f6d1              10.000000
```

```
000008f31610018d898e5f315cdf1bd1             10.000000
00000a3c447250626dbcc628c9cbc460              9.000000
00000b6bf217ec9aef0f68d5c6705897                   NaN
00000b8d3776b13e93ad83676a28e4aa             15.000000

                                  Census_OSBuildRevision  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                    1387
00000176ac758d54827acd545b6315a5                     611
0000019dcefc128c2d4387c1273dae1d                    2189
0000055553dc51b1295785415f1a224d                     371
00000574cefffeca83ec8adf9285b2bf                     371
000007ffedd31948f08e6c16da31f6d1                     286
000008f31610018d898e5f315cdf1bd1                     345
00000a3c447250626dbcc628c9cbc460                     125
00000b6bf217ec9aef0f68d5c6705897                     134
00000b8d3776b13e93ad83676a28e4aa                     192

                                  LocaleEnglishNameIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                           42
00000176ac758d54827acd545b6315a5                           74
0000019dcefc128c2d4387c1273dae1d                           -5
0000055553dc51b1295785415f1a224d                          -85
00000574cefffeca83ec8adf9285b2bf                          -74
000007ffedd31948f08e6c16da31f6d1                          -85
000008f31610018d898e5f315cdf1bd1                          -85
00000a3c447250626dbcc628c9cbc460                          126
00000b6bf217ec9aef0f68d5c6705897                           75
00000b8d3776b13e93ad83676a28e4aa                          -17

                                  Census_ProcessorModelIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                      3064.000000
00000176ac758d54827acd545b6315a5                      3410.000000
0000019dcefc128c2d4387c1273dae1d                      2096.000000
0000055553dc51b1295785415f1a224d                      1985.000000
00000574cefffeca83ec8adf9285b2bf                      3394.000000
000007ffedd31948f08e6c16da31f6d1                      3512.000000
000008f31610018d898e5f315cdf1bd1                      2382.000000
00000a3c447250626dbcc628c9cbc460                      3224.000000
00000b6bf217ec9aef0f68d5c6705897                              NaN
00000b8d3776b13e93ad83676a28e4aa                      3514.000000

                                  Census_SystemVolumeTotalCapacity  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                     123179.000000
```

```
00000176ac758d54827acd545b6315a5                  1882352.000000
0000019dcefc128c2d4387c1273dae1d                    28678.000000
0000055553dc51b1295785415f1a224d                   439345.000000
00000574cefffeca83ec8adf9285b2bf                   461506.000000
000007ffedd31948f08e6c16da31f6d1                   304261.000000
000008f31610018d898e5f315cdf1bd1                   936631.000000
00000a3c447250626dbcc628c9cbc460                   304352.000000
00000b6bf217ec9aef0f68d5c6705897                             NaN
00000b8d3776b13e93ad83676a28e4aa                   476479.000000

                                  AVProductStatesIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                 53447.000000
00000176ac758d54827acd545b6315a5                 53447.000000
0000019dcefc128c2d4387c1273dae1d                 49480.000000
0000055553dc51b1295785415f1a224d                 42160.000000
00000574cefffeca83ec8adf9285b2bf                 53447.000000
000007ffedd31948f08e6c16da31f6d1                 53447.000000
000008f31610018d898e5f315cdf1bd1                  7945.000000
00000a3c447250626dbcc628c9cbc460                 15521.000000
00000b6bf217ec9aef0f68d5c6705897                 53447.000000
00000b8d3776b13e93ad83676a28e4aa                 53447.000000

Census_InternalPrimaryDiagonalDisplaySizeInInches  \
MachineIdentifier
0000010489e3af074adeac69c53e555e
15.500000
00000176ac758d54827acd545b6315a5
15.500000
0000019dcefc128c2d4387c1273dae1d
13.898438
0000055553dc51b1295785415f1a224d
14.000000
00000574cefffeca83ec8adf9285b2bf
15.500000
000007ffedd31948f08e6c16da31f6d1
17.000000
000008f31610018d898e5f315cdf1bd1
15.500000
00000a3c447250626dbcc628c9cbc460
17.000000
00000b6bf217ec9aef0f68d5c6705897
15.500000
00000b8d3776b13e93ad83676a28e4aa
23.203125

                                  CountryIdentifier Census_ActivationChannel  \
```

```
MachineIdentifier
0000010489e3af074adeac69c53e555e               43            OEM:DM
00000176ac758d54827acd545b6315a5               68            Retail
0000019dcefc128c2d4387c1273dae1d              201            OEM:DM
0000055553dc51b1295785415f1a224d               29            OEM:DM
00000574cefffeca83ec8adf9285b2bf              171            Retail
000007ffedd31948f08e6c16da31f6d1               29            Retail
000008f31610018d898e5f315cdf1bd1               29            OEM:DM
00000a3c447250626dbcc628c9cbc460              101            Retail
00000b6bf217ec9aef0f68d5c6705897               21            Retail
00000b8d3776b13e93ad83676a28e4aa              177            Retail

                                   SmartScreen Census_OSInstallTypeName
MachineIdentifier
0000010489e3af074adeac69c53e555e          NaN                     Reset
00000176ac758d54827acd545b6315a5  RequireAdmin                UUPUpgrade
0000019dcefc128c2d4387c1273dae1d  RequireAdmin                     Other
0000055553dc51b1295785415f1a224d  RequireAdmin                   Upgrade
00000574cefffeca83ec8adf9285b2bf  RequireAdmin                    Update
000007ffedd31948f08e6c16da31f6d1          NaN                   Upgrade
000008f31610018d898e5f315cdf1bd1          NaN                   Refresh
00000a3c447250626dbcc628c9cbc460          NaN                   Upgrade
00000b6bf217ec9aef0f68d5c6705897          NaN                  IBSClean
00000b8d3776b13e93ad83676a28e4aa  RequireAdmin                   Upgrade
```

[21]:

```
# For numerical data, fill NaN values with -1
X[numerical_columns] = X[numerical_columns].fillna(value=-1)


from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

for col in select_categorical_columns:
    X[col] = le.fit_transform(X[col])


from sklearn.preprocessing import MinMaxScaler

# create a scaler object
scaler = MinMaxScaler()
# fit and transform the data
X[feature_set] = scaler.fit_transform(X[feature_set])

X.head(10)
```

[21]:

```
                                  Census_FirmwareManufacturerIdentifier  \
MachineIdentifier
```

```
0000010489e3af074adeac69c53e555e                                0.741965
00000176ac758d54827acd545b6315a5                                0.509642
0000019dcefc128c2d4387c1273dae1d                                0.511478
0000055553dc51b1295785415f1a224d                                0.577594
00000574cefffeca83ec8adf9285b2bf                                0.511478
000007ffedd31948f08e6c16da31f6d1                                0.155188
000008f31610018d898e5f315cdf1bd1                                0.131313
00000a3c447250626dbcc628c9cbc460                                0.604224
00000b6bf217ec9aef0f68d5c6705897                                0.000000
00000b8d3776b13e93ad83676a28e4aa                                0.000000

                                  Census_PrimaryDiskTotalCapacity  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                         0.000000
00000176ac758d54827acd545b6315a5                         0.000000
0000019dcefc128c2d4387c1273dae1d                         0.000000
0000055553dc51b1295785415f1a224d                         0.000000
00000574cefffeca83ec8adf9285b2bf                         0.000000
000007ffedd31948f08e6c16da31f6d1                         0.000000
000008f31610018d898e5f315cdf1bd1                         0.000000
00000a3c447250626dbcc628c9cbc460                         0.000000
00000b6bf217ec9aef0f68d5c6705897                         0.000000
00000b8d3776b13e93ad83676a28e4aa                         0.000000

                                  Census_OEMNameIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                  0.437592
00000176ac758d54827acd545b6315a5                  0.359154
0000019dcefc128c2d4387c1273dae1d                  0.095362
0000055553dc51b1295785415f1a224d                  0.434337
00000574cefffeca83ec8adf9285b2bf                  0.095362
000007ffedd31948f08e6c16da31f6d1                  0.322376
000008f31610018d898e5f315cdf1bd1                  0.674532
00000a3c447250626dbcc628c9cbc460                  0.483808
00000b6bf217ec9aef0f68d5c6705897                  0.434337
00000b8d3776b13e93ad83676a28e4aa                  0.000000

                                  Wdft_RegionIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e               0.500000
00000176ac758d54827acd545b6315a5               0.812500
0000019dcefc128c2d4387c1273dae1d               0.750000
0000055553dc51b1295785415f1a224d               0.687500
00000574cefffeca83ec8adf9285b2bf               0.250000
000007ffedd31948f08e6c16da31f6d1               0.687500
000008f31610018d898e5f315cdf1bd1               0.687500
00000a3c447250626dbcc628c9cbc460               0.625000
```

```
00000b6bf217ec9aef0f68d5c6705897              0.000000
00000b8d3776b13e93ad83676a28e4aa              1.000000

                                  Census_OSBuildRevision  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                0.033233
00000176ac758d54827acd545b6315a5                0.014640
0000019dcefc128c2d4387c1273dae1d                0.052449
0000055553dc51b1295785415f1a224d                0.008889
00000574cefffeca83ec8adf9285b2bf                0.008889
000007ffedd31948f08e6c16da31f6d1                0.006853
000008f31610018d898e5f315cdf1bd1                0.008266
00000a3c447250626dbcc628c9cbc460                0.002995
00000b6bf217ec9aef0f68d5c6705897                0.003211
00000b8d3776b13e93ad83676a28e4aa                0.004600

                                  LocaleEnglishNameIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                     0.666667
00000176ac758d54827acd545b6315a5                     0.792157
0000019dcefc128c2d4387c1273dae1d                     0.482353
0000055553dc51b1295785415f1a224d                     0.168627
00000574cefffeca83ec8adf9285b2bf                     0.211765
000007ffedd31948f08e6c16da31f6d1                     0.168627
000008f31610018d898e5f315cdf1bd1                     0.168627
00000a3c447250626dbcc628c9cbc460                     0.996078
00000b6bf217ec9aef0f68d5c6705897                     0.796078
00000b8d3776b13e93ad83676a28e4aa                     0.435294

                                  Census_ProcessorModelIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                         0.684610
00000176ac758d54827acd545b6315a5                         0.761894
0000019dcefc128c2d4387c1273dae1d                         0.468394
0000055553dc51b1295785415f1a224d                         0.443601
00000574cefffeca83ec8adf9285b2bf                         0.758320
000007ffedd31948f08e6c16da31f6d1                         0.784677
000008f31610018d898e5f315cdf1bd1                         0.532276
00000a3c447250626dbcc628c9cbc460                         0.720348
00000b6bf217ec9aef0f68d5c6705897                         0.000000
00000b8d3776b13e93ad83676a28e4aa                         0.785124

                                  Census_SystemVolumeTotalCapacity  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                          0.001292
00000176ac758d54827acd545b6315a5                          0.019736
0000019dcefc128c2d4387c1273dae1d                          0.000301
```

```
0000055553dc51b1295785415f1a224d                         0.004607
00000574cefffeca83ec8adf9285b2bf                         0.004839
000007ffedd31948f08e6c16da31f6d1                         0.003190
000008f31610018d898e5f315cdf1bd1                         0.009821
00000a3c447250626dbcc628c9cbc460                         0.003191
00000b6bf217ec9aef0f68d5c6705897                         0.000000
00000b8d3776b13e93ad83676a28e4aa                         0.004996

                                  AVProductStatesIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                   0.758095
00000176ac758d54827acd545b6315a5                   0.758095
0000019dcefc128c2d4387c1273dae1d                   0.701828
0000055553dc51b1295785415f1a224d                   0.598003
00000574cefffeca83ec8adf9285b2bf                   0.758095
000007ffedd31948f08e6c16da31f6d1                   0.758095
000008f31610018d898e5f315cdf1bd1                   0.112704
00000a3c447250626dbcc628c9cbc460                   0.220161
00000b6bf217ec9aef0f68d5c6705897                   0.758095
00000b8d3776b13e93ad83676a28e4aa                   0.758095

Census_InternalPrimaryDiagonalDisplaySizeInInches  \
MachineIdentifier
0000010489e3af074adeac69c53e555e
0.076834
00000176ac758d54827acd545b6315a5
0.076834
0000019dcefc128c2d4387c1273dae1d
0.069376
0000055553dc51b1295785415f1a224d
0.069849
00000574cefffeca83ec8adf9285b2bf
0.076834
000007ffedd31948f08e6c16da31f6d1
0.083818
000008f31610018d898e5f315cdf1bd1
0.076834
00000a3c447250626dbcc628c9cbc460
0.083818
00000b6bf217ec9aef0f68d5c6705897
0.076834
00000b8d3776b13e93ad83676a28e4aa
0.112704

                                  CountryIdentifier  Census_ActivationChannel  \
MachineIdentifier
0000010489e3af074adeac69c53e555e           0.190045                  0.000000
```

```
00000176ac758d54827acd545b6315a5          0.303167                0.400000
0000019dcefc128c2d4387c1273dae1d          0.904977                0.000000
0000055553dc51b1295785415f1a224d          0.126697                0.000000
00000574cefffeca83ec8adf9285b2bf          0.769231                0.400000
000007ffedd31948f08e6c16da31f6d1          0.126697                0.400000
000008f31610018d898e5f315cdf1bd1          0.126697                0.000000
00000a3c447250626dbcc628c9cbc460          0.452489                0.400000
00000b6bf217ec9aef0f68d5c6705897          0.090498                0.400000
00000b8d3776b13e93ad83676a28e4aa          0.796380                0.400000

                                  SmartScreen  Census_OSInstallTypeName
MachineIdentifier
0000010489e3af074adeac69c53e555e     1.000000                  0.625000
00000176ac758d54827acd545b6315a5     0.619048                  0.750000
0000019dcefc128c2d4387c1273dae1d     0.619048                  0.375000
0000055553dc51b1295785415f1a224d     0.619048                  1.000000
00000574cefffeca83ec8adf9285b2bf     0.619048                  0.875000
000007ffedd31948f08e6c16da31f6d1     1.000000                  1.000000
000008f31610018d898e5f315cdf1bd1     1.000000                  0.500000
00000a3c447250626dbcc628c9cbc460     1.000000                  1.000000
00000b6bf217ec9aef0f68d5c6705897     1.000000                  0.250000
00000b8d3776b13e93ad83676a28e4aa     0.619048                  1.000000
```

**Prediction using Model 0 (Baseline Model)**

[22]:
```python
import joblib
log_reg = joblib.load('log_reg_baseline.sav')1
```

[28]:
```python
numerical_columns =␣
↪['Census_FirmwareManufacturerIdentifier','Census_PrimaryDiskTotalCapacity','Census_OEMNameI
↪'Wdft_RegionIdentifier',
                  'Census_OSBuildRevision','LocaleEnglishNameIdentifier',␣
↪'Census_ProcessorModelIdentifier', 'Census_SystemVolumeTotalCapacity',
                  'AVProductStatesIdentifier',␣
↪'Census_InternalPrimaryDiagonalDisplaySizeInInches', 'CountryIdentifier']


feature_set = numerical_columns

X = data[feature_set]


X.fillna(-1, inplace=True)
```

```
/opt/conda/lib/python3.8/site-packages/pandas/core/frame.py:4462:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return super().fillna(
```

[30]:
```
X.head(10)
```

[30]:
```
                                  Census_FirmwareManufacturerIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                             807.000000
00000176ac758d54827acd545b6315a5                             554.000000
0000019dcefc128c2d4387c1273dae1d                             556.000000
0000055553dc51b1295785415f1a224d                             628.000000
00000574cefffeca83ec8adf9285b2bf                             556.000000
000007ffedd31948f08e6c16da31f6d1                             168.000000
000008f31610018d898e5f315cdf1bd1                             142.000000
00000a3c447250626dbcc628c9cbc460                             657.000000
00000b6bf217ec9aef0f68d5c6705897                              -1.000000
00000b8d3776b13e93ad83676a28e4aa                              -1.000000

                                  Census_PrimaryDiskTotalCapacity  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                    488386.000000
00000176ac758d54827acd545b6315a5                   1907729.000000
0000019dcefc128c2d4387c1273dae1d                     29820.000000
0000055553dc51b1295785415f1a224d                    476940.000000
00000574cefffeca83ec8adf9285b2bf                    476940.000000
000007ffedd31948f08e6c16da31f6d1                    305244.000000
000008f31610018d898e5f315cdf1bd1                    953869.000000
00000a3c447250626dbcc628c9cbc460                    305245.000000
00000b6bf217ec9aef0f68d5c6705897                        -1.000000
00000b8d3776b13e93ad83676a28e4aa                    476940.000000

                                  Census_OEMNameIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e               2688.000000
00000176ac758d54827acd545b6315a5               2206.000000
0000019dcefc128c2d4387c1273dae1d                585.000000
0000055553dc51b1295785415f1a224d               2668.000000
00000574cefffeca83ec8adf9285b2bf                585.000000
000007ffedd31948f08e6c16da31f6d1               1980.000000
000008f31610018d898e5f315cdf1bd1               4144.000000
00000a3c447250626dbcc628c9cbc460               2972.000000
00000b6bf217ec9aef0f68d5c6705897               2668.000000
00000b8d3776b13e93ad83676a28e4aa                 -1.000000

                                  Wdft_RegionIdentifier  \
MachineIdentifier
```

```
0000010489e3af074adeac69c53e555e              7.000000
00000176ac758d54827acd545b6315a5             12.000000
0000019dcefc128c2d4387c1273dae1d             11.000000
0000055553dc51b1295785415f1a224d             10.000000
00000574cefffeca83ec8adf9285b2bf              3.000000
000007ffedd31948f08e6c16da31f6d1             10.000000
000008f31610018d898e5f315cdf1bd1             10.000000
00000a3c447250626dbcc628c9cbc460              9.000000
00000b6bf217ec9aef0f68d5c6705897             -1.000000
00000b8d3776b13e93ad83676a28e4aa             15.000000

                                  Census_OSBuildRevision  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                    1387
00000176ac758d54827acd545b6315a5                     611
0000019dcefc128c2d4387c1273dae1d                    2189
0000055553dc51b1295785415f1a224d                     371
00000574cefffeca83ec8adf9285b2bf                     371
000007ffedd31948f08e6c16da31f6d1                     286
000008f31610018d898e5f315cdf1bd1                     345
00000a3c447250626dbcc628c9cbc460                     125
00000b6bf217ec9aef0f68d5c6705897                     134
00000b8d3776b13e93ad83676a28e4aa                     192

                                  LocaleEnglishNameIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                           42
00000176ac758d54827acd545b6315a5                           74
0000019dcefc128c2d4387c1273dae1d                           -5
0000055553dc51b1295785415f1a224d                          -85
00000574cefffeca83ec8adf9285b2bf                          -74
000007ffedd31948f08e6c16da31f6d1                          -85
000008f31610018d898e5f315cdf1bd1                          -85
00000a3c447250626dbcc628c9cbc460                          126
00000b6bf217ec9aef0f68d5c6705897                           75
00000b8d3776b13e93ad83676a28e4aa                          -17

                                  Census_ProcessorModelIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                      3064.000000
00000176ac758d54827acd545b6315a5                      3410.000000
0000019dcefc128c2d4387c1273dae1d                      2096.000000
0000055553dc51b1295785415f1a224d                      1985.000000
00000574cefffeca83ec8adf9285b2bf                      3394.000000
000007ffedd31948f08e6c16da31f6d1                      3512.000000
000008f31610018d898e5f315cdf1bd1                      2382.000000
00000a3c447250626dbcc628c9cbc460                      3224.000000
```

```
00000b6bf217ec9aef0f68d5c6705897                                  -1.000000
00000b8d3776b13e93ad83676a28e4aa                                3514.000000

                                  Census_SystemVolumeTotalCapacity  \
MachineIdentifier
0000010489e3af074adeac69c53e555e                     123179.000000
00000176ac758d54827acd545b6315a5                    1882352.000000
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0000055553dc51b1295785415f1a224d                     439345.000000
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000007ffedd31948f08e6c16da31f6d1                     304261.000000
000008f31610018d898e5f315cdf1bd1                     936631.000000
00000a3c447250626dbcc628c9cbc460                     304352.000000
00000b6bf217ec9aef0f68d5c6705897                         -1.000000
00000b8d3776b13e93ad83676a28e4aa                     476479.000000

                                  AVProductStatesIdentifier  \
MachineIdentifier
0000010489e3af074adeac69c53e555e               53447.000000
00000176ac758d54827acd545b6315a5               53447.000000
0000019dcefc128c2d4387c1273dae1d               49480.000000
0000055553dc51b1295785415f1a224d               42160.000000
00000574cefffeca83ec8adf9285b2bf               53447.000000
000007ffedd31948f08e6c16da31f6d1               53447.000000
000008f31610018d898e5f315cdf1bd1                7945.000000
00000a3c447250626dbcc628c9cbc460               15521.000000
00000b6bf217ec9aef0f68d5c6705897               53447.000000
00000b8d3776b13e93ad83676a28e4aa               53447.000000

Census_InternalPrimaryDiagonalDisplaySizeInInches  \
MachineIdentifier
0000010489e3af074adeac69c53e555e
15.500000
00000176ac758d54827acd545b6315a5
15.500000
0000019dcefc128c2d4387c1273dae1d
13.898438
0000055553dc51b1295785415f1a224d
14.000000
00000574cefffeca83ec8adf9285b2bf
15.500000
000007ffedd31948f08e6c16da31f6d1
17.000000
000008f31610018d898e5f315cdf1bd1
15.500000
00000a3c447250626dbcc628c9cbc460
17.000000
```

```
00000b6bf217ec9aef0f68d5c6705897
15.500000
00000b8d3776b13e93ad83676a28e4aa
23.203125

                                  CountryIdentifier
MachineIdentifier
0000010489e3af074adeac69c53e555e                 43
00000176ac758d54827acd545b6315a5                 68
0000019dcefc128c2d4387c1273dae1d                201
0000055553dc51b1295785415f1a224d                 29
00000574cefffeca83ec8adf9285b2bf                171
000007ffedd31948f08e6c16da31f6d1                 29
000008f31610018d898e5f315cdf1bd1                 29
00000a3c447250626dbcc628c9cbc460                101
00000b6bf217ec9aef0f68d5c6705897                 21
00000b8d3776b13e93ad83676a28e4aa                177
```

[29]:
```
# Predict using Model 0
y_pred = log_reg.predict_proba(X)[:,1]
res = pd.DataFrame(y_pred)
res.index = X.index # for comparison
res.columns = ["HasDetections"]
res.to_csv("model0_op.csv", chunksize=1000000)
```

**Prediction using Model 1 (Logistic Regression)**

[16]:
```
import joblib
log_reg = joblib.load('log_reg_clean_data.sav')
```

[17]:
```
# Predict using Model 1
y_pred = log_reg.predict_proba(X)[:,1]
res = pd.DataFrame(y_pred)
res.index = X.index # for comparison
res.columns = ["HasDetections"]
res.to_csv("model1_op.csv", chunksize=1000000)
```

[18]:
```
del log_reg
```

**Prediction using Model 2 (Random Forests)**

[21]:
```
import joblib
rf = joblib.load('random_forest_clean_data.sav')
```

[22]:
```
# Predict using Model 2
y_pred = rf.predict_proba(X)[:,1]
res = pd.DataFrame(y_pred)
res.index = X.index # for comparison
res.columns = ["HasDetections"]
```

```python
res.to_csv("model2_op.csv", chunksize=1000000)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    4.6s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    9.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  25 out of  25 | elapsed:  1.7min finished
```

Public Score: 0.60060 ( Random Forests )

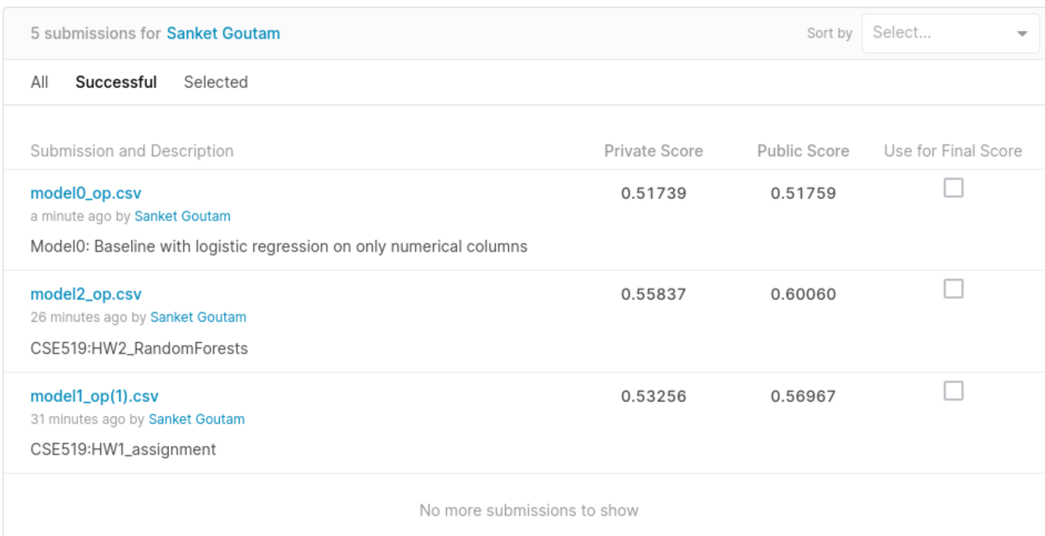
Private Score: 0.55837 ( Random Forests )

Kaggle profile link: https://www.kaggle.com/sanketgoutam

Screenshot(s):

[31]:
```python
from IPython.display import Image
Image(filename='screenshot.png')
```

[31]:



5 submissions for Sanket Goutam                Sort by Select...

All  Successful  Selected

| Submission and Description | Private Score | Public Score | Use for Final Score |
|---|---|---|---|
| model0_op.csv<br>a minute ago by Sanket Goutam<br>Model0: Baseline with logistic regression on only numerical columns | 0.51739 | 0.51759 | ☐ |
| model2_op.csv<br>26 minutes ago by Sanket Goutam<br>CSE519:HW2_RandomForests | 0.55837 | 0.60060 | ☐ |
| model1_op(1).csv<br>31 minutes ago by Sanket Goutam<br>CSE519:HW1_assignment | 0.53256 | 0.56967 | ☐ |

No more submissions to show