JWillis_D209_Data_Mining_PA2

January 8, 2023

0.1 D209 - Data Mining I - PA2

0.1.1 Import Libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from pandas import DataFrame
import sklearn.neighbors
from sklearn.neighbors import KNeighborsClassifier
from sklearn import preprocessing
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split
```

0.1.2 Load Data From medical_clean.csv

[2]:
```
# load data file
df = pd.read_csv('medical_clean.csv')
# quick test the data is present and see the shape
df.head()
```

[2]:
```
   CaseOrder Customer_id                           Interaction  \
0          1     C412403  8cd49b13-f45a-4b47-a2bd-173ffa932c2f
1          2     Z919181  d2450b70-0337-4406-bdbb-bc1037f1734c
2          3     F995323  a2057123-abf5-4a2c-abad-8ffe33512562
3          4     A879973  1dec528d-eb34-4079-adce-0d7a40e82205
4          5     C544523  5885f56b-d6da-43a3-8760-83583af94266

                                UID          City State        County    Zip  \
0  3a83ddb66e2ae73798bdf1d705dc0932           Eva    AL        Morgan  35621
1  176354c5eef714957d486009feabf195      Marianna    FL       Jackson  32446
2  e19a0fa00aeda885b8a436757e889bc9   Sioux Falls    SD     Minnehaha  57110
3  cd17d7b6d152cb6f23957346d11c3f07  New Richland    MN        Waseca  56072
4  d2f0425877b10ed6bb381f3e2579424a    West Point    VA  King William  23181

        Lat        Lng  …  TotalCharge Additional_charges Item1 Item2  Item3  \
```

```
0  34.34960 -86.72508  …  3726.702860       17939.403420     3     3      2
1  30.84513 -85.22907  …  4193.190458       17612.998120     3     4      3
2  43.54321 -96.63772  …  2434.234222       17505.192460     2     4      4
3  43.89744 -93.51479  …  2127.830423       12993.437350     3     5      5
4  37.59894 -76.88958  …  2113.073274        3716.525786     2     1      3

   Item4  Item5 Item6 Item7 Item8
0      2      4     3     3     4
1      4      4     4     3     3
2      4      3     4     3     3
3      3      4     5     5     5
4      3      5     3     4     3

[5 rows x 50 columns]
```

[3]:

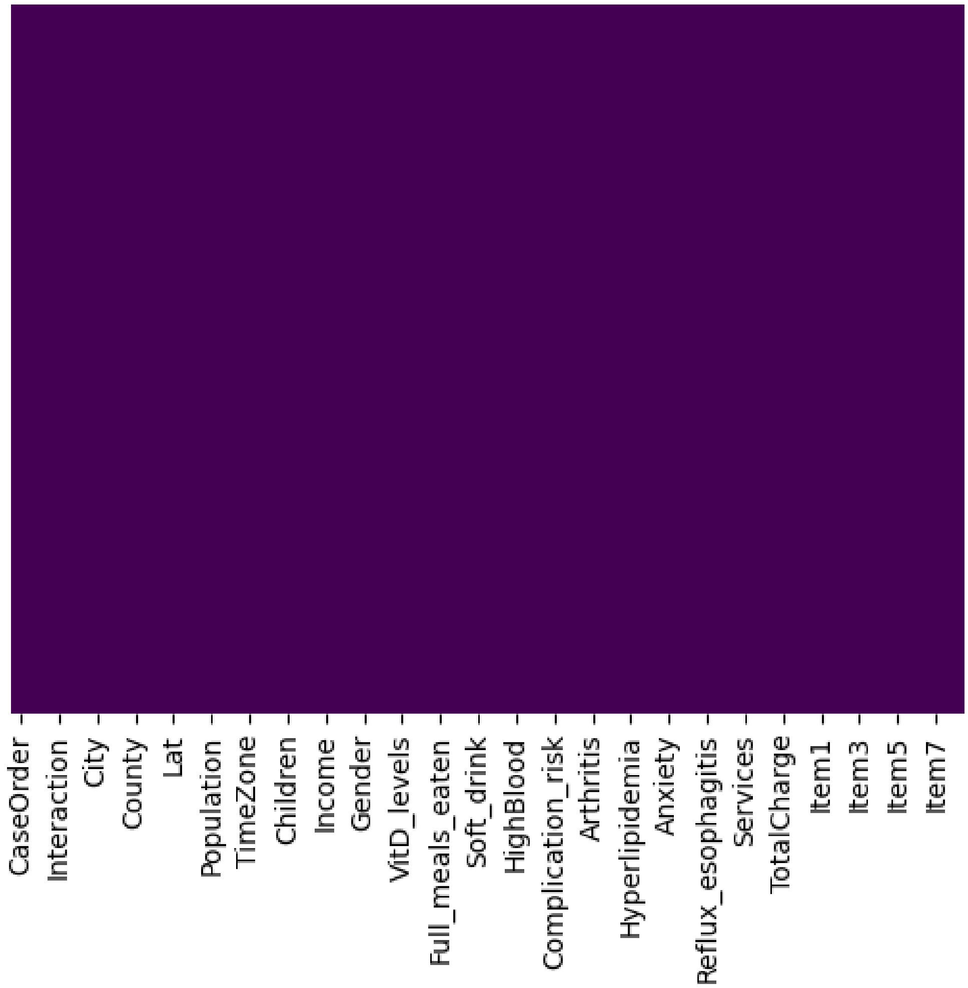
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   CaseOrder           10000 non-null  int64
 1   Customer_id         10000 non-null  object
 2   Interaction         10000 non-null  object
 3   UID                 10000 non-null  object
 4   City                10000 non-null  object
 5   State               10000 non-null  object
 6   County              10000 non-null  object
 7   Zip                 10000 non-null  int64
 8   Lat                 10000 non-null  float64
 9   Lng                 10000 non-null  float64
 10  Population          10000 non-null  int64
 11  Area                10000 non-null  object
 12  TimeZone            10000 non-null  object
 13  Job                 10000 non-null  object
 14  Children            10000 non-null  int64
 15  Age                 10000 non-null  int64
 16  Income              10000 non-null  float64
 17  Marital             10000 non-null  object
 18  Gender              10000 non-null  object
 19  ReAdmis             10000 non-null  object
 20  VitD_levels         10000 non-null  float64
 21  Doc_visits          10000 non-null  int64
 22  Full_meals_eaten    10000 non-null  int64
 23  vitD_supp           10000 non-null  int64
 24  Soft_drink          10000 non-null  object
```

```
 25  Initial_admin       10000 non-null  object
 26  HighBlood           10000 non-null  object
 27  Stroke              10000 non-null  object
 28  Complication_risk   10000 non-null  object
 29  Overweight          10000 non-null  object
 30  Arthritis           10000 non-null  object
 31  Diabetes            10000 non-null  object
 32  Hyperlipidemia      10000 non-null  object
 33  BackPain            10000 non-null  object
 34  Anxiety             10000 non-null  object
 35  Allergic_rhinitis   10000 non-null  object
 36  Reflux_esophagitis  10000 non-null  object
 37  Asthma              10000 non-null  object
 38  Services            10000 non-null  object
 39  Initial_days        10000 non-null  float64
 40  TotalCharge         10000 non-null  float64
 41  Additional_charges  10000 non-null  float64
 42  Item1               10000 non-null  int64
 43  Item2               10000 non-null  int64
 44  Item3               10000 non-null  int64
 45  Item4               10000 non-null  int64
 46  Item5               10000 non-null  int64
 47  Item6               10000 non-null  int64
 48  Item7               10000 non-null  int64
 49  Item8               10000 non-null  int64
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

Look for Missing Values

[4]:
```python
# Mapping to view missing data...none present.
sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap='viridis');
```



[5]:
```
df.describe()
```

[5]:

	CaseOrder	Zip	Lat	Lng	Population	\
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	
mean	5000.50000	50159.323900	38.751099	-91.243080	9965.253800	
std	2886.89568	27469.588208	5.403085	15.205998	14824.758614	
min	1.00000	610.000000	17.967190	-174.209700	0.000000	
25%	2500.75000	27592.000000	35.255120	-97.352982	694.750000	
50%	5000.50000	50207.000000	39.419355	-88.397230	2769.000000	
75%	7500.25000	72411.750000	42.044175	-80.438050	13945.000000	
max	10000.00000	99929.000000	70.560990	-65.290170	122814.000000	

	Children	Age	Income	VitD_levels	Doc_visits	\
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	
mean	2.097200	53.511700	40490.495160	17.964262	5.012200	
std	2.163659	20.638538	28521.153293	2.017231	1.045734	

```
min        0.000000   18.000000     154.080000    9.806483    1.000000
25%        0.000000   36.000000   19598.775000   16.626439    4.000000
50%        1.000000   53.000000   33768.420000   17.951122    5.000000
75%        3.000000   71.000000   54296.402500   19.347963    6.000000
max       10.000000   89.000000  207249.100000   26.394449    9.000000

       …  TotalCharge  Additional_charges         Item1         Item2  \
count  …  10000.000000        10000.000000  10000.000000  10000.000000
mean   …   5312.172769        12934.528587      3.518800      3.506700
std    …   2180.393838         6542.601544      1.031966      1.034825
min    …   1938.312067         3125.703000      1.000000      1.000000
25%    …   3179.374015         7986.487755      3.000000      3.000000
50%    …   5213.952000        11573.977735      4.000000      3.000000
75%    …   7459.699750        15626.490000      4.000000      4.000000
max    …   9180.728000        30566.070000      8.000000      7.000000

              Item3         Item4         Item5         Item6         Item7  \
count  10000.000000  10000.000000  10000.000000  10000.000000  10000.000000
mean       3.511100      3.515100      3.496900      3.522500      3.494000
std        1.032755      1.036282      1.030192      1.032376      1.021405
min        1.000000      1.000000      1.000000      1.000000      1.000000
25%        3.000000      3.000000      3.000000      3.000000      3.000000
50%        4.000000      4.000000      3.000000      4.000000      3.000000
75%        4.000000      4.000000      4.000000      4.000000      4.000000
max        8.000000      7.000000      7.000000      7.000000      7.000000

              Item8
count  10000.000000
mean       3.509700
std        1.042312
min        1.000000
25%        3.000000
50%        3.000000
75%        4.000000
max        7.000000

[8 rows x 23 columns]
```

0.1.3 Describe and Explore Numeric Fields:

[6]:
```python
df.describe(include = [np.number])
```

[6]:
```
         CaseOrder           Zip           Lat           Lng    Population  \
count  10000.00000  10000.000000  10000.000000  10000.000000  10000.000000
mean    5000.50000  50159.323900     38.751099    -91.243080   9965.253800
std     2886.89568  27469.588208      5.403085     15.205998  14824.758614
min        1.00000    610.000000     17.967190   -174.209700      0.000000
```

25%	2500.75000	27592.000000	35.255120	-97.352982	694.750000
50%	5000.50000	50207.000000	39.419355	-88.397230	2769.000000
75%	7500.25000	72411.750000	42.044175	-80.438050	13945.000000
max	10000.00000	99929.000000	70.560990	-65.290170	122814.000000

	Children	Age	Income	VitD_levels	Doc_visits \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	2.097200	53.511700	40490.495160	17.964262	5.012200
std	2.163659	20.638538	28521.153293	2.017231	1.045734
min	0.000000	18.000000	154.080000	9.806483	1.000000
25%	0.000000	36.000000	19598.775000	16.626439	4.000000
50%	1.000000	53.000000	33768.420000	17.951122	5.000000
75%	3.000000	71.000000	54296.402500	19.347963	6.000000
max	10.000000	89.000000	207249.100000	26.394449	9.000000

	…	TotalCharge	Additional_charges	Item1	Item2 \
count	…	10000.000000	10000.000000	10000.000000	10000.000000
mean	…	5312.172769	12934.528587	3.518800	3.506700
std	…	2180.393838	6542.601544	1.031966	1.034825
min	…	1938.312067	3125.703000	1.000000	1.000000
25%	…	3179.374015	7986.487755	3.000000	3.000000
50%	…	5213.952000	11573.977735	4.000000	3.000000
75%	…	7459.699750	15626.490000	4.000000	4.000000
max	…	9180.728000	30566.070000	8.000000	7.000000

	Item3	Item4	Item5	Item6	Item7 \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	3.511100	3.515100	3.496900	3.522500	3.494000
std	1.032755	1.036282	1.030192	1.032376	1.021405
min	1.000000	1.000000	1.000000	1.000000	1.000000
25%	3.000000	3.000000	3.000000	3.000000	3.000000
50%	4.000000	4.000000	3.000000	4.000000	3.000000
75%	4.000000	4.000000	4.000000	4.000000	4.000000
max	8.000000	7.000000	7.000000	7.000000	7.000000

	Item8
count	10000.000000
mean	3.509700
std	1.042312
min	1.000000
25%	3.000000
50%	3.000000
75%	4.000000
max	7.000000

[8 rows x 23 columns]

[7]:
```
df_num = df.select_dtypes(include='number')
df_num.head()
```

[7]:
```
   CaseOrder    Zip       Lat       Lng  Population  Children  Age    Income  \
0          1  35621  34.34960 -86.72508        2951         1   53  86575.93
1          2  32446  30.84513 -85.22907       11303         3   51  46805.99
2          3  57110  43.54321 -96.63772       17125         3   53  14370.14
3          4  56072  43.89744 -93.51479        2162         0   78  39741.49
4          5  23181  37.59894 -76.88958        5287         1   22   1209.56

   VitD_levels  Doc_visits  …  TotalCharge  Additional_charges  Item1  \
0    19.141466           6  …  3726.702860        17939.403420      3
1    18.940352           4  …  4193.190458        17612.998120      3
2    18.057507           4  …  2434.234222        17505.192460      2
3    16.576858           4  …  2127.830423        12993.437350      3
4    17.439069           5  …  2113.073274         3716.525786      2

   Item2  Item3  Item4  Item5  Item6  Item7  Item8
0      3      2      2      4      3      3      4
1      4      3      4      4      4      3      3
2      4      4      4      3      4      3      3
3      5      5      3      4      5      5      5
4      1      3      3      5      3      4      3

[5 rows x 23 columns]
```

0.1.4 Describe and Explore Categorical Fields:

[8]:
```
df.describe(exclude = [np.number])
```

[8]:
```
       Customer_id                           Interaction  \
count        10000                                 10000
unique       10000                                 10000
top        C412403  8cd49b13-f45a-4b47-a2bd-173ffa932c2f
freq             1                                     1

                                     UID     City  State     County   Area  \
count                              10000    10000  10000      10000  10000
unique                             10000     6072     52       1607      3
top     3a83ddb66e2ae73798bdf1d705dc0932  Houston     TX  Jefferson  Rural
freq                                   1       36    553        118   3369

                TimeZone                                  Job  Marital  …  \
count              10000                                10000    10000  …
unique                26                                  639        5  …
top     America/New_York  Outdoor activities/education manager  Widowed  …
freq                3889                                   29     2045  …
```

```
       Overweight Arthritis Diabetes Hyperlipidemia BackPain Anxiety  \
count       10000      10000    10000          10000    10000   10000
unique          2          2        2              2        2       2
top           Yes         No       No             No       No      No
freq         7094       6426     7262           6628     5886    6785

       Allergic_rhinitis Reflux_esophagitis Asthma    Services
count              10000              10000  10000       10000
unique                 2                  2      2           4
top                   No                 No     No  Blood Work
freq                6059               5865   7107        5265

[4 rows x 27 columns]
```

[9]:
```
df_cat = df.select_dtypes(exclude='number')
df_cat.head()
```

[9]:
```
  Customer_id                           Interaction  \
0     C412403  8cd49b13-f45a-4b47-a2bd-173ffa932c2f
1     Z919181  d2450b70-0337-4406-bdbb-bc1037f1734c
2     F995323  a2057123-abf5-4a2c-abad-8ffe33512562
3     A879973  1dec528d-eb34-4079-adce-0d7a40e82205
4     C544523  5885f56b-d6da-43a3-8760-83583af94266

                                UID         City State        County  \
0  3a83ddb66e2ae73798bdf1d705dc0932          Eva    AL        Morgan
1  176354c5eef714957d486009feabf195     Marianna    FL       Jackson
2  e19a0fa00aeda885b8a436757e889bc9  Sioux Falls    SD     Minnehaha
3  cd17d7b6d152cb6f23957346d11c3f07  New Richland    MN        Waseca
4  d2f0425877b10ed6bb381f3e2579424a   West Point    VA  King William

       Area          TimeZone                               Job  Marital  \
0  Suburban   America/Chicago  Psychologist, sport and exercise  Divorced
1     Urban   America/Chicago       Community development worker  Married
2  Suburban   America/Chicago           Chief Executive Officer  Widowed
3  Suburban   America/Chicago               Early years teacher  Married
4     Rural  America/New_York        Health promotion specialist  Widowed

   … Overweight Arthritis Diabetes Hyperlipidemia BackPain Anxiety  \
0  …         No        Yes      Yes             No      Yes     Yes
1  …        Yes         No       No             No       No      No
2  …        Yes         No      Yes             No       No      No
3  …         No        Yes       No             No       No      No
4  …         No         No       No            Yes       No      No

  Allergic_rhinitis Reflux_esophagitis Asthma     Services
```

```
0               Yes                 No     Yes    Blood Work
1                No                Yes      No   Intravenous
2                No                 No      No    Blood Work
3                No                Yes     Yes    Blood Work
4               Yes                 No      No       CT Scan

[5 rows x 27 columns]
```

[10]:
```python
df[['ReAdmis']].describe()
df
```

[10]:
```
      CaseOrder Customer_id                           Interaction  \
0             1     C412403  8cd49b13-f45a-4b47-a2bd-173ffa932c2f
1             2     Z919181  d2450b70-0337-4406-bdbb-bc1037f1734c
2             3     F995323  a2057123-abf5-4a2c-abad-8ffe33512562
3             4     A879973  1dec528d-eb34-4079-adce-0d7a40e82205
4             5     C544523  5885f56b-d6da-43a3-8760-83583af94266
…           …         …                                   …
9995       9996     B863060  a25b594d-0328-486f-a9b9-0567eb0f9723
9996       9997     P712040  70711574-f7b1-4a17-b15f-48c54564b70f
9997       9998     R778890  1d79569d-8e0f-4180-a207-d67ee4527d26
9998       9999     E344109  f5a68e69-2a60-409b-a92f-ac0847b27db0
9999      10000     I569847  bc482c02-f8c9-4423-99de-3db5e62a18d5

                                   UID          City State        County  \
0     3a83ddb66e2ae73798bdf1d705dc0932           Eva    AL        Morgan
1     176354c5eef714957d486009feabf195      Marianna    FL       Jackson
2     e19a0fa00aeda885b8a436757e889bc9   Sioux Falls    SD     Minnehaha
3     cd17d7b6d152cb6f23957346d11c3f07  New Richland    MN        Waseca
4     d2f0425877b10ed6bb381f3e2579424a    West Point    VA  King William
…                                  …           …    …            …
9995  39184dc28cc038871912ccc4500049e5       Norlina    NC        Warren
9996  3cd124ccd43147404292e883bf9ec55c       Milmay    NJ      Atlantic
9997  41b770aeee97a5b9e7f69c906a8119d7     Southside    TN    Montgomery
9998  2bb491ef5b1beb1fed758cc6885c167a         Quinn    SD    Pennington
9999  95663a202338000abdf7e09311c2a8a1    Coraopolis    PA     Allegheny

        Zip       Lat       Lng  … TotalCharge Additional_charges Item1  \
0     35621  34.34960 -86.72508  … 3726.702860       17939.403420     3
1     32446  30.84513 -85.22907  … 4193.190458       17612.998120     3
2     57110  43.54321 -96.63772  … 2434.234222       17505.192460     2
3     56072  43.89744 -93.51479  … 2127.830423       12993.437350     3
4     23181  37.59894 -76.88958  … 2113.073274        3716.525786     2
…       …        …         …  …           …                 …   …
9995  27563  36.42886 -78.23716  … 6850.942000        8927.642000     3
9996   8340  39.43609 -74.87302  … 7741.690000       28507.150000     3
9997  37171  36.36655 -87.29988  … 8276.481000       15281.210000     3
```

```
9998  57775  44.10354 -102.01590  …  7644.483000        7781.678000     5
9999  15108  40.49998  -80.19959  …  7887.553000       11643.190000     4

     Item2  Item3  Item4  Item5 Item6 Item7 Item8
0        3      2      2      4     3     3     4
1        4      3      4      4     4     3     3
2        4      4      4      3     4     3     3
3        5      5      3      4     5     5     5
4        1      3      3      5     3     4     3
…     …    …    …    …    …    …    …
9995     2      2      3      4     3     4     2
9996     3      4      2      5     3     4     4
9997     3      3      4      4     2     3     2
9998     5      3      4      4     3     4     3
9999     3      3      2      3     6     4     3

[10000 rows x 50 columns]
```

[11]:
```python
df[['Gender', 'ReAdmis']].head()
```

[11]:
```
   Gender ReAdmis
0    Male      No
1  Female      No
2  Female      No
3    Male      No
4  Female      No
```

[12]:
```python
df_2num = df.copy()
df_2num.columns
```

[12]:
```
Index(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'State',
       'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job',
       'Children', 'Age', 'Income', 'Marital', 'Gender', 'ReAdmis',
       'VitD_levels', 'Doc_visits', 'Full_meals_eaten', 'vitD_supp',
       'Soft_drink', 'Initial_admin', 'HighBlood', 'Stroke',
       'Complication_risk', 'Overweight', 'Arthritis', 'Diabetes',
       'Hyperlipidemia', 'BackPain', 'Anxiety', 'Allergic_rhinitis',
       'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',
       'TotalCharge', 'Additional_charges', 'Item1', 'Item2', 'Item3', 'Item4',
       'Item5', 'Item6', 'Item7', 'Item8'],
      dtype='object')
```

0.1.5 Transform Catagorical Data To Numerical

[13]:
```
def cat_to_num(series):
    series = series.astype('category')
    return series.cat.codes

df_2num = df_2num.apply(cat_to_num) # Male = 1, ReAdmis Yes = 1
df_2num.head()
```

[13]:
```
   CaseOrder  Customer_id  Interaction   UID  City  State  County   Zip   Lat  \
0          0          887         5453  2240  1675      1     975  2952  1774
1          1         9960         8124   862  3232      9     712  2683   662
2          2         2368         6269  8801  5021     42     951  4944  7305
3          3          320         1167  7953  3782     23    1514  4809  7443
4          4          943         3430  8170  5814     46     766  1778  3174

    Lng  …  TotalCharge  Additional_charges  Item1  Item2  Item3  Item4  \
0  4851  …         3949                7427      2      2      1      1
1  5178  …         4620                7363      2      3      2      3
2  2470  …          384                7337      1      3      3      3
3  3245  …           37                5566      2      4      4      2
4  7357  …           28                 104      1      0      2      2

   Item5  Item6  Item7  Item8
0      3      2      2      3
1      3      3      2      2
2      2      3      2      2
3      3      4      4      4
4      4      2      3      2

[5 rows x 50 columns]
```

[14]:
```
df_2num.shape
```

[14]:
```
(10000, 50)
```

[15]:
```
df[['Gender', 'ReAdmis']].head()
```

[15]:
```
   Gender ReAdmis
0    Male      No
1  Female      No
2  Female      No
3    Male      No
4  Female      No
```

[16]:
```
#df['ReAdmis_Yes'] = df['ReAdmis']
#df['ReAdmis_Yes'] = df['ReAdmis_Yes'].eq('Yes').astype(int)
```

```
#df['ReAdmis_Yes']
```

[17]:
```
df_2num.columns
```

[17]:
```
Index(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'State',
       'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job',
       'Children', 'Age', 'Income', 'Marital', 'Gender', 'ReAdmis',
       'VitD_levels', 'Doc_visits', 'Full_meals_eaten', 'vitD_supp',
       'Soft_drink', 'Initial_admin', 'HighBlood', 'Stroke',
       'Complication_risk', 'Overweight', 'Arthritis', 'Diabetes',
       'Hyperlipidemia', 'BackPain', 'Anxiety', 'Allergic_rhinitis',
       'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',
       'TotalCharge', 'Additional_charges', 'Item1', 'Item2', 'Item3', 'Item4',
       'Item5', 'Item6', 'Item7', 'Item8'],
      dtype='object')
```

[18]:
```
df['Gender'].value_counts()
```

[18]:
```
Female       5018
Male         4768
Nonbinary     214
Name: Gender, dtype: int64
```

[19]:
```
df_2num['Gender'].value_counts() # why is female zero?  Alphabetical sequence?
```

[19]:
```
0    5018
1    4768
2     214
Name: Gender, dtype: int64
```

[20]:
```
df['Initial_admin'].value_counts()
```

[20]:
```
Emergency Admission      5060
Elective Admission       2504
Observation Admission    2436
Name: Initial_admin, dtype: int64
```

[21]:
```
df_2num['Initial_admin'].value_counts() # Seems to be ordered alphabetically.
```

[21]:
```
1    5060
0    2504
2    2436
Name: Initial_admin, dtype: int64
```

[22]:
```
df['Initial_admin'].head()
```

[22]:
```
0    Emergency Admission
1    Emergency Admission
2     Elective Admission
3     Elective Admission
4     Elective Admission
Name: Initial_admin, dtype: object
```

0.1.6 Data Preparation

0.1.7 Prune Data

[23]:
```
df_2num.columns
```

[23]:
```
Index(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'State',
       'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job',
       'Children', 'Age', 'Income', 'Marital', 'Gender', 'ReAdmis',
       'VitD_levels', 'Doc_visits', 'Full_meals_eaten', 'vitD_supp',
       'Soft_drink', 'Initial_admin', 'HighBlood', 'Stroke',
       'Complication_risk', 'Overweight', 'Arthritis', 'Diabetes',
       'Hyperlipidemia', 'BackPain', 'Anxiety', 'Allergic_rhinitis',
       'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',
       'TotalCharge', 'Additional_charges', 'Item1', 'Item2', 'Item3', 'Item4',
       'Item5', 'Item6', 'Item7', 'Item8'],
      dtype='object')
```

[24]:
```
df_2num['Interaction'].head()
```

[24]:
```
0    5453
1    8124
2    6269
3    1167
4    3430
Name: Interaction, dtype: int16
```

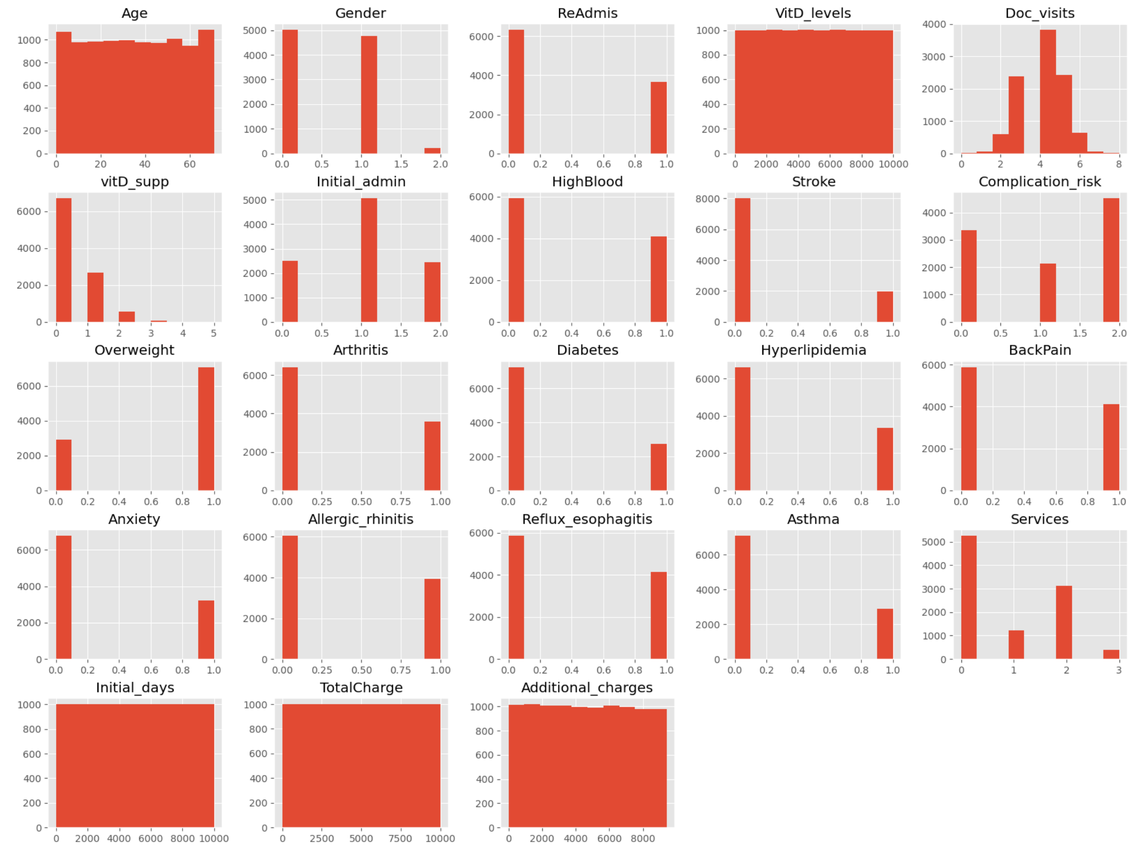
[25]:
```
# Start pruning non-relavent series
pruned_df = df_2num.drop(['CaseOrder', 'Customer_id', 'Interaction', 'UID',␣
 ↪'City', 'State', \
                      'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area',␣
 ↪'TimeZone', 'Job', \
                      'Children', 'Income', 'Marital', 'Full_meals_eaten',␣
 ↪'Soft_drink', \
                     'Item1', 'Item2', 'Item3', 'Item4', 'Item5', 'Item6',␣
 ↪'Item7', 'Item8'], axis=1)
pruned_df.head()
```

[25]:
```
   Age  Gender  ReAdmis  VitD_levels  Doc_visits  vitD_supp  Initial_admin  \
0   35       1        0         7175           5          0              1
```

```
1   33        0       0         6885          3          1             1
2   35        0       0         5219          3          0             0
3   60        1       0         2422          3          0             0
4    4        0       0         3978          4          2             0

   HighBlood  Stroke  Complication_risk  …  Hyperlipidemia  BackPain  \
0          1       0                  2  …               0         1
1          1       0                  0  …               0         0
2          1       0                  2  …               0         0
3          0       1                  2  …               0         0
4          0       0                  1  …               1         0

   Anxiety  Allergic_rhinitis  Reflux_esophagitis  Asthma  Services  \
0        1                  1                   0       1         0
1        0                  0                   1       0         2
2        0                  0                   0       0         0
3        0                  0                   1       1         0
4        0                  1                   0       0         1

   Initial_days  TotalCharge  Additional_charges
0          3234         3949                7427
1          4128         4620                7363
2          1397          384                7337
3           285           37                5566
4           101           28                 104

[5 rows x 23 columns]
```

[26]:
```python
# https://www.datacamp.com/community/tutorials/
 ↪preprocessing-in-data-science-part-1-centering-scaling-and-knn
plt.style.use('ggplot')
# df = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/
 ↪wine-quality/winequality-red.csv ' , sep = ';')
X = pruned_df.drop('ReAdmis', 1).values # drop target variable
y1 = pruned_df['ReAdmis'].values
pd.DataFrame.hist(pruned_df, figsize = [20,15]);
```

```
/var/folders/45/_087y05165x0c7wb_dw4k6nh0000gn/T/ipykernel_62417/922365799.py:4:
FutureWarning: In a future version of pandas all arguments of DataFrame.drop
except for the argument 'labels' will be keyword-only.
  X = pruned_df.drop('ReAdmis', 1).values # drop target variable
```



[27]:
```
# https://realpython.com/knn-python/
# Correlations with target?
#correlation_matrix = pruned_df.corr()

#print(correlation_matrix["ReAdmis_Yes"] > 0.5)
```

0.1.8 Split the Training Data

[28]:
```
# Split dataset into two data groups: train and test
from sklearn.model_selection import train_test_split
train, test = train_test_split(pruned_df, test_size = 0.2) # 80% of data␣
↪assigned to train
```

[29]:
```
print("Train Shape: ", train.shape)
print("Test Shape: ", test.shape)
```

```
Train Shape:  (8000, 23)
Test Shape:  (2000, 23)
```

[30]:

```python
# Notice the first column (row numbers) shows the choices are quite random
print("Train: ", train.head())
print('---------'*10)
print("Test: ", test.head())
```

```
Train:         Age  Gender  ReAdmis  VitD_levels  Doc_visits  vitD_supp
Initial_admin  \
7141   29       0        1         9734           4          2             1
7618   15       1        1          119           2          0             1
6254   49       0        1         7922           4          0             0
7265   16       1        1         1539           4          0             0
2514    7       0        0         8964           4          0             1

      HighBlood  Stroke  Complication_risk  …  Hyperlipidemia  BackPain  \
7141          1       1                  2  …               0         0
7618          0       0                  2  …               0         1
6254          0       0                  0  …               1         0
7265          0       0                  2  …               0         0
2514          1       0                  2  …               0         1

      Anxiety  Allergic_rhinitis  Reflux_esophagitis  Asthma  Services  \
7141        0                  0                   0       0         2
7618        0                  0                   1       0         0
6254        1                  0                   1       0         0
7265        0                  0                   1       0         0
2514        1                  1                   0       0         0

      Initial_days  TotalCharge  Additional_charges
7141          9556         9290                7162
7618          8985         9000                1167
6254          8729         8953                4634
7265          7038         6051                1040
2514          2795         3494                2893

[5 rows x 23 columns]
--------------------------------------------------------------------------------
----------
Test:         Age  Gender  ReAdmis  VitD_levels  Doc_visits  vitD_supp
Initial_admin  \
4184   68       0        0         3245           5          0             1
9309   33       1        0         9710           3          0             0
4963    6       1        0         9499           6          1             1
2320   26       0        0          154           4          0             0
8161   65       0        1         4176           4          0             1

      HighBlood  Stroke  Complication_risk  …  Hyperlipidemia  BackPain  \
4184          1       1                  0  …               0         1
```

```
9309          1        0                    2  ...                 0           1
4963          0        0                    0  ...                 1           0
2320          1        0                    0  ...                 1           1
8161          0        0                    1  ...                 0           0

      Anxiety  Allergic_rhinitis  Reflux_esophagitis  Asthma  Services  \
4184        0                  0                   0       0         0
9309        0                  1                   1       0         0
4963        1                  1                   1       0         3
2320        0                  0                   1       0         2
8161        0                  0                   0       0         1

      Initial_days  TotalCharge  Additional_charges
4184          4893         4965                9379
9309          6136         5870                7254
4963          4837         4962                 713
2320          4591         4591                6775
8161          8203         8141                6115

[5 rows x 23 columns]
```

0.1.9 Build Decision Tree

[31]:
```
pruned_df.columns
```

[31]:
```
Index(['Age', 'Gender', 'ReAdmis', 'VitD_levels', 'Doc_visits', 'vitD_supp',
       'Initial_admin', 'HighBlood', 'Stroke', 'Complication_risk',
       'Overweight', 'Arthritis', 'Diabetes', 'Hyperlipidemia', 'BackPain',
       'Anxiety', 'Allergic_rhinitis', 'Reflux_esophagitis', 'Asthma',
       'Services', 'Initial_days', 'TotalCharge', 'Additional_charges'],
      dtype='object')
```

[32]:
```
# Feed training data into ML Algorithm and Build Decision Tree
from sklearn.tree import DecisionTreeClassifier
clf=DecisionTreeClassifier(max_leaf_nodes=10) # Tried default, 5, 10, 15; 10 &␣
 ↪15 were the same
clf=clf.fit(train[['Age', 'Gender', 'VitD_levels', 'Doc_visits', 'vitD_supp',␣
 ↪'Initial_admin', \
                   'HighBlood', 'Stroke', 'Complication_risk', 'Overweight',␣
 ↪'Arthritis', \
                   'Diabetes', 'Hyperlipidemia', 'BackPain', 'Anxiety',␣
 ↪'Allergic_rhinitis', \
                   'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',␣
 ↪'TotalCharge', \
                   'Additional_charges']], train['ReAdmis'])
```

[33]:
```
clf.feature_importances_
```

[33]:
```
array([0.        , 0.        , 0.00188001, 0.        , 0.        ,
       0.        , 0.        , 0.00102016, 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.00117126, 0.        , 0.98990247,
       0.00602611, 0.        ])
```

[34]:
```
# https://stackoverflow.com/questions/1494492/
↪graphviz-how-to-go-from-dot-to-a-graph
from sklearn import tree
with open("med_data.gif", 'w') as f:
    f = tree.export_graphviz(clf,
                             feature_names=['Age', 'Gender', 'VitD_levels',␣
↪'Doc_visits', 'vitD_supp', 'Initial_admin', \
                   'HighBlood', 'Stroke', 'Complication_risk', 'Overweight',␣
↪'Arthritis', \
                   'Diabetes', 'Hyperlipidemia', 'BackPain', 'Anxiety',␣
↪'Allergic_rhinitis', \
                   'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',␣
↪'TotalCharge', \
                   'Additional_charges'], out_file=f)
```

[35]:
```
predictions = clf.predict(test[['Age', 'Gender', 'VitD_levels', 'Doc_visits',␣
↪'vitD_supp', 'Initial_admin', \
                   'HighBlood', 'Stroke', 'Complication_risk', 'Overweight',␣
↪'Arthritis', \
                   'Diabetes', 'Hyperlipidemia', 'BackPain', 'Anxiety',␣
↪'Allergic_rhinitis', \
                   'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',␣
↪'TotalCharge', \
                   'Additional_charges']])
```

[36]:
```
from sklearn.metrics import accuracy_score
accuracy_score(test['ReAdmis'], predictions)
```

[36]: 0.9755

0.1.10 Random Forest

[37]:
```
n_estimators_selected = 2000
```

[38]:
```
from sklearn.ensemble import RandomForestClassifier
predictors = ['Age', 'Gender', 'VitD_levels', 'Doc_visits', 'vitD_supp',␣
↪'Initial_admin', \
                   'HighBlood', 'Stroke', 'Complication_risk', 'Overweight',␣
↪'Arthritis', \
```

```
                 'Diabetes', 'Hyperlipidemia', 'BackPain', 'Anxiety',␣
↪'Allergic_rhinitis', \
                 'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',␣
↪'TotalCharge', \
                 'Additional_charges']
outcome = 'ReAdmis'

X = pruned_df[predictors]
y = pruned_df[outcome]

rf = RandomForestClassifier(n_estimators=n_estimators_selected, random_state=1,␣
↪oob_score=True)
rf.fit(X,y)
print(rf.oob_decision_function_)
```

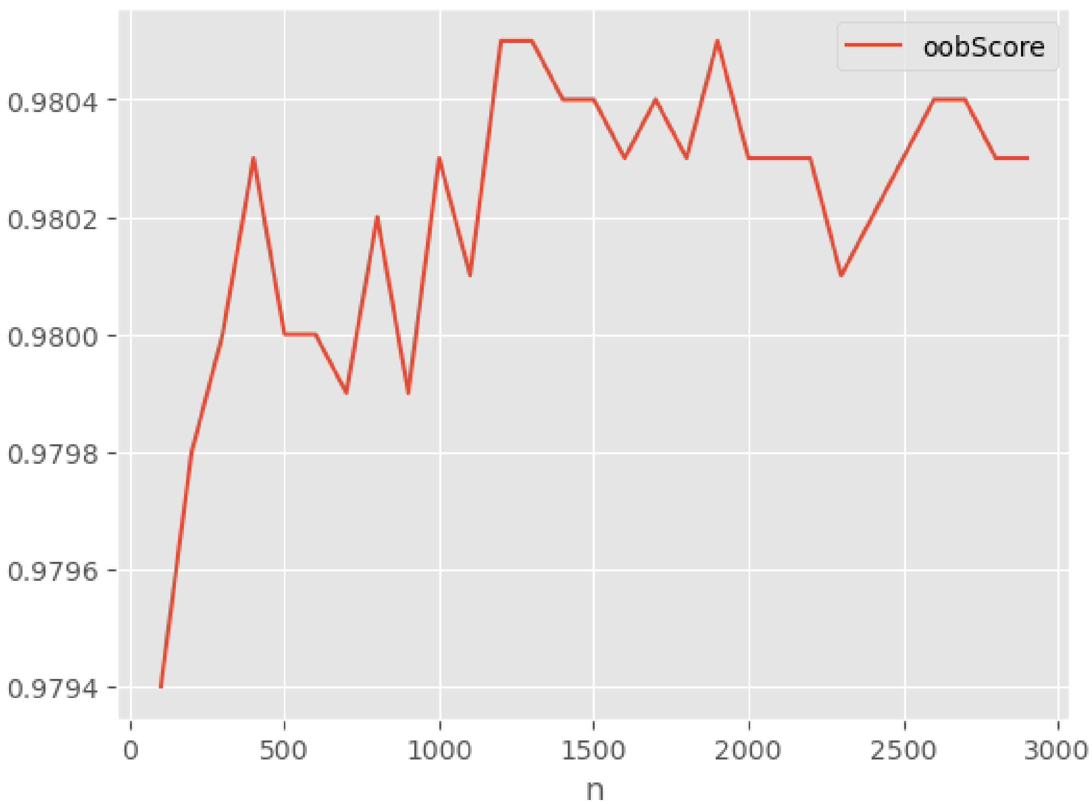
```
[[0.9957204  0.0042796 ]
 [0.99463087 0.00536913]
 [0.99862448 0.00137552]
 …
 [0.00551724 0.99448276]
 [0.00136054 0.99863946]
 [0.00416089 0.99583911]]
```

[39]:
```
n_estimator = list(range(100, 3000, 100)) # Looks to flatten out @1500
oobScores = []
for n in n_estimator:
    rf = RandomForestClassifier(n_estimators=n,
                                criterion='entropy', max_depth=5,
                                random_state=1, oob_score=True)
    rf.fit(X, y)
    oobScores.append(rf.oob_score_)
    print(n) # quick and dirty sense of time
```

```
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300
1400
```

1500
1600
1700
1800
1900
2000
2100
2200
2300
2400
2500
2600
2700
2800
2900

[40]:
```
pd.DataFrame({
    'n': n_estimator,
    'oobScore': oobScores
}).plot(x='n', y='oobScore');
```



0.1.11 OOB Evaluation

[41]:
```python
# Import models and split utility function
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
# Set seed for reproducibility
SEED = 1
# Split data into 70% train and 30% test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.3,
stratify= y,
random_state=SEED)
```

[42]:
```python
# Instantiate a classification-tree 'dt'
dt = DecisionTreeClassifier(max_depth=4,
min_samples_leaf=0.16,
random_state=SEED)
# Instantiate a BaggingClassifier 'bc'; set oob_score = True
bc = BaggingClassifier(base_estimator=dt, n_estimators=300,
oob_score=True, n_jobs=-1)
# Fit 'bc' to the training set
bc.fit(X_train, y_train)
# Predict the test set labels
y_pred = bc.predict(X_test)
```

```
/Users/jasonewillis/opt/anaconda3/lib/python3.9/site-
packages/sklearn/ensemble/_base.py:166: FutureWarning: `base_estimator` was
renamed to `estimator` in version 1.2 and will be removed in 1.4.
  warnings.warn(
```

[43]:
```python
# Evaluate test set accuracy
test_accuracy = accuracy_score(y_test, y_pred)
# Extract the OOB accuracy from 'bc'
oob_accuracy = bc.oob_score_
# Print test set accuracy
print('Test set accuracy: {:.3f}'.format(test_accuracy))
```

```
Test set accuracy: 0.977
```

[44]:
```python
# Print OOB accuracy
print('OOB accuracy: {:.3f}'.format(oob_accuracy))
```

```
OOB accuracy: 0.978
```

[45]:
```python
predictors = ['Age', 'Gender', 'VitD_levels', 'Doc_visits', 'vitD_supp',␣
↪'Initial_admin', \
```

```
                    'HighBlood', 'Stroke', 'Complication_risk', 'Overweight',␣
↪'Arthritis', \
                    'Diabetes', 'Hyperlipidemia', 'BackPain', 'Anxiety',␣
↪'Allergic_rhinitis', \
                    'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',␣
↪'TotalCharge', \
                    'Additional_charges']
outcome = 'ReAdmis'

X = pd.get_dummies(pruned_df[predictors], drop_first=True)
y = pruned_df[outcome]

rf_all = RandomForestClassifier(n_estimators=n_estimators_selected,␣
↪random_state=1)
rf_all.fit(X, y)

rf_all_entropy = RandomForestClassifier(n_estimators=n_estimators_selected,␣
↪random_state=1,
                                        criterion='gini')
print(rf_all_entropy.fit(X, y))
```

```
RandomForestClassifier(n_estimators=2000, random_state=1)
```

[46]:

```
from collections import defaultdict
from sklearn import metrics

rf = RandomForestClassifier(n_estimators=n_estimators_selected)
scores = defaultdict(list)

# crossvalidate the scores on a number of different random splits of the data
for _ in range(3):
    train_X, valid_X, train_y, valid_y = train_test_split(X, y,
                                                          test_size=0.3)
    rf.fit(train_X, train_y)
    acc = metrics.accuracy_score(valid_y, rf.predict(valid_X))
    for column in X.columns:
        X_t = valid_X.copy()
        X_t[column] = np.random.permutation(X_t[column].values)
        shuff_acc = metrics.accuracy_score(valid_y, rf.predict(X_t))
        scores[column].append((acc-shuff_acc)/acc)
print('Features sorted by their score:')
print(sorted([(round(np.mean(score), 4), feat) for
              feat, score in scores.items()], reverse=True))
```

```
Features sorted by their score:
[(0.4375, 'Initial_days'), (0.0088, 'TotalCharge'), (0.0008, 'Stroke'), (0.0005,
'Initial_admin'), (0.0005, 'Complication_risk'), (0.0005, 'Allergic_rhinitis'),
```

```
(0.0003, 'Asthma'), (0.0002, 'Services'), (0.0002, 'Overweight'), (0.0001,
'vitD_supp'), (0.0001, 'VitD_levels'), (0.0001, 'Gender'), (0.0, 'Anxiety'),
(0.0, 'Age'), (-0.0001, 'Hyperlipidemia'), (-0.0001, 'BackPain'), (-0.0001,
'Arthritis'), (-0.0001, 'Additional_charges'), (-0.0002, 'HighBlood'), (-0.0003,
'Diabetes'), (-0.0005, 'Reflux_esophagitis'), (-0.0006, 'Doc_visits')]
```

[47]:
```
train_X, valid_X, train_y, valid_y = train_test_split(X, y, test_size=0.3)
rf.fit(train_X, train_y)
valid_X_predict = rf.predict(valid_X)
acc = metrics.accuracy_score(valid_y, valid_X_predict)

acc
```

[47]:
```
0.9793333333333333
```

[48]:
```
set(rf.predict(valid_X))
```

[48]:
```
{0, 1}
```

[49]:
```
from sklearn.metrics import confusion_matrix

conf_mat = confusion_matrix(valid_y, valid_X_predict)
print(conf_mat)
# TP, FP, FN, TN
```

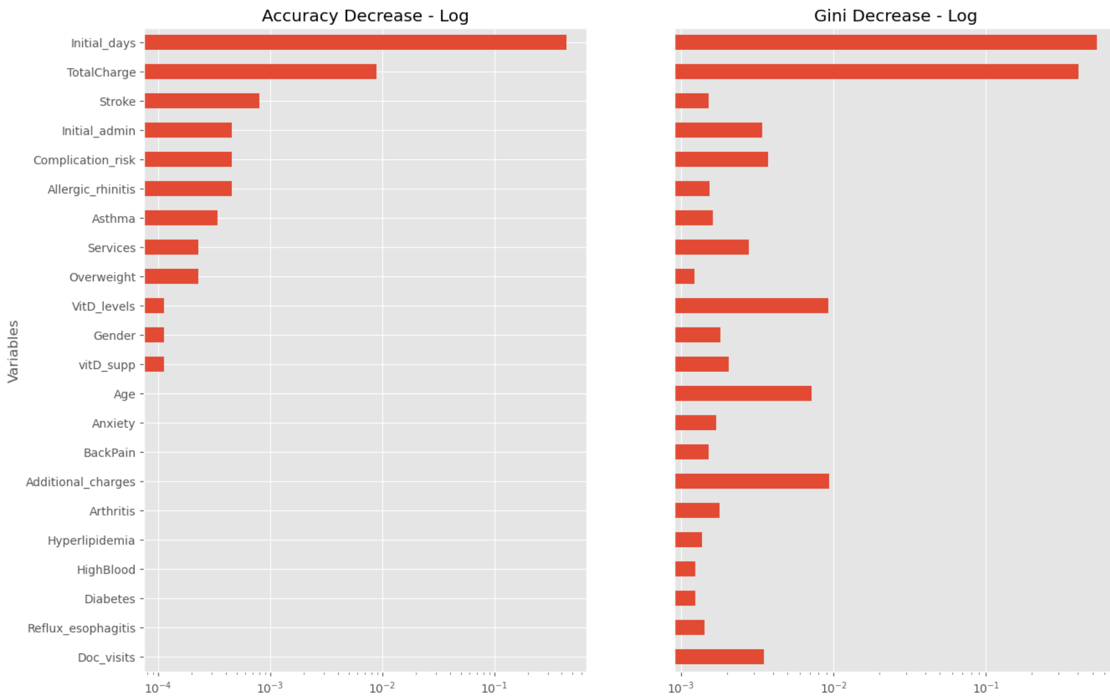
```
[[1862   26]
 [  36 1076]]
```

[57]:
```
#from sklearn.ensemble import RandomForestRegressor

#regressor = RandomForestRegressor(n_estimators=20, random_state=0)
#regressor.fit(train_X, train_y)
#y_pred = regressor.predict(valid_X)

#from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score

#print(confusion_matrix(y_test,y_pred))
#print(classification_report(y_test,y_pred))
#print(accuracy_score(y_test, y_pred))
```

[51]:
```
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score

print(confusion_matrix(y_test,y_pred))
print(classification_report(y_test,y_pred))
print(accuracy_score(y_test, y_pred))
```

```
[[1862   37]
 [  33 1068]]
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1899
           1       0.97      0.97      0.97      1101

    accuracy                           0.98      3000
   macro avg       0.97      0.98      0.97      3000
weighted avg       0.98      0.98      0.98      3000

0.9766666666666667
```

[52]:
```
importances = rf_all.feature_importances_

df = pd.DataFrame({
    'feature': X.columns,
    'Accuracy decrease': [np.mean(scores[column]) for column in
                          X.columns],
    'Gini decrease': rf_all.feature_importances_,
    'Entropy decrease': rf_all_entropy.feature_importances_,
})
df = df.sort_values('Accuracy decrease')

fig, axes = plt.subplots(ncols=2, figsize=(8, 5))
ax = df.plot(kind='barh', x='feature', y='Accuracy decrease', logx=True,␣
 ↪figsize=(15,10), title='Accuracy Decrease - Log',
             legend=False, ax=axes[0])

ax.set_ylabel('Variables')

ax = df.plot(kind='barh', x='feature', y='Gini decrease', logx=True,␣
 ↪title='Gini Decrease - Log',
             legend=False, ax=axes[1])
ax.set_ylabel('')
ax.get_yaxis().set_visible(False)

#plt.tight_layout()
plt.show()
```



0.1.12 Accuracy and MSE

[53]:
```
from sklearn.metrics import mean_squared_error as MSE
from sklearn.model_selection import cross_val_score
```

[55]:
```
from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(train_y, valid_y))
print('Mean Squared Error:', metrics.mean_squared_error(train_y, valid_y))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(train_y,␣
 ↪valid_y)))
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[55], line 2
      1 from sklearn import metrics
----> 2 print('Mean Absolute Error:',␣
 ↪metrics.mean_absolute_error(train_y, valid_y))
      3 print('Mean Squared Error:', metrics.mean_squared_error(train_y,␣
 ↪valid_y))
      4 print('Root Mean Squared Error:', np.sqrt(metrics.
 ↪mean_squared_error(train_y, valid_y)))

File ~/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_regression.py
 ↪196, in mean_absolute_error(y_true, y_pred, sample_weight, multioutput)
```

```
    141 def mean_absolute_error(
    142     y_true, y_pred, *, sample_weight=None, multioutput="uniform_average"
    143 ):
    144     """Mean absolute error regression loss.
    145 
    146     Read more in the :ref:`User Guide <mean_absolute_error>`.
   (…)
    194     0.85…
    195     """
--> 196     y_type, y_true, y_pred, multioutput = _check_reg_targets(
    197         y_true, y_pred, multioutput
    198     )
    199     check_consistent_length(y_true, y_pred, sample_weight)
    200     output_errors = np.average(np.abs(y_pred - y_true), weights=sample_weight, axis=0)

File ~/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_regression.py:100, in _check_reg_targets(y_true, y_pred, multioutput, dtype)
     66 def _check_reg_targets(y_true, y_pred, multioutput, dtype="numeric"):
     67     """Check that y_true and y_pred belong to the same regression task.
     68 
     69     Parameters
   (…)
     98         correct keyword.
     99     """
--> 100     check_consistent_length(y_true, y_pred)
    101     y_true = check_array(y_true, ensure_2d=False, dtype=dtype)
    102     y_pred = check_array(y_pred, ensure_2d=False, dtype=dtype)

File ~/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:397, in check_consistent_length(*arrays)
    395 uniques = np.unique(lengths)
    396 if len(uniques) > 1:
--> 397     raise ValueError(
    398         "Found input variables with inconsistent numbers of samples: %r"
    399         % [int(l) for l in lengths]
    400     )

ValueError: Found input variables with inconsistent numbers of samples: [7000, 3000]
```

0.1.13 Sharding and Exporting Data

[ ]:
```
print("------ Prune Data --------------")
print("pruned_df: ", pruned_df.shape)
print("")
```

```python
print("------ Decision Tree Data ------")
print("train: ", train.shape)
print("test: ", test.shape)
print("")
print("------ Random Forest Data ------")
print("train_X: ", train_X.shape)
print("valid_X: ", valid_X.shape)
print("train_y: ", train_y.shape)
print("valid_y: ", valid_y.shape)
```

[ ]:
```python
# Export to CSV
pruned_df.to_csv('final_cleaned_dataset.csv', index=False)
#
train.to_csv('d_tree_train.csv', index=False)
test.to_csv('d_tree_test.csv', index=False)
#
train_X.to_csv('r_forest_train_X.csv', index=False)
valid_X.to_csv('r_forest_valid_X.csv', index=False)
train_y.to_csv('r_forest_train_y.csv', index=False)
valid_y.to_csv('r_forest_valid_y.csv', index=False)
```

[58]:
```python
# Import DecisionTreeClassifier
from sklearn.tree import DecisionTreeClassifier
# Import train_test_split
from sklearn.model_selection import train_test_split
# Import accuracy_score
from sklearn.metrics import accuracy_score
# Split the dataset into 80% train, 20% test
X_train, X_test, y_train, y_test= train_test_split(X, y,
test_size=0.2,
stratify=y,
random_state=1)
# Instantiate dt
dt = DecisionTreeClassifier(max_depth=2, random_state=1)
```

[59]:
```python
# Fit dt to the training set
dt.fit(X_train,y_train)
# Predict the test set labels
y_pred = dt.predict(X_test)
# Evaluate the test-set accuracy
accuracy_score(y_test, y_pred)
```

[59]: 0.9745

[60]:
```python
# Import DecisionTreeClassifier
from sklearn.tree import DecisionTreeClassifier
# Import train_test_split
```

```python
from sklearn.model_selection import train_test_split
# Import accuracy_score
from sklearn.metrics import accuracy_score
# Split dataset into 80% train, 20% test
X_train, X_test, y_train, y_test= train_test_split(X, y,
test_size=0.2,
stratify=y,
random_state=1)
# Instantiate dt, set 'criterion' to 'gini'
dt = DecisionTreeClassifier(criterion='gini', random_state=1)
```

[61]:
```python
# Fit dt to the training set
dt.fit(X_train,y_train)
# Predict test-set labels
y_pred= dt.predict(X_test)
# Evaluate test-set accuracy
accuracy_score(y_test, y_pred)
```

[61]: 0.967

[62]:
```python
# Import DecisionTreeRegressor
from sklearn.tree import DecisionTreeRegressor
# Import train_test_split
from sklearn.model_selection import train_test_split
# Import mean_squared_error as MSE
from sklearn.metrics import mean_squared_error as MSE
# Split data into 80% train and 20% test
X_train, X_test, y_train, y_test= train_test_split(X, y,
test_size=0.2,
random_state=3)
# Instantiate a DecisionTreeRegressor 'dt'
dt = DecisionTreeRegressor(max_depth=4,
min_samples_leaf=0.1,
random_state=3)
```

[63]:
```python
# Fit 'dt' to the training-set
dt.fit(X_train, y_train)
# Predict test-set labels
y_pred = dt.predict(X_test)
# Compute test-set MSE
mse_dt = MSE(y_test, y_pred)
# Compute test-set RMSE
rmse_dt = mse_dt**(1/2)
# Print rmse_dt
print(rmse_dt)
```

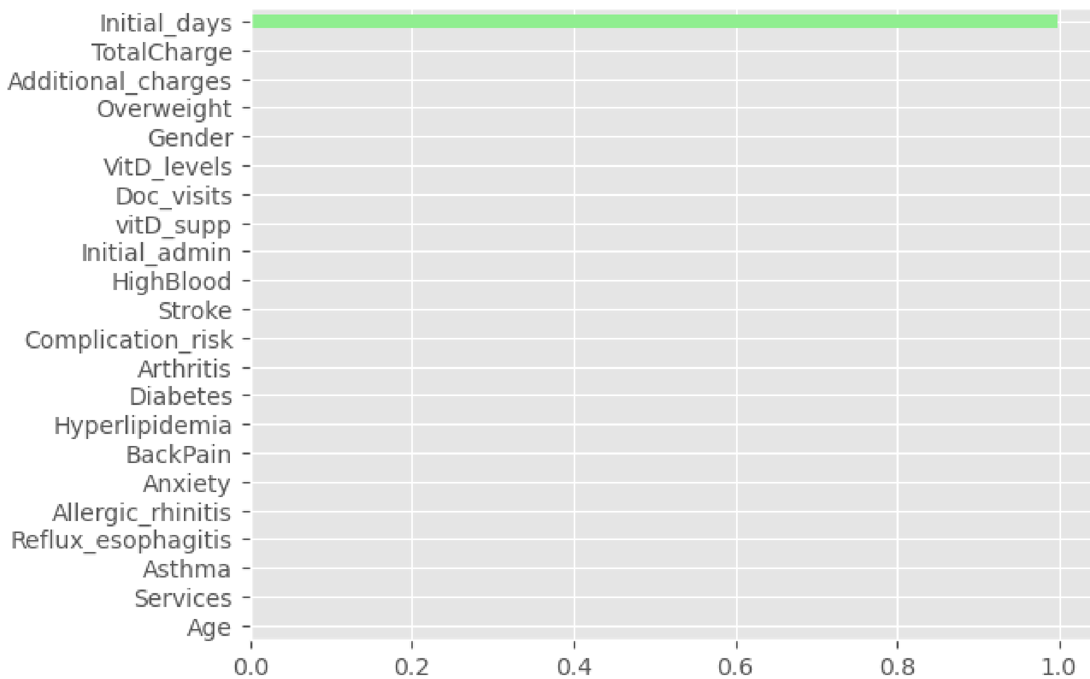
```
0.14757422655650276
```

[64]:
```
from sklearn.ensemble import RandomForestRegressor

SEED = 1
X_train, X_test, y_train, y_test= train_test_split(X, y,
test_size=0.3,
random_state=SEED)

rf = RandomForestRegressor(n_estimators=400,
                           min_samples_leaf=0.12,
                           random_state=SEED)

rf.fit(X_train, y_train)

y_pred = rf.predict(X_test)
```

[65]:
```
rmse_test = MSE(y_test, y_pred)**(1/2)

print('Test set RMSE of rf: {:.2f}'.format(rmse_test))
```

```
Test set RMSE of rf: 0.14
```

[66]:
```
importances_rf = pd.Series(rf.feature_importances_, index = X.columns)

# Sort
sorted_importances_rf = importances_rf.sort_values()

# Horizontal Bar Plot
sorted_importances_rf.plot(kind='barh', color='lightgreen'); plt.show()
```


Initial_days
TotalCharge
Additional_charges
Overweight
Gender
VitD_levels
Doc_visits
vitD_supp
Initial_admin
HighBlood
Stroke
Complication_risk
Arthritis
Diabetes
Hyperlipidemia
BackPain
Anxiety
Allergic_rhinitis
Reflux_esophagitis
Asthma
Services
Age
0.0
0.2
0.4
0.6
0.8
1.0