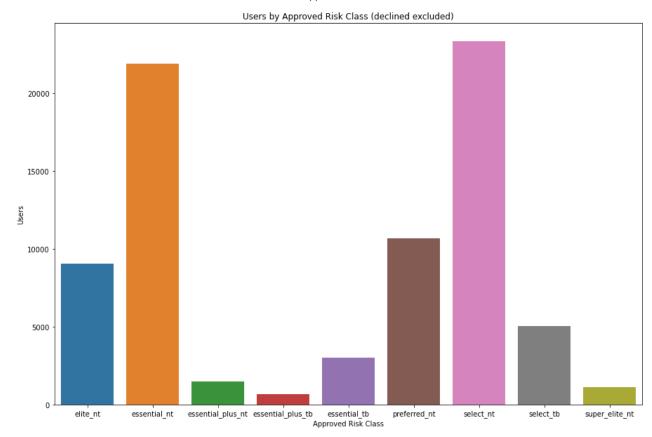
```
In [19]:
           import pandas as pd
           dtypes = {'state': str, 'approved risk class': str, 'alcohol current use': str, 'alcoho
                      'occupation 2019': str,
                      'risky activities': str, 'risky behavior 2019': str, 'valid drivers license a
                      'hiv': str, 'hiv ca': str, 'hiv fl': str,
                      'covid': str, 'previous declined': str, 'previous decline 2019': str, 'chest
                      'family history': str,
                      'medical_collection_ca_2019': str, 'medical_collection_none': str, 'seizure_d
                      'stroke tia last 2019': str,
                      'disability audio visual': str, 'expected travel 90 days': str, 'expected tra
                      'mental_health_missed_work': str, 'seizure_car_accident': str, 'tobacco_2019'
                      'chest pain angina': str, 'chest pain diagnosed': str, 'med conditions': str,
                     'stroke_count': float, 'stroke_last': str, 'stroke_diagnosis': str, 'stroke_di
                      'dui_count': float, 'expected_travel': str,
                     'expected travel fl': str, 'mental health hospitalized': str, 'scuba 130ft': s
                     }
In [20]:
           df = pd.read csv(r'C:\Users\milan\Documents\GitHub\DSC-680\approved risk class.csv', dt
In [21]:
           df.shape
          (173557, 151)
Out[21]:
In [22]:
           df.head()
                  quote_id application_id
Out[22]:
                                          date
                                                         anb
                                                               gender
                                                                       height weight state approved risk cla
                                                     age
                 52df592f-
                               81ce35d2-
                9c61-40ab-
                              f376-4384-
                                         2021-
          0
                                                48.534878
                                                           49
                                                                 male
                                                                         68.0
                                                                                195.0
                                                                                        TX
                                                                                                         Ν
                                         04-08
                     8dc3-
                                   9ead-
             5663562b6346
                            eb7359c393fa
                 8722c617-
                               4acdc655-
                               6fce-4c13-
                eea8-4008-
                                         2021-
          1
                                                42.716825
                                                           43
                                                                 male
                                                                         67.0
                                                                                200.0
                                                                                       NM
                                                                                                         Ν
                                   9c2e-
                                         01-28
                     a735-
                            1bac29df778e
             1970dd1bd9cb
                 39bf00db-
                              1c12bb4d-
                              8070-4c50-
                16d5-49f2-
                                         2021-
                                               54.399474
          2
                                                           54
                                                                 male
                                                                         66.0
                                                                                193.0
                                                                                        KS
                                                                                                         Ν
                                         02-02
                     8007-
                                  b193-
                           907e4ec0183b
             6eb163c4d1ab
                 368be5aa-
                                c2f5fec0-
                8bf6-4063-
                              e747-4b74-
                                         2021-
                                               50.336420
          3
                                                           50
                                                               female
                                                                         63.0
                                                                                140.0
                                                                                        OK
                                                                                                         Ν
                    bd1d-
                                   89fe-
                                         01-18
              4122fafd2093
                             fc79ff6bc725
                 43a8e77e-
                              373879b7-
                6e91-497f-
                               a94f-439f-
                                         2021-
                                                42.725039
                                                           43
                                                               female
                                                                         61.0
                                                                                132.0
                                                                                        IN
                                                                                                         Ν
                     983a-
                                   b4e2-
                                         03-07
             2d09a3c8e870
                           cb068885c06d
```

5 rows × 151 columns

```
In [23]:
          # drop fields with no non null values
          df.drop(['replacement_ins_company_immutable',
           'replacement_ins_policy_number_immutable',
           'alcohol drink count',
           'alcohol drug abuse',
           'alcohol monthly use',
           'occupation',
           'hiv multiselect',
           'chest pain last'
           'chest pain nitro',
           'diabetes before forty',
           'diabetes_kidney_disease',
           'prescribed insulin',
           'medical collection none',
           'stroke',
           'disability_condition',
           'disability condition other',
           'disability_payments',
           'disability payments 2019',
           'dui_history',
           'government_id',
           'depression diagnosed',
           'depression meds',
           'depression_mental_stress',
           'prescribed depression',
           'prescribed_quantity_depression',
           'claim hospital depression',
           'work_missed_depression',
           'when depression diagnosed',
           'rx increase condition',
           'rx increase other',
           'grand mal seizure',
           'how many seizures',
           'prescribed_for_seizures',
           'weight_loss_surgery',
           'active military specify',
           'age diabetes diagnosed',
           'cancer',
           'chronic_kidney_disease',
           'citizen_base',
           'heart disease',
           'legal_alcohol_drugs',
           'legal condition',
           'legal_license',
           'legal none',
           'liver',
           'organ_transplant',
           'peripheral_arterial_disease',
           'previous_insurance',
           'previous insurance reason',
           'reckless_driving_count',
           'skydive_type',
           'suicide depression',
           'travel duration'], axis=1, inplace=True)
```

```
In [24]:
          df.shape
          (173557, 98)
Out[24]:
In [25]:
          df['approved risk class'] = df['approved risk class'].fillna('declined')
In [33]:
          import pandas as pd
          import matplotlib.pyplot as plt
          # Group the data by category and calculate the sum of values
          grouped = df.groupby('approved_risk_class')['application_id'].count().reset_index()
          print(grouped)
          # Create a bar chart from the grouped data
          import seaborn as sns
          import matplotlib.pyplot as plt
          # Create a figure object with the desired size
          fig, ax = plt.subplots(figsize=(15,10))
          # Create the bar plot
          sns.barplot(x="approved_risk_class", y="application_id", data=grouped[grouped['approved
          # Customize the plot
          ax.set_title("Users by Approved Risk Class (declined excluded)")
          ax.set xlabel("Approved Risk Class")
          ax.set ylabel("Users")
          # Display the plot
          plt.show()
           approved_risk_class application_id
```

```
0
             declined
                                 97311
1
             elite nt
                                  9042
2
         essential nt
                                 21910
3
   essential_plus_nt
                                  1468
4
    essential_plus_tb
                                   679
5
         essential_tb
                                  2997
6
         preferred nt
                                 10664
7
            select nt
                                 23326
8
            select tb
                                  5039
9
       super_elite_nt
                                  1121
```



```
In [9]:
          # I am going to remove the super elite and essential plus risk class because there are
          # these risk classes are not necessary
          # I am also going to remove the tobacco risk classes as they generally follow different
          # in terms of risk classification. A separate model could be created for them.
          nt = df[(df['approved risk class'] != 'essential plus tb') & (df['approved risk class']
                  (df['approved risk class'] != 'select tb') & (df['approved risk class'] != 'sup
          nt.shape
         (163721, 94)
Out[9]:
In [10]:
         KeyError
                                                    Traceback (most recent call last)
         ~\AppData\Local\Temp/ipykernel 21008/1915129063.py in <module>
               5 # Group the data by category and calculate the sum of values
          ----> 6 nt.groupby('approved_risk_class')['application_id'].count()
               8 # Create a bar chart from the grouped data
         ~\anaconda3\lib\site-packages\pandas\core\groupby\generic.py in __getitem__(self, key)
            1536
                                  stacklevel=2,
            1537
          -> 1538
                         return super().__getitem__(key)
            1539
                     def _gotitem(self, key, ndim: int, subset=None):
            1540
```

~\anaconda3\lib\site-packages\pandas\core\base.py in getitem (self, key)

```
230
                           else:
              231
                               if key not in self.obj:
           --> 232
                                   raise KeyError(f"Column not found: {key}")
              233
                               subset = self.obj[key]
              234
                               ndim = subset.ndim
          KeyError: 'Column not found: application_id'
  In [ ]:
           # drop id fields, date field, and anb (same as age)
           df.drop(['quote_id', 'application_id', 'date', 'anb'], axis=1, inplace = True)
         examine outliers: age, weight, height, bmi, income
In [151...
           df num = nt.select dtypes(include = "number")
           df num.isnull().sum()
                                            0
          age
Out[151...
          height
                                            0
          weight
                                            0
          mortality_rate
                                        97311
          bmi app state
                                            0
          income_app_state
                                            0
          household income
                                       132727
          current ins value
                                       138843
          diabetes age
                                       153953
          alcohol weekly
                                         9032
          alcohol drink count 2019
                                       163703
          alcohol monthly binge
                                       161189
          alcohol monthly use 2019
                                       163710
          marijuana_monthly_count
                                       144581
          diabetes_hemoglobin
                                       159226
          stroke count
                                       163418
          dui count
                                       159520
          weight loss amount
                                       143623
          skydive count
                                       162636
          dtype: int64
In [152...
           from sklearn.ensemble import IsolationForest
           import numpy as np
           num df = df num[['age', 'height', 'weight', 'bmi app state', 'income app state']]
           X = num df.values
           # Create an instance of the IsolationForest algorithm
           clf = IsolationForest(n_estimators=100, contamination=0.01, random_state=42)
           # Fit the model to the data
           clf.fit(X)
           y_pred = clf.predict(X)
           # Print the indices of the predicted outliers
           outlier indices = np.where(y pred == -1)[0]
           outliers_df = num_df.iloc[outlier_indices]
```

print(outliers df) age height weight bmi app state income app state 215.0 32 54.155801 71.0 29.983138 3380000 150 55.344052 72.0 173.0 23.460455 11783148 238 43.316427 65.0 185.0 30.782249 2704000 533 54.774568 185.0 2496000 63.0 32.767700 557 38.834473 73.0 165.0 7800000 21.766748 172957 50.142029 62.0 140.0 25.603538 2600000 64.0 172972 23.020322 155.0 26.602783 2730000 173016 19.669124 72.0 280.0 37.970679 45614 173024 33.005469 63.0 18720 500.0 88.561350 173244 51.363135 62.0 140.0 25.603538 2908800 [1638 rows x 5 columns] In [153... nt.iloc[outlier indices] Out[153... gender height weight state approved_risk_class mortality_rate bmi_app_state in 32 54.155801 71.0 215.0 OK 123.0 29.983138 male select_nt 55.344052 72.0 173.0 NJ declined NaN 23.460455 150 male 43.316427 65.0 185.0 PA declined 30.782249 238 female NaN 54.774568 female 63.0 185.0 IL declined NaN 32.767700 557 38.834473 73.0 165.0 CA select nt 123.0 21.766748 male 172957 50.142029 female 62.0 140.0 FL declined NaN 25.603538 **172972** 23.020322 male 64.0 155.0 TX declined NaN 26.602783 72.0 **173016** 19.669124 male 280.0 UT essential_nt 145.0 37.970679 **173024** 33.005469 63.0 500.0 declined 88.561350 female VA NaN declined **173244** 51.363135 62.0 140.0 TN NaN 25.603538 female 1638 rows × 94 columns In [154... # look at outliers by risk class outliers = nt.iloc[outlier indices] outliers.groupby('approved_risk_class').count().reset_index() Out[154... approved_risk_class age gender height weight state mortality_rate bmi_app_state income_app_st 0 declined 984 984 984 984 984 0 984 1 85 85 85 elite_nt 85 85 85 85 2 229 229 229 229 229 229 essential_nt 229

Out[157...

| | approved_risk_class | age | gender | height | weight | state | mortality_rate | bmi_app_state | income_app_s |
|---|---------------------|-----|--------|--------|--------|-------|----------------|---------------|--------------|
| 3 | essential_plus_nt | 8 | 8 | 8 | 8 | 8 | 8 | 8 | |
| 4 | preferred_nt | 124 | 124 | 124 | 124 | 124 | 124 | 124 | |
| 5 | select_nt | 208 | 208 | 208 | 208 | 208 | 208 | 208 | |
| | | | | | | | | | |

6 rows × 94 columns

```
In [155... # 1% of our data is outliers
    outliers.shape[0]/nt.shape[0]

Out[155... # drop outliers

    nt_clean = nt.drop(nt.index[outlier_indices])
    nt_clean.shape

Out[156... (162083, 94)
```

check replace insurance and replacement insurance policy number

```
ins = nt_clean[nt_clean['replacement_ins'].notnull()]
ins[['replacement_ins', 'replacement_ins_company', 'replacement_ins_policy_number']]
```

| | replacement_ins | replacement_ins_company | replacement_ins_policy_number |
|--------|-----------------|-------------------------|-------------------------------|
| 10 | no | NaN | NaN |
| 19 | no | NaN | NaN |
| 20 | no | NaN | NaN |
| 39 | no | NaN | NaN |
| 46 | no | NaN | NaN |
| ••• | | | |
| 173534 | no | NaN | NaN |
| 173536 | no | NaN | NaN |
| 173545 | no | NaN | NaN |
| 173547 | yes | Thrivent | 42620 |
| 173549 | no | NaN | NaN |
| | | | |

24515 rows × 3 columns

```
# are there any cases where insurance company is not null, but ins is? No nt_clean[(nt_clean['replacement_ins'].isna()) & (nt_clean['replacement_ins_company'].no
```

```
Out[158...
             age gender height weight state approved_risk_class mortality_rate bmi_app_state income_app_sta
          0 rows × 94 columns
In [159...
            # are there any cases where insurance policy is not null, but ins is? No
            nt_clean[(nt_clean['replacement_ins'].isna()) & (nt_clean['replacement_ins_policy_numbe
Out[159...
             age gender height weight state approved_risk_class mortality_rate bmi_app_state income_app_sta
          0 rows × 94 columns
In [160...
            # drop replacement ins company and replacement ins policy number
            nt_clean.drop(['replacement_ins_company', 'replacement_ins_policy_number'], axis=1, inp
In [161...
            alcohol_cols = nt_clean.filter(like='alcohol')
            alcohol cols
Out[161...
                   alcohol_weekly alcohol_current_use alcohol_drink_count_2019 alcohol_monthly_binge alcohol_m
                0
                              0.0
                                               NaN
                                                                      NaN
                                                                                            NaN
                              0.0
                                               NaN
                1
                                                                      NaN
                                                                                            NaN
                              0.0
                                               NaN
                                                                      NaN
                                                                                            NaN
                3
                            NaN
                                               NaN
                                                                                            NaN
                                                                      NaN
                              0.0
                                               NaN
                                                                      NaN
                                                                                            NaN
           173552
                              0.0
                                               NaN
                                                                      NaN
                                                                                            NaN
           173553
                              1.0
                                               NaN
                                                                      NaN
                                                                                            NaN
           173554
                              0.0
                                               NaN
                                                                      NaN
                                                                                            NaN
           173555
                              0.0
                                               NaN
                                                                      NaN
                                                                                            NaN
           173556
                              0.0
                                               NaN
                                                                      NaN
                                                                                            NaN
          162083 rows × 5 columns
In [162...
            # remove highly correlated and high null columns
            nt_clean.drop(['alcohol_current_use', 'alcohol_drink_count_2019', 'alcohol_monthly_bing'
                                        'alcohol_monthly_use_2019', 'occupation_2019', 'risky_behavio
                                       'previous_decline_2019', 'chest_pain_angina', 'chest_pain_diag
```

```
'medical_collection_2019', 'stroke_tia_last_2019', 'tobacco_20
                                                   'criminal dui years'], axis=1, inplace=True)
In [163...
               nt_clean.shape
              (162083, 76)
Out[163...
In [164...
               nt_clean = nt_clean[(nt_clean['dui_count'] <= 25) | (nt_clean['dui_count'].isna())]</pre>
In [165...
               nt clean.shape
              (162060, 76)
Out[165...
In [166...
               df_num = nt_clean.select_dtypes(include='number')
               corr_mat = df_num.corr()
               import seaborn as sn
               import matplotlib.pyplot as plt
               plt.rcParams['figure.figsize'] = (20, 10)
               sn.heatmap(corr_mat, annot=True)
               plt.show()
                                                                                                                                   1.0
                              1
                                    1
                                                                                                                                  - 0.8
                                          1
                        weight
                                                     0.81
                                                                -0.009
                                                                                  0.0034
                                                                                                               0.0065
                                                                                                                     0.06
                                               1
                    mortality_rate
                                                                                                                                  0.6
                                         0.81
                                                     1
                                                                      -0.014
                   bmi_app_state
                                                           1
                                                                      0.0058
                  income_app_state
                                                                                                                                  0.4
                  household_income
                                         -0 009
                                                                 1
                                                                                                               -0.0018
                                                                       1
                  current_ins_value
                                                                            1
                                                                                                                                  - 0.2
                                                                                   1
                   alcohol_weekly
                                         0.0034
                                                                                             -0.0014
                                                                                                               0.004
                                                                                        1
                                                                                                                                  0.0
                                                                                              1
                diabetes_hemoglobin
                                                                                                    1
                                                                                                                     0.98
                    stroke count
                                                                            0.054
                                                                                                                                   -0.2
                                   0.024
                                                          0.0029
                                                                -0.016
                                                                      -0.068
                                                                                  0.018
                                                                                       -0.0085
                                                                                                               0.0099
                 weight_loss_amount
                                                                            -0.28
                                                                                                    0.98
                                                     0.08
                                                                                       -0.0036
                    skydive count
                              age
                                    reight
                                                      omi_app_state
                                                            icome_app_state
In [167...
               # ~350 users ineligible by age
               nt_clean[(nt_clean['age'] < 18 )| (nt_clean['age'] > 60 ) ]
Out[167...
                                              height weight state approved_risk_class mortality_rate
                                     gender
                                                                                                                  bmi_app_state
                  129
                        60.466676
                                        male
                                                  71.0
                                                          195.0
                                                                    VA
                                                                                      declined
                                                                                                           NaN
                                                                                                                       27.194009
```

| | age | gender | height | weight | state | approved_risk_class | mortality_rate | bmi_app_state | in |
|--------|-----------|--------|--------|--------|-------|---------------------|----------------|---------------|----|
| 299 | 60.384539 | female | 68.0 | 125.0 | IL | declined | NaN | 19.004109 | |
| 372 | 60.365374 | male | 68.0 | 140.0 | NJ | declined | NaN | 21.284602 | |
| 2100 | 60.258595 | female | 65.0 | 130.0 | TX | declined | NaN | 21.630769 | |
| 2296 | 60.121700 | male | 69.0 | 153.0 | SC | declined | NaN | 22.591682 | |
| ••• | | | | | | | | | |
| 171648 | 60.285974 | male | 71.0 | 195.0 | CO | declined | NaN | 27.194009 | |
| 172023 | 60.373587 | male | 66.0 | 180.0 | TX | declined | NaN | 29.049587 | |
| 172923 | 60.403704 | male | 69.0 | 175.0 | MI | preferred_nt | 90.0 | 25.840160 | |
| 172997 | 60.348946 | male | 71.0 | 205.0 | WI | declined | NaN | 28.588574 | |
| 173224 | 60.250382 | female | 66.0 | 189.0 | GA | declined | NaN | 30.502066 | |
| | | | | | | | | | |

352 rows × 76 columns

```
In [168...
# ~ 900 users ineligible by BMI
nt_clean[(nt_clean['bmi_app_state'] < 18.5 )| (nt_clean['bmi_app_state'] > 40 )]
```

Out[168... gender height weight state approved_risk_class mortality_rate bmi_app_state in age 52.118798 829 female 69.0 300.0 TX declined NaN 44.297417 1648 53.797135 female 66.0 250.0 WA declined NaN 40.346648 **4072** 49.046866 male 72.0 350.0 IN declined NaN 47.463349 35.576364 69.0 5813 male 330.0 TX declined NaN 48.727158 37.325886 66.0 6470 female 250.0 MA declined NaN 40.346648

> 172389 31.822693 65.0 245.0 40.765680 female PA declined NaN **172969** 35.529819 male 71.0 334.0 DE declined NaN 46.578457

> **173037** 43.258931 65.0 245.0 declined 40.765680 female PA NaN **173261** 41.933784 270.0 47.823129 63.0 SC declined NaN female **173327** 42.807176 62.0 235.0 declined 42.977367 female MI NaN

876 rows × 76 columns

Dealing with missing values

- Remove household income, medical_collection_ca_2019, expected travel fl, hiv_ca, hiv_fl
- stroke_last, seizure first
- Try converting first and last fields to days since?
- current_ins_value = 0
- replacement ins = False ?
- diabetes age = -1
- alcohol weekly = mean
- remove outliers for marijuana monthly
- occupation description: 'other'
- risky_activities: 'none'
- driver's license: mode
- hiv_pos: mode
- hiv_ca and hiv_fl: drop?
- covid: mode
- previously declined: mode
- previous decline reason: 'none'
- chestpain diagnosis: 'none'
- diabetes complications: 'none'
- diabetes gestational: mode
- diabetes hemogloben: -1
- diabetes hospitalization: mode
- employment status: 'other'
- family history: mode
- final expense: 'none'
- inpatient: 'none'
- med_advice: 'none'
- med conditions: 'none'
- seizure diagnosis: 'none'
- stroke count: 0
- stroke diagnosis: 'none'

- stroke diagnosis multiselect: 'none'
- test_proc_outstanding: False
- test_proc_type: 'none'
- · climbing equipment: False
- disabiliity audio_visual: False
- disability pmts reason: 'none'
- dui count: mean
- expected travel 90 days: 'none'
- expected travel: False
- expected travel muliteselect: 'none'
- mental health diagnosis: 'none'
- mental health hospitalized: False
- mental health missed work: False
- pilot student private: False
- racing 100 mph: False
- rx_increase: False
- scuba_130 ft: False
- seizure car accicent: False
- tb: False
- last worked: ?
- weight loss amount: add mean if weight losss is true, otherwise 0
 - remove outliers
- weight loss reason: 'none'
- cancer type: 'none'
- legal resident: mode
- skydive count: 0
 - remove outliers
- surgery type: 'none'
- travel countries: 'none'

Dealing with missing values

- stroke_last, seizure first
- Try converting first and last fields to days since?
- current_ins_value = 0
- replacement ins = False ?
- diabetes age = -1
- alcohol weekly = mean
- · remove outliers for marijuana monthly
- · occupation description: 'other'
- risky_activities: 'none'
- driver's license: mode
- hiv_pos: mode

- hiv_ca and hiv_fl: drop?
- covid: mode
- previously declined: mode
- previous decline reason: 'none'
- chestpain diagnosis: 'none'
- diabetes complications: 'none'
- diabetes gestational: mode
- diabetes hemogloben: -1
- diabetes hospitalization: mode
- · employment status: 'other'
- family history: mode
- final expense: 'none'
- inpatient: 'none'
- med_advice: 'none'
- med conditions: 'none'
- seizure diagnosis: 'none'
- stroke count: 0
- stroke diagnosis: 'none'
- · stroke diagnosis multiselect: 'none'
- test_proc_outstanding: False
- test_proc_type: 'none'
- climbing equipment: False
- disabiliity audio_visual: False
- disability pmts reason: 'none'
- dui count: mean
- expected travel 90 days: 'none'
- expected travel: False
- expected travel muliteselect: 'none'
- mental health diagnosis: 'none'
- mental health hospitalized: False
- mental health missed work: False
- pilot student private: False
- racing 100 mph: False
- rx_increase: False
- scuba_130 ft: False
- seizure car accicent: False
- tb: False
- last worked: ?
- weight loss amount: add mean if weight losss is true, otherwise 0
 - remove outliers
- weight loss reason: 'none'
- cancer type: 'none'
- legal resident: mode

- skydive count: 0
 - remove outliers
- surgery type: 'none'
- travel countries: 'none'

```
In [173...
```

```
nt_clean.drop(['household_income','medical_collection_ca_2019', 'hiv_ca', 'hiv_fl', 'ex
             axis=1, inplace=True)
# drop dates since it's not worth trying to clean them
nt_clean.drop(['stroke_last', 'seizure_last', 'seizure_first', 'last_worked'], axis=1,
```

- occupation description: 'other'
- risky_activities: 'none'
- previous decline reason: 'none'
- chestpain diagnosis: 'none'
- diabetes complications: 'none'
- · employment status: 'other'
- final expense: 'none'
- inpatient: 'none'
- med_advice: 'none'
- med conditions: 'none'
- seizure diagnosis: 'none'
- stroke diagnosis: 'none'
- stroke diagnosis multiselect: 'none'
- test_proc_type: 'none'
- disability pmts reason: 'none'
- expected travel 90 days: 'none'
- expected travel muliteselect: 'none'
- mental health diagnosis: 'none'
- weight loss reason: 'none'
- cancer type: 'none'
- surgery type: 'none'
- travel countries: 'none'

In [174...

```
fill values = {'occupation description': 'other', 'risky activities': 'none'
 'previous decline reason': 'none'
  'chestpain diagnosis': 'none'
  'diabetes_complications': 'none'
  'employment_status': 'other'
  'final expense': 'none'
  'inpatient': 'none'
  'med_advice': 'none'
  'med_conditions': 'none'
  'seizure diagnosis': 'none'
  'stroke_diagnosis': 'none'
  'stroke_diagnosis_multiselect': 'none'
  'test_proc_type': 'none'
  'disability pmts reason': 'none'
```

```
'expected_travel_90_days': 'none'
  'expected_travel_multiselect': 'none'
  'mental_health_diagnosis': 'none'
 'weight_loss_reason': 'none'
,'cancer_type': 'none'
,'surgery_type': 'none'
,'travel countries': 'none'}
nt_clean.fillna(value = fill_values, inplace=True)
```

- driver's license: mode
- hiv_pos: mode
- · covid: mode
- previously declined: mode
- diabetes gestational: mode
- diabetes hospitalization: mode
- family history: mode
- climbing equipment: False
- disabiliity audio_visual: False
- expected travel: False
- mental health hospitalized: False
- mental health missed work: False
- pilot student private: False
- racing 100 mph: False
- rx_increase: False
- scuba_130 ft: False
- seizure car accicent: False
- tb: False
- legal resident: mode

```
In [175...
           # fill null values with mode in selected columns
           selected_columns = [
            'test_proc_outstanding',
           'valid_drivers_license_app_state',
            'hiv_pos',
            'covid',
            'previous_declined',
            'diabetes_gestational',
            'diabetes_hemoglobin',
            'diabetes hospitalization',
            'family_history',
            'climbing_equipment',
           'disability audio visual',
            'expected_travel',
            'mental_health_hospitalized',
            'mental_health_missed_work',
            'pilot student private',
            'racing_100mph',
            'rx_increase',
            'scuba_130ft',
            'seizure car accident',
```

```
'tb',
             'legal_resident',
             'replacement ins']
            for col in selected columns:
                 if nt clean[col].dtype == bool:
                      nt clean[col].fillna(nt clean[col].mode().iloc[0], inplace=True)
                 elif nt_clean[col].dtype == object:
                     nt_clean[col].fillna(nt_clean[col].mode().iloc[0], inplace=True)
In [176...
             num_fill_values = {'current_ins_value' : 0, 'diabetes_age' : -1, 'diabetes_hemoglobin':
                                   'skydive count': 0, 'dui count':0}
            nt_clean.fillna(value = num_fill_values, inplace=True)
In [177...
            # nt clean[['alcohol weekly']].sort values('alcohol weekly', ascending = False)
            nt clean[nt clean['alcohol weekly'] >= 50]
Out[177...
                         age gender height weight state approved_risk_class mortality_rate bmi_app_state in
              1778 48.882592
                                         64.0
                                                160.0
                                                        WA
                                 male
                                                                       declined
                                                                                         NaN
                                                                                                   27.460938
                                                                                                   24.325260
              7240 30.549566
                                         68.0
                                                160.0
                                                        MO
                                                                       declined
                                                                                         NaN
                               female
              7359 27.546082
                                 male
                                         68.0
                                                170.0
                                                        GΑ
                                                                       declined
                                                                                         NaN
                                                                                                   25.845588
                    51.609547
                                         74.0
                                                198.0
                                                         FL
                                                                       declined
                                                                                         NaN
                                                                                                   25.418919
              7667
                                 male
              7815 26.330452
                               female
                                         64.0
                                                218.0
                                                        OK
                                                                       declined
                                                                                         NaN
                                                                                                   37.415527
                    50.109174
            159400
                                         71.0
                                                150.0
                                                         AR
                                                                       declined
                                                                                         NaN
                                                                                                   20.918469
                                 male
            161994
                    50.109174
                                 male
                                         72.0
                                                235.0
                                                         IN
                                                                       declined
                                                                                         NaN
                                                                                                   31.868248
            167135 34.971286
                                         68.0
                                                220.0
                                                                       declined
                                                                                                   33.447232
                                 male
                                                         IL
                                                                                         NaN
            167862 27.636433
                                 male
                                         74.0
                                                158.0
                                                        NC
                                                                       declined
                                                                                         NaN
                                                                                                   20.283784
            172285 40.249971
                               female
                                         64.0
                                                129.0
                                                         TX
                                                                       declined
                                                                                         NaN
                                                                                                   22.140381
           104 rows × 67 columns
In [178...
            nt_clean[(nt_clean['alcohol_weekly'] < 50) |( nt_clean['alcohol_weekly'].isna())]</pre>
Out[178...
                         age gender height weight state approved_risk_class mortality_rate
                                                                                               bmi_app_state in
                 0 48.534878
                                 male
                                         68.0
                                                195.0
                                                         TX
                                                                       declined
                                                                                         NaN
                                                                                                   29.646410
                    42.716825
                                 male
                                         67.0
                                                200.0
                                                        NM
                                                                       declined
                                                                                         NaN
                                                                                                   31.321007
                    54.399474
                                         66.0
                                                193.0
                                                                       declined
                                                                                                   31.147612
                                 male
                                                         KS
                                                                                         NaN
                    50.336420
                               female
                                         63.0
                                                140.0
                                                        OK
                                                                       declined
                                                                                         NaN
                                                                                                   24.797178
                                                                       declined
                   42.725039
                                         61.0
                                                132.0
                                                         IN
                                                                                         NaN
                                                                                                   24.938457
                               female
```

| | age | gender | height | weight | state | approved_risk_class | mortality_rate | bmi_app_state | in |
|--------|-----------|--------|--------|--------|-------|---------------------|----------------|---------------|----|
| ••• | | | ••• | | | | | | |
| 173552 | 35.020569 | female | 61.0 | 150.0 | ME | declined | NaN | 28.339156 | |
| 173553 | 41.312279 | female | 69.0 | 198.0 | ME | declined | NaN | 29.236295 | |
| 173554 | 40.214378 | male | 72.0 | 196.0 | PA | declined | NaN | 26.579475 | |
| 173555 | 32.887739 | male | 75.0 | 200.0 | PA | declined | NaN | 24.995556 | |
| 173556 | 37.306721 | male | 70.0 | 160.0 | PA | declined | NaN | 22.955102 | |
| | | | | | | | | | |

160730 rows × 67 columns

In [179...

remove users who reported having more than 50 drinks per week
nt_clean = nt_clean[(nt_clean['alcohol_weekly'] < 50) |(nt_clean['alcohol_weekly'].isn
print(nt_clean.shape)</pre>

(160730, 67)

In [180...

fill null values with median for alcohol weekly
nt_clean['alcohol_weekly'].fillna(value=nt_clean['alcohol_weekly'].median(), inplace=Tr

In [181...

remove users who reported smoking marijuana more than 100 times per month
nt_clean[nt_clean['marijuana_monthly_count'] >= 100]

Out[181...

| | age | gender | height | weight | state | approved_risk_class | mortality_rate | bmi_app_state | in |
|--------|-----------|--------|--------|--------|-------|---------------------|----------------|---------------|----|
| 192 | 23.986803 | female | 67.0 | 180.0 | CO | declined | NaN | 28.188906 | |
| 506 | 29.925324 | female | 67.0 | 180.0 | МО | declined | NaN | 28.188906 | |
| 542 | 28.687790 | male | 68.0 | 138.0 | LA | declined | NaN | 20.980536 | |
| 566 | 24.559026 | male | 72.0 | 170.0 | OK | declined | NaN | 23.053627 | |
| 777 | 26.546746 | female | 64.0 | 122.0 | FL | declined | NaN | 20.938965 | |
| ••• | | | | | | | | | |
| 172864 | 27.943079 | female | 70.0 | 196.0 | WA | declined | NaN | 28.120000 | |
| 172909 | 31.778887 | female | 66.0 | 120.0 | CA | declined | NaN | 19.366391 | |
| 172966 | 30.760385 | male | 76.0 | 193.0 | OR | declined | NaN | 23.490132 | |
| 173101 | 26.251052 | female | 62.0 | 115.0 | NM | declined | NaN | 21.031478 | |
| 173390 | 32.208738 | male | 69.0 | 130.0 | OK | declined | NaN | 19.195547 | |
| | | | | | | | | | |

525 rows × 67 columns

4

```
In [182...
            nt_clean[(nt_clean['marijuana_monthly_count'] < 100) | (nt_clean['marijuana_monthly_cou</pre>
                         age gender height weight state approved_risk_class mortality_rate bmi_app_state in
Out[182...
                 0 48.534878
                                         68.0
                                                195.0
                                                        TX
                                                                      declined
                                                                                        NaN
                                                                                                  29.646410
                                 male
                 1 42.716825
                                         67.0
                                                200.0
                                                       NM
                                                                       declined
                                                                                        NaN
                                                                                                  31.321007
                                 male
                 2 54.399474
                                         66.0
                                                193.0
                                                        KS
                                                                      declined
                                                                                        NaN
                                                                                                  31.147612
                                male
                   50.336420
                                         63.0
                                                140.0
                                                                       declined
                               female
                                                        OK
                                                                                        NaN
                                                                                                  24.797178
                   42.725039
                                         61.0
                                               132.0
                                                                       declined
                                                                                                  24.938457
                               female
                                                        IN
                                                                                        NaN
                                                                                                  28.339156
            173552 35.020569
                                         61.0
                                                150.0
                                                                       declined
                               female
                                                        ME
                                                                                        NaN
                                                198.0
            173553 41.312279
                                         69.0
                                                                       declined
                                                                                                  29.236295
                               female
                                                        ME
                                                                                        NaN
            173554 40.214378
                                 male
                                         72.0
                                                196.0
                                                                       declined
                                                                                        NaN
                                                                                                  26.579475
                                                        РΑ
            173555 32.887739
                                         75.0
                                                200.0
                                                                       declined
                                                                                        NaN
                                                                                                  24.995556
                                 male
                                                        РΑ
           173556 37.306721
                                         70.0
                                                160.0
                                                        PA
                                                                       declined
                                                                                        NaN
                                                                                                  22.955102
                                male
           160205 rows × 67 columns
In [183...
            nt clean = nt clean[(nt clean['marijuana monthly count'] < 100) | (nt clean['marijuana</pre>
In [184...
            # fill null values with median in column 'col1'
            nt clean['marijuana monthly count'].fillna(value=nt clean['marijuana monthly count'].me
In [185...
            # check which columns still have nulls
            for col in list(nt clean.columns):
                 if nt_clean[col].isnull().sum() > 0:
                     print(str(col))
                     print(nt clean[col].dtype)
           mortality rate
           float64
           weight loss amount
           float64
In [186...
            nt clean['replacement ins'].isnull().sum()
           0
Out[186...
In [187...
            nt clean[nt clean['marijuana monthly count'].isna()]
Out[187...
                 gender height weight state approved_risk_class mortality_rate bmi_app_state income_app_sta
```

0 rows × 67 columns

```
In [188...
           nt mj = nt clean
In [189...
           # fillna for users who did not lose weight
           nt_mj.loc[~nt_mj['weight_loss'], 'weight_loss_amount'] = nt_mj.loc[~nt_mj['weight_loss']
In [190...
           nt clean.loc[~nt clean['weight loss'], 'weight loss amount']
                     0.0
Out[190...
                     0.0
          1
           2
                     0.0
           4
                     0.0
           5
                     0.0
          173551
                     0.0
           173553
                     0.0
          173554
                     0.0
          173555
                     0.0
           173556
                     0.0
          Name: weight_loss_amount, Length: 140853, dtype: float64
In [191...
           # fillna for users who do not use marijuana
           nt mj.loc[~nt mj['marijuana'], 'marijuana monthly count'] = nt mj.loc[~nt mj['marijuana
In [192...
           nt mj.loc[nt mj['marijuana'] == False]['marijuana monthly count']
                     5.0
Out[192...
          1
                     5.0
                     5.0
                     5.0
           5
                     5.0
                    . . .
          173550
                     5.0
           173551
                     5.0
          173553
                     5.0
          173554
                     5.0
          173555
                     5.0
          Name: marijuana monthly count, Length: 141864, dtype: float64
In [193...
           # factor = pd.factorize(nt_clean['approved_risk_class'])
           # nt clean.approved risk class = factor[0]
           # definitions = factor[1]
           # print(nt_clean.approved_risk_class.head())
           # print(definitions)
          drop mortality rate
In [194...
           nt_clean[nt_clean['approved_risk_class'] == 'essential_plus_nt']
```

Out[194...

| | age | gender | height | weight | state | approved_risk_class | mortality_rate | bmi_app_state ir |
|--------|-----------|--------|--------|--------|-------|---------------------|----------------|------------------|
| 18801 | 49.027701 | male | 67.0 | 220.0 | FL | essential_plus_nt | 200.0 | 34.453108 |
| 18817 | 33.906240 | female | 69.0 | 135.0 | TX | essential_plus_nt | 200.0 | 19.933837 |
| 18945 | 48.901757 | male | 72.0 | 160.0 | DC | essential_plus_nt | 200.0 | 21.697531 |
| 18960 | 41.695586 | female | 66.0 | 170.0 | FL | essential_plus_nt | 200.0 | 27.435721 |
| 19024 | 48.447264 | male | 71.0 | 186.0 | LA | essential_plus_nt | 200.0 | 25.938901 |
| ••• | | ••• | | | | | | |
| 173087 | 51.220764 | female | 64.0 | 175.0 | ME | essential_plus_nt | 200.0 | 30.035400 |
| 173223 | 37.690028 | male | 71.0 | 253.0 | GA | essential_plus_nt | 200.0 | 35.282484 |
| 173276 | 41.462864 | female | 65.0 | 130.0 | NE | essential_plus_nt | 200.0 | 21.630769 |
| 173403 | 44.652525 | male | 67.0 | 165.0 | FL | essential_plus_nt | 200.0 | 25.839831 |
| 173472 | 40.600423 | female | 64.0 | 160.0 | FL | essential_plus_nt | 200.0 | 27.460938 |

1460 rows × 67 columns

```
In [197...
    nt_appRC = nt_clean.drop('mortality_rate', axis=1)
    nt_appRC = nt_appRC[nt_appRC['approved_risk_class'] != 'essential_plus_nt']
    nt_appRC.groupby('approved_risk_class').count()
```

Out[197...

| | _ | _ | _ | _ | | | | |
|---------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| approved_risk_class | | | | | | | | |
| declined | 94513 | 94513 | 94513 | 94513 | 94513 | 94513 | 94513 | 94513 |
| elite_nt | 8931 | 8931 | 8931 | 8931 | 8931 | 8931 | 8931 | 8931 |
| essential_nt | 21681 | 21681 | 21681 | 21681 | 21681 | 21681 | 21681 | 21681 |
| preferred_nt | 10502 | 10502 | 10502 | 10502 | 10502 | 10502 | 10502 | 10502 |
| select_nt | 23118 | 23118 | 23118 | 23118 | 23118 | 23118 | 23118 | 23118 |

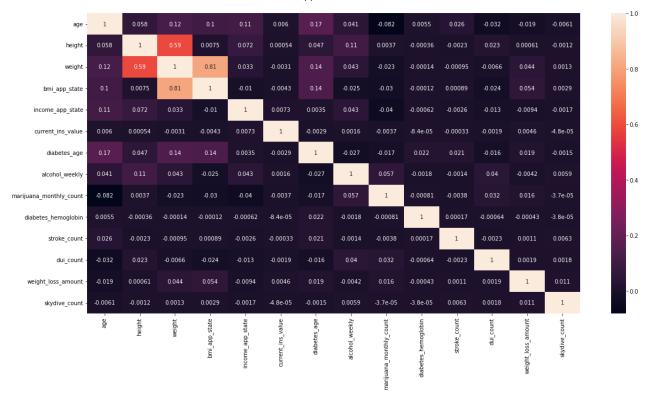
age gender height weight state bmi_app_state income_app_state current_ins

5 rows × 65 columns

```
In [196...

df_num = nt_appRC.select_dtypes(include='number')
    corr_mat = df_num.corr()

import seaborn as sn
    import matplotlib.pyplot as plt
    plt.rcParams['figure.figsize'] = (20, 10)
    sn.heatmap(corr_mat, annot=True)
    plt.show()
```



In [117...

```
import pandas profiling
# import ydata profiling
profile = pandas profiling.ProfileReport(nt appRC)
profile.to file("nt clean.html")
```

C:\Users\milan\AppData\Local\Temp/ipykernel_40260/2879794622.py:1: DeprecationWarning: import pandas profiling` is going to be deprecated by April 1st. Please use `import ydat a profiling` instead.

import pandas_profiling

```
In [119...
           # transform categorical features
           from category encoders import *
           encoder = TargetEncoder()
           factor = pd.factorize(nt_appRC['approved_risk_class'])
           y = factor[0]
           definitions = factor[1]
           X = nt appRC.drop(columns = 'approved risk class')
           enc = TargetEncoder(min_samples_leaf=20, smoothing=10).fit(X,y)
           nt_transformed = enc.transform(X)
           nt transformed
```

C:\Users\milan\anaconda3\lib\site-packages\category_encoders\target_encoder.py:122: Futu reWarning: Default parameter min_samples_leaf will change in version 2.6.See https://git hub.com/scikit-learn-contrib/category encoders/issues/327

warnings.warn("Default parameter min samples leaf will change in version 2.6." C:\Users\milan\anaconda3\lib\site-packages\category encoders\target encoder.py:127: Futu reWarning: Default parameter smoothing will change in version 2.6.See https://github.com/scikit-learn-contrib/category_encoders/issues/327

warnings.warn("Default parameter smoothing will change in version 2.6."

| \cap | 14- | Г1 | 1 | \cap | |
|--------|-----|----|---|--------|-----|
| U | иL | ГΤ | Т | J | ••• |

| 1.015067 | 36400 | | | | | | | |
|---|--|---|--|---|--|---|---|---|
| | | 29.646410 | 1.140601 | 195.0 | 68.0 | 1.029396 | 48.534878 | 0 |
| 1.015067 | 9528 | 31.321007 | 0.998968 | 200.0 | 67.0 | 1.029396 | 42.716825 | 1 |
| 1.015067 | 9396 | 31.147612 | 0.888889 | 193.0 | 66.0 | 1.029396 | 54.399474 | 2 |
| 1.015067 | 82000 | 24.797178 | 0.905008 | 140.0 | 63.0 | 1.014664 | 50.336420 | 3 |
| 1.015067 | 72000 | 24.938457 | 0.751253 | 132.0 | 61.0 | 1.014664 | 42.725039 | 4 |
| | | | | | ••• | | | ••• |
| 1.015067 | 70000 | 28.339156 | 0.985413 | 150.0 | 61.0 | 1.014664 | 35.020569 | 173552 |
| 1.015067 | 169000 | 29.236295 | 0.985413 | 198.0 | 69.0 | 1.014664 | 41.312279 | 173553 |
| 1.015067 | 11772 | 26.579475 | 0.941686 | 196.0 | 72.0 | 1.029396 | 40.214378 | 173554 |
| 1.015067 | 369200 | 24.995556 | 0.941686 | 200.0 | 75.0 | 1.029396 | 32.887739 | 173555 |
| 1.015067 | 36400 | 22.955102 | 0.941686 | 160.0 | 70.0 | 1.029396 | 37.306721 | 173556 |
| 1.015067 1.015067 1.015067 1.015067 1.015067 1.015067 | 9396 82000 72000 70000 169000 11772 369200 | 31.147612 24.797178 24.938457 28.339156 29.236295 26.579475 24.995556 | 0.888889 0.905008 0.751253 0.985413 0.985413 0.941686 0.941686 | 193.0 140.0 132.0 150.0 198.0 196.0 200.0 | 66.0 63.0 61.0 61.0 69.0 72.0 | 1.029396 1.014664 1.014664 1.014664 1.029396 1.029396 | 54.399474 50.336420 42.725039 35.020569 41.312279 40.214378 32.887739 | 2 3 4 173552 173553 173554 |

158745 rows × 65 columns

In [120...

print(definitions)

Index(['declined', 'elite_nt', 'select_nt', 'essential_nt', 'preferred_nt'], dtype='obje
ct')

In [121...

nt_transformed['approved_risk_class'] = y
nt_transformed.head()

Out[121...

| | age | gender | height | weight | state | bmi_app_state | income_app_state | current_ins | current_ |
|---|-----------|----------|--------|--------|----------|---------------|------------------|-------------|----------|
| 0 | 48.534878 | 1.029396 | 68.0 | 195.0 | 1.140601 | 29.646410 | 36400 | 1.015067 | |
| 1 | 42.716825 | 1.029396 | 67.0 | 200.0 | 0.998968 | 31.321007 | 9528 | 1.015067 | |
| 2 | 54.399474 | 1.029396 | 66.0 | 193.0 | 0.888889 | 31.147612 | 9396 | 1.015067 | |
| 3 | 50.336420 | 1.014664 | 63.0 | 140.0 | 0.905008 | 24.797178 | 82000 | 1.015067 | |
| 4 | 42.725039 | 1.014664 | 61.0 | 132.0 | 0.751253 | 24.938457 | 72000 | 1.015067 | |

5 rows × 66 columns

In [122...

nt_transformed.shape

Out[122...

(158745, 66)

```
# save cleaned and transformed dataframe
nt_transformed.to_csv(r'C:\Users\milan\Documents\GitHub\DSC-680\approved_risk_class_cle
```

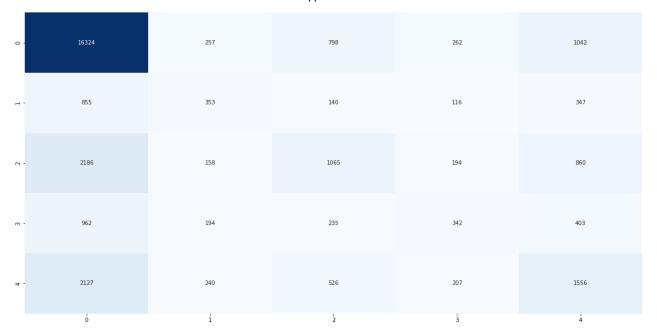
```
In [107...
           from sklearn.ensemble import RandomForestClassifier
           from sklearn.model_selection import train_test_split
           df = pd.read csv(r'C:\Users\milan\Documents\GitHub\DSC-680\approved risk class clean.cs
           y = df['approved risk class']
           X = df.drop('approved_risk_class', axis=1)
           # Split data into training and test sets
           X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
           # # Create random forest classifier with 100 trees
           clf = RandomForestClassifier(n estimators=100, random state=42)
           # # Train the classifier on the training set
           clf.fit(X_train, y_train)
           # # Make predictions on the test set
           y_pred = clf.predict(X_test)
           # # Evaluate the performance of the classifier
           accuracy = clf.score(X_test, y_test)
           print("Accuracy:", accuracy)
```

Accuracy: 0.6186021606979747

```
In [108...
```

```
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn.metrics import confusion_matrix
matrix = confusion_matrix(y_test.values, y_pred)
df = pd.DataFrame(matrix)
sn.heatmap(df, annot = True, cbar = None, cmap = "Blues", fmt='g')
plt.show()

# Note: rows are true values, columns are predicted
# Rows = recall
# Columns = precision
```



In [109...

from sklearn.metrics import classification_report
print(classification_report(y_test.values, y_pred))

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| declined | 0.73 | 0.87 | 0.79 | 18683 |
| elite_nt | 0.29 | 0.19 | 0.23 | 1811 |
| essential_nt | 0.39 | 0.24 | 0.29 | 4463 |
| preferred_nt | 0.31 | 0.16 | 0.21 | 2136 |
| select_nt | 0.37 | 0.33 | 0.35 | 4656 |
| | | | | |
| accuracy | | | 0.62 | 31749 |
| macro avg | 0.42 | 0.36 | 0.38 | 31749 |
| weighted avg | 0.57 | 0.62 | 0.59 | 31749 |

In []:

there are only 295 instances of essential_plus_nt, so I will remove this risk class a

In [124...

nt_transformed.head()

Out[124...

| | age | gender | height | weight | state | bmi_app_state | income_app_state | current_ins | current_ |
|---|-----------|----------|--------|--------|----------|---------------|------------------|-------------|----------|
| 0 | 48.534878 | 1.029396 | 68.0 | 195.0 | 1.140601 | 29.646410 | 36400 | 1.015067 | |
| 1 | 42.716825 | 1.029396 | 67.0 | 200.0 | 0.998968 | 31.321007 | 9528 | 1.015067 | |
| 2 | 54.399474 | 1.029396 | 66.0 | 193.0 | 0.888889 | 31.147612 | 9396 | 1.015067 | |
| 3 | 50.336420 | 1.014664 | 63.0 | 140.0 | 0.905008 | 24.797178 | 82000 | 1.015067 | |
| 4 | 42.725039 | 1.014664 | 61.0 | 132.0 | 0.751253 | 24.938457 | 72000 | 1.015067 | |

5 rows × 66 columns

→

```
In [129...
           train, test = train_test_split(nt_transformed, test_size=0.2, random_state=42)
           features = train.drop('approved risk class', axis=1)
           target = train['approved_risk_class']
           test features = test.drop('approved risk class', axis=1)
           test_target = test['approved_risk_class']
In [130...
           # Create pipeline
           from sklearn.ensemble import RandomForestClassifier
           from sklearn import metrics
           from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
           from sklearn.inspection import permutation importance
           from sklearn.preprocessing import StandardScaler
           from sklearn.pipeline import Pipeline, FeatureUnion
           pipe = Pipeline([
               ('scaler', StandardScaler()),
               ('rf', RandomForestClassifier())
           1)
In [131...
           # Set Parameters
           params = {
               'rf__n_estimators': [120, 140],
                'rf max depth': [30, 50],
               'rf__min_samples_split': [2,3],
               'rf min samples leaf': [3,5]
                  'rf class weight': [{0: 1, 1: 1}, {0: 1, 1:5},{0:1,1:3}, 'balanced']
           }
In [137...
           # GridSearch, Fit, Score
           from sklearn.model_selection import GridSearchCV, TimeSeriesSplit, train_test_split
           RF gs = GridSearchCV(pipe, param grid=params ,scoring = 'f1 weighted', cv = 3)
           RF gs.fit(features, target)
          GridSearchCV(cv=3,
Out[137...
                        estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                                  ('rf', RandomForestClassifier())]),
                        param_grid={'rf__max_depth': [30, 50],
                                    'rf__min_samples_leaf': [3, 5],
                                    'rf__min_samples_split': [2, 3],
                                    'rf__n_estimators': [120, 140]},
                        scoring='f1 weighted')
In [138...
           RF_gs.best_estimator_
          Pipeline(steps=[('scaler', StandardScaler()),
Out[138...
                           ('rf',
                            RandomForestClassifier(max_depth=50, min_samples_leaf=3,
                                                   min_samples_split=3,
                                                   n estimators=120))])
```

```
In [139...
            pipe = Pipeline([("standardizer", StandardScaler()), ("rf", RandomForestClassifier(max_
                                                       min_samples_leaf=3,
                                                       n estimators=120))])
            pipe.fit(features, target)
            rf_preds = pipe.predict(test_features)
            accuracy_score(rf_preds, test_target)
           0.62527953636335
Out[139...
In [140...
            matrix = confusion matrix(test target, rf preds)
            df = pd.DataFrame(matrix)
            sn.heatmap(df, annot = True, cbar = None, cmap = "Blues", fmt='g')
            plt.show()
                    1138
                                                          329
                                                          1522
                    2542
                                       179
                                                                                               114
                    2603
                                                          825
                    1227
                                       136
                                                                            144
In [141...
            from sklearn.metrics import classification report
            print(classification_report(test_target, rf_preds))
                                        recall f1-score
                          precision
                                                            support
                                          0.91
                       0
                               0.69
                                                     0.79
                                                              18683
                       1
                               0.31
                                          0.14
                                                     0.19
                                                               1811
                       2
                               0.38
                                          0.33
                                                     0.35
                                                               4656
                       3
                               0.45
                                          0.19
                                                     0.27
                                                               4463
                               0.41
                                          0.11
                                                     0.18
                                                               2136
                                                     0.63
                                                              31749
               accuracy
              macro avg
                               0.45
                                          0.34
                                                     0.36
                                                              31749
           weighted avg
                               0.57
                                          0.63
                                                     0.58
                                                              31749
  In [ ]:
In [135...
            import sklearn
```

sorted(sklearn.metrics.SCORERS.keys())

```
['accuracy',
Out[135...
            'adjusted_mutual_info_score',
            'adjusted_rand_score',
            'average_precision',
            'balanced_accuracy',
            'completeness_score',
            'explained variance',
            'f1',
            'f1_macro',
            'f1_micro',
            'f1 samples',
            'f1_weighted',
            'fowlkes_mallows_score',
            'homogeneity score',
            'jaccard',
            'jaccard_macro',
            'jaccard_micro',
            'jaccard_samples'
            'jaccard_weighted',
            'max_error',
            'mutual info score',
            'neg_brier_score',
            'neg_log_loss',
            'neg_mean_absolute_error',
            'neg_mean_absolute_percentage_error',
            'neg_mean_gamma_deviance',
            'neg_mean_poisson_deviance',
            'neg_mean_squared_error',
            'neg mean squared log error',
            'neg_median_absolute_error',
            'neg_root_mean_squared_error'
            'normalized_mutual_info_score',
            'precision',
            'precision_macro',
            'precision_micro',
            'precision_samples',
            'precision weighted',
            'r2',
            'rand score',
            'recall',
            'recall_macro',
            'recall micro',
            'recall_samples',
            'recall weighted',
            'roc_auc',
            'roc_auc_ovo',
            'roc auc ovo weighted',
            'roc_auc_ovr',
            'roc_auc_ovr_weighted',
            'top_k_accuracy',
            'v_measure_score']
  In [ ]:
```