12/10/2020

```
The Latest Version
In [1]:
         from sklearn.metrics import classification report, confusion matrix
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.model_selection import KFold, cross_val_score, GridSearchCV
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.preprocessing import MinMaxScaler
         from matplotlib import pyplot
         %matplotlib inline
In [2]:
         data = pd.read csv("COVID-19BehaviorData CAN USA.csv")
In [3]:
         # Data Cleaning
         data["i4_health"].replace(["No, they have not", "Yes, and they tested negative", "Not sur
         data['i3_health'].value_counts()
         data["i3_health"].replace(["No, I have not","Yes, and I tested negative","Not sure"," "
         data["i6_health"].value_counts()
         data["i5_health_1"].replace(["\","No","Yes"],["N/A",'0','1'],inplace=True)
         data["i5_health_2"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
         data["i5_health_3"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
```

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data["i5_health_4"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["i5_health_5"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["i5_health_99"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["i5a_health"].replace([" ","No","Yes","Not sure"],["N/A","2","1","99"],inplace=Tru
data["i8_health"].replace([" ","No","Yes","Not sure"],["N/A",'2','1','99'],inplace=True
data["i6_health"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at all"]
data["i7b_health"].replace([" ","No","Yes"],["N/A",'2','1'],inplace=True)
data["i9_health"].replace([" ","No","Yes","Not sure"],['0','2','1','99'],inplace=True)
data["i10_health"].replace([" ","Very easy","Somewhat easy","Somewhat difficult","Neith
data["i11_health"].replace([" ","Very willing","Somewhat willing","Somewhat unwilling",
data["i12_health_1"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_2"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_3"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_4"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_5"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_6"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_7"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_8"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_9"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at al
data["i12_health_10"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_11"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_12"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_13"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_14"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_15"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_16"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_17"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_18"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_19"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i12_health_20"].replace([" ","Always","Frequently","Sometimes","Rarely","Not at a
data["i14_health_1"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
```

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data["i14_health_2"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["i14_health_3"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["i14_health_4"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["i14_health_5"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["i14_health_6"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["i14_health_7"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["i14_health_8"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["i14_health_9"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["i14_health_10"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["i14_health_96"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["i14_health_98"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["i14_health_99"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_1"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["d1_health_2"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["d1_health_3"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_4"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_5"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_6"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_7"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_8"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["d1_health_9"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["d1_health_10"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_11"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_12"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
data["d1_health_13"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_98"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["d1_health_99"].replace([" ","No","Yes"],["N/A",'0','1'],inplace=True)
           data["gender"].replace([" ","Male","Female"],["N/A",'1','2'],inplace=True)
           data["household_size"].replace(["8 or more", "Prefer not to say", "Don't know"], ["8", '10'
           data["household_children"].replace(["5 or more","Prefer not to say","0","1","2","3","4"
           data["employment_status"].replace(["Full time employment",'Part time employment','Full
           data["qweek"].replace(["week 1","week 2","week 3","week 4","week 5","week 6","week 7","
           data.to csv("cleaned.csv")
In [4]:
           # Cleaned dataset df
           # Raw dataset df_raw
           # full dataset df_full
           df = pd.read_csv("cleaned.csv", index_col=0)
           df_raw = pd.read_csv("COVID-19BehaviorData_CAN_USA.csv")
           df_raw.rename(columns=lambda x: x+'_raw', inplace=True)
           df_full = df.join(df_raw)
In [6]:
           #Make Target Variable If they avoided going out frequently or not
           df["i12 health 6"].replace([1,2], 1,inplace=True)
           df["i12_health_6"].replace([4,5,3], 0, inplace=True)
           #Impute These Variables Using Mode
           df['i11_health'].fillna(df['i11_health'].mode()[0], inplace=True)
           df['i5_health_99'].fillna(df['i5_health_99'].mode()[0], inplace=True)
           df['d1 health 98'].fillna(df['d1 health 98'].mode()[0], inplace=True)
           df['d1_health_99'].fillna(df['d1_health_99'].mode()[0], inplace=True)
In [ ]:
           pd.set_option('display.max_columns', 500)
           df.tail(10)
In [7]:
```

```
# Country Column
           df['Country'] = df['RecordNo'].str[0:3]
           df_raw['Country'] = df_raw['RecordNo_raw'].str[0:3]
           df full['country'] = df full['RecordNo'].str[0:3]
           df_full_usa = df_full.loc[df_full['country'] == 'USA']
           df full can = df full.loc[df full['country'] == 'CAN']
 In [8]:
           # Scaling variables
           min max scaler = MinMaxScaler()
           df["age"]= min_max_scaler.fit_transform(df[["age"]])
           df["i1 health"]= min max scaler.fit transform(df[["i1 health"]])
           df["i2 health"]= min max scaler.fit transform(df[["i2 health"]])
           df["i7a_health"]= min_max_scaler.fit_transform(df[["i7a_health"]])
           df["i13_health"]= min_max_scaler.fit_transform(df[["i13_health"]])
 In [ ]:
           df["i13_health"].tail()
 In [ ]:
           pd.set_option('display.max_rows', 120)
           df.isnull().sum()/len(df)*100
 In [9]:
           plt.figure(figsize=(20,8))
           plt.xticks(np.arange(0, 79+1, 1.0))
           pyplot.bar([x for x in range(len(df.columns))], df.isnull().sum()/len(df)*100)
           plt.xlabel("Feature #")
           plt.ylabel("% Missing")
 Out[9]: Text(0, 0.5, '% Missing')
                 0 1 2 3 4 5 6 7 8 9 1011 12 13 14 15 16 17 18 19 20 21 2223 24 25 2627 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 545 55 5
In [10]:
           # Change type
           for i in range (7,41):
               df[df.columns[i]] = df[df.columns[i]].astype('category')
           for i in range (43,72):
               df[df.columns[i]] = df[df.columns[i]].astype('category')
           df[df.columns[73]] = df[df.columns[73]].astype('category')
           df[df.columns[75]] = df[df.columns[75]].astype('category')
```

```
df[df.columns[76]] = df[df.columns[76]].astype('category')
df[df.columns[77]] = df[df.columns[77]].astype('category')
df[df.columns[78]] = df[df.columns[78]].astype('category')

df[df.columns[0]] = df[df.columns[0]].astype('0')
df[df.columns[1]] = df[df.columns[1]].astype('0')
df[df.columns[56]] = df[df.columns[56]].astype('0')
```

In [11]:

```
df.info()
```

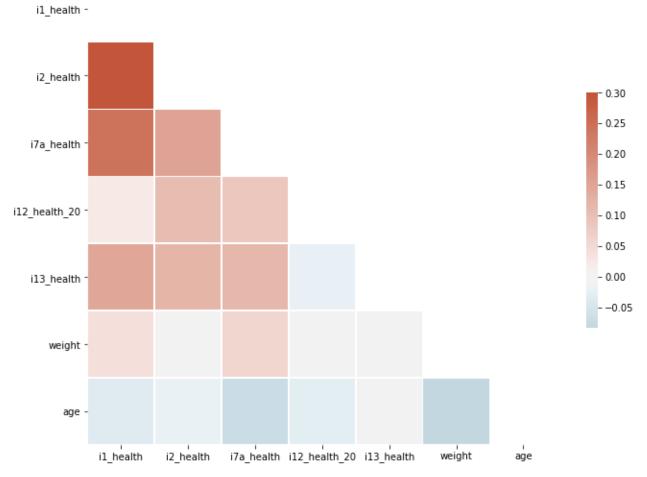
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 28825 entries, 0 to 28824
Data columns (total 80 columns):
     Column
                        Non-Null Count Dtype
---
    _____
                        -----
0
    Index
                        28825 non-null object
1
    RecordNo
                        28825 non-null
                                       object
2
    endtime
                        28825 non-null object
3
     qweek
                        28825 non-null
                                        int64
4
     i1 health
                        28825 non-null float64
5
    i2_health
                        28825 non-null float64
6
                        28825 non-null float64
    i7a health
7
    i3 health
                        28825 non-null category
8
    i4 health
                        28825 non-null category
9
    i5 health 1
                        28106 non-null category
                        28106 non-null category
10
    i5 health 2
11
    i5 health 3
                        28106 non-null
                                        category
12 i5_health_4
                        28106 non-null
                                       category
13 i5 health 5
                        28106 non-null category
14 i5 health 99
                        28825 non-null category
15
   i5a health
                        2606 non-null
                                        category
16 i6 health
                        2606 non-null
                                        category
17 i7b health
                        2316 non-null
                                        category
18 i8 health
                        2266 non-null
                                        category
                        28825 non-null category
19
    i9 health
20 i10 health
                        28825 non-null category
                        28825 non-null category
21 i11 health
22 i12 health 1
                        28825 non-null
                                       category
23 i12 health 2
                        28825 non-null
                                       category
24 i12_health_3
                        28825 non-null
                                       category
25 i12 health 4
                        28825 non-null
                                       category
26 i12 health 5
                        28825 non-null
                                        category
27
    i12_health_6
                        28825 non-null category
                        28825 non-null category
28 i12_health_7
29 i12_health_8
                        28825 non-null category
30 i12 health 9
                        12160 non-null category
                        10146 non-null category
31 i12 health 10
                        28825 non-null category
32 i12 health 11
                        28825 non-null category
33 i12 health 12
34
    i12 health 13
                        28825 non-null
                                       category
                        28825 non-null category
35
    i12 health 14
36 i12 health 15
                        28825 non-null category
37 i12 health 16
                        28825 non-null
                                       category
   i12 health 17
                        28825 non-null
                                        category
39
    i12 health 18
                        28825 non-null
                                        category
40 i12 health 19
                        28825 non-null
                                       category
41
    i12 health 20
                        28825 non-null
                                        int64
42
    i13 health
                        28825 non-null
                                        float64
43
    i14 health 1
                        12160 non-null category
44
                        12160 non-null category
    i14 health 2
45
    i14 health 3
                        12160 non-null
                                        category
                        12160 non-null
46
    i14 health 4
                                        category
                        12160 non-null
47
    i14_health_5
                                        category
```

```
12160 non-null category
         48 i14 health 6
                                12160 non-null category
         49 i14 health 7
         50 i14 health 8
                                12160 non-null
                                                category
                                12160 non-null category
         51 i14 health 9
         52 i14 health 10
                                 12160 non-null category
         53 i14 health 96
                                 12160 non-null category
         54 i14 health 98
                                 12160 non-null category
                                 12160 non-null category
         55 i14 health 99
                                 28825 non-null object
         56 i14_health_other
         57 d1 health 1
                                 26019 non-null category
         58 d1 health 2
                                 26019 non-null
                                                category
         59 d1_health_3
                                 26019 non-null category
         60 d1 health 4
                                 26019 non-null category
         61 d1 health 5
                                26019 non-null category
         62 d1 health 6
                                 26019 non-null category
         63 d1 health 7
                                 26019 non-null category
         64 d1_health_8
                                 26019 non-null category
         65 d1_health_9
                                 26019 non-null category
         66
             d1 health 10
                                 26019 non-null category
             d1 health 11
                                 26019 non-null category
         67
         68 d1 health 12
                                 26019 non-null category
                                 26019 non-null category
         69
             d1 health 13
                                 28825 non-null category
         70 d1 health 98
                                 28825 non-null category
         71 d1 health 99
         72 weight
                                 28825 non-null float64
                                 28825 non-null category
         73 gender
         74 age
                                 28825 non-null float64
         75 region_state
                                 28825 non-null category
         76 household size
                                28825 non-null category
         77 household children 28825 non-null category
                                 28825 non-null category
         78 employment status
             Country
         79
                                 28825 non-null object
        dtypes: category(67), float64(6), int64(2), object(5)
        memory usage: 6.2+ MB
In [ ]:
         df.tail()
In [ ]:
         # EDA
In [ ]:
         plt.figure(figsize=(15,8))
         sns.barplot(x="qweek", y="i7b_health", hue="i12_health_6", palette=["m", "g"], data=df)
In [ ]:
         sns.countplot(x="i9 health raw", data=df raw)
In [ ]:
         sns.countplot(x="i12 health 6 raw", hue="country", data=df full).set title("Avoided goi
In [ ]:
         i12 crosstab = pd.crosstab(df full["i12 health 6 raw"], df full["country"] ,margins = F
         i12 crosstab
In [ ]:
         i12 crosstab.plot(kind = 'bar', stacked = True)
In [ ]:
         i12_crosstab_norm = i12_crosstab.div(i12_crosstab.sum(axis=0), axis=1)
         i12 crosstab norm
```

```
In [ ]:
         i12 crosstab norm.plot(kind = 'bar', stacked = True)
In [ ]:
         def without hue(plot, feature):
             total = len(feature)
             for p in ax.patches:
                 percentage = '{:.1f}%'.format(100 * p.get_height()/total)
                 x = p.get_x() + p.get_width() / 2 - 0.05
                 y = p.get y() + p.get height()
                 ax.annotate(percentage, (x, y), size = 12, ha='center', va='bottom')
             plt.xlabel(" ", size=12)
             plt.ylabel("Count", size=12)
             plt.ylim(0, 7000)
             plt.title("Avoided going out in general in USA", size=12)
             plt.show()
         ax = sns.countplot(x="i12 health 6 raw", data=df full usa, order=df full usa["i12 healt
         without hue(ax, df full usa.i12 health 6)
In [ ]:
         ax = sns.countplot(x="i12_health_6_raw", data=df_full_can, order=df_full_can["i12_healt
         without hue(ax, df full can.i12 health 6)
In [ ]:
         check missing = df full.iloc[:,0:79].isnull()
         count missing = check missing.apply(lambda x: x.value counts())
         with_missing = count_missing.loc[:, np.logical_not(count_missing.isna().any())]
In [ ]:
         with_missing.iloc[1,:].plot(kind='barh', figsize=(40, 30))
In [ ]:
         # ModeL
In [ ]:
         # Compute the correlation matrix
         corr = df raw.corr()
         # Generate a mask for the upper triangle
         mask = np.triu(np.ones like(corr, dtype=bool))
         # Set up the matplotlib figure
         f, ax = plt.subplots(figsize=(11, 9))
         # Generate a custom diverging colormap
         cmap = sns.diverging palette(230, 20, as cmap=True)
         # Draw the heatmap with the mask and correct aspect ratio
         sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
                     square=True, linewidths=.5, cbar kws={"shrink": .5})
In [ ]:
         df.columns
```

```
In [12]:
           df_feats= df[[ 'i1_health', 'i2_health',
                   'i7a_health', 'i3_health', 'i4_health', 'i5_health_99',
                     'i9_health',
                   'i10_health', 'i11_health', 'i12_health_1', 'i12_health_2',
                   'i12_health_3', 'i12_health_4', 'i12_health_5',
                   'i12_health_7', 'i12_health_8',
                   'i12_health_11', 'i12_health_12', 'i12_health_13', 'i12_health_14', 'i12_health_15', 'i12_health_16', 'i12_health_17', 'i12_health_18',
                   'i12_health_19', 'i12_health_20', 'i13_health',
                    'd1_health_98', 'd1_health_99',
                   'weight', 'gender', 'age', 'household_size',
                   'household children', 'employment status', 'i12 health 6']]
In [16]:
           df_feats.isnull().sum()
Out[16]: i1_health
          i2_health
                                  0
          i7a health
                                  0
                                  0
          i3 health
          i4 health
                                  0
          i5_health_99
                                  0
          i9 health
                                  0
          i10 health
                                  0
          i11 health
                                  0
          i12 health 1
                                  0
          i12 health 2
                                  0
                                  0
          i12 health 3
          i12 health 4
                                  0
          i12 health 5
                                  0
          i12 health 7
                                  0
          i12 health 8
                                  0
          i12_health_11
                                  0
          i12_health_12
                                  0
                                  0
          i12_health_13
                                  0
          i12 health 14
                                  0
          i12 health 15
          i12_health_16
                                  0
          i12_health_17
                                  0
          i12 health 18
                                  0
                                  0
          i12 health 19
                                  0
          i12 health 20
                                  0
          i13 health
          d1 health 98
                                  0
                                  0
          d1 health 99
          weight
                                  0
                                  0
          gender
          age
          household_size
                                  0
          household children
                                  0
          employment status
                                  0
          i12 health 6
          dtype: int64
In [13]:
           # Compute the correlation matrix
           corr = df feats.corr()
           # Generate a mask for the upper triangle
           mask = np.triu(np.ones_like(corr, dtype=bool))
           # Set up the matplotlib figure
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1f38f9f38c8>



importance = model1.feature importances

print('Feature: %0d, Score: %.5f' % (i,v))

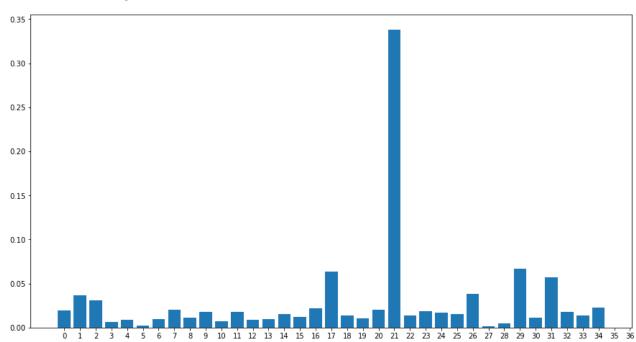
summarize feature importance
for i,v in enumerate(importance):

plot feature importance

```
plt.figure(figsize=(15,8))
plt.xticks(np.arange(0, 55, 1.0))
pyplot.bar([x for x in range(len(importance))], importance)
```

```
Feature: 0, Score: 0.01920
Feature: 1, Score: 0.03669
Feature: 2, Score: 0.03064
Feature: 3, Score: 0.00624
Feature: 4, Score: 0.00921
Feature: 5, Score: 0.00262
Feature: 6, Score: 0.00993
Feature: 7, Score: 0.02013
Feature: 8, Score: 0.01149
Feature: 9, Score: 0.01751
Feature: 10, Score: 0.00722
Feature: 11, Score: 0.01753
Feature: 12, Score: 0.00901
Feature: 13, Score: 0.00933
Feature: 14, Score: 0.01557
Feature: 15, Score: 0.01232
Feature: 16, Score: 0.02209
Feature: 17, Score: 0.06375
Feature: 18, Score: 0.01388
Feature: 19, Score: 0.01022
Feature: 20, Score: 0.02059
Feature: 21, Score: 0.33844
Feature: 22, Score: 0.01334
Feature: 23, Score: 0.01829
Feature: 24, Score: 0.01699
Feature: 25, Score: 0.01528
Feature: 26, Score: 0.03829
Feature: 27, Score: 0.00110
Feature: 28, Score: 0.00455
Feature: 29, Score: 0.06657
Feature: 30, Score: 0.01100
Feature: 31, Score: 0.05684
Feature: 32, Score: 0.01760
Feature: 33, Score: 0.01347
Feature: 34, Score: 0.02307
```

Out[15]: <BarContainer object of 35 artists>



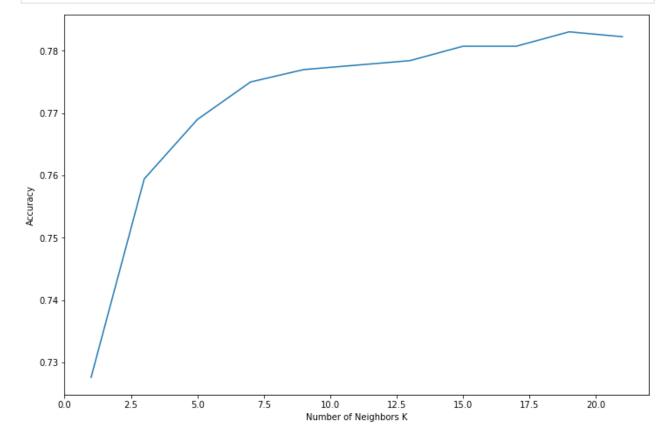
```
graph=[]
In [17]:
        graph2=[]
        print(sum(importance))
        for i in range (35):
            graph.append(X_train.columns[i])
            graph2.append(importance[i])
            print(X_train.columns[i]," ",i, ": ", importance[i])
        0.999999999999999
        i1 health 0: 0.019200790124659504
        i2 health 1: 0.036686946555292026
        i7a health 2: 0.03064250093035997
        i3 health 3: 0.006242163895913354
        i4 health 4: 0.009207985049177537
        i5 health 99 5: 0.0026245949671743793
        i9_health 6: 0.009931495113005624
        i10 health 7 : 0.02012956485676338
        ill health 8: 0.011494545118959743
        i12 health 1 9 : 0.017508732454955638
        i12 health 4 12 :
                         0.009009882785721247
        i12_health_7
                     14: 0.01557076759475509
        i12 health 12
                    17 : 0.06375354114849442
        i12_health_13
                     18: 0.013880937723536595
        i12 health 14
                    19: 0.010217441101093017
        i12 health 15
                     20 : 0.02058506954042459
        i12 health 16
                     21: 0.33844480837679086
                    22 : 0.013342629626018255
        i12 health 17
        i12 health 18 23 : 0.018285504816849863
        i12 health 19 24: 0.016985086313315228
        i12 health 20 25 : 0.015282051002820863
        i13_health 26: 0.0382888358021357
        d1 health 98 27: 0.001099686598628937
        d1 health 99 28: 0.004548393739772186
               29 : 0.0665690231119636
        weight
        gender
              30 : 0.011001560722636299
             31: 0.056836543539419956
        household size 32 : 0.017603393160531156
        household children 33: 0.013466908587988635
        employment status
                         34 : 0.023072242056119442
In [18]:
        model = KNeighborsClassifier(n_neighbors=19)
        model.fit(X train, y train)
         pred = model.predict(X test)
         pred2 = model.predict(X_train)
         print(confusion matrix(y test, pred))
         print(" ")
         print(confusion_matrix(y_train, pred2))
         print("Test")
         print(classification_report(y_test, pred))
         print("Train")
         print(classification report(y train, pred2))
        [[1785 1098]
         [ 439 3885]]
```

```
[[ 5506 3199]
          [ 1188 11725]]
         Test
                        precision
                                     recall f1-score
                                                        support
                    0
                             0.80
                                       0.62
                                                 0.70
                                                           2883
                    1
                             0.78
                                       0.90
                                                 0.83
                                                           4324
                                                 0.79
                                                           7207
             accuracy
                                       0.76
                                                 0.77
                                                           7207
            macro avg
                            0.79
                             0.79
                                       0.79
                                                 0.78
                                                           7207
         weighted avg
         Train
                        precision
                                     recall f1-score
                                                        support
                    0
                             0.82
                                       0.63
                                                 0.72
                                                           8705
                             0.79
                                       0.91
                    1
                                                 0.84
                                                          12913
                                                 0.80
             accuracy
                                                          21618
                            0.80
                                       0.77
                                                 0.78
            macro avg
                                                          21618
         weighted avg
                            0.80
                                       0.80
                                                 0.79
                                                          21618
In [19]:
          num folds = 10
          #scoring (note that Python is set to maximize the MSE function so you need to make it n
          scoring = "accuracy"
          #split for crossvalidation
          kfold = KFold(n splits=num folds, random state=101, shuffle=True)
          cv results = cross val score(model, X train, y train, cv=kfold, scoring=scoring)
          msg = "KNN: %f (%f)" % (cv_results.mean(),cv_results.std())
          print(msg)
         KNN: 0.783051 (0.008929)
In [20]:
          k_{values} = np.array([1,3,5,7,9,13,15,17,19,21])
          param grid = dict(n neighbors=k values)
          #define the grid search cross validation method
          grid=GridSearchCV(estimator=model,param grid=param grid,scoring=scoring,cv=kfold)
          #generate the results of the grid search cross validation method
          grid_result=grid.fit(X_train,y_train)
          #print the best score achieved by any of the specified k values
          print("Best: %f using %s" % (grid result.best score ,grid result.best params ))
         Best: 0.783051 using {'n neighbors': 19}
In [21]:
          means = grid result.cv results ["mean test score"]
          stds = grid_result.cv_results_["std_test_score"]
          params = grid_result.cv_results_["params"]
          for mean, stdev, param in zip(means, stds, params):
              print("%f (%f) with %s" % (mean, stdev, param))
         0.727634 (0.007736) with {'n neighbors': 1}
         0.759460 (0.008357) with {'n_neighbors': 3}
         0.768988 (0.009531) with {'n neighbors': 5}
         0.775002 (0.008954) with {'n neighbors': 7}
         0.776991 (0.011011) with {'n_neighbors': 9}
         0.778425 (0.008877) with {'n_neighbors': 13}
         0.780738 (0.009193) with {'n neighbors': 15}
```

0.780738 (0.009653) with {'n_neighbors': 17} 0.783051 (0.008929) with {'n_neighbors': 19}

```
0.782264 (0.009995) with {'n_neighbors': 21}

In [22]: #plot the accuracy levels at different K
   plt.figure(figsize=(12,8))
   plt.plot(k_values,means)
   plt.xlabel("Number of Neighbors K")
   plt.ylabel("Accuracy")
   plt.savefig('AccuracyChart.png')
```



In []: