H1n1_Classification / Classification Project - H1N1.ipynb

ikuro ensure raw are included 02ebfd3 · 1 minute ago

4899 lines (4899 loc) · 850 KB

Preview Code Blame Raw

Data understanding

As the world struggles to vaccinate the global population against COVID-19, an understanding of how people's backgrounds, opinions, gender, race, age, health behaviors and other features are related to their personal vaccination patterns can provide guidance for future public health efforts. We try to understand better based on data collected to guide public health efforts in predicting whether one has a likelihood of contracting H1N! virus.

More info can be found here > https://www.drivendata.org/competitions/66/flu-shot-learning/page/211/

Problem Statement

The goal is to predict how likely individuals are to receive their H1N1 and seasonal flu vaccines. Specifically, I'll be predicting ONLY one probability - h1n1_vaccine

Specific objectives

```
- Understand if gender has any influence on whether one is likely to contract the virus
- Understand if Race has any influence on contracting the virus
- Determine if Age is a factor in contacting the virus
```

In [343…

```
#import the ecessary libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [344…

```
#Load the datasets
df_label=pd.read_csv('training_set_labels.csv')
df_features=pd.read_csv('training_set_features.csv')
```

In [419…

```
#check that target data has loaded correctly
df_label.head()
```

Out[419…

	respondent_id	h1n1_vaccine	seasonal_vaccine
0	0	0	0
1	1	0	1
2	2	0	0
3	3	0	1
4	4	0	0

In [420…

```
#check that feature data has loaded correctly
df_features.head()
```

Out[420…

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	b
0	0	1.0	0.0	0.0	0.0	0.0	
1	1	3.0	2.0	0.0	1.0	0.0	
2	2	1.0	1.0	0.0	1.0	0.0	
3	3	1.0	1.0	0.0	1.0	0.0	
4	4	2.0	1.0	0.0	1.0	0.0	

5 rows × 36 columns

In [348…

```
#combine the dataset to clean it wholesomely
dataset=pd.concat([df_features,df_label], axis=1)
```

```
#drop repeated column and also seasonal vacine since we are interested in H1N1
dataset.drop(columns=['respondent_id', 'seasonal_vaccine'], inplace=True)
test_df.drop(columns=['respondent_id'], inplace=True)
dataset.head()
```

Out[348…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_
0	1.0	0.0	0.0	0.0	0.0	
1	3.0	2.0	0.0	1.0	0.0	
2	1.0	1.0	0.0	1.0	0.0	
3	1.0	1.0	0.0	1.0	0.0	
4	2.0	1.0	0.0	1.0	0.0	

5 rows × 36 columns

In [349…

```
df=dataset.copy()
```

In [350…

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26707 entries, 0 to 26706
Data columns (total 36 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   h1n1_concern                 26615 non-null  float64
 1   h1n1_knowledge               26591 non-null  float64
 2   behavioral_antiviral_meds    26636 non-null  float64
 3   behavioral_avoidance         26499 non-null  float64
 4   behavioral face mask         26688 non-null  float64
```

```
 5   behavioral_wash_hands        26665 non-null  float64
 6   behavioral_large_gatherings  26620 non-null  float64
 7   behavioral_outside_home      26625 non-null  float64
 8   behavioral_touch_face        26579 non-null  float64
 9   doctor_recc_h1n1             24547 non-null  float64
 10  doctor_recc_seasonal         24547 non-null  float64
 11  chronic_med_condition        25736 non-null  float64
 12  child_under_6_months         25887 non-null  float64
 13  health_worker                25903 non-null  float64
 14  health_insurance             14433 non-null  float64
 15  opinion_h1n1_vacc_effective  26316 non-null  float64
 16  opinion_h1n1_risk            26319 non-null  float64
 17  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 18  opinion_seas_vacc_effective  26245 non-null  float64
 19  opinion_seas_risk            26193 non-null  float64
 20  opinion_seas_sick_from_vacc  26170 non-null  float64
 21  age_group                    26707 non-null  object
 22  education                    25300 non-null  object
 23  race                         26707 non-null  object
 24  sex                          26707 non-null  object
 25  income_poverty               22284 non-null  object
 26  marital_status               25299 non-null  object
 27  rent_or_own                  24665 non-null  object
 28  employment_status            25244 non-null  object
 29  hhs_geo_region               26707 non-null  object
 30  census_msa                   26707 non-null  object
 31  household_adults             26458 non-null  float64
 32  household_children           26458 non-null  float64
 33  employment_industry          13377 non-null  object
 34  employment_occupation        13237 non-null  object
 35  h1n1_vaccine                 26707 non-null  int64
dtypes: float64(23), int64(1), object(12)
memory usage: 7.3+ MB
None
```

In [351…

```
df.shape
```

Out[351… (26707, 36)

In [352…

```
df.describe()
```

Out[352…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_w

count	26615.000000	26591.000000	26636.000000	26499.000000	26688.000000	26(
mean	1.618486	1.262532	0.048844	0.725612	0.068982	
std	0.910311	0.618149	0.215545	0.446214	0.253429	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	1.000000	0.000000	0.000000	0.000000	
50%	2.000000	1.000000	0.000000	1.000000	0.000000	
75%	2.000000	2.000000	0.000000	1.000000	0.000000	
max	3.000000	2.000000	1.000000	1.000000	1.000000	

8 rows × 24 columns

Data Cleaning

In [354…

```
#Lets first clean up the missing before ensuring data is in their correct formats to avoid the problem of NAs

missing= df.isnull().mean()[df.isnull().mean()>0]*100
missing
```

Out[354…

```
h1n1_concern                  0.344479
h1n1_knowledge                0.434343
behavioral_antiviral_meds     0.265848
behavioral_avoidance          0.778822
behavioral_face_mask          0.071142
behavioral_wash_hands         0.157262
behavioral_large_gatherings   0.325757
behavioral_outside_home       0.307036
behavioral_touch_face         0.479275
doctor_recc_h1n1              8.087767
doctor_recc_seasonal          8.087767
chronic_med_condition         3.635751
child_under_6_months          3.070356
health_worker                 3.010447
health_insurance             45.957989
opinion_h1n1_vacc_effective   1.464036
opinion_h1n1_risk             1.452803
```

```
opinion_h1n1_sick_from_vacc     1.479013
opinion_seas_vacc_effective     1.729884
opinion_seas_risk               1.924589
opinion_seas_sick_from_vacc     2.010709
education                       5.268282
income_poverty                 16.561201
marital_status                  5.272026
rent_or_own                     7.645936
employment_status               5.477965
household_adults                0.932340
household_children              0.932340
employment_industry            49.912008
employment_occupation          50.436215
dtype: float64
```

In [355…

```
#For columns with the proportion of missing approximately or above 50%, I will drop them.
df.drop(columns=['employment_occupation','employment_industry','health_insurance'], axis=1, inplace=True)
```

In [356…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26707 entries, 0 to 26706
Data columns (total 33 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   h1n1_concern                 26615 non-null  float64
 1   h1n1_knowledge               26591 non-null  float64
 2   behavioral_antiviral_meds    26636 non-null  float64
 3   behavioral_avoidance         26499 non-null  float64
 4   behavioral_face_mask         26688 non-null  float64
 5   behavioral_wash_hands        26665 non-null  float64
 6   behavioral_large_gatherings  26620 non-null  float64
 7   behavioral_outside_home      26625 non-null  float64
 8   behavioral_touch_face        26579 non-null  float64
 9   doctor_recc_h1n1             24547 non-null  float64
 10  doctor_recc_seasonal         24547 non-null  float64
 11  chronic_med_condition        25736 non-null  float64
 12  child_under_6_months         25887 non-null  float64
 13  health_worker                25903 non-null  float64
 14  opinion_h1n1_vacc_effective  26316 non-null  float64
 15  opinion_h1n1_risk            26319 non-null  float64
 16  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 17  opinion_seas_vacc_effective  26245 non-null  float64
 18  opinion_seas_risk            26193 non-null  float64
```

```
 19  opinion_seas_sick_from_vacc  26170 non-null  float64
 20  age_group                    26707 non-null  object
 21  education                    25300 non-null  object
 22  race                         26707 non-null  object
 23  sex                          26707 non-null  object
 24  income_poverty               22284 non-null  object
 25  marital_status               25299 non-null  object
 26  rent_or_own                  24665 non-null  object
 27  employment_status            25244 non-null  object
 28  hhs_geo_region               26707 non-null  object
 29  census_msa                   26707 non-null  object
 30  household_adults             26458 non-null  float64
 31  household_children           26458 non-null  float64
 32  h1n1_vaccine                 26707 non-null  int64
dtypes: float64(22), int64(1), object(10)
memory usage: 6.7+ MB
```

In [358…

```
missing= df.isnull().mean()[df.isnull().mean()>0]*100
missing
```

Out[358…

```
h1n1_concern                  0.344479
h1n1_knowledge                0.434343
behavioral_antiviral_meds     0.265848
behavioral_avoidance          0.778822
behavioral_face_mask          0.071142
behavioral_wash_hands         0.157262
behavioral_large_gatherings   0.325757
behavioral_outside_home       0.307036
behavioral_touch_face         0.479275
doctor_recc_h1n1              8.087767
doctor_recc_seasonal          8.087767
chronic_med_condition         3.635751
child_under_6_months          3.070356
health_worker                 3.010447
opinion_h1n1_vacc_effective   1.464036
opinion_h1n1_risk             1.452803
opinion_h1n1_sick_from_vacc   1.479013
opinion_seas_vacc_effective   1.729884
opinion_seas_risk             1.924589
opinion_seas_sick_from_vacc   2.010709
education                     5.268282
income_poverty               16.561201
marital_status                5.272026
rent_or_own                   7.645936
```

```
employment_status            5.477965
household_adults             0.932340
household_children           0.932340
dtype: float64
```

In [359…

```
# We inpute income_poverty with mode , since is a categorical variable and drop the rest of missing since they c

df['income_poverty']=df['income_poverty'].fillna(df['income_poverty'].mode()[0])
```

In [360…

```
missing= df.isnull().mean()[df.isnull().mean()>0]*100
missing
```

Out[360…

```
h1n1_concern                 0.344479
h1n1_knowledge               0.434343
behavioral_antiviral_meds    0.265848
behavioral_avoidance         0.778822
behavioral_face_mask         0.071142
behavioral_wash_hands        0.157262
behavioral_large_gatherings  0.325757
behavioral_outside_home      0.307036
behavioral_touch_face        0.479275
doctor_recc_h1n1             8.087767
doctor_recc_seasonal         8.087767
chronic_med_condition        3.635751
child_under_6_months         3.070356
health_worker                3.010447
opinion_h1n1_vacc_effective  1.464036
opinion_h1n1_risk            1.452803
opinion_h1n1_sick_from_vacc  1.479013
opinion_seas_vacc_effective  1.729884
opinion_seas_risk            1.924589
opinion_seas_sick_from_vacc  2.010709
education                    5.268282
marital_status               5.272026
rent_or_own                  7.645936
employment_status            5.477965
household_adults             0.932340
household_children           0.932340
dtype: float64
```

In [361…

```
df=df.dropna()
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 21710 entries, 0 to 26706
Data columns (total 33 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   h1n1_concern                 21710 non-null  float64
 1   h1n1_knowledge               21710 non-null  float64
 2   behavioral_antiviral_meds    21710 non-null  float64
 3   behavioral_avoidance         21710 non-null  float64
 4   behavioral_face_mask         21710 non-null  float64
 5   behavioral_wash_hands        21710 non-null  float64
 6   behavioral_large_gatherings  21710 non-null  float64
 7   behavioral_outside_home      21710 non-null  float64
 8   behavioral_touch_face        21710 non-null  float64
 9   doctor_recc_h1n1             21710 non-null  float64
 10  doctor_recc_seasonal         21710 non-null  float64
 11  chronic_med_condition        21710 non-null  float64
 12  child_under_6_months         21710 non-null  float64
 13  health_worker                21710 non-null  float64
 14  opinion_h1n1_vacc_effective  21710 non-null  float64
 15  opinion_h1n1_risk            21710 non-null  float64
 16  opinion_h1n1_sick_from_vacc  21710 non-null  float64
 17  opinion_seas_vacc_effective  21710 non-null  float64
 18  opinion_seas_risk            21710 non-null  float64
 19  opinion_seas_sick_from_vacc  21710 non-null  float64
 20  age_group                    21710 non-null  object 
 21  education                    21710 non-null  object 
 22  race                         21710 non-null  object 
 23  sex                          21710 non-null  object 
 24  income_poverty               21710 non-null  object 
 25  marital_status               21710 non-null  object 
 26  rent_or_own                  21710 non-null  object 
 27  employment_status            21710 non-null  object 
 28  hhs_geo_region               21710 non-null  object 
 29  census_msa                   21710 non-null  object 
 30  household_adults             21710 non-null  float64
 31  household_children           21710 non-null  float64
 32  h1n1_vaccine                 21710 non-null  int64  
dtypes: float64(22), int64(1), object(10)
memory usage: 5.6+ MB
```

In [362…

```
# Confirm no more missing data
```

```
missing= df.isnull().mean()[df.isnull().mean()>0]*100
missing
```

Out[362…
```
Series([], dtype: float64)
```

In [363…
```
# Check for duplicates
df.duplicated().sum()
```

Out[363…
```
0
```

In [364…
```
num_df=df.select_dtypes(include='number')
```

In [412…
```
# Ensure features are in their correct data formats
binary_cols = [col for col in num_df.columns if num_df[col].nunique() == 2]
print(binary_cols )
```

```
['behavioral_antiviral_meds', 'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_hands', 'behavioral_large_gatherings', 'behavioral_outside_home', 'behavioral_touch_face', 'doctor_recc_h1n1', 'doctor_recc_seasonal', 'chronic_med_condition', 'child_under_6_months', 'health_worker', 'h1n1_vaccine']
```

In [414…
```
df[binary_cols] = df[binary_cols].apply(lambda x: x.astype(int))
```

In [415…
```
order_cols = [col for col in num_df.columns if num_df[col].nunique() > 2]
print(order_cols)
```

```
['h1n1_concern', 'h1n1_knowledge', 'opinion_h1n1_vacc_effective', 'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc', 'opinion_seas_vacc_effective', 'opinion_seas_risk', 'opinion_seas_sick_from_vacc', 'household_adults', 'household_children']
```

In [416…
```
#convert them to int as well

df[order_cols] = df[order_cols].apply(lambda x: x.astype(int))
```

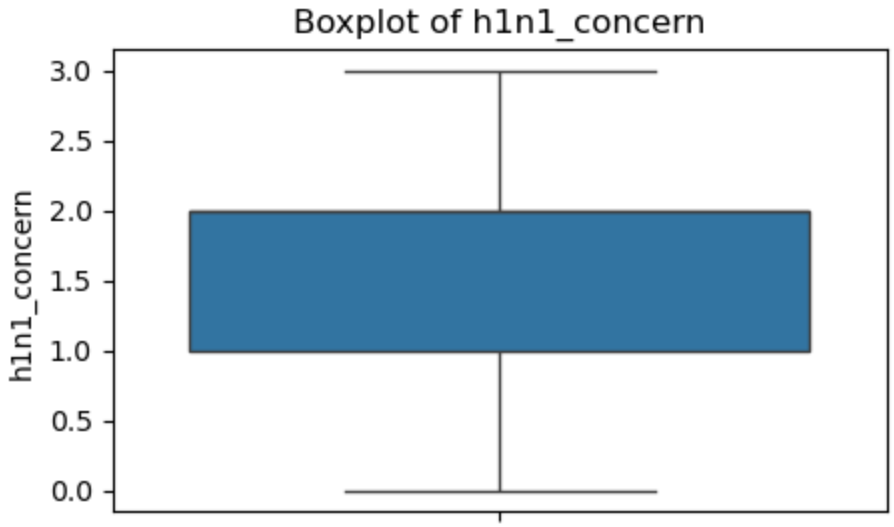
In [417…
```
df.info()
```

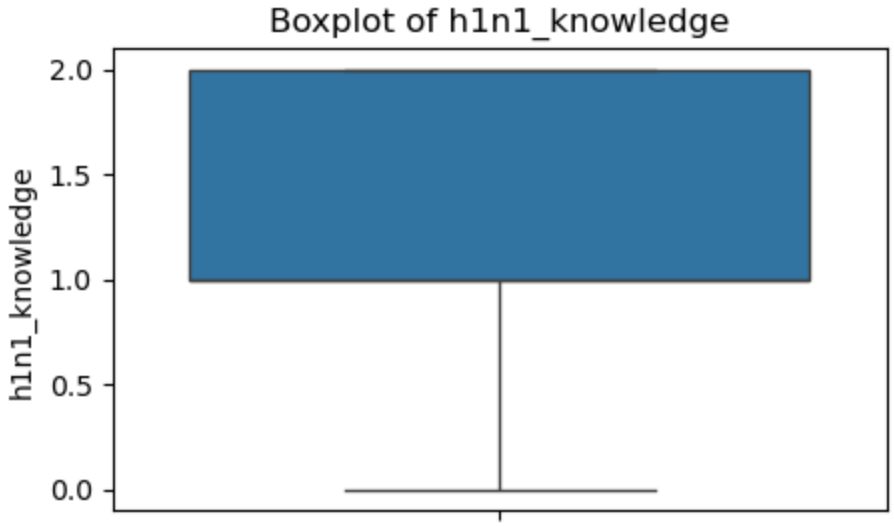
```
<class 'pandas.core.frame.DataFrame'>
Index: 21710 entries, 0 to 26706
```

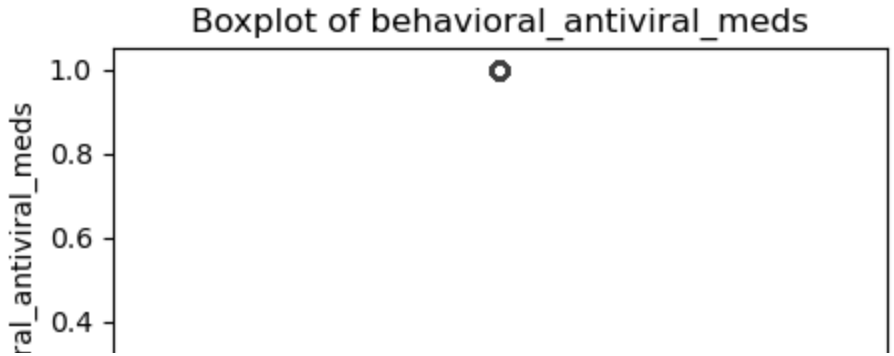
```
Data columns (total 33 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   h1n1_concern                 21710 non-null  int32
 1   h1n1_knowledge               21710 non-null  int32
 2   behavioral_antiviral_meds    21710 non-null  int32
 3   behavioral_avoidance         21710 non-null  int32
 4   behavioral_face_mask         21710 non-null  int32
 5   behavioral_wash_hands        21710 non-null  int32
 6   behavioral_large_gatherings  21710 non-null  int32
 7   behavioral_outside_home      21710 non-null  int32
 8   behavioral_touch_face        21710 non-null  int32
 9   doctor_recc_h1n1             21710 non-null  int32
 10  doctor_recc_seasonal         21710 non-null  int32
 11  chronic_med_condition        21710 non-null  int32
 12  child_under_6_months         21710 non-null  int32
 13  health_worker                21710 non-null  int32
 14  opinion_h1n1_vacc_effective  21710 non-null  int32
 15  opinion_h1n1_risk            21710 non-null  int32
 16  opinion_h1n1_sick_from_vacc  21710 non-null  int32
 17  opinion_seas_vacc_effective  21710 non-null  int32
 18  opinion_seas_risk            21710 non-null  int32
 19  opinion_seas_sick_from_vacc  21710 non-null  int32
 20  age_group                    21710 non-null  object
 21  education                    21710 non-null  object
 22  race                         21710 non-null  object
 23  sex                          21710 non-null  object
 24  income_poverty               21710 non-null  object
 25  marital_status               21710 non-null  object
 26  rent_or_own                  21710 non-null  object
 27  employment_status            21710 non-null  object
 28  hhs_geo_region               21710 non-null  object
 29  census_msa                   21710 non-null  object
 30  household_adults             21710 non-null  int32
 31  household_children           21710 non-null  int32
 32  h1n1_vaccine                 21710 non-null  int32
dtypes: int32(23), object(10)
memory usage: 3.7+ MB
```

In [418…

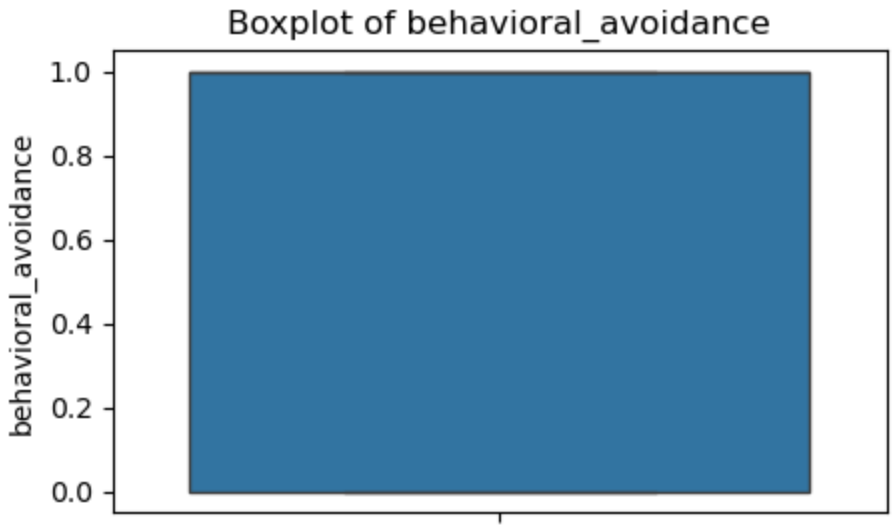
```python
for i in num_df.columns:
    plt.figure(figsize=(5, 3))
    sns.boxplot(y=num_df[i])
    plt.title(f"Boxplot of {i}")
    plt.show()
```

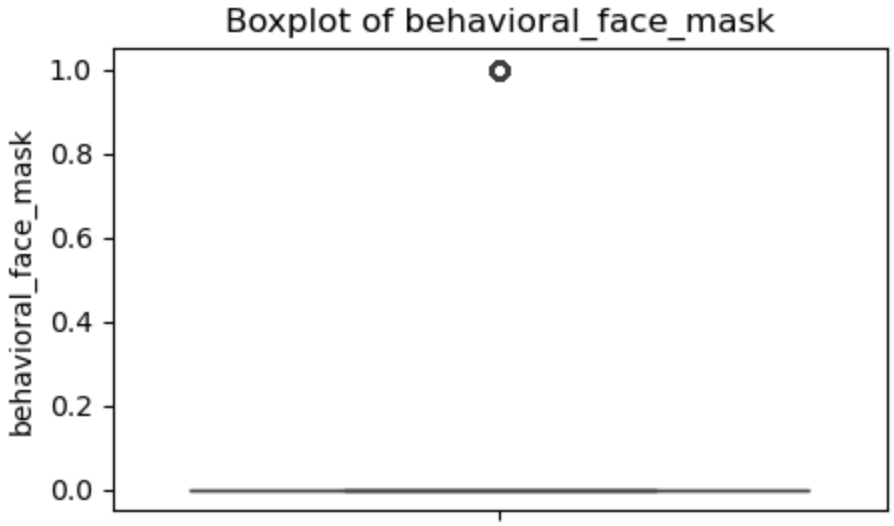

Boxplot of h1n1_concern
h1n1_concern
3.0
2.5
2.0
1.5
1.0
0.5
0.0

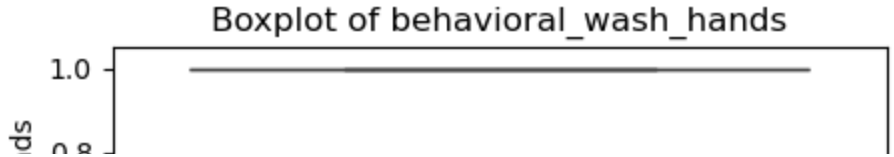

Boxplot of h1n1_knowledge
h1n1_knowledge
2.0
1.5
1.0
0.5
0.0

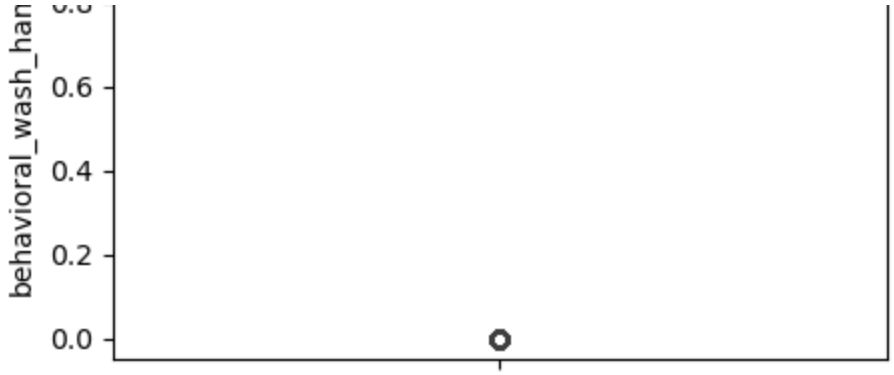

Boxplot of behavioral_antiviral_meds
1.0
0.8
0.6
0.4

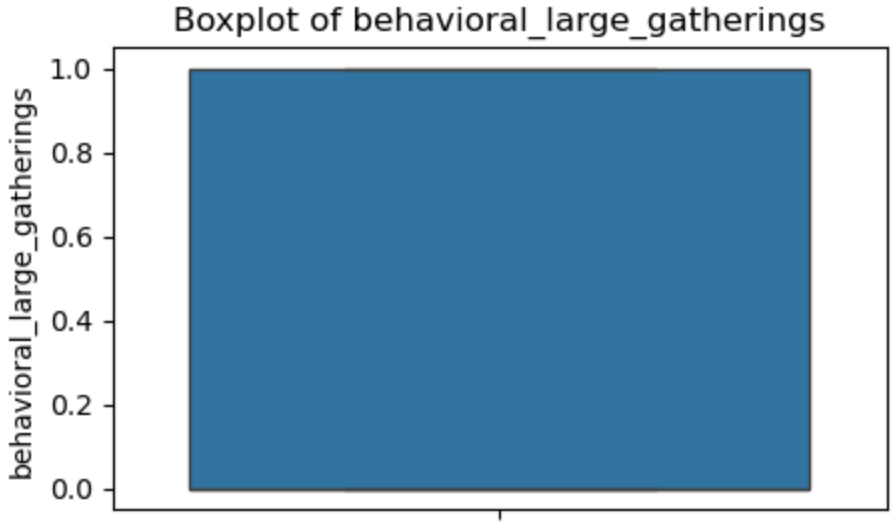

behavio
0.2
0.0

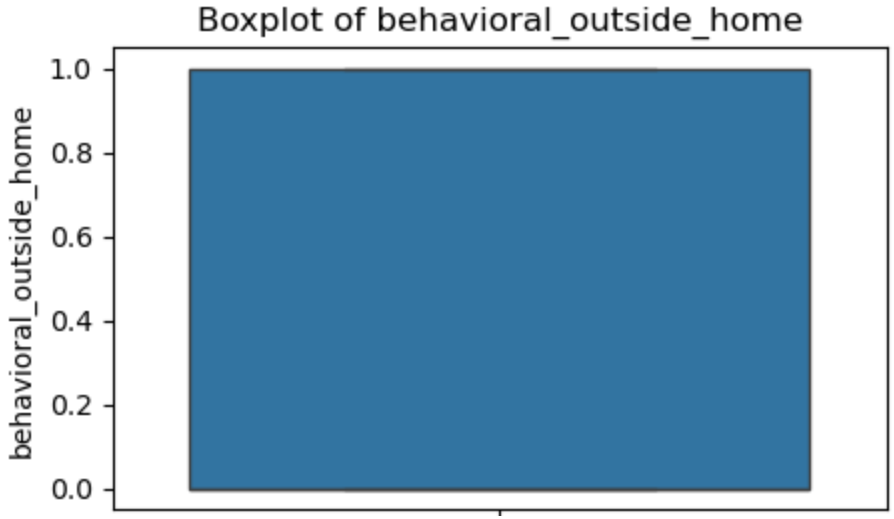

Boxplot of behavioral_avoidance
behavioral_avoidance
1.0
0.8
0.6
0.4
0.2
0.0

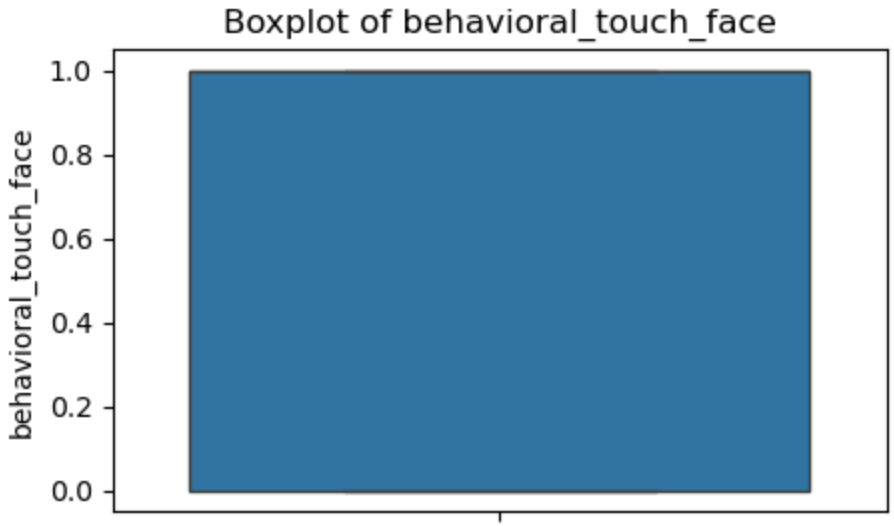

Boxplot of behavioral_face_mask
behavioral_face_mask
1.0
0.8
0.6
0.4
0.2
0.0

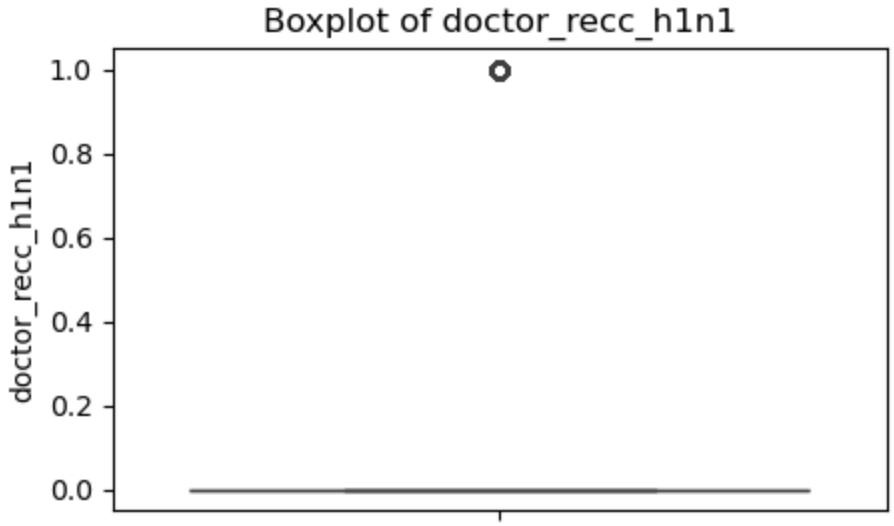

Boxplot of behavioral_wash_hands
1.0

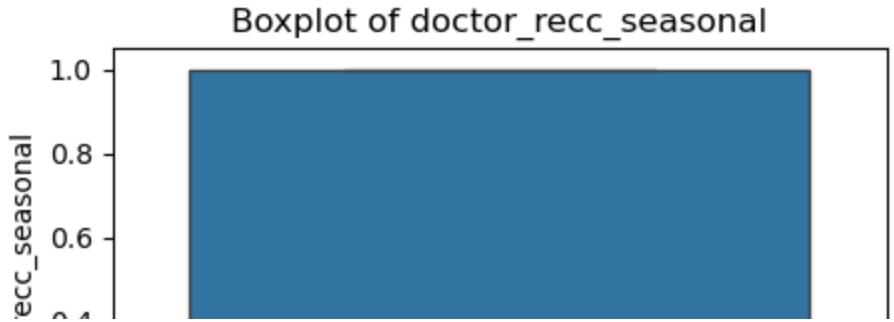

behavioral_wash_han
0.6
0.4
0.2
0.0


Boxplot of behavioral_large_gatherings
behavioral_large_gatherings
1.0
0.8
0.6
0.4
0.2
0.0

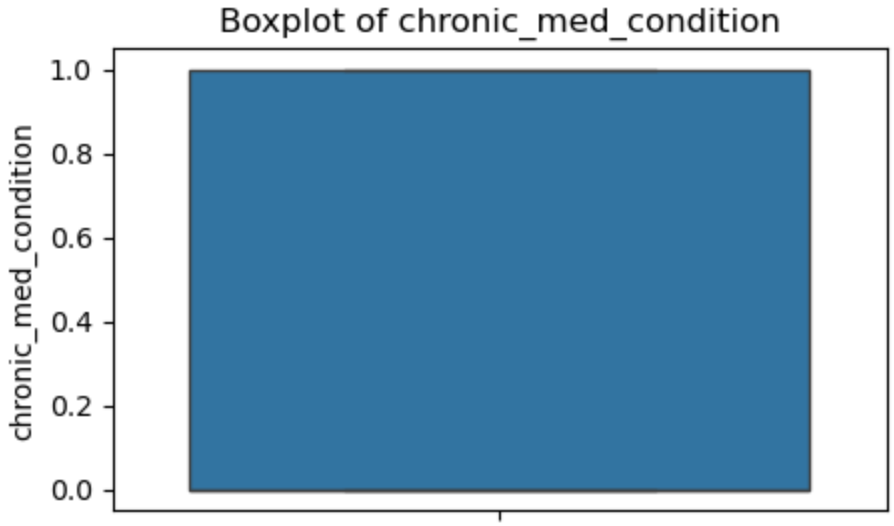

Boxplot of behavioral_outside_home
behavioral_outside_home
1.0
0.8
0.6
0.4
0.2
0.0

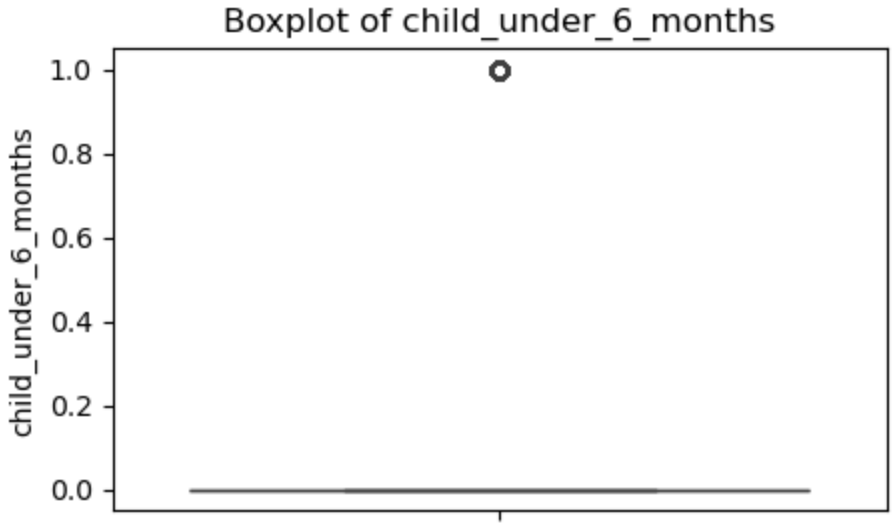

Boxplot of behavioral_touch_face
behavioral_touch_face
1.0
0.8
0.6
0.4
0.2
0.0

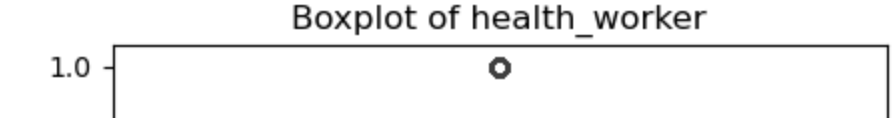

Boxplot of doctor_recc_h1n1
doctor_recc_h1n1
1.0
0.8
0.6
0.4
0.2
0.0


Boxplot of doctor_recc_seasonal
1.0
0.8
0.6

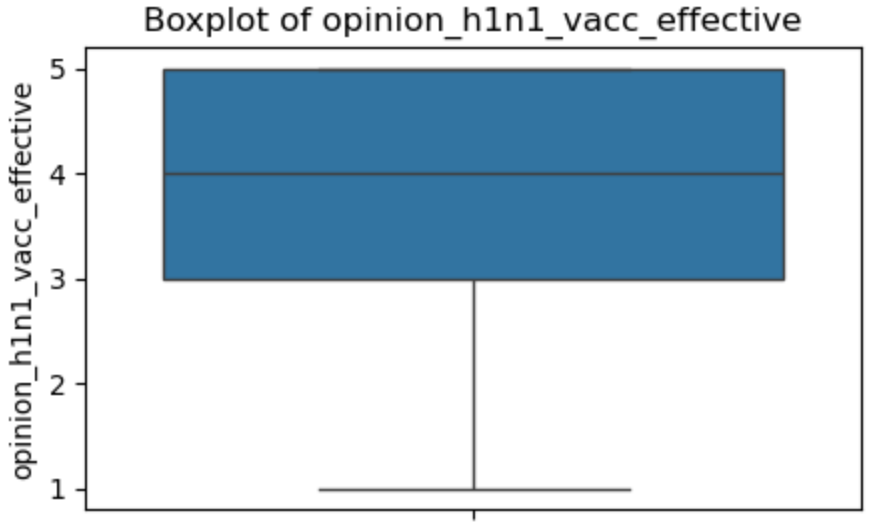

doctor_r
0.4
0.2
0.0

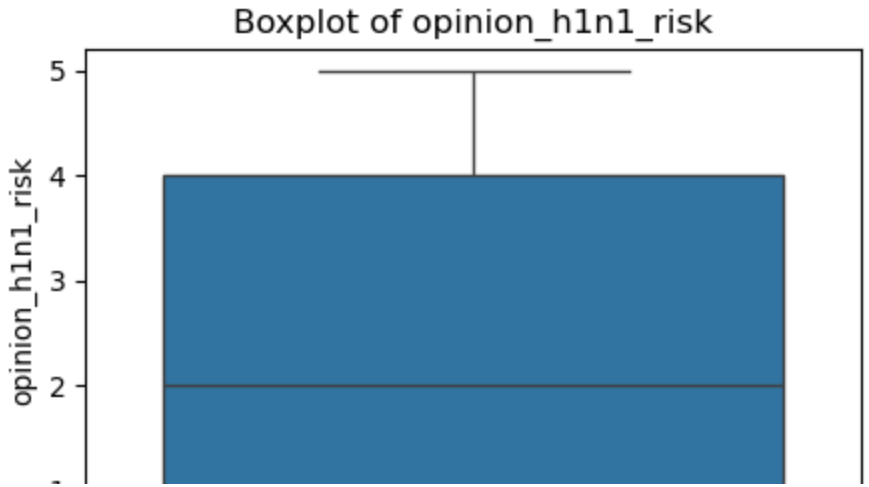

Boxplot of chronic_med_condition
chronic_med_condition
1.0
0.8
0.6
0.4
0.2
0.0

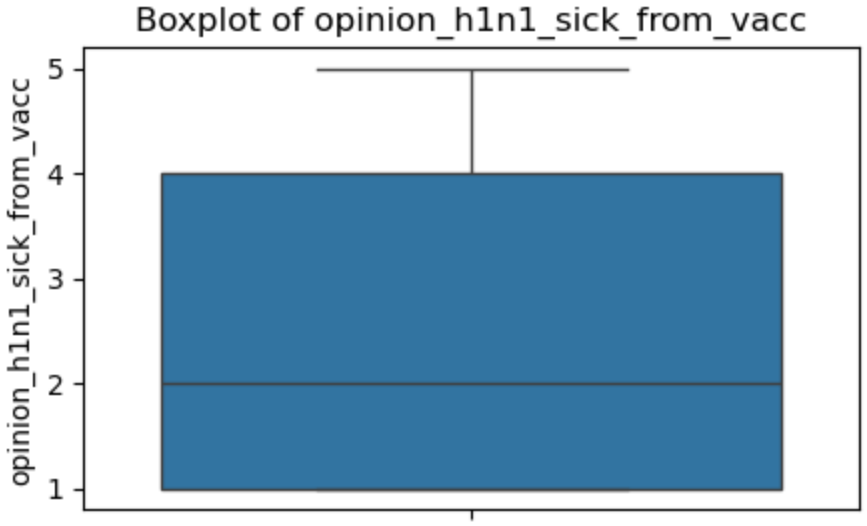

Boxplot of child_under_6_months
child_under_6_months
1.0
0.8
0.6
0.4
0.2
0.0

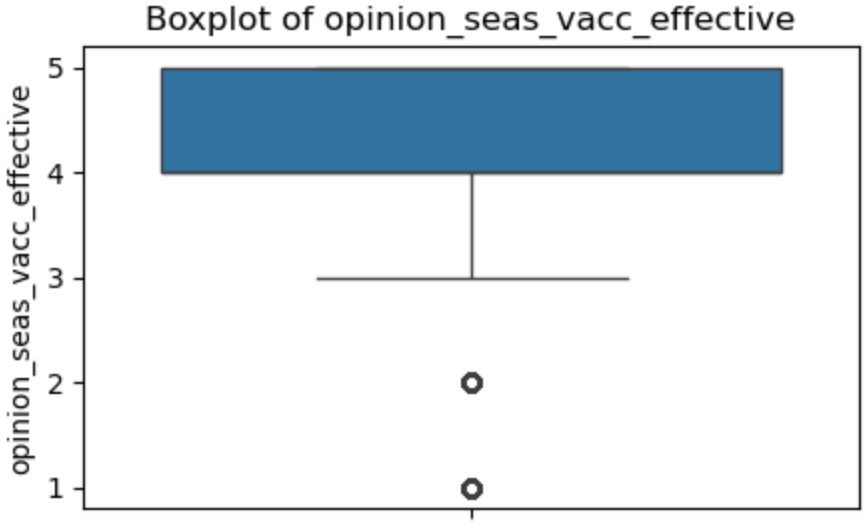

Boxplot of health_worker
1.0

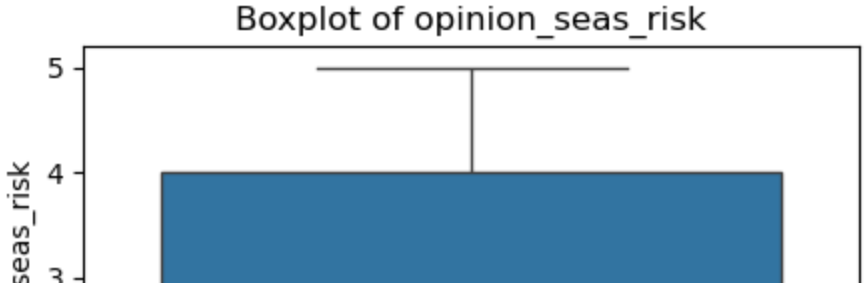

health_worker
0.8
0.6
0.4
0.2
0.0

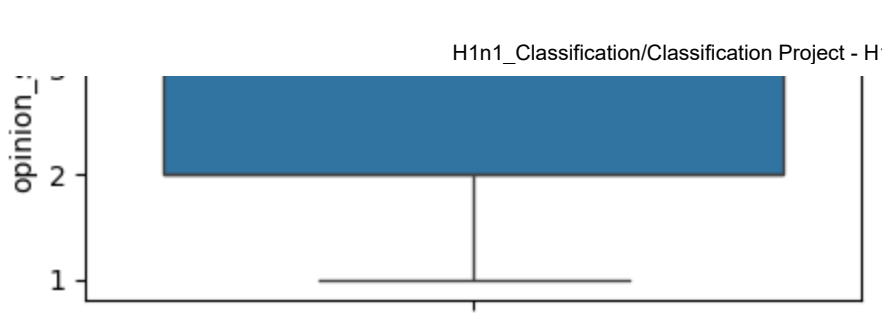

Boxplot of opinion_h1n1_vacc_effective
opinion_h1n1_vacc_effective
5
4
3
2
1

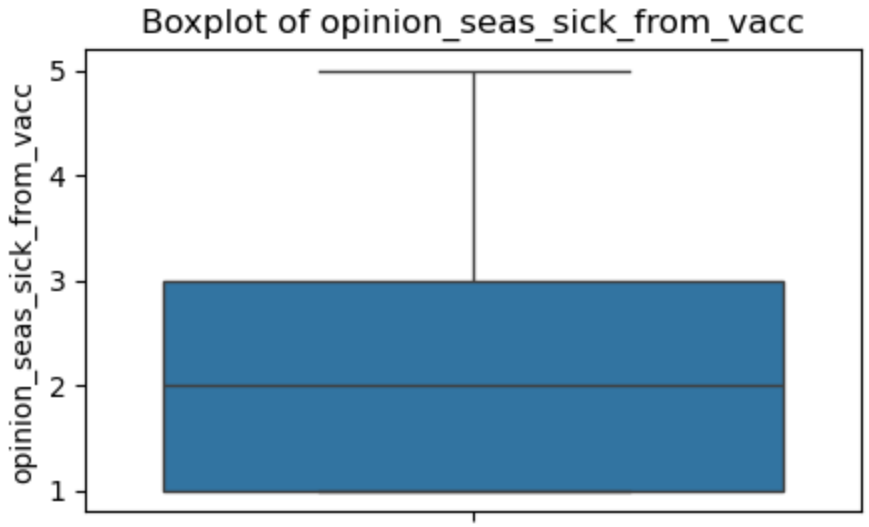

Boxplot of opinion_h1n1_risk
opinion_h1n1_risk
5
4
3
2

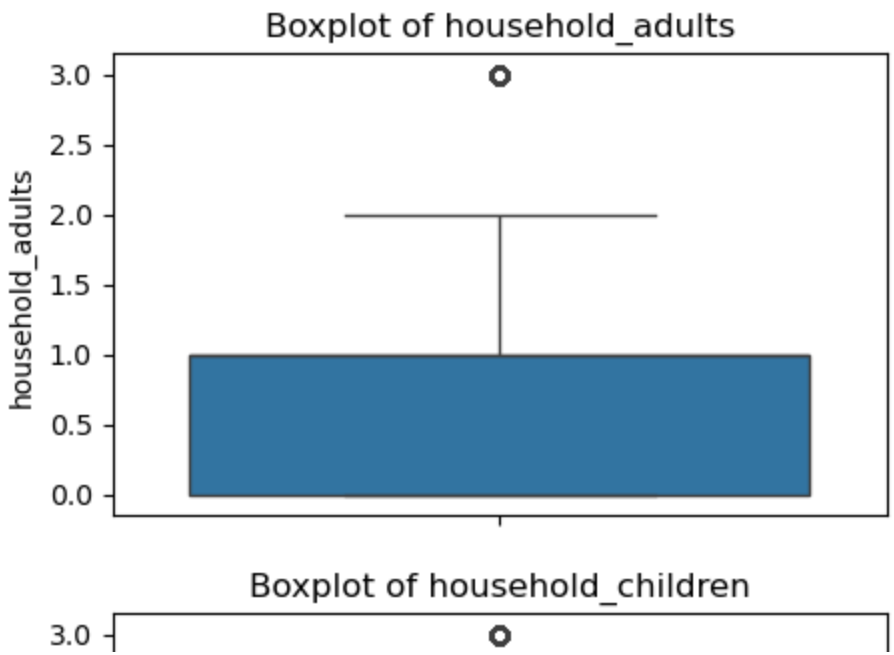

Boxplot of opinion_h1n1_sick_from_vacc
opinion_h1n1_sick_from_vacc
5
4
3
2
1


Boxplot of opinion_seas_vacc_effective
opinion_seas_vacc_effective
5
4
3
2
1

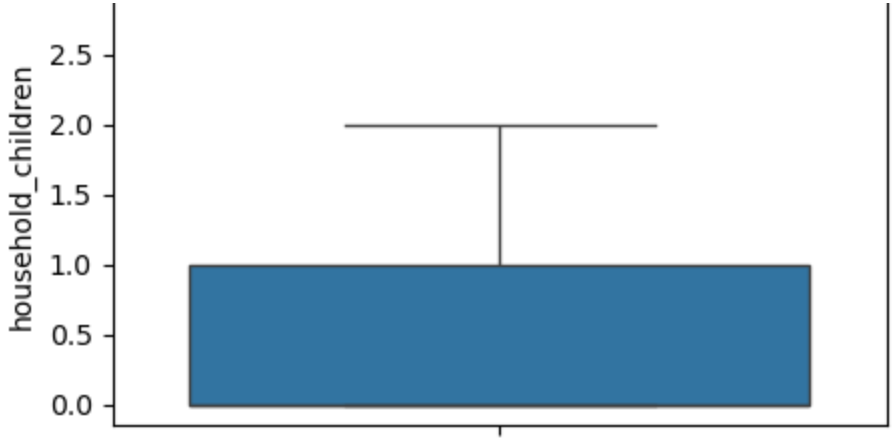

Boxplot of opinion_seas_risk
5
4

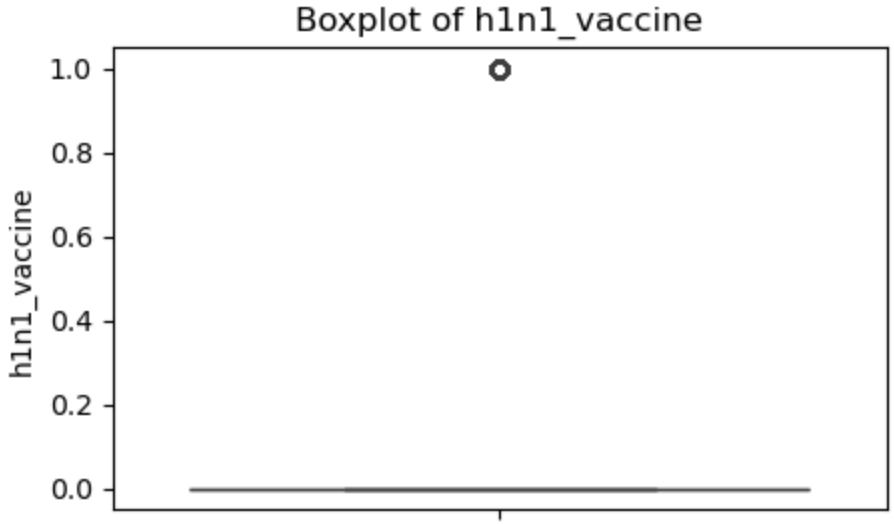

opinion_
2
1


Boxplot of opinion_seas_sick_from_vacc
opinion_seas_sick_from_vacc
5
4
3
2
1


Boxplot of household_adults
household_adults
3.0
2.5
2.0
1.5
1.0
0.5
0.0

Boxplot of household_children
3.0





In [424…

```
# Check class imbalance
df['h1n1_vaccine'].value_counts(normalize=True)
```

Out[424…

```
h1n1_vaccine
0    0.773284
1    0.226716
Name: proportion, dtype: float64
```

From our prior knowledge, this kind of distribution is not good. Reason being, the model might overpredict the most occuring variable

In [425…

```
df.shape
```

Out[425…

```
(21710, 33)
```

EDA

In [426…

```
df_clean=df.copy()

df_clean.head(4)
```

Out[426…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_
0	1	0	0	0	0	
1	3	2	0	1	0	
3	1	1	0	1	0	
4	2	1	0	1	0	

4 rows × 33 columns

In [428…

```
#Extract numerical columns for ease of usage

num_clean_df=df_clean.select_dtypes(include='number')
num_clean_df.columns
```

Out[428…

```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
       'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'doctor_recc_seasonal',
       'chronic_med_condition', 'child_under_6_months', 'health_worker',
       'opinion_h1n1_vacc_effective', 'opinion_h1n1_risk'
```

```
       'opinion_h1n1_sick_from_vacc', 'opinion_seas_vacc_effective',
       'opinion_seas_risk', 'opinion_seas_sick_from_vacc', 'household_adults',
       'household_children', 'h1n1_vaccine'],
      dtype='object')
```

In [429…

```
#Extract categorical columns for ease of usage

cat_clean_df=df_clean.select_dtypes(exclude='number')
cat_clean_df.columns
```

Out[429…

```
Index(['age_group', 'education', 'race', 'sex', 'income_poverty',
       'marital_status', 'rent_or_own', 'employment_status', 'hhs_geo_region',
       'census_msa'],
      dtype='object')
```

In [430…

```
# Lets understand what is in our categorical variables. Sort values ascending to have a better picture
for i in cat_clean_df:
    print(f'The variables \033[1m{i}\033[0m has {cat_clean_df[i].nunique()} items:')
    sorted_values=sorted(cat_clean_df[i].dropna().unique())
    print(f'These are : {sorted_values }\n')
```

```
The variables age_group has 5 items:
These are : ['18 - 34 Years', '35 - 44 Years', '45 - 54 Years', '55 - 64 Years', '65+ Years']

The variables education has 4 items:
These are : ['12 Years', '< 12 Years', 'College Graduate', 'Some College']

The variables race has 4 items:
These are : ['Black', 'Hispanic', 'Other or Multiple', 'White']

The variables sex has 2 items:
These are : ['Female', 'Male']

The variables income_poverty has 3 items:
These are : ['<= $75,000, Above Poverty', '> $75,000', 'Below Poverty']

The variables marital_status has 2 items:
These are : ['Married', 'Not Married']

The variables rent_or_own has 2 items:
These are : ['Own', 'Rent']

The variables employment_status has 3 items:
```

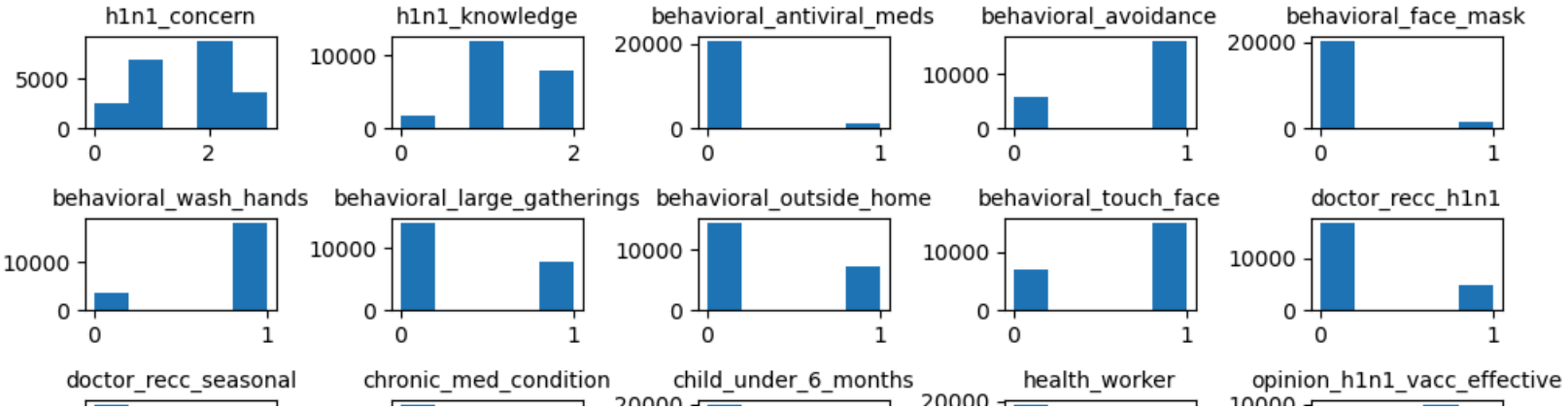
```
These are : [ Employed ,  Not in Labor Force ,  Unemployed ]

The variables hhs_geo_region has 10 items:
These are : ['atmpeygn', 'bhuqouqj', 'dqpwygqj', 'fpwskwrf', 'kbazzjca', 'lrircsnp', 'lzgpxyit', 'mlyzmhmf', 'oxc
hjgsf', 'qufhixun']

The variables census_msa has 3 items:
These are : ['MSA, Not Principle  City', 'MSA, Principle City', 'Non-MSA']
```

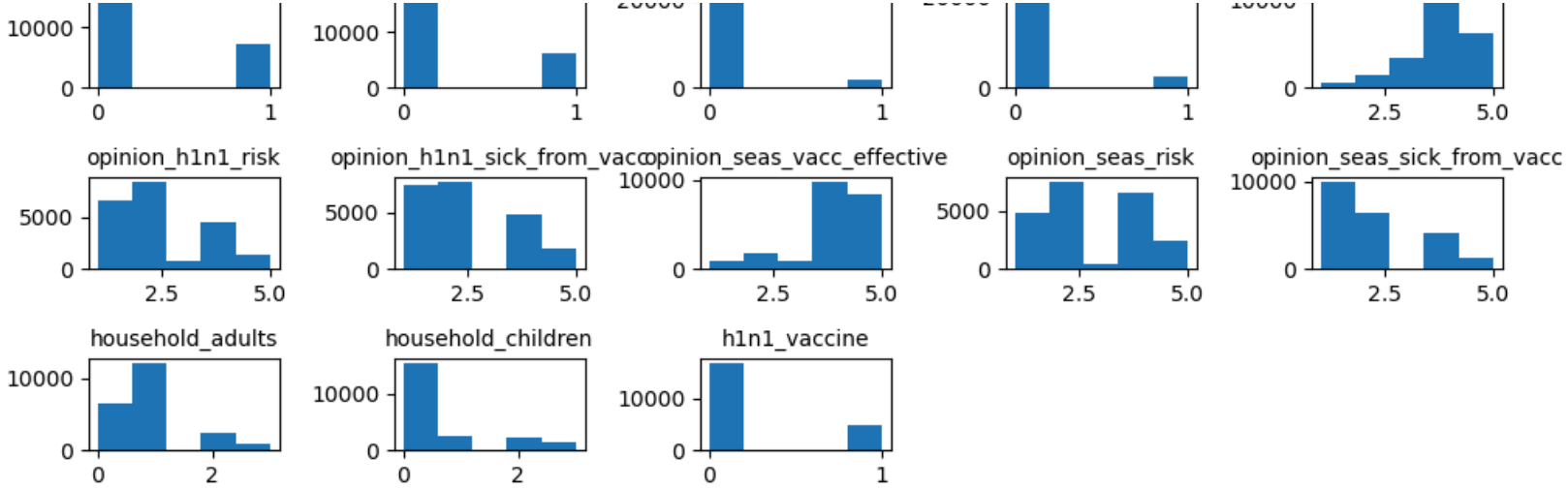
From the above, only geo-region cannot be interpreted directly but the rest are straight forward. We many need to find more about the geo_region codes

Univariate Analysis

In [495…

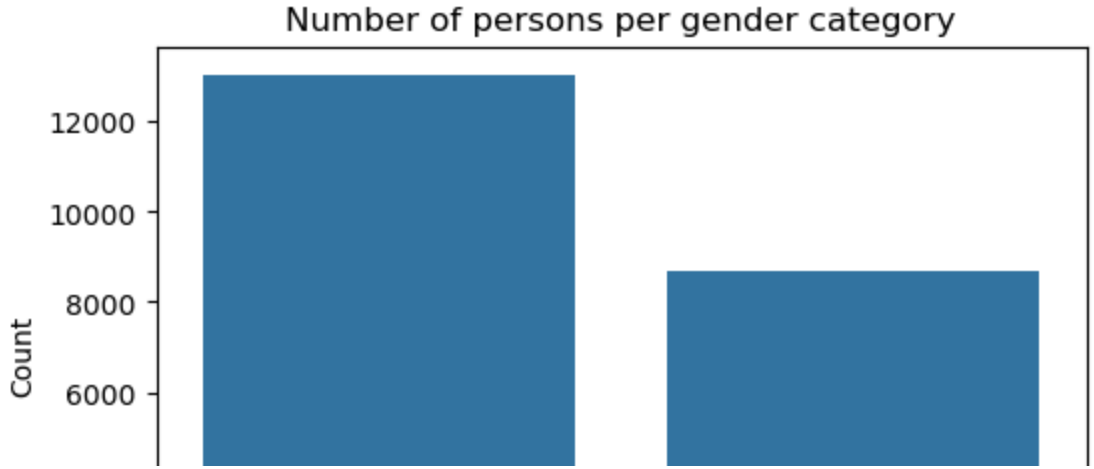
```
#Plot the distributions of numerical data
import matplotlib.pyplot as plt

num_clean_df.hist(bins=5, figsize=(10, 6), grid=False)

for ax in plt.gcf().axes:
    ax.title.set_size(10)

#Export the graph
#plt.savefig("distri.png", dpi=500, bbox_inches="tight")

# Show the plots
plt.tight_layout()
plt.show()
```

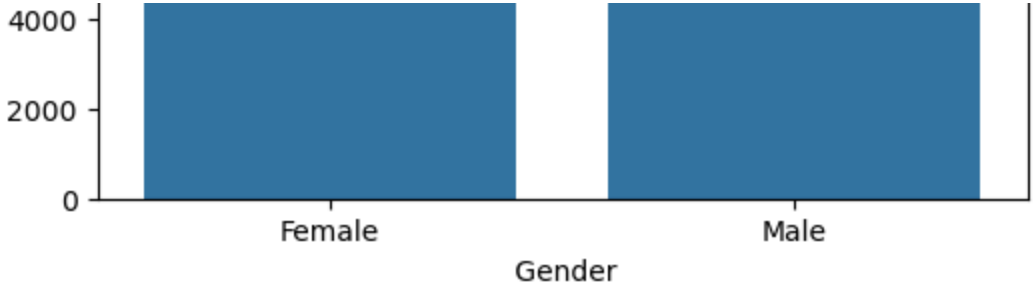




In [496…

```
# check race+gender vs H1n1

gender_piv=df_clean.groupby(['sex'])['h1n1_vaccine'].count().reset_index().sort_values(by='h1n1_vaccine', ascen
plt.figure(figsize=(6,4))
sns.barplot(data=gender_piv, y='h1n1_vaccine', x='sex').set(title="Number of persons per gender category", ylab

#Export the graph
#plt.savefig("Gender.png", dpi=500, bbox_inches="tight")

#Render the output
plt.show()
```





In [438…

```
gender_piv
```

Out[438…

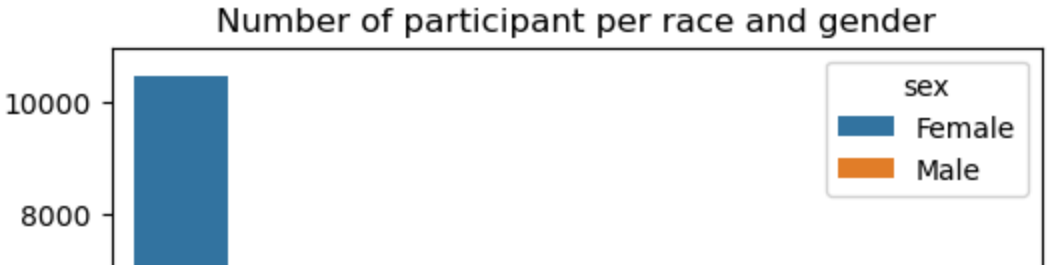
	sex	h1n1_vaccine
0	Female	13018
1	Male	8692

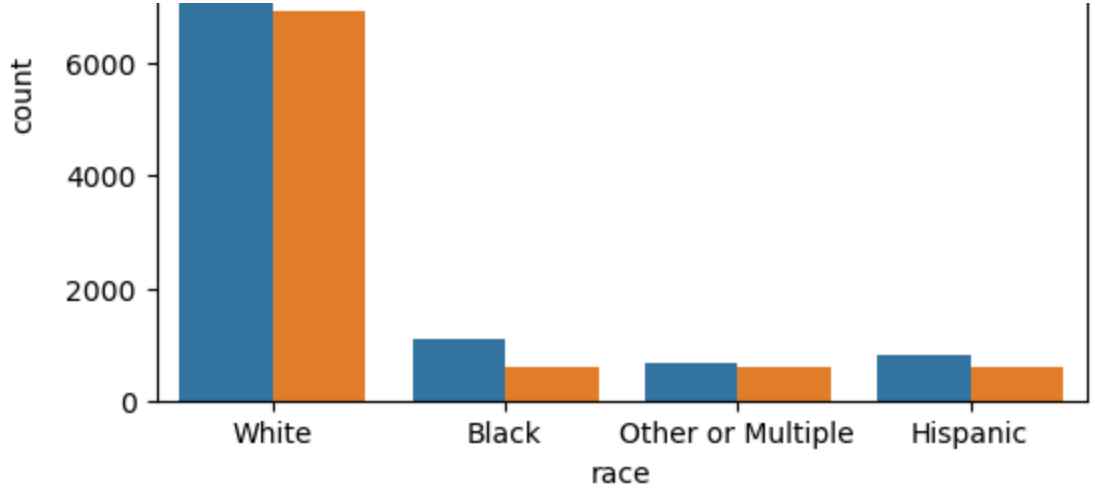
We can see that Female dominated the study at 60% of all resondents

Bivariate Analysis

In [497…

```
# Lets explore race per gender
plt.figure(figsize=(6,4))
sns.countplot(df_clean, x="race", hue="sex", legend=True)
plt.title('Number of participant per race and gender')

#Export the graph
#plt.savefig("RaceGender.png", dpi=500, bbox_inches="tight")

plt.show()
```

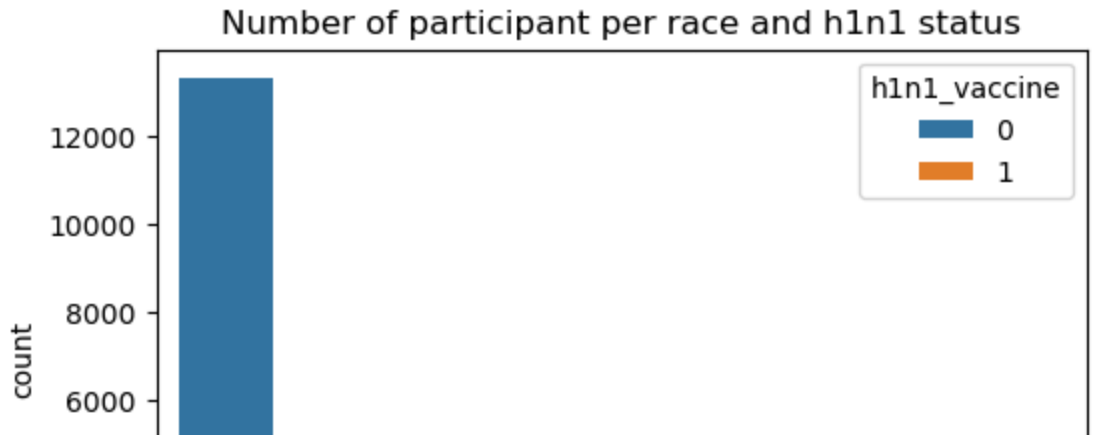


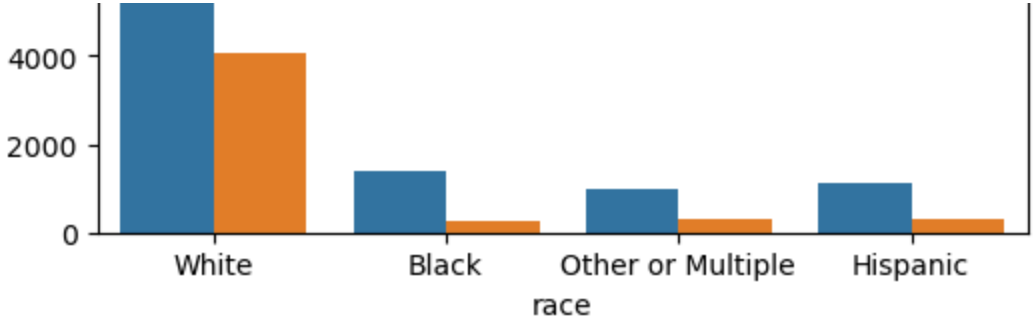


While it is clear that women were the majority, we also sought to understand which race dominated and from the fig above, the white people were the majority and other/multiple race being the minority

In [498…

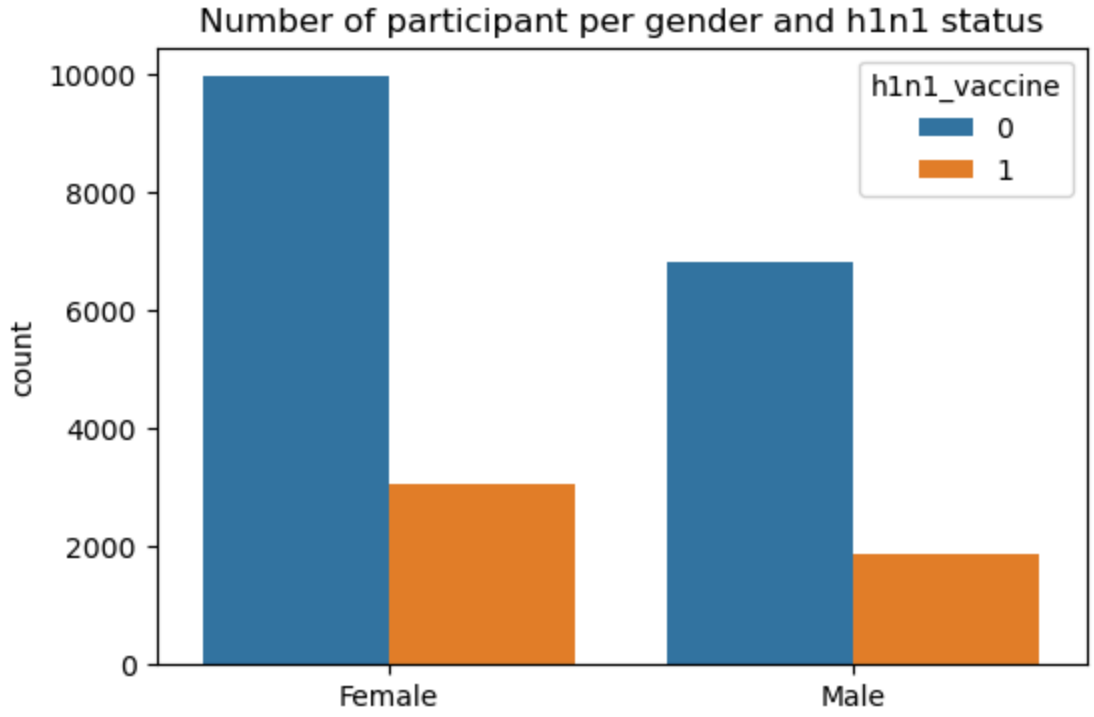
```
# similarly check race with h1n1 variable
plt.figure(figsize=(6,4))
sns.countplot(df_clean, x="race", hue="h1n1_vaccine", legend=True)
plt.title('Number of participant per race and h1n1 status')

#Export the graph
#plt.savefig("Raceh1n1.png", dpi=500, bbox_inches="tight")

plt.show()
```





In [499…

```
#Repeat the above with gender
# check race with h1n1 variable
plt.figure(figsize=(6,4))
sns.countplot(df_clean, x="sex", hue="h1n1_vaccine", legend=True)
plt.title('Number of participant per gender and h1n1 status')

#Export the graph
#plt.savefig("GenderH1n1.png", dpi=500, bbox_inches="tight")

plt.show()
```



sex

In both genders from above graph, it is evident that each gender based on their proportion may have had an equal chances of contracting h1n1. Lets look a pivot table to see how exhibits

In [444…

```
PT=df_clean.pivot_table(index='sex', columns='h1n1_vaccine', aggfunc='size', fill_value=0)

# Convert to proportions
PT = PT.div(PT.sum(axis=1), axis=0)*100


PT
```

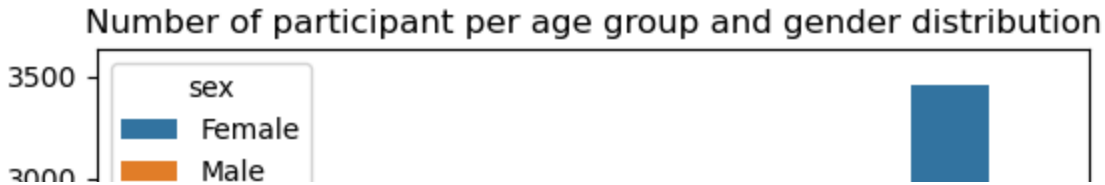
Out[444…

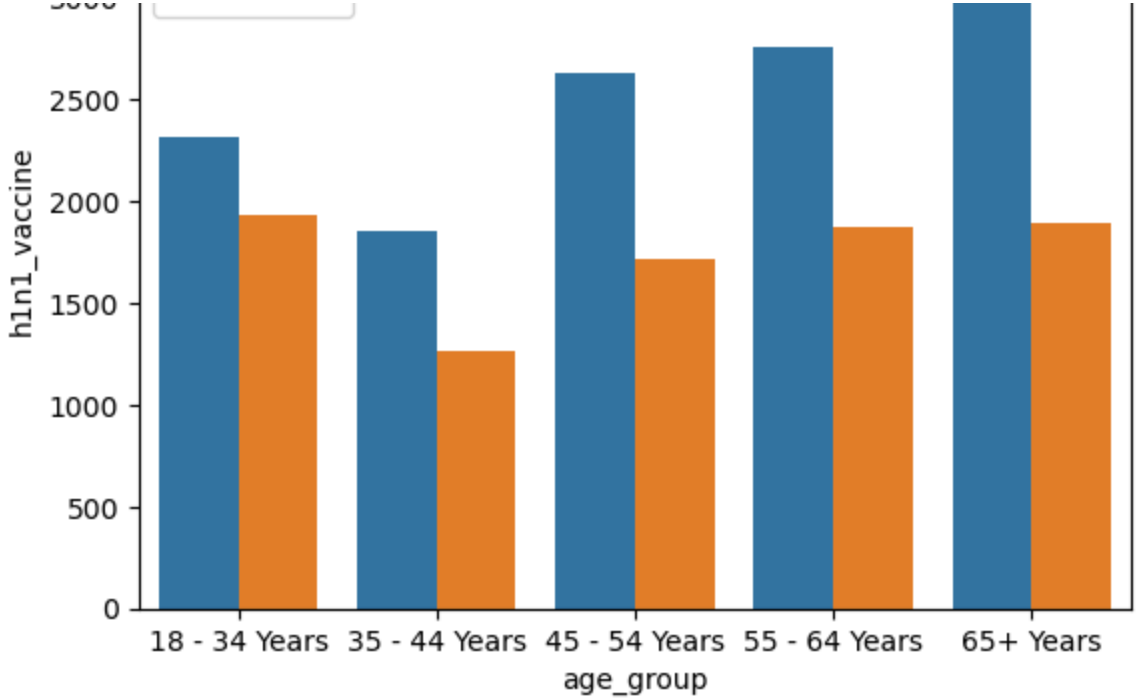
h1n1_vaccine	0	1
sex		
Female	76.532493	23.467507
Male	78.520479	21.479521

Multivariate analysis

In [500…

```
# Further explore the age_group with gender with respect to h1n1
AGG = df_clean.groupby(["age_group", "sex"])["h1n1_vaccine"].count().reset_index()

sns.barplot(data=AGG, x="age_group", y="h1n1_vaccine", hue="sex")
#plt.title('Number of participant per age group and gender distribution')

#Export the graph
plt.savefig("AgeGenderH1n1.png", dpi=500, bbox_inches="tight")

plt.show()
```





In [450…

```
PT1=df_clean.pivot_table(index='age_group', columns=['sex','h1n1_vaccine'], aggfunc='size', fill_value=0)

# Convert to proportions
PT1 = PT1.div(PT1.sum(axis=1), axis=0)*100


PT1
```

Out[450…

sex	Female		Male	
h1n1_vaccine	0	1	0	1
age_group				
18 - 34 Years	42.329412	12.094118	37.764706	7.811765
35 - 44 Years	44.836434	14.592688	33.707505	6.863374
45 - 54 Years	47.014240	13.527791	32.246210	7.211759
55 - 64 Years	43.961979	15.575718	29.833657	10.628645

65+ Years	50.083971	14.480313	25.825714	9.610002

Among all the age_groups, 55-64 males had the highest h1n1_vaccine contraction, while 65+ Females had the highest proportion of zero contraction o h1n1.

Data PreProcessing

In [451…

```
df_clean.describe(include='number')
```

Out[451…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_w
count	21710.000000	21710.000000	21710.000000	21710.000000	21710.000000	21
mean	1.613450	1.289728	0.048503	0.734961	0.067526	
std	0.895736	0.603993	0.214832	0.441364	0.250937	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	1.000000	0.000000	0.000000	0.000000	
50%	2.000000	1.000000	0.000000	1.000000	0.000000	
75%	2.000000	2.000000	0.000000	1.000000	0.000000	
max	3.000000	2.000000	1.000000	1.000000	1.000000	

8 rows × 23 columns

In [452…

```
df_clean.describe(exclude='number')
```

Out[452…

	age_group	education	race	sex	income_poverty	marital_status	rent_or_own	employment_status	hhs_geo_re
count	21710	21710	21710	21710	21710	21710	21710	21710	2
unique	5	4	4	2	3	2	2	3	
top	65+ Years	College Graduate	White	Female	<= $75,000, Above Poverty	Married	Own	Employed	lzg

	Graduate				Above Poverty			
freq	5359	8777	17372	13018	13253	11758	16541	11850

Encoding

In [460…
```
df_encoded = df_clean.copy()
```

In [461…
```
cat_col=df_encoded.select_dtypes(exclude='number')
```

In [462…
```
binary_cols = [col for col in cat_col if df[col].nunique() == 2]
```

In [463…
```
binary_cols
```

Out[463…
```
['sex', 'marital_status', 'rent_or_own']
```

In [464…
```
multi_cols = [col for col in cat_col if df[col].nunique() > 2]
```

In [465…
```
multi_cols
```

Out[465…
```
['age_group',
 'education',
 'race',
 'income_poverty',
 'employment_status',
 'hhs_geo_region',
 'census_msa']
```

In [466…
```
# Label Encoding for binary categorical columns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
# Copy datasets to avoid modifying originals
X_train_encoded = df_encoded.copy()


# Label Encoding for binary categorical columns (Train & Test)
```

```
# Label Encoding for binary categorical columns (Train & Test)
le = LabelEncoder()

for col in binary_cols:
    X_train_encoded[col] = le.fit_transform(X_train_encoded[col])


# One-Hot Encoding for multi-category categorical columns
X_train_encoded = pd.get_dummies(X_train_encoded, columns=multi_cols, drop_first=True)
```

In [467…

```
X_train_encoded.head()
```

Out[467…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_
0	1	0	0	0	0	
1	3	2	0	1	0	
3	1	1	0	1	0	
4	2	1	0	1	0	
5	3	1	0	1	0	

5 rows × 51 columns

In [468…

```
# Convert boolean columns to numeric (0 and 1)
for col in X_train_encoded.select_dtypes(include='bool'):
    X_train_encoded[col] = X_train_encoded[col].astype(int)
X_train_encoded.head(3)
```

Out[468…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_
0	1	0	0	0	0	
1	3	2	0	1	0	
3	1	1	0	1	0	

3 rows × 51 columns

Scaling

In [469…

```
X_train_encoded.head(3)
```

Out[469…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_
0	1	0	0	0	0	
1	3	2	0	1	0	
3	1	1	0	1	0	

3 rows × 51 columns

In [470…

```
from sklearn.preprocessing import MinMaxScaler

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Fit on training data and transform both train & test
X_train_scaled = scaler.fit_transform(X_train_encoded)  # Fit & transform on training


# Convert back to DataFrame for easier analysis
X_train_scaled = pd.DataFrame(X_train_scaled, columns=X_train_encoded.columns)
```

In [ ]:

Modeling

For this modeling exercise, I will focus on >Logistic Regression >Decision Trees >Random Forest >XGBoost

In [472…

```
X_train=X_train_scaled
X_train.head(3)
```

Out[472…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_
0	0.333333	0.0	0.0	0.0	0.0	
1	1.000000	1.0	0.0	1.0	0.0	
2	0.333333	0.5	0.0	1.0	0.0	

3 rows × 51 columns

In [ ]:

Logistic Regression

In [473…

```
#import necessary library
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score, classification_report, con

X=X_train.drop(columns=['h1n1_vaccine'])
y=X_train['h1n1_vaccine']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

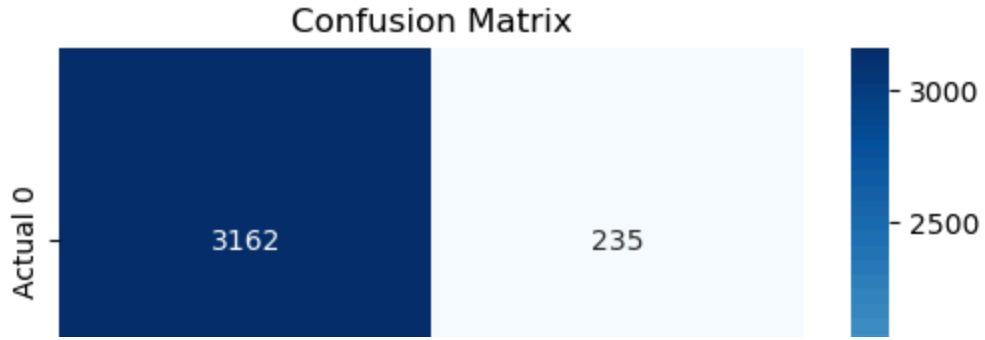
In [478…

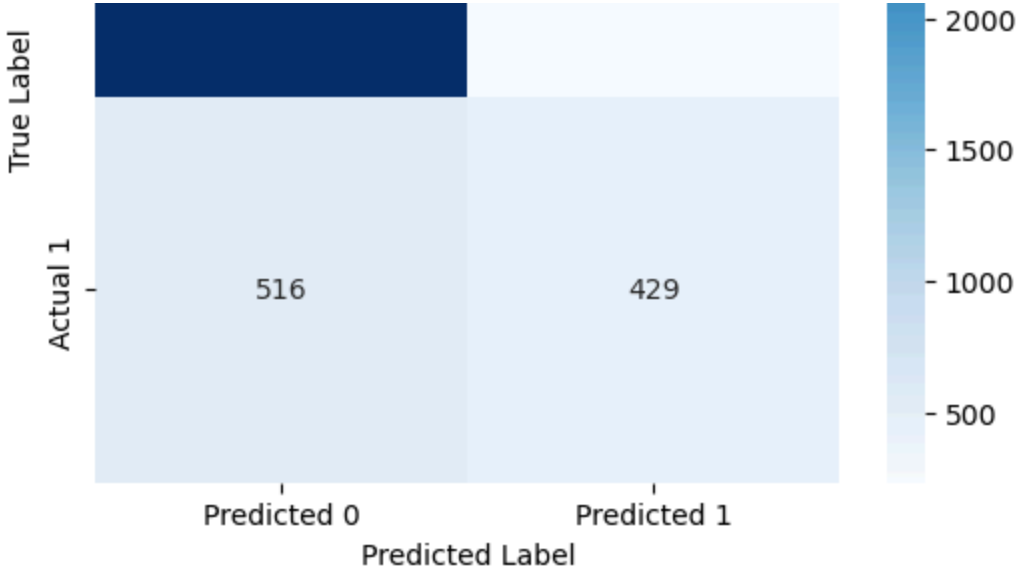
```
# Initialize and train the linear regression model
model = LogisticRegression(random_state=42)
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)
```

In [481…

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)


LR_accuracy=(f"Accuracy: {accuracy}")
LR_Recall=(f"Recall: {recall}")
LR_Precision=(f"Precision: {precision}")
LR_F1=(f"F1-score: {f1}")

# Classification report
print(classification_report(y_test, y_pred))

# Plot confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.93      0.89      3397
         1.0       0.65      0.45      0.53       945

    accuracy                           0.83      4342
   macro avg       0.75      0.69      0.71      4342
weighted avg       0.81      0.83      0.82      4342
```





In [482…

```
print(LR_accuracy)
print(LR_Recall)
print(LR_Precision)
print(LR_F1)
```

```
Accuracy: 0.827038231229848
Recall: 0.45396825396825397
Precision: 0.6460843373493976
F1-score: 0.5332504661280298
```

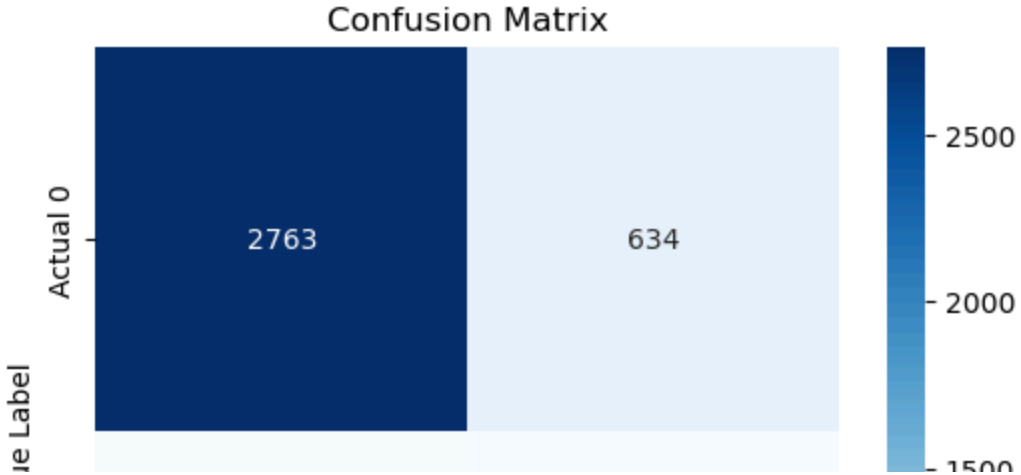
Decision Trees

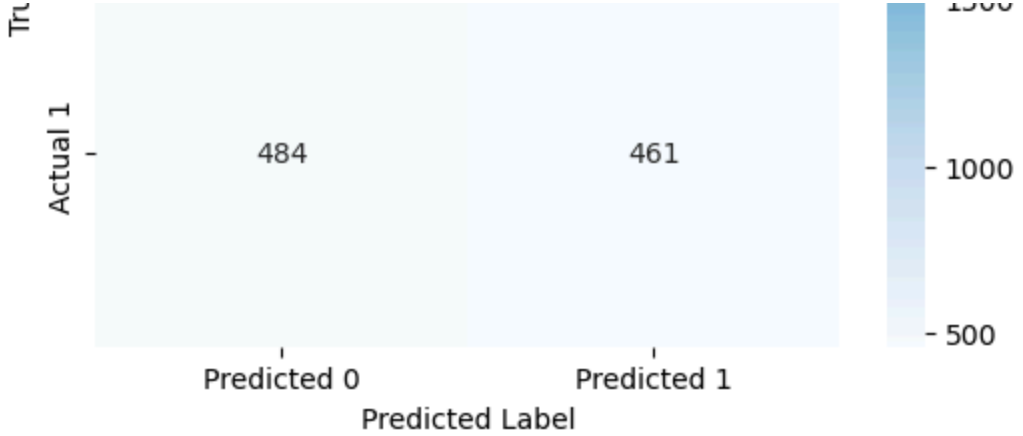
In [483…

```
from sklearn.tree import DecisionTreeClassifier

# Initialize and train the decision tree classifier
dt_model = DecisionTreeClassifier(random_state=42)  # You can adjust hyperparameters here
dt_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = dt_model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
```

```
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

DT_accuracy=(f"Accuracy: {accuracy}")
DT_Recall=(f"Recall: {recall}")
DT_Precision=(f"Precision: {precision}")
DT_F1=(f"F1-score: {f1}")

# Classification report
print(classification_report(y_test, y_pred))

# Plot confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
              precision    recall  f1-score   support

         0.0       0.85      0.81      0.83      3397
         1.0       0.42      0.49      0.45       945

    accuracy                           0.74      4342
   macro avg       0.64      0.65      0.64      4342
weighted avg       0.76      0.74      0.75      4342
```





In [484…

```
print(DT_accuracy)
print(DT_Recall)
print(DT_Precision)
print(DT_F1)
```

```
Accuracy: 0.7425149700598802
Recall: 0.48783068783068784
Precision: 0.42100456621004567
F1-score: 0.4519607843137255
```

The decision performs less better than logistic regression. Accuracy being the best score at 74%

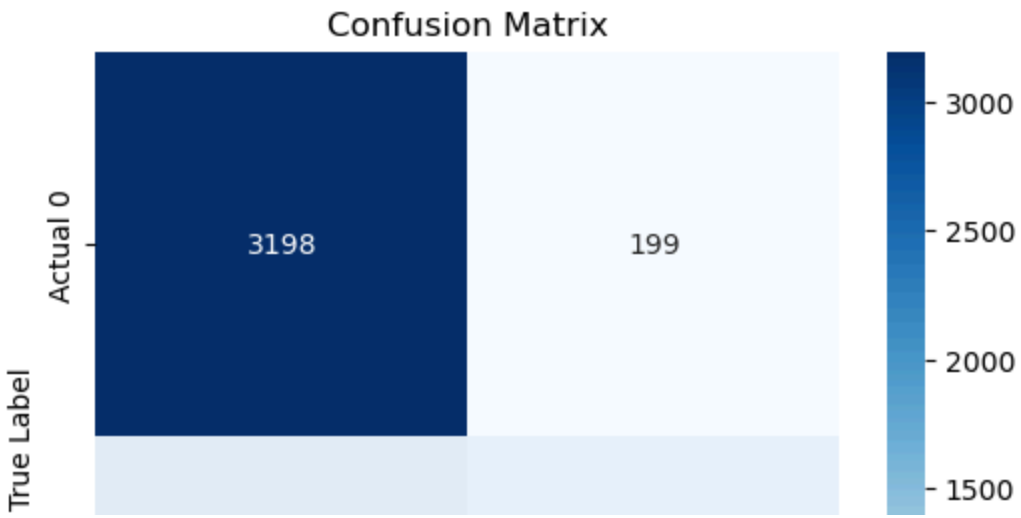
Random Forest

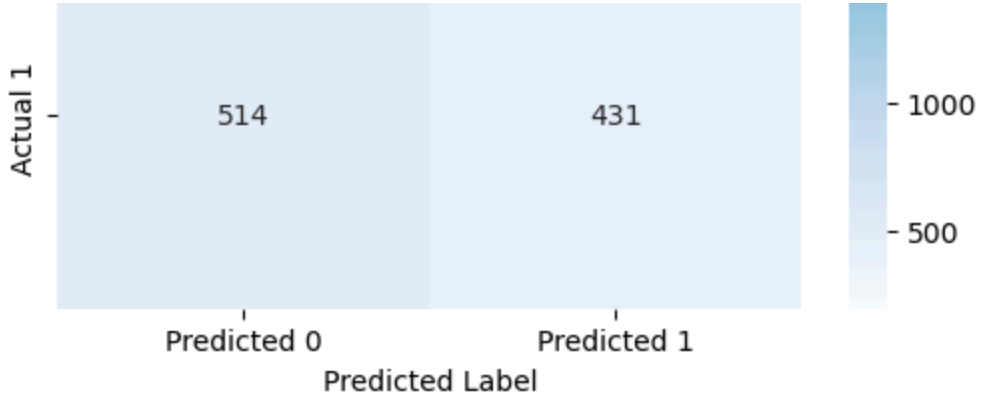
In [485…

```
from sklearn.ensemble import RandomForestClassifier

# Initialize and train the random forest classifier
rf_model = RandomForestClassifier(random_state=42)  # You can adjust hyperparameters here
rf_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = rf_model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
```

```
RF_accuracy=(f"Accuracy: {accuracy}")
RF_Recall=(f"Recall: {recall}")
RF_Precision=(f"Precision: {precision}")
RF_F1=(f"F1-score: {f1}")

# Classification report
print(classification_report(y_test, y_pred))

# Plot confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.94      0.90      3397
         1.0       0.68      0.46      0.55       945

    accuracy                           0.84      4342
   macro avg       0.77      0.70      0.72      4342
weighted avg       0.82      0.84      0.82      4342
```





In [486…

```
print(RF_accuracy)
print(RF_Recall)
print(RF_Precision)
print(RF_F1)
```

```
Accuracy: 0.8357899585444496
Recall: 0.4560846560846561
Precision: 0.6841269841269841
F1-score: 0.5473015873015873
```

There is some improvement in the Random Forest. Accuracy has gone up to 83.5%

XGBoost

In [487…

```
#pip install xgboost
```

In [488…

```
X_train.columns = X_train.columns.astype(str)
X_test.columns = X_test.columns.astype(str)
```

In [489…

```
# Replace "<" and other special characters in column names
X_train.columns = X_train.columns.str.replace(r"[<>\[\]]", "", regex=True)
X_test.columns = X_test.columns.str.replace(r"[<>\[\]]", "", regex=True)
```

In [490…

```
X_train.columns
```

Out[490…

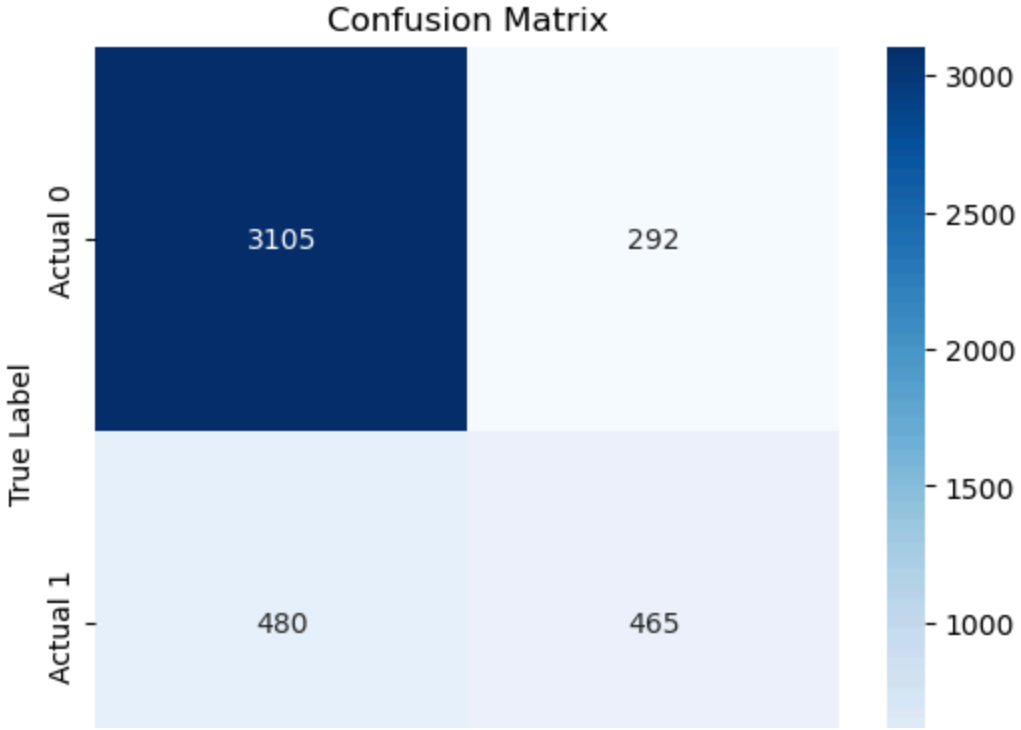
```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
       'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'doctor_recc_seasonal',
       'chronic_med_condition', 'child_under_6_months', 'health_worker',
       'opinion_h1n1_vacc_effective', 'opinion_h1n1_risk',
       'opinion_h1n1_sick_from_vacc', 'opinion_seas_vacc_effective',
       'opinion_seas_risk', 'opinion_seas_sick_from_vacc', 'sex',
       'marital_status', 'rent_or_own', 'household_adults',
       'household_children', 'age_group_35 - 44 Years',
       'age_group_45 - 54 Years', 'age_group_55 - 64 Years',
       'age_group_65+ Years', 'education_ 12 Years',
       'education_College Graduate', 'education_Some College', 'race_Hispanic',
       'race_Other or Multiple', 'race_White', 'income_poverty_ $75,000',
       'income_poverty_Below Poverty', 'employment_status_Not in Labor Force',
       'employment_status_Unemployed', 'hhs_geo_region_bhuqouqj',
       'hhs_geo_region_dqpwygqj', 'hhs_geo_region_fpwskwrf',
       'hhs_geo_region_kbazzjca', 'hhs_geo_region_lrircsnp',
       'hhs_geo_region_lzgpxyit', 'hhs_geo_region_mlyzmhmf',
       'hhs_geo_region_oxchjgsf', 'hhs_geo_region_qufhixun',
       'census_msa_MSA, Principle City', 'census_msa_Non-MSA'],
      dtype='object')
```

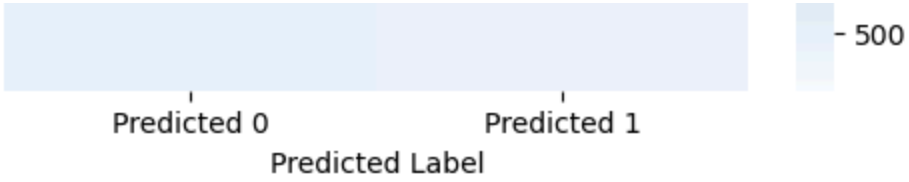
In [491…

```python
import xgboost as xgb
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score, classification_report, con

# Initialize and train the XGBoost classifier
xgb_model = xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb_model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = xgb_model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

XGB_accuracy = f"Accuracy: {accuracy:.4f}"
XGB_Recall = f"Recall: {recall:.4f}"
XGB_Precision = f"Precision: {precision:.4f}"
XGB_F1 = f"F1-score: {f1:.4f}"

# Print classification report
print(classification_report(y_test, y_pred))
```

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

# Plot confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
              precision    recall  f1-score   support

         0.0       0.87      0.91      0.89      3397
         1.0       0.61      0.49      0.55       945

    accuracy                           0.82      4342
   macro avg       0.74      0.70      0.72      4342
weighted avg       0.81      0.82      0.81      4342
```





In [492…

```
print(XGB_accuracy)
print(XGB_Recall)
print(XGB_Precision)
print(XGB_F1)
```

```
Accuracy: 0.8222
Recall: 0.4921
Precision: 0.6143
F1-score: 0.5464
```

XGBoost gives us an accuracy of 82%. The rest of evaluation metrics performing low.

Model Evaluation

In [493…

```
# Define metrics for each model
metrics = {
    "Model": ["Random Forest", "Logistic Regression", "Decision Tree", "XGBoost"],
    "Accuracy": [RF_accuracy, LR_accuracy, DT_accuracy, XGB_accuracy],
    "Recall": [RF_Recall, LR_Recall, DT_Recall, XGB_Recall],
    "Precision": [RF_Precision, LR_Precision, DT_Precision, XGB_Precision],
    "F1-Score": [RF_F1, LR_F1, DT_F1, XGB_F1]
}

# Create a DataFrame
metrics_df = pd.DataFrame(metrics)
```

In [494…

```
# Display the table
metrics_df
```

Out[494…

	Model	Accuracy	Recall	Precision	F1-Score
0	Random Forest	Accuracy: 0.8357899585444496	Recall: 0.4560846560846561	Precision: 0.6841269841269841	F1-score: 0.5473015873015873

1	Logistic Regression	Accuracy: 0.827038231229848	Recall: 0.45396825396825397	Precision: 0.6460843373493976	F1-score: 0.5332504661280298
2	Decision Tree	Accuracy: 0.7425149700598802	Recall: 0.48783068783068784	Precision: 0.42100456621004567	F1-score: 0.4519607843137255
3	XGBoost	Accuracy: 0.8222	Recall: 0.4921	Precision: 0.6143	F1-score: 0.5464

XGBoost seems to be the one doing well in Recall though with very low performace.

Conclusion

Clearly, this models could not achieve any better. This being health related data, our goal would have to focuss on Recall(Sensitivity) so as not to miss out on any opportunity that had H1N1 and wrongly classified. This implies we had many sick patients misclassified as healthy.

In all, the recall was way too low and this can not help in making the correct prediction.

As earlier mentioned above during EDA, we noticed the imbalance and this is what makes this model not to perform any better. This is because the model tends to predict the most occuring value in our target variable.

Recommendation

Use the SMOTE (Synthetic Minority Over-sampling Technique) approach to handle our imbalanced dataset.

More can be read on how to go about this issue and whether more complex model can be of any help in future.

In [ ]:

In [ ]:

The end

In [ ]: