

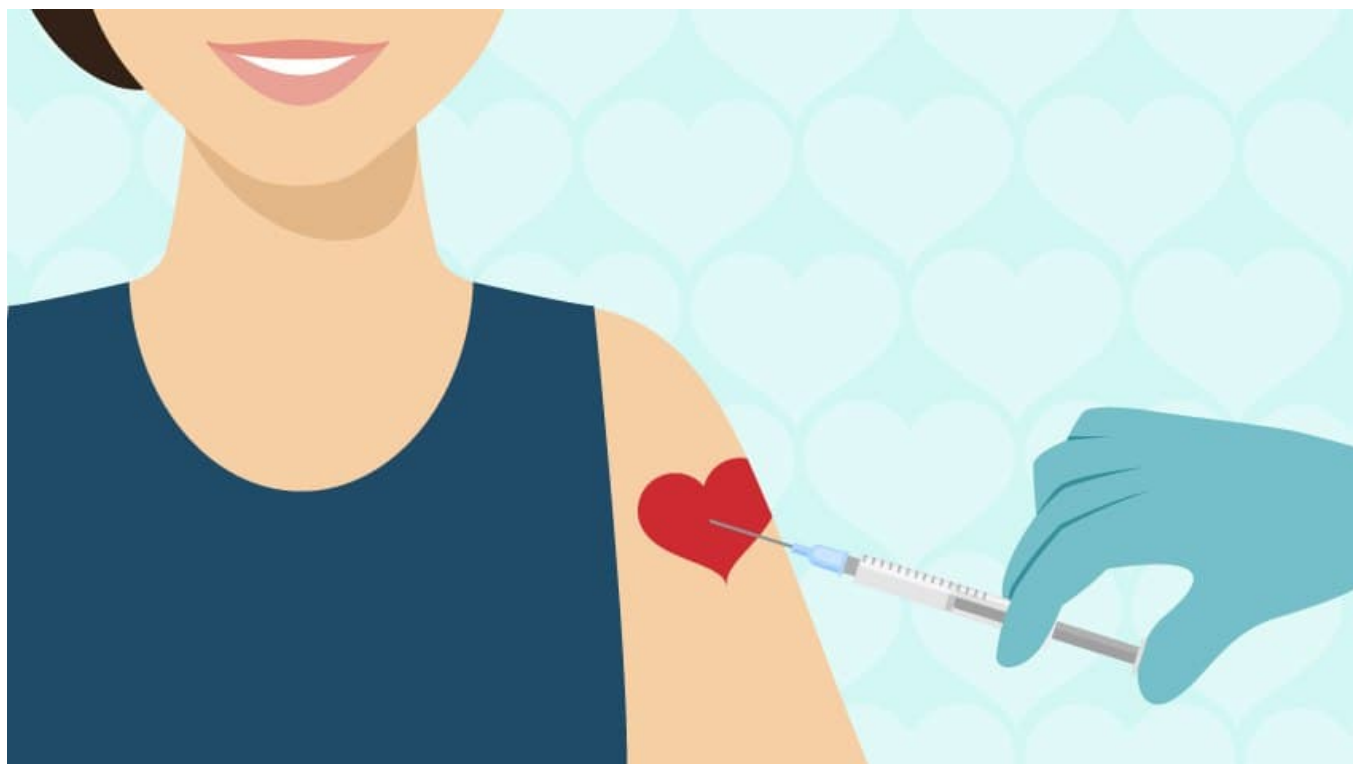
In [1]:

```
# Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import sklearn
import time
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import GridSearchCV
from xgboost import XGBClassifier
#from catboost import CatBoostRegressor
from sklearn.model_selection import KFold
import seaborn as sns
sns.set()

import warnings
warnings.filterwarnings('ignore')
```

Flu Shot Learning: Predict H1N1 and Seasonal Flu Vaccines

Problem Statement



In [2]:

```
# Loading the data and setting index to 'respondent_id' column
url_train_data = 'https://raw.githubusercontent.com/bakhtiyar0309/Flu-Shot-Learning/main/data/training_set_features.csv'
url_test_data = 'https://raw.githubusercontent.com/bakhtiyar0309/Flu-Shot-Learning/main/data/test_set_features.csv'
url_labels = 'https://raw.githubusercontent.com/bakhtiyar0309/Flu-Shot-Learning/main/data/training_set_labels.csv'

df_train = pd.read_csv(url_train_data, index_col='respondent_id') # dataset of training features
df_test = pd.read_csv(url_test_data) # dataset of testing features
df_labels = pd.read_csv(url_labels, index_col='respondent_id') # Labels (targets) for training features
```

Step 1: Prepare DataSet

Task description: Prepare your dataset: encode categorical variables (if any), handle missing variables (if any), generate new features (if you have some intuition that these features can be useful). Preprocess target variable if needed (e.g., combine various classification problems into a single one or convert the target variable to a binary one.)

1.1 Handling Missing Data

In [3]:

```
# Change 'Sex' string column to numeric type
df_train['sex_male'] = df_train['sex'].apply(lambda x: 0.0 if x == 'Female' else 1.0)
df_train = df_train.drop('sex', axis=1)

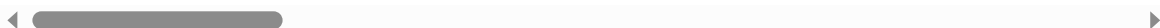
df_test['sex_male'] = df_test['sex'].apply(lambda x: 0.0 if x == 'Female' else 1.0)
df_test = df_test.drop('sex', axis=1)

df_train.head(3)
```

Out[3]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidanc
respondent_id				
0	1.0	0.0	0.0	0
1	3.0	2.0	0.0	1
2	1.0	1.0	0.0	1

3 rows × 35 columns



In [4]:

```
#combine feature data with labels data - required for EDA  
pd.set_option('display.max_columns', 500)  
df = pd.merge(df_train, df_labels, on='respondent_id', how='inner')
```

In [5]:

```
#divide columns into numerical and categorical ones  
num_columns = df_train.select_dtypes('float64').columns  
cat_columns = df_train.select_dtypes('object').columns  
id_column_test = df_test['respondent_id']  
  
df_train_num = df_train.loc[:, num_columns]  
df_train_cat = df_train.loc[:, cat_columns]  
  
df_test_num = df_test.loc[:, num_columns]  
df_test_cat = df_test.loc[:, cat_columns]
```

In [6]:

```
df.isna().sum()
```

Out[6]:

h1n1_concern	92
h1n1_knowledge	116
behavioral_antiviral_meds	71
behavioral_avoidance	208
behavioral_face_mask	19
behavioral_wash_hands	42
behavioral_large_gatherings	87
behavioral_outside_home	82
behavioral_touch_face	128
doctor_recc_h1n1	2160
doctor_recc_seasonal	2160
chronic_med_condition	971
child_under_6_months	820
health_worker	804
health_insurance	12274
opinion_h1n1_vacc_effective	391
opinion_h1n1_risk	388
opinion_h1n1_sick_from_vacc	395
opinion_seas_vacc_effective	462
opinion_seas_risk	514
opinion_seas_sick_from_vacc	537
age_group	0
education	1407
race	0
income_poverty	4423
marital_status	1408
rent_or_own	2042
employment_status	1463
hhs_geo_region	0
census_msa	0
household_adults	249
household_children	249
employment_industry	13330
employment_occupation	13470
sex_male	0
h1n1_vaccine	0
seasonal_vaccine	0
dtype:	int64

In [7]:

[illegible]

In [8]:

```
# Scale numerical columns
scaler_train = StandardScaler()
scaler_test = StandardScaler()

df_train_num_imputed = pd.DataFrame(scaler_train.fit_transform(df_train_num_imputed),
                                     columns = df_train_num_imputed.columns)

df_test_num_imputed = pd.DataFrame(scaler_test.fit_transform(df_test_num_imputed),
                                   columns = df_test_num_imputed.columns)
```

In [9]:

```
# Impute NaNs in categorical columns with 'no_response' values
df_train_cat_imputed = pd.DataFrame(SimpleImputer(missing_values=np.nan, strategy='constant', fill_value = 'no_response').fit_transform(df_train_cat),
                                     columns = df_train_cat.columns)
df_test_cat_imputed = pd.DataFrame(SimpleImputer(missing_values=np.nan, strategy='constant', fill_value = 'no_response').fit_transform(df_test_cat),
                                   columns = df_test_cat.columns)
```

In [10]:

```
# Merge numerical and categorical columns
df_train = pd.concat([df_train_num_imputed, df_train_cat_imputed], axis = 1)
df_test = pd.concat([df_test_num_imputed, df_test_cat_imputed], axis = 1)
```

In [11]:

```
# Check point
df_train.count()
```

Out[11]:

```
h1n1_concern                26707
h1n1_knowledge              26707
behavioral_antiviral_meds    26707
behavioral_avoidance         26707
behavioral_face_mask         26707
behavioral_wash_hands        26707
behavioral_large_gatherings  26707
behavioral_outside_home      26707
behavioral_touch_face        26707
doctor_recc_h1n1            26707
doctor_recc_seasonal        26707
chronic_med_condition        26707
child_under_6_months         26707
health_worker               26707
health_insurance            26707
opinion_h1n1_vacc_effective  26707
opinion_h1n1_risk           26707
opinion_h1n1_sick_from_vacc  26707
opinion_seas_vacc_effective  26707
opinion_seas_risk           26707
opinion_seas_sick_from_vacc  26707
household_adults            26707
household_children          26707
sex_male                   26707
age_group                  26707
education                  26707
race                      26707
income_poverty             26707
marital_status             26707
rent_or_own                26707
employment_status          26707
hhs_geo_region             26707
census_msa                 26707
employment_industry         26707
employment_occupation       26707
dtype: int64
```

1.2 Encode categorical features

In [12]:

```
dummy_columns_train = pd.get_dummies(df_train[cat_columns])
df_train = pd.concat((df_train, dummy_columns_train), axis=1)
df_train = df_train.drop(df_train[cat_columns], axis=1)

dummy_columns_test = pd.get_dummies(df_test[cat_columns])
df_test = pd.concat((df_test, dummy_columns_test), axis=1)
df_test = df_test.drop(df_test[cat_columns], axis=1)
```

Step 2. Exploratory Data Analysis

Task description: Perform an exploratory analysis of the data via visualization with Seaborn. Try to find meaningful patterns in the data which can be used to make a machine learning task more specific or to help with selection and tuning ML models. Perform additional preprocessing of your data if your findings suggest this (again, all steps should be motivated). If there are several options for target variables, you can select some of them after this step with a couple of sentences explaining your choice.

2.1 Target Variables

2.1 Univariate Data Analysis

1. Lets begin our analysis with the target values: H1N1 and Seasonal Flu vaccine distributions

In [13]:

```
# Show all the columns in our dataset
df.columns
```

Out[13]:

```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
      'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_ha
nds',
      'behavioral_large_gatherings', 'behavioral_outside_home',
      'behavioral_touch_face', 'doctor_recc_h1n1', 'doctor_recc_seasona
l',
      'chronic_med_condition', 'child_under_6_months', 'health_worker',
      'health_insurance', 'opinion_h1n1_vacc_effective', 'opinion_h1n1_ri
sk',
      'opinion_h1n1_sick_from_vacc', 'opinion_seas_vacc_effective',
      'opinion_seas_risk', 'opinion_seas_sick_from_vacc', 'age_group',
      'education', 'race', 'income_poverty', 'marital_status', 'rent_or_o
wn',
      'employment_status', 'hhs_geo_region', 'census_msa', 'household_adu
lts',
      'household_children', 'employment_industry', 'employment_occupatio
n',
      'sex_male', 'h1n1_vaccine', 'seasonal_vaccine'],
      dtype='object')
```

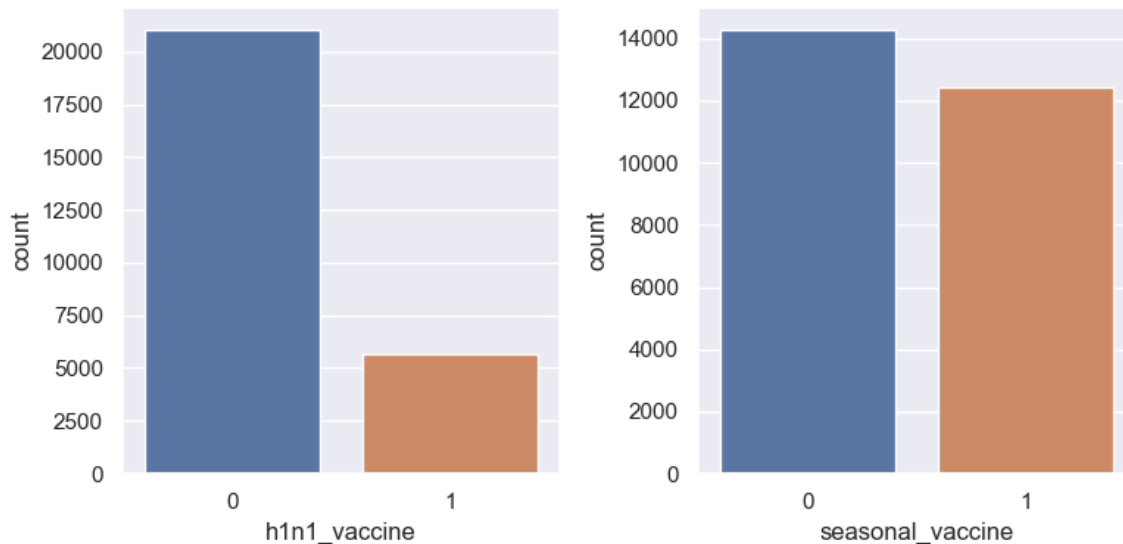
In [16]:

```
# split the data into feature and target variables sets
train = df.drop(['h1n1_vaccine', 'seasonal_vaccine'], axis=1)
labels = df[['h1n1_vaccine', 'seasonal_vaccine']]
```

In [18]:

```
# Distribution plot for target variables
plt.rcParams["figure.figsize"] = [8, 4]
plt.rcParams["figure.autolayout"] = True
f, ax = plt.subplots(1, 2);
sns.countplot(data=labels, x='h1n1_vaccine', ax=ax[0]);
sns.countplot(data=labels, x='seasonal_vaccine', ax=ax[1]);

plt.show();
```

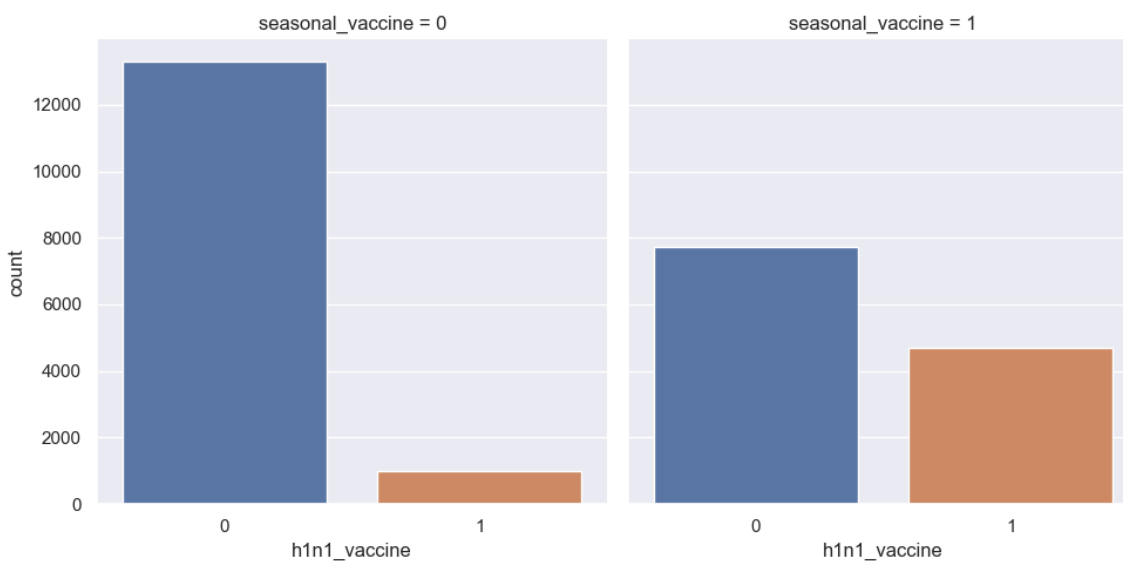


2.2 Bivariate Data Analysis

1. Explore how target variables relate to each other

In [19]:

```
# catplot for h1n1_vaccine and seasonal_vaccine
sns.catplot(x='h1n1_vaccine', col='seasonal_vaccine', kind='count', data=labels);
```



In [20]:

```
pd.crosstab(labels['h1n1_vaccine'], labels['seasonal_vaccine'])
```

Out[20]:

seasonal_vaccine	0	1
h1n1_vaccine		
0	13295	7738
1	977	4697

Observation:

1. We can note that the majority of people who received h1n1_vaccine1 also got the seasonal_vaccine.
2. However, with respect to seasonal_vaccine, smaller portion of them acquired the h1n1_vaccine.

2.2 Analyze how feature variables are related to each other

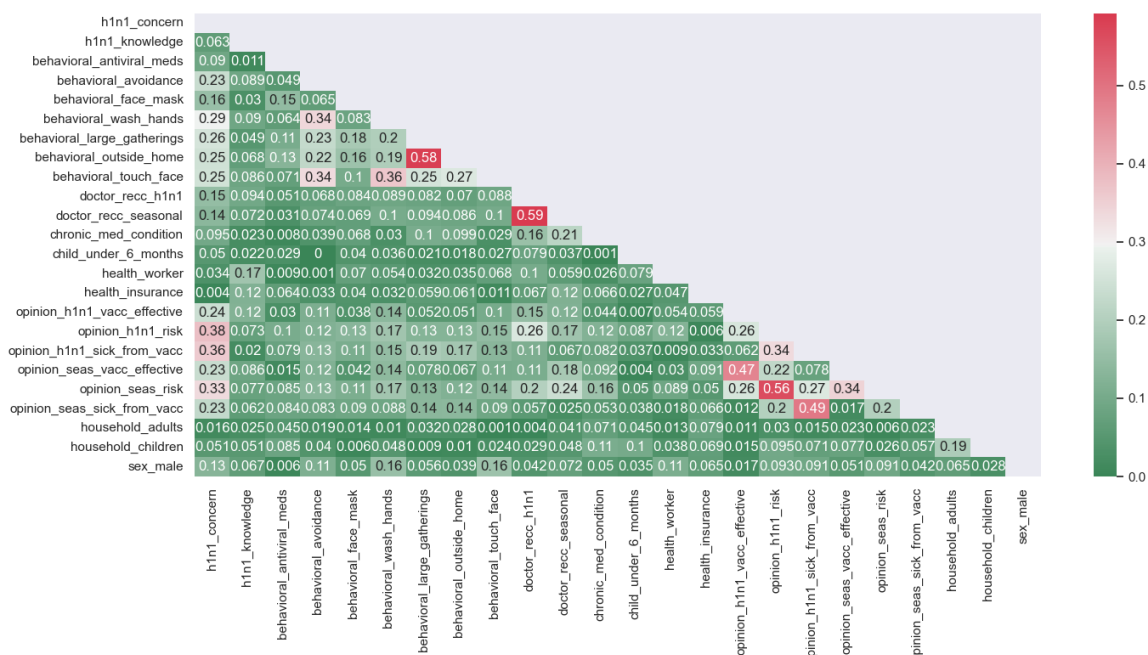
In [21]:

```
#hide_code_in_slideshow()
## plot correlations among variables as an annotated heatmap
corr_matrix = train.corr().abs().round(3)
mask = np.zeros_like(corr_matrix)

# Generate a custom diverging colormap
cmap = sns.diverging_palette(500, 8, as_cmap=True)

## mask the correlations of the variables with themselves along the diagonal and all duplicate correlations to the right of that line
mask[np.triu_indices_from(mask)] = True
mask
plt.figure(figsize=(15,8))

sns.heatmap(corr_matrix, annot=True, cmap=cmap, mask=mask);
```



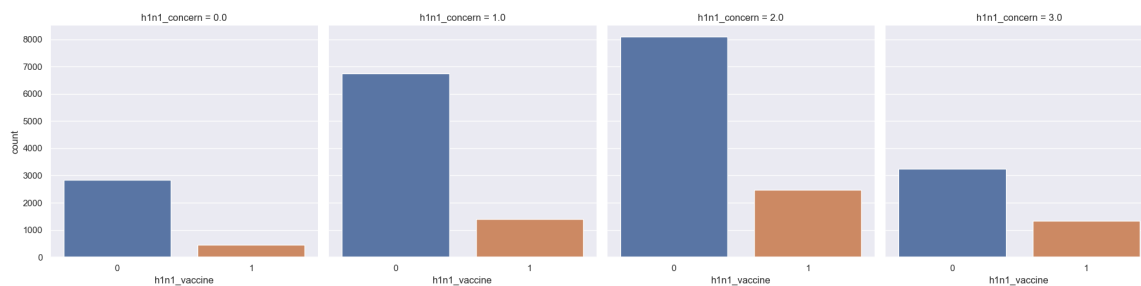
Observations:

1. Respondents opinions on flu vaccine effectiveness are strongly correlated.
2. Respondents concerns on the risk of getting sick with flu, and worries of getting sick from taking vaccine are also strongly related.
3. Level of concern of respondents about the flu shows correlations with their behavioral metrics like avoiding close contact with others having flu-like symptoms or reduing time at large gatherings.
4. People who receive doctors recommendation to take h1n1_vaccine more likely to recive the doctors recommendation to adopt seasonal_vaccine.
5. Doctors recommendation to take flu vaccines are correlated with the opinon of respondents on risks of getting sick with flu.

2.3 Analyze how feature variables are related to target variables

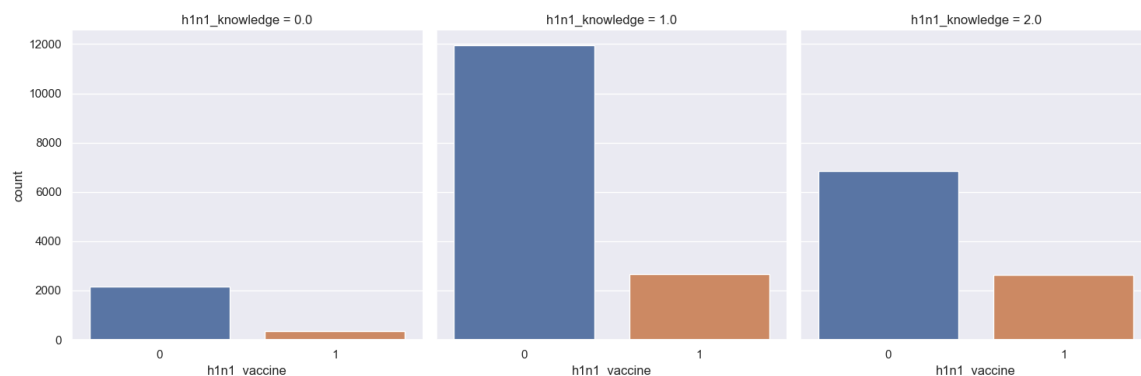
In [22]:

```
# Degree of concern about the virus  
sns.catplot(x='h1n1_vaccine', col='h1n1_concern', kind='count', data=df);
```



In [23]:

```
# Level of knowledge  
sns.catplot(x='h1n1_vaccine', col='h1n1_knowledge', kind='count', data=df);
```



In [24]:

```
# Outputs the percentage for each subgroup
def percent_plot(x, y, ax):
    df1 = df.groupby(x)[y].value_counts(normalize=True)
    df1 = df1.mul(100)
    df1 = df1.rename('percent').reset_index()

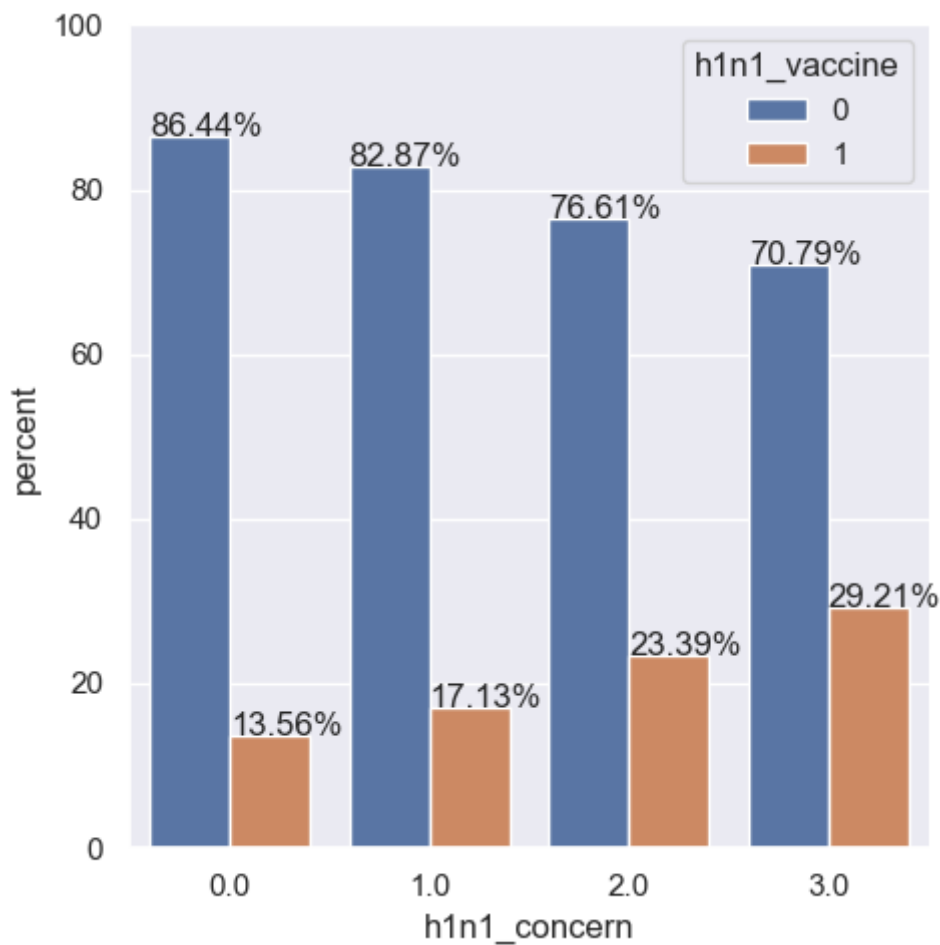
    g = sns.catplot(x=x, y='percent', hue=y, kind='bar', data=df1, legend=False, ax=ax)
    g.ax.set_ylim(0, 100)

    g.fig.get_axes()[0].legend(title=y, loc='upper right')

    for p in g.ax.patches:
        txt = str(p.get_height().round(2)) + '%'
        txt_x = p.get_x()
        txt_y = p.get_height()
        g.ax.text(txt_x, txt_y, txt)
```

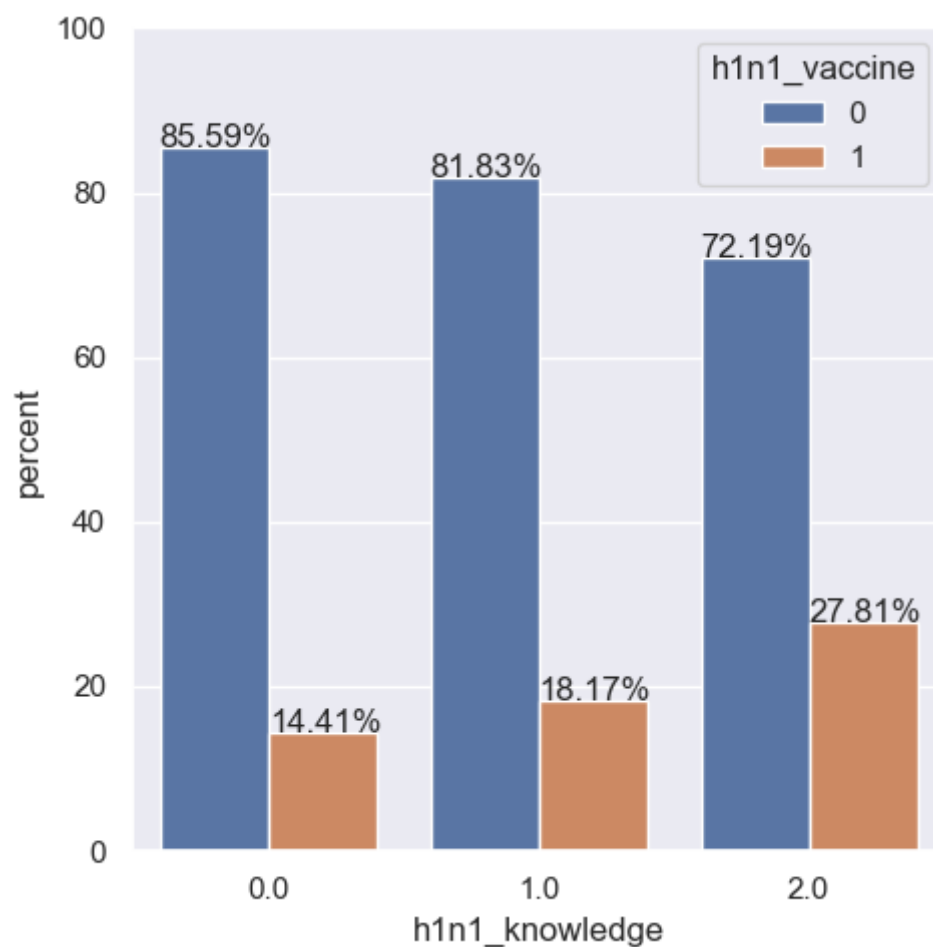
In [25]:

```
#Catplot relative to percentage within each concern level.
percent_plot('h1n1_concern', 'h1n1_vaccine', ax=None)
```



In [26]:

```
#Catplot relative to percentage within each knowledge level.  
percent_plot('h1n1_knowledge', 'h1n1_vaccine', ax=None)
```



Observations:

1. We can observe that the higher the concern for flu virus among respondents and the knowledge level about the virus, thus the greater proportion of people receive the vaccination.

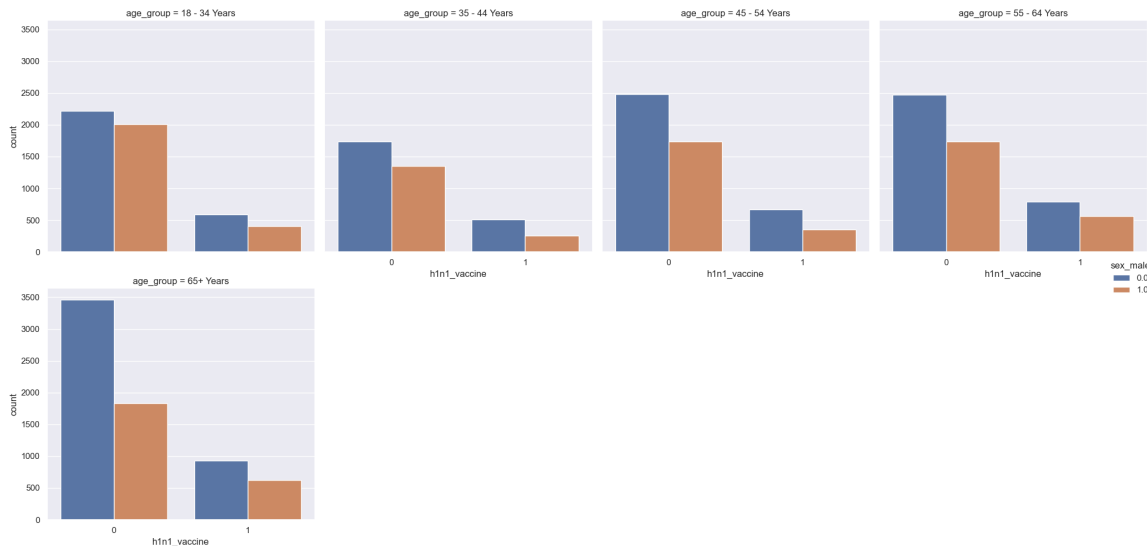
So increasing the knowledge and concern level among population is one of the ways to increase the vaccination rate.

In [27]:

```
# Analyse how vaccination numbers differ by the age and gender categories among respondents
```

```
# for h1n1_vaccine
```

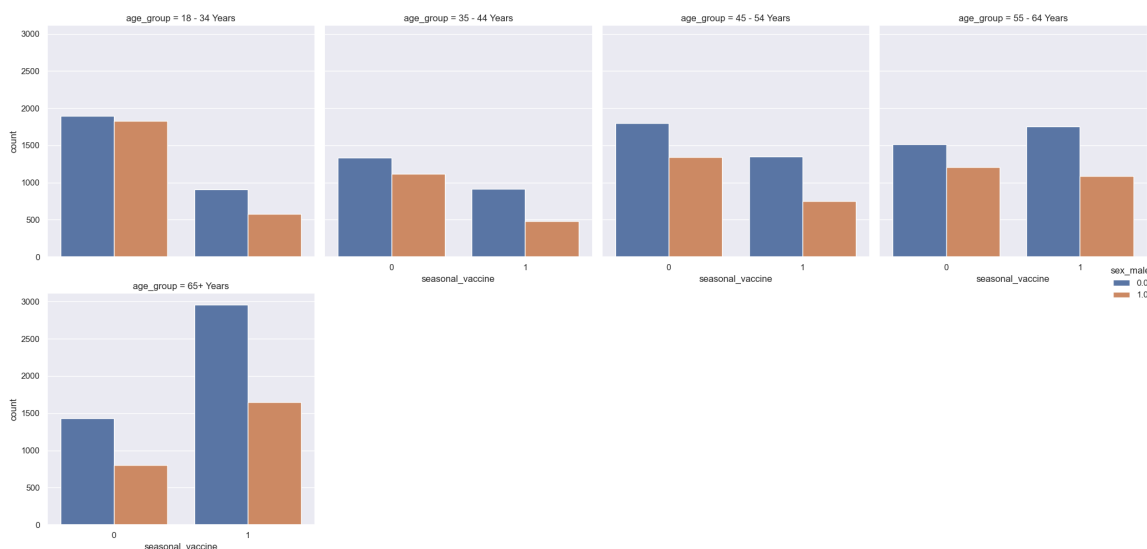
```
sns.catplot(x='h1n1_vaccine', col='age_group', col_wrap = 4, hue='sex_male', col_order = ['18 - 34 Years', '35 - 44 Years', '45 - 54 Years', '55 - 64 Years', '65+ Years'], kind='count', data=df);  
plt.show()
```



In [28]:

```
# similarly for seasonal_vaccine
```

```
sns.catplot(x='seasonal_vaccine', col='age_group', col_wrap = 4, hue='sex_male', col_order = ['18 - 34 Years', '35 - 44 Years', '45 - 54 Years', '55 - 64 Years', '65+ Years'], kind='count', data=df);  
plt.show()
```



Observations:

1. With countplot it is not clear how vaccination rates differs among various age groups.
2. Females received the flu shots (both types) more than men among different age groups.

In [29]:

```
# Plot a histogram of features variables vs target variables
def feature_target_plot(col, target, data, ax=None):
    plot = df.groupby([col])[target].value_counts(normalize=True).reset_index(name='percentage')
    g = sns.histplot(y = col , hue = target , weights= 'percentage',
                     multiple = 'stack', data=plot, shrink = 0.7, ax=ax)
    sns.move_legend(g, "lower center", bbox_to_anchor=(.5, 1), ncol=3, title_fontsize=14)

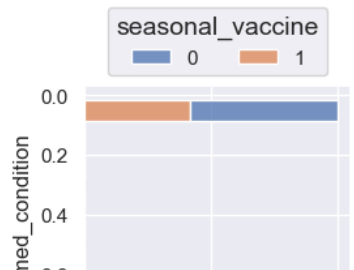
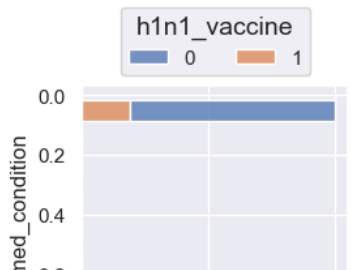
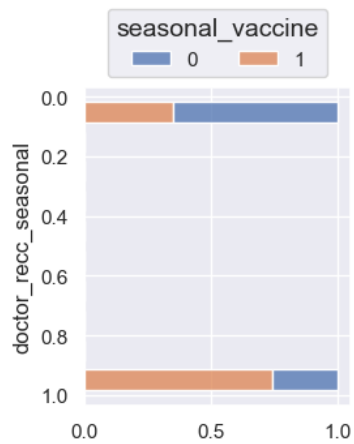
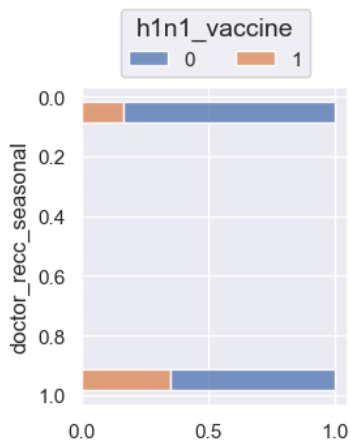
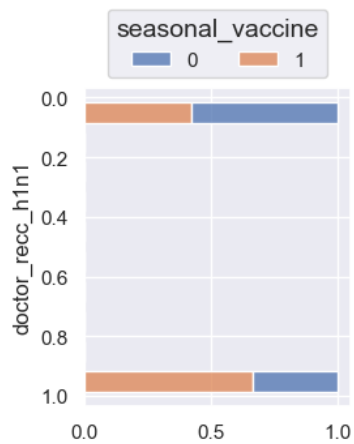
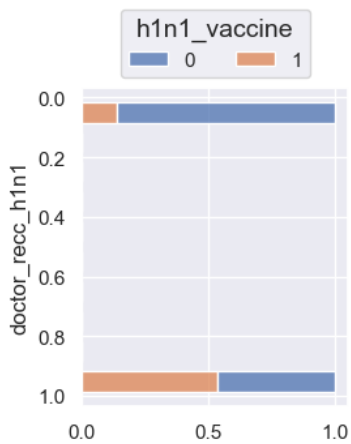
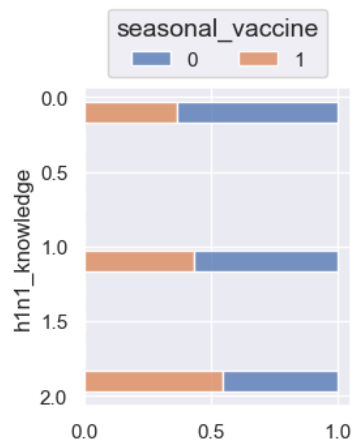
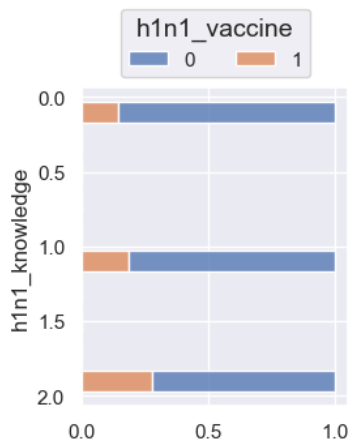
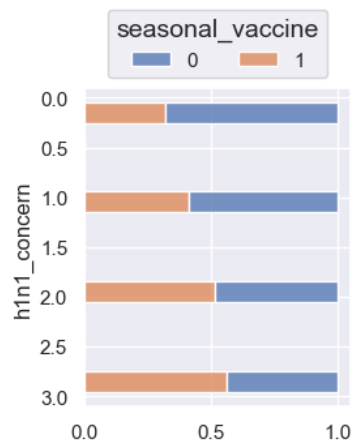
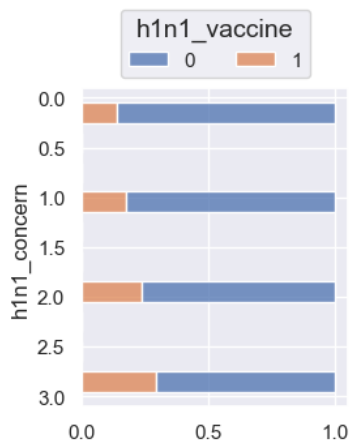
    ax.invert_yaxis()
    ax.set(xlabel=None)
```

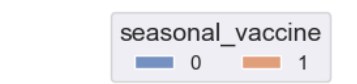
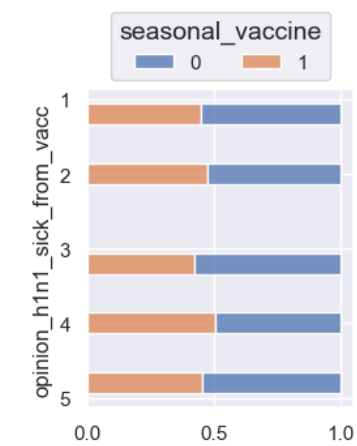
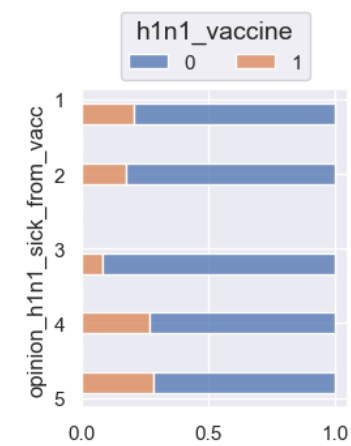
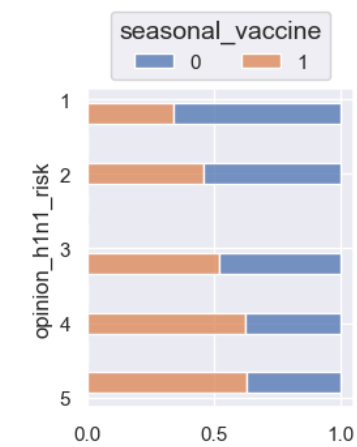
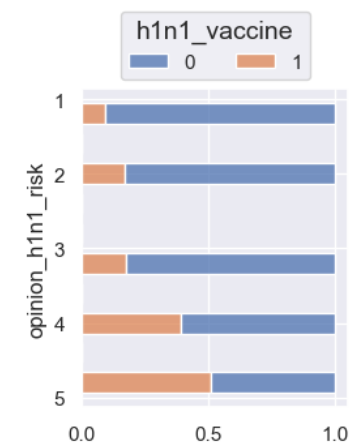
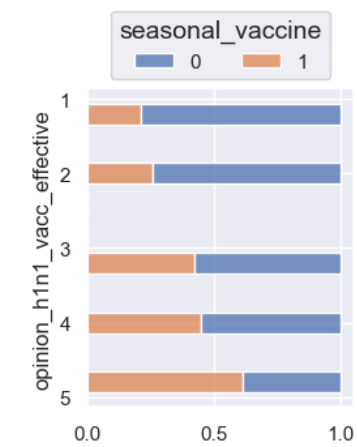
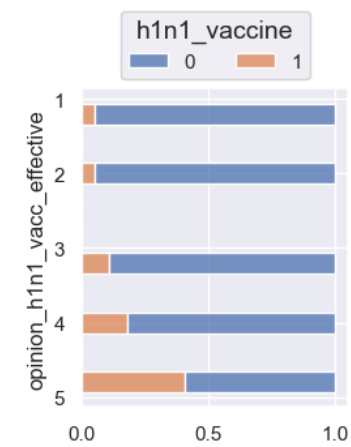
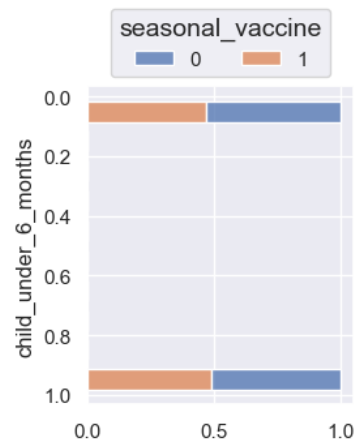
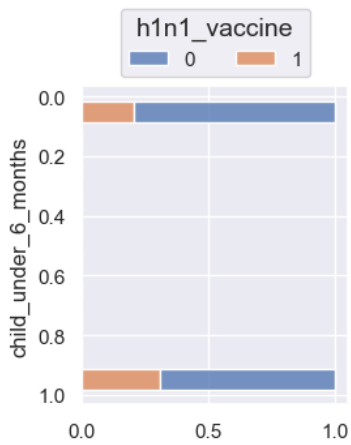
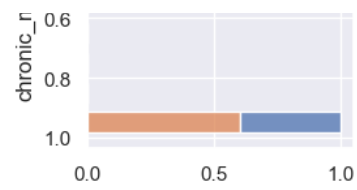
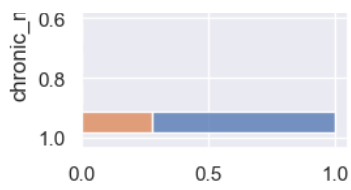
In [30]:

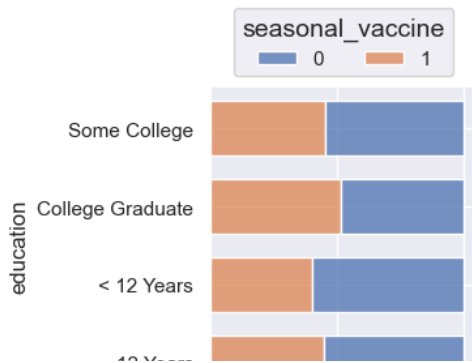
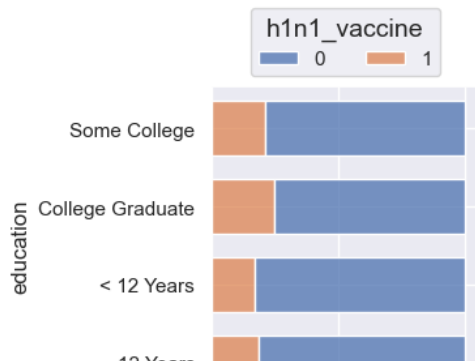
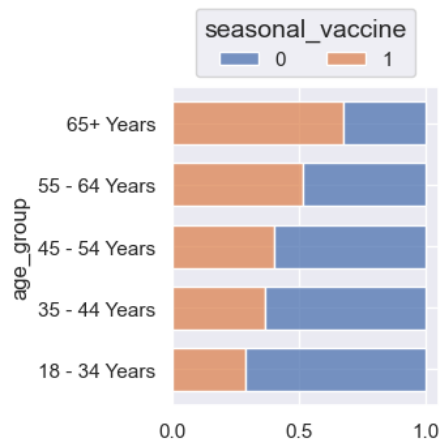
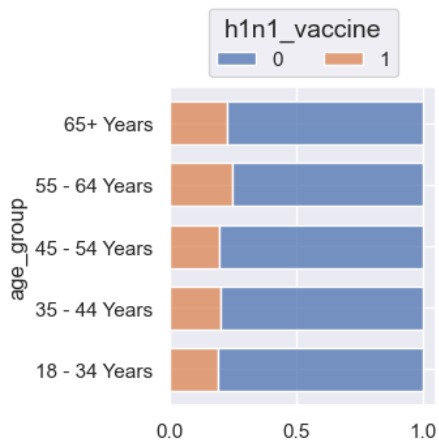
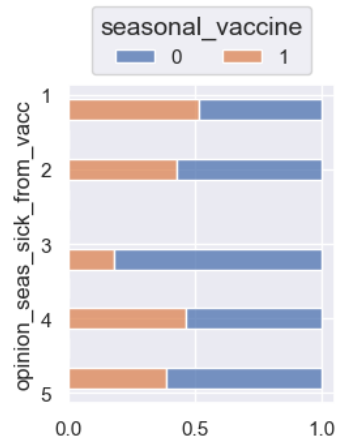
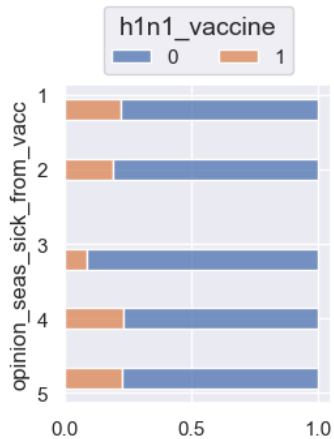
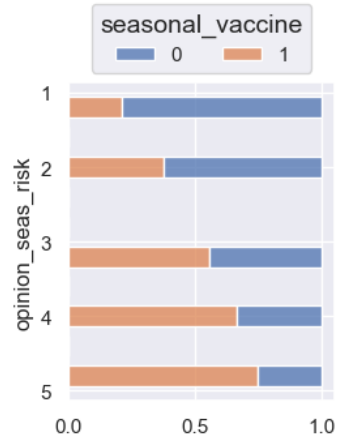
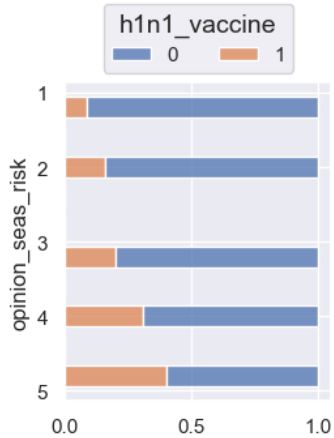
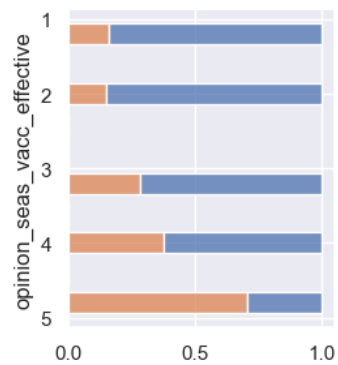
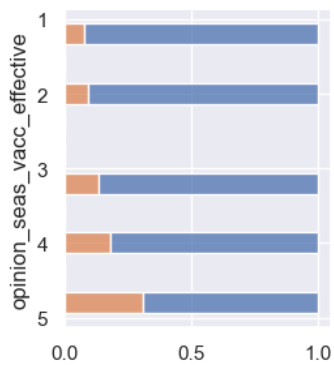
```
# Histogram plotting
cols = [ 'h1n1_concern' , 'h1n1_knowledge', 'doctor_recc_h1n1', 'doctor_recc_seasonal',
         'chronic_med_condition', 'child_under_6_months', 'opinion_h1n1_vacc_e
         ffective',
         'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc', 'opinion_seas_vac
         c_effective',
         'opinion_seas_risk', 'opinion_seas_sick_from_vacc', 'age_group', 'edu
         cation', 'health_insurance', 'health_worker',
         'income_poverty']

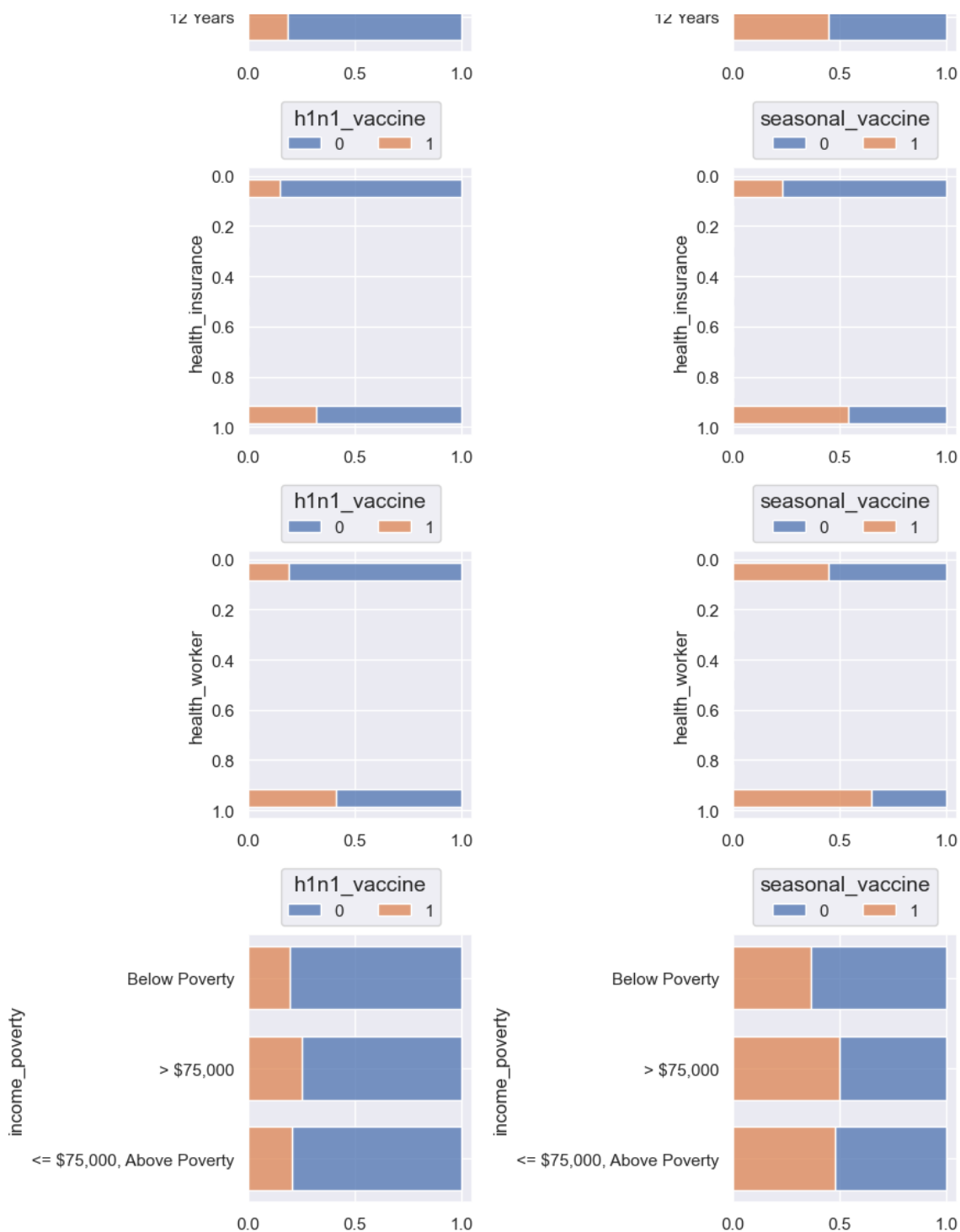
fig, ax = plt.subplots(
    len(cols), 2, figsize=(9, len(cols)*3.5))

for idx, col in enumerate(cols):
    feature_target_plot(
        col, 'h1n1_vaccine', df, ax=ax[idx, 0]
    )
    feature_target_plot(
        col, 'seasonal_vaccine', df, ax=ax[idx, 1]
    )
fig.tight_layout()
```







People are more inclined to have H1N1 and seasonal flu shot if they have:

1. Increased concern and knowledge about H1N1 flu (for both)
2. If their doctor recommended to have a vaccine shot (for both)
3. If they have chronic medical conditions (for both)
4. If they have child under 6 months (only for h1n1_vaccine)
5. Opinion on vaccine effectiveness and risk of getting sick with flu without vaccine (for both)
6. If they are in older population group (only for seasonal vaccine)
7. If they do have health insurance (for both)
8. If they are a health workers

Step 3: Models

Task description: Build a proper cross-validation procedure; select an appropriate measure of quality (the selection of both things should be motivated by your data). Choose an ML model reasonably; look for a good set of hyperparameters. Use the prepared cross-validation procedure to estimate the quality of prediction.

In []:

```
# Rename some columns to further allow XGBoost work with them
df_train = df_train.rename(columns={"education_< 12 Years": "education_less_12_years",
                                   "income_poverty_<= $75,000, Above Poverty": "income_poverty_less_75000_above_poverty",
                                   "income_poverty_> $75,000": "income_poverty_more_75000",
                                   "census_msa_MSA, Not Principle City": "census_msa_MSA_not_principle_city",
                                   "census_msa_MSA, Principle City": "census_msa_MSA_principle_city"})

df_test = df_test.rename(columns={"education_< 12 Years": "education_less_12_years",
                                  "income_poverty_<= $75,000, Above Poverty": "income_poverty_less_75000_above_poverty",
                                  "income_poverty_> $75,000": "income_poverty_more_75000",
                                  "census_msa_MSA, Not Principle City": "census_msa_MSA_not_principle_city",
                                  "census_msa_MSA, Principle City": "census_msa_MSA_principle_city"})
```

In []:

```
# Choose train, validation and test data
X = df_train
X_test = df_test
y_h1n1 = df_labels['h1n1_vaccine']
y_seas = df_labels['seasonal_vaccine']
```

In []:

```
# Split data for H1N1 and seasonal flu
X_h1n1_train, X_h1n1_val, y_h1n1_train, y_h1n1_val = train_test_split(X, y_h1n1, test_size=0.30, random_state=7, shuffle=True, stratify=y_h1n1)
X_seas_train, X_seas_val, y_seas_train, y_seas_val = train_test_split(X, y_seas, test_size=0.30, random_state=7, shuffle=True, stratify=y_seas)
```

1. Comparison of several base machine learning algorithms to find the best one

1. Logistic Regression

In []:

```
# Logistic Regression - baseline model
logistic_clf = LogisticRegression(max_iter=5000, random_state=7)
logistic_clf.fit(X_h1n1_train, y_h1n1_train)
y_pred = logistic_clf.predict_proba(X_h1n1_val)
print('H1N1 Logistic Regression ROC AUC score: {:.3}'.format(roc_auc_score(y_h1n1_val,
y_pred[:, 1])))

logistic_clf = LogisticRegression(max_iter=5000, random_state=7)
logistic_clf.fit(X_seas_train, y_seas_train)
y_pred = logistic_clf.predict_proba(X_seas_val)
print('Seasonal Logistic Regression ROC AUC score: {:.3}'.format(roc_auc_score(y_seas_v
al, y_pred[:, 1])))
```

H1N1 Logistic Regression ROC AUC score: 0.835

Seasonal Logistic Regression ROC AUC score: 0.852

In []:

```
#hyperparameters search
start = time.time()
print("H1N1 started at:", str(time.ctime(int(start))))
#
gs_h1n1 = GridSearchCV(LogisticRegression(max_iter=5000, random_state=7),
                        param_grid={'penalty' : ['l1', 'l2', 'elasticnet', 'none'],
                                     'C' : np.logspace(-2, 2, 5),
                                     'solver' : ['lbfgs', 'newton-cg', 'liblinear', 'sag', 'sag
a']},
                        cv=5, scoring = 'roc_auc', n_jobs = -1)
gs_h1n1.fit(X_h1n1_val, y_h1n1_val)

print("H1N1 ended at:", str(time.ctime(int(time.time()))))
print('Duration: {:.3}'.format((time.time() - start) / 60), 'min')

start = time.time()
print("SEASONAL started at:", str(time.ctime(int(start))))

gs_seas = GridSearchCV(LogisticRegression(max_iter=5000, random_state=7),
                        param_grid={'penalty' : ['l1', 'l2', 'elasticnet', 'none'],
                                     'C' : np.logspace(-2, 2, 5),
                                     'solver' : ['lbfgs', 'newton-cg', 'liblinear', 'sag', 'sag
a']},
                        cv=5, scoring = 'roc_auc', n_jobs = -1)
gs_seas.fit(X_seas_val, y_seas_val)

print("SEASONAL ended at:", str(time.ctime(int(time.time()))))
print('Duration: {:.3}'.format((time.time() - start) / 60), 'min')
```

H1N1 started at: Sun Oct 24 20:46:01 2021

H1N1 ended at: Sun Oct 24 20:54:45 2021

Duration: 8.74 min

SEASONAL started at: Sun Oct 24 20:54:45 2021

SEASONAL ended at: Sun Oct 24 21:16:56 2021

Duration: 22.2 min

In []:

```
print( 'Parameters for H1N1: \npenalty =', gs_h1n1.best_params_['penalty'],
', C =', gs_h1n1.best_params_['C'],
', solver =', gs_h1n1.best_params_['solver'])

print( 'Parameters for Seasonal: \npenalty =', gs_seas.best_params_['penalty'],
', C =', gs_seas.best_params_['C'],
', solver =', gs_seas.best_params_['solver'])
```

Parameters for H1N1:
penalty = l1 , C = 0.1 , solver = saga
Parameters for Seasonal:
penalty = l1 , C = 0.1 , solver = saga

In []:

```
#Scoring the performance of the model with tuned hyperparameters
logistic_clf = LogisticRegression(max_iter=5000, random_state=7, penalty='l1', C=0.1, solver='saga')
logistic_clf.fit(X_h1n1_train, y_h1n1_train)
y_h1n1_pred = logistic_clf.predict_proba(X_h1n1_val)
print('H1N1 Logistic Regression ROC AUC score: {:.3}'.format(roc_auc_score(y_h1n1_val,
y_h1n1_pred[:, 1])))

logistic_clf = LogisticRegression(max_iter=5000, random_state=7, penalty='l1', C=0.1, solver='saga')
logistic_clf.fit(X_seas_train, y_seas_train)
y_seas_pred = logistic_clf.predict_proba(X_seas_val)
print('Seasonal Logistic Regression ROC AUC score: {:.3}'.format(roc_auc_score(y_seas_val,
y_seas_pred[:, 1])))
print('Total Logistic Regression ROC AUC score: {:.3}'.format((roc_auc_score(y_seas_val,
y_seas_pred[:,1]) + roc_auc_score(y_h1n1_val, y_h1n1_pred[:,1]))/2))
```

H1N1 Logistic Regression ROC AUC score: 0.836
Seasonal Logistic Regression ROC AUC score: 0.852
Total Logistic Regression ROC AUC score: 0.844

1. K Neighbors Classifier

In []:

```
#baseline model
knn_clf = KNeighborsClassifier()
knn_clf.fit(X_h1n1_train, y_h1n1_train)
y_pred = knn_clf.predict_proba(X_h1n1_val)
print('H1N1 KNeighborsClassifier ROC AUC score: {:.3}'.format(roc_auc_score(y_h1n1_val,
y_pred[:, 1])))

knn_clf = KNeighborsClassifier()
knn_clf.fit(X_seas_train, y_seas_train)
y_pred = knn_clf.predict_proba(X_seas_val)
print('Seasonal KNeighborsClassifier ROC AUC score: {:.3}'.format(roc_auc_score(y_seas_val,
y_pred[:, 1])))
```

H1N1 KNeighborsClassifier ROC AUC score: 0.741
Seasonal KNeighborsClassifier ROC AUC score: 0.78

In []:

```
#hyperparameters search

start = time.time()
print("H1N1 started at:", str(time.ctime(int(start))))

gs_h1n1 = GridSearchCV(KNeighborsClassifier(),
                       param_grid={'n_neighbors': range(1, 200, 20),
                                    'weights': ['uniform', 'distance'],
                                    'p': range(1, 3)
                                   },
                       cv=5, scoring = 'roc_auc', n_jobs = -1)
gs_h1n1.fit(X_h1n1_val, y_h1n1_val)

print("H1N1 ended at:", str(time.ctime(int(time.time()))))
print('Duration: {:.3}'.format((time.time() - start) / 60), 'min')

start = time.time()
print("SEASONAL started at:", str(time.ctime(int(start))))

gs_seas = GridSearchCV(KNeighborsClassifier(),
                       param_grid={'n_neighbors': range(1, 200, 20),
                                    'weights': ['uniform', 'distance'],
                                    'p': range(1, 3)
                                   },
                       cv=5, scoring = 'roc_auc', n_jobs = -1)
gs_seas.fit(X_seas_val, y_seas_val)

print("SEASONAL ended at:", str(time.ctime(int(time.time()))))
print('Duration: {:.3}'.format((time.time() - start) / 60), 'min')
```

```
H1N1 started at: Sun Oct 24 21:20:38 2021
H1N1 ended at: Sun Oct 24 21:27:01 2021
Duration: 6.38 min
SEASONAL started at: Sun Oct 24 21:27:01 2021
SEASONAL ended at: Sun Oct 24 21:33:22 2021
Duration: 6.35 min
```

In []:

```
print( 'Parameters for H1N1: \nn_neighbors =', gs_h1n1.best_params_['n_neighbors'],
       'weights =', gs_h1n1.best_params_['weights'],
       'p =', gs_h1n1.best_params_['p'])

print( 'Parameters for Seasonal: \nn_neighbors =', gs_seas.best_params_['n_neighbors'],
       'weights =', gs_seas.best_params_['weights'],
       'p =', gs_seas.best_params_['p'])
```

```
Parameters for H1N1:
n_neighbors = 181 weights = distance p = 1
Parameters for Seasonal:
n_neighbors = 181 weights = distance p = 1
```


In []:

```
# Scoring the performance of the model with best parameters
knn_clf = KNeighborsClassifier(n_neighbors=181, weights='distance', p=1)
knn_clf.fit(X_h1n1_train, y_h1n1_train)
y_h1n1_pred = knn_clf.predict_proba(X_h1n1_val)
print('H1N1 KNeighborsClassifier ROC AUC score: {:.3}'.format(roc_auc_score(y_h1n1_val,
y_h1n1_pred[:, 1])))

knn_clf = KNeighborsClassifier(n_neighbors=181, weights='distance', p=1)
knn_clf.fit(X_seas_train, y_seas_train)
y_seas_pred = knn_clf.predict_proba(X_seas_val)
print('Seasonal KNeighborsClassifier ROC AUC score: {:.3}'.format(roc_auc_score(y_seas_val,
y_seas_pred[:, 1])))
print('Total KNeighborsClassifier ROC AUC score: {:.3}'.format((roc_auc_score(y_seas_val,
y_seas_pred[:, 1]) + roc_auc_score(y_h1n1_val, y_h1n1_pred[:, 1]))/2))
```

H1N1 KNeighborsClassifier ROC AUC score: 0.817
Seasonal KNeighborsClassifier ROC AUC score: 0.832
Total KNeighborsClassifier ROC AUC score: 0.824

1. Random Forest Classifier

In []:

```
# Baseline model
rndfor_clf = RandomForestClassifier(random_state=7)
rndfor_clf.fit(X_h1n1_train, y_h1n1_train)
y_h1n1_pred = rndfor_clf.predict_proba(X_h1n1_val)
print('H1N1 Random Forest ROC AUC score: {:.3}'.format(roc_auc_score(y_h1n1_val, y_h1n1
_pred[:, 1])))

rndfor_clf = RandomForestClassifier(random_state=7)
rndfor_clf.fit(X_seas_train, y_seas_train)
y_seas_pred = rndfor_clf.predict_proba(X_seas_val)
print('Seasonal flue Random Forest ROC AUC score: {:.3}'.format(roc_auc_score(y_seas_val,
y_seas_pred[:, 1])))
print('Total Random Forest ROC AUC score: {:.3}'.format((roc_auc_score(y_seas_val, y_se
as_pred[:, 1]) + roc_auc_score(y_h1n1_val, y_h1n1_pred[:, 1]))/2))
```

H1N1 Random Forest ROC AUC score: 0.826
Seasonal flue Random Forest ROC AUC score: 0.851
Total Random Forest ROC AUC score: 0.838

1. XGboost Classifier

In []:

```
# Run base XGboost classifier

xgboost_clf = XGBClassifier(eval_metric='logloss', random_state=7, use_label_encoder=False)
xgboost_clf.fit(X_h1n1_train, y_h1n1_train)
y_h1n1_pred = xgboost_clf.predict_proba(X_h1n1_val)
print('H1N1 Xgboost ROC AUC score: {:.3}'.format(roc_auc_score(y_h1n1_val, y_h1n1_pred[:,1])))

xgboost_clf = XGBClassifier(eval_metric='logloss', random_state=7, use_label_encoder=False)
xgboost_clf.fit(X_seas_train, y_seas_train)
y_seas_pred = xgboost_clf.predict_proba(X_seas_val)
print('Seasonal Xgboost ROC AUC score: {:.3}'.format(roc_auc_score(y_seas_val, y_seas_pred[:,1])))
print('Total Xgboost ROC AUC score: {:.3}'.format((roc_auc_score(y_seas_val, y_seas_pred[:,1]) + roc_auc_score(y_h1n1_val, y_h1n1_pred[:,1]))/2))
```

H1N1 Xgboost ROC AUC score: 0.836
Seasonal Xgboost ROC AUC score: 0.859
Total Xgboost ROC AUC score: 0.847

1. Catboost Regressor

In []:

```
# Run base Catboost regressor

catboost_clf = CatBoostRegressor(depth=5, random_seed=7, silent=True)
catboost_clf.fit(X_h1n1_train, y_h1n1_train)
y_h1n1_pred = catboost_clf.predict(X_h1n1_val)
```

In []:

```
print('H1N1 Catboost ROC AUC score: {:.3}'.format(roc_auc_score(y_h1n1_val, y_h1n1_pred)))
```

H1N1 Catboost ROC AUC score: 0.836

In []:

```
catboost_clf = CatBoostRegressor(depth=5, random_seed=7, silent=True)
catboost_clf.fit(X_seas_train, y_seas_train)
y_seas_pred = catboost_clf.predict(X_seas_val)
```

In []:

```
print('Seasonal flu Catboost ROC AUC score: {:.3}'.format(roc_auc_score(y_seas_val, y_seas_pred)))
print('Total score: {:.3}'.format((roc_auc_score(y_seas_val, y_seas_pred) + roc_auc_score(y_h1n1_val, y_h1n1_pred))/2))
```

Seasonal flu Catboost ROC AUC score: 0.859
Total score: 0.847

ML algorithm	H1N1	Seasonal	Total score
Logistic Regression	0.836	0.852	0.844
KNNeighbours	0.817	0.832	0.823
Random Forest	0.826	0.859	0.843
XGBoost	0.836	0.859	0.847
CatBoost	0.836	0.859	0.847

We can see the CatBoost algorithm is one of the best, so the next step is to tune this algorithm

In []:

```
# # Catboost for seasonal flu grid search
# cv = KFold(n_splits=5, shuffle=True, random_state=7)
# catboost_clf = CatBoostRegressor(random_seed=7, silent=True)

# grid = {
#     'depth': range(1, 11, 2),
#     'l2_leaf_reg': range(1, 29, 7),
#     'bagging_temperature': range(1, 1010, 100),
# }
# gs = GridSearchCV(catboost_clf, param_grid=grid, cv=cv, scoring='roc_auc')
# gs.fit(X_seas_train, y_seas_train)
# print(gs.best_estimator_)
# Best parameters: depth=5, l2_leaf_reg = 3, bagging_temperature=1, random_seed=7, silent=True
```

In []:

```
print('Total score: {:.3}'.format((roc_auc_score(y_seas_val, y_seas_pred) + roc_auc_score(y_h1n1_val, y_h1n1_pred))/2))
```

Total score: 0.847

In []:

```
# Train Catboost regressor with best parameters

# H1N1 Flu
catboost_clf = CatBoostRegressor(depth=5, l2_leaf_reg=3, bagging_temperature=1, random_seed=7, silent=True)
catboost_clf.fit(X_h1n1_train, y_h1n1_train)
y_h1n1_pred = catboost_clf.predict(X_h1n1_val)
y_h1n1_final = catboost_clf.predict(X_test) # Save best estimations

# Seasonal Flu
catboost_clf = CatBoostRegressor(depth=5, l2_leaf_reg=3, bagging_temperature=1, random_seed=7, silent=True)
catboost_clf.fit(X_seas_train, y_seas_train)
y_seas_pred = catboost_clf.predict(X_seas_val)
y_seas_final = catboost_clf.predict(X_test) # Save best estimations
```

In []:

```
print('H1N1 tuned Catboost ROC AUC score: {:.3}'.format(roc_auc_score(y_h1n1_val, y_h1n1_pred)))
print('Seasonal flu tuned Catboost ROC AUC score: {:.3}'.format(roc_auc_score(y_seas_val, y_seas_pred)))
print('Total score: {:.3}'.format((roc_auc_score(y_seas_val, y_seas_pred) + roc_auc_score(y_h1n1_val, y_h1n1_pred))/2))
```

H1N1 tuned Catboost ROC AUC score: 0.839

Seasonal flu tuned Catboost ROC AUC score: 0.86

Total score: 0.849

In []:

```
# Save predictions from the best model in the submission format

y_preds = np.transpose(np.array([id_column_test, y_h1n1_final[:,], y_seas_final[:,]]))
y_preds = pd.DataFrame(y_preds, columns = ['respondent_id', 'h1n1_vaccine', 'seasonal_vaccine'])
y_preds['respondent_id'] = y_preds['respondent_id'].astype('int32')
y_preds.set_index('respondent_id', inplace=True)
y_preds.to_csv('submission.csv')
```

Woohoo! We processed your submission!

Your score for this submission is:

0.8423