Flu Shot Learning: Predicting Seasonal Flu Vaccines

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title

Business Problem

As the COVID-19 virus has spread throughout the world. Countries across the world are working to inoculate their populations and protect against future outbreaks. It is essential to know which populations are at risk of not receiving the vaccines. This information would help public health organizations optimally target their resources to informing and educating individuals about the immunizations.

At this stage of the COVID-19 pandemic, new variants has led to a large number of 'break through' cases. Public health officials have stated the best defense against new strains is to get vaccinated and take the recommended booster shots to greatly decrease the risk of hospitalization.

While we don't know what will ultimately unfold, it is likely that we will need to get regular 'booster' shots to protect us from future variants of the virus, much like the seasonal flu vaccine. If we can learn what factors into an individual's choice to receive the seasonal flu vaccine, we can help governments inoculate their constituents.

OBTAIN

A vaccine for the H1N1 flu virus became publicly available in October 2009. In late 2009 and early 2010, the United States conducted the National 2009 H1N1 Flu Survey. This phone survey asked respondents whether they had received the H1N1 and seasonal flu vaccines, in conjunction with questions about themselves. These additional questions covered their social, economic, and demographic background, opinions on risks of illness and vaccine effectiveness, and behaviors towards mitigating transmission. A better understanding of how these characteristics are associated with personal vaccination patterns can provide guidance for future public health efforts.

We will be using a dataset from Data Driven competition (drivendata.org/competitions/66/flu-shot-learning/data/) that contains data provided courtesy of the United States National Center for Health Statistics, U.S. Department of Health and Human Services (DHHS), National Center for Health Statistics and the National 2009 H1N1 Flu Survey.

The dataset includes approximately 26,707 survey responses relating to the H1N1 and seasonal flu to train various machine learning algorithms in order to predict how likely an individual is to receive a vaccine.

Imports

In [1]:
```
## Data Handling
import pandas as pd
pd.set_option('display.max_columns', None)
import numpy as np
from random import randint

## Data Visualizations
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

## Settings
from IPython.display import display
%matplotlib inline
sns.set_style("darkgrid")
pd.set_option('display.max_columns', None)
pd.set_option('display.float_format', lambda x: f'{x:,.2f}')
pd.set_option('max_rows', 100)
import warnings
warnings.filterwarnings('ignore')

## Scikit-Learn
from sklearn.compose import ColumnTransformer
from sklearn.dummy import DummyClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.impute import SimpleImputer
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.compose import ColumnTransformer, make_column_transformer
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSe
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler, L
from sklearn.pipeline import Pipeline
from sklearn import metrics
from sklearn.multioutput import ClassifierChain
from sklearn.impute import KNNImputer
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score, plot_confusion_matrix, cla
from sklearn.feature_selection import SelectFromModel
```

```
from sklearn.svm import LinearSVC

from sklearn import set_config
set_config(display='diagram')

import missingno
```

In [2]:
```
# Data Source
# https://www.drivendata.org/competitions/66/flu- -learning/data/
```

In [3]:
```
## Reading csv data and loading into a DataFrame

features_df = pd.read_csv('data/training_set_features.csv',index_col=0)
features_df
```

Out[3]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance
respondent_id				
0	1.00	0.00	0.00	0.00
1	3.00	2.00	0.00	1.00
2	1.00	1.00	0.00	1.00
3	1.00	1.00	0.00	1.00
4	2.00	1.00	0.00	1.00
...	...	...	...	...
26702	2.00	0.00	0.00	1.00
26703	1.00	2.00	0.00	1.00
26704	2.00	2.00	0.00	1.00
26705	1.00	1.00	0.00	0.00
26706	0.00	0.00	0.00	1.00

26707 rows × 35 columns

In [6]:
```
labels_df = pd.read_csv('data/training_set_labels.csv',index_col=0)
seas_labels_df = labels_df.drop('h1n1_vaccine',axis=1)
seas_labels_df
```

Out[6]:

	seasonal_vaccine
respondent_id	
0	0

	seasonal_vaccine
respondent_id	
1	1
2	0
3	1
4	0
...	...
26702	0
26703	0
26704	1
26705	0
26706	0

26707 rows × 1 columns

In [7]:
```
# Confirming features and the labels rows match up.
np.testing.assert_array_equal(features_df.index.values, labels_df.index.values)
```

The assertion ran without an error, indicating the features and labels line up correctly.

In [8]:
```
# Joining Features and Labels Dataframes
joined_df = features_df.join(labels_df)
joined_df
```

Out[8]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance
respondent_id				
0	1.00	0.00	0.00	0.00
1	3.00	2.00	0.00	1.00
2	1.00	1.00	0.00	1.00
3	1.00	1.00	0.00	1.00
4	2.00	1.00	0.00	1.00
...	...	...	...	...
26702	2.00	0.00	0.00	1.00
26703	1.00	2.00	0.00	1.00
26704	2.00	2.00	0.00	1.00

respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance
26705	1.00	1.00	0.00	0.00
26706	0.00	0.00	0.00	1.00

26707 rows × 37 columns

The raw dataset contains 29 features, 1 target, and 26,707 instances.

In [10]:
```
# Dropping Features Specific to H1N1
seas_feats_df =features_df.drop(columns=['h1n1_concern','h1n1_knowledge','doctor
                   'opinion_h1n1_vacc_effective','opinion_h1n1_risk',
                   'opinion_h1n1_sick_from_vacc'],axis=1)
```

In [12]:
```
# Joining Seasonal Vaccine Features and Seasonal Label Dataframes
seas_joined_df = seas_feats_df.join(seas_labels_df)
seas_joined_df
```

Out[12]:

respondent_id	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral
0	0.00	0.00	0.00	
1	0.00	1.00	0.00	
2	0.00	1.00	0.00	
3	0.00	1.00	0.00	
4	0.00	1.00	0.00	
...	...	...	...	
26702	0.00	1.00	0.00	
26703	0.00	1.00	0.00	
26704	0.00	1.00	1.00	
26705	0.00	0.00	0.00	
26706	0.00	1.00	0.00	

26707 rows × 30 columns

Data Glossary

behavioral_antiviral_meds - Has taken antiviral medications. (binary)

behavioral_avoidance - Has avoided close contact with others with flu-like symptoms. (binary)

behavioral_face_mask - Has bought a face mask. (binary)

behavioral_wash_hands - Has frequently washed hands or used hand sanitizer. (binary)

behavioral_large_gatherings - Has reduced time at large gatherings. (binary)

behavioral_outside_home - Has reduced contact with people outside of own household. (binary)

behavioral_touch_face - Has avoided touching eyes, nose, or mouth. (binary)

doctor_recc_h1n1 - H1N1 flu vaccine was recommended by doctor. (binary)

doctor_recc_seasonal - Seasonal flu vaccine was recommended by doctor. (binary)

chronic_med_condition - Has any of the following chronic medical conditions: asthma or an other lung condition, diabetes, a heart condition, a kidney condition, sickle cell anemia or other anemia, a neurological or neuromuscular condition, a liver condition, or a weakened immune system caused by a chronic illness or by medicines taken for a chronic illness. (binary)

child_under_6_months - Has regular close contact with a child under the age of six months. (binary)

health_worker - Is a healthcare worker. (binary)

health_insurance - Has health insurance. (binary)

opinion_seas_vacc_effective - Respondent's opinion about seasonal flu vaccine effectiveness.\ 1 = Not at all effective; 2 = Not very effective; 3 = Don't know; 4 = Somewhat effective; 5 = Very effective.

opinion_seas_risk - Respondent's opinion about risk of getting sick with seasonal flu without vaccine.\ 1 = Very Low; 2 = Somewhat low; 3 = Don't know; 4 = Somewhat high; 5 = Very high.

opinion_seas_sick_from_vacc - Respondent's worry of getting sick from taking seasonal flu vaccine.\ 1 = Not at all worried; 2 = Not very worried; 3 = Don't know; 4 = Somewhat worried; 5 = Very worried.

age_group - Age group of respondent.

education - Self-reported education level.

race - Race of respondent.

sex - Sex of respondent.

income_poverty - Household annual income of respondent with respect to 2008 Census poverty thresholds.

marital_status - Marital status of respondent.

rent_or_own - Housing situation of respondent.

employment_status - Employment status of respondent.

hhs_geo_region - Respondent's residence using a 10-region geographic classification defined by the U.S. Dept. of Health and Human Services. Values are represented as short random character strings.

census_msa - Respondent's residence within metropolitan statistical areas (MSA) as defined by the U.S. Census.

household_adults - Number of other adults in household, top-coded to 3.

household_children - Number of children in household, top-coded to 3.

employment_industry - Type of industry respondent is employed in. Values are represented as short random character strings.

employment_occupation - Type of occupation of respondent. Values are represented as short random character strings.

In [13]:
```
seas_feats_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 29 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   behavioral_antiviral_meds    26636 non-null  float64
 1   behavioral_avoidance         26499 non-null  float64
 2   behavioral_face_mask         26688 non-null  float64
 3   behavioral_wash_hands        26665 non-null  float64
 4   behavioral_large_gatherings  26620 non-null  float64
 5   behavioral_outside_home      26625 non-null  float64
 6   behavioral_touch_face        26579 non-null  float64
 7   doctor_recc_seasonal         24547 non-null  float64
 8   chronic_med_condition        25736 non-null  float64
 9   child_under_6_months         25887 non-null  float64
 10  health_worker                25903 non-null  float64
 11  health_insurance             14433 non-null  float64
 12  opinion_seas_vacc_effective  26245 non-null  float64
 13  opinion_seas_risk            26193 non-null  float64
 14  opinion_seas_sick_from_vacc  26170 non-null  float64
 15  age_group                    26707 non-null  object 
 16  education                    25300 non-null  object 
 17  race                         26707 non-null  object 
 18  sex                          26707 non-null  object 
 19  income_poverty               22284 non-null  object 
 20  marital_status               25299 non-null  object 
 21  rent_or_own                  24665 non-null  object 
 22  employment_status            25244 non-null  object 
 23  hhs_geo_region               26707 non-null  object 
 24  census_msa                   26707 non-null  object 
```

```
 25  household_adults            26458 non-null  float64
 26  household_children          26458 non-null  float64
 27  employment_industry         13377 non-null  object
 28  employment_occupation       13237 non-null  object
dtypes: float64(17), object(12)
memory usage: 7.4+ MB
```

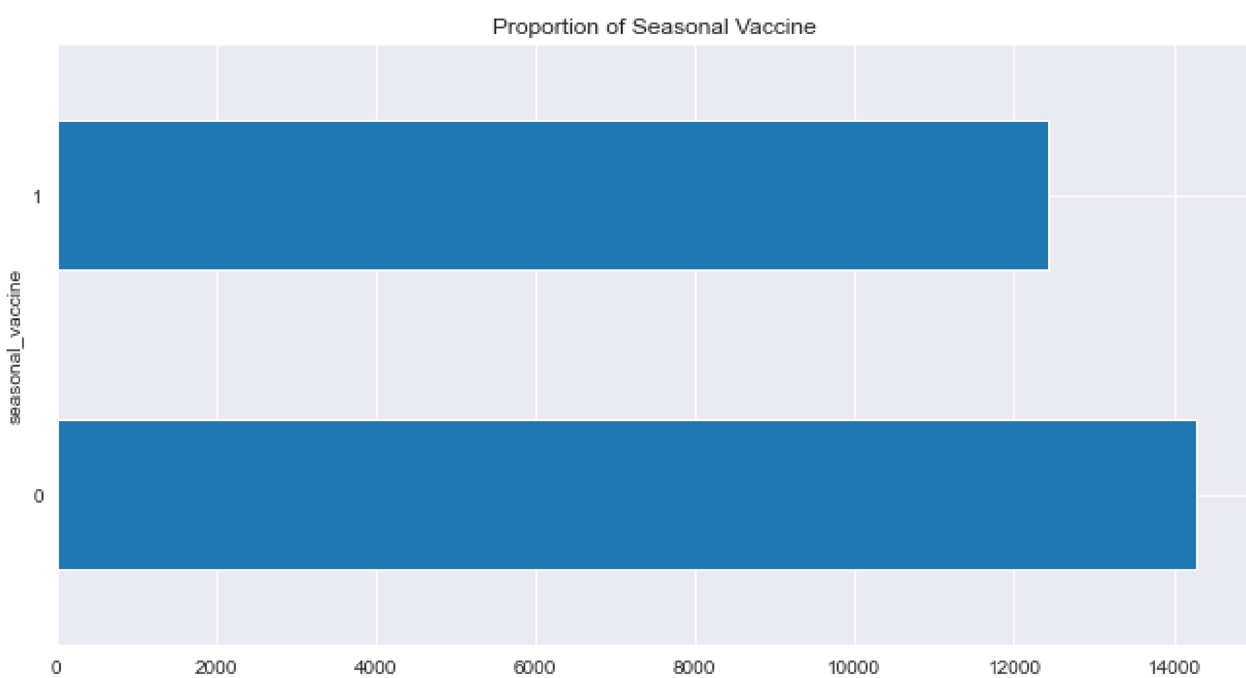
Most of the data fields are stored as floats. Confirming with the data glossary, some fields are actually binary or ordinal categories. The other data fields are stored as objects but most are also able to be encoded into ordinal and nominal categorical variables.

In [14]:
```
print(seas_labels_df['seasonal_vaccine'].value_counts(dropna=False))
```

```
0    14272
1    12435
Name: seasonal_vaccine, dtype: int64
```

Looks like there are target responses for every record in the dataset which is great. We won't have to drop any rows. See target proportions visualized below.

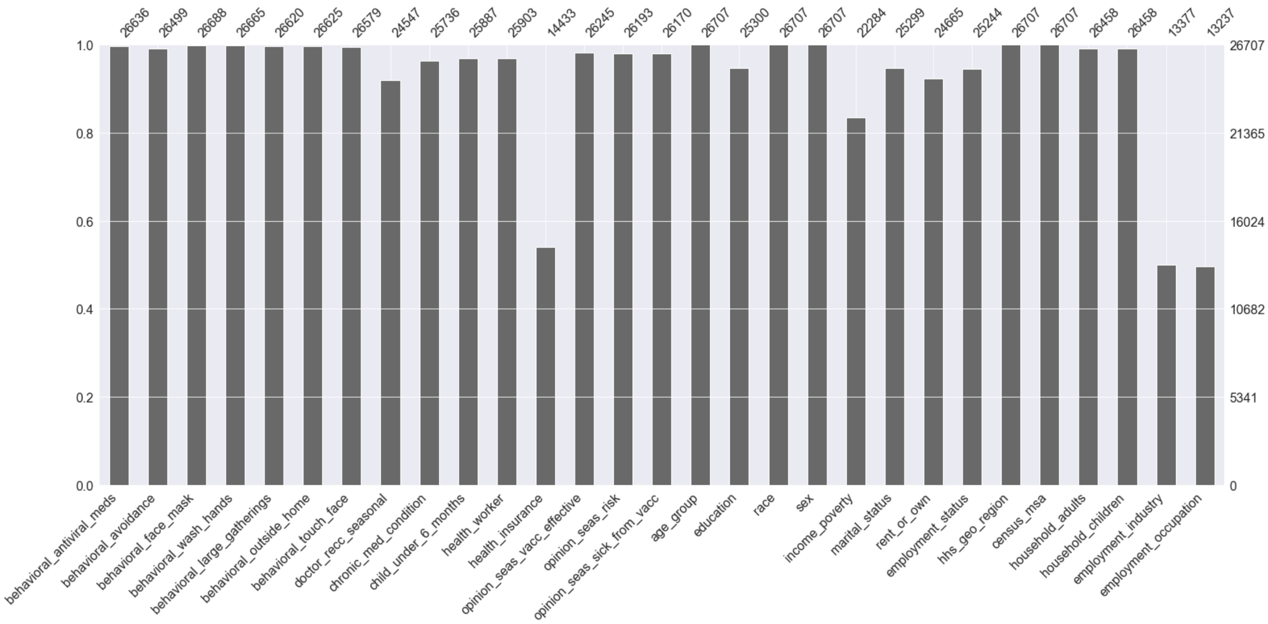
In [15]:
```
fig, ax = plt.subplots(figsize=(9.2, 5))

n_obs = labels_df.shape

(seas_labels_df['seasonal_vaccine']
    .value_counts()
    .plot.barh(title="Proportion of Seasonal Vaccine", ax=ax)
)
ax.set_ylabel("seasonal_vaccine")

fig.tight_layout()
```



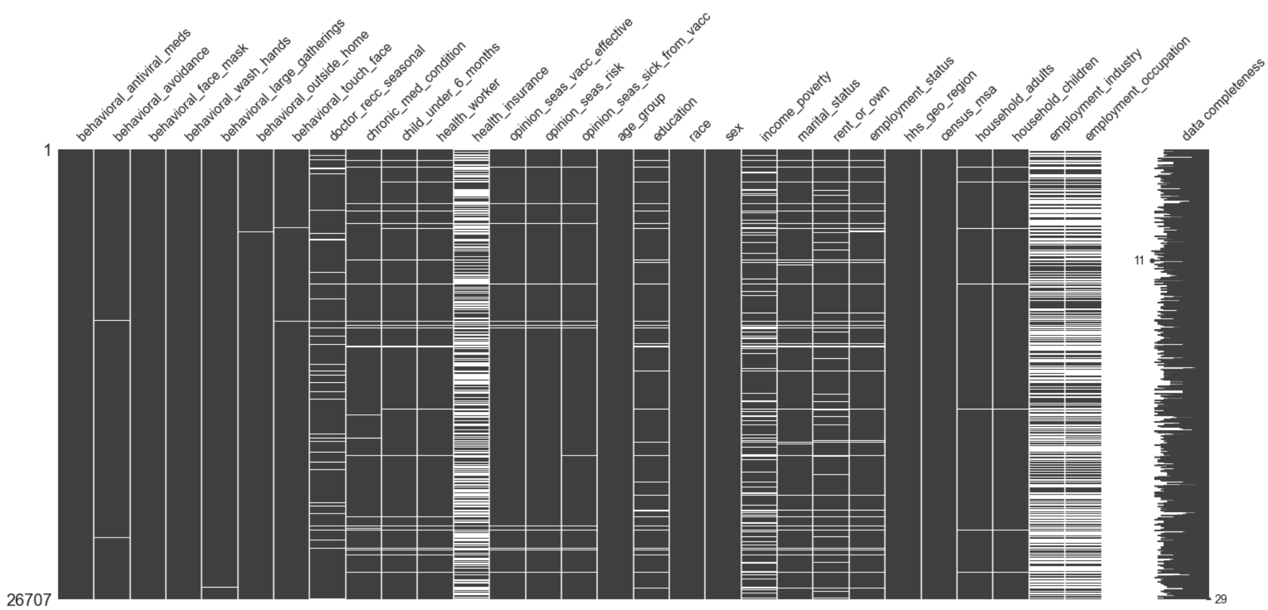
SCRUB

Often times with survey collected data, there are some going to be missing responses. In order to process the data, each field will need to be evaluated to determine how missing values should be treated.

In [16]:
```
missingno.bar(seas_feats_df);
```



In [17]:
```
missingno.matrix(seas_feats_df, labels=True);
```



After inspecting the visualization, it is evident that the features missing the most responses are health insurance and employment details. Since these are categorical variables, we can create a new category and impute for the missing values.

Instead of performing any manual updates to the remaining values, I will test different imputation methods as part of my modeling pipeline. </br></br> Potential methods would include:

Imputing the string "MISSING" Imputing the most frequent value for string values Using the mean, median, or mode for numeric datatypes The benefit of including this step in a pipeline is that I will be able to include these different methods in a GridSearchCV as part of my hyperparameter turning steps.

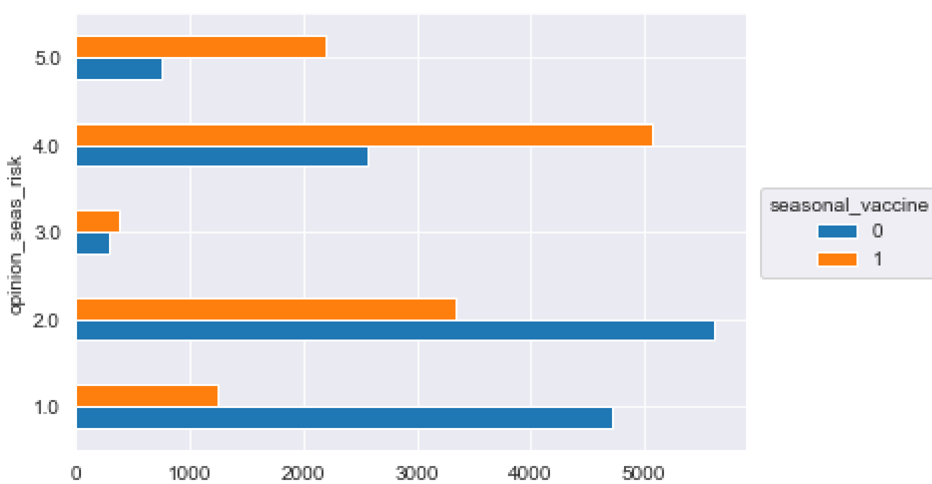
EXPLORE

In [18]:
```
counts = (joined_df[['opinion_seas_risk', 'seasonal_vaccine']]
              .groupby(['opinion_seas_risk', 'seasonal_vaccine'])
              .size()
              .unstack('seasonal_vaccine')
         )
counts
```

Out[18]:

seasonal_vaccine	0	1
opinion_seas_risk		
1.00	4723	1251
2.00	5613	3341
3.00	300	377
4.00	2568	5062
5.00	755	2203

In [19]:
```
ax = counts.plot.barh()
ax.legend(
    loc='center right',
    bbox_to_anchor=(1.3, 0.5),
    title='seasonal_vaccine'
);
```



In [20]:
```
seasonal_concern_counts = counts.sum(axis='columns')
seasonal_concern_counts
```

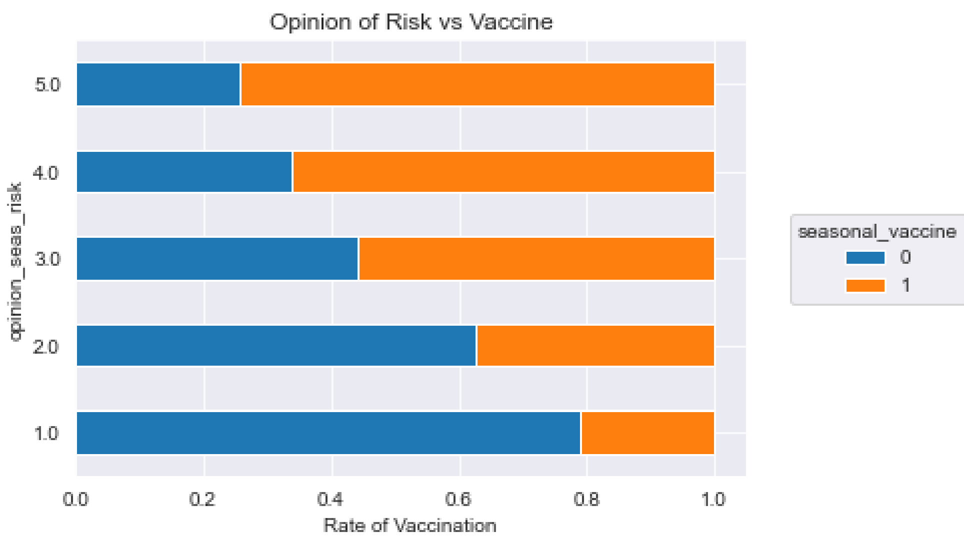
Out[20]:
```
opinion_seas_risk
1.00    5974
2.00    8954
3.00     677
4.00    7630
5.00    2958
dtype: int64
```

In [21]:
```
props = counts.div(seasonal_concern_counts, axis='index')
props
```

Out[21]:

seasonal_vaccine	0	1
opinion_seas_risk		
1.00	0.79	0.21
2.00	0.63	0.37
3.00	0.44	0.56
4.00	0.34	0.66
5.00	0.26	0.74

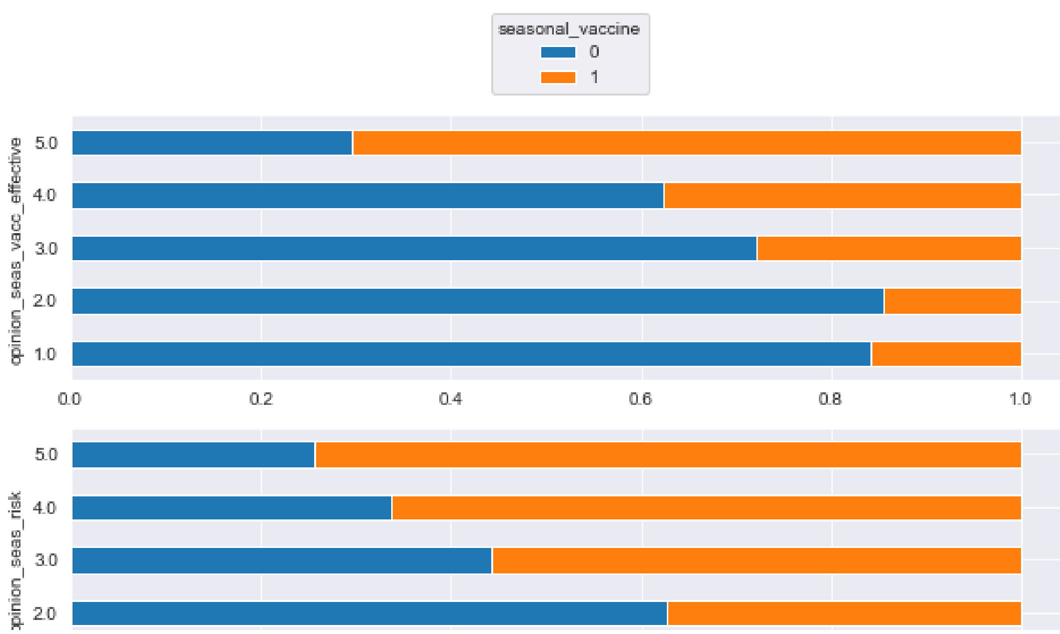
In [22]:
```
# Prototyping Stack Barh plot
ax = props.plot.barh(stacked=True)
ax.set_title('Opinion of Risk vs Vaccine')
ax.set_xlabel('Rate of Vaccination')
ax.legend(
    loc='center left',
    bbox_to_anchor=(1.05, 0.5),
    title='seasonal_vaccine'
);
```

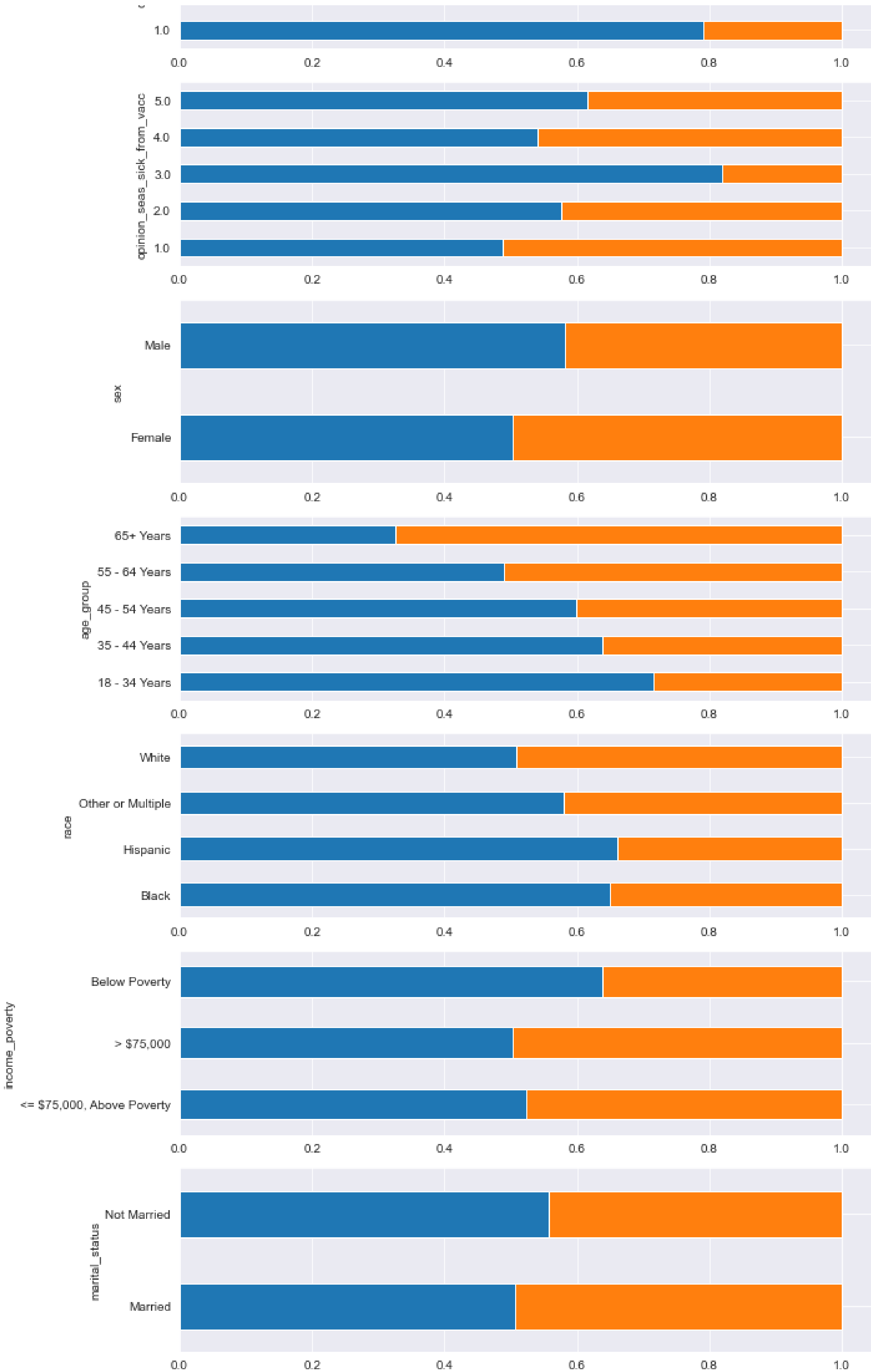


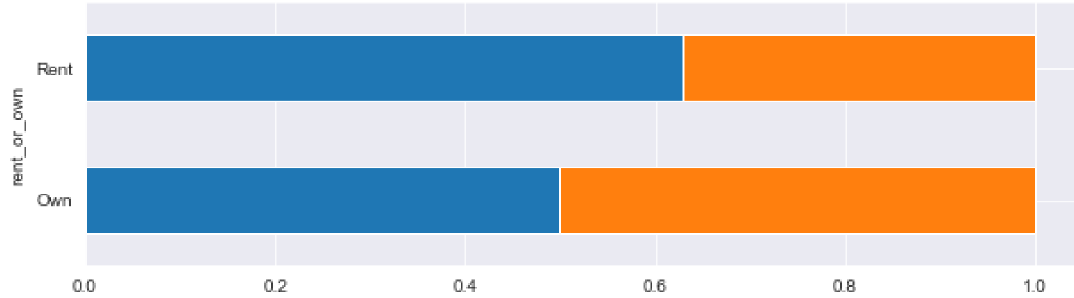
In [23]:
```
def vaccination_rate_plot(col, target, data, ax=None):
    """Stacked bar chart of vaccination rate for `target` against
    `col`.

    Args:
        col (string): column name of feature variable
        target (string): column name of target variable
        data (pandas DataFrame): dataframe that contains columns
            `col` and `target`
        ax (matplotlib axes object, optional): matplotlib axes
            object to attach plot to
    """
    counts = (joined_df[[target, col]]
                  .groupby([target, col])
                  .size()
```

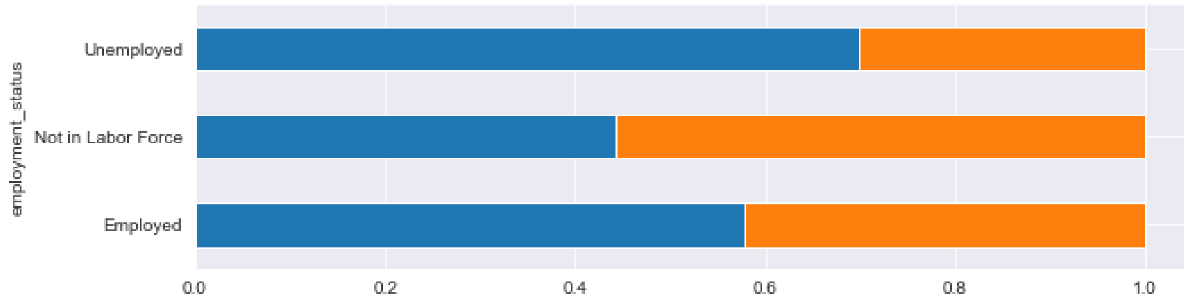
```
                .unstack(target)
            )
    group_counts = counts.sum(axis='columns')
    props = counts.div(group_counts, axis='index')

    props.plot(kind="barh", stacked=True, ax=ax)

    ax.legend().remove()
```

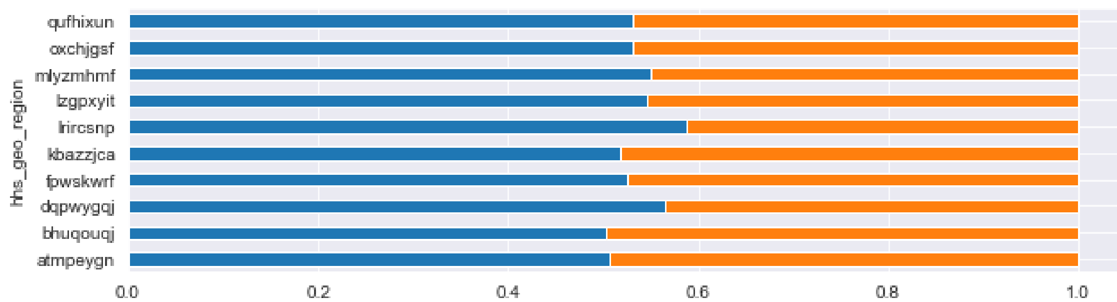
In [25]:
```
# Loop through several columns and plot against both h1n1_vaccine and seasonal_v

cols_to_plot = [
    'opinion_seas_vacc_effective',
    'opinion_seas_risk',
    'opinion_seas_sick_from_vacc',
    'sex',
    'age_group',
    'race',
    'income_poverty',
    'marital_status',
    'rent_or_own',
    'employment_status',
    'hhs_geo_region',
    'census_msa',
]

fig, ax = plt.subplots(
    len(cols_to_plot), figsize=(10,len(cols_to_plot)*2.5)
)
for idx, col in enumerate(cols_to_plot):

    vaccination_rate_plot(
        col, 'seasonal_vaccine', joined_df, ax=ax[idx]
    )


ax[0].legend(
    loc='lower center', bbox_to_anchor=(0.5, 1.05), title='seasonal_vaccine'
)
fig.tight_layout()
```

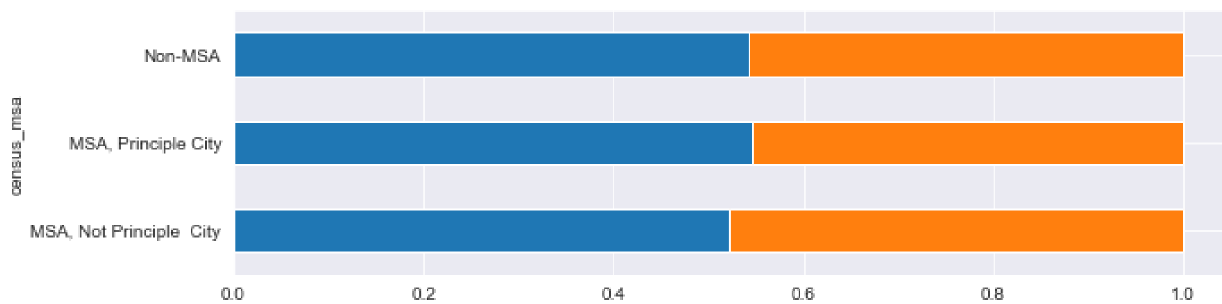



1.0
0.0
0.2
0.4
0.6
0.8
1.0
opinion_seas_sick_from_vacc
5.0
4.0
3.0
2.0
1.0
sex
Male
Female
age_group
65+ Years
55 - 64 Years
45 - 54 Years
35 - 44 Years
18 - 34 Years
race
White
Other or Multiple
Hispanic
Black
income_poverty
Below Poverty
> $75,000
<= $75,000, Above Poverty
marital_status
Not Married
Married









After investigating the relationship among each feature and the target, a few columns stood out. First, the older someone is, the more likely they are to receive the vaccine. This is backed up by those not in the workforce having a higher likelihood of getting the shot than those employed and unemployed. Which is because most retired people are older.

Also, the more someone is concerned about getting sick and the more effective they believe a vaccine to be, the more likely that are to get vaccinated.

MODEL

Preprocessing

Perform Train-Test-Split

In [26]:
```
X_train, X_test, y_train, y_test = train_test_split(
```

```
    seas_feats_df,
    seas_labels_df,
    test_size =.25,
    random_state=42
)

X_train.head()
```

Out[26]:

	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral
respondent_id				
25194	0.00	0.00	0.00	
14006	0.00	1.00	0.00	
11285	0.00	0.00	0.00	
2900	0.00	0.00	0.00	
19083	1.00	1.00	0.00	

In [27]:

```
y_train['seasonal_vaccine'].value_counts(normalize=True)
```

Out[27]:

```
0    0.53
1    0.47
Name: seasonal_vaccine, dtype: float64
```

In [28]:

```
y_test['seasonal_vaccine'].value_counts(normalize=True)
```

Out[28]:

```
0    0.54
1    0.46
Name: seasonal_vaccine, dtype: float64
```

Impute Missing Values, Scaling and Encoding Pipelines

There are two important data preprocessing steps before jumping to the logistic regression:

Scaling: Transform all features to be on the same scale. This matters when using regularization, which we will discuss in the next section. We will use StandardScaler, also known as Z-score scaling. This scales and shifts features so that they have zero mean and unit variance. NA Imputation: Logistic regression does not handle NA values. We will use median imputation, which fills missing values with the median from the training data, implemented with SimpleImputer.

In [89]:

```
# Copying the train test split
X_train_tf = X_train.copy()
X_test_tf = X_test.copy()
```

In [90]:

```
# Breaking out numerical and categorical columns to determine which
# columns need to be sclaed and which need to be encoded.
#  make cat_cols and num_cols
cat_cols = X_train_tf.select_dtypes('O').columns.tolist()
```

```
num_cols = X_train_tf.select_dtypes('number').columns.tolist()
num_cols,cat_cols
```

Out[90]:
```
(['behavioral_antiviral_meds',
  'behavioral_avoidance',
  'behavioral_face_mask',
  'behavioral_wash_hands',
  'behavioral_large_gatherings',
  'behavioral_outside_home',
  'behavioral_touch_face',
  'doctor_recc_seasonal',
  'chronic_med_condition',
  'child_under_6_months',
  'health_worker',
  'health_insurance',
  'opinion_seas_vacc_effective',
  'opinion_seas_risk',
  'opinion_seas_sick_from_vacc',
  'household_adults',
  'household_children'],
 ['age_group',
  'education',
  'race',
  'sex',
  'income_poverty',
  'marital_status',
  'rent_or_own',
  'employment_status',
  'hhs_geo_region',
  'census_msa',
  'employment_industry',
  'employment_occupation'])
```

Numerical Columns

In [91]:
```
# Create a transformer pipeline that will impute missing values using the
# median and then standardize all numerical columns

num_tf = Pipeline(steps=[
    ('imputer',SimpleImputer(strategy='median')),
    ('scaler',StandardScaler())])
```

In [92]:
```
X_train_num_tf = num_tf.fit_transform(X_train[num_cols])
X_test_num_tf = num_tf.transform(X_test[num_cols])
X_train_num_tf
```

Out[92]:
```
array([[-0.22644649, -1.62924603, -0.27402537, ..., -0.08933262,
         0.15110623,  0.50597212],
       [-0.22644649,  0.61378084, -0.27402537, ...,  1.42512566,
         1.48974303,  0.50597212],
       [-0.22644649, -1.62924603, -0.27402537, ..., -0.84656177,
        -1.18753056,  0.50597212],
       ...,
       [-0.22644649,  0.61378084, -0.27402537, ..., -0.08933262,
         0.15110623, -0.57309747],
       [-0.22644649,  0.61378084, -0.27402537, ...,  1.42512566,
         0.15110623, -0.57309747],
       [-0.22644649, -1.62924603, -0.27402537, ..., -0.08933262,
        -1.18753056, -0.57309747]])
```

Categorical Columns

In [93]:
```
# Create a transformer pipeline that will impute missing values using a
```

```python
# constany placeholder 'Unknown' and then OneHotEncode all numerical columns

cat_tf = Pipeline(steps=[
    ('imputer',SimpleImputer(strategy='constant',fill_value='Unknown')),
    ('ohe',OneHotEncoder(sparse=False,handle_unknown='ignore'))])
```

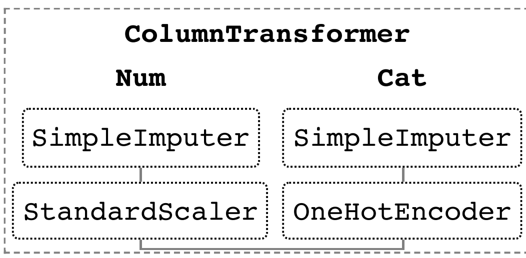
In [94]:
```python
X_train_cat_tf =cat_tf.fit_transform(X_train[cat_cols])
X_test_cat_tf =cat_tf.transform(X_test[cat_cols])

X_train_cat_tf
```

Out[94]:
```
array([[1., 0., 0., ..., 0., 0., 0.],
       [0., 0., 1., ..., 0., 0., 0.],
       [0., 0., 1., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 1., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 0.]])
```

Combining together with ColumnTransformer

In [95]:
```python
# Join both numerical and categorical Pipelines using ColumnTransformer
preprocessor = ColumnTransformer(transformers=[
    ('Num',num_tf,num_cols),
    ('Cat',cat_tf,cat_cols)])
preprocessor
```

Out[95]:



In [96]:
```python
## Get X_train and X_test from column transformer
X_train_tf = preprocessor.fit_transform(X_train)
X_test_tf = preprocessor.transform(X_test)
```

In [97]:
```python
cat_features = list(preprocessor.named_transformers_['Cat'].named_steps['ohe']
                    .get_feature_names(cat_cols))
```

In [98]:
```python
X_cols = num_cols+cat_features
```

In [99]:
```python
X_train_df = pd.DataFrame(preprocessor.transform(X_train),
                          index=X_train.index, columns=X_cols)
X_test_df = pd.DataFrame(preprocessor.transform(X_test),
                          index=X_test.index, columns=X_cols)


## Tranform X_train and X_test and make into DataFrames
X_train_df
```

Out[99]:

	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral
respondent_id				

respondent_id	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral
25194	-0.23	-1.63	-0.27	
14006	-0.23	0.61	-0.27	
11285	-0.23	-1.63	-0.27	
2900	-0.23	-1.63	-0.27	
19083	4.42	0.61	-0.27	
...	...	...	...	
21575	-0.23	-1.63	-0.27	
5390	-0.23	-1.63	-0.27	
860	-0.23	0.61	-0.27	
15795	-0.23	0.61	-0.27	
23654	-0.23	-1.63	-0.27	

20030 rows × 106 columns

In [100…

```
# Confirming Preprocessing CT
X_train_df.describe().round(2)
```

Out[100…

	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_h
count	20,030.00	20,030.00	20,030.00	20,03
mean	-0.00	0.00	-0.00	
std	1.00	1.00	1.00	
min	-0.23	-1.63	-0.27	
25%	-0.23	-1.63	-0.27	
50%	-0.23	0.61	-0.27	
75%	-0.23	0.61	-0.27	
max	4.42	0.61	3.65	

Logistic Regression

Fitting Model

In [101…

```
# Fit a vanilla Logistic Regression to the Pipeline
lr_estimator = LogisticRegression()
```

In [102…

```
# Combine preprocessing steps and model
full_pipeline = Pipeline([
```

```
    ("preprocessor", preprocessor),
    ("estimator", lr_estimator),
])
```

In [103…

```
%%time

# Train model
full_pipeline.fit(X_train, y_train)

# Predict on evaluation set
preds = pd.DataFrame(full_pipeline.predict(X_test))
preds.columns = seas_labels_df.columns
```

```
CPU times: user 1.13 s, sys: 69.4 ms, total: 1.2 s
Wall time: 797 ms
```

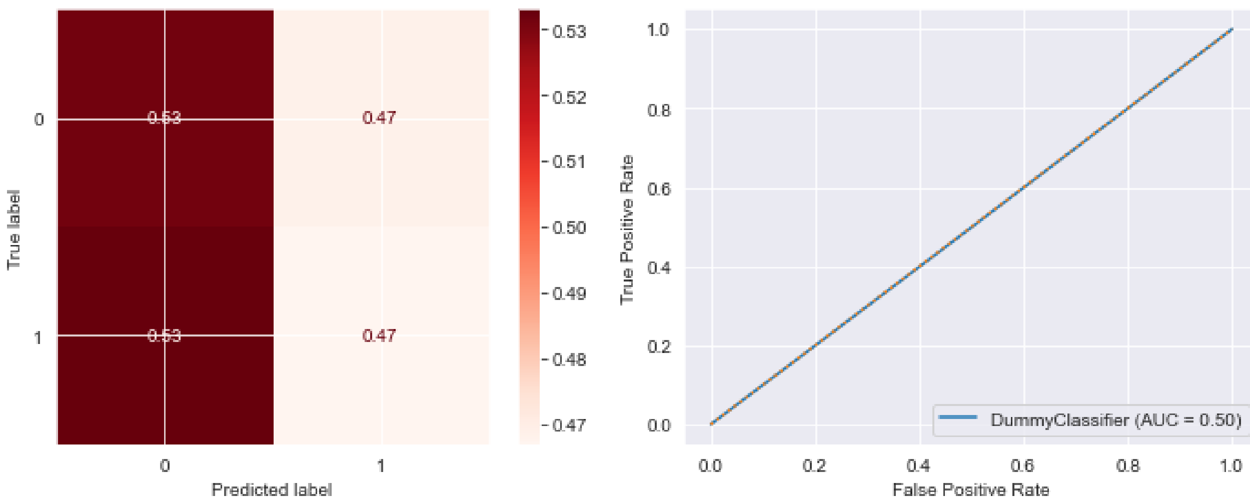
Evaluating Model Performance

In [104…

```
### Function to produce the model's coefficients
# Adapted from https://github.com/jirvingphd/Online-DS-FT-022221-Cohort-Notes-FL

def eval_clf(model, X_test_tf,y_test,cmap='Reds',
                            normalize='true',classes=None,figsize=(10,4),
                            X_train = None, y_train = None,):
    """Evaluates a scikit-learn binary classification model.

    Args:
        model ([type]): [description]
        X_test_tf ([type]): [description]
        y_test ([type]): [description]
        cmap (str, optional): [description]. Defaults to 'Reds'.
        normalize (str, optional): [description]. Defaults to 'true'.
        classes ([type], optional): [description]. Defaults to None.
        figsize (tuple, optional): [description]. Defaults to (8,4).
        X_train ([type], optional): [description]. Defaults to None.
        y_train ([type], optional): [description]. Defaults to None.
    """


    y_hat_test = model.predict(X_test_tf)
    print(metrics.classification_report(y_test, y_hat_test,target_names=classes)


    fig,ax = plt.subplots(ncols=2,figsize=figsize)
    plt.grid(False)
    metrics.plot_confusion_matrix(model, X_test_tf,y_test,cmap=cmap,
                                  normalize=normalize,display_labels=classes,
                                 ax=ax[0])

    curve = metrics.plot_roc_curve(model,X_test_tf,y_test,ax=ax[1])
    curve.ax_.grid()
    curve.ax_.plot([0,1],[0,1],ls=':')
    fig.tight_layout()
    plt.show()

    ## Add comparing Scores if X_train and y_train provided.
    if (X_train is not None) & (y_train is not None):
        print(f"Training Score = {model.score(X_train,y_train):.2f}")
        print(f"Test Score = {model.score(X_test_tf,y_test):.2f}")
```

In [46]:
```
## Creating baseline classifier model

base = DummyClassifier(strategy='stratified', random_state = 42)

base.fit(X_train_df, y_train)

eval_clf(base,X_test_tf,y_test,X_train=X_train_df,y_train=y_train)
```

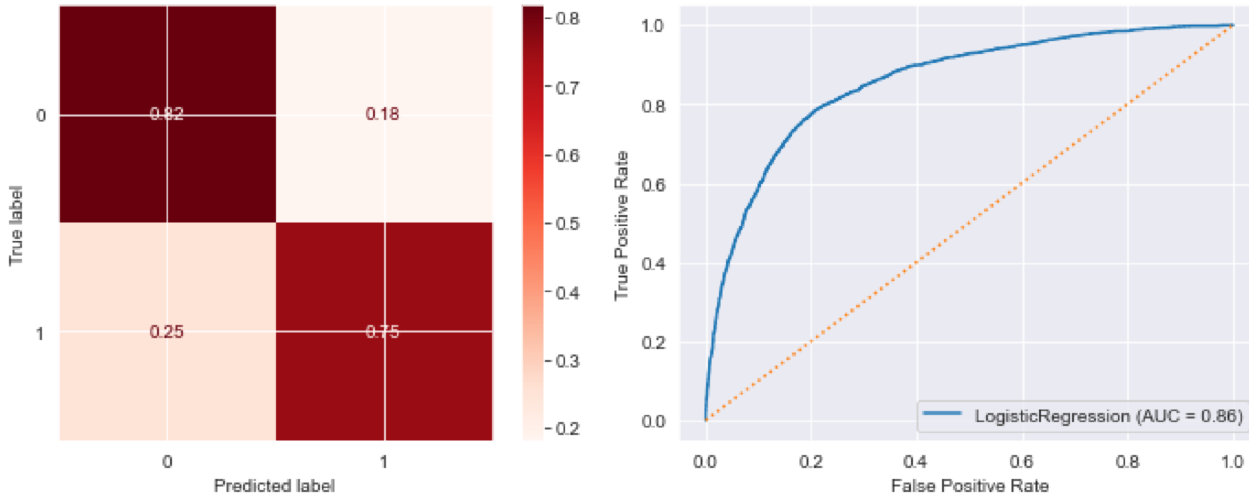
```
              precision    recall  f1-score   support

           0       0.54      0.53      0.54      3634
           1       0.45      0.47      0.46      3043

    accuracy                           0.50      6677
   macro avg       0.50      0.50      0.50      6677
weighted avg       0.50      0.50      0.50      6677
```




```
Training Score = 0.51
Test Score = 0.50
```

In [105…
```
eval_clf(lr_estimator,X_test_tf,y_test,X_train=X_train_df,y_train=y_train)
```

```
              precision    recall  f1-score   support

           0       0.80      0.82      0.81      3634
           1       0.78      0.75      0.76      3043

    accuracy                           0.79      6677
   macro avg       0.79      0.78      0.79      6677
weighted avg       0.79      0.79      0.79      6677
```




```
Training Score = 0.78
Test Score = 0.79
```

Hyperparameter Tuning With GridSearch

In [106…

```
# Logistic regression, optimized for accuracy
logreg = LogisticRegression(max_iter=600, class_weight='balanced')

param_grid = {
     'C':[0.01, 1, 100, 1e6],
     'penalty': ['l1', 'l2', 'elasticnet', 'none'],
     'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
}

logreg_gs = GridSearchCV(logreg, param_grid, scoring='accuracy', n_jobs=-1,
                         verbose=True)


logreg_gs.fit(X_train_df, y_train)

print(logreg_gs.best_estimator_)
print(logreg_gs.best_score_)
```

```
Fitting 5 folds for each of 80 candidates, totalling 400 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   11.6s
[Parallel(n_jobs=-1)]: Done 244 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 400 out of 400 | elapsed:  2.5min finished
LogisticRegression(C=1, class_weight='balanced', max_iter=600, penalty='l1',
                   solver='liblinear')
0.7768347478781827
```

In [107…

```
logreg2 = LogisticRegression(max_iter=600, penalty='l1', solver='liblinear',C=1,
```

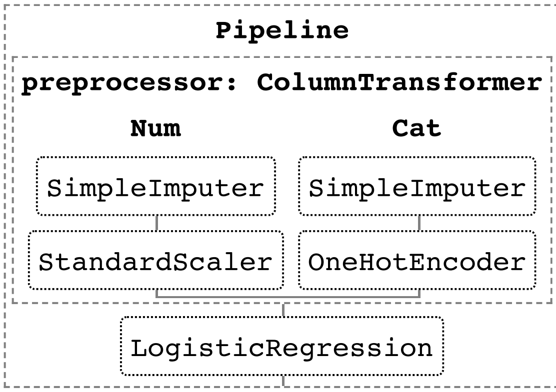
In [108…

```
# Re-run full pipeline with GS best parameter results
full_pipeline_2 = Pipeline([
    ("preprocessor", preprocessor),
    ("estimator", logreg2),
])
```

In [109…

```
# Train model
full_pipeline_2.fit(X_train, y_train)
```

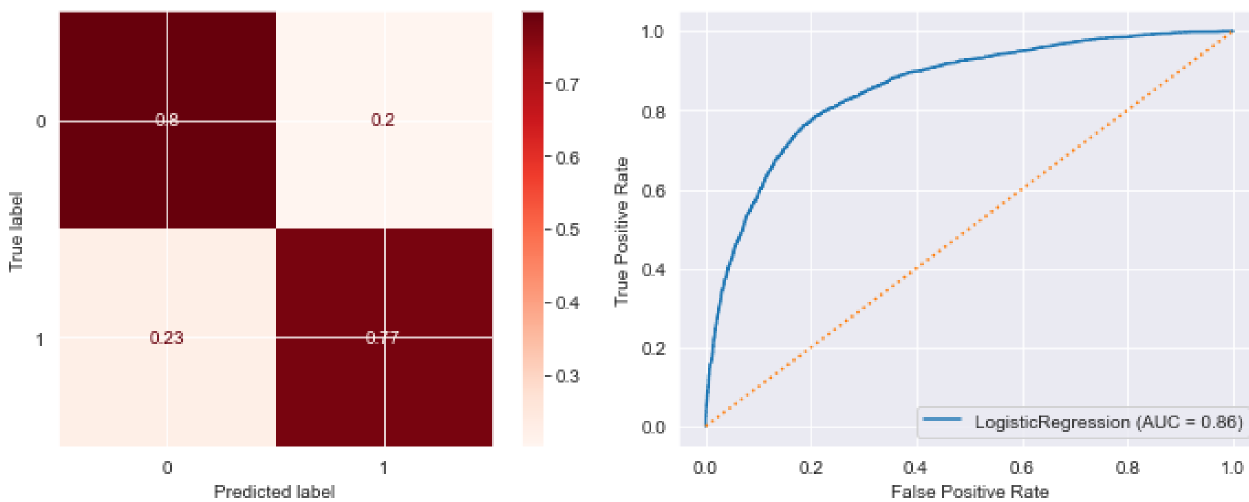
Out[109…



In [110…

```
eval_clf(logreg2,X_test_df,y_test)
```

```
              precision    recall  f1-score   support

           0       0.81      0.80      0.80      3634
           1       0.76      0.77      0.77      3043

    accuracy                           0.79      6677
   macro avg       0.79      0.79      0.79      6677
weighted avg       0.79      0.79      0.79      6677
```



Imputer Tuning With GridSearch

In [111…

```
# Gridsearch Imputation Methods
gs_pipe = Pipeline([('ct',preprocessor),
                    ('clf',LogisticRegression())])
```

In [112…

```
## Setting up params grid to change imputer params.
params = {'ct__Cat__imputer__strategy':['median','mean','most_frequent','constan
       'ct__Cat__imputer__fill_value':[0,-999]}
```

In [113…

```
gridsearch = GridSearchCV(gs_pipe,params,n_jobs=-1,verbose=True,scoring='accurac
```

In [114…

```
gridsearch.fit(X_train,y_train)
gridsearch.best_params_
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:   10.8s finished
```

Out[114…
```
{'ct__Cat__imputer__fill_value': 0,
 'ct__Cat__imputer__strategy': 'most_frequent'}
```

In [115…
```
params = {'ct__Num__imputer':[SimpleImputer(),KNNImputer()]}
```

In [116…
```
gridsearch = GridSearchCV(gs_pipe,params)
```

In [117…
```
gridsearch.fit(X_train,y_train)
gridsearch.best_params_
```

Out[117…
```
{'ct__Num__imputer': KNNImputer()}
```

In [118…
```
# Modify transformer pipeline with GridSearch best params

num_tf_2 = Pipeline(steps=[
    ('imputer',KNNImputer()),
    ('scaler',StandardScaler())])
```

In [128…
```
X_train_num_tf_2 = num_tf_2.fit_transform(X_train[num_cols])
X_test_num_tf_2 = num_tf_2.transform(X_test[num_cols])
X_train_num_tf_2
```

Out[128…
```
array([[-0.22748413, -1.62115853, -0.27417699, ..., -0.09232227,
         0.15267519,  0.50139475],
       [-0.22748413,  0.62090495, -0.27417699, ...,  1.4178574 ,
         1.49018567,  0.50139475],
       [-0.22748413, -1.62115853, -0.27417699, ..., -0.8474121 ,
        -1.1848353 ,  0.50139475],
       ...,
       [-0.22748413,  0.62090495, -0.27417699, ..., -0.09232227,
         0.15267519, -0.57846771],
       [-0.22748413,  0.62090495, -0.27417699, ...,  1.4178574 ,
         0.15267519, -0.57846771],
       [-0.22748413, -1.62115853, -0.27417699, ..., -0.09232227,
        -1.1848353 , -0.57846771]])
```

In [120…
```
# Update Categorical transformer pipeline to impute missing values with 'most
# frequent' and then OneHotEncode all numerical columns

cat_tf_2 = Pipeline(steps=[
    ('imputer',SimpleImputer(strategy='most_frequent')),
    ('ohe',OneHotEncoder(sparse=False,handle_unknown='ignore'))])
```

In [121…
```
X_train_cat_tf_2 =cat_tf_2.fit_transform(X_train[cat_cols])
X_test_cat_tf_2 =cat_tf_2.transform(X_test[cat_cols])

X_train_cat_tf_2
```

Out[121…
```
array([[1., 0., 0., ..., 0., 1., 0.],
       [0., 0., 1., ..., 0., 0., 0.],
       [0., 0., 1., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 1., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 0.]])
```

In [131…
```
# Join both numerical and categorical Pipelines using ColumnTransformer
preprocessor_2 = ColumnTransformer(transformers=[
    ('Num',num_tf_2,num_cols),
```

```
    ('Cat',cat_tf_2,cat_cols)])
preprocessor_2
```

Out[131…

```
ColumnTransformer
   Num              Cat
KNNImputer      SimpleImputer
StandardScaler  OneHotEncoder
```

In [124…

```
## Get X_train and X_test from column transformer
X_train_tf_2 = preprocessor_2.fit_transform(X_train)
X_test_tf_2 = preprocessor_2.transform(X_test)
```

In [125…

```
cat_features_2 = list(preprocessor_2.named_transformers_['Cat'].named_steps['ohe
                   .get_feature_names(cat_cols))
```

In [136…

```
X_cols_2 = num_cols+cat_features_2
```

In [137…

```
X_train_df_2 = pd.DataFrame(preprocessor_2.transform(X_train),
                            index=X_train.index, columns=X_cols_2)
X_test_df_2 = pd.DataFrame(preprocessor_2.transform(X_test),
                           index=X_test.index, columns=X_cols_2)


## Tranform X_train and X_test and make into DataFrames
X_train_df_2
```

Out[137…

	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral
respondent_id				
25194	-0.23	-1.62	-0.27	
14006	-0.23	0.62	-0.27	
11285	-0.23	-1.62	-0.27	
2900	-0.23	-1.62	-0.27	
19083	4.41	0.62	-0.27	
...	...	...	...	
21575	-0.23	-1.62	-0.27	
5390	-0.23	-1.62	-0.27	
860	-0.23	0.62	-0.27	
15795	-0.23	0.62	-0.27	
23654	-0.23	-1.62	-0.27	

20030 rows × 99 columns

In [138…

```
# Combine preprocessing steps and model
```

```
full_pipeline_3 = Pipeline([
    ("preprocessor", preprocessor_2),
    ("estimator", logreg2),
])
```

In [139…

```
# Train model with upodated parameter
full_pipeline_3.fit(X_train, y_train)
```

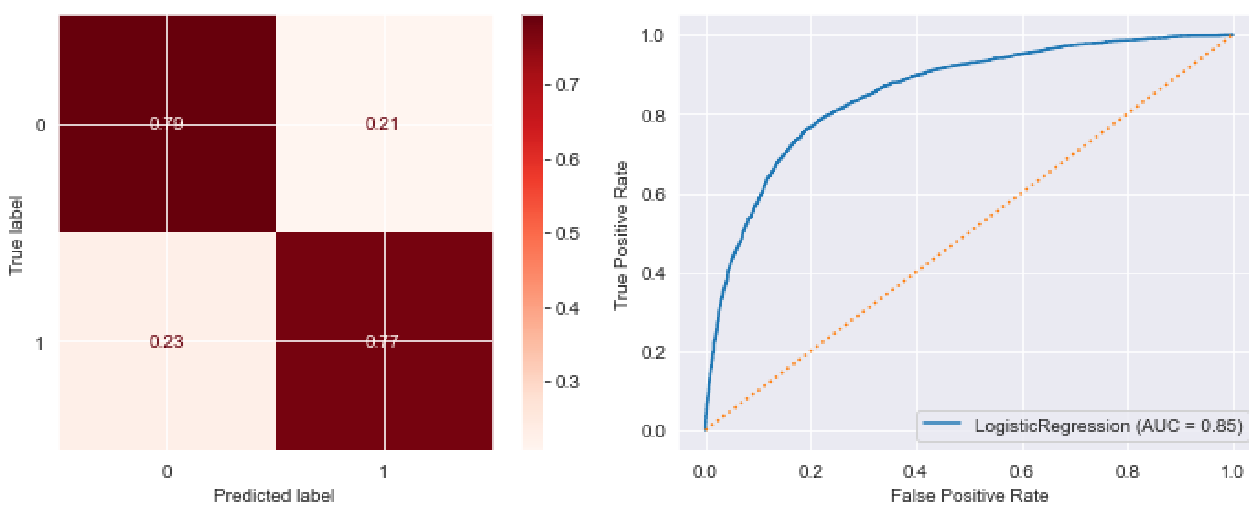
Out[139…

```
Pipeline
preprocessor: ColumnTransformer
      Num               Cat
  KNNImputer      SimpleImputer
StandardScaler    OneHotEncoder
     LogisticRegression
```

In [141…

```
eval_clf(logreg2,X_test_tf_2,y_test)
```

```
              precision    recall  f1-score   support

           0       0.81      0.79      0.80      3634
           1       0.76      0.77      0.77      3043

    accuracy                           0.78      6677
   macro avg       0.78      0.78      0.78      6677
weighted avg       0.78      0.78      0.78      6677
```



Performance is not as great as the previous iteration.

DecisionTree

Fitting Model

In [72]:

```
## Create, fit, and evaluate a vanilla DecisionTreeClassifier
dt_clf = DecisionTreeClassifier(criterion='entropy')
dt_clf.fit(X_train_df, y_train)
```

Out[72]:

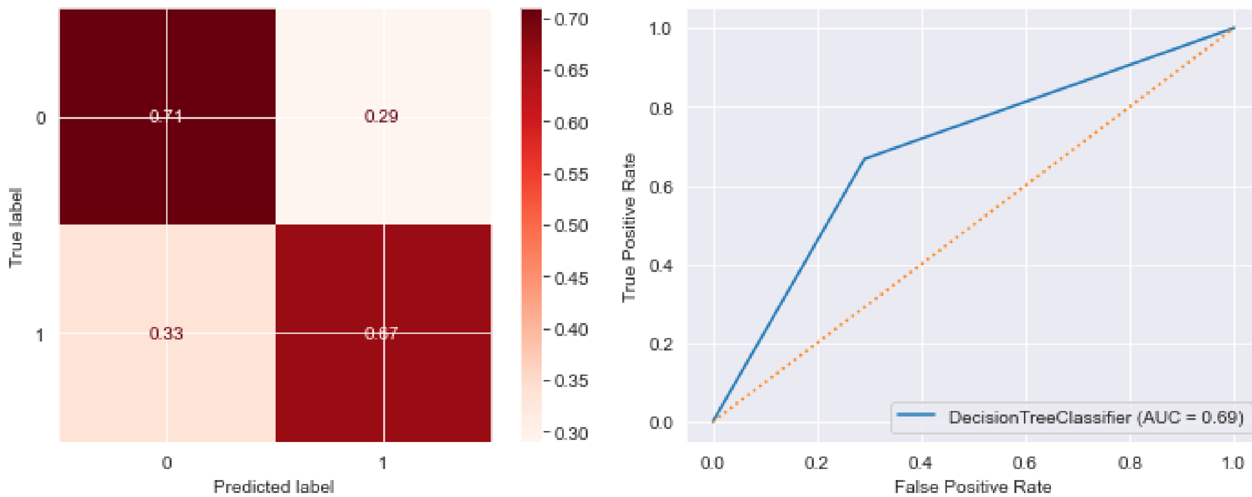
```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy')
```

Evaluating Model Performance

In [73]:

```
eval_clf(dt_clf, X_test_df,y_test,X_train=X_train_df,y_train=y_train)
```

```
              precision    recall  f1-score   support

           0       0.72      0.71      0.71      3634
           1       0.66      0.67      0.66      3043

    accuracy                           0.69      6677
   macro avg       0.69      0.69      0.69      6677
weighted avg       0.69      0.69      0.69      6677
```




```
Training Score = 1.00
Test Score = 0.69
```

The vanilla model is highly overfit, will need to prune the decision tree.

Hyperparameter Tuning

In [143…

```
params = {'max_depth':[None,3,5,10,20],
          'min_samples_leaf':[1,2,3,5],
          'criterion':['entropy','ginie']}


## Instantiate & Fit GridSearchCV
gridsearch = GridSearchCV(DecisionTreeClassifier(),params,n_jobs=-1)
gridsearch.fit(X_train_df,y_train)
```

Out[143…

```
GridSearchCV
DecisionTreeClassifier
```

In [144…

```
gridsearch.best_params_
```

Out[144…

```
{'criterion': 'entropy', 'max_depth': 5, 'min_samples_leaf': 1}
```

In [145…

```
# Fit classifier with best parameters
dt_clf_2 = DecisionTreeClassifier(criterion='entropy', max_depth=5,
                                  min_samples_leaf=1)
dt_clf_2.fit(X_train_df, y_train)
```

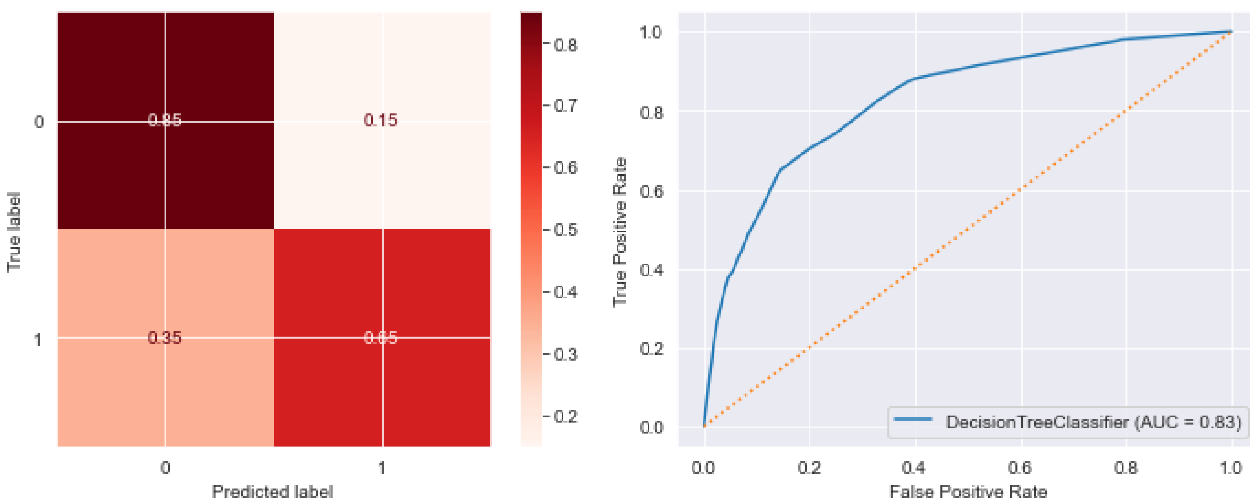
Out[145…

```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=5)
```

In [146…

```
## Evaluate with the classifier
eval_clf(dt_clf_2,X_test_df,y_test,X_train=X_train_df,y_train=y_train)
```

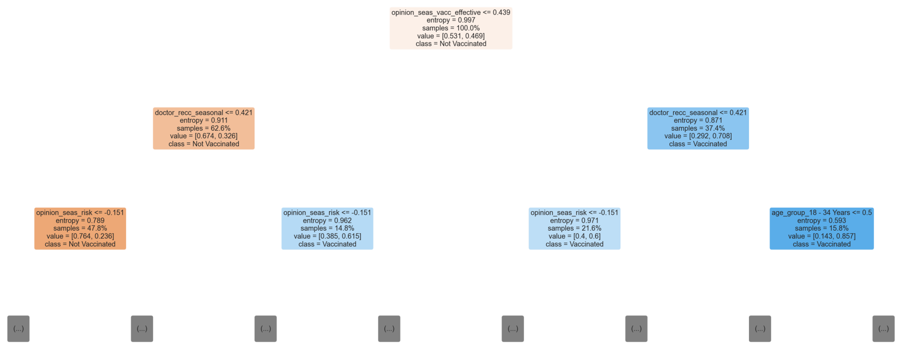
```
              precision    recall  f1-score   support

           0       0.75      0.85      0.79      3634
           1       0.78      0.65      0.71      3043

    accuracy                           0.76      6677
   macro avg       0.77      0.75      0.75      6677
weighted avg       0.76      0.76      0.76      6677
```




```
Training Score = 0.76
Test Score = 0.76
```

In [147…

```
# Visualize Decision Tree with Sci-kit learn plot tree
from sklearn.tree import plot_tree

fig,ax = plt.subplots(figsize=(60,25))
plot_tree(dt_clf_2,max_depth=2,filled=True,rounded=True,proportion=True,
          feature_names=X_train_df.columns,
          class_names=['Not Vaccinated','Vaccinated'],ax=ax);
fig.tight_layout()
fig.savefig('vax_tree.pdf', dpi=300,orientation='landscape')
```



Random Forest

Fitting Model

In [148…
```
rf = RandomForestClassifier(class_weight='balanced')
```

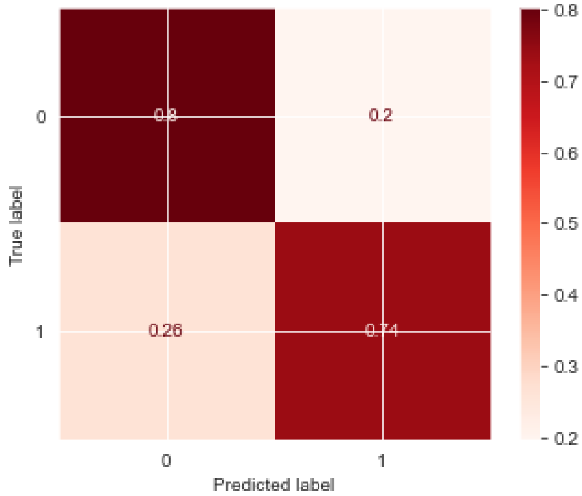
In [149…
```
rf.fit(X_train_df,y_train)
```

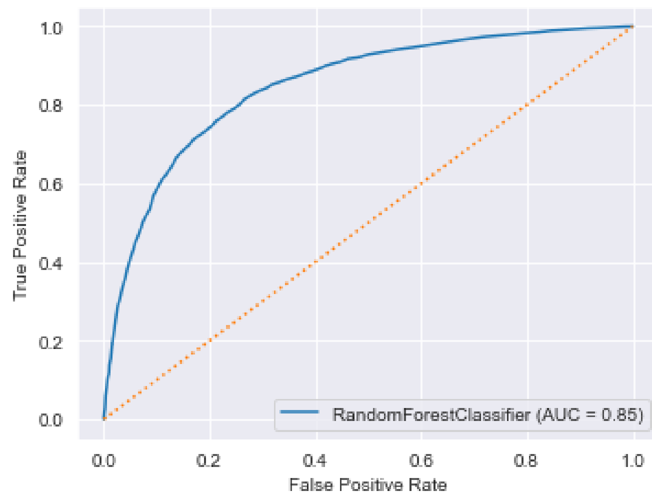
Out[149…
```
RandomForestClassifier
RandomForestClassifier(class_weight='balanced')
```

Evaluating Model Performance

In [150…
```
eval_clf(rf,X_test_tf,y_test)
```

```
              precision    recall  f1-score   support

           0       0.79      0.80      0.79      3634
           1       0.76      0.74      0.75      3043

    accuracy                           0.77      6677
   macro avg       0.77      0.77      0.77      6677
weighted avg       0.77      0.77      0.77      6677
```





Hyperparameter Tuning

In [151…

```
param_grid = {
    'n_estimators':[10, 50, 100],
    'criterion':['gini', 'entropy'],
    'max_depth': [3, 5, 10, 30],
    'min_samples_split': [1, 5, 20],
    'min_impurity_decrease': [0, 0.01, 0.02],
    'max_features': [10, 20],
    'max_leaf_nodes': [6000, 2000, 500]
}
```

In [152…

```
gs_rf = GridSearchCV(rf, param_grid, scoring='accuracy',cv=3,verbose=True,n_jobs
```

In [165…

```
gs_rf.fit(X_train_df, y_train)

print(gs_rf.best_estimator_)
print(gs_rf.best_score_)
```

```
Fitting 3 folds for each of 1296 candidates, totalling 3888 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   12.6s
[Parallel(n_jobs=-1)]: Done 192 tasks      | elapsed:   36.7s
[Parallel(n_jobs=-1)]: Done 442 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done 792 tasks      | elapsed:  2.7min
[Parallel(n_jobs=-1)]: Done 1242 tasks      | elapsed:  4.5min
[Parallel(n_jobs=-1)]: Done 1792 tasks      | elapsed:  7.1min
[Parallel(n_jobs=-1)]: Done 2442 tasks      | elapsed:  9.7min
[Parallel(n_jobs=-1)]: Done 3192 tasks      | elapsed: 12.7min
[Parallel(n_jobs=-1)]: Done 3888 out of 3888 | elapsed: 16.5min finished
RandomForestClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=30, max_features=20, max_leaf_nodes=2000,
                       min_impurity_decrease=0, min_samples_split=20)
0.7770346840168859
```

In [167…

```
# Review model performance for a model with these optimal params
rf_tuned = RandomForestClassifier(class_weight='balanced', criterion='entropy',
                            max_depth=30,
                            max_features=20,
                            max_leaf_nodes=500,
                            min_impurity_decrease=0,
                            min_samples_split=20)
```

```
rf_tuned.fit(X_train_df, y_train)
```

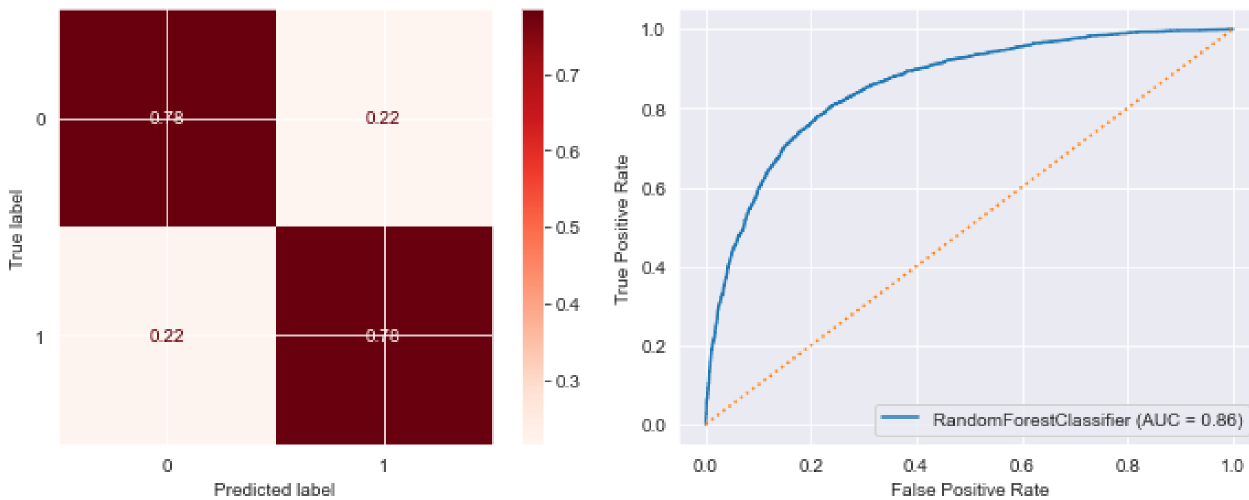
Out[167…

```
                    RandomForestClassifier
RandomForestClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=30, max_features=20, max_leaf_nodes=50
0,
                       min_impurity_decrease=0, min_samples_split=20)
```

In [168…

```
eval_clf(rf_tuned, X_test_df, y_test, X_train=X_train_df, y_train=y_train)
```

```
              precision    recall  f1-score   support

           0       0.81      0.78      0.80      3634
           1       0.75      0.78      0.77      3043

    accuracy                           0.78      6677
   macro avg       0.78      0.78      0.78      6677
weighted avg       0.78      0.78      0.78      6677
```




```
Training Score = 0.83
Test Score = 0.78
```

In [169…

```
clf = Pipeline([
  ('feature_selection', SelectFromModel(LinearSVC(penalty="l2"))),
  ('classification', RandomForestClassifier(class_weight='balanced', max_depth=3
                        max_leaf_nodes=500, min_impurity_decrease=0,
                        min_samples_split=20))
])

clf.fit(X_train_df, y_train)
```

Out[169…

```
          Pipeline
feature_selection: SelectFromModel
         LinearSVC
   RandomForestClassifier
```

In [157…

```
print('Trainging Score:'+str(clf.score(X_train_df, y_train)))
```

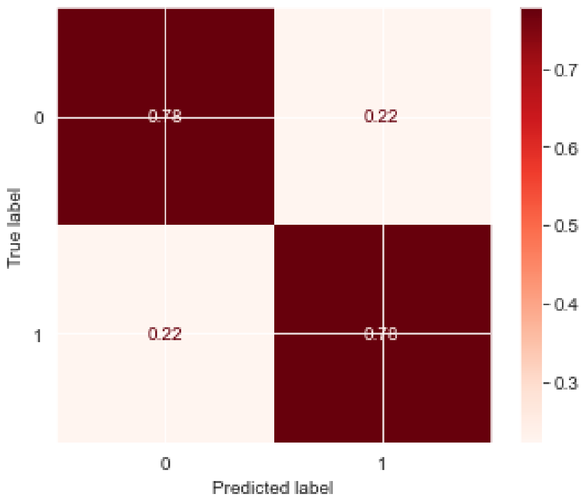
```
print('Testing Score:'+str(clf.score(X_test_df, y_test)))
```

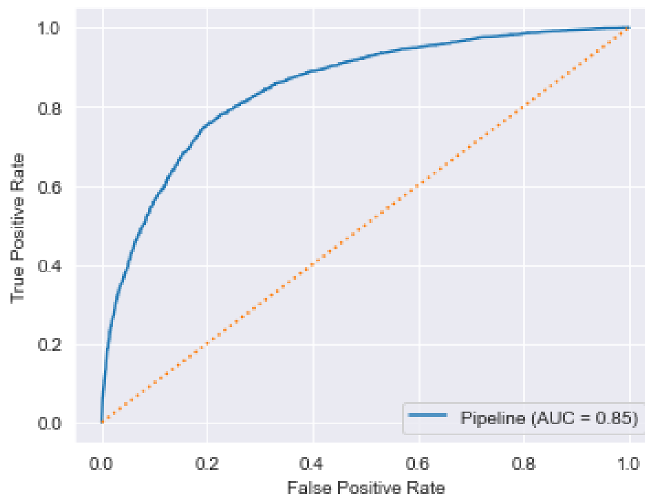
```
Trainging Score:0.8043934098851723
Testing Score:0.776845888872248
```

In [158…

```
eval_clf(clf,X_test_df, y_test, X_train=X_train_df, y_train=y_train)
```

```
              precision    recall  f1-score   support

           0       0.81      0.78      0.79      3634
           1       0.74      0.78      0.76      3043

    accuracy                           0.78      6677
   macro avg       0.78      0.78      0.78      6677
weighted avg       0.78      0.78      0.78      6677
```






```
Training Score = 0.80
Test Score = 0.78
```

XGBoost

Fitting Model

In [159…

```
from xgboost import XGBClassifier
```

In [160…

```
bst = XGBClassifier()
```

In [161…

```
bst.fit(X_train_df[num_cols],y_train)
```

Out[161…

XGBClassifier

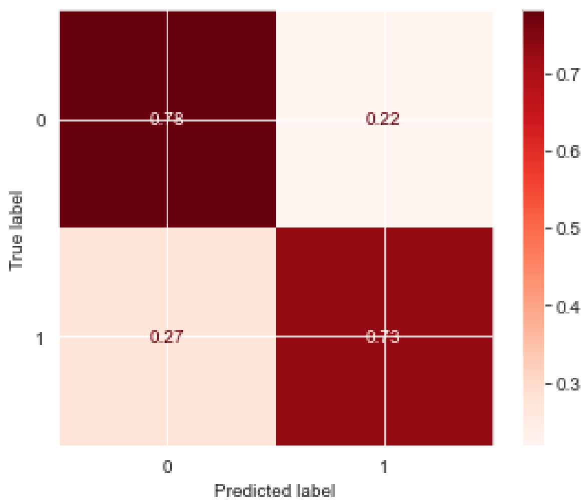
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-
1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints
='()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1, random_s
tate=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=
1,
```

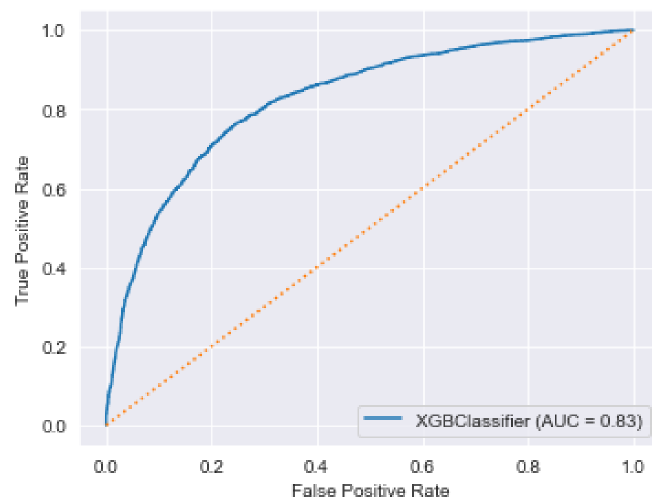
Evaluating Model Performance

In [162…

```
eval_clf(bst,
         X_test_df[num_cols],
         y_test,
         X_train=X_train_df[num_cols],
         y_train=y_train
        )
```

```
              precision    recall  f1-score   support

           0       0.78      0.78      0.78      3634
           1       0.74      0.73      0.73      3043

    accuracy                           0.76      6677
   macro avg       0.76      0.76      0.76      6677
weighted avg       0.76      0.76      0.76      6677
```






```
Training Score = 0.81
Test Score = 0.76
```

Hyperparameter Tuning

In [163…

```
params = {
    'learning_rate': [0.1, 0.2],
    'max_depth': [6],
    'min_child_weight': [1, 2],
    'subsample': [0.5, 0.7],
    'n_estimators': [100],
}
```

In [166…

```
grid_boost= GridSearchCV(bst,
                         params,
                         scoring='accuracy',
                         n_jobs=-1,
                         verbose=True)
grid_boost.fit(X_train_df[num_cols], y_train)

best_parameters = grid_boost.best_params_
best_parameters
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
```

```
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:   49.9s finished
```

Out[166…

```
{'learning_rate': 0.1,
 'max_depth': 6,
 'min_child_weight': 2,
 'n_estimators': 100,
 'subsample': 0.7}
```

In [170…

```
best_xgb = XGBClassifier(learning_rate=0.1, max_depth=6, min_child_weight=1,
                         n_estimators=100, subsample=0.7)
best_xgb.fit(X_train_df[num_cols], y_train)
```

Out[170…

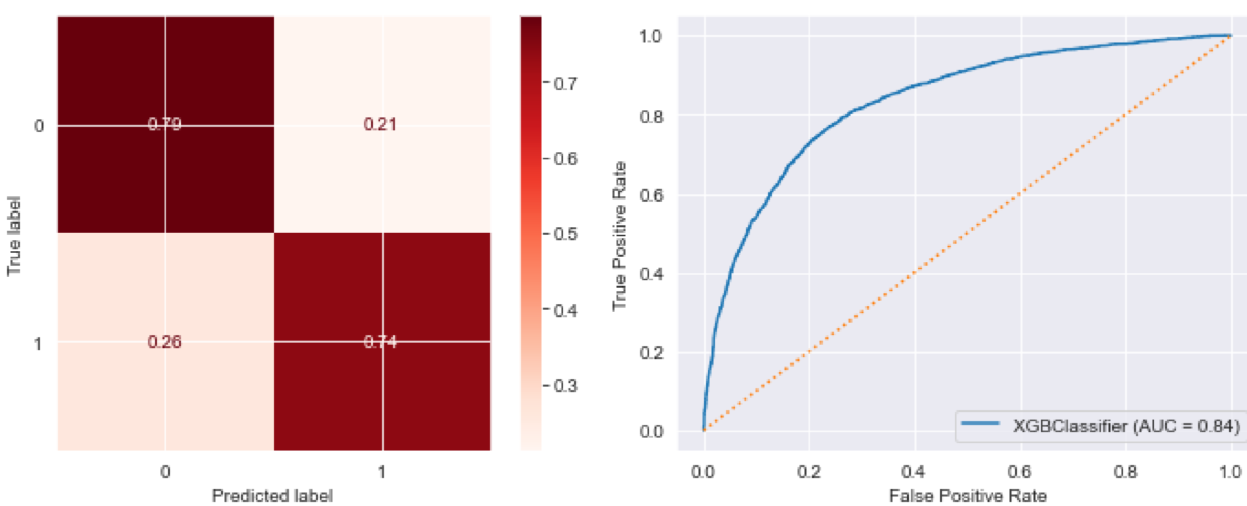
XGBClassifier

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-
1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.1, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints
='()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1, random_s
tate=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=
0.7,
```

In [171…

```
eval_clf(best_xgb, X_test_df[num_cols], y_test)
```

```
              precision    recall  f1-score   support

           0       0.78      0.79      0.79      3634
           1       0.74      0.74      0.74      3043

    accuracy                           0.77      6677
   macro avg       0.76      0.76      0.76      6677
weighted avg       0.77      0.77      0.77      6677
```



iNTERPRET

After fitting and tuning 4 different classification models, we can parse out feature importances that have the most impact on determining whether someone will receive the vaccine or not. For this interpretation process, we will examine the feature importances of all 4 models to see if there is any patterns to recognize. If the models share some of the top features, we can interpret that as it being critical to their chance of getting vaccinated.

Comparing Feature Importances

In [173…

```
#accessing feature importance values of the tuned logistic regression model and
logreg_importances_df = pd.Series(logreg2.coef_[0], index=X_train_df_2.columns).
#parsing the series to a dataframe
logregcv_importances_df = logreg_importances_df.reset_index()
logregcv_importances_df.columns = ['LogReg-Attribute', 'LogReg-Importance']
top_lr = logregcv_importances_df.head(15)
top_lr
```

Out[173…

	LogReg-Attribute	LogReg-Importance
0	employment_occupation_dcjcmpih	2.07
1	age_group_65+ Years	0.91
2	employment_industry_haxffmxo	0.77
3	opinion_seas_risk	0.73
4	employment_industry_msuufmds	0.64
5	opinion_seas_vacc_effective	0.61
6	doctor_recc_seasonal	0.57
7	employment_industry_arjwrbjb	0.30
8	employment_occupation_vlluhbov	0.25
9	employment_industry_mfikgejo	0.25
10	employment_occupation_haliazsg	0.22
11	employment_occupation_cmhcxjea	0.22
12	health_worker	0.20
13	employment_occupation_xzmlyyjv	0.17
14	employment_industry_phxvnwax	0.16

In [174…

```
# accessing feature importance values of the tuned random forest model and sorti
dt_importances_df = pd.Series(dt_clf_2.feature_importances_, index=X_train_df.co
#parsing the series to a dataframe
dt_importances_df = dt_importances_df.reset_index()
dt_importances_df.columns = ['DT-Attribute', 'DT-Importance']
top_dt = dt_importances_df.head(15)
top_dt
```

Out[174…

	DT-Attribute	DT-Importance
0	opinion_seas_vacc_effective	0.39
1	doctor_recc_seasonal	0.27
2	opinion_seas_risk	0.18
3	age_group_65+ Years	0.08

	DT-Attribute	DT-Importance
4	age_group_18 - 34 Years	0.04
5	health_worker	0.02
6	opinion_seas_sick_from_vacc	0.01
7	employment_industry_fcxhlnwr	0.00
8	household_children	0.00
9	income_poverty_> $75,000	0.00
10	income_poverty_Below Poverty	0.00
11	income_poverty_Unknown	0.00
12	marital_status_Married	0.00
13	marital_status_Not Married	0.00
14	income_poverty_<= $75,000, Above Poverty	0.00

In [175…

```
# accessing feature importance values of the tuned random forest model and sorti
rf_importances_df = pd.Series(rf_tuned.feature_importances_, index=X_train_df.co
#parsing the series to a dataframe
rf_importances_df = rf_importances_df.reset_index()
rf_importances_df.columns = ['RF-Attribute', 'RF-Importance']
top_rf = rf_importances_df.head(15)
top_rf
```

Out[175…

	RF-Attribute	RF-Importance
0	opinion_seas_vacc_effective	0.18
1	opinion_seas_risk	0.17
2	doctor_recc_seasonal	0.15
3	age_group_65+ Years	0.05
4	opinion_seas_sick_from_vacc	0.03
5	age_group_18 - 34 Years	0.03
6	health_worker	0.02
7	household_children	0.01
8	chronic_med_condition	0.01
9	employment_industry_fcxhlnwr	0.01
10	household_adults	0.01
11	employment_status_Not in Labor Force	0.01
12	health_insurance	0.01
13	rent_or_own_Rent	0.01
14	race_White	0.01

In [176…

```
#parsing feature importances to a series and sorting
xgb_importances_df = pd.Series(best_xgb.feature_importances_, index=X_train_df[n
```

```
#parsing the series to a dataframe
xgb_importances_df = xgb_importances_df.reset_index()
xgb_importances_df.columns=['XGB-Attribute', 'XGB-Importance']
top_xgb = xgb_importances_df.head(15)
top_xgb
```

Out[176…

	XGB-Attribute	XGB-Importance
0	doctor_recc_seasonal	0.31
1	opinion_seas_vacc_effective	0.21
2	opinion_seas_risk	0.11
3	health_insurance	0.05
4	health_worker	0.04
5	opinion_seas_sick_from_vacc	0.04
6	household_children	0.03
7	behavioral_touch_face	0.03
8	chronic_med_condition	0.03
9	household_adults	0.02
10	behavioral_wash_hands	0.02
11	behavioral_outside_home	0.02
12	behavioral_avoidance	0.02
13	behavioral_face_mask	0.02
14	behavioral_antiviral_meds	0.02

In [177…

```
#Concatenating feature importances into a single dataframe
importances_df = pd.concat([top_lr, top_dt, top_rf, top_xgb], axis=1)
importances_df
```

Out[177…

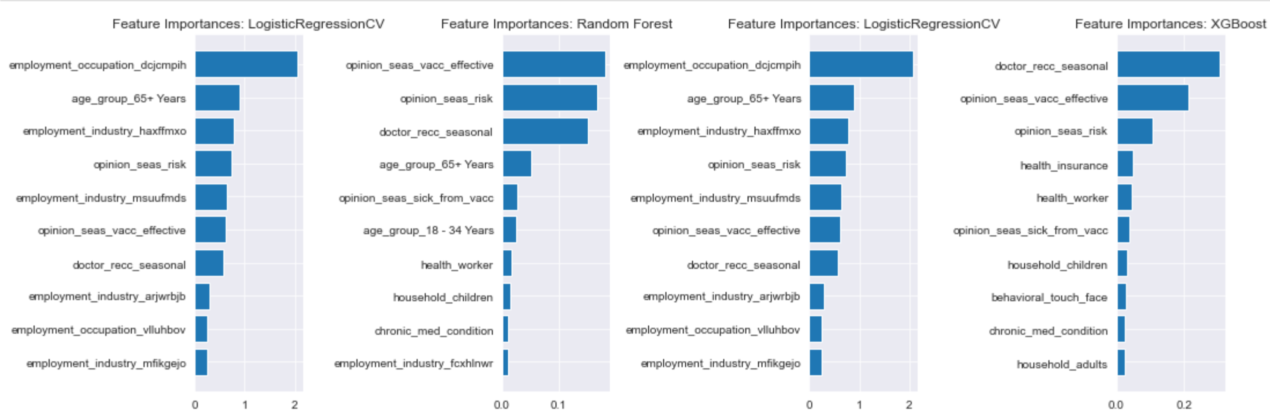
	LogReg-Attribute	LogReg-Importance	DT-Attribute	DT-Importance	
0	employment_occupation_dcjcmpih	2.07	opinion_seas_vacc_effective	0.39	opin
1	age_group_65+ Years	0.91	doctor_recc_seasonal	0.27	
2	employment_industry_haxffmxo	0.77	opinion_seas_risk	0.18	
3	opinion_seas_risk	0.73	age_group_65+ Years	0.08	
4	employment_industry_msuufmds	0.64	age_group_18 - 34 Years	0.04	opinic
5	opinion_seas_vacc_effective	0.61	health_worker	0.02	
6	doctor_recc_seasonal	0.57	opinion_seas_sick_from_vacc	0.01	
7	employment_industry_arjwrbjb	0.30	employment_industry_fcxhlnwr	0.00	
8	employment_occupation_vlluhbov	0.25	household_children	0.00	
9	employment_industry_mfikgejo	0.25	income_poverty_> $75,000	0.00	employ
10	employment_occupation_haliazsg	0.22	income_poverty_Below Poverty	0.00	

	LogReg-Attribute	LogReg-Importance	DT-Attribute	DT-Importance	
11	employment_occupation_cmhcxjea	0.22	income_poverty_Unknown	0.00	en
12	health_worker	0.20	marital_status_Married	0.00	
13	employment_occupation_xzmlyyjv	0.17	marital_status_Not Married	0.00	
14	employment_industry_phxvnwax	0.16	income_poverty_<= $75,000, Above Poverty	0.00	

Feature Importance Comparison

In [178…

```
#plotting feature importances for all models for comparison

fig, ax = plt.subplots(ncols=4, figsize=(15,5))

logregcv_importances_df = logregcv_importances_df.sort_values(by='LogReg-Importa
ax[0].barh(logregcv_importances_df['LogReg-Attribute'], logregcv_importances_df[
ax[0].set_title('Feature Importances: LogisticRegressionCV')
plt.tight_layout()

rf_importances_df = rf_importances_df.sort_values(by='RF-Importance', ascending=
ax[1].barh(rf_importances_df['RF-Attribute'], rf_importances_df['RF-Importance']
ax[1].set_title('Feature Importances: Random Forest')

dr_importances_df = logregcv_importances_df.sort_values(by='LogReg-Importance',
ax[2].barh(logregcv_importances_df['LogReg-Attribute'], logregcv_importances_df[
ax[2].set_title('Feature Importances: LogisticRegressionCV')
plt.tight_layout()

xgb_importances_df = xgb_importances_df.sort_values(by='XGB-Importance', ascendi
ax[3].barh(xgb_importances_df['XGB-Attribute'], xgb_importances_df['XGB-Importan
ax[3].set_title('Feature Importances: XGBoost');
```



CONCLUSIONS & RECOMMENDATIONS

Best Model Results

Out of the 4 tuned classifier models, the Logistic Regression model was the best one in identifying vaccinations. It had a 79% accuracy score for identifying who received the vaccine compared to 53% by a baseline Dummy Classifier model. The next best performer was the RandomForest model at a very 78% accuracy.

Takeaways and Recommendations

In the midst of a pandemic with mutanting and evolving strains, it is vital to keep global populations up to date with immunizations. In order for public health groups to most effectively vaccinate their communities, it is essential to know both what and what does not lead someone to get a seasonal shot.

The most consistent top feature across all 4 models are:

> 1) A respondent's opinion about risk of getting sick with seasonal flu without vaccine\ 2) Respondent's opinion about seasonal flu vaccine effectiveness.\ 3) If the seasonal flu vaccine was recommended by their doctor.

According to the WHO there are about 3 to 5 million cases of severe illness and 290,000 to 650,000 deaths from seasonal flu, worldwide that occur every year. The more the public is aware of this, the more like they are to get vaccinated.

Someone is also more likely to get a shot if they believe it will be effective at protecting them. The more trusted public figures, celebrities, family member speak up about the vaccines effectiveness will only improve society's vaccination rates. The same must also be said for the opposite. Social media platforms must be held accountant for the spread of misinformation.

And lastly, there is a much greater chance of somone getting vaccinated if it was recommnded by their doctor.

Based off these findings Public Health Organizations can prioritize their messaging and actions to improve the likelihood that and individual will receive the flu vaccine.

Future Work

This project was limited by the features of this dataset. All of the columns were discrete, categorical variables. I believe the logistic regression and tree based models would have performed much better are predicting vaccines if they had continuous data for some features.

Also this survey data is aged over 10 years and based around the h1n1 flu. It would be advisable to update with more recent responses.

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