Preparing for Future Pandemics Vaccine Needs

This project aims to help health providers prepare for the vaccination needs for future pandemics. From community clinics to health care providers with hospitals and offices across regions, they will need to know the amount of vaccines needed. The goals are to understand the indicators for receiving pandemic vaccines and build a model that will predict those who will get a pandemic vaccine.

Business Question

How many vaccines healthcare providers need to purchase or request, depending on the national distribution plan, so that all patients who want a vaccine receive one and will not collect a large surplus.

To answer this question we are going to build a model trained on data of who received the h1n1 vaccine, to use to predict individuals who will likely receive a future pandemic vaccination.

While overall accuracy is important, because health care providers would rather have slightly more vaccines than needed, rather than being short and not having vaccines for individuals that requested them, we will focus on achieving a high recall score.

Data Understanding

The data comes from an over 26,000 person phone survey conducted in 2010, a year after the H1N1 outbreak, in which participants were asked about receiving the H1N1 vaccine, the seasonal flu vaccine, opinions about vaccines, behaviors around transmitting illness, and demographic information.

First join the training data and the targets and take a look at the dataset.

In [1]:

```python
# Import Libraries

import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder, FunctionTransformer, OrdinalEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer,  make_column_selector as selector
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB, GaussianNB

from sklearn.metrics import plot_confusion_matrix, recall_score,\
    accuracy_score, precision_score, f1_score

from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImPipeline

from sklearn.dummy import DummyClassifier
```

In [2]:

```python
# Set Options

pd.set_option('max_columns', None)
sns.set_palette("colorblind")
sns.set_style("darkgrid")

```

In [3]:

```
# Read in csv data files

df = pd.read_csv('data/training_set_features.csv')
df_tars = pd.read_csv('data/training_set_labels.csv')

df_tars.head()
```

Out[3]:

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

In [4]:

```
# Join together the files on "respondent_id"

df = df.join(df_tars, on='respondent_id', rsuffix='_tars')
```

In [5]:

```
# Sanity check ids match

df.loc[:, ['respondent_id', 'respondent_id_tars']]
```

Out[5]:

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

26707 rows × 2 columns

In [6]:

```
# Drop repeated column and sheck shape, then investigate the dataframe

df = df.drop('respondent_id_tars', axis=1)
df.shape
```

Out[6]: (26707, 38)

In [7]:

```
df.head()
```

Out[7]:

_h1n1_risk	opinion_h1n1_sick_from_vacc	opinion_seas_vacc_effective	opinion_seas_risk	opinion_seas_sick_from_vacc	age_group	education	race	sex
1.0	2.0	2.0	1.0	2.0	55 - 64 Years	< 12 Years	White	Female
4.0	4.0	4.0	2.0	4.0	35 - 44 Years	12 Years	White	Male
1.0	1.0	4.0	1.0	2.0	18 - 34 Years	College Graduate	White	Male
3.0	5.0	5.0	4.0	1.0	65+ Years	12 Years	White	Female
3.0	2.0	3.0	1.0	4.0	45 - 54 Years	Some College	White	Female

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26707 entries, 0 to 26706
Data columns (total 38 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   respondent_id                26707 non-null  int64  
 1   h1n1_concern                 26615 non-null  float64
 2   h1n1_knowledge               26591 non-null  float64
 3   behavioral_antiviral_meds    26636 non-null  float64
 4   behavioral_avoidance         26499 non-null  float64
 5   behavioral_face_mask         26688 non-null  float64
 6   behavioral_wash_hands        26665 non-null  float64
 7   behavioral_large_gatherings  26620 non-null  float64
 8   behavioral_outside_home      26625 non-null  float64
 9   behavioral_touch_face        26579 non-null  float64
 10  doctor_recc_h1n1             24547 non-null  float64
 11  doctor_recc_seasonal         24547 non-null  float64
 12  chronic_med_condition        25736 non-null  float64
 13  child_under_6_months         25887 non-null  float64
 14  health_worker                25903 non-null  float64
 15  health_insurance             14433 non-null  float64
 16  opinion_h1n1_vacc_effective  26316 non-null  float64
 17  opinion_h1n1_risk            26319 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 19  opinion_seas_vacc_effective  26245 non-null  float64
 20  opinion_seas_risk            26193 non-null  float64
 21  opinion_seas_sick_from_vacc  26170 non-null  float64
 22  age_group                    26707 non-null  object 
 23  education                    25300 non-null  object 
 24  race                         26707 non-null  object 
 25  sex                          26707 non-null  object 
 26  income_poverty               22284 non-null  object 
 27  marital_status               25299 non-null  object 
 28  rent_or_own                  24665 non-null  object 
 29  employment_status            25244 non-null  object 
 30  hhs_geo_region               26707 non-null  object 
 31  census_msa                   26707 non-null  object 
 32  household_adults             26458 non-null  float64
 33  household_children           26458 non-null  float64
 34  employment_industry          13377 non-null  object 
 35  employment_occupation        13237 non-null  object 
 36  h1n1_vaccine                 26707 non-null  int64  
 37  seasonal_vaccine             26707 non-null  int64  
dtypes: float64(23), int64(3), object(12)
memory usage: 7.7+ MB
```

In [9]:
```
df.describe()
```

Out[9]:

m_vacc	opinion_seas_vacc_effective	opinion_seas_risk	opinion_seas_sick_from_vacc	household_adults	household_children	h1n1_vaccine	seasonal_vaccine
.000000	26245.000000	26193.000000	26170.000000	26458.000000	26458.000000	26707.000000	26707.000000
.357670	4.025986	2.719162	2.118112	0.886499	0.534583	0.212454	0.465608
.362766	1.086565	1.385055	1.332950	0.753422	0.928173	0.409052	0.498825
.000000	1.000000	1.000000	1.000000	0.000000	0.000000	0.000000	0.000000
.000000	4.000000	2.000000	1.000000	0.000000	0.000000	0.000000	0.000000
.000000	4.000000	2.000000	2.000000	1.000000	0.000000	0.000000	0.000000
.000000	5.000000	4.000000	4.000000	1.000000	1.000000	0.000000	1.000000
.000000	5.000000	5.000000	5.000000	3.000000	3.000000	1.000000	1.000000

In [10]:
```
df.select_dtypes(include='object').describe()
```

Out[10]:

	age_group	education	race	sex	income_poverty	marital_status	rent_or_own	employment_status	hhs_geo_region	census_msa	employment
count	26707	25300	26707	26707	22284	25299	24665	25244	26707	26707	
unique	5	4	4	2	3	2	2	3	10	3	
top	65+ Years	College Graduate	White	Female	<= $75,000, Above Poverty	Married	Own	Employed	lzgpxyit	MSA, Not Principle City	
freq	6843	10097	21222	15858	12777	13555	18736	13560	4297	11645	

The dataset now has 26707 rows (survey respondents), and 38 columns (variables including id and targets).

It has 12 objects and 26 numeric indicators. Indicators related to behavioral questions are binary,indicators related to opinion questions are a five point scale, numerical and string indicators related to demographics are of varying numbers of response choices, amd respondent ID is a unique identifier. The targets are binary, 0 or 1.

'health_insurance', 'employment_industry', and 'employment_occupation' all have over 50% nulls. Other columns contain a small percentage of nulls.

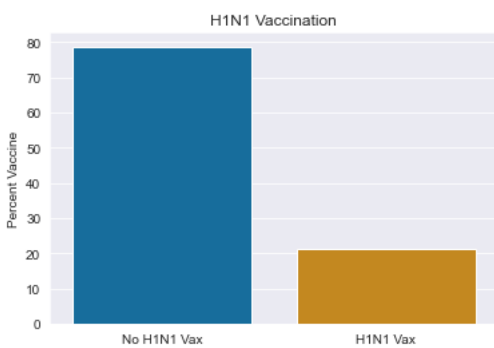
Data Preperation

What are the numbers for the targets? How many respondents received the vaccines?

In [11]:

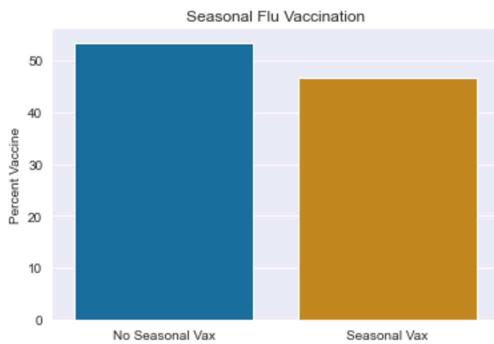
```
# Look at the percent of respondents who have recieved the H1N1 Vaccine

# Get Proportions
vax_prop = df.h1n1_vaccine.value_counts(normalize=True)
print(vax_prop)


# Chart
fig, ax = plt.subplots()

sns.barplot(x=vax_prop.index, y=vax_prop.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent Vaccine')
ax.set_title("H1N1 Vaccination")

ax.set_xticklabels(['No H1N1 Vax', 'H1N1 Vax'])

plt.savefig('images/vaccine_percents.png', bbox_inches='tight', dpi=300)
```

```
0    0.787546
1    0.212454
Name: h1n1_vaccine, dtype: float64
```



In [12]:
```
# Look at the proportion of respondents who have recieved seasonal flu Vaccine for comparison

# Get Proportions
vax_prop_seasonal = df.seasonal_vaccine.value_counts(normalize=True)
print(vax_prop_seasonal)


# Chart
fig, ax = plt.subplots()

sns.barplot(x=vax_prop_seasonal.index, y=vax_prop_seasonal.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent Vaccine')
ax.set_title("Seasonal Flu Vaccination")

ax.set_xticklabels(['No Seasonal Vax', 'Seasonal Vax'])

plt.savefig('images/seasonal_vax_percents.png', bbox_inches='tight', dpi=300)
```

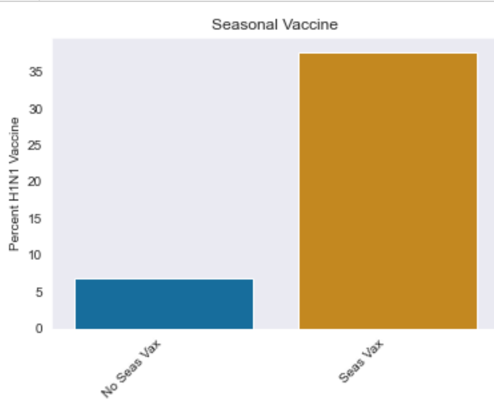
```
0    0.534392
1    0.465608
Name: seasonal_vaccine, dtype: float64
```



In [113]:
```
h1n1_rates_house_seas_vax = df.groupby('seasonal_vaccine').mean().h1n1_vaccine
print(h1n1_rates_house_seas_vax, ': ', h1n1_rates_house_seas_vax.max() - \
      h1n1_rates_house_seas_vax.min())
```

```
seasonal_vaccine
0    0.068456
1    0.377724
Name: h1n1_vaccine, dtype: float64 :  0.3092684481726502
```

In [115]:
```
# Visualize percent of no seasonal vaccination and seasonal vaccination with H1N1 vaccination

fig, ax = plt.subplots()

sns.barplot(x=h1n1_rates_house_seas_vax.index, y=h1n1_rates_house_seas_vax.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Seasonal Vaccine')
plt.xticks(rotation=45, ha="right")

ax.set_xticklabels(['No Seas Vax', 'Seas Vax'])
plt.savefig('images/doc_recs_vax_perc.png', bbox_inches='tight', dpi=300)
```



What percentage of each question response recieved the H1N1 vaccine?

In [13]:

```
# Get percents of H1N1 vaccinated by response by indicator

# Get percent of vaccinated lkjsdaflk

h1n1_rates_house_adlts = df.groupby('household_adults').mean().h1n1_vaccine
h1n1_rates_house_child = df.groupby('household_children').mean().h1n1_vaccine
h1n1_rates_for_bar_numerical = [h1n1_rates_house_adlts, h1n1_rates_house_child]
h1n1_rates_beh_virmeds = df.groupby('behavioral_antiviral_meds').mean().h1n1_vaccine
h1n1_rates_beh_avoid = df.groupby('behavioral_avoidance').mean().h1n1_vaccine
h1n1_rates_beh_facemask = df.groupby('behavioral_face_mask').mean().h1n1_vaccine
h1n1_rates_beh_washhands = df.groupby('behavioral_wash_hands').mean().h1n1_vaccine
h1n1_rates_beh_gatherings = df.groupby('behavioral_large_gatherings').mean().h1n1_vaccine
h1n1_rates_beh_outside = df.groupby('behavioral_outside_home').mean().h1n1_vaccine
h1n1_rates_beh_touchface = df.groupby('behavioral_touch_face').mean().h1n1_vaccine
h1n1_rates_docrec = df.groupby('doctor_recc_h1n1').mean().h1n1_vaccine
h1n1_rates_chroncond = df.groupby('chronic_med_condition').mean().h1n1_vaccine
h1n1_rates_childund6 = df.groupby('child_under_6_months').mean().h1n1_vaccine
h1n1_rates_healthworker = df.groupby('health_worker').mean().h1n1_vaccine
h1n1_rates_insurance = df.groupby('health_insurance').mean().h1n1_vaccine
h1n1_rates_age = df.groupby('age_group').mean().h1n1_vaccine
h1n1_rates_education = df.groupby('education').mean().h1n1_vaccine
h1n1_rates_race = df.groupby('race').mean().h1n1_vaccine
h1n1_rates_sex = df.groupby('sex').mean().h1n1_vaccine
h1n1_rates_income = df.groupby('income_poverty').mean().h1n1_vaccine
h1n1_rates_marital = df.groupby('marital_status').mean().h1n1_vaccine
h1n1_rates_own = df.groupby('rent_or_own').mean().h1n1_vaccine
h1n1_rates_employment_status = df.groupby('employment_status').mean().h1n1_vaccine
h1n1_rates_geo = df.groupby('hhs_geo_region').mean().h1n1_vaccine.sort_values(ascending=False)
h1n1_rates_census = df.groupby('census_msa').mean().h1n1_vaccine
h1n1_rates_employment_industry = df.groupby('employment_industry').mean().h1n1_vaccine.sort_values(ascending=False)
h1n1_rates_employment_occupation = df.groupby('employment_occupation').mean().h1n1_vaccine.sort_values(ascending=False)
h1n1_rates_houseadlt = df.groupby('household_adults').mean().h1n1_vaccine
h1n1_rates_housechld = df.groupby('household_children').mean().h1n1_vaccine
h1n1_rates_concern = df.groupby('h1n1_concern').mean().h1n1_vaccine
h1n1_rates_knowledge = df.groupby('h1n1_knowledge').mean().h1n1_vaccine
h1n1_rates_op_effective = df.groupby('opinion_h1n1_vacc_effective').mean().h1n1_vaccine
h1n1_rates_op_risk = df.groupby('opinion_h1n1_risk').mean().h1n1_vaccine
h1n1_rates_op_sickfromvac = df.groupby('opinion_h1n1_sick_from_vacc').mean().h1n1_vaccine



h1n1_rates_for_bars = [h1n1_rates_beh_virmeds, h1n1_rates_beh_avoid,
                      h1n1_rates_beh_facemask, h1n1_rates_beh_washhands,
                       h1n1_rates_beh_gatherings, h1n1_rates_beh_outside,
                       h1n1_rates_beh_touchface, h1n1_rates_docrec,
                       h1n1_rates_chroncond, h1n1_rates_childund6,
                       h1n1_rates_healthworker, h1n1_rates_insurance,
                       h1n1_rates_beh_virmeds, h1n1_rates_beh_avoid,
                       h1n1_rates_beh_facemask, h1n1_rates_beh_washhands,
                       h1n1_rates_beh_gatherings, h1n1_rates_beh_outside,
                       h1n1_rates_beh_touchface, h1n1_rates_docrec,
                       h1n1_rates_chroncond, h1n1_rates_childund6,
                       h1n1_rates_healthworker, h1n1_rates_insurance,
                       h1n1_rates_age, h1n1_rates_education,
                       h1n1_rates_race, h1n1_rates_sex,
                       h1n1_rates_income, h1n1_rates_marital,
                       h1n1_rates_own, h1n1_rates_employment_status,
                       h1n1_rates_geo, h1n1_rates_census,
                       h1n1_rates_employment_industry, h1n1_rates_employment_occupation,
                       h1n1_rates_houseadlt, h1n1_rates_housechld,
                       h1n1_rates_concern, h1n1_rates_knowledge,
                       h1n1_rates_op_effective, h1n1_rates_op_risk,
                       h1n1_rates_op_sickfromvac
                      ]
```

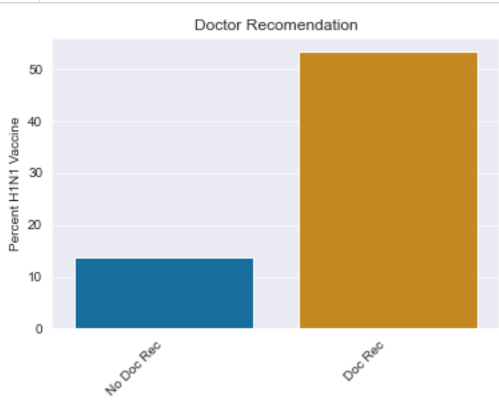
In [14]:
```
# Print percentages by choice and difference between highest and lowest percent by indicator

for i in h1n1_rates_for_bars:
    print(i, ': ', i.max() - i.min(), '\n')
```

```
4.0    0.176410
5.0    0.404828
Name: h1n1_vaccine, dtype: float64 :  0.35742429292073363

opinion_h1n1_risk
1.0    0.088340
2.0    0.167960
3.0    0.173679
4.0    0.392102
5.0    0.510857
Name: h1n1_vaccine, dtype: float64 :  0.42251705193688244

opinion_h1n1_sick_from_vacc
1.0    0.204601
2.0    0.173184
3.0    0.081081
4.0    0.264274
5.0    0.280293
Name: h1n1_vaccine, dtype: float64 :  0.19921155723624862
```

Get another look at indicators with the largest difference in percentage between lowest and highest percentage choices with bar plot visualizations.

In [26]:
```
# Create vizualizations of percentages by choice by indicators
```

In [27]:
```
# Visualize proportion of no doc recomended and doc recomended with H1N1 vaccination

fig, ax = plt.subplots()

sns.barplot(x=h1n1_rates_docrec.index, y=h1n1_rates_docrec.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Doctor Recomendation')
plt.xticks(rotation=45, ha="right")

ax.set_xticklabels(['No Doc Rec', 'Doc Rec'])
plt.savefig('images/doc_recs_vax_perc.png', bbox_inches='tight', dpi=300)
```



Who did doctors recommend get the vacccine?

In [28]:

```
# Get percents of doctor response by response by indicator

doctor_recc_rates_age = df.groupby('age_group').mean().doctor_recc_h1n1
print(doctor_recc_rates_age, '\n')
doctor_recc_rates_education = df.groupby('education').mean().doctor_recc_h1n1
print(doctor_recc_rates_education, '\n')
doctor_recc_rates_race = df.groupby('race').mean().doctor_recc_h1n1
print(doctor_recc_rates_race, '\n')
doctor_recc_rates_sex = df.groupby('sex').mean().doctor_recc_h1n1
print(doctor_recc_rates_sex, '\n')
doctor_recc_rates_income = df.groupby('income_poverty').mean().doctor_recc_h1n1
print(doctor_recc_rates_income, '\n')
doctor_recc_rates_marital = df.groupby('marital_status').mean().doctor_recc_h1n1
```

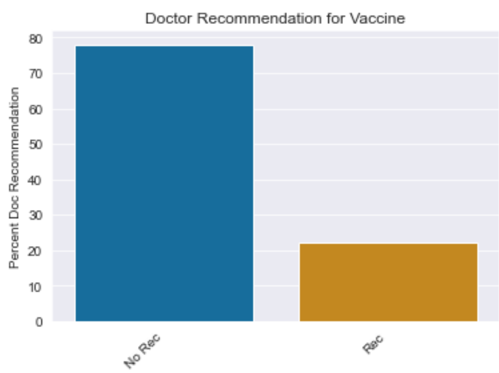
```
age_group
18 - 34 Years    0.217536
35 - 44 Years    0.221251
45 - 54 Years    0.203341
55 - 64 Years    0.234421
65+ Years        0.223545
Name: doctor_recc_h1n1, dtype: float64

education
12 Years            0.202480
< 12 Years          0.200841
College Graduate    0.228896
Some College        0.232847
Name: doctor_recc_h1n1, dtype: float64

race
Black                0.229102
Hispanic             0.242517
Other or Multiple    0.230717
White                0.216785
Name: doctor_recc_h1n1, dtype: float64

sex
Female    0.234831
Male      0.198994
Name: doctor_recc_h1n1, dtype: float64

income_poverty
<= $75,000, Above Poverty    0.216136
> $75,000                    0.235202
Below Poverty                0.235459
Name: doctor_recc_h1n1, dtype: float64
```

Nothing jumps out as an imbalance in percent of doctor recommendations, but all percentages are low. What was the overall percentage of those that responded when they received a doctor recommendation?

In [29]:

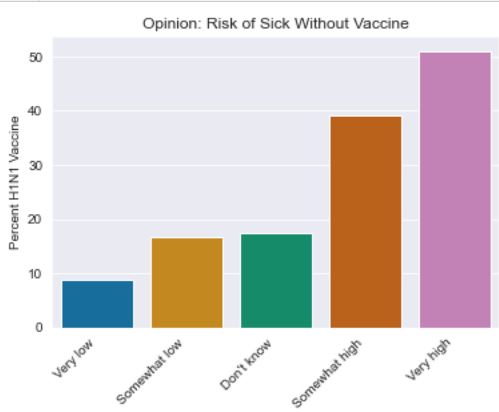
```
# Look at the percent of respondents who recieved a doctor recommendation to get the vaccine

# Get percents
doc_recc_prop = df.doctor_recc_h1n1.value_counts(normalize=True)
print(doc_recc_prop)


# Chart
fig, ax = plt.subplots()

sns.barplot(x=doc_recc_prop.index, y=doc_recc_prop.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent Doc Recommendation')
ax.set_title("Doctor Recommendation for Vaccine")

plt.xticks(rotation=45, ha="right")

ax.set_xticklabels(['No Rec', 'Rec'])

plt.savefig('images/perc_doc_recs.png', bbox_inches='tight', dpi=300)
```

```
0.0    0.779688
1.0    0.220312
Name: doctor_recc_h1n1, dtype: float64
```



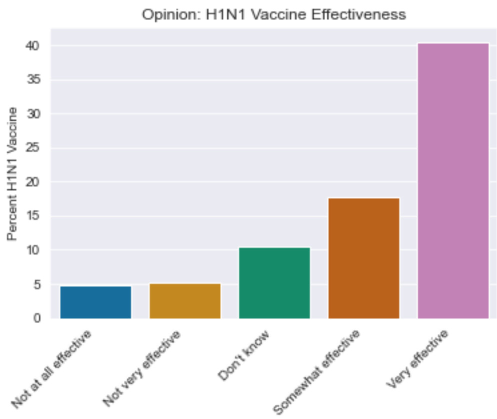
In [30]:

```
# Visualize proportion of level of respons opinion about risk of getting sick with H1N1 without vaccine with H1N1 vaccinc

fig, ax = plt.subplots()

sns.barplot(x=h1n1_rates_op_risk.index, y=h1n1_rates_op_risk.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Opinion: Risk of Sick Without Vaccine')
plt.xticks(rotation=45, ha="right")

ax.set_xticklabels(['Very low', 'Somewhat low', "Don't know", 'Somewhat high', 'Very high'])

plt.savefig('images/op_sick_without_vax.png', bbox_inches='tight', dpi=300)
```



In [31]:

```
# Visualize proportion of level of respons opinion about seasonal flu vaccine effectiveness with H1N1 vaccination

fig, ax = plt.subplots()

sns.barplot(x=h1n1_rates_op_effective.index, y=h1n1_rates_op_effective.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Opinion: H1N1 Vaccine Effectiveness')
plt.xticks(rotation=45, ha="right")

ax.set_xticklabels(['Not at all effective', 'Not very effective', "Don't know", 'Somewhat effective', 'Very effective'])

plt.savefig('images/op_vax_effective.png', bbox_inches='tight', dpi=300)
```

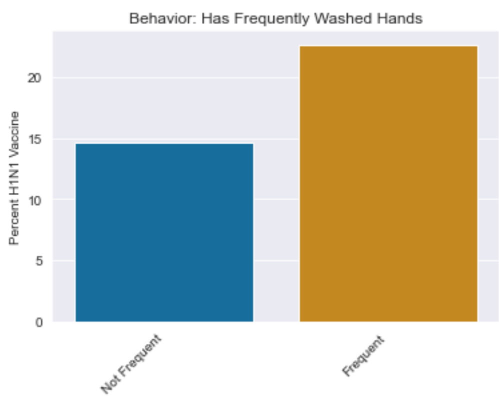


In [32]:

```
# Visualize proportion of level of respons opinion about seasonal flu vaccine effectiveness with H1N1 vaccination

fig, ax = plt.subplots()

sns.barplot(x=h1n1_rates_beh_facemask.index, y=h1n1_rates_beh_facemask.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Behavior: Purchased Facemask')
plt.xticks(rotation=45, ha="right")

ax.set_xticklabels(['No Facemask', 'Purchased Facemask'])

plt.savefig('images/beh_facemask.png', bbox_inches='tight', dpi=300)
```

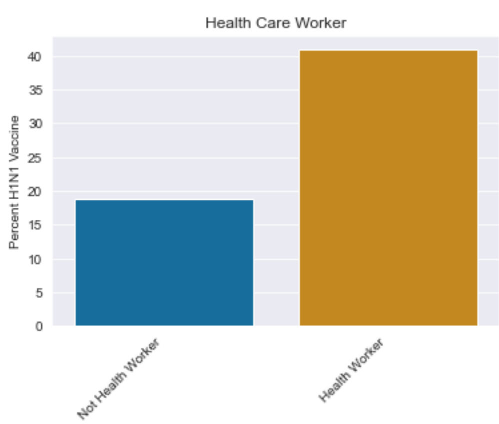
In [33]:
```
# Visualize proportion of level of respons opinion about seasonal flu vaccine effectiveness with H1N1 vaccination

fig, ax = plt.subplots()

sns.barplot(x=h1n1_rates_beh_washhands.index, y=h1n1_rates_beh_washhands.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Behavior: Has Frequently Washed Hands')
plt.xticks(rotation=45, ha="right")

ax.set_xticklabels(['Not Frequent', 'Frequent'])
```

Out[33]:
```
[Text(0, 0, 'Not Frequent'), Text(1, 0, 'Frequent')]
```



In [34]:
```
# Visualize proportion of not health care worker and health care worker with H1N1 vaccination

fig, ax = plt.subplots()

sns.barplot(x=h1n1_rates_healthworker.index, y=h1n1_rates_healthworker.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Health Care Worker')
plt.xticks(rotation=45, ha="right")

ax.set_xticklabels(['Not Health Worker', 'Health Worker'])
```

Out[34]:
```
[Text(0, 0, 'Not Health Worker'), Text(1, 0, 'Health Worker')]
```

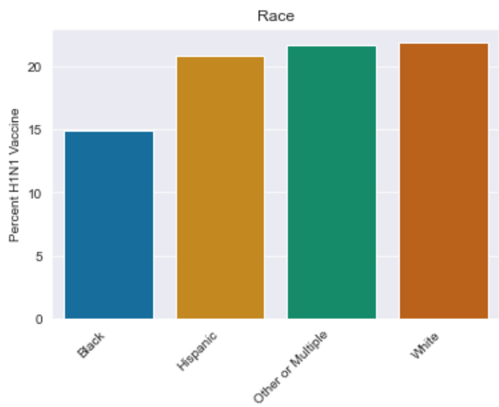


In [35]:

```python
# Visualize proportion of not health care worker and health care worker with H1N1 vaccination

fig, ax = plt.subplots()

sns.barplot(x=h1n1_rates_race.index, y=h1n1_rates_race.values*100)

ax.set_xlabel('')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Race')
plt.xticks(rotation=45, ha="right")
```

Out[35]:

```
(array([0, 1, 2, 3]),
 [Text(0, 0, 'Black'),
  Text(1, 0, 'Hispanic'),
  Text(2, 0, 'Other or Multiple'),
  Text(3, 0, 'White')])
```



Let's have some fun, as a reminder that human behavior is a difficult thing to predict. Are there respondents that are surprising to find did not receive the H1N1 vaccine? Let's see if anyone who gave the most vaccine positive responses to the questions likeliness to get sick from vaccine, the vaccine is effective, and received a doctor's recommendation and still did not get an H1N1 vaccine.

In [37]:

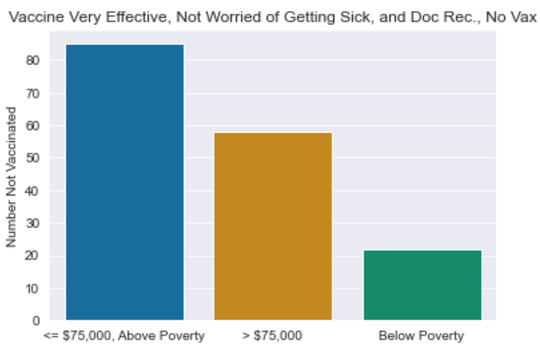
```python
df_y_no_vax = df[(df['h1n1_vaccine'] == 0) &
                                (df['opinion_h1n1_sick_from_vacc'] == 1) &
                                (df['opinion_h1n1_vacc_effective'] == 5) &
                                (df['doctor_recc_h1n1'] == 1)]
```

In [38]:

```python
y_no_vax_norm = df_y_no_vax.income_poverty.value_counts(normalize=True)
print(y_no_vax_norm, '\n')
y_no_vax = df_y_no_vax.income_poverty.value_counts()
print(y_no_vax)
```

```
<= $75,000, Above Poverty    0.515152
> $75,000                    0.351515
Below Poverty                0.133333
Name: income_poverty, dtype: float64

<= $75,000, Above Poverty    85
> $75,000                    58
Below Poverty                22
Name: income_poverty, dtype: int64
```

In [39]:
```python
# Chart
fig, ax = plt.subplots()

sns.barplot(x=y_no_vax.index, y=y_no_vax.values)

ax.set_xlabel('')
ax.set_ylabel('Number Not Vaccinated')
ax.set_title("Vaccine Very Effective, Not Worried of Getting Sick, and Doc Rec., No Vax")

ax.set_xticklabels(['<= $75,000, Above Poverty', '> $75,000', 'Below Poverty',])

plt.savefig('images/###.png', bbox_inches='tight', dpi=300)
```



In [ ]:
```python
# Proportion of those who *&%*&^% who got h1n1 vaccine

likely_vax.groupby('income_poverty').mean().h1n1_vaccine
```

Modeling

```
Having explored the data some, build first models; a dummy model and first simple model.
```

In [41]:
```python
X = df.drop(['respondent_id', 'h1n1_vaccine'], axis=1)
y = df.h1n1_vaccine

X_train, X_test, y_train, y_test = train_test_split(X,y,random_state=42)
```

In [42]:
```python
print(X_train.shape)
print(y_train.shape)
```

```
(20030, 36)
(20030,)
```

Set up transformer pipelines and a cross validation class for modeling.

In [43]:
```python
# Numeric Pipeline, impute missing data and scale

num_pipe = Pipeline([
    ('num_impute', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

# Categorical Pipeline, impute missing data and encode categoricals

cat_pipe = Pipeline([
    ('cat_impute', SimpleImputer(strategy='most_frequent')),
    ('ohe', OneHotEncoder(sparse=False, handle_unknown='ignore'))
])

# Create column transformer to use in model pieplines

CT = ColumnTransformer([
    ('num_trans', num_pipe, selector(dtype_include=np.number)),
    ('cat_trans', cat_pipe, selector(dtype_include=object)),
], remainder='passthrough')
```

In [183]:

```
class ModelWithCV():
    '''Structure to save the model and more easily see its crossvalidation'''

    def __init__(self, model, model_name, X, y, cv_now=True):
        self.model = model
        self.name = model_name
        self.X = X
        self.y = y
        # For CV results
        self.cv_results = None
        self.cv_mean = None
        self.cv_median = None
        self.cv_std = None
        #
        if cv_now:
            self.cross_validate()

    def cross_validate(self, X=None, y=None, kfolds=10):
        '''
        Perform cross-validation and return results.

        Args:
          X:
            Optional; Training data to perform CV on. Otherwise use X from object
          y:
            Optional; Training data to perform CV on. Otherwise use y from object
          kfolds:
            Optional; Number of folds for CV (default is 10)
        '''

        cv_X = X if X else self.X
        cv_y = y if y else self.y

        self.cv_results = cross_val_score(self.model, cv_X, cv_y, scoring='recall', cv=kfolds)
        self.cv_mean = np.mean(self.cv_results)
        self.cv_median = np.median(self.cv_results)
        self.cv_std = np.std(self.cv_results)


    def print_cv_summary(self):
        cv_summary = (
        f'''CV Results for `{self.name}` model:
            {self.cv_mean:.5f} ± {self.cv_std:.5f} recall accuracy
        ''')
        print(cv_summary)


    def plot_cv(self, ax):
        '''
        Plot the cross-validation values using the array of results and given
        Axis for plotting.
        '''
        ax.set_title(f'CV Results for `{self.name}` Model')
        # Thinner violinplot with higher bw
        sns.violinplot(y=self.cv_results, ax=ax, bw=.4)
        sns.swarmplot(
                y=self.cv_results,
                color='orange',
                size=10,
                alpha= 0.8,
                ax=ax
        )

        return ax
```

There is a class imbalance for the target, use SMOTE to create synthetic data to balance the classes.
Use ModelWithCV class to cross validate.

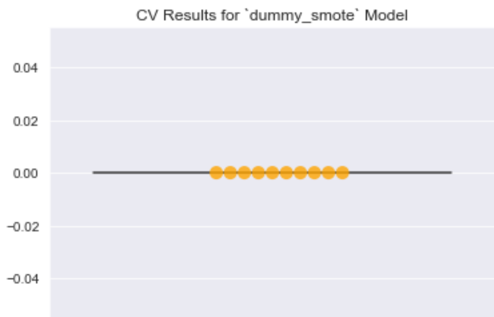
In [185]:

```
# Create Dummy/Baseline

dummy_smote_model = ImPipeline([
    ('ct', CT),
    ('sm', SMOTE(random_state=42)),
    ('dummy', DummyClassifier(strategy='most_frequent', random_state=42))
])

# Use the class with our dummy pipe

dummy_smoted_model_pipe = ModelWithCV(dummy_smote_model, model_name='dummy_smote', X=X_train, y=y_train)
```

In [186]:
```
dummy_smoted_model_pipe.cv_mean
```
Out[186]: 0.0

In [187]:
```
dummy_smoted_model_pipe.print_cv_summary()
```
```
CV Results for `dummy_smote` model:
            0.00000 ± 0.00000 recall accuracy
```

In [188]:
```
sns.set_style("darkgrid")
fig,ax = plt.subplots()

dummy_smoted_model_pipe.plot_cv(ax=ax)
```
Out[188]: <AxesSubplot:title={'center':'CV Results for `dummy_smote` Model'}>



Our dummy model should have given us a .50 after creating synthetic data, however it did not. This is something to look into fixing. Going with what it produced without synthetic data, it is expected to have a recall score of 0 as it only predicted the most frequent outcome of not getting the vaccine.

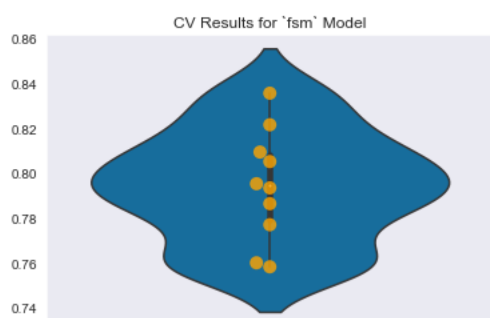
The first simple logistic regression model will be sent all data and use SMOTE to balance the classes.

In [191]:
```
# Use the class with logreg pipe

logreg_fsm = ImPipeline([
    ('ct', CT),
    ('sm', SMOTE(random_state=42)),
    ('logreg_fsm', LogisticRegression(random_state=42, max_iter=1000))
])
```

In [192]:
```
fsm_model_pipe = ModelWithCV(logreg_fsm, model_name='fsm', X=X_train, y=y_train)
```

In [193]:
```
fsm_model_pipe.print_cv_summary()
```
```
CV Results for `fsm` model:
            0.79422 ± 0.02376 recall accuracy
```

In [194]:
```
fig,ax = plt.subplots()

fsm_model_pipe.plot_cv(ax=ax)
```
Out[194]: <AxesSubplot:title={'center':'CV Results for `fsm` Model'}>



Make adjustments to the features, drop those with high percentage fo nulls, and sum behavorial group to reduce features and create stronger indicator. To reduce features, combine the behavioral questions into a behaviorial sum category.

In [195]:

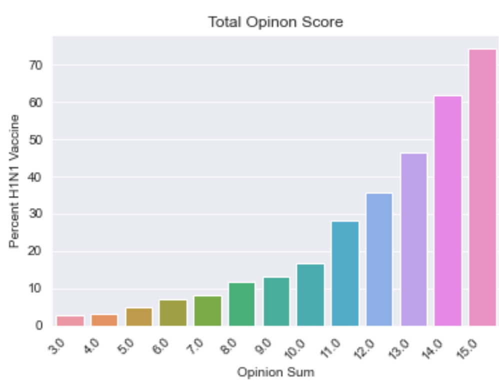
```
# Create Behavorial Sum

sns.set_style("darkgrid")

#Proportional Behavorial Sum
df['beh_sum'] = df.behavioral_antiviral_meds + df.behavioral_avoidance + \
                df.behavioral_face_mask + df.behavioral_wash_hands + \
                df.behavioral_large_gatherings + df.behavioral_outside_home + \
                df.behavioral_touch_face

beh_sum = df.groupby('beh_sum').mean().h1n1_vaccine
print(beh_sum)
print(beh_sum.max() - beh_sum.min())

fig, ax = plt.subplots()

sns.barplot(x=beh_sum.index, y=beh_sum.values*100)

ax.set_xlabel('Behavorial Sum')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Total Behavior Score')
plt.xticks(rotation=45, ha="right")

plt.savefig('images/beh_totals.png', bbox_inches='tight', dpi=300)
```

```
beh_sum
0.0    0.120429
1.0    0.162809
2.0    0.207301
3.0    0.227935
4.0    0.227830
5.0    0.230254
6.0    0.284333
7.0    0.333333
Name: h1n1_vaccine, dtype: float64
0.2129042743377214
```

In [196]:

```
# Ceate Opinion Sum

#Proportional Opinion Sum
df['op_sum'] = df.opinion_h1n1_vacc_effective + df.opinion_h1n1_risk + \
                (6 - df.opinion_h1n1_sick_from_vacc)

op_sum = df.groupby('op_sum').mean().h1n1_vaccine
print(op_sum)
print(op_sum.max() - op_sum.min())

fig, ax = plt.subplots()

sns.barplot(x=op_sum.index, y=op_sum.values*100)

ax.set_xlabel('Opinion Sum')
ax.set_ylabel('Percent H1N1 Vaccine')
ax.set_title('Total Opinon Score')
plt.xticks(rotation=45, ha="right")

plt.savefig('images/op_totals.png', bbox_inches='tight', dpi=300)
```

```
op_sum
3.0     0.026316
4.0     0.032051
5.0     0.049470
6.0     0.070288
7.0     0.081171
8.0     0.115534
9.0     0.132679
10.0    0.165134
11.0    0.282563
12.0    0.357179
13.0    0.463612
14.0    0.617964
15.0    0.742308
Name: h1n1_vaccine, dtype: float64
0.7159919028340082
```



In [197]:

```
# Create dataframe with new features

df_fm = df.copy(['h1n1_concern', 'h1n1_knowledge', 'beh_sum', \
                 'doctor_recc_h1n1', 'chronic_med_condition', 'child_under_6_months', \
                 'health_worker', 'opinion_h1n1_vacc_effective', 'opinion_h1n1_risk', \
                 'opinion_h1n1_sick_from_vacc', 'age_group', 'education', 'race', 'sex', \
                 'income_poverty', 'marital_status', 'rent_or_own', 'employment_status', \
                 'hhs_geo_region', 'household_adults', 'household_children', 'seasonal_vaccine', \
                 'h1n1_vaccine'])
```

In [199]:

```
df_fm.head()
```

Out[199]:

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

In [66]:
```
# Create new train test split with new dataframe

X = df_fm.drop(['respondent_id', 'h1n1_vaccine'], axis=1)
y = df_fm.h1n1_vaccine

X_clean_train, X_clean_test, y_clean_train, y_clean_test = train_test_split(X,y,random_state=42)
```

The next model will be the same model type and parmeters with the adjusted data.

In [200]:
```
fsm_clean_model_pipe = ModelWithCV(logreg_fsm, model_name='fsm_clean', X=X_clean_train, y=y_clean_train)
```

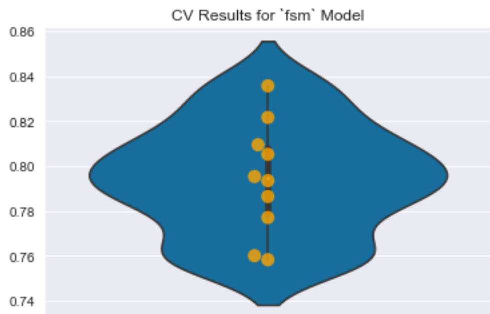
In [201]:
```
fsm_clean_model_pipe.cv_mean
```

Out[201]:
```
0.7949229494614747
```

In [ ]:
```
fsm_clean_model_pipe.
```

In [202]:
```
fig,ax = plt.subplots()

fsm_model_pipe.plot_cv(ax=ax)
```

Out[202]:
```
<AxesSubplot:title={'center':'CV Results for `fsm` Model'}>
```




```
This simple model with the adjusted features produced almost exactly the same results, but with less features will help run future models faster.
```

Use grid search to find the best parameters for a logistic regression model.

In [204]:
```
# Logistic Regression

lr = LogisticRegression(random_state=42, max_iter=1000)

lr_model_pipe = ImPipeline([
    ('ct', CT),
    ('sm', SMOTE(random_state=42)),
    ('lr', lr)
])

lr_params = {
    'ct__num_trans__num_impute__strategy' : ['mean', 'median'],
    'lr__penalty' : ['l1', 'l2', 'elasticnet'],
    'lr__C' : [100, 10, 1.0, 0.1, 0.01],
    'lr__solver' : ['lbfgs', 'liblinear', 'saga'],
}
```

In [205]:
```
gs_lr = GridSearchCV(estimator=lr_model_pipe, param_grid=lr_params, scoring='recall', cv=10, verbose=2)

gs_lr.fit(X_clean_train, y_clean_train)
```

Out[205]:
```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('ct',
                                        ColumnTransformer(remainder='passthrough',
                                                          transformers=[('num_trans',
                                                                         Pipeline(steps=[('num_impute',
                                                                                          SimpleImputer()),
                                                                                         ('scaler',
                                                                                          StandardScaler())]),
                                                                         <sklearn.compose._column_transformer.make_column
_selector object at 0x0000028A1471A790>),
                                                                        ('cat_trans',
                                                                         Pipeline(steps=[('cat_impute',
                                                                                          SimpleImputer(strategy='...
                                                                         <sklearn.compose._column_transformer.make_column
_selector object at 0x0000028A1471A850>)])),
                                       ('sm', SMOTE(random_state=42)),
                                       ('lr',
                                        LogisticRegression(max_iter=1000,
                                                           random_state=42))]),
             param_grid={'ct__num_trans__num_impute__strategy': ['mean',
```

In [146]:
```
gs_lr.best_params_
```

Out[146]:
```
{'ct__num_trans__num_impute__strategy': 'mean',
 'lr__C': 0.01,
 'lr__penalty': 'l1',
 'lr__solver': 'liblinear'}
```

In [147]:
```
gs_lr.best_score_
```

Out[147]:
```
0.8076128141397405
```

Use grid search to find the best parameters for a random forest classifier model.

In [150]:
```
# Random Forest Classsifier

rfc = RandomForestClassifier(random_state=42)

rfc_model_pipe = ImPipeline([
    ('ct', CT),
    ('sm', SMOTE(random_state=42)),
    ('rfc', rfc)])

rfc_params = {
    'ct__num_trans__num_impute__strategy' : ['mean', 'median'],
    'rfc__criterion' : ['gini', 'entropy', 'log_loss'],
    'rfc__max_depth' : [9, 11, 13, 15],
    'rfc__min_samples_leaf' : [1, 5, 15,]
}
```

In [151]:
```
gs_rfc = GridSearchCV(estimator=rfc_model_pipe, param_grid=rfc_params, scoring='recall', cv=10, verbose=2)

gs_rfc.fit(X_clean_train, y_clean_train)
```

Out[151]:
```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('ct',
                                        ColumnTransformer(remainder='passthrough',
                                                          transformers=[('num_trans',
                                                                         Pipeline(steps=[('num_impute',
                                                                                          SimpleImputer()),
                                                                                         ('scaler',
                                                                                          StandardScaler())]),
                                                                         <sklearn.compose._column_transformer.make_column
_selector object at 0x0000028A1471A790>),
                                                                        ('cat_trans',
                                                                         Pipeline(steps=[('cat_impute',
                                                                                          SimpleImputer(strategy='...
                                                                         <sklearn.compose._column_transformer.make_column
_selector object at 0x0000028A1471A850>)])),
                                       ('sm', SMOTE(random_state=42)),
                                       ('rfc',
                                        RandomForestClassifier(random_state=42))]),
             param_grid={'ct__num_trans__num_impute__strategy': ['mean',
```

In [152]:
```
gs_rfc.best_params_
```

Out[152]:
```
{'ct__num_trans__num_impute__strategy': 'mean',
 'rfc__criterion': 'entropy',
 'rfc__max_depth': 11,
 'rfc__min_samples_leaf': 15}
```

In [153]:
```
gs_rfc.best_score_
```

Out[153]:
```
0.62602209334438
```

Because the best parameters had a parameter, min_sample_leaf, at the far end of our options, run another model with the best parameters but increasing the options for min_sample_leaf.

In [ ]:
```

```

In [174]:
```
rfc_params_adj_leafs = {
    'ct__num_trans__num_impute__strategy' : ['mean'],
    'rfc__criterion' : [ 'entropy'],
    'rfc__max_depth' : [11],
    'rfc__min_samples_leaf' : [15, 17, 19, 21, 23]
}
```

In [175]:
```
gs_rfc = GridSearchCV(estimator=rfc_model_pipe, param_grid=rfc_params_adj_leafs, scoring='recall', cv=10, verbose=2)

gs_rfc.fit(X_clean_train, y_clean_train)
```

```
                                                           transformers=[('num_trans',
                                                                          Pipeline(steps=[('num_impute',
                                                                                           SimpleImputer()),
                                                                                          ('scaler',
                                                                                           StandardScaler())]),
                                                                          <sklearn.compose._column_transformer.make_column
_selector object at 0x0000028A1471A790>),
                                                                         ('cat_trans',
                                                                          Pipeline(steps=[('cat_impute',
                                                                                           SimpleImputer(strategy='...
                                                                                                         sparse=False))]),
                                                                          <sklearn.compose._column_transformer.make_column
_selector object at 0x0000028A1471A850>)])),
                                       ('sm', SMOTE(random_state=42)),
                                       ('rfc',
                                        RandomForestClassifier(random_state=42))]),
             param_grid={'ct__num_trans__num_impute__strategy': ['mean'],
                         'rfc__criterion': ['entropy'], 'rfc__max_depth': [11],
                         'rfc__min_samples_leaf': [15, 17, 19, 21, 23]},
             scoring='recall', verbose=2)
```

In [179]:
```
gs_rfc.best_params_
```

Out[179]:
```
{'ct__num_trans__num_impute__strategy': 'mean',
 'rfc__criterion': 'entropy',
 'rfc__max_depth': 11,
 'rfc__min_samples_leaf': 21}
```

In [176]:
```
gs_rfc.best_score_
```

Out[176]:
```
0.6295476387738195
```

In [ ]:
```

```

Use grid search to find the best parameters for a k-nearest neighbors classifier model.

In [180]:
```
# K-Nearest Neighbors Classifier

knn = KNeighborsClassifier()

knn_model_pipe = ImPipeline([
    ('ct', CT),
    ('sm', SMOTE(random_state=42)),
    ('knn', knn)])

knn_params = {
    'ct__num_trans__num_impute__strategy' : ['mean', 'median'],
    'knn__n_neighbors' : [1, 3, 5, 7, 9, 11],
    'knn__weights' : ['uniform', 'distance'],
    'knn__leaf_size' : [5, 10, 20, 30, 40],
    'knn__metric' : ['minkowski', 'cityblock']
}
```

In [181]:
```
gs_knn = GridSearchCV(estimator=knn_model_pipe, param_grid=knn_params, scoring='recall', cv=10, verbose=2)

gs_knn.fit(X_clean_train, y_clean_train)
```

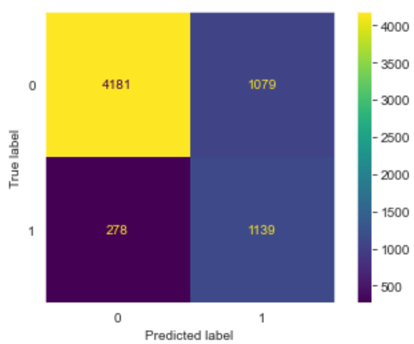
...

In [ ]:
```
gs_rfc.best_score_
```

Evlauation

The logistic regression model with a numerical impute strategy of 'mean, C: .01, penalty: l1, and solver: liblinear, was our best performing model on trained data and cross validation. Now compare the test data.

In [210]:
```
sns.set_style("dark")
gs_lr.best_estimator_.fit(X_clean_train, y_clean_train)
y_pred = gs_lr.best_estimator_.predict(X_clean_test)
plot_confusion_matrix(estimator=gs_lr.best_estimator_, X=X_clean_test, y_true=y_clean_test)

plt.savefig('images/cm_log_reg.png', bbox_inches='tight', dpi=300)
```



In [211]:
```
recall_score(y_clean_test, y_pred)
```

Out[211]: 0.8038108680310515

In [212]:
```
precision_score(y_clean_test, y_pred)
```

Out[212]: 0.5135256988277728