SRS Case Study: COVID-19 Vaccination Likelihood

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June 1, 2022

In this notebook, I tried to show how I would go about working through a problem. The goal is to understand a person's chances of getting the COVID-19 Vaccine.

The provided 2020 sampled survey dataset contains thirty variables with the respondednts sociodemographic characteristics, attituide or beliefs towards COVID vaccine.

Here is a list of variables. I reorganized the variables with categories in blue.

Variable Name	Description
CaseId (Unique)	Unique identifier
#Location information	
FIPS	FIPS code of respondent's county
P_ZIP	ZIP code of respondent
STATE	Respondent's state of residence
REGION4	Respondent's census region of residence
METRO	urban/rural identifier
#Age, gender, race	
GENDER	Respondent's gender (1=Male; 2=Female)
RACETHNICITY	Respondent's race/ethnicity (simplified)
cmu_age_cats	Respondent's age (categorized)
# Socio economic	
d_EDUC5	Highest level of education of respondent (categorized)
d_INCOME4	Respondent's household income (categorized)
HOUSING	Home ownership status:
state_med_hh_income	Median household income of respondent's state of residence
#Target	
intent_to_vaccinate	When a COVID-19 vaccine is available to you, how likely are you to take it? 0 = Extremely unlikely; 10 = Extremely likely
#Opinion	
d_believes_nat_gt_vacc	believes natural immunity is stronger than vaccine immunity
d_childhood_vaccines_have_harmful_side_effects	believes childhood vaccine is harmful
d_comm_covid_exaggerated	reference community thinks that threat of COVID-19 is exaggerated
d_comm_expect_vacc	reference community expects me to take COVID-19 vaccine
#Occupation	
frontline_HCW	respondent is a frontline health care worker
essential_worker	respondent is an essential worker
#Health	
has_comorbidity	has one or more comorbidities with COVID-19
#Beliefs or experiences	
conspiratorial_thinking	Index of conspiratorial thinking (0=no conspiratorial beliefs, 3=frequent conspiratorial beliefs)
trust_in_gov	Index of trust in information from government (0=no trust, 5=complete trust)
trust_in_sci	Index of trust in information from scientists (0=no trust, 3=complete trust)
personal_covid_exp	Respondent has had a personal exposure to COVID-19
d_Q2_1	How much would you guess the COVID-19 vaccine might cost you out of pocket? Your best guess is fine. (categorized)
#Source of information	
d_get_info_fox	gets information on COVID-19 from Fox News
d_get_info_socm	gets information on COVID-19 from social media
d_get_info_scientists	gets information on COVID-19 from scientists
d_get_info_church	gets information on COVID-19 from church

Analysis plan

• Understand nature of the data .info() .describe() • Histograms and boxplots • Value counts • Missing data • inferential stats • Explore interesting themes • Feature engineering • Feature selection • Scaling? Numerical variables • Model Baseline • Model comparison with CV

```
# import required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from scipy import stats
from sklearn.preprocessing import StandardScaler
```

```
# Here we import the data
df = pd.read_excel('covid.xlsx')
```

```
#Check columns and data shape
df.columns
df.shape
```

```
(825, 30)
```

```
#quick look at our data types & null counts
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 825 entries, 0 to 824
Data columns (total 30 columns):
 #   Column                                      Non-Null Count  Dtype
---  ------                                      --------------  -----
 0   CaseId                                      825 non-null    int64
 1   FIPS                                        812 non-null    float64
 2   P_ZIP                                       812 non-null    float64
 3   GENDER                                      825 non-null    int64
 4   RACETHNICITY                                825 non-null    object
 5   cmu_age_cats                                816 non-null    object
 6   d_EDUC5                                     825 non-null    object
 7   d_INCOME4                                   825 non-null    object
 8   STATE                                       825 non-null    object
 9   REGION4                                     825 non-null    object
 10  METRO                                       825 non-null    int64
 11  HOUSING                                     825 non-null    int64
 12  intent_to_vaccinate                         825 non-null    int64
 13  d_believes_nat_gt_vacc                      824 non-null    object
 14  d_childhood_vaccines_have_harmful_side_effects  823 non-null    object
 15  d_comm_covid_exaggerated                    819 non-null    object
 16  d_comm_expect_vacc                          825 non-null    object
 17  frontline_HCW                               825 non-null    int64
 18  essential_worker                            825 non-null    int64
 19  has_comorbidity                             825 non-null    object
 20  conspiratorial_thinking                     819 non-null    float64
 21  trust_in_gov                                819 non-null    float64
 22  trust_in_sci                                825 non-null    int64
 23  personal_covid_exp                          814 non-null    object
 24  state_med_hh_income                         825 non-null    int64
 25  d_Q2_1                                      825 non-null    object
 26  d_get_info_fox                              825 non-null    object
 27  d_get_info_socm                             825 non-null    object
 28  d_get_info_scientists                       825 non-null    object
 29  d_get_info_church                           825 non-null    object
dtypes: float64(4), int64(9), object(17)
memory usage: 193.5+ KB
```

We can see that some values are missining and even for numeric datatype for many categorical features.

Removing missing data

As the % missingness is small, I decide to drop entire rows to save time. But we can interpolate those values based on neighborhood models or descriptive stats.

```
# Removed missing values
df.isnull().mean()
df.dropna(inplace=True)
df.shape
```

```
(777, 30)
```

Feature Engineering

We can see that many categorical variables have a numeric data type. So here I changed the data types.

```
#Changin data types
categories=['FIPS', 'P_ZIP', 'GENDER', 'RACETHNICITY', 'cmu_age_cats',
       'd_EDUC5', 'd_INCOME4', 'STATE', 'REGION4', 'METRO', 'HOUSING',
       'intent_to_vaccinate', 'd_believes_nat_gt_vacc',
       'd_childhood_vaccines_have_harmful_side_effects',
       'd_comm_covid_exaggerated', 'd_comm_expect_vacc', 'frontline_HCW',
       'essential_worker', 'has_comorbidity', 'conspiratorial_thinking',
```

```
       'trust_in_gov', 'trust_in_sci', 'personal_covid_exp',
        'd_Q2_1', 'd_get_info_fox', 'd_get_info_socm',
       'd_get_info_scientists', 'd_get_info_church']

for col_name in categories:
  df[col_name] = df[col_name].astype('category')

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 777 entries, 0 to 824
Data columns (total 30 columns):
 #   Column                                        Non-Null Count  Dtype
---  ------                                        --------------  -----
 0   CaseId                                        777 non-null    int64
 1   FIPS                                          777 non-null    category
 2   P_ZIP                                         777 non-null    category
 3   GENDER                                        777 non-null    category
 4   RACETHNICITY                                  777 non-null    category
 5   cmu_age_cats                                  777 non-null    category
 6   d_EDUC5                                       777 non-null    category
 7   d_INCOME4                                     777 non-null    category
 8   STATE                                         777 non-null    category
 9   REGION4                                       777 non-null    category
 10  METRO                                         777 non-null    category
 11  HOUSING                                       777 non-null    category
 12  intent_to_vaccinate                           777 non-null    category
 13  d_believes_nat_gt_vacc                        777 non-null    category
 14  d_childhood_vaccines_have_harmful_side_effects  777 non-null    category
 15  d_comm_covid_exaggerated                      777 non-null    category
 16  d_comm_expect_vacc                            777 non-null    category
 17  frontline_HCW                                 777 non-null    category
 18  essential_worker                              777 non-null    category
 19  has_comorbidity                               777 non-null    category
 20  conspiratorial_thinking                       777 non-null    category
 21  trust_in_gov                                  777 non-null    category
 22  trust_in_sci                                  777 non-null    category
 23  personal_covid_exp                            777 non-null    category
 24  state_med_hh_income                           777 non-null    int64
 25  d_Q2_1                                        777 non-null    category
 26  d_get_info_fox                                777 non-null    category
 27  d_get_info_socm                               777 non-null    category
 28  d_get_info_scientists                         777 non-null    category
 29  d_get_info_church                             777 non-null    category
dtypes: category(28), int64(2)
memory usage: 89.1 KB
```

Here I created new binary variable from intent_to_vaccinate. This is done by recoding original **0-5** categories to **0** and **6-10** to **1**. Where **0 = Intent to take vaccine is extremely unlikely; 1 = Intent to take vaccine is extremely likely**

I assumed categories 99, 77, and 98 are errors: removed 3 records from the data.

This binary variable solves unbalanaced target variable problem.

Note: Dividing the intent into 3 classes might result better i.e "extremely unlikely", "Not sure","extremely likely" in ML models. But to simplify plotting and interpretation, I'm using a binary variable

```
# creating binary intent variabl
intent = [0,1,2,3,4,5,6,7,8,9,10,99,77,98]
binary_intent = [0,0,0,0,0,0,1,1,1,1,1,99,99,99]

df['binary_intent'] = df['intent_to_vaccinate'].replace(intent, binary_intent)

df=df[df.binary_intent!=99]
```

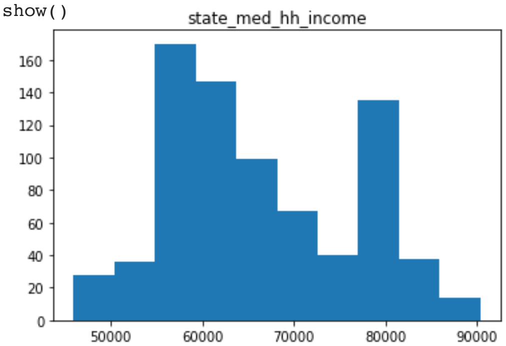
Brief Data Exploration

1) For numeric data: Made histograms to understand distribution. Used box-cox to make it close to normal distribution. Pivot table comparing intent to vaccinate.

2) For Categorical Data: Made bar charts to understand balance of classes. Made pivot tables to understand relationship with intent to vaccinate.

```
#distributions for all numeric variables
plt.hist(df['state_med_hh_income'])
```

```
plt.title('state_med_hh_income')
plt.show()
```



Inferential Stats

H0: No difference in HH income based on the binary intent H1: There is a difference in the HH income based on the binary intent

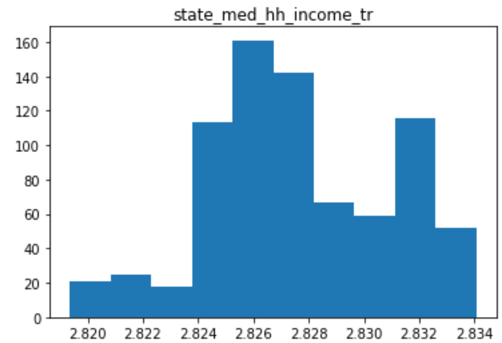
Statistically we can see there is not much difference in HH income values.

```
# Inferential Statistics
import scipy.stats as stats
from scipy.stats import ttest_ind

df.state_med_hh_income.groupby(df.binary_intent).mean()

Unlinkely=df[df.binary_intent==0]
likely=df[df.binary_intent==1]

ttest_ind(Unlinkely.state_med_hh_income,likely.state_med_hh_income,equal_var=False)
```

```
Ttest_indResult(statistic=-0.07518368250454896, pvalue=0.940088763919518)
```

Box-Cox transformation transforms state_med_hh_income. So that it closely resembles a normal distribution.

```
# Box cox transformation
df['state_med_hh_income_1'] = stats.boxcox(df['state_med_hh_income'])[0]
#distributions for all numeric variables
plt.hist(df['state_med_hh_income_1'])
plt.title('state_med_hh_income_tr')
plt.show()
```

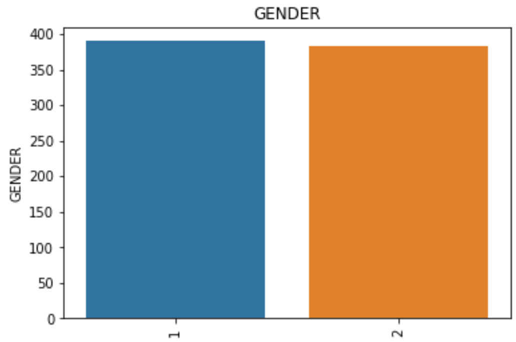



```
#Pivot analyses
pd.pivot_table(df, index = ['intent_to_vaccinate'], values = ['state_med_hh_income'],aggfunc=['mean','count'])
```

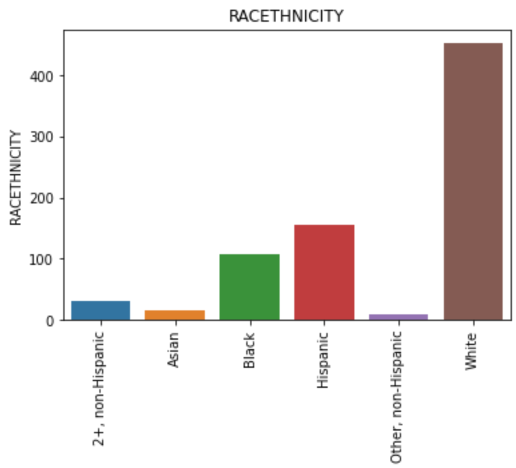
	mean	count
	state_med_hh_income	state_med_hh_income
intent_to_vaccinate		
0	65797.417266	139
1	69885.038462	26
2	65475.551724	29
3	66218.585366	41
4	68213.062500	32
5	66627.142857	77
6	67485.156250	32
7	69344.547170	53
[illegible]	[illegible]	[illegible]

```
# Making barplots for categorical variables
categories=['GENDER', 'RACETHNICITY', 'cmu_age_cats',
       'd_EDUC5', 'd_INCOME4', 'STATE', 'REGION4', 'METRO', 'HOUSING',
       'intent_to_vaccinate', 'd_believes_nat_gt_vacc',
       'd_childhood_vaccines_have_harmful_side_effects',
       'd_comm_covid_exaggerated', 'd_comm_expect_vacc', 'frontline_HCW',
       'essential_worker', 'has_comorbidity', 'conspiratorial_thinking',
       'trust_in_gov', 'trust_in_sci', 'personal_covid_exp',
        'd_Q2_1', 'd_get_info_fox', 'd_get_info_socm',
       'd_get_info_scientists', 'd_get_info_church','binary_intent']
for i in categories:
    sns.barplot(df[i].value_counts().index,df[i].value_counts()).set_title(i)
    plt.xticks(rotation=90)
    plt.show()
```

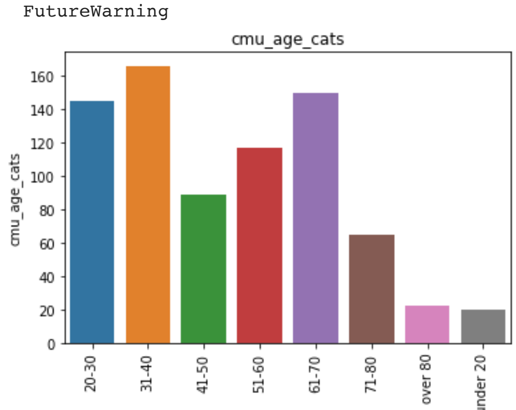
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args
  FutureWarning
```



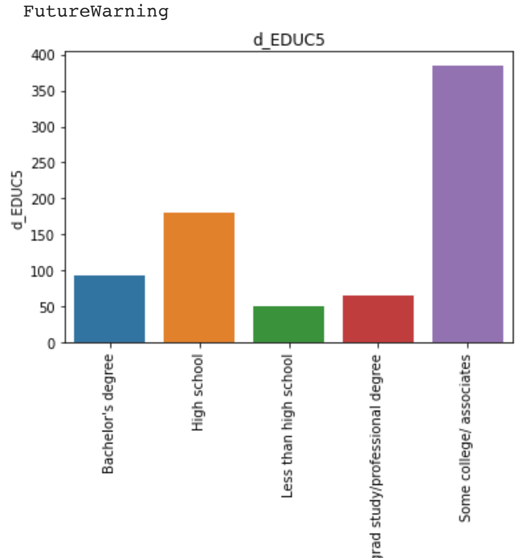

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args
  FutureWarning
```




```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args
  FutureWarning
```

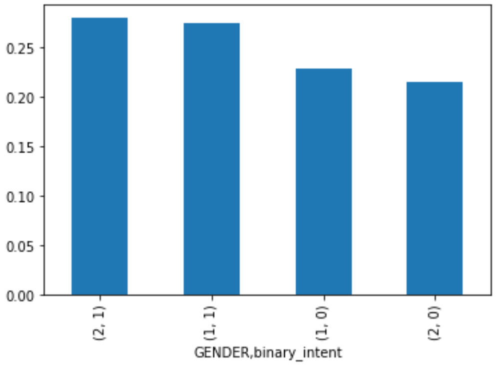


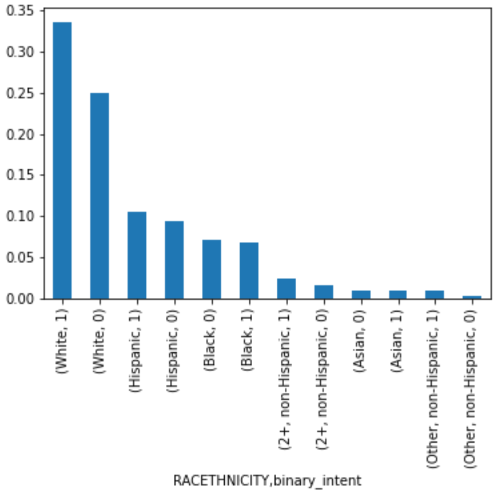

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args
  FutureWarning
```

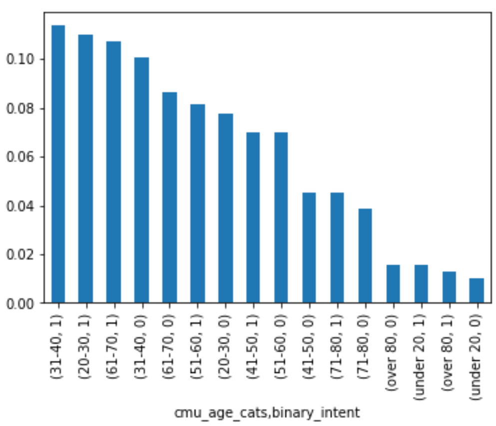


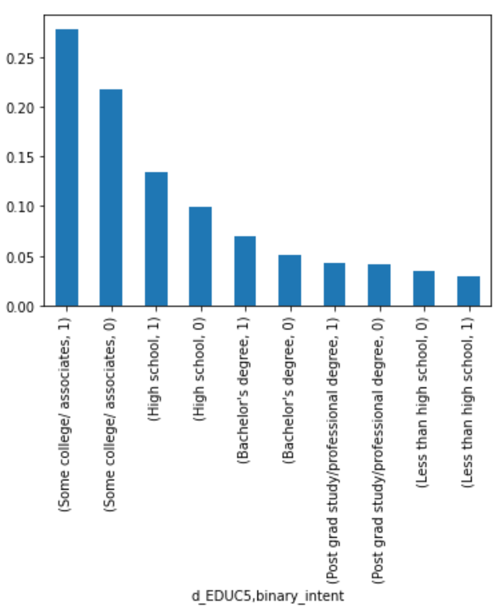
These plots tell us about individual distribution.

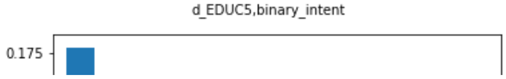
```
# comparison of individual catagorical varables with intent_to_vaccine binary variable
categories=['GENDER', 'RACETHNICITY', 'cmu_age_cats',
       'd_EDUC5', 'd_INCOME4', 'REGION4', 'METRO', 'HOUSING', 'd_believes_nat_gt_vacc',
       'd_childhood_vaccines_have_harmful_side_effects',
       'd_comm_covid_exaggerated', 'd_comm_expect_vacc', 'frontline_HCW',
       'essential_worker', 'has_comorbidity', 'conspiratorial_thinking',
       'trust_in_gov', 'trust_in_sci', 'personal_covid_exp',
        'd_Q2_1', 'd_get_info_fox', 'd_get_info_socm',
       'd_get_info_scientists', 'd_get_info_church']

for i in categories:
    df[[i,'binary_intent']].value_counts(normalize=True).plot(kind='bar')
    plt.xticks(rotation=90)
    plt.show()
```


0.00
0.05
0.10
0.15
0.20
0.25
(2, 1)
(1, 1)
(1, 0)
(2, 0)
GENDER,binary_intent


0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
(White, 1)
(White, 0)
(Hispanic, 1)
(Hispanic, 0)
(Black, 0)
(Black, 1)
(2+, non-Hispanic, 1)
(2+, non-Hispanic, 0)
(Asian, 0)
(Asian, 1)
(Other, non-Hispanic, 1)
(Other, non-Hispanic, 0)
RACETHNICITY,binary_intent


0.00
0.02
0.04
0.06
0.08
0.10
(31-40, 1)
(20-30, 1)
(61-70, 1)
(31-40, 0)
(61-70, 0)
(51-60, 1)
(20-30, 0)
(41-50, 1)
(51-60, 0)
(41-50, 0)
(71-80, 1)
(71-80, 0)
(over 80, 0)
(under 20, 1)
(over 80, 1)
(under 20, 0)
cmu_age_cats,binary_intent


0.00
0.05
0.10
0.15
0.20
0.25
(Some college/ associates, 1)
(Some college/ associates, 0)
(High school, 1)
(High school, 0)
(Bachelor's degree, 1)
(Bachelor's degree, 0)
(Post grad study/professional degree, 1)
(Post grad study/professional degree, 0)
(Less than high school, 0)
(Less than high school, 1)
d_EDUC5,binary_intent


0.175

These plots help understand the relationship between each categorical variable and the intent to vaccinate variable.

Note these trends are affected by population. But I still used it to understand the data.

Age and intent

There is no clear trend in the age category. But it is interesting to see old and young age groups not inclined towards vaccination.

Gender and intent

There is not much difference between Male VS females.

Signigican experice and intent

Shows a clear trend, those with more experience more likely to be vaccinated

Education and intent

Interestingly post graduates % is less than undergraduates. But otherwise educated people are interested in the covid vaccine.

comorbidity and work information

Shows inclination towards vaccine

I will explore others using the RF model

Feature Selection

Feature Selection is the process where we can automatically or manually select those features that contribute most to intent to vaccinate.

Here I used random forest classifier, to select top performing features.

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectFromModel
from sklearn import metrics

# encoding the levels of categorical features into numeric values
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
cols = df.columns.tolist()
for column in cols:
    if df[column].dtype == 'category':
        df[column] = le.fit_transform(df[column])

X = df.drop(['binary_intent','CaseId','state_med_hh_income','intent_to_vaccinate'], 1)       # feature matrix
y = df['binary_intent']               # target feature

X_train,X_test,y_train,y_test = train_test_split(X,y,random_state = 42,test_size =0.20,stratify=y)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(619, 28)
(155, 28)
(619,)
(155,)
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:14: FutureWarning: In a future version of pandas all arguments o
```

Finding best parameters

To select the best parameters from the listed hyperparameters, I used GridSearchCV is a library function. It helps to loop through predefined hyperparameters and fit estimator (model) on the training set.

```
from sklearn.model_selection import GridSearchCV
# Create the parameter grid based on the results of random search
param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}
# Create a based model
rf = RandomForestClassifier()
# Instantiate the grid search model
grid_search = GridSearchCV(estimator = rf, param_grid = param_grid,
                          cv = 3, n_jobs = -1, verbose = 2)
# Fit the grid search to the data
grid_search.fit(X_train, y_train)
```

```
# Best parameters used for the model selection
grid_search.best_params_
```

```
{'bootstrap': True,
 'max_depth': 80,
 'max_features': 2,
 'min_samples_leaf': 4,
 'min_samples_split': 10,
 'n_estimators': 200}
```

```
# model with the best paramteres
rf_w = RandomForestClassifier(bootstrap=True,max_depth=80,max_features=2,min_samples_leaf=4,min_samples_split=10, n_estimators=20(
rf_w.fit(X_train, y_train)
y_pred_rf_w = rf_w.predict(X_test)

#In classification, this function computes subset accuracy:
#the set of labels predicted for a sample must exactly match the corresponding set of labels in y_true.

# accuracy of the model
metrics.accuracy_score(y_test,y_pred_rf_w)
```

```
0.5548387096774193
```

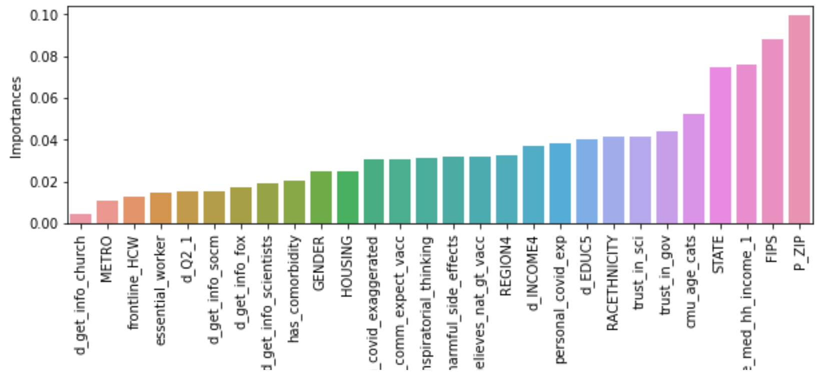
In this case, model accuracy found to be between 50 and 56%. That means: ~55% of the predicted labels (intent to vaccinate) by the current model match with true value.

Plot the feature importances in bars.

Here goal is to see which features are contributing more in determinig likelihood of intent. It is important to note that model accuracy is not great. There is scope for lot of improvement. Due to limited time for the analysis, I will select important features based on this base model only.

```
# get the importance of the resulting features.
importances = rf_w.feature_importances_
# create a data frame for visualization.
final_df = pd.DataFrame({"Features": X_train.columns, "Importances":importances})
final_df.set_index('Importances')

# sort in ascending order to better visualization.
final_df = final_df.sort_values('Importances')

# plot the feature importances in bars.
plt.figure(figsize=(10,3))
plt.xticks(rotation=90)
sns.barplot(x="Features",y= "Importances", data=final_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f649b9dabd0>
```




```
# Here I used cutoff value >0.029
final_list=final_df.sort_values(by=['Importances'], ascending=False).head(17)
final_list.Features
final_df=df[["P_ZIP","FIPS","state_med_hh_income_1","STATE","cmu_age_cats","trust_in_gov","trust_in_sci","RACETHNICITY",
"personal_covid_exp","d_INCOME4","REGION4","d_believes_nat_gt_vacc","d_childhood_vaccines_have_harmful_side_effects","conspiratori
"d_comm_covid_exaggerated","binary_intent"]]
```

Model Building (Baseline Validation Performance)

Before going further, I like to see how different models perform with default parameters. I tried the following models using 5 fold cross validation to get a baseline.

With a validation set basline, we can see how much tuning improves each of the models. Just because a model has a high basline on this validation set doesn't mean that it will actually do better on the eventual test set.

```
from sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn import tree
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
```

```
X = final_df.drop(['binary_intent'], 1)       # feature matrix
y = final_df['binary_intent']               # target feature

X_train,X_test,y_train,y_test = train_test_split(X,y,random_state = 42,test_size =0.20,stratify=y)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarning: In a future version of pandas all arguments of
  """Entry point for launching an IPython kernel.
```

```
#Naive Bayes as a baseline
gnb = GaussianNB()
cv = cross_val_score(gnb,X_train,y_train,cv=5)
print(cv)
print(cv.mean())
```

```
[0.52419355 0.5483871  0.51612903 0.53225806 0.52845528]
0.5298846052976659
```

```
# logistic regression
lr = LogisticRegression(max_iter = 2000)
cv = cross_val_score(lr,X_train,y_train,cv=5)
print(cv)
print(cv.mean())
```

```
[0.50806452 0.52419355 0.56451613 0.56451613 0.53658537]
0.5395751376868607
```

trust_in_gov,binary_intent

```
# tree models
dt = tree.DecisionTreeClassifier(random_state = 1)
cv = cross_val_score(dt,X_train,y_train,cv=5)
print(cv)
print(cv.mean())
```

```
[0.49193548 0.48387097 0.5483871  0.52419355 0.48780488]
0.5072383949645948
```

```
#K nearest neighbor
knn = KNeighborsClassifier()
cv = cross_val_score(knn,X_train,y_train,cv=5)
print(cv)
print(cv.mean())
```

```
[0.55645161 0.51612903 0.49193548 0.53225806 0.59349593]
0.5380540257015474
```

```
# Random forest
rf = RandomForestClassifier(random_state = 1)
cv = cross_val_score(rf,X_train,y_train,cv=5)
print(cv)
print(cv.mean())
```

```
[0.49193548 0.56451613 0.49193548 0.47580645 0.56097561]
0.5170338316286389
```

```
# support vector machines
svc = SVC(probability = True)
cv = cross_val_score(svc,X_train,y_train,cv=5)
print(cv)
print(cv.mean())
```

```
[0.55645161 0.55645161 0.55645161 0.55645161 0.55284553]
0.5557303960136375
```

```
# boosted classifier
from xgboost import XGBClassifier
xgb = XGBClassifier(random_state =1)
cv = cross_val_score(xgb,X_train,y_train,cv=5)
print(cv)
print(cv.mean())
```

```
[0.50806452 0.49193548 0.49193548 0.53225806 0.54471545]
0.5137817991083138
```

Voting classifier

Takes all of the inputs and averages the results. For a "hard" voting classifier each classifier gets 1 vote "yes" or "no" and the result is just a popular vote. For this, you generally want odd numbers

"soft" classifier averages the confidence of each of the models. If a the average confidence is > 50% that it is a 1 it will be counted as such

```
from sklearn.ensemble import VotingClassifier
voting_clf = VotingClassifier(estimators = [('lr',lr),('knn',knn),('rf',rf),('gnb',gnb),('svc',svc),('xgb',xgb)], voting = 'soft')
```

```
cv = cross_val_score(voting_clf,X_train,y_train,cv=5)
print(cv)
print(cv.mean())
```

```
[0.56451613 0.54032258 0.53225806 0.52419355 0.5203252 ]
0.5363231051665356
```

Model Tuned Performance

After getting the baselines, let's see if we can improve on the indivdual model results!I mainly used grid search to tune the models. I only used best performing baseline models SVC, logistic regression, and KNN to save testing time.

```
from sklearn.model_selection import GridSearchCV
#Performance reporting function
def clf_performance(classifier, model_name):
    print(model_name)
    print('Best Score: ' + str(classifier.best_score_))
    print('Best Parameters: ' + str(classifier.best_params_))
```

```
svc = SVC(probability = True)
param_grid = tuned_parameters = [{'kernel': ['rbf'], 'gamma': [.1,.5,1,2,5],
                                  'C': [.1, 1, 10, 100, 1000]},
                                 {'kernel': ['linear'], 'C': [.1, 1, 10, 100]},
                                 {'kernel': ['poly'], 'degree' : [2,3,4,5], 'C': [.1, 1, 10, 100]}]
clf_svc = GridSearchCV(svc, param_grid = param_grid, cv = 2, verbose = True, n_jobs = -1)
best_clf_svc = clf_svc.fit(X_train,y_train)
clf_performance(best_clf_svc,'SVC')
```

```
Fitting 2 folds for each of 45 candidates, totalling 90 fits
SVC
Best Score: 0.5831976197932978
Best Parameters: {'C': 0.1, 'kernel': 'linear'}
```

```
lr = LogisticRegression()
param_grid = {'max_iter' : [2000],
              'penalty' : ['l1', 'l2'],
              'C' : np.logspace(-4, 4, 20),
              'solver' : ['liblinear']}

clf_lr = GridSearchCV(lr, param_grid = param_grid, cv = 2, verbose = True, n_jobs = -1)
best_clf_lr = clf_lr.fit(X_train,y_train)
clf_performance(best_clf_lr,'Logistic Regression')
```

```
Fitting 2 folds for each of 40 candidates, totalling 80 fits
Logistic Regression
Best Score: 0.583192400041758
Best Parameters: {'C': 0.012742749857031334, 'max_iter': 2000, 'penalty': 'l2', 'solver': 'liblinear'}
```

```
knn = KNeighborsClassifier()
param_grid = {'n_neighbors' : [3,5,7],
              'weights' : ['uniform', 'distance'],
              'algorithm' : ['auto', 'ball_tree','kd_tree'],
              'p' : [1,2]}
clf_knn = GridSearchCV(knn, param_grid = param_grid, cv = 2, verbose = True, n_jobs = -1)
best_clf_knn = clf_knn.fit(X_train,y_train)
clf_performance(best_clf_knn,'KNN')
```

```
Fitting 2 folds for each of 36 candidates, totalling 72 fits
KNN
Best Score: 0.5234158054076625
Best Parameters: {'algorithm': 'ball_tree', 'n_neighbors': 7, 'p': 2, 'weights': 'distance'}
```

Double-click (or enter) to edit

Interpreting the model's relevant performance metrics.

This study focuses on how a persons environment and beliefs affect their willingness to take the COVID-19 vaccine. People bear several reservations, but overall suervey sample population show inclination towards getting the COVID-19 vaccine. Geographic locations (FIPS, ZIP, State), Median household income, Education, Age, Race and Trust (on goverment, Scientists) appears to be the key determinants of vaccination intent. Among others, beliefs and personal experiences are ranked higher within Random Forest model. This study intends to estimate what drives the perception of the masses towards COVID-19 vaccination. Six models, e.g., Naive Bayes, random forest (RF), a support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), and eXtreme Gradient Boosting (XGboost), were used for forecasting the overall predilection toward the COVID-19 vaccine. A voting classifier was used at the end of this study to determine the accuracy of all the classifiers. The results prove that the SVM and Logit model after hyperparameter tuning produces the best forecasting results (accuracy: 52%) and that KNN (accuracy: 52%) did not improve much after tuning and produced the worst prediction toward the intent to be vaccinated by the COVID-19 vaccine. When using the voting classifier, the proposed system provided an overall accuracy of 56%.

Thus, the results show that the studied prediction technique is a promising, with improvements feature engineering and additonal supporting data to propose coverage-enhancing policy responses.

Recommendation regarding putting the model in production and How should it be used?

In my opinion, having a model with consistently good performance (at least 80% or more -accuracy/f1 score) is essential for production. As the metrics show that the current model is not performing well (accuracy obtained after tuning SVC: ~59%), I would not recommend putting the model in production.

Without consistent performance, we will not be able to set up the tests to determine if the model is behaving as expected. I recommend improving the current model by adding new data, thorough feature engineering, and parameter tuning.

What additional data would augment this exercise if available? Why is it important? How would you source it? What analyses would you run on it?

I would integrate deprivation measures derived from census data. As, the knowledge of socioeconomic characteristics of neighborhoods is necessary to identify unique health needs and enhance the identification of socioeconomically disadvantaged populations.

Also, in addition, I would augment data derived from sentiment analysis. It is classification of the sentiments that are expressed in the text source example Twitter. This data wold be helpful in understanding the opinion of the people about a variety of topics related to COVID vaccine.