Introduction

This is a case study on using arrest data from the Chicago Police Dept (https://home.chicagopolice.org/statistics-data/).

The scenario: you are the new mayor of a mid-sized city in the southern United States. You campaigned on a promise to reduce crime and now it's time to make good.

You have two promising programs aimed at those at highest risk of re-arrest.

For the final project we are going to decide between these two programs.

```
1) A custom notification program
Under this program, police officers visit the homes of high-risk individuals and
notify them of their status. They additionally warn these individuals that the
police is keeping a closer eye on them. The custom notification program is
relatively cheap to run, so it can serve 1,000 individuals, but it will likely lead
to more people being arrested.

2) A summer jobs program
Under this program, social workers visit the homes of high-risk individuals and
offer them a slot in a summer jobs program which has been shown to be effective in
increasing employment and reducing criminal justice involvement. The summer jobs
program is expensive to run, so it can serve 500 individuals, but many of those
served will likely not have been re-arrested even without the program.
```

In [2]:

```
# load modules
import pandas as pd
import numpy as np

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

# load data analysis and model libraries
import seaborn as sns
from sklearn.metrics import roc_auc_score as auc
from sklearn.ensemble import RandomForestClassifier as RF_clf
from sklearn.linear_model import LogisticRegression as LR_clf
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
```

Part 1

Load data

I will work with the following dataset (previously explored and cleaned from other projects): (if you would like to see the EDA and cleaning process let me know and I will upload those notebooks as well)

- **Xy**: Has the following columns
  - `ArresteeID` : Unique ID for an arrestee
  - `outcome__rearrested_in_2019` : The outcome to predict

- `charges__NIBRS_Group_X__YYYY` : This is a count of the number of charges of type X in the year YYYY.
    - X is either A, B or C
    - YYYY is either 2016, 2017, or 2018
- `arrests__race__XXXX` : Where XXXX is either Black, Hispanic, Other, or White

- **arrests** :
    - `IncidentNum` : Unique ID for an incident
    - `ArrestYr` : Year of arrest
    - `ArrestNumber` : Unique ID for an arrest
    - `ArWeapon` : Any weapons identified by the arresting officer
    - `arr_age` : Current age of arrestee
    - `arr_gender` : Gender of arrestee at incident
    - `ArresteeID` : Unique ID for an arrestee
- **charges** :
    - `ArrestNumber` : Unique ID for an arrest
    - `ArChgNumID` : Unique ID for an arrest charge
    - `Severity` : Misdemeanor or Felony
    - `NIBRS_Group` : Is charge of type A (most severe), B (less severe), or C (traffic incident)
    - `NIBRS_Crime_Category` : The category of the charge
- **incidents** :
    - `IncidentNum` : Unique ID for an incident
    - `incident_type` : Free text field describing the incident
    - `vic_type` : Whether the victim was a person, business, law enforcement, or the government
    - `mo` : Free text field briefly describing the incident
    - `weapon_used` : Free text field listing the type of weapon if any
    - `gang_related` : Indication if the incident was gang-related

Both datasets have the following columns:

- **`outcome__rearrested_in_2019`** : The actual outcome
- **`race__Black`** : A binary-valued column with 1=Black 0=Not Black
- **`race__White`** : A binary-valued column with 1=White 0=Not White
- **`race__Hispanic`** : A binary-valued column with 1=Hispanic or Latino 0=Not Hispanic or Latino
- **`gender__M`** : A binary-valued column with 1=Male gender and 0=Non-Male
- **`network__any_1st_deg_nabe__all`** : A binary-valued column that tells us whether the person has ever been arrested with someone else
- ** `prediction` : The models predicted probability of the outcome

Prediction Setup

I will be predicting whether someone arrested in 2018 will be re-arrested in 2019.

In [3]:

```
# loading data
Xy = pd.read_csv('.data/Xy_final_project.csv')
arrests = pd.read_csv('.data/arrests_final_project.csv')
charges = pd.read_csv('.data/charges_final_project.csv')
incidents = pd.read_csv('.data/incidents_final_project.csv')

# initial look at the data
Xy.head()
```

```
arrests.head()
charges.head()
incidents.head()
```

Out[3]:

	ArresteeID	outcome__rearrested_in_2019	charges__NIBRS_Group_A__2016	charges__NIBRS_Group_A__2017	charges_
0	2549297	0	0.0	0.0	
1	2777109	0	0.0	0.0	
2	2785936	0	0.0	0.0	
3	2856607	0	0.0	0.0	
4	2921408	0	0.0	0.0	

Out[3]:

	IncidentNum	ArrestYr	ArrestNumber	ArWeapon	arr_age	arr_gender	ArresteeID
0	104552-2020	2020	20-018820	Unarmed	51.0	Male	102468259
1	104552-2020	2020	20-018820	Unarmed	51.0	Male	8607720
2	104552-2020	2020	20-018820	Unarmed	51.0	Male	102253069
3	104552-2020	2020	20-018820	Unarmed	51.0	Male	102366171
4	104552-2020	2020	20-018820	Unarmed	51.0	Male	102315487

Out[3]:

	ArrestNumber	ArChgNumID	Severity	NIBRS_Group	NIBRS_Crime_Category
0	14-036903	14-036903-01	F	A	DRUG/ NARCOTIC VIOLATIONS
1	16-012390	16-012390-01	M	B	DRIVING UNDER THE INFLUENCE
2	15-048343	15-048343-01	M	B	PUBLIC INTOXICATION
3	16-015720	16-015720-03	M	C	TRAFFIC VIOLATION - NON HAZARDOUS
4	15-040648	15-040648-01	M	B	DRIVING UNDER THE INFLUENCE

Out[3]:

	IncidentNum	incident_type	vic_type	mo	weapon_used	gang_related
0	207055-2018	ASSAULT -PUB SERV (PEACE OFFICER/JUDGE)	Law Enforcement Offi	A/P BIT OFFICER ON THE LEFT HAND CAUSING INJURY	Personal Weapons (Hands-Feet ETC)	UNK
1	243817-2018	TRAF VIO -OPERATE MOTOR VEH W/O FIN RESP	Government	A/P WAS UNABLE TO PROVIDE PROOF OF INSURANCE	NaN	NaN
2	245226-2018	OTHER OFFENSE - MISDEMEANOR	Government	AP WAS IN POSSESSION OF DRUG PARAPHERNALIA	NaN	NaN
3	133767-2019	POSS MARIJUANA <2OZ	Government	A/P WAS IN POSSESSION OF MARIJUANA.	NaN	NaN
4	273676-2018	POSS CONT SUB PEN GRP 1 <1G	Government	AP WAS IN POSSESSION OF COCAINE	NaN	NaN

Learning about our outcome

1) Using `Xy` , what is the share of 2018 arrestees were arrested in 2019. Would you say this is a high or low base rate?

2) Repeat 1) but now by the three race categories. Which race group has the highest base rate?

In [4]:

```
# use value_counts normalize function to see share of arrestees rearreseted in 2019
Xy.outcome__rearrested_in_2019.value_counts(normalize=True)
```

Out[4]:

```
0    0.927714
1    0.072286
Name: outcome__rearrested_in_2019, dtype: float64
```

I would consider this a fairly low base rate since I know the national recidivism rate is fairly high.

In [5]:

```
# Using loc to filter and value_counts normalize
# Black group
Xy.loc[Xy.arrests__race__Black == 1].outcome__rearrested_in_2019.value_counts(normalize=Tr

# Hispanic Group
Xy.loc[Xy.arrests__race__Hispanic == 1].outcome__rearrested_in_2019.value_counts(normalize

# White Group
Xy.loc[Xy.arrests__race__White == 1].outcome__rearrested_in_2019.value_counts(normalize=Tr

# Other Group
Xy.loc[Xy.arrests__race__Other == 1].outcome__rearrested_in_2019.value_counts(normalize=Tr
```

Out[5]:

```
0    0.915995
1    0.084005
Name: outcome__rearrested_in_2019, dtype: float64
```

Out[5]:

```
0    0.940905
1    0.059095
Name: outcome__rearrested_in_2019, dtype: float64
```

Out[5]:

```
0    0.93343
1    0.06657
Name: outcome__rearrested_in_2019, dtype: float64
```

Out[5]:

```
0    0.932367
1    0.067633
Name: outcome__rearrested_in_2019, dtype: float64
```

The highest rearrest base rate belongs to the black arrestee race group

Feature Generation

1) Create a feature (or features) using the `incidents` data frame and merge these features into Xy.

2) Create one or more features using any of the data frames. Merge these features in with Xy as well.

3) Use sns.regplot to create two separate plots that show the relationship between the features you created and the outcome. Based on these plots, which feature is more predictive of the outcome?

In [6]:

```
##-----------------------------------------------------------------------------
# Creating featues using the incidents data frame
# Looking at the mo for key words to extract features from
incidents.mo.value_counts().head(50)
```

Out[6]:

```
PUBLIC INTOXICATION                                                    977
AP WAS INTOXICATED IN PUBLIC                                           300
AP WAS INTOXICATED                                                     217
A/P WAS DRIVING WHILE INTOXICATED.                                     202
AP WAS IN POSSESSION OF MARIJUANA                                      172
DWI                                                                    148
THE ARRESTED PERSON WAS ARRESTED FOR DRIVING WHILE INTOXICATED.        144
AP WAS INTOXICATED IN A PUBLIC PLACE                                   122
AP WAS ARRESTED FOR PUBLIC INTOXICATION                                108
```

```
A/P WAS INTOXICATED IN PUBLIC                                          105
PUBLIC INTOX                                                            90
AP WAS ARRESTED FOR DWI.                                                81
CRIMINAL TRESPASS                                                       75
A/P WAS PLACED UNDER ARREST FOR DWI.                                    75
AP WAS INTOXICATED IN PUBLIC.                                           75
AP WAS INTOXICATED IN A PUBLIC PLACE.                                   69
A/P WAS DRIVING A MOTOR VEH WHILE INTOXICATED FROM ALCOHOL.             67
A/P WAS INTOXICATED IN A PUBLIC PLACE                                   66
AP WAS ARRESTED FOR PUBLIC INTOXICATION.                                65
PUBLIC INTOXICATION ARREST                                              59
A/P WAS IN POSSESSION OF MARIJUANA                                      56
SUSP WAS INTOXICATED IN PUBLIC                                          54
AP ARRESTED FOR PUBLIC INTOXICATION                                     52
PUBLIC INTOXICATION.                                                    51
AP ARRESTED FOR PI                                                      45
AP WAS IN POSSESSION OF MARIJUANA.                                      42
A/P WAS DRIVING A MOTOR VEH WHILE INTOXICATED FROM ALCOHOL/DRUGS.       41
AP WAS DRIVING WHILE INTOXICATED                                        39
FOUND PROPERTY                                                          37
AP WAS INTOXICATED AND CAUSING A DISTURBANCE.                           37
APOWW                                                                   37
A/P WAS ARRESTED FOR PUBLIC INTOXICATION                                36
SUSPECT WAS INTOXICATED IN PUBLIC                                       34
AP WAS PUBLICLY INTOXICATED                                             32
AP WAS IN POSSESSION OF COCAINE                                         32
CRIMINAL TRESPASS WARNING                                               31
AP WAS IN POSSESSION OF DRUG PARAPHERNALIA                              29
AP WAS IN POSSESSION OF METHAMPHETAMINE                                 28
POSSESSION OF MARIJUANA                                                 27
POSS OF MARIJUANA                                                       27
AP WAS INTOXICATED IN PUBLIC AND A DANGER TO HIMSELF                    25
AP WAS INTOXICATED IN A PUBLIC AREA                                     25
AP WAS IN POSSESSION OF HEROIN                                          25
THE AP WAS INTOXICATED IN PUBLIC                                        24
AP WAS IN POSS OF MARIJUANA                                             23
A/P WAS INTOXICATED IN PUBLIC. NFI                                      23
DRIVING WHILE INTOXICATED                                               22
A/P WAS INTOXICATED IN PUBLIC.                                          22
AP WAS INTOXICATED.                                                     21
AP DROVE A MOTOR VEHICLE WHILE INTOXICATED.                             21
Name: mo, dtype: int64
```

In [7]:

```python
# Most incidents appear to be alcohol related
incidents.mo.str.contains('INTOX|DWI|ALCOHOL|PI').value_counts()
```

Out[7]:

```
False    9600
True     7447
Name: mo, dtype: int64
```

In [8]:

```python
# Good amount of drug related incidents as well
incidents.mo.str.contains('POSS|DRUG|NARC|PARA').value_counts()
```

Out[8]:

```
False    13642
True      3405
Name: mo, dtype: int64
```

In [9]:

```python
# Mapping incidents to new columns related to alcohol and drugs based on key words
incidents['alcohol_related'] = incidents.mo.str.contains('INTOX|DWI|ALCOHOL|PI').map({True
                                                                                      False : 0}
incidents['drug_related'] = incidents.mo.str.contains('POSS|DRUG|NARC|PARA').map({True : 1
                                                                                      False : 0}
```

In [10]:
```
incidents['alcohol_related'].value_counts()
```

Out[10]:
```
0.0    9600
1.0    7447
Name: alcohol_related, dtype: int64
```

In [11]:
```
incidents['drug_related'].value_counts()
```

Out[11]:
```
0.0    13642
1.0     3405
Name: drug_related, dtype: int64
```

In [12]:
```
# creating df merging incidents with the new columns with the arrests df (to relate to Ar
arrests_incidents = pd.merge(arrests,incidents, on="IncidentNum", how="left")
```

In [13]:
```
arrests_incidents.head()
```

Out[13]:

	IncidentNum	ArrestYr	ArrestNumber	ArWeapon	arr_age	arr_gender	ArresteeID	incident_type	vic_type	mo
0	104552-2020	2020	20-018820	Unarmed	51.0	Male	102468259	NaN	NaN	NaN
1	104552-2020	2020	20-018820	Unarmed	51.0	Male	8607720	NaN	NaN	NaN
2	104552-2020	2020	20-018820	Unarmed	51.0	Male	102253069	NaN	NaN	NaN
3	104552-2020	2020	20-018820	Unarmed	51.0	Male	102366171	NaN	NaN	NaN
4	104552-2020	2020	20-018820	Unarmed	51.0	Male	102315487	NaN	NaN	NaN

In [14]:
```
# Creating two new df with columns grouped on ArresteeID
alcohol_related = arrests_incidents.groupby('ArresteeID')['alcohol_related'].sum().reset_i

drug_related = arrests_incidents.groupby('ArresteeID')['drug_related'].sum().reset_index(n
```

In [15]:
```
# Merging the alcohol related df to Xy
Xy = pd.merge(Xy, alcohol_related, on="ArresteeID", how='left')
Xy.head()
```

Out[15]:

	ArresteeID	outcome__rearrested_in_2019	charges__NIBRS_Group_A__2016	charges__NIBRS_Group_A__2017	cha
0	2549297	0	0.0	0.0	
1	2777109	0	0.0	0.0	
2	2785936	0	0.0	0.0	
3	2856607	0	0.0	0.0	
4	2921408	0	0.0	0.0	
...	...	...	...	...	
12238	102720805	0	0.0	0.0	
12239	102724697	0	0.0	0.0	
12240	102730586	0	0.0	0.0	
12241	102758342	0	0.0	0.0	
12242	102765292	0	NaN	NaN	

12243 rows × 16 columns

In [16]:
```
# Merging the drug related df to Xy
Xy = pd.merge(Xy, drug_related, on="ArresteeID", how='left')
Xy.head()
```

Out[16]:

	ArresteeID	outcome__rearrested_in_2019	charges__NIBRS_Group_A__2016	charges__NIBRS_Group_A__2017	charges_
0	2549297	0	0.0	0.0	
1	2777109	0	0.0	0.0	
2	2785936	0	0.0	0.0	
3	2856607	0	0.0	0.0	
4	2921408	0	0.0	0.0	

In [ ]:
```
##---------------------------------------------------------------------------
## Feature Building using remaining df
## Creating a feature to indicate age upon first arrest
```

In [18]:
```
# Merging arrests and charges df for ease of feature building
arrest_charges = pd.merge(arrests, charges, on="ArrestNumber", how='left')
arrest_charges.head()
```

Out[18]:

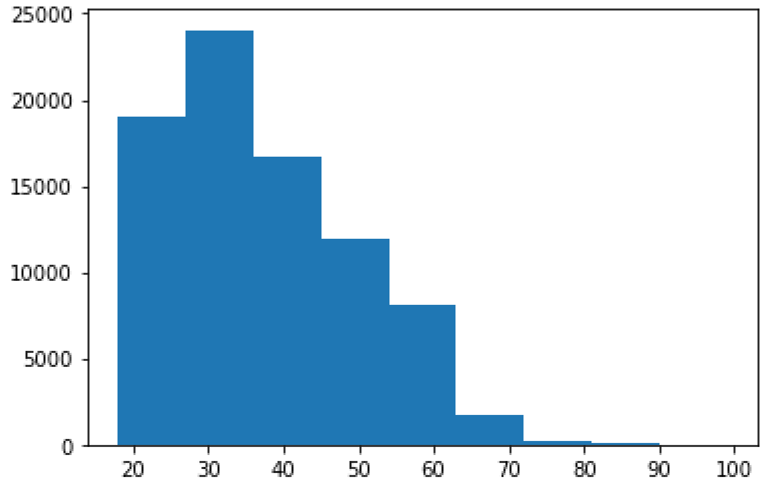
	IncidentNum	ArrestYr	ArrestNumber	ArWeapon	arr_age	arr_gender	ArresteeID	ArChgNumID	Severity	NIBRS
0	104552-2020	2020	20-018820	Unarmed	51.0	Male	102468259	20-018820-01	M	
1	104552-2020	2020	20-018820	Unarmed	51.0	Male	8607720	20-018820-01	M	
2	104552-2020	2020	20-018820	Unarmed	51.0	Male	102253069	20-018820-01	M	
3	104552-2020	2020	20-018820	Unarmed	51.0	Male	102366171	20-018820-01	M	
4	104552-2020	2020	20-018820	Unarmed	51.0	Male	102315487	20-018820-01	M	

In [44]:
```
# I want to create a feature that looks at what age an arrestee is first arrested. I first
# Looking at different bin sizes. 9 seems like the best distribution and nice round number

import matplotlib.pyplot as plt

plt.hist(arrests.arr_age, bins=9)
plt.show()
```

Out[44]:
```
(array([1.8976e+04, 2.4040e+04, 1.6741e+04, 1.1934e+04, 8.1130e+03,
        1.6860e+03, 1.7200e+02, 7.2000e+01, 4.0000e+00]),
 array([18., 27., 36., 45., 54., 63., 72., 81., 90., 99.]),
 <BarContainer object of 9 artists>)
```



In [19]:

```
# using agg function to separate min (did max incase I wanted to make another feature)

arrest_charges_nums = arrest_charges.groupby(['ArresteeID'])['arr_age'].agg([('min', np.mi
```

In [20]:

```
# Creating a function to make bins for the ages (used bins from above)
def make_bins_age(df):
   label_names = ["18-26", "27-35","36-44", "45-54","54-62","63-71","72-80","81-89","90-9
   cut_points = [18., 27., 36., 45., 54., 63., 72., 81., 90., 99.]
   df["first_arrested_age_group"] = pd.cut(df["min"], cut_points, labels=label_names)
   return df
```

In [21]:

```
# run the function to separate the min column into the bins
first_age_arrest = make_bins_age(arrest_charges_nums)
first_age_arrest.first_arrested_age_group.value_counts()
```

Out[21]:

```
27-35    16893
18-26    16800
36-44    10767
45-54     6868
54-62     4419
63-71      910
72-80      128
81-89       43
90-99        3
Name: first_arrested_age_group, dtype: int64
```

In [22]:

```
# the values match up
first_age_arrest.shape
arrest_charges.ArresteeID.nunique()
```

Out[22]:

```
(57816, 3)
```

Out[22]:

```
57816
```

In [23]:

```
# Merging this new column back into the arrest_charges df
arrest_charges = pd.merge(arrest_charges, first_age_arrest, on="ArresteeID", how="left")
arrest_charges.head()
```

Out[23]:

	IncidentNum	ArrestYr	ArrestNumber	ArWeapon	arr_age	arr_gender	ArresteeID	ArChgNumID	Severity	NIBR
0	104552-2020	2020	20-018820	Unarmed	51.0	Male	102468259	20-018820-01	M	

	IncidentNum	ArrestYr	ArrestNumber	ArWeapon	arr_age	arr_gender	ArresteeID	ArChgNumID	Severity	NIBR!
1	104552-2020	2020	20-018820	Unarmed	51.0	Male	8607720	20-018820-01	M	
2	104552-2020	2020	20-018820	Unarmed	51.0	Male	102253069	20-018820-01	M	
3	104552-2020	2020	20-018820	Unarmed	51.0	Male	102366171	20-018820-01	M	
4	104552-2020	2020	20-018820	Unarmed	51.0	Male	102315487	20-018820-01	M	

In [24]:

```
# Creating a new df and one hot encode the new column
arr_ages_group = pd.concat([arrest_charges[['ArresteeID']],
                    pd.get_dummies(arrest_charges.first_arrested_age_group, prefix='first_arı
                    axis=1)
arr_ages_group.head()
```

Out[24]:

	ArresteeID	first_arr_age__18-26	first_arr_age__27-35	first_arr_age__36-44	first_arr_age__45-54	first_arr_age__54-62	first_arr_ag
0	102468259	0	0	0	1	0	
1	8607720	0	0	0	1	0	
2	102253069	0	0	0	1	0	
3	102366171	0	0	0	1	0	
4	102315487	0	0	0	1	0	

In [25]:

```
# merging new feature into the Xy df
Xy = pd.merge(Xy, arr_ages_group, on="ArresteeID", how="left")
Xy.head()
```

Out[25]:

	ArresteeID	outcome__rearrested_in_2019	charges__NIBRS_Group_A__2016	charges__NIBRS_Group_A__2017	charges_
0	2549297	0	0.0	0.0	
1	2777109	0	0.0	0.0	
2	2785936	0	0.0	0.0	
3	2785936	0	0.0	0.0	
4	2785936	0	0.0	0.0	

5 rows × 26 columns

In [135…

```
# Adding severity feature
severity = pd.concat([arrest_charges[['ArresteeID']],
                      pd.get_dummies(arrest_charges.Severity, prefix='Severity_')],
                      axis=1)
severity = severity.groupby(['ArresteeID']).sum()
```

Out[135…

	Severity__F	Severity__M	Severity__N
ArresteeID			

	Severity__F	Severity__M	Severity__N
ArresteeID			
2549297	0	1	0
2759851	0	0	0
2762756	0	1	0
2777109	0	1	0
2785936	2	3	0
...	...	...	...
102780909	0	0	0
102781002	0	0	0
102781047	0	0	0
102781058	0	0	0
102781095	0	0	0

57816 rows × 3 columns

In [136…

```
Xy = pd.merge(Xy, severity, on="ArresteeID", how="left")
Xy
```

Out[136…

	ArresteeID	outcome__rearrested_in_2019	charges__NIBRS_Group_A__2016	charges__NIBRS_Group_A__2017	cha
0	2549297	0	0.0	0.0	
1	2777109	0	0.0	0.0	
2	2785936	0	0.0	0.0	
3	2785936	0	0.0	0.0	
4	2785936	0	0.0	0.0	
...	...	...	...	...	
24860	102730586	0	0.0	0.0	
24861	102758342	0	0.0	0.0	
24862	102758342	0	0.0	0.0	
24863	102765292	0	NaN	NaN	
24864	102765292	0	NaN	NaN	

24865 rows × 29 columns

In [137…

```
Xy.columns
```

Out[137…

```
Index(['ArresteeID', 'outcome__rearrested_in_2019',
       'charges__NIBRS_Group_A__2016', 'charges__NIBRS_Group_A__2017',
       'charges__NIBRS_Group_A__2018', 'charges__NIBRS_Group_B__2016',
       'charges__NIBRS_Group_B__2017', 'charges__NIBRS_Group_B__2018',
       'charges__NIBRS_Group_C__2016', 'charges__NIBRS_Group_C__2017',
       'charges__NIBRS_Group_C__2018', 'arrests__race__Black',
```

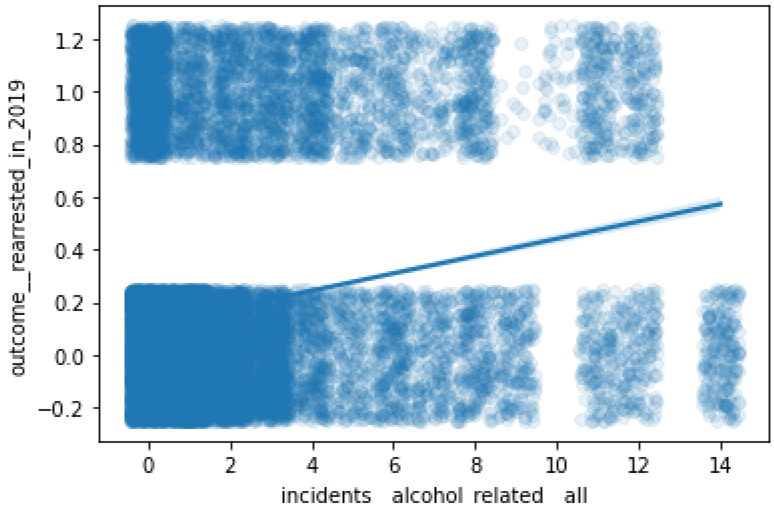
```
 'arrests__race__Hispanic', 'arrests__race__Other',
 'arrests__race__White', 'incidents__alcohol_related__all',
 'incidents__drug_related__all', 'first_arr_age__18-26',
 'first_arr_age__27-35', 'first_arr_age__36-44', 'first_arr_age__45-54',
 'first_arr_age__54-62', 'first_arr_age__63-71', 'first_arr_age__72-80',
 'first_arr_age__81-89', 'first_arr_age__90-99', 'Severity__F',
 'Severity__M', 'Severity__N'],
dtype='object')
```

In [47]:

```
# Using sns.regplot to see how well the relationship with features and outcome
# For the incidents alcohol related feature, there appears to be a positive relationship b
# incidents and outcome to be rearrested
sns.regplot(data=Xy, x="incidents__alcohol_related__all",y='outcome__rearrested_in_2019',
        x_jitter=.45, y_jitter=.25, scatter_kws={'alpha':0.1},)
```

Out[47]:

```
<AxesSubplot:xlabel='incidents__alcohol_related__all', ylabel='outcome__rearrested_in_201
9'>
```

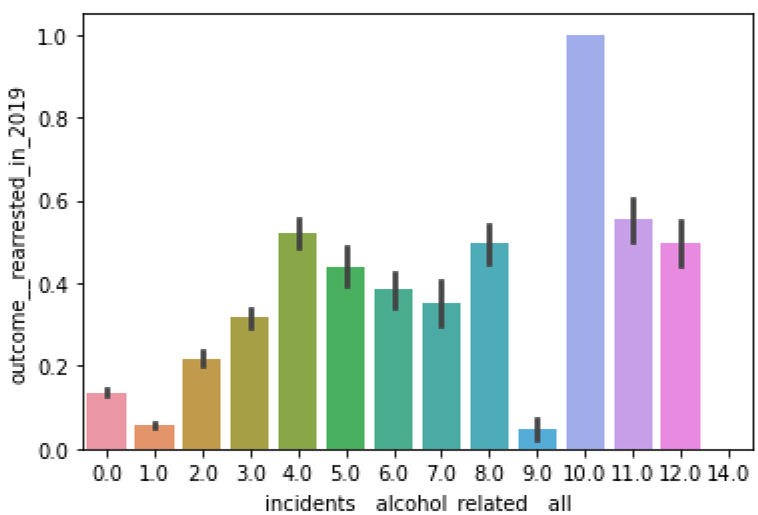


In [48]:

```
# This can also be seen in a bar plot where there's a slight positive correlation
sns.barplot(data=Xy, x="incidents__alcohol_related__all",y='outcome__rearrested_in_2019')
```

Out[48]:

```
<AxesSubplot:xlabel='incidents__alcohol_related__all', ylabel='outcome__rearrested_in_201
9'>
```

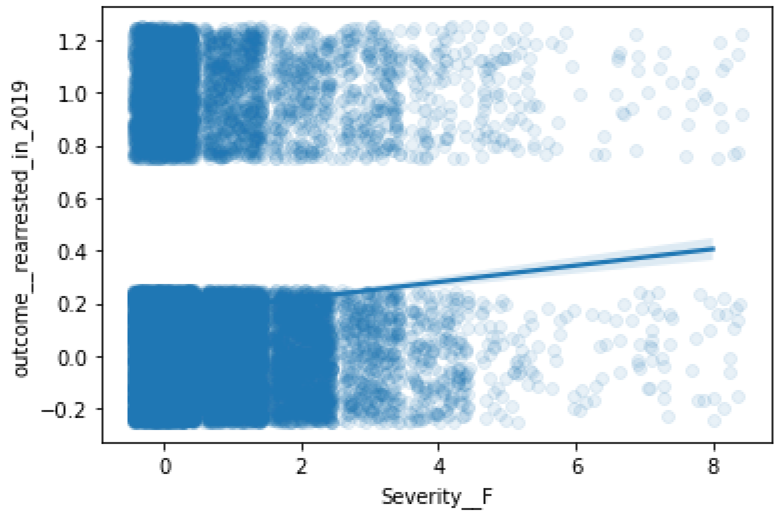


In [138…

```
# For the incidents severity felony, there appears to be a positive relationship between i
# incidents and outcome to be rearrested though less pronounced than the alcohol features
sns.regplot(data=Xy, x="Severity__F",y='outcome__rearrested_in_2019',
        x_jitter=.45, y_jitter=.25, scatter_kws={'alpha':0.1},)
```

Out[138…

```
<AxesSubplot:xlabel='Severity__F', ylabel='outcome__rearrested_in_2019'>
```

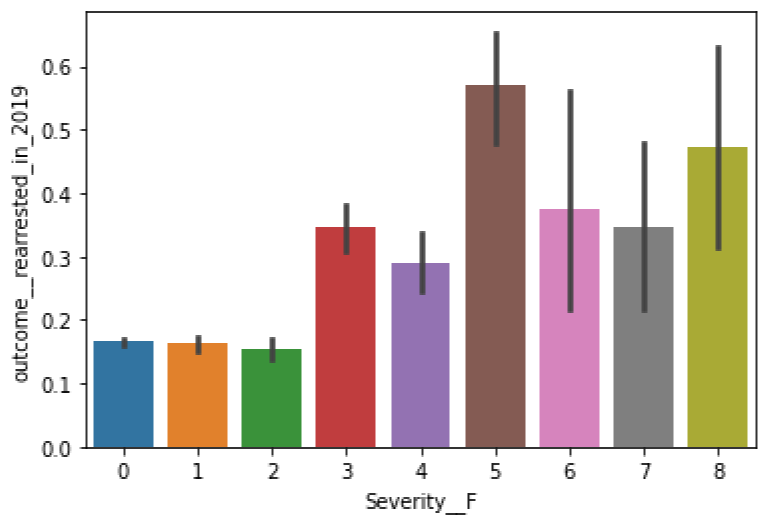


In [139…

```
sns.barplot(data=Xy, x="Severity__F",y='outcome__rearrested_in_2019')
```

Out[139…

```
<AxesSubplot:xlabel='Severity__F', ylabel='outcome__rearrested_in_2019'>
```



Build models

We are going to build two models.

1) The first one will NOT include any of the features that you built.

These are the set of features to include in the first model.

```
feature_names = ['charges__NIBRS_Group_A__2016', 'charges__NIBRS_Group_A__2017',
       'charges__NIBRS_Group_A__2018', 'charges__NIBRS_Group_B__2016',
       'charges__NIBRS_Group_B__2017', 'charges__NIBRS_Group_B__2018',
       'charges__NIBRS_Group_C__2016', 'charges__NIBRS_Group_C__2017',
       'charges__NIBRS_Group_C__2018', 'arrests__race__Black',
       'arrests__race__Hispanic', 'arrests__race__Other',
       'arrests__race__White']
```

2) The second model WILL include the features you built (and include the features from 1))

Using the algorithm of your choice (e.g. decision trees, logistic regression, random forest, etc), train a model to predict `outcome__rearrested_in_2019` for both 1) and 2).

Note:

- Perform hyperparameter tuning.
- Make sure you have created a holdout/test set before training the models.
- Make sure to show the selected hyperparameters after tuning for both models.

Generate predictions for your test/holdout set.

The predictions from 1) should be in a column called `predictions_standard`

The predictions from 2) should be in a column called `predictions_augmented`

In [62]:
```
# Creating feature names array and outcome for model 1, splittig into train and test, size

feature_names_1 = ['charges__NIBRS_Group_A__2016', 'charges__NIBRS_Group_A__2017',
       'charges__NIBRS_Group_A__2018', 'charges__NIBRS_Group_B__2016',
       'charges__NIBRS_Group_B__2017', 'charges__NIBRS_Group_B__2018',
       'charges__NIBRS_Group_C__2016', 'charges__NIBRS_Group_C__2017',
       'charges__NIBRS_Group_C__2018', 'arrests__race__Black',
       'arrests__race__Hispanic', 'arrests__race__Other',
       'arrests__race__White']

outcome_1 = 'outcome__rearrested_in_2019'

X_train, X_test, y_train, y_test = train_test_split(Xy[feature_names_1], Xy[outcome_1], te
```

In [63]:
```
# filling in the null values of the train and test data

X_train.fillna(0, inplace=True)
X_test.fillna(0, inplace=True)
```

In [71]:
```
# Running a random forest classifier model
# tuning parameters incude max depth, max features, and n estimators
# Fitting the model and showing best parameters

rf_model_1 = RF_clf()

param_grid_1 = {'max_depth' : [1, 5, 10, 20],
                'max_features' : [1, 2, 3, 4],
                'n_estimators' : [100,200,500]}

model_1 = GridSearchCV(estimator=rf_model_1, param_grid=param_grid_1, cv=5, scoring='avera

model_1.fit(X_train[feature_names_1], y_train)

model_1.best_params_
```

Out[71]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [1, 5, 10, 20],
                         'max_features': [1, 2, 3, 4],
                         'n_estimators': [100, 200, 500]},
             scoring='average_precision')
```

Out[71]:
```
{'max_depth': 20, 'max_features': 1, 'n_estimators': 500}
```

In [72]:
```
# Results from the first dataset
test_results_1 = pd.DataFrame({'outcome__rearrested_in_2019' : y_test,
                              'predictions_standard' : model_1.predict_proba(X_test)[:, 1]}
test_results_1
```

Out[72]:

	outcome__rearrested_in_2019	predictions_standard
9570	0	0.116503
10191	0	0.117341
18500	0	0.117341
5312	1	1.000000
17690	0	0.411400
...	...	...
3060	0	0.411400
23298	1	0.230099
17287	0	0.116503
8853	0	0.194358
1758	0	0.116503

7460 rows × 2 columns

In [140…

```
# Creating feature names array and outcome for model 2, splittig into train and test, size

feature_names_2 = [
        'charges__NIBRS_Group_A__2016', 'charges__NIBRS_Group_A__2017',
        'charges__NIBRS_Group_A__2018', 'charges__NIBRS_Group_B__2016',
        'charges__NIBRS_Group_B__2017', 'charges__NIBRS_Group_B__2018',
        'charges__NIBRS_Group_C__2016', 'charges__NIBRS_Group_C__2017',
        'charges__NIBRS_Group_C__2018', 'arrests__race__Black',
        'arrests__race__Hispanic', 'arrests__race__Other',
        'arrests__race__White', 'incidents__alcohol_related__all',
        'incidents__drug_related__all', 'first_arr_age__18-26',
        'first_arr_age__27-35', 'first_arr_age__36-44', 'first_arr_age__45-54',
        'first_arr_age__54-62', 'first_arr_age__63-71', 'first_arr_age__72-80',
        'first_arr_age__81-89', 'first_arr_age__90-99', 'Severity__F',
        'Severity__M', 'Severity__N']

outcome_2 = 'outcome__rearrested_in_2019'

X_train, X_test, y_train, y_test = train_test_split(Xy[feature_names_2], Xy[outcome_2], te
```

In [141…

```
# filling in the null values of the train and test data

X_train.fillna(0, inplace=True)
X_test.fillna(0, inplace=True)
```

In [176…

```
# Running a random forest classifier model
# tuning parameters incude max depth, max features, and n estimators
# Fitting the model and showing best parameters

rf_model_2 = RF_clf()

param_grid_2 = {'max_depth' : [1, 3, 5, 8],
                'max_features' : [1, 2, 3, 4, 5],
                'n_estimators' : [200]}

model_2 = GridSearchCV(estimator=rf_model_2, param_grid=param_grid_2, cv=5, scoring='avera
```

```
model_2.fit(X_train[feature_names_2], y_train)

model_2.best_params_
```

Out[176…

```
GridSearchCV(cv=5, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [1, 3, 5, 8],
                         'max_features': [1, 2, 3, 4, 5],
                         'n_estimators': [200]},
             scoring='average_precision')
```

Out[176…

```
{'max_depth': 8, 'max_features': 5, 'n_estimators': 200}
```

In [177…

```
# Results from the second dataset
test_results_2 = pd.DataFrame({'outcome__rearrested_in_2019' : y_test,
                               'predictions_augmented' : model_2.predict_proba(X_test)[:, 1]
test_results_2
```

Out[177…

	outcome__rearrested_in_2019	predictions_augmented
17382	0	0.270452
7099	0	0.037391
5126	0	0.094115
17928	0	0.053577
20543	0	0.073596
...	...	...
22248	0	0.085435
24359	1	0.713650
4602	0	0.221163
1898	0	0.043406
20895	0	0.025871

7460 rows × 2 columns

Model performance

We are now going to compute precision, recall, and AUC for **both** sets of predictions.

1) Compute precision and recall using the appropriate threshold for the summer jobs program.

2) Compute precision and recall using the appropriate threshold for the custom notification program.

3) Compute AUC

4) Based on your results here, are your features improving performance? And where in the distribution is performance being improved? Justify your answer using the results from 1), 2) , and 3) and the meaning of the performance metrics

In [178…

```
# Setting the thresholds for the two programs
notification_thresh = 1000
summer_job_thresh = 500
```

In [179…
```
# Sorting the two test results
test_results_1 = test_results_1.sort_values('predictions_standard', ascending=False)
test_results_2 = test_results_2.sort_values('predictions_augmented', ascending=False)
```

In [180…
```
# Setting yhat thresholds for the first model
test_results_1['yhat_not'] = 0
test_results_1.yhat_not[:notification_thresh] = 1
test_results_1['yhat_sum'] = 0
test_results_1.yhat_sum[:summer_job_thresh] = 1

# Thresholds for the second model
test_results_2['yhat_not'] = 0
test_results_2.yhat_not[:notification_thresh] = 1
test_results_2['yhat_sum'] = 0
test_results_2.yhat_sum[:summer_job_thresh] = 1
```

```
C:\Users\Smoo9\AppData\Local\Continuum\anaconda3\envs\inst_414_f2021\lib\site-packages\ipy
kernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports until
C:\Users\Smoo9\AppData\Local\Continuum\anaconda3\envs\inst_414_f2021\lib\site-packages\ipy
kernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  """
C:\Users\Smoo9\AppData\Local\Continuum\anaconda3\envs\inst_414_f2021\lib\site-packages\ipy
kernel_launcher.py:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  if __name__ == '__main__':
C:\Users\Smoo9\AppData\Local\Continuum\anaconda3\envs\inst_414_f2021\lib\site-packages\ipy
kernel_launcher.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  # This is added back by InteractiveShellApp.init_path()
```

In [181…
```
# model 1 notification
cm_model_1_not = pd.crosstab(test_results_1.yhat_not, test_results_1.outcome__rearrested_i
print("Model 1 Notification System")
cm_model_1_not
# model 1 summer program
cm_model_1_sum = pd.crosstab(test_results_1.yhat_sum, test_results_1.outcome__rearrested_i
print("Model 1 Summer Jobs Program")
cm_model_1_sum
# model 2 notification
cm_model_2_not = pd.crosstab(test_results_2.yhat_not, test_results_2.outcome__rearrested_i
print("Model 2 Notification System")
cm_model_2_not
# model 2 summer program
cm_model_2_sum = pd.crosstab(test_results_2.yhat_sum, test_results_2.outcome__rearrested_i
print("Model 2 Summer Program")
cm_model_2_sum
```

```
Model 1 Notification System
```

Out[181…

outcome__rearrested_in_2019	0	1
yhat_not		
0	5825	635
1	360	640

```
Model 1 Summer Jobs Program
```

Out[181…

outcome__rearrested_in_2019	0	1
yhat_sum		
0	6132	828
1	53	447

```
Model 2 Notification System
```

Out[181…

outcome__rearrested_in_2019	0	1
yhat_not		
0	6080	380
1	70	930

```
Model 2 Summer Program
```

Out[181…

outcome__rearrested_in_2019	0	1
yhat_sum		
0	6150	810
1	0	500

In [182…

```
# model 1 notification metrics
print("Model 1 Notification System Performance Metrics")
ppv = cm_model_1_not.iloc[1,1] / cm_model_1_not.iloc[1, :].sum()
print('precision:', ppv)

tnr = cm_model_1_not.iloc[1, 1] / cm_model_1_not.iloc[:, 1].sum()
print('recall:', tnr)

print('AUC:', auc(test_results_1.outcome__rearrested_in_2019, test_results_1.predictions_s
```

```
Model 1 Notification System Performance Metrics
precision: 0.64
recall: 0.5019607843137255
AUC: 0.8375276681408215
```

In [183…

```
# model 2 notification metrics
print("Model 2 Notification System Performance Metrics")
ppv = cm_model_2_not.iloc[1,1] / cm_model_2_not.iloc[1, :].sum()
print('precision:', ppv)

tnr = cm_model_2_not.iloc[1, 1] / cm_model_2_not.iloc[:, 1].sum()
print('recall:', tnr)

print('AUC:', auc(test_results_2.outcome__rearrested_in_2019, test_results_2.predictions_a
```

```
Model 2 Notification System Performance Metrics
precision: 0.93
recall: 0.7099236641221374
AUC: 0.9554244398932539
```

In [184…

```
# model 1 summer job program metrics
print("Model 1 Summer Job Program Performance Metrics")
ppv = cm_model_1_sum.iloc[1,1] / cm_model_1_sum.iloc[1, :].sum()
print('precision:', ppv)

tnr = cm_model_1_sum.iloc[1, 1] / cm_model_1_sum.iloc[:, 1].sum()
print('recall:', tnr)

print('AUC:', auc(test_results_1.outcome__rearrested_in_2019, test_results_1.predictions_s
```

```
Model 1 Summer Job Program Performance Metrics
precision: 0.894
recall: 0.35058823529411764
AUC: 0.8375276681408215
```

In [185…

```
# model 2 summer job program metrics
print("Model 2 Notification System Performance Metrics")
ppv = cm_model_2_sum.iloc[1,1] / cm_model_2_sum.iloc[1, :].sum()
print('precision:', ppv)

tnr = cm_model_2_sum.iloc[1, 1] / cm_model_2_sum.iloc[:, 1].sum()
print('recall:', tnr)

print('AUC:', auc(test_results_2.outcome__rearrested_in_2019, test_results_2.predictions_a
```

```
Model 2 Notification System Performance Metrics
precision: 1.0
recall: 0.3816793893129771
AUC: 0.9554244398932539
```

Based on the performance metrics, the augmented model has much better precision in both the notification and summer job program - meaning that a higher proportion of positive identifications were correct. The recall is also much higher for the second model in the notification system and only slightly higher in the summer job program - meaning in both cases, the augmented model correctly identified a higher proprotion of actual positive outcomes.

In both models, the area under the curve is fairly high. The second model is higher, showing a higher probability to rank a random positive outcome higher than a negative one - i.e. it distinguishes better between positive and negative classes.

Part 2

Now we are going to decide whether to select the custom notification or summer jobs program.

We are only going to use `prediction_standard` or `prediction_augmented` in this section, so also first decide which one you would prefer to use.

The same algorithm will be used for both programs, all that will be different is which threshold will be used (500 for summer jobs, 1000 for custom notifications).

Total Impact

We first want to know what the potential for total impact is.

- So compute:
  - the number of arrests in 2019.

- the number of arrests that would be accounted for by the top 500 in predicted risk.
    - the number of arrests that would be accounted for by the top 1,000 in predicted risk.

- Custom notifications **reduce the chance of re-arrest by 50%** (meaning that the number of arrests accounted for by the top 1,000 would be cut in half). Compute what percentage of 2019 arrests would be eliminated if the custom notification program targeted the top 1,000 and reduced re-arrest by 50%.

- Summer jobs reduce the chance of re-arrest by 100% (meaning the number arrests accounted for by the top 500 would go down to zero. Compute what percentage of 2019 arrests would be eliminated if the summer jobs program targeted the top 500 and reduced re-arrest by 100%.

Jurisdictions typically care about reducing felonies much more than reducing misdemeanors.

Compute the number of felony arrests that would be prevented by summer jobs Compute the number of felony arrests that would be prevented by custom notifications

In [186…

```
# Sum the number of rearrested in 2019 to find the number of arrests.
tot_rearrest = test_results_2.outcome__rearrested_in_2019.sum()
tot_rearrest
```

Out[186…

```
1310
```

In [187…

```
# Sum predictions_augmented for first 500
tot_summer = test_results_2.predictions_augmented.iloc[:500].sum()
tot_summer
```

Out[187…

```
400.25944460234797
```

In [188…

```
# Sum preditions_augmented for first 1000
tot_notif = test_results_2.predictions_augmented.iloc[:1000].sum()
tot_notif
```

Out[188…

```
640.752297854804
```

In [189…

```
# Compute percentage of 2019 arrests eliminated by custom notification system
print("Percentage of rearrestes eliminated by Custom Notifications:")
(tot_notif/2)/tot_rearrest

# Compute percentage of 2019 rearrests eliminated by Summer Jobs Program
print("Percentage of rearrests eliminated by Summer Jobs Program")
tot_summer/tot_rearrest
```

```
Percentage of rearrestes eliminated by Custom Notifications:
```

Out[189…

```
0.24456194574610843
```

```
Percentage of rearrests eliminated by Summer Jobs Program
```

Out[189…

```
0.3055415607651511
```

In [214…

```
##---------------------------------------------------------------------------
# Create a new test results df with the severity_f felonies added
test_results_w_felonies = pd.DataFrame({'outcome__rearrested_in_2019' : y_test,
                                        'Severity_F' : X_test['Severity__F'],
                                        'prediction' : model_2.predict_proba(X_test)[:, 1]})
test_results_w_felonies
```

Out[214…

	outcome__rearrested_in_2019	Severity_F	prediction
17382	0	0	0.270452
7099	0	0	0.037391
5126	0	0	0.094115
17928	0	1	0.053577
20543	0	1	0.073596
...	...	...	...
22248	0	1	0.085435
24359	1	1	0.713650
4602	0	0	0.221163
1898	0	1	0.043406
20895	0	0	0.025871

7460 rows × 3 columns

In [216…

```
# Filter test results to only have the results with felonies associated with them
test_results_w_felonies = test_results_w_felonies[test_results_w_felonies.Severity_F == 1]
```

In [218…

```
# total the number of rearrests with felonies
tot_rearrest_felonies = test_results_w_felonies.outcome__rearrested_in_2019.sum()
tot_rearrest_felonies
```

Out[218…

```
268
```

In [220…

```
# Total number of rearrests using the custom notifications
tot_notif_felonies = test_results_w_felonies.prediction.iloc[:1000].sum()
tot_notif_felonies
```

Out[220…

```
149.33498808107646
```

In [221…

```
# Total number of rearrests using the summer job program
tot_summer_felonies = test_results_w_felonies.prediction.iloc[:500].sum()
tot_summer_felonies
```

Out[221…

```
76.1251088242983
```

In [224…

```
# Compute percentage of 2019 felony arrests eliminated by custom notification system
print("Percentage of felony rearrestes eliminated by Custom Notifications:")
(tot_notif_felonies/2)/tot_rearrest_felonies

# Compute percentage of 2019 felony rearrests eliminated by Summer Jobs Program
print("Percentage of felony rearrests eliminated by Summer Jobs Program")
tot_summer_felonies/tot_rearrest_felonies
```

```
Percentage of felony rearrestes eliminated by Custom Notifications:
```

Out[224…

```
0.27861005239006803
```

```
Percentage of felony rearrests eliminated by Summer Jobs Program
```

Out[224…

```
0.2840489135235011
```

Calculating Cost

- Let's assume that it costs the city $1,000 for each person enrolled in the custom notification program. First calculate the total cost of the program. Then divide this number by the total number of re-arrests prevented from part 3.1. This figure is the **cost per re-arrest prevented**
- Let's assume that it costs the city $5,000 for each person enrolled in the summer jobs program program. First calculate the total cost of the program. Then divide this number by the total number re-arrests prevented from part 3.1.

In [190…

```
# Total cost for each program
notif_cost = 1000 * 1000
summ_cost = 500 * 5000

# cost per re-arrest prevented notif
print("Cost per re-arrest prevented Custom Notifications:")
notif_cost/(tot_notif/2)

# cost per re-arrest prevented summer
print("Cost per re-arrest prevented Summer Jobs:")
summ_cost/tot_summer
```

```
Cost per re-arrest prevented Custom Notifications:
```

Out[190…

```
3121.3309834328593
```

```
Cost per re-arrest prevented Summer Jobs:
```

Out[190…

```
6245.948805739523
```

Fairness

As a mayoral candidate, you campaigned on injecting more fairness into the criminal justice process, so you would like this program to be as fair as possible.

You care about two things: 1) If a program is going to potentially limit people's civil liberties, you want the False Positive Rates across groups to be as close to each other as possible.

2) If a program involves the offer of a service (and is not punitive), you want the group with the highest base rate to also have the highest precision. (The mayor's reasoning here is that the groups most likely to be re-arrested are also among the most disadvantaged socio-economically, therefore, it is the mayor's belief that scarce resources should be allocated to the True Positives of those groups first.)

FPR balance

- Compute the false positive rate for for Black individuals in the top 1000
- Compute the false positive rate for for Hispanic individuals in the top 1000
- Compute the false positive rate for for White individuals in the top 1000

Precision

- Compute the precision for Black individuals in the top 500

- Compute the precision for Hispanic individuals in the top 500
- Compute the precision for White individuals in the top 500

In [191…

```python
# Creating a df with predicted results along with the race features
test_results_w_race = pd.DataFrame({'outcome__rearrested_in_2019' : y_test,
                                    'race__Black' : X_test['arrests__race__Black'],
                                    'race__White' : X_test['arrests__race__Hispanic'],
                                    'race__Hispanic' : X_test['arrests__race__White'],
                                    'prediction' : model_2.predict_proba(X_test)[:, 1]})
test_results_w_race.head()
```

Out[191…

	outcome__rearrested_in_2019	race__Black	race__White	race__Hispanic	prediction
17382	0	0	0	1	0.270452
7099	0	0	0	1	0.037391
5126	0	1	0	0	0.094115
17928	0	1	0	0	0.053577
20543	0	1	0	0	0.073596

In [192…

```python
# Setting up the yhat for the first 1000 predictions sorted
test_results_w_race = test_results_w_race.sort_values('prediction', ascending=False)

test_results_w_race['yhat_1'] = 0
test_results_w_race.yhat_1[:1000] = 1
```

```
C:\Users\Smoo9\AppData\Local\Continuum\anaconda3\envs\inst_414_f2021\lib\site-packages\ipy
kernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  """
```

In [193…

```python
# Crosstab with the race features

confusion_matrix_Black = pd.crosstab(test_results_w_race[test_results_w_race.race__Black==
                                     test_results_w_race[test_results_w_race.race__Black==
confusion_matrix_Hispanic = pd.crosstab(test_results_w_race[test_results_w_race.race__Hisp
                                     test_results_w_race[test_results_w_race.race__Hispani
confusion_matrix_White = pd.crosstab(test_results_w_race[test_results_w_race.race__White==
                                     test_results_w_race[test_results_w_race.race__White==
```

In [194…

```python
#fpr
print('FPR, Black:', confusion_matrix_Black.iloc[1, 0] / confusion_matrix_Black.iloc[:, 0]
print('FPR, Hispanic:', confusion_matrix_White.iloc[1, 0] / confusion_matrix_White.iloc[:,
print('FPR, White:', confusion_matrix_Hispanic.iloc[1, 0] / confusion_matrix_Hispanic.iloc
```

```
FPR, Black: 0.009900990099009901
FPR, Hispanic: 0.008695652173913044
FPR, White: 0.019261637239165328
```

In [195…

```python
# Same as above except for the first 500

test_results_w_race['yhat_2'] = 0
test_results_w_race.yhat_2[:500] = 1
```

```
C:\Users\Smoo9\AppData\Local\Continuum\anaconda3\envs\inst_414_f2021\lib\site-packages\ipy
kernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

In [196…

```
# Same confusion matrix with yhat 2

confusion_matrix_Black = pd.crosstab(test_results_w_race[test_results_w_race.race__Black==
                                     test_results_w_race[test_results_w_race.race__Black==
confusion_matrix_Hispanic = pd.crosstab(test_results_w_race[test_results_w_race.race__Hisp
                                     test_results_w_race[test_results_w_race.race__Hispani
confusion_matrix_White = pd.crosstab(test_results_w_race[test_results_w_race.race__White==
                                     test_results_w_race[test_results_w_race.race__White==
```

In [197…

```
# So I'm assuming at this point most all the metrics point to overfitting, but I really do

print('PPV, Black:', confusion_matrix_Black.iloc[1, 1] / confusion_matrix_Black.iloc[1, :]
print('PPV, Hispanic:', confusion_matrix_White.iloc[1, 1] / confusion_matrix_White.iloc[1,
print('PPV, White:', confusion_matrix_Hispanic.iloc[1, 1] / confusion_matrix_Hispanic.iloc
```

```
PPV, Black: 1.0
PPV, Hispanic: 1.0
PPV, White: 1.0
```

Part 3: Putting It All Together

Now you have to make a choice. Decide whether you will use the algorithm to target the custom notification program or the summer jobs program.

You should mention the following dimensions when you describe your reason for choosing one program over the other:

- Predictive performance
- Potential for impact
- Cost Effectiveness
- Fairness considerations

You must cite numbers from your analysis above to receive full credit.

Would the impact on felony arrests change your answer above, why or why not?

Based on the analysis of the model, I decided to go with the algorithm for the custom notification program.

Performance Metrics:

Both the notification program and summer jobs program have the same high AUC - 0.9554; indicating that the model does a good job of distinguishing the difference between positive and negative classes. In fact, it's nearly 1 indicating a near perfectly calibrated model. They both have high precision (0.93 for the notification system and 1.0 for the summer jobs program) indicating that a high proportion of positive indentifications were correct.

The big difference is in the recall (0.7099 for the notification system and 0.3817 for the summer job program) where the notification system identified a higher proportion of actual positive outcomes.

Potential for Impact:

Based on the percentage of rearrests eliminated for each program, they came out fairly similarly with the summer program being better: 0.2446 for the notification system and 0.3055 for the summer jobs program. The Summer jobs program was slightly more than 6.0% better at eliminating rearrests.

Cost Effectiveness:

Cost effectiveness accounts for the biggest difference between the two programs. The cost per re-arrest prevented for the notification system came out to be $3121.33 per arrest prevented and the summer jobs program was \$6245.95, making the summer program twice as expensive per arrest prevented

Fairness Considerations:

The false positive rate for each of the featured races were as follows: Black: 0.0099 Hispanic: 0.0087 White: 0.0193 I would consider these all very similar as they are less than a percentage point apart. However from a relative standpoint, white arrestees were incorrectly considered positive at twice the rate as black and hispanic arrestees. The precision for all three were the same. Black: 1.0 Hispanic: 1.0 White: 1.0 The model seems to be over fitting because I find it unlikely that all three would have perfect precision. But I've adujusted the hyper parameters a number of times to no effect.

It's likely I did something wrong in the process, but based on the analysis the custom notification system would come out on top as being much cheaper and accurate than the summer job program.

The impact on felony arrests would not change my choice as the two systems were evenly comparable (0.2786 for the custom notification system and 0.2840 for the summer job program. This is less than a 1% difference and not very impactful.