Terry Stop Analysis

In the 1968 Supreme Court case "Terry v. Ohio", the court found that a police officer was not in vilation of the "unresonable search and seizur clause of the Fourth Amendment after he stopped and frisked suspect only because their behavior was suspicious. Thus the phrase "Terry Stops" are in reference to stops made of suspicious drivers.

This is an analysis of over 48,000 Terry Stops, with a goal of predicting if an arrest will be made based off time of day, whether a suspect was frisked, and racial & gender demographics of both the suspects and officers.

The overall goal of the analysis is to have the highest possible recall, to minimize false positives, accidentally classifying subject who were not arrested as arrested.

In [1]:
```
mport the necessary libraries.


port pandas as pd
port numpy as np
port seaborn as sns
port datetime
port matplotlib.pyplot as plt
atplotlib inline
om sklearn.pipeline import Pipeline
om sklearn.preprocessing import OneHotEncoder, StandardScaler
om sklearn.model_selection import train_test_split, GridSearchCV
om sklearn.linear_model import LogisticRegression
om sklearn.metrics import plot_confusion_matrix
om sklearn.neighbors import KNeighborsClassifier
om sklearn.metrics import precision_score, recall_score, accuracy_score,
om xgboost import XGBClassifier
om sklearn.tree import DecisionTreeClassifier
```

Step 1: Cleaning the Data

In [2]:
```
# Import and look at the rows of our dataset.

pd.set_option('display.max_columns', None)
df = pd.read_csv('Terry_Stops.csv')
df.head()
```

Out[2]:

	Subject Age Group	Subject ID	GO / SC Num	Terry Stop ID	Stop Resolution	Weapon Type	Officer ID	Officer YOB	Officer Gender	Of I
0	-	-1	20140000120677	92317	Arrest	None	7500	1984	M	Bla Af Ame
1	-	-1	20150000001463	28806	Field Contact	None	5670	1965	M	V
2	-	-1	20150000001516	29599	Field Contact	None	4844	1961	M	V
3	-	-1	20150000001670	32260	Field Contact	None	7539	1963	M	V
4	-	-1	20150000001739	33155	Field Contact	None	6973	1977	M	V

In [3]:
```
# For ease of analysis, let's add underscores to each column name
renamed_columns = ['Subject_Age_Group','Subject_ID', 'GO_SC_Num', 'Terry
                   'Stop_Resolution', 'Weapon_Type', 'Officer_ID', 'Offi
                  'Officer_Gender', 'Officer_Race', 'Subject_Perceived_R
                  'Subject_Perceived_Gender', 'Reported_Date', 'Reported
                   'Initial_Call_Type', 'Final_Call_Type', 'Call_Type',
                  'Arrest_Flag', 'Frisk_Flag','Precinct', 'Sector', 'Bea
df.columns = renamed_columns
df.head()
```

Out[3]:

	Subject_Age_Group	Subject_ID	GO_SC_Num	Terry_Stop_ID	Stop_Resolution	Weapon_Typ
0	-	-1	20140000120677	92317	Arrest	Non
1	-	-1	20150000001463	28806	Field Contact	Non
2	-	-1	20150000001516	29599	Field Contact	Non
3	-	-1	20150000001670	32260	Field Contact	Non
4	-	-1	20150000001739	33155	Field Contact	Non

In [4]:
```
# Looking at the initial data, 'Subject_ID, GO_SC_Num', 'Terry_Stop_ID',
# individual indentifiers so it's okay to drop those
```

In [5]:
```
df = df.drop(['Subject_ID','GO_SC_Num', 'Terry_Stop_ID', 'Officer_ID'],
```

In [6]:
```
# Take a look to see if there are any null values in the data

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

Out[6]:
```
Subject_Age_Group            0
Stop_Resolution              0
Weapon_Type                  0
Officer_YOB                  0
Officer_Gender               0
Officer_Race                 0
Subject_Perceived_Race       0
Subject_Perceived_Gender     0
Reported_Date                0
Reported_Time                0
Initial_Call_Type            0
Final_Call_Type              0
Call_Type                    0
Officer_Squad              605
Arrest_Flag                  0
Frisk_Flag                   0
Precinct                     0
Sector                       0
Beat                         0
dtype: int64
```

In [7]:
```
# Interesting, because upon initial analysis, there are empty entries
# in 'Subject Age Group', all of the 'Call Type' columns

df.info()
```

```
Stop_Resolution             48094 non-null object
Weapon_Type                 48094 non-null object
Officer_YOB                 48094 non-null int64
Officer_Gender              48094 non-null object
Officer_Race                48094 non-null object
Subject_Perceived_Race      48094 non-null object
Subject_Perceived_Gender    48094 non-null object
Reported_Date               48094 non-null object
Reported_Time               48094 non-null object
Initial_Call_Type           48094 non-null object
Final_Call_Type             48094 non-null object
Call_Type                   48094 non-null object
Officer_Squad               47489 non-null object
Arrest_Flag                 48094 non-null object
Frisk_Flag                  48094 non-null object
Precinct                    48094 non-null object
Sector                      48094 non-null object
Beat                        48094 non-null object
dtypes: int64(1), object(18)
memory usage: 7.0+ MB
```

In [8]:
```
# investigate the columns that are mostly '-' to see if there is data
# or if it's mostly null values
```

In [9]:
```
print('Subject Age Group:' , '\n', df['Subject_Age_Group'].value_counts(
print('Initial Call Type:', '\n', df['Initial_Call_Type'].value_counts()
print('Final Call Type:', '\n',  df['Final_Call_Type'].value_counts(), '
print('Call Type:', "\n", df['Call_Type'].value_counts(),'\n')
```

```
Subject Age Group:
 26 - 35          16012
36 - 45          10262
18 - 25           9590
46 - 55           6225
56 and Above      2448
1 - 17            1986
-                 1571
Name: Subject_Age_Group, dtype: int64

Initial Call Type:
 -                                                   13207
SUSPICIOUS STOP - OFFICER INITIATED ONVIEW          3221
SUSPICIOUS PERSON, VEHICLE OR INCIDENT              3078
DISTURBANCE, MISCELLANEOUS/OTHER                    2477
ASLT - IP/JO - WITH OR W/O WPNS (NO SHOOTINGS)      2070
                                                   ...
PREPLANNED EVENT                                       1
-ASSIGNED DUTY - STAKEOUT                              1
ALARM - RESIDENTIAL - SILENT/AUD PANIC/DURESS          1
WARRANT PICKUP - FROM OTHER AGENCY                     1
ORDER - ASSIST DV VIC W/SRVC OF COURT ORDER            1
Name: Initial_Call_Type, Length: 168, dtype: int64

Final Call Type:
 -                                                     13207
--SUSPICIOUS CIRCUM. - SUSPICIOUS PERSON              3873
--PROWLER - TRESPASS                                  3381
--DISTURBANCE - OTHER                                 2775
--ASSAULTS, OTHER                                     2344
                                                     ...
SHOTS -DELAY/INCLUDES HEARD/NO ASSAULT                   1
MVC - UNK INJURIES                                       1
MVC - REPORT, NON INJ/NON BLKG OR AFTER FACT INJ         1
FIGHT - VERBAL/ORAL (NO WEAPONS)                         1
ESCAPE - PRISONER                                        1
Name: Final_Call_Type, Length: 211, dtype: int64

Call Type:
 911                               21844
-                                13207
ONVIEW                            9280
TELEPHONE OTHER, NOT 911          3399
ALARM CALL (NOT POLICE ALARM)      355
TEXT MESSAGE                         8
SCHEDULED EVENT (RECURRING)          1
Name: Call_Type, dtype: int64
```

In [10]:
```
l "Call Type" is mostly unnecessary and can be dropped. Also 'Initial_Cal
missing over 13k columns so it's okay to drop those
```

In [11]:
```
df = df.drop(['Call_Type','Initial_Call_Type', 'Final_Call_Type'], axis=
```

In [12]:
```
df['Subject_Age_Group'].value_counts()
```

Out[12]:
```
26 - 35         16012
36 - 45         10262
18 - 25          9590
46 - 55          6225
56 and Above     2448
1 - 17           1986
-                1571
Name: Subject_Age_Group, dtype: int64
```

In [13]:
```
df = df = df[df.Subject_Age_Group != '-']
```

In [14]:
```
df['Subject_Age_Group'].value_counts()
```

Out[14]:
```
26 - 35         16012
36 - 45         10262
18 - 25          9590
46 - 55          6225
56 and Above     2448
1 - 17           1986
Name: Subject_Age_Group, dtype: int64
```

In [15]:
```
df['Officer_YOB'].value_counts()
```

Out[15]:
```
1986    3261
1987    2934
1984    2691
1991    2659
1985    2440
1992    2426
1990    2274
1988    2114
1989    2010
1982    1833
1983    1681
1979    1493
1993    1482
1981    1406
1995    1232
1971    1182
1978    1137
1977     994
1976     993
1994     905
1973     904
1980     809
1967     701
1996     687
1968     590
1970     559
1969     539
1974     533
1975     521
1997     451
1962     449
1964     431
1972     413
1965     412
1963     236
1958     215
1961     206
1966     178
1959     167
1960     128
1954      44
1957      43
1998      36
1953      33
1900      31
1955      21
1956      17
1948      10
1949       5
1952       4
1946       2
1951       1
Name: Officer_YOB, dtype: int64
```

In [16]:
```
def officer_yob_decade(x):
    if (x <= 1959):
        return '1900-1960'
    elif (x > 1959) and (x <= 1969):
        return '1960s'
    elif (x > 1969) and (x <= 1979):
        return '1970s'
    elif (x > 1979) and (x <= 1989):
        return '1980s'
    elif (x > 1989) and (x <= 1999):
        return '1990s'
```

In [17]:
```
df['Officer_Age_By_Decade'] = df['Officer_YOB'].apply(officer_yob_decade
df['Officer_Age_By_Decade'].value_counts()
```

Out[17]:
```
1980s        21179
1990s        12152
1970s         8729
1960s         3870
1900-1960      593
Name: Officer_Age_By_Decade, dtype: int64
```

In [18]:
```
# Explore "Arrest Flag" and "Stop Resolution
#a s they both have arrest data that will serve
# as the target variable for this exploration.
```

In [19]:
```
df['Arrest_Flag'].value_counts()
```

Out[19]:
```
N    42843
Y     3680
Name: Arrest_Flag, dtype: int64
```

In [20]:
```
df['Stop_Resolution'].value_counts()
```

Out[20]:
```
Field Contact                 18637
Offense Report                15287
Arrest                        11706
Referred for Prosecution        719
Citation / Infraction           174
Name: Stop_Resolution, dtype: int64
```

In [21]:
```
# It seems there is a discrepency in Arrest data between 'Stop Resolutic
# and "Arrest_Flag". I am making the executive decision to base this
# exploration around "Stop Resolution" as it reads as more thorough
# in it's reporting of resoltion rather than a simple 'Yes'/'No' in
# 'Arrest Flag'.
```

In [22]:
```
df['Stop_Resolution'] = df['Stop_Resolution'].apply(lambda x: 'Yes' if x
df['Stop_Resolution'].value_counts()
```

Out[22]:
```
No     34817
Yes    11706
Name: Stop_Resolution, dtype: int64
```

In [23]:
```
df = df.drop('Arrest_Flag', axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 46523 entries, 124 to 48093
Data columns (total 16 columns):
Subject_Age_Group            46523 non-null object
Stop_Resolution              46523 non-null object
Weapon_Type                  46523 non-null object
Officer_YOB                  46523 non-null int64
Officer_Gender               46523 non-null object
Officer_Race                 46523 non-null object
Subject_Perceived_Race       46523 non-null object
Subject_Perceived_Gender     46523 non-null object
Reported_Date                46523 non-null object
Reported_Time                46523 non-null object
Officer_Squad                45936 non-null object
Frisk_Flag                   46523 non-null object
Precinct                     46523 non-null object
Sector                       46523 non-null object
Beat                         46523 non-null object
Officer_Age_By_Decade        46523 non-null object
dtypes: int64(1), object(15)
memory usage: 6.0+ MB
```

In [24]:
```
# Now explore factors like the races and genders of both the officers
# and the people pulled over
```

In [25]:
```
('Officer Gender:' , '\n', df['Officer_Gender'].value_counts(),'\n')
('Officer Race:', '\n', df['Officer_Race'].value_counts(),'\n')
('Subject Perceived Gender:', '\n',  df['Subject_Perceived_Gender'].valu
('Subject Perceived Race:', "\n", df['Subject_Perceived_Race'].value_cou
```

```
Officer Gender:
 M    41154
F     5344
N       25
Name: Officer_Gender, dtype: int64

Officer Race:
 White                                  35173
Hispanic or Latino                     2679
Two or More Races                      2669
Asian                                  1987
Black or African American              1790
Not Specified                          1447
Nat Hawaiian/Oth Pac Islander           437
American Indian/Alaska Native           310
Unknown                                  31
Name: Officer_Race, dtype: int64

Subject Perceived Gender:
 Male                                                            36887
Female                                                          9489
Unable to Determine                                              108
Unknown                                                           17
-                                                                 16
Gender Diverse (gender non-conforming and/or transgender)          6
Name: Subject_Perceived_Gender, dtype: int64

Subject Perceived Race:
 White                                           23078
Black or African American                      13943
Unknown                                         2466
Hispanic                                        1659
Asian                                           1540
-                                               1471
American Indian or Alaska Native                1352
Multi-Racial                                     801
Other                                            150
Native Hawaiian or Other Pacific Islander         63
Name: Subject_Perceived_Race, dtype: int64
```

In [26]:
```
# There seem to be many different ways to say "unknown" in these columns
# Let's combine the redundant values together
```

In [27]:
```
'Officer_Race'] = df['Officer_Race'].apply(lambda x: "Other" if x in ['N
'Subject_Perceived_Gender'] = df['Subject_Perceived_Gender'].apply(lambd
'Subject_Perceived_Race'] = df['Subject_Perceived_Race'].apply(lambda x:
```

In [28]:
```
print(df['Officer_Race'].value_counts(), '\n')
print(df['Subject_Perceived_Gender'].value_counts(), '\n')
print(df['Subject_Perceived_Race'].value_counts(), '\n')
```

```
White                               35173
Hispanic or Latino                   2679
Two or More Races                    2669
Asian                                1987
Black or African American            1790
Other                                1478
Nat Hawaiian/Oth Pac Islander         437
American Indian/Alaska Native         310
Name: Officer_Race, dtype: int64

Male              36887
Female             9489
Unknown/GNC         147
Name: Subject_Perceived_Gender, dtype: int64

White                                        23078
Black or African American                    13943
Unknown                                       4087
Hispanic                                      1659
Asian                                         1540
American Indian or Alaska Native              1352
Multi-Racial                                   801
Native Hawaiian or Other Pacific Islander       63
Name: Subject_Perceived_Race, dtype: int64
```

In [29]:
```
# Also let's clean up the gender columns of both the officer and the
# subject. Entries outside of the gender binary are miniscule compared
# to Male and Female.

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 46523 entries, 124 to 48093
Data columns (total 16 columns):
Subject_Age_Group           46523 non-null object
Stop_Resolution             46523 non-null object
Weapon_Type                 46523 non-null object
Officer_YOB                 46523 non-null int64
Officer_Gender              46523 non-null object
Officer_Race                46523 non-null object
Subject_Perceived_Race      46523 non-null object
Subject_Perceived_Gender    46523 non-null object
Reported_Date               46523 non-null object
Reported_Time               46523 non-null object
Officer_Squad               45936 non-null object
Frisk_Flag                  46523 non-null object
Precinct                    46523 non-null object
Sector                      46523 non-null object
Beat                        46523 non-null object
Officer_Age_By_Decade       46523 non-null object
dtypes: int64(1), object(15)
memory usage: 6.0+ MB
```

In [30]:
```
df = df[df.Officer_Gender != 'N']
df = df[df.Subject_Perceived_Gender != 'Unknown/GNC']
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 46351 entries, 124 to 48093
Data columns (total 16 columns):
Subject_Age_Group           46351 non-null object
Stop_Resolution             46351 non-null object
Weapon_Type                 46351 non-null object
Officer_YOB                 46351 non-null int64
Officer_Gender              46351 non-null object
Officer_Race                46351 non-null object
Subject_Perceived_Race      46351 non-null object
Subject_Perceived_Gender    46351 non-null object
Reported_Date               46351 non-null object
Reported_Time               46351 non-null object
Officer_Squad               45794 non-null object
Frisk_Flag                  46351 non-null object
Precinct                    46351 non-null object
Sector                      46351 non-null object
Beat                        46351 non-null object
Officer_Age_By_Decade       46351 non-null object
dtypes: int64(1), object(15)
memory usage: 6.0+ MB
```

In [31]:
```
df['Weapon_Type'].value_counts()
```

Out[31]:
```
None                                    31478
-                                       12076
Lethal Cutting Instrument                1452
Knife/Cutting/Stabbing Instrument         671
Handgun                                   285
Firearm Other                              92
Blunt Object/Striking Implement            89
Club, Blackjack, Brass Knuckles            48
Firearm                                    43
Mace/Pepper Spray                          30
Other Firearm                              22
Firearm (unk type)                         15
Taser/Stun Gun                             10
None/Not Applicable                         9
Club                                        9
Fire/Incendiary Device                      7
Rifle                                       6
Shotgun                                     3
Automatic Handgun                           2
Personal Weapons (hands, feet, etc.)        2
Blackjack                                   1
Brass Knuckles                              1
Name: Weapon_Type, dtype: int64
```

In [32]:
```
df = df.drop('Weapon_Type', axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 46351 entries, 124 to 48093
Data columns (total 15 columns):
Subject_Age_Group           46351 non-null object
Stop_Resolution             46351 non-null object
Officer_YOB                 46351 non-null int64
Officer_Gender              46351 non-null object
Officer_Race                46351 non-null object
Subject_Perceived_Race      46351 non-null object
Subject_Perceived_Gender    46351 non-null object
Reported_Date               46351 non-null object
Reported_Time               46351 non-null object
Officer_Squad               45794 non-null object
Frisk_Flag                  46351 non-null object
Precinct                    46351 non-null object
Sector                      46351 non-null object
Beat                        46351 non-null object
Officer_Age_By_Decade       46351 non-null object
dtypes: int64(1), object(14)
memory usage: 5.7+ MB
```

In [33]:
```
# Drop Weapon type, there are far more null values than there are weapon
```

In [34]:
```
df['Reported_Time'].value_counts()
```

Out[34]:
```
03:09:00    50
02:56:00    49
19:01:00    48
19:18:00    48
03:13:00    48
            ..
14:54:22     1
00:11:30     1
22:24:46     1
03:07:36     1
21:19:26     1
Name: Reported_Time, Length: 13183, dtype: int64
```

In [35]:
```
# There are 13K different times, let's create a new column that is just
# the hours of the stops.
```

In [36]:
```
df['Reported_Time'] = pd.to_datetime(df['Reported_Time'])
df['Reported_Hour'] = df['Reported_Time'].apply(lambda x: x.hour)
```

In [37]:
```
df['Reported_Hour'].value_counts()
```

Out[37]:
```
18    2830
2     2678
19    2545
3     2473
17    2472
23    2318
1     2318
16    2220
0     2111
15    2111
14    2040
22    1977
11    1908
13    1825
10    1808
21    1671
12    1557
5     1490
9     1442
4     1429
20    1411
8     1282
7     1247
6     1188
Name: Reported_Hour, dtype: int64
```

In [38]:
```
def time_of_day(x):
    if (x > 4) and (x <= 11):
        return 'Morning'
    elif (x > 12) and (x <= 19):
        return 'Afternoon'
    else:
        return "Night"
```

In [39]:
```
df['Time_of_Day'] = df['Reported_Hour'].apply(time_of_day)
```

In [40]:
```
df['Time_of_Day'].value_counts()
```

Out[40]:
```
Night        19943
Afternoon    16043
Morning      10365
Name: Time_of_Day, dtype: int64
```

In [41]:
```
# Now that those are divided, let's divide them into AM and PM and
# create a new column. 0 is AM, 1 is PM
```

In [42]:
```
f['Reported_AM_or_PM'] = df['Reported_Hour'].apply(lambda x: 0 if x <12 e
f['Reported_AM_or_PM'] = df['Reported_AM_or_PM'].astype(int)
```

In [43]:
```
df['Reported_AM_or_PM'].value_counts()
```

Out[43]:
```
1    24977
0    21374
Name: Reported_AM_or_PM, dtype: int64
```

In [44]:
```
df = df.drop(['Reported_Time'], axis=1)
```

In [ ]:

In [45]:
```
df['Frisk_Flag'].value_counts()
```

Out[45]:
```
N    35460
Y    10498
-      393
Name: Frisk_Flag, dtype: int64
```

In [46]:
```
df = df[df.Frisk_Flag != '-']
df['Frisk_Flag'] = df['Frisk_Flag'].apply(lambda x: "0" if x =='N' else
```

In [47]:
```
df['Frisk_Flag'].value_counts()
```

Out[47]:
```
0    35460
1    10498
Name: Frisk_Flag, dtype: int64
```

In [48]:
```
# Let's explore dates
```

In [49]:
```
df['Reported_Date'].value_counts()
```

Out[49]:
```
2015-10-01T00:00:00    87
2015-09-29T00:00:00    64
2015-05-28T00:00:00    54
2015-08-04T00:00:00    53
2019-04-26T00:00:00    52
                       ..
2015-03-24T00:00:00     1
2015-04-14T00:00:00     1
2015-05-13T00:00:00     1
2015-03-15T00:00:00     1
2015-05-10T00:00:00     1
Name: Reported_Date, Length: 2296, dtype: int64
```

In [50]:
```
df['Reported_Date'] = pd.DatetimeIndex(df['Reported_Date']).month
```

In [51]:
```
df['Reported_Date'].value_counts()
```

Out[51]:
```
5     4818
6     4258
7     4025
4     3979
8     3943
10    3903
1     3763
3     3745
9     3571
11    3443
2     3261
12    3249
Name: Reported_Date, dtype: int64
```

In [52]:
```
df['Precinct'].value_counts()
```

Out[52]:
```
West         11311
North        10158
-             9368
East          6077
South         5480
Southwest     2213
SouthWest     1124
Unknown        172
OOJ             34
FK ERROR        21
Name: Precinct, dtype: int64
```

In [53]:
```
df = df[df.Precinct != '-']
df = df[df.Precinct != 'Unknown']
df = df[df.Precinct != 'OOJ']
df = df[df.Precinct != 'FK ERROR']
df['Precinct'] = df['Precinct'].apply(lambda x: 'SouthWest' if x in ['So
df['Precinct'].value_counts()
```

Out[53]:
```
West         11311
North        10158
East          6077
South         5480
SouthWest     3337
Name: Precinct, dtype: int64
```

In [54]:
```
df['Beat'].value_counts()
```

Out[54]:
```
N3      1129
E2      1041
K3       978
M2       835
M3       768
        ...
C2        90
U3        85
N1        76
J2        72
99         2
Name: Beat, Length: 103, dtype: int64
```

In [55]:
```
df['Sector'].value_counts()
```

Out[55]:
```
E         2230
M         2195
N         2105
K         1741
K         1700
B         1611
L         1558
D         1468
R         1374
F         1327
M         1285
S         1284
U         1247
D         1161
O         1090
J         1088
G         1047
C          991
E          944
Q          936
W          885
Q          821
N          719
F          690
R          633
O          617
B          534
S          483
G          466
U          454
L          448
W          433
C          398
J          394
-            6
Name: Sector, dtype: int64
```

In [56]:
```
df['Officer_Squad'].value_counts()
```

Out[56]:
```
TRAINING - FIELD TRAINING SQUAD                        4055
WEST PCT 1ST W - DAVID/MARY                            1213
WEST PCT 2ND W - D/M RELIEF                             816
SOUTHWEST PCT 2ND W - FRANK                             741
WEST PCT 1ST W - KING/QUEEN                             736
                                                       ...
CANINE - NIGHT SQUAD                                      1
BURG/THEFT/JUV - WEST                                     1
CANINE - DAY SQUAD                                        1
COMMUNITY OUTREACH - YOUTH VIOLENCE-SCHOOLS DETAIL        1
TRAF - MOTORCYCLE UNIT - T2 SQUAD                         1
Name: Officer_Squad, Length: 156, dtype: int64
```

In [57]:
```
# Dropping 'Officer Squad', 'Beat' and 'Sector' for reasons similar to C
```

In [58]:
```
df = df.drop(['Beat', 'Sector', 'Officer_Squad'], axis=1)
```

In [59]:
```
df.columns
```

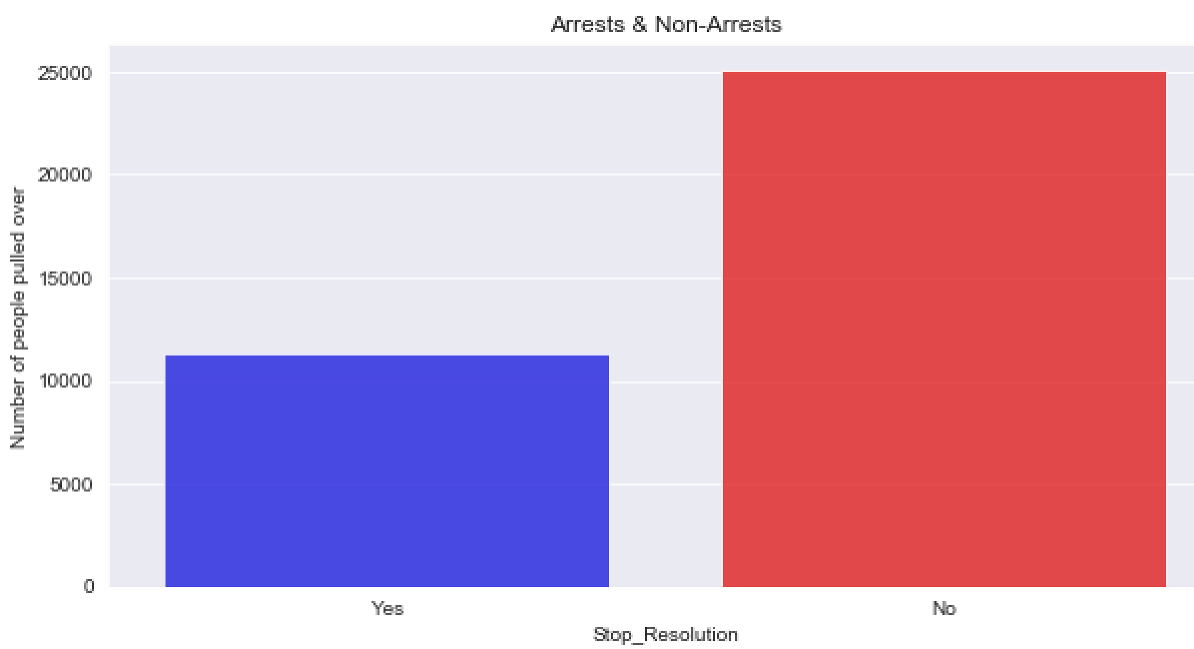
Out[59]:
```
Index(['Subject_Age_Group', 'Stop_Resolution', 'Officer_YOB', 'Officer_G
nder',
       'Officer_Race', 'Subject_Perceived_Race', 'Subject_Perceived_Gend
r',
       'Reported_Date', 'Frisk_Flag', 'Precinct', 'Officer_Age_By_Decad
e',
       'Reported_Hour', 'Time_of_Day', 'Reported_AM_or_PM'],
      dtype='object')
```

Step 2: Visualize the Data

In [60]:
```
# Begin visualization of cleaned data, starting with a visualizaiton of
# our target variable, Stop Resolution.
```

In [61]:
```
arrests = df['Stop_Resolution']=='Yes'
non_arrests = df['Stop_Resolution']=='No'
y = df['Stop_Resolution']
num_of_arrests = df[arrests].shape[0]
num_of_nonarrests = df[non_arrests].shape[0]

print('Target Variable: Stop Resolution')
print('Total Arrests: ', num_of_arrests)
print('Total of Non-arrests: ', num_of_nonarrests)

sns.set_style('darkgrid');
plt.figure(figsize = (10,5));
sns.countplot(df['Stop_Resolution'], alpha = .80, palette= ['blue', 'red
plt.title('Arrests & Non-Arrests');

plt.ylabel('Number of people pulled over');
plt.show()
```

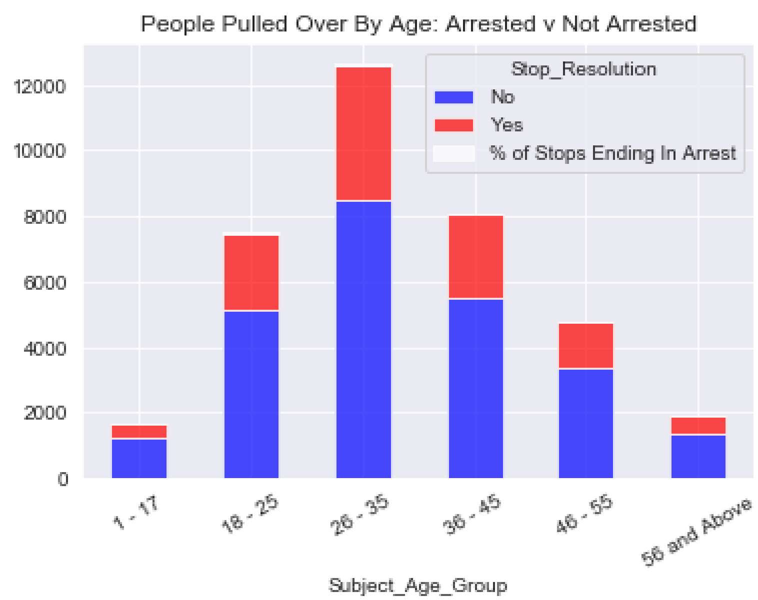
```
Target Variable: Stop Resolution
Total Arrests:  11278
Total of Non-arrests:  25085
```



In [62]:
```
# Create bar charts to compare different columns against the arrrest dat
```

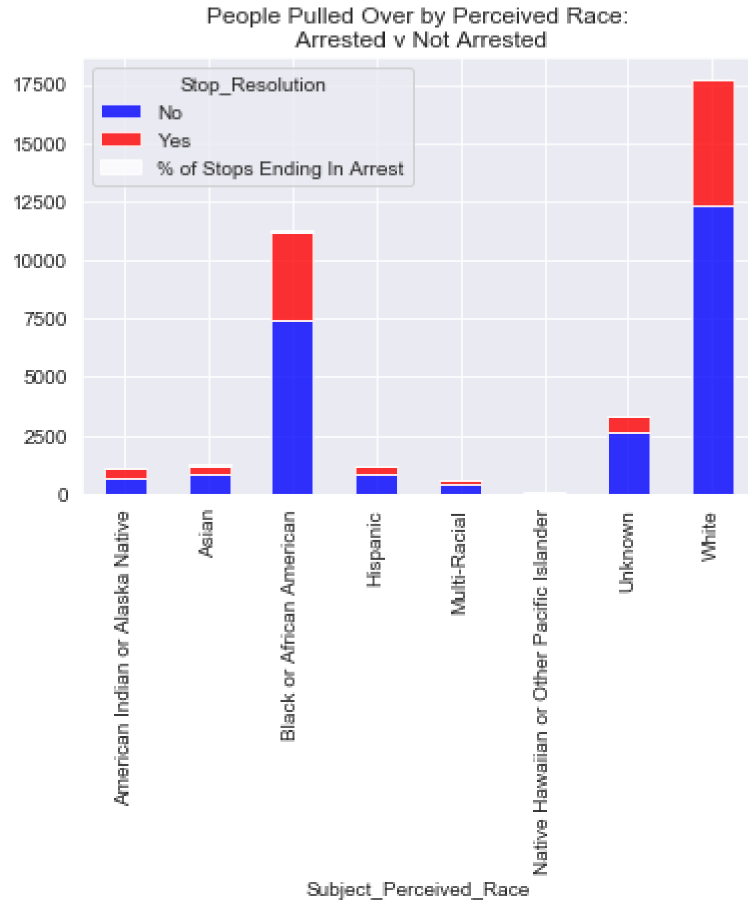
In [63]:
```
subject_age_group = df.groupby(['Subject_Age_Group', 'Stop_Resolution'])
subject_age_group['% of Stops Ending In Arrest'] = (subject_age_group['Y
print('Subject Age Group\n')
print(subject_age_group)

viz_1 = subject_age_group.plot(kind = 'bar', stacked = True,
                               title = "People Pulled Over By Age: Arrested
                               color = ['blue', 'red', 'white'], alpha = .70
```

```
Subject Age Group

Stop_Resolution        No   Yes  % of Stops Ending In Arrest
Subject_Age_Group
1 - 17               1204   420                    25.862069
18 - 25              5155  2304                    30.888859
26 - 35              8480  4132                    32.762448
36 - 45              5511  2542                    31.565876
46 - 55              3391  1357                    28.580455
56 and Above         1344   523                    28.012855
```



In [64]:
```
subject_perceived_race = df.groupby(['Subject_Perceived_Race', 'Stop_Res
subject_perceived_race['% of Stops Ending In Arrest'] = (subject_perceiv
print('Subject Perceived Race\n')
print(subject_perceived_race)

viz_2 = subject_perceived_race.plot(kind = 'bar', stacked = True,
                                    title = 'People Pulled Over by Percei
                                    color = ['blue', 'red','white'], alph
```

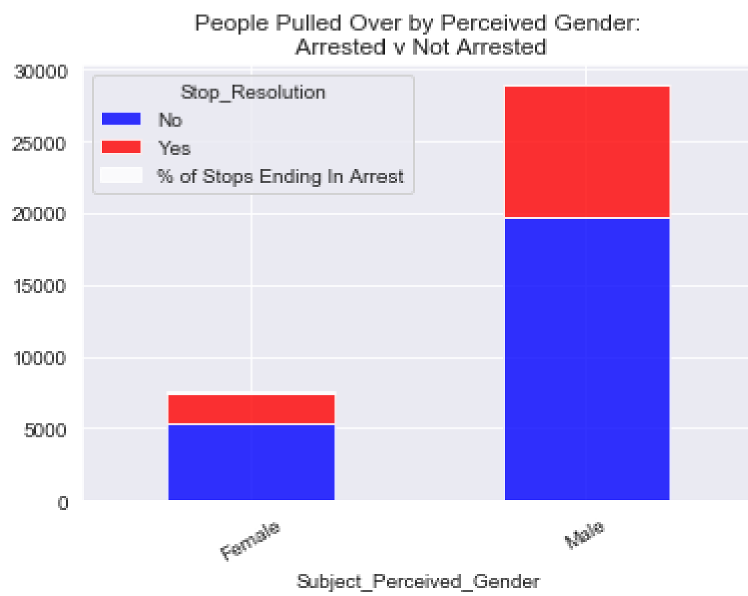
```
Subject Perceived Race

Stop_Resolution                               No   Yes  \
Subject_Perceived_Race
American Indian or Alaska Native             669   386
Asian                                        801   417
Black or African American                   7444  3795
Hispanic                                     811   379
Multi-Racial                                 404   155
Native Hawaiian or Other Pacific Islander     41    18
Unknown                                     2612   721
White                                      12303  5407

Stop_Resolution                            % of Stops Ending In Arrest
Subject_Perceived_Race
American Indian or Alaska Native                             36.587678
Asian                                                        34.236453
Black or African American                                    33.766349
Hispanic                                                     31.848739
Multi-Racial                                                 27.728086
Native Hawaiian or Other Pacific Islander                    30.508475
Unknown                                                      21.632163
White                                                        30.530774
```



In [65]:
```
# It appears American Inidan/Native Alaskan have the highest percentage
# of arrests made after a Terry stop with nearly 37%. While important tc
# there were only 669 total stops of 36363 total in the data set.
# The next highest was Asian with 34.2% , with Black, white, and Native
# at around 30% each.
```

In [66]:
```
er', 'Stop_Resolution']).Subject_Perceived_Gender.count().unstack()
ject_perceived_gender['Yes'] / (subject_perceived_gender.sum(axis=1)))*1(





True,
 by Perceived Gender:\n Arrested v Not Arrested',
te'], alpha = .80, rot = 30)
```

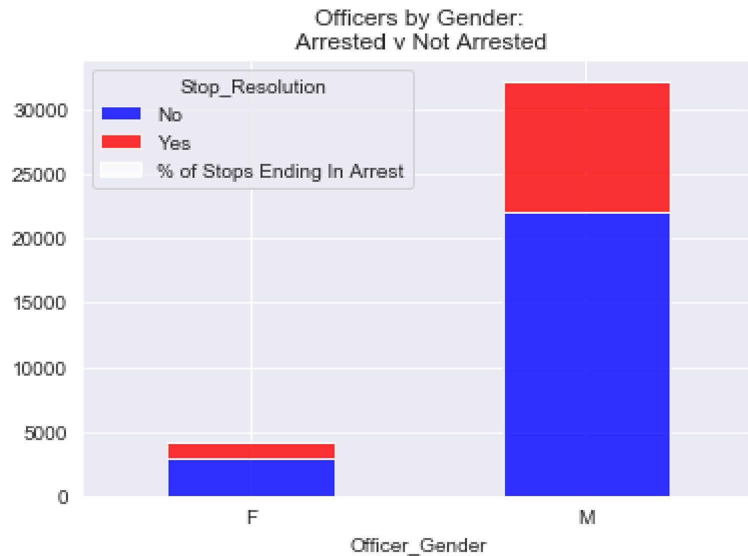
```
Subject Perceived Gender

Stop_Resolution              No    Yes   % of Stops Ending In Arrest
Subject_Perceived_Gender
Female                     5356   2151                     28.653257
Male                      19729   9127                     31.629470
```



In [67]:
```
ale subjects were arrest 31% of the arrests while female subjects were
rrested 28.65%. While the male subjects were stopped nearly 4 times the ı
f female, their arrest percentage was surprisingly close
```

In [68]:
```
der = df.groupby(['Officer_Gender', 'Stop_Resolution']).Officer_Gender.c
der['% of Stops Ending In Arrest'] = (officer_gender['Yes'] / (officer_g

cer Gender\n')
er_gender)

icer_gender.plot(kind = 'bar', stacked = True,
                        title = 'Officers by Gender:\n Arrested v Not Ar
                        color = ['blue', 'red','white'], alpha = .80, ro
```

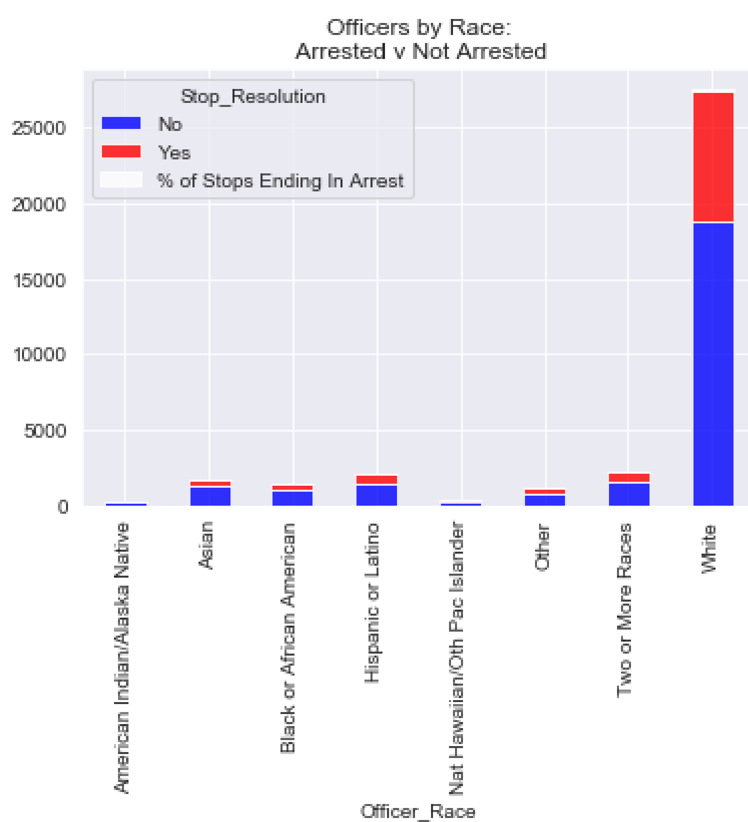
```
Officer Gender

Stop_Resolution     No    Yes  % of Stops Ending In Arrest
Officer_Gender
F                 2972   1177                    28.368282
M                22113  10101                    31.355932
```



In [69]:
```
# Male cops arrested individuals 31% of those pulled over, while male of
# arrested at a rate of 28%.
```

In [70]:
```
icer_race = df.groupby(['Officer_Race', 'Stop_Resolution']).Subject_Perc
icer_race['% of Stops Ending In Arrest'] = (officer_race['Yes'] / (offic

nt('Officer Race\n')
nt(officer_race)

_5 = officer_race.plot(kind = 'bar', stacked = True,
                              title = 'Officers by Race:\n Arrested v 
                              color = ['blue', 'red','white'], alpha =
```

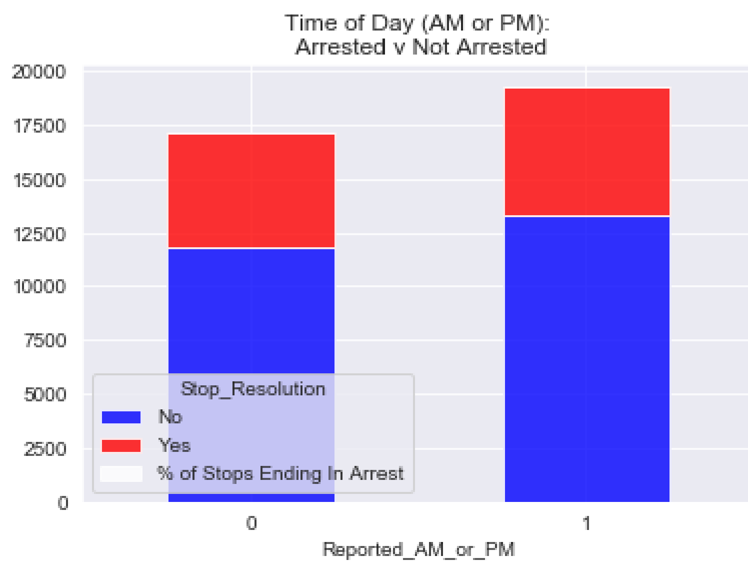
```
Officer Race

Stop_Resolution                      No   Yes  % of Stops Ending In Arrest
Officer_Race
American Indian/Alaska Native       149    69                    31.651376
Asian                              1203   446                    27.046695
Black or African American          1023   323                    23.997028
Hispanic or Latino                 1407   653                    31.699029
Nat Hawaiian/Oth Pac Islander       246    84                    25.454545
Other                               767   341                    30.776173
Two or More Races                  1526   677                    30.730822
White                             18764  8685                    31.640497
```



In [71]:
```
# While white officers make up nearly 3 times the cops of all other race
# combined, they were actually in the middle of the pack in terms of
# arrests made. Officers of two + races, Hispanic/Latino, and Asian offi
# were arresting at around ~25%.
```

In [72]:
```
am_or_pm = df.groupby(['Reported_AM_or_PM', 'Stop_Resolution']).Reported
am_or_pm['% of Stops Ending In Arrest'] = (am_or_pm['Yes'] / (am_or_pm.s

print('Reported AM or PM\n')
print(am_or_pm)

viz_6 = am_or_pm.plot(kind = 'bar', stacked = True,
                                title = 'Time of Day (AM or PM):\n Ar
                                color = ['blue', 'red','white'], alph
```

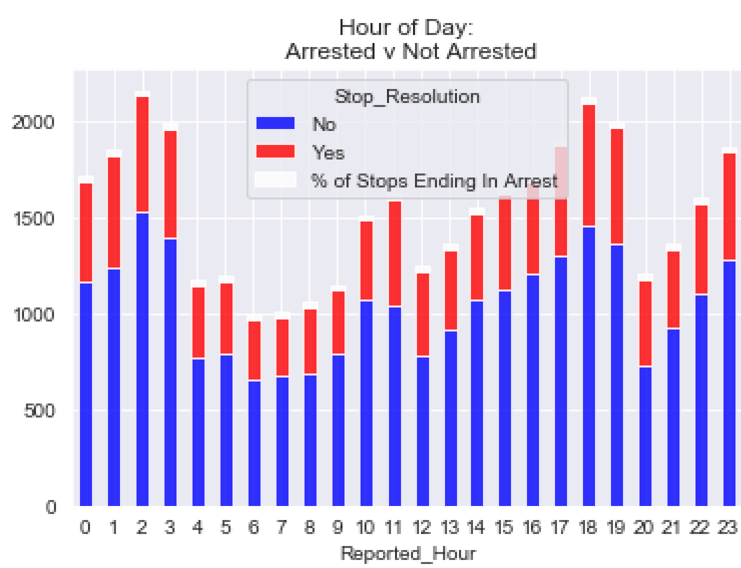
```
0                    11821   5286                          30.899632
1                    13264   5992                          31.117574
```



In [73]:
```
There are more Terry stops in the PM hours than AM, however the percenta
are less than 0.3% apart.
```

In [74]:
```
hour_of_day = df.groupby(['Reported_Hour', 'Stop_Resolution']).Reported_
hour_of_day['% of Stops Ending In Arrest'] = (hour_of_day['Yes'] / (hour

print('Reported Hour\n')
print(hour_of_day)

viz_7 = hour_of_day.plot(kind = 'bar', stacked = True,
                                    title = 'Hour of Day:\n Arrested v No
                                    color = ['blue', 'red','white'], alph
```

```
Reported Hour

Stop_Resolution    No  Yes  % of Stops Ending In Arrest
Reported_Hour
0                1170  517                    30.646117
1                1237  587                    32.182018
2                1527  606                    28.410689
3                1400  565                    28.753181
4                 766  377                    32.983377
5                 795  374                    31.993157
6                 651  320                    32.955716
7                 679  300                    30.643514
8                 687  347                    33.558994
9                 788  332                    29.642857
10               1078  409                    27.505044
11               1043  552                    34.608150
12                776  441                    36.236647
13                917  415                    31.156156
14               1076  443                    29.163924
15               1129  495                    30.480296
16               1205  488                    28.824572
17               1304  572                    30.490405
18               1456  637                    30.434783
19               1367  606                    30.714648
20                725  448                    38.192668
21                925  412                    30.815258
22               1100  478                    30.291508
23               1284  557                    30.255296
```



In [75]:
```
# Looking at the data, arrests ebb and flow depending on time of day,
# with peaks at midnight to 3am and 4pm to 7pm. However the highest
# percentage of arrests made at 11am and 12pm, over 1 percentage point
#away from the next two closest hours at 9am and 8pm.
```

Step 3: Model the Data

In [76]:
```
# Now that we've cleaned and visualized the data, now let's fit it into
# model. First starting with converting the target variable to binary,
# OneHotEncoding, then normalizing the data with StandardScalar
```

In [77]:
```
df['Stop_Resolution'] = df['Stop_Resolution'].apply(lambda x: 0 if x=='N

df['Stop_Resolution'].value_counts()
```

Out[77]:
```
0    25085
1    11278
Name: Stop_Resolution, dtype: int64
```

In [78]:
```
ne_hot_df = pd.get_dummies(df)

 = one_hot_df['Stop_Resolution']
ne_hot_df.drop('Stop_Resolution', axis=1, inplace=True)

_train, X_test, y_train, y_test = train_test_split(one_hot_df, y, test_s
```

In [79]:
```
scaler = StandardScaler()

scaled_data_train = scaler.fit_transform(X_train)
scaled_data_test = scaler.transform(X_test)

scaled_df_train = pd.DataFrame(scaled_data_train, columns=one_hot_df.col
```

In [80]:
```
scaled_df_train.head()
```

Out[80]:

	Officer_YOB	Reported_Date	Reported_Hour	Reported_AM_or_PM	Subject_Age_Group_1 - 17	Sub
0	0.386363	-0.726015	-1.070069	-1.060617	-0.216547	
1	0.731738	-1.025905	-1.486164	-1.060617	-0.216547	
2	-2.146385	-0.426125	0.178215	0.942847	-0.216547	
3	0.731738	1.373217	1.426499	0.942847	-0.216547	
4	1.307362	0.773437	0.871706	0.942847	-0.216547	

In [81]:
```
# Now that the data is OneHotEncoded and normalized, let's fit a model,
# starting with a Logistic Regression model.
```

In [82]:
```
logreg = LogisticRegression(fit_intercept=False, C=1e12, solver='libline
logreg.fit(scaled_data_train, y_train)
```

Out[82]:
```
LogisticRegression(C=1000000000000.0, fit_intercept=False, solver='libli
ear')
```

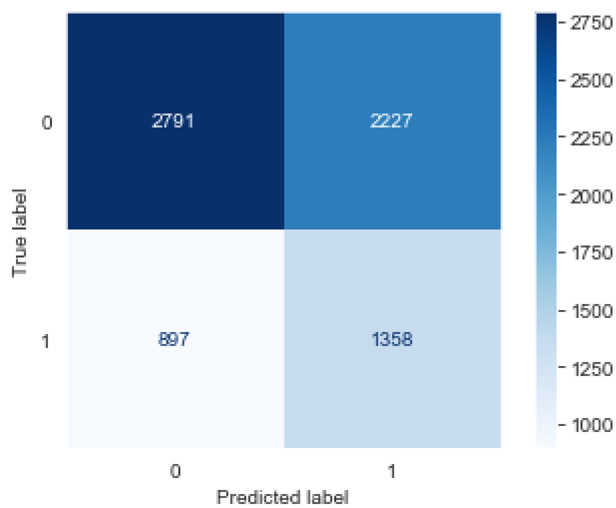
In [83]:
```
y_hat_train = logreg.predict(scaled_data_train)
y_hat_test = logreg.predict(scaled_data_test)
```

In [84]:
```
print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.5704661075209679
```

In [85]:
```
Looking at the initial model, both the training and the test, both had a
accuracy of 57%. We can definitely make this better using more sophistic
modeling. Next let's look at a confusion matrix to see where we can
see how the model is performing
```

In [86]:
```
plot_confusion_matrix(logreg, scaled_data_test, y_test,
                      cmap=plt.cm.Blues)
plt.grid(False)
plt.show()
```



In [87]:
```
# The model is correctly predicting stops ending in no arrest 2791 times
# while inccorectly predicting stops that were arrests as non arrest 897
# times.

# Next let's check the Precision, Recall, Accuracy, and F1 scores.
```

In [88]:
```
print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.5704661075209679
Testing Precision:  0.3788005578800558
Testing Recall:  0.6022172949002217
Testing F1-Score:  0.4650684931506849
```

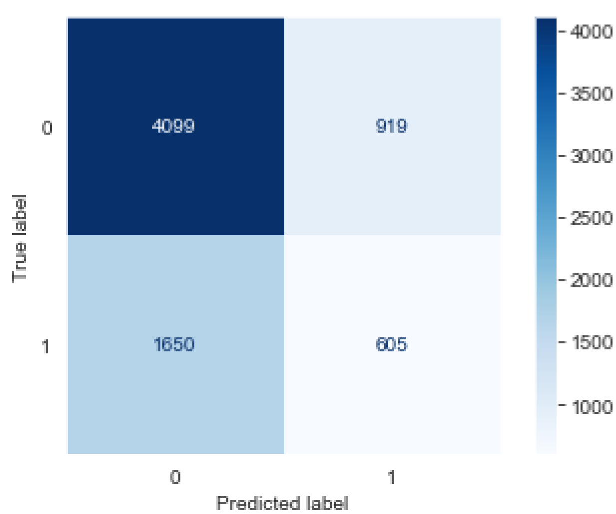
In [89]:
```
# Not too bad for a first start except for the precision.
# This time, we'll fit a K Nearest-Neighbors model to see if the data
# works better in that context.
```

In [90]:
```
clf = KNeighborsClassifier()
clf.fit(scaled_data_train, y_train)
y_hat_train = clf.predict(scaled_data_train)
y_hat_test = clf.predict(scaled_data_test)
```

In [91]:
```
print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.6467757459095284
Testing Precision:  0.3969816272965879
Testing Recall:  0.2682926829268293
Testing F1-Score:  0.3201905265943371
```

In [92]:
```
plot_confusion_matrix(clf, scaled_data_test, y_test,
                      cmap=plt.cm.Blues)
plt.grid(False)
plt.show()
```



In [93]:
```
The accuracy and precision went down
slightly in comparison to the Logistic Regression output.
A confusion matrix shows that it has only predicted '0', not
a great sign.
Since KNN has a default "neighbors" of 5, let's use GridSearchCV to
see if we can find a the best number of neighbors and run that
model one more time.

Source of following code: Eijaz Allibhai (https://towardsdatascience.com
```

In [106]:
```
clf2 = KNeighborsClassifier()
param_grid = {'n_neighbors': np.arange(1,25)}
clf_gscv = GridSearchCV(clf2, param_grid, cv=5)
clf_gscv.fit(scaled_data_train, y_train)
```

Out[106]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': array([ 1,  2,  3,  4,  5,  6,
7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24])})
```

In [95]:
```
clf_gscv.best_params_
```

Out[95]:
```
{'n_neighbors': 24}
```

In [96]:
```
# Let's rerun the KNN model to see exactly how this 24 is the best neigh
```

In [97]:
```
clf = KNeighborsClassifier(n_neighbors=24)
clf.fit(scaled_data_train, y_train)
y_hat_test = clf.predict(scaled_data_test)
```

In [98]:
```
print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.6837618589302901
Testing Precision:  0.4403183023872679
Testing Recall:  0.07361419068736141
Testing F1-Score:  0.12613981762917933
```

In [99]:
```
# Accuracy and precision are up but recall and F1 are not great.
# Let's move on to XGBoost
```

In [100]:
```
xgbc = XGBClassifier()
xgbc.fit(scaled_data_train, y_train)
y_hat_test = xgbc.predict(scaled_data_test)
```

In [101]:
```
print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.6902241165956277
Testing Precision:  0.5098039215686274
Testing Recall:  0.023059866962305987
Testing F1-Score:  0.044123886296139156
```

In [102]:
```
# Accuracy and Precision are up, but everything else is worse.
# Let's try tuning XGBoost using GridSearchCV
# to see if we get better results.
```

In [109]:
```
param_grid = {
    'learning rate': [0.1, 0.2, 0.3, 0.4, 0.5],
    'max_depth': [6],
    'min_child_weight': [1, 2, 3, 4, 5],
    'subsample': [0.5, 0.7, 0.9],
    'n_estimators': [100],
}
```

In [110]:
```
xgbc = XGBClassifier()
grid_xgbc = GridSearchCV(xgbc, param_grid, scoring='accuracy', cv=None,
grid_xgbc.fit(scaled_data_train, y_train)

best_parameters = grid_xgbc.best_params_
```

In [111]:
```
print(best_parameters)
```

```
{'learning rate': 0.1, 'max_depth': 6, 'min_child_weight': 2, 'n_estimat
rs': 100, 'subsample': 0.9}
```

In [112]:
```
xgbc = XGBClassifier(n_estimators=100, max_depth=6, learning_rate=0.1,
                     min_child_weight=2, subsample=0.9)
xgbc.fit(scaled_data_train, y_train)
y_hat_test = xgbc.predict(scaled_data_test)
```

In [113]:
```
print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.690774095971401
Testing Precision:  0.5081081081081081
Testing Recall:  0.08337028824833703
Testing F1-Score:  0.14323809523809525
```

In [114]:
```
# This is the highest our accuracy has been but barely. Was the 30
# minutes of loading this GridSearch worth it?
# Let's move to a decision tree and see if we can get better than
# 69% accuracy.
```

In [115]:
```
SEED=1
dtc = DecisionTreeClassifier(criterion='entropy', random_state=SEED)
dtc.fit(scaled_data_train, y_train)
```

Out[115]:
```
DecisionTreeClassifier(criterion='entropy', random_state=1)
```

In [116]:
```
y_hat_test = dtc.predict(scaled_data_test)

print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.6187267977450845
Testing Precision:  0.38748913987836664
Testing Recall:  0.39556541019955654
Testing F1-Score:  0.39148562650866797
```

In [117]:
```
SEED=1
dtc = DecisionTreeClassifier(criterion='gini', random_state=SEED)
dtc.fit(scaled_data_train, y_train)
```

Out[117]:
```
DecisionTreeClassifier(random_state=1)
```

In [118]:
```
y_hat_test = dtc.predict(scaled_data_test)

print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.6147394472707274
Testing Precision:  0.38580375782881005
Testing Recall:  0.4097560975609756
Testing F1-Score:  0.3974193548387097
```

In [119]:
```
# The difference between 'gini' and 'entropy' were basically non existen
# Let's try another GridSearch to see instead of manually changing param
# Hopefully we can find the best decision tree.
```

In [121]:
```
dtc_param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 2, 3, 4, 5],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 3, 4, 5]
}

dtc_grid = GridSearchCV(dtc, dtc_param_grid, cv=3, return_train_score=Tr

dtc_grid.fit(scaled_data_train, y_train)
```

Out[121]:
```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(random_state=1),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [None, 2, 3, 4, 5],
                         'min_samples_leaf': [1, 2, 3, 4, 5],
                         'min_samples_split': [2, 5, 10]},
             return_train_score=True)
```

In [122]:
```
dtc_grid.best_params_
```

Out[122]:
```
{'criterion': 'gini',
 'max_depth': 2,
 'min_samples_leaf': 1,
 'min_samples_split': 2}
```

In [123]:
```
dtc = DecisionTreeClassifier(criterion='gini', max_depth=2,
                             min_samples_leaf=1, min_samples_split=2,
                             random_state=SEED)
dtc.fit(scaled_data_train, y_train)
```

Out[123]:
```
DecisionTreeClassifier(max_depth=2, random_state=1)
```

In [124]:
```
y_hat_test = dtc.predict(scaled_data_test)

print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Testing Accuracy:  0.6899491269077409
Testing Precision:  0.0
Testing Recall:  0.0
Testing F1-Score:  0.0

/Users/Garseed/anaconda3/envs/learn-env/lib/python3.6/site-packages/skle
rn/metrics/_classification.py:1248: UndefinedMetricWarning: Precision is
ill-defined and being set to 0.0 due to no predicted samples. Use `zero_
ivision` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [125]:
```
# It seems as though we were unable to get enough data for testing
# metrics outside of Accuracy, probably deue to the low samples.
```

In [126]:
```
# After running 7 models, the highest accuracy achieved was from an
# XGBoost model with the best parameters found through GridSearchCV,
# and even at that it was only able to be 69% accurate.
```