Introduction

The Kepler mission was designed to locate Earth sized planets using an objects transit data as it orbits a star. The goal of this model is to utilize the Kepler telescope's data to help classify whether an object is a confirmed exoplanet, or a false positive. There are a number of objects which are classified as "candidates" and require additional research. This model can help point to which candidates can likely be confirmed exoplanets.

Imports

In [1]:
```
import numpy as np
import pandas as pd
from functions import *

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.pipeline import Pipeline

# Classification Models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoosti
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
import xgboost as xgb

from sklearn.metrics import plot_confusion_matrix, classification_report,accuracy_score

# Scalers
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import Normalizer
from sklearn.preprocessing import RobustScaler

# Categorical Create Dummies
from sklearn.preprocessing import OneHotEncoder
```

EDA

In [2]:
```
df = pd.read_csv(r'Data\KeplerData.csv',skiprows=76)
```

In [3]:
```
import random
random.seed(40521)
```

In [4]:
```
df.head()
```

Out[4]:

	kepid	kepoi_name	kepler_name	koi_disposition	koi_pdisposition	koi_score	koi_fpflag_nt	koi_fp
0	10797460	K00752.01	Kepler-227 b	CONFIRMED	CANDIDATE	1.000	0	

	kepid	kepoi_name	kepler_name	koi_disposition	koi_pdisposition	koi_score	koi_fpflag_nt	koi_fp
1	10797460	K00752.02	Kepler-227 c	CONFIRMED	CANDIDATE	0.969	0	
2	10811496	K00753.01	NaN	CANDIDATE	CANDIDATE	0.000	0	
3	10848459	K00754.01	NaN	FALSE POSITIVE	FALSE POSITIVE	0.000	0	
4	10854555	K00755.01	Kepler-664 b	CONFIRMED	CANDIDATE	1.000	0	

5 rows × 70 columns

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9564 entries, 0 to 9563
Data columns (total 70 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   kepid              9564 non-null   int64  
 1   kepoi_name         9564 non-null   object 
 2   kepler_name        2365 non-null   object 
 3   koi_disposition    9564 non-null   object 
 4   koi_pdisposition   9564 non-null   object 
 5   koi_score          8054 non-null   float64
 6   koi_fpflag_nt      9564 non-null   int64  
 7   koi_fpflag_ss      9564 non-null   int64  
 8   koi_fpflag_co      9564 non-null   int64  
 9   koi_fpflag_ec      9564 non-null   int64  
 10  koi_disp_prov      9564 non-null   object 
 11  koi_period         9564 non-null   float64
 12  koi_time0bk        9564 non-null   float64
 13  koi_time0          9564 non-null   float64
 14  koi_eccen          9201 non-null   float64
 15  koi_longp          0 non-null      float64
 16  koi_impact         9201 non-null   float64
 17  koi_duration       9564 non-null   float64
 18  koi_ingress        0 non-null      float64
 19  koi_depth          9201 non-null   float64
 20  koi_ror            9201 non-null   float64
 21  koi_srho           9243 non-null   float64
 22  koi_fittype        9564 non-null   object 
 23  koi_prad           9201 non-null   float64
 24  koi_sma            9201 non-null   float64
 25  koi_incl           9200 non-null   float64
 26  koi_teq            9201 non-null   float64
 27  koi_insol          9243 non-null   float64
 28  koi_dor            9201 non-null   float64
 29  koi_limbdark_mod   9201 non-null   object 
 30  koi_max_sngle_ev   8422 non-null   float64
 31  koi_max_mult_ev    8422 non-null   float64
 32  koi_model_snr      9201 non-null   float64
 33  koi_count          9564 non-null   int64  
 34  koi_num_transits   8422 non-null   float64
 35  koi_tce_plnt_num   9218 non-null   float64
 36  koi_tce_delivname  9218 non-null   object 
 37  koi_quarters       8422 non-null   float64
 38  koi_bin_oedp_sig   8054 non-null   float64
 39  koi_trans_mod      9201 non-null   object 
 40  koi_steff          9201 non-null   float64
 41  koi_slogg          9201 non-null   float64
 42  koi_smet           9178 non-null   float64
```

```
 43  koi_srad           9201 non-null   float64
 44  koi_smass          9201 non-null   float64
 45  koi_sage           0 non-null      float64
 46  koi_sparprov       9201 non-null   object
 47  ra                 9564 non-null   float64
 48  dec                9564 non-null   float64
 49  koi_kepmag         9563 non-null   float64
 50  koi_gmag           9523 non-null   float64
 51  koi_rmag           9555 non-null   float64
 52  koi_imag           9410 non-null   float64
 53  koi_zmag           8951 non-null   float64
 54  koi_jmag           9539 non-null   float64
 55  koi_hmag           9539 non-null   float64
 56  koi_kmag           9539 non-null   float64
 57  koi_fwm_stat_sig   8488 non-null   float64
 58  koi_fwm_sra        9058 non-null   float64
 59  koi_fwm_sdec       9058 non-null   float64
 60  koi_fwm_srao       9109 non-null   float64
 61  koi_fwm_sdeco      9109 non-null   float64
 62  koi_fwm_prao       8734 non-null   float64
 63  koi_fwm_pdeco      8747 non-null   float64
 64  koi_dicco_mra      8965 non-null   float64
 65  koi_dicco_mdec     8965 non-null   float64
 66  koi_dicco_msky     8965 non-null   float64
 67  koi_dikco_mra      8994 non-null   float64
 68  koi_dikco_mdec     8994 non-null   float64
 69  koi_dikco_msky     8994 non-null   float64
dtypes: float64(54), int64(6), object(10)
memory usage: 5.1+ MB
```

In [6]:
```
df.describe()
```

Out[6]:

	kepid	koi_score	koi_fpflag_nt	koi_fpflag_ss	koi_fpflag_co	koi_fpflag_ec	koi_perio
count	9.564000e+03	8054.000000	9564.000000	9564.000000	9564.000000	9564.000000	9564.00000
mean	7.690628e+06	0.480829	0.208595	0.232748	0.197512	0.120033	75.67135
std	2.653459e+06	0.476928	4.767290	0.422605	0.398142	0.325018	1334.74404
min	7.574500e+05	0.000000	0.000000	0.000000	0.000000	0.000000	0.24184
25%	5.556034e+06	0.000000	0.000000	0.000000	0.000000	0.000000	2.73368
50%	7.906892e+06	0.334000	0.000000	0.000000	0.000000	0.000000	9.75283
75%	9.873066e+06	0.998000	0.000000	0.000000	0.000000	0.000000	40.71517
max	1.293514e+07	1.000000	465.000000	1.000000	1.000000	1.000000	129995.77840

8 rows × 60 columns

In [7]:
```
df.koi_pdisposition.value_counts()
```

Out[7]:
```
FALSE POSITIVE    4847
CANDIDATE         4717
Name: koi_pdisposition, dtype: int64
```

In [8]:
```
(df.koi_disposition == df.koi_pdisposition).value_counts()
```

Out[8]:
```
True     7200
False    2364
```

```
dtype: int64
```

In [9]:
```
df_FP = df.loc[df.koi_disposition == "FALSE POSITIVE"]
```

In [10]:
```
(df_FP.koi_disposition == df_FP.koi_pdisposition).value_counts()
```

Out[10]:
```
True     4839
False       1
dtype: int64
```

In [11]:
```
for col in df.columns:
    print(df[col].isna().value_counts())
```

```
False    9564
Name: kepid, dtype: int64
False    9564
Name: kepoi_name, dtype: int64
True     7199
False    2365
Name: kepler_name, dtype: int64
False    9564
Name: koi_disposition, dtype: int64
False    9564
Name: koi_pdisposition, dtype: int64
False    8054
True     1510
Name: koi_score, dtype: int64
False    9564
Name: koi_fpflag_nt, dtype: int64
False    9564
Name: koi_fpflag_ss, dtype: int64
False    9564
Name: koi_fpflag_co, dtype: int64
False    9564
Name: koi_fpflag_ec, dtype: int64
False    9564
Name: koi_disp_prov, dtype: int64
False    9564
Name: koi_period, dtype: int64
False    9564
Name: koi_time0bk, dtype: int64
False    9564
Name: koi_time0, dtype: int64
False    9201
True      363
Name: koi_eccen, dtype: int64
True    9564
Name: koi_longp, dtype: int64
False    9201
True      363
Name: koi_impact, dtype: int64
False    9564
Name: koi_duration, dtype: int64
True    9564
Name: koi_ingress, dtype: int64
False    9201
True      363
Name: koi_depth, dtype: int64
False    9201
True      363
Name: koi_ror, dtype: int64
False    9243
True      321
Name: koi_srho, dtype: int64
```

```
False    9564
Name: koi_fittype, dtype: int64
False    9201
True      363
Name: koi_prad, dtype: int64
False    9201
True      363
Name: koi_sma, dtype: int64
False    9200
True      364
Name: koi_incl, dtype: int64
False    9201
True      363
Name: koi_teq, dtype: int64
False    9243
True      321
Name: koi_insol, dtype: int64
False    9201
True      363
Name: koi_dor, dtype: int64
False    9201
True      363
Name: koi_limbdark_mod, dtype: int64
False    8422
True     1142
Name: koi_max_sngle_ev, dtype: int64
False    8422
True     1142
Name: koi_max_mult_ev, dtype: int64
False    9201
True      363
Name: koi_model_snr, dtype: int64
False    9564
Name: koi_count, dtype: int64
False    8422
True     1142
Name: koi_num_transits, dtype: int64
False    9218
True      346
Name: koi_tce_plnt_num, dtype: int64
False    9218
True      346
Name: koi_tce_delivname, dtype: int64
False    8422
True     1142
Name: koi_quarters, dtype: int64
False    8054
True     1510
Name: koi_bin_oedp_sig, dtype: int64
False    9201
True      363
Name: koi_trans_mod, dtype: int64
False    9201
True      363
Name: koi_steff, dtype: int64
False    9201
True      363
Name: koi_slogg, dtype: int64
False    9178
True      386
Name: koi_smet, dtype: int64
False    9201
True      363
Name: koi_srad, dtype: int64
False    9201
```

```
True      363
Name: koi_smass, dtype: int64
True    9564
Name: koi_sage, dtype: int64
False    9201
True      363
Name: koi_sparprov, dtype: int64
False    9564
Name: ra, dtype: int64
False    9564
Name: dec, dtype: int64
False    9563
True        1
Name: koi_kepmag, dtype: int64
False    9523
True       41
Name: koi_gmag, dtype: int64
False    9555
True        9
Name: koi_rmag, dtype: int64
False    9410
True      154
Name: koi_imag, dtype: int64
False    8951
True      613
Name: koi_zmag, dtype: int64
False    9539
True       25
Name: koi_jmag, dtype: int64
False    9539
True       25
Name: koi_hmag, dtype: int64
False    9539
True       25
Name: koi_kmag, dtype: int64
False    8488
True     1076
Name: koi_fwm_stat_sig, dtype: int64
False    9058
True      506
Name: koi_fwm_sra, dtype: int64
False    9058
True      506
Name: koi_fwm_sdec, dtype: int64
False    9109
True      455
Name: koi_fwm_srao, dtype: int64
False    9109
True      455
Name: koi_fwm_sdeco, dtype: int64
False    8734
True      830
Name: koi_fwm_prao, dtype: int64
False    8747
True      817
Name: koi_fwm_pdeco, dtype: int64
False    8965
True      599
Name: koi_dicco_mra, dtype: int64
False    8965
True      599
Name: koi_dicco_mdec, dtype: int64
False    8965
True      599
Name: koi_dicco_msky, dtype: int64
```

```
False    8994
True      570
Name: koi_dikco_mra, dtype: int64
False    8994
True      570
Name: koi_dikco_mdec, dtype: int64
False    8994
True      570
Name: koi_dikco_msky, dtype: int64
```

Drop obvious columns (ID etc) and rows of missing data

Initial Column Drop

In [12]:
```
len(df.columns)
```

Out[12]: 70

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

Out[13]:

	kepid	kepoi_name	kepler_name	koi_disposition	koi_pdisposition	koi_score	koi_fpflag_nt	koi_fp
0	10797460	K00752.01	Kepler-227 b	CONFIRMED	CANDIDATE	1.000	0	
1	10797460	K00752.02	Kepler-227 c	CONFIRMED	CANDIDATE	0.969	0	
2	10811496	K00753.01	NaN	CANDIDATE	CANDIDATE	0.000	0	
3	10848459	K00754.01	NaN	FALSE POSITIVE	FALSE POSITIVE	0.000	0	
4	10854555	K00755.01	Kepler-664 b	CONFIRMED	CANDIDATE	1.000	0	

5 rows × 70 columns

In [14]:
```
drop_initial = ['kepid','kepler_name','koi_ingress','koi_longp','koi_sage'] #'kepoi_nam
```

In [15]:
```
df_initial_drop = df.drop(drop_initial,axis=1)
```

In [16]:
```
df_initial_drop.head()
```

Out[16]:

	kepoi_name	koi_disposition	koi_pdisposition	koi_score	koi_fpflag_nt	koi_fpflag_ss	koi_fpflag_co	k
0	K00752.01	CONFIRMED	CANDIDATE	1.000	0	0	0	
1	K00752.02	CONFIRMED	CANDIDATE	0.969	0	0	0	
2	K00753.01	CANDIDATE	CANDIDATE	0.000	0	0	0	
3	K00754.01	FALSE POSITIVE	FALSE POSITIVE	0.000	0	1	0	
4	K00755.01	CONFIRMED	CANDIDATE	1.000	0	0	0	

5 rows × 65 columns

Drop rows of missing data

In [17]:
```
for col in df_initial_drop.columns:
    print(df_initial_drop[col].isna().value_counts())
```

```
False    9564
Name: kepoi_name, dtype: int64
False    9564
Name: koi_disposition, dtype: int64
False    9564
Name: koi_pdisposition, dtype: int64
False    8054
True     1510
Name: koi_score, dtype: int64
False    9564
Name: koi_fpflag_nt, dtype: int64
False    9564
Name: koi_fpflag_ss, dtype: int64
False    9564
Name: koi_fpflag_co, dtype: int64
False    9564
Name: koi_fpflag_ec, dtype: int64
False    9564
Name: koi_disp_prov, dtype: int64
False    9564
Name: koi_period, dtype: int64
False    9564
Name: koi_time0bk, dtype: int64
False    9564
Name: koi_time0, dtype: int64
False    9201
True      363
Name: koi_eccen, dtype: int64
False    9201
True      363
Name: koi_impact, dtype: int64
False    9564
Name: koi_duration, dtype: int64
False    9201
True      363
Name: koi_depth, dtype: int64
False    9201
True      363
Name: koi_ror, dtype: int64
False    9243
True      321
Name: koi_srho, dtype: int64
False    9564
Name: koi_fittype, dtype: int64
False    9201
True      363
Name: koi_prad, dtype: int64
False    9201
True      363
Name: koi_sma, dtype: int64
False    9200
True      364
Name: koi_incl, dtype: int64
False    9201
True      363
Name: koi_teq, dtype: int64
False    9243
True      321
Name: koi_insol, dtype: int64
False    9201
True      363
```

```
Name: koi_dor, dtype: int64
False    9201
True      363
Name: koi_limbdark_mod, dtype: int64
False    8422
True     1142
Name: koi_max_sngle_ev, dtype: int64
False    8422
True     1142
Name: koi_max_mult_ev, dtype: int64
False    9201
True      363
Name: koi_model_snr, dtype: int64
False    9564
Name: koi_count, dtype: int64
False    8422
True     1142
Name: koi_num_transits, dtype: int64
False    9218
True      346
Name: koi_tce_plnt_num, dtype: int64
False    9218
True      346
Name: koi_tce_delivname, dtype: int64
False    8422
True     1142
Name: koi_quarters, dtype: int64
False    8054
True     1510
Name: koi_bin_oedp_sig, dtype: int64
False    9201
True      363
Name: koi_trans_mod, dtype: int64
False    9201
True      363
Name: koi_steff, dtype: int64
False    9201
True      363
Name: koi_slogg, dtype: int64
False    9178
True      386
Name: koi_smet, dtype: int64
False    9201
True      363
Name: koi_srad, dtype: int64
False    9201
True      363
Name: koi_smass, dtype: int64
False    9201
True      363
Name: koi_sparprov, dtype: int64
False    9564
Name: ra, dtype: int64
False    9564
Name: dec, dtype: int64
False    9563
True        1
Name: koi_kepmag, dtype: int64
False    9523
True       41
Name: koi_gmag, dtype: int64
False    9555
True        9
Name: koi_rmag, dtype: int64
False    9410
```

```
True      154
Name: koi_imag, dtype: int64
False    8951
True      613
Name: koi_zmag, dtype: int64
False    9539
True       25
Name: koi_jmag, dtype: int64
False    9539
True       25
Name: koi_hmag, dtype: int64
False    9539
True       25
Name: koi_kmag, dtype: int64
False    8488
True     1076
Name: koi_fwm_stat_sig, dtype: int64
False    9058
True      506
Name: koi_fwm_sra, dtype: int64
False    9058
True      506
Name: koi_fwm_sdec, dtype: int64
False    9109
True      455
Name: koi_fwm_srao, dtype: int64
False    9109
True      455
Name: koi_fwm_sdeco, dtype: int64
False    8734
True      830
Name: koi_fwm_prao, dtype: int64
False    8747
True      817
Name: koi_fwm_pdeco, dtype: int64
False    8965
True      599
Name: koi_dicco_mra, dtype: int64
False    8965
True      599
Name: koi_dicco_mdec, dtype: int64
False    8965
True      599
Name: koi_dicco_msky, dtype: int64
False    8994
True      570
Name: koi_dikco_mra, dtype: int64
False    8994
True      570
Name: koi_dikco_mdec, dtype: int64
False    8994
True      570
Name: koi_dikco_msky, dtype: int64
```

In [18]:

```
df_initial_drop = df_initial_drop.dropna(subset=
                                         ['koi_score','koi_quarters','koi_fwm_stat_sig'
                                          'koi_dicco_mra','koi_model_snr','koi_zmag',
                                          'koi_fwm_sra','koi_smet','koi_gmag','koi_rmag
                                          'koi_imag'], how='any')
```

In [19]:

```
for col in df_initial_drop.columns:
    print(df_initial_drop[col].isna().value_counts())
```

```
False    6682
```

```
Name: kepoi_name, dtype: int64
False    6682
Name: koi_disposition, dtype: int64
False    6682
Name: koi_pdisposition, dtype: int64
False    6682
Name: koi_score, dtype: int64
False    6682
Name: koi_fpflag_nt, dtype: int64
False    6682
Name: koi_fpflag_ss, dtype: int64
False    6682
Name: koi_fpflag_co, dtype: int64
False    6682
Name: koi_fpflag_ec, dtype: int64
False    6682
Name: koi_disp_prov, dtype: int64
False    6682
Name: koi_period, dtype: int64
False    6682
Name: koi_time0bk, dtype: int64
False    6682
Name: koi_time0, dtype: int64
False    6682
Name: koi_eccen, dtype: int64
False    6682
Name: koi_impact, dtype: int64
False    6682
Name: koi_duration, dtype: int64
False    6682
Name: koi_depth, dtype: int64
False    6682
Name: koi_ror, dtype: int64
False    6682
Name: koi_srho, dtype: int64
False    6682
Name: koi_fittype, dtype: int64
False    6682
Name: koi_prad, dtype: int64
False    6682
Name: koi_sma, dtype: int64
False    6682
Name: koi_incl, dtype: int64
False    6682
Name: koi_teq, dtype: int64
False    6682
Name: koi_insol, dtype: int64
False    6682
Name: koi_dor, dtype: int64
False    6682
Name: koi_limbdark_mod, dtype: int64
False    6682
Name: koi_max_sngle_ev, dtype: int64
False    6682
Name: koi_max_mult_ev, dtype: int64
False    6682
Name: koi_model_snr, dtype: int64
False    6682
Name: koi_count, dtype: int64
False    6682
Name: koi_num_transits, dtype: int64
False    6682
Name: koi_tce_plnt_num, dtype: int64
False    6682
Name: koi_tce_delivname, dtype: int64
```

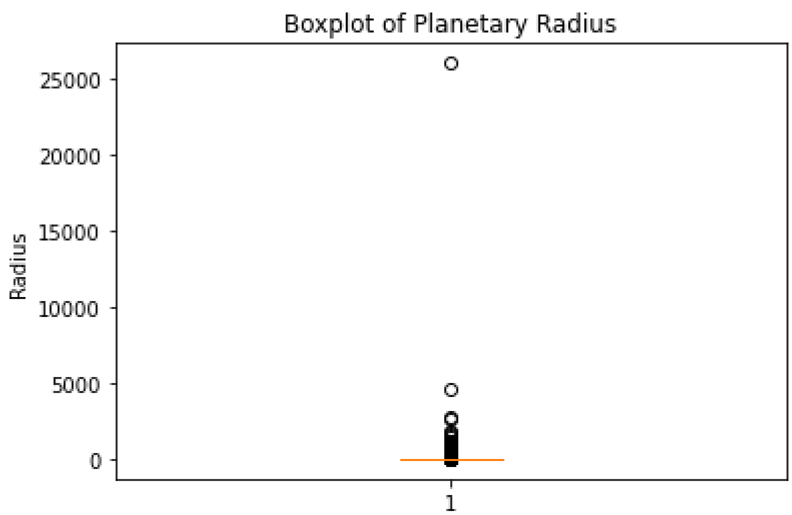
```
False    6682
Name: koi_quarters, dtype: int64
False    6682
Name: koi_bin_oedp_sig, dtype: int64
False    6682
Name: koi_trans_mod, dtype: int64
False    6682
Name: koi_steff, dtype: int64
False    6682
Name: koi_slogg, dtype: int64
False    6682
Name: koi_smet, dtype: int64
False    6682
Name: koi_srad, dtype: int64
False    6682
Name: koi_smass, dtype: int64
False    6682
Name: koi_sparprov, dtype: int64
False    6682
Name: ra, dtype: int64
False    6682
Name: dec, dtype: int64
False    6682
Name: koi_kepmag, dtype: int64
False    6682
Name: koi_gmag, dtype: int64
False    6682
Name: koi_rmag, dtype: int64
False    6682
Name: koi_imag, dtype: int64
False    6682
Name: koi_zmag, dtype: int64
False    6682
Name: koi_jmag, dtype: int64
False    6682
Name: koi_hmag, dtype: int64
False    6682
Name: koi_kmag, dtype: int64
False    6682
Name: koi_fwm_stat_sig, dtype: int64
False    6682
Name: koi_fwm_sra, dtype: int64
False    6682
Name: koi_fwm_sdec, dtype: int64
False    6682
Name: koi_fwm_srao, dtype: int64
False    6682
Name: koi_fwm_sdeco, dtype: int64
False    6682
Name: koi_fwm_prao, dtype: int64
False    6682
Name: koi_fwm_pdeco, dtype: int64
False    6682
Name: koi_dicco_mra, dtype: int64
False    6682
Name: koi_dicco_mdec, dtype: int64
False    6682
Name: koi_dicco_msky, dtype: int64
False    6682
Name: koi_dikco_mra, dtype: int64
False    6682
Name: koi_dikco_mdec, dtype: int64
False    6682
Name: koi_dikco_msky, dtype: int64
```

Plots of Some Best Features After Modeling

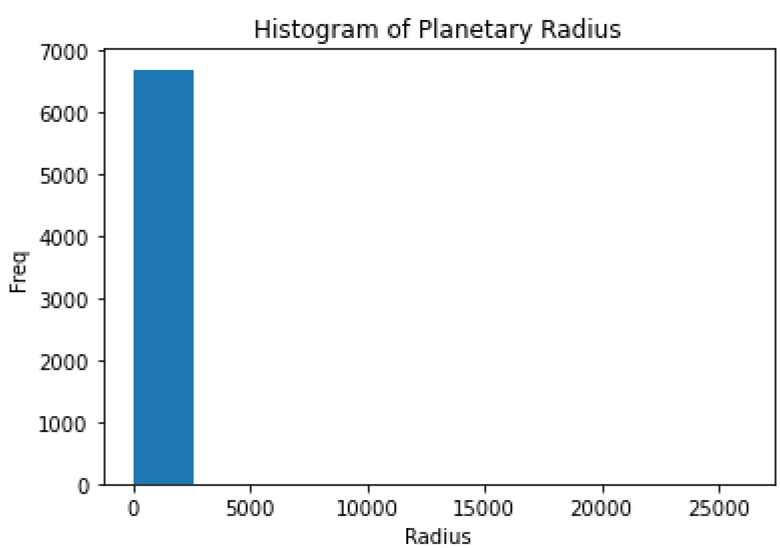
In [20]:
```
len(df_initial_drop.columns)
```

Out[20]: 65

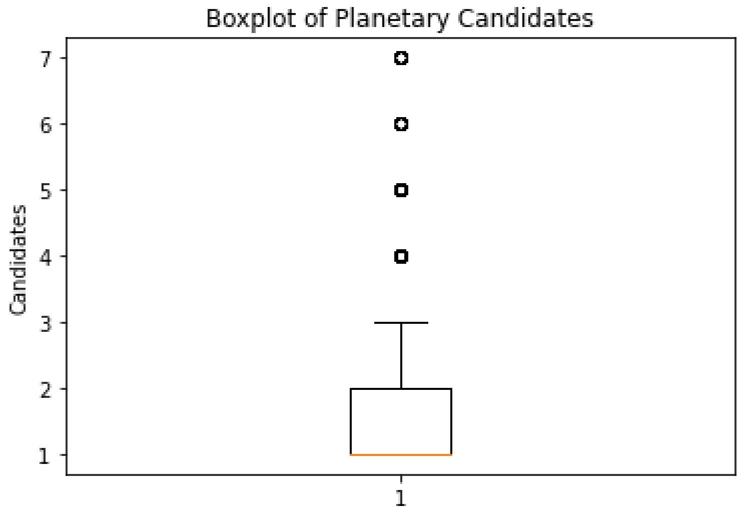
In [21]:
```
fig1,ax = plt.subplots()
plt.boxplot(df_initial_drop.koi_prad);
plt.title("Boxplot of Planetary Radius")
plt.ylabel("Radius");
```



In [22]:
```
plt.hist(df_initial_drop.koi_prad);
plt.title("Histogram of Planetary Radius")
plt.xlabel("Radius")
plt.ylabel("Freq");
```

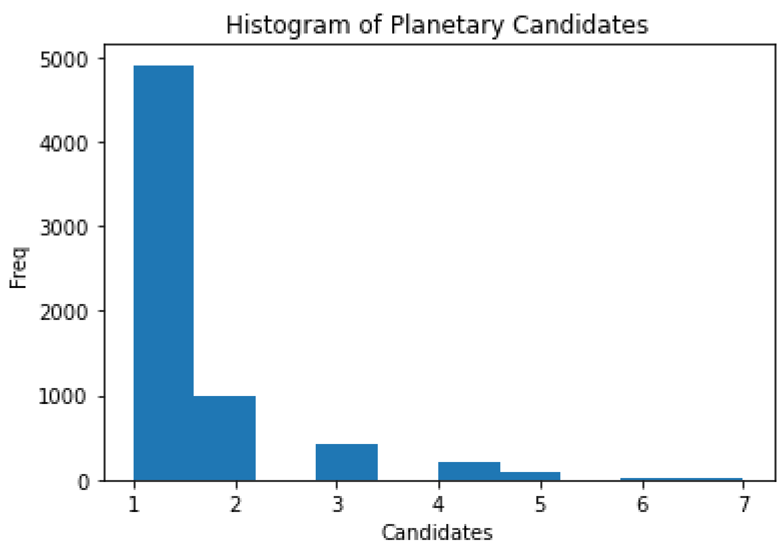


In [23]:
```
plt.boxplot(df_initial_drop.koi_count)
plt.title("Boxplot of Planetary Candidates")
plt.ylabel("Candidates");
```



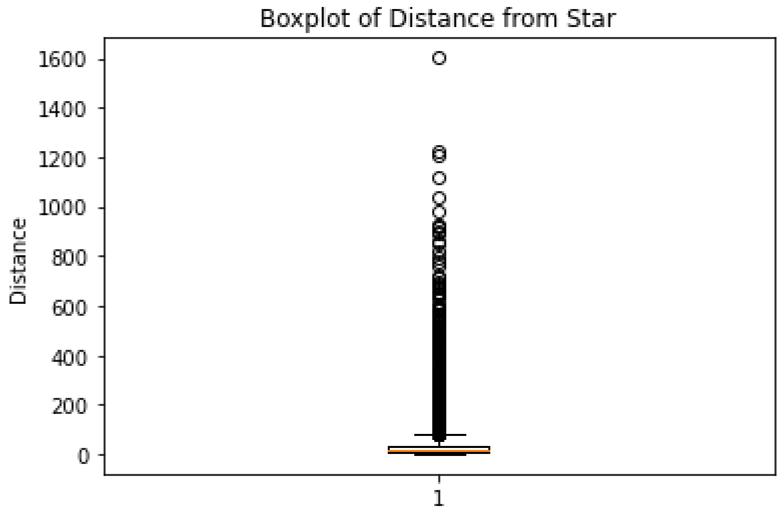
In [24]:

```
plt.hist(df_initial_drop.koi_count)
plt.title("Histogram of Planetary Candidates")
plt.xlabel("Candidates")
plt.ylabel("Freq");
```

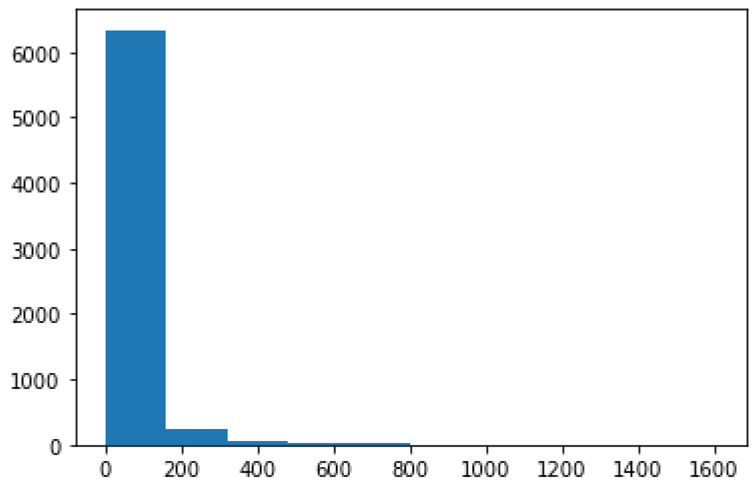


In [151…

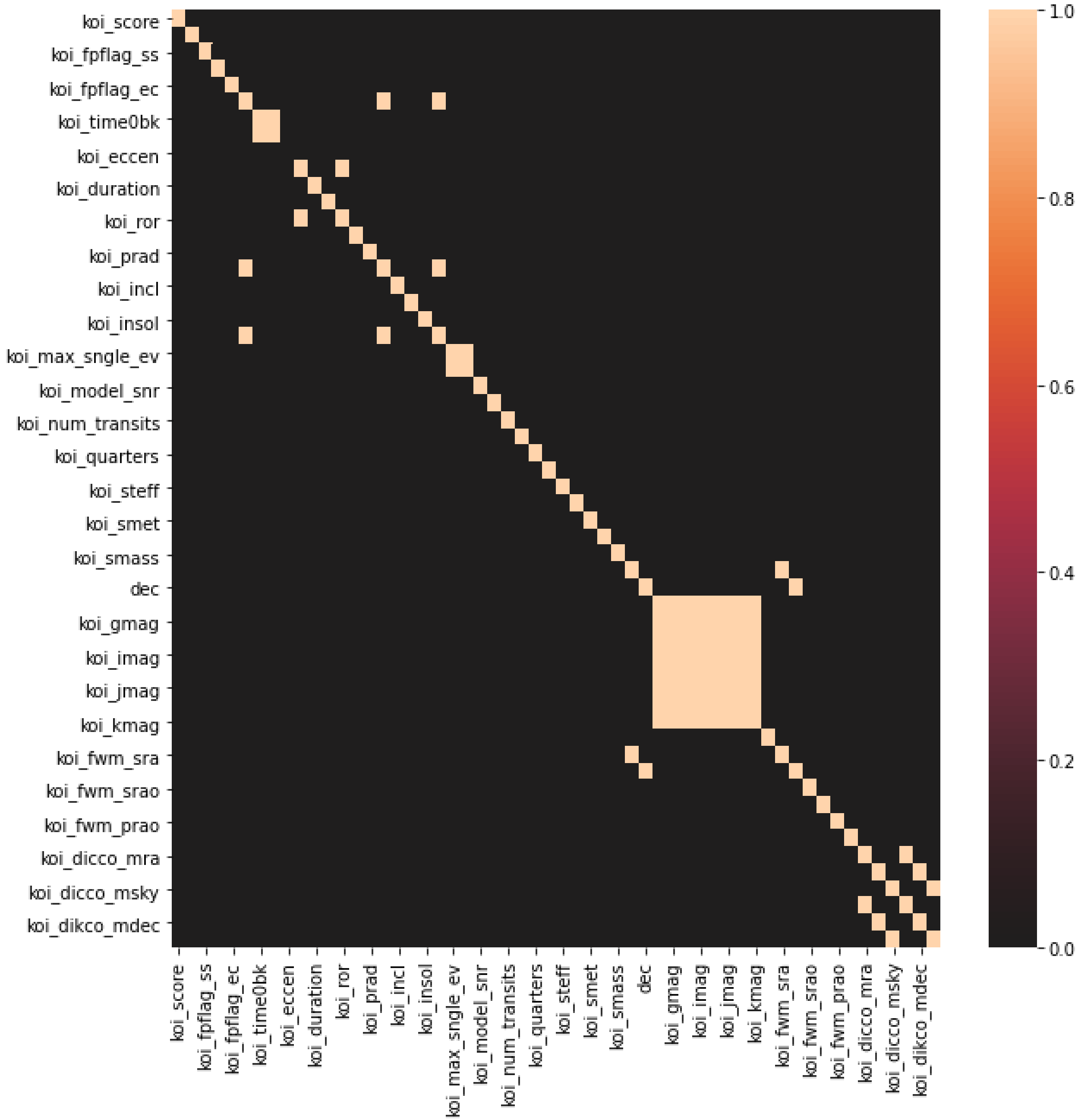
```
plt.boxplot(df_initial_drop.koi_dor)
plt.title("Boxplot of Distance from Star")
plt.ylabel('Distance');
```



In [26]:
```
plt.hist(df_initial_drop.koi_dor);
```

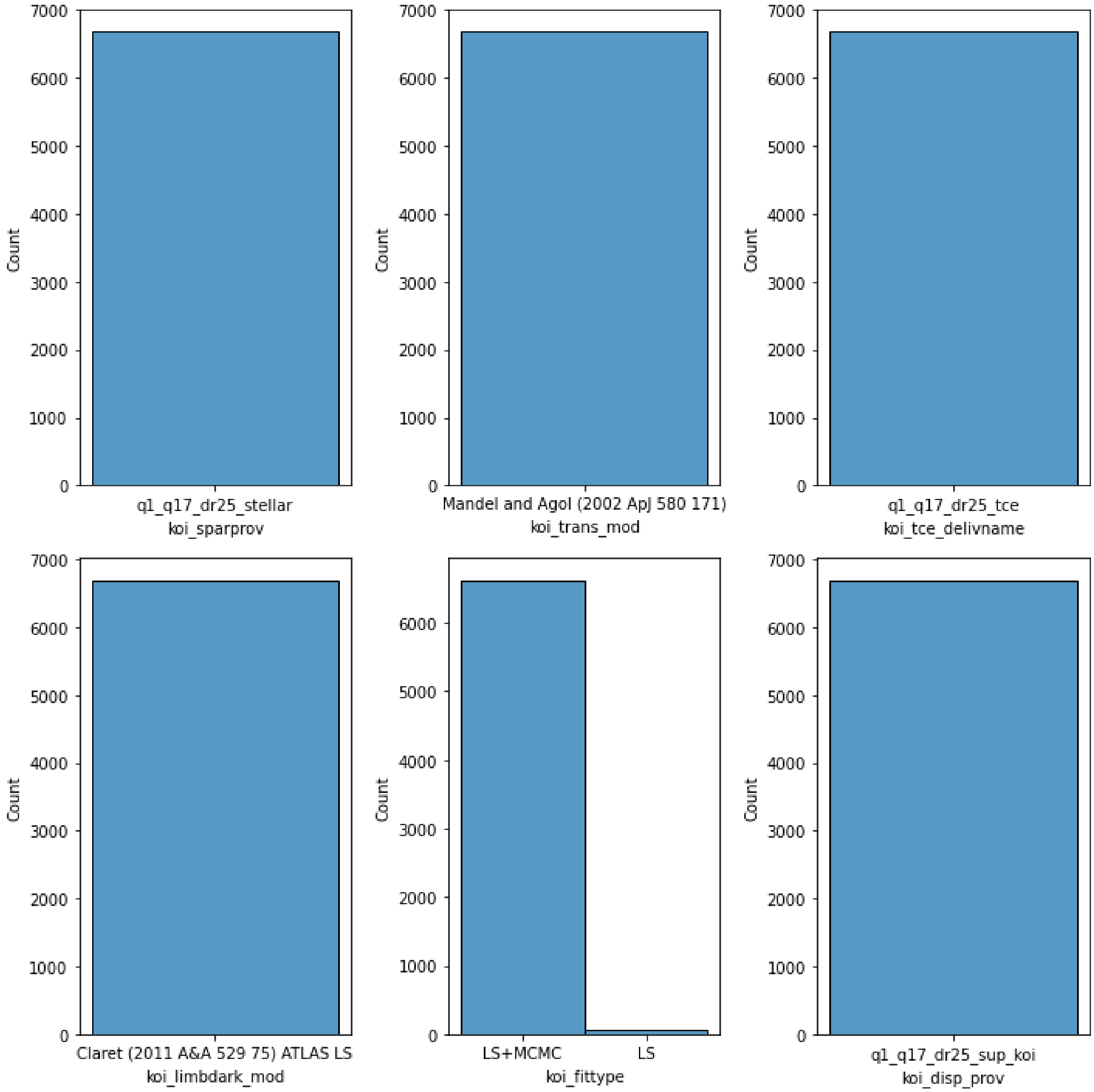


In [27]:
```
fig,hs = plt.subplots(figsize=(10,10))
sns.heatmap(df_initial_drop.corr()>.75, center=0);
```



In [28]:

```
add_drops = ['koi_sparprov','koi_trans_mod','koi_tce_delivname','koi_limbdark_mod','koi
dropped_df = df_initial_drop.loc[:,add_drops]
fig, axes = plt.subplots(figsize=(10,10),nrows=2,ncols=3)
for i in range(len(add_drops)):
    row = i%3
    col = i//3
    axis = axes[col,row]
    name = add_drops[i]
    sns.histplot(dropped_df,x=name,ax=axis)
    plt.tight_layout()
```



In [29]:

```
add_drops = ['koi_sparprov','koi_trans_mod','koi_tce_delivname','koi_limbdark_mod','koi
df_initial_drop = df_initial_drop.drop(add_drops,axis=1)
```

In [30]:

```
df_initial_drop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6682 entries, 0 to 9563
Data columns (total 59 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   kepoi_name        6682 non-null   object
 1   koi_disposition   6682 non-null   object
 2   koi_pdisposition  6682 non-null   object
 3   koi_score         6682 non-null   float64
 4   koi_fpflag_nt     6682 non-null   int64
 5   koi_fpflag_ss     6682 non-null   int64
 6   koi_fpflag_co     6682 non-null   int64
 7   koi_fpflag_ec     6682 non-null   int64
 8   koi_period        6682 non-null   float64
 9   koi_time0bk       6682 non-null   float64
 10  koi_time0         6682 non-null   float64
```

```
 11  koi_eccen         6682 non-null   float64
 12  koi_impact        6682 non-null   float64
 13  koi_duration      6682 non-null   float64
 14  koi_depth         6682 non-null   float64
 15  koi_ror           6682 non-null   float64
 16  koi_srho          6682 non-null   float64
 17  koi_prad          6682 non-null   float64
 18  koi_sma           6682 non-null   float64
 19  koi_incl          6682 non-null   float64
 20  koi_teq           6682 non-null   float64
 21  koi_insol         6682 non-null   float64
 22  koi_dor           6682 non-null   float64
 23  koi_max_sngle_ev  6682 non-null   float64
 24  koi_max_mult_ev   6682 non-null   float64
 25  koi_model_snr     6682 non-null   float64
 26  koi_count         6682 non-null   int64
 27  koi_num_transits  6682 non-null   float64
 28  koi_tce_plnt_num  6682 non-null   float64
 29  koi_quarters      6682 non-null   float64
 30  koi_bin_oedp_sig  6682 non-null   float64
 31  koi_steff         6682 non-null   float64
 32  koi_slogg         6682 non-null   float64
 33  koi_smet          6682 non-null   float64
 34  koi_srad          6682 non-null   float64
 35  koi_smass         6682 non-null   float64
 36  ra                6682 non-null   float64
 37  dec               6682 non-null   float64
 38  koi_kepmag        6682 non-null   float64
 39  koi_gmag          6682 non-null   float64
 40  koi_rmag          6682 non-null   float64
 41  koi_imag          6682 non-null   float64
 42  koi_zmag          6682 non-null   float64
 43  koi_jmag          6682 non-null   float64
 44  koi_hmag          6682 non-null   float64
 45  koi_kmag          6682 non-null   float64
 46  koi_fwm_stat_sig  6682 non-null   float64
 47  koi_fwm_sra       6682 non-null   float64
 48  koi_fwm_sdec      6682 non-null   float64
 49  koi_fwm_srao      6682 non-null   float64
 50  koi_fwm_sdeco     6682 non-null   float64
 51  koi_fwm_prao      6682 non-null   float64
 52  koi_fwm_pdeco     6682 non-null   float64
 53  koi_dicco_mra     6682 non-null   float64
 54  koi_dicco_mdec    6682 non-null   float64
 55  koi_dicco_msky    6682 non-null   float64
 56  koi_dikco_mra     6682 non-null   float64
 57  koi_dikco_mdec    6682 non-null   float64
 58  koi_dikco_msky    6682 non-null   float64
dtypes: float64(51), int64(5), object(3)
memory usage: 3.1+ MB
```

In [31]:

```
df_initial_drop.koi_disposition.value_counts()
```

Out[31]:

```
FALSE POSITIVE    2938
CONFIRMED         2155
CANDIDATE         1589
Name: koi_disposition, dtype: int64
```

EDA Results

- Using 55 initial features for modeling
- Several features contain outliers, plan will be to use a robust scaler to scale the outliers

- A few features are also multicollinear, removing from model
- Will remove candidates to predict at the end of the model
- Target Variable: koi_disposition
- Classes in target variable are close in weight, not planning on any balancing

Build initial model with pipeline and log regression

Removing Candidates from Data

- Will be using final model to predict if Confirmed or False Positive at end

In [32]:
```
candidates_df = df_initial_drop.loc[df_initial_drop['koi_disposition'] == 'CANDIDATE']
df_processed = df_initial_drop.loc[df_initial_drop['koi_disposition'] != 'CANDIDATE']
```

In [33]:
```
len(candidates_df)
```

Out[33]:
```
1589
```

In [34]:
```
len(df_processed)
```

Out[34]:
```
5093
```

In [35]:
```
df_processed.koi_disposition.value_counts()
```

Out[35]:
```
FALSE POSITIVE    2938
CONFIRMED         2155
Name: koi_disposition, dtype: int64
```

Train Test Data

In [36]:
```
X = df_processed.drop(['koi_disposition','koi_pdisposition','kepoi_name'],axis=1)
y = df_processed['koi_disposition']
```

In [37]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

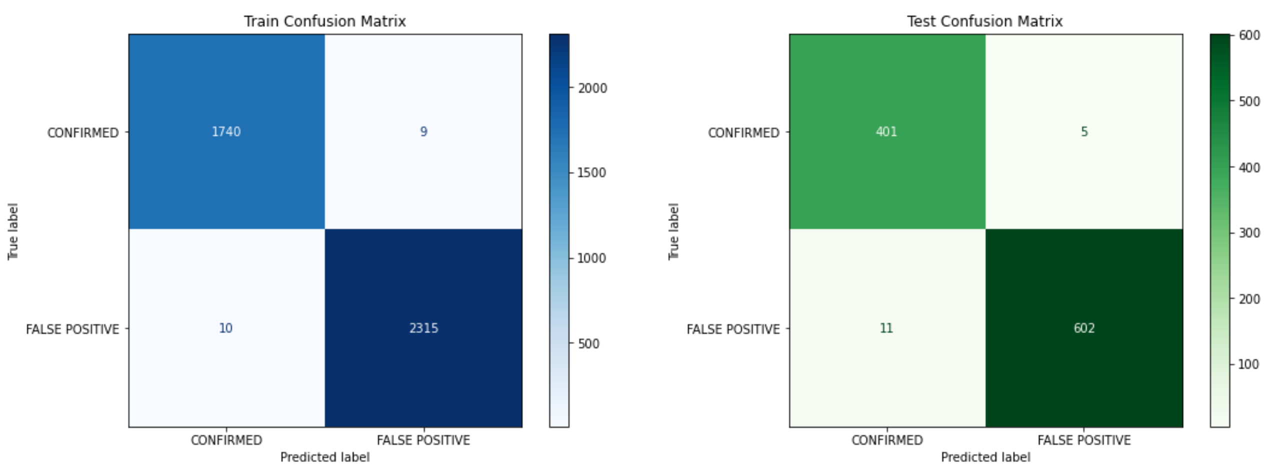
Initial Logistic Regression Model

In [38]:
```
initial_pipeline = Pipeline([('ss', StandardScaler()),
                             ('log',LogisticRegression(random_state=40521))])
```

In [39]:
```
initial_model = run_class_model(initial_pipeline, X_train, y_train, X_test, y_test)
```

```
********************************************************

     Classification Report: Train

                precision    recall  f1-score   support

     CONFIRMED       0.99      0.99      0.99      1749
FALSE POSITIVE       1.00      1.00      1.00      2325
```

```
    accuracy                           1.00      4074
   macro avg       1.00      1.00      1.00      4074
weighted avg       1.00      1.00      1.00      4074

*******************************************************

     Classification Report: Test

                precision    recall  f1-score   support

     CONFIRMED       0.97      0.99      0.98       406
FALSE POSITIVE       0.99      0.98      0.99       613

      accuracy                           0.98      1019
     macro avg       0.98      0.98      0.98      1019
  weighted avg       0.98      0.98      0.98      1019

*******************************************************
```



Initial Findings/Results

- Performs well for an initial model, primarily looking for accuracy
- Model is able to predict too well. After further investigation, there are columns included in the model which are already used to calculate the disposition (target variable) and should be removed

In [40]:
```
df_processed.head()
```

Out[40]:

	kepoi_name	koi_disposition	koi_pdisposition	koi_score	koi_fpflag_nt	koi_fpflag_ss	koi_fpflag_co	k
0	K00752.01	CONFIRMED	CANDIDATE	1.000	0	0	0	
1	K00752.02	CONFIRMED	CANDIDATE	0.969	0	0	0	
3	K00754.01	FALSE POSITIVE	FALSE POSITIVE	0.000	0	1	0	
4	K00755.01	CONFIRMED	CANDIDATE	1.000	0	0	0	
8	K00114.01	FALSE POSITIVE	FALSE POSITIVE	0.000	0	1	1	

5 rows × 59 columns

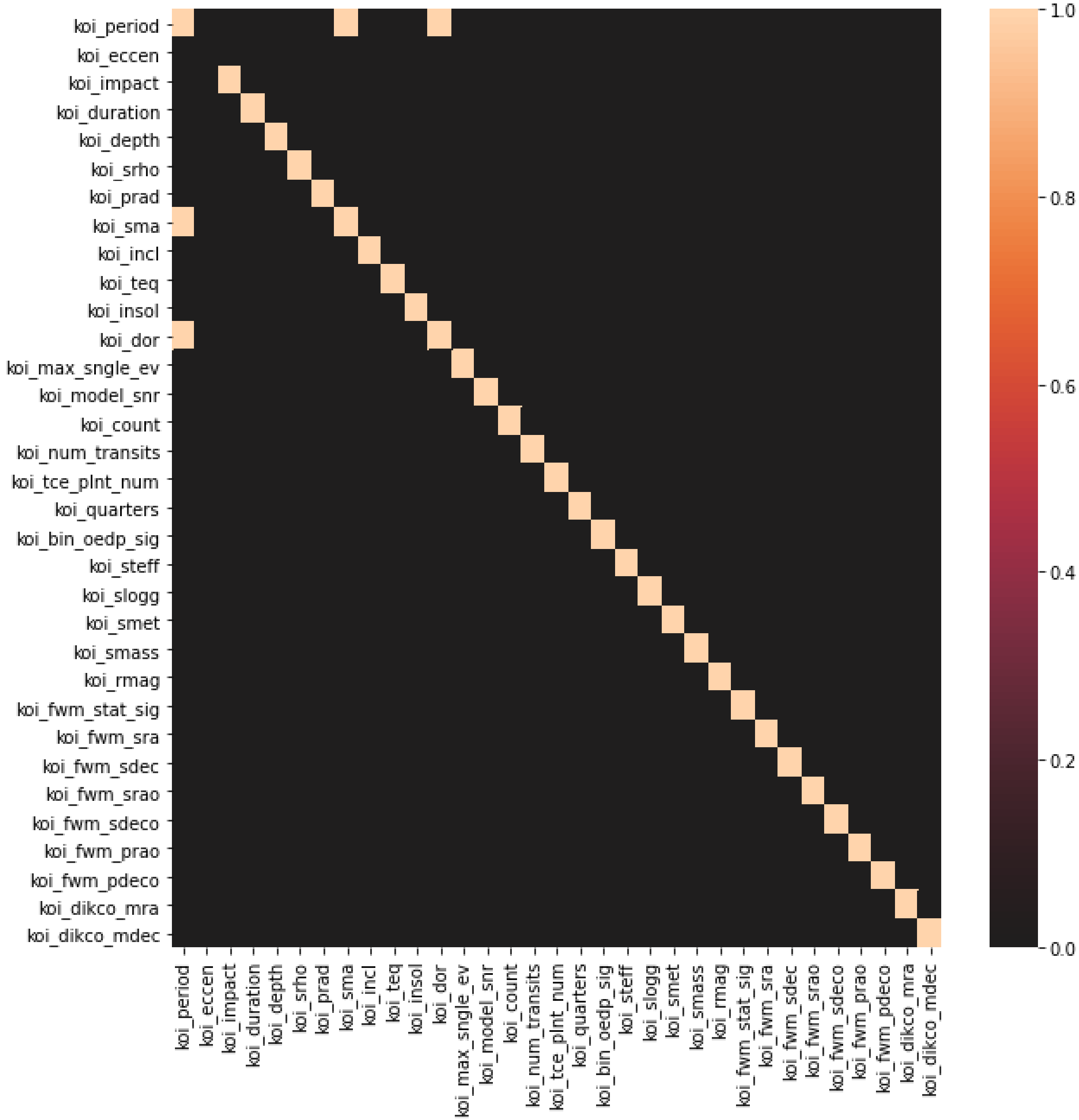
Confounding Features Removal and Initial Model Rebuild

In [41]:
```
X.columns
```

Out[41]:
```
Index(['koi_score', 'koi_fpflag_nt', 'koi_fpflag_ss', 'koi_fpflag_co',
       'koi_fpflag_ec', 'koi_period', 'koi_time0bk', 'koi_time0', 'koi_eccen',
       'koi_impact', 'koi_duration', 'koi_depth', 'koi_ror', 'koi_srho',
       'koi_prad', 'koi_sma', 'koi_incl', 'koi_teq', 'koi_insol', 'koi_dor',
       'koi_max_sngle_ev', 'koi_max_mult_ev', 'koi_model_snr', 'koi_count',
       'koi_num_transits', 'koi_tce_plnt_num', 'koi_quarters',
       'koi_bin_oedp_sig', 'koi_steff', 'koi_slogg', 'koi_smet', 'koi_srad',
       'koi_smass', 'ra', 'dec', 'koi_kepmag', 'koi_gmag', 'koi_rmag',
       'koi_imag', 'koi_zmag', 'koi_jmag', 'koi_hmag', 'koi_kmag',
       'koi_fwm_stat_sig', 'koi_fwm_sra', 'koi_fwm_sdec', 'koi_fwm_srao',
       'koi_fwm_sdeco', 'koi_fwm_prao', 'koi_fwm_pdeco', 'koi_dicco_mra',
       'koi_dicco_mdec', 'koi_dicco_msky', 'koi_dikco_mra', 'koi_dikco_mdec',
       'koi_dikco_msky'],
      dtype='object')
```

In [42]:
```
c_features = ['koi_score','koi_max_mult_ev','koi_fpflag_nt','koi_fpflag_ss','koi_fpflag
              'ra','dec','koi_kepmag','koi_gmag','koi_hmag','koi_imag','koi_jmag','koi_
             'koi_dicco_mra','koi_dicco_mdec','koi_dicco_msky','koi_time0','koi_time0bk
             ]
df_revised = df_processed.drop(c_features,axis=1)
candidates_revised = candidates_df.drop(c_features,axis=1)
```

In [43]:
```
fig,hs = plt.subplots(figsize=(10,10))
sns.heatmap(df_revised.corr()>.75, center=0);
```



Train Test Data Rebuilt

In [44]:
```
X_r = df_revised.drop(['koi_disposition','koi_pdisposition','kepoi_name'],axis=1)
y_r = df_revised['koi_disposition']
```

In [45]:
```
X_train_r, X_test_r, y_train_r, y_test_r = train_test_split(X_r, y_r, test_size=0.2)
```

In [46]:
```
y_r.value_counts()
```

Out[46]:
```
FALSE POSITIVE    2938
CONFIRMED         2155
Name: koi_disposition, dtype: int64
```

In [47]:
```
len(X_r.columns)
```

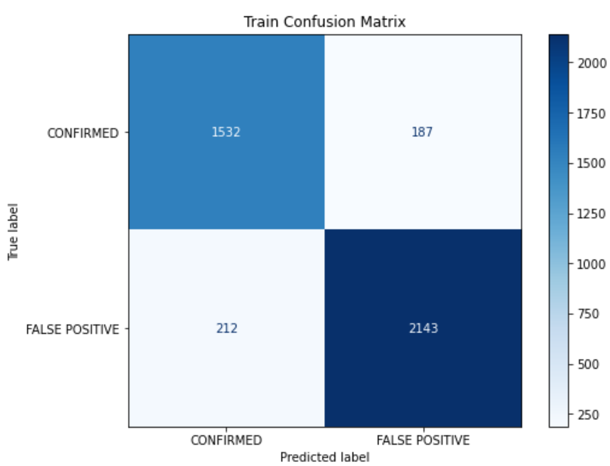
Out[47]:
```
33
```

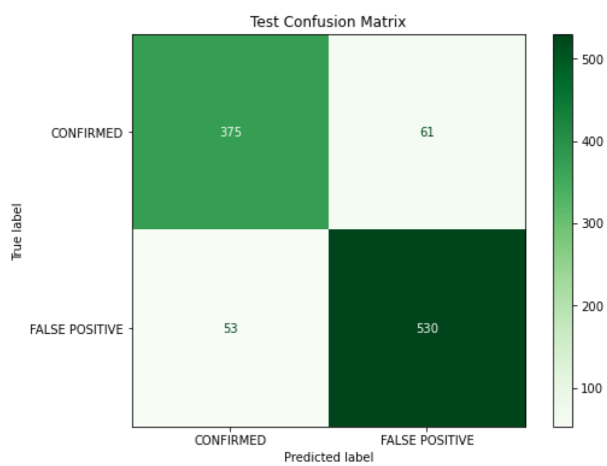
Remodel

In [48]:
```
remodel_pipeline = Pipeline([('ss', StandardScaler()),
                             ('log',LogisticRegression(random_state=40521))])
```

In [49]:
```
remodel = run_class_model(remodel_pipeline, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

                precision    recall  f1-score   support

     CONFIRMED       0.88      0.89      0.88      1719
FALSE POSITIVE       0.92      0.91      0.91      2355

      accuracy                           0.90      4074
     macro avg       0.90      0.90      0.90      4074
  weighted avg       0.90      0.90      0.90      4074

********************************************************

     Classification Report: Test

                precision    recall  f1-score   support

     CONFIRMED       0.88      0.86      0.87       436
FALSE POSITIVE       0.90      0.91      0.90       583

      accuracy                           0.89      1019
     macro avg       0.89      0.88      0.89      1019
  weighted avg       0.89      0.89      0.89      1019

********************************************************
```





Remodeled Findings

- Model performed worse overall which was expected
- Base Model Accuracy is 89%

List of models

- Logistic Regression
- K Nearest Neighbors
- Gaussian Naive Bayes
- Random Forest
- ADA Boost
- Gradient Boost
- XG Boost
- Support Vector Machines

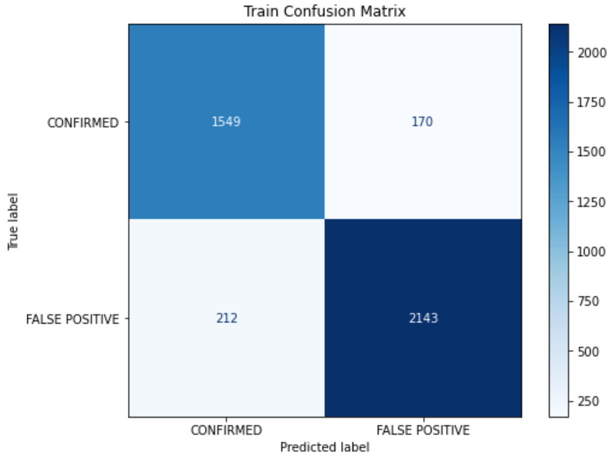
Model 1 - Logistic Regression

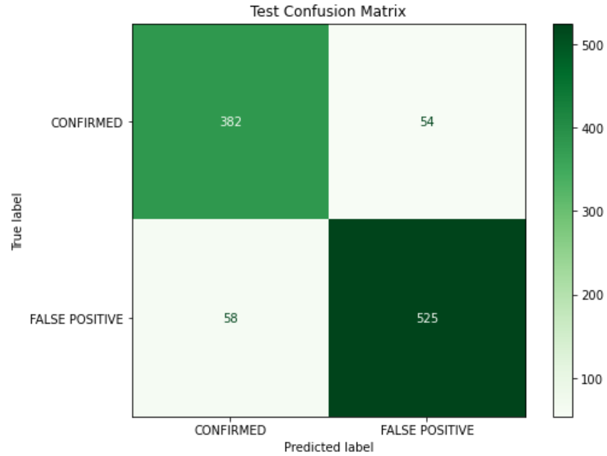
In [50]:
```
log_pipe = Pipeline([('ss', StandardScaler()),
                     ('log', LogisticRegression(random_state=40521))])
log_grid = [{'log__C': [0,10],
             'log__solver': ['newton-cg','sag','saga','lbfgs','liblinear']}]
```

In [51]:
```
log_gridsearch = GridSearchCV(estimator=log_pipe,
                              param_grid=log_grid,
                              scoring='accuracy',
                              cv=5)
```

In [52]:
```
gslog_model = run_class_model(log_gridsearch, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

                precision    recall  f1-score   support

     CONFIRMED       0.88      0.90      0.89      1719
FALSE POSITIVE       0.93      0.91      0.92      2355

      accuracy                           0.91      4074
     macro avg       0.90      0.91      0.90      4074
  weighted avg       0.91      0.91      0.91      4074

********************************************************

     Classification Report: Test

                precision    recall  f1-score   support

     CONFIRMED       0.87      0.88      0.87       436
FALSE POSITIVE       0.91      0.90      0.90       583

      accuracy                           0.89      1019
     macro avg       0.89      0.89      0.89      1019
  weighted avg       0.89      0.89      0.89      1019

********************************************************
```





In [53]:
```
gslog_model.best_params_
```

Out[53]:
```
{'log__C': 10, 'log__solver': 'newton-cg'}
```

In [54]:
```
accuracy_score(y_test_r, gslog_model.predict(X_test_r))
```

Out[54]:
```
0.8900883218842002
```

Logistic Results

- Performs roughly the same as the base log model

Model 2 - KNN

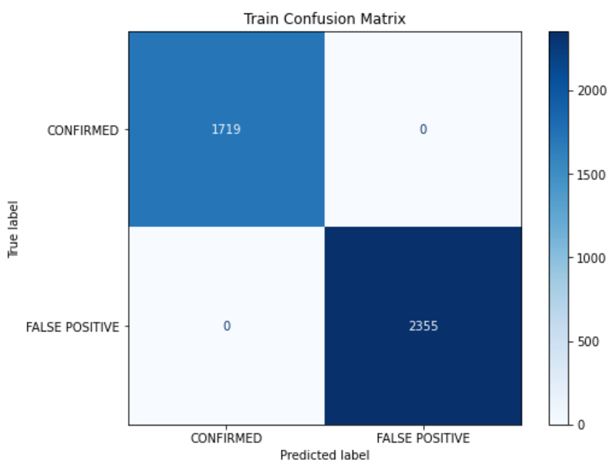
In [55]:
```
knn_pipe = Pipeline([('rb', RobustScaler()),
                     ('knn', KNeighborsClassifier())])
knn_grid = [{'knn__n_neighbors': [2,5],
             'knn__weights' : ['uniform', 'distance'],
             'knn__leaf_size': [30,50]
            }]
```

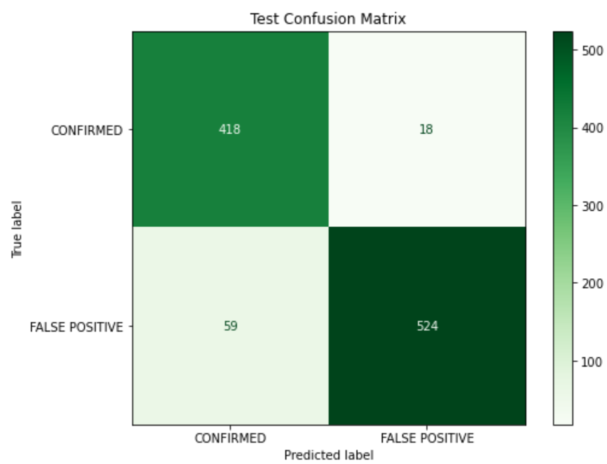
In [56]:
```
knn_gridsearch = GridSearchCV(estimator=knn_pipe,
                              param_grid=knn_grid,
                              scoring='accuracy',
                              cv=5)
```

In [57]:
```
gsknn_model = run_class_model(knn_gridsearch, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

                precision    recall  f1-score   support

     CONFIRMED       1.00      1.00      1.00      1719
FALSE POSITIVE       1.00      1.00      1.00      2355

      accuracy                           1.00      4074
     macro avg       1.00      1.00      1.00      4074
  weighted avg       1.00      1.00      1.00      4074

********************************************************
```

```
        Classification Report: Test

                   precision    recall  f1-score   support

      CONFIRMED       0.88      0.96      0.92       436
 FALSE POSITIVE       0.97      0.90      0.93       583

       accuracy                           0.92      1019
      macro avg       0.92      0.93      0.92      1019
   weighted avg       0.93      0.92      0.92      1019

********************************************************
```





In [58]:
```
gsknn_model.best_params_
```

Out[58]:
```
{'knn__leaf_size': 30, 'knn__n_neighbors': 2, 'knn__weights': 'distance'}
```

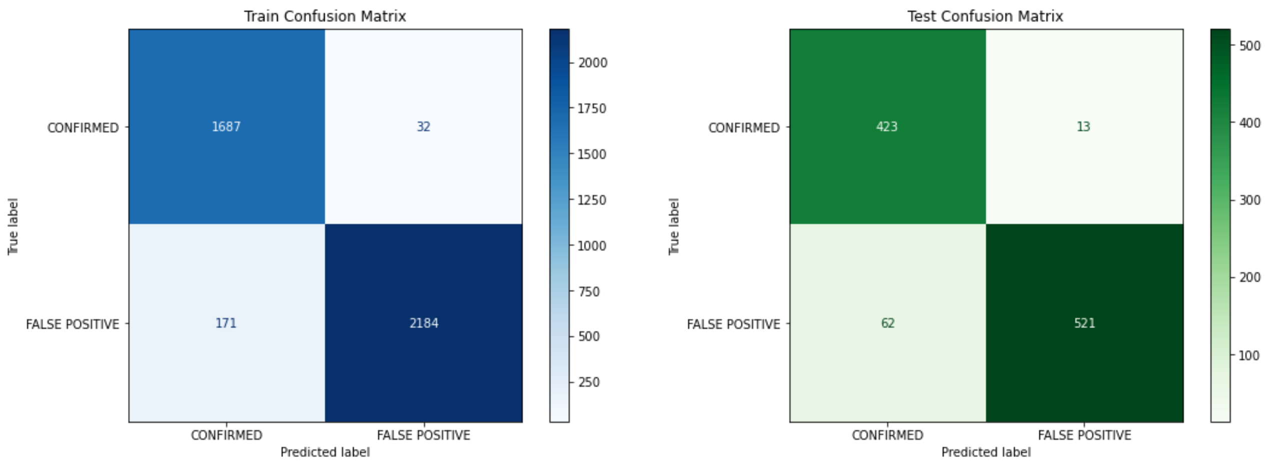
In [117…
```
knn_grid2 = [{'knn__n_neighbors': [3,5],
              'knn__weights' : ['uniform', 'distance'],
              'knn__leaf_size': [40,50]
             }]
```

In [118…
```
knn_gridsearch2 = GridSearchCV(estimator=knn_pipe,
                               param_grid=knn_grid2,
                               scoring='accuracy',
                               cv=5)
```

In [119…
```
gsknn_model2 = run_class_model(knn_gridsearch2, X_train_r, y_train_r, X_test_r, y_test_
```

```
********************************************************

        Classification Report: Train

                   precision    recall  f1-score   support

      CONFIRMED       0.91      0.98      0.94      1719
 FALSE POSITIVE       0.99      0.93      0.96      2355

       accuracy                           0.95      4074
      macro avg       0.95      0.95      0.95      4074
   weighted avg       0.95      0.95      0.95      4074

********************************************************

        Classification Report: Test
```

```
              precision    recall  f1-score   support

     CONFIRMED       0.87      0.97      0.92       436
FALSE POSITIVE       0.98      0.89      0.93       583

      accuracy                           0.93      1019
     macro avg       0.92      0.93      0.93      1019
  weighted avg       0.93      0.93      0.93      1019

********************************************************
```



In [120…

```
gsknn_model2.best_params_
```

Out[120…

```
{'knn__leaf_size': 40, 'knn__n_neighbors': 3, 'knn__weights': 'uniform'}
```

KNN Results

- Too overfit
- Reducing overfit does not improve the test performance substantially.

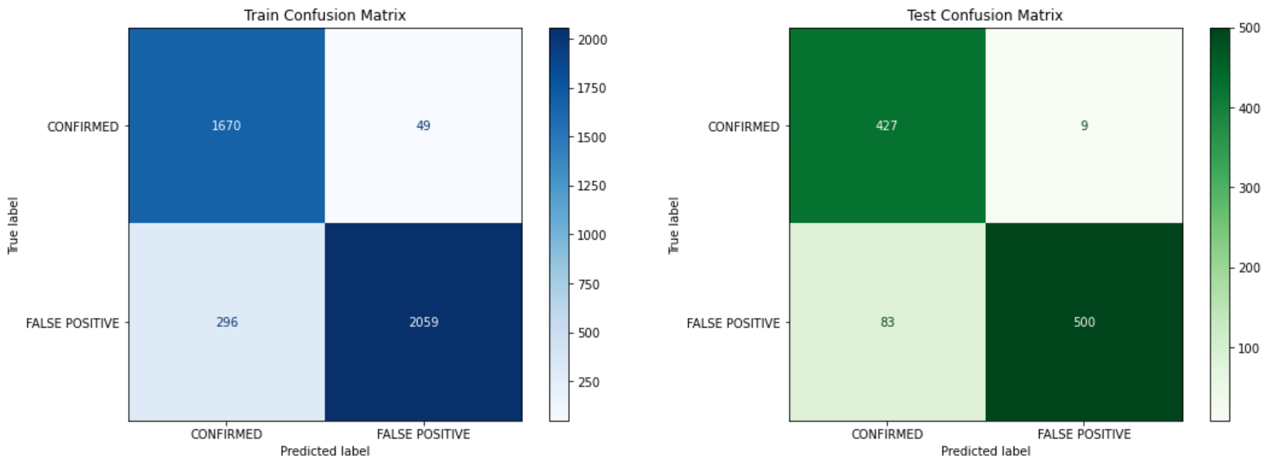
Gaussian Naive Bayes

In [63]:

```
gnb_pipe = Pipeline([('ss', StandardScaler()),
                     ('gnb', GaussianNB())])
gnb_model = run_class_model(gnb_pipe, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

              precision    recall  f1-score   support

     CONFIRMED       0.85      0.97      0.91      1719
FALSE POSITIVE       0.98      0.87      0.92      2355

      accuracy                           0.92      4074
     macro avg       0.91      0.92      0.91      4074
  weighted avg       0.92      0.92      0.92      4074

********************************************************

     Classification Report: Test
```

```
               precision    recall  f1-score   support

     CONFIRMED       0.84      0.98      0.90       436
FALSE POSITIVE       0.98      0.86      0.92       583

      accuracy                           0.91      1019
     macro avg       0.91      0.92      0.91      1019
  weighted avg       0.92      0.91      0.91      1019

********************************************************
```



GNB Results

- Performs better than Logistic but worse than KNN

Random Forest Classifer

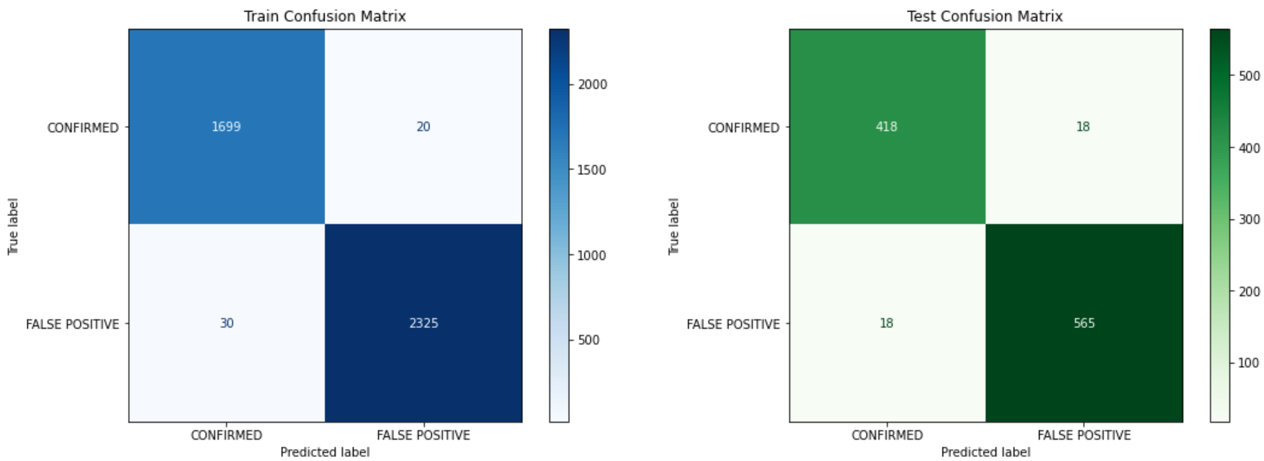
In [64]:
```
rf_pipe = Pipeline([('rb', RobustScaler()),
                    ('RF', RandomForestClassifier(random_state=40521))])
rf_grid = [{'RF__max_depth': [2,11],
            'RF__min_samples_split': [3,7],
            'RF__min_samples_leaf': [3,7],
            'RF__oob_score': [True,False],
           }]
```

In [65]:
```
gs_rf = GridSearchCV(estimator = rf_pipe,
                     param_grid = rf_grid,
                     scoring = 'accuracy',
                     cv = 3)
```

In [66]:
```
gsrf_model = run_class_model(gs_rf, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

               precision    recall  f1-score   support

     CONFIRMED       0.98      0.99      0.99      1719
FALSE POSITIVE       0.99      0.99      0.99      2355

      accuracy                           0.99      4074
     macro avg       0.99      0.99      0.99      4074
  weighted avg       0.99      0.99      0.99      4074
```

```
*******************************************************

     Classification Report: Test

                  precision    recall  f1-score   support

     CONFIRMED       0.96      0.96      0.96       436
FALSE POSITIVE       0.97      0.97      0.97       583

      accuracy                           0.96      1019
     macro avg       0.96      0.96      0.96      1019
  weighted avg       0.96      0.96      0.96      1019

*******************************************************
```



In [67]:
```
gsrf_model.best_params_
```

Out[67]:
```
{'RF__max_depth': 11,
 'RF__min_samples_leaf': 3,
 'RF__min_samples_split': 3,
 'RF__oob_score': True}
```

In [121…
```
accuracy_score(y_test_r,gsrf_model.predict(X_test_r))
```

Out[121…
```
0.9646712463199215
```

RF Results

- Best performing model so far

ADA Boost

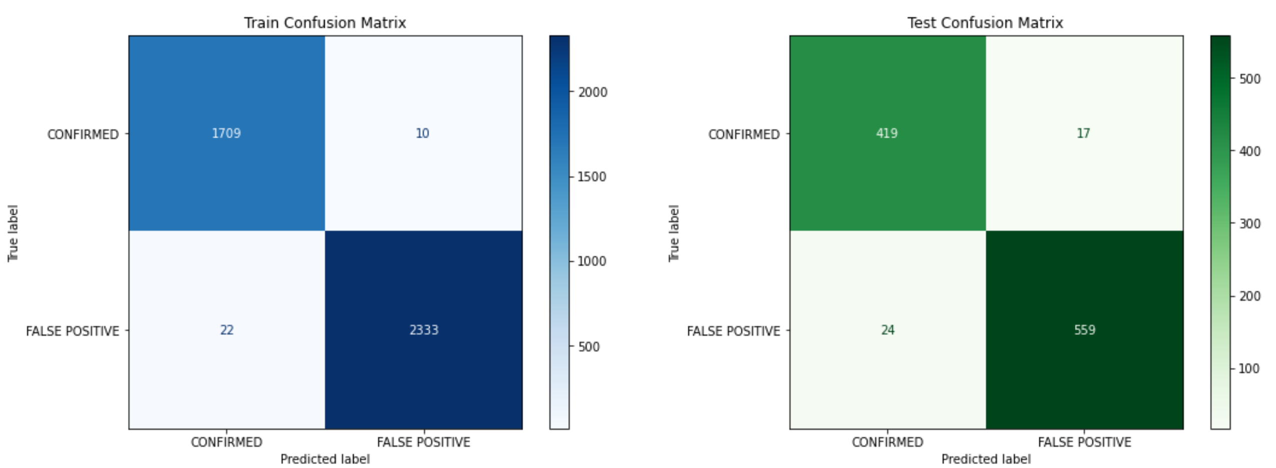
In [69]:
```
ada_pipe = Pipeline([('rb', RobustScaler()),
                    #('ss', StandardScaler()),
                    ('ada', AdaBoostClassifier(random_state=40521))])
ada_grid = [{'ada__learning_rate': [1.5,1.0],
             'ada__n_estimators': [150,100,50]
           }]
```

In [70]:
```
gs_ada = GridSearchCV(estimator = ada_pipe,
                      param_grid = ada_grid,
```

```
                        scoring = 'accuracy',
                        cv = 3)
```

In [71]:
```
gsada_model = run_class_model(gs_ada, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

                precision    recall  f1-score   support

     CONFIRMED       0.99      0.99      0.99      1719
FALSE POSITIVE       1.00      0.99      0.99      2355

      accuracy                           0.99      4074
     macro avg       0.99      0.99      0.99      4074
  weighted avg       0.99      0.99      0.99      4074

********************************************************

     Classification Report: Test

                precision    recall  f1-score   support

     CONFIRMED       0.95      0.96      0.95       436
FALSE POSITIVE       0.97      0.96      0.96       583

      accuracy                           0.96      1019
     macro avg       0.96      0.96      0.96      1019
  weighted avg       0.96      0.96      0.96      1019

********************************************************
```



In [72]:
```
gsada_model.best_params_
```

Out[72]:
```
{'ada__learning_rate': 1.0, 'ada__n_estimators': 150}
```

ADA Boost Results

- Performs well too, similar to Random Forest.

Gradient Boost

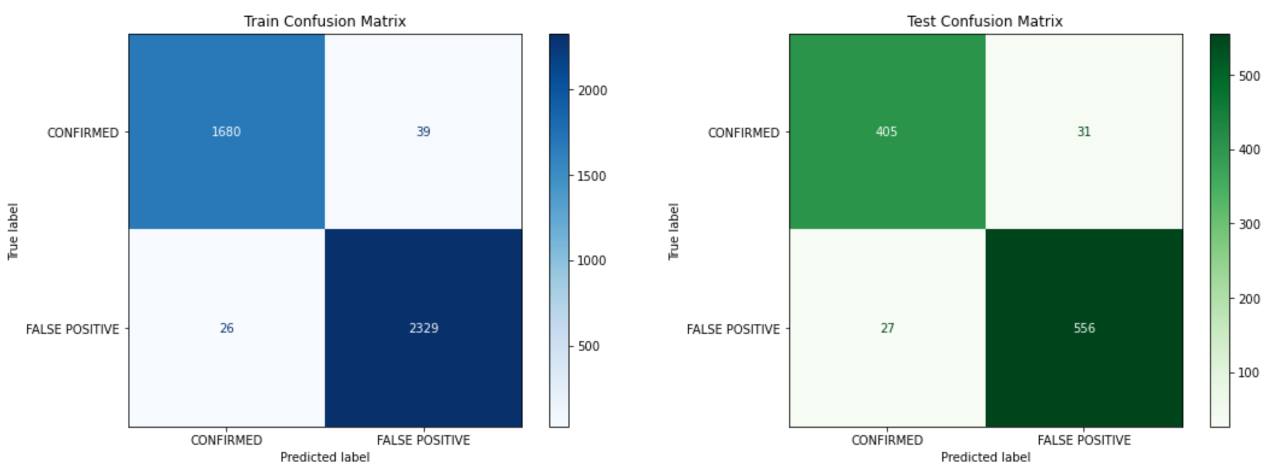
In [73]:
```
gra_pipe = Pipeline([('rb', RobustScaler()),
```

```
                    ('gra', GradientBoostingClassifier(random_state=40521,subsample=.65
gra_grid = [{'gra__learning_rate': [1.5,1.0],
             'gra__n_estimators': [150,100,50]
           }]
```

In [74]:
```
gs_gra = GridSearchCV(estimator = gra_pipe,
                      param_grid = gra_grid,
                      scoring = 'accuracy',
                      cv = 3)
```

In [75]:
```
gsgra_model = run_class_model(gs_gra, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

                precision    recall  f1-score   support

     CONFIRMED       0.98      0.98      0.98      1719
FALSE POSITIVE       0.98      0.99      0.99      2355

      accuracy                           0.98      4074
     macro avg       0.98      0.98      0.98      4074
  weighted avg       0.98      0.98      0.98      4074

********************************************************

     Classification Report: Test

                precision    recall  f1-score   support

     CONFIRMED       0.94      0.93      0.93       436
FALSE POSITIVE       0.95      0.95      0.95       583

      accuracy                           0.94      1019
     macro avg       0.94      0.94      0.94      1019
  weighted avg       0.94      0.94      0.94      1019

********************************************************
```



In [76]:
```
gsgra_model.best_params_
```

Out[76]: {'gra__learning_rate': 1.0, 'gra__n_estimators': 150}

Gradient Boost Results

- Does not perform as well as Random Forest or ADA boost

XG Boost

In [127…

```
test_xg_pipe = Pipeline([('rb', RobustScaler()),
                        ('xg', xgb.XGBClassifier(random_state=40521,
                                                 min_child_weight=3,subsample=.65))])
```

In [133…

```
test_xg_grid = [{'xg__learning_rate': [2,1.5,1.0],
                 'xg__n_estimators': [150,100,50],
                 'xg__gamma': [.5,1,2],
                 'xg__max_depth': [1,2],
                 'xg__colsample_bytree': [.6,.7],
           }]
```

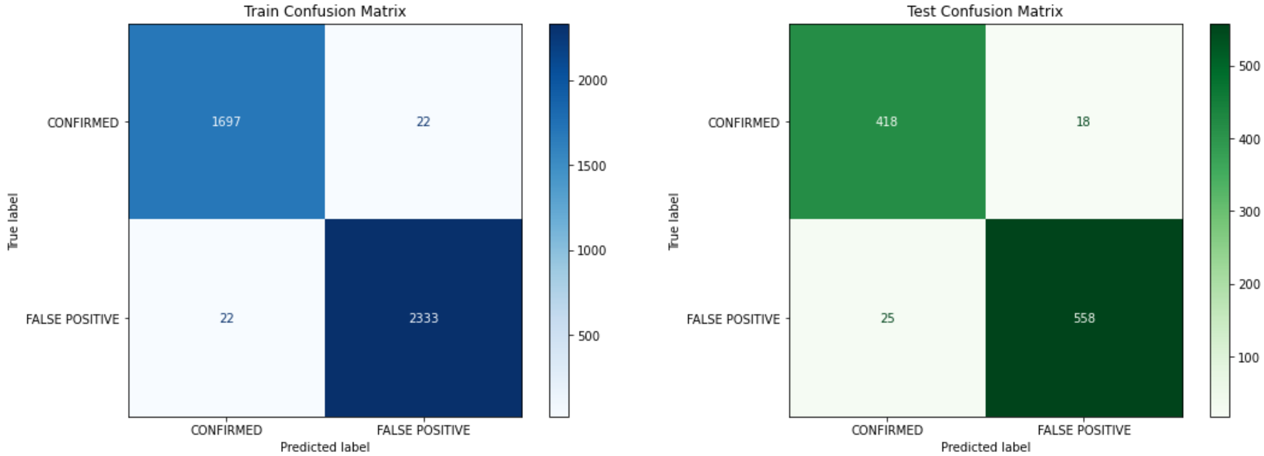
In [134…

```
gs_xg_test = GridSearchCV(estimator = test_xg_pipe,
                     param_grid = test_xg_grid,
                     scoring = 'accuracy',
                     cv = 3)
```

In [135…

```
gsxg_model = run_class_model(gs_xg_test, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

                precision    recall  f1-score   support

     CONFIRMED       0.99      0.99      0.99      1719
FALSE POSITIVE       0.99      0.99      0.99      2355

      accuracy                           0.99      4074
     macro avg       0.99      0.99      0.99      4074
  weighted avg       0.99      0.99      0.99      4074

********************************************************

     Classification Report: Test

                precision    recall  f1-score   support

     CONFIRMED       0.94      0.96      0.95       436
FALSE POSITIVE       0.97      0.96      0.96       583

      accuracy                           0.96      1019
     macro avg       0.96      0.96      0.96      1019
  weighted avg       0.96      0.96      0.96      1019

********************************************************
```



In [136…

```
gsxg_model.best_params_
```

Out[136…

```
{'xg__colsample_bytree': 0.6,
 'xg__gamma': 1,
 'xg__learning_rate': 1.0,
 'xg__max_depth': 2,
 'xg__n_estimators': 50}
```

In [137…

```
accuracy_score(y_test_r,gsxg_model.predict(X_test_r))
```

Out[137…

```
0.957801766437684
```

XG Boost Results

- Also appears overfit, but test data remains well and balanced

Support Vector Machines

In [83]:

```
svm_pipe = Pipeline([#('rb', RobustScaler()),
                     ('mms',MinMaxScaler(feature_range=(-1,1))),
                     ('ss', StandardScaler()),
                     ('svm', SVC(random_state=40521))])
svm_grid = [{'svm__C': [1.5,1.0,.5],
             'svm__gamma': ['scale','auto'],
             'svm__kernel': ['linear','poly','rbf','sigmoid'],
            }]
```

In [84]:

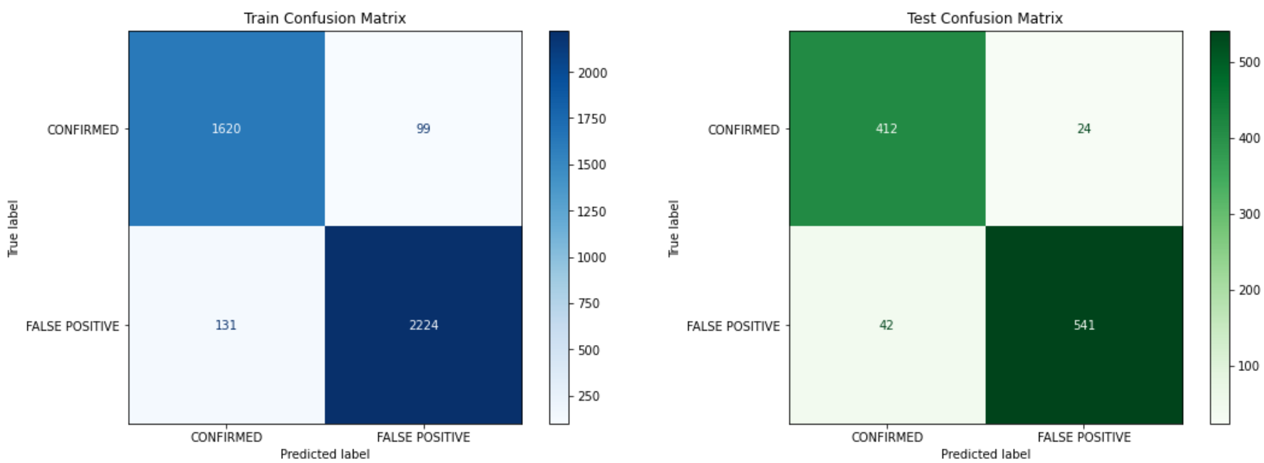
```
gs_svm = GridSearchCV(estimator = svm_pipe,
                     param_grid = svm_grid,
                     scoring = 'accuracy',
                     cv = 3)
```

In [85]:

```
gssvm_model = run_class_model(gs_svm, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
********************************************************

     Classification Report: Train

                precision    recall  f1-score   support

     CONFIRMED       0.93      0.94      0.93      1719
FALSE POSITIVE       0.96      0.94      0.95      2355
```

```
    accuracy                           0.94      4074
   macro avg       0.94      0.94      0.94      4074
weighted avg       0.94      0.94      0.94      4074

*******************************************************

     Classification Report: Test

                precision    recall  f1-score   support

     CONFIRMED       0.91      0.94      0.93       436
FALSE POSITIVE       0.96      0.93      0.94       583

      accuracy                           0.94      1019
     macro avg       0.93      0.94      0.93      1019
  weighted avg       0.94      0.94      0.94      1019

*******************************************************
```



In [86]:
```
gssvm_model.best_params_
```

Out[86]:
```
{'svm__C': 1.5, 'svm__gamma': 'auto', 'svm__kernel': 'rbf'}
```

SVM Results

- Performs slightly worse than the others
- Difficult to hypertune parameters due to long run times

Table of Classification Results

In [138…
```
all_models = [gslog_model,gsknn_model,gnb_model,gsrf_model,
              gsada_model,gsgra_model,gsxg_model,gssvm_model]
model_names = ['Logistic Regression',
               'K Nearest Neighbors',
               'Gaussian Naive Bayes',
               'Random Forest',
               'ADA Boost',
               'Gradient Boost',
               'XG Boost',
               'Support Vector Machines'
              ]
```

In [139…
```
model_table = pd.DataFrame({"Models": model_names})
```

In [140…
```
model_table['Accuracy'] = [round(accuracy_score(y_test_r,all_models[m].predict(X_test_r
                           for m in range(len(all_models))]
```

In [141…
```
model_table['F1 Score'] = [round(f1_score(y_test_r,all_models[m].predict(X_test_r),
                                  pos_label='CONFIRMED'),4)
                                   for m in range(len(all_models))]
```

In [142…
```
model_table['Precision'] = [round(precision_score(y_test_r,all_models[m].predict(X_test
                                          pos_label='CONFIRMED'),4)
                                            for m in range(len(all_models))]
```

In [143…
```
model_table['Recall'] = [round(recall_score(y_test_r,all_models[m].predict(X_test_r),
                                    pos_label='CONFIRMED'),4)
                                     for m in range(len(all_models))]
```

In [144…
```
model_table.sort_values(by="Accuracy")
```

Out[144…

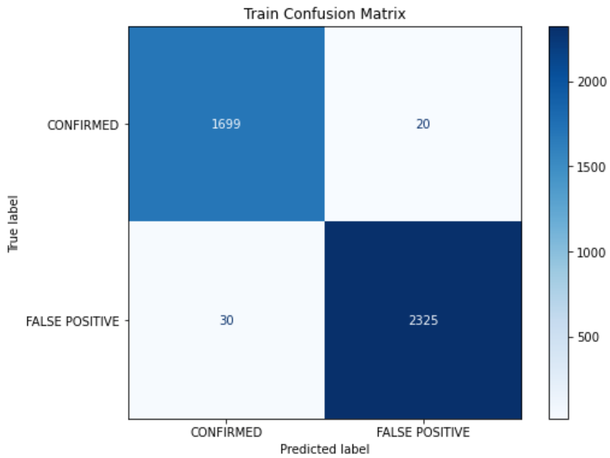
	Models	Accuracy	F1 Score	Precision	Recall
0	Logistic Regression	0.8901	0.8721	0.8682	0.8761
2	Gaussian Naive Bayes	0.9097	0.9027	0.8373	0.9794
1	K Nearest Neighbors	0.9244	0.9157	0.8763	0.9587
7	Support Vector Machines	0.9352	0.9258	0.9075	0.9450
5	Gradient Boost	0.9431	0.9332	0.9375	0.9289
6	XG Boost	0.9578	0.9511	0.9436	0.9587
4	ADA Boost	0.9598	0.9534	0.9458	0.9610
3	Random Forest	0.9647	0.9587	0.9587	0.9587

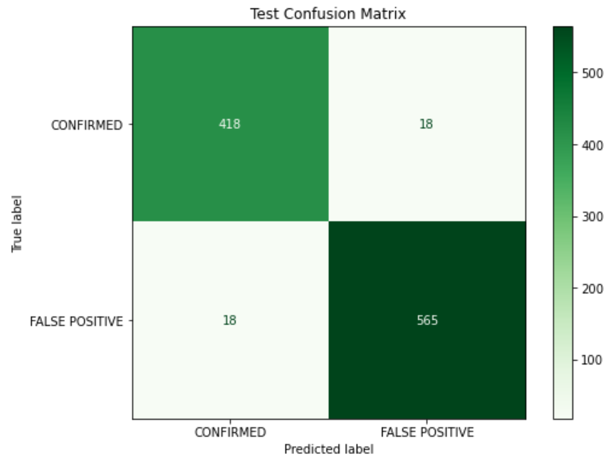
Best Model - Random Forest Rerun

In [94]:
```
gsrf_model = run_class_model(gs_rf, X_train_r, y_train_r, X_test_r, y_test_r)
```

```
************************************************************

     Classification Report: Train

                 precision    recall  f1-score   support

     CONFIRMED       0.98      0.99      0.99      1719
FALSE POSITIVE       0.99      0.99      0.99      2355

      accuracy                           0.99      4074
     macro avg       0.99      0.99      0.99      4074
  weighted avg       0.99      0.99      0.99      4074

************************************************************

     Classification Report: Test

                 precision    recall  f1-score   support
```

```
      CONFIRMED       0.96      0.96      0.96       436
 FALSE POSITIVE       0.97      0.97      0.97       583

       accuracy                           0.96      1019
      macro avg       0.96      0.96      0.96      1019
   weighted avg       0.96      0.96      0.96      1019

*******************************************************
```





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

Out[95]:
```
{'RF__max_depth': 11,
 'RF__min_samples_leaf': 3,
 'RF__min_samples_split': 3,
 'RF__oob_score': True}
```

Most Important Features

In [96]:
```
gsrf_model.best_estimator_.named_steps["RF"].feature_importances_
```

Out[96]:
```
array([0.02132519, 0.        , 0.04537372, 0.01609932, 0.03796122,
       0.0113826 , 0.11547089, 0.02126385, 0.0479246 , 0.01948668,
       0.02989431, 0.06794475, 0.03224734, 0.06299863, 0.09390651,
       0.01697461, 0.00345279, 0.00102787, 0.00528168, 0.00636405,
       0.00605211, 0.01986917, 0.00405767, 0.00303346, 0.11261167,
       0.00429279, 0.00342672, 0.02674703, 0.02134808, 0.0182259 ,
       0.01195475, 0.04636913, 0.06563091])
```

In [97]:
```
features = pd.DataFrame(columns=['Features','Coef'])
```

In [98]:
```
features['Features'] = X_r.columns
```

In [99]:
```
features['Coef']= gsrf_model.best_estimator_.named_steps["RF"].feature_importances_
```

In [100…
```
features.sort_values(by='Coef').tail(5)
```

Out[100…

	Features	Coef
32	koi_dikco_mdec	0.065631
11	koi_dor	0.067945
14	koi_count	0.093907

	Features	Coef
24	koi_fwm_stat_sig	0.112612
6	koi_prad	0.115471

In [101…

```
features.sort_values(by='Coef').head(5)
```

Out[101…

	Features	Coef
1	koi_eccen	0.000000
17	koi_quarters	0.001028
23	koi_rmag	0.003033
26	koi_fwm_sdec	0.003427
16	koi_tce_plnt_num	0.003453

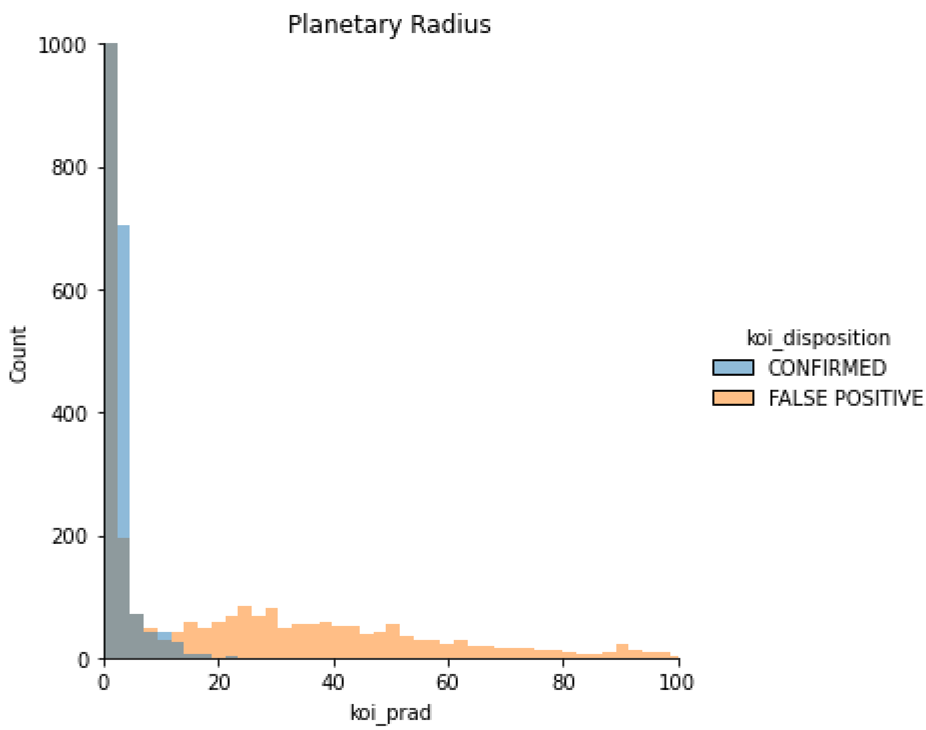
In [102…

```
best_features = ['koi_prad','koi_count','koi_dor']
```

RePlot the distrubutions and relationship with the target variable

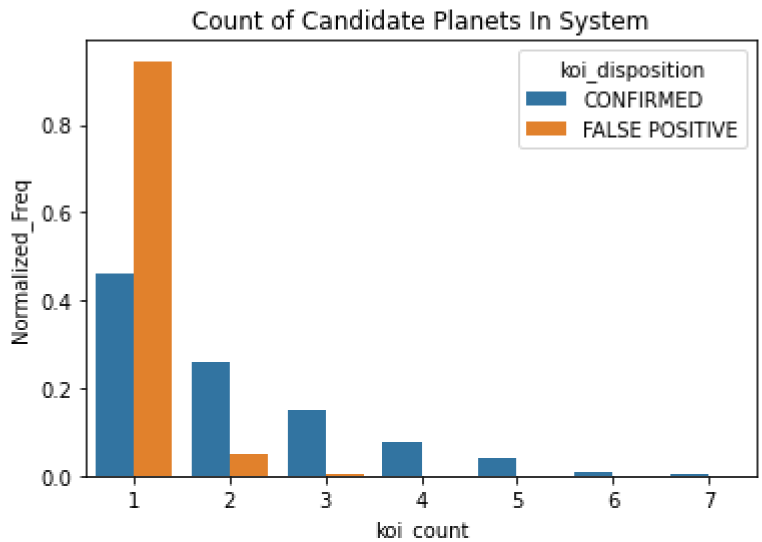
In [146…

```
sns.displot(data=df_revised,x='koi_prad',hue='koi_disposition')
        .set(xlim=(0,100),ylim=(0,1000),title="Planetary Radius");
```

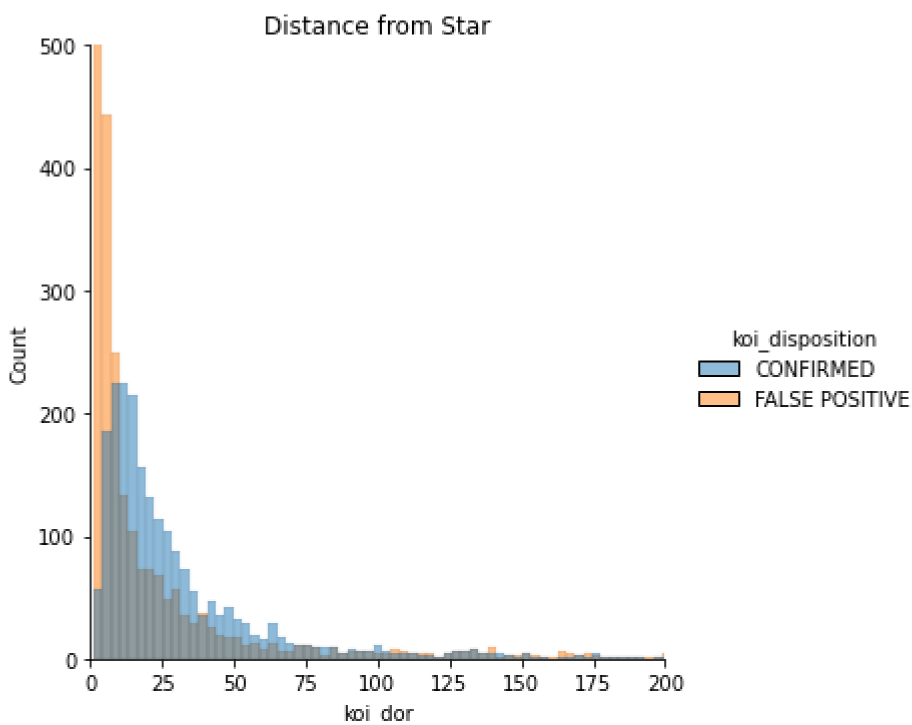


In [150…

```
sns.barplot(data=df_revised['koi_count']
 .groupby(df_revised['koi_disposition'])
 .value_counts(normalize=True)
 .rename("Normalized_Freq")
 .reset_index(),x='koi_count',y='Normalized_Freq',hue='koi_disposition')
            .set(title="Count of Candidate Planets In System");
```



In [148…
```
sns.displot(data=df_revised,x='koi_dor',hue='koi_disposition')
          .set(xlim=(0,200),ylim=(0,500),title = "Distance from Star");
```



Important Feature Descriptions

koi_dor: The distance between the planet and the star at mid-transit divided by the stellar radius.koi_count: Number of planets candidates identified in a system.koi_prad: The radius of the planet. Planetary radius is the product of the planet star radius ratio and the stellar radius.

Using model to predict candidates

In [106…
```
candidates_revised
```

Out[106…

	kepoi_name	koi_disposition	koi_pdisposition	koi_period	koi_eccen	koi_impact	koi_duration	kc

	kepoi_name	koi_disposition	koi_pdisposition	koi_period	koi_eccen	koi_impact	koi_duration	kc
2	K00753.01	CANDIDATE	CANDIDATE	19.899140	0.0	0.969	1.78220	
37	K00760.01	CANDIDATE	CANDIDATE	4.959319	0.0	0.831	2.22739	
58	K00777.01	CANDIDATE	CANDIDATE	40.419504	0.0	0.911	3.36200	
62	K00780.02	CANDIDATE	CANDIDATE	7.240661	0.0	1.198	0.55800	
63	K00115.03	CANDIDATE	CANDIDATE	3.435916	0.0	0.624	3.13300	
...	...	...	...	...	...	...	...	
9536	K08297.01	CANDIDATE	CANDIDATE	229.957537	0.0	1.175	7.59000	
9542	K07982.01	CANDIDATE	CANDIDATE	376.379890	0.0	0.305	13.99000	
9552	K08193.01	CANDIDATE	CANDIDATE	367.947848	0.0	0.902	4.24900	
9560	K07986.01	CANDIDATE	CANDIDATE	1.739849	0.0	0.043	3.11400	
9562	K07988.01	CANDIDATE	CANDIDATE	333.486169	0.0	0.214	3.19900	

1589 rows × 36 columns

In [107…
```
predictions = gsxg_model.best_estimator_.predict(candidates_revised.drop(
    ['kepoi_name','koi_disposition','koi_pdisposition'],axis=1))
```

In [108…
```
candidates_predictions = candidates_revised.copy()
```

In [109…
```
candidates_predictions['Predictions'] = predictions
```

In [110…
```
candidates_predictions.Predictions.value_counts()
```

Out[110…
```
CONFIRMED         916
FALSE POSITIVE    673
Name: Predictions, dtype: int64
```

In [2]:
```
916/(916+673)
```

Out[2]:
```
0.5764631843926998
```

In [112…
```
candidates_predictions.loc[:,['kepoi_name','koi_disposition','Predictions']].head()
```

Out[112…

	kepoi_name	koi_disposition	Predictions
2	K00753.01	CANDIDATE	FALSE POSITIVE
37	K00760.01	CANDIDATE	CONFIRMED
58	K00777.01	CANDIDATE	CONFIRMED
62	K00780.02	CANDIDATE	FALSE POSITIVE
63	K00115.03	CANDIDATE	CONFIRMED

Final Results and Conclusion

1. Best performing classifier model for this dataset is Random Forest Classifier with an accuracy of 97%. However, other models performed just as well.
2. Important features in determining the disposition include: a. Distance of Planet from Star (7%) b. Number of planet candidates in the system (9%) c. Planetary Radius (11%)
3. 33 features and ~5,100 rows of data were used in training the model a. Of these data points, ~2,900 were false positive, 2,200 were confirmed exoplanets
4. ~1,600 candidate exoplanets were run through the model a. Of these planets, 57% are predicted to be confirmed exoplanets b. Additional data should be collected on these predictions and focus should be placed on these.