Obtaining Data

In [1]:
```
#Importing libraries needed
import pandas as pd
import numpy as np


#For visualization
import matplotlib.pyplot as plt
from matplotlib import pyplot
%matplotlib inline
import seaborn as sns
import shap

# For our modeling steps
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import normalize
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import log_loss
from sklearn.metrics import precision_recall_fscore_support
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score, recall_score, f1_score, a
from sklearn.model_selection import GridSearchCV, cross_val_score
import xgboost as xgb
from xgboost import XGBClassifier, plot_importance
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_
from sklearn import svm, datasets
from sklearn import metrics



# For demonstrative purposes
from scipy.special import logit, expit

import warnings
warnings.filterwarnings('ignore')
```

```
pandas.Int64Index is deprecated and will be removed from pandas in a futu
re version. Use pandas.Index with the appropriate dtype instead.
```

In [2]:
```
#opening the datasets
bottom =  pd.read_csv(r'data\bottom_hurricane.csv')
middle =  pd.read_csv(r'data\middle_hurricane.csv')
top =  pd.read_csv(r'data\top_hurricane.csv')
all_df = pd.read_csv(r'data\all_hurricane.csv')
```

Data Processing

In [3]:
```
#let's get rid of duplicate cities by only grabbing the cities with th
bottom = bottom.sort_values('AWND', ascending=False).drop_duplicates([
middle = middle.sort_values('AWND', ascending=False).drop_duplicates([
top = top.sort_values('AWND', ascending=False).drop_duplicates(['Hurri
all_df = all_df.sort_values('AWND', ascending=False).drop_duplicates([
```

In [4]:
```
#We want to use data from hurricane Ian to test our mode
#let's save a dataframe that has just Ian
all_ian = all_df.loc[all_df['HurricaneName'] == 'ian']
all_ian.head()
```

Out[4]:

	City	HurricaneName	DATE	AWND	WSF2	SizeRank	before
3	Apalachicola	ian	9/28/2022	38.027300	57.93571	12877	65287.07867
98	Fort Pierce	ian	9/28/2022	50.039453	100.66050	529	79706.02938
179	Lakeland	ian	9/28/2022	51.538176	105.13430	105	92333.43871
188	Leesburg	ian	9/29/2022	48.540730	91.48921	1024	89188.23594
203	Miami	ian	9/28/2022	41.539233	69.56759	20	187941.97110

In [5]:
```
#removing ian from the other datasets
bottom = bottom.drop(bottom[bottom['HurricaneName'] == 'ian'].index)
middle = middle.drop(middle[middle['HurricaneName'] == 'ian'].index)
top = top.drop(top[top['HurricaneName'] == 'ian'].index)
all_df = all_df.drop(all_df[all_df['HurricaneName'] == 'ian'].index)
```

In [6]:
```
#saving the all dataset for use in later analysis
all_df.to_csv(r'data\wind_modeling.csv', index=False)
```

Comparing Crosstabs by Target Variable

We can see by comparing the crosstabs by our target variable that the standard deviations for wind features are not hugely different. However, the standard deviation for SizeRank and before prices are. This indicates that SizeRank and before prices will probably have more of an impact on our target variable.

Bottom Tier Home Values

In [7]:
```
#check crosstabs
bottom[bottom['increase'] == 0].describe()
```

Out[7]:

	AWND	WSF2	SizeRank	before	after	percent	increas
count	96.000000	96.000000	96.000000	96.000000	96.000000	96.000000	96
mean	16.828333	31.587500	778.479167	95519.992225	109226.353419	15.737500	0
std	7.510509	13.880939	1933.043703	36589.222256	38580.694737	7.428945	0
min	4.700000	0.000000	12.000000	35072.914710	42936.584540	1.715556	0
25%	12.750000	23.000000	109.000000	67085.771493	77117.054463	9.294061	0
50%	14.430000	26.950000	219.000000	87921.154230	106197.766650	13.545954	0
75%	19.460000	36.000000	714.000000	124777.238250	137188.222700	21.427859	0
max	40.260000	79.000000	12877.000000	187941.971100	204898.395000	31.148843	0

In [8]:
```
#check crosstabs
bottom[bottom['increase'] == 1].describe()
```

Out[8]:

	AWND	WSF2	SizeRank	before	after	percent	increas
count	45.00000	45.000000	45.000000	45.000000	45.000000	45.000000	45.
mean	19.71000	36.360000	1614.733333	81869.675339	99918.350911	22.208175	1.
std	7.55599	14.072933	3251.236781	22972.899025	28216.775660	6.973273	0.
min	5.82000	13.000000	12.000000	33025.679010	41196.088340	12.376811	1.
25%	13.87000	25.900000	105.000000	65732.062590	78209.741850	17.496982	1.
50%	19.46000	31.100000	350.000000	79706.029380	97547.957590	19.823318	1.
75%	23.71000	52.100000	1343.000000	94132.640630	113361.292200	24.912005	1.
max	40.71000	70.900000	12877.000000	137614.499600	166366.441400	38.720009	1.

Middle Tier Home Values

In [9]:
```
#check crosstabs
middle[middle['increase'] == 0].describe()
```

Out[9]:

	AWND	WSF2	SizeRank	before	after	percent	inc
count	106.000000	106.000000	106.000000	106.000000	106.000000	106.000000	
mean	17.192736	32.578302	1196.764151	178788.700647	200015.445600	12.739620	
std	7.398756	13.286456	2875.059325	57253.054213	60012.616564	8.166830	
min	4.700000	10.100000	12.000000	47433.413480	55475.026340	-0.304135	
25%	12.750000	23.900000	106.000000	140195.814075	158385.796575	6.516116	
50%	14.760000	29.100000	219.000000	168077.713500	188779.652850	10.175417	
75%	20.525000	36.900000	744.000000	214175.896200	235810.160275	19.340890	
max	38.920000	79.000000	12877.000000	328091.109800	346404.378100	30.423110	

In [10]:
```
#check crosstabs
middle[middle['increase'] == 1].describe()
```

Out[10]:

	AWND	WSF2	SizeRank	before	after	percent	increa
count	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000	33
mean	19.468182	33.951515	2376.212121	152609.677086	183012.972018	19.750077	1
std	9.052282	16.306749	3966.086317	45215.695236	58301.939354	9.054438	0
min	4.470000	0.000000	12.000000	38971.285380	48205.342730	8.693131	1
25%	13.650000	23.900000	299.000000	131341.028200	147305.080700	11.724797	1
50%	16.780000	30.000000	529.000000	153995.650000	185899.410500	14.943632	1
75%	24.610000	46.100000	1644.000000	184197.828400	211150.410200	27.524342	1
max	40.710000	70.900000	12877.000000	237636.125500	316361.491800	34.925821	1

Top Tier Home Values

In [11]:
```
#check crosstabs
top[top['increase'] == 0].describe()
```

Out[11]:

	AWND	WSF2	SizeRank	before	after	percent	incr
count	114.000000	114.000000	114.000000	114.000000	114.000000	114.000000	
mean	17.763947	33.115789	1225.184211	328449.969281	360988.239664	10.473163	
std	7.852753	13.802145	2961.979981	113947.912364	122569.498236	8.631772	
min	4.470000	8.100000	12.000000	98118.000900	119490.997200	-4.161603	
25%	12.970000	23.900000	93.000000	246799.050675	271226.589675	4.737962	
50%	15.100000	29.100000	190.000000	315968.313150	350767.209850	5.958488	
75%	20.800000	38.000000	744.000000	382389.195500	418708.970725	17.504185	
max	40.260000	79.000000	12877.000000	671004.028700	768214.341700	27.655345	

In [12]:
```
#check crosstabs
top[top['increase'] == 1].describe()
```

Out[12]:

	AWND	WSF2	SizeRank	before	after	percent	increa
count	28.000000	28.000000	28.000000	28.000000	28.000000	28.000000	28
mean	17.624286	32.192857	2354.142857	273379.316779	326346.226943	18.132019	1
std	7.603506	14.464181	3809.242403	76774.203448	110181.403979	10.229255	0
min	5.820000	13.000000	16.000000	130756.896600	140391.373400	6.722834	1
25%	13.142500	23.675000	299.000000	231229.432300	255309.653800	7.967553	1
50%	14.875000	28.000000	636.500000	252692.063600	311156.525200	18.205906	1
75%	21.922500	34.325000	1927.000000	315217.170000	372749.758575	28.046185	1
max	40.710000	70.900000	12877.000000	457389.673300	605350.754900	33.863819	1

All Home Values

In [13]:
```
#check crosstabs
all_df[all_df['increase'] == 0].describe()
```

Out[13]:

	AWND	WSF2	SizeRank	before	after	percent	inc
count	258.000000	258.000000	258.000000	258.000000	258.000000	258.000000	
mean	13.768992	27.177907	1191.391473	212575.987928	234000.852403	11.890184	
std	6.939955	12.531378	2873.375161	124254.783285	131099.520669	8.078201	
min	2.910000	0.000000	12.000000	45314.651590	52157.021900	-4.161603	
25%	8.720000	18.100000	106.000000	117276.771100	135580.557625	5.582217	
50%	12.190000	23.900000	219.000000	184998.996100	205368.325550	9.188158	
75%	16.722500	31.100000	744.000000	278446.944025	311384.740025	17.445984	
max	38.920000	79.000000	12877.000000	638691.713200	669502.004200	30.676022	

In [14]:
```
#check crosstabs
all_df[all_df['increase'] == 1].describe()
```

Out[14]:

	AWND	WSF2	SizeRank	before	after	percent	increas
count	86.000000	86.000000	86.000000	86.000000	86.000000	86.000000	86
mean	14.880814	27.886047	1861.965116	146638.094252	174430.381725	19.463055	1
std	7.205503	13.217672	3396.683491	83327.546857	100276.415300	8.625308	0
min	4.920000	6.900000	12.000000	44457.567490	55432.846820	6.722834	1
25%	9.282500	18.100000	107.750000	80030.413350	93270.193108	12.500773	1
50%	13.650000	24.500000	462.000000	126538.414750	148023.322150	17.719562	1
75%	18.570000	31.775000	1410.000000	190034.211300	219513.525825	25.149288	1
max	40.710000	70.900000	12877.000000	372909.443500	488064.017600	38.720009	1

Baseline Model

Examining Class Imbalance

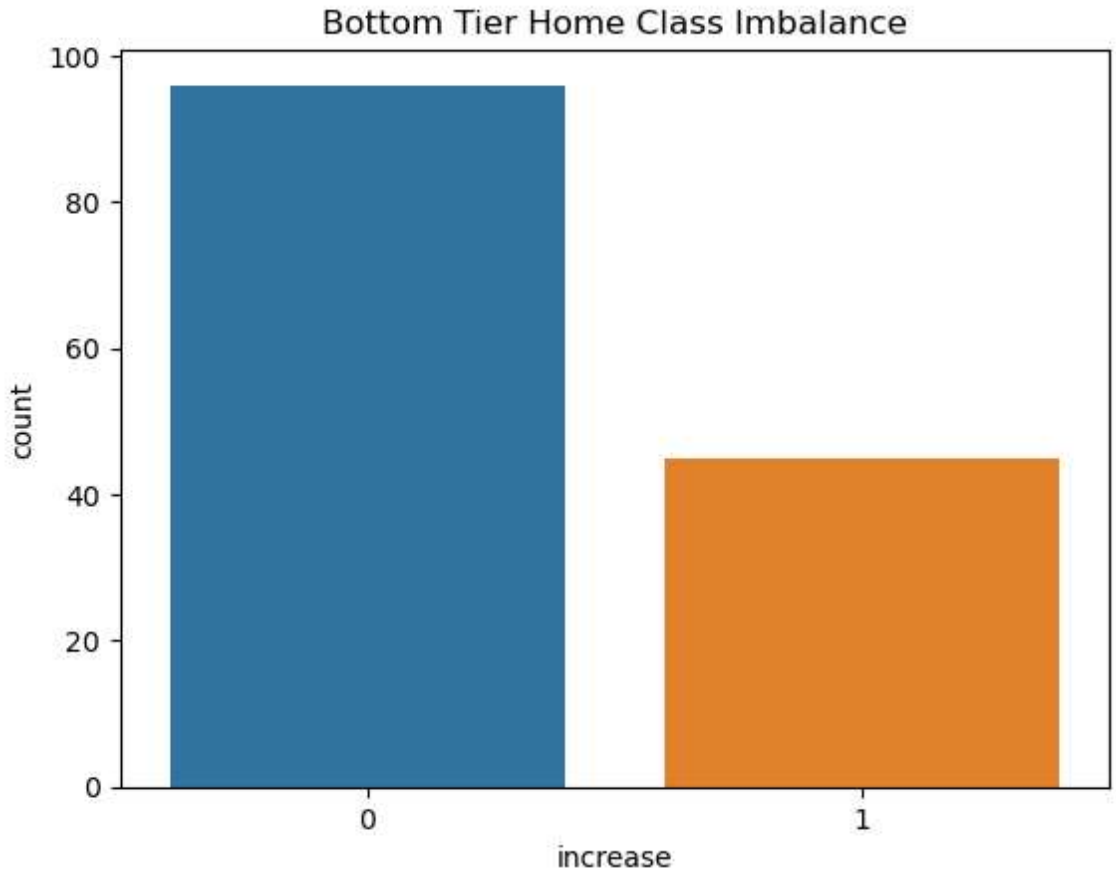
In order to know what a good accuracy is for our models, we must know what the majority class percent is. This will tell us if our model performs any better than just selecting the majority class each time. From the count plots below we can see that the average class imbalance is 74%, which makes sense because our cutoff value was the 75th percentile.

Dataset	Increase	No Increase	No Increase as Percent
Bottom Tier	45	96	68%
Middle Tier	33	106	76%
Top Tier	28	114	80%
All	89	255	74%

Bottom Tier Class Imabalance

In [15]:
```
# Checking the balance of target variable 'increase'
sns.countplot(x='increase', data=bottom).set(title='Bottom Tier Home C
print(bottom['increase'].value_counts())
#checking ratio to see what accuracy is like
percent_bottom = (len(bottom['increase']) - bottom['increase'].sum())/
print("majority percent is {}".format(percent_bottom),"%")

```

```
0    96
1    45
Name: increase, dtype: int64
majority percent is 68.08510638297872 %
```

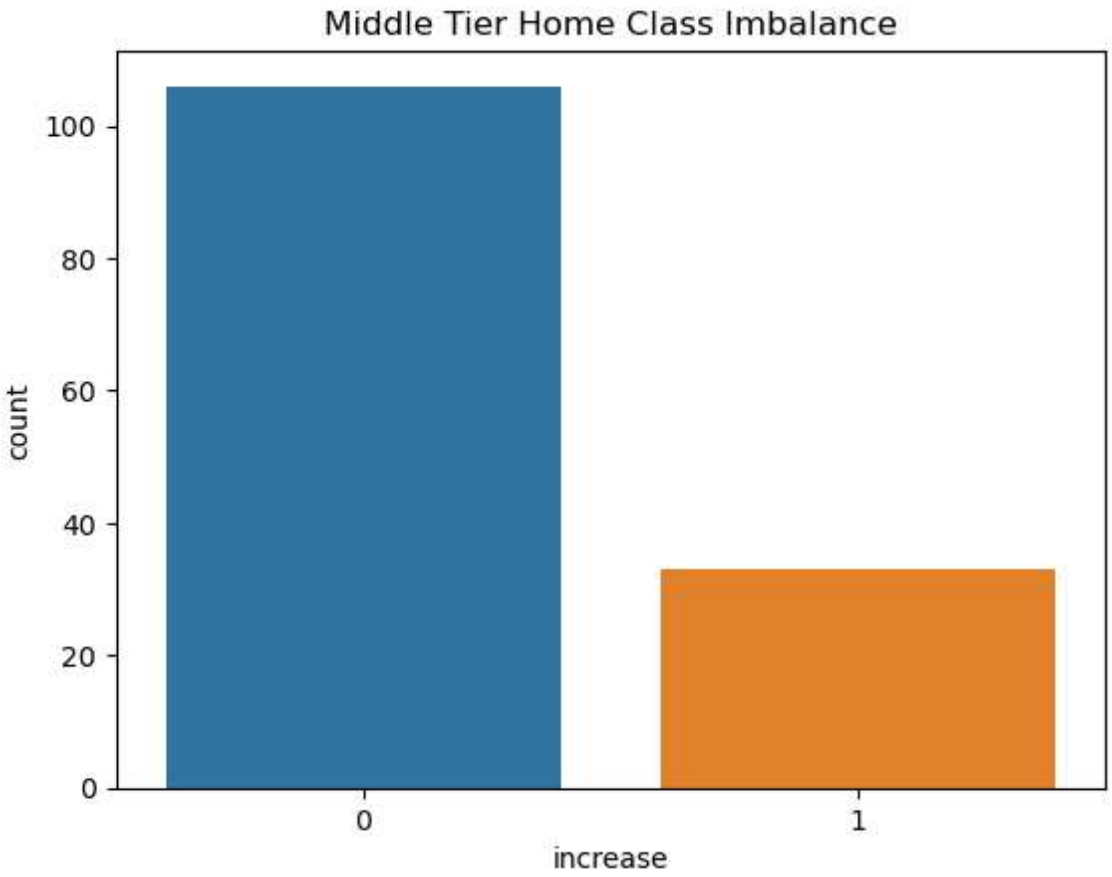


Middle Tier Class Imbalance

In [16]:

```
# Checking the balance of target variable 'increase'
sns.countplot(x='increase', data=middle).set(title='Middle Tier Home C
print(middle['increase'].value_counts())
#checking ratio to see what accuracy is like
percent = (len(middle['increase']) - middle['increase'].sum())/(len(mi
print("majority percent is {}".format(percent),"%")
```

```
0    106
1     33
Name: increase, dtype: int64
majority percent is 76.2589928057554 %
```

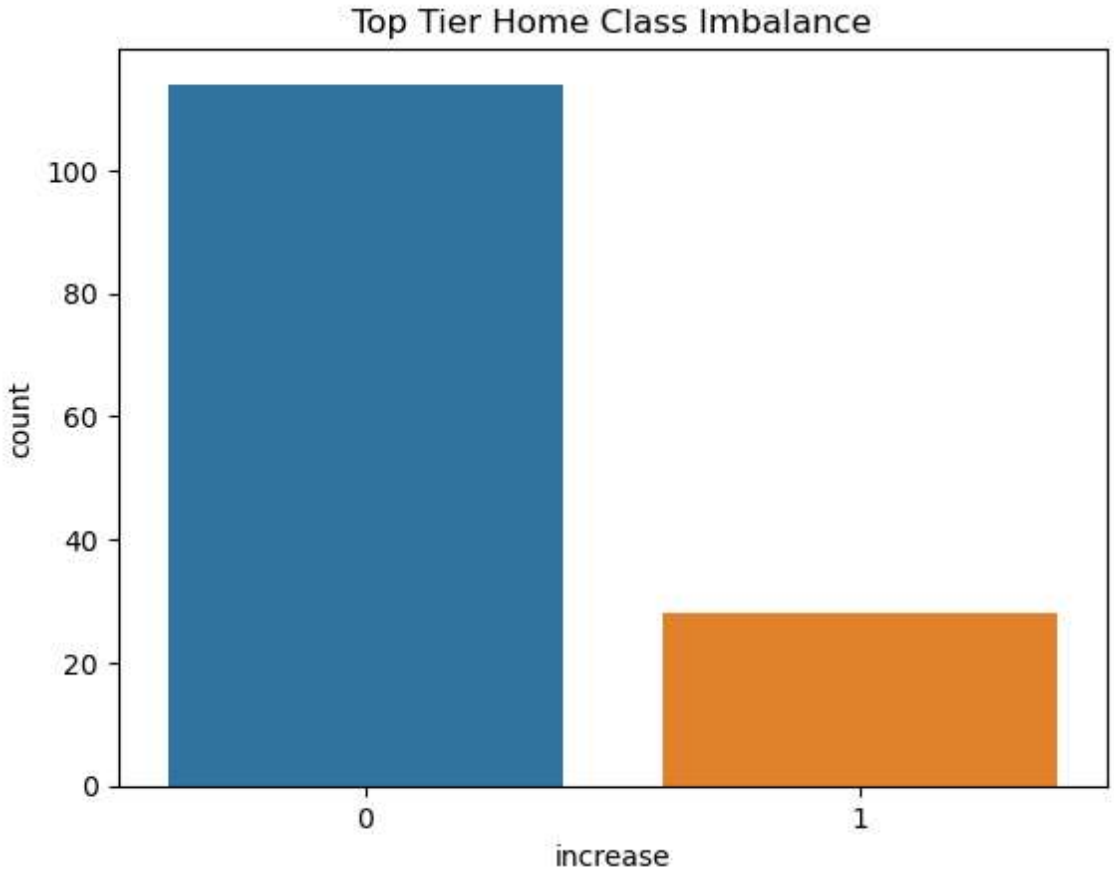


Top Tier Class Imbalance

In [17]:

```
# Checking the balance of target variable 'increase'
sns.countplot(x='increase', data=top).set(title='Top Tier Home Class I
print(top['increase'].value_counts())
#checking ratio to see what accuracy is like
percent = (len(top['increase']) - top['increase'].sum())/(len(top['inc
print("majority percent is {}".format(percent),"%")
```

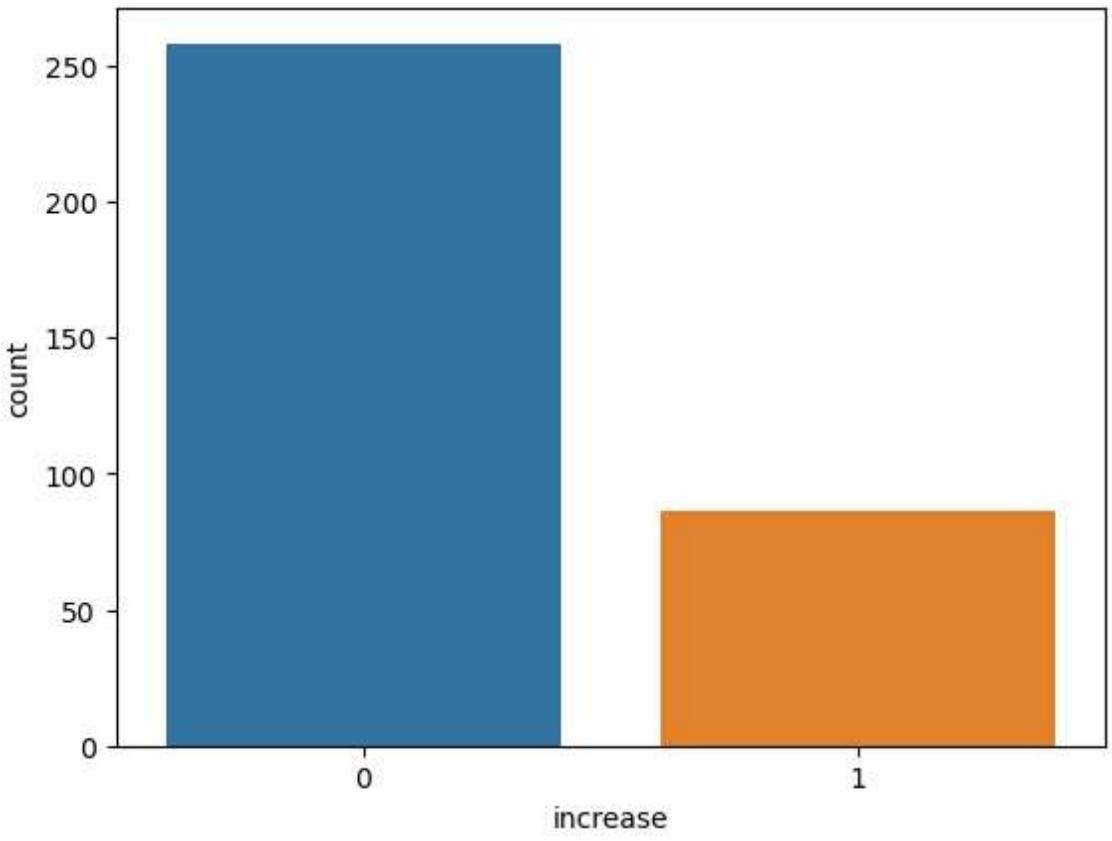
```
0    114
1     28
Name: increase, dtype: int64
majority percent is 80.28169014084507 %
```



All Homes Class Imbalance

In [18]:
```
# Checking the balance of target variable 'increase'
sns.countplot(x='increase', data=all_df);
print(all_df['increase'].value_counts())
#checking ratio to see what accuracy is like
percent = (len(all_df['increase']) - all_df['increase'].sum())/(len(al
print("majority percent is {}".format(percent),"%")
```

```
0    258
1     86
Name: increase, dtype: int64
majority percent is 75.0 %
```

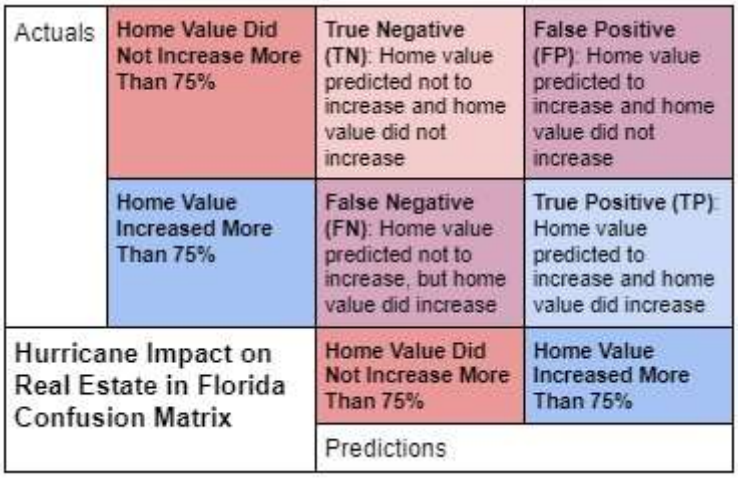


Modeling

Of equal concern to the business problem was the model predicting False Negatives or False Positives. In this situation both are of equal importance to our real estate client. If the model predicts that the home value will not increase but it does (false negative) then our client could lose out on a possible higher return on a home. However, if the model predicts that the home value will increase but it does not (false positive) then our client may have invested money into a home that does not pay off.

For the scope of this project we will be using accuracy and F1 score to assess our model performance. Since we had a class imbalance we could not solely rely on accuracy to communicate model performance. Since, precision and recall were of equal importance for our business problem F1 score was used to assess model performance.

- **Model accuracy** is a machine learning classification model performance metric that takes the ratio of true positives and true negatives to all positives and negative results. It communicates how often our model will correctly predict an outcome out of the total number of predictions made. However, accuracy metrics are not always reliable for imbalance datasets. Accuracy Score = (TP + TN)/ (TP + FN + TN + FP)
- **Model F1 Score** is a model performance metric that gives equal weight to both the Precision and Recall for measuring performance. F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Recall Score/)
- **ROC-AUC** The Receiver Operator Characteristic (ROC) curve is used to assess a model's ability to correctly classify by plotting the true positive rate against the false positive rate. A curve that 'peaks' more quickly communicates that there is a good true positive rate and a low false positive rate. The area under the curve (AUC) is derived from ROC and has a baseline chance of 50% accuracy, hence, an AUC closer to 1 signifies a better classification model.



Works Cited

Filho M. How To Get Feature Importance In Logistic Regression. forecastegy.com. Published March 30, 2023. Accessed July 10, 2023. https://forecastegy.com/posts/feature-importance-in-logistic-regression/#feature-importance-in-binary-logistic-regression (https://forecastegy.com/posts/feature-importance-in-logistic-regression/#feature-importance-in-binary-logistic-regression)

Kumar A. Accuracy, Precision, Recall & F1-Score - Python Examples. Data Analytics. Published

Logistic Regresion

We chose to use a logistic regression model because this is a classification issue and this model works well with categorical data. The model had a default penalty of L2.

A logistic regression model was iterated through with our scaled data. We removed collinear variables and used SMOTE to adjust for the class imbalance. The logistic regression model that performed the best was our SMOTE model with no colinear features and had an accuracy of

0.74 which was slightly better than our baseline accuracy of 0.68 and an F1 score of 0.68.

In [19]:
```
#establishing model
logreg = LogisticRegression(random_state=56)
```

Model 1: Bottom Tier Housing

We will use the bottom tier housing for modeling since it has the best class imbalance.

Selecting Our Target Variable and Features

Our target variable is increase and for our first iteration of modeling we will use all the available features.

In [20]:
```
#y is prediction variable
#X is features
y = bottom['increase']
X = bottom.drop(['City', 'HurricaneName', 'DATE', 'after', 'percent',
```

Train/Test Split

In order to know how well our model performs we need to test it on data it has not seen. We will use a train/test split to save 30% of our dataset for testing the model.

In [21]:
```
#performing train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
```

Scaling Our Data

Currently our dataset contains features that are measured in various way (price, speed, size), in order for our machine learning models to interpret these features they need to be on the same scale, so we will perform scaling.

In [22]:
```
#initiating Standard Scaler
sc = StandardScaler()
#fitting
sc.fit(X_train)
#tranforming X train and test
X_train = sc.transform(X_train)
X_test= sc.transform(X_test)
```

Training Data

Currently, this model is performing as well as the baseline model.

In [23]:
```
#fitting the model unto our training data
logreg.fit(X_train, y_train)
y_pred_train = logreg.predict(X_train)
```

In [24]:
```
#Printing Accuracy
print('Accuracy: %.3f' % accuracy_score(y_train, y_pred_train))
```

```
Accuracy: 0.684
```

In [25]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
print('F1 Score: %.3f' % f1_score(y_train, y_pred_train))
```

```
F1 Score: 0.311
```

Testing Data

The accuracy is slightly better than the baseline model and of 43 predictions 9 were false negatives and 2 were false positives. The AUC value is good and shows that the model is classifying correctly. The most important features were before and AWND.

In [26]:
```
#fitting the model unto our test data
logreg.fit(X_test, y_test)
y_pred_test = logreg.predict(X_test)
```

In [27]:
```
#Printing Accuracy
accuracy_1 = accuracy_score(y_test, y_pred_test)
print(accuracy_1)
```

```
0.7441860465116279
```

In [28]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
F1_1 = f1_score(y_test, y_pred_test)
print(F1_1)
```

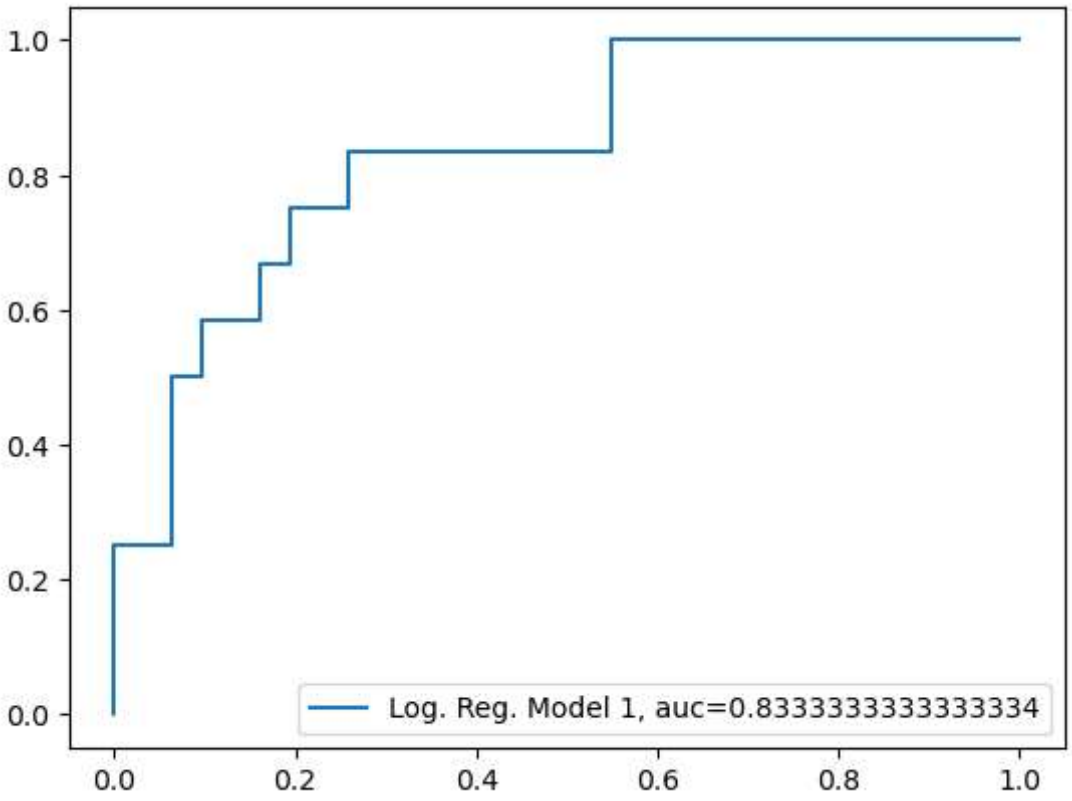
```
0.35294117647058826
```

In [29]:
```
#initiating dictionary to keep model accuracy and F1 score
model_dict = {}
#recording baseline model accuracy
model_dict['Baseline Accuracy'] = percent_bottom
#recording model 1 values
model_dict['LGRModel1_Accuracy'] = accuracy_1
model_dict['LGRModel1_F1'] = F1_1
model_dict
```

Out[29]:
```
{'Baseline Accuracy': 68.08510638297872,
 'LGRModel1_Accuracy': 0.7441860465116279,
 'LGRModel1_F1': 0.35294117647058826}
```

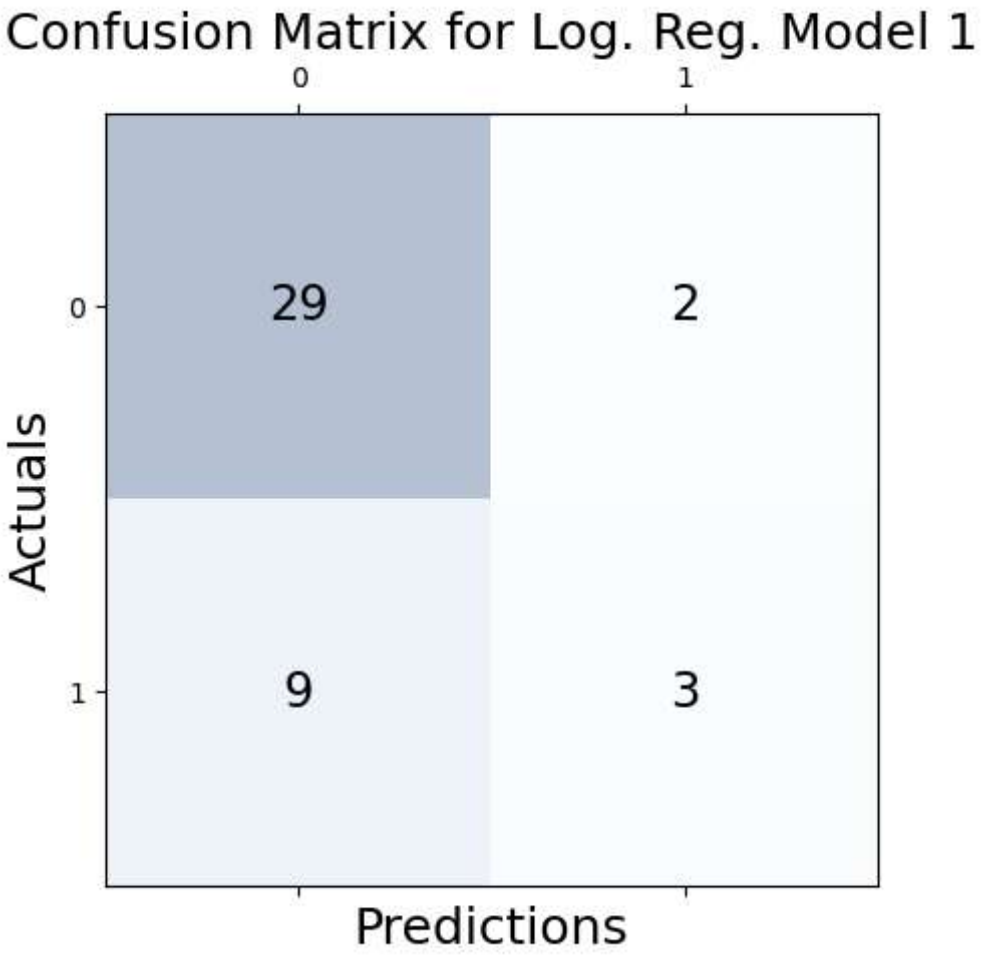
In [30]:

```
#let's check out the AUC curve
#getting probability
y_pred_prob = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_prob)
auc = metrics.roc_auc_score(y_test, y_pred_prob)

#plotting
plt.plot(fpr,tpr,label="Log. Reg. Model 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

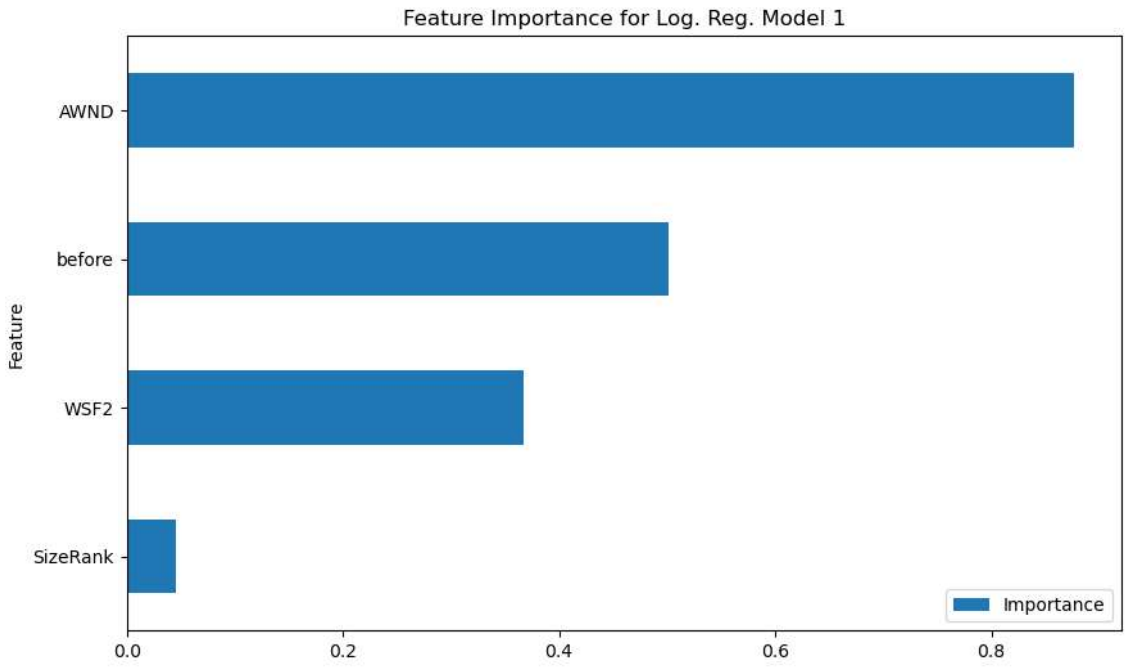


In [31]:

```
#getting confusion matrix values
conf_matrix = confusion_matrix(y_true=y_test, y_pred=y_pred_test)
#plotting
fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center'
#assigning labels
plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix for Log. Reg. Model 1', fontsize=18)
plt.show()
```



In [32]:
```
#checking out feature importance
#initiating model
model = LogisticRegression()
#fitting model
model.fit(X_train, y_train)
#getting coefficients
coefficients = model.coef_[0]
#plotting
feature_importance = pd.DataFrame({'Feature': X.columns, 'Importance':
feature_importance = feature_importance.sort_values('Importance', asce
feature_importance.plot(x='Feature', y='Importance', title='Feature Im
```



Model 2: Bottom Tier Housing Without Colinear Variables

We will use the bottom tier housing for modeling since it has the best class imbalance.

Selecting Our Target Variable and Features

Our target variable is increase and for our second iteration of modeling we will drop WSF2 because it's highly correlated with AWND.

In [33]:
```
#y is prediction variable
#X is features
y = bottom['increase']
X = bottom.drop(['City', 'HurricaneName', 'DATE', 'after', 'percent',
```

Train/Test Split

In [34]:
```
#performing train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
```

Scaling Our Data

In [35]:
```
#initiating Standard Scaler
sc = StandardScaler()
#fitting
sc.fit(X_train)
#tranforming X train and test
X_train = sc.transform(X_train)
X_test= sc.transform(X_test)
```

Training Data

The performance of this model is not better than the baseline model.

In [36]:
```
#fitting the model unto our training data
logreg.fit(X_train, y_train)
y_pred_train = logreg.predict(X_train)
```

In [37]:
```
#Printing Accuracy
print('Accuracy: %.3f' % accuracy_score(y_train, y_pred_train))
```

```
Accuracy: 0.684
```

In [38]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
print('F1 Score: %.3f' % f1_score(y_train, y_pred_train))
```

```
F1 Score: 0.311
```

Testing Data

Testing this model we do get better slightly better accuracy than before, meaning that dropping colinear features is effective in improving model performance. And we had one less false positive.

In [39]:
```
#fitting the model unto our test data
logreg.fit(X_test, y_test)
y_pred_test = logreg.predict(X_test)
```

In [40]:
```
#Printing Accuracy
accuracy_2 = accuracy_score(y_test, y_pred_test)
print(accuracy_2)
```

```
0.7674418604651163
```

In [41]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
F1_2 = f1_score(y_test, y_pred_test)
print(F1_2)
```

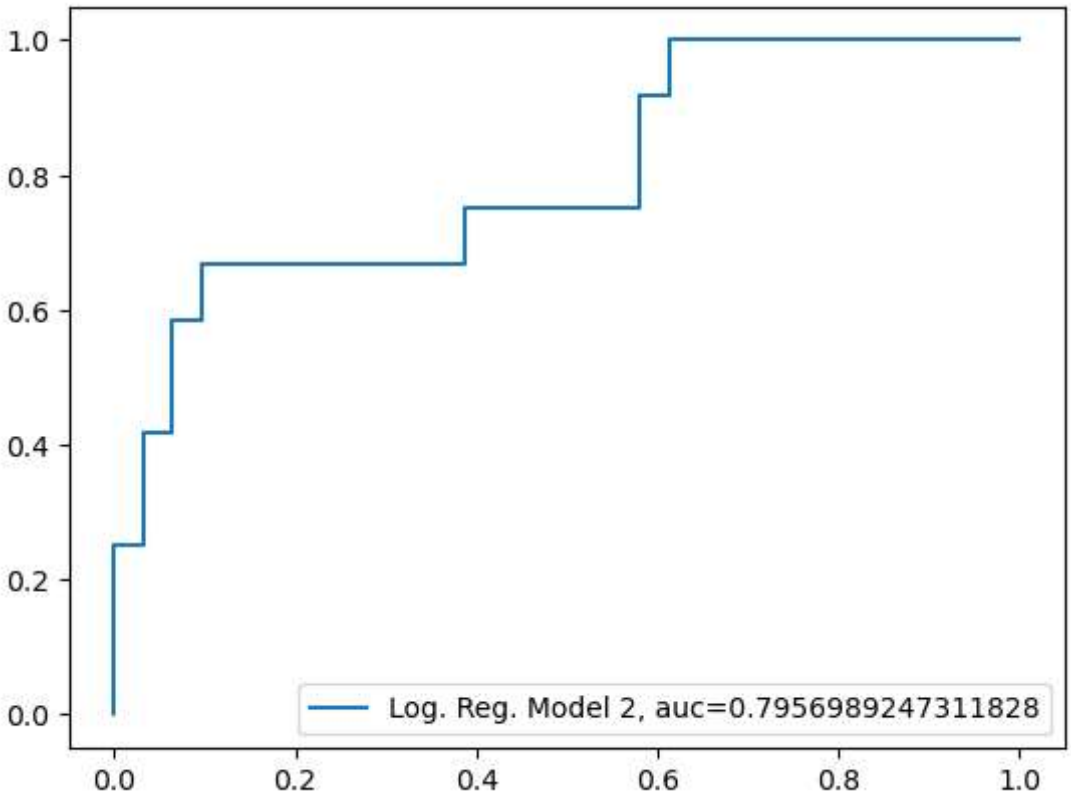
```
0.375
```

Saving to Dictionary

In [42]:
```
#adding to model dictionary
model_dict['LGRModel2_Accuracy'] = accuracy_2
model_dict['LGRModel2_F1'] = F1_2
model_dict
```

Out[42]:
```
{'Baseline Accuracy': 68.08510638297872,
 'LGRModel1_Accuracy': 0.7441860465116279,
 'LGRModel1_F1': 0.35294117647058826,
 'LGRModel2_Accuracy': 0.7674418604651163,
 'LGRModel2_F1': 0.375}
```

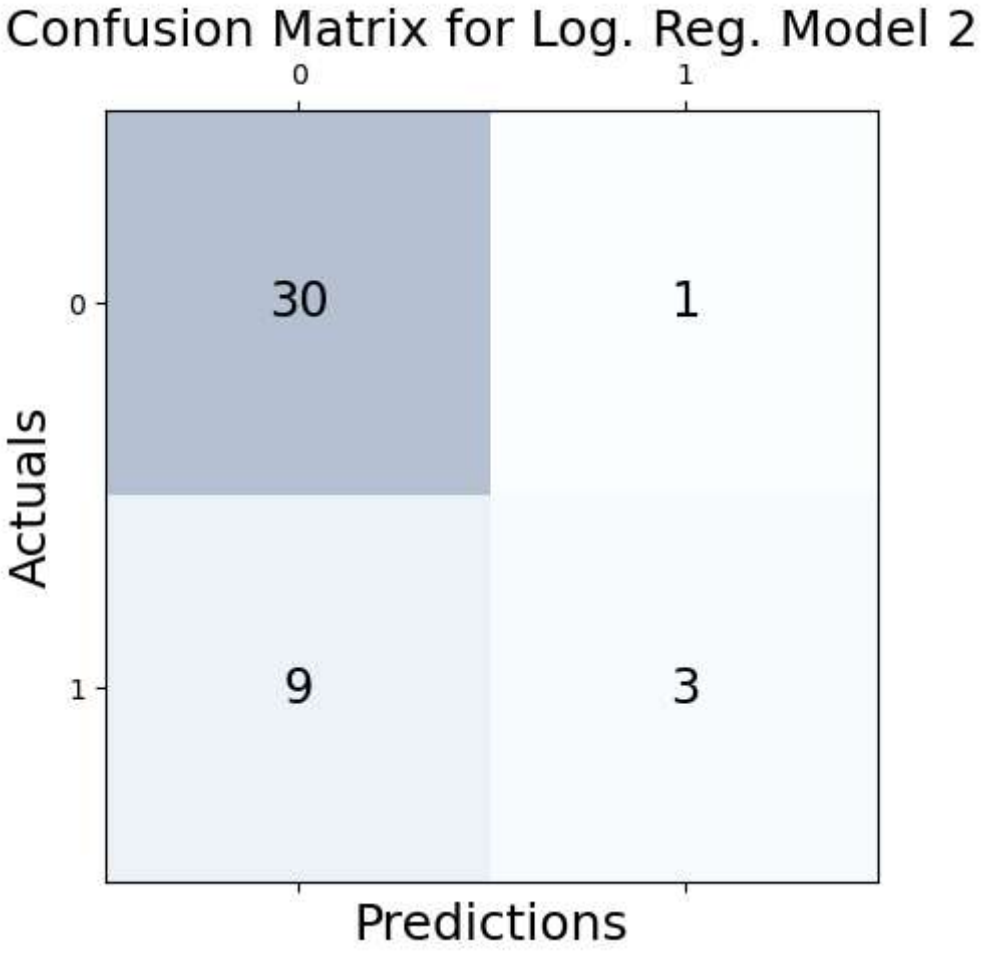
In [43]:
```
#let's check out the AUC curve
#getting probability
y_pred_prob = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_prob)
auc = metrics.roc_auc_score(y_test, y_pred_prob)

#plotting
plt.plot(fpr,tpr,label="Log. Reg. Model 2, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



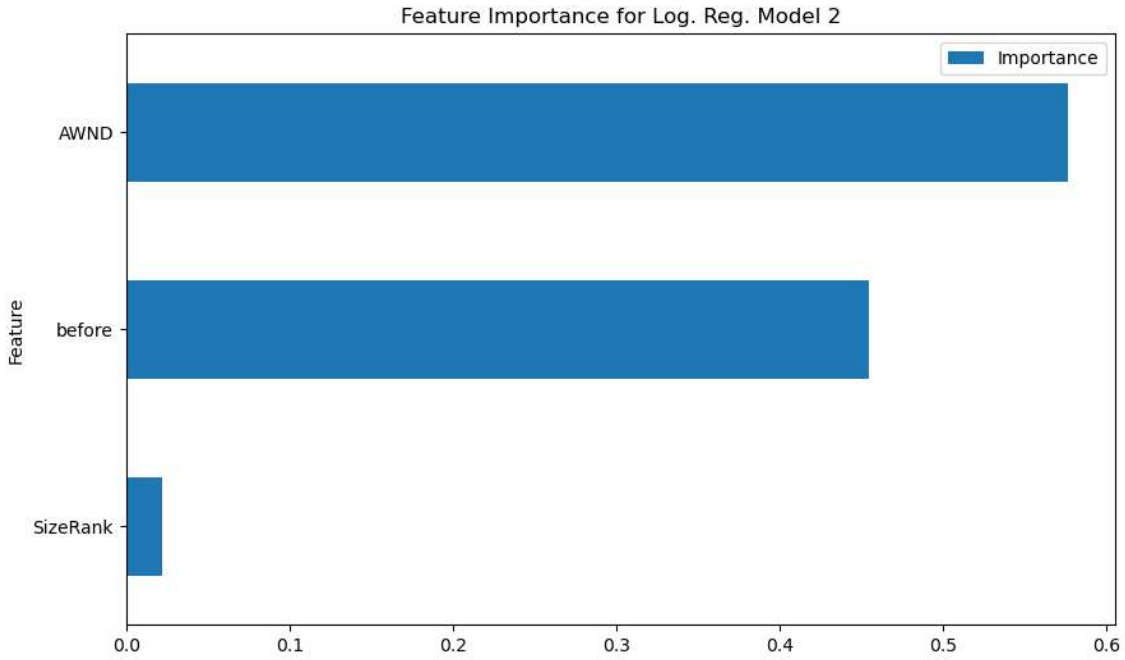
Confusion Matrix

In [44]:

```
#getting confusion matrix values
conf_matrix = confusion_matrix(y_true=y_test, y_pred=y_pred_test)
#plotting
fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center'
#assigning labels
plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix for Log. Reg. Model 2', fontsize=18)
plt.show()
```



In [45]:
```
#initiating model
model = LogisticRegression()
#fitting model
model.fit(X_train, y_train)
#getting coefficients
coefficients = model.coef_[0]
#plotting
feature_importance = pd.DataFrame({'Feature': X.columns, 'Importance':
feature_importance = feature_importance.sort_values('Importance', asce
feature_importance.plot(x='Feature', y='Importance', kind='barh', titl
```



Model 3: Bottom Tier Housing with Synthetic Minority Oversampling Technique (SMOTE)

Due to the class imbalance in our dataset SMOTE may be effective in improving our model performance. SMOTE can be used to increase the number of cases in our dataset in a balanced way.

In [46]:
```
#y is prediction variable
#X is features
y = bottom['increase']
X = bottom.drop(['City', 'HurricaneName', 'DATE', 'after', 'percent',
```

Train/Test Split

In [47]:
```
#performing train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
```

Scaling Our Data

In [48]:
```
#initiating Standard Scaler
sc = StandardScaler()
#fitting
sc.fit(X_train)
#tranforming X train and test
X_train = sc.transform(X_train)
X_test= sc.transform(X_test)
```

SMOTE

In [49]:
```
# Create instance of smotec
from imblearn.over_sampling import SMOTE,SMOTENC
# set sampling_strategy to 0.8 to avoid oversampling
smote = SMOTE(sampling_strategy=0.8, random_state=56)
```

In [50]:
```
# Create resampled version of the train dataset
SMOTE_X_train, SMOTE_y_train = smote.fit_resample(X_train, y_train)
# Create resampled version of the test dataset
SMOTE_X_test, SMOTE_y_test = smote.fit_resample(X_test, y_test)
```

In [51]:
```
#before smote
print('Before Smote\n', y_train.value_counts())

#after smote
print('\nAfter Smote\n', SMOTE_y_train.value_counts())
```

```
Before Smote
 0    65
1    33
Name: increase, dtype: int64

After Smote
 0    65
1    52
Name: increase, dtype: int64
```

Training Data

Our accuracy is worse than the baseline and previous models, but the F1 score is improving.

In [52]:
```
#fitting the model unto our training data
logreg.fit(SMOTE_X_train, SMOTE_y_train)
y_pred_train = logreg.predict(SMOTE_X_train)
```

Checking Metrics

In [53]:
```
#Printing Accuracy
print('Accuracy: %.3f' % accuracy_score(SMOTE_y_train, y_pred_train))
```

```
Accuracy: 0.641
```

In [54]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
print('F1 Score: %.3f' % f1_score(SMOTE_y_train, y_pred_train))
```

```
F1 Score: 0.553
```

Testing Data

The model accuracy on the testing data is better than the baseline, but slightly worse than the previous model. However, the F1 score did improve

In [55]:
```
#fitting the model unto our test data
logreg.fit(SMOTE_X_test, SMOTE_y_test)
y_pred_test = logreg.predict(SMOTE_X_test)
```

Checking Metrics

In [56]:
```
#Printing Accuracy
accuracy_3 = accuracy_score(SMOTE_y_test, y_pred_test)
print(accuracy_3)
```

```
0.7454545454545455
```

In [57]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
F1_3 = f1_score(SMOTE_y_test, y_pred_test)
print(F1_3)
```

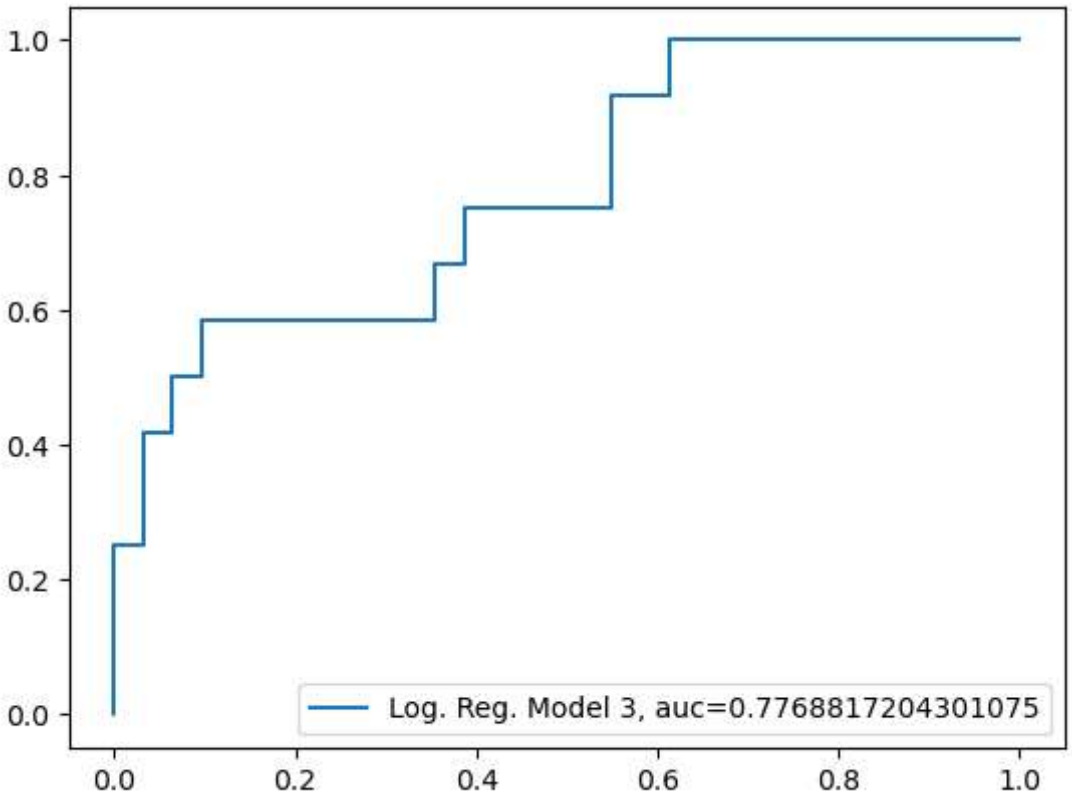
```
0.6818181818181818
```

In [58]:
```
#adding metrics to dictionary
model_dict['LGRModel3_Accuracy'] = accuracy_3
model_dict['LGRModel3_F1'] = F1_3
model_dict
```

Out[58]:
```
{'Baseline Accuracy': 68.08510638297872,
 'LGRModel1_Accuracy': 0.7441860465116279,
 'LGRModel1_F1': 0.35294117647058826,
 'LGRModel2_Accuracy': 0.7674418604651163,
 'LGRModel2_F1': 0.375,
 'LGRModel3_Accuracy': 0.7454545454545455,
 'LGRModel3_F1': 0.6818181818181818}
```

In [59]:

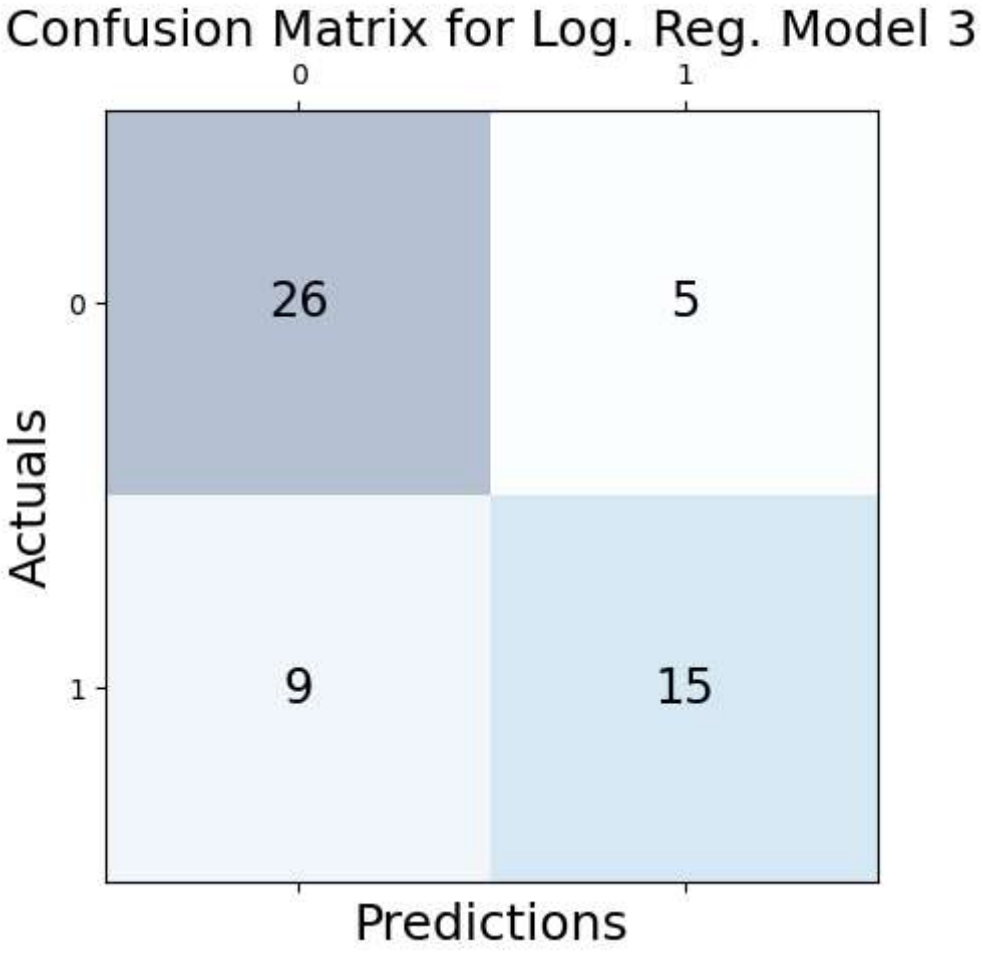
```
#let's check out the AUC curve
#getting probability
y_pred_prob = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_prob)
auc = metrics.roc_auc_score(y_test, y_pred_prob)

#plotting
plt.plot(fpr,tpr,label="Log. Reg. Model 3, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



Confusion Matrix

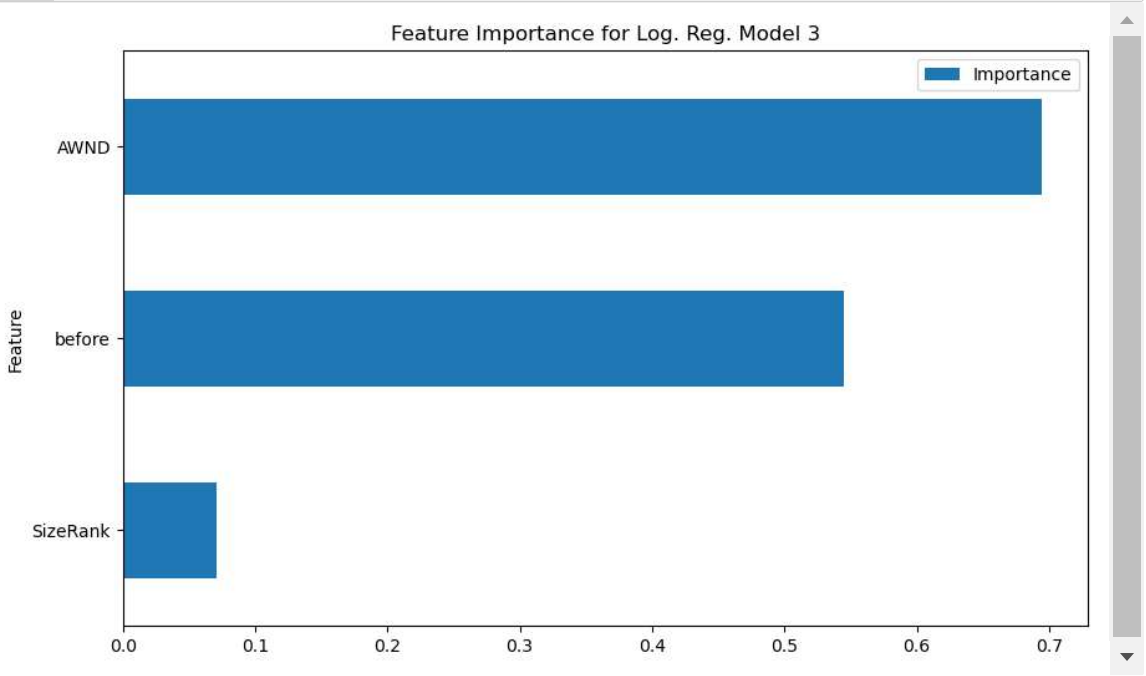
In [60]:

```
#getting confusion matrix values
conf_matrix = confusion_matrix(y_true=SMOTE_y_test, y_pred=y_pred_test
#plotting
fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center'
#assigning labels
plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix for Log. Reg. Model 3', fontsize=18)
plt.show()
```



Feature Importance

In [61]:
```
#initiating model
model = LogisticRegression()
#fitting model
model.fit(SMOTE_X_train, SMOTE_y_train)
#getting coefficients
coefficients = model.coef_[0]
#plotting feature_importance
feature_importance = pd.DataFrame({'Feature': X.columns, 'Importance':
feature_importance = feature_importance.sort_values('Importance', asce
feature_importance.plot(x='Feature', y='Importance', kind='barh', titl
```



XGBoost

In [62]:
```
#initiating model
xgb = XGBClassifier(random_state=56)
```

Selecting Our Target Variable and Features

Let's first run the model with all features.

In [63]:
```
#y is prediction variable
#X is features
y_boost = bottom['increase']
X_boost = bottom.drop(['City', 'HurricaneName', 'DATE', 'after', 'perc
```

Train/Test Split

In [64]:
```
#train/test splits with 30% test size
XG_X_train, XG_X_test, XG_y_train, XG_y_test = train_test_split(X_boos
```

Training Data

Using XG Boost we get perfect accuracy.

In [65]:
```
#fitting the model
xgb.fit(XG_X_train, XG_y_train);
```

In [66]:
```
#getting predictions
y_pred_train = xgb.predict(XG_X_train)
```

In [67]:
```
#Printing Accuracy
print('Accuracy: %.3f' % accuracy_score(XG_y_train, y_pred_train))
```

```
Accuracy: 1.000
```

In [68]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
print('F1 Score: %.3f' % f1_score(XG_y_train, y_pred_train))
```

```
F1 Score: 1.000
```

Testing Data

In [69]:
```
#fitting the model
xgb.fit(XG_X_test, XG_y_test);
```

In [70]:
```
#getting predictions
y_pred_test = xgb.predict(XG_X_test)
```

In [71]:
```
#Printing Accuracy
accuracy_XG1 = accuracy_score(XG_y_test, y_pred_test)
print(accuracy_XG1)
```

```
1.0
```

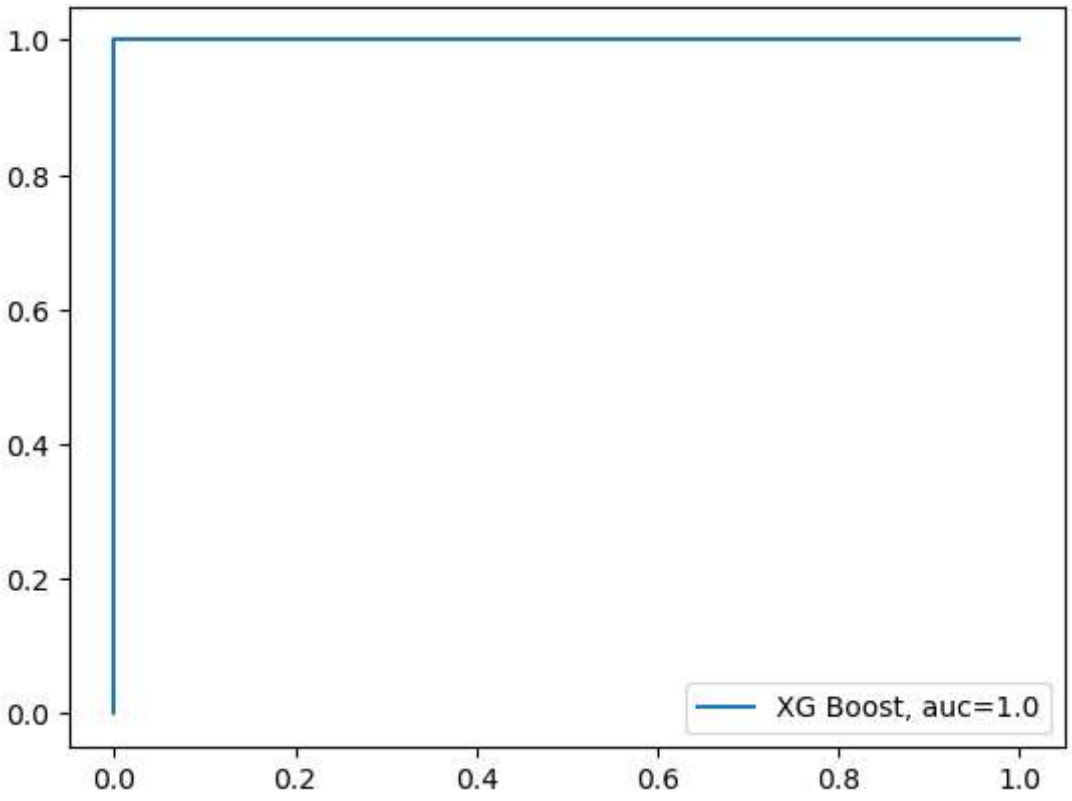
In [72]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
F1_XG1 = f1_score(XG_y_test, y_pred_test)
print(F1_XG1)
```

```
1.0
```

In [73]:
```
#adding values to dictionary
model_dict['XGBoost_Accuracy'] = accuracy_XG1
model_dict['XGBoost_F1'] = F1_XG1
model_dict
```

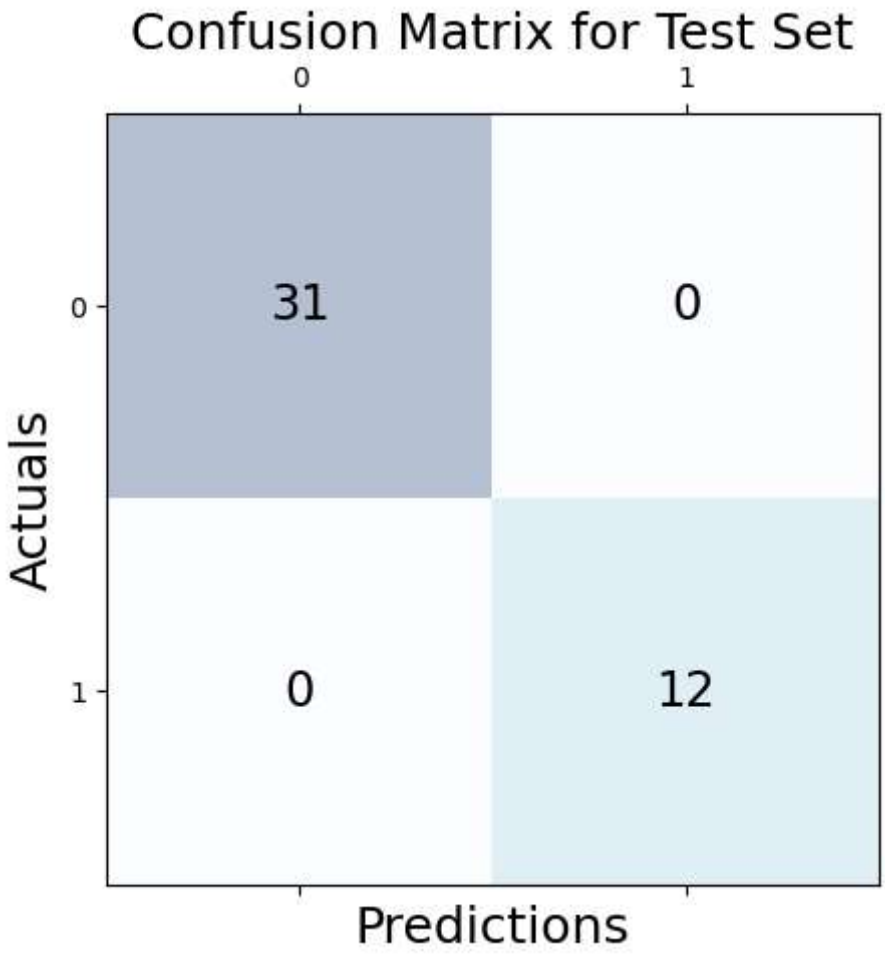
Out[73]:
```
{'Baseline Accuracy': 68.08510638297872,
 'LGRModel1_Accuracy': 0.7441860465116279,
 'LGRModel1_F1': 0.35294117647058826,
 'LGRModel2_Accuracy': 0.7674418604651163,
 'LGRModel2_F1': 0.375,
 'LGRModel3_Accuracy': 0.7454545454545455,
 'LGRModel3_F1': 0.6818181818181818,
 'XGBoost_Accuracy': 1.0,
 'XGBoost_F1': 1.0}
```

In [74]:
```
#let's check out the AUC curve
#getting probability
y_pred_prob = xgb.predict_proba(XG_X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(XG_y_test,  y_pred_prob)
auc = metrics.roc_auc_score(XG_y_test, y_pred_prob)

#plotting
plt.plot(fpr,tpr,label="XG Boost, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



In [75]:

```
#checking confusion matrix
conf_matrix = confusion_matrix(y_true=XG_y_test, y_pred=y_pred_test)

#plotting confusion matrix
fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center'

#assigning labels
plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix for Test Set', fontsize=18)
plt.show()
```



Feature Importance using SHAP (SHapley Additive exPlanations)

SHAP is used to explain the output of machine learning models. Using a beeswarm plot can reveal the importance of features and their relationship with the predicted outcome.

shap_values: is the average contribution of each of the features to the prediction for each sample based on alll the possible features.

From the plot below we can interpret that:

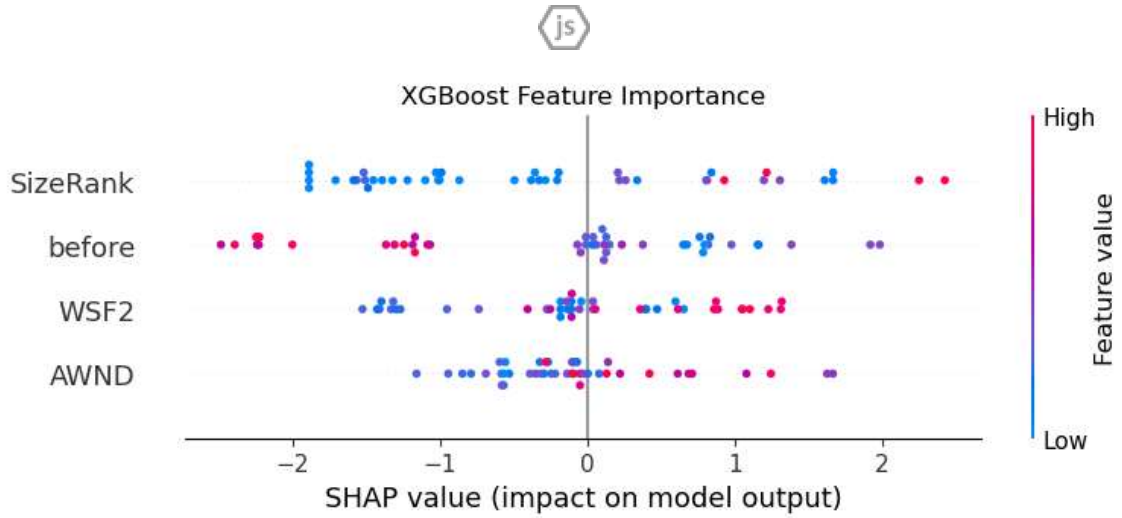
- larger SizeRank values have a higher impact on feature value
- smaller before values have a higher impact on feature value
- higher WSF2 and AWND values have higher impact on feature value

Works Cited

Classification Feature Selection : SHAP Tutorial. kaggle.com. Accessed July 6, 2023. https://www.kaggle.com/code/ritzig/classification-feature-selection-shap-tutorial#SHAP (https://www.kaggle.com/code/ritzig/classification-feature-selection-shap-tutorial#SHAP)

In [76]:

```
#Using SHAP to assess feature importance
#creating an explainer for our model
explainer = shap.TreeExplainer(xgb)

# finding out the shap values using the explainer
shap_values = explainer.shap_values(XG_X_test)

#creating a beeswarm plot
shap.initjs()
plt.title("XGBoost Feature Importance", y=1)
shap.summary_plot(shap_values, XG_X_test)
```



Best Model: XGBoost

We ran two types of models, logistic regression and XG Boost. The best logisitc regression model (model 3 with SMOTE) had an accuracy of 74% which is only slightly better than the majority percent of 68% and an F1 score of 0.68 on the testing data. Our best model was XGBoost which had a perfect accuracy and F1 score with the included features:

- AWND
- WSF2
- SizeRank
- before

While the logistic regression models had AWND as the top feature, the XG Boost model had SizeRank as the top feature.

In [77]:
```
#pulling up model accuracy and F1 score for all models
model_dict
```

Out[77]:
```
{'Baseline Accuracy': 68.08510638297872,
 'LGRModel1_Accuracy': 0.7441860465116279,
 'LGRModel1_F1': 0.35294117647058826,
 'LGRModel2_Accuracy': 0.7674418604651163,
 'LGRModel2_F1': 0.375,
 'LGRModel3_Accuracy': 0.7454545454545455,
 'LGRModel3_F1': 0.6818181818181818,
 'XGBoost_Accuracy': 1.0,
 'XGBoost_F1': 1.0}
```

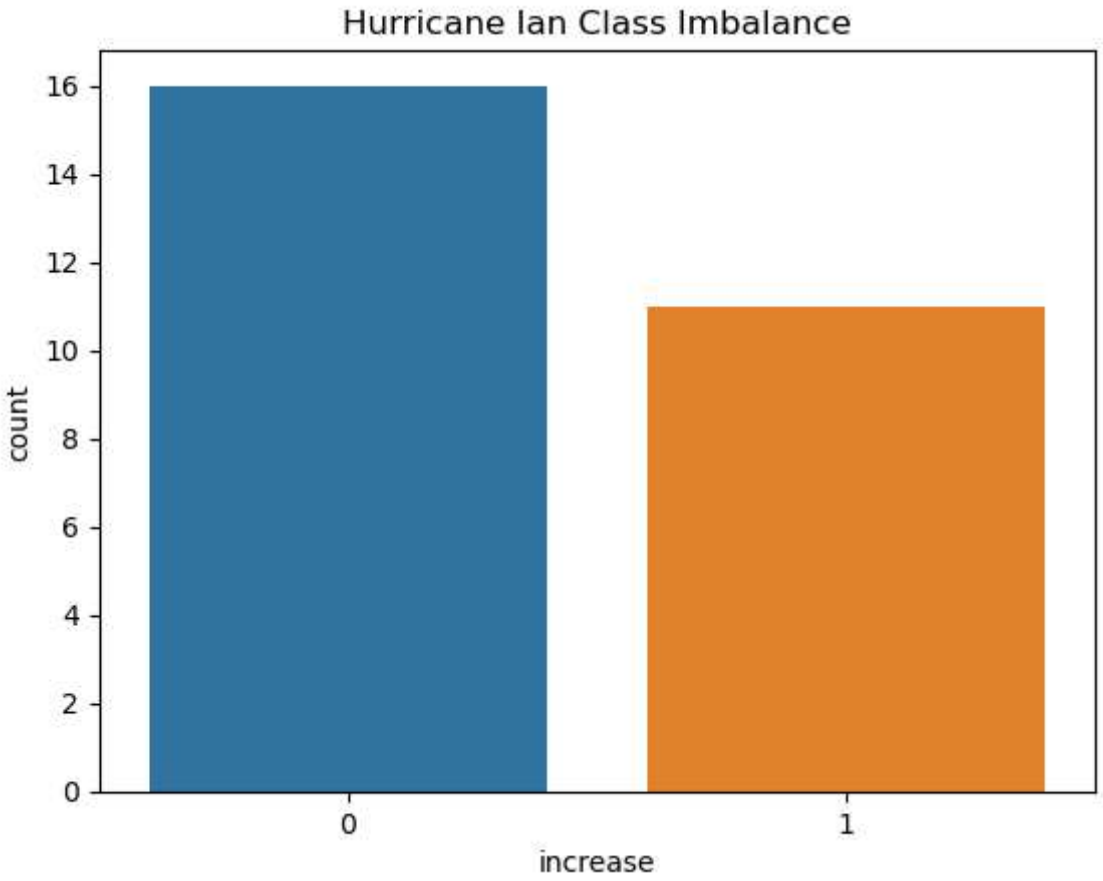
Model Validation

In order to know how the model would perform on real world data we will validate it using data from Hurricane Ian. This is data the model has never seen. The model performed with 74% accuracy which is better than the baseline accuracy of 59%. And had an F1 score of 0.533 and an AUC value of 0.92. Of 27 predictions 7 were false negatives and none were false positives.

XGBoost on Hurricane Ian Data

In [78]:
```
# Checking the balance of target variable 'increase'
#plotting
sns.countplot(x='increase', data=all_ian).set(title='Hurricane Ian Cla
#print value counts
print(all_ian['increase'].value_counts())
#checking ratio to see what accuracy is like
percent = (len(all_ian['increase']) - all_ian['increase'].sum())/(len(
print("majority percent is {}".format(percent),"%")
```

```
0    16
1    11
Name: increase, dtype: int64
majority percent is 59.25925925925925 %
```



Selecting Our Target Variable and Features

In [79]:
```
#y is target variable
#X is features
y_ian = all_ian['increase']
X_ian = all_ian.drop(['City', 'HurricaneName', 'DATE', 'after', 'perce
```

In [80]:
```
#getting prediction
y_pred = xgb.predict(X_ian)
```

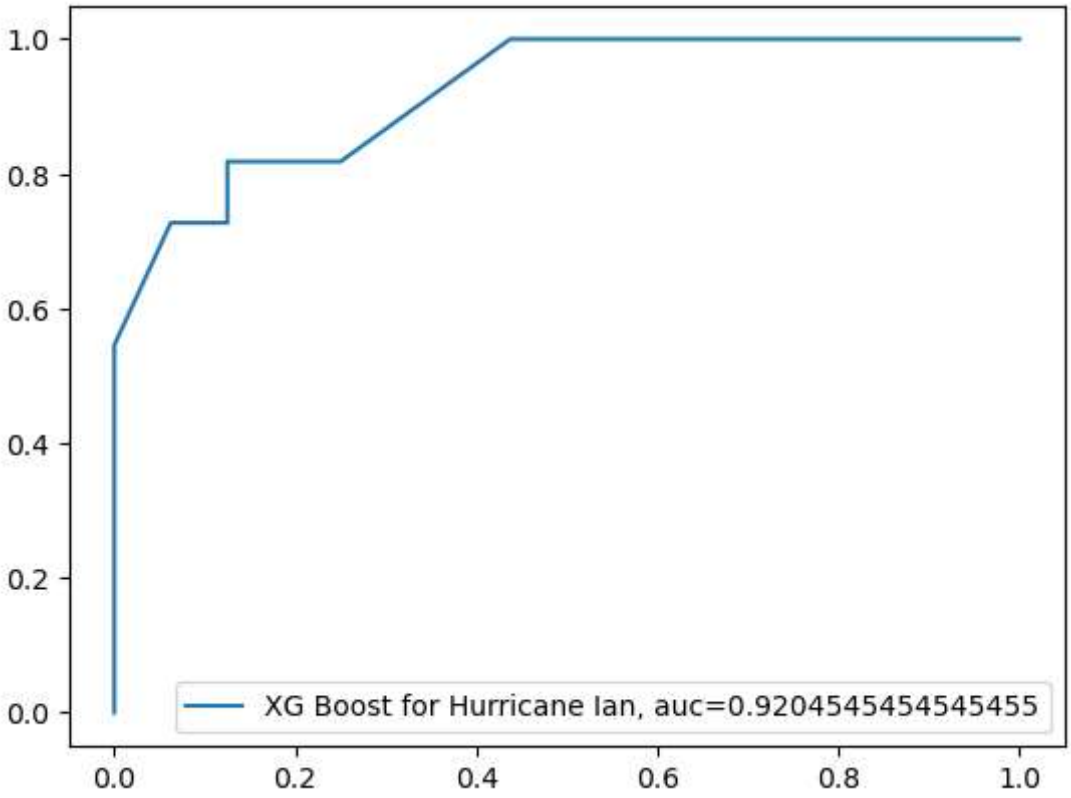
In [81]:
```
#Printing Accuracy
print('Accuracy: %.3f' % accuracy_score(y_ian, y_pred))
```

```
Accuracy: 0.741
```

In [82]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
print('F1 Score: %.3f' % f1_score(y_ian, y_pred))
```

```
F1 Score: 0.533
```

In [83]:
```
#let's check out the AUC curve
#getting probability
y_pred_prob = xgb.predict_proba(X_ian)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_ian,  y_pred_prob)
auc = metrics.roc_auc_score(y_ian, y_pred_prob)

#plotting
plt.plot(fpr,tpr,label="XG Boost for Hurricane Ian, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



Confusion Matrix

As seen below 7 false negatives were predicted. Meaning home value was predicted not to increase, but it did.

In [84]:

```
conf_matrix = confusion_matrix(y_true=y_ian, y_pred=y_pred)

fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center'

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix for Validation Set', fontsize=18)
plt.show()
```