What brings people to parks?

Using social media, amenities and park accessibility to predict park visitation rates

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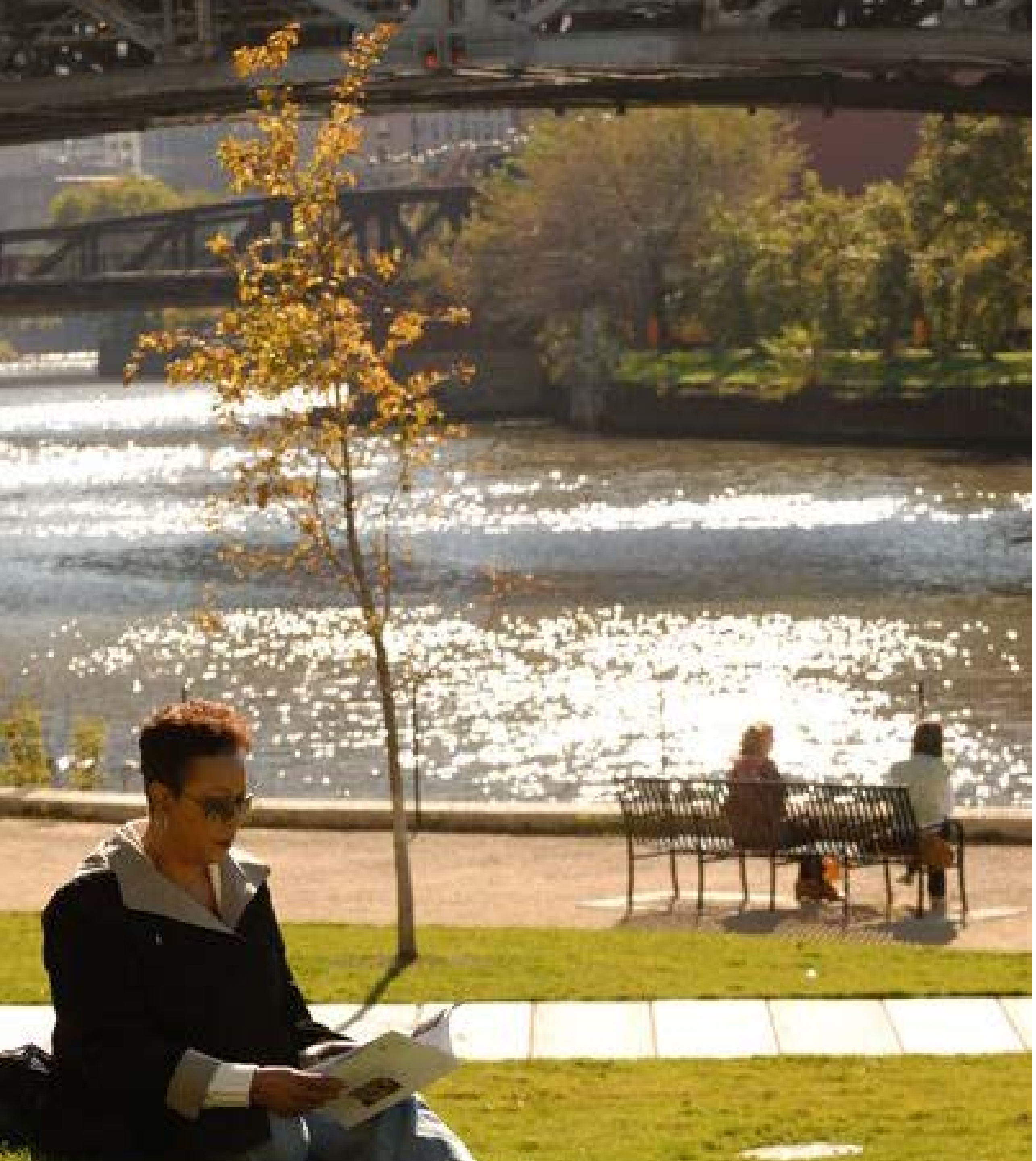

What brings people to parks?

Why do park users choose one over the other?

- **Hypothesis:** Park usage (i.e. the number of geolocated tweets within a park boundary) can be predicted through park size, the number and types of amenities in the park, and the number of people living with a 10-minute walk of the park.

What brings people to parks?

Who cares and why?

- City officials
- Park professionals
- Community members
- Conservation organizations
- Landscape architects
- Social equity organizations

What brings people to parks?

Data Sources

- NYC Parks and Recreation Department
    - Park locations
    - General park attributes (e.g. park size, park type)
    - Park amenities
- The Trust for Public Land's ParkServe® database
    - 10-minute walk park statistics
- Twitter Streaming API

NYC Parks

Image source: *Friends of the High Line*

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What brings people to parks?

Data Wrangling

- Get amenity count for each park (total and for each amenity)
- Join 10-minute walk statistics

```
# group by park ID and get the count of amenities of interest
athletics_count_df = athletics_df.groupby('gispropnum')[['handball','tennis','basketball','adult_soft', 't
rack_and']].apply(lambda x: x[x=='Yes'].count())
athletics_count_df.head()
```

	handball	tennis	basketball	adult_soft	track_and
gispropnum					
B001	2	0	2	0	0
B007	6	8	4	3	0
B008	12	0	6	2	0
B012	1	0	2	0	0
B016	4	0	3	0	0

```
parks_features_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1705 entries, 0 to 1704
Data columns (total 33 columns):
GISPROPNUM          1705 non-null object
BOROUGH             1705 non-null object
ACRES               1705 non-null float64
SIGNNAME            1705 non-null object
TYPECATEGO          1705 non-null object
handball            1705 non-null float64
tennis              1705 non-null float64
basketball          1705 non-null float64
adult_soft          1705 non-null float64
track_and           1705 non-null float64
play_area_count     1705 non-null float64
preserve_count      1705 non-null float64
spray_count         1705 non-null float64
OBJECTID            1705 non-null int64
TPL_P_NAME          1705 non-null object
FREQUENCY           1705 non-null int64
SUM_SVCAREA         1705 non-null float64
SUM_TOTPOPSVCA      1705 non-null int64
SUM_KIDSVCA         1705 non-null int64
SUM_YOUNGPROSVCA    1705 non-null int64
SUM_SENIORSVCA      1705 non-null int64
SUM_HHILOWSVCA      1705 non-null int64
SUM_HHIMEDSVCA      1705 non-null int64
SUM_HHIHIGHSVCA     1705 non-null int64
SUM_TOTHHSVCA       1705 non-null int64
SUM_WHITE_SVC       1705 non-null int64
SUM_BLACK_SVC       1705 non-null int64
SUM_AMERINDSVC      1705 non-null int64
SUM_ASIAN_SVC       1705 non-null int64
SUM_PACIFICSVC      1705 non-null int64
SUM_OTHRACESVC      1705 non-null int64
SUM_RACE2UPSVC      1705 non-null int64
SUM_HISP_SVC        1705 non-null int64
```

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What brings people to parks?

Data Wrangling

- Choose random sample of 1,705 NYC parks
- Collect geolocated tweets in JSON and parse to CSV

```
In [12]: #take random sample of parks in parks csv
         testy_test = np.random.choice(parks_df.index, 100)
         print(testy_test)
         parks_rand_s = pd.Series(testy_test)

['M007' 'M280' 'Q444' 'M358' 'X336' 'R028' 'Q009' 'X289' 'M278' 'B429'
 'B357' 'M256' 'R098' 'M249' 'B058' 'B085' 'B337' 'B357' 'M017' 'B042'
 'R165' 'R020' 'X536' 'Q561' 'R505' 'B590' 'B261' 'B324' 'M517' 'M025'
 'R117' 'Q266' 'R126' 'B582' 'M079' 'B334' 'B219' 'Q523' 'X292' 'B302'
 'M365' 'Q267' 'M238' 'QT20' 'B121' 'Q354' 'Q544' 'M241' 'X137' 'X291'
 'B359' 'X201' 'X131' 'X365' 'B251' 'Q557' 'Q471' 'R524' 'B432' 'Q051'
 'X508' 'B209' 'Q102' 'X126' 'X266A' 'Q536' 'B565' 'X302' 'B210W' 'Q563'
 'M231' 'M082' 'Q293' 'Q294' 'B154' 'X515' 'M402' 'X180' 'M323' 'B223NA'
 'M127' 'M194' 'BT10' 'B019' 'Q362' 'R059' 'B265' 'X259' 'BT03' 'X040'
 'X080' 'Q165' 'M130' 'X182' 'B210P' 'Q475' 'M198' 'R079' 'Q011' 'X365']

In [13]: parks_rand_s.to_csv(r'Y:/Springboard/Parks_RandSample.csv')
```

```
out_file.write(str(tweet['id_str'])+ ',' + str(tweet['user']['screen_name']) + ',' +
               str(tweet['text']).replace(',',' ').replace("\n",'').replace("\r","").replace('"','').lstrip().lstrip('-') +
               ','+ d.strftime('%Y%m%d') + ',' + str(tweet['geo']['coordinates'][0]) + ',' + str(tweet['geo']['coordinates'][1]) + "\n")
```

Above code snippet originally obtained from Natural Capital Project and modified for use in this project

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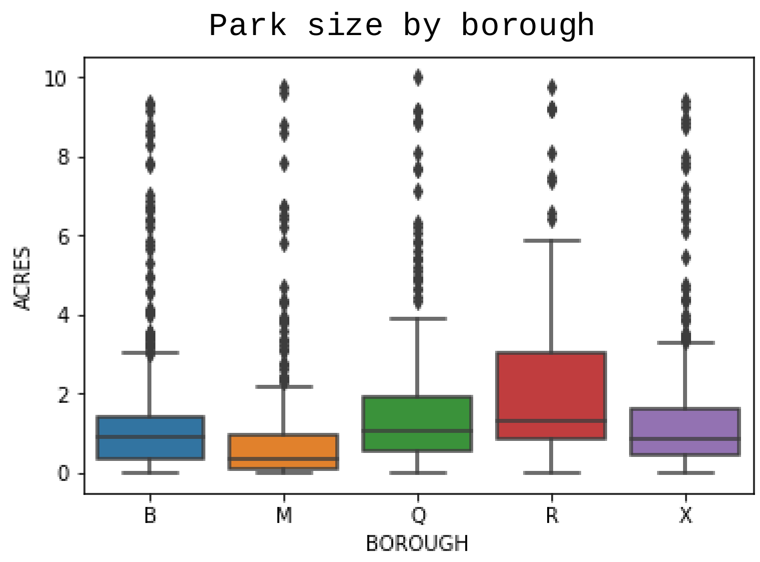
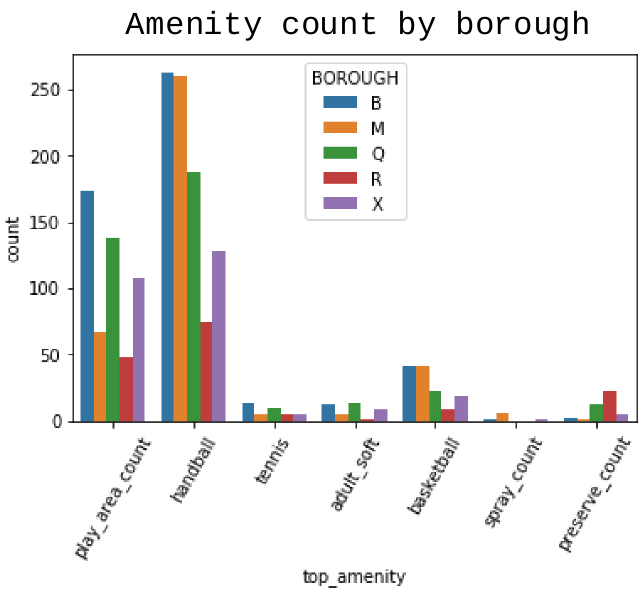
What brings people to parks?

Initial Findings – Park attributes

- Amenity count does not appear to be strongly correlated with park size
- Manhattan has the lowest median # of park amenities and Queens has the highest.
- Staten Island has the largest parks on average
- No strong correlation between # of people within a 10-minute walk and park size, or # of people within a 10-minute walk and amenity count.
- Handball courts are the most popular amenities in NYC parks.





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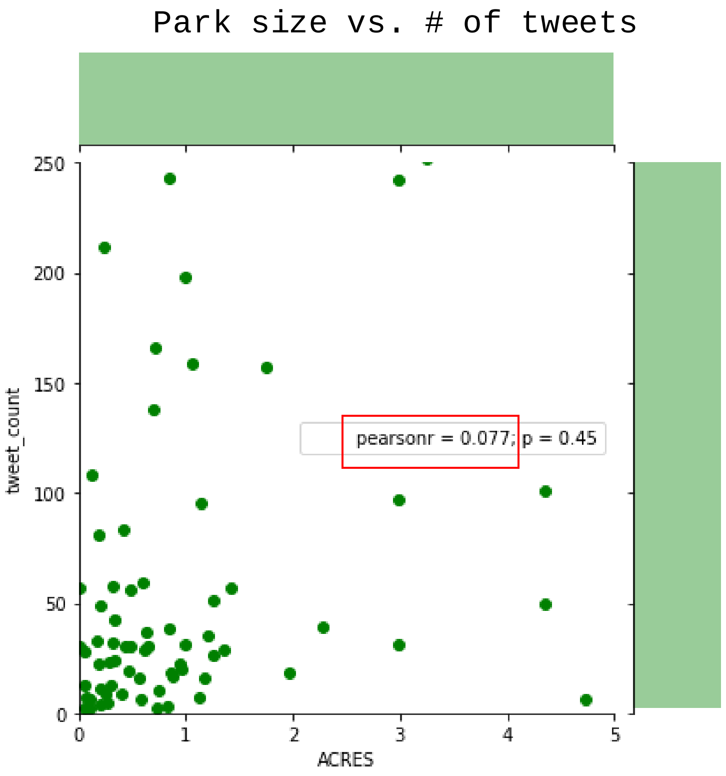
What brings people to parks?

Initial Findings – Park attributes and tweets

- The number of tweets within a park boundary is **not linearly correlated** with park size, total number of park amenities, or number of people living within a 10-minute walk of a park.
- I **did not find any significant difference** in means for small vs. large parks and # of tweets, parks with many amenities vs parks with few amenities and # of tweets, or parks with many people living within a 10-minute walk vs. parks with few people living within a 10-minute walk and # of tweets.




```
# run significance test for mean park usage per year and total # of park amenities

fewAmenities = parksInfo.loc[parksInfo.total_amenities<1]['tweet_count']
manyAmenities= parksInfo.loc[parksInfo.total_amenities>5]['tweet_count']

# null = available amenities does not impact the # of tweets
# alt = parks with more amenities have more tweets

sample_diff_means = diff_of_means(fewAmenities,manyAmenities)
print(sample_diff_means)

# Acquire permutation samples
perm_replicates = draw_perm_reps(fewAmenities, manyAmenities, diff_of_means, 1000)
print(np.percentile(perm_replicates, [0.5,99.5]))

# Compute and print p-value: p
p = np.sum(perm_replicates <= sample_diff_means) / float(len(perm_replicates))
print('p-value = {}'.format(p))
```

```
165.98255814
[-1210.96947674   966.0840298 ]
p-value = 0.504
```

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Predicting park visitation

Machine Learning – Random Forest Regressor

```
from sklearn.preprocessing import normalize

y = np.array(parksInfo.tweet_count)
X = parksInfo_dummied
#X_norm = normalize(X)

from sklearn.model_selection import train_test_split

train_X, test_X, train_y, test_y = train_test_split(X, y,
```

```
from sklearn.model_selection import GridSearchCV

# Create the parameter grid using list of set values
param_grid = {'n_estimators': [100, 200, 300, 1000, 5000]}

rf = RandomForestRegressor()

grid_search = GridSearchCV(estimator = rf, param_grid = param_grid)

grid_search.fit(train_X, train_y)
grid_search.best_params_
```

```
{'n_estimators': 100}
```

```
rf = RandomForestRegressor(n_estimators = 100)
# Train the model on training data
rf.fit(train_X, train_y)
predict_test = rf.predict(test_X)

print "Train R-squared :: ", rf.score(train_X, train_y)
print "Test R-squared  :: ", rf.score(test_X, test_y)
```

```
Train R-squared ::  0.8653115296513108
Test R-squared  ::  0.25302542372881365
```

- Results are not too great.

  Let’s try to do better than this!

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Predicting park visitation

Machine Learning – Random Forest Classifier

```
# look at distribution of tweets counts to determine class thresholds
parksInfo_dummied.tweet_count.describe()
```

```
count       98.00000
mean       568.55102
std       2435.58974
min          2.00000
25%         22.00000
50%         53.50000
75%        242.75000
max      22373.00000
Name: tweet_count, dtype: float64
```

```
# in the future, use pandas.cut
def label_tweets (row):
   if row['tweet_count'] <= 30:
     return 0
   if row['tweet_count'] > 30 and row['tweet_count'] <= 200:
     return 1
   else:
     return 2

parksInfo_dummied['tweet_class'] = parksInfo_dummied.apply(lambda row: label_tweets (row),axis=1)
parksInfo_dummied.head()
```

```
# Create the parameter grid based on the results of range
param_grid = {'n_estimators': range(1,50)}
# Create a based model
rf = RandomForestClassifier()
# Instantiate the grid search model
grid_search = GridSearchCV(estimator = rf, param_grid =

grid_search.fit(train_X, train_y)
grid_search.best_params_
```

```
{'n_estimators': 17}
```

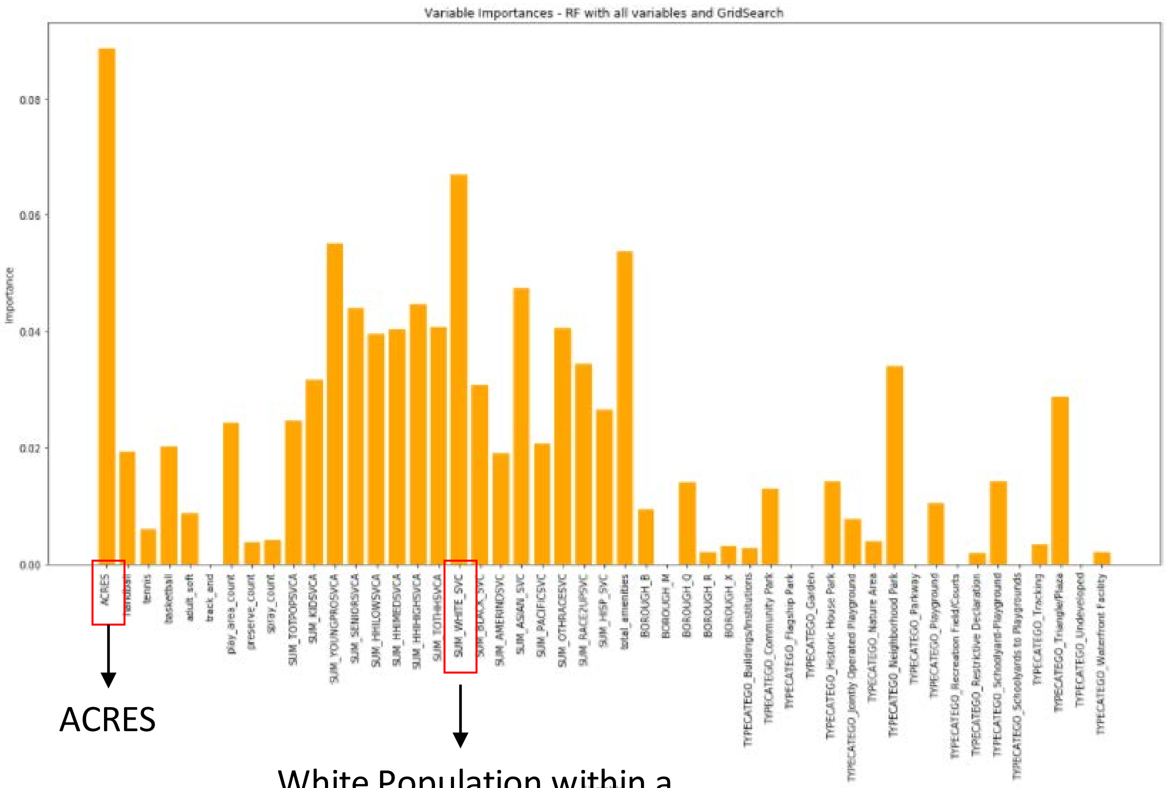
```
rf = RandomForestClassifier(n_estimators=17)
# Train the model on training data
rf.fit(train_X, train_y)

predict_test = rf.predict(test_X)

print "Train Accuracy :: ", accuracy_score(train_y, rf.p
print "Test Accuracy  :: ", accuracy_score(test_y, predi
```

```
Train Accuracy ::  0.9871794871794872
Test Accuracy  ::  0.65
```

OK, but not good enough!



ACRES

White Population within a 10-minute walk

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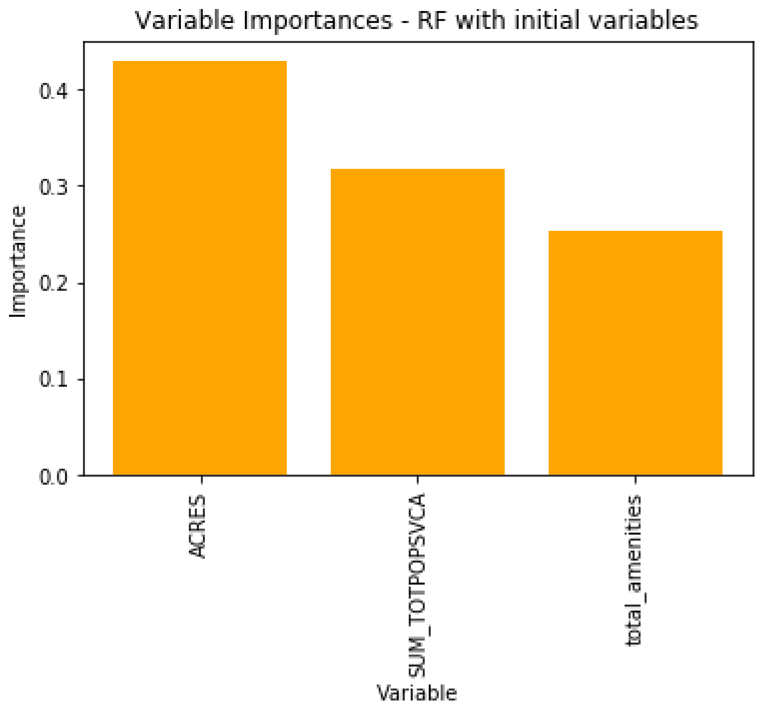
Predicting park visitation

Machine Learning – Random Forest Classifier

Let's look at the accuracy with the 3 initial variables of interest...

```
: parksInfo_sub = parksInfo_dummied[['ACRES','SUM_TOTPOPSVCA','total_amenities',]]

  y = np.array(parksInfo_dummied.tweet_class)
  X = parksInfo_sub

  train_X, test_X, train_y, test_y = train_test_split(X, y, test_size = 0.2, random_state = 42)

  # Create the parameter grid based on the results of range
  param_grid = {'n_estimators': range(1,50)}
  # Create a based model
  rf = RandomForestClassifier()
  # Instantiate the grid search model
  grid_search = GridSearchCV(estimator = rf, param_grid = param_grid)

  grid_search.fit(train_X, train_y)
  grid_search.best_params_

: {'n_estimators': 43}

: rf = RandomForestClassifier(n_estimators=43)
  rf.fit(train_X, train_y)

  predict_test = rf.predict(test_X)


  print "Train Accuracy :: ", accuracy_score(train_y, rf.predict(train_X))
  print "Test Accuracy  :: ", accuracy_score(test_y, predict_test)

  Train Accuracy ::  0.9871794871794872
  Test Accuracy  ::  0.45
```



Definitely not good enough!

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Predicting park visitation

Conclusions and Next Steps

Datasets for further investigation:

- **Public transportation**
- **More amenities**
- **Crime statistics**
- **Park programming/rental facilities**

Using the data at hand, park size, the number and type of amenities, and the number of people living within a 10-minute walk of the park **are not reliable predictors of park usage**, yet bringing more variables into the analysis strengthens the model.

Questions for further consideration:

- **Is the number of tweets within a park truly representative of park usage/visitation?**
- **Define local perception of a high-quality park. Are high quality parks more likely to have a higher number of tweets?**
- **Can the number of tweets predict park attributes, such as park type (e.g. community, pocket, regional) and park size?**

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Thank you.

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