CS 109A/STAT 121A/AC 209A/CSCI E-109A:

Spotify Final Project: Group 31

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In [1]:
```
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
from sklearn import linear_model
from sklearn.preprocessing import PolynomialFeatures
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.tree import export_graphviz
from sklearn.neighbors import KNeighborsRegressor
from IPython.display import display
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score
import statsmodels.api as sm
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import LassoCV
import operator
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

```
/Users/emilychen1/anaconda/lib/python3.6/site-packages/statsmodels/compa
t/pandas.py:56: FutureWarning: The pandas.core.datetools module is deprec
ated and will be removed in a future version. Please use the pandas.tseri
es module instead.
  from pandas.core import datetools
```

Spotify Predictors Only

Shotgun Phase

Shotgun Phase

In [2]:
```
# read csv of spotify predictors
df = pd.read_csv('spotify_predictors.csv')
df = df.dropna()
df = df.drop(['Unnamed: 0'], 1)
```

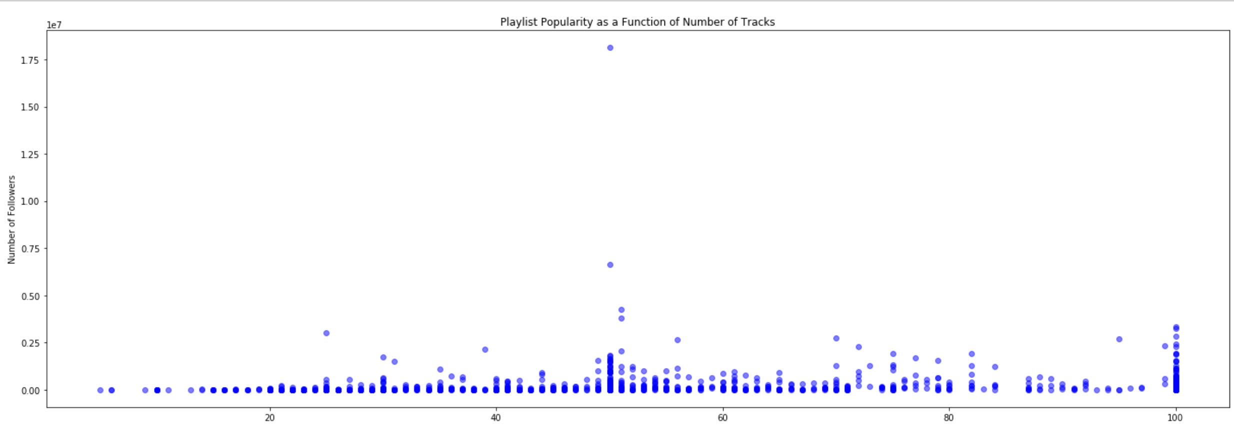
In [3]:
```
# split data
np.random.seed(9001)
msk = np.random.rand(len(df)) < 0.75
data_train = df[msk]
data_test = df[~msk]

pd.set_option('display.max_columns', 100)
data_train.head()
```

Out[3]:

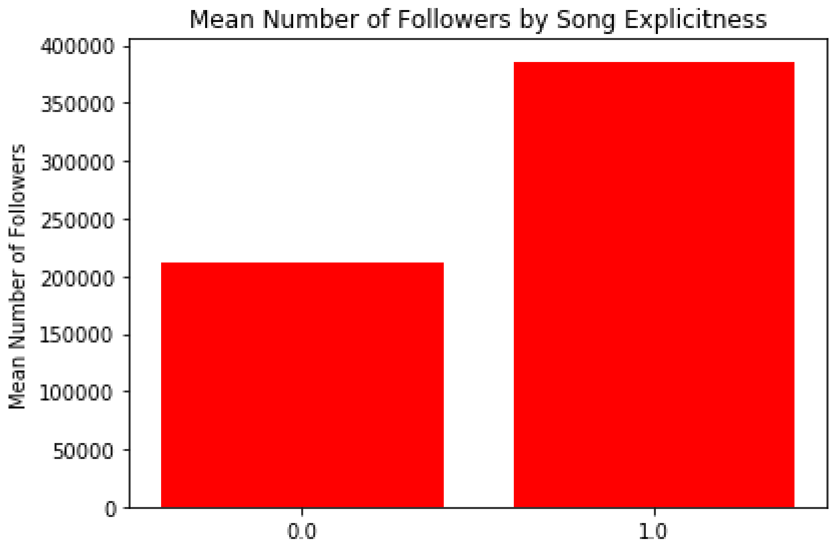
	followers	majority_artist_genres	name	owner	track_ids	num_tracks	av
0	18129916	pop	Today's Top Hits	spotify	['0tBbt8CrmxbjRP0pueQkyU', ' 2amzBJRBPOGszBem4...	50	
3	3787551	indie r&b	Are & Be	spotify	['6gU9OKjOE7ghfEd55oRO57', ' 25wStx3LyTjYmHTd3...	51	
5	4254642	contemporary country	Hot Country	spotify	['54EWDYWhs4w6SODnxabuoh', ' 7rdK9NSJIRBZAiXC0...	51	
6	6639722	latin	¡Viva Latino!	spotify	['2hl6q70unbviGo3g1R7uFx', ' 2SmgFAhQkQCQPyBiB...	50	
9	3323766	focus	Peaceful Piano	spotify	['1JoAjYal3zvhXVx41HH7Fc', ' 7ih16mauHrpUMOIeW...	100	

EDA

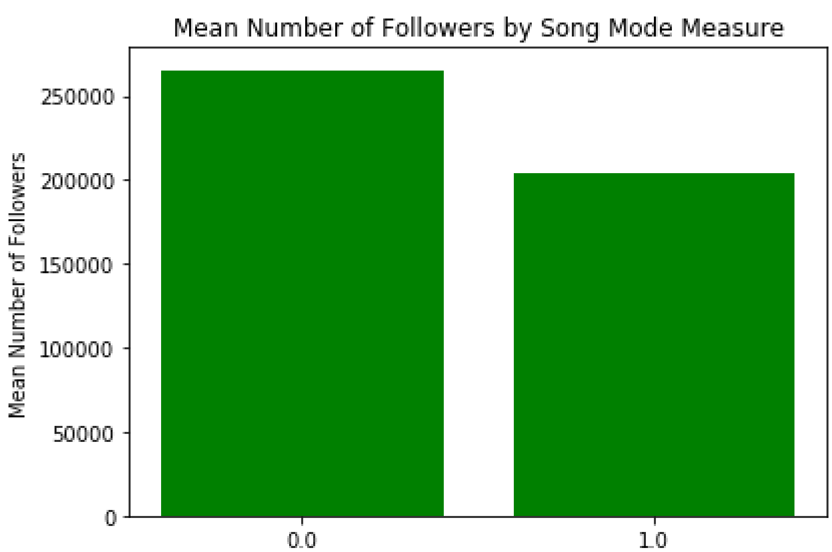
In [4]:
```
plt.figure(figsize=(20,7))
plt.scatter(data_train['num_tracks'], data_train['followers'], color='b', al
plt.xlabel('Number of Tracks')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Number of Tracks')

plt.tight_layout()
plt.savefig('num_tracks.png')
```



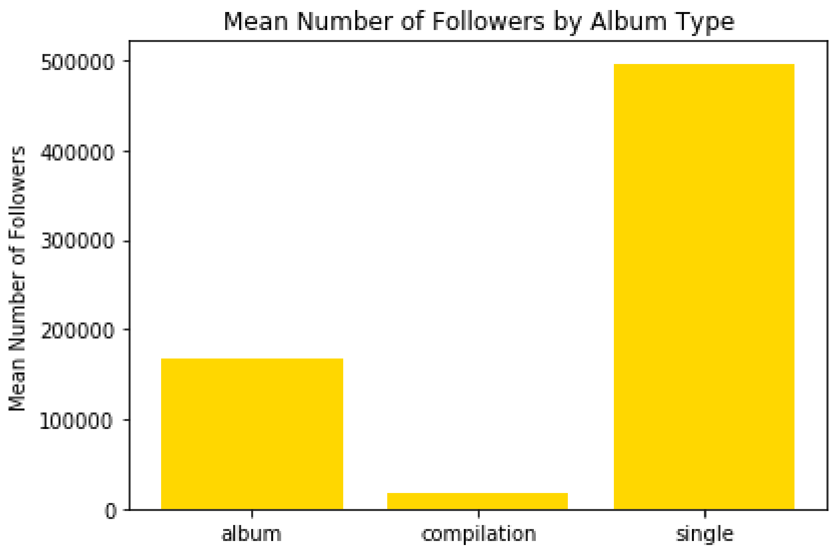
In [5]:
```
by_explicit = data_train.groupby('majority_explicit')
explicit_means = by_explicit['followers'].mean()
plt.bar(range(len(explicit_means)),explicit_means,tick_label=list(explicit_m
plt.ylabel('Mean Number of Followers')
plt.title('Mean Number of Followers by Song Explicitness')

plt.tight_layout()
plt.savefig('explicit.png')
```



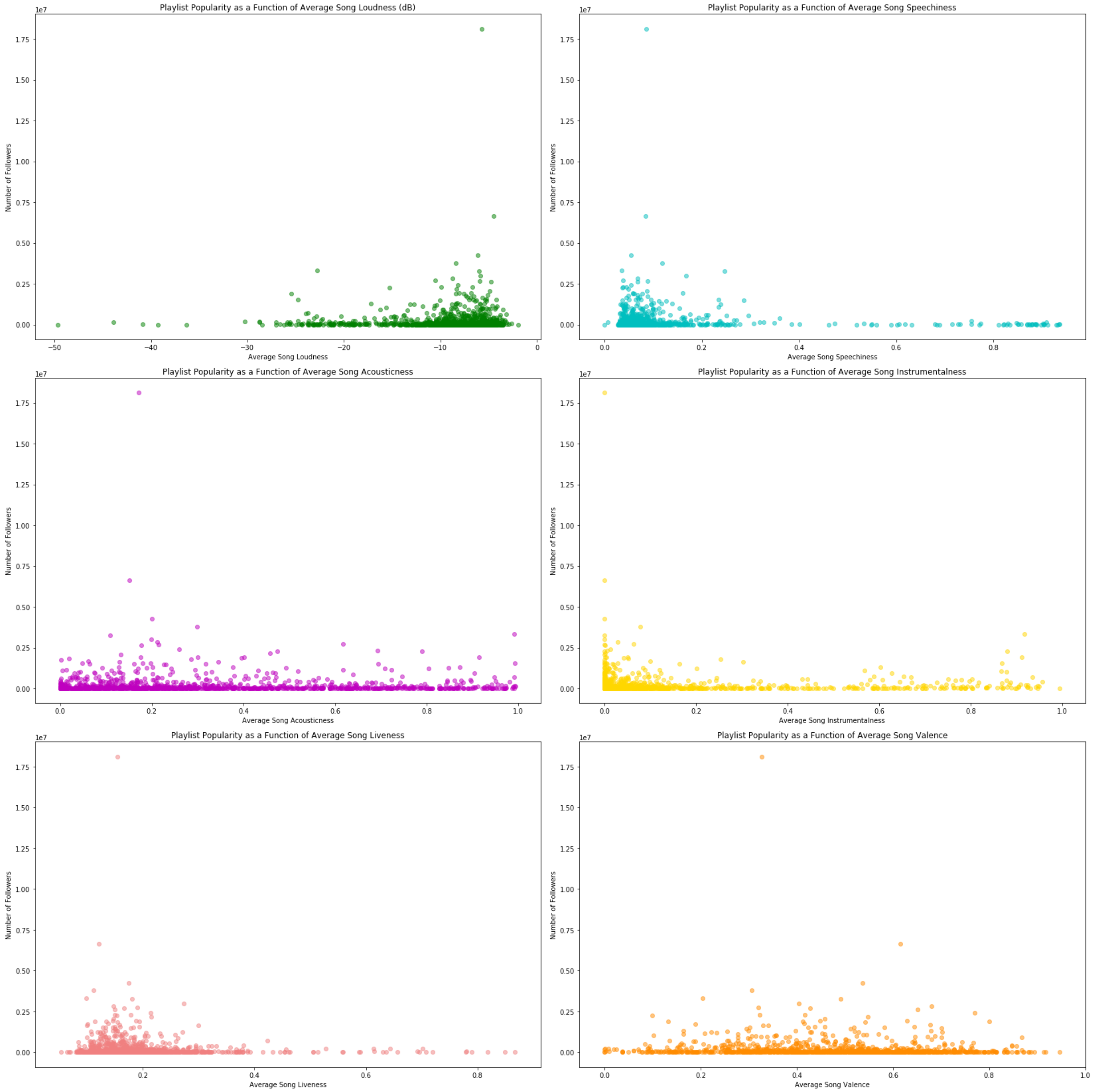
In [6]:
```
by_mode = data_train.groupby('majority_mode')
mode_means = by_mode['followers'].mean()
plt.bar(range(len(mode_means)),mode_means,tick_label=list(mode_means.index),
plt.ylabel('Mean Number of Followers')
plt.title('Mean Number of Followers by Song Mode Measure')

plt.tight_layout()
plt.savefig('mode.png')
```



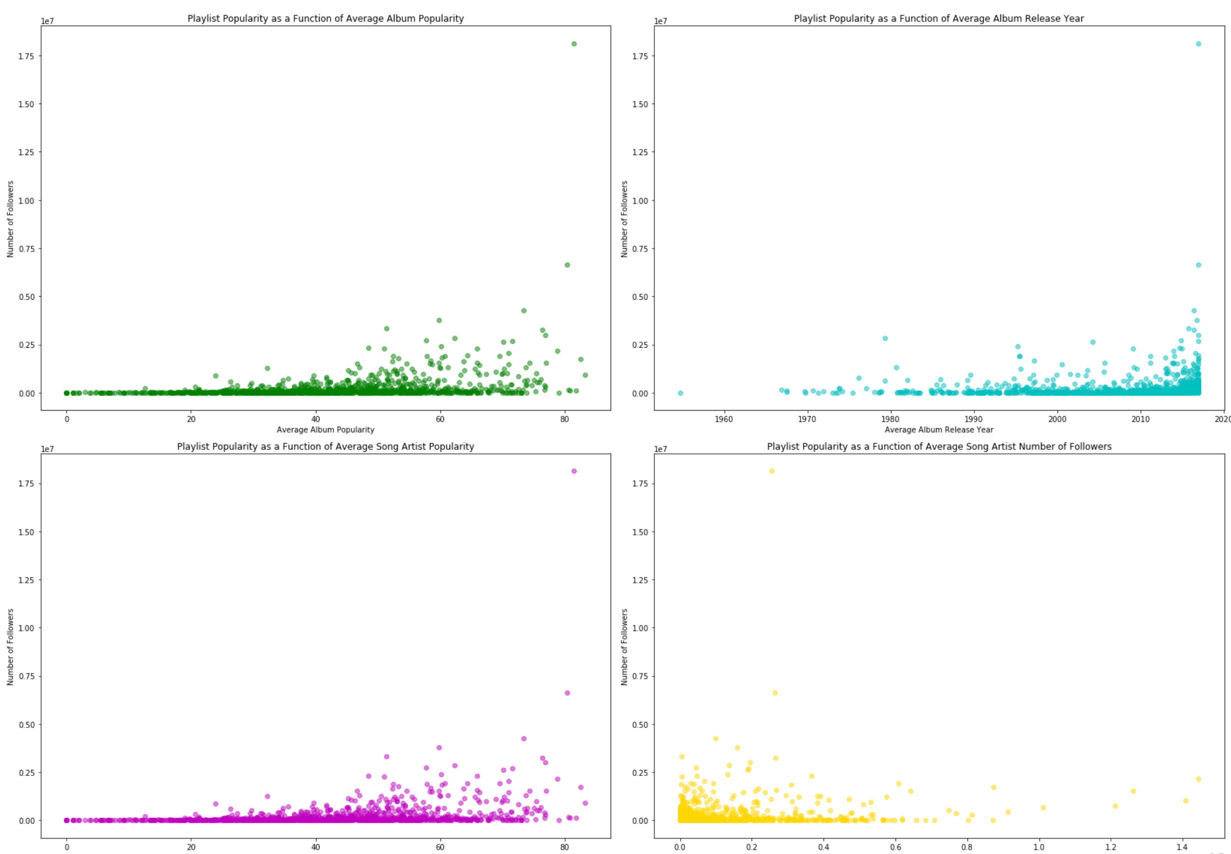
In [7]:
```
by_album_type = data_train.groupby('majority_album_type')
album_type_means = by_album_type['followers'].mean()
plt.bar(range(len(album_type_means)),album_type_means,tick_label=list(album_
plt.ylabel('Mean Number of Followers')
plt.title('Mean Number of Followers by Album Type')

plt.tight_layout()
plt.savefig('album_type.png')
```



In [8]:
```
fig, ax = plt.subplots(3, 2, figsize=(23, 23))

plt.subplot(3, 2, 1)
plt.scatter(data_train['avg_loudness'], data_train['followers'], color='g',
plt.xlabel('Average Song Loudness')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Loudness (dB)')

plt.subplot(3, 2, 2)
plt.scatter(data_train['avg_speechiness'], data_train['followers'], color='c
plt.xlabel('Average Song Speechiness')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Speechiness')

plt.subplot(3, 2, 3)
plt.scatter(data_train['avg_acousticness'], data_train['followers'], color='
plt.xlabel('Average Song Acousticness')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Acousticness')

plt.subplot(3, 2, 4)
plt.scatter(data_train['avg_instrumentalness'], data_train['followers'], col
plt.xlabel('Average Song Instrumentalness')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Instrumentalnes

plt.subplot(3, 2, 5)
plt.scatter(data_train['avg_liveness'], data_train['followers'], color='ligh
plt.xlabel('Average Song Liveness')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Liveness')

plt.subplot(3, 2, 6)
plt.scatter(data_train['avg_valence'], data_train['followers'], color='darkc
plt.xlabel('Average Song Valence')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Valence')

plt.tight_layout()
plt.savefig('audio_features.png')
```


Playlist Popularity as a Function of Average Song Loudness (dB)
Number of Followers
Average Song Loudness
Playlist Popularity as a Function of Average Song Speechiness
Number of Followers
Average Song Speechiness
Playlist Popularity as a Function of Average Song Acousticness
Number of Followers
Average Song Acousticness
Playlist Popularity as a Function of Average Song Instrumentalness
Number of Followers
Average Song Instrumentalness
Playlist Popularity as a Function of Average Song Liveness
Number of Followers
Average Song Liveness
Playlist Popularity as a Function of Average Song Valence
Number of Followers
Average Song Valence

In [9]:
```
fig, ax = plt.subplots(2, 2, figsize=(23, 16))

plt.subplot(2, 2, 1)
plt.scatter(data_train['avg_album_popularity'], data_train['followers'], col
plt.xlabel('Average Album Popularity')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Album Popularity')

plt.subplot(2, 2, 2)
plt.scatter(data_train['avg_album_release_year'], data_train['followers'], c
plt.xlabel('Average Album Release Year')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Album Release Year')

plt.subplot(2, 2, 3)
plt.scatter(data_train['avg_album_popularity'], data_train['followers'], col
plt.xlabel('Average Song Artist Popularity')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Artist Populari

plt.subplot(2, 2, 4)
plt.scatter(data_train['avg_artist_followers'], data_train['followers'], col
plt.xlabel('Average Song Artist Number of Followers')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Artist Number c

plt.tight_layout()
plt.savefig('audio_info.png')
```



In [10]:
```
# one-hot encoding for categorical predictors
data_train = pd.get_dummies(data_train, columns=['majority_album_type'], drc
data_test = pd.get_dummies(data_test, columns=['majority_album_type'], drop_

# get column names
column_headers = list(data_train.columns.values)

# get variables
X_train = data_train.iloc[:,5:]
y_train = data_train.iloc[:,0]

X_test = data_test.iloc[:,5:]
y_test = data_test.iloc[:,0]
```

Linear Regression

In [11]:
```
X_train2 = sm.add_constant(X_train.values)
model = sm.OLS(y_train.values, X_train2)
results = model.fit()

y_hat_train = results.predict(X_train2)

# test case
X_test2 = sm.add_constant(X_test.values)
y_hat_test = results.predict(X_test2)

r2_score_train = r2_score(y_train, y_hat_train)
r2_score_test = r2_score(y_test, y_hat_test)

print('R^2 Values for Train, Test Using Linear Regression:', r2_score_train,
```

```
R^2 Values for Train, Test Using Linear Regression: 0.168225035255 0.1812
77116647
```

Polynomial Terms Regression

In [12]:
```
r2_train_poly = []
r2_test_poly = []

# make dataframes to add polynomial terms to
cont = ['avg_album_popularity', 'avg_album_release_year', 'avg_artist_popula
X_binary_only = X_train.drop(['avg_album_popularity', 'avg_album_release_yea
X_test_bin_only = X_test.drop(['avg_album_popularity', 'avg_album_release_ye
X_poly = X_binary_only.copy()
X_test_poly = X_test_bin_only.copy()

X_poly_test_all = X_test.copy()
X_poly_train_all = X_train.copy()

# function to create and add polynomial terms to dataframe
def add_poly_features(train, test, poly_train, poly_test, polylist):
    for col in polylist:
        for i in range(2,4):
            poly_train[col + '_' + str(i)] = train[col]**i
            poly_test[col + '_' + str(i)] = test[col]**i

add_poly_features(X_train, X_test, X_poly_train_all, X_poly_test_all,cont)

# polynomial term regression
poly_regression_model = linear_model.LinearRegression(fit_intercept=False)
poly_regression_model.fit(X_poly_train_all, y_train)

y_hat_train = poly_regression_model.predict(X_poly_train_all)
y_hat_test = poly_regression_model.predict(X_poly_test_all)


r2_train_poly.append( r2_score(y_train, y_hat_train))
r2_test_poly.append( r2_score(y_test, y_hat_test))

print('R^2 Values for Train, Test Using Polynomial Regression:', r2_train_pc
```

```
R^2 Values for Train, Test Using Polynomial Regression: [0.21866516189664
709] [0.18486578914356244]
```

kNN Regression

In [13]:
```
# try multiple k's
K = [1, 2, 4,8, 10, 50, 100, 250, 500, 600, 700, 800, 900, 1000]
r2_test_knn = []
r2_train_knn = []

# try each different k and calculate R^2
for i,k in enumerate(K):
    knn_model = KNeighborsRegressor(n_neighbors=k)
    knn_model.fit(X_train, y_train)
    predicted_pickups_train = knn_model.predict(X_train)
    predicted_pickups = knn_model.predict(X_test)

    r2_train_knn.append( r2_score(y_train, predicted_pickups_train))
    r2_test_knn.append( r2_score(y_test, predicted_pickups))

print('R^2 Values for Train Using kNN Regression:', r2_train_knn)
print()
print('R^2 Values for Test Using kNN Regression:', r2_test_knn)
```

```
R^2 Values for Train Using kNN Regression: [0.99999999826605368, 0.673615
57405130701, 0.26014861730618322, 0.14666628473394638, 0.1244182265963514
9, 0.042620591885406456, 0.029105850221909146, 0.022963572284714795, 0.01
3139851669411118, 0.011592111214729361, 0.0092869321588529008, 0.00779488
62622220227, 0.0073745784743184384, 0.0056233810101773418]

R^2 Values for Test Using kNN Regression: [-0.75715473073802242, -0.25301
680053630093, -0.30348630520483377, -0.094250067982748709, -0.12328060001
080909, -0.021899414008623497, -0.013522963401996657, 0.00454740789181340
42, 0.0031360746980091392, 0.0017065831673064302, 0.0013485495695024774,
0.0014863803700982947, 0.00016419258602440312, -0.00075057625934760175]
```

Random Forest Regression

In [14]:

```
r2_train_rf = []
r2_test_rf = []

# check multiple depths to see which depth is best
for i in range(1, 20):
    rf_reg = RandomForestRegressor(max_depth=i)
    rf_reg.fit(X_train, y_train)

    rf_yhat_train = rf_reg.predict(X_train)
    rf_yhat_test = rf_reg.predict(X_test)

    r2_train_rf.append( r2_score(y_train, rf_yhat_train))
    r2_test_rf.append( r2_score(y_test, rf_yhat_test))

print('R^2 Values for Train Using Random Forest Regression:', r2_train_rf)
print()
print('R^2 Values for Test Using Random Forest Regression:', r2_test_rf)
```

```
R^2 Values for Train Using Random Forest Regression: [0.4972029675643434
6, 0.61270131485010926, 0.68781757760996243, 0.66572656890709236, 0.72579
428734652485, 0.76220222715670116, 0.83028968917612855, 0.896006876471702
85, 0.82751658981528342, 0.90397467822481714, 0.82688300968743556, 0.8093
2068679634084, 0.80088932016355352, 0.8318520139901675, 0.847601697642013
65, 0.87436773242829824, 0.9327280066845034, 0.86419104646927214, 0.93431
964941287748]

R^2 Values for Test Using Random Forest Regression: [0.06568853013213538
1, 0.11686894621887656, 0.24313162668286292, 0.28709485521131284, 0.26626
07744323261, 0.34904452912818174, 0.29851039695836878, 0.306595779031037
3, 0.36954388468561639, 0.2522709301908852, 0.23787368602781456, 0.268863
89619395945, 0.24574812074392371, 0.33606857579939109, 0.2528143675855637
5, 0.27813440591777383, 0.33600838787033338, 0.26840161712604982, 0.27994
817289037111]
```

In [15]:

```
# get best depth
index, value = max(enumerate(r2_test_rf), key=operator.itemgetter(1))
best_depth = index + 1

print('Best Depth for Random Forest Tree Depth:', best_depth )
```

```
Best Depth for Random Forest Tree Depth: 9
```

Fine Tuning Phase

Ridge and Lasso for Polynomial Term Regression

In [16]:
```
# Ridge Regression on Polynomial Term Regression
lambdas = [.001,.005,1,5,10,50,100,500,1000]
ridge = RidgeCV(alphas=lambdas, fit_intercept=False, normalize=True, cv=10)
ridge.fit(X_poly_train_all, y_train)

print("Ridge train R^2: ", ridge.score(X_poly_train_all, y_train))
print('Ridge test R^2', ridge.score(X_poly_test_all, y_test))
```

```
Ridge train R^2:  0.311660608922
Ridge test R^2 0.26309415895
```

In [17]:
```
# Lasso Regression on Polynomial Term Regression
lasso = LassoCV(alphas=lambdas, fit_intercept=False, normalize=True, cv=10)
lasso.fit(X_poly_train_all, y_train)

print("Lasso train R^2: ", lasso.score(X_poly_train_all, y_train))
print('Lasso test R^2', lasso.score(X_poly_test_all, y_test))
```

```
Lasso train R^2:  0.309383380859
Lasso test R^2 0.26803387052
```

In [18]:
```
# Fine Tuning Random Forest: Initial Run with max_depth set to the optimal d
r2_train_rf = []
r2_test_rf = []

rf_reg = RandomForestRegressor(max_depth=best_depth)
rf_reg.fit(X_train, y_train)

rf_yhat_train = rf_reg.predict(X_train)
rf_yhat_test = rf_reg.predict(X_test)

r2_train_rf.append( r2_score(y_train, rf_yhat_train))
r2_test_rf.append( r2_score(y_test, rf_yhat_test))

print('R^2 Values for Train, Test Using Random Forest Regression:', r2_train
```

```
R^2 Values for Train, Test Using Random Forest Regression: [0.89587077404
69255] [0.2907008705635209]
```

In [19]:
```
# step 1: fine tune the number of trees
r2_train_rf_trees = []
r2_test_rf_trees = []

# create list of tree numbers we will test
trees = [2**x for x in range(8)]  # 2, 4, 8, 16, 32, ...

# test the tree numbers keeping max_depth at 9
for n_trees in trees:
    rf = RandomForestRegressor(n_estimators=n_trees, max_depth=best_depth, r
    rf.fit(X_train, y_train)

    rf_yhat_train = rf.predict(X_train)
    rf_yhat_test = rf.predict(X_test)

    r2_train_rf_trees.append(r2_score(y_train, rf_yhat_train))
    r2_test_rf_trees.append(r2_score(y_test, rf_yhat_test))

print('R^2 Values for Train Using Random Forest Regression:', r2_train_rf_tr
print()
print('R^2 Values for Test Using Random Forest Regression:', r2_test_rf_tree
```

```
R^2 Values for Train Using Random Forest Regression: [0.5679748228780785
4, 0.80234289053068186, 0.77059992272949063, 0.70152777008931655, 0.90530
980473216849, 0.85275109969795582, 0.88201649617753375, 0.857432928988192
12]

R^2 Values for Test Using Random Forest Regression: [0.07571505945058421,
0.10618906817465157, 0.14651476417606069, 0.32637513644207894, 0.27808610
681013535, 0.33125284656270726, 0.26565927221011654, 0.2952721502433362]
```

In [20]:
```
# get best number of trees
index, value = max(enumerate(r2_test_rf_trees), key=operator.itemgetter(1))
best_tree = trees[index]

print('Random Forest Best Number of Trees:',best_tree)
print('R^2 Value:',value)
```

```
Random Forest Best Number of Trees: 32
R^2 Value: 0.331252846563
```

In [21]:
```
# step 2: fine tune the number of predictors used
r2_train_rf_feat = []
r2_test_rf_feat = []

# 19 = len(list(X_train)) is the maximum number of predictors we have
for i in range(1, len(list(X_train))):
    rf = RandomForestRegressor(n_estimators=32, max_depth=9, max_features=i)
    rf.fit(X_train, y_train)

    rf_yhat_train = rf.predict(X_train)
    rf_yhat_test = rf.predict(X_test)

    r2_train_rf_feat.append(r2_score(y_train, rf_yhat_train))
    r2_test_rf_feat.append(r2_score(y_test, rf_yhat_test))

print('R^2 Values for Train Using Random Forest Regression:', r2_train_rf_fe
print()
print('R^2 Values for Test Using Random Forest Regression:', r2_test_rf_feat
```

```
R^2 Values for Train Using Random Forest Regression: [0.8256661111085228
4, 0.77028153913388597, 0.81294981310663916, 0.82230984221503411, 0.86399
928188978148, 0.84900428685973228, 0.86796979785964978, 0.869998626197293
62, 0.8765343315962304, 0.83978169521855706, 0.88528359486999786, 0.87353
484950923743, 0.82726533523158174, 0.85297023789094073, 0.890513635028307
83, 0.88520795662651808, 0.85059256851215825, 0.86209711928116417]

R^2 Values for Test Using Random Forest Regression: [0.15794790583084561,
0.19010823363449014, 0.21701001115604357, 0.32057835078781416, 0.26955495
98488991, 0.29352389205363116, 0.23822094648134462, 0.22518511833625854,
0.26129543627494345, 0.26912500788228744, 0.28568486755867872, 0.28869981
484340268, 0.29008893080067877, 0.28629686174585578, 0.26584568328217706,
0.27836093527718631, 0.28419643148861906, 0.27408654680703304]
```

In [22]:
```
# get best number of predictors
index, value = max(enumerate(r2_test_rf_feat), key=operator.itemgetter(1))

print('Random Forest Number of Predictors for Best Value:',index+1)
print('Best R^2 Value Using Only Spotify Predictors:',value)
```

```
Random Forest Number of Predictors for Best Value: 4
Best R^2 Value Using Only Spotify Predictors: 0.320578350788
```

Combined Predictors

Shotgun Phase

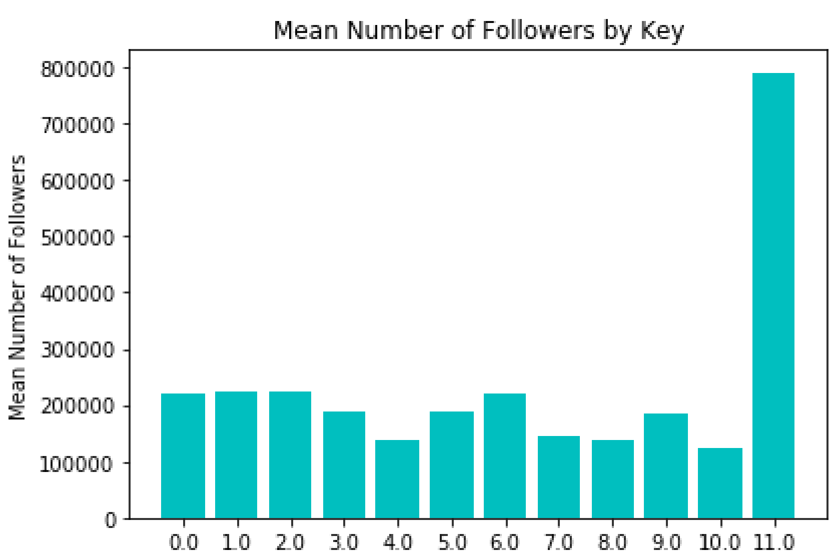
In [23]:
```
# read csv that combines previous csv from spotify with few additional colur
df = pd.read_csv('final_dataset.csv')
df = df.dropna()
df = df.drop(['Unnamed: 0'], 1)
```

In [24]:
```
# split data
np.random.seed(9001)
msk = np.random.rand(len(df)) < 0.75
data_train = df[msk]
data_test = df[~msk]

column_headers = list(data_train.columns.values)

pd.set_option('display.max_columns', 100)
data_train.head()
```

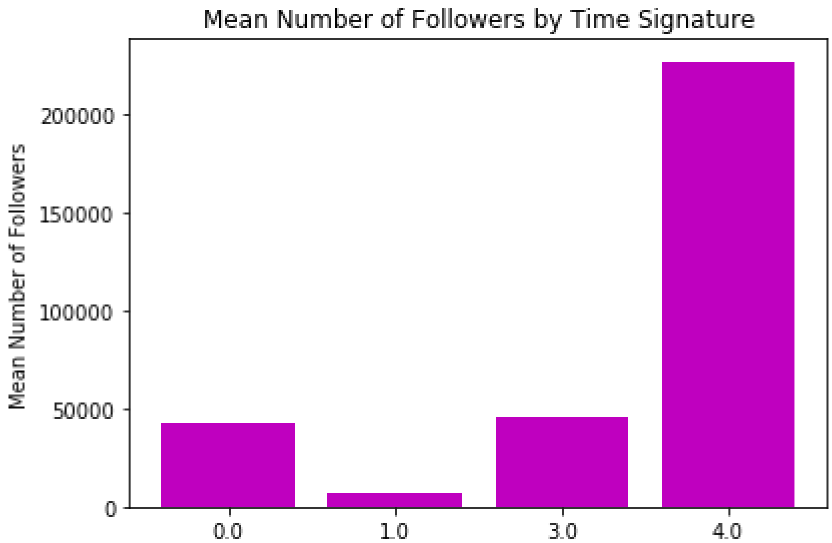
Out[24]:

	followers	majority_artist_genres	name	owner	track_ids	num_tracks	av
0	18129916	pop	Today's Top Hits	spotify	['0tBbt8CrmxbjRP0pueQkyU', ' 2amzBJRBPOGszBem4...	50	
3	3787551	indie r&b	Are & Be	spotify	['6gU9OKjOE7ghfEd55oRO57', ' 25wStx3LyTjYmHTd3...	51	
5	4254642	contemporary country	Hot Country	spotify	['54EWDYWhs4w6SODnxabuoh', ' 7rdK9NSJIRBZAiXC0...	51	
6	6639722	latin	¡Viva Latino!	spotify	['2hl6q70unbviGo3g1R7uFx', ' 2SmgFAhQkQCQPyBiB...	50	
9	3323766	focus	Peaceful Piano	spotify	['1JoAjYal3zvhXVx41HH7Fc', ' 7ih16mauHrpUMOleW...	100	

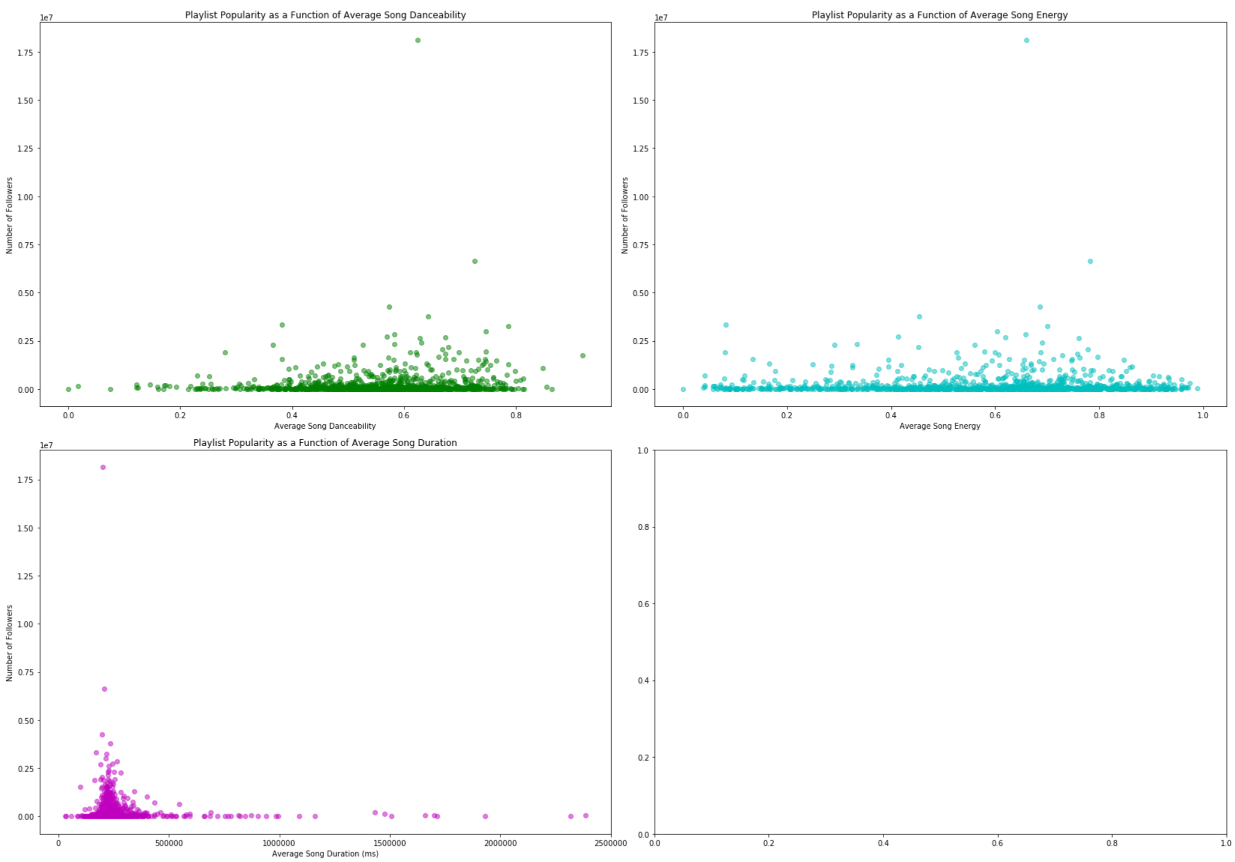
In [25]:
```
by_key = data_train.groupby('majority_key')
key_means = by_key['followers'].mean()
plt.bar(range(len(key_means)),key_means,tick_label=list(key_means.index), co
plt.ylabel('Mean Number of Followers')
plt.title('Mean Number of Followers by Key')

plt.tight_layout()
plt.savefig('key.png')
```



In [26]:
```
by_time_sig = data_train.groupby('majority_time_signature')
time_sig_means = by_time_sig['followers'].mean()
plt.bar(range(len(time_sig_means)),time_sig_means,tick_label=list(time_sig_m
plt.ylabel('Mean Number of Followers')
plt.title('Mean Number of Followers by Time Signature')

plt.tight_layout()
plt.savefig('time_signature.png')
```



In [27]:
```
fig, ax = plt.subplots(2, 2, figsize=(23, 16))

plt.subplot(2, 2, 1)
plt.scatter(data_train['avg_danceability'], data_train['followers'], color='
plt.xlabel('Average Song Danceability')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Danceability')

plt.subplot(2, 2, 2)
plt.scatter(data_train['avg_energy'], data_train['followers'], color='c', al
plt.xlabel('Average Song Energy')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Energy')

plt.subplot(2, 2, 3)
plt.scatter(data_train['avg_duration_ms'], data_train['followers'], color='m
plt.xlabel('Average Song Duration (ms)')
plt.ylabel('Number of Followers')
plt.title('Playlist Popularity as a Function of Average Song Duration')

plt.tight_layout()
plt.savefig('audio_features_additional.png')
```



In [28]:
```
# one-hot encoding for categorical predictors
data_train = pd.get_dummies(data_train, columns=['majority_key','majority_ti
data_test = pd.get_dummies(data_test, columns=['majority_key','majority_time

# get column names
column_headers = list(data_train.columns.values)

# get variables
X_train = data_train.iloc[:,5:]
y_train = data_train.iloc[:,0]

X_test = data_test.iloc[:,5:]
y_test = data_test.iloc[:,0]
```

Linear Regression

In [29]:
```
X_train2 = sm.add_constant(X_train.values)
model = sm.OLS(y_train.values, X_train2)
results = model.fit()

y_hat_train = results.predict(X_train2)

# test case
X_test2 = sm.add_constant(X_test.values)
y_hat_test = results.predict(X_test2)

r2_score_train = r2_score(y_train, y_hat_train)
r2_score_test = r2_score(y_test, y_hat_test)

print('R^2 Values for Train, Test Using Linear Regression:', r2_score_train,
```

```
R^2 Values for Train, Test Using Linear Regression: 0.188062242633 0.1279
95346803
```

Polynomial Terms Regression

In [30]:
```
r2_train_poly = []
r2_test_poly = []

# set up dataframe to add polynomial terms to
cont = ['avg_album_popularity', 'avg_album_release_year', 'avg_artist_popula
X_binary_only = X_train.drop(['avg_album_popularity', 'avg_album_release_yea
X_test_bin_only = X_test.drop(['avg_album_popularity', 'avg_album_release_ye
X_poly = X_binary_only.copy()
X_test_poly = X_test_bin_only.copy()

X_poly_test_all = X_test.copy()
X_poly_train_all = X_train.copy()

# function to create and add polynomial terms to dataframe
def add_poly_features(train, test, poly_train, poly_test, polylist):
    for col in polylist:
        for i in range(2,4):
            poly_train[col + '_' + str(i)] = train[col]**i
            poly_test[col + '_' + str(i)] = test[col]**i

add_poly_features(X_train, X_test, X_poly_train_all, X_poly_test_all,cont)

# regress and calculate R^2
poly_regression_model = linear_model.LinearRegression(fit_intercept=False)
poly_regression_model.fit(X_poly_train_all, y_train)

y_hat_train = poly_regression_model.predict(X_poly_train_all)
y_hat_test = poly_regression_model.predict(X_poly_test_all)

r2_train_poly.append( r2_score(y_train, y_hat_train))
r2_test_poly.append( r2_score(y_test, y_hat_test))

print('R^2 Values for Train, Test Using Polynomial Regression:', r2_train_po
```

```
R^2 Values for Train, Test Using Polynomial Regression: [0.22365592656318
156] [0.19078809329451474]
```

kNN Regression

In [31]:
```
# test different k's
K = [1, 2, 4,8, 10, 50, 100, 250, 500, 600, 700, 800, 900, 1000]

r2_test_knn = []
r2_train_knn = []

# test different k's and regress
for i,k in enumerate(K):
    knn_model = KNeighborsRegressor(n_neighbors=k)
    knn_model.fit(X_train, y_train)
    predicted_pickups_train = knn_model.predict(X_train)
    predicted_pickups = knn_model.predict(X_test)

    r2_train_knn.append( r2_score(y_train, predicted_pickups_train))
    r2_test_knn.append( r2_score(y_test, predicted_pickups))

print('R^2 Values for Train Using KNN Regression:', r2_train_knn)
print()
print('R^2 Values for Test Using KNN Regression:', r2_test_knn)
```

```
R^2 Values for Train Using KNN Regression: [0.99999999826605368, 0.707052
95578349214, 0.26384447277586165, 0.14062785261746957, 0.1681539974643767
6, 0.041790871252071704, 0.026784122297934254, 0.022334620712726183, 0.01
3199508562418361, 0.011615787116215581, 0.0092690893153853926, 0.00792706
98554815278, 0.0074171109814979985, 0.0056618388771036976]

R^2 Values for Test Using KNN Regression: [-0.87195646189656983, -0.32627
859453665375, -0.1542926908927027, -0.089021508792754611, -0.118099359389
08334, -0.020776306046869086, -0.010578038605963069, 0.003168592302538741
9, 0.0036867169843481928, 0.0026448150105176094, 0.0015801451321187931,
0.0015217888123526535, 0.00056359830487651141, -0.0006410793680169391]
```

Random Forest Regression

In [32]:
```
r2_train_rf = []
r2_test_rf = []

# check multiple depths to see which depth is best
for i in range(1, 20):
    rf_reg = RandomForestRegressor(max_depth=i)
    rf_reg.fit(X_train, y_train)

    rf_yhat_train = rf_reg.predict(X_train)
    rf_yhat_test = rf_reg.predict(X_test)

    r2_train_rf.append( r2_score(y_train, rf_yhat_train))
    r2_test_rf.append( r2_score(y_test, rf_yhat_test))

print('R^2 Values for Train Using Random Forest Regression:', r2_train_rf)
print()
print('R^2 Values for Test Using Random Forest Regression:', r2_test_rf)
```

```
R^2 Values for Train Using Random Forest Regression: [0.4972029675643434
6, 0.61053350899380598, 0.68024242103697308, 0.67417419454609795, 0.72703
450561074345, 0.76129438982654363, 0.82826168965869496, 0.890758780290849
54, 0.82731366848664911, 0.90645817073650103, 0.82926781510319325, 0.7930
1657823217642, 0.78252458746760933, 0.79662562095222622, 0.84607245407198
439, 0.86602676866652106, 0.92853095764601801, 0.83285277634645305, 0.934
5492041547051]

R^2 Values for Test Using Random Forest Regression: [0.06568853013213538
1, 0.11955126119857296, 0.23689289946392322, 0.26770594423792349, 0.26822
437144144051, 0.30804616302553378, 0.29194690047452032, 0.309430286910503
56, 0.36153466389056399, 0.30359581277335412, 0.22811542159418852, 0.2441
3334080333959, 0.17365091726726267, 0.2942474156517787, 0.235500124709304
93, 0.25922089750101251, 0.24252559131939444, 0.26024406499389796, 0.2573
2779460683675]
```

In [33]:
```
# get best depth
index, value = max(enumerate(r2_test_rf), key=operator.itemgetter(1))
best_depth2 = index + 1

print('Best Depth for Random Forest Tree Depth:', best_depth2 )
```

```
Best Depth for Random Forest Tree Depth: 9
```

Fine Tuning Phase

Ridge and Lasso on Polynomial Term Regression

In [34]:
```
# Ridge Regression on Polynomial Term Regression
lambdas = [.001,.005,1,5,10,50,100,500,1000]
ridge = RidgeCV(alphas=lambdas, fit_intercept=False, normalize=True, cv=10)
ridge.fit(X_poly_train_all, y_train)

print("Ridge train R^2: ", ridge.score(X_poly_train_all, y_train))
print('Ridge test R^2', ridge.score(X_poly_test_all, y_test))
```

```
Ridge train R^2:  0.326717798114
Ridge test R^2 0.256967193697
```

In [35]:
```
# Lasso Regression on Polynomial Term Regression
lasso = LassoCV(alphas=lambdas, fit_intercept=False, normalize=True, cv=10)
lasso.fit(X_poly_train_all, y_train)

print("Lasso train R^2: ", lasso.score(X_poly_train_all, y_train))
print('Lasso test R^2', lasso.score(X_poly_test_all, y_test))
```

```
Lasso train R^2:  0.330738827492
Lasso test R^2 0.222855946887
```

In [36]:
```
# Fine Tuning Random Forest: get R^2 values for optimal depth that we calcul
r2_train_rf = []
r2_test_rf = []

rf_reg = RandomForestRegressor(max_depth=best_depth2)
rf_reg.fit(X_train, y_train)

rf_yhat_train = rf_reg.predict(X_train)
rf_yhat_test = rf_reg.predict(X_test)

r2_train_rf.append( r2_score(y_train, rf_yhat_train))
r2_test_rf.append(r2_score(y_test, rf_yhat_test))

print('R^2 Values for Train, Test Using Random Forest Regression:', r2_trair
```

```
R^2 Values for Train, Test Using Random Forest Regression: [0.90262541883
850489] [0.24087108131907387]
```

In [37]:

```
# step 1: fine tuning number of trees
r2_train_rf_trees = []
r2_test_rf_trees = []

# will try various number of trees
trees = [2**x for x in range(8)]  # 2, 4, 8, 16, 32, ...

# try different trees with optimal depth
for n_trees in trees:
    rf = RandomForestRegressor(n_estimators=n_trees, max_depth=best_depth2,
    rf.fit(X_train, y_train)

    rf_yhat_train = rf.predict(X_train)
    rf_yhat_test = rf.predict(X_test)

    r2_train_rf_trees.append(r2_score(y_train, rf_yhat_train))
    r2_test_rf_trees.append(r2_score(y_test, rf_yhat_test))

print('R^2 Values for Train Using Random Forest Regression:', r2_train_rf_tr
print()
print('R^2 Values for Test Using Random Forest Regression:', r2_test_rf_tree
```

```
R^2 Values for Train Using Random Forest Regression: [0.5749220817996074
7, 0.79613269275111742, 0.74639675519356485, 0.70857324665172727, 0.90271
868614388662, 0.85278439937628614, 0.88376628817650682, 0.858920594385434
78]

R^2 Values for Test Using Random Forest Regression: [-0.01909679333220193
3, 0.063317838578937025, 0.1650974481859171, 0.28993793816624602, 0.25554
733422998355, 0.30215898703465505, 0.26622004029166813, 0.269570026149657
3]
```

In [38]:

```
# get best number of trees
index, value = max(enumerate(r2_test_rf_trees), key=operator.itemgetter(1))
best_trees2 = trees[index]

print('Random Forest Best Number of Trees:',best_trees2)
print('R^2 Value:',value)
```

```
Random Forest Best Number of Trees: 32
R^2 Value: 0.302158987035
```

In [39]:
```
# step 2: fine tuning number of predictors used
r2_train_rf_feat = []
r2_test_rf_feat = []

# 38 = len(list(X_train)) is the maximum number of predictors we have
for i in range(1, len(list(X_train))):
    rf = RandomForestRegressor(n_estimators=best_trees2, max_depth=best_dept
    rf.fit(X_train, y_train)

    rf_yhat_train = rf.predict(X_train)
    rf_yhat_test = rf.predict(X_test)

    r2_train_rf_feat.append(r2_score(y_train, rf_yhat_train))
    r2_test_rf_feat.append(r2_score(y_test, rf_yhat_test))

print('R^2 Values for Train Using Random Forest Regression:', r2_train_rf_fe
print()
print('R^2 Values for Test Using Random Forest Regression:', r2_test_rf_feat
```

```
R^2 Values for Train Using Random Forest Regression: [0.7563398811340179
6, 0.70946280665336514, 0.74961922274263015, 0.79715576473639183, 0.85743
741826413333, 0.83103940853478919, 0.88522452216497172, 0.857773869835969
93, 0.88534598066540782, 0.84321293307864076, 0.88287446763216326, 0.8753
5793526961547, 0.81132008668654254, 0.84070341093556755, 0.90326674743422
597, 0.87555445691910205, 0.85607681263792534, 0.84174249333054441, 0.861
04110520470523, 0.84989793225520183, 0.86331742273837153, 0.8637480581369
6498, 0.91830319188432075, 0.87902292764811663, 0.81898358578364983, 0.81
512189037245752, 0.88782640132252211, 0.85056039360514102, 0.852543215367
83029, 0.85774173971159018, 0.78129295743555305, 0.8484575148908714, 0.82
38652173578408, 0.89008544896313146, 0.90070565416255888, 0.8781677309396
7326, 0.8643900597449834]

R^2 Values for Test Using Random Forest Regression: [0.13685407984731046,
0.13056892014350696, 0.20169352611776525, 0.17519220035219507, 0.17637356
446846342, 0.19977953355757672, 0.19916545541152464, 0.19710749640464198,
0.24704056223281323, 0.20284096428194665, 0.23951639299763949, 0.28502083
413380452, 0.1718507125250972, 0.24473154530435814, 0.25582648336544878,
0.26182614979885499, 0.21486595984387513, 0.26392864716334097, 0.27670487
697996038, 0.26839906679688541, 0.22897224146566386, 0.21466243502811977,
0.25629771936123813, 0.25013958498328981, 0.23611616488848763, 0.29951831
281468189, 0.24439258739783642, 0.28019120208068038, 0.25150094389644284,
0.28236049961817022, 0.25970156426833924, 0.2782170560177093, 0.283850269
53194825, 0.23285751371026409, 0.24946118929459549, 0.26824313258624244,
0.25621452521169175]
```

In [40]:
```
# get best number of predictors and best R^2 value
index, value = max(enumerate(r2_test_rf_feat), key=operator.itemgetter(1))

print('RandomForest Number of Predictors for Best Value:',index+1)
print('Final Best R^2 Value:',value)
```

```
RandomForest Number of Predictors for Best Value: 26
Final Best R^2 Value: 0.299518312815
```