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

Midterm - 2017

Harvard University
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INSTRUCTIONS

- You must submit the Midterm on your own**. No group submissions are allowed.** You may use any print or online resources but **you may not work or consult with others**.
- Restart the kernel and run the whole notebook again before you submit.
- Please submit both a notebook and a pdf.

Flight Delays

The U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics tracks the on-time performance of domestic flights operated by large air carriers. Summary information on the number of on-time, delayed, canceled, and diverted flights are published in DOT's monthly Air Travel Consumer Report and in this dataset of 2015 flight delays and cancellations.

Data

Each entry of the flights.csv file corresponds to a flight. More than 5,800,000 flights were recorded in 2015. These flights are described according to 31 variables. Further details of these variables can be found here (https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236&DB_Short_Name=On-Time), if you are interested (not needed to answer these questions).

Name	Type	DESCRIPTION
DATE	object	The date in python datetime format
MONTH	int64	The month of the year(1-12)
DAY	int64	The day of the month
DAY_OF_WEEK	int64	The day of the week(1-7, MON-SUN)
AIRLINE	object	An identifier for the airline
FLIGHT_NUMBER	int64	The flight number
TAIL_NUMBER	object	The tail number (aircraft) corresponding to this flight
ORIGIN_AIRPORT	object	The code for origin airport
DESTINATION_AIRPORT	object	The code for destination airport
SCHED_DEP	object	The departure time in python datetime.time format
SCHED_ARR	object	The arrival time in python datetime.time format
DEPARTURE_DELAY	float64	The delay incurred at the origin (mins)
ARRIVAL_DELAY	float64	The delay when the flight reached the (mins) destination
DISTANCE	int64	Distance in miles between origin and destination
SCHEDULED_TIME	float64	Scheduled time of flight (minutes)
ELAPSED_TIME	float64	Actual time of flight (minutes)
AIR_SYSTEM_DELAY	float64	What part of the delay was NASD?(mins)
SECURITY_DELAY	float64	What part of the delay was due to security problems? (mins)
AIRLINE_DELAY	float64	What part of the delay is due to the airline? (mins)
LATE_AIRCRAFT_DELAY	float64	What part of the delay is due to previous flight(s) being late(mins)
WEATHER_DELAY	float64	Delay due to extreme weather events(min)

You can read more about the various weather delays here (https://www.rita.dot.gov/bts/help/aviation/html/understanding.html) if you are so inclined.

Data/Caveats

The data file, flights.csv, is found here (https://drive.google.com/file/d/0B9dVesTppCgHY0IwZHk3SGhjd00/view?usp=sharing) (note, it is about 70MB).

This data is already preprocessed, reduced, partially cleaned and therefore not identical to the original dataset.

Problem Description

We will build two separate models: one model that classifies whether a flight will be delayed and a second model that predicts the length of delay given that a flight is truly delayed. Only consider models taught in class so far.

Consider the following: This is a large dataset; think of strategies on how to solve this problem. Create a manageable subsample of the data that you can use to train and test/validate, but eventually you should predict on all the data (excluding the training set).

Questions

1. (5pts) Create a new variable, `DELAY_OR_NOT`: a boolean/indicator variable which indicates any arrival delay under 15 mins as a 0, and any delay at or above 15 mins as a 1 (`ARRIVAL_DELAY >= 15`).
2. (5pts) Make sure you understand the data variable descriptions before you start the analysis. Consider all the columns and determine and list which of these predictors should not be used.
3. (15pts) Perform EDA to gain intuition of the factors that affect delay and provide visuals: do delays vary across airlines, or time of departure, or airport (do, at the very least, Chicago (ORD), Boston (BOS), and your favorite another airport), or airport traffic?
4. (20pts) Build a classification model that classifies delays according to `DELAY_OR_NOT`. This is an unbalanced dataset, thus consider the appropriate performance metric when reporting your results.
5. (5pts) Given your model, comment on the importance of factors as related to whether a flight is delayed.
6. (5pts) Evaluate your model(s) on your test set, and finally provide a visual to show which airlines are predicted to have the most delays using all the data excluding the training and test set.
7. (15pts) Build a regression model that predicts the length of delay (on the log scale) given that a flight is truly delayed.
8. (20pts) Write a report (in the last markdown cell in your notebook with your findings (without code)). Describe the main design decisions you have made with justifications. Clearly explain your methodology and results. This should not be more than 300 words. You may use up to 5 diagrams.

209 Additional questions

1. (10pts) Engineer two additional features that will help improve the classification model's performance.
2. (5pts) Add one additional feature from a data source not given to you. Do this only after you complete the rest of the exam.

Deliverable:

A well presented notebook with well structured and documented code to answer questions 1-7 (plus additional questions for 209 students) with brief explanations and/or clarifications (10pts for overall presenation). The last cell should contain the report for question 8.

Hints

1. For the classification model, an AUC of approximately 0.6 should be your base model.
2. $R^2 > 0.03$ for the regression is good, $R^2 > 0.05$ very good, and $R^2 > 0.1$ is impressive (measured on the log scale).

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import statsmodels.api as sm
from statsmodels.api import OLS
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.tree import DecisionTreeClassifier
from sklearn.utils import resample
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import r2_score
import sklearn.metrics as metrics
import seaborn.apionly as sns
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import Imputer
from sklearn.metrics import mean_squared_error
from sklearn.tree import export_graphviz
from IPython.display import Image
from IPython.display import display
import copy
%matplotlib inline
```

Part 1:

Create a new variable, DELAY_OR_NOT: a boolean/indicator variable which indicates any arrival delay under 15 mins as a 0, and any delay at or above 15 mins as a 1 (ARRIVAL_DELAY >= 15).

In [2]:
```
# load in data
data = pd.read_csv('cs109a_midterm.csv')

print("Size of dataset: ", data.shape)
data.head()
```

```
Size of dataset:  (804941, 21)
```

Out[2]:

	DATE	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	ORI
0	2015-09-19	9	19	6	AA	394	N3FMAA	ORD
1	2015-10-28	10	28	3	AA	375	N4YDAA	112
2	2015-08-19	8	19	3	MQ	3648	N512MQ	XNA
3	2015-12-01	12	1	2	WN	4096	N912WN	PHX
4	2015-09-15	9	15	2	WN	285	N7718B	MCI

5 rows × 21 columns

In [3]:
```
# pre-processing, add new column DELAY_OR_NOT
print('Num flights delayed by 15+ mins: ', sum(data['ARRIVAL_DELAY'] >=
15.0))
delay_list = []
for x in data['ARRIVAL_DELAY']:
    # 1 if delay >= 15m
    if x >= 15.0:
        delay_list.append(1)
    else:
        delay_list.append(0)

# add in new column of 1s and 0s
data['DELAY_OR_NOT'] = delay_list
print('Num flights delayed by 15+ mins: ', sum(data['DELAY_OR_NOT']))
print('Column names: ', list(data.columns.values))
```

```
Num flights delayed by 15+ mins:  82107
Num flights delayed by 15+ mins:  82107
Column names:  ['DATE', 'MONTH', 'DAY', 'DAY_OF_WEEK', 'AIRLINE', 'FLIG
HT_NUMBER', 'TAIL_NUMBER', 'ORIGIN_AIRPORT', 'DESTINATION_AIRPORT', 'SC
HED_DEP', 'SCHED_ARR', 'DEPARTURE_DELAY', 'ARRIVAL_DELAY', 'DISTANCE',
 'SCHEDULED_TIME', 'ELAPSED_TIME', 'AIR_SYSTEM_DELAY', 'SECURITY_DELA
Y', 'AIRLINE_DELAY', 'LATE_AIRCRAFT_DELAY', 'WEATHER_DELAY', 'DELAY_OR_
NOT']
```

Some intermediate Pre-Processing for our data

In [4]:
```
# pre-processing, turn SCHED_DEP into a usable time float

dept_floats = []
for x in data['SCHED_DEP']:
    # split by colon to get hours and minutes
    spl = x.split(":")
    # 60*hours + minutes
    total = int(spl[0]) * 60 + int(spl[1])
    dept_floats.append(total / (24 * 60))
# set new columnn
data['SCHED_DEP_FLOAT'] = dept_floats
data['SCHED_DEP_FLOAT'].head()
```

Out[4]:
```
0    0.302083
1    0.843750
2    0.515278
3    0.472222
4    0.590278
Name: SCHED_DEP_FLOAT, dtype: float64
```

In [5]:
```
# pre-processing, add columns for airport traffic, both origin and desti
nation

origin_traffic = []
origin_airport_traffic = {}
destination_traffic = []
destination_airport_traffic = {}
airports = list(set(data['ORIGIN_AIRPORT']))

# iterate thru airports, count number of flights (traffic proxy)
for airport in airports:
    origin_airport_data = (data[(data['ORIGIN_AIRPORT'] == airport)])
    destination_airport_data = (data[(data['DESTINATION_AIRPORT'] == air
port)])

    origin_airport_traffic[airport] = len(origin_airport_data)
    destination_airport_traffic[airport] = len(destination_airport_data)

for x in data['ORIGIN_AIRPORT']:
    origin_traffic.append(origin_airport_traffic[x])

for y in data['DESTINATION_AIRPORT']:
    destination_traffic.append(destination_airport_traffic[y])

data['DESTINATION_TRAFFIC'] = destination_traffic
data['ORIGIN_TRAFFIC'] = origin_traffic
data.head()
```

Out[5]:

	DATE	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	ORI
0	2015-09-19	9	19	6	AA	394	N3FMAA	ORD
1	2015-10-28	10	28	3	AA	375	N4YDAA	112
2	2015-08-19	8	19	3	MQ	3648	N512MQ	XNA
3	2015-12-01	12	1	2	WN	4096	N912WN	PHX
4	2015-09-15	9	15	2	WN	285	N7718B	MCI

5 rows × 25 columns

In [6]:
```
# split into train/test and do not touch test data until our final test

# split into train and rest
np.random.seed(9001)
msk = np.random.rand(len(data)) < 0.25
data_train = data[msk]
rest = data[~msk]

# split rest into test and remainder
np.random.seed(9001)
msk2 = np.random.rand(len(rest)) < 0.33
data_test = rest[msk2]
remaining_data = rest[~msk2]
orig_remaining_data = copy.deepcopy(remaining_data)

print(len(data_train))
print(len(data_test))
print(len(remaining_data))
print()
print("So 1/4 of our data is for training, 1/4 is for testing, and 1/2 i
s not being used, ")
print("but will be visualized later")
```

```
200870
199163
404908

So 1/4 of our data is for training, 1/4 is for testing, and 1/2 is not
 being used,
but will be visualized later
```

Part 1 Comments: Now we have 4 new (hopefully) predictive variables that can be used for our models, DELAY_OR_NOT as a classification response variable, and SCHED_DEP_FLOAT, ORIGIN_AIRPORT, DESTINATION_AIRPORT as predictors. All are in suitable numeric form.

Part 2:

Make sure you understand the data variable descriptions before you start the analysis. Consider all the columns and determine and list which of these predictors should not be used.

INITIAL INSTINCTS: DATE should be eliminated, since its contents are held in other, non-object categories. I also think DAY is likely not helpful since we have day of the week, but there is no harm in using it (perhaps the ends of months tend to be more delayed than the beginning for some reason). DAY_OF_WEEK, MONTH, and AIRLINE all seem like crucial information, and will be good predictors to one-hot. FLIGHT_NUMBER seems like unneeded information since they seem fairly random, as well as TAIL_NUMBER. Origin airport certainly seems important, Destination less so. We also only need one of SCHED_DEP and SCHED_ARR, because SCHED_DEP + SCHEDULED_TIME = SCHED_ARR. DEPARTURE_DELAY and ARRIVAL_DELAY are almost certainly very similar, and ARRIVAL_DELAY is the basis for the column that we are predicting on, so it doesn't seem appropriate to use either of these columns for prediction. DISTANCE seems like an appropriate predictor to use, although I do not know if it will be predictive. We should not use both ELAPSED_TIME and SCHEDULED_TIME because knowing both gives us too much information about the delay, and I think SCHEDULED_TIME is a more fair variable to use because it does not reveal information about the actual flight. Finally, all of the columns about specific delays should not be used, as these columns sum up to the total delay, so it is not appropriate to use direct information about delay to predict delay. If we used these columns, or columns like ARRIVAL_DELAY and DEPARTURE_DELAY, we would be able to get incredibly high accuracy without actually learning anything about what causes delays, so we would not adequately answer the question.

FINAL DECISION:

LIST OF PREDICTORS NOT TO USE:

DATE

FLIGHT_NUMBER

TAIL_NUMBER

SCHED_ARR

DEPARTURE_DELAY

ARRIVAL_DELAY

ELAPSED_TIME

AIR_SYSTEM_DELAY

SECURITY_DELAY

AIRLINE_DELAY

LATE_AIRCRAFT_DELAY

WEATHER_DELAY

SCHED_DEP (use SCHED_DEP_FLOAT instead)

ORIGIN_AIRPORT (use ORIGIN_TRAFFIC instead)

DESTINATION_AIRPORT (use DESTINATION_TRAFFIC instead)

LIST OF PREDICTORS TO USE:

MONTH (predictor to one-hot)

DAY

DAY_OF_WEEK (predictor to one-hot)

AIRLINE (predictor to one-hot)

SCHED_DEP_FLOAT (predictor that I made)

DISTANCE

SCHEDULED_TIME (predictor that I made)

ORIGIN_TRAFFIC (predictor that I made)

DESTINATION_TRAFFIC (predictor that I made)

RESPONSE VARIABLE:

DELAY_OR_NOT for classification problem

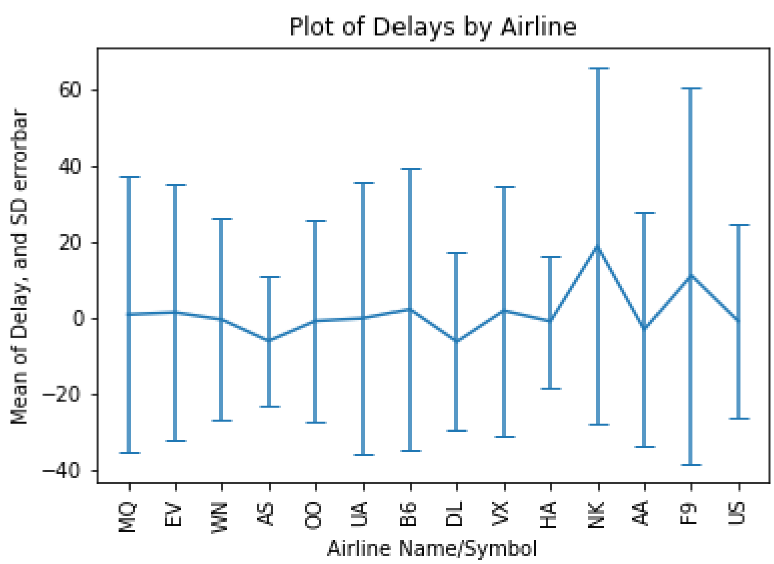
ARRIVAL_DELAY for regression problem

Part 3:

Perform EDA to gain intuition of the factors that affect delay and provide visuals: do delays vary across airlines, or time of departure, or airport (do, at the very least, Chicago (ORD), Boston (BOS), and your favorite another airport), or airport traffic?

Delays across airlines

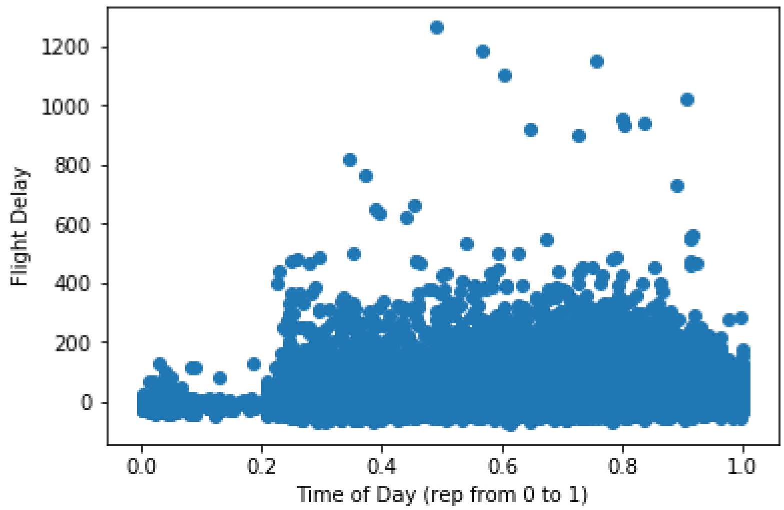
In [7]:
```
# visualize on training data

# delays across airlines:
airlines = set(data_train['AIRLINE'])

# take mean and sd of delays for each
ave_delay = []
delay_sd = []
for air in airlines:
    air_vals = data_train[data_train['AIRLINE'] == air]
['ARRIVAL_DELAY'].values
    ave_delay.append(np.mean(air_vals))
    delay_sd.append(np.std(air_vals))

#plt.plot(data_train['AIRLINE'], data_train['ARRIVAL_DELAY'])
plt.figure(1)
plt.errorbar(range(len(airlines)), ave_delay, delay_sd, capsize = 5, cap
thick = 1)
plt.xticks(range(len(airlines)), airlines, rotation='vertical')
plt.title('Plot of Delays by Airline')
plt.xlabel('Airline Name/Symbol')
plt.ylabel('Mean of Delay, and SD errorbar')
plt.show()
```



Comments: Here we can see that some of the highest delayed airlines are NK (Spirit) and F9 (Frontier), along with a few others. Delta (DL) and AS (Alaskan Air). I would say delays definitely vary across airlines!

Delay by departure time

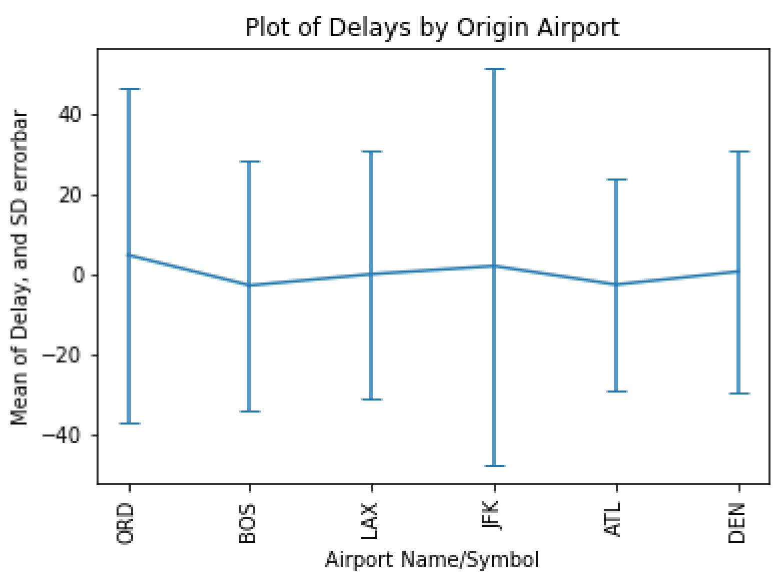
In [8]:
```
# delays by departure time

# sort the data by deparute (from 0 to 1)
sorted_dept = data_train.sort_values(by='SCHED_DEP_FLOAT', axis=0)

plt.figure(2)
plt.scatter(sorted_dept['SCHED_DEP_FLOAT'],
sorted_dept['ARRIVAL_DELAY'])
plt.xlabel('Time of Day (rep from 0 to 1)')
plt.ylabel('Flight Delay')
plt.show()
```



Comments: Time of departure clearly has a relationship with delay. For flights between midnight and about 5am, there are almost never delays, and after, there still may be trends in the delays.

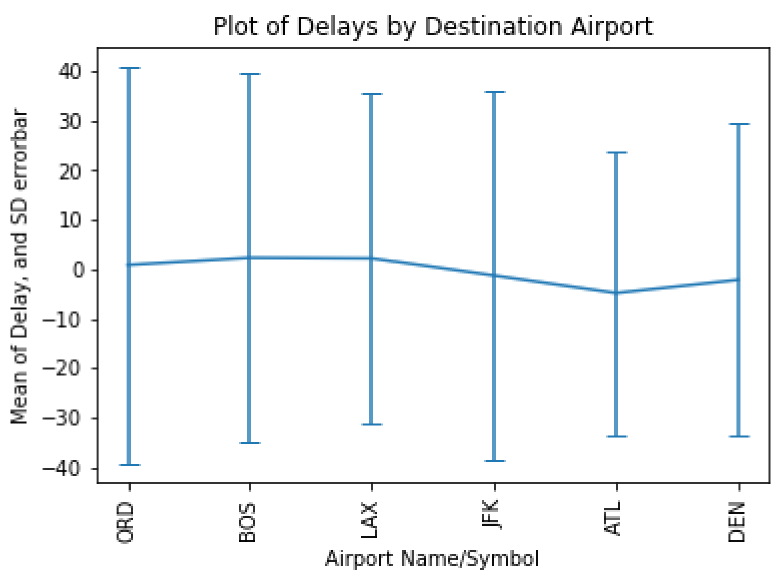
Delays for major airports

In [9]:
```
# delay by airport for major airport as origin

major_airports = ['ORD', 'BOS', 'LAX', 'JFK', 'ATL', 'DEN']

# collect mean and sd for each airport
ave_delay = []
delay_sd = []
for airport in major_airports:
    air_vals = data_train[data_train['ORIGIN_AIRPORT'] == airport]['ARRI
VAL_DELAY'].values
    ave_delay.append(np.mean(air_vals))
    delay_sd.append(np.std(air_vals))

plt.figure(3)
plt.errorbar(range(len(major_airports)), ave_delay, delay_sd, capsize =
5, capthick = 1)
plt.xticks(range(len(major_airports)), major_airports, rotation='vertica
l')
plt.title('Plot of Delays by Origin Airport')
plt.xlabel('Airport Name/Symbol')
plt.ylabel('Mean of Delay, and SD errorbar')
plt.show()

print("ORD ave delay: ", ave_delay[0])
```




```
ORD ave delay:  5.00126698917
```

In [10]:
```
# delay by airport for major airport as destination

# collect mean and sd for each airport
ave_delay2 = []
delay_sd2 = []
for airport in major_airports:
    air_vals = data_train[data_train['DESTINATION_AIRPORT'] == airport]
['ARRIVAL_DELAY'].values
    ave_delay2.append(np.mean(air_vals))
    delay_sd2.append(np.std(air_vals))

plt.figure(4)
plt.errorbar(range(len(major_airports)), ave_delay2, delay_sd2, capsize
= 5, capthick = 1)
plt.xticks(range(len(major_airports)), major_airports, rotation='vertica
l')
plt.title('Plot of Delays by Destination Airport')
plt.xlabel('Airport Name/Symbol')
plt.ylabel('Mean of Delay, and SD errorbar')
plt.show()

print("ORD Ave Delay: ", ave_delay2[0])
```

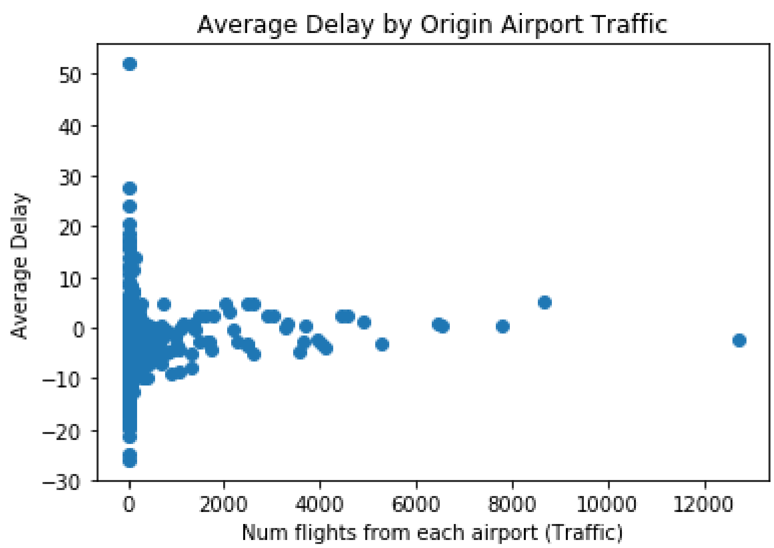



```
ORD Ave Delay:  0.879399697689
```

Comments: It is clear that airport of departure/origin also can impact delay time, since we see different average delays for each of these major airports, with ORD and JFK as the highest delay time for origin, and LAX and BOS as the highest delays for destination. It is interesting that these airports rank differently for origin and destination, and it seems like airports could definitely influence delays, which makes sense.

Delays by airport traffic

In [11]:
```
# delay time by origin airport traffic

# collect number of flights (traffic), and mean of the delays
airports = list(set(data_train['ORIGIN_AIRPORT']))
num_flights = []
ave_delay = []
for airport in airports:
    airport_data = data_train[(data_train['ORIGIN_AIRPORT'] == airport)]
['ARRIVAL_DELAY'].values
    num_flights.append(len(airport_data))
    ave_delay.append(np.mean(airport_data))

plt.figure(5)
plt.scatter(num_flights, ave_delay)
plt.title("Average Delay by Origin Airport Traffic")
plt.xlabel("Num flights from each airport (Traffic)")
plt.ylabel("Average Delay")
plt.show()
```



Comments: This is a small sample size, and it is difficult to determine the relationship here. For very small airports, there is no clear trend, but as traffic increases, there is perhaps a small positive relationship between traffic and delays.

Intermediate Pre-Processing: One-hot encoding

In [12]:
```
# pre-processing, one-hot for origin_airport, destination_airport, airli
nes, etc.

categorical_columns_g2cols = ['AIRLINE', 'DAY_OF_WEEK', 'MONTH']
data_train = pd.get_dummies(data_train, columns=categorical_columns_g2co
ls, drop_first=False)
data_test = pd.get_dummies(data_test,
columns=categorical_columns_g2cols, drop_first=False)
remaining_data = pd.get_dummies(remaining_data, columns=categorical_colu
mns_g2cols, drop_first=False)
data_train.head()
```

Out[12]:

	DATE	DAY	FLIGHT_NUMBER	TAIL_NUMBER	ORIGIN_AIRPORT	DESTINATION_AIRI
0	2015-09-19	19	394	N3FMAA	ORD	LGA
5	2015-01-29	29	2784	N966WN	DTW	MDW
13	2015-11-24	24	525	N193JB	JFK	TPA
18	2015-06-19	19	5033	N872AS	ABE	ATL
21	2015-02-07	7	4647	N14920	ORD	CRW

5 rows × 55 columns

Part 4:

Build a classification model that classifies delays according to DELAY_OR_NOT. This is an unbalanced dataset, thus consider the appropriate performance metric when reporting your results.

In [13]:
```
# get the list of predictors to use for the classification model
predictors_remove = ['ARRIVAL_DELAY', 'DATE', 'FLIGHT_NUMBER', 'TAIL_NUMBER', 'SCHED_ARR', 'DEPARTURE_DELAY', 'ELAPSED_TIME',
'AIR_SYSTEM_DELAY', 'SECURITY_DELAY', 'AIRLINE_DELAY', 'LATE_AIRCRAFT_DELAY', 'WEATHER_DELAY', 'DESTINATION_AIRPORT', 'SCHED_DEP', 'DELAY_OR_NOT', 'ORIGIN_AIRPORT']
predictors_all = list(data_train.columns.values)
for x in predictors_remove:
    predictors_all.remove(x)
preds_class = predictors_all
print("Classification Problem Predictors: ", preds_class)
```

```
Classification Problem Predictors:  ['DAY', 'DISTANCE', 'SCHEDULED_TIME', 'SCHED_DEP_FLOAT', 'DESTINATION_TRAFFIC', 'ORIGIN_TRAFFIC', 'AIRLINE_AA', 'AIRLINE_AS', 'AIRLINE_B6', 'AIRLINE_DL', 'AIRLINE_EV', 'AIRLINE_F9', 'AIRLINE_HA', 'AIRLINE_MQ', 'AIRLINE_NK', 'AIRLINE_OO', 'AIRLINE_UA', 'AIRLINE_US', 'AIRLINE_VX', 'AIRLINE_WN', 'DAY_OF_WEEK_1', 'DAY_OF_WEEK_2', 'DAY_OF_WEEK_3', 'DAY_OF_WEEK_4', 'DAY_OF_WEEK_5', 'DAY_OF_WEEK_6', 'DAY_OF_WEEK_7', 'MONTH_1', 'MONTH_2', 'MONTH_3', 'MONTH_4', 'MONTH_5', 'MONTH_6', 'MONTH_7', 'MONTH_8', 'MONTH_9', 'MONTH_10', 'MONTH_11', 'MONTH_12']
```

In [14]:
```
# split training set into training and validation
np.random.seed(9001)
msk = np.random.rand(len(data_train)) < 0.75
train_data = data_train[msk]
valid_data = data_train[~msk]

# split into predictors and response (X and y)
X_train = train_data[preds_class]
Y_train = train_data['DELAY_OR_NOT']
X_valid = valid_data[preds_class]
Y_valid = valid_data['DELAY_OR_NOT']
X_test = data_test[preds_class]
Y_test = data_test['DELAY_OR_NOT']
X_remain = remaining_data[preds_class]
Y_remain = remaining_data['DELAY_OR_NOT']
```

In [15]:
```
# pre-processing step, normalize all predictors to be between 0 and 1

def normalize_columns(X, X_min, X_max):
    return (X-X_min)/(X_max-X_min)

# normalize all predictors between 0 and 1 for easy use
normal_predictors = copy.deepcopy(preds_class)
for pred in normal_predictors:
    X_train[pred] = normalize_columns(X=X_train[pred],
X_min=min(X_train[pred].values), X_max=max(X_train[pred].values))
    X_test[pred] = normalize_columns(X=X_test[pred], X_min=min(X_test[pr
ed].values), X_max=max(X_test[pred].values))
    X_valid[pred] = normalize_columns(X=X_valid[pred],
X_min=min(X_valid[pred].values), X_max=max(X_valid[pred].values))
    X_remain[pred] = normalize_columns(X=X_remain[pred], X_min=min(X_rem
ain[pred].values), X_max=max(X_remain[pred].values))

X_train.head()
```

```
/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/ipykernel/_
_main__.py:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/ipykernel/_
_main__.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/ipykernel/_
_main__.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/ipykernel/_
_main__.py:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
```

Out[15]:

	DAY	DISTANCE	SCHEDULED_TIME	SCHED_DEP_FLOAT	DESTINATION_TRAFF
0	0.600000	0.141761	0.176737	0.301808	0.218260
18	0.600000	0.133481	0.166163	0.501391	1.000000
27	0.000000	0.129443	0.161631	0.851182	0.011727
46	0.800000	0.193861	0.222054	0.892907	0.013611
52	0.466667	0.256866	0.293051	0.810153	0.192479

5 rows × 39 columns

Simple Logistic Regression with CV

In [16]:
```
# logistic regression model
logregcv = LogisticRegressionCV(penalty='l2') # By default LBGFS induces
 L2 norm.
logregcv.fit(X_train, Y_train)
print("Accuracy Score: ", logregcv.score(X_valid, Y_valid))
print("But this is not the best measure since this is an unbalanced data
set, so use AUC instead")
```

```
Accuracy Score:  0.907104154124
But this is not the best measure since this is an unbalanced dataset, s
o use AUC instead
```

LDA

In [17]:
```
# lda model
lda = LinearDiscriminantAnalysis()
lda.fit(X_train, Y_train)
print("Accuracy Score: ", lda.score(X_valid, Y_valid))
```

```
Accuracy Score:  0.905277945013

/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/sklearn/dis
criminant_analysis.py:387: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
```

QDA

In [18]:
```
# qda model
qda = QuadraticDiscriminantAnalysis()
qda.fit(X_train, Y_train)
print("Accuracy Score: ", qda.score(X_valid, Y_valid))
```

```
/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/sklearn/dis
criminant_analysis.py:695: UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")

Accuracy Score:  0.676359622717
```

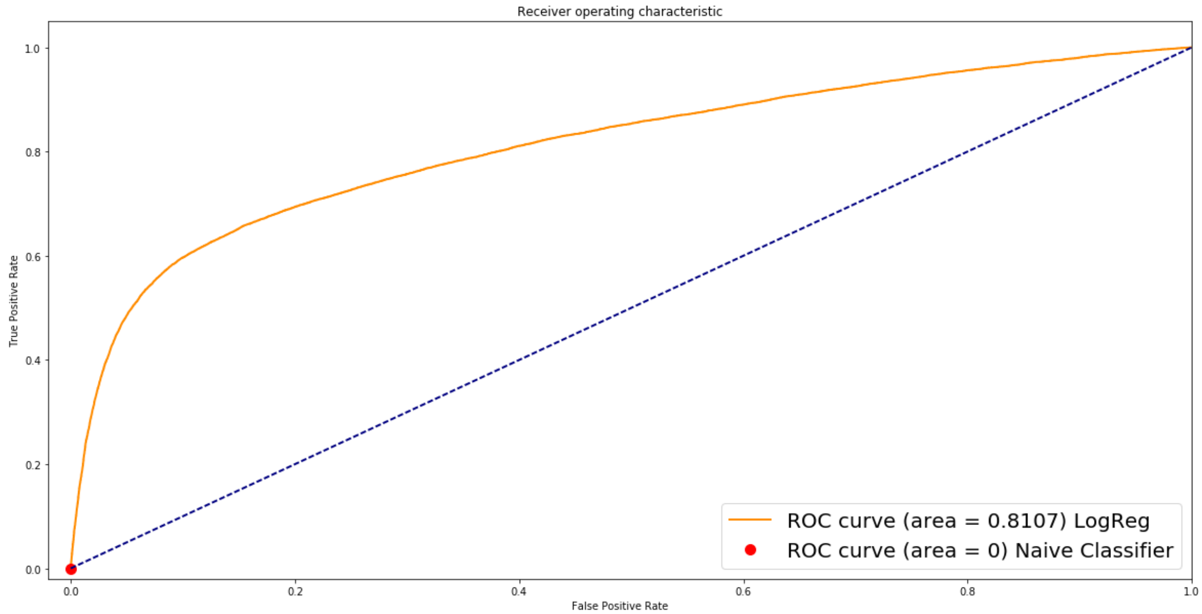
Logistic with Poly Terms

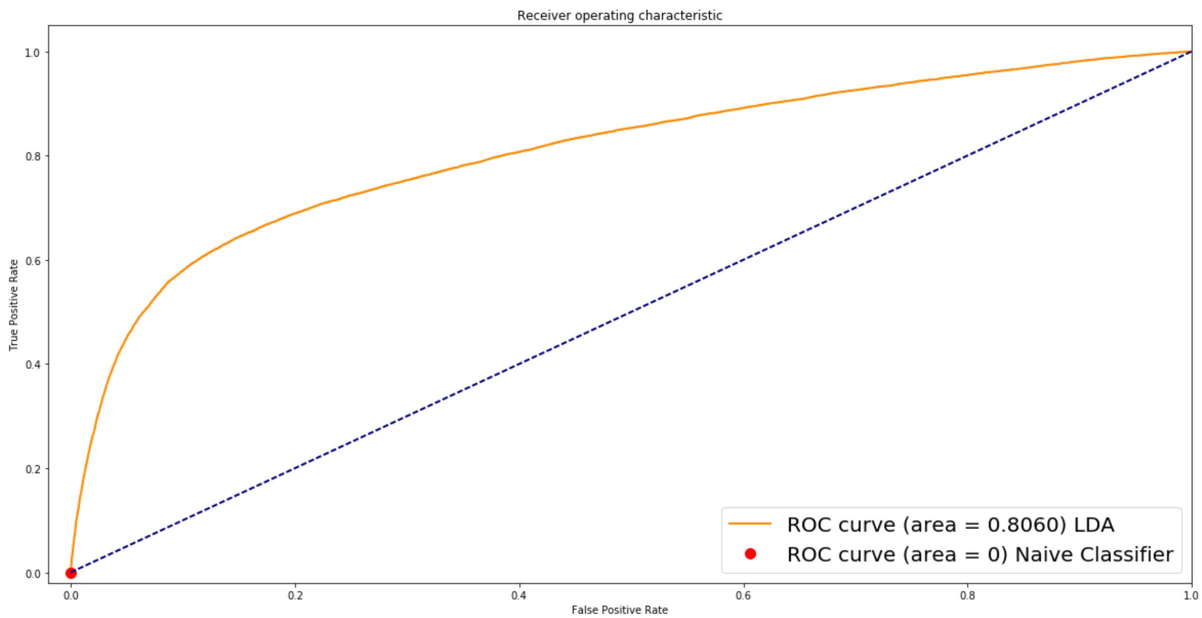
In [19]:
```
# logistic model with polynomial terms

# including all polynomial terms and interaction terms makes this model
 too slow to run
# include polynomial terms
#poly = PolynomialFeatures(degree = 2, include_bias = False, interaction
_only=True)
X_train_poly = copy.deepcopy(X_train)
X_valid_poly = copy.deepcopy(X_valid)
X_test_poly = copy.deepcopy(X_test)

preds = X_train.columns.values
for predictor in ['DAY', 'DISTANCE', 'SCHEDULED_TIME',
'SCHED_DEP_FLOAT', 'ORIGIN_TRAFFIC', 'DESTINATION_TRAFFIC']:
    title = predictor + "_2"
    title2 = predictor + "_3"
    X_train_poly[title] = X_train_poly[predictor] ** 2
    X_valid_poly[title] = X_valid_poly[predictor] ** 2
    X_test_poly[title] = X_test_poly[predictor] ** 2
    X_train_poly[title2] = X_train_poly[predictor] ** 3
    X_valid_poly[title2] = X_valid_poly[predictor] ** 3
    X_test_poly[title2] = X_test_poly[predictor] ** 3

lr_poly = LogisticRegressionCV(penalty='l2') # By default LBGFS induces
 L2 norm.
lr_poly.fit(X_train_poly, Y_train)
print("Accuracy Score: ", lr_poly.score(X_valid_poly, Y_valid))
print("So our accuracy on the validation data is boosted very slightly b
y adding these polynomial terms. A more careful analysis of which polyno
mial terms are significant, and what interaction terms might be useful a
nd could boost performance even more.")
```

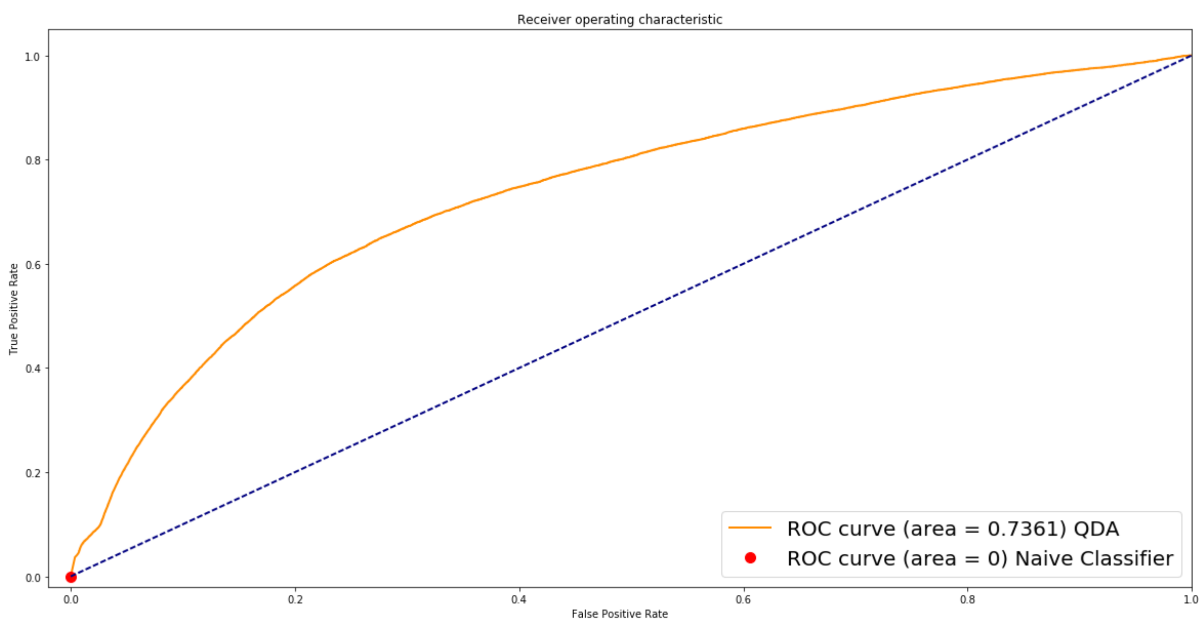
```
Accuracy Score:  0.907645996388
So our accuracy on the validation data is boosted very slightly by addi
ng these polynomial terms. A more careful analysis of which polynomial
 terms are significant, and what interaction terms might be useful and
 could boost performance even more.
```

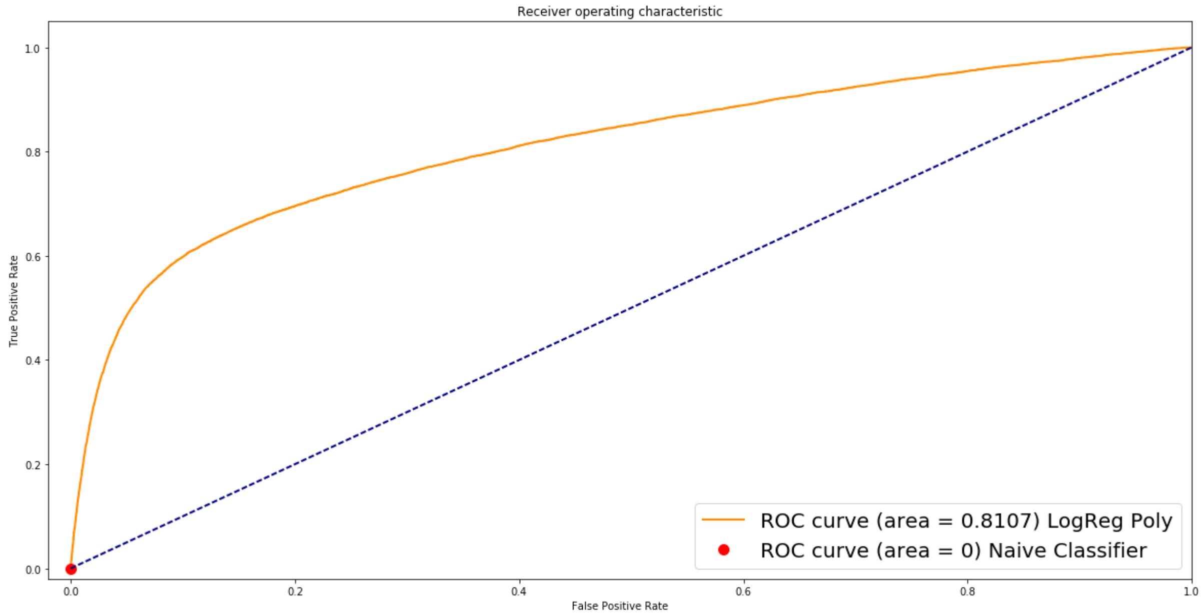
In [20]:
```
# pre-written function to display ROC curve for a model
def roc_curve(model, X, Y, title):
    preds = model.predict_proba(X)[:,1]
    fpr, tpr, thresholds = metrics.roc_curve(Y, preds)
    fpr_2, tpr_2, thresholds_2 = metrics.roc_curve(Y, [0 for y in Y])
    roc_auc_2 = metrics.auc(fpr_2, tpr_2)
    plt.figure(figsize=(20,10))
    lw = 2
    roc_auc = metrics.auc(fpr, tpr)
    plt.plot(fpr, tpr, color='darkorange',
             lw=lw, label='ROC curve (area = %0.4f) {}'.format(title) %
roc_auc)
    plt.plot([0], [0], marker='o', markersize=10, lw = 0, color="red", l
abel ='ROC curve (area = 0) Naive Classifier')
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([-0.02, 1.0])
    plt.ylim([-0.02, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic')
    plt.legend(loc="lower right", prop={'size':20})
    plt.show()
```

In [21]:
```
roc_curve(logregcv, X_train, Y_train, 'LogReg')
roc_curve(lda, X_train, Y_train, 'LDA')
roc_curve(qda, X_train, Y_train, 'QDA')
roc_curve(lr_poly, X_train_poly, Y_train, 'LogReg Poly')
```


Receiver operating characteristic
True Positive Rate
False Positive Rate
ROC curve (area = 0.8107) LogReg
ROC curve (area = 0) Naive Classifier


Receiver operating characteristic
True Positive Rate
False Positive Rate
ROC curve (area = 0.8060) LDA
ROC curve (area = 0) Naive Classifier


Receiver operating characteristic
True Positive Rate
False Positive Rate
ROC curve (area = 0.7361) QDA
ROC curve (area = 0) Naive Classifier



Comments: simply logistic regression seems to be the best model on this set, since it is essentially tied with the polynomial term logistic regression for performance, but is simpler and more efficient.

In [22]:
```
# simple Logistic Regression on this set seems to be the best model
# so we will display these coefficients
for i in range(len(preds_class)):
    print('Coefficient for {}: {}'.format(preds_class[i],
logregcv.coef_[0][i]))
```

```
Coefficient for DAY: -0.06269070719774932
Coefficient for DISTANCE: -4.558243764638298
Coefficient for SCHEDULED_TIME: 5.767905730776717
Coefficient for SCHED_DEP_FLOAT: 5.698700833814338
Coefficient for DESTINATION_TRAFFIC: 0.3396044742333251
Coefficient for ORIGIN_TRAFFIC: 0.1942135552111503
Coefficient for AIRLINE_AA: -0.2593064805775563
Coefficient for AIRLINE_AS: -1.4436199566641605
Coefficient for AIRLINE_B6: 0.43598416587614236
Coefficient for AIRLINE_DL: -1.3419955005380593
Coefficient for AIRLINE_EV: 0.2209625273208871
Coefficient for AIRLINE_F9: 1.0041565731139335
Coefficient for AIRLINE_HA: -1.163603166813929
Coefficient for AIRLINE_MQ: 0.44526013645062457
Coefficient for AIRLINE_NK: 1.9375211086609228
Coefficient for AIRLINE_OO: -0.15428480283811524
Coefficient for AIRLINE_UA: 0.25256220061344303
Coefficient for AIRLINE_US: -0.42895273464612005
Coefficient for AIRLINE_VX: 0.22881308221786215
Coefficient for AIRLINE_WN: 0.08520019592304194
Coefficient for DAY_OF_WEEK_1: 0.3602462116976932
Coefficient for DAY_OF_WEEK_2: -0.17578255603801204
Coefficient for DAY_OF_WEEK_3: 0.005160988003684378
Coefficient for DAY_OF_WEEK_4: 0.432149925018257
Coefficient for DAY_OF_WEEK_5: 0.14535779156860695
Coefficient for DAY_OF_WEEK_6: -0.6077916541226109
Coefficient for DAY_OF_WEEK_7: -0.3406433580287143
Coefficient for MONTH_1: 0.49692568125881903
Coefficient for MONTH_2: 0.7050009715197869
Coefficient for MONTH_3: 0.2040801014884996
Coefficient for MONTH_4: -0.3131102834793226
Coefficient for MONTH_5: -0.0012880227292928399
Coefficient for MONTH_6: 0.9017134118446098
Coefficient for MONTH_7: 0.5666865113384386
Coefficient for MONTH_8: 0.06425421978245628
Coefficient for MONTH_9: -1.1369091154248119
Coefficient for MONTH_10: -1.1934731524753
Coefficient for MONTH_11: -0.6787931850395097
Coefficient for MONTH_12: 0.20361021001460658
```

Part 5:

Given your model, comment on the importance of factors as related to whether a flight is delayed.

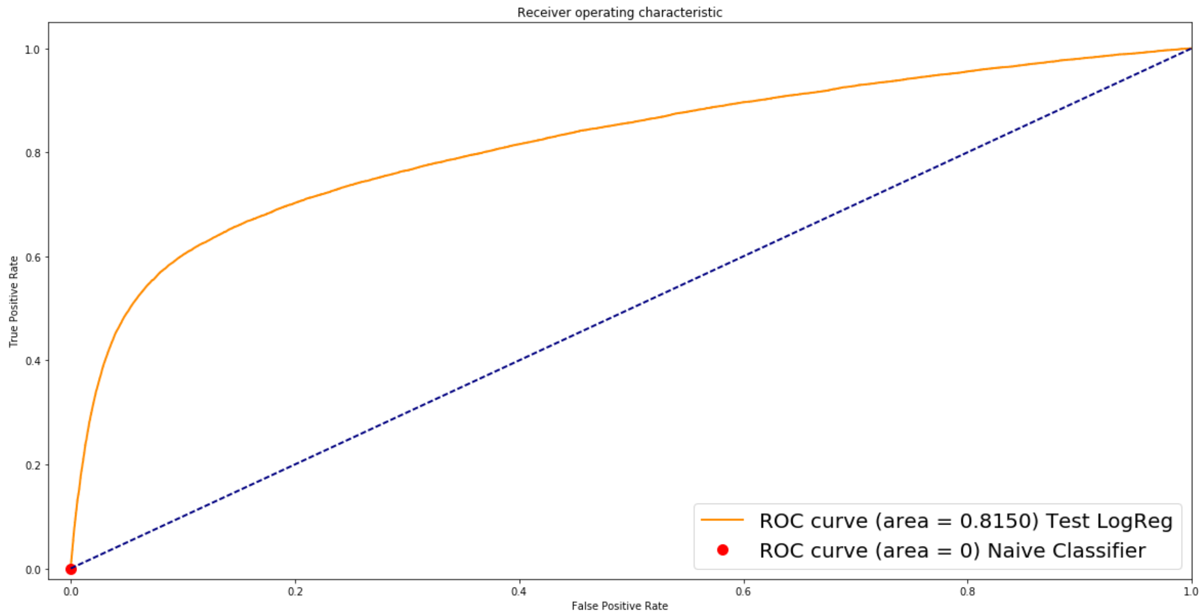
The original model that I tested did not use the SCHED_DEP_FLOAT, ORIGIN_TRAFFIC, DESTINATION_TRAFFIC or the airlines/day_of_week/month one-hot data, and had an AUC of 0.59, as specified in the hint section of this assignment. When training these classification models, I used these one-hot encoded columns, and the other predictors that I designed, and this immediately improved the performance of the classifier by a significant amount. In addition, with this task in mind, I tried 4 different models- Simple Logistic, LDA, QDA, and Logistic with polynomial terms. QDA performed poorly, but the rest performed well, with Simple and Polynomial logistic essentially tied for performance, and since Simple Logistic is an efficient and transparent model, I chose this as the best model, and displayed its predictor coefficients above (it had Classification rate of 0.907104154124, and AUC of 0.8107). Based on the coefficients, there are a few columns that have more predictive power than others. SCHED_DEP (the departure time) has a very large coefficient, and it is positive, so the later the departure time is, the more likely there is a delay, which makes sense. Similarly, SCHEDULED_TIME has a large positive coefficient, so perhaps longer flights tend to be more delayed. At the same time, DISTANCE has a large negative coefficient, so this information in contradictory, and perhaps the effects of distance and scheduled time essentially cancel out. In addition, Spirit Airlines (NK) and Frontier (F9) are much more likely to delay a flight, with significant coefficients, and Delta (DL), Alaskan Air (AS), US Airways (US), and Hawaiian Air (HA) are less likely to delay flights with a significant coefficient. Most other predictors show relatively low values, meaning a somewhat insignificant direct connection to flight delays. We must remember that there is likely some degree of collinearity between these predictors so certain effects that we may expect out of one predictor may be captured by another, but in general, these large coefficient values indicate significant predictive impact.

Part 6:

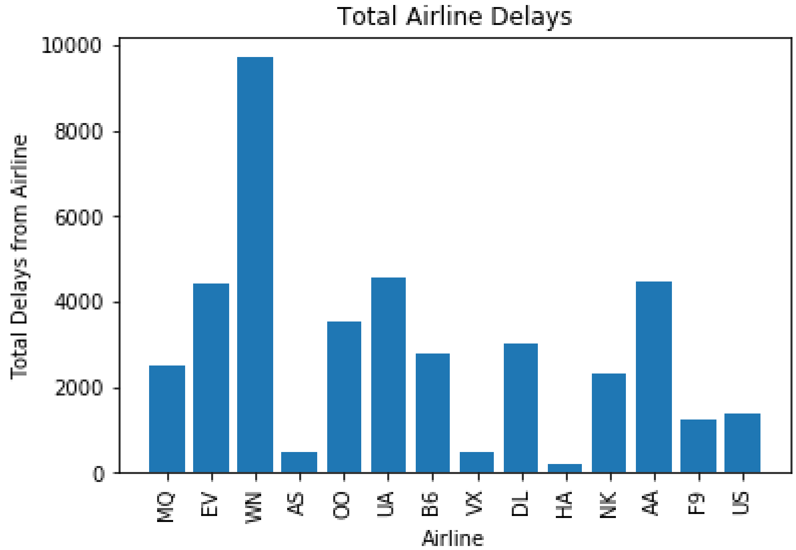
Evaluate your model(s) on your test set, and finally provide a visual to show which airlines are predicted to have the most delays using all the data excluding the training and test set.

In [23]:
```
print("Accuracy Score for Test Data: ", logregcv.score(X_test, Y_test))
roc_curve(logregcv, X_test, Y_test, 'Test LogReg')
```

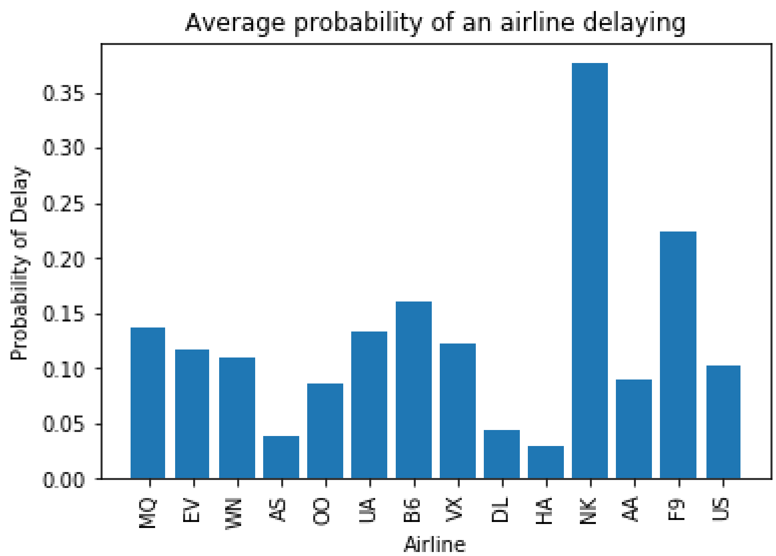
```
Accuracy Score for Test Data:  0.905599935731
```



In [24]:
```
remaining_data.head()

orig_remaining_data['prediction'] = logregcv.predict(remaining_data[pred
s_class])
airlines = list(set(orig_remaining_data['AIRLINE'].values))
sum_delays = []
prob_delay = []
for airline in airlines:
    airline_data = orig_remaining_data[orig_remaining_data['AIRLINE'] ==
 airline]
    sum_delays.append(sum(airline_data['DELAY_OR_NOT']))
    if(len(airline_data) == 0):
        prob_delay.append(0)
    else:
        prob_delay.append(sum(airline_data['DELAY_OR_NOT'])/len(airline_
data))

plt.figure(6)
plt.bar(range(len(airlines)), sum_delays)
plt.xlabel('Airline')
plt.ylabel('Total Delays from Airline')
plt.title('Total Airline Delays')
plt.xticks(range(len(airlines)), airlines, rotation='vertical')
plt.show()

print("But this is a flawed measurement because some airlines will simpl
y have way more flights than others. Instead, we can print out delays/#f
lights to get the probability that a flight is delayed")

plt.figure(7)
plt.bar(range(len(airlines)), prob_delay)
plt.xlabel('Airline')
plt.ylabel('Probability of Delay')
plt.title('Average probability of an airline delaying')
plt.xticks(range(len(airlines)), airlines, rotation='vertical')
plt.show()
```




```
But this is a flawed measurement because some airlines will simply have
way more flights than others. Instead, we can print out delays/#flights
to get the probability that a flight is delayed
```



Comments: Here, we see that the AUC for the test set is actually higher than on the training data, at 0.8150, and the Classification Accuracy is 0.905599935731 showing a solid performance for the logistic regression model with the selected predictors. In addition, our predicted probabilities of delaying flights match both the observations made about the coefficients, and the EDA performed earlier (low delays for HA, DL, AS, and high delays for NK and F9).

Part 7:

Build a regression model that predicts the length of delay (on the log scale) given that a flight is truly delayed.

In [25]:
```
# save a copy of the data, with our premade categories, but no one-hot
data2 = copy.deepcopy(data)
data2.head()
```

Out[25]:

	DATE	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	ORI
0	2015-09-19	9	19	6	AA	394	N3FMAA	ORD
1	2015-10-28	10	28	3	AA	375	N4YDAA	112
2	2015-08-19	8	19	3	MQ	3648	N512MQ	XNA
3	2015-12-01	12	1	2	WN	4096	N912WN	PHX
4	2015-09-15	9	15	2	WN	285	N7718B	MCI

5 rows × 25 columns

In [26]:
```
# RE-DO PRE PROCESSING ON NEW DATA

# first, only take data that has been delayed
data_delay = data2[data2['DELAY_OR_NOT'] == 1]

# split into train/test and do not touch test data until our final test
# less data, so no need to deal with remaining, just split 50/50 train/t
est

np.random.seed(9001)
msk = np.random.rand(len(data_delay)) < 0.5
data_train2 = data_delay[msk]
data_test2 = data_delay[~msk]

print(len(data_train2))
print(len(data_test2))
```

```
41042
41065
```

In [27]:
```
# pre-processing, one-hot for airline, day_of_week, month
categorical_columns_g2cols = ['AIRLINE','DAY_OF_WEEK', 'MONTH']
data_train2 = pd.get_dummies(data_train2, columns=categorical_columns_g2
cols, drop_first=True)
data_test2 = pd.get_dummies(data_test2, columns=categorical_columns_g2co
ls, drop_first=True)

data_train2.head()
```

Out[27]:

	DATE	DAY	FLIGHT_NUMBER	TAIL_NUMBER	ORIGIN_AIRPORT	DESTINATION_AIF
19	2015-01-04	4	958	N211WN	PHL	ATL
70	2015-08-19	19	6144	N11539	ABE	ORD
123	2015-03-14	14	1673	N256WN	BDL	MDW
151	2015-11-12	12	2701	N283JB	BUF	JFK
158	2015-07-05	5	1579	N65832	LAX	DEN

5 rows × 52 columns

In [28]:
```
# get the regression problem predictors
predictors_remove = ['ARRIVAL_DELAY', 'DATE', 'FLIGHT_NUMBER', 'TAIL_NUM
BER', 'SCHED_ARR', 'DEPARTURE_DELAY', 'ELAPSED_TIME',
'AIR_SYSTEM_DELAY', 'SECURITY_DELAY', 'AIRLINE_DELAY', 'LATE_AIRCRAFT_DE
LAY', 'WEATHER_DELAY', 'SCHED_DEP', 'DELAY_OR_NOT', 'ORIGIN_AIRPORT', 'D
ESTINATION_AIRPORT']
predictors_all = list(data_train2.columns.values)
for x in predictors_remove:
    predictors_all.remove(x)
preds_reg = predictors_all
print("Regression Problem Predictors: ", preds_reg)
```

```
Regression Problem Predictors:  ['DAY', 'DISTANCE', 'SCHEDULED_TIME',
 'SCHED_DEP_FLOAT', 'DESTINATION_TRAFFIC', 'ORIGIN_TRAFFIC', 'AIRLINE_A
S', 'AIRLINE_B6', 'AIRLINE_DL', 'AIRLINE_EV', 'AIRLINE_F9', 'AIRLINE_H
A', 'AIRLINE_MQ', 'AIRLINE_NK', 'AIRLINE_OO', 'AIRLINE_UA', 'AIRLINE_U
S', 'AIRLINE_VX', 'AIRLINE_WN', 'DAY_OF_WEEK_2', 'DAY_OF_WEEK_3', 'DAY_
OF_WEEK_4', 'DAY_OF_WEEK_5', 'DAY_OF_WEEK_6', 'DAY_OF_WEEK_7', 'MONTH_
2', 'MONTH_3', 'MONTH_4', 'MONTH_5', 'MONTH_6', 'MONTH_7', 'MONTH_8',
 'MONTH_9', 'MONTH_10', 'MONTH_11', 'MONTH_12']
```

In [29]:

```
# split training data into train and validation
np.random.seed(9001)
msk4 = np.random.rand(len(data_train2)) < 0.75
train_data2 = data_train2[msk4]
valid_data2 = data_train2[~msk4]

# split data into predictors and response (X and y)
# make sure to use log scale for the response variable
X_train2 = train_data2[preds_reg]
Y_train2 = np.log10(train_data2['ARRIVAL_DELAY'].values)
X_valid2 = valid_data2[preds_reg]
Y_valid2 = np.log10(valid_data2['ARRIVAL_DELAY'].values)
X_test2 = data_test2[preds_reg]
Y_test2 = np.log10(data_test2['ARRIVAL_DELAY'].values)
```

In [30]:
```
# pre-processing step, normalize all predictors to be between 0 and 1

def normalize_columns(X, X_min, X_max):
    return (X-X_min)/(X_max-X_min)

normal_predictors = copy.deepcopy(preds_reg)
for pred in normal_predictors:
    X_train2[pred] = normalize_columns(X=X_train2[pred], X_min=min(X_tra
in2[pred].values), X_max=max(X_train2[pred].values))
    X_test2[pred] = normalize_columns(X=X_test2[pred],
X_min=min(X_test2[pred].values), X_max=max(X_test2[pred].values))
    X_valid2[pred] = normalize_columns(X=X_valid2[pred], X_min=min(X_val
id2[pred].values), X_max=max(X_valid2[pred].values))

X_train2.head()
```

```
/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/ipykernel/_
_main__.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/ipykernel/_
_main__.py:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
/Users/joshkuppersmith/anaconda/lib/python3.6/site-packages/ipykernel/_
_main__.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
```

Out[30]:

	DAY	DISTANCE	SCHEDULED_TIME	SCHED_DEP_FLOAT	DESTINATION_TRAF
19	0.100000	0.128231	0.174507	0.774373	1.000000
151	0.366667	0.054523	0.104704	0.771588	0.230073
166	0.833333	0.194871	0.247344	0.784123	0.008440
172	0.133333	0.031906	0.060698	0.607242	0.166744
249	0.566667	0.300081	0.291351	0.541086	0.313031

5 rows × 36 columns

In [31]:

```
# OLS MODEL
print('Predictors: ', X_train2.columns.values)
ols = LinearRegression(fit_intercept=True)
ols.fit(X_train2, Y_train2)
print()
print('OLS Train Score', r2_score(Y_train2, ols.predict(X_train2)))
print('OLS Valid Score', r2_score(Y_valid2, ols.predict(X_valid2)))
print('OLS Test Score', r2_score(Y_test2, ols.predict(X_test2)))
```

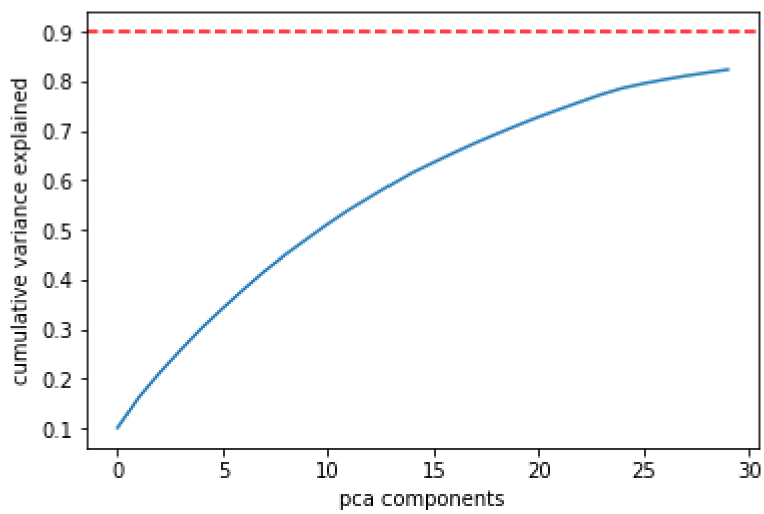
```
Predictors:  ['DAY' 'DISTANCE' 'SCHEDULED_TIME' 'SCHED_DEP_FLOAT' 'DEST
INATION_TRAFFIC'
 'ORIGIN_TRAFFIC' 'AIRLINE_AS' 'AIRLINE_B6' 'AIRLINE_DL' 'AIRLINE_EV'
 'AIRLINE_F9' 'AIRLINE_HA' 'AIRLINE_MQ' 'AIRLINE_NK' 'AIRLINE_OO'
 'AIRLINE_UA' 'AIRLINE_US' 'AIRLINE_VX' 'AIRLINE_WN' 'DAY_OF_WEEK_2'
 'DAY_OF_WEEK_3' 'DAY_OF_WEEK_4' 'DAY_OF_WEEK_5' 'DAY_OF_WEEK_6'
 'DAY_OF_WEEK_7' 'MONTH_2' 'MONTH_3' 'MONTH_4' 'MONTH_5' 'MONTH_6'
 'MONTH_7' 'MONTH_8' 'MONTH_9' 'MONTH_10' 'MONTH_11' 'MONTH_12']

OLS Train Score 0.0373735789644
OLS Valid Score 0.025059813133
OLS Test Score 0.0381651306603
```

In [32]:
```
# OLS with polynomial terms

X_train3 = copy.deepcopy(X_train2)
X_valid3 = copy.deepcopy(X_valid2)
X_test3 = copy.deepcopy(X_test2)

# add polynomial terms
for predictor in ['DAY', 'DISTANCE', 'SCHEDULED_TIME',
'SCHED_DEP_FLOAT', 'ORIGIN_TRAFFIC', 'DESTINATION_TRAFFIC']:
    title = predictor + "_2"
    title2 = predictor + "_3"
    X_train3[title] = X_train3[predictor] ** 2
    X_valid3[title] = X_valid3[predictor] ** 2
    X_test3[title] = X_test3[predictor] ** 2
    X_train3[title2] = X_train3[predictor] ** 3
    X_valid3[title2] = X_valid3[predictor] ** 3
    X_test3[title2] = X_test3[predictor] ** 3

# add some intuitive interaction terms
string = "INTER_"
term_num = 1
# terms between airlines and all other factors
airlines = ['AIRLINE_AS', 'AIRLINE_B6', 'AIRLINE_DL', 'AIRLINE_EV', 'AIR
LINE_F9', 'AIRLINE_HA', 'AIRLINE_MQ', 'AIRLINE_NK', 'AIRLINE_OO', 'AIRLI
NE_UA', 'AIRLINE_US', 'AIRLINE_VX', 'AIRLINE_WN']
others = ['DAY', 'DISTANCE', 'SCHEDULED_TIME', 'SCHED_DEP_FLOAT', 'DESTI
NATION_TRAFFIC', 'ORIGIN_TRAFFIC', 'DAY_OF_WEEK_2','DAY_OF_WEEK_3', 'DAY
_OF_WEEK_4', 'DAY_OF_WEEK_5', 'DAY_OF_WEEK_6','DAY_OF_WEEK_7']
for airline in airlines:
    for other in others:
        title = string + str(term_num)
        X_train3[title] = X_train3[airline]* X_train3[other]
        X_valid3[title] = X_valid3[airline]*X_valid3[other]
        X_test3[title] = X_test3[airline]*X_test3[other]
```

```
        term_num += 1

# a few more potentially interesting interaction terms
string = "INTER_2_"
term_num = 1
# terms between days of the week and other factors
days_of_week = ['DAY_OF_WEEK_2','DAY_OF_WEEK_3', 'DAY_OF_WEEK_4', 'DAY_O
F_WEEK_5', 'DAY_OF_WEEK_6','DAY_OF_WEEK_7']
others2 = ['DISTANCE', 'SCHEDULED_TIME', 'SCHED_DEP_FLOAT', 'DESTINATION
_TRAFFIC','ORIGIN_TRAFFIC']
for day in airlines:
    for other in others2:
        title = string + str(term_num)
        X_train3[title] = X_train3[day]* X_train3[other]
        X_valid3[title] = X_valid3[day]*X_valid3[other]
        X_test3[title] = X_test3[day]*X_test3[other]
        term_num += 1

# OLS model
ols2 = LinearRegression(fit_intercept=True)
ols2.fit(X_train3, Y_train2)
print('OLS Train Score', r2_score(Y_train2, ols2.predict(X_train3)))
print('OLS Valid Score', r2_score(Y_valid2, ols2.predict(X_valid3)))
print('OLS Test Score', r2_score(Y_test2, ols2.predict(X_test3)))
```

```
OLS Train Score 0.0472546966959
OLS Valid Score 0.0275138714838
OLS Test Score 0.0401109787072
```

In [ ]:
```
# try using PCA to reduce dimensionality
pca = PCA()
pca.fit(X_train3)
var_c = np.cumsum(pca.explained_variance_ratio_)
plt.plot(range(30), var_c[0:30])
plt.axhline(0.9,ls='--',color='red')
plt.xlabel("pca components")
plt.ylabel("cumulative variance explained")
plt.show()

# so let's try 20 PCA components to try to avoid overfitting
pca_comp = 20
X_train_pca = pca.transform(X_train3)[:,:pca_comp]
X_test_pca = pca.transform(X_test3)[:,:pca_comp]
X_valid_pca = pca.transform(X_valid3)[:,:pca_comp]

# OLS model. Uses PCA
ols2 = LinearRegression(fit_intercept=True)
ols2.fit(X_train_pca, Y_train2)
print('OLS Train Score', r2_score(Y_train2, ols2.predict(X_train_pca)))
print('OLS Valid Score', r2_score(Y_valid2, ols2.predict(X_valid_pca)))
print('OLS Test Score', r2_score(Y_test2, ols2.predict(X_test_pca)))

print()
print("As expected, using PCA to reduce dimensionality simply gives us l
ess information to predict on, so it hurts our model.")
```




```
OLS Train Score 0.0231679300927
OLS Valid Score 0.0197212042953
OLS Test Score 0.0248779123648

As expected, using PCA to reduce dimensionality simply gives us less in
formation to predict on, so it hurts our model.
```

In [ ]:
```
# KNN model with many values of k
valid_scores = []

# The code below is commented out because it takes a long time to run
# however, this loop was used to determine the best n_neighbors value fo
r
# knn, which ended up being 81.

#ns = range(1,301,10)
#for n in ns:
#    knn = KNeighborsRegressor(n_neighbors=n)
#    knn.fit(X_train2, Y_train2)
#    valid_scores.append(r2_score(Y_valid2, knn.predict(X_valid2)))
#index = valid_scores.index(max(valid_scores))
#best_n = ns[index]

print("N = {}".format(81))
knn = KNeighborsRegressor(n_neighbors=81)
knn.fit(X_train2, Y_train2)
print('KNN Train Score', r2_score(Y_train2, knn.predict(X_train2)))
print('KNN Valid Score', r2_score(Y_valid2, knn.predict(X_valid2)))
print('KNN Test Score', r2_score(Y_test2, knn.predict(X_test2)))

# so we see significant overfitting here, with high training score and l
ow test and validation
```

```
N = 81
```

Comments: OLS with several added polynomial and interaction terms is the best model here, with the highest r2 value. KNN overfits, and PCA hurts performance because it limits predictive information. A possible next step to help performance is to run predictor selection on the interaction term dataset to find the best set of predictors (avoid overfitting), and boost this OLS model even further.

Part 8:

Write a report (in the last markdown cell in your notebook with your findings (without code)). Describe the main design decisions you have made with justifications. Clearly explain your methodology and results. This should not be more than 300 words. You may use up to 5 diagrams.