Data Science Decal Project 1

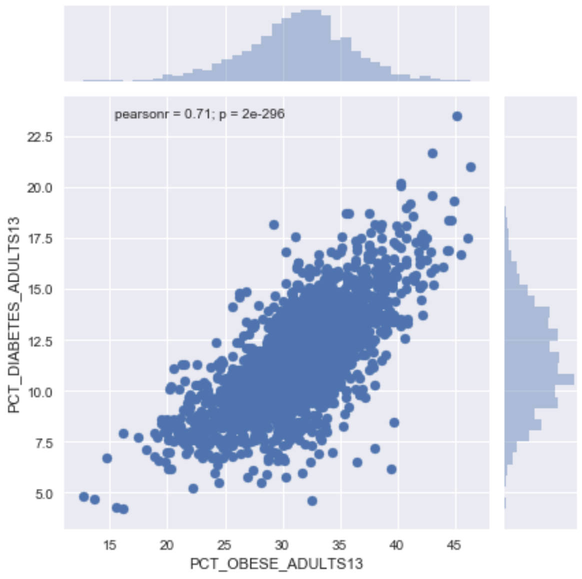
By: An Wang, Andrew Wang, Skyler Ruesga

The first part of the project was picking the dataset to work with. While the school finances was one sheet and very simple to convert to a CSV, we found that the food access dataset was neater and more interesting. We found the food access dataset better documented and easier to follow as well. To clean our dataset, we simply dropped null rows from our dataset, since are only interested in counties that have values for both food access and health data.

To understand the data we utilized seaborn to make graphs. We quickly were able to recognize patterns in the data. It was apparent that there was some correlation between obesity and diabetes as well as fast food restaurants and full service restaurants. From what we observed, counties with higher obesity rates tend to have higher diabetes rates, and counties that have more full service restaurants tend to spend more on full service restaurants than compared to fast food restaurants. This may be that full service restaurants are more expensive than fast food, so likely cannot indicate that counties may consume more full service restaurant food if more of these restaurants are available. We also plotted obesity rates vs diabetes rates, which showed a clear linear correlation, so we decided to analyze further, checking if increases in the number of fast food restaurants in a county had any relation on obesity or diabetes rates.

For linear regression, we used scikit learn’s library to create a linear regression model to create a function that tries to find a correlation between obesity and diabetes.

We first created a graph mapping each county’s percentage of obesity against each county’s percentage of diabetes (that is percentage of the county suffering from diabetes and obesity).



As you can see, there seems to be a solid linear relationship between the two. We then split up the obesity data into two segments. The first segment is our training data containing 80% of our data points while the second segment is our testing data which contains 20% of our data points. We do likewise with our diabetes data, splitting it 4:1, then train our model on the training data. Once the model has been trained we test it’s performance by feeding it the obesity testing data and recording its results. These results should be some prediction as to the percent of the population that has diabetes. We can then compare this predicted data against our real diabetes testing data to ascertain the accuracy of our model. We end up with a MSE of 3.827 and a model accuracy of 0.462. While this initially seems like a poor result and might make us want to reconsider the model, these results in fact reinforce what we do see in the data. The original data, while seeming to portray some linear relationship, is in no way strictly linear and seems to have a large degree of variance from point to point. This suggests that even though there is some relation between obesity and diabetes, neither is the sole determining factor of the other, and thus any model that solely relies on one of these parameters to predict the other is bound to have only around a 46.2% accuracy.

For logistic regression, we also used scikit learn for the modeling. We decided to make our predictor variable the percent change in the number of fast food restaurants per county from 2009 to 2014, and the binary variable (outcome) would be whether there is a positive or nonpositive increase in obesity. We also did the same logistic regression with diabetes as our outcome variable. We chose our specific predictor variable because we want to see if an increase in the number of fast food restaurants in counties can be attributed towards the increase in obesity and diabetes rates in those counties. For obesity rates, we first subtracted the obesity rates in 2008 from the obesity rates in 2013 to get the difference in obesity rates for each county. We then mapped this difference to a true or false value based on whether the difference was greater than 0, indicating whether there was a positive increase (true) or a nonpositive increase (false). We found that our mean squared error of our logistic regression was about 0.2201 and yielded an R2-score of about 0.7799. This results in a somewhat accurate predictor of obesity rates, but still not reliable since fast food is not the only factor in increasing obesity rates. We then performed logistic regression on diabetes rates in counties. For diabetes rates, we used the same function to map the difference in diabetes rates from 2008 to 2013 to binary values. We calculated the MSE to be about

0.1349, and the R2-score to be about 0.8651. This indicates that an increase in the number of fast food restaurants in a county is a better predictor for increases in diabetes rates rather than increases in obesity rates (since the MSE for diabetes is lower and R2-score for diabetes is higher), yet is still not a complete predictor since it is just a single contributing factor to diabetes rates.

Fast food and health

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_squared_error
import seaborn as sns
#ssl error on osx fix
import ssl
ssl._create_default_https_context = ssl._create_unverified_context
%matplotlib inline
```

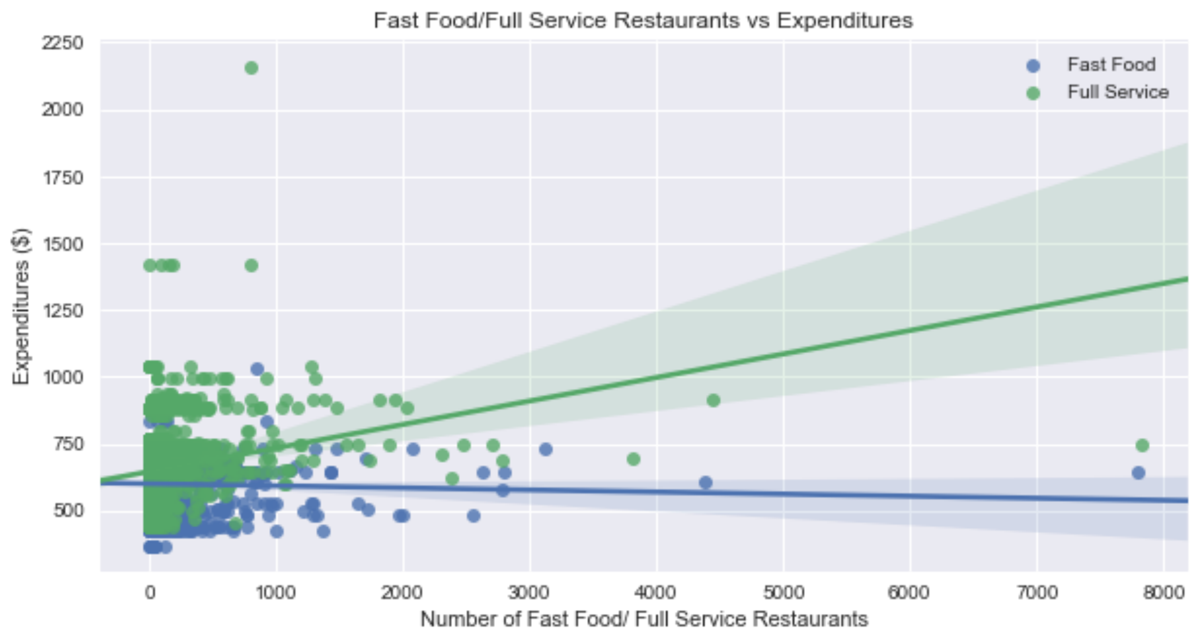
```
/usr/local/anaconda3/lib/python3.6/site-packages/statsmodels/compat/pan
das.py:56: FutureWarning: The pandas.core.datetools module is deprecate
d and will be removed in a future version. Please use the pandas.tserie
s module instead.
  from pandas.core import datetools
```

In [2]:
```
# load county population data
df_county = pd.read_csv('data/county.csv', index_col=False)
df_county = df_county.dropna()

# load restaurant data
df_restaurants = pd.read_csv('data/restaurants.csv', index_col=False)
df_restaurants = df_restaurants.dropna()

# load grocery store data
df_stores = pd.read_csv('data/stores.csv', index_col=False)
df_stores = df_stores.dropna()

# load health data
df_health = pd.read_csv('data/health.csv', index_col=False)
df_health = df_health.dropna()
```

In [3]:
```
# restaurants in 2009 and 2014
# Fast food, full service, and expenditures per capita on fast food and
 restaurants (2007 and 2012)
rests_09 = df_restaurants[['FIPS', 'State', 'County', 'FFR09', 'PC_FFRSA
LES07', 'FSR09', 'PC_FSRSALES07']]
rests_14 = df_restaurants[['FIPS', 'State', 'County', 'FFR14', 'PC_FFRSA
LES12', 'FSR14', 'PC_FSRSALES12']]
print("Average % change in number of fast food restaurants per 1000 pop:
 ", np.mean(df_restaurants['PCH_FFRPTH_09_14']))
# This shows that the average consumption in fast food is slightly incre
asing

print("Average % change in number of full service restaurants per 1000 p
op: ", np.mean(df_restaurants['PCH_FSRPTH_09_14']))
# This hsows that the average consumption in full service restaurants in
 increasing, but not as much as fast food
```

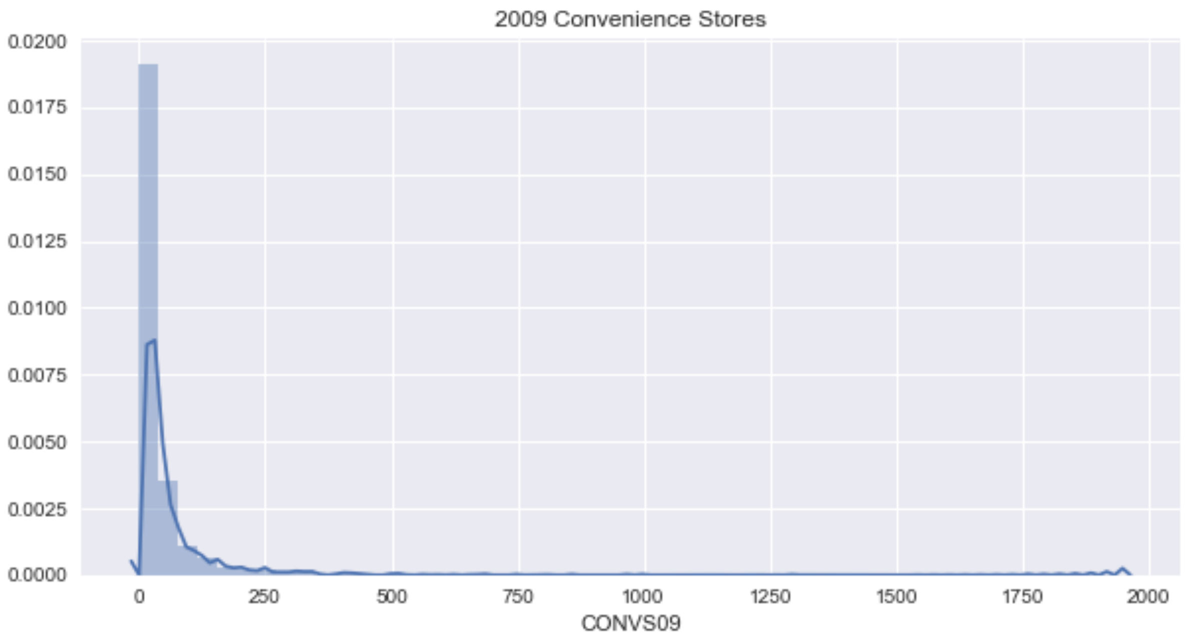
```
Average % change in number of fast food restaurants per 1000 pop:  4.80
59159891103445
Average % change in number of full service restaurants per 1000 pop:
 3.679059409120473
```

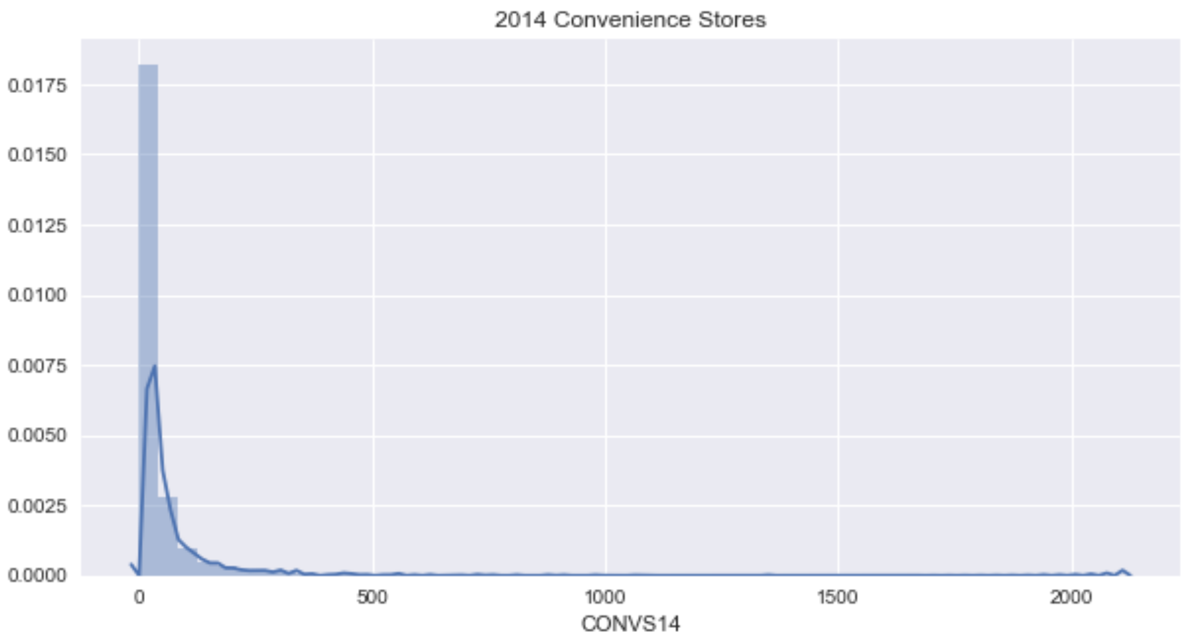
In [4]:
```
plt.figure(figsize=(10,5))
plt.title("Fast Food/Full Service Restaurants vs Expenditures")
sns.regplot(x = 'FFR14', y = 'PC_FFRSALES12', data = rests_14, label='Fa
st Food')
sns.regplot(x = 'FSR14', y = 'PC_FSRSALES12', data = rests_14, label='Fu
ll Service')
plt.ylabel("Expenditures ($)")
plt.xlabel("Number of Fast Food/ Full Service Restaurants")
plt.legend()
plt.show()
# This shows that there is more expenditure per capita in restaurants th
an fast food for counties with
# more full service restaurants, which perhaps is a way to combat high f
ast food consumption
```



In [5]:
```
# stores in 2009 and 2014
# Grocery, Supermarket, Convenience, and Specialized stores
stores_09 = df_stores[['FIPS', 'State', 'County', 'GROC09', 'SUPERC09',
'CONVS09', 'SPECS09']]
stores_14 = df_stores[['FIPS', 'State', 'County', 'GROC14', 'SUPERC14',
'CONVS14', 'SPECS14']]
```

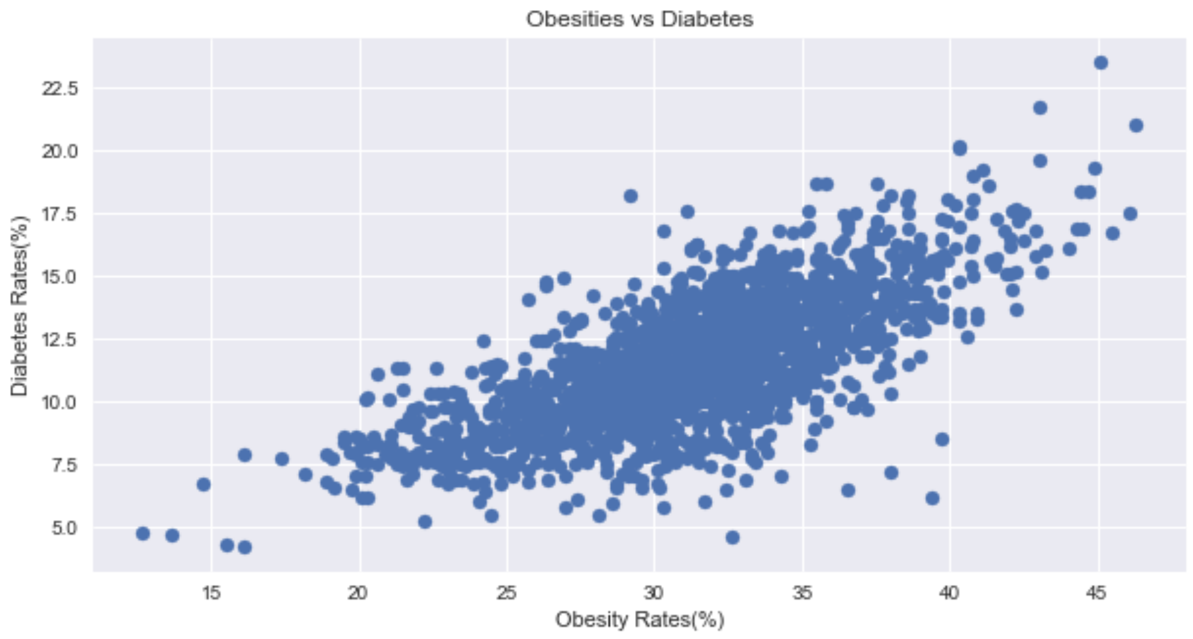
In [6]:
```
plt.figure(figsize=(10,5))
plt.title("2009 Convenience Stores")
sns.distplot(stores_09.dropna().CONVS09, hist='True')
plt.show()

plt.figure(figsize=(10,5))
plt.title("2014 Convenience Stores")
sns.distplot(stores_14.dropna().CONVS14, hist='True')
plt.show()
```





In [7]:
```
# health in 2008-09 and 2013-14
# Diabetes rate, Obesity rate, rec and facities count
health_0809 = df_health[['FIPS', 'State', 'County', 'PCT_DIABETES_ADULTS
08', 'PCT_OBESE_ADULTS08', 'RECFAC09']]
health_1314 = df_health[['FIPS', 'State', 'County', 'PCT_DIABETES_ADULTS
13', 'PCT_OBESE_ADULTS13', 'RECFAC14']]
```

In [8]:
```
plt.figure(figsize=(10,5))
plt.title("Obesities vs Diabetes")
# sns.barplot('PCT_OBESE_ADULTS13', 'PCT_DIABETES_ADULTS13', data = heal
th_1314)
# I think the below is better for visualizing trend
plt.scatter(health_1314['PCT_OBESE_ADULTS13'], health_1314['PCT_DIABETES
_ADULTS13'])
plt.xlabel("Obesity Rates(%)")
plt.ylabel("Diabetes Rates(%)")
plt.show()
```

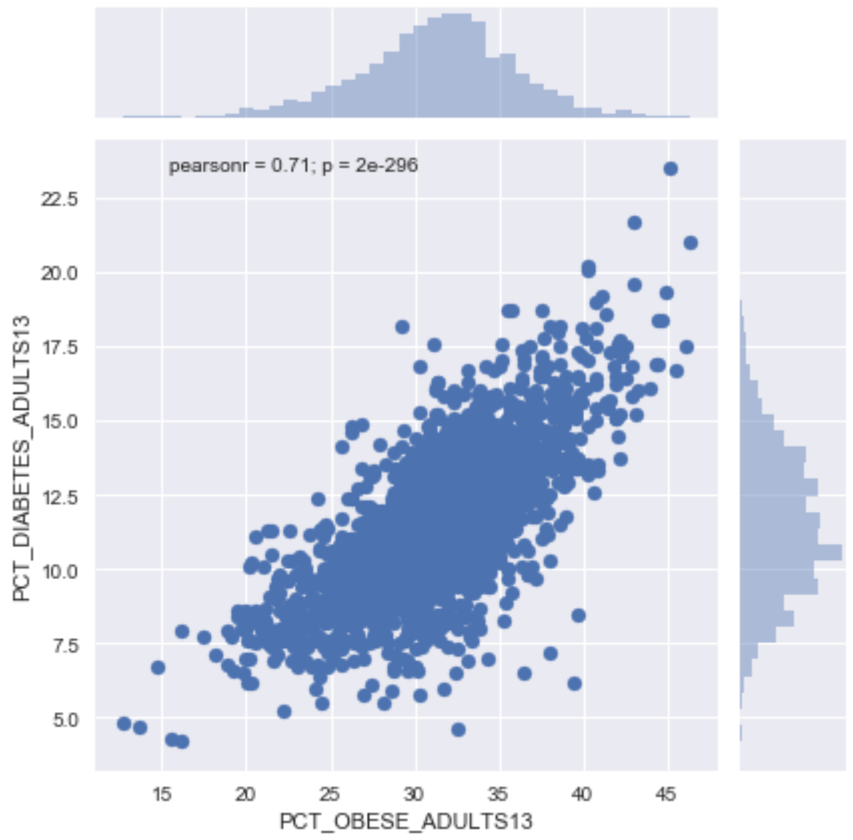


In [9]:
```
split = int(health_1314.shape[0] * 0.8)
diabetes_train = health_1314["PCT_DIABETES_ADULTS13"][:split]
diabetes_valid = health_1314["PCT_DIABETES_ADULTS13"][split:]
obesity_train = health_1314["PCT_OBESE_ADULTS13"][:split]
obesity_valid = health_1314["PCT_OBESE_ADULTS13"][split:]
```

In [10]:
```
myOLS = sm.OLS(diabetes_train, obesity_train).fit()
diabetes_hat = myOLS.predict(obesity_valid)
mse = 1/len(diabetes_valid)*np.dot((diabetes_valid - diabetes_hat),(diab
etes_valid - diabetes_hat))
print("The MSE for the model obesity~diabetes is:", mse)
```

```
The MSE for the model obesity~diabetes is: 3.85752534133
```

```
In [11]: sns.jointplot('PCT_OBESE_ADULTS13', 'PCT_DIABETES_ADULTS13', data = heal
         th_1314)
         plt.show()
```



Linear Regression

```
In [12]: linreg = LinearRegression()

         #80-20 train-test split
         split = int(len(health_1314.PCT_OBESE_ADULTS13) * 0.8)

         X = health_1314.PCT_OBESE_ADULTS13.values.reshape(-1,1)
         X_train, X_test = (X[:split], X[split:])

         y = health_1314.PCT_DIABETES_ADULTS13.values.reshape(-1,1)
         y_train, y_test = (y[:split], y[split:])

         model = linreg.fit(X_train, y_train)
         y_pred = model.predict(X_test)

         print("%change in obesity vs. %change in diabetes MSE: ", mean_squared_e
         rror(y_test, y_pred))
         print("%change in obesity vs. %change in diabetes R2-score: ", model.sco
         re(X_test, y_test))
```

```
%change in obesity vs. %change in diabetes MSE:  3.82727404393
%change in obesity vs. %change in diabetes R2-score:  0.46232564056
```

Logistic Regression

In [13]:
```
def change(diff):
        return diff > 0

logreg = LogisticRegression()
df_rest_health = df_restaurants[['County', 'PCH_FFR_09_14']].merge(
    df_health[['County', 'PCT_OBESE_ADULTS08', 'PCT_OBESE_ADULTS13',
               'PCT_DIABETES_ADULTS08', 'PCT_DIABETES_ADULTS13']]).dropn
a()

#80-20 train-test split
split = int(len(df_rest_health) * 0.8)

X = df_rest_health.PCH_FFR_09_14.values.reshape(-1,1)
X_train, X_test = (X[:split], X[split:])

y_obesity =  np.ravel(df_rest_health.PCT_OBESE_ADULTS13.sub(df_rest_heal
th.PCT_OBESE_ADULTS08).map(change))
y_obesity_train, y_obesity_test = (y_obesity[:split], y_obesity[split:])

model_obesity = logreg.fit(X_train, y_obesity_train)
y_obesity_pred = model_obesity.predict(X_test)
print("Fast food restaurant % change vs. change in obesity MSE: ",
      mean_squared_error(y_obesity_test, y_obesity_pred))
print("Fast food restaurant % change vs. change in obesity R2-score: ",
      model_obesity.score(X_test, y_obesity_test))
print()

y_diabetes =  np.ravel(df_rest_health.PCT_DIABETES_ADULTS13.sub(df_rest_
health.PCT_DIABETES_ADULTS08).map(change))
y_diabetes_train, y_diabetes_test = (y_diabetes[:split], y_diabetes[spli
t:])

model_diabetes = logreg.fit(X_train, y_diabetes_train)
y_diabetes_pred = model_diabetes.predict(X_test)
print("Fast food restaurant % change vs. change in diabetes MSE: ",
      mean_squared_error(y_diabetes_test, y_diabetes_pred))
print("Fast food restaurant % change vs. change in diabetes R2-score: ",
      model_diabetes.score(X_test, y_diabetes_test))
```

```
Fast food restaurant % change vs. change in obesity MSE:  0.22010582010
6
Fast food restaurant % change vs. change in obesity R2-score:  0.779894
179894

Fast food restaurant % change vs. change in diabetes MSE:  0.1349206349
21
Fast food restaurant % change vs. change in diabetes R2-score:  0.86507
9365079
```

```
/usr/local/anaconda3/lib/python3.6/site-packages/sklearn/metrics/regres
sion.py:232: DeprecationWarning: numpy boolean subtract, the `-` operat
or, is deprecated, use the bitwise_xor, the `^` operator, or the logica
l_xor function instead.
  output_errors = np.average((y_true - y_pred) ** 2, axis=0,
/usr/local/anaconda3/lib/python3.6/site-packages/sklearn/metrics/regres
sion.py:232: DeprecationWarning: numpy boolean subtract, the `-` operat
or, is deprecated, use the bitwise_xor, the `^` operator, or the logica
l_xor function instead.
  output_errors = np.average((y_true - y_pred) ** 2, axis=0,
```

Links used

https://github.com/mlberkeley/Data-Science-Decal-Fall-2017/blob/master/Day4-LogisticRegression/Finished_Logistic_Regression.ipynb (https://github.com/mlberkeley/Data-Science-Decal-Fall-2017/blob/master/Day4-LogisticRegression/Finished_Logistic_Regression.ipynb)

http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html (http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)

http://scikit-learn.org/stable/auto_examples/linear_model/plot_iris_logistic.html (http://scikit-learn.org/stable/auto_examples/linear_model/plot_iris_logistic.html)

http://nbviewer.jupyter.org/gist/justmarkham/6d5c061ca5aee67c4316471f8c2ae976 (http://nbviewer.jupyter.org/gist/justmarkham/6d5c061ca5aee67c4316471f8c2ae976)

```
In [ ]:
```