Proj1Food

October 4, 2017

In [2]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import missingno as msno
from sklearn.feature_selection import RFECV
from sklearn.linear_model import LinearRegression
from sklearn import linear_model
from sklearn.metrics import mean_squared_error, r2_score
from collections import defaultdict
from mpl_toolkits.mplot3d import Axes3D

foodSep = {'ACCESS':pd.DataFrame, 'STORES':pd.DataFrame, 'RESTAURANTS':pd.D
        'INSECURITY':pd.DataFrame, 'PRICES_TAXES':pd.DataFrame,
        'LOCAL':pd.DataFrame, 'HEALTH':pd.DataFrame, 'SOCIOECONOMIC':pd.Dat
for k, n in foodSep.items():
    foodSep[k] = pd.read_csv(k + '.csv')
```

```
/home/porrster/home/porrster/Documents/anaconda2/envs/universe/lib/python3.5/site-p
  from pandas.core import datetools
```

In [3]:
```
foodSep['ACCESS'].head()
```

Out[3]:

	FIPS	State	County	LACCESS_POP10	LACCESS_POP15	PCH_LACCESS_POP_10_15
0	1001	AL	Autauga	18428.439685	17496.693038	-5.056026
1	1003	AL	Baldwin	35210.814078	30561.264430	-13.204891
2	1005	AL	Barbour	5722.305602	6069.523628	6.067799
3	1007	AL	Bibb	1044.867327	969.378841	-7.224696
4	1009	AL	Blount	1548.175559	3724.428242	140.568857

	PCT_LACCESS_POP10	PCT_LACCESS_POP15	LACCESS_LOWI10	LACCESS_LOWI15	\
0	33.769657	32.062255	5344.427472	6543.676824	
1	19.318473	16.767489	9952.144027	9886.831137	
2	20.840972	22.105560	3135.676086	2948.790251	
3	4.559753	4.230324	491.449066	596.162829	

```
4           2.700840           6.497380      609.027708     1650.959482

            ...           LACCESS_HISP15  PCT_LACCESS_HISP15  \
0           ...               471.136164            0.863345
1           ...              1377.874834            0.755973
2           ...               509.377525            1.855183
3           ...                 8.596762            0.037516
4           ...               497.489891            0.867886

   LACCESS_NHASIAN15  PCT_LACCESS_NHASIAN15  LACCESS_NHNA15  \
0          86.767975               0.159000       61.169869
1         212.946378               0.116833      181.649648
2          17.096410               0.062266       39.960527
3           1.994318               0.008703        2.513097
4           8.428994               0.014705       28.938242

   PCT_LACCESS_NHNA15  LACCESS_NHPI15  PCT_LACCESS_NHPI15  LACCESS_MULTIR15
0            0.112092        8.817961            0.016159        482.84863
1            0.099662       14.819634            0.008131       1127.69609
2            0.145539        8.082376            0.029436        462.38265
3            0.010967        0.000000            0.000000          5.25924
4            0.050484        1.062851            0.001854        202.91418

   PCT_LACCESS_MULTIR15
0              0.884808
1              0.618712
2              1.684025
3              0.022951
4              0.353990

[5 rows x 44 columns]
```

In [4]:
```python
#combine all separate categories into one dataframe
# for simplicity. All categories have same number of rows
food = pd.concat(foodSep, axis=1)
```

In [5]:
```python
#confirm combination
print(foodSep['ACCESS'].shape)
print(food.shape)
```

```
(3143, 44)
(3143, 304)
```

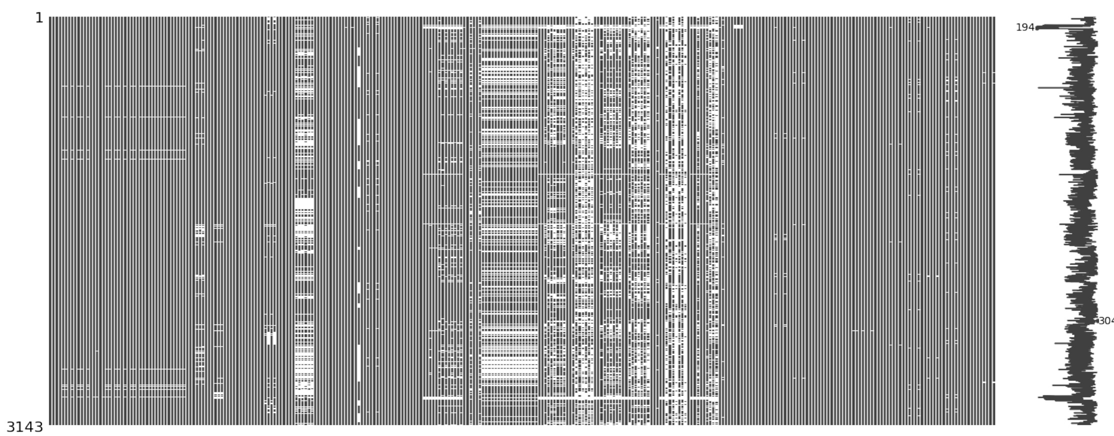
In [6]:
```python
food.describe()
```

Out[6]:
```
                  ACCESS                                                  \
                    FIPS  LACCESS_POP10  LACCESS_POP15 PCH_LACCESS_POP_10_15
count   3143.000000    3143.000000    3124.000000           3.117000e+03
```

```
mean   30390.411709   20156.653242   19287.747386           7.180008e+03
std    15164.717720   51308.865791   47803.525596           3.955676e+05
min     1001.000000       0.000000       0.000000          -1.000000e+02
25%    18178.000000    1661.076794    1631.358726          -1.091343e+01
50%    29177.000000    4097.827186    4131.174278          -6.239322e-02
75%    45082.000000   12954.123206   13119.029389           7.262080e+00
max    56045.000000  886068.668386  740267.412661           2.208376e+07

                                                                           \
       PCT_LACCESS_POP10 PCT_LACCESS_POP15 LACCESS_LOWI10 LACCESS_LOWI15
count        3143.000000       3124.000000    3143.000000    3123.000000
mean           23.559330         23.084470    5551.776559    5833.959524
std            20.250176         19.602745   13862.922934   13989.348252
min             0.000000          0.000000       0.000000       0.000000
25%            10.847099         10.927326     592.983070     608.235919
50%            19.685956         19.200682    1500.780036    1636.858816
75%            29.581054         28.862231    4591.067541    4859.016156
max           100.000001        100.000001  292541.789025  259479.516033

                                                         ...        \
       PCH_LACCESS_LOWI_10_15 PCT_LACCESS_LOWI10         ...
count            3.115000e+03        3143.000000         ...
mean             7.318957e+03           8.374953         ...
std              4.004692e+05           8.214988         ...
min             -1.000000e+02           0.000000         ...
25%             -1.232638e+01           3.442171         ...
50%              3.486028e+00           6.150772         ...
75%              2.352342e+01          10.324935         ...
max              2.234893e+07          72.274456         ...

                STORES                                                 \
       PCH_SNAPS_12_16   SNAPSPTH12   SNAPSPTH16 PCH_SNAPSPTH_12_16
count      3140.000000  3143.000000  3141.000000        3138.000000
mean         19.774565     0.880064     1.025253          20.079051
std          32.074488     0.387638     0.451670          39.262939
min        -100.000000     0.000000     0.000000        -100.000000
25%           5.405406     0.629603     0.750265           5.136099
50%          15.915190     0.818400     0.965336          15.206350
75%          28.979172     1.066786     1.234080          28.328855
max        1100.000000     6.658001     6.695621        1135.312012

                                                                           \
            WICS08       WICS12 PCH_WICS_08_12    WICSPTH08    WICSPTH12
count  3143.000000  3143.000000    3124.000000  3143.000000  3143.000000
mean     14.371619    15.109131      -1.901222     0.255593     0.230473
std      49.856567    55.831489      25.937208     0.257250     0.211762
min       0.000000     0.000000    -100.000000     0.000000     0.000000
25%       3.000000     3.000000     -12.500000     0.123272     0.118920
```

```
50%       5.000000     5.000000      0.000000     0.189785     0.177336
75%      11.000000    11.000000      0.000000     0.296110     0.268129
max    1285.000000  1602.000000    300.000000     4.618937     2.994012

      PCH_WICSPTH_08_12
count        3124.000000
mean           -3.995745
std            25.580415
min          -100.000000
25%           -15.333640
50%            -2.383872
75%             3.158470
max           294.070300

[8 rows x 286 columns]
```

In [7]: `msno.matrix(food)`

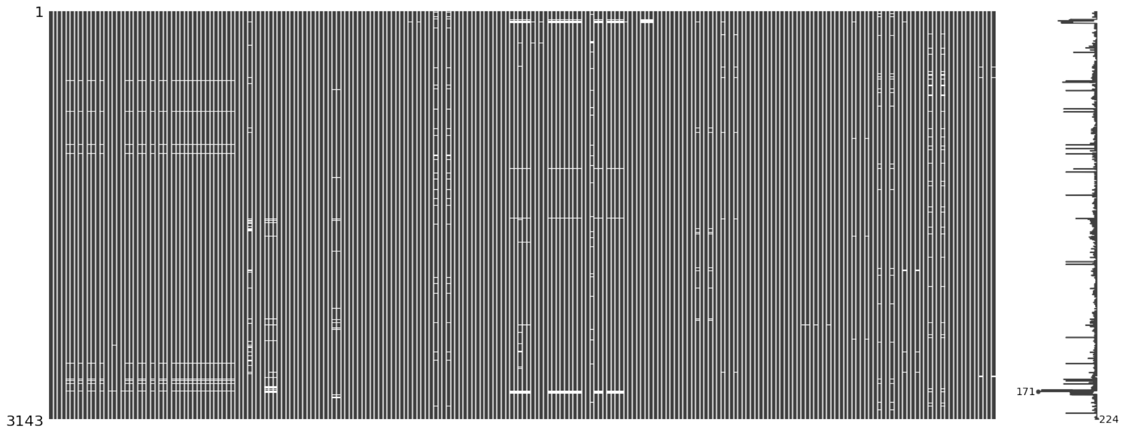


In [8]:
```
#Lets remove categories which have too much missing information,
# here we removed all columns with more than 200 missing values
```

In [9]:
```
food_clean = food[[x[0] for x in food.items() if sum(pd.isnull(food[x[0]]))
food_clean.shape
```

Out[9]: (3143, 224)

In [10]: `msno.matrix(food_clean)`




```
In [11]: # now lets remove rows with particularly large numbers of missing values
         print(sum(sum(pd.isnull([food_clean[x[0]] for x in food_clean.items()]))))
         for i, row in food_clean.iterrows():
             if sum(pd.isnull(row)) > 25:
                 food_clean = food_clean.drop(i)
         print(food_clean.shape)
         print(sum(sum(pd.isnull([food_clean[x[0]] for x in food_clean.items()]))))
```

```
3942
(3115, 224)
3064
```

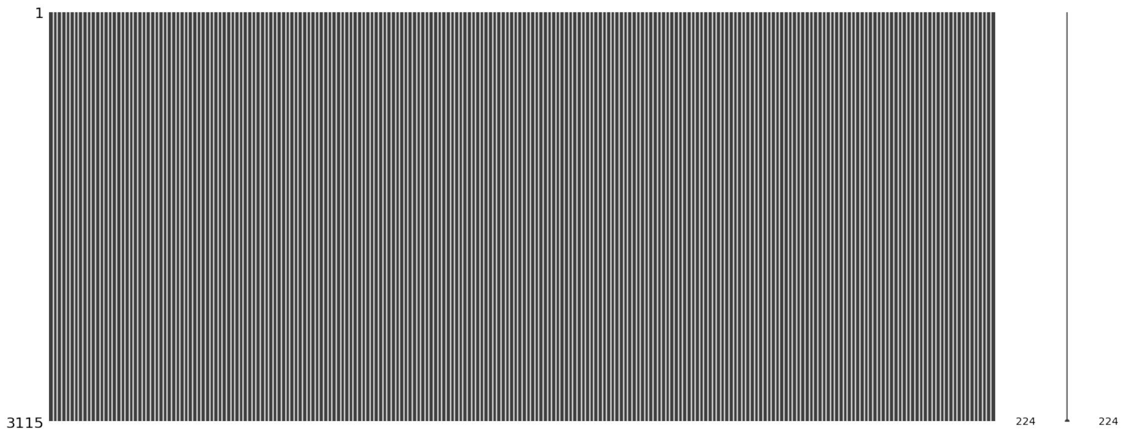
```
In [12]: #Replace missing values with average for category.
         # logic is that since the missing values make up such a
         # small part of the dataset (about .4%), it would not
         # skew the results too much, while still retaining a large
         # amount of data that would have been lost had we simply removed
         # the entire rows
```

```
In [13]: #Need to correct key index values because we dropped rows
         # (ex. [0:"foo", 1:'foo', 2:'foo'] >*drop item 1*> [0:'foo', 2:'foo'], <-
         food_clean = food_clean.assign(index = range(len(food_clean[('ACCESS', 'LA
         food_clean = food_clean.set_index('index')
         food_clean.drop('index', axis=1)

         for index, (k, a) in enumerate(food_clean.items()):
             #skip over first three categories
             if sum(pd.isnull(a)) != 0 and index > 2:
                 average = 0
                 for num, val in a.items():
                     if not pd.isnull(val):
                         average += val
```

```
                average /= (len(a) - sum(pd.isnull(a)))
                for i in range(len(a)):
                    if pd.isnull(a[i]):
                        a[i] = average
                food_clean[k] = a
```

```
/home/porrster/home/porrster/Documents/anaconda2/envs/universe/lib/python3.5/site-p
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
```

In [14]:
```
msno.matrix(food_clean) #Now we have a clean dataset :)
```



In [15]:
```
#Now lets try to calculate farm to school program using logistic
# regression
def sigmoid(X, w):
    """
    Compute the elementwise sigmoid of the product Xw
    Data in X should be rows, weights are a column.
    """
    return 1 / (1 + np.exp(-np.dot(X, w)))

def gradient(X, y, w, onept, lamb=0):
    """
    Compute gradient of regularized loss function.
    Accomodate for if X is just one data point.
    """
    if onept:
        return 2 * lamb * w - ((y - sigmoid(X, w)) * X).reshape(w.size, 1)
    return 2 * lamb * w - np.dot(X.T, y - sigmoid(X, w)) / y.size

def loss(X, y, w, lamb=0):
```

```
    """
    Compute total loss for the data in X, labels in y, params w
    """
    sumcost = 0
    for i in range(X.shape[0]):
        sumcost += y[i] * np.log(sigmoid(X[i], w)) + (1 - y[i]) * np.log(1
    return lamb * np.linalg.norm(w)**2 - sumcost / y.size

def accuracy(X, y, w):
    """
    Compute accuracy for data in X, labels in y, params w
    """
    results = np.round(sigmoid(X, w))
    score = sum([results[i] == y[i] for i in range(y.size)]) / y.size
    return score[0]
```

In [16]:

```
#Using variables we deemed relevant to the variable we're trying to predic
# it indicates that farmers are selling locally. Farms with direct sales b
# the ability to support a farm to school program. Low access to stores an
# likely to participate in farm to school program. Food insecurity would i
# which may prompt engagement in the farm to school program.
half = len(food_clean[('LOCAL', 'FMRKT09')]) // 2
food_train = food_clean[0:half]
food_val = food_clean[half:]

datTrain = food_train[[('LOCAL', 'FMRKT09'), ('LOCAL', 'PCT_LOCLFARM07'),
            ('INSECURITY', 'FOODINSEC_10_12')]]
datVal = food_val[[('LOCAL', 'FMRKT09'), ('LOCAL', 'PCT_LOCLFARM07'), ('AC
            ('INSECURITY', 'FOODINSEC_10_12')]]
#Need to get dataset into 2D np array format to be comnpatible with the fu
logTrain = np.zeros((len(datTrain[('LOCAL', 'FMRKT09')]), 4))
logVal = np.zeros((len(datVal[('LOCAL', 'FMRKT09')]), 4))

for i, row in datTrain.iterrows():
    logTrain[i] = [row[x] for x in range(len(row))]
for i, row in datVal.iterrows():
    logVal[i - half] = [row[x] for x in range(len(row))]

datTrain = food_train[('LOCAL', 'FARM_TO_SCHOOL09')] #2013 set has too man
datVal = food_val[('LOCAL', 'FARM_TO_SCHOOL09')]

logLabelsTrain = np.zeros(len(datTrain))
logLabelsVal = np.zeros(len(datVal))

for k, a in datTrain.items():
    logLabelsTrain[k] = a
for k, a in datVal.items():
    logLabelsVal[k - half] = a
```

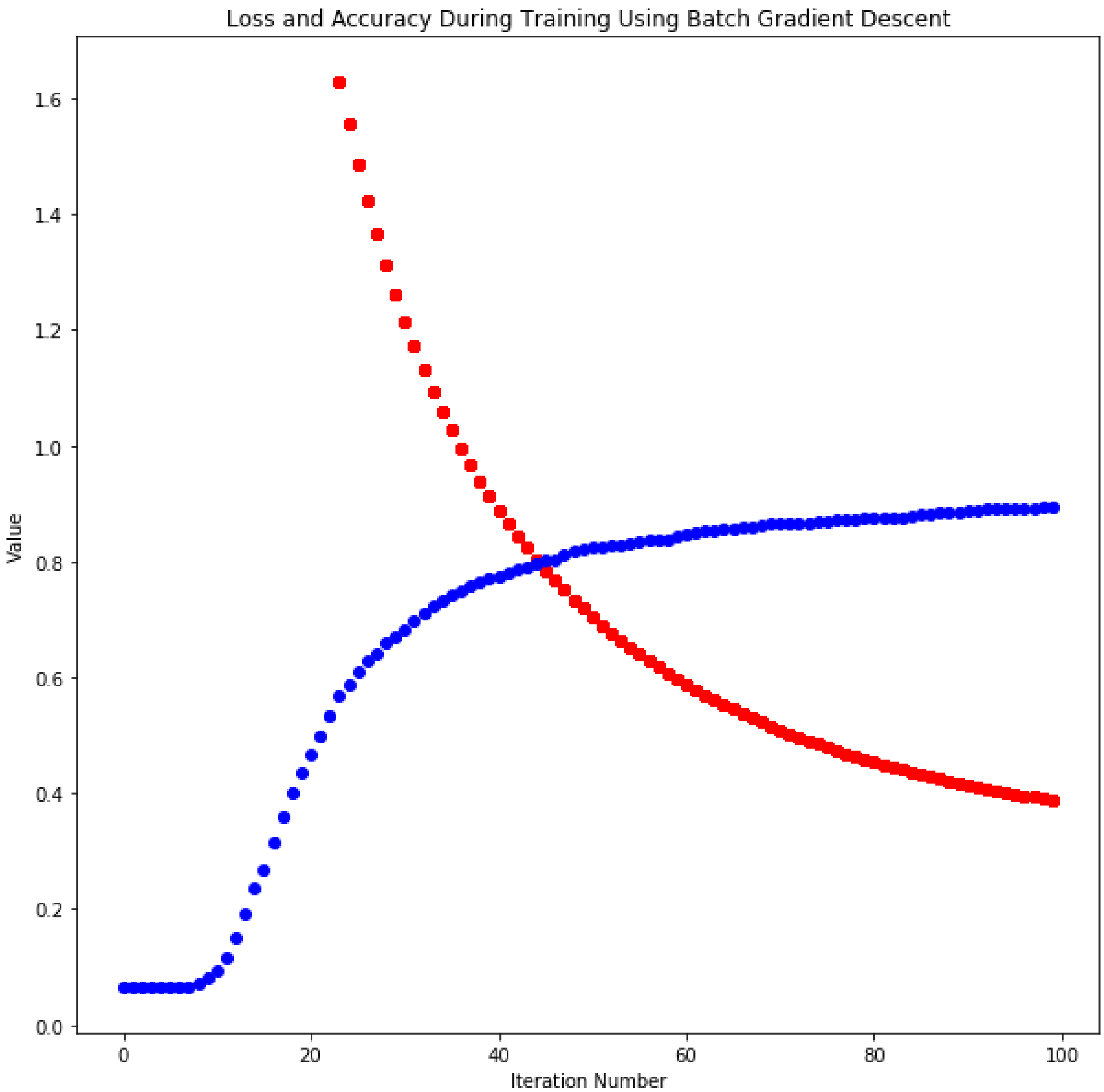
```
logTrain = np.concatenate([logTrain, np.ones((logTrain.shape[0], 1))], axi
logVal = np.concatenate([logVal, np.ones((logVal.shape[0], 1))], axis=1)
logTrain.shape
```

Out[16]: (1557, 5)

In [19]:
```
weights = np.asarray([np.random.rand() for i in range(logTrain.shape[1])])
weights /= np.linalg.norm(weights)
losses = []
accuracies = []
epsilon = 0.001
num_iterations = 100

for i in range(num_iterations):
    diff = epsilon * gradient(logTrain, logLabelsTrain, weights, False)
    weights = weights - diff
    losses.append(loss(logTrain, logLabelsTrain, weights))
    accuracies.append(accuracy(logTrain, logLabelsTrain, weights))
```

```
/home/porrster/home/porrster/Documents/anaconda2/envs/universe/lib/python3.5/site-p
/home/porrster/home/porrster/Documents/anaconda2/envs/universe/lib/python3.5/site-p
```

In [20]:
```
#Visual of loss over time
plt.figure(figsize=[10,10])
plt.plot(np.arange(num_iterations), losses, 'ro')
plt.plot(np.arange(num_iterations), accuracies, 'bo')
plt.title('Loss and Accuracy During Training Using Batch Gradient Descent'
plt.ylabel('Value')
plt.xlabel('Iteration Number')
plt.show()
accuracy0 = accuracy(logTrain, logLabelsTrain, weights)
accuracy1 = accuracy(logVal, logLabelsVal, weights)
print("Accuracy for training data: %.3f" % accuracy0)
print("Accuracy for validation data: %.3f" % accuracy1)
```




```
Accuracy for training data: 0.893
Accuracy for validation data: 0.879
```

In [21]:
```
# Here we will calculate a linear regression using multiple variables
#to predict adult obeseity rates. We will also use recursive feature
#elimination to remove irrelivant variables
```

In [22]:
```
new_filtered = pd.concat([food_clean['STORES']['GROC09'], food_clean['STOR
                          food_clean['RESTAURANTS']['FSR09'], food_clean['PRICES_TAX
                          food_clean['PRICES_TAXES']['CHIPSTAX_STORES14'], food_clea
                          food_clean['HEALTH']['PCT_OBESE_ADULTS13']], axis=1)
target_filtered = pd.concat([new_filtered['PCT_OBESE_ADULTS13']], axis=1)
regr_dataset = pd.concat([new_filtered['FFR09'], new_filtered['CONVS09'],
```

```
                             new_filtered['CHIPSTAX_STORES14'], new_filtered['
                             new_filtered['FSR09']], axis=1)

        #add bias variable
        regr_dataset = sm.add_constant(regr_dataset)

        regr_dataset.head()
```

Out[22]:

```
              const  FFR09  CONVS09  SODATAX_STORES14  CHIPSTAX_STORES14  RECFAC(
        index
        0       1.0     30       29               4.0                4.0
        1       1.0    112      119               4.0                4.0          1
        2       1.0     21       14               4.0                4.0
        3       1.0      7       19               4.0                4.0
        4       1.0     24       31               4.0                4.0

              GROC09  FSR09
        index
        0          6     34
        1         24    202
        2          5     12
        3          6      6
        4          6     19
```

In [23]:

```
# Create linear regression object
regr = linear_model.LinearRegression()

#Perform recurrent feature elimation to find most relevant
# variables
myRFE = RFECV(regr, step = 1, cv = 5)
myRFE = myRFE.fit(regr_dataset, target_filtered)

print(myRFE.support_)
print(myRFE.ranking_)
```

```
[False False False  True  True  True False False]
[6 2 4 1 1 1 5 3]


/home/porrster/home/porrster/Documents/anaconda2/envs/universe/lib/python3.5/site-p
  y = column_or_1d(y, warn=True)
```

In [24]:

```
#Create new dataframe based on most relevant variables
regr_dataset = pd.concat([regr_dataset['SODATAX_STORES14'], regr_dataset['
                          regr_dataset['RECFAC09']], axis=1)
regr_dataset = sm.add_constant(regr_dataset)
```

In [25]:

```
# Split the data into training/testing sets
training_set = regr_dataset[:half]
```

```python
test_set = regr_dataset[half:]
# Split the targets into training/testing sets
target_training_set = target_filtered[:half]
target_test_set = target_filtered[half:]
# Train the model using the training sets
regr = sm.OLS(target_training_set, training_set).fit()
# Make predictions using the testing set
obesity_pred = regr.predict(test_set)

# Some stats about the model
print(regr.summary())
# The coefficients
print('Coefficients: \n', regr.params)
# The mean squared error
print("Mean squared error: %.2f"
      % mean_squared_error(target_test_set, obesity_pred))
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     PCT_OBESE_ADULTS13   R-squared:                       0.149
Model:                            OLS   Adj. R-squared:                  0.148
Method:                 Least Squares   F-statistic:                     90.86
Date:                Wed, 04 Oct 2017   Prob (F-statistic):           3.59e-54
Time:                        01:32:05   Log-Likelihood:                -4545.2
No. Observations:                1557   AIC:                             9098.
Df Residuals:                    1553   BIC:                             9120.
Df Model:                           3
Covariance Type:            nonrobust
======================================================================================
                       coef    std err          t      P>|t|      [0.025      0.97
--------------------------------------------------------------------------------------
const               32.0309      0.206    155.753      0.000      31.628      32.4
SODATAX_STORES14    -0.1888      0.043     -4.391      0.000      -0.273      -0.1
CHIPSTAX_STORES14    0.5205      0.052      9.970      0.000       0.418       0.6
RECFAC09            -0.0401      0.003    -11.684      0.000      -0.047      -0.0
==============================================================================
Omnibus:                      111.242   Durbin-Watson:                   0.970
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              200.161
Skew:                          -0.507   Prob(JB):                     3.43e-44
Kurtosis:                       4.434   Cond. No.                         63.9
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly sp
Coefficients:
 const                32.030902
SODATAX_STORES14     -0.188783
CHIPSTAX_STORES14     0.520523
```

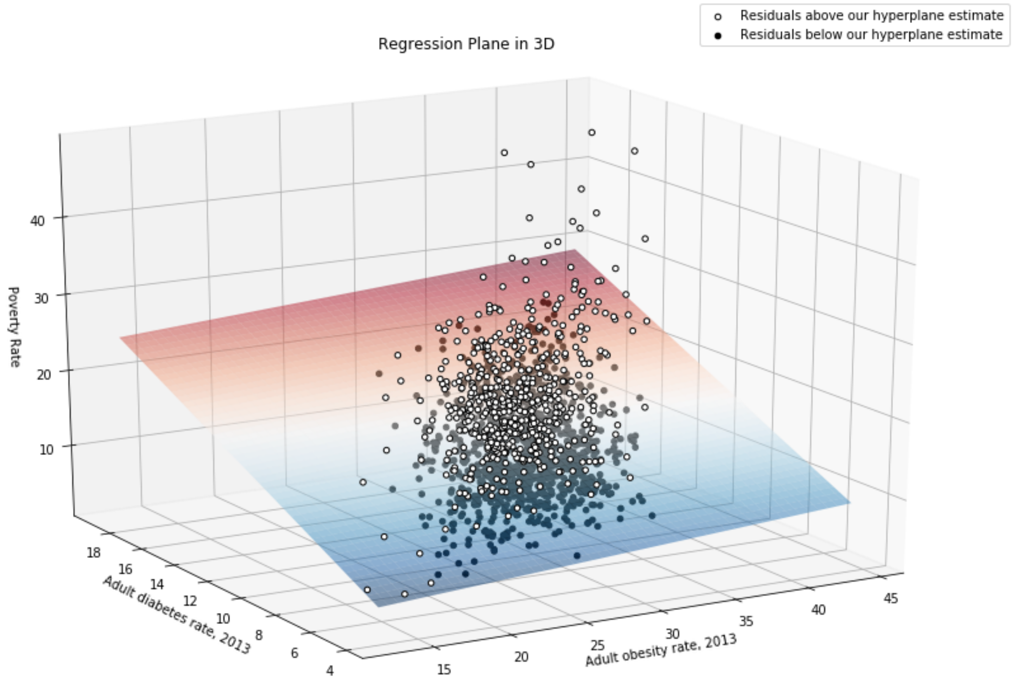
```
RECFAC09            -0.040100
dtype: float64
Mean squared error: 16.38
```

In [26]:
```
# Here we are going to predict levels of poverty rates based on levels of
#This will provide some insight on the connection between health and
#social status.
dat = food_clean[[('HEALTH', 'PCT_OBESE_ADULTS13'), ('HEALTH', 'PCT_DIABET
poverty = food_clean[('SOCIOECONOMIC','POVRATE15')]
#Add constant
dat = sm.add_constant(dat)
```

In [27]:
```
#Split into training and validation sets
dat_train = dat[0:half]
dat_val = dat[half:]

labels_train = poverty[0:half]
labels_val = poverty[half:]
```

In [28]:
```
# Let's take a look at Diabetes vs Poverty
myMLR = sm.OLS(labels_train, dat_train).fit()
#Make some predictions
prediction = myMLR.predict(dat_val)

#Make a visual model
obese = ('HEALTH', 'PCT_OBESE_ADULTS13')
diab = ('HEALTH', 'PCT_DIABETES_ADULTS13')
x1, x2 = np.meshgrid(np.linspace(dat_val[obese].min(), dat_val[obese].max
                       np.linspace(dat_val[diab].min(), dat_val[diab].max
x3 = myMLR.params[0] + myMLR.params[1] * x1 + myMLR.params[2] * x2
#Create figure
fig = plt.figure(figsize=(12, 8))
my3D = Axes3D(fig, azim=-120, elev=20)
#Plot the plane
surf = my3D.plot_surface(x1, x2, x3, cmap=plt.cm.RdBu_r, alpha=0.5, linewi
#Plot data points
resid = labels_val - prediction
my3D.scatter(dat_val[resid >= 0][obese], dat_val[resid >= 0][diab], labels
            label="Residuals above our hyperplane estimate")
my3D.scatter(dat_val[resid < 0][obese], dat_val[resid < 0][diab], labels_v
            label="Residuals below our hyperplane estimate")
# set axis labels
my3D.set_xlabel('Adult obesity rate, 2013')
my3D.set_ylabel('Adult diabetes rate, 2013')
my3D.set_zlabel('Poverty Rate')
my3D.set_title('Regression Plane in 3D')
my3D.legend()
```

```
plt.show()
```




```
In [29]: #Now lets calculate some stats.
         mse = 1/len(prediction) * np.dot((labels_val.T - prediction.T), (labels_va
         print(mse)
```

```
27.0901878236
```

```
In [ ]:
```

```
In [ ]:
```