In [2]:

```python
# Connor Lewis
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# Due: February 7, 2017 17:00

import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import numpy as np
from scipy.linalg import orth
from scipy.misc import imread
import sympy
```

In [3]:

```python
# Problem 1: Linear Algebra in Python
v1 = np.array([1,2,3,4])
v2 = np.array([0,1,0,1])
v3 = np.array([1,4,3,6])
v4 = np.array([2,11,6,15])

#https://docs.scipy.org/doc/numpy/reference/generated/numpy.vstack.html
matrix = np.vstack((v1,v2,v3,v4))
print("Origional Matrix: \n" + str(matrix))

#http://docs.sympy.org/dev/tutorial/matrices.html
reduce = sympy.Matrix(matrix).rref()
print("RREF form: \n" + str(reduce))
```

```
Origional Matrix:
[[ 1  2  3  4]
 [ 0  1  0  1]
 [ 1  4  3  6]
 [ 2 11  6 15]]
RREF form:
(Matrix([
[1, 0, 3, 2],
[0, 1, 0, 1],
[0, 0, 0, 0],
[0, 0, 0, 0]]), [0, 1])
```

In [4]:
```
# Problem 1: Linear Algebra in Python - Question 1
in_s = np.array([1,1,3,3])
matrix2 = np.vstack((matrix,in_s))
reduce2 = sympy.Matrix(matrix2).rref()
print(str(in_s) + " is in the span of S")

print("RREF of matrix and new vector in S: \n" + str(reduce2))

not_in_s = np.array([1,0,5,2])
matrix3 = np.vstack((matrix, not_in_s))
reduce3 = sympy.Matrix(matrix3).rref()
print(str(not_in_s) + " is not in the span of S")
print("RREF of matrix and new vector not in S: \n" + str(reduce3))
# To check if a vector is in S, we concatenate the vector onto the matrix
# and reduce the matrix. If it is the same as the origional matrix reduced
# then it is in the span of S. Otherwise, it is outsie.
```

```
[1 1 3 3] is in the span of S
RREF of matrix and new vector in S:
(Matrix([
[1, 0, 3, 2],
[0, 1, 0, 1],
[0, 0, 0, 0],
[0, 0, 0, 0],
[0, 0, 0, 0]]), [0, 1])
[1 0 5 2] is not in the span of S
RREF of matrix and new vector not in S:
(Matrix([
[1, 0, 0, 2],
[0, 1, 0, 1],
[0, 0, 1, 0],
[0, 0, 0, 0],
[0, 0, 0, 0]]), [0, 1, 2])
```

In [5]:
```
# Problem 1: Linear Algebra in Python - Question 2
print("The Dimension of the Subspace S is: " + str(np.linalg.matrix_rank(matrix)))
```

```
The Dimension of the Subspace S is: 2
```

In [6]:
```
# Problem 1: Linear Algebra in Python - Question 3
print("An orthonormal basis of for the span of S is: \n" + str(orth(matrix)))
```

```
An orthonormal basis of for the span of S is:
[[-0.24011927  0.8581727 ]
 [-0.05990306 -0.29094143]
 [-0.35992538  0.27628983]
 [-0.89955994 -0.32024463]]
```

In [7]:
```
# Problem 1: Linear Algebra in Python - Question 4
z = np.array([1,0,0,0])
matrix4 = np.vstack((v1,v2)).transpose()
matrix5 = (matrix4.transpose().dot(matrix4))
matrix6 = matrix5.dot(matrix4.transpose())
minx_s = matrix6[:, 0]
print(minx_s)
```

```
[30  6]
```

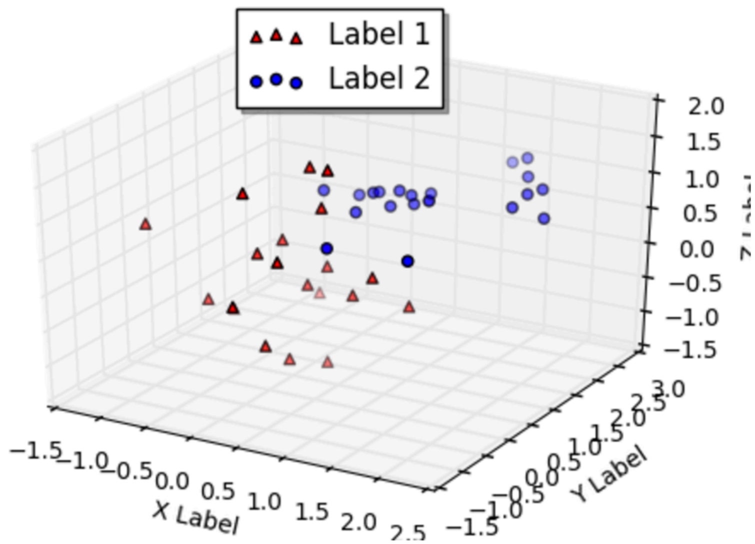
Problem 2: PCA

2. The points look like they generally follow a vector going from left to right. The points labeled 'Label 1' are more dispersed than those labeled 'Label 2'. The ones labeled 'Label 2' are clearly more tightly grouped.

4. Yes, PCA did make it easier to distinguish the two labels in two dimensions.

In [8]:

```
# Problem 2: PCA - Question 1
mean1 = [0,0,0]
n = 20
d = 3
cov_Matrix1 = [[0.5,0,0],[0,0.5,0],[0,0,0.7]]
mean2 = [1,1,1]
cov_Matrix2 = [[0.5,0,0],[0,0.5,0],[0,0,0.01]]

data1 = np.random.multivariate_normal(mean1, cov_Matrix1, n)
data2 = np.random.multivariate_normal(mean2, cov_Matrix2, n)
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.scatter(data1[:,0], data1[:,1], data1[:,2], c='r', marker='^', label="Label 1")
ax.scatter(data2[:,0], data2[:,1], data2[:,2], c='b', marker='o', label="Label 2")
ax.set_xlabel('X Label')
ax.set_ylabel('Y Label')
ax.set_zlabel('Z Label')
legend = ax.legend(loc='upper center', shadow=True)
plt.show()
```



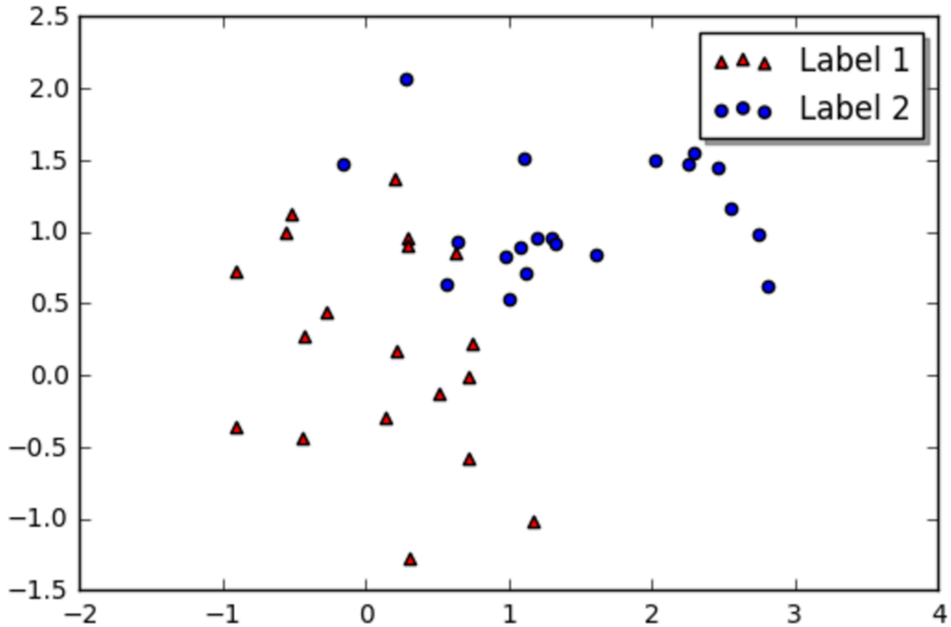
In [33]:

```
# Problem 2: PCA - Question 3
data_Agg = np.vstack((data1,data2))

mean = [None] *3
mean[0] = data_Agg[0].mean()
mean[1] = data_Agg[1].mean()
mean[2] = data_Agg[2].mean()

data_Agg_Norm = data_Agg - mean
cov = data_Agg_Norm.transpose().dot(data_Agg_Norm)
print(cov/39)
```

```
[[ 0.76372968  0.4916334   0.63862193]
 [ 0.4916334   0.92017048  0.45611048]
 [ 0.63862193  0.45611048  1.3417359 ]]
```

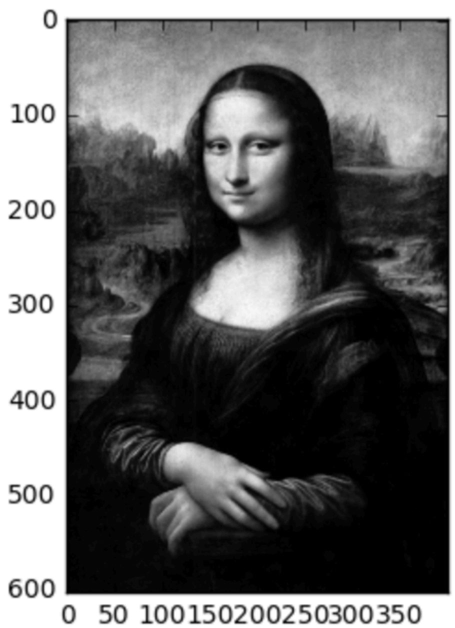
In [34]:

```
# Problem 2: PCA - Question 4
data_Agg_Square = np.hstack((data_Agg,np.zeros(shape=(40,37))))

eigen = (np.linalg.eig(cov))
eigenValues = eigen[0]
eigenVectors = eigen[1]
topTwo = np.zeros((2,3))
topTwo[0] = np.argmax(eigenValues)
eigenValues[np.argmax(eigenValues)] = -10
topTwo[1] = np.argmax(eigenValues)

topTwo[0] = eigenVectors[int(topTwo[0][0])]
topTwo[1] = eigenVectors[int(topTwo[1][0])]

finalData = data_Agg.dot(topTwo.transpose())


plt.scatter(finalData[0:19,0], finalData[0:19,1], c='r', marker='^', label="Label 1")

plt.scatter(finalData[20:,0], finalData[20:,1], c='b', marker='o', label="Label 2")
ax.set_xlabel('X Label')
ax.set_ylabel('Y Label')
ax.set_zlabel('Z Label')
legend = plt.legend(loc='upper right', shadow=True)
plt.show()
```



In [35]:

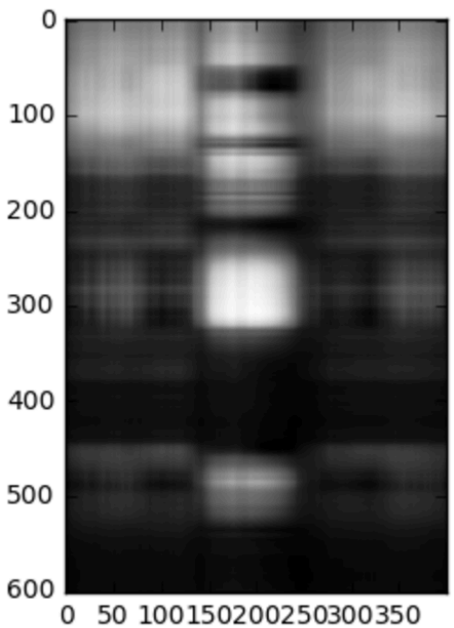
```
# Problem 3: Low Rank Approximation of Mona
#http://sebastianraschka.com/Articles/2014_pca_step_by_step.html
mona_lisa = imread('./input/mona_lisa.png', flatten=True)

plt.imshow(mona_lisa, cmap='Greys_r')

plt.show()

print(mona_lisa.shape)
```




```
(603, 400)
```

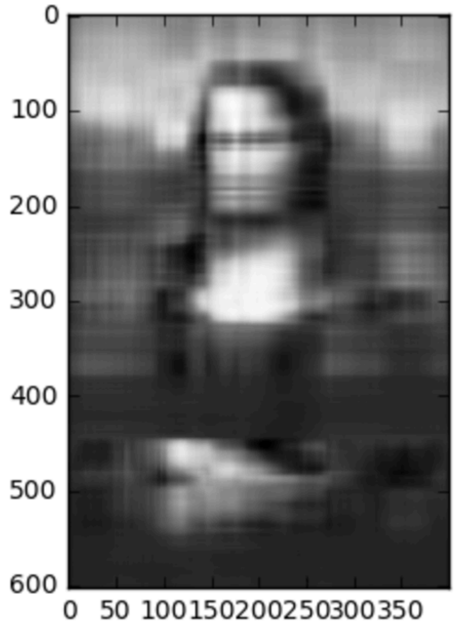
In [36]:

```python
# Problem 3: Low Rank Approximation of Mona
u, s, v = np.linalg.svd(mona_lisa)

rank2 = np.copy(s)
rank2[2:] = 0

S = np.zeros(mona_lisa.shape)
result = np.diag(rank2)
S[:400, :400] = result
rank2_approx = u.dot(S.dot(v))
plt.imshow(rank2_approx, cmap='Greys_r')
plt.show()
```

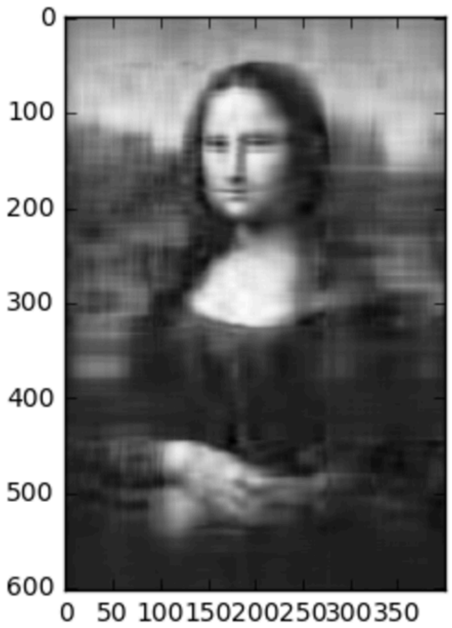


In [37]:

```
# Problem 3: Low Rank Approximation of Mona
rank5 = np.copy(s)
rank5[5:] = 0

S = np.zeros(mona_lisa.shape)
result = np.diag(rank5)
S[:400, :400] = result
rank5_approx = u.dot(S.dot(v))
plt.imshow(rank5_approx, cmap='Greys_r')
plt.show()
```



In [38]:
```
# Problem 3: Low Rank Approximation of Mona
rank10 = np.copy(s)
rank10[10:] = 0

S = np.zeros(mona_lisa.shape)
result = np.diag(rank10)
S[:400, :400] = result
rank10_approx = u.dot(S.dot(v))
plt.imshow(rank10_approx, cmap='Greys_r')
plt.show()
```



In [39]:
```
# Problem 3: Low Rank Approximation of Mona
#Bits is compressed Mona Lisa?
rank2 = 603 * 400 * 16 * 2 / 400
rank5 = 603 * 400 * 16 * 5 / 400
rank10 = 603 * 400 * 16 * 10 / 400
print("Rank 2:", int(rank2), "bits")
print("Rank 5:", int(rank5), "bits")
print("Rank 10:", int(rank10), "bits")
```

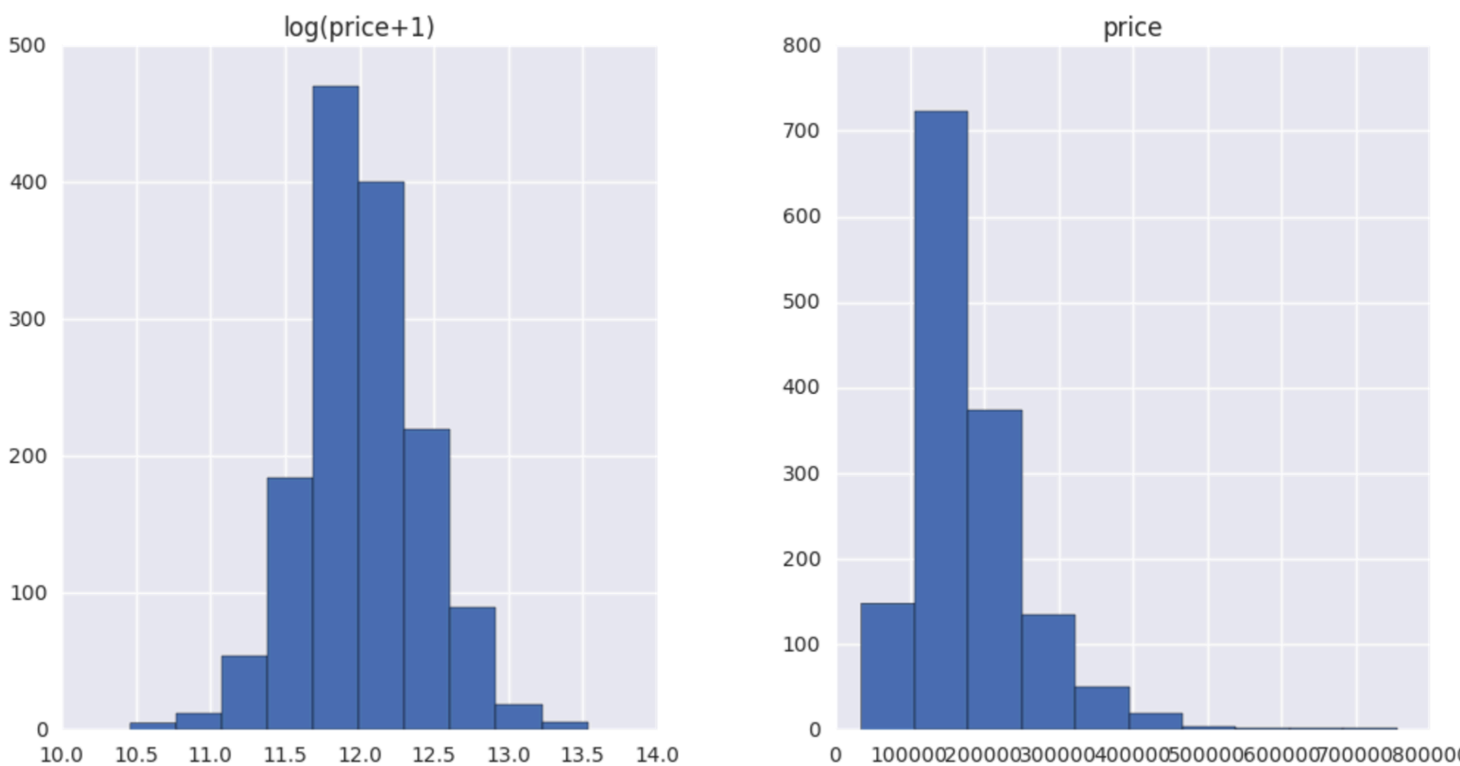
```
('Rank 2:', 19296, 'bits')
('Rank 5:', 48240, 'bits')
('Rank 10:', 96480, 'bits')
```

In [43]:

```
# Problem 4: Starting in Kaggle
# Kaggle username: MSpearing
# The code in this module is copied from:
# https://www.kaggle.com/apapiu/house-prices-advanced-regression-techniques/regularized-linear-models

# Trying our a linear model
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
from scipy.stats import skew
from scipy.stats.stats import pearsonr

%config InlineBackend.figure_format = 'png' # 'retina' #set 'png' here when working on notebook
%matplotlib inline
```

In [44]:

```
# Problem 4: Starting in Kaggle
# The code in this module is copied from:
# https://www.kaggle.com/apapiu/house-prices-advanced-regression-techniques/regularized-linear-models

train = pd.read_csv("./input/train.csv")
test = pd.read_csv("./input/test.csv")
train.head()
all_data = pd.concat((train.loc[:,'MSSubClass':'SaleCondition'],test.loc[:,'MSSubClass': 'SaleCondition']))

# Preprocessing the data
matplotlib.rcParams['figure.figsize'] = (12.0,6.0)
prices = pd.DataFrame({"price":train["SalePrice"], "log(price+1)":np.log1p(train["SalePrice"])})
prices.hist()

train["SalePrice"] = np.log1p(train["SalePrice"])

numeric_feats = all_data.dtypes[all_data.dtypes != "object"].index

skewed_feats = train[numeric_feats].apply(lambda x: skew(x.dropna()))
skewed_feats = skewed_feats[skewed_feats > 0.75]
skewed_feats = skewed_feats.index

all_data[skewed_feats] = np.log1p(all_data[skewed_feats])

all_data = pd.get_dummies(all_data)

#filling NA's with the mean of the column
all_data = all_data.fillna(all_data.mean())

# Creating matrices for sklearn
X_train = all_data[:train.shape[0]]
X_test = all_data[train.shape[0]:]
y = train.SalePrice
```



In [28]:

```
# Problem 4: Starting in Kaggle
# Run a ridge Regression using alpha = 0.1
# Make a submission of this prediction
from sklearn.linear_model import Ridge
from sklearn.cross_validation import cross_val_score
alpha = 0.1
# Run the ridge regression 5 times and cross validate
ridge = np.sqrt(-cross_val_score(Ridge(alpha=alpha),X_train, y, scoring = "mean_squared_error", cv=5))

# Take the mean of the 5 samples
ridge = ridge.mean()
print("RMSE with alpha = " + str(alpha) + " is: " + str(ridge))
```

```
RMSE with alpha = 0.1 is: 0.137775382772
```

In [33]:

```
# The code in this module is copied from:
# https://www.kaggle.com/apapiu/house-prices-advanced-regression-techniques/regularized-linear-models
# Models
from sklearn.linear_model import Ridge, RidgeCV, ElasticNet, LassoCV, LassoLarsCV
from sklearn.cross_validation import cross_val_score

def rmse_cv(model):
    rmse = np.sqrt(-cross_val_score(model, X_train, y, scoring="mean_squared_error", cv = 5))
    return(rmse)

model_ridge = Ridge()

alphas = [0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 50, 75]
cv_ridge = [rmse_cv(Ridge(alpha = alpha)).mean() for alpha in alphas]

cv_ridge = pd.Series(cv_ridge, index = alphas)
cv_ridge.plot(title = "Validation - Just Do It")
plt.xlabel("alpha")
plt.ylabel("rmse")

cv_ridge.min()
```

Out[33]:

```
0.12733734668670743
```