Grashof_David_Assignment5

May 5, 2019

0.0.1 1.0 | Assignment 3: Unsupervised Learning and PCA

0.0.2 Overview:

Kaggle User Name: DavidGrashof Submission (Non-PCA) Score: .9075 Submission (PCA) Score: .9075 Submission (Combo PCA) Score: .9075 This assignment followed much the same pattern as previous machine learning model exercises. A dataset was provided with a train and test set with the objective of optimizing the predictive power of a RandomForestClassifier. The added wrinkle was the inclusion of PCA to simplify the training and test data by removing columns of data while still capturing 95% of variance for each row in the dataset. Going into this assignment, my expectation was that the PCA would significantly reduce the amount of time required to fit the model to the data due to the decreased number of columns all while maintaing the same level of accuracy.

After completing some initial exploratory analysis of the dataset, I fit the training data to a random forest regressor and then applied the model to the test set. The model was fit in 1:18 (m:s) and achieved an accuracy of .9075 when submitted to the Kaggle competition. Next, I applied Principal Component Analysis to the data and retrained the model. The design flaw in this assignment was the instruction to apply principal component analysis to both the training and test data set. By applying to both datasets at once, you are accounting for some of the variance that will be present in the test set and influencing the training set which will be used to fit the model. This practice would be similar to scaling training and test data together or even fitting a model on the test and training set together; it produces biased results that do not translate to a productionalized model. As such, I applied fit_transform to the training data and fit only to the test data. In fitting this model, I was suprised to find that the PCA data (column count from 784 to 320) took significantly longer to fit. This ran contrary to my expectations given the smaller dataset. The results were submitted to the Kaggle competition and achieved the same accuracy score of .9075 showing that nearly half the data could be discarded while still accurately representing the data.

0.0.3 1.1 | Load Modules

```
In [1]: import pandas as pd
        import datetime
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.preprocessing import StandardScaler #scale any continuous fields
        from sklearn.decomposition import PCA
        ################################################
        from sklearn.model_selection import GridSearchCV
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics #to evaluate model performances

import warnings
warnings.filterwarnings("ignore")
```

0.0.4 1.2 | Import Train Data

```
In [2]: file = "C:/Users/David/OneDrive/MSDS/MSDS422/Week5/train.csv"
        train = pd.read_csv(file,sep = ',')
        train.head()
```

Out[2]:

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	\
0	1	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	
3	4	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	

	pixel8	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	\
0	0	...	0	0	0	0	0	0	
1	0	...	0	0	0	0	0	0	
2	0	...	0	0	0	0	0	0	
3	0	...	0	0	0	0	0	0	
4	0	...	0	0	0	0	0	0	

	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

[5 rows x 785 columns]

0.0.5 1.3 | Data Pre-Processing

```
In [3]: #isolate labels and pixel fields
        xtrain = train.ix[:,1:]
        ytrain = train.ix[:,0]

        xtrain.describe()
        #looks like most pixels are just white space and can be reduced
```

Out[3]:

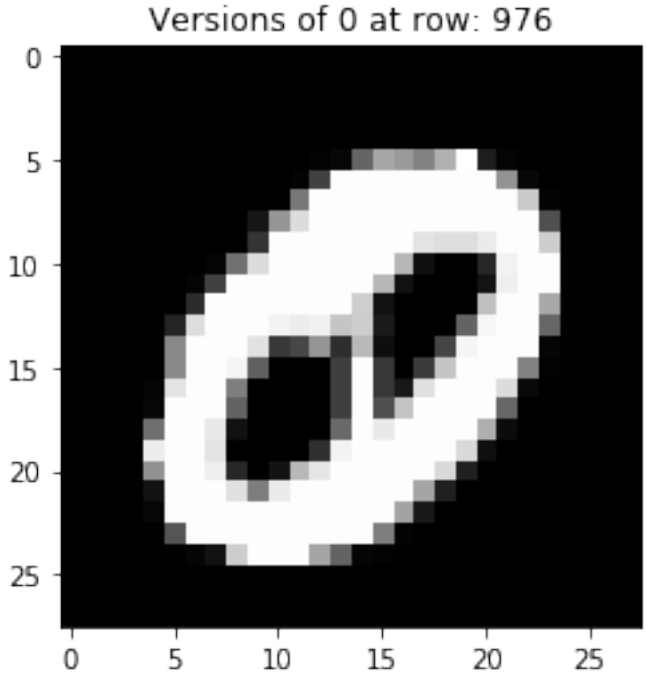
	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	\
count	42000.0	42000.0	42000.0	42000.0	42000.0	42000.0	42000.0	42000.0	
mean	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
std	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

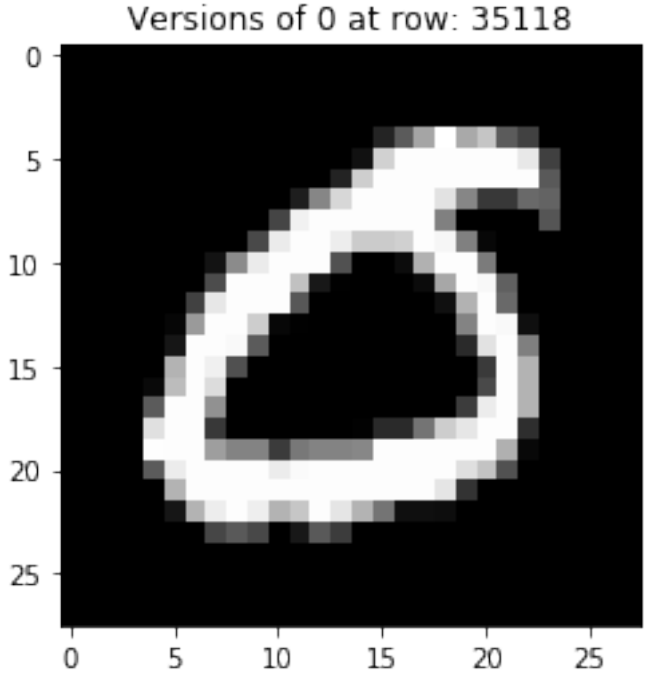
```
25%       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0
50%       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0
75%       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0
max       0.0      0.0      0.0      0.0      0.0      0.0      0.0      0.0

       pixel8   pixel9  ...      pixel774      pixel775      pixel776  \
count  42000.0  42000.0  ...  42000.000000  42000.000000  42000.000000
mean       0.0      0.0  ...      0.219286      0.117095      0.059024
std        0.0      0.0  ...      6.312890      4.633819      3.274488
min        0.0      0.0  ...      0.000000      0.000000      0.000000
25%        0.0      0.0  ...      0.000000      0.000000      0.000000
50%        0.0      0.0  ...      0.000000      0.000000      0.000000
75%        0.0      0.0  ...      0.000000      0.000000      0.000000
max        0.0      0.0  ...    254.000000    254.000000    253.000000

         pixel777      pixel778      pixel779  pixel780  pixel781  pixel782  \
count  42000.00000  42000.000000  42000.000000   42000.0   42000.0   42000.0
mean       0.02019      0.017238      0.002857       0.0       0.0       0.0
std        1.75987      1.894498      0.414264       0.0       0.0       0.0
min        0.00000      0.000000      0.000000       0.0       0.0       0.0
25%        0.00000      0.000000      0.000000       0.0       0.0       0.0
50%        0.00000      0.000000      0.000000       0.0       0.0       0.0
75%        0.00000      0.000000      0.000000       0.0       0.0       0.0
max      253.00000    254.000000     62.000000       0.0       0.0       0.0

       pixel783
count   42000.0
mean        0.0
std         0.0
min         0.0
25%         0.0
50%         0.0
75%         0.0
max         0.0

[8 rows x 784 columns]
```

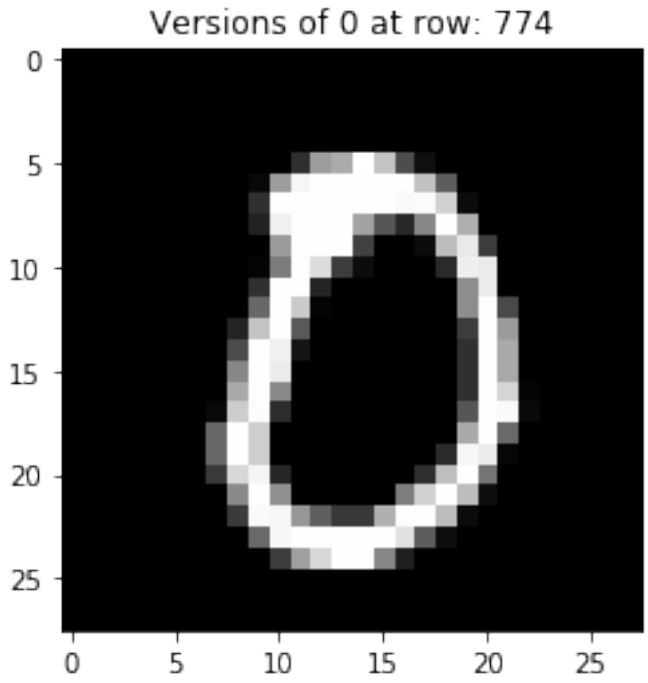
0.0.6 1.4 | EDA

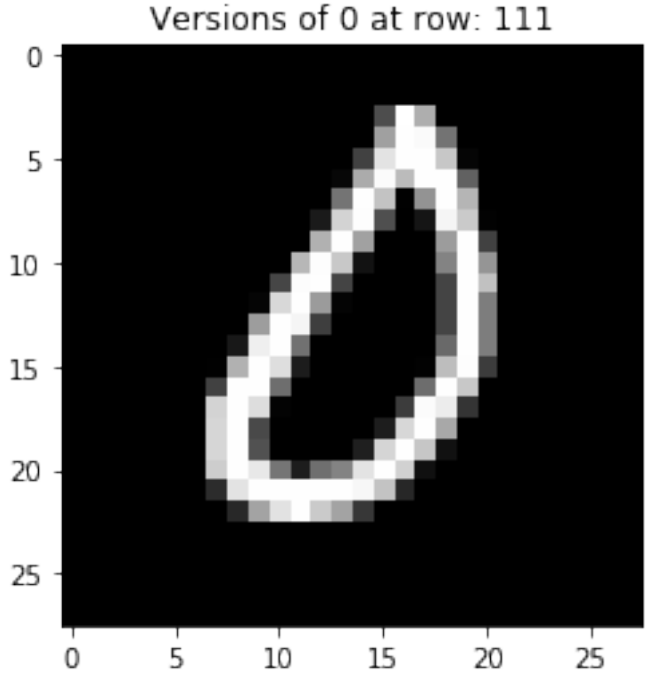
In [5]:
```
#Examine variances in like numbers. Isolate 5 examples of 0
pltdata = train[train['label']==0].sample(5)

#iterate thru each row in pltdata and display
for index,row in pltdata.iterrows():
    pixels = np.array(xtrain.ix[index,:], dtype='uint8')
    pixels = pixels.reshape((28, 28))
    plt.title('Versions of 0 at row: '+str(index))
    plt.imshow(pixels, cmap='gray')
```

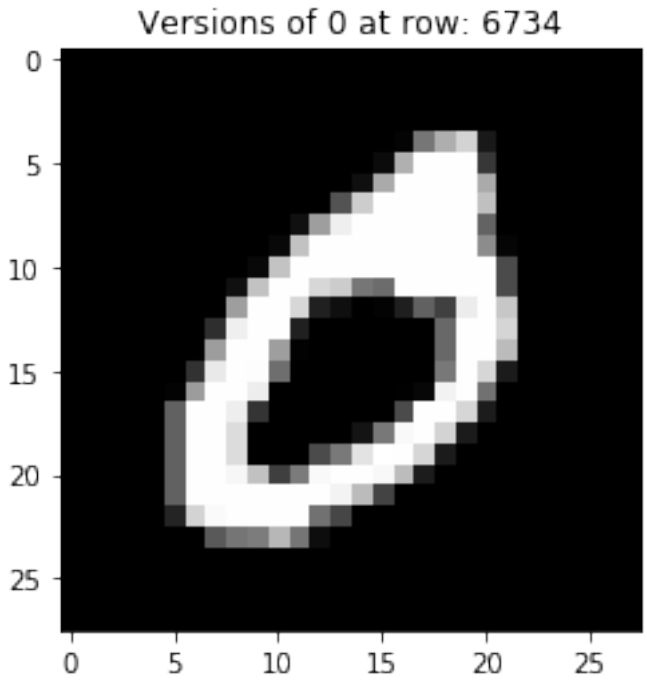
```
plt.show()
```


Versions of 0 at row: 976
0
5
10
15
20
25
0
5
10
15
20
25

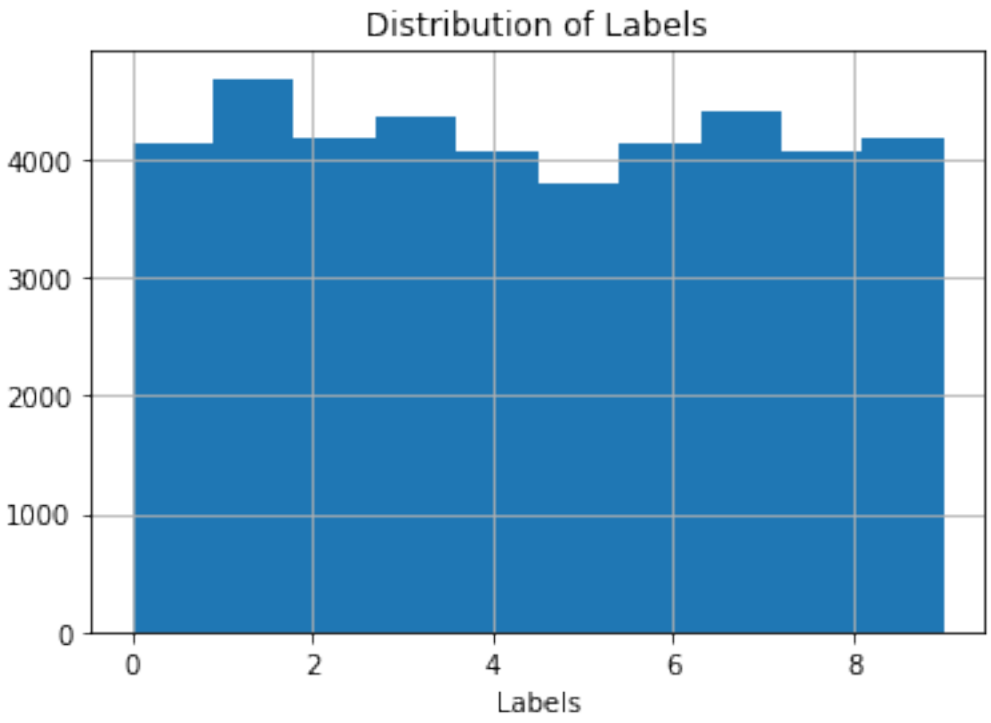

Versions of 0 at row: 35118
0
5
10
15
20
25
0
5
10
15
20
25


Versions of 0 at row: 774
0
5
10
15
20
25
0
5
10
15
20
25


Versions of 0 at row: 111
0
5
10
15
20
25
0
5
10
15
20
25




```
In [7]: #check for imbalanced dataset
        ytrain.hist()
        plt.title('Distribution of Labels')
        plt.xlabel('Labels')

Out[7]: Text(0.5, 0, 'Labels')
```



0.0.7 1.5 | Import Test Data

```
In [8]: file = "C:/Users/David/OneDrive/MSDS/MSDS422/Week5/test.csv"
        xtest = pd.read_csv(file,sep = ',')
        xtest.head()
```

Out[8]:

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	\
0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	

	pixel9	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	\
0	0	...	0	0	0	0	0	0	
1	0	...	0	0	0	0	0	0	
2	0	...	0	0	0	0	0	0	
3	0	...	0	0	0	0	0	0	
4	0	...	0	0	0	0	0	0	

	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0

```
3         0         0         0         0
4         0         0         0         0

[5 rows x 784 columns]
```

In [9]:
```
xtest.describe()
#looks like most pixels are just white space and can be reduced
```

Out[9]:

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	\
count	28000.0	28000.0	28000.0	28000.0	28000.0	28000.0	28000.0	28000.0	
mean	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
std	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
25%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
50%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
75%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
max	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

	pixel8	pixel9	...	pixel774	pixel775	pixel776	\
count	28000.0	28000.0	...	28000.000000	28000.000000	28000.000000	
mean	0.0	0.0	...	0.164607	0.073214	0.028036	
std	0.0	0.0	...	5.473293	3.616811	1.813602	
min	0.0	0.0	...	0.000000	0.000000	0.000000	
25%	0.0	0.0	...	0.000000	0.000000	0.000000	
50%	0.0	0.0	...	0.000000	0.000000	0.000000	
75%	0.0	0.0	...	0.000000	0.000000	0.000000	
max	0.0	0.0	...	253.000000	254.000000	193.000000	

	pixel777	pixel778	pixel779	pixel780	pixel781	pixel782	\
count	28000.000000	28000.000000	28000.0	28000.0	28000.0	28000.0	
mean	0.011250	0.006536	0.0	0.0	0.0	0.0	
std	1.205211	0.807475	0.0	0.0	0.0	0.0	
min	0.000000	0.000000	0.0	0.0	0.0	0.0	
25%	0.000000	0.000000	0.0	0.0	0.0	0.0	
50%	0.000000	0.000000	0.0	0.0	0.0	0.0	
75%	0.000000	0.000000	0.0	0.0	0.0	0.0	
max	187.000000	119.000000	0.0	0.0	0.0	0.0	

	pixel783
count	28000.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

[8 rows x 784 columns]

In [10]:
```
#confirm split went according to plan. both y values are close to the mean value
print("Row count of Xtrain:",len(xtrain))
print("Row count of Ytrain:",len(ytrain))
print("Row count of Xtest:",len(xtest))
```

```
Row count of Xtrain: 42000
Row count of Ytrain: 42000
Row count of Xtest: 28000
```

0.0.8 1.6 | Scale Test and Training Data

In [11]:
```
#scale training data separate from test so as to not influence scaling
xtrain = pd.DataFrame(StandardScaler().fit_transform(xtrain),
                      columns = xtrain.columns, index = xtrain.index)


#scale test data likewise
xtest = pd.DataFrame(StandardScaler().fit_transform(xtest),
                      columns = xtest.columns, index = xtest.index)


print("Test Data shape:",xtest.shape)
print("Training Data shape: ",xtrain.shape)
xtrain.head()
```

```
Test Data shape: (28000, 784)
Training Data shape:  (42000, 784)
```

Out[11]:

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	\
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

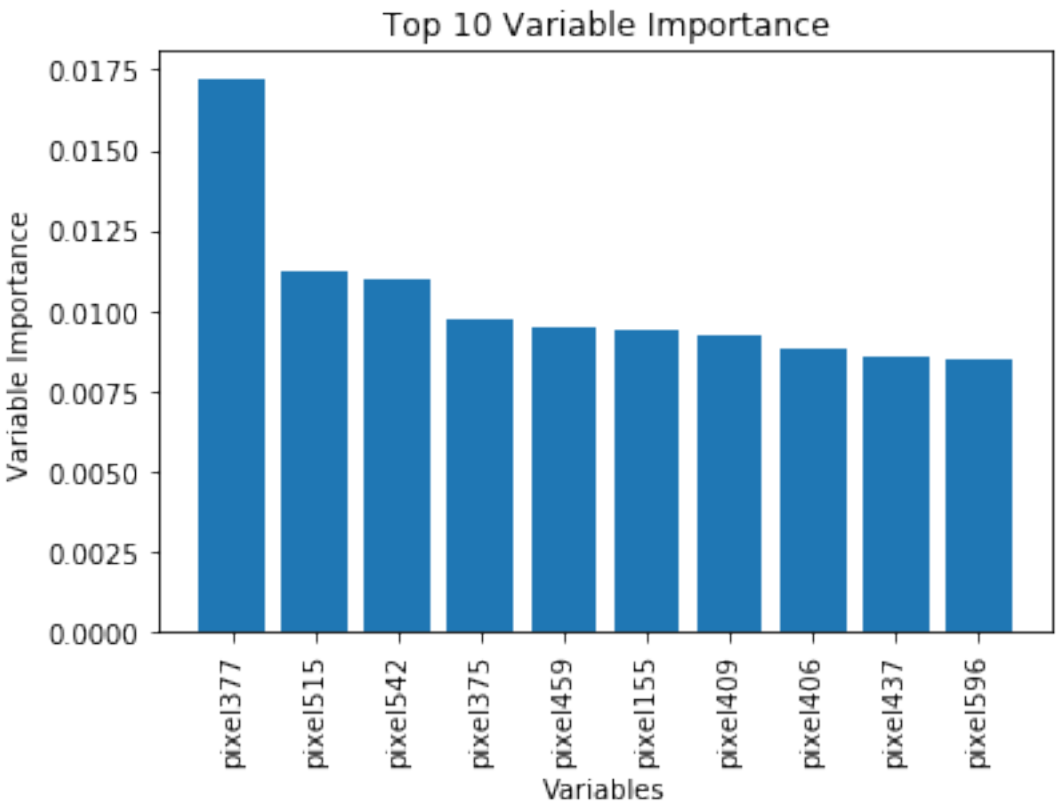
	pixel9	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	\
0	0.0	...	-0.034737	-0.02527	-0.018026	-0.011473	-0.009099	-0.006897	
1	0.0	...	-0.034737	-0.02527	-0.018026	-0.011473	-0.009099	-0.006897	
2	0.0	...	-0.034737	-0.02527	-0.018026	-0.011473	-0.009099	-0.006897	
3	0.0	...	-0.034737	-0.02527	-0.018026	-0.011473	-0.009099	-0.006897	
4	0.0	...	-0.034737	-0.02527	-0.018026	-0.011473	-0.009099	-0.006897	

	pixel780	pixel781	pixel782	pixel783
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0

```
4       0.0       0.0       0.0       0.0

[5 rows x 784 columns]
```

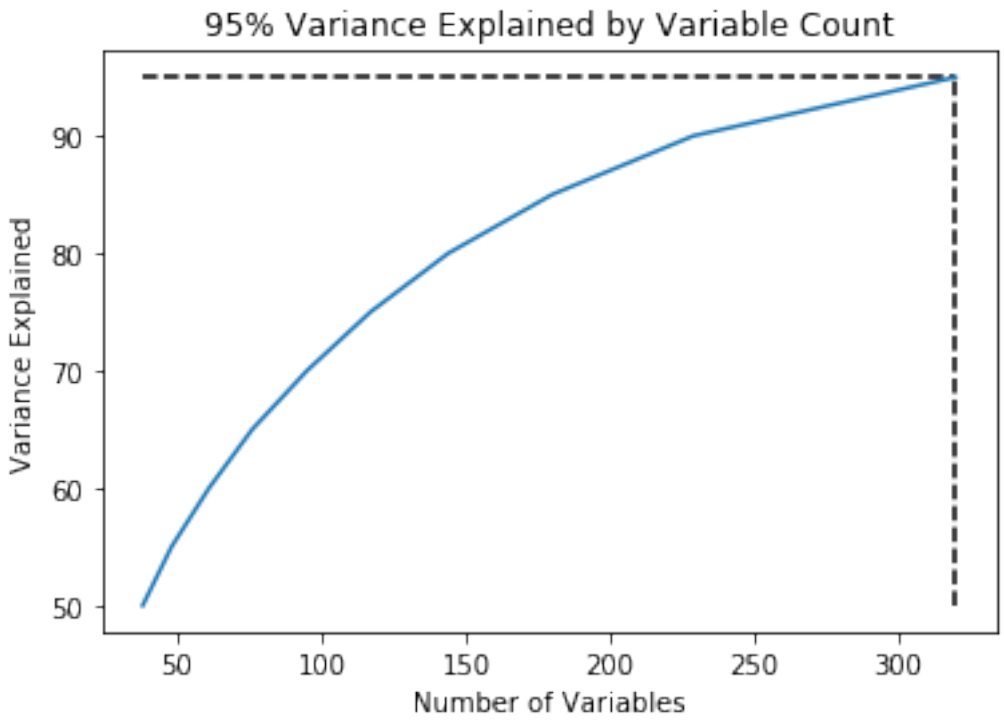
0.0.9 1.7 | Model I: RandomForest Classifier (All Variables)

```
In [12]: start=datetime.datetime.now()

         model1 = RandomForestClassifier(random_state = 42)

         param_grid = [{
             "n_estimators"       :[10],
             "max_features"       :['sqrt'],
             "bootstrap"          :[True],
             "warm_start"         :[True, False],
             }]

         #fit parameters to model for best model
         grid_search = GridSearchCV(model1,param_grid,cv = 5)
         rf = grid_search.fit(xtrain,ytrain)

         end=datetime.datetime.now()
         print("Elapsed Time: ",end-start)

Elapsed Time:  0:01:18.789869


In [13]: #make predictions and export submission
         best_model_rf = rf.best_estimator_
         label = best_model_rf.predict(xtest)
         submission = pd.DataFrame({"ImageID":xtest.index,"Label":label})
         submission.to_csv('C:/Users/David/OneDrive/MSDS/MSDS422/Week5/submissions/submission1

In [14]: #take a look at top variables of importance
         coeff = pd.concat([pd.Series(xtrain.columns),pd.Series(best_model_rf.feature_importanc
         coeff.columns = ['Variable','Variable Importance']
         coeff = coeff.sort_values('Variable Importance',ascending = False).head(10)

         plt.bar(coeff['Variable'],coeff['Variable Importance'])
         plt.title('Top 10 Variable Importance')
         plt.xticks(rotation = 90)
         plt.ylabel('Variable Importance')
         plt.xlabel('Variables')

Out[14]: Text(0.5, 0, 'Variables')
```



0.0.10 1.8 | PCA

```
In [15]: n_components = []
         variable_count = []
         #evaluate variance explained by different numbers of variables
         for i in range(50,100,5):
             pca = PCA(n_components = i/100)
             xtrain_pca=pca.fit_transform(xtrain)
             variable_count.append(len(pca.components_))
             n_components.append(i)

In [16]: #looks like about half of the variables can explain as much as 95 percent of variance
         plt.plot(variable_count,n_components)
         plt.title('95% Variance Explained by Variable Count')
         plt.xlabel('Number of Variables')
         plt.ylabel('Variance Explained')
         plt.hlines(y = 95,xmin = min(variable_count),xmax = max(variable_count),linestyles =
         plt.vlines(x = max(variable_count),ymin = min(n_components),ymax = max(n_components),l

Out[16]: <matplotlib.collections.LineCollection at 0x1f2264ac8d0>
```



0.0.11 1.9 | Model II: Random Forest Regressor (PCA)

```
In [18]: start=datetime.datetime.now()

         model2 = RandomForestClassifier(random_state = 42)

         param_grid = [{
             "n_estimators"       :[10],
             "max_features"       :['sqrt'],
             "bootstrap"          :[True],
             "warm_start"         :[True, False],
             }]

         #fit parameters to model for best model
         grid_search = GridSearchCV(model2,param_grid,cv = 5)
         rf = grid_search.fit(pd.DataFrame(xtrain_pca),ytrain)

         end=datetime.datetime.now()
         print("Elapsed Time: ",end-start)
```

```
Elapsed Time:  0:04:20.705715
```

```
In [19]: #make predictions and export submission
         best_model_rf_2 = rf.best_estimator_
```

```
label_2 = best_model_rf_2.predict(xtest_pca)
submission = pd.DataFrame({"ImageID":xtest.index,"Label":label})
submission.to_csv('C:/Users/David/OneDrive/MSDS/MSDS422/Week5/submissions/submission2
```

0.0.12 2.0 | Addendum (PCA on combined Training and Test Data)

In [28]:
```
start=datetime.datetime.now()

#combine test and training
combo = pd.concat([xtrain,xtest],axis = 0)
pca = PCA(n_components = .95,random_state = 42)
#fit_transform train and test
combo_pca=pca.fit_transform(combo)
xtrain_pca = pca.transform(xtrain)
xtest_pca = pca.transform(xtest)

end=datetime.datetime.now()
print("Elapsed Time: ",end-start)
```

```
Elapsed Time:  0:00:13.332147
```

In [29]:
```
start=datetime.datetime.now()

model3 = RandomForestClassifier(random_state = 42)

param_grid = [{
    "n_estimators"      :[10],
    "max_features"      :['sqrt'],
    "bootstrap"         :[True],
    "warm_start"        :[True, False],
    }]

#fit parameters to model for best model
grid_search = GridSearchCV(model2,param_grid,cv = 5)
rf = grid_search.fit(pd.DataFrame(xtrain_pca),ytrain)

end=datetime.datetime.now()
print("Elapsed Time: ",end-start)
```

```
Elapsed Time:  0:03:59.517650
```

In [31]:
```
#make predictions and export submission
best_model_rf_3 = rf.best_estimator_
label_3 = best_model_rf_3.predict(xtest_pca)
submission = pd.DataFrame({"ImageID":xtest.index,"Label":label})
submission.to_csv('C:/Users/David/OneDrive/MSDS/MSDS422/Week5/submissions/submission3
```

In [ ]: