Assignment 5: Principal Components Analysis

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Objective and data

The MNIST dataset contains gray-scale images of hand-drawn digits, from zero through nine. Each image is 28 pixels in height and 28 pixels in width, for a total of 784 pixels in total. Each pixel has a single pixel-value associated with it, indicating the lightness or darkness of that pixel, with higher numbers meaning darker. This pixel-value is an integer between 0 and 255, inclusive. The training set has 42,000 samples, with a label column indicating the digit drawn. The test set has 28,000 samples, unlabeled. Multi-class classification, with and without dimension reduction, is evaluated for future use. This study ultimately aims to evaluate the effectiveness of using principal components analysis (PCA) for dimension reduction as a preliminary to machine learning classification with this dataset and for comparable computer vision problems in the future.

Initial findings

All 256 values between zero and 255 exist in the train set. The label distribution in the training set appears relatively balanced across zero to nine (Figure 1), which obviates the need for adjustment by up-sampling, down-sampling, or other methods. An initial examination of sample digits shows that darker pixels are generally concentrated in the middle of the 28x28 grid, with consistent white space in the corners of each grid. The images themselves seem quite low-resolution. The zeros stand out most noticeably and distinctively, but many of the other digits are difficult to decipher even by human eyes, for example between threes and sevens.

Study design

A random forest classifier with minimal parameters is fitted to the training set first with a 80/20 train test split. Grid search is applied to tune hyperparameters, then the model is adjusted (increasing n_estimators) and fitted again. This serves as the baseline for multi-class classification on the MNIST data after evaluation on the Kaggle test set. In an attempt to compress the data and find a more informative representation for classification, PCA is then applied to the combined training and test set data to identify principal components that represent 95 percent of the variability in the explanatory features, resulting in 154 principal components. Examining the explained variance ratio, we see that 10 percent of the training dataset's variance lies along the first PC and decreases from there. Employing incremental PCA resulted in relatively similar results, so the original components are used. These components do not lend themselves to a useful visualization of clusters or patterns but they do reduce the dataset substantially while preserving most of its variance. Using the identified principal components, a second random forest model is fitted to the training data and evaluated on Kaggle's unseen test data. The evaluation metric for these methods is categorization accuracy, i.e., the proportion of test images that are correctly classified. Process time is also recorded for the classification, with and without principal components identified and applied. Accuracy and timing both will factor into final assessments of the utility of PCA prior to machine learning classification, in addition to other factors.

Results

The table below shows model fitting and evaluation results, with categorization accuracy and Kaggle score included:

Method	Process Time (seconds)	Accuracy (Train)	Kaggle Score (Test)
Random Forest (RF) classifier (OOB)	7.73	0.9656	
RF after grid search model fitting	23.33	0.9668	0.96471
PCA component identification	5.61		
RF with PCA model fitting	32.40	0.9448	0.94628

Findings and recommendation

The Random Forest classifier, both with and without PCA, generalizes well to the unseen Kaggle test data. With this particular dataset and classification method, compression from PCA resulted in slightly lower categorization accuracy and slower model fitting. As an unsupervised method of processing data for computer vision problems, it is not possible to generalize these results reliably beyond this classification effort's particular data, hyperparameters, and PCA particularities. This study's results are highly data-dependent; even using the same dataset, different hyperparameters, dimension reduction techniques (for example t-SNE or UMAP), and classification methods, like SVM, would almost inevitably result in different process times and categorization accuracy. For analogous image classification problems, it is thus recommended to utilize PCA and/or other appropriate dimension reduction techniques for exploration, compression, and representation. Given other hyperparameters and modeling techniques, PCA may result in faster fitting times as well. In cases where the majority of variance can be explained by a small number of components, PCA may provide the added benefit of cluster visualization and pattern exploration. The results and implementation time required of training with and without dimension reduction, though, would need to be considered in the context of the classification problem and objective and also the nature of the data (e.g., greyscale drawn numbers versus photographs) and its volume and complexity as an input to the tradeoff between accuracy and process time.

Appendix:

Link to Kaggle notebook: https://www.kaggle.com/clairence/random-forest-classification-with-pca?scriptVersionId=28419288

Jupyter notebook:

Objective: Develop a multiclass classifier using the entire MNIST data set for input data. The classifier will be used to predict which of 10 digits is being written.

In [ ]:
```
# https://www.kaggle.com/c/digit-recognizer/data
```

The data files train.csv and test.csv contain gray-scale images of hand-drawn digits, from zero through nine.

Each image is 28 pixels in height and 28 pixels in width, for a total of 784 pixels in total. Each pixel has a single pixel-value associated with it, indicating the lightness or darkness of that pixel, with higher numbers meaning darker. This pixel-value is an integer between 0 and 255, inclusive.

The training data set, (train.csv), has 785 columns. The first column, called "label", is the digit that was drawn by the user. The rest of the columns contain the pixel-values of the associated image.

Each pixel column in the training set has a name like pixelx, where x is an integer between 0 and 783, inclusive. To locate this pixel on the image, suppose that we have decomposed x as x = i * 28 + j, where i and j are integers between 0 and 27, inclusive. Then pixelx is located on row i and column j of a 28 x 28 matrix, (indexing by zero).

For example, pixel31 indicates the pixel that is in the fourth column from the left, and the second row from the top, as in the ascii-diagram below.

The test data set, (test.csv), is the same as the training set, except that it does not contain the "label" column.

Your submission file should be in the following format: For each of the 28000 images in the test set, output a single line containing the ImageId and the digit you predict.

The evaluation metric for this contest is the categorization accuracy, or the proportion of test images that are correctly classified. For example, a categorization accuracy of 0.97 indicates that you have correctly classified all but 3% of the images.

Assignment steps:

(1) Begin by fitting a random forest classifier using the full set of 784 explanatory variables and the model training set (train.csv). Record the time it takes to fit the model and then evaluate the model on the test.csv data by submitting to Kaggle.com. Provide your Kaggle.com score and user ID.

(2) Execute principal components analysis (PCA) on the combined training and test set data together, generating principal components that represent 95 percent of the variability in the explanatory variables. The number of principal components in the solution should be substantially fewer than the 784 explanatory variables. Record the time it takes to identify the principal components.

(3) Using the identified principal components from step (2), use the train.csv to build another random forest classifier. Record the time it takes to fit the model and to evaluate the model on the test.csv data by submitting to Kaggle.com. Provide your Kaggle.com score and user ID.

(4) Submit both the RF Classifier and the PCA RF Classifier to Kaggle.com, and report both scores along with your user name. I MUST have your user name to verify submission status.

Report total elapsed time measures for the training set analysis. It is sufficient to run a single time-elapsed test for this assignment.

In [1]:
```
# Import dependencies
import numpy as np
import pandas as pd
import os
import random
import time

# ML imports
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import KFold, train_test_split, cross_val_score, cross_val_predict, GridSearchCV
from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score, classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA, IncrementalPCA
# from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA

# Visualizations
import matplotlib.pyplot as plt  # static plotting
import seaborn as sns  # pretty plotting, including heat map
%matplotlib inline
```

In [2]:
```
# Initialize process time list for code timing across entire program
process_time = []
```

Import and inspect training data

In [3]:
```
# Import train and test datasets

# The training data set, (train.csv), has 785 columns. The first column, called "label", is the
# digit that was drawn by the user. The rest of the columns contain the pixel-values of the associated image.
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

In [4]:
```
# 42,000 images
# Each image has 784 features (each image is 28 x 28 pixels) and 1 label feature (785 total)
# Each feature represents one pixel's intensity from 0 (white) to 255 (black)
train.shape
```

Out[4]:
```
(42000, 785)
```

In [5]:
```
# 28,000 images, contains 784 features and no label
test.shape
```

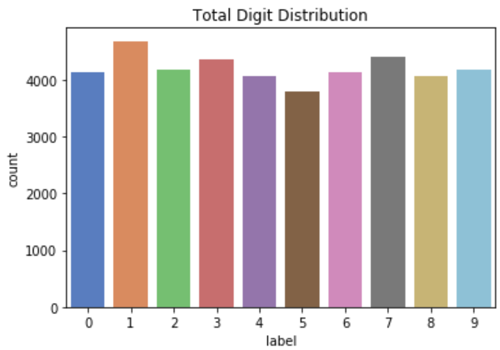
Out[5]:
```
(28000, 784)
```

In [6]:
```
# Inspect class balances for train set, seems relatively balanced
print(train['label'].value_counts(ascending=False))
print('--------------------')
print(train['label'].value_counts(normalize=True))
```

```
1    4684
7    4401
3    4351
9    4188
2    4177
6    4137
0    4132
4    4072
8    4063
5    3795
Name: label, dtype: int64
--------------------
1    0.111524
7    0.104786
3    0.103595
9    0.099714
2    0.099452
6    0.098500
0    0.098381
4    0.096952
8    0.096738
5    0.090357
Name: label, dtype: float64
```

Figure 1: Label Distribution in Train Set

In [51]:
```
# Plot label distribution from Kaggle train set
mn_plot_total = sns.countplot(train['label'], palette="muted").set_title('Total Digit Distribution')
```



In [7]:
```
# Save the labels to a Pandas series target
y = train['label']

# Drop the label feature
X = train.drop("label",axis=1)
```

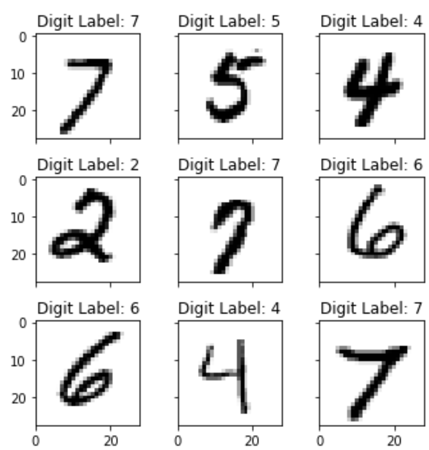
In [8]:
```
# Confirm that all 256 values between the min-max of 0-255 exist in the train set
len(np.unique(X))
```

Out[8]:
```
256
```

In [13]:
```
# View images
images_to_plot = 9
random_indices = random.sample(range(42000), images_to_plot)

sample_images = X.loc[random_indices, :]
sample_labels = y.loc[random_indices]
```

In [14]:
```
# Plot examples
plt.clf()
plt.style.use('seaborn-muted')

fig, axes = plt.subplots(3,3,
                         figsize=(5,5),
                         sharex=True, sharey=True,
                         subplot_kw=dict(adjustable='box', aspect='equal')) #https://stackoverflow.com/q/44703433/1870
832

for i in range(images_to_plot):

    # axes (subplot) objects are stored in 2d array, accessed with axes[row,col]
    subplot_row = i//3
    subplot_col = i%3
    ax = axes[subplot_row, subplot_col]

    # plot image on subplot
    plottable_image = np.reshape(sample_images.iloc[i,:].values, (28,28))
    ax.imshow(plottable_image, cmap='gray_r')

    ax.set_title('Digit Label: {}'.format(sample_labels.iloc[i]))
    ax.set_xbound([0,28])

plt.tight_layout()
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



Step 1: Fit a Random Forest classifier and evaluate on test set

- OOB model
- Train and evaluate
- Grid search
- Train and evaluate
- Predict
- Confusion matrix

1. Train test split and distribution of labels

In [9]:
```
# Assign classifier
# Use default criterion (gini)
cls_rf = RandomForestClassifier(random_state=1, n_jobs=-1, n_estimators=90)
```

In [10]:
```
# Split train and test set 90/10
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.20, random_state=1)
```

In [11]:
```
# Check split
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(33600, 784)
(33600,)
(8400, 784)
(8400,)
```

Figure 2: Label Distribution in Training Set

In [32]:
```
# Evaluate distribution of labels across train set
mn_plt_trn = sns.countplot(y_train, palette="muted").set_title('Train Digit')
```

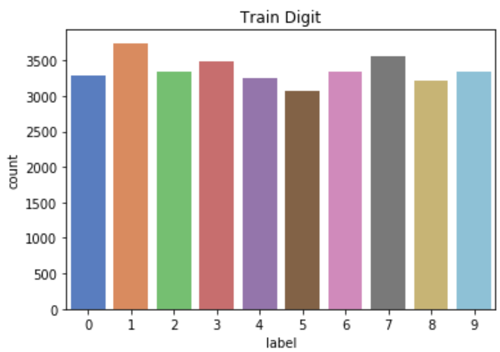
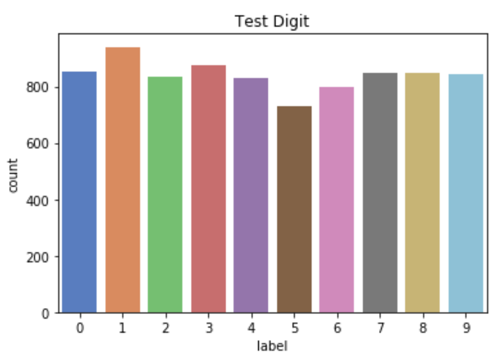


Figure 3: Label Distribution in Test Set

In [33]:
```
# Evaluate distribution of labels across test set
mn_plt_tst = sns.countplot(y_test, palette="muted").set_title('Test Digit')
```



2. Initial classification with Random Forest

In [12]:
```
# Fit model and run on test set with timing
start_time = time.time()
cls_rf.fit(X_train, y_train)
print('Accuracy: ', cls_rf.score(X_test, y_test))

# Timing
elapsed_time = time.time() - start_time
print('Formatted time: ', time.strftime("%H:%M:%S", time.gmtime(elapsed_time)))
print('Time in seconds: ', elapsed_time)
process_time.append(elapsed_time)
```

```
Accuracy:  0.9655952380952381
Formatted time:  00:00:07
Time in seconds:  7.7275731563568115
```

3. Grid search for fine-tuning

Try n_estimator hyperparameter

In [36]:
```
# cls_rf = RandomForestClassifier()

param_grid = {
    'bootstrap': [True],
    'max_depth': range(2,10),
    'n_estimators': [100,150,200,250,300,400,500]
}

grid_search_rf = GridSearchCV(estimator=cls_rf, param_grid=param_grid, cv=3,
                              return_train_score=True, n_jobs=-1, verbose=2)

grid_search_rf.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 40 candidates, totalling 120 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed:  7.7min finished
```

Out[36]:
```
GridSearchCV(cv=3, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=90, n_jobs=-1,
                                              oob_score=False, random_state=42,
                                              verbose=0, warm_start=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'bootstrap': [True], 'max_depth': range(2, 10),
                         'n_estimators': [100, 150, 200, 250, 300]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
             scoring=None, verbose=2)
```

In [37]:
```
# Display parameter recommendations
print('Test set score: ', grid_search_rf.score(X_test, y_test))
print('Best parameters: ', grid_search_rf.best_params_)
print('Best cross-validation score: ', grid_search_rf.best_score_)
```

```
Test set score:  0.9342857142857143
Best parameters:  {'bootstrap': True, 'max_depth': 9, 'n_estimators': 300}
Best cross-validation score:  0.9366666666666666
```

In [13]:
```
# Adjust model parameters, not using max depth
cls_rf = RandomForestClassifier(random_state=1, n_jobs=-1, n_estimators=300)

# Original
# cls_rf = RandomForestClassifier(random_state=1, n_jobs=-1, n_estimators=90)
```

In [14]:
```
# Fit the tuned parameters with timing
start_time = time.time()
cls_rf.fit(X_train, y_train)
elapsed_time = time.time() - start_time

# Results with tuning
print('Accuracy: ', cls_rf.score(X_test, y_test))

# Timing
print('Formatted time: ', time.strftime("%H:%M:%S", time.gmtime(elapsed_time)))
print('Time in seconds: ', elapsed_time)
process_time.append(elapsed_time)
```

```
Accuracy:  0.9667857142857142
Formatted time:  00:00:23
Time in seconds:  23.325534105300903
```

In [15]:
```
# F1 score
pred = cls_rf.predict(X_test)
print('F1 accuracy: ', f1_score(pred, y_test, average='macro'))
```

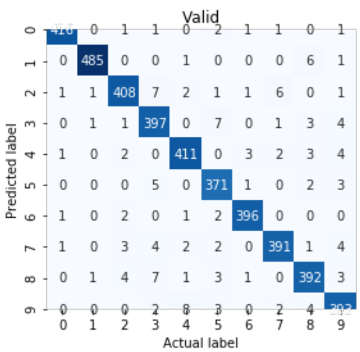
```
F1 accuracy:  0.9665596424569133
```

In [16]:
```
# Print classification report
target_names = ['class 0', 'class 1', 'class 2', 'class 3', 'class 4', 'class 5', 'class 6', 'class 7',
                'class 8', 'class 9']
print(classification_report(y_test, pred, target_names=target_names))
```

```
              precision    recall  f1-score   support

     class 0       0.98      0.99      0.99       853
     class 1       0.99      0.98      0.98       940
     class 2       0.96      0.97      0.97       835
     class 3       0.97      0.94      0.95       873
     class 4       0.96      0.97      0.96       829
     class 5       0.96      0.96      0.96       731
     class 6       0.98      0.98      0.98       800
     class 7       0.97      0.96      0.97       850
     class 8       0.96      0.96      0.96       846
     class 9       0.95      0.94      0.94       843

    accuracy                           0.97      8400
   macro avg       0.97      0.97      0.97      8400
weighted avg       0.97      0.97      0.97      8400
```

3. Confusion matrix

In [49]:
```
# Plot confusion matrix of actual versus predicted labels
rf_cm = confusion_matrix(y_test, pred)
rf_cm_plt=sns.heatmap(rf_cm.T, square=True, annot=True, fmt='d', cbar=False, cmap="Blues")
plt.xlabel('Actual label')
plt.ylabel('Predicted label')
plt.title("Valid");
```



4. Evaluate model on test set for Kaggle

In [17]:
```
# Submission code
testData = pd.read_csv("test.csv")
start_time = time.time()
pred = cls_rf.predict(testData)
elapsed_time = time.time() - start_time
print('Formatted time: ', time.strftime("%H:%M:%S", time.gmtime(elapsed_time)))
print('Time in seconds: ', elapsed_time)
process_time.append(elapsed_time)

# Create Dataframe
data = pred
df_1 = pd.DataFrame(pred)
df_1['ImageID'] = df_1.index + 1
df_1.columns = ['Label', 'ImageID']
submission = df_1[['ImageID', 'Label']]

# Output to csv
submission.to_csv('Boetticher_RF_predictions_8020.csv',header=True, index=False)
```

```
Formatted time:  00:00:01
Time in seconds:  1.1097159385681152
```

Kaggle ID: Claire Boetticher
Kaggle username: clairence

Step 2: Principal Components Analysis

1. Data preparation and PC identification

In [18]:
```
# Combine training and test set for PCA
x = np.concatenate((X_train, X_test), axis=0)
```

In [19]:
```
# Fit model using PCA, generating principal components that represent 95 percent of the variability in
# the explanatory features
start_time = time.time()
pca = PCA(.95)
pca.fit(x)
totimages = pca.transform(x)
# pca.n_components_

# Timing
elapsed_time = time.time() - start_time
print('Formatted time: ', time.strftime("%H:%M:%S", time.gmtime(elapsed_time)))
print('Time in seconds: ', elapsed_time)
process_time.append(elapsed_time)
```

```
Formatted time:  00:00:05
Time in seconds:  5.606950998306274
```

In [20]:
```
# Output number of principal components explaining 95% of variability in the explanatory features: 154
print('Principal components count: ', pca.n_components_)
```

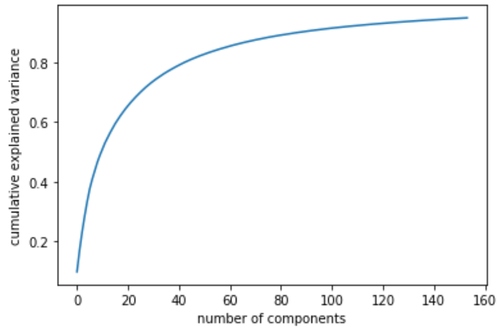
```
Principal components count:  154
```

2. Explained variance ratio and visualization

In [21]:
```
# Explained variance ratio for 154 PCs
# 10% of the train dataset's variance lies along the first PC
# 7% along the second
# 6% along the third, etc.
pca.explained_variance_ratio_
```

Out[21]:
```
array([0.09748938, 0.07160266, 0.06145903, 0.05379302, 0.04894262,
       0.04303214, 0.03277051, 0.02892103, 0.02766902, 0.02348871,
       0.02099325, 0.02059001, 0.01702553, 0.01692787, 0.01581126,
       0.0148324 , 0.01319688, 0.01282727, 0.01187976, 0.01152755,
       0.01072191, 0.01015199, 0.00964902, 0.00912846, 0.00887641,
       0.00838766, 0.00811856, 0.00777406, 0.00740635, 0.00686661,
       0.00657982, 0.00638799, 0.00599367, 0.00588913, 0.00564335,
       0.00540967, 0.00509222, 0.00487505, 0.00475569, 0.00466545,
       0.00452952, 0.00444989, 0.00418255, 0.00397506, 0.00384542,
       0.00374919, 0.00361013, 0.00348522, 0.00336488, 0.00320738,
       0.00315467, 0.00309146, 0.00293709, 0.00286541, 0.00280759,
       0.00269618, 0.00265831, 0.00256299, 0.00253821, 0.00246178,
       0.00239716, 0.0023874 , 0.00227591, 0.00221518, 0.00213934,
       0.00206133, 0.00202851, 0.00195977, 0.00193639, 0.00188485,
       0.00186751, 0.0018167 , 0.00176891, 0.00172592, 0.00166121,
       0.0016331 , 0.00160601, 0.00154472, 0.0014685 , 0.00142376,
       0.00141098, 0.00140228, 0.00138835, 0.00135417, 0.00132307,
       0.0013078 , 0.00129674, 0.0012424 , 0.00122249, 0.00119624,
       0.0011584 , 0.00113859, 0.00112263, 0.00110475, 0.00108133,
       0.00107413, 0.00103866, 0.00103322, 0.00101495, 0.00099997,
       0.00097482, 0.00094506, 0.00093864, 0.00091222, 0.00090731,
       0.00088887, 0.0008637 , 0.00084423, 0.00083554, 0.00081665,
       0.00078768, 0.00078156, 0.00077746, 0.00077193, 0.00075784,
       0.00075022, 0.00073448, 0.00072577, 0.00071532, 0.00070032,
       0.00069305, 0.00068574, 0.00067993, 0.00066572, 0.00065614,
       0.0006448 , 0.00063539, 0.00062612, 0.00061851, 0.00060574,
       0.00060385, 0.00059145, 0.0005859 , 0.00058463, 0.00057548,
       0.00056972, 0.0005645 , 0.00055317, 0.00053434, 0.00052578,
       0.00052197, 0.00051119, 0.00050514, 0.00049992, 0.00049532,
       0.00049235, 0.0004844 , 0.00047669, 0.00047467, 0.00046789,
       0.0004653 , 0.00046136, 0.00045634, 0.00045176])
```

In [22]:
```
#Explained variance plot
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
plt.show()
```



In [22]:
```
# Reform the training and testing images
# Training: up to 33,600
# Testing: 33,600 to 42,000
trainimages = totimages[0:33600, :]
testimages = totimages[33600:42000, :]
```

In [23]:
```
# Convert to integers
trainimages = trainimages.astype(int)
testimages = testimages.astype(int)
```

3. Test Incremental PCA

In [24]:
```
# Time component identification
start_time = time.time()

n_batches = 100
inc_pca = IncrementalPCA(n_components=154)
for X_batch in np.array_split(X_train, n_batches):
    inc_pca.partial_fit(X_batch)

X_reduced = inc_pca.transform(X_train)

# Timing
elapsed_time = time.time() - start_time
print('Formatted time: ', time.strftime("%H:%M:%S", time.gmtime(elapsed_time)))
print('Time in seconds: ', elapsed_time)
process_time.append(elapsed_time)
```

```
Formatted time:  00:00:08
Time in seconds:  8.207072019577026
```

In [32]:
```
# Explained variance ratio for 154 PCs with incremental PCA
# 10% of the train dataset's variance lies along the first PC
# 7% along the second
# 6% along the third, etc.
# Not drastically different than PCA and took longer
inc_pca.explained_variance_ratio_
```

Out[32]:
```
array([0.0974987 , 0.07141142, 0.06151824, 0.05388163, 0.04890098,
       0.04318881, 0.03282591, 0.02884297, 0.0276572 , 0.02350486,
       0.02100847, 0.02057254, 0.0170844 , 0.01697231, 0.01571694,
       0.01481204, 0.01322833, 0.01281248, 0.01185411, 0.0115275 ,
       0.01073516, 0.01014294, 0.00964169, 0.00912906, 0.00885071,
       0.00839414, 0.00812626, 0.00777431, 0.00738998, 0.00686648,
       0.00657795, 0.00636188, 0.00599267, 0.00587324, 0.00562946,
       0.00542793, 0.00508767, 0.00489156, 0.00474121, 0.00466481,
       0.00454451, 0.00446174, 0.00417216, 0.00396312, 0.00385106,
       0.00375317, 0.00362015, 0.00348357, 0.00336826, 0.00320721,
       0.00315766, 0.00308749, 0.00292497, 0.00286046, 0.00281125,
       0.00268951, 0.00265246, 0.00257036, 0.0025385 , 0.00244912,
       0.00240386, 0.00238819, 0.00227269, 0.00220696, 0.00213842,
       0.00207173, 0.00202547, 0.00195977, 0.00193556, 0.00188451,
       0.00186966, 0.00181152, 0.00176677, 0.00172303, 0.0016659 ,
       0.00163342, 0.00160367, 0.00154687, 0.00146551, 0.00142234,
       0.00140977, 0.00140012, 0.0013862 , 0.00135238, 0.00132266,
       0.00131378, 0.00129288, 0.00123952, 0.00122102, 0.0011996 ,
       0.00115537, 0.00113975, 0.00111659, 0.00110452, 0.00107816,
       0.00106763, 0.00103541, 0.00102944, 0.00101433, 0.00099765,
       0.0009733 , 0.00094301, 0.00093513, 0.00091001, 0.00090182,
       0.00088084, 0.00086275, 0.00084047, 0.00083399, 0.00081642,
       0.00078296, 0.00077758, 0.00077628, 0.0007637 , 0.00075262,
       0.00074332, 0.00072606, 0.0007161 , 0.00070858, 0.00069437,
       0.00068603, 0.000678  , 0.00067524, 0.00066127, 0.00064644,
       0.00063779, 0.00063105, 0.00062343, 0.00060675, 0.00059727,
       0.00059467, 0.00058163, 0.00057402, 0.00056586, 0.00055703,
       0.00055221, 0.00054657, 0.00054022, 0.0005191 , 0.00051785,
       0.00050122, 0.00048903, 0.0004854 , 0.00047305, 0.00046864,
       0.00046417, 0.00045361, 0.00044847, 0.00044269, 0.00043785,
       0.00043312, 0.00042279, 0.00042026, 0.00040192])
```

Step 3: Random Forest Classifier with Principal Components

1. Fit model with principal components

In [30]:
```
# Fit the model
start_time = time.time()
cls_rf2 = RandomForestClassifier(random_state=1, n_jobs=-1, n_estimators=300)
cls_rf2.fit(trainimages, y_train)
elapsed_time = time.time() - start_time
print('Accuracy: ', cls_rf2.score(testimages, y_test))

# Timing
print('Formatted time: ', time.strftime("%H:%M:%S", time.gmtime(elapsed_time)))
print('Time in seconds: ', elapsed_time)
process_time.append(elapsed_time)
```

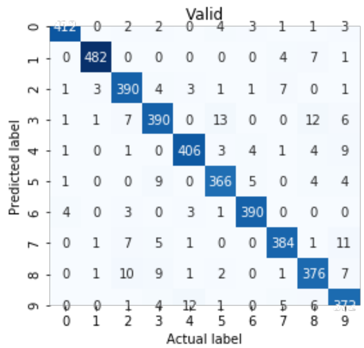
```
Accuracy:  0.9448809523809524
Formatted time:  00:00:32
Time in seconds:  32.40455889701843
```

In [31]:
```
# Predict a second time with principal components
pred2 = cls_rf2.predict(testimages)
print('F1 accuracy: ', f1_score(pred2, y_test, average='macro'))
```

```
F1 accuracy:  0.9444212610466947
```

2. Confusion matrix

In [50]:
```
# Plot confusion matrix of actual versus predicted labels
rf_cm = confusion_matrix(y_test, pred2)
rf_cm_plt=sns.heatmap(rf_cm.T, square=True, annot=True, fmt='d', cbar=False, cmap="Blues")
plt.xlabel('Actual label')
plt.ylabel('Predicted label')
plt.title("Valid");
```



3. Evaluate model on test set for Kaggle

In [27]:
```
# Submission code with timing
x_test = pd.read_csv("test.csv")
start_time = time.time()
pred_PCA = cls_rf2.predict(pca.transform(x_test))
elapsed_time = time.time() - start_time
print('Formatted time: ', time.strftime("%H:%M:%S", time.gmtime(elapsed_time)))
print('Time in seconds: ', elapsed_time)
process_time.append(elapsed_time)

# Create Dataframe
data = pred_PCA
df_1 = pd.DataFrame(pred_PCA)
df_1['ImageID'] = df_1.index + 1
df_1.columns = ['Label', 'ImageID']
submission = df_1[['ImageID', 'Label']]

# Output to csv
submission.to_csv('Boetticher_RF__PCA_predictions_2_8020.csv',header=True, index=False)
```

```
Formatted time:  00:00:01
Time in seconds:  1.0840649604797363
```

Kaggle ID: Claire Boetticher
Kaggle username: clairence

Processing time for entire study

In [28]:

```
# Final process_time addition for entire program
# Find sum of elements in process_time list
total = 0

# Iterate over each element in process_time list and add them in variable total
for ele in range(0, len(process_time)):
    total = total + process_time[ele]

# Conversion
def convert(seconds):
    min, sec = divmod(seconds, 60)
    hour, min = divmod(min, 60)
    return "%d:%02d:%02d" % (hour, min, sec)

# Time output
n = total
convert(n)

# Results
print("Total time of model fitting and evalation for study (in seconds): ", total)
print('Formatted time: ', time.strftime("%H:%M:%S", time.gmtime(total)))
```

```
Total time of model fitting and evalation for study (in seconds):  80.17386531829834
Formatted time:  00:01:20
```

In [ ]: