mmn_12_computer_vision

December 13, 2018

1 MMN 12 Computer Vision

1.1 Preparatory Setup

1.1.1 Library Imports

```
In [184]: import numpy as np
          import cv2
          import matplotlib.pyplot as plt
          from mpl_toolkits.mplot3d import Axes3D
          import seaborn as sns
          import pandas as pd
          from sklearn.utils import shuffle
          from sklearn.model_selection import train_test_split
          from sklearn.neighbors import KNeighborsClassifier
          from sklearn.preprocessing import StandardScaler, label_binarize
          from sklearn.metrics import roc_curve, auc, classification_report, confusion_matrix
          from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
          from sklearn.svm import SVC, LinearSVC
          from scipy.stats import uniform, expon, randint
          from sklearn.decomposition import PCA,TruncatedSVD
          from sklearn.manifold import TSNE
          import os
          %matplotlib inline
```

1.1.2 Plot Style Setup

```
In [2]: # change rcParams so figure aesthetics match jupyterthemes style
        # NOTE: or use plt.style.use(['dark_background']) to get dark plots without installing
        from jupyterthemes import jtplot
        jtplot.style()
```

1.2 Iris Dataset

link to Iris dataset source website

1.2.1 Overview

The dataset consists of 150 samples. Each sample is assigned to 1 of 3 possible classes, and holds a value for each of the 4 attributes.

Note: this is not the original dataset in neither shape, form, or format. We've done some pre-processing (outside notebook scope) for convenience.

Classes

- Iris Setosa
- Iris Versicolour
- Iris Virginica

Attributes

1. sepal length in cm
2. sepal width in cm
3. petal length in cm
4. petal width in cm

1.2.2 Dataset Exploration

In [10]:
```
# load dataset
iris_data = pd.read_csv('./iris_dataset.csv', index_col='id')
```

In [11]:
```
# number of samples
iris_data.species.count()
```

Out[11]:
```
150
```

In [12]:
```
# showcase a few random samples
iris_data.sample(5)
```

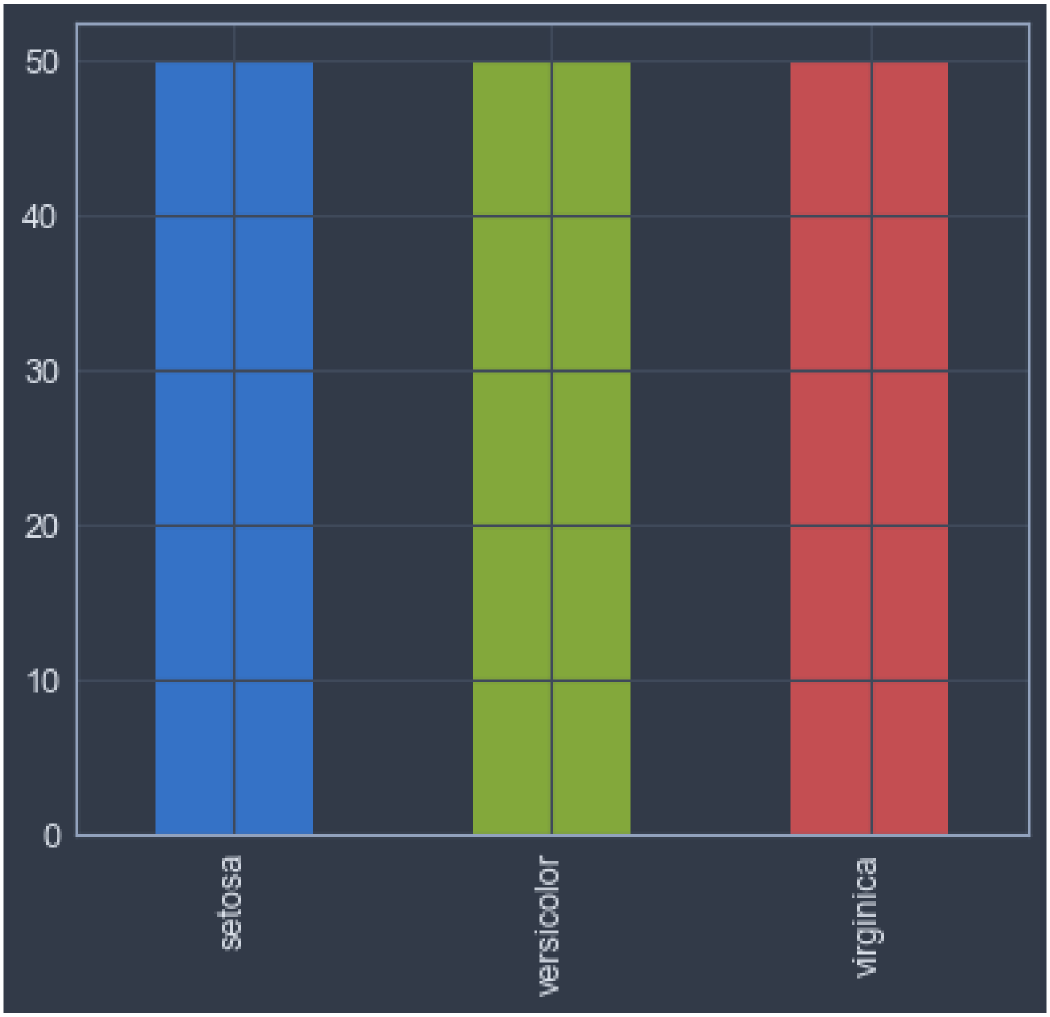
Out[12]:
```
     sepal_length  sepal_width  petal_length  petal_width     species
id
104           6.5          3.0           5.8          2.2   virginica
74            6.4          2.9           4.3          1.3  versicolor
69            5.6          2.5           3.9          1.1  versicolor
30            4.8          3.1           1.6          0.2      setosa
36            5.5          3.5           1.3          0.2      setosa
```

In [6]:
```
# unique classes
pd.unique(iris_data.species)
```

Out[6]:
```
array(['setosa', 'versicolor', 'virginica'], dtype=object)
```

In [8]:
```
# number of samples in each class
iris_data.species.value_counts().plot.bar()
```

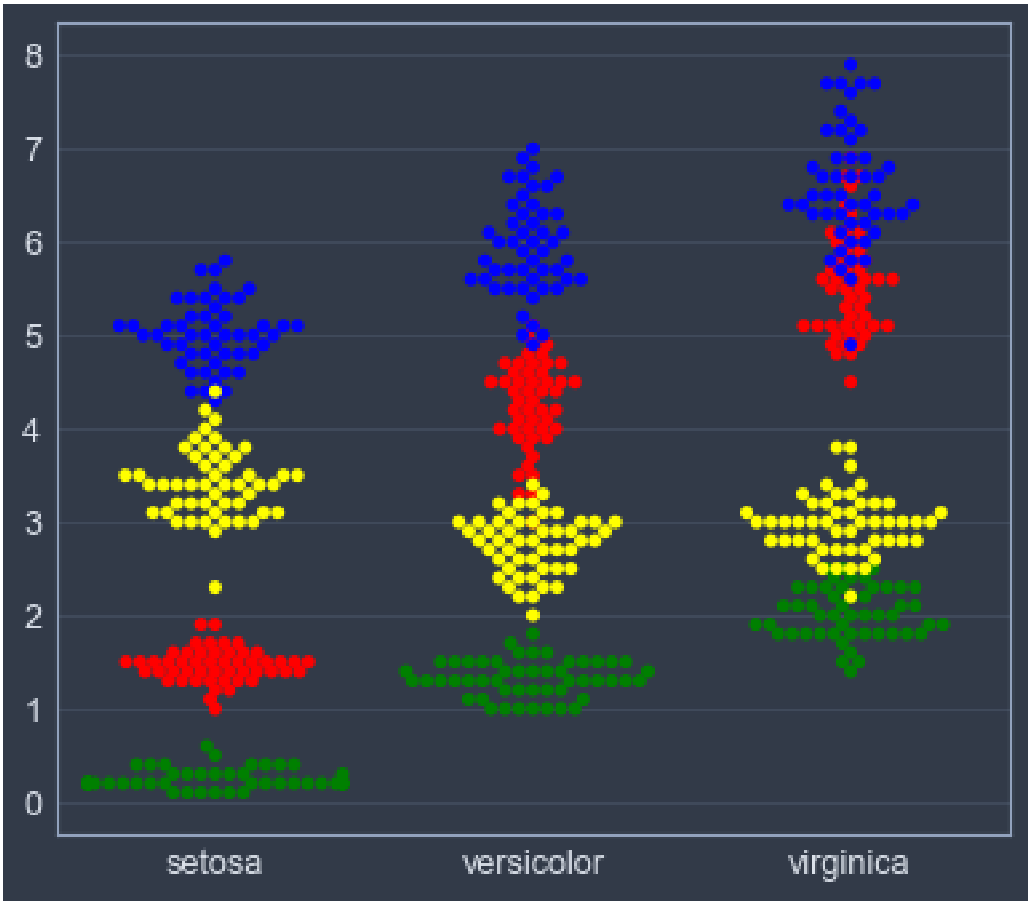
Out[8]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x115a50978>
```



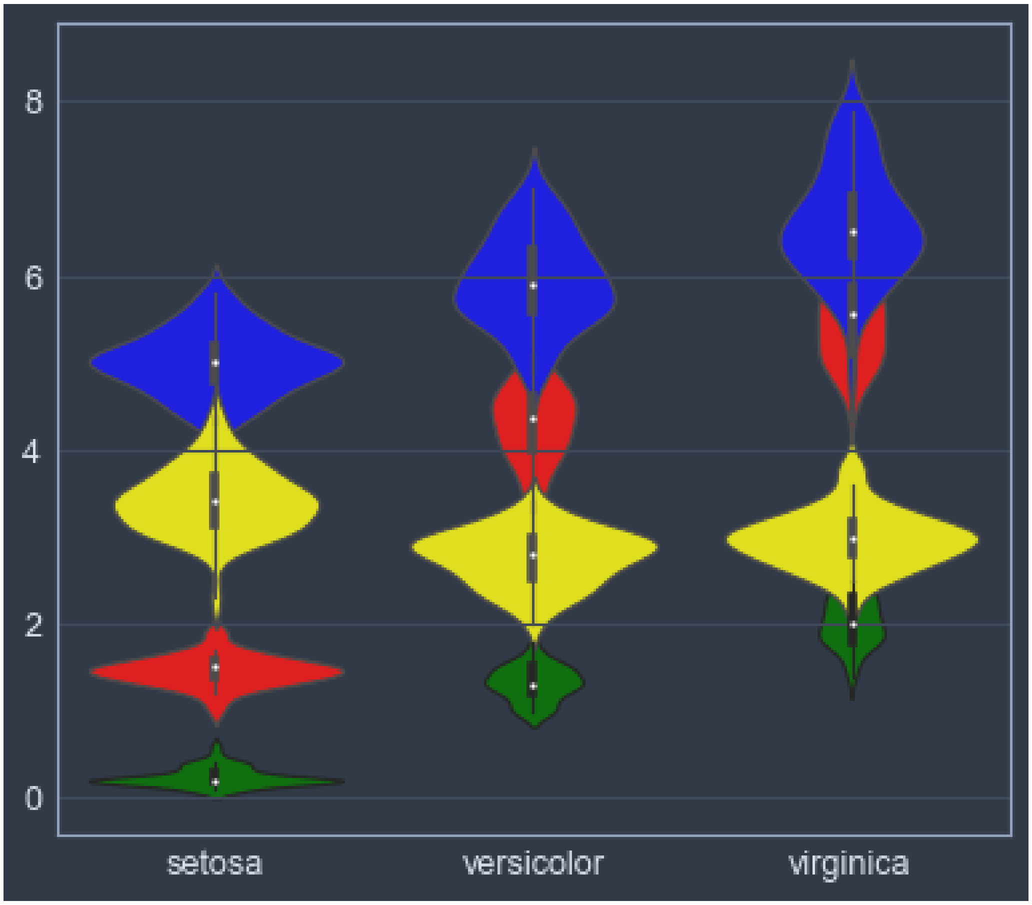

```
In [21]: # x_name = 'sepal_width'; y_name = 'sepal_length'
         # for species in pd.unique(iris_data.species):
         #     x = iris_data[iris_data.species==species][x_name]
         #     y = iris_data[iris_data.species==species][y_name]
         #     plt.scatter(x,y, label=species)
         # plt.xlabel(x_name); plt.ylabel(y_name); plt.legend()
```

```
In [22]: sns.swarmplot(x="species", y='petal_length', color='red', data=iris_data)
         sns.swarmplot(x="species", y="petal_width", color='green', data=iris_data)
         sns.swarmplot(x="species", y="sepal_length", color='blue', data=iris_data)
         sns.swarmplot(x="species", y="sepal_width", color='yellow', data=iris_data)
         plt.xlabel(''); plt.ylabel('')
```

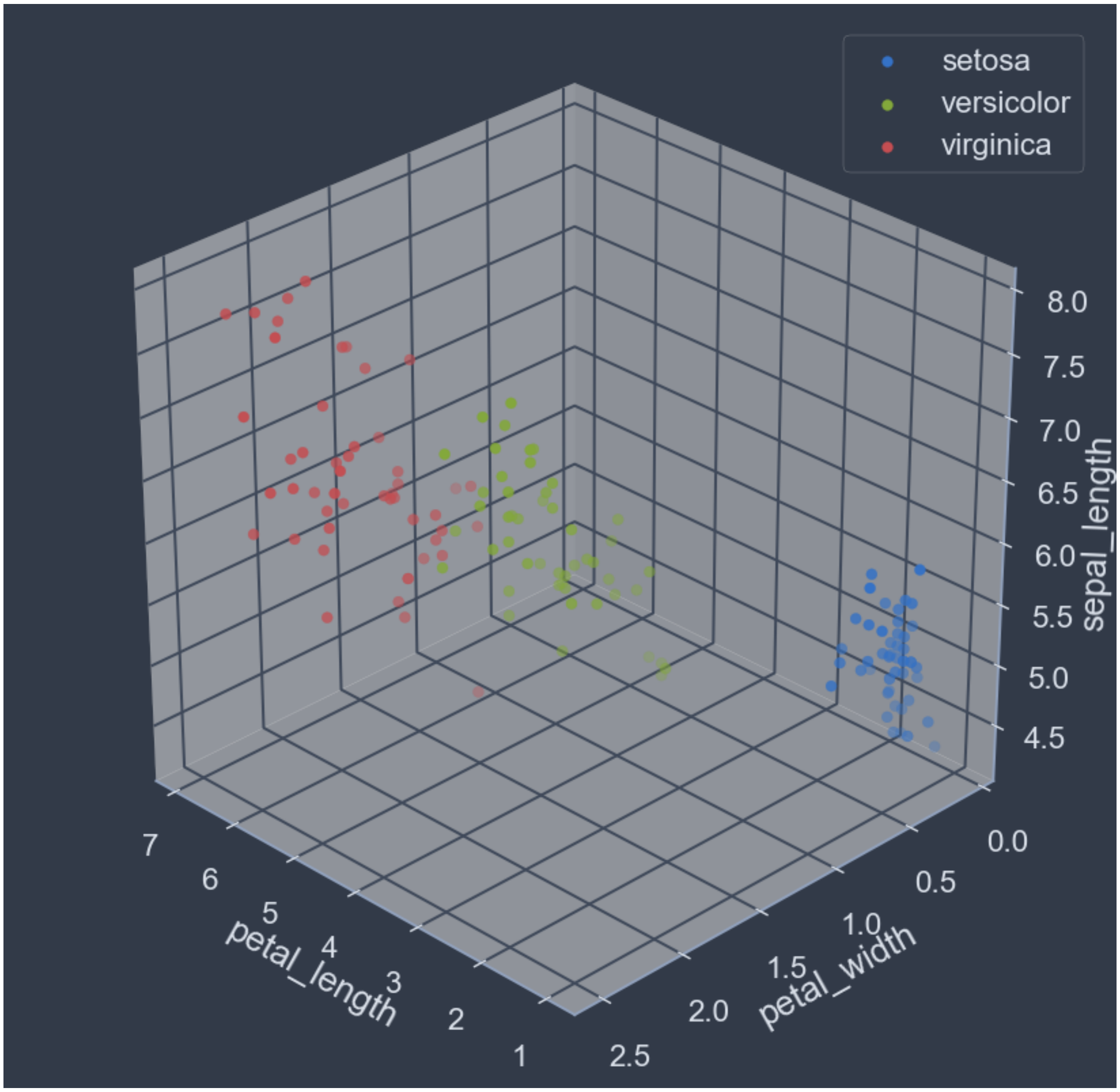
```
Out[22]: Text(0,0.5,'')
```




```
In [13]: sns.violinplot(x="species", y='petal_length', color='red', data=iris_data)
         sns.violinplot(x="species", y="petal_width", color='green', data=iris_data)
         sns.violinplot(x="species", y="sepal_length", color='blue', data=iris_data)
         sns.violinplot(x="species", y="sepal_width", color='yellow', data=iris_data)
         plt.xlabel(''); plt.ylabel('')

Out[13]: Text(0,0.5,'')
```




```
In [14]: fig= plt.figure(figsize=(8,8), dpi=128); ax = fig.add_subplot(111, projection='3d')
         x_name = 'petal_length'; y_name = 'petal_width'; z_name='sepal_length'
         for species in pd.unique(iris_data.species):
             x = iris_data[iris_data.species==species][x_name]
             y = iris_data[iris_data.species==species][y_name]
             z = iris_data[iris_data.species==species][z_name]
             ax.scatter(x,y,z,label=species)
         ax.view_init(30, 135)
         ax.set_xlabel(x_name); ax.set_ylabel(y_name); ax.set_zlabel(z_name)
         plt.legend()
         plt.show()
```



Exploration Notes

- The class 'setosa' is linearly well separated.
- The classes 'versicolor' and 'virginica' are likely not linearly separable.
- Classes seem to have good boundaries overall.
- Data forms some well defined clusters.
- Classes are mostly easily distinguishable by looking at cluster membership.

1.2.3 Classifier Selection

Judging by our exploratory analysis, not all classes can be completely separated via a hyperplane. However, the classes do seem to have well defined boundaries and are generally easily distinguishable. Therefore, some form of non-linear classification approach will likely yield better results: commonly by space partitioning via curved hyper-surface class boundaries.

Both SVMs (non-linear, via a feature space transform) and k-NN can be suitable for the task. However, due to the shape of the data, using an SVM will require an extensive hyper-parameter search as well as kernel comparison against various metrics, with no clear foreseeable benefits. Meanwhile, the data distribution looks well suited for a kNN to be quickly and easily trained without much tunning or computation.

By way of the above rationale, we'll choose to utilize the kNN algorithm.

1.2.4 Classifier Training

```
In [119]: # separate data into features and labels
          X = iris_data.drop(columns='species')
          y = iris_data.species
          print('features: ', X.shape); print('labels: ', y.shape)
```

```
features:  (150, 4)
labels:  (150,)
```

```
In [120]: # training validation split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1)
          print('train split: ', X_train.shape, y_train.shape)
          print('test split: ', X_test.shape, y_test.shape)
```

```
train split:  (135, 4) (135,)
test split:  (15, 4) (15,)
```

```
In [121]: # randomization
          X_train, y_train = shuffle(X_train, y_train)

In [122]: # normalization
          sc = StandardScaler()
          sc.fit(X_train)
          X_train_norm = sc.transform(X_train)
          X_test_norm = sc.transform(X_test)

In [123]: # choose k-nearest-neighbors param
          k = int(round(np.sqrt(X_train.shape[0])))
          k

Out[123]: 12

In [124]: # train classifier
          knn = KNeighborsClassifier(n_neighbors=k, metric='euclidean')
          knn.fit(X_train_norm, y_train)

Out[124]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='euclidean',
                     metric_params=None, n_jobs=1, n_neighbors=12, p=2,
                     weights='uniform')
```

1.2.5 Classifier Validation

TODO: ROC, AUC, metrics, k values, visualize boundaries, SVM comparison, plot all 6 scatters, make 3d code more compact

```
In [125]: # score classifier
          print('Train Accuracy: {:.2f}'.format(knn.score(X_train_norm, y_train)))
          print('Test Accuracy: {:.2f}'.format(knn.score(X_test_norm, y_test)))
```

```
Train Accuracy: 0.96
Test Accuracy: 1.00
```

1.3 MNIST Dataset

link to MNIST dataset source website

1.3.1 Overview

The dataset consists of 60,000 labeled samples. Each sample is a grayscale 28x28 pixel PNG image. Each image is labeled as a single digit from the range [0,9].

Note: this is not the original dataset in neither shape, form, format. We've done some pre-processing to it (outside scope of this notebook) for convenience.

1.3.2 Dataset Exploration

```
In [3]: # MNIST image directory and imag file extension
        IMG_DIR = './mnist-images/'; IMG_FILE_EXTENSION ='.png'
        # load file paths sorted by numerical value of file name, excluding the extension suff
        fpaths = sorted(os.listdir(IMG_DIR), key=lambda x: int(x[:-len(IMG_FILE_EXTENSION)]))
        # load images
        X = np.array([cv2.imread(IMG_DIR+fp, cv2.IMREAD_GRAYSCALE) for fp in fpaths],dtype=np.u
        # load labels
        y = np.loadtxt('mnist_labels.txt',dtype=np.uint8)
```

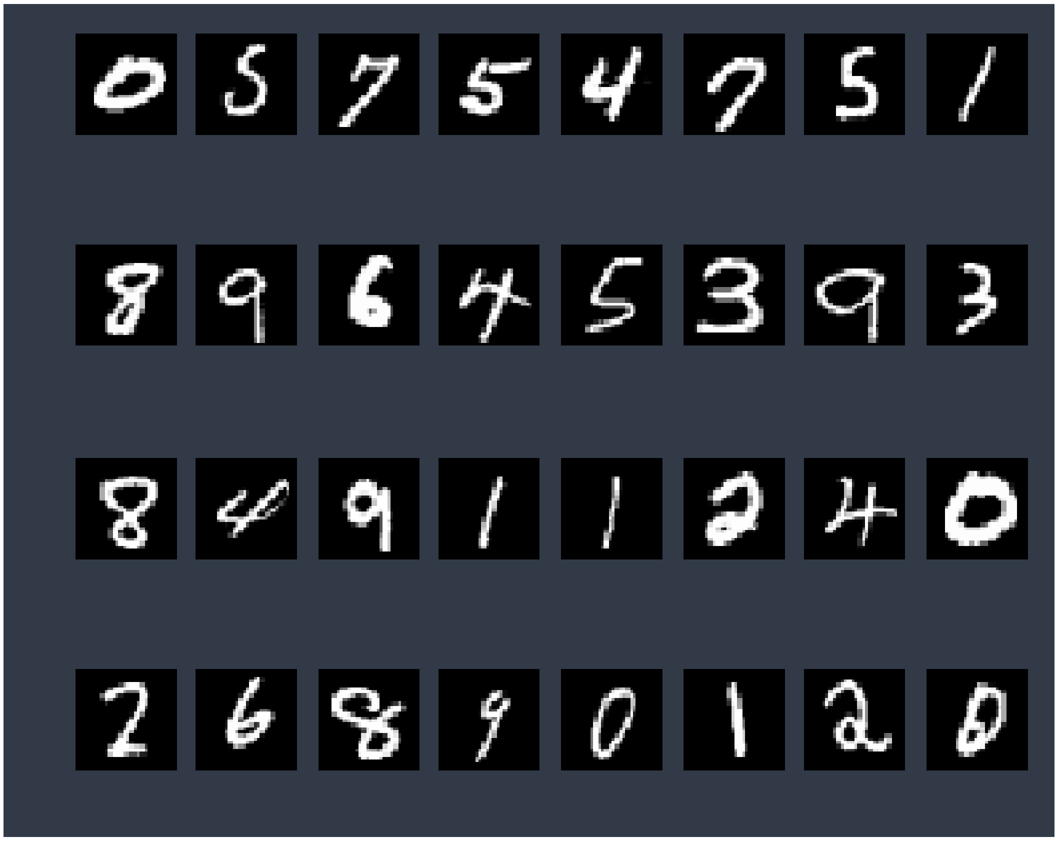
```
In [4]: # count and shape
        print('X: ', X.shape,'\ny: ', y.shape)
```

```
X:  (60000, 28, 28)
y:  (60000,)
```

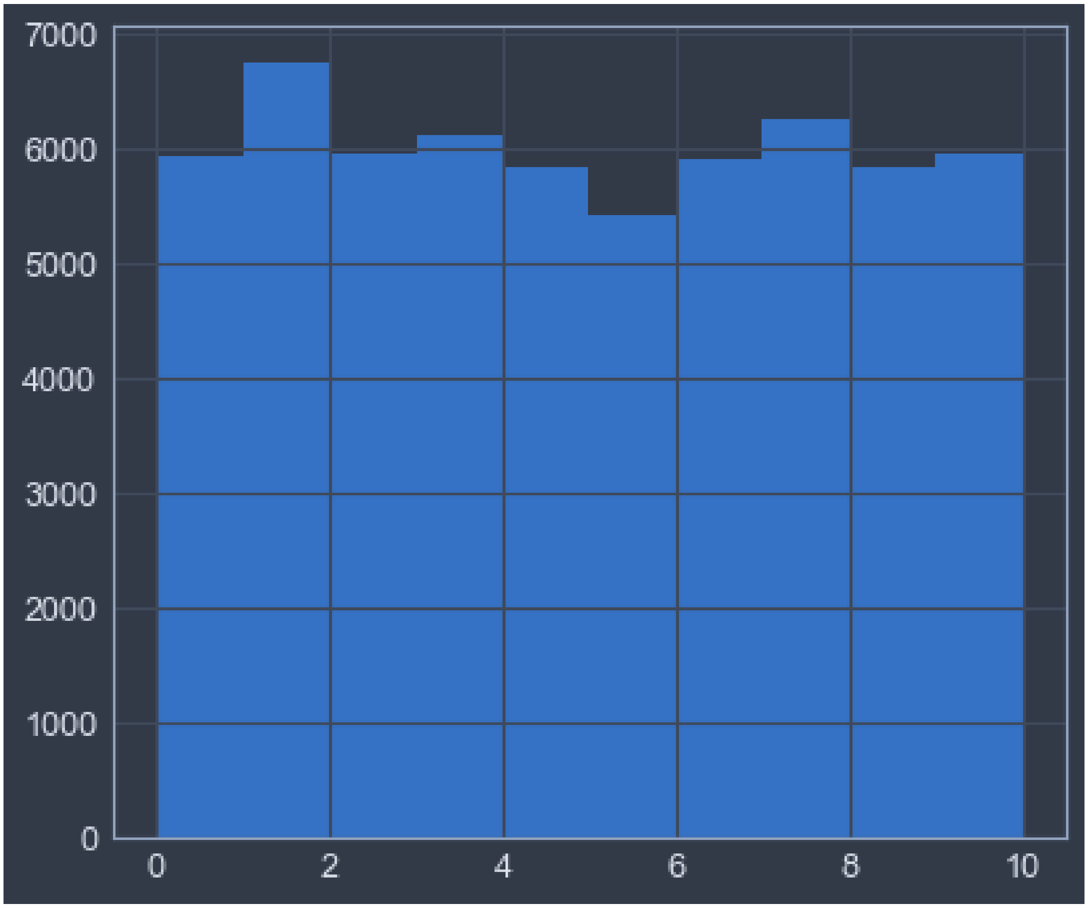
```
In [5]: # unique classes
        np.unique(y)
```

```
Out[5]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
```

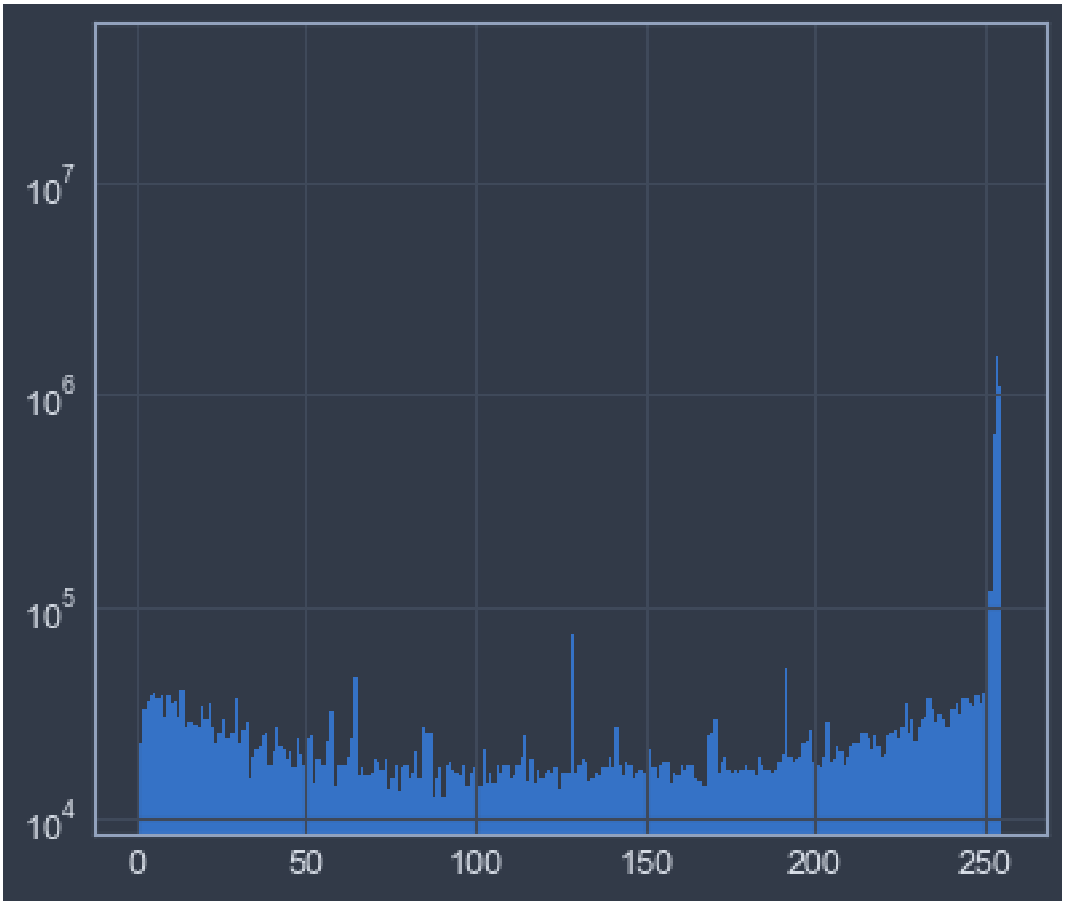
```
In [201]: # showcase a few samples
          for ax in plt.subplots(4,8)[1].ravel():
              rnd = np.random.randint(0,y.shape[0])
              ax.set_axis_off()
              ax.imshow(X[rnd],cmap='gray')
```



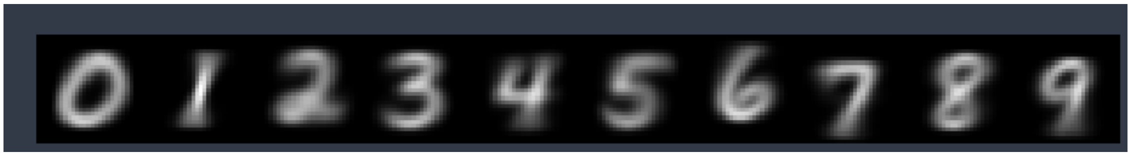
```
In [202]: # plot class sample counts
          plt.hist(y, bins=range(11))

Out[202]: (array([ 5923.,  6742.,  5958.,  6131.,  5842.,  5421.,  5918.,  6265.,
                   5851.,  5949.]),
           array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
           <a list of 10 Patch objects>)
```




```
In [203]: # plot logarithmic grayscale color histogram
          hist = plt.hist(X.flatten(), bins=range(256), log=True)
```

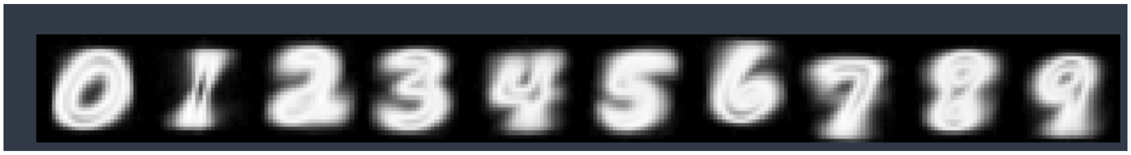



```
In [6]: # compute and show average pixel values for each digit class
        avgs = np.hstack([np.mean(X[y==i], axis=0) for i in range(10)])
        plt.matshow(avgs,cmap='gray'); plt.axis('off');
```



```
In [7]: # compute and show median pixel values for each digit class
        medians = np.hstack([np.median(X[y==i], axis=0) for i in range(10)])
        plt.matshow(medians,cmap='gray'); plt.axis('off');
```

```
In [8]: # compute and show standard diviation of pixel values for each digit class
        stds = np.hstack([np.std(X[y==i], axis=0) for i in range(10)])
        plt.matshow(stds,cmap='gray'); plt.axis('off');
```



1.3.3 Preprocessing

```
In [256]: # training validation split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
          print('train split: ', X_train.shape, y_train.shape)
          print('test split: ', X_test.shape, y_test.shape)
```

```
train split:  (42000, 28, 28) (42000,)
test split:  (18000, 28, 28) (18000,)
```

```
In [257]: # randomization
          X_train, y_train = shuffle(X_train, y_train)

In [258]: # threshold and binarize the images
          X_train = np.where(X_train>127,1,0).astype(np.bool)
          X_test = np.where(X_test>127,1,0).astype(np.bool)
          plt.matshow(np.hstack(X_train[:10]*255),cmap='gray'); plt.axis('off');
```

```
In [259]: # flatten images to match classifier,preprocessors,etc expected input shapes
          X_train = X_train.reshape(len(X_train), -1)
          X_test = X_test.reshape(len(X_test), -1)
          print('X_train:', X_train.shape,' X_test:', X_test.shape)
```

```
X_train: (42000, 784)  X_test: (18000, 784)
```

```
In [260]: # standarize and perform PCA dimensionality reduction
          pca = PCA(0.65, whiten=True)
          X_train = pca.fit_transform(X_train)
          X_test = pca.transform(X_test)
          print('X_train:', X_train.shape,' X_test:', X_test.shape)
```

```
X_train: (42000, 34)  X_test: (18000, 34)
```

```
In [261]: # plot inverse PCA result
          plt.matshow(np.hstack(pca.inverse_transform(X_train[:10]).reshape(-1,28,28)),cmap='g
```

```
In [262]: # tsne = TSNE(n_components=2, n_iter=250)
          # tsne.fit(X_train)
```

1.3.4 Classifier Selection

MNIST is a larger dataset with many more dimensions and training samples (~5m even in binary form). Although it's still not large enough to make kNN classification computationaly unfeasible, it's probably a better direction to utilize something like a linear or polynomial SVM since it's likely to be a much more efficient classifier.

1.3.5 Classifier Training

```
In [271]: # setup SVM hyperparam search
          hyperparams = {'kernel':['linear', 'poly','rbf'],'C':expon(scale=10), 'gamma':expon(s
          rand_search = RandomizedSearchCV(SVC( ), hyperparams, n_jobs=-1)
```

```
In [272]: %%capture
          rand_search.fit(X_train,y_train)
```

1.3.6 Classifier Validation

```
In [273]: # rand_search.best_params_
          # rand_search.best_estimator_
          # rand_search.score(X_test, y_test)
          y_pred = rand_search.predict(X_test)
          print(classification_report(y_test,y_pred))
```

```
             precision    recall  f1-score   support
```

0	0.99	0.99	0.99	1771
1	0.99	0.99	0.99	1970
2	0.97	0.97	0.97	1812
3	0.96	0.97	0.97	1807
4	0.96	0.98	0.97	1749
5	0.97	0.96	0.96	1589
6	0.98	0.99	0.98	1804
7	0.97	0.97	0.97	1874
8	0.97	0.96	0.97	1786
9	0.97	0.96	0.97	1838
avg / total	0.97	0.97	0.97	18000