Assignment 6: Neural Networks
Claire Boetticher, MSDS 422, SEC 56
Kaggle ID: Claire Boetticher // Kaggle username: clairence
Google Colab link: https://colab.research.google.com/drive/1HEn3V7gPopvoxZSw9-39goeJnI2Os2MJ

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. The label distribution in the training and testing sets appears relatively balanced across zero to nine (Figures 1-2), which obviates the need for adjustment by up-sampling, down-sampling, or other methods. This benchmark study aims to compare and evaluate two neural network types (simple multilayer perceptrons and convolutional neural networks) with various architectures (shallow and deep) and optimizers (SGD and Adam) to determine their potential utility in multi-class classification problems on the MNIST dataset of hand-drawn digits and for future analogous Optical Character Recognition (OCR) efforts. The data is split into 55,000 training images, 10,000 testing images, and 5,000 validation images.

Study design

Keras, a high-level neural network library, is used for training in this study to take advantage of fast prototyping and ease of extensibility. The study examines the following neural network models using the MNIST dataset, assessing both processing time and performance across treatments. The benchmark study employs 2 MLPs and 2 CNNs, with network architecture defined as follows:

Type of Neural Net	Layers	Network Architecture	Trainable Parameters
Simple MLP 1	2	1 Dense, ReLU activation, 784 nodes 1 Dense, Softmax activation, 10 output nodes	623,390
Simple MLP 2	3	1 Dense, ReLU activation, 784 nodes 1 Dense, ReLU activation, 784 nodes 1 Dense, Softmax activation, 10 output nodes	1,238,730
CNN 3	5	1 Convolutional 2D, ReLU activation 1 Max Pooling, ReLU activation 1 Flatten layer to provide features to the classifier 1 Dense, ReLU activation, 100 nodes 1 Dense, Softmax activation, 10 output nodes	542,230
CNN 4	7	1 Convolutional 2D, ReLU activation 1 Batch Normalization 1 Max Pooling, ReLU activation 1 Flatten layer to provide features to the classifier 1 Dense, ReLU activation, 100 nodes 1 Batch Normalization 1 Dense, Softmax activation, 10 output nodes	542,494

Simple MLP 1 serves as a baseline model under the assumption of reasonable performance on this proscribed dataset. The simple MLP 2 model extends the baseline with the addition of 1 additional layer with the same number of nodes. A CNN model serves as a contrast to the MLP models, both with and without batch normalization to examine potential effects on processing time and performance. After various tuning efforts on the baseline model, the following hyperparameters are employed across all four study models:

- Learning rate: 0.01
- Activation: ReLU
- Optimizer: Adam (MLP models 1 and 2) and stochastic gradient descent (SGD) (CNN models 3 and 4)
- Batch size: 200
- Epochs: 10

Results

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

Type of Neural Net	Processing Time (in seconds)	Acc (Train)	Acc (Validation)	Acc (Test)	Kaggle Score (Test)
Simple MLP 1	58.21	1.00	0.984	0.9813	0.9957
Simple MLP 2	105.02	0.997	0.985	0.9816	0.9943
CNN 3	109.39	0.99	0.985	0.9819	0.9903
CNN 4	204.19	0.999	0.988	0.987	0.9963

Simple MLP model 1 performs best in terms of processing time, training accuracy, and score on unseen Kaggle data. The extended architecture of MLP model 2 only adds minor improvement by way of validation and test accuracy and takes almost twice as long to fit. For the more complex CNNs, model 3 only takes slightly longer than simple MLP model 2 and performs a bit better on the test set but worse on the Kaggle data. CNN model 4, with batch normalization, takes the longest amount of processing time but results in slightly better performance across training, validation, test, and Kaggle sets as compared to model 3, without batch normalization. Confusion matrices (Figures 4, 6, 8, 10) for each model reflect these performance levels and identify which digits prove challenging for individual models: models 1, 2, and 3 all exhibit minor confusion between 4s and 9s; models 1 and 3 also exhibit confusion between 2s and 7s (both understandable given the nature of handwriting and the general shape of these digits).

Findings and recommendation

For this study's classification task, the simple MLP model 1 performs well on training and validation, processes efficiently, and generalizes well on unseen data. For this dataset and comparable OCR problems with handwritten or typed digits, the simplicity of the MLP seems an appropriate baseline. For other OCR tasks, these 10 digits may not be representative of the range of challenges of punctuation, formulae, or other characters that may appear with the digits themselves for a financial institution. Additionally, tolerance for error may be high in financial transactions. For those scenarios, CNNs may be preferable given flexibility and extensibility. Model 4, though most time-consuming, seems to perform and generalize best of this study's models; if processing time were a higher priority, model 3 seems to perform adequately as a CNN and could be tuned for higher performance. The extensive flexibility of neural networks also means that options abound for alternatives to model training and evaluation for OCR tasks. Hyperparameter adjustments could be evaluated for faster processing time and increased performance, including the number of hidden layers, the number of nodes per layer (and whether these are consistent or varied), and the learning rate. Alternate optimizers beyond SGD and Adam and smaller batch sizes (this study utilized 200, but further tests could limit to 32) could be tested as well. Finally, in terms of performance, this study used CPUs but GPUs could potentially perform better. Ultimately, these four tests provide a usable suite of baseline models for more complex OCR problems depending on the data, error tolerance, and the criticality of performance versus processing time factors.

In [96]:
```
import keras
import tensorflow as tf

import os
import time
import numpy as np
import pandas as pd
from datetime import datetime

from keras.models import Sequential, load_model
from keras.layers import Conv2D, MaxPooling2D, Dense, Flatten, Dropout, Activation
from keras.optimizers import Adam, SGD
from keras.callbacks import TensorBoard
from keras.datasets import mnist
from keras.utils import np_utils
from keras.layers import BatchNormalization
from keras import backend as K
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix

import matplotlib.pyplot as plt
import seaborn as sns
%config InlineBackend.figure_format = 'svg'
```

In [ ]:
```
# from google.colab import drive
# drive.mount('/content/gdrive')
```

In [ ]:
```
# Saving in Colab
# os.getcwd()
# %cd /content/gdrive/My Drive/MSDS422_weeksix
# !pwd
# !ls
# print('Working Directory')
# # print(os.getcwd())
# work_dir = "/content/gdrive/My Drive/MSDS422_weeksix"
# chp_id = "ann"
```

In [ ]:
```
# # Saving models locally after fitting
# save_dir = "/results/"
# model_name = 'keras_mnist_model_1.h5'
# model_path = os.path.join(save_dir, model_name)
# model.save(model_path)
# print('Saved trained model at %s ' % model_path)
```

In [ ]:
```
# # Loading saved model
# mnist_model = load_model()
# scores = mnist_model.evaluate(X_test, Y_test, verbose=2)
```

Load data

In [114]:
```
# Load data
(X_train, y_train), (X_test, y_test) = mnist.load_data()

# Flatten 28*28 images to a 784 vector for each image
num_pixels = X_train.shape[1] * X_train.shape[2]
X_train = X_train.reshape((X_train.shape[0], num_pixels)).astype('float32')
X_test = X_test.reshape((X_test.shape[0], num_pixels)).astype('float32')

# Normalize inputs from 0-255 to 0-1
X_train = X_train / 255.0
X_test = X_test / 255.0
```

In [13]:
```
# Examine shape and data type
print(X_train.shape)
# (60000, 28, 28)
print(X_train.dtype)
# dtype('uint8')
```

```
(60000, 784)
float32
```

In [5]:
```
# Confirm that all 256 values between the min-max of 0-255 exist in the train set
len(np.unique(X_train))
```

Out[5]:
```
256
```

In [8]:
```
# Plot distribtion of test and train
def dist_plot(var1, var2, var3):
    plt.figure(figsize=(6, 4))
    tmp_plt=sns.countplot(var1, palette="muted").set_title(var2)
    tmp_fig = tmp_plt.get_figure()
    tmp_fig.savefig(var3 + ".png",
        bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
        orientation='portrait', papertype=None, format=None,
        transparent=True, pad_inches=0.25)
    return(tmp_plt)
```

Figure 1: Train Digit Distribution

In [253]:
```
mn_plt_trn=dist_plot(y_train, 'Train Digit Distribution', "TrainDistMNIST")
```

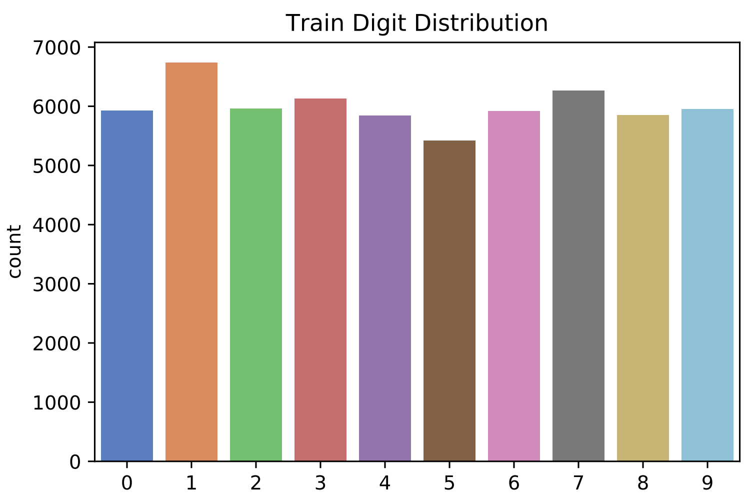
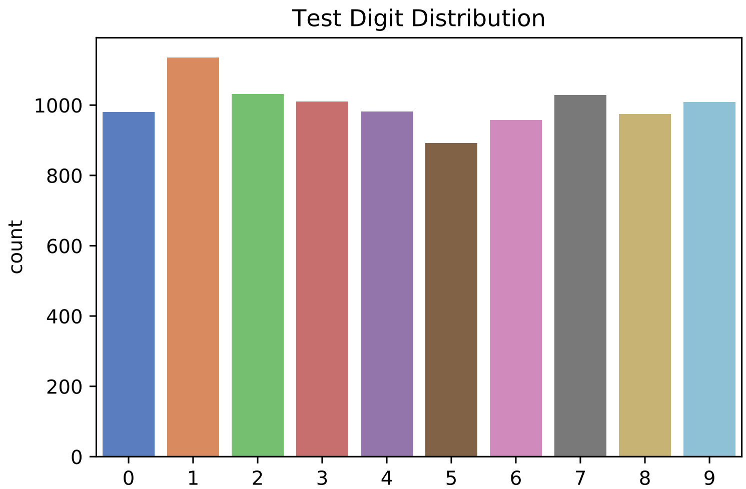


Figure 2: Test Digit Distribution

In [254]:
```
mn_plt_test=dist_plot(y_test, 'Test Digit Distribution', "TestDistMNIST")
```



In [115]:
```
# # One hot encode outputs
y_train = np_utils.to_categorical(y_train)
y_test = np_utils.to_categorical(y_test)
num_classes = y_test.shape[1]

# Validation data
X_valid, X_train = X_train[:5000], X_train[5000:]
y_valid, y_train = y_train[:5000], y_train[5000:]
```

Experiment design

Baseline: simple multilayer perceptron

- 2 layers, 784 neurons

Model 2 simple multi-layer perceptron

- 4 layers, 784 neurons

Model 3:

- Simple convolutional neural net

Model 4:

- Simple convolutional neural net with batch normalization

Network Architecture:

Model 1: baseline

Simple multi-layer perceptron

- 2 layers, 784 neurons

In [117]:
```
Define baseline model
def baseline_model():
    # create model
    model = Sequential()
    model.add(Dense(num_pixels, input_dim=num_pixels, kernel_initializer='normal', activation='relu
'))
    model.add(Dense(10, kernel_initializer='normal', activation='softmax'))
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

# Fit the model
model = baseline_model()
model = load_model('results/keras_mnist_model_1.h5')
start_time = time.time()
history = model.fit(X_train, y_train, validation_data=(X_valid, y_valid), epochs=10, batch_size=200,
verbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# # Saving models locally after fitting
# save_dir = "results/"
# model_name = 'keras_mnist_model_1.h5'
# model_path = os.path.join(save_dir, model_name)
# model.save(model_path)
# print('Saved trained model at %s ' % model_path)
# print('--------------------------')

# # Final evaluation of the model
# Loading saved model
# mnist_model = load_model('results/keras_mnist_model_1.h5')
# scores = mnist_model.evaluate(X_test, y_test, verbose=0)

# # Load current model
# scores = model.evaluate(X_test, y_test, verbose=0)

print('Testing scores:')
print("Baseline Error: %.2f%%" % (100-scores[1]*100))
print("Accuracy score: %.4f%%" % scores[1])
print("Loss: %.4f%%" % scores[0])
```

```
Train on 55000 samples, validate on 5000 samples
Epoch 1/10
 - 7s - loss: 0.0064 - acc: 0.9991 - val_loss: 0.0568 - val_acc: 0.9832
Epoch 2/10
 - 6s - loss: 0.0042 - acc: 0.9996 - val_loss: 0.0565 - val_acc: 0.9844
Epoch 3/10
 - 6s - loss: 0.0032 - acc: 0.9997 - val_loss: 0.0608 - val_acc: 0.9834
Epoch 4/10
 - 6s - loss: 0.0030 - acc: 0.9997 - val_loss: 0.0609 - val_acc: 0.9856
Epoch 5/10
 - 6s - loss: 0.0065 - acc: 0.9985 - val_loss: 0.0696 - val_acc: 0.9830
Epoch 6/10
 - 6s - loss: 0.0088 - acc: 0.9975 - val_loss: 0.0749 - val_acc: 0.9822
Epoch 7/10
 - 6s - loss: 0.0060 - acc: 0.9984 - val_loss: 0.0681 - val_acc: 0.9838
Epoch 8/10
 - 6s - loss: 0.0016 - acc: 0.9998 - val_loss: 0.0631 - val_acc: 0.9844
Epoch 9/10
 - 6s - loss: 6.7766e-04 - acc: 1.0000 - val_loss: 0.0630 - val_acc: 0.9858
Epoch 10/10
 - 6s - loss: 4.7501e-04 - acc: 1.0000 - val_loss: 0.0652 - val_acc: 0.9842
--------------------------
Training time in seconds:  58.21
--------------------------
Testing scores:
Baseline Error: 1.87%
Accuracy score: 0.9813%
Loss: 0.0633%
```

In [130]:
```
# Model architecture
model = baseline_model()
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_22 (Dense)             (None, 784)               615440
_________________________________________________________________
dense_23 (Dense)             (None, 10)                7850
=================================================================
Total params: 623,290
Trainable params: 623,290
Non-trainable params: 0
_________________________________________________________________
```

Figure 3: Learning Curves - Model 1

In [17]:
```
# Plot learning curves for baseline model
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```

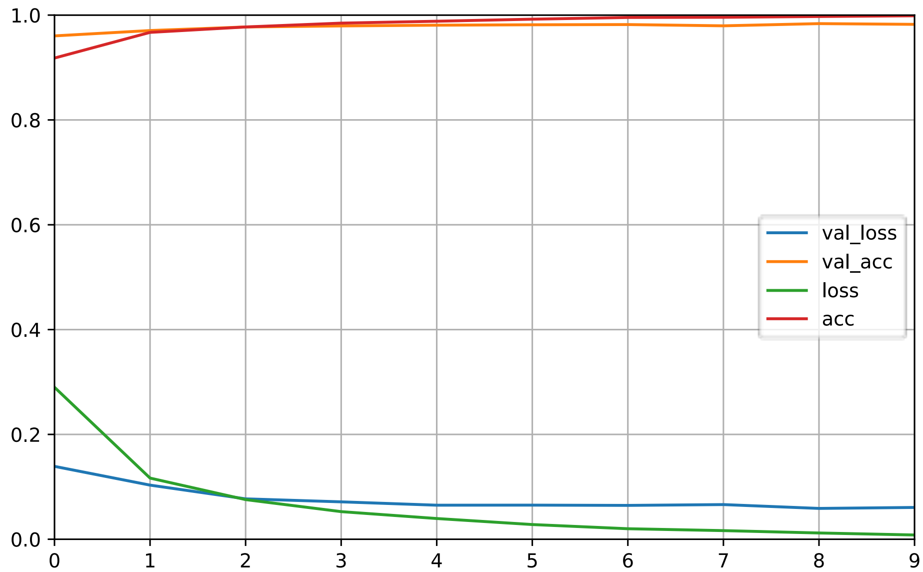


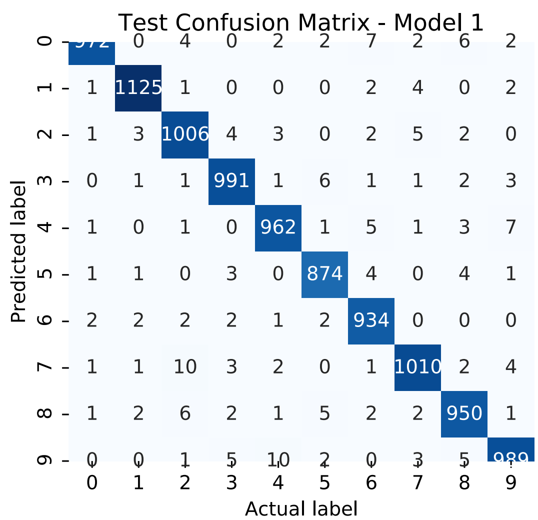
Figure 4: Confusion Matrix - Model 1

In [82]:
```
# Confusion matrix

# Reverse one hot encoding for y_test
y_test_rev = np.argmax(y_test, axis=1, out=None)

# Predictions
y_pred = model.predict_classes(X_test)

#  Plot
m1_tst = confusion_matrix(y_test_rev, y_pred)
m1_tst_plt=sns.heatmap(m1_tst.T, square=True, annot=True, fmt='d', cbar=False, cmap="Blues")
plt.xlabel('Actual label')
plt.ylabel('Predicted label')
plt.title("Test Confusion Matrix - Model 1");
```



In [97]:
```
# Model prediction on Kaggle test data
X_kaggle = pd.read_csv("test.csv")

# predictions = model.predict_classes(X_kaggle, verbose=0)

# Using saved model
mnist_model = load_model('results/keras_mnist_model_1.h5')
predictions = mnist_model.predict_classes(X_kaggle, verbose=0)

# Submission
submissions = pd.DataFrame({"ImageId": list(range(1,len(predictions)+1)),
    "Label": predictions})

submissions.to_csv("MLP1_CB.csv", index=False, header=True)
```

Kaggle submission for Model 1 Kaggle ID: Claire Boetticher
Kaggle username: clairence

Model 2 training and evaluation

In [118]:
```
# Model 2
def model_2():
    # create model
    model = Sequential()
    model.add(Dense(num_pixels, input_dim=num_pixels, kernel_initializer='normal', activation='relu
'))
    model.add(Dense(num_pixels, input_dim=num_pixels, kernel_initializer='normal', activation='relu
'))
    model.add(Dense(num_classes, kernel_initializer='normal', activation='softmax'))
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

# Fit the model
model = model_2()
# model = load_model('results/keras_mnist_model_2.h5')
start_time = time.time()
history = model.fit(X_train, y_train, validation_data=(X_valid, y_valid), epochs=10, batch_size=200,
verbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# # Saving models locally after fitting
# save_dir = "results/"
# model_name = 'keras_mnist_model_2.h5'
# model_path = os.path.join(save_dir, model_name)
# model.save(model_path)
# print('Saved trained model at %s ' % model_path)
# print('--------------------------')

# # Final evaluation of the model
# # Loading saved model
mnist_model = load_model('results/keras_mnist_model_2.h5')
scores = mnist_model.evaluate(X_test, y_test, verbose=0)

# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
print("Baseline Error: %.2f%%" % (100-scores[1]*100))
print("Accuracy score: %.4f%%" % scores[1])
print("Loss: %.4f%%" % scores[0])
```

```
Train on 55000 samples, validate on 5000 samples
Epoch 1/10
 - 12s - loss: 0.0099 - acc: 0.9966 - val_loss: 0.0821 - val_acc: 0.9818
Epoch 2/10
 - 11s - loss: 0.0114 - acc: 0.9966 - val_loss: 0.0779 - val_acc: 0.9852
Epoch 3/10
 - 10s - loss: 0.0110 - acc: 0.9964 - val_loss: 0.0813 - val_acc: 0.9850
Epoch 4/10
 - 10s - loss: 0.0092 - acc: 0.9970 - val_loss: 0.0887 - val_acc: 0.9826
Epoch 5/10
 - 11s - loss: 0.0074 - acc: 0.9973 - val_loss: 0.0923 - val_acc: 0.9830
Epoch 6/10
 - 10s - loss: 0.0122 - acc: 0.9962 - val_loss: 0.1052 - val_acc: 0.9794
Epoch 7/10
 - 10s - loss: 0.0055 - acc: 0.9983 - val_loss: 0.0891 - val_acc: 0.9838
Epoch 8/10
 - 10s - loss: 0.0049 - acc: 0.9984 - val_loss: 0.0905 - val_acc: 0.9822
Epoch 9/10
 - 10s - loss: 0.0105 - acc: 0.9970 - val_loss: 0.1017 - val_acc: 0.9844
Epoch 10/10
 - 11s - loss: 0.0095 - acc: 0.9971 - val_loss: 0.0872 - val_acc: 0.9846
--------------------------
Training time in seconds:  105.02
--------------------------
Testing scores:
Baseline Error: 1.84%
Accuracy score: 0.9816%
Loss: 0.0848%
```

In [131]:
```
# Model architecture
model = model_2()
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_24 (Dense)             (None, 784)               615440
_________________________________________________________________
dense_25 (Dense)             (None, 784)               615440
_________________________________________________________________
dense_26 (Dense)             (None, 10)                7850
=================================================================
Total params: 1,238,730
Trainable params: 1,238,730
Non-trainable params: 0
_________________________________________________________________
```

Figure 5: Learning Curves - Model 2

In [84]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```

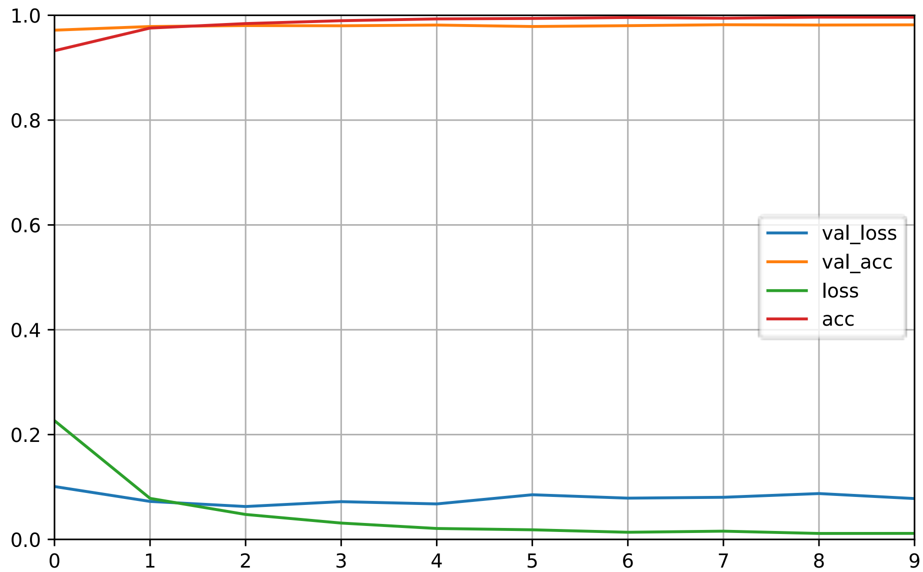


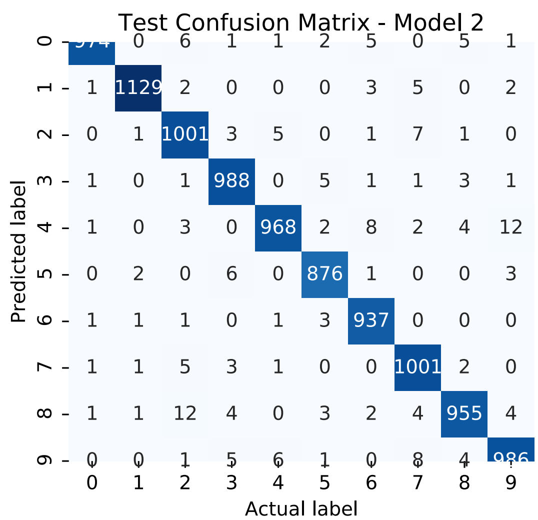
Figure 6: Confusion Matrix - Model 2

In [85]:
```
# Confusion matrix

# Reverse one hot encoding for y_test
# y_test_rev = np.argmax(y_test, axis=1, out=None)

# Predictions
y_pred = model.predict_classes(X_test)

#  Plot
m1_tst = confusion_matrix(y_test_rev, y_pred)
m1_tst_plt=sns.heatmap(m1_tst.T, square=True, annot=True, fmt='d', cbar=False, cmap="Blues")
plt.xlabel('Actual label')
plt.ylabel('Predicted label')
plt.title("Test Confusion Matrix - Model 2");
```



In [98]:
```
# Model prediction on Kaggle test data
X_kaggle = pd.read_csv("test.csv")

# Current model
# predictions = model.predict_classes(X_kaggle, verbose=0)

# Using saved model
mnist_model = load_model('results/keras_mnist_model_2.h5')
predictions = mnist_model.predict_classes(X_kaggle, verbose=0)

# Submission
submissions = pd.DataFrame({"ImageId": list(range(1,len(predictions)+1)),
    "Label": predictions})

submissions.to_csv("MLP2_CB.csv", index=False, header=True)
```

Kaggle submission for Model 2 Kaggle ID: Claire Boetticher
Kaggle username: clairence

Model 3: simple CNN training and evaluation

In [100]:

```
# Data prep for CNN
(X_train, y_train), (X_test, y_test) = mnist.load_data()

# Reshape dataset to have a single channel
X_train = X_train.reshape((X_train.shape[0], 28, 28, 1))
X_train = X_train.astype('float32') / 255.0
X_test = X_test.reshape((X_test.shape[0], 28, 28, 1))
X_test = X_test.astype('float32') / 255.0

# One hot encode outputs
y_train = np_utils.to_categorical(y_train)
y_test = np_utils.to_categorical(y_test)
num_classes = y_test.shape[1]

# Validation data
X_valid, X_train = X_train[:5000], X_train[5000:]
y_valid, y_train = y_train[:5000], y_train[5000:]
```

In [101]:
```
def model_3():
    model = Sequential()
    model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', input_shape=(28,
28, 1)))
    model.add(MaxPooling2D((2, 2)))
    model.add(Flatten())
    model.add(Dense(100, activation='relu', kernel_initializer='he_uniform'))
    model.add(Dense(10, activation='softmax'))
    # compile model
    opt = SGD(lr=0.01, momentum=0.9)
    model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])
    return model

# Fit the model
model = model_3()
start_time = time.time()
history = model.fit(X_train, y_train, validation_data=(X_valid, y_valid), epochs=10, batch_size=200,
verbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Saving models locally after fitting
save_dir = "results/"
model_name = 'keras_mnist_model_3.h5'
model_path = os.path.join(save_dir, model_name)
model.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')

# # Final evaluation of the model
# # Loading saved model
# mnist_model = load_model('results/keras_mnist_model_2.h5')
# scores = mnist_model.evaluate(X_test, Y_test, verbose=0)

# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
print("Baseline Error: %.2f%%" % (100-scores[1]*100))
print("Accuracy score: %.4f%%" % scores[1])
print("Loss: %.4f%%" % scores[0])
```

```
Train on 55000 samples, validate on 5000 samples
Epoch 1/10
 - 12s - loss: 0.3221 - acc: 0.9024 - val_loss: 0.1537 - val_acc: 0.9554
Epoch 2/10
 - 10s - loss: 0.1492 - acc: 0.9561 - val_loss: 0.1193 - val_acc: 0.9638
Epoch 3/10
 - 10s - loss: 0.1089 - acc: 0.9683 - val_loss: 0.0931 - val_acc: 0.9756
Epoch 4/10
 - 11s - loss: 0.0842 - acc: 0.9759 - val_loss: 0.0803 - val_acc: 0.9772
Epoch 5/10
 - 10s - loss: 0.0724 - acc: 0.9786 - val_loss: 0.0693 - val_acc: 0.9800
Epoch 6/10
 - 11s - loss: 0.0604 - acc: 0.9826 - val_loss: 0.0673 - val_acc: 0.9816
Epoch 7/10
 - 12s - loss: 0.0524 - acc: 0.9840 - val_loss: 0.0614 - val_acc: 0.9826
Epoch 8/10
 - 11s - loss: 0.0458 - acc: 0.9869 - val_loss: 0.0567 - val_acc: 0.9836
Epoch 9/10
 - 11s - loss: 0.0401 - acc: 0.9885 - val_loss: 0.0563 - val_acc: 0.9836
Epoch 10/10
 - 11s - loss: 0.0356 - acc: 0.9898 - val_loss: 0.0549 - val_acc: 0.9854
--------------------------
Training time in seconds:  109.39
--------------------------
Saved trained model at results/keras_mnist_model_3.h5
--------------------------
Testing scores:
Baseline Error: 1.81%
Accuracy score: 0.9819%
Loss: 0.0545%
```

In [132]:
```
# Model architecture
model = model_3()
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_5 (Conv2D)            (None, 26, 26, 32)        320       
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 13, 13, 32)        0         
_________________________________________________________________
flatten_5 (Flatten)          (None, 5408)              0         
_________________________________________________________________
dense_27 (Dense)             (None, 100)               540900    
_________________________________________________________________
dense_28 (Dense)             (None, 10)                1010      
=================================================================
Total params: 542,230
Trainable params: 542,230
Non-trainable params: 0
_________________________________________________________________
```

Figure 7: Learning Curves - Model 3

In [88]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```

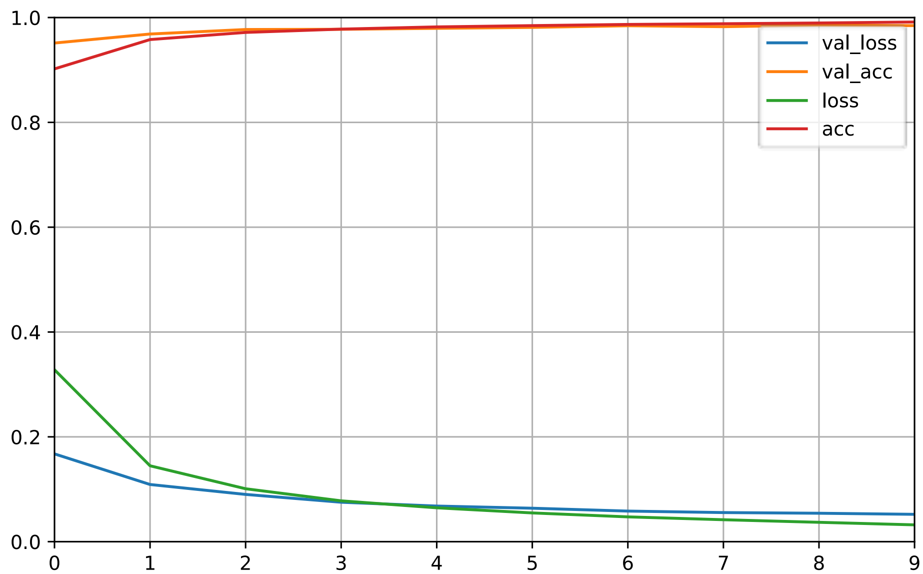


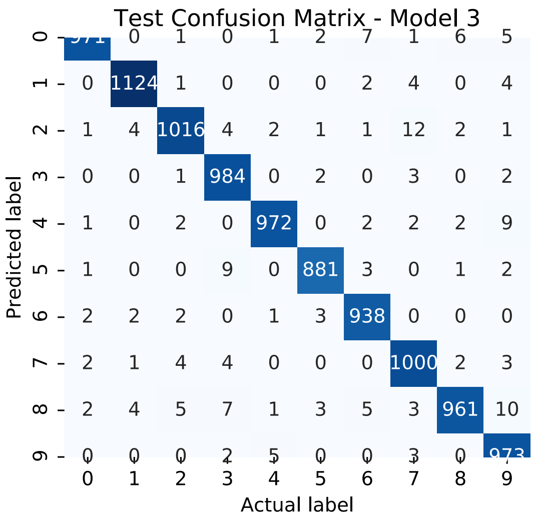
Figure 8: Confusion Matrix - Model 3

In [89]:
```python
# Confusion matrix

# Reverse one hot encoding for y_test
# y_test_rev = np.argmax(y_test, axis=1, out=None)

# Predictions
y_pred = model.predict_classes(X_test)

#  Plot
m1_tst = confusion_matrix(y_test_rev, y_pred)
m1_tst_plt=sns.heatmap(m1_tst.T, square=True, annot=True, fmt='d', cbar=False, cmap="Blues")
plt.xlabel('Actual label')
plt.ylabel('Predicted label')
plt.title("Test Confusion Matrix - Model 3");
```



In [111]:
```python
# Model prediction on Kaggle test data
df_kaggle = pd.read_csv("test.csv").as_matrix()

print('Dimensions of the dataframe', df_kaggle.shape)

# Reshape to be samples pixels width, height
X_kaggle = df_kaggle.reshape(df_kaggle.shape[0], 28, 28, 1).astype('float32')

# Normalize_inputs
X_kaggle = X_kaggle/255.0

# Predict and create DataFrame
prediction = pd.DataFrame()
imageid = []
for i in range(len(X_kaggle)):
    i = i + 1
    imageid.append(i)
prediction["ImageId"] = imageid
prediction["Label"] = model.predict_classes(X_kaggle, verbose=0)

# Output to csv
prediction.to_csv("CNN3_CB.csv", index=False)
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: FutureWarning: Method .as_matrix wil
l be removed in a future version. Use .values instead.


Dimensions of the dataframe (28000, 784)
   ImageId  Label
0        1      2
1        2      0
```

Kaggle submission for Model 3 Kaggle ID: Claire Boetticher
Kaggle username: clairence

In [ ]:
```
# # Model prediction on Kaggle test data
# X_kaggle = pd.read_csv("test.csv")

# X_test = x_test.reshape(x_test.shape[0], 28, 28,1)

# X_kaggle = X_kaggle.reshape((X_test.shape[0], 28, 28, 1))
# # X_kaggle = X_kaggle.astype('float32') / 255.0

# # # Current model
# predictions = model.predict_classes(X_kaggle, verbose=0)

# # # Using saved model
# # # mnist_model = load_model('results/keras_mnist_model_3.h5')
# # # predictions = mnist_model.predict_classes(X_kaggle, verbose=0)

# # # Submission
# submissions = pd.DataFrame({"ImageId": list(range(1,len(predictions)+1)),
#     "Label": predictions})

# submissions.to_csv("CNN3_CB.csv", index=False, header=True)
```

Model 4: simple CNN with batch normalization training and evaluation

In [112]:
```
def model_4():
    model = Sequential()
    model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', input_shape=(28,
28, 1)))
    model.add(BatchNormalization())
    model.add(MaxPooling2D((2, 2)))
    model.add(Flatten())
    model.add(Dense(100, activation='relu', kernel_initializer='he_uniform'))
    model.add(BatchNormalization())
    model.add(Dense(10, activation='softmax'))
    # compile model
    opt = SGD(lr=0.01, momentum=0.9)
    model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])
    return model

# Fit the model
model = model_4()
start_time = time.time()
history = model.fit(X_train, y_train, validation_data=(X_valid, y_valid), epochs=10, batch_size=200,
verbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Saving models locally after fitting
save_dir = "results/"
model_name = 'keras_mnist_model_4.h5'
model_path = os.path.join(save_dir, model_name)
model.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')

# # Final evaluation of the model
# # Loading saved model
# mnist_model = load_model('results/keras_mnist_model_4.h5')
# scores = mnist_model.evaluate(X_test, Y_test, verbose=0)

# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
print("Baseline Error: %.2f%%" % (100-scores[1]*100))
print("Accuracy score: %.4f%%" % scores[1])
print("Loss: %.4f%%" % scores[0])
```

```
Train on 55000 samples, validate on 5000 samples
Epoch 1/10
 - 27s - loss: 0.1823 - acc: 0.9464 - val_loss: 0.0842 - val_acc: 0.9762
Epoch 2/10
 - 20s - loss: 0.0622 - acc: 0.9833 - val_loss: 0.0652 - val_acc: 0.9802
Epoch 3/10
 - 21s - loss: 0.0401 - acc: 0.9899 - val_loss: 0.0538 - val_acc: 0.9846
Epoch 4/10
 - 19s - loss: 0.0279 - acc: 0.9934 - val_loss: 0.0476 - val_acc: 0.9852
Epoch 5/10
 - 19s - loss: 0.0197 - acc: 0.9962 - val_loss: 0.0465 - val_acc: 0.9870
Epoch 6/10
 - 19s - loss: 0.0141 - acc: 0.9979 - val_loss: 0.0450 - val_acc: 0.9868
Epoch 7/10
 - 20s - loss: 0.0104 - acc: 0.9987 - val_loss: 0.0428 - val_acc: 0.9888
Epoch 8/10
 - 20s - loss: 0.0078 - acc: 0.9995 - val_loss: 0.0409 - val_acc: 0.9878
Epoch 9/10
 - 19s - loss: 0.0062 - acc: 0.9996 - val_loss: 0.0414 - val_acc: 0.9884
Epoch 10/10
 - 19s - loss: 0.0049 - acc: 0.9999 - val_loss: 0.0413 - val_acc: 0.9882
--------------------------
Training time in seconds:  204.19
--------------------------
Saved trained model at results/keras_mnist_model_4.h5
--------------------------
Testing scores:
Baseline Error: 1.31%
Accuracy score: 0.9869%
Loss: 0.0385%
```

In [133]:
```
# Model architecture
model = model_4()
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_6 (Conv2D)            (None, 26, 26, 32)        320       
_________________________________________________________________
batch_normalization_5 (Batch (None, 26, 26, 32)        128       
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 13, 13, 32)        0         
_________________________________________________________________
flatten_6 (Flatten)          (None, 5408)              0         
_________________________________________________________________
dense_29 (Dense)             (None, 100)               540900    
_________________________________________________________________
batch_normalization_6 (Batch (None, 100)               400       
_________________________________________________________________
dense_30 (Dense)             (None, 10)                1010      
=================================================================
Total params: 542,758
Trainable params: 542,494
Non-trainable params: 264
_________________________________________________________________
```

Figure 9: Learning Curves - Model 4

In [93]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```

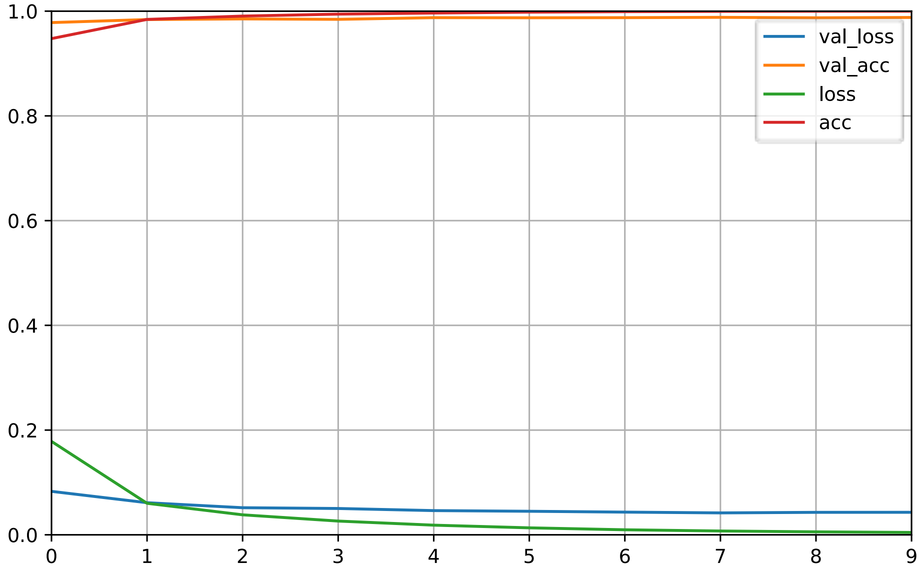


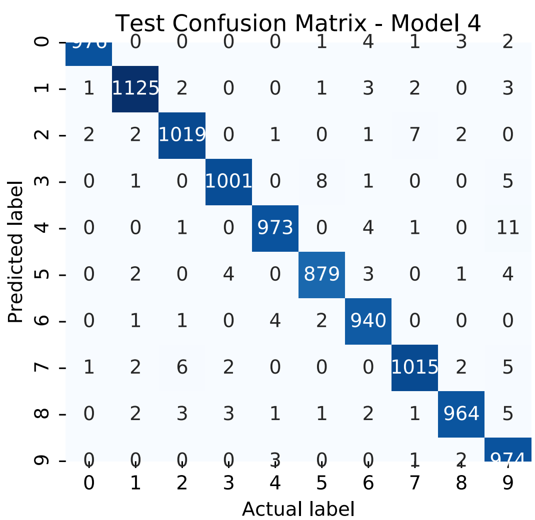
Figure 10: Confusion Matrix - Model 4

In [94]:
```
# Confusion matrix

# Reverse one hot encoding for y_test
# y_test_rev = np.argmax(y_test, axis=1, out=None)

# Predictions
y_pred = model.predict_classes(X_test)

#  Plot
m1_tst = confusion_matrix(y_test_rev, y_pred)
m1_tst_plt=sns.heatmap(m1_tst.T, square=True, annot=True, fmt='d', cbar=False, cmap="Blues")
plt.xlabel('Actual label')
plt.ylabel('Predicted label')
plt.title("Test Confusion Matrix - Model 4");
```



In [113]:
```
# Model prediction on Kaggle test data
df_kaggle = pd.read_csv("test.csv").as_matrix()

print('Dimensions of the dataframe', df_kaggle.shape)

# Reshape to be samples pixels width, height
X_kaggle = df_kaggle.reshape(df_kaggle.shape[0], 28, 28, 1).astype('float32')

# Normalize_inputs
X_kaggle = X_kaggle/255.0

# Predict and create DataFrame
prediction = pd.DataFrame()
imageid = []
for i in range(len(X_kaggle)):
    i = i + 1
    imageid.append(i)
prediction["ImageId"] = imageid
prediction["Label"] = model.predict_classes(X_kaggle, verbose=0)

# Output to csv
prediction.to_csv("CNN4_CB.csv", index=False)
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: FutureWarning: Method .as_matrix wil
l be removed in a future version. Use .values instead.


Dimensions of the dataframe (28000, 784)
```

Kaggle submission for Model 4 Kaggle ID: Claire Boetticher
Kaggle username: clairence

In [ ]: