# Capstone Project

October 6, 2020

# 1 Capstone Project

## 1.1 Image classifier for the SVHN dataset

### 1.1.1 Instructions

In this notebook, you will create a neural network that classifies real-world images digits. You will use concepts from throughout this course in building, training, testing, validating and saving your Tensorflow classifier model.

This project is peer-assessed. Within this notebook you will find instructions in each section for how to complete the project. Pay close attention to the instructions as the peer review will be carried out according to a grading rubric that checks key parts of the project instructions. Feel free to add extra cells into the notebook as required.

### 1.1.2 How to submit

When you have completed the Capstone project notebook, you will submit a pdf of the notebook for peer review. First ensure that the notebook has been fully executed from beginning to end, and all of the cell outputs are visible. This is important, as the grading rubric depends on the reviewer being able to view the outputs of your notebook. Save the notebook as a pdf (File -> Download as -> PDF via LaTeX). You should then submit this pdf for review.

### 1.1.3 Let's get started!

We'll start by running some imports, and loading the dataset. For this project you are free to make further imports throughout the notebook as you wish.

```
In [1]: import math
        import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        from matplotlib import gridspec
        from scipy.io import loadmat

        # Tensorflow and Keras imports
        import tensorflow as tf
        from tensorflow.keras.models import load_model
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, LeakyReLU
from tensorflow.keras.layers import BatchNormalization, Dropout
from tensorflow.keras.layers import Conv2D, MaxPooling2D

from tensorflow.keras import regularizers
from tensorflow.keras.callbacks import LearningRateScheduler
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import ModelCheckpoint

from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.metrics import confusion_matrix
```

For the capstone project, you will use the SVHN dataset. This is an image dataset of over 600,000 digit images in all, and is a harder dataset than MNIST as the numbers appear in the context of natural scene images. SVHN is obtained from house numbers in Google Street View images.

- Y. Netzer, T. Wang, A. Coates, A. Bissacco, B. Wu and A. Y. Ng. "Reading Digits in Natural Images with Unsupervised Feature Learning". NIPS Workshop on Deep Learning and Unsupervised Feature Learning, 2011.

Your goal is to develop an end-to-end workflow for building, training, validating, evaluating and saving a neural network that classifies a real-world image into one of ten classes.

```
In [2]: # Run this cell to load the dataset

        train = loadmat('data/train_32x32.mat')
        test = loadmat('data/test_32x32.mat')
```

Both `train` and `test` are dictionaries with keys `X` and `y` for the input images and labels respectively.

## 1.2 1. Inspect and preprocess the dataset

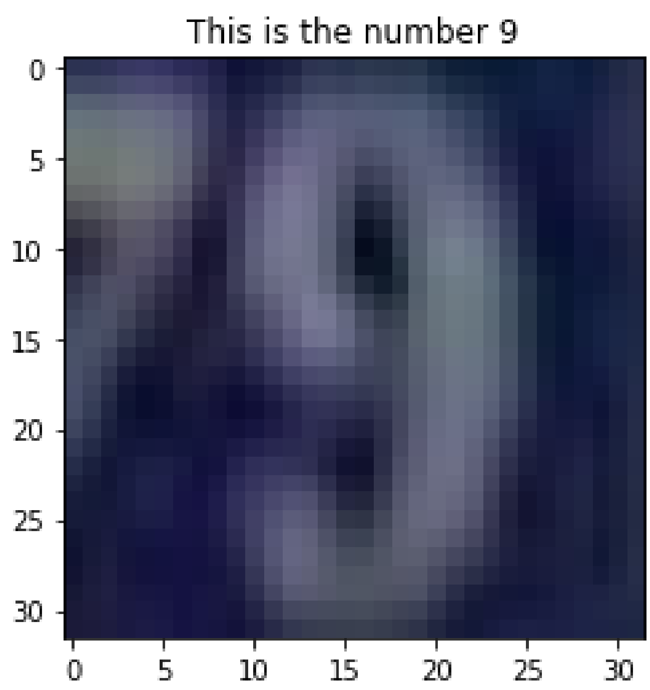
- Extract the training and testing images and labels separately from the train and test dictionaries loaded for you.
- Select a random sample of images and corresponding labels from the dataset (at least 10), and display them in a figure.
- Convert the training and test images to grayscale by taking the average across all colour channels for each pixel. *Hint: retain the channel dimension, which will now have size 1.*
- Select a random sample of the grayscale images and corresponding labels from the dataset (at least 10), and display them in a figure.

In [3]:
```
X_train, X_test = train['X'], test['X']
y_train, y_test = train['y'], test['y']

new_order = [3,0,1,2]
X_train = X_train.transpose(new_order)
X_test = X_test.transpose(new_order)
```

In [4]:
```
def rectify_labels(old_labels):
    corrected_labels = np.where(old_labels == 10, 0, old_labels) # replace 10 by 0
    return corrected_labels
```

In [5]:
```
y_train = rectify_labels(y_train)
y_test = rectify_labels(y_test)
```

In [6]:
```
plt.imshow(X_train[35,:,:,:])
img_id = 'This is the number ' + str(y_train[35][0])
plt.title(img_id)
plt.show()
```



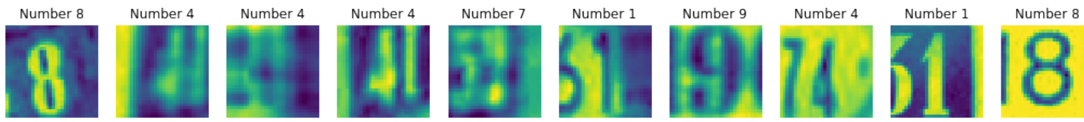
```
In [7]: def show_images(X_data, y_data, num_figs):
            num_examples = X_data.shape[0]
            sample = np.random.choice(range(num_examples), size=num_figs)

            n_rows = int(math.ceil(num_figs / 10))
            gs = gridspec.GridSpec(n_rows, 10)
            fig = plt.figure(figsize=(18,4))

            for i,j in enumerate(sample):
                if X_data.shape[-1] == 3:
                    image = X_data[j,:,:,:]
                elif X_data.shape[-1] == 1:
                    image = X_data[j,:,:,0]
                else:
                    raise ValueError('Wrong dimension of the input data...')
                img_label = 'Number ' + str(y_data[j][0])
                ax = fig.add_subplot(gs[i])
                ax.set_axis_off()
                ax.imshow(image)
                ax.set_title(img_label)

            plt.show()
```

```
In [8]: show_images(X_train, y_train, 15)
```


```
In [9]: def average_colors(data):
            data_grayscale = np.average(data, axis = -1)[...,np.newaxis]
            return data_grayscale
```

```
In [10]: X_train = average_colors(X_train)
         X_test = average_colors(X_test)
```

```
In [11]: show_images(X_train, y_train, 10)
```




```
In [12]: X_train = X_train / 255.0
         X_test = X_test / 255.0
```

### 1.3 2. MLP neural network classifier

- Build an MLP classifier model using the Sequential API. Your model should use only Flatten and Dense layers, with the final layer having a 10-way softmax output.
- You should design and build the model yourself. Feel free to experiment with different MLP architectures. *Hint: to achieve a reasonable accuracy you won't need to use more than 4 or 5 layers.*
- Print out the model summary (using the summary() method)
- Compile and train the model (we recommend a maximum of 30 epochs), making use of both training and validation sets during the training run.
- Your model should track at least one appropriate metric, and use at least two callbacks during training, one of which should be a ModelCheckpoint callback.
- As a guide, you should aim to achieve a final categorical cross entropy training loss of less than 1.0 (the validation loss might be higher).
- Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets.
- Compute and display the loss and accuracy of the trained model on the test set.

```
In [13]: def leaky_relu(x):
             return tf.nn.leaky_relu(x, alpha=0.15)

         def get_model(neurons_per_layers, wd, train_data):
             model = Sequential()
             for i, n_neurons in enumerate(neurons_per_layers):
                 if i == 0:
                     model.add(Flatten(input_shape=train_data.shape[1:]))
                     model.add(Dense(n_neurons, kernel_regularizer=regularizers.l2(wd),
                                     activation=leaky_relu))
                 else:
                     model.add(Dense(n_neurons, kernel_regularizer=regularizers.l2(wd),
                                     activation=leaky_relu))

             model.add(Dense(10, activation='softmax', name="out_layer"))
             return model
```

```
In [14]: nn_arch = [100, 50]
         weight_decay = 1e-6
         model = get_model(nn_arch, weight_decay, X_train)
         model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense (Dense)                (None, 100)               102500
_________________________________________________________________
dense_1 (Dense)              (None, 50)                5050
_________________________________________________________________
out_layer (Dense)            (None, 10)                510
=================================================================
Total params: 108,060
Trainable params: 108,060
Non-trainable params: 0
_________________________________________________________________
```

```
In [15]: opt = tf.keras.optimizers.Adam(learning_rate=0.01)
         loss = tf.keras.losses.SparseCategoricalCrossentropy()

         model.compile(optimizer = opt, loss = loss, metrics = ['accuracy'])
```

```
In [16]: def lr_decay(epoch, lr):
             if epoch <= 3:
                 return lr
             else:
                 lr = lr * np.exp(-1.5/epoch)
                 return lr

         # learning schedule callback
         lrate = LearningRateScheduler(lr_decay, verbose=1)
         earlystop = EarlyStopping(patience=3)
         mlp_checkpoint_best = 'nn_checkpoints_best/checkpoint'
         checkpoint_best = ModelCheckpoint(filepath=mlp_checkpoint_best, save_freq='epoch',
                                           save_weights_only=False, monitor='val_accuracy',
                                           save_best_only=True, verbose=1)

         my_callbacks = [lrate, earlystop, checkpoint_best]
```

```
In [17]: history = model.fit(X_train, y_train, epochs = 30, validation_split=0.15,
                             batch_size = 100, callbacks=my_callbacks, verbose = 1)
```

```
Train on 62268 samples, validate on 10989 samples

Epoch 00001: LearningRateScheduler reducing learning rate to 0.009999999776482582.
Epoch 1/30
61900/62268 [============================>.] - ETA: 0s - loss: 2.3114 - accuracy: 0.1861
Epoch 00001: val_accuracy improved from -inf to 0.21704, saving model to nn_checkpoints_best/cl
```

```
WARNING:tensorflow:From /opt/conda/lib/python3.7/site-packages/tensorflow_core/python/ops/resou
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 19s 312us/sample - loss: 2.3108 - accuracy: 0.18

Epoch 00002: LearningRateScheduler reducing learning rate to 0.009999999776482582.
Epoch 2/30
62200/62268 [============================>.] - ETA: 0s - loss: 1.9402 - accuracy: 0.3119 ETA: 1
Epoch 00002: val_accuracy improved from 0.21704 to 0.43116, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 270us/sample - loss: 1.9400 - accuracy: 0.31

Epoch 00003: LearningRateScheduler reducing learning rate to 0.009999999776482582.
Epoch 3/30
62000/62268 [============================>.] - ETA: 0s - loss: 1.4946 - accuracy: 0.5008
Epoch 00003: val_accuracy improved from 0.43116 to 0.56183, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 275us/sample - loss: 1.4935 - accuracy: 0.50

Epoch 00004: LearningRateScheduler reducing learning rate to 0.009999999776482582.
Epoch 4/30
62000/62268 [============================>.] - ETA: 0s - loss: 1.3262 - accuracy: 0.5732
Epoch 00004: val_accuracy improved from 0.56183 to 0.59077, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 279us/sample - loss: 1.3263 - accuracy: 0.57

Epoch 00005: LearningRateScheduler reducing learning rate to 0.006872892634288598.
Epoch 5/30
62200/62268 [============================>.] - ETA: 0s - loss: 1.1849 - accuracy: 0.6300
Epoch 00005: val_accuracy improved from 0.59077 to 0.63008, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 276us/sample - loss: 1.1848 - accuracy: 0.63

Epoch 00006: LearningRateScheduler reducing learning rate to 0.005091564248681657.
Epoch 6/30
62000/62268 [============================>.] - ETA: 0s - loss: 1.0912 - accuracy: 0.6665
Epoch 00006: val_accuracy improved from 0.63008 to 0.65283, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 279us/sample - loss: 1.0907 - accuracy: 0.66

Epoch 00007: LearningRateScheduler reducing learning rate to 0.003965314235977213.
Epoch 7/30
62100/62268 [============================>.] - ETA: 0s - loss: 1.0200 - accuracy: 0.6938
Epoch 00007: val_accuracy improved from 0.65283 to 0.68405, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 274us/sample - loss: 1.0200 - accuracy: 0.69
```

```
Epoch 00008: LearningRateScheduler reducing learning rate to 0.0032004753115511507.
Epoch 8/30
61900/62268 [============================>.] - ETA: 0s - loss: 0.9602 - accuracy: 0.7107
Epoch 00008: val_accuracy improved from 0.68405 to 0.70962, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 277us/sample - loss: 0.9599 - accuracy: 0.7

Epoch 00009: LearningRateScheduler reducing learning rate to 0.002653287264908044.
Epoch 9/30
62100/62268 [============================>.] - ETA: 0s - loss: 0.9099 - accuracy: 0.7285
Epoch 00009: val_accuracy improved from 0.70962 to 0.71763, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 273us/sample - loss: 0.9098 - accuracy: 0.7

Epoch 00010: LearningRateScheduler reducing learning rate to 0.0022459591747814355.
Epoch 10/30
62100/62268 [============================>.] - ETA: 0s - loss: 0.8721 - accuracy: 0.7419
Epoch 00010: val_accuracy improved from 0.71763 to 0.73346, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 18s 285us/sample - loss: 0.8721 - accuracy: 0.7

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0019331149356105692.
Epoch 11/30
61800/62268 [============================>.] - ETA: 0s - loss: 0.8398 - accuracy: 0.7487
Epoch 00011: val_accuracy improved from 0.73346 to 0.73756, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 274us/sample - loss: 0.8399 - accuracy: 0.7

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0016866916899998582.
Epoch 12/30
62000/62268 [============================>.] - ETA: 0s - loss: 0.8054 - accuracy: 0.7604
Epoch 00012: val_accuracy improved from 0.73756 to 0.75576, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 278us/sample - loss: 0.8054 - accuracy: 0.7

Epoch 00013: LearningRateScheduler reducing learning rate to 0.0014885001618388336.
Epoch 13/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.7757 - accuracy: 0.7697
Epoch 00013: val_accuracy did not improve from 0.75576
62268/62268 [==============================] - 16s 250us/sample - loss: 0.7757 - accuracy: 0.7

Epoch 00014: LearningRateScheduler reducing learning rate to 0.0013262884372625512.
Epoch 14/30
62100/62268 [============================>.] - ETA: 0s - loss: 0.7505 - accuracy: 0.7776 ETA:
Epoch 00014: val_accuracy did not improve from 0.75576
62268/62268 [==============================] - 15s 241us/sample - loss: 0.7508 - accuracy: 0.7

Epoch 00015: LearningRateScheduler reducing learning rate to 0.001191533987088959.
```

```
Epoch 15/30
62000/62268 [============================>.] - ETA: 0s - loss: 0.7246 - accuracy: 0.7853
Epoch 00015: val_accuracy improved from 0.75576 to 0.77368, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 16s 264us/sample - loss: 0.7251 - accuracy: 0.78

Epoch 00016: LearningRateScheduler reducing learning rate to 0.0010781445349850964.
Epoch 16/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.7076 - accuracy: 0.7900
Epoch 00016: val_accuracy did not improve from 0.77368
62268/62268 [==============================] - 15s 245us/sample - loss: 0.7074 - accuracy: 0.79

Epoch 00017: LearningRateScheduler reducing learning rate to 0.000981661766327396.
Epoch 17/30
61900/62268 [============================>.] - ETA: 0s - loss: 0.6906 - accuracy: 0.7955
Epoch 00017: val_accuracy improved from 0.77368 to 0.77641, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 268us/sample - loss: 0.6899 - accuracy: 0.79

Epoch 00018: LearningRateScheduler reducing learning rate to 0.0008987559040903719.
Epoch 18/30
62100/62268 [============================>.] - ETA: 0s - loss: 0.6753 - accuracy: 0.8009 ETA: 
Epoch 00018: val_accuracy improved from 0.77641 to 0.78488, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 271us/sample - loss: 0.6750 - accuracy: 0.80

Epoch 00019: LearningRateScheduler reducing learning rate to 0.000826895357137767.
Epoch 19/30
62000/62268 [============================>.] - ETA: 0s - loss: 0.6590 - accuracy: 0.8064
Epoch 00019: val_accuracy improved from 0.78488 to 0.78688, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 270us/sample - loss: 0.6589 - accuracy: 0.80

Epoch 00020: LearningRateScheduler reducing learning rate to 0.0007641245358877472.
Epoch 20/30
61900/62268 [============================>.] - ETA: 0s - loss: 0.6489 - accuracy: 0.8088 ETA:
Epoch 00020: val_accuracy improved from 0.78688 to 0.79134, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 269us/sample - loss: 0.6490 - accuracy: 0.80

Epoch 00021: LearningRateScheduler reducing learning rate to 0.0007089115843053009.
Epoch 21/30
61900/62268 [============================>.] - ETA: 0s - loss: 0.6355 - accuracy: 0.8134
Epoch 00021: val_accuracy improved from 0.79134 to 0.79361, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 277us/sample - loss: 0.6352 - accuracy: 0.81

Epoch 00022: LearningRateScheduler reducing learning rate to 0.0006600411749978975.
```

```
Epoch 22/30
62000/62268 [============================>.] - ETA: 0s - loss: 0.6284 - accuracy: 0.8156 ETA: 
Epoch 00022: val_accuracy improved from 0.79361 to 0.79743, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 265us/sample - loss: 0.6279 - accuracy: 0.8

Epoch 00023: LearningRateScheduler reducing learning rate to 0.0006165382703631737.
Epoch 23/30
62000/62268 [============================>.] - ETA: 0s - loss: 0.6166 - accuracy: 0.8190 ETA: 
Epoch 00023: val_accuracy improved from 0.79743 to 0.79934, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 270us/sample - loss: 0.6166 - accuracy: 0.8

Epoch 00024: LearningRateScheduler reducing learning rate to 0.0005776123807018673.
Epoch 24/30
61900/62268 [============================>.] - ETA: 0s - loss: 0.6086 - accuracy: 0.8212
Epoch 00024: val_accuracy did not improve from 0.79934
62268/62268 [==============================] - 15s 247us/sample - loss: 0.6083 - accuracy: 0.8

Epoch 00025: LearningRateScheduler reducing learning rate to 0.0005426166080451965.
Epoch 25/30
62200/62268 [============================>.] - ETA: 0s - loss: 0.6008 - accuracy: 0.8237
Epoch 00025: val_accuracy improved from 0.79934 to 0.80116, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 269us/sample - loss: 0.6010 - accuracy: 0.8

Epoch 00026: LearningRateScheduler reducing learning rate to 0.0005110170579727344.
Epoch 26/30
62000/62268 [============================>.] - ETA: 0s - loss: 0.5944 - accuracy: 0.8265
Epoch 00026: val_accuracy improved from 0.80116 to 0.80144, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 16s 261us/sample - loss: 0.5942 - accuracy: 0.8

Epoch 00027: LearningRateScheduler reducing learning rate to 0.0004823696071240638.
Epoch 27/30
61900/62268 [============================>.] - ETA: 0s - loss: 0.5880 - accuracy: 0.8278
Epoch 00027: val_accuracy improved from 0.80144 to 0.80653, saving model to nn_checkpoints_bes
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 16s 259us/sample - loss: 0.5883 - accuracy: 0.8

Epoch 00028: LearningRateScheduler reducing learning rate to 0.0004563020836763124.
Epoch 28/30
61800/62268 [============================>.] - ETA: 0s - loss: 0.5819 - accuracy: 0.8302
Epoch 00028: val_accuracy did not improve from 0.80653
62268/62268 [==============================] - 15s 245us/sample - loss: 0.5818 - accuracy: 0.8

Epoch 00029: LearningRateScheduler reducing learning rate to 0.0004325005561633849.
Epoch 29/30
```

```
61800/62268 [============================>.] - ETA: 0s - loss: 0.5755 - accuracy: 0.8319
Epoch 00029: val_accuracy did not improve from 0.80653
62268/62268 [==============================] - 15s 249us/sample - loss: 0.5762 - accuracy: 0.83

Epoch 00030: LearningRateScheduler reducing learning rate to 0.0004106985446929329.
Epoch 30/30
61900/62268 [============================>.] - ETA: 0s - loss: 0.5712 - accuracy: 0.8320 ETA:
Epoch 00030: val_accuracy improved from 0.80653 to 0.80917, saving model to nn_checkpoints_best
INFO:tensorflow:Assets written to: nn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 17s 268us/sample - loss: 0.5710 - accuracy: 0.83
```

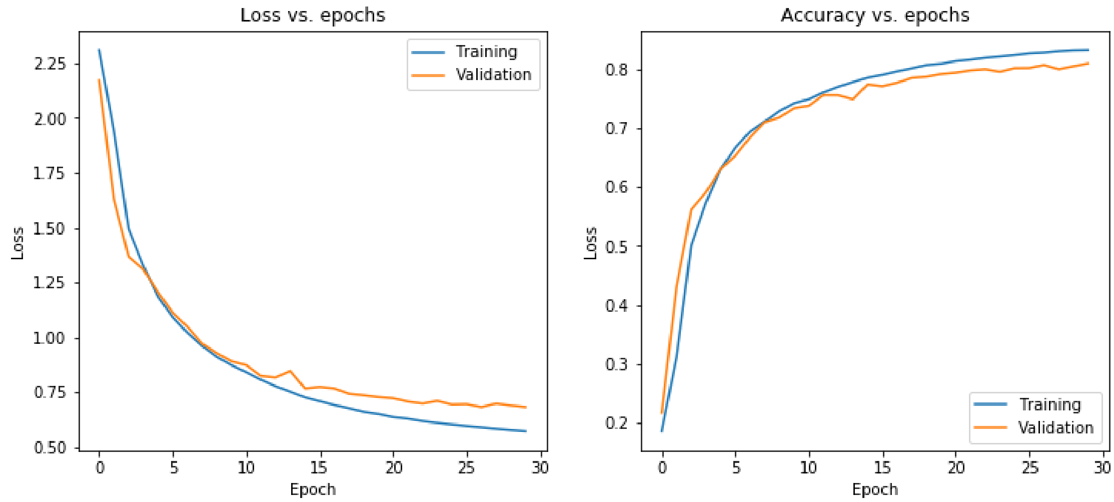
In [18]:
```python
df_hist = pd.DataFrame(history.history)
df_hist.head(10)
```

Out[18]:

| | loss | accuracy | val_loss | val_accuracy | lr |
|---|---|---|---|---|---|
| 0 | 2.310797 | 0.186131 | 2.172417 | 0.217035 | 0.010000 |
| 1 | 1.939972 | 0.312070 | 1.629429 | 0.431158 | 0.010000 |
| 2 | 1.493482 | 0.501140 | 1.367031 | 0.561835 | 0.010000 |
| 3 | 1.326325 | 0.573232 | 1.309591 | 0.590773 | 0.010000 |
| 4 | 1.184806 | 0.630019 | 1.205127 | 0.630085 | 0.006873 |
| 5 | 1.090663 | 0.666602 | 1.111646 | 0.652835 | 0.005092 |
| 6 | 1.019994 | 0.693791 | 1.047261 | 0.684048 | 0.003965 |
| 7 | 0.959919 | 0.710863 | 0.970394 | 0.709619 | 0.003200 |
| 8 | 0.909784 | 0.728448 | 0.926577 | 0.717627 | 0.002653 |
| 9 | 0.872070 | 0.741874 | 0.889884 | 0.733461 | 0.002246 |

In [19]:
```python
def plot_results(history):
    fig = plt.figure(figsize=(12, 5))

    fig.add_subplot(121)

    plt.plot(history['loss'])
    plt.plot(history['val_loss'])
    plt.title('Loss vs. epochs')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['Training', 'Validation'], loc='upper right')

    fig.add_subplot(122)

    plt.plot(history['accuracy'])
    plt.plot(history['val_accuracy'])
    plt.title('Accuracy vs. epochs')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['Training', 'Validation'], loc='lower right')

    plt.show()
```

```
In [20]: plot_results(df_hist)
```




```
In [21]: def get_test_accuracy(model, X_test, y_test):
             test_loss, test_acc = model.evaluate(x=X_test, y=y_test, verbose=0)
             print('accuracy: {acc:0.3f}'.format(acc=test_acc))
             print('loss: {loss:0.3f}'.format(loss=test_loss))

         get_test_accuracy(model, X_test, y_test)
```

```
accuracy: 0.793
loss: 0.781
```

### 1.4 3. CNN neural network classifier

- Build a CNN classifier model using the Sequential API. Your model should use the Conv2D, MaxPool2D, BatchNormalization, Flatten, Dense and Dropout layers. The final layer should again have a 10-way softmax output.
- You should design and build the model yourself. Feel free to experiment with different CNN architectures. *Hint: to achieve a reasonable accuracy you won't need to use more than 2 or 3 convolutional layers and 2 fully connected layers.)*
- The CNN model should use fewer trainable parameters than your MLP model.
- Compile and train the model (we recommend a maximum of 30 epochs), making use of both training and validation sets during the training run.
- Your model should track at least one appropriate metric, and use at least two callbacks during training, one of which should be a ModelCheckpoint callback.
- You should aim to beat the MLP model performance with fewer parameters!
- Plot the learning curves for loss vs epoch and accuracy vs epoch for both training and validation sets.
- Compute and display the loss and accuracy of the trained model on the test set.

In [22]:
```
def get_cnn_model(train_data, wd, dprate, lr):
    model = Sequential()
    # Convolutional layers
    model.add(Conv2D(filters=24, kernel_size=(3,3), padding='SAME', activation='relu'
                     input_shape = train_data.shape[1:], name='conv_1'))
    model.add(MaxPooling2D(pool_size=(2,2)))
    model.add(BatchNormalization())
    model.add(Dropout(dprate))

    model.add(Conv2D(filters=16, kernel_size=(3,3), padding='SAME',
                     activation='relu', name='conv_2'))
    model.add(MaxPooling2D(pool_size=(3,3)))
    model.add(BatchNormalization())
    model.add(Dropout(dprate*0.5))


    model.add(Flatten())
    # Fully connected layers
    model.add(Dense(50, activation=leaky_relu, kernel_regularizer=regularizers.l2(wd)

    # Output layer
    model.add(Dense(10, activation='softmax'))

    params = {'optimizer': tf.keras.optimizers.Adam(learning_rate=lr),
              'loss': tf.keras.losses.SparseCategoricalCrossentropy(),
              'metrics': ['accuracy']}

    model.compile(**params)

    return model
```

In [23]:
```
weight_decay = 1e-6
dropout_rate = 0.5
opt_lr = 0.01
cnn_model = get_cnn_model(X_train, weight_decay, dropout_rate, opt_lr)
cnn_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv_1 (Conv2D)              (None, 32, 32, 24)        240
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 16, 16, 24)        0
_________________________________________________________________
batch_normalization (BatchNo (None, 16, 16, 24)        96
_________________________________________________________________
dropout (Dropout)            (None, 16, 16, 24)        0
```

```
_________________________________________________________________
conv_2 (Conv2D)              (None, 16, 16, 16)        3472
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 5, 5, 16)          0
_________________________________________________________________
batch_normalization_1 (Batch (None, 5, 5, 16)          64
_________________________________________________________________
dropout_1 (Dropout)          (None, 5, 5, 16)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 400)               0
_________________________________________________________________
fc_1 (Dense)                 (None, 50)                20050
_________________________________________________________________
dense_2 (Dense)              (None, 10)                510
=================================================================
Total params: 24,432
Trainable params: 24,352
Non-trainable params: 80
_________________________________________________________________
```

```
In [24]: cnn_checkpoint_best = 'cnn_checkpoints_best/checkpoint'
         checkpoint_best = ModelCheckpoint(filepath=cnn_checkpoint_best, save_freq='epoch',
                                           save_weights_only=False, monitor='val_accuracy',
                                           save_best_only=True, verbose=1)

         my_callbacks = [lrate, earlystop, checkpoint_best]
```

```
In [25]: history = cnn_model.fit(X_train, y_train, epochs = 20, validation_split=0.15,
                                 batch_size = 64, callbacks=my_callbacks, verbose = 1)
```

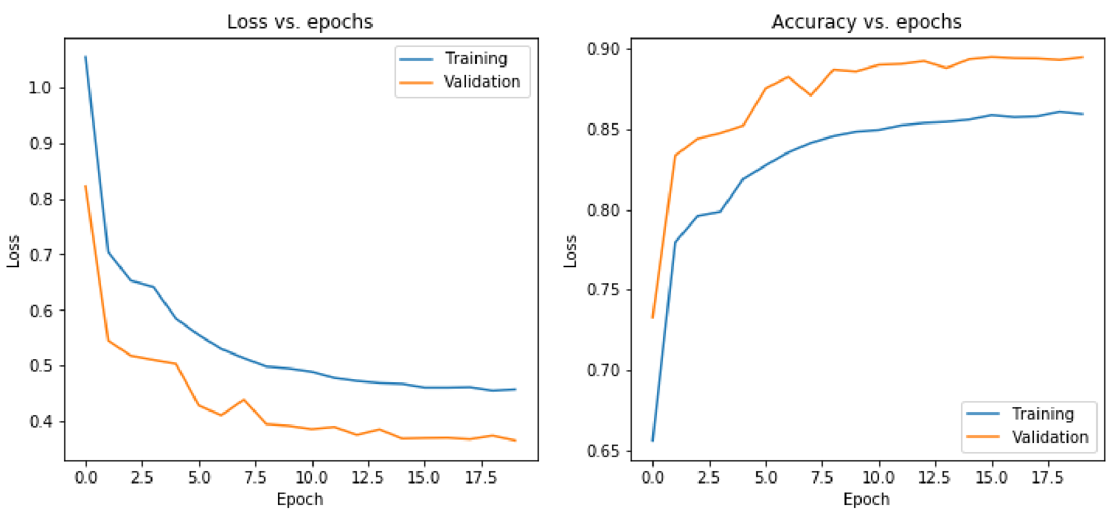
```
Train on 62268 samples, validate on 10989 samples

Epoch 00001: LearningRateScheduler reducing learning rate to 0.009999999776482582.
Epoch 1/20
62208/62268 [============================>.] - ETA: 0s - loss: 1.0542 - accuracy: 0.6558
Epoch 00001: val_accuracy improved from -inf to 0.73273, saving model to cnn_checkpoints_best/c
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 283s 5ms/sample - loss: 1.0539 - accuracy: 0.656

Epoch 00002: LearningRateScheduler reducing learning rate to 0.009999999776482582.
Epoch 2/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.7037 - accuracy: 0.7795
Epoch 00002: val_accuracy improved from 0.73273 to 0.83347, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 277s 4ms/sample - loss: 0.7037 - accuracy: 0.779

Epoch 00003: LearningRateScheduler reducing learning rate to 0.009999999776482582.
```

```
Epoch 3/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.6529 - accuracy: 0.7958
Epoch 00003: val_accuracy improved from 0.83347 to 0.84393, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 268s 4ms/sample - loss: 0.6527 - accuracy: 0.795

Epoch 00004: LearningRateScheduler reducing learning rate to 0.009999999776482582.
Epoch 4/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.6411 - accuracy: 0.7985
Epoch 00004: val_accuracy improved from 0.84393 to 0.84739, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 257s 4ms/sample - loss: 0.6412 - accuracy: 0.798

Epoch 00005: LearningRateScheduler reducing learning rate to 0.006872892634288598.
Epoch 5/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.5845 - accuracy: 0.8188
Epoch 00005: val_accuracy improved from 0.84739 to 0.85203, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 247s 4ms/sample - loss: 0.5845 - accuracy: 0.818

Epoch 00006: LearningRateScheduler reducing learning rate to 0.005091564248681657.
Epoch 6/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.5550 - accuracy: 0.8274
Epoch 00006: val_accuracy improved from 0.85203 to 0.87524, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 256s 4ms/sample - loss: 0.5551 - accuracy: 0.827

Epoch 00007: LearningRateScheduler reducing learning rate to 0.003965314235977213.
Epoch 7/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.5301 - accuracy: 0.8355
Epoch 00007: val_accuracy improved from 0.87524 to 0.88243, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 258s 4ms/sample - loss: 0.5303 - accuracy: 0.835

Epoch 00008: LearningRateScheduler reducing learning rate to 0.0032004753115511507.
Epoch 8/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.5136 - accuracy: 0.8413
Epoch 00008: val_accuracy did not improve from 0.88243
62268/62268 [==============================] - 258s 4ms/sample - loss: 0.5135 - accuracy: 0.841

Epoch 00009: LearningRateScheduler reducing learning rate to 0.002653287264908044.
Epoch 9/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4984 - accuracy: 0.8456
Epoch 00009: val_accuracy improved from 0.88243 to 0.88698, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 257s 4ms/sample - loss: 0.4985 - accuracy: 0.845

Epoch 00010: LearningRateScheduler reducing learning rate to 0.002245959174781435 5.
```

```
Epoch 10/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4951 - accuracy: 0.8482
Epoch 00010: val_accuracy did not improve from 0.88698
62268/62268 [==============================] - 253s 4ms/sample - loss: 0.4949 - accuracy: 0.848

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0019331149356105692.
Epoch 11/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4894 - accuracy: 0.8492
Epoch 00011: val_accuracy improved from 0.88698 to 0.88998, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 255s 4ms/sample - loss: 0.4892 - accuracy: 0.849

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0016866916899998582.
Epoch 12/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4778 - accuracy: 0.8523
Epoch 00012: val_accuracy improved from 0.88998 to 0.89053, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 259s 4ms/sample - loss: 0.4781 - accuracy: 0.852

Epoch 00013: LearningRateScheduler reducing learning rate to 0.0014885001618388336.
Epoch 13/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4728 - accuracy: 0.8537
Epoch 00013: val_accuracy improved from 0.89053 to 0.89235, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 259s 4ms/sample - loss: 0.4727 - accuracy: 0.853

Epoch 00014: LearningRateScheduler reducing learning rate to 0.0013262884372625512.
Epoch 14/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4691 - accuracy: 0.8545
Epoch 00014: val_accuracy did not improve from 0.89235
62268/62268 [==============================] - 255s 4ms/sample - loss: 0.4690 - accuracy: 0.854

Epoch 00015: LearningRateScheduler reducing learning rate to 0.001191533987088959.
Epoch 15/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4674 - accuracy: 0.8558
Epoch 00015: val_accuracy improved from 0.89235 to 0.89353, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 257s 4ms/sample - loss: 0.4674 - accuracy: 0.855

Epoch 00016: LearningRateScheduler reducing learning rate to 0.0010781445349850964.
Epoch 16/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4608 - accuracy: 0.8586
Epoch 00016: val_accuracy improved from 0.89353 to 0.89489, saving model to cnn_checkpoints_bes
INFO:tensorflow:Assets written to: cnn_checkpoints_best/checkpoint/assets
62268/62268 [==============================] - 264s 4ms/sample - loss: 0.4606 - accuracy: 0.858

Epoch 00017: LearningRateScheduler reducing learning rate to 0.0009816617663273967.
Epoch 17/20
```

```
62208/62268 [============================>.] - ETA: 0s - loss: 0.4606 - accuracy: 0.8574
Epoch 00017: val_accuracy did not improve from 0.89489
62268/62268 [==============================] - 258s 4ms/sample - loss: 0.4606 - accuracy: 0.85

Epoch 00018: LearningRateScheduler reducing learning rate to 0.0008987559040903719.
Epoch 18/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4613 - accuracy: 0.8579 ETA:
Epoch 00018: val_accuracy did not improve from 0.89489
62268/62268 [==============================] - 254s 4ms/sample - loss: 0.4614 - accuracy: 0.85

Epoch 00019: LearningRateScheduler reducing learning rate to 0.0008268953357137767.
Epoch 19/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4553 - accuracy: 0.8607
Epoch 00019: val_accuracy did not improve from 0.89489
62268/62268 [==============================] - 258s 4ms/sample - loss: 0.4551 - accuracy: 0.86

Epoch 00020: LearningRateScheduler reducing learning rate to 0.0007641245358877472.
Epoch 20/20
62208/62268 [============================>.] - ETA: 0s - loss: 0.4574 - accuracy: 0.8594
Epoch 00020: val_accuracy did not improve from 0.89489
62268/62268 [==============================] - 258s 4ms/sample - loss: 0.4574 - accuracy: 0.85
```

In [26]:
```python
df_hist = pd.DataFrame(history.history)
plot_results(df_hist)
```




In [27]:
```python
def get_test_accuracy(model, X_test, y_test):
    test_loss, test_acc = model.evaluate(x=X_test, y=y_test, verbose=0)
    print('accuracy: {acc:0.3f}'.format(acc=test_acc))
    print('loss: {loss:0.3f}'.format(loss=test_loss))
```

```
get_test_accuracy(cnn_model, X_test, y_test)
```

```
accuracy: 0.886
loss: 0.395
```

### 1.5 4. Get model predictions

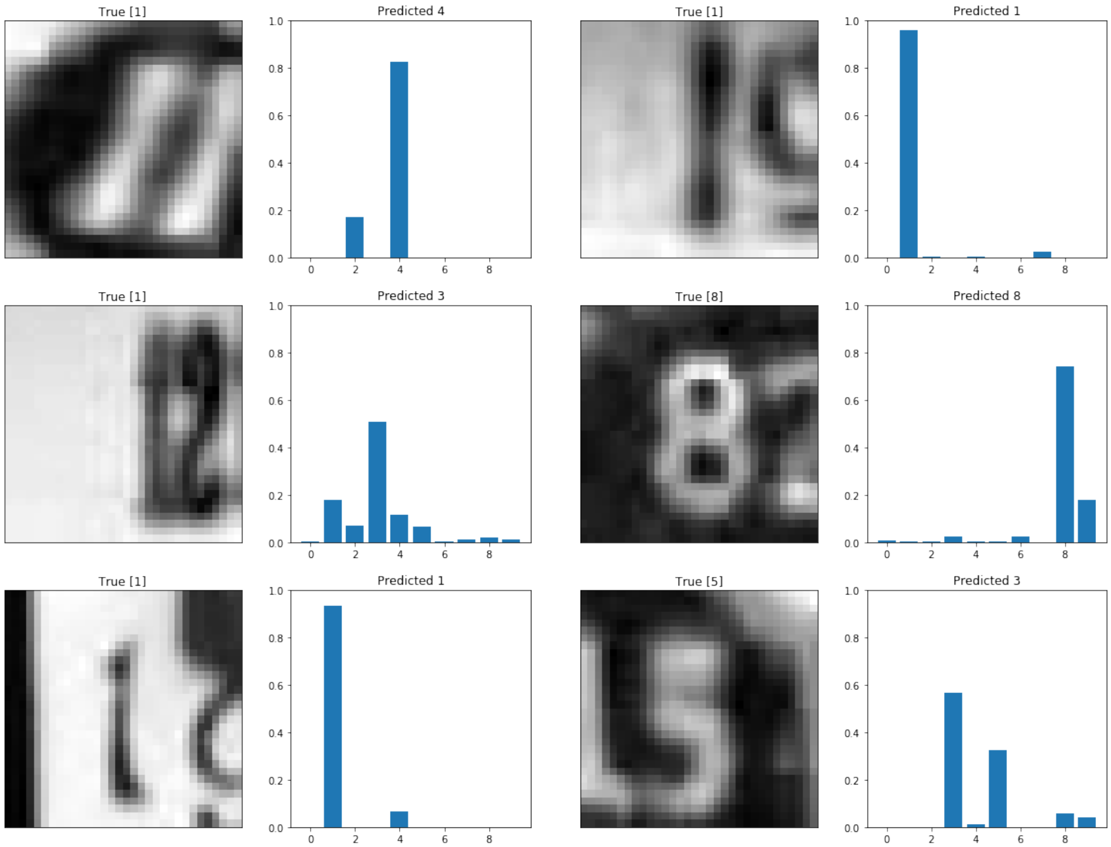
- Load the best weights for the MLP and CNN models that you saved during the training run.
- Randomly select 5 images and corresponding labels from the test set and display the images with their labels.
- Alongside the image and label, show each model's predictive distribution as a bar chart, and the final model prediction given by the label with maximum probability.

In [28]:
```
MLP_model = load_model(mlp_checkpoint_best)
CNN_model = load_model(cnn_checkpoint_best)
```

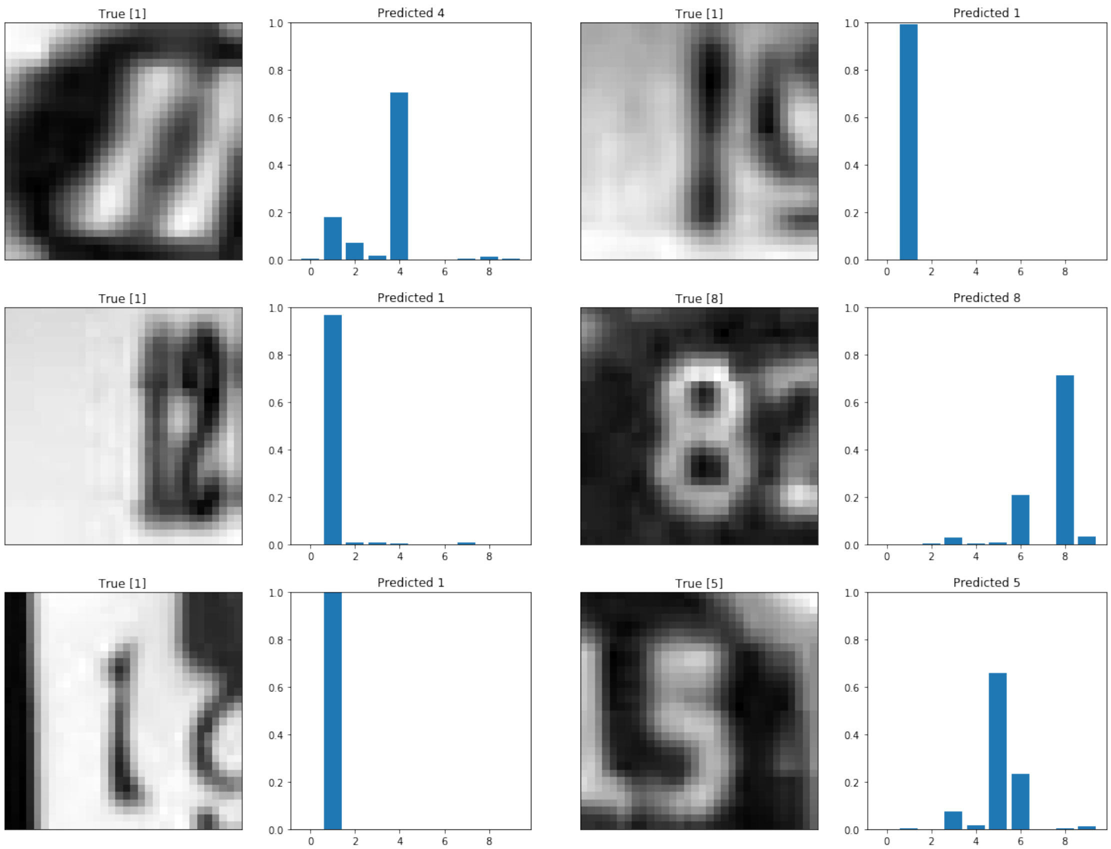
In [29]:
```
num_examples = X_test.shape[0]
sample = np.random.choice(range(num_examples), size=6)
X6_test = X_test[sample]
y6_true_labels = y_test[sample]
y6_pred_mlp = MLP_model.predict(X6_test)
y6_pred_cnn = CNN_model.predict(X6_test)
```

In [30]:
```
def plot_predictions(n_rows, n_cols, test_images, y_true, y_pred):

    plt.figure(figsize=(20, 15))
    n = 0
    for i in range(1,n_rows*n_cols+1): # Displaying 6 samples

        if i%2 != 0:
            plt.subplot(n_rows, n_cols, i)
            plt.xticks([])
            plt.yticks([])
            plt.imshow(test_images[n][:,:,0], cmap='gray') # Plot image selected from
            true_label = y_true[n]
            plt.title('True {}'.format(true_label)) # Dsiplaying Label

        else:
            plt.subplot(n_rows, n_cols, i)
            plt.bar(range(10), y_pred[n].flatten())
            plt.ylim([0, 1])
            pred_label = np.argmax(y_pred[n])
            plt.title('Predicted {}'.format(pred_label)) # Dsiplaying Label
            n += 1

    plt.show()
```

```
In [31]: plot_predictions(3, 4, X6_test, y6_true_labels, y6_pred_mlp)
```




```
In [32]: plot_predictions(3, 4, X6_test, y6_true_labels, y6_pred_cnn)
```




```
In [33]: y_pred_mlp = MLP_model.predict(X_test)
         y_pred_cnn = CNN_model.predict(X_test)
```

```
In [34]: # Convert the true labels and predicted labels into binary matrices,
         # where the hot index (ones) indicates the actual class
         y_pred_mlp_bin = np.zeros(y_pred_mlp.shape)
         y_pred_mlp_bin[np.arange(len(y_pred_mlp)), y_pred_mlp.argmax(1)] = 1

         y_pred_cnn_bin = np.zeros(y_pred_cnn.shape)
         y_pred_cnn_bin[np.arange(len(y_pred_cnn)), y_pred_cnn.argmax(1)] = 1

         mlb = MultiLabelBinarizer()
         y_test_bin = mlb.fit_transform(y_test)
```

```
In [35]: def cm_plot(y_true, y_pred, labels, ymap=None, cmap='BuPu', figsize=(16,12)):
             if ymap is not None:
                 y_pred = [ymap[yi] for yi in y_pred]
                 y_true = [ymap[yi] for yi in y_true]
                 labels = [ymap[yi] for yi in labels]
             cm = confusion_matrix(y_true, y_pred, labels=labels)
             cm_sum = np.sum(cm, axis=1, keepdims=True)
```

```
    cm_perc = cm / cm_sum.astype(float) * 100
    annot = np.empty_like(cm).astype(str)
    nrows, ncols = cm.shape
    for i in range(nrows):
        for j in range(ncols):
            c = cm[i, j]
            p = cm_perc[i, j]
            if i == j:
                s = cm_sum[i]
                annot[i, j] = '%.1f%%\n%d/%d' % (p, c, s)
            elif c <= 0.5:
                annot[i, j] = ''
            else:
                annot[i, j] = '%.1f%%\n%d' % (p, c)
    cm = pd.DataFrame(cm, index=labels, columns=labels)
    cm.index.name = 'Real'
    cm.columns.name = 'Prediction'
    fig, ax = plt.subplots(figsize=figsize)
    sns.heatmap(cm, annot=annot, fmt='', ax=ax, linewidth=0.2, cmap = cmap)
    plt.ylim(len(cm)+0.05, -0.05)
    plt.show()
```

```
In [36]: cm_plot(y_test_bin.argmax(axis=1), y_pred_cnn_bin.argmax(axis=1), labels=None, ymap=N
                 cmap='terrain_r', figsize=(15,9))
```