Deep Learning Project Part2

```
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```

- Images have been preprocessed on Part1
- We will load the data and start evaluating it
- We will define all our methods necessary
- Create the Model
- Train the Model
- Show predictions and accuracy results
- Show a Confusion Matrix of the results
- Show picture examples of incorrect and correct images
- Show a plot of Validations vs Losses

Preprocessors

In [1]:

```
#Preprocessors used
from __future__ import absolute_import
from __future__ import print_function
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
from datetime import timedelta
from keras import regularizers
import tensorflow as tf
import seaborn as sns
import numpy as np
import h5py
import time
import os
```

```
Using TensorFlow backend.
```

Import and load the data

In [2]:
```
# default figure size for images
%matplotlib inline
plt.rcParams['figure.figsize'] = (16.0, 4.0)

h5f = h5py.File('SVHN_grey.h5', 'r')

# Load the training, test and validation set
X_train = h5f['X_train'][:]
y_train = h5f['y_train'][:]
X_test = h5f['X_test'][:]
y_test = h5f['y_test'][:]
X_val = h5f['X_val'][:]
y_val = h5f['y_val'][:]

h5f.close()

print('Training set', X_train.shape, y_train.shape)
print('Validation set', X_val.shape, y_val.shape)
print('Test set', X_test.shape, y_test.shape)
```

```
Training set (63733, 32, 32, 1) (63733, 10)
Validation set (9524, 32, 32, 1) (9524, 10)
Test set (26032, 32, 32, 1) (26032, 10)
```

Defined Methods

In [3]:
```
def get_batch(X, y, batch_size=512):
    for i in np.arange(0, y.shape[0], batch_size):
        end = min(X.shape[0], i + batch_size)
        yield(X[i:end],y[i:end])
```

In [4]:
```
def plot_images(images, nrows, ncols, cls_true, mode=None):
    # Initialize the subplotgrid
    fig, axes = plt.subplots(nrows, ncols)

    # Randomly select nrows * ncols images
    rs = np.random.choice(images.shape[0], nrows*ncols)
    print("T = True, P = Prediction")
    for i, ax in zip(rs, axes.flat):

        if mode is None:
            title = "T: {0}".format(np.argmax(cls_true[i]))

        else:
            title = "T: {0}, P: {1}".format(np.argmax(cls_true[i]), mode[i])

        # Display the image
        ax.imshow(images[i,:,:,0], cmap='binary')
        ax.set_title(title)
        ax.set_xticks([])
        ax.set_yticks([])
```

In [5]:

```
def model(features):
    weight_decay = 2e-4

# INPUT->[CONV->RELU->CONV->RELU->POOL]->DROPOUT->[FC->RELU]->FC
    input_layer = tf.reshape(features, [-1, 32, 32, 1], name='Reshaped_Input'

    conv1 = tf.layers.conv2d( inputs=input_layer, filters=32,
        kernel_size=[5, 5], padding="same",
        kernel_regularizer=regularizers.l2(weight_decay),
        activation=tf.nn.relu)

    pool1 = tf.layers.max_pooling2d(inputs=conv1, pool_size=[2, 2],
            strides=2)

    conv2 = tf.layers.conv2d( inputs=pool1,filters=64,
            kernel_size=[5, 5], padding="same",
            kernel_regularizer=regularizers.l2(weight_decay),
            activation=tf.nn.relu)

    pool2 = tf.layers.max_pooling2d(inputs=conv2, pool_size=[2, 2],
            strides=2)

    pool2_flat = tf.reshape(pool2, [-1, 8 * 8 * 64])
    dense = tf.layers.dense(inputs=pool2_flat, units=256,
            activation=tf.nn.relu)
    dropout = tf.layers.dropout(inputs=dense, rate=0.8)

    logits = tf.layers.dense(inputs=dropout, units=10)

    return logits
```

Building the Model

In [6]:

```
max_epochs = 10
num_examples = X_train.shape[0]
```

In [7]:

```
# Method to flatten results for Confusion Matrix
def flatten(lists):
    flat = []
    for numbers in lists:
        for x in numbers:
            flat.append(x)
    return np.asarray(flat)
```

In [8]:

```
tf.logging.set_verbosity(tf.logging.INFO)

# Our application logic will be added here
x = tf.placeholder(tf.float32, shape = [None, 32, 32, 1], name='Input_Data')
y = tf.placeholder(tf.float32, shape = [None, 10], name='Input_Labels')
y_cls = tf.argmax(y, 1)

discard_rate = tf.placeholder(tf.float32, name='Discard_rate')
os.environ['TF_CPP_MIN_LOG_LEVEL']='2'
```

In [9]:

```
#with tf.name_scope('Model Prediction'):
prediction = model(x)
prediction_cls = tf.argmax(prediction, 1)
#with tf.name_scope('loss'):
loss = tf.reduce_mean(tf.losses.softmax_cross_entropy(onehot_labels=y, logits

optimizer = tf.train.AdamOptimizer().minimize(loss)
```

```
WARNING: Logging before flag parsing goes to stderr.
W1203 17:09:33.333313  1888 deprecation.py:323] From <ipython-input-5-36aa2
b28cf27>:9: conv2d (from tensorflow.python.layers.convolutional) is depreca
ted and will be removed in a future version.
Instructions for updating:
Use `tf.keras.layers.Conv2D` instead.
W1203 17:09:33.336306  1888 deprecation.py:506] From C:\Users\jguim\Anacond
a3\lib\site-packages\tensorflow\python\ops\init_ops.py:1251: calling Varian
ceScaling.__init__ (from tensorflow.python.ops.init_ops) with dtype is depr
ecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to
the constructor
W1203 17:09:33.514797  1888 deprecation.py:323] From <ipython-input-5-36aa2
b28cf27>:11: max_pooling2d (from tensorflow.python.layers.pooling) is depre
cated and will be removed in a future version.
Instructions for updating:
Use keras.layers.MaxPooling2D instead.
W1203 17:09:33.645449  1888 deprecation.py:323] From <ipython-input-5-36aa2
b28cf27>:20: dense (from tensorflow.python.layers.core) is deprecated and w
ill be removed in a future version.
Instructions for updating:
Use keras.layers.dense instead.
W1203 17:09:33.954648  1888 deprecation.py:323] From <ipython-input-5-36aa2
b28cf27>:21: dropout (from tensorflow.python.layers.core) is deprecated and
will be removed in a future version.
Instructions for updating:
Use keras.layers.dropout instead.
W1203 17:09:34.063331  1888 deprecation.py:323] From C:\Users\jguim\Anacond
a3\lib\site-packages\tensorflow\python\ops\losses\losses_impl.py:121: add_d
ispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

In [10]:
```
# Predicted class equals the true class of each image?
correct_prediction = tf.equal(prediction_cls, y_cls)

# Cast predictions to float and calculate the mean
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
```

In [11]:
```
sess = tf.Session()
```

In [12]:
```
sess.run(tf.global_variables_initializer())
```

In [13]:
```
batch_size = 512
toss = 0.6
accu = 0.0
```

In [14]:

```
train_loss = []
valid_loss = []
start_time = time.time()
for epoch in range(max_epochs):
    print ('Training .........')
    epoch_loss = 0
    print ()
    print ('Epoch ', epoch+1 , ': ........ \n')
    step = 0

    ## Training epochs ....
    for (epoch_x , epoch_y) in get_batch(X_train, y_train, batch_size):
        _, train_accu, c = sess.run([optimizer, accuracy, loss],
        feed_dict={x: epoch_x, y: epoch_y, discard_rate: toss})
        train_loss.append(c)

        if(step%40 == 0):
            print ("Step:", step, ".....", "\nMini-Batch Loss   : ", c)
            print('Mini-Batch Accuracy :' , train_accu*100.0, '%')

            ## Validating prediction and summaries
            accu = 0.0
            for (epoch_x , epoch_y) in get_batch(X_val, y_val, 512):
                correct, _c = sess.run([correct_prediction, loss], feed_dict=
                valid_loss.append(_c)
                accu+= np.sum(correct[correct == True])
            print('Validation Accuracy :' , accu*100.0/y_val.shape[0], '%')
            print ()
        step = step + 1


    print ('Epoch', epoch+1, 'completed out of ', max_epochs)


# Calculate net time
time_diff = time.time() - start_time

# Testing prediction and summaries

for (epoch_x , epoch_y) in get_batch(X_test, y_test, 512):
    correct = sess.run([correct_prediction],
    feed_dict={x: epoch_x, y: epoch_y, discard_rate: toss})
    accu+= np.sum(correct[correct == True])

print("Time usage: " + str(timedelta(seconds=int(round(time_diff)))))
print ("\n\n")
```

```
Step: 0 .....
Mini-Batch Loss   :  0.25864834
Mini-Batch Accuracy : 92.1875 %
Validation Accuracy : 88.7757244855103 %

Step: 40 .....
Mini-Batch Loss   :  0.13602126
Mini-Batch Accuracy : 96.2890625 %

Validation Accuracy : 88.62872742545149 %
```

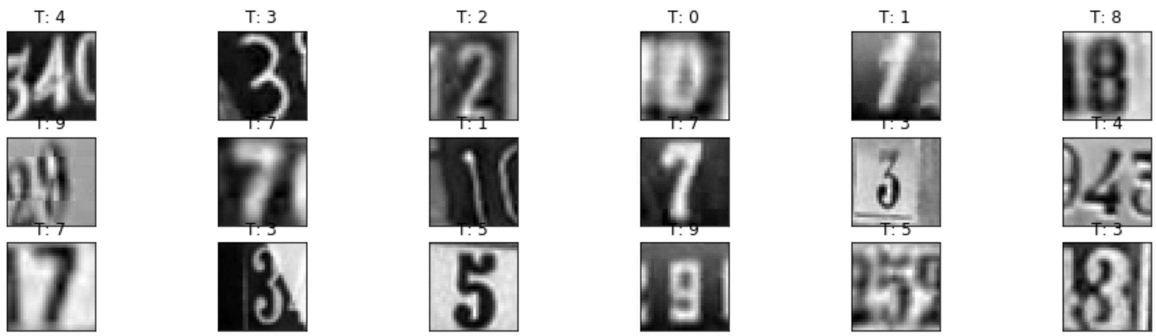
```
Step: 80 .....
Mini-Batch Loss    :  0.14437835
Mini-Batch Accuracy : 94.53125 %
Validation Accuracy : 88.68122637547249 %

Step: 120 .....
Mini-Batch Loss    :  0.1806235
Mini-Batch Accuracy : 95.5078125 %
Validation Accuracy : 88.67072658546829 %
```

Model Visualization

In [15]:
```
plot_images(X_train, 3, 6, y_train);
```

```
T = True, P = Prediction
```



In [16]:
```
test_pred = []
for (epoch_x , epoch_y) in get_batch(X_test, y_test, 512):
    correct = sess.run([prediction_cls],
    feed_dict={x: epoch_x, y: epoch_y, discard_rate: 0.0})
    test_pred.append((np.asarray(correct, dtype=int)).T)
```

Confusion Matrix

In [17]:
```
flat_array = flatten(test_pred)
flat_array = (flat_array.T)
flat_array = flat_array[0]
flat_array.shape
```

Out[17]:
```
(26032,)
```

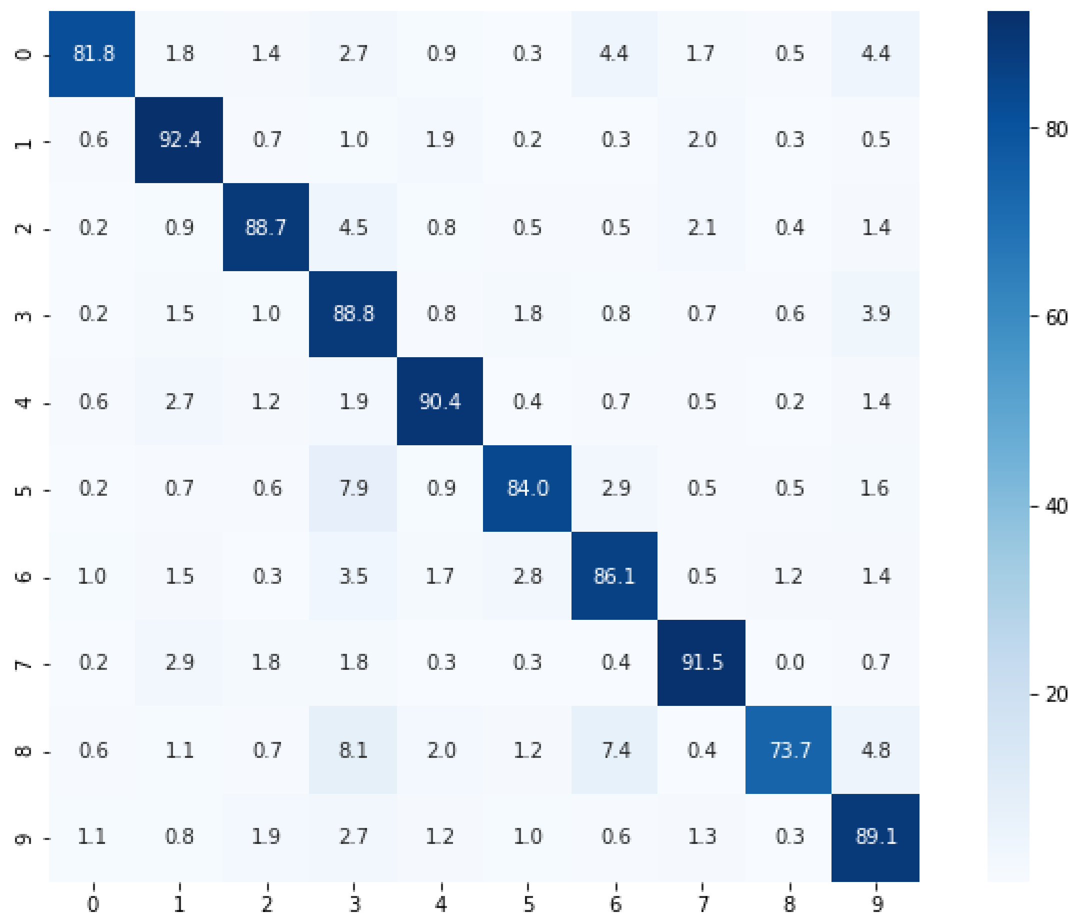
In [18]:

```
#Set the figure size
plt.figure(figsize=(12, 8))

#Calculate the confusion matrix
cm = confusion_matrix(y_true=np.argmax(y_test, axis=1), y_pred=flat_array)

#Normalize the confusion matrix
cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis] * 100.0

#Show
sns.heatmap(cm, annot=True, cmap='Blues', fmt='.1f', square=True);
```



Classified picture examples

```
First set of images are incorrect examples
Second set of images are correct examples
```

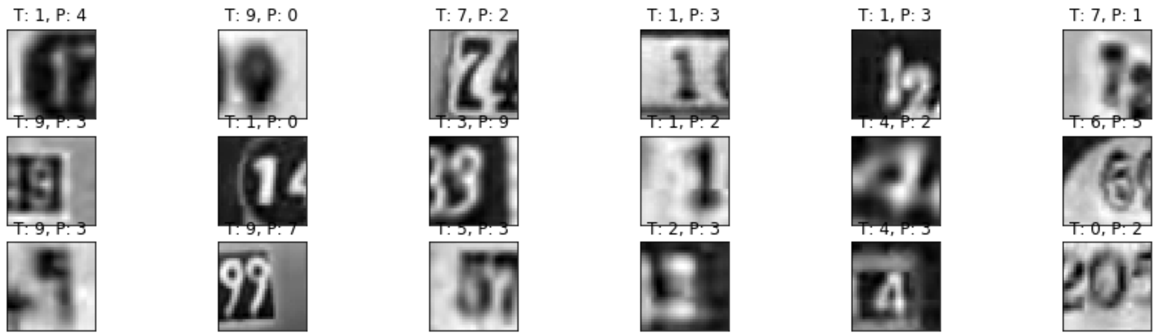
In [19]:

```
# Find incorrectly classified examples
incorrect = flat_array != np.argmax(y_test, axis=1)

images = X_test[incorrect]
cls_true = y_test[incorrect]
mode = flat_array[incorrect]

plot_images(images, 3, 6, cls_true, mode);
```

```
T = True, P = Prediction
```



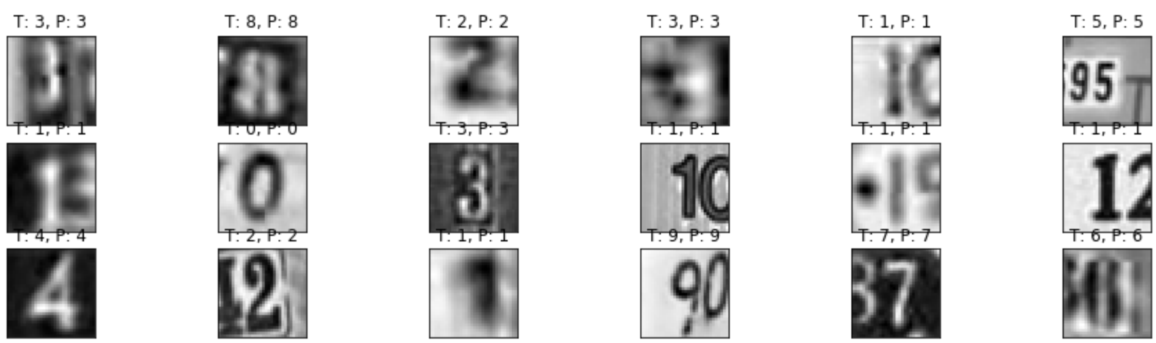
In [20]:

```
# Find correctly classified examples
correct = np.invert(incorrect)

images = X_test[correct]
cls_true = y_test[correct]
mode = flat_array[correct]

plot_images(images, 3, 6, cls_true, mode);
```

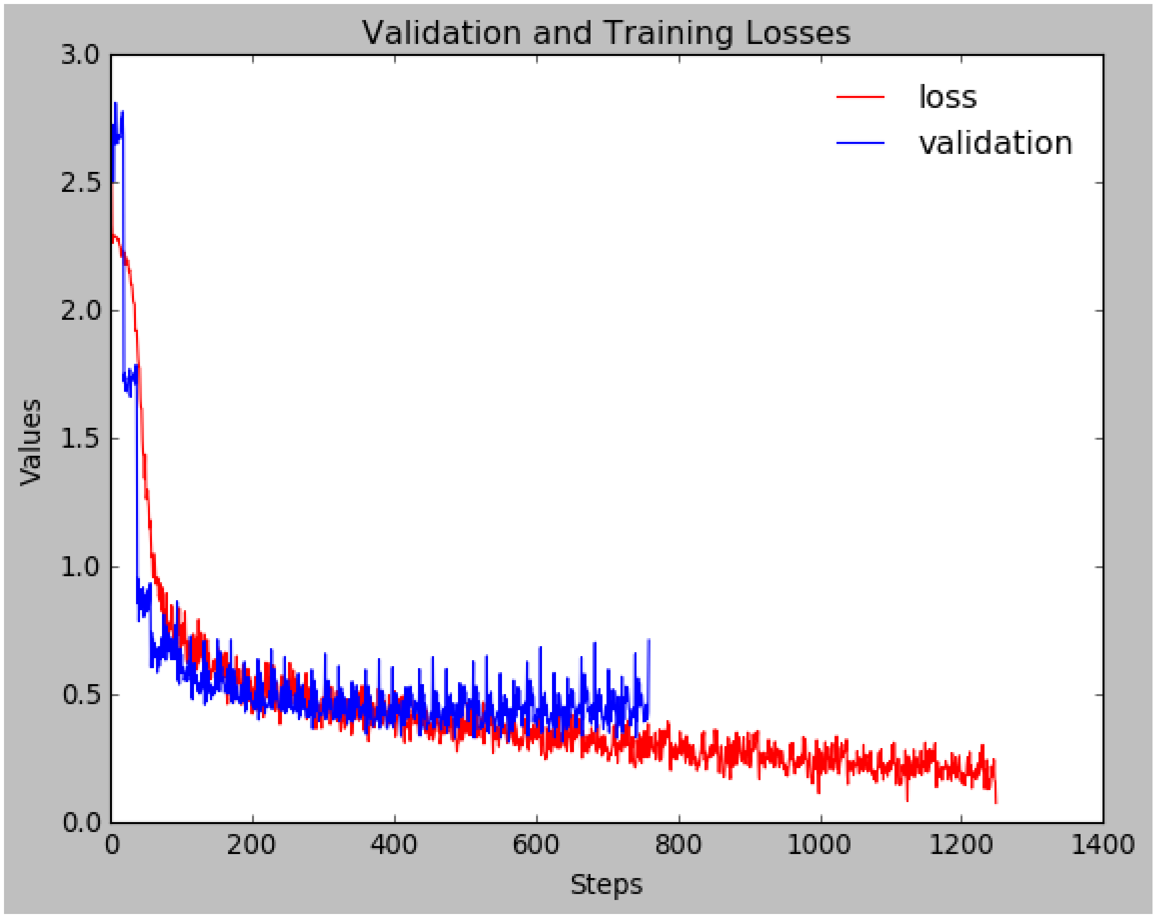
```
T = True, P = Prediction
```



Plot Validatiosn vs Losses

In [21]:
```
plt.style.use('classic')
plt.title("Validation and Training Losses")
plt.xlabel("Steps")
plt.ylabel("Values")
plt.plot(train_loss ,'r', label = 'loss')
plt.plot(valid_loss, 'b', label = 'validation')
plt.legend(loc='upper right', frameon=False)
```

Out[21]:
```
<matplotlib.legend.Legend at 0x19348d375c0>
```



Final Comments:

Project was achieved with an accuracy of 88.6% using 10 epochs A much higher accuracy can be achieved by adding more epochs but.. That would require higher computational power and time.

In [ ]:
```

```