OCR_assign3

February 17, 2020

[ ]:
```python
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

np.random.seed(2)

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
import itertools

from keras.utils.np_utils import to_categorical  # convert to one-hot-encoding
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPool2D
from keras.optimizers import RMSprop
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ReduceLROnPlateau

sns.set(style='white', context='notebook', palette='deep')

# Load the data
train = pd.read_csv("./input/train.csv")
test = pd.read_csv("./input/test.csv")

Y_train = train["label"]

# Drop 'label' column
X_train = train.drop(labels=["label"], axis=1)

# free some space
del train

g = sns.countplot(Y_train)

Y_train.value_counts()

# Check the data
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```python
X_train.isnull().any().describe()

test.isnull().any().describe()

# Normalize the data
X_train = X_train / 255.0
test = test / 255.0

# Reshape image in 3 dimensions (height = 28px, width = 28px , canal = 1)
X_train = X_train.values.reshape(-1, 28, 28, 1)
test = test.values.reshape(-1, 28, 28, 1)

# Encode labels to one hot vectors (ex : 2 -> [0,0,1,0,0,0,0,0,0,0])
Y_train = to_categorical(Y_train, num_classes=10)

# Set the random seed
random_seed = 2

# Split the train and the validation set for the fitting
X_train, X_val, Y_train, Y_val = train_test_split(X_train, Y_train, test_size=0.1, random_state=random_seed)

# Some examples
g = plt.imshow(X_train[0][:, :, 0])

# Set the CNN model
# my CNN architechture is In -> [[Conv2D->relu]*2 -> MaxPool2D -> Dropout]*2 -> Flatten -> Dense -> Dropout -> Out

model = Sequential()

model.add(Conv2D(filters=32, kernel_size=(5, 5), padding='Same',
                 activation='relu', input_shape=(28, 28, 1)))
model.add(Conv2D(filters=32, kernel_size=(5, 5), padding='Same',
                 activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(filters=64, kernel_size=(3, 3), padding='Same',
                 activation='relu'))
model.add(Conv2D(filters=64, kernel_size=(3, 3), padding='Same',
                 activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(256, activation="relu"))
```

```
model.add(Dropout(0.5))
model.add(Dense(10, activation="softmax"))

# Define the optimizer
optimizer = RMSprop(lr=0.001, rho=0.9, epsilon=1e-08, decay=0.0)

# Compile the model
model.compile(optimizer=optimizer, loss="categorical_crossentropy",␣
↪metrics=["accuracy"])

# Set a learning rate annealer
learning_rate_reduction = ReduceLROnPlateau(monitor='val_acc',
                                            patience=3,
                                            verbose=1,
                                            factor=0.5,
                                            min_lr=0.00001)

epochs = 10  # Turn epochs to 30 to get 0.9967 accuracy
batch_size = 86

# Without data augmentation i obtained an accuracy of 0.98114
# history = model.fit(X_train, Y_train, batch_size = batch_size, epochs =␣
↪epochs,
#           validation_data = (X_val, Y_val), verbose = 2)

# With data augmentation to prevent overfitting (accuracy 0.99286)

datagen = ImageDataGenerator(
    featurewise_center=False,  # set input mean to 0 over the dataset
    samplewise_center=False,  # set each sample mean to 0
    featurewise_std_normalization=False,  # divide inputs by std of the dataset
    samplewise_std_normalization=False,  # divide each input by its std
    zca_whitening=False,  # apply ZCA whitening
    rotation_range=10,  # randomly rotate images in the range (degrees, 0 to␣
↪180)
    zoom_range=0.1,  # Randomly zoom image
    width_shift_range=0.1,  # randomly shift images horizontally (fraction of␣
↪total width)
    height_shift_range=0.1,  # randomly shift images vertically (fraction of␣
↪total height)
    horizontal_flip=False,  # randomly flip images
    vertical_flip=False)  # randomly flip images

datagen.fit(X_train)

# Fit the model
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history = model.fit_generator(datagen.flow(X_train, Y_train,␣
↪batch_size=batch_size),
                              epochs=epochs, validation_data=(X_val, Y_val),
                              verbose=2, steps_per_epoch=X_train.shape[0] //␣
↪batch_size
                              , callbacks=[learning_rate_reduction])

# Plot the loss and accuracy curves for training and validation
fig, ax = plt.subplots(2, 1)
ax[0].plot(history.history['loss'], color='b', label="Training loss")
ax[0].plot(history.history['val_loss'], color='r', label="validation loss",␣
↪axes=ax[0])
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(history.history['acc'], color='b', label="Training accuracy")
ax[1].plot(history.history['val_acc'], color='r', label="Validation accuracy")
legend = ax[1].legend(loc='best', shadow=True)



# Look at confusion matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
```

```python
    plt.xlabel('Predicted label')


# Predict the values from the validation dataset
Y_pred = model.predict(X_val)
# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_pred, axis=1)
# Convert validation observations to one hot vectors
Y_true = np.argmax(Y_val, axis=1)
# compute the confusion matrix
confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)
# plot the confusion matrix
plot_confusion_matrix(confusion_mtx, classes=range(10))

# Display some error results

# Errors are difference between predicted labels and true labels
errors = (Y_pred_classes - Y_true != 0)

Y_pred_classes_errors = Y_pred_classes[errors]
Y_pred_errors = Y_pred[errors]
Y_true_errors = Y_true[errors]
X_val_errors = X_val[errors]


def display_errors(errors_index, img_errors, pred_errors, obs_errors):
    """ This function shows 6 images with their predicted and real labels"""
    n = 0
    nrows = 2
    ncols = 3
    fig, ax = plt.subplots(nrows, ncols, sharex=True, sharey=True)
    for row in range(nrows):
        for col in range(ncols):
            error = errors_index[n]
            ax[row, col].imshow((img_errors[error]).reshape((28, 28)))
            ax[row, col].set_title("Predicted label :{}\nTrue label :{}".
 ↪format(pred_errors[error], obs_errors[error]))
            n += 1


# Probabilities of the wrong predicted numbers
Y_pred_errors_prob = np.max(Y_pred_errors, axis=1)

# Predicted probabilities of the true values in the error set
true_prob_errors = np.diagonal(np.take(Y_pred_errors, Y_true_errors, axis=1))

# Difference between the probability of the predicted label and the true label
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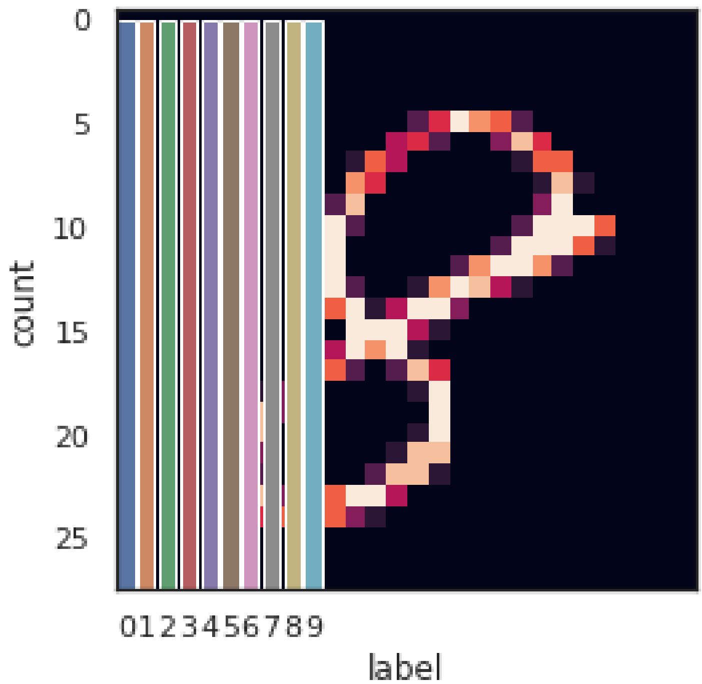
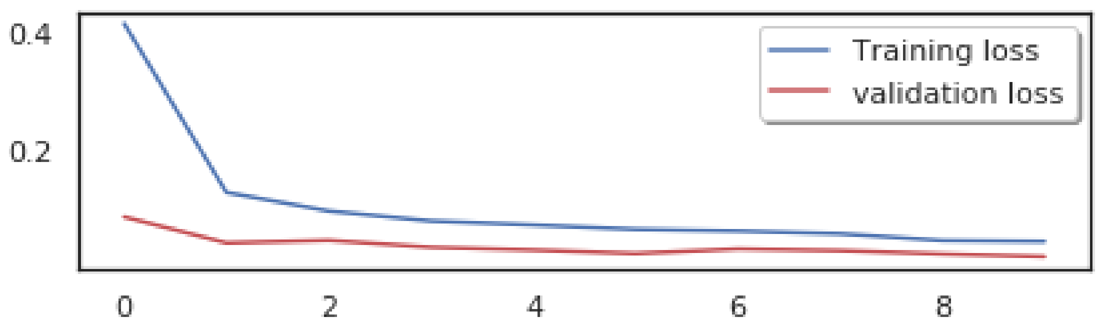
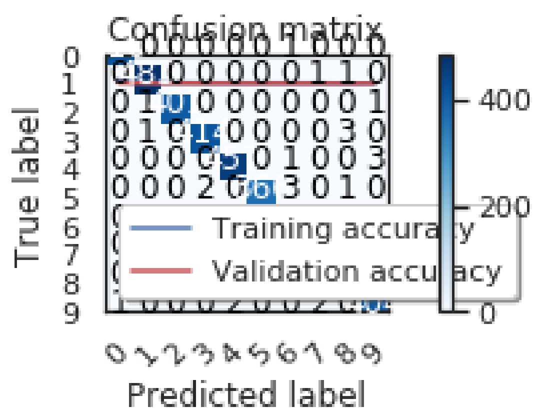
```python
delta_pred_true_errors = Y_pred_errors_prob - true_prob_errors

# Sorted list of the delta prob errors
sorted_dela_errors = np.argsort(delta_pred_true_errors)

# Top 6 errors
most_important_errors = sorted_dela_errors[-6:]

# Show the top 6 errors
display_errors(most_important_errors, X_val_errors, Y_pred_classes_errors,␣
 ↪Y_true_errors)

# predict results
results = model.predict(test)

# select the indix with the maximum probability
results = np.argmax(results, axis=1)

results = pd.Series(results, name="Label")

submission = pd.concat([pd.Series(range(1, 28001), name="ImageId"), results],␣
 ↪axis=1)

submission.to_csv("./input/cnn_mnist_datagen.csv", index=False)
```

```
Epoch 1/10
 - 67s - loss: 0.4141 - acc: 0.8679 - val_loss: 0.0870 - val_acc: 0.9738
Epoch 2/10
 - 64s - loss: 0.1285 - acc: 0.9614 - val_loss: 0.0430 - val_acc: 0.9871
Epoch 3/10
 - 64s - loss: 0.0970 - acc: 0.9717 - val_loss: 0.0474 - val_acc: 0.9862
Epoch 4/10
 - 65s - loss: 0.0800 - acc: 0.9775 - val_loss: 0.0356 - val_acc: 0.9890
Epoch 5/10
 - 64s - loss: 0.0733 - acc: 0.9785 - val_loss: 0.0310 - val_acc: 0.9921
Epoch 6/10
 - 63s - loss: 0.0660 - acc: 0.9807 - val_loss: 0.0250 - val_acc: 0.9919
Epoch 7/10
 - 63s - loss: 0.0631 - acc: 0.9808 - val_loss: 0.0328 - val_acc: 0.9907
Epoch 8/10
 - 63s - loss: 0.0585 - acc: 0.9831 - val_loss: 0.0300 - val_acc: 0.9907

Epoch 00008: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
Epoch 9/10
 - 63s - loss: 0.0474 - acc: 0.9864 - val_loss: 0.0242 - val_acc: 0.9950
Epoch 10/10
 - 63s - loss: 0.0456 - acc: 0.9871 - val_loss: 0.0199 - val_acc: 0.9936
```


count
label
0
5
10
15
20
25
0123456789


Training loss
validation loss
0.4
0.2
0
2
4
6
8


Confusion matrix
True label
Predicted label
Training accuracy
Validation accuracy
400
200
0

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