Digit_identification

February 23, 2025

1 Digit Identification: PyTorch vs. TensorFlow

The purpose of this notebook is to compare deep learning models built by PyTorch and TensorFlow for identifying handwritten digits.

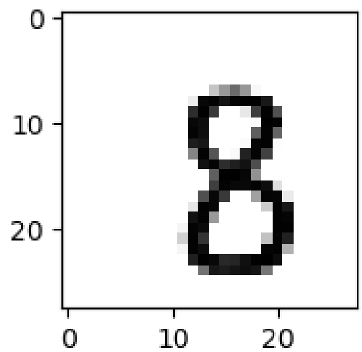
The collection used in this notebook is found in Kaggle and is not from the MINST dataset. There are 10773 images of each of the ten digits in PNG format. In the following, I will, first, make a DataFrame of the images' pixel data and build neural network models using PyTorch and TensorFlow.

[1]:
```
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout

import torch
from torch import nn

from PIL import Image

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import time
import warnings
warnings.filterwarnings(action='ignore')
```

1.1 Build Image Dataset

[62]:
```
# getting image dimensions

img = Image.open('8/8/110.png')
plt.figure(figsize=(2,2))
plt.imshow(img)
img_arr = np.asarray(img)
img_arr.shape
```

[62]: (28, 28, 4)



Now that we know the dimensions of the images, 28 * 28 * 4, we can make a function to convert each image folder into a DataFrame.

[3]:
```
# A function to convert image data to pandas DataFrame

def image_to_dataframe(path, img_count, img_label):
    '''
    path (str): the file path of images
    img_count (int): the number of images in the path folder
    img_label (int): the digit that images represent
    '''

    df = pd.DataFrame(columns = [i for i in range(3136)]) # 24 * 24 * 4 = 3136
    for i in range(img_count):
        img = np.asarray(Image.open(path+str(i)+'.png'))
        df.loc[len(df)] = img.reshape(-1)

    df['digit'] = img_label
    return df
```

[4]:
```
# Dataframe of ten digits images
time_start = time.time()
```

```python
df_0 = image_to_dataframe('0/0/', 10772, 0)
df_1 = image_to_dataframe('1/1/', 10772, 1)
df_2 = image_to_dataframe('2/2/', 10772, 2)
df_3 = image_to_dataframe('3/3/', 10772, 3)
df_4 = image_to_dataframe('4/4/', 10772, 4)
df_5 = image_to_dataframe('5/5/', 10772, 5)
df_6 = image_to_dataframe('6/6/', 10772, 6)
df_7 = image_to_dataframe('7/7/', 10772, 7)
df_8 = image_to_dataframe('8/8/', 10772, 8)
df_9 = image_to_dataframe('9/9/', 10772, 9)

print('Time Elapsed: {} seconds'.format(time.time() - time_start))
```

```
Time Elapsed: 322.1026051044464 seconds
```

[5]:
```python
df_all = pd.concat([df_0, df_1, df_2, df_3, df_4, df_5, df_6, df_7, df_8, df_9],
                   ignore_index = True)

#shuffle the dataframe
df_digits = df_all.sample(frac=1).reset_index(drop=True)
```

[6]:
```python
df_digits
```

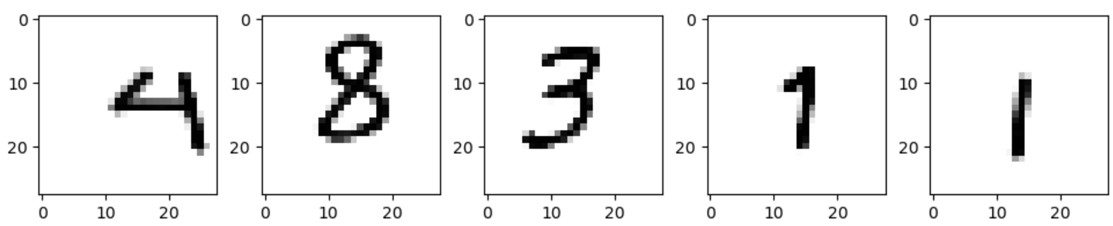
[6]:
```
        0  1  2  3  4  5  6  7  8  9  …  3127  3128  3129  3130  3131  3132  \
0       0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
1       0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
2       0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
3       0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
4       0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
…     .. .. .. .. .. .. .. .. .. .. …   …     …     …     …     …     …
107715  0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
107716  0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
107717  0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
107718  0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0
107719  0  0  0  0  0  0  0  0  0  0  …     0     0     0     0     0     0

        3133  3134  3135  digit
0          0     0     0      0
1          0     0     0      7
2          0     0     0      9
3          0     0     0      0
4          0     0     0      5
…        …     …     …      …
107715     0     0     0      9
107716     0     0     0      9
107717     0     0     0      7
```

```
107718      0      0      0       8
107719      0      0      0       2

[107720 rows x 3137 columns]
```

Now we have a dataset of all image pixel data and it is better to save the whole in a `.csv` file for later applications.

[7]:
```
df_digits.to_csv('Digits.csv')
```

[55]:
```
# visualizing sample images
plt.figure(figsize=(12,2))

for i in range(1,6):
    plt.subplot(1,5,i)
    plt.imshow(df_digits.iloc[120+i,:3136].values.reshape(28,28,4))

plt.show()
```



1.2 Split data into train and test sets

Rows in `df_digits` dataframe are numpy arrays, but for the PyTorch model, we must convert them into tensors before splitting into train and test sets.

[9]:
```
# Spliitng data into train and test sets

# set the hyperparameters for data creation
NUM_CLASSES = 10
RANDOM_SEED = 42

X = df_digits.drop('digit', axis=1)
y = df_digits['digit']


# 2. Converting data into tensors
X = torch.tensor(X.to_numpy()).type(torch.float)
y = torch.from_numpy(y.to_numpy()).type(torch.LongTensor) # Must be LongTensor
 --> see documentation
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
                                                    random_state = RANDOM_SEED)

X.shape, y.shape, X_train.shape, y_train.shape
```

[9]:
```
(torch.Size([107720, 3136]),
 torch.Size([107720]),
 torch.Size([86176, 3136]),
 torch.Size([86176]))
```

1.3 PyTorch Model

[10]:
```
class DigitIdentification(nn.Module):
    def __init__(self, input_features, output_features, hidden_sizes = [784,␣
 ↪128, 64]):
        super().__init__()
        self.linear_layers = nn.Sequential(
            nn.Linear(input_features, hidden_sizes[0]),
            nn.ReLU(),
            nn.Linear(hidden_sizes[0], hidden_sizes[1]),
            nn.ReLU(),
            nn.Linear(hidden_sizes[1], hidden_sizes[2]),
            nn.ReLU(),
            nn.Linear(hidden_sizes[2], output_features),
            nn.LogSoftmax(dim=1)
        )

    def forward(self, x):
        return self.linear_layers(x)

model_1 = DigitIdentification(input_features = X.shape[1],
                              output_features = 10,
                              hidden_sizes = [784, 128, 64])

model_1
```

[10]:
```
DigitIdentification(
  (linear_layers): Sequential(
    (0): Linear(in_features=3136, out_features=784, bias=True)
    (1): ReLU()
    (2): Linear(in_features=784, out_features=128, bias=True)
    (3): ReLU()
    (4): Linear(in_features=128, out_features=64, bias=True)
```

```
    (5): ReLU()
    (6): Linear(in_features=64, out_features=10, bias=True)
    (7): LogSoftmax(dim=1)
  )
)
```

Before making the train and test loop, we need to define the loss function, the optimizer, and the accuracy function.

[11]:
```python
# loss function, optimizer, and accuracy function
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params = model_1.parameters(),
                            lr = 0.01)

# accuracy
def accuracy_fn(y_true, y_pred):
    correct = torch.eq(y_true, y_pred).sum().item()
    acc = (correct/len(y_pred)) * 100
    return acc
```

Here we can test our PyTorch model, but it will not give us accurate output, because it is not trained yet. The raw outputs of the model are not in the form of image pixel information. We must first, turn them into prediction probabilities (a magnitude between `0` and `1`), using the `softmax` method and then into pixel info using the `argmax` method, as shown in the following cells.

[12]:
```python
## The raw outputs of the model
y_logits = model_1(X_train)
y_logits.shape, y_logits[:5]
```

[12]:
```
(torch.Size([86176, 10]),
 tensor([[-5.1979, -4.6856, -2.4525, -3.3985, -7.0550, -5.5446, -2.2908,
-0.3357,
          -4.9027, -3.2833],
         [-3.0618, -2.0845, -2.3167, -2.1066, -2.7275, -3.0778, -2.2317,
-1.4449,
          -2.3083, -2.9079],
         [-2.7523, -2.8164, -2.2060, -3.2555, -4.0429, -1.2428, -2.6844,
-1.4407,
          -4.0013, -2.3200],
         [-2.8761, -3.2436, -1.8326, -2.2755, -2.9935, -3.2544, -2.3929,
-1.1862,
          -2.8402, -2.3227],
         [-3.6663, -3.2958, -1.8373, -2.6964, -3.0803, -4.0806, -3.2070,
-0.6103,
          -3.3094, -3.5874]], grad_fn=<SliceBackward0>))
```

```
[13]: ## raw outputs into prediction probabilities
y_pred_probs = torch.softmax(y_logits, dim=1)
y_pred_probs[:5]
```

```
[13]: tensor([[0.0055, 0.0092, 0.0861, 0.0334, 0.0009, 0.0039, 0.1012, 0.7149, 0.0074,
          0.0375],
         [0.0468, 0.1244, 0.0986, 0.1217, 0.0654, 0.0461, 0.1073, 0.2358, 0.0994,
          0.0546],
         [0.0638, 0.0598, 0.1101, 0.0386, 0.0175, 0.2886, 0.0683, 0.2368, 0.0183,
          0.0983],
         [0.0564, 0.0390, 0.1600, 0.1027, 0.0501, 0.0386, 0.0914, 0.3054, 0.0584,
          0.0980],
         [0.0256, 0.0370, 0.1592, 0.0674, 0.0459, 0.0169, 0.0405, 0.5432, 0.0365,
          0.0277]], grad_fn=<SliceBackward0>)
```

```
[14]: ## Finally, we will have image info as output.
y_preds = torch.argmax(y_pred_probs, dim=1)
y_preds[:10], y_train[:10]
```

```
[14]: (tensor([7, 7, 5, 7, 7, 7, 7, 7, 7, 7]),
 tensor([0, 1, 4, 1, 9, 2, 4, 8, 1, 9]))
```

1.3.1 Creating training and testing loops

```
[15]: torch.manual_seed(42)
epochs = 100

time_start = time.time()

for epoch in range(epochs):
    # Trining
    model_1.train()

    # Forward pass
    y_logits = model_1(X_train)
    y_preds = torch.softmax(y_logits, dim=1).argmax(dim=1)

    loss = loss_fn(y_logits, y_train)
    acc = accuracy_fn(y_train, y_preds)

    # Optimizer
    optimizer.zero_grad()

    # Backpropagation
    loss.backward()

    # Optimizer step
```

```
    optimizer.step()

    ## Testing loop
    model_1.eval()
    with torch.inference_mode():
        test_logits = model_1(X_test)
        test_preds = torch.softmax(test_logits, dim=1).argmax(dim=1)
        test_loss = loss_fn(test_logits, y_test)
        test_acc = accuracy_fn(y_test, test_preds)

    ## Printing results, after every ten epochs
    if epoch % 10 == 0:
        print(f'Epoch: {epoch} | Loss: {loss:.4f}, Acc: {acc:.2f}% | Test Loss:␣
 ↪{test_loss:.4f}, Test Acc: {test_acc:.2f}%')

print('-'*20)
print('Time Elapsed: {} seconds'.format(time.time() - time_start))
```

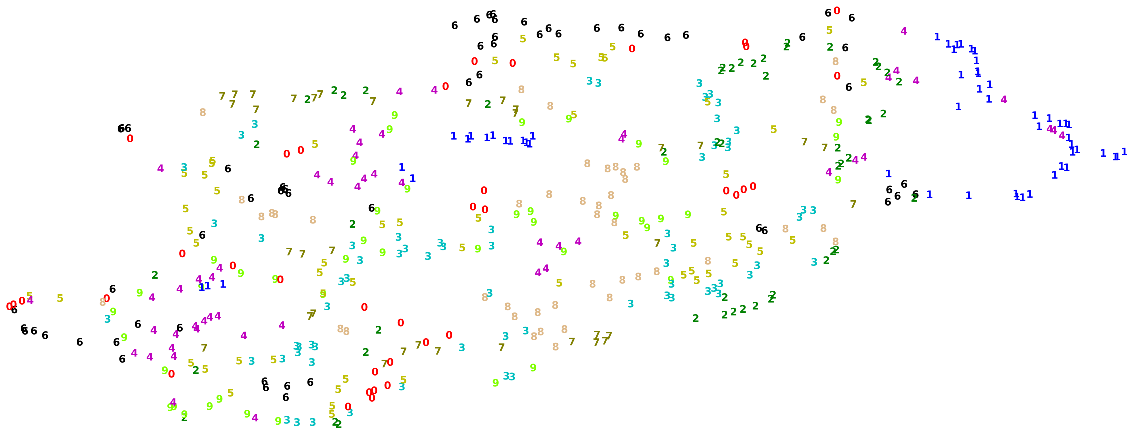
```
Epoch: 0 | Loss: 2.8490, Acc: 10.86% | Test Loss: 2.7807, Test Acc: 11.14%
Epoch: 10 | Loss: 1.8657, Acc: 31.91% | Test Loss: 2.0796, Test Acc: 38.67%
Epoch: 20 | Loss: 1.0565, Acc: 72.52% | Test Loss: 1.0842, Test Acc: 68.76%
Epoch: 30 | Loss: 1.0628, Acc: 68.34% | Test Loss: 0.8513, Test Acc: 74.92%
Epoch: 40 | Loss: 0.4573, Acc: 90.05% | Test Loss: 0.4585, Test Acc: 89.57%
Epoch: 50 | Loss: 0.4990, Acc: 87.52% | Test Loss: 0.4219, Test Acc: 89.74%
Epoch: 60 | Loss: 0.2463, Acc: 95.44% | Test Loss: 0.2469, Test Acc: 95.30%
Epoch: 70 | Loss: 0.1901, Acc: 96.73% | Test Loss: 0.1931, Test Acc: 96.58%
Epoch: 80 | Loss: 0.1527, Acc: 97.56% | Test Loss: 0.1569, Test Acc: 97.33%
Epoch: 90 | Loss: 0.1259, Acc: 98.12% | Test Loss: 0.1307, Test Acc: 97.91%
--------------------
Time Elapsed: 94.18707394599915 seconds
```

1.3.2 Visualizing

For visualization, we must use a dimensionality reduction method. We can use UMAP. It is fast and can handle large datasets with high-dimensional data. UMAP can provide a better big-picture view of your data as well as preserve local neighbor similarities. We assing each digit a unique color.

[16]:
```
import umap
umap_results = umap.UMAP(n_neighbors = 5,
                        min_dist = 0.3,
                        metric = 'correlation').fit_transform(X_test[:500])

plt.figure(figsize=(10,5))
colours = ["r","b","g","c","m","y","k","olive","burlywood","chartreuse"]
for i in range(umap_results.shape[0]):
    plt.text(umap_results[i, 0], umap_results[i, 1], test_preds.numpy()[i],
             color=colours[int(test_preds[i])],
             fontdict={'weight': 'bold', 'size': 70})
```

```
        )

plt.xticks([])
plt.yticks([])
plt.axis('off')
plt.show()
```



1.4 Tensorflow model

Now it is time to use TensorFlow and Keras. We can see the difference between the two libraries, `PyTorch` and `TensorFlow`. There are differences in reading data, the format used in the model, and the hyperparameters and optimizers, as we can see below.

[17]:
```
import tensorflow as tf
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Input
from tensorflow.keras import losses
```

1.4.1 Split data into train and test sets

[18]:
```python
X_tf = df_digits.drop('digit', axis=1)
y_tf = df_digits['digit']

X_tf_train, X_tf_test, y_tf_train, y_tf_test = train_test_split(
    X_tf, y_tf, test_size = 0.2,
    random_state = 42
    )
```

[19]:
```python
X_tf_train.shape, X_tf_test.shape, y_tf_train.shape, y_tf_test.shape
```

[19]:
```
((86176, 3136), (21544, 3136), (86176,), (21544,))
```

[20]:
```python
y_tf_train = to_categorical(y_tf_train, 10)
y_tf_test = to_categorical(y_tf_test, 10)

y_tf_train.shape, y_tf_test.shape
```

[20]:
```
((86176, 10), (21544, 10))
```

[24]:
```python
tf.random.set_seed(42)

model_tf = Sequential()
model_tf.add(Dense(784, input_shape=(3136,), activation='relu'))
model_tf.add(Dense(128, activation='relu'))
model_tf.add(Dense(64, activation='relu'))
model_tf.add(Dense(10, activation='softmax'))
model_tf.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 784)	2,459,408
dense_5 (Dense)	(None, 128)	100,480
dense_6 (Dense)	(None, 64)	8,256
dense_7 (Dense)	(None, 10)	650

Total params: 2,568,794 (9.80 MB)

Trainable params: 2,568,794 (9.80 MB)

```
 Non-trainable params: 0 (0.00 B)
```

In the following training session, we use `Adam` as the optimizer. The reason for this is that, the default `learning rate` of `SGD` is too high and does not converge, something that `Adam` adjusts itself well. Later we will see that by tuning this hyperparameter, `SGD` optimizer also works perfectly. The best loss function for multiclass prediction is `CategoricalCrossentroy`.

[25]:
```
## Adam optimizer works by the default learning rate

model_tf.compile(loss=losses.CategoricalCrossentropy(),
                optimizer='adam',
                metrics=['accuracy'])

time_start = time.time()
model_tf.fit(X_tf_train, y_tf_train,
             batch_size=128,
             epochs = 10,
             verbose =1)

print('-'*50)
score_1 = model_tf.evaluate(X_tf_test, y_tf_test, verbose=0)
print('Test score:', score_1[0])
print('Test accuracy:', score_1[1])

print('_'*20)
print('Time Elapsed: {}'.format(time.time() - time_start))
```

```
Epoch 1/10
674/674             5s 7ms/step -
accuracy: 0.8229 - loss: 2.8638
Epoch 2/10
674/674             5s 7ms/step -
accuracy: 0.9916 - loss: 0.0347
Epoch 3/10
674/674             5s 7ms/step -
accuracy: 0.9883 - loss: 0.0588
Epoch 4/10
674/674             5s 7ms/step -
accuracy: 0.9957 - loss: 0.0235
Epoch 5/10
674/674             5s 7ms/step -
accuracy: 0.9952 - loss: 0.0341
Epoch 6/10
674/674             5s 7ms/step -
accuracy: 0.9935 - loss: 0.0505
Epoch 7/10
674/674             5s 7ms/step -
```

```
accuracy: 0.9959 - loss: 0.0340
Epoch 8/10
674/674              5s 7ms/step -
accuracy: 0.9964 - loss: 0.0360
Epoch 9/10
674/674              5s 7ms/step -
accuracy: 0.9967 - loss: 0.0423
Epoch 10/10
674/674              5s 7ms/step -
accuracy: 0.9980 - loss: 0.0217
--------------------------------------------------
Test score: 0.06887882947921753
Test accuracy: 0.9924340844154358

--------------------
Time Elapsed: 48.84316110610962
```

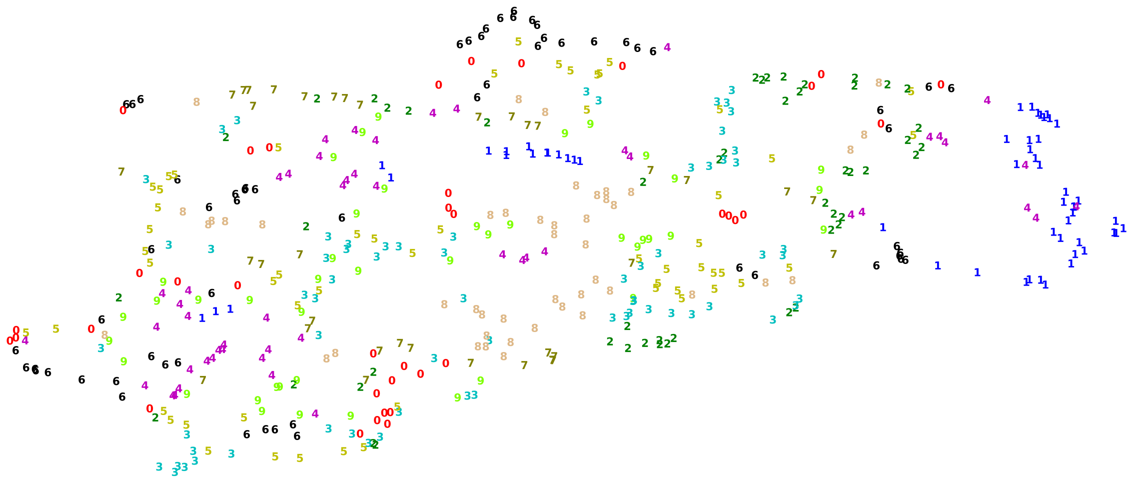
1.4.2 Making Predictions

[27]:
```
y_tf_preds = model_tf.predict(X_tf_test)
predictions = np.argmax(y_tf_preds, axis=1)
predictions.shape
```

```
674/674              1s 1ms/step
```

[27]:
```
(21544,)
```

[28]:
```
umap_tf_results = umap.UMAP(n_neighbors = 5,
                        min_dist = 0.3,
                        metric = 'correlation').fit_transform(X_tf_test[:500])

plt.figure(figsize=(10,5))
colours = ["r","b","g","c","m","y","k","olive","burlywood","chartreuse"]
for i in range(umap_tf_results.shape[0]):
    plt.text(umap_tf_results[i, 0], umap_tf_results[i, 1], predictions[i],
             color=colours[predictions[i]],
             fontdict={'weight': 'bold', 'size': 70}
        )

plt.xticks([])
plt.yticks([])
plt.axis('off')
plt.show()
```



The only difference between the following model and the previous one is the optimizer. In this model we will use SGD, but as I mentioned earlier we have to set the learning rate ourselves.

[50]:
```
## model 2

tf.random.set_seed(42)

model_tf2 = Sequential()
model_tf2.add(Dense(784, input_shape=(3136,), activation='relu'))
model_tf2.add(Dense(128, activation='relu'))
model_tf2.add(Dense(64, activation='relu'))
model_tf2.add(Dense(10, activation='softmax'))
model_tf2.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_8 (Dense)	(None, 784)	2,459,408
dense_9 (Dense)	(None, 128)	100,480
dense_10 (Dense)	(None, 64)	8,256
dense_11 (Dense)	(None, 10)	650

Total params: 2,568,794 (9.80 MB)

Trainable params: 2,568,794 (9.80 MB)

Non-trainable params: 0 (0.00 B)

[51]:
```
## training with batch_size = 512
## SGD optimizer works on learning rates lower than the default.

model_tf2.compile(loss=losses.CategoricalCrossentropy(),
                optimizer=tf.keras.optimizers.SGD(learning_rate=0.001), # low␣
 ↪learning_rate
                metrics=['accuracy'])

time_start = time.time()
model_tf2.fit(X_tf_train, y_tf_train,
             batch_size=512,
             epochs = 10,
             verbose =1)

print('-'*50)
score_2 = model_tf2.evaluate(X_tf_test, y_tf_test, verbose=0)
print('Test score:', score_2[0])
print('Test accuracy:', score_2[1])

print('_'*20)
print('Time Elapsed: {}'.format(time.time() - time_start))
```

```
Epoch 1/10
169/169            2s 11ms/step -
accuracy: 0.4740 - loss: 5.9643
Epoch 2/10
169/169            2s 12ms/step -
accuracy: 0.8716 - loss: 0.4374
Epoch 3/10
169/169            2s 11ms/step -
accuracy: 0.9403 - loss: 0.2002
Epoch 4/10
169/169            2s 11ms/step -
accuracy: 0.9670 - loss: 0.1156
Epoch 5/10
169/169            2s 11ms/step -
accuracy: 0.9798 - loss: 0.0749
Epoch 6/10
169/169            2s 11ms/step -
accuracy: 0.9866 - loss: 0.0524
Epoch 7/10
```

```
169/169              2s 11ms/step -
accuracy: 0.9913 - loss: 0.0387
Epoch 8/10
169/169              2s 11ms/step -
accuracy: 0.9939 - loss: 0.0296
Epoch 9/10
169/169              2s 12ms/step -
accuracy: 0.9957 - loss: 0.0233
Epoch 10/10
169/169              2s 12ms/step -
accuracy: 0.9969 - loss: 0.0189
--------------------------------------------------
Test score: 0.047796934843063354
Test accuracy: 0.9860286116600037
--------------------
Time Elapsed: 20.757277011871338
```

[46]:
```
model_tf2.optimizer.learning_rate
```

[46]:
```
<KerasVariable shape=(), dtype=float32, path=adam/learning_rate>
```

Both PyTorch and TensorFlow have their own advantages, but considering the time of processing, it seems the TensorFlow models will converge in a significantly shorter amount of time.

[ ]:
```
```