

Comparision of Optimizers

Fashion MNIST

The dataset we will use to start is the Fashion MNIST dataset. This dataset contains 60000 images of different clothing items.

In []:

```
import tensorflow as tf
from tensorflow import keras
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In []:

```
data = keras.datasets.fashion_mnist #Loading the dataset
```

In []:

```
(train_images, train_labels), (test_images, test_labels) = data.load_data()
```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz>

32768/29515 [=====] - 0s 0us/step

40960/29515 [=====] - 0s 0us/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz>

26427392/26421880 [=====] - 0s 0us/step

26435584/26421880 [=====] - 0s 0us/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz>

16384/5148 [=====] - 0s 0us/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz>

4423680/4422102 [=====] - 0s 0us/step

4431872/4422102 [=====] - 0s 0us/step

In []:

```
#assigning classes
```

```
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
```

Pre-processing images

We do this by dividing each image by 255. Since each image is greyscale we are simply scaling the pixel values down to make computations easier for our model.

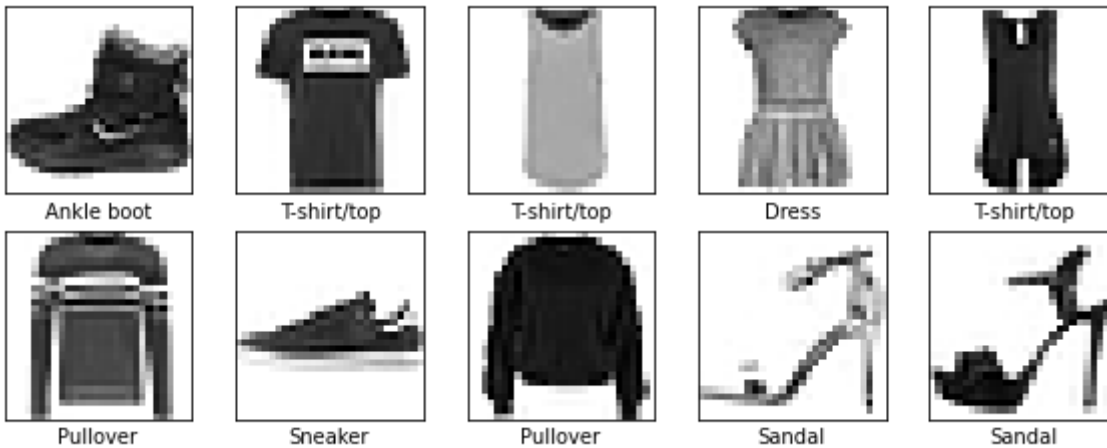
In []:

```

train_images = train_images/255.0
test_images = test_images/255.0

plt.figure(figsize=(10,10))
for i in range(10):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(train_images[i], cmap=plt.cm.binary)
    plt.xlabel(class_names[train_labels[i]])
plt.show()

```



Creating Models

Adam Optimizer

In []:

```

modeladm = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(10)
])

```

RMS optimizer

In []:

```

modelrms = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(10)
])

```

Adagrad optimizer

In []:

```
modeladgrad = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(10)
])
```

SGD optimizers

In []:

```
modelsgd = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(10)
])
```

SGDM optimizer

In []:

```
modelsgdm = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(10)
])
```

Compiling the model with different optimizers

In []:

```
modeladm.compile(optimizer='adam',
                 loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                 metrics=['accuracy'])
modelrms.compile(optimizer='RMSprop',
                 loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                 metrics=['accuracy'])
modeladgrad.compile(optimizer='adagrad',
                   loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                   metrics=['accuracy'])
modelsgd.compile(optimizer='SGD',
                 loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                 metrics=['accuracy'])
opt = tf.keras.optimizers.SGD(learning_rate=0.1, momentum=0.9)
modelsgdm.compile(optimizer=opt,
                  loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                  metrics=['accuracy'])
```

Fitting the model

SGD

In []:

```
hist4=modelsgd.fit(train_images, train_labels, epochs=10)
```

```
Epoch 1/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.7362 -
accuracy: 0.7665
Epoch 2/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.5079 -
accuracy: 0.8269
Epoch 3/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.4645 -
accuracy: 0.8404
Epoch 4/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.4400 -
accuracy: 0.8487
Epoch 5/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.4215 -
accuracy: 0.8548
Epoch 6/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.4079 -
accuracy: 0.8596
Epoch 7/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.3960 -
accuracy: 0.8634
Epoch 8/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.3869 -
accuracy: 0.8655
Epoch 9/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.3785 -
accuracy: 0.8679
Epoch 10/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.3711 -
accuracy: 0.8708
```

SGDM

In []:

```
hist5=modelsgdm.fit(train_images, train_labels, epochs=10)
```

```
Epoch 1/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.7853 -
accuracy: 0.7133
Epoch 2/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.7553 -
accuracy: 0.7110
Epoch 3/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.7148 -
accuracy: 0.7350
Epoch 4/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.6829 -
accuracy: 0.7499
Epoch 5/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.7145 -
accuracy: 0.7428
Epoch 6/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.6809 -
accuracy: 0.7466
Epoch 7/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.7253 -
accuracy: 0.7313
Epoch 8/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.6448 -
accuracy: 0.7670
Epoch 9/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.6561 -
accuracy: 0.7565
Epoch 10/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.6462 -
accuracy: 0.7710
```

Adgrad

In []:

```
hist3=modeladgrad.fit(train_images, train_labels, epochs=10)
```

Epoch 1/10

1875/1875 [=====] - 5s 2ms/step - loss: 1.0645 -
accuracy: 0.6781

Epoch 2/10

1875/1875 [=====] - 4s 2ms/step - loss: 0.7186 -
accuracy: 0.7706

Epoch 3/10

1875/1875 [=====] - 5s 2ms/step - loss: 0.6421 -
accuracy: 0.7951

Epoch 4/10

1875/1875 [=====] - 4s 2ms/step - loss: 0.6014 -
accuracy: 0.8071

Epoch 5/10

1875/1875 [=====] - 4s 2ms/step - loss: 0.5744 -
accuracy: 0.8154

Epoch 6/10

1875/1875 [=====] - 4s 2ms/step - loss: 0.5550 -
accuracy: 0.8207

Epoch 7/10

1875/1875 [=====] - 4s 2ms/step - loss: 0.5396 -
accuracy: 0.8247

Epoch 8/10

1875/1875 [=====] - 4s 2ms/step - loss: 0.5277 -
accuracy: 0.8280

Epoch 9/10

1875/1875 [=====] - 5s 2ms/step - loss: 0.5178 -
accuracy: 0.8305

Epoch 10/10

1875/1875 [=====] - 5s 2ms/step - loss: 0.5092 -
accuracy: 0.8326

RMS prop

In []:

```
hist2=modelrms.fit(train_images, train_labels, epochs=10)
```

Epoch 1/10

1875/1875 [=====] - 6s 3ms/step - loss: 0.5065 -
accuracy: 0.8194

Epoch 2/10

1875/1875 [=====] - 5s 3ms/step - loss: 0.3788 -
accuracy: 0.8645

Epoch 3/10

1875/1875 [=====] - 6s 3ms/step - loss: 0.3446 -
accuracy: 0.8782

Epoch 4/10

1875/1875 [=====] - 6s 3ms/step - loss: 0.3302 -
accuracy: 0.8829

Epoch 5/10

1875/1875 [=====] - 6s 3ms/step - loss: 0.3153 -
accuracy: 0.8897

Epoch 6/10

1875/1875 [=====] - 5s 3ms/step - loss: 0.3076 -
accuracy: 0.8931

Epoch 7/10

1875/1875 [=====] - 5s 3ms/step - loss: 0.2967 -
accuracy: 0.8970

Epoch 8/10

1875/1875 [=====] - 5s 3ms/step - loss: 0.2930 -
accuracy: 0.9000

Epoch 9/10

1875/1875 [=====] - 5s 3ms/step - loss: 0.2856 -
accuracy: 0.9016

Epoch 10/10

1875/1875 [=====] - 5s 3ms/step - loss: 0.2787 -
accuracy: 0.9033

Adam

In []:

```
hist1=modeladm.fit(train_images, train_labels, epochs=10)
```

```
Epoch 1/10
1875/1875 [=====] - 5s 2ms/step - loss: 0.4985 -
accuracy: 0.8242
Epoch 2/10
1875/1875 [=====] - 5s 2ms/step - loss: 0.3745 -
accuracy: 0.8652
Epoch 3/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.3377 -
accuracy: 0.8774
Epoch 4/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.3145 -
accuracy: 0.8844
Epoch 5/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.2955 -
accuracy: 0.8909
Epoch 6/10
1875/1875 [=====] - 5s 2ms/step - loss: 0.2820 -
accuracy: 0.8960
Epoch 7/10
1875/1875 [=====] - 5s 3ms/step - loss: 0.2693 -
accuracy: 0.9005
Epoch 8/10
1875/1875 [=====] - 5s 2ms/step - loss: 0.2577 -
accuracy: 0.9047
Epoch 9/10
1875/1875 [=====] - 5s 2ms/step - loss: 0.2479 -
accuracy: 0.9078
Epoch 10/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.2406 -
accuracy: 0.9098
```

Plotting accuracies with respect to epochs

In []:

```
ep=np.arange(1,11,1)

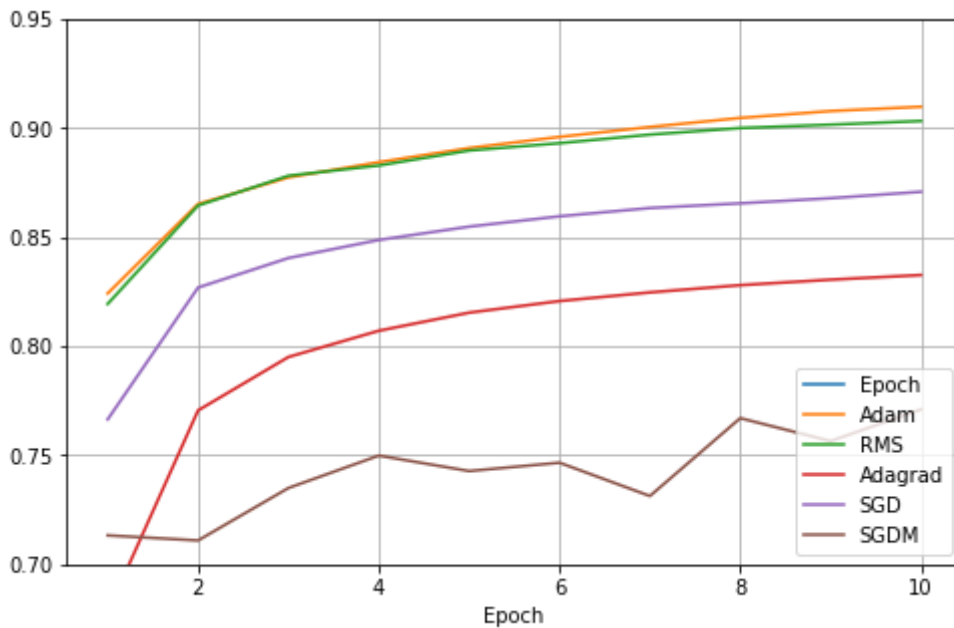
acc1=hist1.history['accuracy']
acc2=hist2.history['accuracy']
acc3=hist3.history['accuracy']
acc4=hist4.history['accuracy']
acc5=hist5.history['accuracy']
list_of_tuples = list(zip(ep,acc1,acc2,acc3,acc4,acc5))
```

In []:

```
df = pd.DataFrame(list_of_tuples, columns = ['Epoch', 'Adam', 'RMS', 'Adagrad', 'SGD', 'SGD
M'])
```


In []:

```
df.index = df['Epoch']
df.plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(.7, .95) # set the vertical range to [0-1]
plt.show()
```



Validation using test set

In []:

```
modeladm.evaluate(test_images, test_labels)
modelrms.evaluate(test_images, test_labels)
modeladgrad.evaluate(test_images, test_labels)
modelsgd.evaluate(test_images, test_labels)
```

```
313/313 [=====] - 1s 2ms/step - loss: 0.3500 - ac
curacy: 0.8747
313/313 [=====] - 1s 2ms/step - loss: 0.3881 - ac
curacy: 0.8815
313/313 [=====] - 1s 2ms/step - loss: 0.5320 - ac
curacy: 0.8174
313/313 [=====] - 1s 3ms/step - loss: 0.4090 - ac
curacy: 0.8554
```

Out[]:

```
[0.40901100635528564, 0.855400025844574]
```