```
import tensorflow as tf
from tensorflow import keras
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
import random
from tensorflow.compiler.tf2xla.python import xla
```

```
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()

print("4 Random Training samples and labels")
idx1, idx2, idx3, idx4 = random.sample(range(0, x_train.shape[0]), 4)

img1 = (x_train[idx1], y_train[idx1])
img2 = (x_train[idx2], y_train[idx2])
img3 = (x_train[idx3], y_train[idx3])
img4 = (x_train[idx4], y_train[idx4])

imgs = [img1, img2, img3, img4]

plt.figure(figsize=(10, 10))

for idx, item in enumerate(imgs):
    image, label = item[0], item[1]
    plt.subplot(2, 2, idx + 1)
    plt.imshow(image, cmap="gray")
    plt.title(f"Label : {label}")
plt.show()
```

module: random

Open in tab View source

Random variable generators.

bytes

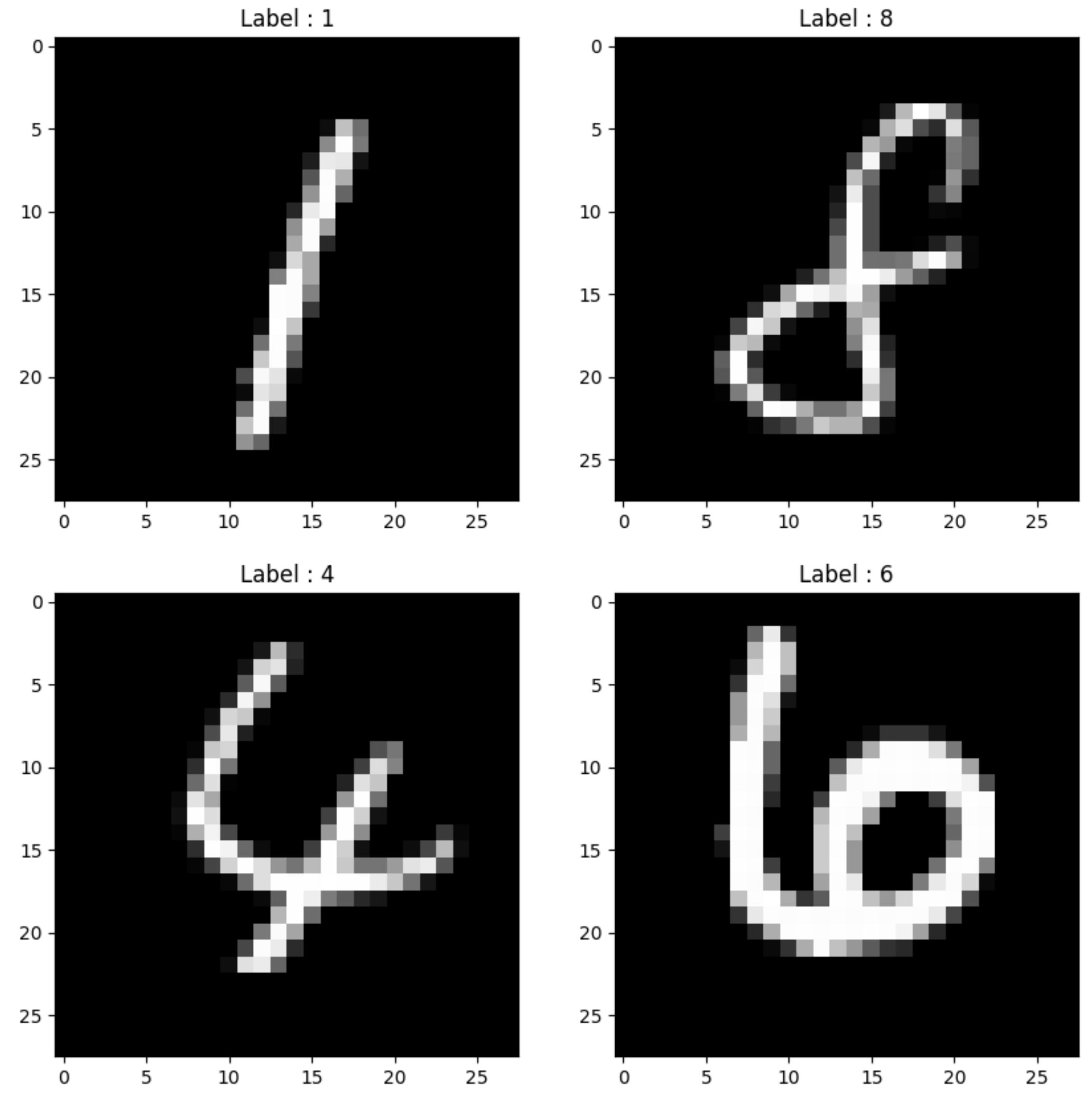
uniform bytes (values between 0 and 255)

integers

uniform within range

sequences

```
4 Random Training samples and labels
```



```
class FFDense(keras.layers.Layer):
    """
    A custom ForwardForward-enabled Dense layer. It has an implementation of the
    Forward-Forward network internally for use.
    This layer must be used in conjunction with the `FFNetwork` model.
    """

    def __init__(
        self,
        units,
        optimizer,
        loss_metric,
        num_epochs=50,
        use_bias=True,
        kernel_initializer="glorot_uniform",
        bias_initializer="zeros",
        kernel_regularizer=None,
        bias_regularizer=None,
        **kwargs,
    ):
        super().__init__(**kwargs)
        self.dense = keras.layers.Dense(
            units=units,
            use_bias=use_bias,
            kernel_initializer=kernel_initializer,
            bias_initializer=bias_initializer,
            kernel_regularizer=kernel_regularizer,
            bias_regularizer=bias_regularizer,
        )
        self.relu = keras.layers.ReLU()
        self.optimizer = optimizer
        self.loss_metric = loss_metric
        self.threshold = 1.5
        self.num_epochs = num_epochs

    # We perform a normalization step before we run the input through the Dense
    # layer.

    def call(self, x):
        x_norm = tf.norm(x, ord=2, axis=1, keepdims=True)
        x_norm = x_norm + 1e-4
        x_dir = x / x_norm
        res = self.dense(x_dir)
        return self.relu(res)

    # The Forward-Forward algorithm is below. We first perform the Dense-layer
    # operation and then get a Mean Square value for all positive and negative
    # samples respectively.
    # The custom loss function finds the distance between the Mean-squared
    # result and the threshold value we set (a hyperparameter) that will define
    # whether the prediction is positive or negative in nature. Once the loss is
    # calculated, we get a mean across the entire batch combined and perform a
    # gradient calculation and optimization step. This does not technically
    # qualify as backpropagation since there is no gradient being
    # sent to any previous layer and is completely local in nature.

    def forward_forward(self, x_pos, x_neg):
        for i in range(self.num_epochs):
            with tf.GradientTape() as tape:
                g_pos = tf.math.reduce_mean(tf.math.pow(self.call(x_pos), 2), 1)
                g_neg = tf.math.reduce_mean(tf.math.pow(self.call(x_neg), 2), 1)

                loss = tf.math.log(
                    1
                    + tf.math.exp(
                        tf.concat([-g_pos + self.threshold, g_neg - self.threshold], 0)
                    )
                )
                mean_loss = tf.cast(tf.math.reduce_mean(loss), tf.float32)
                self.loss_metric.update_state([mean_loss])
            gradients = tape.gradient(mean_loss, self.dense.trainable_weights)
            self.optimizer.apply_gradients(zip(gradients, self.dense.trainable_weights))
        return (
            tf.stop_gradient(self.call(x_pos)),
            tf.stop_gradient(self.call(x_neg)),
            self.loss_metric.result(),
        )
```

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```
class FFNetwork(keras.Model):
    """
    A [`keras.Model`](/api/models/model#model-class) that supports a `FFDense` network creation. This model
    can work for any kind of classification task. It has an internal
    implementation with some details specific to the MNIST dataset which can be
    changed as per the use-case.
    """

    # Since each layer runs gradient-calculation and optimization locally, each
    # layer has its own optimizer that we pass. As a standard choice, we pass
    # the `Adam` optimizer with a default learning rate of 0.03 as that was
    # found to be the best rate after experimentation.
    # Loss is tracked using `loss_var` and `loss_count` variables.
    # Use legacy optimizer for Layer Optimizer to fix issue
    # https://github.com/keras-team/keras-io/issues/1241

    def __init__(
        self,
        dims,
        layer_optimizer=keras.optimizers.legacy.Adam(learning_rate=0.03),
        **kwargs,
    ):
        super().__init__(**kwargs)
        self.layer_optimizer = layer_optimizer
        self.loss_var = tf.Variable(0.0, trainable=False, dtype=tf.float32)
        self.loss_count = tf.Variable(0.0, trainable=False, dtype=tf.float32)
        self.layer_list = [keras.Input(shape=(dims[0],))]
        for d in range(len(dims) - 1):
            self.layer_list += [
                FFDense(
                    dims[d + 1],
                    optimizer=self.layer_optimizer,
                    loss_metric=keras.metrics.Mean(),
                )
            ]

    # This function makes a dynamic change to the image wherein the labels are
    # put on top of the original image (for this example, as MNIST has 10
    # unique labels, we take the top-left corner's first 10 pixels). This
    # function returns the original data tensor with the first 10 pixels being
    # a pixel-based one-hot representation of the labels.

    @tf.function(reduce_retracing=True)
    def overlay_y_on_x(self, data):
        X_sample, y_sample = data
        max_sample = tf.reduce_max(X_sample, axis=0, keepdims=True)
        max_sample = tf.cast(max_sample, dtype=tf.float64)
        X_zeros = tf.zeros([10], dtype=tf.float64)
        X_update = xla.dynamic_update_slice(X_zeros, max_sample, [y_sample])
        X_sample = xla.dynamic_update_slice(X_sample, X_update, [0])
        return X_sample, y_sample

    # A custom `predict_one_sample` performs predictions by passing the images
    # through the network, measures the results produced by each layer (i.e.
    # how high/low the output values are with respect to the set threshold for
    # each label) and then simply finding the label with the highest values.
    # In such a case, the images are tested for their 'goodness' with all
    # labels.

    @tf.function(reduce_retracing=True)
    def predict_one_sample(self, x):
        goodness_per_label = []
        x = tf.reshape(x, [tf.shape(x)[0] * tf.shape(x)[1]])
        for label in range(10):
            h, label = self.overlay_y_on_x(data=(x, label))
            h = tf.reshape(h, [-1, tf.shape(h)[0]])
            goodness = []
            for layer_idx in range(1, len(self.layer_list)):
                layer = self.layer_list[layer_idx]
                h = layer(h)
                goodness += [tf.math.reduce_mean(tf.math.pow(h, 2), 1)]
            goodness_per_label += [
                tf.expand_dims(tf.reduce_sum(goodness, keepdims=True), 1)
            ]
        goodness_per_label = tf.concat(goodness_per_label, 1)
        return tf.cast(tf.argmax(goodness_per_label, 1), tf.float64)

    def predict(self, data):
        x = data
```

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Open in tab View source
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```
        preds = list()
        preds = tf.map_fn(fn=self.predict_one_sample, elems=x)
        return np.asarray(preds, dtype=int)

    # This custom `train_step` function overrides the internal `train_step`
    # implementation. We take all the input image tensors, flatten them and
    # subsequently produce positive and negative samples on the images.
    # A positive sample is an image that has the right label encoded on it with
    # the `overlay_y_on_x` function. A negative sample is an image that has an
    # erroneous label present on it.
    # With the samples ready, we pass them through each `FFLayer` and perform
    # the Forward-Forward computation on it. The returned loss is the final
    # loss value over all the layers.

    @tf.function(jit_compile=True)
    def train_step(self, data):
        x, y = data

        # Flatten op
        x = tf.reshape(x, [-1, tf.shape(x)[1] * tf.shape(x)[2]])

        x_pos, y = tf.map_fn(fn=self.overlay_y_on_x, elems=(x, y))

        random_y = tf.random.shuffle(y)
        x_neg, y = tf.map_fn(fn=self.overlay_y_on_x, elems=(x, random_y))

        h_pos, h_neg = x_pos, x_neg

        for idx, layer in enumerate(self.layers):
            if isinstance(layer, FFDense):
                print(f"Training layer {idx+1} now : ")
                h_pos, h_neg, loss = layer.forward_forward(h_pos, h_neg)
                self.loss_var.assign_add(loss)
                self.loss_count.assign_add(1.0)
            else:
                print(f"Passing layer {idx+1} now : ")
                x = layer(x)
        mean_res = tf.math.divide(self.loss_var, self.loss_count)
        return {"FinalLoss": mean_res}
```

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Open in tab View source

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```
x_train = x_train.astype(float) / 255
x_test = x_test.astype(float) / 255
y_train = y_train.astype(int)
y_test = y_test.astype(int)

train_dataset = tf.data.Dataset.from_tensor_slices((x_train, y_train))
test_dataset = tf.data.Dataset.from_tensor_slices((x_test, y_test))

train_dataset = train_dataset.batch(60000)
test_dataset = test_dataset.batch(10000)


model = FFNetwork(dims=[784, 500, 500])

model.compile(
    optimizer=keras.optimizers.Adam(learning_rate=0.03),
    loss="mse",
    jit_compile=True,
    metrics=[keras.metrics.Mean()],
)

epochs = 5
history = model.fit(train_dataset, epochs=epochs)
```

```
Epoch 1/5
Training layer 1 now : 
Training layer 2 now : 
Training layer 1 now : 
Training layer 2 now : 
1/1 [==============================] - 427s 427s/step - FinalLoss: 0.7280
Epoch 2/5
1/1 [==============================] - 268s 268s/step - FinalLoss: 0.7084
Epoch 3/5
1/1 [==============================] - 283s 283s/step - FinalLoss: 0.7029
Epoch 4/5
1/1 [==============================] - 267s 267s/step - FinalLoss: 0.6805
Epoch 5/5
1/1 [==============================] - 269s 269s/step - FinalLoss: 0.6566
```

```
preds = model.predict(tf.convert_to_tensor(x_test))

preds = preds.reshape((preds.shape[0], preds.shape[1]))

results = accuracy_score(preds, y_test)

print(f"Test Accuracy score : {results*100}%")

plt.plot(range(len(history.history["FinalLoss"])), history.history["FinalLoss"])
plt.title("Loss over training")
plt.show()
```

```
Test Accuracy score : 79.81%
```