Introduction to Keras and TensorFlow

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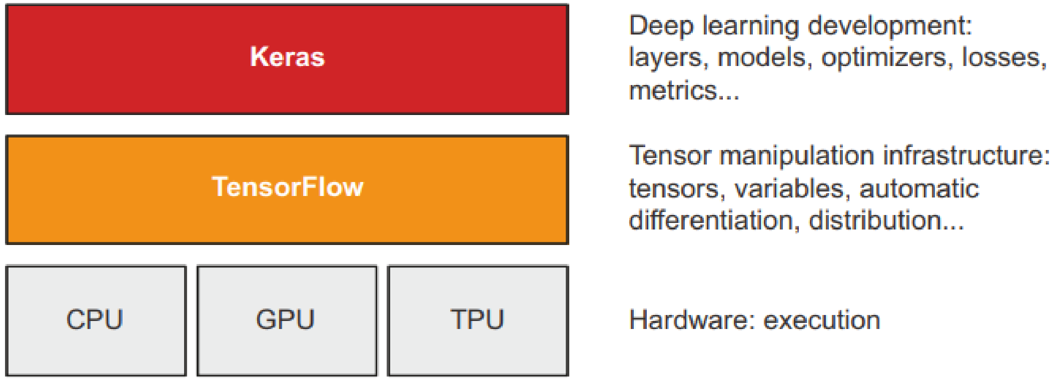
What’s TensorFlow?

- TensorFlow is a Python-based, free, open source machine learning platform, developed primarily by Google.
- It can automatically compute the gradient of any differentiable expression
- It can run not only on CPUs, but also on GPUs and TPUs, highly parallel hardware accelerators.
- Computation defined in TensorFlow can be easily distributed across many machines.
- TensorFlow programs can be exported to other runtimes, such as C++, JavaScript or TensorFlow Lite (on mobile or embedded devices), etc.
- TensorFlow scales fairly well
  - Oak Ridge National Lab have used it to train a 1.1 exaFLOPS extreme weather forecasting model on the 27,000 GPUs of the IBM Summit supercomputer

What’s Keras?

- Keras is a deep learning API for Python, built on top of TensorFlow, to define and train any kind of deep learning model.
- Through TensorFlow, Keras can run on top of different types of hardware—CPU, GPU, TPU and can be seamlessly scaled to thousands of machines.
- Keras prioritizes the developer experience-an API for human beings, not machines.
- Keras is easy to learn for beginners and highly productive for experts
- Keras has a large and diverse user base-Google, Netflix, Uber, CERN, NASA, Yelp, Instacart, Square and used in Waymo self-driving cars and YouTube recommendations

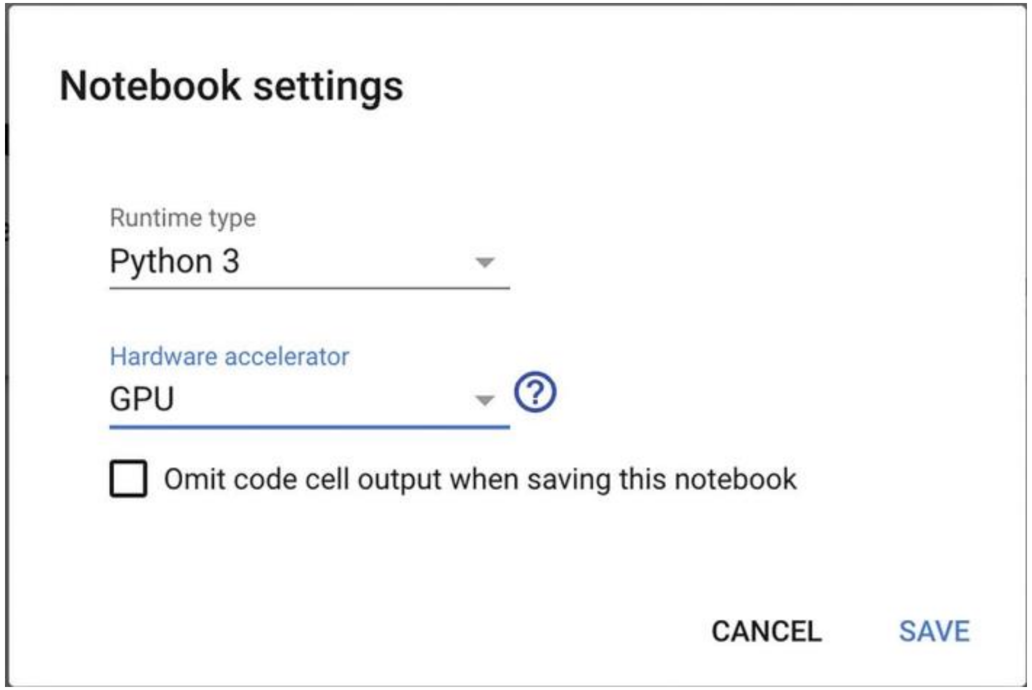


Setting up a deep learning workspace

- Highly recommended to run deep learning code on a modern NVIDIA GPU rather than computer's CPU
- To do deep learning on a GPU, you have three options:
  - Buy and install a physical NVIDIA GPU on your workstation.
  - Use GPU instances on Google Cloud or AWS EC2.
  - Use the free GPU runtime from Colaboratory.
- Jupyter notebooks: The preferred way to run deep learning experiments
- Colaboratory: a free Jupyter notebook service in the cloud, execute Keras scripts right away.
  - Gives access to a free (but limited) GPU runtime and even a TPU runtime.

Using The GPU Runtime With Colab

- select Runtime > Change Runtime Type in the menu and select GPU for the Hardware Accelerator.



First steps with TensorFlow

- First, low-level tensor manipulation. This requires TensorFlow APIs:
  - Tensors
  - Tensor operations such as addition, relu, matmul
  - Backpropagation, a way to compute the gradient of math expressions
- Second, high-level deep learning concepts. This requires Keras APIs.
  - Layers, which are combined into a model
  - A loss function, which defines the feedback signal used for learning
  - An optimizer, which determines how learning proceeds
  - Metrics to evaluate model performance, such as accuracy
  - A training loop that performs mini-batch stochastic gradient descent

Constant tensors and variables

Listing 3.1 All-ones or all-zeros tensors

```
>>> import tensorflow as tf
>>> x = tf.ones(shape=(2, 1))
>>> print(x)
tf.Tensor(
[[1.]
 [1.]], shape=(2, 1), dtype=float32)
>>> x = tf.zeros(shape=(2, 1))
>>> print(x)
tf.Tensor(
[[0.]
 [0.]], shape=(2, 1), dtype=float32)
```

Equivalent to np.ones(shape=(2, 1))

Equivalent to np.zeros(shape=(2, 1))

Unlike NumPy arrays, TensorFlow tensors aren't assignable.

Listing 3.3 NumPy arrays are assignable

```
import numpy as np
x = np.ones(shape=(2, 2))
x[0, 0] = 0.
```

Listing 3.4 TensorFlow tensors are not assignable

```
x = tf.ones(shape=(2, 2))
x[0, 0] = 0.
```

This will fail, as a tensor isn't assignable.

Creating a TensorFlow variable

- To create a variable, you need to provide some initial value, such as a random tensor.

Listing 3.5 Creating a TensorFlow variable

```
>>> v = tf.Variable(initial_value=tf.random.normal(shape=(3, 1)))
>>> print(v)
array([[-0.75133973],
       [-0.4872893 ],
       [ 1.6626885 ]], dtype=float32)>
```

Listing 3.6 Assigning a value to a TensorFlow variable

```
>>> v.assign(tf.ones((3, 1)))
array([[1.],
       [1.],
       [1.]], dtype=float32)>
```

Listing 3.8 Using `assign_add()`

```
>>> v.assign_add(tf.ones((3, 1)))
array([[2.],
       [2.],
       [2.]], dtype=float32)>
```

Tensor operations: Doing math in TensorFlow

Listing 3.9 A few basic math operations

```
a = tf.ones((2, 2))
b = tf.square(a)
c = tf.sqrt(a)
d = b + c
e = tf.matmul(a, b)
e *= d
```

- `b = tf.square(a)`: Take the square.
- `c = tf.sqrt(a)`: Take the square root.
- `d = b + c`: Add two tensors (element-wise).
- `e = tf.matmul(a, b)`: Take the product of two tensors (as discussed in chapter 2).
- `e *= d`: Multiply two tensors (element-wise).

Like NumPy

Listing 3.10 Using the `GradientTape`

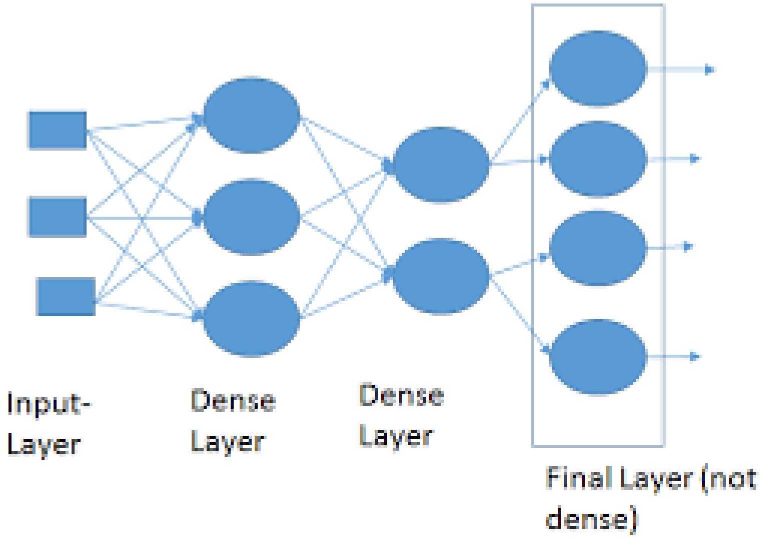
NumPy Can't Do

```
input_var = tf.Variable(initial_value=3.)
with tf.GradientTape() as tape:
   result = tf.square(input_var)
gradient = tape.gradient(result, input_var)
```

Anatomy of a neural network: Understanding core Keras APIs

Layers: The building blocks of deep learning

- A layer is a data processing module that takes as input one or more tensors and that outputs one or more tensors.
- In Keras, a Layer is an object that encapsulates some state (weights) and some computation (a forward pass).



Listing 3.22 A `Dense` layer implemented as a `Layer` subclass

```
from tensorflow import keras

class SimpleDense(keras.layers.Layer):
```

All Keras layers inherit from the base Layer class.

The “compile” step: Configuring the learning process

- Once the model architecture is defined, we have to choose three more things
  - ***Loss function*** — a measure of success that will be minimized during training.
  - ***Optimizer***—Determines how the network will be updated based on the loss function.
  - ***Metrics***—The measures of success you want to monitor during training and validation, such as classification accuracy.
- Use the built-in compile() and fit() methods to start training model
  - The compile() method configures the training process.
  - The fit() method implements the training loop itself

The “compile” step…

```
model = keras.Sequential([keras.layers.Dense(1)])
model.compile(optimizer="rmsprop",
              loss="mean_squared_error",
              metrics=["accuracy"])
```

Define a linear classifier.

Specify the optimizer by name: RMSprop (it’s case-insensitive).

Specify the loss by name: mean squared error.

Specify a list of metrics: in this case, only accuracy.

The “compile” step: Keras Options

- Optimizers:
  - SGD (with or without momentum)
  - RMSprop
  - Adam
  - Adagrad
- Losses:
  - CategoricalCrossentropy
  - SparseCategoricalCrossentropy
  - BinaryCrossentropy
  - MeanSquaredError
  - KLDivergence
  - CosineSimilarity

The “compile” step: Keras Options

- Metrics:
  - CategoricalAccuracy
  - SparseCategoricalAccuracy
  - BinaryAccuracy
  - AUC
  - Precision
  - Recall

Understanding the fit() method

Listing 3.23 Calling `fit()` with NumPy data

```
history = model.fit(
    inputs,
    targets,
    epochs=5,
    batch_size=128
)
```

The input examples, as a NumPy array

The corresponding training targets, as a NumPy array

The training loop will iterate over the data 5 times.

The training loop will iterate over the data in batches of 128 examples.

```
>>> history.history
{"binary_accuracy": [0.855, 0.9565, 0.9555, 0.95, 0.951],
 "loss": [0.6573270302042366,
          0.07434618508815766,
          0.07687718723714351,
          0.07412414988875389,
          0.07617757616937161]}
```

Monitoring loss and metrics on validation data

```
model.fit(
    training_inputs,
    training_targets,
    epochs=5,
    batch_size=16,
    validation_data=(val_inputs, val_targets)
)
```

Training data, used to update the weights of the model

Validation data, used only to monitor the validation loss and metrics

Inference: Using a model after training

```
predictions = model(new_inputs)
```

Takes a NumPy array or TensorFlow tensor and returns a TensorFlow tensor

```
predictions = model.predict(new_inputs, batch_size=128)
```

Takes a NumPy array or a Dataset and returns a NumPy array

```
>>> predictions = model.predict(val_inputs, batch_size=128)
>>> print(predictions[:10])
[[0.3590725 ]
 [0.82706255]
 [0.74428225]
 [0.682058  ]
 [0.7312616 ]
 [0.6059811 ]
 [0.78046083]
 [0.025846  ]
 [0.16594526]
 [0.72068727]]
```

Results of *predict()* on some validation data with the linear model we trained earlier. we get scalar scores that correspond to the model's prediction for each input sample.

Digit Recognition Example: Model configuration

```
from tensorflow.keras.datasets import mnist
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 2s 0us/step
```

```
from tensorflow import keras
from tensorflow.keras import layers
model = keras.Sequential([
layers.Dense(512, activation="relu"),
layers.Dense(10, activation="softmax")
])
```

- Here, our model consists of a sequence of two Dense layers. The second (and last) layer is a 10-way *softmax classification* layer, which means it will return an array of 10 probability scores (summing to 1).
- Each score will be the probability that the current digit image belongs to one of our 10 digit classes.

Digit Recognition Example: …Data preprocessing

```
model.compile(optimizer="rmsprop",
loss="sparse_categorical_crossentropy",
metrics=["accuracy"])
```

```
train_images = train_images.reshape((60000, 28 * 28))
train_images = train_images.astype("float32") / 255
test_images = test_images.reshape((10000, 28 * 28))
test_images = test_images.astype("float32") / 255
```

- Before training, the data is reshaped into the shape the model expects and scaled it so that all values are in the [0, 1] interval.

Digit Recognition Example: Training the model

```
model.fit(train_images, train_labels, epochs=5, batch_size=128)
```

```
Epoch 1/5
469/469 [==============================] - 4s 3ms/step - loss: 0.2559 - accuracy: 0.9253
Epoch 2/5
469/469 [==============================] - 1s 3ms/step - loss: 0.1030 - accuracy: 0.9697
Epoch 3/5
469/469 [==============================] - 1s 3ms/step - loss: 0.0683 - accuracy: 0.9797
Epoch 4/5
469/469 [==============================] - 1s 3ms/step - loss: 0.0488 - accuracy: 0.9852
Epoch 5/5
469/469 [==============================] - 2s 4ms/step - loss: 0.0371 - accuracy: 0.9893
<keras.callbacks.History at 0x7f0750517040>
```

Training accuracy

Digit Recognition Example: Model testing

```
test_digits = test_images[0:10]
predictions = model.predict(test_digits)
predictions[0]
```

```
1/1 [==============================] - 0s 60ms/step
array([3.8975578e-09, 4.2572078e-11, 5.4741922e-06, 7.7760007e-05,
       6.4008993e-12, 5.3976187e-08, 3.1037809e-15, 9.9991536e-01,
       2.4116693e-07, 1.1648450e-06], dtype=float32)
```

```
test_labels[0]
```

```
7
```

average accuracy over the entire test set

```
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f"test_acc: {test_acc}")
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.0670 - accuracy: 0.9797
test_acc: 0.9797000288963318
```

- Test-set accuracy turns out to be 97.8%—that’s a bit lower than the training set accuracy (98.9%).
- This gap is an example of overfitting: the fact that machine learning models tend to perform worse on new data than on their training data.

Summary

- TensorFlow is an industry-strength numerical computing framework that can run on CPU, GPU, or TPU. It can automatically compute the gradient of any differentiable expression.
- Key TensorFlow objects include tensors, variables, tensor operations, and the gradient tape.
- The central class of Keras is the Layer. A *layer* encapsulates some weights and some computation. Layers are assembled into *models*.
- Before you start training a model, you need to pick an *optimizer*, a *loss*, and some *metrics*, which you specify via the *model.compile()* method.
- To train a model, you can use the *fit()* method, which runs mini-batch gradient descent for you. You can also use it to monitor your loss and metrics on *validation data*.
- Once your model is trained, you use the *model.predict()* method to generate predictions on new inputs.