

Keras

In this module we will introduce Keras (<https://keras.io/>), a high level API for Neural Networks.

To be specific

- we will mostly restrict ourselves to the Keras Sequential model
- this will greatly simplify your learning and coding
- it will restrict the type of Deep Learning programs that you can write
 - but not a meaningful restriction for the simple programs that you will write in this course

After we introduce the high level Keras API

- we will review the history of Deep Learning programming to see how we got here
- this will give you greater insight into what Keras does "under the covers"
 - appreciate history
 - aid your diagnostics

Note:

The code snippets in this notebook are *fragments* of a larger [notebook](#) ([DNN TensorFlow example.ipynb](#)).

- are illustrative: will not actually execute in this notebook but will in the complete notebook

Confusion warning:

- There are two similar *but different* packages that implement Keras
 - one built into TensorFlow (the one we will use)
 - a separate project

Later in this module we will explain the difference and why it's important to distinguish between them.

The Keras Sequential Model

Reference: [Getting started with the Keras Sequential Model \(https://keras.io/getting-started/sequential-model-guide/\)](https://keras.io/getting-started/sequential-model-guide/).

Keras has two programming models

- Sequential
- Functional

We will start with the Sequential model

The Sequential model allows you to build Neural Networks (NN) that are composed of a *sequence* of layers

- just like our cartoon
- a very prevalent paradigm

This will likely be sufficient in your initial studies

- but it restricts the architecture of the Neural Networks that you can build
- use the Functional API for full generality
 - but it might appear more complicated

Let's jump into some code.

Some old friends, in new clothing:

```
import tensorflow as tf from tensorflow.keras.models import Model, Sequential from tensorflow.keras
import layers # Regression reg_model = Sequential([ layers.Dense(1, activation=None,
input_dim=x.shape[1]) ] ) reg_model.compile(optimizer='rmsprop', loss='mse') reg_model.fit(x, y,
nb_epoch=10, validation_data=(x_val, y_val))
```



```
# Classification class_model = Sequential([ layers.Dense(1, activation="sigmoid", input_dim=x.shape[1]) ] )  
class_model.compile(optimizer='rmsprop', loss='binary_crossentropy') class_model.fit(x, y, nb_epoch=10,  
validation_data=(x_val, y_val))
```

TL;DR

- Both examples are a single layer
 - Dense, with 1 unit ("neuron")
- Regression example
 - No activation
 - MSE cost
- Binary classification example
 - Sigmoid activation
 - Binary cross entropy cost

Hopefully you get the idea.

Let's explore a slightly more complicated model.

```
import tensorflow as tf from tensorflow.keras.models import Model, Sequential from tensorflow.keras
import layers mnist_model = Sequential([ layers.Dense(n_hidden_1, activation=tf.nn.relu,
name="hidden1", input_shape=(input_size,)), layers.Dense(n_hidden_2, activation=tf.nn.relu,
name="hidden2") layers.Dense(output_size,activation=tf.nn.softmax, name="outputs") ] )
```

This defines a NN with three layers

- we will explain the layers in detail later

To use the model, you first need to "compile" it

```
metrics = [ "acc" ] mnist_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',  
metrics=metrics)
```

"Compiling" is quite significant as we will demonstrate later

- For now: *it is where you define the Cost/Loss function*

Next, just as in `sklearn` : you "fit" the model to the training data.

```
history = mnist_model.fit(X_train, y_train, epochs=n_epochs, batch_size=batch_size, validation_data=(X_valid, y_valid), shuffle=True )
```


Once the model is fit, you can predict, just like `sklearn` .

Here we evaluate the model on the Test dataset.

```
test_loss, test_accuracy = mnist_model.evaluate(X_test, y_test) print("Test dataset: loss={tl:5.4f},  
accuracy={ta:5.4f}".format(tl=test_loss, ta=test_accuracy))
```

The idea is quite simple

- Keras Sequential implements an sklearn-like API
 - define a model
 - fit the model
 - predict

We have glossed over a lot of details

- What does each layer do ?
- Why do we need to "compile" ?
 - and why does it need an optimizer ?

The Keras Functional Model

- More verbose than Sequential
- Also more flexible
 - you can define more complex computation graphs (multiple inputs/outputs, shared layers)

```
from keras.layers import Input, Dense from keras.models import Model # This returns a tensor inputs =  
Input(shape=(784,)) # a layer instance is callable on a tensor, and returns a tensor x = Dense(32,  
activation='relu')(inputs) predictions = Dense(10, activation='softmax')(x) # This creates a model that  
includes # the Input layer and Dense layers model = Model(inputs=inputs, outputs=predictions)
```

Highlights:

- Manually invoke a single layer at a time
 - Passing as input the output of the prior layer.
- You must define an `Input` layer (placeholder for the input/define its shape)
 - `Sequential` uses the `input_shape=` parameter to the first layer
- You "wrap" the graph into a "model" by a `Model` statement
 - looks like a function definition
 - names the input and output formal parameters
 - a `Model` acts just like a layer (but with internals that you create)

```
model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy']) model.fit(data,  
labels) # starts training
```


As a beginner, you will probably exclusively use the Sequential model.

Keep the Functional API in the back of your mind.

Let's code !

Lets see a working notebook.

Two options

- Run on your local machine: [DNN Tensorflow example Notebook local \(DNN TensorFlow example.ipynb\)](#) (local)
 - Tensorflow version 2+ only !
- Run on Google Colab: [DNN Tensorflow example Notebook from github \(https://colab.research.google.com/github/kenperry-public/ML_Spring_2020/blob/master/DNN_TensorFlow_example.ipynb\)](#) (Colab)

```
In [1]: print("Done")
```

Done