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/)

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_Fall_2021/blob/master/DNN_TensorFlow_example.ipynb) (**Colab**)

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

```
Done
```