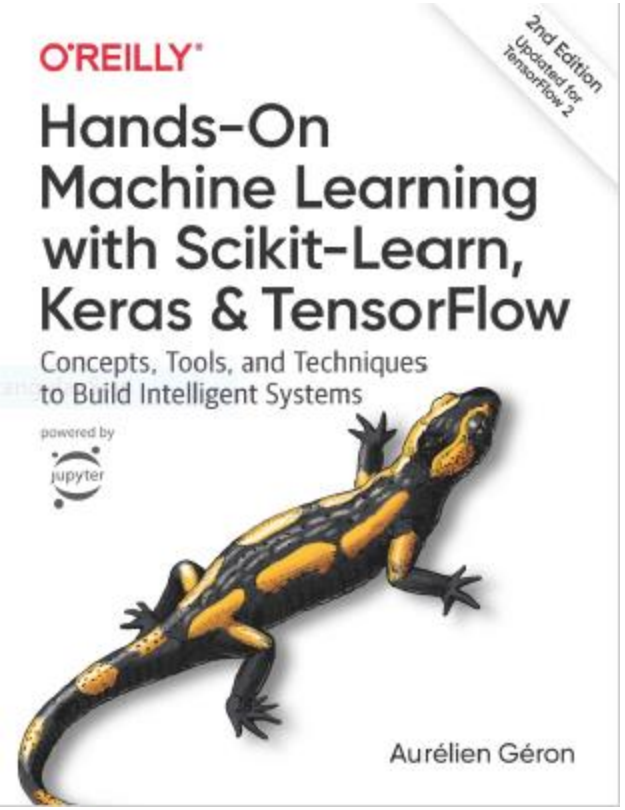
Artificial Neural Networks with Keras

Prof. Gheith Abandah

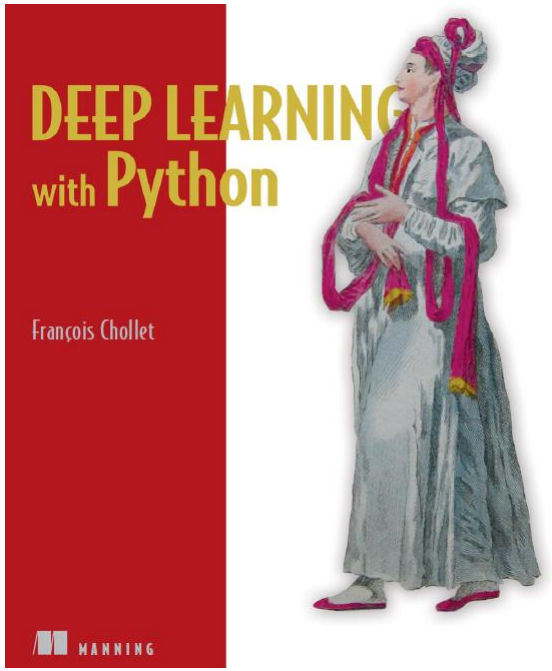
Reference

- Chapter 10: **Introduction to Artificial Neural Networks with Keras**



- Aurélien Géron, **Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow**, O'Reilly, 2nd Edition, 2019
  - Material: https://github.com/ageron/handson-ml2

Reference



- **Deep Learning with Python**, by François Chollet, Manning Pub. 2018
- **Introduction to Keras** by Francois Chollet, March 9th, 2018 (slides)

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1. Introduction
2. Keras API Styles
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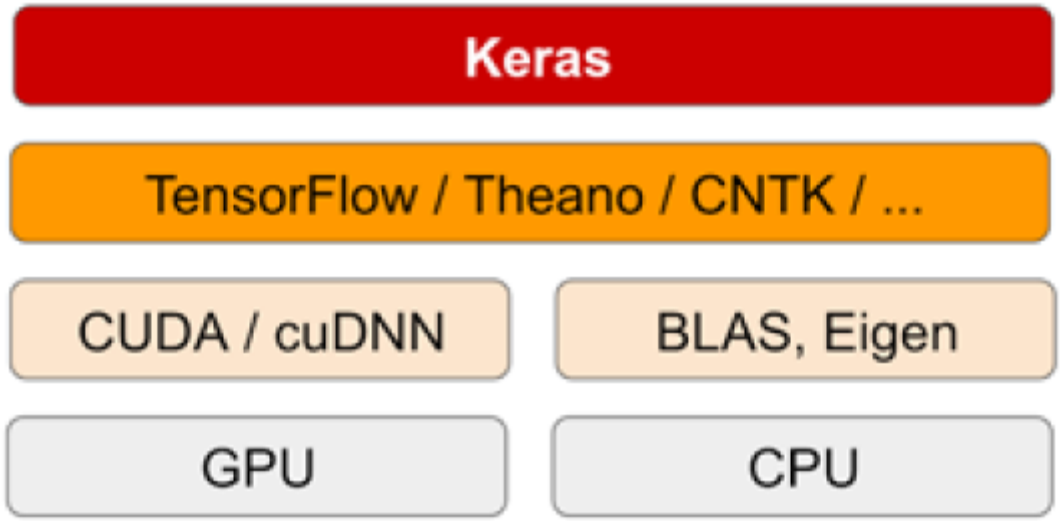
Introduction

- YouTube Video: *Keras Explained* from Siraj Raval

https://youtu.be/j_pJmXJwMLA

1. Introduction

- **Keras** is a high-level API to build and train deep learning models.



1. Introduction – Advantages

- **User friendly**: Keras has a simple, consistent interface optimized for common use cases. It provides clear and actionable feedback for user errors.
- **Modular and composable**: Keras models are made by connecting configurable building blocks together, with few restrictions.
- **Easy to extend**: Write custom building blocks to express new ideas for research. Create new layers, loss functions, and develop state-of-the-art models.

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2. Keras API Styles

1. **The Sequential Model**
   - Dead simple
   - Only for single-input, single-output, sequential layer stacks
   - Good for 70+% of use cases
2. **The functional API**
   - Like playing with Lego bricks
   - Multi-input, multi-output, arbitrary static graph topologies
   - Good for 95% of use cases
3. **Model subclassing**
   - Maximum flexibility
   - Larger potential error surface

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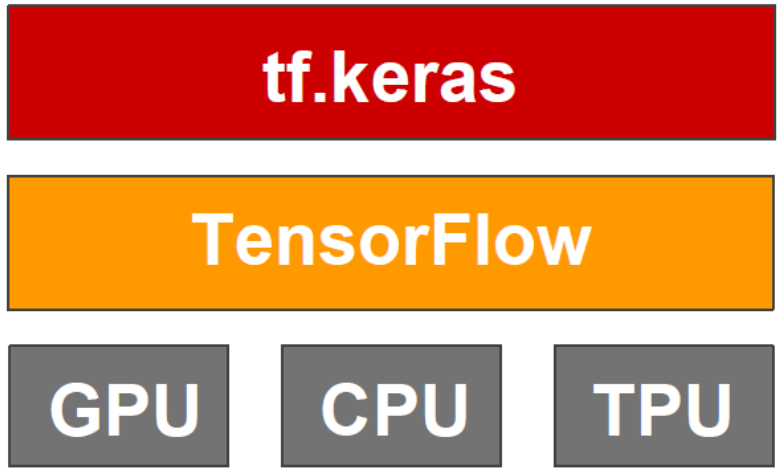
3. TensorFlow Keras

- Keras is the official high-level API of TensorFlow
- tensorflow.keras (tf.keras) module
- Part of core TensorFlow since v1.4
- Full Keras API
- With useful extra features such as **tf.data**



3. TensorFlow Keras

- To install TensorFlow

```
$ pip install --upgrade tensorflow
```

- To import Keras from TensorFlow

```
>>> import tensorflow as tf
>>> from tensorflow.keras import Layers
>>> from tensorflow import keras
>>> tf.__version__
'2.1.0'
>>> keras.__version__
'2.2.4-tf'
```

- Dense
- Activations
- Dropout
- Conv1D, 2D, 3D
- Polling
- RNN, LSTM, GRU
- …

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4. Image Classifier Using the Sequential Model

- **Fashion MNIST** is similar to MNIST (70,000 grayscale images of 28×28 pixels each, with 10 classes).

4. Fashion MNIST

1. **Get and prepare the dataset**.
2. **Build sequential model** of layers that maps your inputs to your targets.
3. **Compile the model and configure the learning process** by choosing a loss function, an optimizer, and some metrics to monitor.
4. **Train the model** by calling the `fit()` method of your model.
5. **Evaluate and use** the model.

4.1 Get and Prepare the Dataset

```
import tensorflow as tf
from tensorflow import keras

# Get the Fashion MNIST
fashion_mnist = keras.datasets.fashion_mnist
(X_train_full, y_train_full), (X_test, y_test) =
                fashion_mnist.load_data()

# Prepare the data train (55000), val (5000), test (10000)
X_valid = X_train_full[:5000] / 255.
X_train = X_train_full[5000:] / 255.
y_valid, y_train = y_train_full[:5000], y_train_full[5000:]
X_test = X_test / 255.
```

4.2 Build the Model

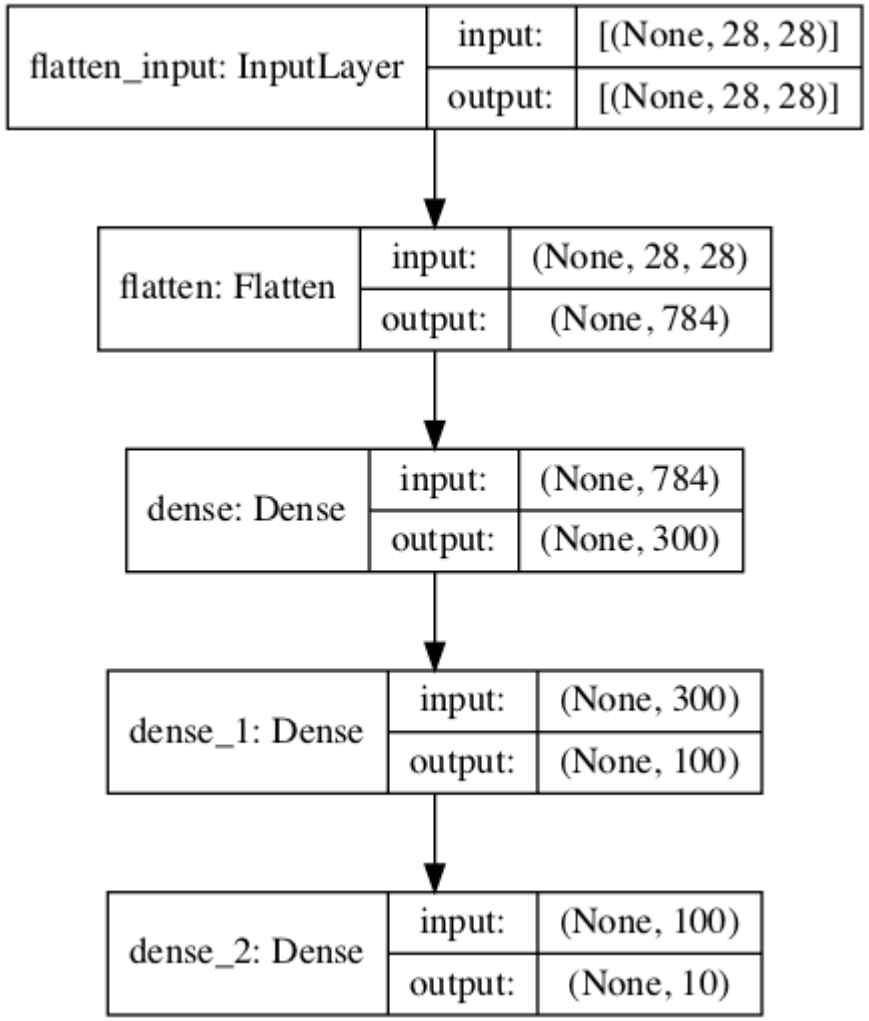
The default is no activation function, i.e., linear layer.

```
model = keras.models.Sequential()
model.add(keras.layers.Flatten(input_shape=[28, 28]))
model.add(keras.layers.Dense(300, activation="relu"))
model.add(keras.layers.Dense(100, activation="relu"))
model.add(keras.layers.Dense(10, activation="softmax"))
```

```
>>> model.summary()
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_1 (Flatten)          (None, 784)               0
_________________________________________________________________
dense_3 (Dense)              (None, 300)               235500
_________________________________________________________________
dense_4 (Dense)              (None, 100)               30100
_________________________________________________________________
dense_5 (Dense)              (None, 10)                1010
=================================================================
Total params: 266,610
Trainable params: 266,610
Non-trainable params: 0
```

4.2 Build the Model

```
# Plot the model
keras.utils.plot_model(
        model,
        "my_model.png",
        show_shapes=True)
```



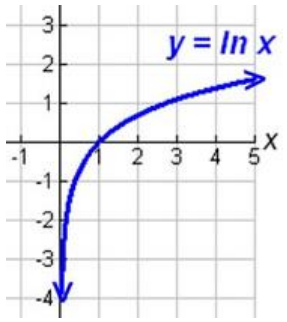
4.3 Compile the Model

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

# For sparse labels (0-9):
loss = "sparse_categorical_crossentropy"
# For one-hot labels:
loss = "categorical_crossentropy"
# For binary labels:
loss = "binary_crossentropy"
# For regression:
loss = "mean_squared_error"
```

Stochastic Gradient Descent

$$-\sum_{c=1}^{M} y_{o,c} \log(p_{o,c})$$



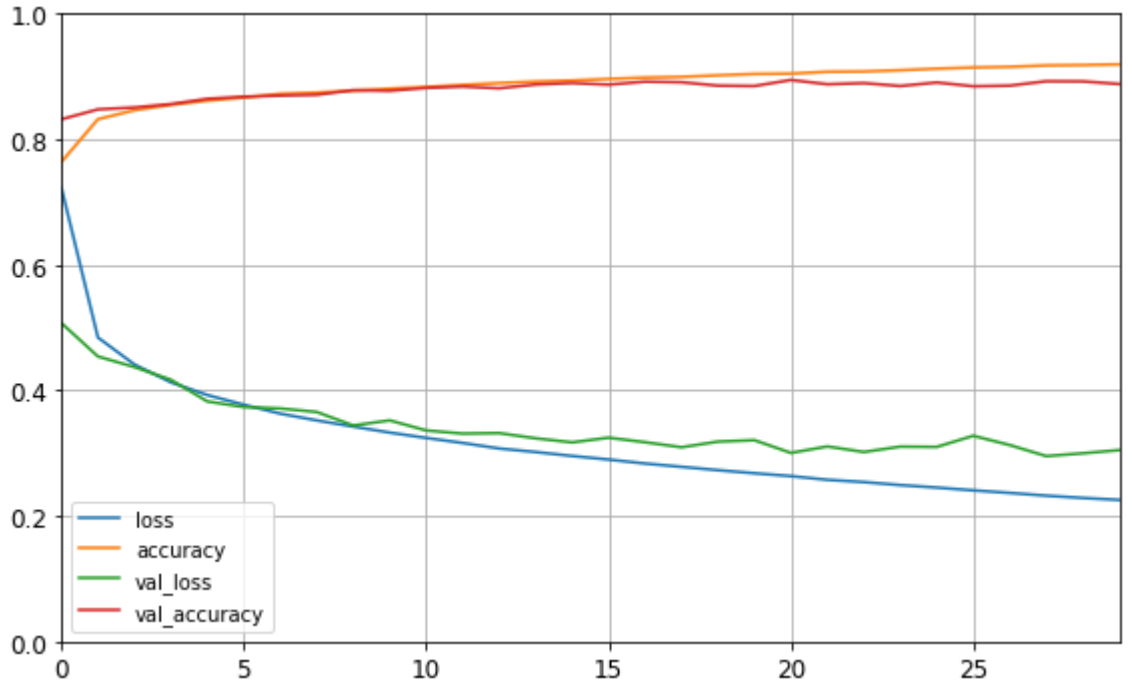
4.4 Train the Model

```
# Train the model
history = model.fit(X_train, y_train, epochs=30,
                    validation_data=(X_valid, y_valid))
```

```
Train on 55000 samples, validate on 5000 samples
Epoch 1/30
55000/55000 [==============================] - 2s 44us/sample - loss: 0.7226 - accuracy: 0.7641 - val_loss:
0.5073 - val_accuracy: 0.8320
Epoch 2/30
55000/55000 [==============================] - 2s 39us/sample - loss: 0.4844 - accuracy: 0.8321 - val_loss:
0.4541 - val_accuracy: 0.8478
…
Epoch 30/30
55000/55000 [==============================] - 2s 39us/sample - loss: 0.2256 - accuracy: 0.9195 - val_loss:
0.3049 - val_accuracy: 0.8882
```

4.4 Train the Model

```
import pandas as pd
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1)
save_fig("keras_learning_curves_plot")
plt.show()
```



4.5 Evaluate and Use the Model

```
model.evaluate(X_test, y_test)
10000/10000 [==============================] - 0s 21us/sample - loss: 0.3378 -
accuracy: 0.8781
[0.3378701770782473, 0.8781]

X_new = X_test[:3]
y_proba = model.predict(X_new)
y_proba.round(2)
array([[0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.01, 0.  , 0.99],
       [0.  , 0.  , 0.99, 0.  , 0.01, 0.  , 0.  , 0.  , 0.  , 0.  ],
       [0.  , 1.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  ]],
      dtype=float32)

model.predict_classes(X_new)
array([9, 2, 1])
```

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5. Example - MNIST

1. **Define your training data**: input tensors and target tensors.
2. **Define a network** of layers (or **model**) that maps your inputs to your targets.
3. **Configure the learning process** by choosing a loss function, an optimizer, and some metrics to monitor.
4. **Iterate on your training data** by calling the `fit()` method of your model.

5. Example – Prepare the data

```
from keras.datasets import mnist
(train_images, train_labels), (test_images, test_labels) =
      mnist.load_data()
#(60000, 28, 28), (60000), #(10000, 28, 28), (10000)
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

from keras.utils import to_categorical    #one hot
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
```

5. Example – Define and configure the network

```
from keras import models
from keras import layers

network = models.Sequential()
network.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
network.add(layers.Dense(10, activation='softmax'))

network.compile(optimizer='rmsprop',
                loss='categorical_crossentropy',
                metrics=['accuracy'])
```

5. Example – Training and evaluation

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

```
Epoch 1/5
60000/60000 [==============================] - 2s - loss: 0.2577 - acc: 0.9245
Epoch 2/5
60000/60000 [==============================] - 1s - loss: 0.1042 - acc: 0.9690
Epoch 3/5
60000/60000 [==============================] - 1s - loss: 0.0687 - acc: 0.9793
Epoch 4/5
60000/60000 [==============================] - 1s - loss: 0.0508 - acc: 0.9848
Epoch 5/5
60000/60000 [==============================] - 1s - loss: 0.0382 - acc: 0.9890
```

```
test_loss, test_acc = network.evaluate(test_images, test_labels)
```

```
9536/10000 [===========================>..] - ETA: 0s
```

```
test_acc: 0.9777
```

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6. Regression Using the Sequential Model

- Solve the **California housing** problem using a regression neural network.
- Scikit-Learn has `fetch_california_housing()` function to load the data
- This dataset contains **only numerical features** and there are **no missing values**.

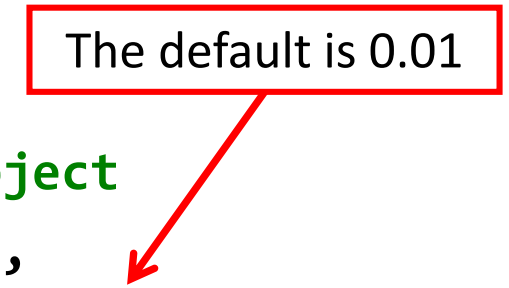
6.1 Get and Prepare the Dataset

```
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

housing = fetch_california_housing()

X_train_full, X_test, y_train_full, y_test =
       train_test_split(housing.data, housing.target, random_state=42)
X_train, X_valid, y_train, y_valid = train_test_split(X_train_full,
                    y_train_full, random_state=42)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_valid = scaler.transform(X_valid)
X_test = scaler.transform(X_test)
```

The default is 75% : 25%

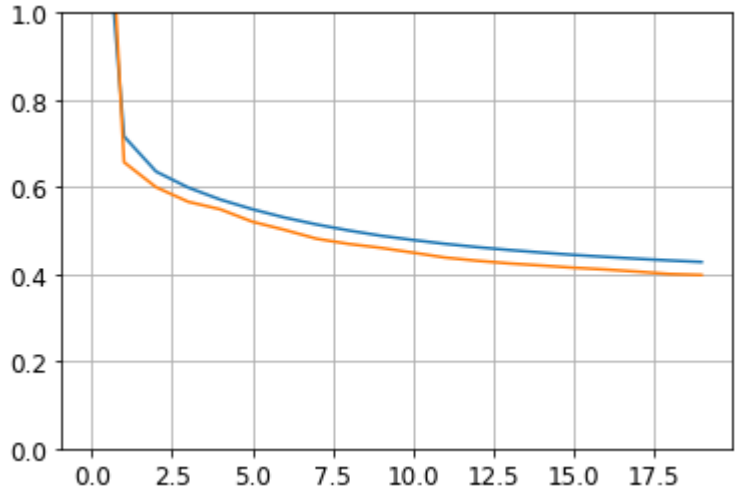
6.2 Build and Compile the Model

```
# Building by passing a list of layers when creating
#  the Sequential model
model = keras.models.Sequential([
        keras.layers.Dense(30, activation="relu",
                input_shape=X_train.shape[1:]),
        keras.layers.Dense(1)
])

# Compile with creating an optimizer object
model.compile(loss="mean_squared_error",
        optimizer=keras.optimizers.SGD(lr=1e-3))
```



6.3 Train and Evaluate the Model

```
history = model.fit(X_train, y_train, epochs=20,
        validation_data=(X_valid, y_valid))
```




```
mse_test = model.evaluate(X_test, y_test)
5160/5160 [==============================] - 0s
15us/sample - loss: 0.421
```

6.4 Save and Restore the Model

- After training a model save it to a file.

```
model.save("my_keras_model.h5")
```

- In the production program, load the trained model.

```
model = keras.models.load_model("my_keras_model.h5")
```

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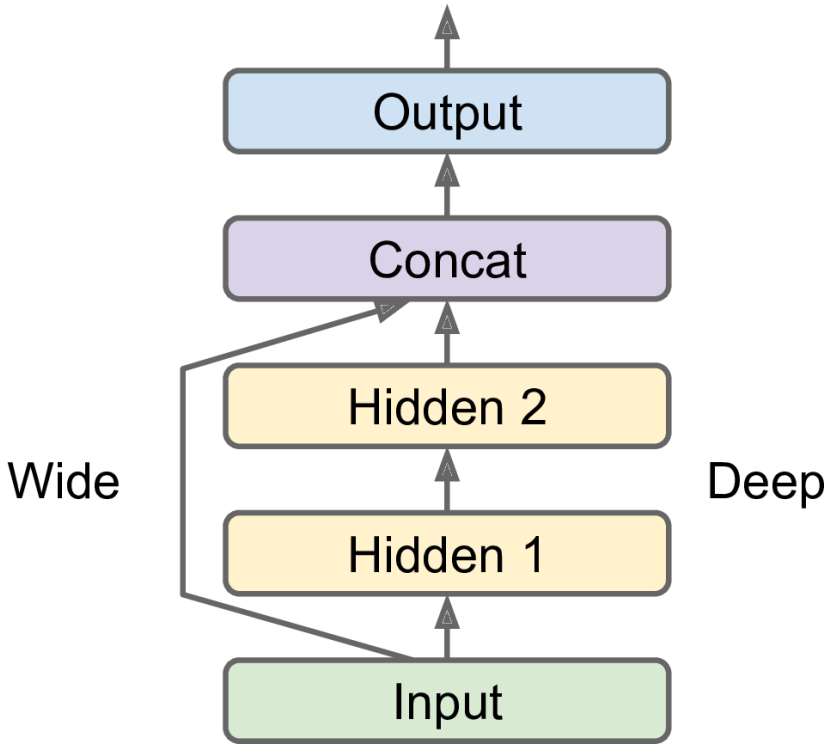
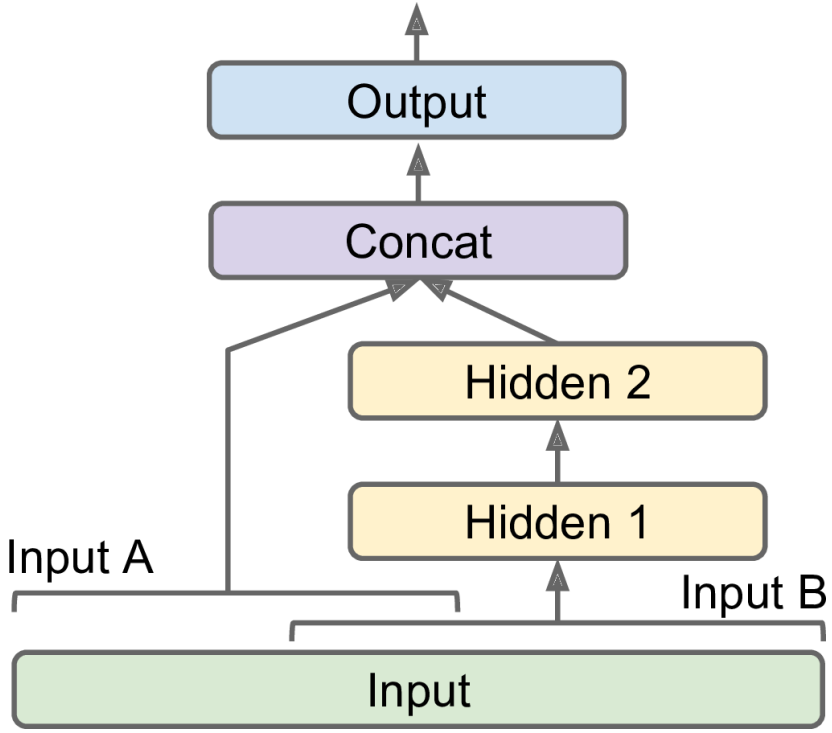
7. Using the Functional API

- Keras functional API can be used to build arbitrary **static graph topologies**.
- Create a layer and as soon as it is created, **call it like a function**, passing it the input.
- Example 1: the **wide and deep** network that learns both deep patterns (using the deep path) and simple rules (through the short path).



7. Using the Functional API

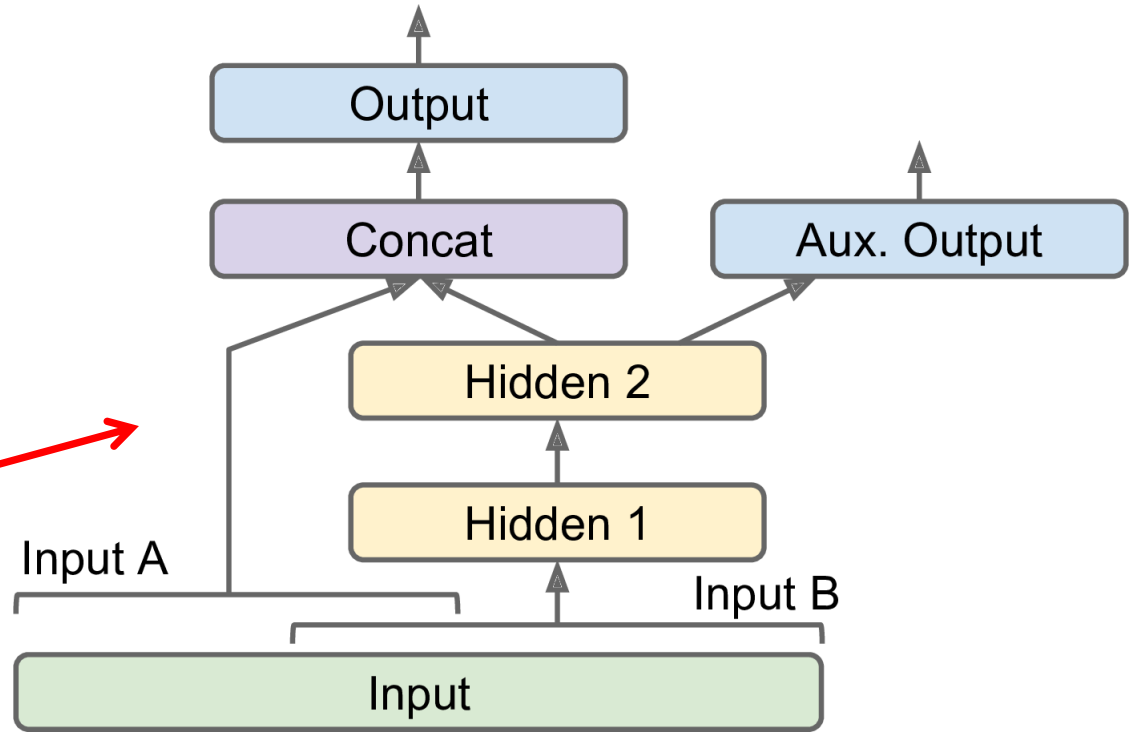
2. **Multi-input**: You can send a subset of the features through the wide path, and a different subset (possibly overlapping) through the deep path.



7. Using the Functional API

3. Multiple Outputs

- To **locate and classify** the main object in a picture.
- **Multiple independent tasks** to perform based on the same data.
- **Regularization technique** (to ensure that the deep network learns something useful on its own).



7.1 Auxiliary Output for Regularization

```
# Build the model
input_A = keras.layers.Input(shape=[5], name="wide_input")
input_B = keras.layers.Input(shape=[6], name="deep_input")

hidden1 = keras.layers.Dense(30, activation="relu")(input_B)
hidden2 = keras.layers.Dense(30, activation="relu")(hidden1)

concat = keras.layers.concatenate([input_A, hidden2])

output = keras.layers.Dense(1, name="main_output")(concat)

aux_output = keras.layers.Dense(1, name="aux_output")(hidden2)

model = keras.models.Model(inputs=[input_A, input_B],
                           outputs=[output, aux_output])
```

7.1 Auxiliary Output for Regularization

```
# Split the input
X_train_A, X_train_B = X_train[:, :5], X_train[:, 2:]
X_valid_A, X_valid_B = X_valid[:, :5], X_valid[:, 2:]
X_test_A,  X_test_B  = X_test[:, :5],  X_test[:, 2:]

# Take some test samples
X_new_A, X_new_B = X_test_A[:3], X_test_B[:3]
```

7.1 Auxiliary Output for Regularization

```
# Compile, train, evaluate, and predict
model.compile(loss=["mse", "mse"], loss_weights=[0.9, 0.1],
              optimizer=keras.optimizers.SGD(lr=1e-3))

history = model.fit([X_train_A, X_train_B], [y_train, y_train], epochs=20,
                    validation_data=([X_valid_A, X_valid_B], [y_valid, y_valid]))

total_loss, main_loss, aux_loss = model.evaluate([X_test_A, X_test_B],
                                                 [y_test, y_test])

y_pred_main, y_pred_aux = model.predict([X_new_A, X_new_B])
```

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8. Using Callbacks

- The `fit()` method accepts a `callbacks` argument that lets you specify a list of objects that Keras will call during training
  - at the start and end of **training**
  - at the start and end of each **epoch**
  - before and after processing each **batch**
- There are many callbacks available in the `keras.callbacks` package. See

https://keras.io/callbacks/

8.1 Saving Best Model

- **Save your best model** when its performance on the validation set is the best so far.

```
checkpoint_cb = keras.callbacks.ModelCheckpoint(
        "my_keras_model.h5", save_best_only=True)
history = model.fit(X_train, y_train, epochs=10,
        validation_data=(X_valid, y_valid),
        callbacks=[checkpoint_cb])

# rollback to best model
model = keras.models.load_model("my_keras_model.h5")
mse_test = model.evaluate(X_test, y_test)
```

8.2 Early Stopping

- Interrupt training when there is no progress on the validation set for a number of epochs (defined by the **patience** argument)
- Optionally roll back to the best model.

```
early_stopping_cb = keras.callbacks.EarlyStopping(
        patience=10, restore_best_weights=True)

history = model.fit(X_train, y_train, epochs=100,
        validation_data=(X_valid, y_valid),
        callbacks=[checkpoint_cb, early_stopping_cb])
```

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9. Visualization Using TensorBoard

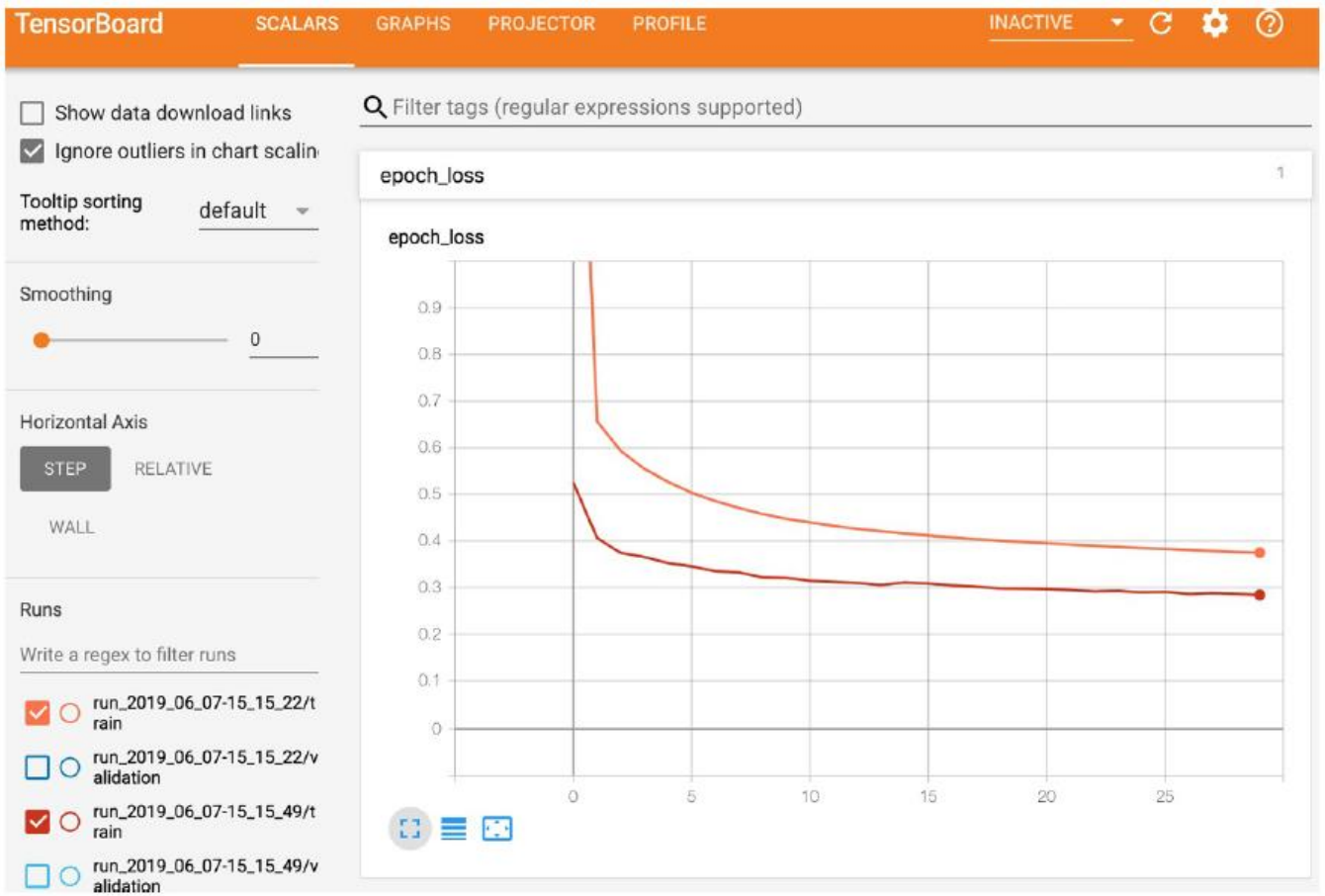
- TensorBoard is a great **interactive visualization tool** that comes with TensorFlow.
- Use it using its callback

```
tensorboard_cb =
        keras.callbacks.TensorBoard(run_logdir)
history = model.fit(X_train, y_train, epochs=30,
        validation_data=(X_valid, y_valid),
        callbacks=[tensorboard_cb])
```

- Start TensorBoard server

```
$ tensorboard --logdir=./my_logs --port=6006
```

9. Open http://localhost:6006



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10. Fine-Tuning Neural Network Hyperparameters

- **Number of Hidden Layers**
  - One hidden layer can theoretically model even the most complex functions, provided it has enough neurons.
  - But for complex problems, deep networks have a much higher parameter efficiency than shallow ones.
- **Number of Neurons per Hidden Layer**
  - **Pyramid** across layers or **same** size
  - **Stretch pants**: pick a model with more layers and neurons than you actually need, then use early stopping and other regularization techniques to prevent it from overfitting.
- Better to increase the number of layers instead of the number of neurons per layer.

10. Fine-Tuning Neural Network Hyperparameters

- **Learning Rate**: the optimal LR is about half of the maximum LR.
- **Optimizer**: There are other than the Mini-batch Gradient Descent optimizer.
- **Batch Size**
  - Larger gives better speed up with hardware accelerators.
  - Smaller makes the models more general.
- **Activation Functions**

11. Tutorials

- https://keras.io/
- https://www.tensorflow.org/guide/keras
- Keras Tutorial: Deep Learning in Python from DataCamp, https://www.datacamp.com/community/tutorials/deep-learning-python
- Keras Tutorial: The Ultimate Beginner's Guide to Deep Learning in Python, from EliteDataScience, https://elitedatascience.com/keras-tutorial-deep-learning-in-python

12. Exercise

From Chapter 10, solve exercise:

- 10. Train a deep MLP on the **MNIST** dataset (you can load it using `keras.datasets.mnist.load_data()`. See if you can get over **98%** precision. Try searching for the optimal learning rate by using the approach presented in this chapter (i.e., by growing the learning rate exponentially, plotting the error, and finding the point where the error shoots up). Try adding all the bells and whistles—save checkpoints, use **early stopping**, and plot learning curves using **TensorBoard**.

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