# PO: Introduction to Keras

Natural Language Understanding

Interuniversity Master's Degree in Artificial Intelligence
Academic Year 2023-2024





# Objectives PO

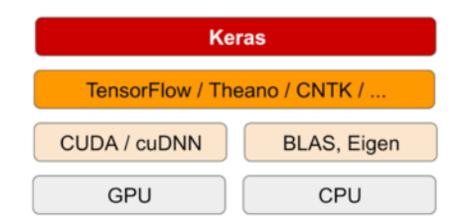
- Introduce Keras and programming environments for Python notebooks
- Get acquainted with basic libraries useful for NLU (preprocessing, tokenization, embeddings, etc.)
- Be able to train and use neural network models for classification problems in a text domain

## Python and notebooks

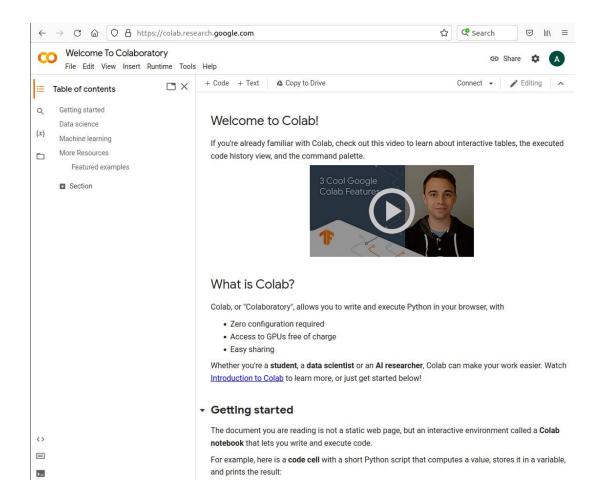
- Jupyter notebooks
  - https://jupyter.org
  - Great to run deep learning experiments
  - Combine interactive and incremental running and documenting (text-editing) into a single Web GUI
  - Requires installing libraries in your local computer
- Google Colaboratory
  - https://colab.research.google.com/
  - Looks like an online notebook, you can upload your own jupyter notebooks
  - No configuration and installation needed (Keras available already)
  - Access to GPU/TPU free of charge (if really needed)

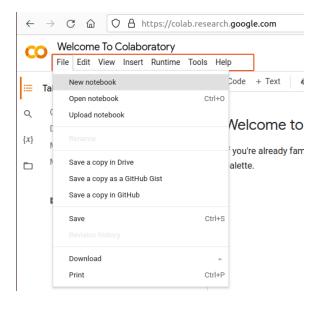
### **KERAS**

- The Python Deep Learning API
- URL: <a href="https://keras.io/">https://keras.io/</a>
- Model-level library with <u>high-level</u> building blocks for developing deep-learning models
  - user-friendly API
  - same code to run seamlessly on CPU or GPU
  - built-in support for convolutional networks, recurrent networks (for sequence processing)...

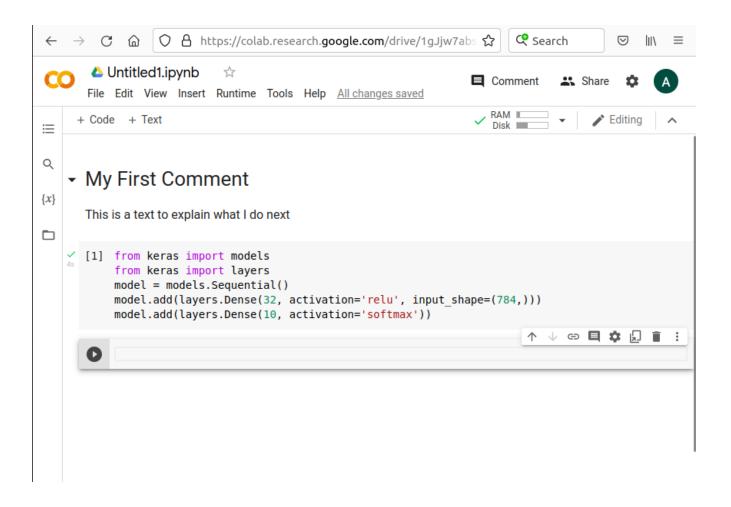


### Colab





### Colab environment



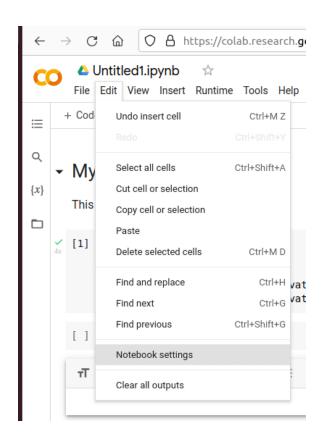
### Text cells

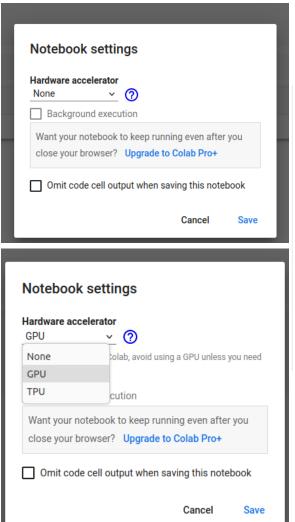
- Formatting and style in Markdown

### Code cells

- control on order to run cells interactively
- GPU/TPU may be available

# Colab GPU/TPU use \*





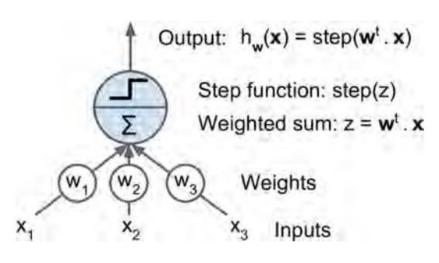
```
import tensorflow
    from tensorflow.python.client import device lib
   print ("Current keras version: ", tensorflow.keras. version )
   print ("Available resources: ", device lib.list local devices())
Current keras version: 2.8.0
   Available resources: [name: "/device:CPU:0"
    device type: "CPU"
   memory limit: 268435456
   locality {
    incarnation: 9468665601269294226
   xla global id: -1
    , name: "/device:GPU:0"
   device type: "GPU"
   memory limit: 14444920832
   locality {
     bus id: 1
     links {
   incarnation: 3319789702893679343
   physical device desc: "device: 0, name: Tesla T4, pci bus id: 0000:00:04.0, compute capability: 7.5"
   xla global id: 416903419
```

\*enable it only if really necessary

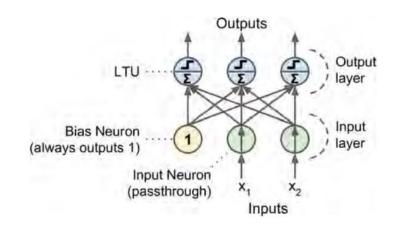
# Part I

Formative assignment (P0\_part1.ipynb)

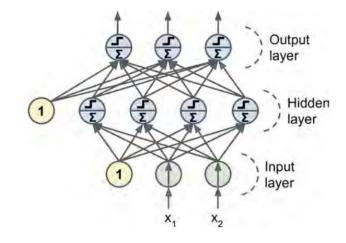
# The Perceptron and Artificial Neural Networks



$$(z = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n = \mathbf{w}^T \cdot \mathbf{x})$$



Perceptron



Multi-layer Perceptron

Liner Threshold unit

## Workflow overview

### Define data

• Define your training data: input tensors and target tensors

#### Define layers

• Define a network of layers (or model)

### Configure

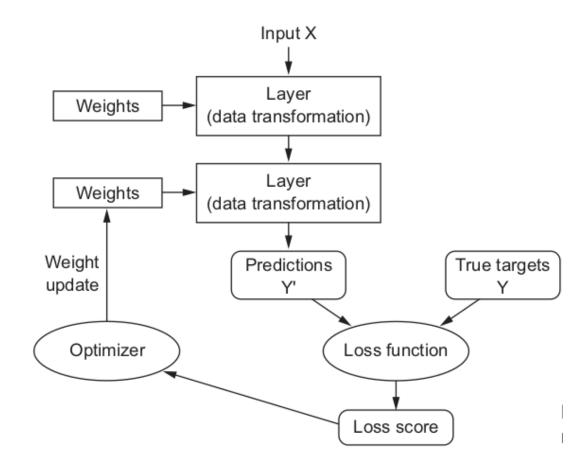
• Configure the learning process by choosing a loss functions, an optimizer and some metrics to monitor and guide the learning process

#### Trair

• Train your model using the fit method

#### Evaluate

• Evaluate your model with the test data



## Inspecting the provided Keras code

### Three Examples

- Example 1: Prediction of patients with diabetes
- Example 2: Digit recognition with the MNIST dataset
- Example 3: Classifying sentiment of movie reviews

### Your goal

- To inspect and run the code, looking at how the workflow is adapted to different problems in Keras
- Discuss with your partner key aspects about the code and outcomes
- Try out small changes to the provided code

## Example 3: Classifying movie reviews

- Internet Movie Database (IMDB)
- Dataset: <a href="https://ai.stanford.edu/~amaas/data/sentiment/">https://ai.stanford.edu/~amaas/data/sentiment/</a>
  - Included in Keras already, will be downloaded first time you use it
- 50K polarized reviews
  - 25K for training, 25K for testing, each with 50-50% negative/positive review labels
- The goal is to learn to classify whether a review is positive or negative based on the text
  - Binary classification problem

### Define Data

from keras.datasets import imdb

- train data and test data are lists of reviews
- each review is a list of word indices (encoding a sequence of words)
- train\_labels and test\_labels are lists of 0s and 1s, where 0 stands for negative and 1 stands for positive

```
# only keep the top num_words most frequent. Discard rare words.
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=10000)

word_index = imdb.get_word_index()
reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])
decoded_review = ' '.join([reverse_word_index.get(i - 3, '?') for i in train_data[0]])
```

print(decoded\_review)

word\_index maps words to integers

### Define Data

```
import numpy as np
def vectorize sequences(sequences, dimension=10000):
  results = np.zeros((len(sequences), dimension))
  for i, sequence in enumerate(sequences):
    results[i, sequence] = 1.
  return results
x train = vectorize sequences(train data)
x_test = vectorize_sequences(test_data)
y_train = np.asarray(train_labels).astype('float32')
y test = np.asarray(test_labels).astype('float32')
```

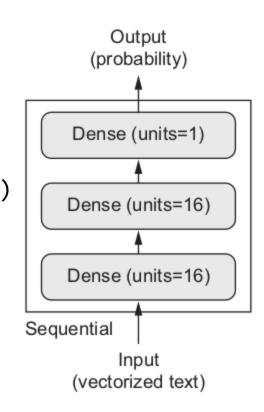
- Numpy has a bunch of useful operations to deal with vectors, arrays, tensors
- Remember that NNs don't work with words but with numbers as input
- Vectorize to keep length manageable and get a specific data representation
  - Kind of one-hot encoding with 0s and 1s whether terms/tokens are or not present in a given review
- Also vectorize labels

# Define Layers

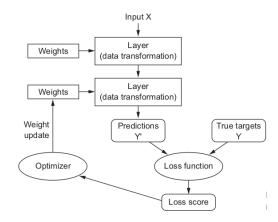
```
from keras import models
from keras import layers

model = models.Sequential()
model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
model.summary()
```

- Input layer is set to 10000 tokens in agreement with the vectorization done before
- Dense layers, fully connected
- Output layer with a neuron with a sigmoid function



# Configure



model.compile(optimizer='rmsprop', loss='binary\_crossentropy',metrics=['accuracy'])

-----

from keras import optimizers
model.compile(optimizer=optimizers.rmsprop\_v2.RMSprop(learning\_rate=0.001),loss='binary\_crossentropy
', metrics=['accuracy'])

Activation functions

1.0

0.5

0.0

-0.5

-1.0

-4

-2

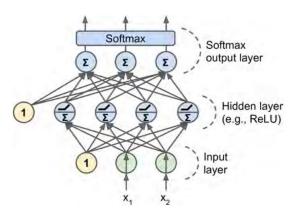
0

2

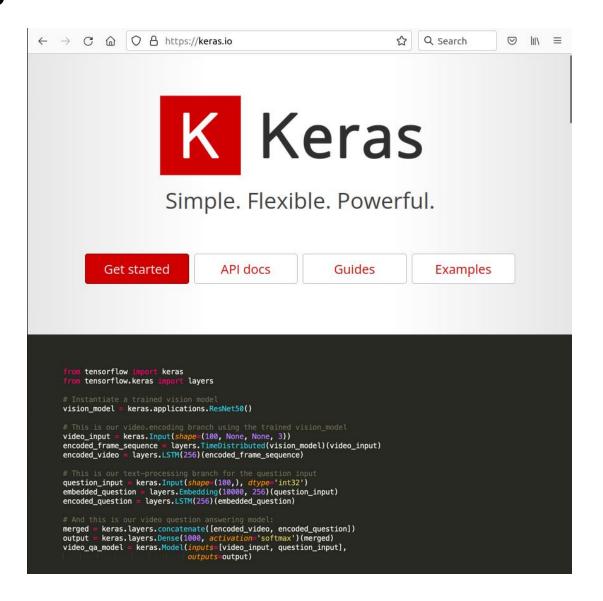
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Table 4.1 Choosing the right last-layer activation and loss function for your model

Problem type	Last-layer activation	Loss function
Binary classification	sigmoid	binary_crossentropy
Multiclass, single-label classification	softmax	categorical_crossentropy
Multiclass, multilabel classification	sigmoid	binary_crossentropy
Regression to arbitrary values	None	mse
Regression to values between 0 and 1	sigmoid	mse or binary_crossentropy



### Resources



### Train

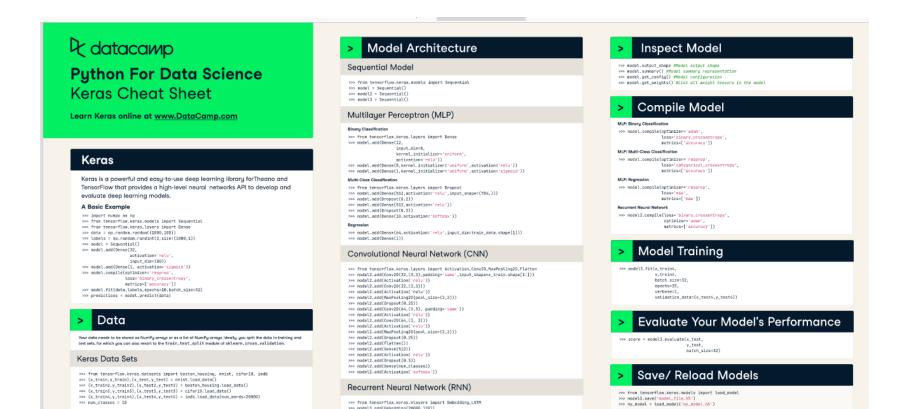
```
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]

history = model.fit(partial_x_train,partial_y_train,epochs=20,batch_size=512, validation_data=(x_val, y_val))
```

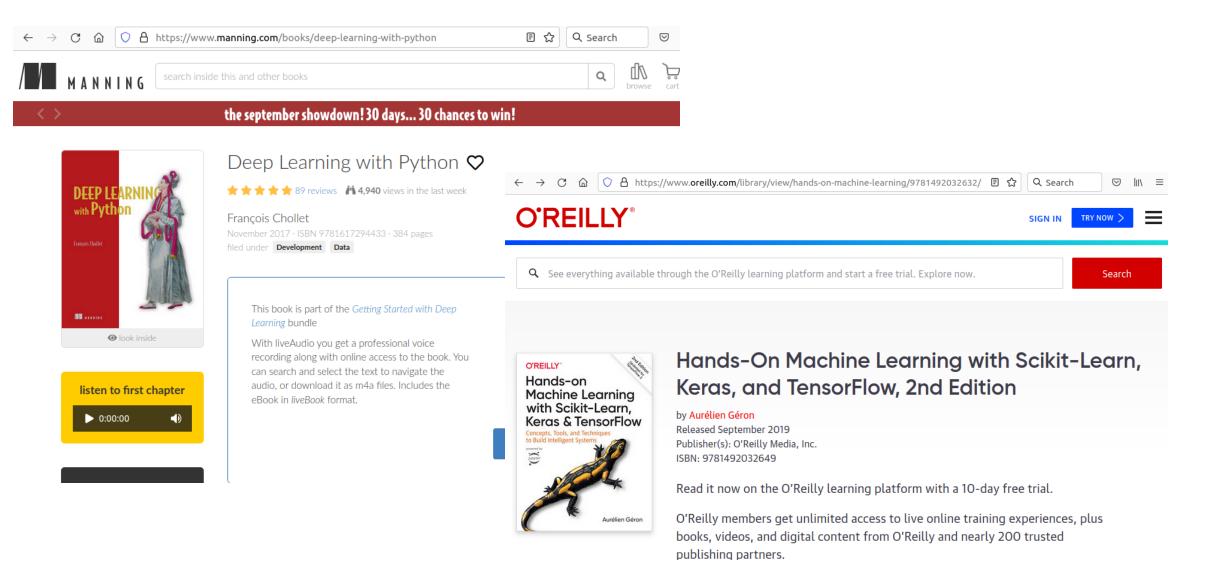
- We can set a subset for validation as in the example or using the
- With .fit() train for 20 epochs in minibatches of 512 samples
- model.fit() returns a History object.
  - •Try history\_dict = history.history,... for plotting training/validation loss/accuracy history

### Resources

• Cheatsheet Keras: <a href="https://www.datacamp.com/cheat-sheet/keras-cheat-sheet-neural-networks-in-python">https://www.datacamp.com/cheat-sheet/keras-cheat-sheet/keras-cheat-sheet-neural-networks-in-python</a>



### Resources



# Working with text input

- Texts are composed of documents, paragraphs, words, characters,...
  - Sample review: "A thrilling movie. Absolutely recommended for those loving action..."
  - Tokenization: how to get from raw text to words (or tokens)
  - Words as tokens?
    - What about US, USA, United States of America? Mr. Jones vs. Indiana Jones? Absolutely vs. Absolutely vs. Absolute? Pictured/picturing vs. picture vs. pictur?
- Regardless how we tokenize, input must be numbers to feed NNs
  - We need Encodings and Embeddings

### One-hot encoding

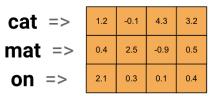
# One-hot Encoding

- Raw text = "The cat sat on the mat"
- Word-level Tokens = "cat", "mat", "on", "sat", "the"
- Length of vocabulary = 5
- One-hot vector for "cat" token = [1, 0, 0, 0, 0]

the => **sat** =>

- A sentence can be encoded using one-hot vectors: [1,1,1,1,1] \*
- or a sequence of integer indexes: [5, 1, 4, 2, 3]
- What would it happen if...
  - switched the vector for "cat" and "the"?
  - there were several documents?
  - there were many documents leading to (a realistic situation with) thousands tokens?
    - Can we handle unlimited number of tokens?
    - Advantages and disadvantages of one-hot binary encoding vs. Sequences?
    - Can we keep the order of the word tokens in our chosen representation or are they like bag of words?

# Word Embeddings



- Lower-dimension and dense representation
- Vector values are learned from data (so not intended for humans)
- But enables meaningful vector arithmetic operations in properly trained embeddings (e.g., what is the "king man + woman? => queen)

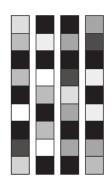
- What would it happen if...
  - there were several documents?
  - there were many documents leading to thousands tokens?
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    - Advantages and disadvantages of one-hot encoding vs. Word embedding?
    - Can we keep the order of the word tokens in our chosen representation?

## One-hot Encoding vs. Word Embeddings



One-hot word vectors:

- Sparse
- High-dimensional
- Hardcoded



Word embeddings:

- Dense
- Lower-dimensional
- Learned from data
- Find out more about these practical issues:
  - <a href="https://www.tensorflow.org/text/guide/word">https://www.tensorflow.org/text/guide/word</a> embeddings

# Part II

Summative assignment (P0\_student\_assignment\_part2.ipynb)

# P0 Final Assignment

