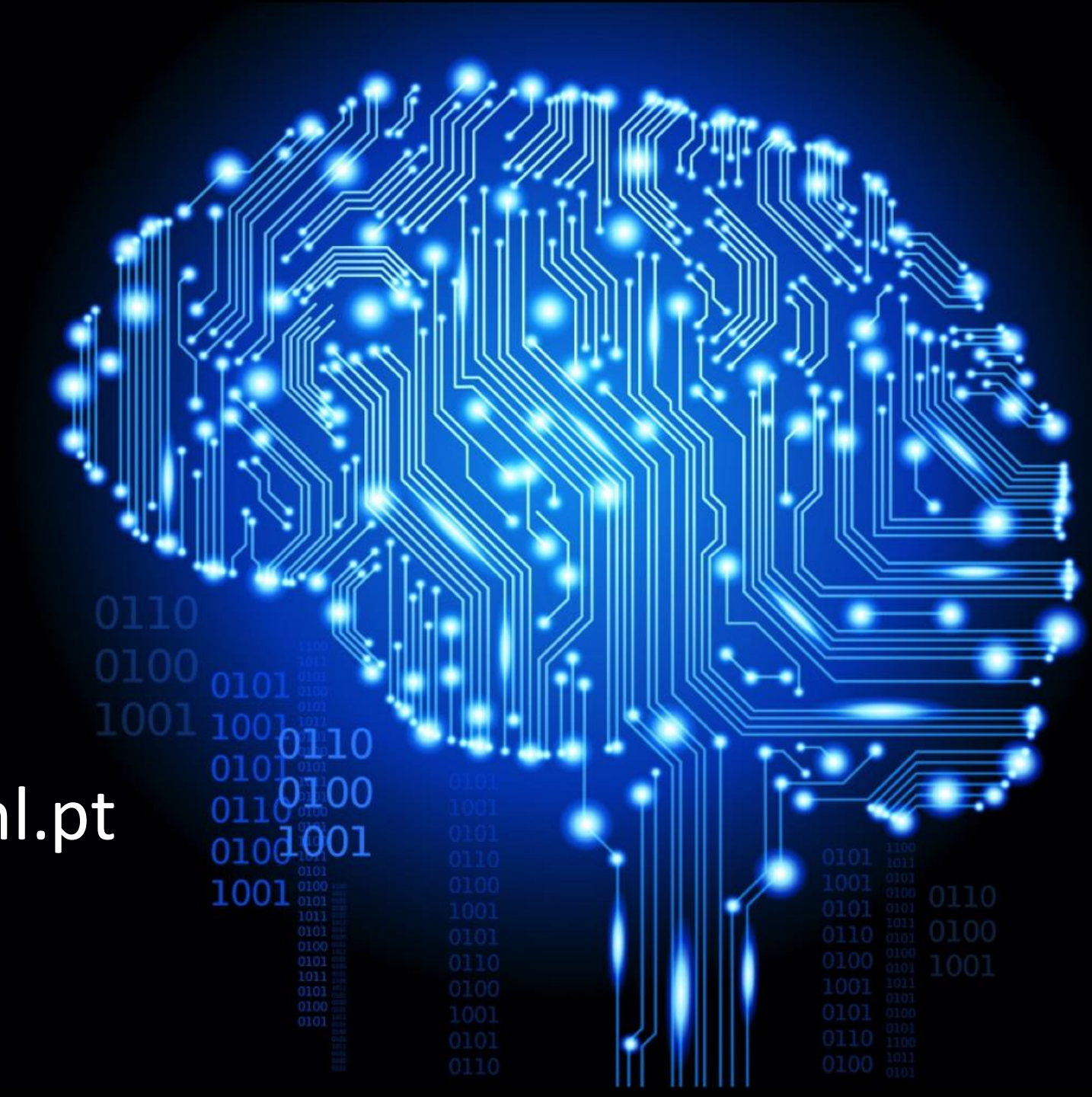
DEEP LEARNING

Spring 2021

MAURO CASTELLI
mcastelli@novaims.unl.pt



Outline

- Course Introduction
- Evaluation Method
- Book
- Deep Learning Introduction

Course Introduction

- This is a 7 weeks intensive course on Deep Learning
- We will cover the most important Deep Learning concepts
- Highly Practical Course
- Assume some knowledge of Machine Learning and NNs

Evaluation Method

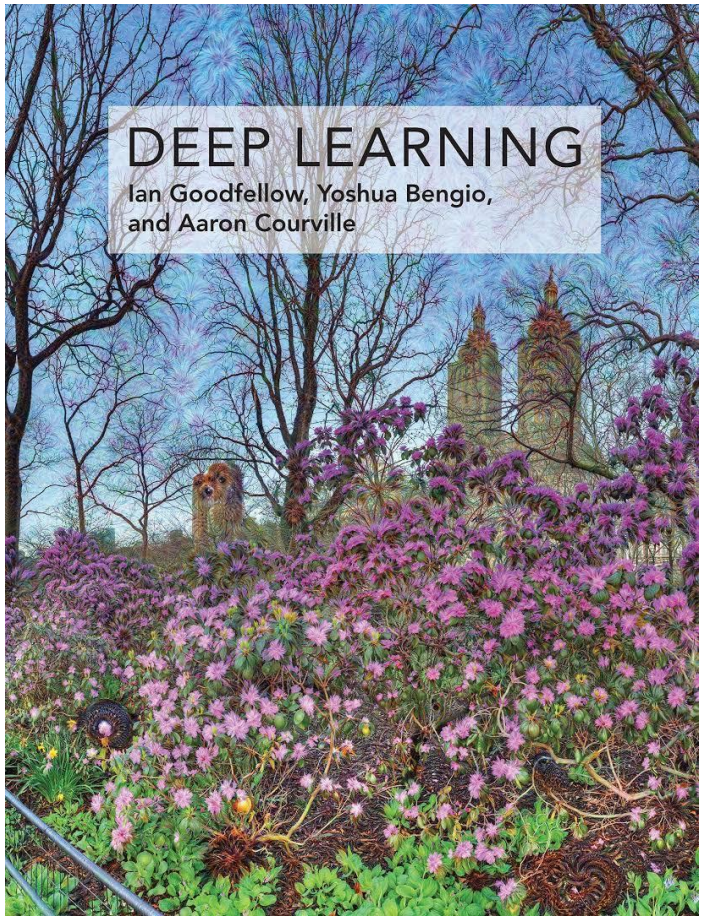
- For both the first and second epochs you have to deliver a project.
- The project is the same for the two epochs.
- You will work in a team of 3 students.
- More details later...

Book

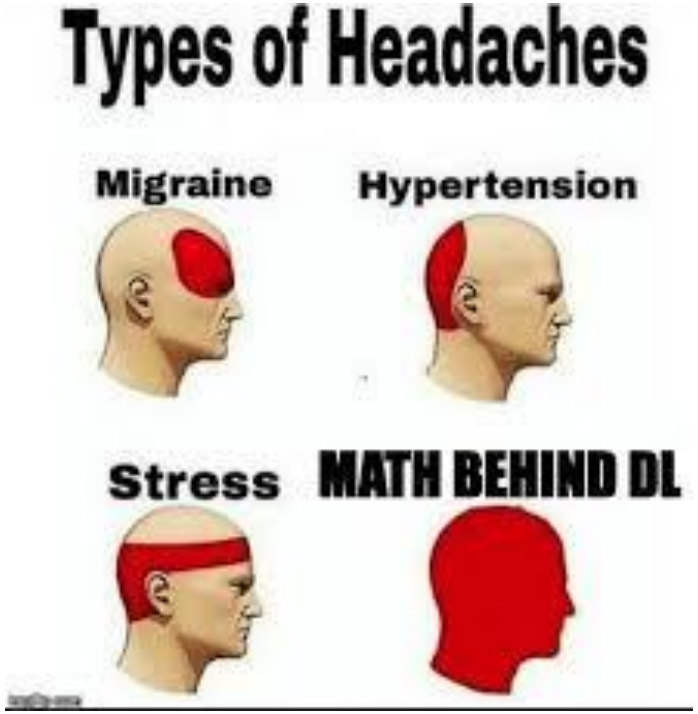
Deep Learning

By Goodfellow, Bengio, and Courville

MIT Press



Let’s start!!



I will try to hide the mathematical details, but sometimes we Really need them ;-)

Why deep learning? Why now?

- The two key ideas of deep learning for computer vision—convolutional neural networks and backpropagation—were already well understood in 1989.

- The Long Short-Term Memory (LSTM) algorithm, which is fundamental to deep learning for timeseries, was developed in 1997 and has barely changed since.

- *So…why did deep learning only take off after 2012? What changed in these two decades?*

Why deep learning? Why now?

Three technical forces are driving advances in machine learning:

- ✓Hardware
- ✓Datasets and benchmarks
- ✓Algorithmic advances

Because ML is guided by experimental findings rather than by theory, algorithmic advances only become possible when appropriate data and hardware are available to try new ideas (or scale up old ideas, as is often the case).

Data

If there's one dataset that has been a catalyst for the rise of deep learning, it's the ImageNet dataset, consisting of 1.4 million images that have been hand annotated with 1000 image categories (1 category per image).

What makes ImageNet special isn't just its large size, but also the yearly competition associated with it.

Having common benchmarks that researchers compete to beat has greatly helped the recent rise of deep learning.

Algorithms

Until the late 2000s, we were missing a reliable way to train very deep neural networks. As a result, neural networks were still fairly shallow.

The key issue was that of *gradient propagation* through deep stacks of layers. The feedback signal used to train neural networks would fade away as the number of layers increased.

This changed around 2009–2010 with the advent of several simple but important algorithmic improvements that allowed for better gradient propagation.

Algorithms

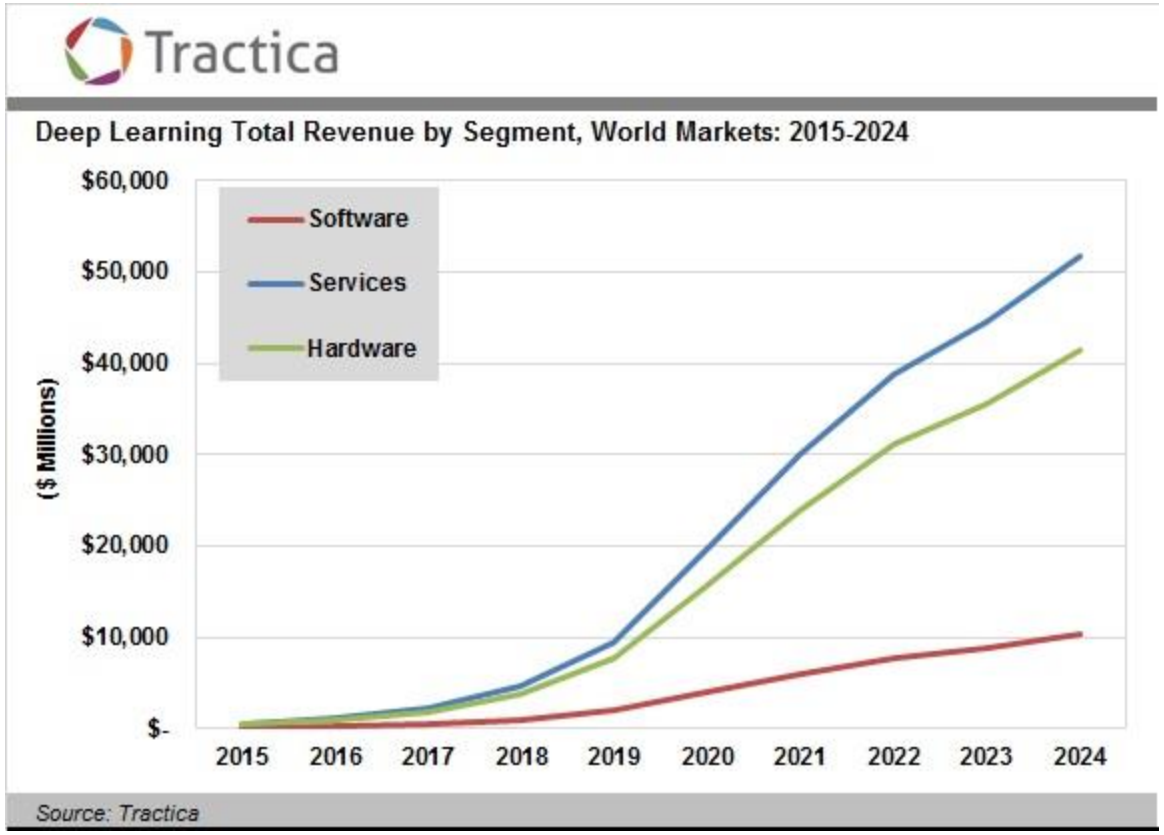
- Better *activation functions* for neural layers
- Better *weight-initialization schemes*
- Better *optimization schemes*, such as RMSProp and Adam

Only when these improvements began to allow for training models with 10 or more layers did deep learning start to shine.

Finally, in 2014, 2015, and 2016, even more advanced ways to help gradient propagation were discovered, such as batch normalization.

Today we can train from scratch models that are thousands of layers deep.

Investment in Deep Learning



Will it continue?

Is there anything special about deep neural networks that makes them the “right” approach for companies to be investing in and for researchers to flock to?

Or…is deep learning just a “trendy” ML technique that may not last?

Will we still be using deep neural networks in 20 years?

Will it continue?

Deep learning has several properties that justify its status as an AI revolution, and it's here to stay. We may not be using neural networks two decades from now, but whatever we use will directly inherit from modern deep learning and its core concepts.

These important properties can be broadly sorted into three categories:

- *Simplicity*—Deep learning removes the need for feature engineering, replacing complex, brittle, engineering-heavy pipelines with simple, end-to-end trainable models that are typically built using only five or six different tensor operations.
- *Scalability*—Deep learning is highly amenable to parallelization on GPUs, so it can take full advantage of Moore's law. In addition, deep-learning models are trained by iterating over small batches of data, allowing them to be trained on datasets of arbitrary size.
- *Versatility and reusability*

Will it continue?

Deep learning has only been in the spotlight for a few years, and we haven't yet established the full scope of what it can do. With every passing month, we learn about new use cases and engineering improvements that lift previous limitations.

Following a scientific revolution, progress generally follows a sigmoid curve: it starts with a period of fast progress, which gradually stabilizes as researchers hit hard limitations, and then further improvements become incremental. Deep learning in 2019 seems to be in the first half of that sigmoid, with much more progress to come in the next few years.

Keras

Keras

- In this course we will use Keras.

- Keras is a powerful and easy-to-use open source deep learning library for Theano and TensorFlow that provides a high-level neural networks API to develop and evaluate deep learning models.

- Easy to install with Anaconda distribution.

- Already available in Google Colab or Microsoft Azure.

Why use Keras?

Here are some of the areas in which Keras compares favorably to existing alternatives.

- ✓ Keras is an API designed for human beings, not machines. It offers consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear and actionable feedback upon user error.

- ✓ This makes Keras easy to learn and easy to use. As a Keras user, you are more productive, allowing you to try more ideas faster.

- ✓ This ease of use does not come at the cost of reduced flexibility: because Keras integrates with lower-level deep learning languages (in particular TensorFlow), it enables you to implement anything you could have built in the base language.

Why use Keras?

Keras has broad adoption in the industry and the research community