Lecture4 DL Project

1. Deep Learning Frameworks

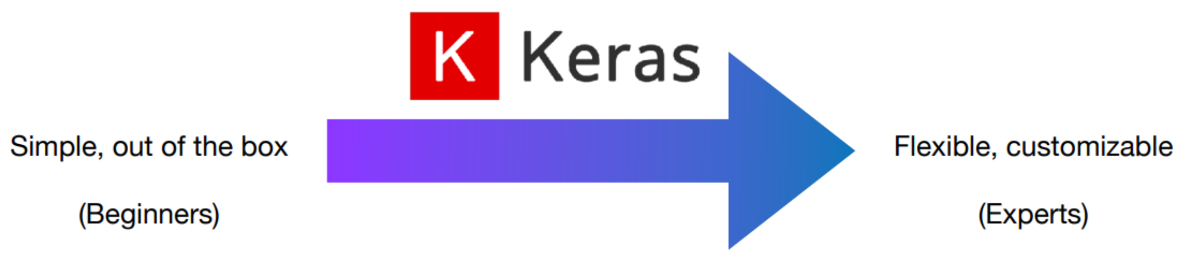
Common

- They automatically compute gradients of differentiable expressions
- They can run on CPUs, GPUs, TPUs
- Computations can be easily distributed across many machines

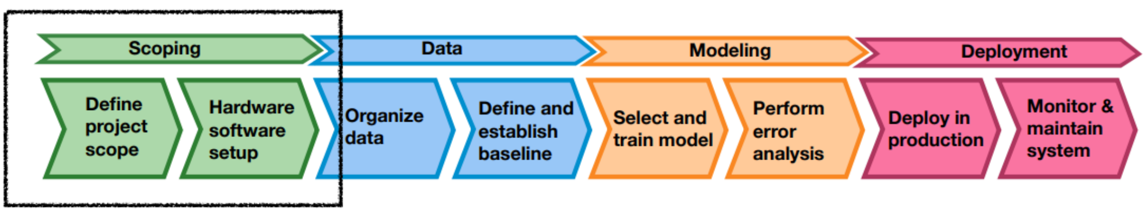
Difference

- Pytorch is a bit easier to debug and do customized operation with. (Researcher's choice)
- TensorFlow programs can be exported to other runtimes such as C++, Java-Script (for web apps) or TensorFlow Lite (for mobiles and embedded devices).

Deep Learning Layers	Description
Keras 3.0	Deep learning development: layers, models, optimizers, losses, metrics
TensorFlow, Pytorch, Jax	Tensor manipulation infrastructure: tensors, variables, automatic differentiation, distribution
CPU / GPU / TPU	Hardware: execution.



2. Setting up a Deep Learning Project

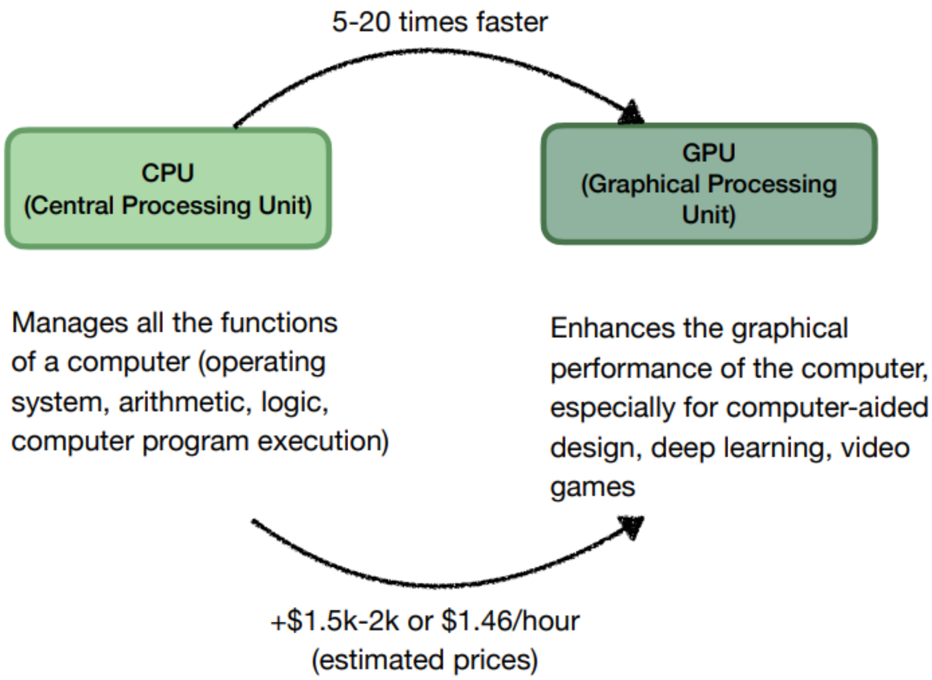


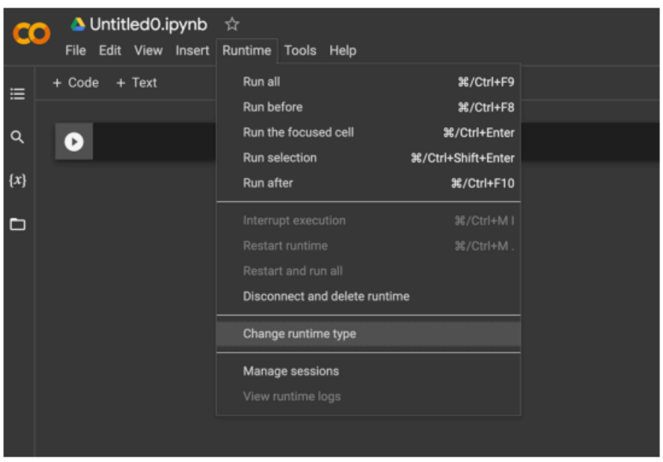
Scoping

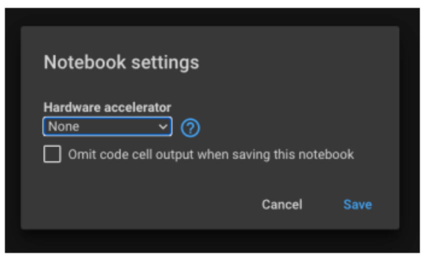
Define project scope

- What is the project about?
  - E.g.: classification of fashion items
- Do you have data for this problem?
  - E.g. Yes! The Fashion-MNIST dataset
- Decide on metrics.
  - E.g.: accuracy
- Estimate resources and timeline.
  - E.g.: Your laptops, and from today's class until EOW

Hardware Execution







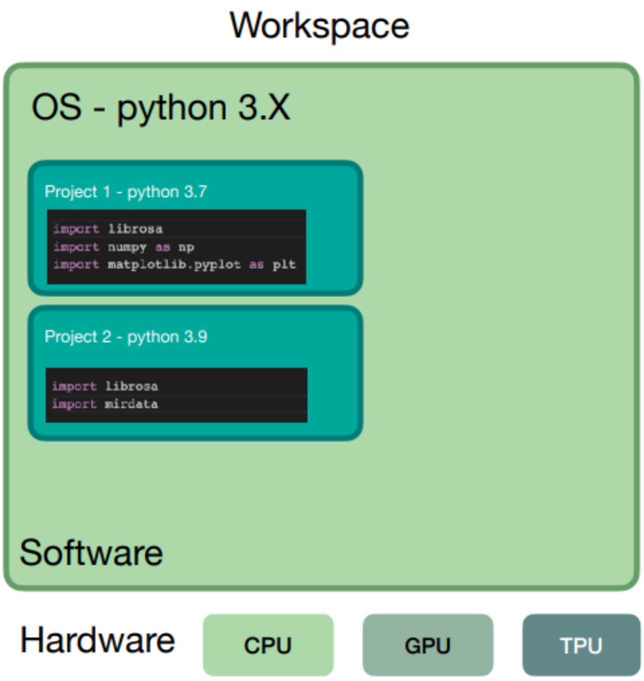
Usage constrains, e.g. maximum runtime of 12hrs, limited RAM (~12 GB)

Local vs. Remote & Conda

- Different projects have different software needs in terms of
  - e.g. Python version and packages versions
- It's important to have those well defined for reproducibility

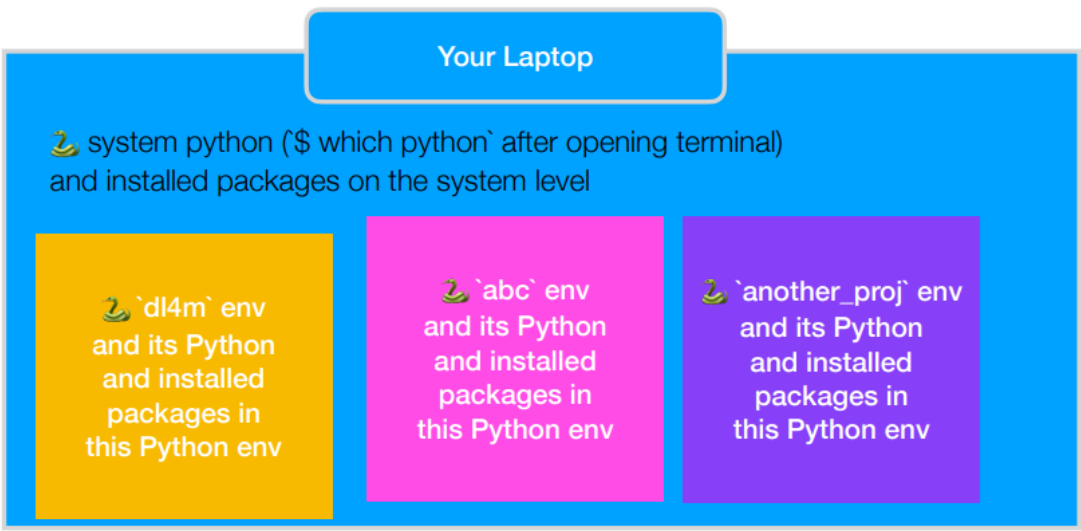
Conda

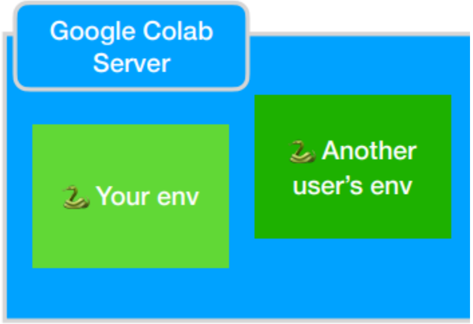
- a package and environment management system to create and switch environments in your local computer
- For Windows user: is recommended to use TensorFlow with a Unix workstation
- Keras and TensorFlow will automatically execute on GPU if available



- Install Miniconda: `https://docs.conda.io/en/latest/miniconda.html`
- Create an environment: `conda create -n [env_name] python=[version]`
- Activate environment: `conda activate [env_name]`
- Install packages: `pip install [package_name]`

Python and Python Environments





Why many environments?

- one environment per project
- Different versions of Python and installed packages act differently, whereas we want a consistent behavior within a project
  - I.e., reproducibility

How should we do?

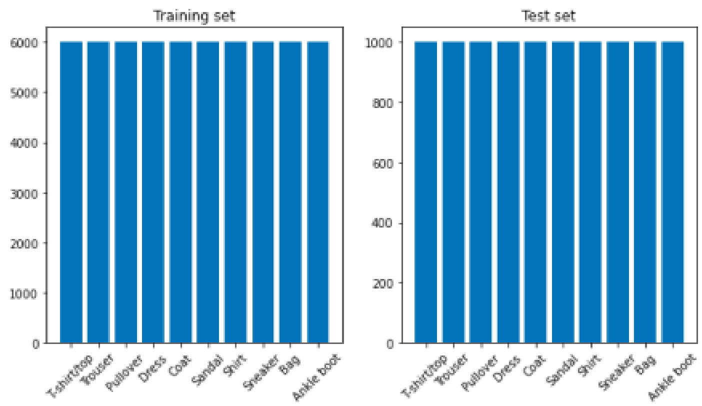
- Perhaps it's okay during this semester to use one env for all the homework etc.
- Colab has some default setup and pre-installed packages for convenience.

Python Packages

- There are several packages we will use:
  - **Numpy** (standard numerical computation tool in python)
  - **TensorFlow**, **Keras** (specialized in deep learning)
  - **Matplotlib** (image plotting)
  - **Jupyter** (easier visualization and prototyping)
- Some audio/image specific packages
  - mirdata
  - soundata
  - librosa
  - kapre (with TF), torchaudio (with Pytorch)

Data

Organize Data



Dataset statistics:

- How is the distribution of classes?
- How are the items labeled?

Define and Establish a Baseline

Provides a benchmark to:

- Measure progress
    - as a starting point to measure progress.
- Avoid pitfalls
    - are complex models needed or simple is enough? Overfitting?
- Set expectations
    - what is achievable with the data and resources available?
- Provide a reference for future work

You can have multiple baselines, some common ones are:

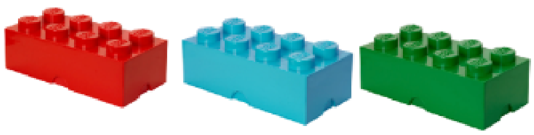
- rule-based models
- previous research
- a minimal model (e.g. linear regression)
- human-level performance

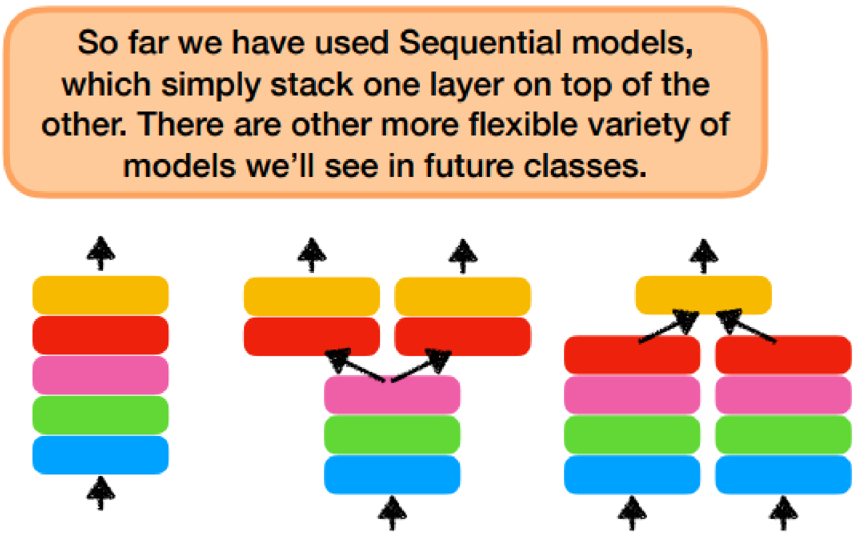
Modeling

Model Definition

Different types of layers are appropriate for different tensor formats and different data processing.

- **Simple vector data** (samples, features): are usually processed by **densely connected layers** (also known and **fully connected** or **dense layers**)
- **Sequence data** (samples, time steps, features) are usually processed by **recurrent layers**, such as **LSTMs** or **GRUs**
- **Image data** (samples, hight, width, channels) are usually processed by **convolutional layers**





Layers are connected like LEGO bricks

- Layers will only "clip" together when they are "**compatible**"
- Keras dynamically builds layers to be compatible with the output of the previous layer

Compilation Step

In the compilation step you define the **optimizer** and **loss function** for your model.

- **Optimizer**: ideally a version of **SGD with momentum** and **adaptive learning rate** (e.g. Adam)
- **Loss function**: choose a loss that is appropriate for your problem.

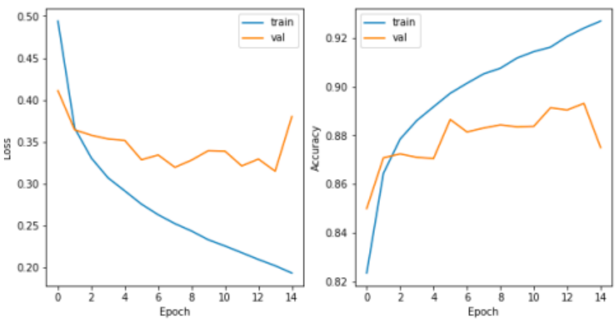
Some Examples

- **Regression problems**: mean squared error (MSE), mean absolute error (MAE), Huber loss.
- **Binary or multi-label classification problems**: binary cross-entropy.
- **Multi-class classification problems**: categorical cross-entropy, sparse categorical cross-entropy.
- **Imbalanced classification problems**: weighted cross-entropy, focal loss.

Monitoring the loss

The goal of learning is that **models perform well in general and not only in the training data**

Validation set: a subset of the training data to “keep an eye” on how the model performs on unseen data. Is given to the model in the fit( ) method



The model will typically do much better in the training set (overfitting). We monitor the validation loss to mitigate this.

Model Evaluation

Once trained, you want to make predictions on new data (the **test set**). This is called **inference**.

You can obtain predictions by simply doing:

$$y_{pred} = \begin{array}{c} \begin{array}{ccc} \text{Class1} & \text{Class2} & \text{Class3} \end{array} \\ \begin{bmatrix} 0.25 & 0.45 & 0.10 \\ 0.70 & 0.56 & 0.32 \end{bmatrix} \end{array} \begin{array}{l} \\ \text{Item1} \\ \text{Item2} \end{array} \longrightarrow y_{pred} = \begin{array}{c} \text{ClassID} \\ \begin{bmatrix} 1 \\ 0 \end{bmatrix} \end{array} \begin{array}{l} \\ \text{Item1} \\ \text{Item2} \end{array}$$

```
# Make predictions using the model
y_pred = model.predict(x_text)

# Convert the predicted probabiliies to the class labels
y_pred = np.argmax(y_pred, axis=1)
```

To evaluate accuracy

$$y_{pred} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \longleftrightarrow y_{true} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \longrightarrow \text{acc} = 0.5$$

```
# Calculate the accuracy by comparing the predicted labels with the ground truth labels
test_acc = np.mean(y_pred == y_test)
```

3. Remember these terms

- TensorFlow
- Keras
- PyTorch
- CPU
- GPU
- TPU
- Workspace
- Environment
- Preprocessing
- Baseline
- Normalization
- Reshape
- Validation loss
- Monitor loss
- Accuracy
- Inference