MF810: Environment setup and fundamentals

Desirable properties of a program or code

Some important features of a program and its source code:

Efficiency The most obvious: Do what we want without taking too long.

Correctness Do what we want in all circumstances, including edge cases.

Note that in unexpected cases it is often better to abort than to just continue.

Robustness Handle edge cases, unexpected inputs, or errors gracefully.

Maintainability Adding features, changing features, or fixing bugs should be easy.

Readability Somebody else (or future you) should be able to understand the code.

Not only about **what** the code does, but also **why**.

Helps maintainability.

Portability The program should run correctly on other computers than the developer's.

Today

- Docker and Linux basics
- Python Docker setup
- Intro to Pytorch
- Intro to neural networks
- Neural neural networks in Pytorch

Portability: Docker and Linux

- When moving code from one computer to another, it can fail to run. Some • Dependencies are not installed. Pucleage Xexist on another reasons include

 - Package versions differ.
 - Files are not in the right location.) solve problem
 - Etc.
- These issues are solved by containers. They also provide some safety/security benefits if used correctly.)
- **Docker** is a system for running containers.
- Docker is built on features of the Linux kernel. To be proficient Docker users, we must build basic understanding of Linux topics.

What is Linux?

Linux

- Linux typically refers to an operative system, like Windows or macOS.
- Strictly speaking, Linux is the Linux kernel.
- A kernel is the piece of software that coordinates everything in the background and communicates with the hardware. As far as software is concerned, the kernel is the computer!
- Examples include: the Windows NT Kernel on Windows; XNU on Apple devices; the Linux kernel on Android, etc.
- The Linux kernel provides features to run kernels inside the kernel itself, which is what makes Docker and containerization possible.

¹This is technically not what happens, but it is *similar* to doing so.

Foundations

Let us look at basics of how a Linux environment works.

Windows and macOS are in many ways very similar, but details differ.

We will discuss

- Users, groups, and permissions.
- Filesystems and file permissions.
- Environment variables.
- The "command line."

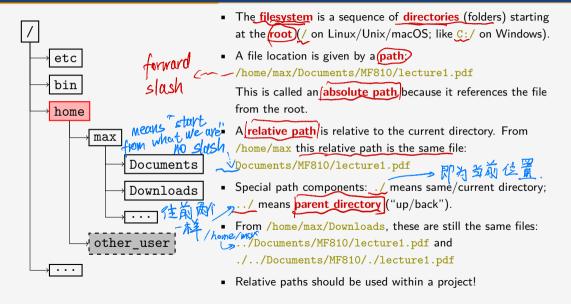
Users and groups

- When setting up a new computer, you must enter a (user)name. In this process, the OS sets up a user (account) for you.
- Systems typically have one super user² and one or more regular users.
- The purpose of multiple users is to restrict users from doing certain things:
 - One users should not be able to read other users' files.
 Only the super user (admin) should be granted unlimited access to the computer.

 - Etc.
- Different users have different permissions.
- Users can be members of groups, which may include multiple users. Groups are another tool to grant permissions. For instance, users who are members of the printer group are allowed to use the printers.

²root user on Linux/Unix/macOS or *Administrator* on Windows.

Filesystems



Files and file permissions

- A directory may contain a number of files.
- There are three main types of files: regular files, symlinks (references/shortcuts), and directories.
- Each file has an <u>owner</u>, a <u>group owner</u>, and two sets of permissions: owner permissions and group permissions.
- A file listing may look like

```
owner group size date filename rw indicates that the owner (max) may read (r) and write (w) to the file.

therefore indicates that all members of the group users may read (r) but not write (w) to the file.
```

 Permissions are central to the system and a great protection against accidental mistakes.

Docker images

- Docker images and containers are like classes and objects in object-oriented programming: containers are specific instances of images.
- Images can be created in two ways:
 - By downloading an existing image, e.g.
 docker pull ubuntu or docker pull python:slim.
 - By extending an existing image in a Dockerfile and building it:
 docker build -t image_name path_to_Dockerfile_dir
 We will use the name my_python_im and the path will be . if run from the same directory as the Dockerfile.
- Containers are created from an image using either docker run or docker create.
- Making changes to a container does not change the image it was created from!

Containers: docker run example

Once set up, we run any Python script by entering

```
docker run --rm -it my_python_im -v "$PWD":/workdir python scriptname.py
```

- docker run creates and runs a container from an image.
- --rm deletes the container after termination.
- -it specifies interactive mode (as opposed to running in the background).
- python_image is the name we have given our Python image.
 - -v "\$PWD":/workdir makes the current directory (\$PWD) available in the container at the /workdir path.
 - python specifies that the container should execute the Python executable.
 - scriptname.py is the script file we want python to run.
- This is long, but we can make a shortcut as e.g. dockpy scriptname.py
- Like this, your code can be sent to a friend or a cloud computer and run exactly like it does on your computer!

Deep learning libraries and neural

networks

Differentiation and optimization

- What are famous libraries like Tensorflow and Pytorch?
- Short answer:
 They are numerical libraries with extra support for differentiating special functions.
- Consider an abstract problem of minimizing a function L as a function of θ :

$$\min_{\theta \in \mathbb{R}^P} L(\theta).$$

ullet If L is smooth, the first order condition at the minimum states

$$\nabla_{\theta} L(\theta) \Big|_{\theta = \theta^*} = \nabla_{\theta} L(\theta^*) = 0.$$

• Gradients are intimately connected to optimization, and that is the interest in numerical libraries with differentiation support.

Gradient descent

- lacksquare Recall from calculus, that the gradient $\nabla_{ heta}L$ is a vector pointing in the direction in which the function L is most increasing (steepest).
- Similarly, $-\nabla_{\theta}L = \nabla_{\theta}(-L)$ is the direction in which -L is most increasing, i.e., $-\nabla_{\theta}L$ is the direction that L is most decreasing.
- If we from any point θ move a small distance $\epsilon \nabla_{\theta} L(\theta)$ along the gradient to θ' , we should have $L(\theta') \leq L(\theta)$. • We have discovered gradient descent: $\theta_{n+1} = \theta_n - \epsilon \nabla_{\theta} L(\theta_n)$.

$$\theta_{n+1} = \theta_n - \epsilon \nabla_{\theta} L(\theta_n).$$

- Because our deep learning library can compute gradients, this is trivial to implement!

Our first example: linear regression

Consider the problem of least squares linear regression:

$$\min_{\theta \in \mathbb{R}^P} \sum_{i=1}^N \ell(y_i, f(x_i; \theta)) \qquad \min_{\theta \in \mathbb{R}^P} \sum_{i$$

- Define

$$L(\theta) = \sum_{i=1}^{N} \ell(y_i, f(x_i; \theta))$$

so that

$$L(\theta) = \sum_{i=1}^{N} \ell(y_i, f(x_i; \theta))$$
Some as min (0) $i=1$

$$U$$
 so take gradient
$$\nabla_{\theta} L(\theta) = \sum_{i=1}^{N} \partial_{y'} \ell(y_i, f(x_i; \theta)) \nabla_{\theta} f(x_i; \theta) = \sum_{i=1}^{N} 2(y_i - x_i \cdot \theta) x_i.$$

These expressions are much simpler on matrix form.

x is vector

Linear regression gradient descent

With

$$\nabla_{\theta} L(\theta) = \sum_{i=1}^{N} 2(y_i - x_i \cdot \theta) x_i$$

gradient descent is equivalent to iterating

Start with
$$\theta_{n+1} = \underbrace{\theta_n^{\nu}}_{-\frac{\nu}{2}} - \underbrace{\sum_{i=1}^{N} 2(y_i - x_i \cdot \theta) x_i}_{\text{stines with}}.$$

• For linear regression, this method converges to the minimizer θ^* .

 $^{^3}$ If ϵ is decreasing at an appropriate rate.

Linear/dense layers

- The function $f(x;\theta) = \theta \cdot x = \theta x$ maps $x \in \mathbb{R}^P$ to \mathbb{R} .
- lacksquare Generalize this to \mathbb{R}^P to \mathbb{R}^k by taking $\theta \in \mathbb{R}^{P imes k}$

$$\mathbb{R}^P \to \mathbb{R}^k$$
 $x \mapsto \theta x$.

- It is useful to apply another function σ to the output.
- Often $\sigma : \mathbb{R} \to \mathbb{R}$, in which case this is done element-by-element, and we write σ . for such **broadcasting**:

$$\sigma(x) = (\sigma(x_1), \dots, \sigma(x_k)), \quad x \in \mathbb{R}^k.$$

We write just $\sigma(x)$ to mean $\sigma(x)$ in this case.

- The transformation $x \mapsto \theta x$ is called a **linear layer**.
- The function $f(x;\theta) = \sigma(\theta x)$ is called just a layer or a dense layer.

Neural networks

- The function $[x \mapsto \sigma(\theta x)]$ is an example of a trivial (artificial) neural network (ANN or NN).
- Let $\theta=(w_1,w_2)$ and define $h_1(x;w_1)=\sigma_1(w_1x)$ and $h_2(x;w_2)=\sigma_2(w_2x)$. The composition (assuming $w_1\in\mathbb{R}^{k_0\times k_1}$ and $w_2\in\mathbb{R}^{k_1\times k_2}$)

$$(h_2 \circ h_1)(x) = h_2(h_1(x)) = \sigma_2(w_2\sigma_1(w_1x))$$

is a two-layer neural network.

- The function h_1 is called a **hidden layer** and the function h_2 is called the **output** layer.
- The parameters w_1 and w_2 are called weights.
- The functions σ_1 and σ_2 are called **activation functions**.

Neuron bias

- For reasons we discuss later, it is common to work with affine transformations instead of linear.
- Let $heta=((w_1,b_1),\ldots,(w_d,b_d))$ and define each adding h . $h_i(x)=\sigma_i(b_i+w_ix)$.
- The term b_i is called a **neuron bias**, often **bias** for short.
- The composition $h_d \circ h_{d-1} \circ \cdots \circ h_2 \circ h_1$ is a **neural network** of **depth** d.
- Because $h_d(x)$ is often a linear transformation to a scalar $(\mathbb{R}^{k_{d-1}} \to \mathbb{R}^{k_d} = \mathbb{R})$, it is customary to speak of the number of **hidden layers**, which here is d-1.
- Like before, the weights must satisfy $w_i \in \mathbb{R}^{k_{i-1} \times k_i}$ and $b \in \mathbb{R}^{k_i}$. The value k_i is called the width of layer i.
- The number of parameters in this network is $P = \sum_{i=0}^{d} (k_{i-1} + 1)k_i.$

MLPs and more

- This type of neural network is called a multilinear perceptron (MLP).
- An MLP is a feedforward neural network in which all neurons in two adjacent layers are connected to each other (called fully connected or dense).
- There are many other examples of layers. Some examples include
 Convolutional layers Feedforward but not fully connected.
 - Commonly used to find spatial patterns, like in images.

Recurrent layers Not feedforward.

Used for sequential data like natural language processing (NLP) and time series.

Dropout layers Randomly omits connections: feedforward but not dense. Used for regularization.

- Such common structures are included in the libraries and can be used directly.
- There are no restrictions on general layers; custom layers are often created.