fastai

A deep learning library for fast implementation & research

Marie-Hélène Burle
training@westgrid.ca

April 14, 2021

WestGrid Training Modules 2021

WestGrid Training Modules 2021 Basics Programming Parallel Cloud ML SciVis MATLAB

WEST GRID

Training Modules 2021

Remote computing basics	April 27 & May 4
Programming tools	May 11, 18 & 25
Parallel coding	June 1 & 8
Compute Canada cloud	June 22 & 29
Machine learning	July 6
Scientific visualization	July 13
MATLAB	July 21 & 27

Information

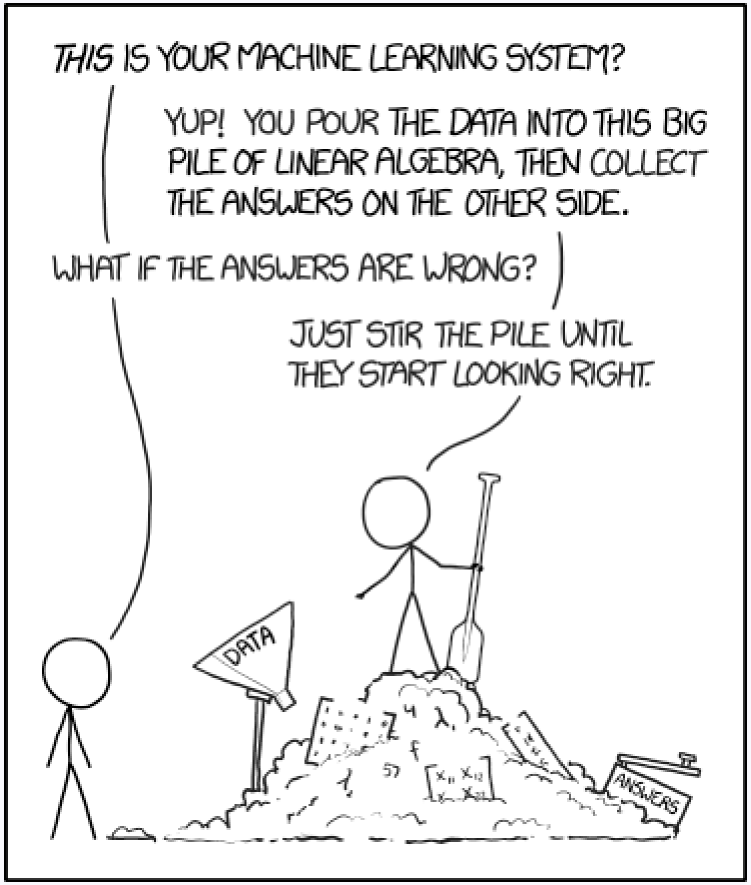
https://wgtm21.netlify.app/

Machine learning

Computer programs whose performance at a task improves with experience

Dominant approach:

Feeding vast amounts of data to algorithms



From xkcd.com

History

1943: Warren McCulloch & Walter Pitts—mathematical model of artificial neuron.

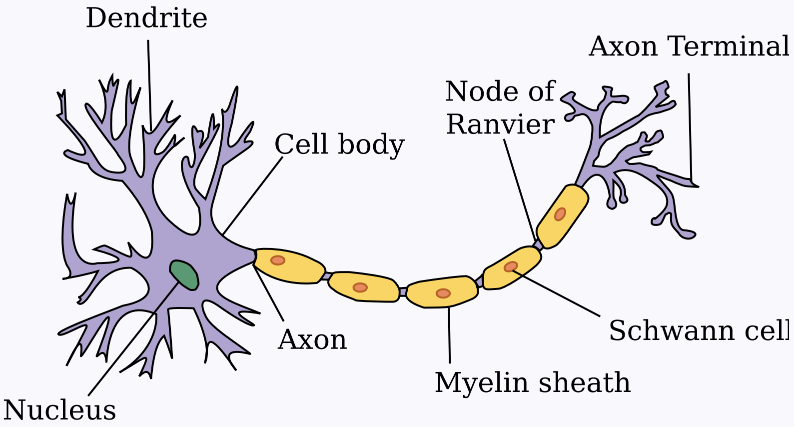
1961: Frank Rosenblatt—perceptron.

1961: Arthur Samuel's checkers program.

1986: James McClelland, David Rumelhart & PDP Research Group—book: "Parallel Distributed Processing".

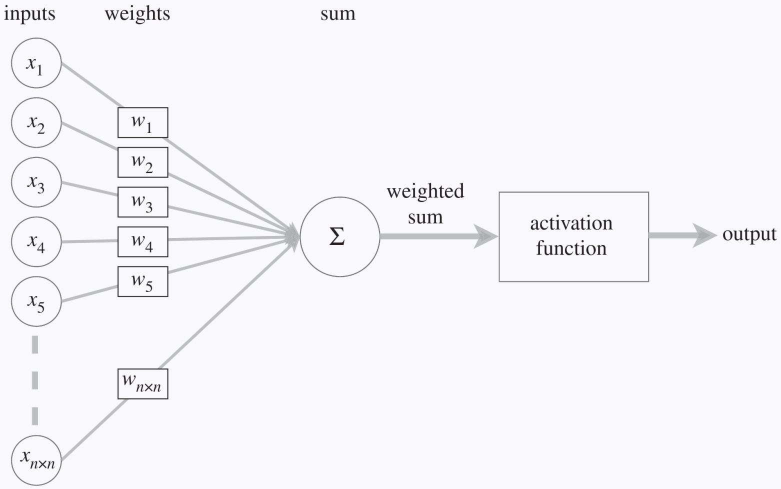
Neurons

Biological



Schematic from Dhp1080, Wikipedia

Artificial



Modified from O.C. Akgun & J. Mei 2019

Neural networks

A NN is a parameterized function which can, in theory, solve any problem to any level of accuracy.

The learning process is the mapping of input data to output data (in a training set) through the adjustment of the parameters.

Neural networks

Biological

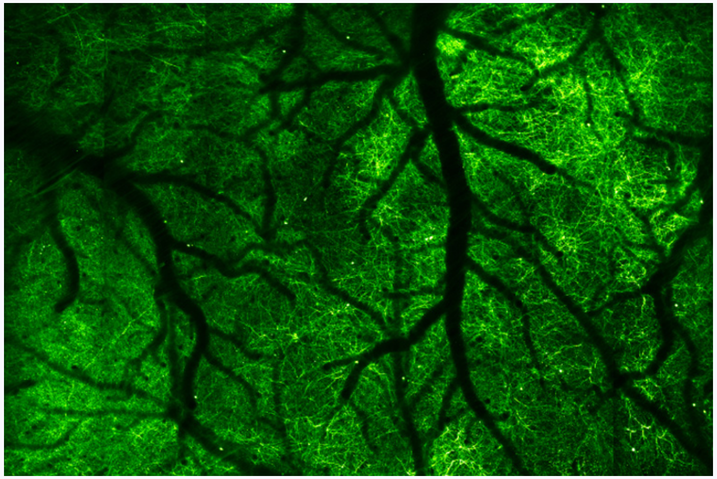
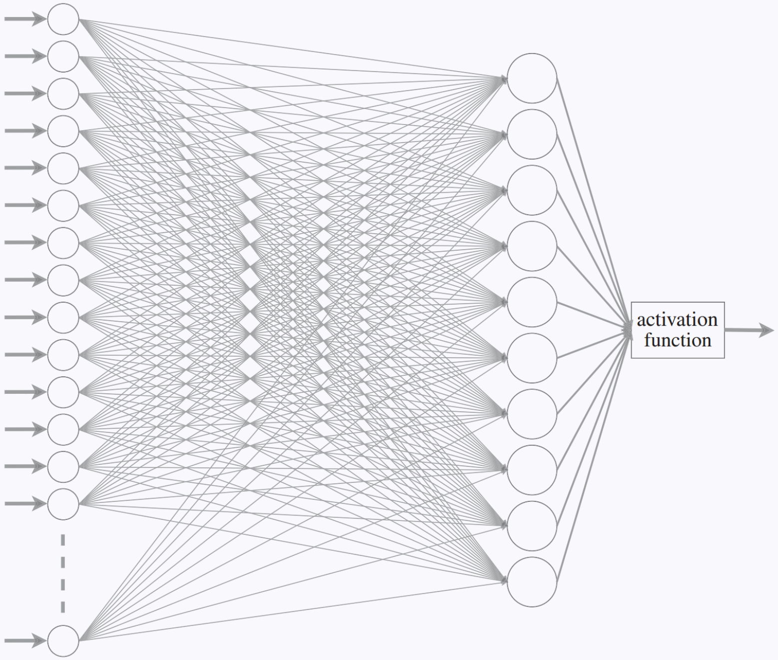


Image by Na Ji, UC Berkeley

Artificial



Modified from O.C. Akgun & J. Mei 2019

Neural networks

Single layer of artificial neurons → Unable to learn even some of the simple mathematical functions (Marvin Minsky & Seymour Papert).

Two layers → Theoretically can approximate any math model, but in practice very slow.

More layers → Deeper networks

Neural networks

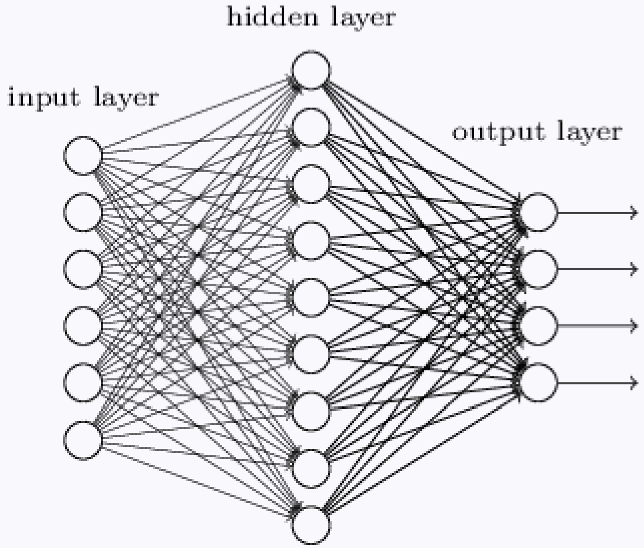
Single layer of artificial neurons → Unable to learn even some of the simple mathematical functions (Marvin Minsky & Seymour Papert).

Two layers → Theoretically can approximate any math model, but in practice very slow.

More layers → Deeper networks → **deep learning**.

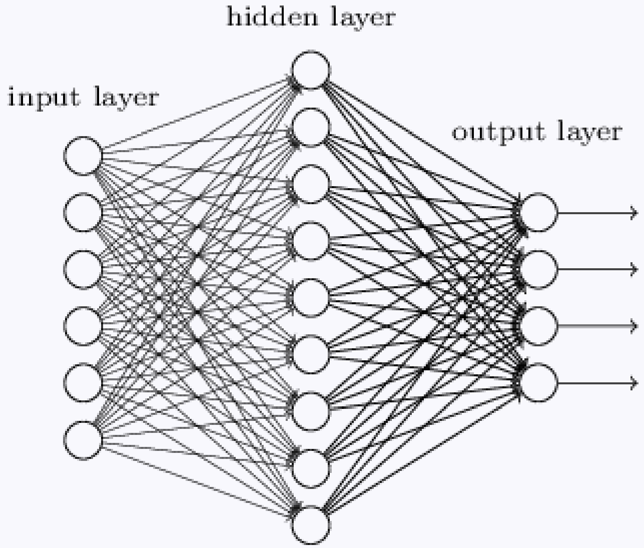
Types of NN

Fully-connected, feedforward, single-layer NN



From "Neural Networks and Deep Learning" free online book, Chapter 5

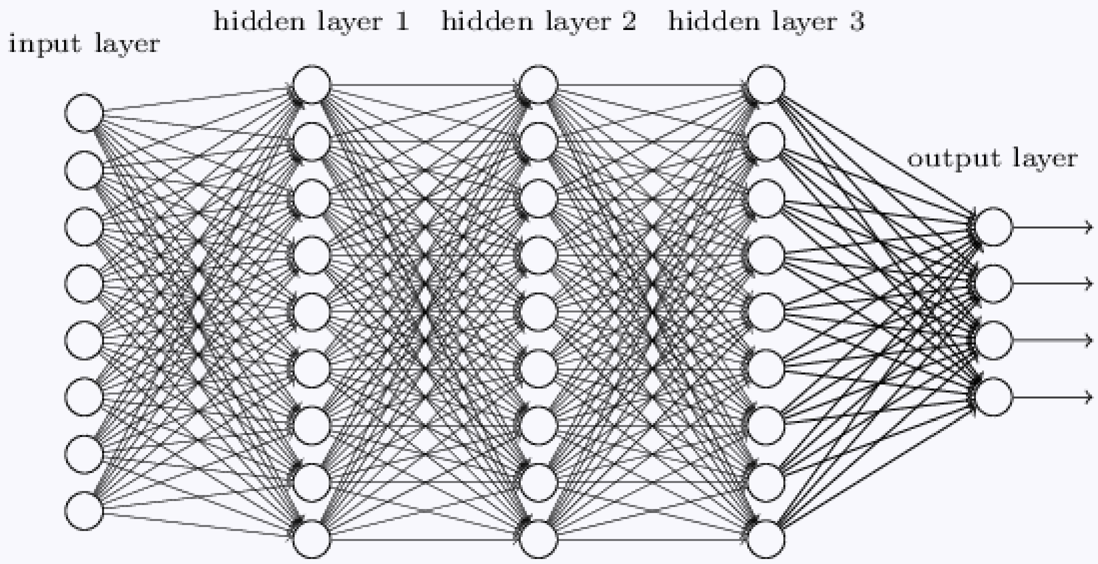
Fully-connected, feedforward, single-layer NN



From "Neural Networks and Deep Learning" free online book, Chapter 5

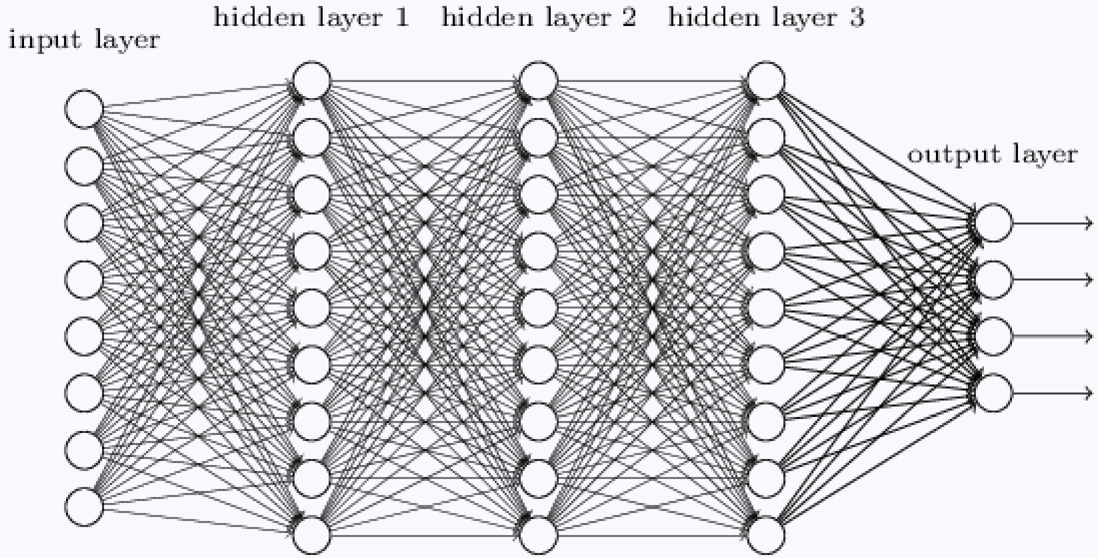
Each neuron receives input from every element of the previous layer.

Fully-connected, feedforward, deep NN



From "Neural Networks and Deep Learning" free online book, Chapter 5

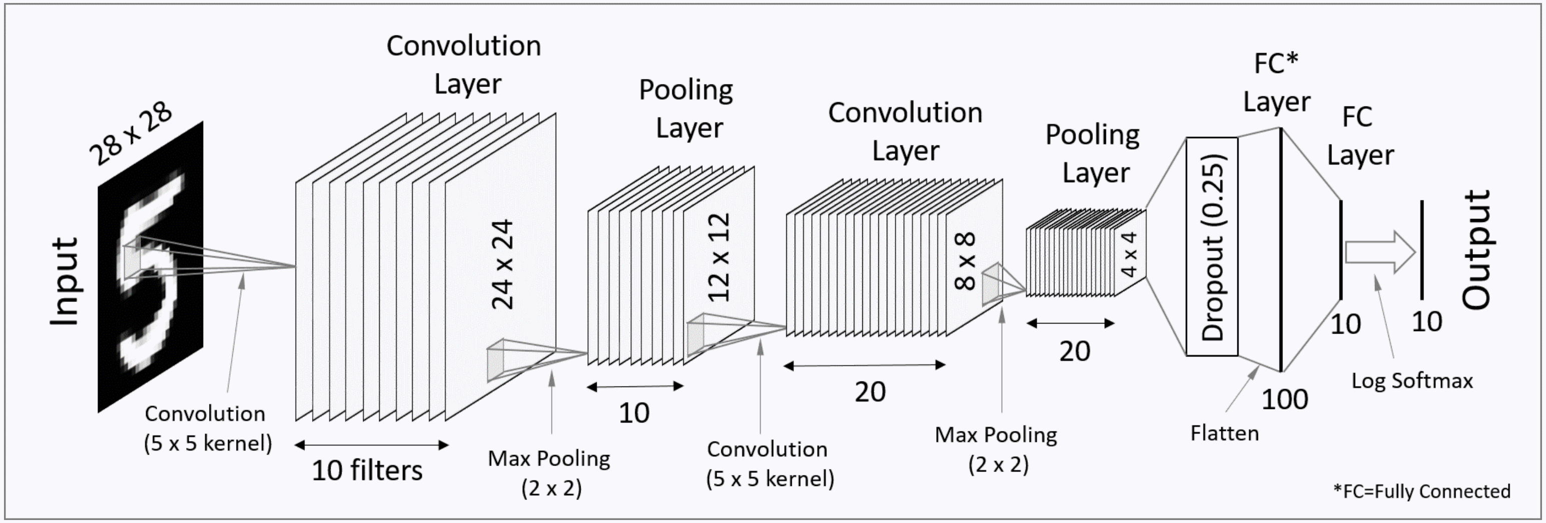
Fully-connected, feedforward, deep NN



From "Neural Networks and Deep Learning" free online book, Chapter 5

Data with large input sizes (e.g. images) would require a huge number of neurons.

Convolutional neural network (CNN)



From Programming Journeys by Rensu Theart

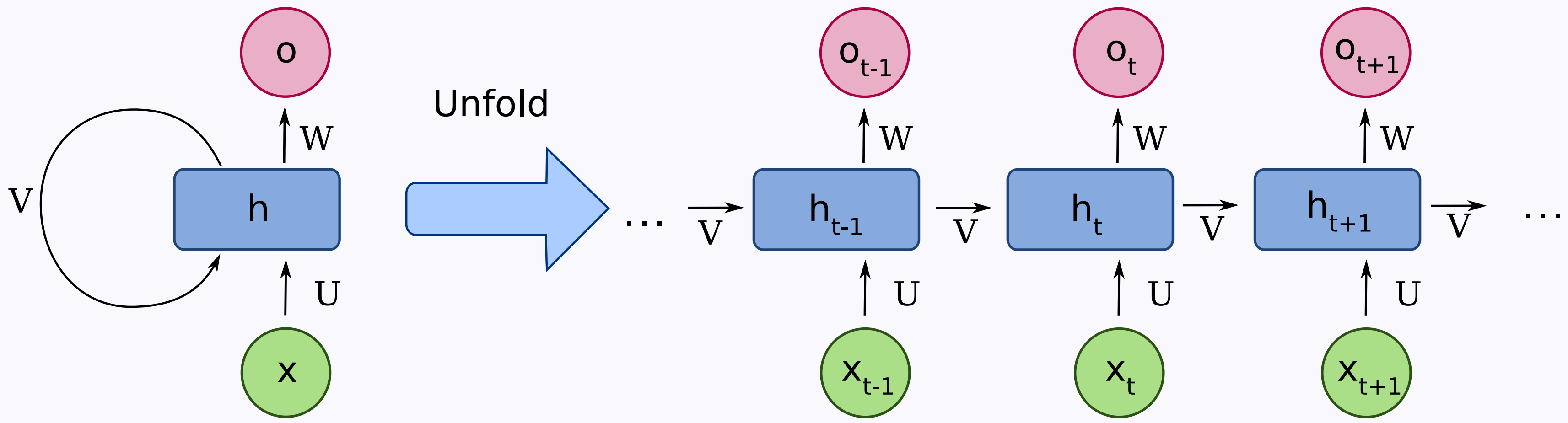
Used for spatially structured data.

Convolution layers → each neuron receives input only from a subarea of the previous layer.

Pooling → combines the outputs of neurons in a subarea to reduce the data dimensions.

Not fully connected.

Recurrent neural network (RNN)



From fdeloche, Wikipedia

Used for chain structured data (e.g. text).

Not feedforward.

General principles

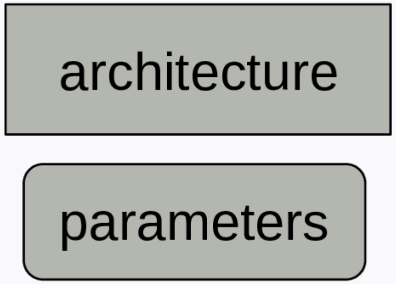
General principles

Derived from **Arthur Samuel**'s approach.

Building a model

First, we need an architecture (size, depth, types of layers, etc.).
This is set before training and does not change.

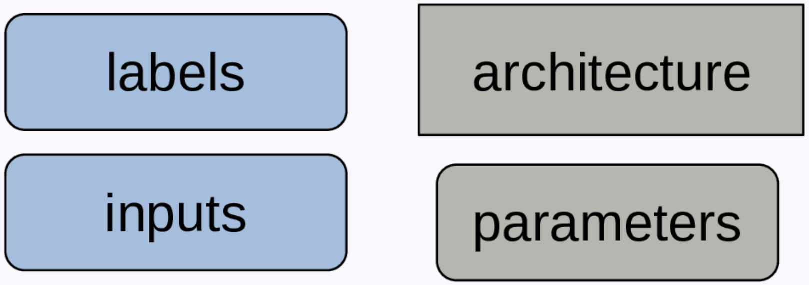
Building a model



A model also comprises parameters.

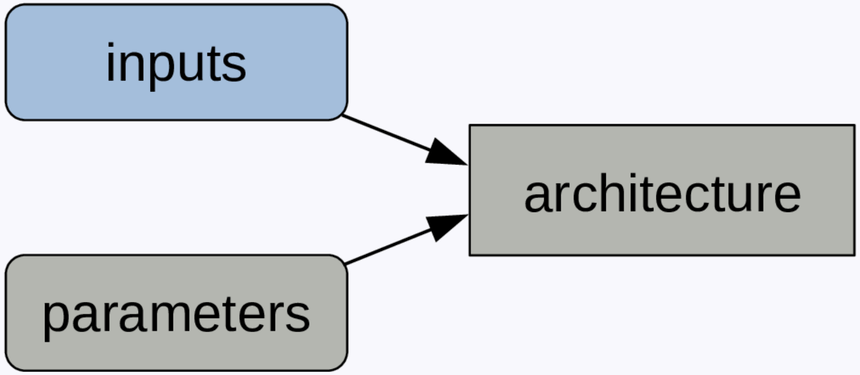
Those are set to some initial values, but will change during training.

Training a model



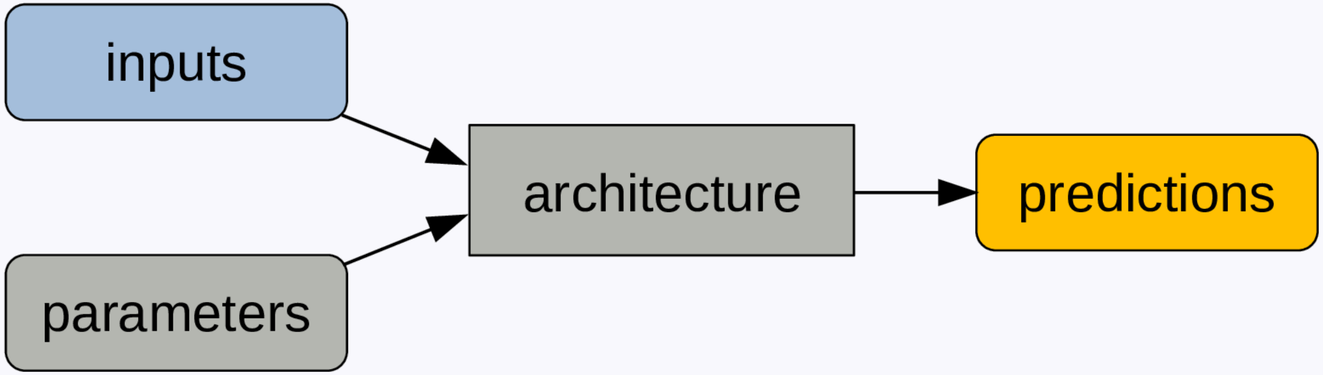
To train the model, we need labelled data in the form of input/output pairs.

Training a model



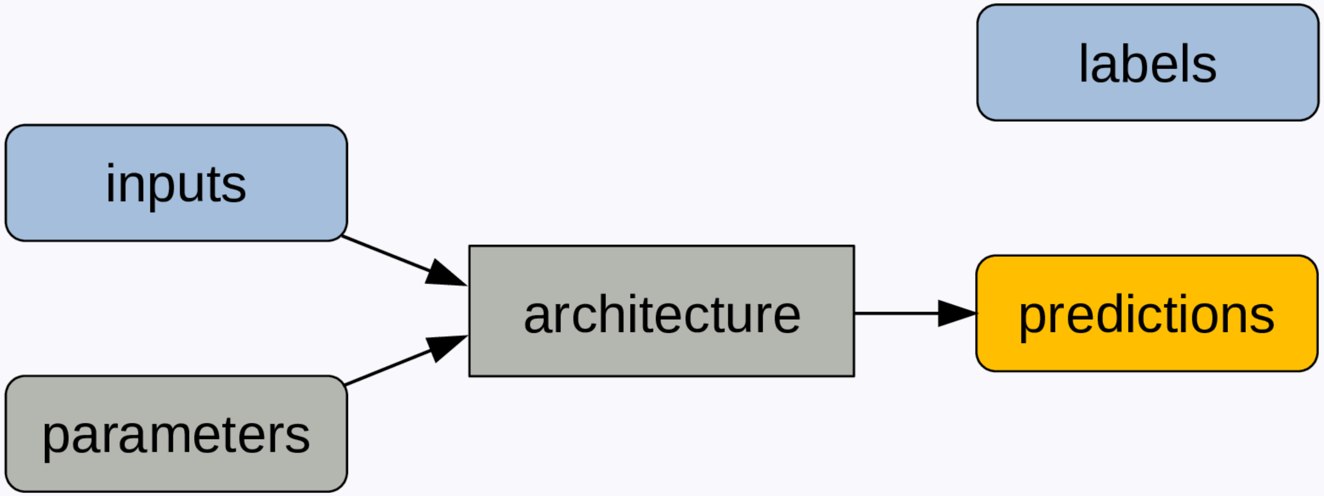
Inputs and parameters are fed to the architecture.

Training a model



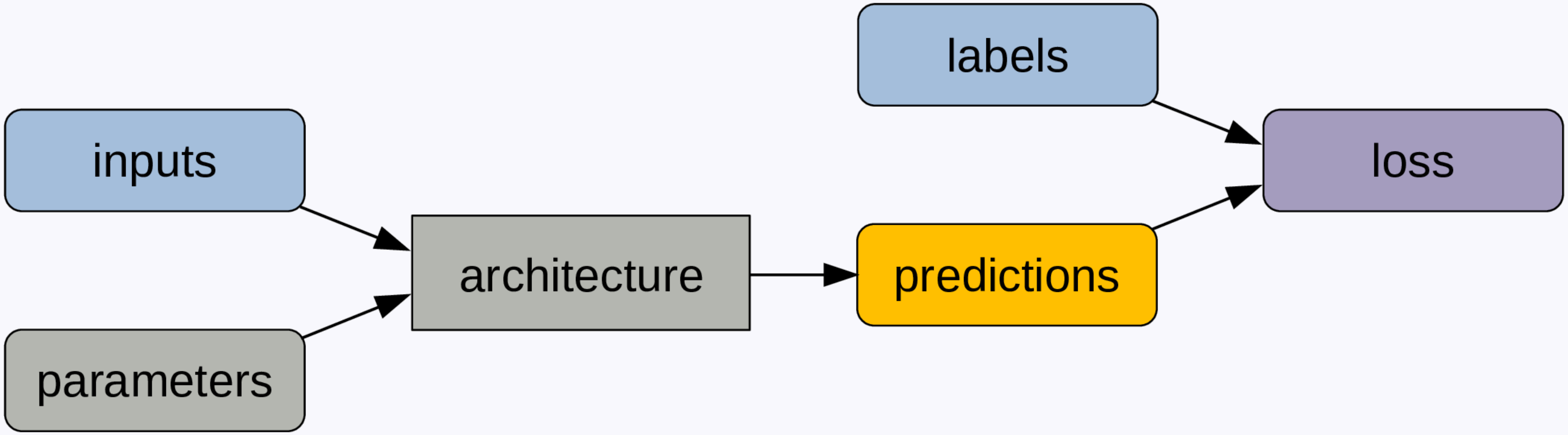
We get predictions as outputs.

Training a model



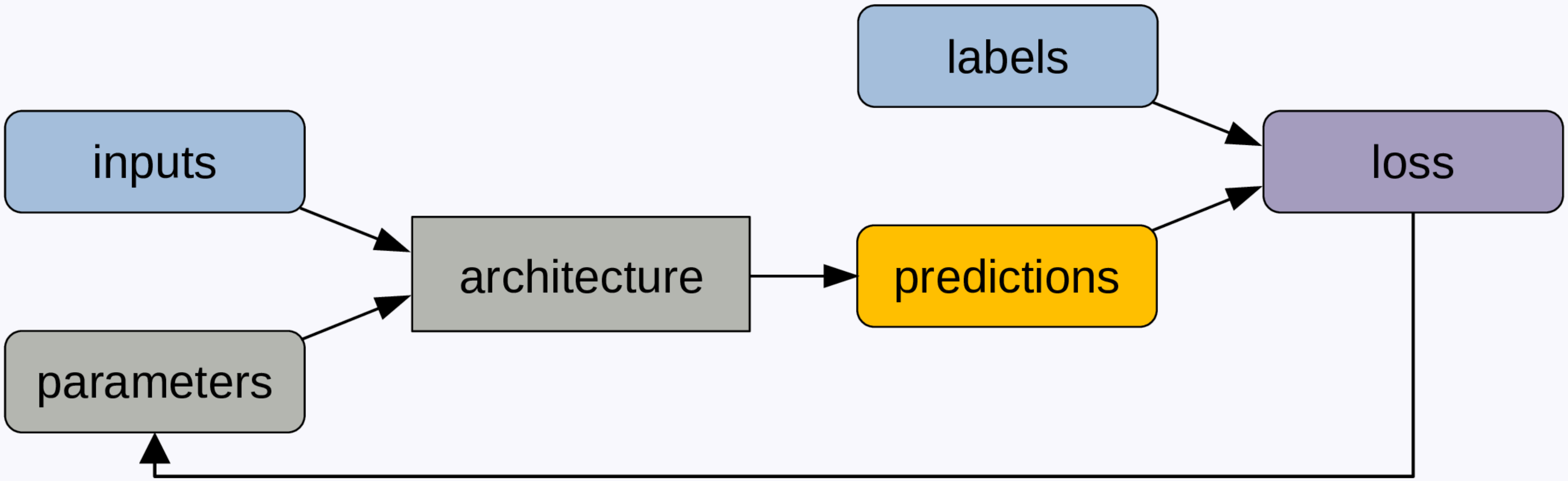
A metric (e.g. error rate) compares predictions and labels and is a measure of model performance.

Training a model



Because it is not always sensitive enough to changes in parameter values, we compute a loss function …

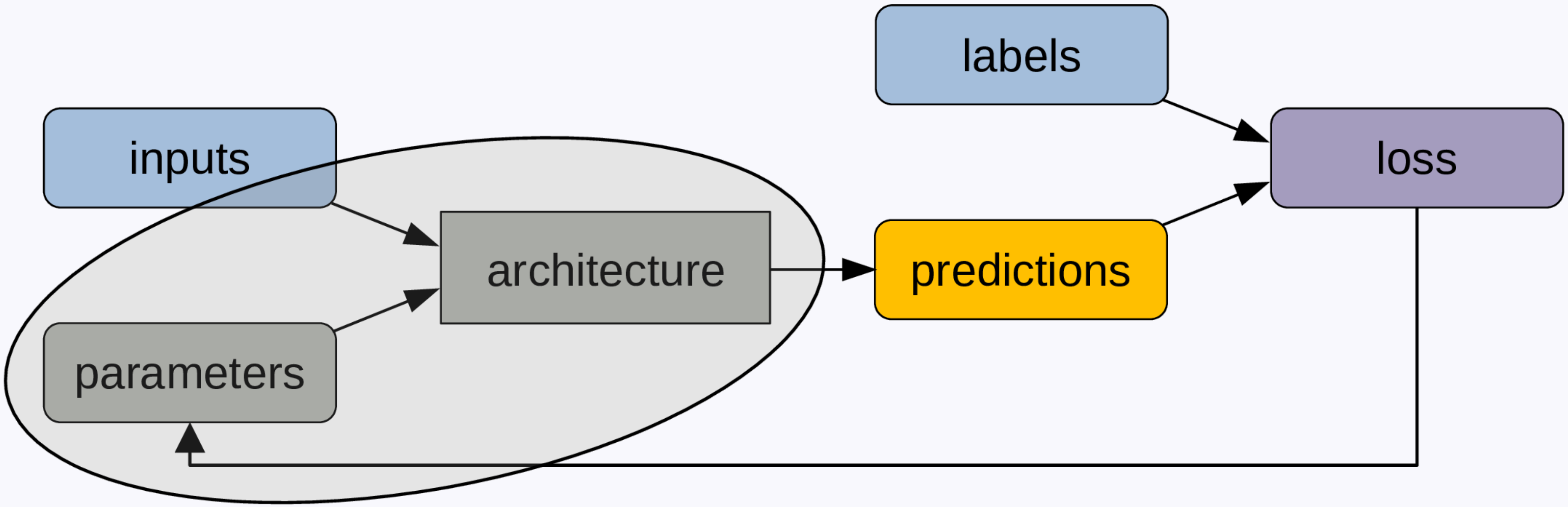
Training a model



… which allows to adjust the parameters slightly through backpropagation.

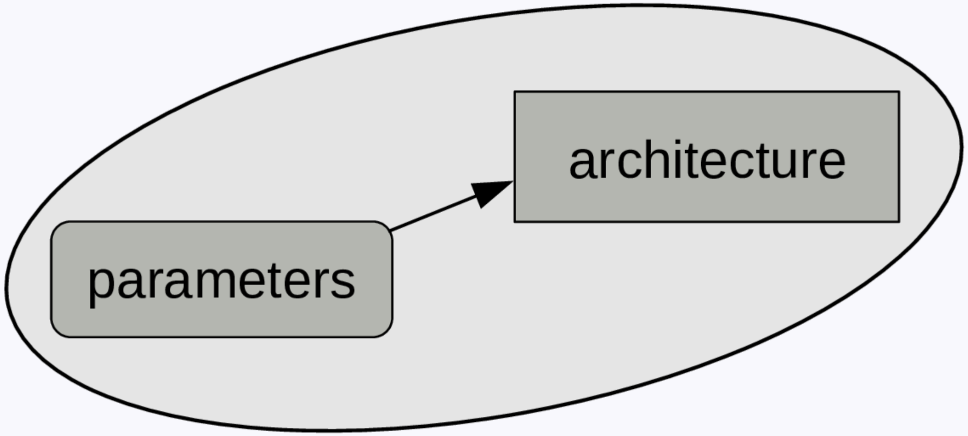
This cycle gets repeated for a number of steps.

Using a model



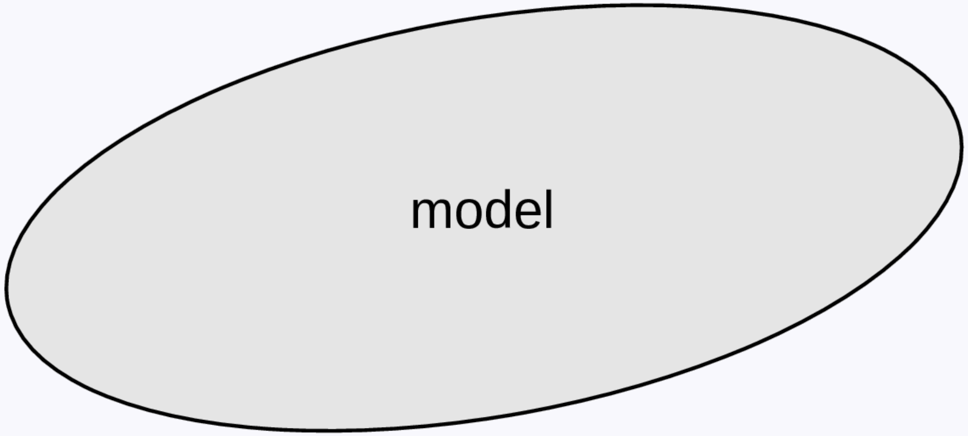
At the end of the training process, what matters is the combination of architecture and trained parameters.

Using a model



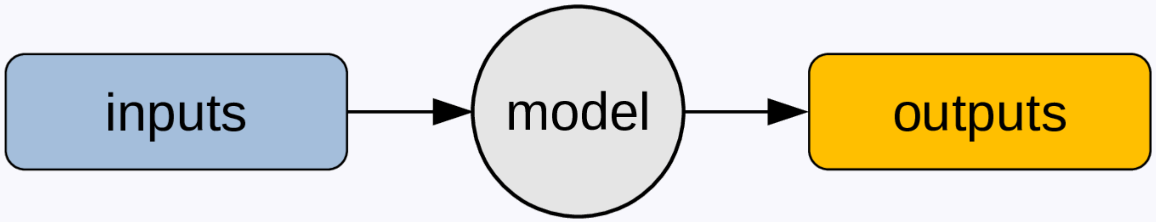
That’s what constitute a model.

Using a model



A model can be considered as a regular program …

Using a model

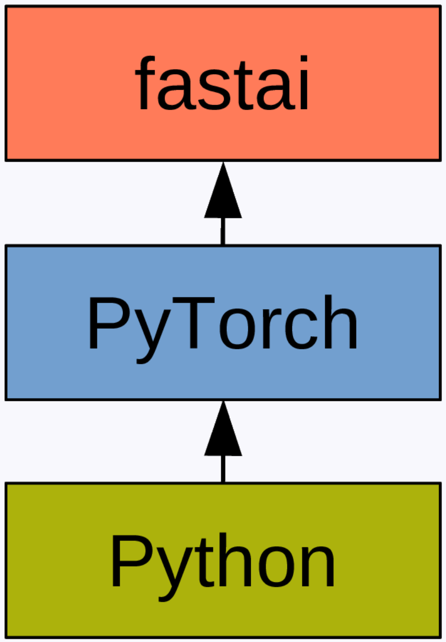


… and be used to obtain outputs from inputs.

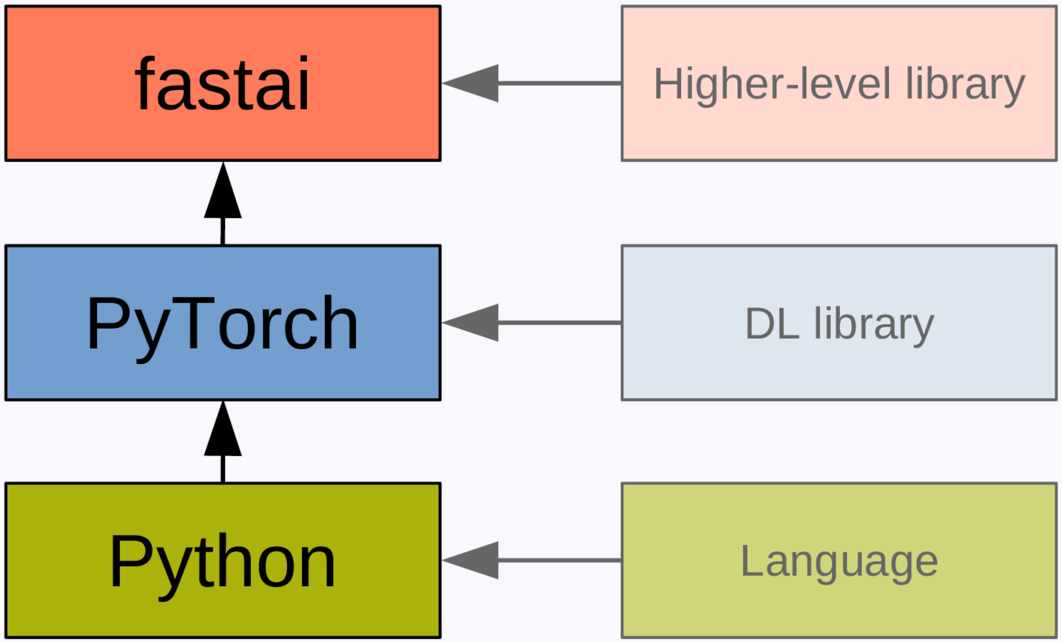
fastai

What is fastai?

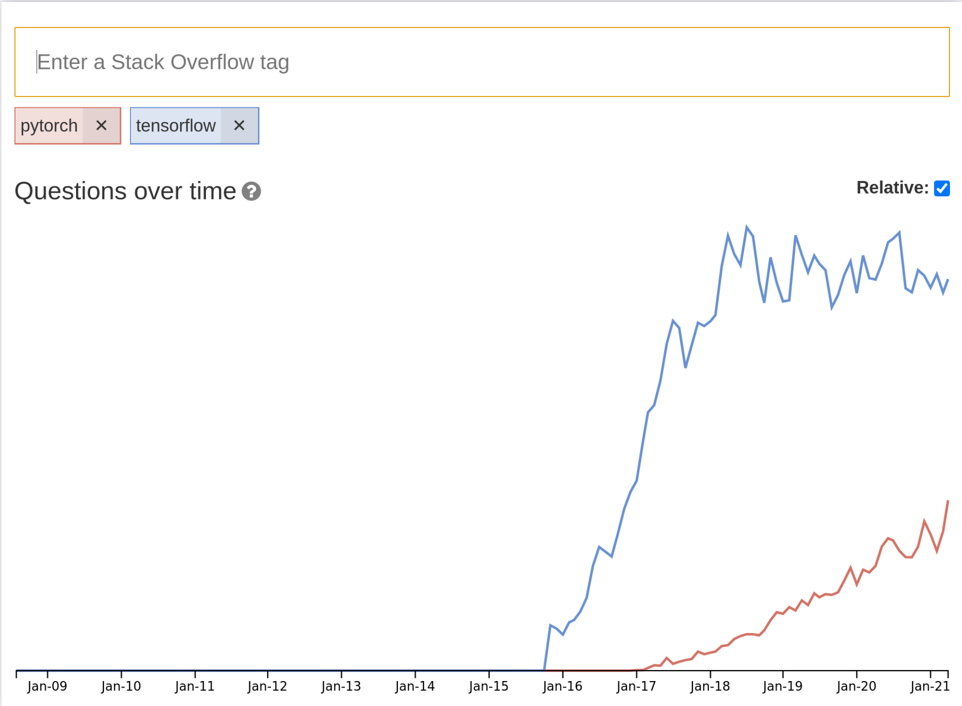
What is fastai?



What is fastai?



PyTorch



- Very Pythonic.
- Widely used in research.

fastai

fastai is a deep learning library that builds on top of PyTorch, adding a higher level of functionality.

> *[It] is organized around two main design goals: to be approachable and rapidly productive, while also being deeply hackable and configurable.*

Resources

Documentation

Manual

Tutorials

Peer-reviewed paper

Book

Paperback version

Free MOOC version of part 1 of the book

Jupyter notebooks version of the book

Getting help

Discourse forum

Basic workflow

- DataLoaders

Create iterators with the training and validation data.

- Learner

Train the model.

- Predict or visualize

Get predictions from our model.

Example: identifying painters

Two main types of models

- Classification

- Regression

Two main types of models

- Classification

- Regression

Load domain specific library

In our case, we need the `vision` library:

```
from fastai.vision.all import *
```

Other domains available:

```
from fastai.text.all import *
from fastai.tabular.all import *
from fastai.collab import *
```

> Note that `import *` is not recommended in Python outside the context of fastai.

DataLoaders

A fastai class.

A simple wrapper around the PyTorch `DataLoader` class with added functionality (a `DataLoader` creates batches of data and sends them to the CPU or GPU as you iterate through it).

Creates an object of class DataLoaders which contains a validation DataLoader and a training DataLoader.

DataLoaders

Using `search_images_bing`, a convenience function to download images from the Bing API (free registration required).

```
key = os.environ.get('AZURE_SEARCH_KEY', '<your-private-key>')
```

DataLoaders

Let's download paintings from Monet:

```
monet = search_images_bing(key, 'monet')
ims = monet.attrgot('content_url')
path = Path('dataset')
fns = get_image_files(path)
fns
```

> (#65) [Path('dataset/monet/Image_63.jpg'),Path('dataset/monet/Image_31.jpg')...]

Note that this last output is of a fastai class `L`: a Python list with added functionality.

DataLoaders

We can do the same with Van Gogh:

```
vangogh = search_images_bing(key, 'vangogh')
ims = vangogh.attrgot('content_url')
path = Path('dataset')
fns = get_image_files(path)
fns
```

> (#89) [Path('dataset/vangogh/Image_13.jpg'),Path('dataset/vangogh/Image_42.jpg')...]

DataLoaders

Data block API:

```
paintings = DataBlock(
    blocks=(ImageBlock, CategoryBlock),
    get_items=get_image_files,
    splitter=RandomSplitter(valid_pct=0.2, seed=42),
    get_y=parent_label,
    item_tfms=Resize(128))
```

DataLoaders

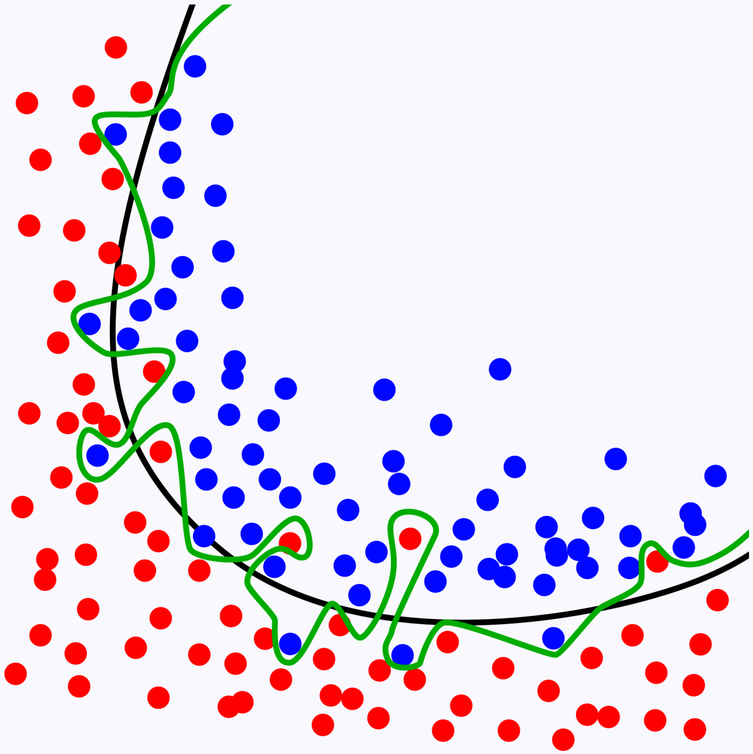
- **blocks**: types of inputs and labels
- **get_items**: how to get the list of items
- **splitter**: how to split the data between a validation set and a training set
- **get_y**: how to label the data
- **item_tfms**: item transformation
- **batch_tfms**: transformation of the whole batch. Very fast as this happens in the GPU

DataLoaders

- **blocks**: types of inputs and labels
- **get_items**: how to get the list of items
- **splitter**: how to split the data between a validation set and a training set
- **get_y**: how to label the data
- **item_tfms**: item transformation
- **batch_tfms**: transformation of the whole batch. Very fast as this happens in the GPU

`valid_pct=0.2`: keep a validation set (20% of the data) to test the model.

Major pitfall: over-fitting



From Chabacano, Wikipedia

Major pitfall: over-fitting

- Training too long

- Training without enough data

- Too many parameters

DataLoaders

```
dls = paintings.dataloaders(path)
```

We now have our `DataLoaders` object `dls`.

Let's have a look at 4 items:

```
dls.valid.show_batch(max_n=4, nrows=1)
```

DataLoaders

```
dls = paintings.dataloaders(path)
```

We now have our `DataLoaders` object `dls`.

Let's have a look at 4 items:

```
dls.valid.show_batch(max_n=4, nrows=1)
```

DataLoaders

To standardize the size of images, `Resize` cropped them, but there are alternative methods:

```
paintings = paintings.new(item_tfms=Resize(128, ResizeMethod.Squish))
dls = paintings.dataloaders(path)
dls.valid.show_batch(max_n=4, nrows=1)
```

DataLoaders

To standardize the size of images, `Resize` cropped them, but there are alternative methods:

Squish

```
paintings = paintings.new(item_tfms=Resize(128, ResizeMethod.Squish))
dls = paintings.dataloaders(path)
dls.valid.show_batch(max_n=4, nrows=1)
```

DataLoaders

To standardize the size of images, `Resize` cropped them, but there are alternative methods:

Pad

```
paintings = paintings.new(item_tfms=Resize(128, ResizeMethod.Pad,
                                            pad_mode='zeros'))
dls = paintings.dataloaders(path)
dls.valid.show_batch(max_n=4, nrows=1)
```

Learner

```
learn = cnn_learner(dls, resnet18, metrics=error_rate)
learn.fine_tune(4)
```

Transfer learning

Repurposing pretrained models.

- Less data needed

- Less computing time needed

- Leads to better accuracy

Results

epoch	train_loss	valid_loss	error_rate	time
0	0.398155	0.167293	0.068152	00:03
1	0.204518	0.135118	0.050011	00:02
2	0.199835	0.099103	0.040012	00:05
3	0.179214	0.046119	0.025813	00:03

Getting into a lower level

Gradient descent

For each function, there is another function representing, not the values, but the rate of change of the values of the first function.

We need the gradients of the parameters with respect to the loss function to know in which direction and with which magnitude to adjust them at each step.

Automatic differentiation

To start tracking all operations performed on our model parameters:

```
params = tensor.requires_grad_()
```

> Underscore at the end of a method in PyTorch: in place operation.

Gradient descent

Get the values predicted by our model with our parameters:

```
preds = model(params)
```

Calculate the loss:

```
loss = loss_func(preds, targets)
```

Backpropagation:

```
loss.backward()
```

Gradient descent

Get the gradients:

```
params.grad
```

Update the parameters:

```
params.data -= params.grad.data * lr
```

- `.data` stops the gradient from being calculated on this operation.
- `lr`: learning rate.

> **Which learning rate?**
> Usually between 0.0001 and 1.
> Deeper networks are more bumpy and require lower learning rates (e.g. 0.01 instead of 0.1).

Gradient descent

Get the gradients:

```
params.grad
```

Update the parameters:

```
params.data -= params.grad.data * lr
```

- `.data` stops the gradient from being calculated on this operation.
- `lr`: learning rate.

Reset the gradient:

```
params.grad = None
```

Gradient descent

Putting it all together:

```python
def apply_step(params, prn=True):
    preds = model(params)
    loss = loss_func(preds, targets)
    loss.backward()
    params.data -= params.grad.data * lr
    params.grad = None
    if prn: print(loss.item())
    return preds

for i in range(4): apply_step(params)
```

Data bias

Bias is always present in data.

Document the limitations and scope of your data as best as possible.

Problems to watch for:

- *Out of domain data*: data used for training are not relevant to the model application.
- *Domain shift*: model becoming inadapted as conditions evolve.
- *Feedback loop*: initial bias exacerbated over the time.

The last one is particularly problematic whenever the model outputs the next round of data based on interactions of the current round of data with the real world.

Solution: ensure there are human circuit breakers and oversight.

Questions?