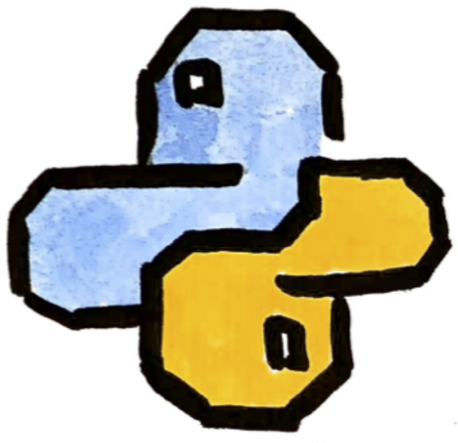
END 2 END DATA SCIENCE

Mark Keinhörster &
Dr. Shirin Glander

Convolutional Neural Nets

Computer Vision



About this Workshop

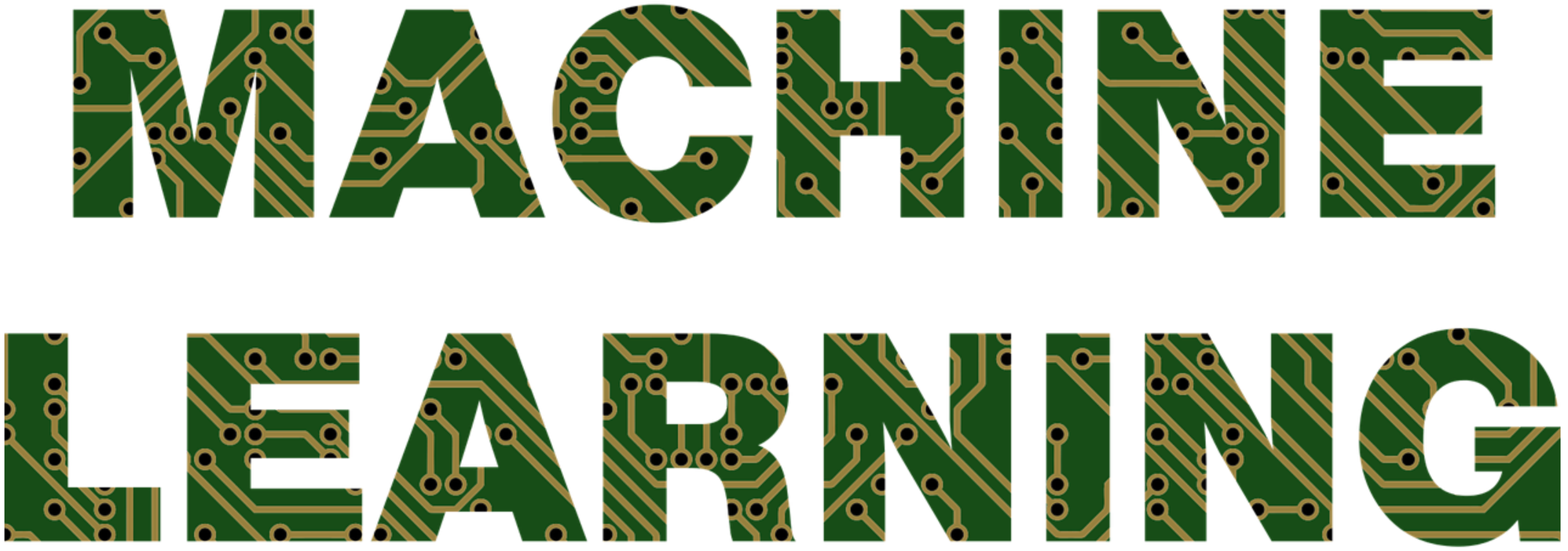
- Learn what neural nets are and what the big deal is with deep learning
- Interactively build a model that differentiates between fruits on images
- Get a glimpse of production-readiness
- Learn about Luigi pipelines and their main components
- Write your production ready pipeline
- Get an overview of luigis modules

About us

Data Architect

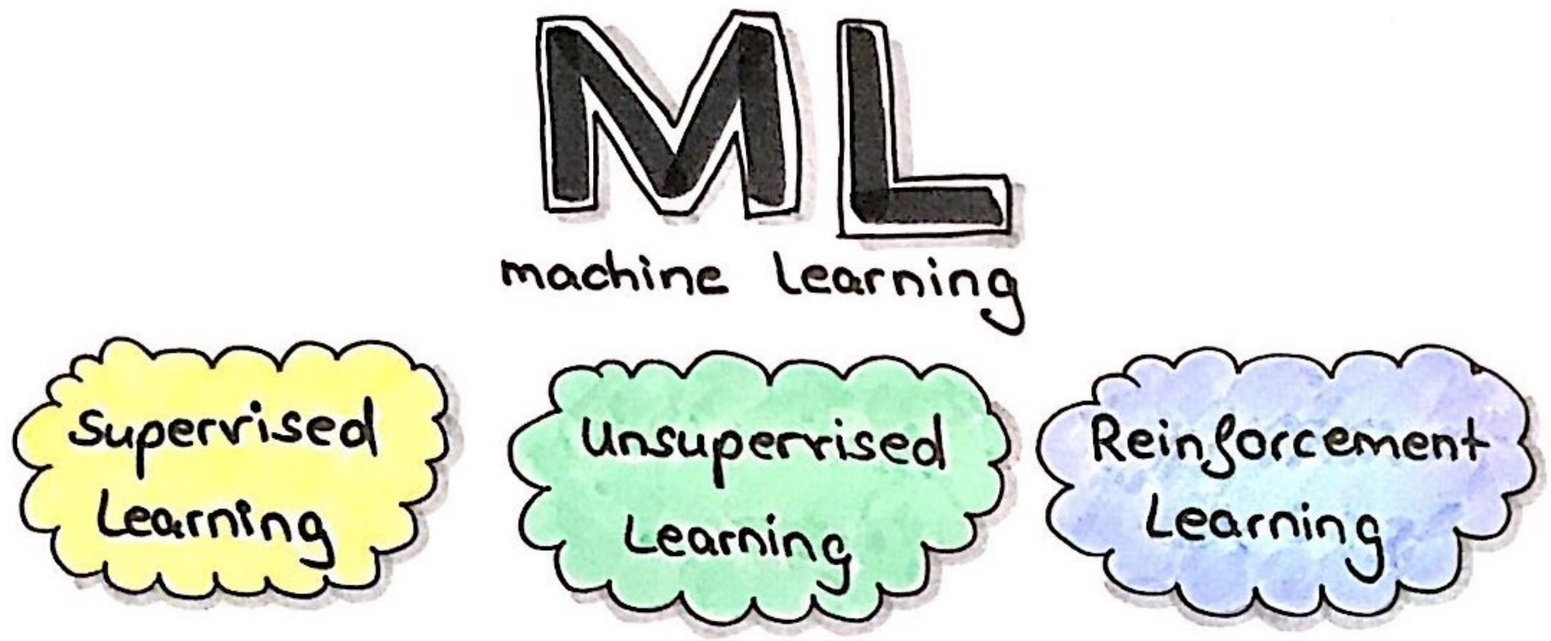
Data Scientist

codecentric



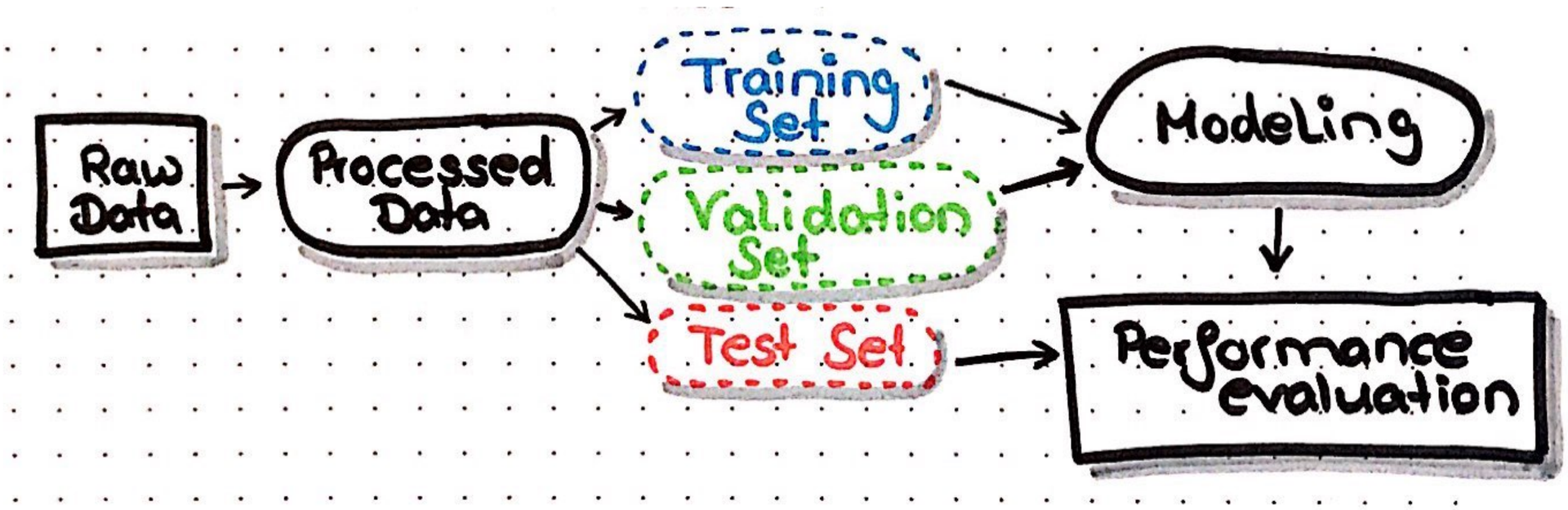
https://pixabay.com/de/a-ich-ai-anatomie-2729781/

What is Machine Learning (ML)



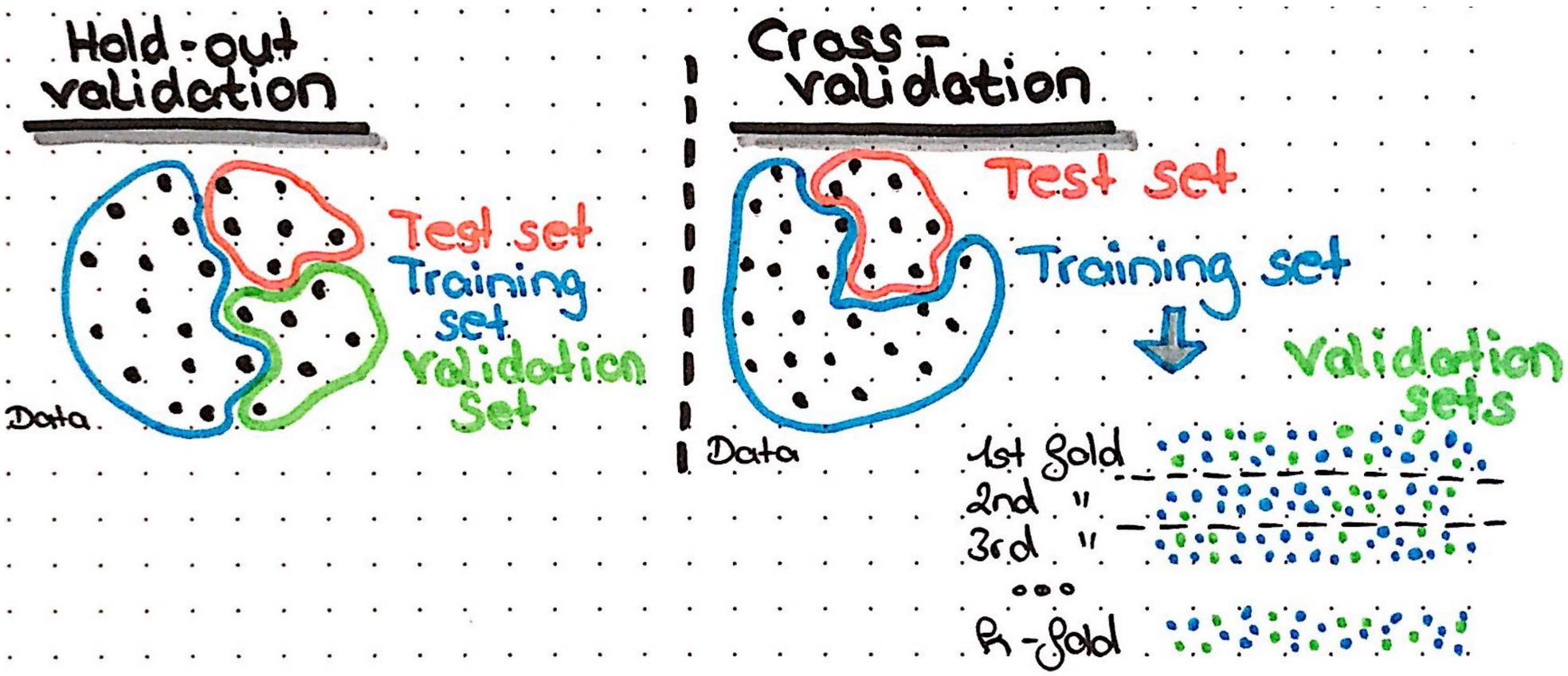
Labelled data	unlabelled data	self-generating data
• Classification or • Regression	• Clustering • Dimensionality reduction • Anomaly Detection	reward + punishment • Real-time Learning

A typical ML Workflow

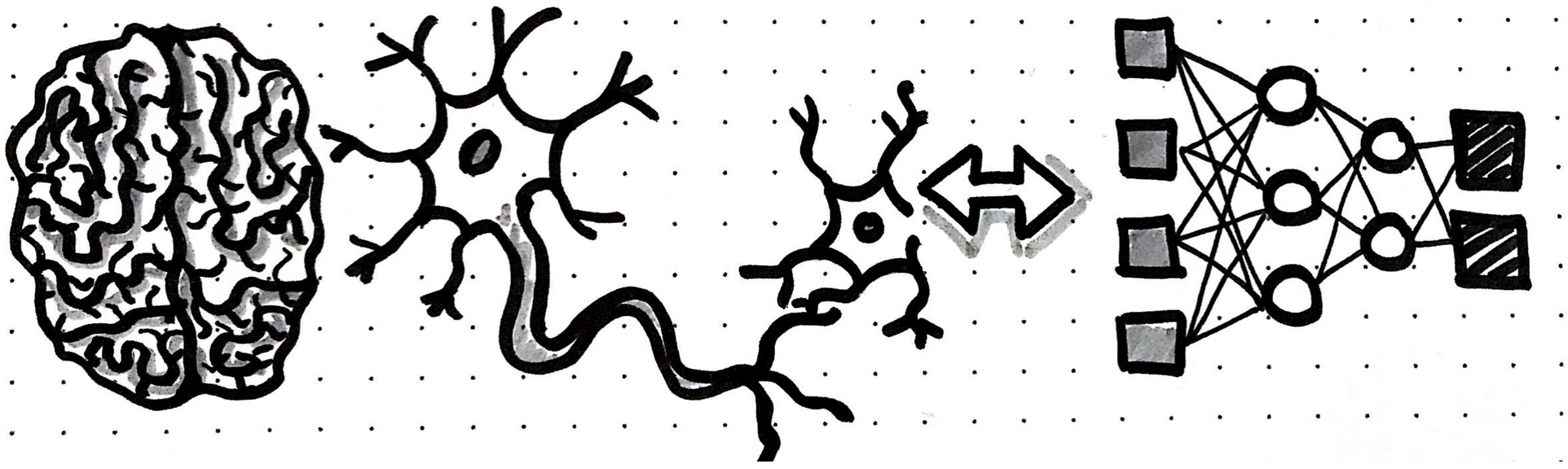


Why use validation and test data?

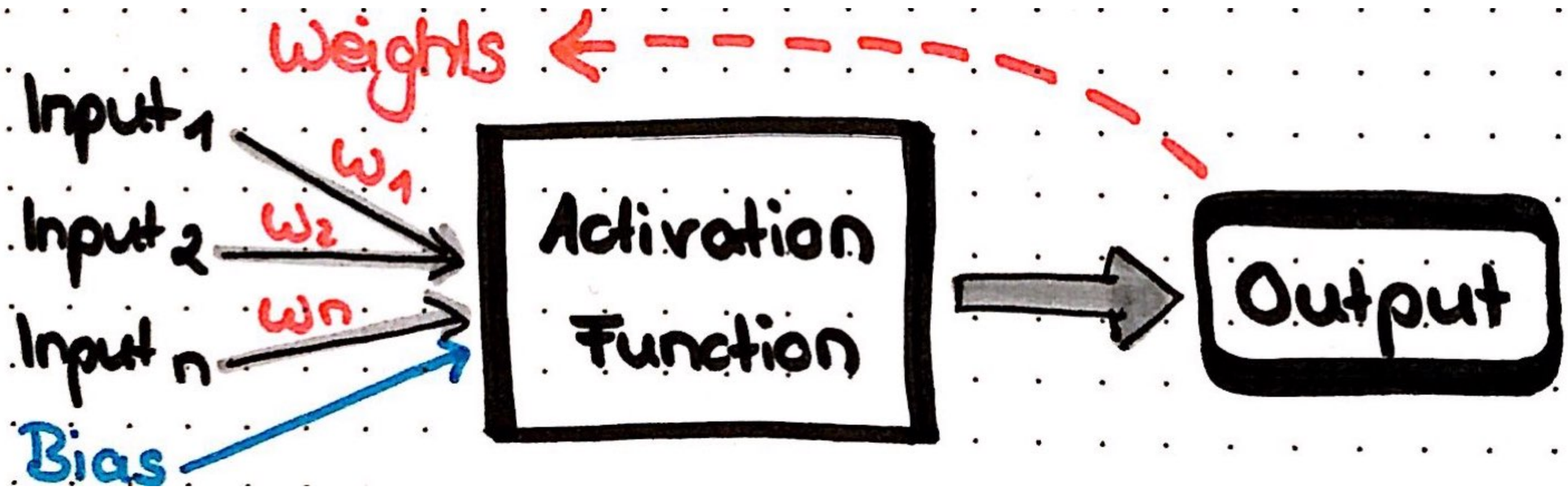
Validation methods



What are neural nets?

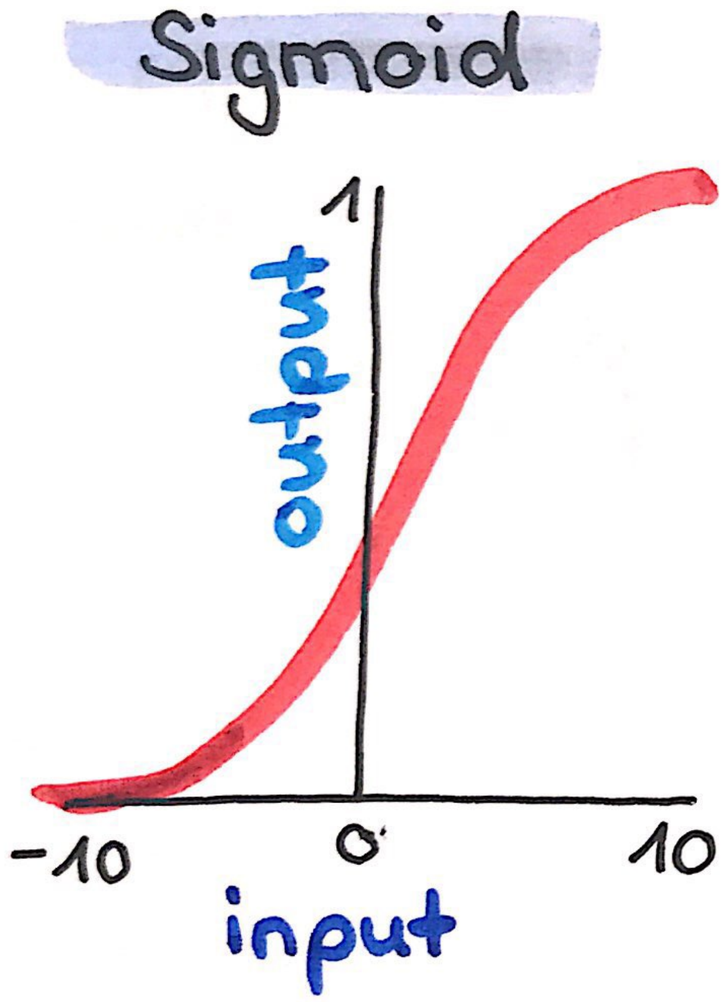


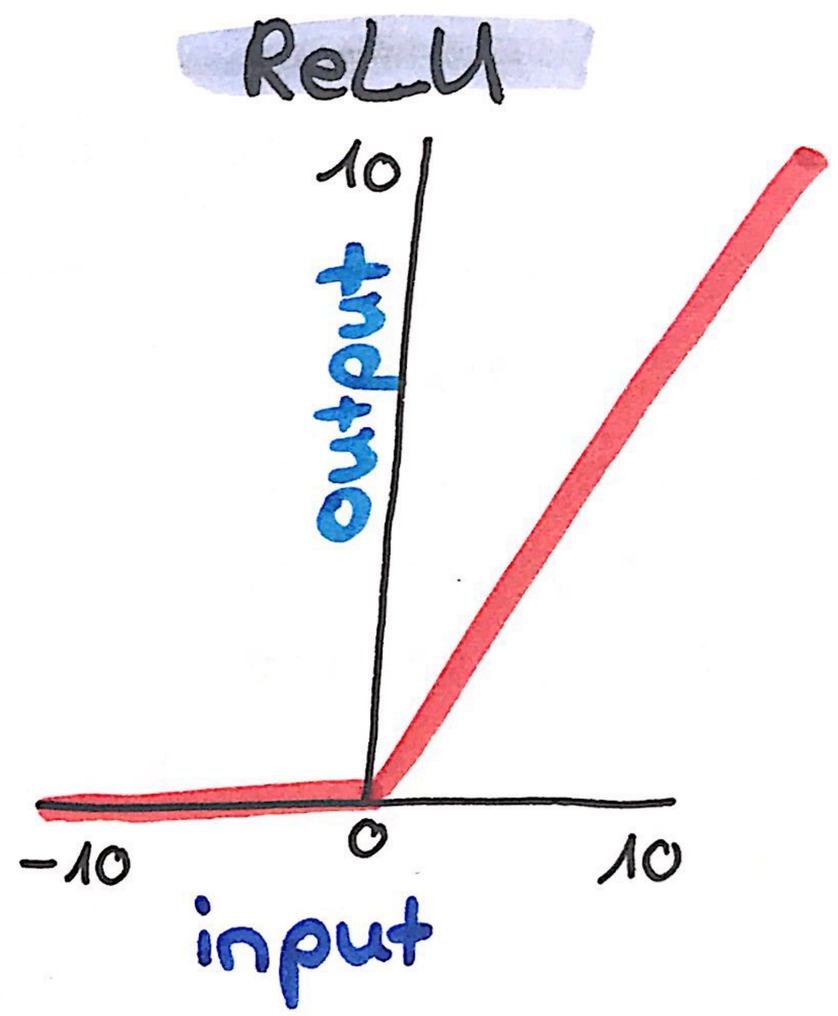
Perceptrons



Activation functions normalise input

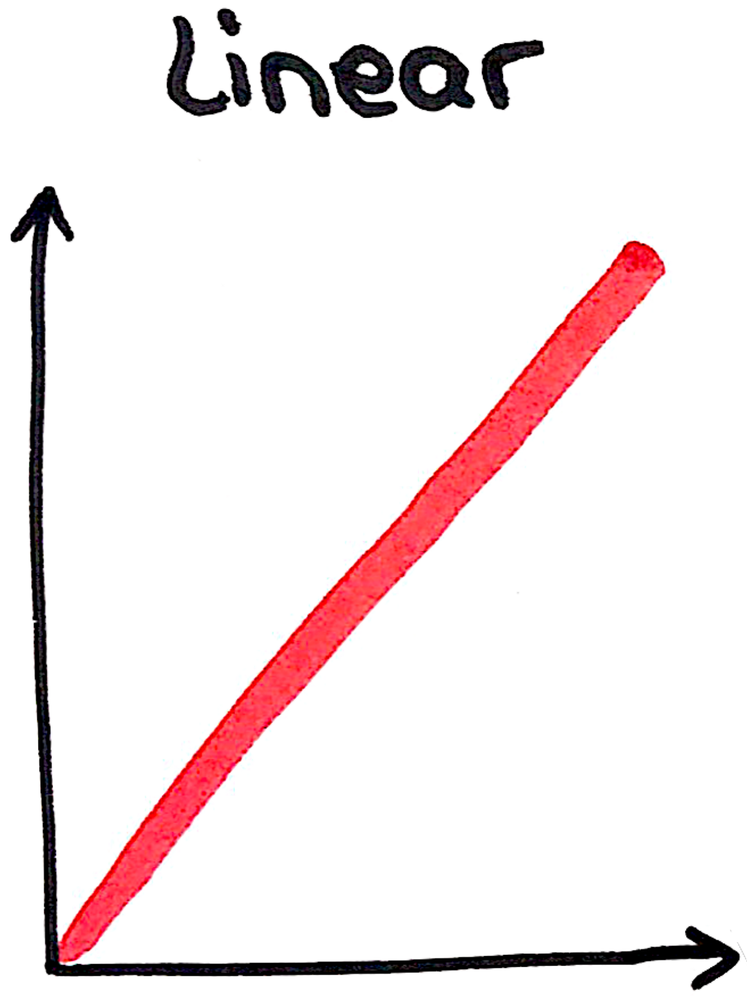
- every problem can be described with a mathematical function

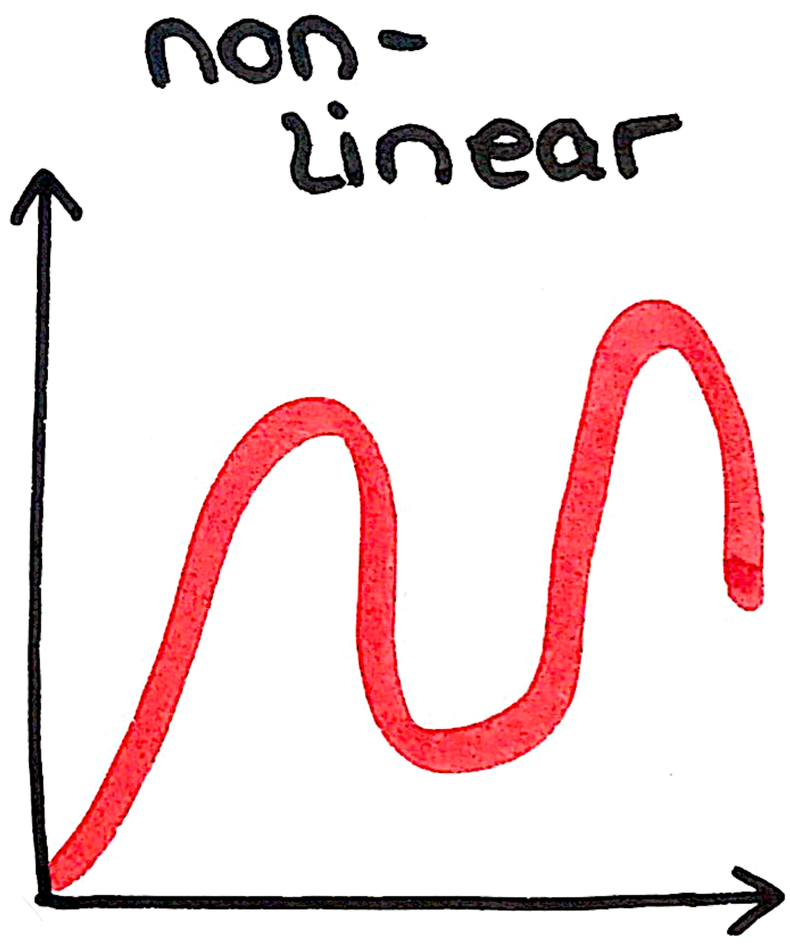




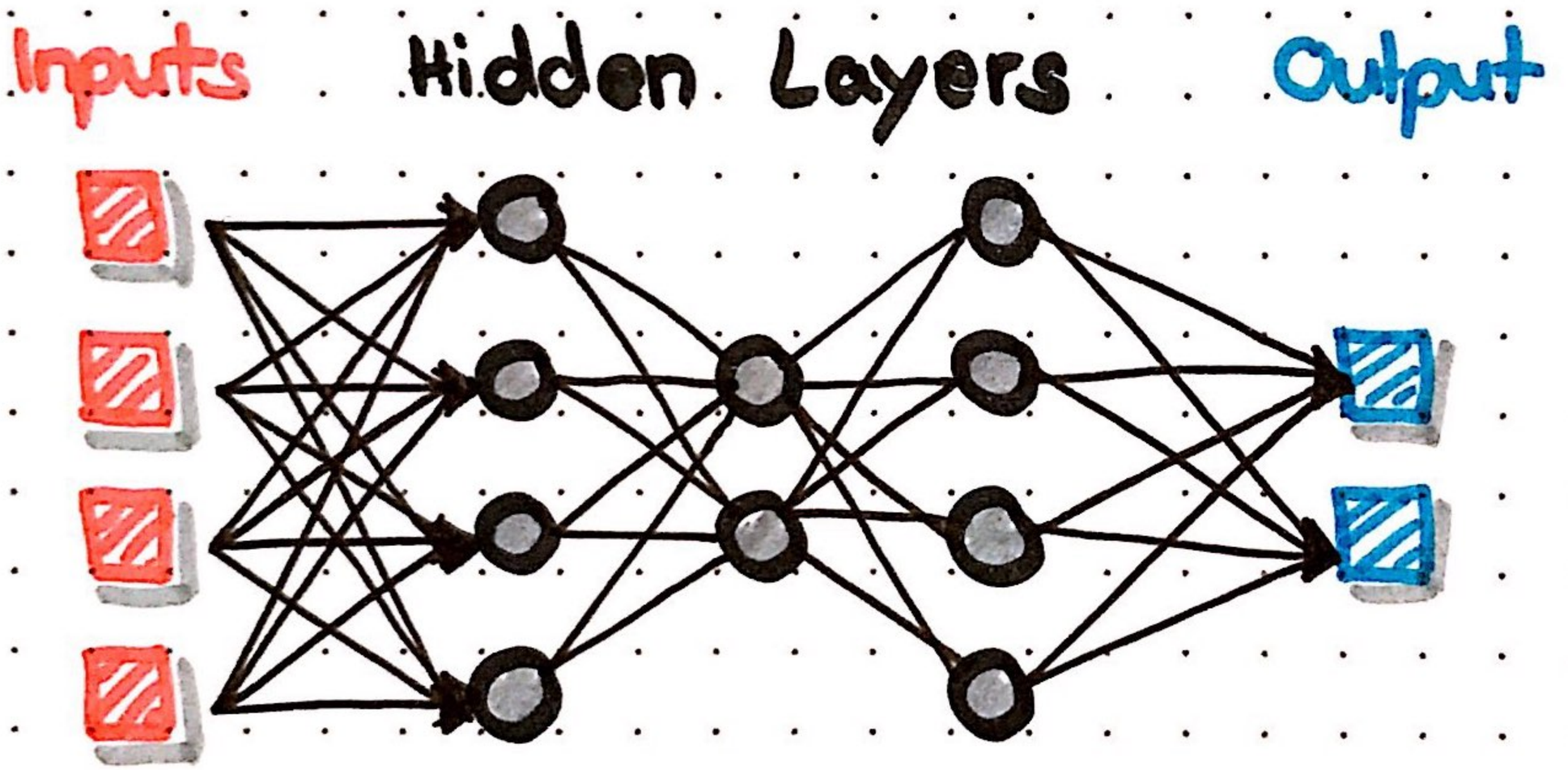
Activation functions make non-linearity possible

- non-linear activation functions allow us to approximate ANY mathematical formula with neural nets

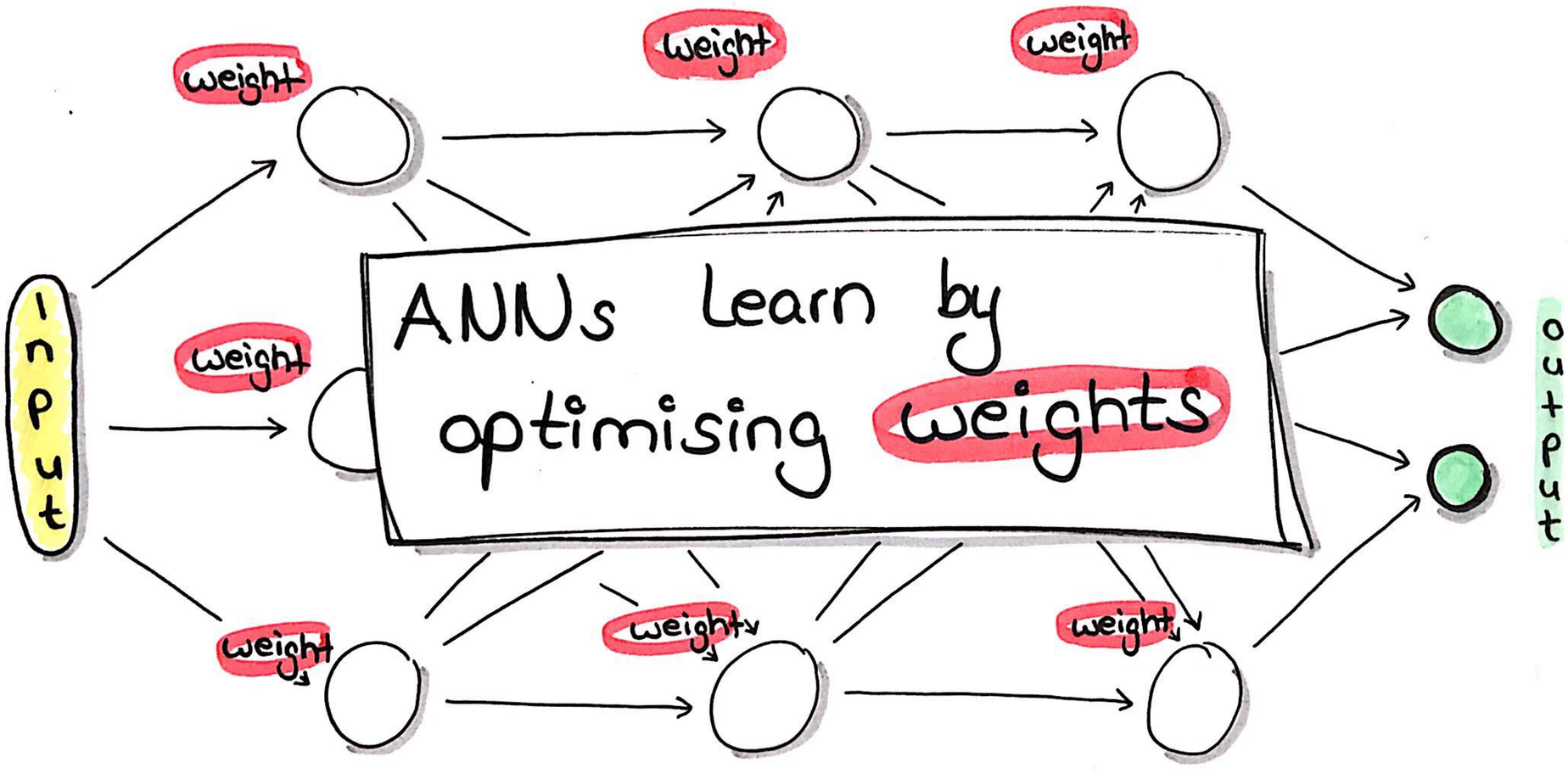




Multi-Layer Perceptrons

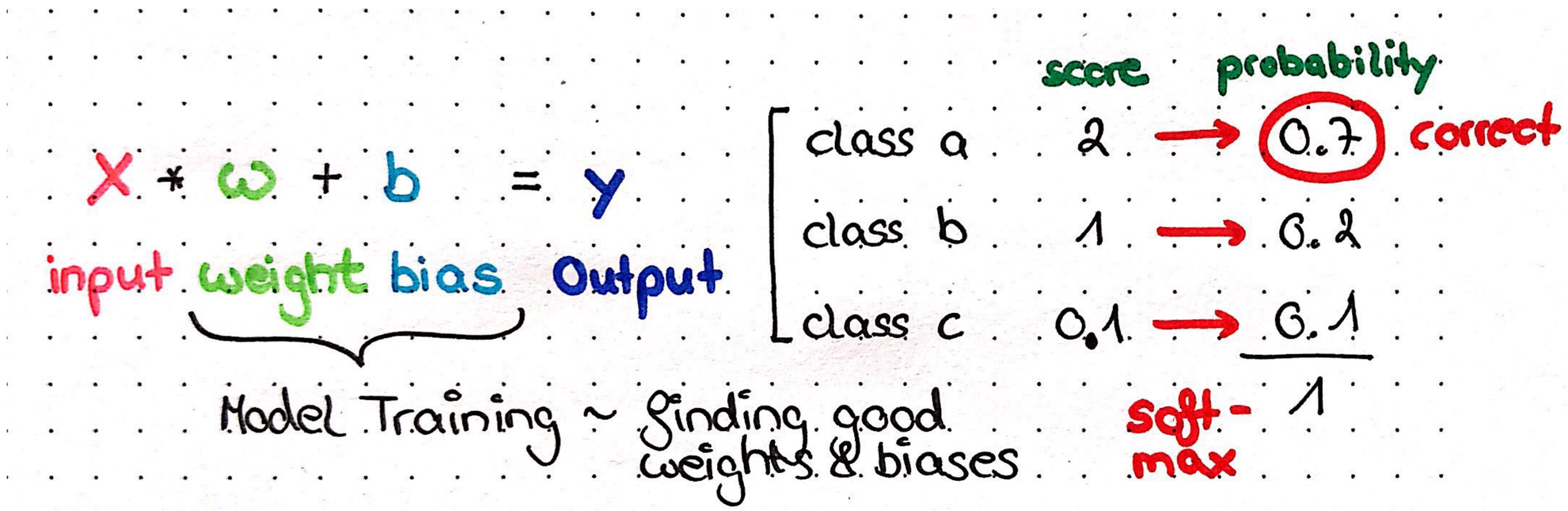


How does a neural net learn?



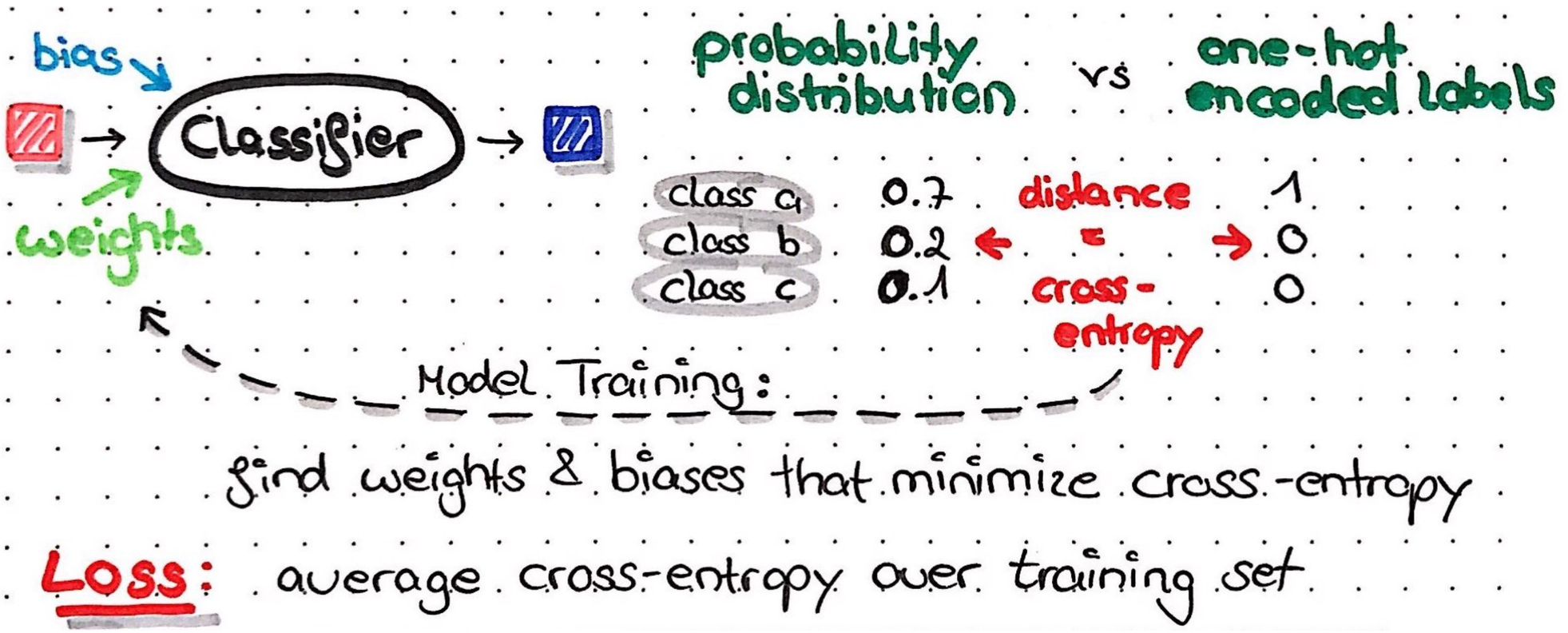
How does a neural net learn?

The Softmax function



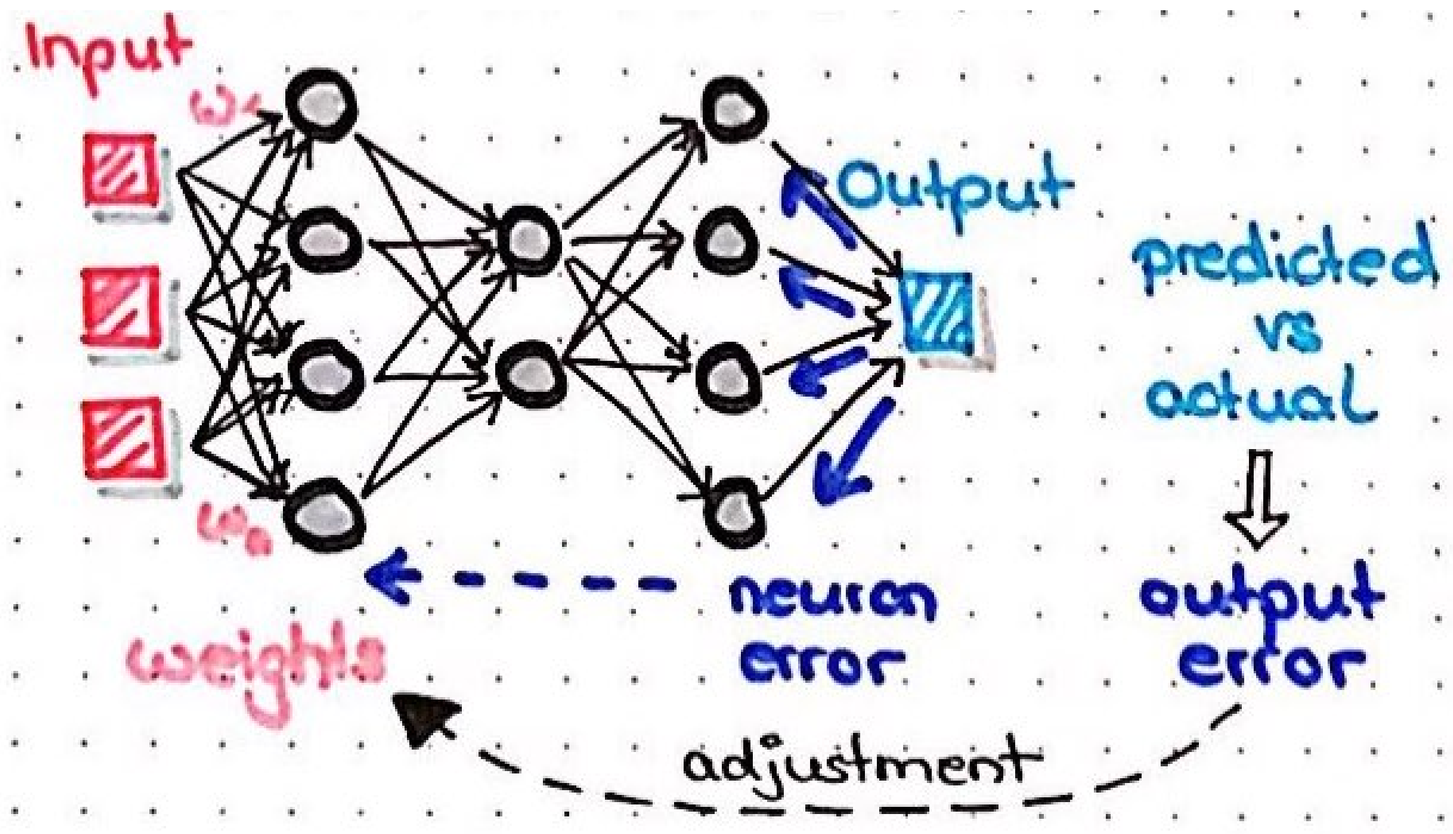
How does a neural net learn?

Cross-entropy



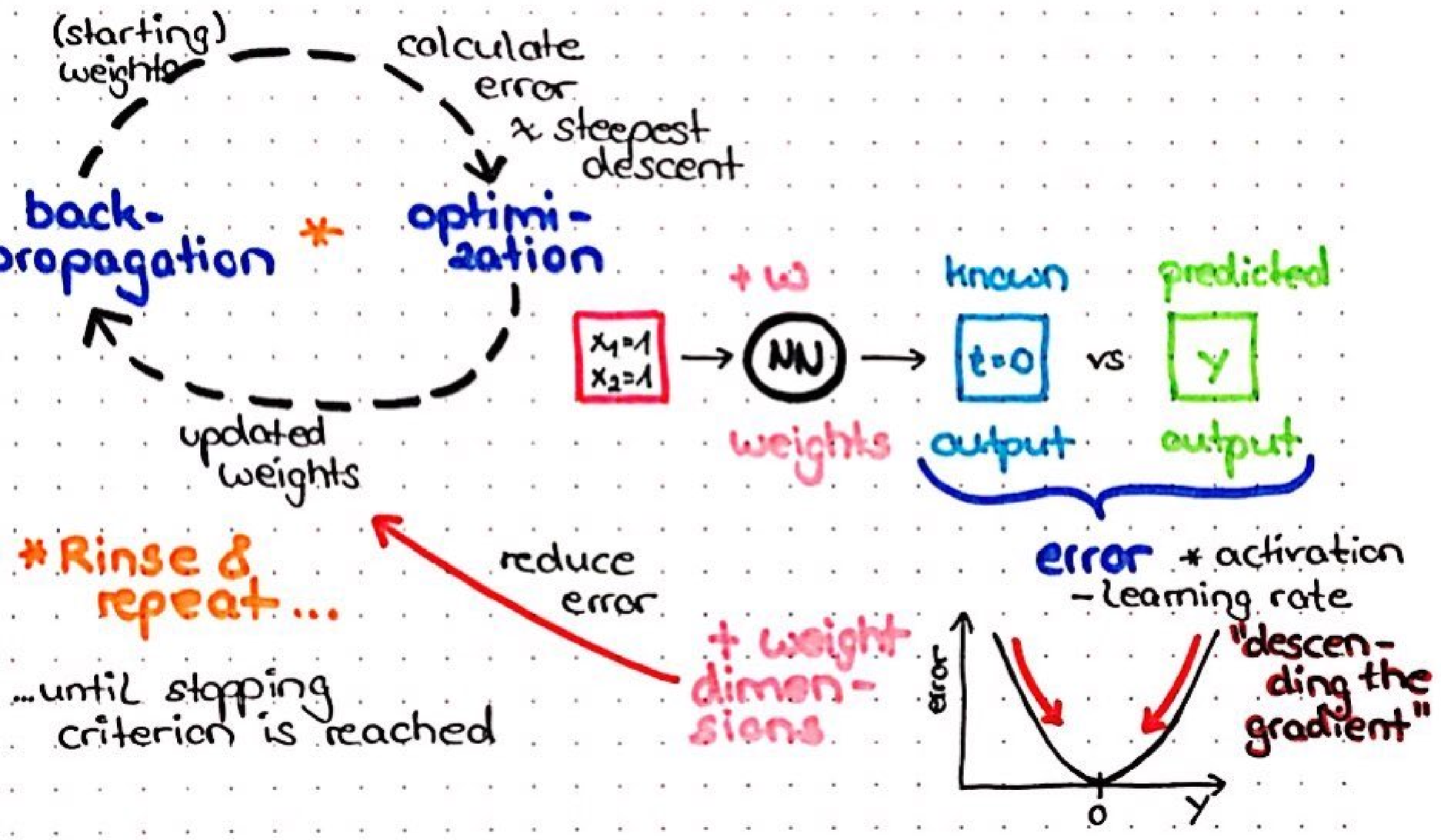
How does a neural net learn?

Backpropagation

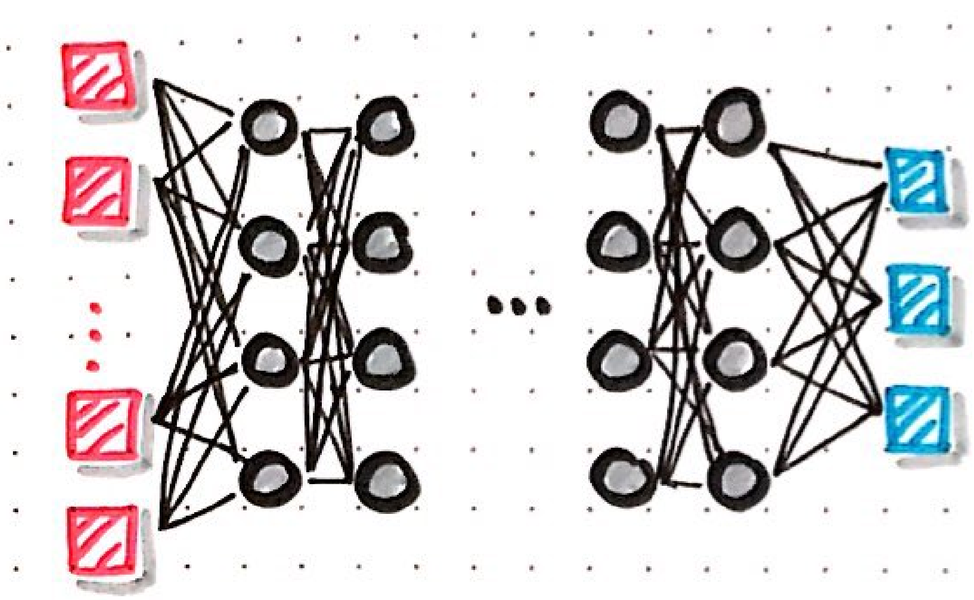


How does a neural net learn?

Gradient descent optimization



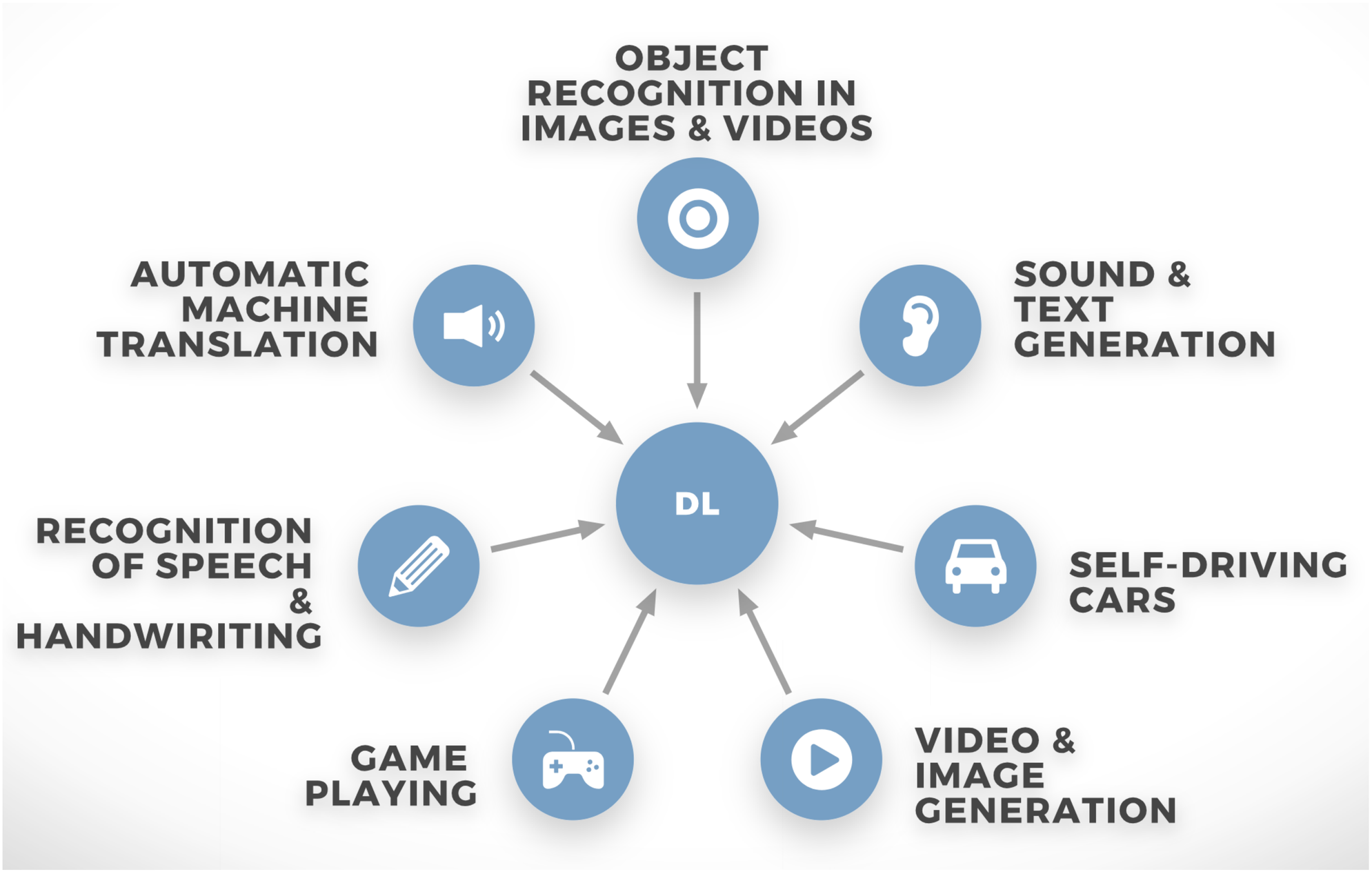
Deep Learning



- supervised, semi-supervised or unsupervised
- NLP, speech recognition
- image recognition
- object classification
- recommender systems

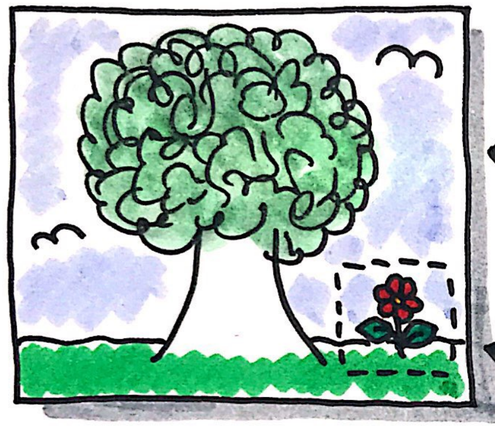
etc.

Deep Learning in the wild



How does a computer learn to "see"?

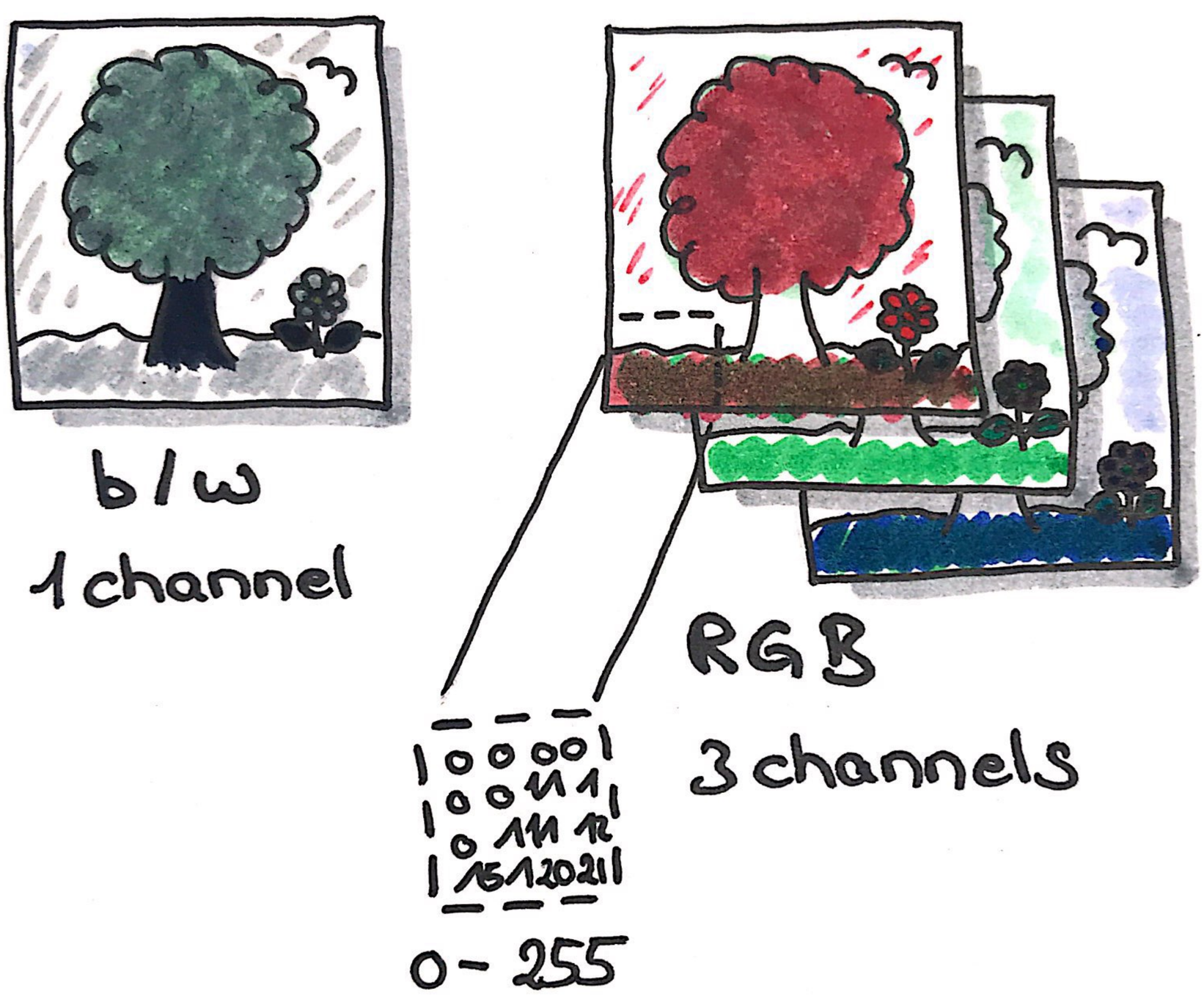
Convolutional
Neural
Nets



- image classification
  class = tree
- object detection
  flower

Computer
Vision

How does a computer learn to ”see”?



Jupyter Lab and Python

- i(nteractive) Python
- browser based notebook
- code + markdown + output

Jupyter tips'n'tricks

- ?: search documentation

In [5]:
```
len?
```

- ??: look at source code

In [6]:
```
len??
```

- tab: autocomplete
- shift + tab: look at function call

In [ ]:
```
import numpy as np
np.arr
```

```
array
array2string
array_equal
array_equiv
array_precision
array_repr
array_split
array_str
array_type
arrayprint
```

In [ ]:

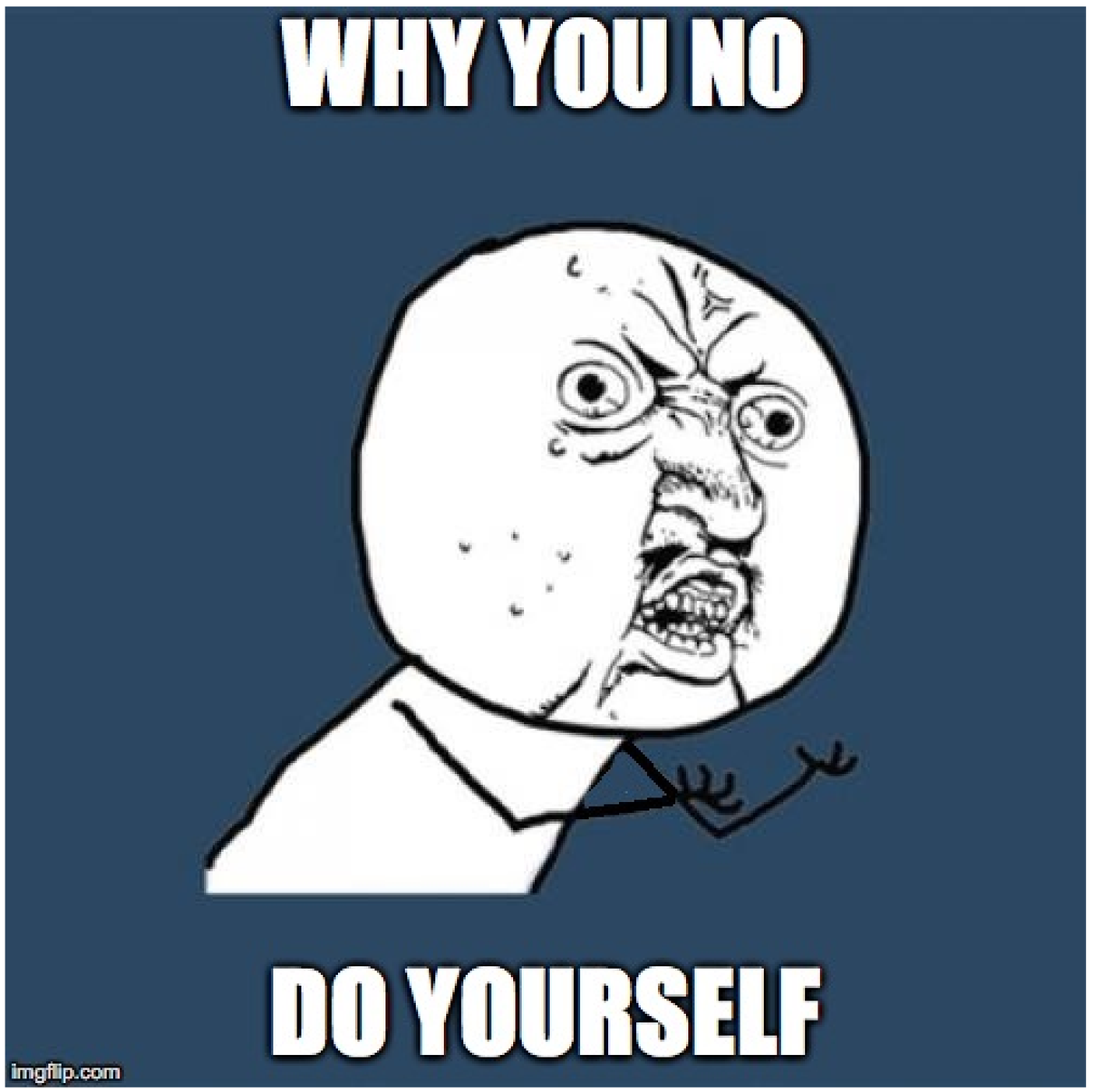
In [ ]:

In [ ]:

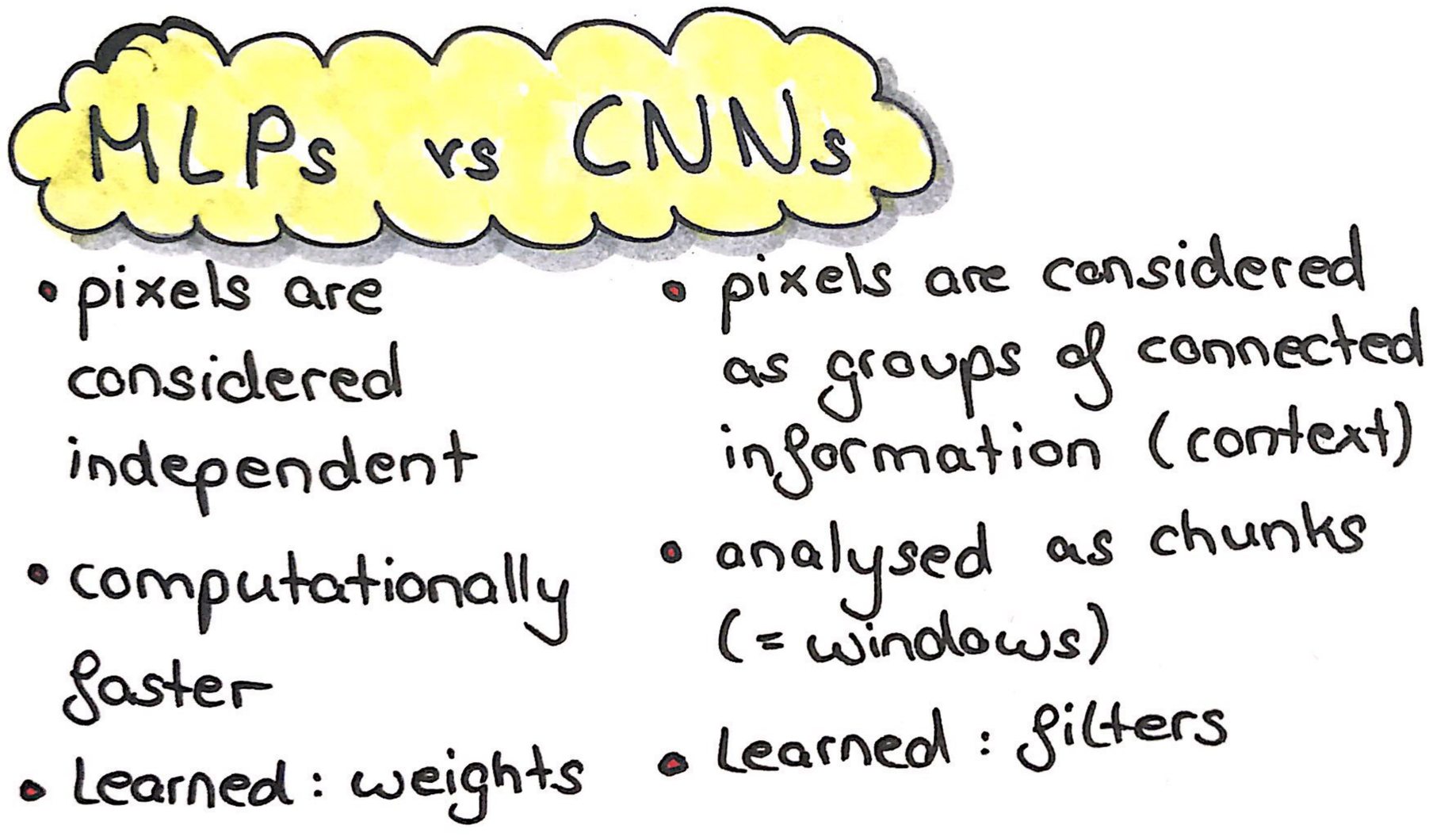
Visualization with Matplotlib

- Matplotlib is a Python 2D plotting library
- Can be used in Python scripts, Python/IPython shells, Jupyter notebooks

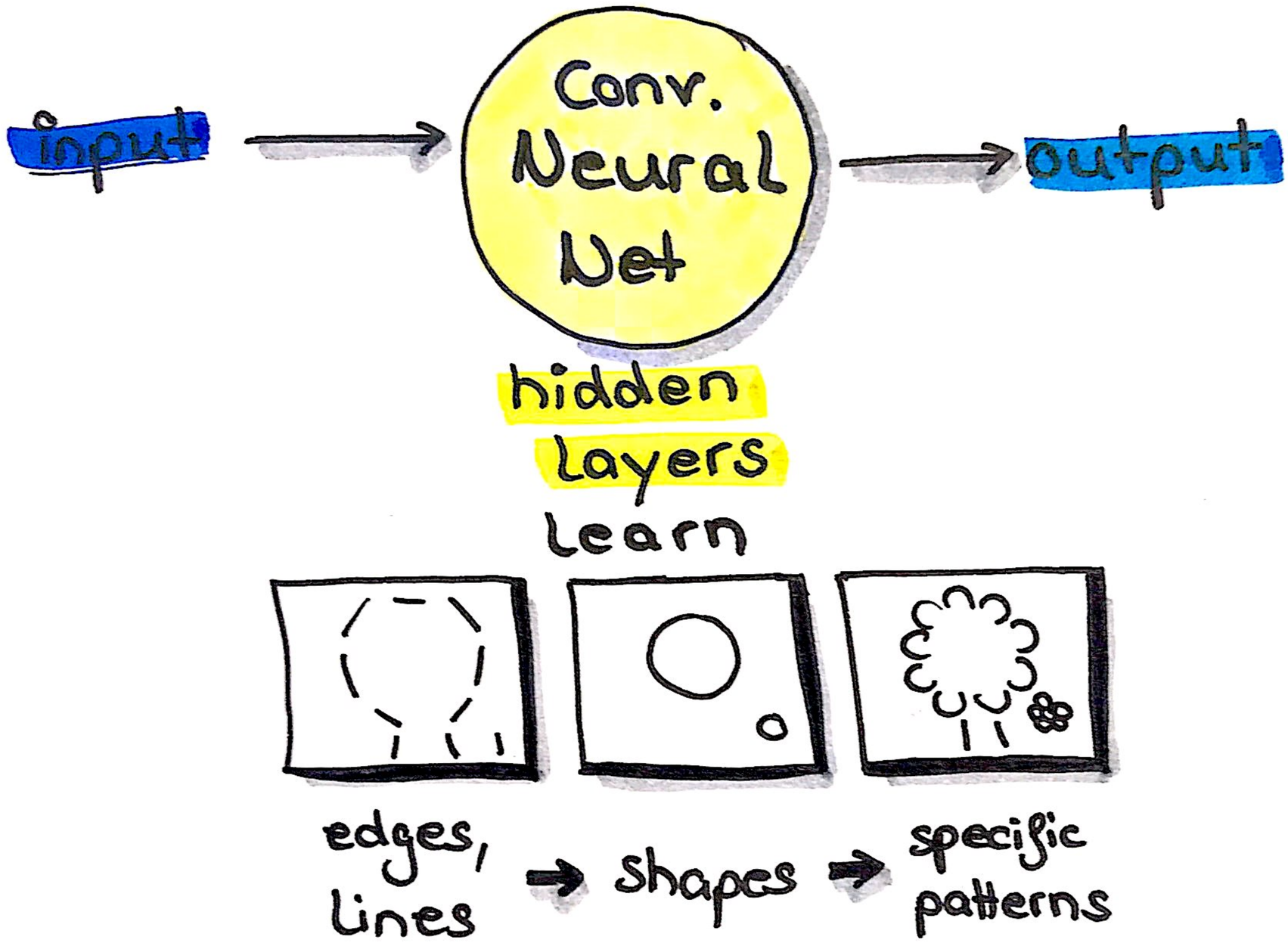
Matplotlib



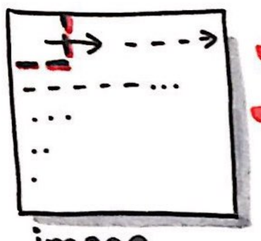
Convolutional Neural Nets



ConvNets


input
Conv.
Neural
Net
output
hidden
layers
learn
edges,
lines
shapes
specific
patterns

ConvNets

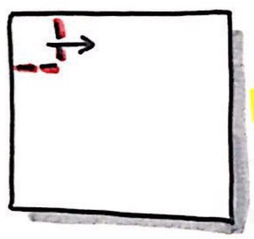


sliding window

↳ window **size** (e.g. 3×3 pixels)

image

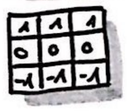
↓



apply **filters** to every sliding window

e.g.

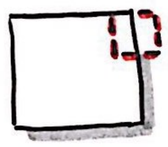
vertical lines



horizontal lines

- **Filters**
  detect shapes & patterns in window chunks
- multiple filters are combined
- filters are learned

padding



- fake pixels are created at the edge of images to incorporate border pixels

stride

- how much overlap to have in sliding window

Convolutional Layers

apply filters

↓

output

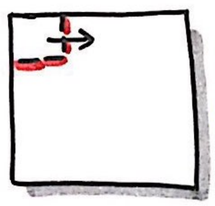
=

feature maps

↓

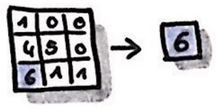
stacks of **feature maps**

→



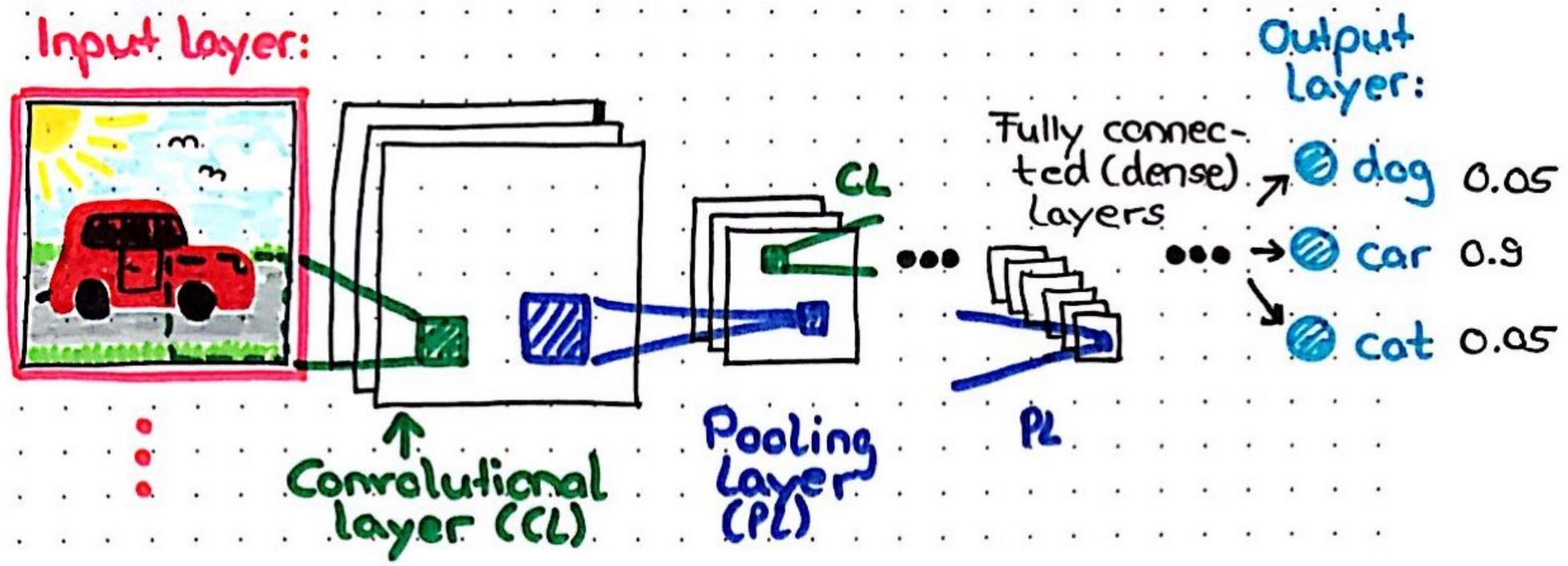
Pooling Layers

e.g. max pooling

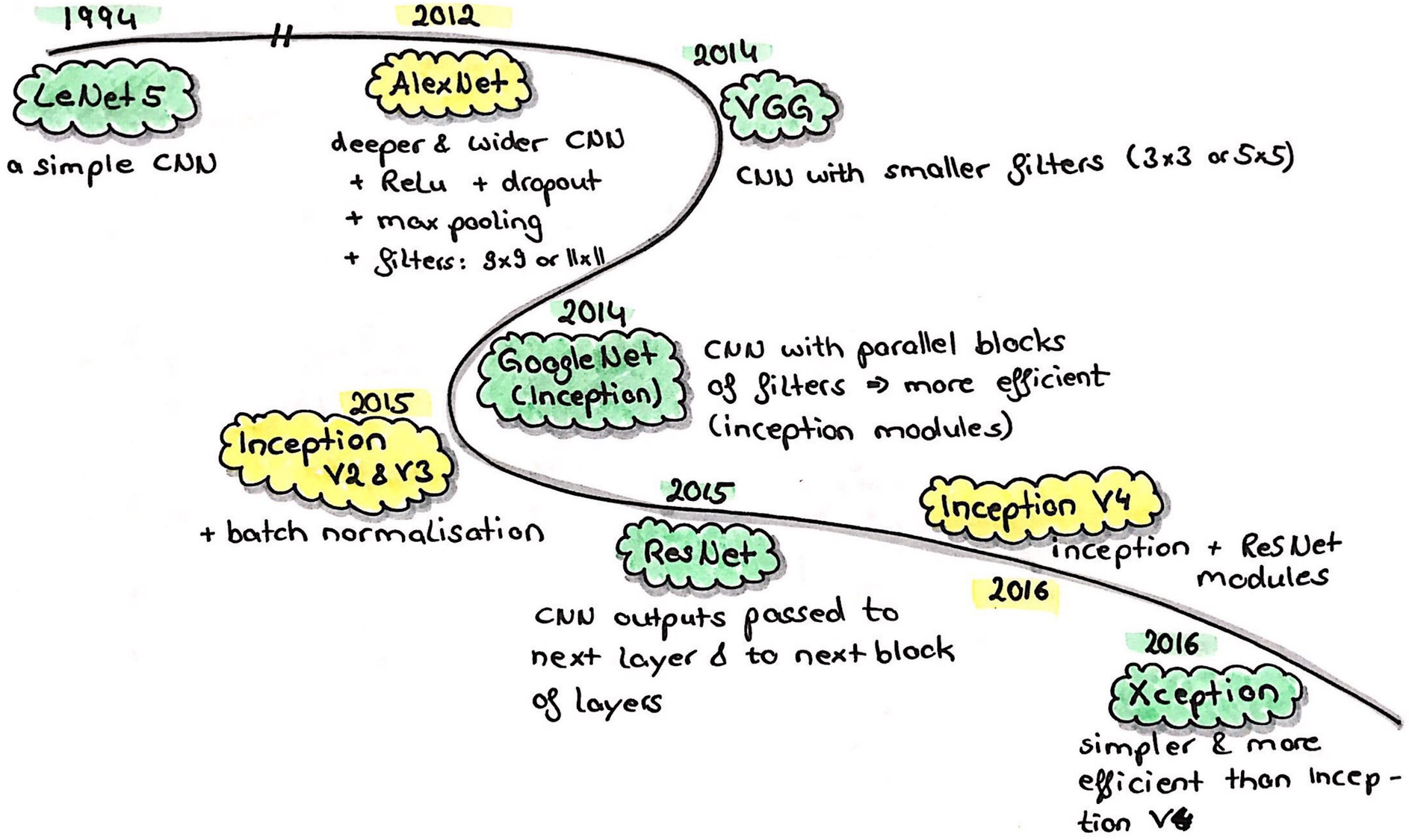


- reduces compute time
- boils information down

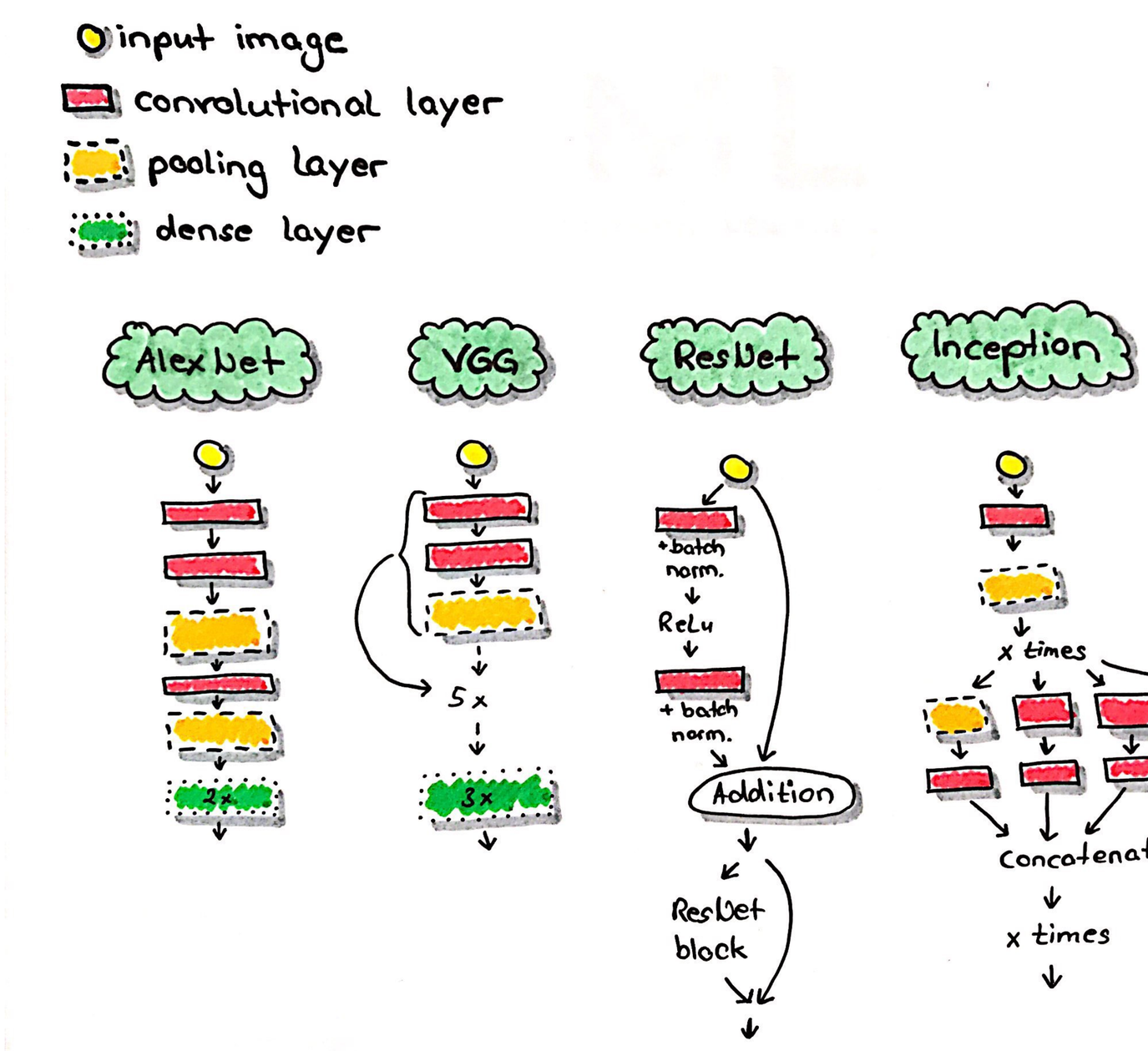
ConvNets


Input layer:
Output layer:
Fully connec-ted (dense) layers
CL
PL
dog 0.05
car 0.9
cat 0.05
Convolutional layer (CL)
Pooling layer (PL)

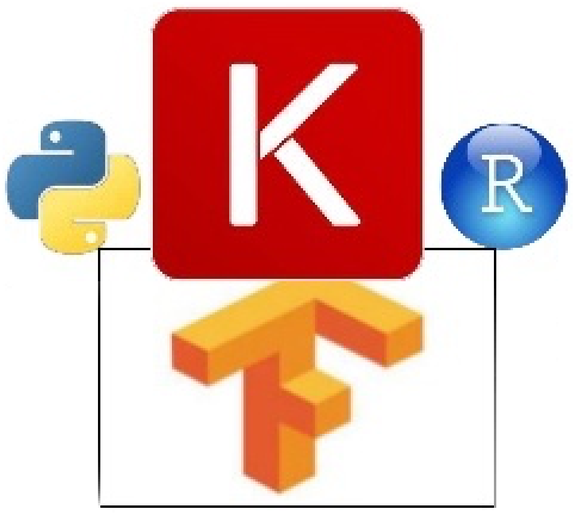
Evolution of neural nets for image recognition



CNN architectures

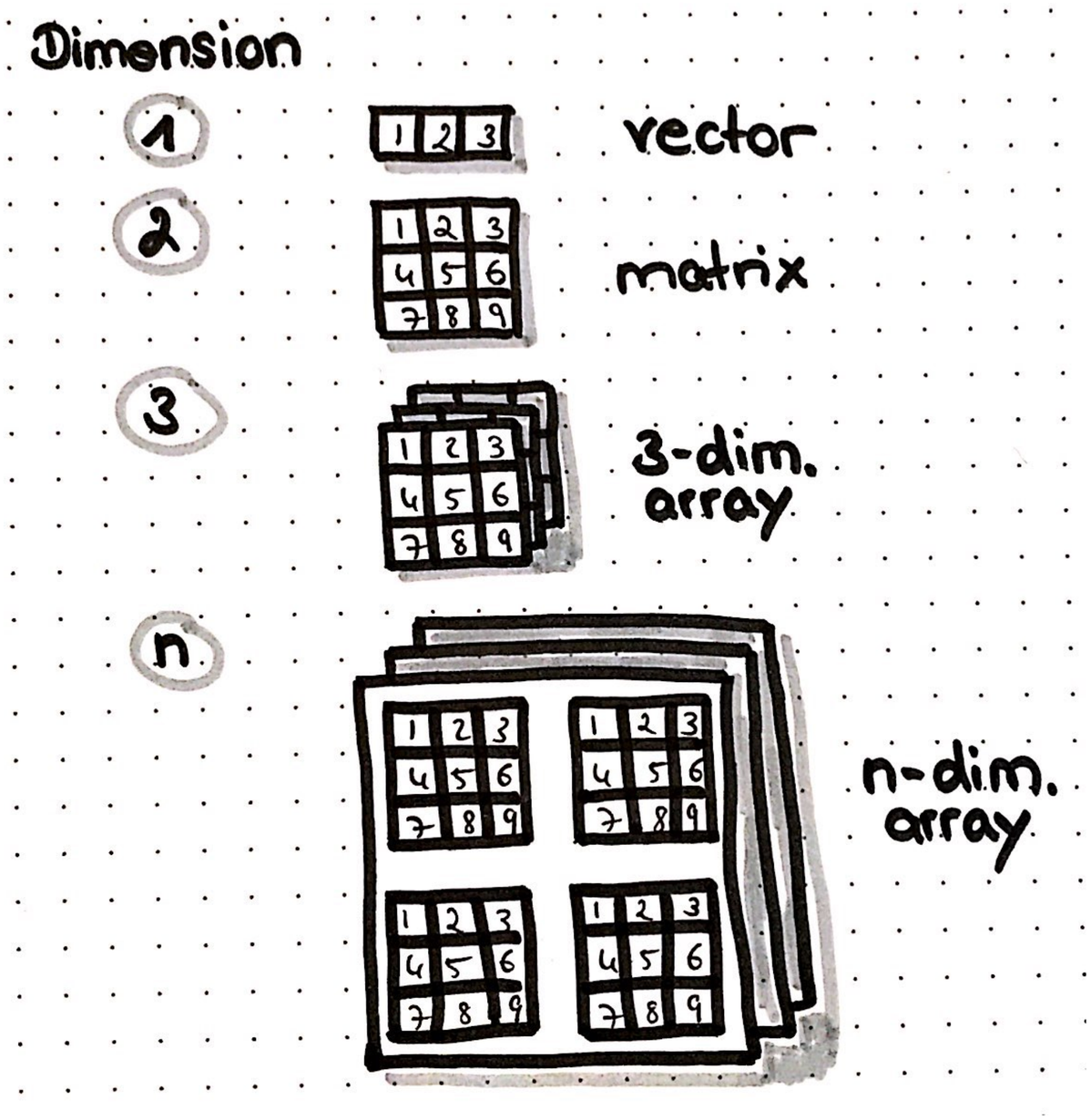


Introduction to TensorFlow



What are tensors?

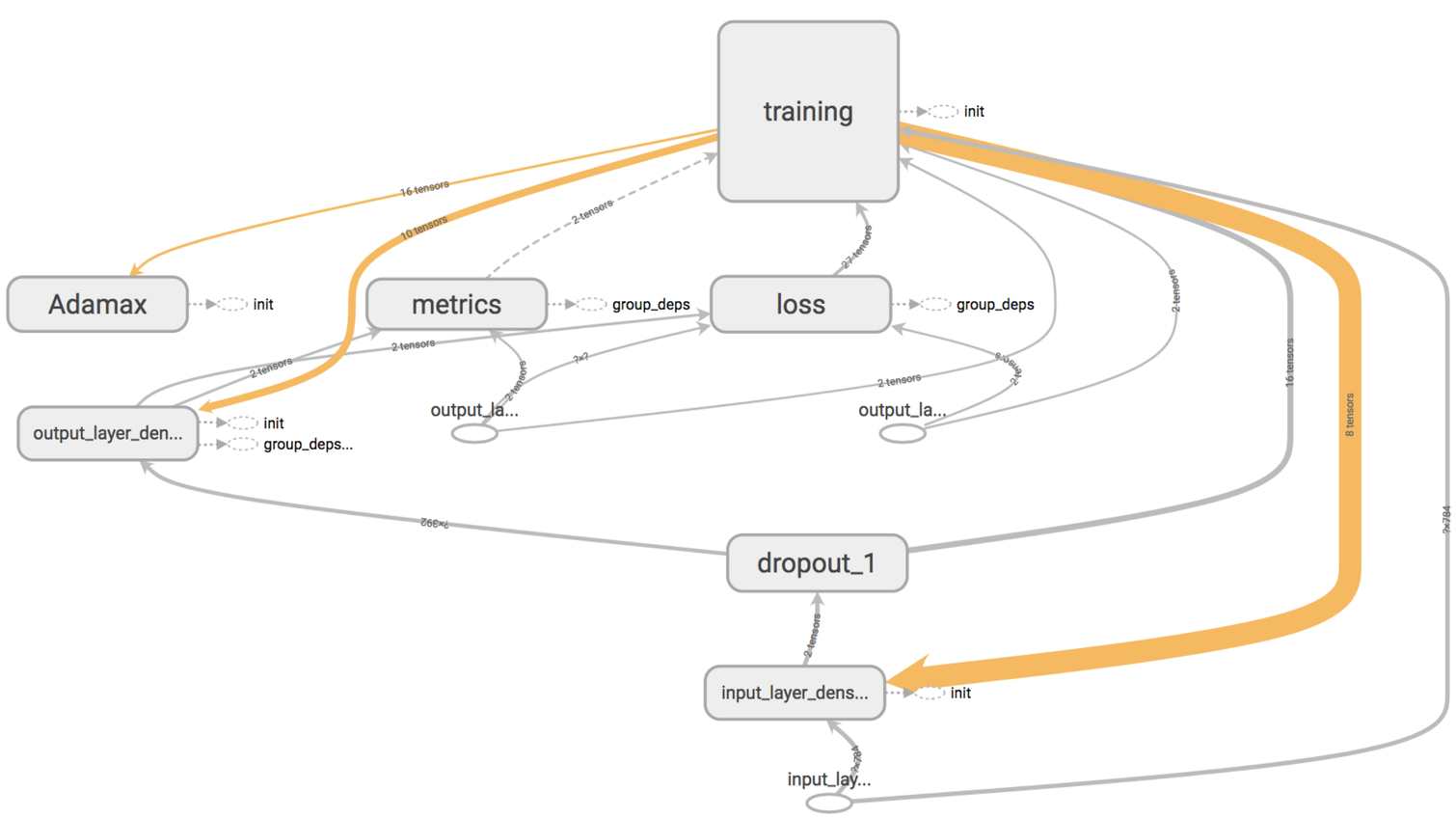
Tensors = multidimensional arrays



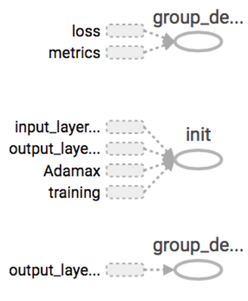
Tensor "Flow"

Graphs in TensorBoard

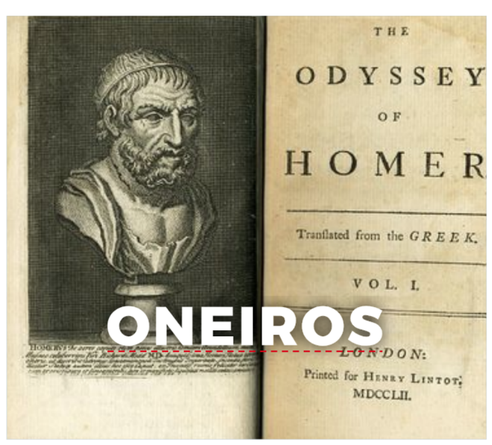
Main Graph

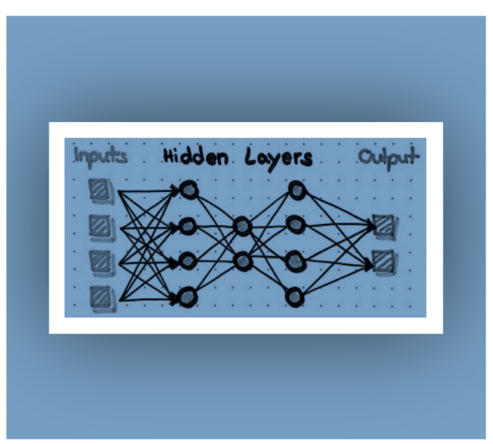


Auxiliary Nodes



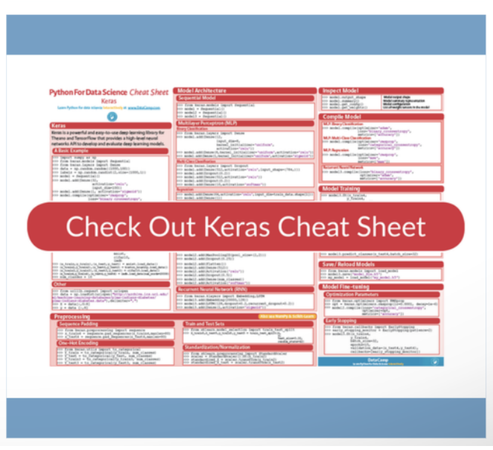
Keras High-Level API for TensorFlow

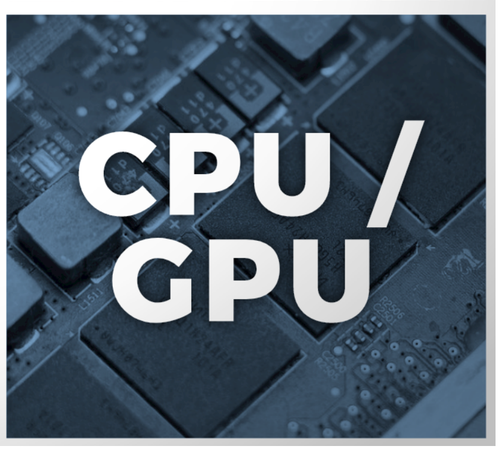




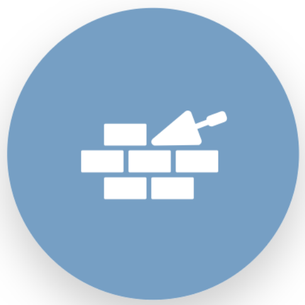
"Oneiroi are beyond our unravelling -
who can be sure what tale they tell?
Not all that men look for comes to pass.
Two gates there are that give passage to fleeting Oneiroi;
one is made of horn, one of ivory.
The Oneiroi that pass through sawn ivory are deceitful,
bearing a message that will not be fulfilled;
those that come out through polished horn have truth behind them,
to be accomplished for men who see them."

Homer, Odyssey 19. 562 ff (Shewring translation).





Keras APIs



SEQUENTIAL MODELS

simple

suitable for most cases

linear order of layers

only one direction from input to output

FUNCTIONAL API

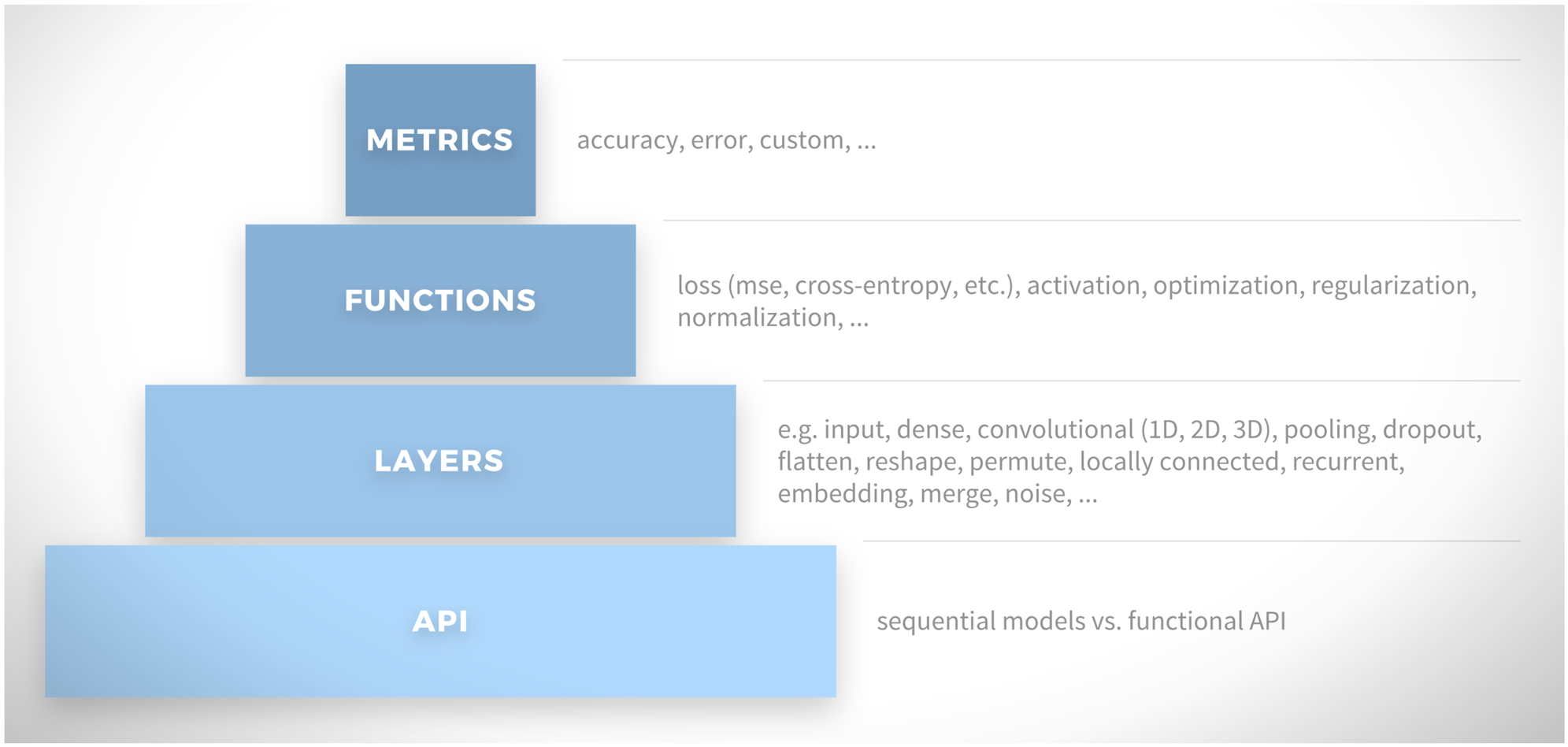
more complex

suitable for complex models

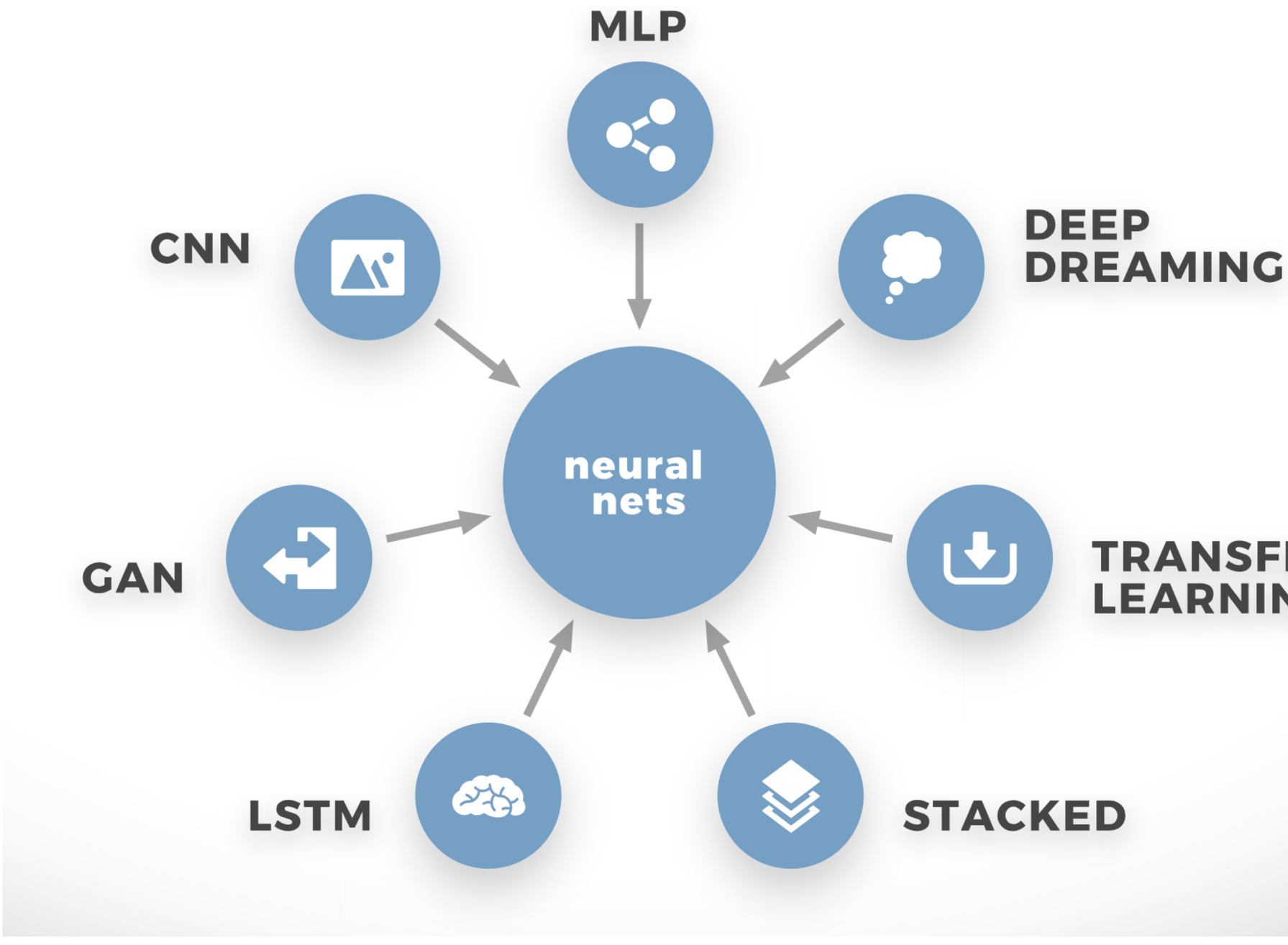
can have multiple in- or outputs

layers can be non-sequential, e.g. LSTM

Keras layers

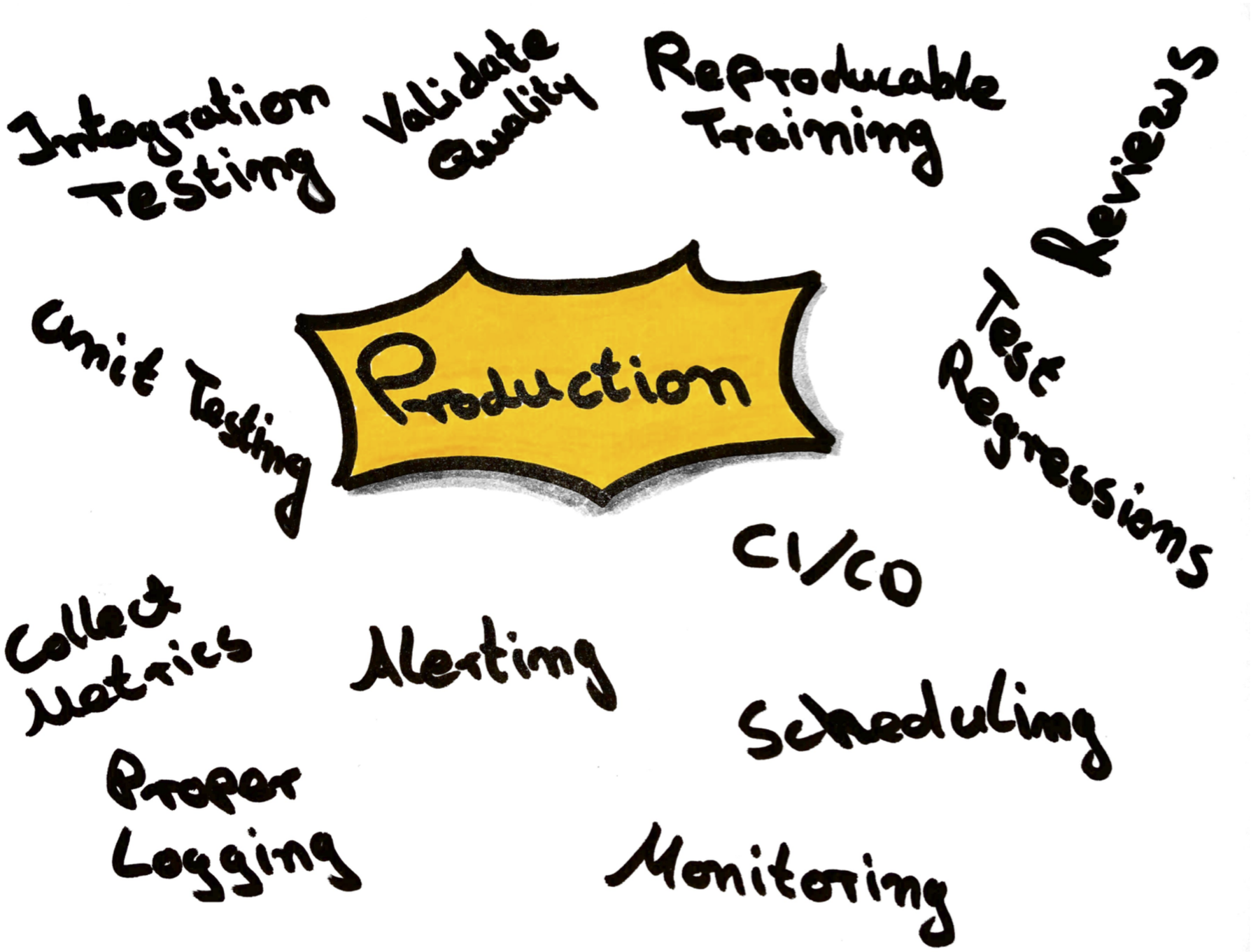


Endless possibilities



It works, now DEPLOY it!

Production ready



A bit about Luigi

Luigi helps to stitch long running tasks together into pipelines

It contains a wide toolbox of task templates (e.g. Hive, Pig, Spark, Python)

How to compose workflows?

A workflow consists of Targets, Tasks and Parameters

Targets correspond to a file or a database entry or some other kind of checkpoint

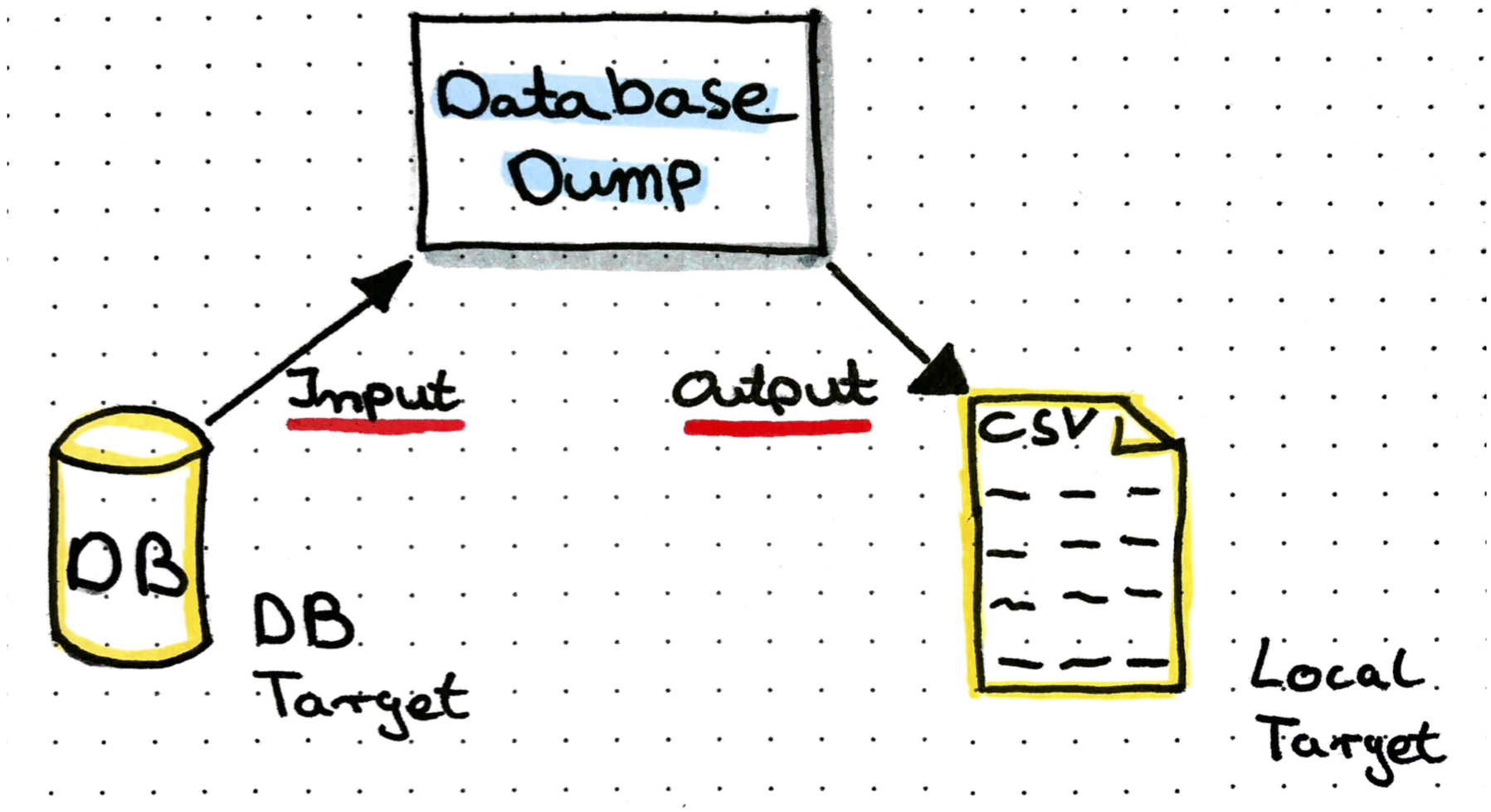
Tasks consume Targets of other tasks, run a computation, then output a target

Parameters take care of task parameterization

Targets

- Files on disk or database entries
- Checkpoints that prevent tasks from multiple executions
- A lot of implementations already exist in the Luigi framework
- LocalTarget (File), RemoteTarget (SSH), HDFSTarget, MySqlTarget, ...

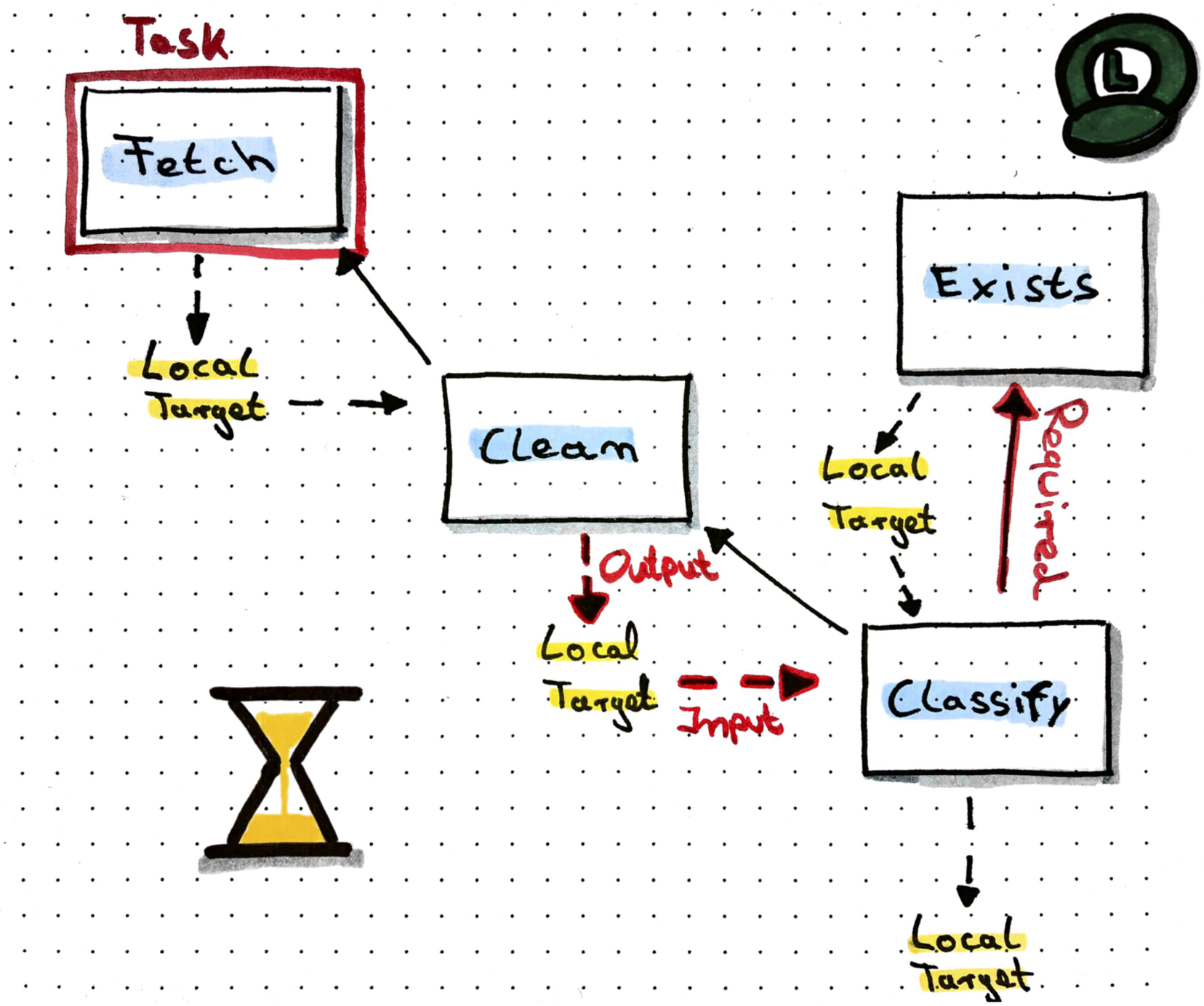
Targets



Tasks

- Implement the actual processing
- Consume targets, process data and save results in new target
- Respect dependencies to other tasks
- Implemented via Python-Classes

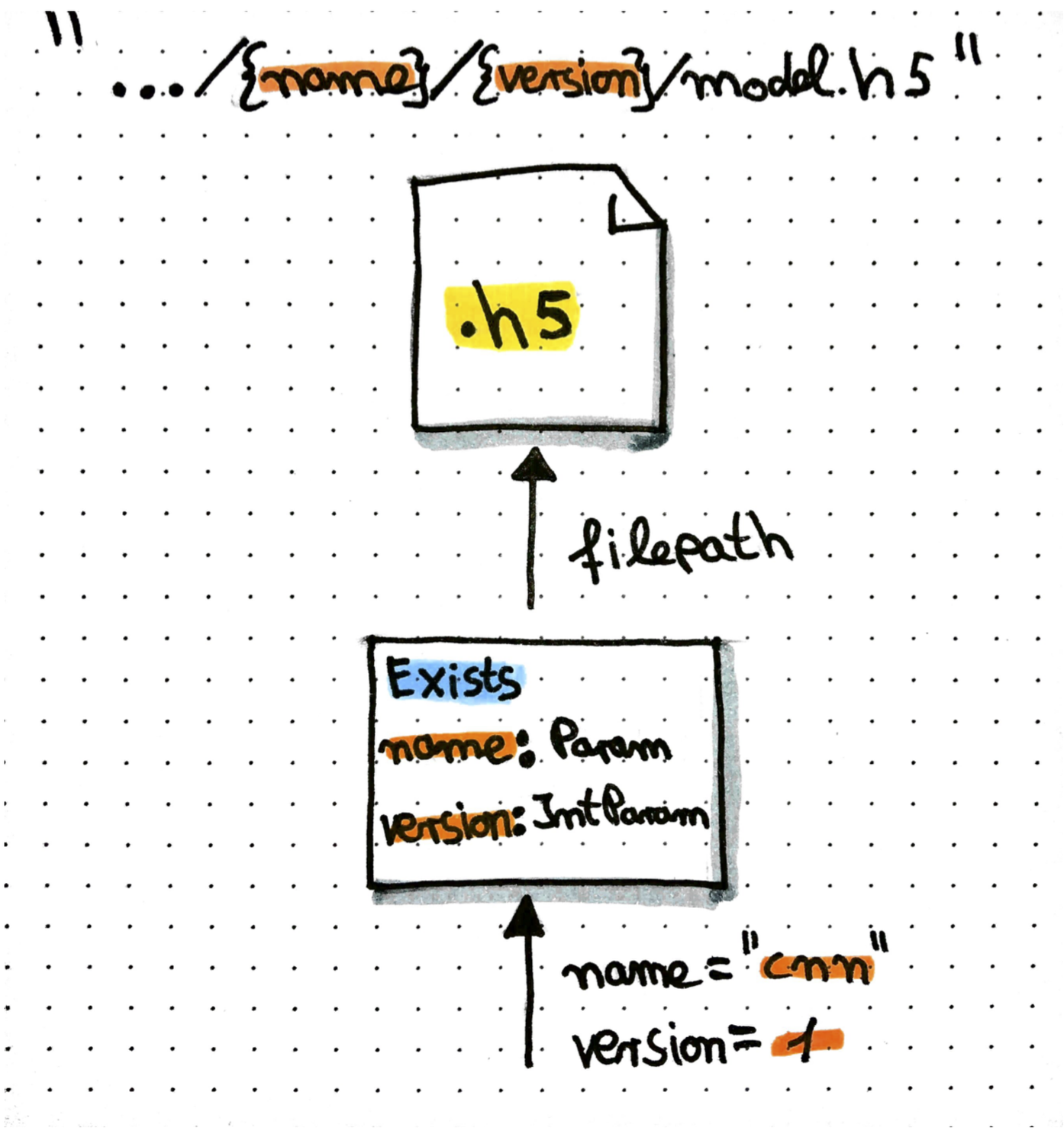
Tasks

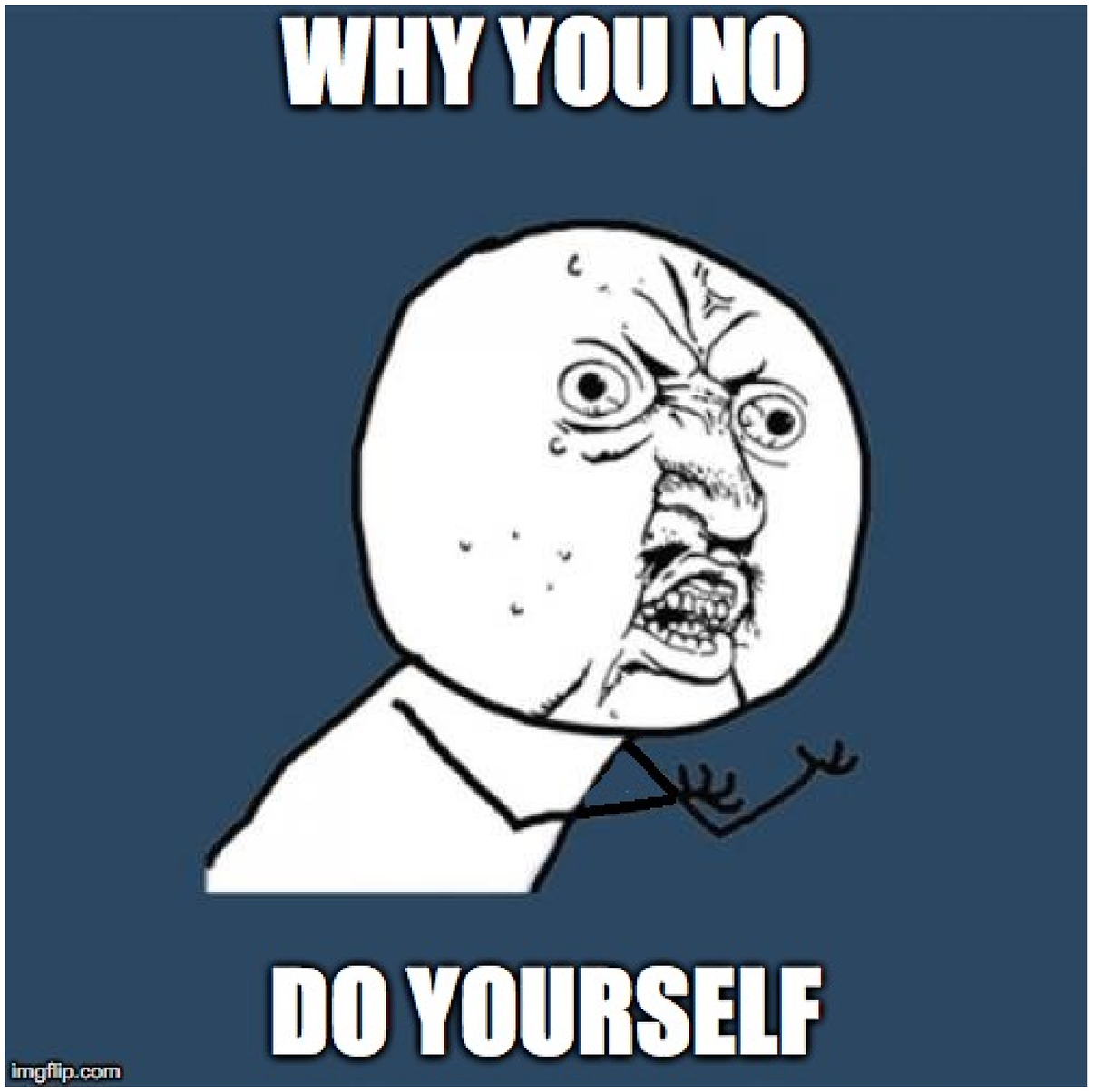

Task
Fetch
Local Target
Clean
Output
Local Target
Input
Local Target
Classify
Exists
Local Target
Required
Local Target

Parameters

- like constructur parameters
- Luigi takes care of parameter validation
- Again, a lot of implementations already exist in the Luigi framework
- IntParameter, BoolParameter, DateParameter, etc...

Parameters


"../{name}/{version}/model.h5"
.h5
filepath
Exists
name: Param
version: IntParam
name = "cnn"
version = 1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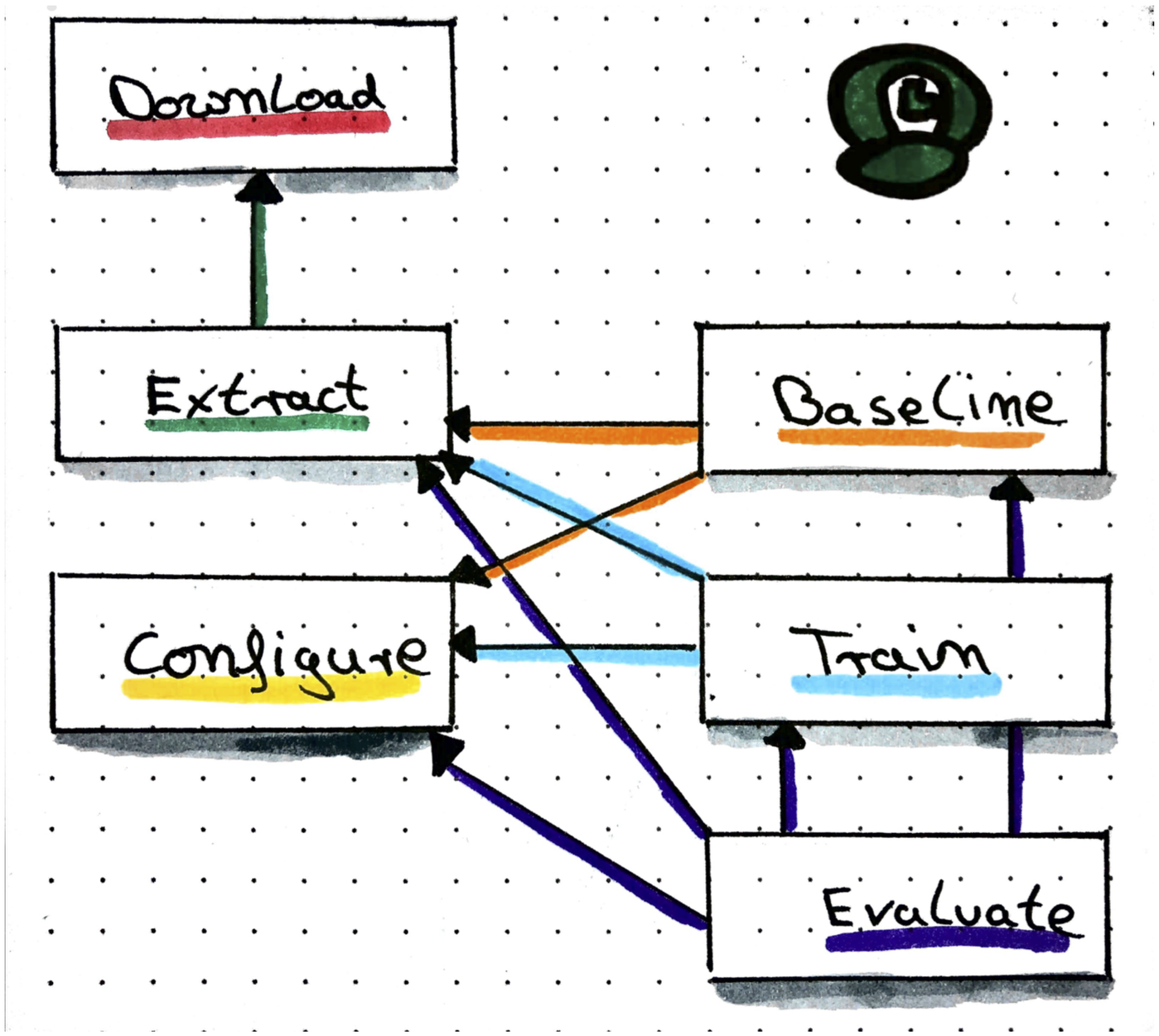
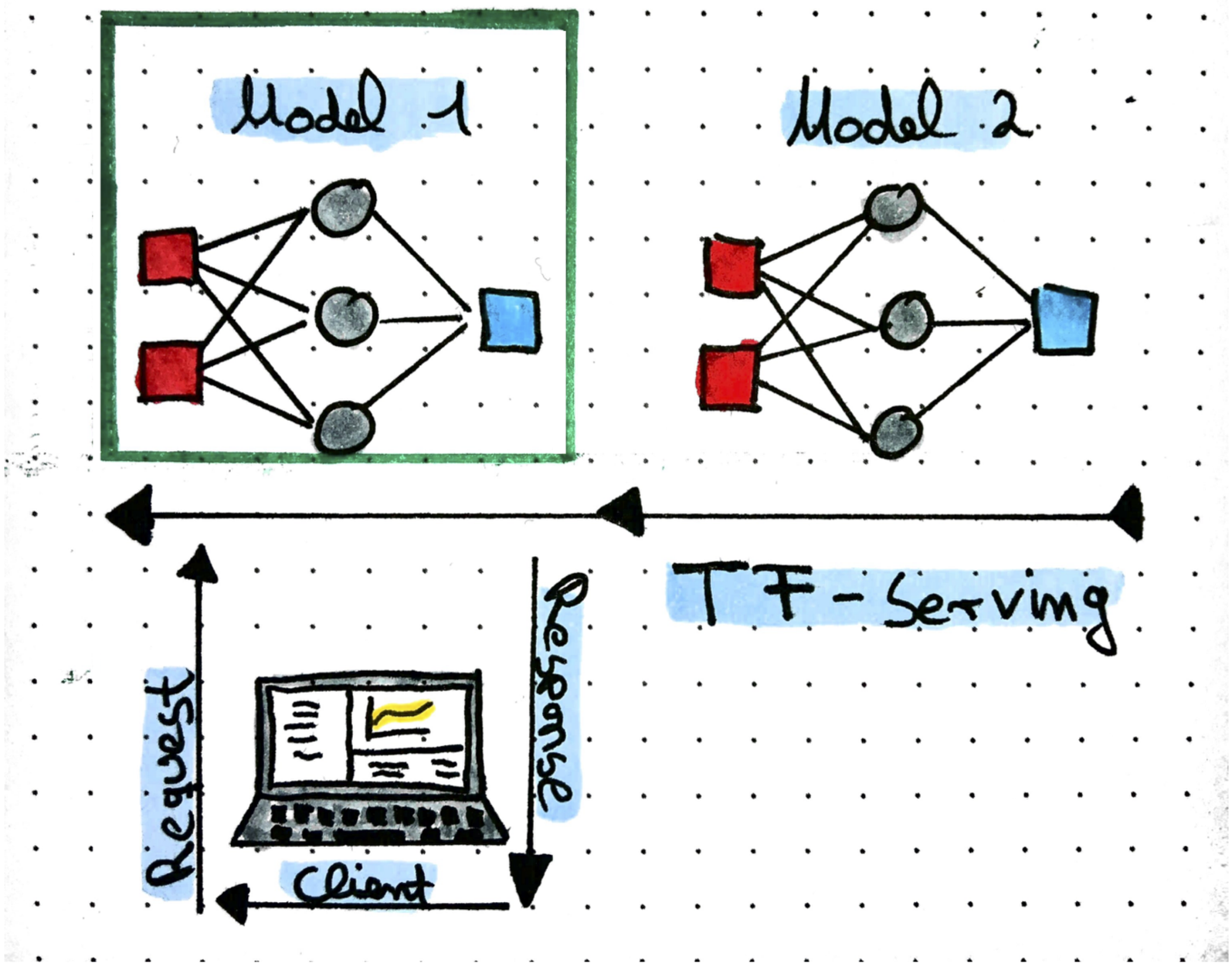
How would a production-ready Workflow look like?

- Download the dataset
- Extract the data
- Create a preprocessing configuration
- Run the baseline validation
- Train the model
- Evaluate the model

Workflow



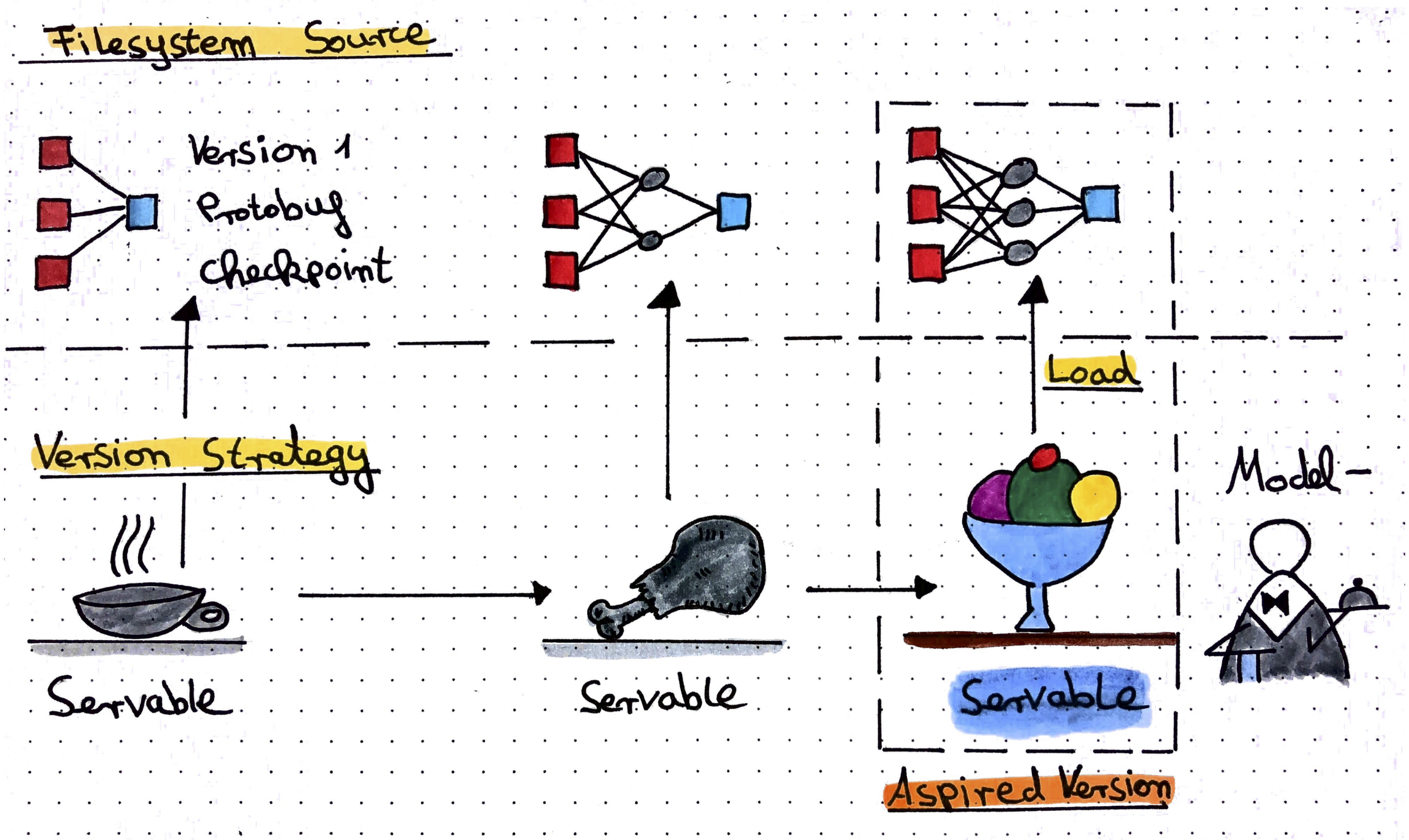
TensorFlow Serving



TensorFlow Serving

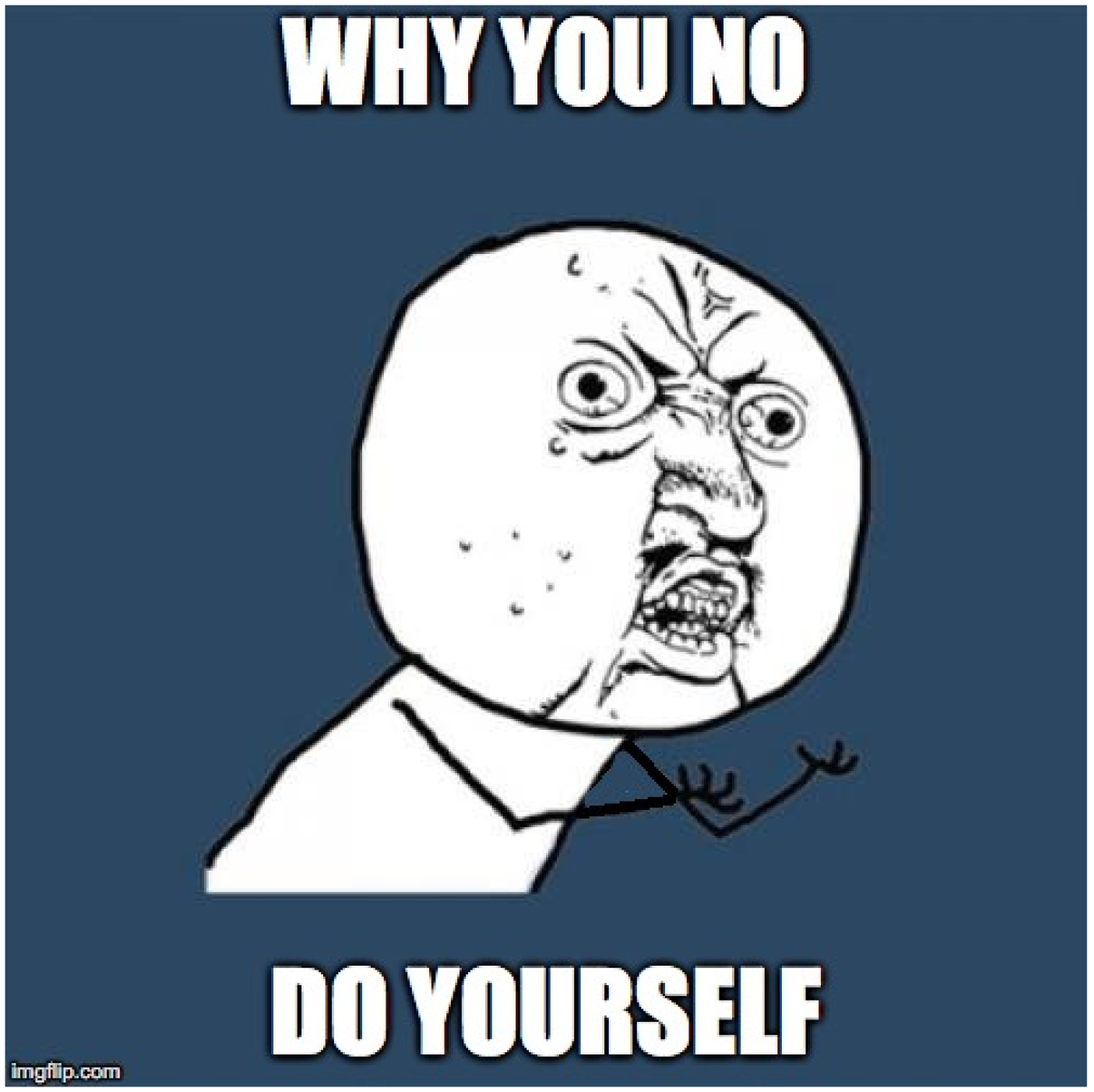
- ModelServer as Server-runtime for ML models
- Can natively handle TensorFlow graphs
- Highly flexible
- Designed for production use

TensorFlow Serving in Detail



TensorFlow Serving Components

- Protobuf file for graph, checkpoint files for weights
- Version strategy defines how many models are loaded into memory
- Clients request inferences via gRPC
- TF-Serving consists of pluggable components, namely sources, loaders and version strategies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