

End2End Data Science

From Keras to Production!

Contents

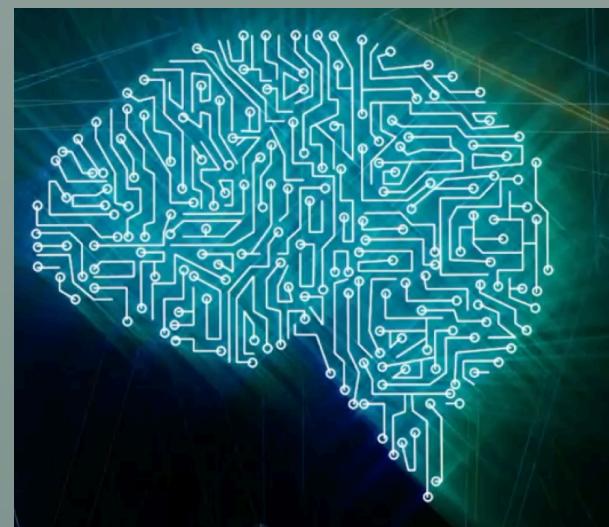
- Learn what neural nets are and what's the big deal with deep learning
- Work with Keras to apply existing models on your own data
- Build your own fruit classification model!

- Get a glimpse of production-readiness
- Version your data and models with DVC
- Deploy your model with Tensorflow Serving
- Learn about Luigi/Airflow and write your own pipeline

What is Deep Learning?

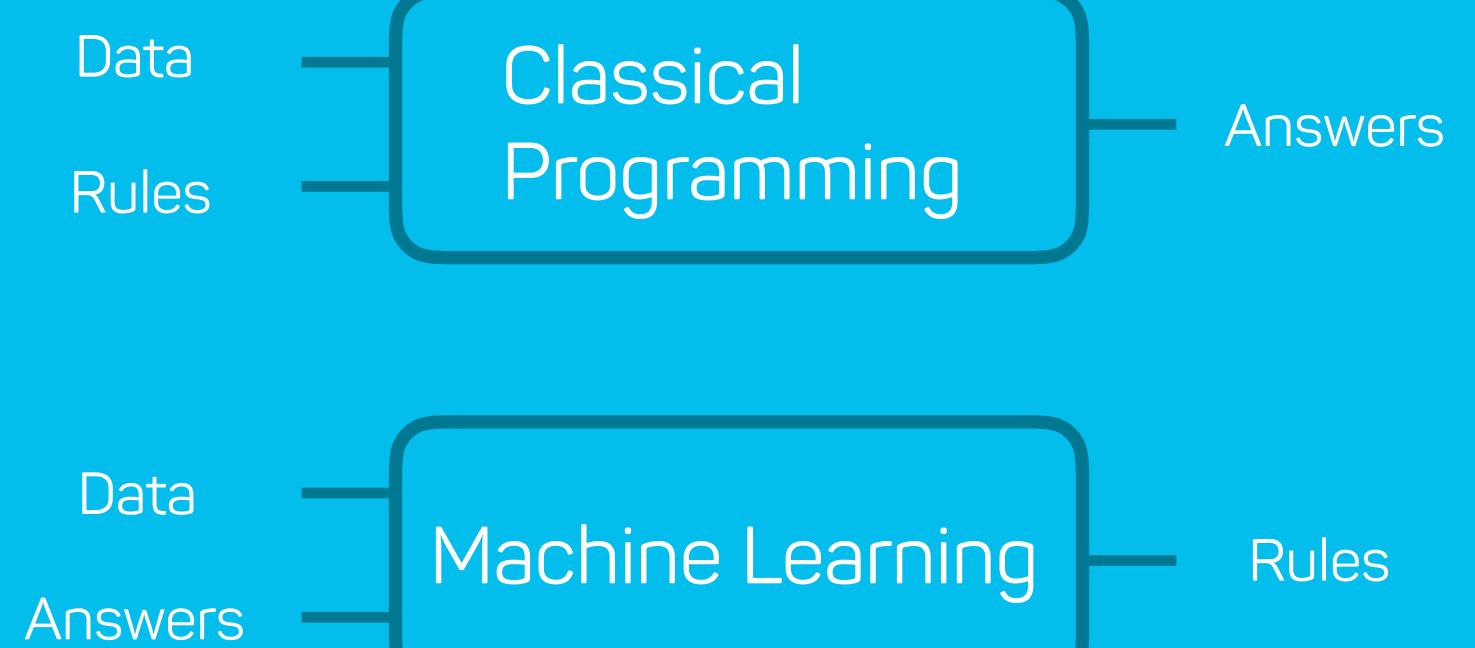
Artificial Intelligence

Any technique that enables computers to mimic human behavior



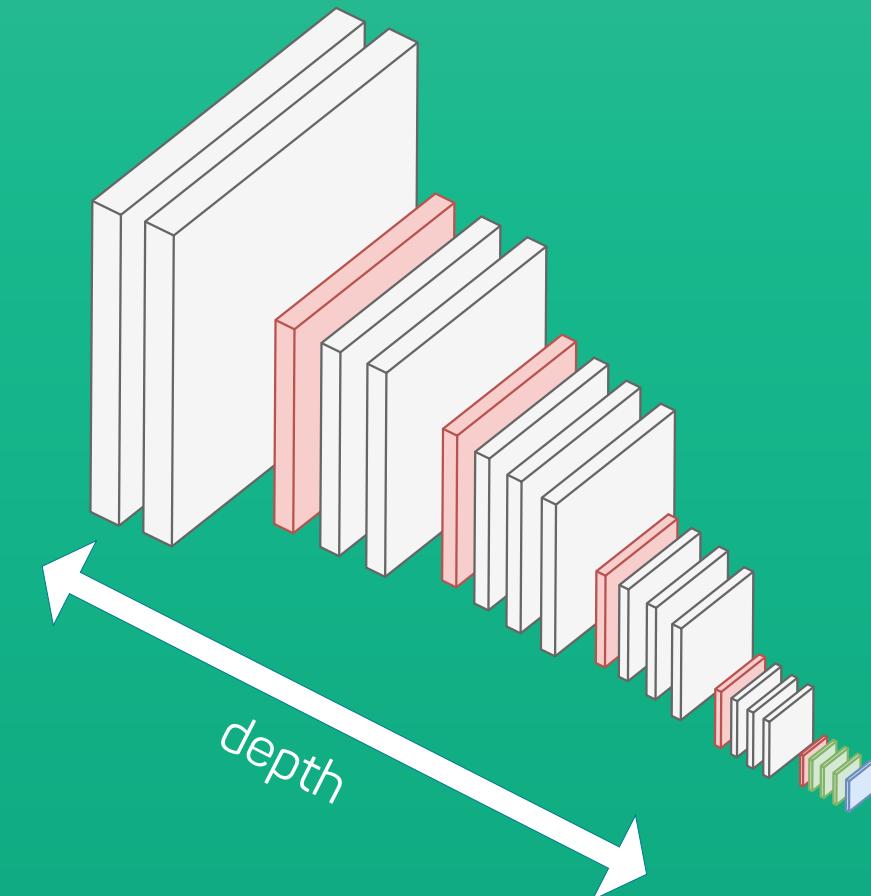
Machine Learning

Ability to learn rules from data



Deep Learning

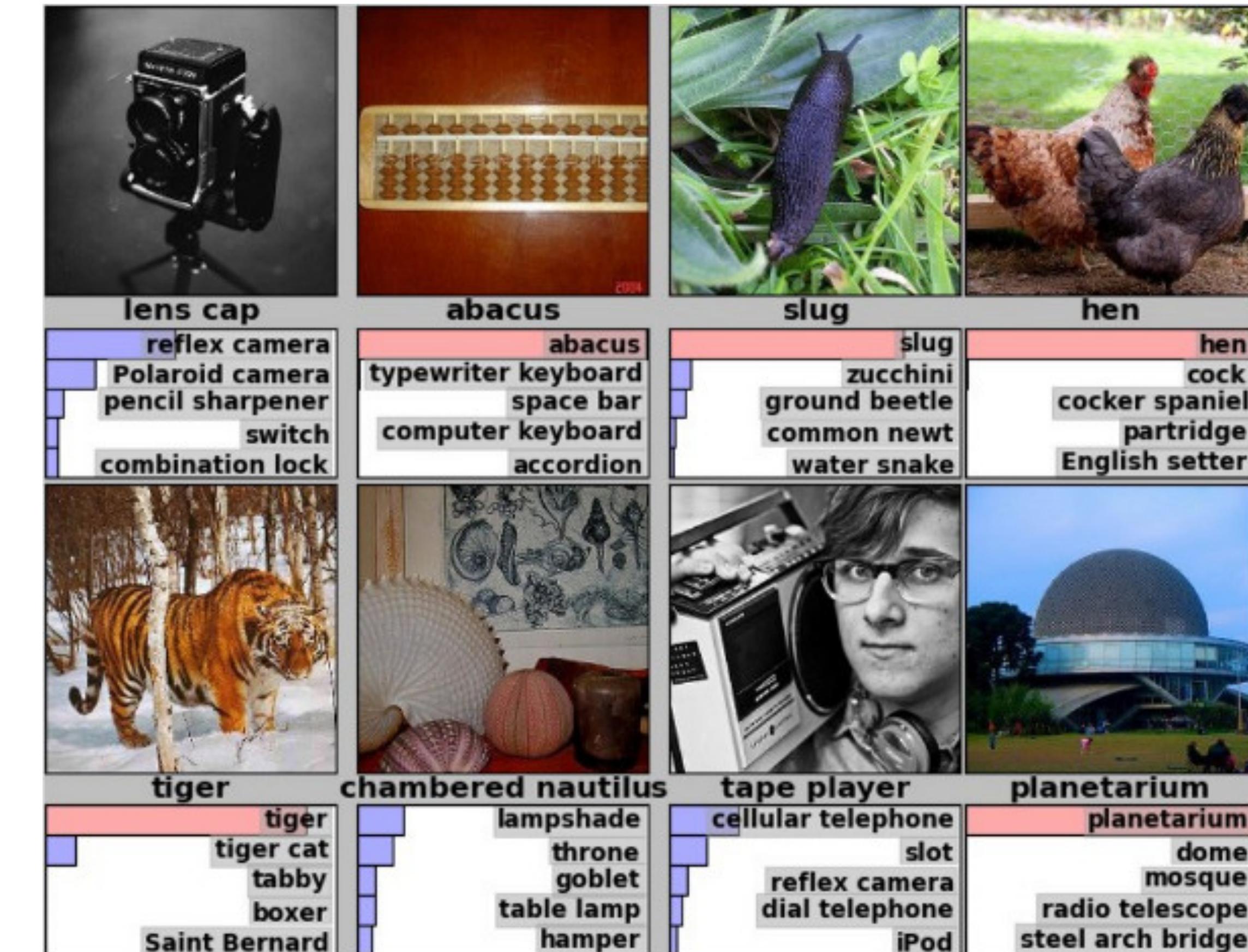
Apply machine learning with „deep“ neural networks



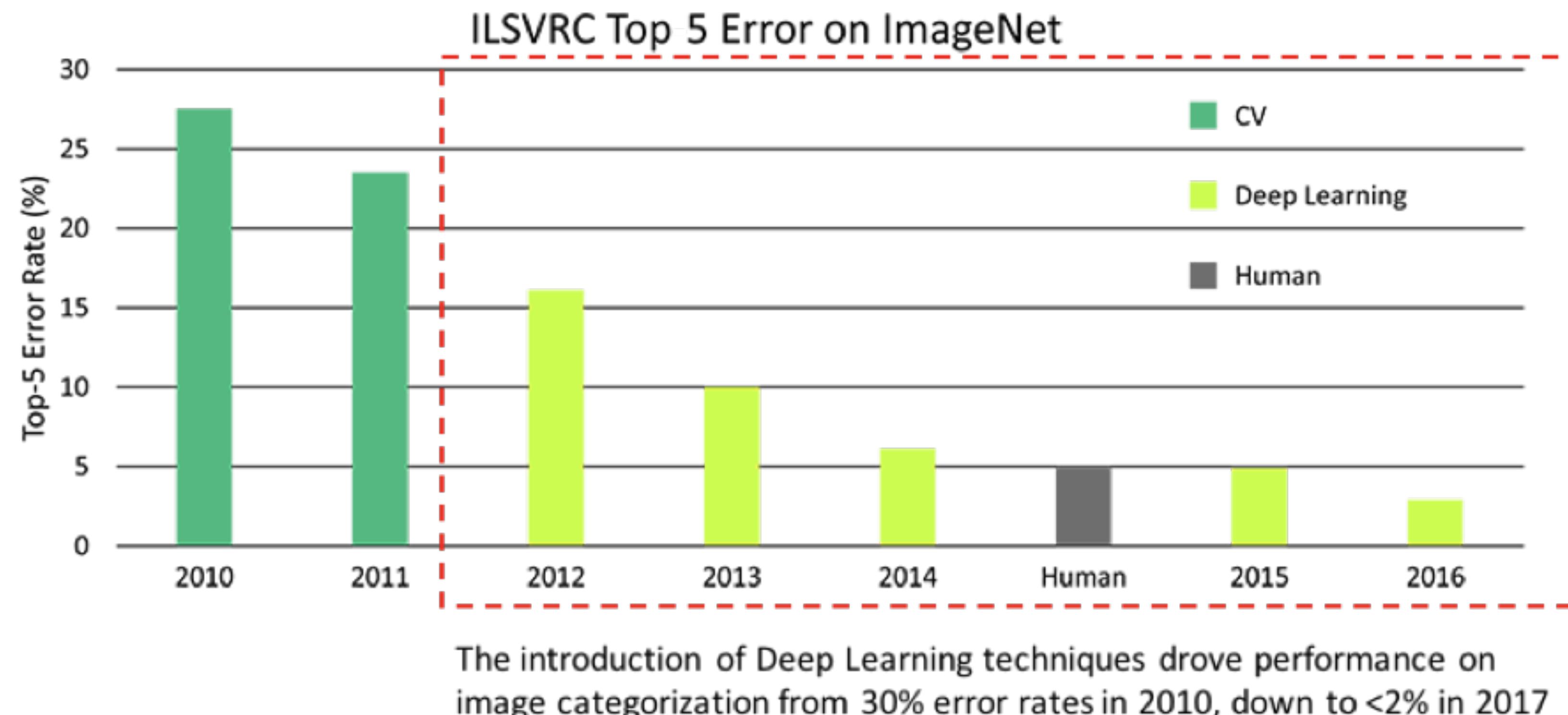
Deep Learning Achievements - ImageNet



- 1000 categories
- train set: 1.2 M
- test set: 100 k



Deep Learning Achievements - ImageNet



<https://medium.com/obvious-ventures/our-investment-in-darwinai-d5ea1a7af32e>

Deep Learning Achievements - Speech Recognition

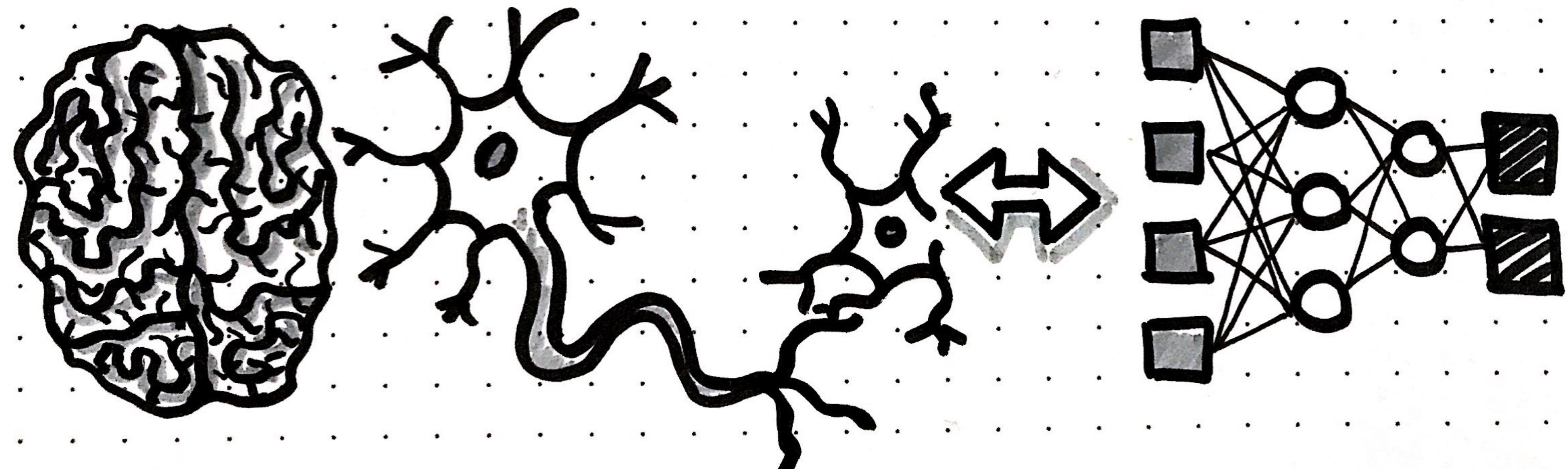


2006
Microsoft

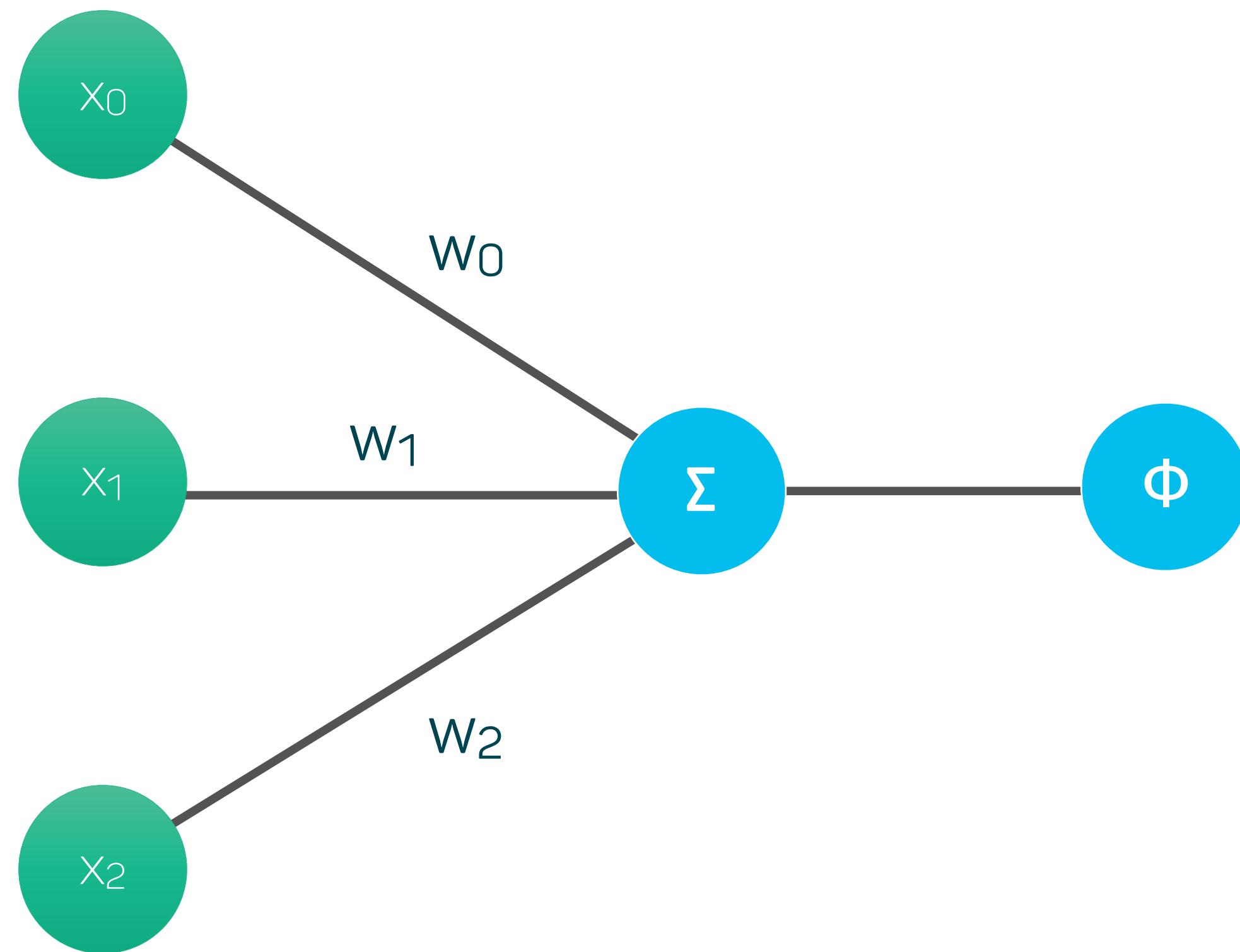


2018
Google

Neural Networks: Inspired by Nature



Fundamentals of Deep Learning - Perceptron



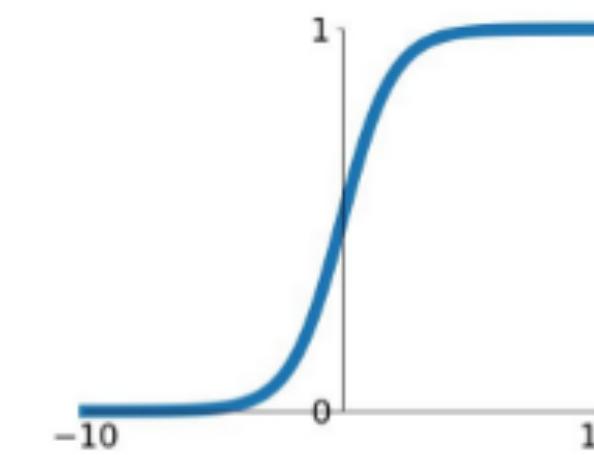
$$f(x) = \phi\left(\sum_i w_i x_i + b\right)$$

Fundamentals of Deep Learning

Activation Functions

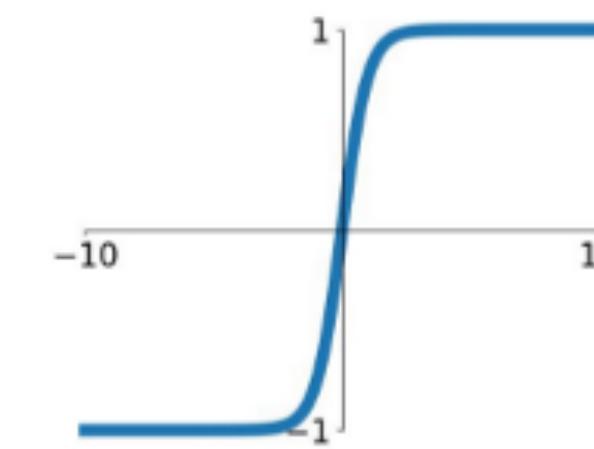
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



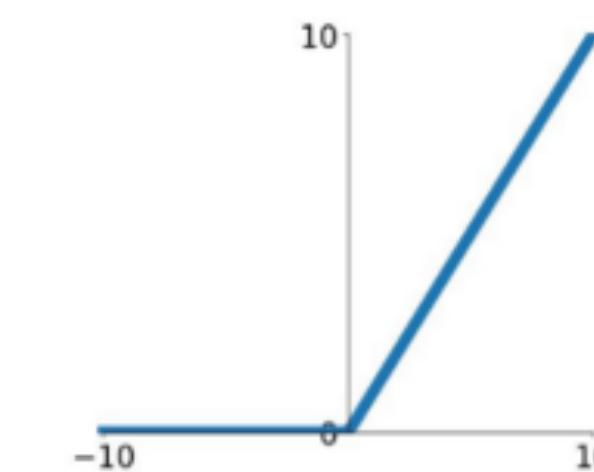
tanh

$$\tanh(x)$$



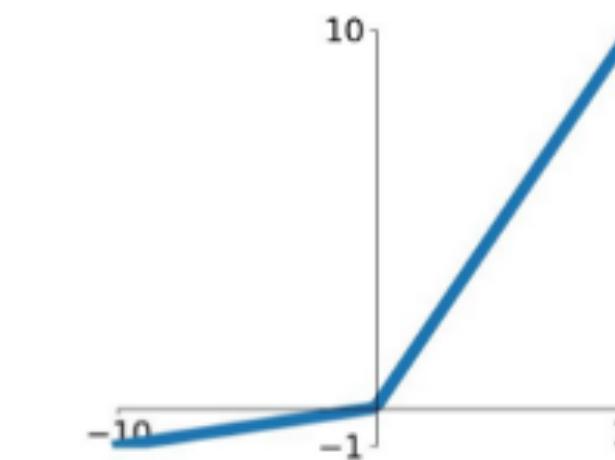
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

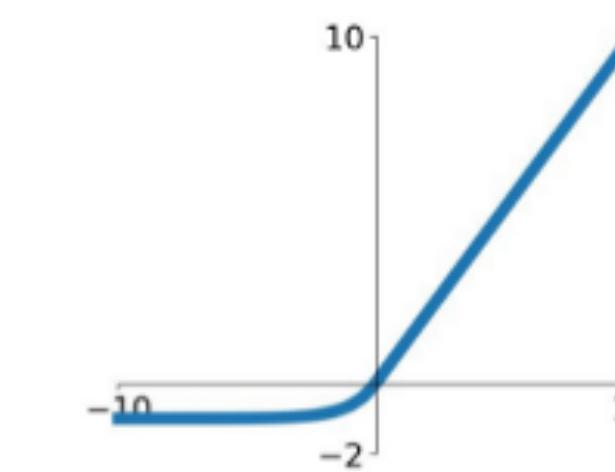


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

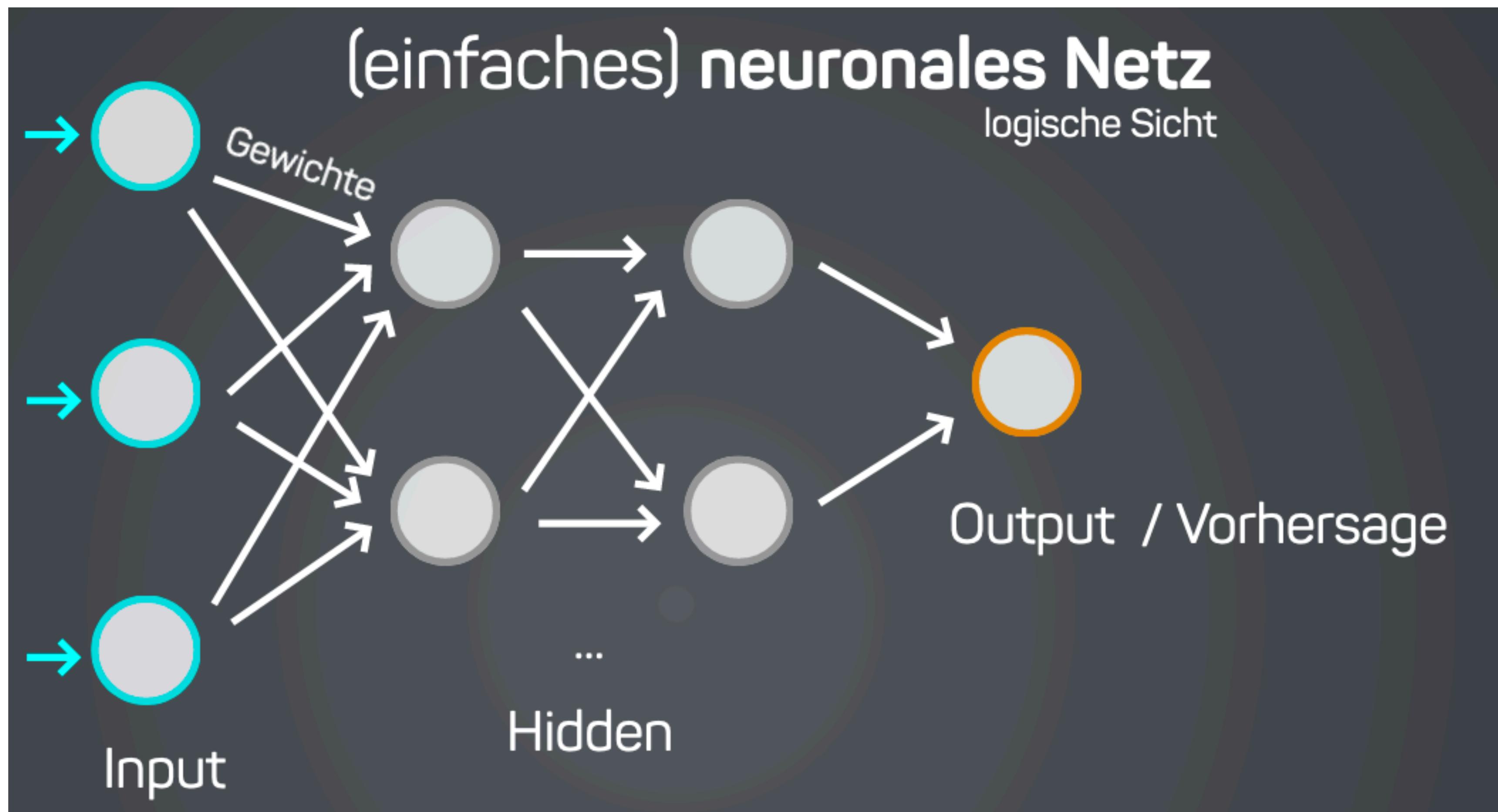
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

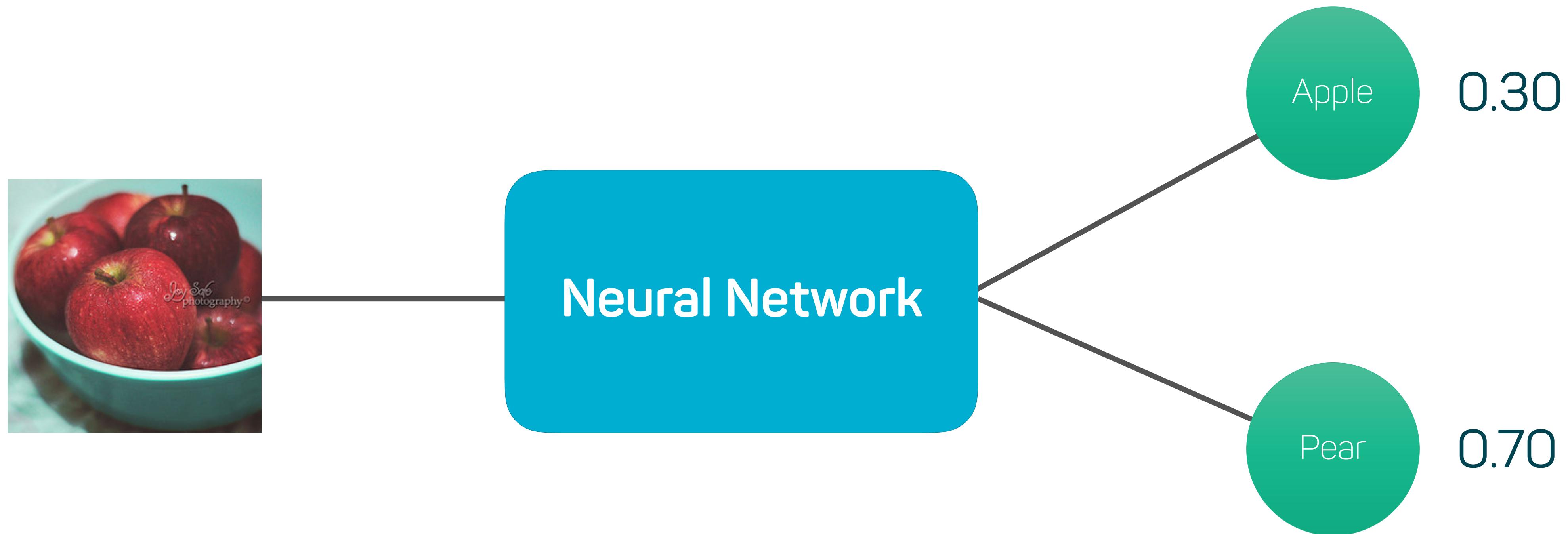


https://cdn-images-1.medium.com/max/1200/1*ZafDv3VUm60Eh100eJu1vw.png

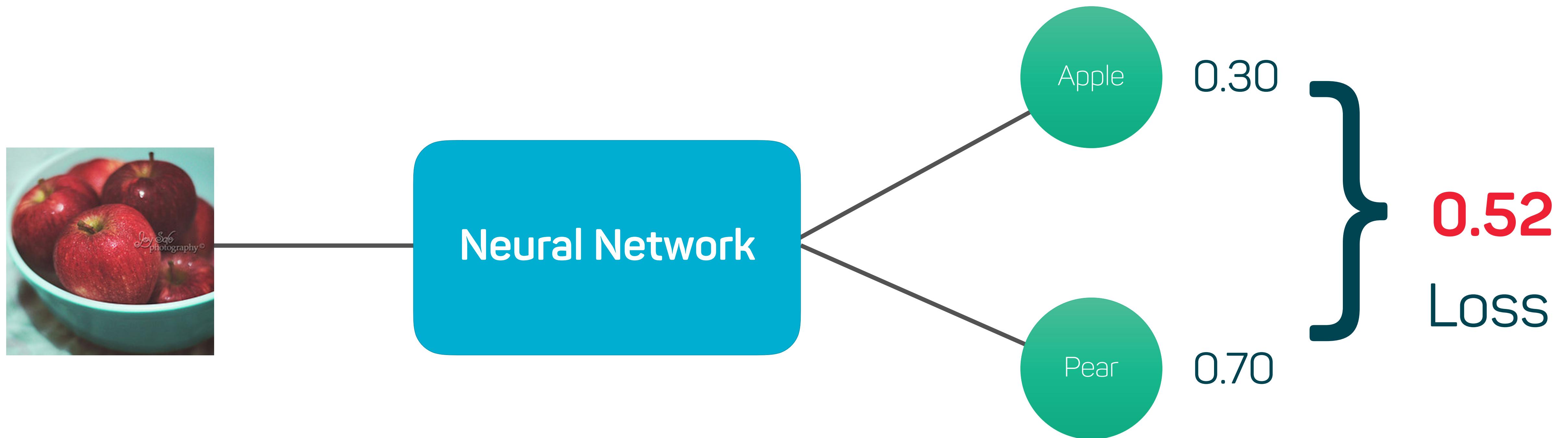
Fundamentals of Deep Learning



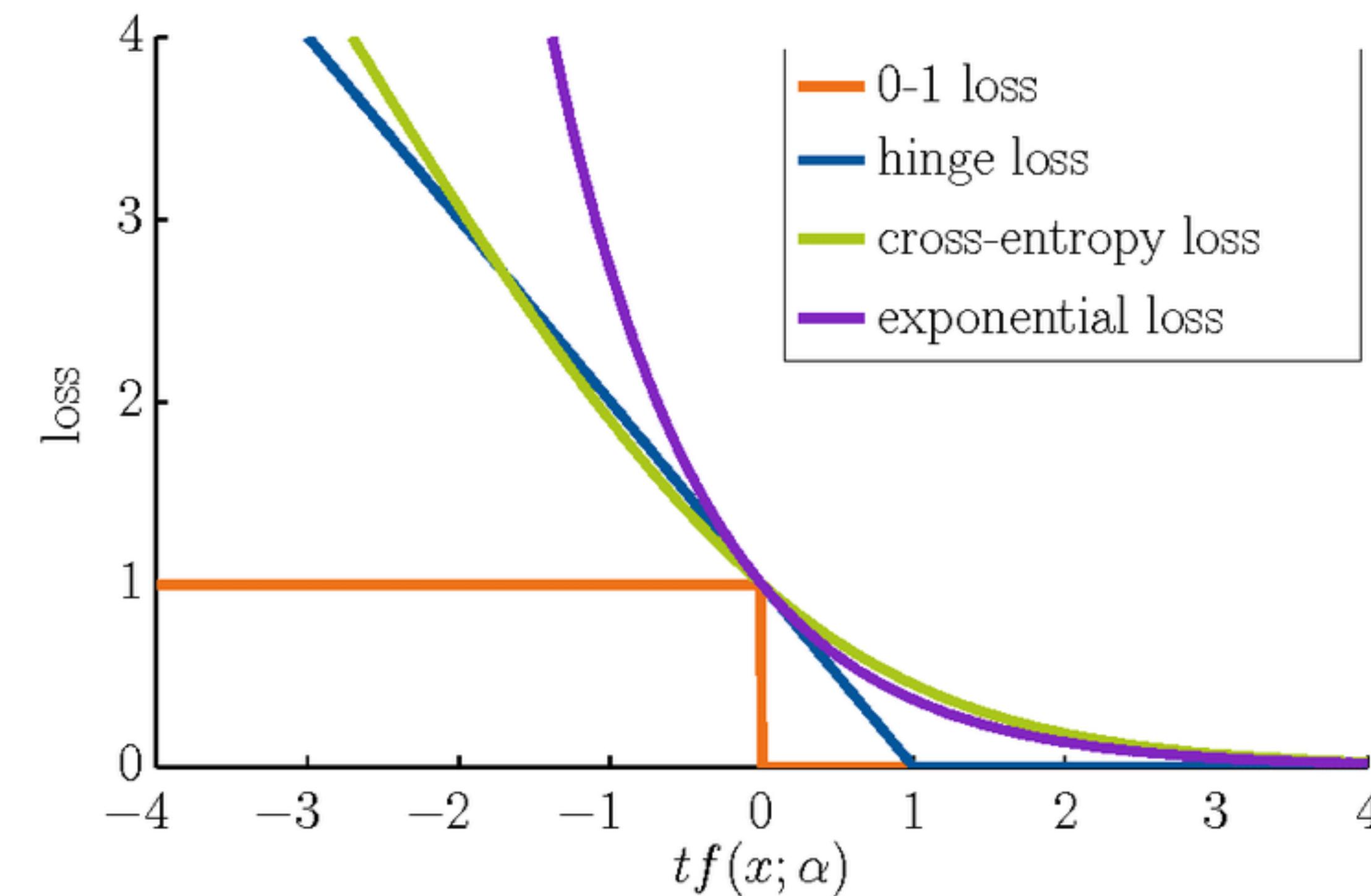
Fundamentals of Deep Learning



Fundamentals of Deep Learning - Loss Function

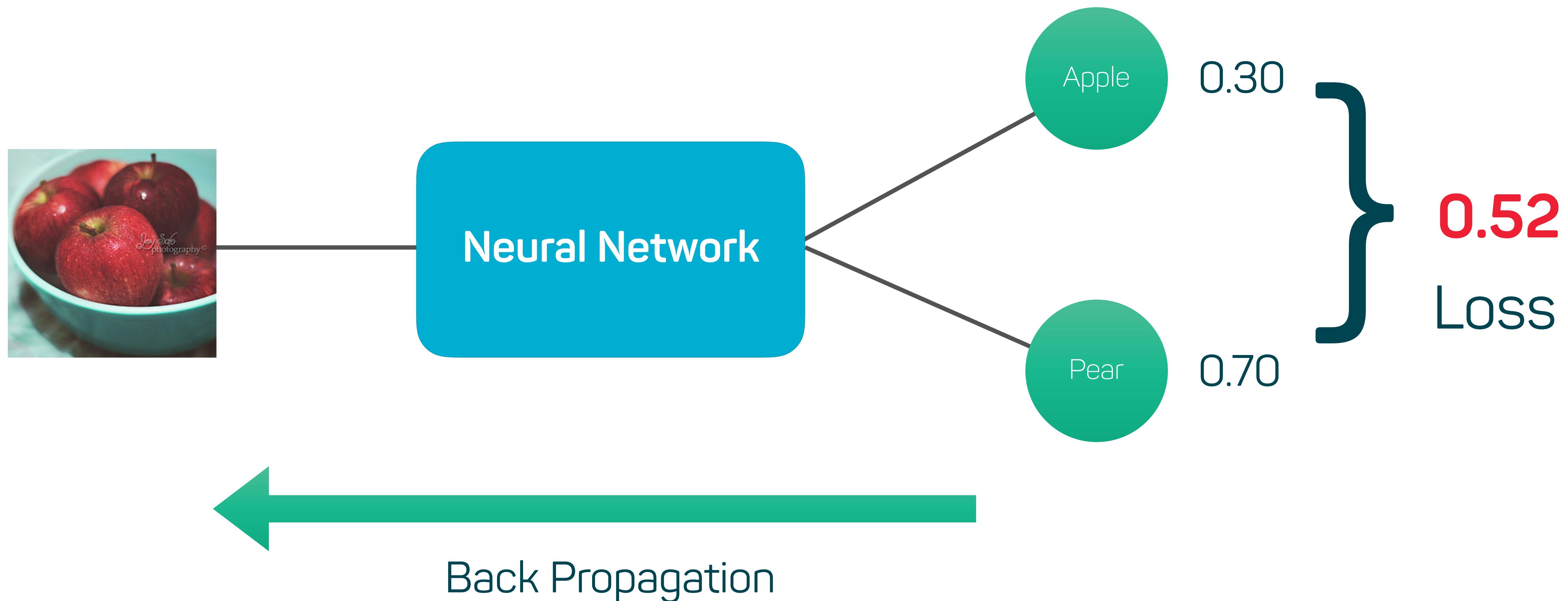


Fundamentals of Deep Learning - Loss Functions

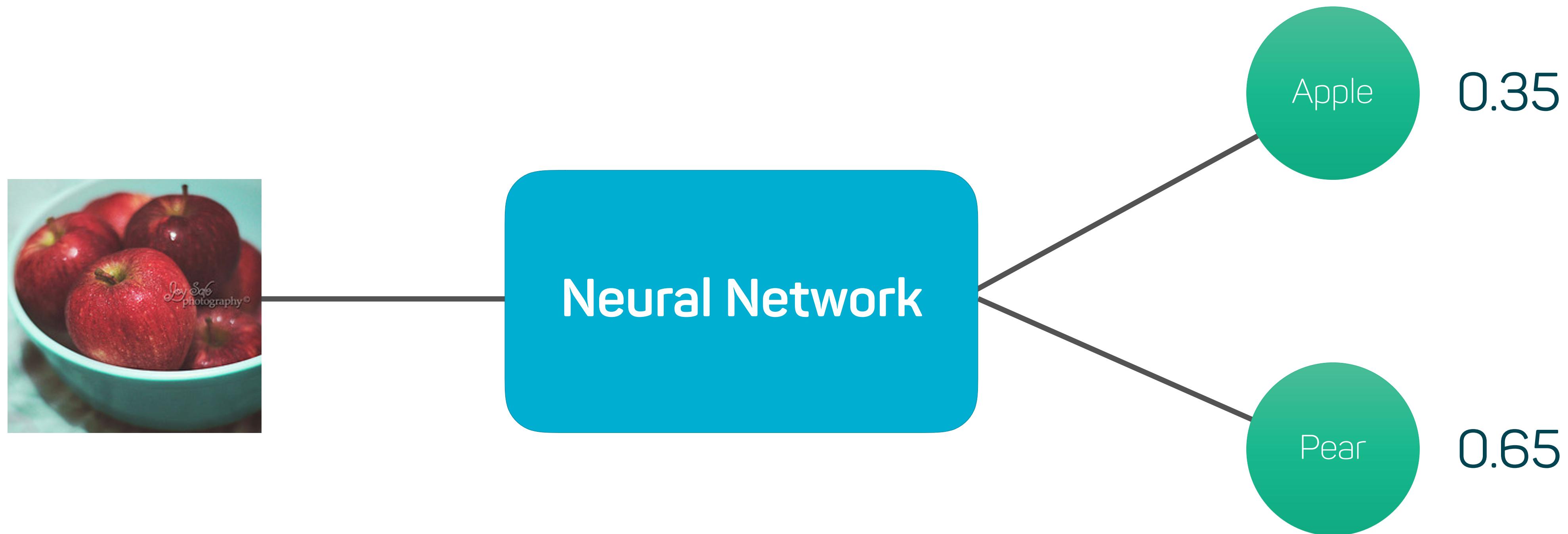


Any loss function returns a scalar value!

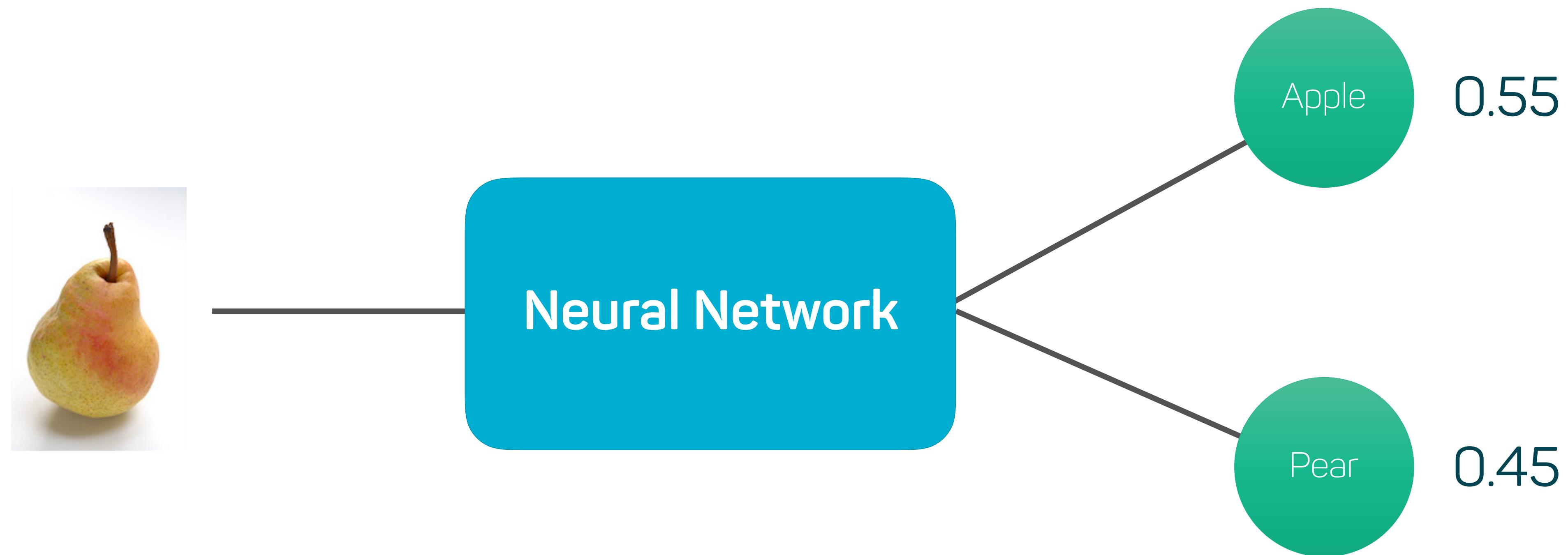
Fundamentals of Deep Learning



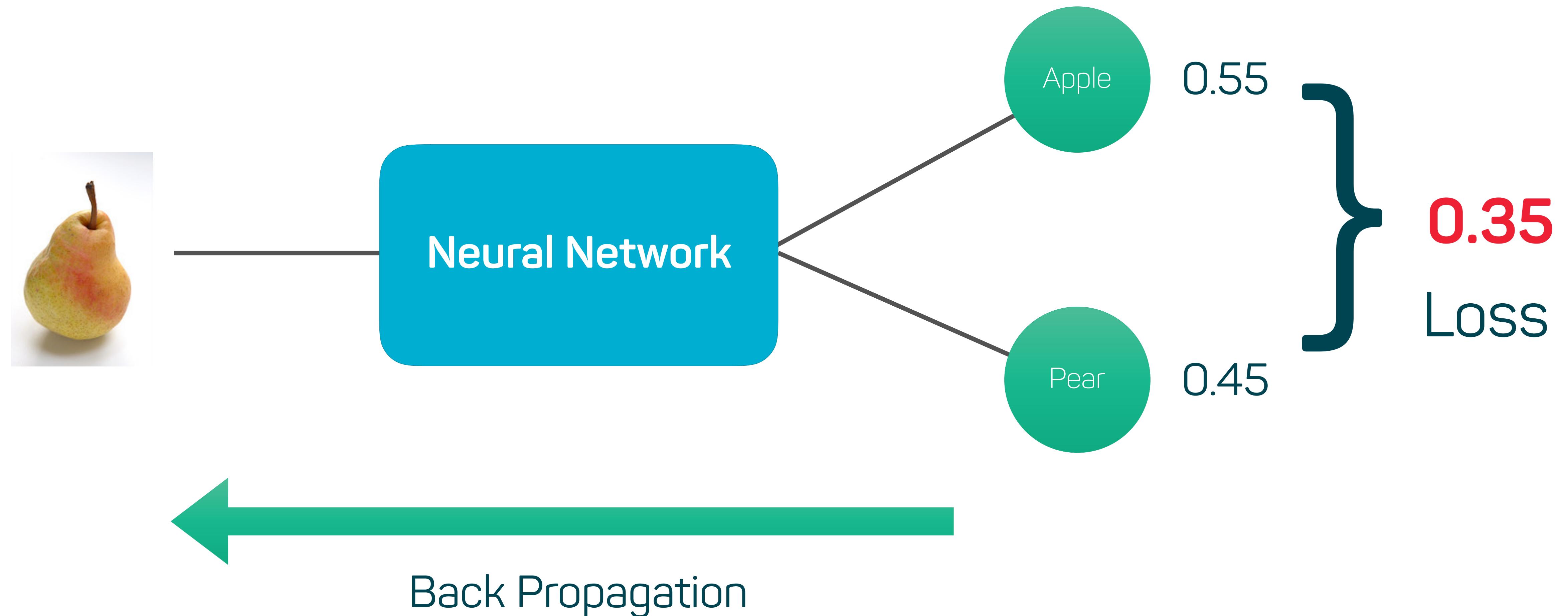
Fundamentals of Deep Learning



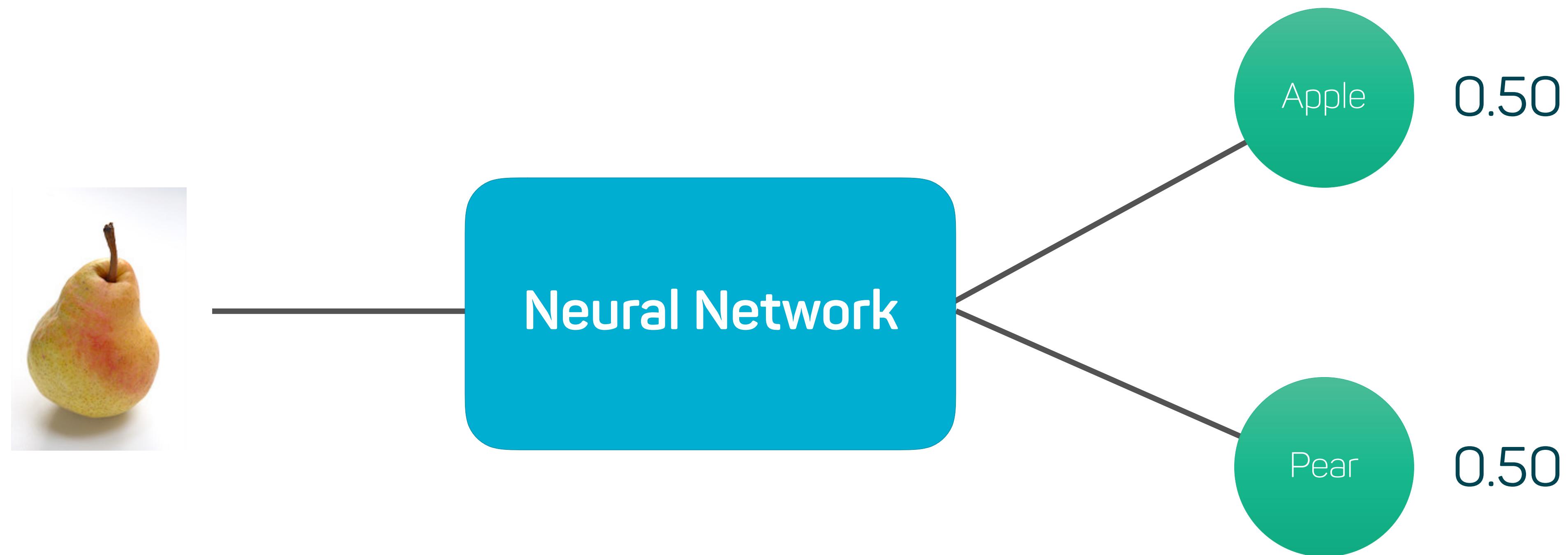
Fundamentals of Deep Learning



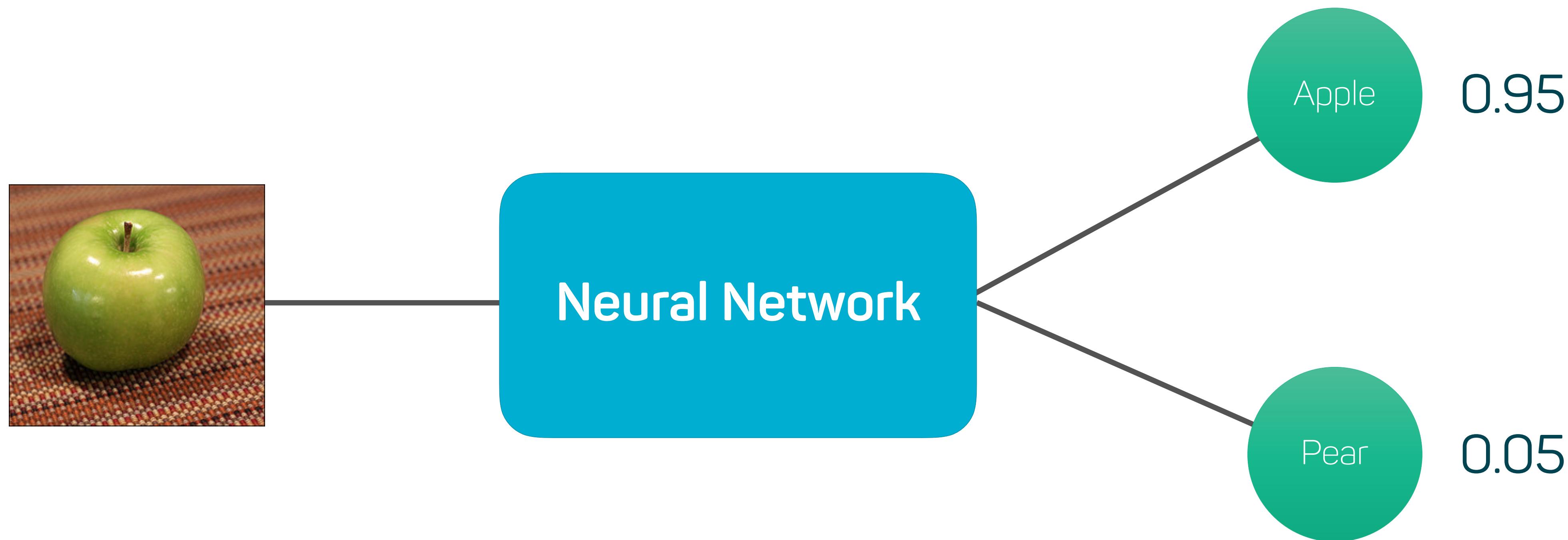
Fundamentals of Deep Learning



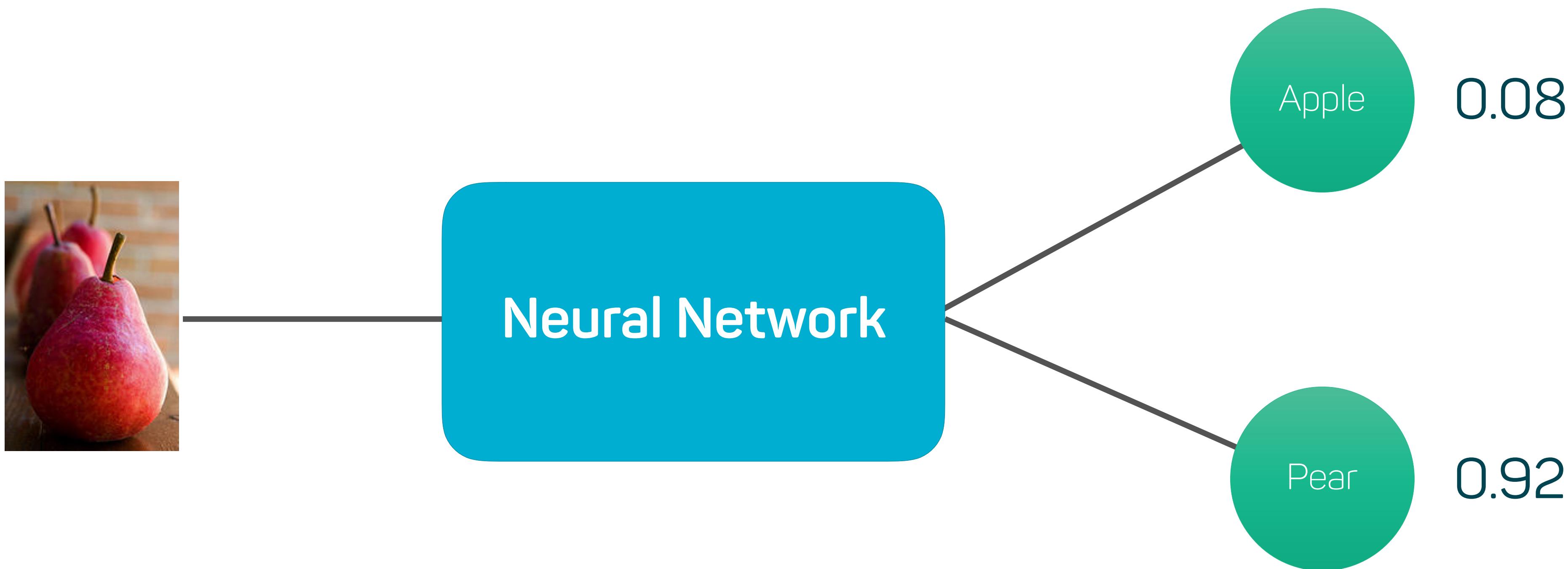
Fundamentals of Deep Learning



Fundamentals of Deep Learning

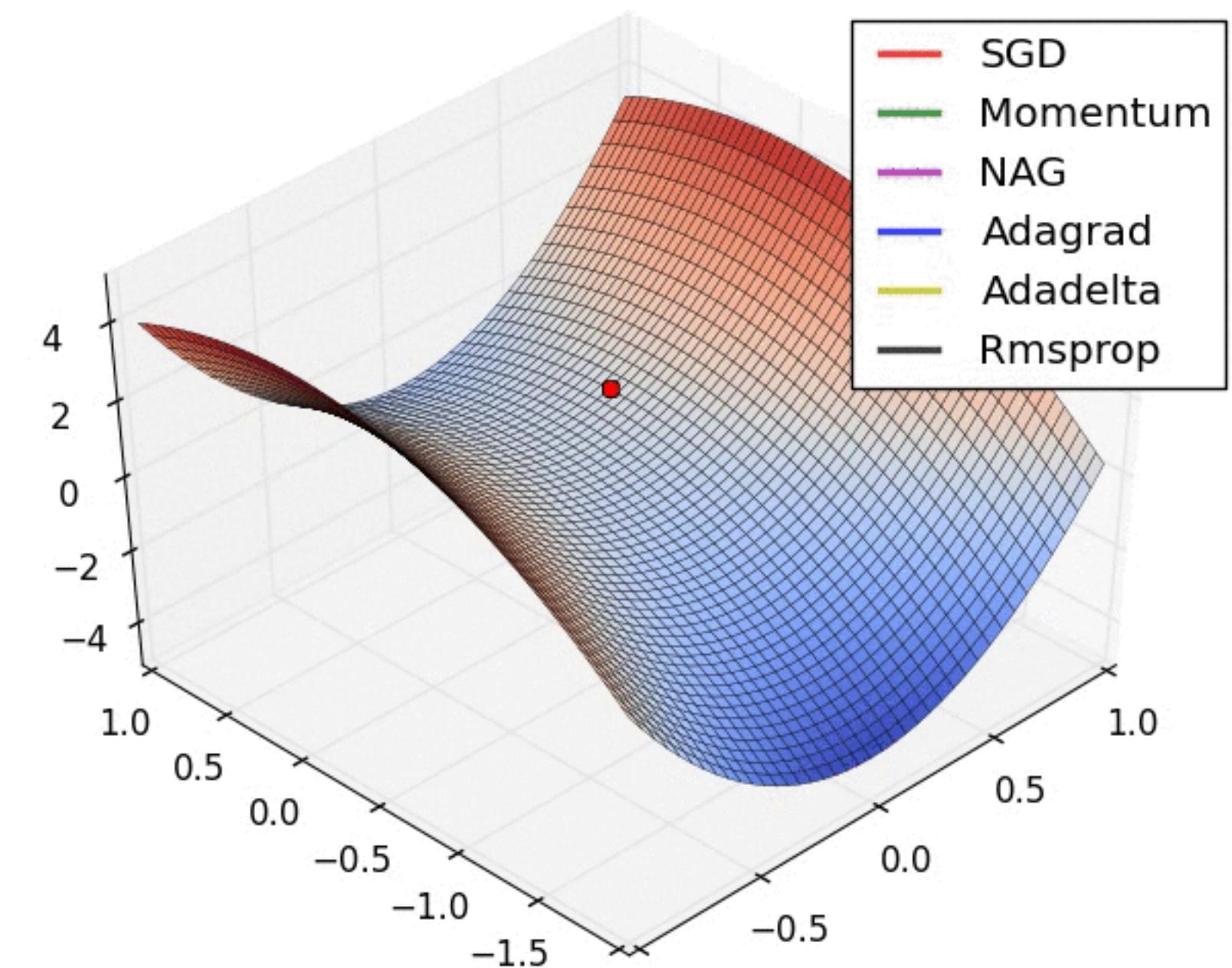


Fundamentals of Deep Learning

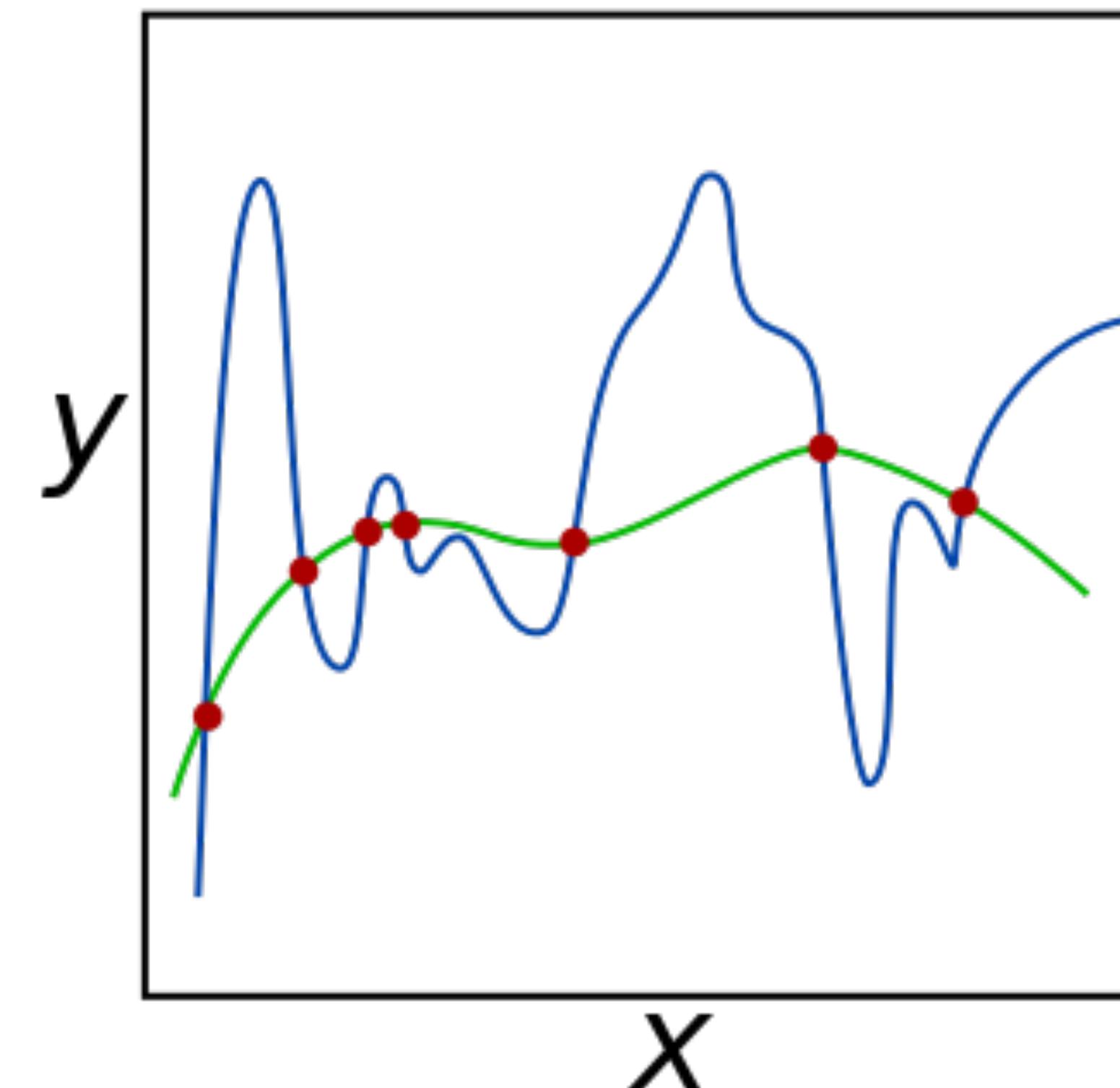


Fundamentals of Deep Learning - Optimizer

- Strategy to minimize loss
- Core idea: **stochastic gradient descent**
- Momentum: Also consider past gradients
- AdaGrad/**RMSProp**/AdaDelta: Adaptive learning rate based on past gradients
- **Adam**/RAdam: Momentum + RMSProp

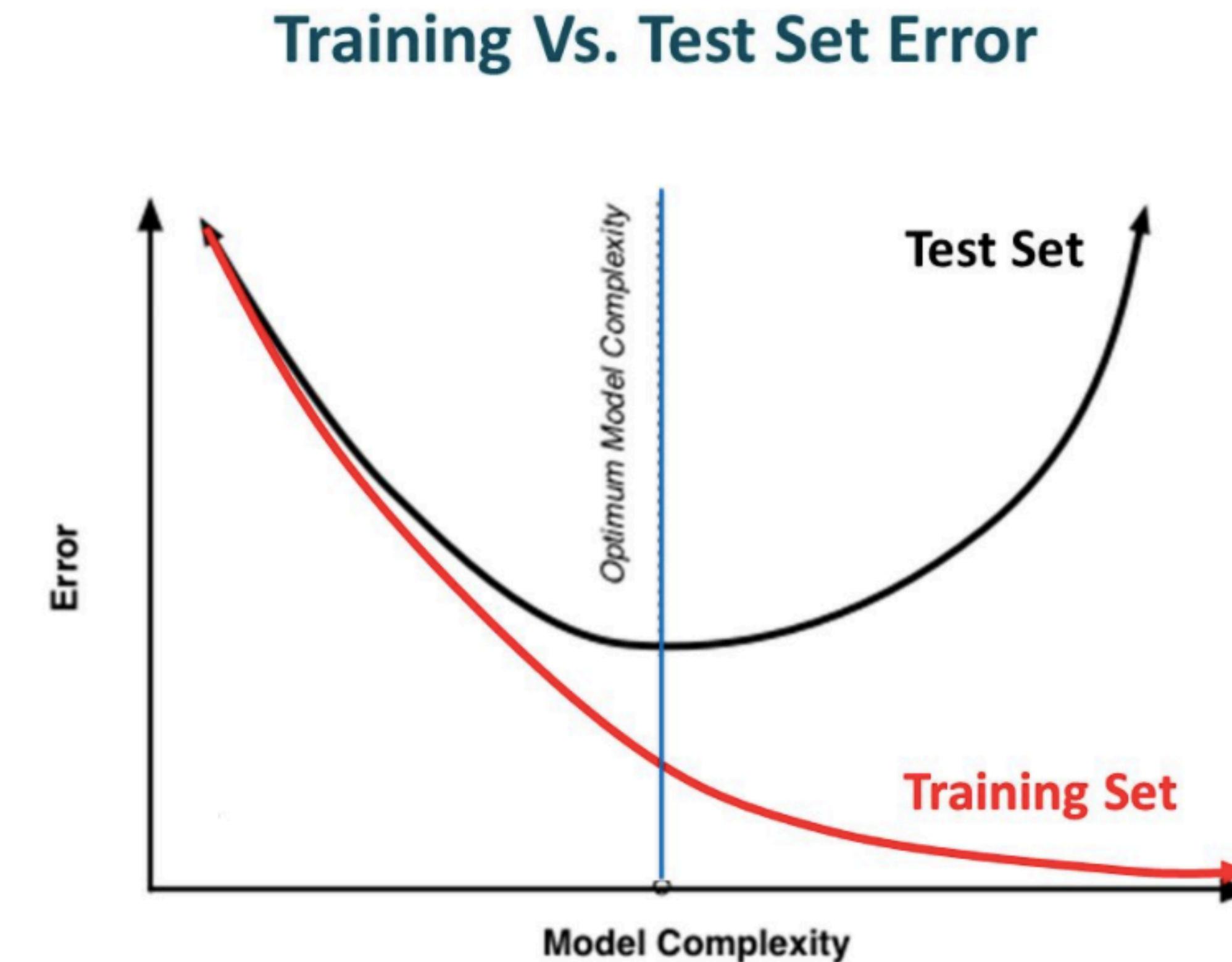


Fundamentals of Deep Learning - Overfitting



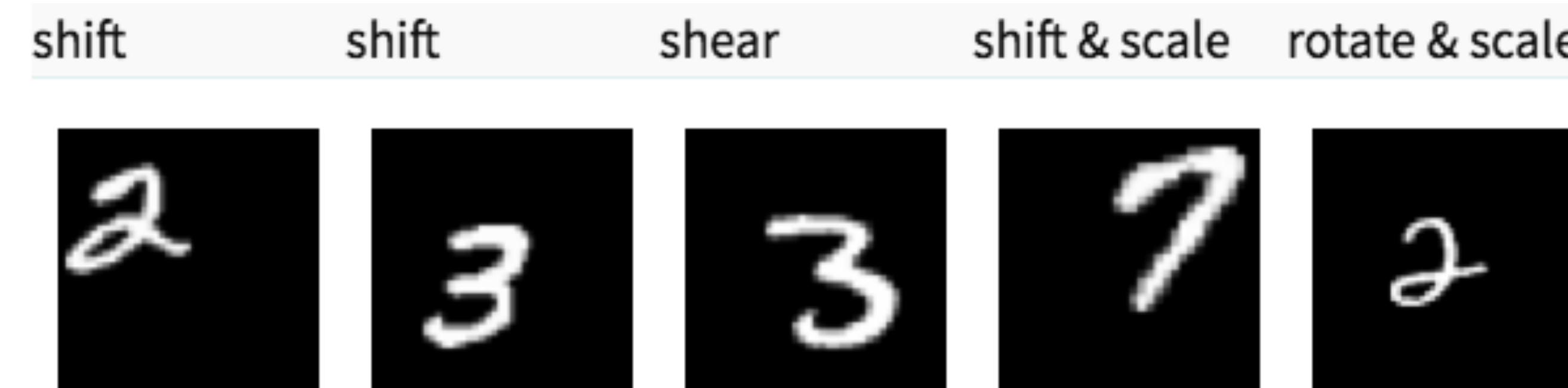
[https://en.wikipedia.org/wiki/Regularization_\(mathematics\)](https://en.wikipedia.org/wiki/Regularization_(mathematics))

Fundamentals of Deep Learning - Overfitting



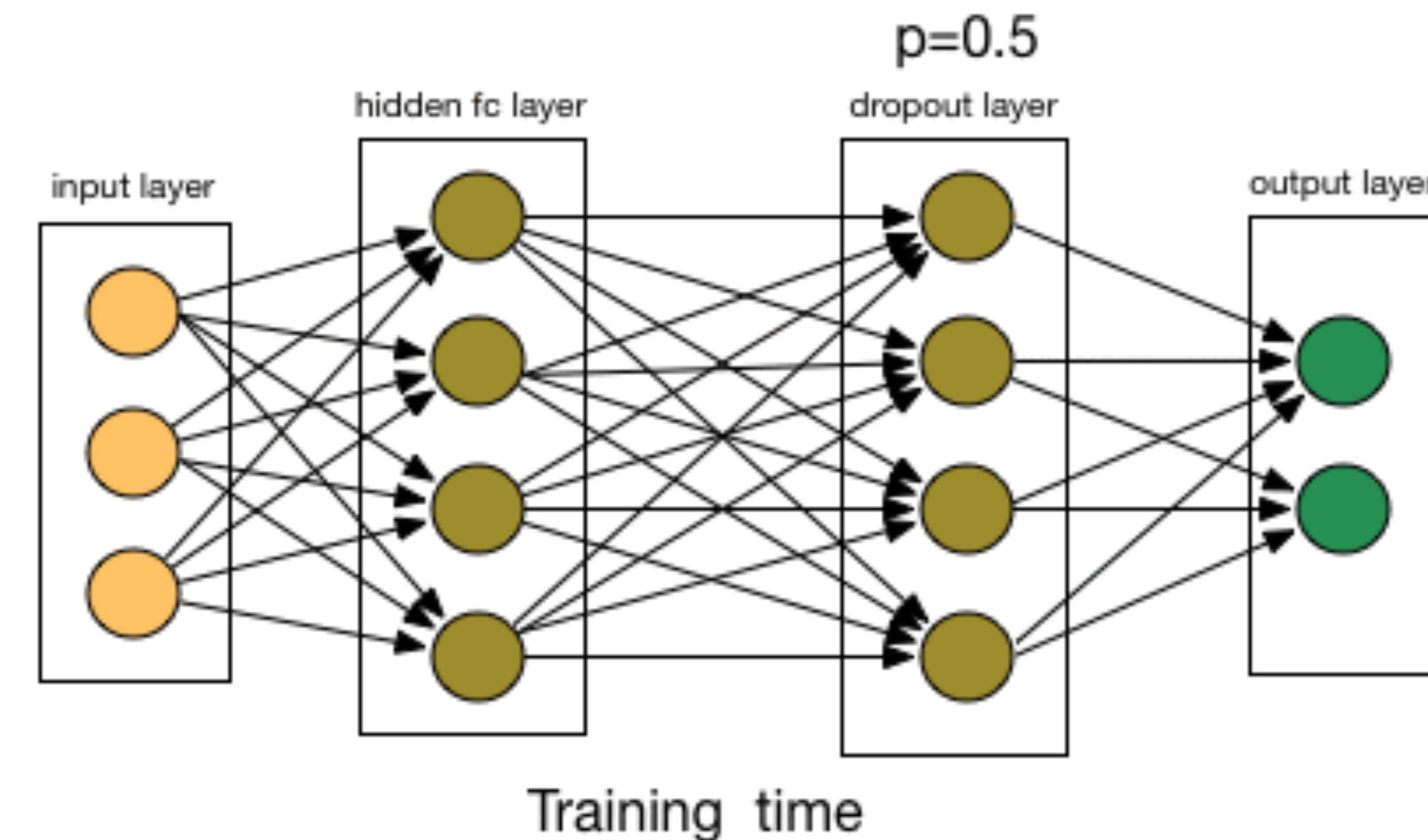
<https://www.analyticsvidhya.com/blog/2018/04/fundamentals-deep-learning-regularization-techniques/>

Fundamentals of Deep Learning - Data Augmentation



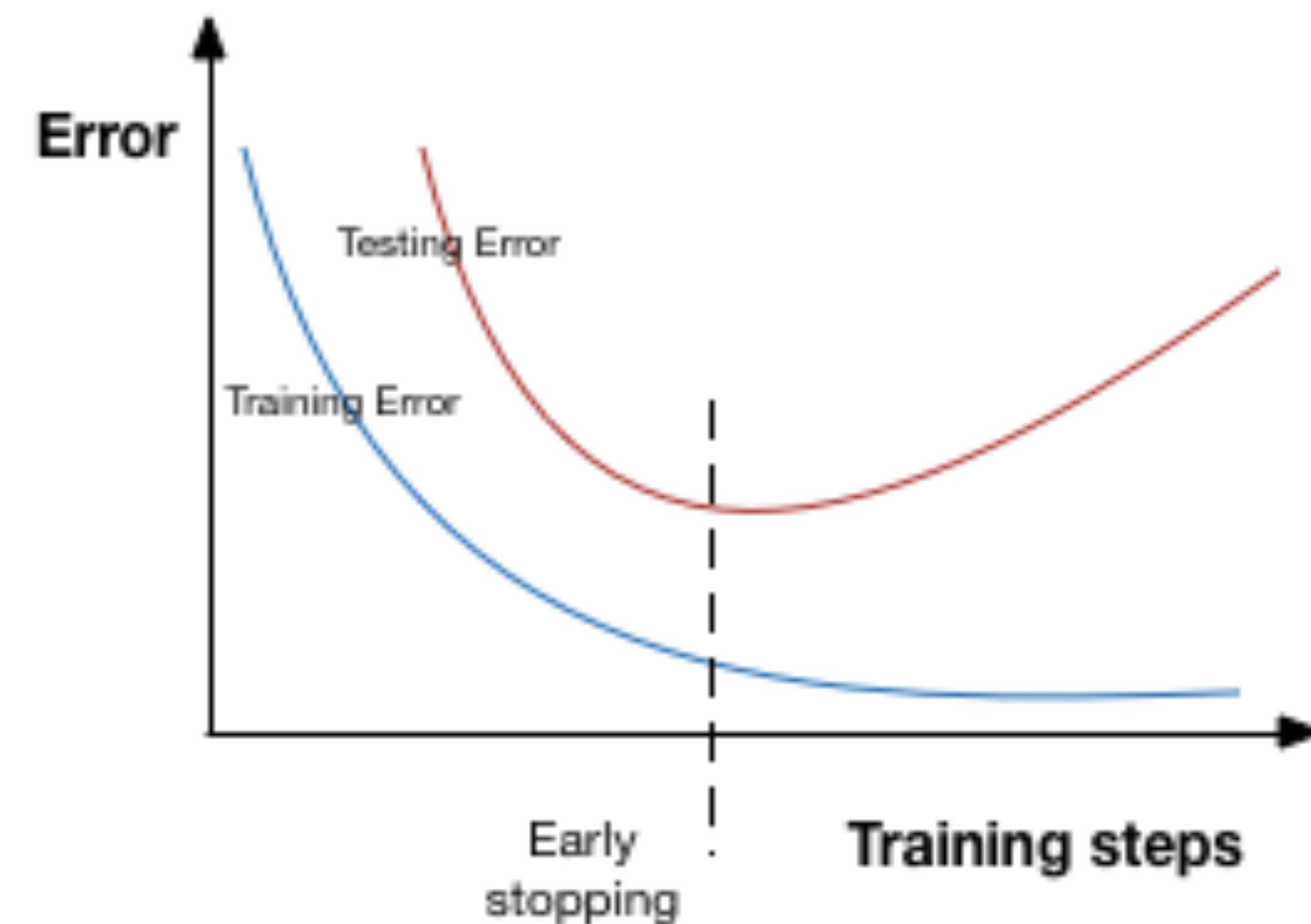
<https://www.analyticsvidhya.com/blog/2018/04/fundamentals-deep-learning-regularization-techniques/>

Fundamentals of Deep Learning - Dropout



<https://www.analyticsvidhya.com/blog/2018/04/fundamentals-deep-learning-regularization-techniques/>

Fundamentals of Deep Learning - Early Stopping

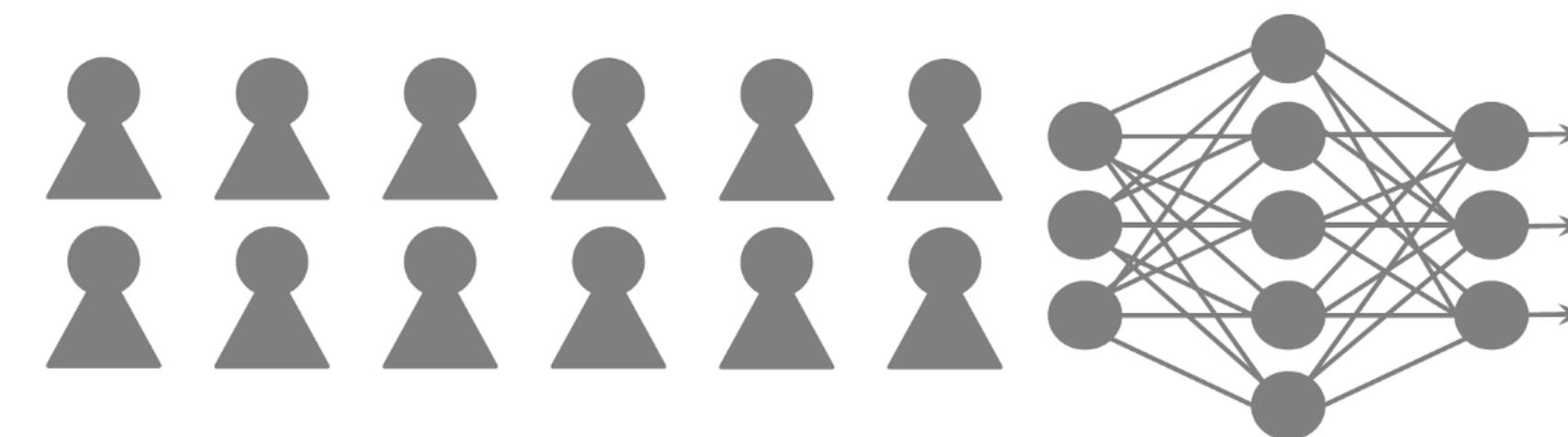


<https://www.analyticsvidhya.com/blog/2018/04/fundamentals-deep-learning-regularization-techniques/>

Fundamentals of Deep Learning - Pretraining

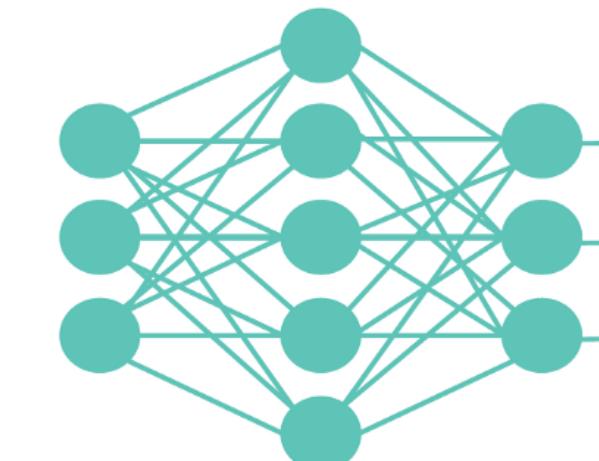
1

Pre-training: cheap large datasets on related domain



2

Fine-tuning: expensive well-labeled data



Performance
boost!

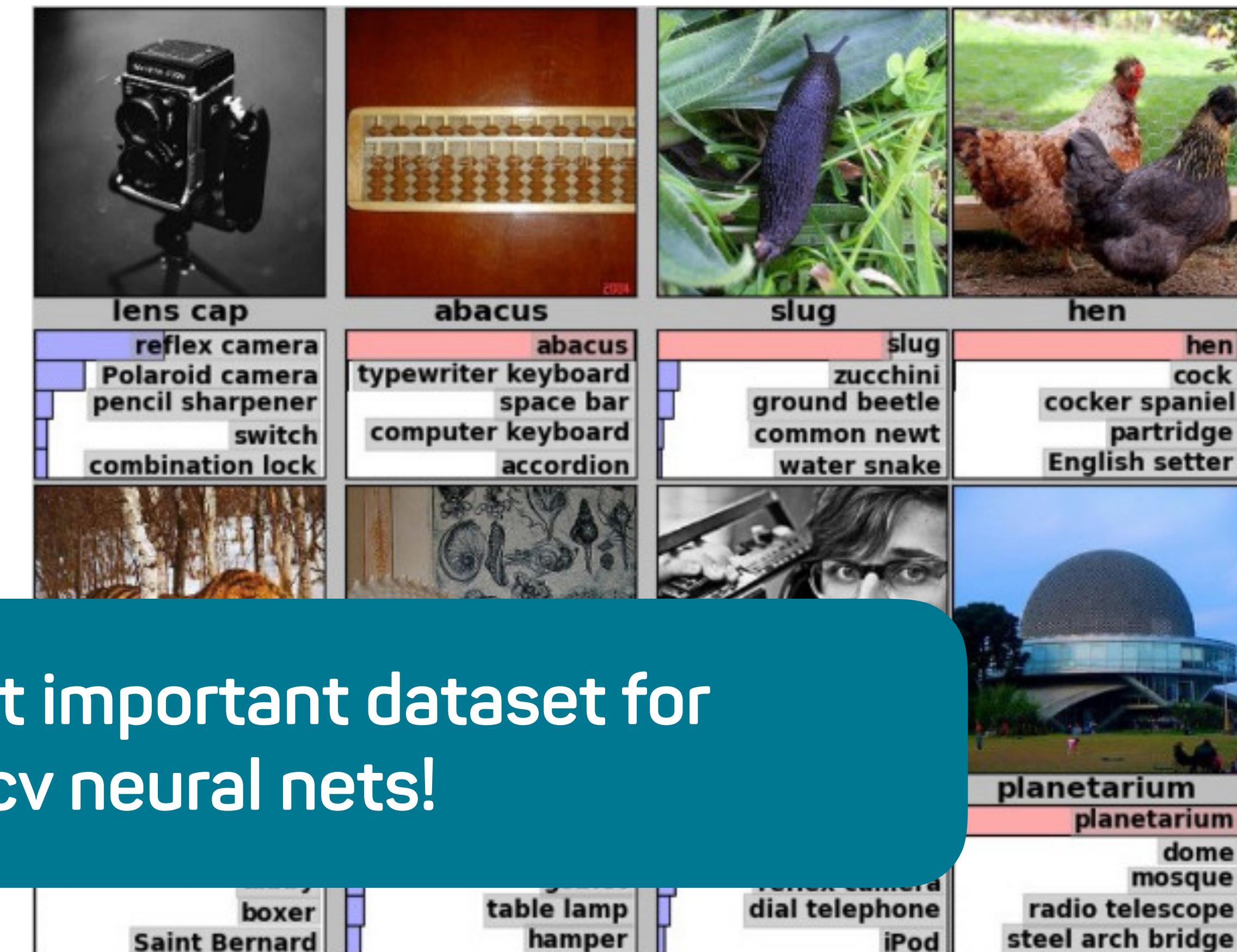
<https://medium.com/merantix/applying-deep-learning-to-real-world-problems-ba2d86ac5837>

Deep Learning Achievements - Pretraining

IMAGENET

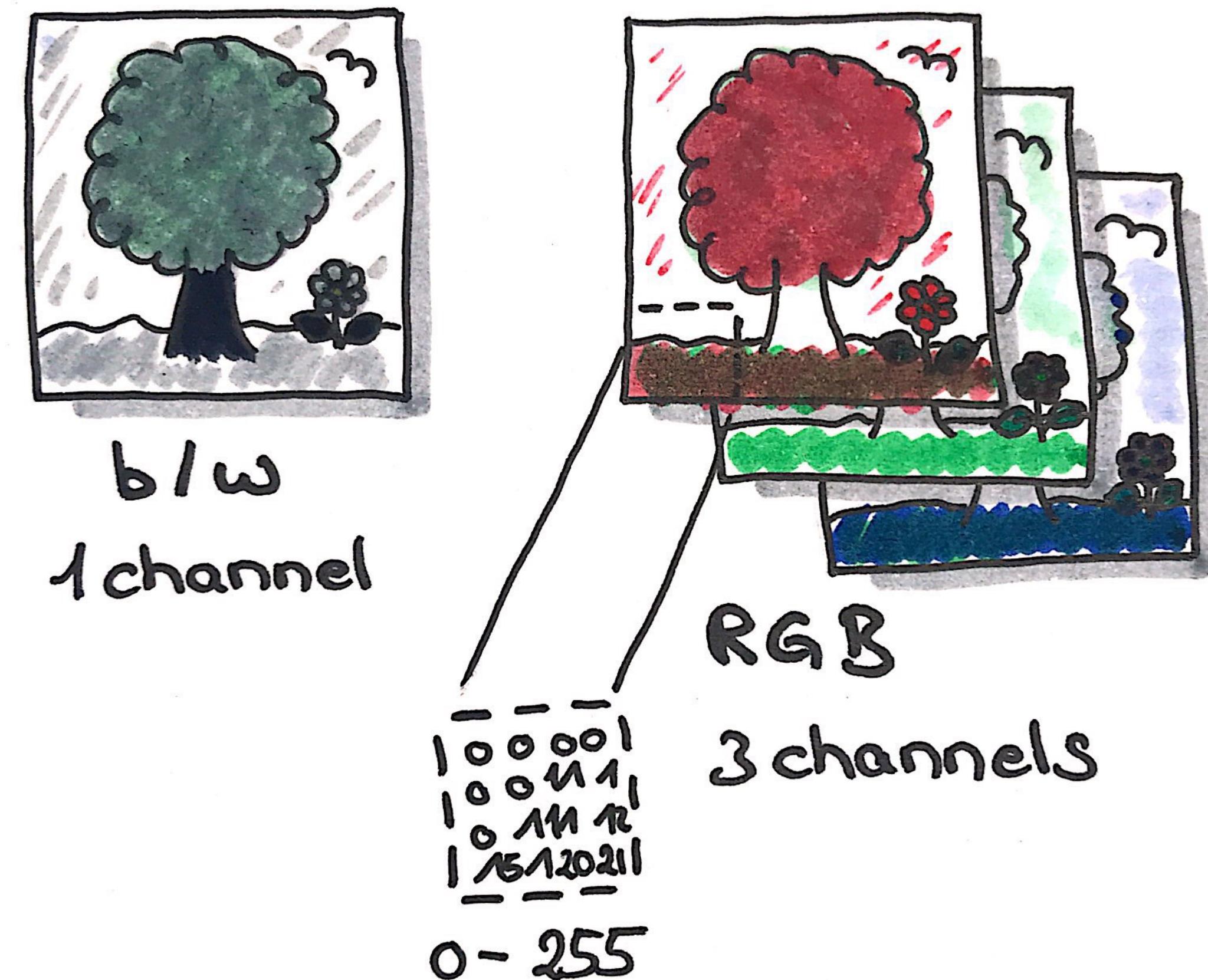
- 1000 categories
- training
- testing

ImageNet is the most important dataset for pretraining cv neural nets!



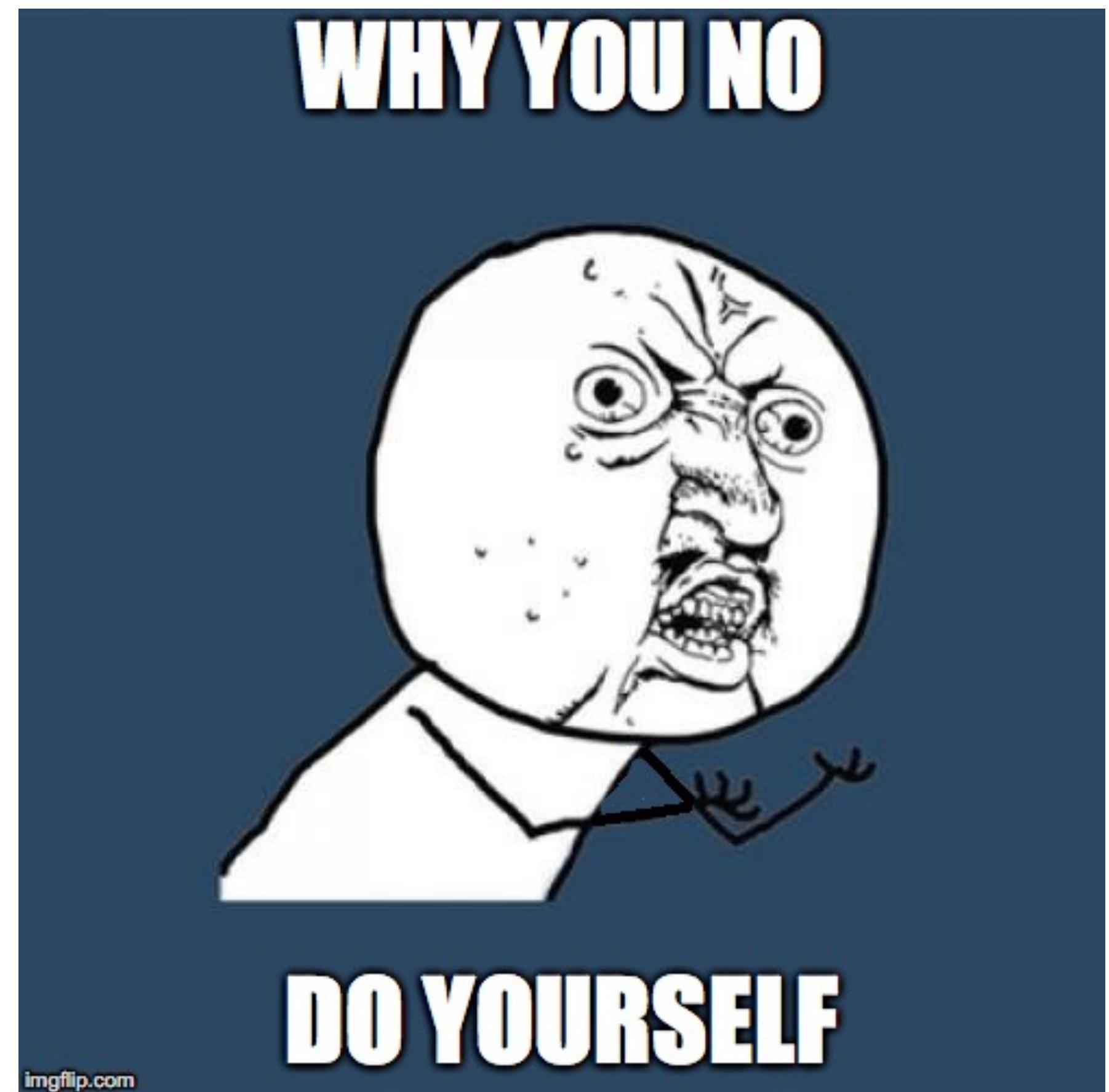
<https://medium.com/obvious-ventures/our-investment-in-darwinai-d5ea1a7af32e>

The Structure of an Image



Let's get Practical: JupyterLab, Python + Matplotlib

- Jupyter = Julia + Python + R
 - Interactive browser-based environment for script-based languages
- Matplotlib: Python spinoff of Matlabs plotting library



Jupyter tips'n'tricks

- ?: search documentation

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

- ??: look at source code

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

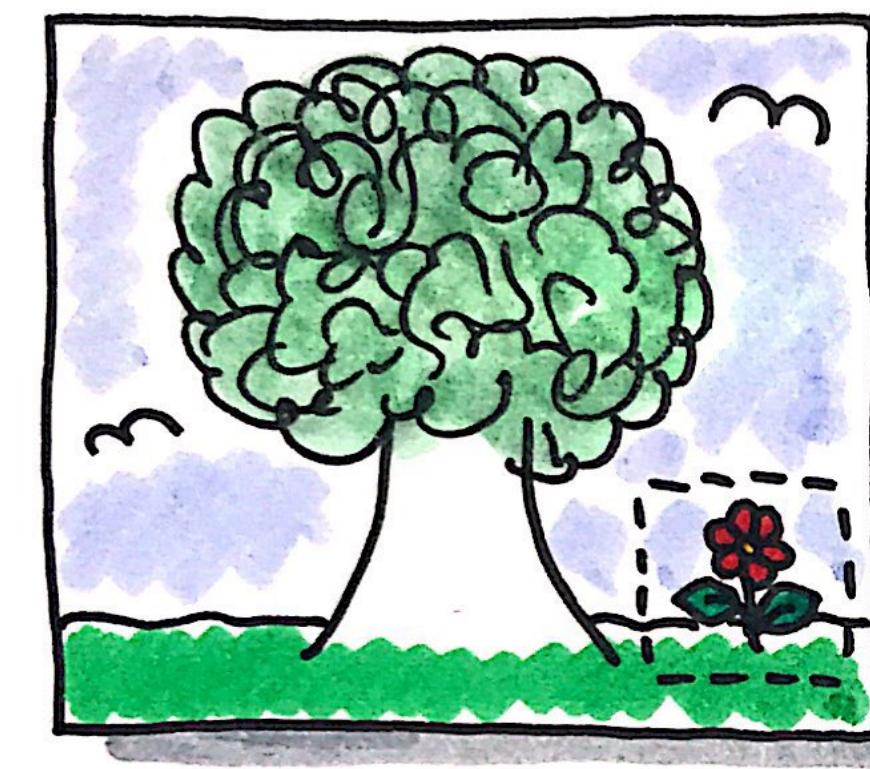
- tab: autocomplete
- shift + tab: look at function call

A screenshot of a Jupyter Notebook interface. In the top cell, the code `import numpy as np` is written, followed by `np.arr`. A dropdown menu is open, showing various methods available for the `array` class. The methods listed are: array, array2string, array_equal, array_equiv, array_precision, array_repr, array_split, array_str, array_type, and arrayprint. The method `array` is highlighted with a gray background.

```
In [ ]:  
import numpy as np  
np.arr  
In [ ]:  
array  
array2string  
array_equal  
array_equiv  
array_precision  
array_repr  
array_split  
array_str  
array_type  
arrayprint
```

How does a Computer Learn to See?

Convolutional Neural Nets



- image classification
class = tree

- object detection
flower

Computer
Vision

Convolutional Neural Networks (CNNs)

Fully Connected

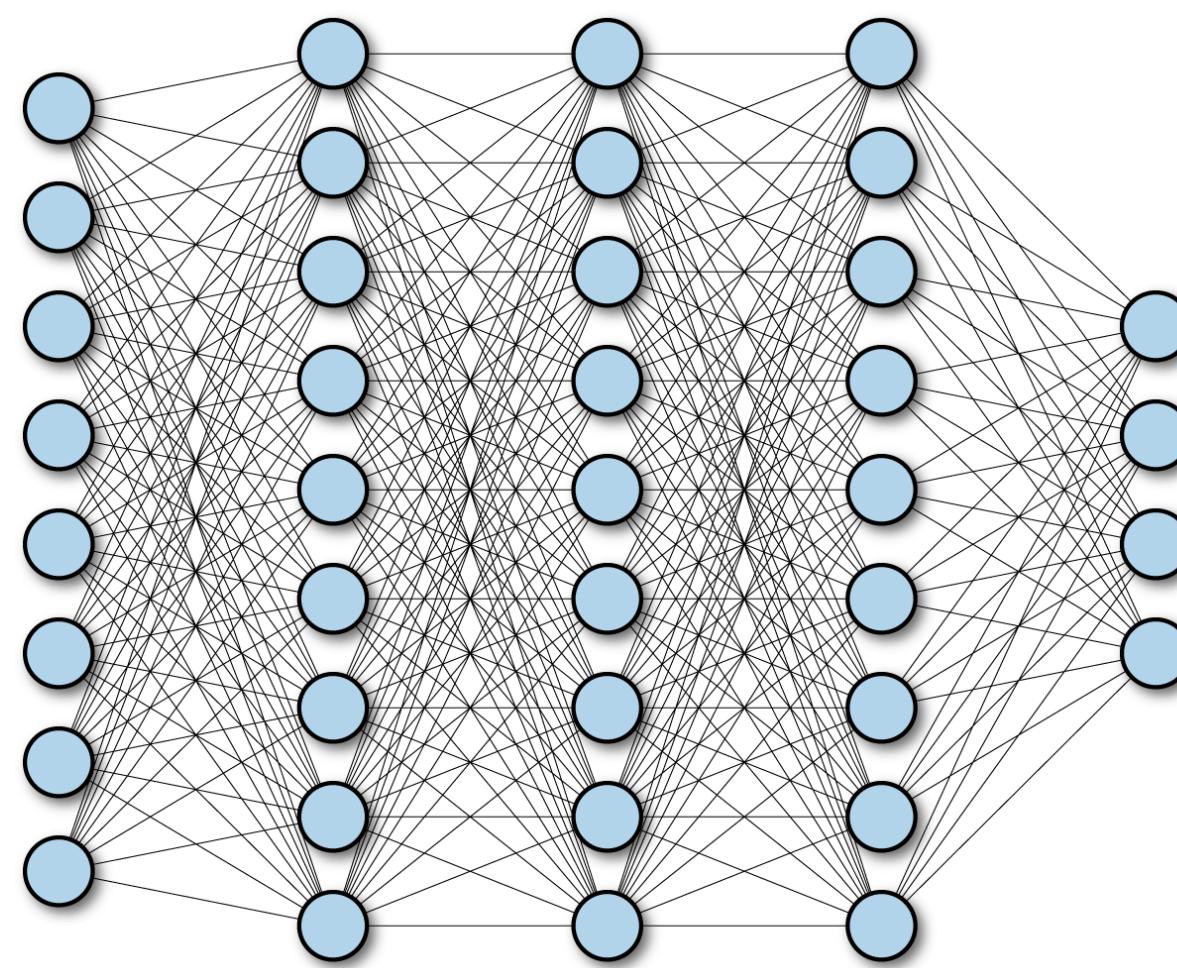


image: www.kdnuggets.com

CNNs

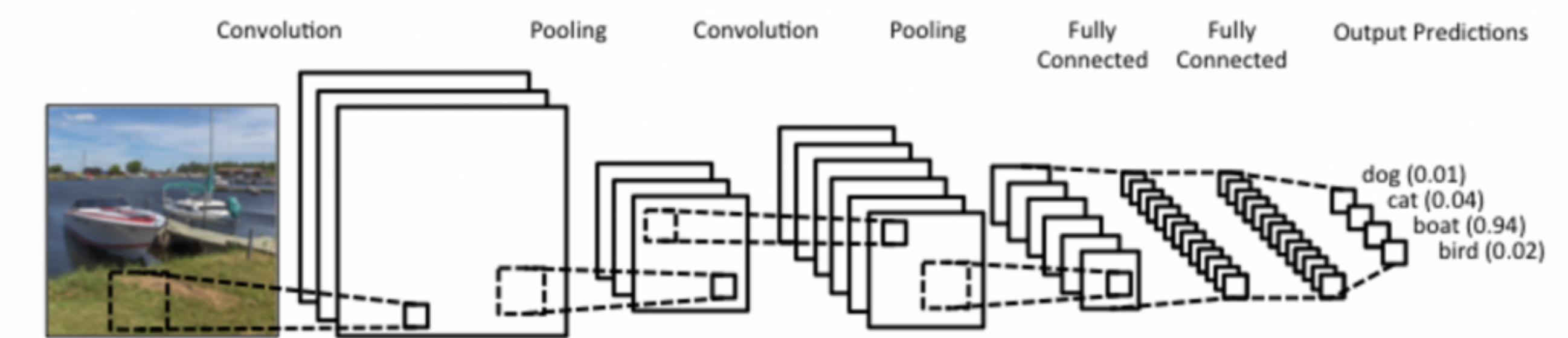


image: www.kdnuggets.com

Convolutional Neural Networks (CNNs)

Fully Connected

Input Image
(128x128x3)



Connections First Layer
(512 nodes)

25.165.824
weights

CNNs

Connections First Layer
(Kernel 3x3, Filters 16)

432
weights

Convolutional Layer

Input

3 ₀	3 ₁	2 ₂	1	0
0 ₂	0 ₂	1 ₀	3	1
3 ₀	1 ₁	2 ₂	2	3
2	0	0	2	2
2	0	0	0	1

Output

12	12	17
10	17	19
9	6	14

Kernel

$$\begin{pmatrix} 0 & 1 & 2 \\ 2 & 2 & 0 \\ 0 & 1 & 2 \end{pmatrix}$$

Input



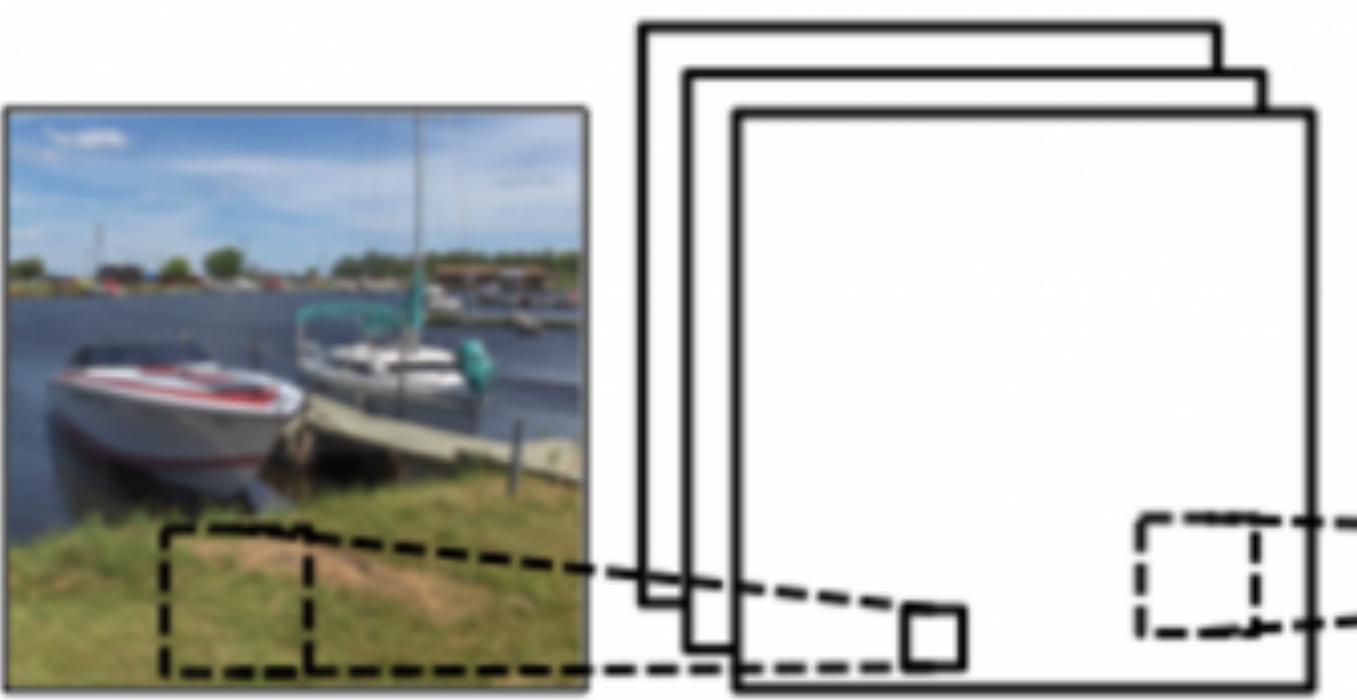
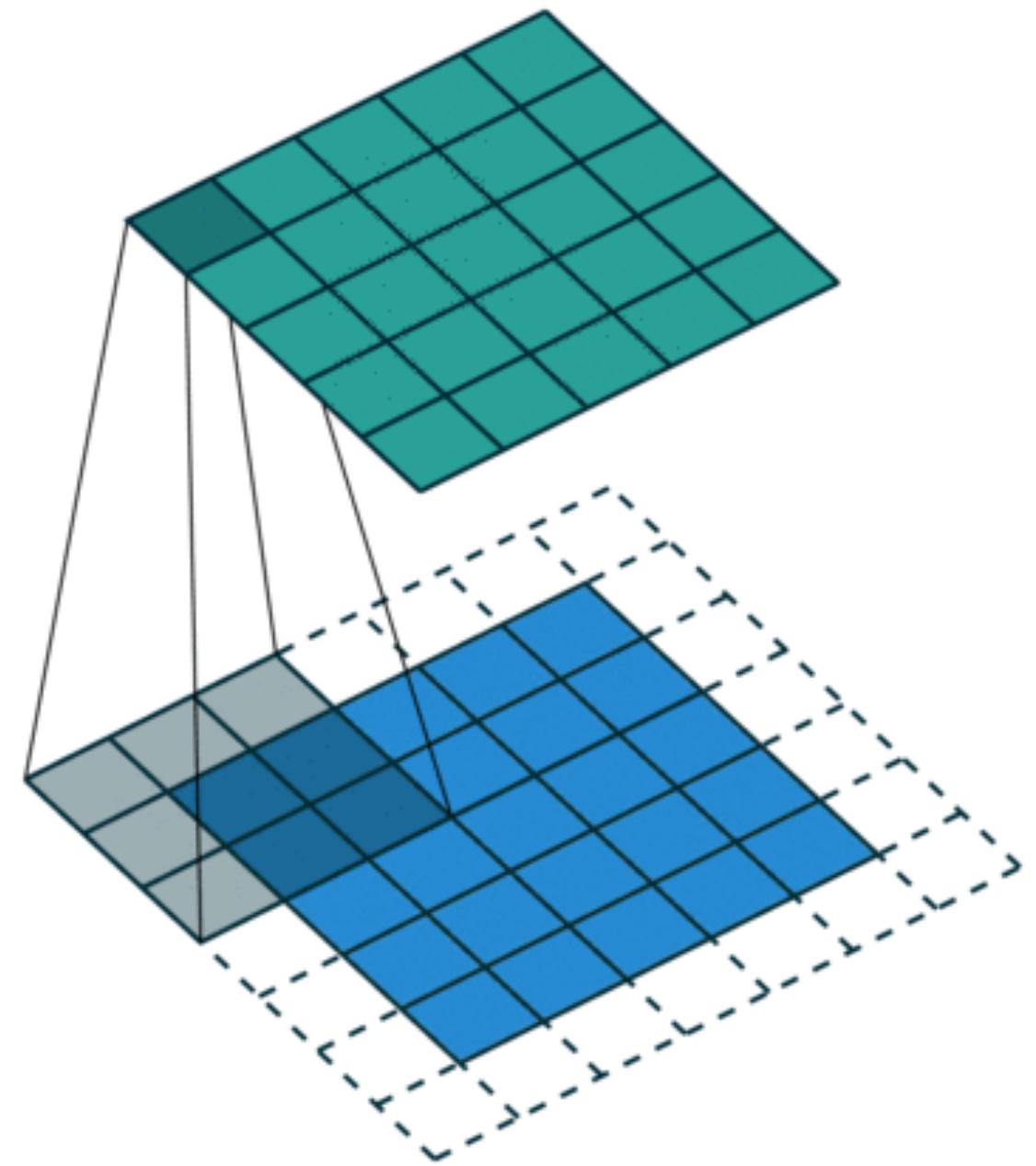
Output



Kernel is learned

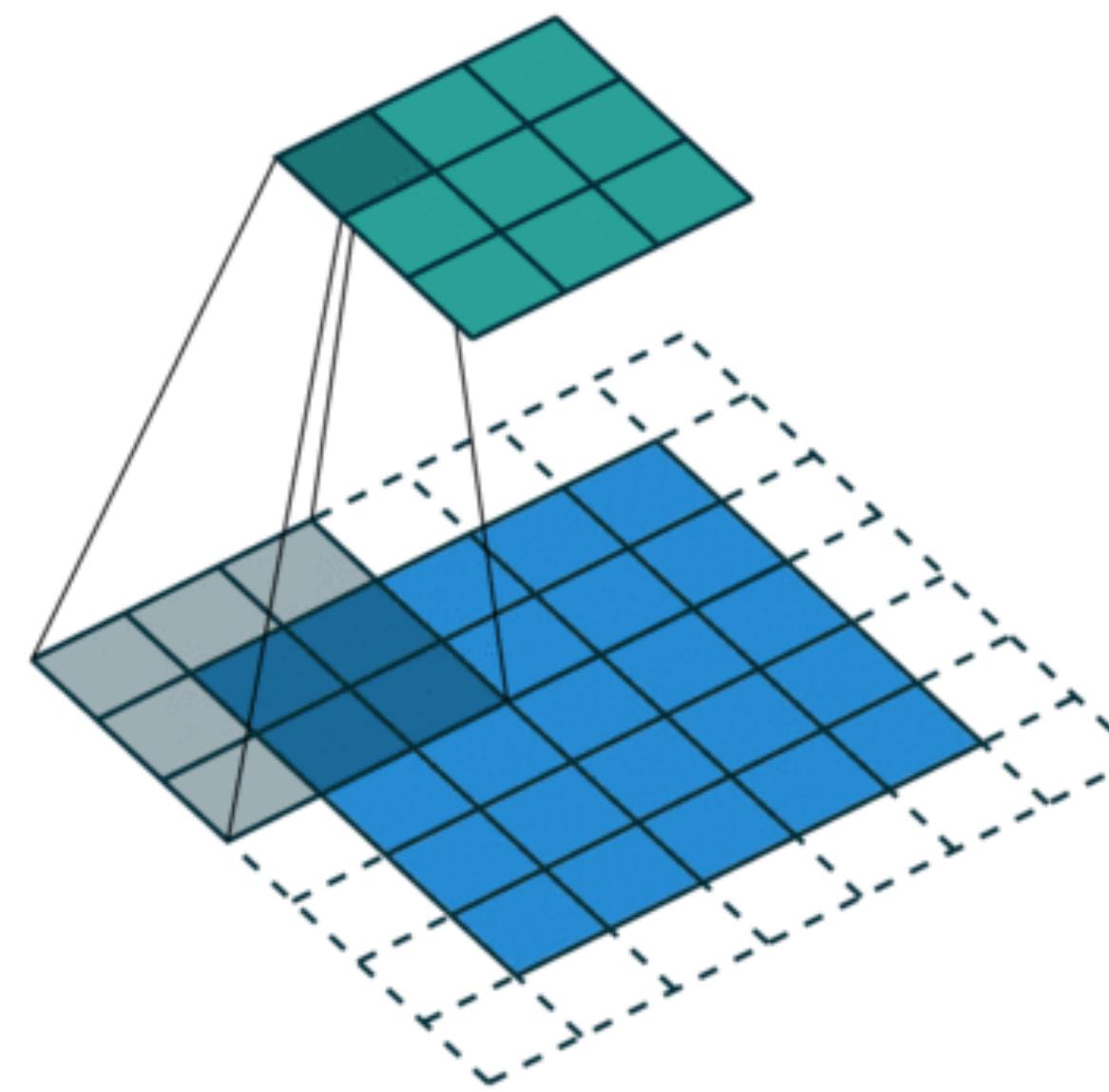
image: www.deeplearning.net

Convolutional Layer - Zero Padding



Convolutional Layer - Strides and Pooling Layer

Stride of 2



Maxpool

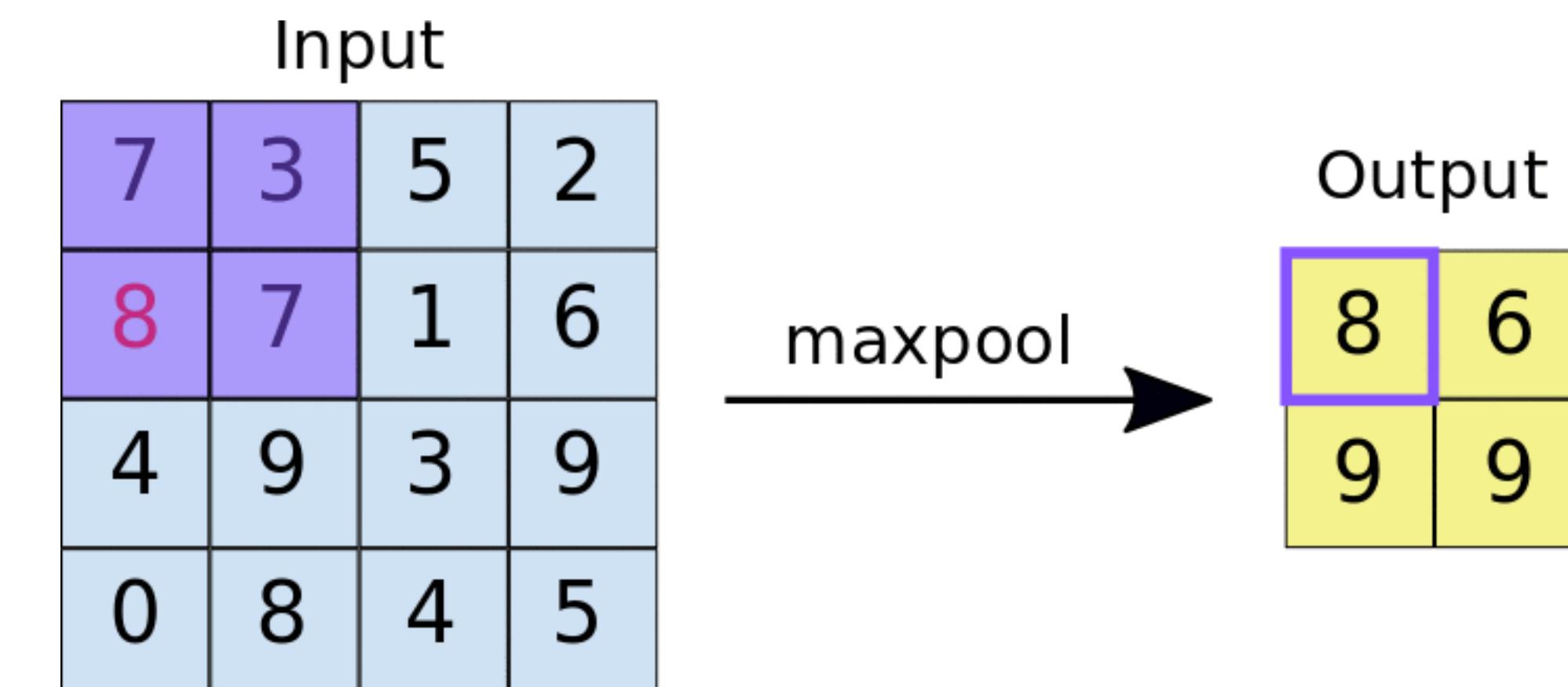
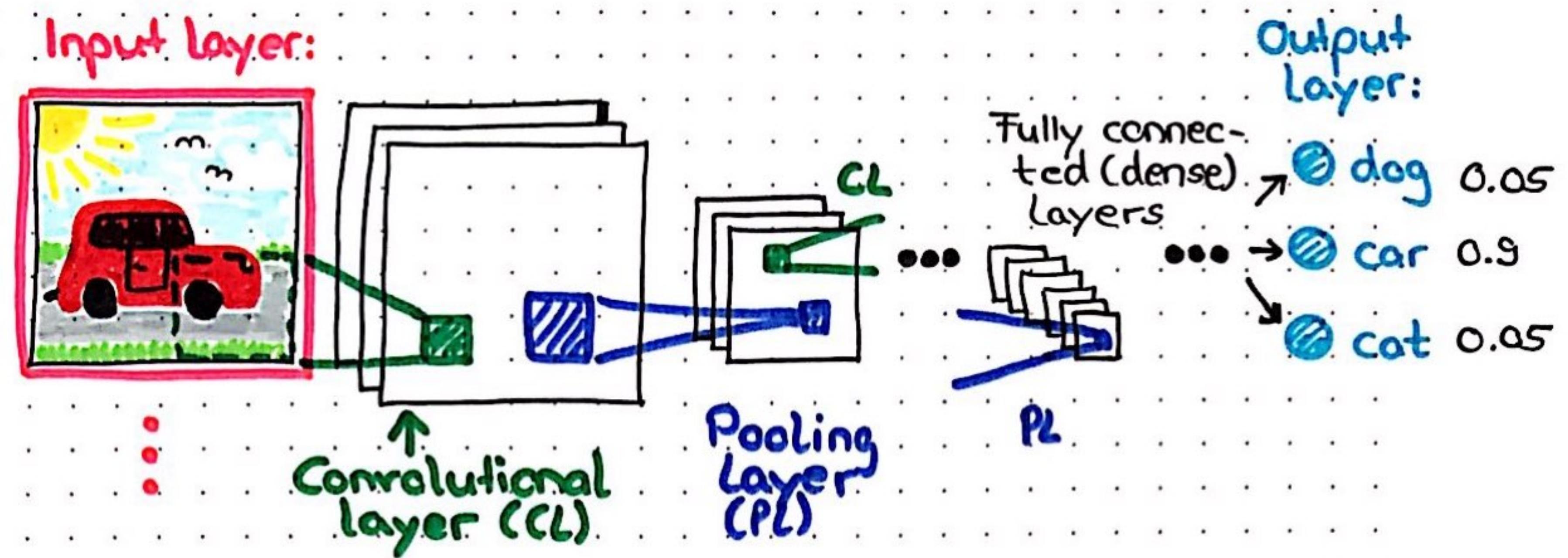
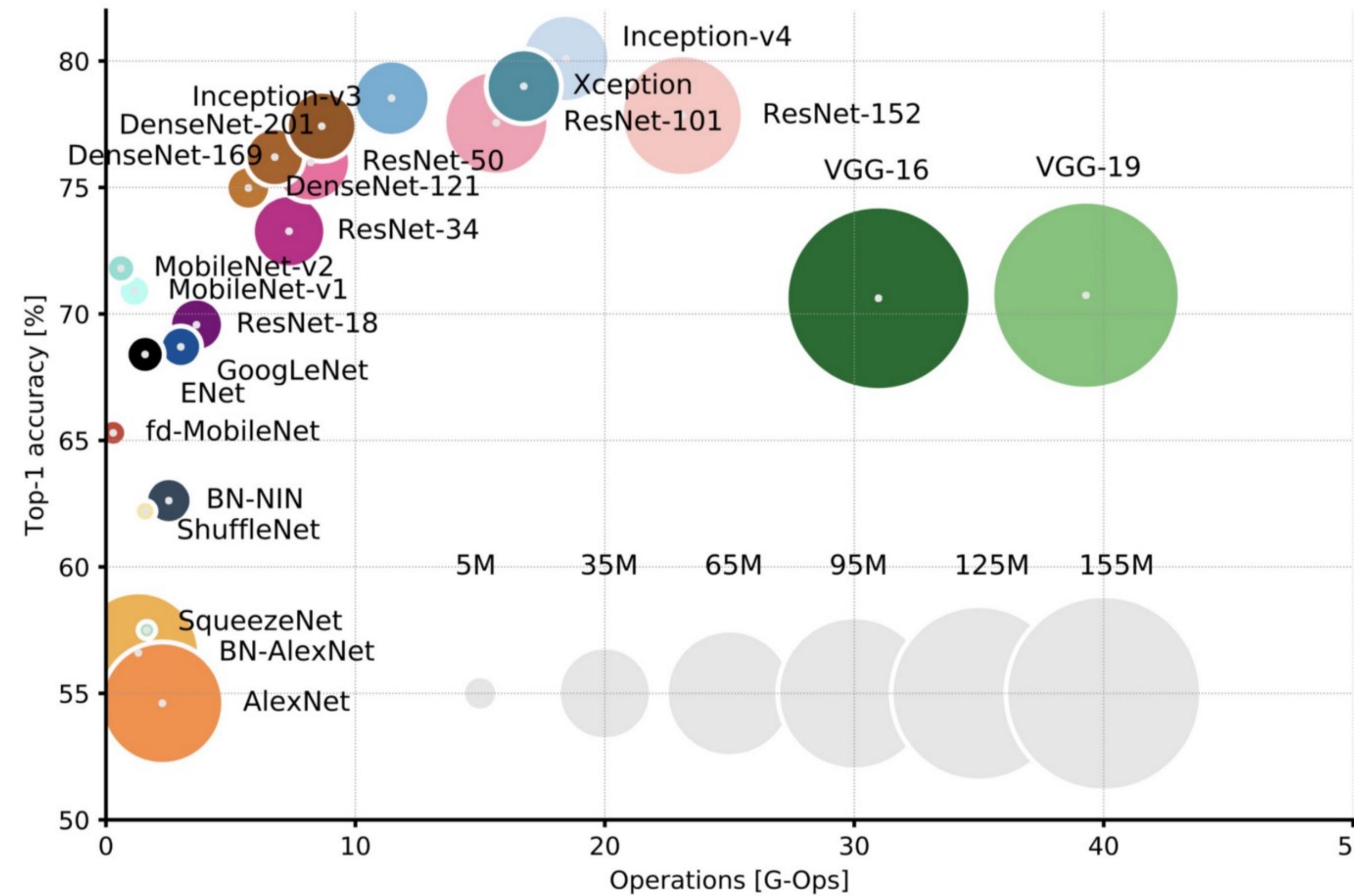


image: developers.google.com

Convolutional Neural Network



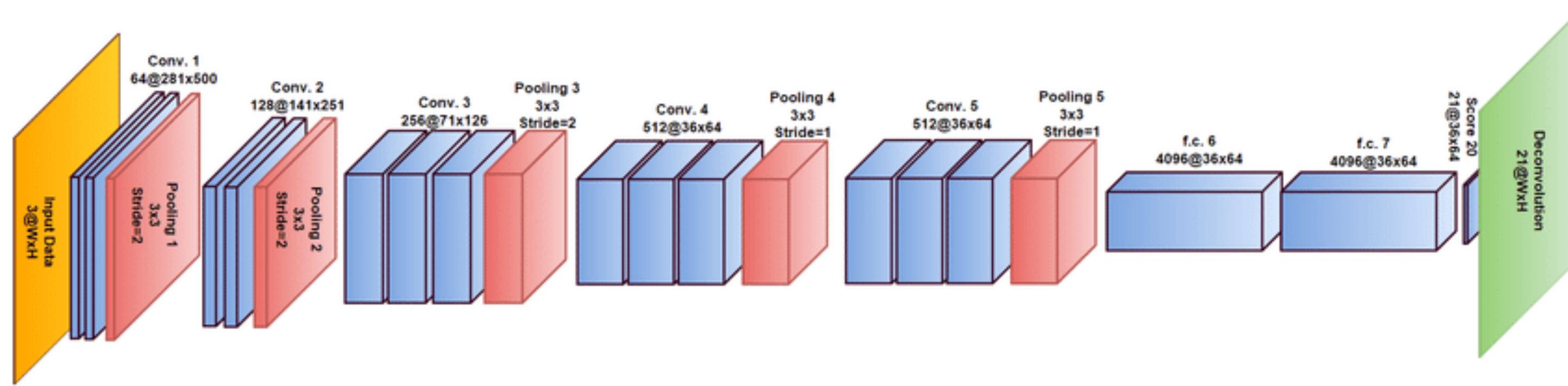
Important CNN Architectures



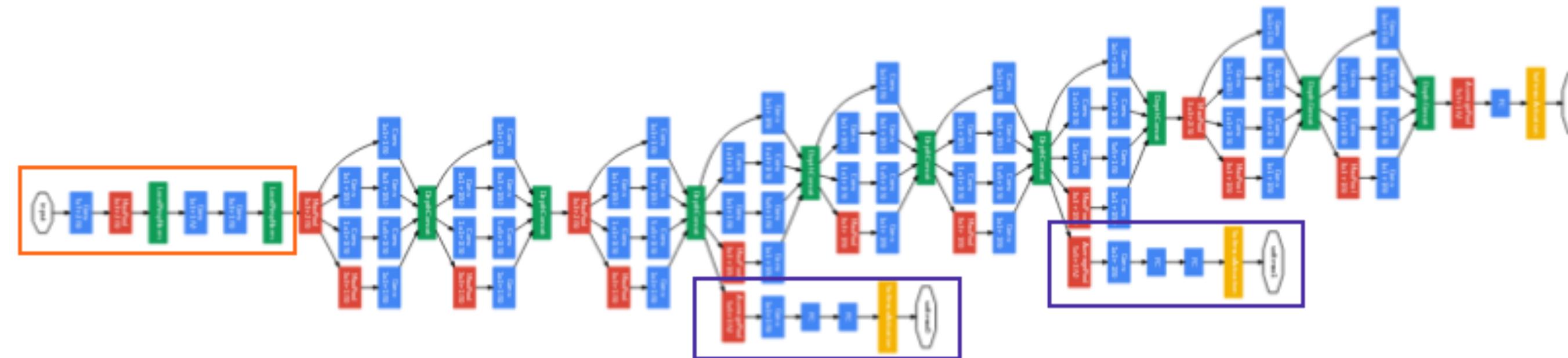
Relevant Architectures

- AlexNet (2012)
- VGG-16 (2014)
- Inception (2014)
- ResNet (2015)
- MobileNet (2017)

Important CNN Architectures

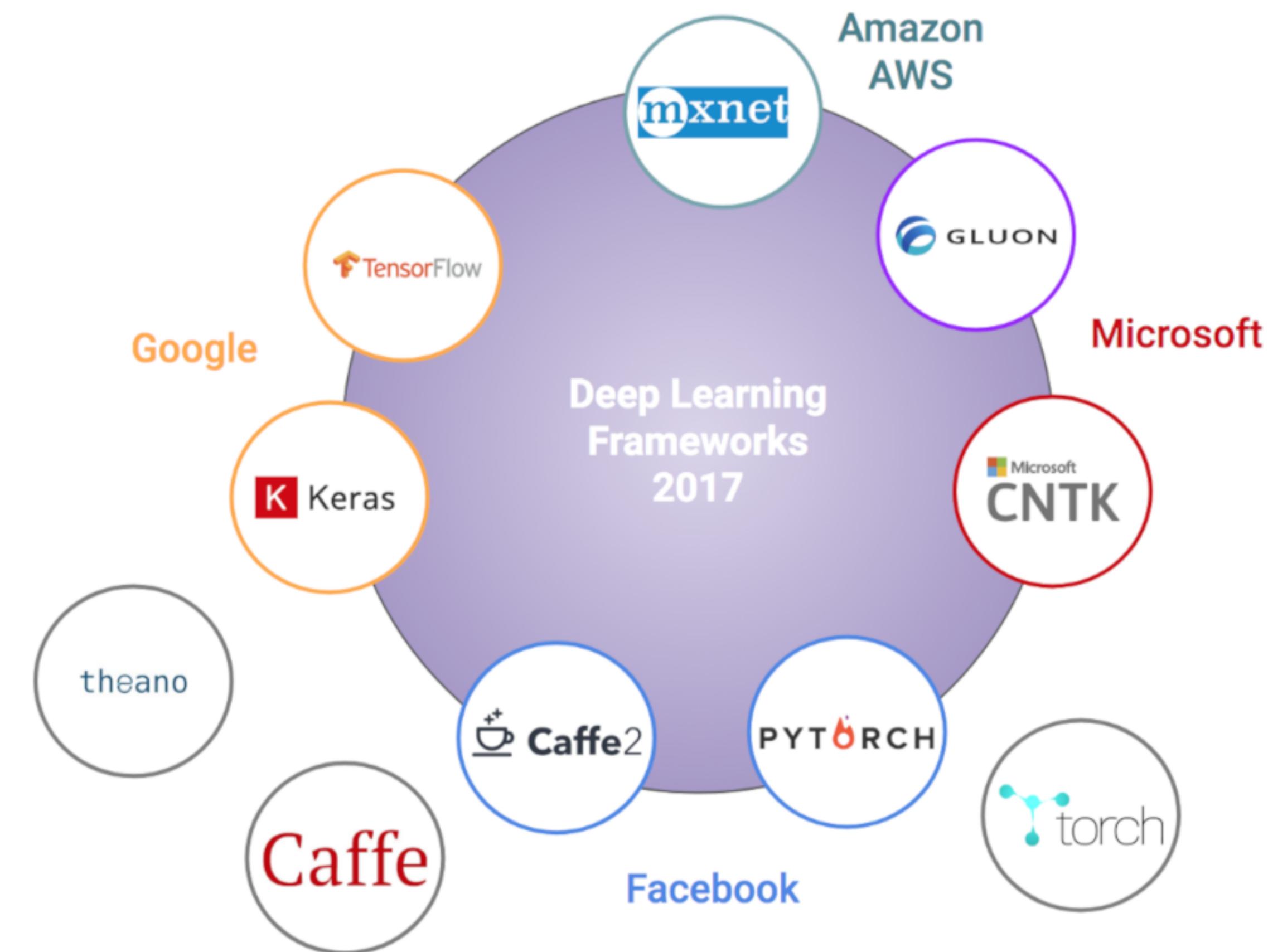


VGG



Inception

Deep Learning Frameworks



<https://devopedia.org/deep-learning-frameworks>

Tensorflow



Tensorflow

- Tensors = Multidimensional Arrays

Dimension

1

1	2	3
---	---	---

vector

2

1	2	3
4	5	6
7	8	9

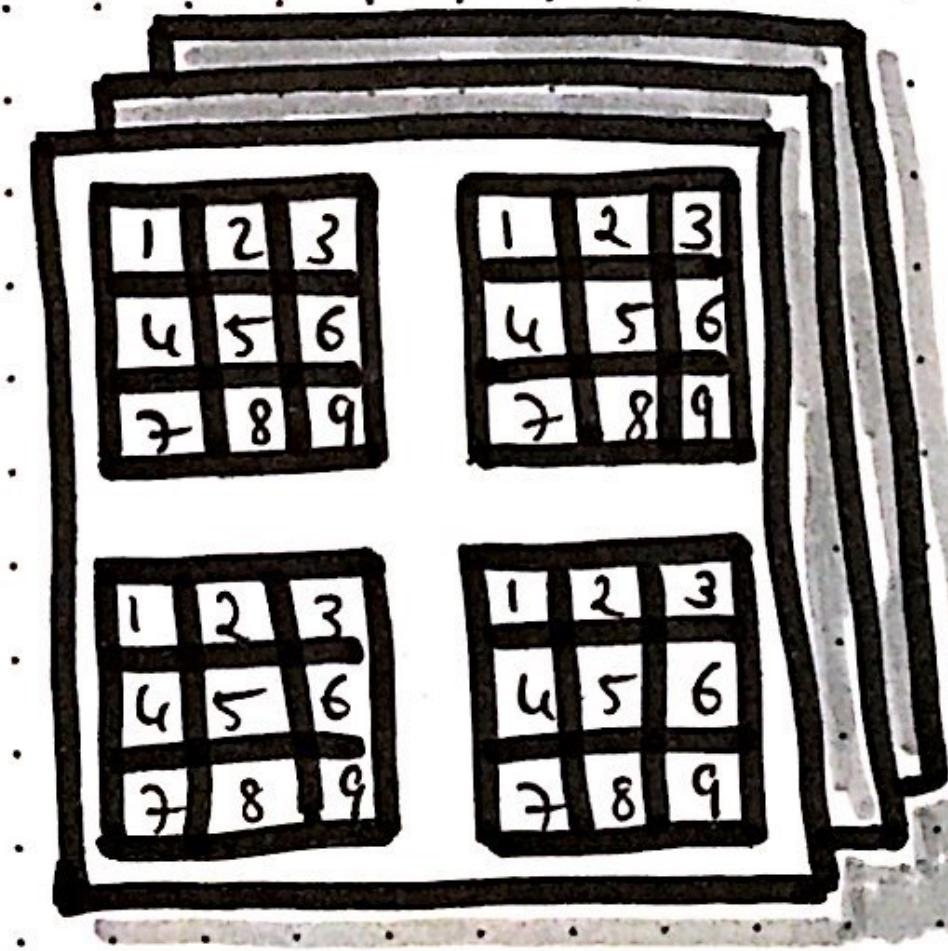
matrix

3

1	2	3
4	5	6
7	8	9

3-dim.
array

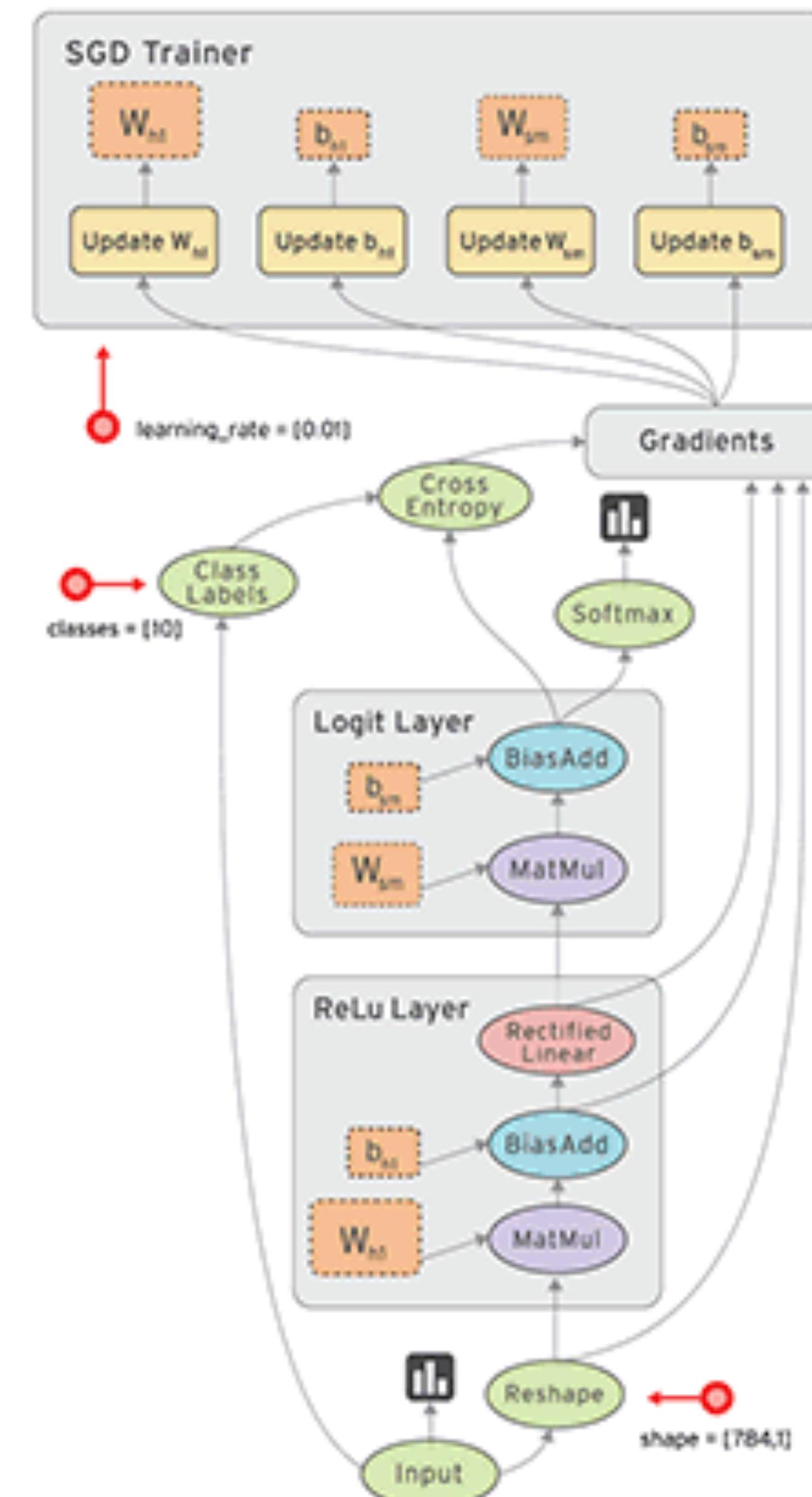
n



n-dim.
array

Tensor-“Flow”

- Compilation of static dataflow graph

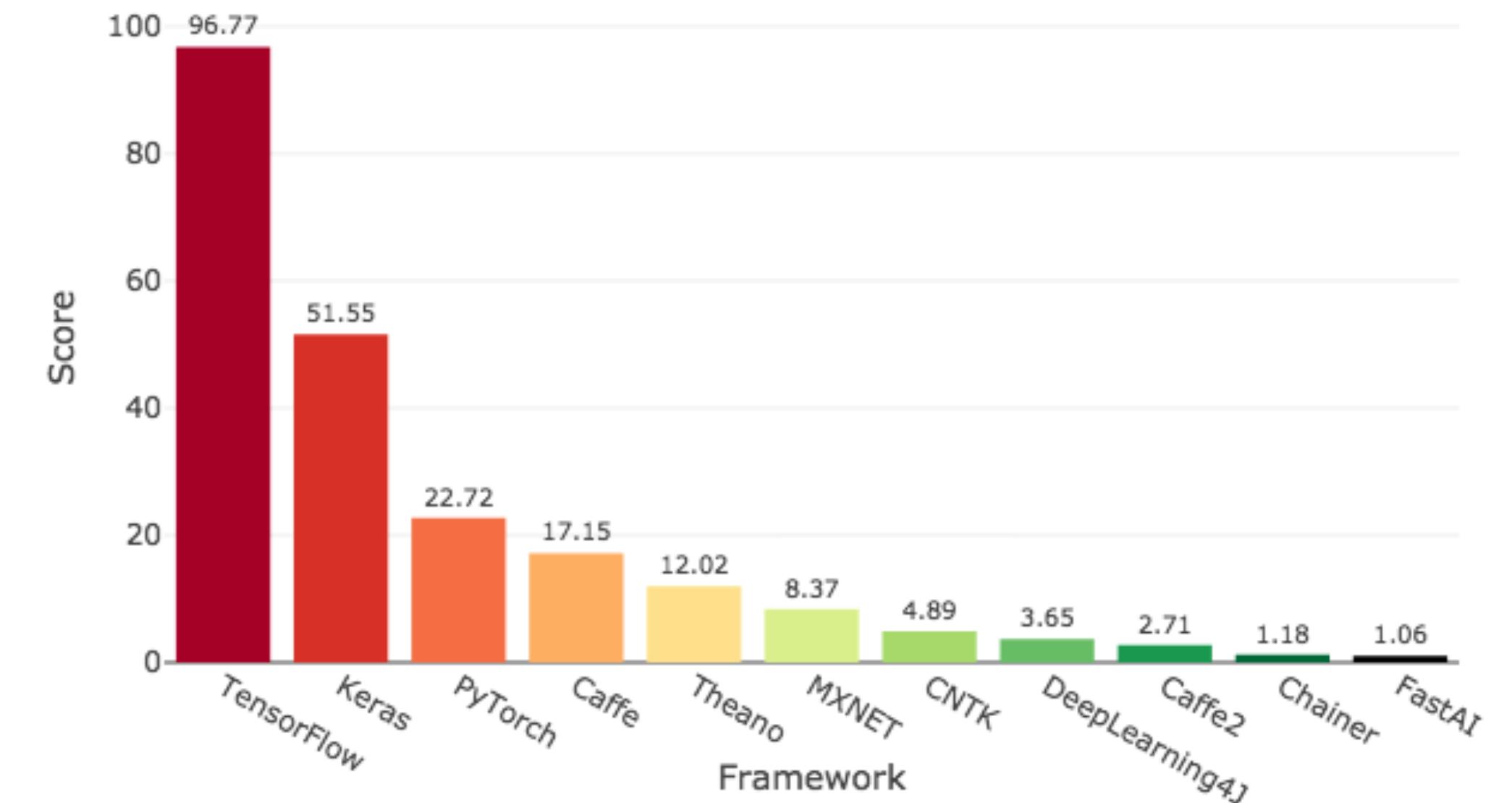


Keras

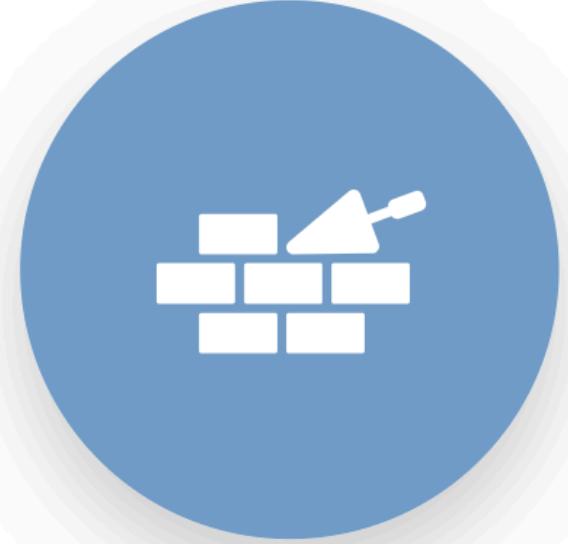
- High-level API for Tensorflow, Theano and CNTK
- Part of Tensorflow Core API since v1.4
- User-friendly, extensible and flexible



Deep Learning Framework Power Scores 2018



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

Let's get Practical: Keras





Experiment worked!

And now??

Just Deploy it, Okay?

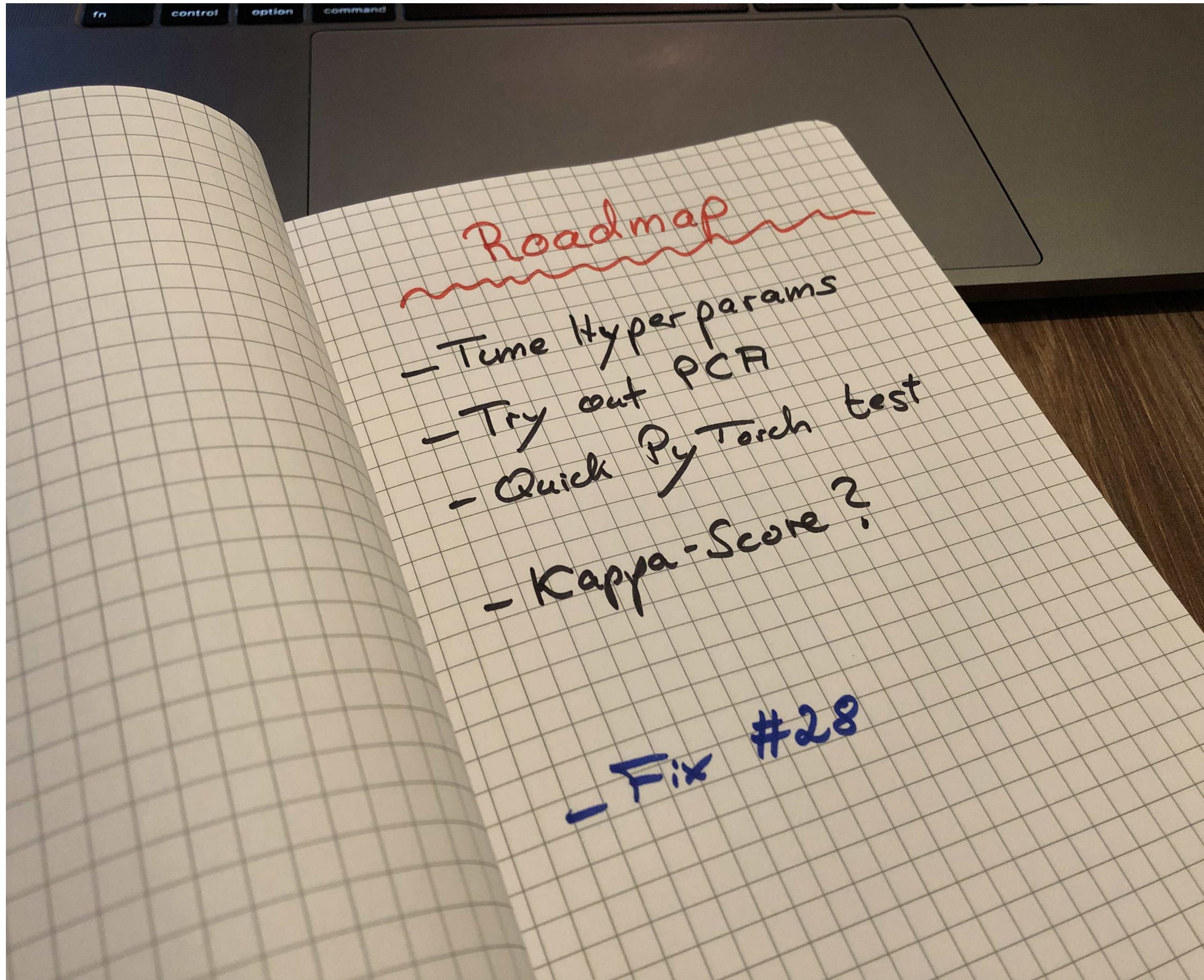


Production-Ready Data Science



Versioning and Reproducable Training

- Data Science is experiment-driven ...



A STORY TOLD IN FILE NAMES:				
Filename	Date Modified	Size	Type	
data_2010.05.28_test.dat	3:37 PM 5/28/2010	420 KB	DAT file	
data_2010.05.28_re-test.dat	4:29 PM 5/28/2010	421 KB	DAT file	
data_2010.05.28_re-re-test.dat	5:43 PM 5/28/2010	420 KB	DAT file	
data_2010.05.28_calibrate.dat	7:17 PM 5/28/2010	1,256 KB	DAT file	
data_2010.05.28_huh??.dat	7:20 PM 5/28/2010	30 KB	DAT file	
data_2010.05.28_WTF.dat	9:58 PM 5/28/2010	30 KB	DAT file	
data_2010.05.29_aaarrgh.dat	12:37 AM 5/29/2010	30 KB	DAT file	
data_2010.05.29_#\$@*!&!.dat	2:40 AM 5/29/2010	0 KB	DAT file	
data_2010.05.29_crap.dat	3:22 AM 5/29/2010	437 KB	DAT file	
data_2010.05.29_notbad.dat	4:16 AM 5/29/2010	670 KB	DAT file	
data_2010.05.29_woohoo!!_.dat	4:47 AM 5/29/2010	1,349 KB	DAT file	
data_2010.05.29_USETHISONE.dat	5:08 AM 5/29/2010	2,894 KB	DAT file	
analysis_graphs.xls	7:13 AM 5/29/2010	455 KB	XLS file	
ThesisOutline.doc	7:26 AM 5/29/2010	38 KB	DOC file	
Notes_Meeting_with_ProfSmith.txt	11:38 AM 5/29/2010	1,673 KB	TXT file	
JUNK...	2:45 PM 5/29/2010		Folder	
data_2010.05.30_startingover.dat	8:37 AM 5/30/2010	420 KB	DAT file	

Reproducible Training

- ... and collaborative!

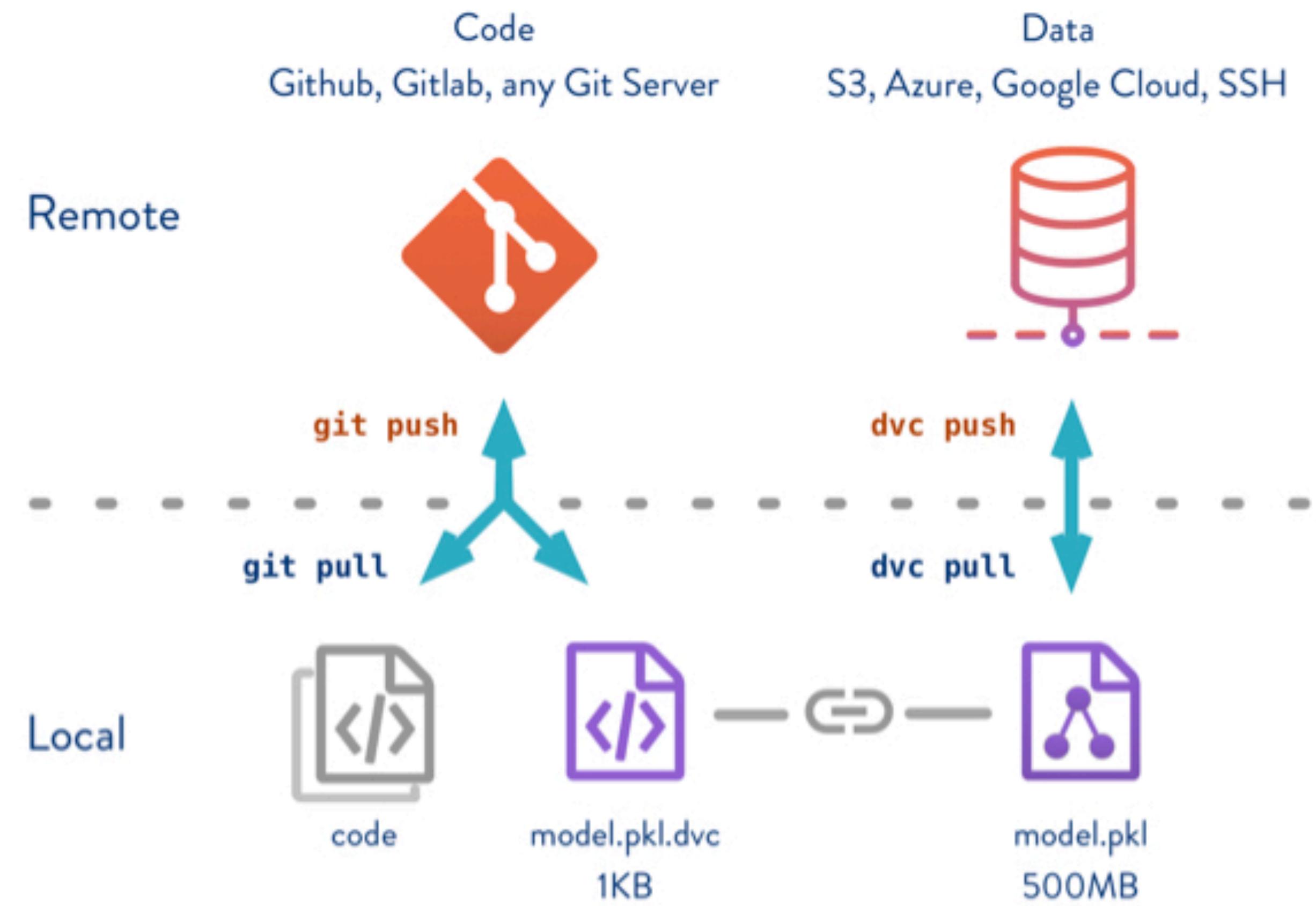
```
Tims-MacBook-Pro:code tsabsch$ git log --graph --decorate --oneline
*   fc88d36 (HEAD -> master) Merge branch 'tim_fix_zerodivisionerror'
|\ \
| * 2cc23f0 (tim_fix_zerodivisionerror) Fix ZeroDivisionError
* |   e486d76 Merge branch 'mark_batchnorm'
|\ \
| | \
| | / \
| | / \
| | / \
| | * b988f6e (mark_batchnorm) Decrease BN threshold
| | * c83736d Add batch normalisation
* |   f80b108 Add preprocessing
| |
* a87aa63 Add simple tensorflow model
* 7c0d21e Initial commit
Tims-MacBook-Pro:code tsabsch$
```



DVC to the Rescue!



- **Large File Storage**, similar to git-lfs
- Metadata in git (name, hashsum etc.)
- Contents in cache + remote storage

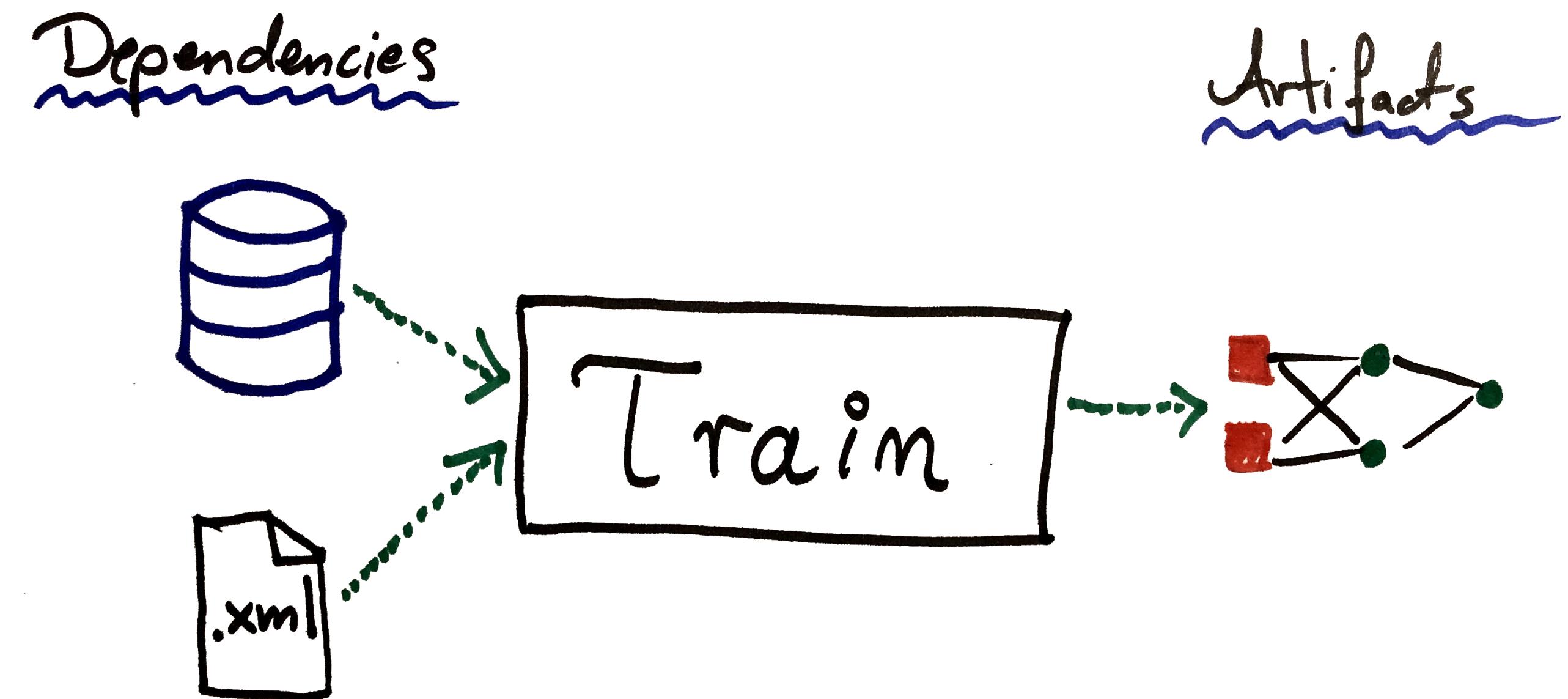


<https://dvc.org>



DVC to the Rescue!

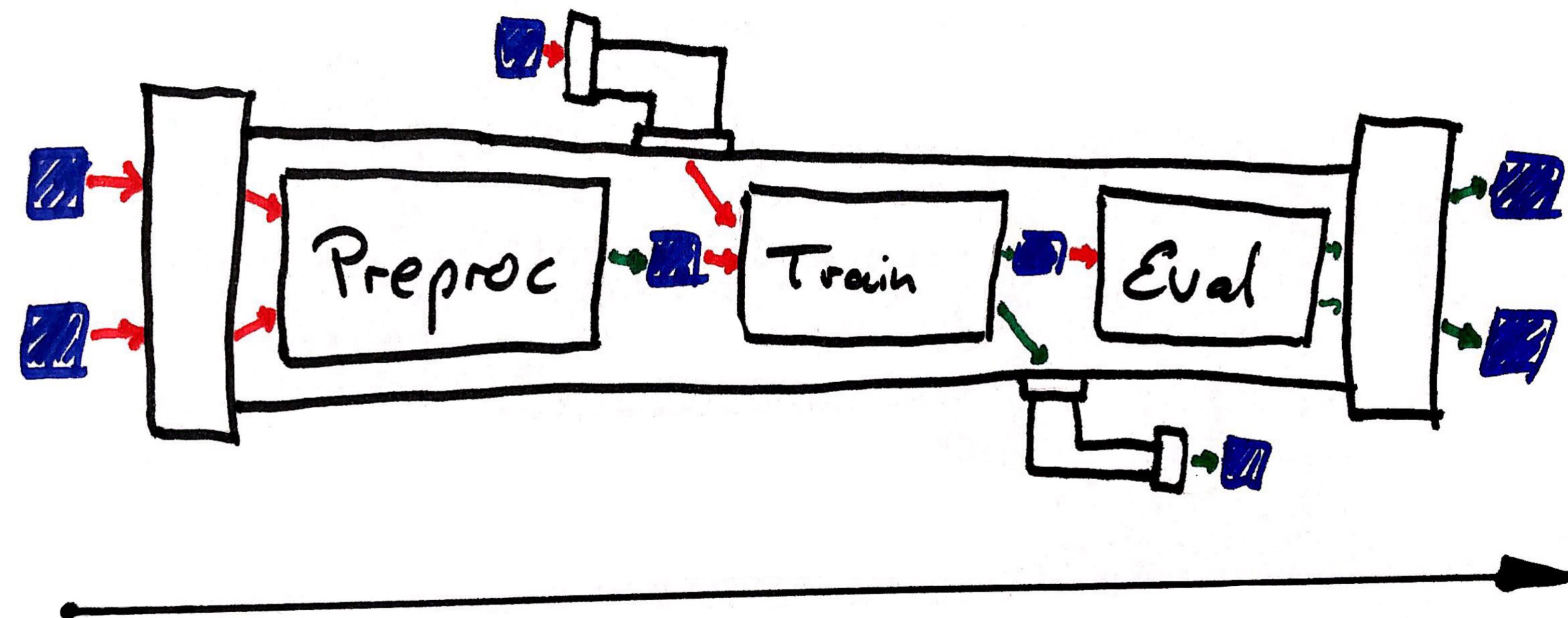
- **Pipelines**
- Optimise reproduction by splitting your process into stages
- Stages store dependencies, processing and output artefacts



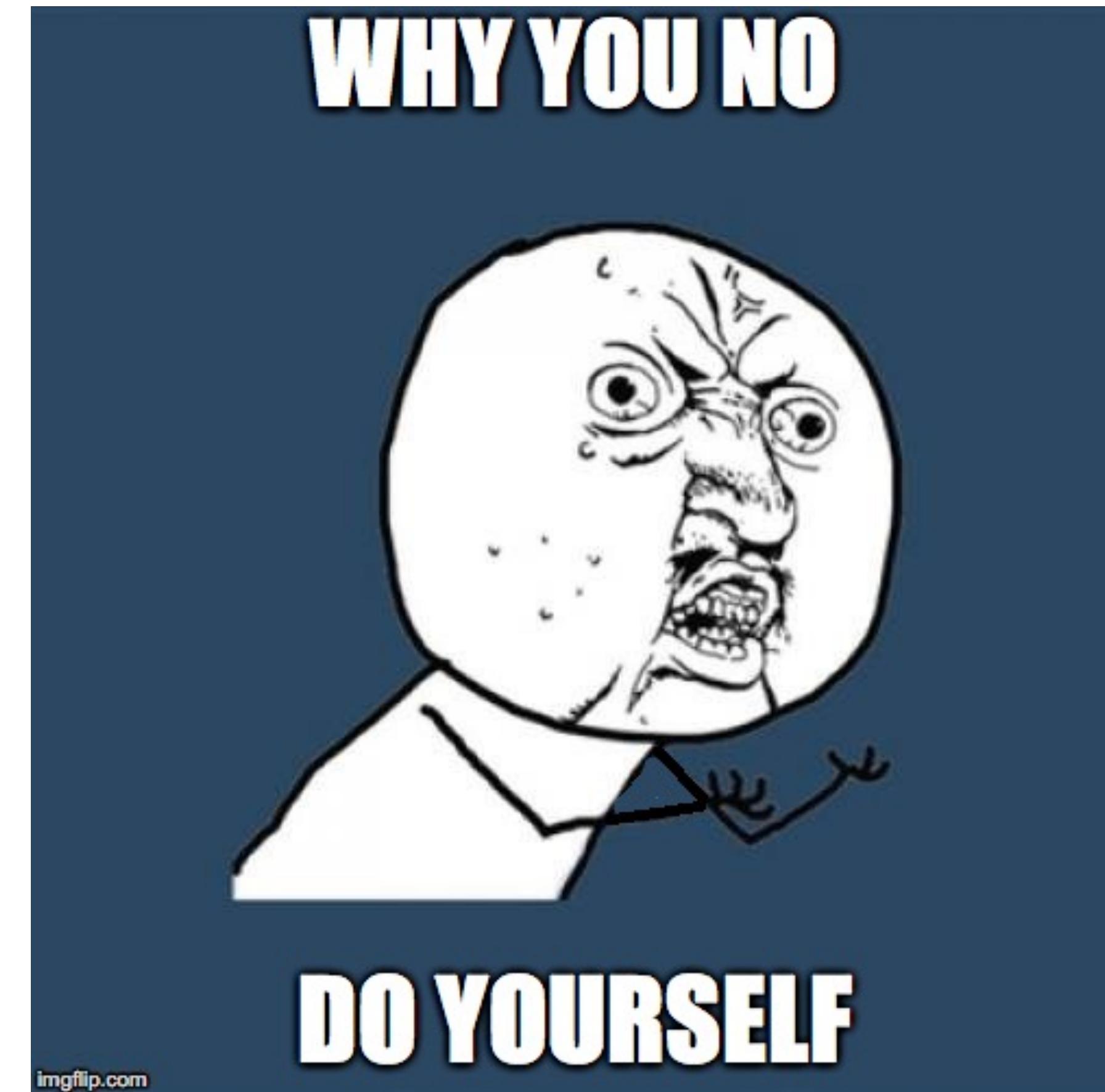


DVC to the Rescue!

- **Pipelines**
- Connect stages to a pipelines via dependencies



Let's get Practical: DVC

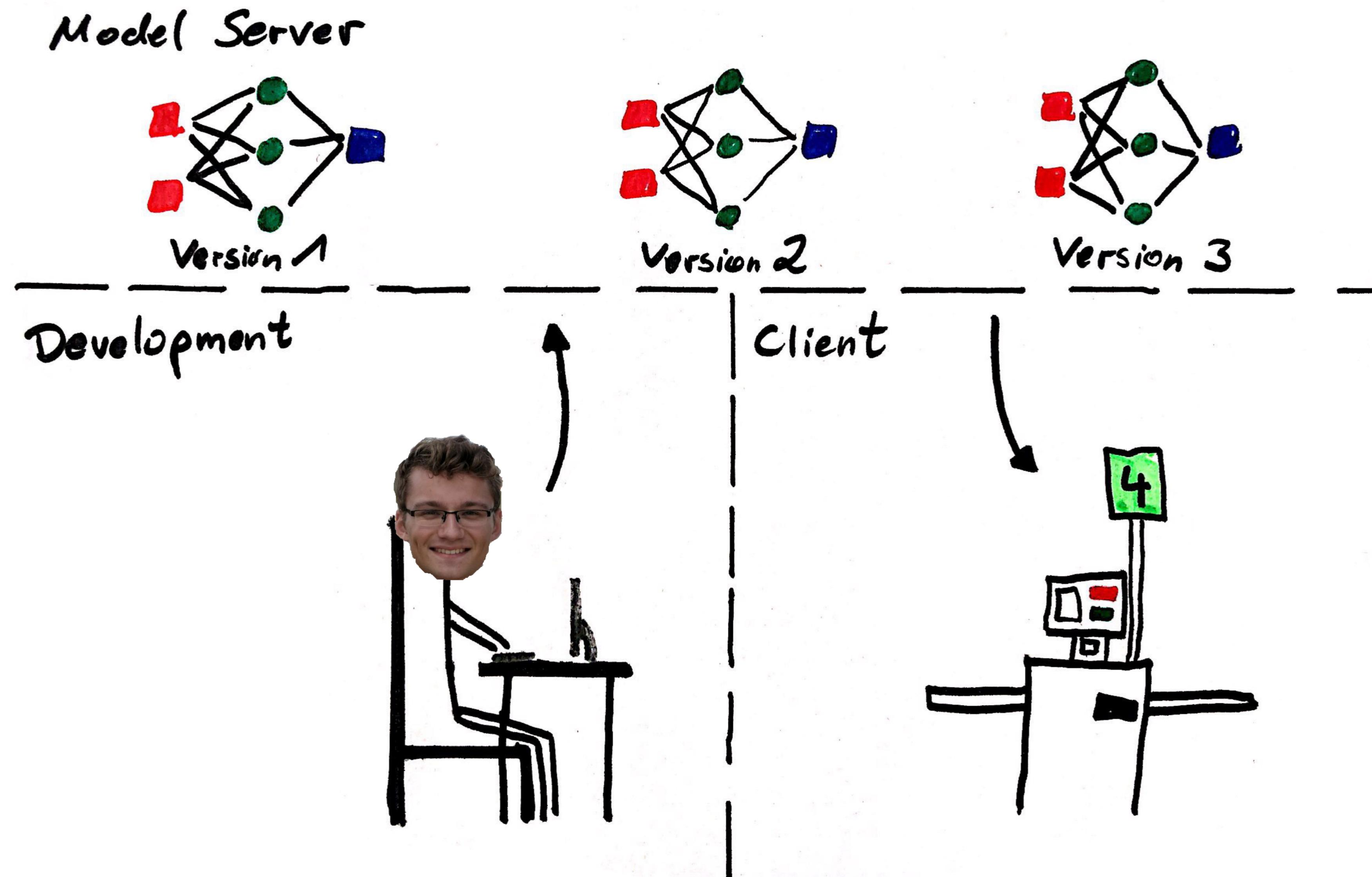


Model Serving with Tensorflow Serving

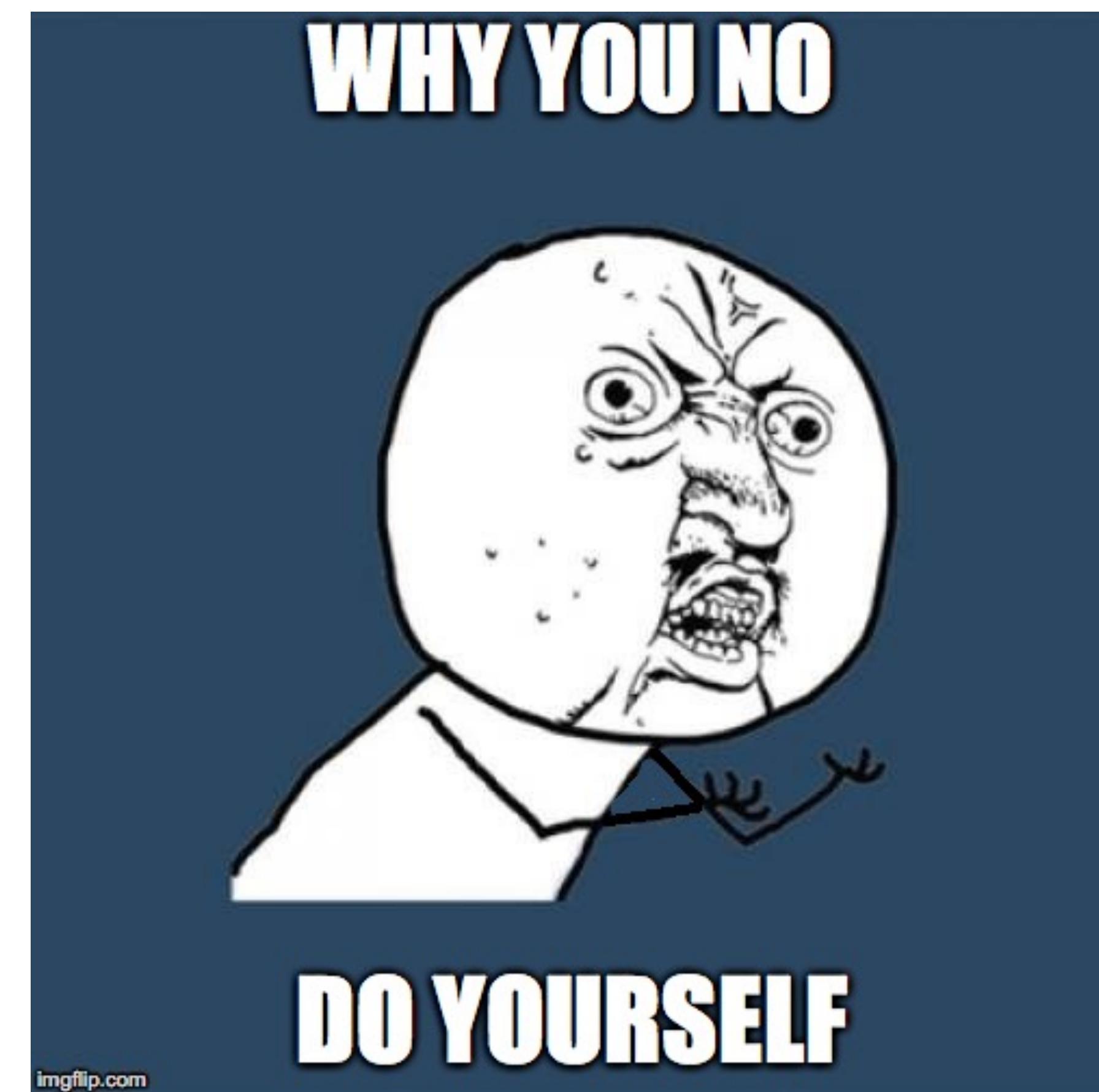
- Lightweight model server for Tensorflow graphs
- Useful for
 - Distributed model applications
 - Fast and continuous delivery
 - Model versioning



Tensorflow Serving



Let's get Practical: Tensorflow Serving



Preprocessing and the Deployment

- Preprocessing and model are tightly coupled
- How can the client "be sure" to do the right thing?

Possible solutions

- The client just knows
- Wrapper service around model and expose API
- Integrate preprocessing into the model

Preprocessing and the Deployment

```
import tensorflow as tf
from keras.layers import Lambda

def preprocess(x):
    resized = tf.image.resize_images(x, size=[100, 100])
    max_color = tf.constant(255, dtype=tf.float32)
    rescaled = tf.divide(resized, max_color)
    return rescaled

additional = Lambda(preprocess, output_shape=(100, 100, 3), name="preprocessing")
```

Preprocessing and the Deployment

```
from keras.models import Sequential
from keras.layers import InputLayer

prod_model = Sequential()
prod_model.add(InputLayer(input_shape=(None, None, 3)))
prod_model.add(additional)

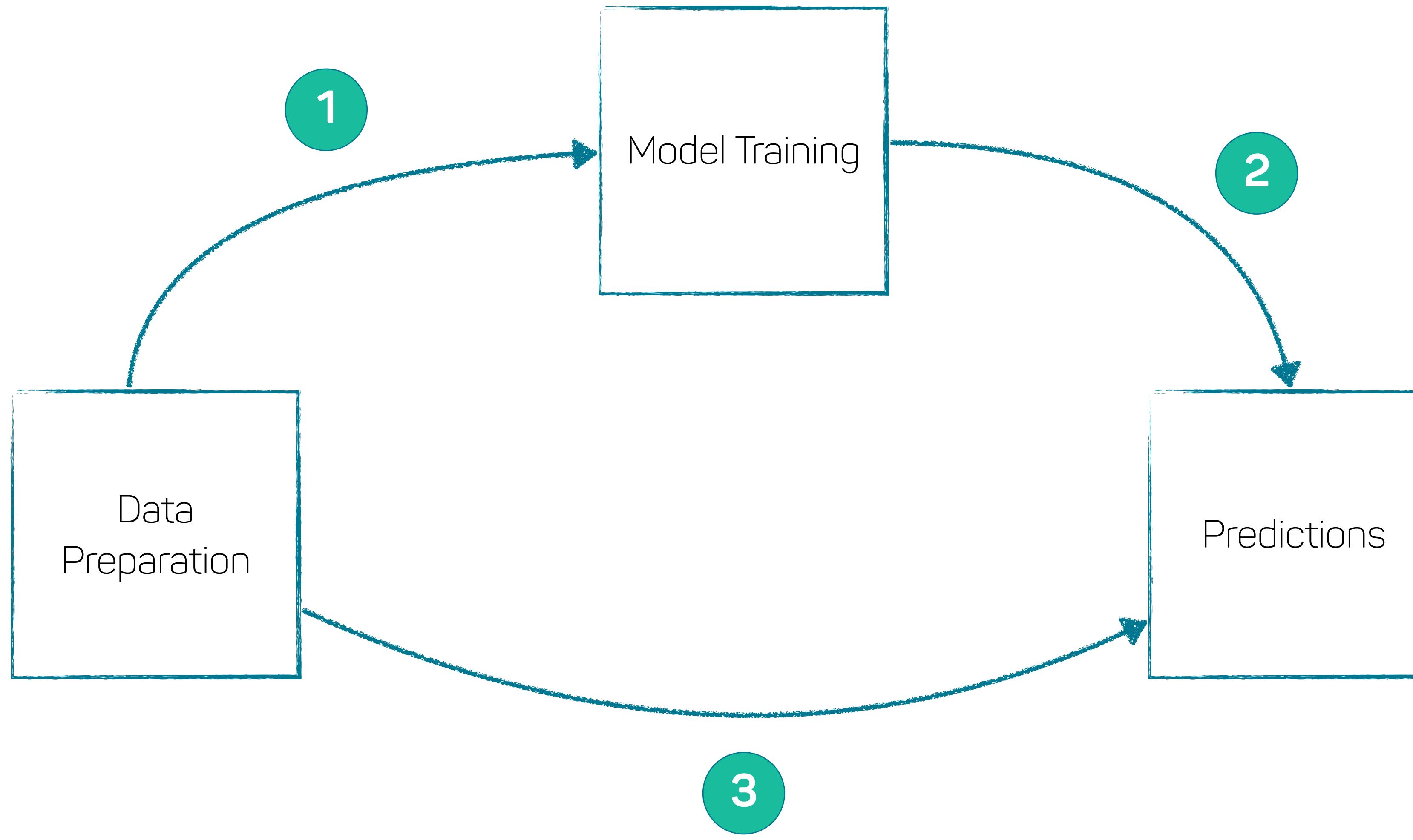
for layer in model.layers:
    prod_model.add(layer)
```

Workflow Management with Luigi/Airflow

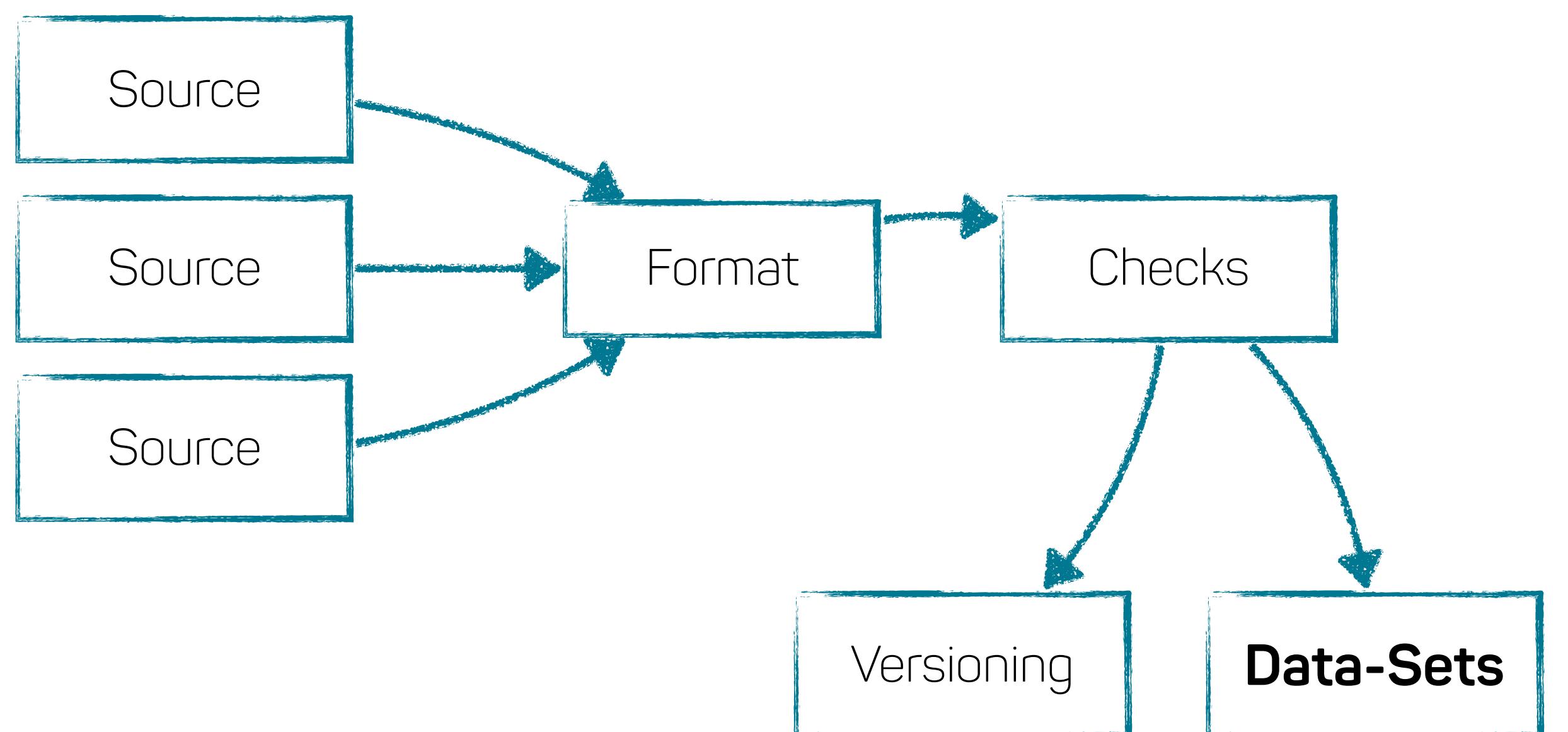
- DVC pipelines are useful for research & development, but intended for manual use
- What about more complex workflows?
- What about an automated & scheduled process?



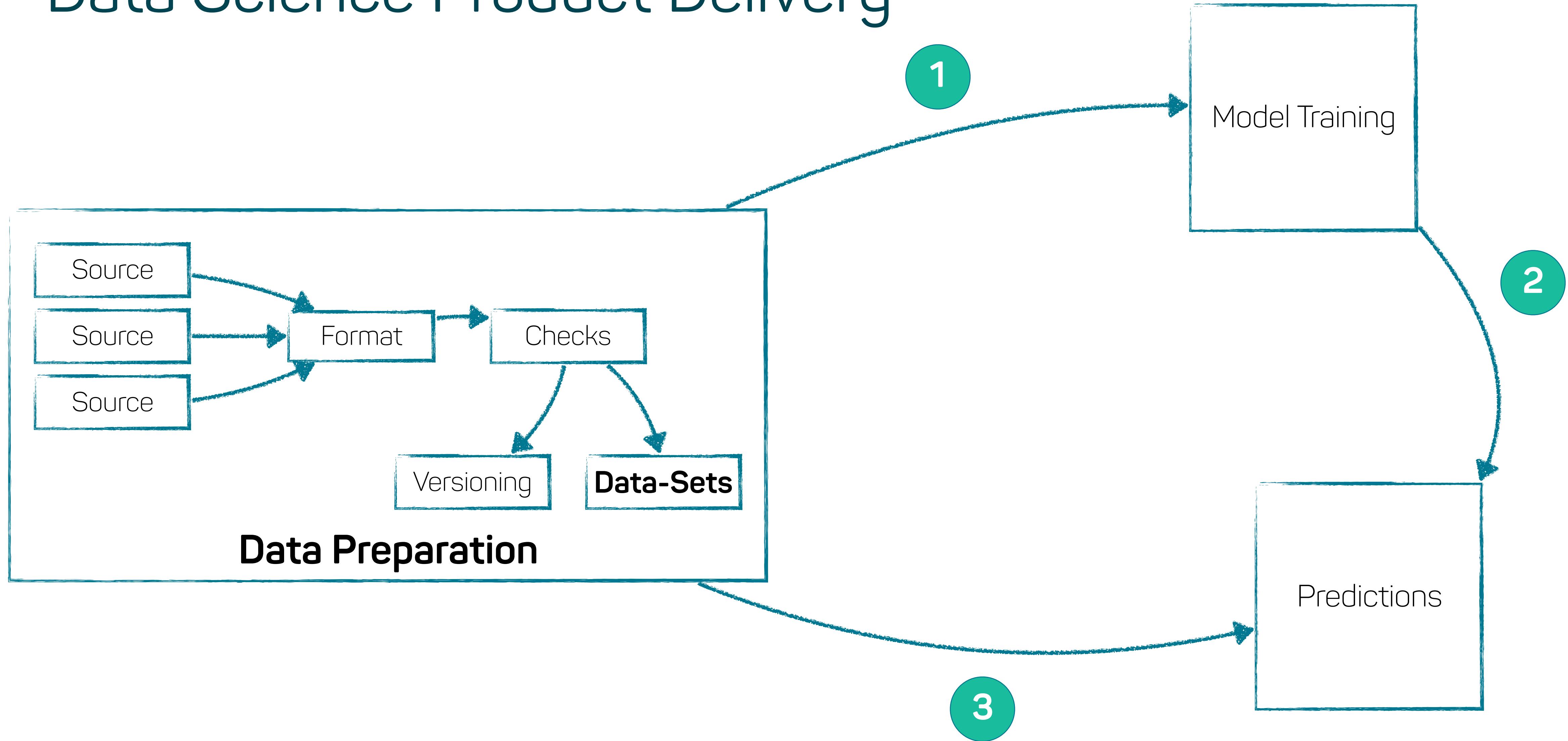
Data Science Product Delivery



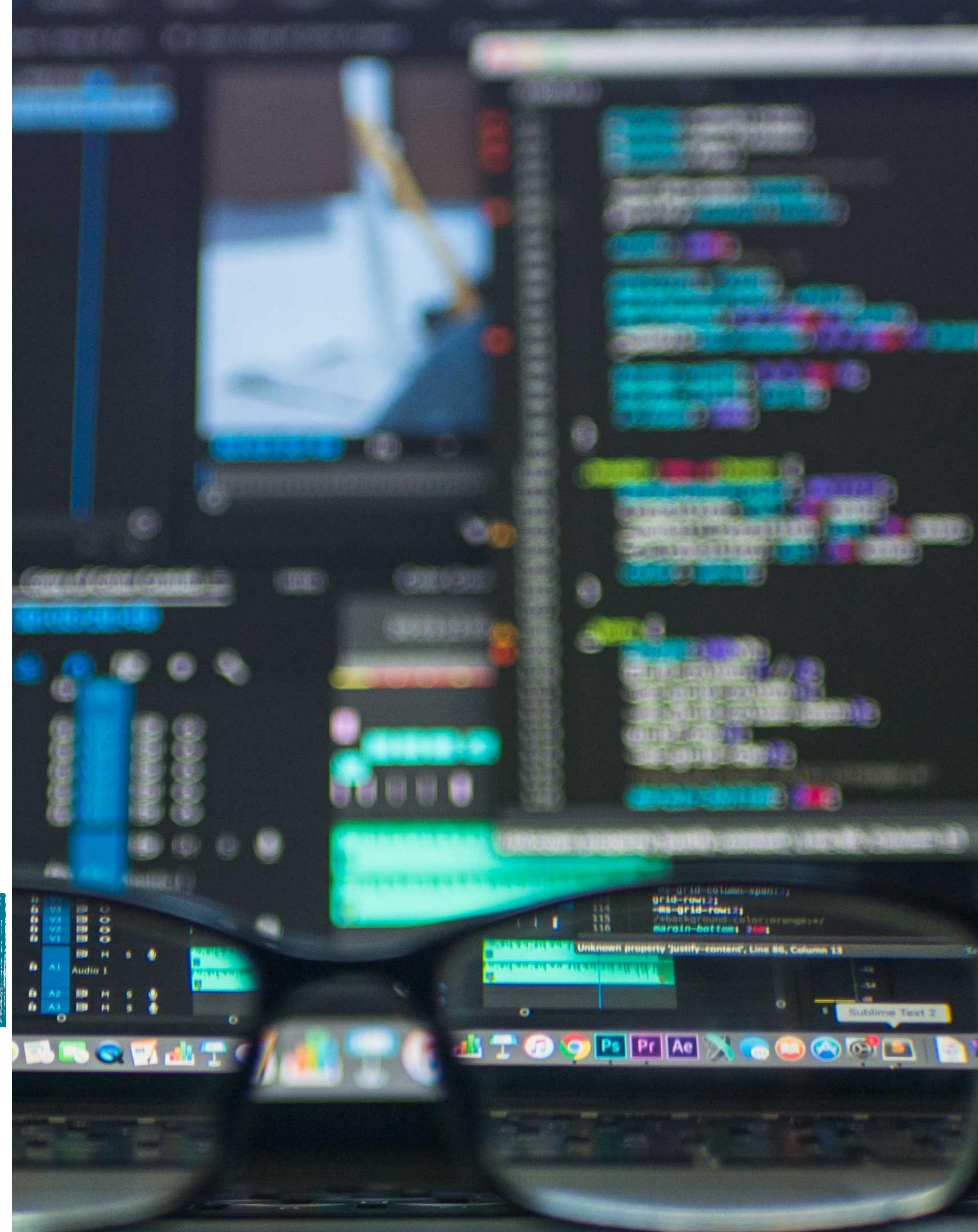
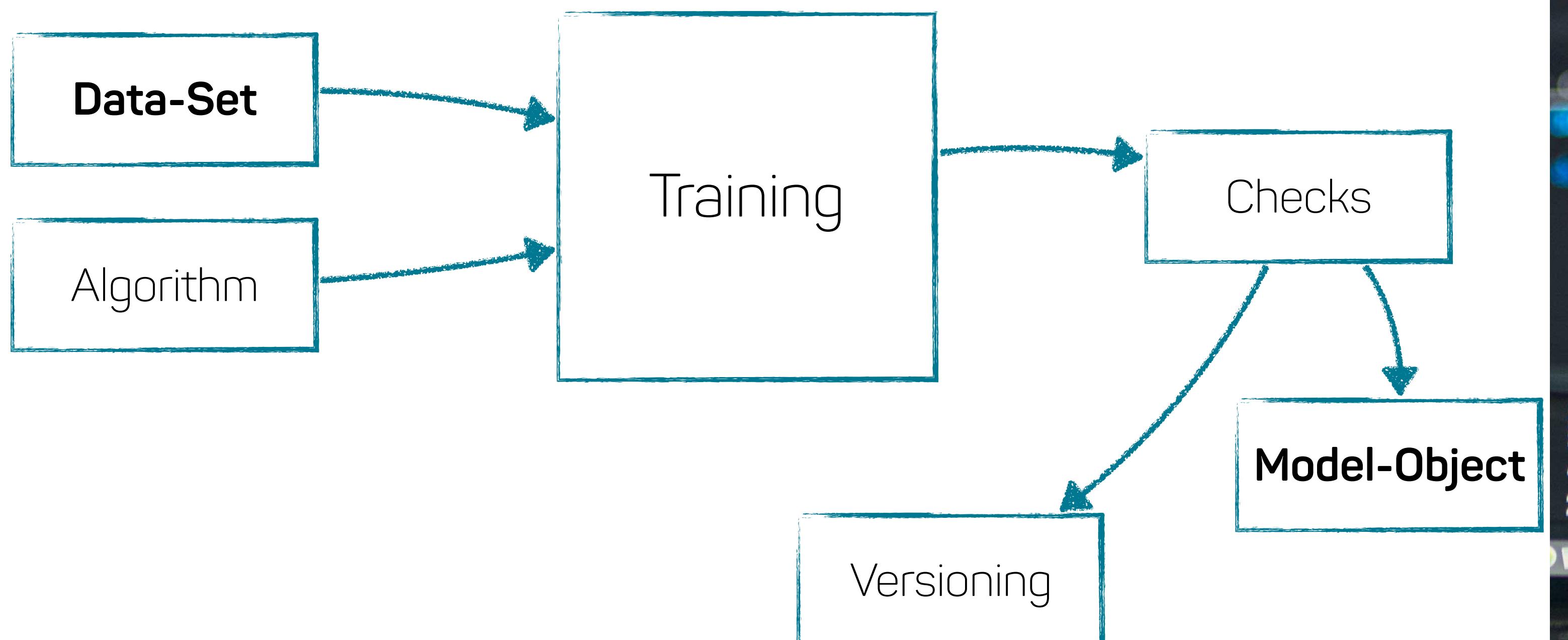
Data Preparation



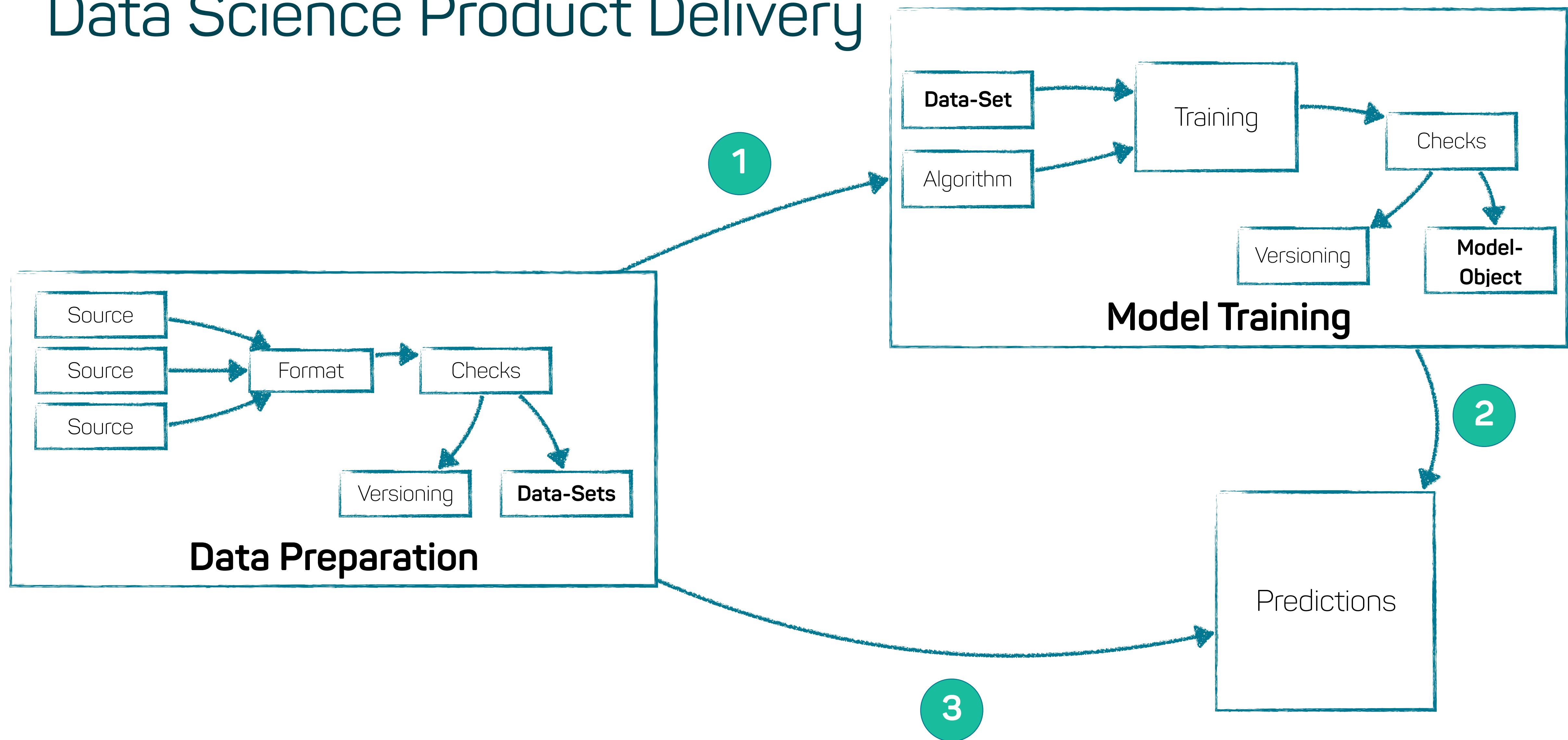
Data Science Product Delivery



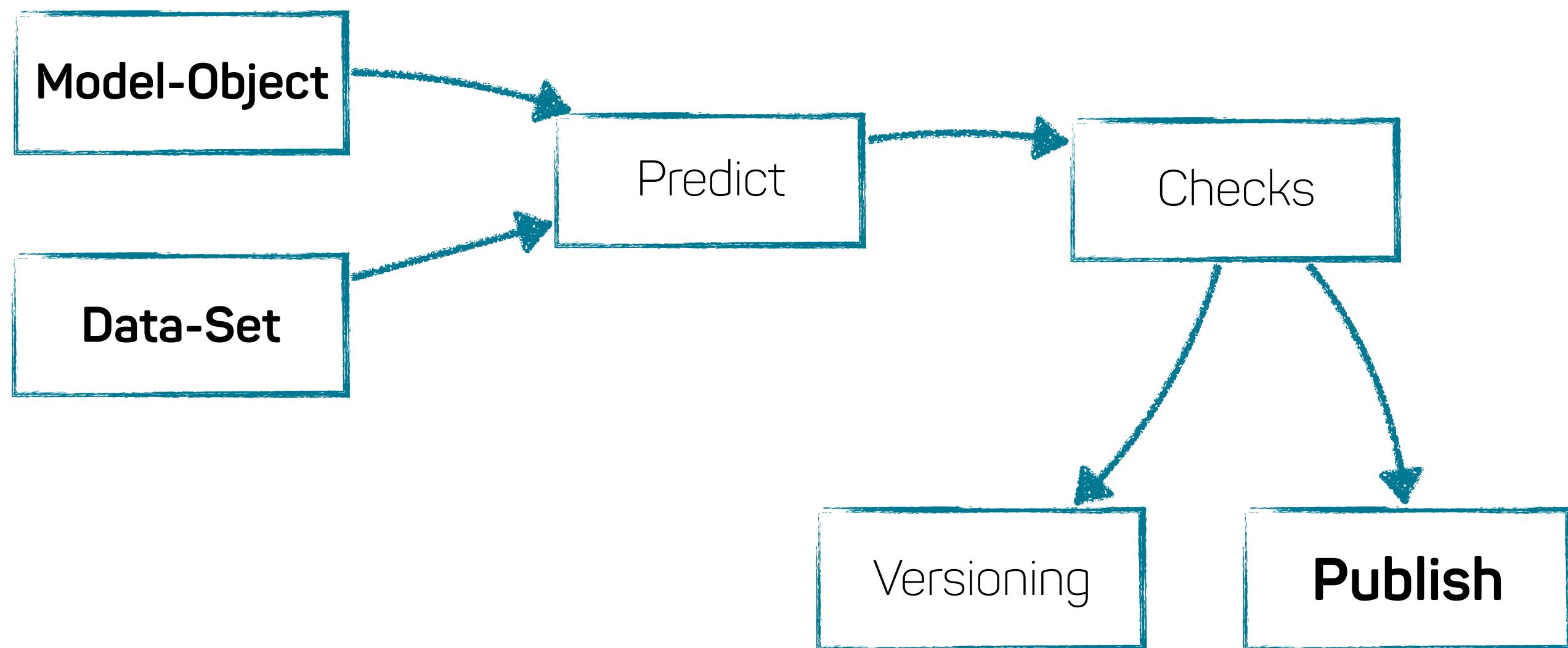
Model Training



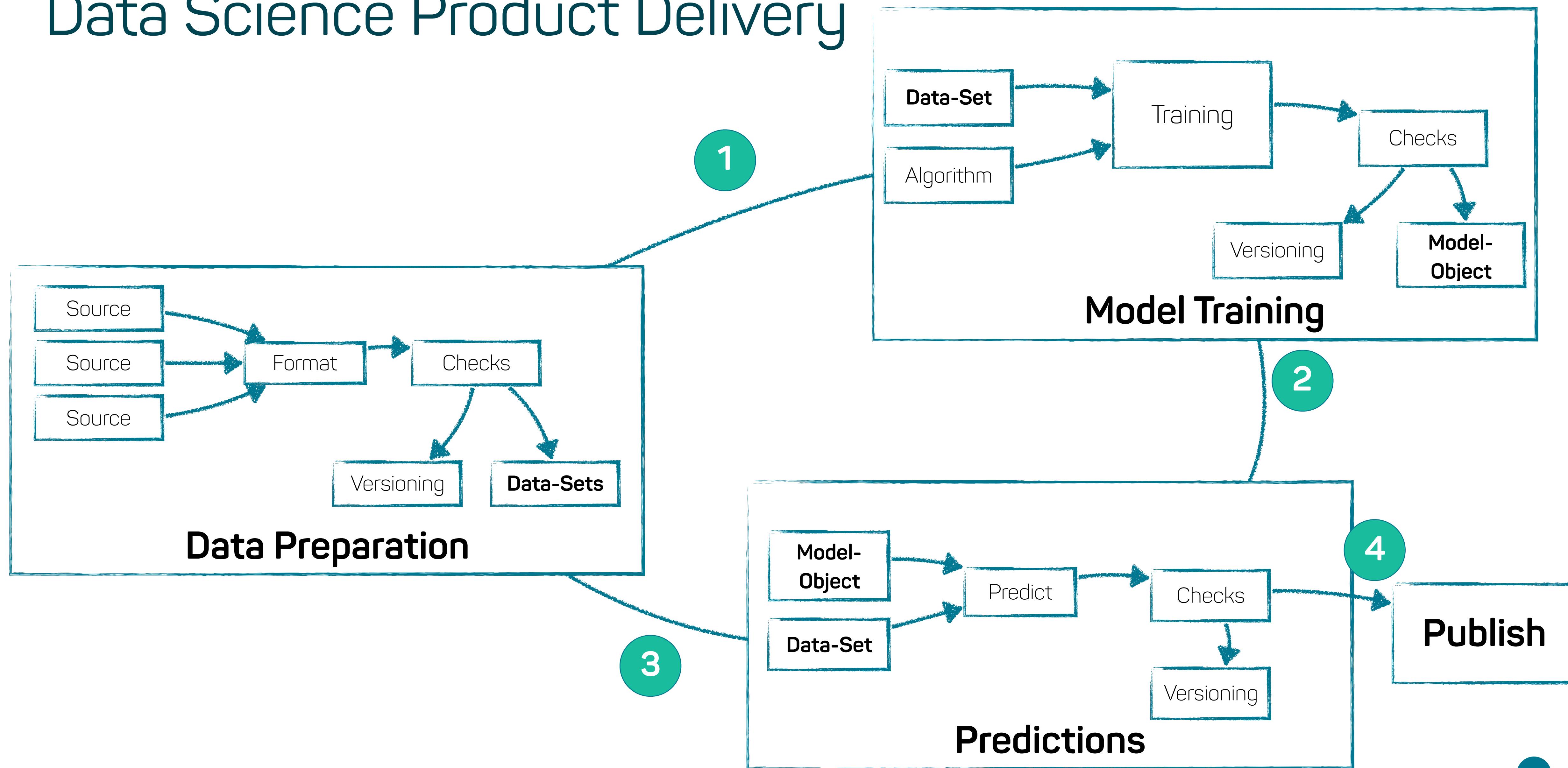
Data Science Product Delivery



Predictions



Data Science Product Delivery



Let's get Practical: Airflow

- Developed by AirBnB, now Apache Foundation
- **Write, schedule** and **monitor** workflows
- Write: Workflows are defined as Directed Acyclic Graphs, defined and written in Python
- Schedule: Provides own scheduler, allows for cron-style scheduling
- Monitor: Inspect and interact via webserver / UI

