Deep Learning

Equancy
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course given by
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Nice to meet you!

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R&D in Deep Learning/Image Processing

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Disclaimer

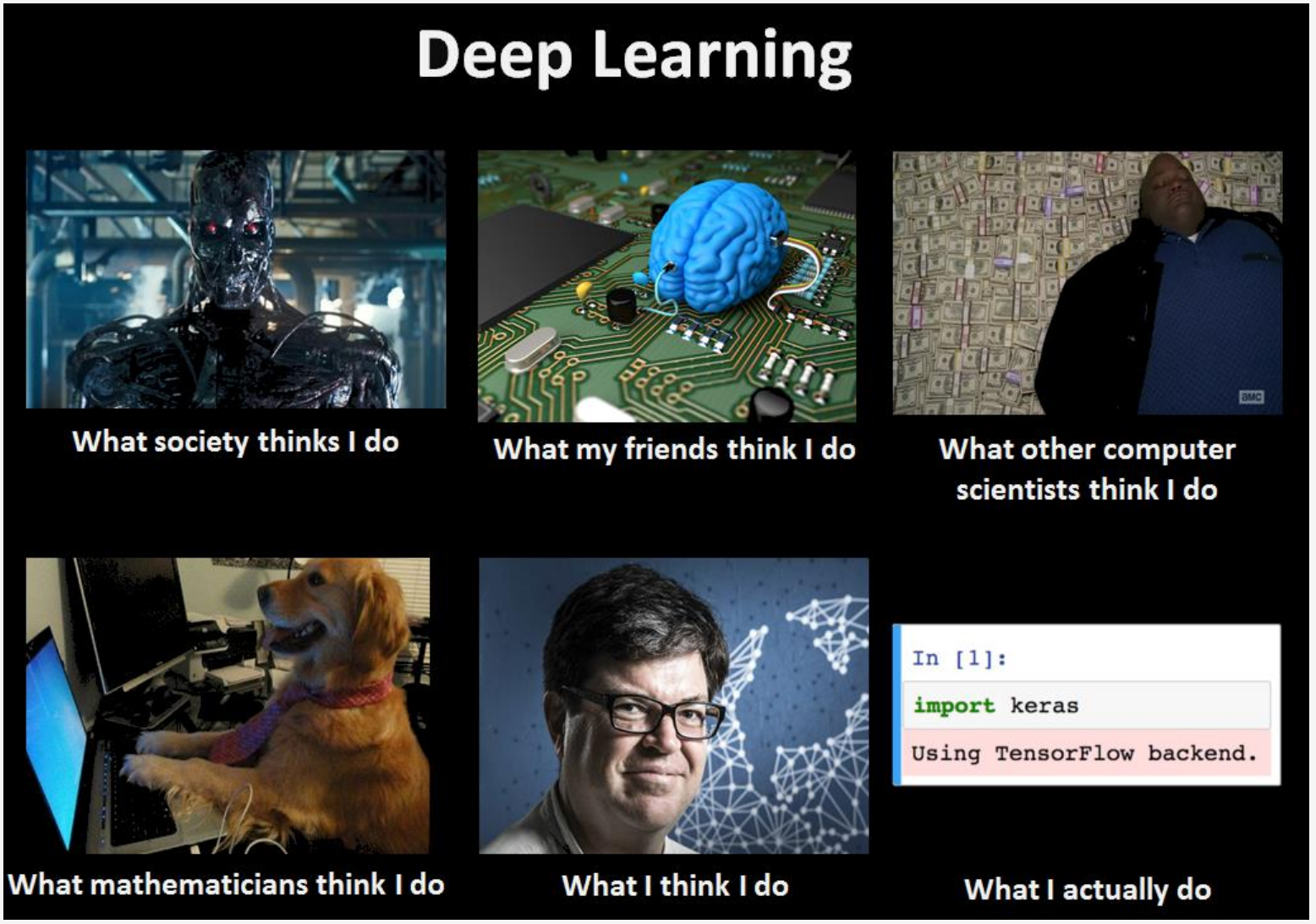
- First steps in Deep Learning (DL)

- Goals:
  - Learning foundations of DL
  - Understanding/managing neural networks
  - Lead successfully DL projects

- You'll master not only the theory, but also see how to apply it in the industry by learning keras and tensorflow

Disclaimer

- No need to be afraid, it’s not that complicated !



AGENDA

- Introduction
- Challenges Motivating Deep Learning: ML vs DL
- Theory of Deep Neural Networks
  - Neural Networks
  - Regularization for DL
  - Optimization for Training DL models
  - CNN
  - RNN
  - Transfer Learning, Reinforcement Learning
- Practicing : train your own networks using keras
  - Image Classification
  - Sentiment Analysis
  - Fisheries kaggle competition
- Conclusion

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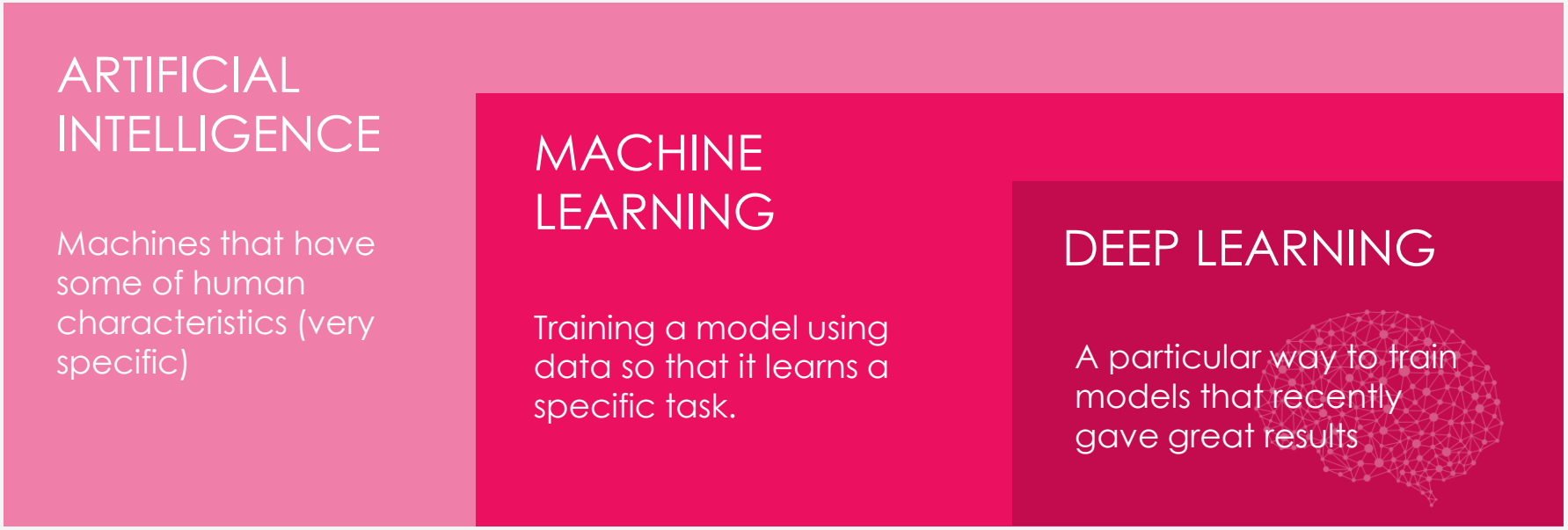
Introduction

What's Deep Learning ?

A subset of Machine Learning

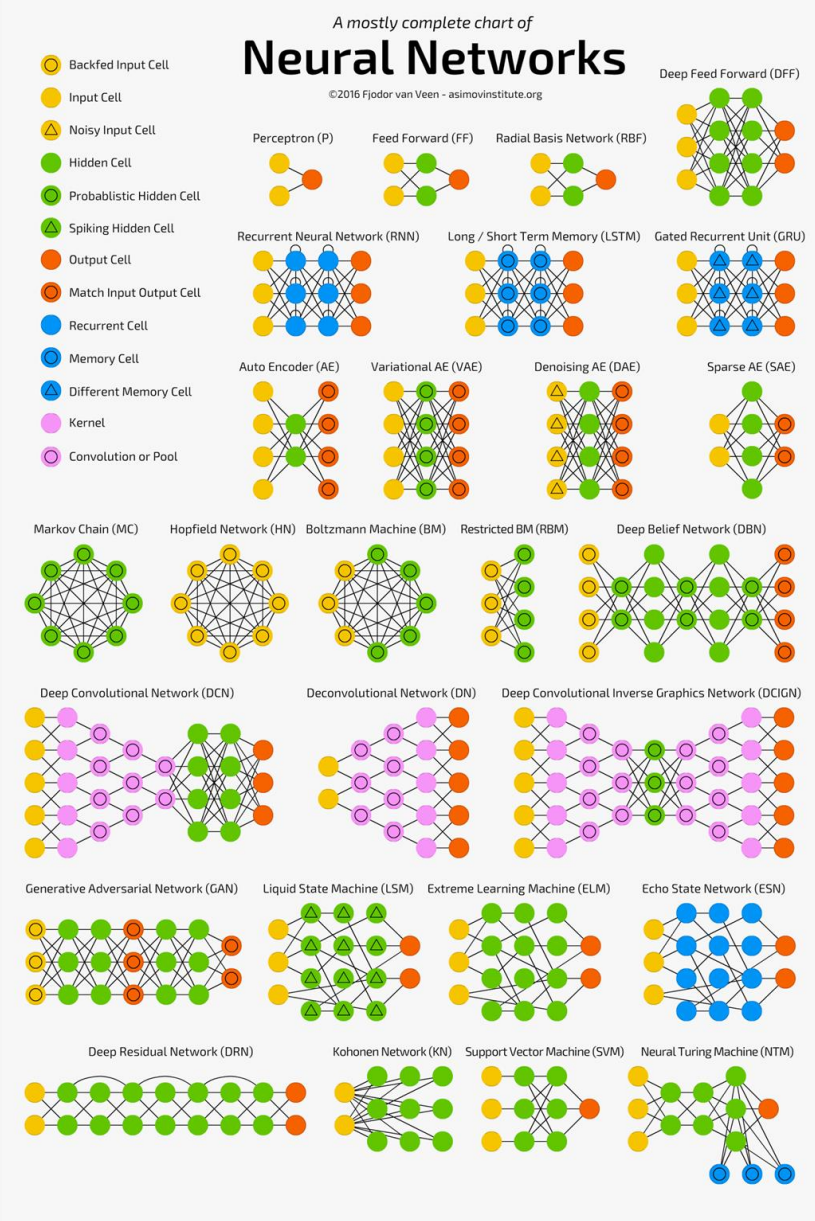


- Used when classical ML algorithms do not succeed
- To solve central problems in AI:
  - Image recognition
  - Natural Language Processing (Part of Speech, Named Entity Recognition, …)

Neural Networks

The core of Deep Learning

- Using Deep Learning often implies training Deep Neural Networks
- Incredibly large number of possible networks …
- Heavy theory & mathematical foundations
- Highly flexible & sensitive algorithms



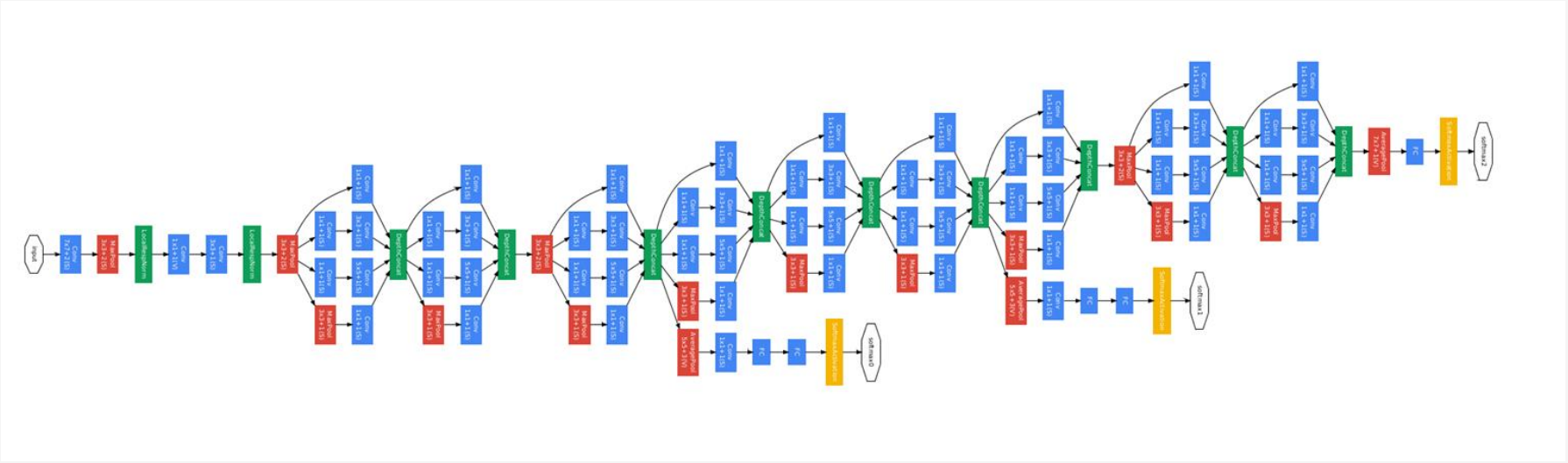
Why Deep ?

Complex and deep models

- The Deepness refers to the complexity of the Neural Networks
- To simplify! Each time we want to describe a modern deep network

It looks like this ...

GoogleNet - Inception



Who’s using DL ?

All major companies

facebook

Microsoft

YAHOO!

Google

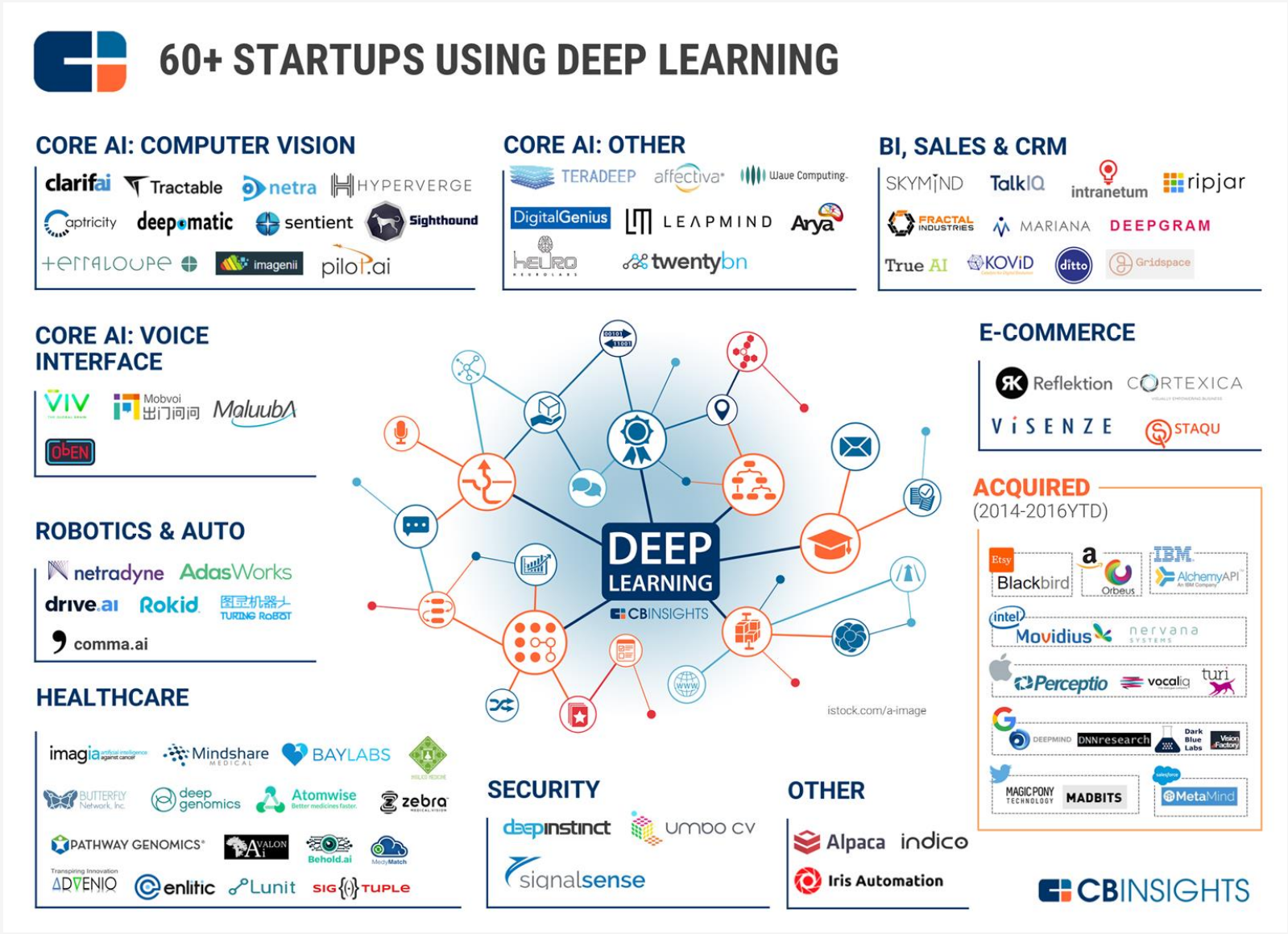
IBM

NVIDIA

Baidu 百度

Who's using DL ?

Specialized start-ups … it's booming!



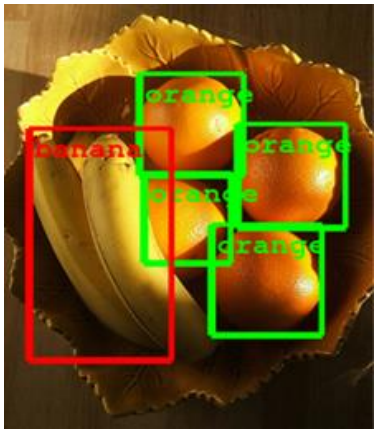
What for ?

Image recognition

Image Classification

Persian cat : 0.45
Egyptian cat : 0.22
Hamster : 0.09
Lynx : 0.04

Object detection



Artist Imitations

Image Segmentation

Caption Generation

The man at bat readies to swing at the pitch while the umpire looks on.

Image Generation

What for ?

Natural Language Processing

Part of Speech Tagging

Text:
The grand jury commented on a number of other topics

Legend:
article, adjective, noun, preposition, verb

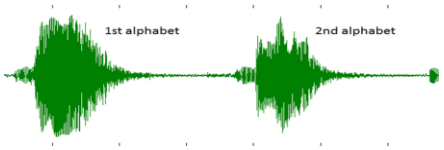
Named Entity Recognition

Text:
Apple CEO Tim Cook introduces the latest iphone version at the Cupertino Flint Center event in California

Legend:
Organization, Location, Person

Speech Recognition

Audio:



Text:
Winter is coming !

Translation

French → Chinese

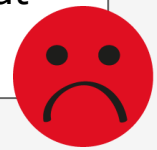
Bonjour à tous !

大家好 ！

Sentiment Analysis

Text 1:
Today was a great class about Deep Learning ! #cepe #dl

Text 2:
We've had trouble understanding what the guy was talking about #equancy #cepe. It was bad.



Is it new ?

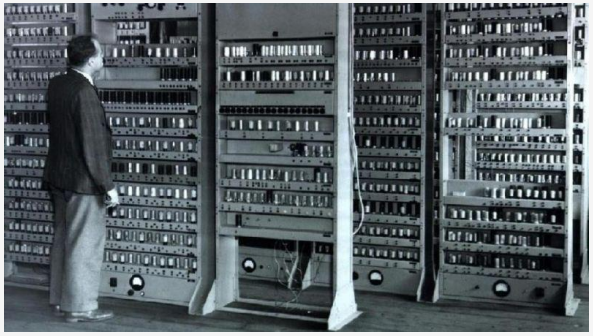
Not really … but we can finally exploit it!

- Neural Networks - studied since the end of the 1950’s
- Computationally heavy
- A reborn in the second part of 2000’s:
  - Significant computational power
  - Explosion of Data
  - Highly implicated community

Is it new ?

Not really … but we can finally exploit it!

Significant computational power



…

amazon web services

Google Cloud Platform

Microsoft Azure

IBM

NVIDIA

TESLA

AMD

GPU

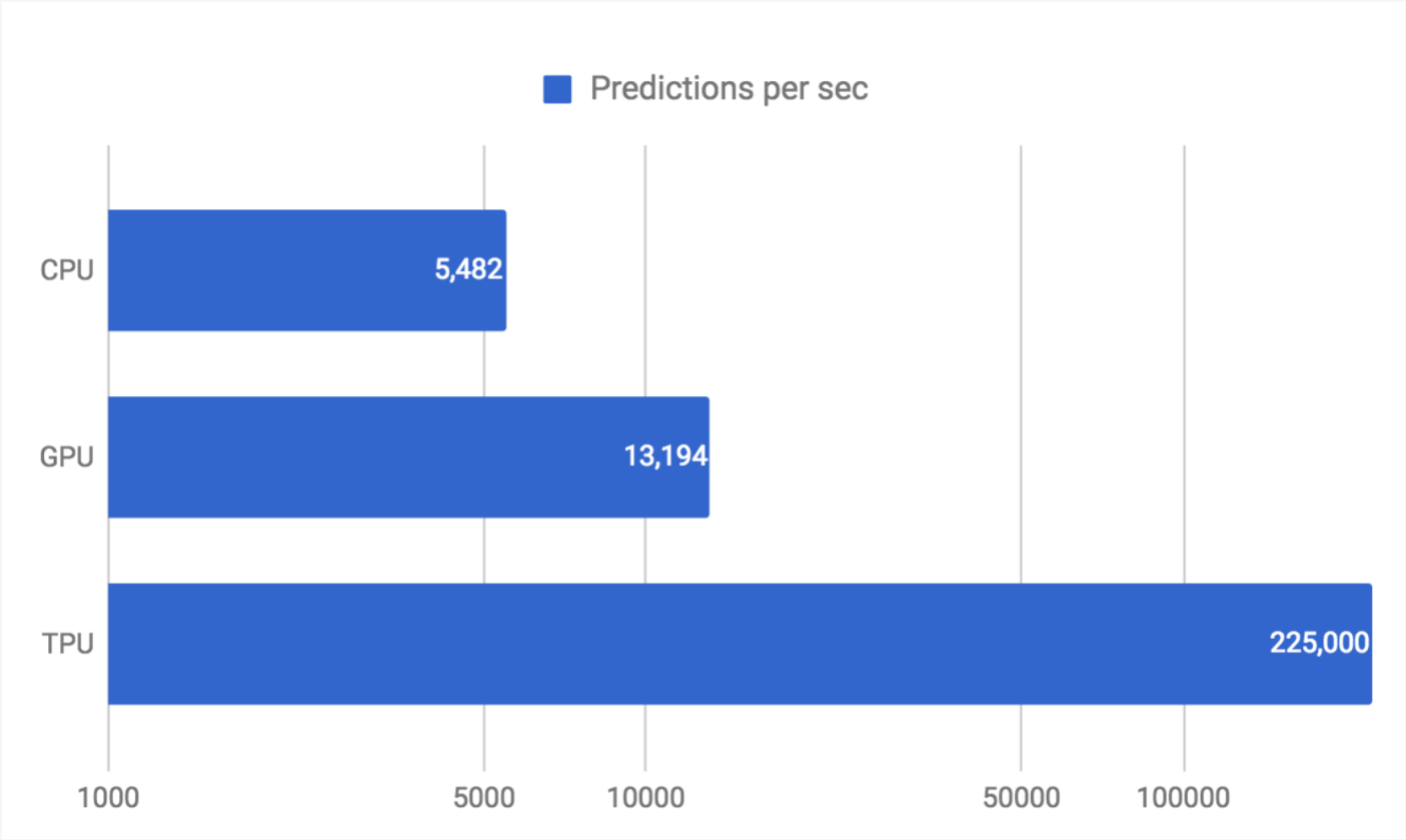
CPU

Cloud TPU

Is it new ?

Not really … but we can finally exploit it!

Significant computational power
TPU … always faster



Is it new ?

Not really … but we can finally exploit it!

Explosion of DataSets

kaggle™

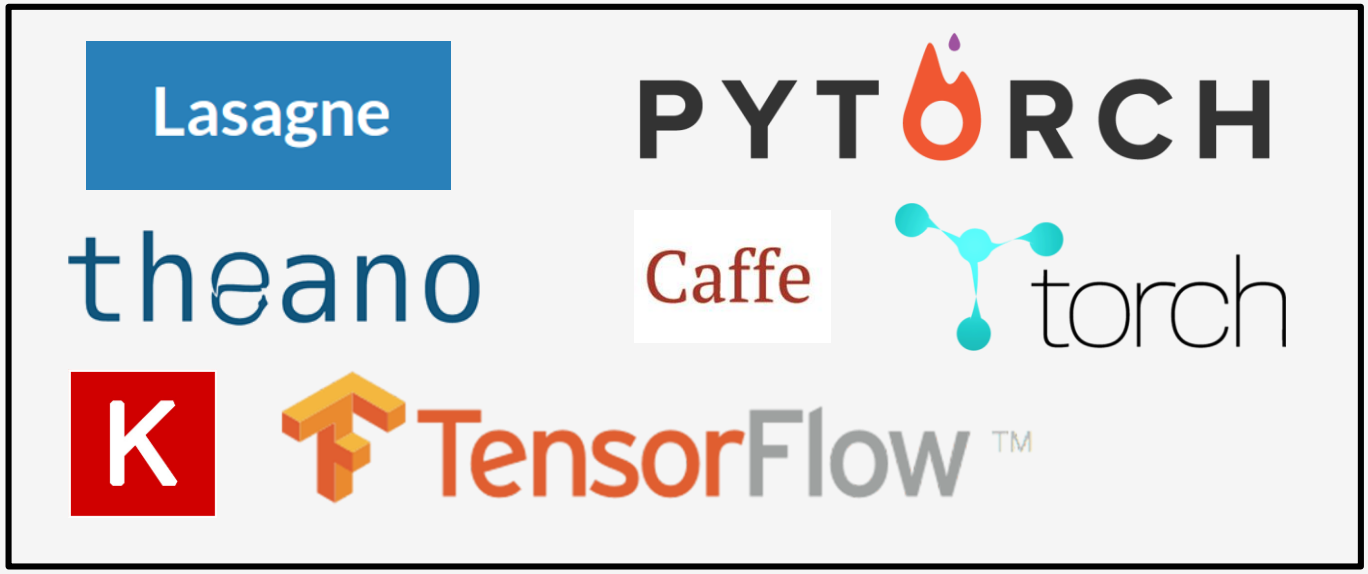
1627 Hosted Datasets	**276** Commercial Competitions	**1919** Student Competitions	**1M** Data Scientist	**4M** ML models submitted

Is it new ?

Not really … but we can finally exploit it!

Active and implicated community of deep learners
companies, researchers, scientists …

large choice of available tools !




2
Challenges motivating Deep Learning: ML vs DL

Reminders

Reminders

ML reminders/basics

- Remember DL is a subset of ML
- To understand DL, strong ML basics are necessary:
  - complexity, overfitting and underfitting
  - model selection & model generalization
  - regularization
  - bias/variance tradeoff
  - gradient-descent optimization
- Let’s quickly review these key concepts

Reminders: Complexity, overfitting and underfitting

- Central challenge in ML: perform well on *new unseen* inputs (i.e. **generalization**)
- In optimization ⇒ Minimize the **training error**
- In ML ⇒ Minimize **test/generalization error** as well
- In other terms, the goals are to get:
  1. smallest training error
  2. smallest gap between training and test error
- Let's define $L\big(y,\ f(x)\big)$ and $\mathrm{EPE} \equiv \mathrm{E}[L\big(y,\ f(x)\big)|x = x_0]$

Reminders: Complexity, overfitting and underfitting

- Let's take the example of *MSE*: $L(y,\ f(x)) = \frac{1}{N}\sum_i^N (y_i\ -\ \hat{y}_i)^2$

- **Training error** can be expressed as:

$$\frac{1}{N}\sum_i^N (y_i\ -\ \hat{y}_i)^2$$

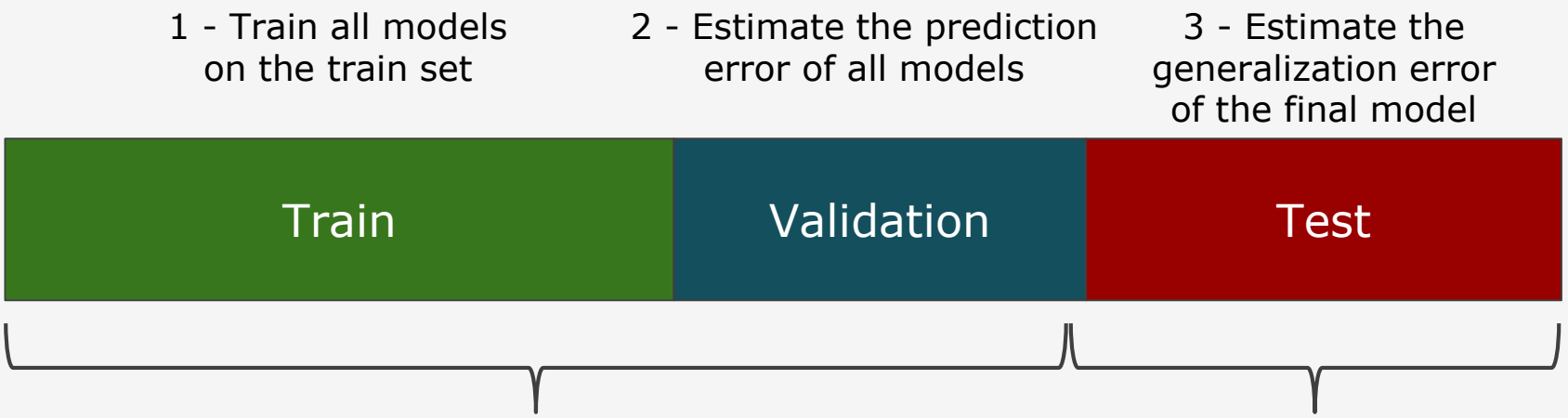
- **Test error** can be expressed as:

$$EPE = \sigma^2 + \left[Bias^2\left(\hat{f}(x_0)\right) + Var_\tau\left(\hat{f}(x_0)\right)\right]$$

- How to assess these error terms ?

Reminders: Complexity, overfitting and underfitting

In rich data context



$$training\ error = \frac{1}{N}\sum_{i}^{N}(y_i - \hat{y_i})^2$$

$$EPE = \sigma^2 + \left[Bias^2\left(\hat{f}(x_0)\right) + Var_\tau\left(\hat{f}(x_0)\right)\right]$$

Reminders: Complexity, overfitting and underfitting

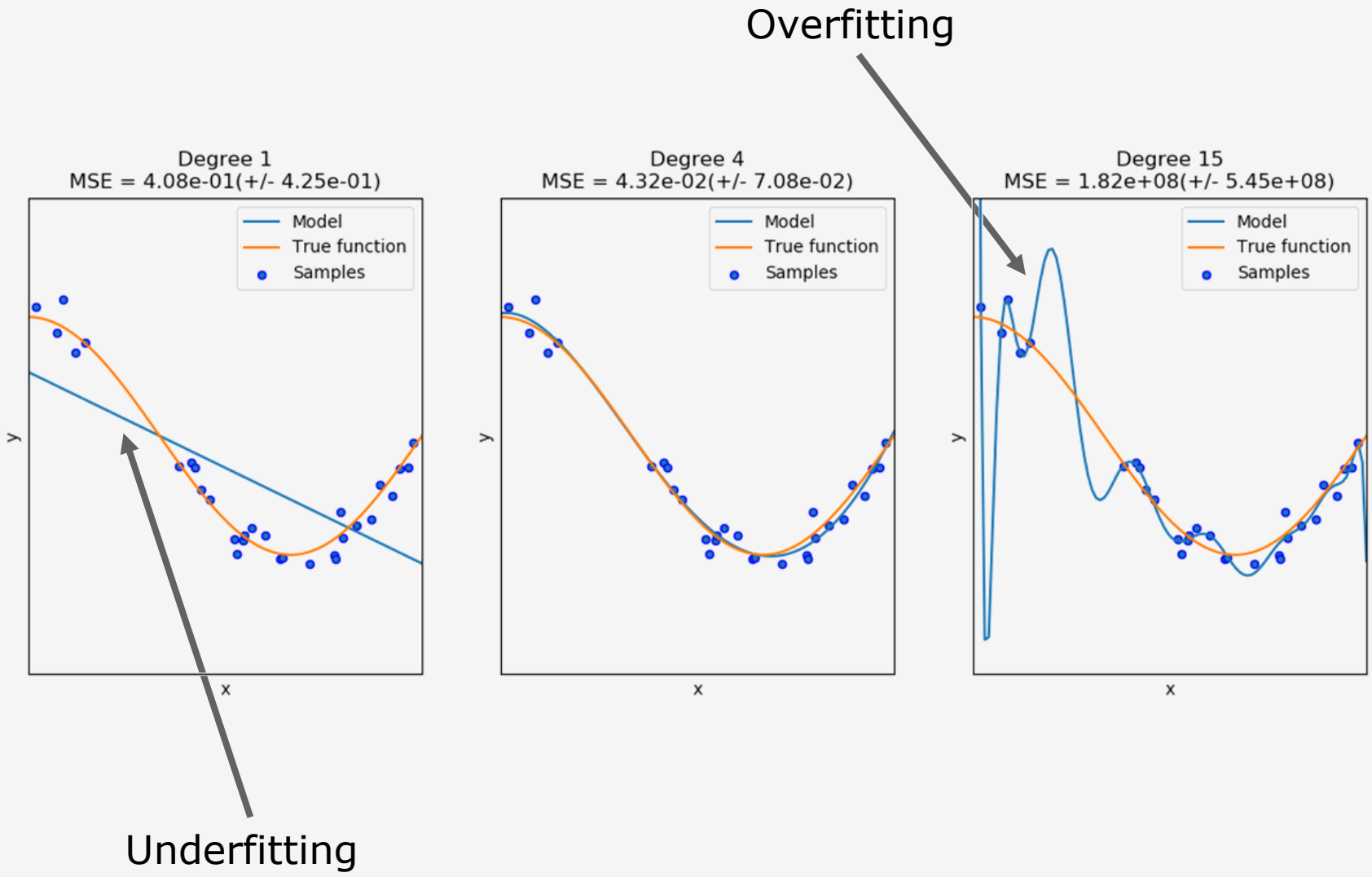
K-folds cross-validation

Reminders: Complexity, overfitting and underfitting

- **Underfitting:** “model unable to obtain a sufficiently low training error”
- **Overfitting:** ”training error sufficiently low, but gap between training and test errors is too large”
- **Complexity:** model complexity (i.e. capacity)

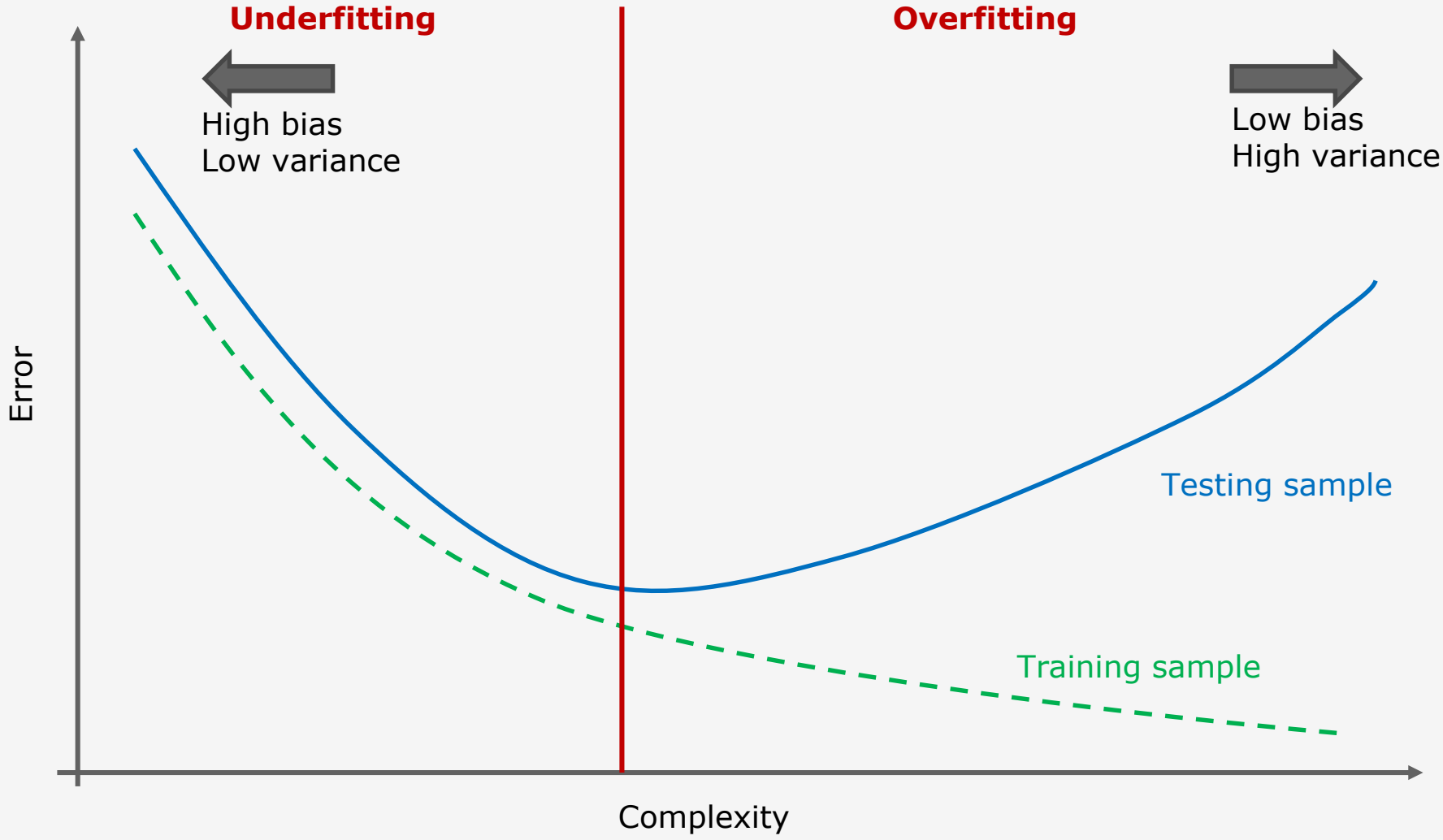
Reminders: Complexity, overfitting and underfitting

Illustration: fitting a polynomial regression



Reminders: Complexity, overfitting and underfitting

Overfitting and underfitting are linked with complexity



Reminders: Regularization

- To tackle overfitting and underfitting:
  - Increase or decrease the model capacity
  - Increase the training examples (more data)
  - Regularization

- **Regularization:** ”any modification we make to a learning algorithm that is intended to reduce its generalization error but not its training error”

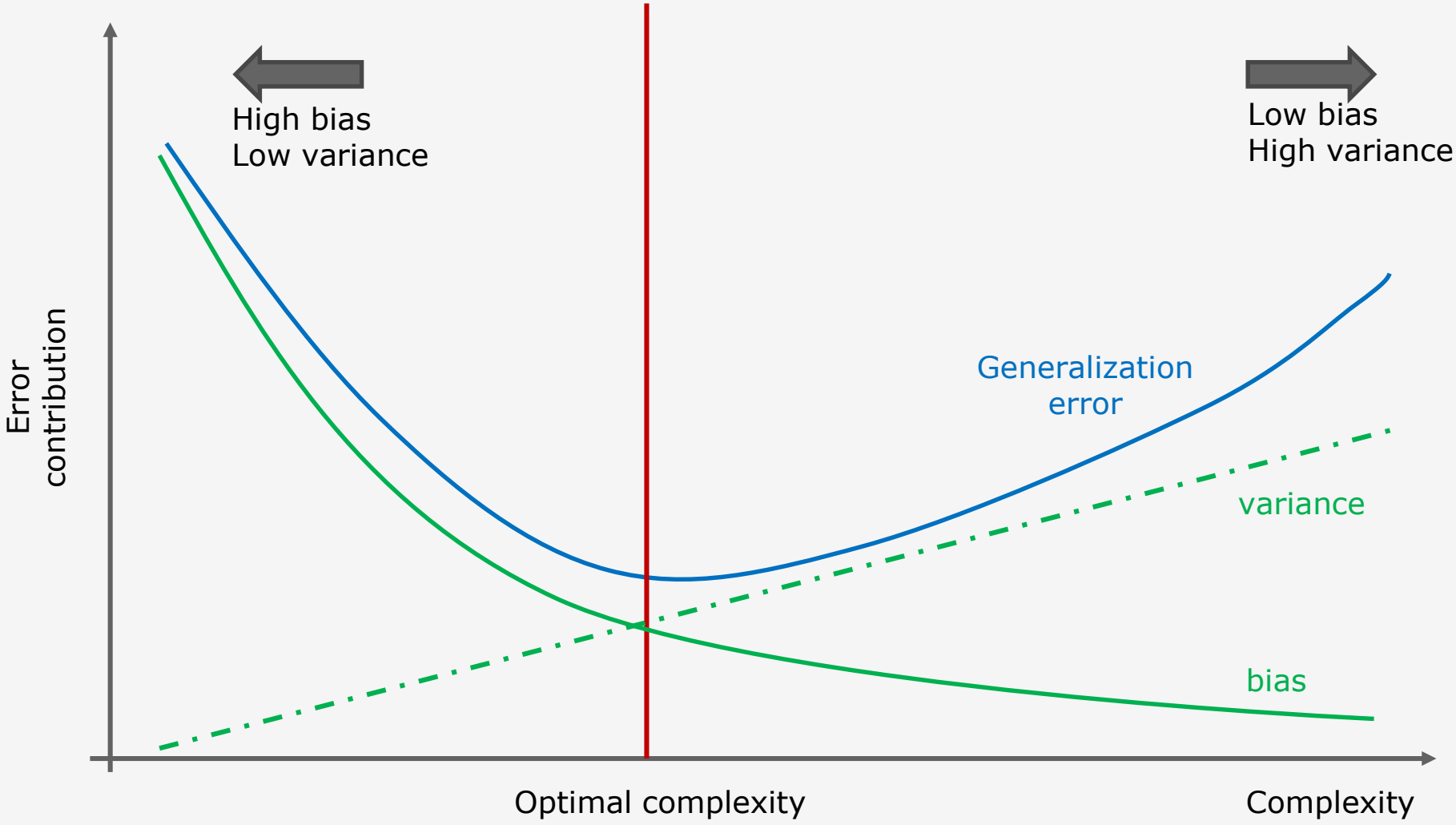
- Regularization to reduce overfitting

$$L\big(y, f(x)\big) = MSE_{train} + \lambda w^T w$$

- L1 or L2 regularization

Reminders: bias/variance tradeoff

A question of 'arbitrage'



Reminders: Gradient Descent optimization

Basic Gradient Descent

- Gradient-based optimization is very important in Deep Learning
- Gradient Descent to find *Global Minimum* of a given function with parameters
- Let's consider a cost/loss function

$$L(\theta) \; with \; input \; parameters \; \theta \in \Theta$$

- Such as

$$\min L(\theta)$$

- Gradient Descent:

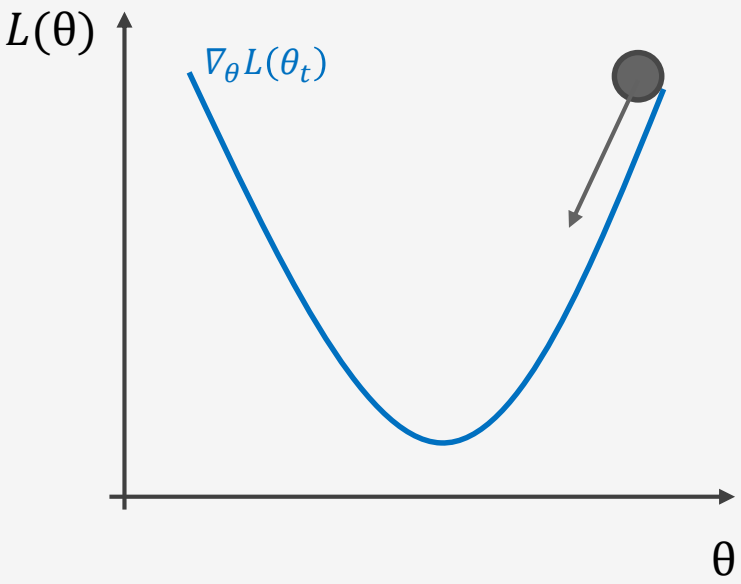
$$\theta_{t+1} = \theta_t \; - \lambda \, \nabla_\theta L(\theta_t)$$

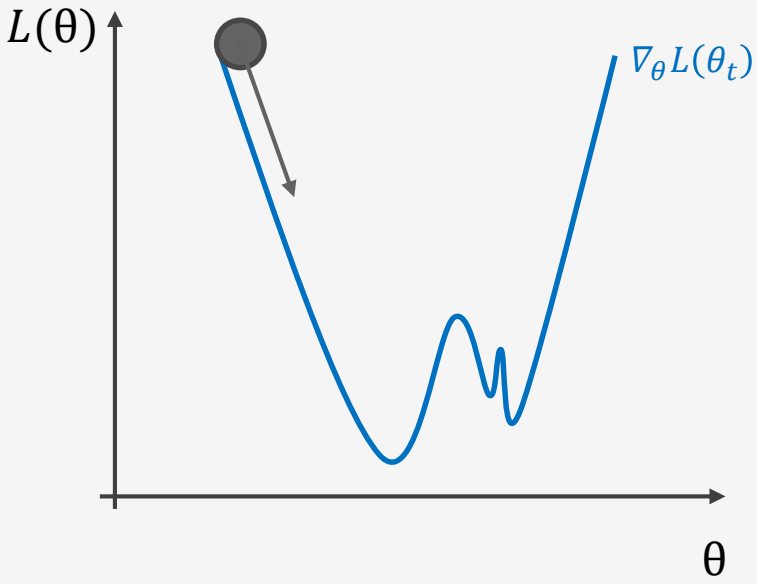
$$with \; \nabla_\theta L(\theta_t) \; as \; the \; gradient \; of \; L(\theta) \; w.r.t. to \; \theta$$
$$and \; \lambda \; as \; the \; learning \; rate$$

Reminders: Gradient Descent optimization

Basic Gradient Descent

See it as a ball rolling down …



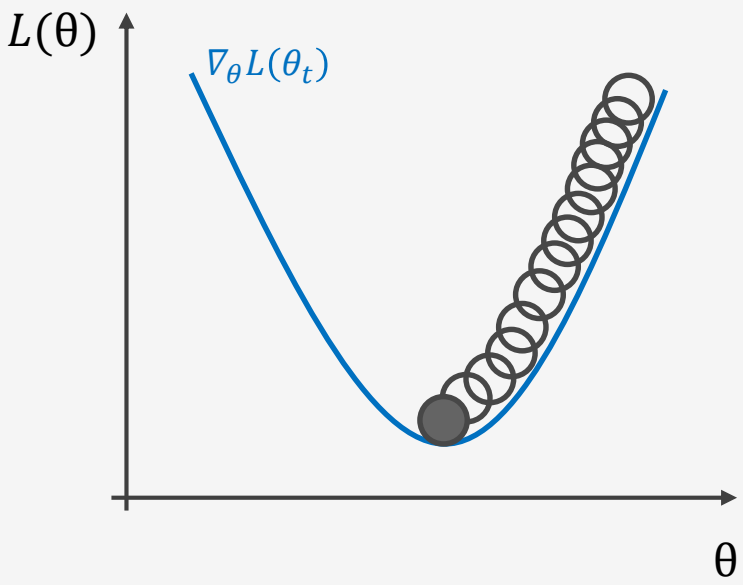


Reminders: Gradient Descent optimization

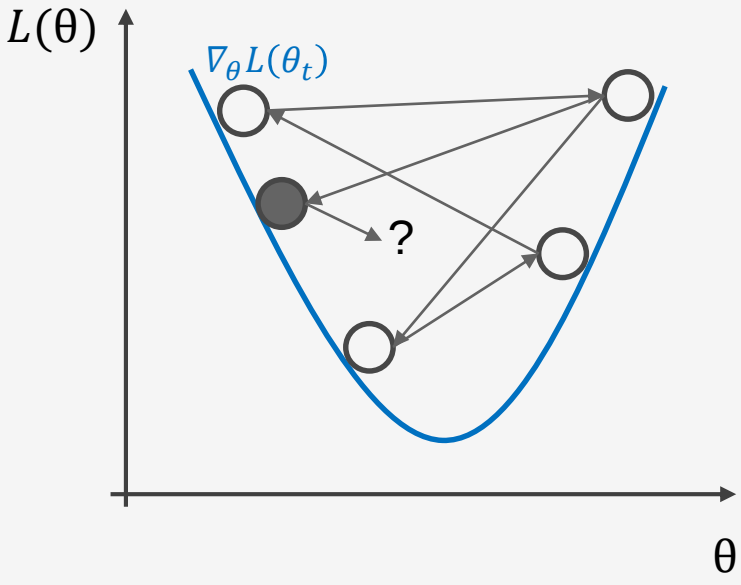
Basic Gradient Descent

Choice of the learning rate λ

λ too **small** …. Descent too **slow**



λ too **large** …. Target **missed**

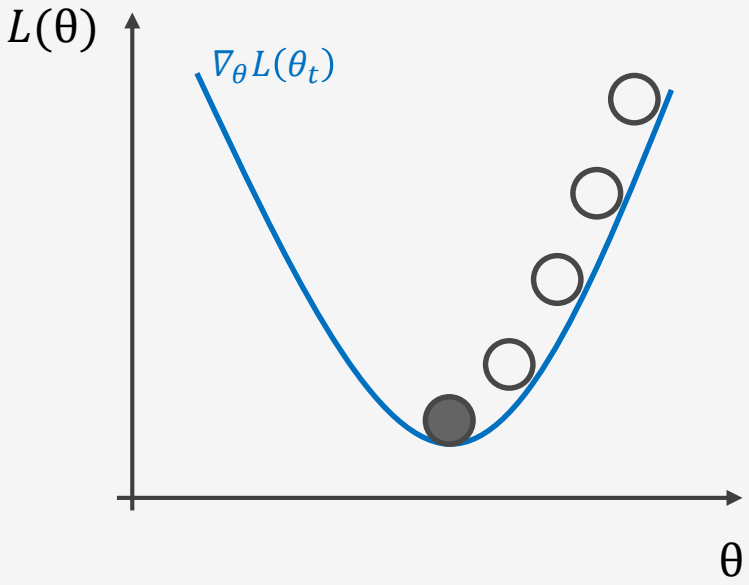


Reminders: Gradient Descent optimization

Basic Gradient Descent

Choice of the learning rate λ

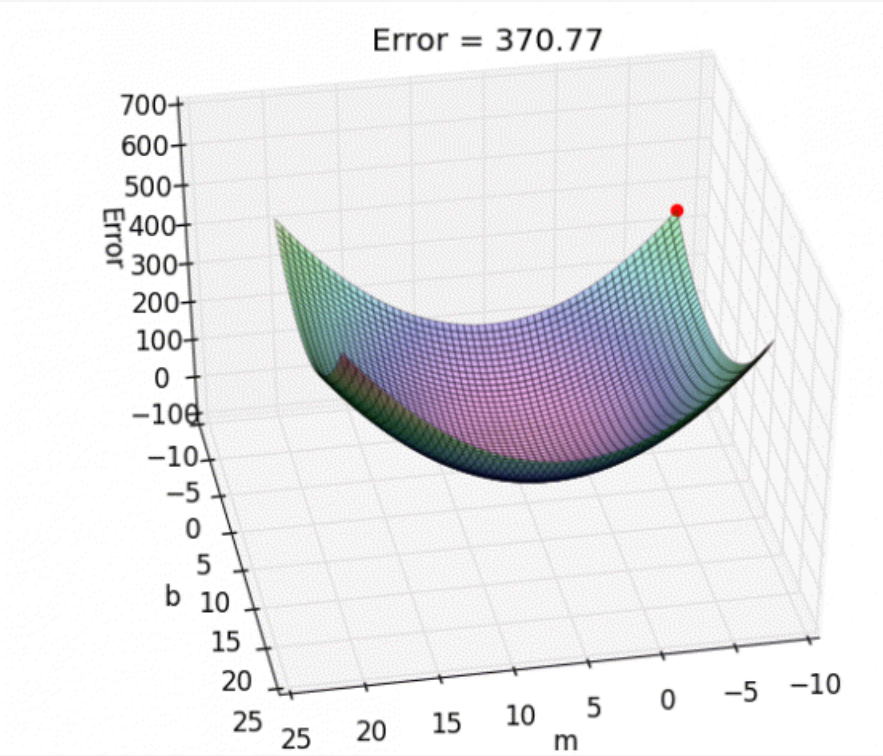
Tradeoff between
speed and *precision*

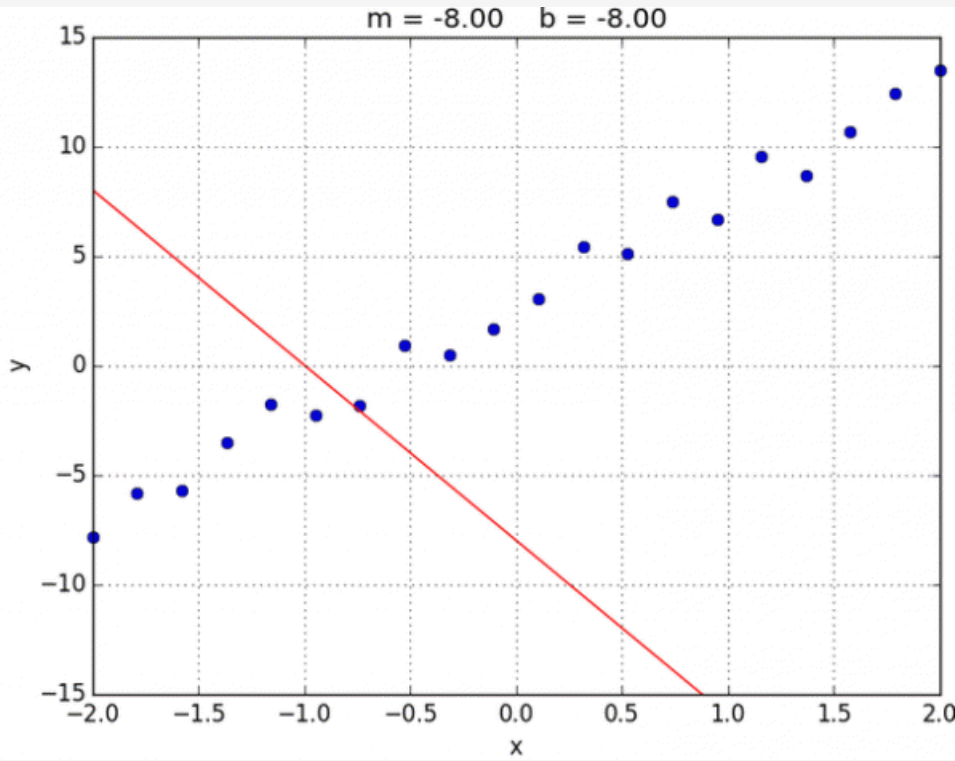


Reminders: Gradient Descent optimization

Illustration of Gradient Descent

- Let's consider a linear regression with $f(x) = m * x + b$
- With $m, b \equiv \theta$ and $L(\theta) = MSE$





The Challenges motivating DL

Challenges motivating Deep Learning

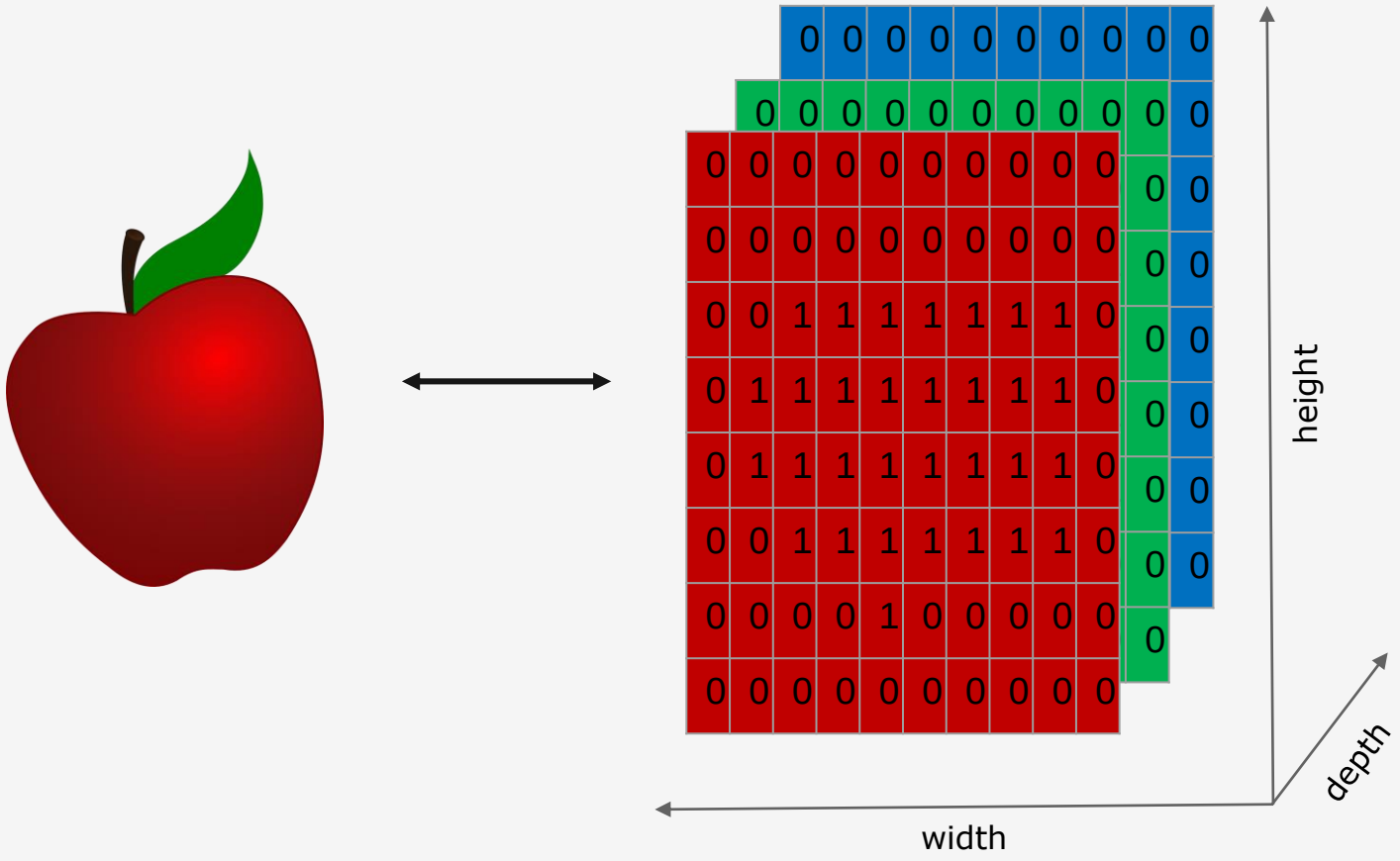
- ML works well in wide variety of problems
- Unfortunately, they haven’t succeed in solving core AI problems (e.g. image recognition, speech recognition, etc …)

But Why ?

Challenges motivating Deep Learning

Failure of ML: example of image recognition

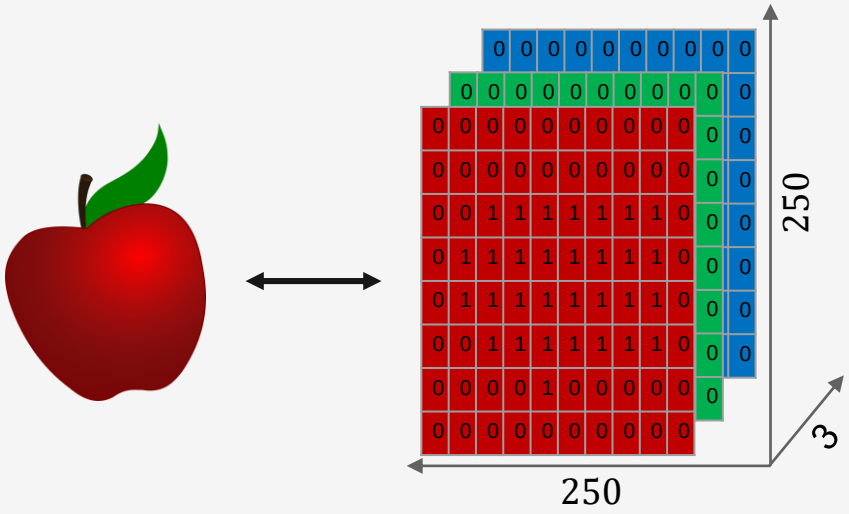
Image = RGB matrix



Challenges motivating Deep Learning

Failure of ML: example of image recognition

With classical ML model



Reshape/flatten:

$250 * 250 * 3 = 187\,500$

Vector of dimension 187500

High dimensional space

...

Complicated for ML models

Challenges motivating Deep Learning

Challenge 1: The curse of dimensionality

- Many ML problems' complexity increase with the number of dimensions in the data
- The number of possible set of configurations increases exponentially with the number of variables
- When can we qualify the issue of high-dimensional ?

$$number\ of\ variables(x) \gg number\ of\ training\ examples\ (n)$$

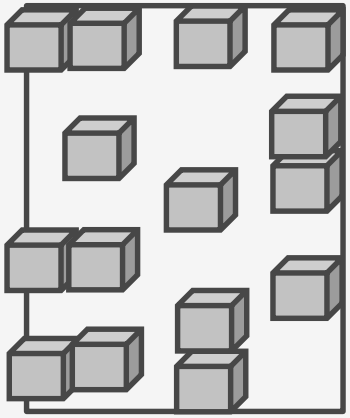
Challenges motivating Deep Learning

Challenge 1: The curse of dimensionality

1 dim

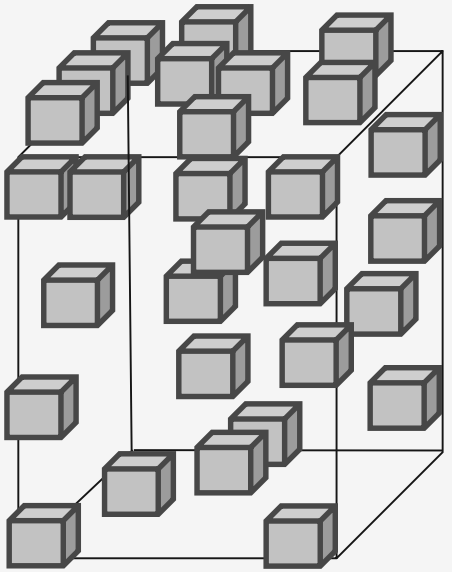
4
regions of
interest

2 dims



4 * 4 = 16
regions of
interest

3 dims



4 * 4 * 4 = 64
regions of
interest

Challenges motivating Deep Learning

Challenge 1: The curse of dimensionality

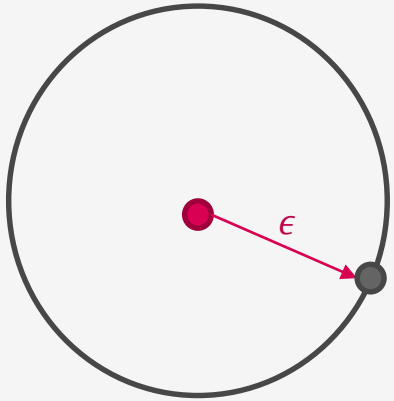
- Traditional ML approach insufficient for these spaces
- **DL challenge**: generalize well in high-dimensional spaces while keeping the computational cost low

Challenges motivating Deep Learning

Challenge 2: Local constancy and smoothness regularization

- ML algorithms must be guided by *prior beliefs* about the kind of function to learn
- **Local constancy prior :** ”the function we learn should not change very much within a small region”:

$$f^*(x) \approx f^*(x + \epsilon)$$



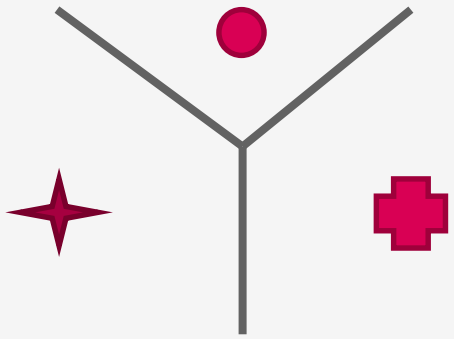
- Intuition: if we know a good answer for an input x, the answer is also good in the small neighborhood of x

Challenges motivating Deep Learning

Challenge 2: Local constancy and smoothness regularization

- **Limitation**: ”to distinguish *O(k)* regions in the input space, we need *O(k)* examples”
- *Nearest neighbors*, *local kernel* and *tree* based methods suffer from the limitations of this prior

Example of knn



Challenges motivating Deep Learning

Challenge 2: Local constancy and smoothness regularization

- Challenge
  - Can we represent a complicated function efficiently?
  - Can it generalize well to new inputs ?
- DL allows to represent

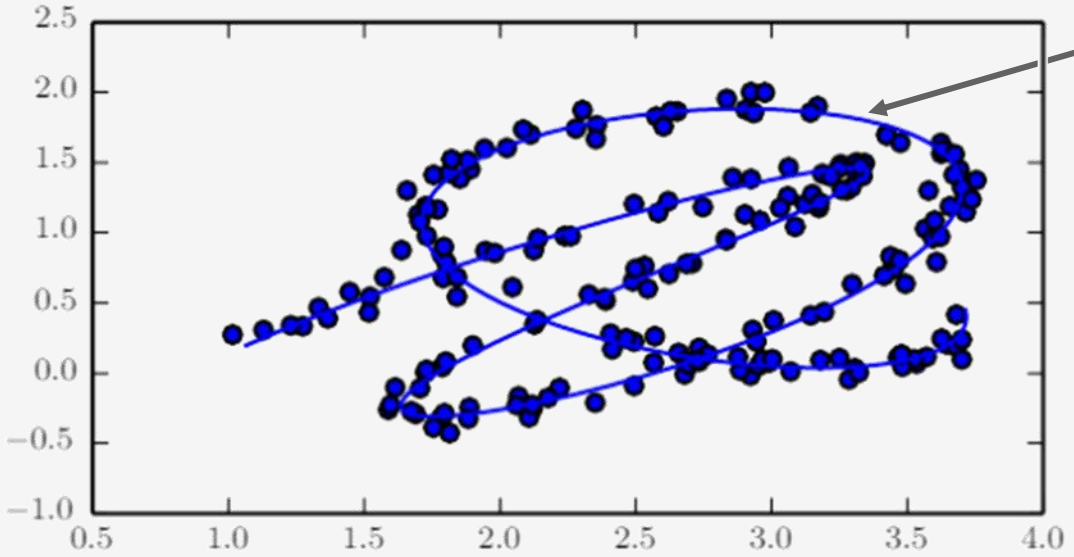
$$O\left(2^k\right) regions\ with\ O(k)\ examples$$

as it can introduce additional assumptions about the underlying data-generating distribution

Challenges motivating Deep Learning

Challenge 3: Manifold learning

- **Manifold** is a connected region: a set of points associated with a neighborhood around each point. Its is an Euclidean space.
- It is possible to move from neighborhood to another one on the manifold



Manifold to infer

Concentration of points near a one-dimensional manifold

Challenges motivating Deep Learning

Challenge 3: Manifold learning

- ML seem hopeless if want to learn interesting variations across all R^n
- Manifold learning algorithms consider that
  - R^n inputs are invalid
  - Interesting variations occur only along a collection of manifolds
    - Along the directions of the manifold
    - When passing from one manifold to another
- Necessary assumption for processing images, audio or texts

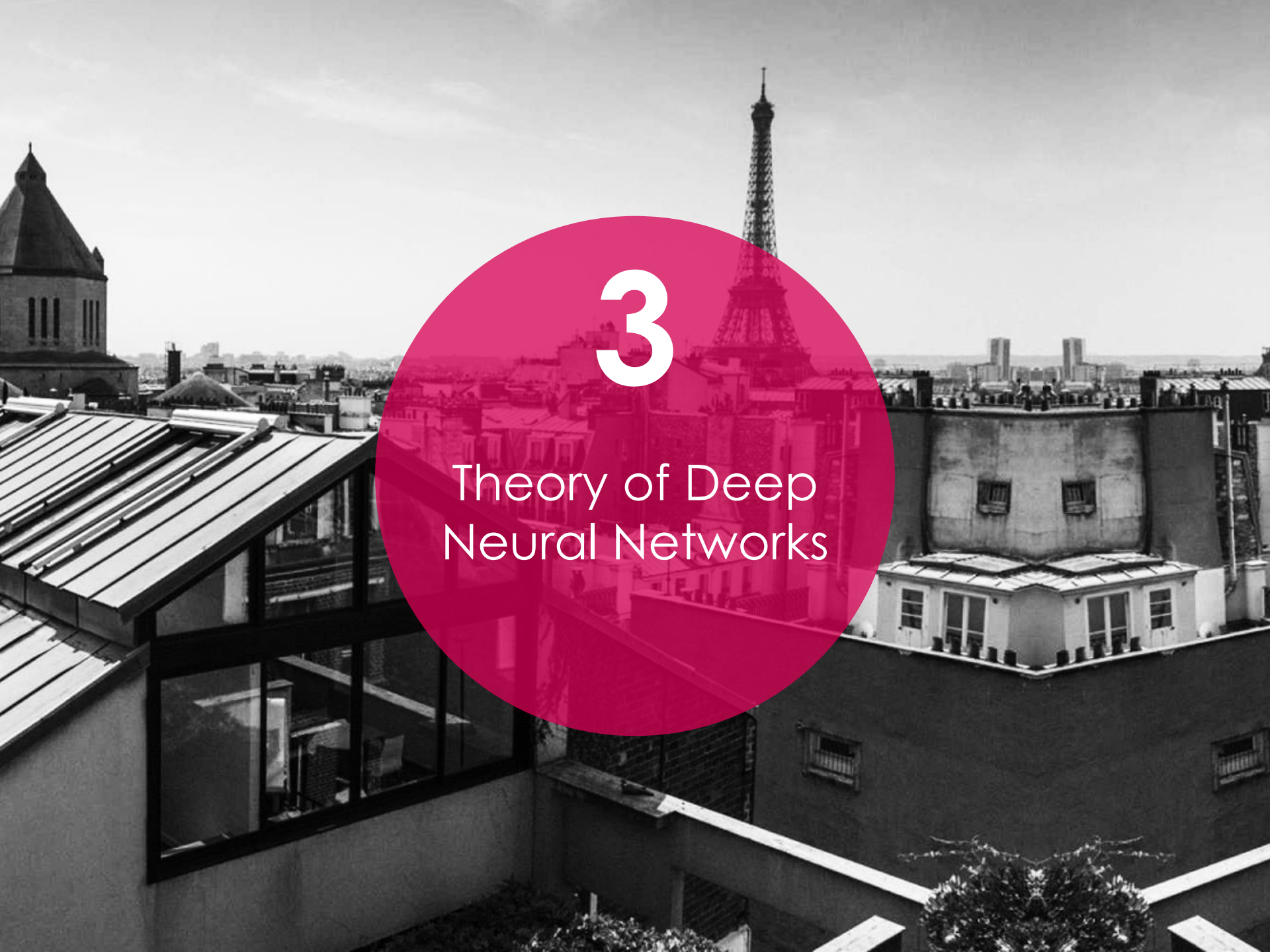
Challenges motivating Deep Learning

To summarize so far …

- Deep learning is motivated by its ability to
  - Learn in high-dimensional spaces
  - Learn very compicated functions efficiently and still be able to generalize well
  - Allow manifold learning

    ➔ Solve core AI issues

- We've seen:
  - Basic reminders of ML
  - Reasons to interest in DL



3

Theory of Deep Neural Networks

Deep Forward Neural Networks

Deep Forward Neural Networks

Perceptron

- Simplest neuron possible
- Introduced by *Rosenblatt* in the late 50's
- *« A device that makes decisions by weighting up evidence »*
- Takes input *X*, transformes it and fires a binary output (0 or 1)

Deep Forward Neural Networks

Perceptron

What does it mean in maths ?

- Let's consider:
  - Inputs $X\ (x_1,\ x_2,\ x_3, \dots, x_n)$
  - Binary output $f(x)$
  - Set of weights $W(w_1,\ w_2,\ w_3, \dots, w_n)$
  - Bias b

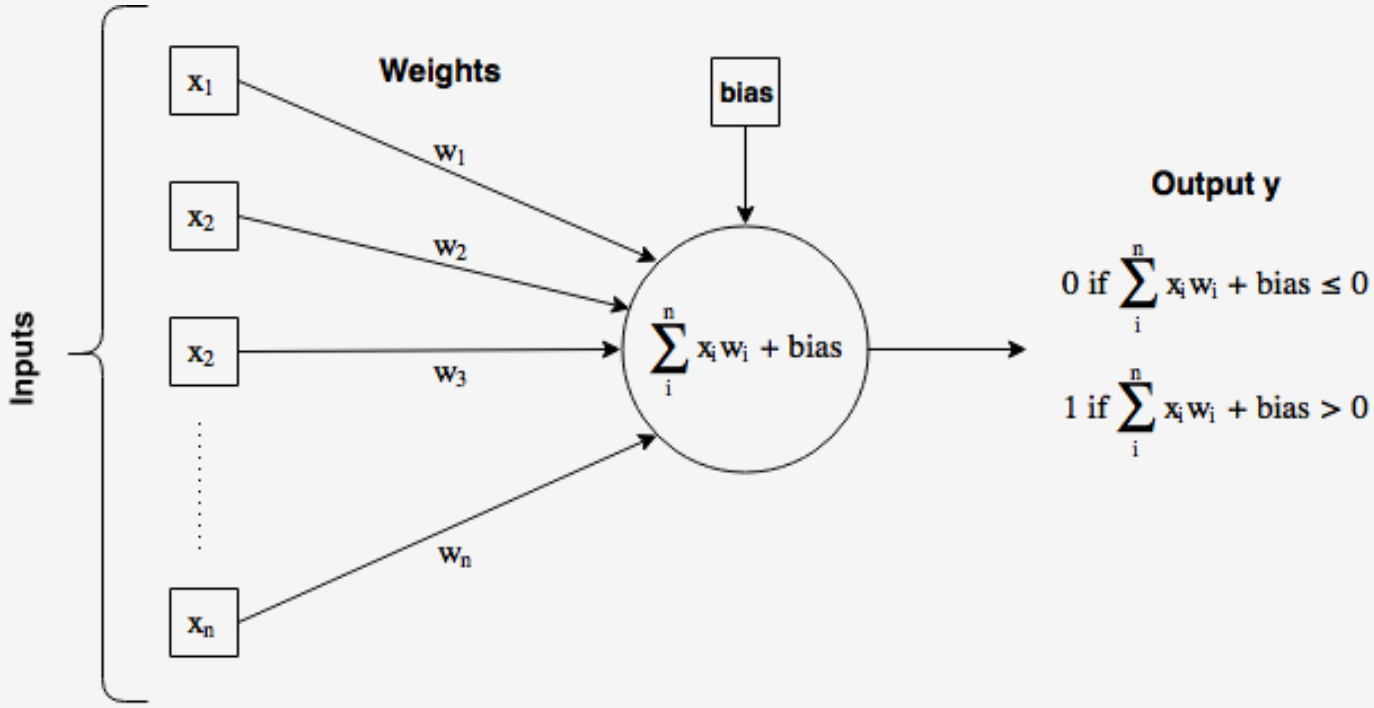
- The perceptron can be expressed:

$$f(x) = \begin{cases} 0\ if \sum_{i=1}^{n} x_i w_i + b \ \leq 0 \\ 1\ if \sum_{i=1}^{n} x_i w_i + b > 0 \end{cases}$$

Deep Forward Neural Networks

Perceptron

Flow of information in a perceptron with weights W and bias b



Deep Forward Neural Networks

Perceptron

- A perceptron fires only binary outputs
- How can we get continuous outputs ?

Deep Forward Neural Networks

Neuron with activation

- **Activation** term σ
- such as

$$f(x) = \sigma\left(\sum_{i=1}^{n} x_i w_i + b\right)$$

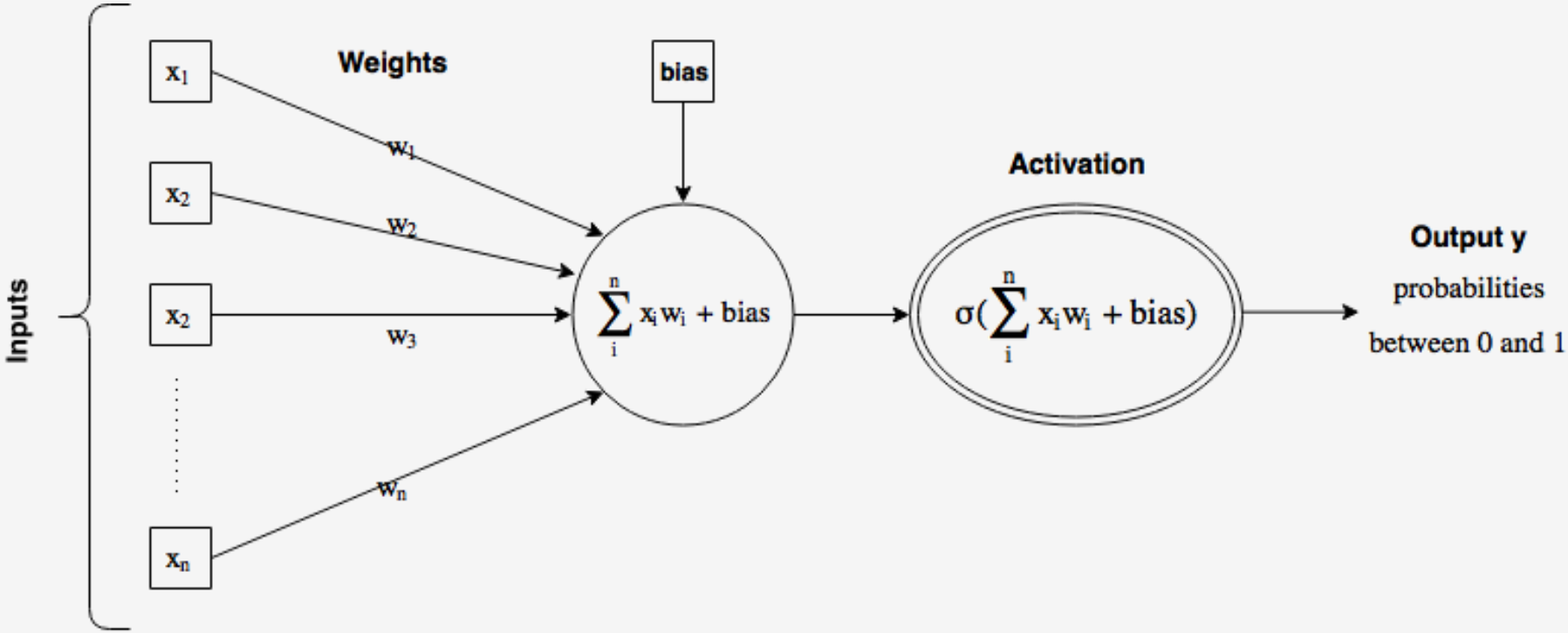
- Sigmoid activation function (i.e. logit) ➔ famous

$$\sigma\left(\sum_{i=1}^{n} x_i w_i + b\right) = \frac{1}{1 + e^{-\sum_{i=1}^{n} x_i w_i + b}}$$

Deep Forward Neural Networks

Neuron with activation

Flow of information in a neuron with activation



Deep Forward Neural Networks

Neuron with activation

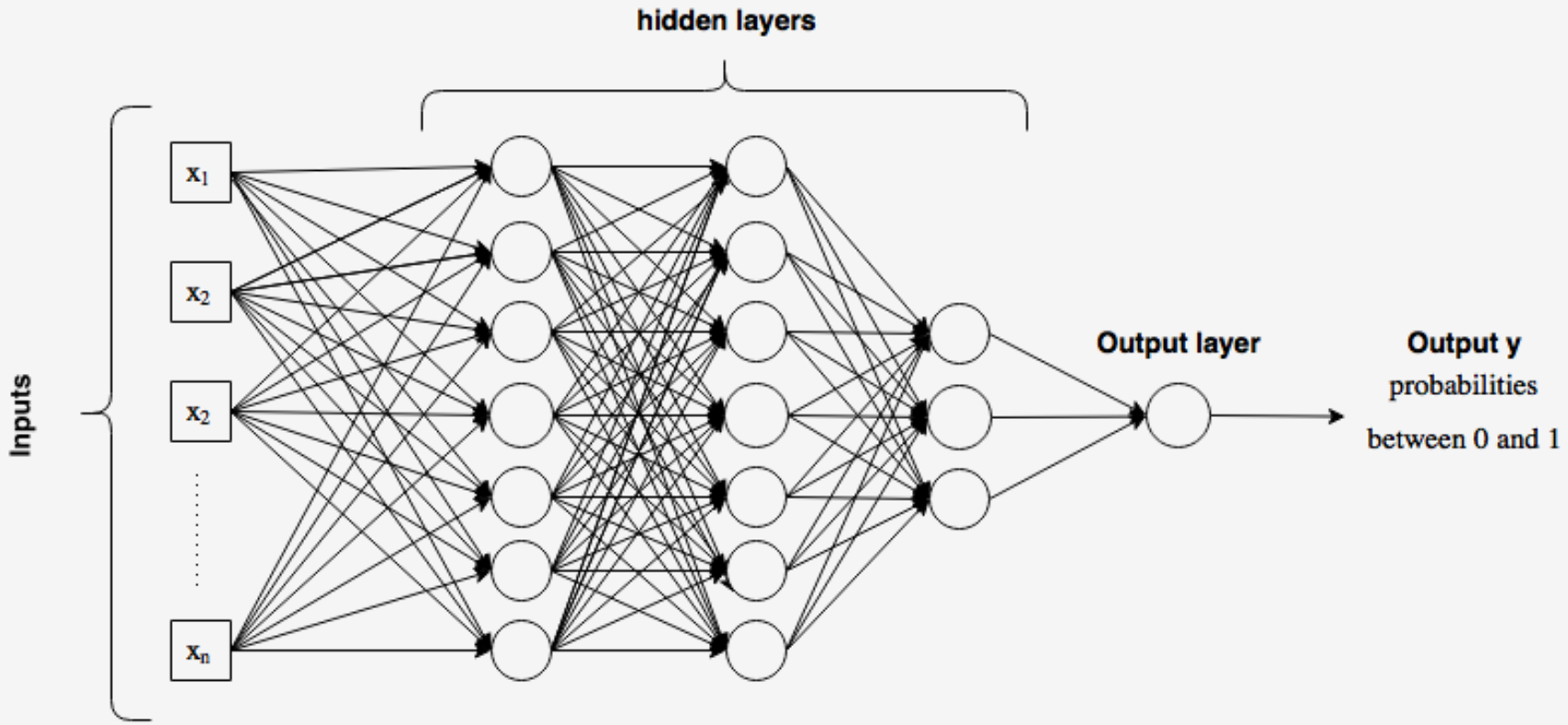
A single neuron might not be the strongest model of decision making

...

However, a set of neurons constituting together a sufficiently complex network could make sophisticated decisions

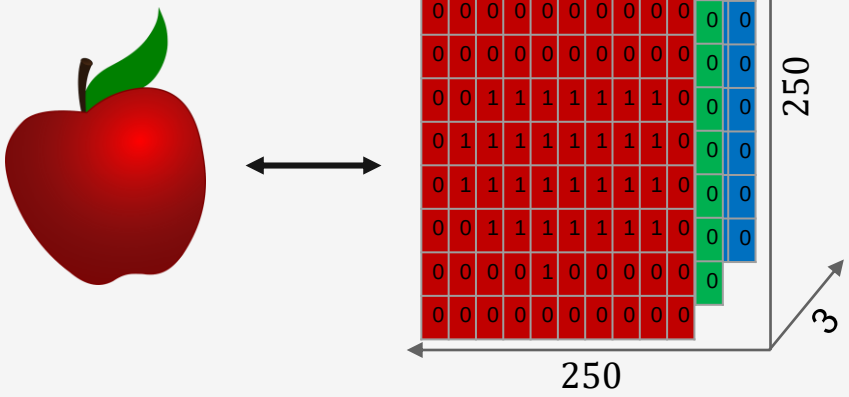
Deep Forward Neural Networks

Multilayer Perceptron



Deep Forward Neural Networks

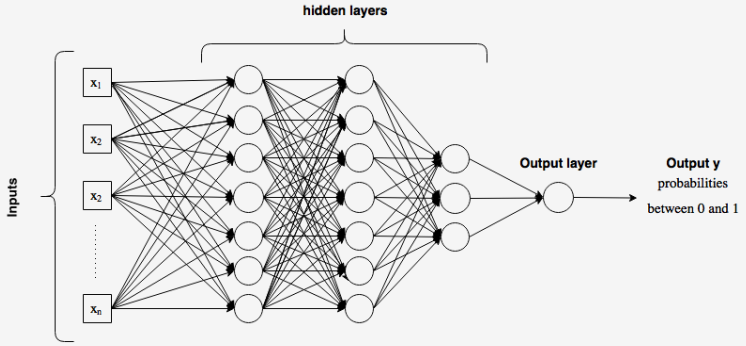
Multilayer Perceptron



Reshape/flatten:

$$250 * 250 * 3 = 187\,500$$

Vector of dimension 187500 as input



MLP can process the flattened image if it is complex enough ...

Deep Forward Neural Networks

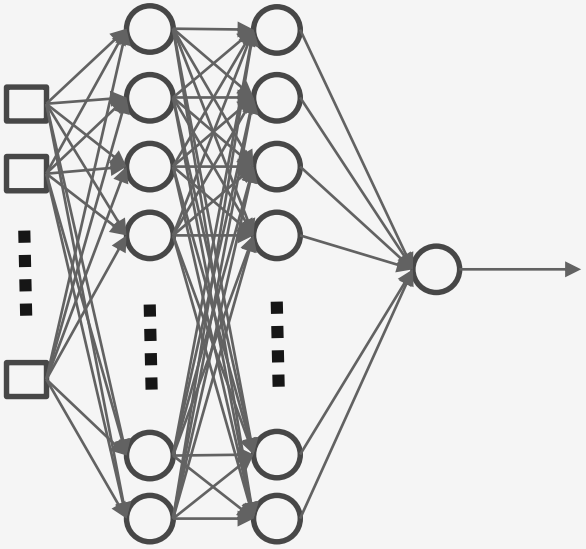
Multilayer Perceptron - design

If it is complex enough ?!

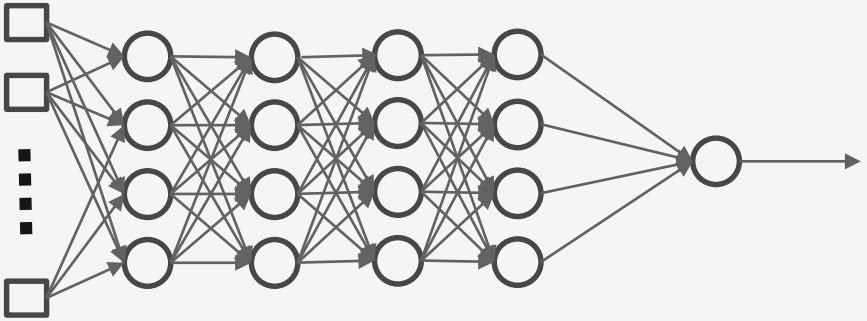
…

How to make it ‘more’ complex ?

More neurons per layer



More layers



Deep Forward Neural Networks

Multilayer Perceptron – complexity, overfitting and underfitting

Be careful !!

If **too complex**
…
if too many layers,
too many neurons

Risk of **overfitting**

If **not sufficiently complex**
…
too few layers,
too few neurons

Risk of **underfitting**

Deep Forward Neural Networks

Universal approximation theorem

Feedforward networks (such as MLP) allow the learning of highly non-linear function.

"According to the **universal approximation theorem** (Hornik et al. (1989)) any feedforward network with a linear output layer and at least one hidden layer with any “squashing” activation function (such as the logistic sigmoid activation function) **can approximate any Borel measurable function** from one finite-dimensional space to another with any desired non-zero amount of error, **provided that the network is given enough hidden units**"

Deep Forward Neural Networks

Universal approximation theorem

- The learning process is critical as it can fail because:
  - Underfitting ➔ unable to find the optimal parameters
  - Overfitting ➔ the algorithm chooses the wrong function
- Can lead to bad accuracy and bad generalization

Deep Forward Neural Networks

Limitations of Multilayer Perceptron

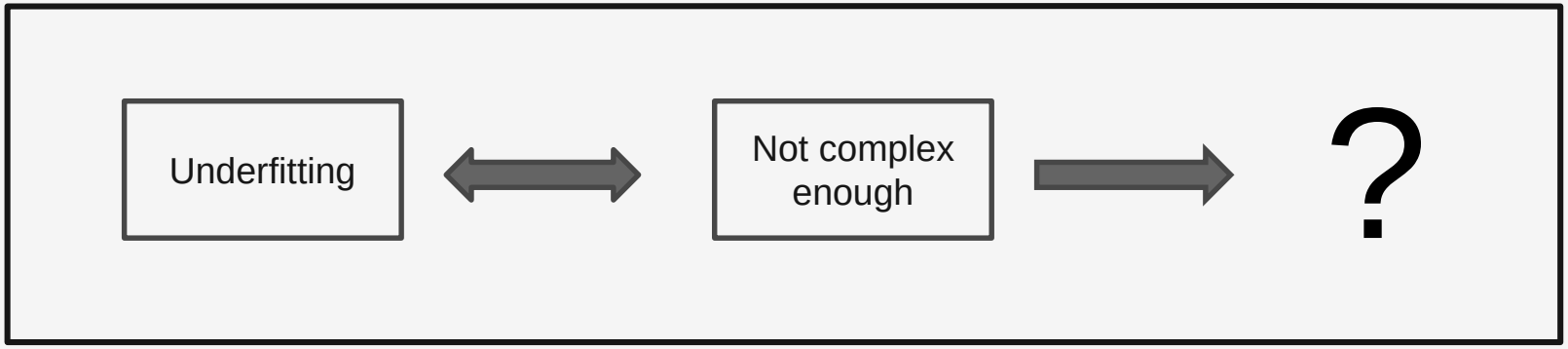
The overparametrized model has 3 main inconvenient:

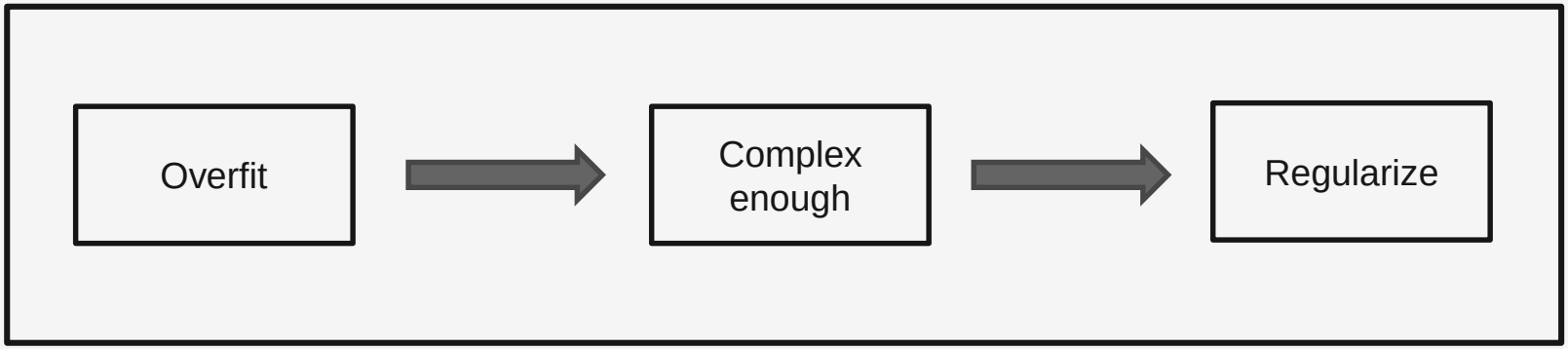
- **Non-convex and unstable loss function**
  more than one local minima possible – random weight initialization can lead to different accuracy
- **Overfitting**
- **Sensitivity to feature scaling**
  between 0 and 1

Regularization for DL

Regularization for DL

Should we first look to overfit ?

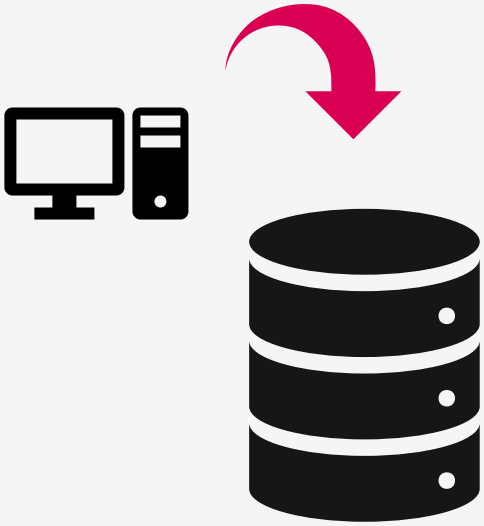




Regularization for DL

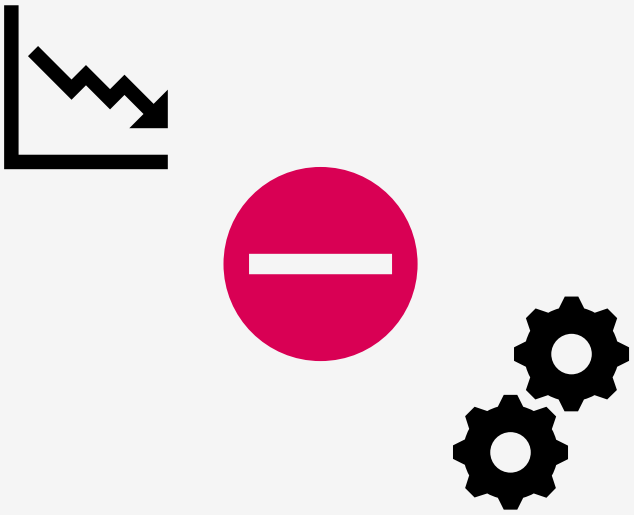
First easy options

Add more data



Not always possible …

Stop the process when validation accuracy drops or stagnates



Regularization for DL

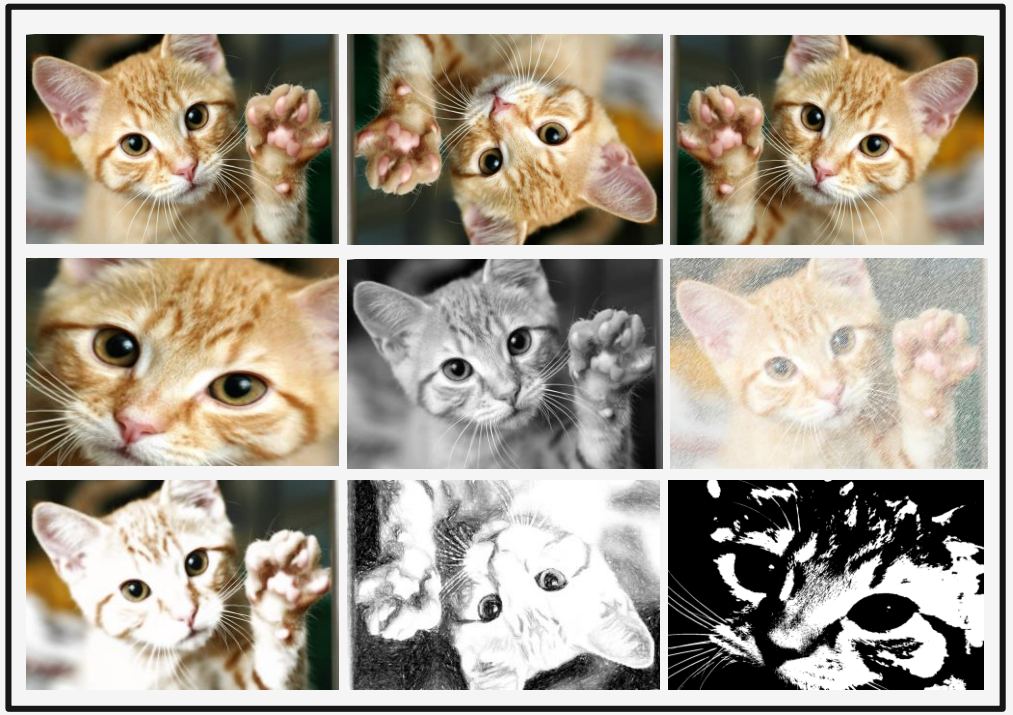
Data Augmentation

Blow artificially your training set !

Initial image

Random transformations

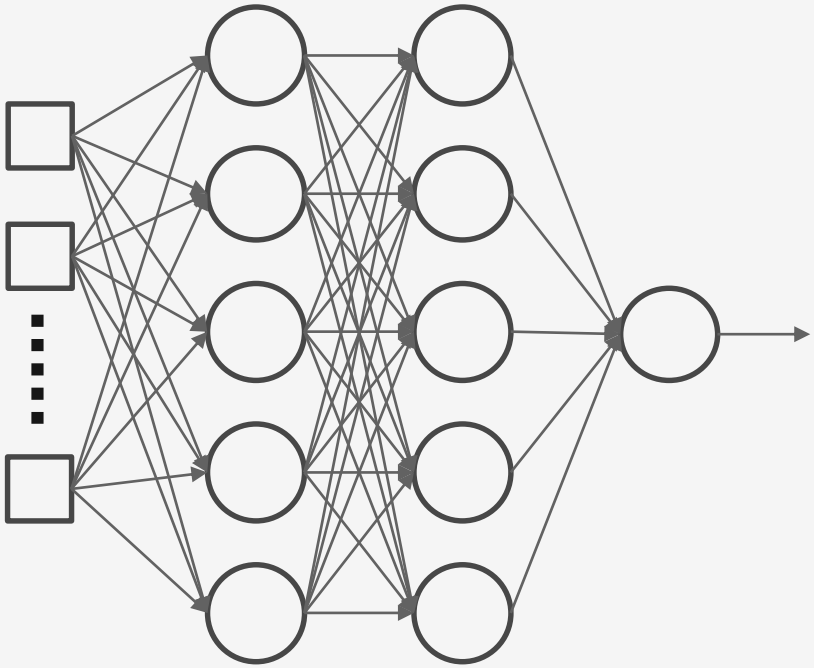
New set of images



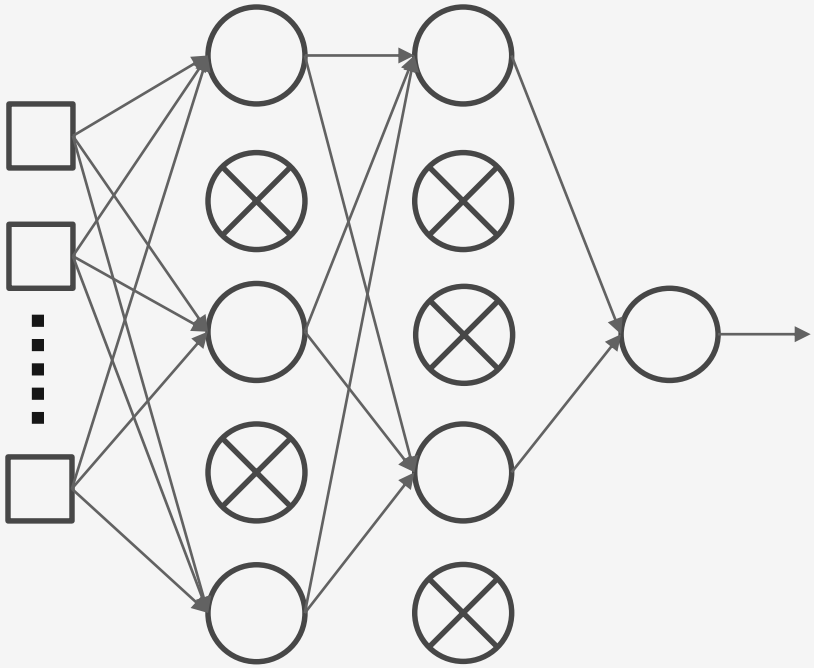
Regularization for DL

Dropout

Overfitting model



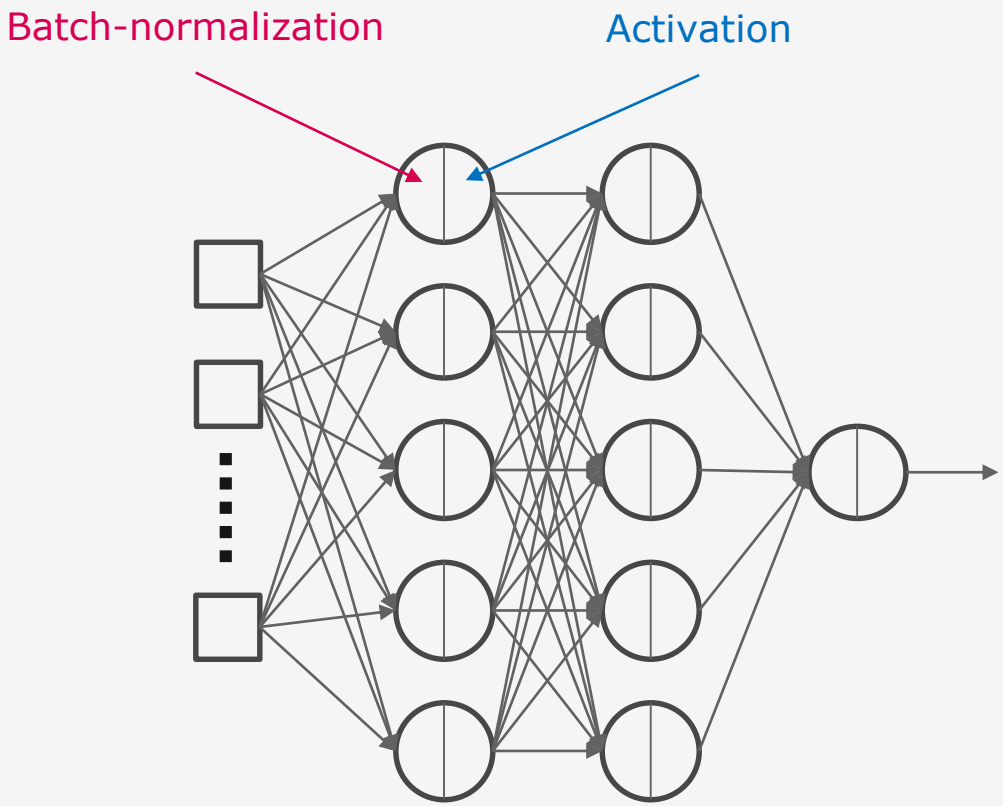
Dropout regularized model



It avoids units too co-adapt too strongly

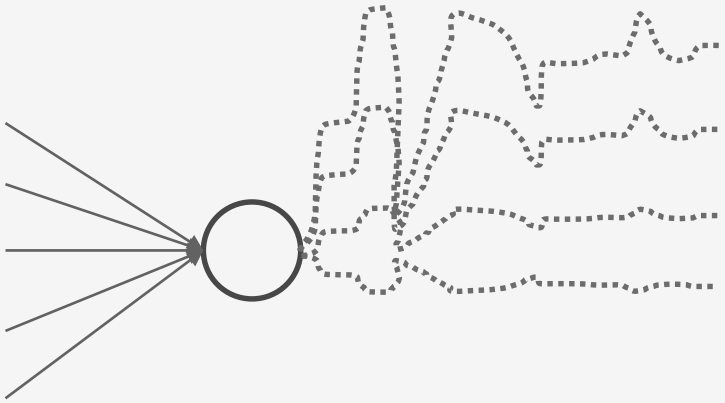
Regularization for DL

Batch-Normalization



Regularization for DL

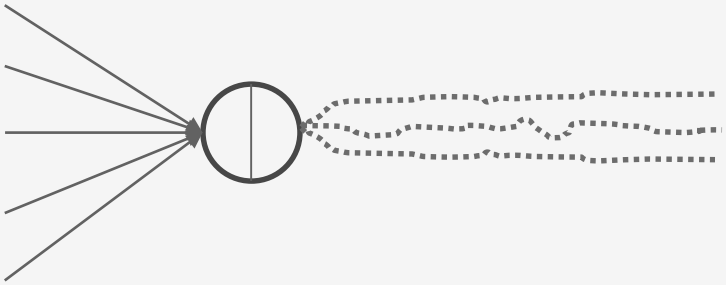
Batch-Normalization



Normal case without BN

- Internal covariance
- Layer's need to adapt to inputs' distribution

➔ Learning requires lower λ ➔ slower process



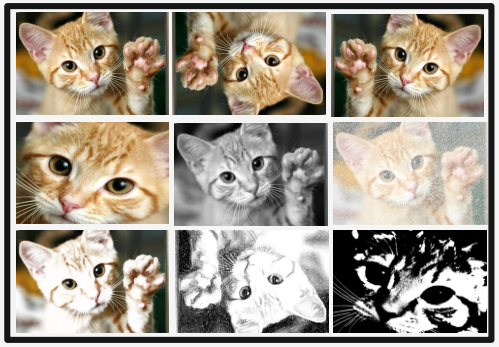
With BN

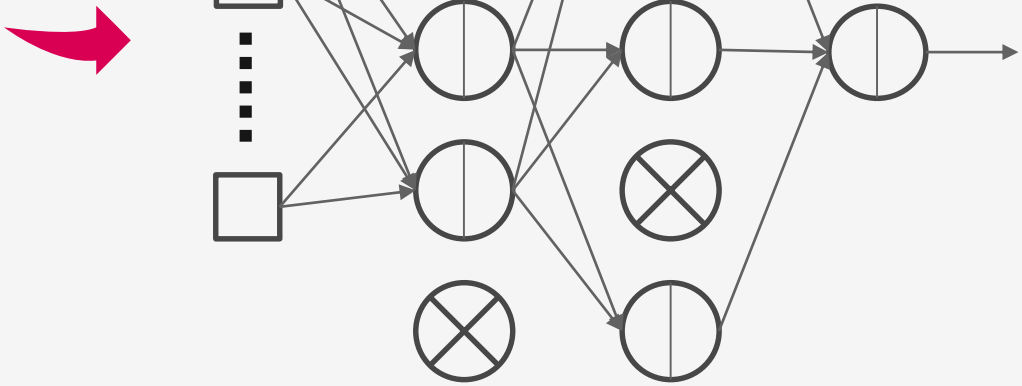
- Initially treats the internal covariance issue
- Allows higher λ ➔ faster learning process
- It has also proven to significantly reduce overfitting

Regularization for DL

Combine all methods

Data Augmentation + BN + Dropout
It should work !

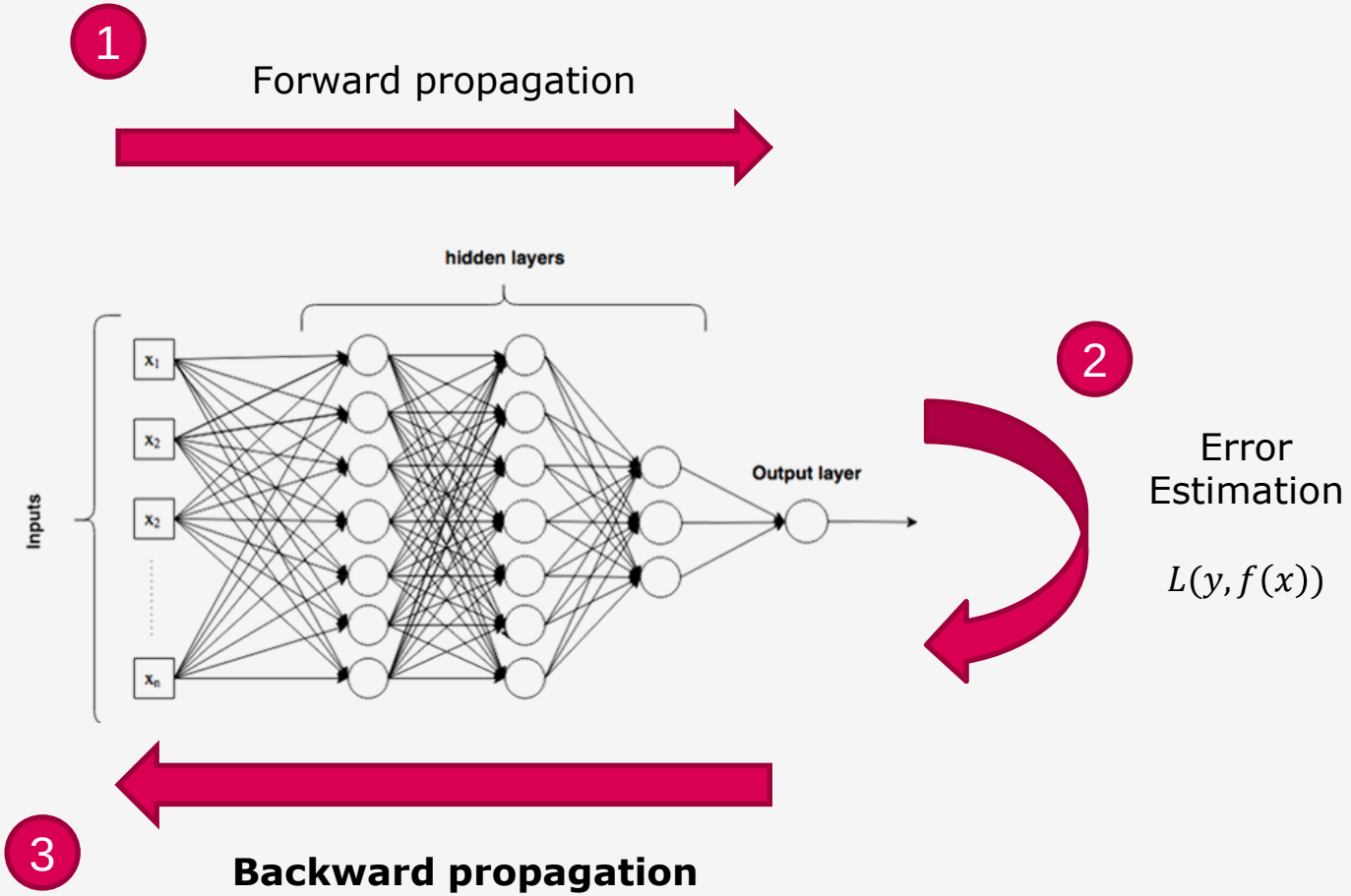




Training Deep Neural Networks

Training Deep Neural Networks

Back-propagation



- **Numerical computation of the gradient**
- **Weight actualization**

Training Deep Neural Networks

Stochastic Gradient Descent

- Recurrent issue in ML: large training set is good for generalization
- Gradient Descent with large datasets is computationally heavy

Stochastic Gradient Descent (SGD) with *mini-batches*

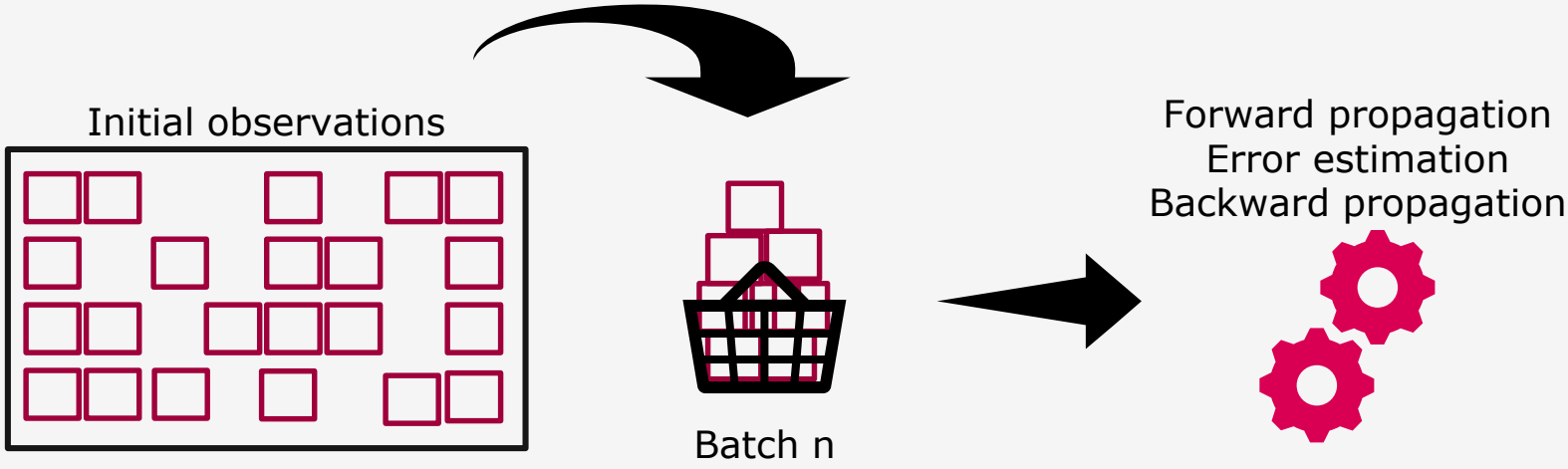
- Update of parameters for each mini-batch *i*

$$\theta_{t+1} = \theta_t - \lambda \nabla_\theta L(\theta_t; x_i; y_i)$$

Training Deep Neural Networks

Stochastic Gradient Descent

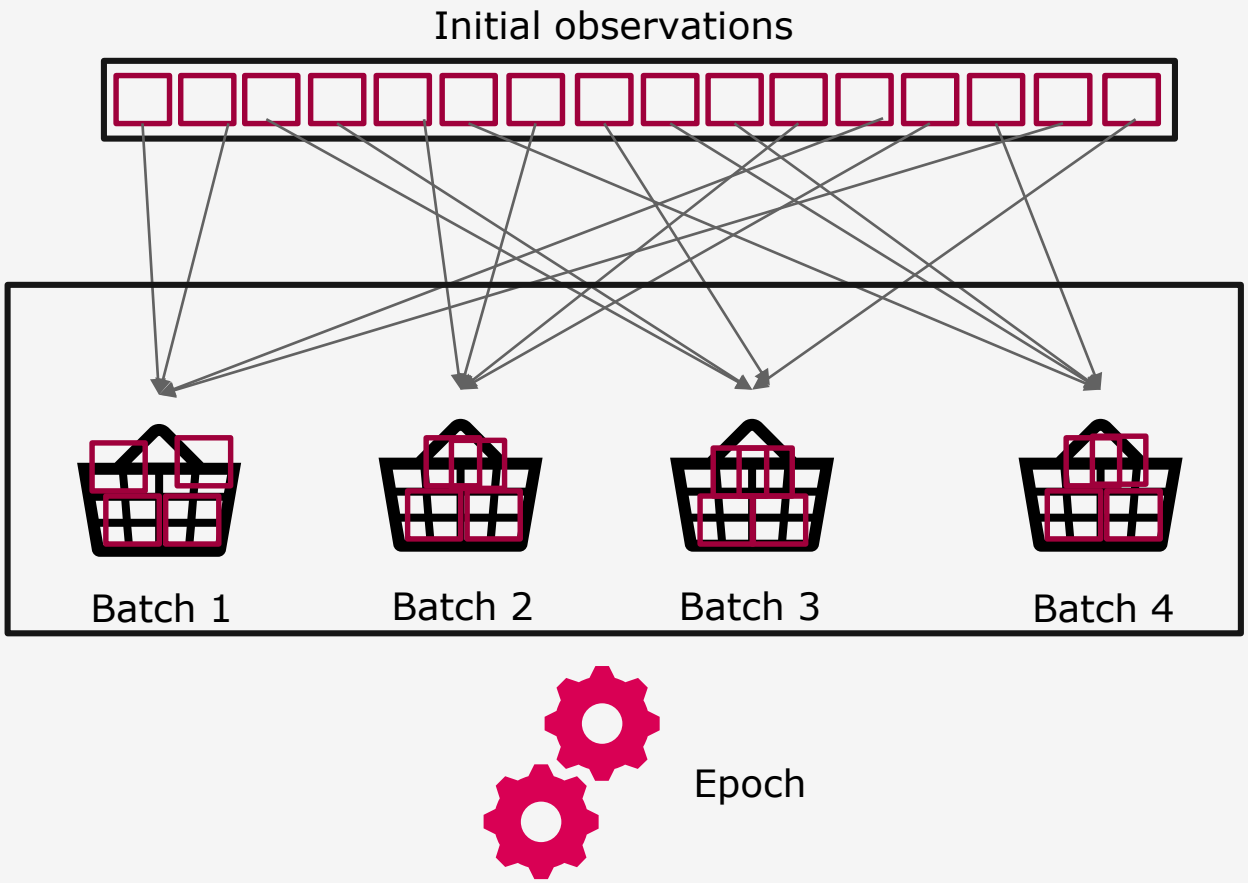
Batch/mini-batch learning



Training Deep Neural Networks

Stochastic Gradient Descent

Constituting an epoch



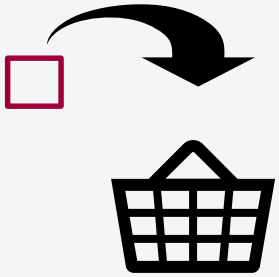
Training Deep Neural Networks

Stochastic Gradient Descent

Which batch size (bs) ?

If batch size too small

- Learning too small
- Regularizing effect expected (generalization error best with bs 1)



If batch size too large

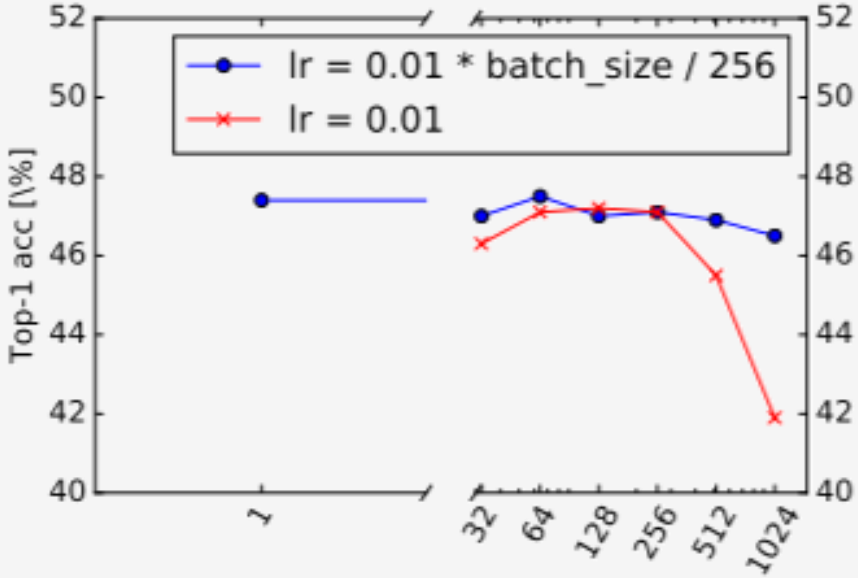
- Large bs ➔ Better estimate of the gradient
- Faster learning
- Too large ➔ degradation of the gen. accuracy

Training Deep Neural Networks

Stochastic Gradient Descent

Which batch size (bs) ?

Batch size and initial learning rate
impact to the accuracy

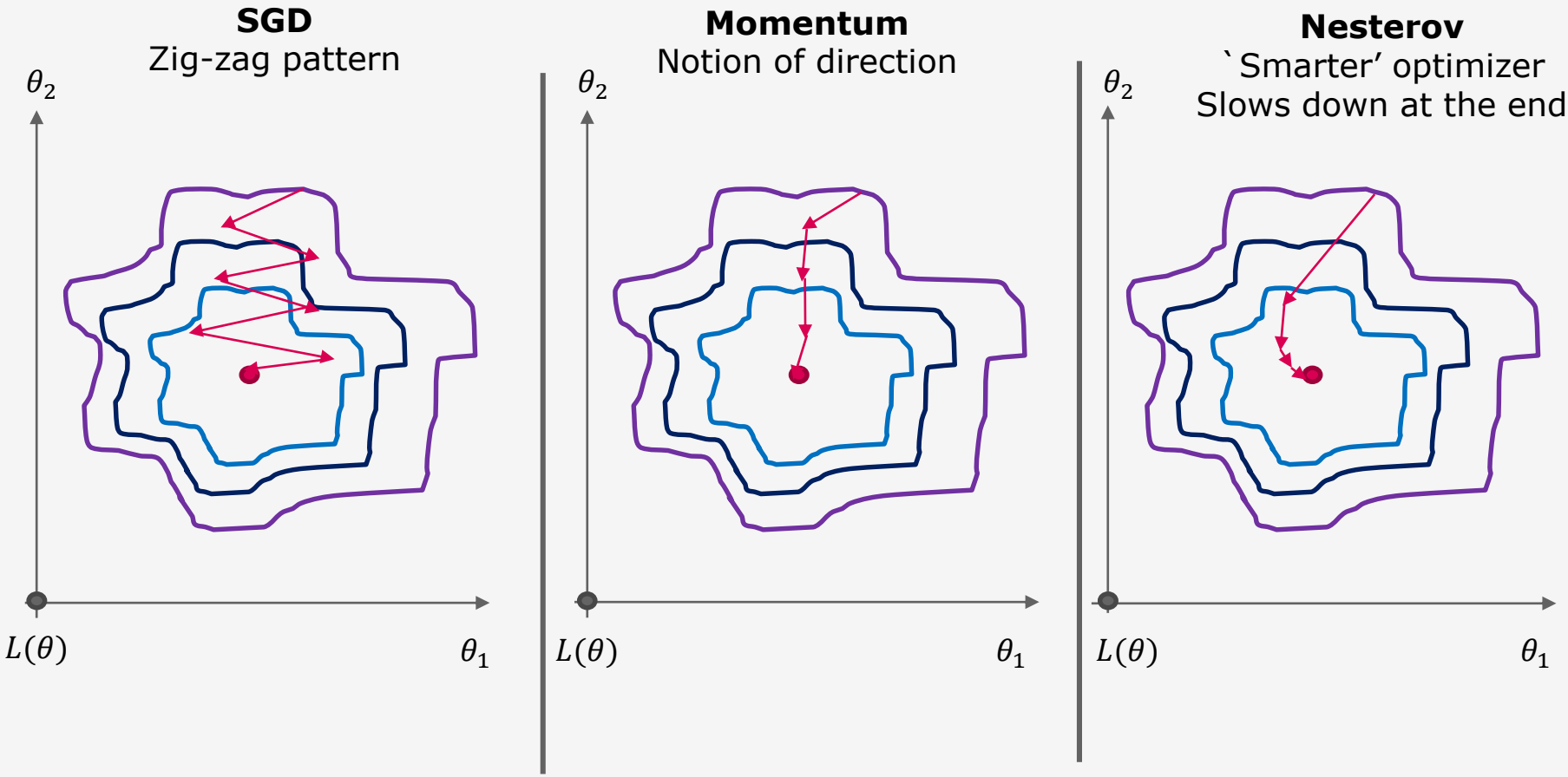


https://arxiv.org/pdf/1606.02228.pdf

Training Deep Neural Networks

Stochastic Gradient Descent

- Stochastic Gradient Descent is a “first order method”
- Such as **Nesterov** and **Momentum**



Training Deep Neural Networks

Adaptive optimizers

- *Second order moment* methods
- They minimize $J(\theta)$ not only by estimating the Gradient but also by estimating the **Hessian matrix** and using the **Newton's method**
- They **adapt the learning rate** λ at each step:

Adagrad, Adadelta, **Adamax**, **RMSprop**, **Adam**

.... For detailed description

Training Deep Neural Networks

Choosing the right optimization algorithm

Adaptive (second order moment)

Adapted for Sparse input data

No tuning Required for λ

Faster convergence

First order moment

Slow convergence

Can get stuck In saddle paths

Too reliant on Robust intialization

Adaptive = best option

In particular Adam

Introducing Keras

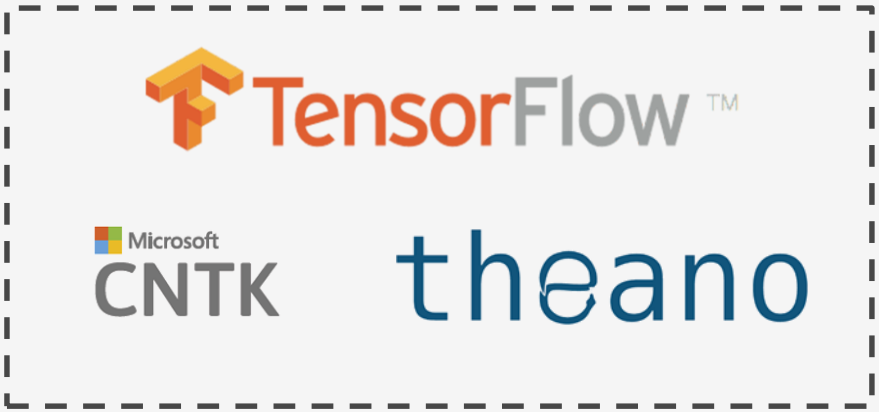
A little bit of practice !

Introducing Keras

Deep Learning specialized library

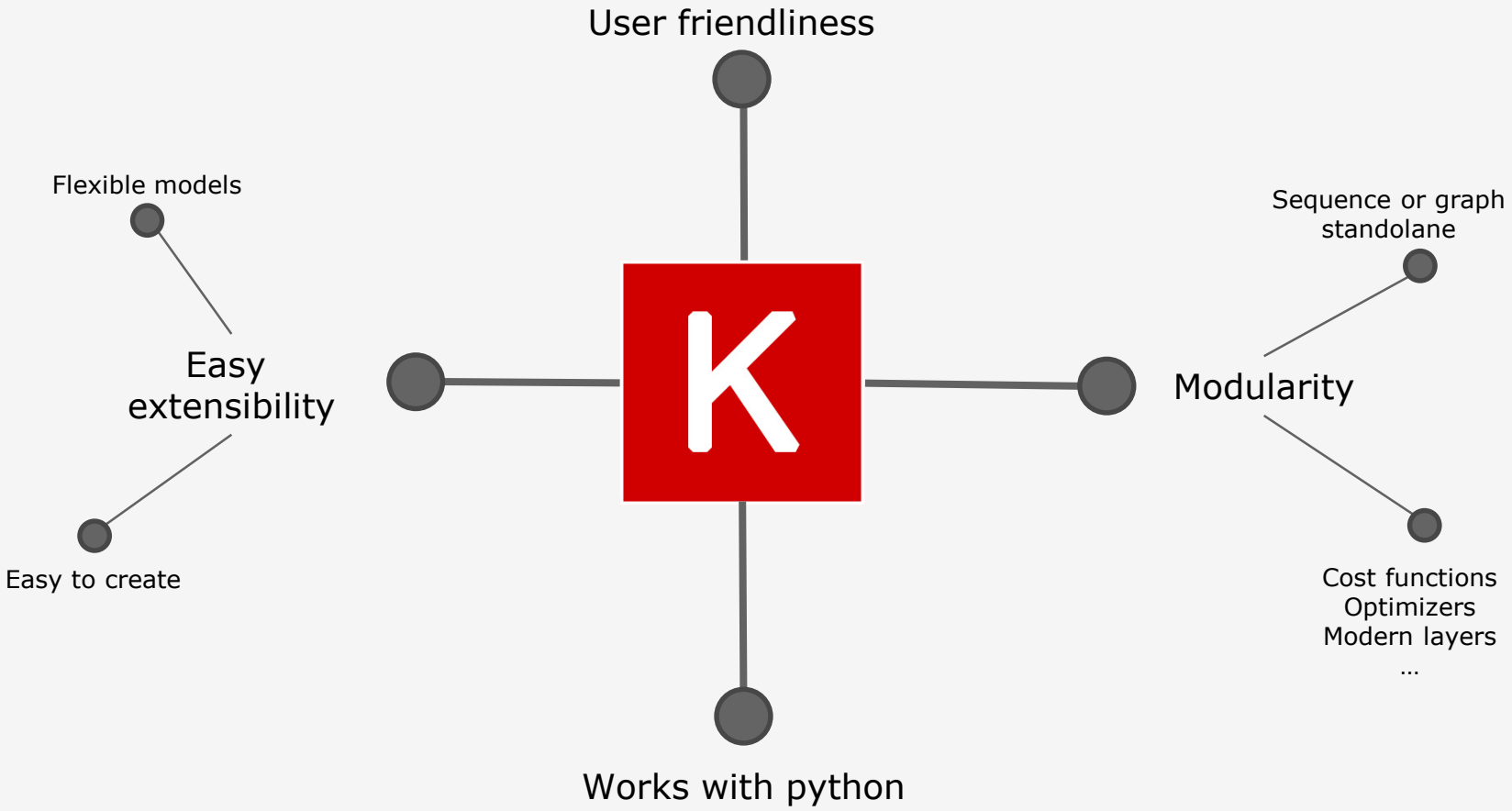
Wrapper designed for fast implementation

On CPU or GPU



https://keras.io/

Introducing Keras



Introducing keras

Design, train and predict

1 – Declare a **Sequential** model

```
import keras
from keras.models import Sequential

model = sequential()
```

2 – Stack all layers

```
from keras.layers import Dense, Activation

model.add(Dense(units=64,input_dim=100))
model.add(Activation('Relu'))
model.add(Dense(units=32))
model.add(Activation('Relu'))
model.add(Dense(units=10))
model.add(Activation('softmax'))
```

3 – Configure its learning process

```
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

4.A – Fit your model – automatic batch

```
model.fit(x_train, y_train,
          epochs=10,
          batch_size=32)
```

4.B – Or fit on your own batch

```
model.train_on_batch(x_batch,y_batch)
```

5 – Evaluate on your validation set

```
loss_metrics = model.evaluate(X_val, y_val,
                              batch_size=32)
```

6 – Make your own predictions

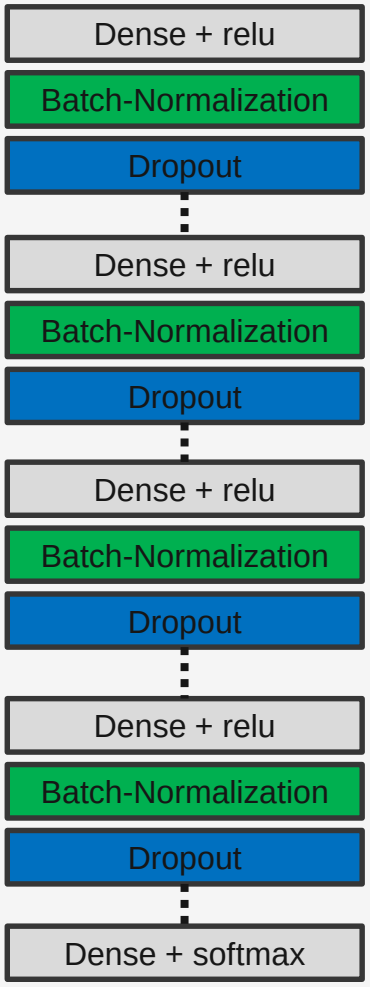
```
preds = model.predict(x_test,
                      batch_size=32)
```

Introducing keras

Data augmentation, Dropout, Batch-Normalization

A - Dropout and Normalization

```
from keras.layers import Dense, Dropout
from keras.layers.normalization import BatchNormalization

model.add(Dense(units=128,input_dim=100, activation='Relu'))
model.add(BatchNormalization())
model.add(Dropout(0.25))

model.add(Dense(units=128, activation='Relu'))
model.add(BatchNormalization())
model.add(Dropout(0.25))

model.add(Dense(units=64, activation='Relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

model.add(Dense(units=64, activation='Relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

model.add(Dense(units=10, activation='softmax'))
```



Introducing keras

Data augmentation, Dropout, Batch-Normalization

B – Data Augmentation

1 – Declare all possible transformations

```
from keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(rescale=1./255,
                    shear_range=0.2,
                    zoom_range=0.2,
                    horizontal_flip=True)

test_datagen = ImageDataGenerator(rescale=1./255)
```

2 – Generate batches (flow from directory)

```
train_generator = train_datagen.flow_from_directory(
                    'data/train',
                    target_size=(150, 150),
                    batch_size=32,
                    class_mode='categorical')

validation_generator = test_datagen.flow_from_directory(
                    'data/validation',
                    target_size=(150, 150),
                    batch_size=32,
                    class_mode='categorical')
```

3 – Fit on these generated batches

```
model.fit_generator( train_generator,
                    steps_per_epoch=2000,
                    epochs=50,
                    validation_data=validation_generator,
                    validation_steps=800)
```

4 – predict on the test set

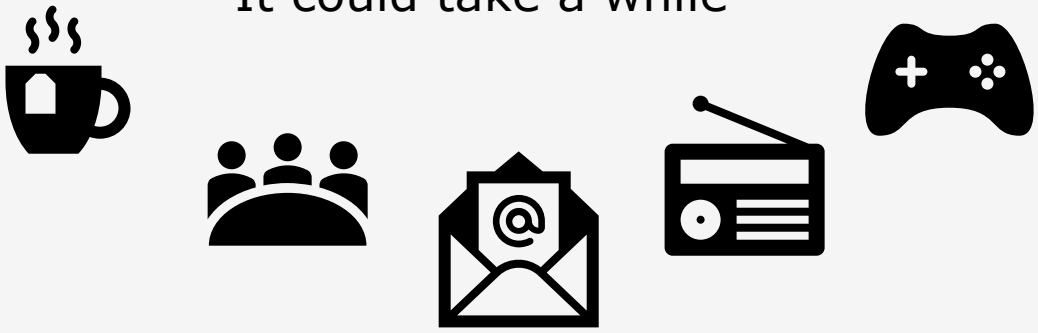
```
test_generator = test_datagen.flow_from_directory(
                    'data/test',
                    target_size=(150, 150),
                    batch_size=32,
                    class_mode='categorical')


model.predict_generator( test_generator,
                    steps=total_size/batch_size)
```

Introducing keras

Design, train and predict

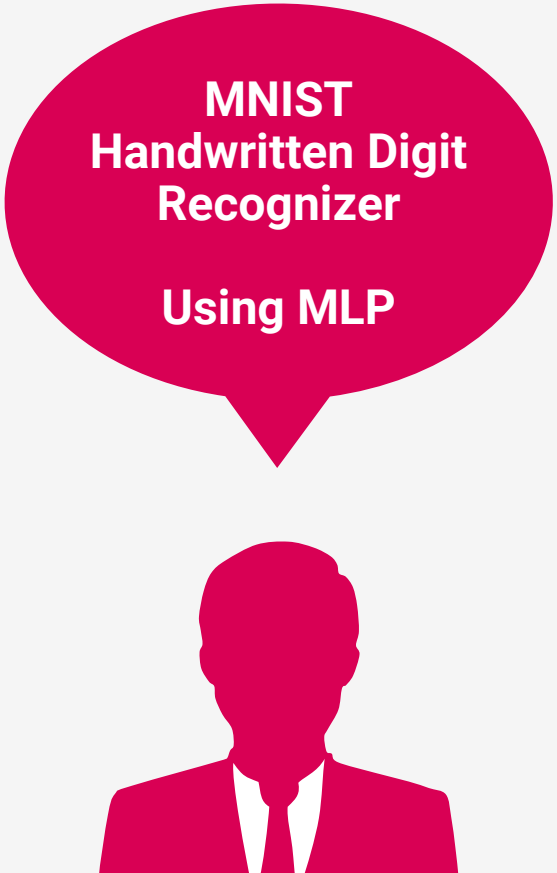
Quiet easy right ?!?

Just need to wait the
model to run !
....
It could take a while



Study case n°1

Design, train and predict

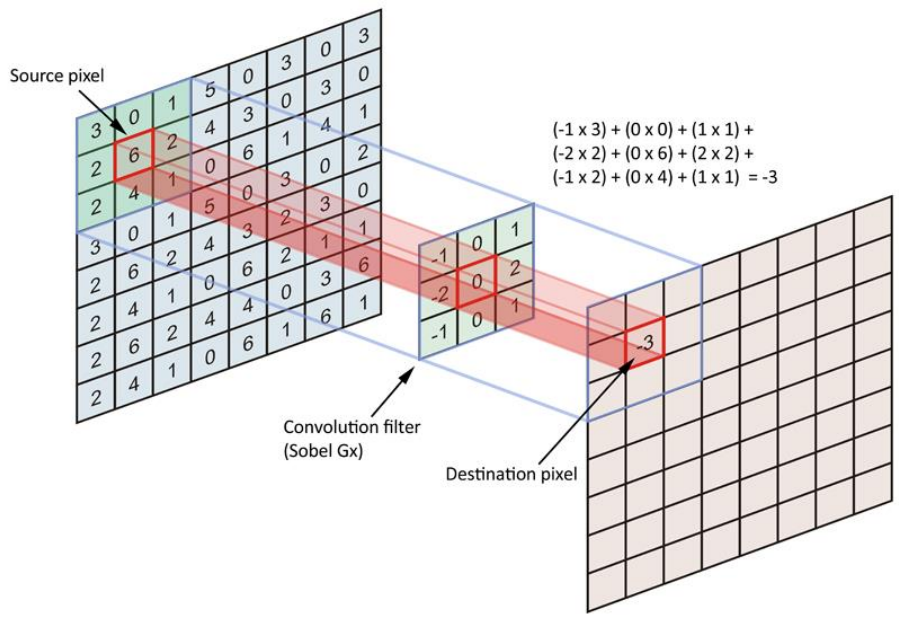


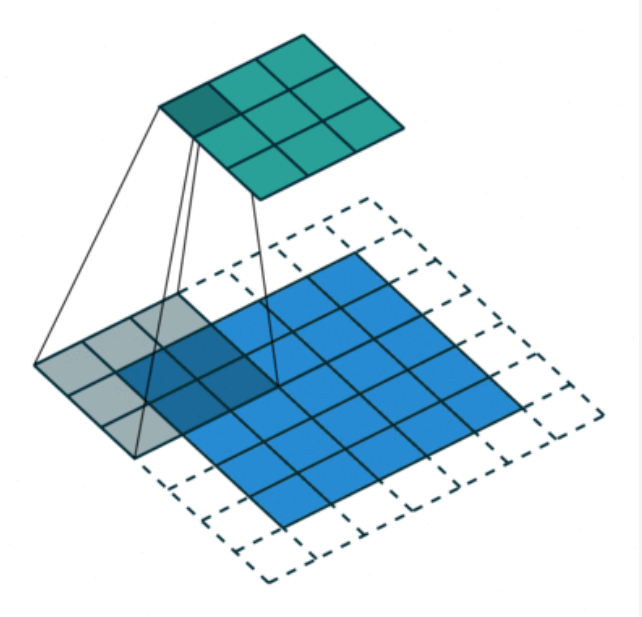
Convolutional Neural Networks

Convolutional Neural Networks

Convolution as core mechanism of CNNs

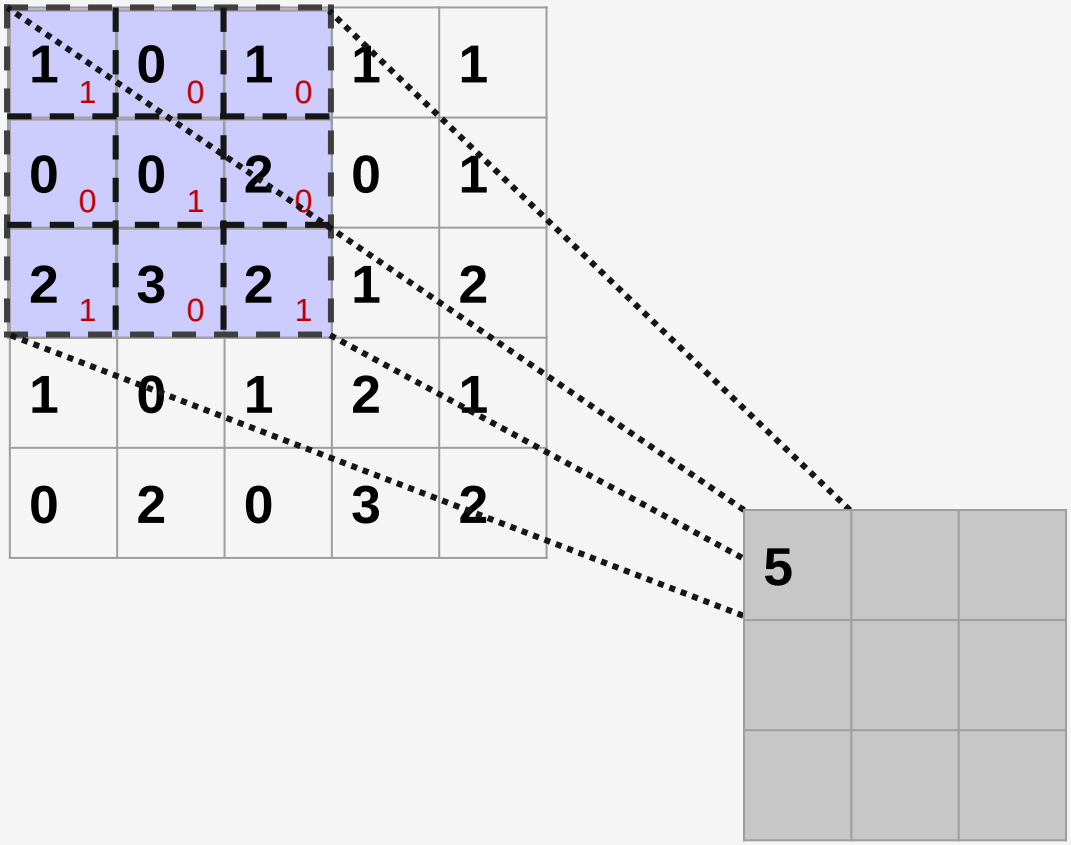
Convolution ≡ Cross-Correlation





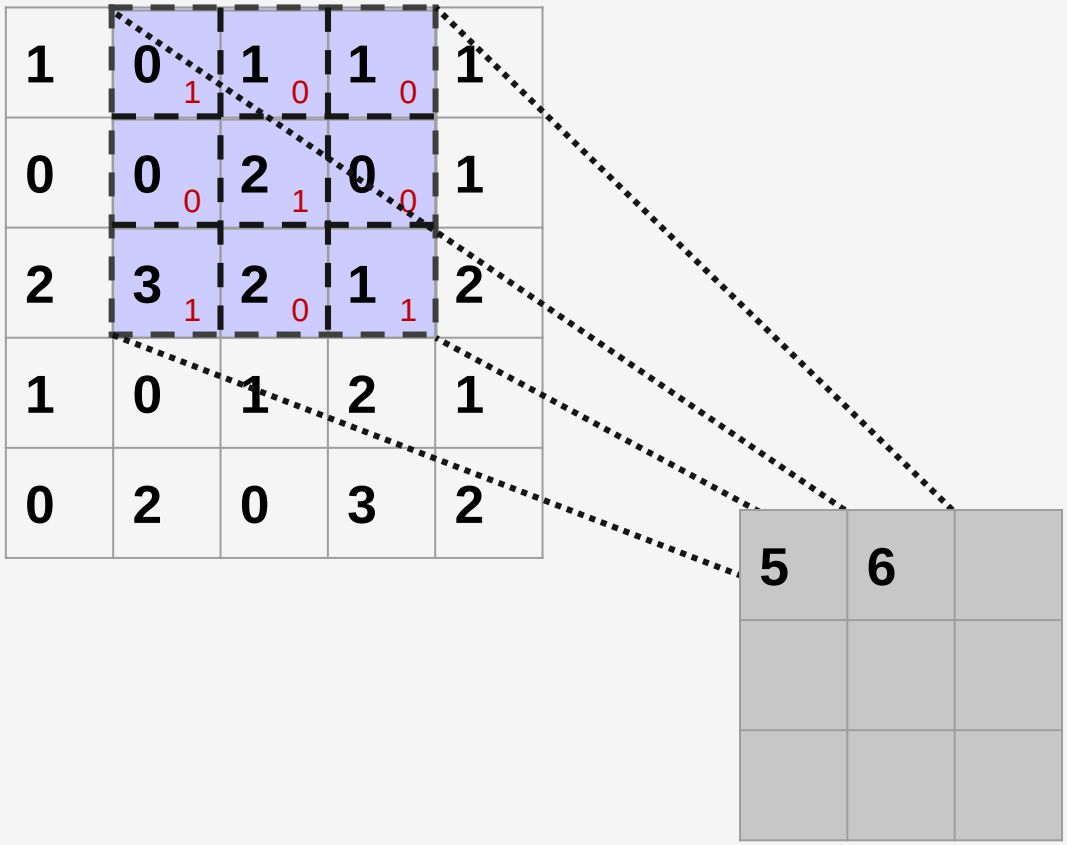
Convolutional Neural Networks

Convolution as core mechanism of CNNs



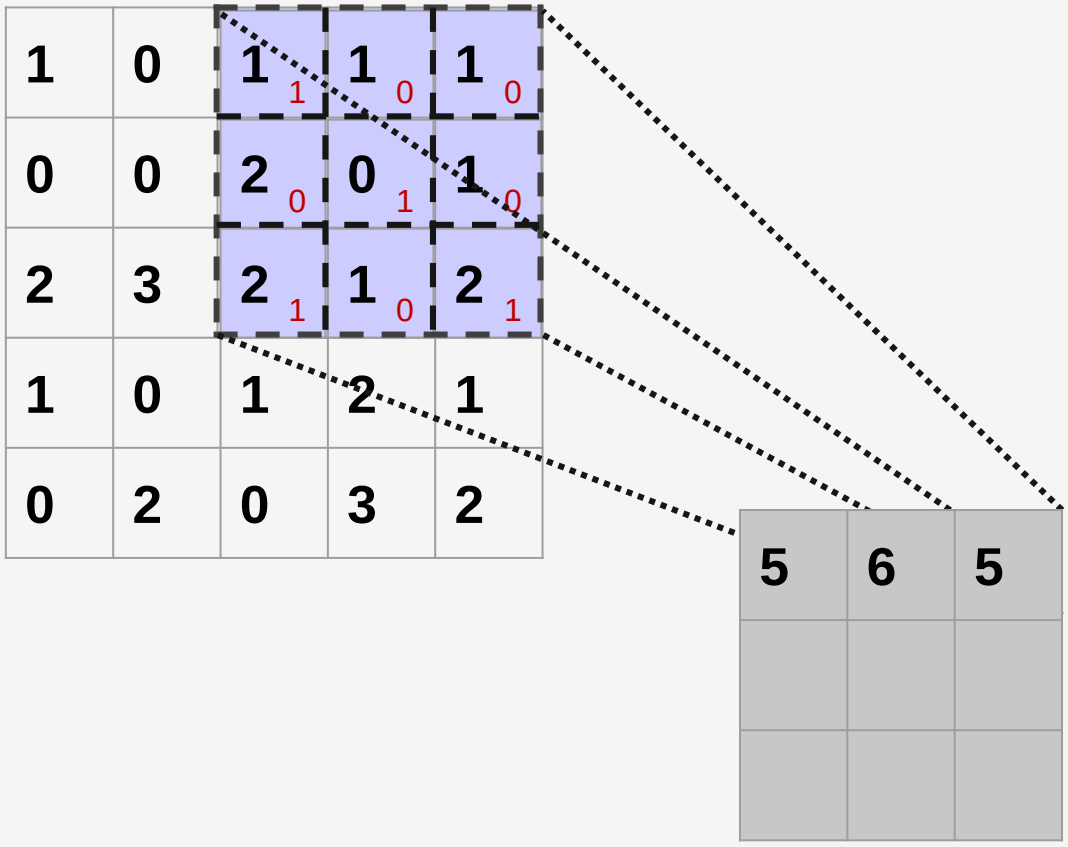
Convolutional Neural Networks

Convolution as core mechanism of CNNs



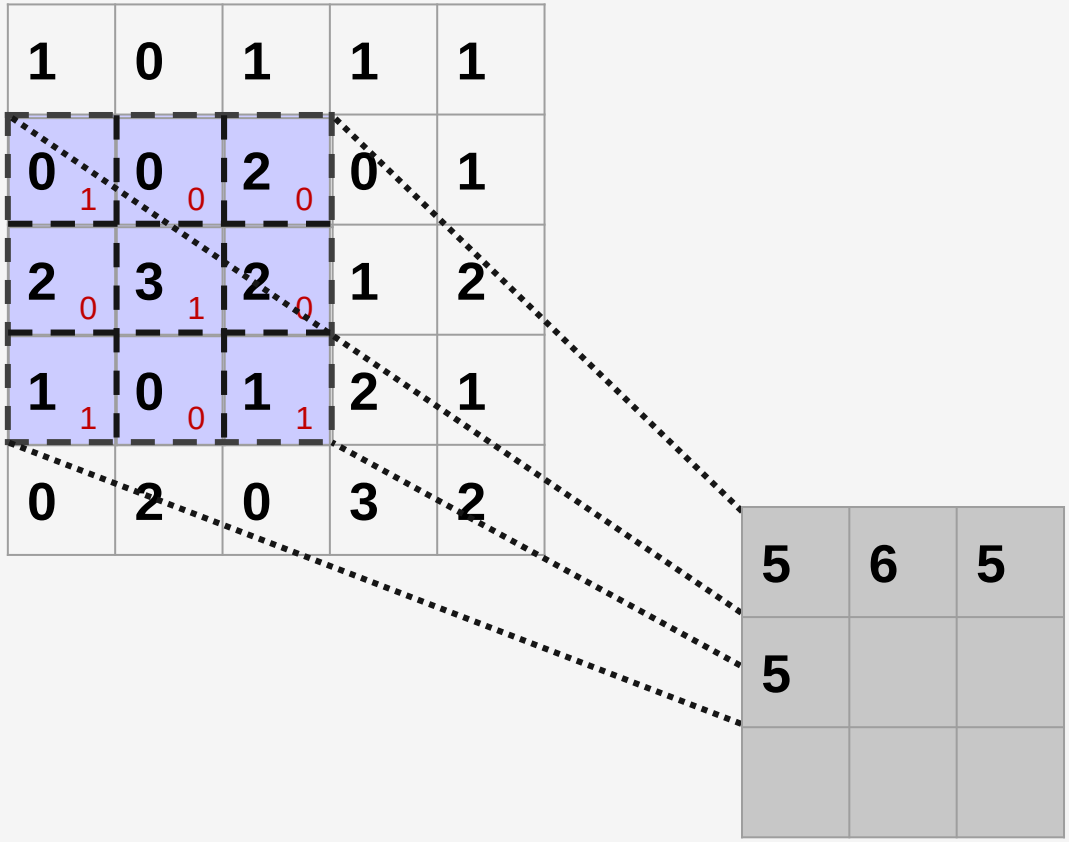
Convolutional Neural Networks

Convolution as core mechanism of CNNs



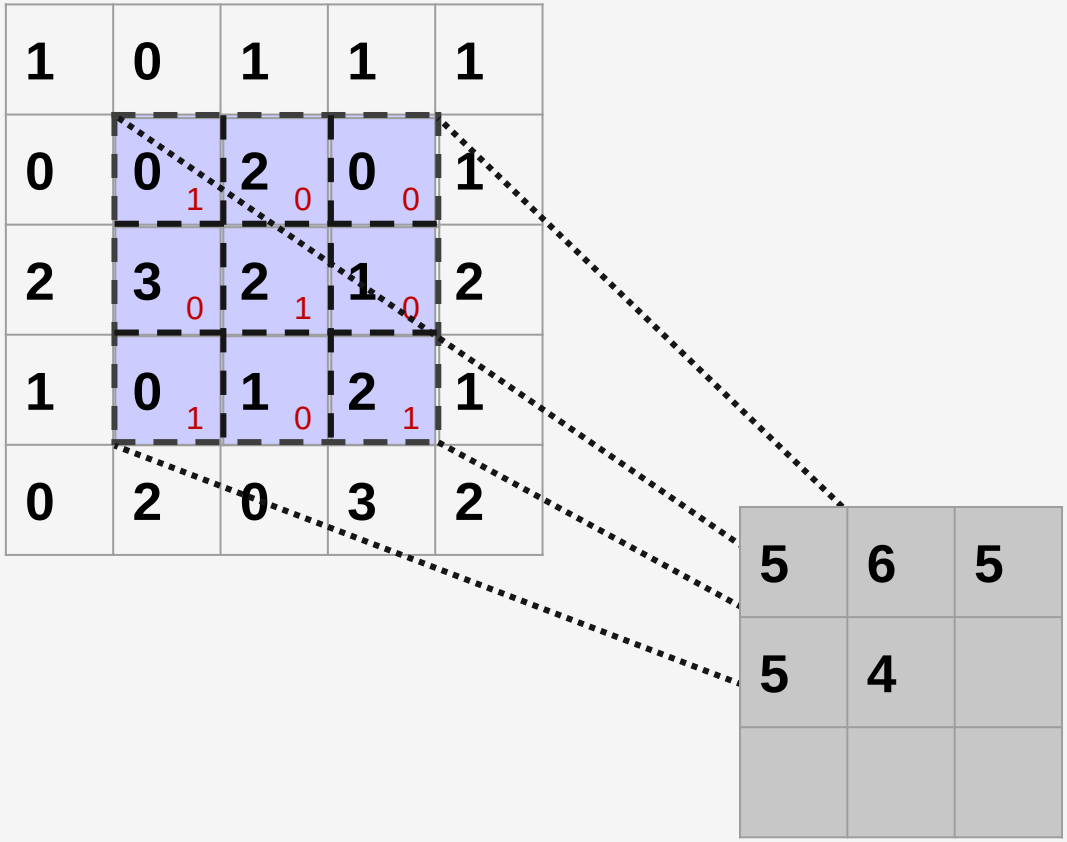
Convolutional Neural Networks

Convolution as core mechanism of CNNs



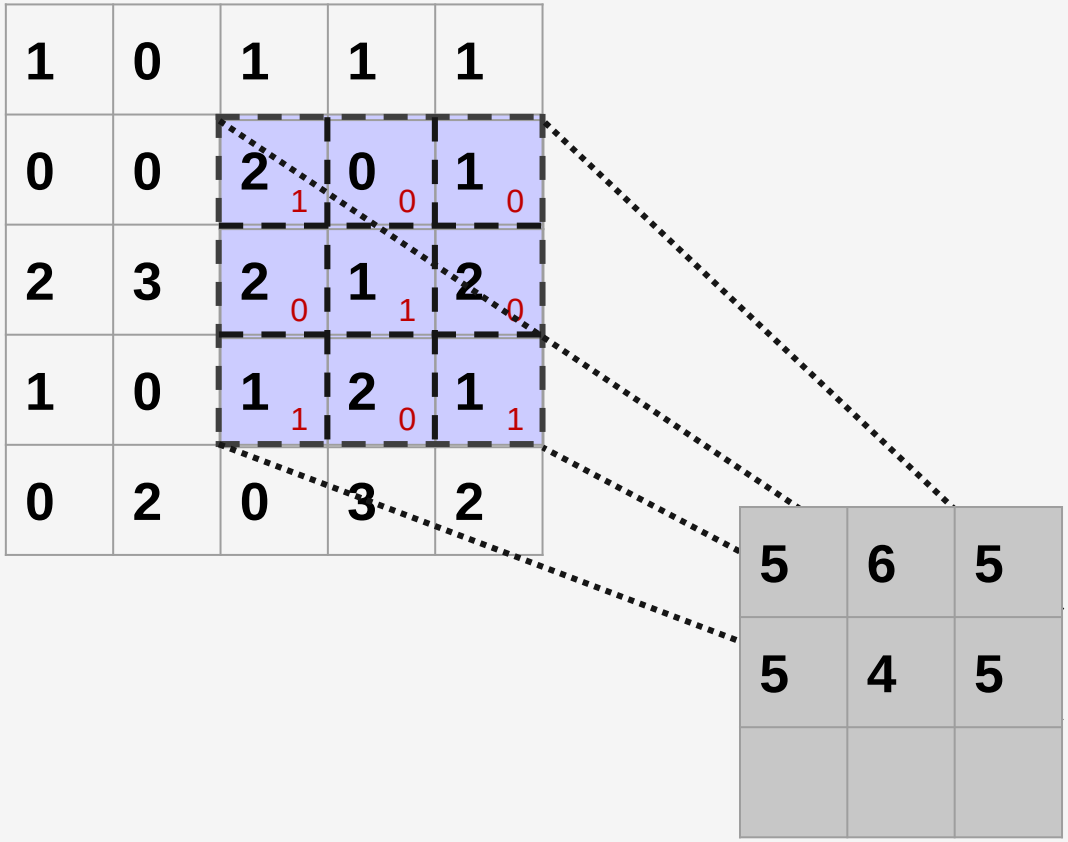
Convolutional Neural Networks

Convolution as core mechanism of CNNs



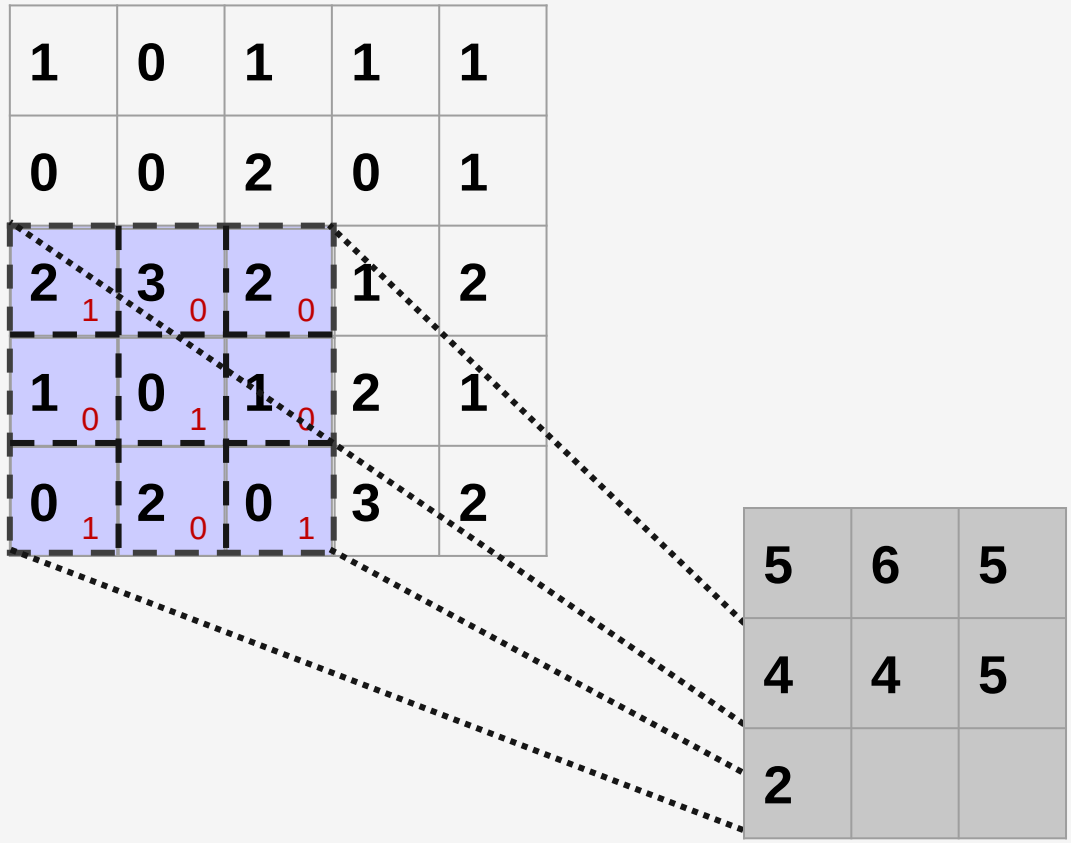
Convolutional Neural Networks

Convolution as core mechanism of CNNs



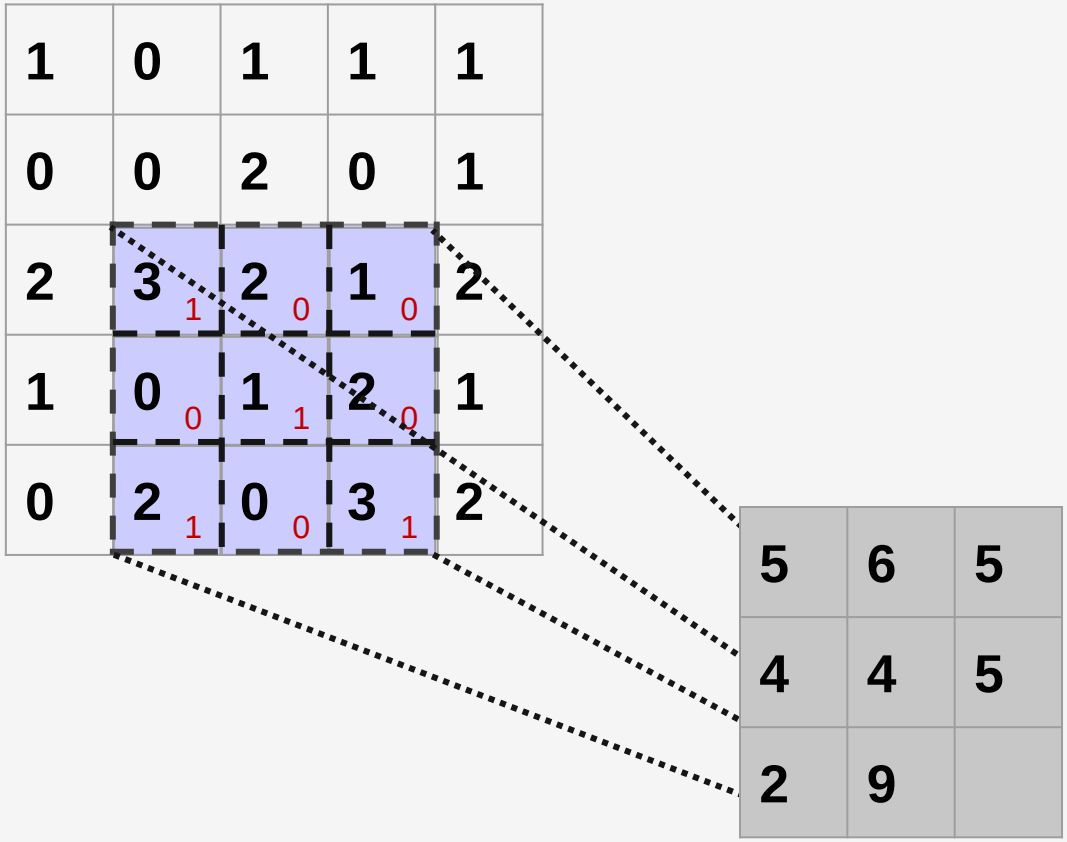
Convolutional Neural Networks

Convolution as core mechanism of CNNs



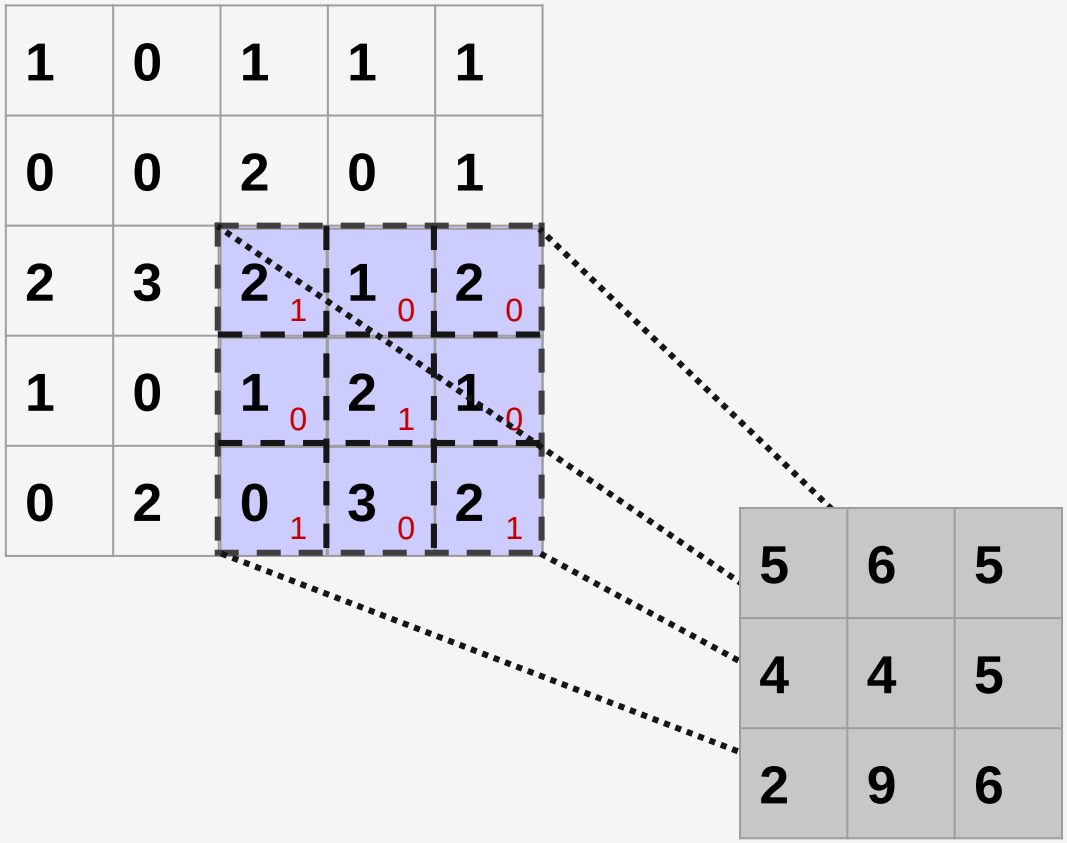
Convolutional Neural Networks

Convolution as core mechanism of CNNs



Convolutional Neural Networks

Convolution as core mechanism of CNNs



Convolutional Neural Networks

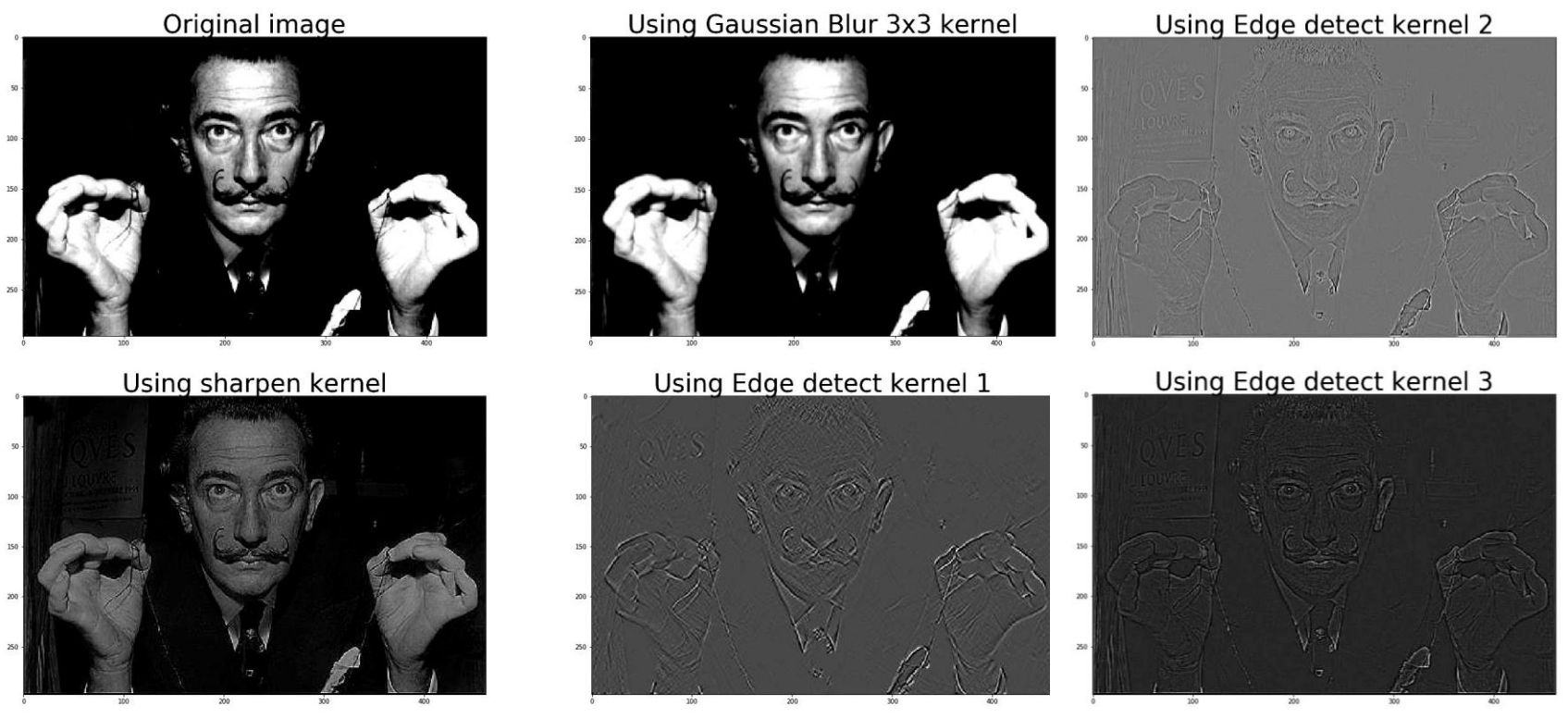
Convolution as core mechanism of CNNs

- Notion of **moving average**
- Represents a **filter**
- Importance of *shape* and *weights* of the filter matrix (kernel)
- Each kernel extracts a specific kind of features (edge, color, shape …)

Convolutional Neural Networks

Convolution as core mechanism of CNNs

Using different kernels



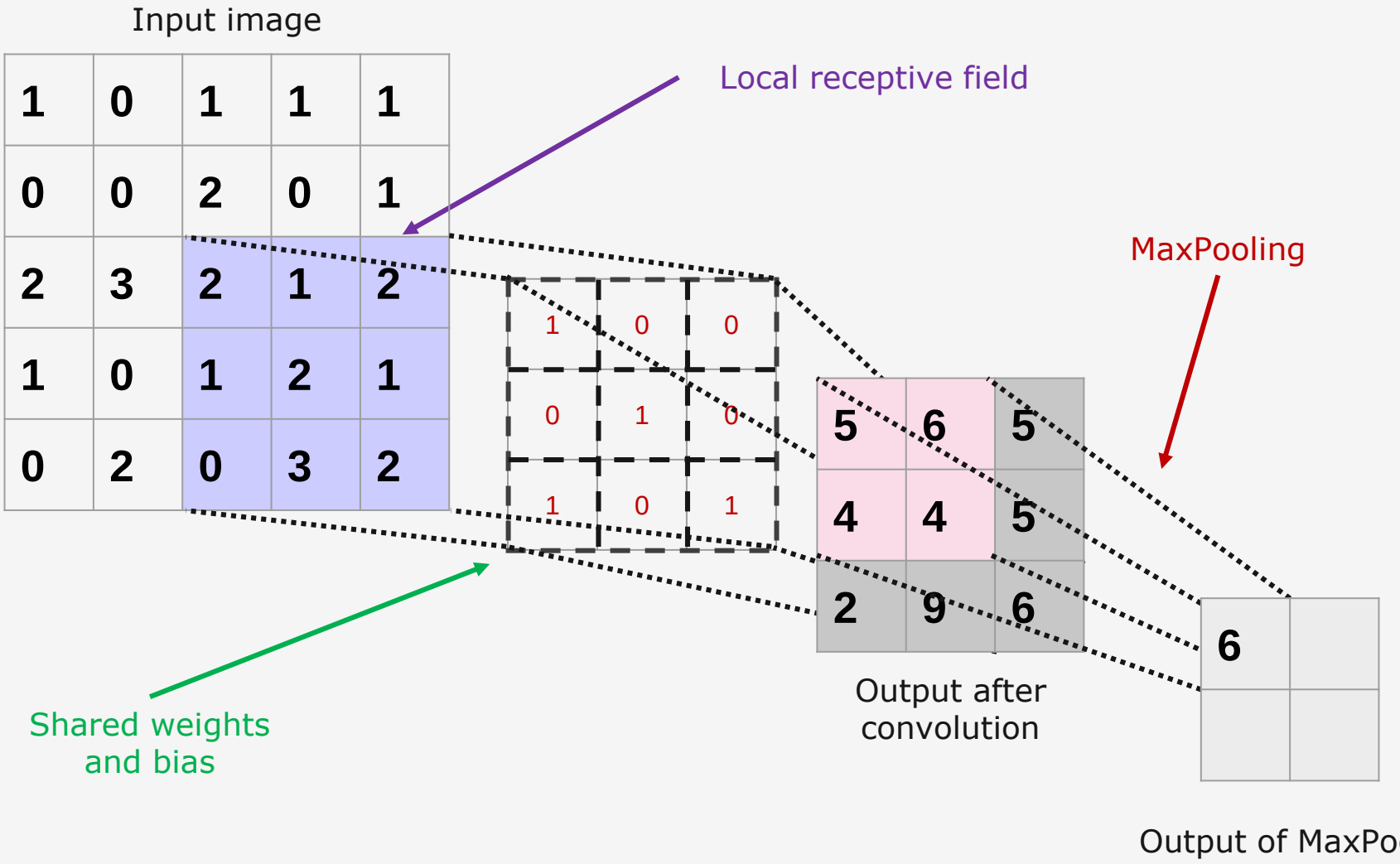
Convolutional Neural Networks

CNN

- Particular kind of deep forward networks
  ➔ **Weights** and **bias** to learn as well
- Convolutional layers filter inputs for useful information
- They automatically adjust to extract the information useful for the Computer Vision task (classification, object detection, …)
- Basic CNN are based on three main ideas:
  - Local receptive fields
  - Shared weights and bias
  - Pooling layers

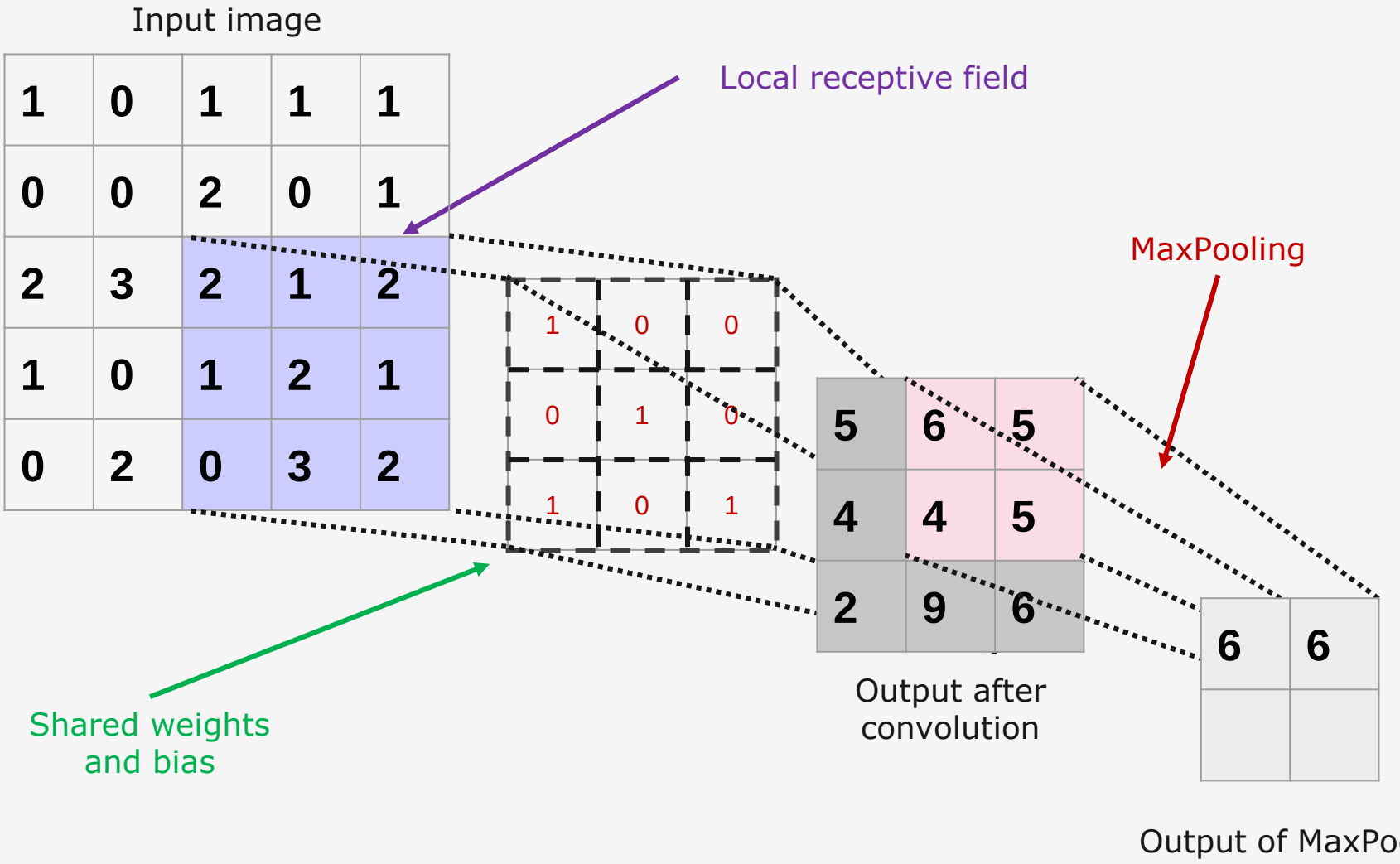
Convolutional Neural Networks

CNN – Basics



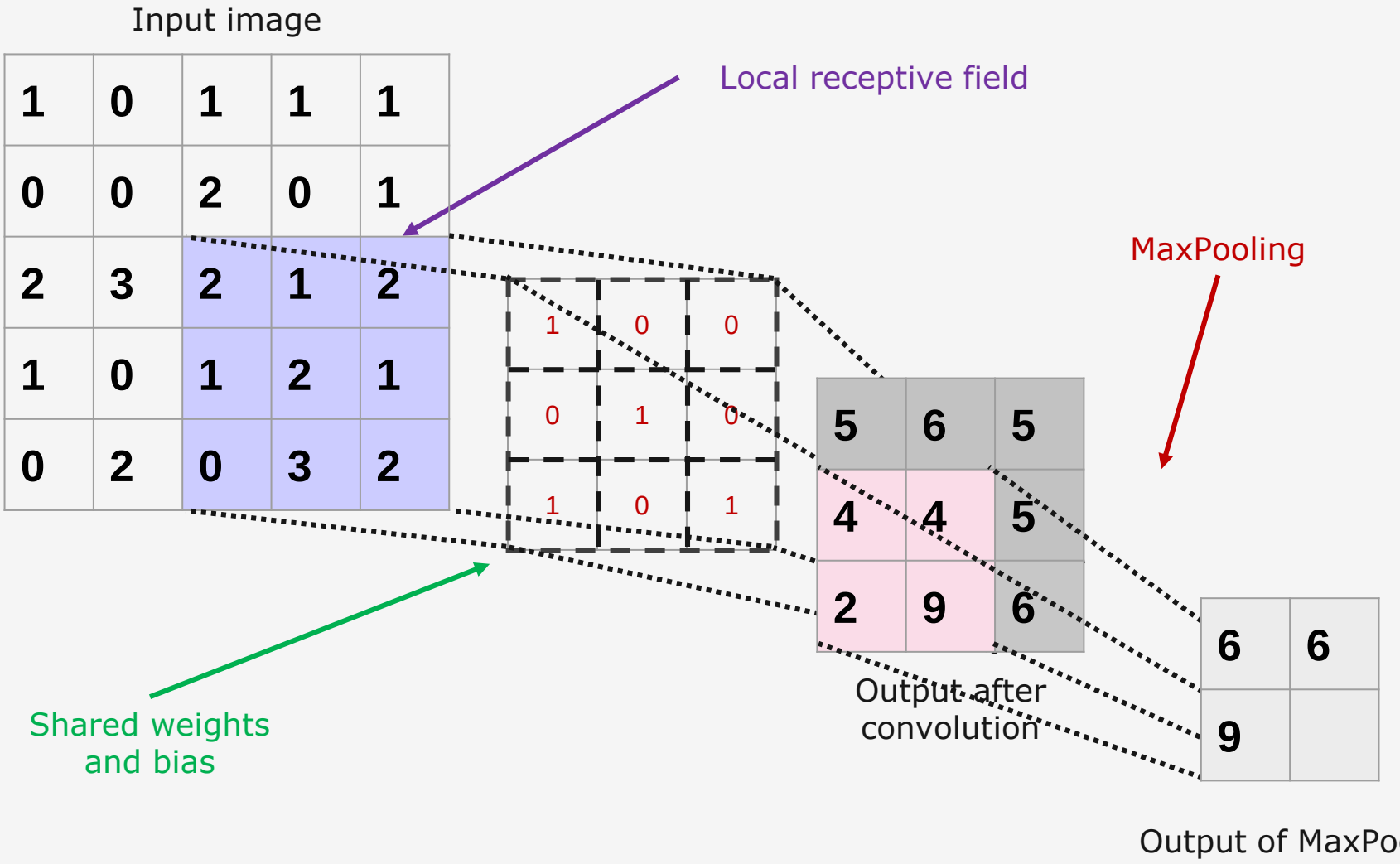
Convolutional Neural Networks

CNN – Basics



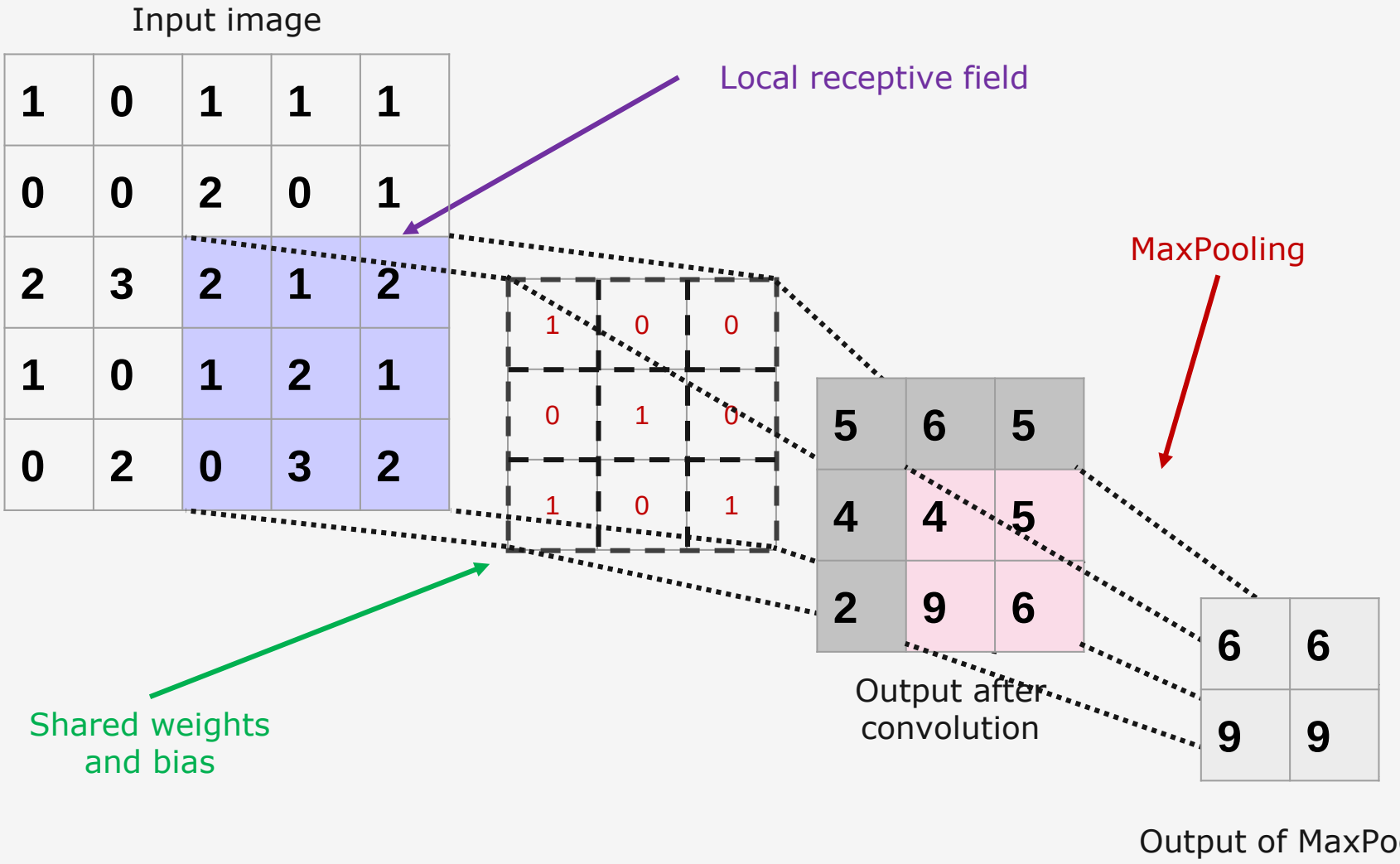
Convolutional Neural Networks

CNN – Basics



Convolutional Neural Networks

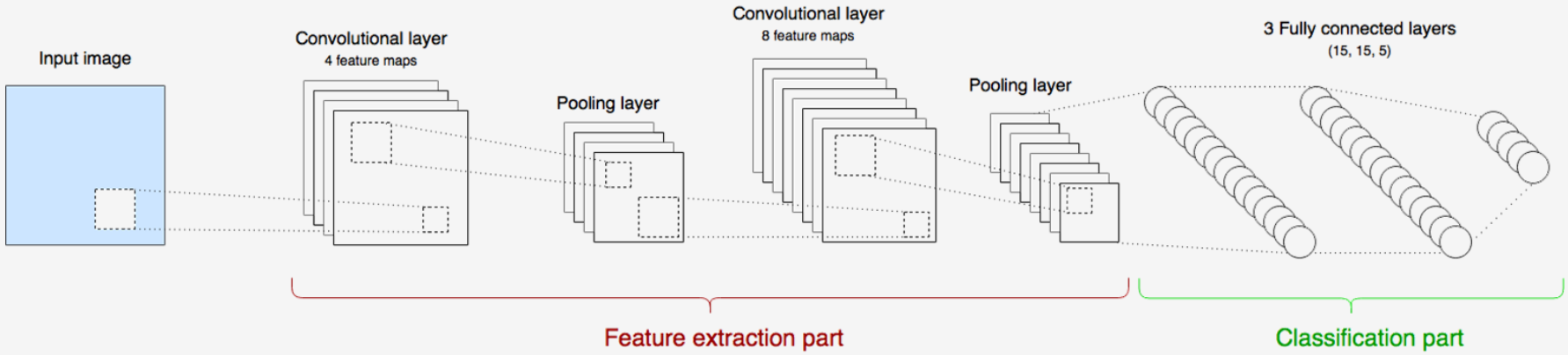
CNN - Basics



Convolutional Neural Networks

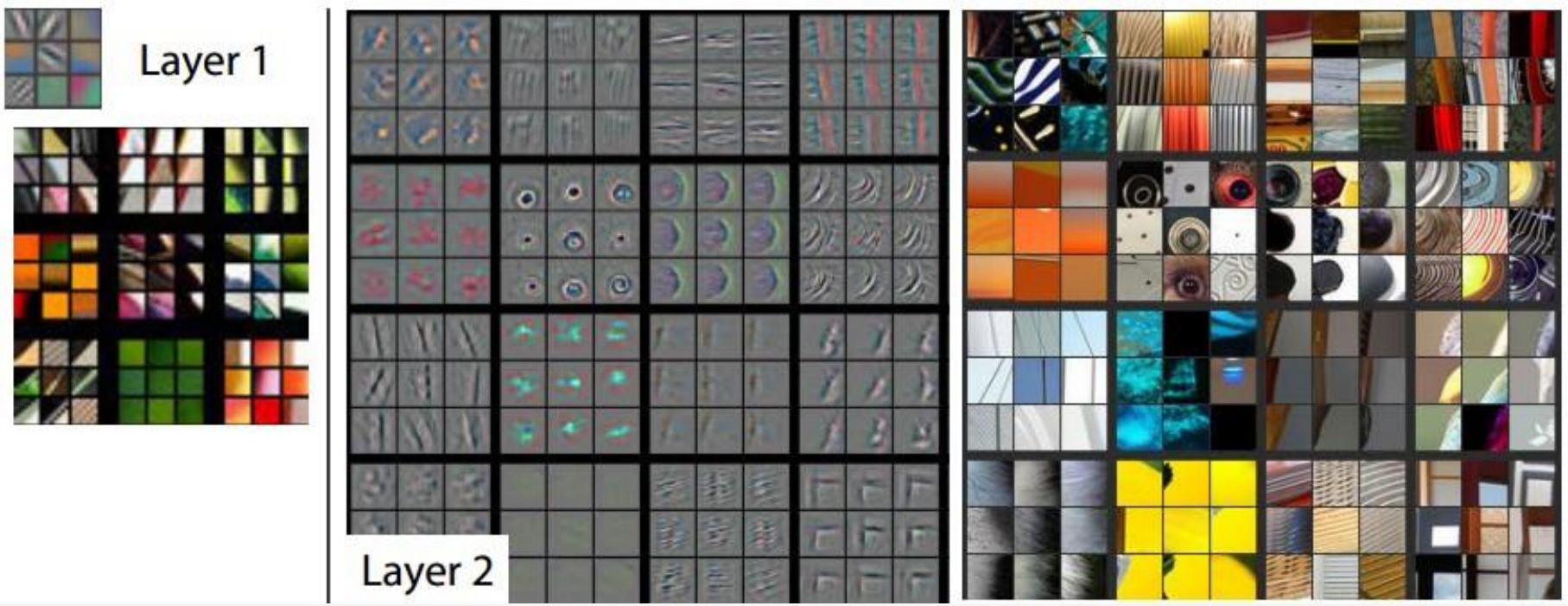
CNN

Illustration of a small CNN



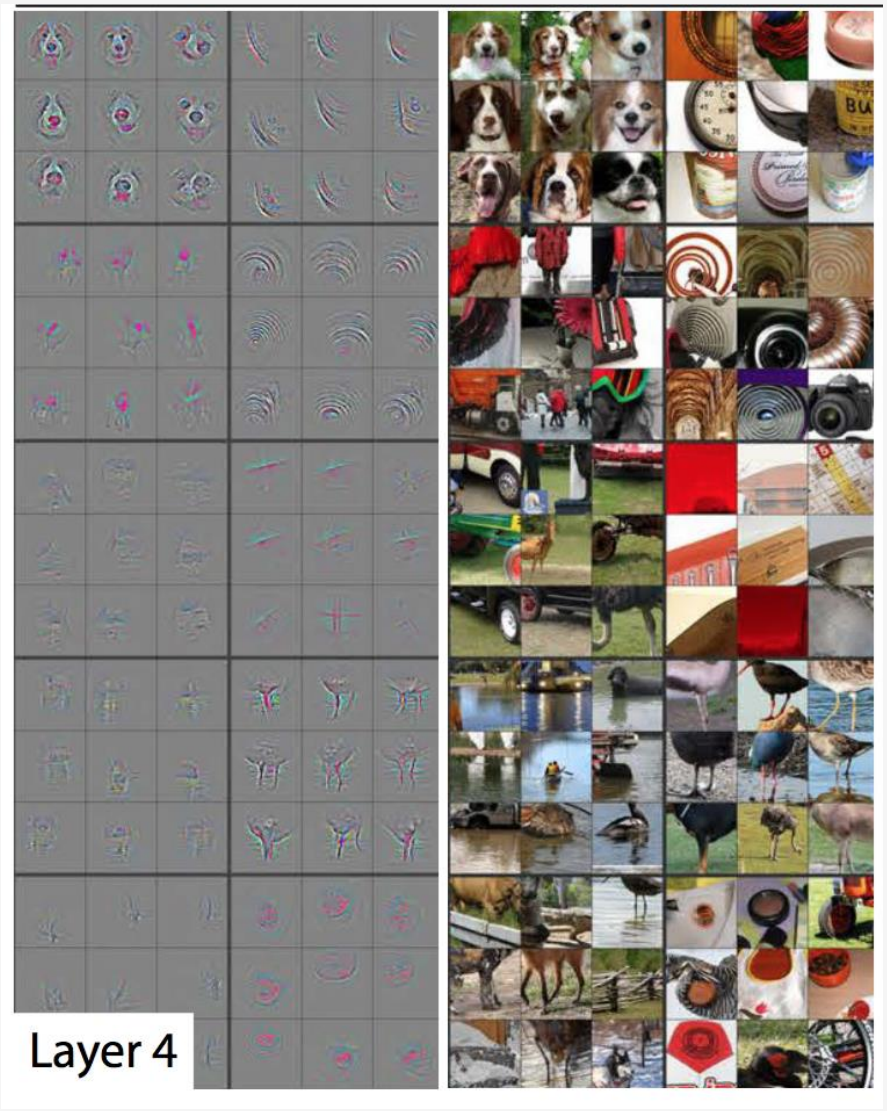
Convolutional Neural Networks

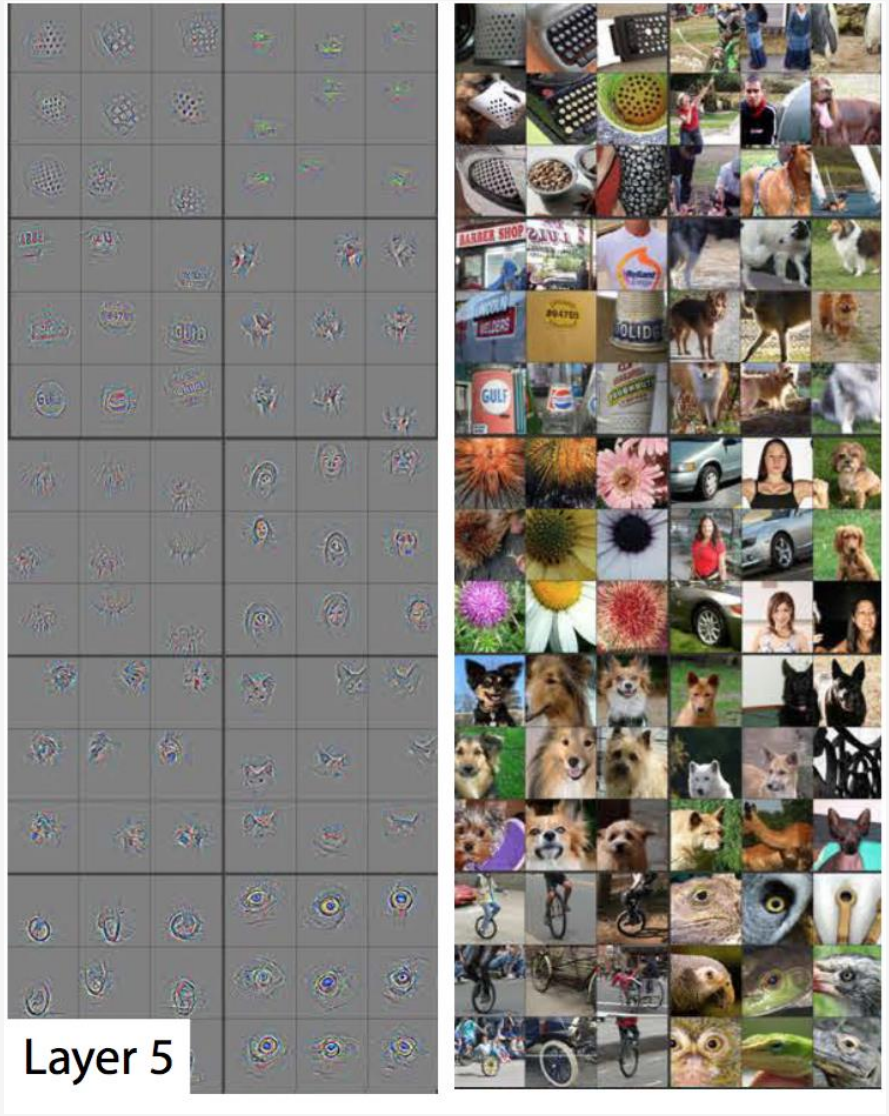
CNN – illustration of what layers see



Convolutional Neural Networks

CNN – illustration of what layers see





Convolutional Neural Networks

Famous CNN architectures

IMAGENET

Large Vision Recognition Challenge (ILSVRC 2010 – 2017)

http://www.image-net.org/

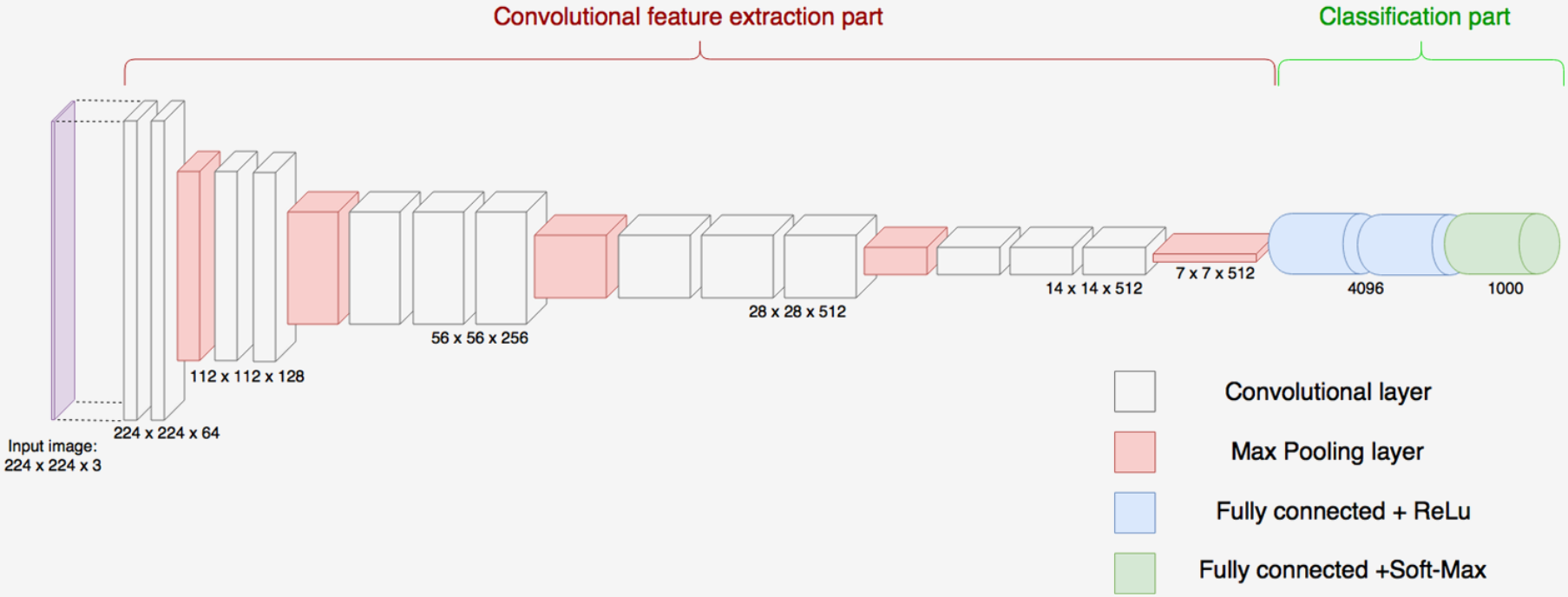
1000 Object classes	**+ 1,2 M** Training images	**+ 100 k** Test images

Convolutional Neural Networks

Famous CNN architectures

Very Deep CNN – VGG16

top-5 test error of around 8% (2014)

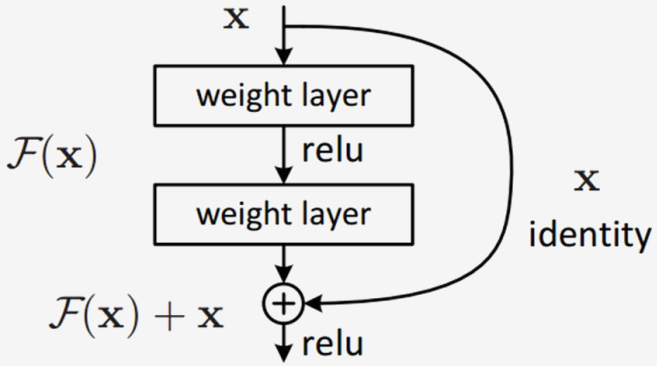


Convolutional Neural Networks

Famous CNN architectures

Residual Networks - ResNet

top-5 test error of around 3.57 % (2015)



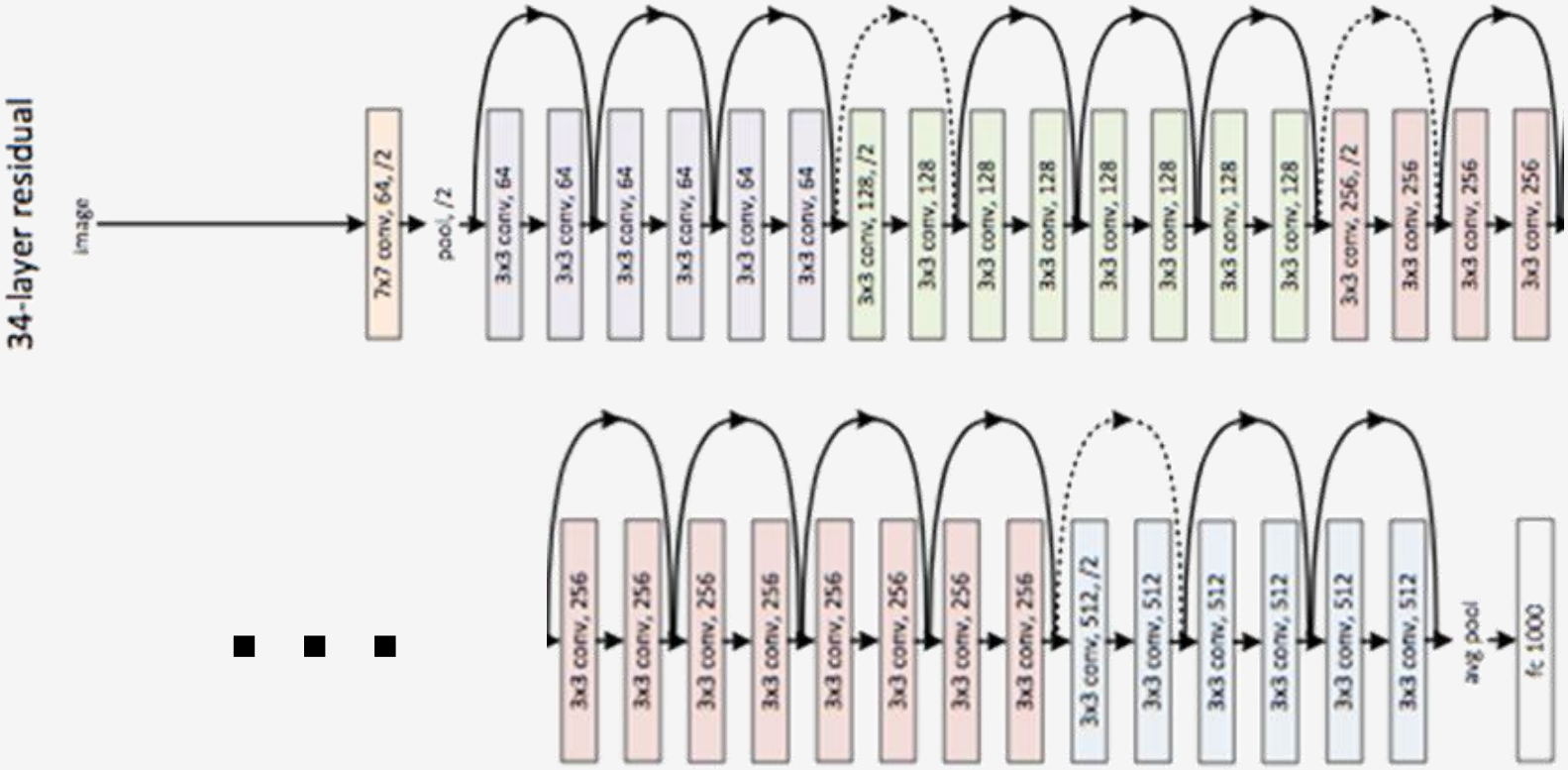
- with 152 layers it is **8 times** deeper than VGG16
- Residual Learning intuition: multiple non-linear function can asymptotically approximate the residual function $F(x) = H(x) - x$
- It is then possible to fit: $H(x) \coloneqq F(x) + x$
- Ease training of **critically Deep models**
- Tackles the degradation of the learning process we usually meet with critically deep networks

Convolutional Neural Networks

Famous CNN architectures

Residual Networks - ResNet

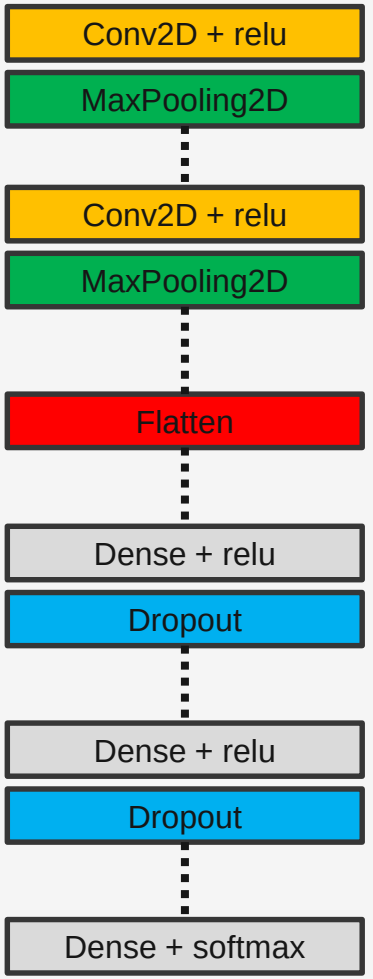
top-5 test error of around 3.57 % (2015)



Convolutional Neural Network

Building a CNN

```
from keras.layers import Dense, MaxPooling2D, Conv2D, Flatten

def deep_conv_model():
    model = Sequential()
    model.add(Conv2D(64, (5,5), input_shape = (28,28,1), activation = 'relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(64, (5, 5),activation = 'relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.25))
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.25))
    model.add(Dense(10, activation='softmax'))

    model.compile(optimizer='adam',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model

model = deep_conv_model()
model.summary()
```



Study case n°2

Design, train and predict

Transfer Learning

Transfer Learning

General intuition

"Inspired by human beings' capabilities to transfer knowledge across tasks, transfer learning aims to leverage knowledge from a source domain to improve the learning performance or minimize the number of labeled examples required in a target domain." (Wei et al. (2014))

If able to recognize lions and tigers

After training the classification part of the CNN

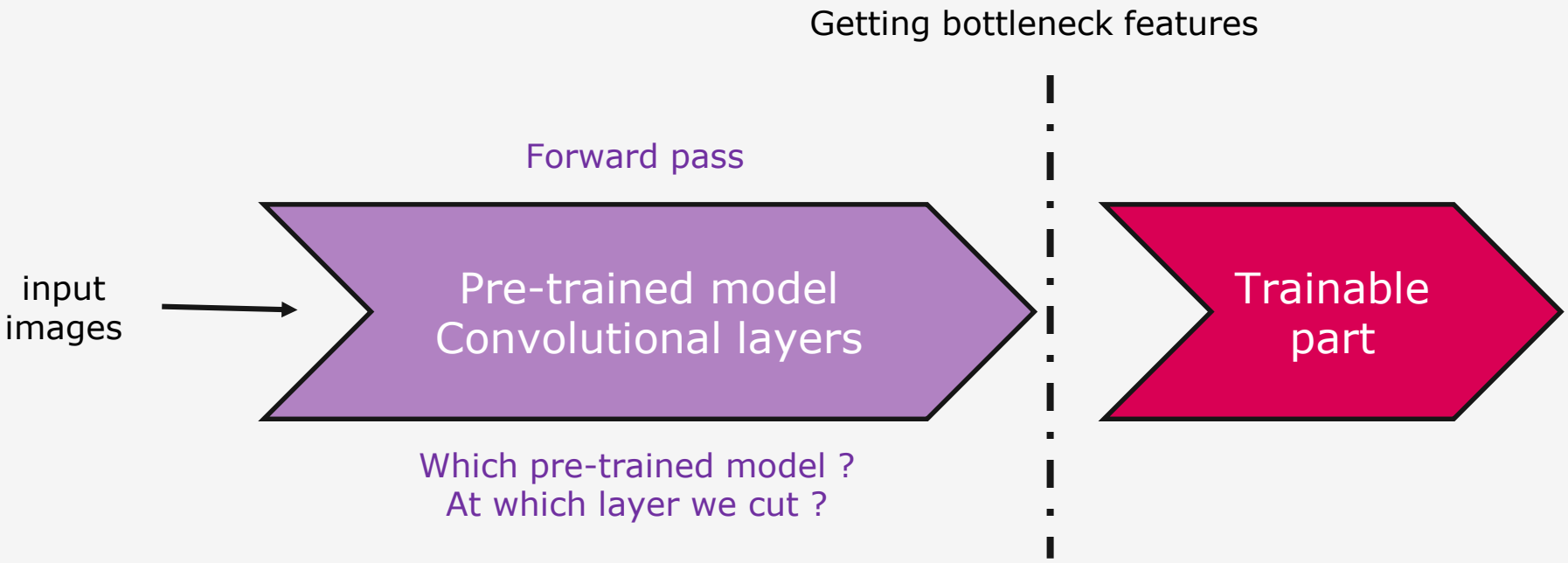
Transfer Learning approach

You can also recognize cats and dogs

Transfer Learning

General Scheme

Transfer knowledge from one domain-to-another
in the case of CNN

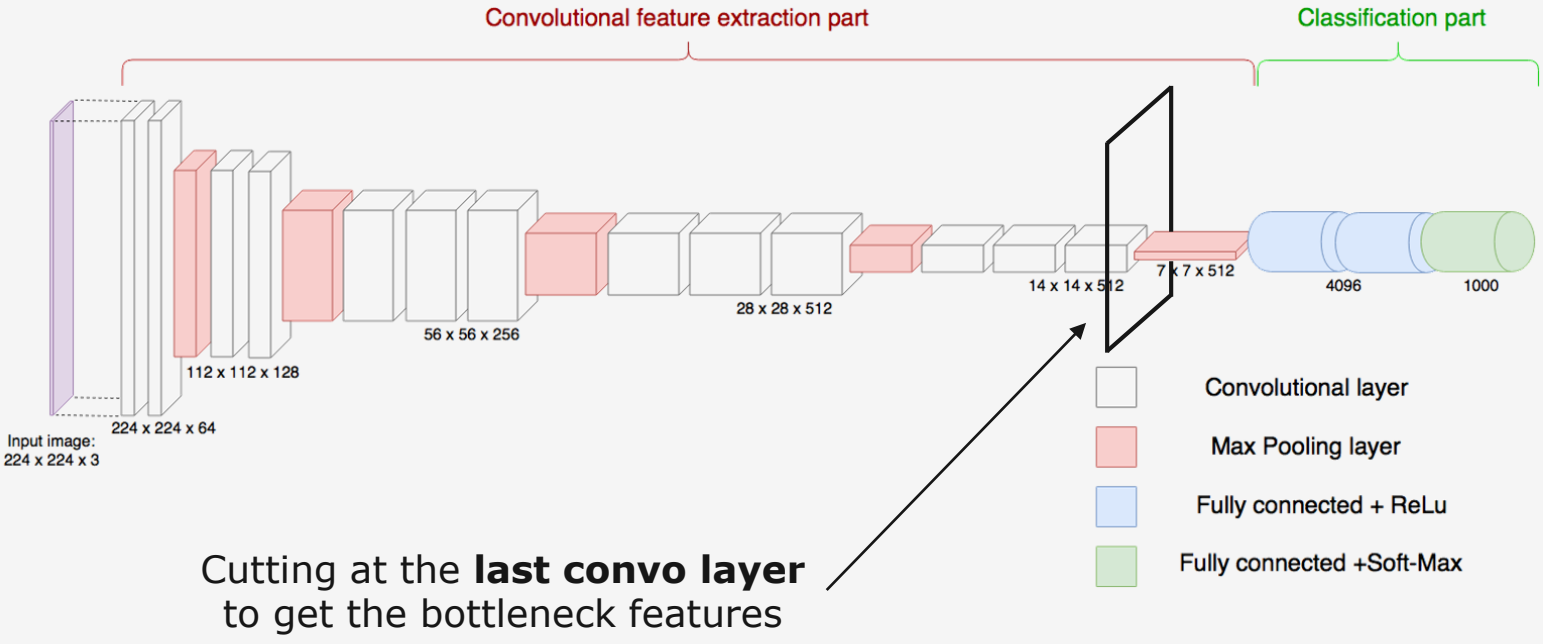


Transfer Learning

General Scheme

- Models famous for having outperformed state-of-the-art results in ImageNet competition
- Weights for VGG16, VGG19, Inception, ResNet50 and Xception are available in keras

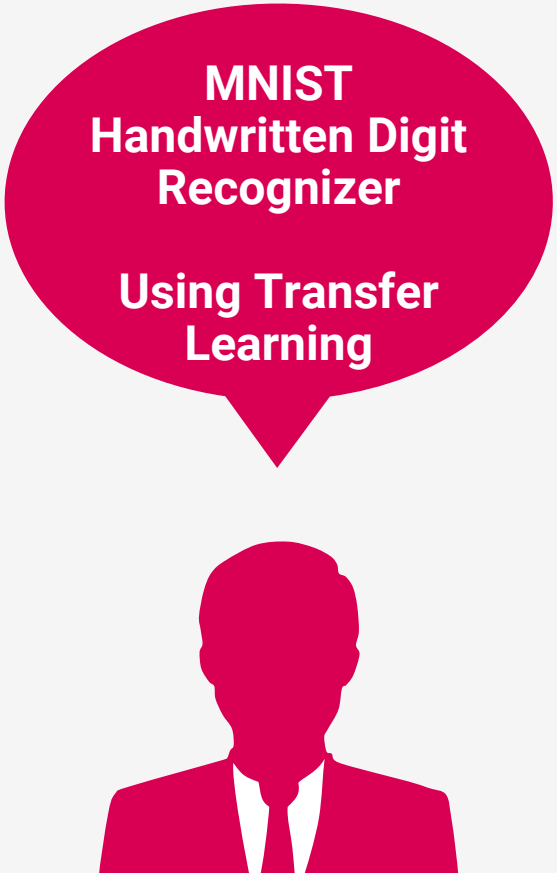
VGG 16 as starting point



Cutting at the **last convo layer**
to get the bottleneck features

Study case n°3

Design, train and predict

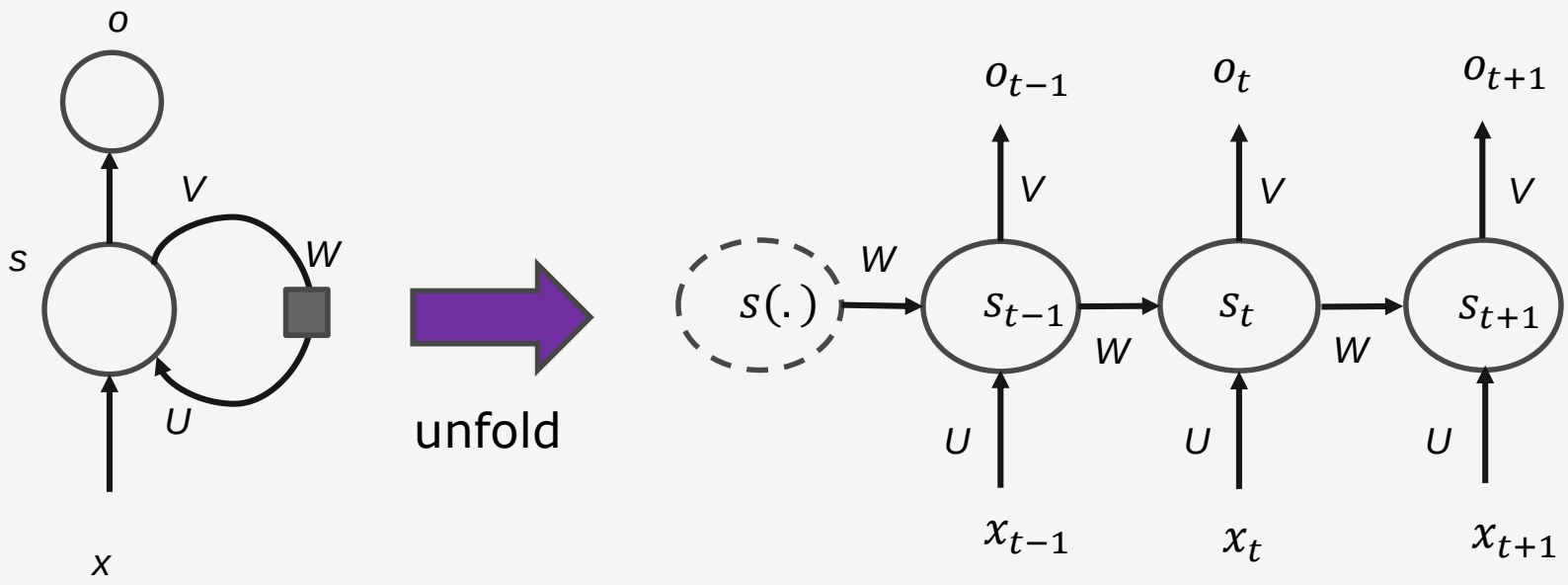


Recurrent Neural Networks

Recurrent Neural Networks

What's a RNN?

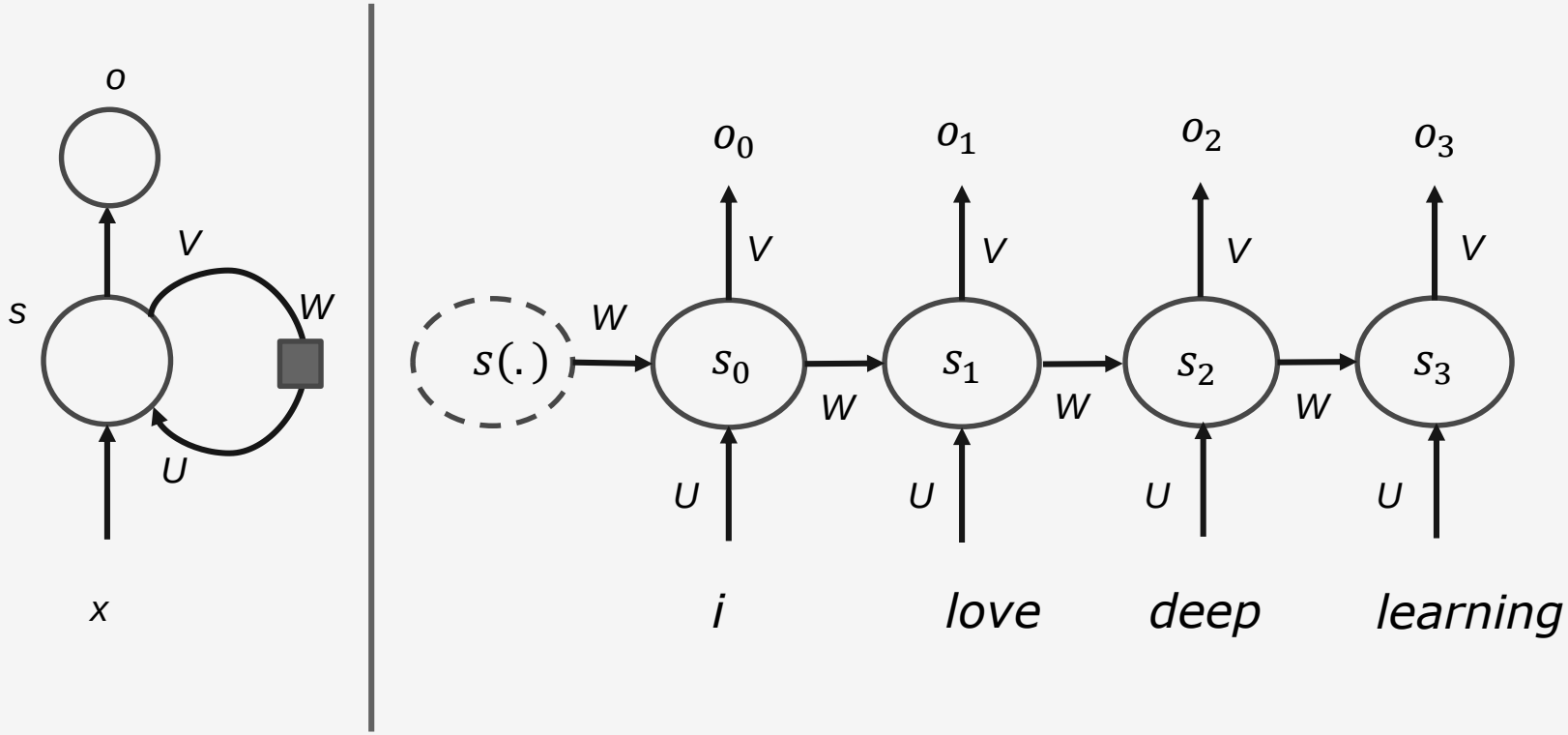
- Adapted to sequence treatment tasks: NLP, etc …
- Inputs are not independent anymore ➔ notion of memory



Recurrent Neural Networks

Illustration: example with a sentence

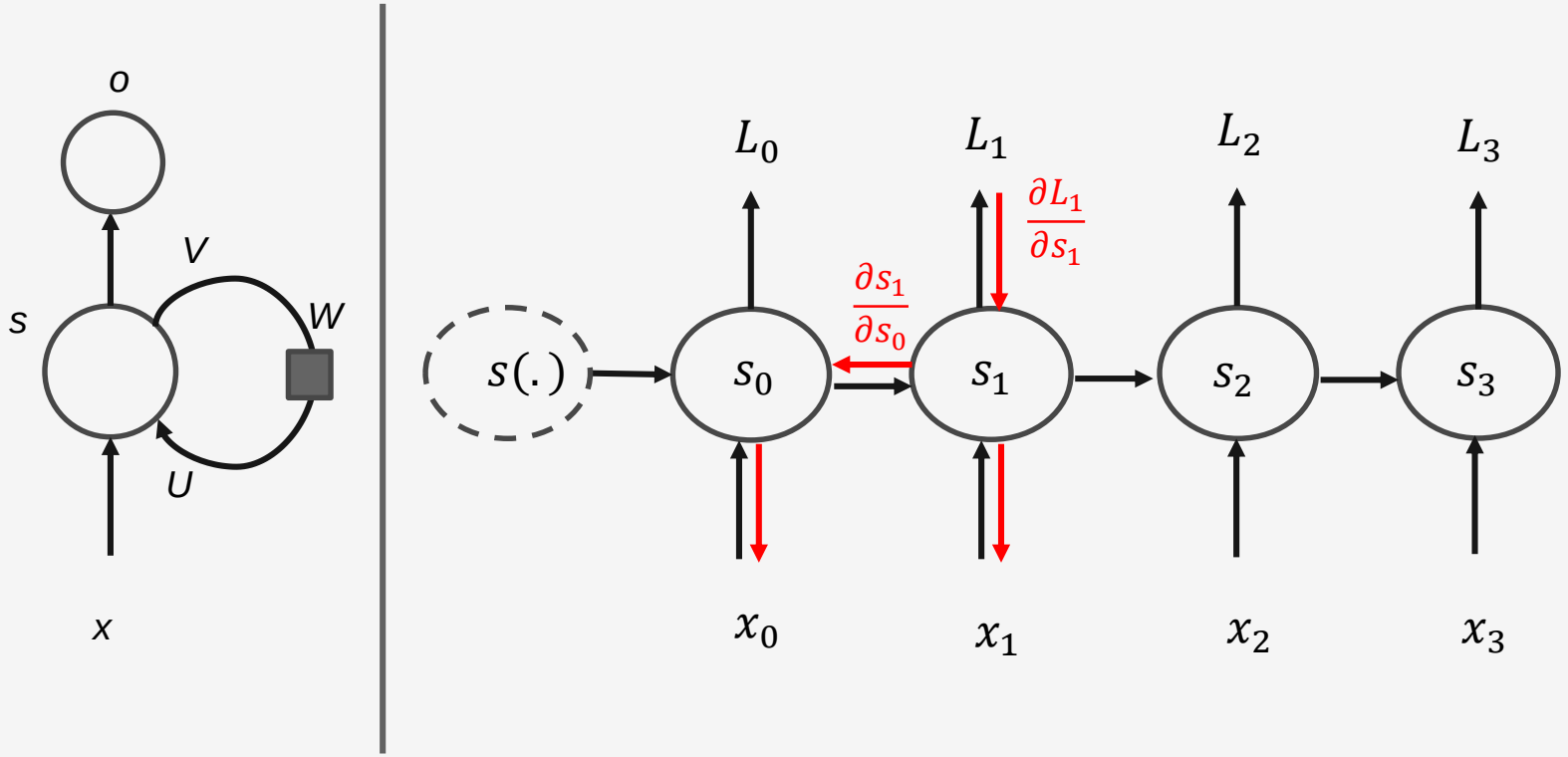
Sentence: «i love deep learning »



Training a Recurrent Neural Networks

Back-Propagation Through Time (BPTT)

Sentence: «i love deep learning »



Training a Recurrent Neural Networks

Back-Propagation Through Time (BPTT)

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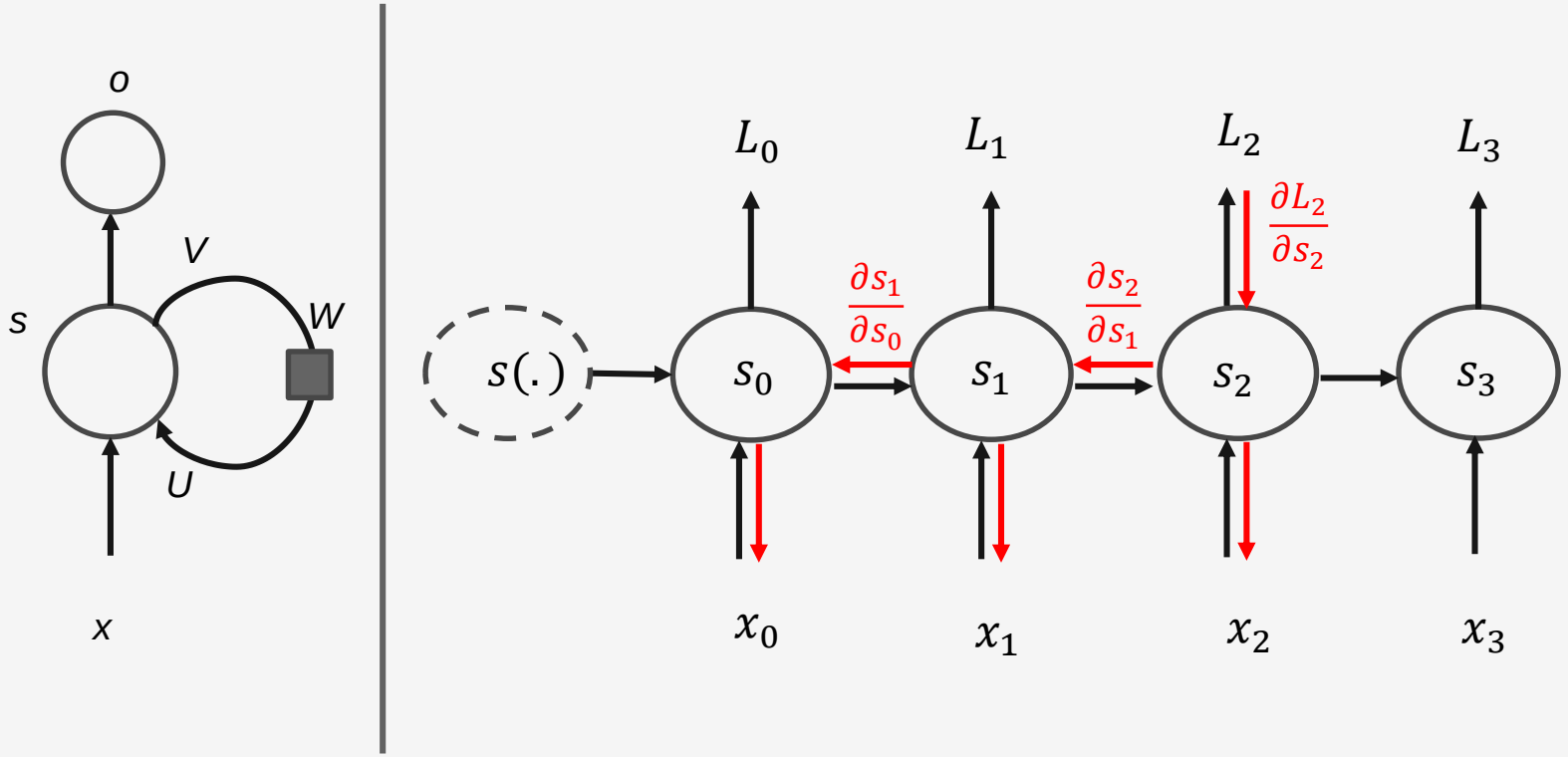
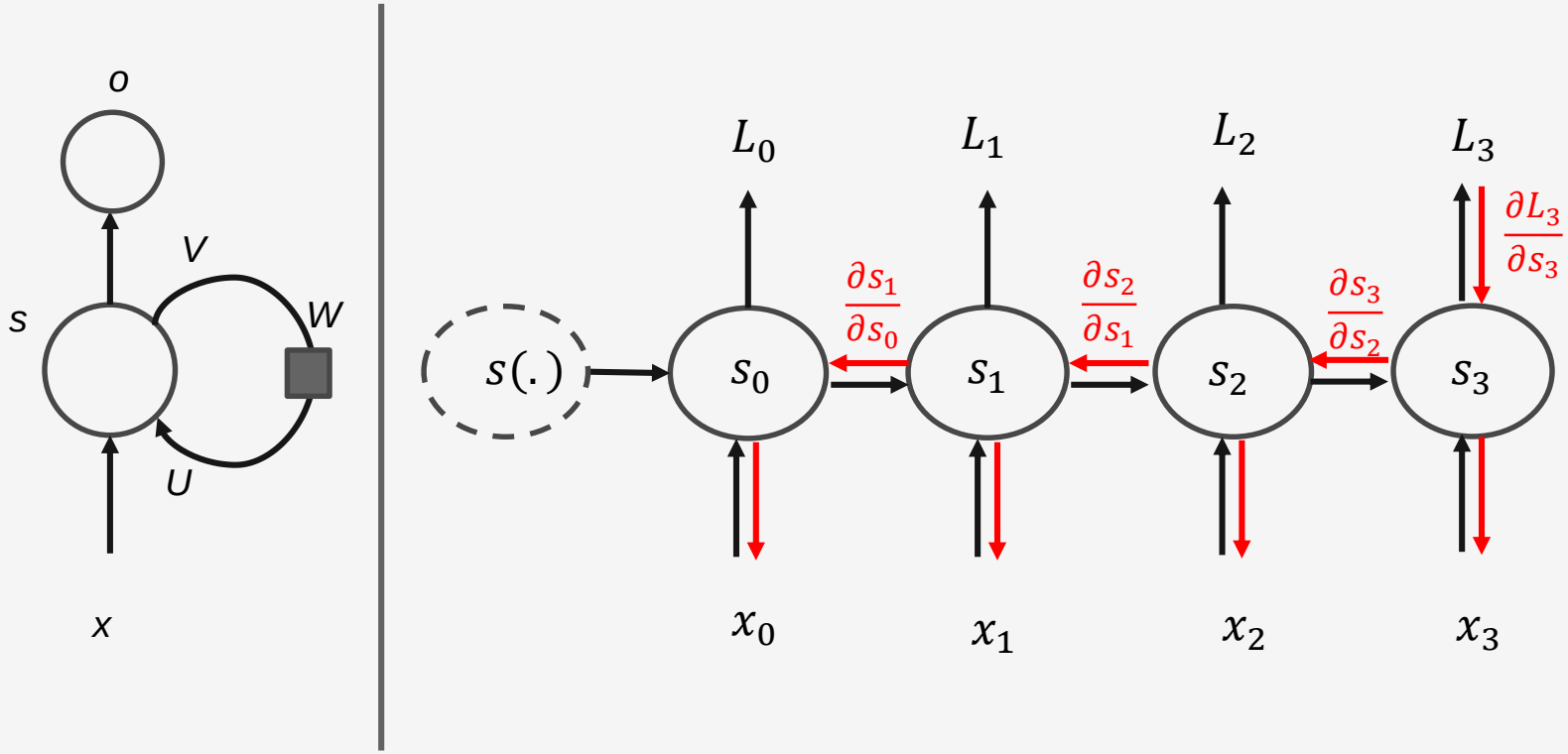


Training a Recurrent Neural Networks

Back-Propagation Through Time (BPTT)

Sentence: «i love deep learning »



Complexified RNNs

Gated Recurrent Units (GRU)

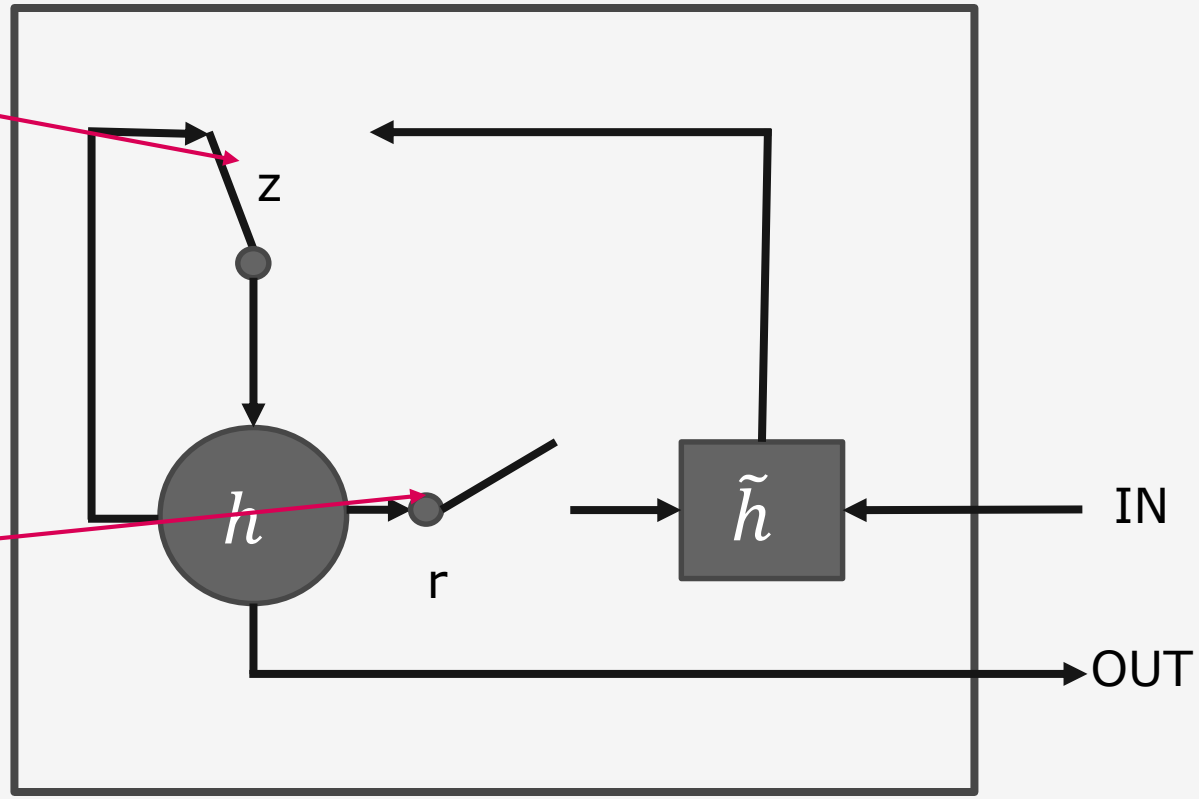
Z = update gate

How much of the previous memory to keep around

r = reset gate

How much of the new input to combine with the previous memory

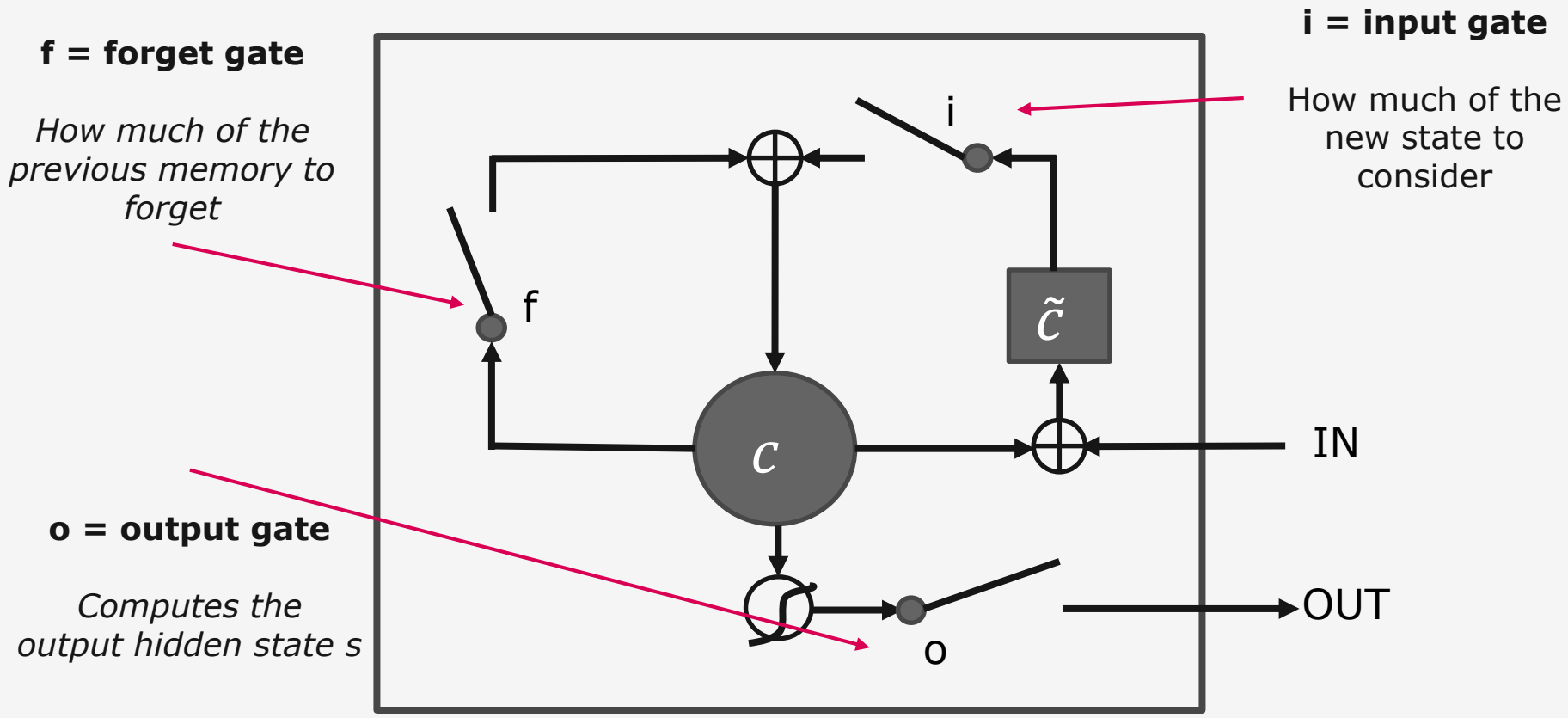
Illustration of a GRU



Complexified RNNs

Long Short Term Memory (LSTM)

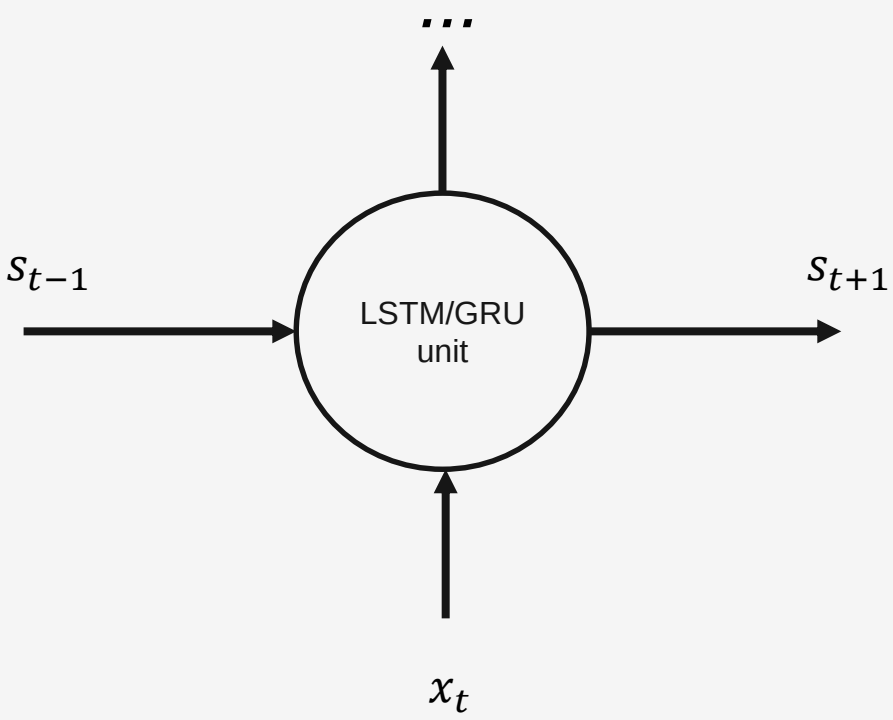
Illustration of a GRU



Complexified RNNs

LSTM/GRU units

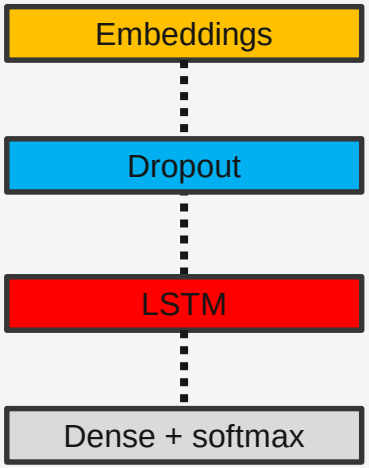
You can also stick to the simplest version !!!



Complexified RNNs

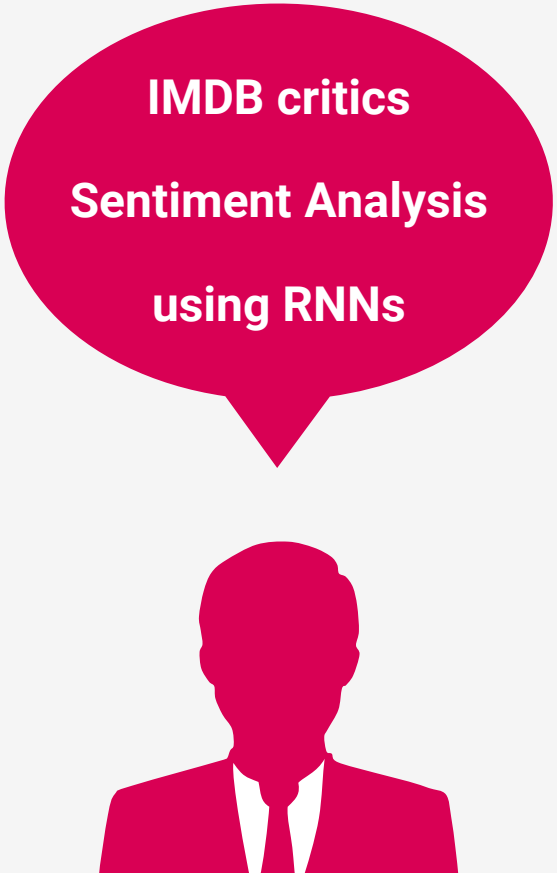
Sentiment Analysis

```
from keras.layers import Dense, MaxPooling2D, Conv2D, Flatten

def sentiment_analysis_model():
    model = Sequential()
    model.add(Embedding(vocab_size=2000, 5, input_length=500))
    model.add(Dropout(0.2))
    model.add(LSTM(50))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])

    return model

model = sentiment_analysis_model()
model.summary()
```



Study case n°4

Design, train and predict



4

Practice: Design and train your own network

The Nature Conservancy

kaggle

ALB: Albacore tuna (*Thunnus alalunga*)

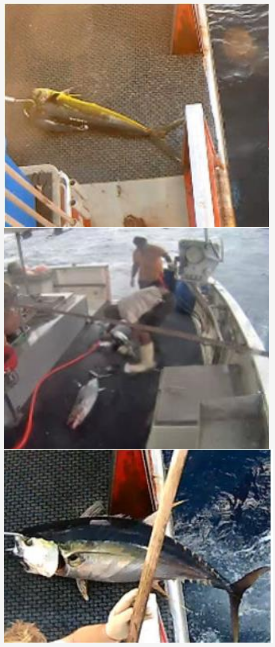
BET: Bigeye tuna (*Thunnus obesus*)

DOL: Dolphinfish, Mahi Mahi (Coryphaena hippurus)

LAG: Opah, Moonfish (*Lampris guttatus*)

SHARK: Various: Silky, Shortfin Mako

YFT: Yellowfin tuna (*Thunnus albacares*)



5

Conclusion

Conclusion

- Useful in AI
- The most powerful tool in the rest years in the AI enivronment
- Evoluating very fast … need to constantly update the knowledge

Tips

- Courses online available:
  - http://course.fast.ai/ , free course given by Jeremy Howard
  - https://fr.coursera.org/specializations/deep-learning course given by Andrew NG
- Books:
  - “The Elements of Statistical Learning”, by T. Hastie, R. Tibshirani and J. Friedman
  - “Deep Learning”, by I. Goodfellow, Y. Bengio and A. Courville
- Research papers at: http://www.arxiv-sanity.com/

Thanks

It was a big pleasure to animate this course!
Sincere thanks!