

Deep Learning for Natural Language Processing

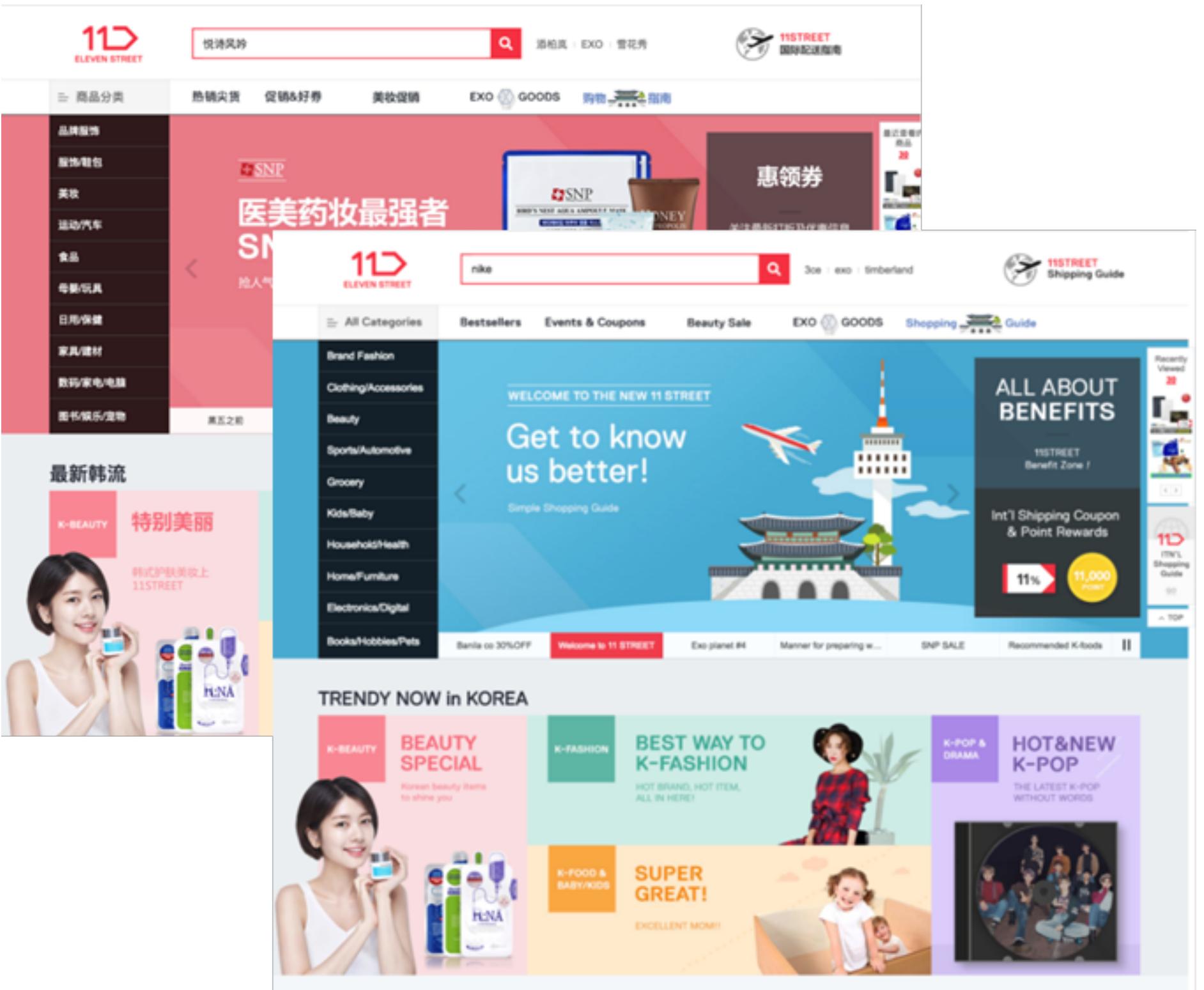
Week 1 Introduction to PyTorch

Course introduction



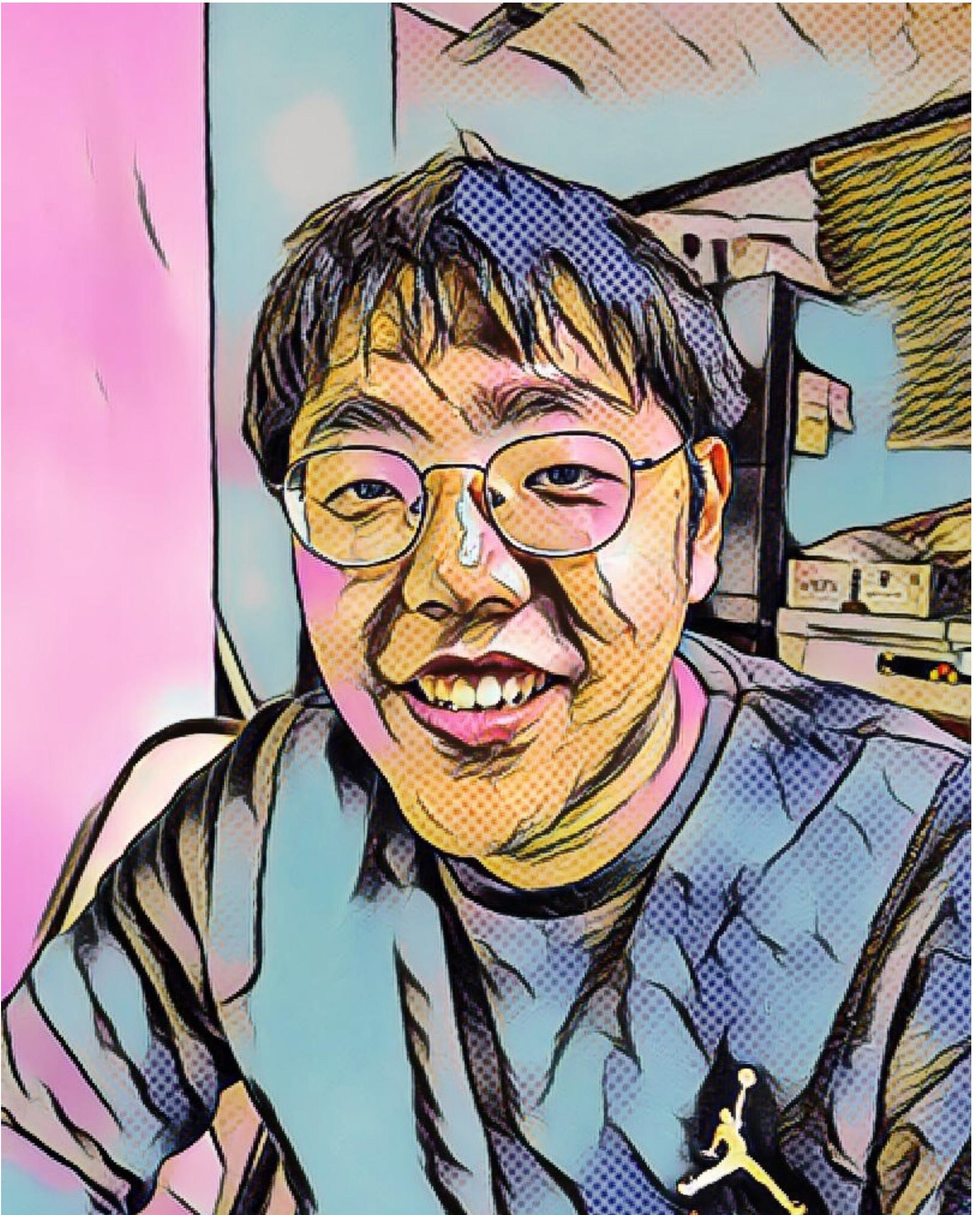
Ki Hyun Kim

- Machine Learning Engineer, MakinaRocks
- Generative Learning, Unsupervised Learning, Anomaly Detection
- Machine Learning Researcher, SKPlanet
 - Neural Machine Translation
- Researcher, ETRI
 - Language Modeling for Speech Recognition, Automatic Speech Translation



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오상준

- Deep Learning Engineer, Deep Bio Inc.
- Biomedical Lab 랩장, 모두의연구소
- Docker Contents Creator, 모두를 위한 딥러닝 Season 2
- Co-founder and Research Engineer, QuantumSurf
- GitHub: <https://github.com/juneoh>
- Email: me@juneoh.net



A typical DL project workflow

1. Obtain and cleanse data
2. Choose a baseline model — e.g. ResNet, DenseNet, MobileNet, NASNet, MNASNet
3. Train to overfit
4. Tune and optimize — hard example mining, model pruning, custom loss functions, etc.
5. Deploy — e.g. using Open Neural Network Exchange Format (ONNX)

Machine Learning in Research

we spend months trying hard to design an algorithm complex enough to gain 0.3% improvement over previous best models

Machine Learning in Engineering

we use a simple algorithm and spend one week annotating more data to gain 3% improvement over previous week's result.



Definitions

- baseline: reference benchmark
- Proof-of-Concept (POC): a quick working prototype for an idea
- binary classification: A or not A
- multi-class classification: A, B, or C
- one-hot encoding: A as $(1, 0, 0)$, B as $(0, 1, 0)$, C as $(0, 0, 1)$



Who this course is for

In order to follow the hands-on sessions, you are expected to:

- know basic Python programming (data structures, OOP, etc.)
 - e.g. watched 무작정 따라하는 파이썬 프로그래밍 (YouTube)
- have heard of the basics of machine learning and/or deep learning
 - e.g. watched 모두를 위한 딥러닝/머신러닝 or PyTorch Zero to All

Who this course is for

And preferably, to fully catch the theory:

- understand the basic concepts of related topics in mathematics (statistics, probability, calculus, and linear algebra)
- e.g. watched Machine Learning by Andrew Ng (Coursera)

But even if not, **just ask!**

What this course does NOT offer

- Basic programming and mathematics
- (왕초보) 프로그래밍 첫걸음 시작하기 (Fast campus)
- (초보) 파이썬으로 개발 시작하기 (Fast campus)
- (중고급) 파이썬 완전 정복 CAMP (Fast campus)
- (초급) 딥러닝을 위한 최적화와 수치해석 CAMP (Fast campus)

What this course does NOT offer

- *Everything* deep learning can do
 - (초급) PyTorch로 시작하는 딥러닝 입문 CAMP (Fast campus)
- Deeper topics of NLP: Sequence-to-Sequence, Neural Machine Translation
 - (고급) PyTorch를 활용한 자연어처리 심화 CAMP (Fast campus)

What this course DOES offer

- A rapid understanding of core concepts in deep NLP for intuition and insight
- Hands-on sessions with working project codebase to freely exploit
- Real-life tips and thorough support from field experts
- A comprehensive guide of how you should study further

The goal

A rapid, focused deep NLP bootcamp:

the journey from a beginner in deep learning to a junior NLP researcher, capable of building business-level text classification models.

Syllabus

Week 1 Introduction to PyTorch - 오상준

- (Theory) Introduction to Deep Learning
- (Practice) Hello PyTorch!

Week 2 Introduction to NLP - 김기현

- (Theory) Deeper Introduction to Deep Learning
- (Theory) Introduction to Natural Language Processing

Syllabus

Week 3 Word Sense Disambiguation - 김기현

- (Theory) Word Sense Disambiguation
- (Practice) Word Sense Disambiguation Excercise

Week 4 Word Vector Embedding - 오상준

- (Theory) Geometry of Deep Learning
- (Practice) Word Vector Embedding

Syllabus

Week 5 Deep Artificial Neural Networks - 오상준

- (Theory) Deep Neural Networks
- (Practice) Cryptocurrency Price Prediction

Week 6 Text Classification with PyTorch - 김기현

- (Theory) Naïve Bayes
- (Practice) Text Classification Excercise

Course mechanics

- Materials
 - By e-mail and GitHub
- Questions
 - Any time: during, before, or after lectures
 - In person, by email, or via Facebook (TBD)
- Fast campus regulations
 - Absences up to 2 times
 - 3 e-mail surveys: 1st, 3rd, 6th week

Complementary materials

Intermediate

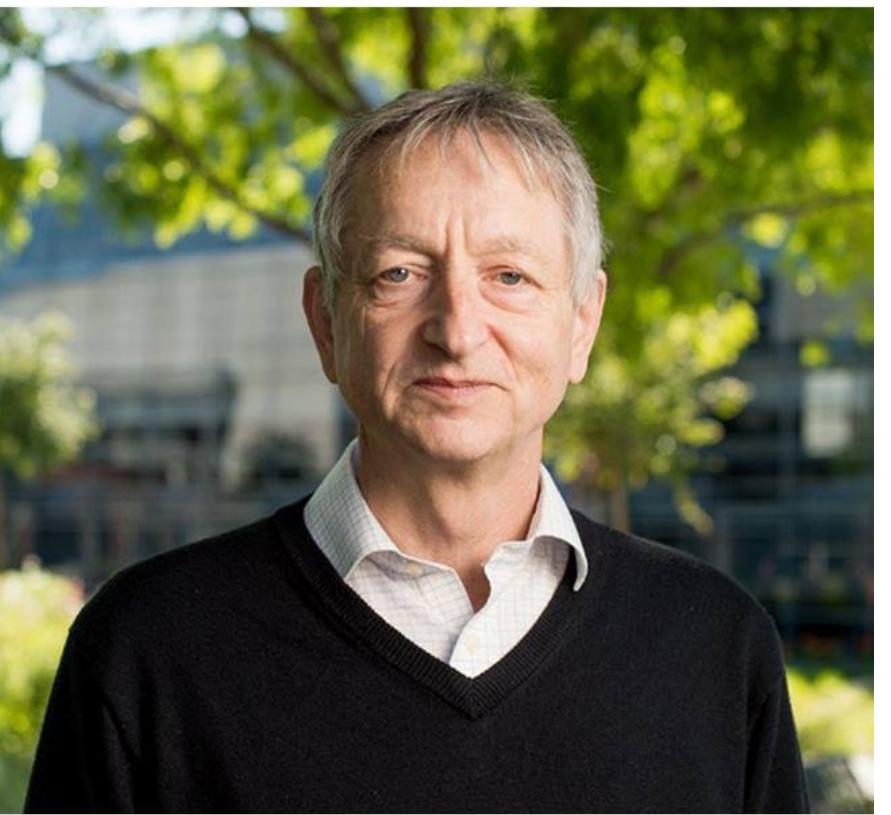
The materials below cover the theoretical parts of this course. They are recommended for further commitment.

- Deep Learning Book by Ian Goodfellow et al.
 - A thorough look at the basics, from linear algebra and calculus
- CS231n: Convolutional Neural Networks for Visual Recognition at Stanford

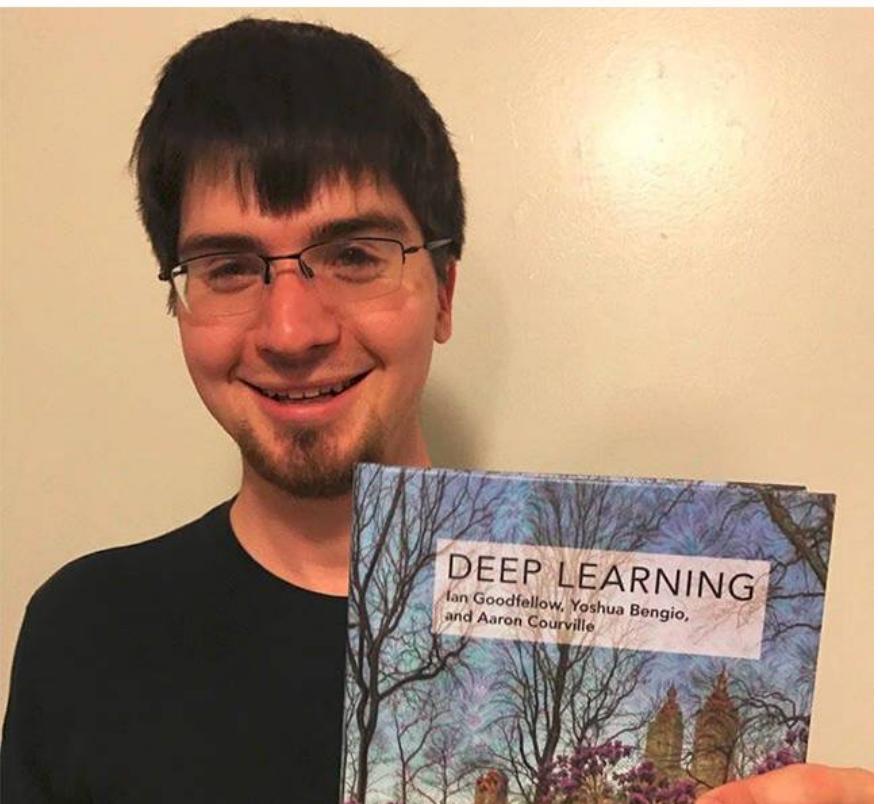
one taught me
love



one taught me
patience



one taught me
pain



Complementary materials

Intermediate

- CS224d: Deep Learning for Natural Language Processing at Stanford
- Oxford Deep NLP 2017
- Google 머신러닝 단기집중과정

Complementary materials

Advanced

- Pattern Recognition and Machine Learning 우리말 정리

Other

- 라온피플 머신러닝 아카데미
- colah's blog

Complementary materials

Tips and trends

- The official PyTorch forums
- PyTorch KR (Facebook)
- TensorFlow KR (Facebook)
- PR12 딥러닝 논문읽기 모임 (YouTube)
- Two Minute Papers (YouTube)
- Machine Learning (Reddit)
- Google AI Blog

Introduction to Deep Learning

- Genealogy
- Timeline
- Neural networks
- Activation functions and non-linearity
- Loss functions
- Regularization methods



SK Telecom

이젠, 빠빠라고 하지 않는다!

초고속 인공지능, 스피드012 - 빠빠라고 하기엔 너무 똑똑하다!

파워 VDSL로 더 강해지!

Mbps를 20배, 평균 속도는 30Mbps
1Mbps마다 3Mbps.
인터넷 사용 기쁨이 더욱 강해졌다.

지역변경의 날은 지도으로!

전국 어디에서나 내가 있는 위치
활용한 지역을 지도으로 한시
언급시키자 즉시 통신된다.

세계 표준 시각을 확장으로!

인터넷을 교체하고, 브라우저 대신 게임
위선을 통해 세계관과 접두한 시간을 즐기세요.

모든 서비스를 빠빠하나로!

전국 어디에서나 빠빠 인터넷 속도 상위
정보, 결제, 험마서비스를 모두 링크 수 있다.

검색시 수령하고 빠빠지!

총화기 홈페이지 전화기를 사용하는 자동전환서비스로
전화기 번호로 편리하게 통화를 사용하세요.

마우스 움직이는 속도!

총화기 또는 전자제작 번호를 빠져
마우스 움직임 스스로 세로 100% 제한을 벗어나

빠빠를 빠빠도 빠빠는 그대로!

인터넷이나 휴대폰 스스로 선택하게 됨
인터넷 고속도로와는 그대로 사용할 수 있다.

초고속 인공지능

SPEED 012



when someone says Sophia is an AI





Giedrius Trump

when someone says Sophia
is an AI



1h

Haha

Reply



Yann LeCun

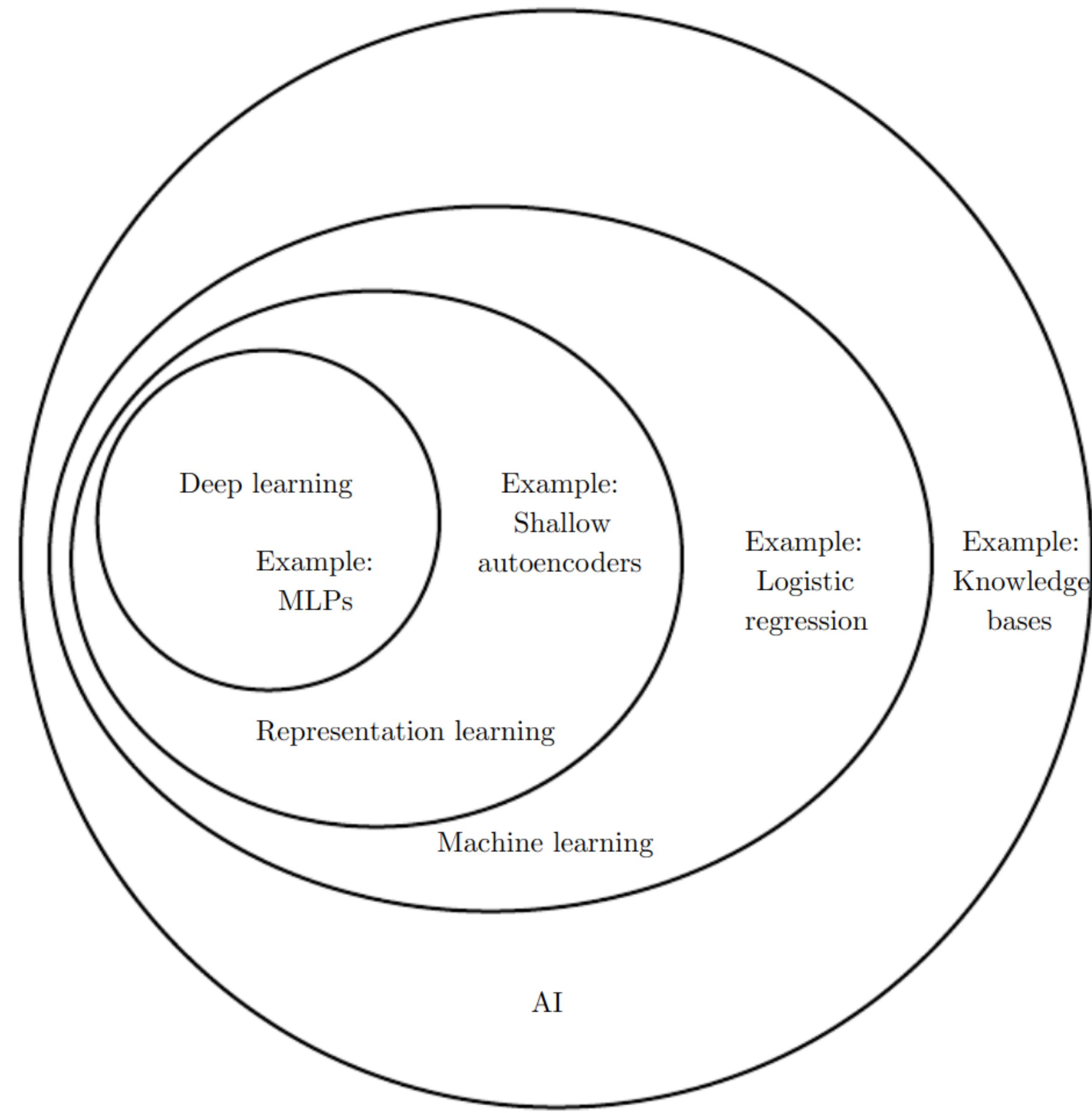
Exactly, except that Geoff and Andrew
would push me into the fight.

1h

Like

Reply

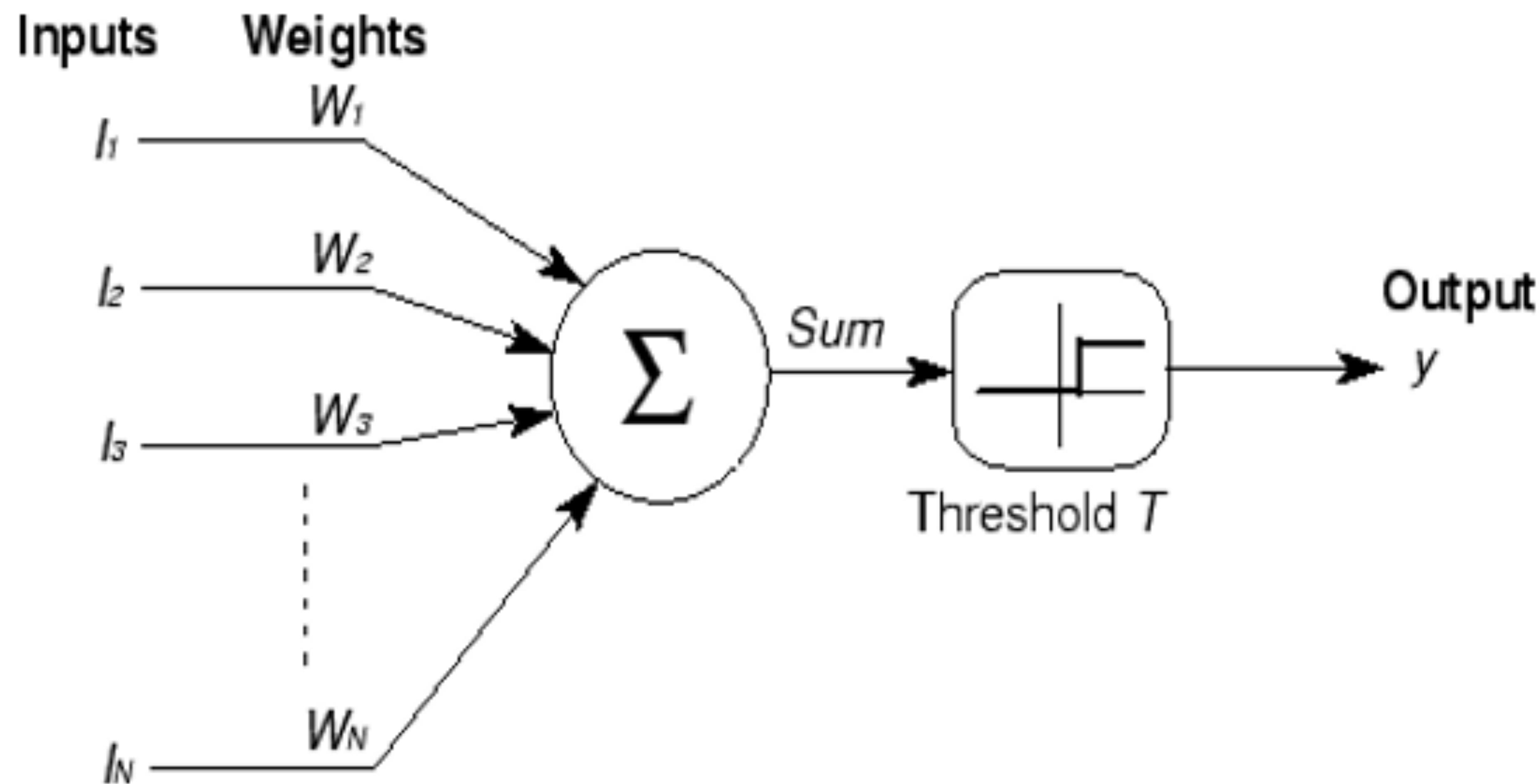




Timeline

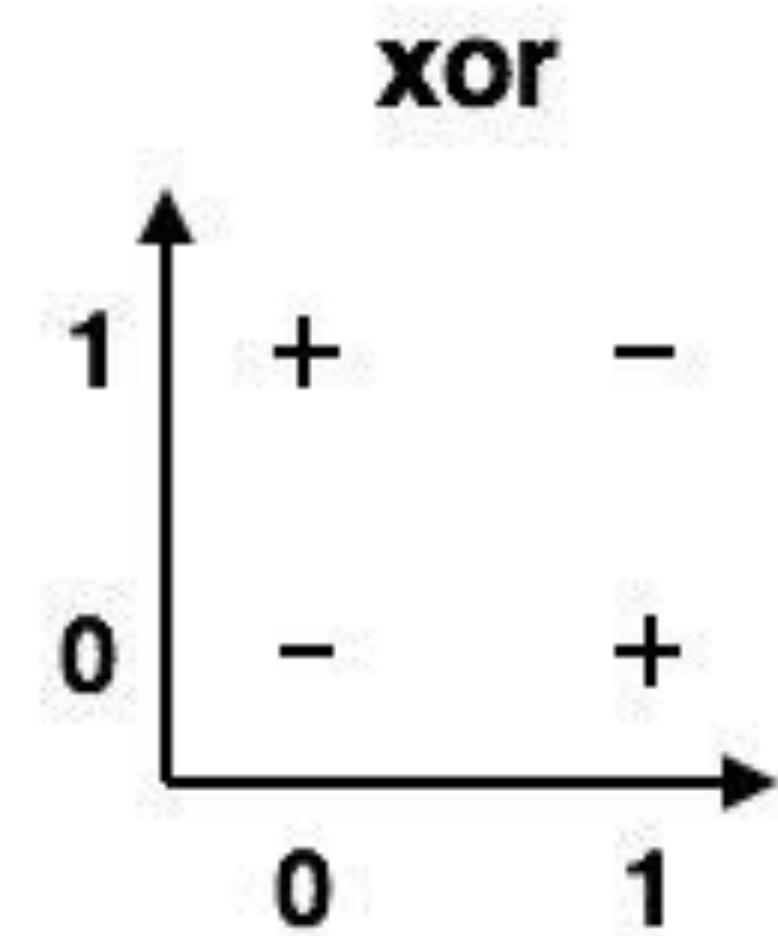
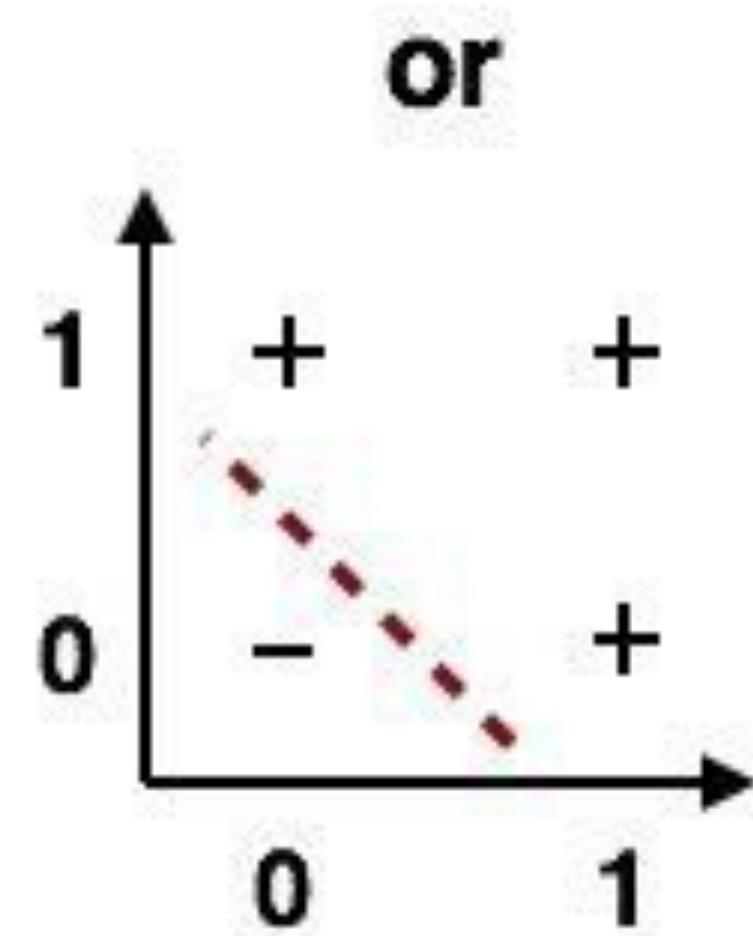
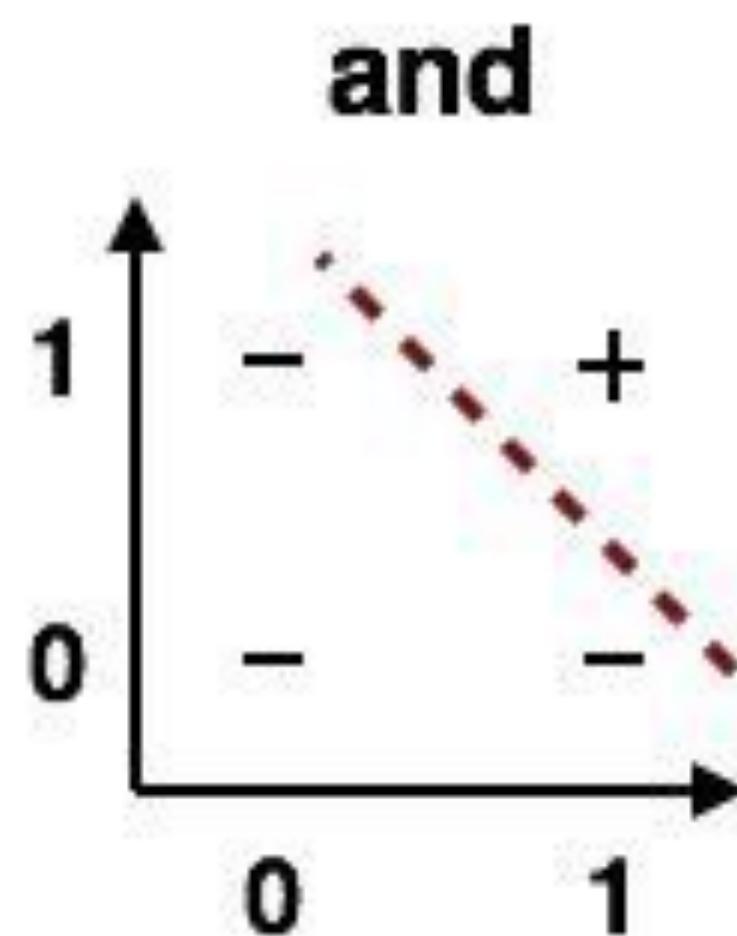
- **Cybernetics** 1940s-1960s
 - McCulloch-Pitts neuron
 - McCulloch and Pitts, 1942. A Logical Calculus of the Ideas Immanent in Nervous Activity
 - Hebbian Learning
 - Hebb, 1949. The Organization of Behaviour.
 - Perceptron
 - Rosenblatt, 1958. The Perceptron: A Probabilistic Model for Information Storage and Organization

Timeline



Timeline

BRACE YOURSELVES



Timeline

- **Connectionism** 1980s-1990s
 - Backpropagation
 - Rumelhart et al., 1986. Learning Representations by Back-propagating Errors.
 - Convolutional Neural Networks
 - Fukushima, 1980. Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position.

Timeline

- **Deep Learning** 2006-
 - Deep Neural Networks
 - Hinton et al., 2006. A Fast Learning Algorithm for Deep Belief Nets.
 - Rectified Linear Units
 - Golorot et al., 2011. Deep Sparse Rectifier Neural Networks.
 - AlexNet
 - Krizhevsky et al, 2012. ImageNet Classification with Deep Convolutional Neural Networks.

And God said,



"Let there be light!"

ImageNet Classification with Deep Convolutional Neural Networks

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Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

Abstract

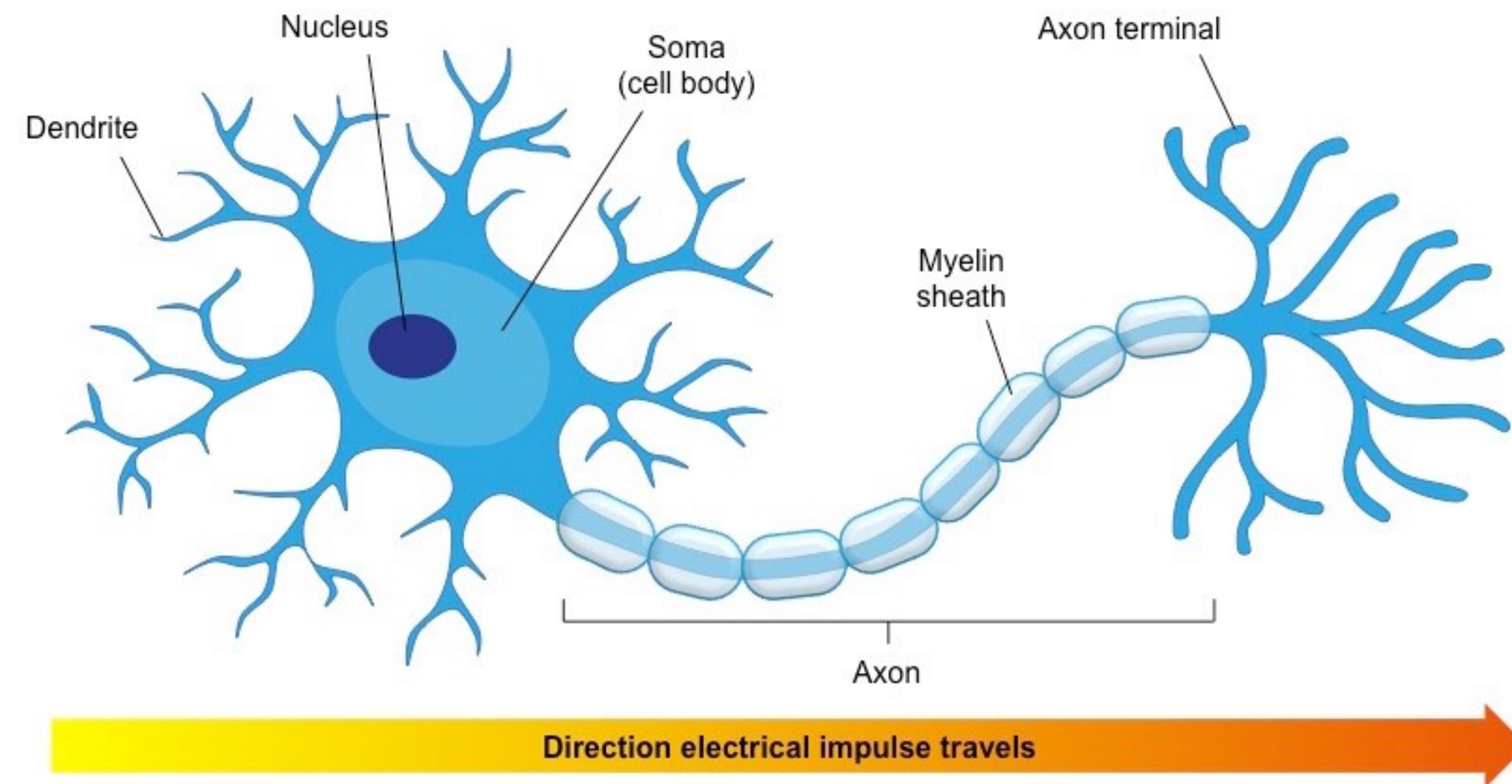
We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

Introduction

Current approaches to object recognition make essential use of machine learning methods. To improve their performance, we can collect larger datasets, learn more powerful models, and use better techniques for preventing overfitting. Until recently, datasets of labeled images were relatively small — on the order of tens of thousands of images (e.g., NORB [16], Caltech-101/256 [8, 9], and CIFAR-10/100 [12]). Simple recognition tasks can be solved quite well with datasets of this size, especially if they are augmented with label-preserving transformations. For example, the current error rate on the MNIST digit recognition task [1] has been reduced to 0.3%

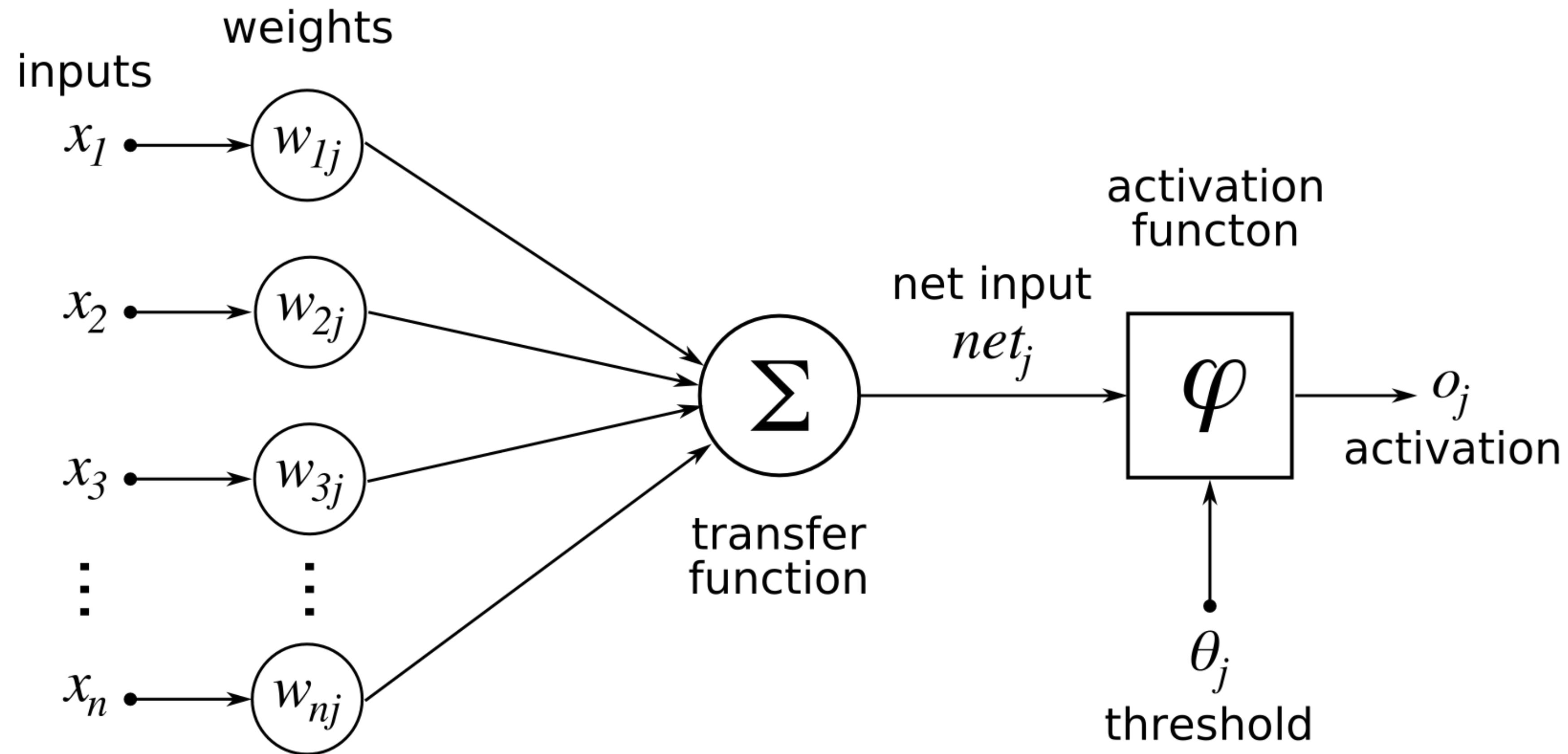
Neural networks

- Feed-forward networks



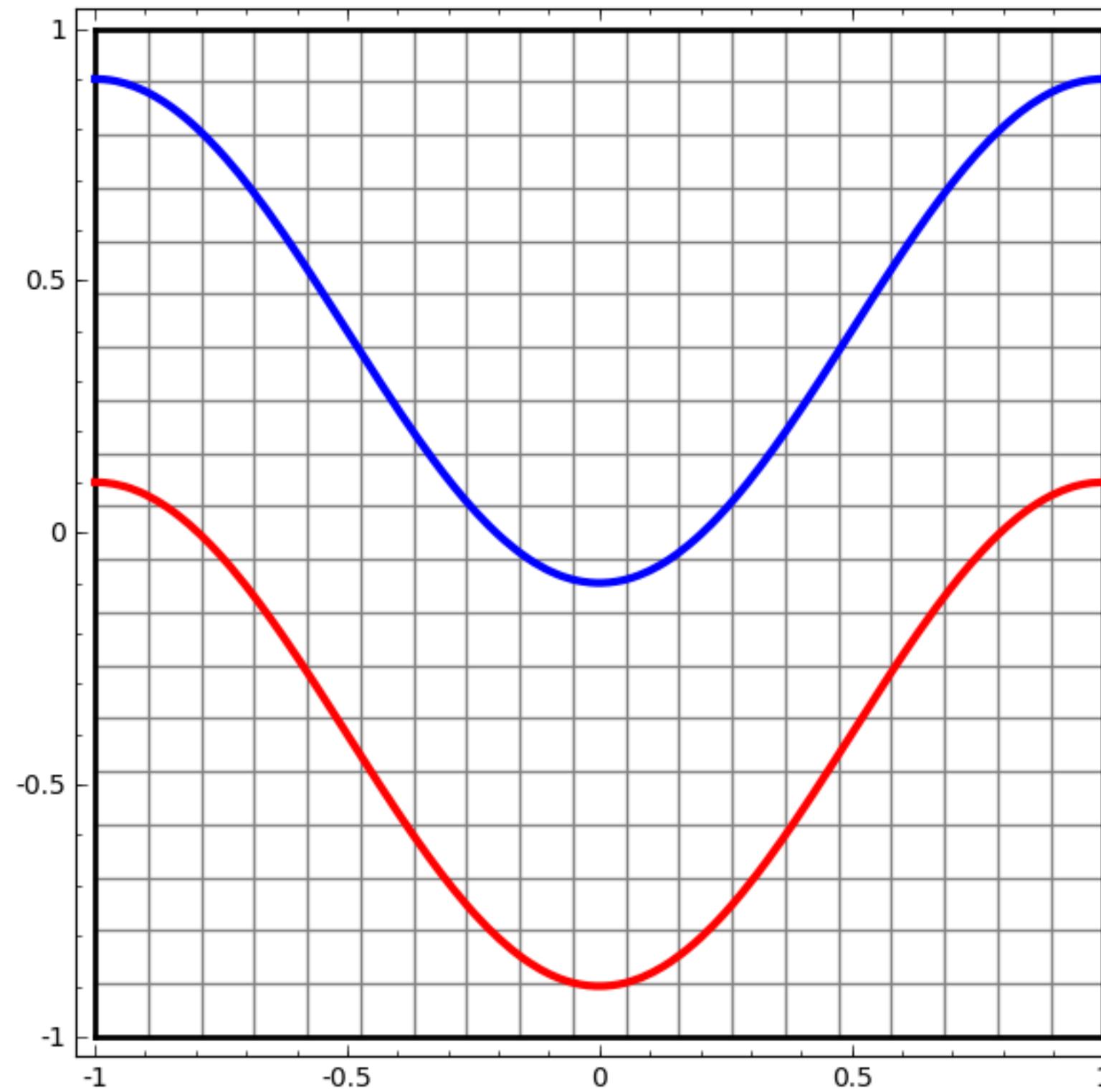
Neural networks

- Feed-forward networks



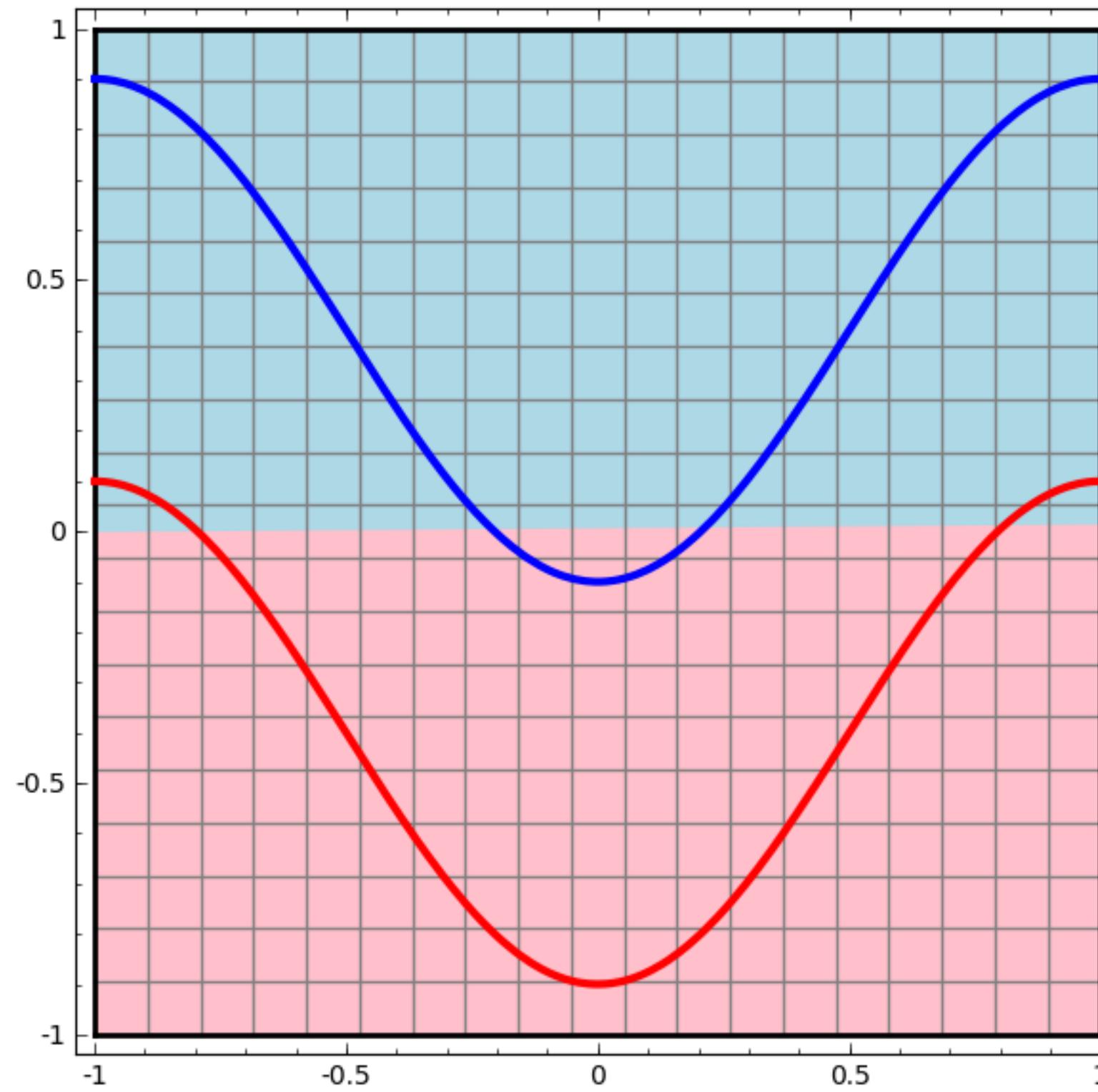
Neural networks

Problem: draw a single straight line to separate colors.



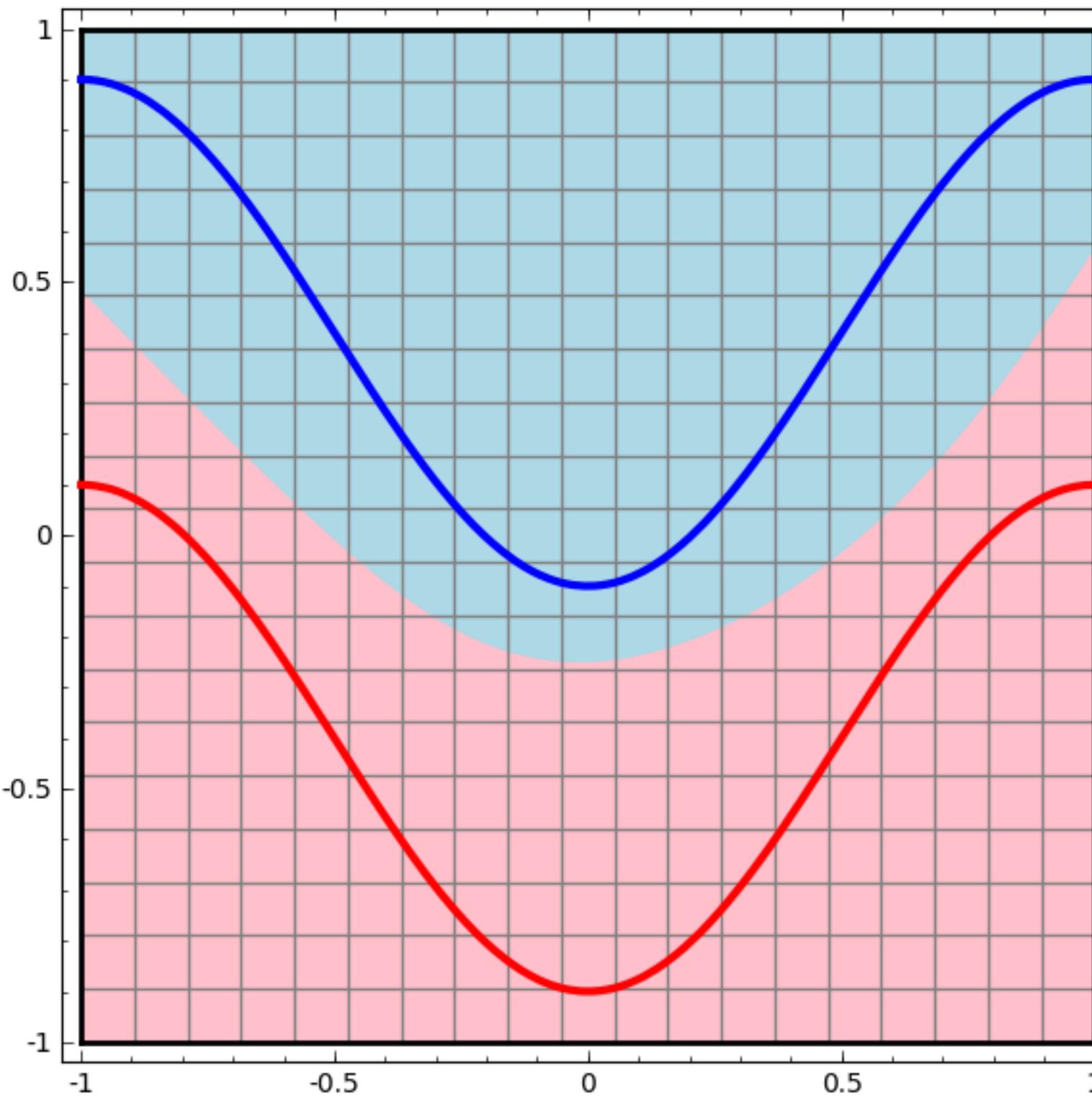
Neural networks

Problem: draw a single straight line to separate colors.



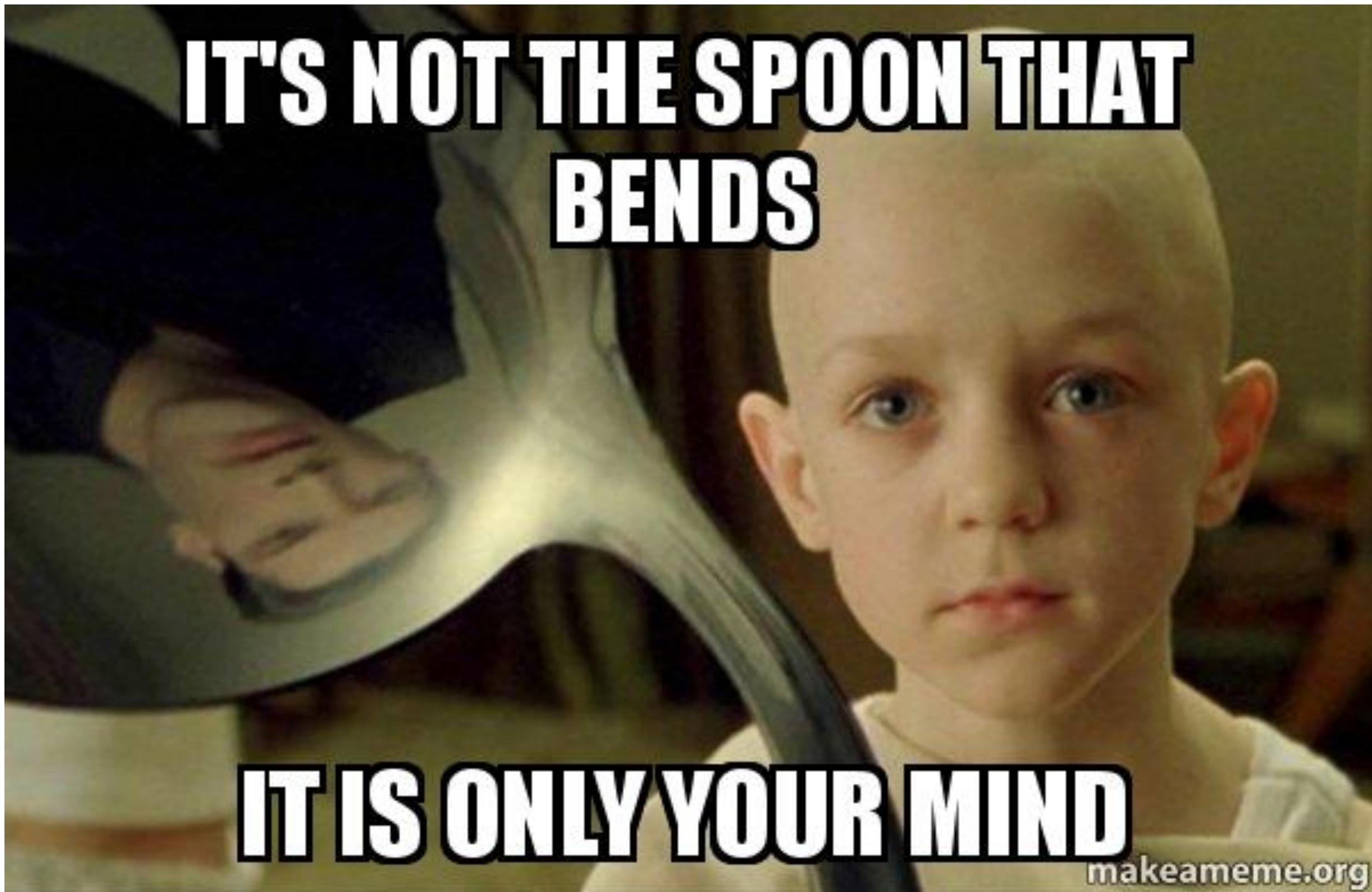
Neural networks

Problem: draw a single straight line to separate colors.



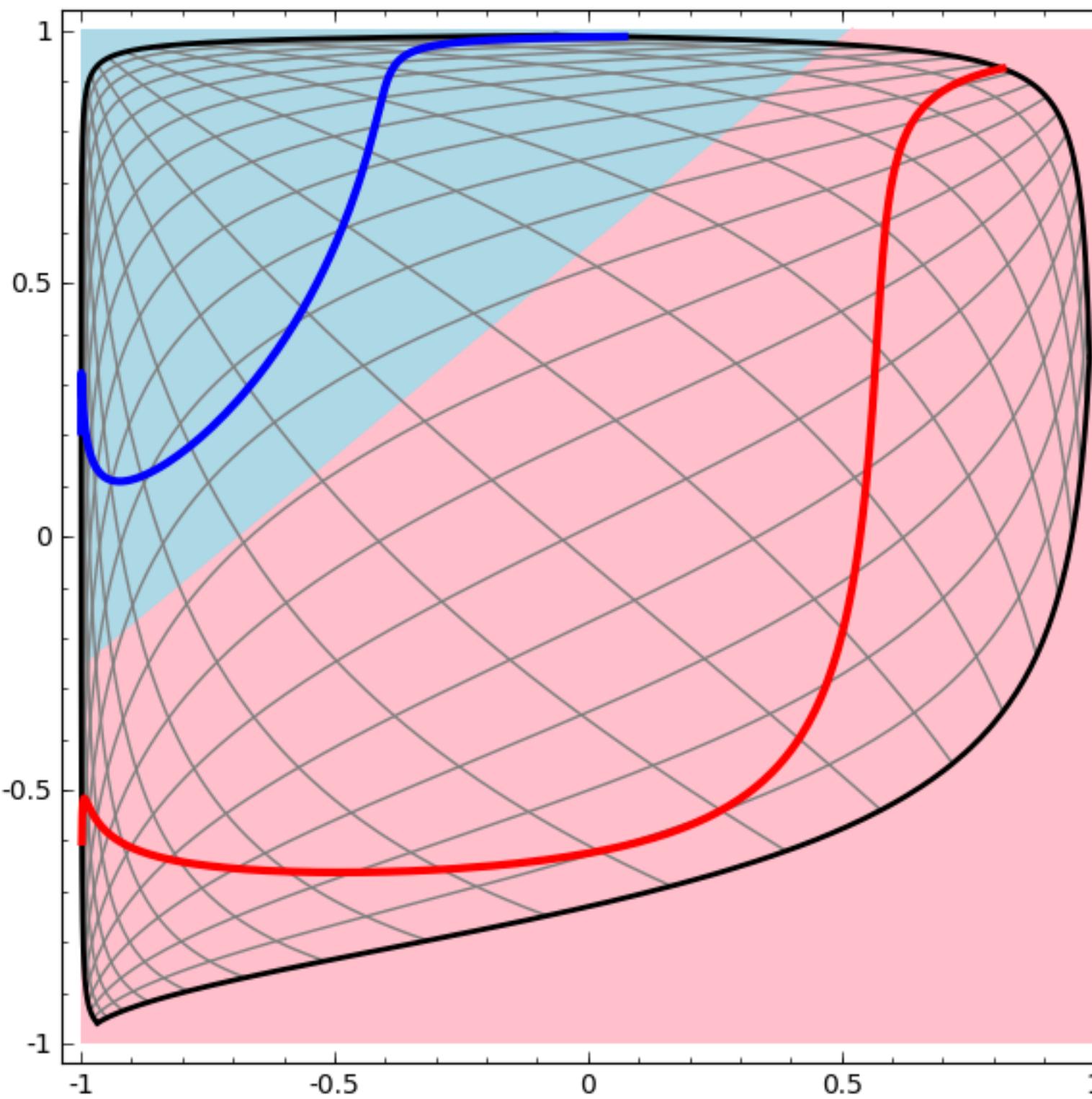
Neural networks

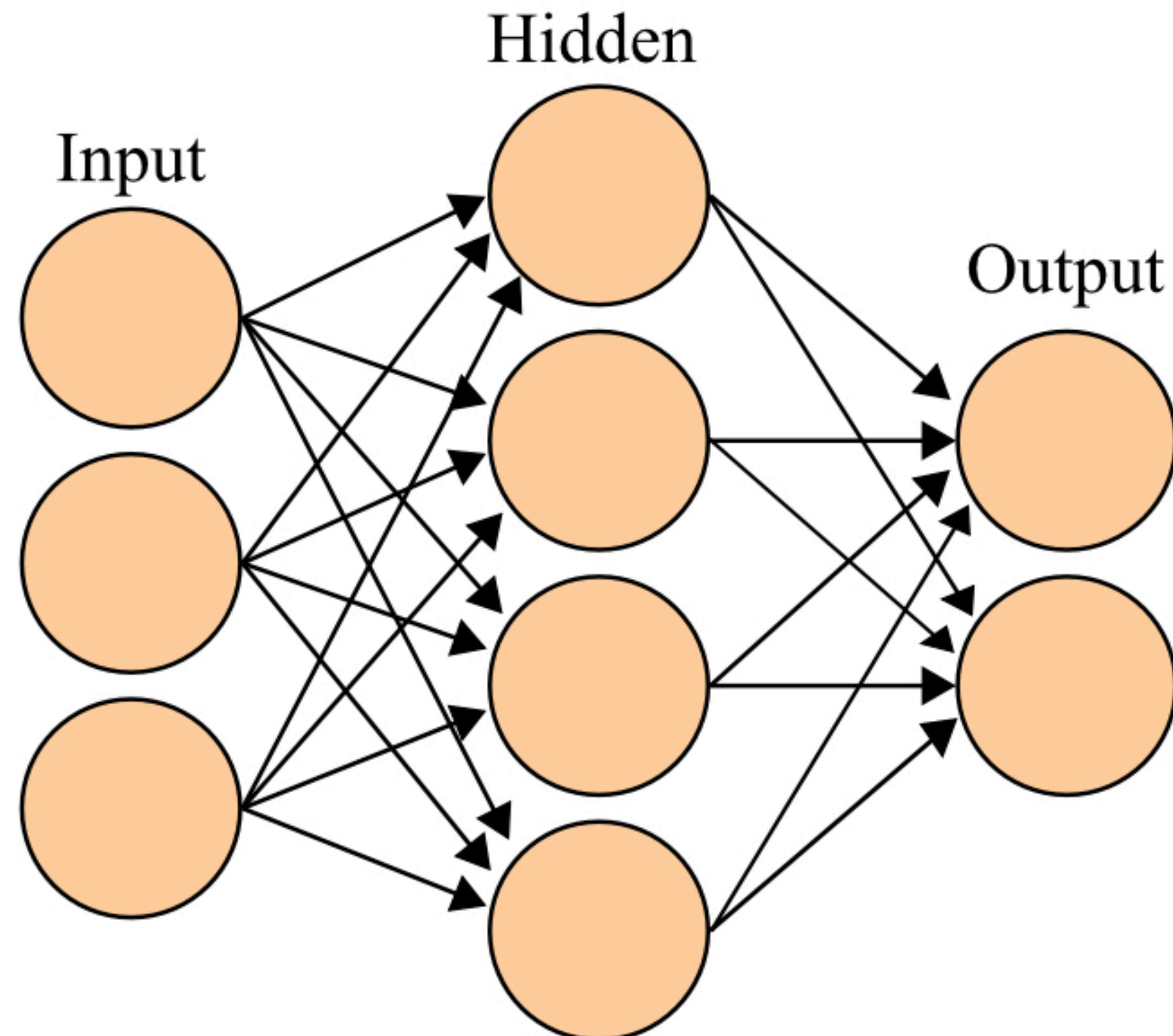
Problem: draw a single straight line to separate colors.



Neural networks

Problem: draw a single straight line to separate colors.

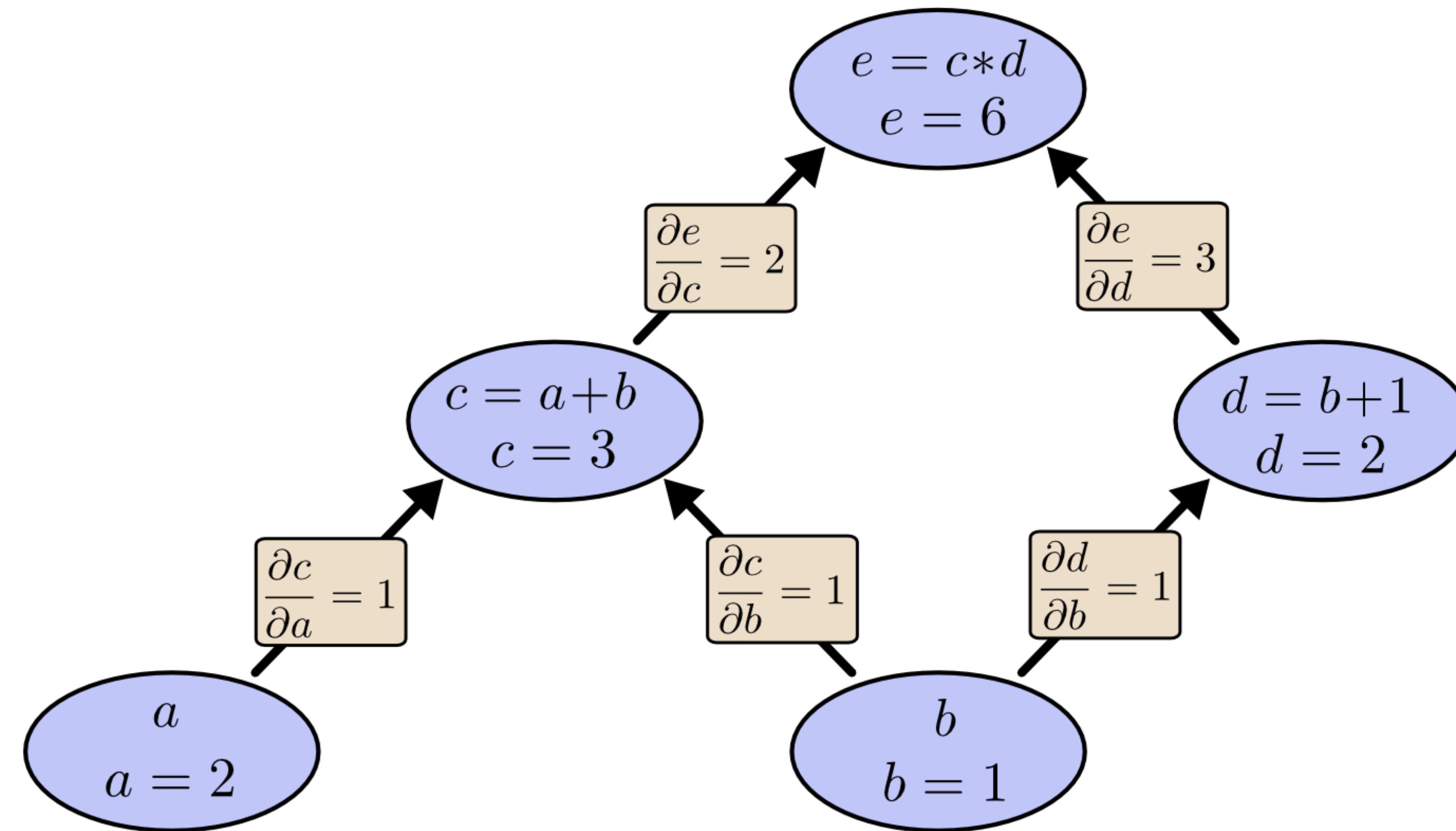




The hidden layer learns a **representation**, so that the data is linearly separable.

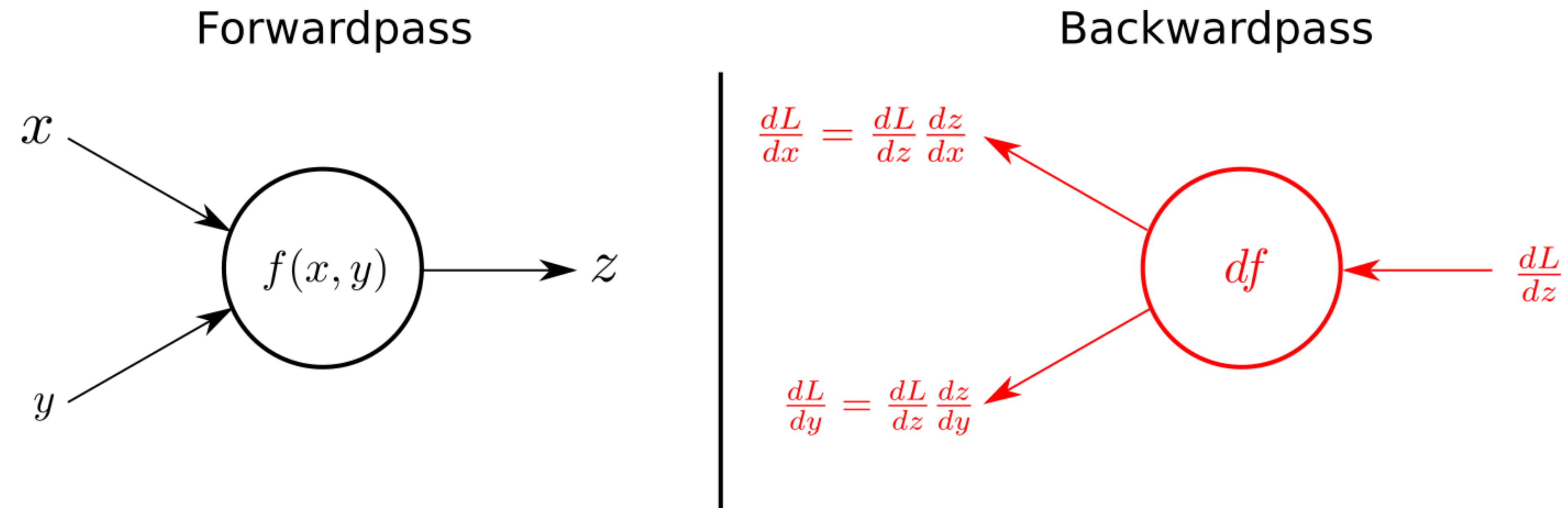
Neural networks

- Backpropagation



Neural Networks

- Backpropagation

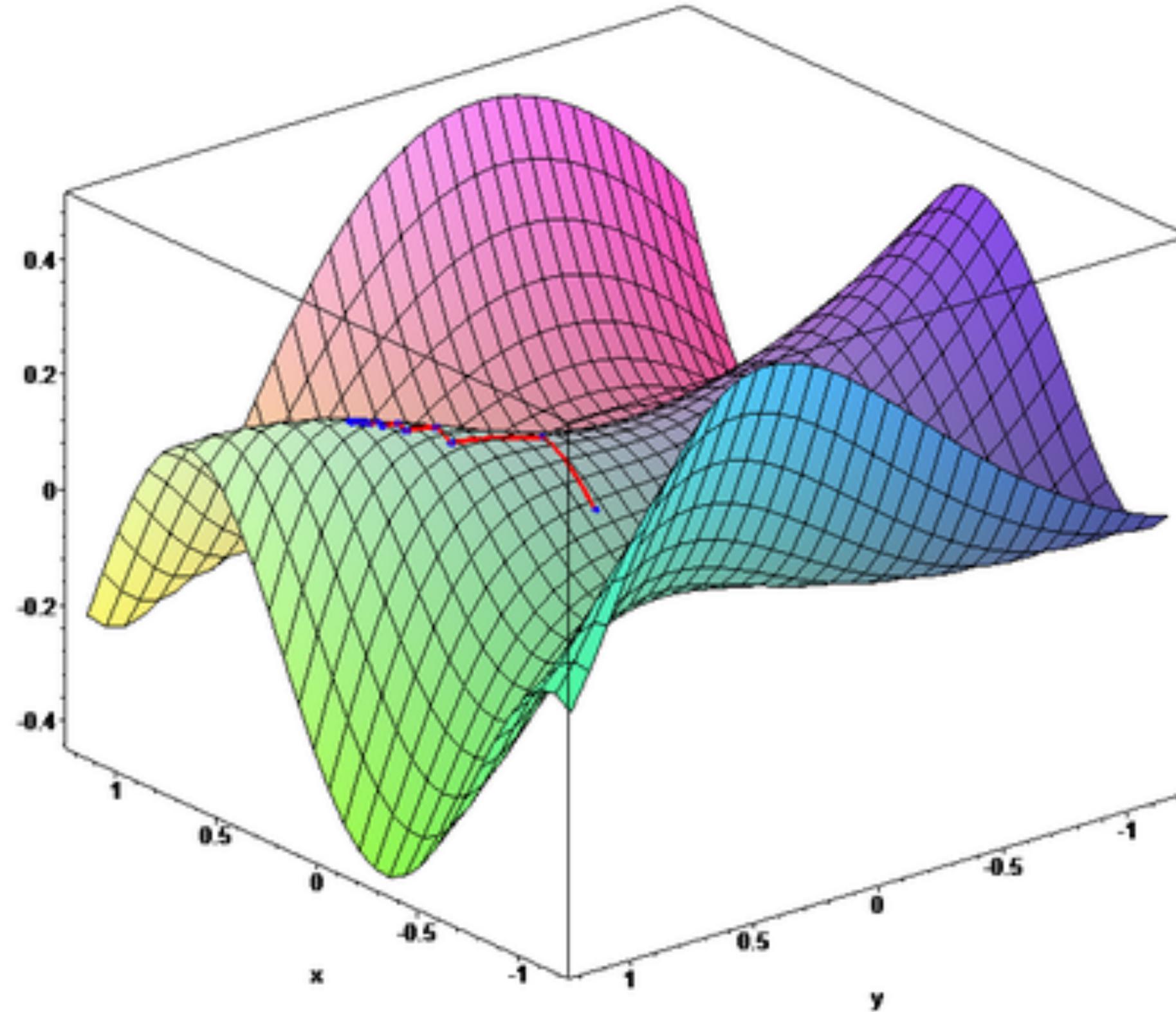


**IT IS FRIDAY, ALL MY FRIENDS ARE
AT PARTY**



Neural networks

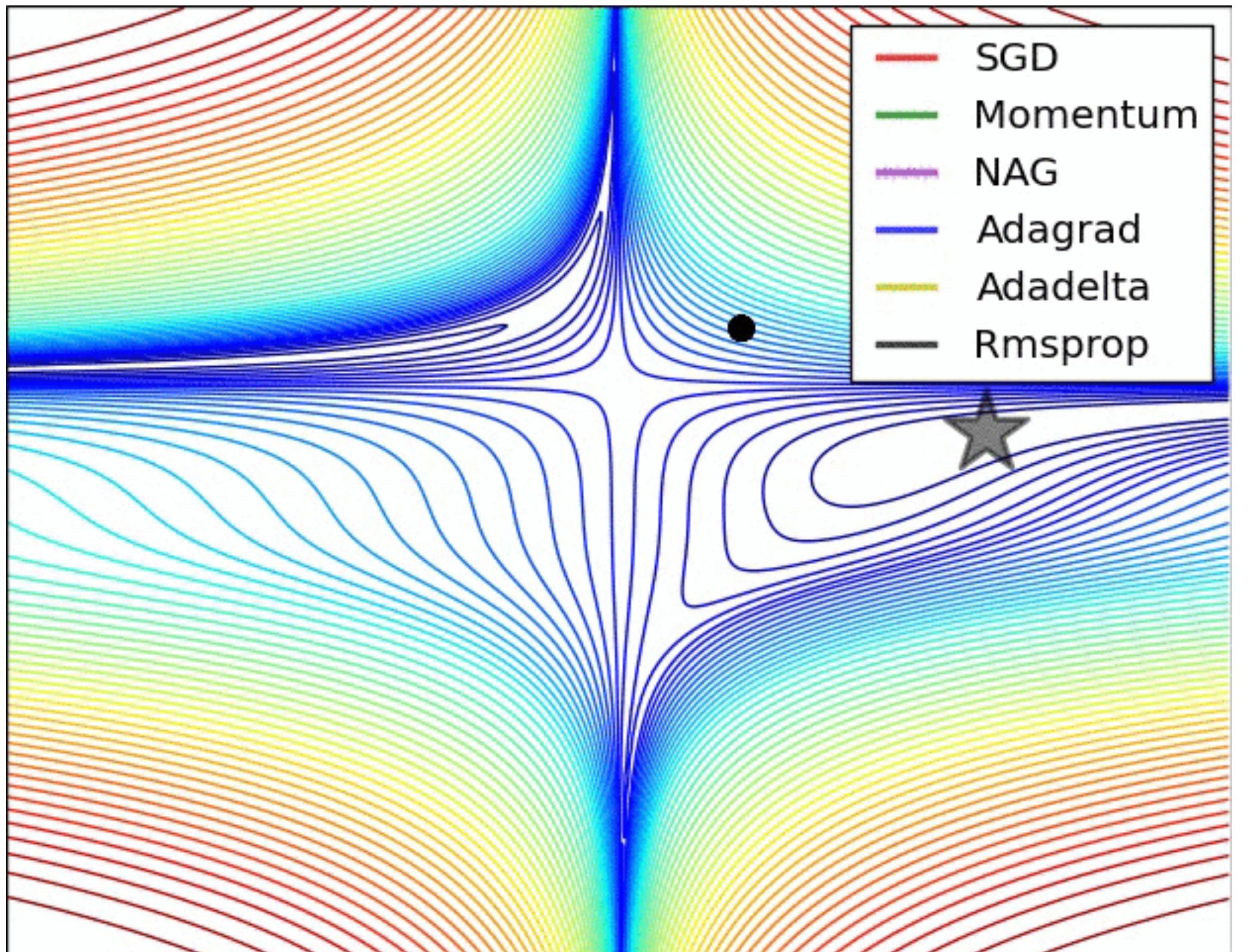
- Gradient descent



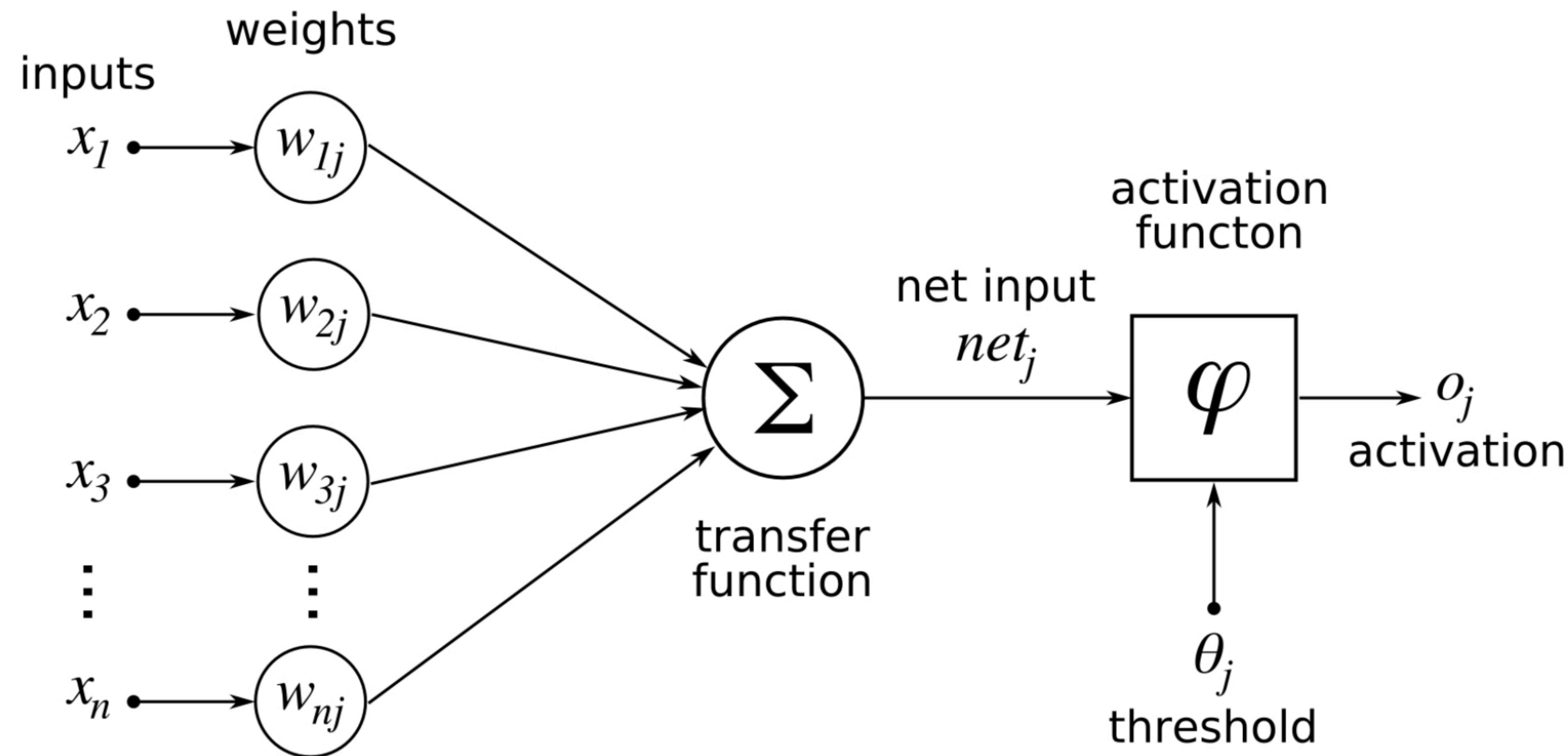
```
def updated_weights(weights, gradients, learning_rate):  
    return weights - learning_rate * (gradients - weights)
```

Neural networks

- Gradient descent
 - **Stochastic Gradient Descent (SGD)** is steady and stable.
 - **Adam** is fast, but sometimes wacky.

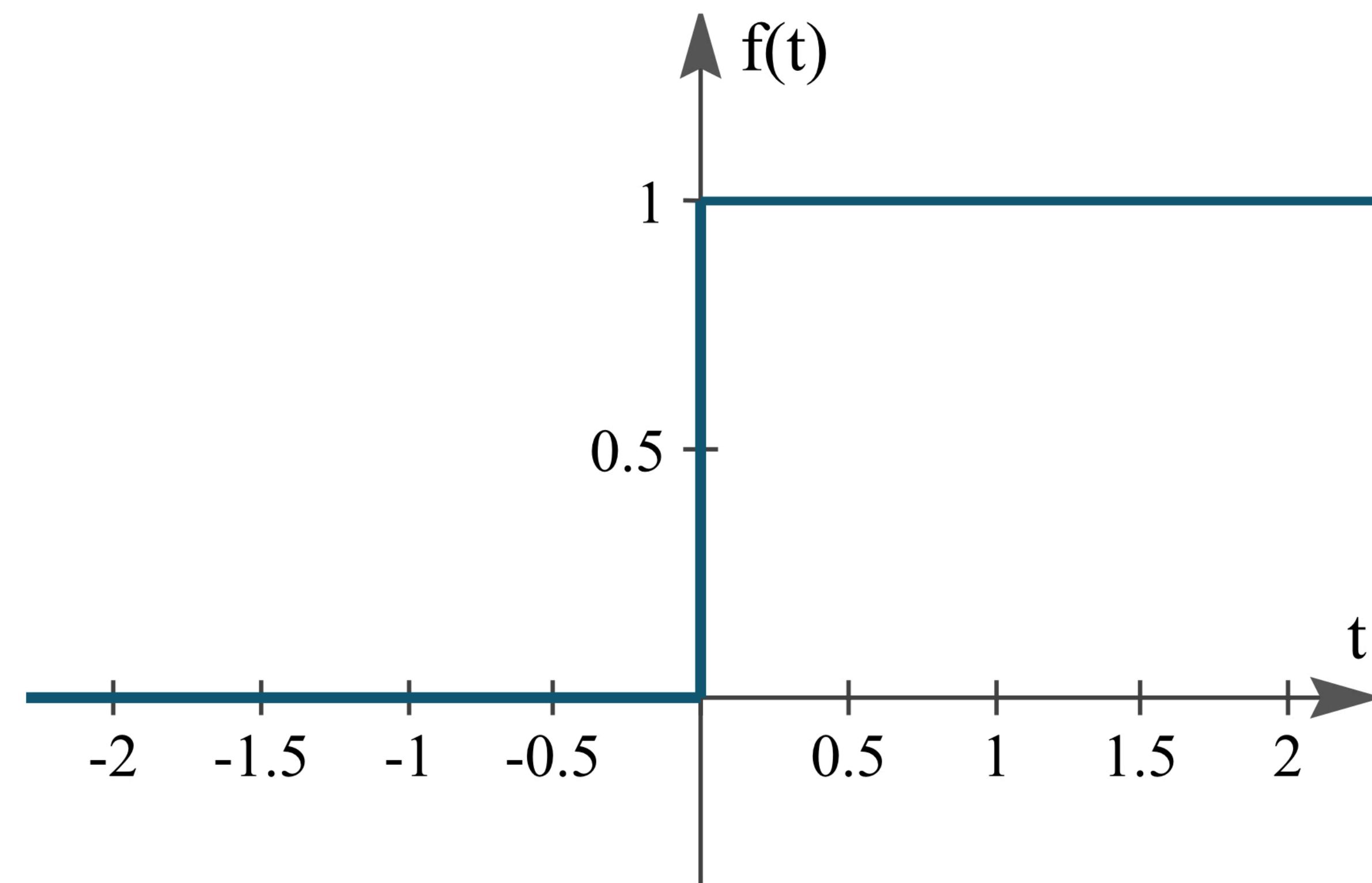


Activation functions and non-linearity



Activation functions and non-linearity

- Step function



Activation functions and non-linearity

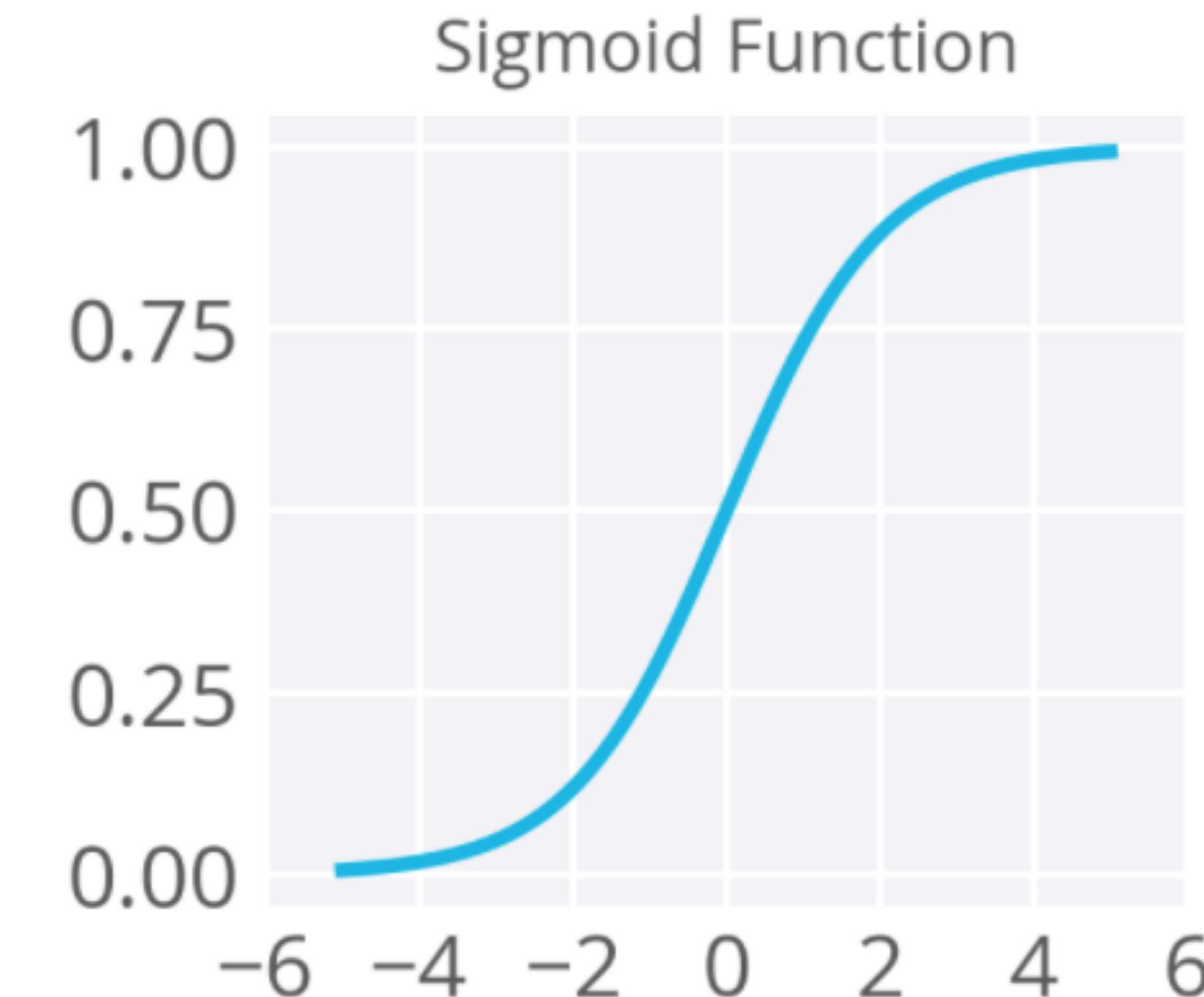


I'm afraid you couldn't be more wrong.

Activation functions and non-linearity

- Sigmoid function

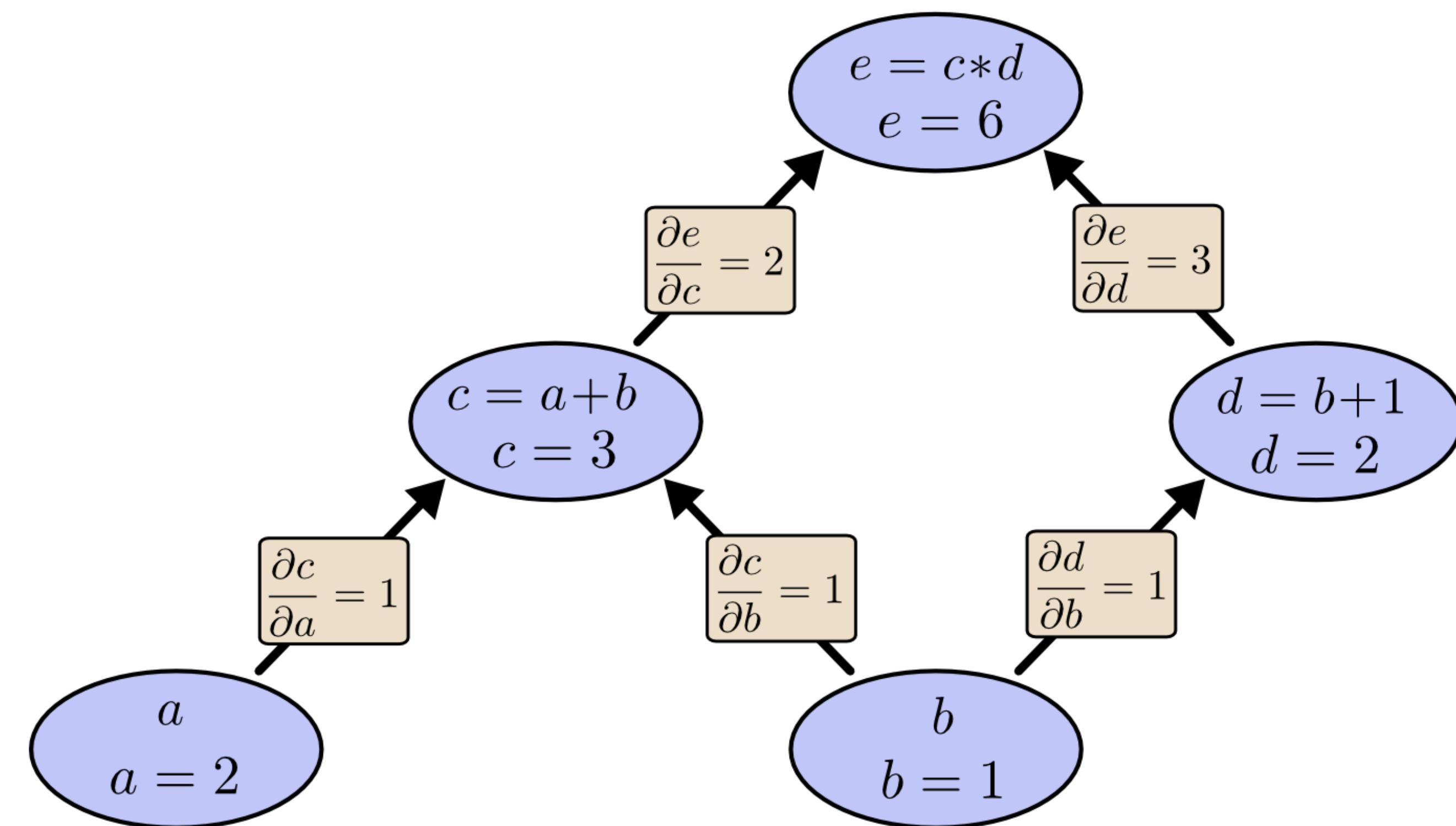
$$\frac{1}{1 + e^{-x}}$$



```
def sigmoid(inputs):  
    return 1.0 / (1.0 + exp(-inputs))
```

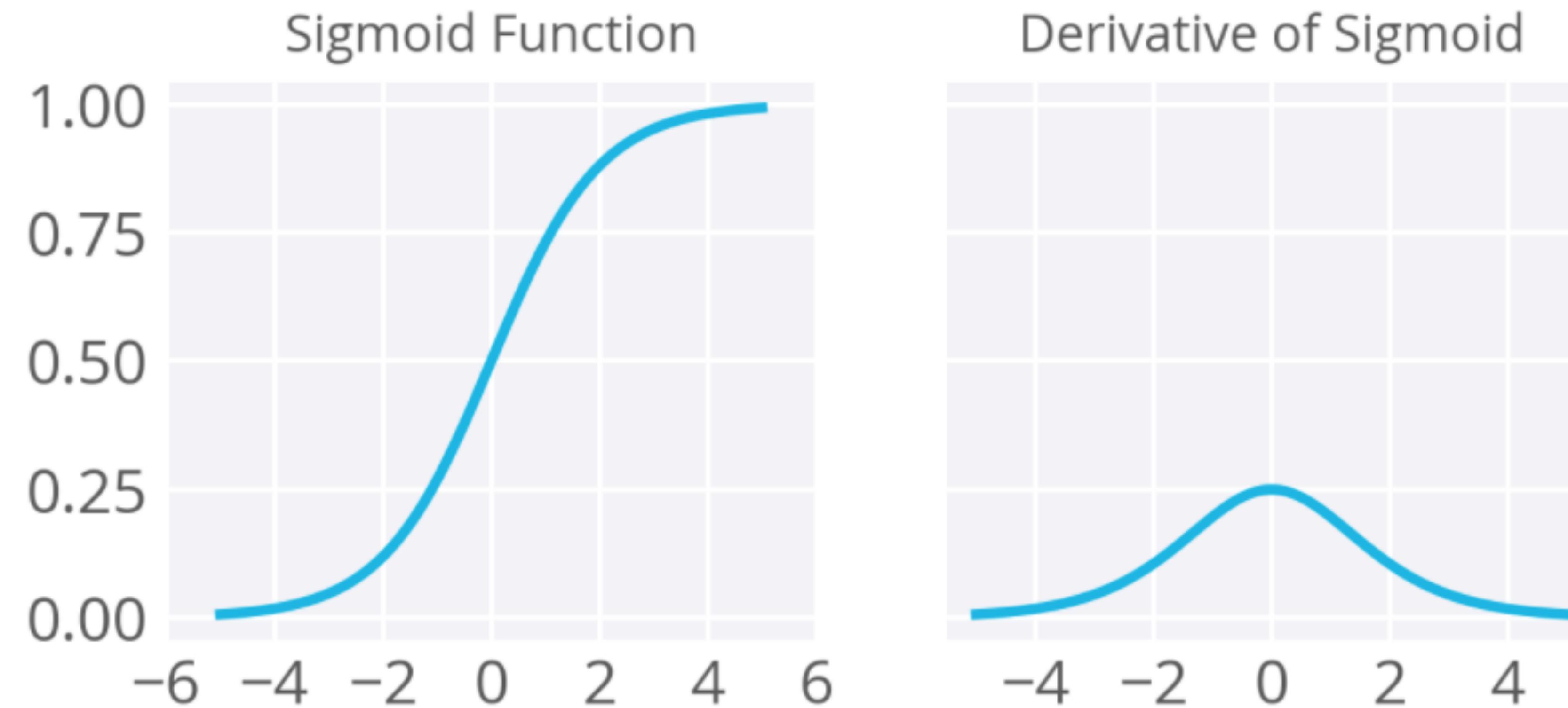
Activation functions and non-linearity

- Sigmoid function



Activation functions and non-linearity

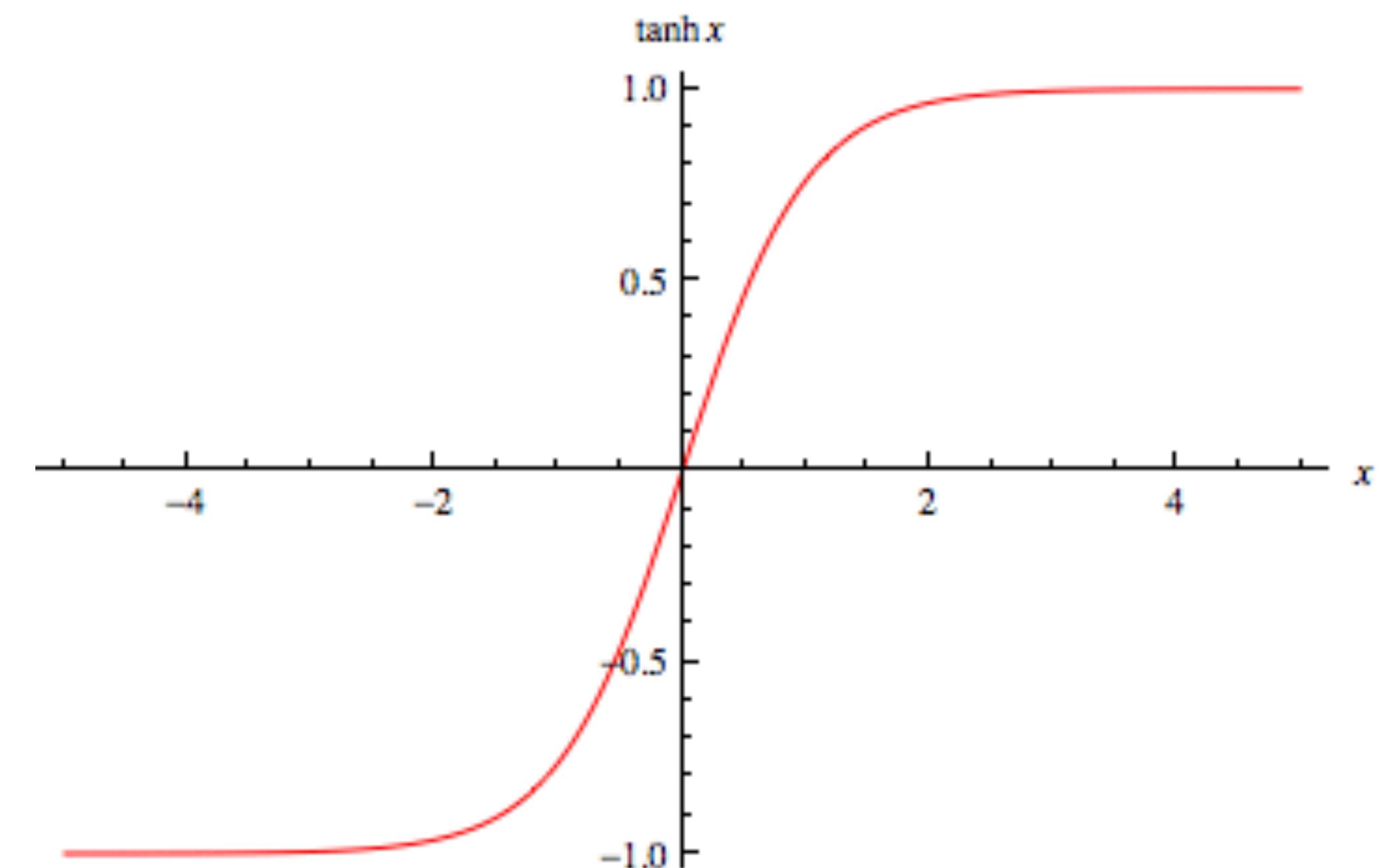
- Sigmoid function



Activation functions and non-linearity

- Hyperbolic Tangent (tanh)

$$\frac{e^x - e^{-x}}{e^x + e^{-x}}$$

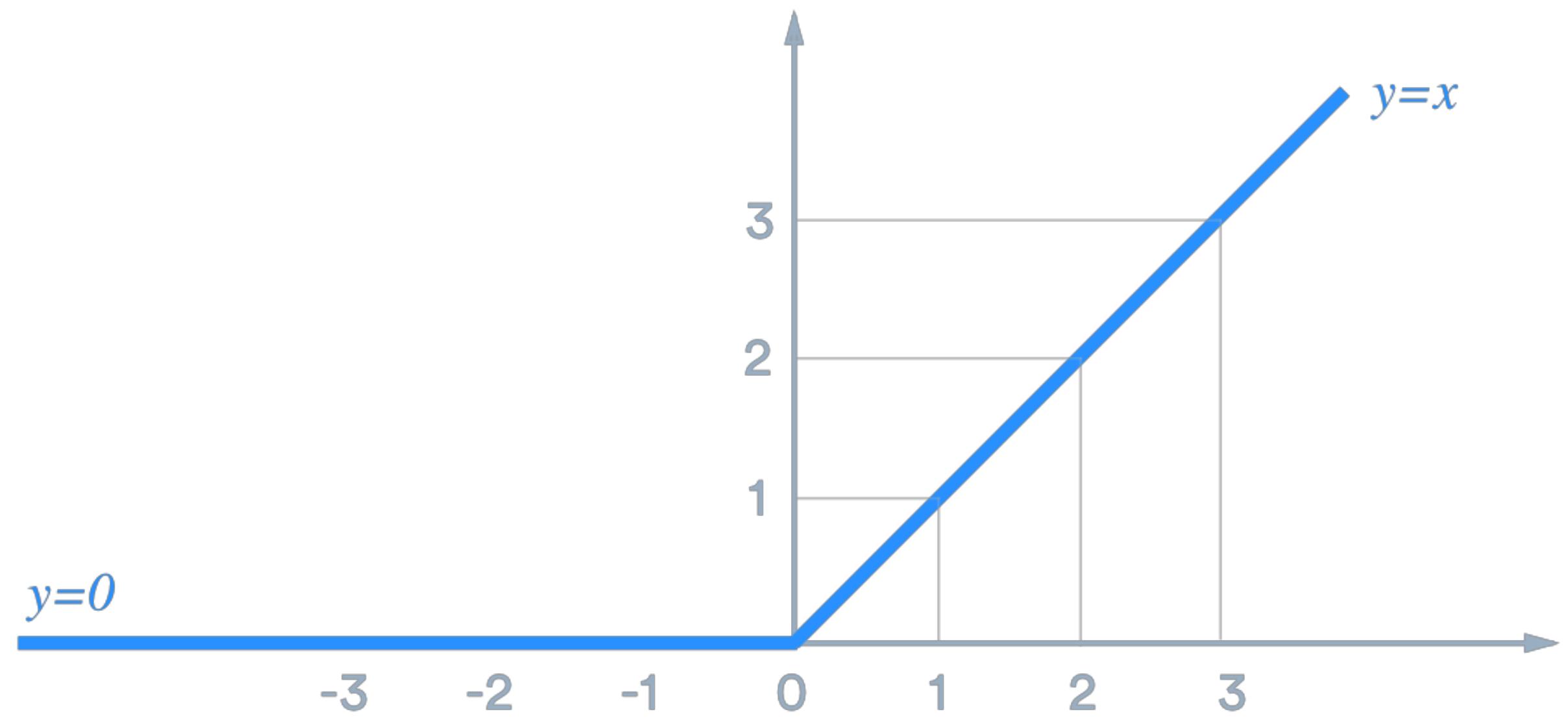


```
def tanh(inputs):  
    return (exp(inputs) - exp(-inputs)) / (exp(inputs) + exp(-inputs))
```

Activation functions and non-linearity

- Rectified Linear Units (ReLU)

$$\max(0, x)$$



```
def relu(inputs):  
    return max(0, inputs)
```

Activation functions and non-linearity

- Softmax function



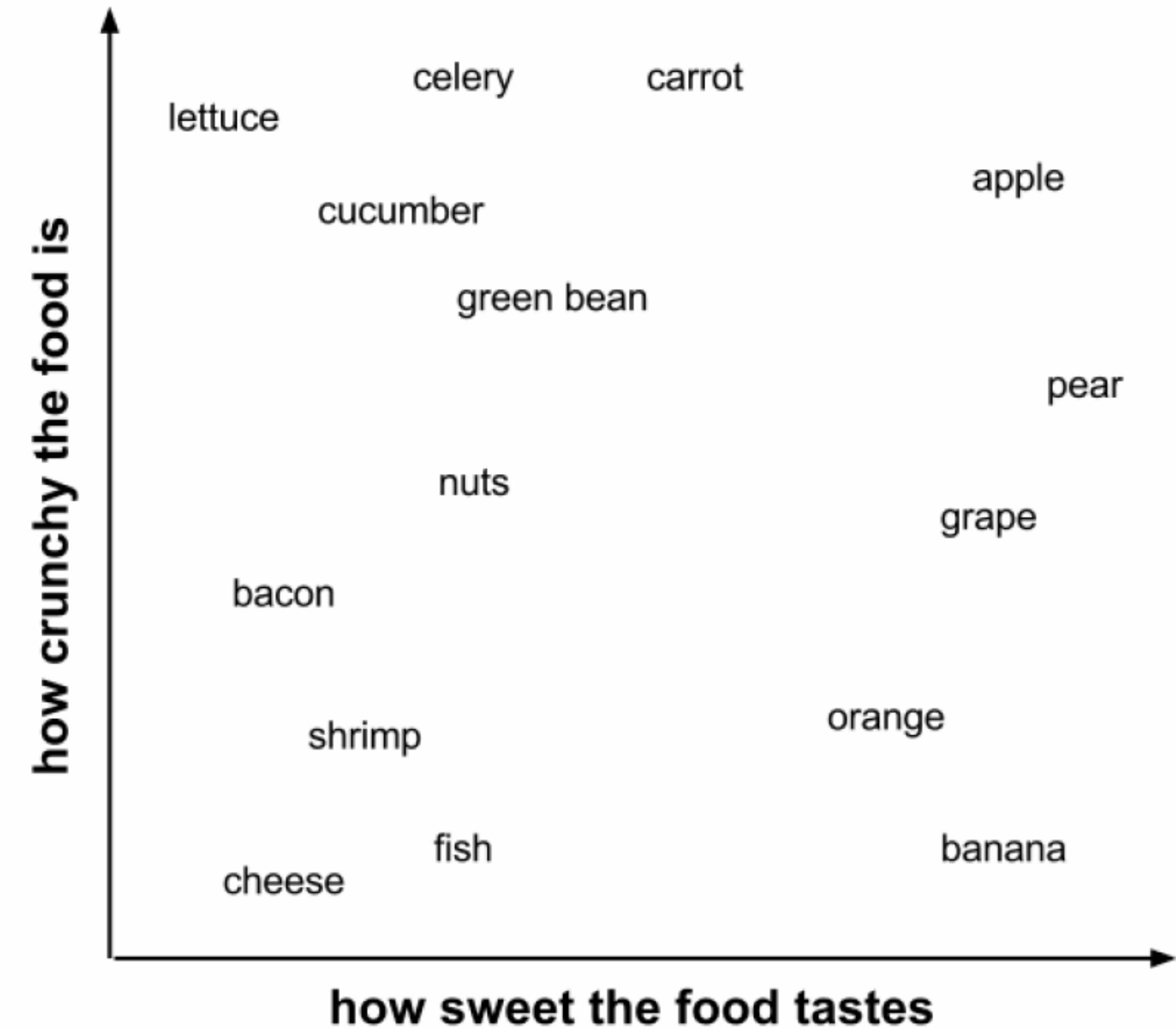
cat	3.2	1.3	2.2
car	5.1	4.9	2.5
frog	-1.7	2.0	-3.1



http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture03.pdf

Activation functions and non-linearity

- Where activation functions are used:
 - in-between layers: **ReLU** and its variants
 - after the final layer: **sigmoid** (binary) or **softmax** (multiclass)



K-Nearest Neighbors

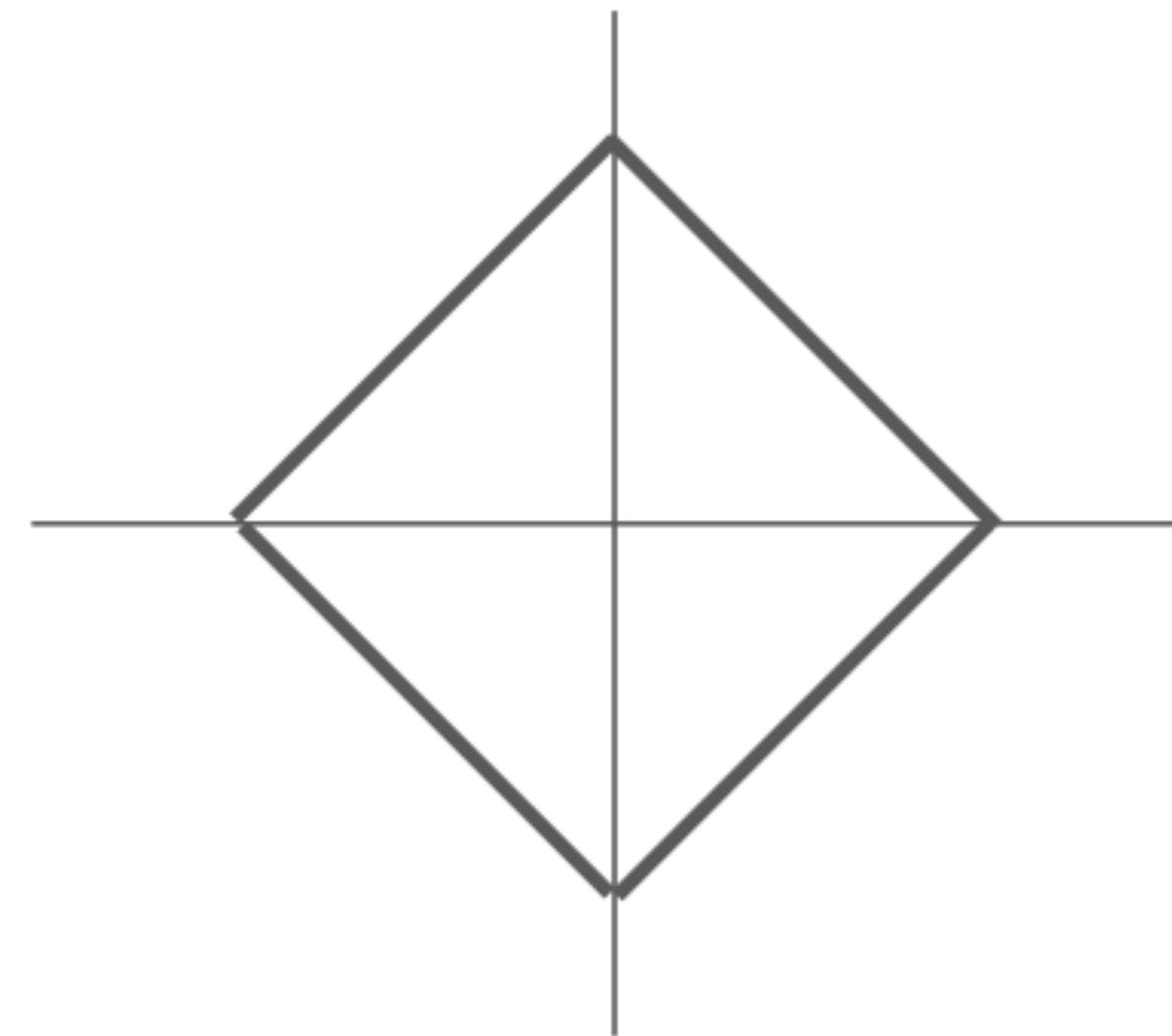
Loss functions

- L1 Loss

$$\sum_{i=1}^n |y_i - \hat{y}_i|$$

L1 (Manhattan) distance

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$



```
def l1_loss(targets, outputs):  
    return sum(abs(targets - outputs))
```

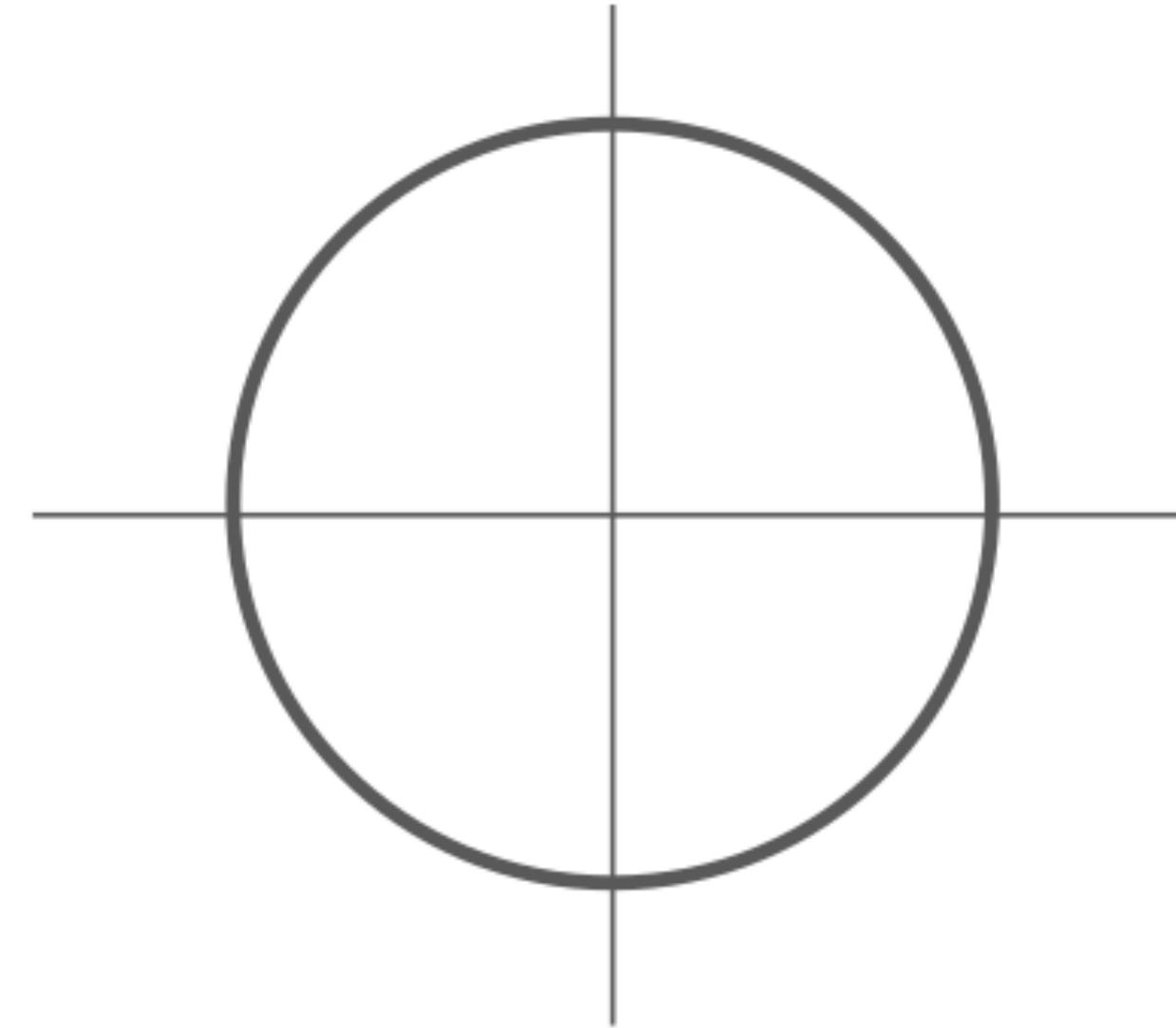
Loss functions

- L2 Loss

$$\sum_{i=1}^n (y_i - \hat{y}_i)^2$$

L2 (Euclidean) distance

$$d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2}$$



```
def l2_loss(targets, outputs):  
    return sum((targets - outputs)**2))
```

Loss functions

- Mean squared error (MSE)

$$\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

		상세 점수										엔
		야구순위	1	2	3	4	5	6	7	8	9	10
순위	현재	두	슬	한	넥	기	삼	롯	엘	클	한	엔
1		기	두	엔	롯	슬	엘	삼	넥	클	한	32
1		기	엔	두	엘	넥	슬	삼	롯	클	한	32
5		엔	기	롯	두	엘	넥	슬	삼	한	클	38
1		기	두	엔	엘	슬	롯	넥	삼	한	클	32
4		기	두	엔	엘	롯	슬	넥	삼	클	한	34

```
def mean_square_error(targets, outputs):  
    return mean(sqrt((targets - outputs)**2))
```

Loss functions

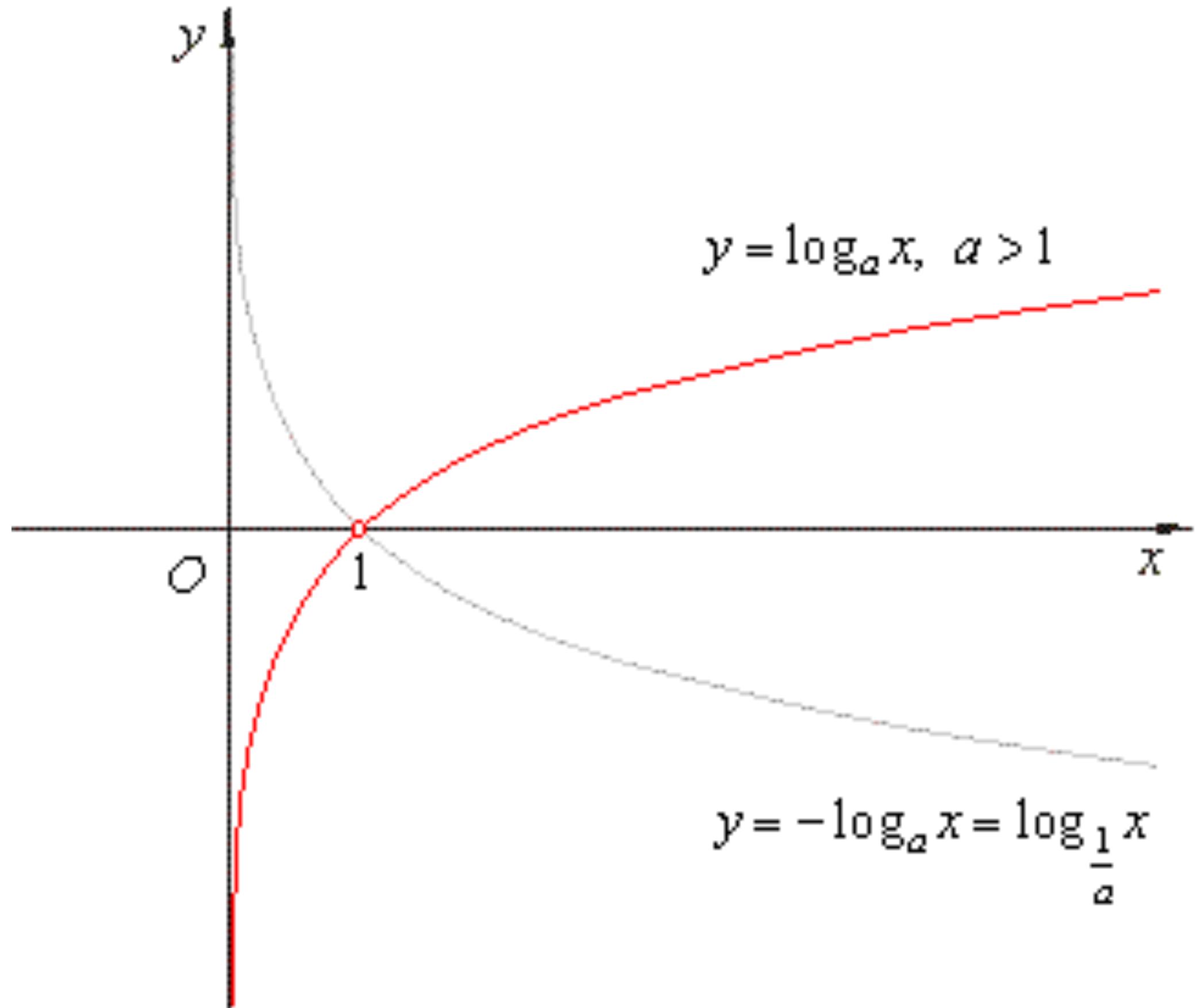
- Cross Entropy

Entropy (in information theory)

= amount of information in an event

= amount of surprise

$$h[x] = \mathbb{E}[-\log P(x)]$$



Loss functions

- Cross Entropy

$$D(\hat{\mathbf{y}}, \mathbf{y}) = - \sum_j y_j \ln \hat{y}_j$$

Diagram illustrating the Cross Entropy Loss function. On the left, a vector $\hat{\mathbf{y}}$ is shown with values $[0.1, 0.5, 0.4]$. On the right, a vector \mathbf{y} is shown with values $[0, 1, 0]$. A red curved arrow points from $\hat{\mathbf{y}}$ to the term y_j in the formula, and a blue curved arrow points from \mathbf{y} to the term $\ln \hat{y}_j$.

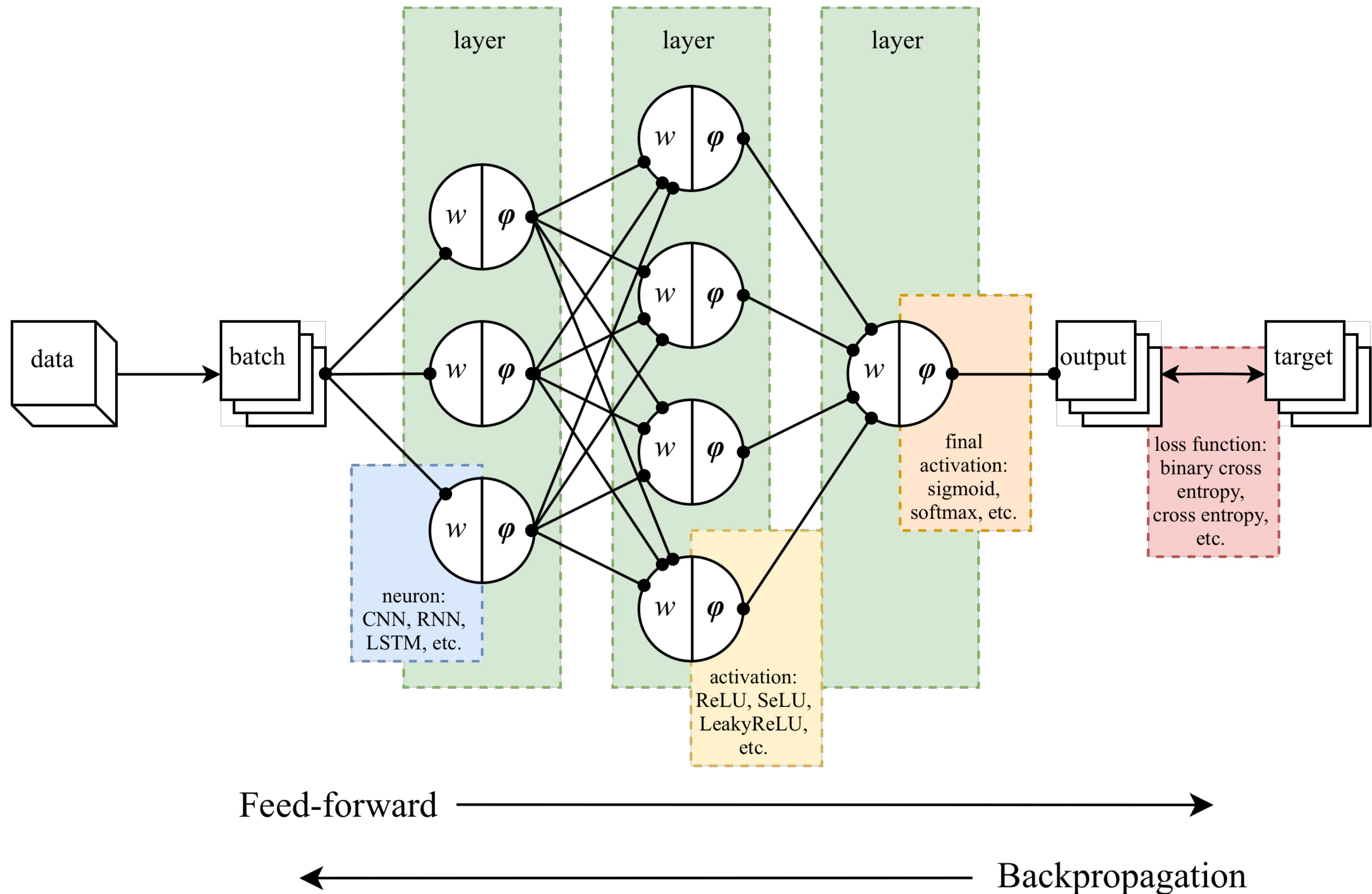
```
def cross_entropy_loss(targets, outputs):  
    return -sum(targets * log(outputs))
```

Loss functions

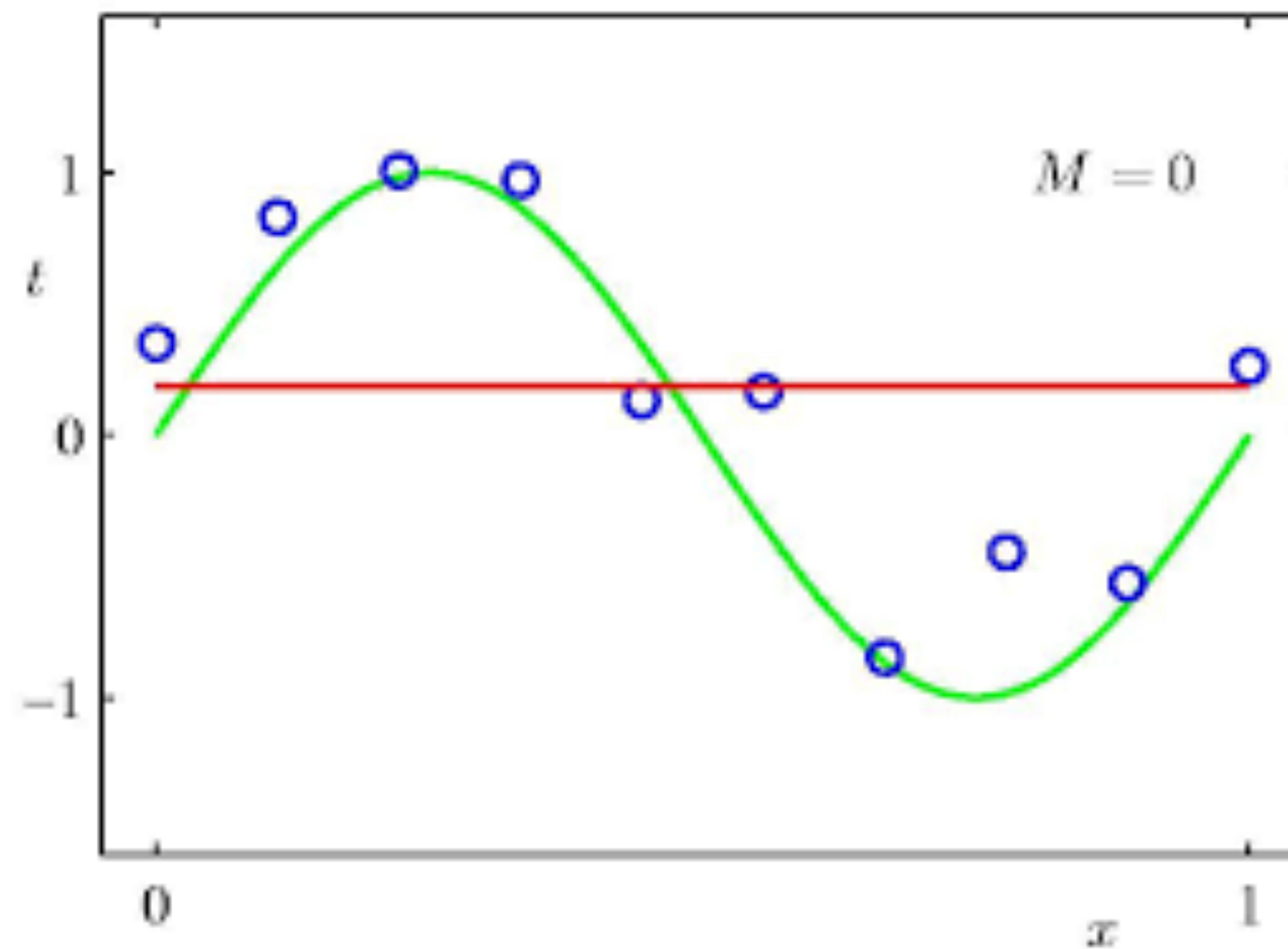
- Binary Cross Entropy

$$-\frac{1}{n} \sum_{i=1}^n [y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)]$$

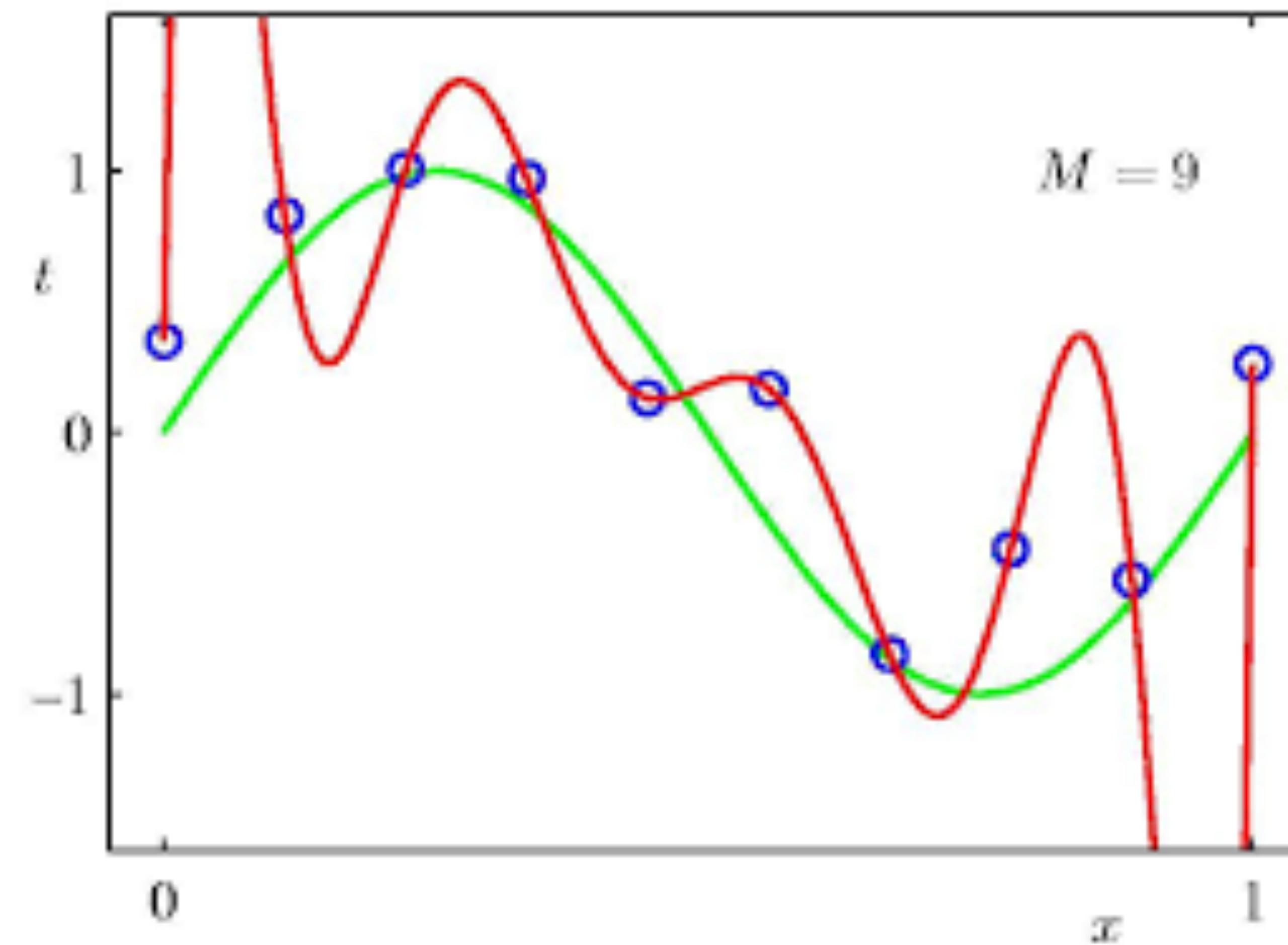
```
def binary_cross_entropy_loss(targets, outputs):
    return -mean(targets * log(outputs) + (1 - targets) * log(1 - outputs))
```



Regularization methods



Regularization methods



Regularization methods

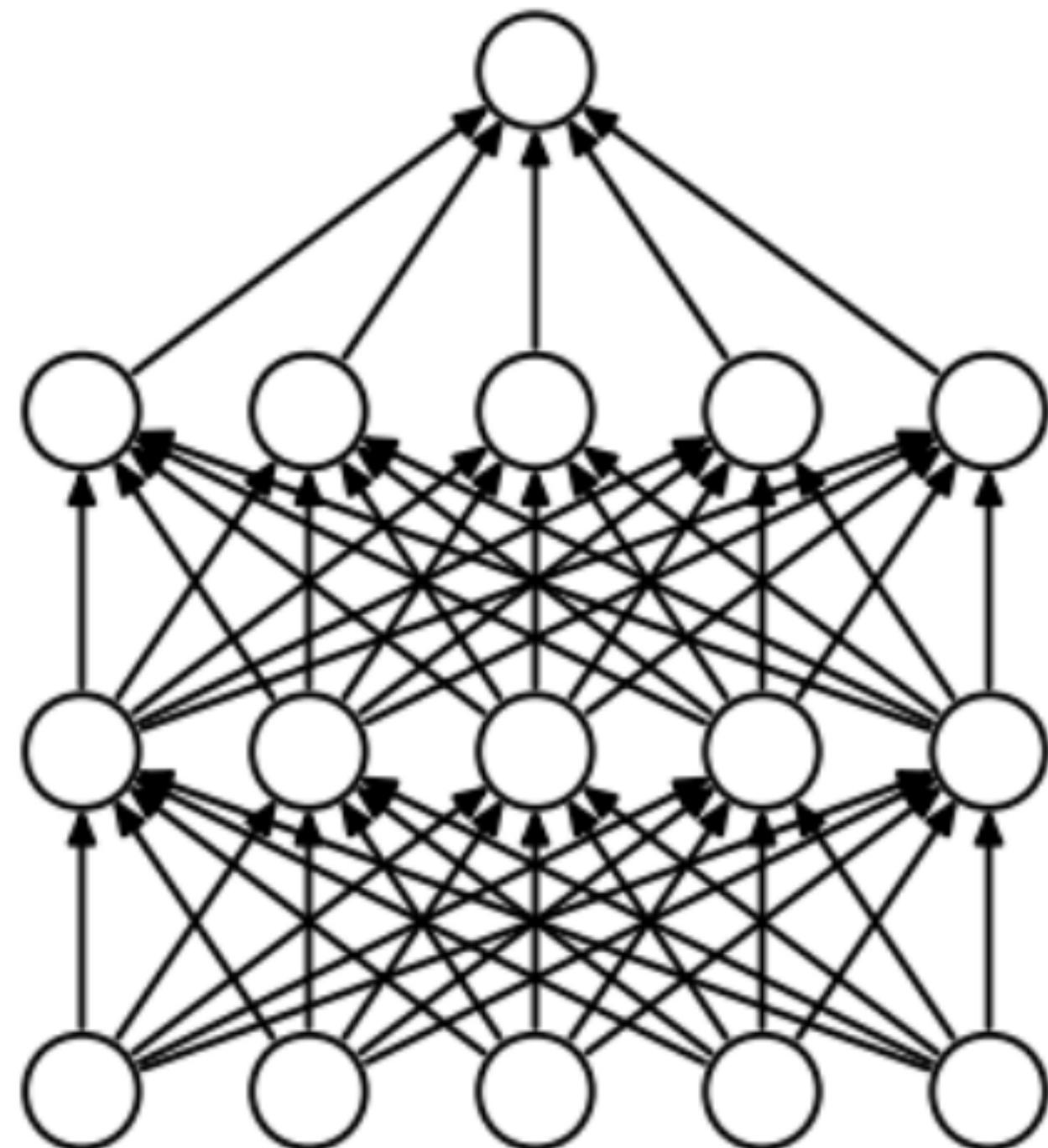
- Weight decay

$$W \leftarrow W - \lambda \left(\frac{\partial L}{\partial W} + \gamma \|W\| \right)$$

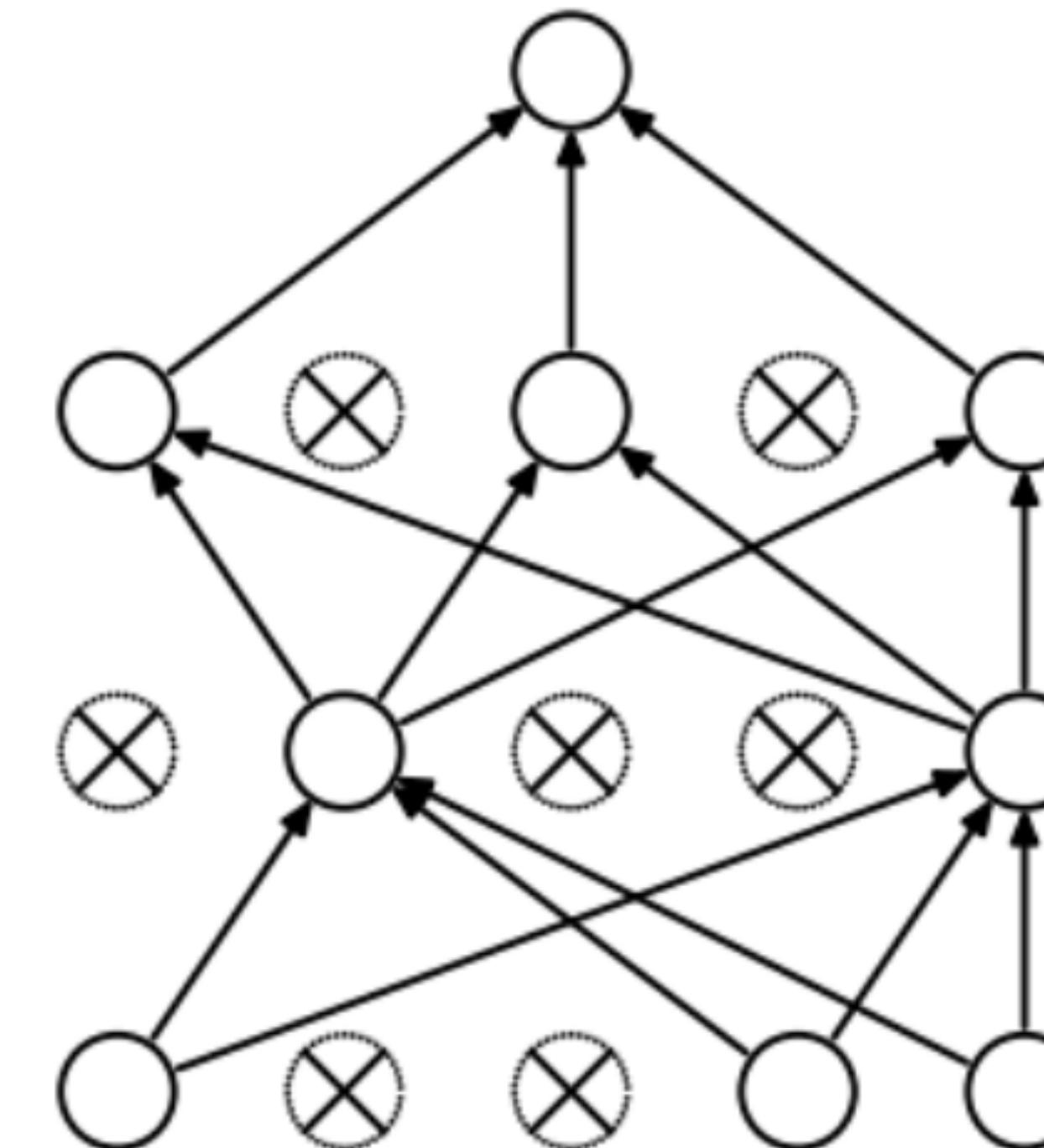
```
def update_weights(weights, gradients, learning_rate, weight_decay):  
    weight_penalty = weight_decay * sum(sqrt(weights ** 2))  
    return weights - learning_rate * (gradients @ weights + weight_penalty)
```

Regularization methods

- Dropout



(a) Standard Neural Net



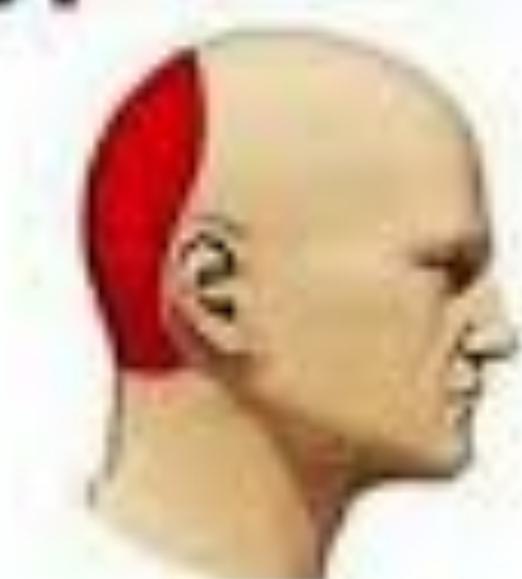
(b) After applying dropout.

Types of Headaches

Migraine



Hypertension



Stress



MATH BEHIND DL



Hello PyTorch!

PyTorch, Anaconda, Jupyter Notebook

Installation

PyTorch source code structure

Tensors

Modules

Image classification with PyTorch



PyTorch

- Deep learning framework
 - TensorFlow, Keras, Torch, Chainer, MXNet
- Python-native, NumPy-friendly
- Dynamic graphs
- Official website: <https://pytorch.org/>
- Documentation: <https://pytorch.org/docs/stable/index.html>
- Source code: <https://github.com/pytorch/pytorch>

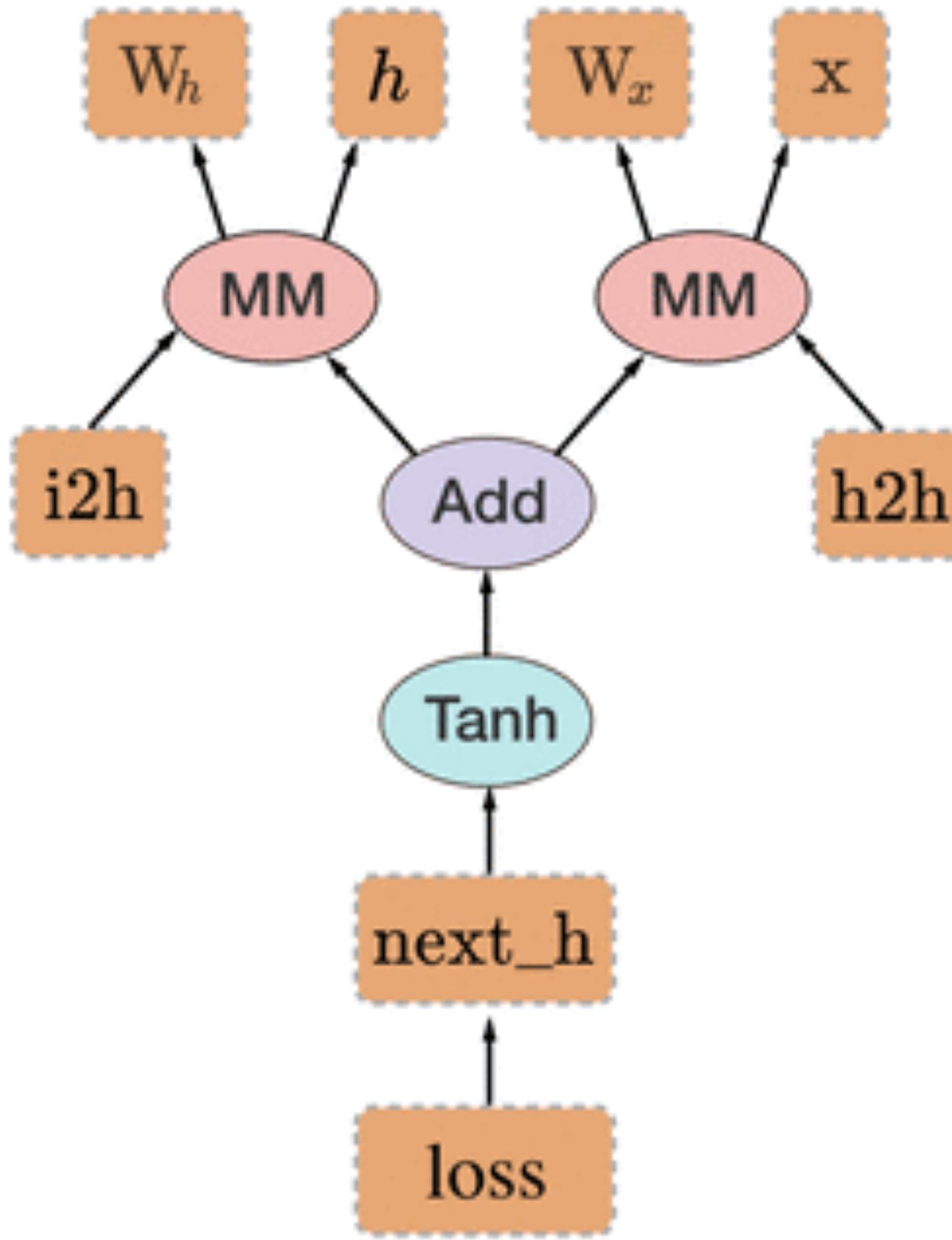


Back-propagation
uses the dynamically created graph

```
x = torch.randn(1, 10)
prev_h = torch.randn(1, 20)
W_h = torch.randn(20, 20)
W_x = torch.randn(20, 10)

i2h = torch.mm(W_x, x.t())
h2h = torch.mm(W_h, prev_h.t())
next_h = i2h + h2h
next_h = next_h.tanh()

loss = next_h.sum()
loss.backward() # compute gradients!
```



Anaconda

- Python package manager + virtual environment manager
- Accessed via the terminal (Ubuntu and macOS) or Anaconda Prompt (Windows)
- <https://www.anaconda.com/download/>



Jupyter Notebook

The screenshot shows a Jupyter Notebook interface. At the top, there's a header with the Jupyter logo, the title "Untitled", and a note about the last checkpoint. On the right side of the header are a Python logo icon and a "Logout" button. Below the header is a menu bar with options: File, Edit, View, Insert, Cell, Kernel, Widgets, and Help. To the right of the menu bar are buttons for "Trusted" and "Python 3". The main area contains a code cell labeled "In [1]:" containing the text "import this". Below the cell, the "Zen of Python" by Tim Peters is displayed as a block of text.

```
In [1]: import this

The Zen of Python, by Tim Peters

Beautiful is better than ugly.
Explicit is better than implicit.
Simple is better than complex.
Complex is better than complicated.
Flat is better than nested.
Sparse is better than dense.
Readability counts.
Special cases aren't special enough to break the rules.
Although practicality beats purity.
Errors should never pass silently.
Unless explicitly silenced.
In the face of ambiguity, refuse the temptation to guess.
There should be one-- and preferably only one --obvious way to do it.
Although that way may not be obvious at first unless you're Dutch.
Now is better than never.
Although never is often better than *right* now.
If the implementation is hard to explain, it's a bad idea.
If the implementation is easy to explain, it may be a good idea.
Namespaces are one honking great idea -- let's do more of those!
```

Installation

1. Install Anaconda from <https://www.anaconda.com/download/>
2. Run the installation commands:

- Ubuntu:

```
conda install -y pytorch-cpu torchvision-cpu -c pytorch
```

- macOS:

```
conda install -y pytorch torchvision -c pytorch
```

- Windows:

```
conda install -y pytorch-cpu -c pytorch
pip3 install torchvision
```

 12,270 commits	 326 branches	 19 releases	 837 contributors	 View license
Branch: v0.4.1 ▾	New pull request	Create new file	Upload files	Find file
Clone or download ▾				
This branch is 17 commits ahead, 2436 commits behind master.			Pull request	Compare
 soumith fix lint				Latest commit a24163a on 26 Jul
 .circleci	Dummy CircleCI config. (#9537)			4 months ago
 .github	updated the environment collection script URL to the raw version on G...			7 months ago
 .jenkins	Skip PyTorch ROCm tests in the script. (#9467)			4 months ago
 aten	ATEN tests are failing on cuda 9.2. Disable compiling by setting ATEN...			4 months ago
 binaries	Update from Facebook (#8887)			5 months ago
 caffe	Fix public protobuf interface (#1961)			9 months ago
 caffe2	build fixes for static cuda linkage			4 months ago
 cmake	A reasonable way to detect Python include dirs and library			4 months ago
 conda	Fixing missing PyCObject_Type bug (#8467)			5 months ago
 docker	Minor cleanup to scripts			4 months ago
 docs	Add scatter_add_ doc (#9630)			4 months ago
 modules	Additional operator information values (#9153)			4 months ago
 scripts	Install typing for Mac (#9271)			4 months ago
 test	fix for cpp_extensions TEST_CUDNN logic			4 months ago
 third_party	Update onnx to onnx/onnx@b2817a6 (#9476)			4 months ago
 tools	build fixes for static cuda linkage			4 months ago
 torch	fix lint			4 months ago

Branch: v0.4.1 ▾

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This branch is 17 commits ahead, 2436 commits behind master.

[Pull request](#) [Compare](#) **soumith** fix lint

Latest commit a24163a on 26 Jul

..

 [_thnn](#)

Update from Facebook (#8887)

5 months ago

 [autograd](#)

Fix segmentation fault in grad_fn (#9292)

4 months ago

 [backends](#)

Move _cudnn_init_dropout_state to TensorOptions and enable cuDNN drop...

5 months ago

 [contrib](#)

Add code for TensorBoard visualization of JIT GraphExecutors (#8050)

6 months ago

 [csrc](#)

fix small literals being flushed to 0 by std::to_string

4 months ago

 [cuda](#)

Move nccl scatter and gather to C++ (#9117)

4 months ago

 [distributed](#)

Distributed Data Parallel Module Implementation (#8584)

5 months ago

 [distributions](#)

cherry pick #9500 and #9590 into 0.4.1 (#9599)

4 months ago

 [for_onnx](#)

Codemod Toffee -> ONNX, toffee -> onnx. Change file names to match

a year ago

 [jit](#)

move batchop import to init to avoid debugging confusions (#9425)

4 months ago

 [legacy](#)

cherry pick #9500 and #9590 into 0.4.1 (#9599)

4 months ago

 [lib](#)

Delete flag from THTensor. (#9494)

4 months ago

 [multiprocessing](#)

Eliminate storage views. (#9466)

4 months ago

 [nn](#)

Fixed a missing '=' in LPPoolNd repr function (#9629)

4 months ago

 [onnx](#)

Add support for .norm() pytorch onnx export and ReduceL1/ReduceL2 caf...

4 months ago

 [optim](#)

cherry pick #9500 and #9590 into 0.4.1 (#9599)

4 months ago

 [sparse](#)

Delete dead Tensor code paths (#5417)

9 months ago

 [testing](#)

Codemod to update our codebase to 0.4 standard (#6641)

7 months ago

 [utils](#)

fix lint

4 months ago

Branch: v0.4.1 ▾

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This branch is 17 commits ahead, 2436 commits behind master.

 [Pull request](#) [Compare](#)

vmirly and SsnL	Fixed a missing '=' in LPPoolNd repr function (#9629) ...	Latest commit 76c16a5 on 21 Jul
..		
_functions	Implement 2D and 3D alpha_dropout (#9073)	4 months ago
backends	Implement MarginRankingLoss as native function and add reduce=True ar...	8 months ago
modules	Fixed a missing '=' in LPPoolNd repr function (#9629)	4 months ago
parallel	Distributed Data Parallel Module Implementation (#8584)	5 months ago
utils	cherry pick #9500 and #9590 into 0.4.1 (#9599)	4 months ago
__init__.py	Add weight normalization implementation (#1945)	a year ago
functional.py	Implement 2D and 3D alpha_dropout (#9073)	4 months ago
grad.py	Codemod to update our codebase to 0.4 standard (#6641)	7 months ago
init.py	Fix #8692 (#8699)	5 months ago
parameter.py	Fix serialization for Parameters (#8633)	5 months ago

Branch: v0.4.1 ▾

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This branch is 17 commits ahead, 2436 commits behind master.

[Pull request](#) [Compare](#)vmirly and SsnL Fixed a missing '=' in LPPoolNd repr function ([#9629](#)) [...](#)

Latest commit 76c16a5 on 21 Jul

..

__init__.py	Implement 2D and 3D alpha_dropout (#9073)	4 months ago
activation.py	copy paste documentation error fixed in Softmin (#7324)	6 months ago
adaptive.py	Add utf-8 header to Python file with Unicode. (#8131)	5 months ago
batchnorm.py	Fix loading 0.4 BN checkpoints (#9004)	5 months ago
container.py	Add ModuleDict and ParameterDict containers (#8463)	4 months ago
conv.py	Update extension docs, fix Fold/Unfold docs (#9239)	4 months ago
distance.py	implement TripletMarginLoss as a native function (#5680)	8 months ago
dropout.py	Implement 2D and 3D alpha_dropout (#9073)	4 months ago
fold.py	Update extension docs, fix Fold/Unfold docs (#9239)	4 months ago
instancenorm.py	Fix loading 0.4 BN checkpoints (#9004)	5 months ago
linear.py	Fix the comments: code and comments dimensions mis-match (#9070)	5 months ago
loss.py	docs fixes (#9607)	4 months ago
module.py	Fix loading 0.4 BN checkpoints (#9004)	5 months ago
normalization.py	Update extension docs, fix Fold/Unfold docs (#9239)	4 months ago

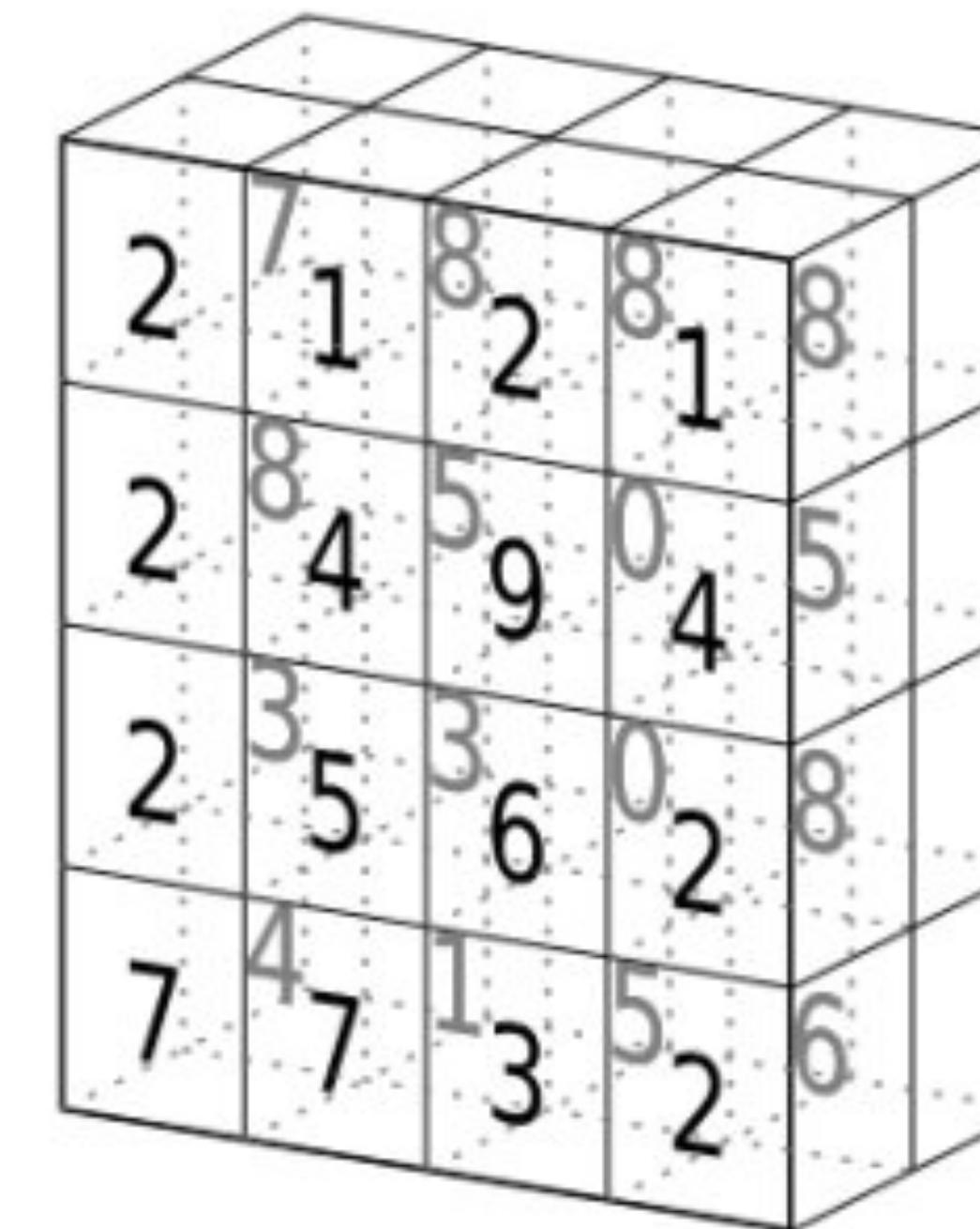
Tensors: PyTorch's core data structure

't'
'e'
'n'
's'
'o'
'r'

tensor of dimensions [6]
(vector of dimension 6)

3	1	4	1
5	9	2	6
5	3	5	8
9	7	9	3
2	3	8	4
6	2	6	4

tensor of dimensions [6,4]
(matrix 6 by 4)



tensor of dimensions [4,4,2]

Tensors: PyTorch's core data structure

- Creating tensors
 - with pre-existing data: `torch.tensor()`
 - with specific size: `torch.ones()`, `torch.zeros()`, `torch.rand()`

```
import torch

tensor = torch.tensor([[1, 2, 3], [4, 5, 6]])
print(tensor)
zeros = torch.zeros(2, 3)
print(zeros)
```

Tensors: PyTorch's core data structure

torch.tensor(data, dtype=None, device=None, requires_grad=False) → Tensor

Constructs a tensor with data.

- data (array_like) – Initial data for the tensor. Can be a list, tuple, NumPy ndarray, scalar, and other types.
- dtype (torch.dtype, optional) – the desired data type of returned tensor. Default: if None, infers data type from data.
- device (torch.device, optional) – the desired device of returned tensor. Default: if None, uses the current device for the default tensor type. device will be the CPU for CPU tensor types and the current CUDA device for CUDA tensor types.

Tensors: PyTorch's core data structure

torch.tensor(data, dtype=None, device=None, requires_grad=False) → Tensor

- `requires_grad` (bool, optional) – If autograd should record operations on the returned tensor. Default: False.

Tensors: PyTorch's core data structure

Data type	dtype	CPU tensor
32-bit floating point	<code>torch.float32</code> or <code>torch.float</code>	<code>torch.FloatTensor</code>
64-bit floating point	<code>torch.float64</code> or <code>torch.double</code>	<code>torch.DoubleTensor</code>
16-bit floating point	<code>torch.float16</code> or <code>torch.half</code>	<code>torch.HalfTensor</code>
8-bit integer (unsigned)	<code>torch.uint8</code>	<code>torch.ByteTensor</code>
8-bit integer (signed)	<code>torch.int8</code>	<code>torch.CharTensor</code>
16-bit integer (signed)	<code>torch.int16</code> or <code>torch.short</code>	<code>torch.ShortTensor</code>
32-bit integer (signed)	<code>torch.int32</code> or <code>torch.int</code>	<code>torch.IntTensor</code>
64-bit integer (signed)	<code>torch.int64</code> or <code>torch.long</code>	<code>torch.LongTensor</code>

Tensors: PyTorch's core data structure

torch.zeros(*sizes, out=None, dtype=None, layout=torch.strided, device=None, requires_grad=False) → Tensor

Returns a tensor filled with the scalar value 0, with the shape defined by the variable argument sizes.

- sizes (int...) – a sequence of integers defining the shape of the output tensor. Can be a variable number of arguments or a collection like a list or tuple.
- out (Tensor, optional) – the output tensor
- dtype (torch.dtype, optional) – the desired data type of returned tensor. Default: if None, uses a global default.

Tensors: PyTorch's core data structure

torch.zeros(*sizes, out=None, dtype=None, layout=torch.strided, device=None, requires_grad=False) → Tensor

- layout (torch.layout, optional) – the desired layout of returned Tensor. Default: torch.strided.
- device (torch.device, optional) – the desired device of returned tensor. Default: if None, uses the current device for the default tensor type (see `torch.set_default_tensor_type()`). device will be the CPU for CPU tensor types and the current CUDA device for CUDA tensor types.
- requires_grad (bool, optional) – If autograd should record operations on the returned tensor. Default: False.

Tensors: PyTorch's core data structure

- Transposing tensors: Tensor.t()

```
tensor = torch.tensor([[1, 2, 3], [4, 5, 6]])  
  
transposed = tensor.t()  
print(transposed)
```

Tensors: PyTorch's core data structure

- Reshaping tensors

```
tensor = torch.Tensor([[1, 2, 3], [4, 5, 6]])
```

```
reshaped = tensor.view(3, 2)  
print(reshaped)
```

```
reshaped = tensor.view(6, 1)  
print(reshaped)
```

```
reshaped = tensor.view(2, -1)  
print(reshaped)
```

Tensors: PyTorch's core data structure

Tensor.t() → Tensor

Expects self to be a matrix (2-D tensor) and transposes dimensions 0 and 1.

Tensor.view(*args) → Tensor

Returns a new tensor with the same data as the self tensor but of a different size.

- args (torch.Size or int...) – the desired size

Tensors: PyTorch's core data structure

- Broadcasting

```
tensor = torch.Tensor([[1, 2, 3], [4, 5, 6]])
```

```
changed = tensor + 1  
print(changed)
```

Tensors: PyTorch's core data structure

- In-place operations (marked by an underscore)

```
tensor = torch.Tensor([[1, 2, 3], [4, 5, 6])  
  
changed = tensor - 1  
tensor.add_(1)  
  
print(changed)  
print(tensor)
```

Modules: the building block of PyTorch

torch.nn.Module

- Base class for all neural network modules
- The Python magic method `__call__()` executes `forward()` method
- If `backward()` method is not defined, the `backward` is automatically created by `forward()`
- Submodules can be assigned as regular attributes

Modules: the building block of PyTorch

```
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Image classification with PyTorch

- FashionMNIST
 - Zalando's clothing product images
 - 28-pixel-square grayscale images
 - 60k examples for training, 10k samples for testing
 - 10 classes
 - <https://github.com/zalandoresearch/fashion-mnist>

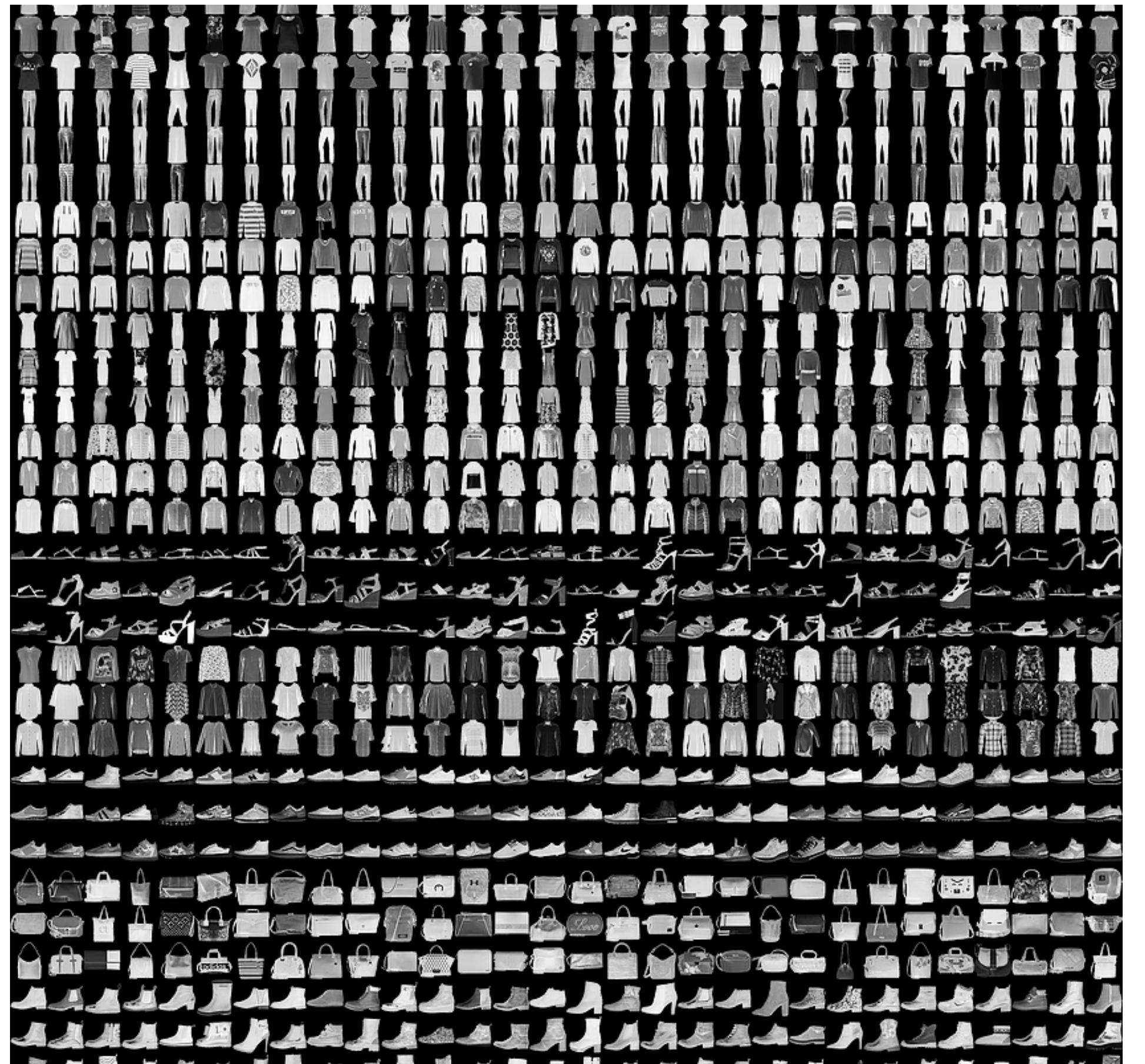


Image classification with PyTorch

- ResNet
 - He et al., Deep Residual Learning for Image Recognition. 2015.
 - [torchvision.models.resnet](#)
 - The PyTorch reference implementation of the ResNet
 - A great example of building PyTorch models with Python OOP

plain net

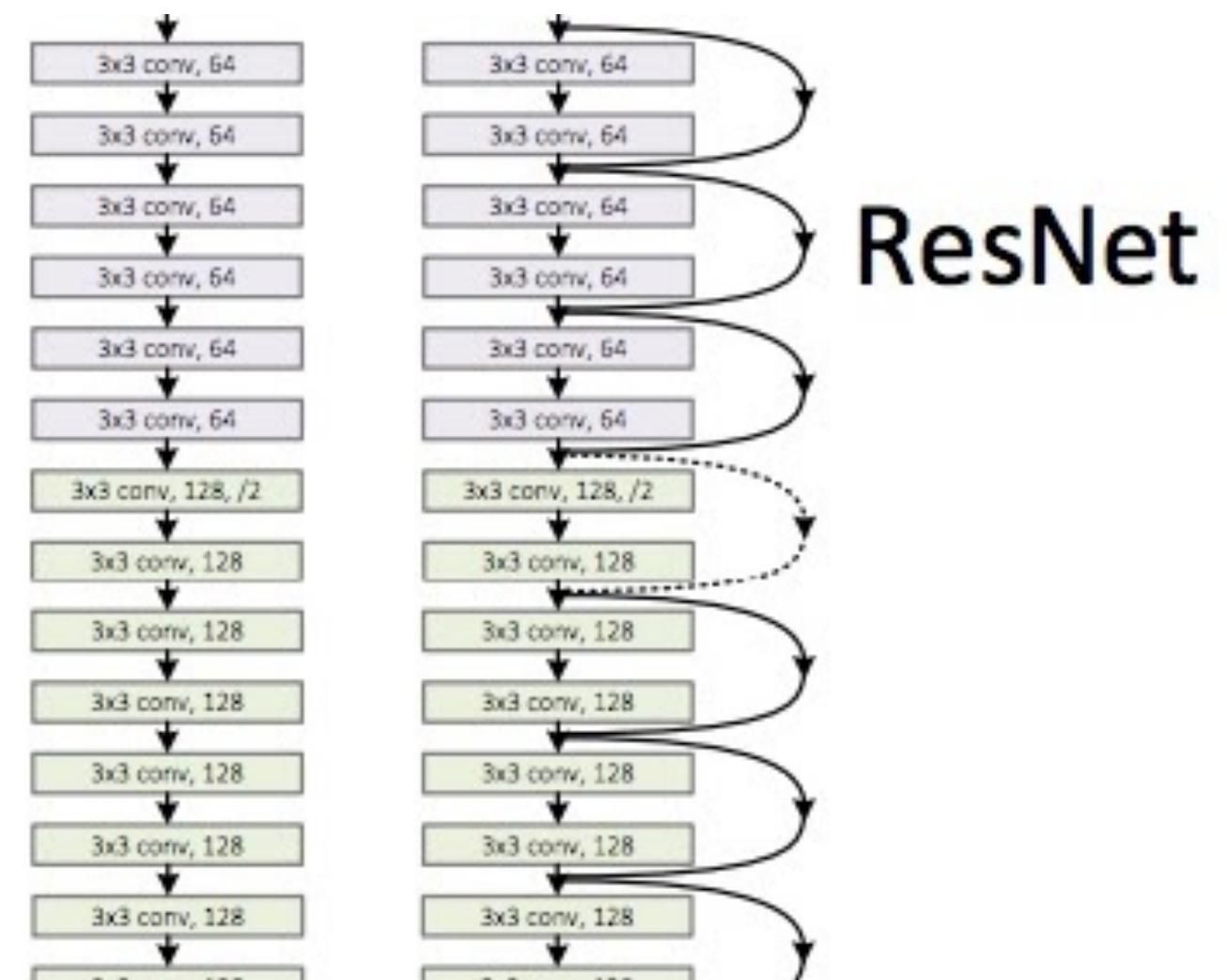


Image classification with PyTorch

git clone or download https://github.com/juneoh/sample_pytorch_project

- Dockerfile – if you want to use Docker.
- README.md – the repository description.
- main.py – the main code.
- requirements.txt – the package requirements to run this example, for pip.

Image classification with PyTorch

- The process
 1. Prepare the data: training, validation, test.
 2. Create the model and the loss function.
 3. Create the optimizer and attach it to the model.
 4. For each epoch, train, evaluate and save model.
 5. Finally, evaluate the model on the test dataset.

Image classification with PyTorch

- The process
- 🤔 Why not use cross-validation?



Yoshua Bengio, My lab has been one of the three that started the deep learning approach, back in 2006, along with Hinton's...

Answered Jan 20, 2016 · Upvoted by Naran Bayanbat, [MSCS with focus in machine learning](#) and Boxun Zhang, [Data Scientist at Spotify; PhD in Computer Science](#) · Author has 172 answers and 3.6m answer views

We mostly have large datasets when it is not worth the trouble to do something like k-fold cross-validation. We just use a train/valid/test split. Cross-validation becomes useful when the dataset is tiny (like hundreds of examples), but then you can't typically learn a complex model.

36.6k Views · View Upvoters

Code review

Thank you!