technische universität dortmund

lehrstuhl physik e5

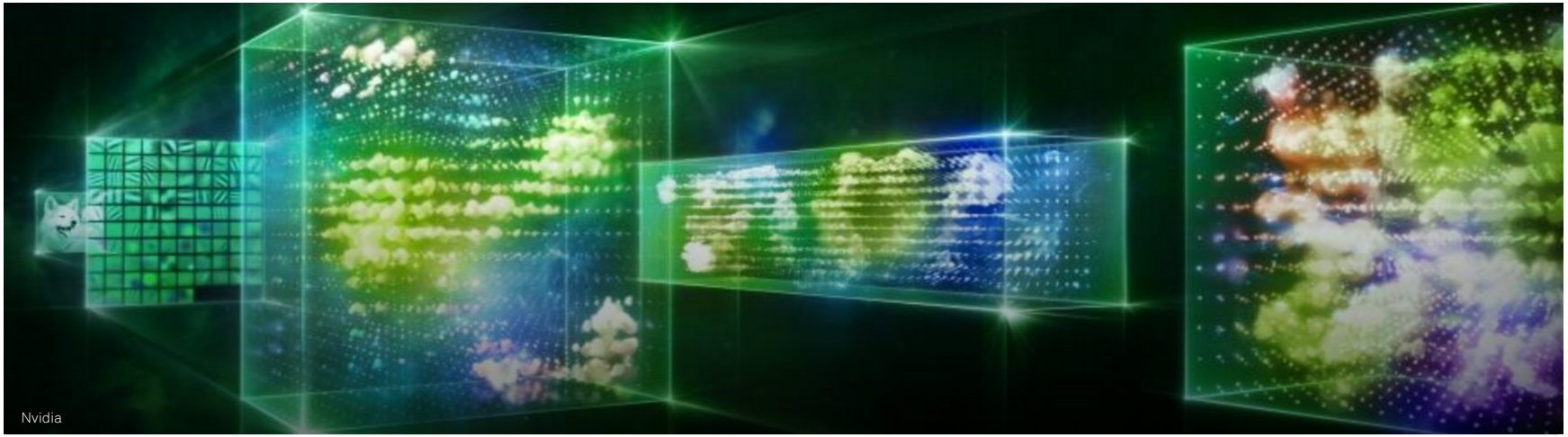


Image Classification Using Deep Learning Algorithms

Konrad Mielke

konrad.mielke@tu-dortmund.de

Torino

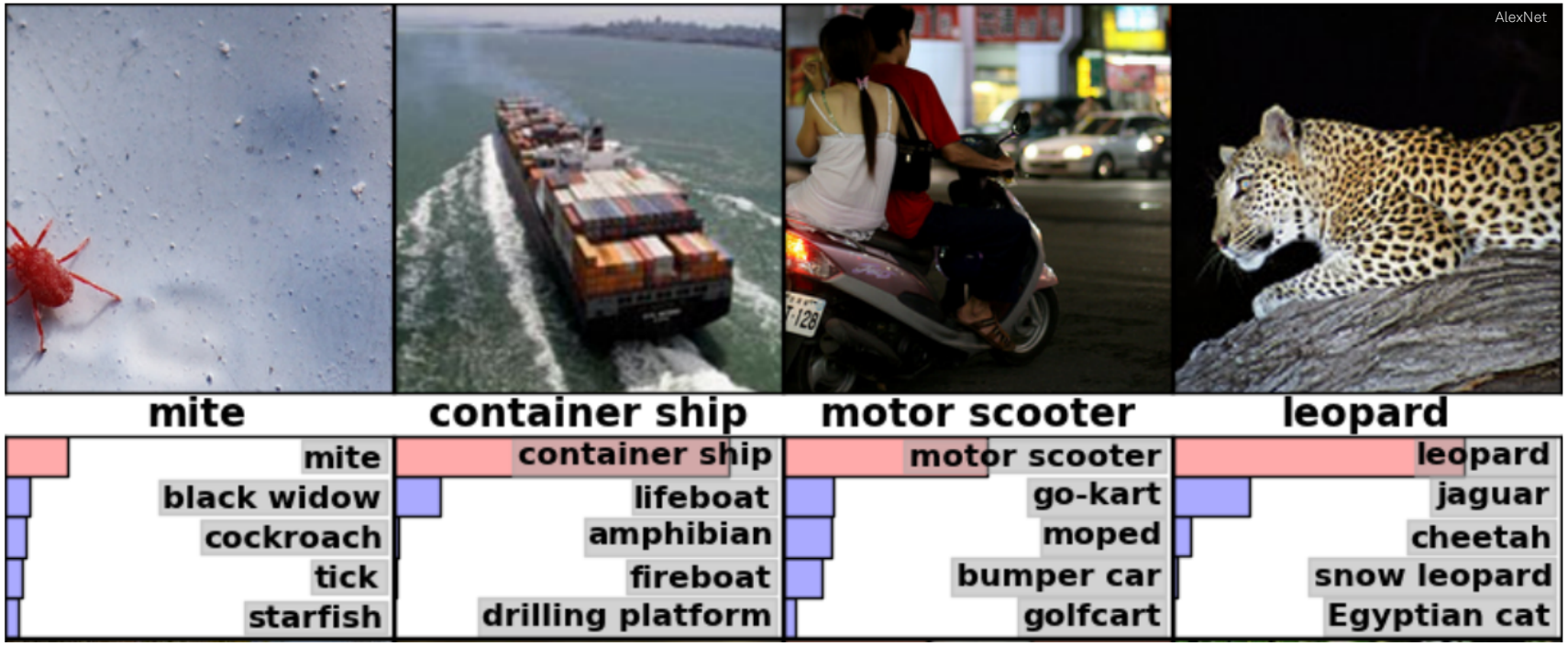
June 26th, 2017

ImageNet

- Image database containing labeled images
- More than fourteen million images
- More than twenty thousand different labels

ImageNet Recognition Challenge

Annual competition in which research teams submit programs that classify images



ImageNet Recognition Challenge 2012

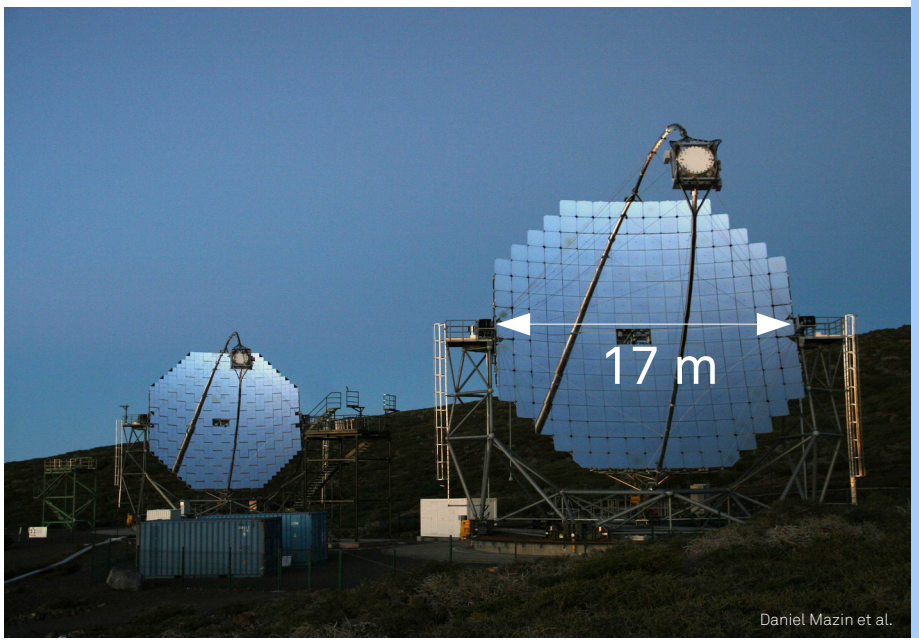
- Competition won by Krizhevsky/Sutskever/Hinton

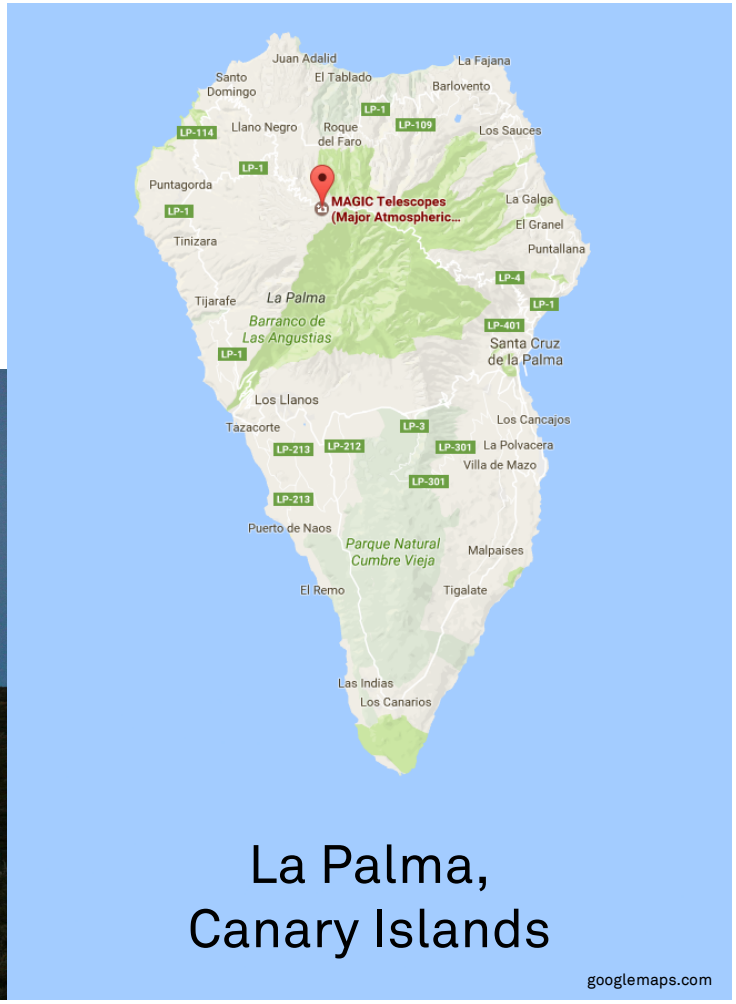
> We trained a large, deep convolutional neural network to classify the [...] images [with an error rate] considerably better than the previous state-of-the-art.

- Today, Deep Learning is by far the most successful image classification technique

The MAGIC Telescopes

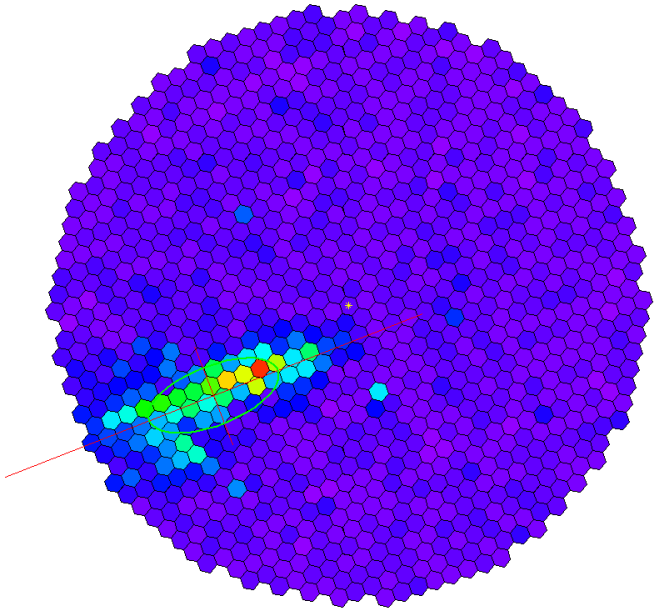
- Imaging Air Cherenkov Telescopes (IACTs)
- Energy range: 50 GeV – 50 TeV
- 1039 pixels/PMTs per telescope



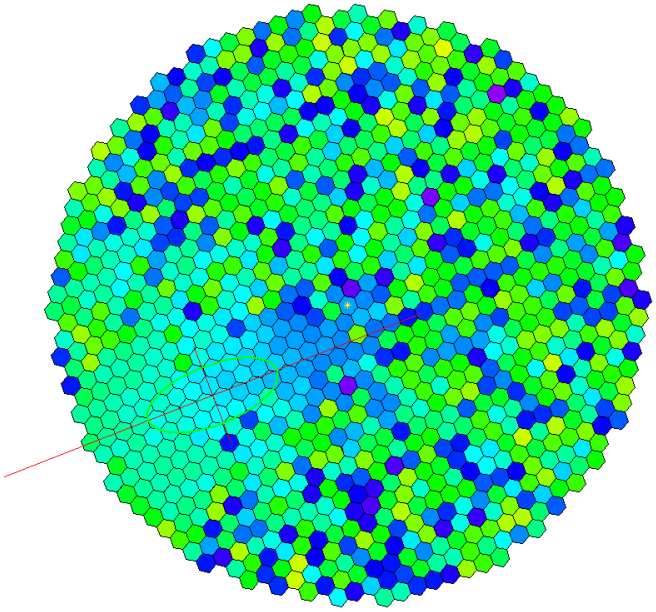


Usage in Physics: Energy Estimation for MAGIC

Photon Charge



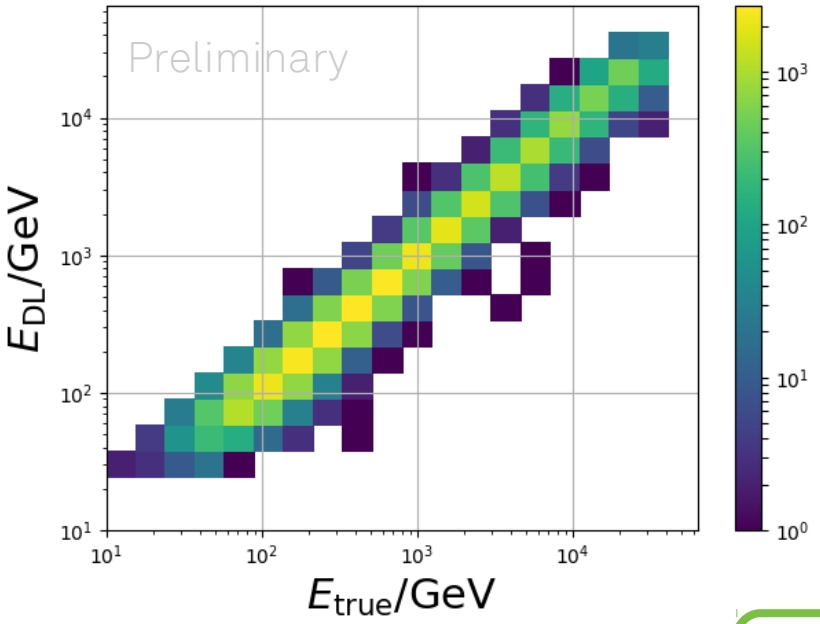
Arrival Time



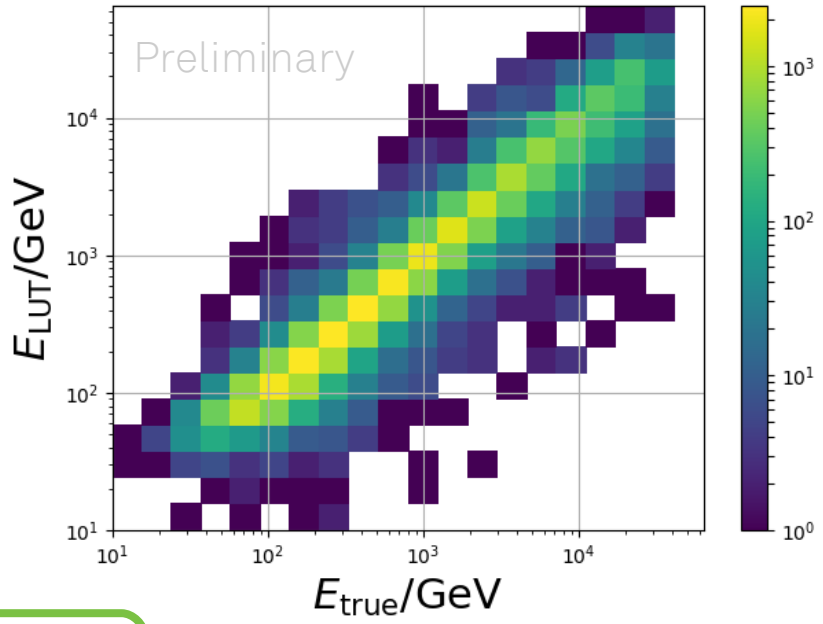
→ Estimate the Energy

Usage in Physics: Performance

Deep Learning

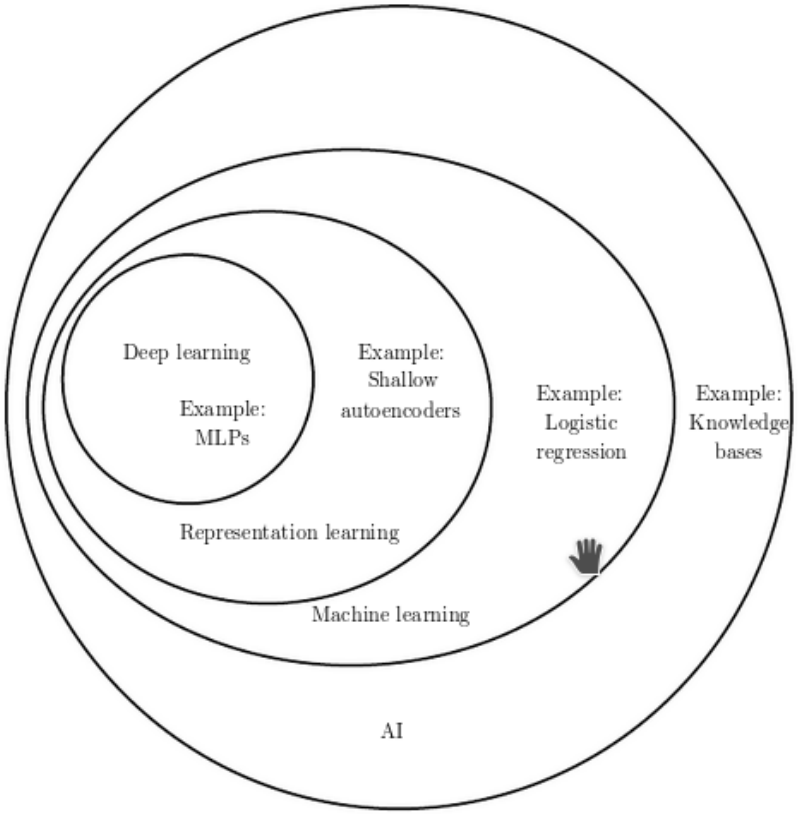


Standard Method (Lookup Tables)



Zenith range:
5° - 35°

Deep Learning Dependencies



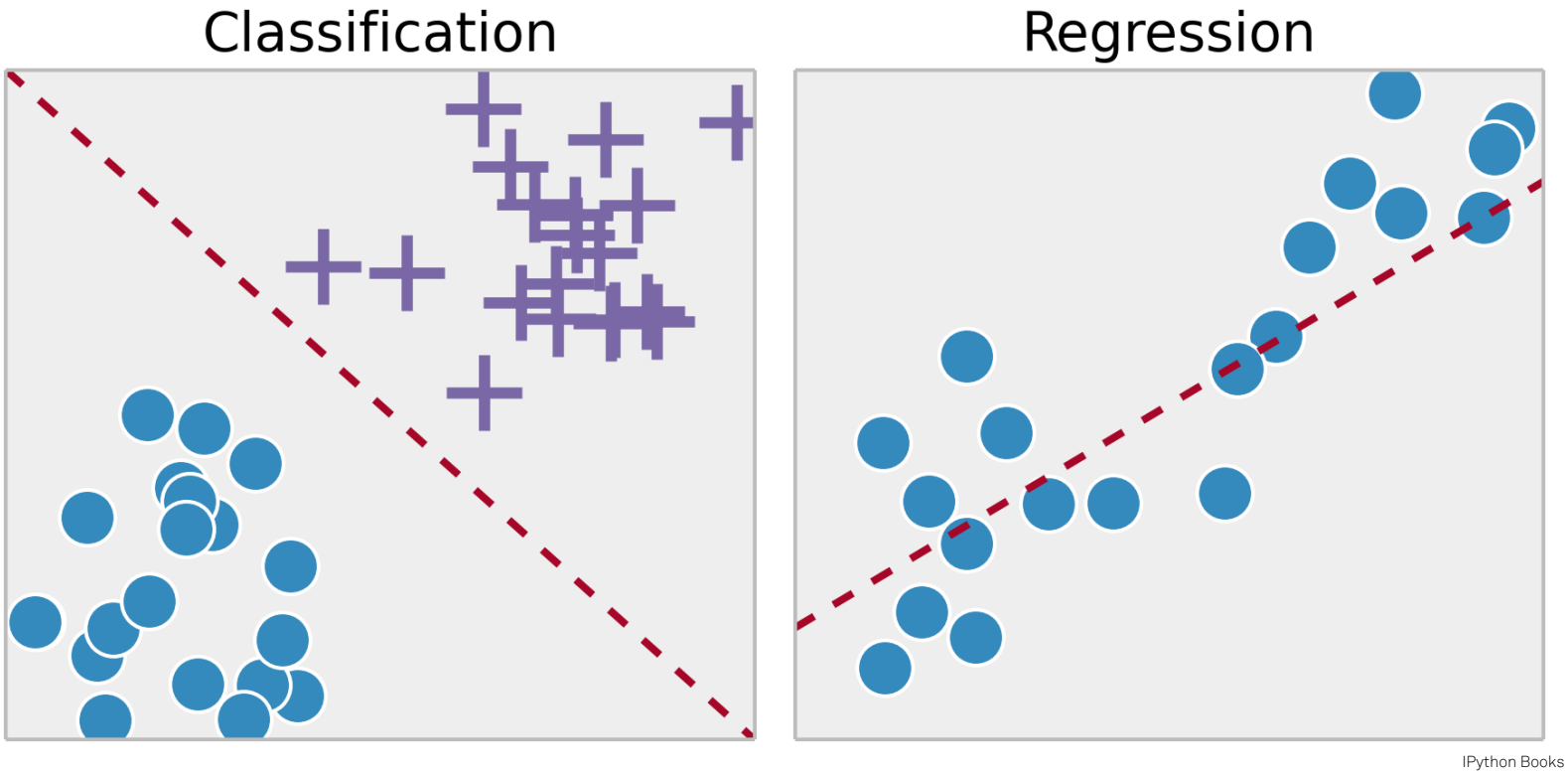
Deeplearningbook

Machine Learning: Supervised Learning

- Based on labeled data: Truth is known
  - E.g. MC simulation
- Divide data in training data and test data
- Train a model to later apply it new data
  - Training data used to train model
  - Test data used to evaluate its performance

- Weakly supervised learning: Only ratio of labels known
- Unsupervised learning: No labels known

Machine Learning: Classification & Regression

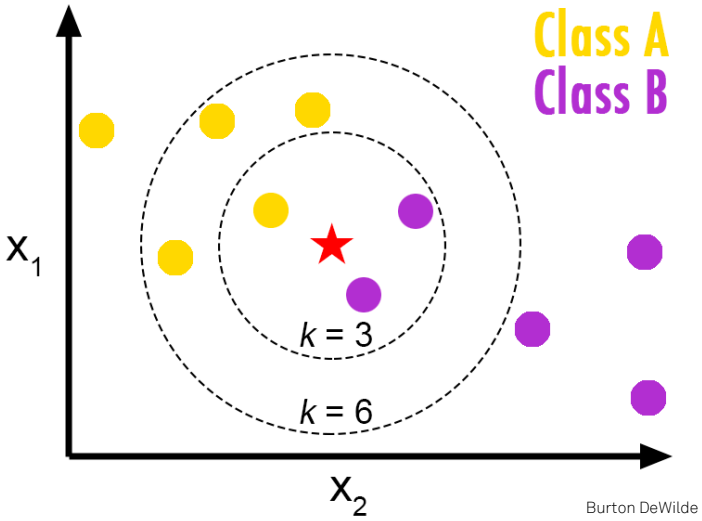


IPython Books

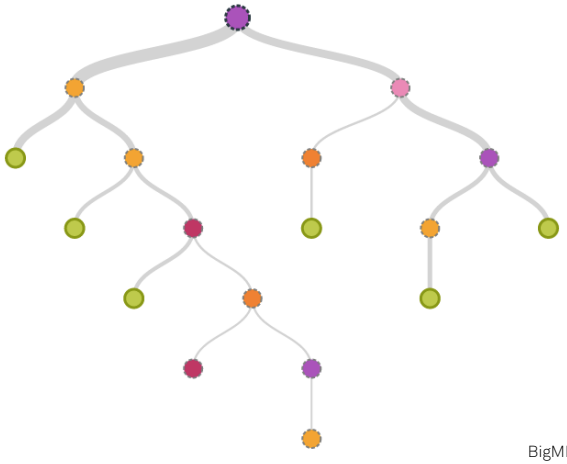
Machine Learning: Classification

Different Classification Algorithms:

- Naive Bayes
- k Nearest Neighbors (kNN)
- Decision Tree
- Random Forest
- Boosted Decision Trees
- Logistic Regression
- Neural Networks



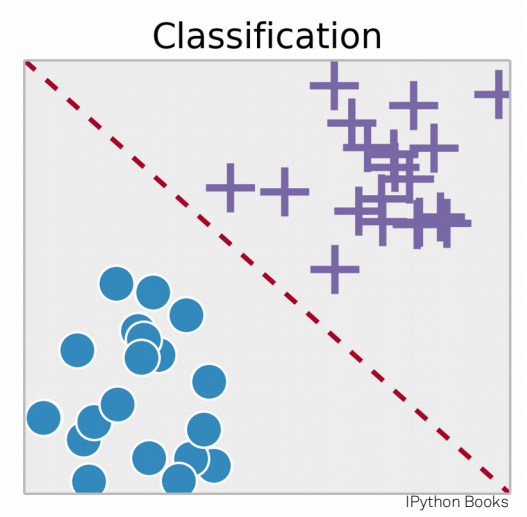
Burton DeWilde



BigML

Machine Learning: Classification Performance

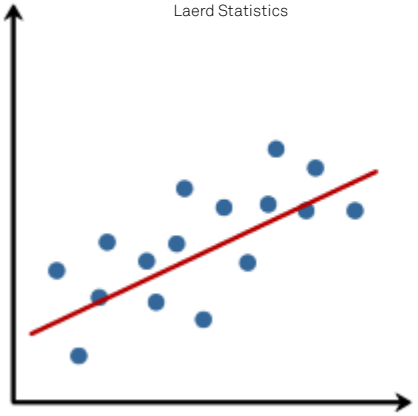
- Definitions:
  - True positive (tp): Signal event classified as signal
  - False positive (fp): Background event classified as signal
  - False negative (fn): Signal event classified as background
  - True negative (tn): Background event classified as background
- Performance Measures:
  - Efficiency: tp/(tp + fn)
  - Purity: tp/(tp + fp)

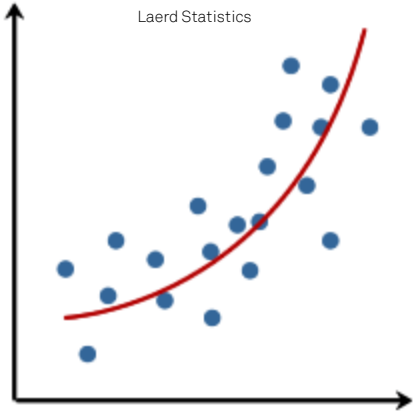


Machine Learning: Regression

Different Regression Algorithms:

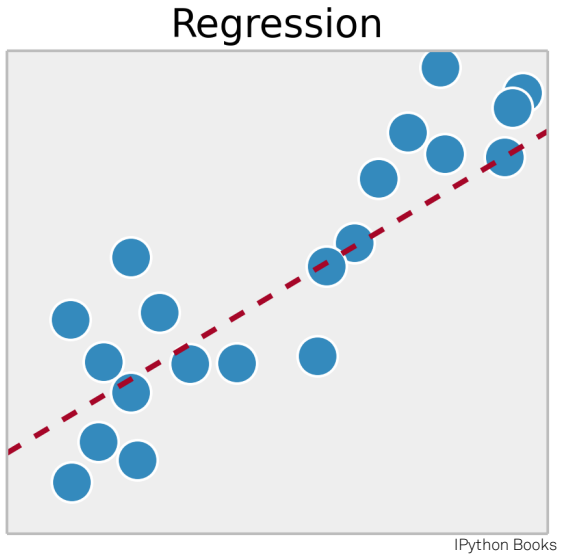
- Linear Regression
- Polynomial Regression
- Neural Networks





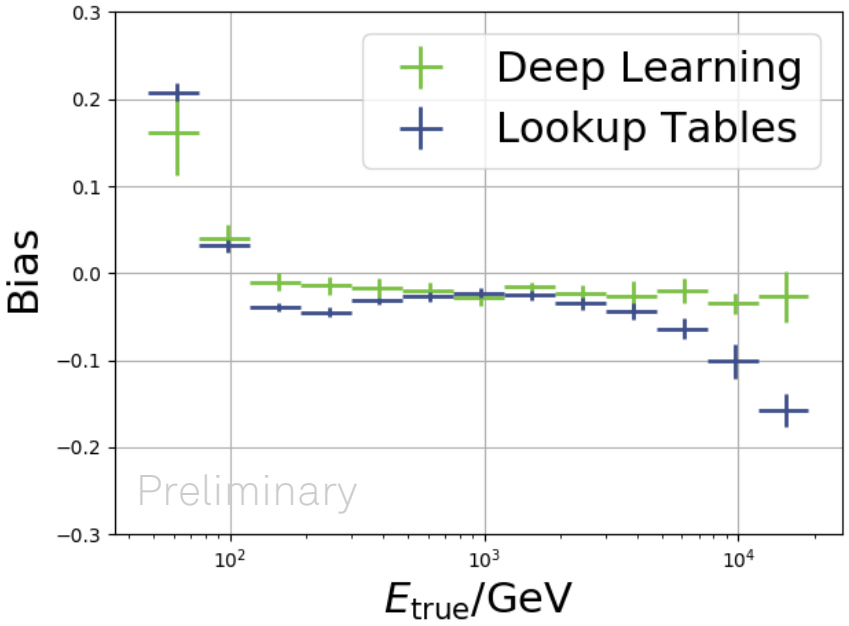
Machine Learning: Regression Performance

- Calculate the relative error of the regression for every event
  → Gaussian distribution
- Performance Measures:
  - Bias: Shift of distribution in relation to zero
  - Resolution: Width of distribution

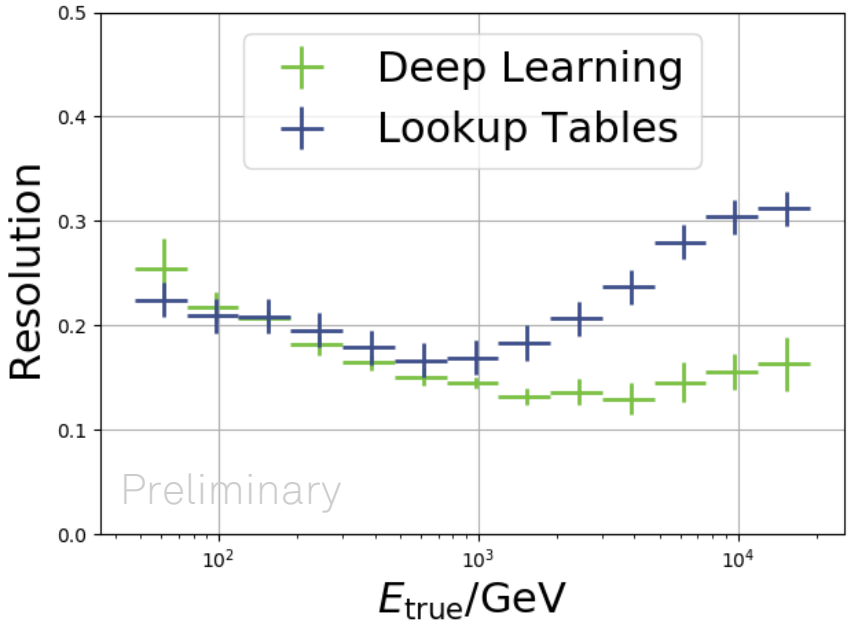


Machine Learning: Example for Regression Performance

Energy Bias



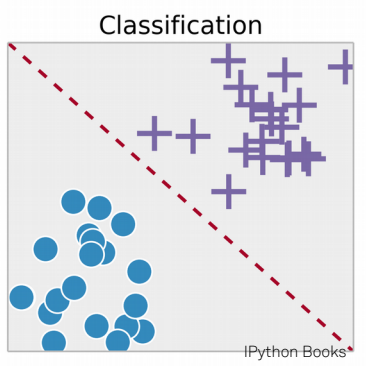
Energy Resolution



Generalization

How well does a learned model generalize on unknown (test) data?

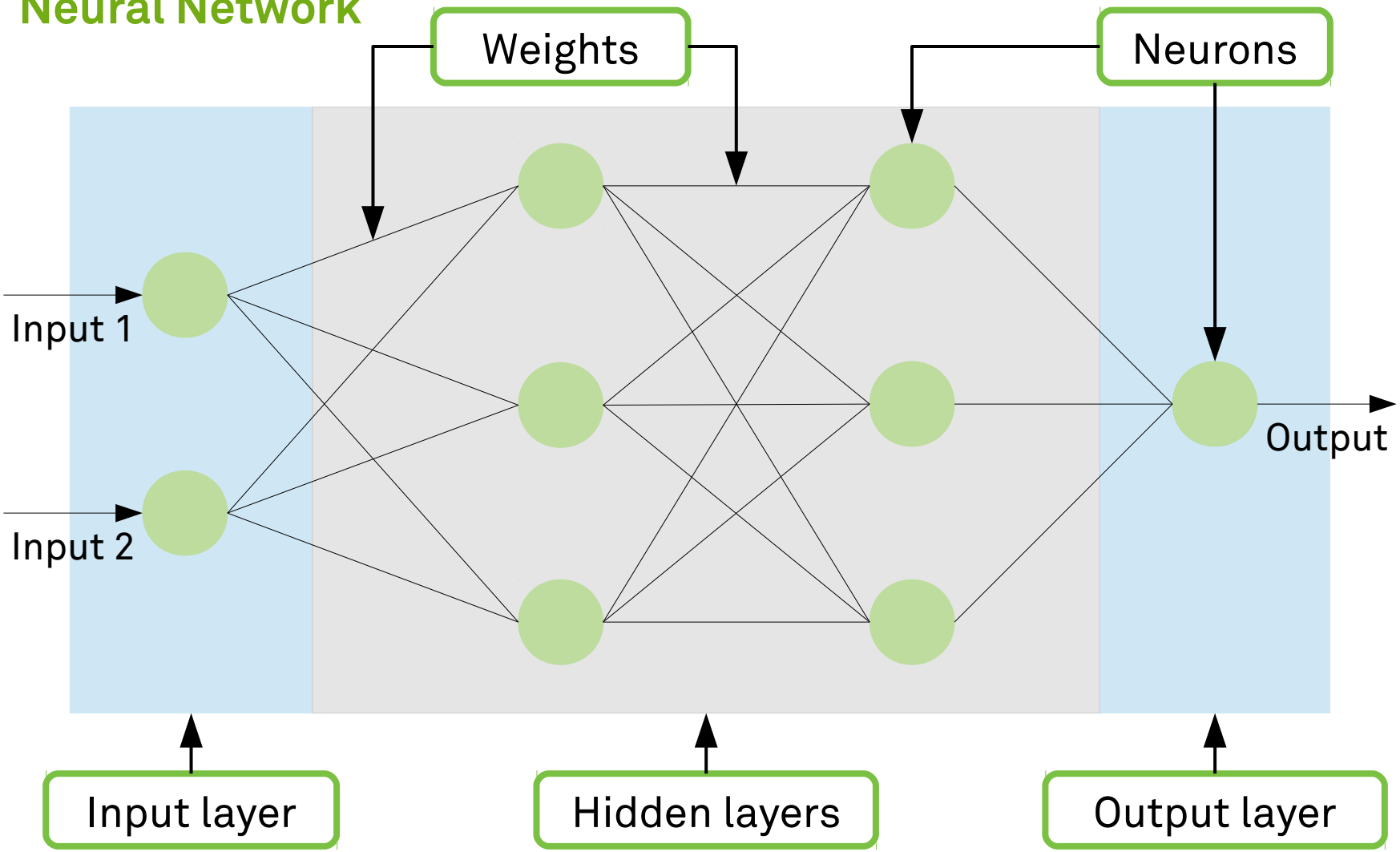
- Underfitting:
  - Model is too simple to fit the data
  - Solution: Increase the models complexity
- Overfitting:
  - Model is too complex and fits irrelevant noise
  - Solutions:
    - Increase dataset size
    - Decrease the models complexity
    - Regularization



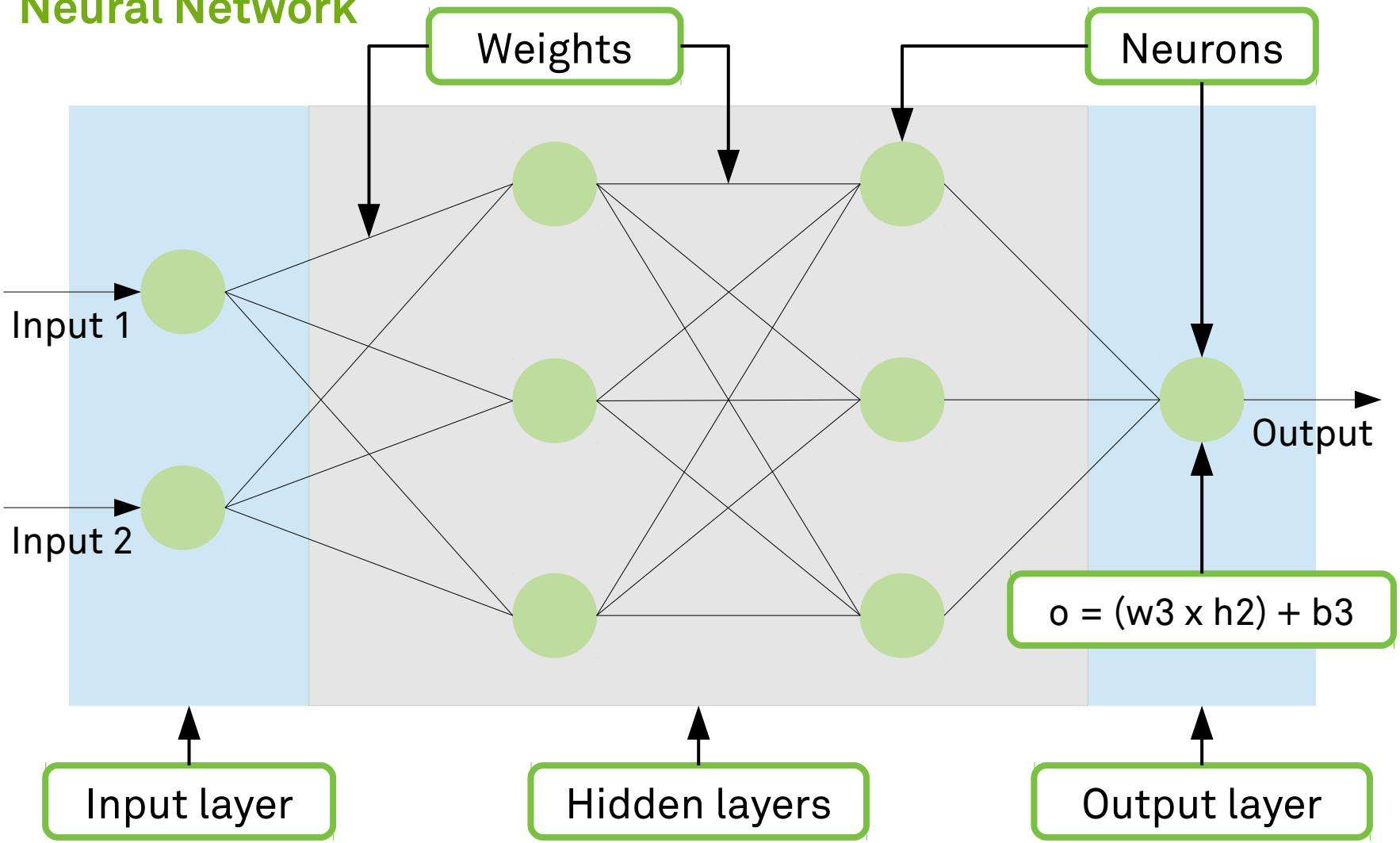
Deep Learning

Konrad Mielke
konrad.mielke@tu-dortmund.de

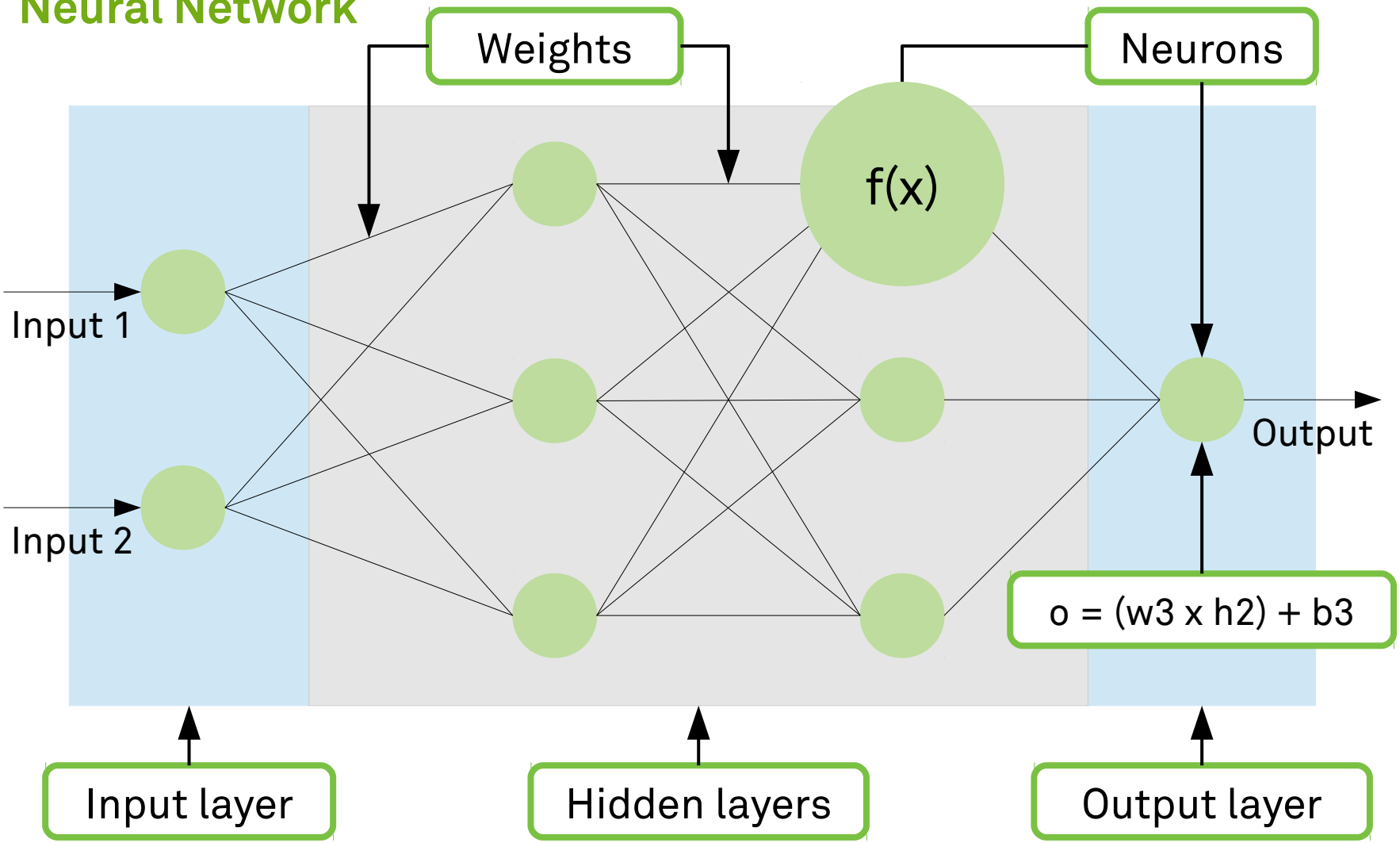
Neural Network



Neural Network



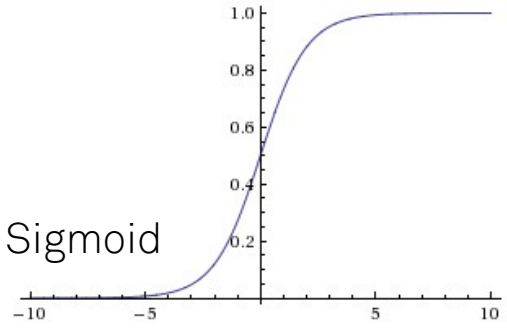
Neural Network



Activation Function & Loss Function

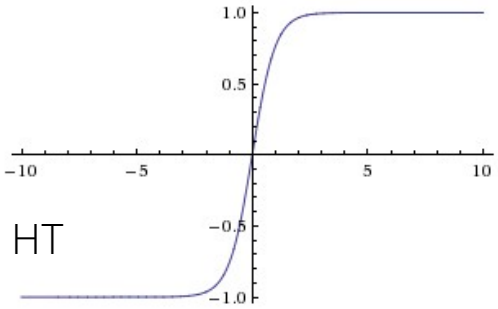
Activation Functions:

- Sigmoid function
- Hyperbolic Tangent (HT)
- Rectified Linear Unit (ReLU)
- Leaky ReLU



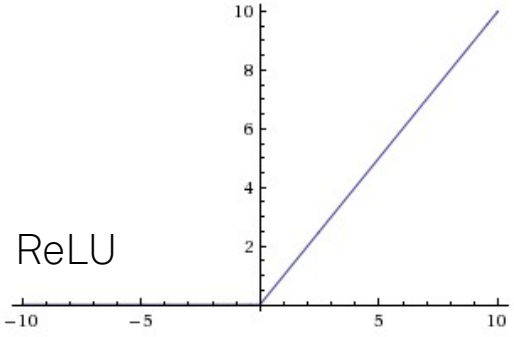
Loss Functions for Regression:

- L1 norm
- L2 norm

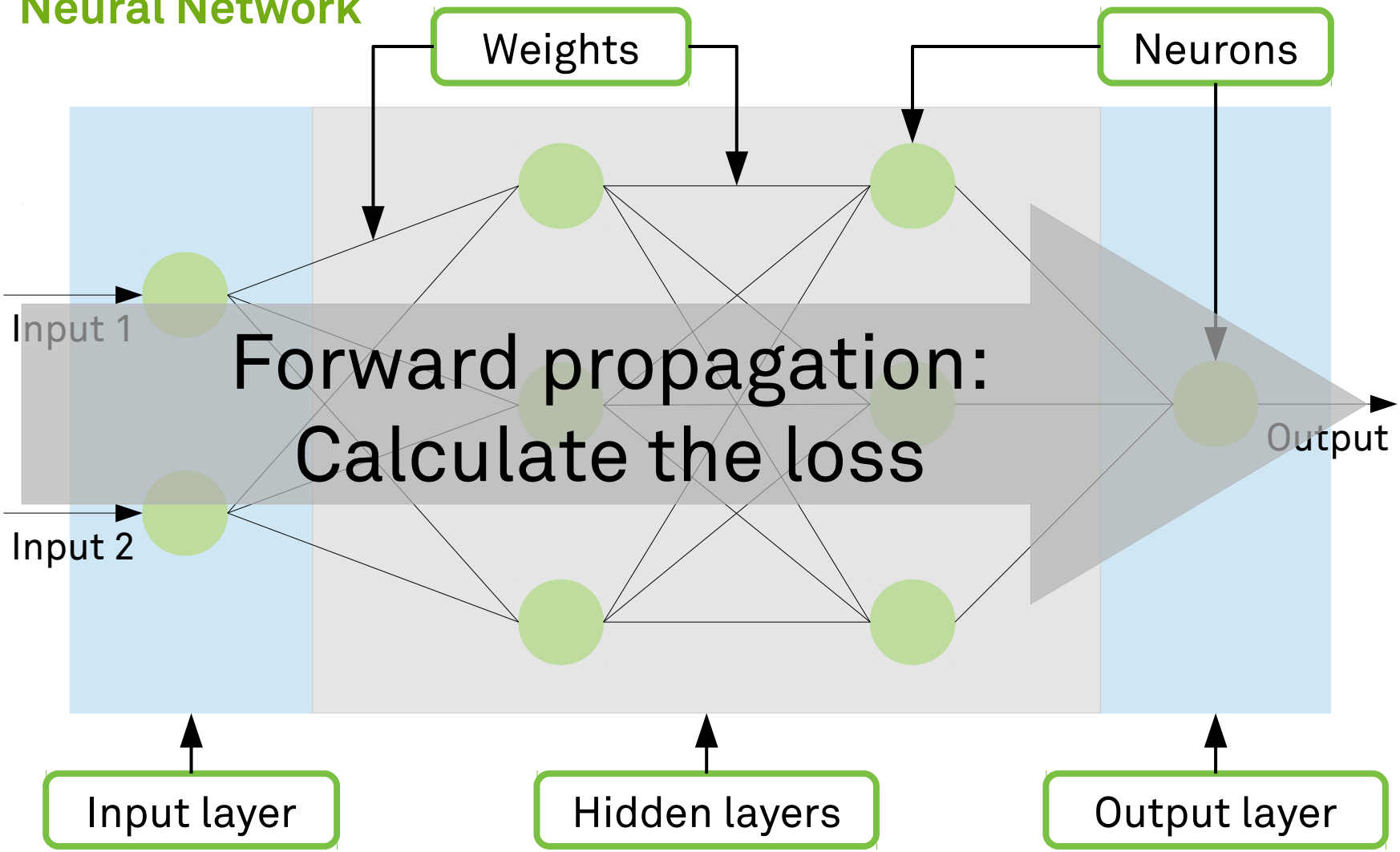


Loss Functions for Classification:

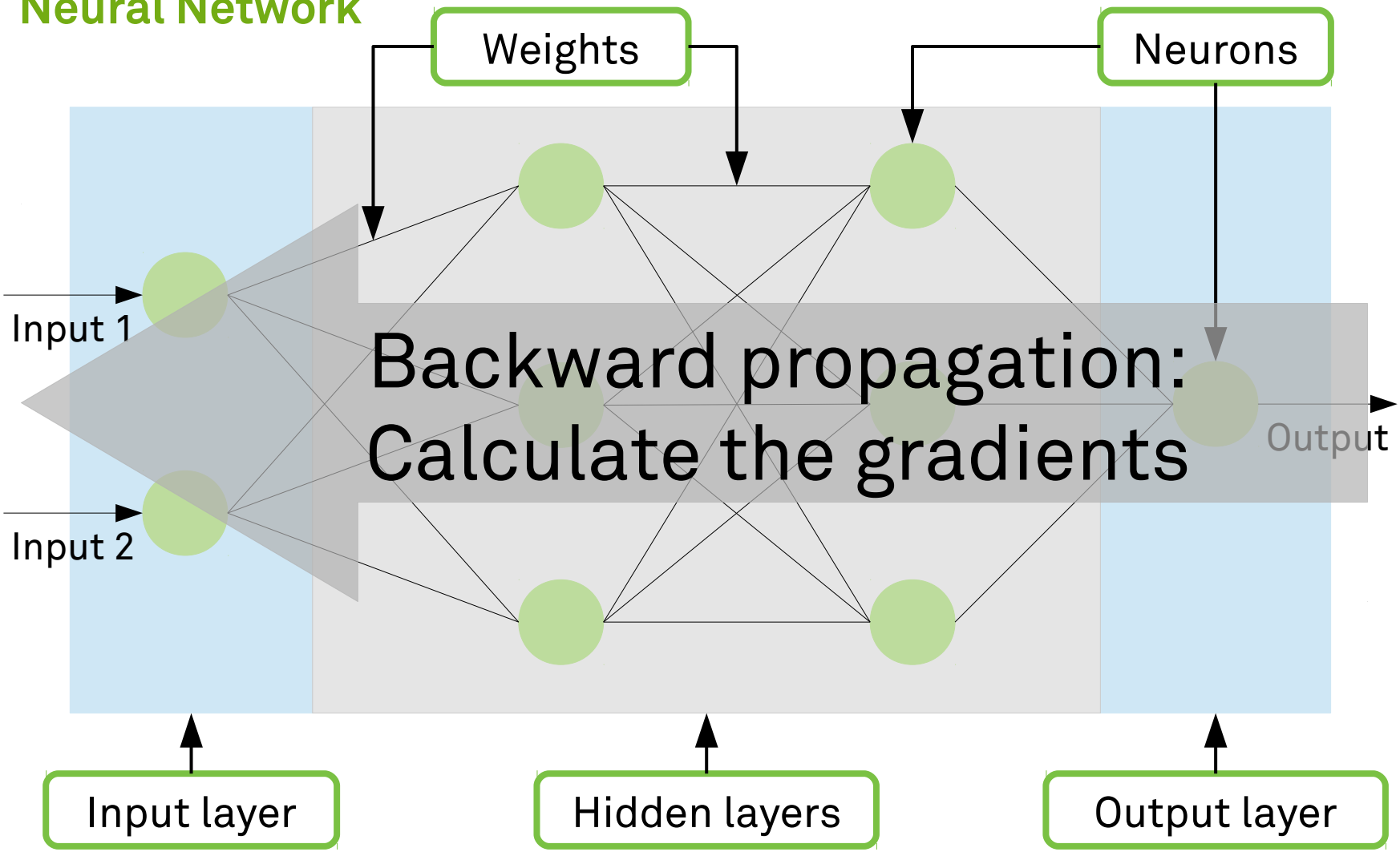
- Zero-One loss
- Cross entropy



Neural Network



Neural Network

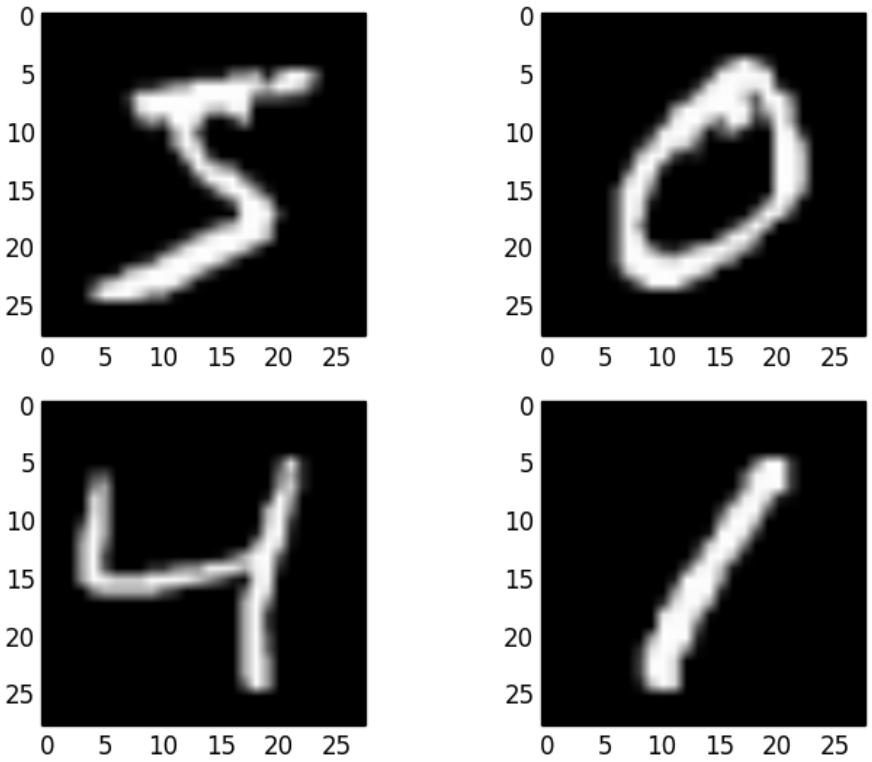


Now: What is Deep Learning?

Definition 1:
Deep Learning is the use of a neural network with several layers of neurons between input and output.

Definition 2:
Deep learning allows the computer to build complex concepts out of simpler concepts.

MNIST Classification Using Deep Learning



MNIST

Image Recognition Techniques

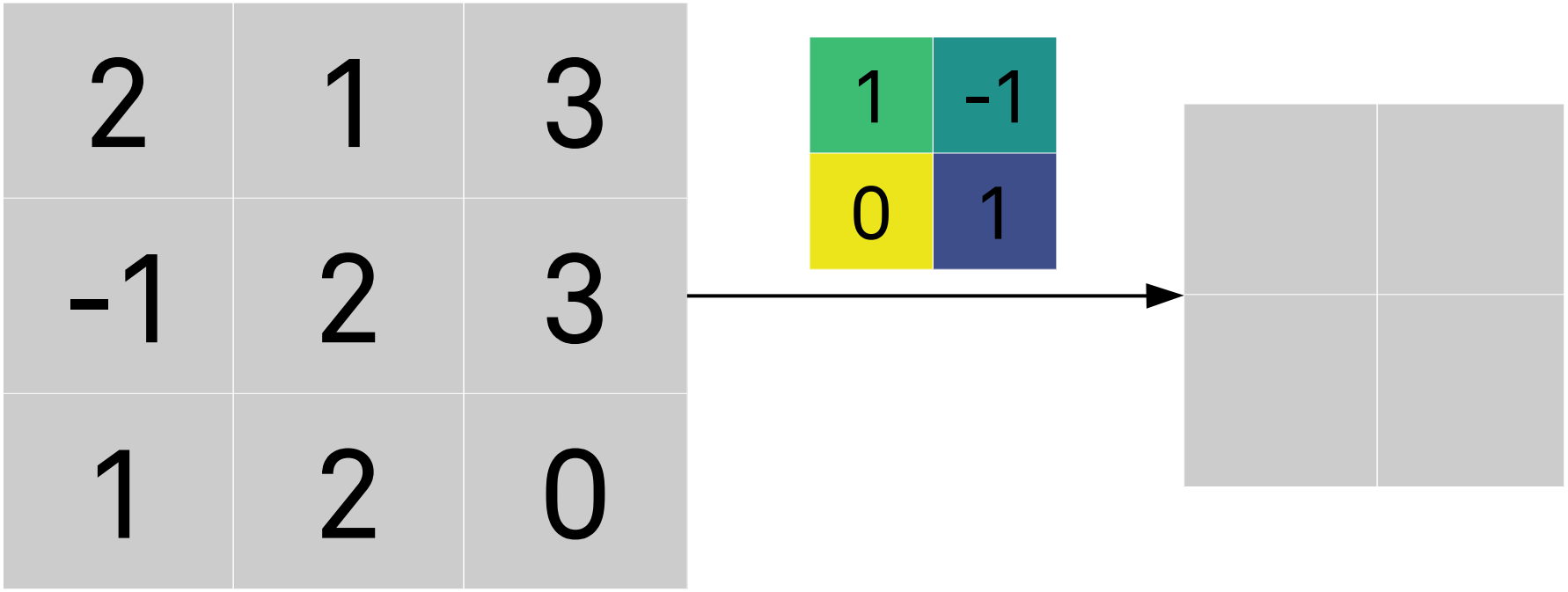
Konrad Mielke
konrad.mielke@tu-dortmund.de

Main Problems with MNIST Classification

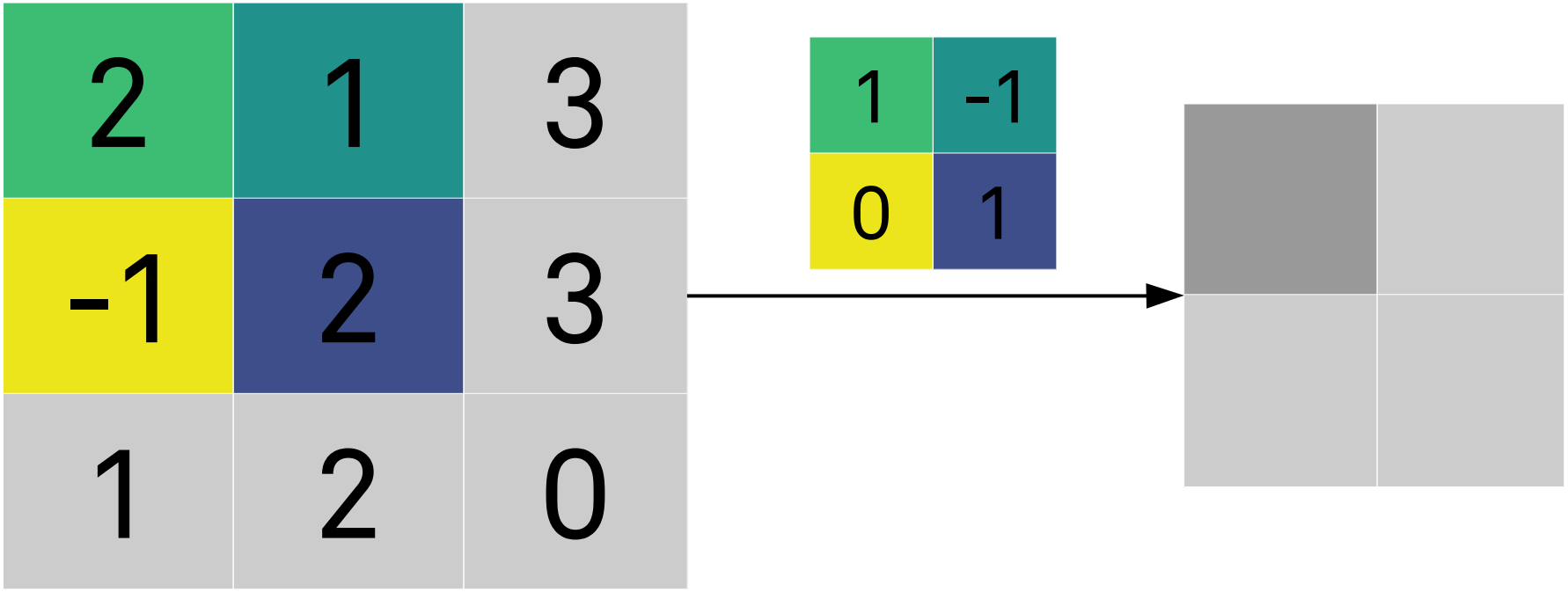
- Input is too high dimensional
  → Too many parameters
- Image character of input ignored
  → Not using useful information

- Solution: Convolution and Pooling

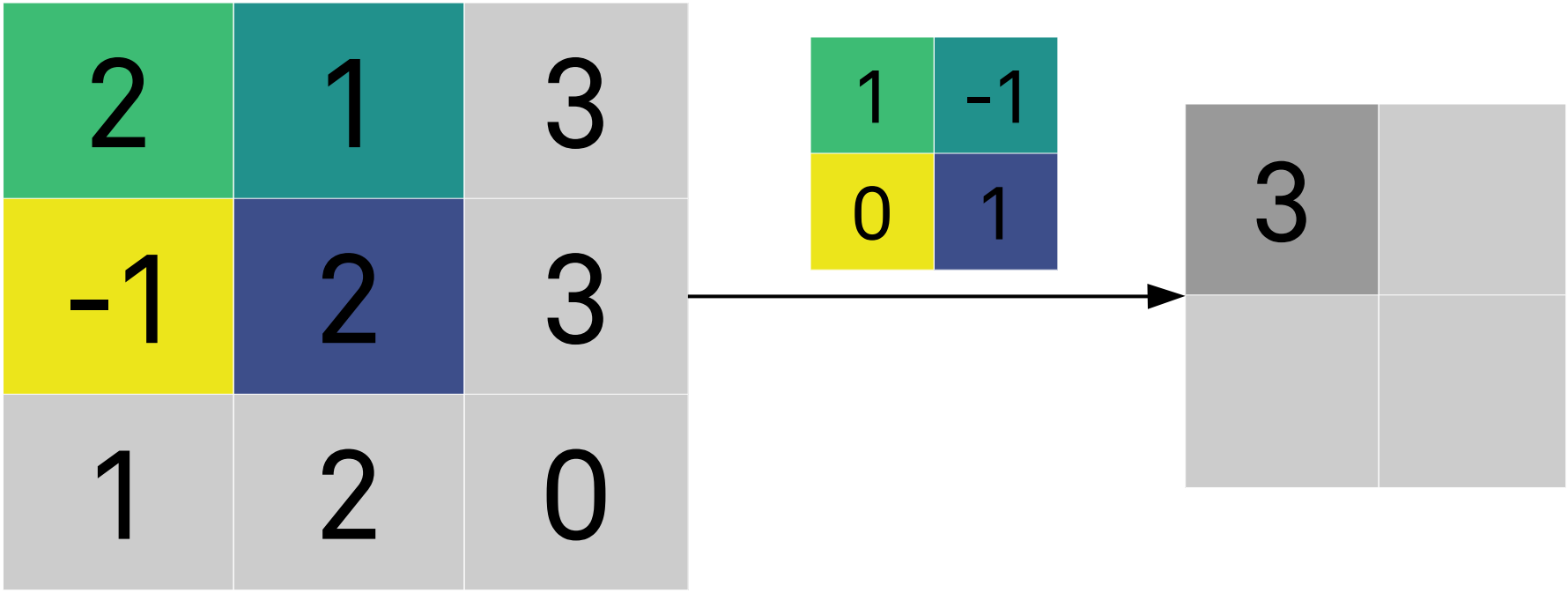
Convolution: Basic Idea



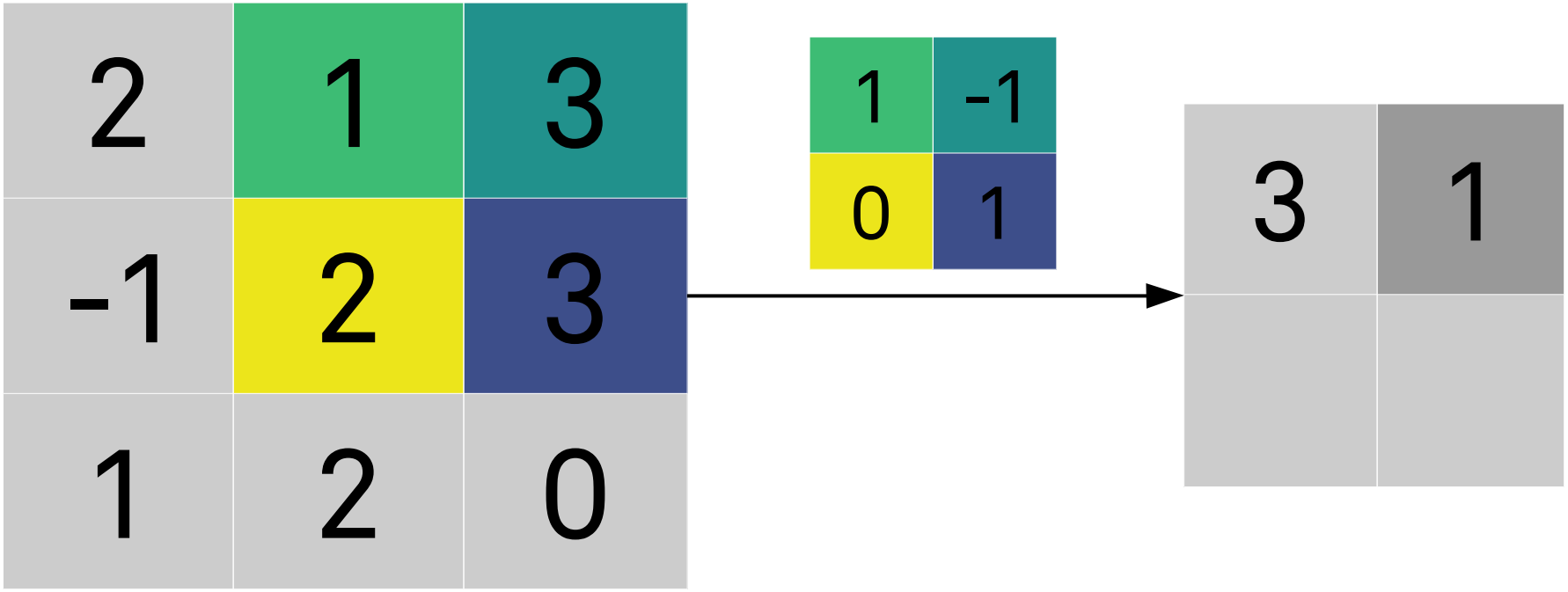
Convolution: Basic Idea



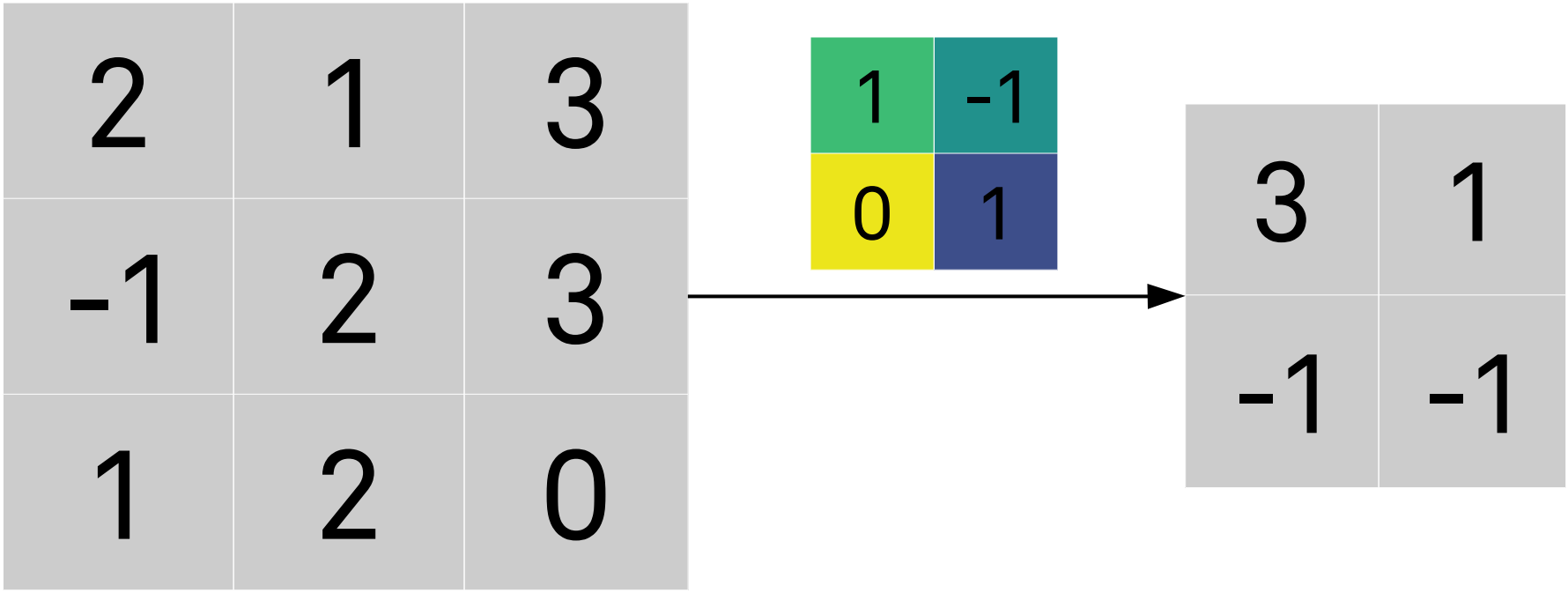
Convolution: Basic Idea



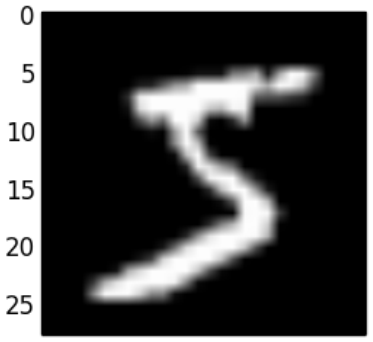
Convolution: Basic Idea



Convolution: Basic Idea



Convolution: Benefits

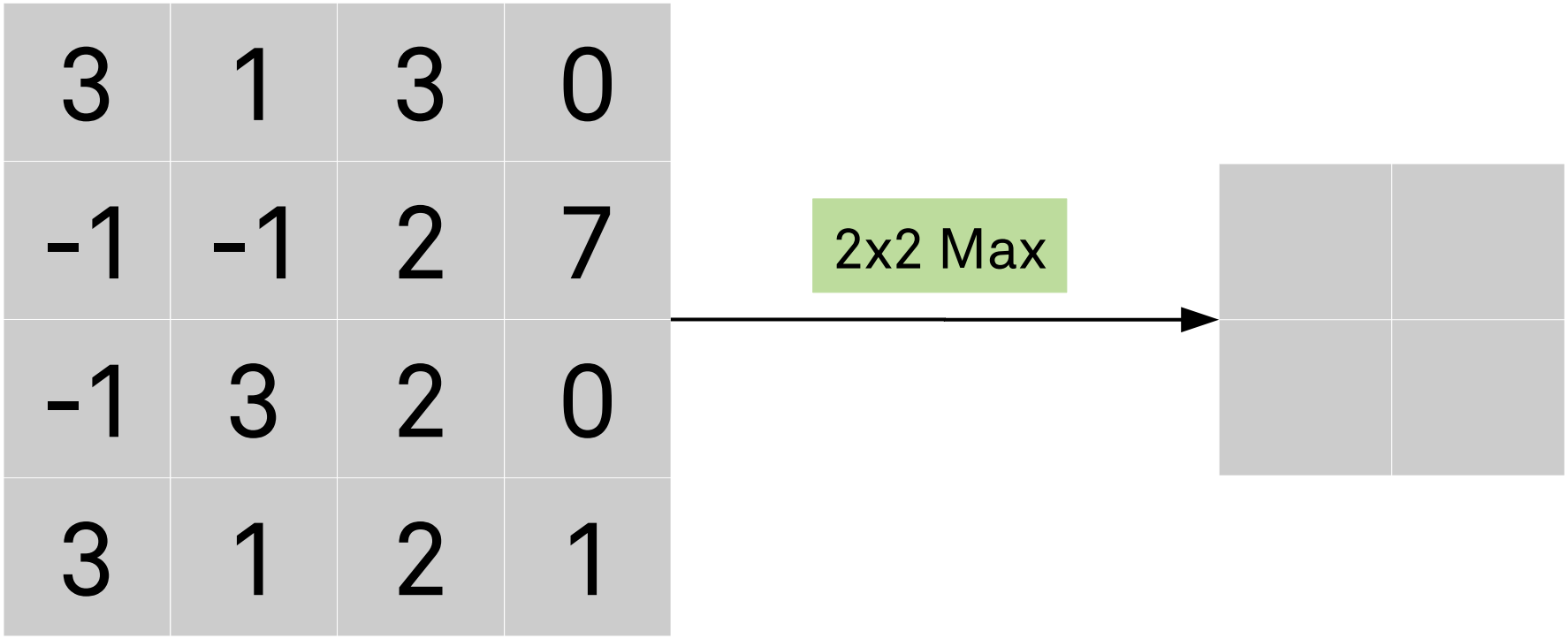


MNIST

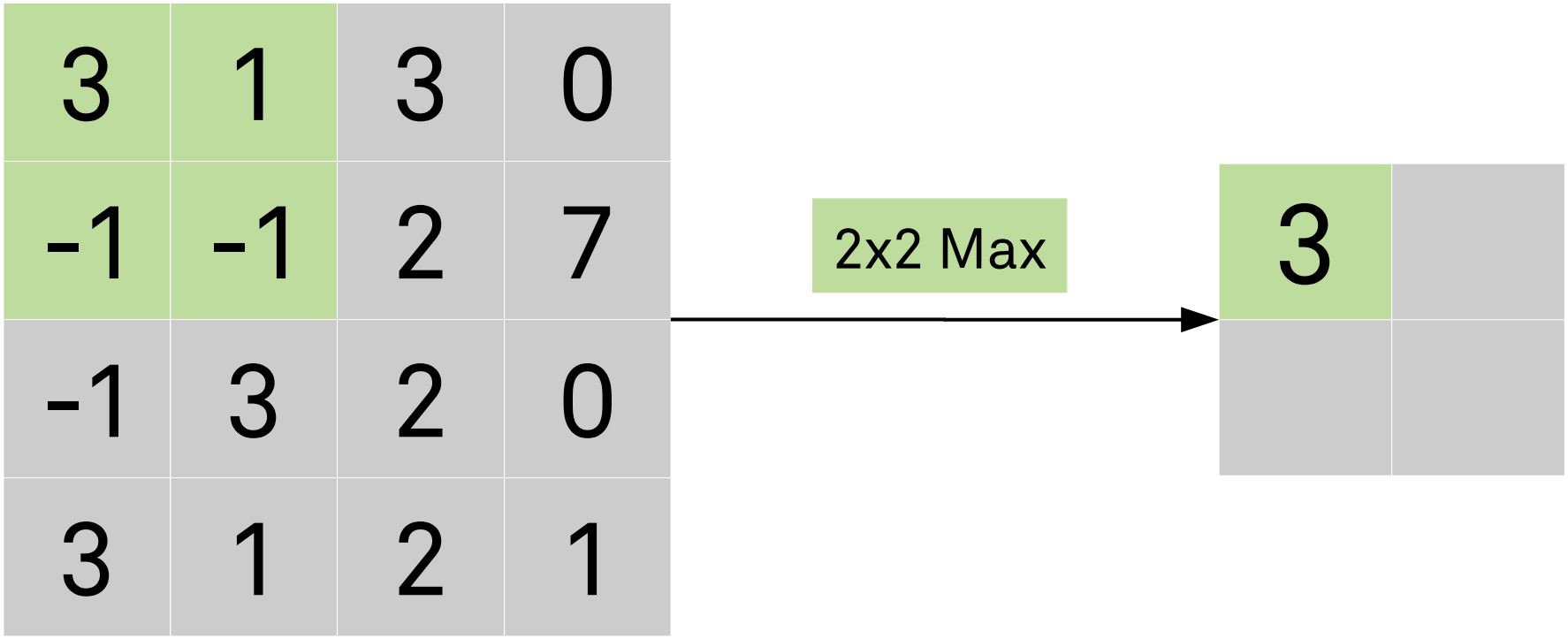
- Position of digital in picture not important
- Local correlation between pixels very important

  → Both adressed by convolution

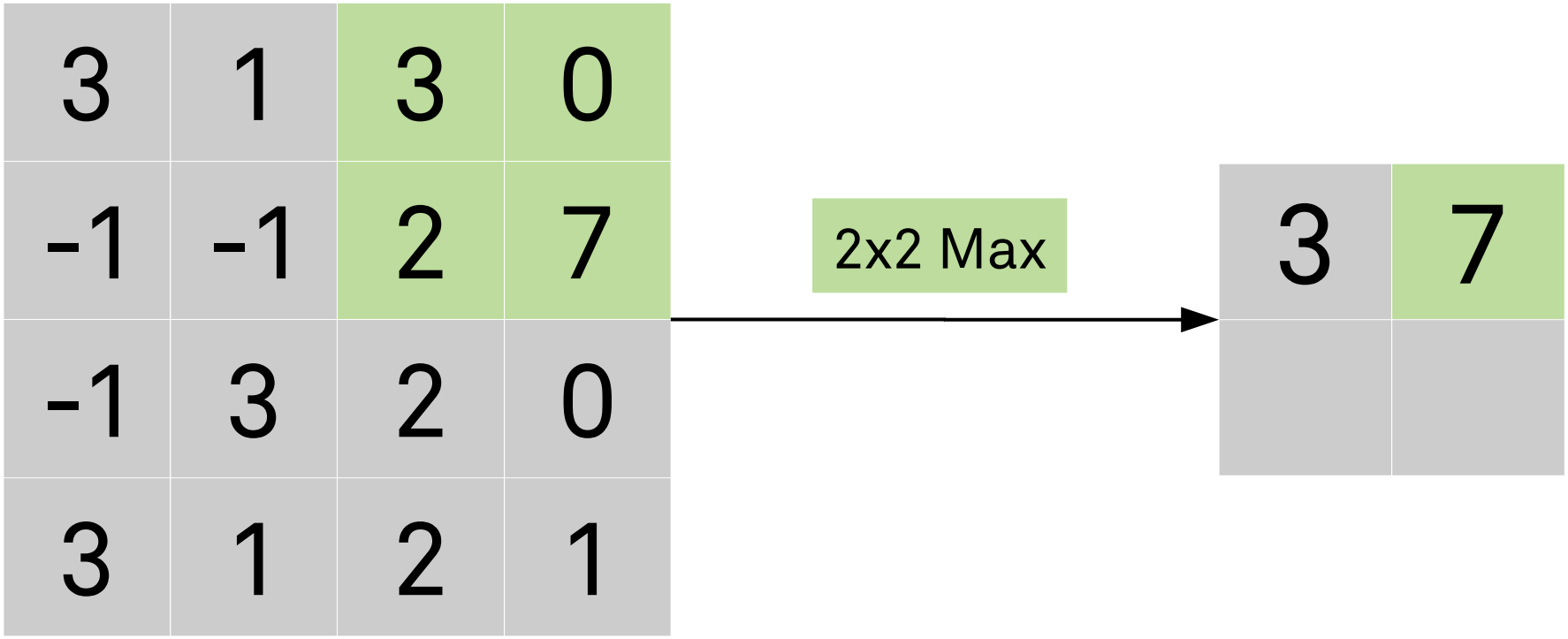
Pooling



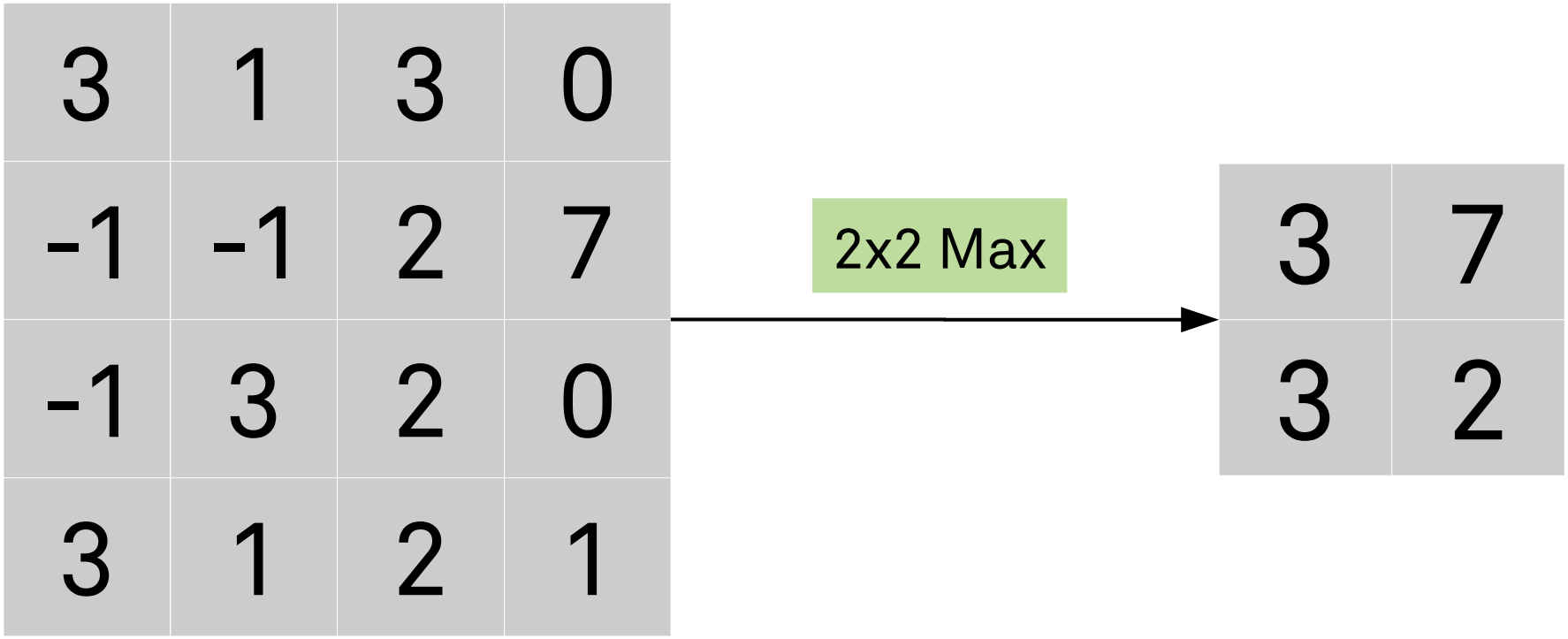
Pooling



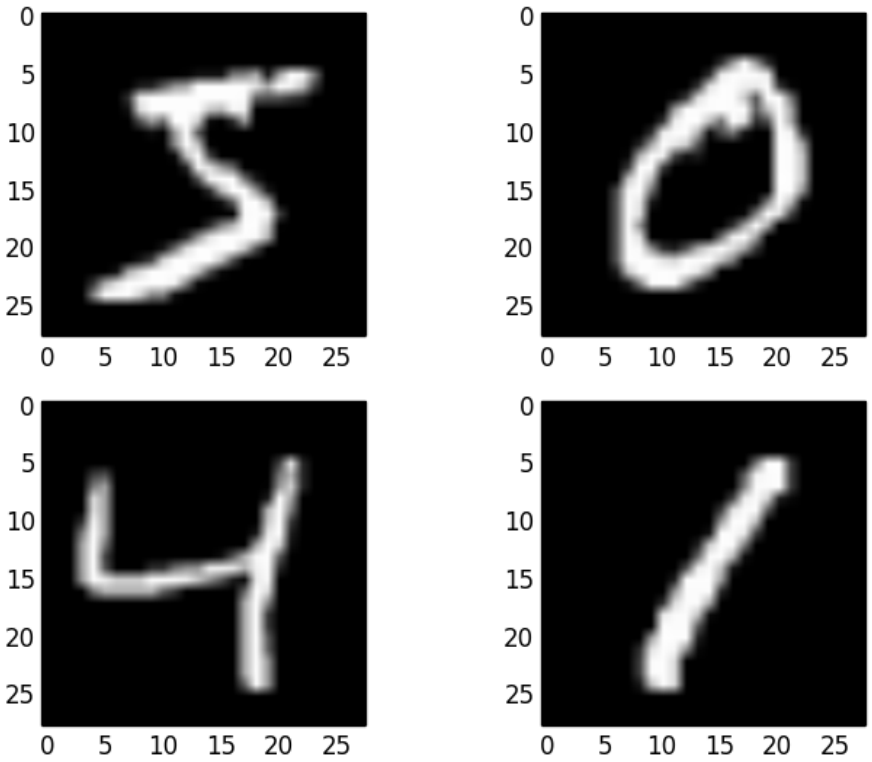
Pooling



Pooling



MNIST Classification Using Convolution & Pooling



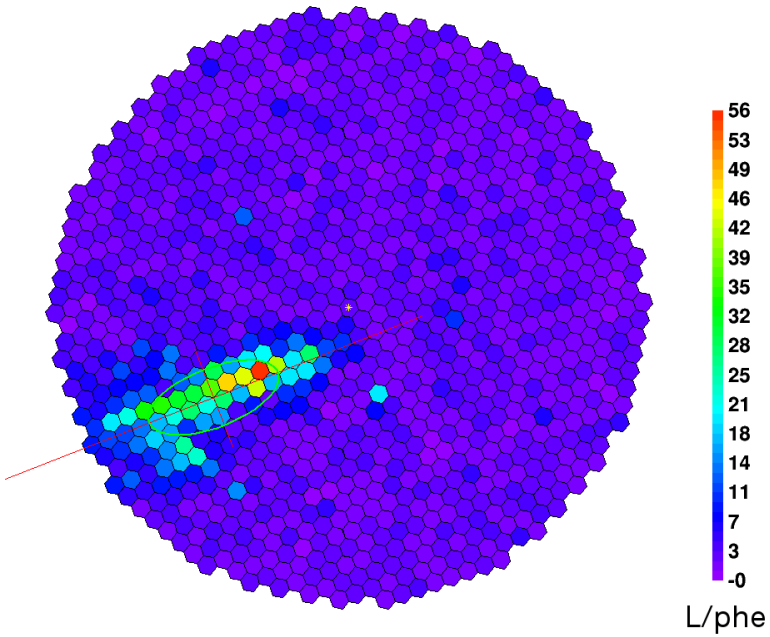
MNIST

Optimization

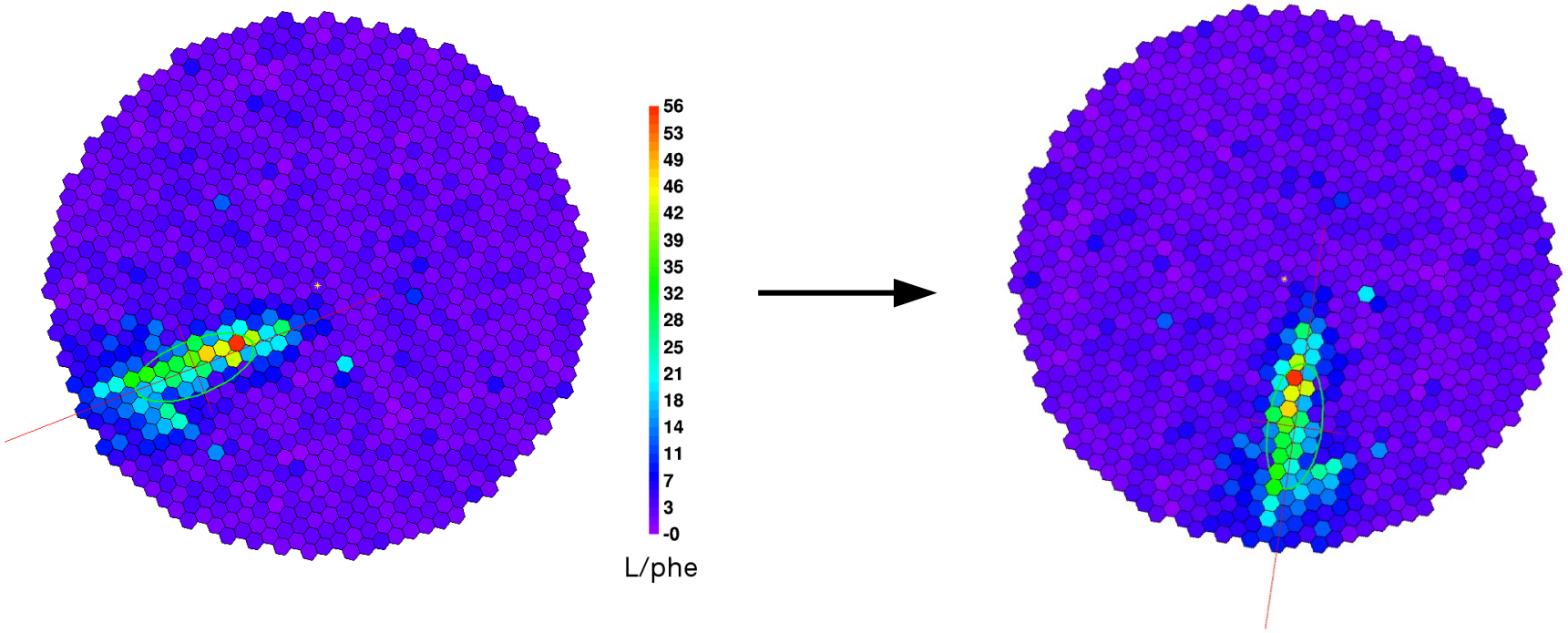
Optimization

- Data augmentation and normalization
- Network architecture and size
- Loss function
- Learning algorithm
- Weight initialization
- Hyperparameters: E.g. Learning rate
- Regularization

Data Augmentation: Example



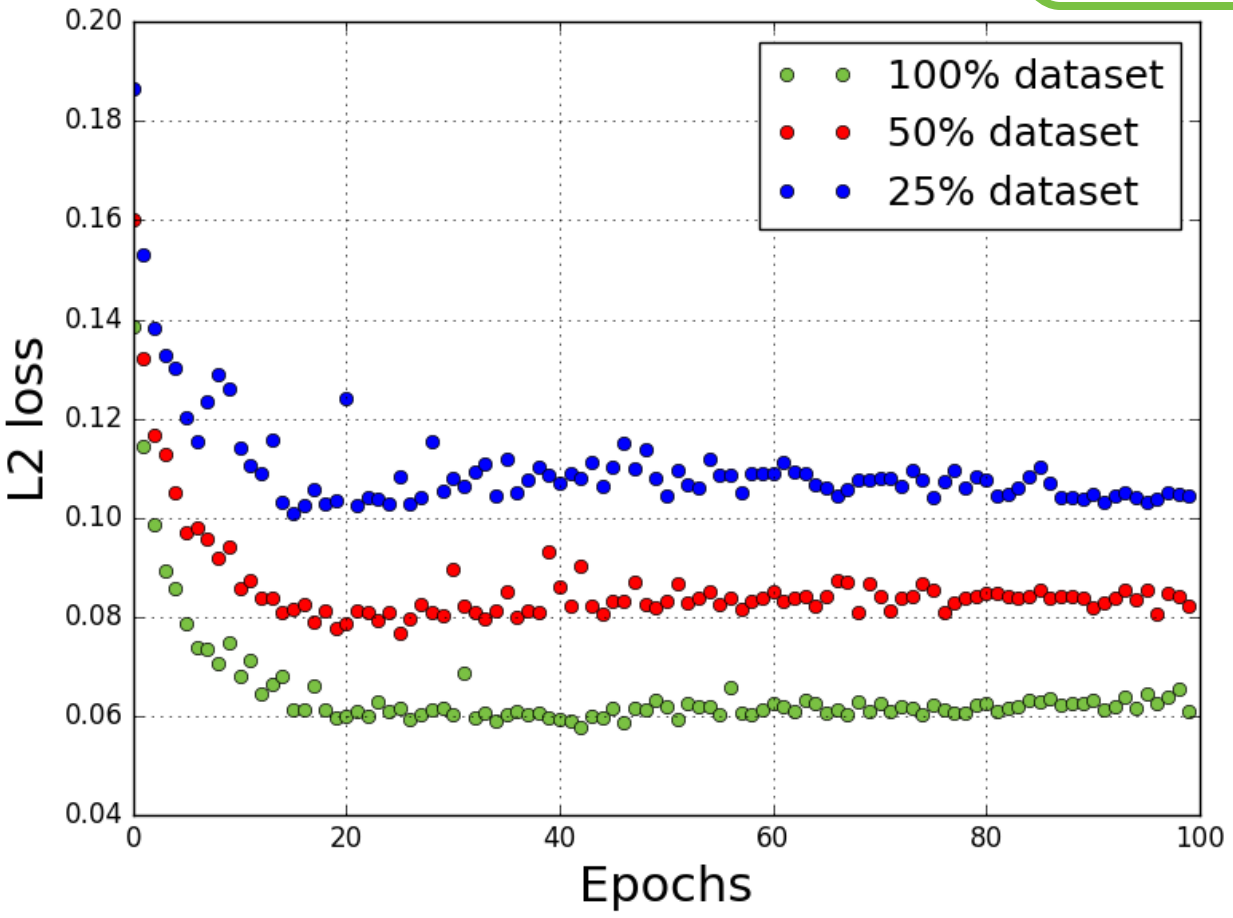
Data Augmentation: Example



→ Very cheap method to generate more data

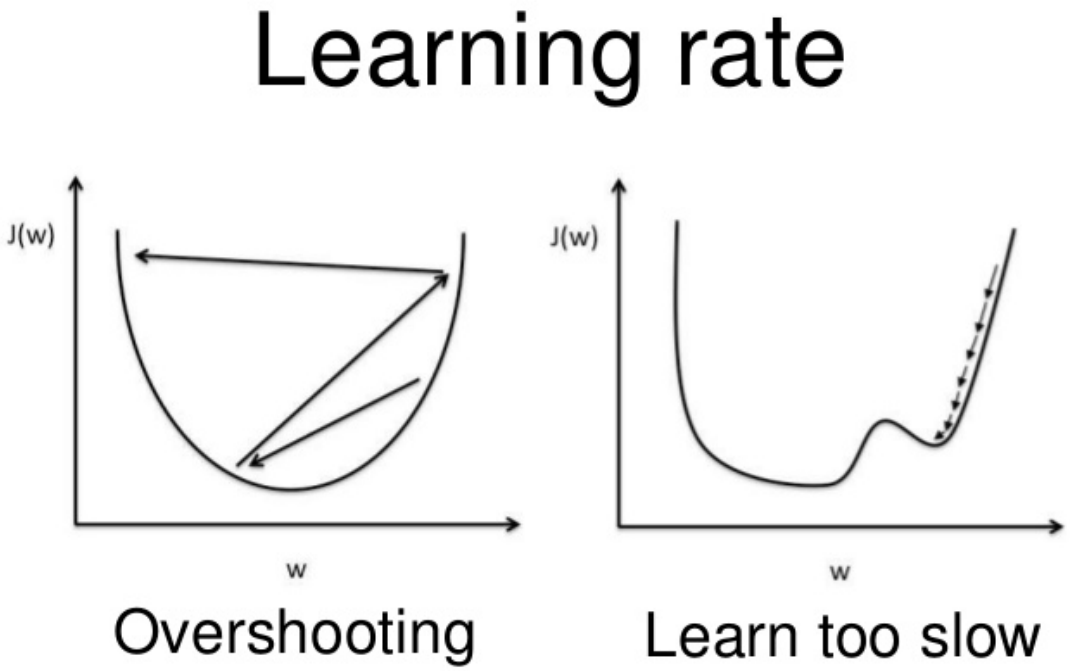
Effect of Dataset Size

Epoch: One pass through the entire dataset



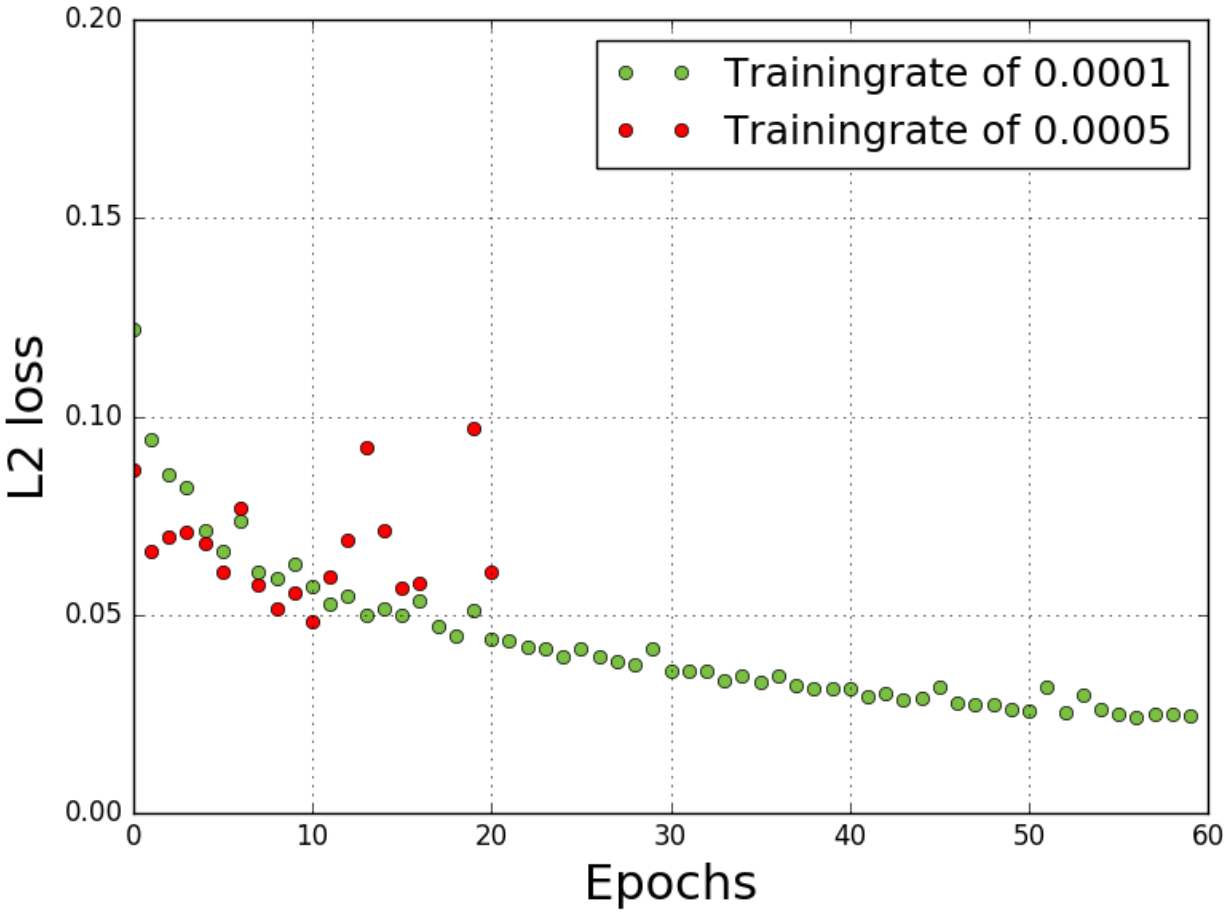
Learning Rate

How quickly to update the parameters?

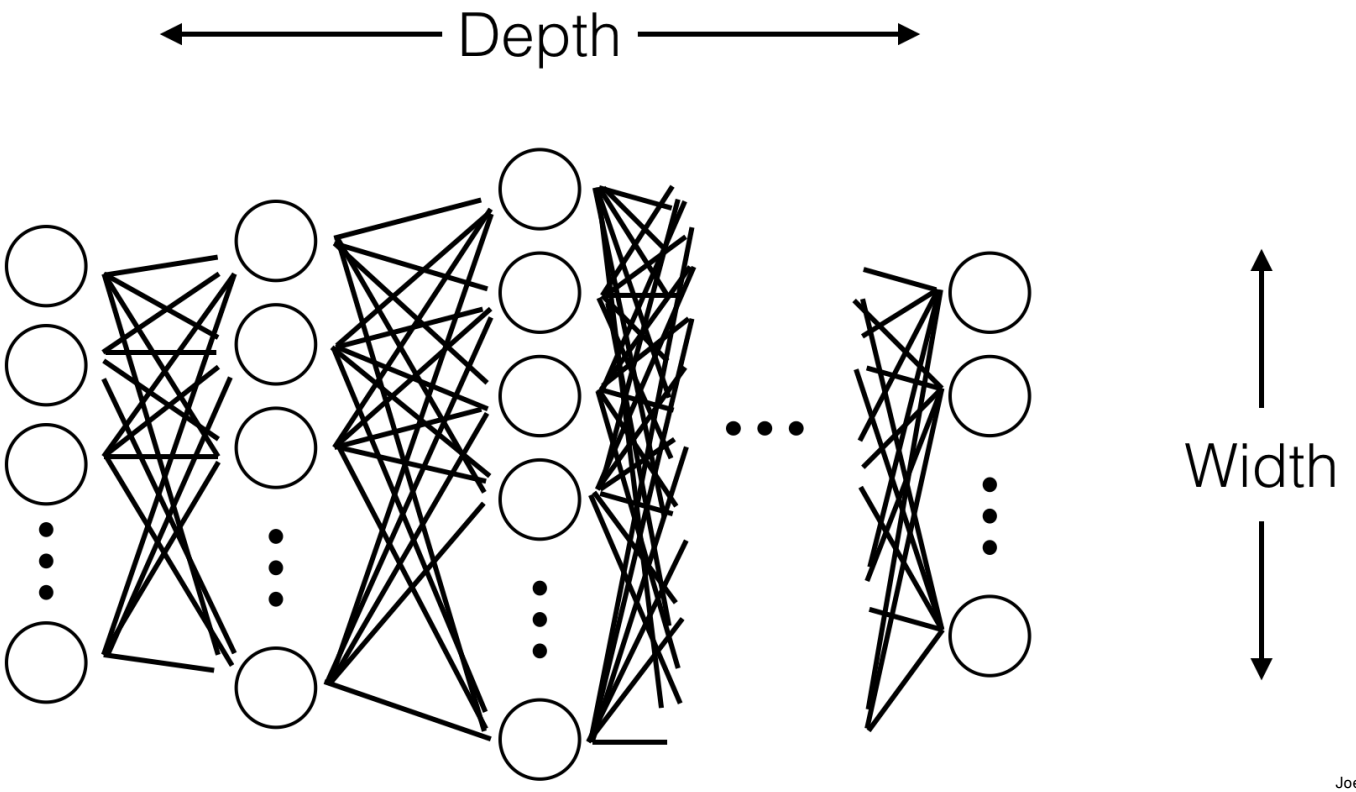


Jonas Degrave

Effect of Learning Rate

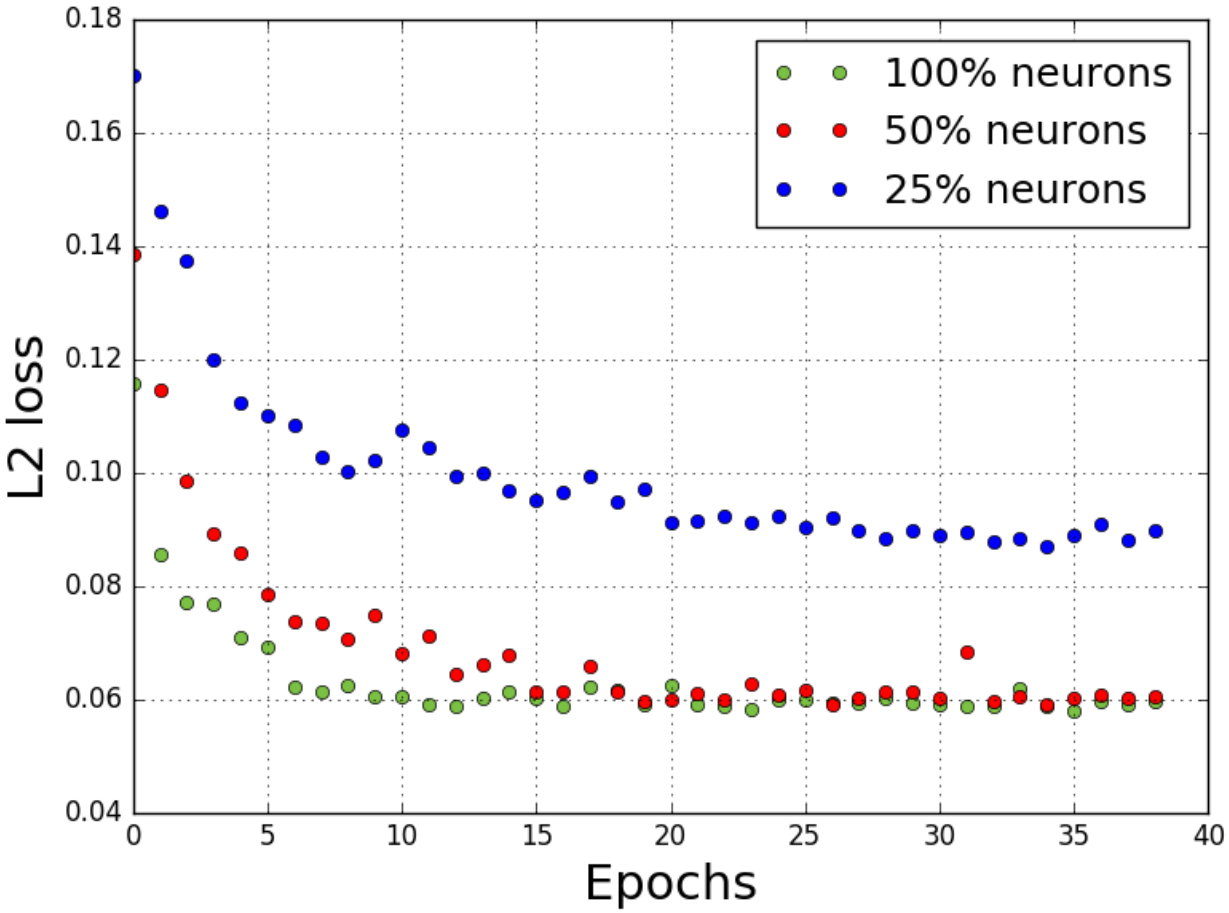


Network Size: Depth and Width

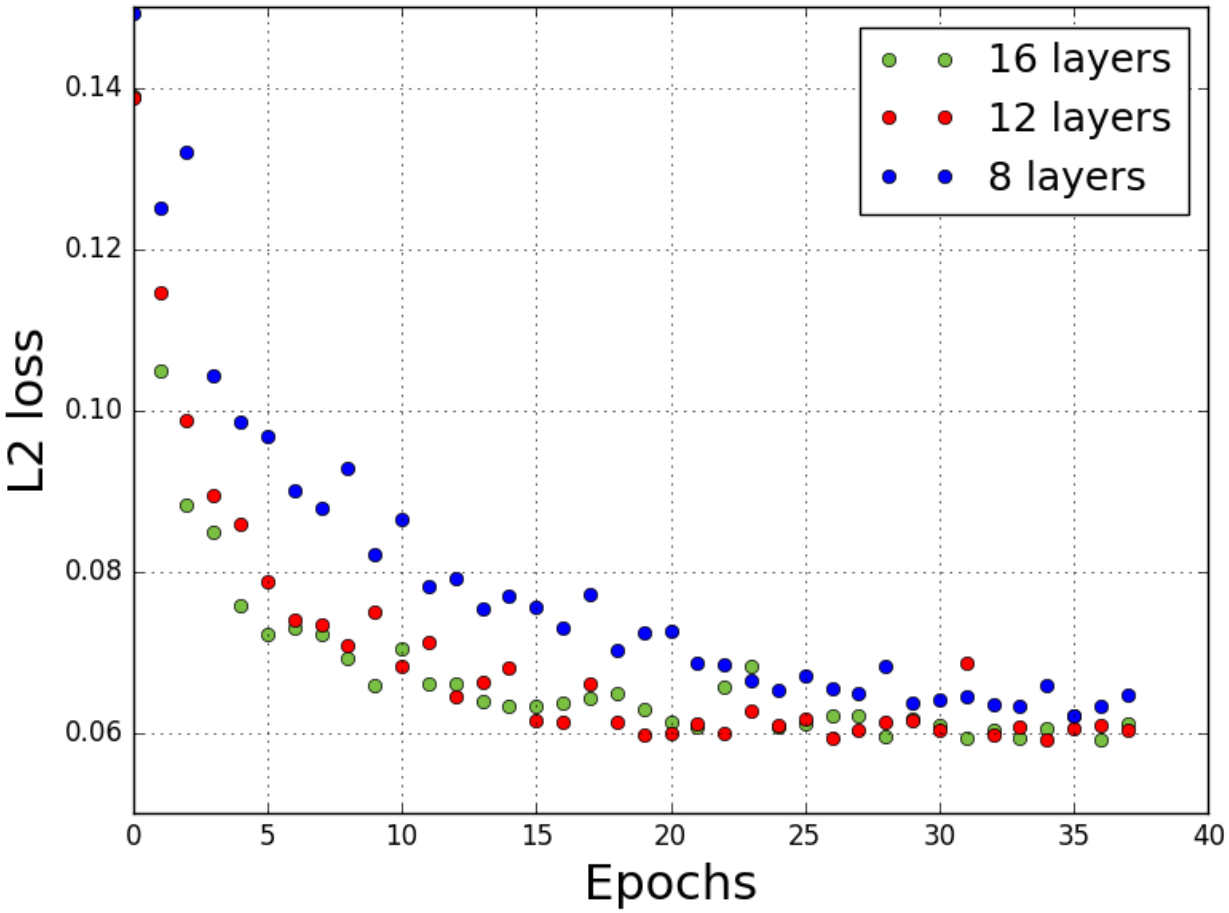


Joe Marino

Effect of Network Width



Effect of Network Depth



ImageNet Recognition Challenge 2012

- Competition won by Krizhevsky/Sutskever/Hinton

> We trained a large, deep convolutional neural network to classify the [...] images [with an error rate] considerably better than the previous state-of-the-art.

- **Why is it so much better than the old neural networks?**

ImageNet Recognition Challenge 2012

- Competition won by Krizhevsky/Sutskever/Hinton

> We trained a large, deep convolutional neural network to classify the [...] images [with an error rate] considerably better than the previous state-of-the-art.

- **Why is it so much better than the old neural networks?**

Lots of small improvements

ImageNet Recognition Challenge 2012

- Competition won by Krizhevsky/Sutskever/Hinton

> We trained a large, deep convolutional neural network to classify the [...] images [with an error rate] considerably better than the previous state-of-the-art.

- **Why is it so much better than the old neural networks?**

Lots of small improvements

Drastically better computers and bigger datasets

Thank you for your attention!