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Deep Learning Tutorial

HAP Workshop – Big Data Science in Astroparticle Physics

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Tutorial Overview

- Deep Learning Fundamentals
  - → Neural Networks
  - → Optimization
  - → Generalization
- Image Classification
- TensorFlow & Keras
- Practice Session 1: Image Classification with Neural Networks

Coffee break

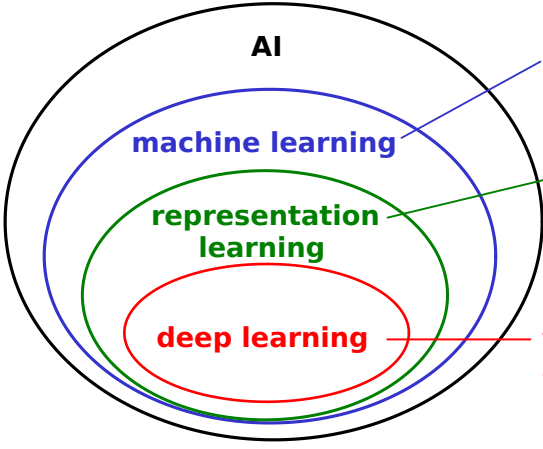
- Convolutional Networks
- Practice Session 2: Image Classification with Convolution Networks
- Image Recognition on Air Shower Footprints
- Practice Session 3: Air Showers Reconstruction

Machine Learning

"**Machine learning** is the subfield of computer science that gives computers the ability to learn without being explicitly programmed." *Arthur Samuel, 1959*

- **Supervised learning**: With data $\{x, y\}$ learn to predict $y(x)$
  - → Regression task: $y \in \mathbb{R}$, e.g. predicting house prices
  - → Classification task: y discrete, e.g. signal or background
- **Unsupervised learning**: Find structures or patterns in dataset $\{x\}$
  Example: Estimate distribution $p(x)$
- **Reinforcement learning**: Interaction with dynamic environment
  Example: Game playing and control problems

What is Deep Learning



infer statistical dependencies to give ability to predict

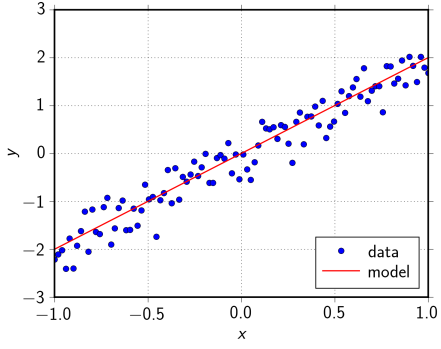
finding data representations that improve machine learning

represent data as hierarchy of features where each new layer is a more abstract representation based on less abstract ones

Deep learning is the state-of-the-art approach for everything related to computer vision, speech recognition, natural language processing and many AI tasks in general.

Primer: Linear Regression

Let's define the terminology based on simple linear regression (supervised learning).



- **Data** set $\{x_i, y_i\} \quad i = 1 \dots N$
  and want to predict $y = f(x)$
- Define **model**
  $y_{\mathrm{m}}(x; \theta) = Wx + b$ with parameters $\theta = (W, b)$
- Define **objective** function (also called loss or cost) that quantifies distance between model and data
  $J(\theta|x, y) = \frac{1}{N} \sum_{i=1}^{N} (y_{\mathrm{m}}(x_i) - y_i)^2$
- **Train** the model by optimizing the parameters
  $\hat{\theta} = \arg\min J(\theta)$ e.g. through gradient descent

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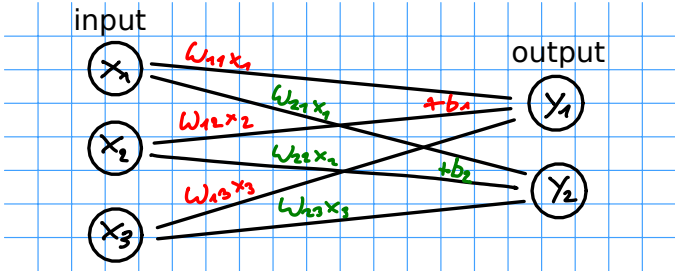
Neural Networks

Multidimensional Linear Model

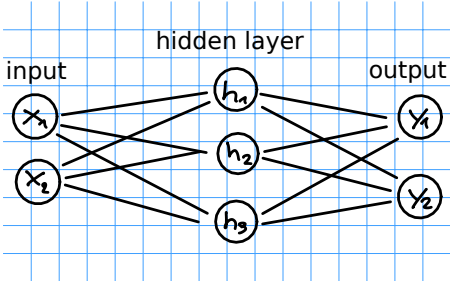
General case: Predict multiple outputs $\mathbf{y} = (y_1 \dots y_n)$ from multiple inputs $\mathbf{x} = (x_1 \dots x_m)$ using linear function $\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{b}$

Example: $x \in \mathbb{R}^3$, $y \in \mathbb{R}^2$

$$\begin{pmatrix} W_{1,1} & W_{1,2} & W_{1,3} \\ W_{2,1} & W_{2,2} & W_{2,3} \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$$



Nonlinear Models



$\mathbf{Wx} + \mathbf{b}$ only describes linear transformation.
Idea: Create a network by applying several linear transformations

$$h' = W^{(1)}x + b^{(1)}$$
$$y = W^{(2)}h' + b^{(2)}$$

Problem: the model is still linear ...

$$\begin{aligned} y &= W^{(2)}\left(W^{(1)}x + b^{(1)}\right) + b^{(2)} \\ &= \underbrace{W^{(2)}W^{(1)}}_{W}x + \underbrace{W^{(2)}b^{(1)} + b^{(2)}}_{b} \end{aligned}$$

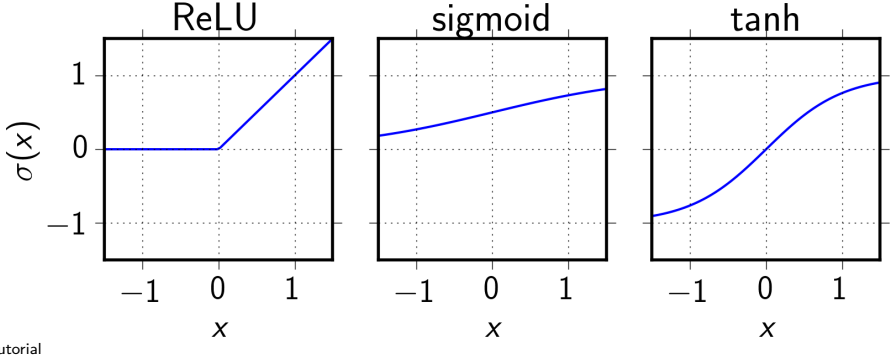
Solution: Apply non-linear **activation** σ to each element of $h' \longrightarrow h = \sigma(h') = \sigma(Wx + b)$

Activation Function

Through the activation function the layer $\sigma(Wx + b)$ becomes a non-linear mapping. Basically any kind of non-linearity can be used.

Some choices are

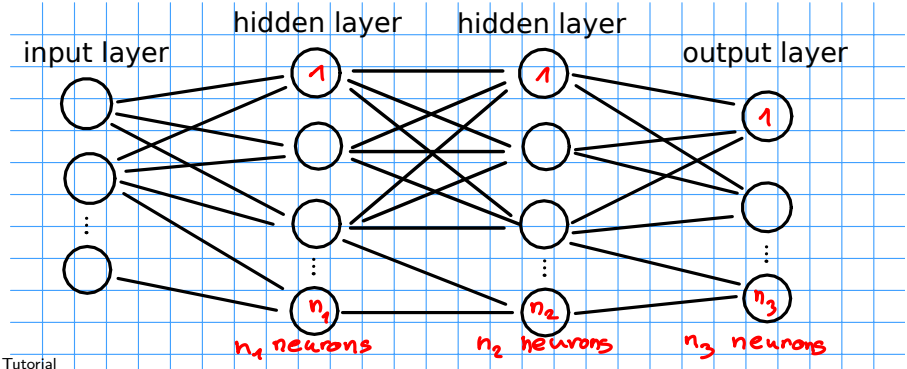
- $\sigma(x) = \max(0, x)$ rectified linear unit (**ReLU**)
- $\sigma(x) = \frac{1}{1+e^{-x}}$ sigmoid function
- $\sigma(x) = \tanh(x)$



Neural Networks

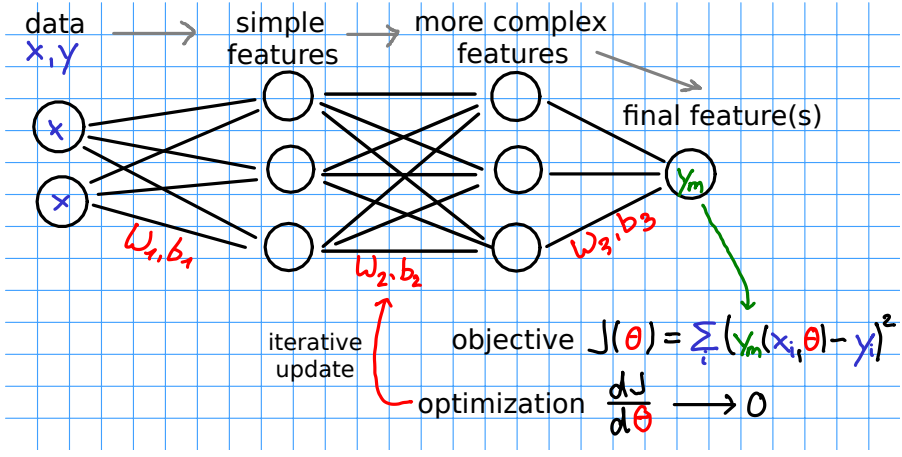
Basic unit $\sigma(Wx + b)$ called **neuron** in analogy with the brain

- Non-linear activation according to a number of inputs (= outputs of previous layer)
- Strength of connection between neurons specified by **W**
- **Depth**: number of weighted layers (don't count input here)
- **Width**: number of neurons per layer



Feature Learning

Each new layer extracts more complex features about the data. Learning these features is an **automatic** process when training the model.



$\longrightarrow$ No need for hand-crafted features, network learns meaningful features from data itself.

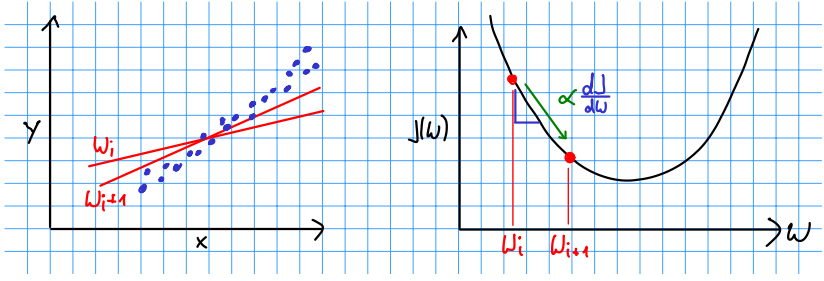
Optimization

Gradient Descent

Minimize objective function $J(\theta)$ by iteratively updating θ in negative direction of gradient. Update proportional to gradient $\frac{dJ}{d\theta}$ and learning rate α:

$$\theta \longrightarrow \theta - \alpha \frac{dJ}{d\theta}$$

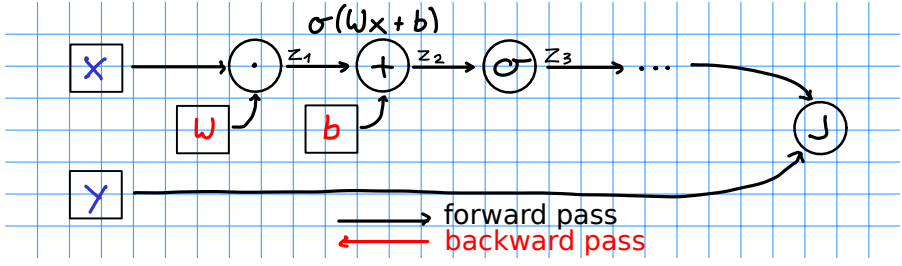
Example: Linear regression with mean squared error $J \sim \sum_{i=1}^{N} (y_{\mathrm{m}}(x_i) - y_i)^2$



Gradient can be evaluated numerically (expensive) or analytically (cheap).

Computation Graph

- A network is a series of simple operations → computation graph
- Each operation knows how to calculate
  - → its local output (forward pass)
  - → its local derivative (backward pass)
- Use chain rule to evaluate derivative $\frac{dJ(\theta|x,y)}{d\theta}$ for each parameter through multiplying the local derivatives
- Allows to evaluate the analytic gradient in automated way (**backprop**)



Stochastic Gradient Descent

For large datasets evaluating $J(\theta|x, y)$ and $\frac{dJ}{d\theta}$ is prohibitively expensive

Idea: Only use small subset of data in each iteration (**mini-batch**)

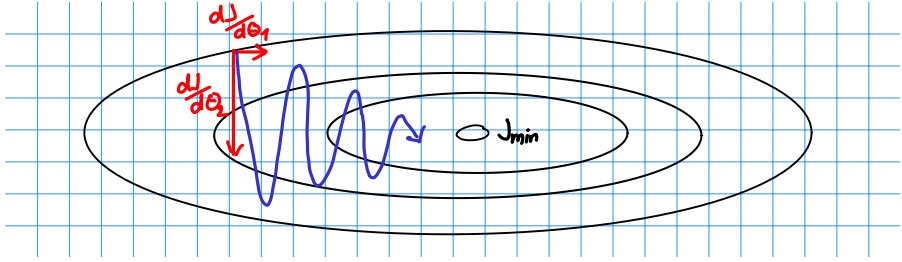
- Smaller batches $\rightarrow$ more parameter updates per compute
- Stochasticity in objective function helps escaping local minima
- **Batch size** is typically small, say 16 - 256 samples (hyperparameter!)
- **Epoch** $\equiv$ full pass through the training data

Stochastic gradient descent (**SGD**): Loop

- Sample random mini-batch of data
- Calculate objective J and gradient $\frac{dJ}{d\theta}$
- Update parameters $\theta \rightarrow \theta - \alpha \frac{dJ}{d\theta}$

Improved Optimizers

Typical situation: $\frac{dJ}{d\theta_1} \ll \frac{dJ}{d\theta_2}$ leading to slow learning in θ_1

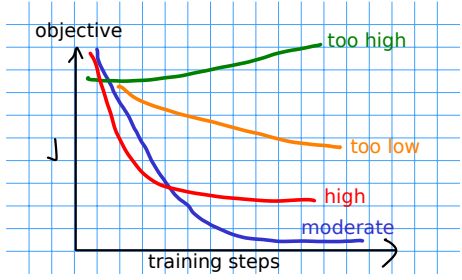


Improve learning with modified parameter update

- **Momentum**: build up momentum
- **Adagrad**: scale down by $1/\sqrt{\text{sum of past gradients}}$
- **RMSProp**: similar to Adagrad but with decay of scale factor
- **Adam**: combination of RMSProp and momentum

Learning Rate

In gradient-based optimizers ($\theta \rightarrow \theta - \alpha \frac{dJ}{d\theta}$) learning rate α determines speed of training



Best learning rate decreases over time (implicitly done in Adagrad, RMSProp and Adam)

- Typically start with $\alpha = 10^{-3}$ (for standard objective functions)
- Reduce learning rate $\alpha/10$ when objective stops decreasing

Parameter Initialization

Need to provide initial weights W and biases b at start of training.
Set weights to small random values to break symmetry $W \sim \mathcal{N}(\mu = 0, \sigma)$.
Scale of initial weights σ is critical for deeper nets.

- Weights too large $\rightarrow$ exploding signals and gradients
- Weights too small $\rightarrow$ vanishing signals and gradients

To keep the expected signal constant, scale initial weights with number of ingoing n_{in} and outgoing connections n_{out} of neuron.

- **Xavier**: $\sigma^2(W) = \frac{2}{n_{\text{in}}+n_{\text{out}}}$ (X. Glorot & Y. Bengio)
- **He**: for ReLU use $\sigma^2(W) = \frac{2}{n_{\text{in}}}$ (He et. al)

Batch Normalization: feature normalization operation inside the network

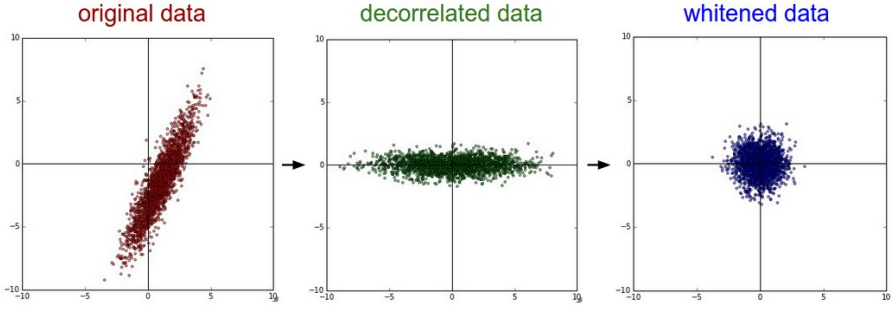
- Reduces problem of vanishing / exploding signals and gradients
- Reduces sensitivity to bad initialization

Data Preprocessing

Highly beneficial if input features $x_1, x_2 \dots x_n$ of dataset are on same scale.

Preprocessing options:

- Limit input features to range $x_i \in [-1, 1]$
- Standard normalize: $\text{mean}(x_i) = 0$, $\text{std}(x_i) = 1$
- Whitening: Decorrelate and standard normalize



taken from http://cs231n.github.io/neural-networks-2/

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Generalization

Universal Approximation Theorem

Many network design considerations: How many layers, how many nodes per layer, which kind of connections, ... ?

Universal approximation theorem

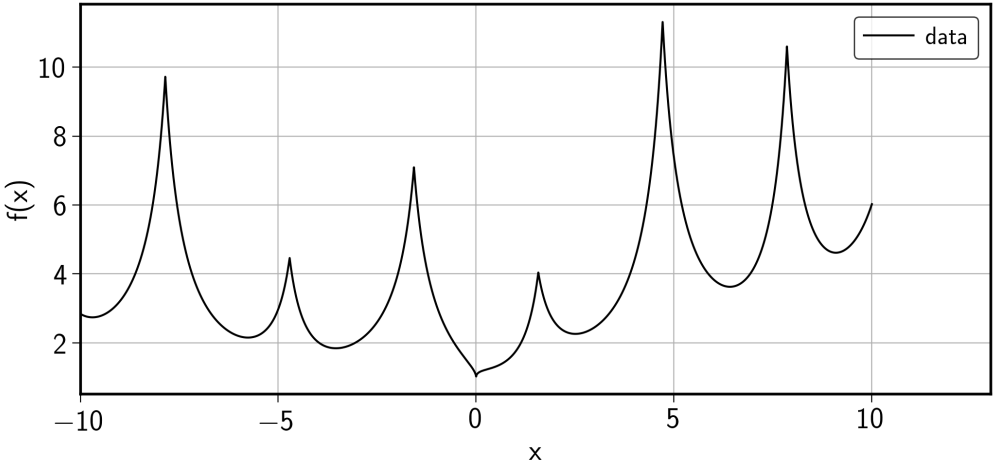
A feed-forward network with a linear output and at least one hidden layer with a finite number of nodes can approximate any function to arbitrary precision.

Caveats

- It doesn't specify how many nodes are needed
- There's no statement on how to train the network

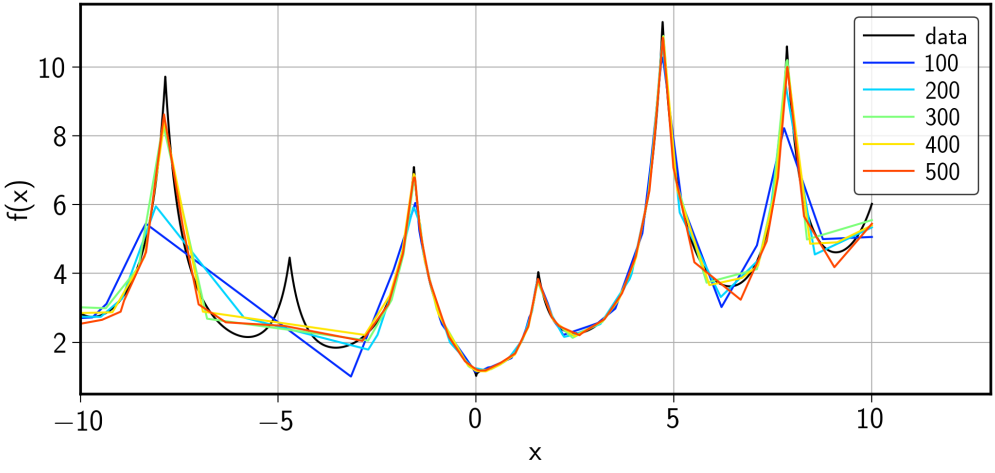
1D Function Fitting

Try to fit some complicated function with neural network



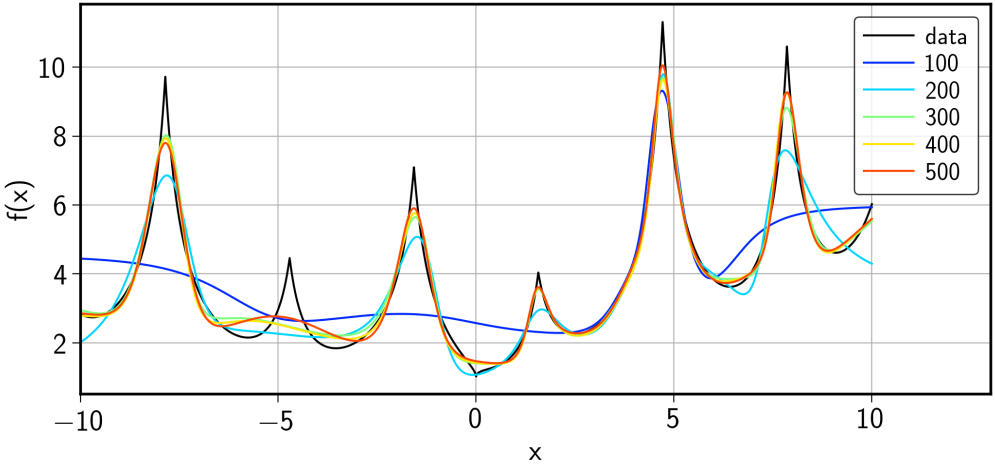
1D Function Fitting 1

Train network with 3 hidden layers of 20 neurons and **ReLU** as activation
Fit after different number of training iterations:



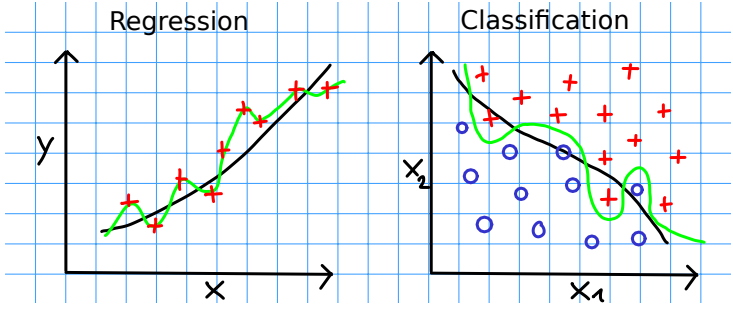
1D Function Fitting 2

Train network with 3 hidden layers of 20 neurons and **sigmoid** as activation
Fit after different number of training iterations:



Overfitting

If a complex enough network can learn any function, how do we know that it's not overfitting, i.e. fine-tuning to statistical fluctuations?



Validation

Unknown true distribution $p(x, y)$ from which data $\{x, y\}$ is drawn.
Trained model provides prediction $y_{\mathrm{m}}(x)$ based on this limited dataset.

Generalization

How good is our estimator when faced with new data?

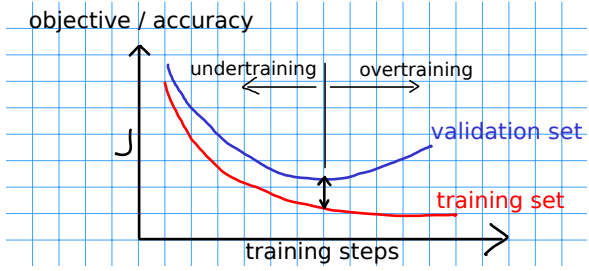
Validation

Since $p(x, y)$ unknown, estimate generalization error on fraction of data not used during training. $\longrightarrow$ Typically split data into **training**, **validation** and **test** set.

- Validation set: Evaluate performance for given set of hyper-parameters.
- Test set: Estimate final performance. Use only once, or risk of "look elsewhere effect"

Over-/Undertraining

During training, monitor the objective or another accuracy metric separately for the training and validation sets. Typical observation:



- Training loss decreases continuously ($\rightarrow 0$ if model complex enough)
- Validation loss has minimum $\rightarrow$ network starts to **overtrain**
- Validation loss higher than training loss $\rightarrow$ **generalization gap**

$\longrightarrow$ **Early stopping**: Stop training when validation error stops to decrease

Regularization and Capacity

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Regularization

Methods to reduce the validation error, possibly at the expense of higher training error.

- Early stopping
- Parameter norm penalties: add term to objective to penalize large weights
  - → L^2 norm: $J + \lambda \sum W^2$
  - → L^1 norm: $J + \lambda \sum |W|$
  - → Need careful tuning of λ
- Data augmentation: generate artificial data samples
- Ensemble methods: combination of multiple networks (special case: Dropout)

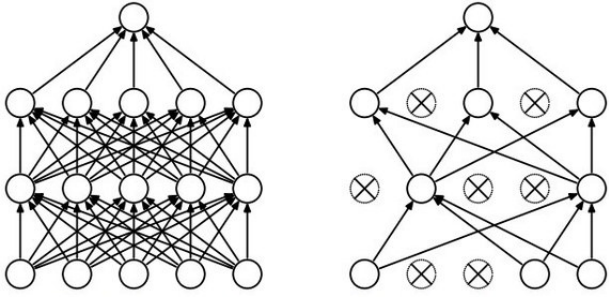
Model capacity

Complexity of functions that the network can represent. Effective capacity determined by

- Network architecture
- Training & regularization

Dropout

Randomly turn off a fraction (say $p = 0.5$) of neurons in each training step

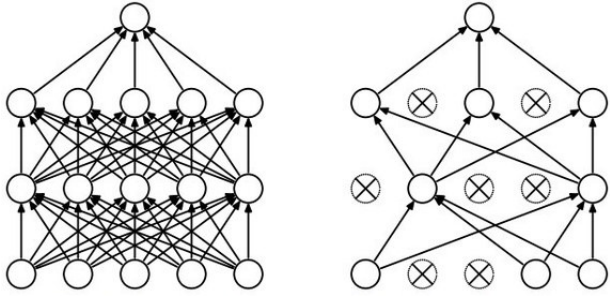


(a) Standard Neural Net

(b) After applying dropout.

Dropout

Randomly turn off a fraction (say $p = 0.5$) of neurons in each training step

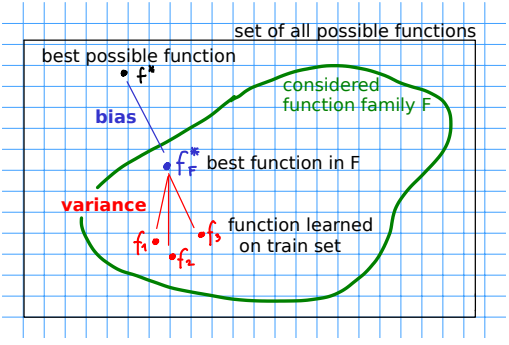


(a) Standard Neural Net (b) After applying dropout.

- Forces network to learn redundant representations, more robust predictions
- At test time use all neurons: large ensemble of models that share parameters
- Very effective regularization method. Easy to tune (hyperparameter p)

Bias and Variance Dilemma

- **Model Bias**: Error when approximating f^* with given model
- **Model Variance**: Error when training model using limited dataset



Effective capacity trades off bias against variance

- Choose more complex F: bias↓ variance↑
- Choose simpler F: bias↑ variance↓
- Optimal choice depends on size of dataset

Ensemble methods

- **Ensemble averaging**: Train multiple networks and combine their predictions
  $\Rightarrow$ variance↓, free boost in test performance

Summary

- Neural networks: layers of connected neurons $\sigma(Wx + b)$
  - → Linear transformation $Wx + b$
  - → Non-linear activation σ
  - → Universal approximation theorem: can fit any function
- Optimization
  - → Stochastic gradient descent on mini-batches of data
  - → Optimizers: Adam, learn rate, data preprocessing, parameter initialization
- Generalization
  - → Split data into training, validation and test set
    - » Validation set for monitoring training and tuning hyperparameters
    - » Estimate generalization error with test set
  - → Regularization to control overfitting
    - » early stopping, dropout, data augmentation
  - → Bias / variance, ensemble averaging

Image Classification

Image Classification

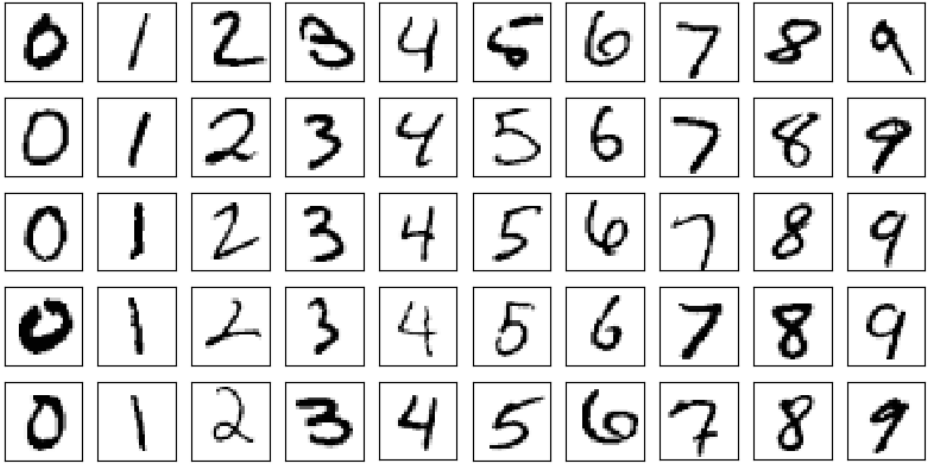
What do these images show?

Very easy for humans, very hard for classical machine learning methods. Challenges are

- High dimensional input $\mathbf{x} \in \mathbb{R}^{10^3-10^7}$
- Many possible classes depending on task
- Need to deal with multiple variations
  - → viewing angle, occlusion, deformation, light conditions, object variations ...

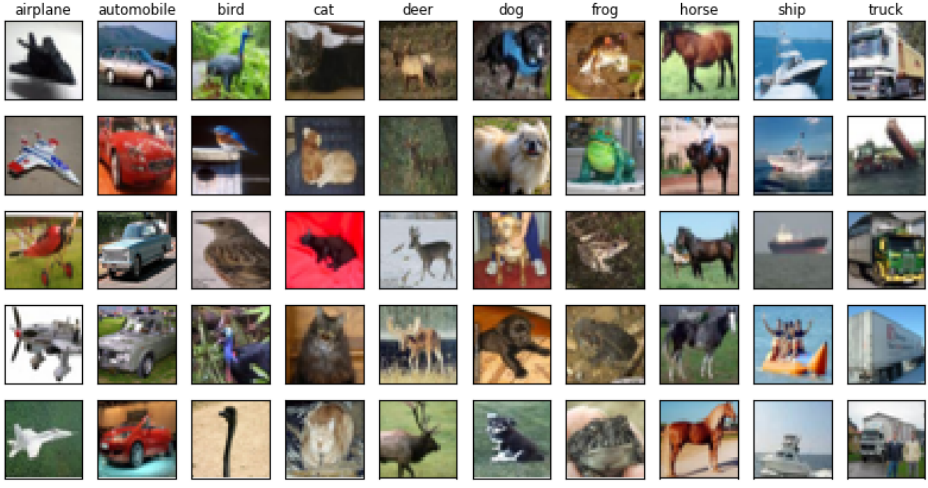
MNIST

Hand-written digit dataset, 28 x 28 pixels (grayscale)



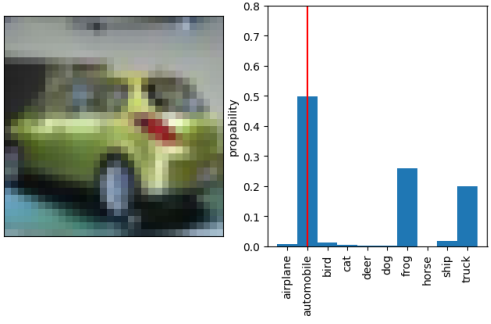
CIFAR-10

Tiny natural image dataset, 32 x 32 pixels (8-bit RGB), 10 categories



CIFAR-10 Classification Task

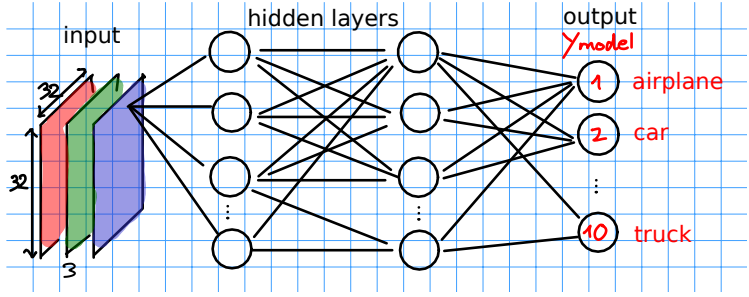
- Input $\mathbf{x} = (x_1, \dots x_{3072})$ for $32 \times 32 \times 3 = 3072$ features
- Output $\mathbf{y} = (y_1, \dots y_{10})$, one variable for each category (**one-hot encoding**)
  Categories: airplane, car, bird, cat, deer, dog, frog, horse, ship, truck
  Image $\mathbf{x}^i$ showing a car has $\mathbf{y}^i = (0, 1, 0 \dots 0)$.



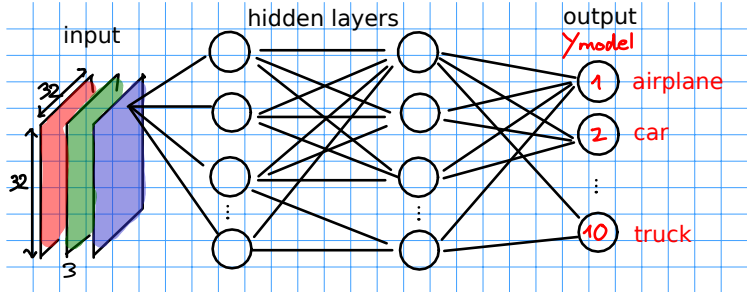
Model predicts probability for each class
$\rightarrow \mathbf{y}_{\text{model}}(\mathbf{x}^i|\theta) = (p_{\text{airplane}}, p_{\text{car}} \dots)$

- Take highest p_j as predicted category
- Value of $\max(p_j)$ gives measure of certainty

Classification Layer



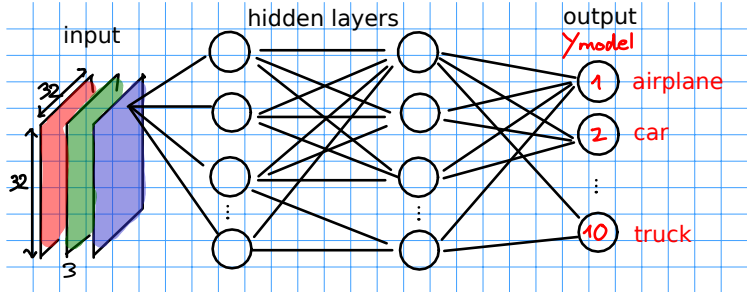
Classification Layer



Softmax as activation, $y_{\text{model},j} = \sigma(z_j) = e^{z_j} / \sum e^{z_j}$, thus

- Pre-activation outputs are unnormalized log-probabilities $z_j \sim \log(p_j)$
- Softmax takes out the log and normalizes $\sum_j p_j = 1$

Classification Layer



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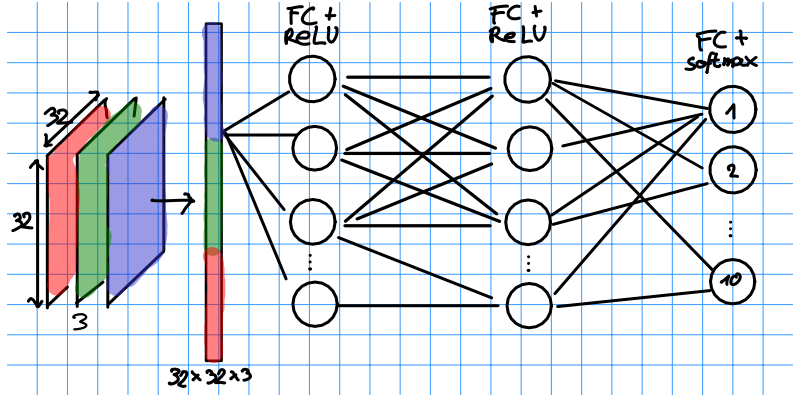
Categorial cross-entropy as objective function $J(\theta) = -\frac{1}{n} \sum_i \sum_j \mathbf{y}^i \log\left(\mathbf{y}_{\text{model}}(\mathbf{x}^i|\theta)\right)$

- Since $y_j = 0$ for all but the true class, only the predicted probability for the correct classification contributes
- Corresponds to maximum likelihood

First Ansatz: Fully Connected Network

- Input layer: Flatten image to $32 \times 32 \times 3 = 3072$ vector
- Some hidden layers: Fully connected with ReLU, dropout for regularization
- Classification layer: Fully connected with softmax



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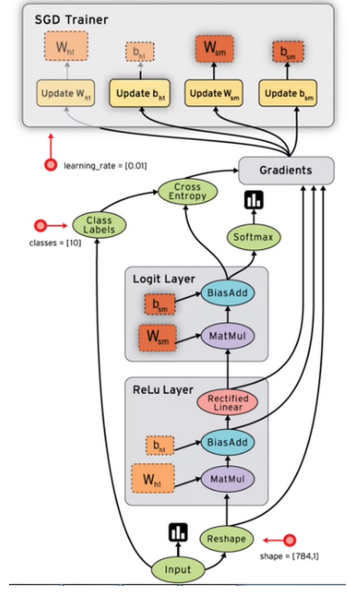
TensorFlow & Keras

What is TensorFlow

- Open source software library for numerical computation using data flow graphs. Nodes in the graph represent mathematical operations, while edges represent tensors communicated between them.
- Deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API.
- Originally developed at Google Brain, but general enough for application in variety of domains.
- Most popular deep learning framework
- Stable API since last week (version 1.0)



TensorFlow Example

```
import tensorflow as tf

x = tf.placeholder(tf.float32, [None, 3072])
y = tf.placeholder(tf.float32, [None, 10])

# hidden layer: h1 = ReLU(W1*x + b1)
W1 = tf.Variable(tf.random_normal([256, 3072]))
b1 = tf.Variable(tf.random_normal([256]))
h1 = tf.nn.relu(tf.matmul(x, W1) + b1)

# output layer: y = softmax(W2*h1 + b2)
W2 = tf.Variable(tf.random_normal([256, 10]))
b2 = tf.Variable(tf.random_normal([10]))
ym = tf.nn.softmax(tf.matmul(h1, W2) + b2)
```

TensorFlow is **low-level** framework: very verbose, focus on maximum flexibility

Keras Example

Keras as high-level library on top of TensorFlow.

- More readable
- Default settings follow best practices
- Quicker prototyping

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

model = Sequential([
  Dense(256, activation='relu', input_shape=(3072)),
  Dense(10, activation='softmax')
  ])
```

"Keras is gaining official Google support ... If you want a high-level object-oriented TF API to use for the long term, Keras is the way to go." *F. Chollet, a few days ago*

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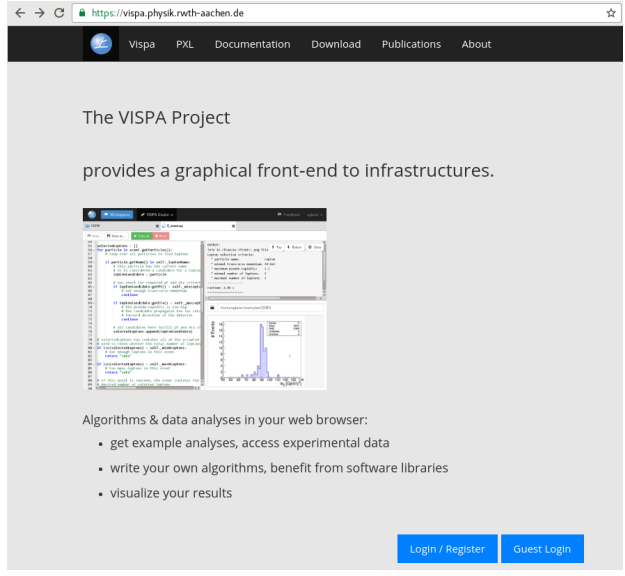
Practice Session 1: Image Classification with Neural Networks

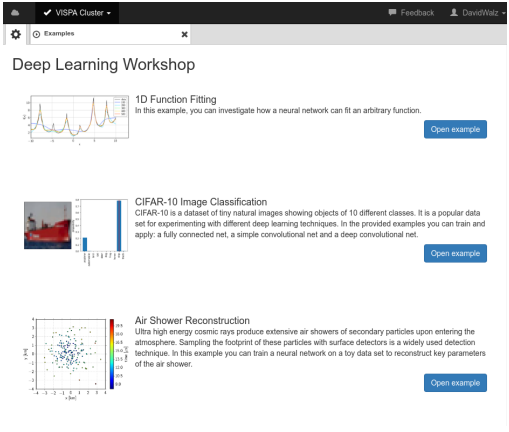
VISPA

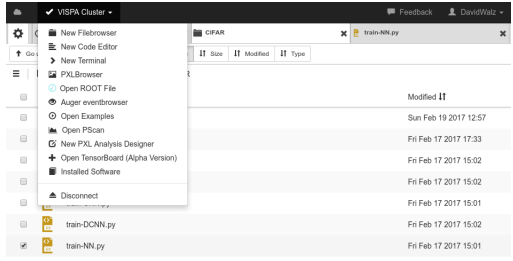
- Open `vispa.rwth-aachen.de`
- Register a new or login with your existing account
- *Note:* Guest accounts work as well, but data is lost when logging out



Deep Learning Examples

Open the CIFAR-10 example





Note: File browser, code editor and terminal tabs can be opened under “VISPA Cluster”

Code Example: train-NN.py

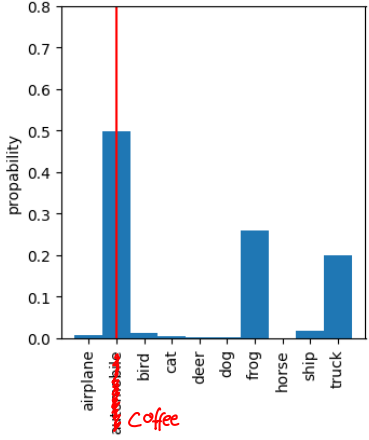
```
# define 3 layer network
model = Sequential([
    Flatten(input_shape=(32, 32, 3)),
    Dense(256, activation='relu'),
    Dropout(0.3),
    Dense(256, activatio n='relu'),
    Dropout(0.3),
    Dense(10, activation='softmax') ])

# set objective and optimizer, set up computation graph
model.compile(loss='categorical_crossentropy',
    optimizer=keras.optimizers.Adam(lr=1E-3),
    metrics=['accuracy'])

# training
results = model.fit(X_train, Y_train,
  batch_size=32, nb_epoch=25,
  validation_data=(X_valid, Y_valid))
```

Practice Time: `train-NN.py`

- `pygpu %file` executes your script on the VISPA GPU cluster
  - → 20 × GeForce GTX 1080
  - → 2 jobs per GPU → 40 jobs in parallel
  - → Type `condor_q` in terminal to query job status
- Familiarize yourself with data preprocessing etc.
- Run and inspect the training results
  - → `condor/` → log, error and standard output files
  - → `train-NN-XYZ/` → plots, training history, trained model
- Experiment with your model
  - → Modify the network layout: Add more layers, neurons
  - → Tune hyperparameters: dropout, learning rate, batch size

Note: We'll get to `train-CNN.py` and `train-DCNN.py` after the coffee break!

Coffee Break



Results: CIFAR-10 with Dense Neural Network

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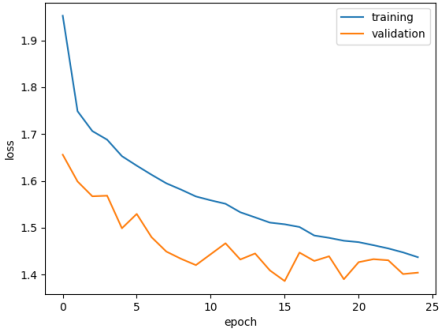
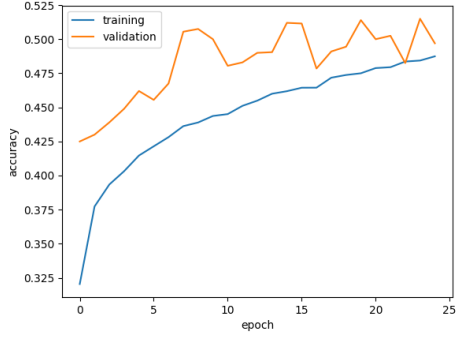
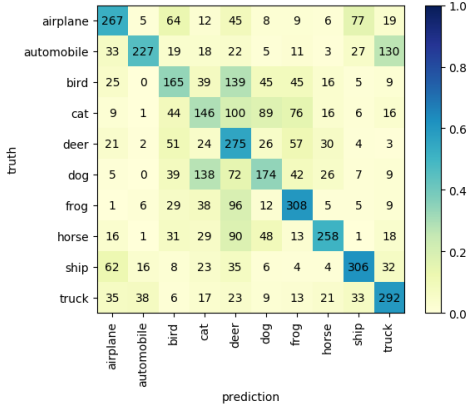
Objective

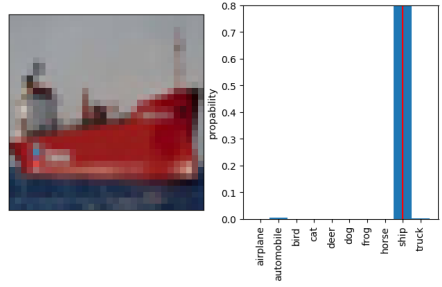


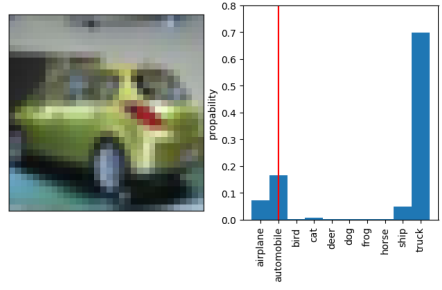
Accuracy



Results: CIFAR-10 with Dense Neural Network







Results: CIFAR-10 with Dense Neural Network

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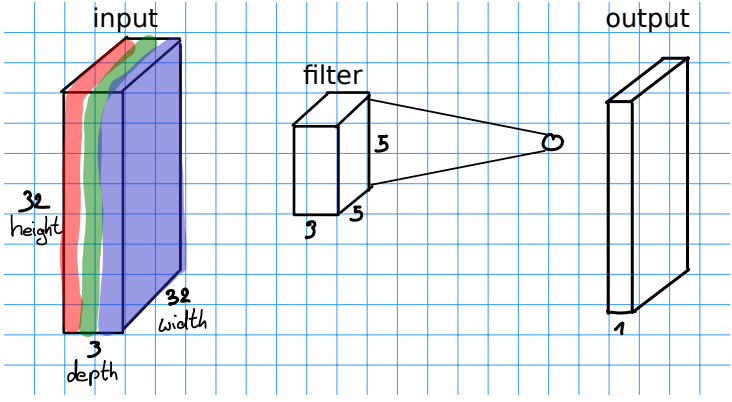
```
Layer                                Output Shape              Param
=================================================================
Flatten                              (None, 3072)              0
Dense                                (None, 256)               786688
Activation                           (None, 256)               0
Dropout                              (None, 256)               0
Dense                                (None, 256)               65792
Activation                           (None, 256)               0
Dropout                              (None, 256)               0
Dense                                (None, 10)                2570
Activation                           (None, 10)                0
=================================================================
Trainable params: 855,050
```

High dimensional input $\longrightarrow$ many parameters in fully connected layers

Convolutional Networks

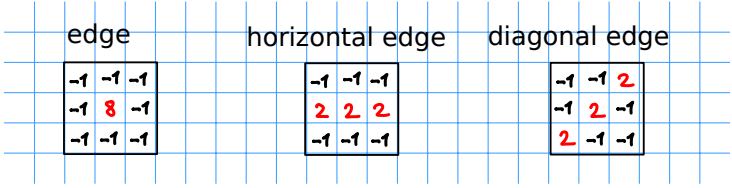
2D Convolution Operation

- Consider input **volume**, e.g. color image
- Use convolution filter with much smaller width and height, but same depth as input
- Slide **filter** w spatially over input **volume** and calculate $w^T x + b$ to get one output value at each position

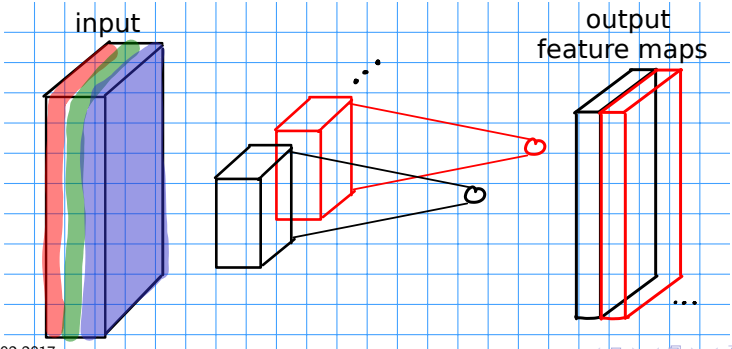


2D Convolution: Filters

Each filter scans the input for the presence of one feature



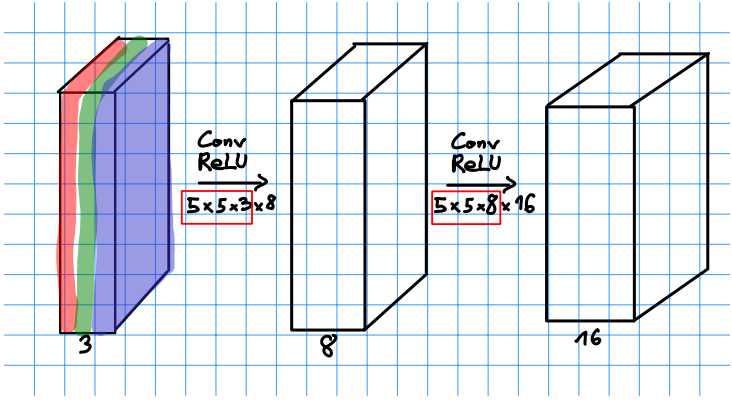
Use multiple filters and stack the output feature maps depth-wise



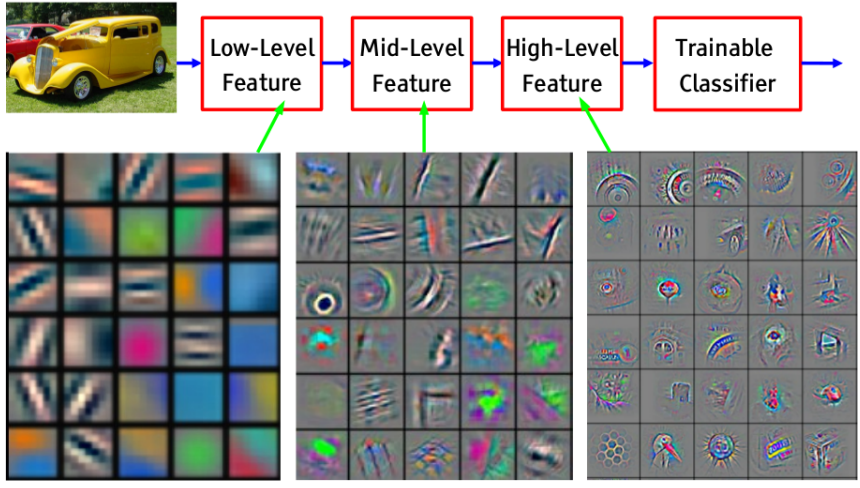
Convolution Stack

Stack multiple layers of convolution + activation

- Each convolution acts on the feature map of the previous layer
- Receptive field increases
- Complexity of features increases



Hierarchical Feature Extraction



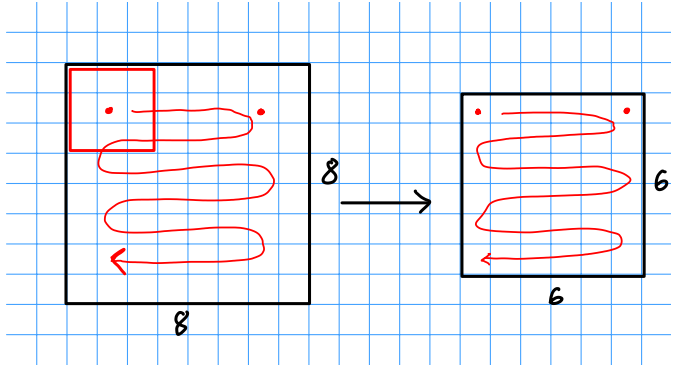
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

slide from Yann Le Cun

Spatial Output Size

Standard convolution reduces the output size.
$\longrightarrow$ Sets an upper bound to the number of convolution layers.

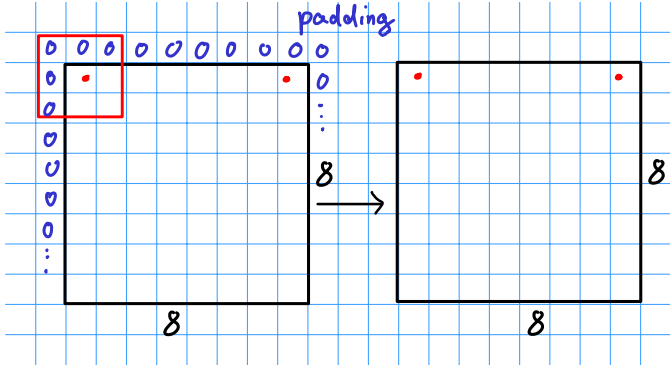
Example: Convolution with 3x3 filter



Padding

Padding the input with zeros prevents the spatial extent from shrinking too fast
$\longrightarrow$ Necessary for deep stacks of many convolution layers

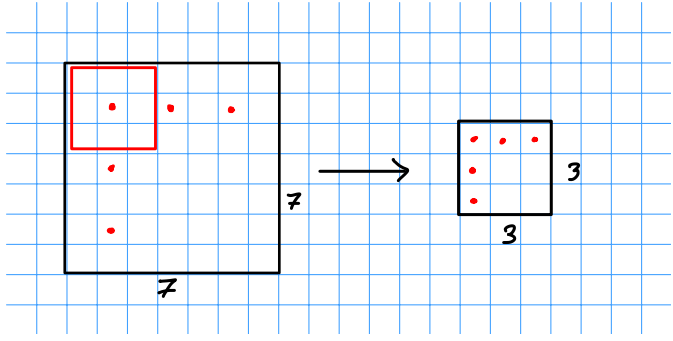
Example: Convolution with 3x3 filter and padding of one



Striding

Using a larger **stride** when sliding over the input reduces the output size

Example: Convolution with 3×3 filter and stride of 2

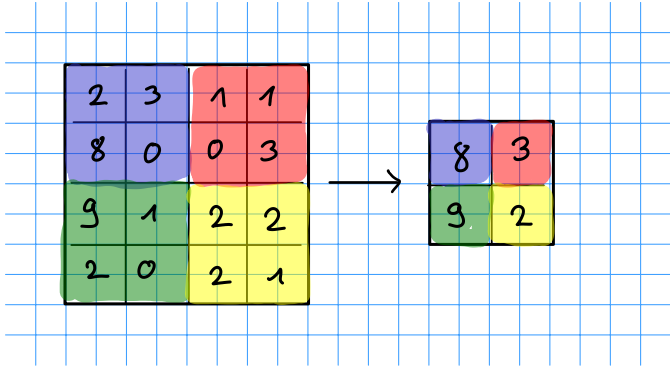


Pooling

Sub-sample the input to reduce the output size

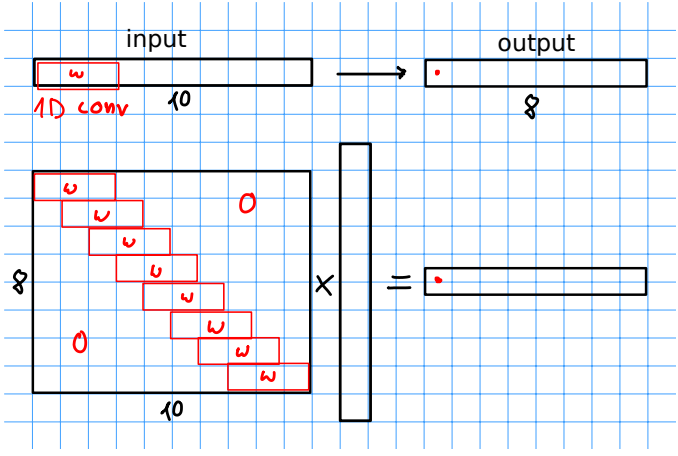
- **AveragePooling**: Take the mean of each patch
- **MaxPooling**: Take the maximum of each patch (better)
- Pooling is more precise than striding but also a little more expensive

Example: MaxPooling on 2×2 patches



Convolution vs Dense Layers

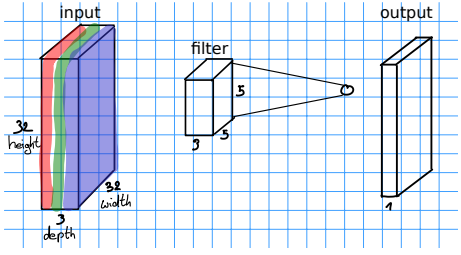
Convolutions are a special case of dense (fully connected) weight layers.



Number of parameters greatly reduced due to **sparsity** and **weight sharing**.
Convolution: Strong prior for **local correlation** and **translational invariance**.

Summary: 2D Convolution

- Acts on a 3D input volume: $W \times H \times D$ (width, height, depth)
- Slides small filter over input volume and compute dot product and bias add
- Hyperparameters:
  - → Size of filters F, typically 3 or 5
  - → Number of filters K
  - → Zero padding to maintain spatial extent
  - → Stride or MaxPooling to reduce spatial extent
- Small number of parameters: $F^2 \cdot D \cdot K$ (weights) and K (biases)



Convolutions in Keras

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```
# Input example: CIFAR-10
X = ...  # X.shape = (60000,32,32,3), feature axis last


# Convolution layer example
keras.layers.Convolution2D(
  16, 3, 3,              # applies 16 (3x3) filters
  subsample=(1, 1),      # no striding, use (2,2) for stride 2
  border_mode='valid',   # no padding, use 'same' for padding
  activation=None)


# MaxPooling layer example
keras.layers.MaxPooling2D(
  pool_size=(2, 2),      # (2x2) pooling
  strides=None,          # no striding
  border_mode='valid')   # no padding, use 'same' for padding
```

Practice Session 2: Image Classification with ConvNets

CIFAR-10 with Convolutional Networks

Inspect, run and evaluate

- `train-CNN.py` simple convolutional net
- `train-DCNN.py` deep convolutional net, $\sim$ 10-20 min runtime

Extras

- Visualize trained convolutional filters and activation in first layer
- `test-ensemble.py` form ensemble average over multiple models

Results: CIFAR-10 with Simple Convolutional Network

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Layer	Output Shape	Param
Convolution2D	(None, 14, 14, 32)	2432
Activation	(None, 14, 14, 32)	0
Dropout	(None, 14, 14, 32)	0
Convolution2D	(None, 5, 5, 64)	51264
Activation	(None, 5, 5, 64)	0
Dropout	(None, 5, 5, 64)	0
Convolution2D	(None, 1, 1, 128)	204928
Activation	(None, 1, 1, 128)	0
Dropout	(None, 1, 1, 128)	0
Flatten	(None, 128)	0
Dense	(None, 128)	16512
Activation	(None, 128)	0
Dropout	(None, 128)	0
Dense	(None, 10)	1290
Activation	(None, 10)	0

Trainable params: 276,426

Test accuracy: ~ 75%

Results: CIFAR-10 with Deep Convolutional Network

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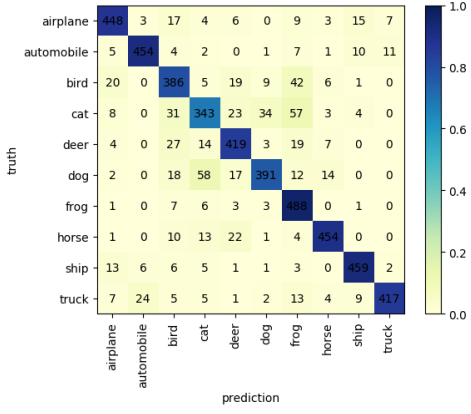
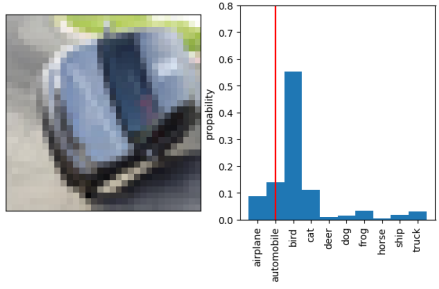
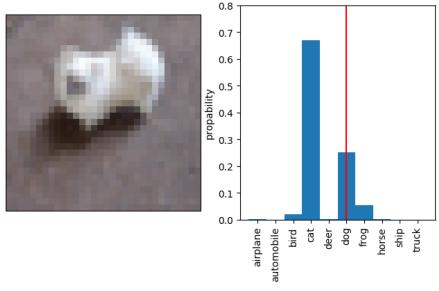
```
Layer                                 Output Shape              Param
=================================================================
Convolution2D                         (None, 32, 32, 32)        896
BatchNormalization                    (None, 32, 32, 32)        128
... 8 more convolution blocks ...
Convolution2D                         (None, 4, 4, 256)         590080
BatchNormalization                    (None, 4, 4, 256)         1024
Activation                            (None, 4, 4, 256)         0
MaxPooling2D                          (None, 2, 2, 256)         0
Flatten                               (None, 1024)              0
Dropout                               (None, 1024)              0
Dense                                 (None, 256)               262400
BatchNormalization                    (None, 256)               1024
Activation                            (None, 256)               0
Dropout                               (None, 256)               0
Dense                                 (None, 10)                2570
Activation                            (None, 10)                0
=================================================================
Trainable params: 2,178,090
Test accuracy: ~ 88%
```

Results: CIFAR-10 with Deep Convolutional Network







Human level accuracy $\sim$ 95%, need data augmentation to reach this level

Image Recognition on Air Shower Footprints

Deep Learning Applications in Astroparticle Physics

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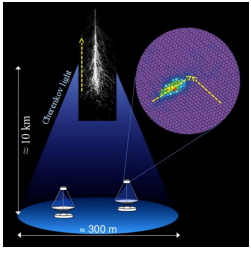
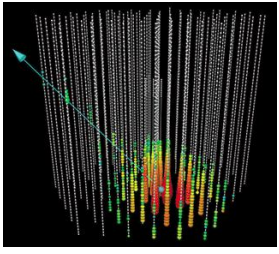
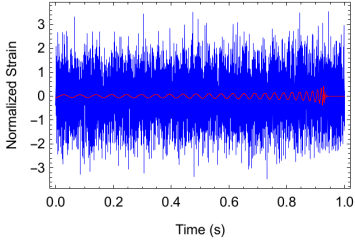
Applications in astroparticle experiments: Cherenkov telescopes, gamma & cosmic ray satellites, neutrino & cosmic ray observatories, dark matter & gravitational wave detectors

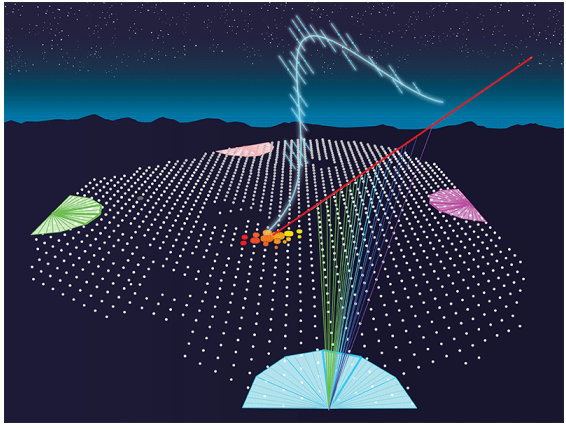






- Event reconstruction
- Signal classification & background rejection
- Pattern recognition on signal distributions, e.g. gamma or cosmic ray skies

Air Shower Detection at the Pierre Auger Observatory



https://physics.aps.org/articles/v9/125

- **Fluorescence detector**
  - → Fluorescence light traces longitudinal shower development
  - → 2D image
- **Surface detector**
  - → Water Cherenkov tanks detect passage of charged particles
  - → 2D image sequence
- **Radio detector**
  - → Radio footprint with time information
  - → Pulse measured in 2 or 3 polarizations
  - → 2D image sequence / time traces

Air Shower Footprint – Toy Data Generator

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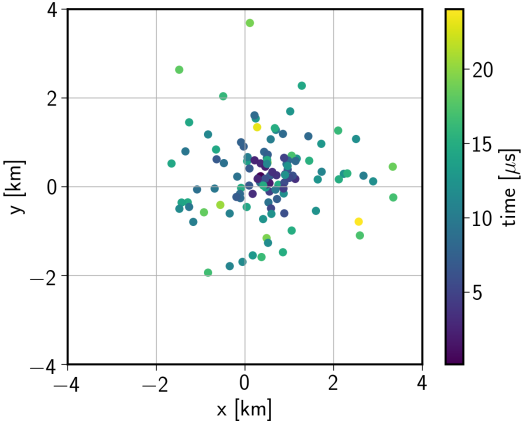
Simulation of spatial and time distribution of air shower muons on ground

Procedure

- Random number muon $\propto \frac{E}{E_0} A^{0.15}$
- Random production depth $\propto \mathcal{N}(\mu, \sigma(X_{\max}, A))$
- Random direction $\propto$ Normal distribution with opening angle
- Calculate arrival on ground (x, y, t)
- Add random offset to (x, y, t) per event

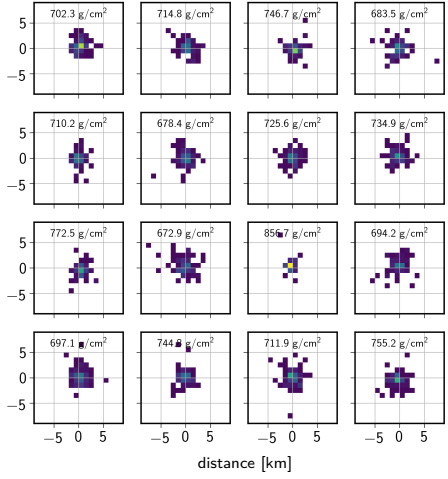
Shower footprint



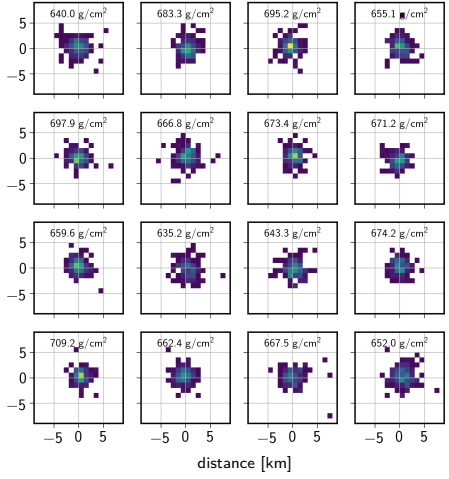
Toy Data

40.000 vertical showers, same energy, 25% protons, helium, nitrogen, iron

Protons ($A = 1$)

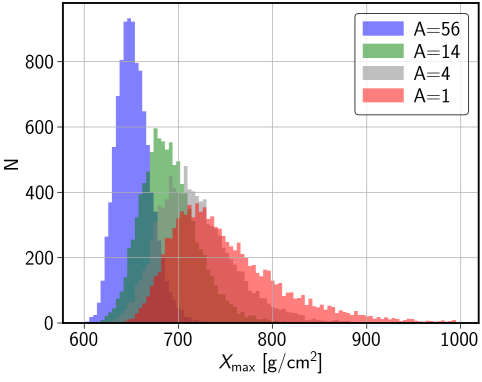


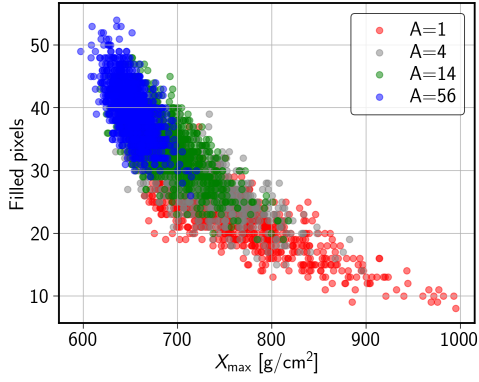
Iron ($A = 56$)



Toy Data

40.000 vertical showers, same energy, 25% protons, helium, nitrogen, iron





$\longrightarrow$ No clear separation possible on either $X_{\max}$or number of filled pixels

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Practice Session 3: Air Showers Reconstruction

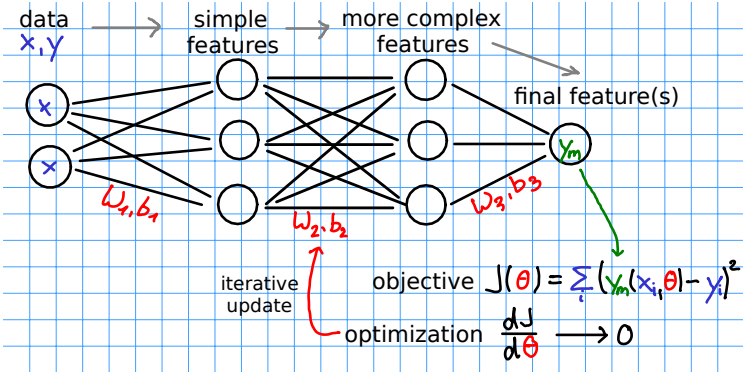
Toy Air Shower Reconstruction

- Toy data generator: `generate_data.py`
- Regression Task: `train-Xmax.py` – reconstruct $X_{\max}$
- Classification Task: `train-A.py` – separate the four different species $A = 1, 4, 14, 56$

Links & Resources

- TensorFlow Tutorial
  `https://www.tensorflow.org/get_started/get_started`
- Deep Learning (Goodfellow, Bengio and Courville)
  MIT Press, ISBN: 0262035618
  `http://www.deeplearningbook.org/`
- Neural Networks and Deep Learning (Nielson)
  `http://neuralnetworksanddeeplearning.com/`
- CS231n - Convolutional Neural Networks for Visual Recognition (Kaparthy)
  `http://cs231n.stanford.edu/syllabus.html`
- Deep Learning by Google (Vanhoucke), Udacity
  `https://www.udacity.com/course/deep-learning--ud730`

The Physicist's Toolbox



- With deep learning we have a powerful new tool at our disposal!
- Availability of deep learning frameworks and GPUs make this previously very challenging method accessible to anyone with scripting abilities and a gaming PC