base.camp

Digitaltag 2020
19.06.2020

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Eugen Ruppert
ruppert at informatik.uni-hamburg.de

DIGITALTAG 2020
DEEP LEARNING – DIE REVOLUTION IN DER KÜNSTLICHEN INTELLIGENZ

Zoom

Zoom
Nettiquette

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- Turn on your video
- If available, use a headset
- Please mute your microphone when not in the conversation
  mute on/off: Alt + a – Push to Talk: Space
- We want to record the session and make it available for people who could not join today
  We take privacy seriously. Thus, we will blur/black out your faces, so don't worry about asking questions and giving feedback!

Introduction

base.camp
Creative Lab at UHH

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- Focus areas: **B**ig Data, **A**rtificial Intelligence, **Se**curity (BASE)
- Offering students possibilities
  - student projects
    (focus on practice and iterative development)
  - hackathons
  - workshops
- Organizing events
- Networking for interdisciplinary events and courses

`https://basecamp.informatik.uni-hamburg.de/`

base.camp Talks
Idea

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- lecture series on current and general topics for Computer Science
- practically oriented
- easy to follow
- interactive examples, not just theoretical knowledge

`https://www.inf.uni-hamburg.de/inst/basecamp/events/basecamp-talks.html`

base.camp Talks
Machine Learning Talks

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- practical introduction to ML
- understand the key terms for ML
- understand how to perform a ML project
- code examples
- **not** a full lecture about ML and learning theory, partial derivatives, etc.

Machine Learning and AI – What is it?

Machine Learning and AI – What is it?

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- finding regularities in data
- classification based on training:
  - SPAM classification
  - image recognition (tagging people in photos)
  - text categorization (invoice, technical issue report, contract cancelation)
- emergent ‘intelligent’ systems (Artificial Intelligence)
- distinction between weak and strong AI
- our topic: useful AI – reduce human effort

Machine Learning and AI – What is it?
Strong AI: Chess

IBM Deep Blue:
https://en.wikipedia.org/wiki/Deep_Blue_(chess_computer)

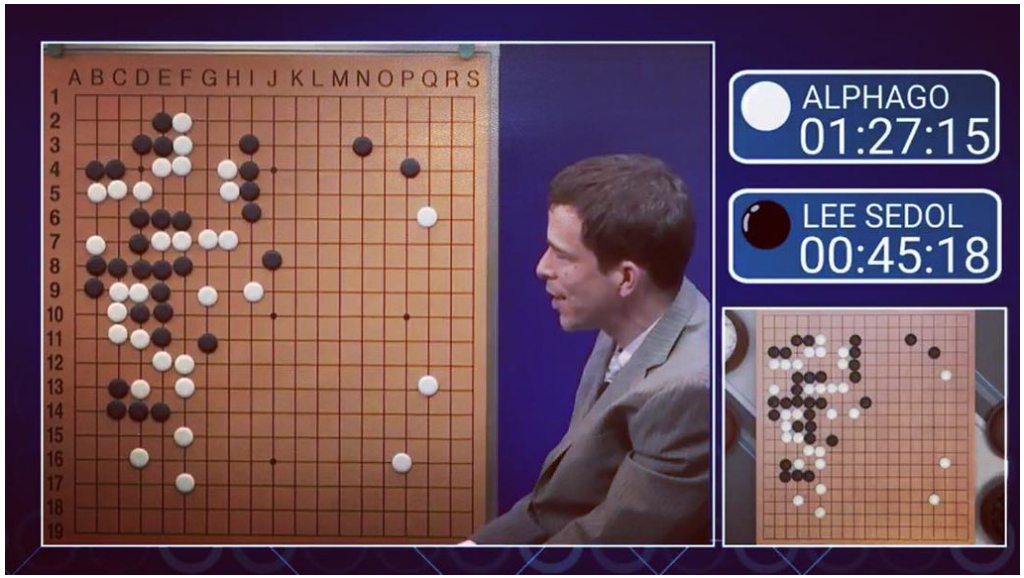
Machine Learning and AI – What is it?

Strong AI: Question Answering

IBM Watson Jeopardy

`https://en.wikipedia.org/wiki/Watson_(computer)`

Machine Learning and AI – What is it?
Strong AI: Go



Google Research: Alpha Go

`https://en.wikipedia.org/wiki/AlphaGo`

Easy vs Hard Problems
Language identification

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?

Computerspiele machen Spaß und sind ein Riesenmarkt. Und sie sind “Treiber für innovative Technologien”, sagt der zuständige Minister Dobrindt.

?

It’s easy to travel the world and feel oddly at home, particularly if you’re in one of the planet’s 24,000 Starbucks.

Easy vs Hard Problems
Language identification

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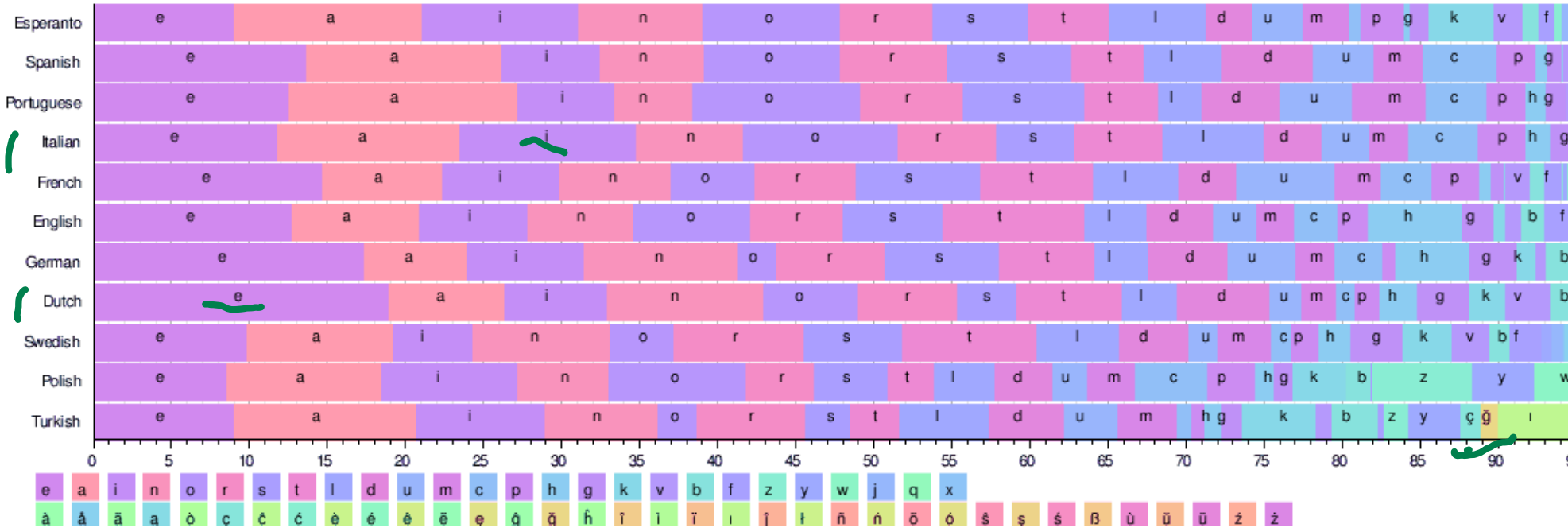
?

Dörtnala gelip Uzak Asya'dan Akdeniz'e bir kısrak başı gibi uzanan bu memleket, bizim.
Bilekler kan içinde, dişler kenetli, ayaklar çıplak Ve ipek bir halıya benzeyen toprak bu cehennem, bu cennet bizim. Kapansın el kapıları, bir daha açılmasın, Yok edin insanın insana kulluğunu, bu dâvet bizim....
Yaşamak bir ağaç gibi tek ve hür ve bir orman gibi kardeşçesine, bu hasret bizim...

Easy vs Hard Problems
Language identification



Easy vs Hard Problems
Language understanding

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Früher stellten die Frauen der Inseln am Wochenende Kopftücher mit Blumentmotiven her, die ihre Männer an den folgenden Montagen auf dem Markt im Zentrum der Hauptinsel verkauften.

`https://slideplayer.org/slide/645960/`

Easy vs Hard Problems
Language understanding

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Früher stellten die Frauen der Inseln am Wochenende Kopftücher mit Blumentmotiven her, die ihre Männer an den folgenden Montagen auf dem Markt im Zentrum der Hauptinsel verkauften.

- more than 250,000 interpretations possible!

`https://slideplayer.org/slide/645960/`

Hands on

Hands on

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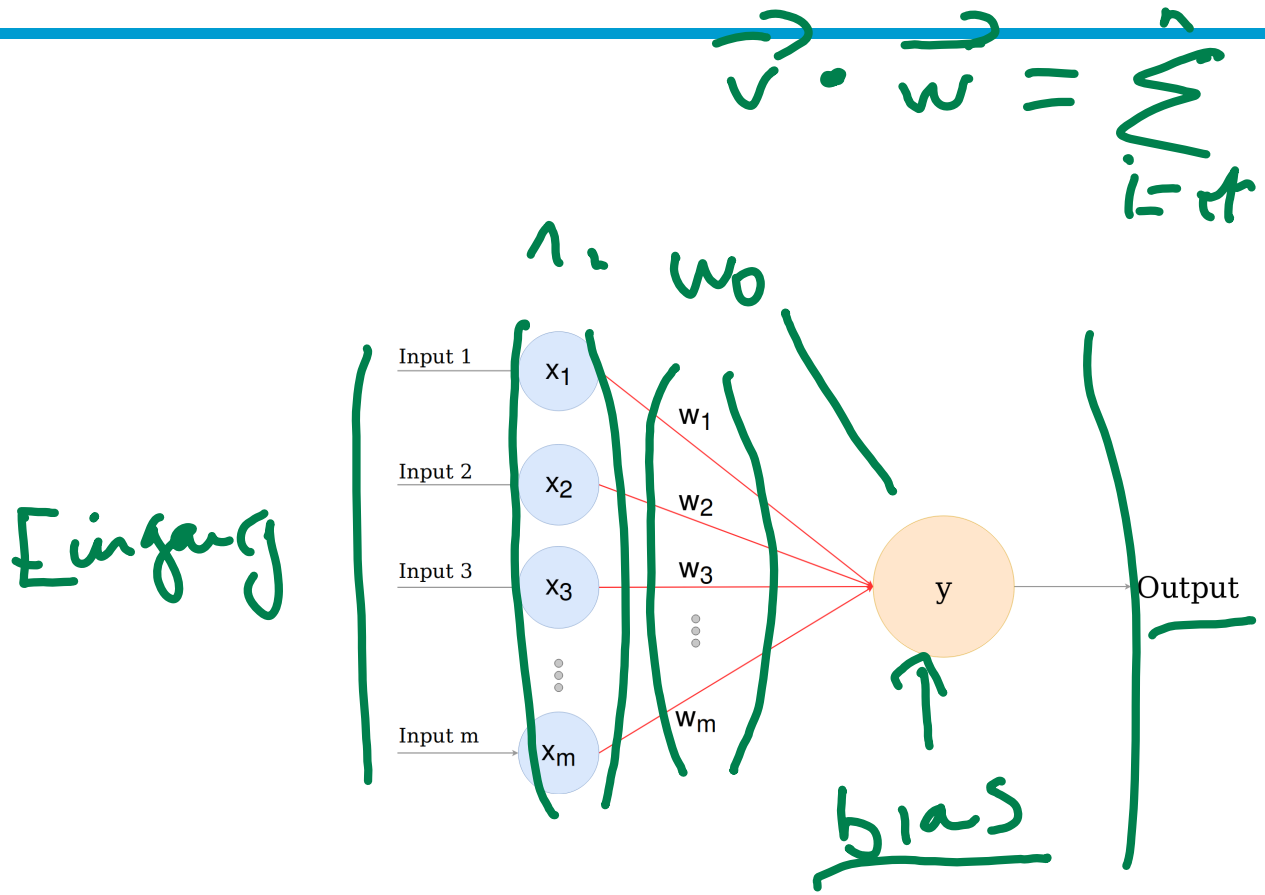
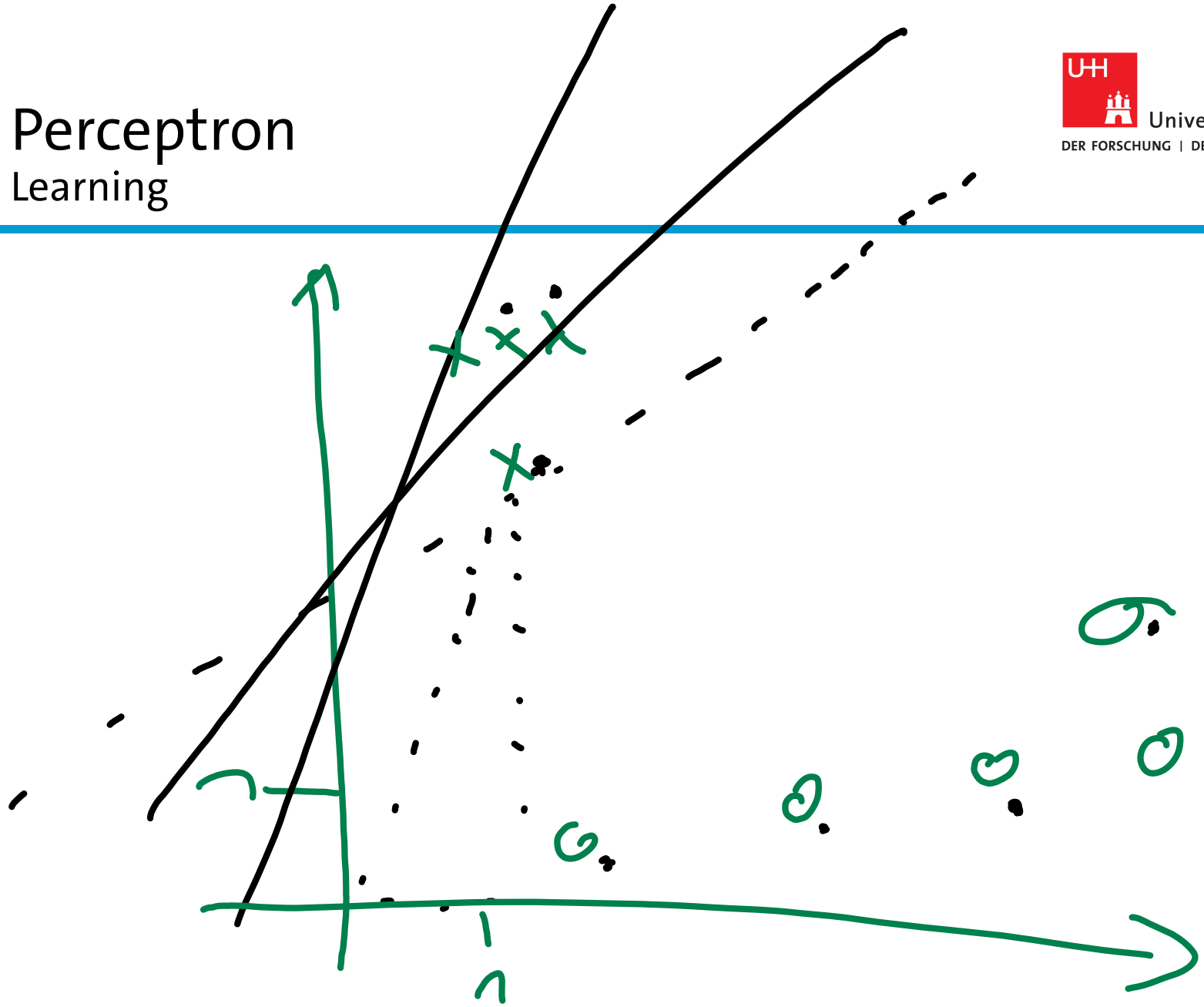
- `https://ltdemos.informatik.uni-hamburg.de/rserver/`
- code: `https://git.informatik.uni-hamburg.de/base.camp/ml-deep-learning` `0-shoe-size.py`

Perceptron

Perceptron
Overview



Perceptron
Learning



SGD Algorithm for Perceptron

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for $t = 1, \ldots, T$ **do**
  for $i = 1, \ldots, n$ **do**
    if $y_i \langle x_i, w^{(t)} \rangle \leq 0$ **then**
      update $w^{(t+1)} = w^{(t)} + \eta^{(t)} y_i x_i$
    end if
  end for
end for

Perceptron
Evaluation

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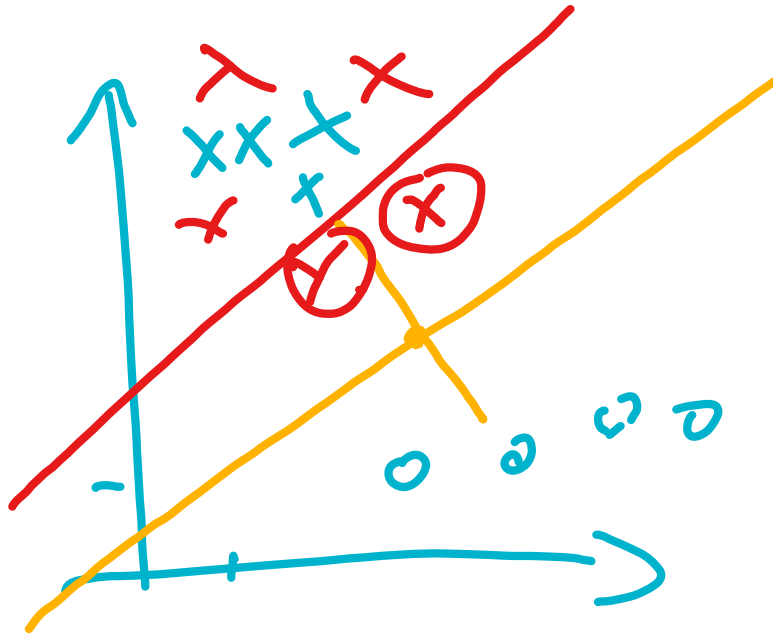
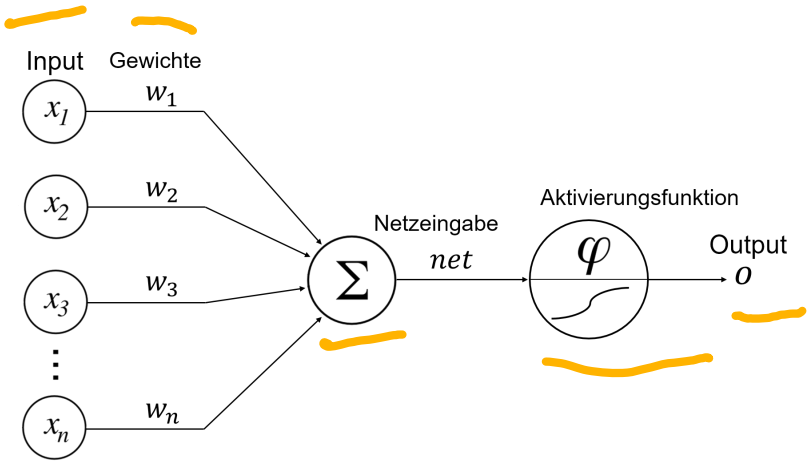
- fast and simple
- separates separable problems
- not very robust as a single classifier



Perceptron
Sneek Peek into the Future



Hands on

Hands on

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- `https://ltdemos.informatik.uni-hamburg.de/rserver/`
- code: `https://git.informatik.uni-hamburg.de/base.camp/ml-deep-learning` `1-perceptron.py`

Machine Learning

Supervised ML Setup

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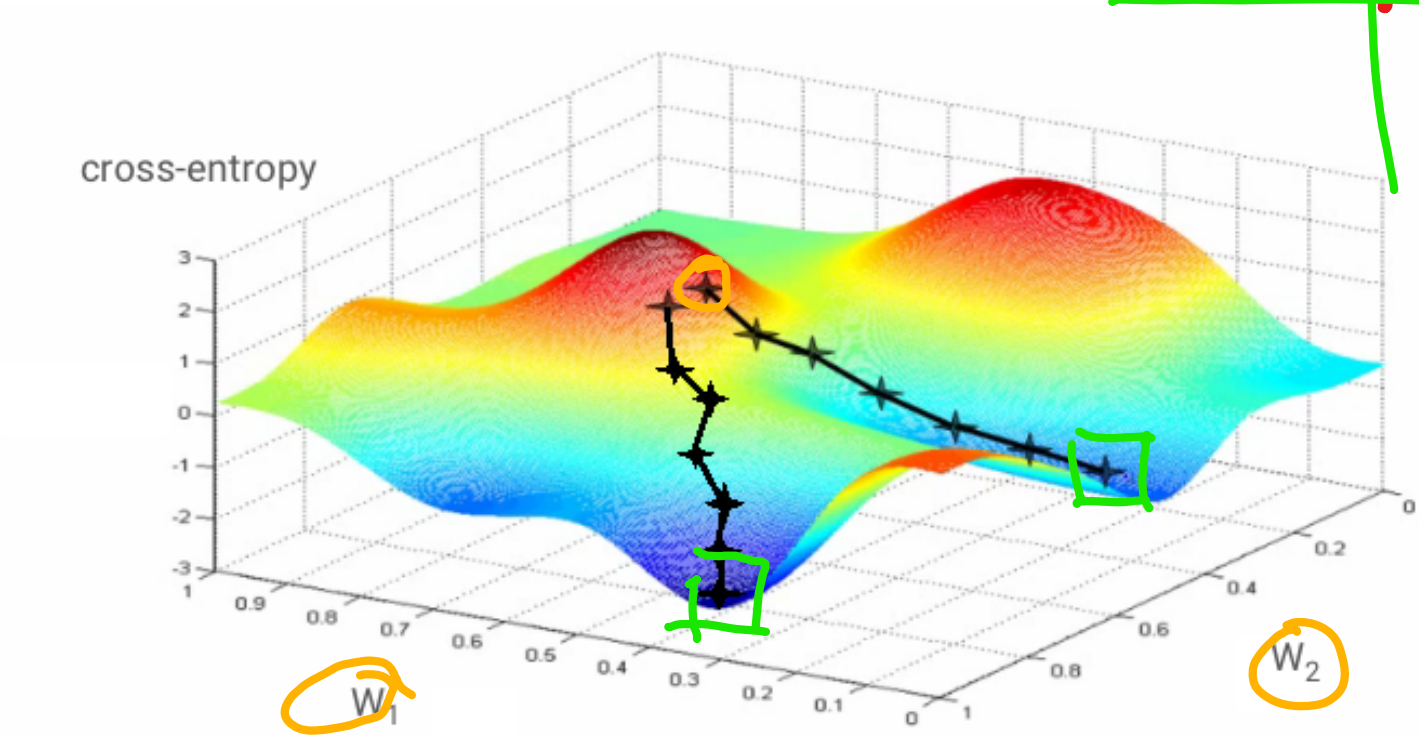
- problem identification
- data collection and annotation
- selection of ML algorithm
- training and evaluation

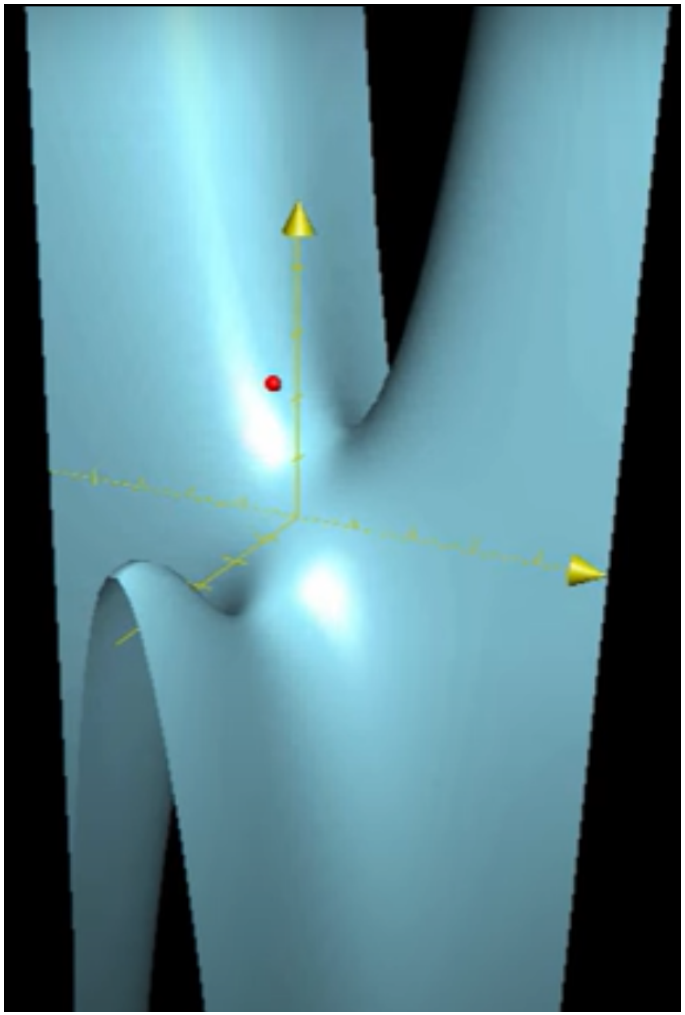
Training
Loss or Cost Function

- errors during training are accumulated into a Loss
- ideal Loss functon scales with the magnitude of error
- training algorithm tries to minimize the Loss
- assumption: as all data is drawn independentdly, this will reduce errors on test data
- gradient of the error can be computed, so that a Gradient Descent algorithm can improve the model

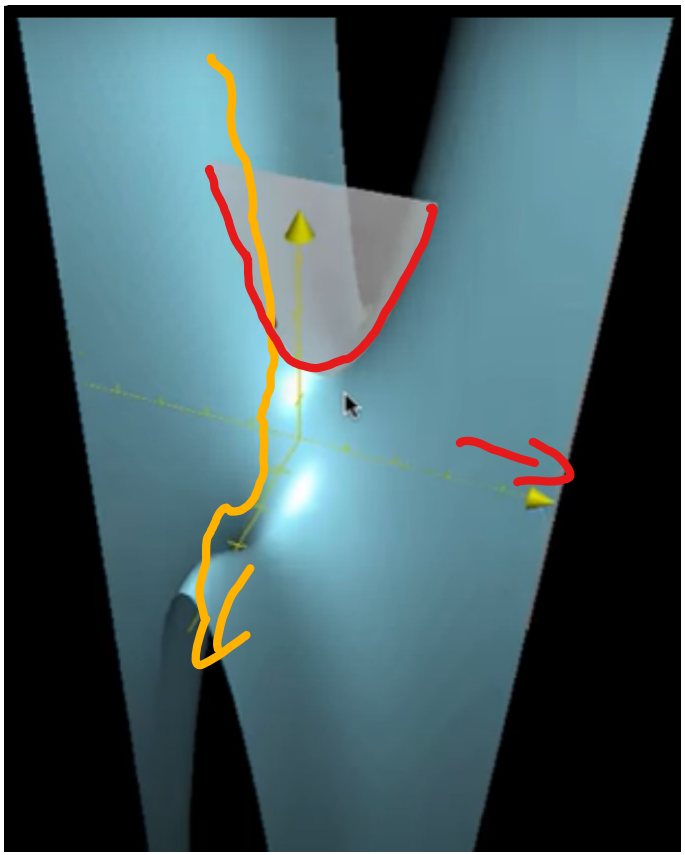
Stochastic Gradient Descent



Stochastic Gradient Descent
Partial Derivatives



Stochastic Gradient Descent
Partial Derivatives



https://towardsdatascience.com/
a-quick-introduction-to-derivatives-for-machine-learning-people

Baselines

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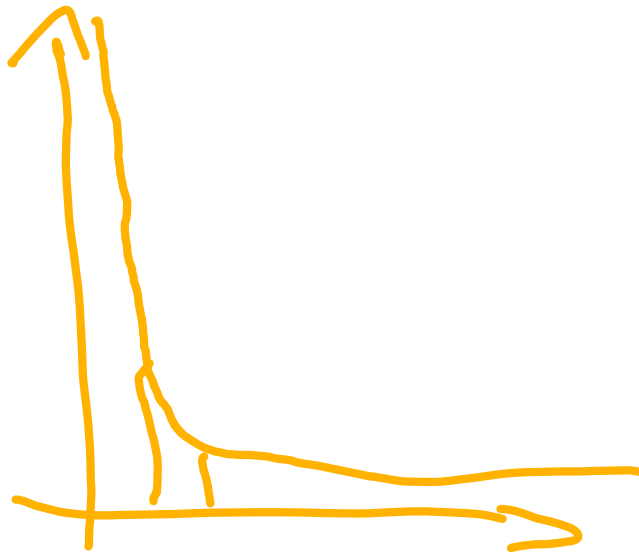
- complex ML models need to be justified
- baselines can provide justification
- simple baselines
  - random
  - most frequent class
- strong baselines
  - perceptron
  - related work
  - simple neural networks



Deep Learning

Deep Learning

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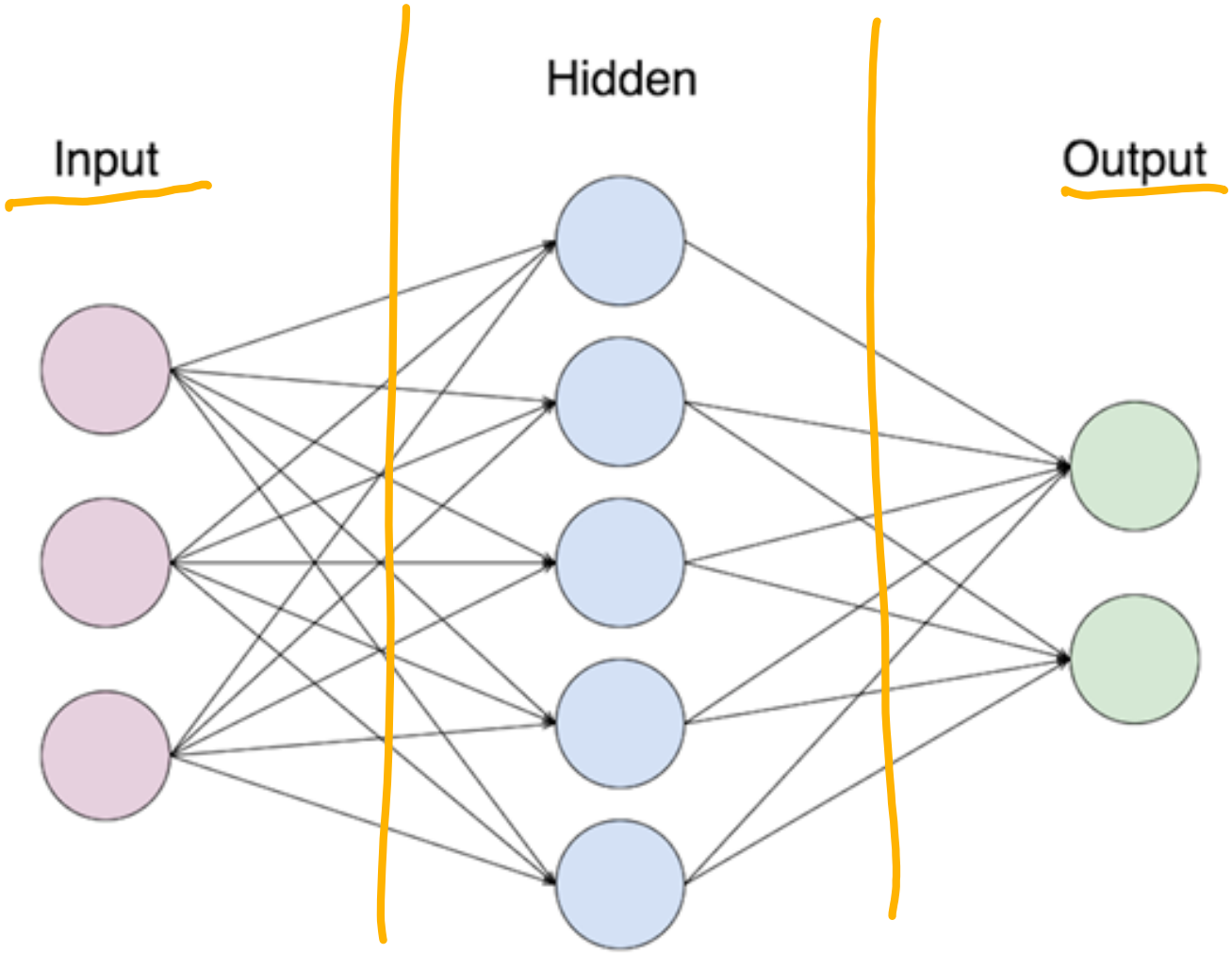
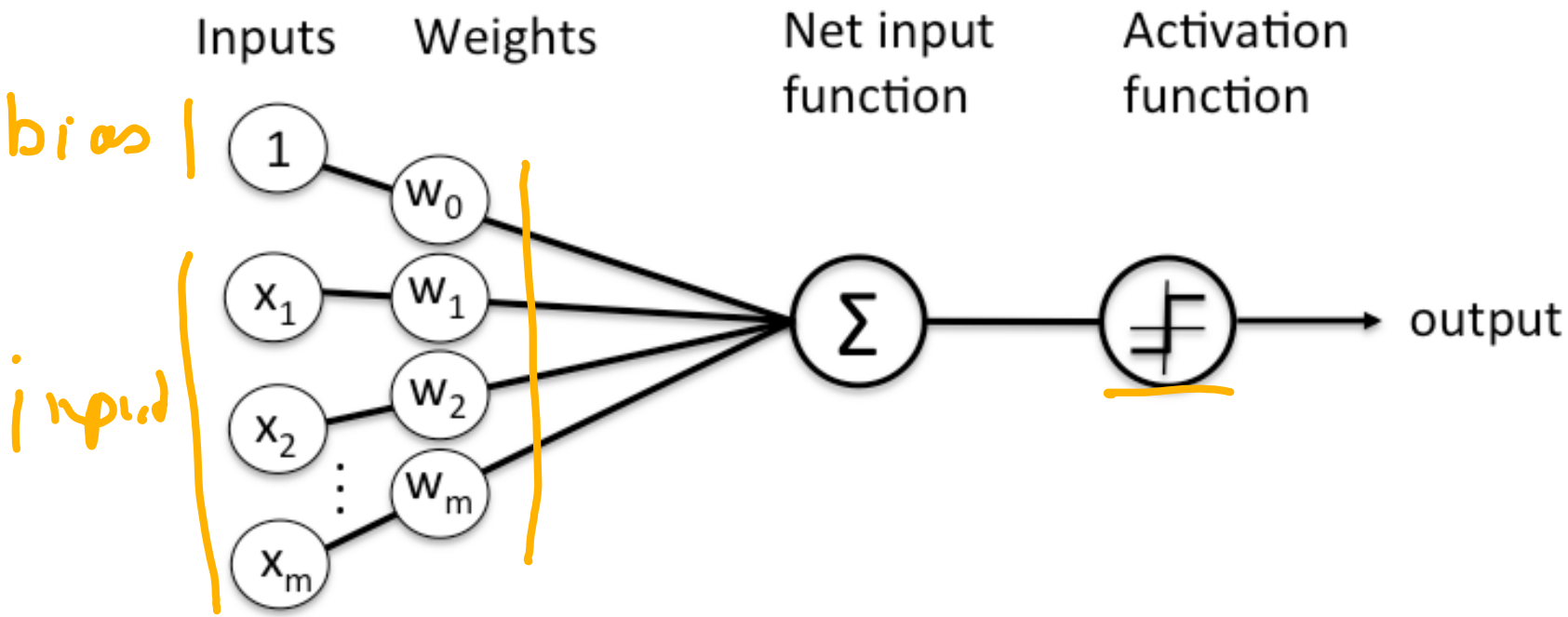
- ML with Deep Neural Networks
- inspired by neurons in the brain
- ‘automatic’ feature extraction
- several layers of processing, e.g. image recognition: lines – shapes – eyes – face – person
- large parameter space – benefits greatly from GPUs

Neural Network

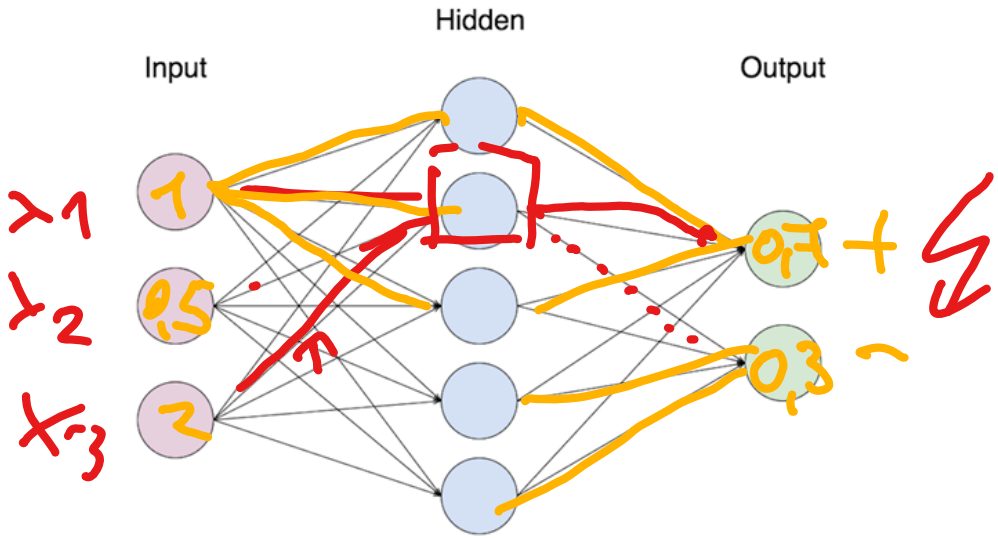


Neuron / Perceptron

- weighted sum of inputs
- bias
- activation function

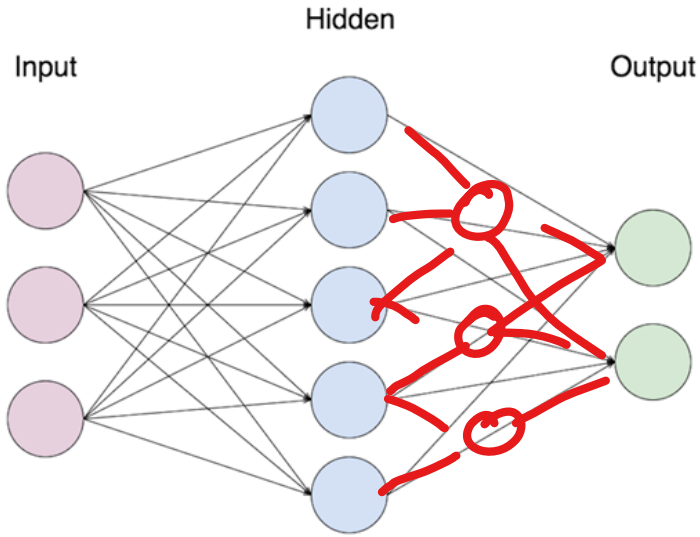


Forward and Back Propagation



- input is fed through the network (forward propagation)
- error is computed on the output layer
- error is back-propagated through all layers
- gradient of the error is identified, weights are updated

Batches and Epochs



- we compile loss on batches of input elements
  e.g. 1 batch = 100 input examples
- more robustness, stronger direction of the gradientIterations
- 1 epoch = all input examples have been processed
- with complex neural nets, many epochs are required

MNIST – Deep Learning “Hello World”

MNIST

- Yann Lecun (Google Labs) 1998
- 60,000 training digits
- 10,000 evaluation digits
- dimension: 28x28 pixels (784 overall)
- `http://yann.lecun.com/exdb/mnist/`

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. ”Gradient-based learning applied to document recognition.” Proceedings of the IEEE, 86(11):2278-2324, November 1998.

Getting Started with Tensorflow

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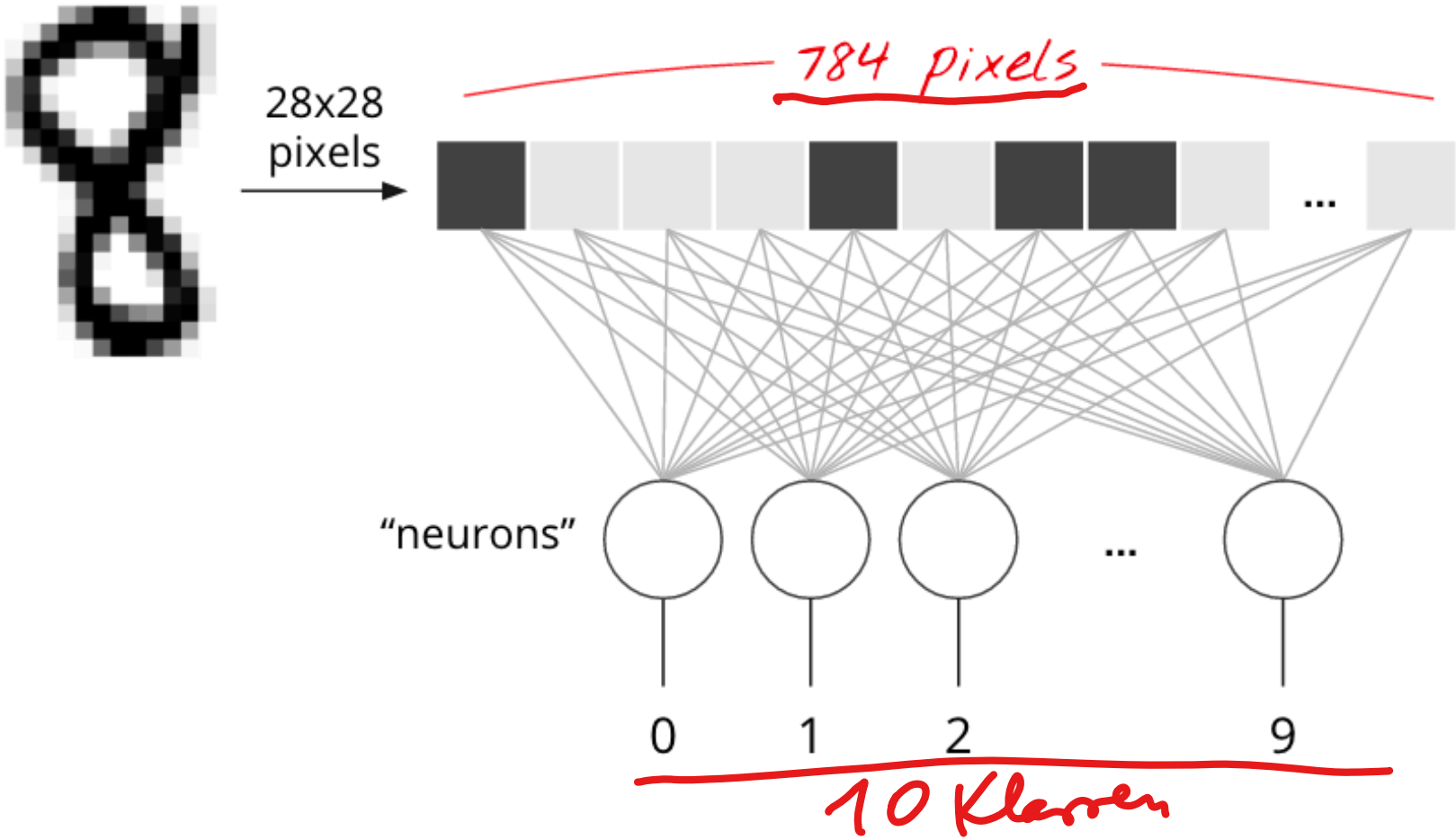
```
pip3 install tensorflow
```

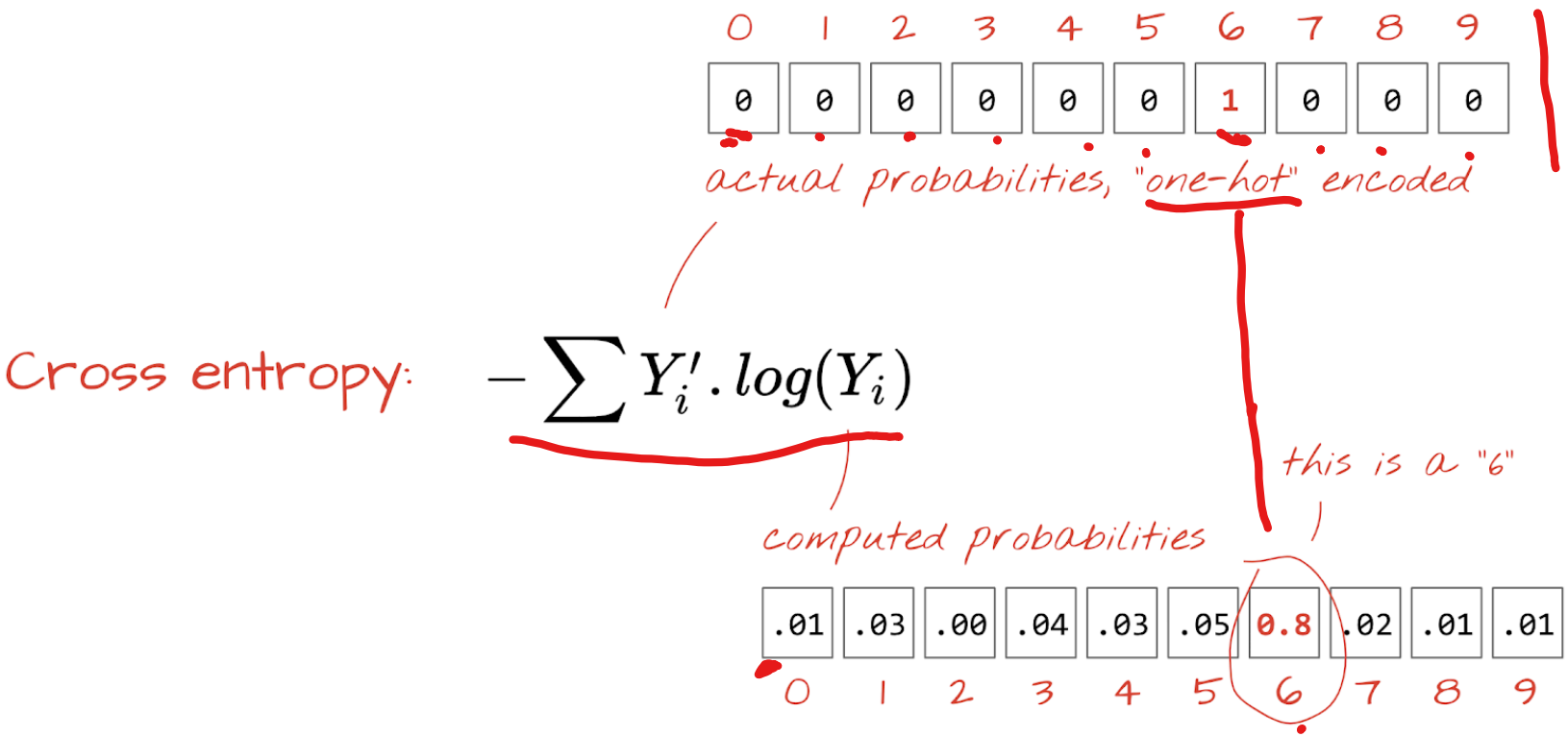
Tensor: multi-dimensional table:

- grayscale image [28, 28]
- color image [28, 28, 3]
- training batch [100, 28, 28, 3]

Dense Layer Classifier

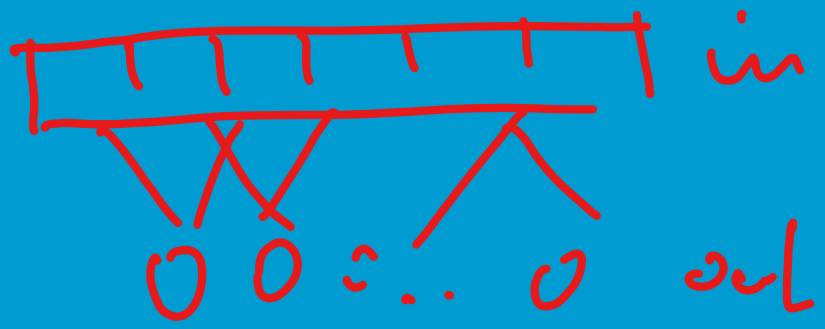


Cross Entropy Loss



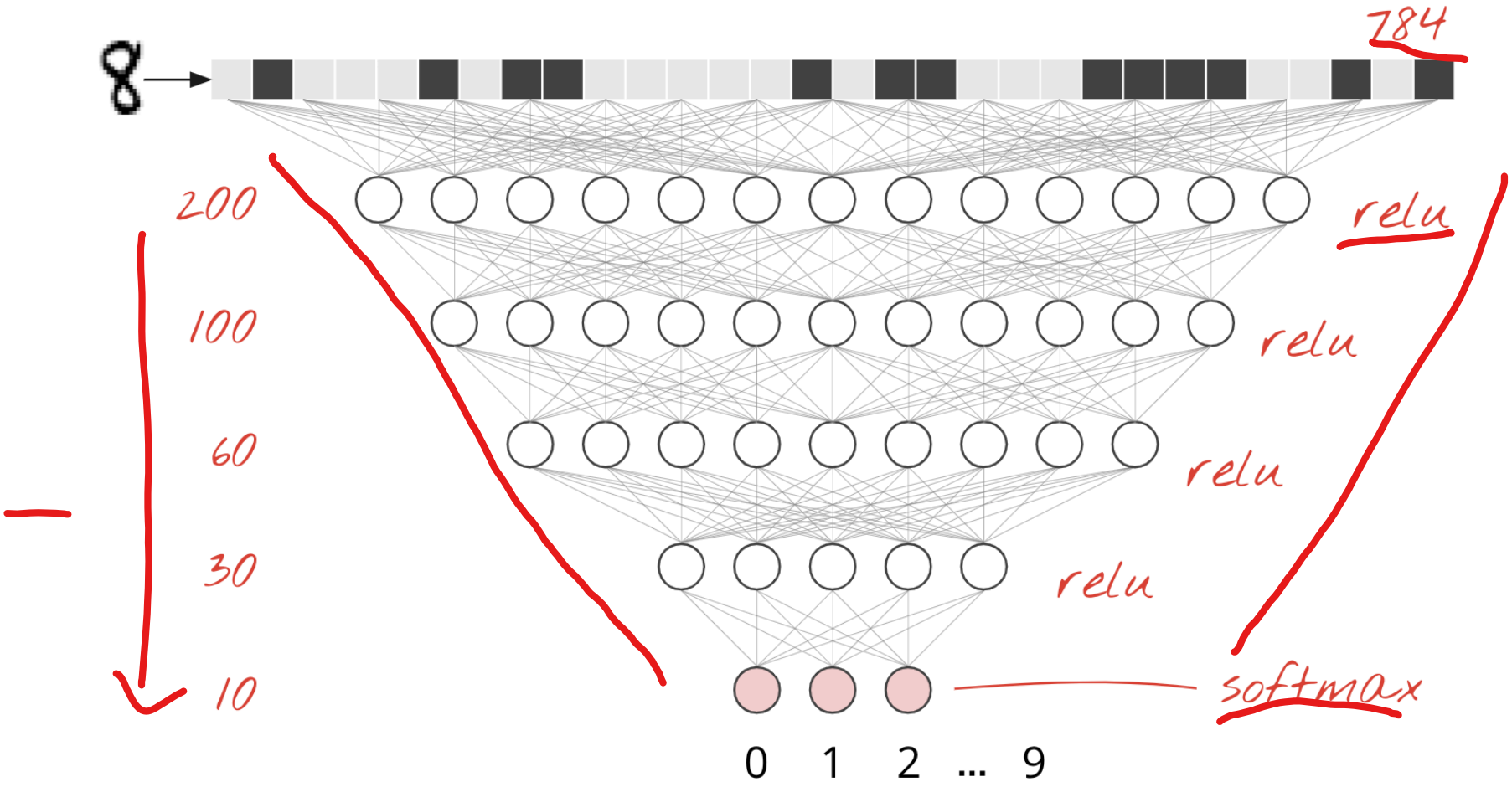
Off we Go!

https://git.informatik.uni-hamburg.de/base.camp/ml-deep-learning/number-recognition-1.py



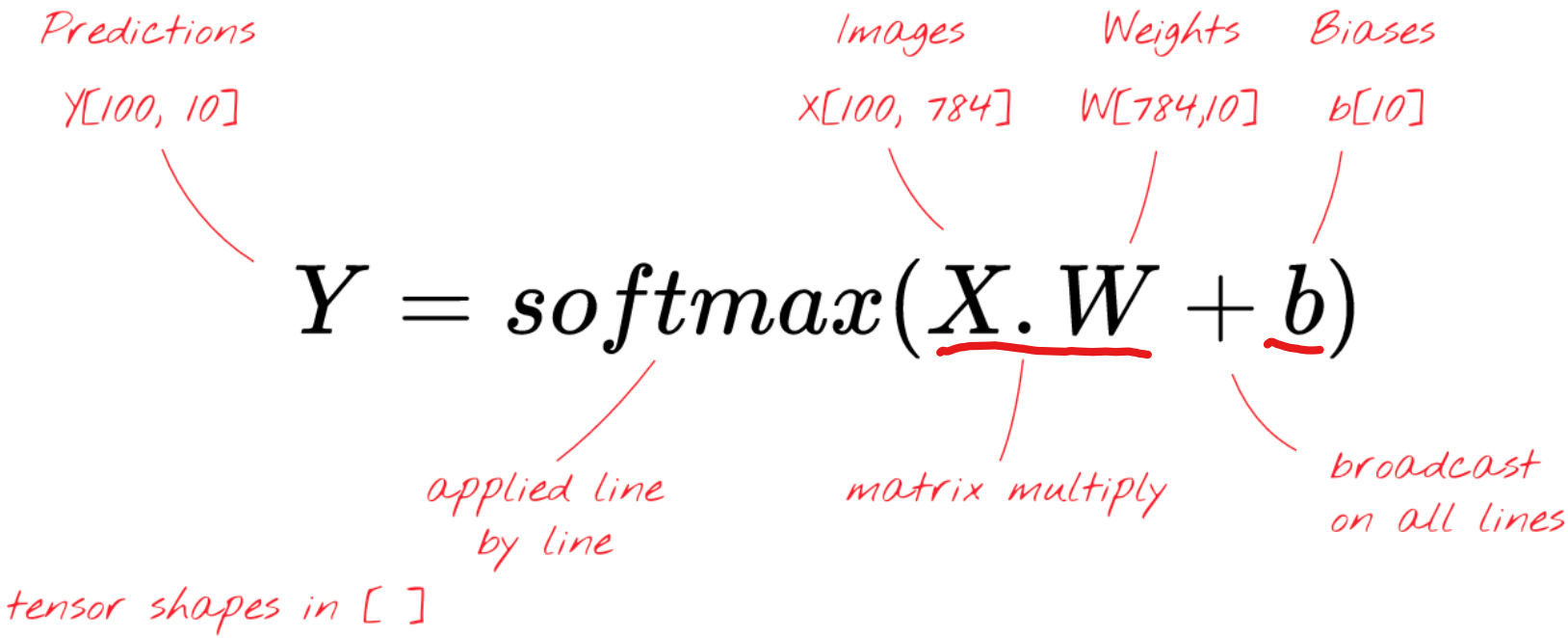
We need to go deeper!

Deep Neural Network

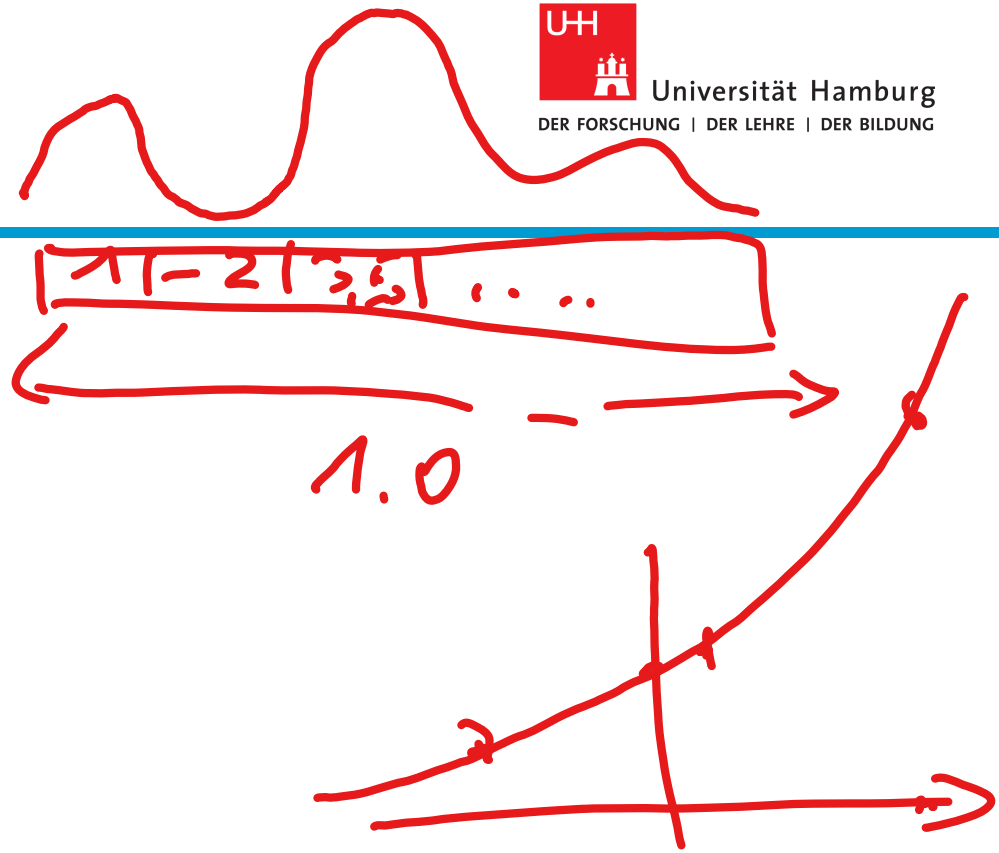


Activation Functions

Softmax Activation



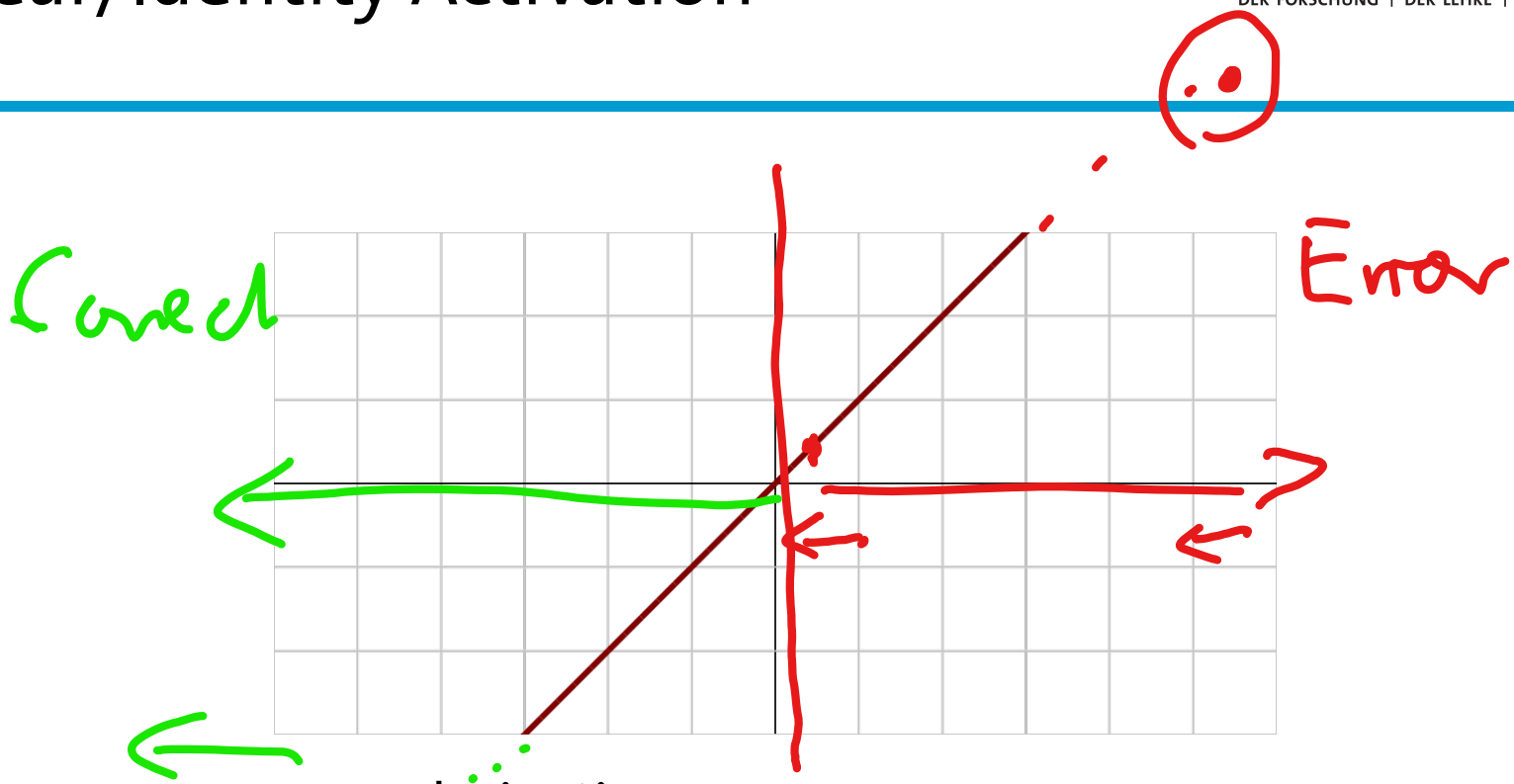
Softmax Activation



$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

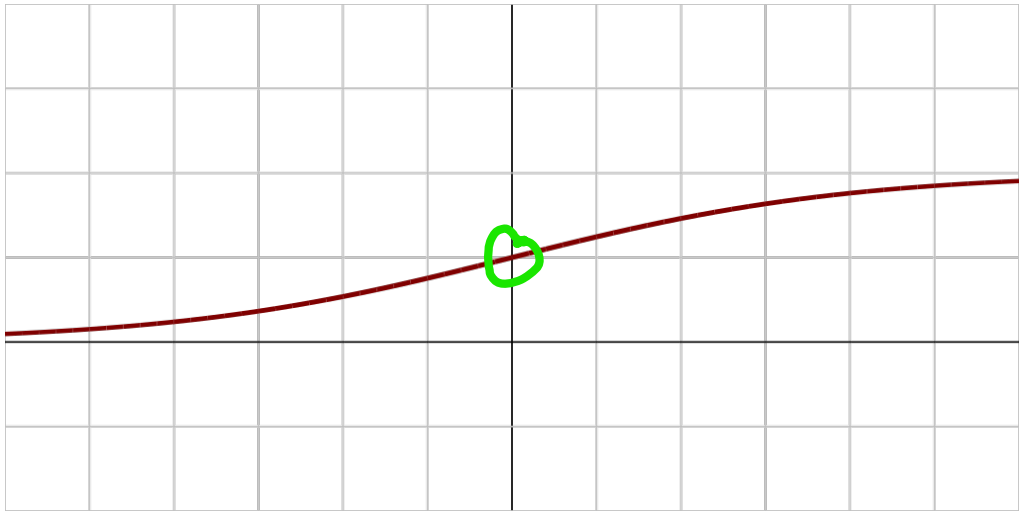
- on output layer
- transforms activations into probability distribution
- exponential funciton to increase contrast and give the highest activation a value close to 1.0

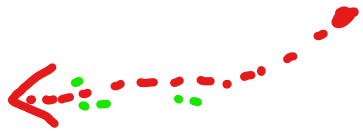
Linear/Identity Activation



- \+ easy derivation
- – uniformity does not help differentiation
- – correct classifications contribute to learning
  $\rightarrow$ overfitting

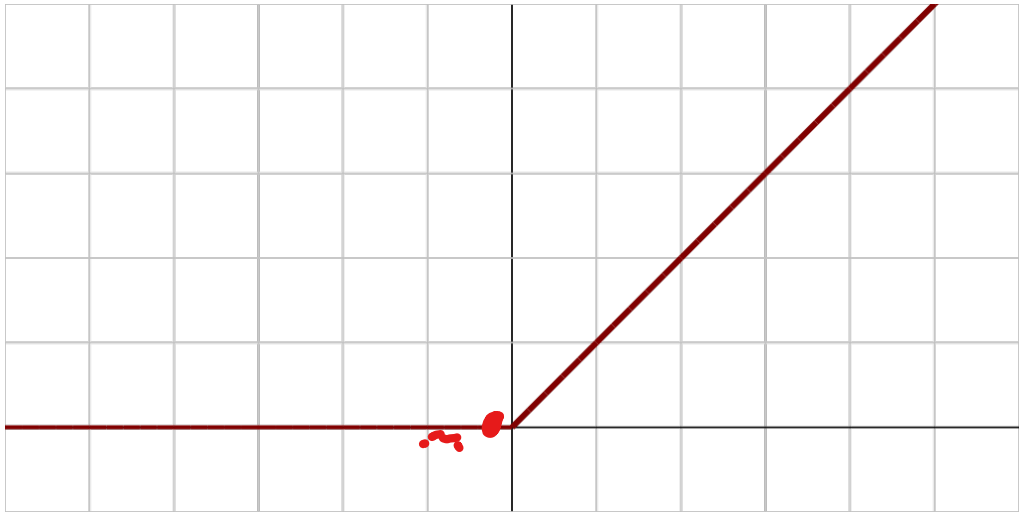
Sigmoid Activation





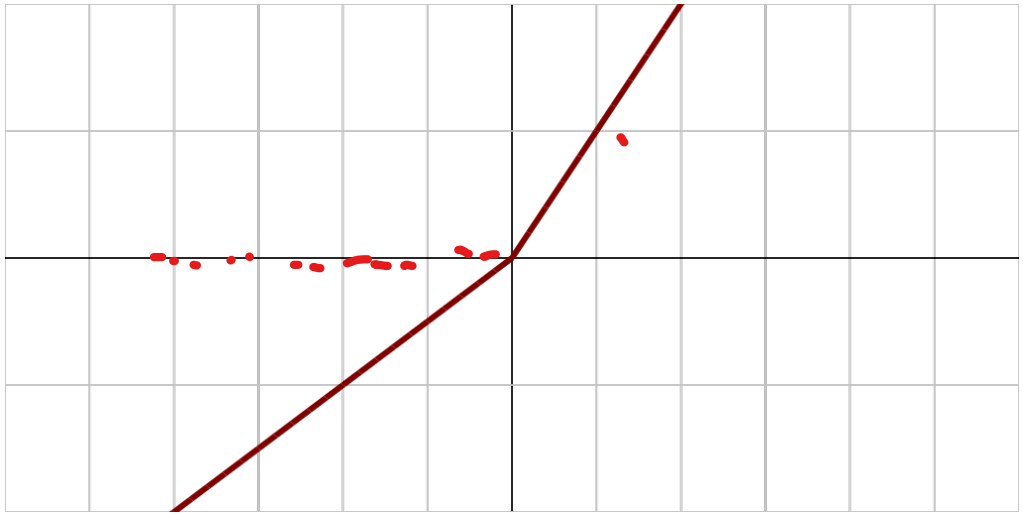
+ non-linear
+ strong differentiation at decision boundary
+ similar to brain neuron activation
– gradient becomes zero on large errors

Rectified Linear Unit (ReLU) Activation



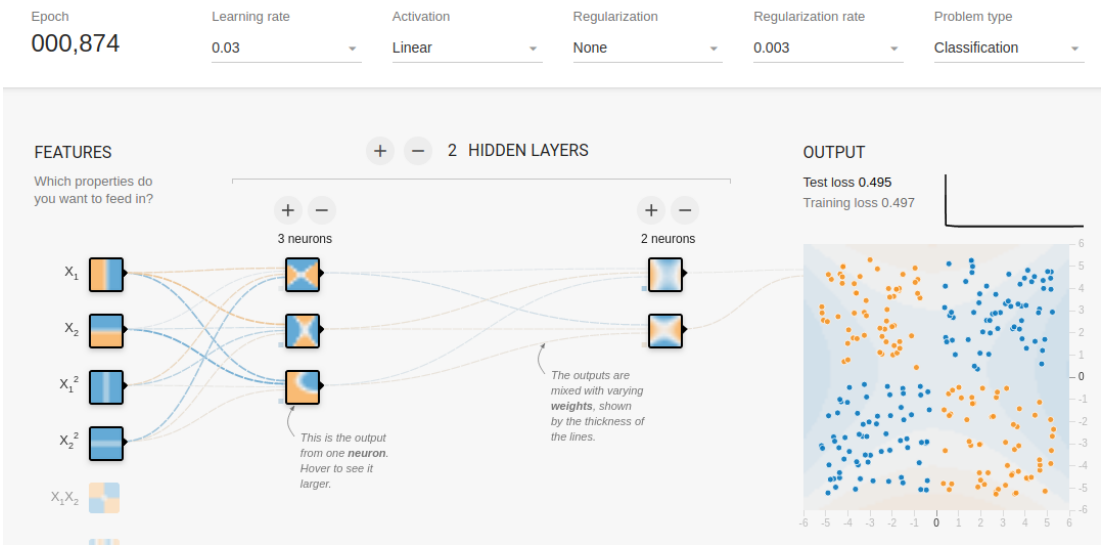
+ non-linear
+ can handle all errors margins
+ usually faster conversion than sigmoid
– cannot learn from positive examples

Leaky ReLU Activation



+ non-linear
+ can handle all errors margins
+ similar to brain neuron activation
+ usually faster conversion than sigmoid
+ learning from positive examples at a lower rate

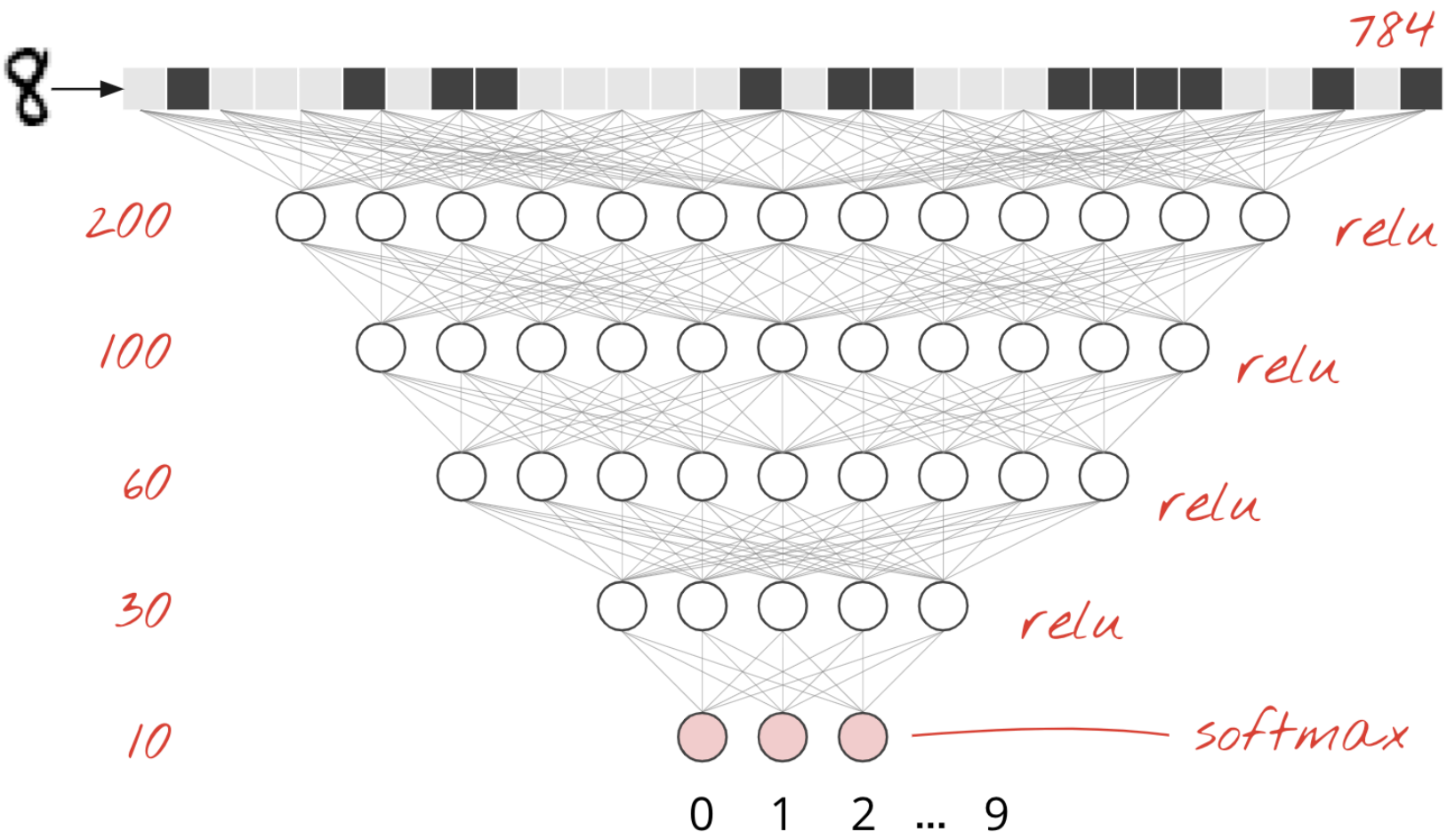
Universality



- non-linear data requires non-linear activation functions
- non-linear data requires non-linear feature representation
- you can **approximate any non-linear function** with non-linear activation functions

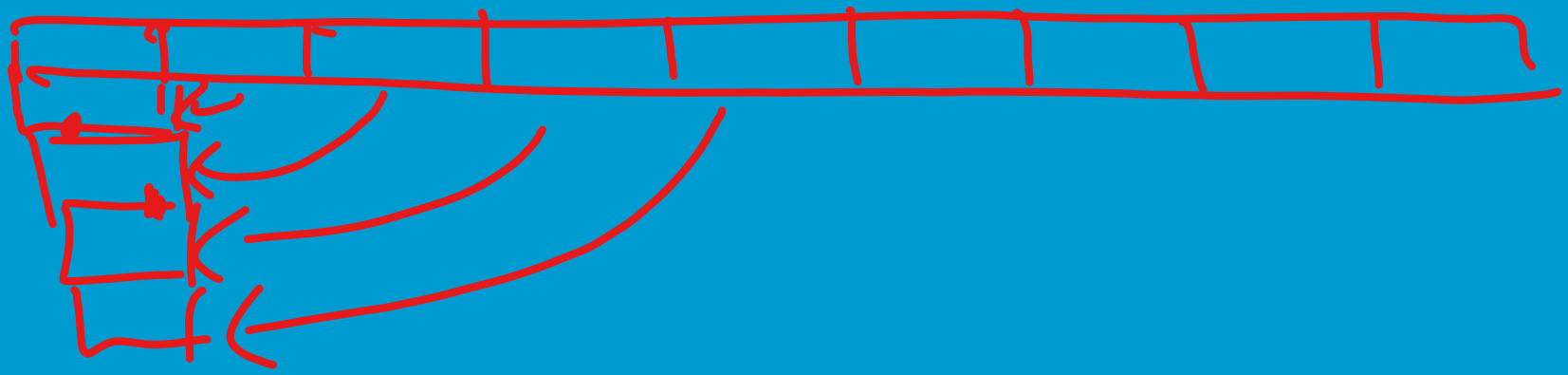
`http://playground.tensorflow.org/`

Deep Neural Network



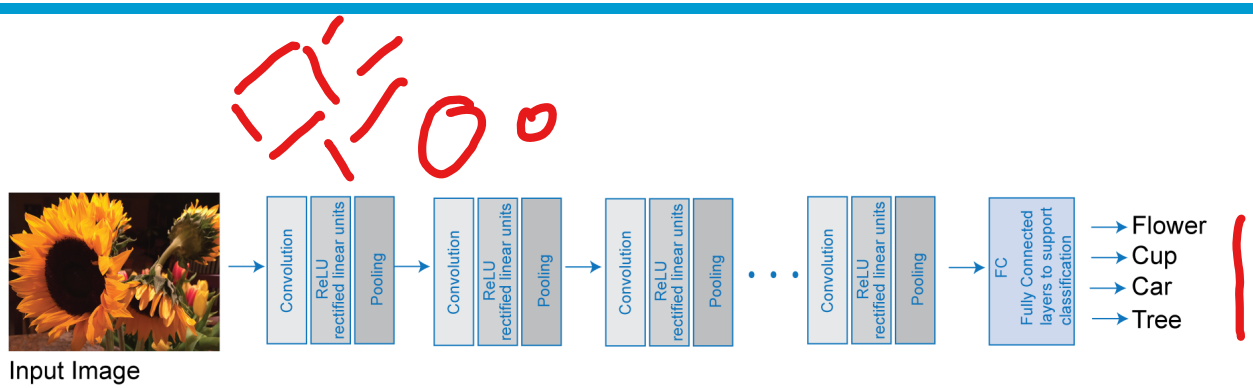
Let’s do it!

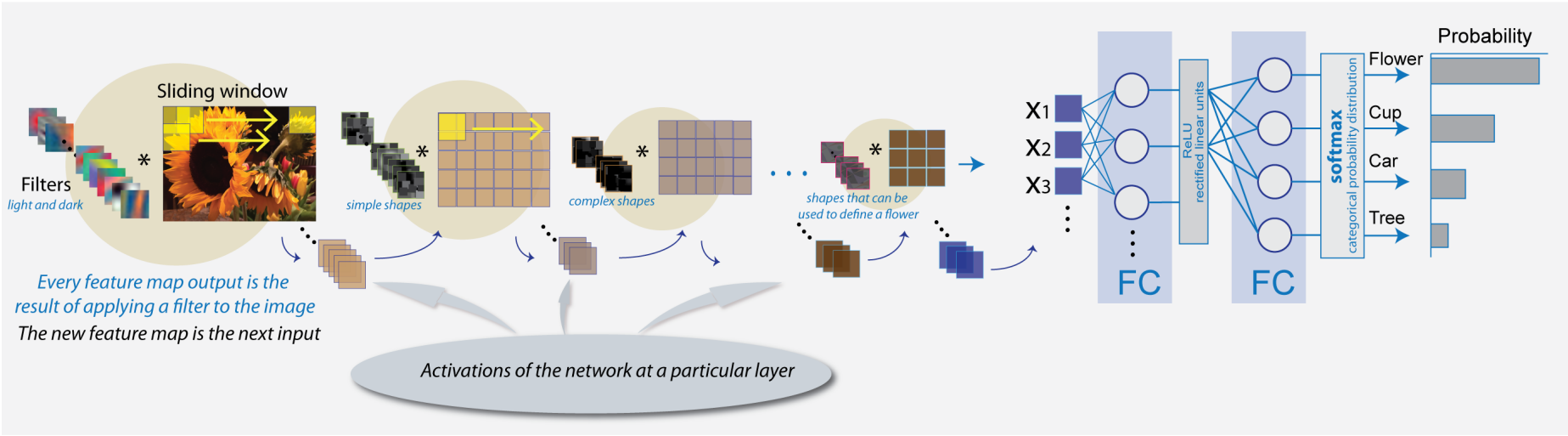
https://git.informatik.uni-hamburg.de/base.camp/ml-deep-learning/
number-recognition-2.py number-recognition-3.py



I see 1-dimensional people?

Convolutional Neural Network





Layers

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- Dense Layer (fully connected) ✓
- Output Layer (w. number of classes) ~
- Convolutional Layer
- Pooling Layer

Convolutional Layer

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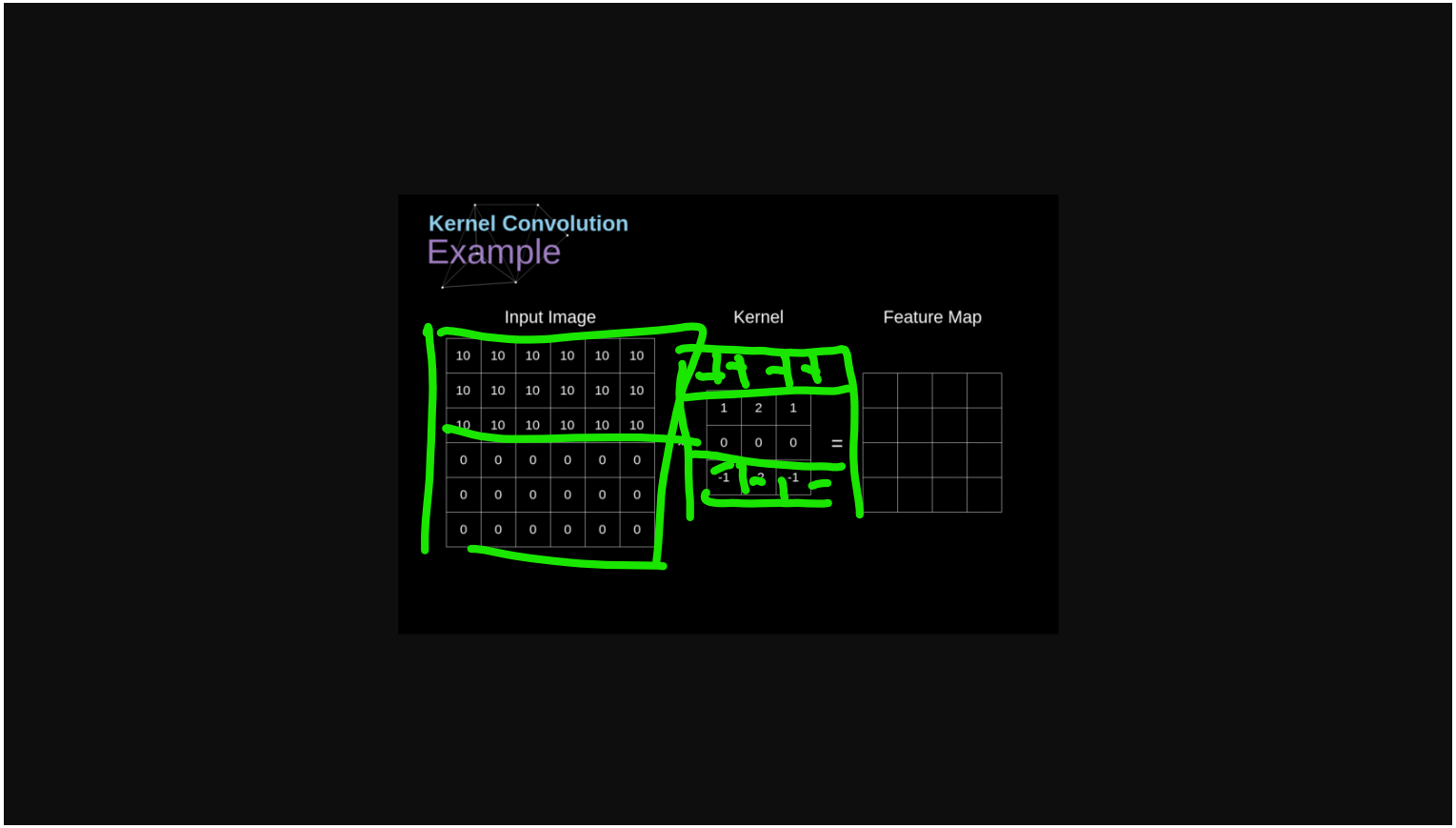
- automatically learned filters (also: kernels)
- identifying features in tensors
- important for image recognition and signal processing

Convolutional Layer



Pooling Layer

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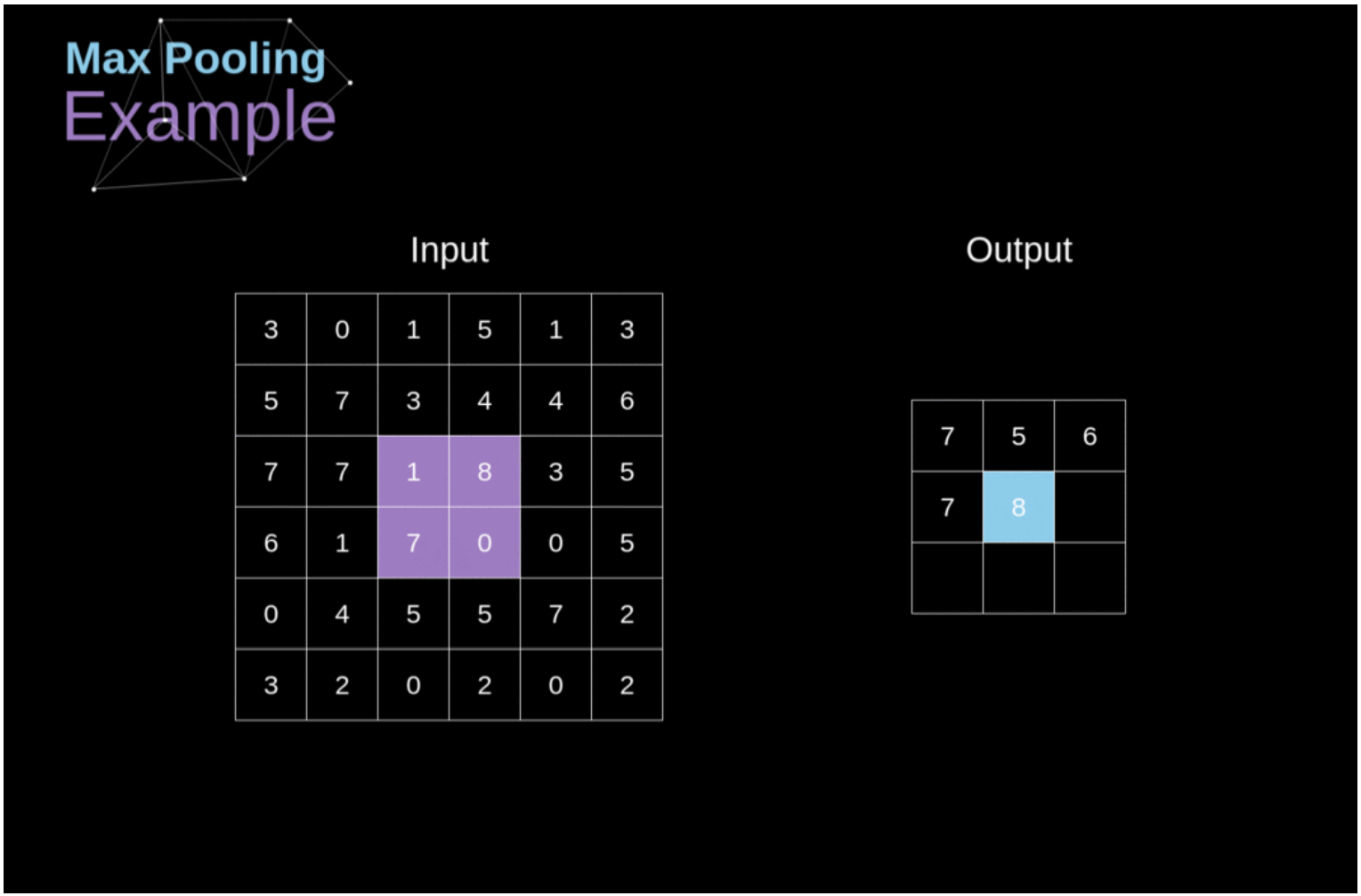
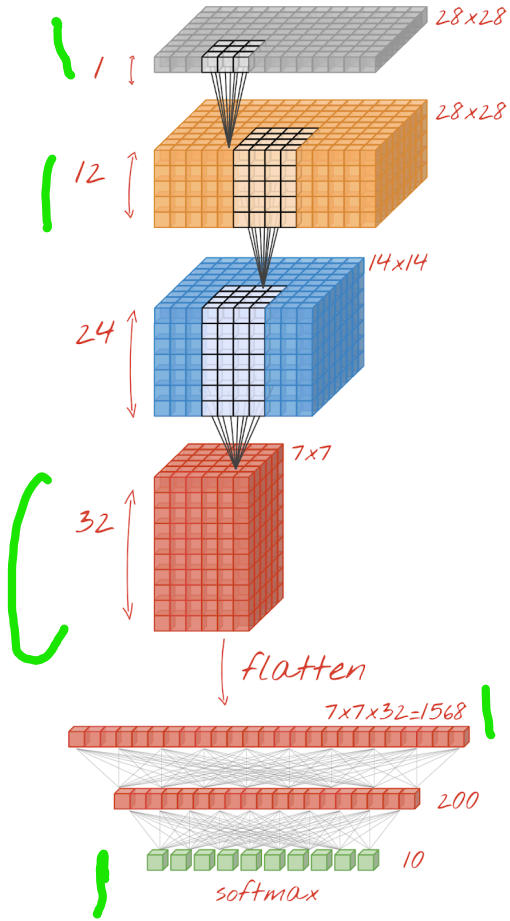
- max pooling or average pooling
- identifying important points in tensor
- or: blurring the image for further processing (e.g. with convolutions)

Pooling Layer



CNN



Convolutional 3x3 filters=12
$W_1[3, 3, 1, 12]$

Convolutional 6x6 filters=24
$W_2[6, 6, 12, 24]$ stride 2

Convolutional 6x6 filters=32
$W_3[6, 6, 24, 32]$ stride 2

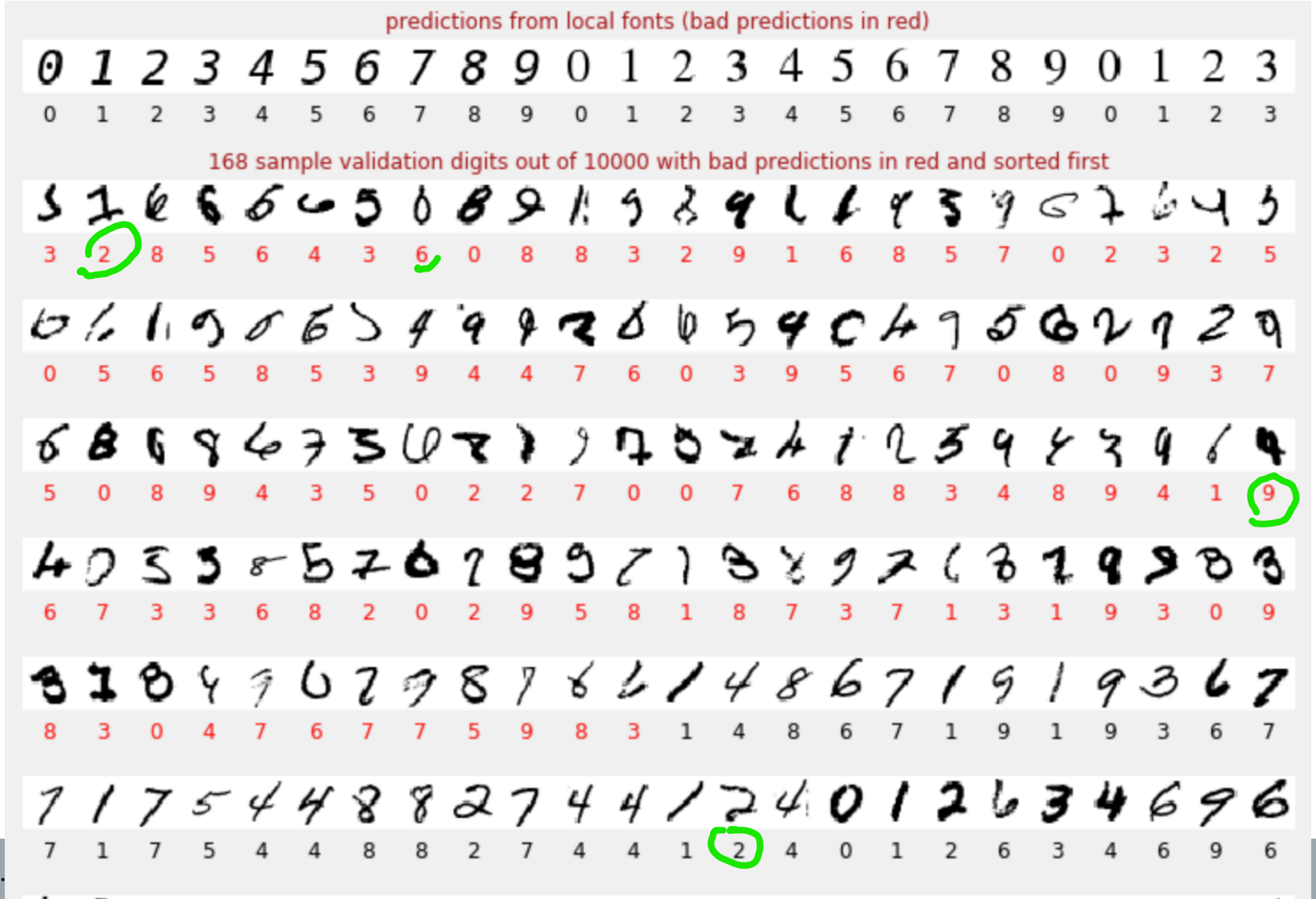
Dense layer
$W_4[1568, 200]$

Softmax dense layer
$W_5[200, 10]$

Let’s do it!

```
https://git.informatik.uni-hamburg.de/base.camp/
ml-deep-learning/
number-recognition-4.py
```

MNIST Results



MNIST Results

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Approach	Error rate
Linear	7.6 – 12.0
KNN	0.5 – 5.0
SVM	0.6 – 1.4
Neural Nets	0.4 – 4.7
Convolutional Nets	0.2 – 1.7
Dense	7.3
Deep Network	1.7 – 2.1
Convolutional Network	1.1

Resources

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- Tensorflow Playground
  `http://playground.tensorflow.org/`
- Tensorflow Tutorial
  `https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/`
  Code: `https://github.com/GoogleCloudPlatform/tensorflow-without-a-phd/tree/master/tensorflow-mnist-tutorial`
- *Neural Networks and Deep Learning* book
  `http://neuralnetworksanddeeplearning.com/`
- Github Repository of examples in the slides:
  `https://github.com/basecamp-uhh/mnist-tutorial`

Conclusion

Conclusion

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- neural networks offer powerful ML techniques
- no feature engineering required
- but: network engineering and hyperparameter tuning
- not a means to solve everything but a nice tool in the toolbelt

Conclusion
Decision for algorithm

- Classification performance
- Online Learning possibility
- Training/classification time
- Availability of data
- Explainability

Conclusion

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Take-away points:

- idea about neural networks
- knowledge to aid in understanding papers and lectures
- motivation to try out neural networks

Conclusion
Impact

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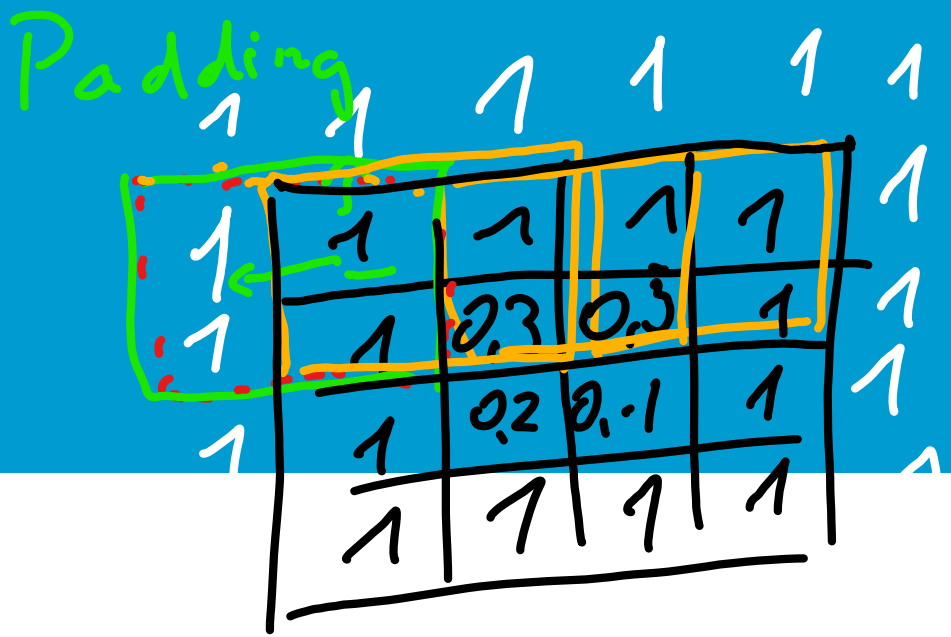
- AI has a large impact on the world
- ethical considerations are important
- Big Data and privacy issues
- misuse opportunities

Interesting talks from the EIT (Prof. Judith Simon and Prof. Ingrid Schneider)
Taming the Machines:
`https://www.inf.uni-hamburg.de/en/inst/ab/eit/taming-the-machines/lecture2go.html`



Fin

w.o. padding 3x3

with padding 5x5

SGD Algorithm for Perceptron

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for $t = 1, \ldots, T$ **do**
  for $i = 1, \ldots, n$ **do**
    if $y_i \langle x_i, w^{(t)} \rangle \leq 0$ **then**
      update $w^{(t+1)} = w^{(t)} + \eta^{(t)} y_i x_i$
    end if
  end for
end for

Perceptron example

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Consider the following data points, characterized by two features F and G; the variable Y represents the label:

	F	G	Y
$\mathbf{x}_1$	-1	2	$-$
$\mathbf{x}_2$	3	0	$-$
$\mathbf{x}_3$	0	4	$+$
$\mathbf{x}_4$	1	5	$+$
$\mathbf{x}_5$	2	2	$+$

Perceptron example

In the first step we fold the distance to the hyperplane ρ into x_i. This adds a new component -1 to every data point:

	X	Y
$\mathbf{x}_1$	$(-1, 2, -1)$	$-$
$\mathbf{x}_2$	$(3, 0, -1)$	$-$
$\mathbf{x}_3$	$(0, 4, -1)$	$+$
$\mathbf{x}_4$	$(1, 5, -1)$	$+$
$\mathbf{x}_5$	$(2, 2, -1)$	$+$

Perceptron example

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Then we fold the label into the instance: $x_i \cdot y_i$

	X
$\mathbf{x}_1$	$(1, -2, 1)$
$\mathbf{x}_2$	$(-3, 0, 1)$
$\mathbf{x}_3$	$(0, 4, -1)$
$\mathbf{x}_4$	$(1, 5, -1)$
$\mathbf{x}_5$	$(2, 2, -1)$

Perceptron example

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Now we can apply the SGD algorithm to compute a weight vector w which classifies all examples x_i correctly. The learning rate η is set to 1, so we get the following update instruction for a misclassified x_i:

$$w^{(t+1)} = w^{(t)} + y_i x_i \tag{1}$$

Perceptron example

w	x_i	$x_i \cdot w$	w	x_i	$x_i \cdot w$
$(0, 0, 0)$	$(1, -2, 1)$	0	$(-2, 2, 3)$	$(1, 5, -1)$	$+5$
$(1, -2, 1)$	$(-3, 0, 1)$	-2	$(-2, 2, 3)$	$(2, 2, -1)$	-3
$(-2, -2, 2)$	$(0, 4, -1)$	-10	$(0, 4, 2)$	$(1, -2, 1)$	-6
$(-2, 2, 1)$	$(1, 5, -1)$	$+7$	$(1, 2, 3)$	$(-3, 0, 1)$	0
$(-2, 2, 1)$	$(2, 2, -1)$	-1	$(-2, 2, 4)$	$(0, 4, -1)$	$+4$
$(0, 4, 0)$	$(1, -2, 1)$	-8	$(-2, 2, 4)$	$(1, 5, -1)$	$+4$
$(1, 2, 1)$	$(-3, 0, 1)$	-2	$(-2, 2, 4)$	$(2, 2, -1)$	-4
$(-2, 2, 2)$	$(0, 4, -1)$	$+6$	$(0, 4, 3)$	$(1, -2, 1)$	-5
$(-2, 2, 2)$	$(1, 5, -1)$	$+6$	$(1, 2, 4)$	$(-3, 0, 1)$	$+1$
$(-2, 2, 2)$	$(2, 2, -1)$	-2	$(1, 2, 4)$	$(0, 4, -1)$	$+4$
$(0, 4, 1)$	$(1, -2, 1)$	-7	$(1, 2, 4)$	$(1, 5, -1)$	$+7$
$(1, 2, 2)$	$(-3, 0, 1)$	-1	$(1, 2, 4)$	$(2, 2, -1)$	$+2$
$(-2, 2, 3)$	$(0, 4, -1)$	$+5$	$(1, 2, 4)$	$(1, -2, 1)$	$+1$

Perceptron example

At this point, all five examples are correctly classified, and we are done. In terms of the original data points (attributes *F* and *G*), the prediction is:

$$f(x) = x \cdot (1, 2) - 4 \tag{2}$$

We arrive at (2) if we compute the dot product of *x* and *w* and extract the constant -4, which is the same for all possible data points:

$$\begin{aligned} f(x) &= \langle x, w \rangle \\ &= \langle (F, G, -1), (1, 2, 4) \rangle \\ &= \langle (F, G), (1, 2) \rangle - 4 \end{aligned} \tag{3}$$

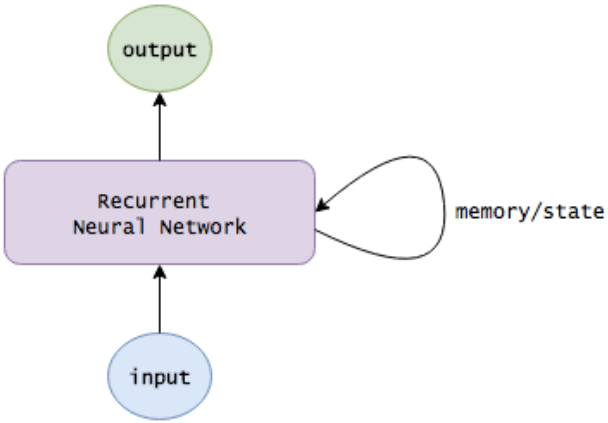
Perceptron example

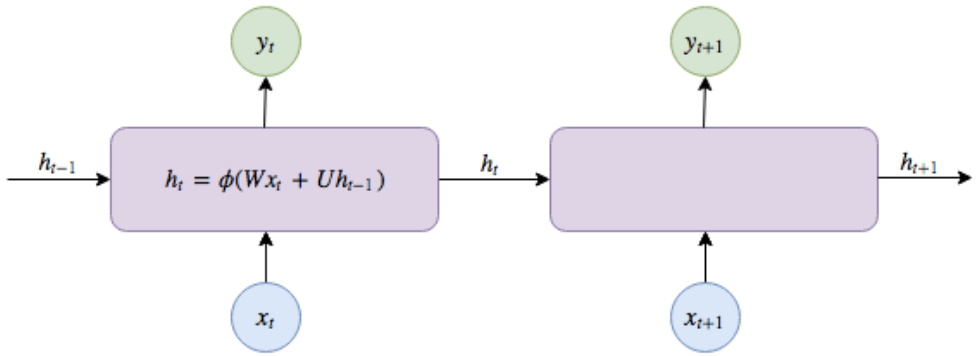
We can confirm that the prediction (2) correctly classifies all the original examples:

$\boldsymbol{x}$	$f(\boldsymbol{x})$	Y
$(-1, 2)$	-1	$-$
$(3, 0)$	-1	$-$
$(0, 4)$	$+4$	$+$
$(1, 5)$	$+7$	$+$
$(2, 2)$	$+2$	$+$

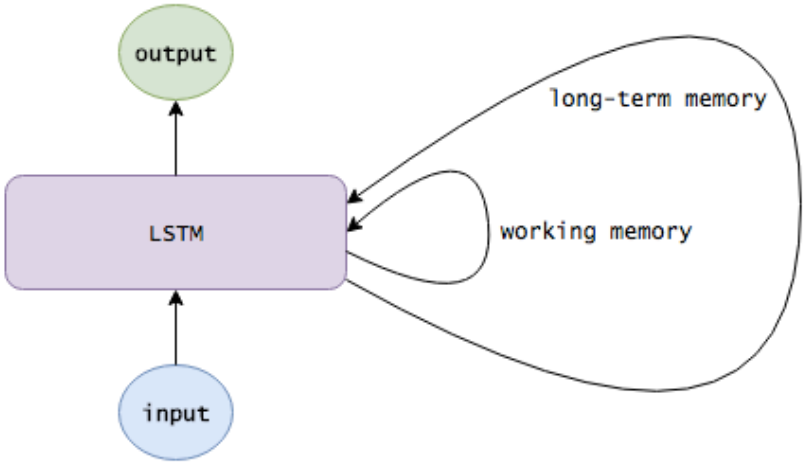
RNN, LSTM and others

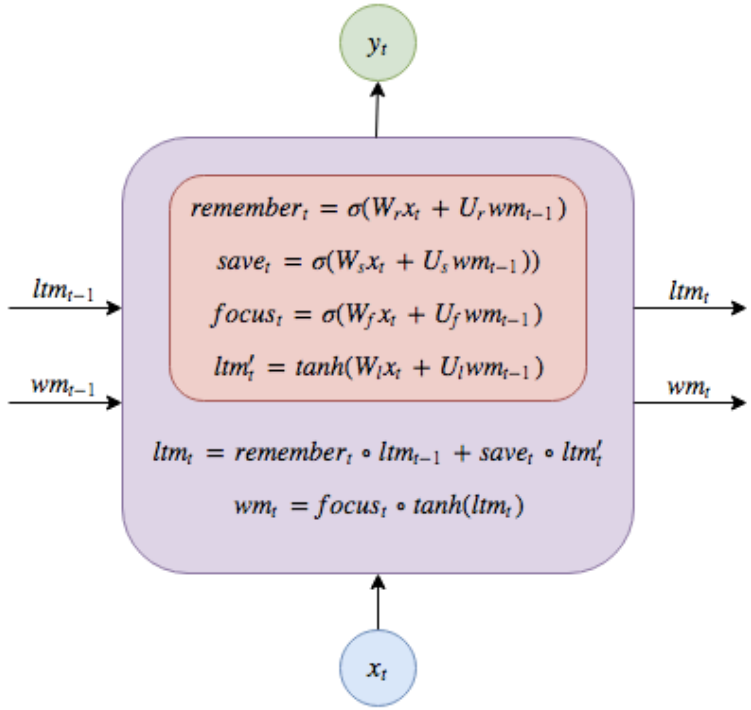
Recurrent Neural Networks





Long Short-Term Memory





Long Short-Term Memory

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- LSTMs solve RNN problems like vanishing/exploding gradient
- input gate
- keep gate
- forget gate
- long-range dependencies are captured

LSTM to generate Code

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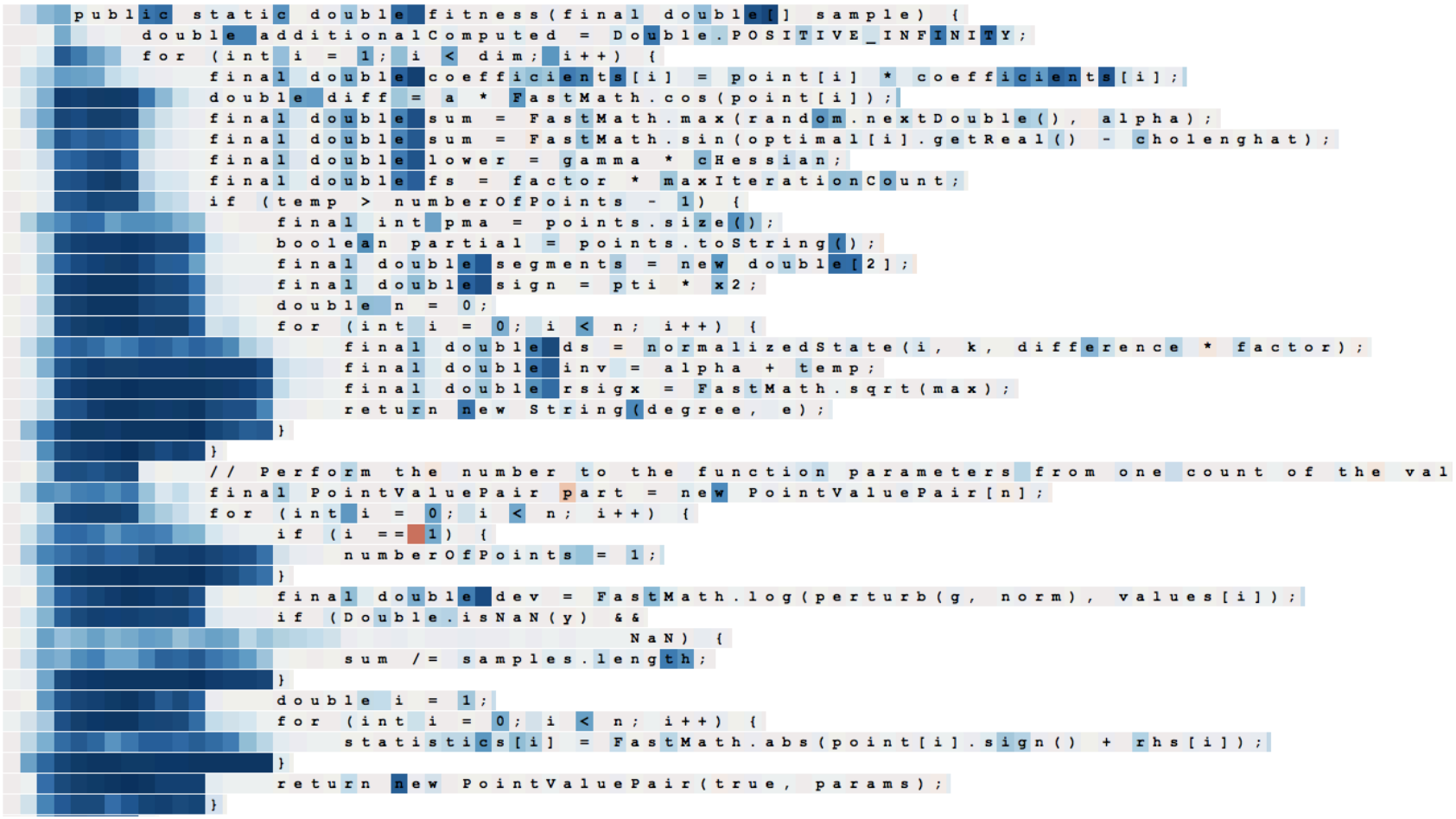

Other Interesting Approaches

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- Reinforcement Learning, automated learning in a situated environment
- Adversarial Learning, co-training 2 neural nets
- transfer learning
- embeddings (text, speech, graphs, images)

Reinforcement Learning

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- subfield of machine learning
- decision making and motor control
- agents reach goals in complex environments

`https://gym.openai.com/`

Frameworks, Tools and Resources

Tensorflow

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- by Google Brain team
- big ecosystem
- can model any kind of data flow
- mature

`https://www.tensorflow.org/`

Keras

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- by Google research
- modular
- extensible
- user-friendly (building blocks)
- rather an interface for Tensorflow

`https://keras.io/`

Keras

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```
model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=[28, 28, 1]),
    tf.keras.layers.Dense(200, activation="relu"),
    tf.keras.layers.Dense(60, activation="relu"),
    tf.keras.layers.Dense(10, activation='softmax') # classifyi
])

# this configures the training of the model. Keras calls it "c
model.compile(
  optimizer='adam',
  loss= 'categorical_crossentropy',
  metrics=['accuracy']) # % of correct answers

# train the model
model.fit(dataset, ... )
```

PyTorch

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- by Facebook research
- automatic differentiation
- hot topic

`https://pytorch.org/`

PyTorch

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```
input_size = 784
hidden_sizes = [128, 64]
output_size = 10

# Build a feed-forward network
model = nn.Sequential(nn.Linear(input_size, hidden_sizes[0]),
                      nn.ReLU(),
                      nn.Linear(hidden_sizes[0], hidden_sizes[
                      nn.ReLU(),
                      nn.Linear(hidden_sizes[1], output_size),
                      nn.LogSoftmax(dim=1))

# Train
logps = model(images)
loss = criterion(logps, labels)
loss.backward()
optimizer.step()
```

Ludwig

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- by UBER AI LAbs
- automatic encoders for many data types
- no need for programming

`https://uber.github.io/ludwig/`

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- MNIST example:
  `https://uber.github.io/ludwig/examples/#image-classification-mnist`