



# Künstliche Intelligenz

Förderung oder Überforderung?

Denis Jordan  
Marcel Steiner-Curtis

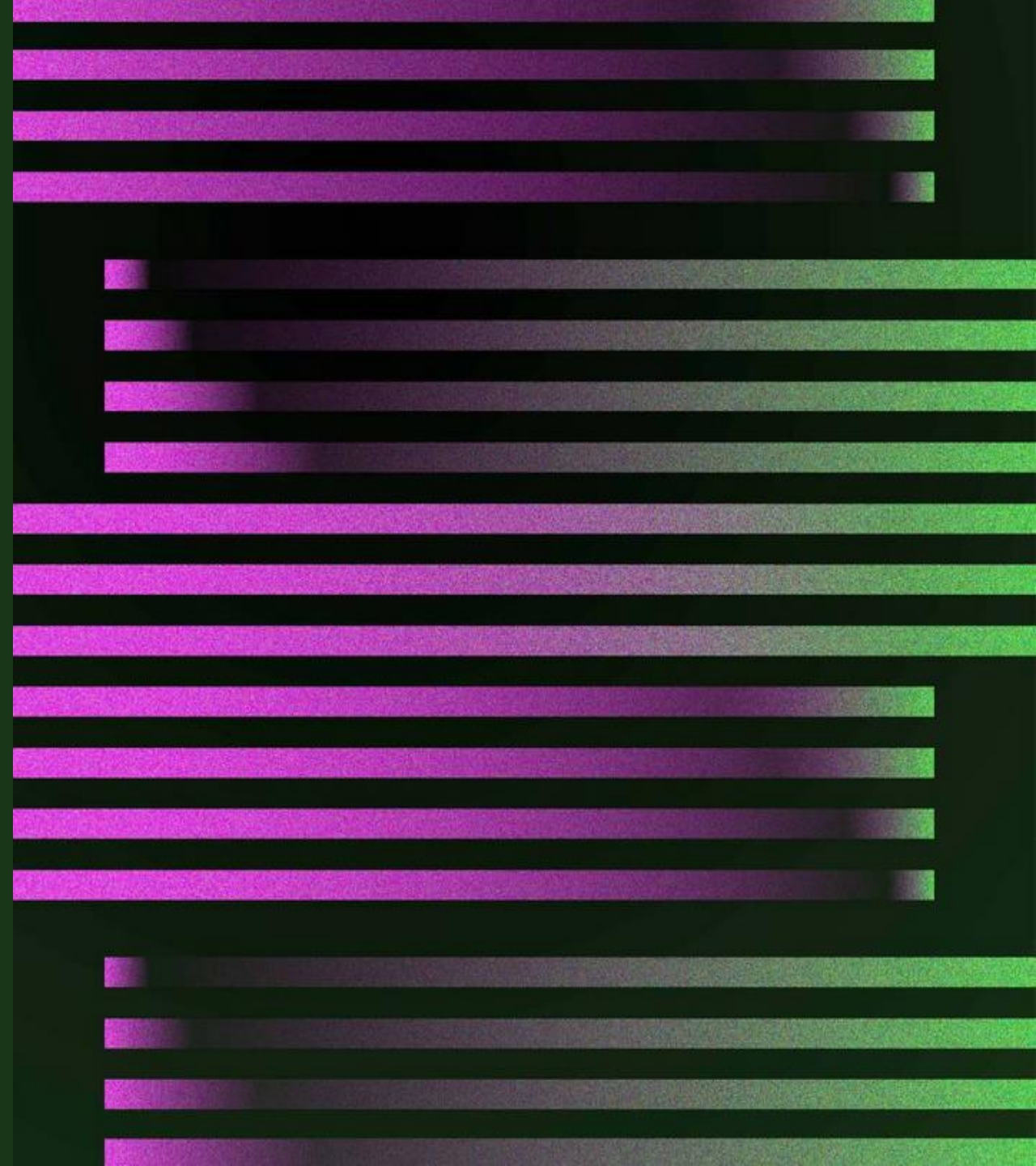
Assemblée générale OSIG / SOGI  
14.03.2024, FHNW MuttENZ



# ChatGPT: Optimizing Language Models for Dialogue

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to [InstructGPT](#), which is trained to follow an instruction in a prompt and provide a detailed response.

[TRY CHATGPT ↗](#)





Solve the following with R: The annual maximum sea levels [in cm] in Venice, 1931-1981 have been recorded by P. A. Pirazzoli. The data set

Year	SeaLevel
1931	103
1932	78
1933	121
1934	116
1935	115
⋮	⋮
1978	132
1979	166
1980	134
1981	138

contains the annual maximum tides at Venice for the 51 years.

- Represent the data in a scatter diagram sea level versus year and describe the functional context in words.
- Fit a straight line to the data points. Give the estimated parameter values.
- Add the model in the scatter diagram. Comment on the solution.
- Does the data support the hypothesis that Venice sinks? Make a statistical test.



I'll provide you with the R code to perform these tasks and interpret the results. However, I cannot execute the code as I'm an AI text model. You can execute the code in your local R environment or use an online R compiler like RStudio or Jupyter Notebook.

First, let's input the data into a data frame:

R

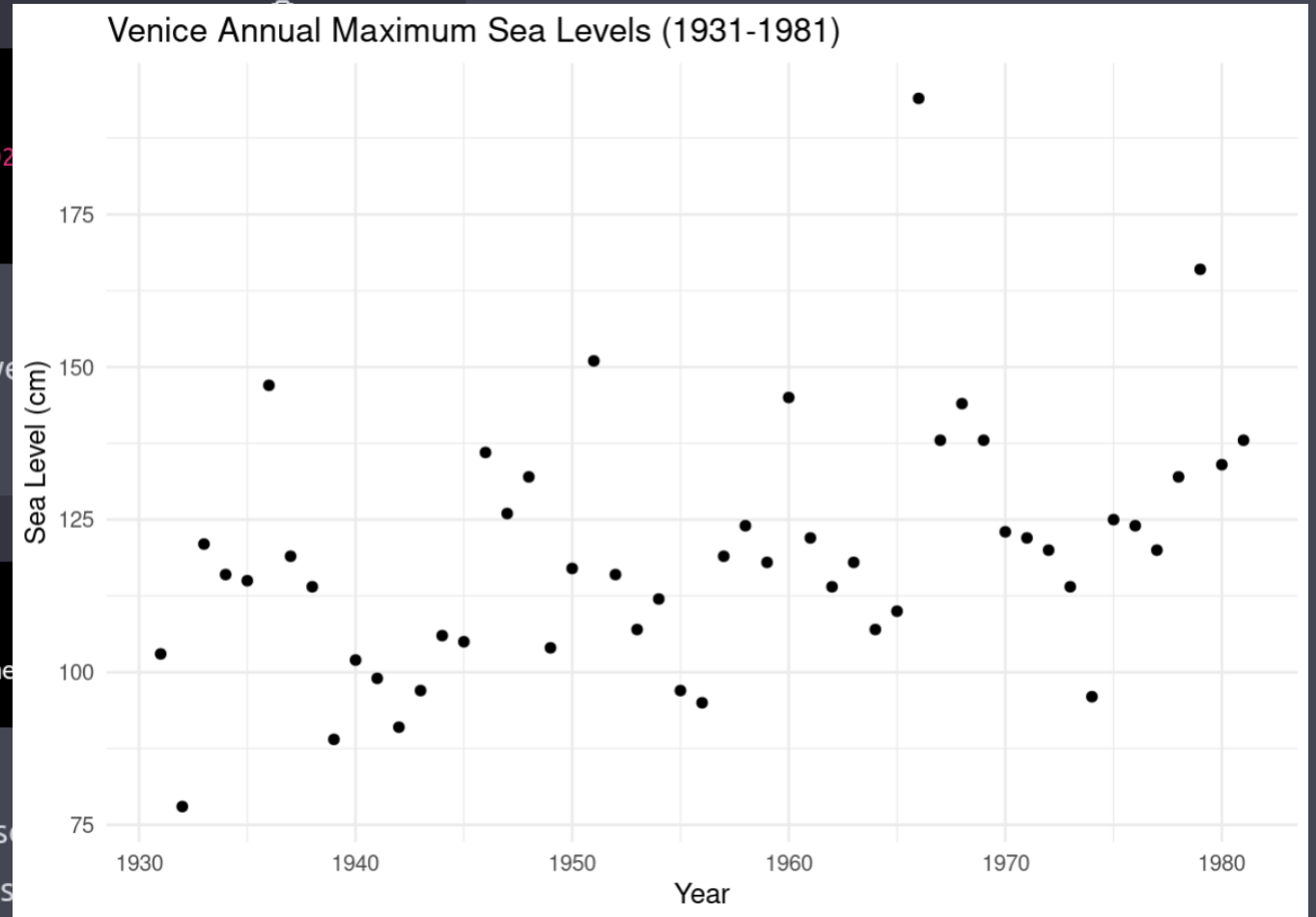
```
Year <- c(1931:1981)
SeaLevel <- c(103, 78, 121, 116, 115, 147, 119, 114, 89, 102)
data <- data.frame(Year, SeaLevel)
```

a. Represent the data in a scatter diagram sea level versus year. Provide a functional context in words.

R


```
library(ggplot2)
ggplot(data, aes(x=Year, y=SeaLevel)) + geom_point() + theme_minimal()
```

This code will create a scatter plot of the annual maximum sea level from 1931 to 1981. You should see a general upward trend in sea levels, which indicates a sinking phenomenon.



b. Fit a straight line to the data points. Give the estimated parameter values.

R

 Copy code

```
linear_model <- lm(SeaLevel ~ Year, data)
summary(linear_model)
```

The output will provide the estimated parameter values (intercept and slope) for the regression line.

Call:

```
lm(formula = SeaLevel ~ Year, data = data)
```

Residuals:

Min	1Q	Median	3Q	Max
-33.813	-11.211	-3.309	9.515	68.722

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	-989.3822	346.4770	-2.856	0.00628	**
Year	0.5670	0.1771	3.201	0.00241	**

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 18.62 on 49 degrees of freedom

Multiple R-squared: 0.1729, Adjusted R-squared: 0.1561

F-statistic: 10.25 on 1 and 49 DF, p-value: 0.002406

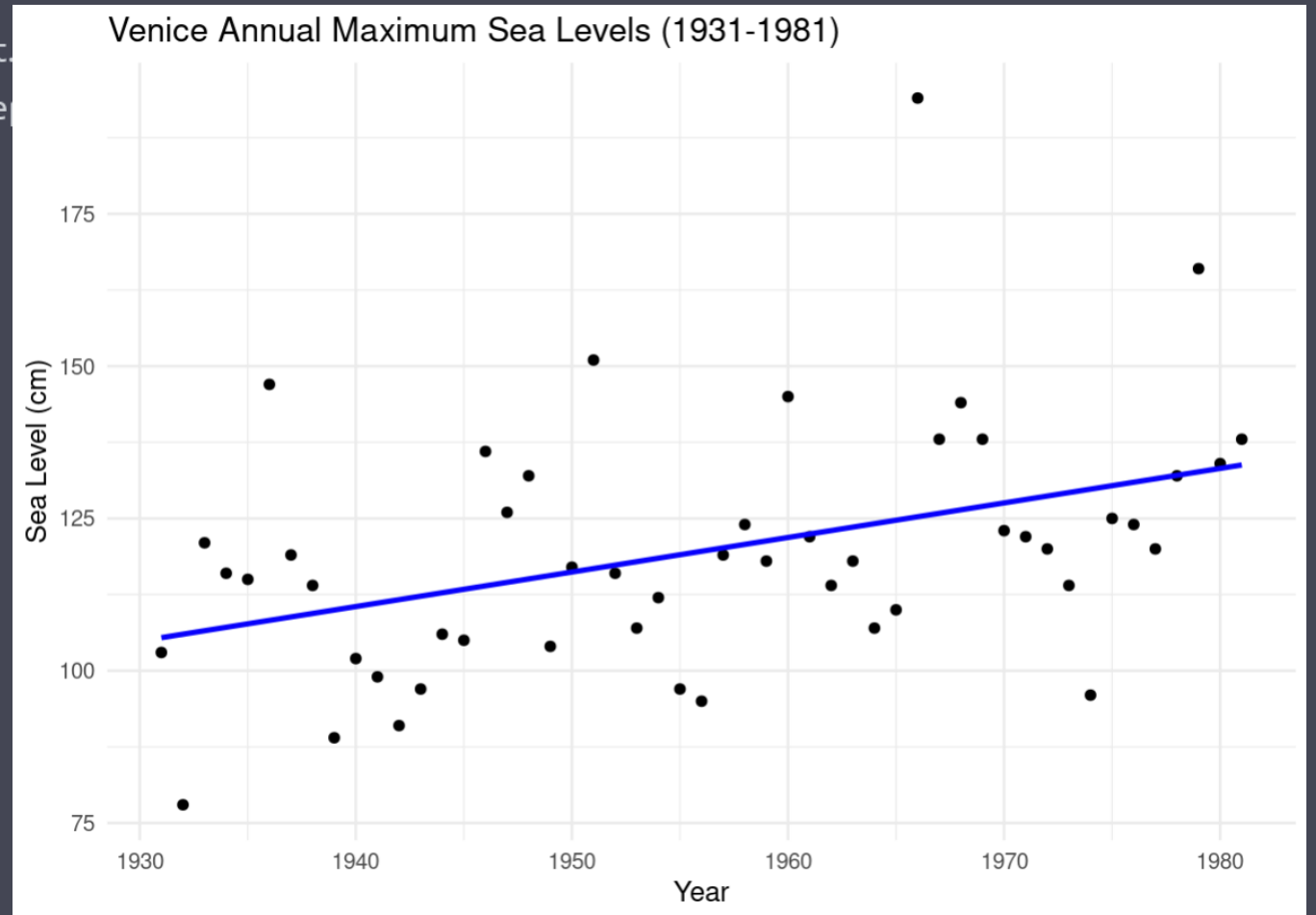
c. Add the model in the scatter diagram. Comment on the solution.

R

Copy code


```
ggplot(data, aes(x=Year, y=SeaLevel)) + geom_point() + geom_smooth(method = "lm", se = FALSE)
```

This code will add the fitted linear model to the scatter plot. Evaluate how well the line represents the data. Comment on the solution if the trend is captured accurately.



d. Does the data support the hypothesis that Venice sinks? Make a statistical test.

R

 Copy code

```
# Perform a t-test on the slope of the linear regression model
slope_test <- summary(linear_model)$coefficients["Year", "t value"]
slope_pvalue <- summary(linear_model)$coefficients["Year", "Pr(>|t|)"]

slope_test
slope_pvalue
```

The t-test will give you the t-value and p-value for the slope of the fitted line. If the p-value is less than a significance level (e.g., 0.05), you can reject the null hypothesis that the slope is equal to zero, suggesting a significant relationship between the year and sea level, which might support the hypothesis that Venice is sinking.

```
> # Perform a t-test on the slope of the linear regression model
> slope_test <- summary(linear_model)$coefficients["Year", "t value"]
> slope_pvalue <- summary(linear_model)$coefficients["Year", "Pr(>|t|)"]
>
> slope_test
[1] 3.200852
> slope_pvalue
[1] 0.002406147
```



0-677



REVOX  
high fidelity

REVERSE PLAY STOP REC  
MONITOR  
STEREO CH I CH II MONO  
HAB INPUT EC

VOLUME BALANCE

PHONES MIC CH I MIC CH II

CHANNEL I CHANNEL II  
RECORD  
MIC HI RADIO MIC HI RADIO  
MIC LO AUX MIC LO AUX

LEVEL LEVEL

POWER  
3 1/2 0 OFF 0 3 1/2





## ReVox A77 rechter Wickelmotor wird feurig heiss. Was ist defekt?



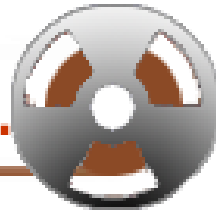
Wenn der rechte Wickelmotor Ihres ReVox A77 Tonbandgeräts übermäßig heiß wird, kann dies auf ein mechanisches oder elektrisches Problem hinweisen. Es ist wichtig zu beachten, dass ich keine Echtzeitinformationen habe und nicht auf dem neuesten Stand der Technik bin, da meine Daten nur bis September 2021 reichen. Dennoch kann ich Ihnen einige allgemeine Hinweise geben:



1. **Mechanische Probleme:** Ein heiß laufender Motor könnte auf übermäßige Reibung oder Blockaden im Mechanismus hinweisen. Überprüfen Sie, ob der Motor leichtgängig läuft, oder ob es Anzeichen für mechanische Probleme wie abgenutzte Lager, Riemen oder Zahnräder gibt.
2. **Elektrische Probleme:** Überhitzung kann auch auf elektrische Probleme hinweisen. Möglicherweise fließt zu viel Strom durch den Motor, was zu einer Überlastung führen kann. Dies könnte auf defekte elektrische Komponenten wie Transistoren, Kondensatoren oder Widerstände zurückzuführen sein.
3. **Lüftung:** Stellen Sie sicher, dass die Lüftungsöffnungen des Geräts nicht blockiert sind.



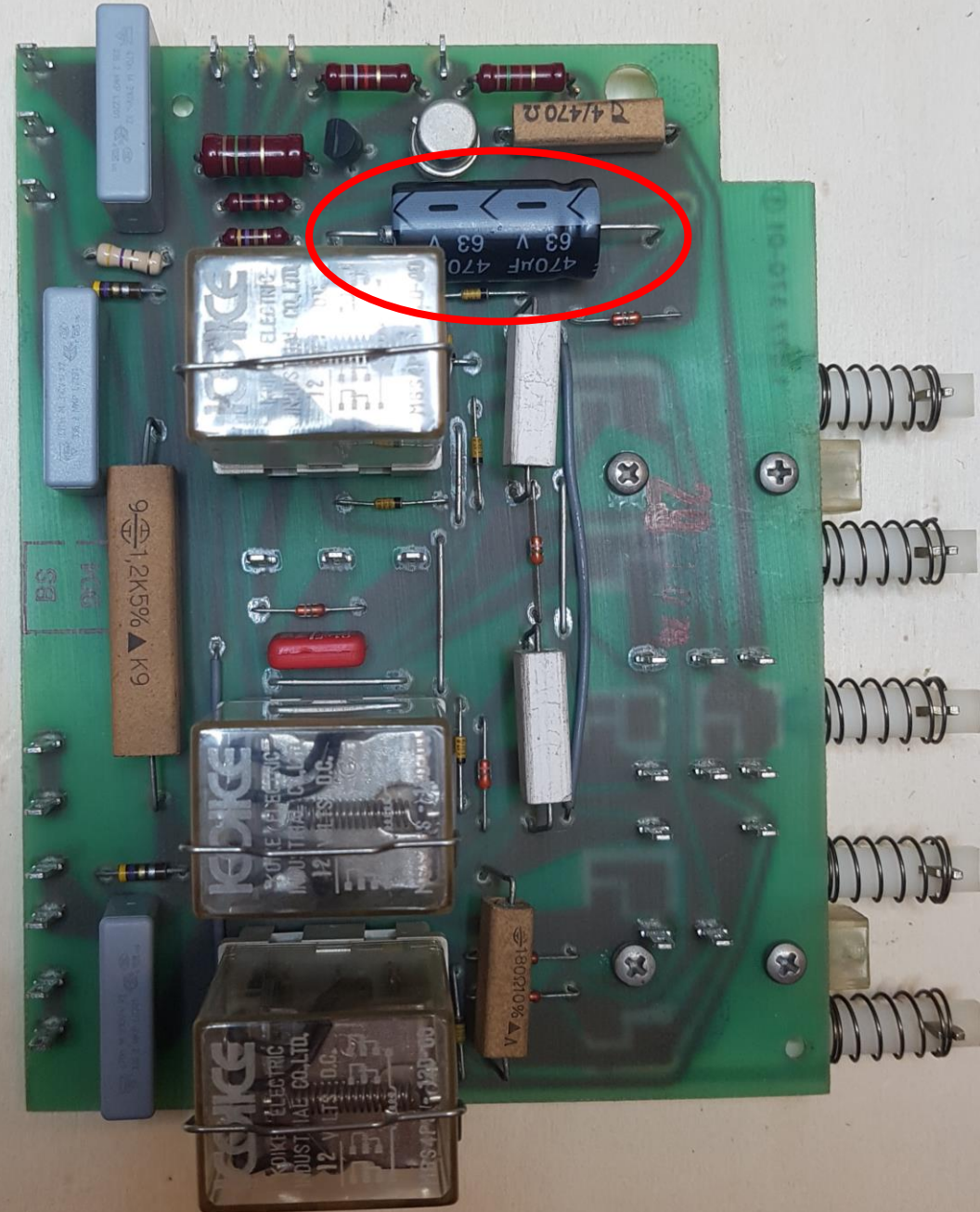
# ...:BANDMASCHINENFORUM:...:

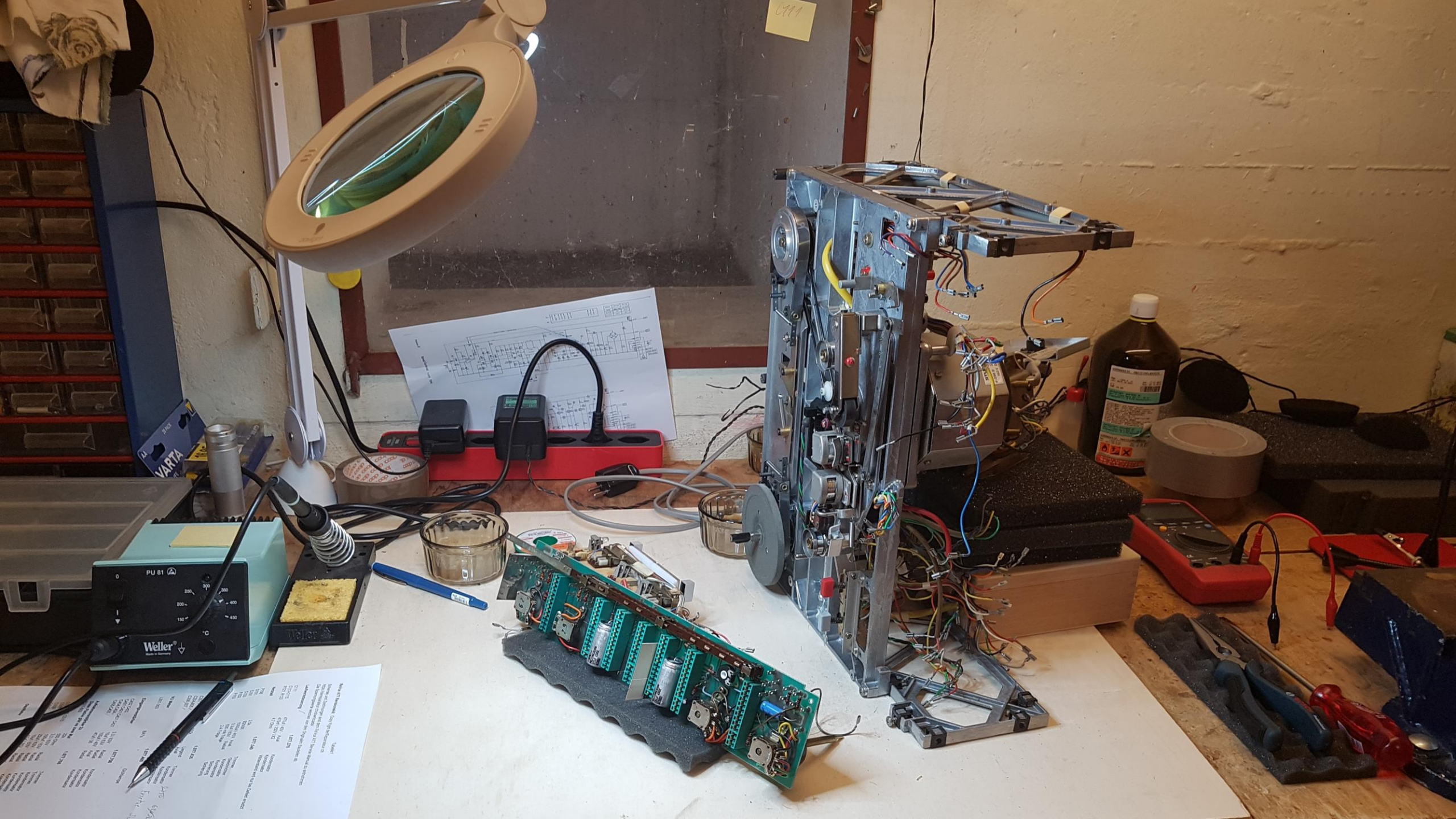


kaimex

Hast du schon mal den C111 500 µF überprüft ?

MfG Kai





0111



Weller  
PU 81  
230V  
300W  
200-400  
150-450

Handwritten notes and a checklist on a piece of paper, including a list of components and their specifications.

Part No.	Part Name	Quantity	Remarks
1	Resistor	1	
2	Capacitor	1	
3	IC	1	
4	Diode	1	
5	Transistor	1	
6	Relay	1	
7	Switch	1	
8	Motor	1	
9	Speaker	1	
10	Power Supply	1	
11	Chassis	1	
12	PCB	1	
13	Wires	1	
14	Tools	1	
15	Components	1	

Label on a bottle of liquid, possibly a cleaning agent or solder flux.

Red digital multimeter with black and red test leads.

Black foam tool tray containing several screwdrivers and other hand tools.

Ist das Glas  
halb voll ...

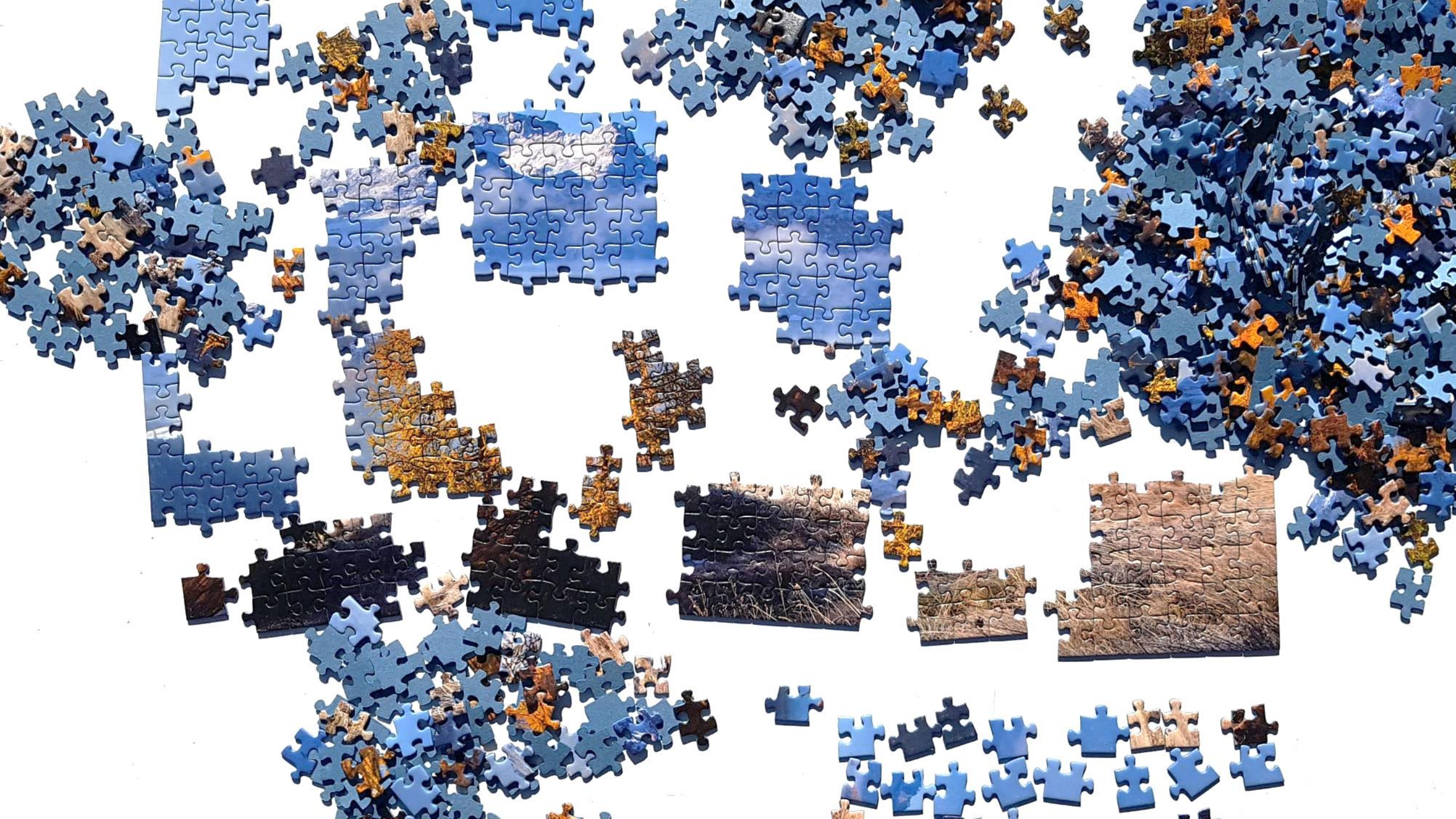


... oder  
halb leer ?

A photograph of a dirt road that splits into two paths. The road is unpaved and appears to be in a rural or forested area. The background is hazy and foggy, with trees on either side. The text 'Unterricht neu denken' is overlaid in red in the upper center.

# Unterricht neu denken

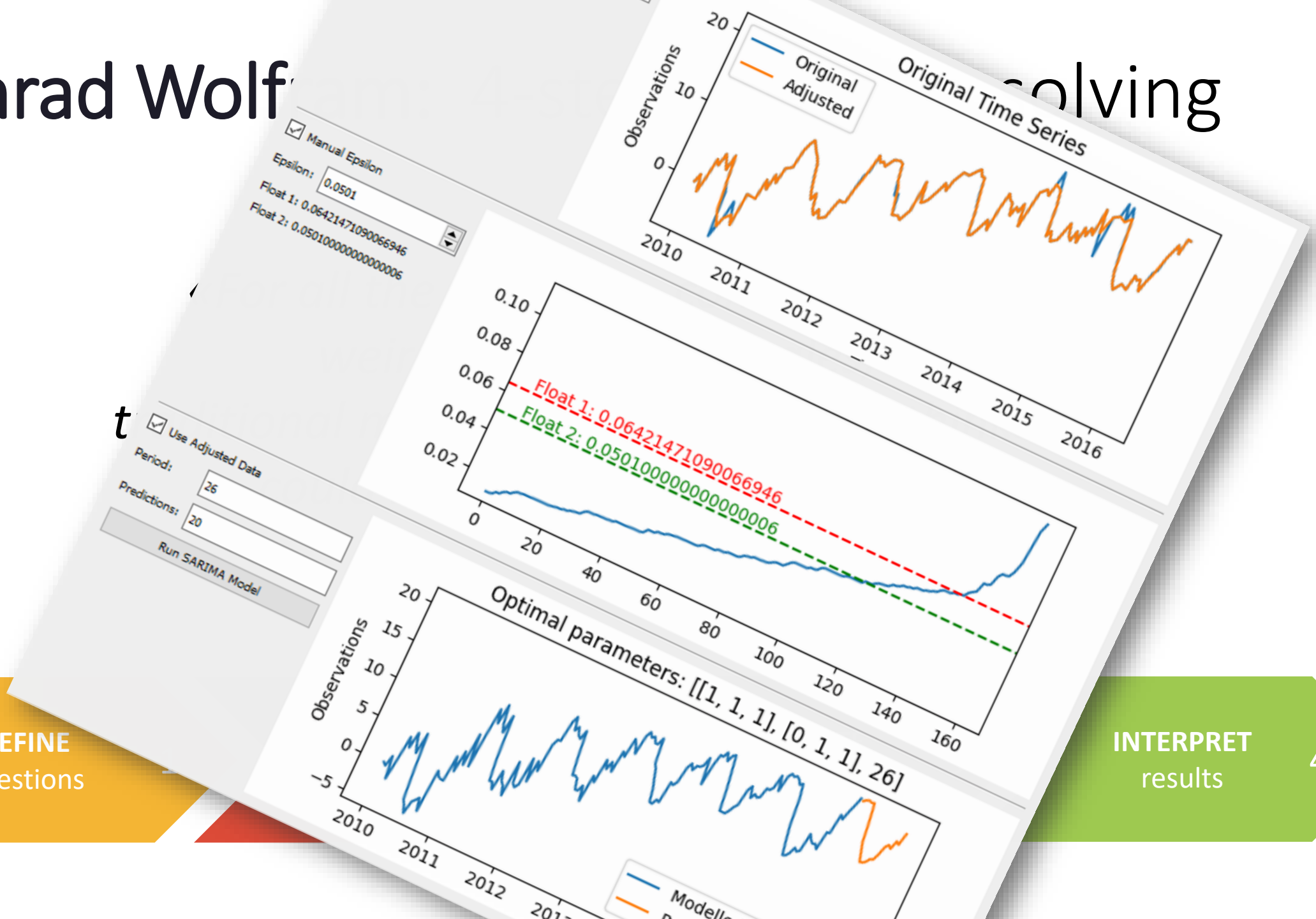
FHNW  
Fellowships  
«Hochschullehre 2025»



# Conrad Wolfram: 4-step problem-solving

*«For all the mystique, complexity and weird symbolic squiggles, traditional maths or computational thinking could be characterised as this»*





DEFINE  
questions

INTERPRET  
results



# Conrad Wolfram:

«For all the  
we  
traditional  
could

## Calling Bullshit

The Art of  
Scepticism  
in a  
Data-Driven  
World

CARL T. BERGSTROM  
& JEVIN D. W...

DEFINE  
questions

1

3

INTERPRET  
results

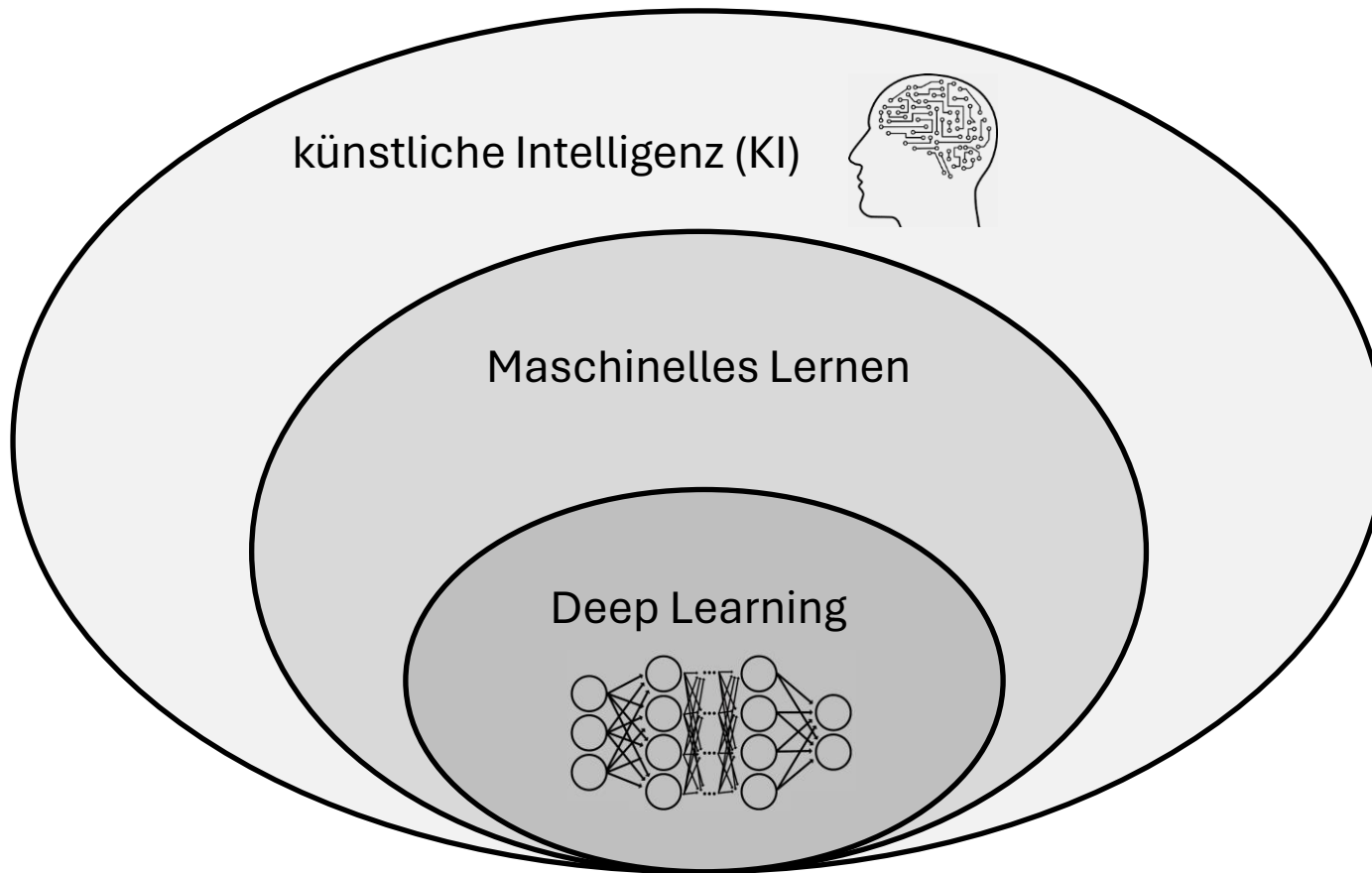
4

*«Prediction  
is very  
difficult,  
especially  
about the  
future.»*

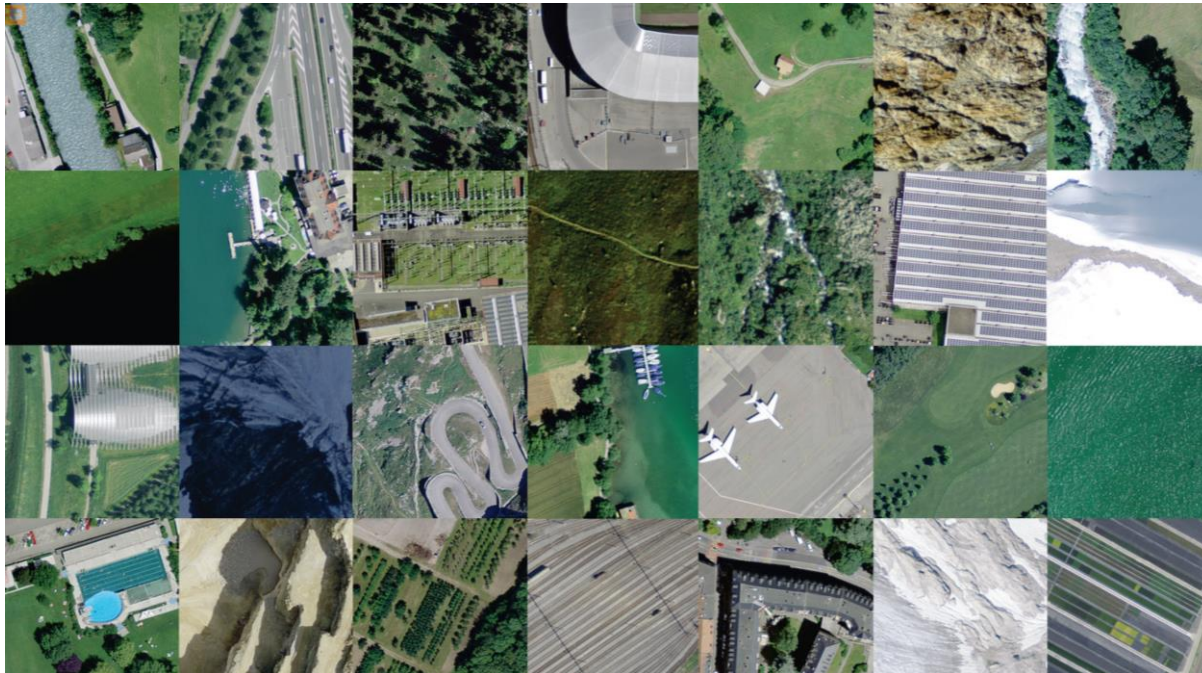
Niels Bohr  
1885-1962



## Künstliche Intelligenz – einige Begriffe



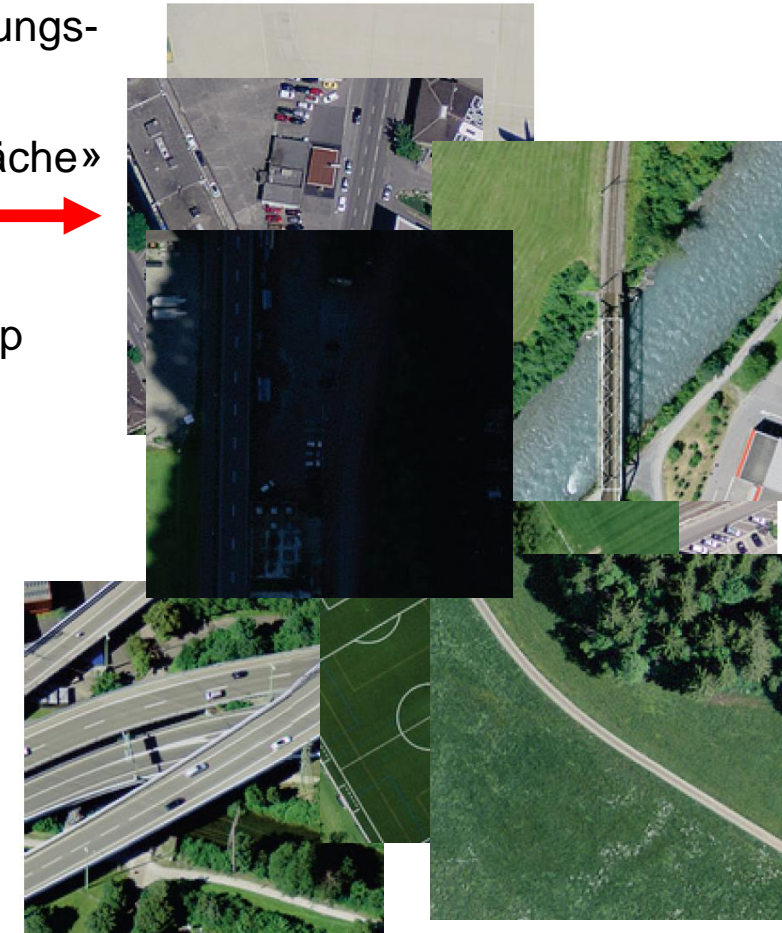
## Deep Learning am IGEO – Arealstatistik der Schweiz (BFS)



Bodenbedeckungs-  
Klasse 11  
«befestigte Fläche»



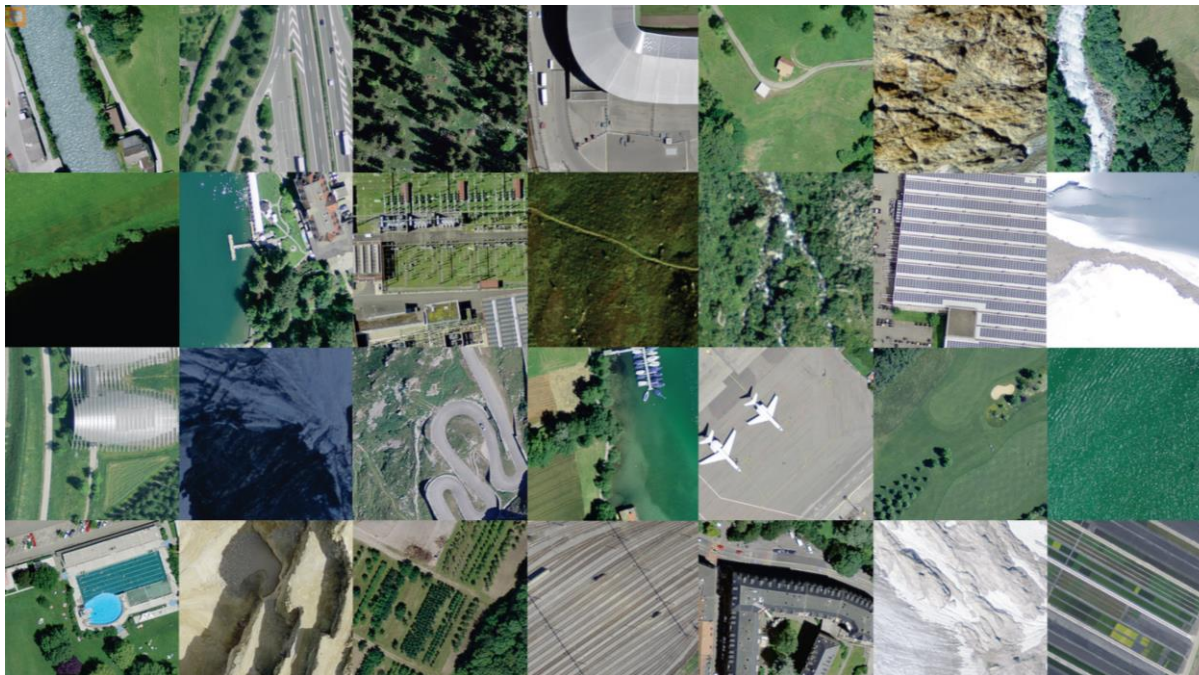
- manuell
- KI mit Deep Learning



Swissimage (swisstopo) als 100m x 100m Patches, amtliche Daten, ...

- 4.2 Mio Patches für die gesamte CH
- 72 Bodenbedeckungs- und Bodennutzungsklassen

## Deep Learning am IGEO – Arealstatistik der Schweiz (BFS)

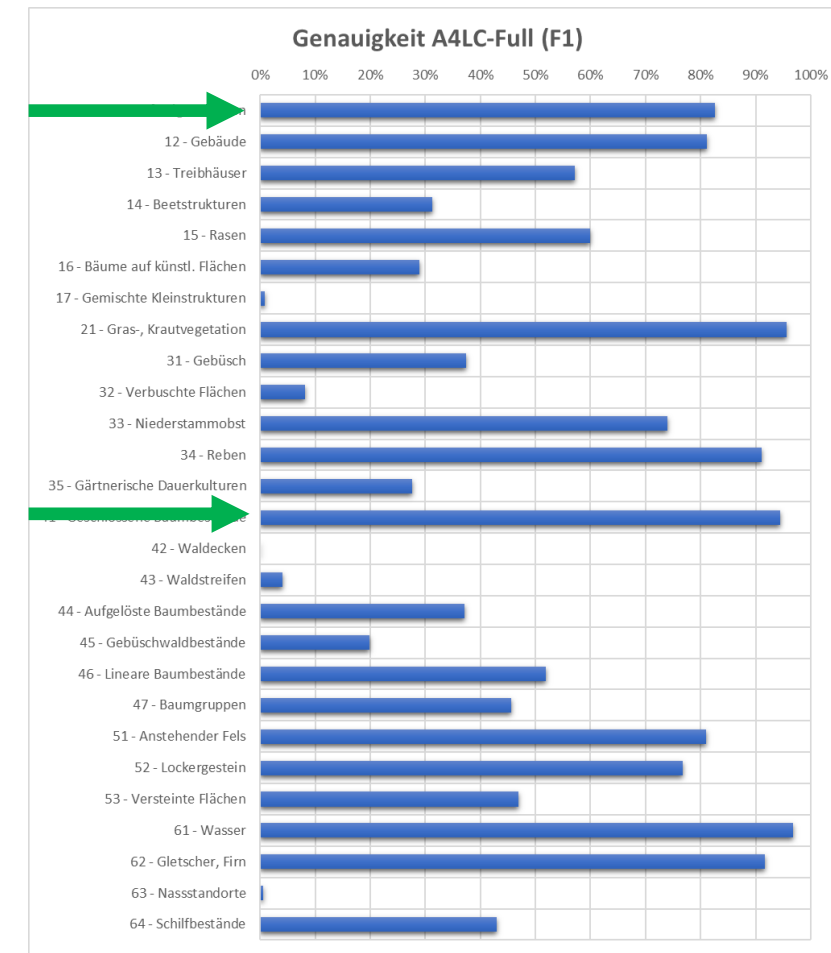
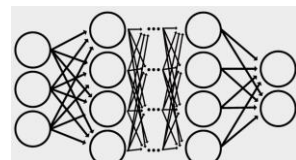


befestigte Fläche

Wald

- RGB und FCIR Orthofotos
- Satellitenbilder (Zeitreihen)
- Höhenmodelle, amtliche Daten

Deep Learning



## Deep Learning – Was ist die Grundidee?

### Neuronale Signalprozessierung des Gehirns



### Neuron und Aktionspotenzial

**Dendritenbaum**

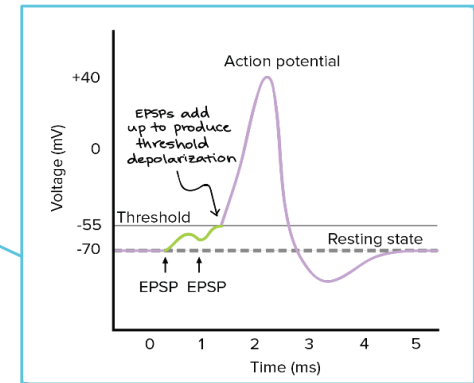
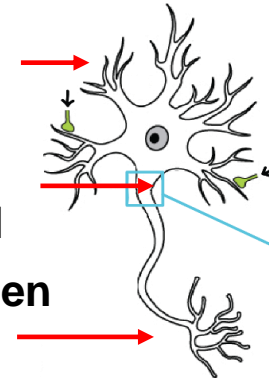
→ Input (Reize)

**Soma, Axonhügel**

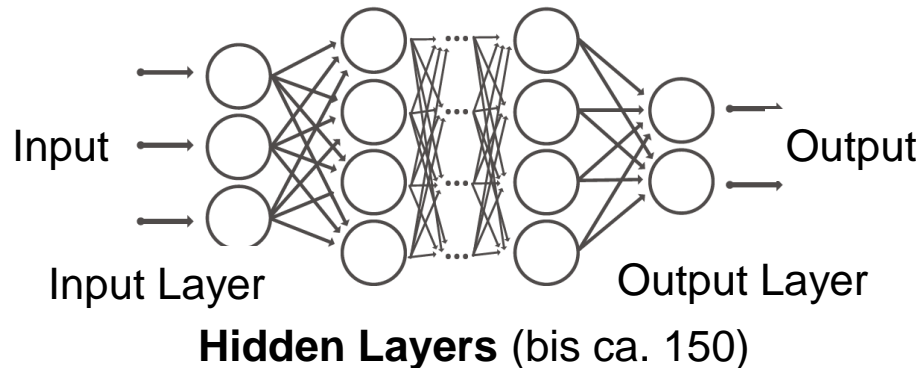
→ Aktionspotenzial

**Axon und Synapsen**

→ Schnittstellen



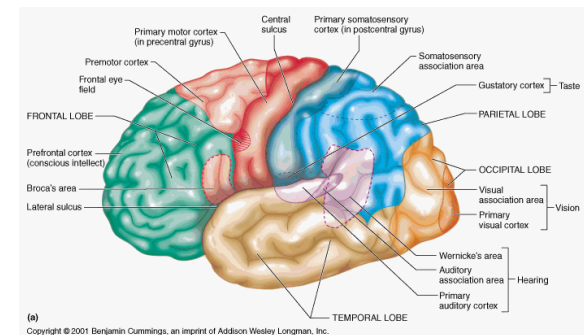
### Deep Neural Network (DNN)



### Funktionelle Einheiten des Kortex

Layer ↔

kortikale Schichten



höhere Schichten



niedrigere Schichten

## Deep Learning – Was ist die Grundidee?

### Neuronale Signalprozessierung des Gehirns



### Neuron und Aktionspotenzial

**Dendritenbaum**

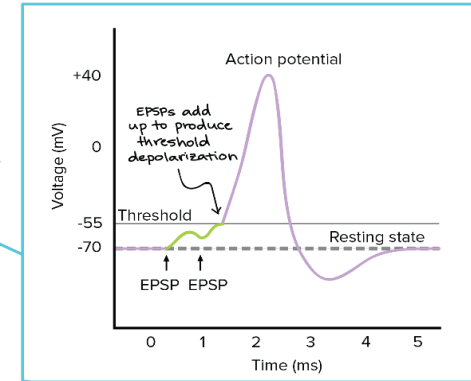
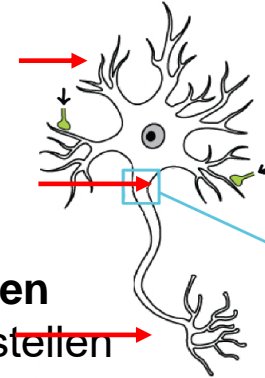
→ Input (Reize)

**Soma, Axonhügel**

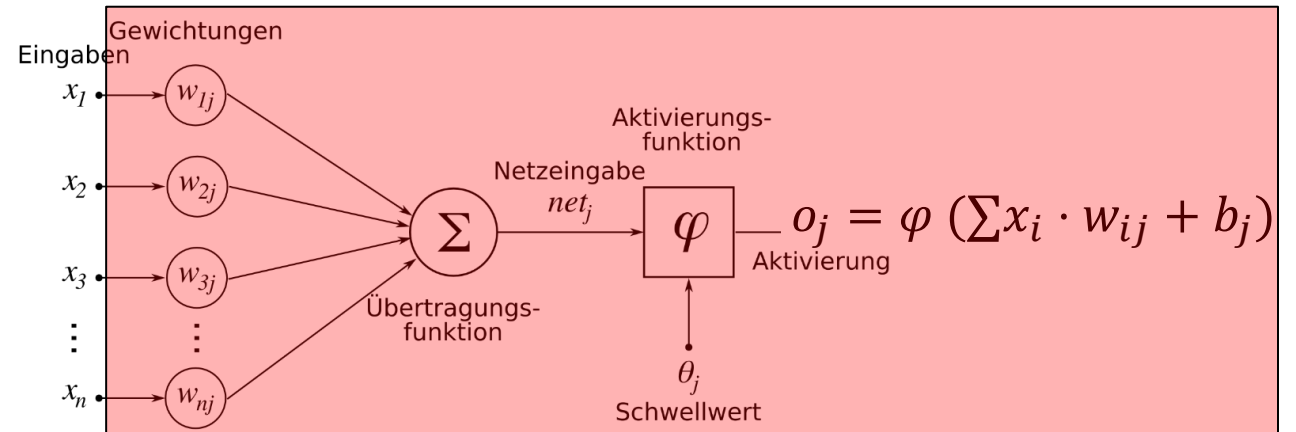
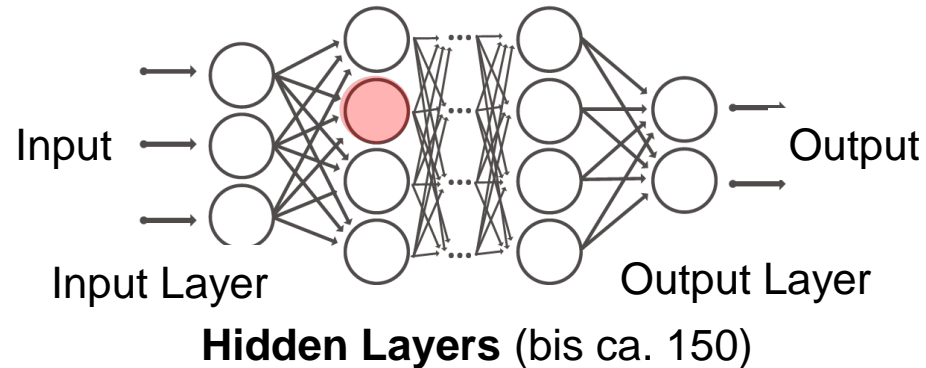
→ Aktionspotenzial

**Axon und Synapsen**

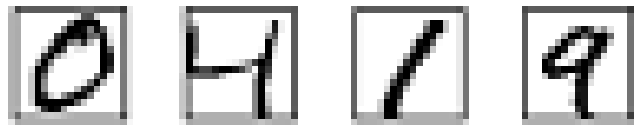
→ Leitung, Schnittstellen



### Deep Neural Network (DNN)

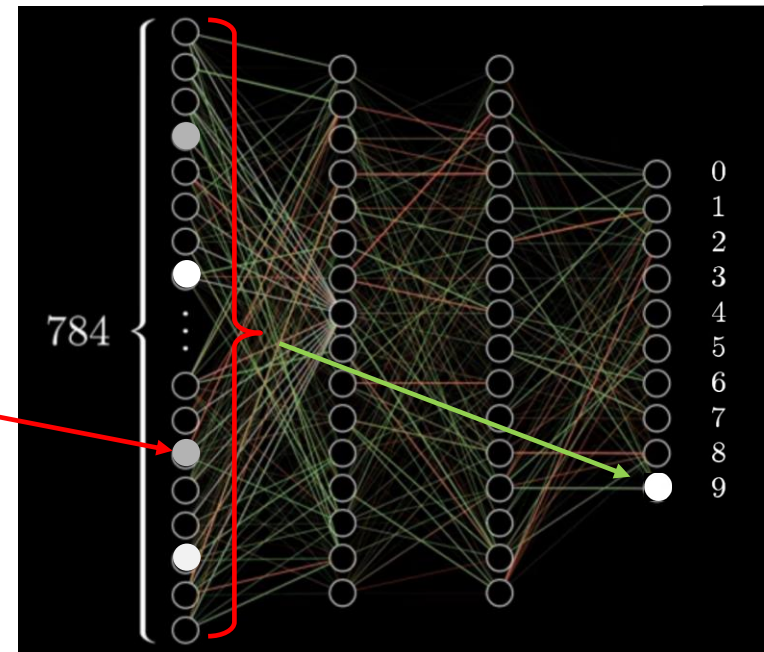
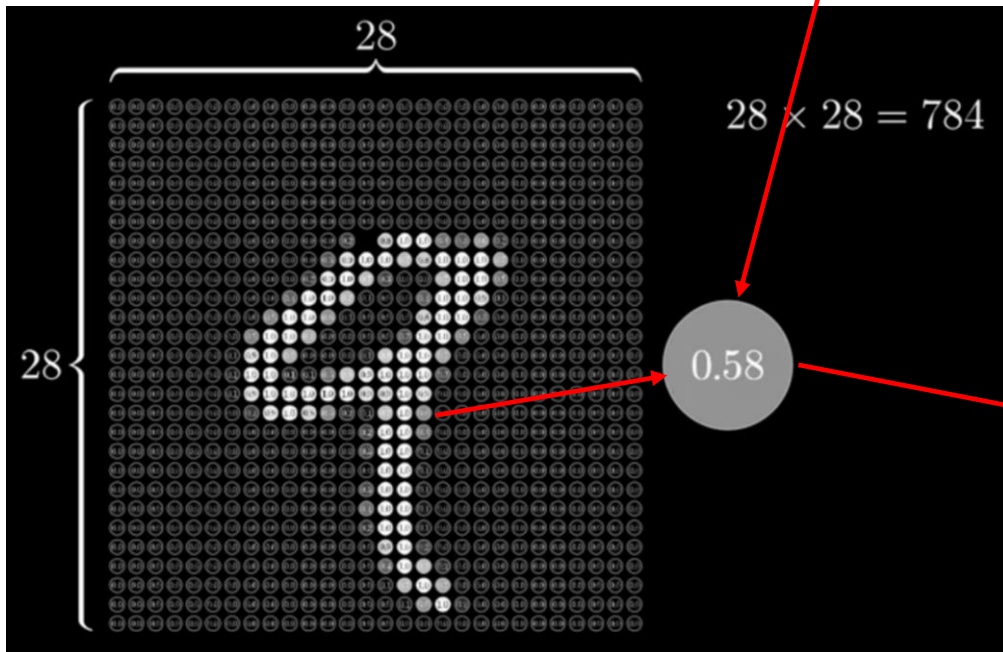
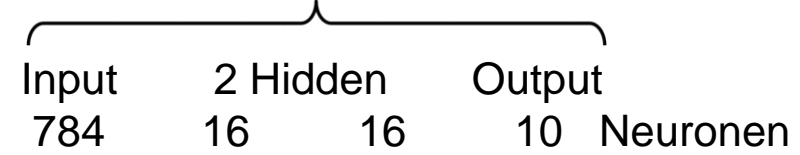


## Deep Learning – Wie wird gelernt?



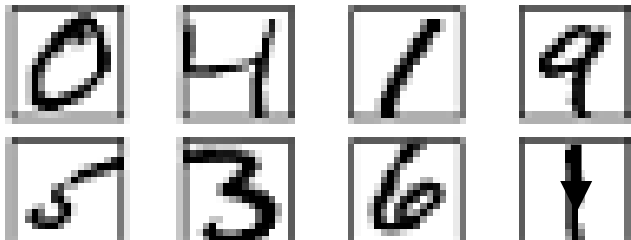
Wert eines der 784 Neuronen

Layers

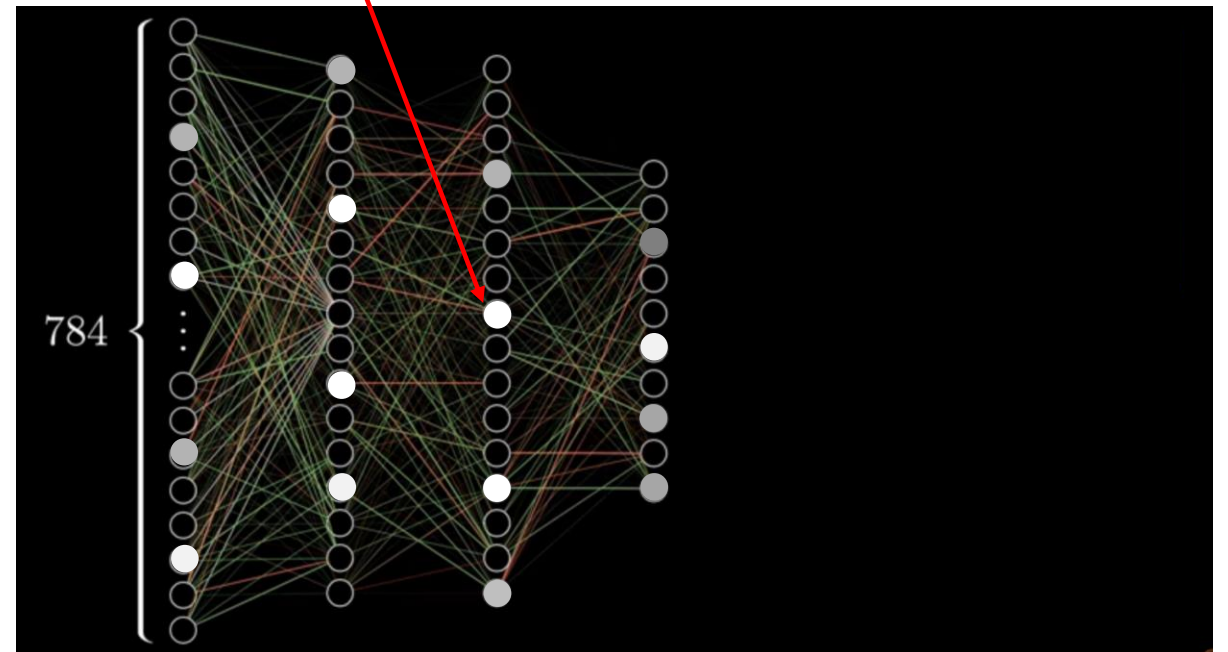
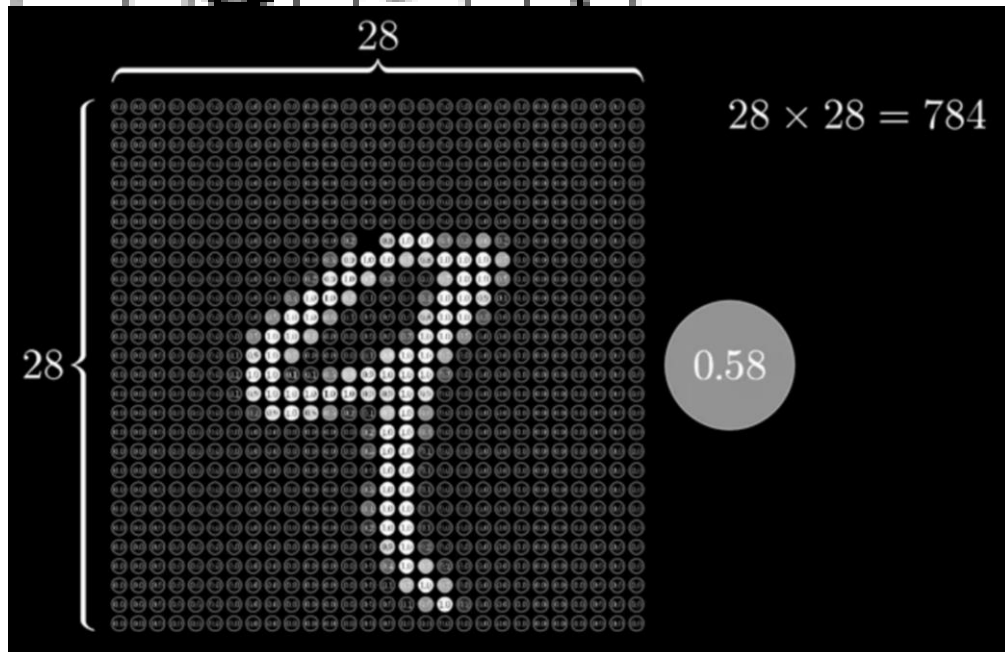




## Deep Learning – Wie wird gelernt?



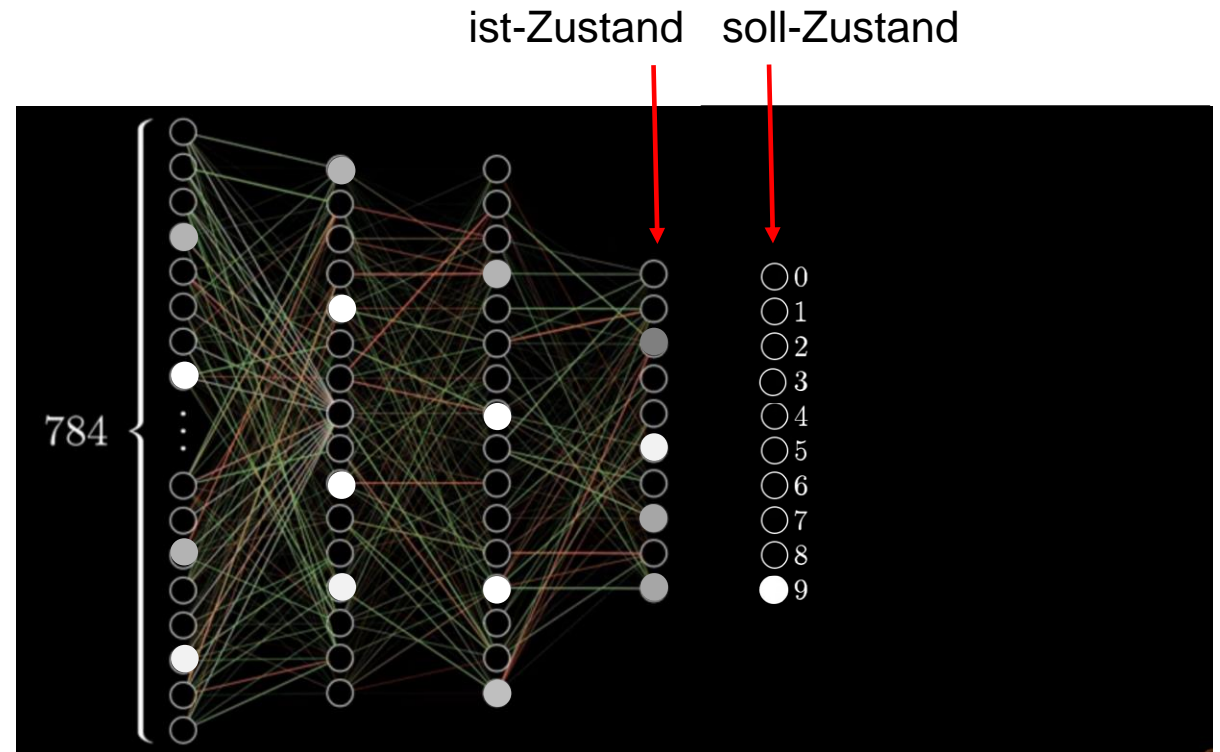
→ **Optimierungsstrategie erforderlich:** alle  $w_{ij}, b_j$  in  
$$o_j = \varphi (\sum x_i \cdot w_{ij} + b_j)$$
 optimal festlegen



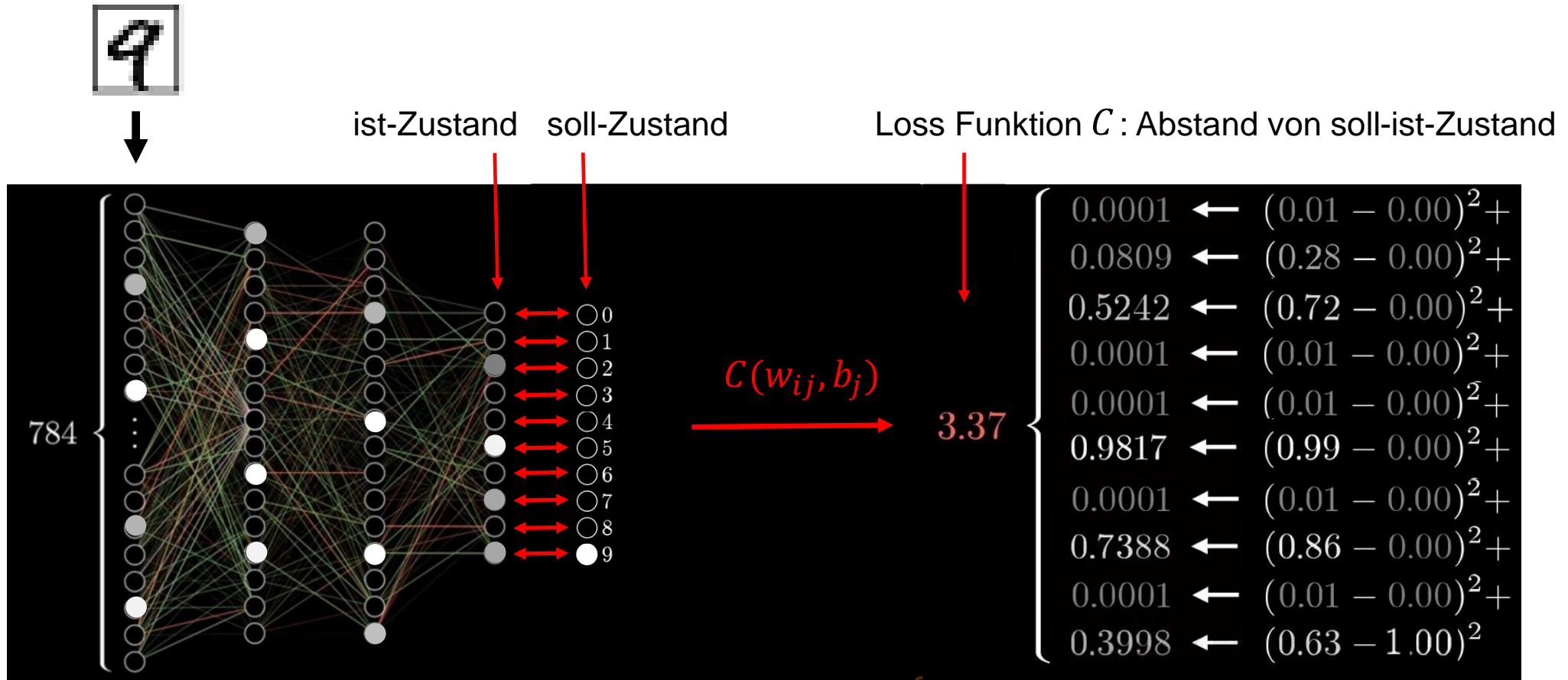
## Deep Learning – Wie wird gelernt?



→ Optimierungsstrategie: iterativer Trainingsprozess

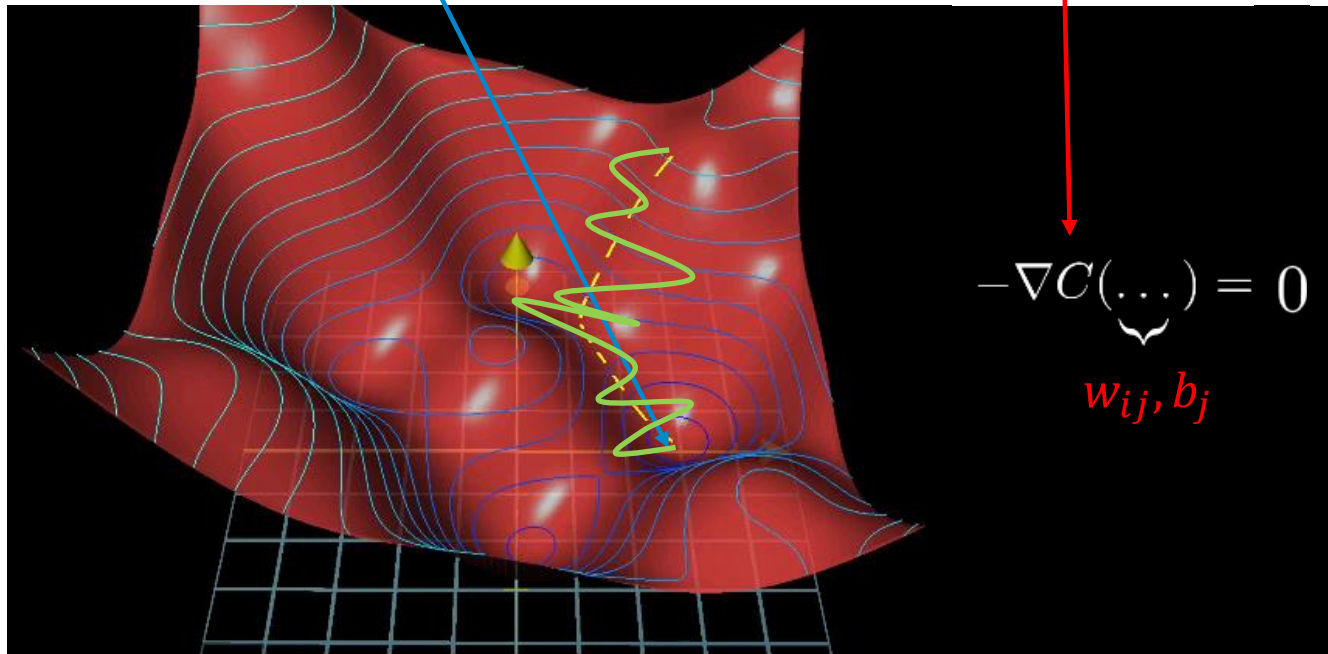


## Deep Learning – Wie wird gelernt?



## Deep Learning – Wie wird gelernt?

Minimum der **Loss-Funktion**  $C(w_{ij}, b_j)$  → Gradient zeigt schnellsten Weg zum Minimum



Lernen ist rechenintensiv

- **Gradient Descent** mit
- **Backpropagation** und
  - **Mini-Batches**
  - in jedem Iterationsschritt:  
Satz besserer Modellparameter

Achtung **Overfitting**

→ **Training** und **Validierung**

**DNN's** sind universelle **Funktionen**

→ erledigen jede Aufgabe, die ein Automat kann (Turing complete)

→ haben **keine Intelligenz**

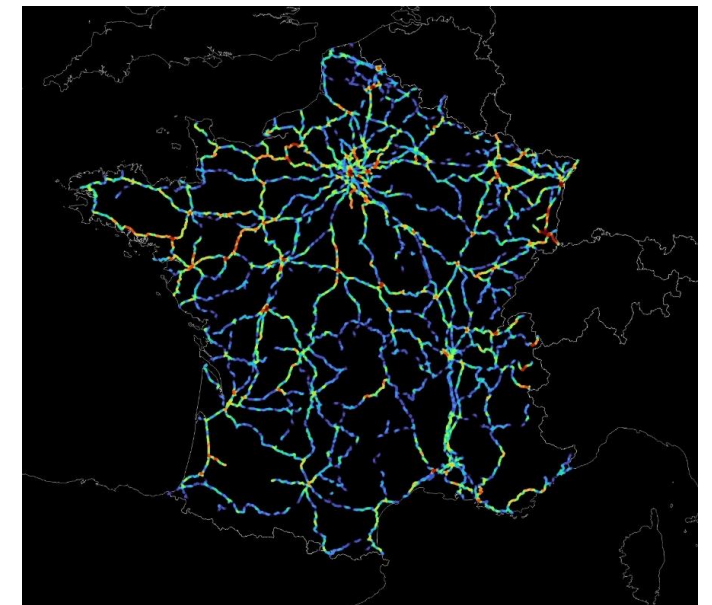
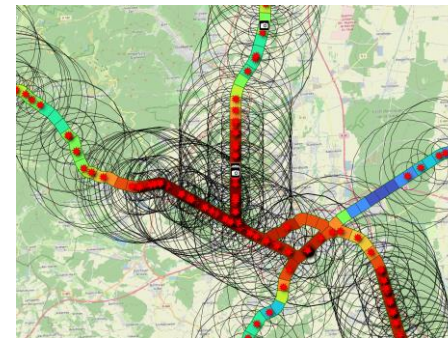
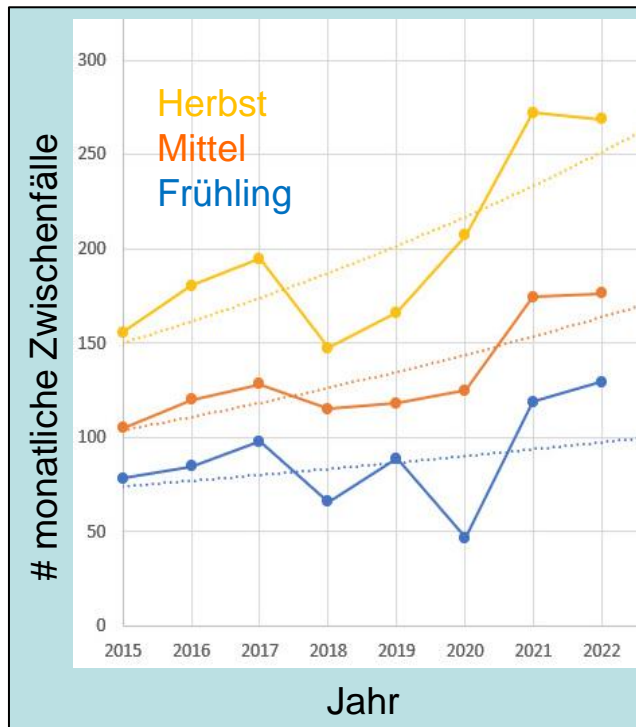
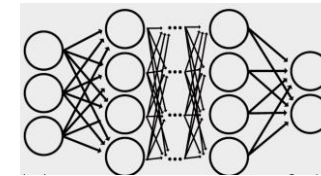
## Deep Learning IGEO – Wildtier Habitatsmodelle SNCF



- Kamerafallen
- Satellitenbilder (Zeitreihen)
- Klimadaten, Jagd, ...



DNN



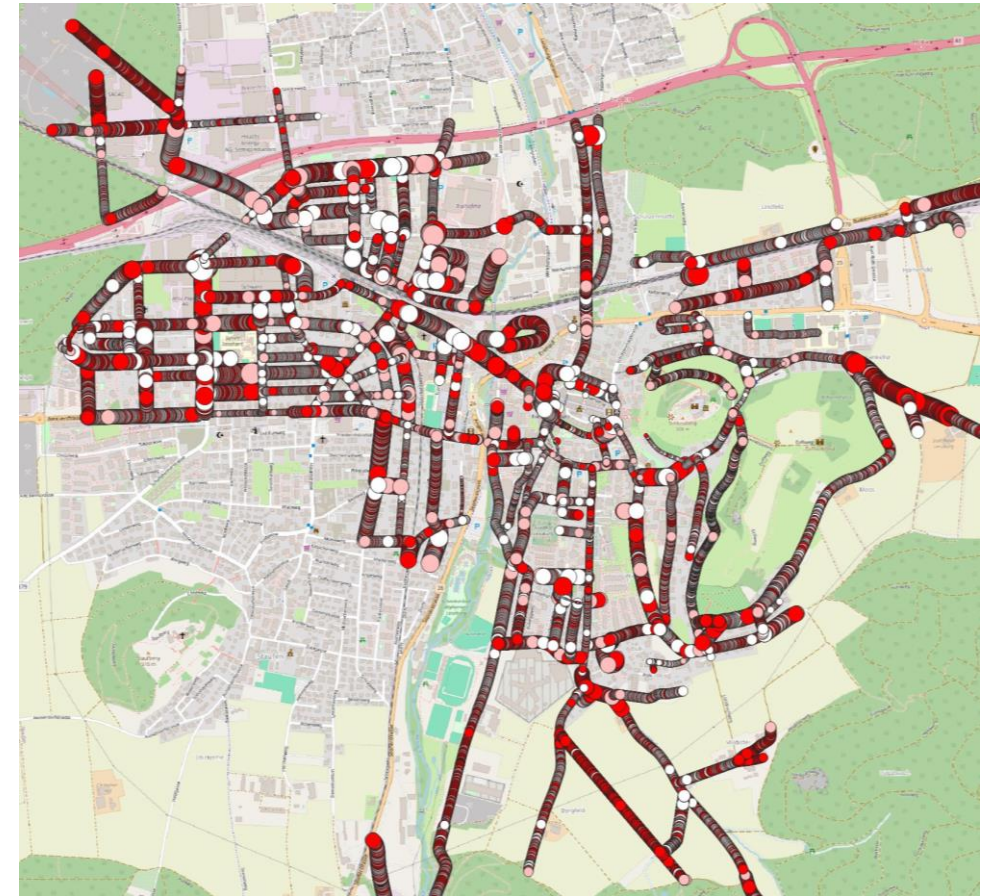
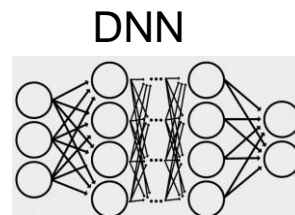
Adrian Meyer (MSc Biologie und Geoinformatik, Doktorand)

Prof. Dr. Denis Jordan

## Deep Learning am IGEO – Strassenzustandsbeurteilung kommunaler Strassen



- hochauflösende Mobile Mapping Bilder (iNovitas)
- Referenzdaten (WIF)



Prof. Dr. Stephan Nebiker

Elia Ferrari (MSc Geomatik, wiss. Mitarbeiter)

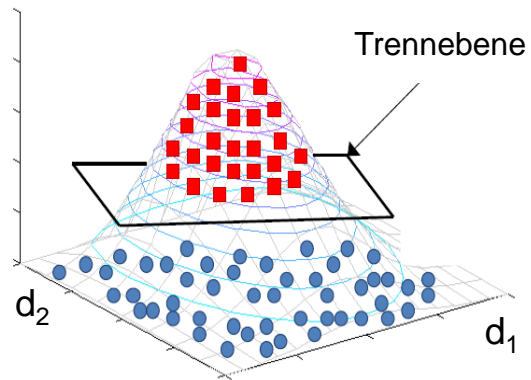
Jonas Meyer (MSc Geomatik, wiss. Mitarbeiter)

Prof. Dr. Denis Jordan

## Deep Learning am IGEO – in der Lehre

### Modul im Bachelor-Studiengang

- Methoden
- Programmierung
- Anwendung Geosciences
- Geschichte
- Ethik und Recht



```

from keras.layers import Dense
fc = Dense(3)(inputs)

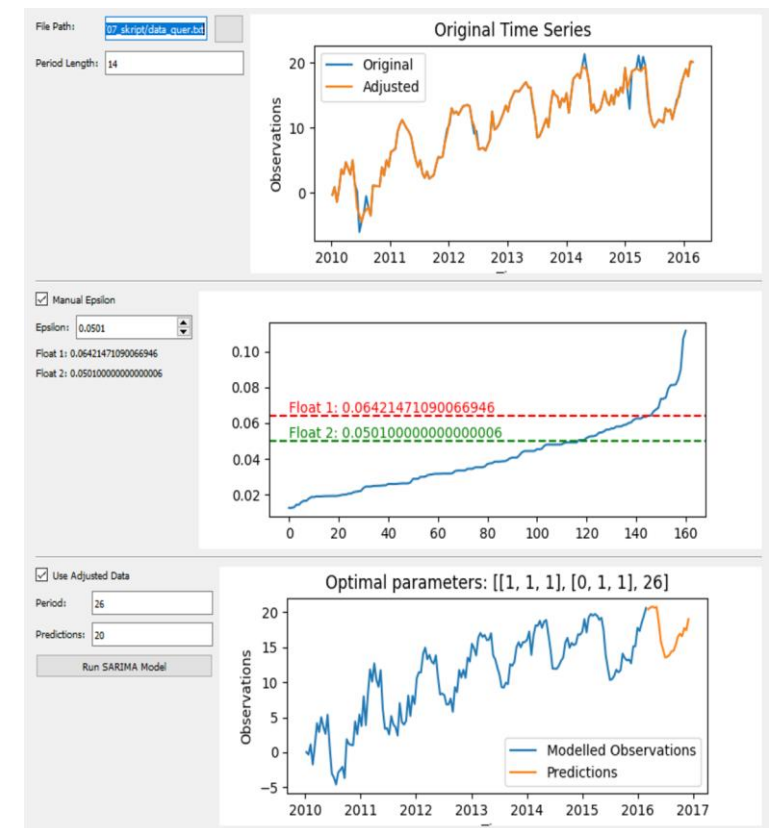
from keras.models import Model
predictions = Dense(3, activation='softmax')(fc)
classifier = Model(inputs=inputs, outputs=predictions)

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

```

### Studierendenarbeiten im Bachelor- und Masterstudiengang

- Bachelorthesen
  - Masterprojekte
  - Masterthesen
- mit forschungs- und praxisorientierten Problemstellungen

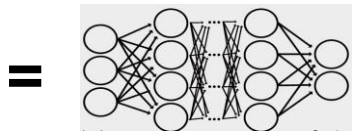


# Künstliche Intelligenz – Förderung oder Überforderung?

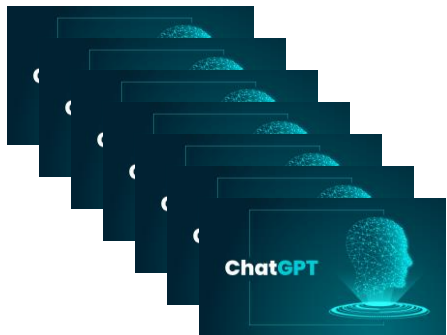
## künstliche Intelligenz



- emotionslos-simpel
- inhaltlicher bullshit?
- fordernd
- ggf. **fördernd**



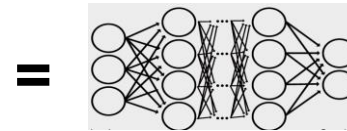
heute **176(?) Milliarden** Neuronen (ChatGPT 3)



## menschliche Intelligenz (exemplarisch)



- emotional
- individuell
- komplex
- ggf. **überfordernd**
- **viel spannender**



mit je **100 Milliarden** Neuronen

