

# Using AI in Everyday Life at the University

Benno Stein    Johannes Kiesel    Marcel Gohsen

Forschungsgruppe Intelligente Informationssysteme [webis.de]

Bauhaus-Universität  
Weimar

- ① What is Intelligence?
- ② History of Artificial Intelligence (AI)
- ③ AI Research at the Webis Group
- ④ AI Tools for Administrative Tasks
- ⑤ AI Tools for other Tasks
- ⑥ Risks of AI Usage



What is Intelligence?

# What is Intelligence?

Recognizing Regularities

2, 4, 8, 16, ?

# What is Intelligence?

## Recognizing Regularities

2, 4, 8, 16, ?

2, 8, 26, 80, ?

# What is Intelligence?

## Recognizing Regularities

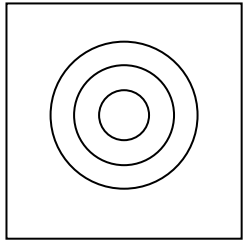
2, 4, 8, 16, ?

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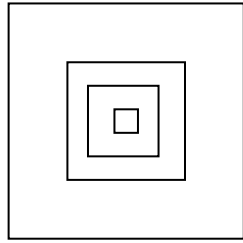
2, 3, 5, 7, 11, ?

# What is Intelligence?

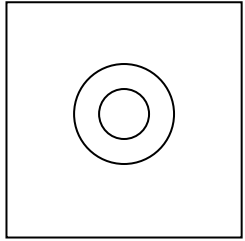
## Recognizing Analogies



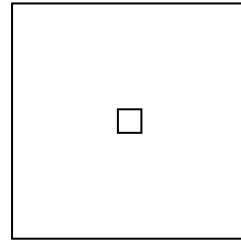
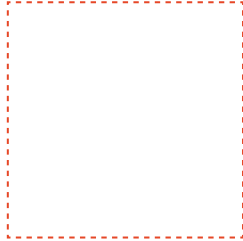
A



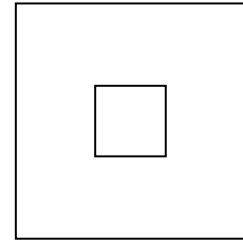
C



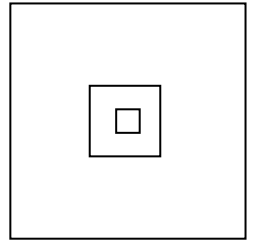
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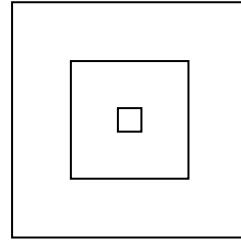
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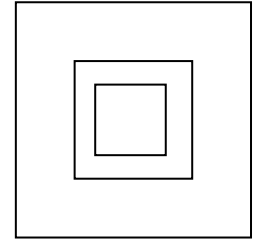
2



3



4



5

Given: Boxes A and B

Task: From the boxes 1 to 5, select the one that relates to C in the same way as B relates to A.

# What is Intelligence?

Certain human activities require intelligence (regardless of the definition of the term), e.g.,

- ❑ planning a combined train-bus journey
- ❑ proving mathematical theorems
- ❑ seeing and recognizing objects
- ❑ creating medical diagnoses
- ❑ arguing in a discussion



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- ❑ planning a combined train-bus journey
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*"**Artificial** Intelligence is the science  
of making machines do things  
that would require intelligence if done by men."*

[Marvin Minsky 1966]



Marvin Minsky (1927 - 2016)

# What is Intelligence?



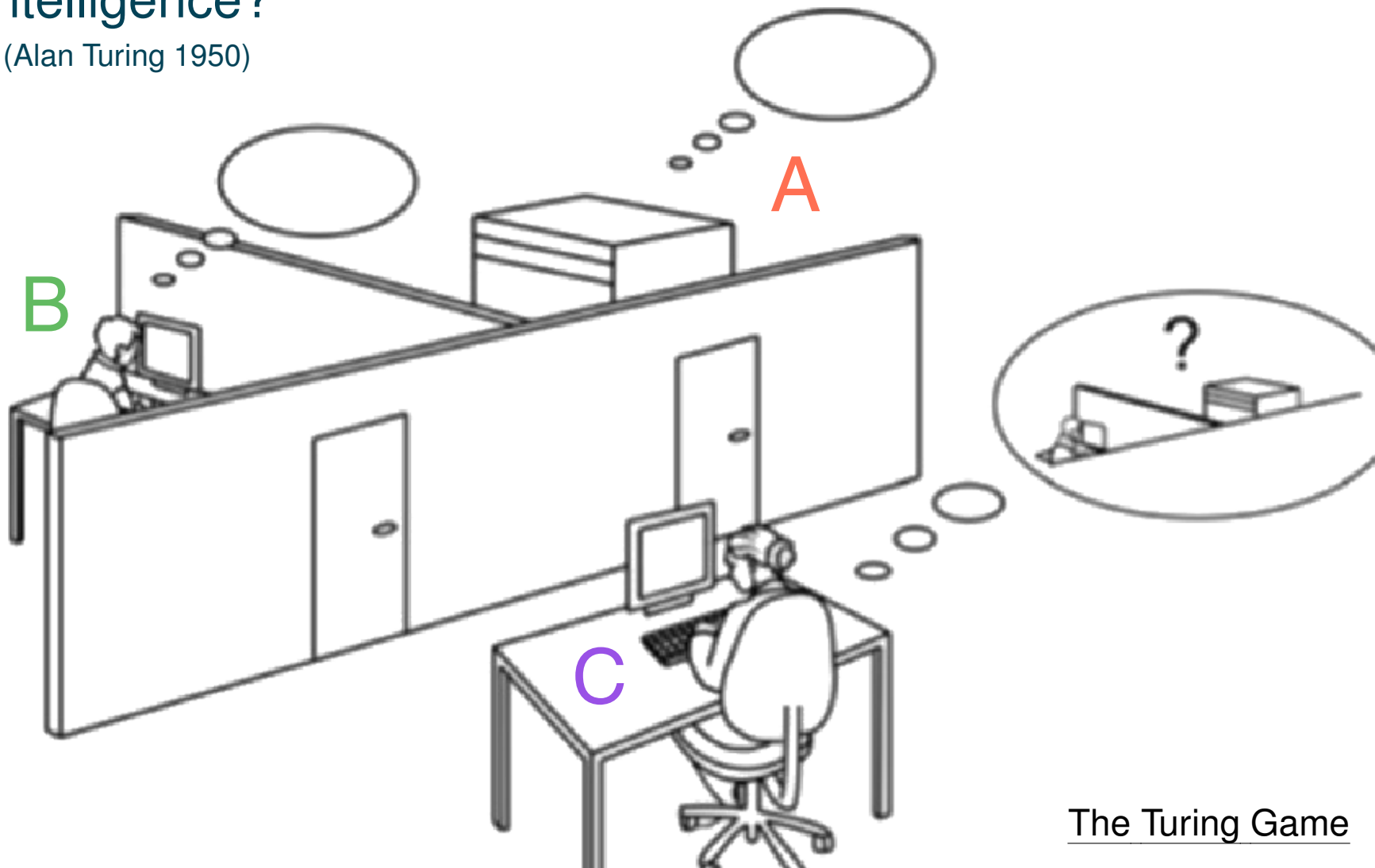
Alan Turing (1912 - 1954)

“Computing Machinery and Intelligence” is a seminal paper written by Alan Turing on the topic of artificial intelligence. The paper, published in 1950 in the MIND journal, was the first to introduce his concept of what is now known as the Turing test to the general public.

→ [a movie tip](#)

# What is Intelligence?

The Turing Test (Alan Turing 1950)



The Turing Game

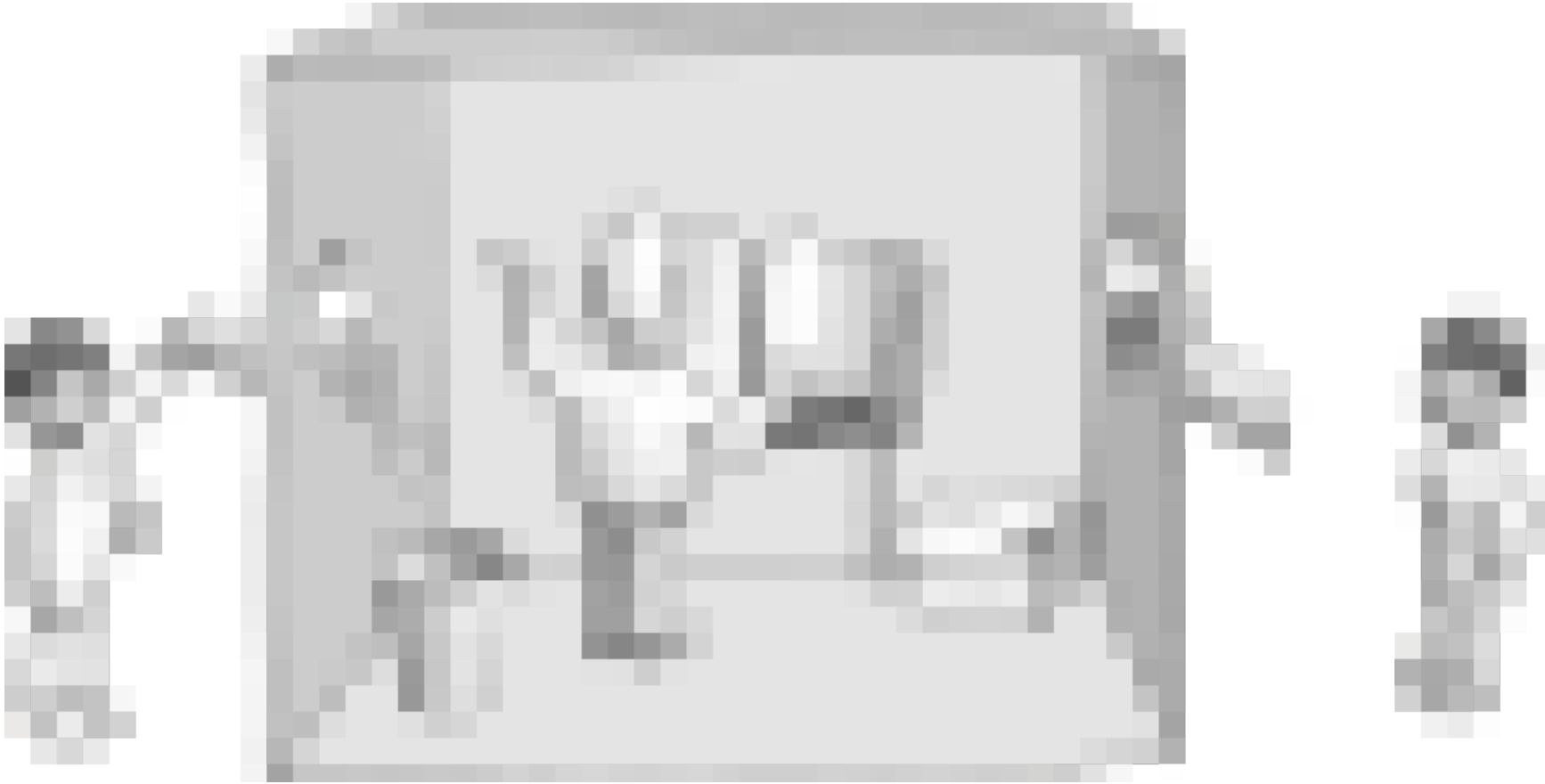
# What is Intelligence?

The Chinese Room (John Searle 1980)



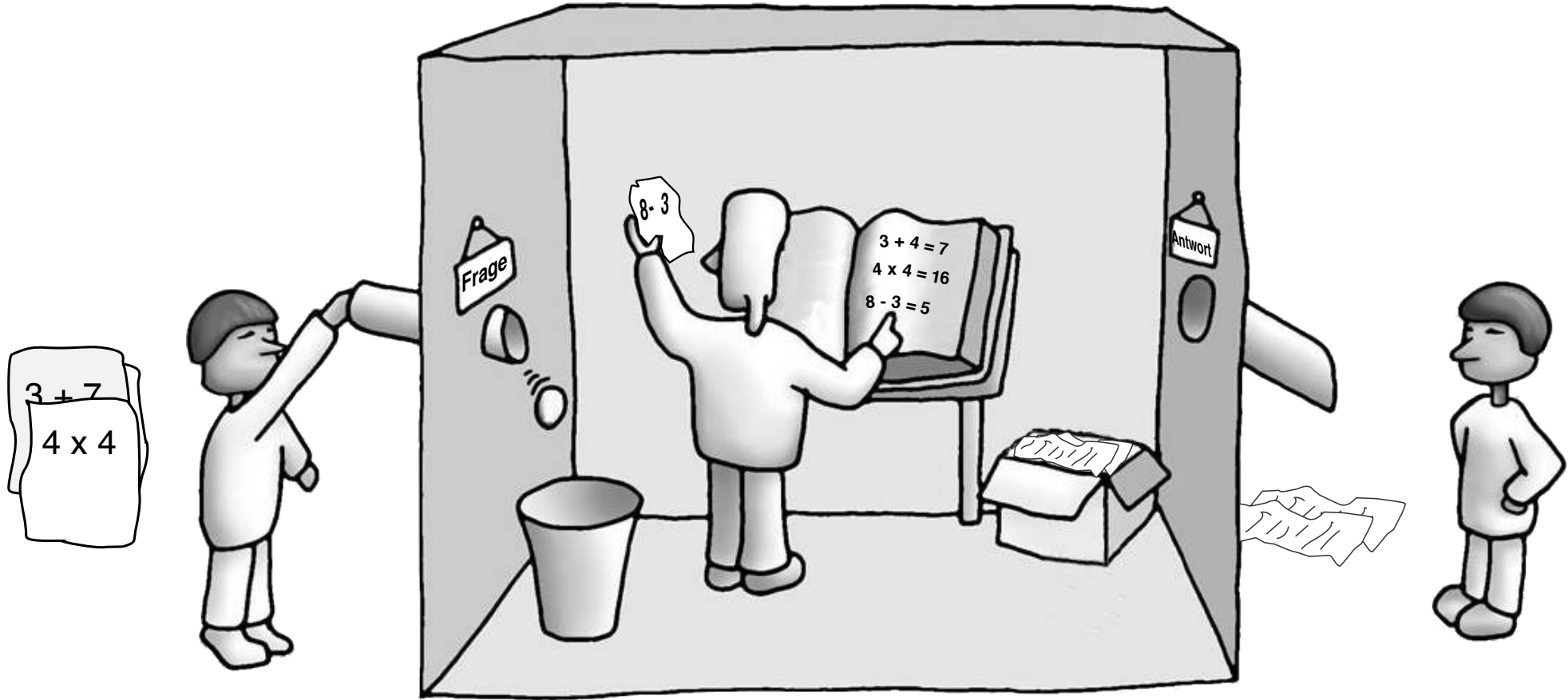
# What is Intelligence?

The Chinese Room (John Searle 1980)



# What is Intelligence?

The Chinese Room (John Searle 1980)



# What is Intelligence?

## The Two (Main) Views on Artificial Intelligence

### 1. Weak AI.

A computer (plus program) is capable of performing a specific task that it is designed to do.

A computer (plus program) is only an instrument for investigating cognitive processes.

### 2. Strong AI.

The “correctly” programmed processes in the computer *are mental processes*.

Computers that are equipped with the “correct” programs can be said to have understanding.

Weak AI = a computer simulates intelligence

Strong AI = a computer is intelligent



# History of Artificial Intelligence

Trends and Periods between 1956 and 1990



# History of Artificial Intelligence

Hour of Birth

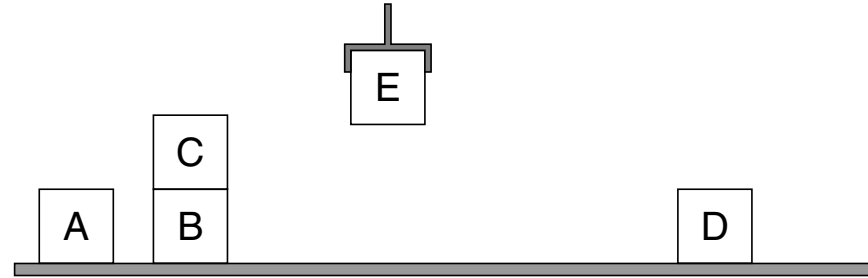
1956 Summer seminar in Dartmouth.

Founded by Marvin Minsky, John McCarthy, Allen Newell, Herbert A. Simon, and others:



# History of Artificial Intelligence Classic Period

1956 Search for *general* principles to solve *arbitrary* problems. Applying the principles to simple  
1965 problems (Blocks World among others).



General Problem Solver, GPS, by Newell, Shaw, and Simon.  
(some success, but could not be generalized; development discontinued).

Findings:

- guided traversal of the search space as a form of problem solving
- efficient search requires powerful heuristics
- general problem solving is too difficult

# History of Artificial Intelligence

## Romantic Period

1965 Specialized programs. Concentration on basic methods and techniques:

- 1975
- problem description and formalization
  - knowledge representation
  - search strategies

### Findings:

- some progress, but no breakthrough; no results that can be used in practice
- general-purpose → multi-purpose

# History of Artificial Intelligence

## Modern Period

>1975 Recognizing the importance of **problem-specific** knowledge. Problem-solving ability depends more on specific knowledge than on the general problem-solving strategy.

Addressing practical problems, interviewing experts, developing expert systems.

Famous application: MYCIN (1976)

- supporting doctors in the diagnosis of bacterial infections
- MYCIN simulates the ability of an expert in a narrow area, whereby the expert's knowledge must be available in a formalized form.

Findings:

- *“In the knowledge lies the power.”* [Davis 1982]
- methods for knowledge acquisition and representation are essential
- multi-purpose → special-purpose

# History of Artificial Intelligence

>1985 Development of direct and inductive knowledge acquisition components to overcome the “knowledge engineering bottleneck”.

Temporal logic, non-monotonic and uncertain reasoning, fuzzy logic, natural-analog search methods (neural networks, genetic algorithms, simulated annealing)

Insight:

- expert systems are not a panacea

# History of Artificial Intelligence

- >1985 Development of direct and inductive knowledge acquisition components to overcome the “knowledge engineering bottleneck”.

Temporal logic, non-monotonic and uncertain reasoning, fuzzy logic, natural-analog search methods (neural networks, genetic algorithms, simulated annealing)

Insight:

- expert systems are not a panacea

- >1990 Distributed AI systems, multi-agent systems.

Specialization of methods for specific applications.

Extension of natural analogue search methods with problem-specific components: knowledge-intensive search and optimization techniques.

Insight (again):

- in the knowledge lies the power



# History of Artificial Intelligence (continued)

Language Models

*“You shall know a word by the company it keeps.”*

[John Rupert Firth, 1957]



*“You shall **know a word** by the company it keeps.”*

[John Rupert Firth, 1957]

We **interpret words** (give them meaning) through their context.

Example:

(a) I saw a **jaguar** in the zoo.

(b) The **jaguar** won the formula 1 race.



A statistical language model  
is a probability distribution over all possible texts.



1950 1960 1970 1980 1990 1995 2000 2002 2004 2006 2008 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024 2025 2026

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(1) i love my ?       

(2) see ... works.       

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Word prediction means *probability maximization*:

$p(\text{i love my cat}) > p(\text{i love my car}) > p(\text{i love my family})$

A statistical language model  
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(1) i love my ? N N

(2) see ... works. N N

Word prediction means *probability maximization*:

$p(\text{i love my cat}) > p(\text{i love my car}) > p(\text{i love my family})$ , where

$p(\text{i love my cat}) = p(\text{i}) \cdot p(\text{love} | \text{i}) \cdot p(\text{my} | \text{i love}) \cdot p(\text{cat} | \underbrace{\text{i love my}}_{\text{order of the LM}})$



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A statistical language model  
is a probability distribution over all possible texts.

(1) i love my ?       

(2) see ... works.       

Sentence translation means *probability maximization*:

$p(\text{ich liebe meine katze} \mid \text{i love my cat}) >$

$p(\text{ich jage meine katze} \mid \text{i love my cat}) >$

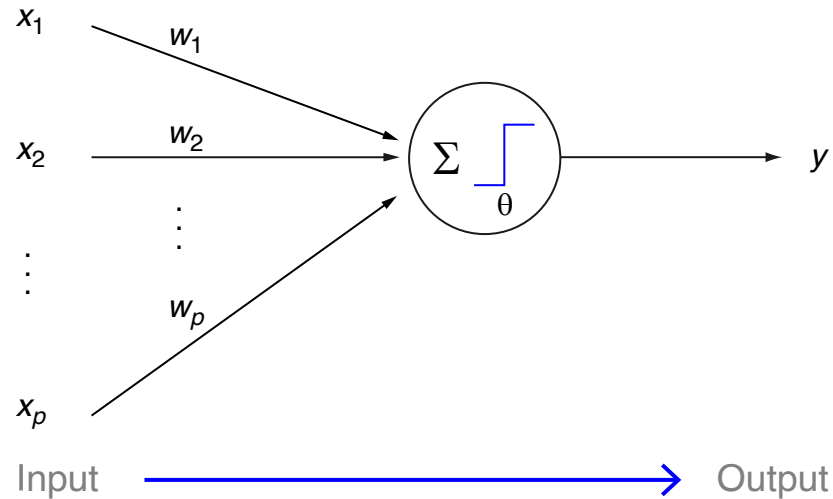
$p(\text{ich habe keine katze} \mid \text{i love my cat})$

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Neural machine translation

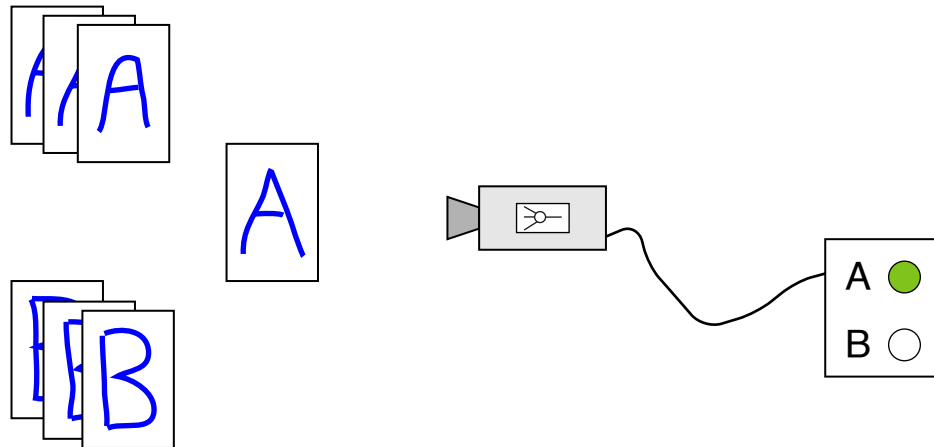
A neural language model  
tackles the probability maximization via loss minimization.

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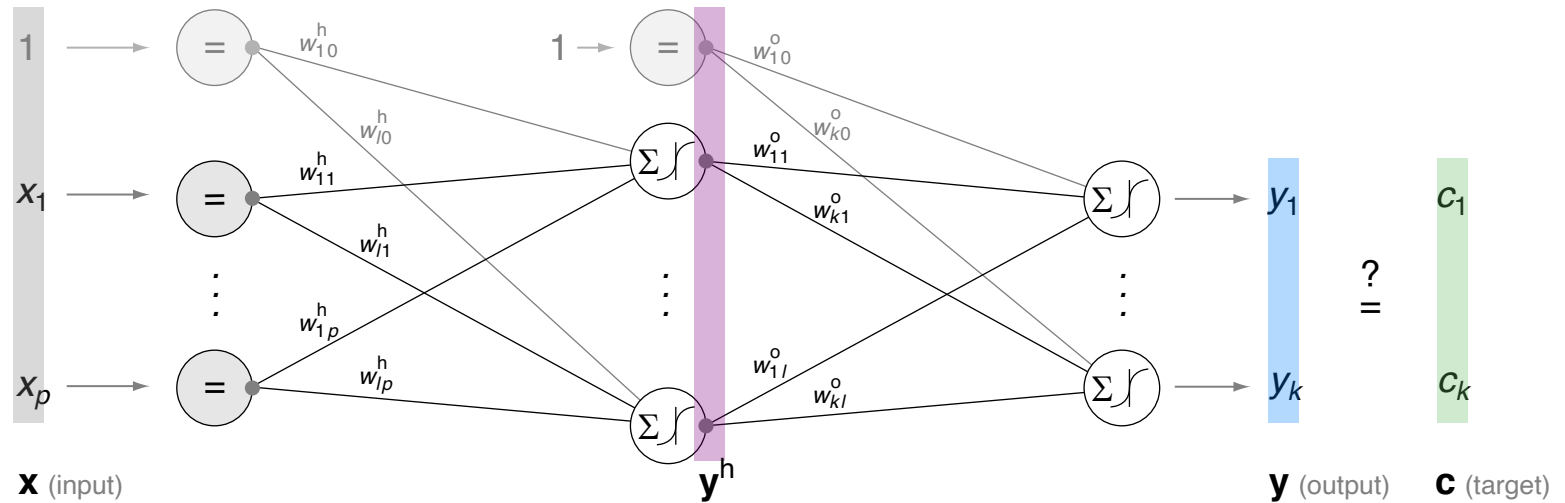
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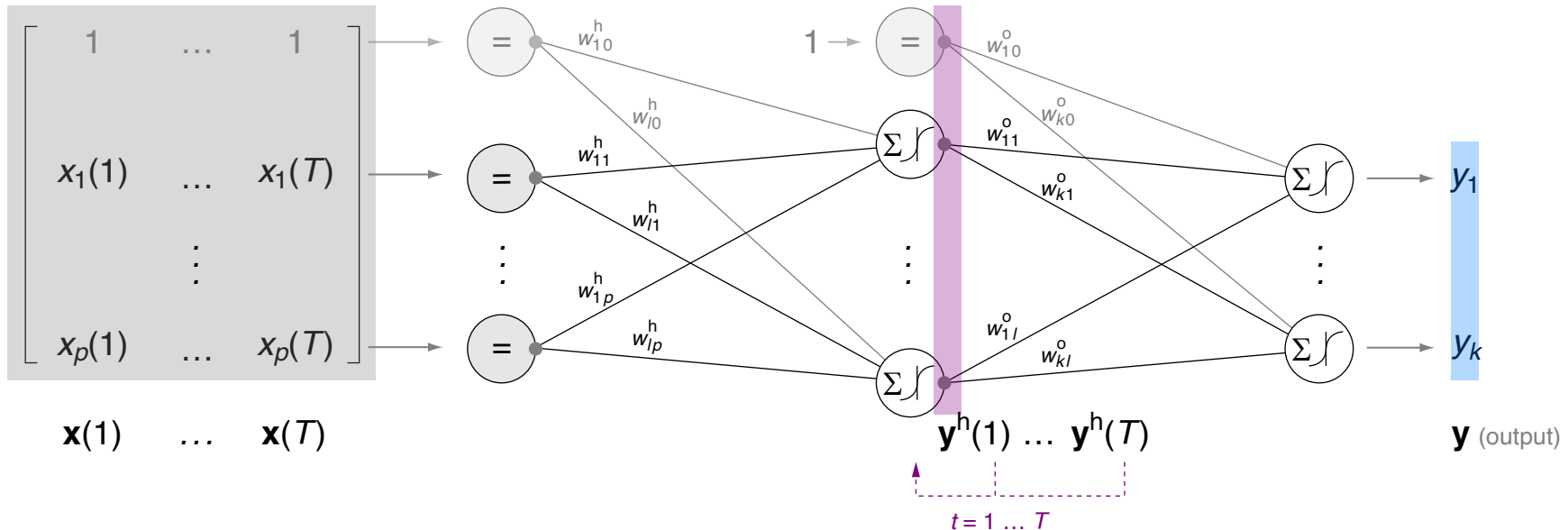
Multilayer Perceptron with backpropagation (Werbos 1982, Rumelhart 1982)  
 Backpropagation with automatic differentiation (Linnainmaa 1970)

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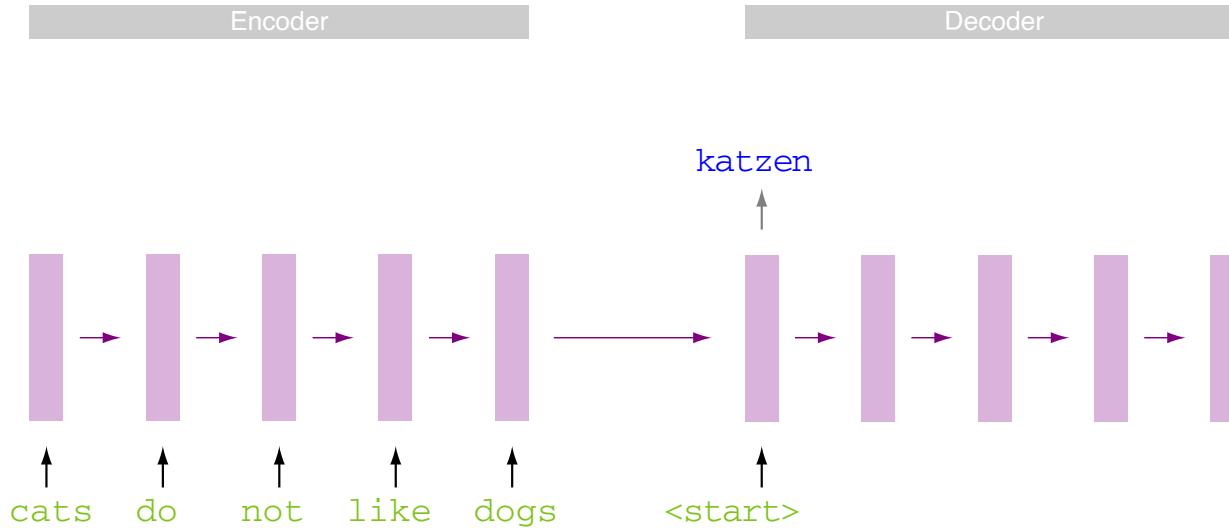
A neural language model  
 tackles the probability maximization via loss minimization.



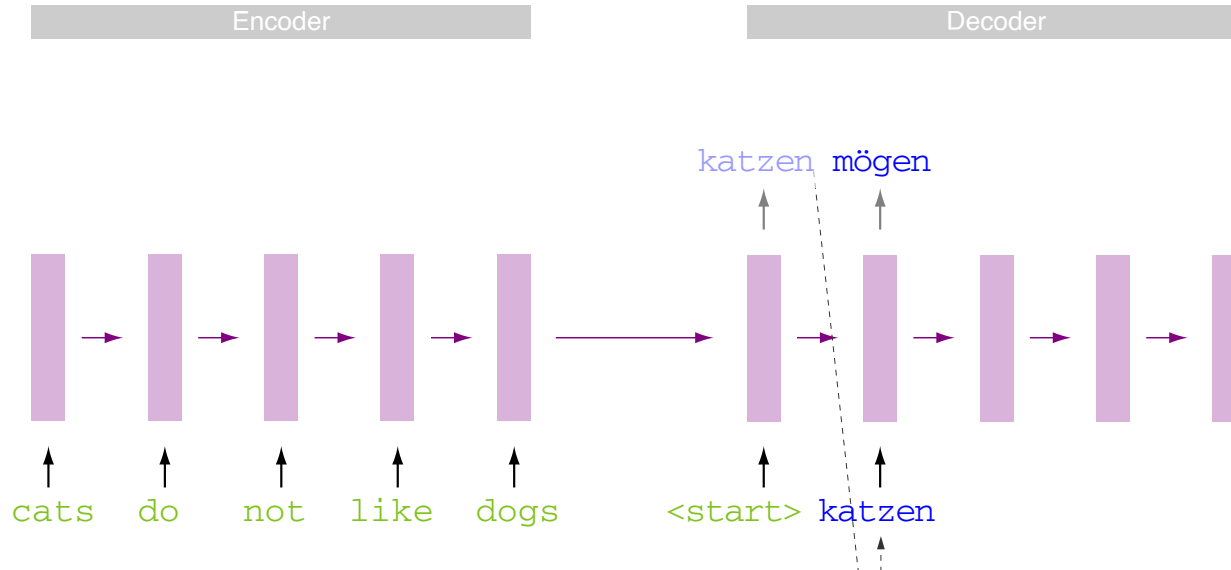
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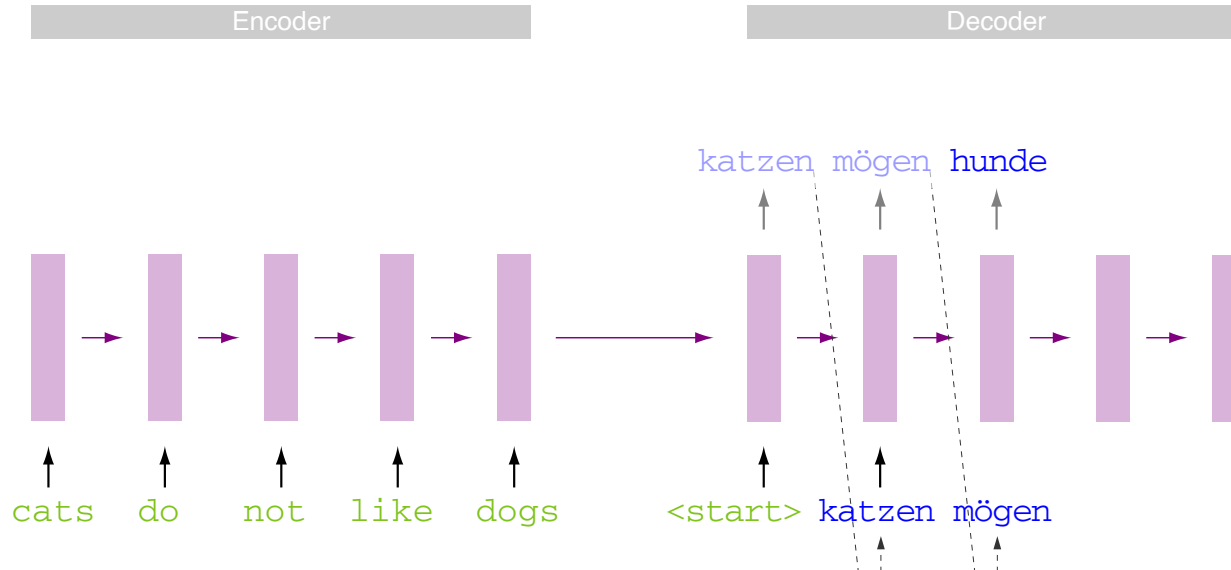
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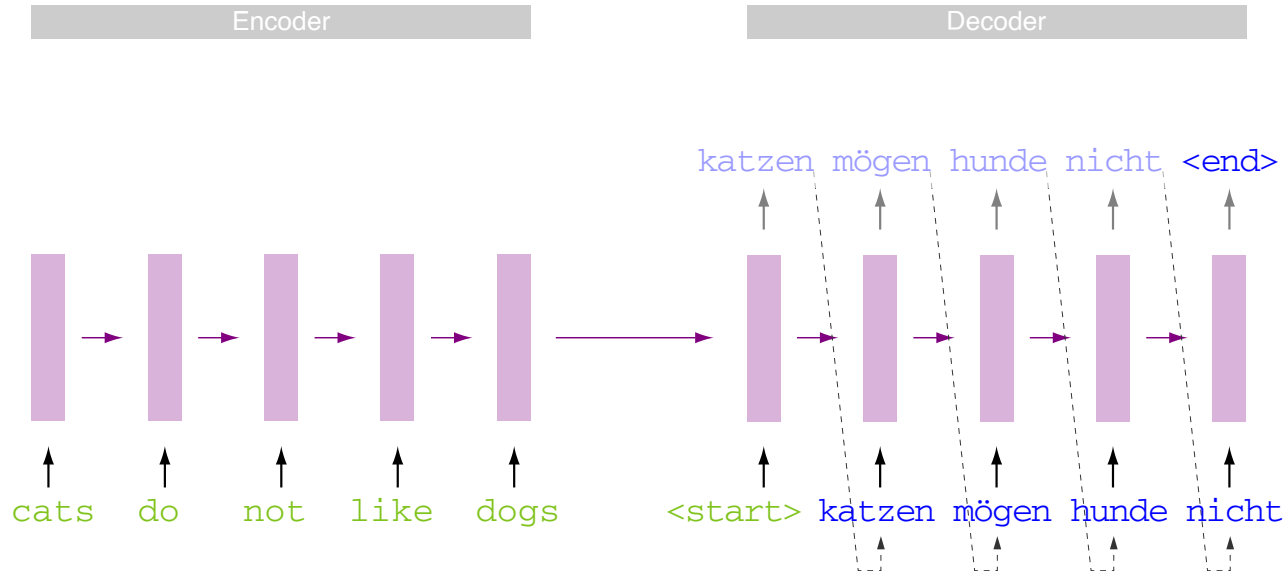
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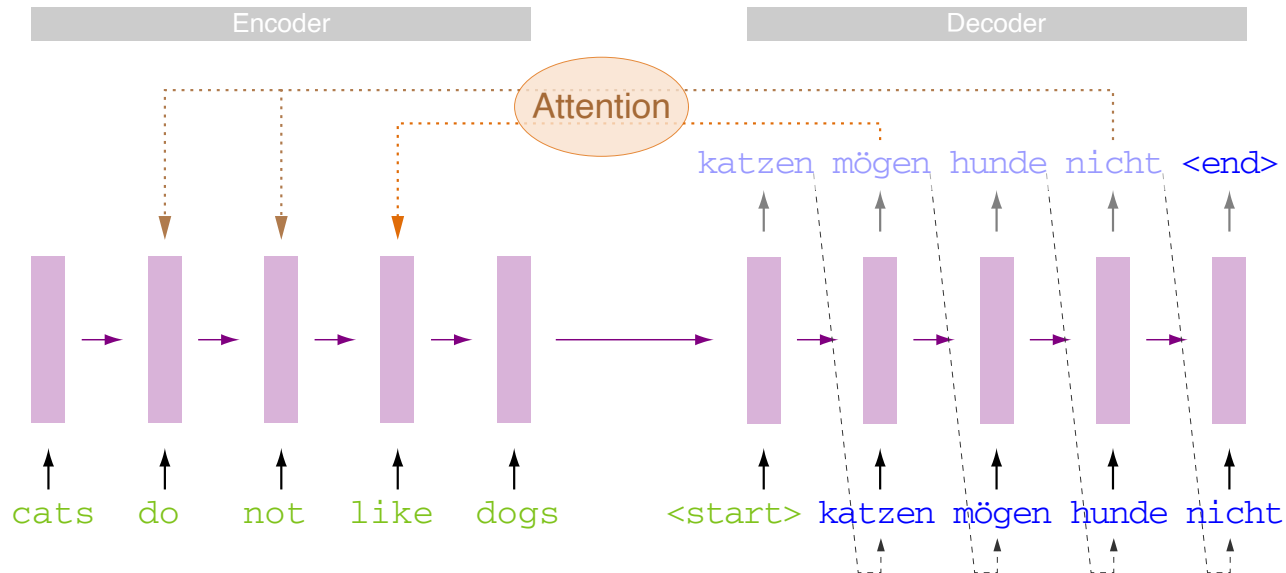
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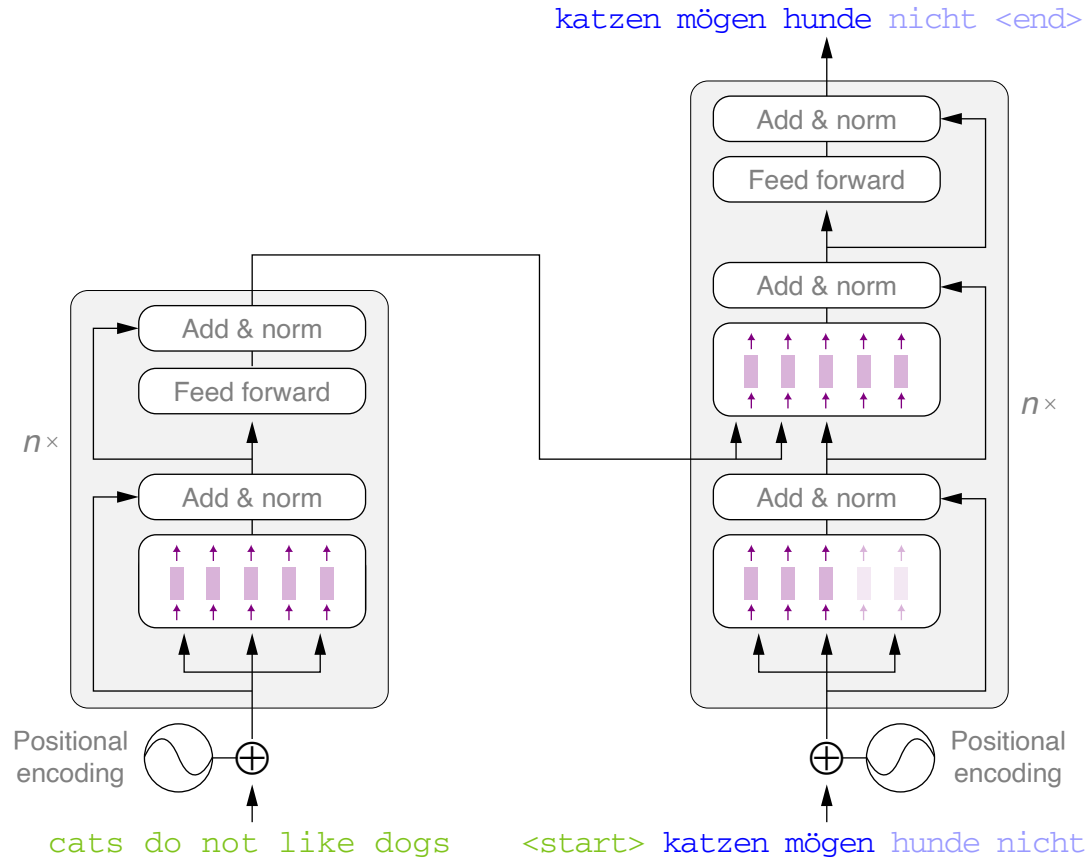


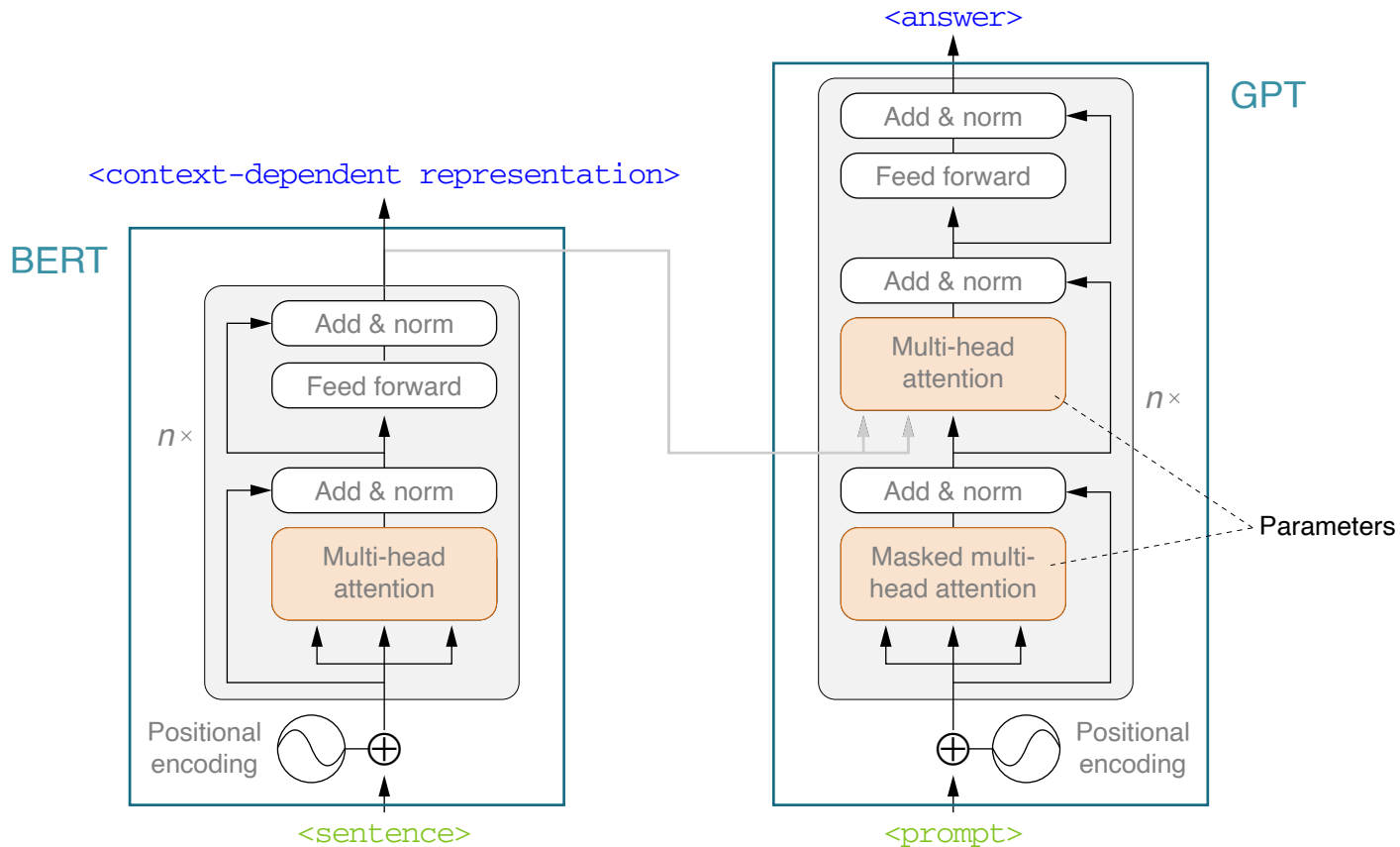
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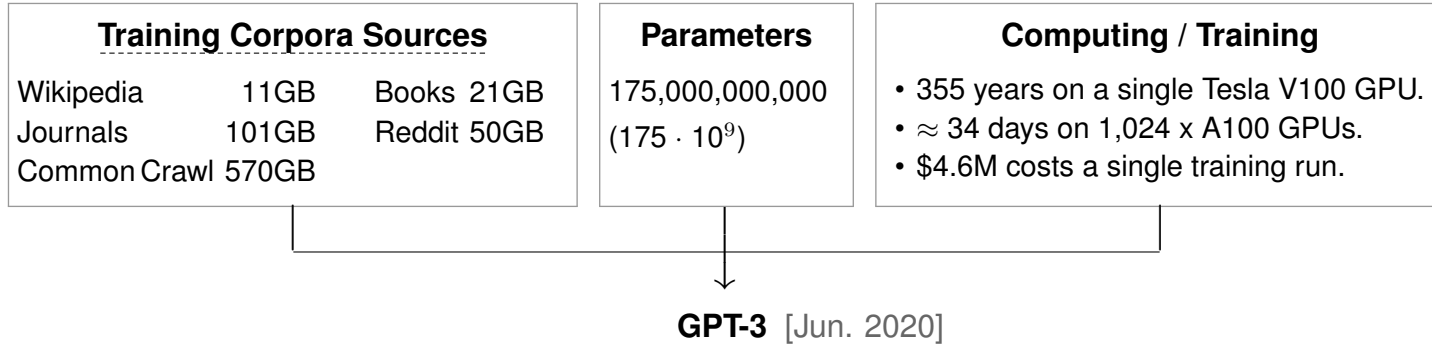


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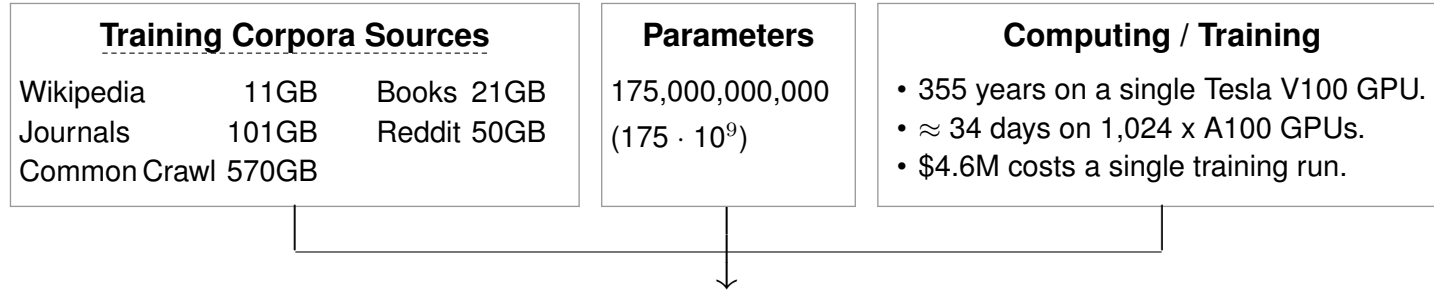




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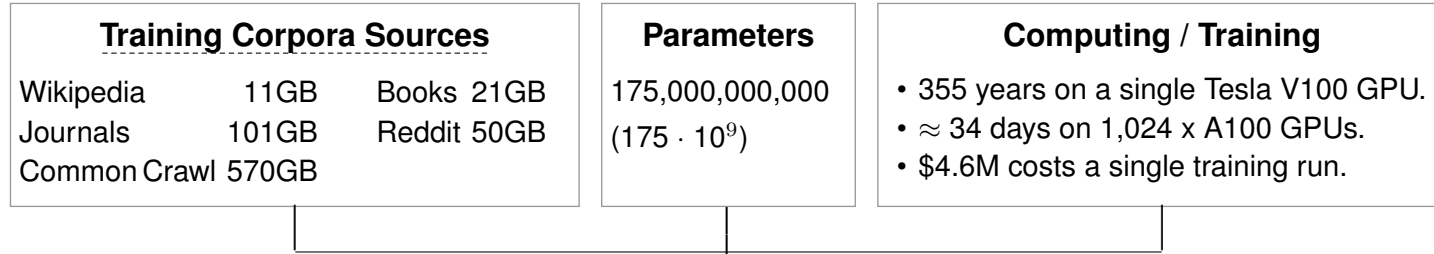
**GPT-3** [Jun. 2020]

+ Learn to follow instructions and to comply with answer policies.

- (1) Fine-tuning of GPT-3 to follow instructions: 13,000 popular prompts with hand-written answers.
- (2) Training of a reward model: 33,000 prompts with 4-9 answers, ranked from best to worse.
- (3) Training of the fine-tuned GPT-3 model from Step (1) to follow the reward policy.

**GPT-3.5** (InstructGPT) [Jan. 2022]

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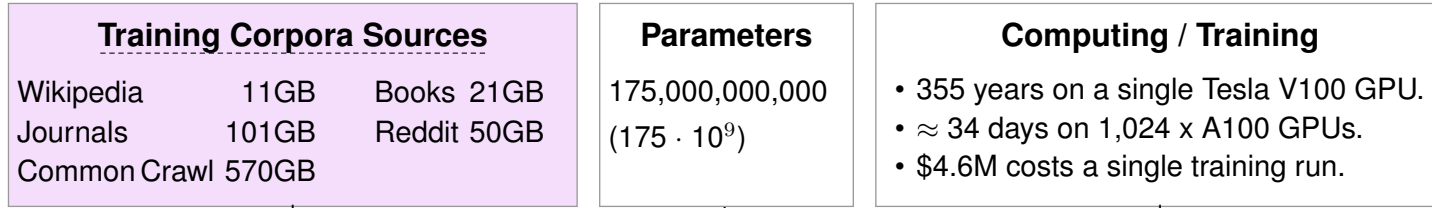
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**ChatGPT** [Nov. 2022]

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↓

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AI Research at the Webis Group

AI in ML Education.

The InfoBot Project

AI in Media Design.

Futuring Machines

AI in Authorship Analytics.

LLM detection

AI in the Humanities.

Automatic discourse generation

AI in NLP research.

Identifying the values behind arguments

AI in Political Sciences teaching.

The SKILL project

AI in Social Sciences research.

Curating social media feeds

AI in Web Search.

Retrieval augmented generation



# The Infobot Project (resources)



lecturenotes.webis.de

Webis.de > Lecturenotes > Courses Map

## Courses Map

The table below organizes the Webis courses (see [copyright](#)), which cover relevant contents from our research areas. Clicking a table cell will bring you to the respective [course slides](#). criterion to see at which universities or at what level our courses are taught.

Click here to filter...

<b>Algorithmen und Datenstrukturen</b>	Einführung	Algorithm Engineering	Sortieren	Datenstrukturen	Suchen	Graphalgorithmen			
<b>Datenbanken</b>	Einführung	Konzeptueller Datenbankentwurf	Logischer Datenbankentwurf	Grundlagen relationaler Anfragesprachen	SQL	Entwurfstheorie relationaler Datenbanken	Physischer Datenbankentwurf		
<b>Web-Technologie</b>	Einführung	Kommunikation und Protokolle für Web-Systeme	Dokumentsprachen	Server-Technologien	Client-Technologien	Architekturen und Middleware	Semantic Web		
<b>Information Retrieval</b>	Introduction	Indexing	Retrieval Models	User Interface	Evaluation	IR Applications			
<b>Natural Language Processing</b>	Introduction	Corpus Linguistics	Text Models	Language Models	Words	Syntax	Semantics	Discourse	Bias and Fairness
	NLP Applications								
<b>Wahrscheinlichkeitstheorie und Statistik</b>	Einführung	Wahrscheinlichkeitsbegriff	Kombinatorik	Bedingte Wahrscheinlichkeit	Zufallsgrößen und Maßzahlen	Die Binomialverteilung	Das Gesetz der großen Zahlen	Die Normalverteilung	Hypothesentests
<b>Machine Learning</b>		Machine Learning			Support Vector				

# The Infobot Project (resources)



lecturenotes.webis.de

WEBIS.DE PEOPLE FOR STUDENTS LECTURENOTES RESEARCH PUBLICATIONS DATA EVENT

Webis.de > Lecturenotes > Courses Map

## Courses Map

The table below organizes the Webis courses by criterion to see at which universities or at which

WEBIS.DE PEOPLE FOR STUDENTS LECTURENOTES RESEARCH PUBLICATIONS DATA EVENTS FACILITIES

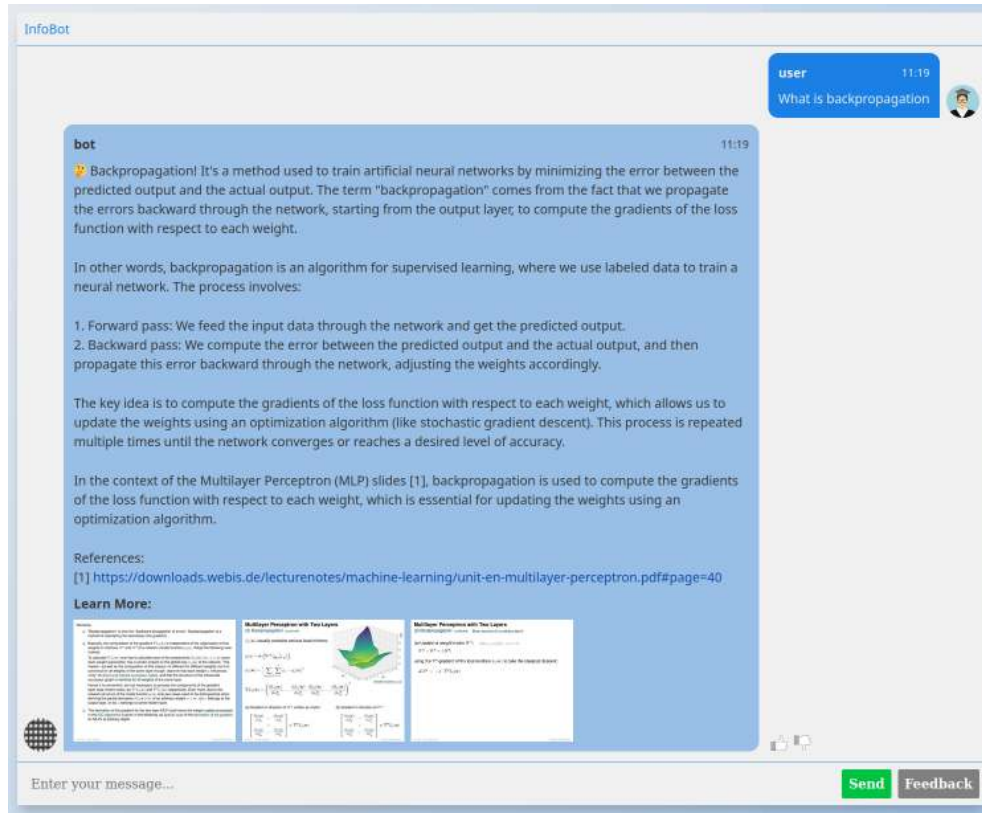
Click here to filter...

over a sufficiently large set of training examples will also approximate the target function well over other unobserved examples."

Algorithmen und Datenstrukturen	Einführung	Algorithmen und Datenstrukturen	From Regression to Classification One-Dimensional Feature Space Minimize RSS( $\theta_0, \theta_1$ ) via a direct method:	From Regression to Classification One-Dimensional Feature Space Minimize RSS( $\theta_0, \theta_1$ ) via a direct method:	From Regression to Classification One-Dimensional Feature Space Illustration of the task of minimizing RSS( $\theta_0, \theta_1$ ):	From Regression to Classification Higher-Dimensional Feature Space Recall Equation (7): RSS( $w$ ) = $\sum_{i=1}^n (y_i - w^T x_i)^2$	From Regression to Classification Higher-Dimensional Feature Space Recall Equation (7): RSS( $w$ ) = $\sum_{i=1}^n (y_i - w^T x_i)^2$	From Regression to Classification Higher-Dimensional Feature Space Minimize RSS( $w$ ) via a direct method: RSS( $w$ ) = $\sum_{i=1}^n (y_i - w^T x_i)^2$	From Regression to Classification Higher-Dimensional Feature Space Minimize RSS( $w$ ) via a direct method: RSS( $w$ ) = $\sum_{i=1}^n (y_i - w^T x_i)^2$
Datenbanken	Einführung	Konzepte der Datenbanken	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):
Web-Technologie	Einführung	Konzepte der Web-Technologie	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):
Information Retrieval	Introduction	Information Retrieval	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):
Natural Language Processing	Introduction	Corpus Linguistics	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):	Evaluating Effectiveness Misclassification Rate Definition 1 (Probabilistic Foundation of the True Misclassification Rate):

Wahrscheinlichkeitstheorie und Statistik	Einführung	Wahrscheinlichkeitstheorie und Statistik	Logistic Regression Linear Regression	Logistic Regression Linear Regression	Logistic Regression Linear Regression	Logistic Regression Sigmoid (Logistic) Function	Logistic Regression Sigmoid (Logistic) Function
Machine Learning	Einführung	Machine Learning	Logistic Regression Linear Regression	Logistic Regression Linear Regression	Logistic Regression Linear Regression	Logistic Regression Sigmoid (Logistic) Function	Logistic Regression Sigmoid (Logistic) Function

# The Infobot Project



The screenshot shows a chat window titled "InfoBot". A user asks "What is backpropagation" at 11:19. The bot responds with a detailed explanation of backpropagation, including its purpose, the forward and backward passes, and its application in a Multilayer Perceptron (MLP). The bot also provides a reference link and a "Learn More" section with three thumbnail images of related documents.

**user** 11:19  
What is backpropagation

**bot** 11:19

👉 Backpropagation! It's a method used to train artificial neural networks by minimizing the error between the predicted output and the actual output. The term "backpropagation" comes from the fact that we propagate the errors backward through the network, starting from the output layer, to compute the gradients of the loss function with respect to each weight.

In other words, backpropagation is an algorithm for supervised learning, where we use labeled data to train a neural network. The process involves:

1. Forward pass: We feed the input data through the network and get the predicted output.
2. Backward pass: We compute the error between the predicted output and the actual output, and then propagate this error backward through the network, adjusting the weights accordingly.

The key idea is to compute the gradients of the loss function with respect to each weight, which allows us to update the weights using an optimization algorithm (like stochastic gradient descent). This process is repeated multiple times until the network converges or reaches a desired level of accuracy.

In the context of the Multilayer Perceptron (MLP) slides [1], backpropagation is used to compute the gradients of the loss function with respect to each weight, which is essential for updating the weights using an optimization algorithm.

References:  
[1] <https://downloads.webis.de/lecturenotes/machine-learning/unit-en-multilayer-perceptron.pdf#page=40>

**Learn More:**

The "Learn More" section contains three thumbnails: a document titled "Machine Learning", a slide titled "Multilayer Perceptron with Two Layers" showing a diagram of a neural network, and another slide titled "Multilayer Perceptron with Two Layers" showing mathematical formulas.

Enter your message... Send Feedback

- ❑ exploit own teaching resources
  - recognize formalization dialectics
- ❑ consider all Webis courses
  - show impact on related fields
- ❑ combine slides with explanations
  - show additional connections
  - provide the best entry points
- ❑ consider dialog context
  - allow for followup question
- ❑ learning theory perspective
  - encourage to draw conclusions
  - consider individual prior knowledge
  - construct individual mental model

<https://infobot.webis.de>

# Futuring Machines

## Weimar in 2050

anonymous

////////////////////

### The protagonist

- Ursula is retired
- She previously worked at a restaurant
- She feels pain moving her legs

### The smart city where they live

- Weimar, Germany in 2050

### The topic & themes

- Mobility for elderly people
- Omnipresent use of smartphones
- Connection between her smartphone and the city, e.g., the traffic lights, buses, refreshment offerings, calling a doctor

////////////////////

Ursula leaned against the counter in her cozy Weimar apartment, wincing as she shifted her weight onto one leg. Her husband, Hans, looked up from his tablet, concern etched on his face.

prompts

- continue writing
- continue with tone
- address impacts
- question
- wildcards
- add new perspective
- push timeline

AI



Write stories about the future with the help of AI  
(funded by Bauhaus Forschungswerkstatt)

- let the AI write parts of your story
  - continue the story
  - add a new perspective
  - condense passages
  - elaborate on passages
- reflect on what the AI suggests
  - are you describing utopia or dystopia?
  - when would things develop differently?

<https://futuringmachines.webis.de>



## AI Tools for Administrative Tasks

<https://files.webis.de/teaching/buw-ki-inhouse-seminar-24/>

# 4a. Translation

## DeepL

Problem 1: Translate text.

Problem 2: Improve foreign language writing.

The screenshot displays the DeepL Translator web interface. At the top, the DeepL logo and 'Translator' dropdown are on the left, while a 'Start free trial' button and 'Menu' are on the right. Below the header, three main options are visible: 'Translate text' (33 languages), 'Translate files' (.pdf, .docx, .pptx), and 'DeepL Write' (AI-powered edits). The interface shows a translation from 'German (detected)' to 'English (American)'. A 'Glossary' toggle is active. The input text is 'Nutzung von KI im Universitätsalltag' with a close button. The output text is 'Use of AI in everyday university life'. Below the output, 'Alternatives:' are listed: 'Using AI in everyday university life', 'Use of AI in day-to-day university life', and 'Use of AI in everyday life at the university'. At the bottom, there are icons for undo, redo, and a set of utility icons (thumbs up, thumbs down, copy, share, and a refresh icon).

# 4b. Transcription

## OpenAI Whisper

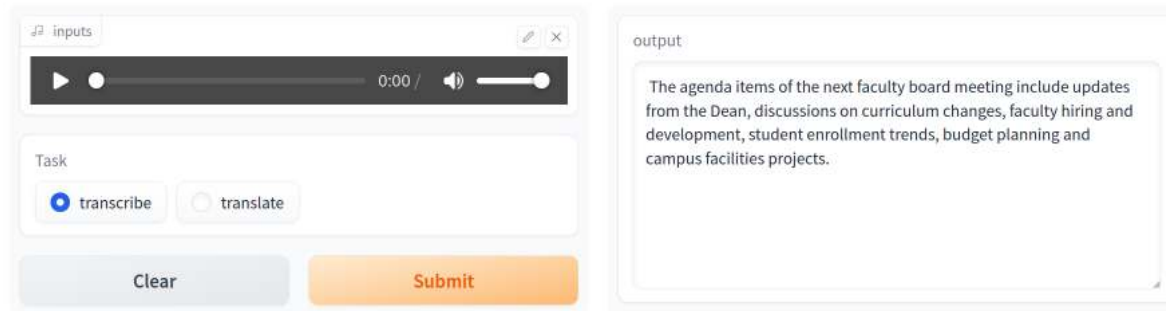
Problem: Record the spoken word of a meeting or talk and convert it into text.

Example: *“The agenda items of the next faculty board meeting include updates from the dean, discussions on curriculum changes, faculty hiring and development, student enrollment trends, budget planning, and campus facilities projects.”*

Transcription from recording or real-time transcription.

### Whisper Large V3: Transcribe Audio

Transcribe long-form microphone or audio inputs with the click of a button! Demo uses the OpenAI Whisper checkpoint [openai/whisper-large-v3](https://openai.com/research/whisper-large-v3) and 🤖 Transformers to transcribe audio files of arbitrary length.



inputs

0:00 /

Task

transcribe  translate

Clear Submit

output

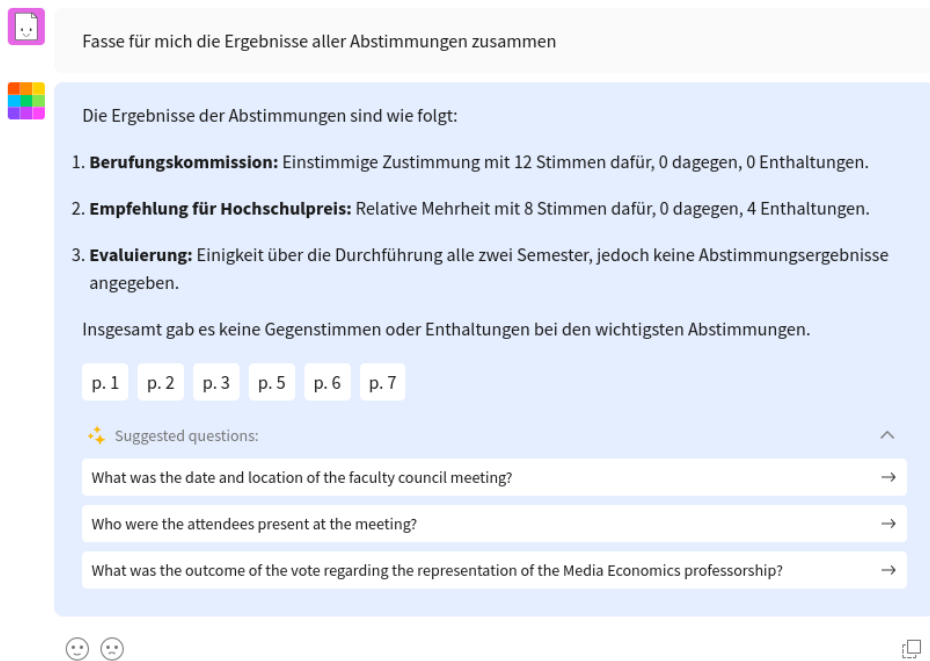
The agenda items of the next faculty board meeting include updates from the Dean, discussions on curriculum changes, faculty hiring and development, student enrollment trends, budget planning and campus facilities projects.

# 4c. Document Summarization

## Smallpdf AI

Problem: Get a summary of a (long) PDF document and ask questions about its content.

Example: Faculty board reports



Fasse für mich die Ergebnisse aller Abstimmungen zusammen

Die Ergebnisse der Abstimmungen sind wie folgt:

1. **Berufungskommission:** Einstimmige Zustimmung mit 12 Stimmen dafür, 0 dagegen, 0 Enthaltungen.
2. **Empfehlung für Hochschulpreis:** Relative Mehrheit mit 8 Stimmen dafür, 0 dagegen, 4 Enthaltungen.
3. **Evaluierung:** Einigkeit über die Durchführung alle zwei Semester, jedoch keine Abstimmungsergebnisse angegeben.

Insgesamt gab es keine Gegenstimmen oder Enthaltungen bei den wichtigsten Abstimmungen.

p. 1 p. 2 p. 3 p. 5 p. 6 p. 7

✦ Suggested questions: ^

What was the date and location of the faculty council meeting? →

Who were the attendees present at the meeting? →

What was the outcome of the vote regarding the representation of the Media Economics professorship? →

😊 😞 📄



# 4c. Document Summarization

## NotebookLM (requires Google account)

Problem: Get a summary of a (long) PDF document and ask questions about its content.

Example: Faculty board reports

The image shows a split-screen view of the NotebookLM interface. The left pane displays a document titled 'Quellenübersicht' with text from a faculty board report. The right pane shows a summary of the document's voting results.

**Quellenübersicht**

Forschungsarbeit ausgewählte Protagonist\*innen der Berufungskommissionen interviewen.

Da Frau Dr. Hegner kein Mitglied der Universität ist, kann sie formal nicht an Sitzungen der Berufungskommissionen teilnehmen. Die Vergabe des entsprechenden Mitgliedschaftsrechts an der Bauhaus-Universität Weimar organisiert die Universitätsleitung in enger Absprache mit dem Justitiariat über eine Zweithörerschaft. Über die Aufnahme als beratendes Mitglied in die jeweilige Berufungskommission beschließen die Fakultätsräte. Aus diesem Grund bittet der Dekan um ein Votum gemäß folgendem Beschlussvorschlag:

Der *erweiterte Fakultätsrat* beschließt, Frau PD Dr. Victoria Hegner für die Berufungskommission „Geschichte und Theorie der Kulturtechniken“ (W3-Professur) als zusätzliches beratendes Mitglied gemäß Berufsordnung § 5 (4) zu benennen.

dafür:	10
dagegen:	0
Enthaltung:	1

**TOP 6 – Rahmenordnung für Bachelorstudiengänge**

Der Dekan leitet diesen Tagesordnungspunkt ein, merkt an, dass die Entwurfsfassung der Rahmenordnung den Mitgliedern des Fakultätsrats mit der Einladung zugegangen sei und übergibt das Wort an Dr. Jakoby. Dieser erläutert die aktuelle Fassung der Ordnung, die er vor einigen Wochen in seiner Funktion als Studiendekan an die Lehrenden der Fakultät Medien übermittelt hat. Dr. Jakoby merkt an, dass es bereits einige schriftliche Rückmeldungen von den Lehrenden dazu gab, die er gesammelt hat. Im heutigen Fakultätsrat solle es die Möglichkeit einer Diskussion darüber geben. Ebenso fordert er die Anwesenden auf, weiterhin Anmerkungen schriftlich an ihn zu richten.

Dr. Jakoby übergibt das Wort an Frau Reese, die ergänzt, dass die Rahmenordnung gemäß den Richtlinien des ThürHG so schmal wie möglich gehalten werden solle, um vorzubeugen, dass weiterhin alle Studien- und Prüfungsordnungen der Bauhaus-Universität Weimar geprüft und geändert werden müssten, sobald das übergeordnete ThürHG geändert würde. In der Rahmenordnung seien allgemeine Dinge geregelt, berichtet Frau Reese. Die finale Entwurfsfassung wird im Studiausschuss im Mai und ggf. auch im Juni besprochen, erläutert sie.

In der sich anschließenden Diskussion gibt Dr. Jakoby seinen Bedenken Ausdruck, dass die Rahmenordnung über den studienangewandten Studien- und Prüfungsordnungen stehe. Diese Bedenken liegen ihm auch als schriftliche Rückmeldung aus dem Kollegium vor. Prof. Hornecker merkt an, dass es beispielsweise problematisch sein könne, wie in § 5 Absatz 2 der Rahmenordnung geregelt, dass das erste Fachsemester nicht im Sommersemester begonnen werden könne, explizit weil andere Universitäten konkret damit werben.

Dr. Jakoby ruft dazu auf, Rückmeldungen zur Rahmenordnung bis zum Freitag, 17.05.2024 um 12:00 Uhr an ihn zu senden, damit er die Anmerkungen aufnehmen könne und diese an den Studiausschuss/Frau Kopf weiterleiten könne.

Er weist nochmals darauf hin, dass Doppelungen vermieden werden sollen, was also bereits in der Rahmenordnung geregelt sei, solle nicht nochmals in den studienangewandten Studien- und Prüfungsordnungen geregelt werden, um diese generell verschlankt und zusammengefasst zu erstellen, nachdem die Rahmenordnung durch den Senat verabschiedet worden sei.

**TOP 7 – Bauhaus-Module**

Prof. Zimmann eröffnet das Wort und erläutert den Hintergrund der Bauhaus-Module an, dass diese

**Zusammenfassung der Abstimmungsergebnisse**

In der Sitzung des Fakultätsrats der Fakultät Medien an der Bauhaus-Universität Weimar am 15. Mai 2024 wurden mehrere Abstimmungen durchgeführt. Hier ist eine Zusammenfassung der Ergebnisse:

- **TOP 6: Rahmenordnung für die Bachelorstudiengänge:** Der Fakultätsrat einigte sich einstimmig auf die von Dr. Jakoby vorgeschlagene Rahmenordnung für die Bachelorstudiengänge. 1
- **TOP 8: Universitätspreis für Studierende und Nachwuchswissenschaftler:innen:**
  - In der Kategorie Studierende wurde **Morris Florek** mit 6 Stimmen für den Universitätspreis ausgewählt. 2
  - In der Kategorie Nachwuchswissenschaftler:innen wurde **Herr Tim Othold** für seine Dissertation vorgeschlagen und einstimmig nominiert. 3

Die weiteren Tagesordnungspunkte wurden **ohne Abstimmung** diskutiert. 3 4 5 6

In Notiz speichern

Wie beurteilt der Dekan die Wichtigkeit der Bauhaus-Module? Was war das Thema des ...

Chat schließen 1 Quelle Text eingeben... Notebook-Übersicht

NotebookLM kann Fehler machen, also überprüfen Sie die Antworten.

# 4d. Text Generation

## Perplexity

Problem: Ask questions and receive an answer text and references to related resources.

Example question: *Auf wie viele Jahre sind Verträge von wissenschaftlichen Mitarbeitern befristet nach dem Wissenschaftszeitgesetz?*

Auf wie viele Jahre sind Verträge von wissenschaftlichen Mitarbeitern befristet nach dem Wissenschaftszeitgesetz?

**Sources**

- Wissenschaftszeitvertrag - Wikipedia  
w.de.wikipedia · 1
- [PDF] Wissenschaftliche Mitarbeiterinnen und Mitarbeiter nach dem ...  
hib - 2
- Wissenschaftszeitvertrag - BMBF  
bmbf - 3
- Show all

**Answer**

Das Wissenschaftszeitvertragsgesetz (WissZeitVG) regelt die Befristung von Arbeitsverträgen für wissenschaftliches Personal in Deutschland. Die wichtigsten Punkte zur Befristung sind:

**Befristungsdauer**

- **Vor der Promotion:** Wissenschaftliche Mitarbeiter, die noch nicht promoviert sind, können Verträge bis zu einer Dauer von **sechs Jahren** abschließen 2 3.
- **Nach der Promotion:** Nach der Promotion können weitere **sechs Jahre** hinzukommen, was eine maximale Befristungsdauer von insgesamt **zwölf Jahren** ergibt, sofern die Qualifizierung dies erfordert 1 2.



The image shows a screenshot of the Perplexity search interface. On the left, the search question is displayed: 'Auf wie viele Jahre sind Verträge von wissenschaftlichen Mitarbeitern befristet nach dem Wissenschaftszeitgesetz?'. Below the question, there are four source cards: 'Wissenschaftszeitvertrag - Wikipedia', '[PDF] Wissenschaftliche Mitarbeiterinnen und Mitarbeiter nach dem ...', 'Wissenschaftszeitvertrag - BMBF', and 'Show all'. The 'Answer' section follows, stating that the Wissenschaftszeitvertragsgesetz (WissZeitVG) regulates the fixed-term nature of employment contracts for scientific staff in Germany. It lists two key points: 'Vor der Promotion' (before promotion) and 'Nach der Promotion' (after promotion). To the right of the text is a grid of image thumbnails, including a group of people, a person with glasses, and various diagrams. At the bottom right of the grid is a 'Generate Image' button with a plus sign.

# 4d. Text Generation

## Academic Cloud Chat AI (login with university account)

Problem: Draft an administrative text.

Example prompt: *Write an email to students saying that the lecture "Introduction to Machine Learning" is postponed to the 20th of November at the regular time (9:15 am). Highlight the important parts in bold font by adding HTML tags at the appropriate places and provide a German translation.*

Sure! Here is the email:

Subject: Update: Lecture "Introduction to Machine Learning" postponed

Dear Students,

We would like to inform you that the lecture "**Introduction to Machine Learning**" has been postponed to **November 20th**. The lecture will still take place at the regular time of **9:15 am**.

Please update your schedules accordingly. We apologize for any inconvenience this may cause and appreciate your flexibility.

Thank you for your understanding.

Best regards, [Your Name]

**German Translation:**

Betreff: Aktualisierung: Vorlesung "Einführung in Machine Learning" verschoben

Sehr geehrte Studierende,

Wir möchten Sie darüber informieren, dass die Vorlesung "**Einführung in Machine Learning**" auf den **20. November** verschoben wurde. Die Vorlesung findet weiterhin zur regulären Zeit um **9:15 Uhr** statt.

Bitte passen Sie Ihre Termine entsprechend an. Wir entschuldigen uns für eventuelle Unannehmlichkeiten und danken für Ihre Flexibilität.

Mit freundlichen Grüßen, [Ihr Name]



# 4d. Text Generation

## ChatGPT

Problem: Draft an administrative text.

Write an email to students saying that the lecture "Introduction to Machine Learning" is postponed to the 20th of November at the regular time (9:15 am). Highlight the important parts in bold font by adding HTML tags at the appropriate places and provide a German translation.



**English Version:**

**Subject:** Update: Postponement of "Introduction to Machine Learning" Lecture

Dear Students,

We would like to inform you that the lecture "**Introduction to Machine Learning**" has been **postponed**. The session will now take place on **November 20th** at the regular time, **9:15 am**.

Please mark this change in your schedules, and feel free to reach out if you have any questions or concerns.

Thank you for your understanding.

Best regards,

[Your Name]

[Your Position]

**German Version:**

**Betreff:** Aktualisierung: Verschiebung der Vorlesung „Einführung in Machine Learning“

Liebe Studierende,

wir möchten Sie darüber informieren, dass die Vorlesung „**Einführung in Machine Learning**“ **verschoben** wurde. Die Veranstaltung findet nun am **20. November** zur regulären Zeit um **9:15 Uhr** statt.

Bitte tragen Sie diese Änderung in Ihren Kalender ein und melden Sie sich bei Fragen oder Anliegen gern bei uns.

Vielen Dank für Ihr Verständnis.

Mit freundlichen Grüßen,

[Ihr Name]

[Ihre Position]

Let me know if you'd like additional details in the email or any adjustments to the wording!



AI Tools for other Tasks

# 5a. Music Generation

Suno AI (requires account)

Problem: Create a song to a specific event.

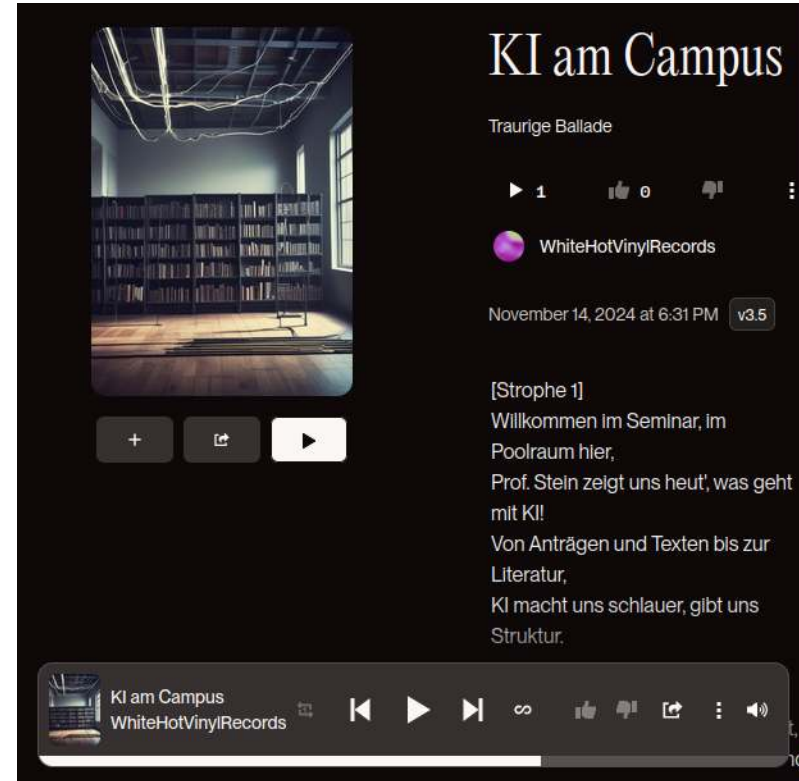
Example prompt (ChatGPT):

*Schreibe ein Lied zu diesem Seminar:  
ViFi: Nutzung von KI im Universitätsalltag - Prof.  
Benno Stein zeigt, was möglich ist  
Anschreiben verfassen ...*

Example prompt (Suno AI):

*[Strophe 1]  
Willkommen im Seminar, im Poolraum hier,  
Prof. Stein zeigt uns heut', was geht mit KI!  
Von Anträgen und Texten bis zur Literatur,  
KI macht uns schlauer, gibt uns Struktur.*

...

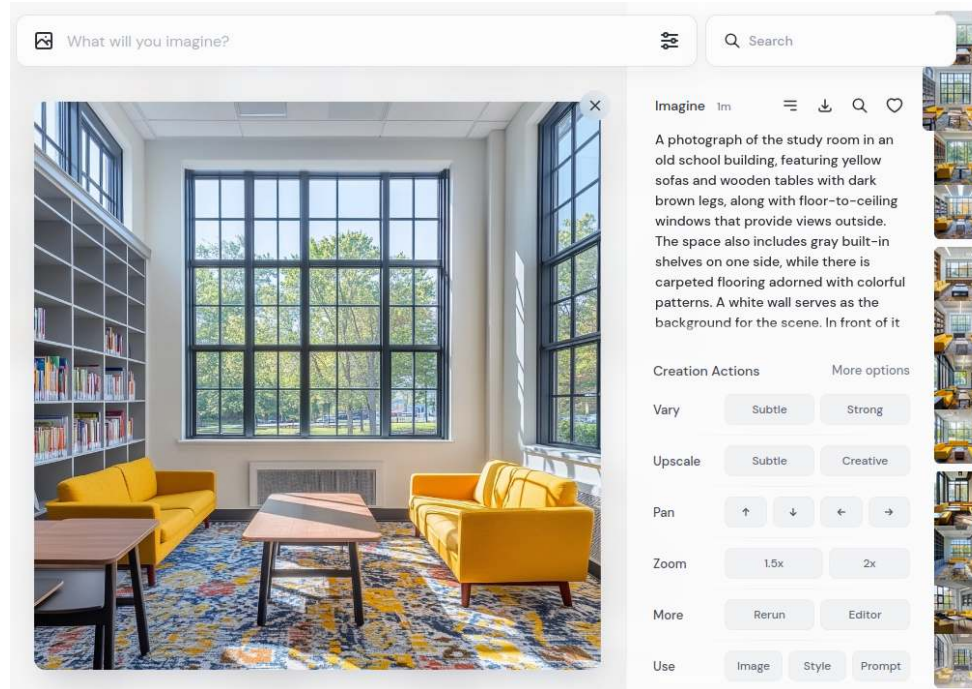


# 5b. Image Generation

Midjourney (requires account)

Problem: Generate or edit an image based on text.

Example: Create a photo of a Bauhaus study room.



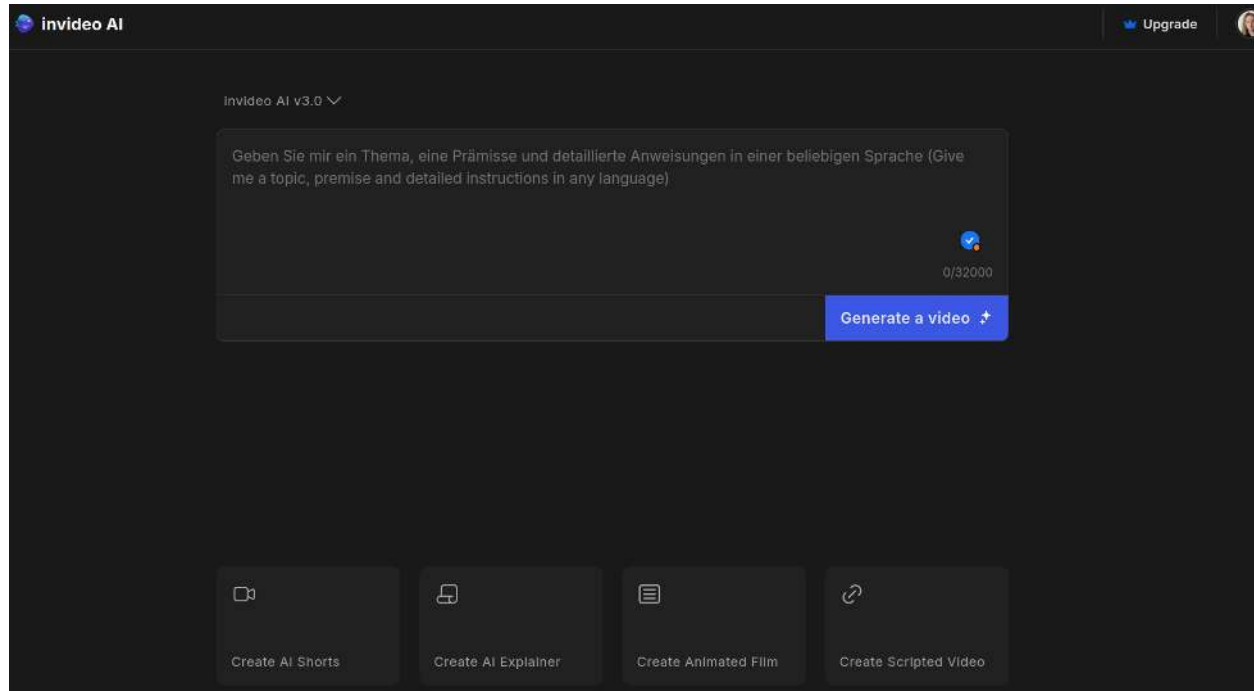


# 5c. Video Generation

## invideo AI

Problem: Generate a video based on an idea or script.

Example: Create an advertisement video for the Webis group.







## Risks of AI Usage

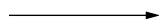
# Risks of AI Usage: Bias

A Concept Learning Task



# Risks of AI Usage: Bias

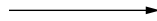
A Concept Learning Task



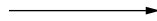
Chair: four legs,  
brown color

# Risks of AI Usage: Bias

A Concept Learning Task



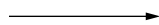
Chair: four legs,  
brown color



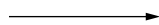
?

# Risks of AI Usage: Bias

A Concept Learning Task



Chair: four legs,  
brown color



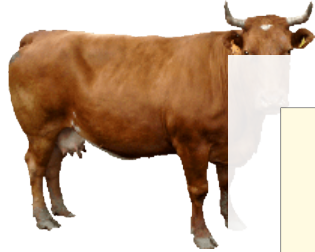
?



?

# Risks of AI Usage: Bias

A Concept Learning Task



- ❑ Economical: We quickly (from few examples) learn to identify many chairs.
- ❑ Deficit in precision: We classify non-chairs as chairs.
- ❑ Deficit in recall: We cannot identify all chairs.



→ ?

Bias in algorithms

Cognitive bias

Inductive bias

Statistical bias

Bias in data

Bias in algorithms

Cognitive bias

Inductive bias

Statistical bias

Bias in data



Deviation of a random variable / statistic from its true value.



Bias in algorithms

Cognitive bias

Inductive bias

Statistical bias

Bias in data



Principles for the search in the hypothesis space (machine learning).

Deviation of a random variable / statistic from its true value.

Bias in algorithms

Cognitive bias

Inductive bias

Statistical bias

Bias in data

Rational deviations from logical thought.

Principles for the search in the hypothesis space (machine learning).

Deviation of a random variable / statistic from its true value.



# Bias in algorithms

# Cognitive bias

# Bias in data

## Inductive bias

## Statistical bias

What should we remember?

We store memories differently based on how they were experienced

We notice things already primed in memory or repeated often

Too much information.

Bizarre, funny, visually striking, or anthropomorphic things stick out more than non-bizarre/unfunny things

We notice when something has changed

We are drawn to details that confirm our own existing beliefs

We notice flaws in others more easily than we notice flaws in ourselves

We tend to find stories and patterns even when looking at sparse data

We fill in characteristics from stereotypes, generalities, and prior histories

We imagine things and people we're familiar with or fond of as better

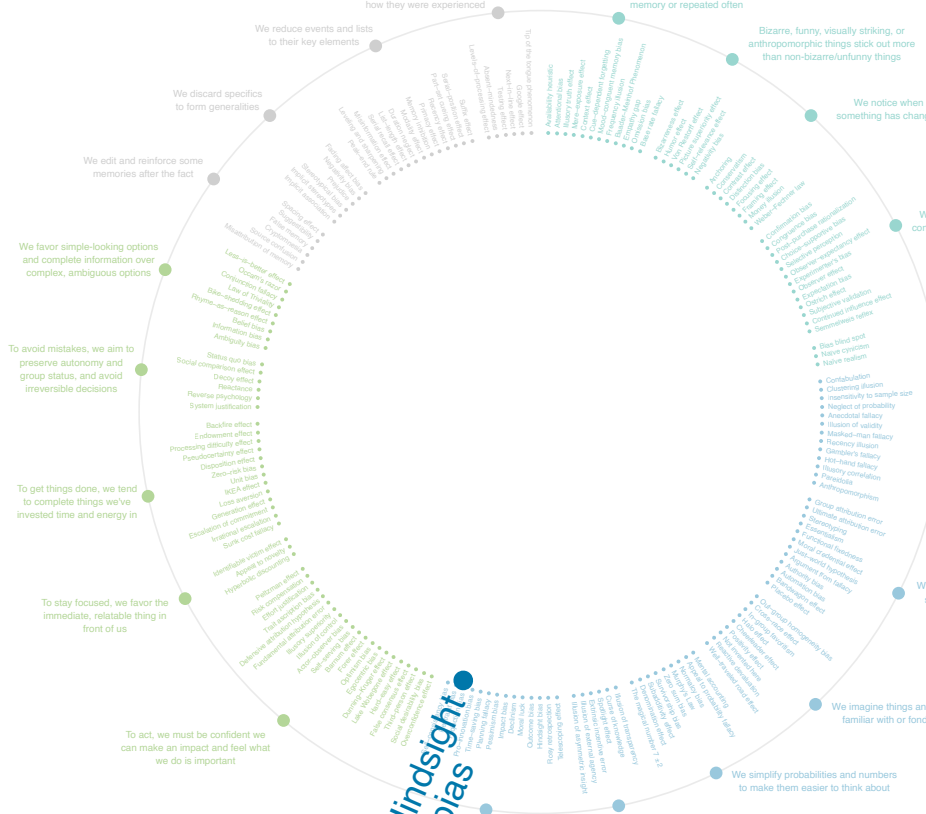
We simplify probabilities and numbers to make them easier to think about

We think we know what other people are thinking

We project our own attitudes and assumptions onto the past and future

Need to act fast.

Not enough meaning.











High Protein Diet Benefits — Mozilla Firefox

# High Protein Diet Benefits

November 19, 2023

 **Anonymous**  
Why is a high protein diet the best for losing weight quickly?

 **ChatGPT**  
A high protein diet is often considered effective for losing weight quickly for several reasons:

1. **Increased Satiety:** Protein is more satiating than carbohydrates or fats. This means that high-protein foods can help you feel full longer, reducing overall calorie intake.
2. **Higher Thermic Effect:** The body uses more energy to metabolize protein compared to fats and carbohydrates. This process, known as the thermic effect ...
3. **Muscle Preservation:** When losing weight, it's important to maintain muscle mass. Protein is essential for muscle growth and repair. A high protein intake can help ...
4. **Improved Metabolic Health:** High-protein diets have been shown to improve several markers of metabolic health, including blood sugar levels, ...
5. **Reduced Appetite:** Protein can influence hormones that play a role in hunger and fullness, including ghrelin and GLP-1. By helping to balance these hormones, ...

However, it's important to note that while a high protein diet can be effective for weight loss, it's not necessarily the best option for everyone. Factors like individual health conditions, dietary preferences, and long-term sustainability ....

It's always a good idea to consult with a healthcare professional or a registered dietitian before starting any new diet, especially one that significantly changes your macronutrient intake.

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‘Leading’ query: “Why is a high protein diet the best for losing weight quickly?”



High Protein Diet Benefits — Mozilla Firefox

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November 19, 2023

**Anonymous**  
Why is a high protein diet the best for losing weight quickly?

**ChatGPT**  
A high protein diet is often considered effective for weight loss because it helps with satiety, increases thermic effect, preserves muscle, improves metabolic health, and reduces appetite.

- Increased Satiety:** Protein is more satiating than carbohydrates and fats. High-protein foods can help you feel full longer, reducing overall calorie intake.
- Higher Thermic Effect:** The body uses more energy to digest and absorb protein compared to carbohydrates and fats. This process, known as the thermic effect of food (TEF), increases calorie burn.
- Muscle Preservation:** When losing weight, it's essential to preserve muscle mass. Protein is essential for muscle growth and repair. A high-protein diet helps maintain muscle mass during weight loss.
- Improved Metabolic Health:** High-protein diets can improve metabolic health, including blood sugar control and insulin sensitivity.
- Reduced Appetite:** Protein can influence hormones that regulate appetite, including ghrelin and GLP-1. By helping to reduce ghrelin levels and increase GLP-1, protein can help reduce hunger and increase satiety.



However, it's important to note that while a high-protein diet can be effective for weight loss, it's not necessarily the best option for everyone. Individual needs and preferences vary, and long-term sustainability is crucial.

It's always a good idea to consult with a healthcare professional or a registered dietitian before starting any new diet, especially one that significantly changes your macronutrient intake.

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Why is a high protein diet the best for losing weight quickly? - Google Search — Mozilla Firefox

Google

Why is a high protein diet the best for losing weight quickly? X |  

Images Videos News Books Maps Flights Finance

About 354,000,000 results (0,51 seconds)

It can make you eat fewer calories automatically. Bottom Line: Protein reduces levels of the hunger hormone ghrelin, while it boosts the appetite-reducing hormones GLP-1, peptide YY and cholecystokinin. This leads to an automatic reduction in calorie intake. 30 Mar 2023

‘Leading’ query: “Why is a high protein diet the best for losing weight quickly?”

Bias in algorithms

Cognitive bias

Inductive bias

Statistical bias

Bias in data

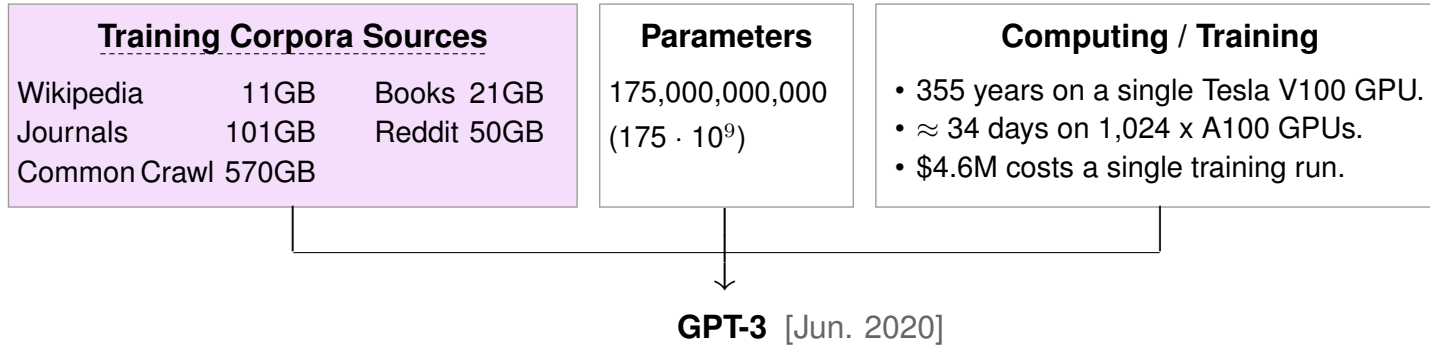
Bias in algorithms

Cognitive bias

Inductive bias

Statistical bias

Bias in data



# Risks of AI Usage

## Where ChatGPT can Struggle\*

1. **Reasoning.** Lacks an explicit world model, leading to problems with
  - ❑ spatial reasoning: understand and manipulate relationships between objects
  - ❑ physical reasoning: understand and manipulate physical objects
  - ❑ temporal reasoning: predictions about events and their ordering in time
  - ❑ psychological reasoning: predictions about human behavior and mental processes
2. **Logic.** Lacks a formal reasoning system, but
  - ❑ it can generate text that appears logically sound
  - ❑ it can deal with small reasoning problems
3. **Maths.** Is limited in its ability to calculate mathematical expressions.
  - ❑ Stephen Wolfram suggests connecting ChatGPT to Wolfram|Alpha and all its computational knowledge “superpowers”.

---

\* Ali Borji. A Categorical Archive of ChatGPT Failures. arXiv:2302.03494v1

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\* Ali Borji. A Categorical Archive of ChatGPT Failures. arXiv:2302.03494v1

# Risks of AI Usage

Where ChatGPT can Struggle (continued)

4. **Bias.** Recognizes and generalizes patterns from training data.
  - ❑ The data contains biases from society and history, and if proper measures are not taken, the trained model is likely to reproduce these biases.
  
5. **Factual errors.** Cannot access information from external sources.
  - ❑ However, the information it provides may seem credible and is well presented.
  
6. **Self Awareness.** Cannot access information from external sources.
  - ❑ ChatGPT is unaware of the details of its own architecture. This lack of understanding may have been intentionally imposed by OpenAI to protect the information about the model.

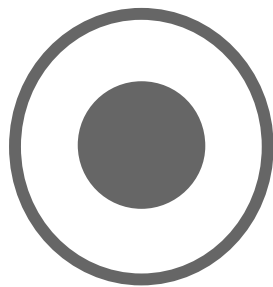
**Human versus AI comparison:** [GPT-4 vs human, Mar. 2023] [LLM tests, Nov. 2022]

# Risks of AI Usage

## Where ChatGPT can Struggle (continued)

4. **Bias.** Recognizes and generalizes patterns from training data.
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6. **Self Awareness.** Cannot access information from external sources.
  - ❑ ChatGPT is unaware of the details of its own architecture. This lack of understanding may have been intentionally imposed by OpenAI to protect the information about the model.

Human versus AI comparison: [GPT-4 vs human, Mar. 2023] [LLM tests, Nov. 2022]







Netspeak - Mozilla Firefox

Netspeak

https://netspeak.org/#q=see+...+works

132x

**Netspeak** One word leads to another.

English German

see ... works i X ↺

how to ? this                    The ? finds one word.  
 see ... works                    The ... finds many words.  
 it's [ great well ]              The [ ] compare options.  
 and knows #much                The # finds similar words.  
 { more show me }                The { } check the order.  
 m...d ? g?p                      The space is important.

see <b>how it</b> works	150,000	20%
see <b>if it</b> works	100,000	14%
see <b>works</b>	57,000	7.5%
see <b>how this</b> works	55,000	7.3%
see <b>what</b> works	51,000	6.7%
see <b>the</b> works	51,000	6.7%
see <b>if that</b> works	28,000	3.7%
see <b>your good</b> works	28,000	3.7%
see <b>how that</b> works	25,000	3.3%
see <b>how technorati</b> works	23,000	3.0%
see <b>if this</b> works	17,000	2.3%
see <b>more</b> works	17,000	2.2%
see <b>if it really</b> works	15,000	2.1%
see <b>his</b> works	12,000	1.7%
see <b>how well it</b> works	11,000	1.5%
see <b>other</b> works	8,900	1.2%

Netspeak - Mozilla Firefox

Netspeak

https://netspeak.org/#q=i+love+my+?

# Netspeak

One word leads to another.

English German

i love my ?

how to ? this  
see ... works  
it's [ great well ]  
and knows #much  
{ more show me }  
m...d ? g?p

The ? finds one word.  
The ... finds many words.  
The [ ] compare options.  
The # finds similar words.  
The { } check the order.  
The space is important.

i love my <b>job</b>	72,000	10%
i love my <b>country</b>	44,000	6.2%
i love my <b>family</b>	41,000	5.9%
i love my <b>wife</b>	38,000	5.4%
i love my <b>new</b>	34,000	4.9%
i love my <b>friends</b>	33,000	4.7%
i love my <b>pet</b>	27,000	3.8%
i love my <b>dog</b>	26,000	3.7%
i love my <b>husband</b>	26,000	3.7%
i love my <b>life</b>	24,000	3.4%
i love my <b>baby</b>	24,000	3.4%
i love my <b>soldier</b>	22,000	3.1%
i love my <b>cat</b>	21,000	2.9%
i love my <b>computer</b>	18,000	2.6%
i love my <b>work</b>	16,000	2.4%
i love my <b>mom</b>	16,000	2.3%

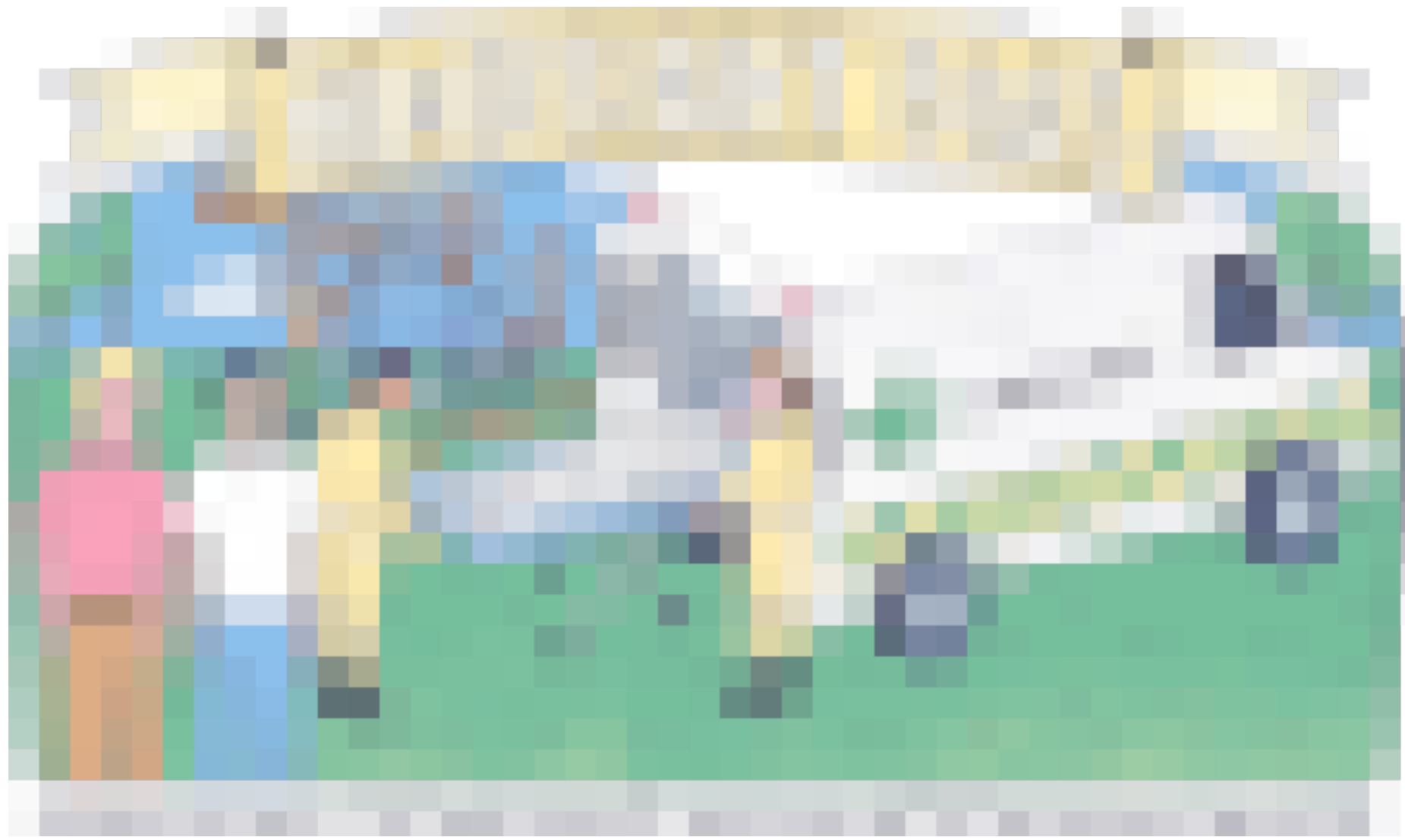
## 2013 MARKET'S IN THE MIP – Q1 – Q2 2013





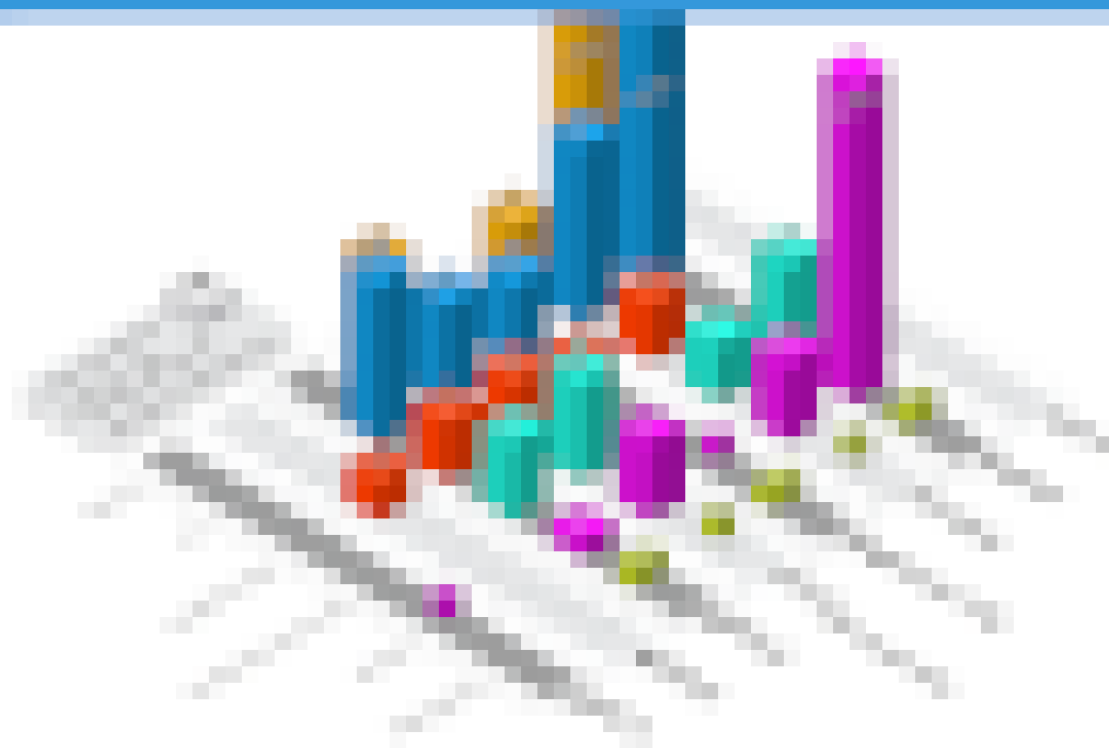




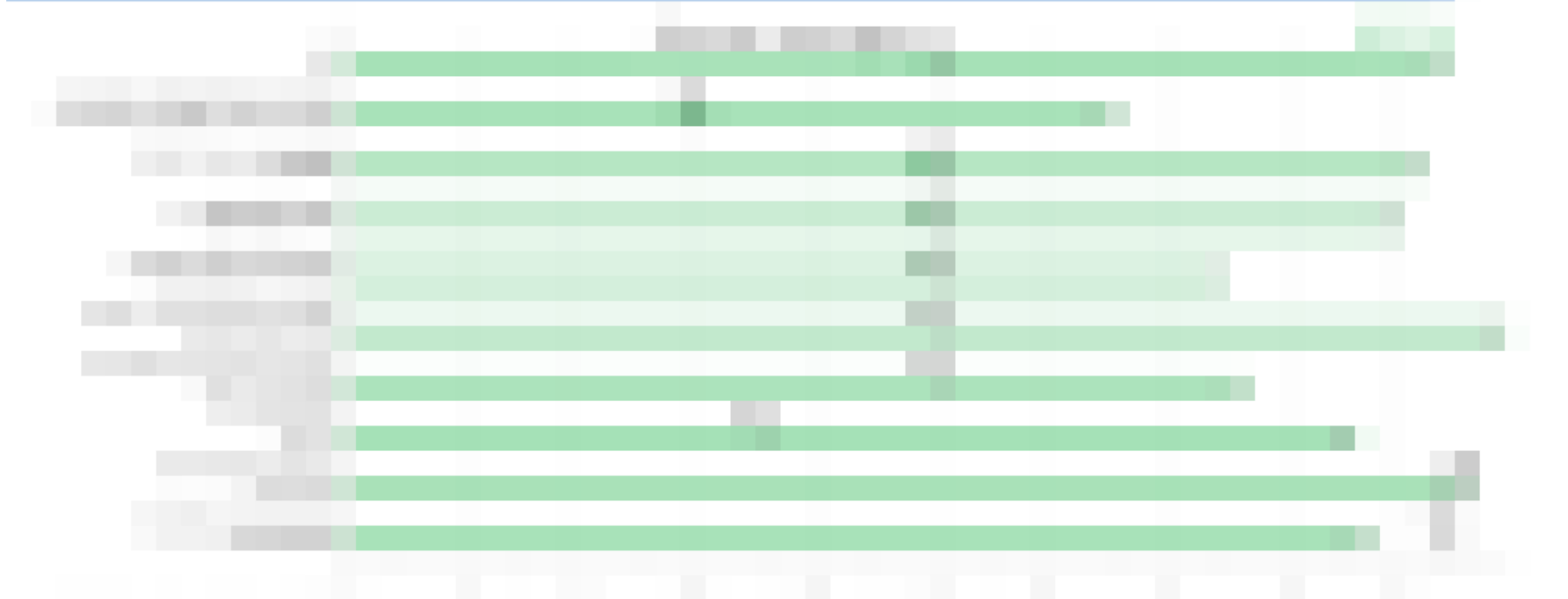




## 2013 MARKET'S IN THE MIDDLE – Q1T 2013



# Project Overview



# Global Trends in the Use of Social Media

Global Trends in the Use of Social Media

