

„AI in Education“: Kritische Perspektiven und Anschlüsse

BMBF-Bildungsforschungstagung: Chance Bildung
Berlin, 15.3.2023



- 1) „Künstliche Intelligenz“ und „Deep Learning“
- 2) Kontrolle vs. Kontrollverlust
- 3) Kontrollsystem vs. Kontrollverlustsystem
- 4) „Artificial Intelligence in Education“:
status quo und best practice
- 5) Fazit

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1961

Steps Toward Artificial Intelligence*

MARVIN MINSKY†, MEMBER, IRE

1966

A view of artificial intelligence

by FRED M. TONGE
University of California, Irvine

INTRODUCTION

By "intelligence" we mean a property of a system ment based on observation of the system's beha agreed to by "most reasonable men" as inte "Artificial intelligence" is then that property as in non-living systems. Work directed toward p such behavior is thereby work in artificial inte

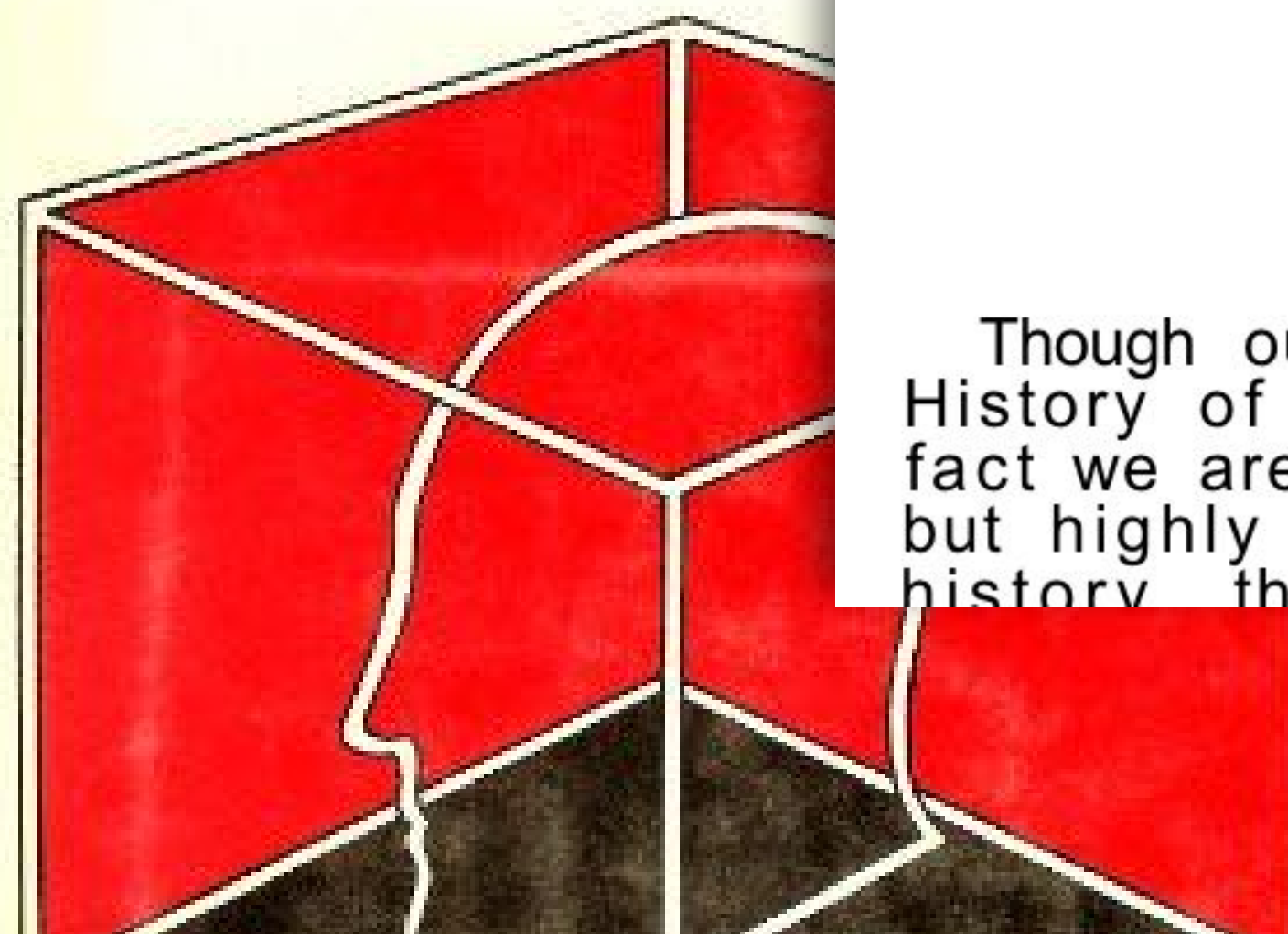
While the above is indeed a loose definition, n ful in suggestiveness than in precision, it shoul for our purposes. It does contain at least on assumption — that, *a priori*, intelligence is not to "living" systems. And it does suggest that, if of whether artificial intelligence does or will eve ever) exist is really worthy of further argumen cern, then some agreement should be reached.

Summary—The prob computers solve really di areas: Search, Pattern Induction.

A computer can do, in

INTRODUCTION TO ARTIFICIAL INTELLIGENCE

PHILIP C. JACKSON



1977

HISTORY OF ARTIFICIAL INTELLIGENCE

P. McCorduck (Session Chairman), Univ. of Pittsburgh! M. Minsky, MIT: O. Selfridge, Bolt Beranek and Newman? H. A. Simon, Carnegie-Mellon University

The Early History

P. McCorduck

Though our discussion is en History of Artificial Intellige fact we are focusing here on c but highly significant moment history the moment when art r

1974

2004

PAMELA McCORDUCK
MACHINES WHO THINK



„Good Old Fashioned AI“ versus Deep Learning

- A. KRR: Wissenrepresentation und Schlussfolgern,
- B. PLAN: Planen
- C. MAS: Multi-Agent Systems
- D. RBT: Robotik
- E. PHIL: Philosophische Fragen
- F. NLP: Prozessieren natürlicher Sprachen
- G. CV: Computer vision
- H. ML: Machine Learning

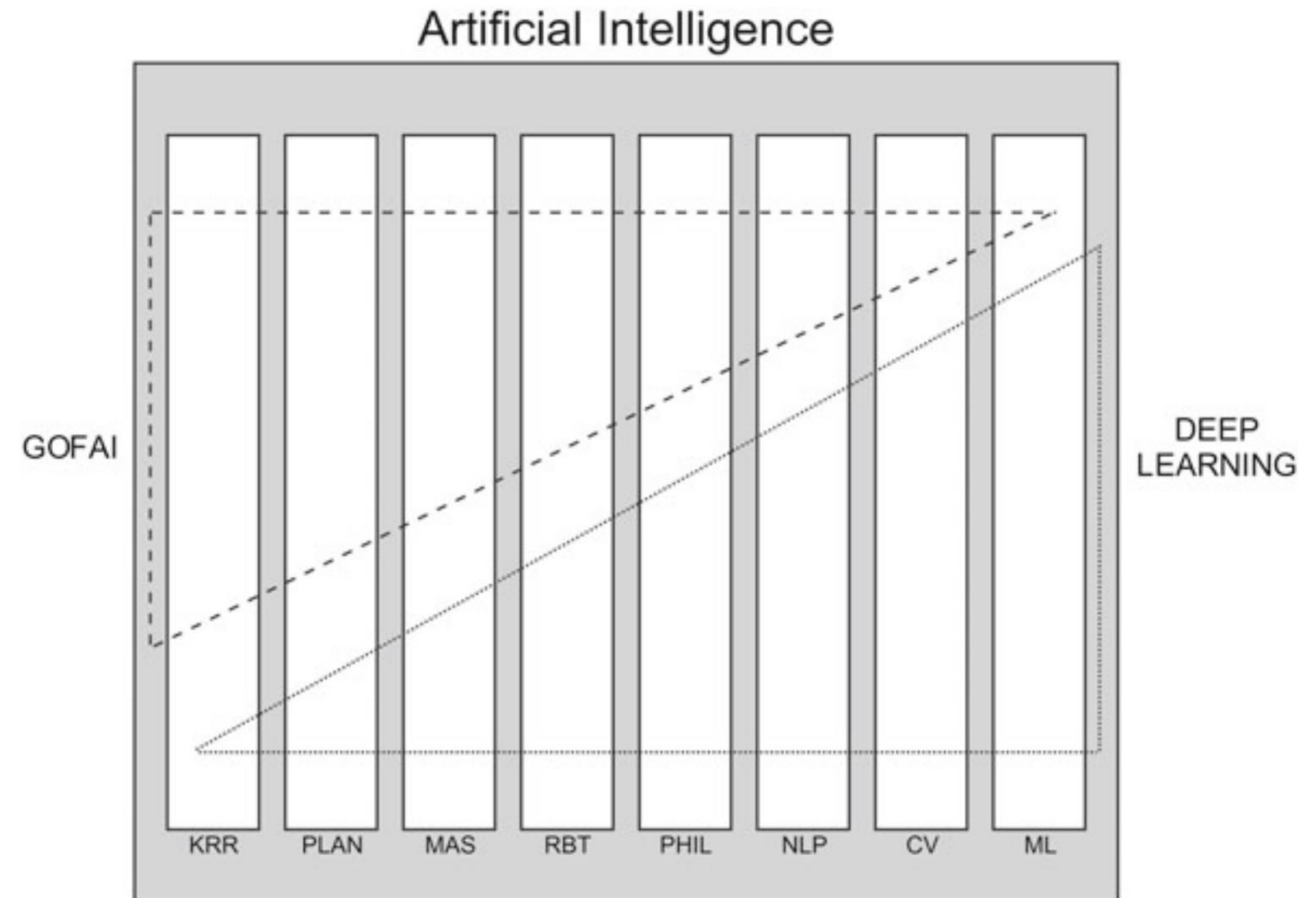
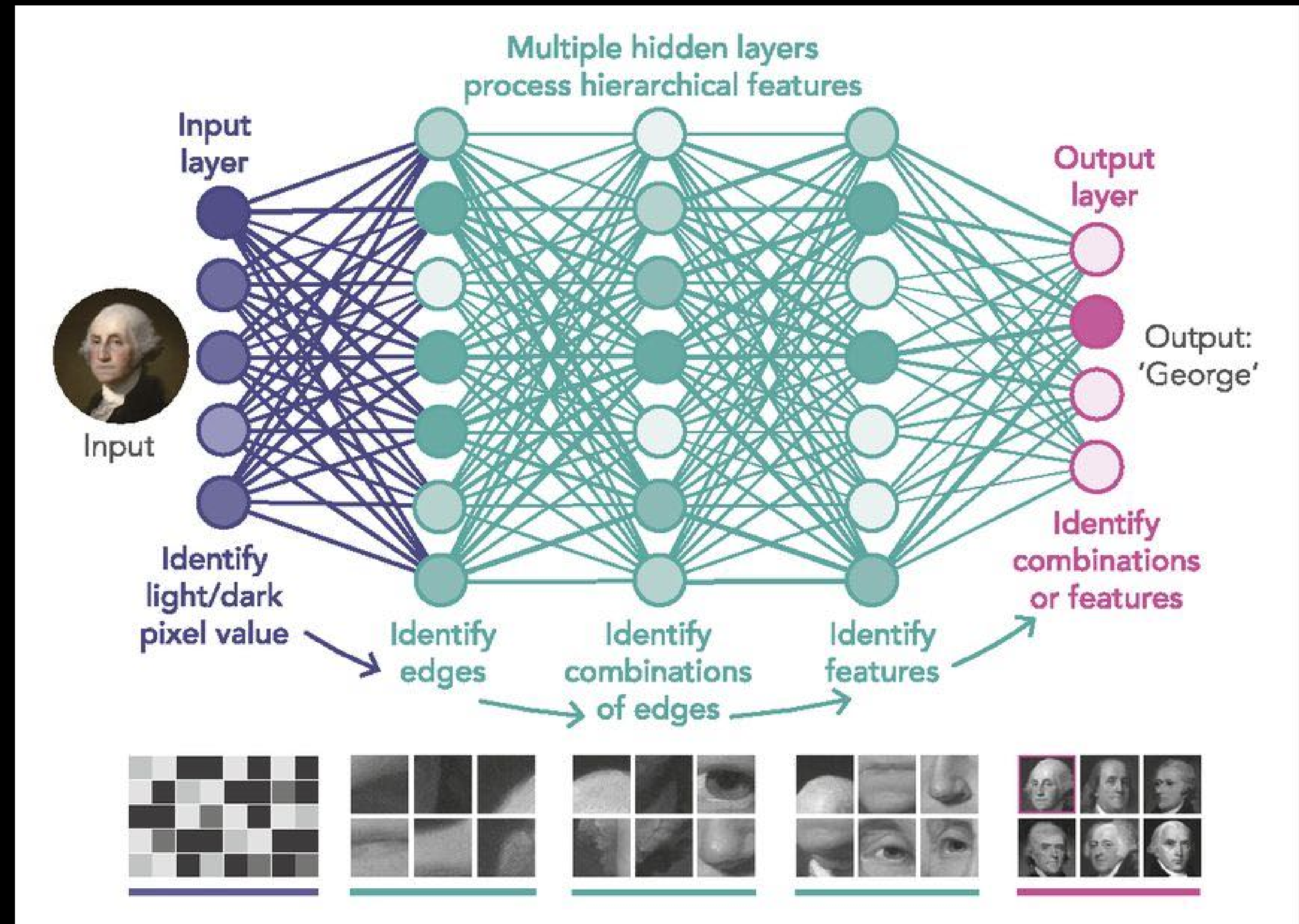
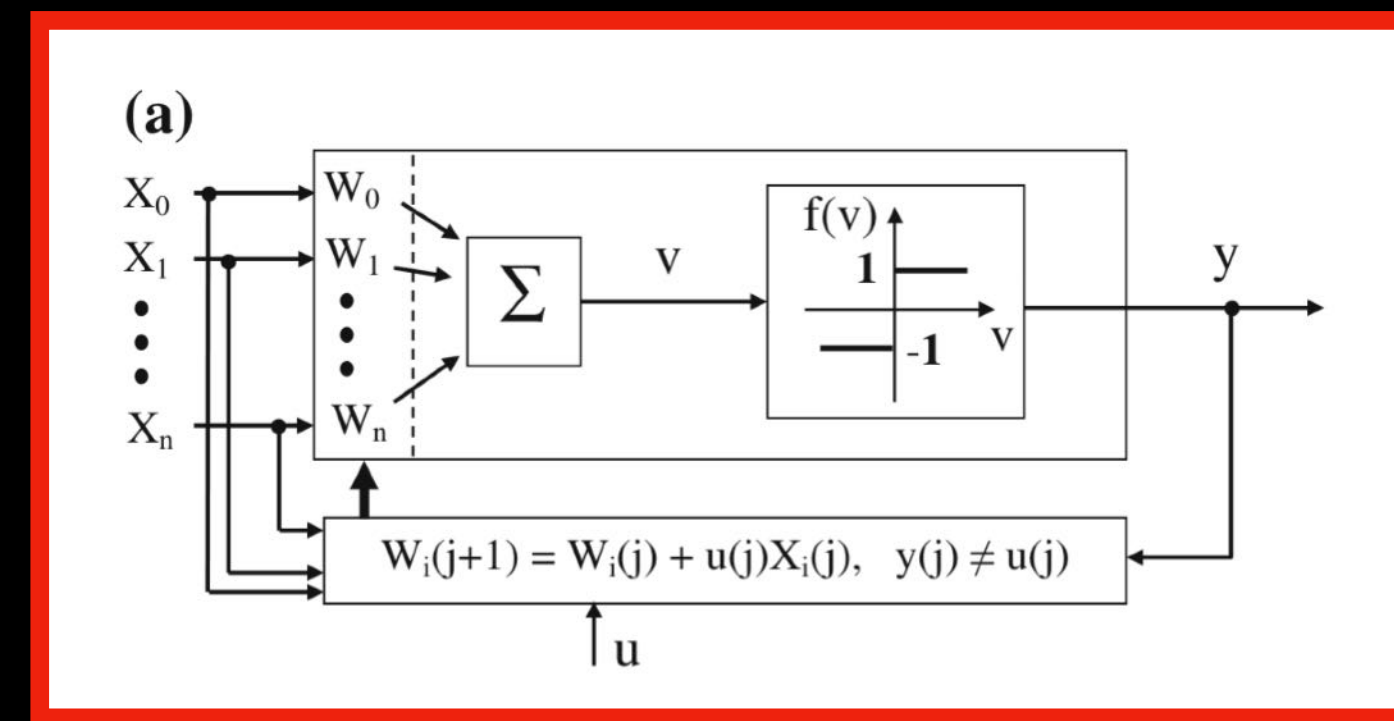


Fig. 1.1 Vertical and horizontal components of AI

Neuronal „feed forward“ Netzwerk



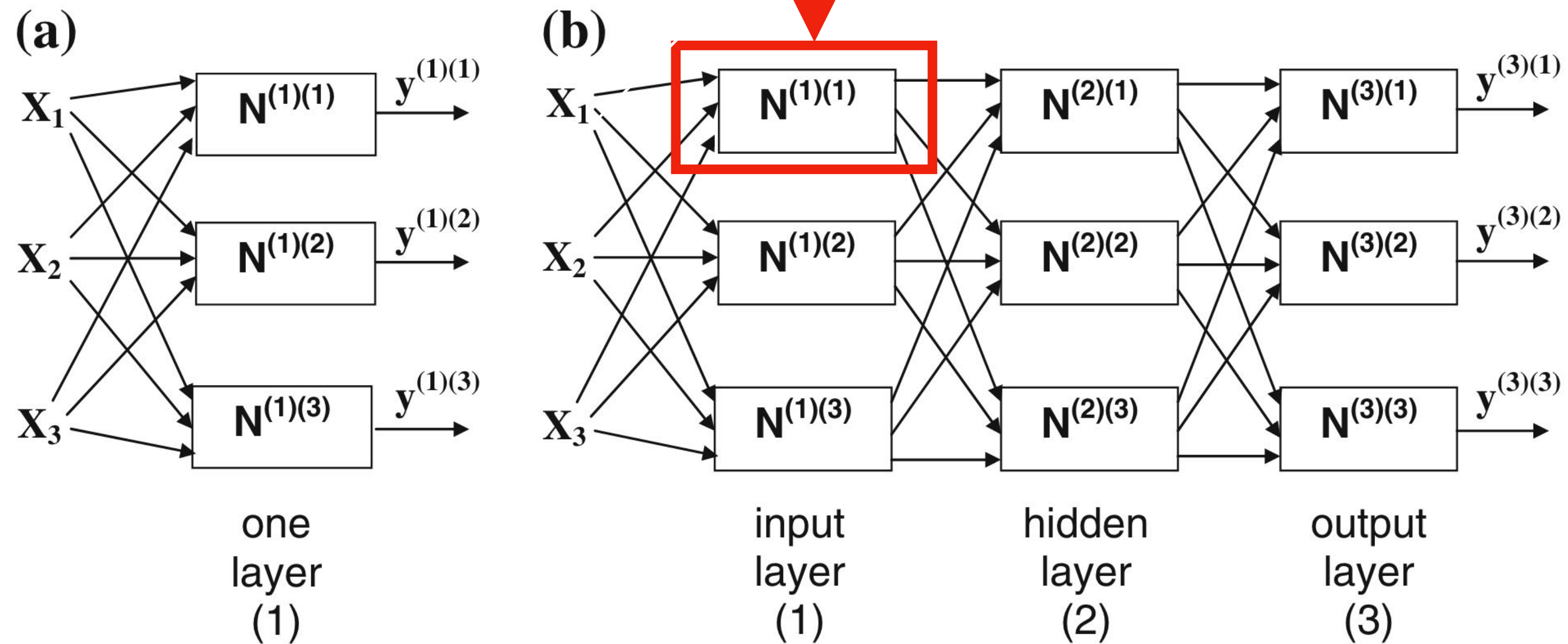
Künstliches Neuron (hier: Perceptron)



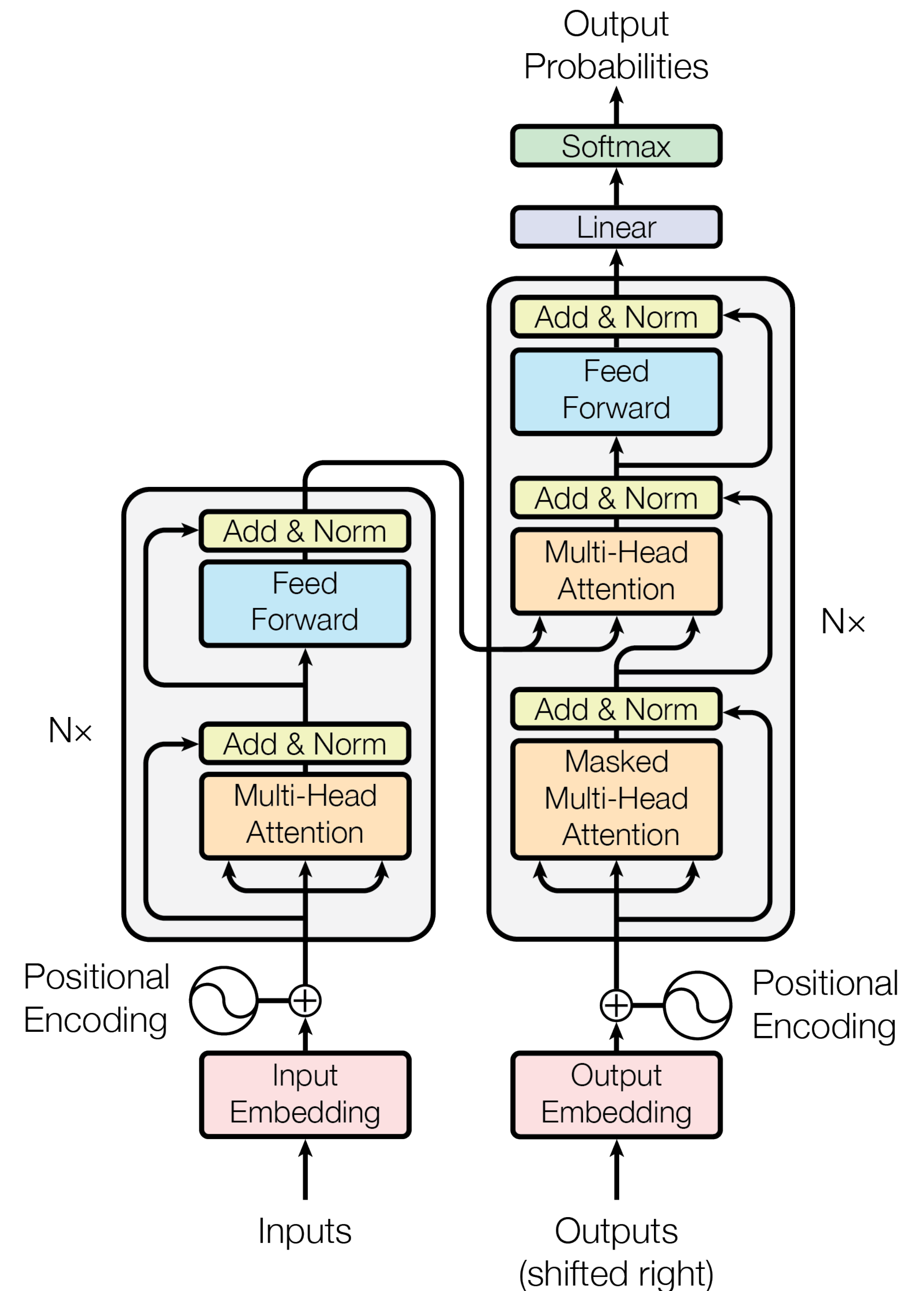
Neuronales „feed forward“ Netzwerk

168

11 Neural Networks

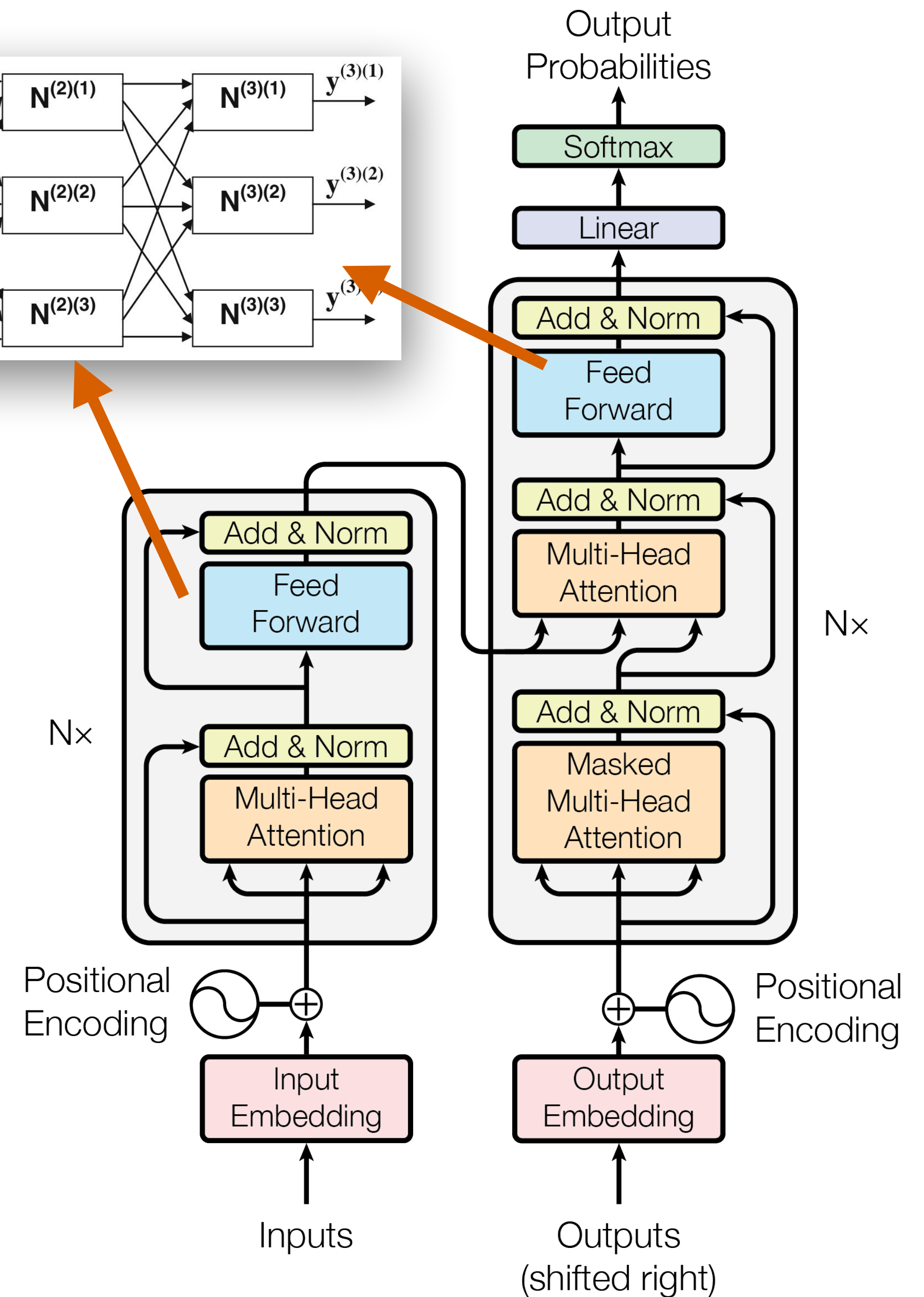
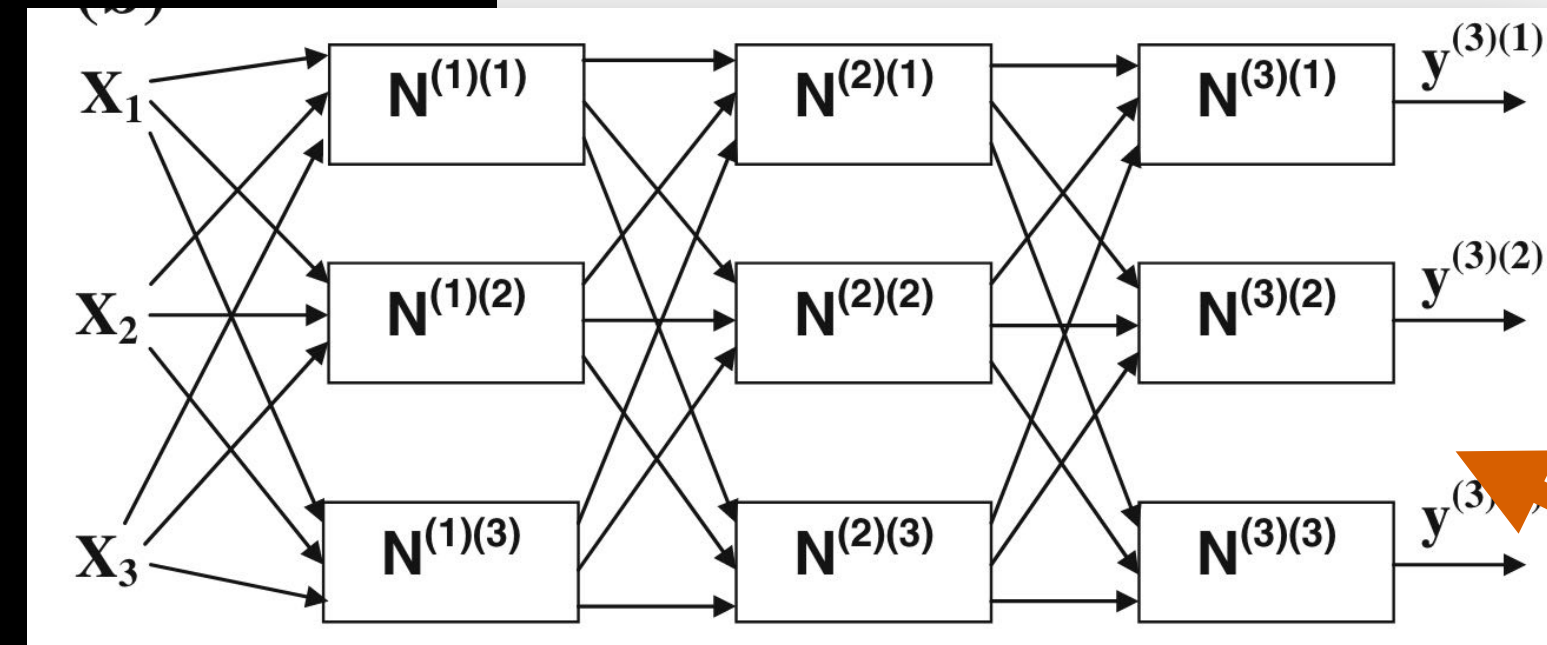


„Transformer Neural Networks“ (TNN): Grundlage von ChatGPT (z.B. BERT; GPT-3)



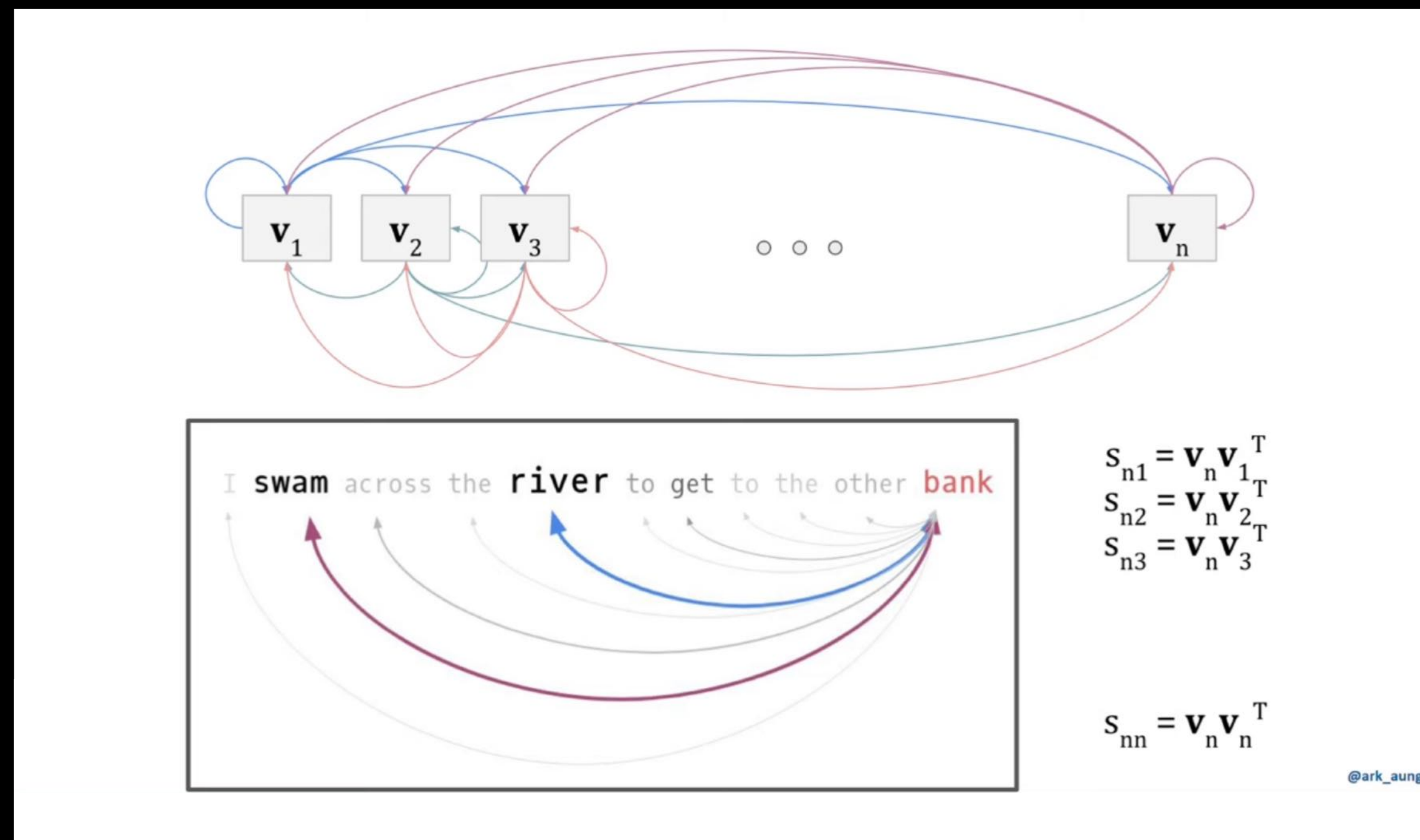
Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention Is All You Need (arXiv:1706.03762). arXiv. <https://doi.org/10.48550/arXiv.1706.03762>

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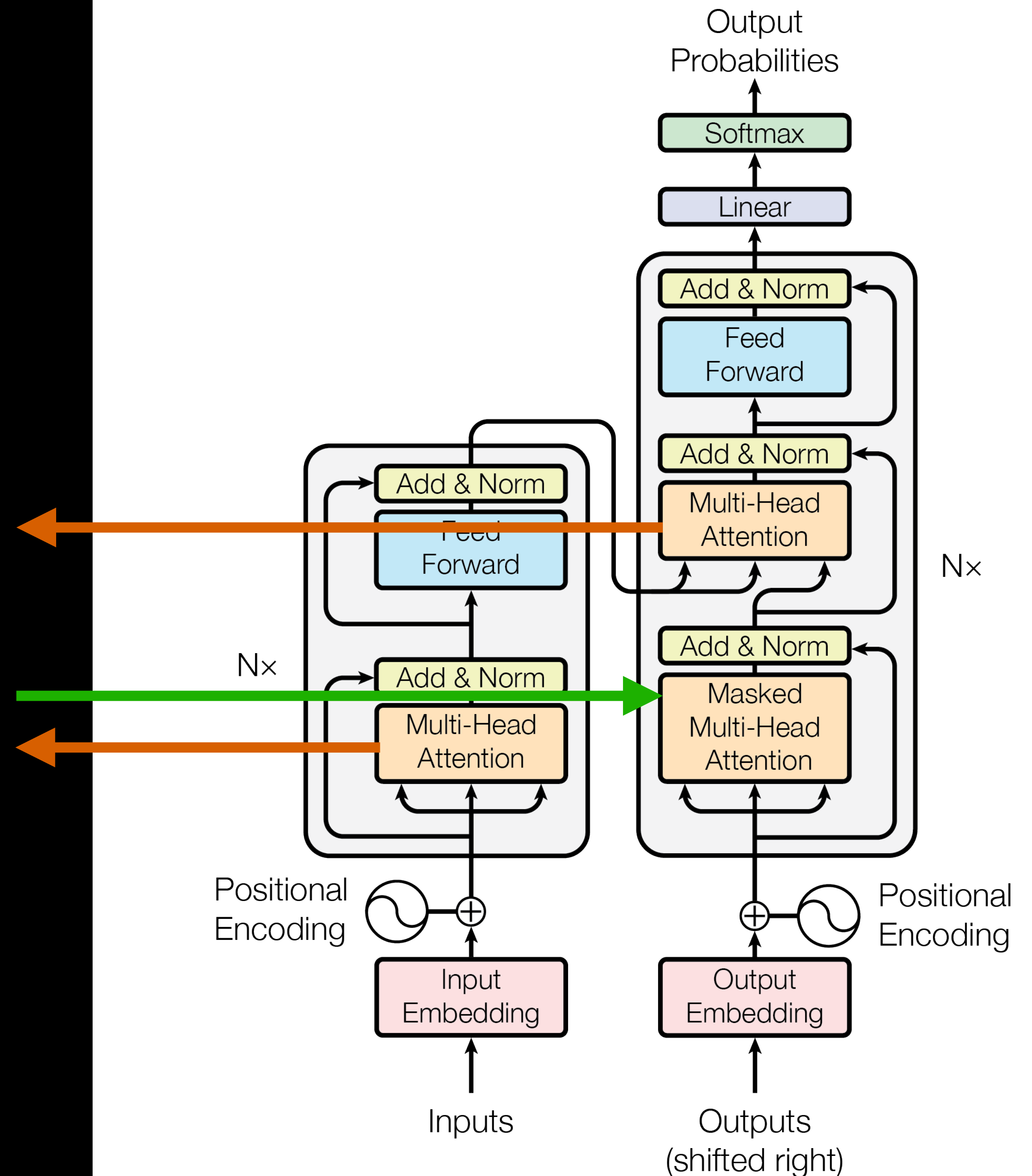


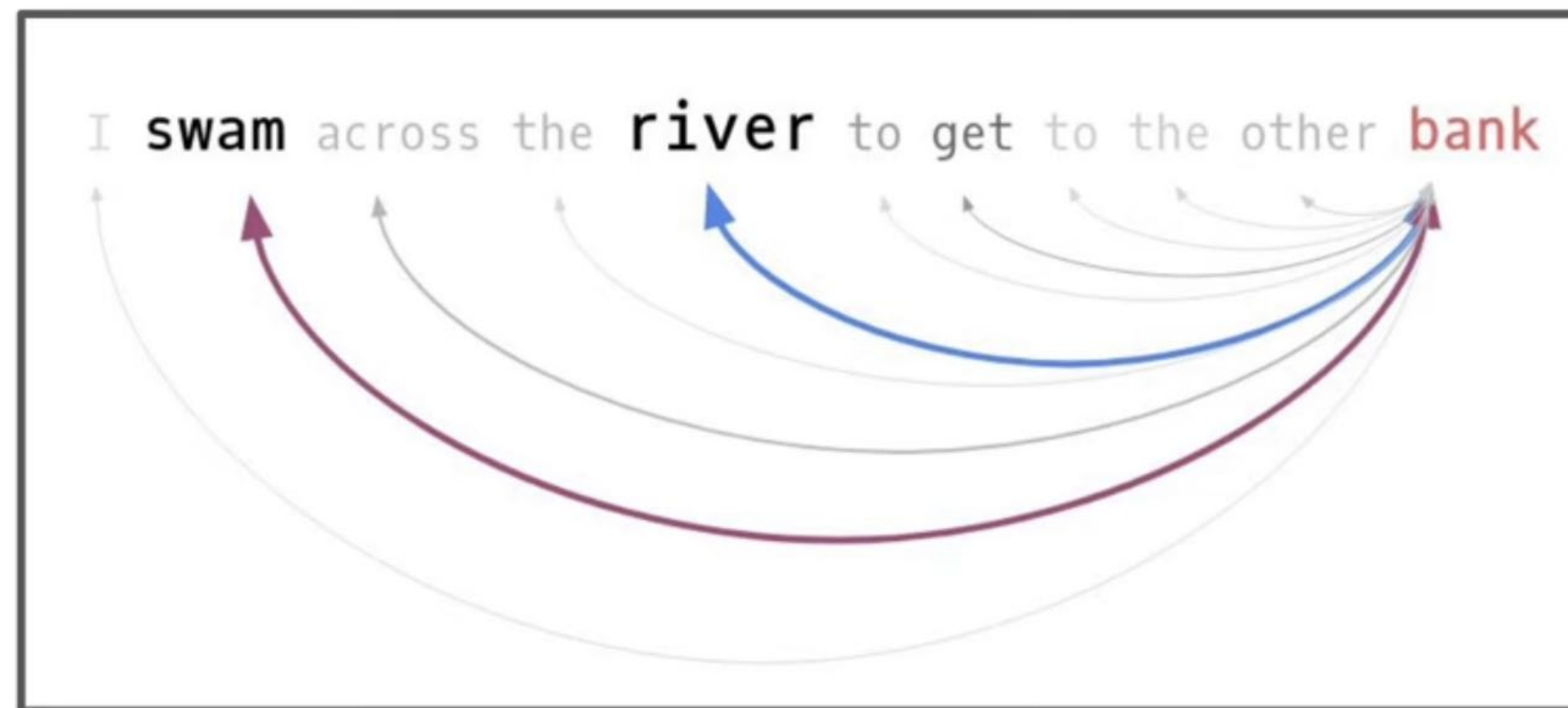
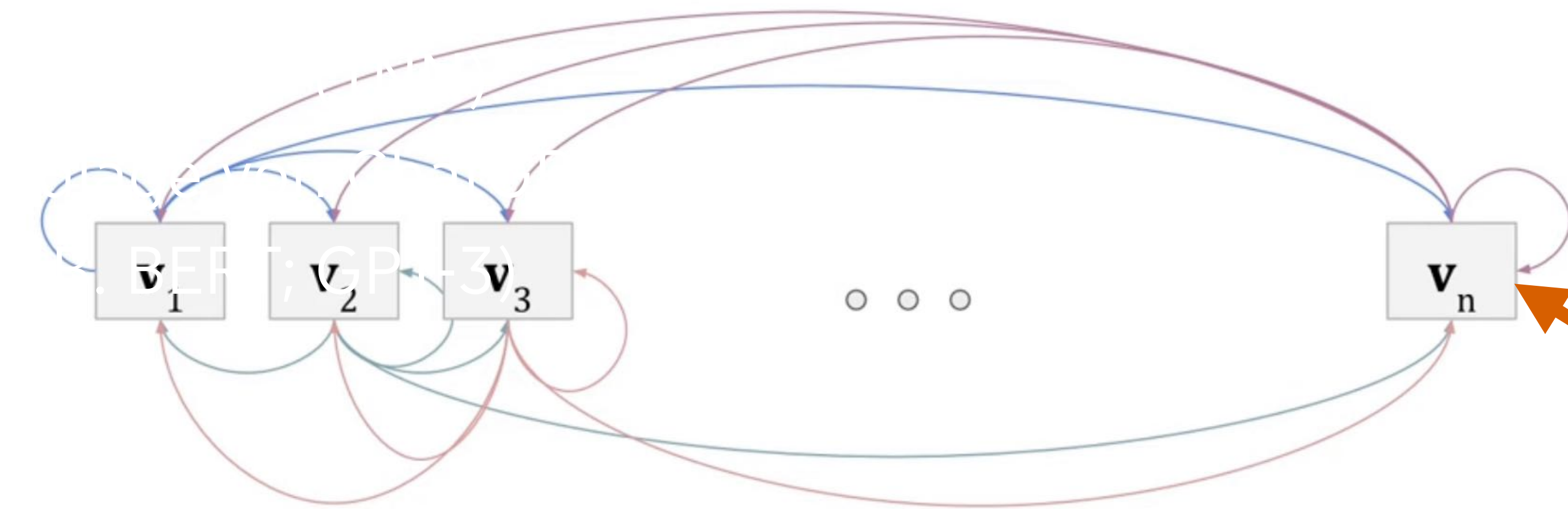
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„Transformer Neural Networks“ (TNN): Grundlage von ChatGPT (z.B. BERT; GPT-3)



Aung, A. M. (Director). (2020, Oktober 17). Intuition Behind Self-Attention Mechanism in Transformer Networks.
<https://www.youtube.com/watch?v=g2BRluln4uc>





$$S_{n1} = \mathbf{v}_n \mathbf{v}_1^T$$

$$S_{n2} = \mathbf{v}_n \mathbf{v}_2^T$$

$$S_{n3} = \mathbf{v}_n \mathbf{v}_3^T$$

$$S_{nn} = \mathbf{v}_n \mathbf{v}_n^T$$

@ark_aung

Add & Norm

Multi-Head
Attention

Jede Einheit (Wort) wird als **Vektor** berechnet, der Beziehungen zu anderen Einheiten (Wörtern) ausdrückt.

DATA

5 tensors found
Word2Vec 10K

Label by
word

Color by
No color map

Edit by
word

Tag selection as

Load

Publish

Download

Label

☒ Sphereize data

Checkpoint: Demo datasets

Metadata: oss_data/word2vec_10000_200d_labels.tsv

UMAP

T-SNE

PCA

CUSTOM

X
Component #1

Y
Component #2

Z
Component #3

PCA is approximate.

Total variance described: 8.5%.

🖼️ 📐 🌙 A

Points: 10000 | Dimension: 200 | Selected 101 points

?

university

word university

count 10195

university

college

school

harvard

institute

universities

professor

graduate

cambridge

stanford

oxford

yale

students

illinois

columbia

faculty

press

mit

princeton

undergraduate

education

academic

student

berkeley

Show All Data

Isolate 101 points

Clear selection

Search
university

by
word

neighbors

distance

COSINE

EUCLIDEAN

Nearest points in the original space:

college

school

harvard

institute

universities

professor

graduate

cambridge

stanford

oxford

yale

students

illinois

columbia

faculty

press

mit

princeton

undergraduate

education

academic

student

berkeley

BOOKMARKS (0)

Word Embeddings

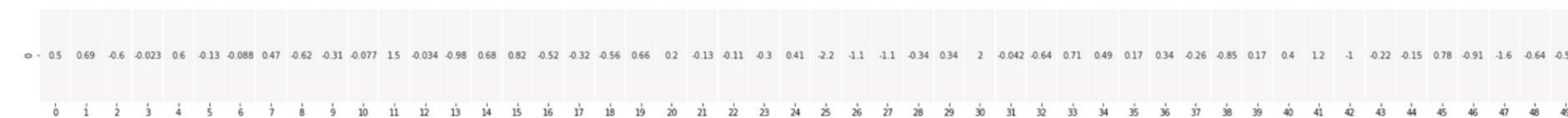
| “The gift of words is the gift of deception and illusion” ~Children of Dune

With this understanding, we can proceed to look at trained word-vector examples (also called word embeddings) and start looking at some of their interesting properties.

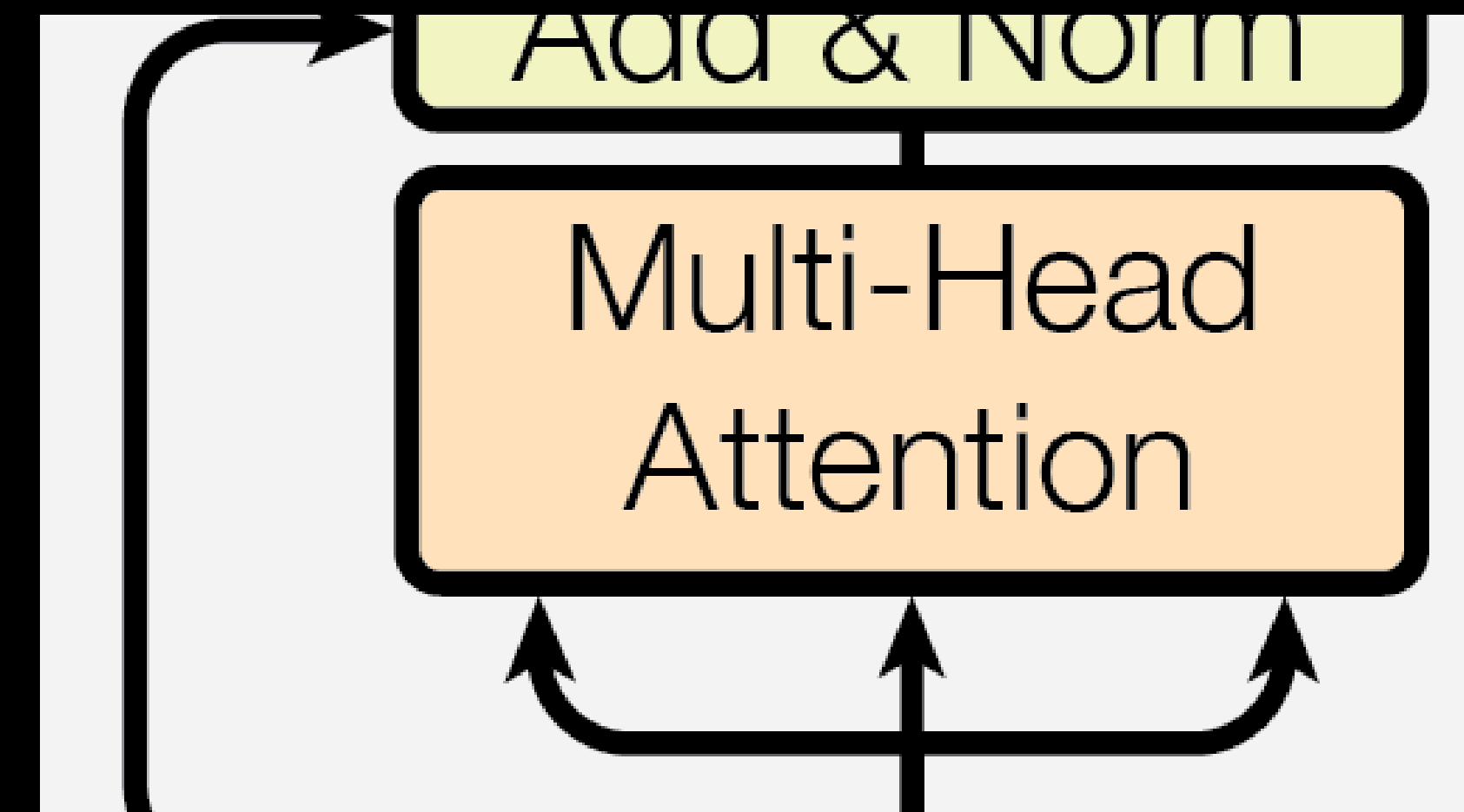
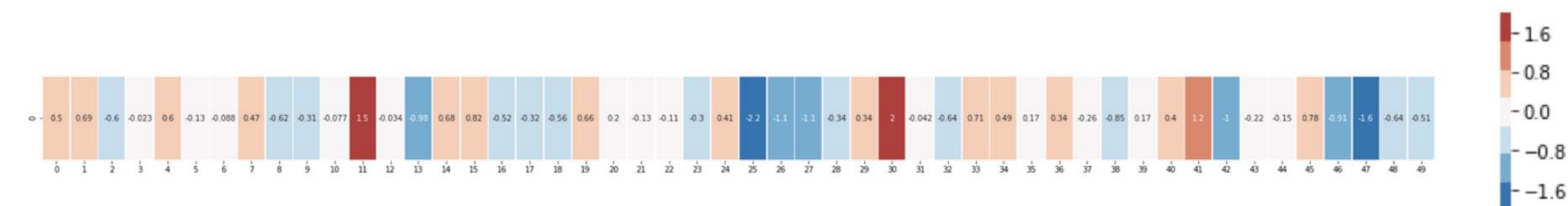
This is a word embedding for the word “king” (GloVe vector trained on Wikipedia):

```
[ 0.50451 , 0.68607 , -0.59517 , -0.022801, 0.60046 , -0.13498 , -0.08813 , 0.47377 , -0.61798 , -0.31012 ,  
-0.076666, 1.493 , -0.034189, -0.98173 , 0.68229 , 0.81722 , -0.51874 , -0.31503 , -0.55809 , 0.66421 , 0.1961  
, -0.13495 , -0.11476 , -0.30344 , 0.41177 , -2.223 , -1.0756 , -1.0783 , -0.34354 , 0.33505 , 1.9927 ,  
-0.04234 , -0.64319 , 0.71125 , 0.49159 , 0.16754 , 0.34344 , -0.25663 , -0.8523 , 0.1661 , 0.40102 , 1.1685 ,  
-1.0137 , -0.21585 , -0.15155 , 0.78321 , -0.91241 , -1.6106 , -0.64426 , -0.51042 ]
```

It’s a list of 50 numbers. We can’t tell much by looking at the values. But let’s visualize it a bit so we can compare it other word vectors. Let’s put all these numbers in one row:



Let’s color code the cells based on their values (red if they’re close to 2, white if they’re close to 0, blue if they’re close to -2):



We'll proceed by ignoring the numbers and only looking at the colors to indicate the values of the cells. Let's now contrast "King" against other words:

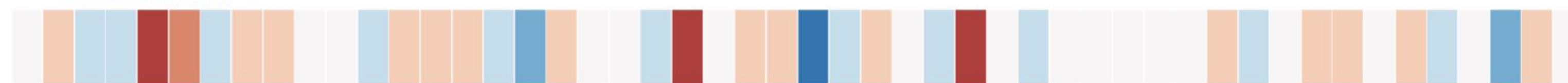
"king"



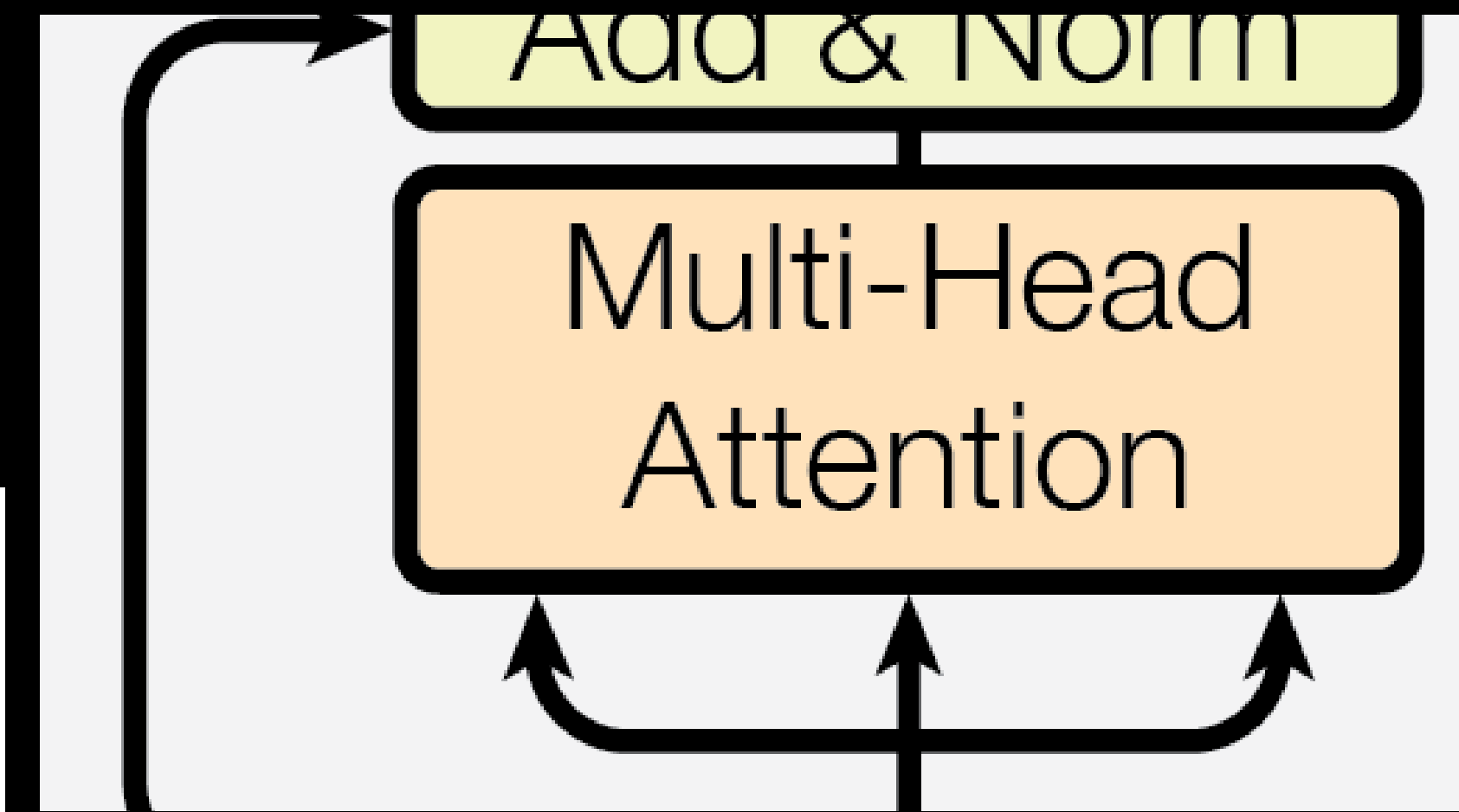
"Man"

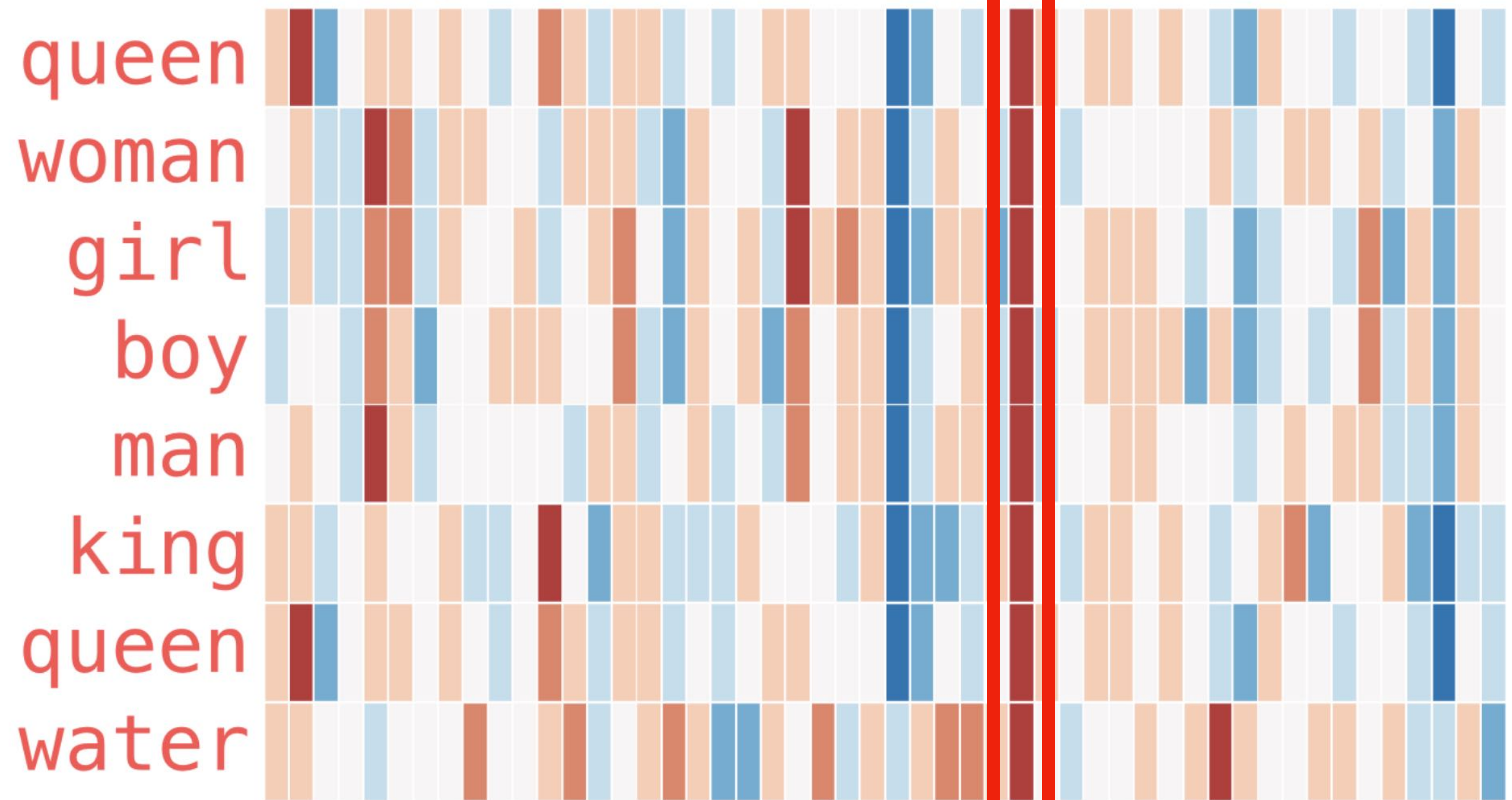


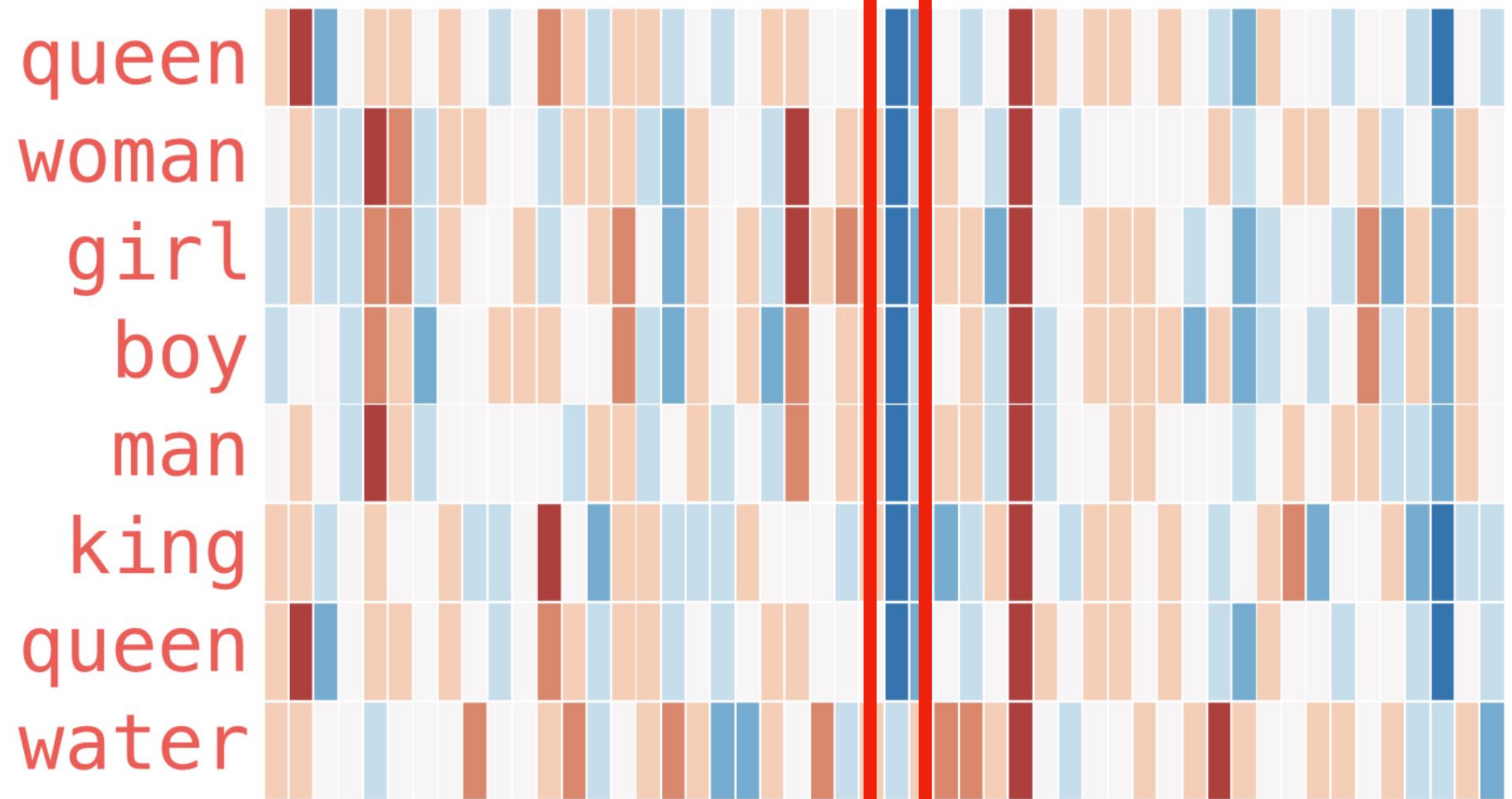
"Woman"

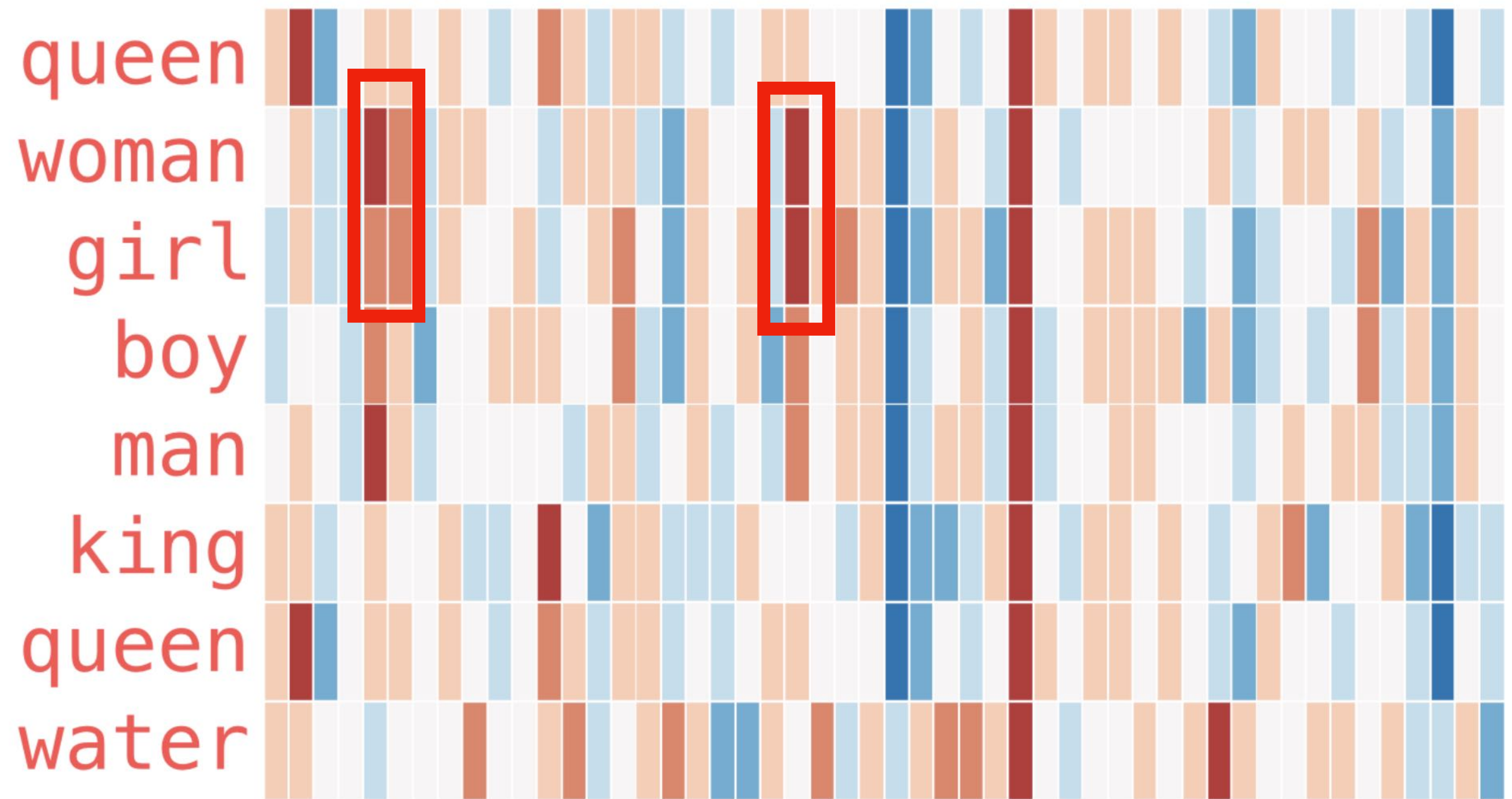


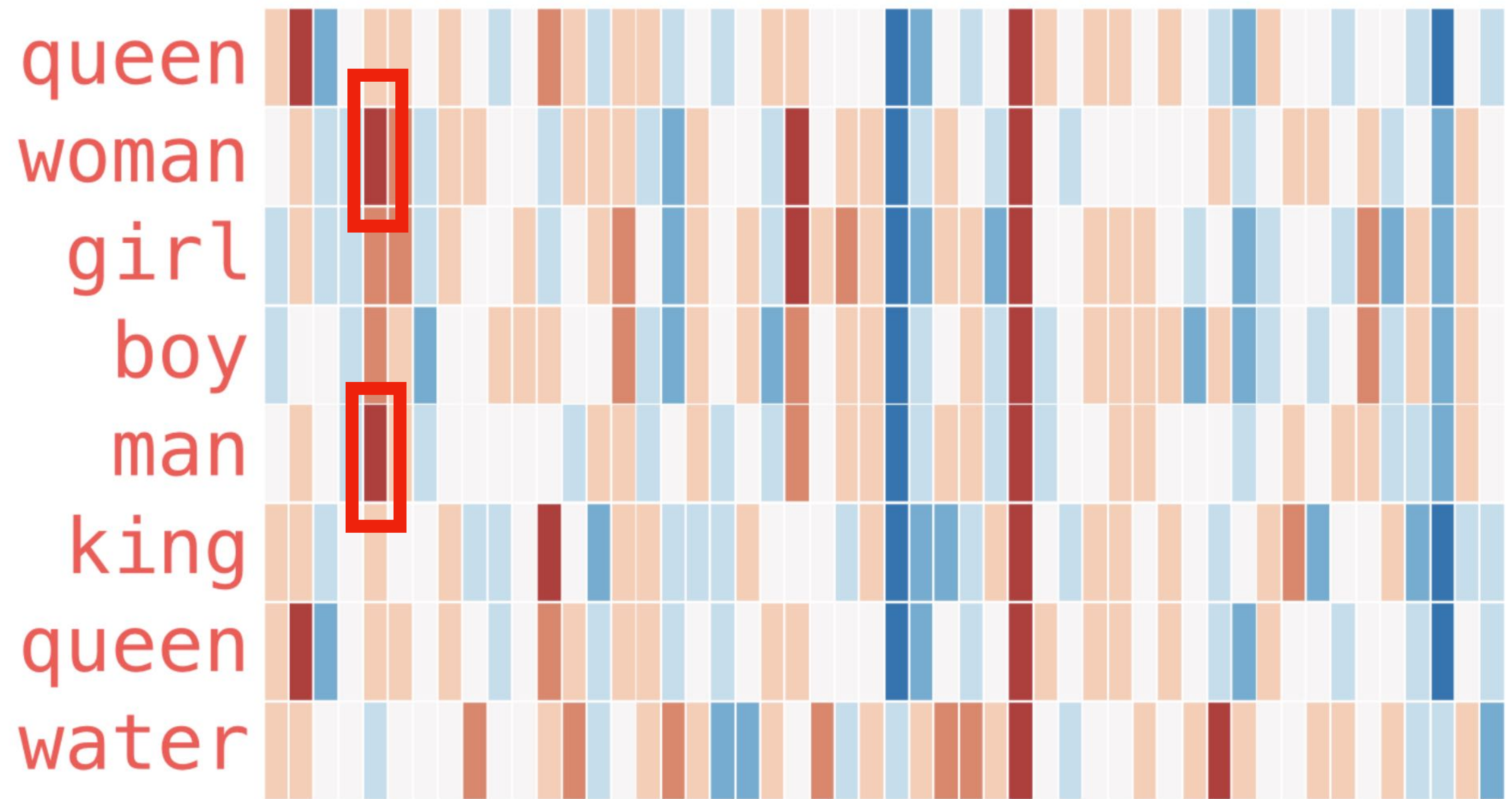
See how "Man" and "Woman" are much more similar to each other than either of them is to "king"? This tells you something. These vector representations capture quite a bit of the information/meaning/associations of these words.

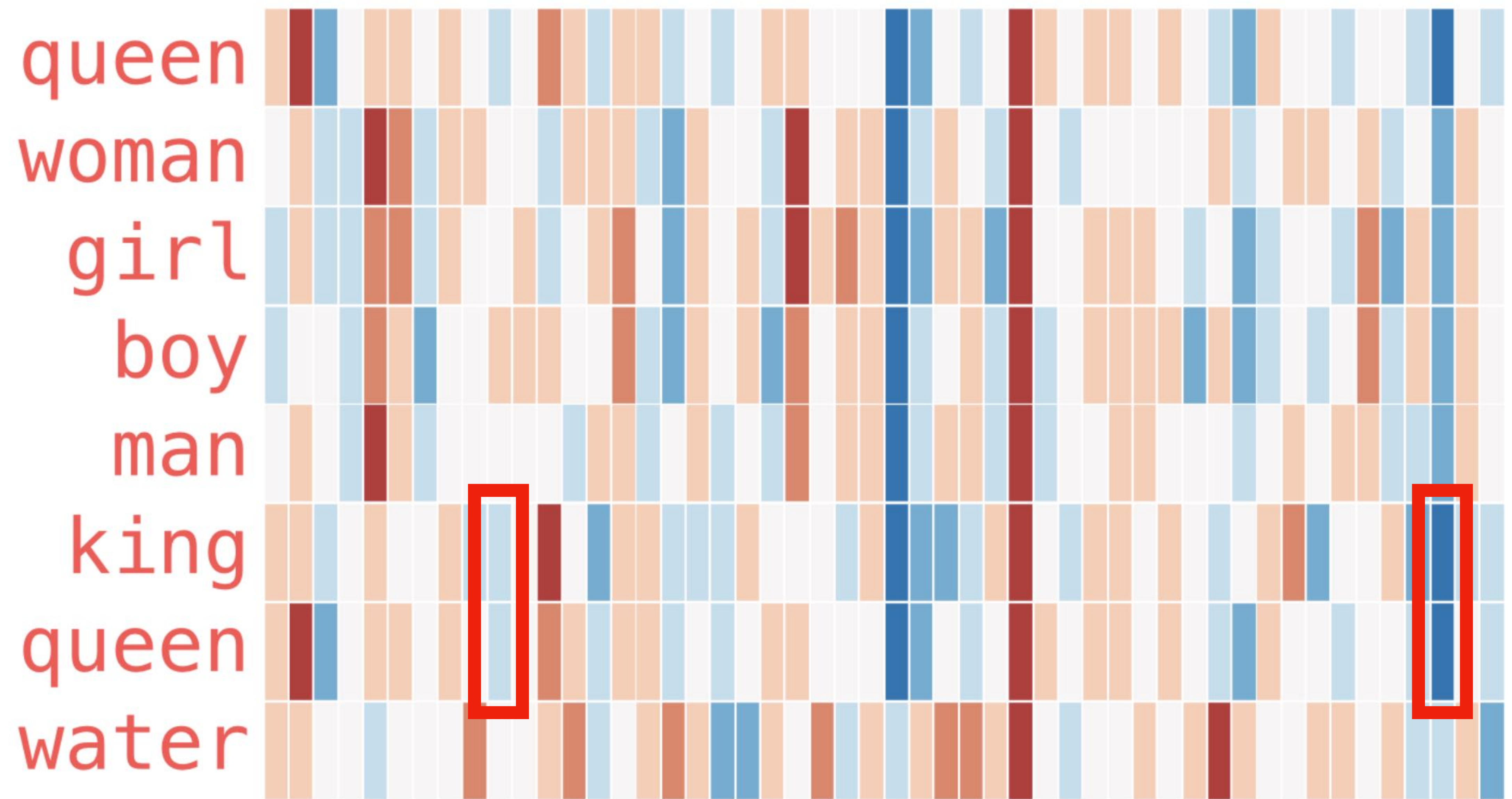










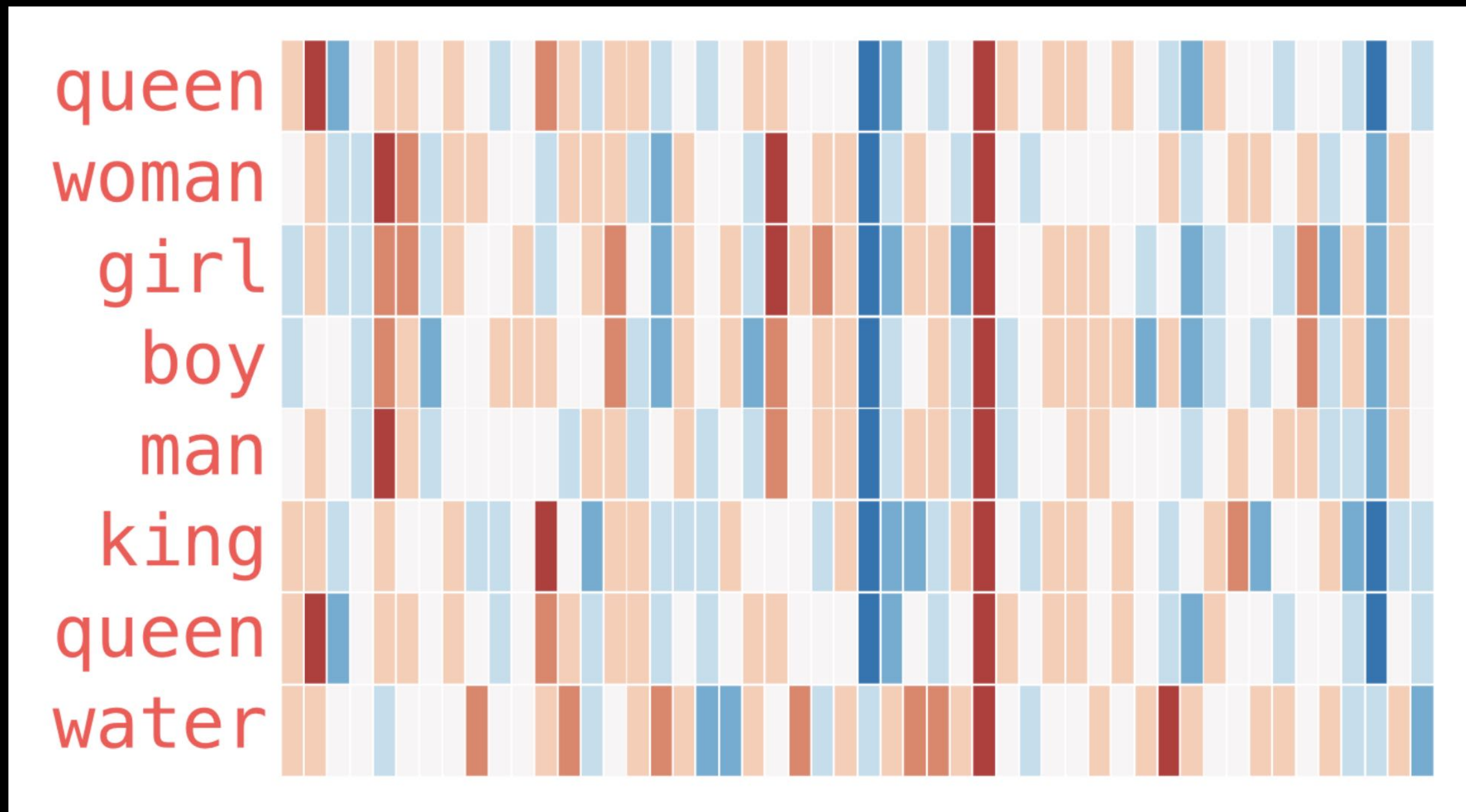


king - man + woman $\approx$ queen

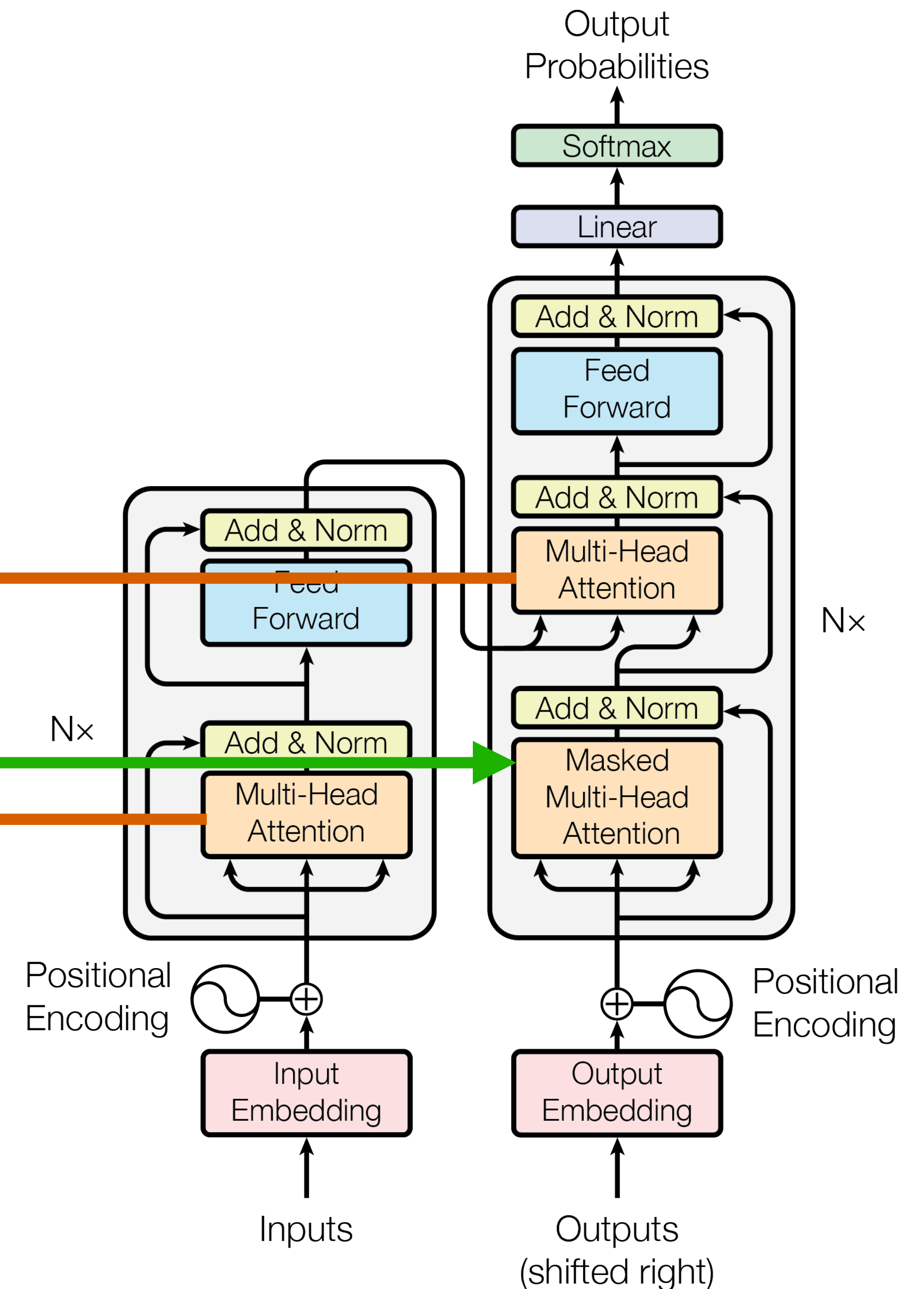


The resulting vector from "king-man+woman" doesn't exactly equal "queen", but "queen" is the closest word to it from the 400,000 word embeddings we have in this collection.

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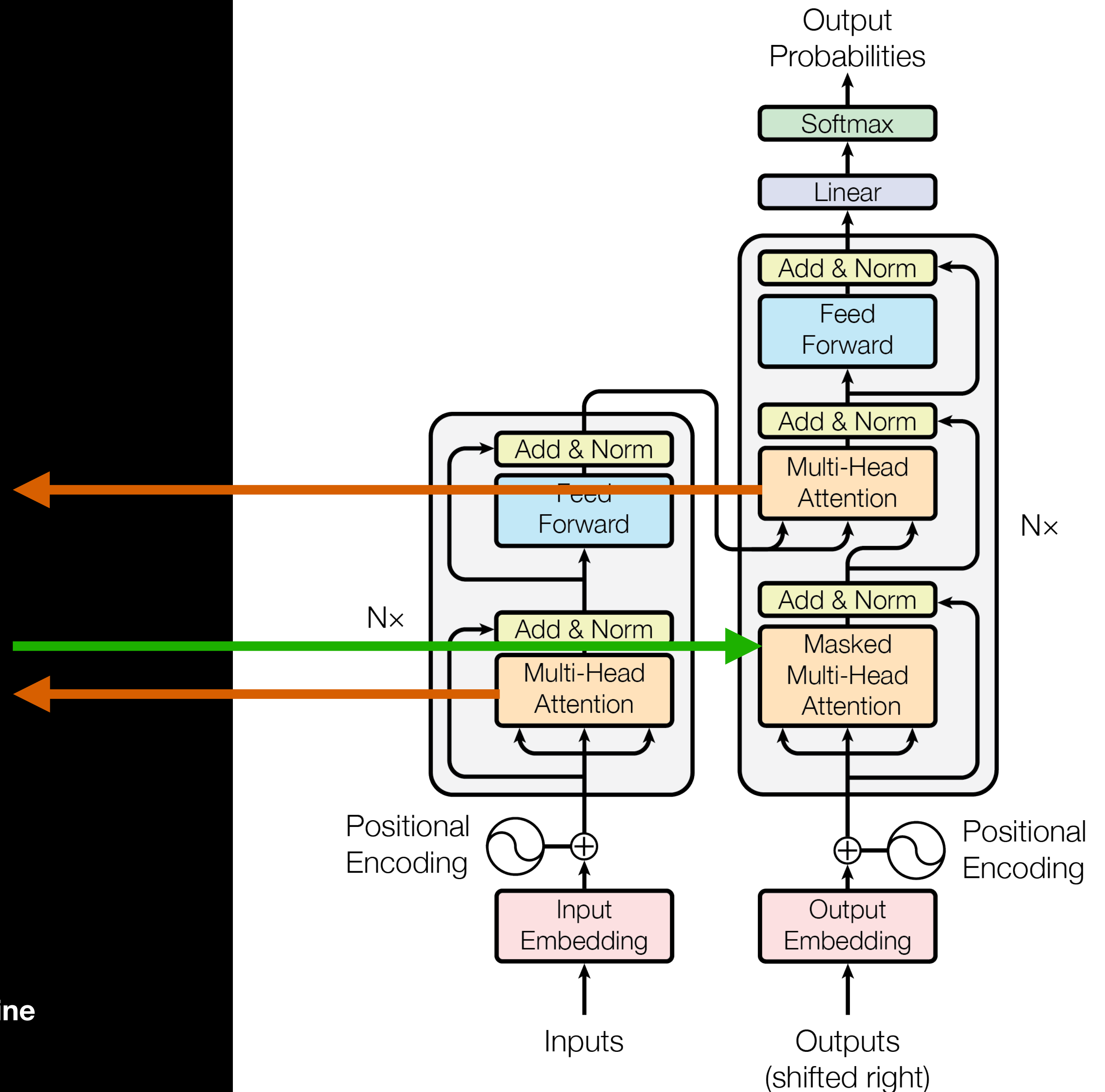
Alammar, J. (2019, März 27). The Illustrated Word2vec. <https://jalammar.github.io/illustrated-word2vec/>



Generelles Merkmal von
KI-Technologien im Kontext
humaner/hermeneutischer
Bedeutungswelten:

„Brute-force“-statistische
Normierung von Bedeutung:
quantitative „Wahrscheinlichkeit“
vs. verhältnismäßige
„Wahr-Scheinlichkeit“

Böhme, G. (1996). Idee und Kosmos: Platons Zeitlehre: eine
Einführung in seine theoretische Philosophie.
Klostermann, S. 18



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KI-Technologien im Kontext
humaner/hermeneutischer
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quantitative „Wahrscheinlichkeit“
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„Wahr-Scheinlichkeit“

Das Problem liegt *nicht* in den
Algorithmen/der KI an sich, sondern ...

- 1) *Produktion*: Versuch, **die Simulation von Bedeutung durch Statistik als User Experience zu installieren**, d.h. zu maskieren: UX ↔ Compliance als Geschäftsmodell
- 2) *Rezeption*: **Anthropomorphisierung der Maschine** (Verwechslung von Wahrscheinlichkeit und „Wahr-Scheinlichkeit“)
- 3) *Politik + Wirtschaft*: **Universalisierung und Automatisierung kybernetischer Steuerungslogiken** (Social Engineering, Subjektengineering, Humanengineering, Militär, Polizei, Rechtssprechung)

Generelles Merkmal von
KI-Technologien im Kontext
humaner/hermeneutischer
Bedeutungswelten:

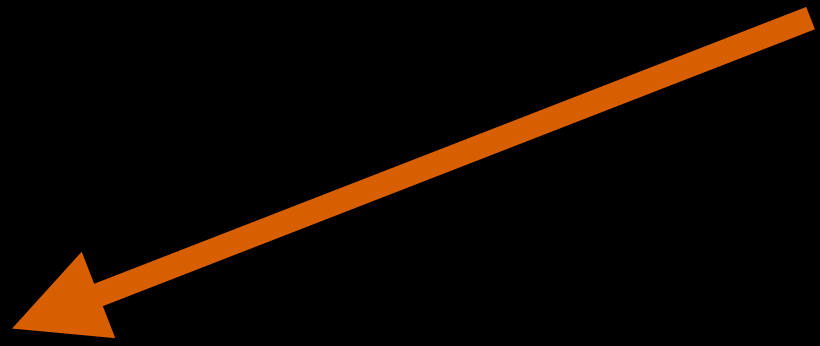
„Brute-force“-statistische
Normierung von Bedeutung:
quantitative „Wahrscheinlichkeit“
vs. verhältnismäßige
„Wahr-Scheinlichkeit“

→ **zu unterscheidende Ebenen
von Analyse und Kritik:**

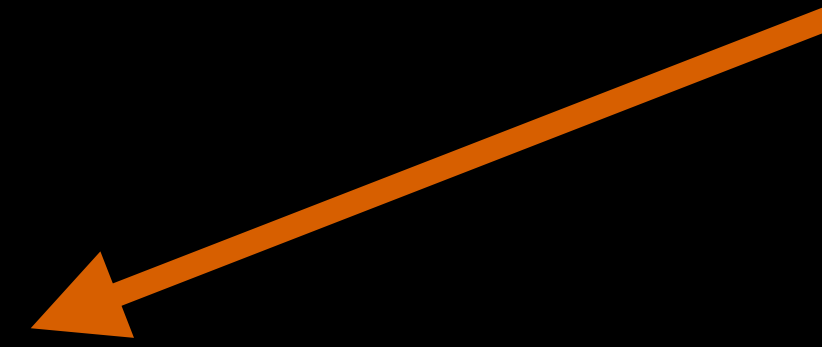
- 1) **Kritische Analytik/Hermeneutik von KI** auf der
Ebene ihrer operativen Logiken (folgender Abschnitt)
 - KI als „andere“, non-humane Intelligenz, aber
welche Art von Alterität mit welchen Implikationen?
- 2) **Kritische Rekonstruktion der Praktiken und
Policies** in Bezug auf Hervorbringung von und
Umgang mit KI, d.h. v.a. ihrer politischen Ökonomie
 - Exklusionen (Datenformate, Daten, Archive)
 - Politiken und Normativitäten, implizite Ideologien
(Ground truths, Firmenpolicies des Trainings und
Finetunings)

Generelles Merkmal von
KI-Technologien im Kontext
humaner/hermeneutischer
Bedeutungswelten:

**2) Kontrolle vs.
Kontrollverlust**



**3) Kontrollsystem vs.
Kontrollverlustsystem**



→ **zu unterscheidende Ebenen
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status quo und best practice
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Mathematik (Mersch)	KI (Mersch)
nicht durchgängig computierbar	universelle Computierbarkeit
Poetik der Findungen	vollständige Berechenbarkeit
Differenz von Berechenbarkeit und Nichtberechenbarkeit	deduktive formale Geschlossenheit
strukturell unvollständig	algorithmische Rationalität
schöpferisches Tätigkeitsfeld	unkreatives, totales Kontrollparadigma

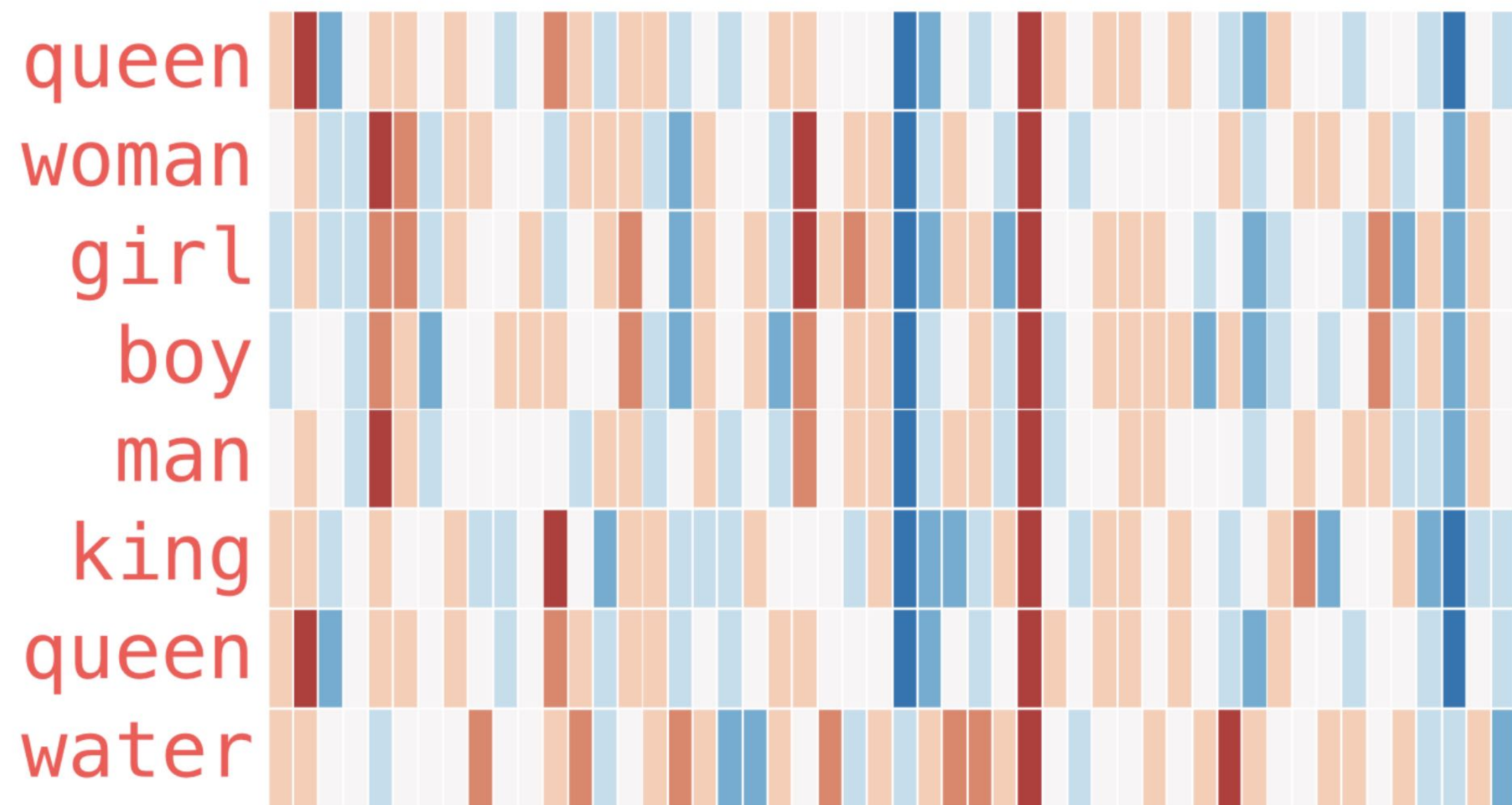
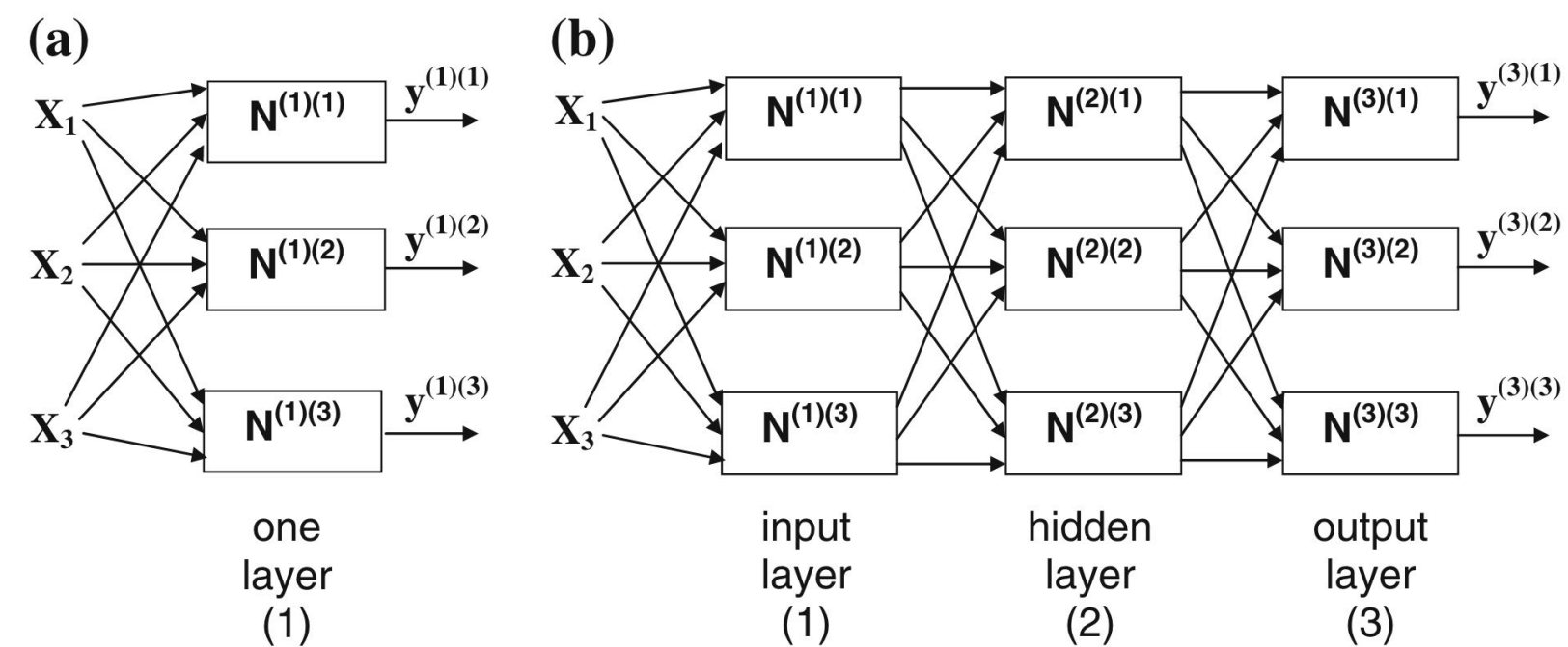
Mersch, D. (2019). Kreativität und Künstliche Intelligenz. Einige Bemerkungen zu einer Kritik algorithmischer Rationalität. Zeitschrift für Medienwissenschaft, 11(2), 65–74. <https://doi.org/10.25969/mediarep/12634>

Parisi, L. (2019). The alien subject of AI. Subjectivity, 12(1), 27–48. <https://doi.org/10.1057/s41286-018-00064-3>

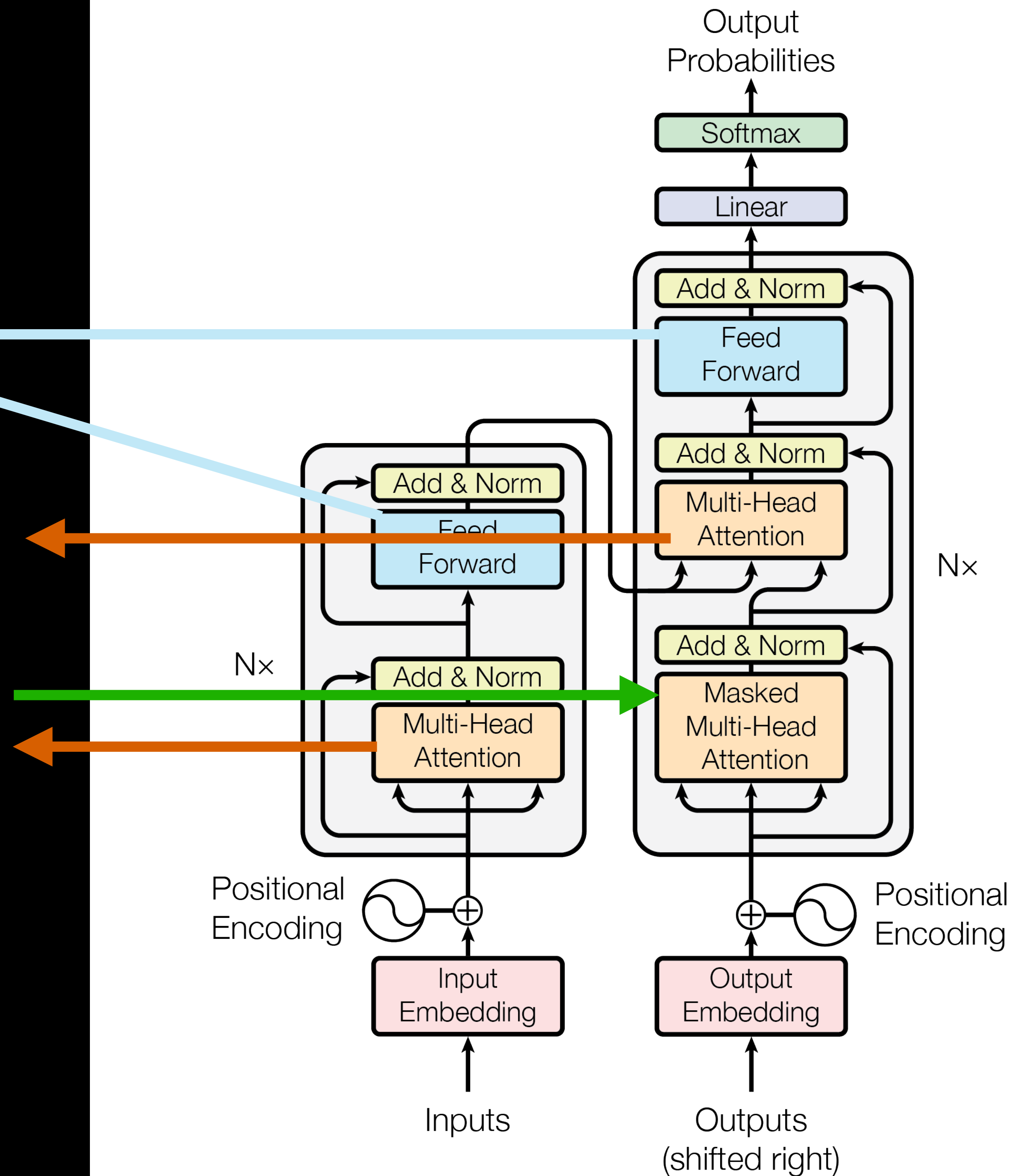
Mathematik (Mersch)	KI (Mersch)	KI (Parisi)
nicht durchgängig computierbar	universelle Computierbarkeit	Unverfügbarkeit als grundsätzliches, immanentes Moment digitaler (Turing-) Maschinen
Poetik der Findungen	vollständige Berechenbarkeit	„Halteproblem“; „Zufälle/Unfälle und Fehler“ als integraler Bestandteil, laufende Arbeit mit kollidierenden Daten“
Differenz von Berechenbarkeit und Nichtberechenbarkeit	deduktive formale Geschlossenheit	affektgeladen durch menschengemachte Daten
strukturell unvollständig	algorithmische Rationalität	„alien space of reasoning“; Hegemonialität nicht grundsätzlich, sondern Folge hegenomnialer Praxis
schöpferisches Tätigkeitsfeld	unkreatives, totales Kontrollparadigma	kreativer Kontrollverlust (wo nicht hegemonial eingehegt)

Mersch, D. (2019). Kreativität und Künstliche Intelligenz. Einige Bemerkungen zu einer Kritik algorithmischer Rationalität. Zeitschrift für Medienwissenschaft, 11(2), 65–74. <https://doi.org/10.25969/mediarep/12634>

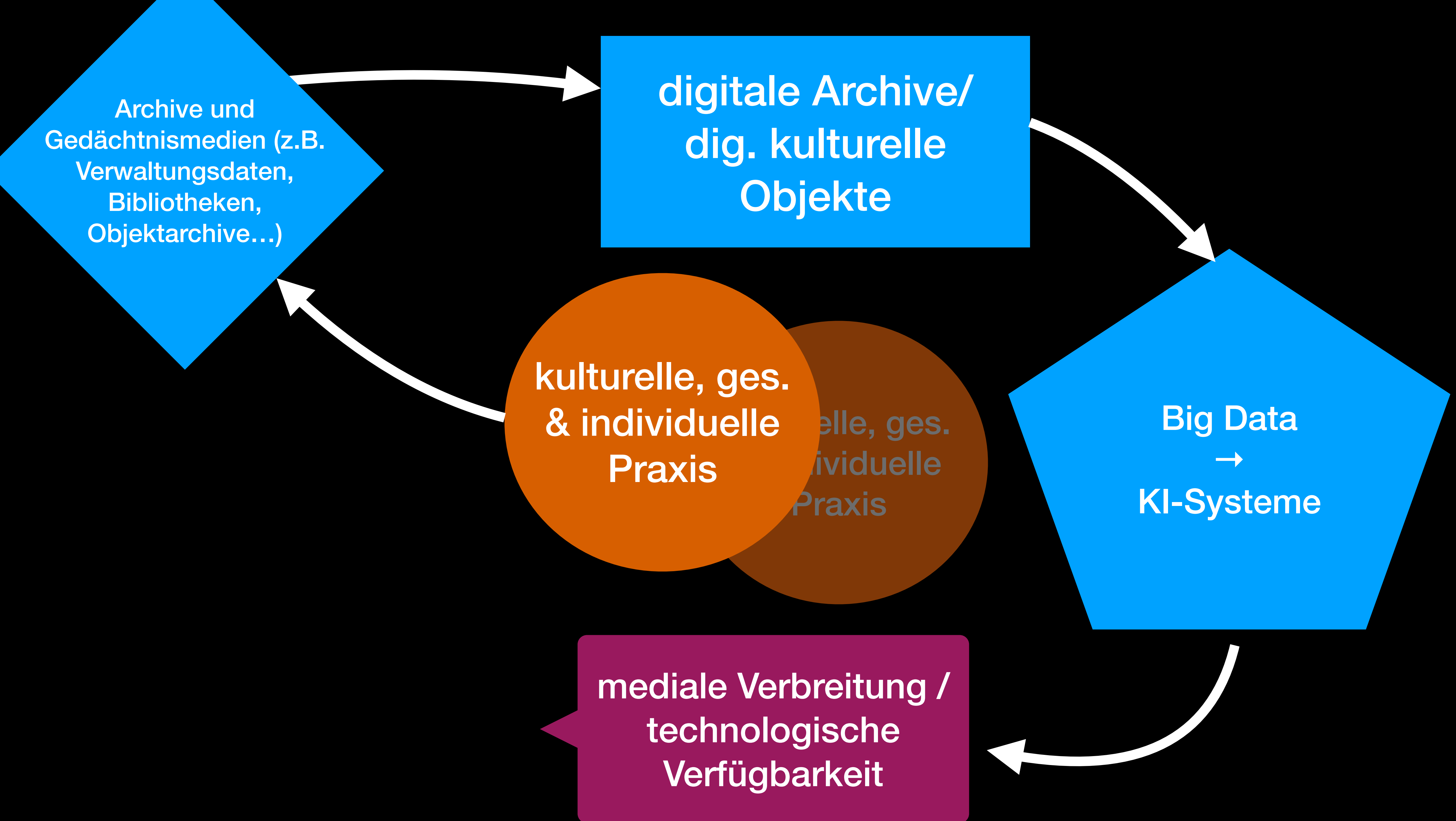
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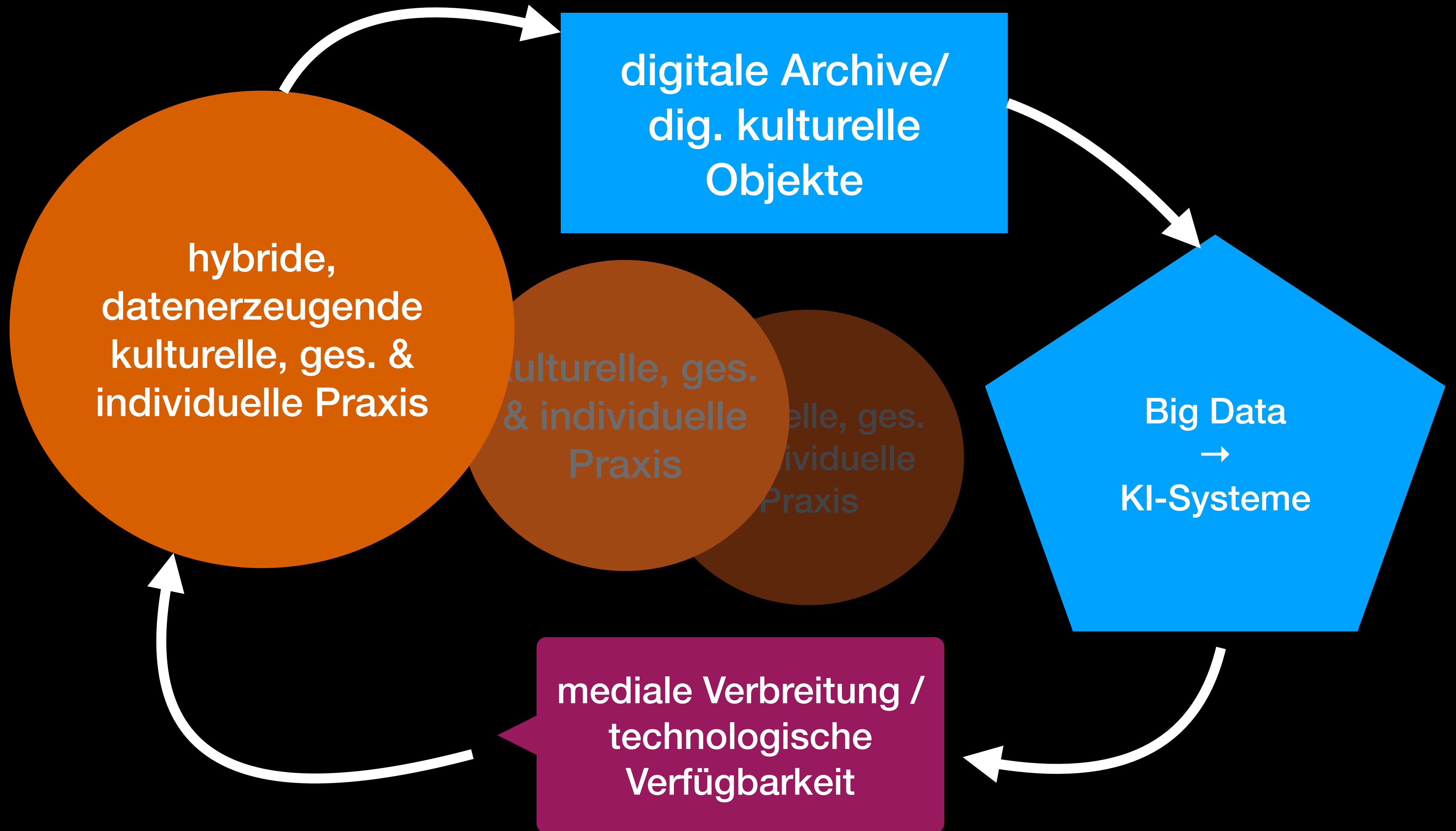


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Martin Donner,
Heidrun Allert

AUF DEM WEG ZUR CYBER POLIS

Neue Formen
von Gemeinschaft,
Selbst und Bildung

[transcript] Digitale Gesellschaft

MedienPädagogik

Zeitschrift für Theorie und Praxis der Medienbildung
www.medienpaed.com

ISSN 1424-3636

Themenheft Nr. 42: Optimierung in der Medienpädagogik.

Forschungsperspektiven im Anschluss an den 27. Kongress der DGfE

Herausgegeben von Patrick Bettinger, Klaus Rummler und Karsten D. Wolf

Optimierung und Subversion

**Kybernetik und neue künstlerisch-ästhetische Medienpraktiken in den
1960er Jahren**

Martin Donner

Zusammenfassung

Der Text fragt im Sinne subjektivationstheoretischer Ansätze nach den Lücken, die das kybernetische Dispositiv dem Selbst eröffnet. Dazu werden zuerst die Grundlagen dieses Dispositivs erörtert. Besonderes Augenmerk wird dabei auf das kybernetische Selbstkonzept und entsprechende Lernverständnisse gelegt. Im Rahmen dessen werden zwei wissenschaftliche Idiome vorgestellt, die mit der Kybernetik verbunden sind, ein repräsentationales und ein performatives. Veranschaulicht wird dies schliesslich an den künstlerisch-ästhetischen Medienpraktiken von Ken Kesey (Einer flog über das Kuckucksnest) und der Aktionskunst-Gruppe Merry Pranksters, die aus der spielerischen Auseinandersetzung mit dem kybernetischen Dispositiv emergieren und als prototypische Anordnungen heutiger Multimedia-Kulturen verstanden werden können. Es stellt sich die Frage, welches der beiden Idiome (medien-)pädagogischen Kontexten in normativer Hinsicht eher angemessen ist.



Dabei ging es Kesey und den Pranksters ganz im Sinne des genannten Forschungsprogramms um nichts anderes als eine «Reprogrammierung» ihres Selbst mit Hilfe von neuen medienästhetischen Praktiken, allerdings nicht, um die bestehende Gesellschaftsordnung zu optimieren, sondern ganz im Gegenteil, um aus dem Gefängnis ihres anerzogenen Denkens ausbrechen und «Herren» ihrer selbst zu werden.

. Als Modell dient nicht mehr das abwägend rasonierende Selbst, sondern das affektiv involvierte und sich in Feedback-Loops konstituierende. Bildungsprozesse entstehen im Guten wie im Schlechten *in situ* in der möglichst instantanen Reaktion und Kommentierung des allgemeinen «Loopgeschehens», in das medial alle möglichen an- und abwesenden Akteure involviert sein können.

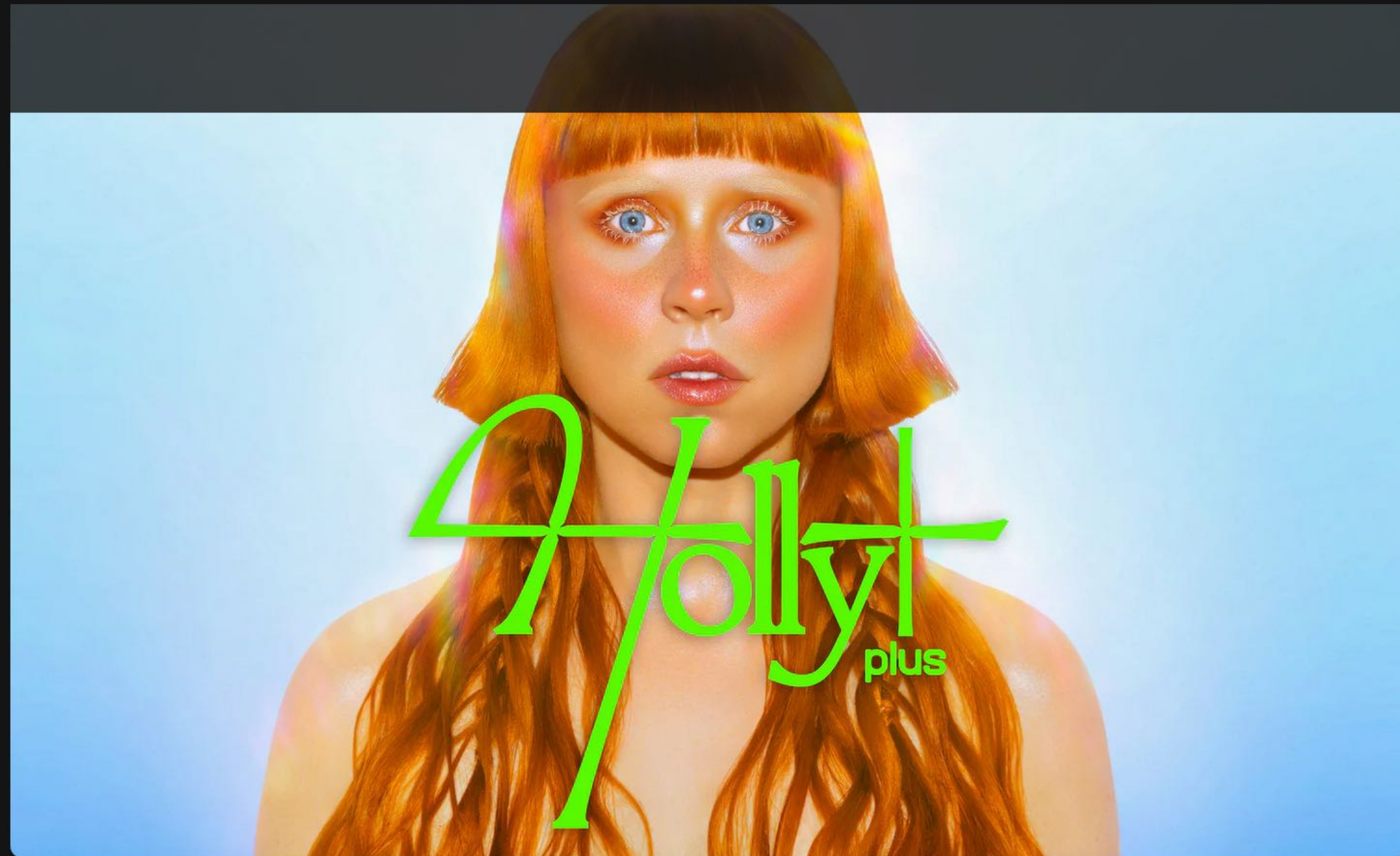
Abb. 5.: Der Prankster-Bus namens *Furthur*, hier u.a. mit Mitgliedern der Gruppen *Jefferson Airplane* und *Grateful Dead*, entnommen aus Babbs und Perry 1993, VII.

artistic creation
as hybrid
aesthetic decision-
making



Screenshot: Holly Herndon & Jlin (feat. Spawn) – Godmother

Quelle: <https://youtu.be/sc9OjL6Mjgo> (Datum: 10.6.2020)



👤 : Andrés Mañón

I'm excited to finally share something I have been working on for the last year ✨ [Holly+](#)

I am releasing [Holly+](#) in collaboration with [Never Before Heard Sounds](#), the first tool of many to allow for others to make artwork with my voice, and will distribute ownership of my digital likeness through the creation of the Holly+ DAO 👯

My voice is precious to me! It is 1 of 1 🥰

Voice Models, in combination with machine learning technology, already allow for anyone to clone a voice to generate music and media, and the opportunities and complications inherent to these techniques will only intensify!

This development raises novel questions about voice ownership that I think can be addressed by DAO governance 💛

Who am I?

I'm an artist and composer 🧑 who has been working with machine learning for many years. My last album [PROTO\(4AD,2019\)](#) was the first to utilize singing neural networks and I completed my Doctorate at [Stanford's Center for Computer Research in Music and Acoustics](#), where my research focus was on the interplay between machine learning and the voice, and the implications of this technology for IP and vocal sovereignty 🧐

Some AI models already know who I am! Here are some images spawned from my likeness using [OpenAI's CLIP model](#) 🤖



- 1) „Künstliche Intelligenz“ und „Deep Learning“
- 2) Kontrolle vs. Kontrollverlust
- 3) Kontrollsystem vs. Kontrollverlustsystem
- 4) „Artificial Intelligence in Education“:
status quo und best practice
- 5) Fazit

AI technology brings virtually unlimited possibilities to education. The 40 articles investigated a wide variety of AI applications in education, including the following types of learning technology:

- Chatbot (Fryer et al., 2017);
- Expert systems (Dias et al., 2015; Hwang et al., 2020);
- Intelligent tutors or agents (Cheung et al., 2003; Chin et al., 2010; Chin et al., 2013; Cung, Xu, Eichhorn, & Warschauer, 2019; Gulz et al., 2020; Köse & Arslan, 2016; Matsuda et al., 2020; McCarthy et al., 2018; McLaren, DeLeeuw, & Mayer, 2011; Tärning, Silvervarg, Gulz, & Haake, 2019);
- Machine learning (Arpaci, 2019; Wei, et al., 2018);
- Personalized learning systems or environments (PLS/E) (Bahçeci & Gürol, 2016; Griol et al., 2014; Köse, 2017; Montalvo et al., 2018; Samarakou et al., 2018; Santos & Notargiacomo, 2018; Xu & Wang, 2006; Walkington & Bernacki, 2019);
- Visualizations (Keshav et al., 2017; Leony, Munoz-Merino, Pardo, & Kloos, 2013; Lou-Escande, Frenoy, Poplimont, Thouvenin Gapenne, & Megalakaki, 2017)

"Ein Großteil der Forschung hat sich auf vier Aspekte der KI beim E-Learning konzentriert, nämlich adaptive Systeme und Personalisierung, Bewertung und Beurteilung, Profiling und Vorhersage sowie intelligente Tutorsysteme" (Tang et al., 2021, S. 14).

Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. *Computers and Education: Artificial Intelligence*, 2, 100025. <https://doi.org/10.1016/j.caeai.2021.100025>

Tang, K.-Y., Chang, C.-Y., & Hwang, G.-J. (2021). Trends in artificial intelligence-supported e-learning: A systematic review and co-citation network analysis (1998–2019). *Interactive Learning Environments*. <https://www.tandfonline.com/doi/abs/10.1080/10494820.2021.1875001>

Dashboard stories: How narratives told by predictive analytics reconfigure roles, risk and sociality in education

Juliane Jarke¹ and Felicitas Macgilchrist^{2,3}

Abstract

In this paper, we explore how the development and affordances of predictive analytics may impact how teachers and other educational actors think about and teach students and, more broadly, how society understands education. Our particular focus is on the data dashboards of learning support systems which are based on Machine Learning (ML). While previous research has focused on how these systems produce credible knowledge, we explore here how they also produce compelling, persuasive and convincing narratives. Our main argument is that particular kinds of stories are written by predictive analytics and written into their data dashboards. Based on a case study of a leading predictive analytics system, we explore how data dashboards imply causality between the ‘facts’ they are visualising. To do so, we analyse the stories they tell according to their spatial and temporal dimensions, characters and events, sequentiality as well as tellability. In the stories we identify, teachers are managers, students are at greater or lesser risk, and students’ sociality is reduced to machine-readable interactions. Overall, only data marked as individual behaviours becomes relevant to the system, rendering structural inequalities invisible. Reflecting on the implications of these systems, we suggest ways in which the uptake of these systems can interrupt such stories and reshape them in other directions.

Keywords

Predictive analytics, learning analytics, education, data visualisation, datafication, storytelling, dashboards, machine learning, artificial intelligence

Introduction

Advances in and promises of Artificial Intelligence (AI) and in particular Machine Learning (ML), a sub-field of AI upon which new approaches to learning analytics are based, have encouraged the hopes and hype around educational technology (edtech) today. Since the beginning of the SARS-2-CoV pandemic, vast sums have been spent implementing new technologies in public and private education. Market reports claim that the education and learning analytics market will grow on average 30% per year over the next few years, reaching \$34.7 billion by 2027 (Meticulous Research, 2021). Educational policies written or updated during the pandemic see Big Data and learning analytics as a priority for strategic action (e.g. European Commission, 2020: 23). Supranational organisations highlight learning analytics, Big Data and machine learning/AI in their hopes for how education can better deal with future global disruptions (OECD, 2020).

Within this nexus of heightened expectations, it is crucial to understand how these technologies play out

on the ground. In this paper, we explore how the development and affordances of AI-powered predictive analytics systems may impact how teachers and educational organisations think about and teach students and, more broadly, how society understands education. Our particular focus is on the data dashboards of learning support systems based on ML. While previous research has focused on how these systems produce authoritative, objective and credible knowledge, we explore here how they also produce compelling,

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Analyse von Dashboards als „storytelling practices“



Figure 2. Engagement dashboard presenting time in content (left) and time in content vs. grade (right) as aggregate over a whole course (Brightspace Tutorials, 2019).³

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Juliane Jarke¹ and Felicitas Macgilchrist^{2,3}

Abstract

In this paper, we explore how the development and affordances of predictive analytics make teachers and other educational professionals into data analysts. Our particular focus is on the data dashboards of learning support systems which are based on Machine Learning (ML). While previous research has focused on how these systems produce credible knowledge, we explore here how they also produce compelling narratives. We ask: ‘What is being written by predictive analytics? How do they do so, and what are the implications?’ In this paper, we explore how data dashboards imply causality between the facts they are visualising. To do so, we analyse the stories they tell according to their spatial and temporal dimensions, characters and events, sequentiality as well as tellability. We argue that these systems render sociality invisible, rendering structural inequalities invisible. Reflecting on the implications of these systems, we suggest ways in which the uptake of these systems can interrupt such stories and reshape them in other directions.

Keywords

Predictive analytics, learning analytics, education, data visualisation, datafication, storytelling, dashboards, machine learning, artificial intelligence

Introduction

Advances in and promises of Artificial Intelligence (AI) and in particular Machine Learning (ML) have led to AI upon which many educational technologies are based, have encouraged the hopes and hype around educational technology (edtech) today. Since the beginning of the 20th century, the education system has been a site of technological innovation. Vast sums have been invested in educational technologies in public and private education. Market reports claim that the education and learning analytics market will grow over the next 10 years, reaching 14.7 billion by 2027 (Education Research, 2021). Educational policies written or updated during the pandemic see Big Data and learning analytics as a priority for strategic planning (European Commission, 2020: 23). Supranational organisations highlight learning analytics, Big Data and machine learning/AI in their hopes for how education can better deal with future global disruptions (OECD, 2020).

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Analyse von Dashboards als „storytelling practices“

„Lehrkräfte werden zu Datenanalysten, die auf Dashboards nach Erkenntnissen suchen. Wenn ‚das, was gezählt wird, zählt‘ [...], und wenn (in Systemen wie diesen) immer mehr Schüleraktivitäten gezählt werden, wird es zu einem immer zeitintensiveren Teil des Lehrens, das Gezählte zu beobachten und auf der Grundlage dieser Daten Entscheidungen zu treffen. Wenn dies die Aufmerksamkeit vom physischen Klassenzimmer ablenkt, ändert sich das, was in der Schule von Bedeutung ist. Weitere Rollen, z. B. die des Lehrers als Betreuer, Berater, Motivator oder Unterstützer, werden in diesem System unsichtbar und für die Geschichte von Höhen und Tiefen, Erfolg und Misserfolg irrelevant.“



Distributed interpretation – teaching reconstructive methods in the social sciences supported by artificial intelligence

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ABSTRACT

This article highlights teaching and learning in reconstructive research supported by artificial intelligence (AI) and machine interpretation in particular. The focus is whether the traditional teaching of methodological competence through research workshops can be supplemented with artificial intelligence (natural language processing, NLP) implemented in computer-assisted qualitative data analysis software (CAQDAS). A case study shows that AI models can be trained to interpret texts. Thus, distributed interpretation by humans and AI becomes possible, opening up new possibilities for teaching qualitative methods. How people deal with these new possibilities is presented based on an explorative evaluation of a group discussion with young researchers. Finally, this contribution discusses the possibilities and limits of this new form of interpretation *together with a machine*.

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documentary method;
prompt engineering;
group discussion;
method skills; method
knowledge

Introduction

The teaching of qualitative research has recently received increased attention (Eisenhart & Jurow, 2014). This paper addresses whether and how AI-supported machine interpretation can support the teaching of procedures related to reconstructive methods in social sciences. It is mainly concerned with teaching method skills of reconstructive approaches to qualitative empirical social research (and their possible support by AI) and not with teaching qualitative methods in general (Eisenhart & Jurow, 2014; Flick, 2014; Denzin & Lincoln, 2018). However, the term reconstructive research (Pfaff et al., 2010) refers to methods this article summarizes under the collective term deep interpretation, which culminates with AI-supported machine interpretation to a practice of distributed interpretation.

Artificial Intelligence (AI), coined by computer scientists McCarthy and Minsky (1955), has been discussed controversially and in many ways. In addition to genuine computer science publications (Chowdhary, 2020; Mackworth & Poole, 2017; Russell & Norvig, 2016; Kaplan, 2016), publications in the intersection of computer science, social and cultural sciences are indirectly relevant for this research (e.g., Bostrom, 2017; Beer, 2017). The debate about AI in education

The participants' examination of the results of machine interpretation is a prerequisite for placing trust in it. However, doing so is countered by today's AIs, which are mainly nontransparent due to their complexity and the sheer volume of data processed in the hidden layers. Their use in an interpretive process insofar presupposes a "risky investment" through the "trusting expectation" (Luhmann, 1979, p. 24) that the use of an AI helps find new perspectives without overextending oneself in the state of almost infinite contingency. Interpreting, especially in a research workshop,

This article highlights that interpreting is multifaceted, a reciprocal relationship of different actors and artifacts as tools that form an interpretive network of distributed intelligence (Pea, 1993). Subsequently, this article proposes the notion of distributed interpretation as a practice of reconstructive research that resembles a neural network consisting of machine interpretation by AI on the one hand and deep interpretation by human interpreters on the other. Reciprocal relations between these entities result in abductive leaps and, thus, creative interpretive performances, which promote method skills. AI becomes an interpretation generator whose potential, but also danger, lies on the one hand in generating an infinite number of machine interpretations—sometimes more, sometimes less accurate. On the other hand it enables abductive leaps and loosens creative blockades by irritating the human interpreters. Machine interpretation thus extends deep interpretation, creating a state of distributed interpretation. The AI takes on the role of an opaque other, in a certain sense, like an oracle, and a hybrid research workshop emerges in which learners acquire method knowledge and skills together with the AI. Some

„Die KI übernimmt die Rolle eines undurchsichtigen Anderen, in gewissem Sinne wie ein Orakel [...].“

„Dieser Artikel schlägt den Begriff des verteilten Interpretierens als eine Praxis der rekonstruktiven Forschung vor, die einem neuronalen Netzwerk ähnelt, das aus maschineller Interpretation durch KI einerseits und tiefer Interpretation durch menschliche Interpreten andererseits besteht. Die wechselseitigen Beziehungen zwischen diesen Einheiten führen zu abduktiven Sprüngen und damit zu kreativen Interpretationsleistungen, die die Methodenkompetenz fördern.“

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