Intelligenza Artificiale

Parte 5

O. Incani, ~~16 novembre 2023~~ ⇨ **6 dicembre 2023**

Sommario

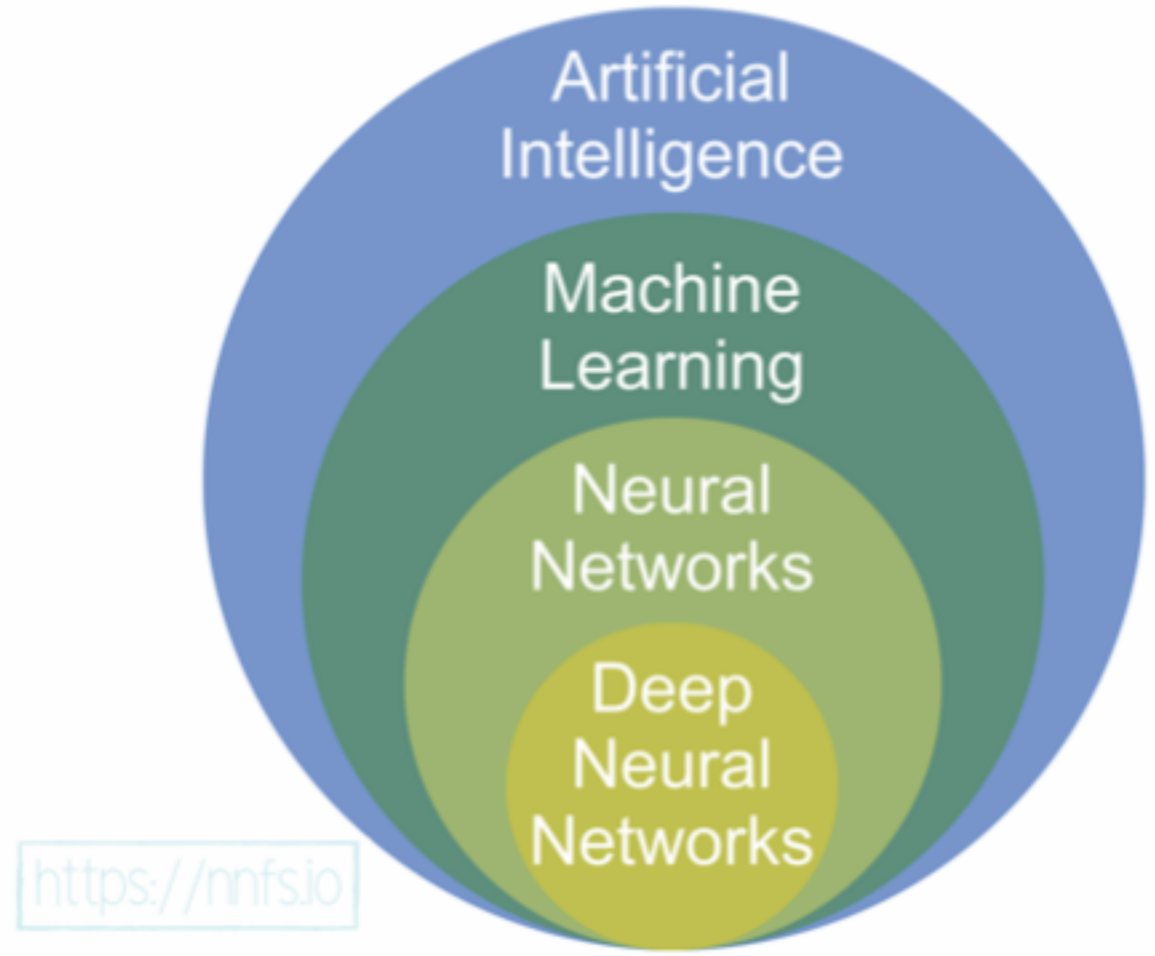
- 1a parte: reti neurali
- 2a parte: IA nella didattica

Neural Networks

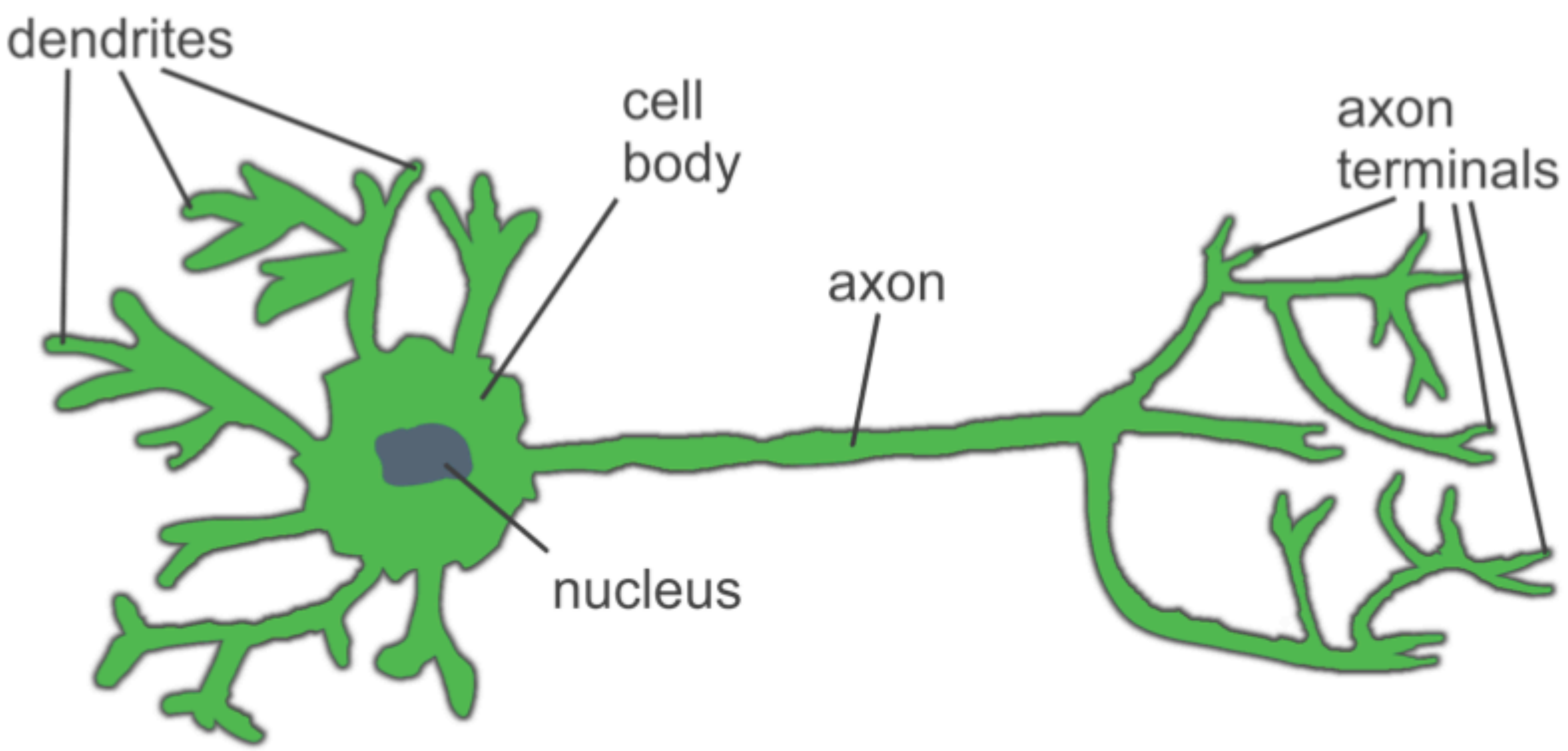
Primer

Neural Network

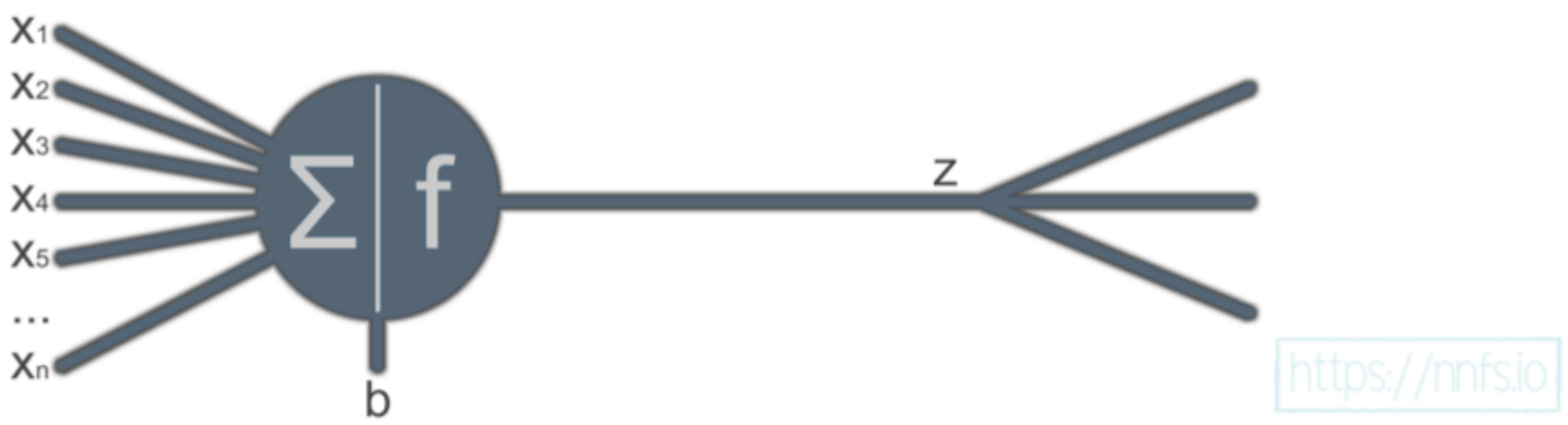
- ’40 del secolo scorso
- ’60 backpropagation
- 2010 vincita di competizioni



Biological vs Artificial Neuron

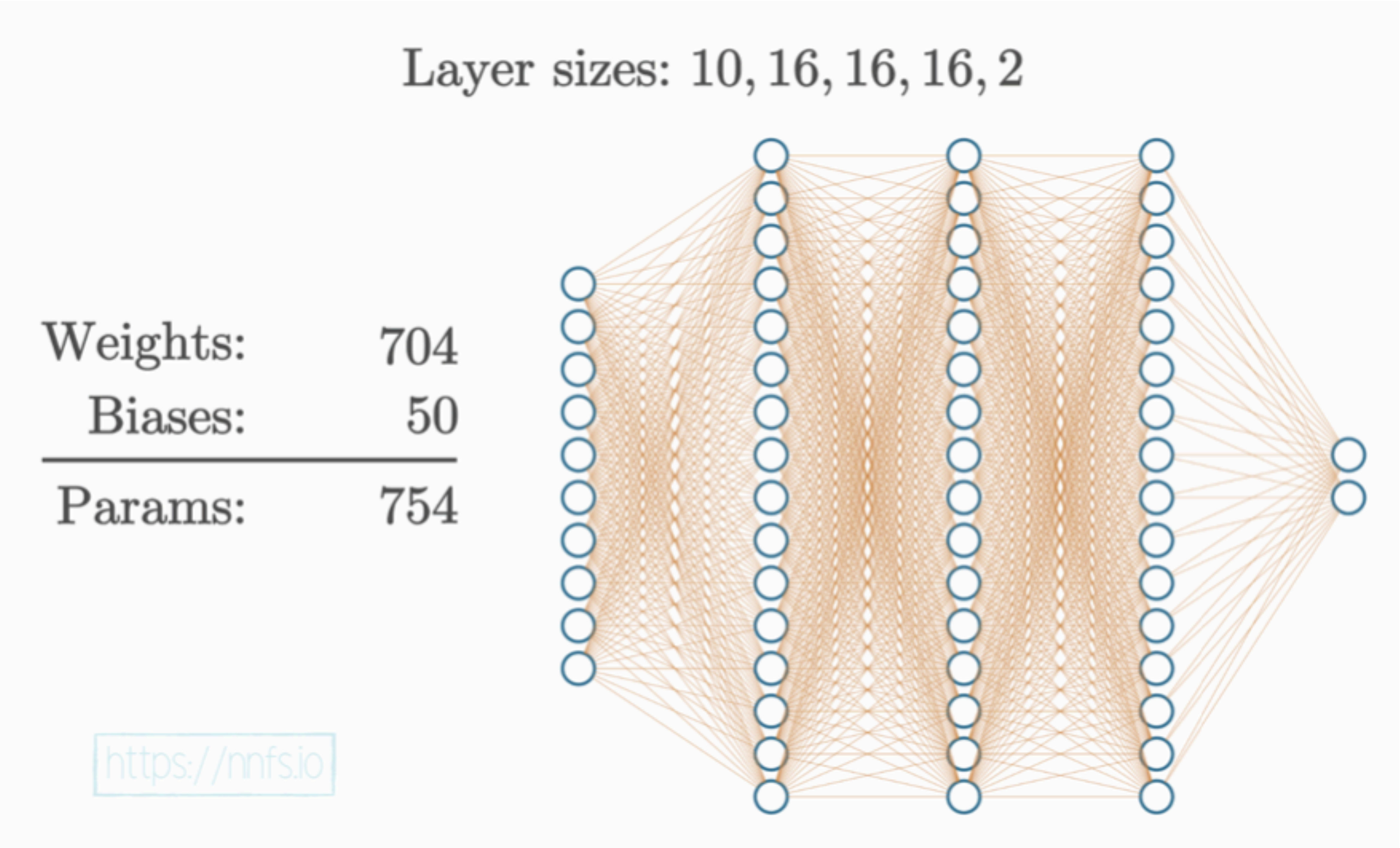


Biological Neuron



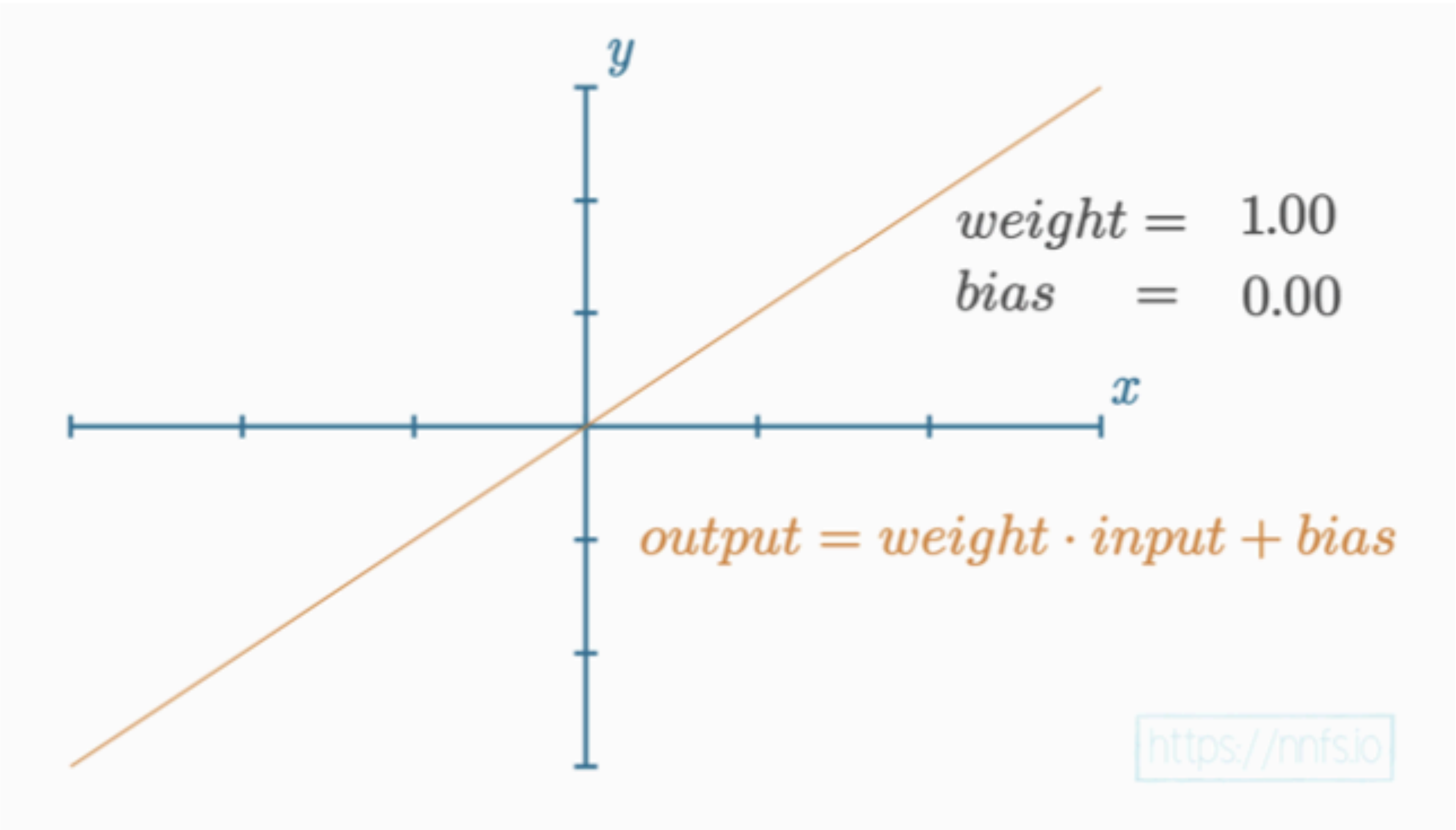
Artificial Neuron

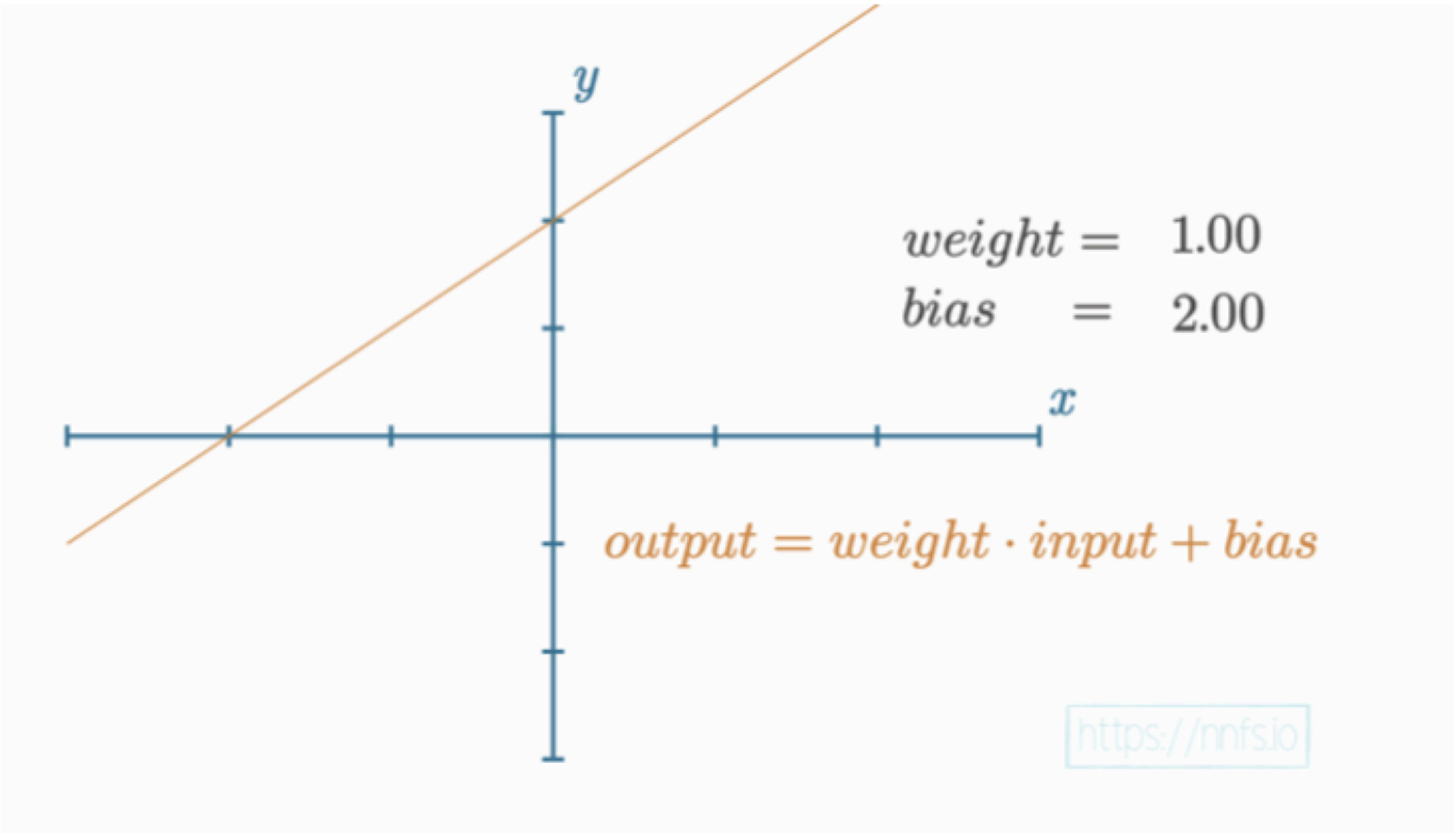
Networks Parameters



www.youtube.com/watch?v=Ls1dJqZtI7w

Bias



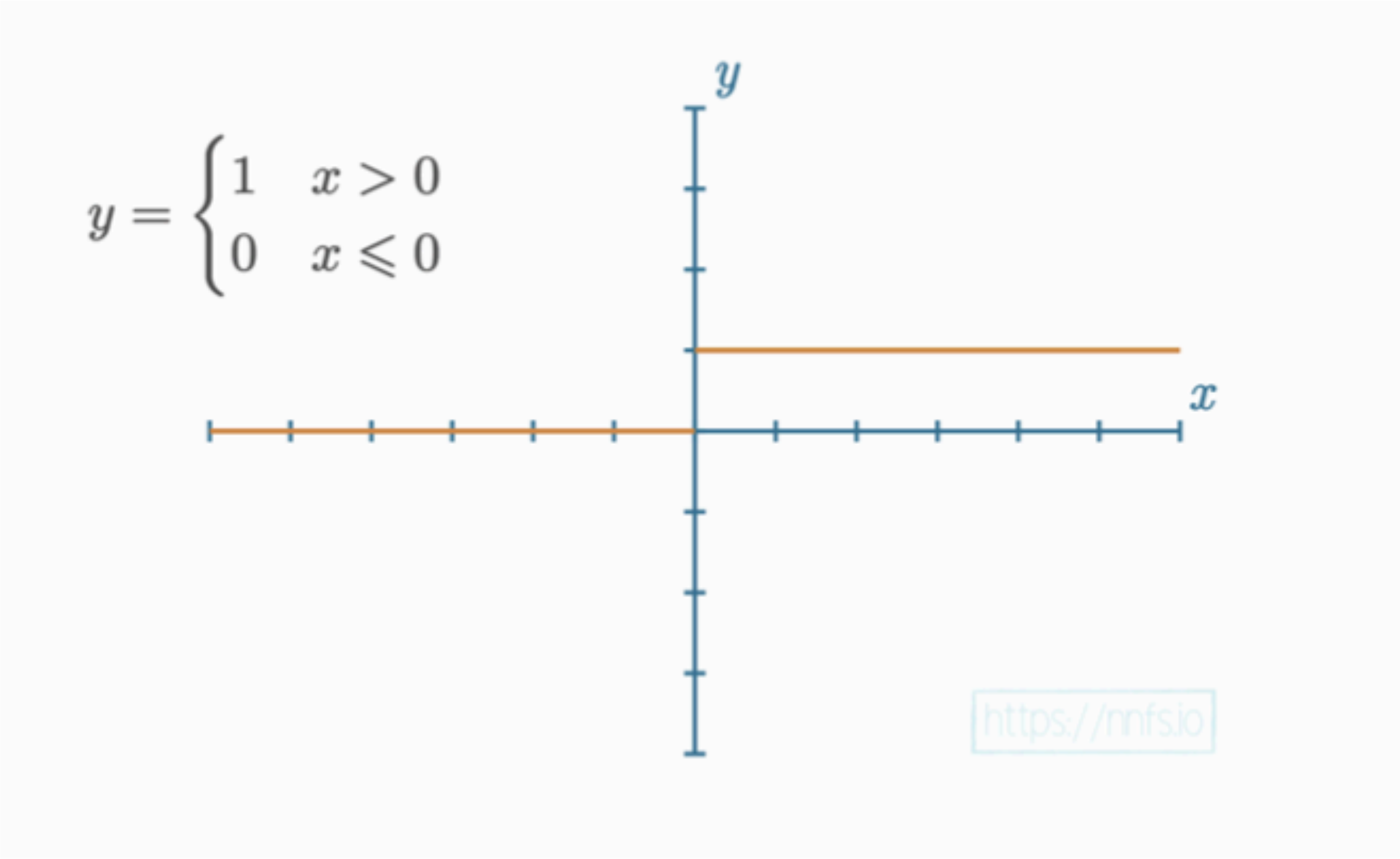


bias $= 0$

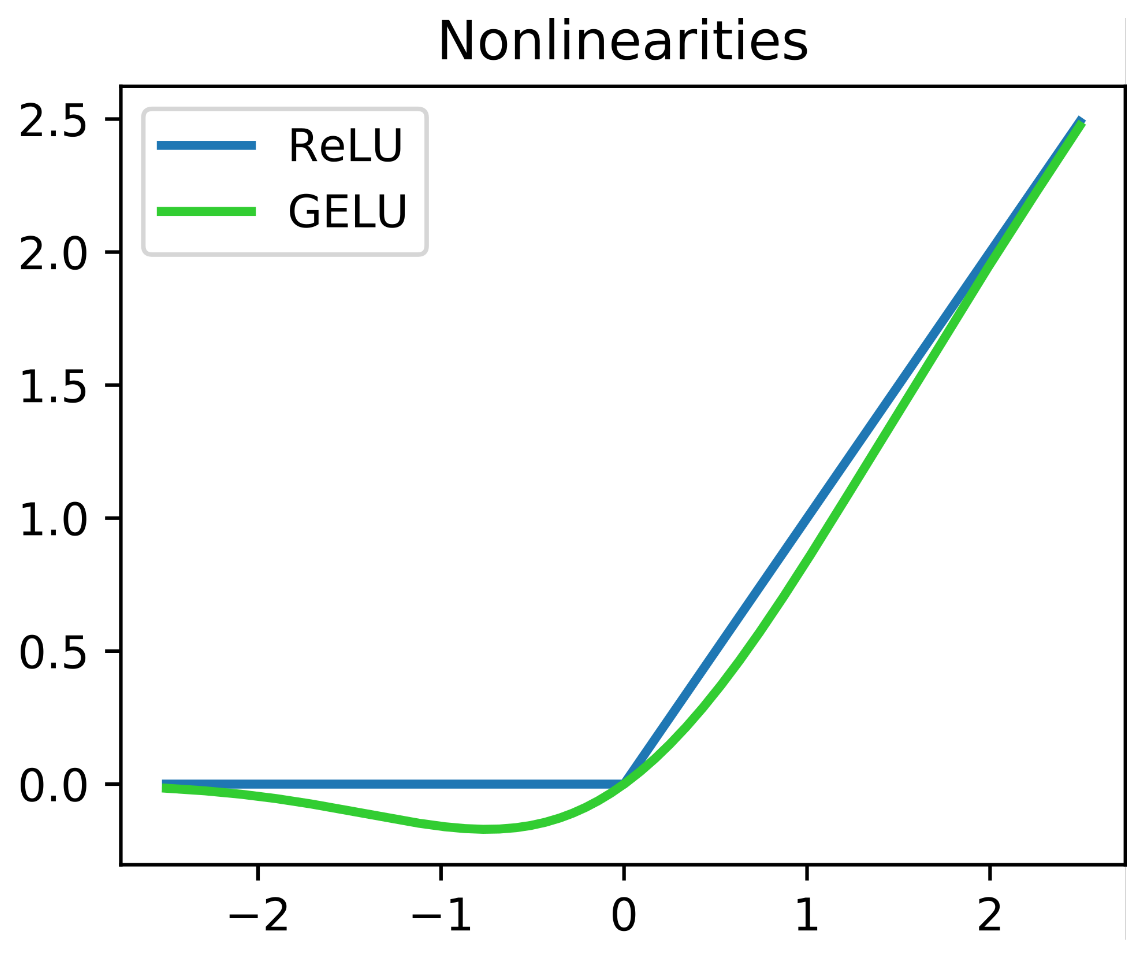
bias $\neq 0$

www.youtube.com/watch?v=SRAFVJ5UbB0

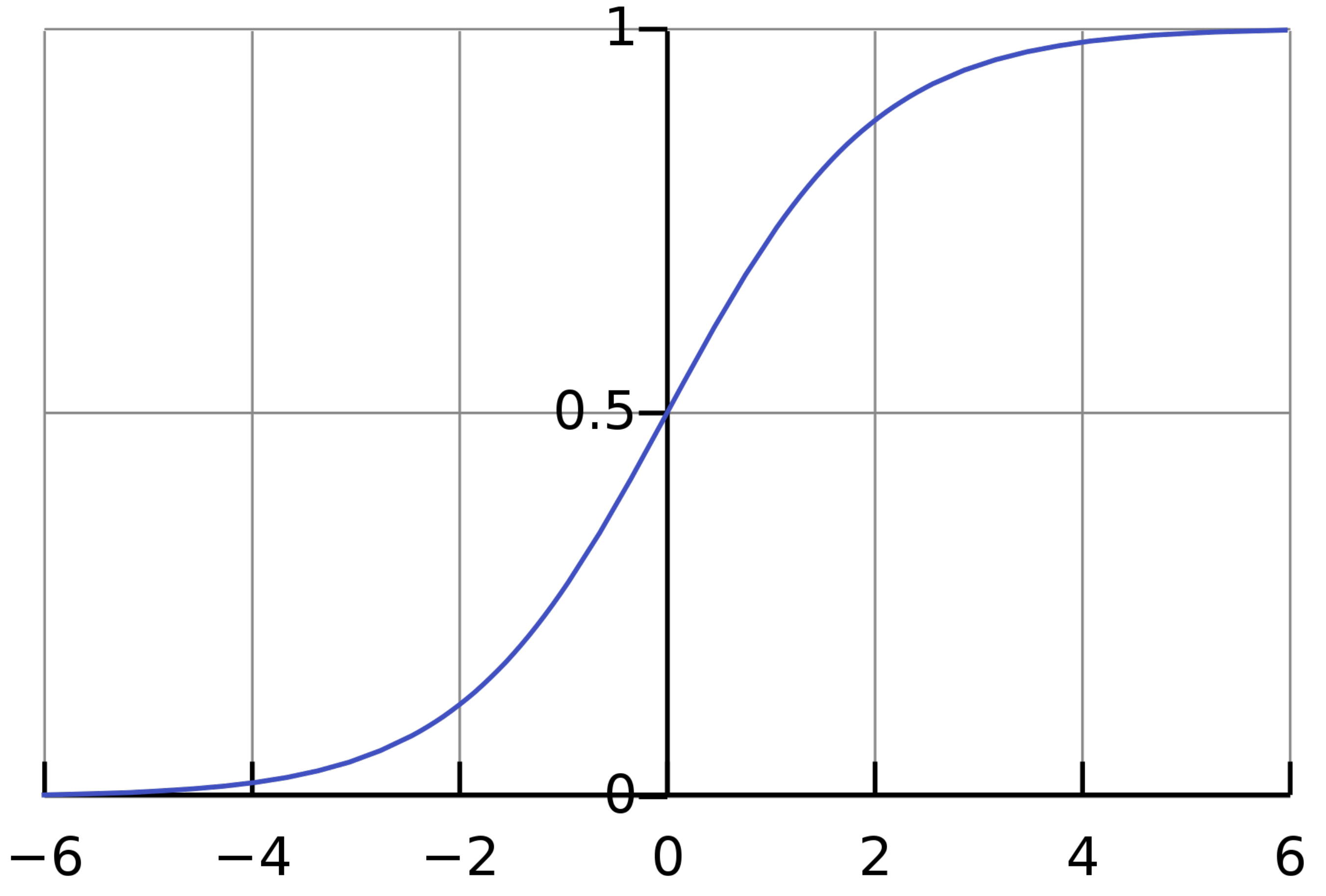
Activation Functions



Step Function

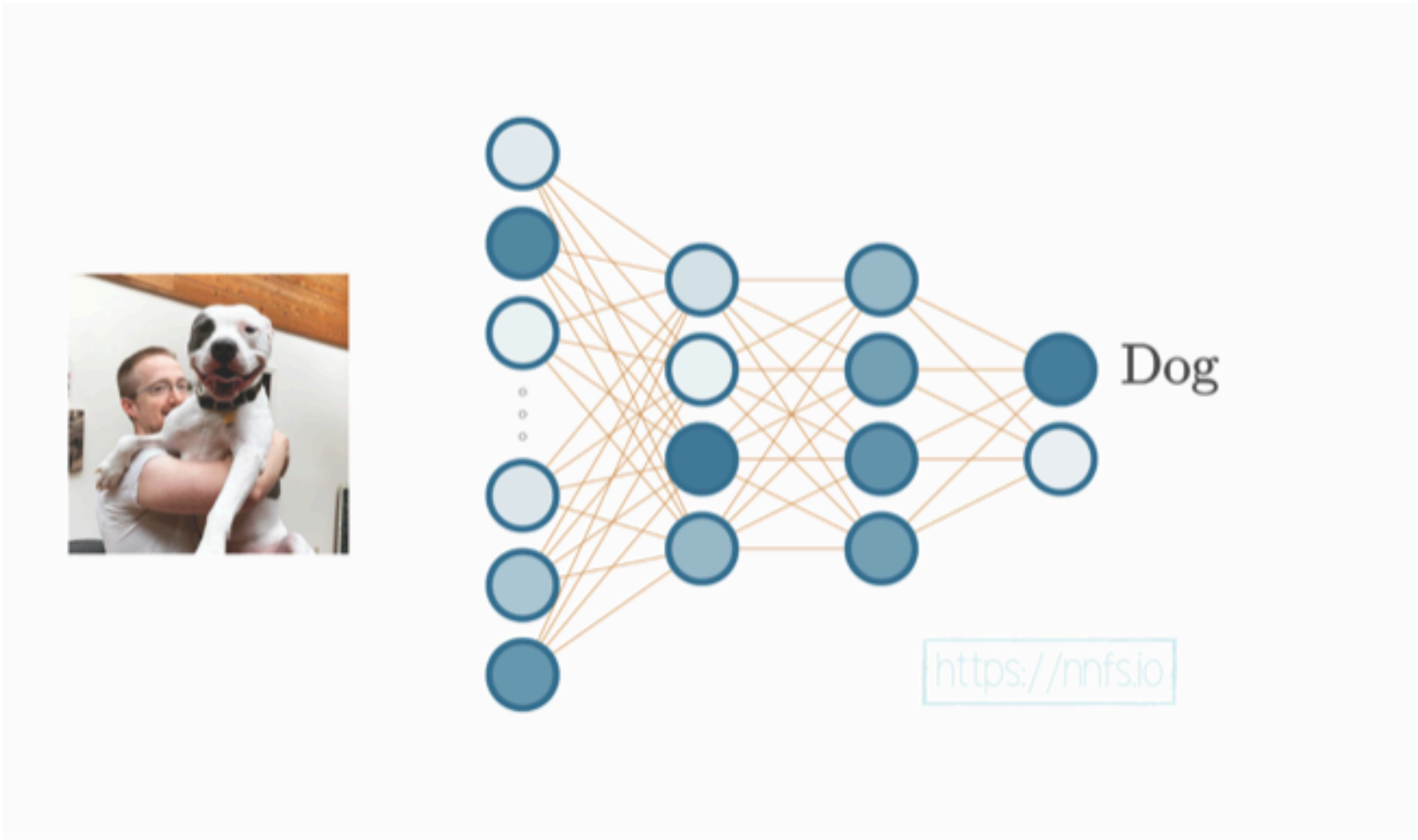


Rectified Linear Unit (ReLU)
Gaussian Error Linear Unit (GELU)



Logistic Function

Classification



www.youtube.com/watch?v=fXSRfzhHPm0

Full formula for the forward pass

$$L = -\sum_{l=1}^{N} y_l log(\forall_{j=1}^{n_3} \frac{e^{\sum_{i=1}^{n_2}(\forall_{j=1}^{n_2} max(0,\sum_{i=1}^{n_1}(\forall_{j=1}^{n_1} max(0,\sum_{i=1}^{n_0} X_i w_{1,i,j}+b_{1,j}))_i w_{2,i,j}+b_{2,j}))_i w_{3,i,j}+b_{3,j}}}{\sum_{k=1}^{n_3} e^{\sum_{i=1}^{n_2}(\forall_{j=1}^{n_2} max(0,\sum_{i=1}^{n_1}(\forall_{j=1}^{n_1} max(0,\sum_{i=1}^{n_0} X_i w_{1,i,j}+b_{1,k}))_i w_{2,i,j}+b_{2,k}))_i w_{3,i,k}+b_{3,k}}})$$

https://nnfs.io

```
loss = -np.log(
    np.sum(
        y * np.exp(
            np.dot(
                np.maximum(
                    0,
                    np.dot(
                        np.maximum(
                            0,
                            np.dot(
                                X,
                                w1.T
                            ) + b1
                        ),
                        w2.T
                    ) + b2
                ),
                w3.T
            ) + b3
        ) /
        np.sum(
            np.exp(
                np.dot(
                    np.maximum(
                        0,
                        np.dot(
                            np.maximum(
                                0,
                                np.dot(
                                    X,
                                    w1.T
                                ) + b1
                            ),
                            w2.T
                        ) + b2
                    ),
                    w3.T
                ) + b3
            ),
            axis=1,
            keepdims=True
        )
    )
)
```

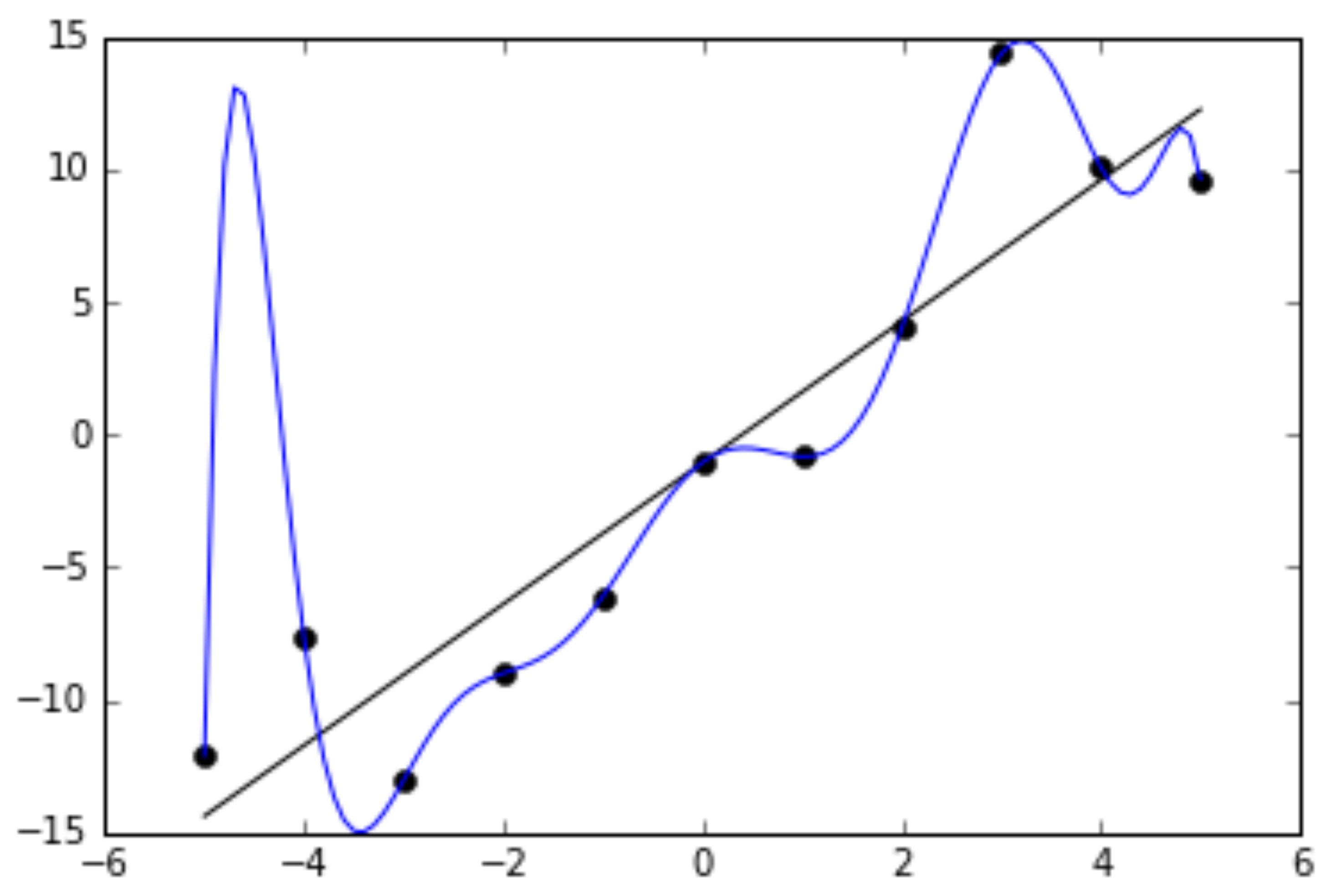
https://nnfs.io

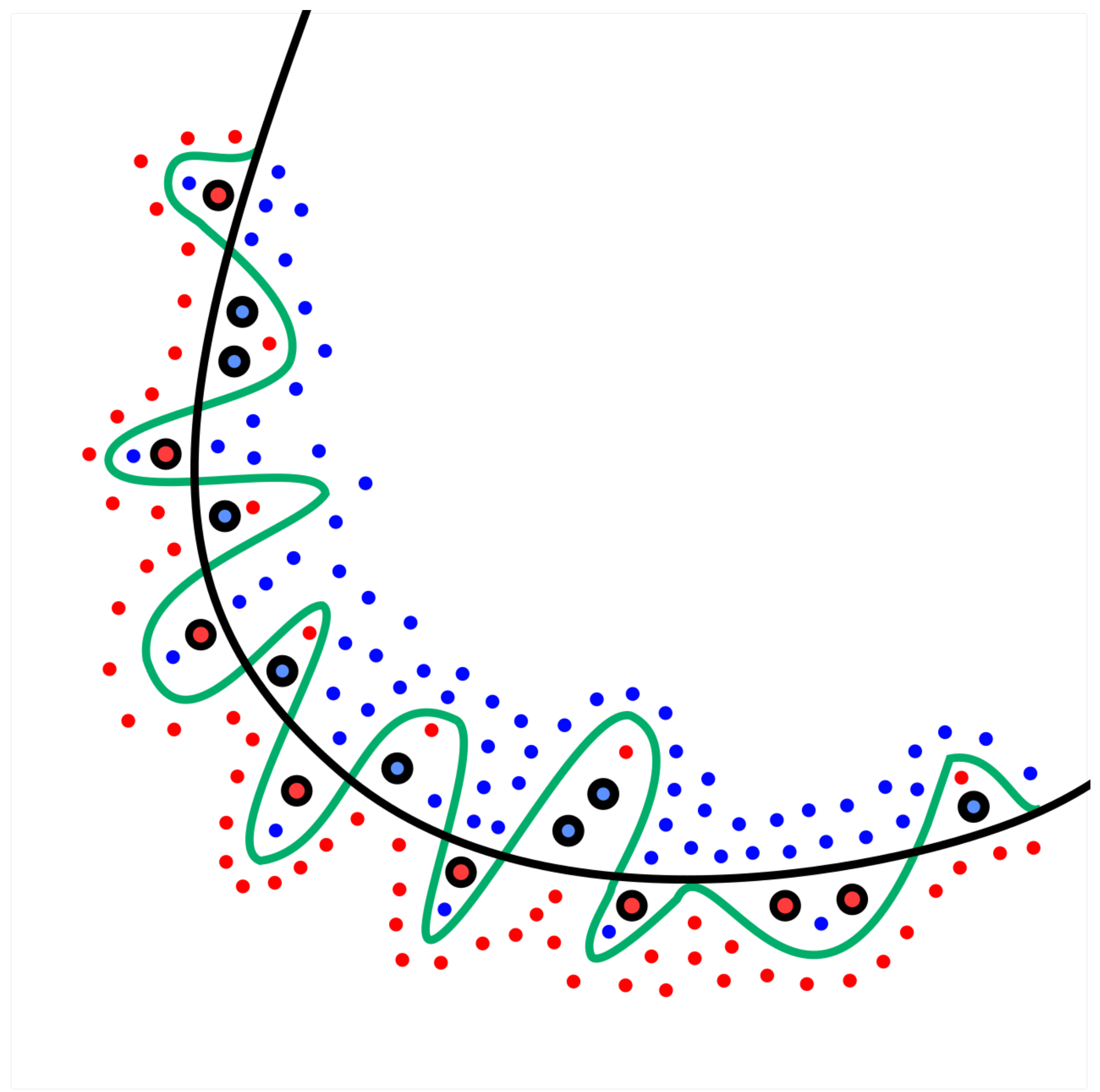
www.youtube.com/watch?v=xtzVuln1PV8

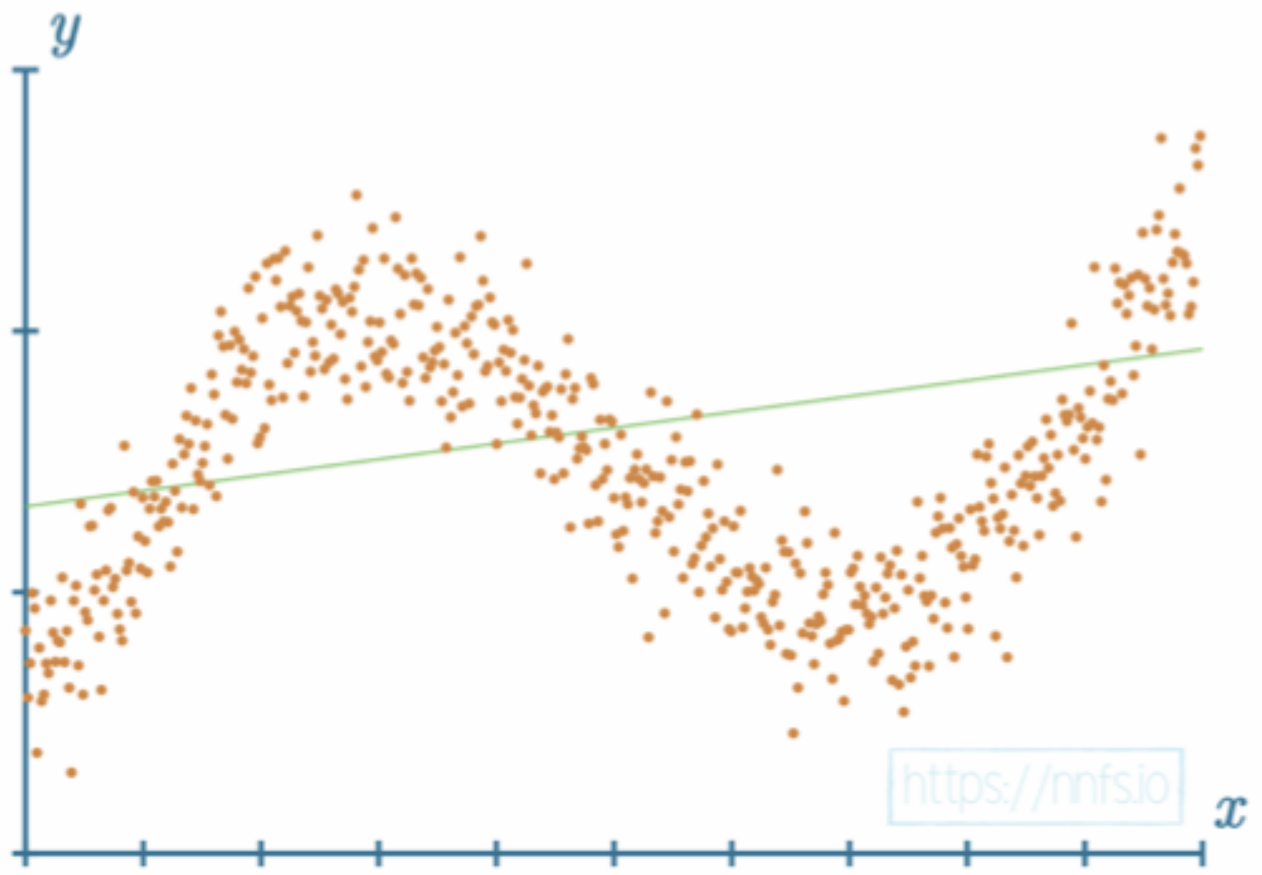
Overfitting

Machine Learning and Data Mining

Overfitting is the production of an analysis which corresponds too closely or exactly to a particular set of data, and may therefore fail to fit additional data or predict future observations reliably.







Generalization
(il “contrario” dell’*overfitting*)

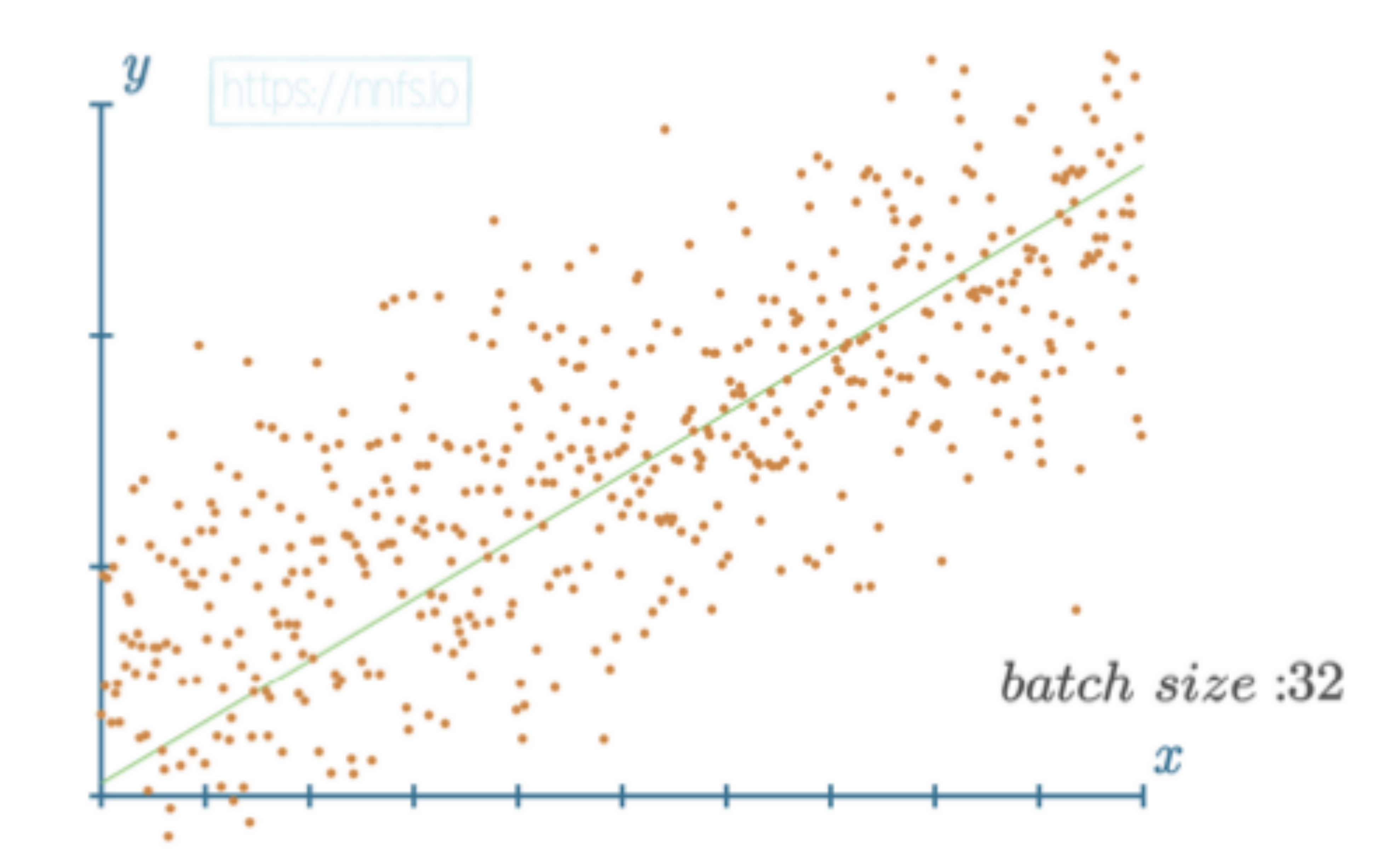
Overfitting: The network basically just “memorizes” the training data

Thus, we tend to use “in-sample” data to train a model and then use “out-of-sample” data to validate a neural network

For example, if there is a dataset of 100,000 samples of data and labels, you will immediately take 10,000 and set them aside to be your “out-of-sample” or “validation” data. You will then train your model with the other 90,000 in-sample or “training” data and finally validate your model with the 10,000 out-of-sample data that the model hasn’t yet seen. The goal is for the model to not only accurately predict on the training data, but also to be similarly accurate while predicting on the withheld out-of-sample validation data.

This is called generalization, which means learning to fit the data instead of memorizing it. The idea is that we “train” (slowly adjusting weights and biases) a neural network on many examples of data. We then take out-of-sample data that the neural network has never been presented with and hope it can accurately predict on these data too.

Fitting



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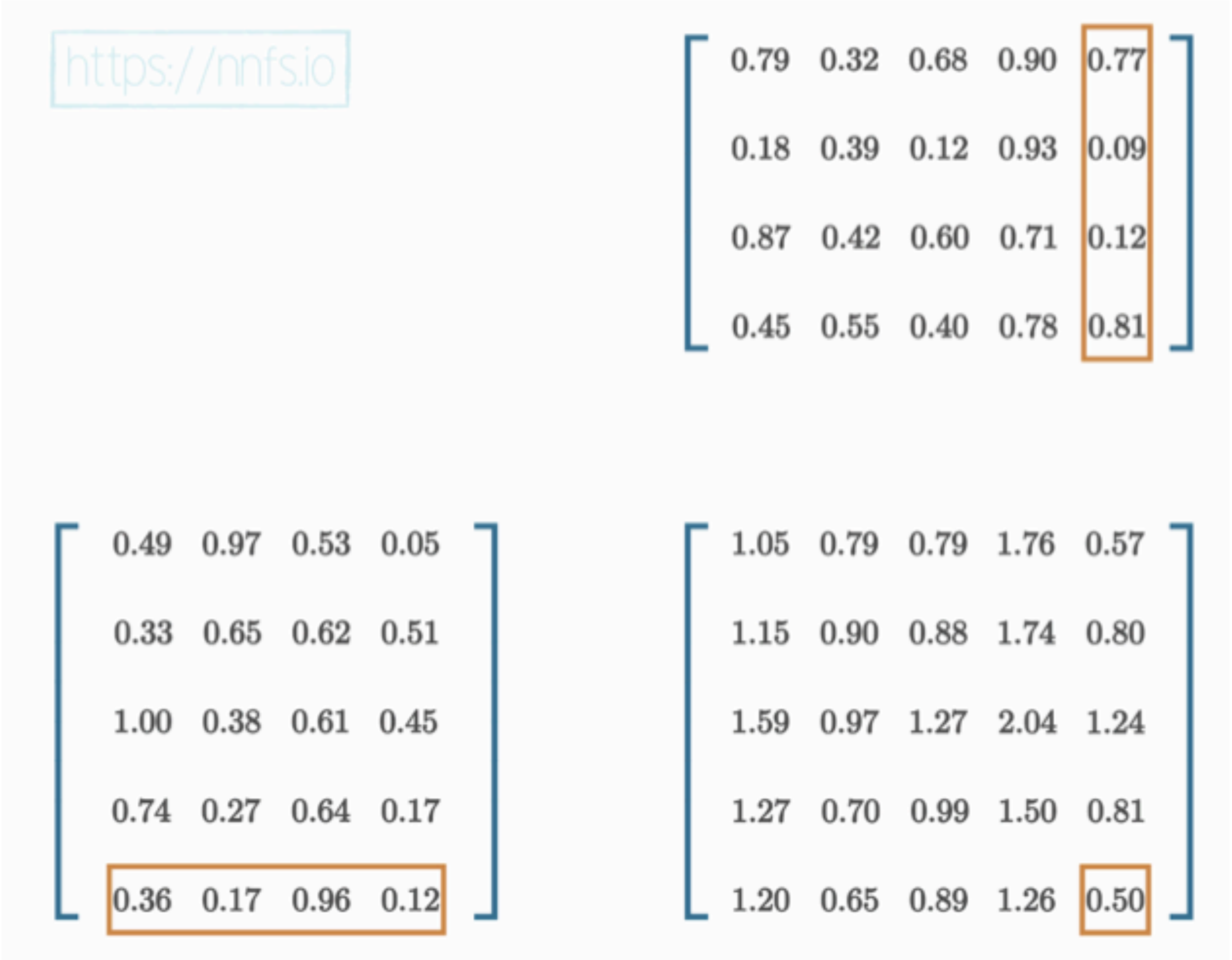
Matrix Product



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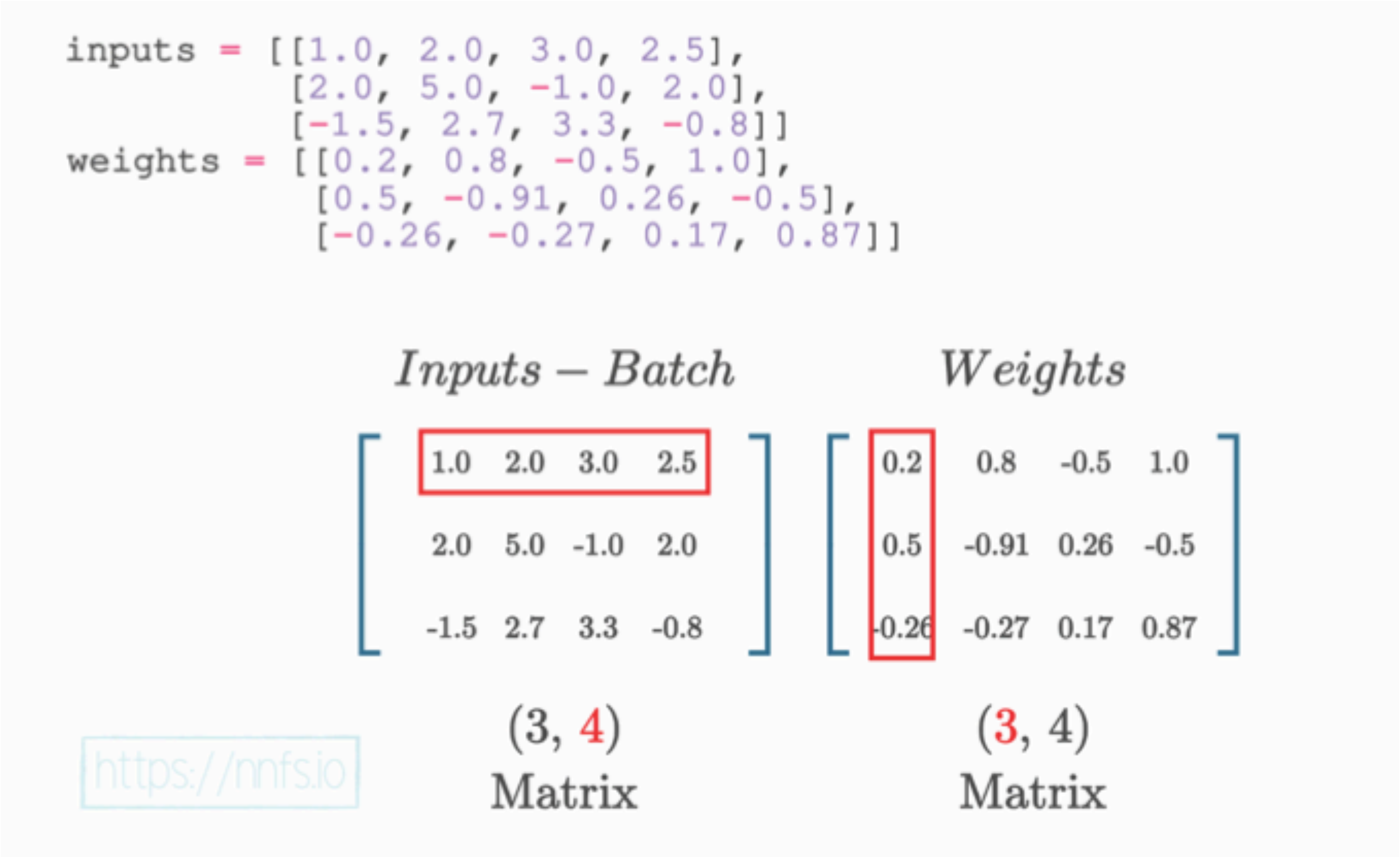
Matrix Transpose



www.youtube.com/watch?v=2c9CJ_7YT8w

Loss Function and Accuracy

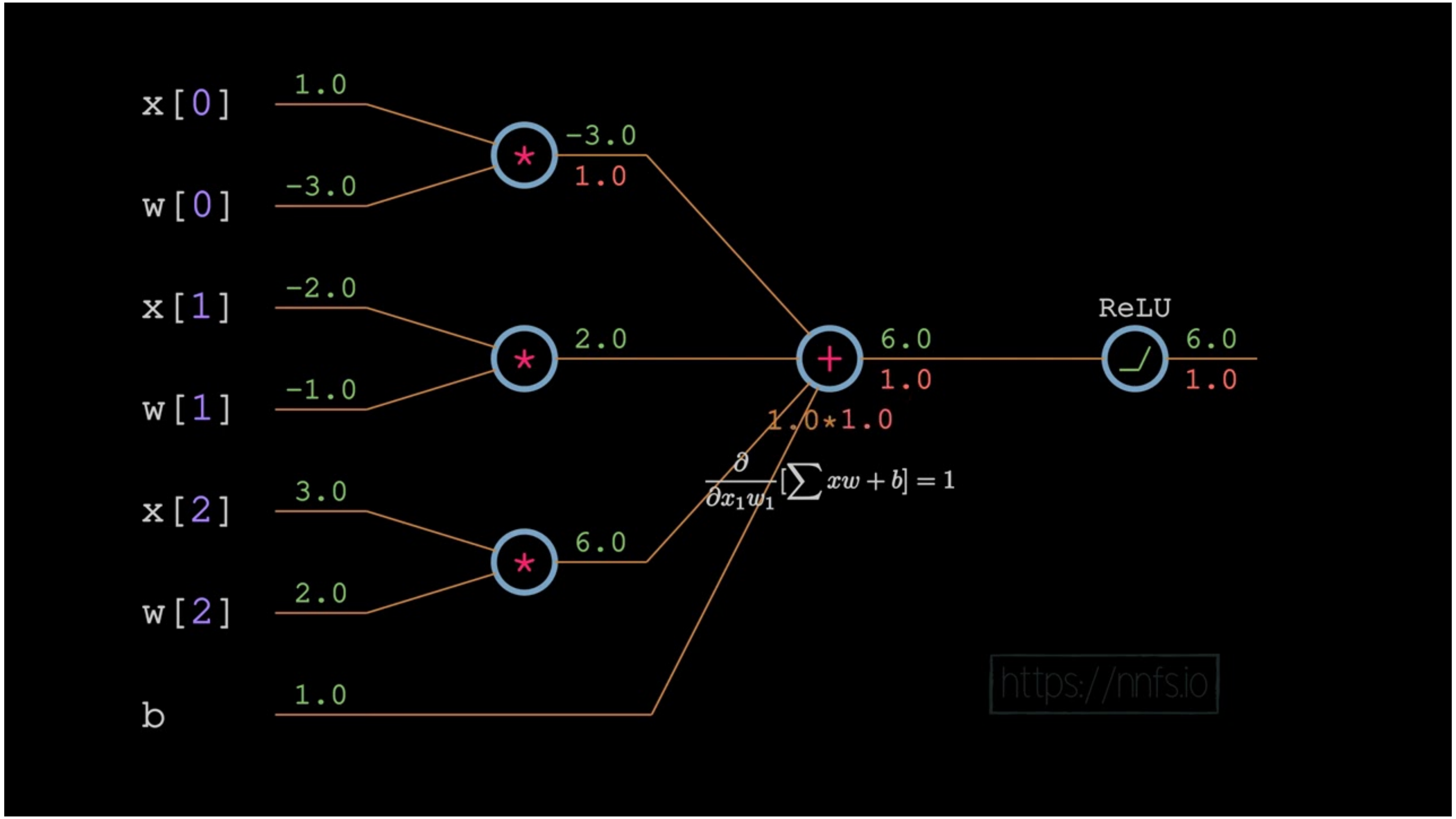
Loss Function:

With a randomly-initialized model, or even a model initialized with more sophisticated approaches, our goal is to train, or teach, a model over time. To train a model, we tweak the weights and biases to improve the model’s accuracy and confidence. To do this, we calculate how much error the model has. The **loss function**, also referred to as the **cost function**, is the algorithm that quantifies how wrong a model is. Loss is the measure of this metric. Since loss is the model’s error, we ideally want it to be 0.

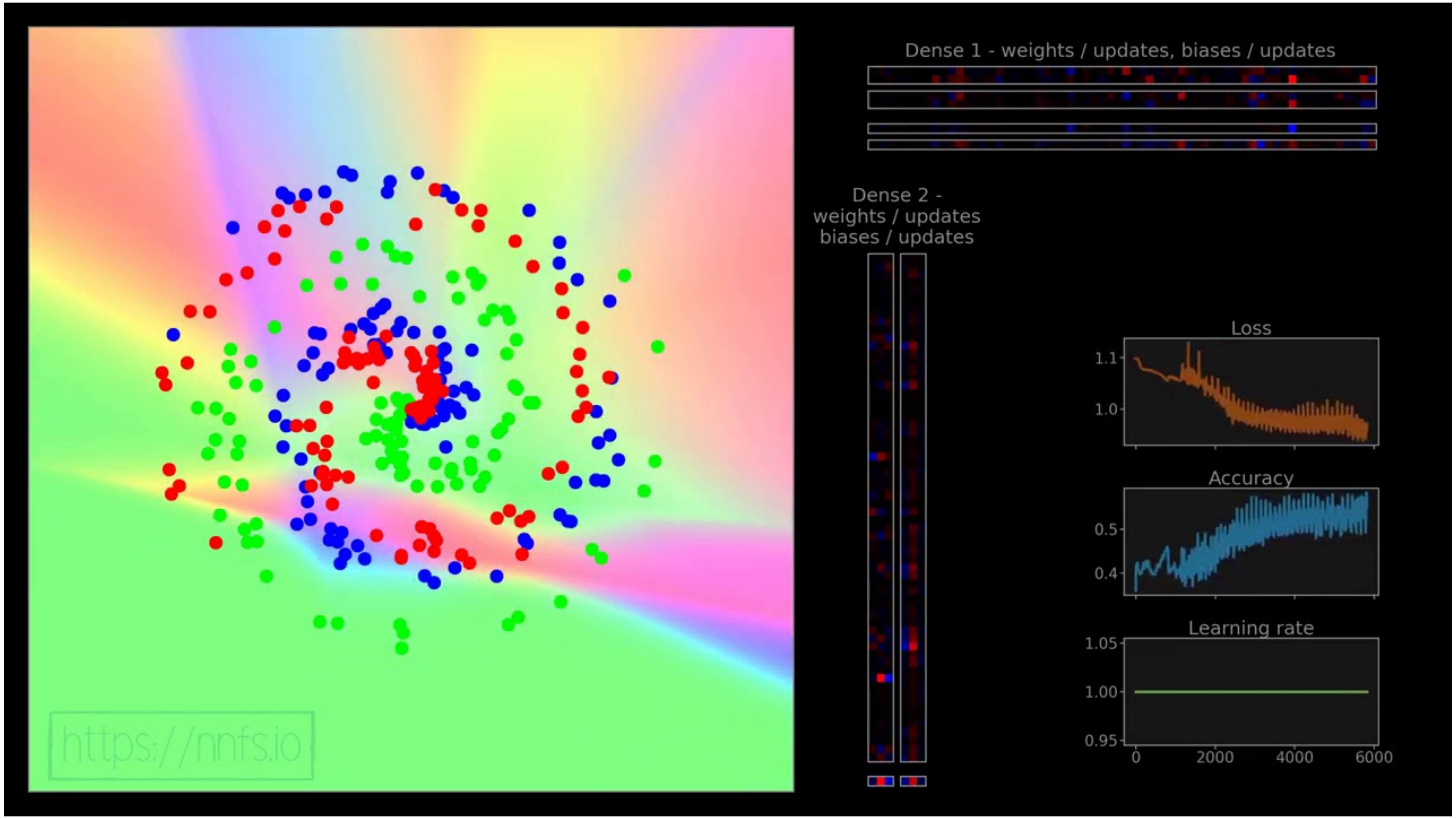
Accuracy:

While loss is a useful metric for optimizing a model, the metric commonly used in practice along with loss is the accuracy, which describes how often the largest confidence is the correct class in terms of a fraction.

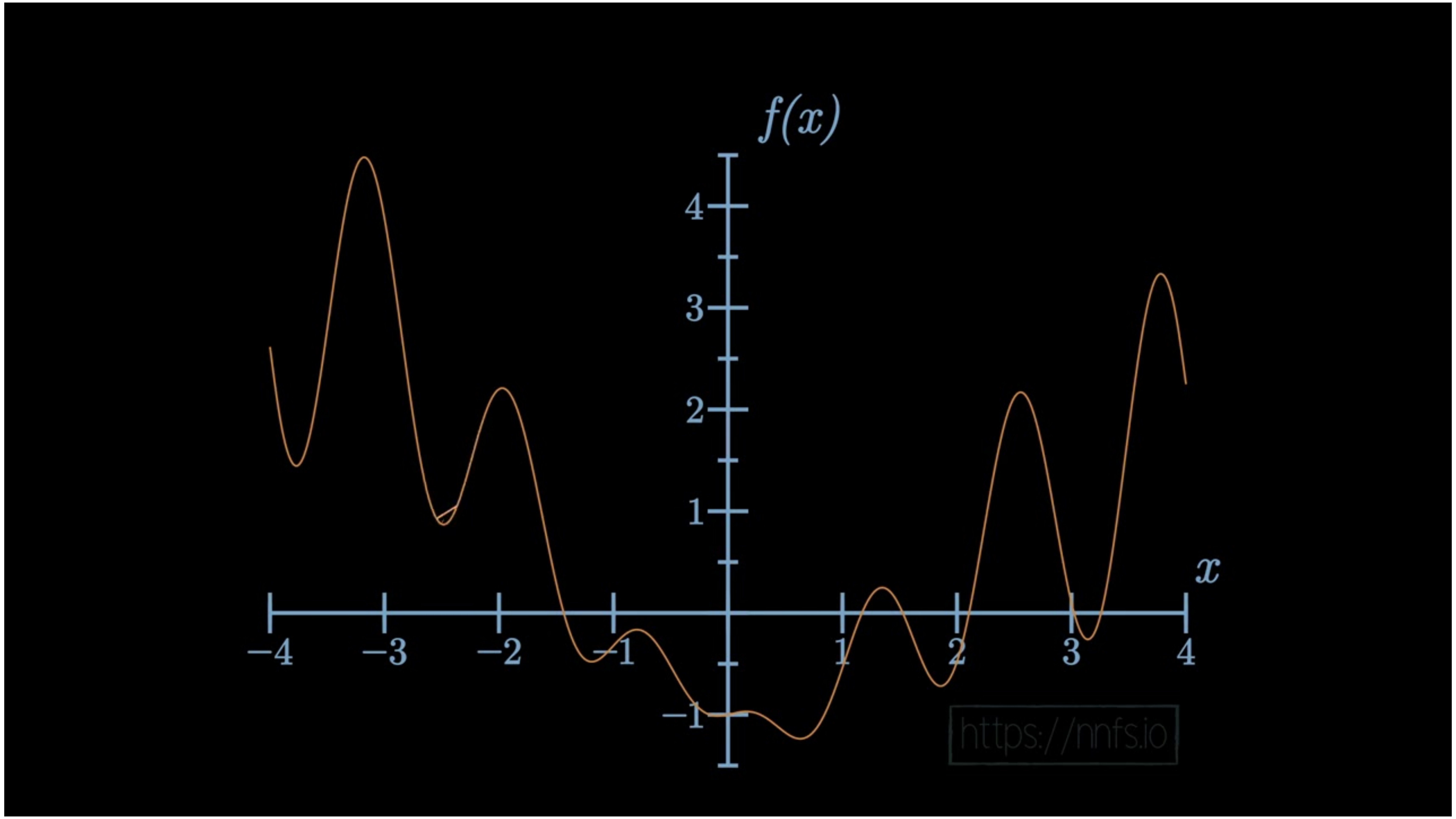
Backpropagation



Stochastic Gradient Descent



Learning Rate

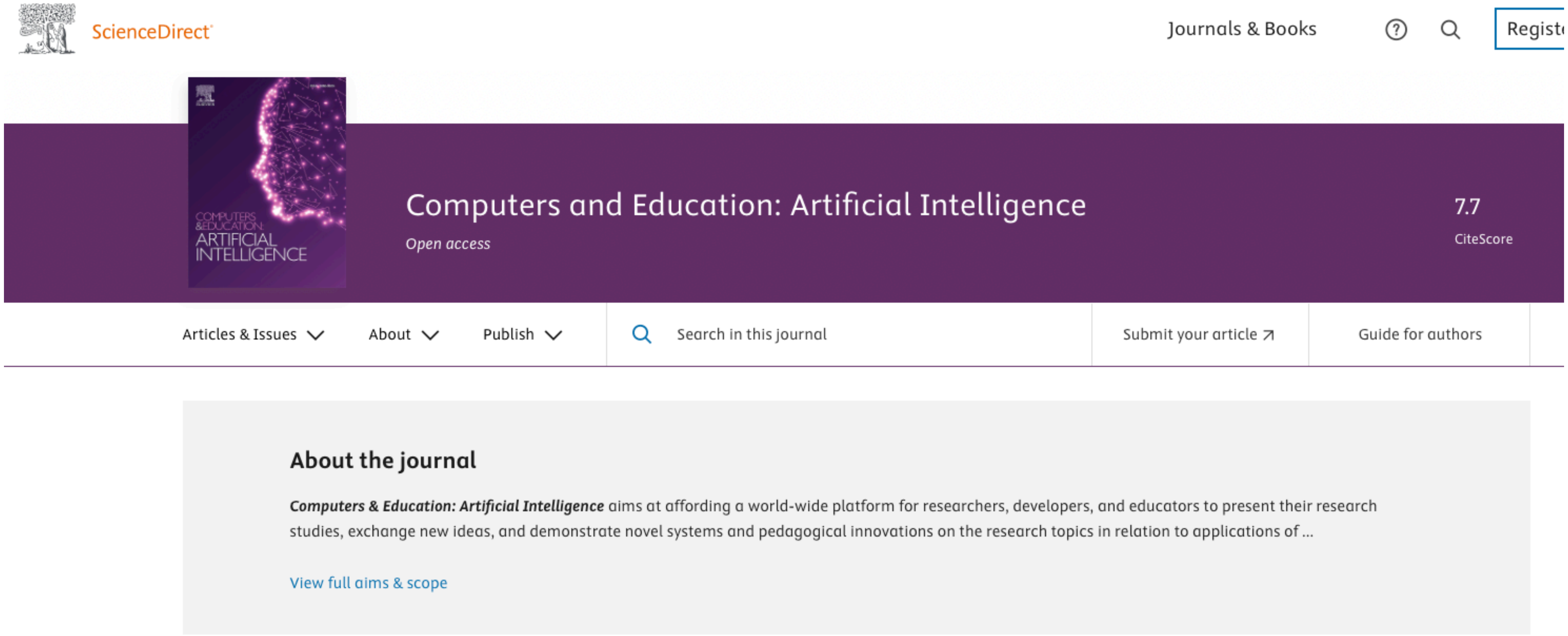


Education

IA nella didattica

Computers & Education: Artificial Intelligence

www.sciencedirect.com/journal/computers-and-education-artificial-intelligence



Computers and Education: Artificial Intelligence
Volume 4, 2023, 100145

Artificial Intelligence teaching and learning in K-12 from 2019 to 2022: A systematic literature review

Saman Rizvi [a, b], Jane Waite [a, b], Sue Sentance [b]

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https://doi.org/10.1016/j.caeai.2023.100145 Get rights and content

Highlights

- There is a paucity of research on a standardised evaluation framework for AI teaching and learning in K-12.
- Mainstream collaborative programming tools used in undergraduate education may be too complex for teaching AI at K-12 level.
- AI teaching and learning outcomes in K-12 may be closely linked with students' prior programming experience.
- Interactive AI resources and AI-driven games may be more versatile and adaptable to be used with different age groups.
- Studies reported minimal gender differences in young children in learning outcomes, perceptions, or participatory behaviours.

www.sciencedirect.com/science/article/pii/S2666920X23000243

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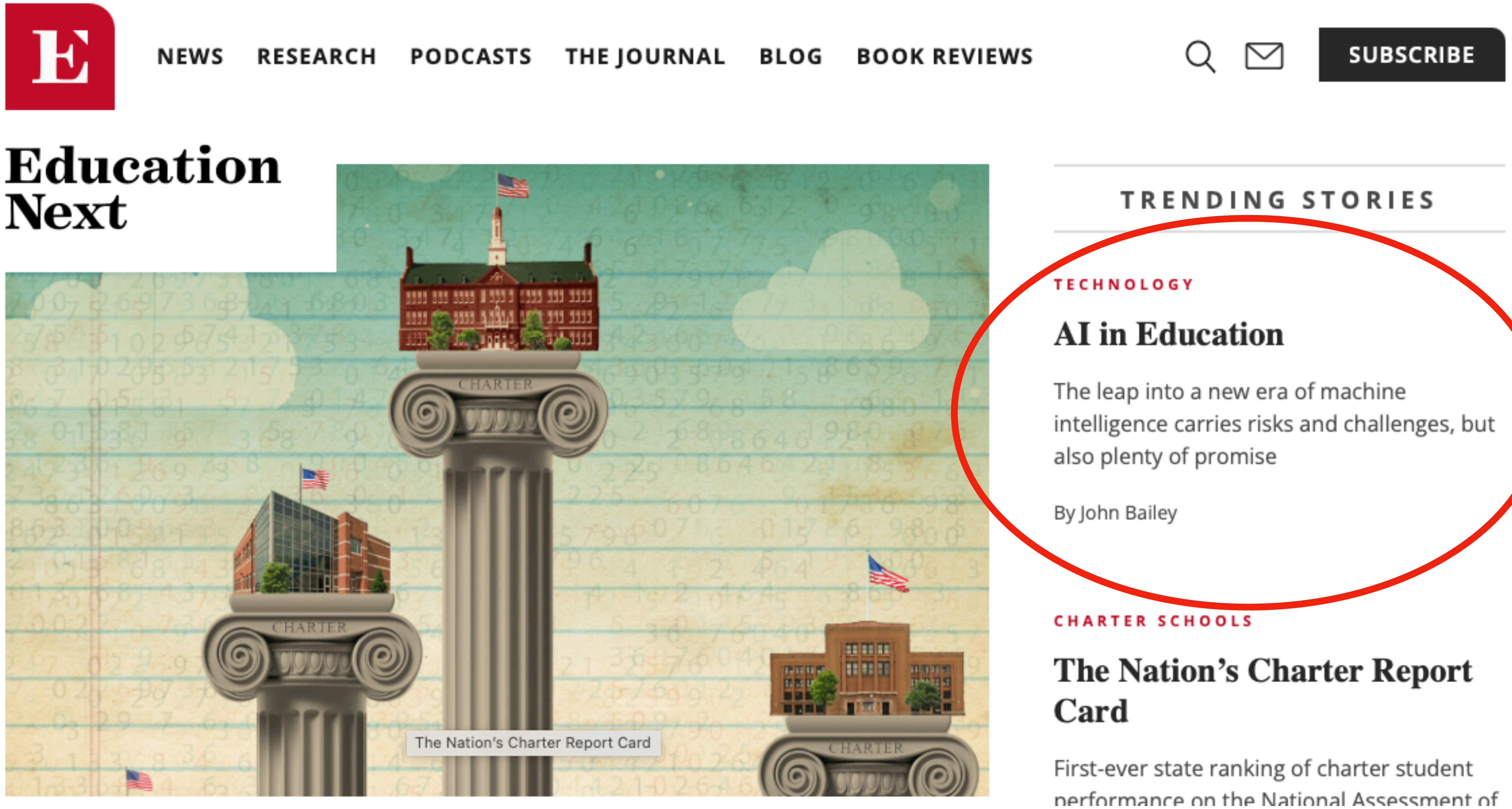

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EDUCATION NEXT'S

About Us

In the stormy seas of school reform, this journal will steer a steady course, presenting the facts as best they can be determined, giving voice (without fear or favor) to worthy research, sound ideas, and responsible arguments. Bold change is needed in American K–12 education, but Education Next partakes of no program, campaign, or ideology. It goes where the evidence points.

Traduzione con Bing:

Nelle tempestose acque della riforma scolastica, questa rivista seguirà un corso costante, presentando i fatti nel modo migliore possibile, dando voce (senza timore o favore) alla ricerca meritevole, alle idee solide e agli argomenti responsabili. È necessario un cambiamento audace nell'istruzione americana K-12, ma Education Next non partecipa a nessun programma, campagna o ideologia. Va dove indicano le prove.

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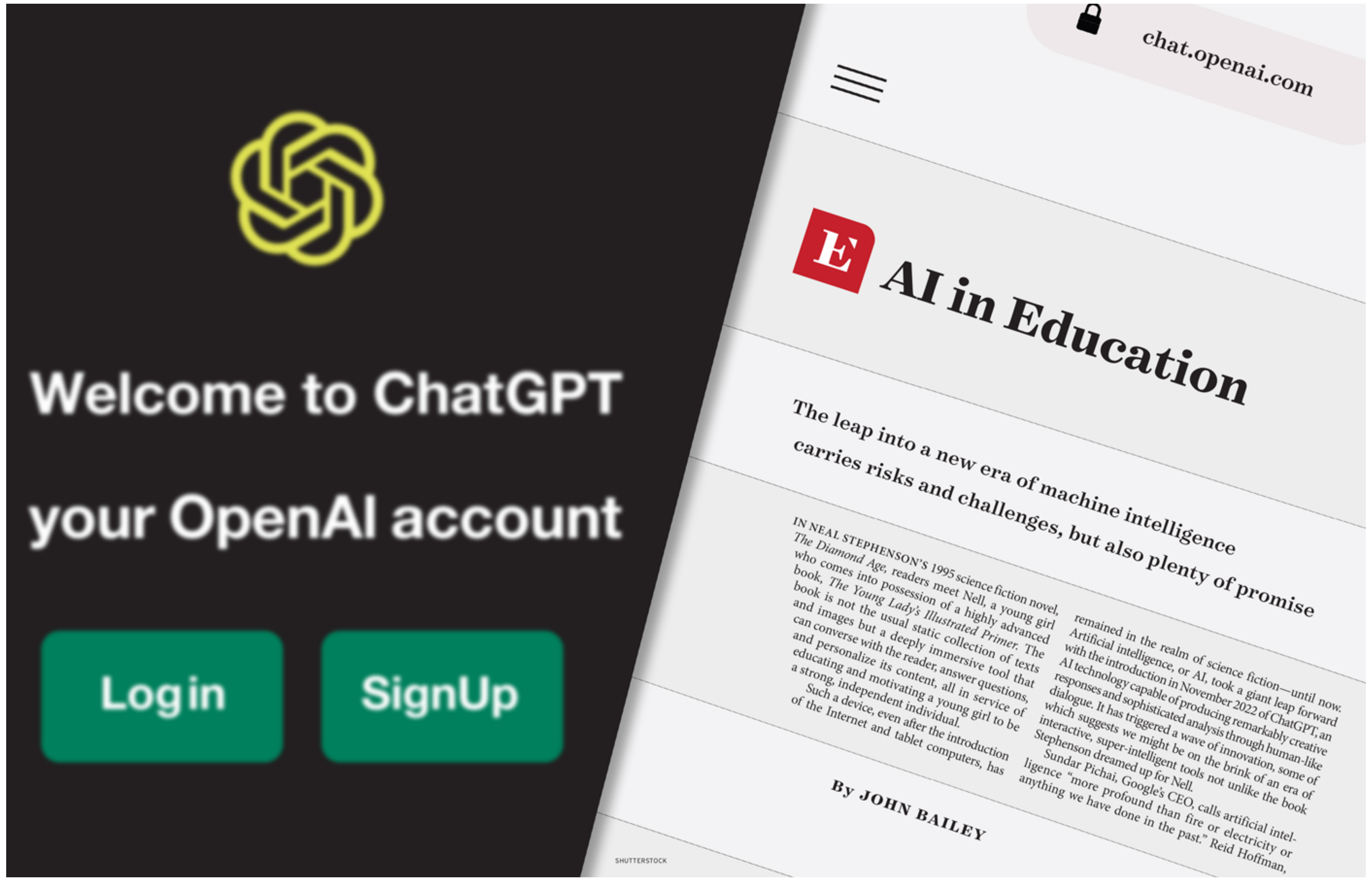
TECHNOLOGY VOL. 23, NO. 4

AI in Education

The leap into a new era of machine intelligence carries risks and challenges, but also plenty of promise

John Bailey



Latest Issue

Fall 2023

Vol. 23, No. 4

www.educationnext.org/a-i-in-education-leap-into-new-era-machine-intelligence-carries-risks-challenges-promises

AI in Education

Artificial Intelligence:

“more profound than fire or electricity or anything we have done in the past”
— Sundar Pichai, Google’s CEO, about AI

“The power to make positive change in the world is about to get the biggest boost it’s ever had”
— Reid Hoffman, LinkedIn founder

“This new wave of AI is as fundamental as the creation of the microprocessor, the personal computer, the Internet, and the mobile phone”
— Bill Gates

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AI in Education

Artificial intelligence took a giant leap forward with the introduction in November 2022 of ChatGPT, an AI technology capable of producing remarkably creative responses and sophisticated analysis through human-like dialogue. It has triggered a wave of innovation, some of which suggests we might be on the brink of an era of interactive, super-intelligent tools.

Traduzione con Bing:

L'intelligenza artificiale ha fatto un enorme passo avanti con l'introduzione nel novembre 2022 di ChatGPT, una tecnologia di intelligenza artificiale in grado di produrre risposte notevolmente creative e analisi sofisticate attraverso il dialogo umano. Ciò ha scatenato una ondata di innovazione, alcune delle quali suggeriscono che potremmo essere sull'orlo di un'era di strumenti interattivi e super intelligenti.

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AI in Education

In the realm of education, this technology will influence how students learn, how teachers work, and ultimately how we structure our education system. Some educators and leaders look forward to these changes with great enthusiasm. **Sal Kahn**, founder of Khan Academy, went so far as to say in a TED talk that AI has the potential to effect “probably the biggest positive transformation that education has ever seen.” But others warn that AI will enable the spread of misinformation, facilitate cheating in school and college, kill whatever vestiges of individual privacy remain, and cause massive job loss. The challenge is to harness the positive potential while avoiding or mitigating the harm.

Traduzione con Bing:

Nel campo dell’istruzione, questa tecnologia influenzerà il modo in cui gli studenti imparano, il modo in cui i docenti lavorano e, in definitiva, il modo in cui strutturiamo il nostro sistema educativo. Alcuni educatori e leader guardano con grande entusiasmo a questi cambiamenti. ***Sal Kahn****, fondatore di Khan Academy, ha persino affermato in una conferenza TED che l’IA ha il potenziale per effettuare “probabilmente la più grande trasformazione positiva che l’istruzione abbia mai visto”. Ma altri mettono in guardia contro il fatto che l’IA faciliterà la diffusione di disinformazione, agevolerà la frode a scuola e all’università, ucciderà ciò che resta della privacy individuale e causerà una massiccia perdita di posti di lavoro. La sfida è quella di sfruttare il potenziale positivo evitando o mitigando i danni.*

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TED Ideas worth spreading

WATCH DISCOVER ATTEND PARTICIPATE ABOUT SIGN IN MEMBERSHIP

How AI could save (not destroy) education

2,601,362 views | Sal Khan | TED2023 • April 2023

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Sal Khan, the founder and CEO of Khan Academy, thinks artificial intelligence could spark the greatest positive transformation education has ever seen. He shares the opportunities he sees for students and educators to collaborate with AI tools -- including the potential of a personal AI tutor for every student and an AI teaching assistant for every teacher -- and demos some exciting new features for their educational chatbot, Khanmigo.

Technology, Education, AI, Teaching, Kids

Transcript (14 Languages)

English

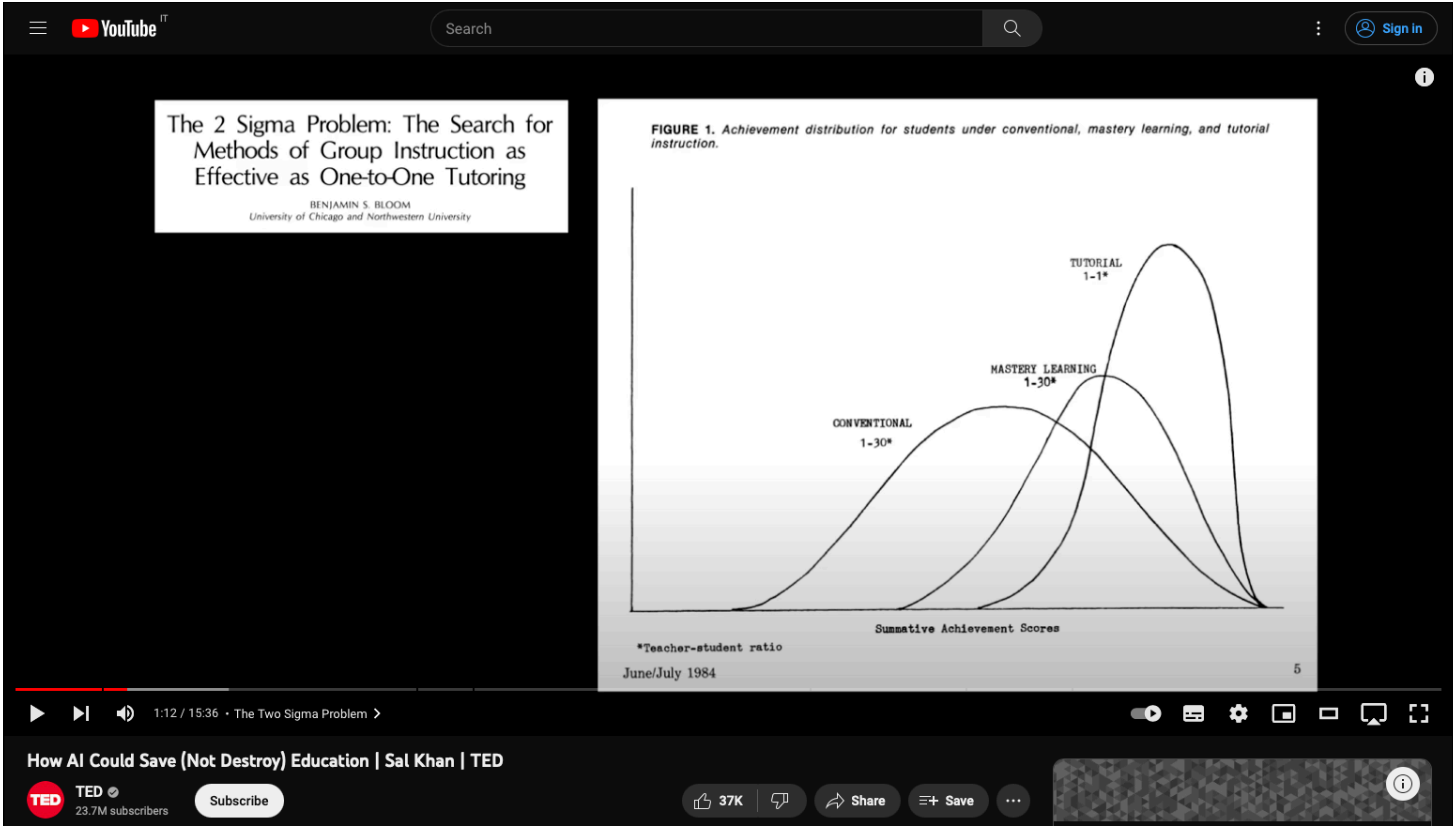
00:01

So anyone who's been paying attention for the last few months has been seeing headlines like this, especially in education. The thesis has been: students are going to be using ChatGPT and other forms of AI to cheat, do their assignments. They're not going to learn. And it's going to completely undermine education as we know it.

00:21

Now, what I'm going to argue today is not only are there ways to mitigate all of that, if we put the right guardrails, we

www.youtube.com/watch?v=hJP5GqnTrNo



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The 2 Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-One Tutoring

BENJAMIN S. BLOOM
University of Chicago and Northwestern University

Two University of Chicago doctoral students in education, Anania (1982, 1983) and Burke (1984), completed dissertations in which they compared student learning under the following three conditions of instruction:

1. *Conventional.* Students learn the subject matter in a class with about 30 students per teacher. Tests are given periodically for marking the students.
2. *Mastery Learning.* Students learn the subject matter in a class with about 30 students per teacher. The instruction is the same as in the conventional class (usually with the same teacher). Formative tests (the same tests used with the conventional group) are given for feedback followed by corrective procedures and parallel formative tests to determine the extent to which the students have mastered the subject matter.
3. *Tutoring.* Students learn the subject matter with a good tutor for each student (or for two or three students simultaneously). This tutoring instruction is followed periodically by formative tests, feedback-corrective procedures, and parallel formative tests as in the mastery learning classes. It should be pointed out that the need for corrective work under tutoring is very small.

The students were randomly assigned the three learning conditions, and their initial aptitude tests scores, previous achievement in the subject, and initial attitudes and interests in the subject were similar. The amount of time for instruction was the same in all three groups except for the corrective work in the mastery learning and tutoring groups. Burke (1984) and Anania (1982, 1983) replicated the study with four different samples of students at grades four, five, and eight and with two different subject matters, Probability and Cartography. In each sub-study, the instructional treatment was limited to 11 periods of instruction over a 3-week block of time.

Most striking were the differences in final achievement measures under the three conditions. Using the standard deviation (sigma) of the control (conventional) class, it was typically found that the average student under tutoring was about two standard deviations above the average of the control class (the average tutored student was above 98% of the students in the control class).[1] The average student under mastery learning was about one standard deviation above the average of the control class (the average mastery learning student was above 84% of the students in the control class).

The variation of the students' achievement also changed under these learning conditions such that about 90% of the tutored students and 70% of the mastery learning students attained the level of summative achievement reached by only the highest 20% of the students under conventional instructional conditions. (See Figure 1.)

There were corresponding changes in students' time on task in the classroom (65% under conventional instruction, 75% under Mastery Learning, and 90+% under tutoring) and students' attitudes and interests (least positive under conventional instruction and most positive under tutoring). There were great reductions in the relations between prior measures (aptitude or achievement) and the summative achievement measures. Typically, the aptitude-achievement correlations changed from +.60 under conventional to +.35 under mastery learning and +.25 under tutoring. It is recognized that the correlations for the mastery learning and tutoring groups were so low because of the restricted range of scores under these learning conditions. However, the most striking of the findings is that under the best learning conditions we can devise (tutoring), the average student is 2 sigma above the average control student taught under conventional group methods of instruction.

The tutoring process demonstrates that *most* of the students do have the potential to reach this high level of learning. I believe an important task of research and instruction is to seek ways of accomplishing this under more practical and realistic conditions than the one-to-one tutoring, which is too costly for most societies to bear on a large scale. This is the "2 sigma" problem. Can researchers and teachers devise teaching-learning conditions that will enable the majority of students under *group instruction* to

Benjamin S. Bloom is Professor of Education, University of Chicago and Northwestern University, 5835 S. Kimbark Avenue, Chicago, Illinois 60637. His areas of specialization are evaluation and the teaching-learning process.

en.wikipedia.org/wiki/Bloom%27s_2_sigma_problem

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Bloom's 2 sigma problem

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From Wikipedia, the free encyclopedia

Bloom's 2 sigma problem refers to the educational phenomenon that the average student tutored one-to-one using mastery learning techniques performed two standard deviations better than students educated in a classroom environment. It was originally observed by educational psychologist Benjamin Bloom and reported in 1984 in the journal *Educational Researcher*.[1][2][3] Bloom's paper analyzed the dissertation results of University of Chicago PhD students Joanne Anania and Joseph Arthur Burke. As quoted by Bloom: "the average tutored student was above 98% of the students in the control class".[1]:4 Additionally, the variation of the students' achievement changed: "about 90% of the tutored students ... attained the level of summative achievement reached by only the highest 20%" of the control class.[1]:4

The phenomenon's associated problem, as described by Bloom, was to "find methods of group instruction as effective as one-to-one tutoring".[1] The phenomenon has also been used to illustrate that factors outside of a teachers' control influences student education outcomes, motivating research in alternative teaching methods,[4] in some cases reporting larger standard deviation improvements than those predicted by the phenomenon.[5][6] The phenomenon has also motivated developments in human-computer interaction for education, including cognitive tutors[6] and learning management systems.[7]

Mastery learning [edit]

Main article: Mastery learning

Mastery learning is an educational philosophy first proposed by Bloom in 1968[8] based on the premise that students must

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AI in Education

Artificial intelligence is a branch of computer science that focuses on creating software capable of mimicking behaviors and processes we would consider "intelligent" if exhibited by humans, including:

- reasoning
- learning
- problem-solving
- exercising creativity

AI systems can be applied to an extensive range of tasks, including:
- language translation
- image recognition
- navigating autonomous vehicles
- detecting and treating cancer

and, in the case of **generative AI**, producing content and knowledge rather than simply searching for and retrieving it.

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AI in Education

Foundation Models:

Foundation models in generative AI are systems trained on a large dataset to learn a broad base of knowledge that can then be adapted to a range of different, more specific purposes.

This learning method is self-supervised, meaning the model learns by finding patterns and relationships in the data it is trained on.

Large Language Models (**LLM**s) are foundation models that have been trained on a vast amount of text data (e.g. web content, books, Wikipedia articles, news articles, social media posts, code snippets, etc).

By doing this analysis across billions of sentences, LLM models develop a statistical understanding of language: how words and phrases are usually combined, what topics are typically discussed together, and what tone or style is appropriate in different contexts.

That allows it to generate human-like text and perform a wide range of tasks, such as writing articles, answering questions, or analyzing unstructured data.

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AI in Education

Large Language Models:

LLMs include:

- **GPT-4** by OpenAI
- **PaLM** by Google
- **LLaMA** by Meta

These LLMs serve as "foundations" for AI applications:

- **ChatGPT** is built on GPT-3.5 and GPT-4,
- **Bard** uses Google's Pathways Language Model 2 (PaLM 2)

November 4, 2023

Grok-1: an AI modeled to answer almost anything and, far harder, even suggest what questions to ask! x.ai

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Some of the best-known applications:

ChatGPT 3.5. The free version of ChatGPT (November 2022). It was trained on data only up to 2021, and while it is very fast, it is prone to inaccuracies.

ChatGPT 4.0. The newest version of ChatGPT, which is more powerful and accurate than ChatGPT 3.5 but also slower, and it requires a paid account. It also has extended capabilities through plug-ins that give it the ability to interface with content from websites, perform more sophisticated mathematical functions, and access other services. A new Code Interpreter feature gives ChatGPT the ability to analyze data, create charts, solve math problems, edit files, and even develop hypotheses to explain data trends.

Microsoft Bing Chat. Powered by OpenAI's ChatGPT technology. It can browse websites and offers source citations with its results.

Google Bard. Google's AI generates text, translates languages, writes different kinds of creative content, and writes and debugs code in more than 20 different programming languages. The tone and style of Bard's replies can be finetuned to be simple, long, short, professional, or casual. Bard also leverages Google Lens to analyze images uploaded with prompts.

Anthropic Claude 2. A chatbot that can generate text, summarize content, and perform other tasks, Claude 2 can analyze texts of roughly 75,000 words and generate responses of more than 3,000 words.

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AI in Education

Uses of AI in Education:

Report of the U.S. Department of Education (May, 2023):

Artificial Intelligence and the Future of Teaching and Learning: Insights and Recommendations

Listening sessions in 2022 with > 700 people, including educators and parents:

- action is required now in order to get ahead of the expected increase of AI in education technology
- future potential risks with AI
- AI may enable achieving educational priorities in better ways, at scale, and with lower costs

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AI in Education

Uses of AI in Education:

Instructional assistants:

- help explain difficult concepts to students
- constructive critiques on student writing
- help students fine-tune their writing skills
- certain kinds of prompts can help children generate more fruitful questions about learning
- customized learning for students with disabilities
- provide translation for English language learners

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AI in Education

Uses of AI in Education:

Teaching assistants:

- administrative tasks that keep teachers from investing more time with their peers or students
- automated routine tasks such as drafting lesson plans, creating differentiated materials, designing worksheets, developing quizzes, and exploring ways of explaining complicated academic materials
- provide educators with recommendations to meet student needs and help teachers reflect, plan, and improve their practice

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AI in Education

Uses of AI in Education:

Parent assistants:

- generate letters requesting individualized education plan or to ask that a child be evaluated for gifted and talented programs
- administrative assistant to choose a school for their child, map out school options within driving distance of home, generate application timelines, compile contact information etc.
- create bedtime stories tailored to a child’s interests

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AI in Education

Uses of AI in Education:

Administrator assistants:

- draft various communications, including materials for parents, newsletters, and other community-engagement documents
- organizing class or bus schedules
- analyze complex data to identify patterns or needs
- ChatGPT can perform sophisticated sentiment analysis that could be useful for measuring school-climate and other survey data

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AI in Education

Challenges and Risks:

Student cheating:

- Students might use AI to solve homework problems or take quizzes
- AI-generated essays threaten to undermine learning as well as the college-entrance process
- Students who use AI to do their work for them may not be learning the content and skills they need

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AI in Education

Challenges and Risks:

Bias in AI algorithms:

- AI systems learn from the data they are trained on. If this data contains biases, those biases can be learned and perpetuated by the AI system.
- For example, if the data include student-performance information that's biased toward one **ethnicity**, **gender**, or **socioeconomic segment**, the AI system could learn to favor students from that group.
- Less cited but still important are potential biases around **political ideology** and possibly even **pedagogical philosophy** that may generate responses not aligned to a community's values.

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AI in Education

Challenges and Risks:

Privacy concerns:

- When students or educators interact with generative-AI tools, their conversations and personal information might be stored and analyzed, posing a risk to their privacy.
- With public AI systems, educators should refrain from inputting or exposing sensitive details about themselves, their colleagues, or their students, including but not limited to private communications, personally identifiable information, health records, academic performance, emotional well-being, and financial information.

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AI in Education

Challenges and Risks:

Decreased social connection:

- There is a risk that more time spent using AI systems will come at the cost of less student interaction with both educators and classmates.
- Children may also begin turning to these conversational AI systems in place of their friends.
- As a result, AI could intensify and worsen the public health crisis of loneliness, isolation, and lack of connection identified by the U.S. Surgeon General.

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AI in Education

Challenges and Risks:

Overreliance on technology:

- Both teachers and students face the risk of becoming overly reliant on AI-driven technology.
- For students, this could stifle learning, especially the development of critical thinking.
- This challenge extends to educators as well.
- While AI can expedite lesson-plan generation, speed does not equate to quality.
- Teachers may be tempted to accept the initial AI-generated content rather than devote time to reviewing and refining it for optimal educational value.

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AI in Education

Challenges and Risks:

Equity issues:

- Not all students have equal access to computer devices and the Internet.
- That imbalance could accelerate a widening of the achievement gap between students from different socioeconomic backgrounds.

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AI in Education

Why AI is different:

- It is wise to be skeptical of new technologies that claim to revolutionize learning.
- In the past, prognosticators have promised that television, the computer, and the Internet, in turn, would transform education.
- Unfortunately, the heralded revolutions fell short of expectations.

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AI in Education

Why AI is different:

- There are some early signs, though, that this technological wave might be different in the benefits it brings to students, teachers, and parents.
- Previous technologies democratized access to content and resources, but AI is democratizing a kind of machine intelligence that can be used to perform a myriad of tasks.
- Moreover, these capabilities are open and affordable—nearly anyone with an Internet connection and a phone now has access to an intelligent assistant.

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AI in Education

Why AI is different:

- Generative AI models keep getting more powerful and are improving rapidly.
- The capabilities of these systems months or years from now will far exceed their current capacity.
- Their capabilities are also expanding through integration with other expert systems.
- Take **math**, for example. GPT-3.5 had some difficulties with certain basic mathematical concepts, but GPT-4 made significant improvement.
- Now, the incorporation of the **Wolfram** plug-in has nearly erased the remaining limitations.

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