CELET 2024, Stockholm University Beata Brzozowska, Faculty of Physics, University of Warsaw

#### Al and its use in radiation research





Simple example: how to recognise numbers

More sophisticated example: how to recognise dicentrics

### Agenda

Basic information about AI

One pixel attack

Some threads

### <u>chat.openai.com</u>



Chatgpt.com			ᠿ	+	ſĊ
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can you prepare for me 10 slides on ma	achine learning?				
les on <b>Machine Learning</b> . You can use this s provide brief descriptions for each slide.	structure to				
ng f ML					
o AI or ML)					
rning?					
set of Artificial Intelligence (AI) that allows s	systems to learn				

from data and improve from experience  $\checkmark$  hout being explicitly programmed."

## bard.google.com



See the latest updates to the <u>Gemini Apps Privacy Hub</u>

Show drafts 🗸 🗸

The question of whether Gemini is better than ChatGPT is subjective and depends on the specific task at hand. Both models have their own strengths and weaknesses.

Some people may find Gemini to be more informative and comprehensive in its responses, while others may prefer ChatGPT's more conversational and engaging style. Ultimately, the best way to decide which model is right for you is to try them

Here are some of the key differences between Gemini and ChatGPT:

• Factual accuracy: Gemini is generally more accurate in its responses, especially

• **Real-time information access:** Gemini has access to the web and can provide

• Diverse tasks: Gemini is capable of performing a wider range of tasks, including

#### Welcome to Gemini

As you try Gemini, please remember:

#### Gemini will not always get it right

Gemini may give inaccurate or offensive responses. When in doubt, use the Google button to double-check Gemini's responses.

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To connect you with useful content, Gemini Apps may share parts of your conversations and other relevant info, like your location, with other services. These services may use that info for their improvement, even if you later delete your Gemini Apps activity. You can turn extensions off at any time on the Extensions page. Learn more in the Gemini Apps Privacy <u>Hub</u>

#### Gemini will get better with your feedback

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**Chapter V: General-Purpose Al** Models

Chapter VI: Measures in Support of Innovation

**Chapter VII: Governance** 

Chapter VIII: EU Database for High-**Risk Al Systems** 

📋 Copy URL **Part of Chapter I: General Provisions** Article 3: Definitions Date of entry into force: Inherited from: According to: 2 February 2025 Article 113(a) Chapter I See here for a full implementation timeline. SUMMARY + For the purposes of this Regulation, the following definitions apply: (1) 'AI system' means a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments; Related: Recital 12

(2) 'risk' means the combination of the probability of an occurrence of harm and the severity of that harm;

## Artificial Intelligence



# Artificial Intelligence (AI)



https://suryamaddula.medium.com/domains-of-artificial-intelligence-8046d0778f1a

#### Performance and interpretability



Lei Xing, The Role of AI in Clinical Radiation Oncology





#### A brain is a supercomputer (H. Markram)

#### **Blue Brain** Project

The goal of the Blue Brain Project is to build biologically detailed digital reconstructions and simulations of the mouse brain.

Cost: billion €



https://www.epfl.ch/research/domains/bluebrain/blue-brains-scientific-milestones/



#### A brain is a supercomputer (H. Markram)

#### **Blue Brain** Project

The goal of the Blue Brain Project is to build biologically detailed digital reconstructions and simulations of the mouse brain.



https://www.ted.com/talks/henry\_markram\_a\_brain\_in\_a\_supercomputer?subtitle=en



#### brain: ~86 000 000 000 neurons, up to 10 000 connections each



Henry Markram @TED, 2009

Axon terminal

Soma (cell body)

Myelin sheath

5

Output points = synapses

Myelinated axon trunk



# Caenorhabditis elegans



#### The body consists of 959 somatic cells, of which 302 are neurons.

https://openworm.org/getting\_started.htm

## Neuron activity



## Artificial neuron activity

- Inputs,  $x_i$
- Output, y
- Activation function, f
- Activation(state), a
- Bias, b
- Threshold,  $\theta$

$$\begin{aligned} a(t+1) &= f(a(t), w_i x_i, \theta, b) \\ y &= g(a(t)) \end{aligned}$$



### Activation functions

#### **Activation Functions**



Leaky ReLU  $\max(0.1x, x)$ 



 $\begin{array}{l} \textbf{Maxout} \\ \max(w_1^T x + b_1, w_2^T x + b_2) \end{array}$ 

ELU  $\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 & -\frac{10}{-2} & -\frac{10}{-2} & 0 \end{cases}$ 



- Matrix multiply at each layer
  - $L_i = f(W_{\{i-1\}}L_{\{i-1\}})$
- Dense vs Sparse



Keith Schubert, The Latest on CNN News: Understanding and Using Convolutional Neural Networks

#### Neural network

## Convolutional Neural Network (CNN)

\*







0	1	2	4		.2	.2	.1
2	5	6	9	*	0	.3	0
1	3	2	6		0	.2	0
0	2	4	1				

0	1	2	4		.2
2	5	6	9	*	0
1	3	2	6		0
0	2	4	1		



0	1	2	4		.2
2	5	6	9	*	0
1	3	2	6		0
0	2	4	1		



0	1	2	4		.2	.2	.1
2	5	6	9	*	0	.3	0
1	3	2	6		0	.2	0
0	2	4	1				

0	1	2	4		.2	.2	.1
2	5	6	9	*	0	.3	0
1	3	2	6		0	.2	0
0	2	4	1				

# Image convolution





# Convolutional Neural Network (CNN)



https://skyengine.ai/se/skyengine-blog/125-what-is-a-convolutional-neural-network



#### Network architecture





# Object classification







cube

# Object classification

#### **DEEP LEARNING (DL)** A deep neural network



The tumor in the image is an oligodendroglioma

The tumor in the image is an astrocytoma





## Deep learning

#### to 'remember and recognise' more than a few patterns



#### neural network must have more parameters (connection weights)

## Model parameters

#### 

Ś

I'm based on GPT-4, which has around 175 billion parameters. These parameters are the weights and biases that the model uses to generate and understand text. The number of parameters influences the model's ability to handle complex tasks, but it's not the only factor that determines how well it performs—training data, architecture, and fine-tuning are also key components.

how many parameters do you have?



## Model parameters



Lei Xing, The Role of AI in Clinical Radiation Oncology

# Training cycle



# Data and training



https://www.analyticsvidhya.com/blog/2023/11/train-test-validation-split/

![](_page_31_Picture_3.jpeg)

### K-fold cross-validation

		Fold 1	Fold 2	Fold 3
	Split 1	test	train	train
	Split 2	train	test	train
Train data	Split 3	train	train	test
	Split 4	train	train	train
	Split 5	train	train	train

![](_page_32_Figure_2.jpeg)

https://towardsdatascience.com/how-to-cross-validation-with-time-series-data-9802a06272c6

![](_page_33_Figure_1.jpeg)

Nassim Abderrahmane. Hardware design of spiking neural networks for energy efficient brain- inspired computing. Artificial Intelligence [cs.AI]. Université Côte d'Azur, 2020. English. NNT: 2020COAZ4082

#### Simple example

Modified National Institute of Standards and Technology (MNIST): database of handwritten digits

![](_page_33_Figure_6.jpeg)

M Inbox (1) - b.b	014Version01	🎽 Deep Learnin	G SimpleMnist.i	📣 My Drive - Go	G rok akademic	🖃 rozkład jazdy 🗧 🚼 referaty-term	ni 🕂 harmonogram G Alexamples/Si
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			In []: import ma	tplotlib.pyplot as p	lt		

#### Simple example

#### More sophisticated example: dicentrics

![](_page_35_Picture_1.jpeg)

Courtesy of M. Głowacki

![](_page_35_Picture_3.jpeg)
### Precision of scoring chromosomal aberrations by CELOD participants



Gałecki et al. Precision of scoring radiation-induced chromosomal aberrations and micronuclei by unexperienced scorers, International Journal of Radiation biology 95(9): 1251–1258, 2019

## Fast and precise scoring of dicentrics

# RENEB data









# RENEB: laboratory network

- Running the European Network of Biological and retrospective Physical dosimetry (7th EU framework EURATOM Fission Programme);
- retrospective dose assessment in small-scale and large-scale nuclear & radiological emergency situations;
- assuring the high-level expertise of laboratories (intercomparison).

8

U. Oestreicher et al. RENEB intercomparisons applying the conventional Dicentric Chromosome Assay (DCA), International Journal of Radiation Biology 93: 20–29, 2017



## Scoring DIC under the microscope



- blood samples collected from the 10 donors;
- irradiated in vitro with <sup>60</sup>Co;
- doses: 0 Gy, 0.25 Gy, 0.75 Gy, 1 Gy, 1.5 Gy, 2.5 Gy, 3 Gy, 4.5 Gy, and 5 Gy

## Datasets

### TRAINING set

- used for the training (including validation),
- spanning over 3000 images in total (all doses),
- 5 experts labeled the chromosomes.

### CALIBRATION set

- consists of 300 images for each dose (0 Gy 4.5 Gy),
- evaluated by an external (6th) expert,
- used to prepare a calibration curve to study the dose-response, as well as to evaluate the parameters of the final model.

### TEST set

- consists of 50 images for each dose,
- no overlap with the CALIBRATION and TRAINING sets,
- evaluated by 5 experts and the model independently to assess their relative performance



## Experts



### TRAINING and TEST sets (5 experts)

### CALIBRATION set (1 expert)



# Labeling by experts

Other Expo	et Boxes
Number of chromosomes: 46	Help
Monocentric (1)	46
Dicentric (2)	0
Acentric (3)	0
Ring (4)	0
Bad split (5)	0
Other (6)	4
Remove label (Delete)	
Find not labeled (Enter) T	o label: 0
Devidence (Lafe) Next (D	( ala a)

# Workflow of the model AB





# Model A: U-Net approach



M. Głowacki, Application of U-net type deep neural network in finding centromeres on microscopic images, Bachelor thesis @ University of Warsaw





## U-net architecture



# Model B: 2-stages image processing

Segmentation: chromosome detection

Classification: dicentric recognition





watershed with hidden bad splits

original

# Images for training



MaskR-CNN



## Chromosome classification

Type
Monocentric
Dicentric
Acentric
Ring

### Final class was chosen as labeled by the most of the experts



Training dataset	Test dataset
$73 \ 283$	$12 \ 264$
605	109
686	84
28	2





### Performance estimation

# $F_1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)}$

- F1-score (predictive performance),
- its values is between 0 and 1,
- F1 = 1 means perfect prediction.

### Model predictions Expert labels





# Expert performance



F1-scores for all pairs of experts per dose For a pair of experts, its two permutations give the same F1-score



# Expert and model performance



### Performance estimation

 $Precision = \frac{TP}{TP+FP}$   $Sensitivity = \frac{TP}{TP+FN}$   $F1-score = \frac{2TP}{2TP+FP+FN}$ 

### Model predictions Expert labels





## Precision and sensitivity of the model



### Dose-effect curve: comparison between experts



× 5

$$y = \alpha D^2 + \beta D + c,$$

$$CV_{\alpha} = \frac{SD\overline{\alpha}}{\overline{\alpha}} \cdot 100\% = 58\%$$

$$CV_{\beta} = \frac{SD\beta}{\overline{\beta}} \cdot 100\% = 110\%$$

TEST set (5 experts)



### Dose-effect curve: comparison between experts

х

5



$$y = \alpha D^2 + \beta D + c,$$

$$CV_{\alpha} = \frac{SD\overline{\alpha}}{\overline{\alpha}} \cdot 100\% = 58\%$$

$$CV_{\beta} = \frac{SD\overline{\beta}}{\overline{\beta}} \cdot 100\% = 110\%$$

TEST set (5 experts)



## Dose-effect curve: comparison between experts





## Dose-effect curve: expert vs. model



$$y = \alpha D^2 + \beta D + c,$$

### CALIBRATION set (1 expert)





## Dose estimation by experts and model





 $RMSE_{exp} = 0.76 Gy$  $RMSE_{mod} = 0.68 Gy$ 



## http://studenci.fuw.edu.pl/~mg394990/MaksChroms/

### Welcome to MaksChroms website!



(22.02.2023) The manual is available! Please see the Downloads section.

(20.01.2023) First beta release of MaksChroms is available! Please see the Downloads section.

About MaksChroms

*MaksChroms* is a software for analysis of chromosomes on microscopic images. It uses four different deep neural networks to autonomously detect and classify chromosomes into one of four categories – monocentric, acentric, dicentric and others. *MaksChroms* allows for manual inspection and custom modification of generated results in a convenient way. It also estimates the radiation dose absorbed by the sample, using embedded dose curve, or based on the calibration data provided by the user. *MaksChroms* prediction results, as well as calibration curve, can by exported to .csv files.

#### Our Team

Member	Contribution	Email address
dr Beata Brzozowska	Project coordination	Beata.Brzozowska@fuw.edu.pl
dr Józef Ginter	Project coordination	Jozef.Ginter@fuw.edu.pl
Maksymilian Głowacki	Software development	m.glowacki10@uw.edu.pl

#### System requirements

MaksChroms was developed and tested on Windows 10 (64-bit). It may work out of the box on other (64-bit) Windows distributions as well. Please report any bugs directly to <u>m.glowacki10@uw.edu.pl</u>.

#### Downloads







300Gy Lab Ab	~	Process	Process All
ample's properties (average	per image):		
D	300Gy La	ab Ab	
Acentrics	1.5050		
nvalid predictions	0.2107		
Monocentrics	43.8027		
Dicentrics	0.7759		
Dose (MC 1.0)	99.0000		
nage statistics:			Dose Curve
D	3.0 Gy b	Lab A - 006	
Acentrics	5		
nvalid predictions	0		
Monocentrics	40		
Dicentrics	2		

Open Viewer Export Set

Dicentrics

Open Viewer		Export Set		Save	Save All
Туре	Mask type	Final Type	Disabled	Hand made	Delete
	0	Acentric ~			Delete
	1	Monocentric ~			Delete
	1	Dicentric ~			Delete
	2	Dicentric ~			Delete
	1	Monocentric ~			Delete



- 0



### Andrzej Wójcik

### 弘前大学 HIROSAKI UNIVERSITY

Yohei Fujishima



Ursula Oestreicher Martin Bucher FACULTY OF PHYSICS UNIVERSITY OF WARSAW

Jan Borkowski Beata Brzozowska Józef Ginter Maksymilian Głowacki Maria Kowalska Maria Szoła Adrianna Tartas

# ROBOTEC M

Paweł Kotowski

Contact: m.glowacki10@student.uw.edu.pl







# Al in medicine

### Segmentation and treatment planning

Radiation dosimetry and quality assurance

### Image reconstruction and multimodality imaging

### Outcome predictions

Lei Xing, The Role of AI in Clinical Radiation Oncology

# Al in medicine



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### A New AI Tool Predicts G

An artificial intelligence tool, scGPT, ca disrupting genes, and pinpoint which g

Carissa Wong, PhD

Aug 21, 2023 | 4 min read

#### PDF VERSION

nature medicine

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<u>nature</u> > <u>nature medicine</u> > <u>articles</u> > article

Article | Published: 19 March 2024

### A visual-language foundation model for computational pathology

Ming Y. Lu, Bowen Chen, Drew F. K. Williamson, Richard J. Chen, Ivy Liang, Tong Ding, Guillaume Jaume, Igor Odintsov, Long Phi Le, Georg Gerber, Anil V. Parwani, Andrew Zhang & Faisal Mahmood ⊠

Nature Medicine 30, 863–874 (2024) Cite this article

30k Accesses | 38 Citations | 157 Altmetric | Metrics

### nature medicine

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NS CATEGO	nature > nature medicine > articles > article					
Article Published: 07 August 2024 <b>A generalist vision–language foundation model for</b> <b>diverse biomedical tasks</b>						
			an, <u>Yixin Liu, Jun Y</u>	u, <u>Zhengliang Liu</u> , <u>Xun Chen</u> , <u>Brian</u>		
Publish with u	s 🛩 Subscribe		<u>n Zhou, Sunyang Fi</u> <u>ang Li, Hongfang Li</u>	u, Wei Liu, Tianming Liu, Xiang Li u & Lichao Sun ⊠		

Lei Xing, The Role of AI in Clinical Radiation Oncology



## Explainable Artificial Intelligence (XAI)

### One pixel attack

- $\bullet$







Ali, Y. M. B. (2023). One-pixel and x-pixel adversarial attacks based on smell bees optimization algorithm. Future Generation Computer Systems, 149, 562-576.

segmenting the image at the first stage; applying a nature-inspired algorithm to find the optimal pixel able to modify the decision of the deep learning model.

Fig. 7. Some adversarial images with their corresponding classes achieved after the attack when using CNN.

# How does it work?

#### input image





**CAT 98%** 

input image





**CAT 98%** 

Klawikowska et al. Explainable AI for Inspecting Adversarial Attacks on Deep Neural Networks, https://doi.org/10.1007/978-3-030-61401-0\_14

FGSM attack

adversarial example





DOG 100%



**DOG 95%** 

#### Fig. 1. Illustration of the FGSM and one-pixel attacks.

# One pixel attack

Name	Number of Data	Number of Class	Original Size of Image	Type of Dataset	Color Information	Type of Image
Derma	10,015	7	600  imes 450	Multi-class	Color	Dermatoscopic
Pneumonia	5856	2	(384~2916) × (127~2713)	Multi-class	Greyscale	X-ray
OCT	109,309	4	(1, 3) × (384~1536) × (277~512)	Multi-class	Greyscale	Optical Coherence Tomography
COVID-19	30,530	3	$1024 \times 1024$	Multi-class	Greyscale	X-ray
Chest	112,120	14	$1024 \times 1024$	Binary-class Multi-label	Greyscale	X-ray



Pneumonia 88% precision, 100% recall

Tsai, M.-J.; Lin, P.-Y.; Lee, M.-E. Adversarial Attacks on Medical Image Classification. Cancers 2023, 15, 4228. https://doi.org/10.3390/ cancers15174228

Normal 100% precision, 65% recall

# Multi-pixel attack



Tsai, M.-J.; Lin, P.-Y.; Lee, M.-E. Adversarial Attacks on Medical Image Classification. Cancers 2023, 15, 4228. https://doi.org/10.3390/ cancers15174228

- the success rate of converting normal images into pneumonia images is positively correlated with the number of perturbed pixels
- transforming pneumonia images into normal images does not yield successful results, even with an increase in the perturbed pixels.

# Al hallucinations

Ethics and Information Technology (2024) 26:38 https://doi.org/10.1007/s10676-024-09775-5

**ORIGINAL PAPER** 

#### **ChatGPT is bullshit**

Michael Townsen Hicks<sup>1</sup> · James Humphries<sup>1</sup> · Joe Slater<sup>1</sup>

Published online: 8 June 2024 © The Author(s) 2024

#### Abstract

Recently, there has been considerable interest in large language models: machine learning systems which produce like text and dialogue. Applications of these systems have been plagued by persistent inaccuracies in their output; 1 often called "AI hallucinations". We argue that these falsehoods, and the overall activity of large language models, understood as bullshit in the sense explored by Frankfurt (On Bullshit, Princeton, 2005): the models are in an in way indifferent to the truth of their outputs. We distinguish two ways in which the models can be said to be bul and argue that they clearly meet at least one of these definitions. We further argue that describing AI misreprese as bullshit is both a more useful and more accurate way of predicting and discussing the behaviour of these syst

Keywords Artificial intelligence · Large language models · LLMs · ChatGPT · Bullshit · Frankfurt · Assertion · Content

> AI/LLM systems do not usually give the sources of the answers and information generated, instead sometimes giving sources that do not exist.



Ethics and Information Technology (2024) 26:46 https://doi.org/10.1007/s10676-024-09785-3

CORRECTION

#### **Correction: ChatGPT is bullshit**

Michael Townsen Hicks<sup>1</sup> · James Humphries<sup>1</sup> · Joe Slater<sup>1</sup>

Published online: 11 July 2024 © The Author(s) 2024

**Correction to: Ethics and Information Technology** (2024) 26:38

https://doi.org/10.1007/s10676-024-09775-5

In this article, there are multiple corrections as listed below,

The sentence beginning, 'Solutions such as...' must be Solutions such as connecting the LLM to a database don't work because, if the models are *trained* on the database, then the words in the database affect the probability that the chatbot will add one or another word to the line of text it is generating.

The sentence beginning, 'We will argue....' must be 'We will argue that these falsehoods aren't hallucinations later.'

The sentence beginning 'In Sect. 3.2 we consider.....' must be 'In our final section, we consider whether ChatGPT having any intentions at all, and we'll go into this in more depth in the next section'.

The sentence beginning, 'In Sect. 1, we argued....' must be 'Earlier, we argued that ChatGPT is not designed to produce true utterances; rather, it is designed to produce text which is indistinguishable from the text produced by humans. It is aimed at being convincing rather than accurate'.

The sentence, 'We will consider these questions in more depth in Sect. 3.2.2.' must be 'We will consider these questions in more depth below.'

The sentence beginning 'We don't think......' must be 'We don't think that ChatGPT is an agent or has intentions in precisely the same way that humans do (see Levinstein and Herrmann (forthcoming) for a discussion of the issues here).



Cornell University  $\exists r \times 1V > cs > arXiv:2311.16822$ 

**Computer Science > Machine Learning** 

[Submitted on 28 Nov 2023 (v1), last revised 17 Jun 2024 (this version, v2)]

#### Large Language Models Suffer From Their Own Output: An Analysis of the Self-Consuming Training Loop

#### Martin Briesch, Dominik Sobania, Franz Rothlauf

Large Language Models (LLM) are already widely used to generate content for a variety of online platforms. As we are not able to safely distinguish LLM-generated content from human-produced content, LLM-generated content is used to train the next generation of LLMs, giving rise to a self-consuming training loop. From the image generation domain we know that such a self-consuming training loop reduces both quality and diversity of images finally ending in a model collapse. However, it is unclear whether this alarming effect can also be observed for LLMs. Therefore, we present the first study investigating the self-consuming training loop for LLMs. I method based on logic expressions that allows us to unambiguously verify the correctness of LLM-generated content, which is difficult for na the self-consuming training loop produces correct outputs, however, the output declines in its diversity depending on the proportion of the u slow down this decline, but not stop it. Given these concerning results, we encourage researchers to study methods to negate this process.

Subjects: Machine Learning (cs.LG); Computation and Language (cs.CL); Neural and Evolutionary Computing (cs.NE)

Cite as: arXiv:2311.16822 [cs.LG] (or arXiv:2311.16822v2 [cs.LG] for this version) https://doi.org/10.48550/arXiv.2311.16822

#### Submission history

From: Martin Briesch [view email] [v1] Tue, 28 Nov 2023 14:36:43 UTC (643 KB) [v2] Mon, 17 Jun 2024 07:07:30 UTC (760 KB)

# Quality of training data

We gratefully acknowledge support <u>member insti</u>

> Search... Help | Ac



train

# Copyrights of training data





Reuters

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Litigation | Copyright | Appellate | Intellectual Property | Litigation

### Artist sues after US rejects copyright for **Al-generated image**

By Blake Brittain



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### **EU AI Act: first regulation on** artificial intelligence

The use of artificial intelligence in the EU will be regulated by the AI Act, the world's first comprehensive AI law. Find out how it will protect you.

> Published: 08-06-2023 Last updated: 18-06-2024 - 16:29 6 min read

#### **Table of contents**

- AI Act: different rules for different risk levels
- Transparency requirements
- Supporting innovation



# Climate change

#### BUSINESS

### AI brings soaring emissions for Google and Microsoft, a major contributor to climate change

JULY 12, 2024 · 5:13 AM ET



**3-Minute Listen** 





"One query to ChatGPT uses approximately as much electricity as could light one light bulb for about 20 minutes,"

#### Al's Dual Role in Climate Change

Al's impact on climate change is multifaceted, with both positive and negative potentials.

#### Negative Impacts:

- Energy Consumption: Training and running AI models, particularly large language models, requires significant computational power, which often relies on energyintensive data centers. 🗸
- **Carbon Footprint:** The energy consumption associated with AI can contribute to greenhouse gas emissions and climate change.

#### **Positive Impacts:**

- Climate Mode understanding
- Renewable E energy system managing ene
- Yes, AI can both positively and negatively impact climate change. While AI technologies have the potential to contribute to sustainability efforts and help mitigate the effects of climate change, they can also have unintended environmental consequences. Here's an overview of how AI impacts climate change from both perspectives:

#### **Positive Impacts of AI on Climate Change:**

- 1. Energy Efficiency Improvements:
  - Smart Grids: AI can optimize electricity distribution through smart grids, reducing energy waste and improving the efficiency of renewable energy sources like wind and solar. This helps lower carbon emissions by ensuring that energy is used more efficiently.
  - Building Management Systems: Al-driven systems can control heating, ventilation, and air conditioning (HVAC) systems in buildings to optimize energy use, reducing the carbon footprint of commercial and residential spaces.
- 2. Renewable Energy Optimization:






https://brain.fuw.edu.pl/edu/index.php/TI/Sztuczna\_Inteligencja Piotr Durka,

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**Moravec** (1988): "it is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility"

**Pinker** (1994): "the main lesson of thirty-five years of AI research is that the hard problems are easy and the easy problems are hard"

Pinker, Steven (September 4, 2007) [1994], The Language Instinct, Perennial Modern Classics, Harper

Moravec, Hans (1988), Mind Children, Harvard University Press





## Thank you for your attention!

Contact: beata.brzozowska@fuw.edu.pl

