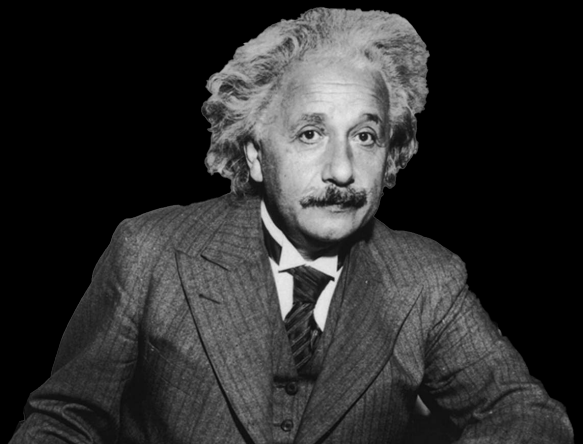
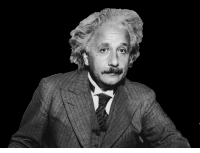
Künstliche Intelligenz oder künstliche Dummheit

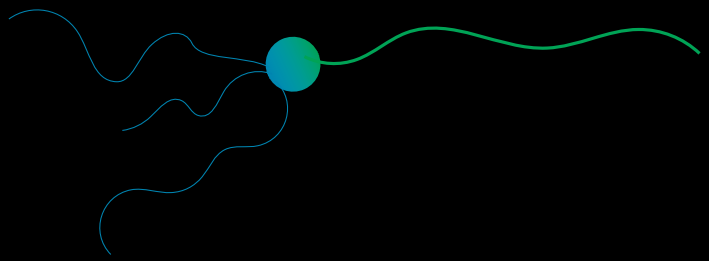
IQWiG Herbstsymposium 2022

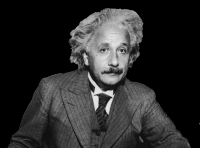
Daniel Truhn



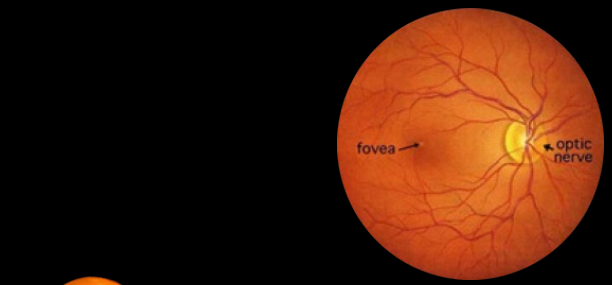


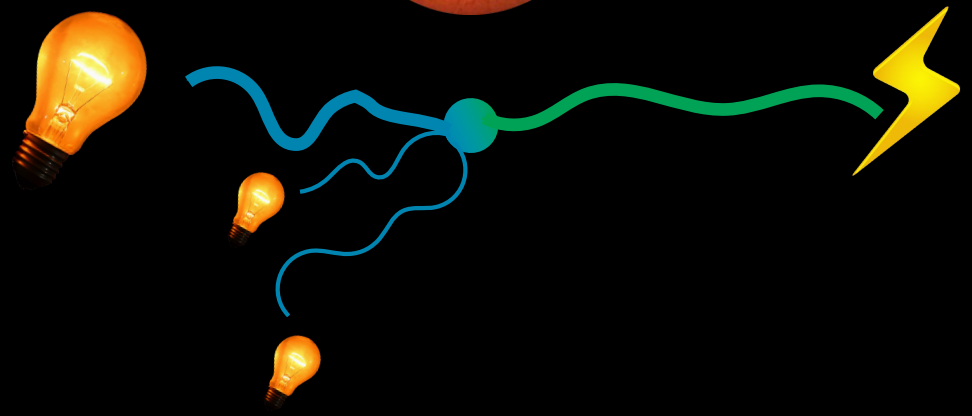
Human Intelligence

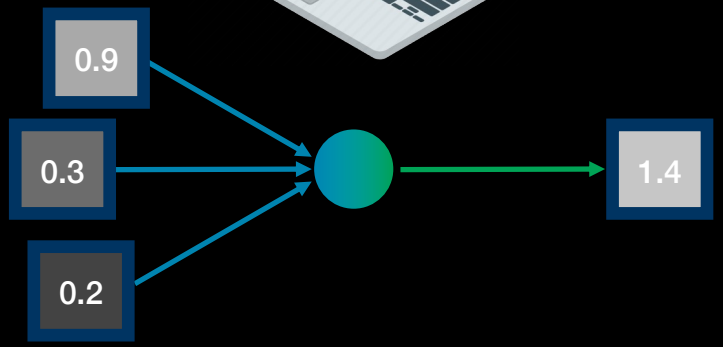


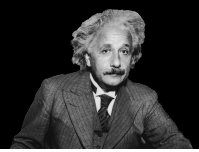


Human Intelligence - Machine Intelligence

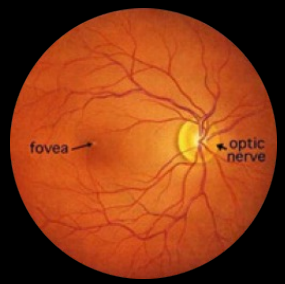


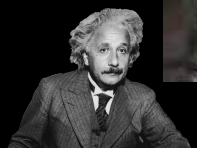




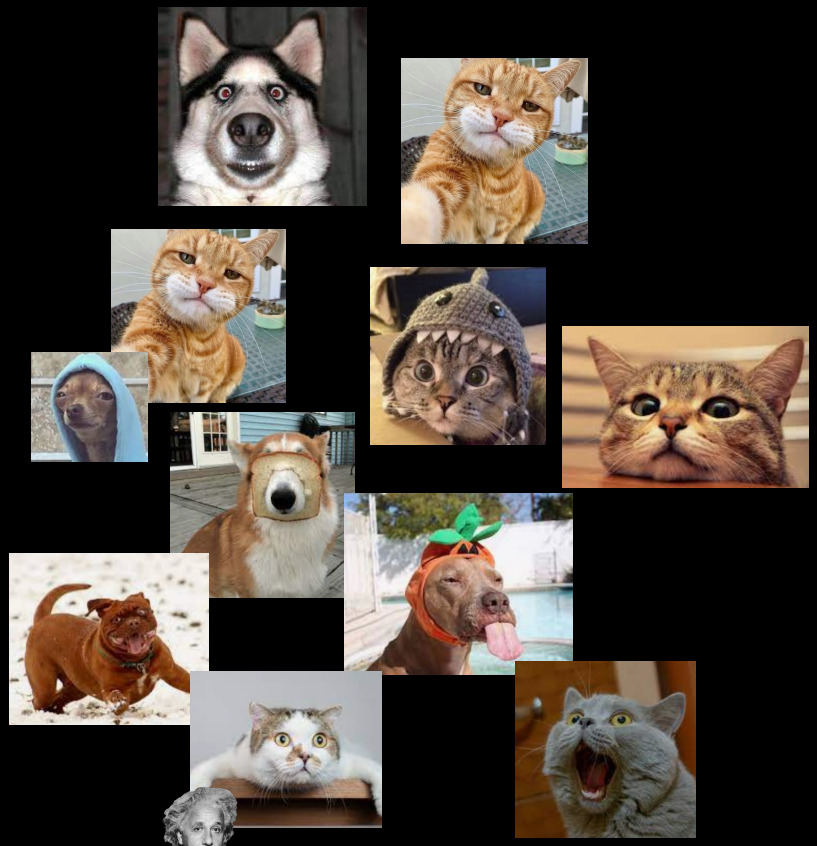


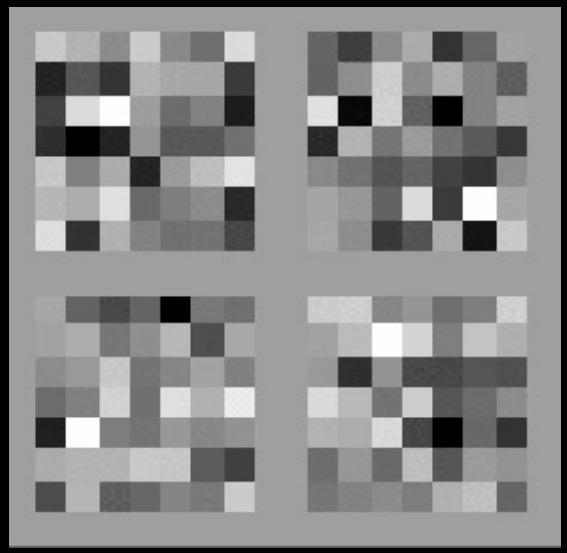
Human Intelligence - Machine Intelligence

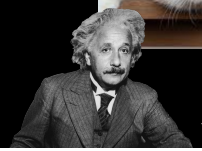




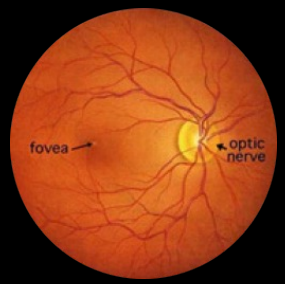
Human Intelligence - Machine Intelligence

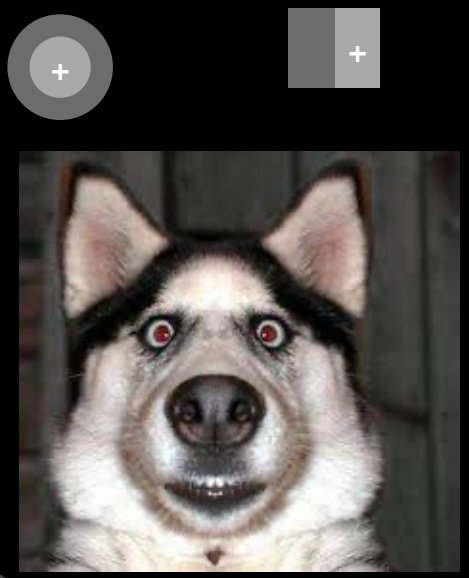


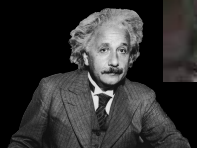


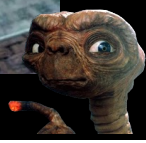


Human Intelligence - Machine Intelligence

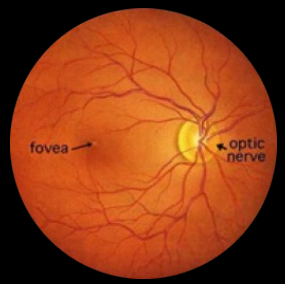


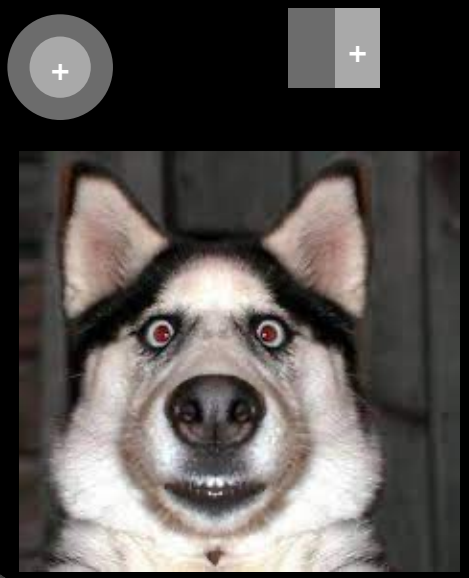


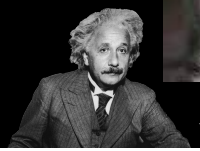


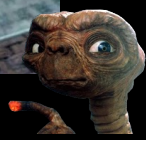


Human Intelligence - Machine Intelligence

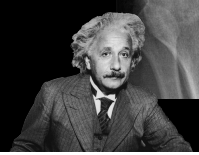








How Does Training Work?



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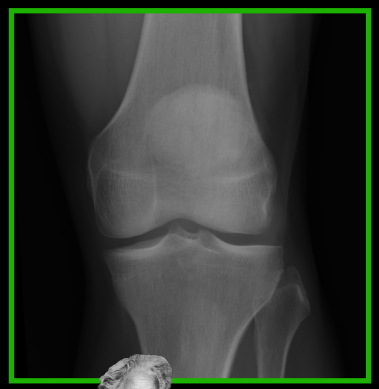

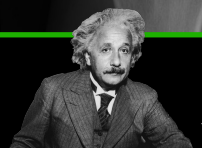

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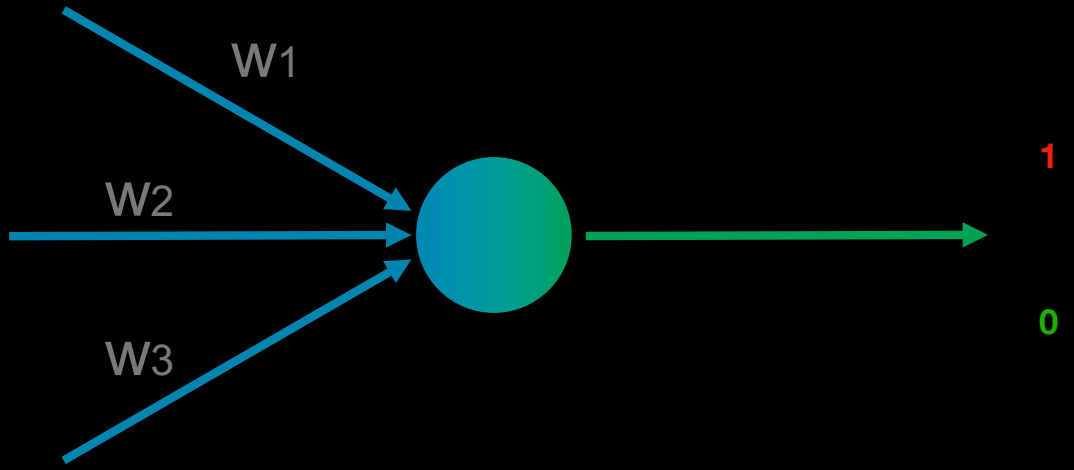

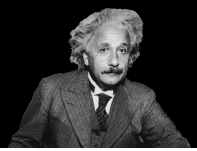

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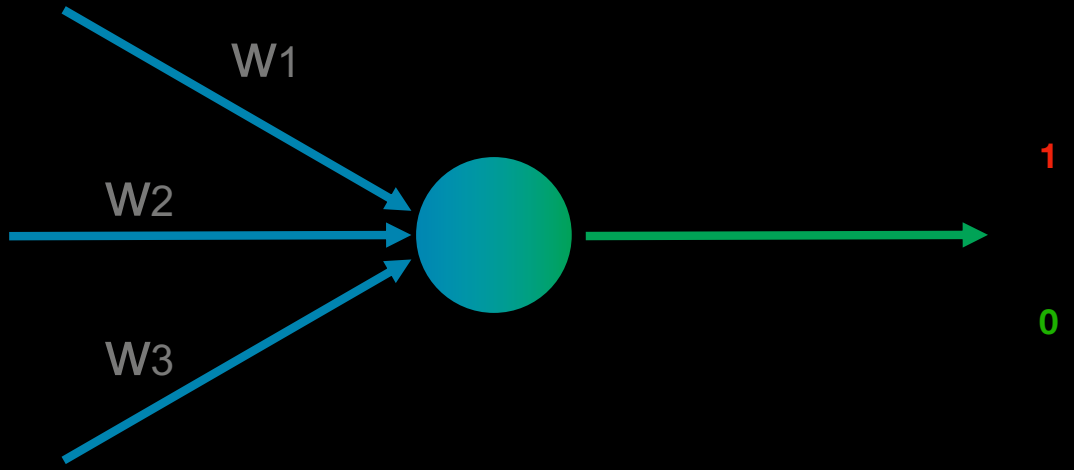

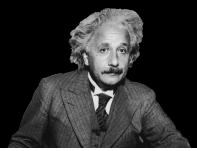

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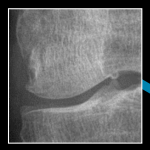
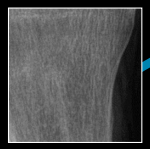




W1

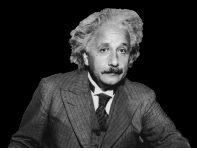
W2

W3

1

0.5

0



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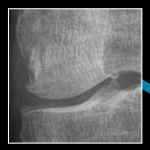
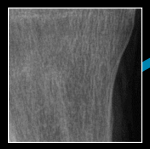




W1

W2

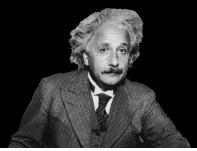
W3

Backpropagation

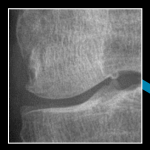
1

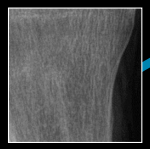
0.5

0



How Does Training Work?





W1

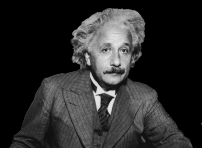
W2

W3

1

0.5

0



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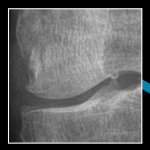
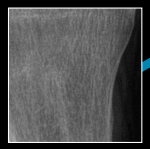




W1

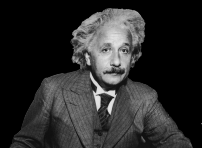
W2

W3

1

0.7

0



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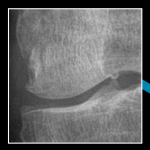
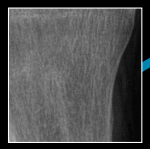




W1

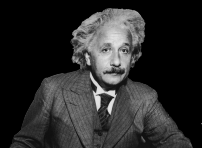
W2

W3

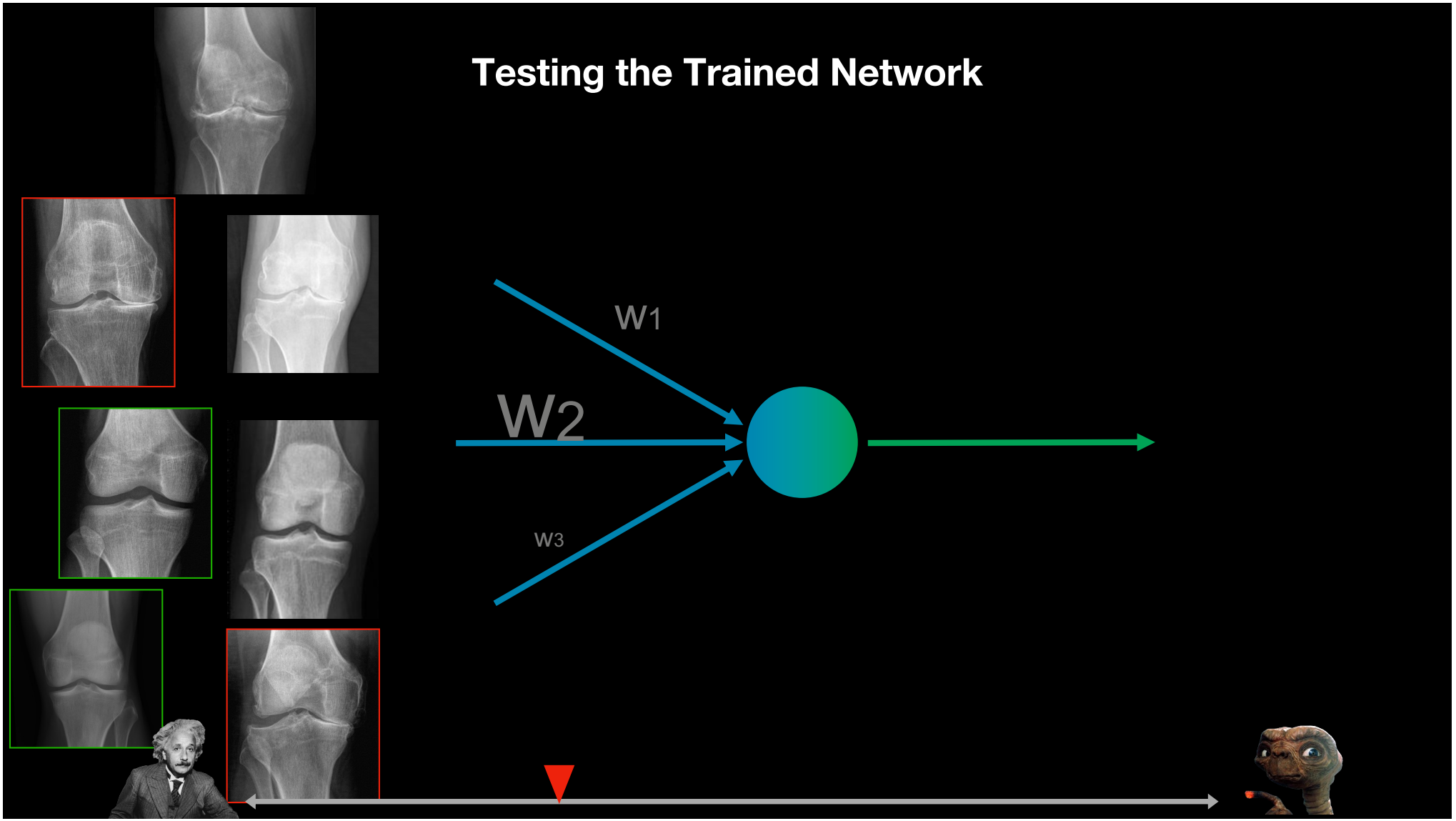
1

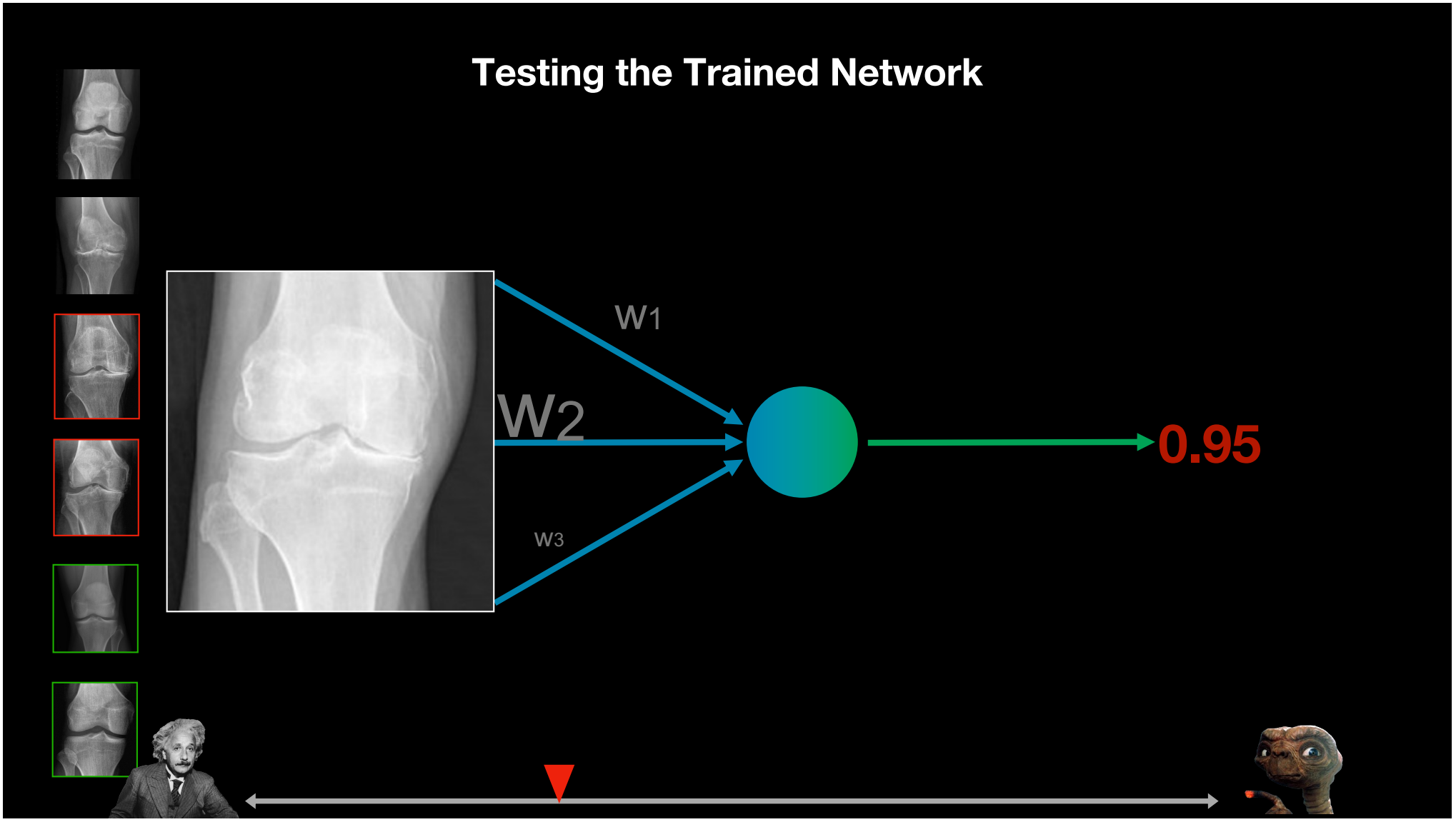
0.8

0

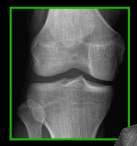


Testing the Trained Network




Testing the Trained Network
W1
W2
W3
0.95

Testing the Trained Network

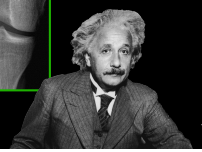


W1

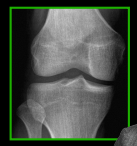
W2

W3

0.10



Testing the Trained Network



0.10

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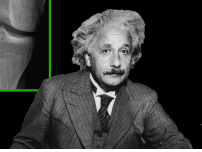

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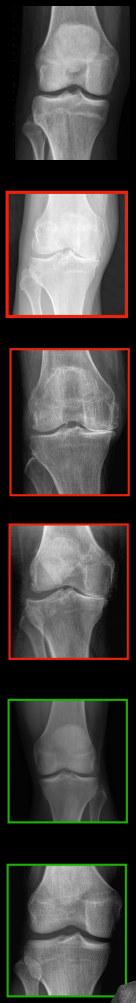
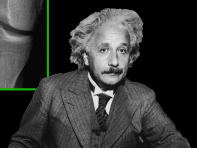




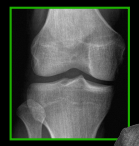
W1

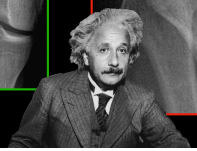
W2

W3

0.10

Testing the Trained Network





W1

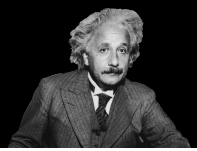
W2

W3

0.10

Training Data

AI performance depends crucially on the data it is trained on.



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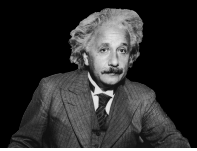
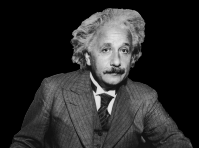
Training Data



Training Data



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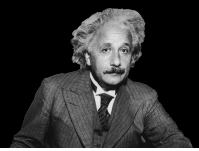

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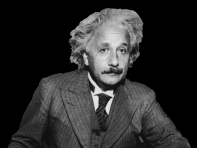
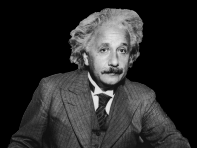


Training Data

Critical Period

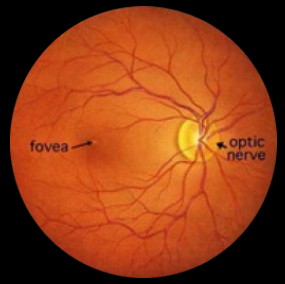
proper stimuli needed

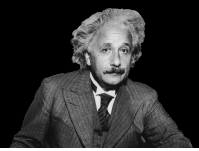


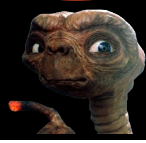
Training Data

Critical Period

proper stimuli needed







Training Data

AI performance depends crucially on the data it is trained on.

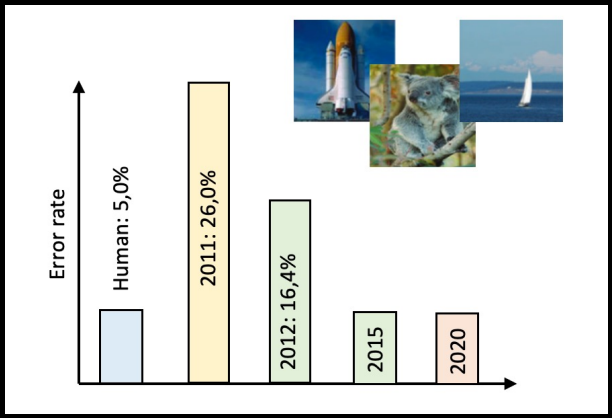
Human performance depends crucially on the data it is trained on.

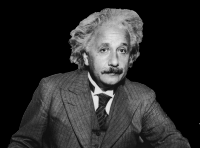
Training Data

AI performance depends crucially on the data it is trained on.

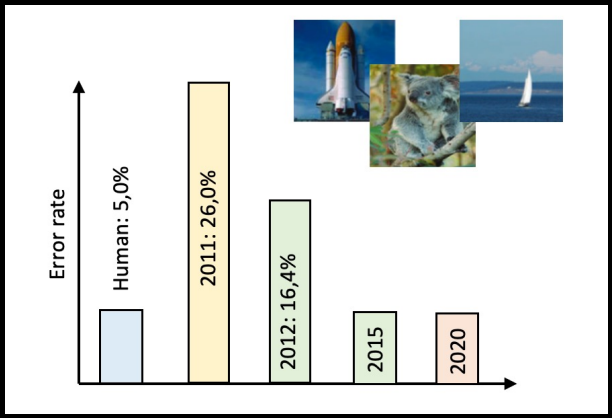
Human performance depends crucially on the data it is trained on.

AI is powerful





AI is powerful



LETTER

doi:10.1038/nature21056

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva[1*], Brett Kuprel[1*], Roberto A. Novoa[2,3], Justin Ko[2], Susan M. Swetter[2,4], Helen M. Blau[5] & Sebastian Thrun[6]

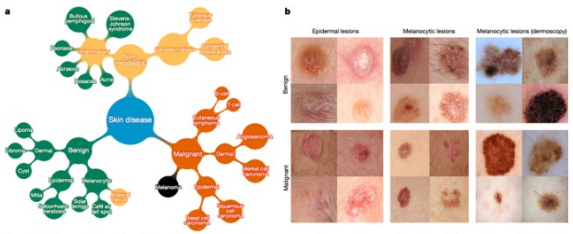
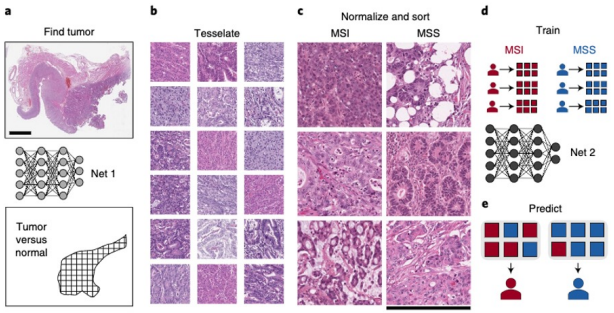


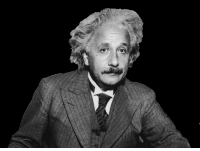
Figure 2 | A schematic illustration of the taxonomy and example test set images. a, A subset of the top of the tree-structured taxonomy of skin disease. The full taxonomy contains 2,032 diseases and is organized based on visual and clinical similarity of diseases. Red indicates malignant, green indicates benign, and orange indicates conditions that can be either. Black indicates melanoma. The first two levels of the taxonomy are used in validation. Testing is restricted to the tasks of **b**. **b**, Malignant and benign example images from two disease classes. These test images highlight the difficulty of malignant versus benign discernment for the three medically critical classification tasks we consider: epidermal lesions, melanocytic lesions and melanocytic lesions visualized with a dermoscope. Example images reprinted with permission from the Edinburgh Dermofit Library (https://licensing.eri.ed.ac.uk/i/software/dermofit-image-library.html).

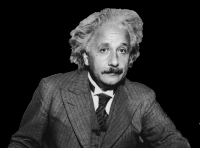
nature medicine

Deep learning can predict microsatellite instability directly from histology in gastrointestinal cancer

Jakob Nikolas Kather[1,2,3,4,5*], Alexander T. Pearson[4], Niels Halama[2,5,6], Dirk Jäger[2,3,5], Jeremias Krause[1], Sven H. Loosen[1], Alexander Marx[7], Peter Boor[8], Frank Tacke[9], Ulf Peter Neumann[10], Heike I. Grabsch[11,12], Takaki Yoshikawa[13,14], Hermann Brenner[2,15,16], Jenny Chang-Claude[17,18], Michael Hoffmeister[15], Christian Trautwein[1] and Tom Luedde[1*]





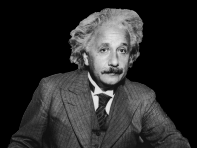


Airplane: 98%

Dog: 84%

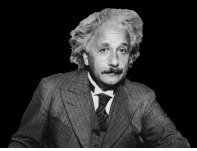
Dog: 93%

Dog: 89%



Dog: 96%

Airplane: 98%



Dog: 96%

Airplane: 98%

Dog: 96%

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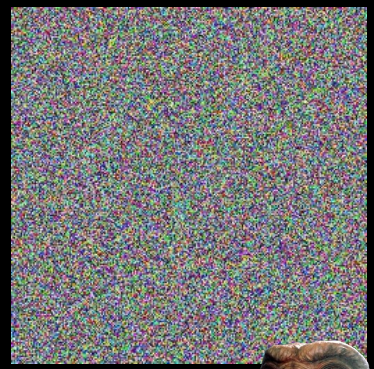
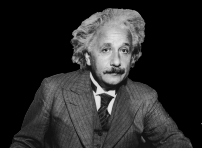
Adversarial Noise





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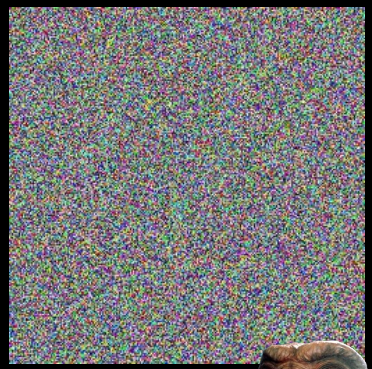
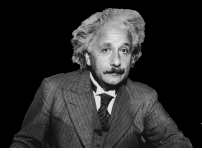
Adversarial Noise

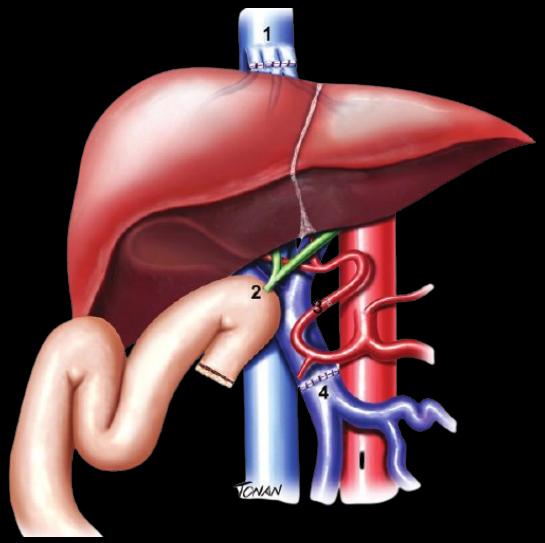




nature COMMUNICATIONS

Advancing diagnostic performance and clinical usability of neural networks via adversarial training and dual batch normalization

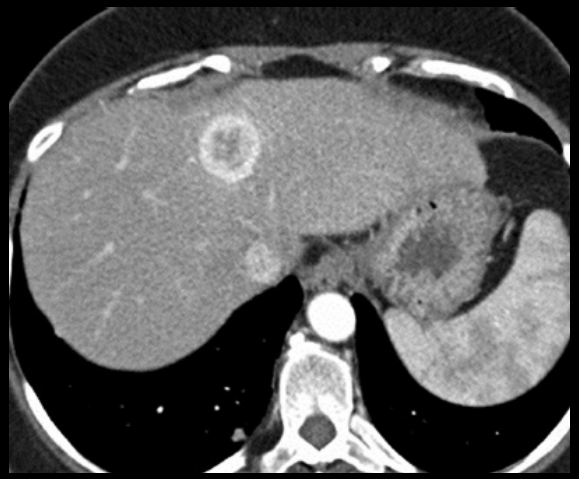
Tianyu Han[1✉], Sven Nebelung[2], Federico Pedersoli[2], Markus Zimmermann[2], Maximilian Schulze-Hagen[2], Michael Ho[3], Christoph Haarburger[3], Fabian Kiessling[4,5,6], Christiane Kuhl[2], Volkmar Schulz[1,5,6,7✉] & Daniel Truhn[2,7✉]

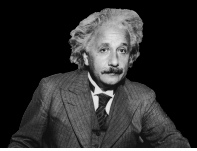


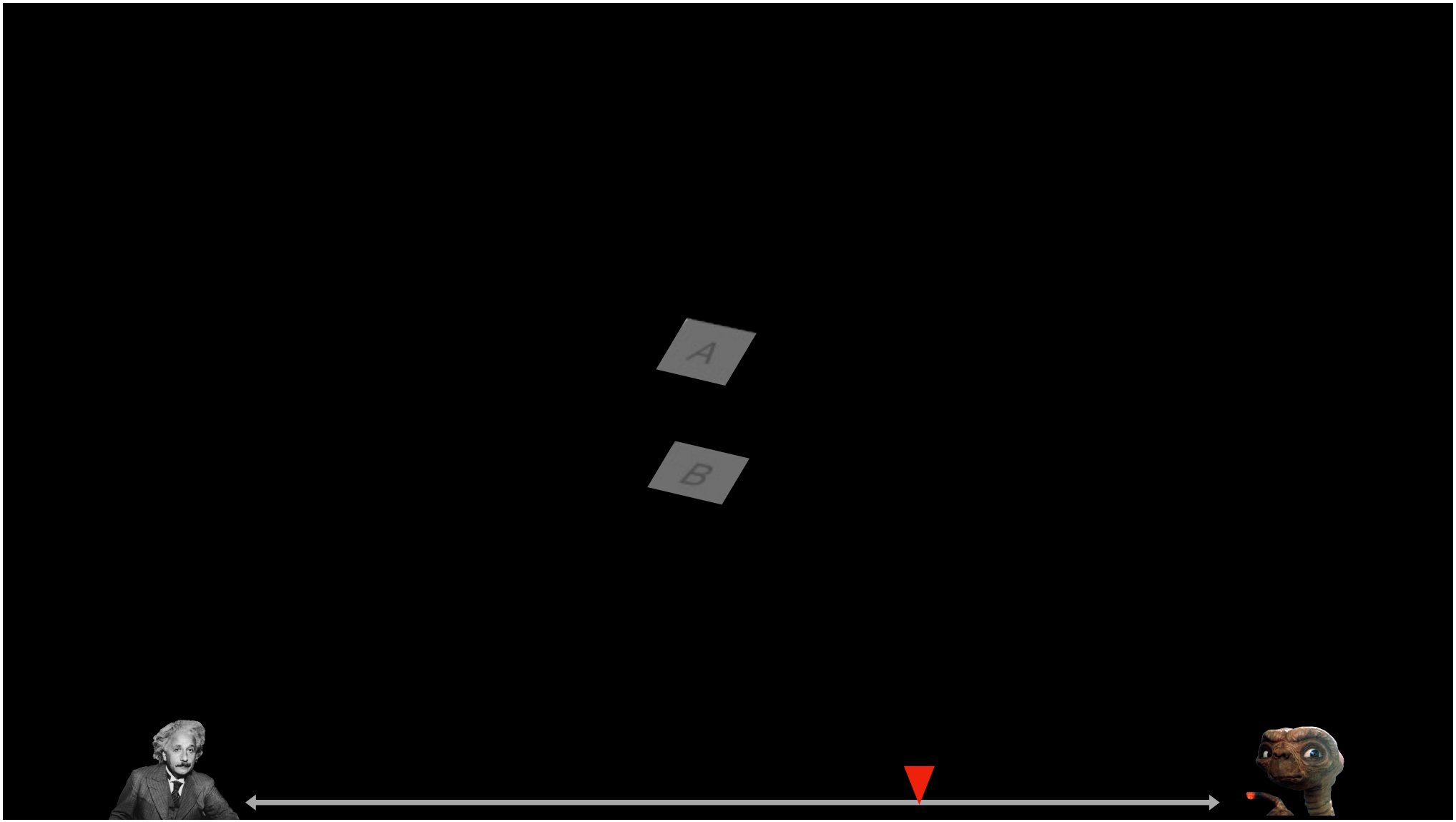
nature COMMUNICATIONS

Adversarial attacks and adversarial robustness in computational pathology

Narmin Ghaffari Laleh (1), Daniel Truhn (2), Gregory Patrick Veldhuizen (1), Tianyu Han (3), Marko van Treeck (1), Roman D. Buelow (4), Rupert Langer (5, 6), Bastian Dislich (5), Peter Boor (4), Volkmar Schulz (3, 7, 8), Jakob Nikolas Kather (1, 9, 10, 11)



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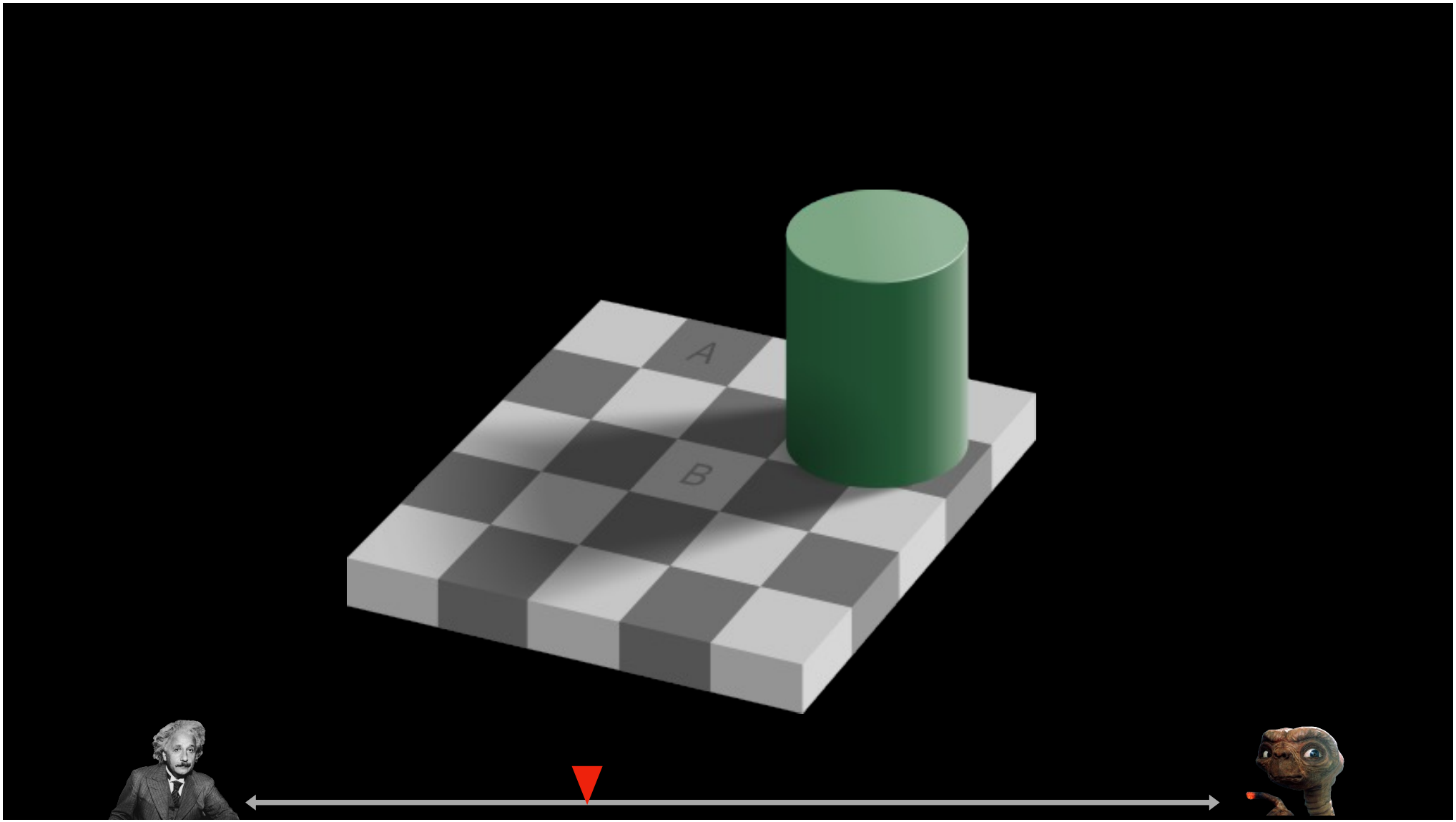
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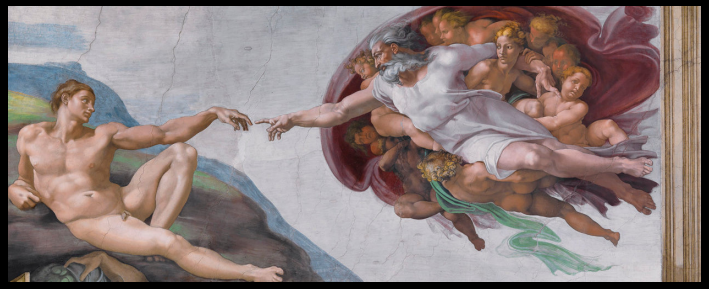

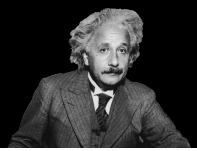

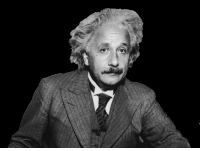

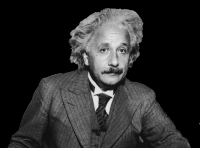

FIRST
PLACE
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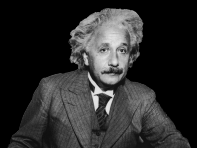
COLORADO
STATE
FAIR
PUEBLO, CO
EMERGING
Jason Allen
Pueblo West
Théâtre D'opéra Spatial
$750
Colorado State Fair



2021

“a hedgehog using a calculator”

“a corgi wearing a red bowtie and a purple party hat”

“robots meditating in a vipassana retreat”

“a fall landscape with a small cottage next to a lake”

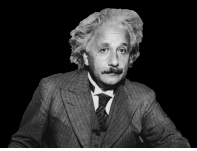
2022

A brain riding a rocketship heading towards the moon.

A dragon fruit wearing karate belt in the snow.

A small cactus wearing a straw hat and neon sunglasses in the Sahara desert.

A photo of a Corgi dog riding a bike in Times Square. It is wearing sunglasses and a beach hat.



npj | digital medicine

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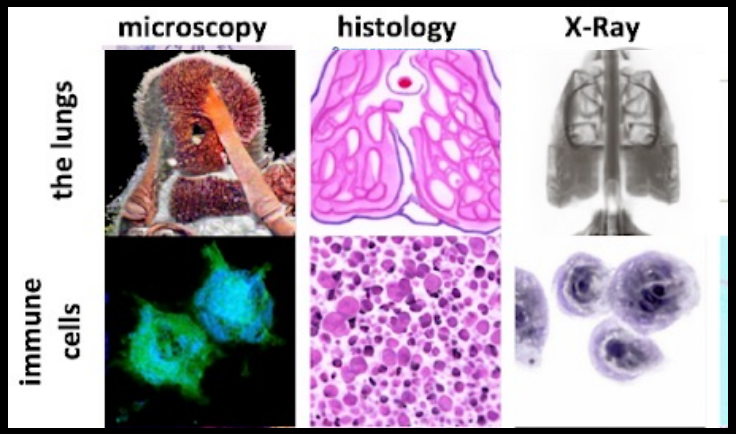
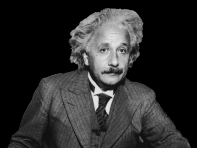
COMMENT OPEN

Check for updates

Medical domain knowledge in domain-agnostic generative AI

Jakob Nikolas Kather[1,2,3,4✉], Narmin Ghaffari Laleh[1], Sebastian Foersch[5] and Daniel Truhn[6]





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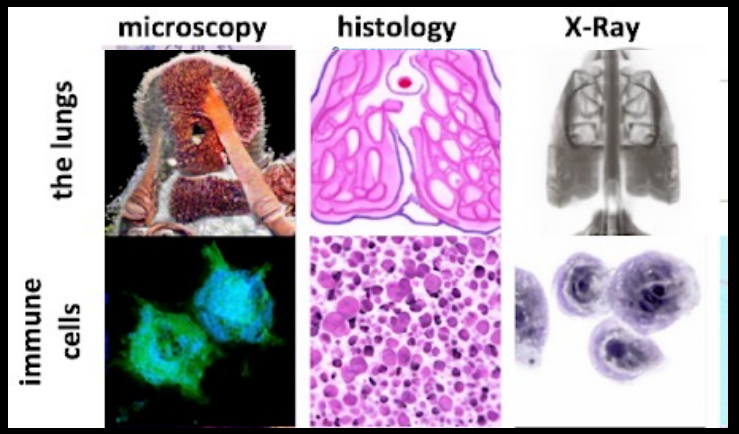
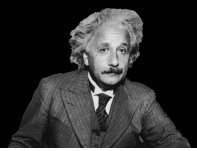


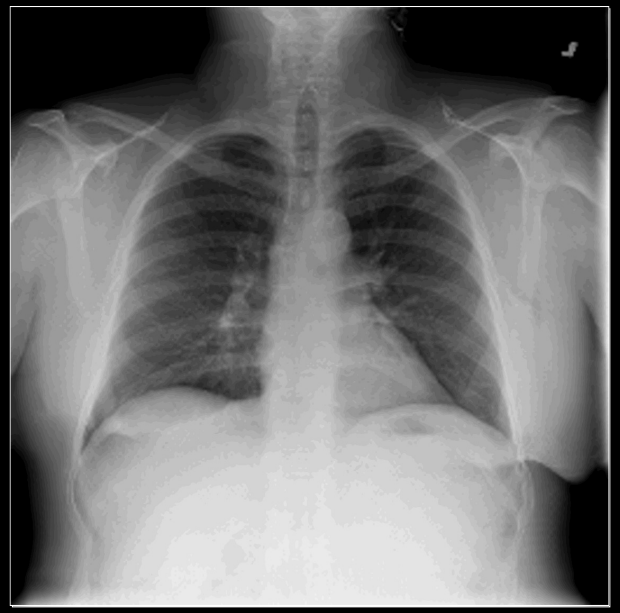


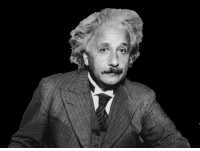
SCIENCE ADVANCES | RESEARCH ARTICLE

COMPUTER SCIENCE

Breaking medical data sharing boundaries by using synthesized radiographs

Tianyu Han[1], Sven Nebelung[2], Christoph Haarburger[3], Nicolas Horst[4], Sebastian Reinartz[1,5], Dorit Merhof[4,6,7], Fabian Kiessling[6,7,8], Volkmar Schulz[1,6,7]*†, Daniel Truhn[3,5]*





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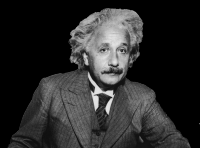

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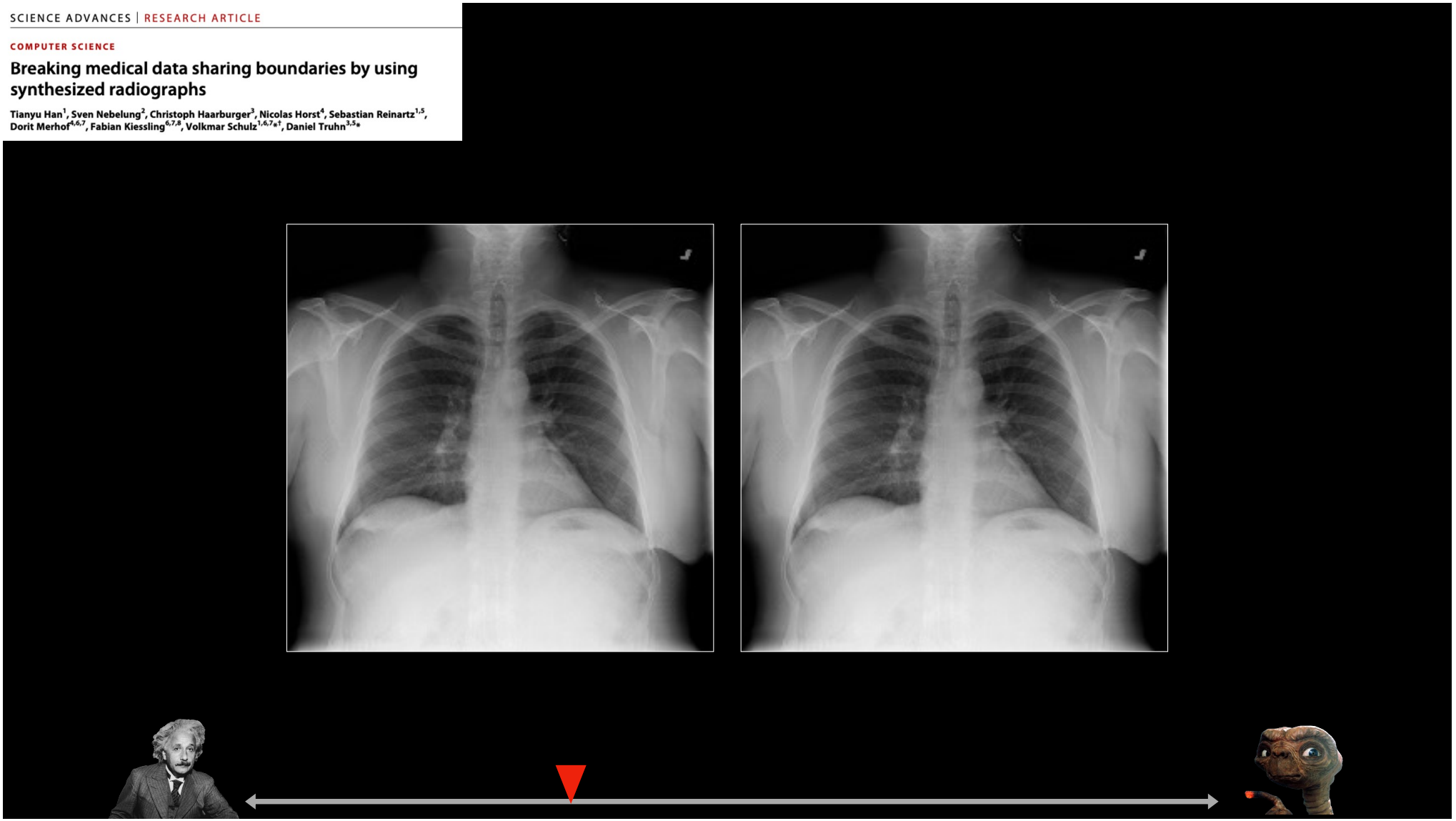

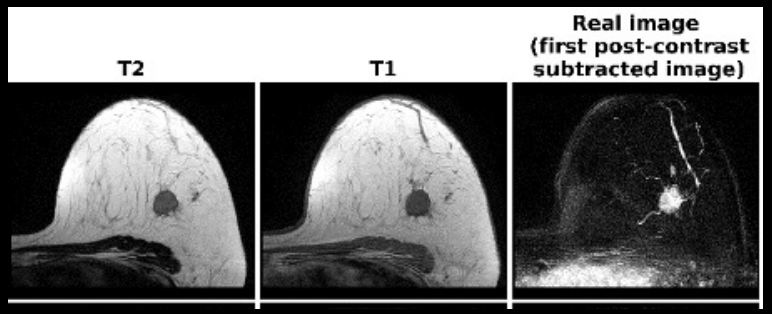
T2
T1
Real image
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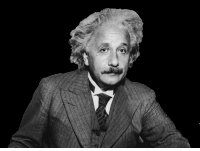

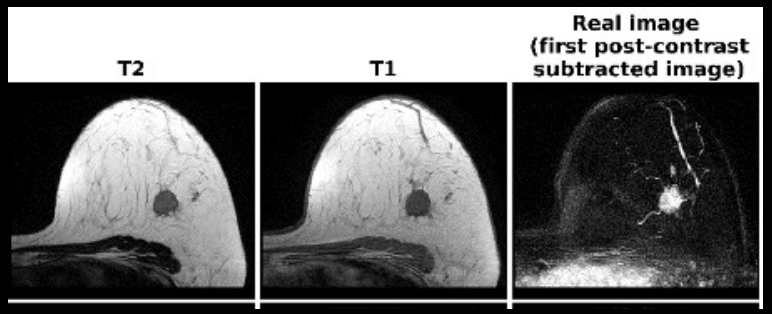
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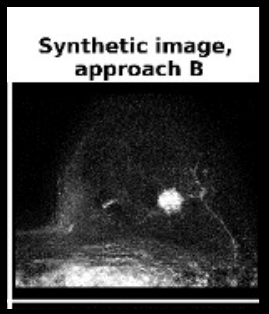
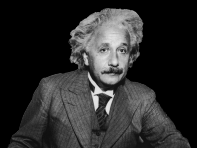
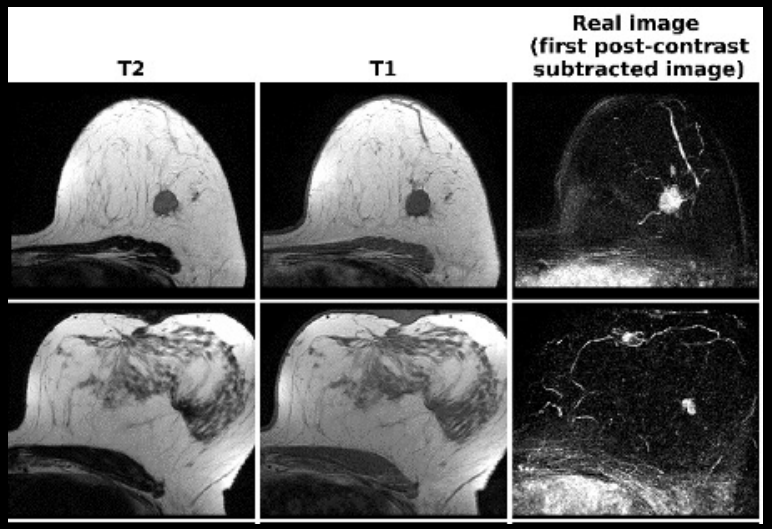
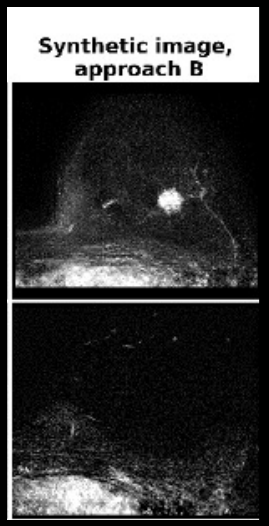
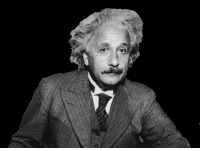
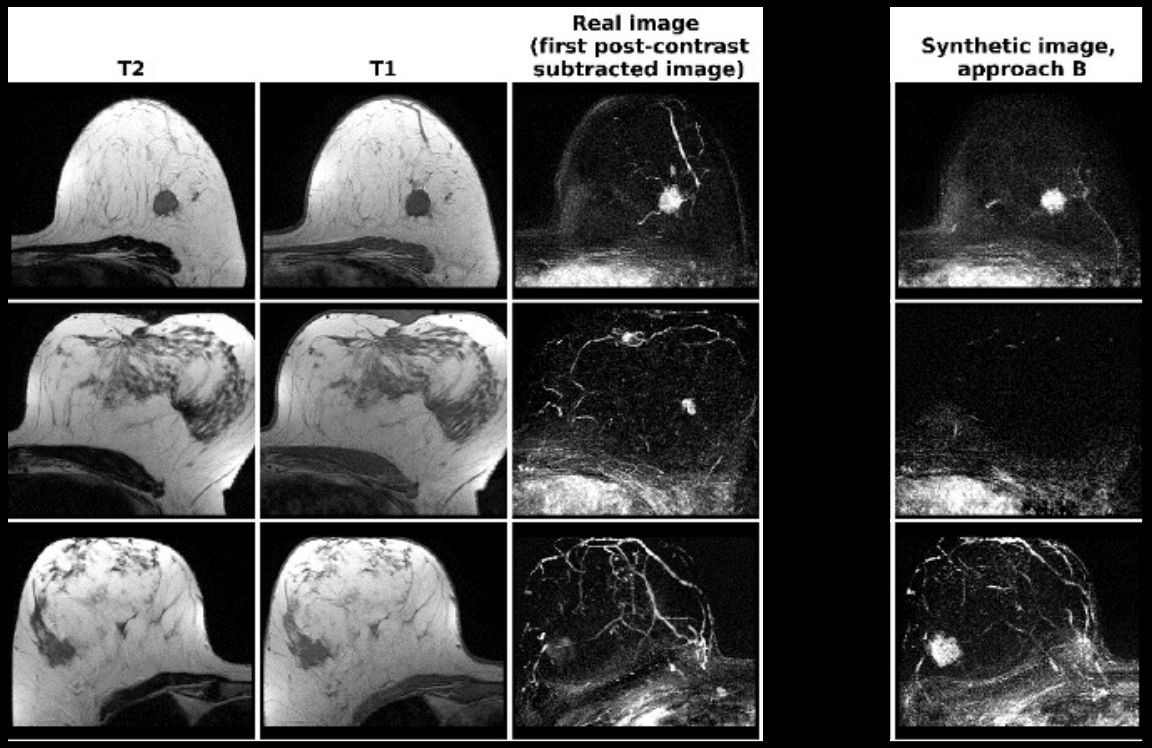

Synthetic image,
approach B




T2
T1
Real image
(first post-contrast
subtracted image)


Synthetic image,
approach B




T2
T1
Real image
(first post-contrast
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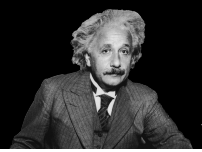
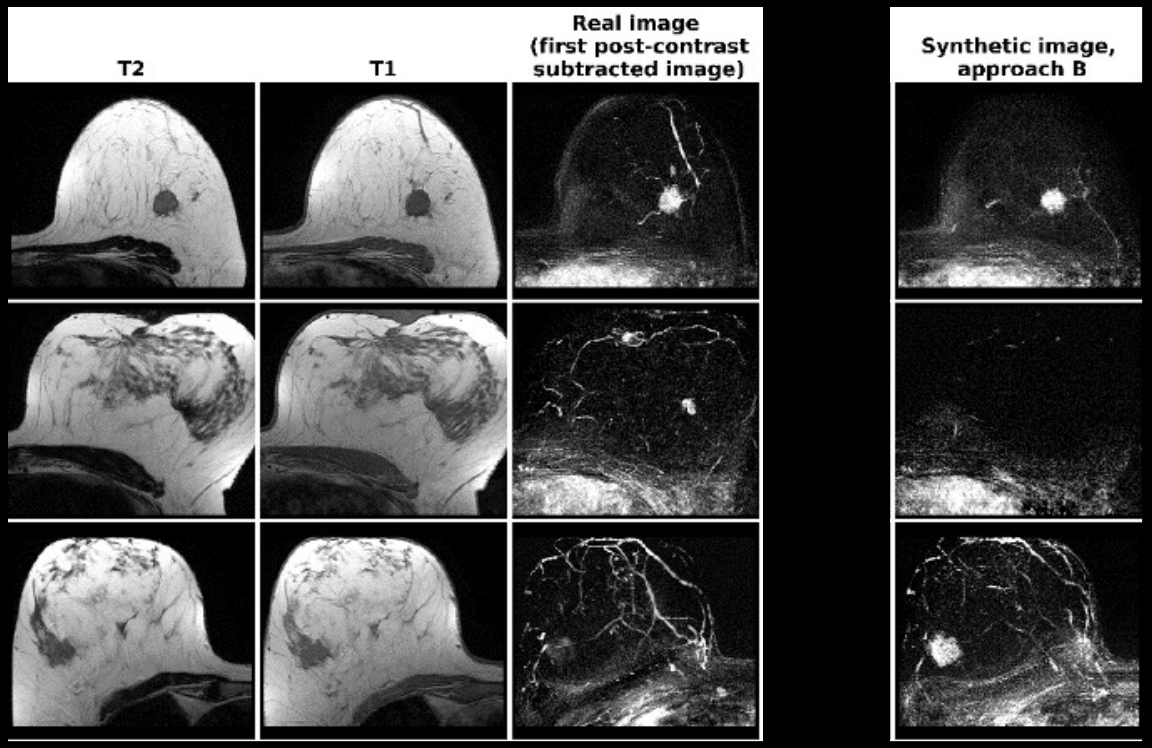
Synthetic image,
approach B

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Synthetic image,
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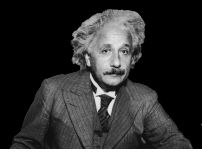

A comic page that depicts how to achieve nuclear fusion to solve the energy crisis.

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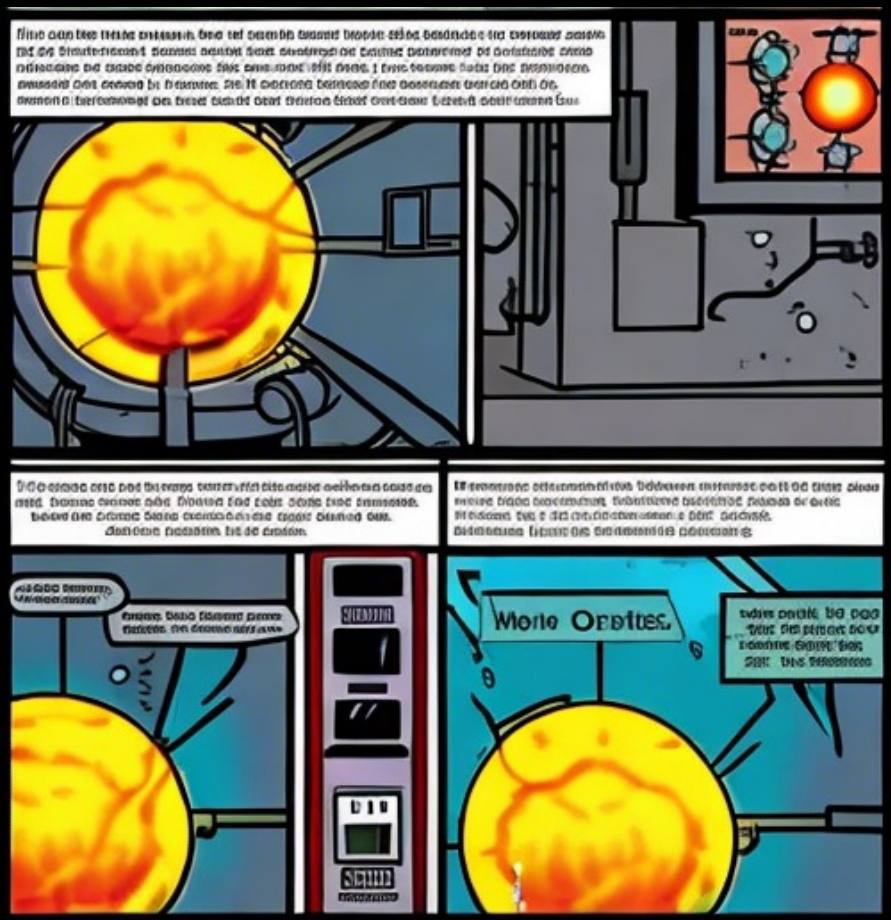

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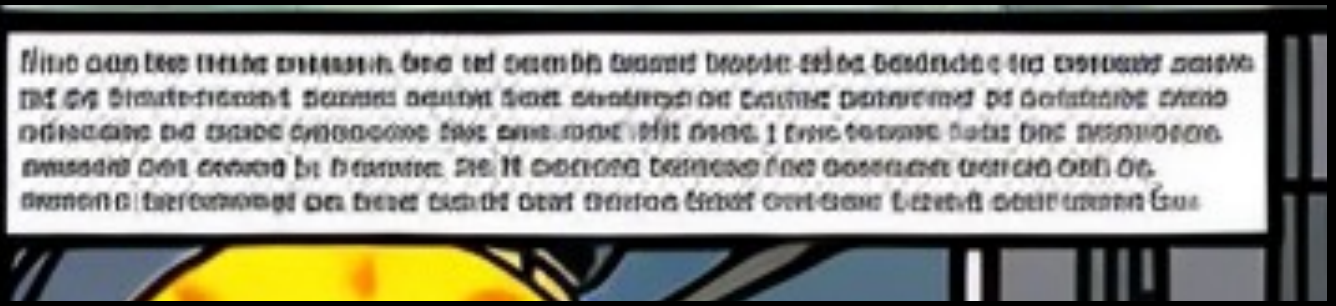
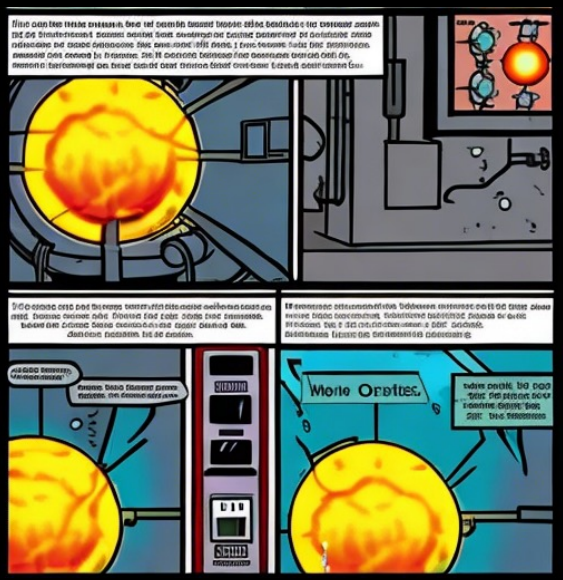
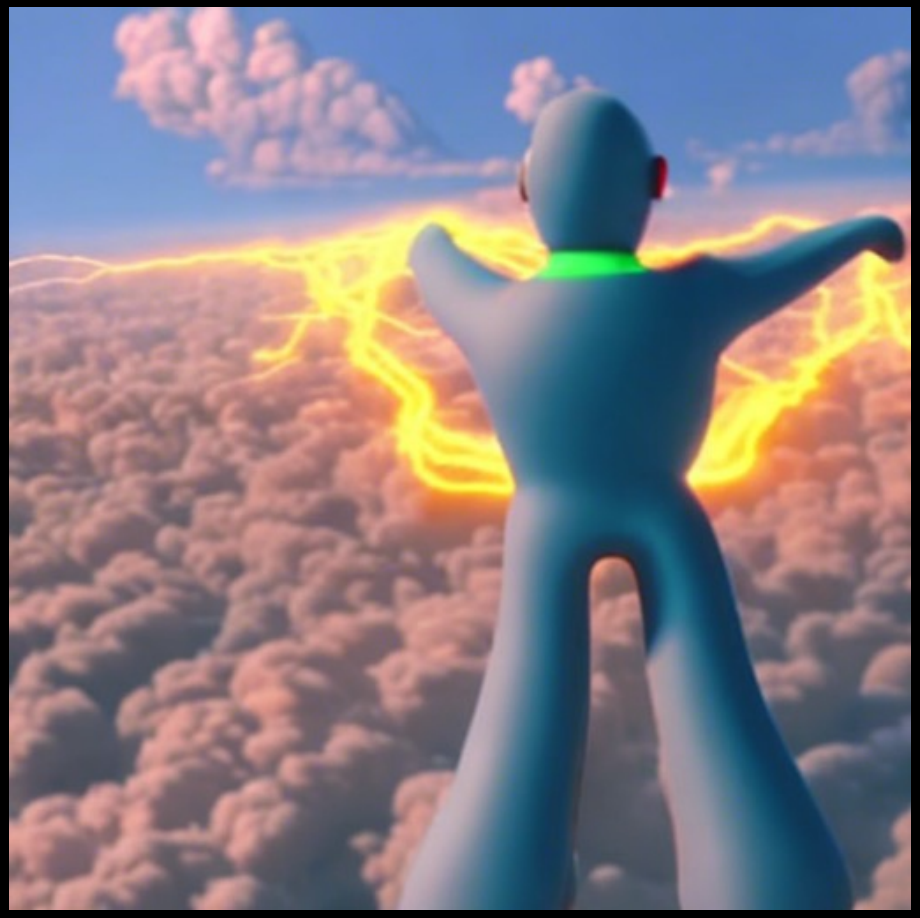




The future of planet earth

The future of planet earth



Medical doctors running from a robot that exhibits artificial intelligence.

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A schematic drawing of how AI imagines its integration into clinical routine.

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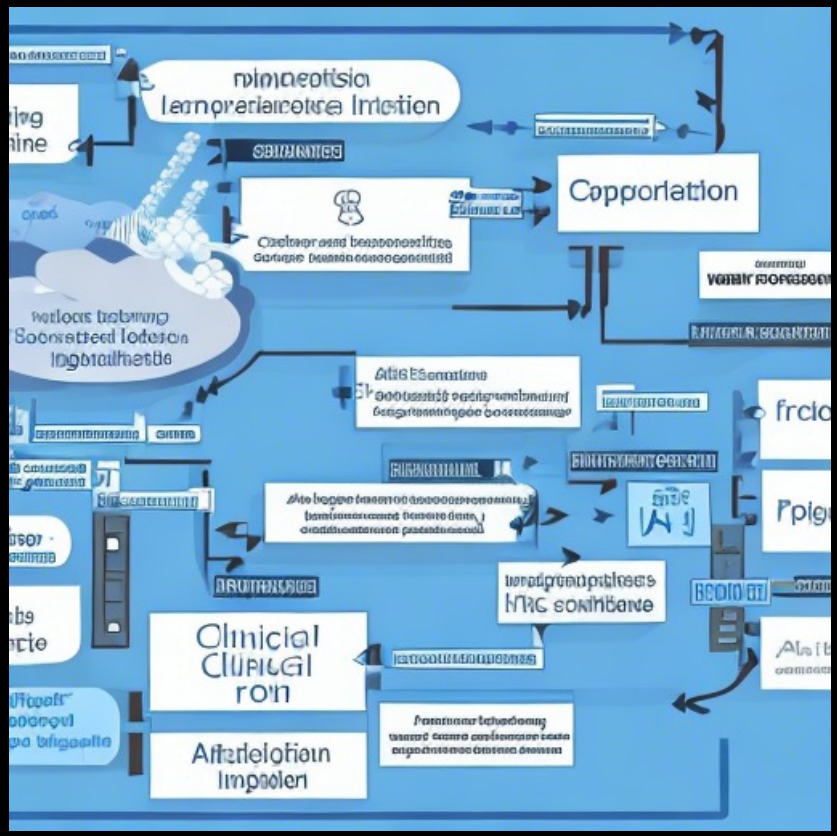
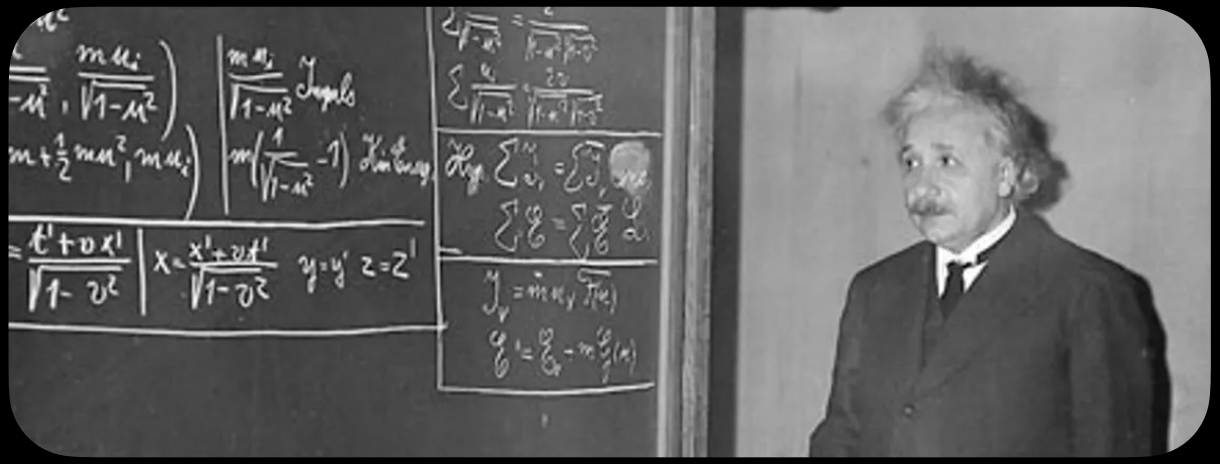
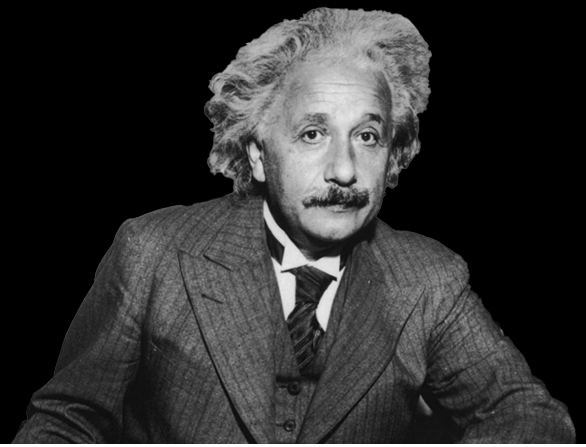
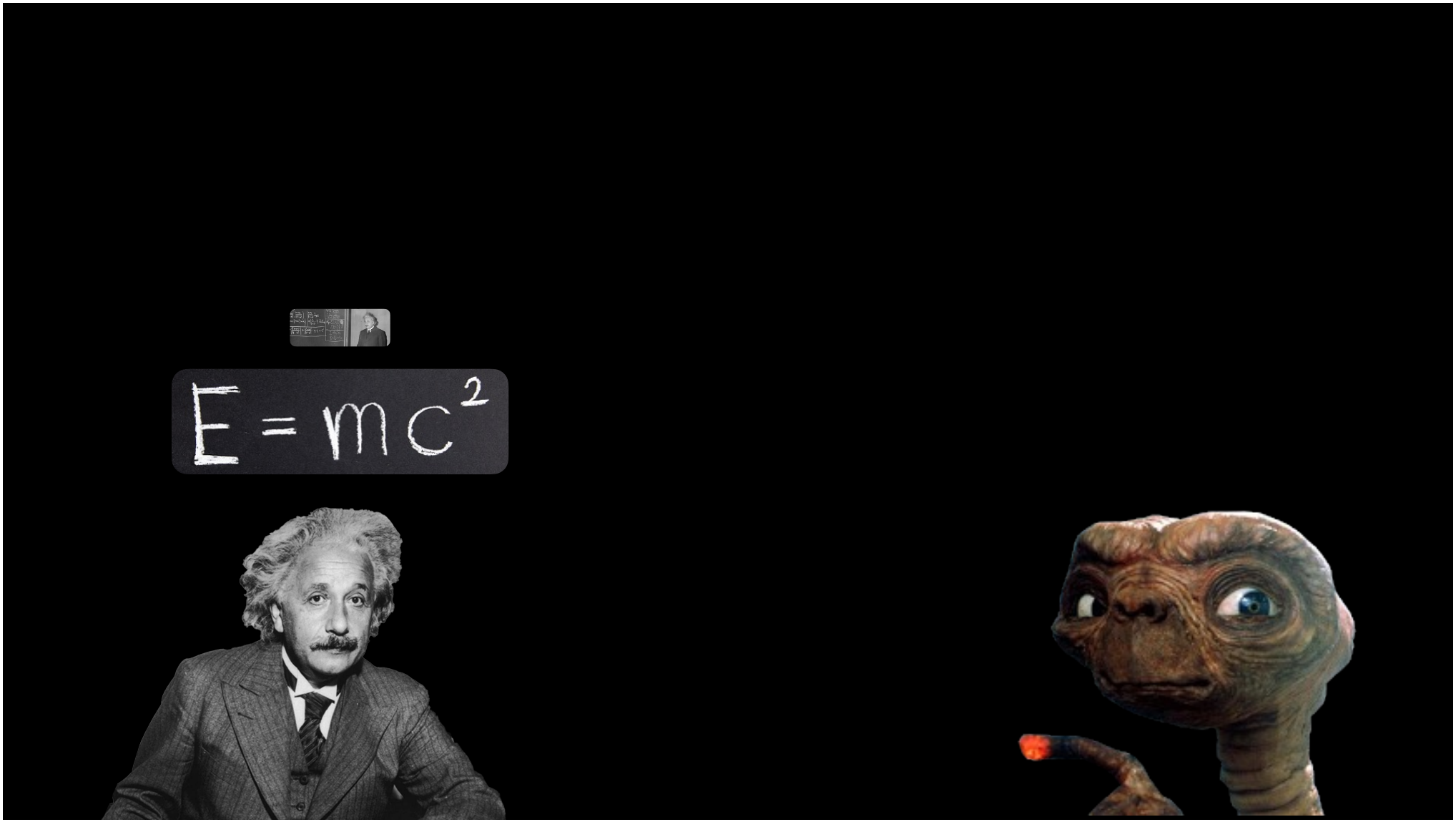


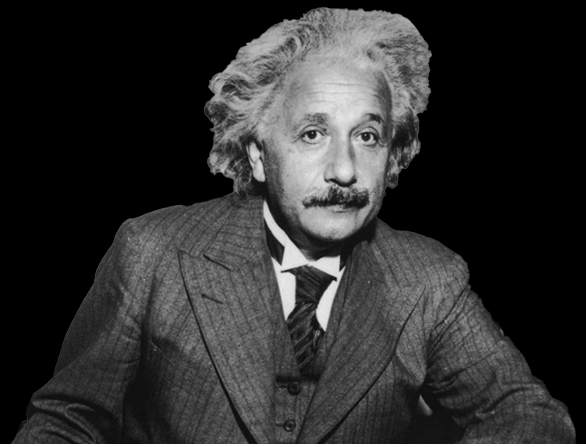


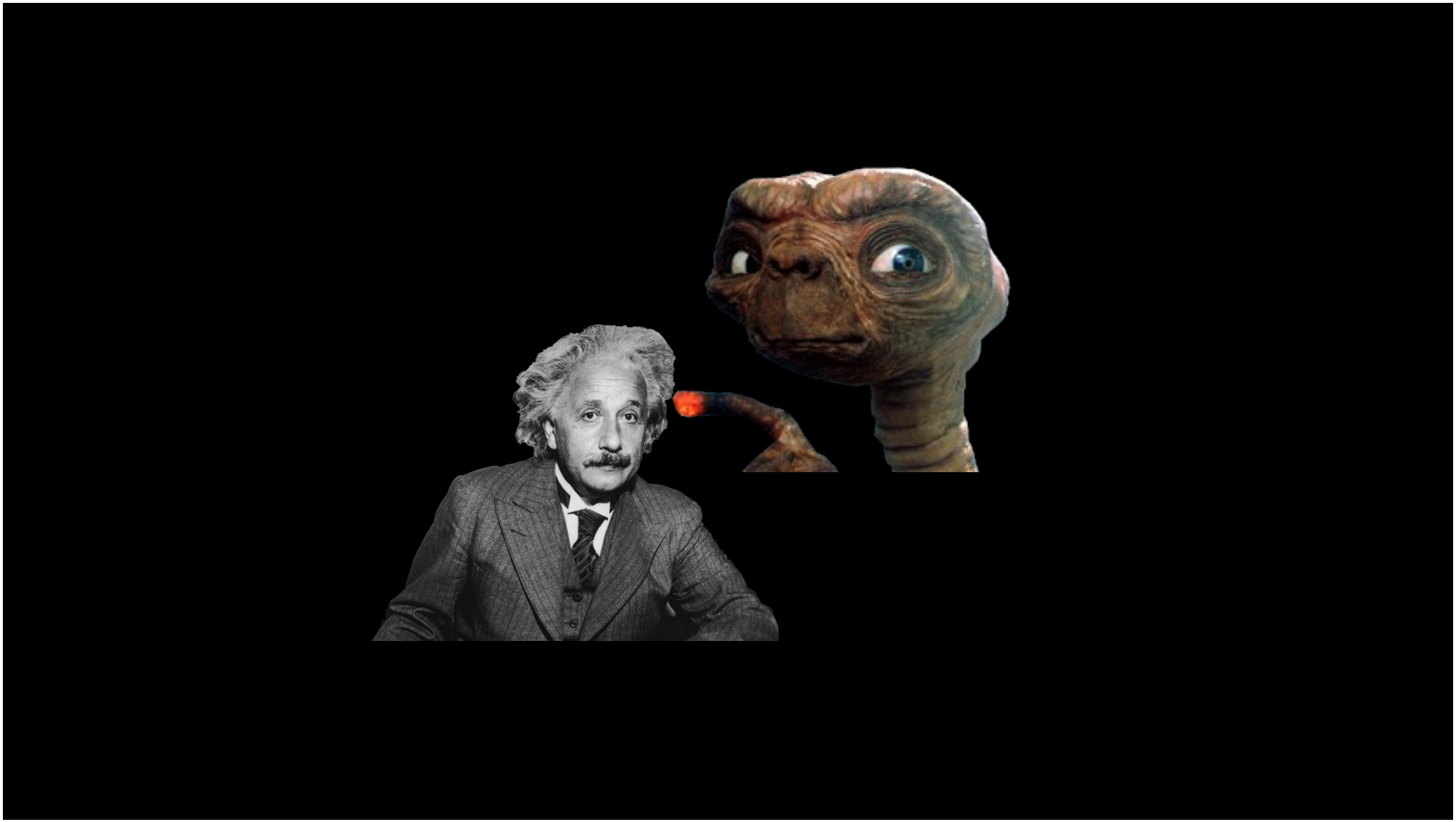


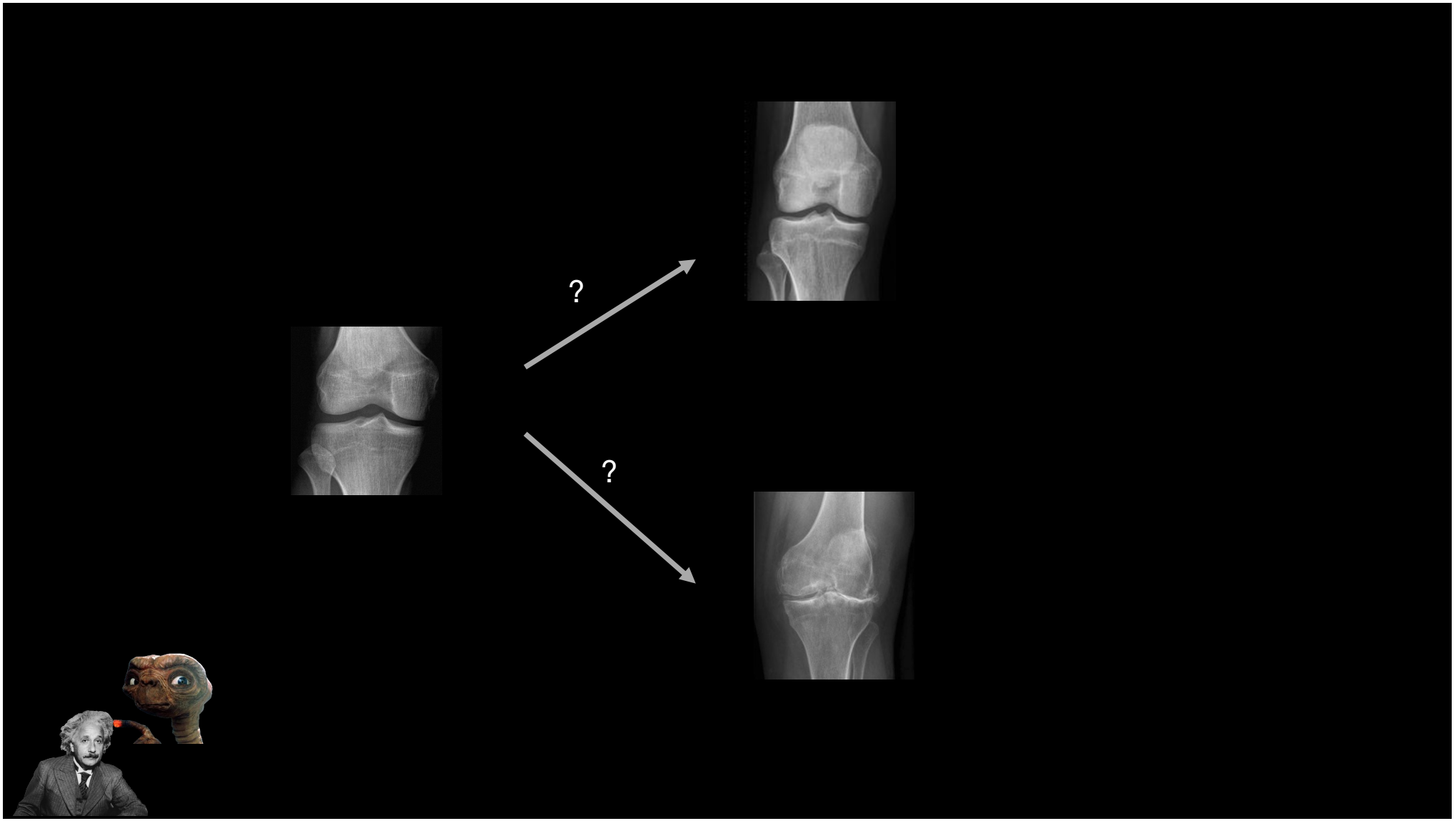

$E = mc^2$

$E = mc^2$

"*Phone home*"







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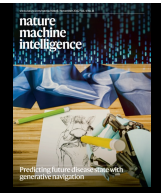
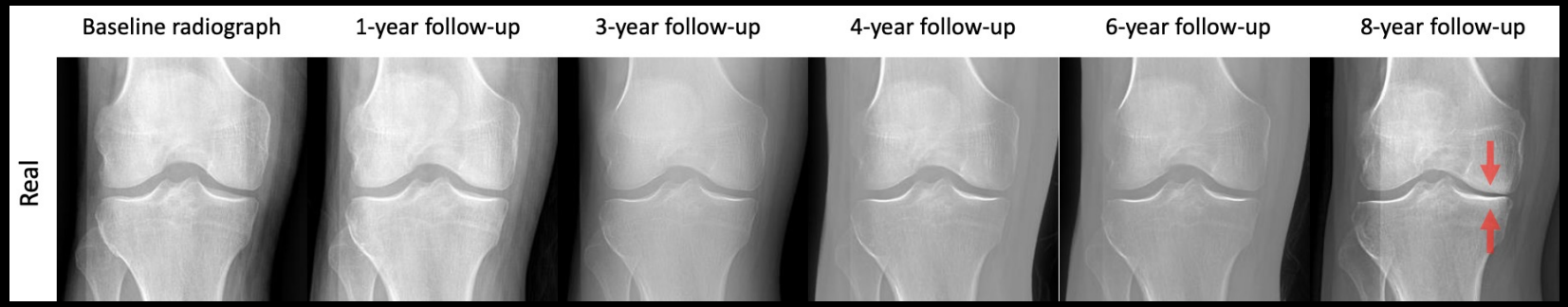
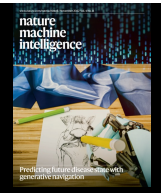
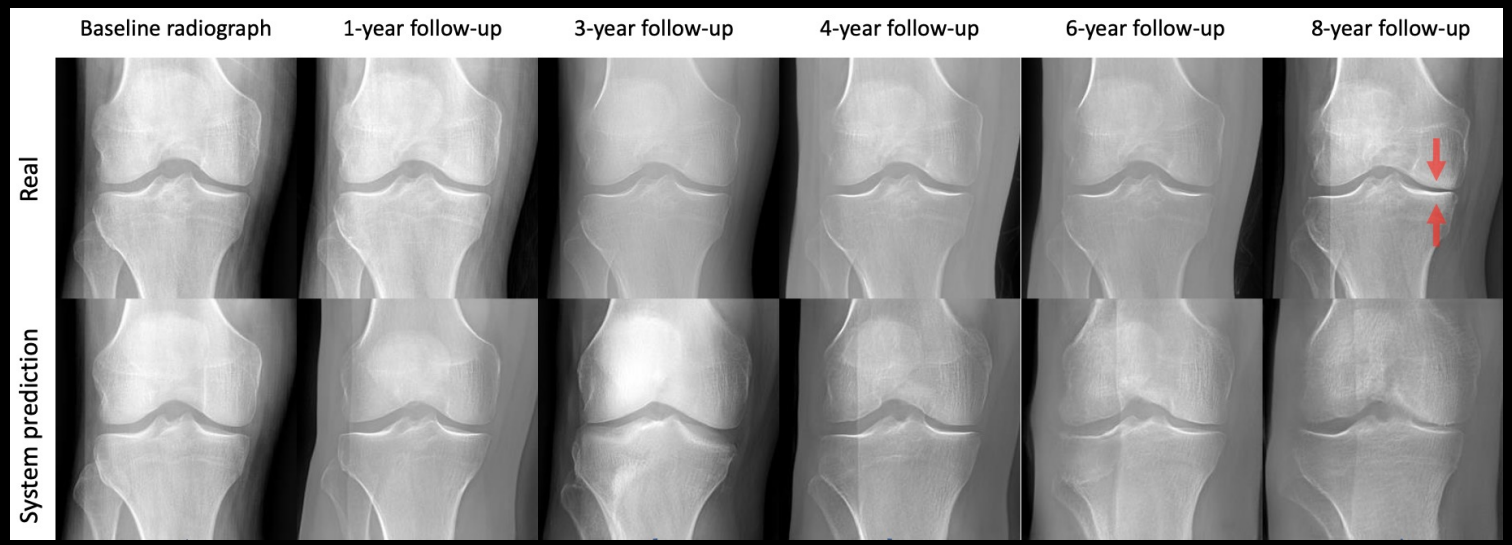
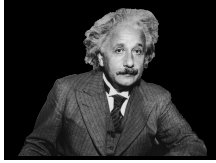
nature machine intelligence
Predicting future disease state with generative navigation


nature
machine
intelligence
Predicting future disease image with generative navigation

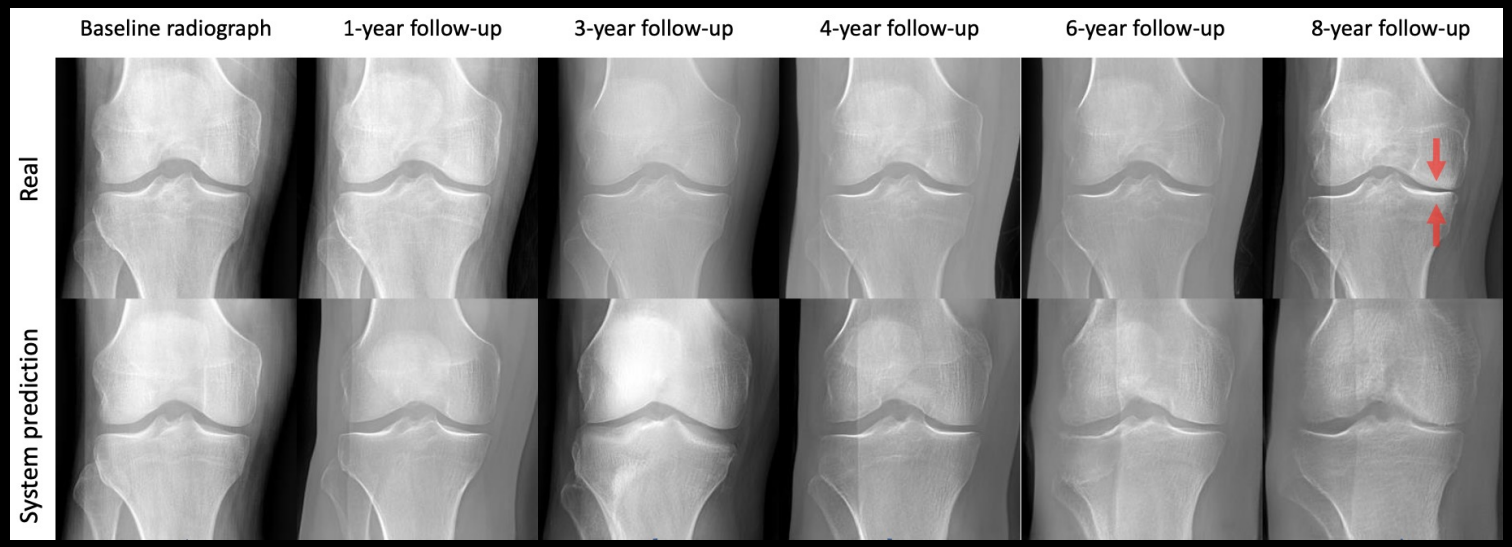

Baseline radiograph
1-year follow-up
3-year follow-up
4-year follow-up
6-year follow-up
8-year follow-up
Real


nature
machine
intelligence
Predicting future disease status with
generative navigation


Baseline radiograph
1-year follow-up
3-year follow-up
4-year follow-up
6-year follow-up
8-year follow-up
Real
System prediction



nature
machine
intelligence
Predicting future disease time with generative navigation


Baseline radiograph
1-year follow-up
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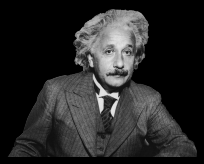
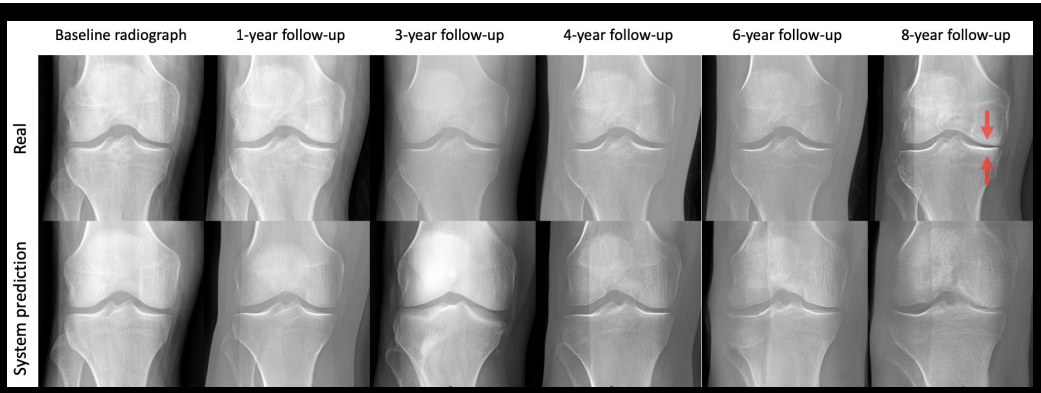
8-year follow-up
Real
System prediction

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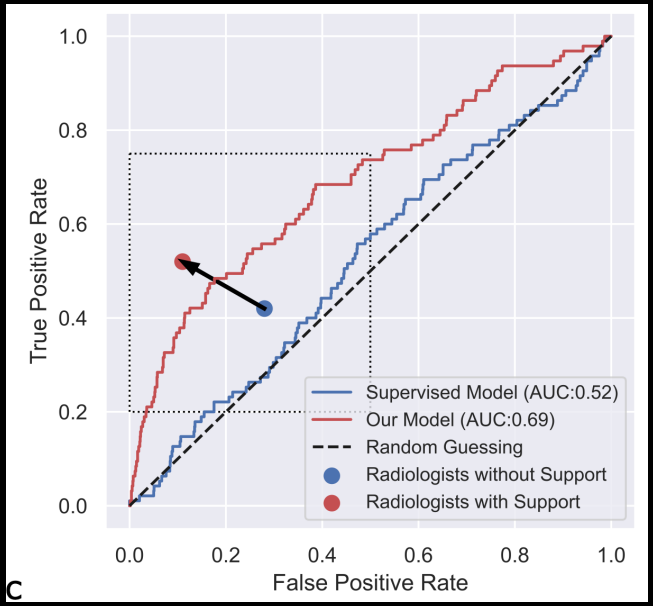
nature machine intelligence
Predicting future disease time with generative navigation


1.0
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True Positive Rate
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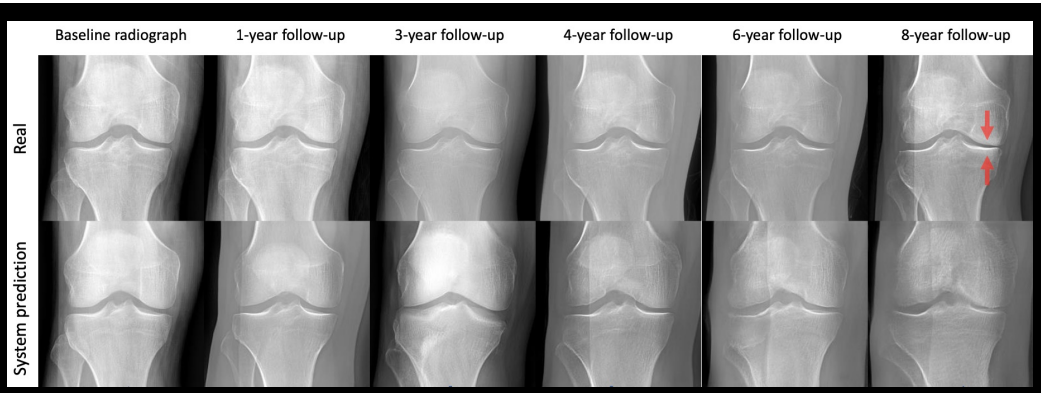
1.0
False Positive Rate
Supervised Model (AUC:0.52)
Our Model (AUC:0.69)
Random Guessing
Radiologists without Support
Radiologists with Support
C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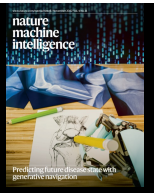
nature machine intelligence
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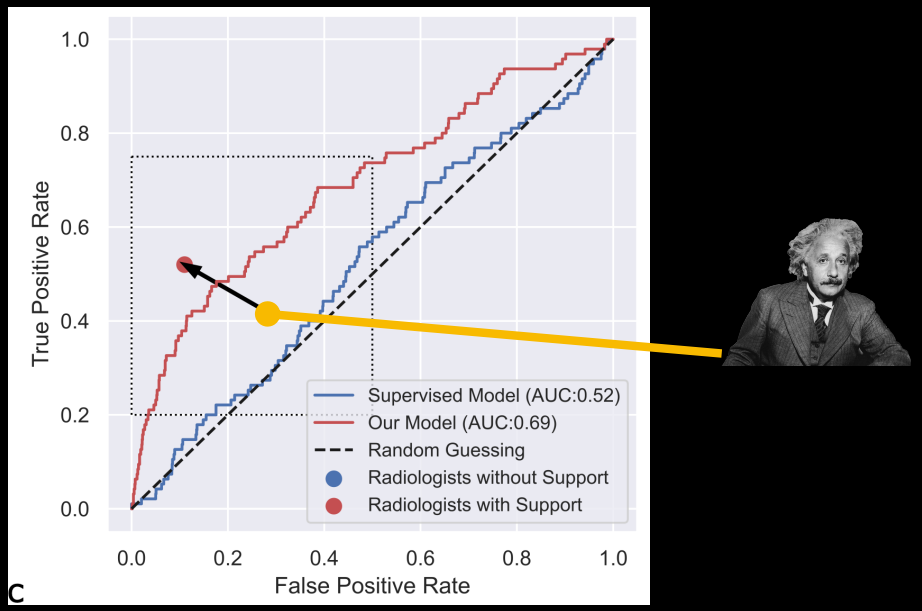
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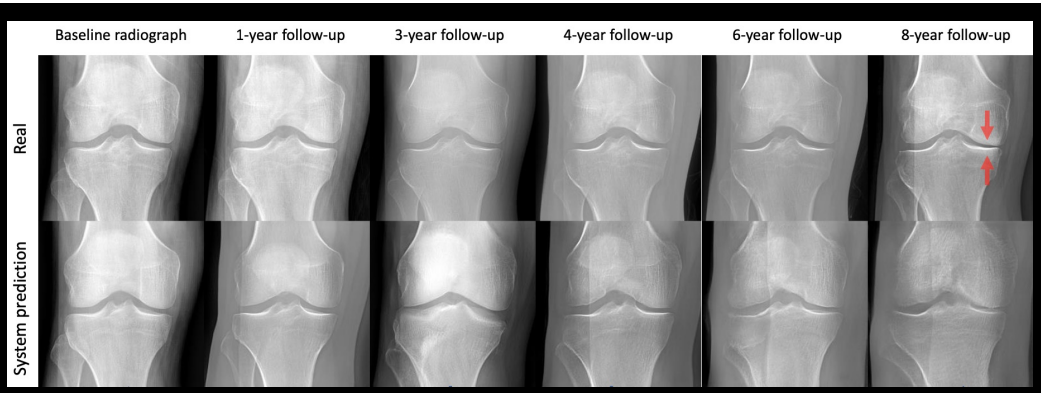
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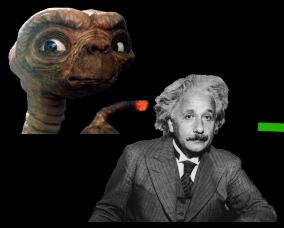

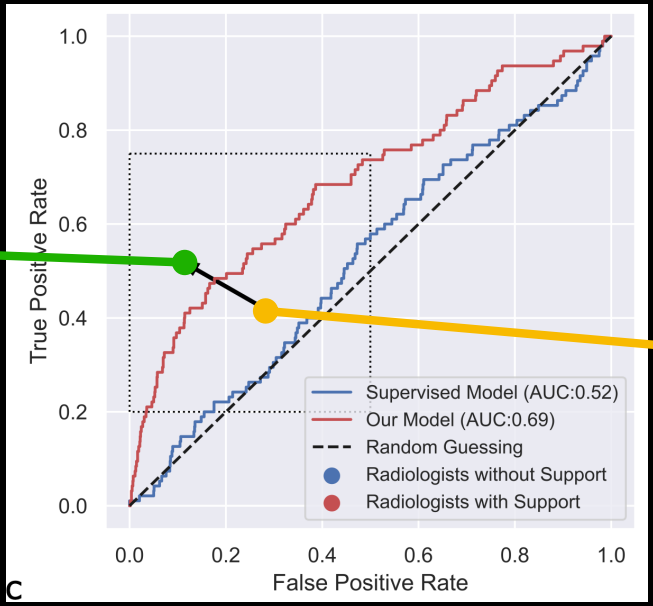
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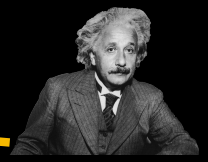
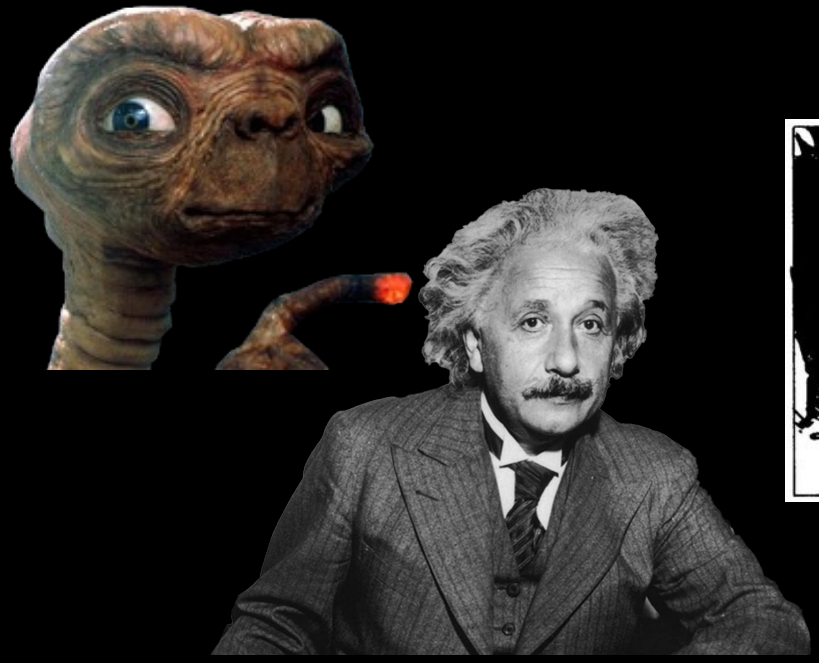
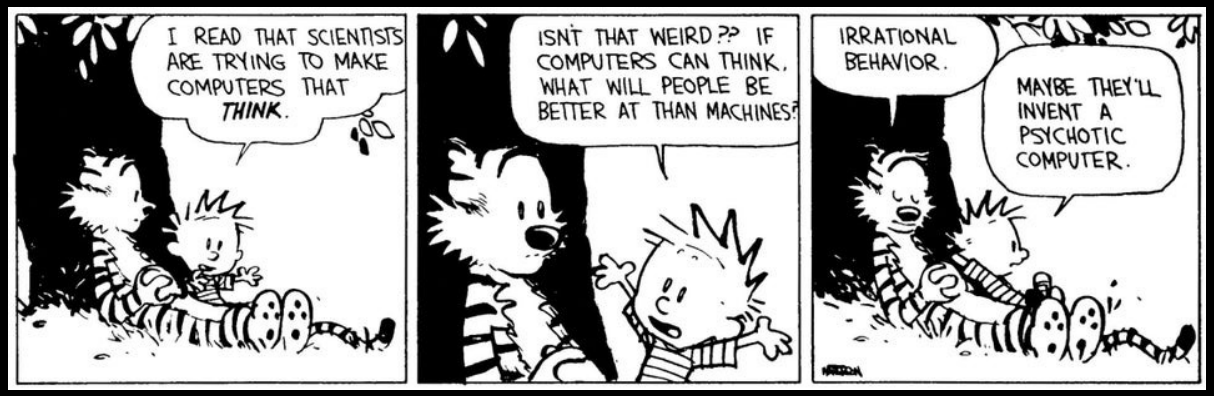


Thank you!




I READ THAT SCIENTISTS ARE TRYING TO MAKE COMPUTERS THAT THINK.
ISN'T THAT WEIRD?? IF COMPUTERS CAN THINK, WHAT WILL PEOPLE BE BETTER AT THAN MACHINES?
IRRATIONAL BEHAVIOR.
MAYBE THEY'LL INVENT A PSYCHOTIC COMPUTER.