

# The Thinking Sidecar: Five Thoughts on Machine Learning, Medicine, and Future Physicians

---

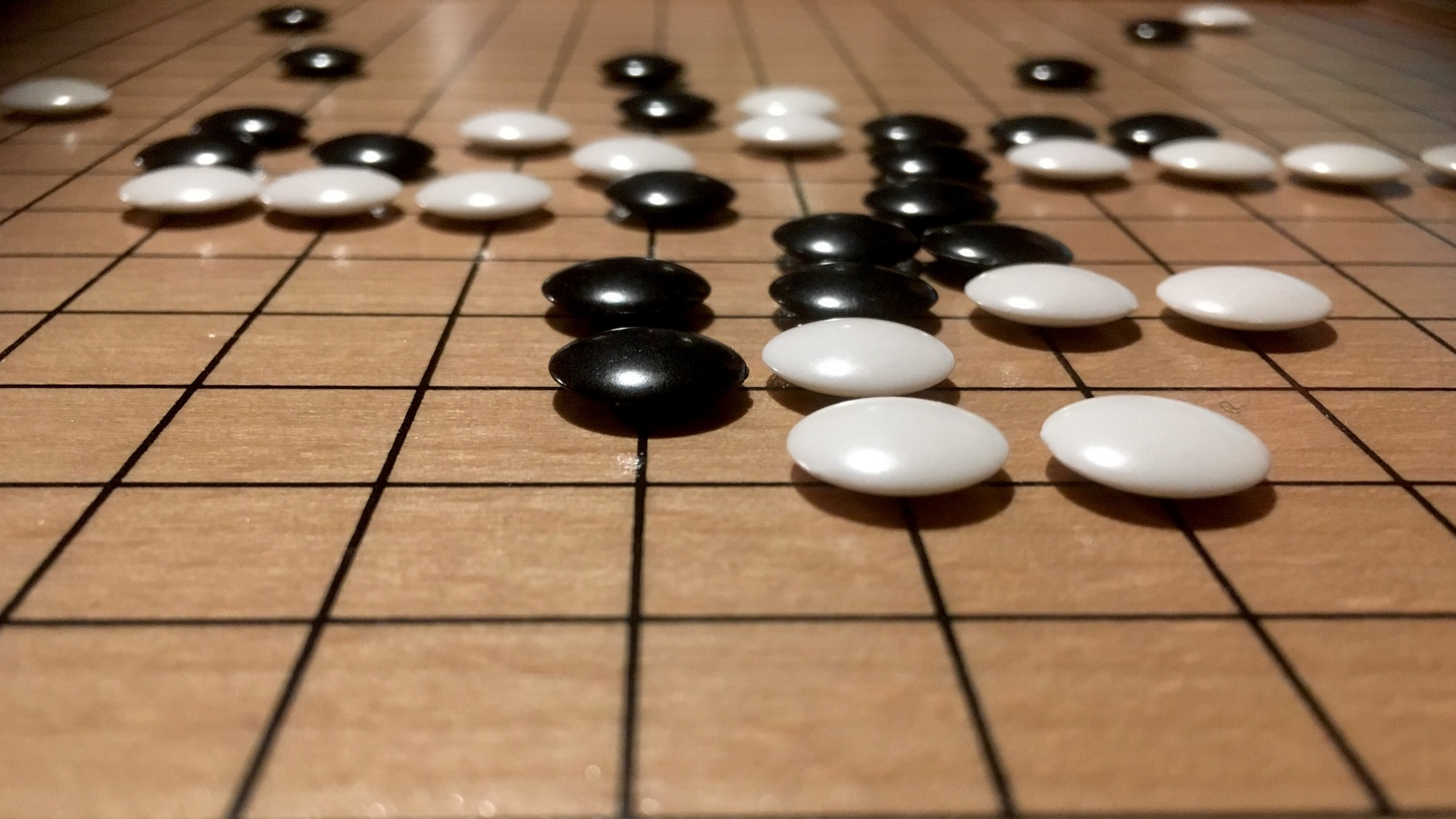
Ruben R. Puentedura, Ph.D.





## 1. A Clockwork World







# nature

THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE



## LESIONS LEARNT

Artificial intelligence powers detection  
of skin cancer from images **PAGES 36 & 115**

 [NATURE.COM/NATURE](https://www.nature.com/nature)

2 February 2017 £10

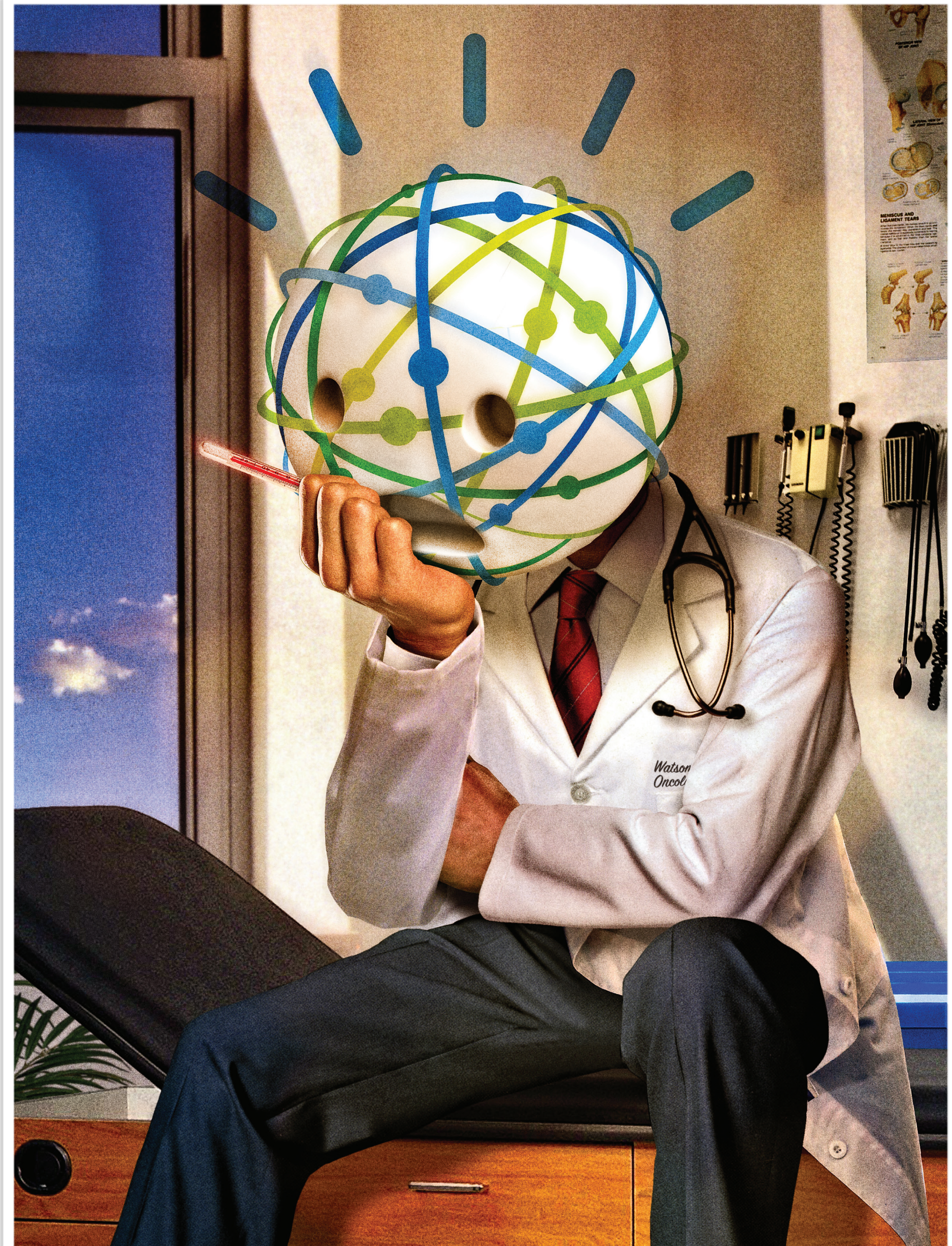
Vol. 542, No. 7639



# IBM Watson, *Heal* Thyself

How IBM overpromised and  
underdelivered on AI health care

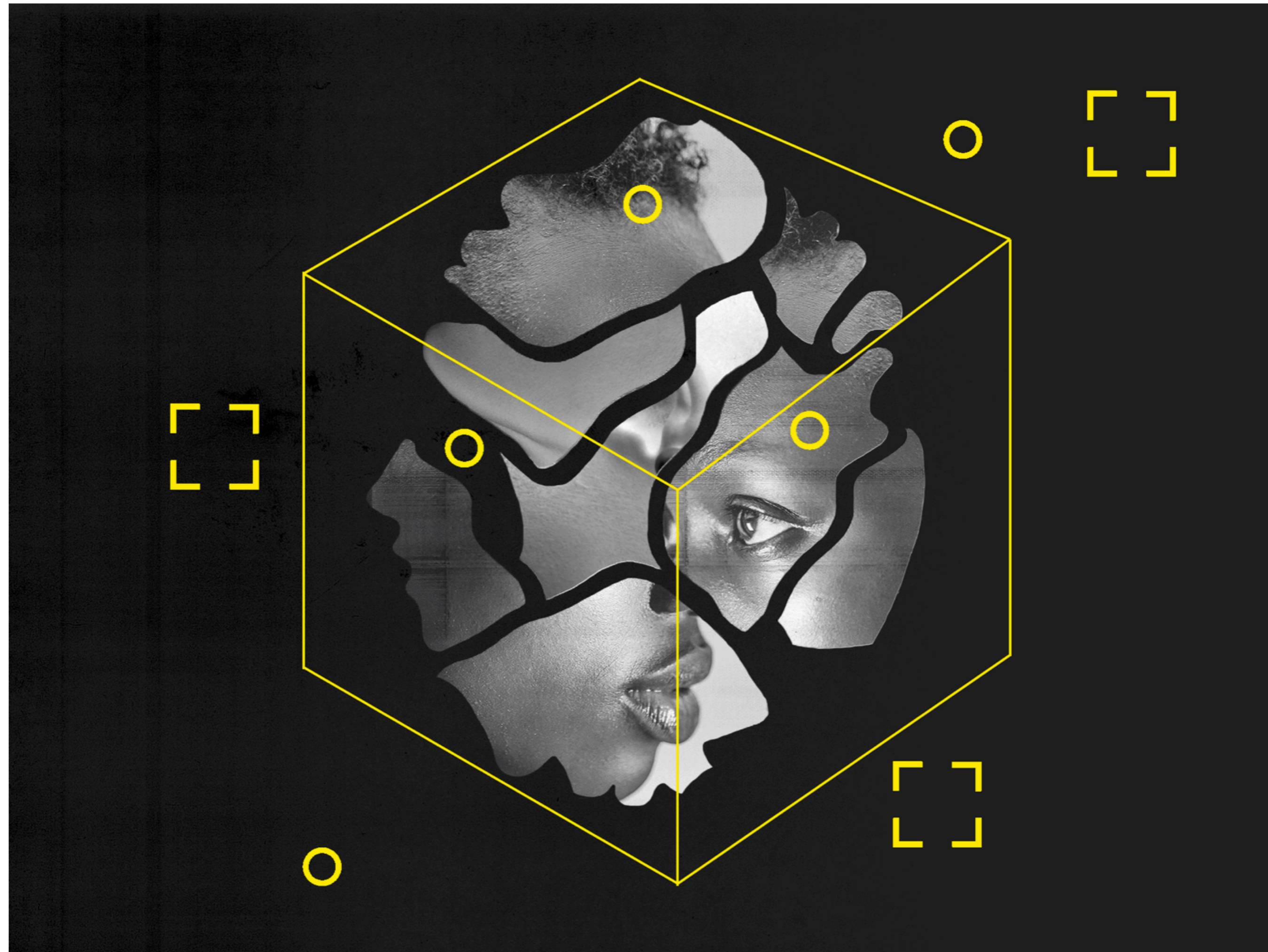
By ELIZA STRICKLAND ILLUSTRATIONS BY EDDIE GUY





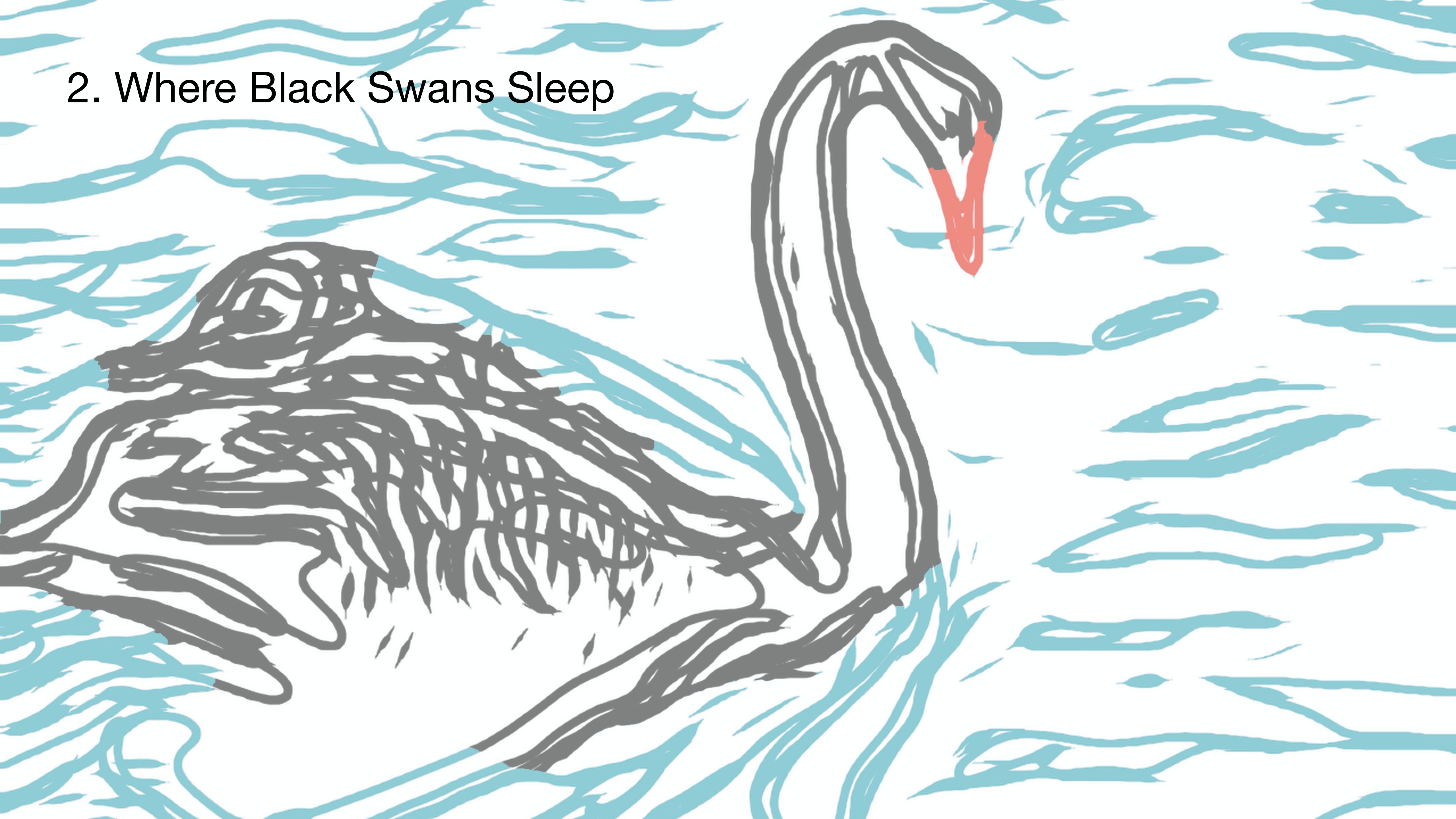
TOM SIMONITE BUSINESS 07.22.19 07:00 AM

# THE BEST ALGORITHMS STRUGGLE TO RECOGNIZE BLACK FACES EQUALLY





## 2. Where Black Swans Sleep





# Black Swan Events

---

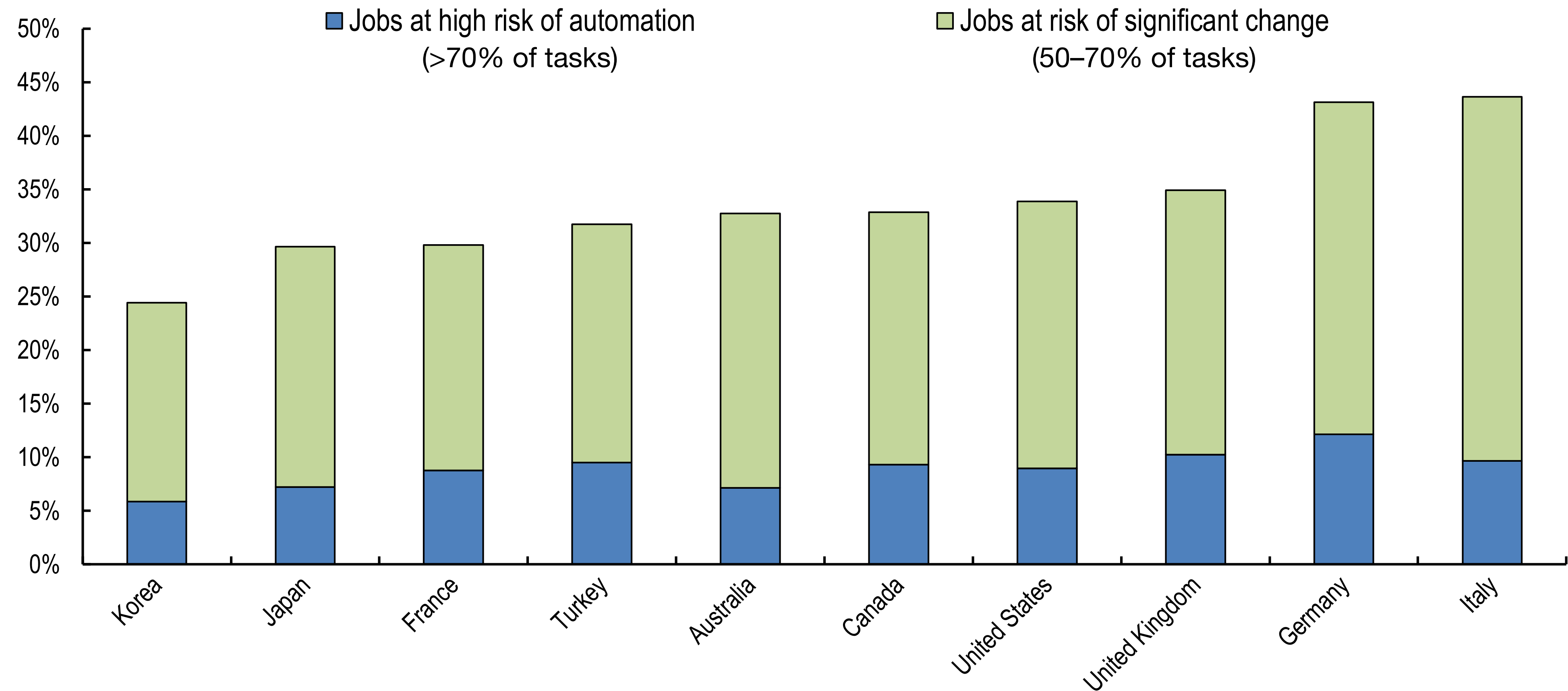
- Cannot be predicted ahead of time
- Have a major effect
- Can be rationalized retrospectively







# Advanced G20 Countries: Jobs at High Risk of Automation

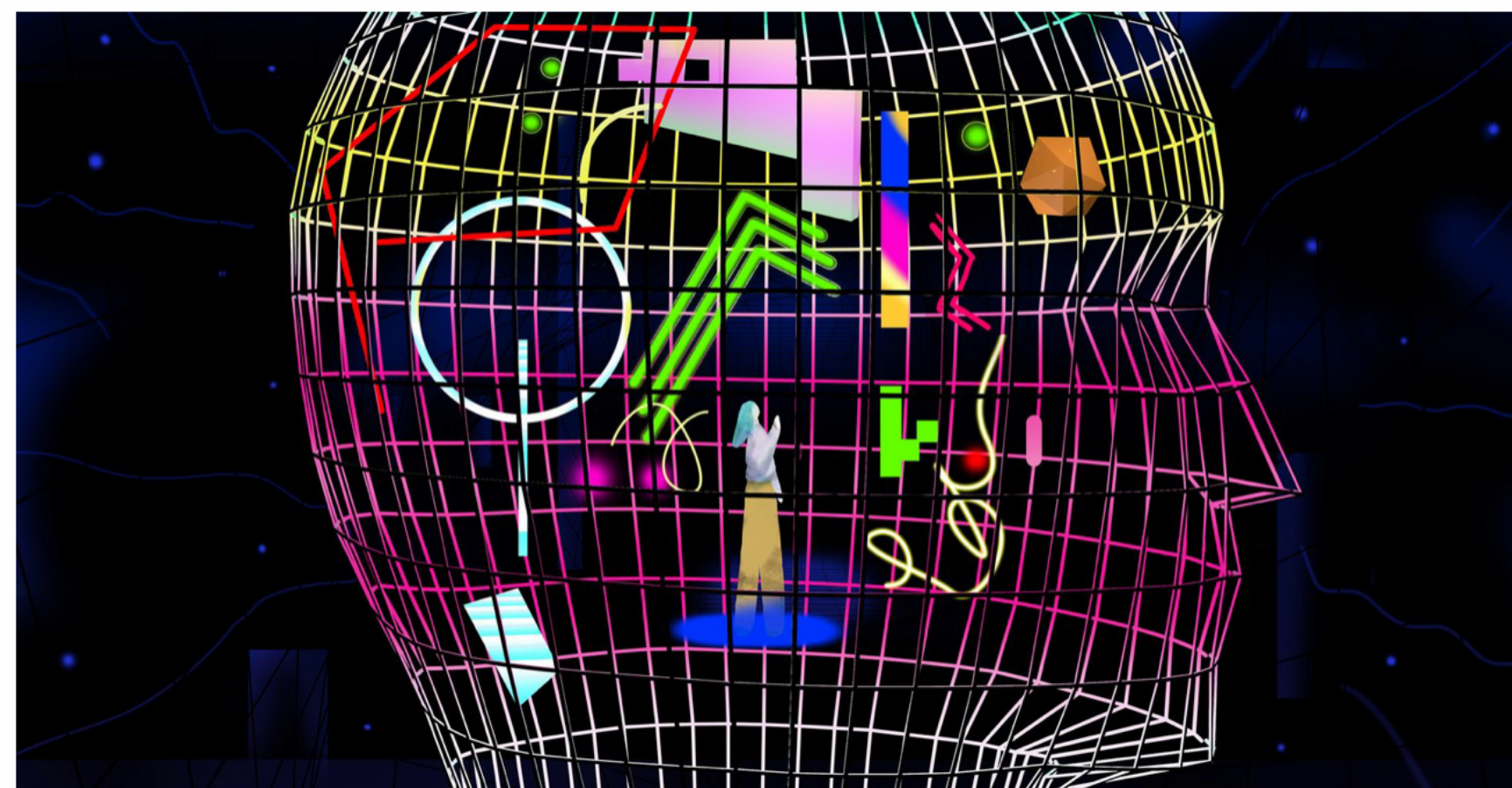




ANNALS OF TECHNOLOGY

# THE HIDDEN COSTS OF AUTOMATED THINKING

By **Jonathan Zittrain** July 23, 2019



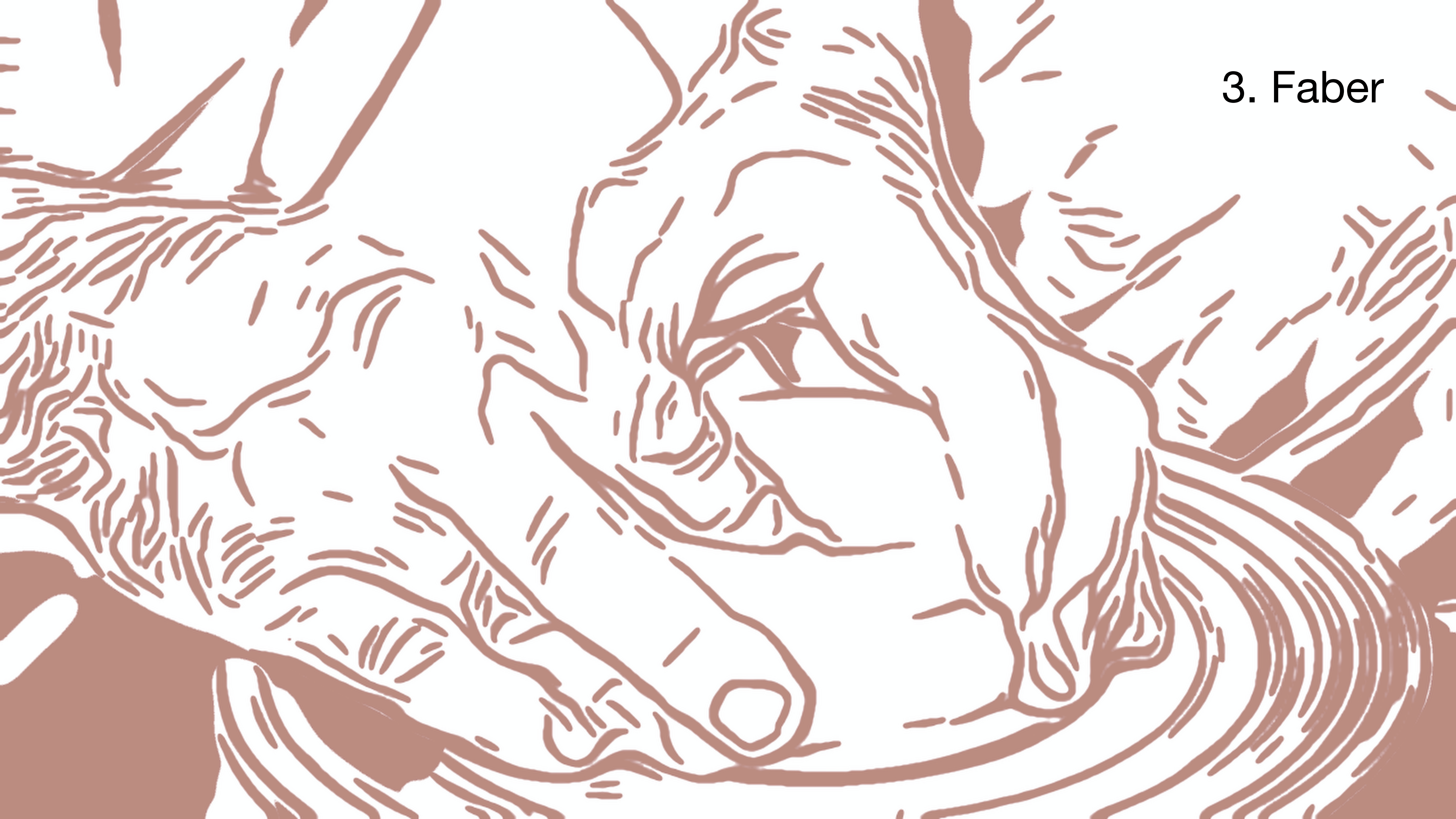
*Overreliance on artificial intelligence may put us in intellectual debt.* Illustration by Jon Han

Like many medications, the wakefulness drug modafinil, which is marketed under the trade name Provigil, comes with a small, tightly folded paper pamphlet. For the most part, its contents—lists of instructions and precautions, a diagram of the drug’s molecular structure—make for anodyne reading. The subsection called “Mechanism of Action,” however, contains a sentence that might induce sleeplessness by itself: “The mechanism(s) through which modafinil promotes wakefulness is unknown.”

Provigil isn’t uniquely mysterious. Many drugs receive regulatory approval, and are widely prescribed, even though no one knows exactly how they work. This mystery is built into the process of drug discovery, which often proceeds by trial and error. Each year, any number of new substances are tested in cultured cells or animals; the best and safest of those are tried out in people.



### 3. Faber







## ImageClassifier



Model accuracy

83%

Training

79%

Validation

79%

Evaluation ⓘ



Predicted  
Positive

True  
Positive



Predictions

Confidence

Positive

85%

Negative

15%



Predicted  
Positive

True  
Positive





# AI in Medical Education -Basic Exercises

---

- Bots
- Recommendation Systems
- Regression and Clustering
- Image Classification
- Object Detection
- Sequence Classification



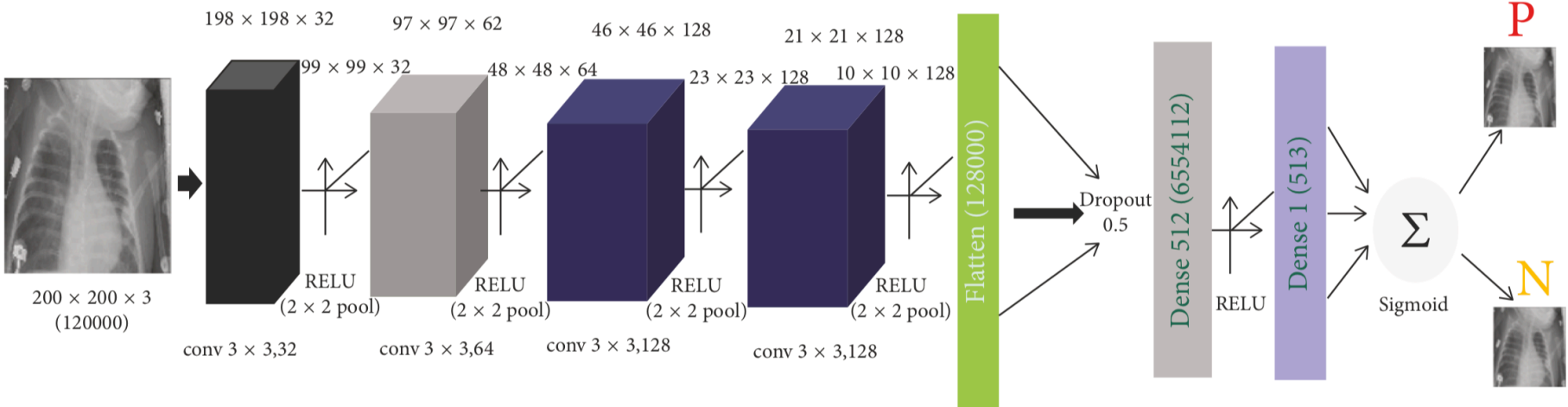
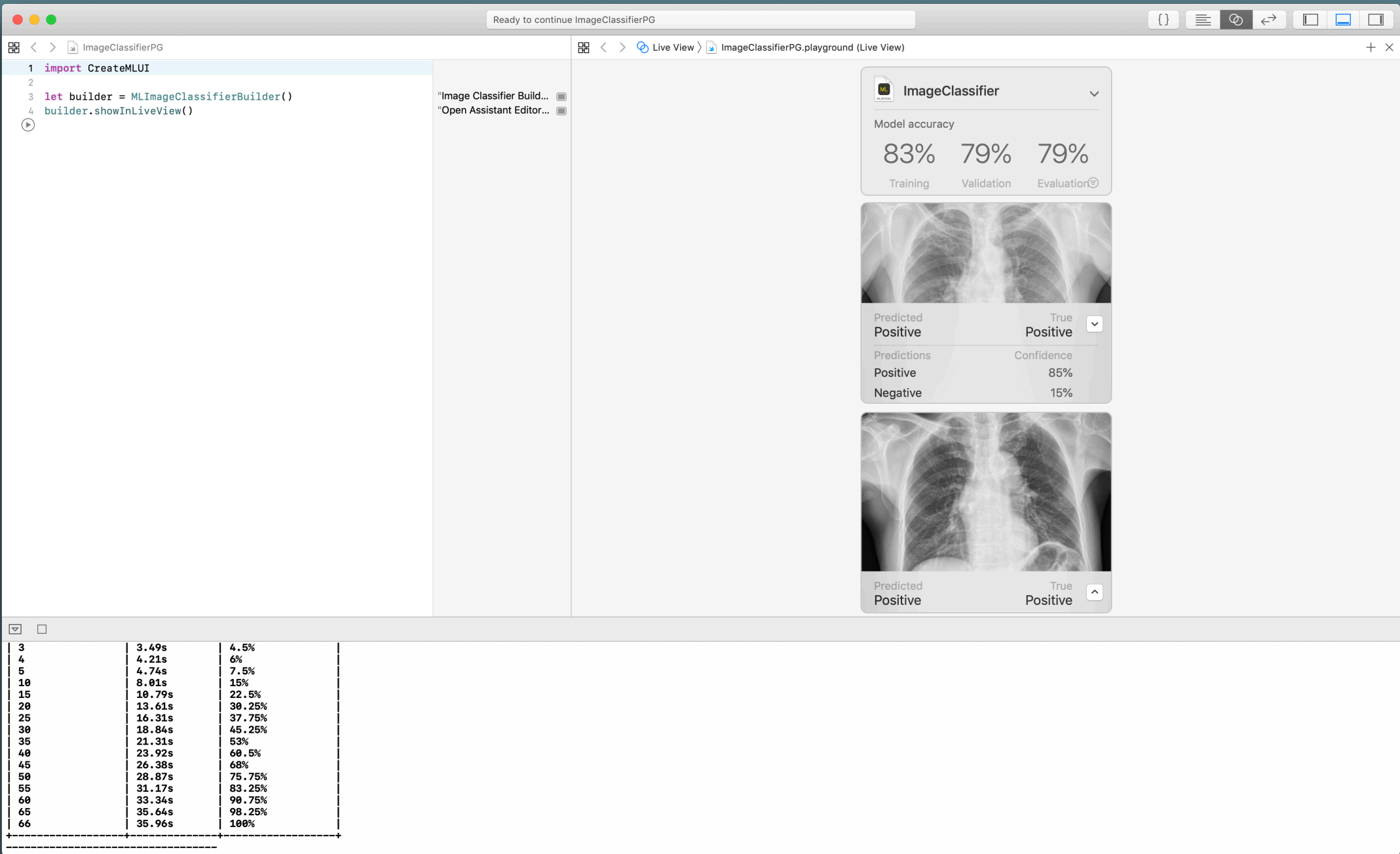
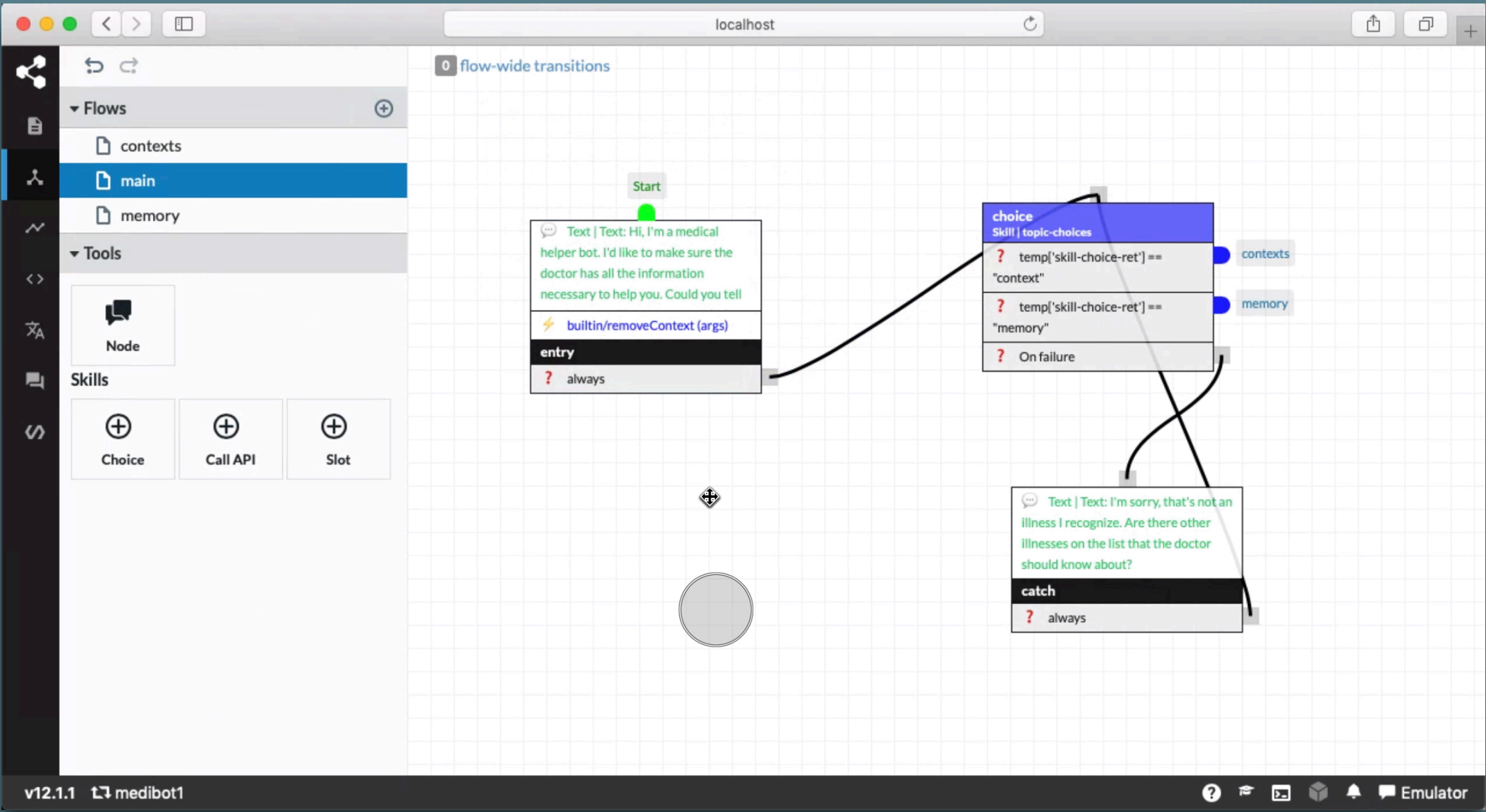
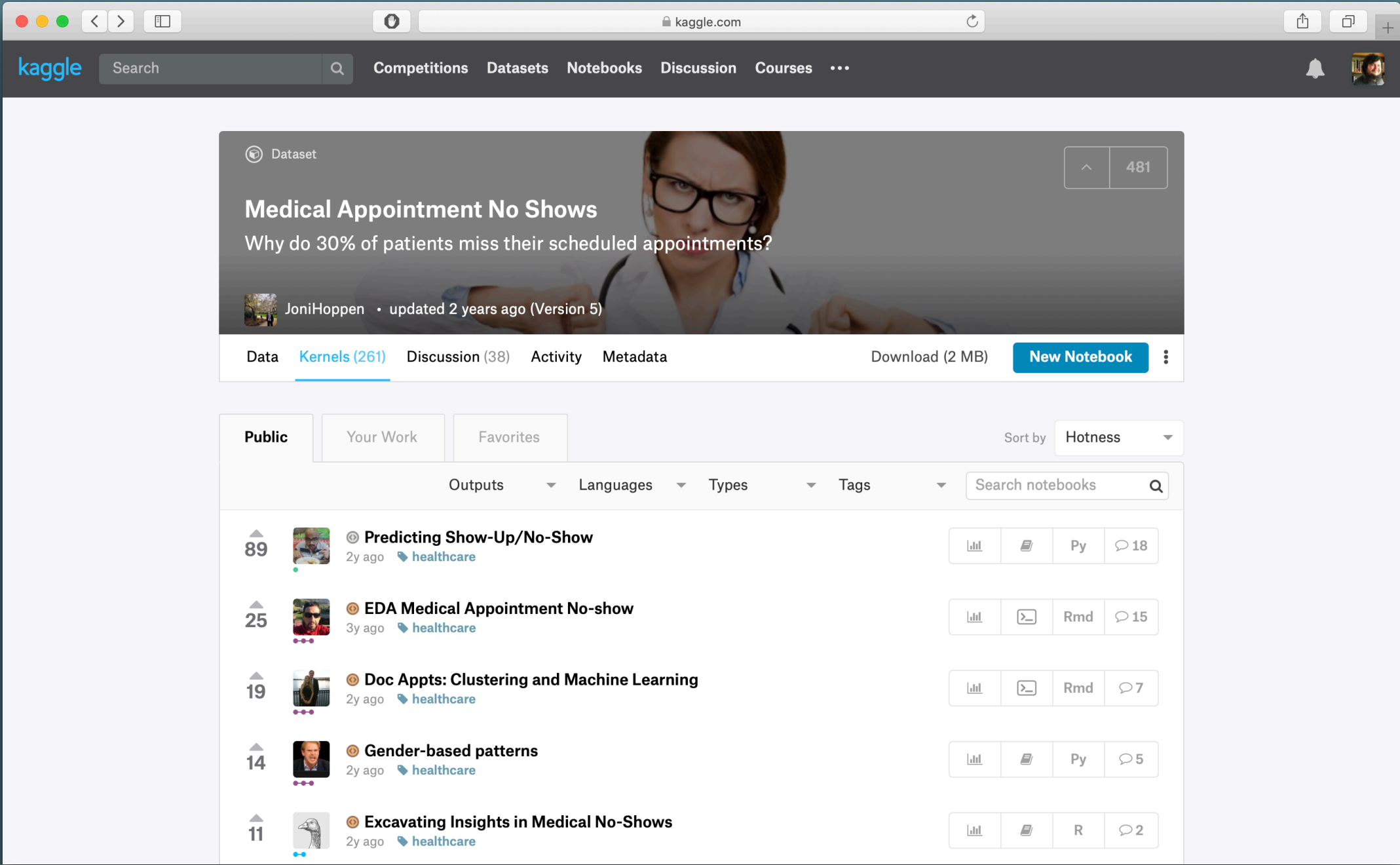


FIGURE 3: The proposed architecture.

TABLE 2: The output of the proposed network architecture.

Layer (type)	Output shape	Turtles
conv2d_9 (conv2D)	(None, 198, 198, 32)	896
max_Pooling2d_9 (MaxPooling2)	(None, 99, 99, 32)	0
conv2d_10 (conv2D)	(None, 97, 97, 64)	18496
max_Pooling2d_10 (MaxPooling2)	(None, 48, 48, 64)	0
conv2d_11 (conv2D)	(None, 46, 46, 128)	73856
max_Pooling2d_11 (MaxPooling2)	(None, 23, 23, 128)	0
conv2d_12 (conv2D)	(None, 21, 21, 128)	147584
max_Pooling2d_12 (MaxPooling2)	(None, 10, 10, 128)	0
flatten_3 (Flatten)	(None, 12800)	0
dropout_3 (Dropout)	(None, 12800)	0
dense_5 (Dense)	(None, 512)	6554112
dense_6 (Dense)	(None, 1)	513

Stephen, Okeke, et al. "An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare." *Journal of healthcare engineering* (2019).







4. Ludens



colab.research.google.com

COMMENT

SHARE

Neural Style Transfer Exploration

File Edit View Insert Runtime Tools Help

CODE TEXT CELL CELL

CONNECTED EDITING

Table of contents Code snippets Files

Neural Style Transfer with tf.keras

Overview

Setup

Import and configure modules

Visualize the input

Prepare the data

Build the Model

Define and create our loss functions (content and style distances)

Content Loss

Style Loss

Apply style transfer to our images

Optimization loop

Visualize outputs

Image Credits

SECTION

Content Image

Style Image

Output Image







## 5. The Thinking Sidecar



# Chess, a *Drosophila* of reasoning

The recent world chess championship saw Magnus Carlsen defend his title against Fabiano Caruana. But it was not a contest between the two strongest chess players on the planet, only the strongest humans. Soon after I lost my rematch against IBM’s Deep Blue in 1997, the short window of human-machine chess competition slammed shut forever. Unlike humans, machines keep getting faster, and today a smartphone chess app can be stronger than Deep Blue. But as we see with the AlphaZero system (see pages 1118 and 1140), machine dominance has not ended the historical role of chess as a laboratory of cognition.

Much as the *Drosophila melanogaster* fruit fly became a model organism for geneticists, chess became a *Drosophila* of reasoning. In the late 19th century, Alfred Binet hoped that understanding why certain people excelled at chess would unlock secrets of human thought. Sixty years later, Alan Turing wondered if a chess-playing machine might illuminate, in the words of Norbert Wiener, “whether this sort of ability represents an essential difference between the potentialities of the machine and the mind.”

Much as airplanes don’t flap their wings like birds, machines don’t generate chess moves like humans do. Early programs that attempted it were weak. Success came with the “minimax” algorithm and Moore’s law, not with the ineffable human combination of pattern recognition and visualization. This prosaic formula dismayed the artificial intelligence (AI) crowd, who realized that profound computational insights were not required to produce a machine capable of defeating the world champion.

But now the chess fruit fly is back under the microscope. Based on a generic game-playing algorithm, AlphaZero incorporates deep learning and other AI techniques like Monte Carlo tree search to play against itself to generate its own chess knowledge. Unlike top traditional programs like Stockfish and Fritz, which employ many preset evaluation functions as well as massive li-

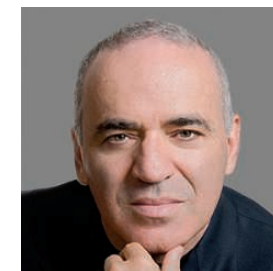
braries of opening and endgame moves, AlphaZero starts out knowing only the rules of chess, with no embedded human strategies. In just a few hours, it plays more games against itself than have been recorded in human chess history. It teaches itself the best way to play, reevaluating such fundamental concepts as the relative values of the pieces. It quickly becomes strong enough to defeat the best chess-playing entities in the world, winning 28, drawing 72, and losing none in a victory over Stockfish.

I admit that I was pleased to see that AlphaZero had a dynamic, open style like my own. The conventional wisdom was that machines would approach perfection with endless dry maneuvering, usually leading to drawn games. But in my observation, AlphaZero prioritizes piece activity over material, preferring positions that to my eye looked risky and aggressive. Programs usually reflect priorities and prejudices of programmers, but because AlphaZero programs itself, I would say that its style reflects the truth. This superior understanding allowed it to outclass the world’s top traditional program despite calculating far fewer positions per second. It’s the embodiment of the cliché, “work smarter, not harder.”

AlphaZero shows us that machines can be the experts, not merely expert tools. Explainability is still an issue—it’s not going to put chess coaches out of business just yet. But the knowledge it generates is information we can all learn from. AlphaZero is surpassing us in a profound and useful way, a model that may be duplicated on any other task or field where virtual knowledge can be generated.

Machine learning systems aren’t perfect, even at a closed system like chess. There will be cases where an AI will fail to detect exceptions to their rules. Therefore, we must work together, to combine our strengths. I know better than most people what it’s like to compete against a machine. Instead of raging against them, it’s better if we’re all on the same side.

—Garry Kasparov



**Garry Kasparov**  
*is the former world chess champion and the author of Deep Thinking: Where Machine Intelligence Ends and Human Creativity Begins. He is chairman of the Human Rights Foundation, New York, NY, USA.*  
[kasparov@hrf.org](mailto:kasparov@hrf.org)



**“...machine dominance has not ended the historical role of chess as a laboratory of cognition.”**

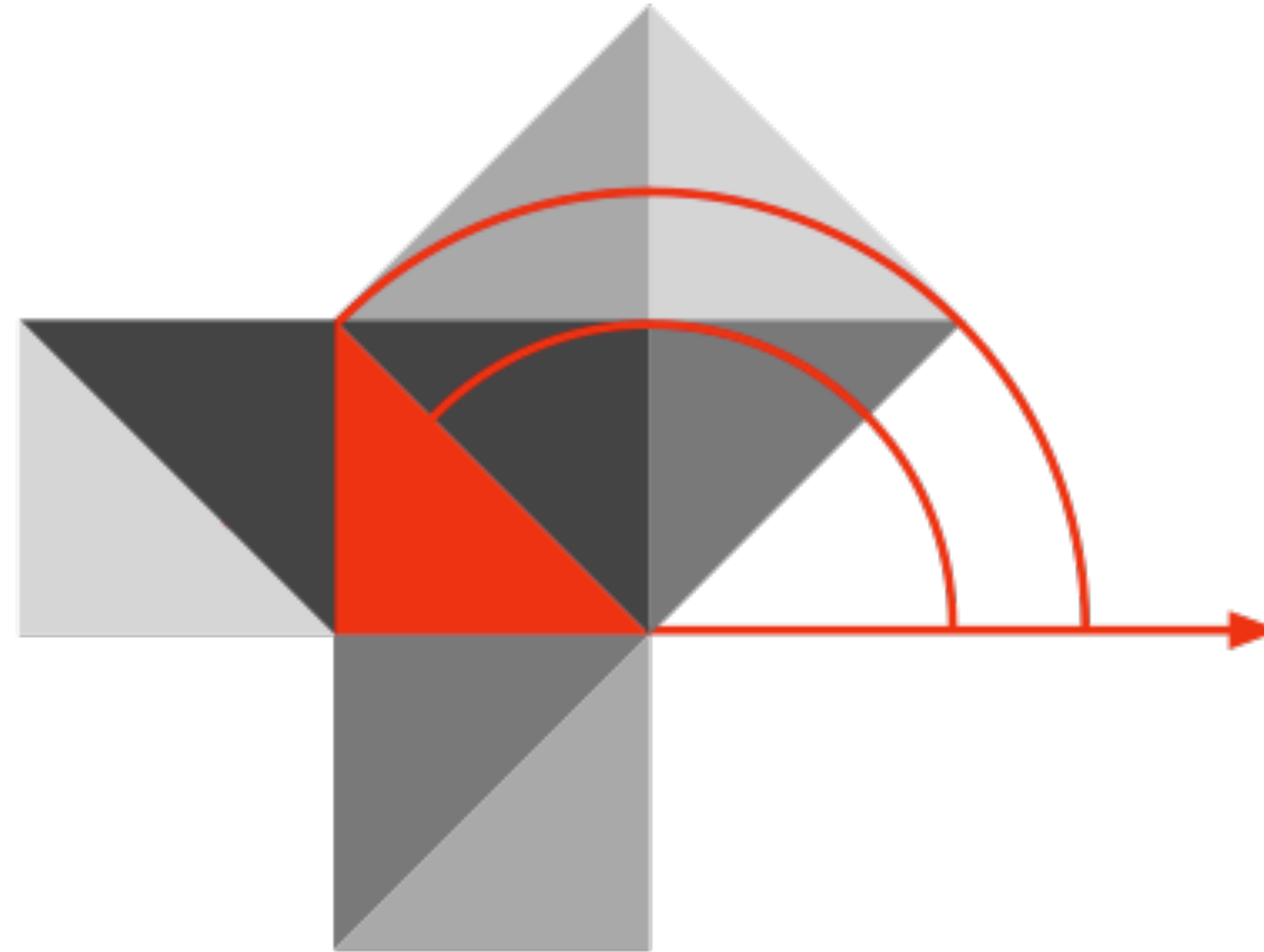
CREDITS: (INSET) DEEPMIND TECHNOLOGIES LIMITED; (RIGHT) IGOR KHOZINSKIY

10.1126/science.aaw2221



# Hippasus

---



Blog: <http://hippasus.com/blog/>

Email: [rubenrp@hippasus.com](mailto:rubenrp@hippasus.com)

Twitter: @rubenrp

This work is licensed under a Creative Commons Attribution-Noncommercial-Share Alike 3.0 License.

