Explaining AI through artistic practice

Dr Terence Broad

AI-ART Workshop
IEEE ICME 2025

Goldsmiths
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ual: creative computing institute

About me

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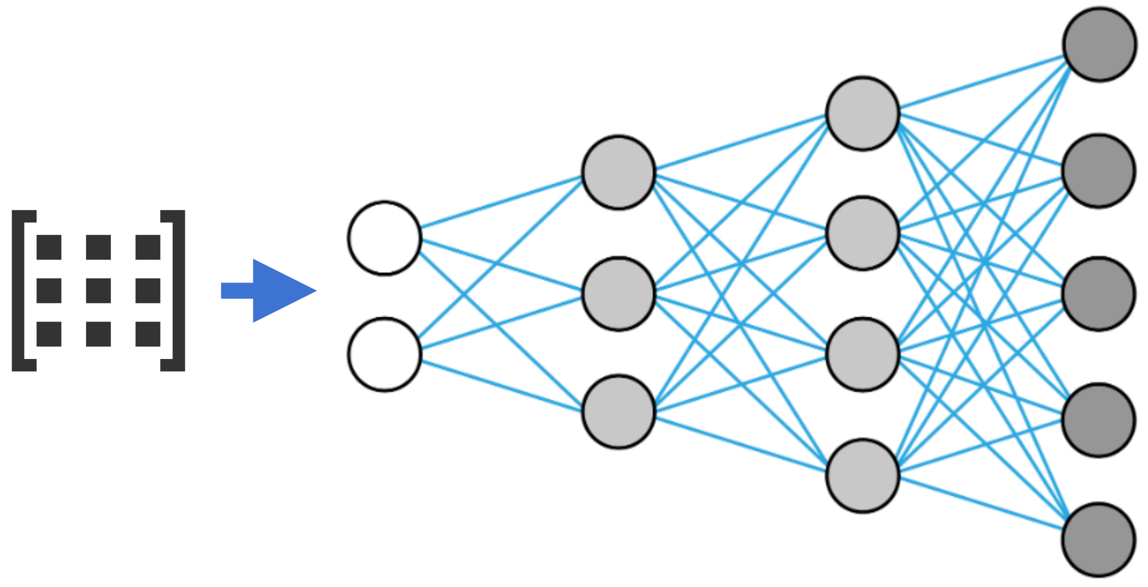
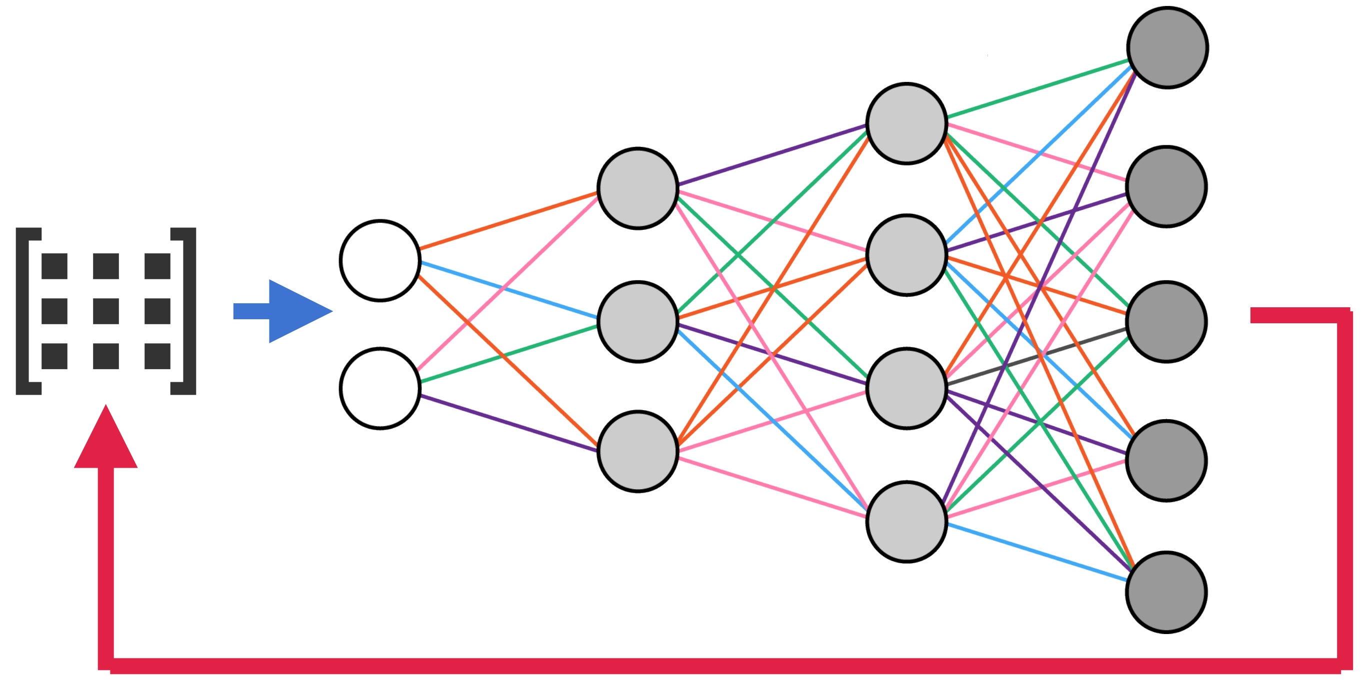
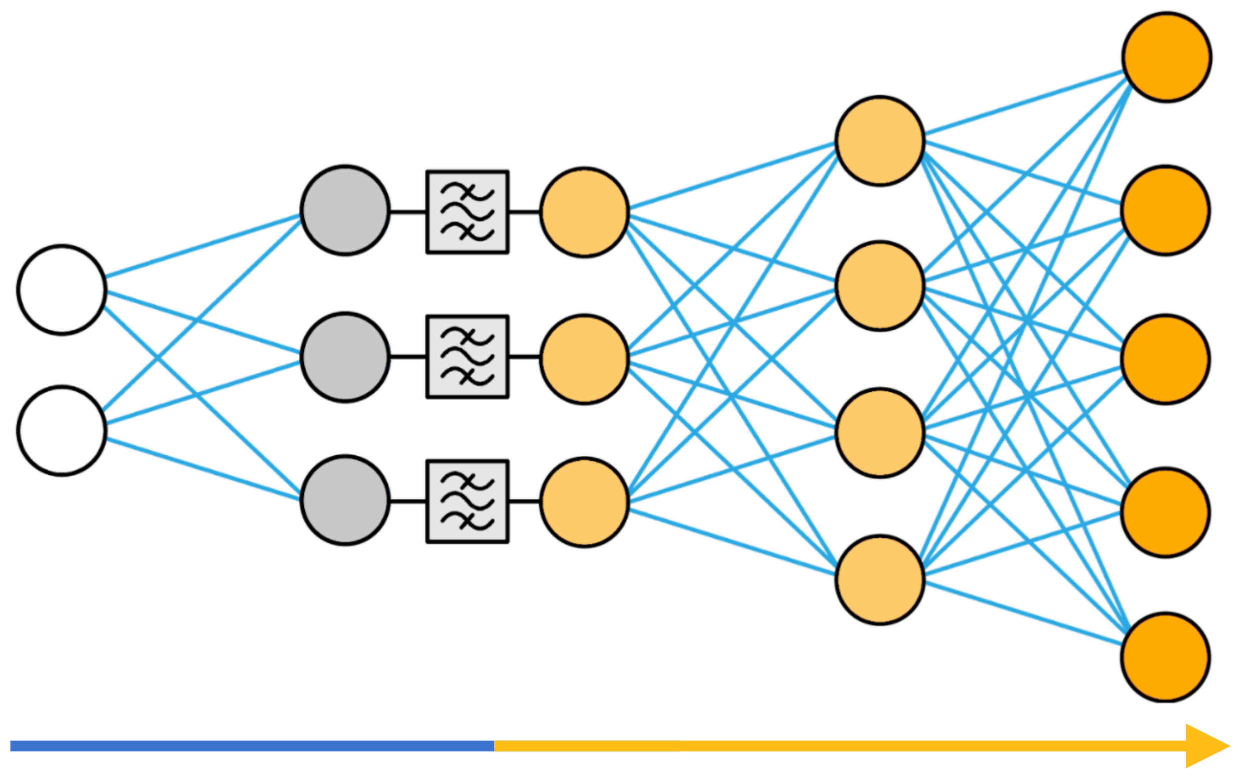
Artistic interventions with AI



In inference

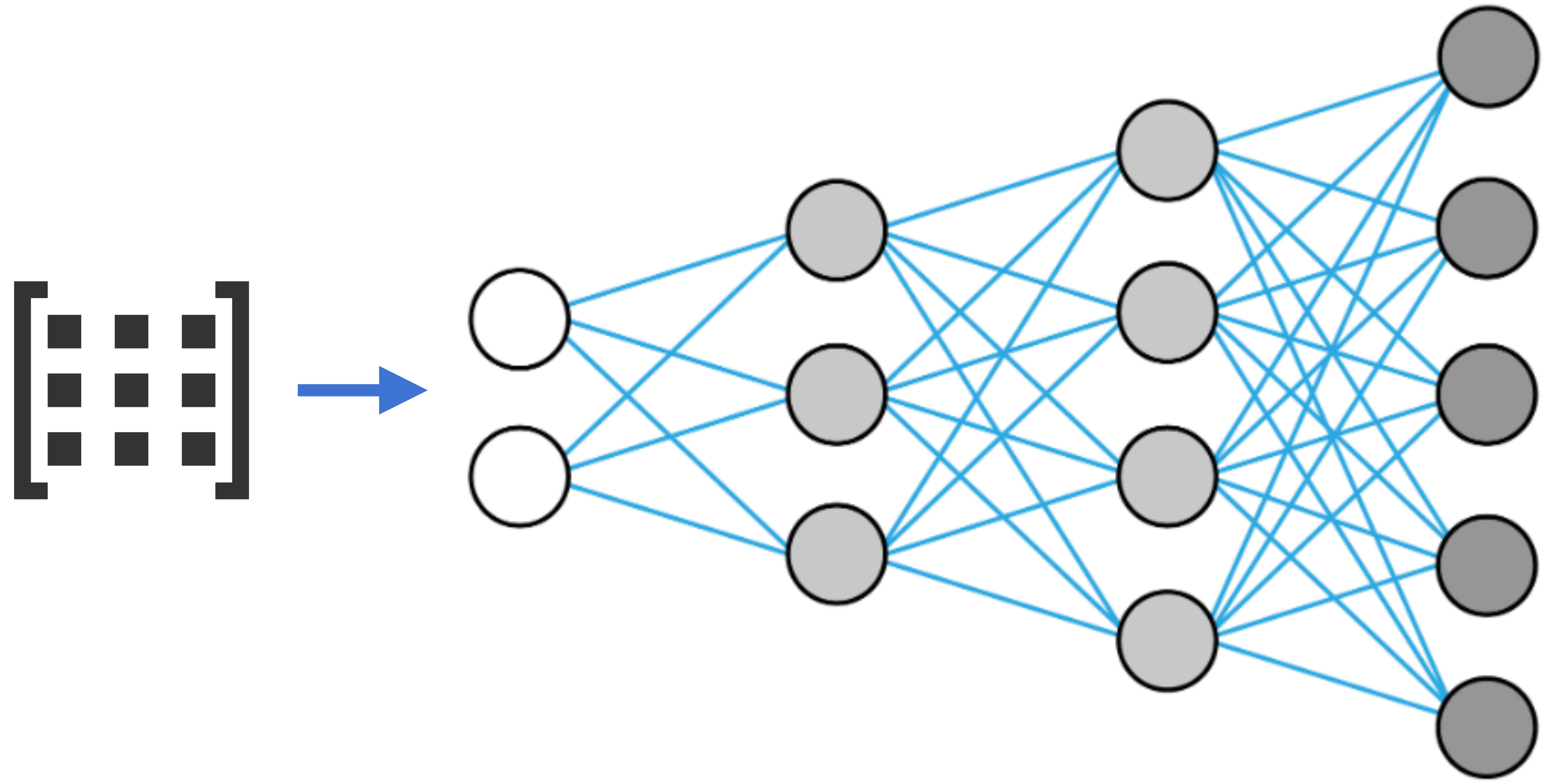


In training



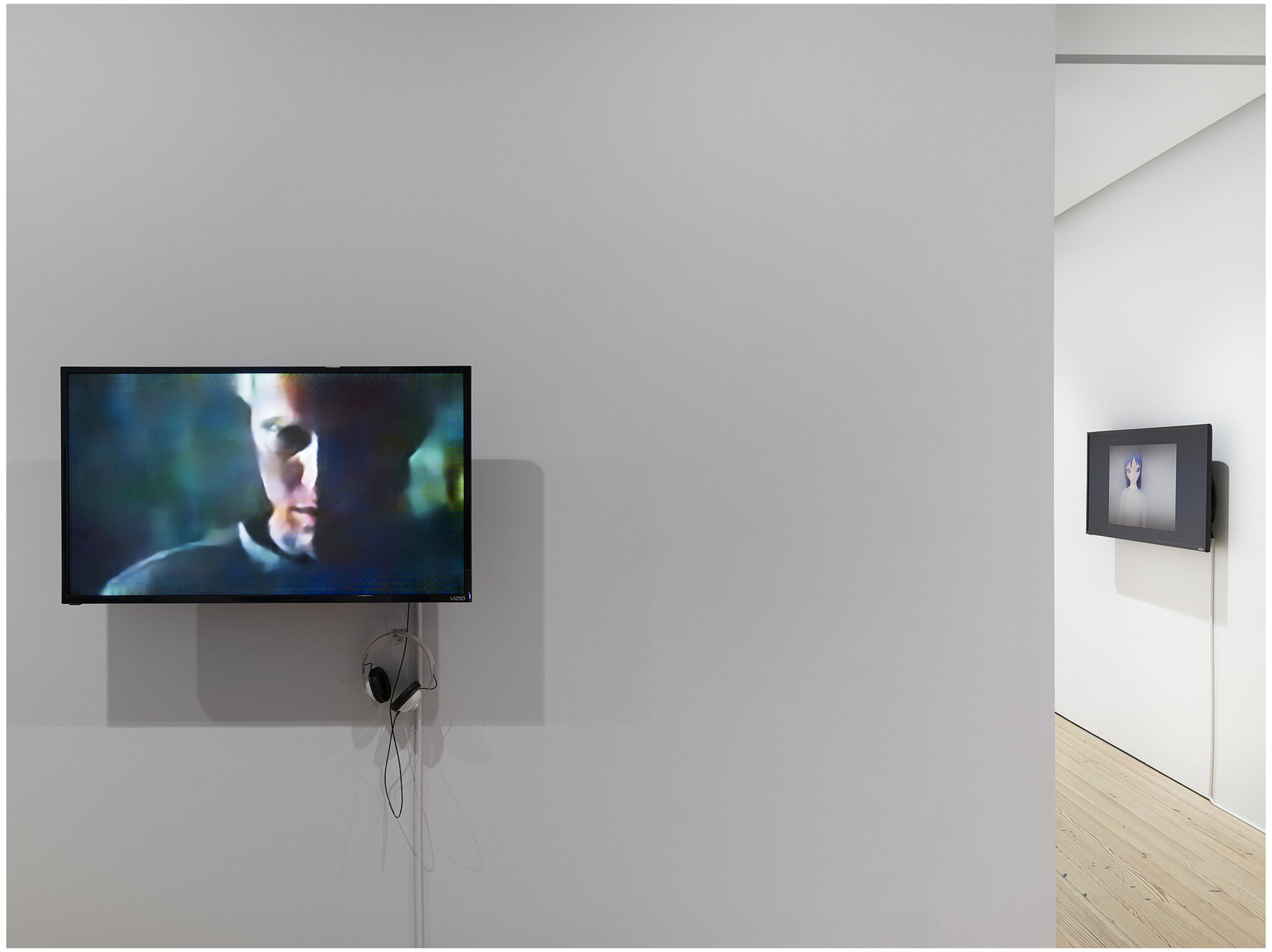
After training

Artistic interventions in inference

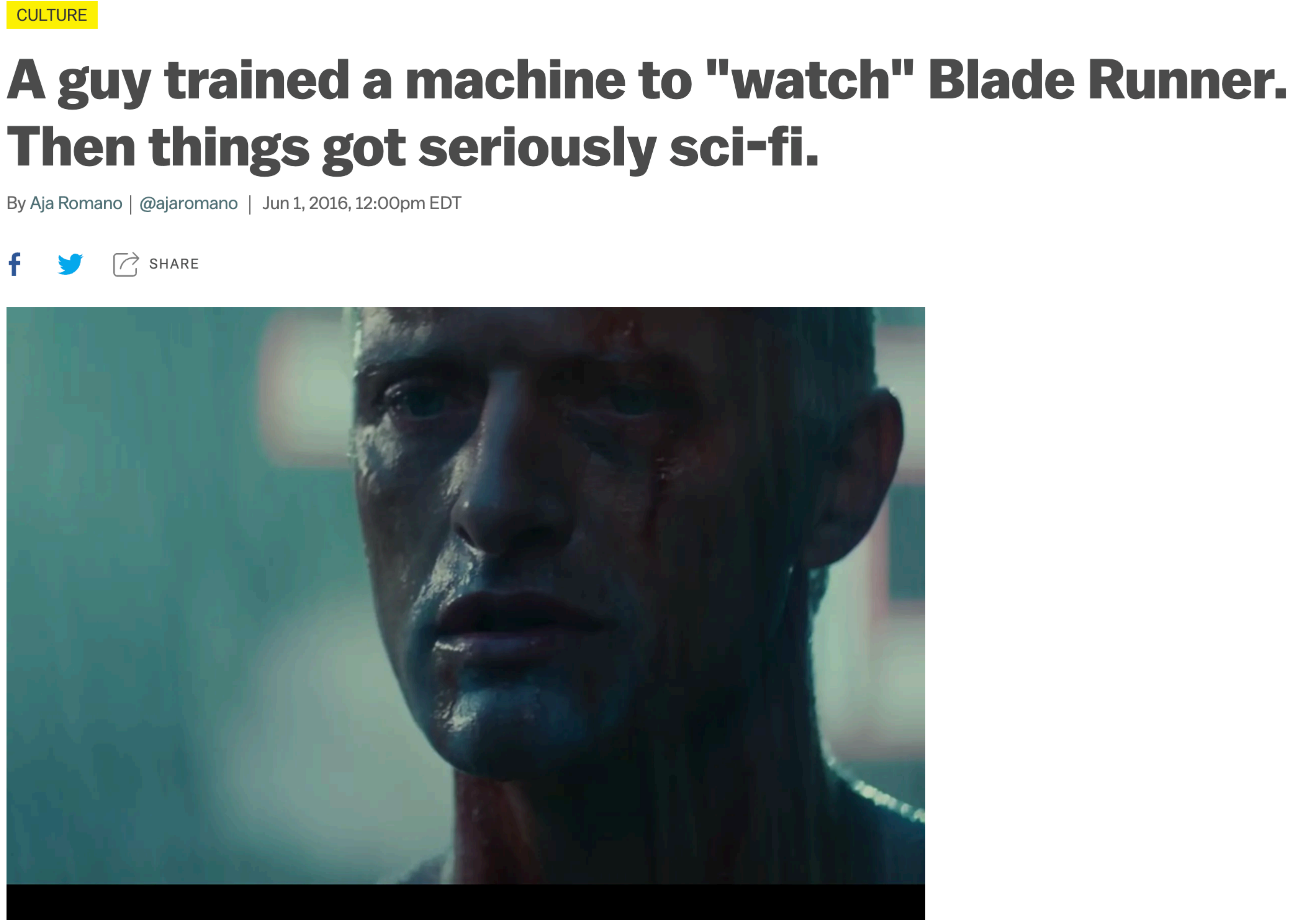


Visualising AI's memory

Blade Runner — Autoencoded (2016)
Terence Broad



Dreamlands: Immersive Cinema and Art, 1905–2016,
Whitney Museum of American Art, New York
2016-17

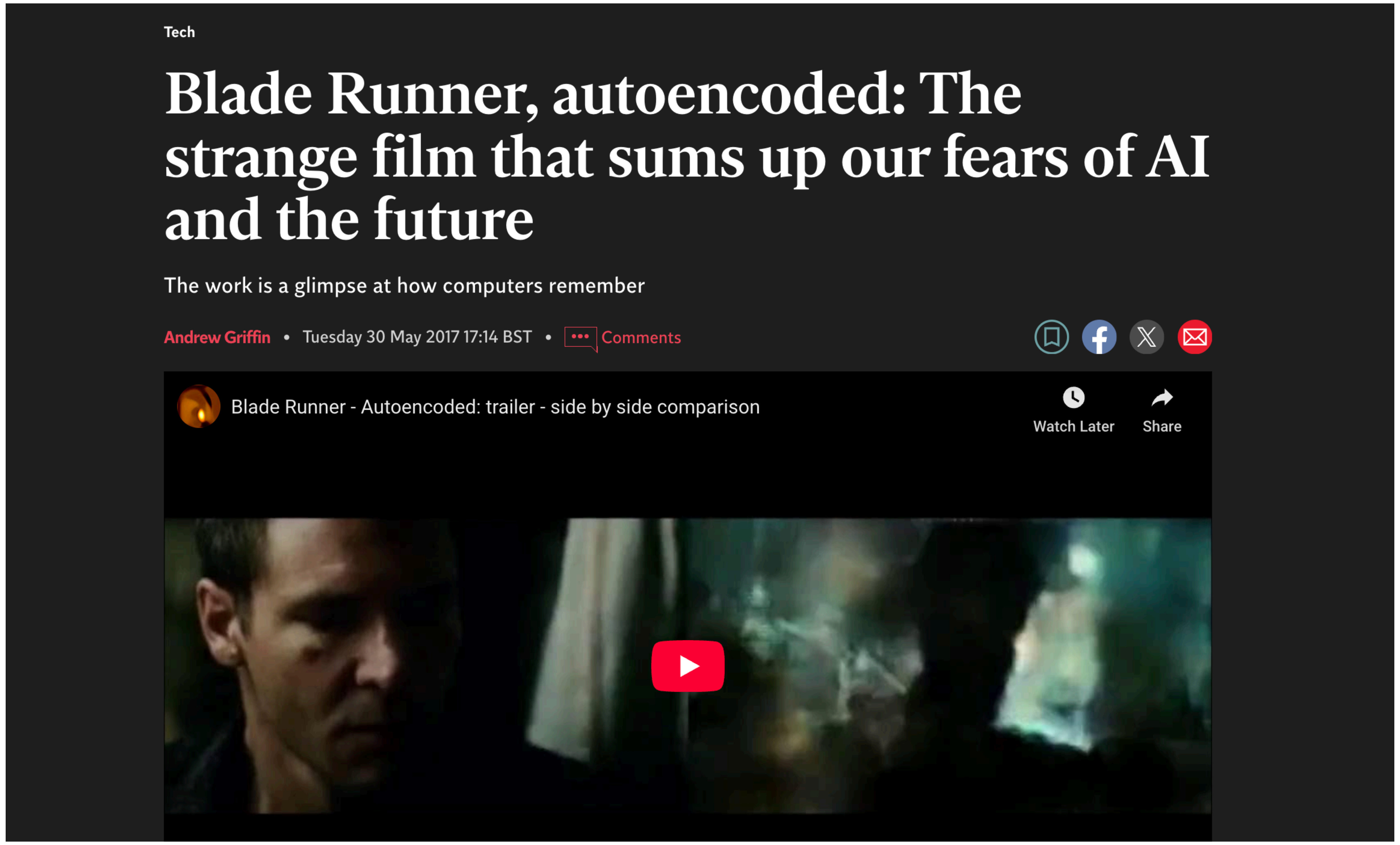

CULTURE

A guy trained a machine to "watch" Blade Runner. Then things got seriously sci-fi.

By Aja Romano | @ajaromano | Jun 1, 2016, 12:00pm EDT

SHARE

Vox (2016)


Tech

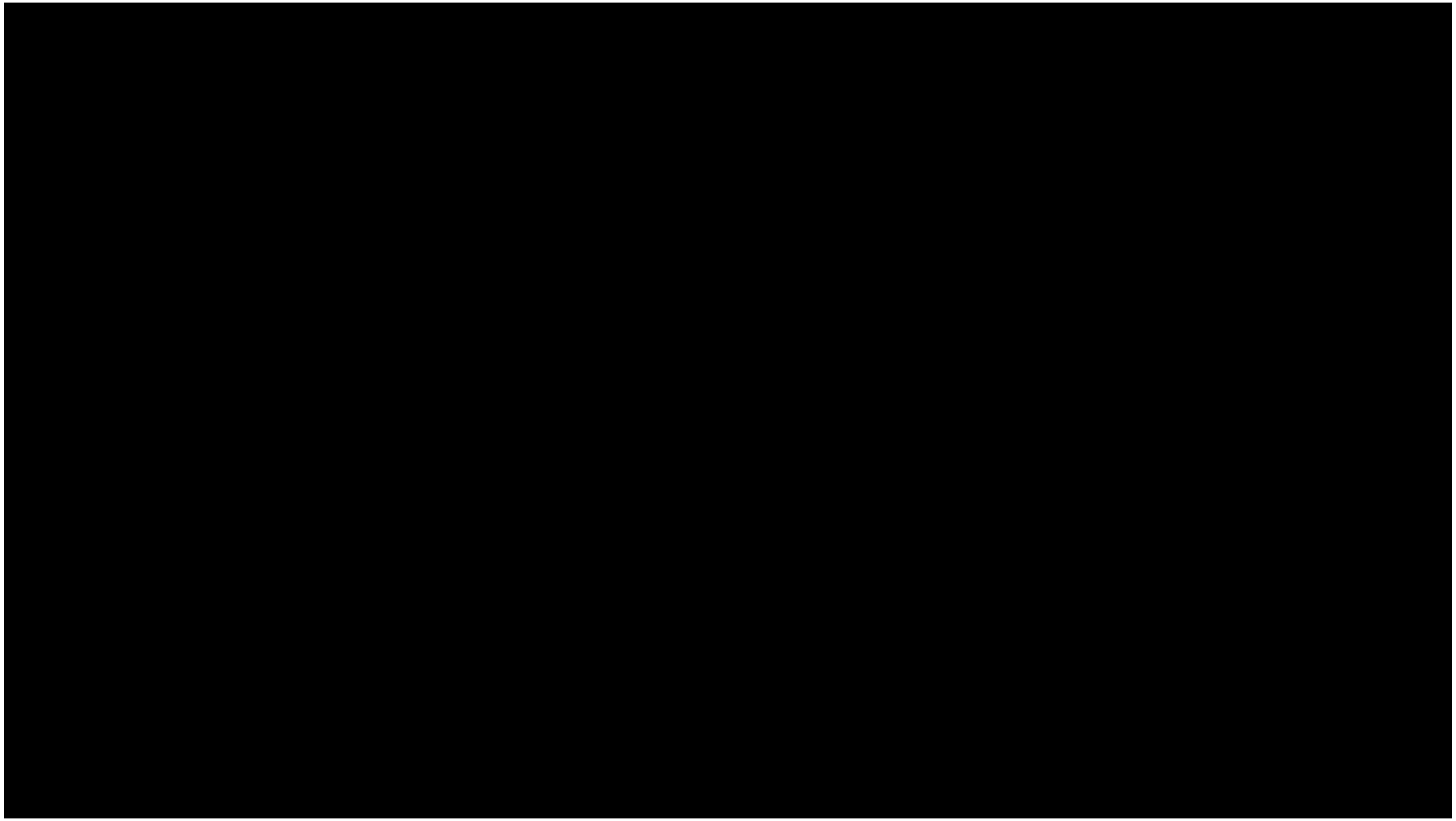
Blade Runner, autoencoded: The strange film that sums up our fears of AI and the future

The work is a glimpse at how computers remember

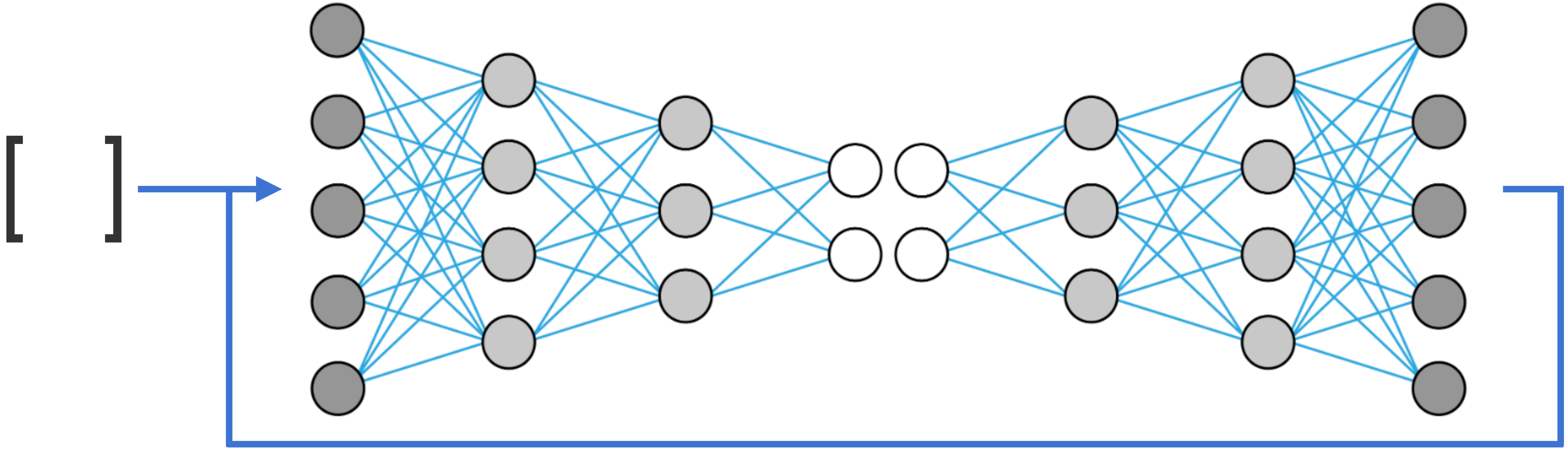
Andrew Griffin • Tuesday 30 May 2017 17:14 BST • Comments

The Indepedent (2017)

Visualising AI's internal hallucinations



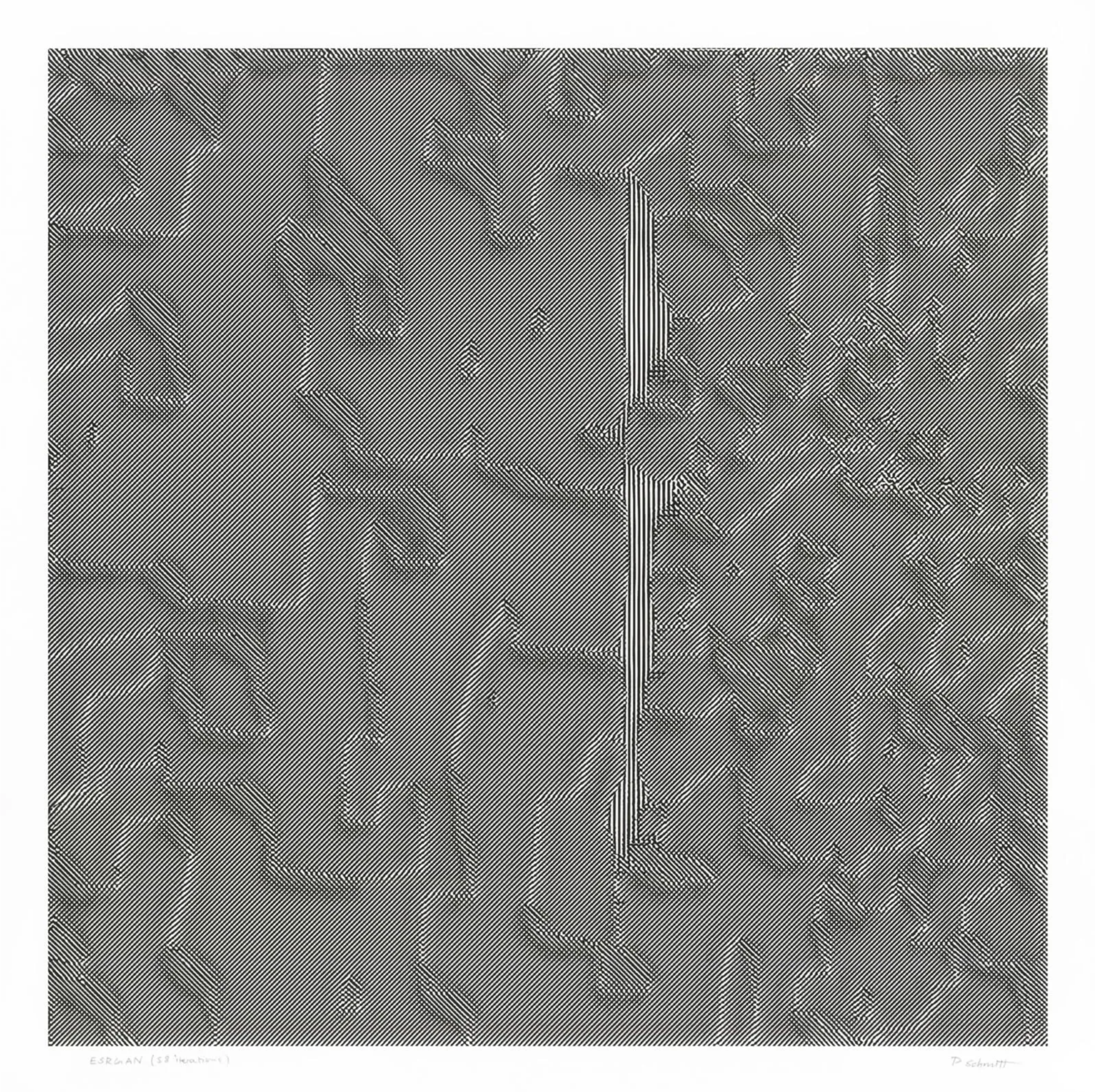
Introspections (2019)
Phillipp Schmitt



Feed uniform array into image translation model then recursively reprocess it

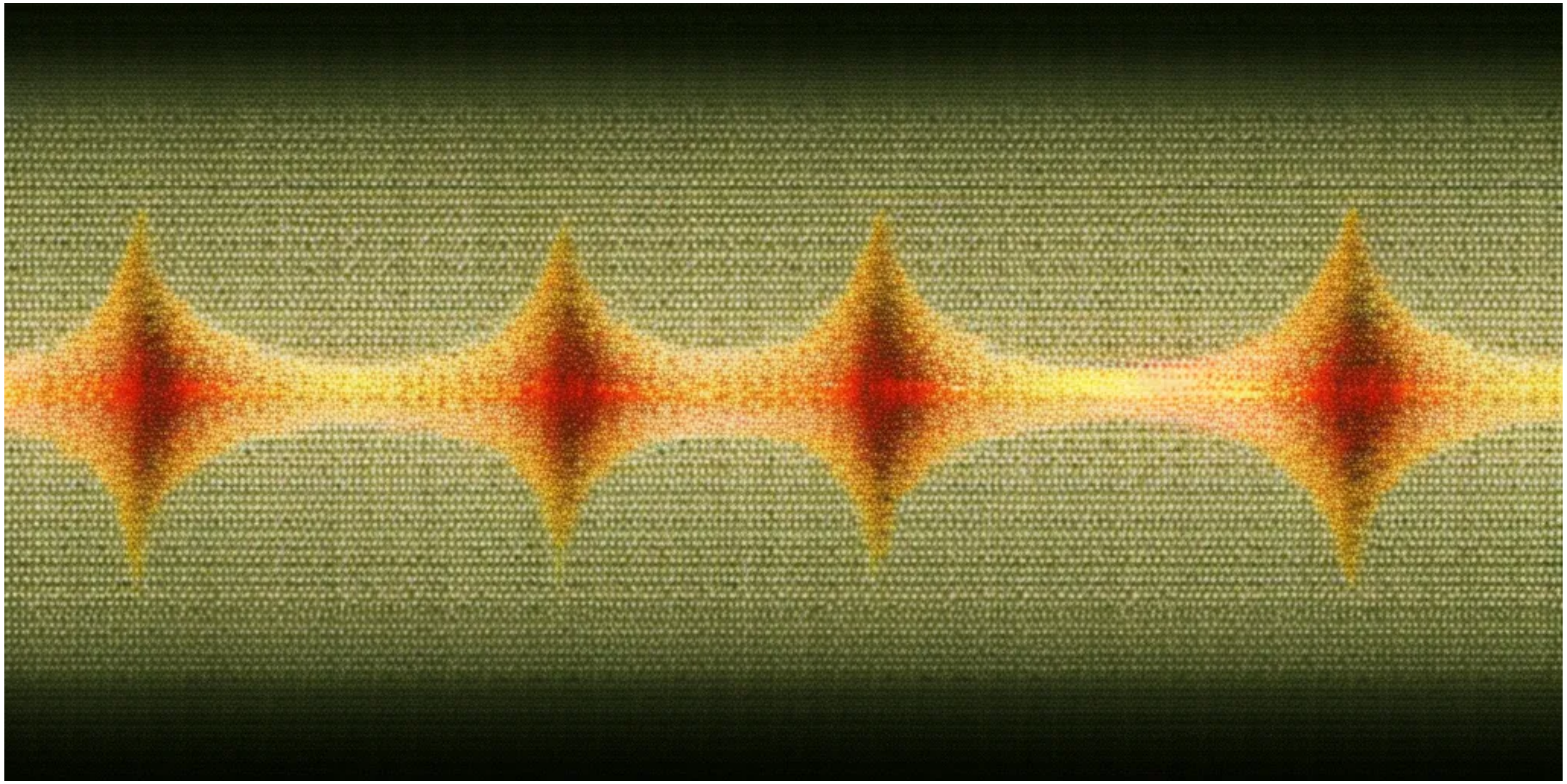
Photo colourisation

PhotoSketch

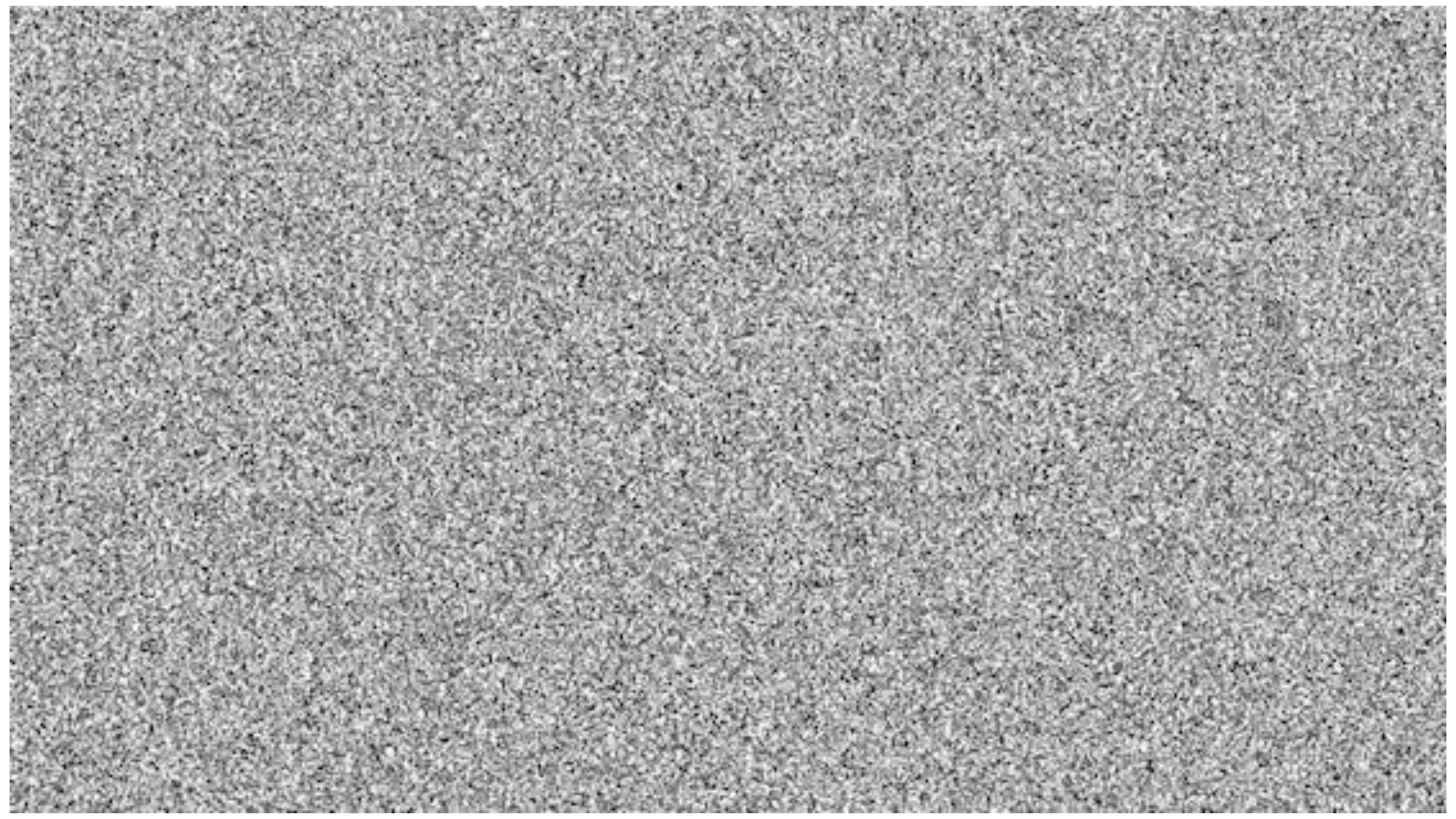


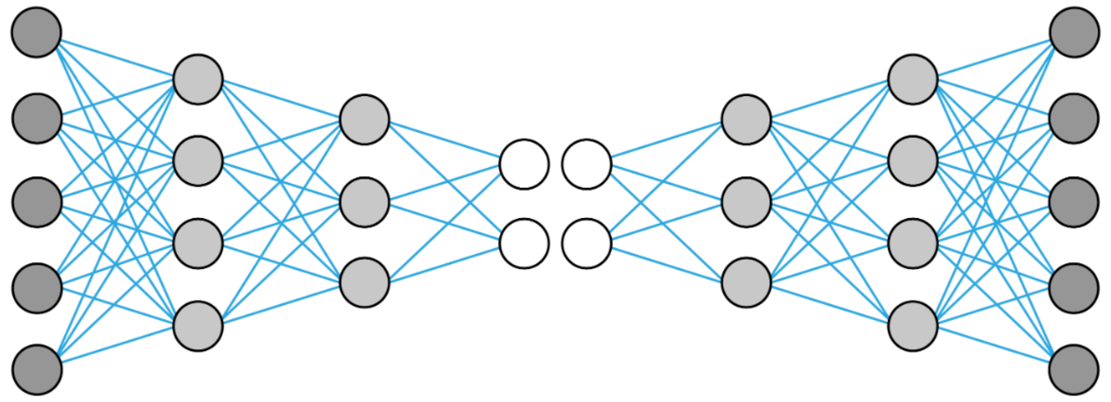
ESRGAN

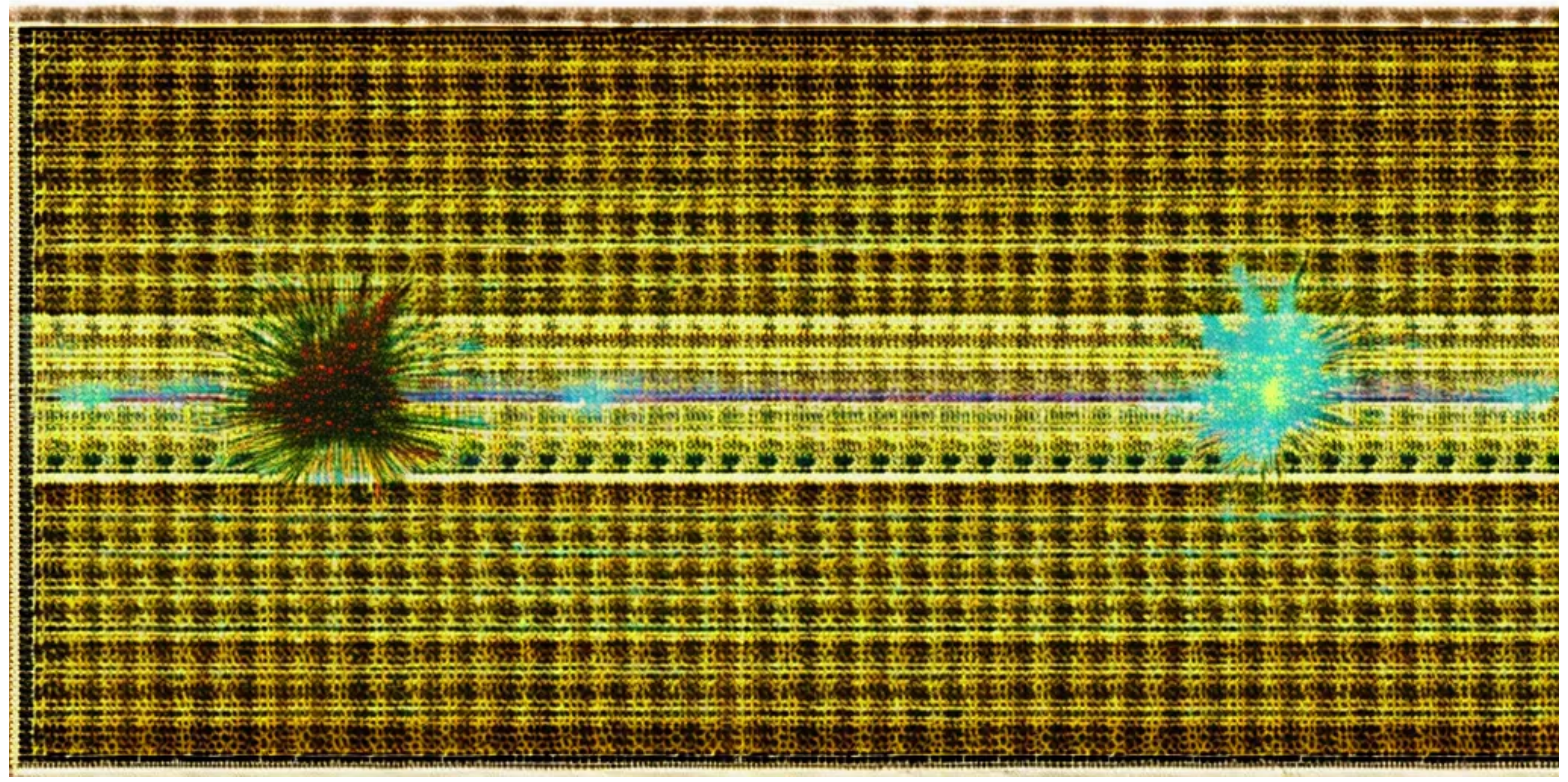
Visualising AI's inabililities



Writing noise into noise (2023)
Eryk Salvaggio



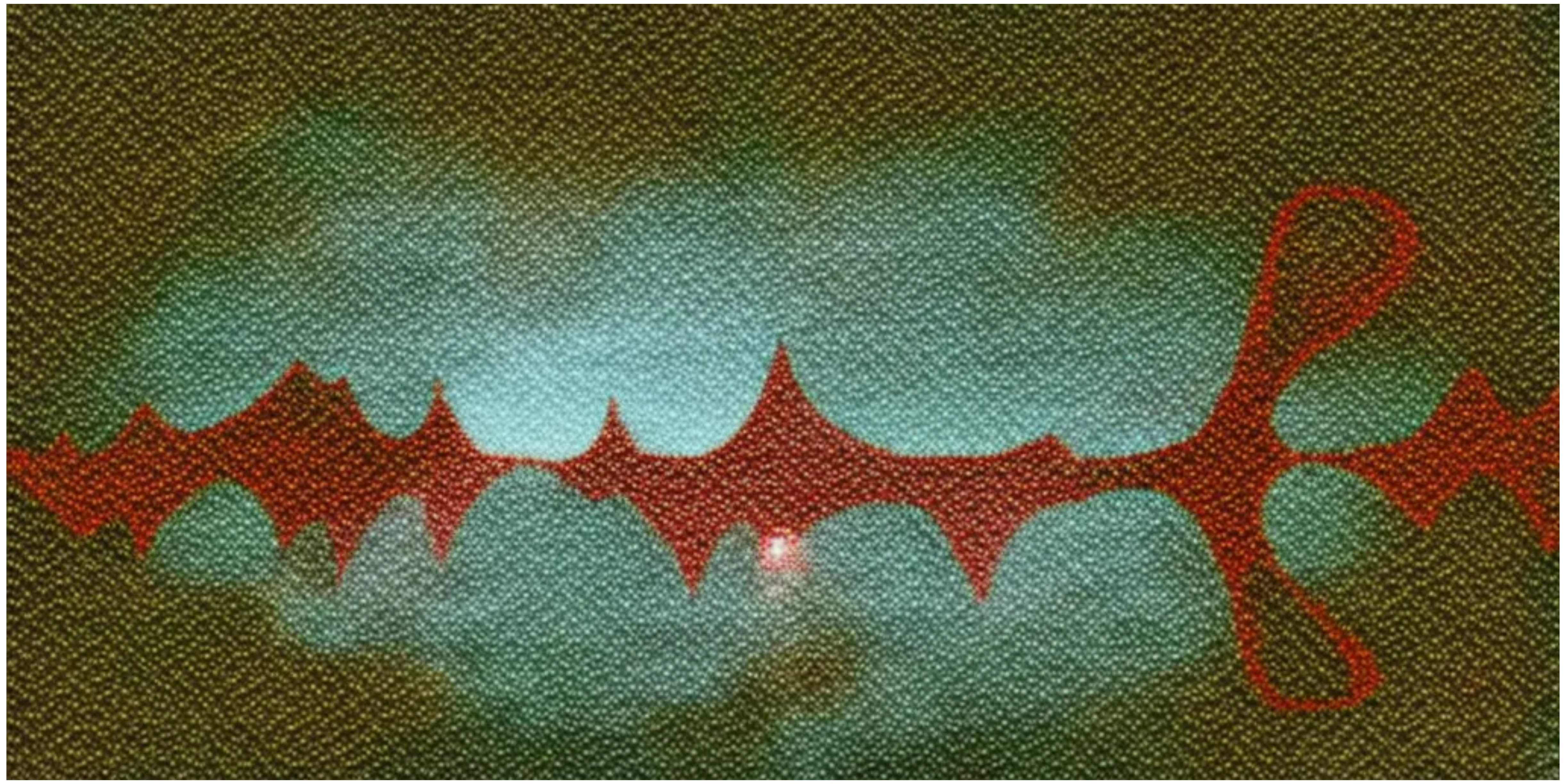
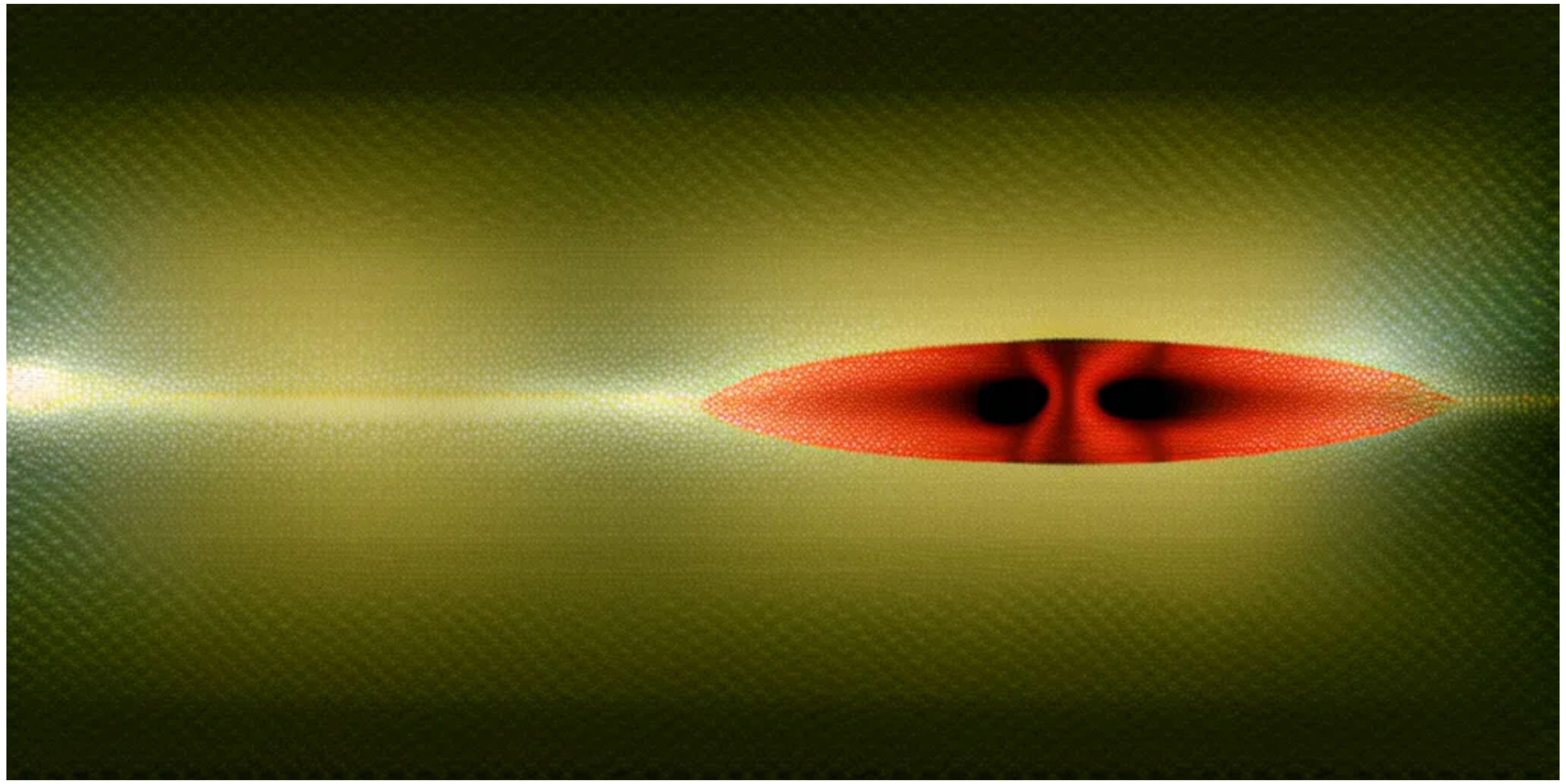
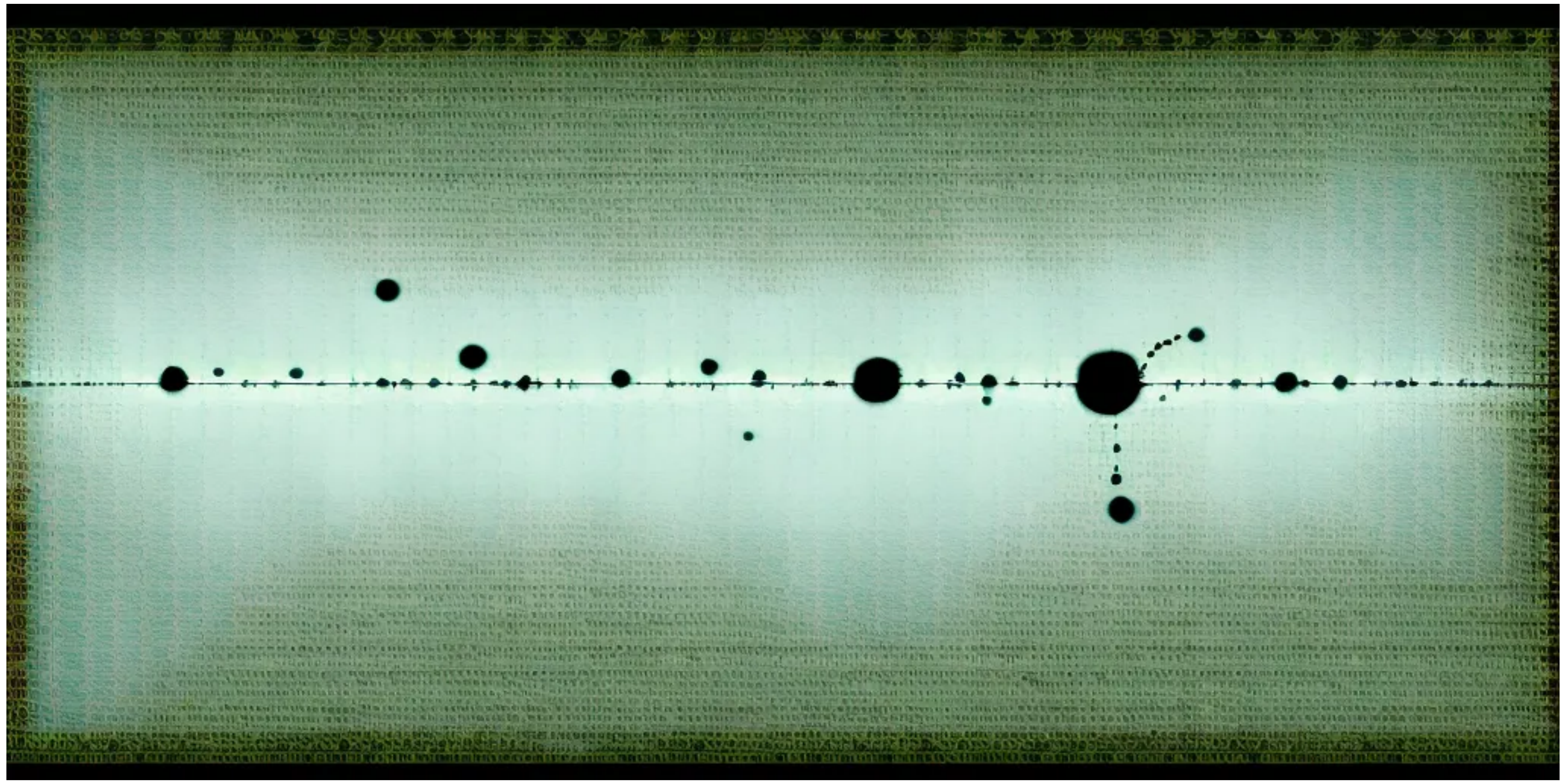
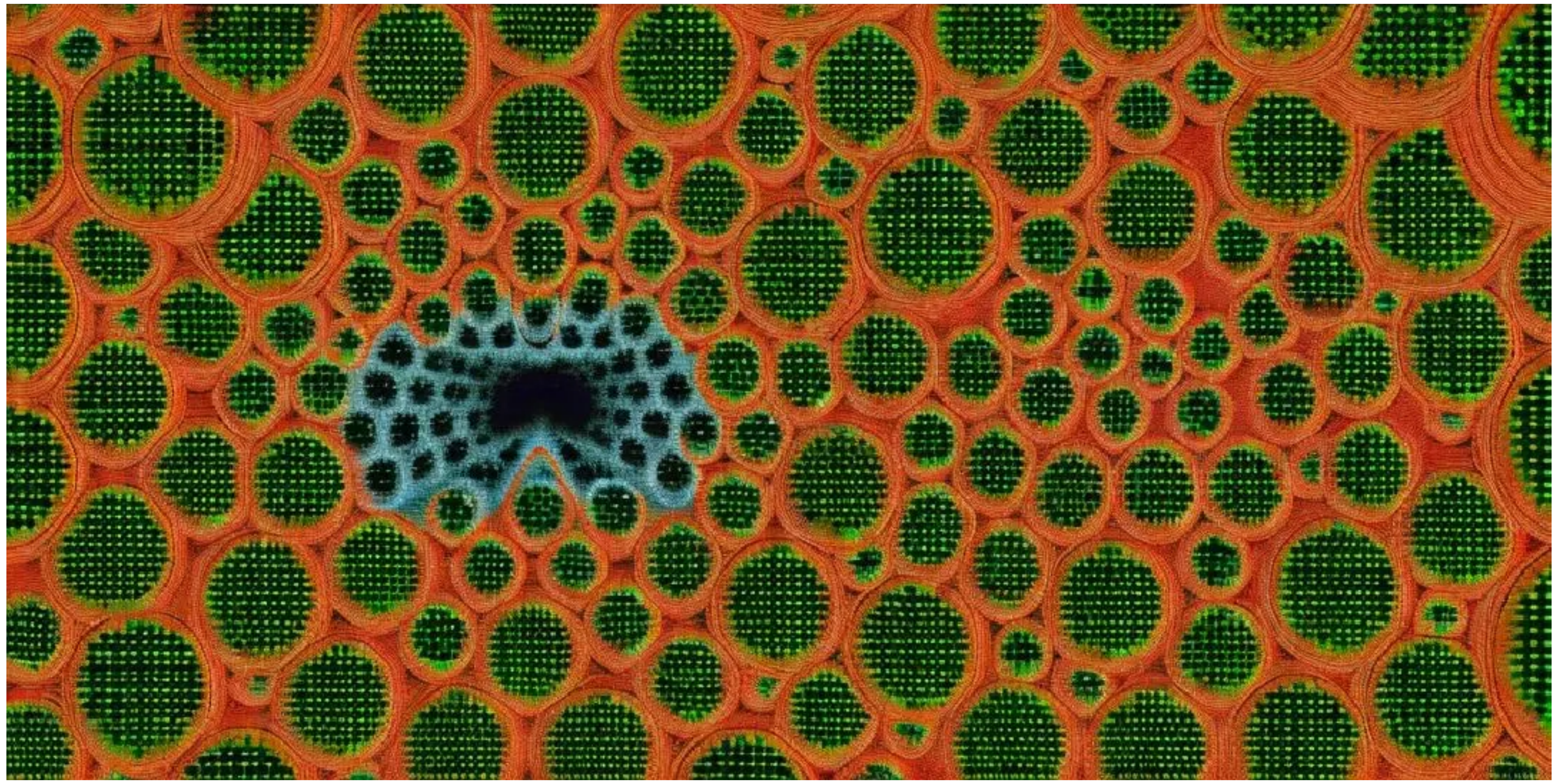




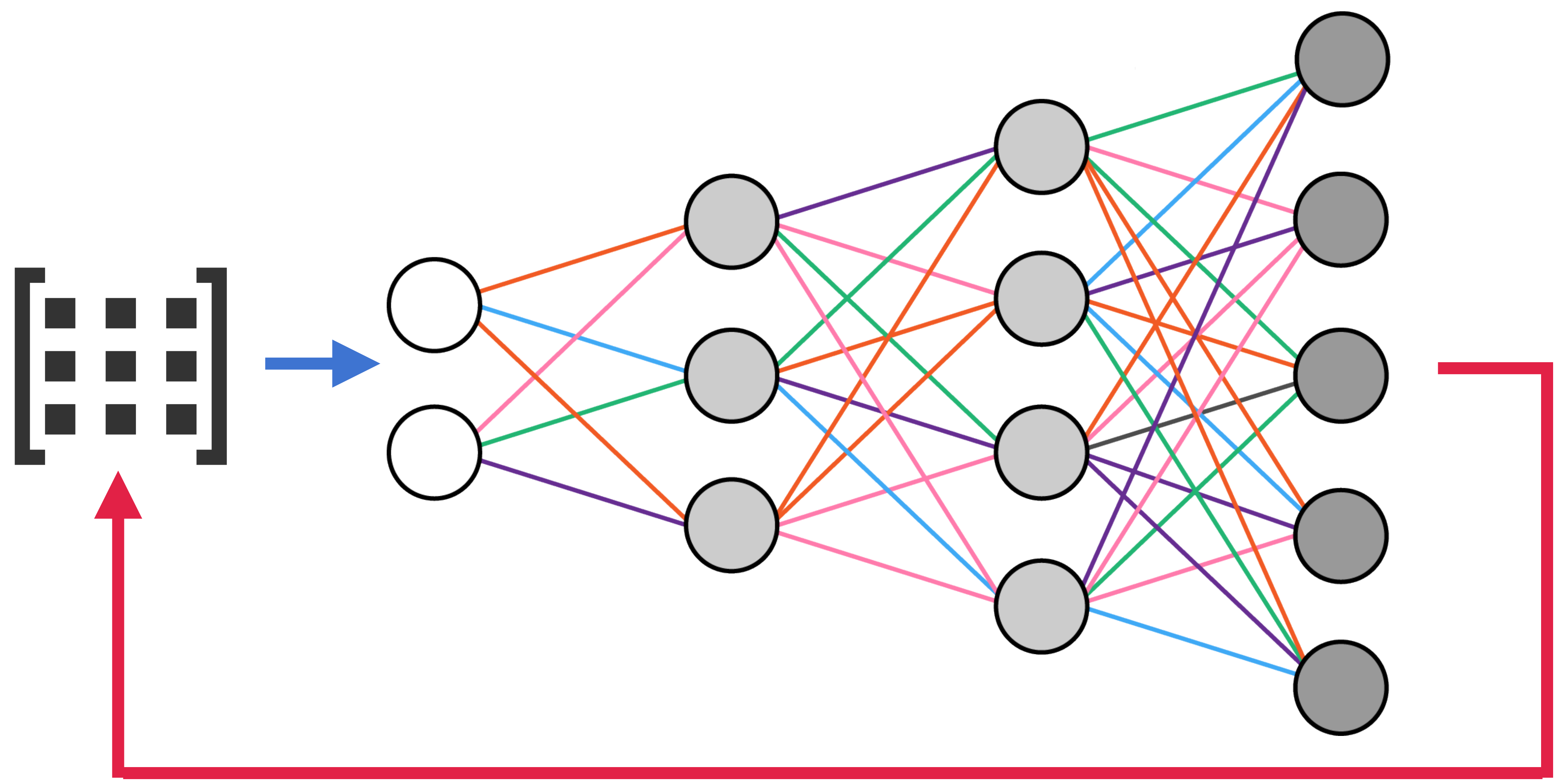
Gaussian noise seed

Denoising diffusion model

Image generated with prompt 'Gaussian noise'

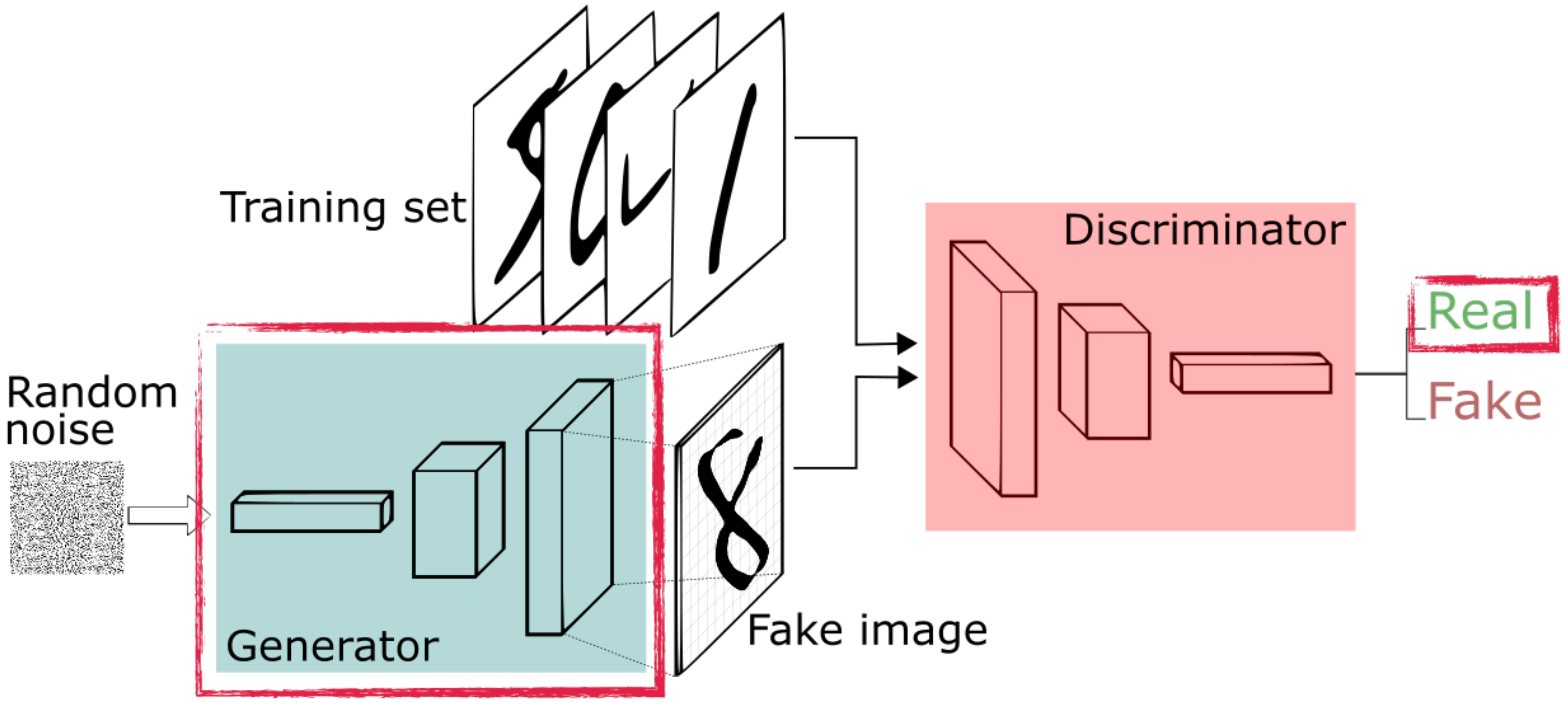
Artistic interventions in training

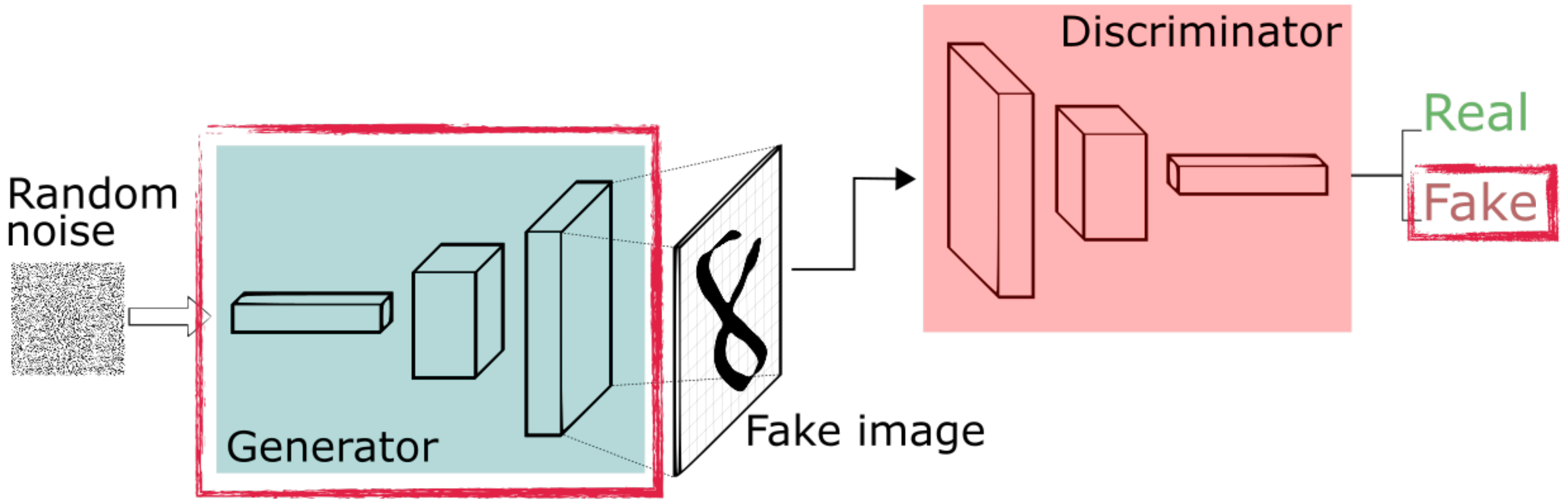


Training away from learned data

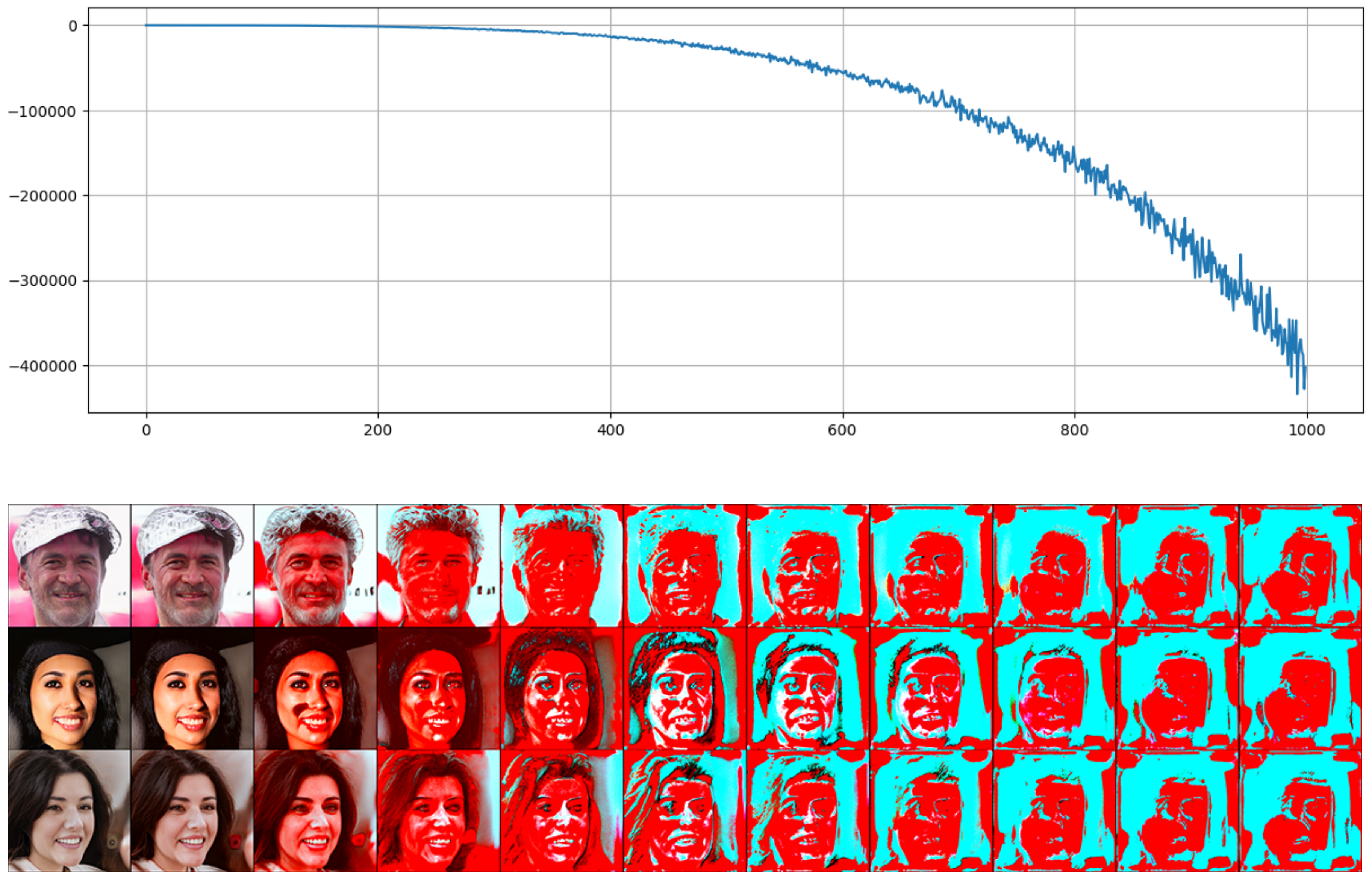
Being Foiled (2019)
Terence Broad

?

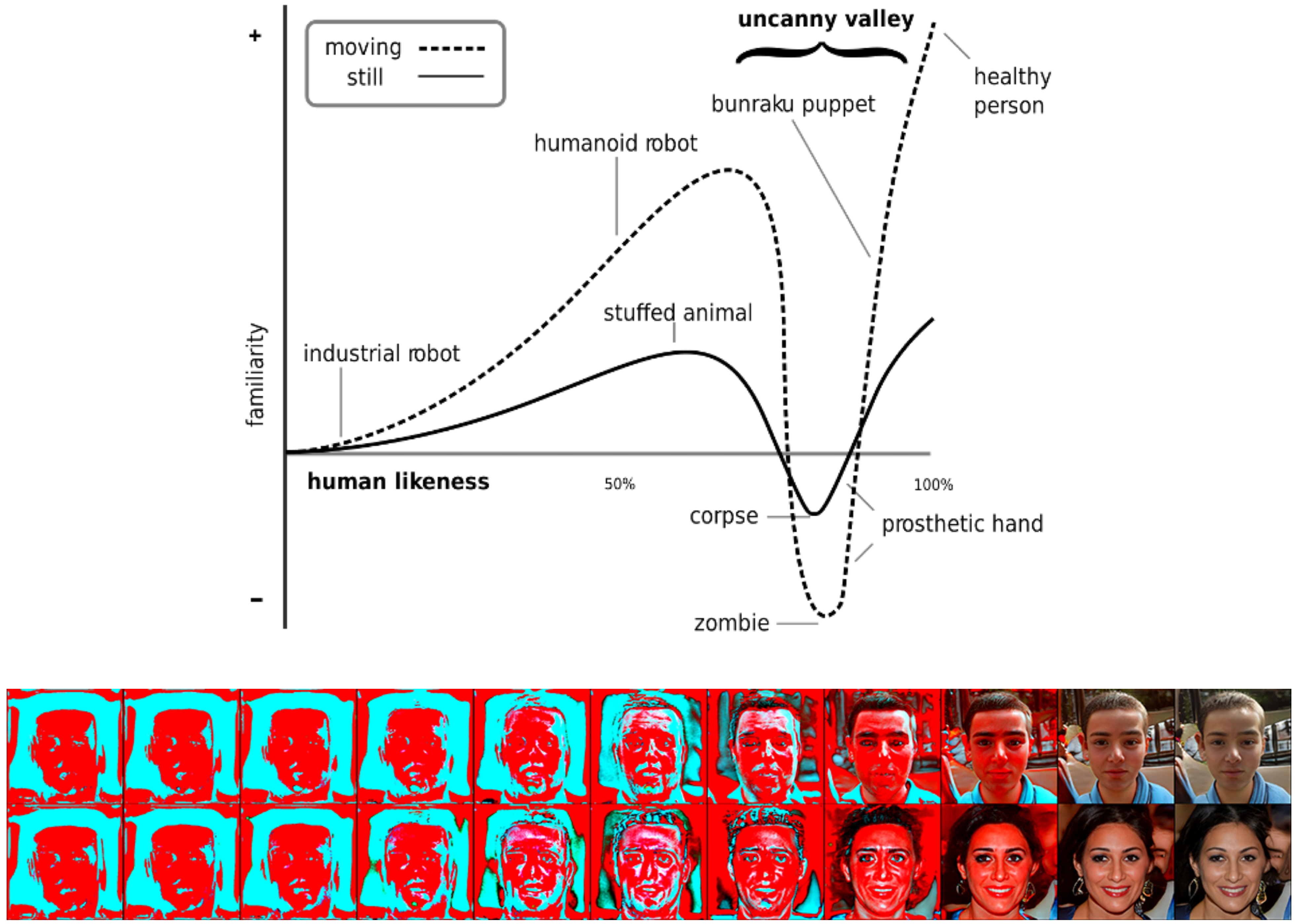




Optimising the generator towards generating ‘fake’ images instead of ‘real’ ones

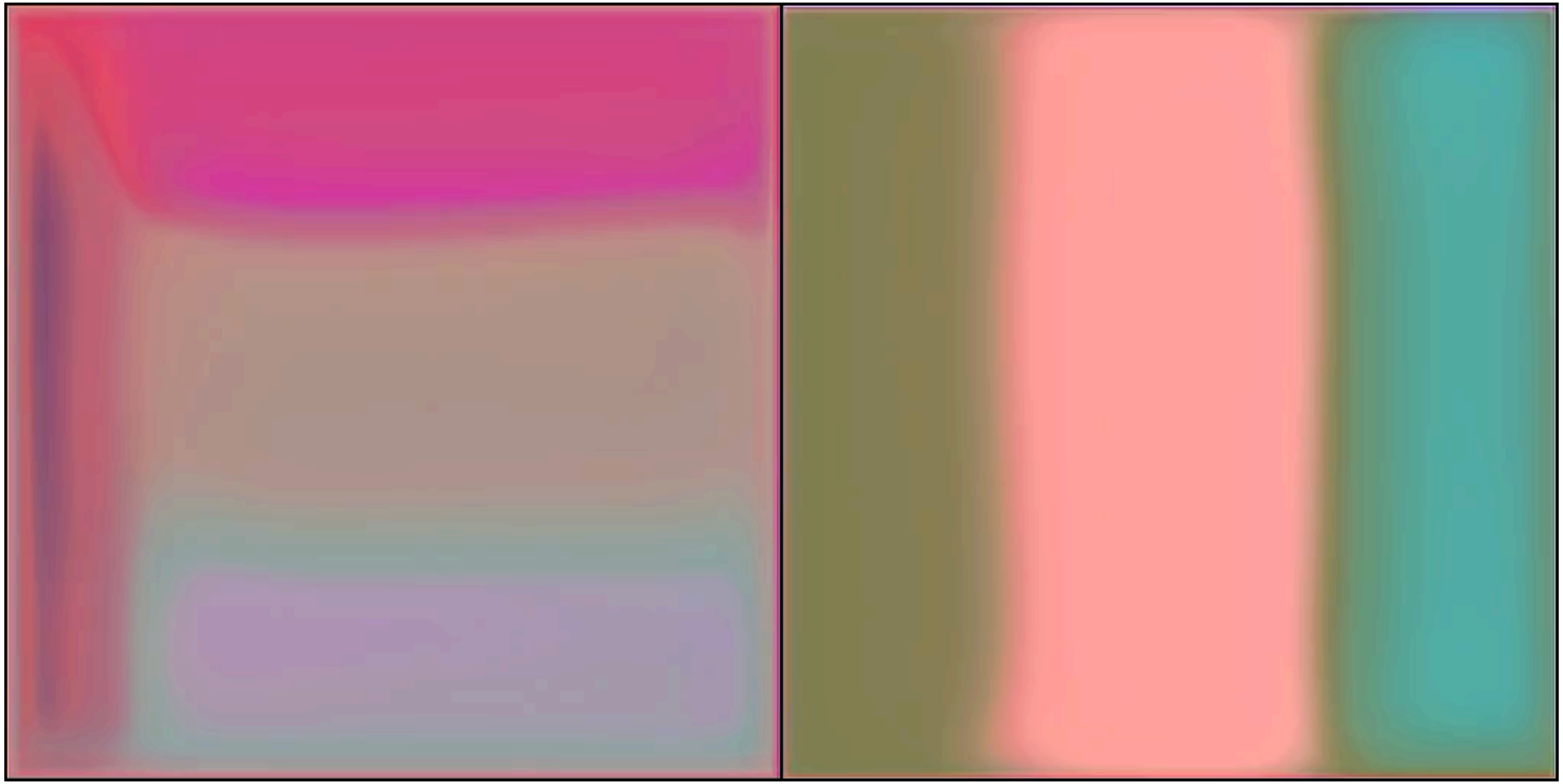


Fine tuning process with inverse loss

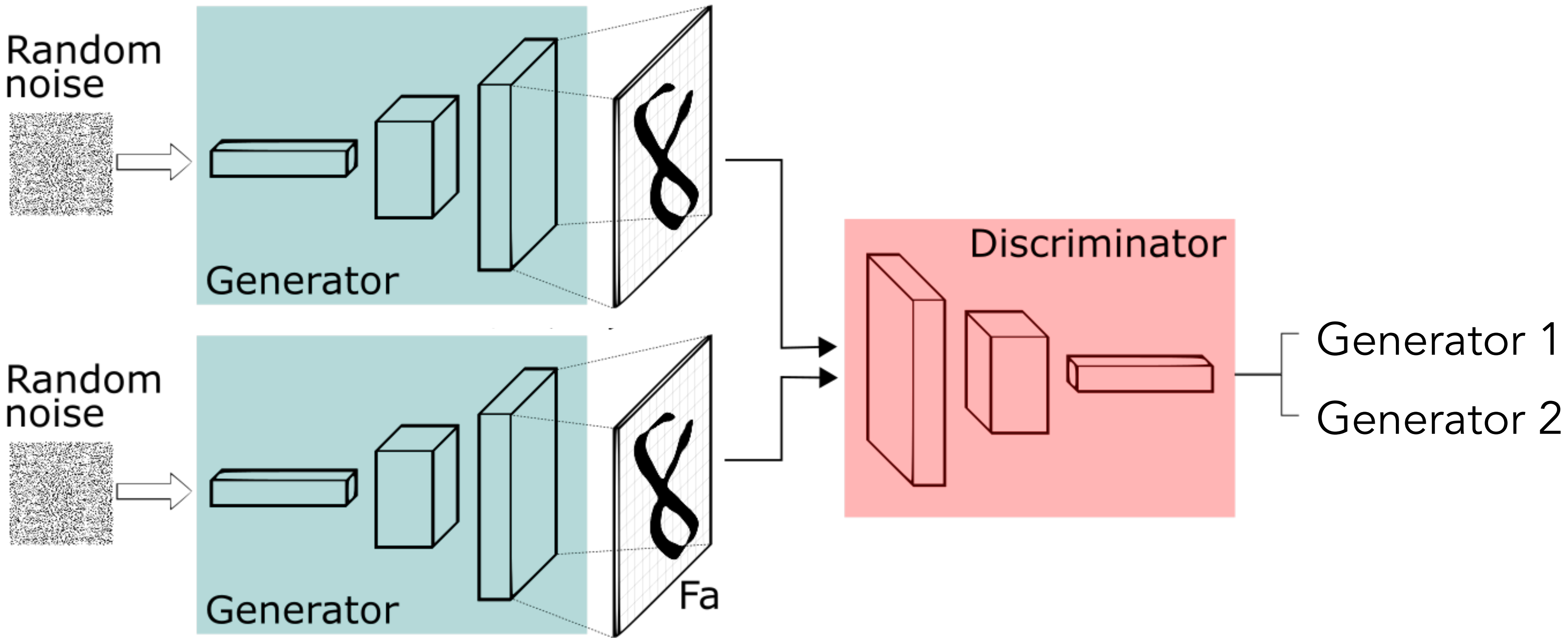


Traversing the uncanny valley

Training without data



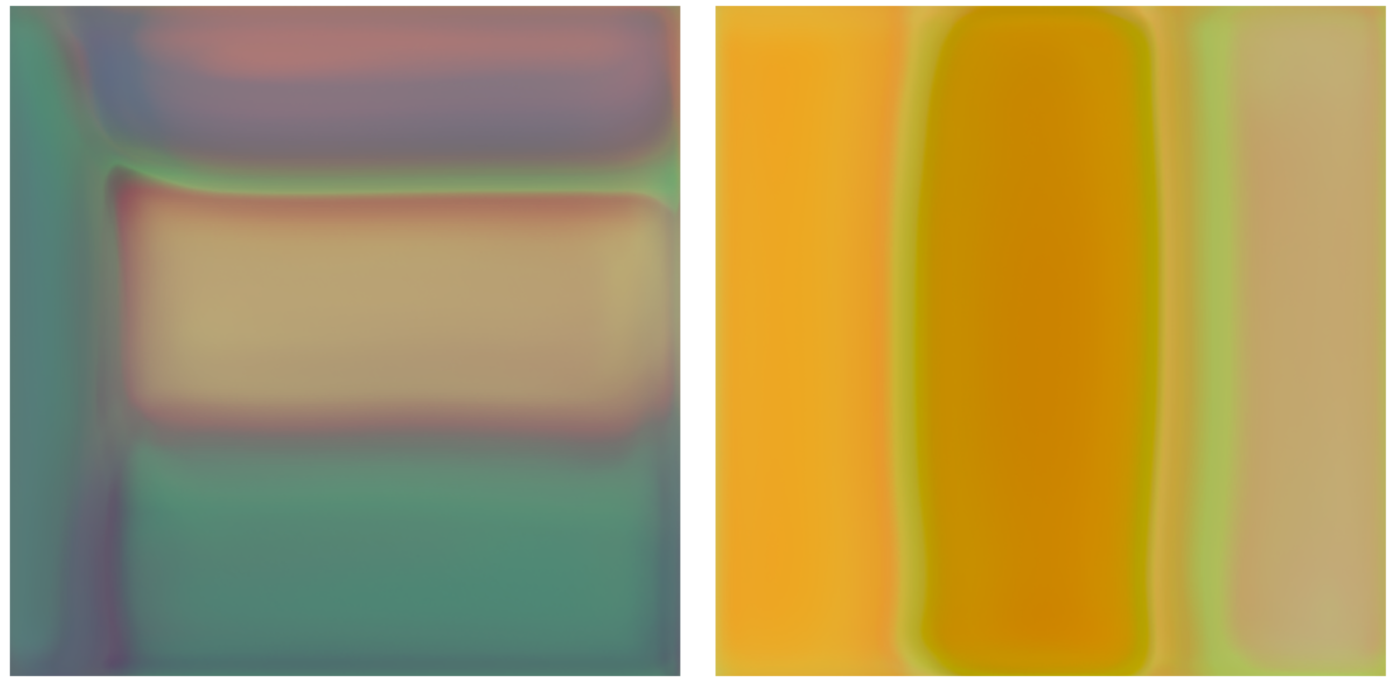
(un)stable equilibrium 1:1 (2019)
Terence Broad



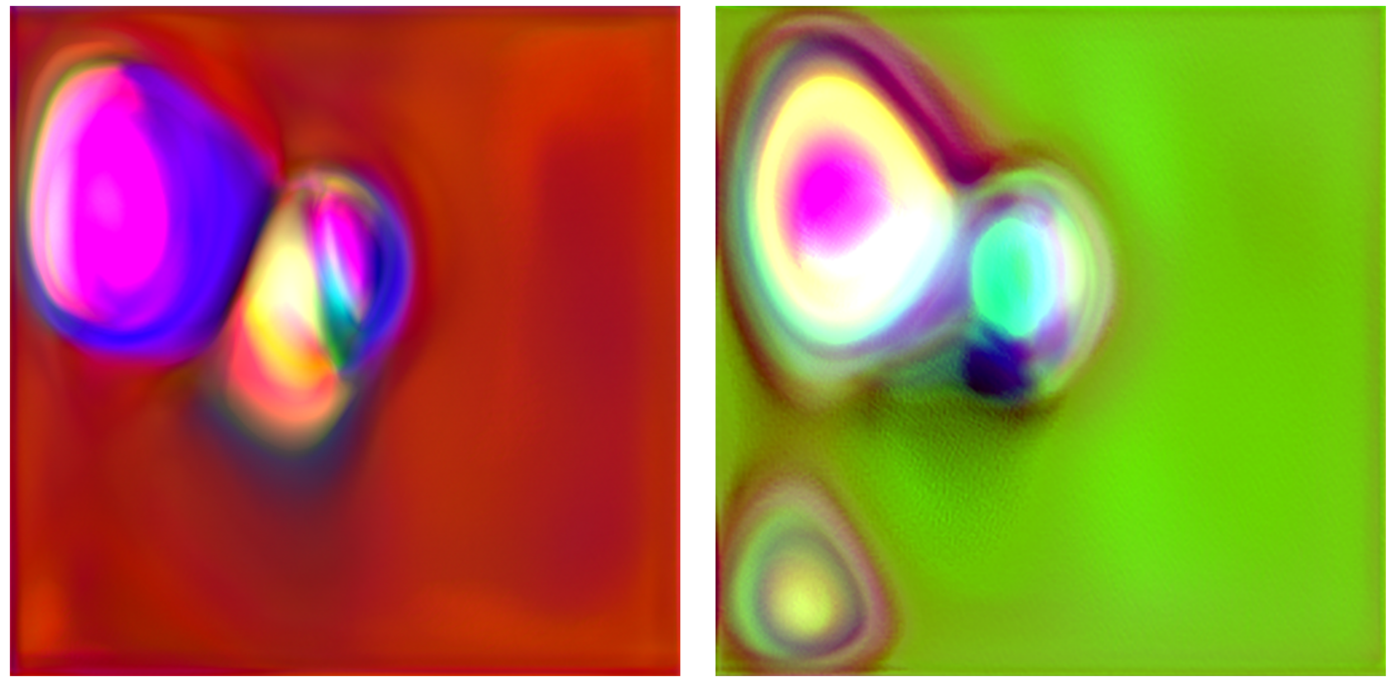
$$+ \, Vdiff = Var(B^{c}_{g_1}) - Var(B^{c}_{g_2})$$

Two generator 'GAN' training regime

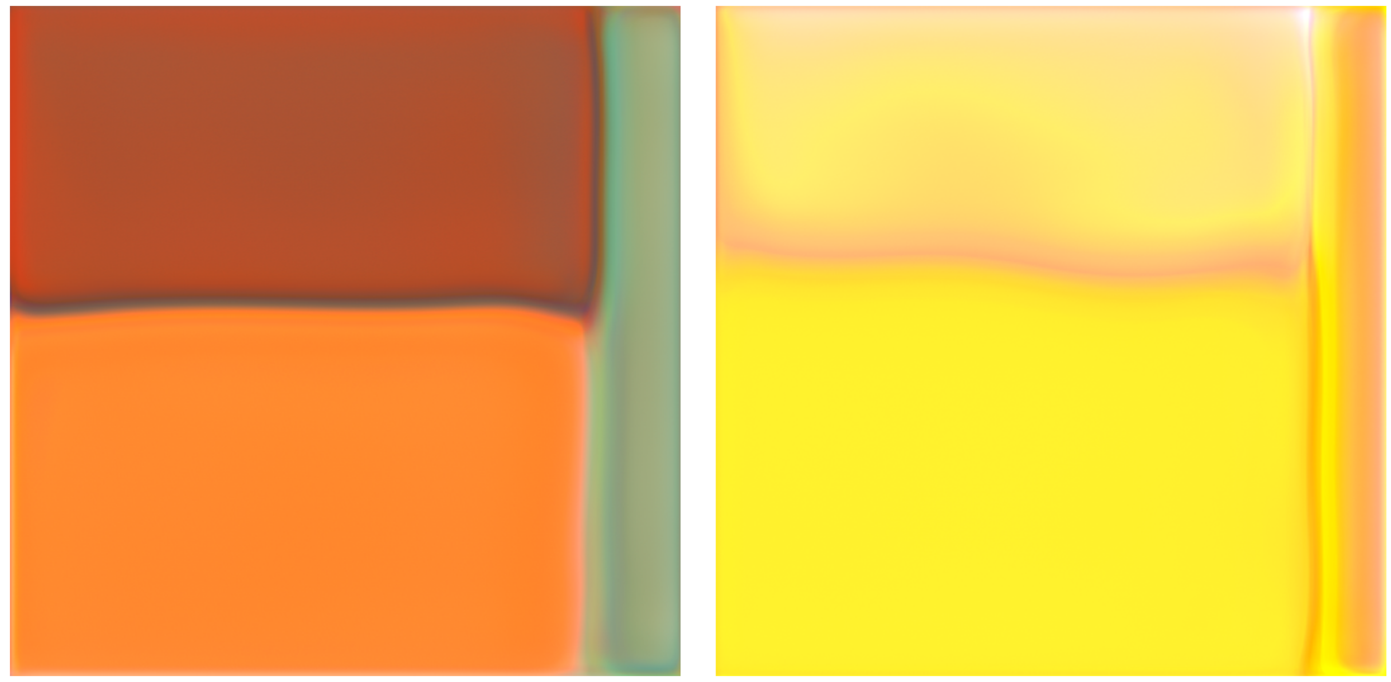
Relative colour variance loss term



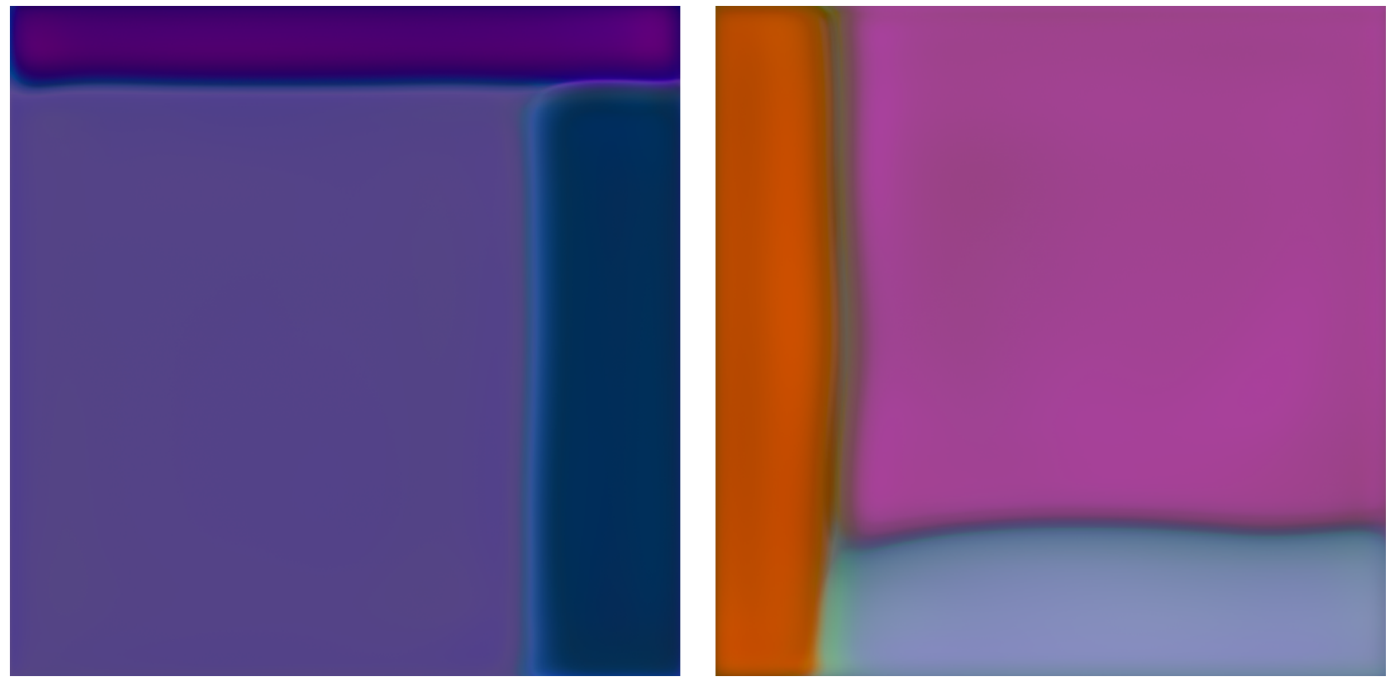
(un)stable equilibrium 1:1



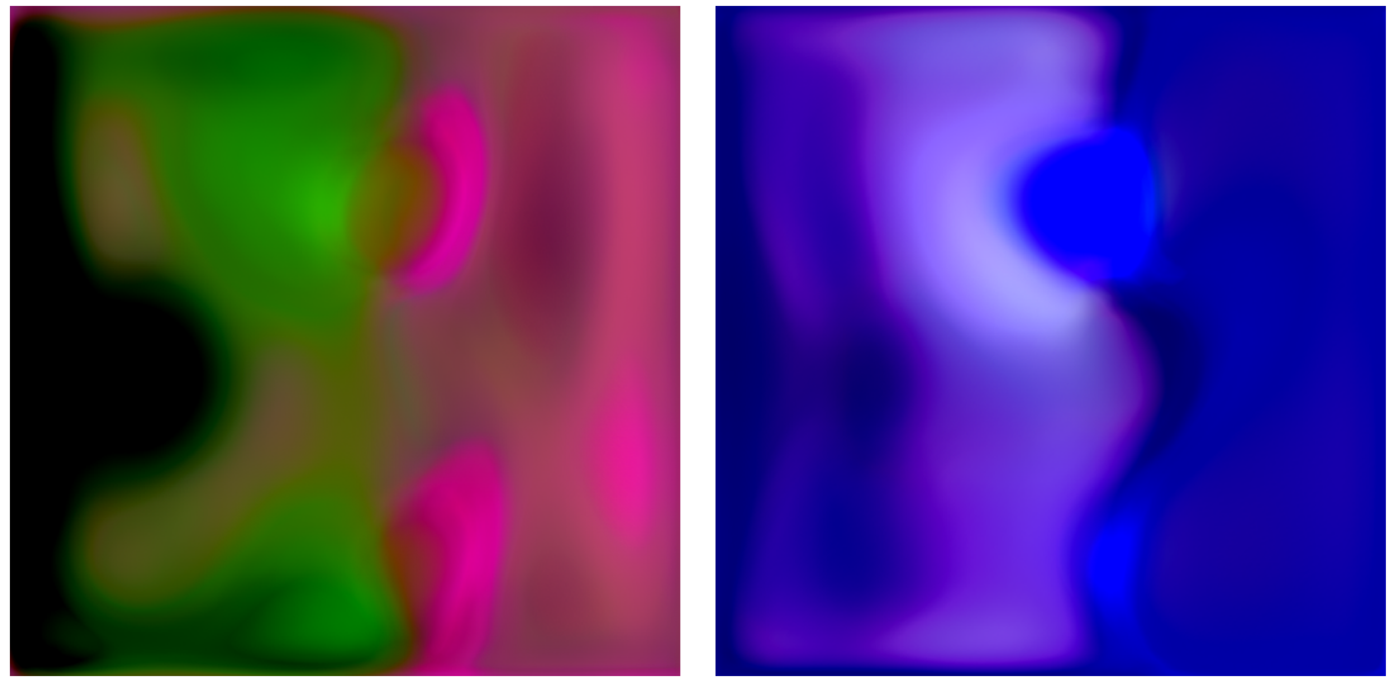
(un)stable equilibrium 1:3



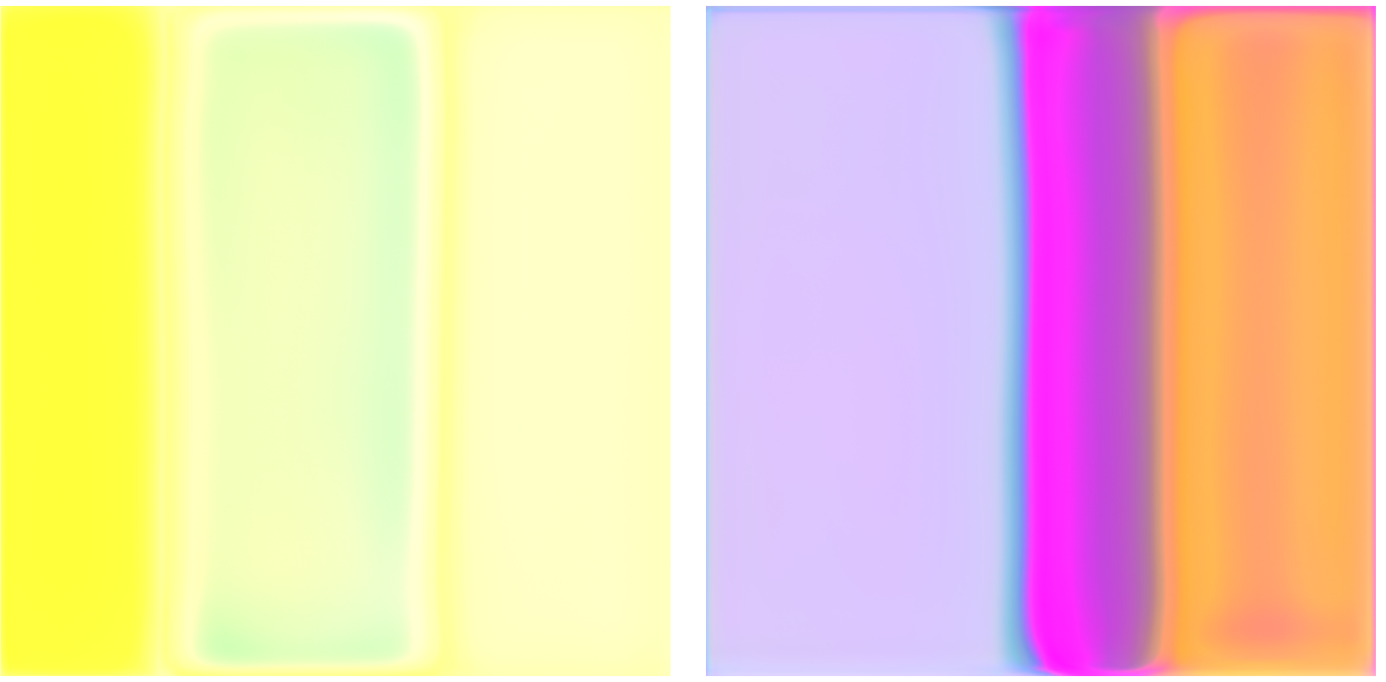
(un)stable equilibrium 1:5



(un)stable equilibrium 1:2



(un)stable equilibrium 1:4



(un)stable equilibrium 1:6

the depot_ digs,
London, 2021

FILE Festival,
Sao Paolo, 2022

TECH / AI

What happens when you feed AI nothing

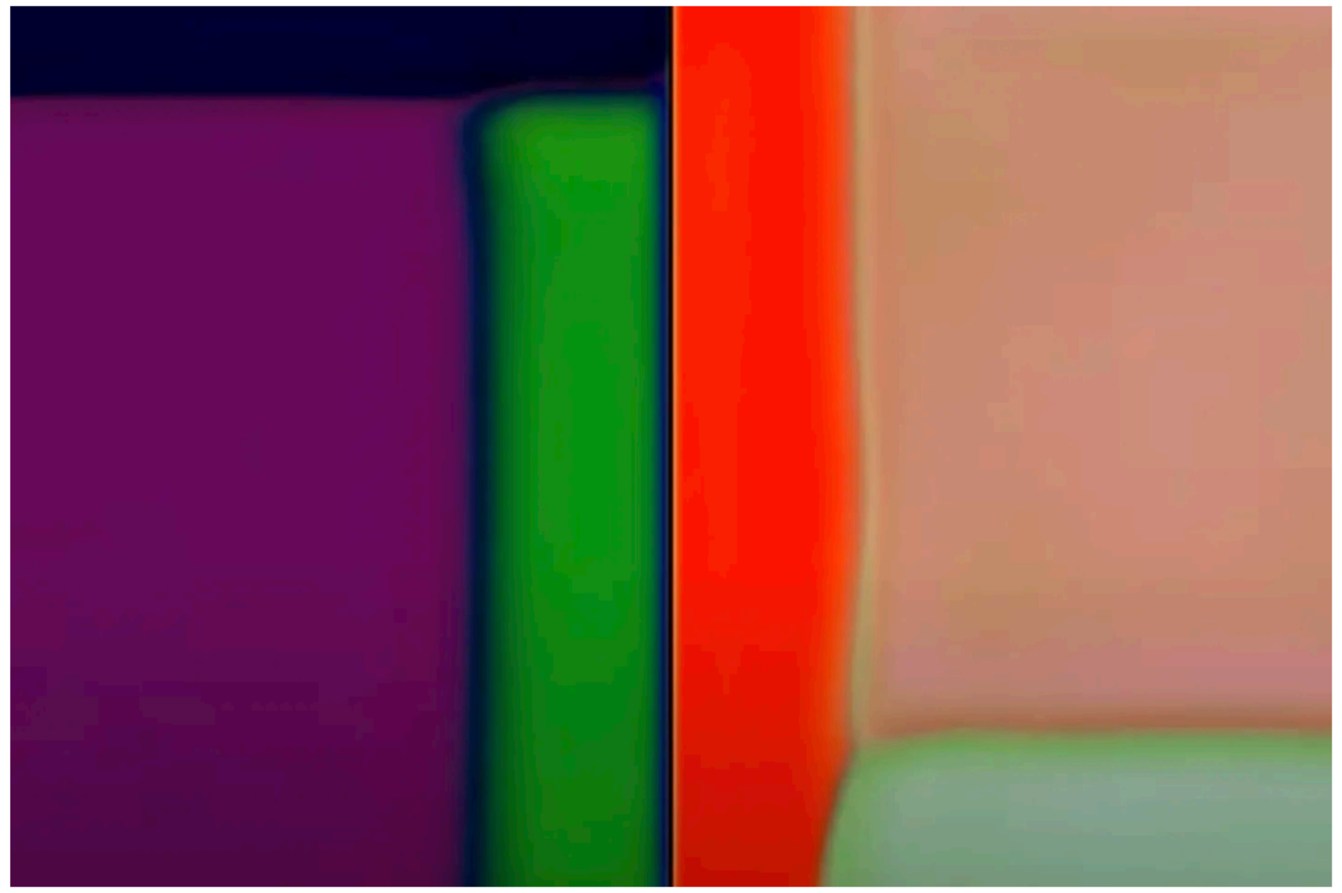


Image: Terence Broad

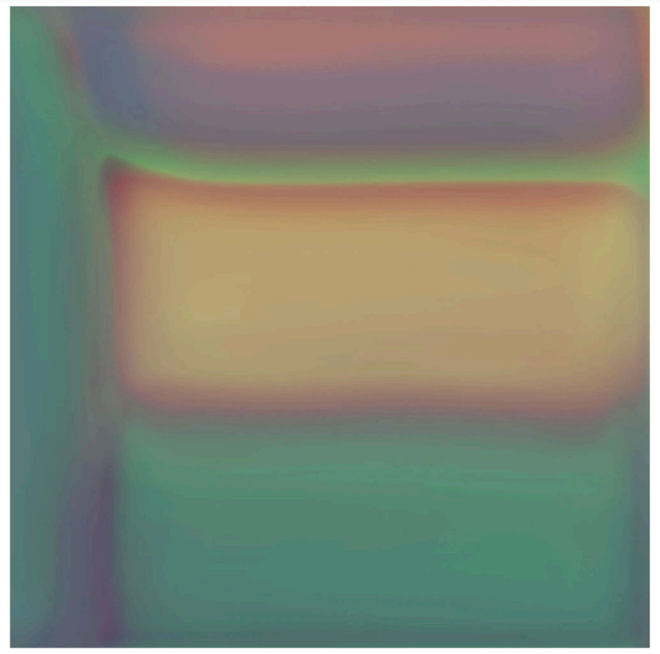
/ Artist Terence Broad makes AI produce images without any training data at all.

by Franklin Schneider
Updated Jun 18, 2025, 4:07 PM GMT+1

14 Comments (14 New)

The Verge (2025)

COURTESY OF TERENCE BROAD



COURTESY OF TERENCE BROAD

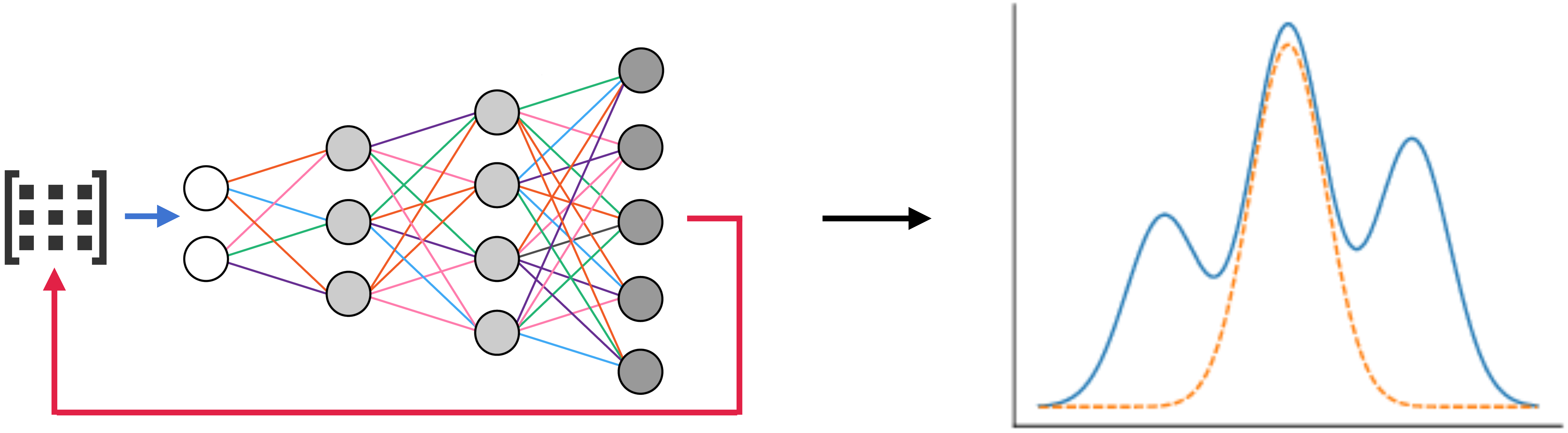
Researcher Terence Broad creates dynamic images using a model trained on no data, which produces almost Rothko-like abstract color fields.

Finding the right balance between surprise and control will be hard, though. Midjourney can surprise, but it gives few levers for controlling what it produces beyond your prompt. Some have claimed that writing prompts is itself a creative act. "But no one struggles with a paintbrush the way they struggle with a prompt," says Cook.

MIT Tech Review (2025)

Training AI on it's own data

Strange Fruit (2020)
Mal Som



Training AI on it’s own generated data leads to mode collapse

Samples from the model on the verge of collapse

The Curse of Recursion: Training on Generated Data Makes Models Forget

Ilia Shumailov* University of Oxford

Zakhar Shumaylov* University of Cambridge

Yiren Zhao Imperial College London

Yarin Gal University of Oxford

Nicolas Papernot University of Toronto & Vector Institute

Ross Anderson University of Cambridge & University of Edinburgh

Abstract

Stable Diffusion revolutionised image creation from descriptive text. `GPT-2`, `GPT-3(.5)` and `GPT-4` demonstrated astonishing performance across a variety of language tasks. `ChatGPT` introduced such language models to the general public. It is now clear that large language models (LLMs) are here to stay, and will bring about drastic change in the whole ecosystem of online text and images. In this paper we consider what the future might hold. What will happen to `GPT-`$\{n\}$ once LLMs contribute much of the language found online? We find that use of model-generated content in training causes irreversible defects in the resulting models, where tails of the original content distribution disappear. We refer to this effect as *model collapse*[1] and show that it can occur in Variational Autoencoders, Gaussian Mixture Models and LLMs. We build theoretical intuition behind the phenomenon and portray its ubiquity amongst all learned generative models. We demonstrate that it has to be taken seriously if we are to sustain the benefits of training from large-scale data scraped from the web. Indeed, the value of data collected about genuine human interactions with systems will be increasingly valuable in the presence of content generated by LLMs in data crawled from the Internet.

1 Introduction

A lot of human communication happens online. Billions of emails are exchanged daily, along with billions of social-media messages and millions of news articles. Almost all of this material was produced and curated only by humans in the early years of the worldwide web, yet since the turn of the century search engines have come to determine what people can find, and in the past decade smart text editors with spelling and grammar correction have helped tweak what we produce. Now, text can not only be groomed and analysed efficiently; it can also be generated – by large language models (LLMs). These models now (arguably) pass a weaker form of the Turing test in the sense that their output cannot be reliably distinguished from text written by humans [Solaiman et al., 2019].

The development of LLMs is quite involved and requires masses of training data. Anecdotally, some powerful recent models are trained using scrapes of much of the Internet, then further fine-tuned with reinforcement learning from human feedback (RLHF) [Griffith et al., 2013, OpenAI, 2023]. This further boosts the effective dataset size. Yet while current LLMs [Devlin et al., 2018, Liu et al., 2019, Brown et al., 2020, Zhang et al., 2022], including `GPT-4`, were trained on predominantly human-generated text, this may change in the future. If most future models' training data is also scraped from the web, then they will inevitably come to train on data produced by their predecessors. In this paper, we investigate what happens when text produced, *e.g.* by a version of `GPT`, forms most of the training dataset of following models. What happens to `GPT` versions `GPT-`$\{n\}$ as generation n increases?[2]

[1] The name is inspired by the Generative Adversarial Networks (GAN) literature on mode collapse, where GANs start producing a limited set of outputs that all trick the discriminator. *Model Collapse* is a process whereby models eventually converge to a state similar to that of a GAN Mode Collapse. The original version of this paper referred to this effect as 'model dementia', but we decided to change this following feedback that it trivialised the medical notion of 'dementia' and could cause offence.

[2] This is not limited to text models; one can also consider what happens when music created by human composers and played by human musicians trains models whose output trains other models.

Self-Consuming Generative Models Go MAD

Sina Alemohammad,[*,†] Josue Casco-Rodriguez,[*,†] Lorenzo Luzi,[†] Ahmed Imtiaz Humayun,[†] Hossein Babaei,[†] Daniel LeJeune,[‡] Ali Siahkoohi,[§] Richard G. Baraniuk[†]

[†] Department of Electrical and Computer Engineering, Rice University

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Abstract

Seismic advances in generative AI algorithms for imagery, text, and other data types has led to the temptation to use synthetic data to train next-generation models. Repeating this process creates an autophagous ("self-consuming") loop whose properties are poorly understood. We conduct a thorough analytical and empirical analysis using state-of-the-art generative image models of three families of autophagous loops that differ in how fixed or fresh real training data is available through the generations of training and in whether the samples from previous-generation models have been biased to trade off data quality versus diversity. Our primary conclusion across all scenarios is that *without enough fresh real data in each generation of an autophagous loop, future generative models are doomed to have their quality (precision) or diversity (recall) progressively decrease.* We term this condition Model Autophagy Disorder (MAD), making analogy to mad cow disease.

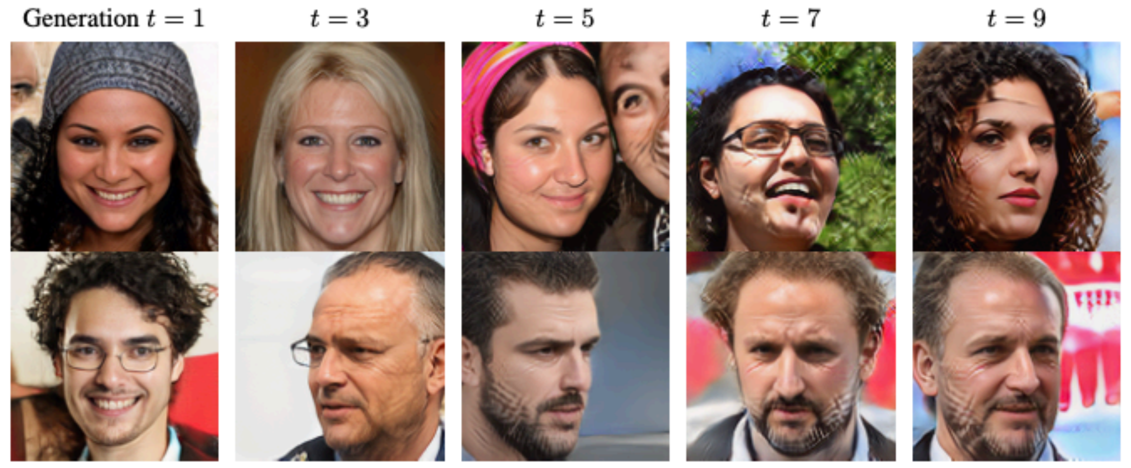

Figure 1: **Training generative artificial intelligence (AI) models on synthetic data progressively amplifies artifacts.** As synthetic data from generative models proliferates on the Internet and in standard training datasets, future models will likely be trained on some mixture of real and synthetic data, forming an *autophagous ("self-consuming") loop*. Here we highlight one potential unintended consequence of autophagous training. We trained a succession of StyleGAN-2 [1] generative models such that the training data for the model at generation $t \geq 2$ was obtained by synthesizing images from the model at generation $t - 1$. This particular setup corresponds to a fully synthetic loop in Figure 3. Note how the cross-hatched artifacts (possibly an architectural *fingerprint*) are progressively amplified in each new generation. Additional samples are provided Appendices C and D.

[*] Equal contribution.

Combining Generative Artificial Intelligence (AI) and the Internet: Heading towards Evolution or Degradation?

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March 3, 2023

Abstract

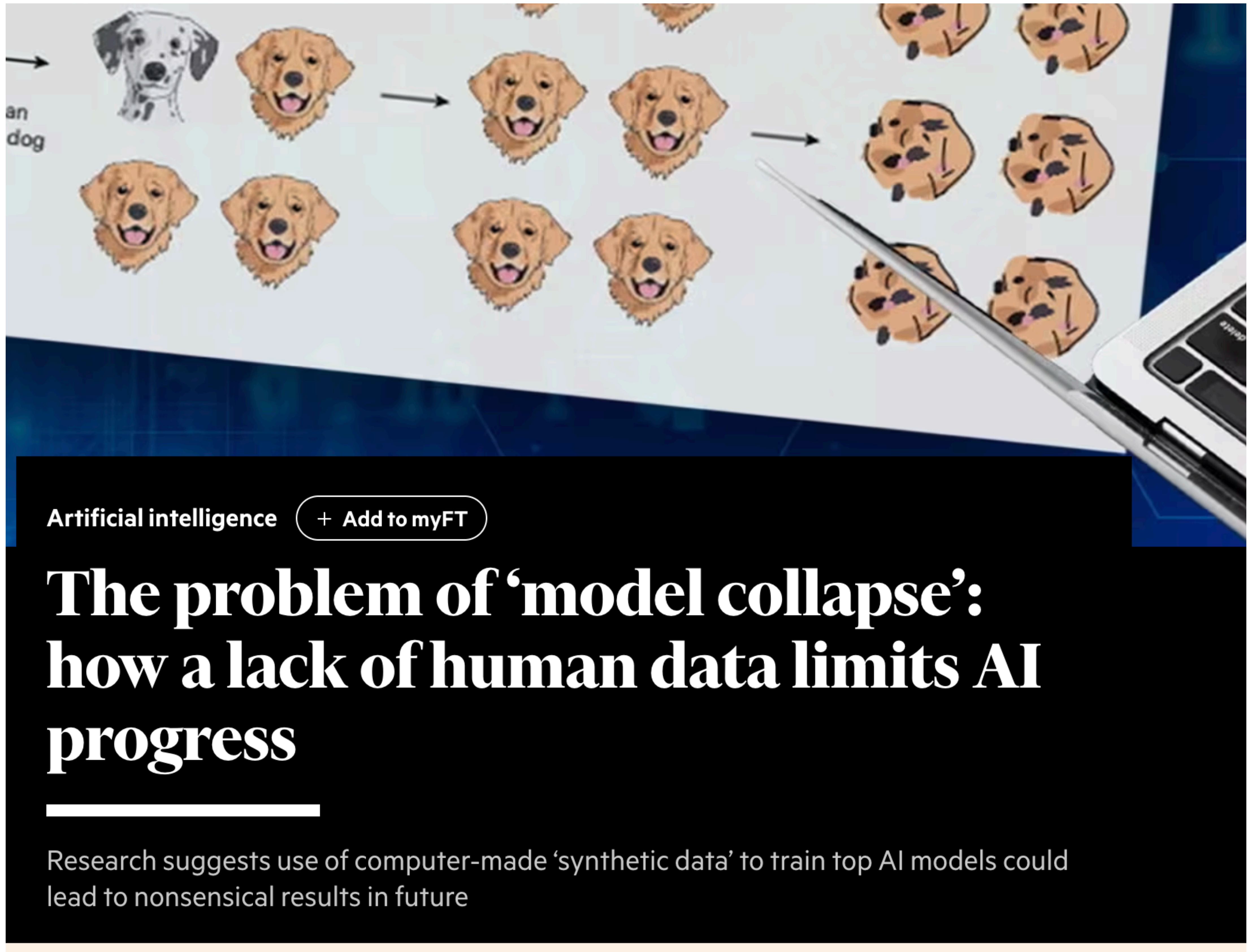
In the span of a few months, generative Artificial Intelligence (AI) tools that can generate realistic images or text have taken the Internet by storm, making them one of the technologies with fastest adoption ever. Some of these generative AI tools such as DALL-E, MidJourney, or ChatGPT have gained wide public notoriety. Interestingly, these tools are possible because of the massive amount of data (text and images) scraped from Internet sites. Now, these generative AI tools are creating massive amounts of new data that are being fed into the Internet. Therefore, future versions of generative AI tools will be trained with Internet data that is a mix of original and AI-generated data. As time goes on, increasing volumes of data generated by different versions of AI will populate the Internet.

This raises a few intriguing questions: how will future versions of generative AI tools behave when trained on a mixture of real and AI generated data? Will they evolve and improve with the new data sets or degenerate? Will evolution introduce biases in subsequent generations of generative AI tools? In this document, we explore these questions and report some initial simulation results using a simple image-generation AI tool. These results suggest that the quality of the generated images degrades as more AI-generated data is used for training thus suggesting that generative AI may degenerate. Although these results are preliminary and cannot be generalised without further study, they serve to illustrate the potential issues of the interaction between generative AI and the Internet.

1 Introduction

Traditional applications of Artificial Intelligence (AI) have focused on the detection or classification of objects, for example detecting pedestrians in the images captured by in-vehicle cameras [1] or classifying the results of a medical

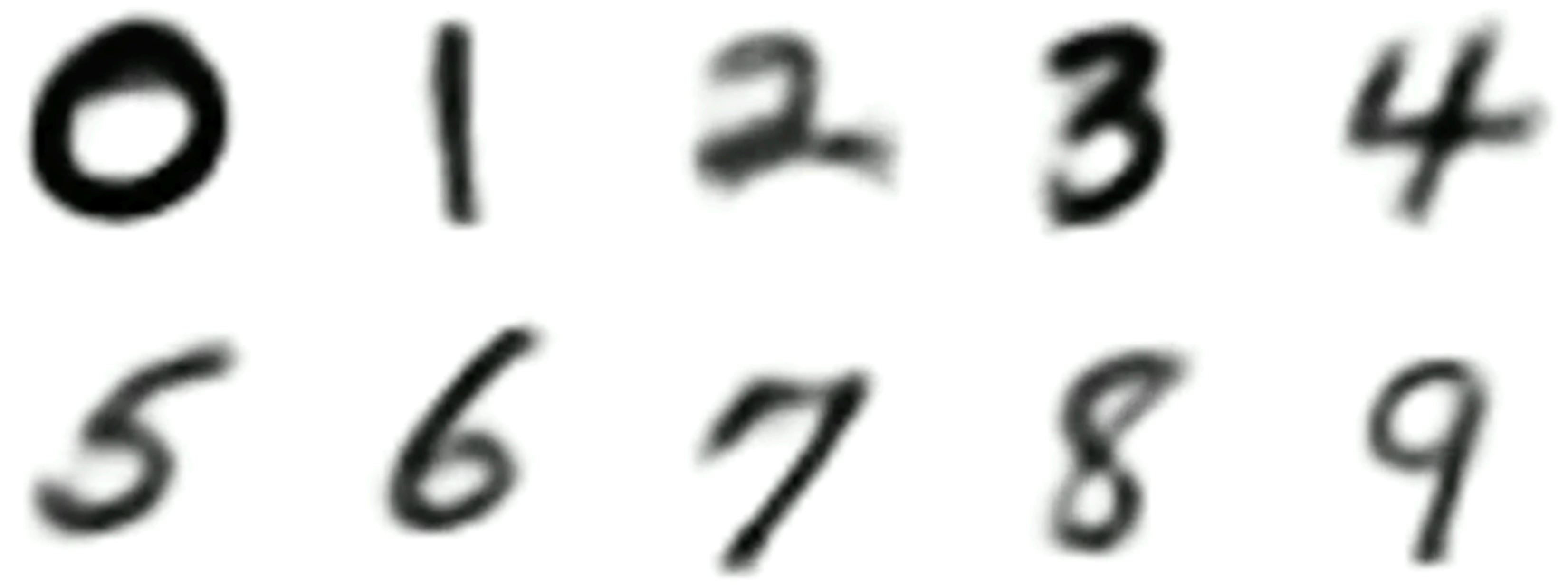
Papers in 2023 that show the same phenomena



Artificial intelligence | + Add to myFT

The problem of 'model collapse': how a lack of human data limits AI progress

Research suggests use of computer-made 'synthetic data' to train top AI models could lead to nonsensical results in future



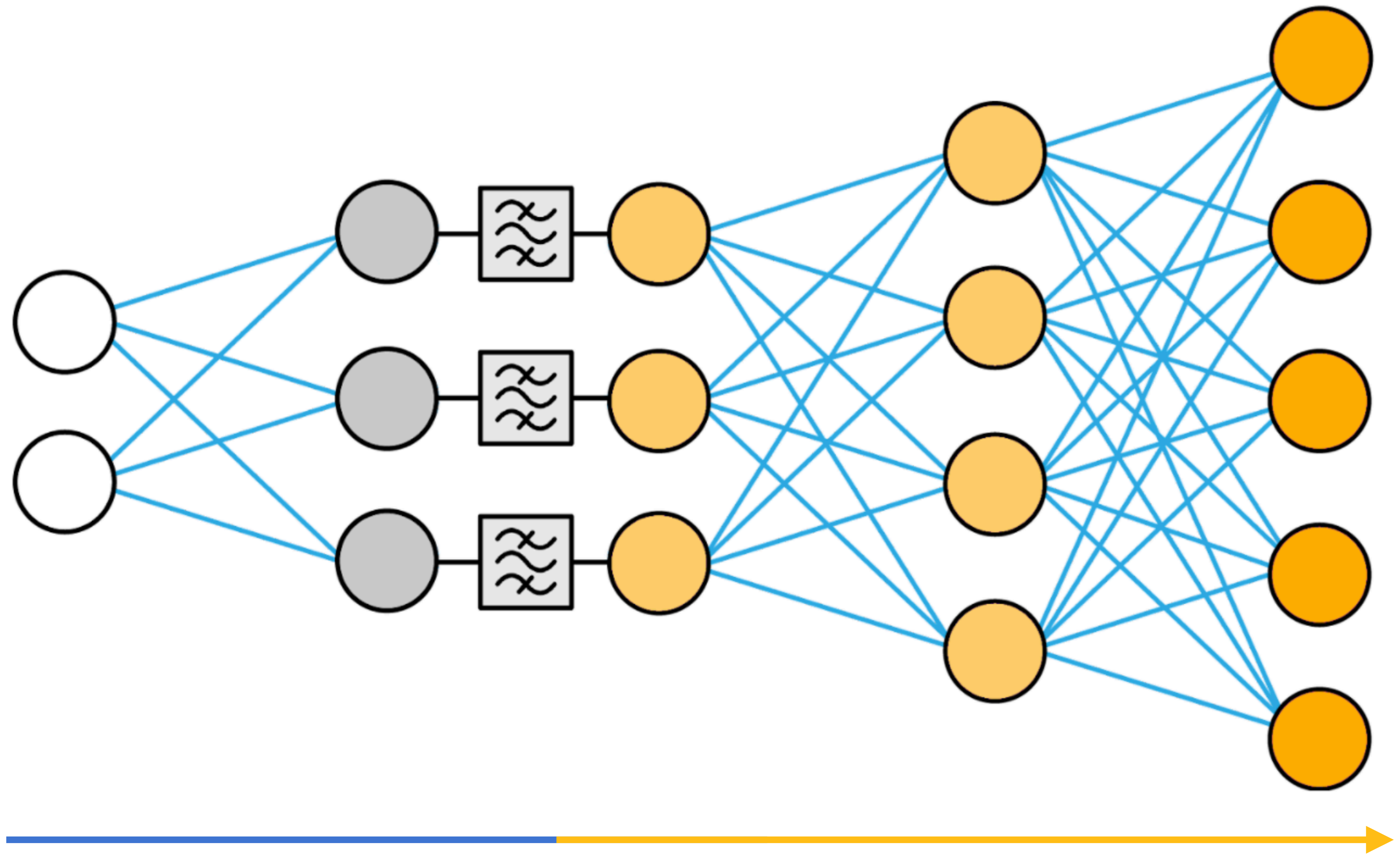
TheUpshot

When A.I.'s Output Is a Threat to A.I. Itself

As A.I.-generated data becomes harder to detect, it's increasingly likely to be ingested by future A.I., leading to worse results.

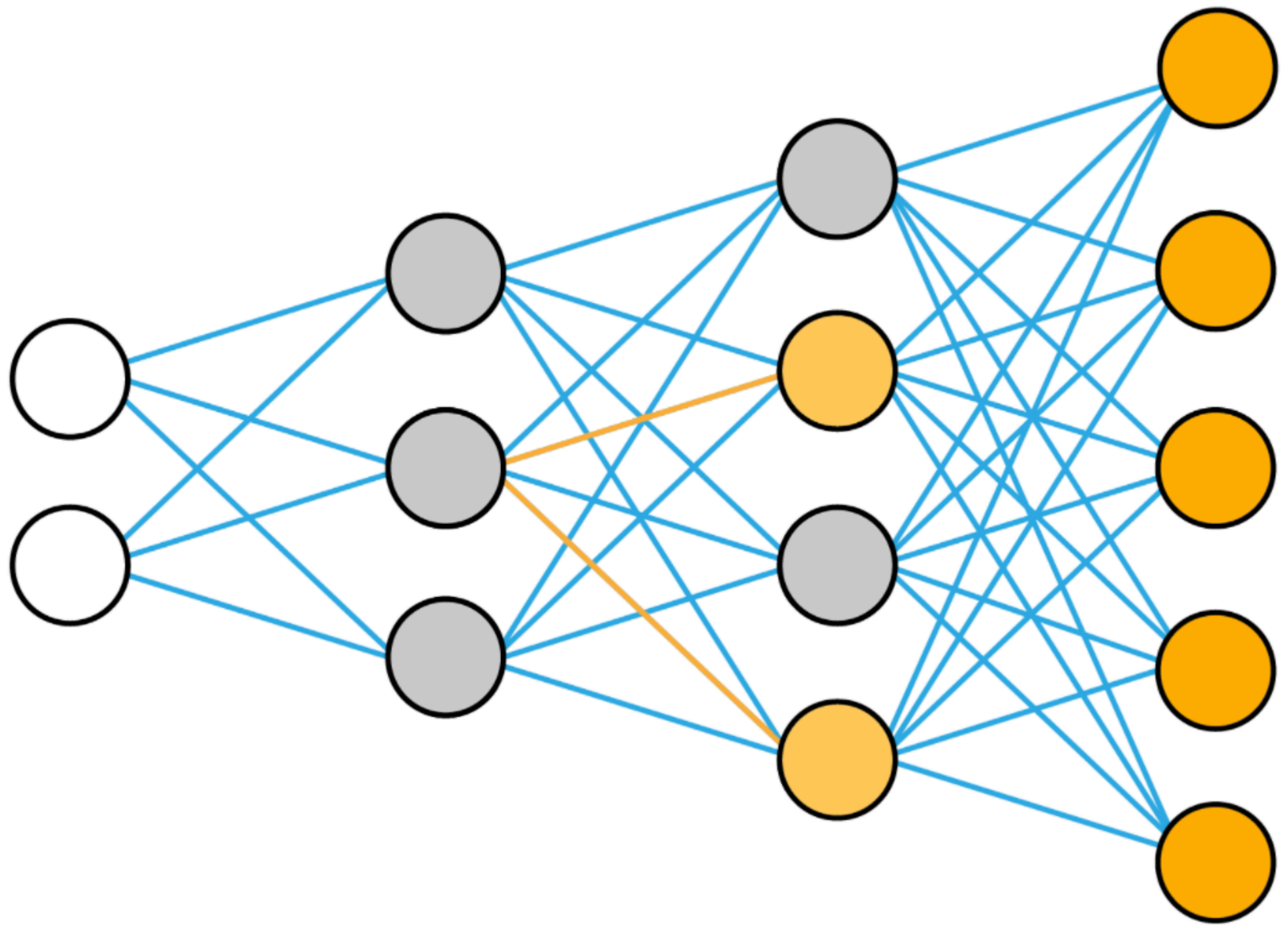
News articles in 2024 about this phenomenon

Artistic interventions after training

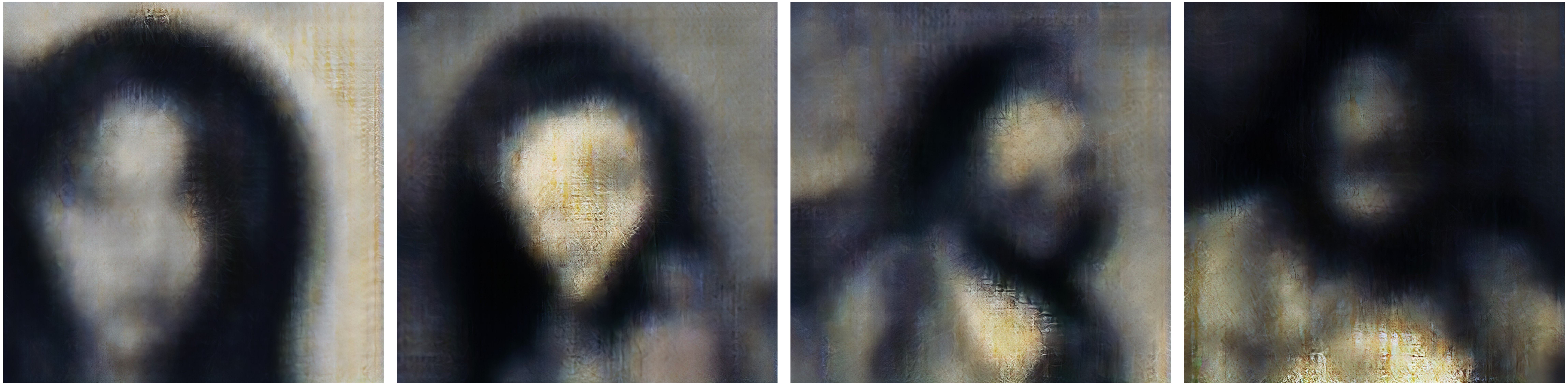


Corrupting the weights of AI models

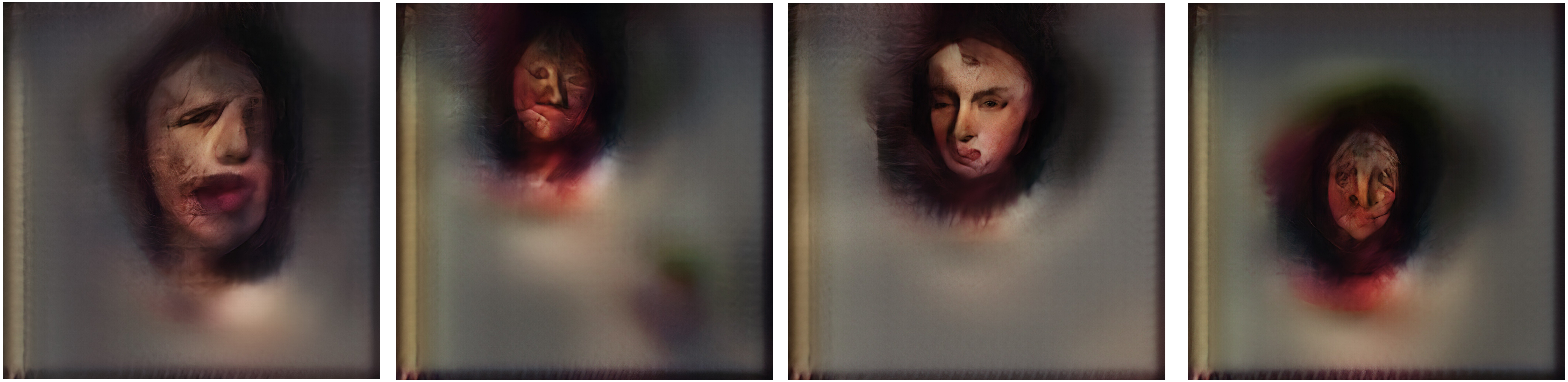
Neural glitch (2018)
Mario Klingemann



Random permutations made to the weights after training



Same permutations, different latents

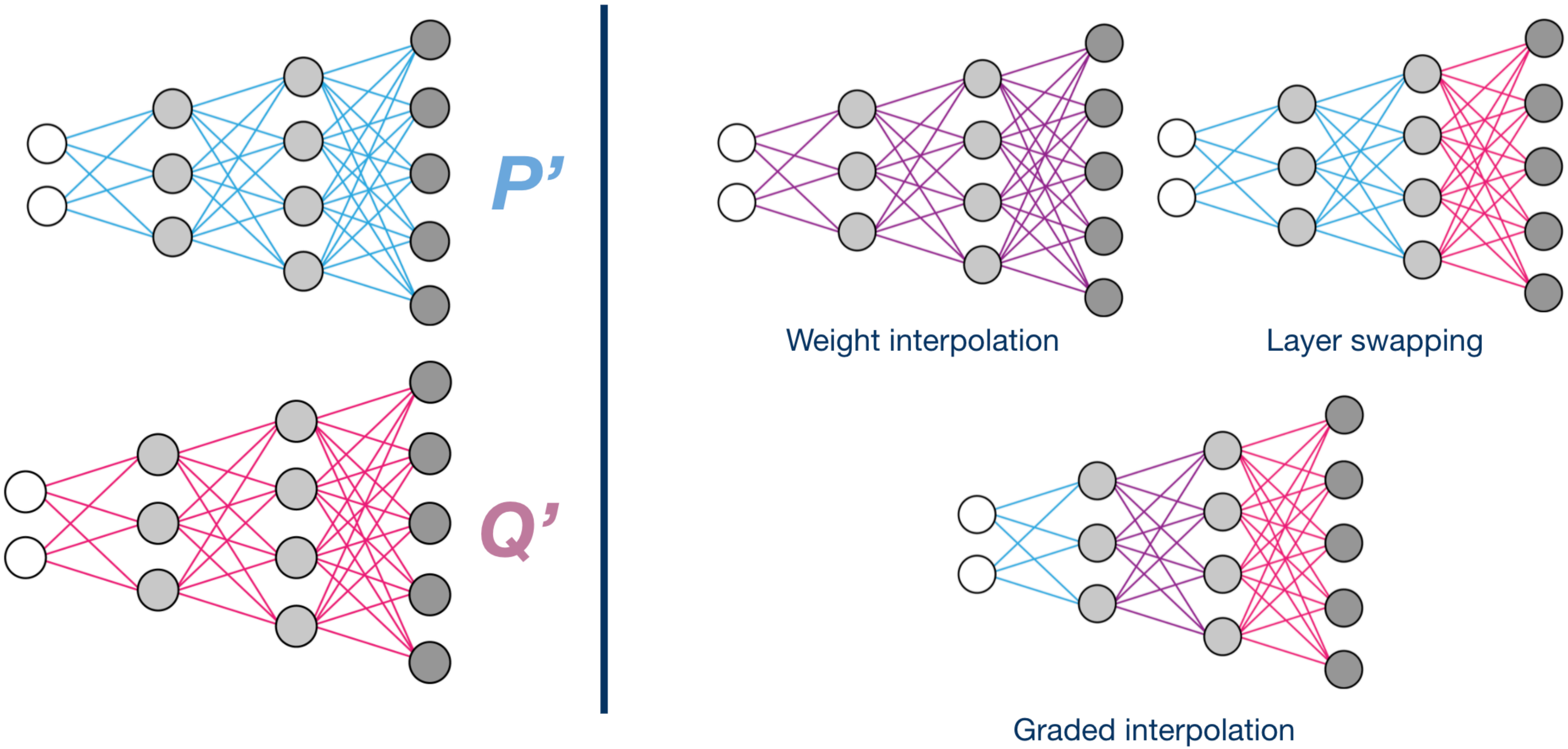


Same latent, different permutations

Gradually erasing the weights with the same latent

Blending the weights of AI models

Real Ukiyo-e (2020)
Justin Pinkney



Different approaches to blending weights of generative networks

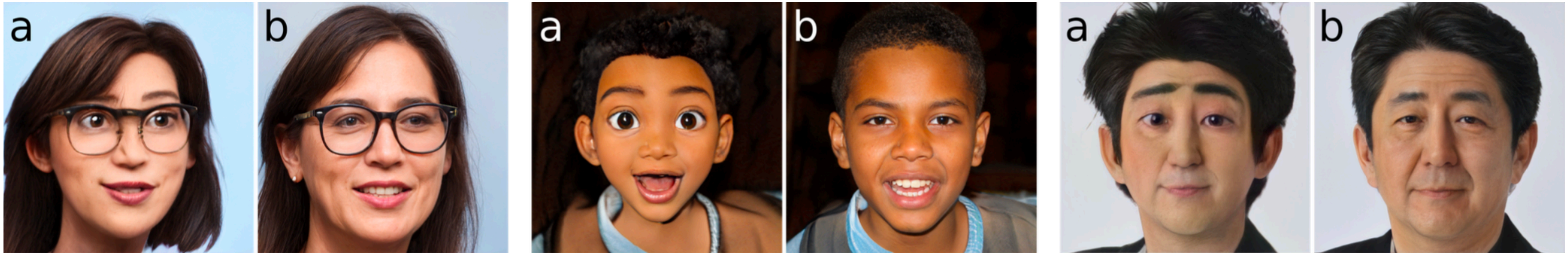
FFHQ stylegan

Ukiyo-e stylegan

Layer swapping (Ukyio-e followed by FFHQ)

Layer swapping (FFHQ followed by Ukiyo-e)

Graded interpolation



Results from 'toonification' model using same approach

TIES-MERGING: Resolving Interference When Merging Models

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Leshem Choshen[2,3] **Colin Raffel**[1] **Mohit Bansal**[1]
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Abstract

Transfer learning – i.e., further fine-tuning a pre-trained model on a downstream task – can confer significant advantages, including improved downstream performance, faster convergence, and better sample efficiency. These advantages have led to a proliferation of task-specific fine-tuned models, which typically can only perform a single task and do not benefit from one another. Recently, model merging techniques have emerged as a solution to combine multiple task-specific models into a single multitask model without performing additional training. However, existing merging methods often ignore the interference between parameters of different models, resulting in large performance drops when merging multiple models. In this paper, we demonstrate that prior merging techniques inadvertently lose valuable information due to two major sources of interference: (a) interference due to redundant parameter values and (b) disagreement on the sign of a given parameter's values across models. To address this, we propose our method, TRIM, ELECT SIGN & MERGE (TIES-MERGING), which introduces three novel steps when merging models: (1) resetting parameters that only changed a small amount during fine-tuning, (2) resolving sign conflicts, and (3) merging only the parameters that are in alignment with the final agreed-upon sign. We find that TIES-MERGING outperforms several existing methods in diverse settings covering a range of modalities, domains, number of tasks, model sizes, architectures, and fine-tuning settings. We further analyze the impact of different types of interference on model parameters, and highlight the importance of resolving sign interference.[1]

1 Introduction

Pre-trained models (PTMs) have become widespread in many real-world applications [91, 6]. Using PTMs typically involves fine-tuning them to specialize on a specific task [69, 12], which can lead to improved performance with less task-specific labeled data. These benefits have resulted in the release of thousands of finetuned checkpoints [81] derived from popular PTMs such as ViT [14] for vision and T5 [58] for language. However, having a separate fine-tuned model for each task has various drawbacks: (1) for each new application, a separate model has to be stored and deployed [17, 89], and (2) models trained in isolation cannot leverage information from related tasks to improve in-domain performance or out-of-domain generalization [66, 58, 75]. Multitask learning [66, 57] could address these concerns but requires costly training and simultaneous access to all tasks [17]. Moreover, it can be complex and resource-intensive to determine how best to mix datasets to ensure that multitask training is beneficial for all tasks [55, 54, 80, 52, 2, 17].

[1] Our code is available at https://github.com/prateeky2806/ties-merging

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Deep Model Fusion: A Survey

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Abstract

Deep model fusion/merging is an emerging technique that merges the parameters or predictions of multiple deep learning models into a single one. It combines the abilities of different models to make up for the biases and errors of a single model to achieve better performance. However, deep model fusion on large-scale deep learning models (e.g., LLMs and foundation models) faces several challenges, including high computational cost, high-dimensional parameter space, interference between different heterogeneous models, etc. Although model fusion has attracted widespread attention due to its potential to solve complex real-world tasks, there is still a lack of complete and detailed survey research on this technique. Accordingly, in order to understand the model fusion method better and promote its development, we present a comprehensive survey to summarize the recent progress. Specifically, we categorize existing deep model fusion methods as four-fold: (1) "Mode connectivity", which connects the solutions in weight space via a path of non-increasing loss, in order to obtain better initialization for model fusion; (2) "Alignment" matches units between neural networks to create better conditions for fusion; (3) "Weight average", a classical model fusion method, averages the weights of multiple models to obtain more accurate results closer to the optimal solution. (4) "Ensemble learning" combines the outputs of diverse models, which is a foundational technique for improving the accuracy and robustness of the final model. In addition, we analyze the challenges faced by deep model fusion and propose possible research directions for model fusion in the future. Our review is helpful in deeply understanding the correlation between different model fusion methods and practical application methods, which can enlighten the research in the field of deep model fusion.

1 Introduction

In recent years, deep neural networks (DNNs) [129] have made remarkable development, which is widely used in computer vision (CV) [175], natural language processing (NLP) [30] and other fields. Generally speaking, a single deep learning model often has certain limitations and cannot fully capture all underlying information behind complex networks [195]. Therefore, the classic ensemble learning [15, 193, 198] combines the outputs of multiple models to improve the final performance of model in deep learning (DL). But it suffers from the high cost of storing and running multiple models at test time [65, 204], especially as the complexity and size of models increase. Especially, for example, GPT-3 [172] has billions of parameters, and PaLM [31] even reaches 540 billion parameters and 780 billion tokens. In addition, from the perspective of loss landscape of DNNs [134, 196], gradient-optimized solutions usually converge to points near the boundary of the wide flat region instead of the central point [99]. It means that a trained network is not exactly

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ADAMERGING: ADAPTIVE MODEL MERGING FOR MULTI-TASK LEARNING

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ABSTRACT

Multi-task learning (MTL) aims to empower a model to tackle multiple tasks simultaneously. A recent development known as task arithmetic has revealed that several models, each fine-tuned for distinct tasks, can be directly merged into a single model to execute MTL without necessitating a retraining process using the initial training data. Nevertheless, this direct addition of models often leads to a significant deterioration in the overall performance of the merged model. This decline occurs due to potential conflicts and intricate correlations among the multiple tasks. Consequently, the challenge emerges of how to merge pre-trained models more effectively without using their original training data. This paper introduces an innovative technique called Adaptive Model Merging (`AdaMerging`). This approach aims to autonomously learn the coefficients for model merging, either in a task-wise or layer-wise manner, without relying on the original training data. Specifically, our `AdaMerging` method operates as an automatic, unsupervised task arithmetic scheme. It leverages entropy minimization on unlabeled test samples from the multi-task setup as a surrogate objective function to iteratively refine the merging coefficients of the multiple models. Our experimental findings across eight tasks demonstrate the efficacy of the AdaMerging scheme we put forth. Compared to the current state-of-the-art task arithmetic merging scheme, AdaMerging showcases a remarkable 11% improvement in performance. Notably, AdaMerging also exhibits superior generalization capabilities when applied to unseen downstream tasks. Furthermore, it displays a significantly enhanced robustness to data distribution shifts that may occur during the testing phase. The code is available at AdaMerging.

1 INTRODUCTION

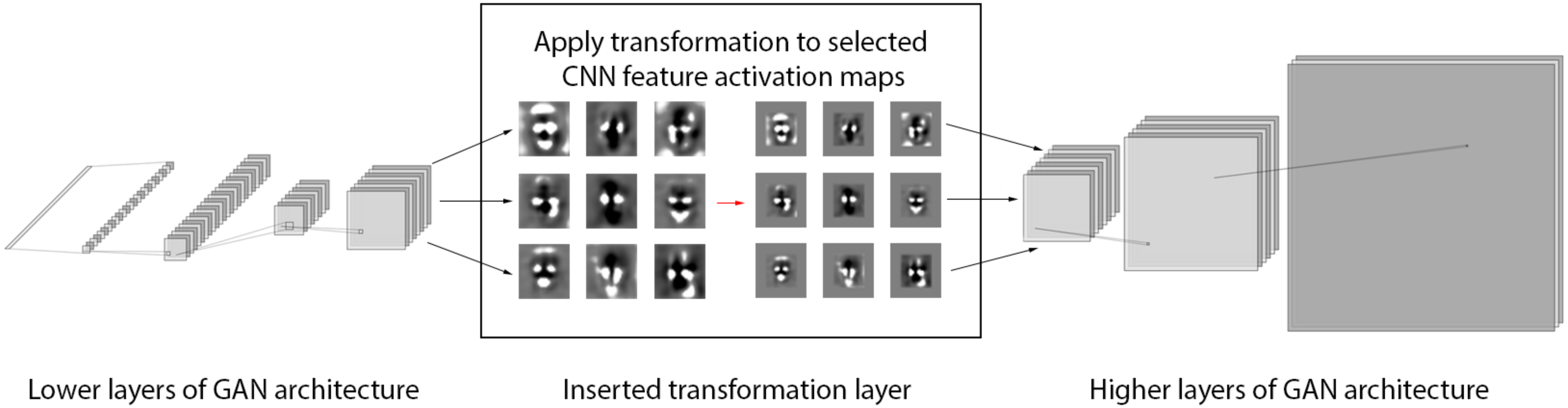
Multi-task learning (MTL) is a technique that enables the transfer of knowledge (Wu et al., 2020; Wang et al., 2023; Jiang et al., 2024) among multiple tasks by efficiently sharing model parameters, leading to improvements in overall performance (Caruana, 1997; Liu et al., 2019b; Vandenhende et al., 2021) across a variety of tasks. Consequently, it has garnered significant attention in fields such as computer vision (Misra et al., 2016; Chen et al., 2018; 2020), natural language processing (Collobert & Weston, 2008; Dong et al., 2015), and recommendation systems (Ma et al., 2018; Yang et al., 2023; Song et al., 2024). In the context of foundation models, there are two key considerations. On the one hand, it is highly inefficient to pursue the traditional MTL approach for large pre-trained models by collecting a large volume of training data due to the high data labeling and computation cost. On the other hand, the advent of pre-trained models' popularity (Qiu et al., 2020) has led to a prevalent practice among downstream tasks. These tasks independently fine-tune the same pre-trained model, such as ViT (Dosovitskiy et al., 2021) or BERT (Devlin et al., 2019), and subsequently release these fine-tuned models, often without disclosing the specifics of their original training data. Consequently, there has emerged a recent trend in the research community, focused on exploring methodologies for effectively merging multiple independently trained models without relying on their training data for the purpose of MTL (Matena & Raffel, 2022; Jin et al., 2023; Ainsworth et al., 2023; Ilharco et al., 2023; Huang et al., 2023; Ortiz-Jimenez et al., 2023; Yadav et al., 2023; Li et al., 2023).

*Corresponding author

Model fusion papers from 2023 onwards

Hacking the computational graph of AI models

Disembodied gaze (2020)
Terence Broad



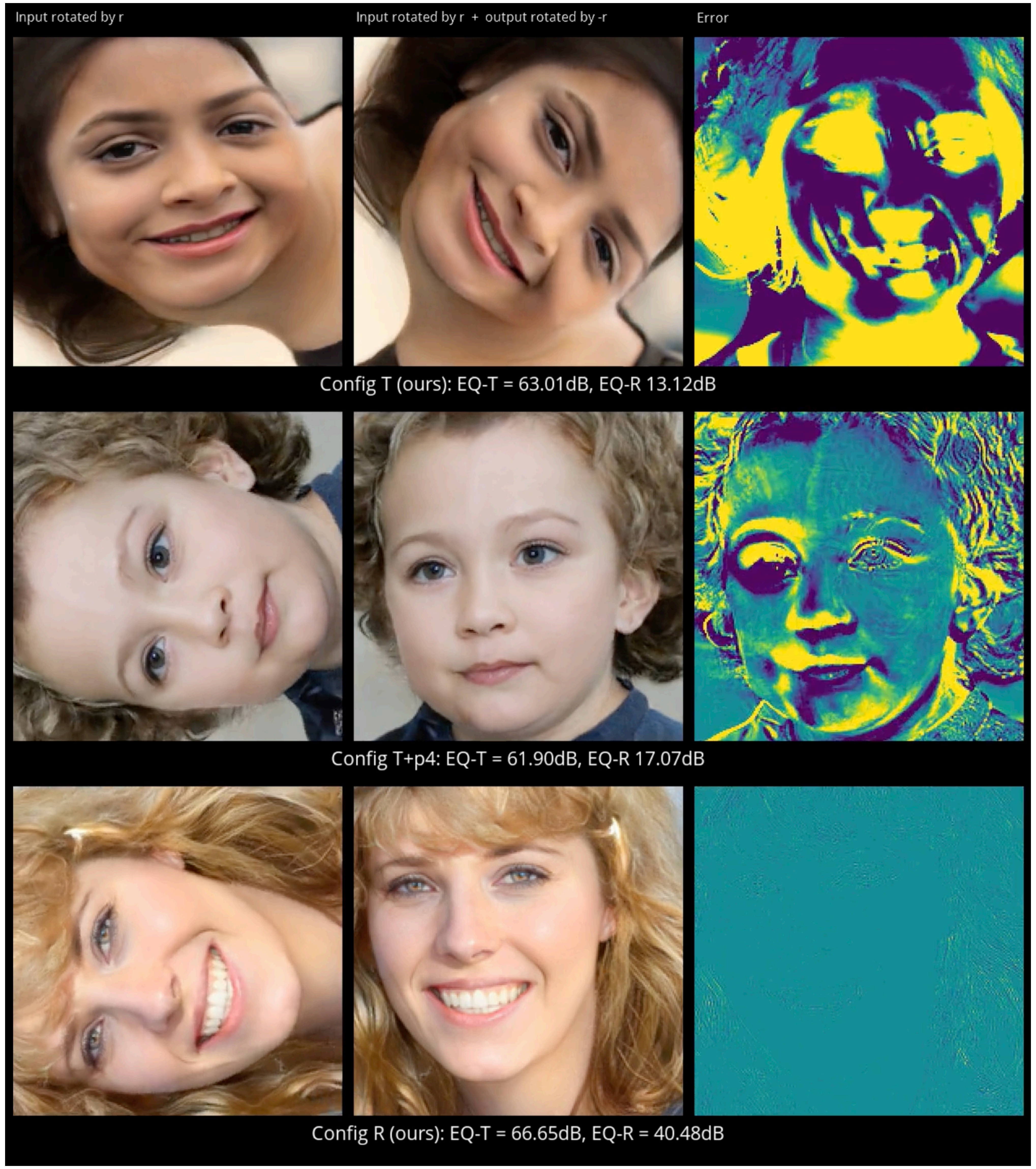

Unaltered Result


Manipulated Result

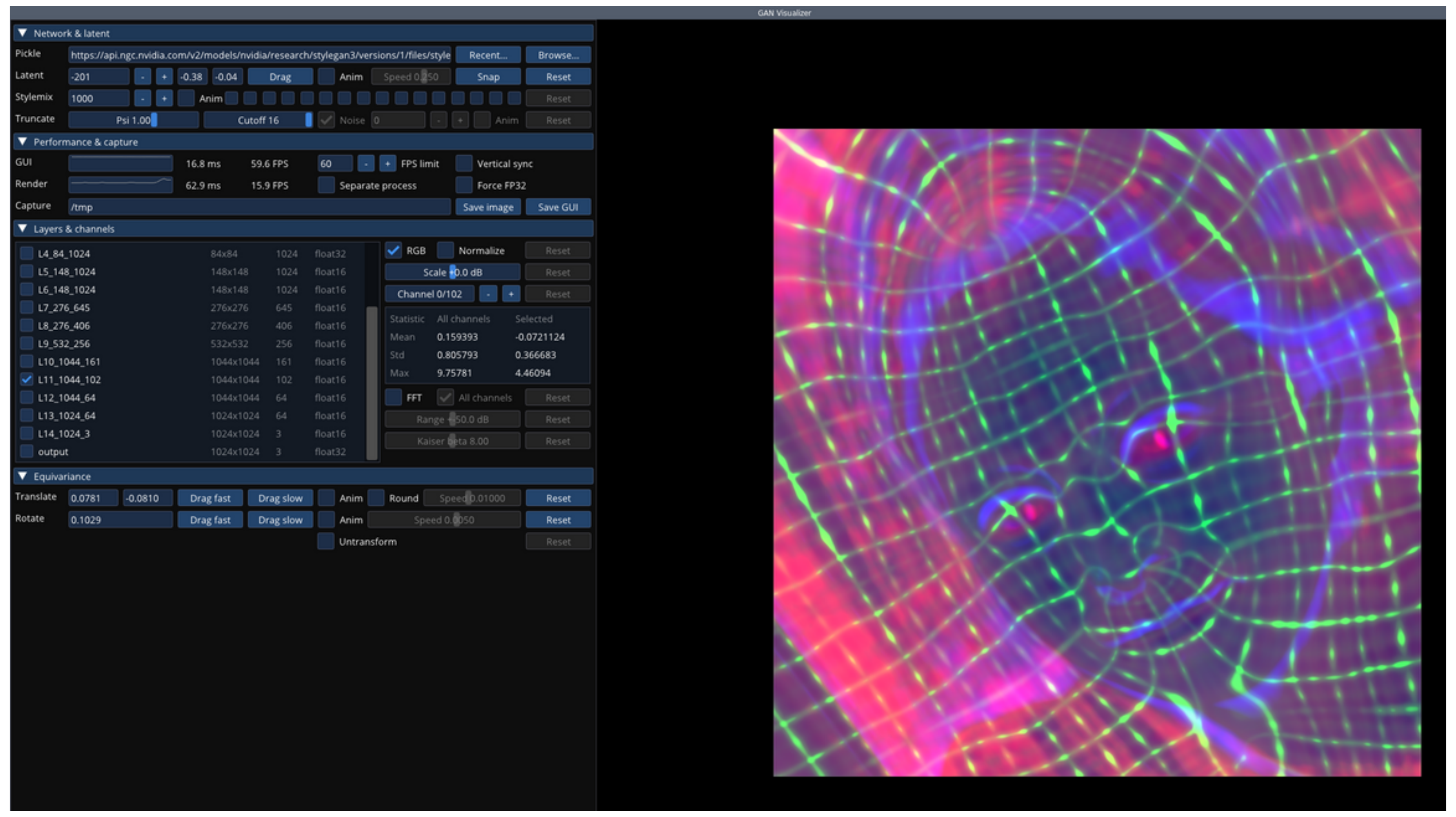
Insert deterministically controllable filters into a network after training
Aka Network Bending

Teratome (2020)
Terence Broad

Fragments of self (2021)

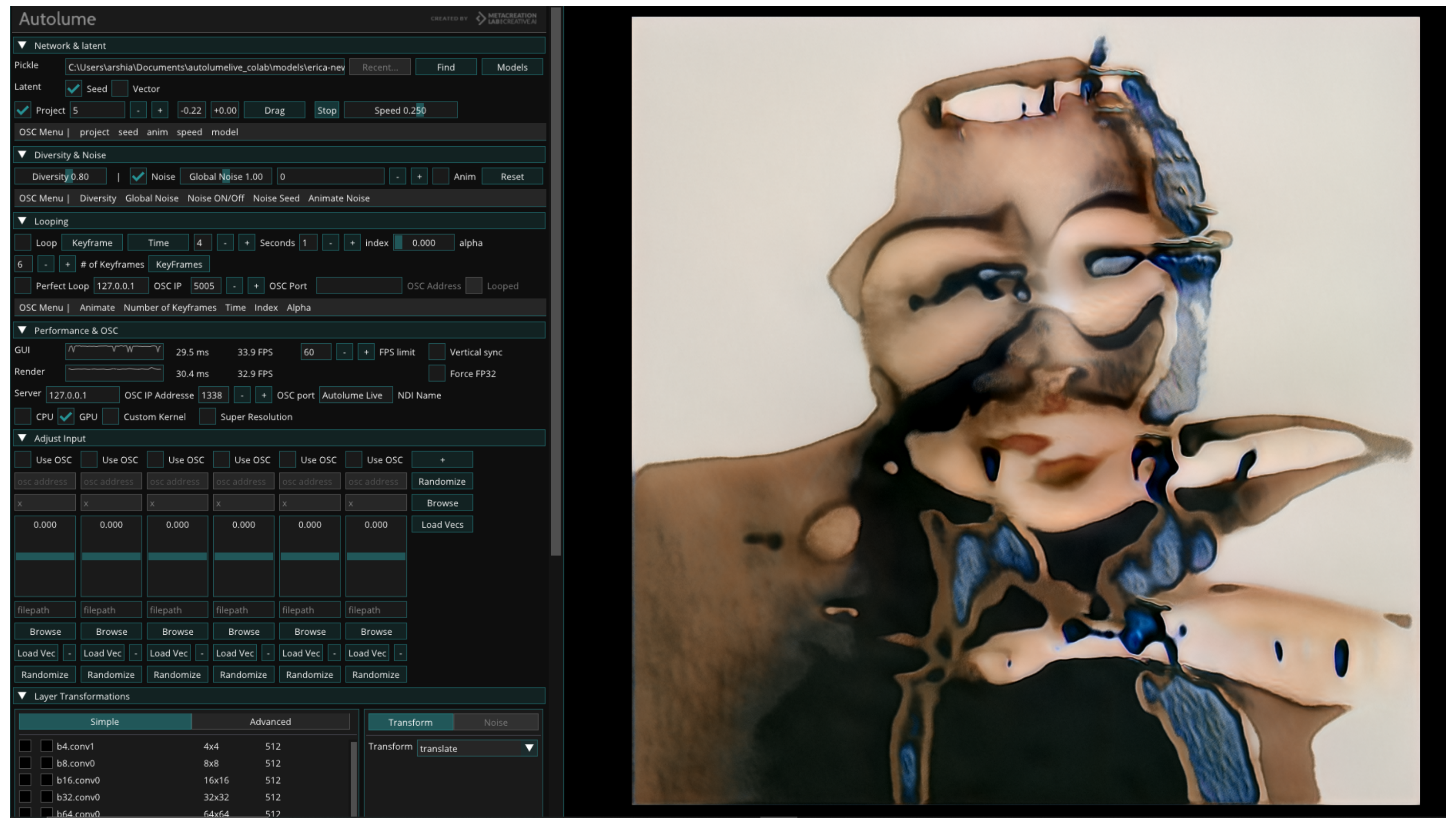


Network bending in StyleGAN3
Image courtesy of NVIDIA

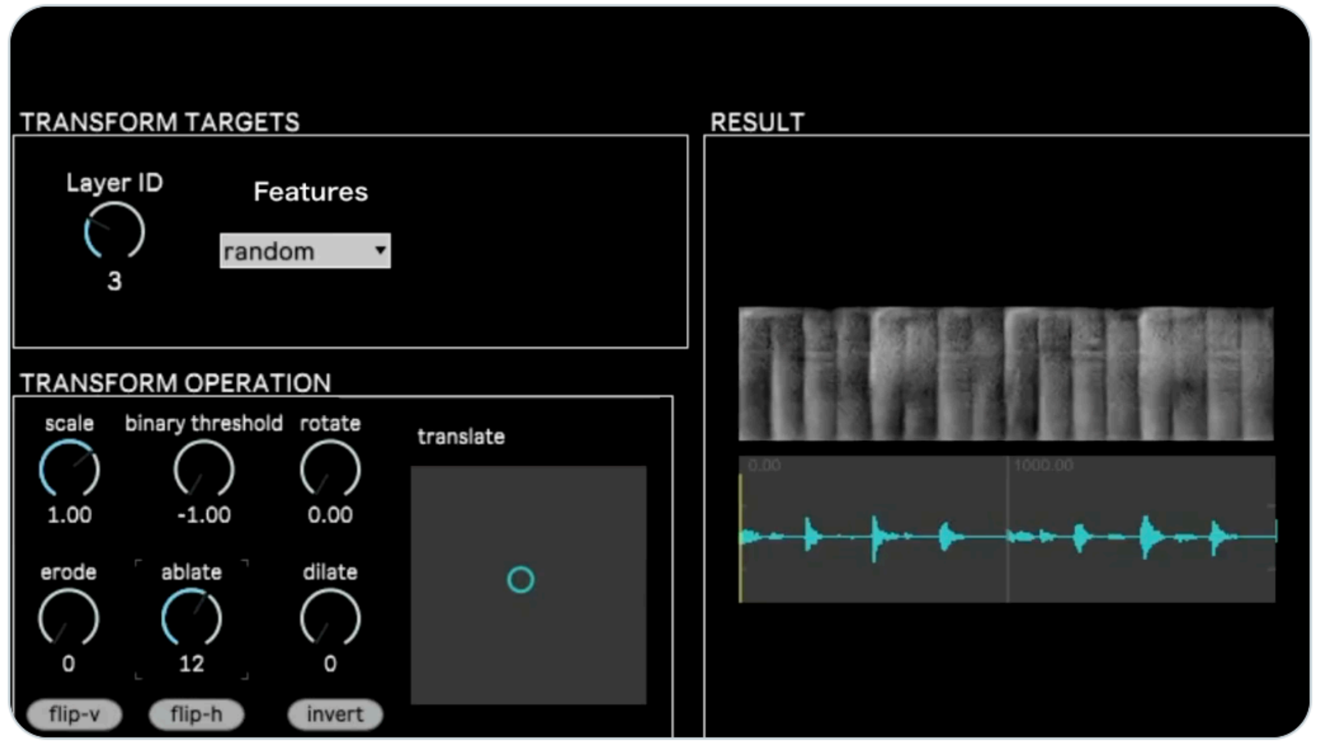


StyleGAN3 visualiser
NVIDIA

StyleGAN-Canvas
Shuoyang Zheng

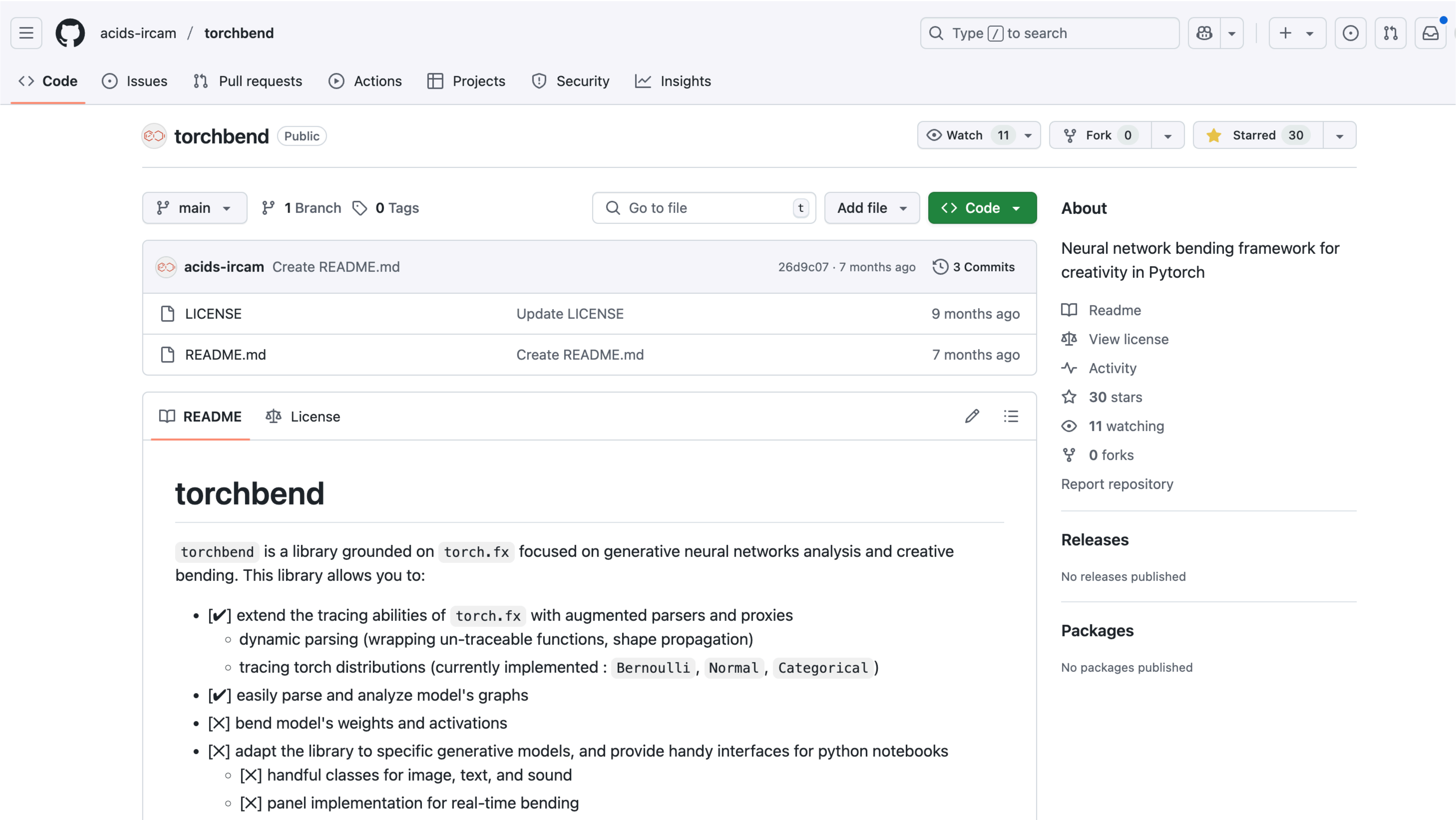


Autolume
Simon Fasier University



LoopGAN interface
Nao Tokui

User interfaces developed for network bending



Torchbend library (forthcoming)
IRCAM

Closing remarks

Artistic interventions provide accessible and ways of understanding and demistifying generative AI

Artists play a crucial role in not only explaining existing technologies, but asking questions that further the development of AI itself

Moving beyond the paradigm of imitation-based learning toward actively diverging from data is in navigating the current backlash against generative AI

My papers discussed in this talk

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- Yang, E., Wang, Z., Shen, L., Liu, S., Guo, G., Wang, X. and Tao, D., 2023. Adamerging: Adaptive model merging for multi-task learning. arXiv preprint arXiv:2310.02575.

Link to slides:

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