Autonomous and Adaptive Systems

AI and Creativity: Generative Machine Learning

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What is Creativity?

Source: Wikimedia

"Creativity can be defined as the ability to generate novel, and valuable, ideas. Valuable, here, has many meanings: interesting, useful, beautiful, simple, richly complex, and so on. Ideas covers many meaning too: not only ideas as such (concepts, theories, interpretations, stories), but also artifacts such as graphic images, sculptures, houses and jet engines. Computer models have been designed to generate ideas in all these areas and more."

Margaret A. Boden

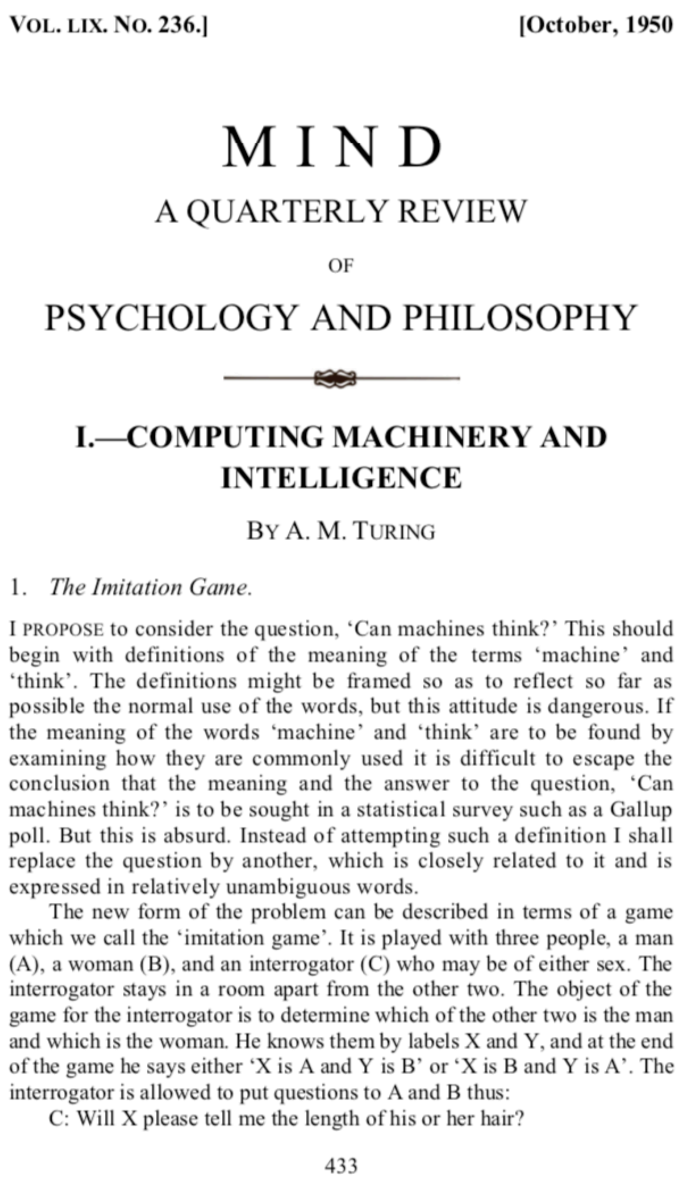
Ada Lovelace's Objection

Source: Computer History Museum

"The Analytical Engine has no pretensions whatever to originate anything. It can do whatever we know how to order it to perform; but it has no power of anticipating any analytical relations or truths."

Ada Lovelace

Turing’s Response



VOL. LIX. NO. 236.] [October, 1950

MIND

A QUARTERLY REVIEW

OF

PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. *The Imitation Game.*

I PROPOSE to consider the question, ‘Can machines think?’ This should begin with definitions of the meaning of the terms ‘machine’ and ‘think’. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words ‘machine’ and ‘think’ are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, ‘Can machines think?’ is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

The new form of the problem can be described in terms of a game which we call the ‘imitation game’. It is played with three people, a man (A), a woman (B), and an interrogator (C) who may be of either sex. The interrogator stays in a room apart from the other two. The object of the game for the interrogator is to determine which of the other two is the man and which is the woman. He knows them by labels X and Y, and at the end of the game he says either ‘X is A and Y is B’ or ‘X is B and Y is A’. The interrogator is allowed to put questions to A and B thus:

C: Will X please tell me the length of his or her hair?

- Ada Lovelace’s objection can be seen as the assertion that computers cannot surprise us.

- Alan Turing in his Mind paper argues that actually computers are still able to surprise us. He also underlines the fact that Ada Lovelace lived in a period where neurological phenomena were not known.

Can an (artificial) agent be creative?

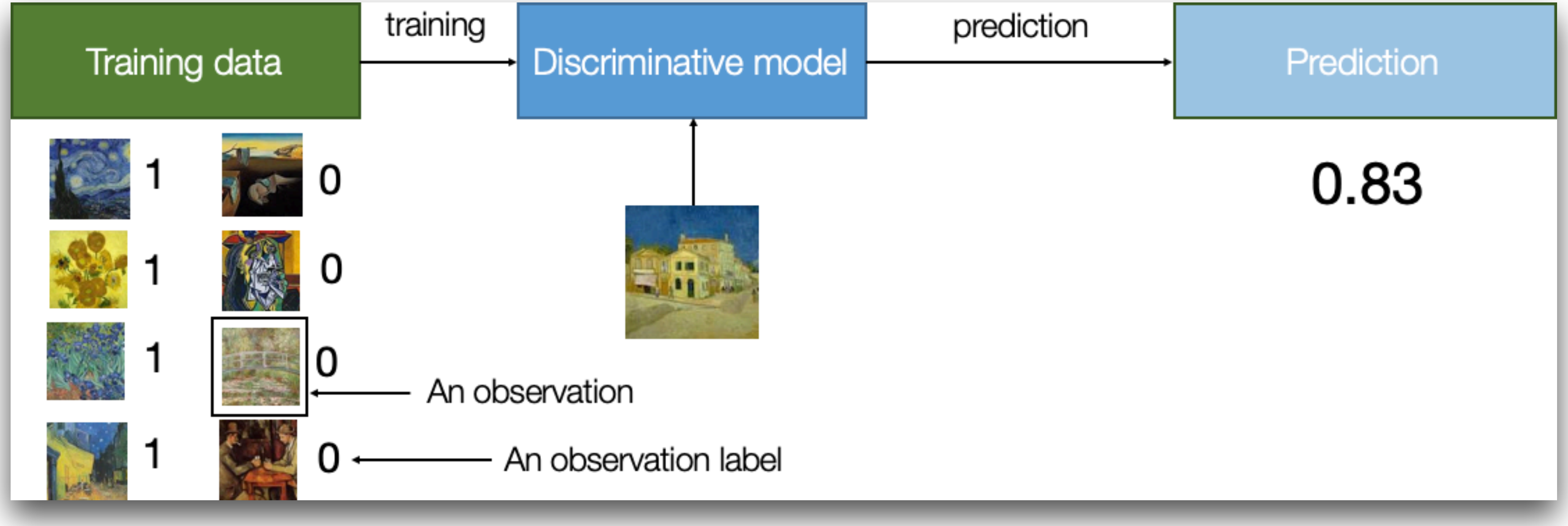
Generative Modeling

- A generative model describes how a dataset is generated for example through a probabilistic model. Through sampling of this model, we generate new data.

- The goal is to generated data are variations of the existing ones, but not “too far” from the original dataset.

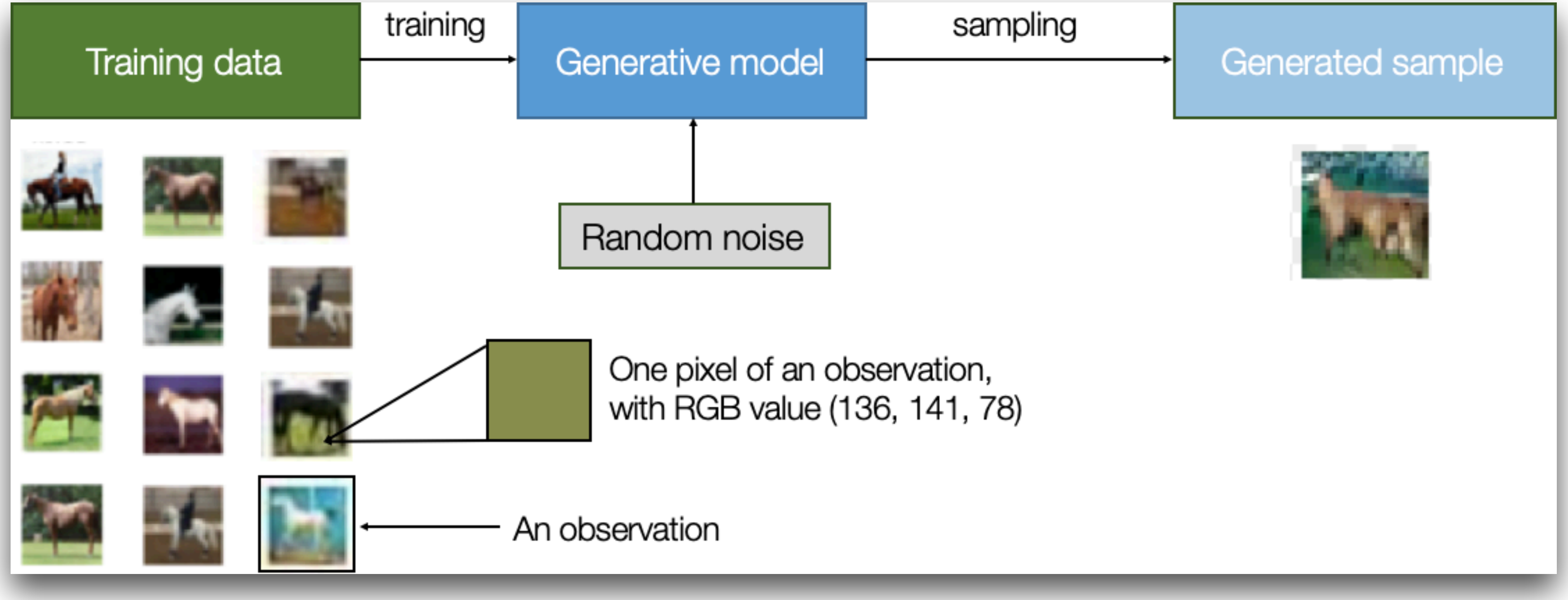
- A generative model is usually probabilistic rather than deterministic in nature.

Discriminative Model



Source: David Foster. Generative Deep Learning. O'Reilly. 2019.

Generative Model



Source: David Foster. Generative Deep Learning. O'Reilly. 2019.

Generative Modelling Framework

- Given a dataset $\mathbf{X}$, we assume that the observation have been according to some *unknown* distribution p_{data}.

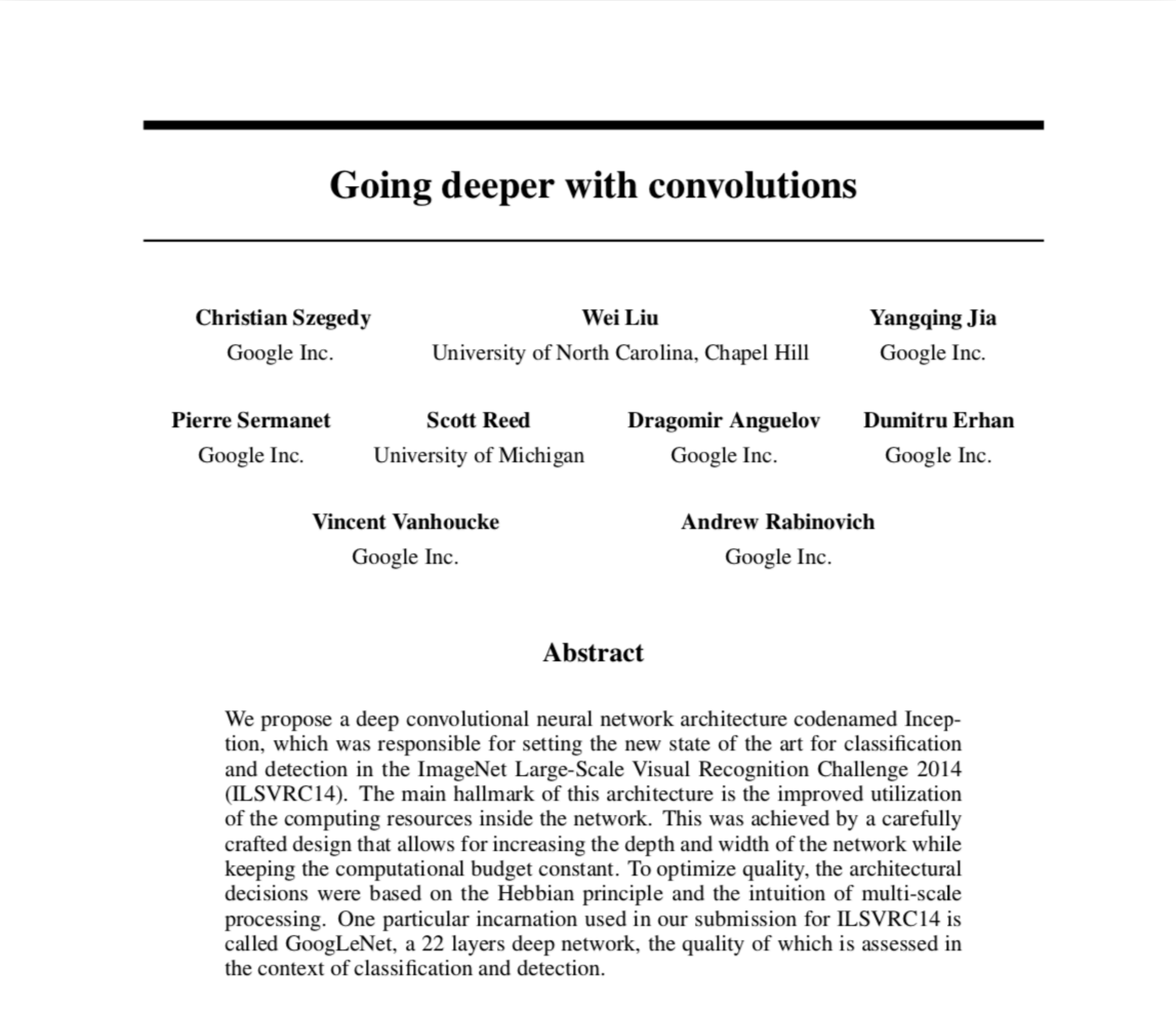
- The goal is to create a generative model p_{model} that can be used to generate samples that look like they were drawn from p_{data}.

- We achieved our goal if the generated data are also suitably different from the observations in $\mathbf{X}$.

  - The model should not simply reproduce the things that have already been seen.

DeepDream

- Developed by Alexander Mordvintsev, Christopher Olah and Mike Tika in 2015.
- This movement is also called inceptionism from Chris Nolan’s movie “Inception” (but a bit indirectly).
- The idea is to try to exploit the “patterns” that are learnt by neural network “in reverse”.
- This is used to generate images that are composed by the patterns that are detected by the different layers.



Going deeper with convolutions

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Vincent Vanhoucke
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Abstract

We propose a deep convolutional neural network architecture codenamed Inception, which was responsible for setting the new state of the art for classification and detection in the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14). The main hallmark of this architecture is the improved utilization of the computing resources inside the network. This was achieved by a carefully crafted design that allows for increasing the depth and width of the network while keeping the computational budget constant. To optimize quality, the architectural decisions were based on the Hebbian principle and the intuition of multi-scale processing. One particular incarnation used in our submission for ILSVRC14 is called GoogLeNet, a 22 layers deep network, the quality of which is assessed in the context of classification and detection.

WE NEED TO GO
DEEPER

DeepDream

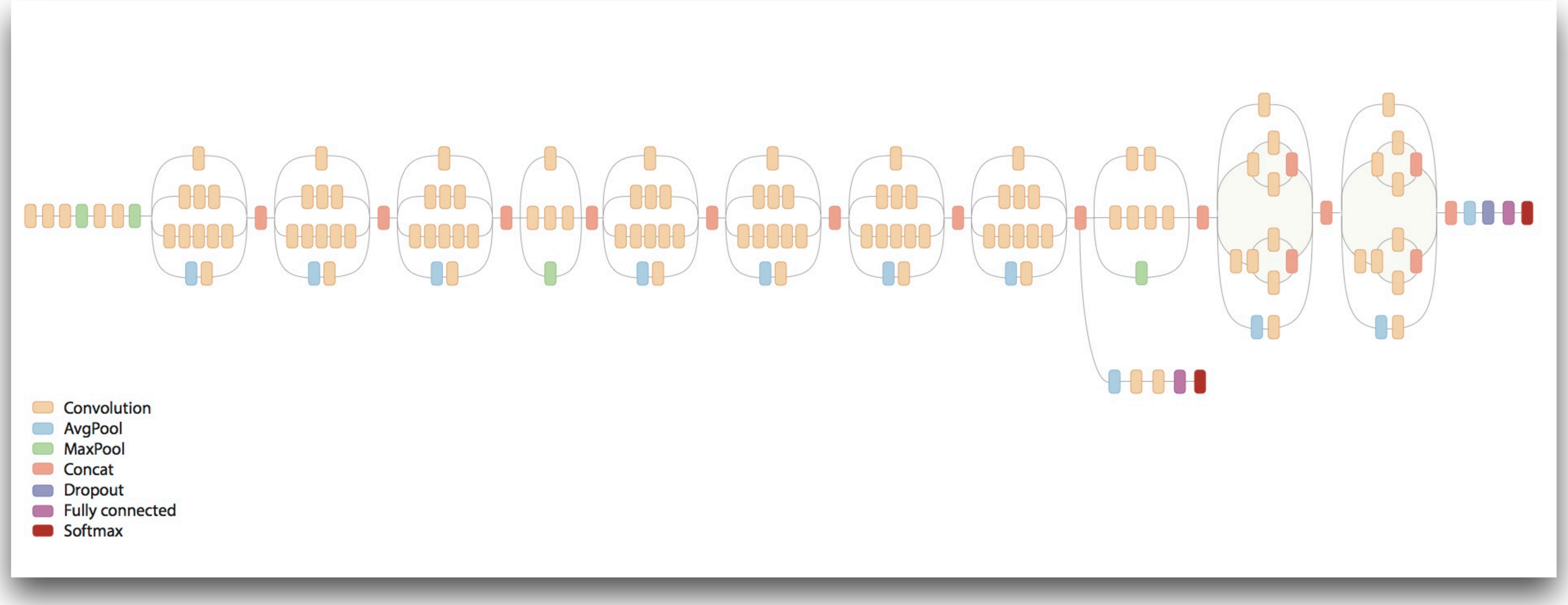
- Interpretability is still an open question in deep learning.

- In case of images, we know that each layer progressively extracts higher and higher-level features of the images, until the final layer makes a decision on what an image actually shows.

    - First layer for edges and corners, then intermediate layers interpret the basic features and are used to extract shapes and components (windows, leaves, etc). A final layer might extract buildings or trees.

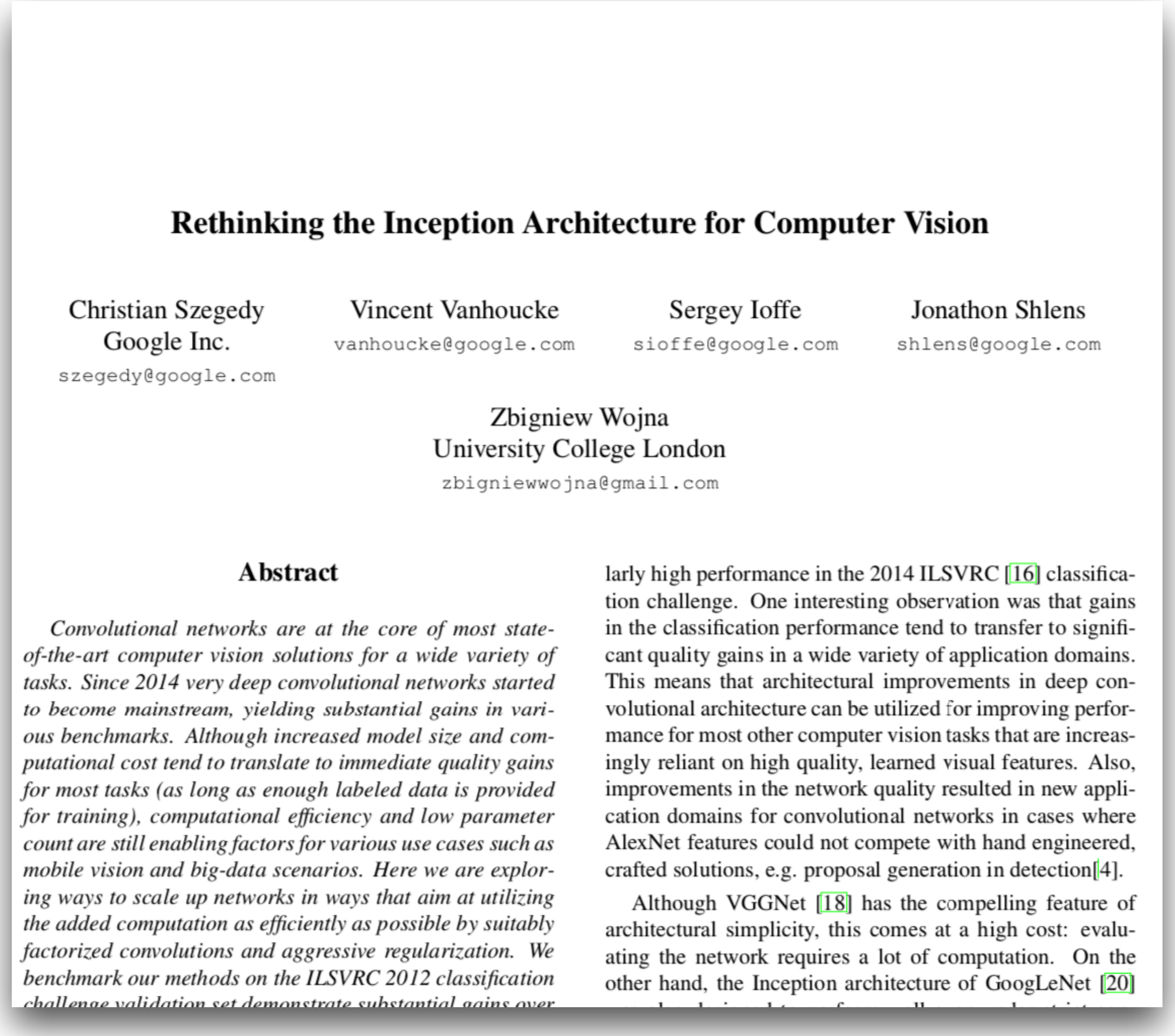
- One way to visualise this is to turn the network upside down and ask to enhance an input image so that the role of each layer can be interpreted.

Inception Network



Source: Inception in TensorFlow
https://github.com/tensorflow/models/tree/master/research/inception

Inception Network



Rethinking the Inception Architecture for Computer Vision

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Abstract

Convolutional networks are at the core of most state-of-the-art computer vision solutions for a wide variety of tasks. Since 2014 very deep convolutional networks started to become mainstream, yielding substantial gains in various benchmarks. Although increased model size and computational cost tend to translate to immediate quality gains for most tasks (as long as enough labeled data is provided for training), computational efficiency and low parameter count are still enabling factors for various use cases such as mobile vision and big-data scenarios. Here we are exploring ways to scale up networks in ways that aim at utilizing the added computation as efficiently as possible by suitably factorized convolutions and aggressive regularization. We benchmark our methods on the ILSVRC 2012 classification challenge validation set demonstrate substantial gains over

larly high performance in the 2014 ILSVRC [16] classification challenge. One interesting observation was that gains in the classification performance tend to transfer to significant quality gains in a wide variety of application domains. This means that architectural improvements in deep convolutional architecture can be utilized for improving performance for most other computer vision tasks that are increasingly reliant on high quality, learned visual features. Also, improvements in the network quality resulted in new application domains for convolutional networks in cases where AlexNet features could not compete with hand engineered, crafted solutions, e.g. proposal generation in detection[4].

Although VGGNet [18] has the compelling feature of architectural simplicity, this comes at a high cost: evaluating the network requires a lot of computation. On the other hand, the Inception architecture of GoogLeNet [20]

DeepDream

- The idea of DeepDream is to choose a layer (or layers) and mimimise the loss in a way that the image increasingly “excites” the layers.

- The complexity of the features incorporated depends on the layer we chose.

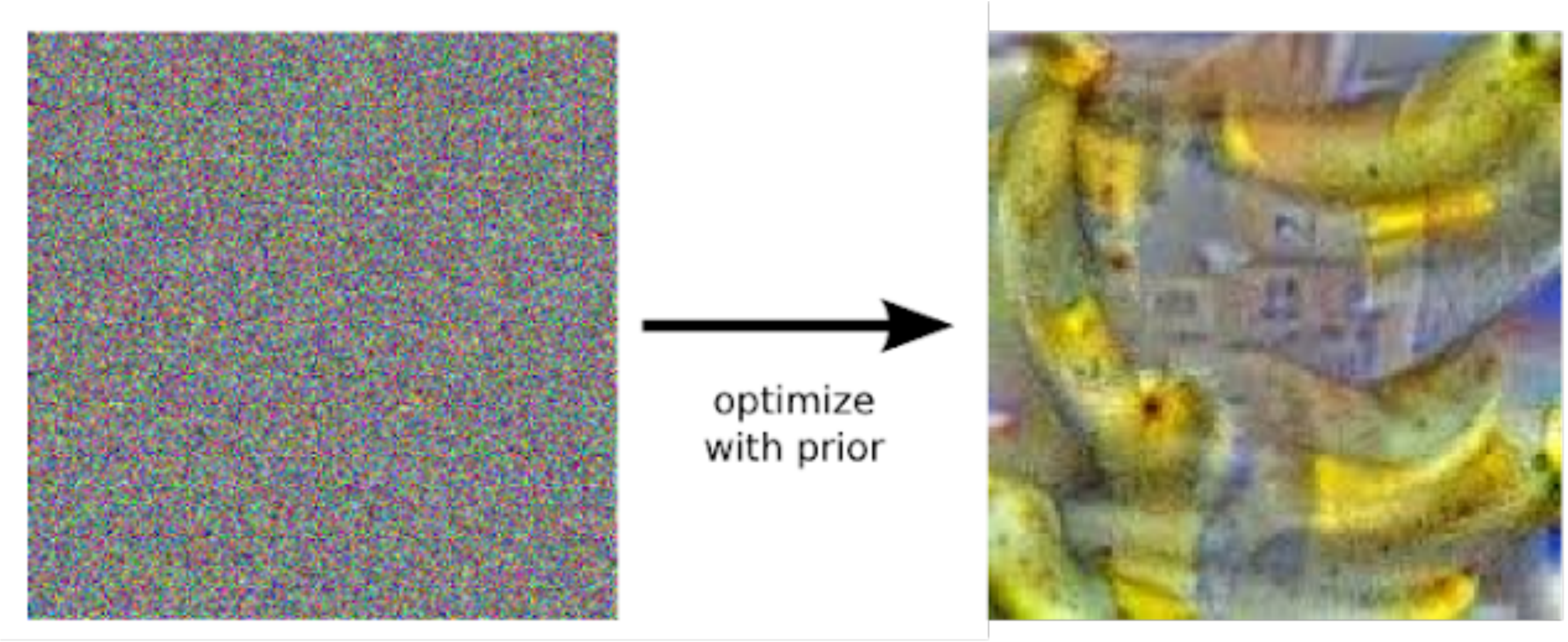
- We use the InceptionV3 architecture.

  - For DeepDream the layers of interest are those where the convolutions are concatenated.

- Once we have calculated the loss for the chosen layers, we calculate the gradients (using gradient ascent) to the input images.

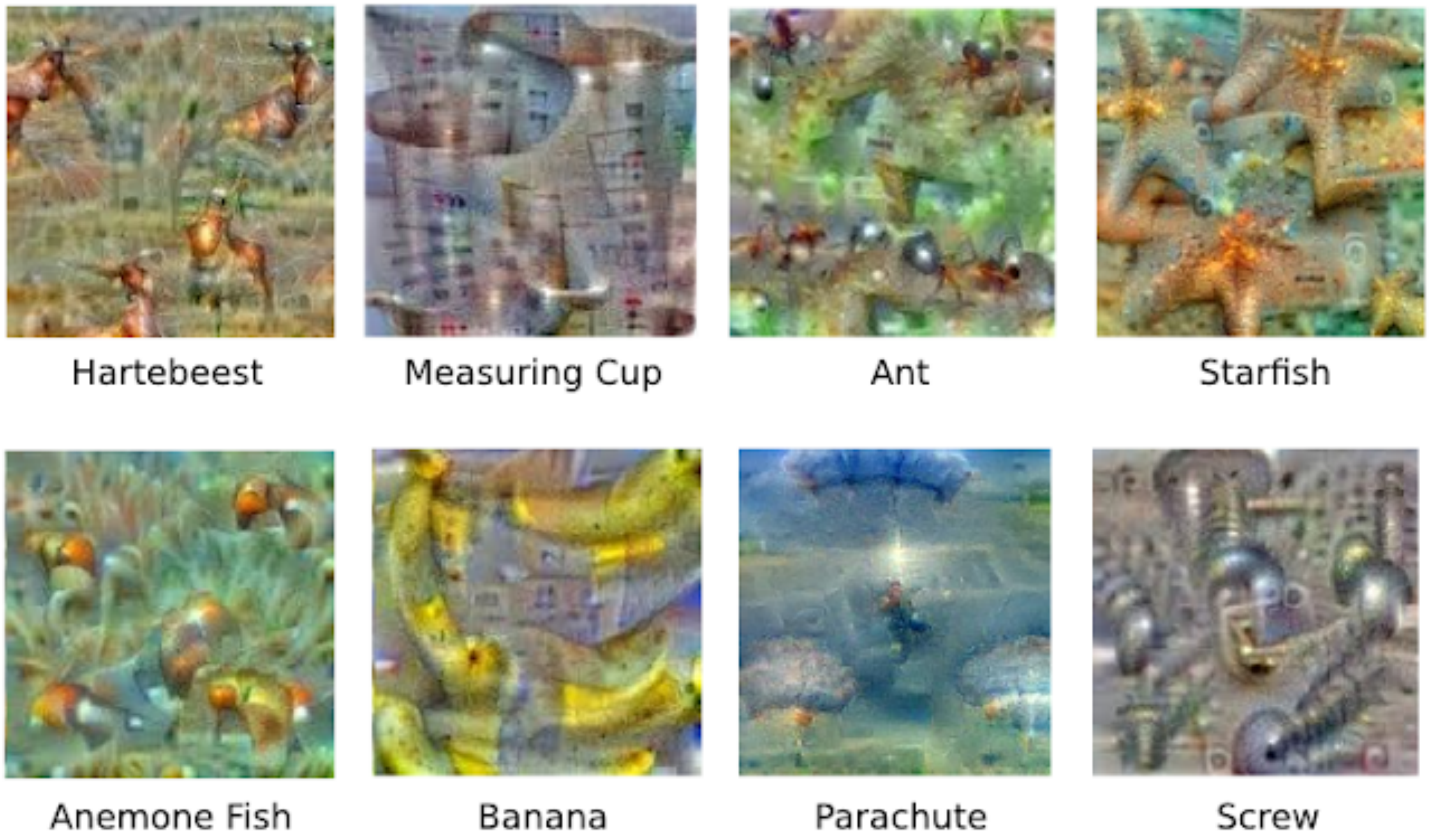
- If we consider a “noise” image, the shapes that are identified by that specific layer will appear.

DeepDream



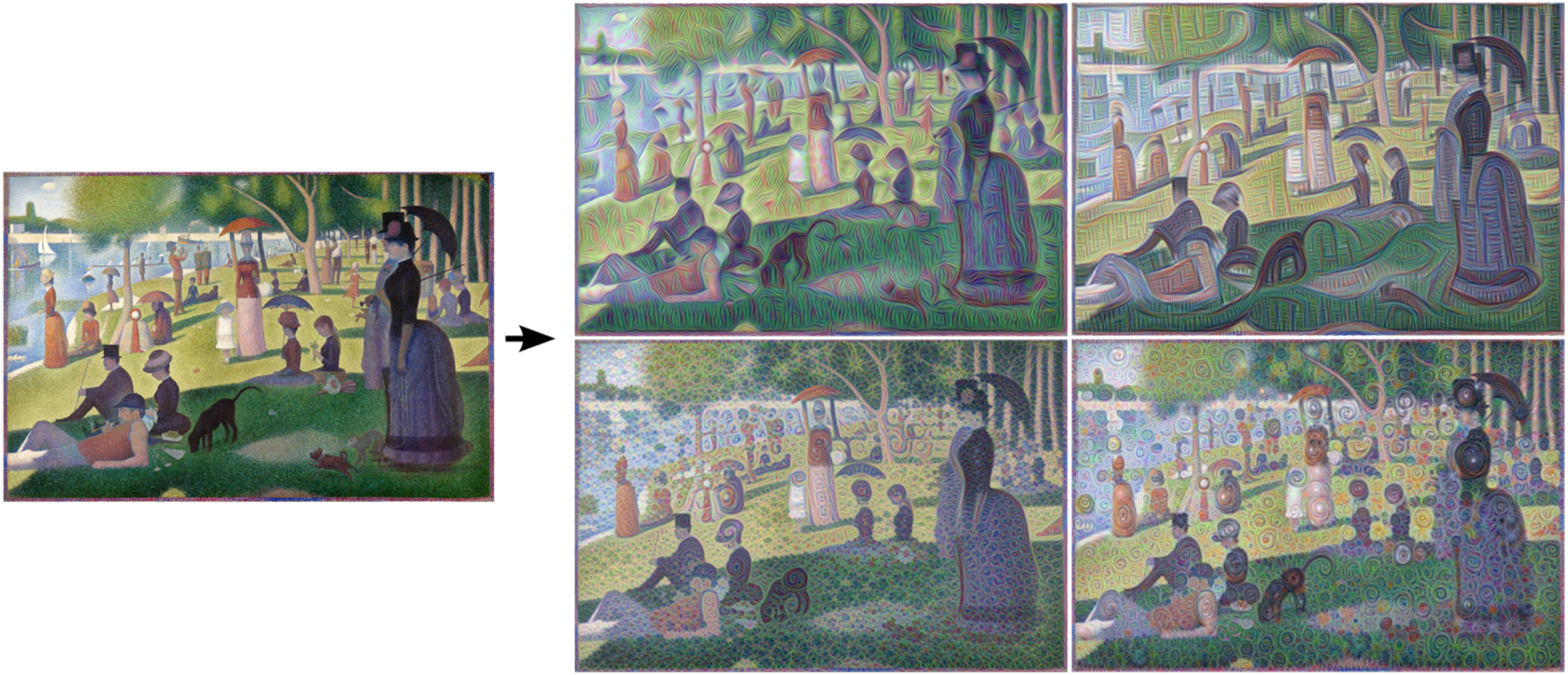
Source: Inceptionism: Going Deeper into Neural Networks
https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

DeepDream



Source: Inceptionism: Going Deeper into Neural Networks
https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

DeepDream



Source: Inceptionism: Going Deeper into Neural Networks
https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

DeepDream

Source: Inceptionism: Going Deeper into Neural Networks
https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

TensorFlow DeepDream Colab

https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/generative/deepdream.ipynb

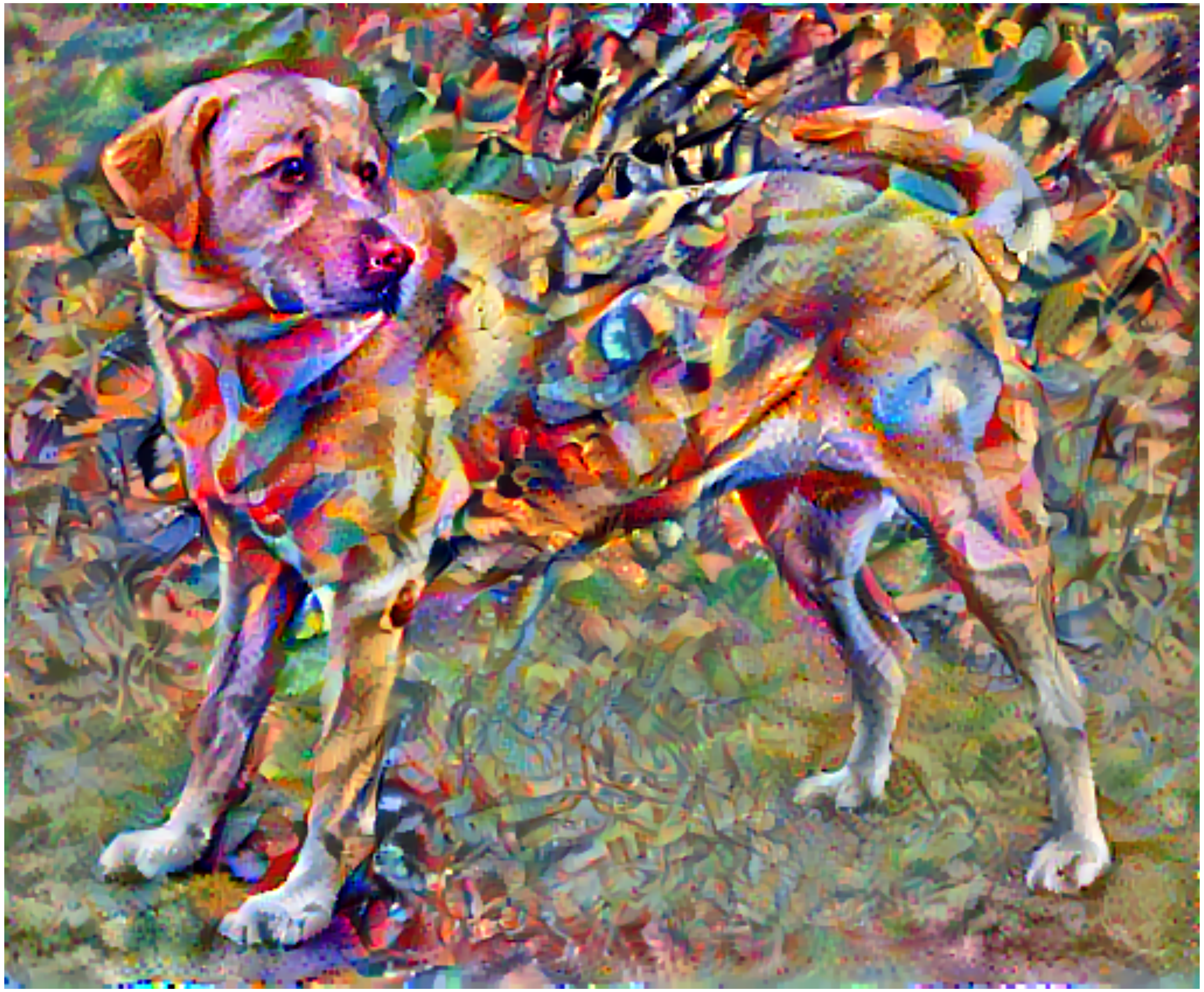
Neural Style Transfer

Source:TensorFlow Neural Style Transfer
https://www.tensorflow.org/tutorials/generative/style_transfer

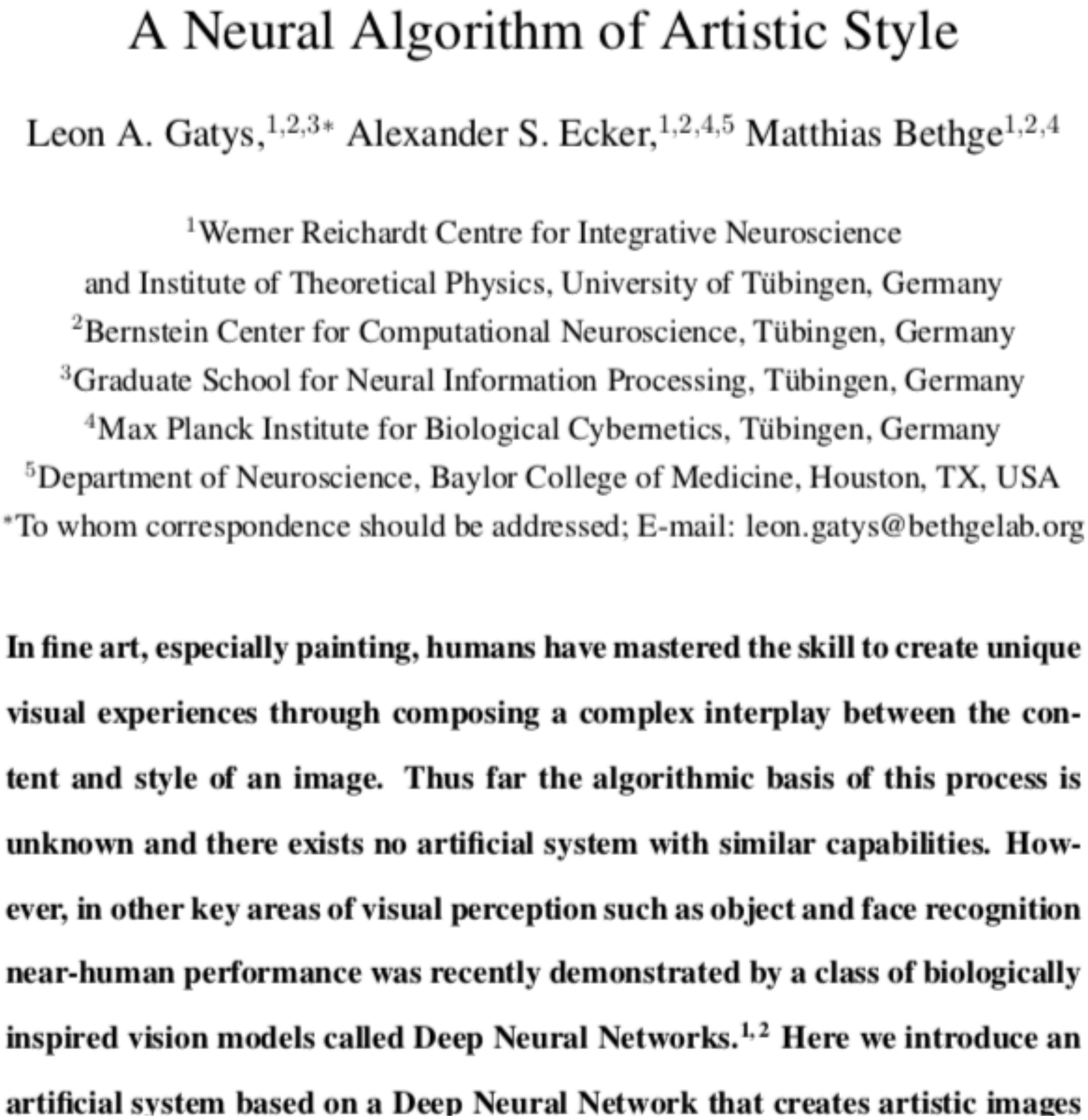
Neural Style Transfer

Source:TensorFlow Neural Style Transfer
https://www.tensorflow.org/tutorials/generative/style_transfer

Neural Style Transfer



Source:TensorFlow Neural Style Transfer
https://www.tensorflow.org/tutorials/generative/style_transfer



A Neural Algorithm of Artistic Style

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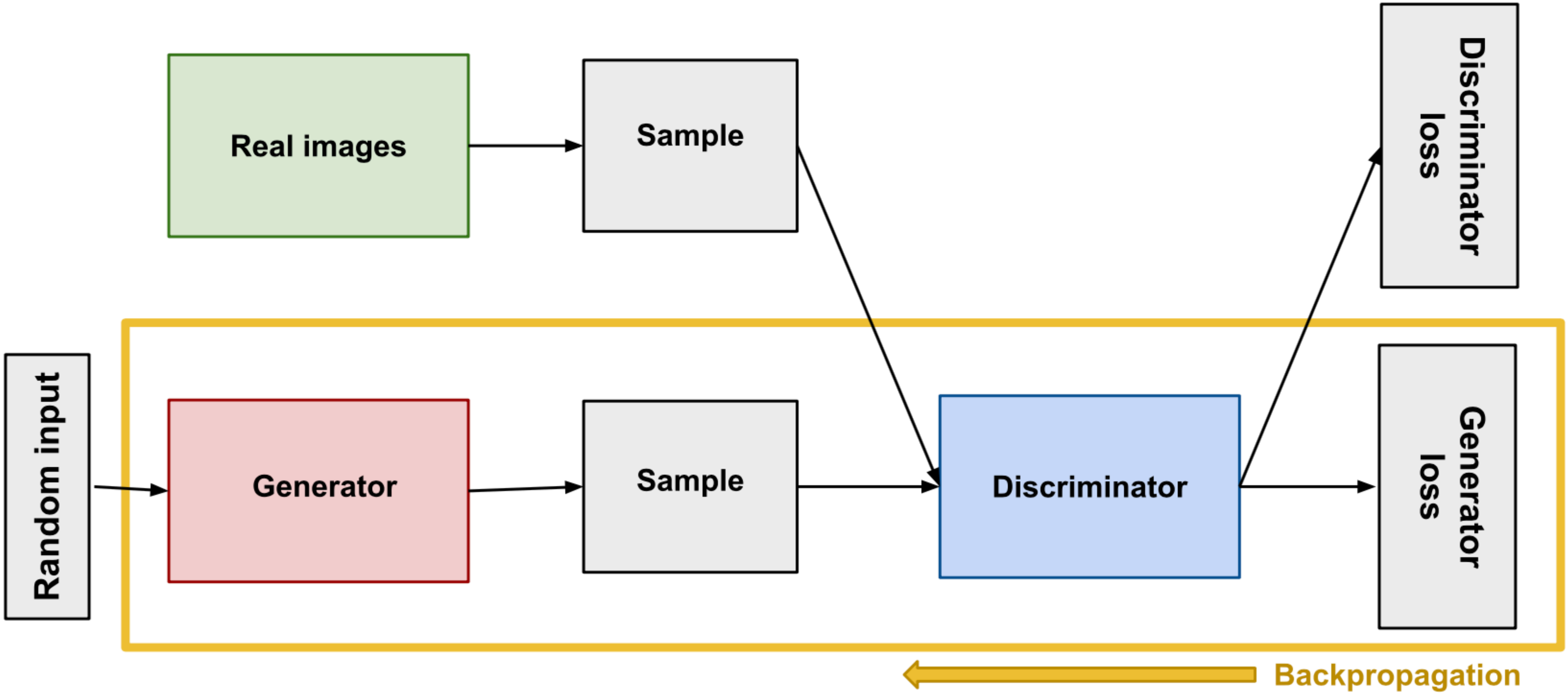
In fine art, especially painting, humans have mastered the skill to create unique visual experiences through composing a complex interplay between the content and style of an image. Thus far the algorithmic basis of this process is unknown and there exists no artificial system with similar capabilities. However, in other key areas of visual perception such as object and face recognition near-human performance was recently demonstrated by a class of biologically inspired vision models called Deep Neural Networks.[1,2] Here we introduce an artificial system based on a Deep Neural Network that creates artistic images

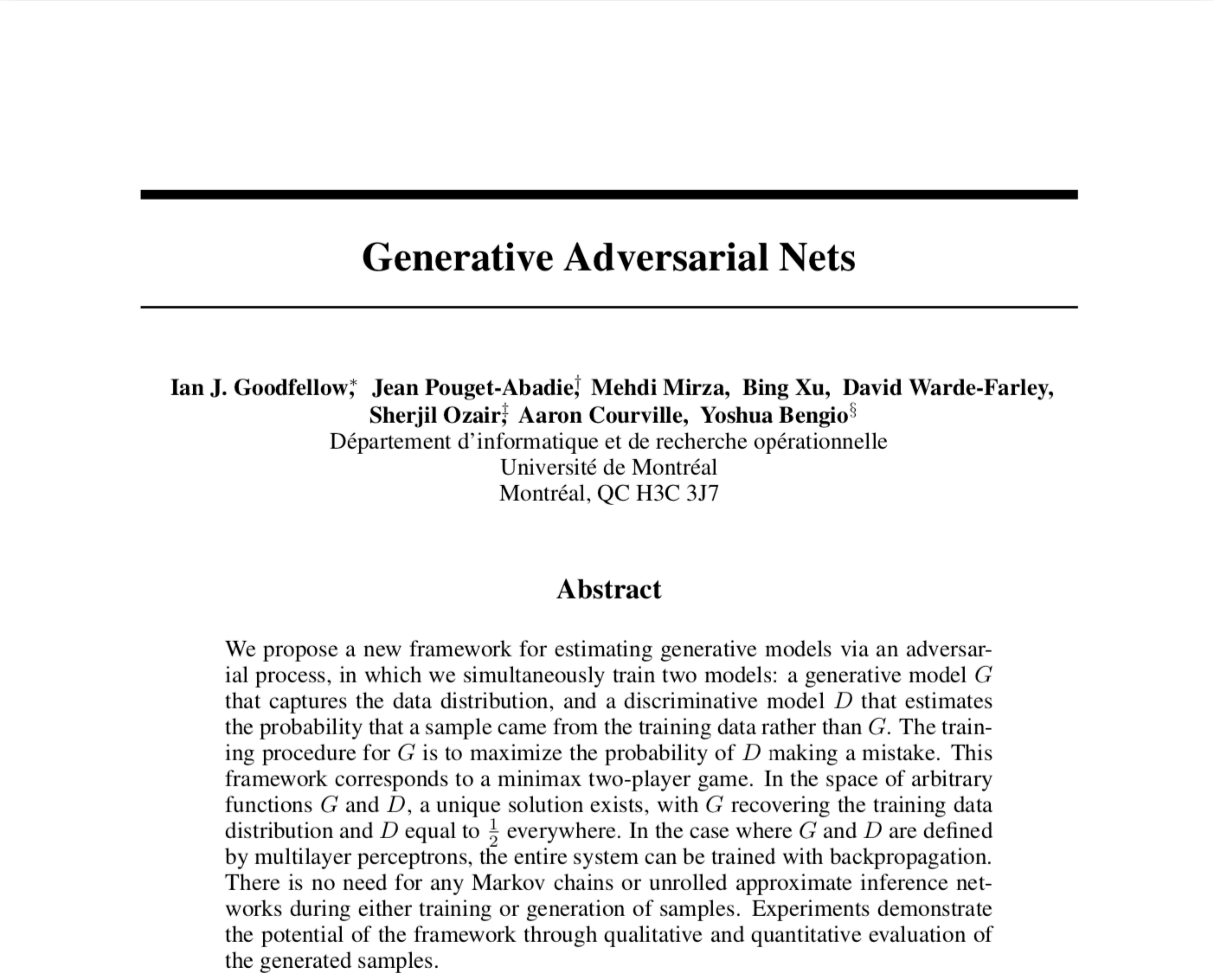
Generative Adversarial Networks (GANs)

- A Generative Adversarial Network (GAN) is a class of machine learning techniques in which two neural networks play against each other.
- The *generative network* generates candidates, while the *discriminative network* evaluate them.
- The generative network tries to create new samples that look similar from the true data (an original distribution, for example portraits). The goal of the discriminator is to identify if the data given in input are from the original distribution or not.
- The generative network's training objective is to increase the error rate of the discriminative network (i.e., to fool the discriminative network)
- Indeed, the discriminative network's training objective is to minimise its error rate in discriminating the input.
- This is used for images, videogame generation, scientific images, etc.

Generative Adversarial Networks (GANs)



Source: https://developers.google.com/machine-learning/gan/generator



Generative Adversarial Nets

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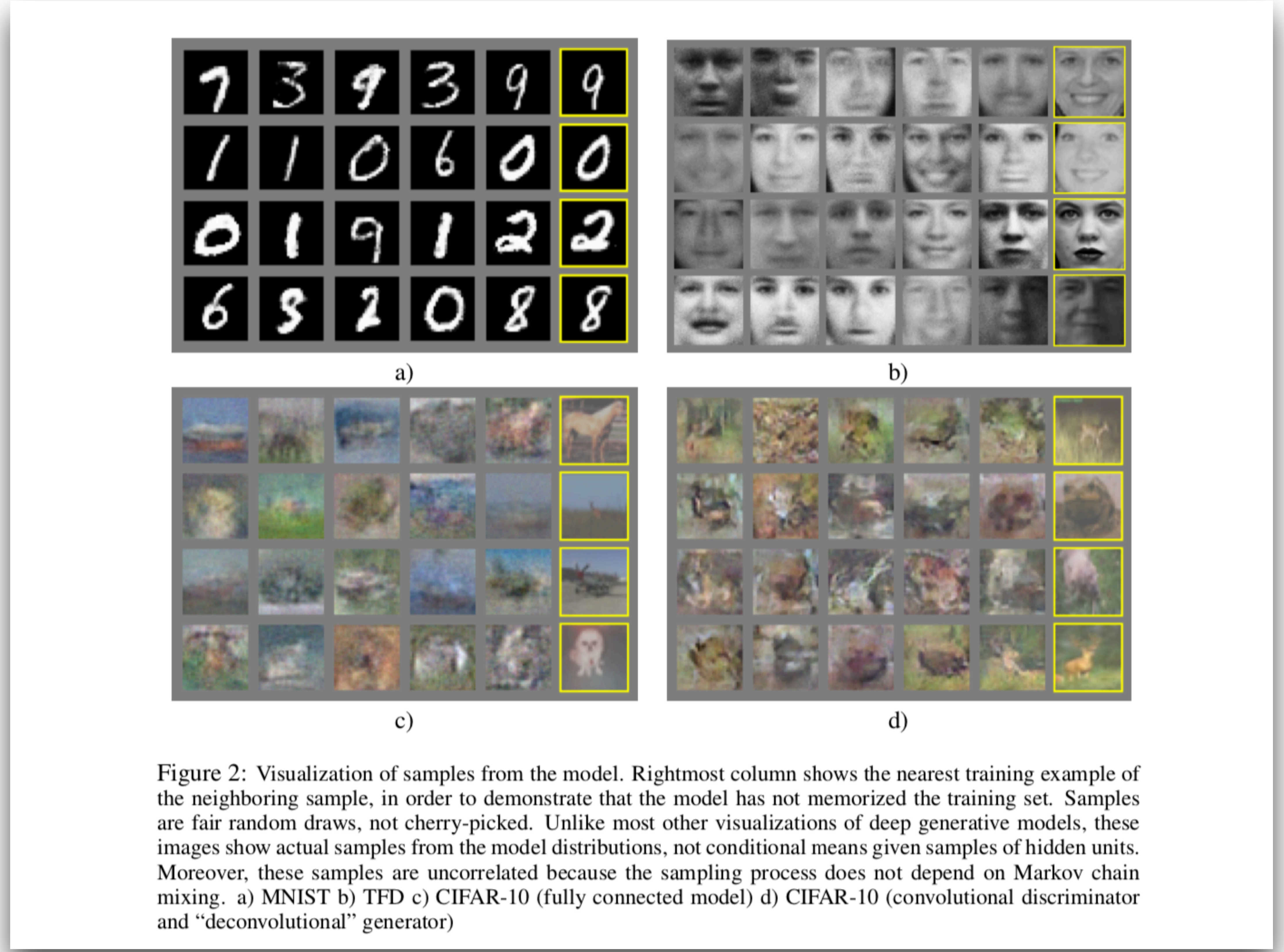
Abstract

We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to $\frac{1}{2}$ everywhere. In the case where G and D are defined by multilayer perceptrons, the entire system can be trained with backpropagation. There is no need for any Markov chains or unrolled approximate inference networks during either training or generation of samples. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated samples.



a)

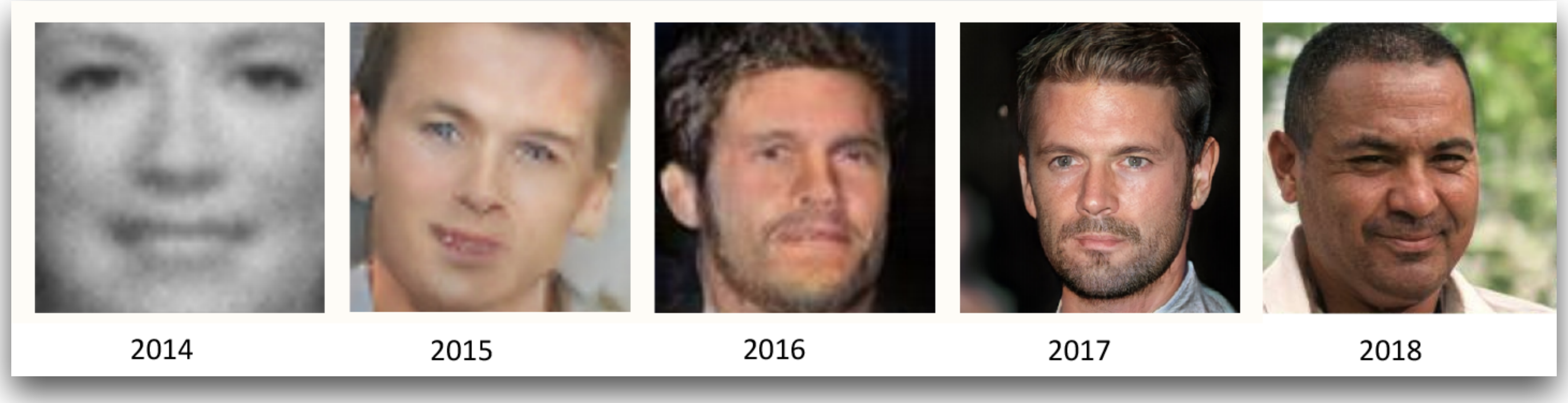
b)

c)

d)

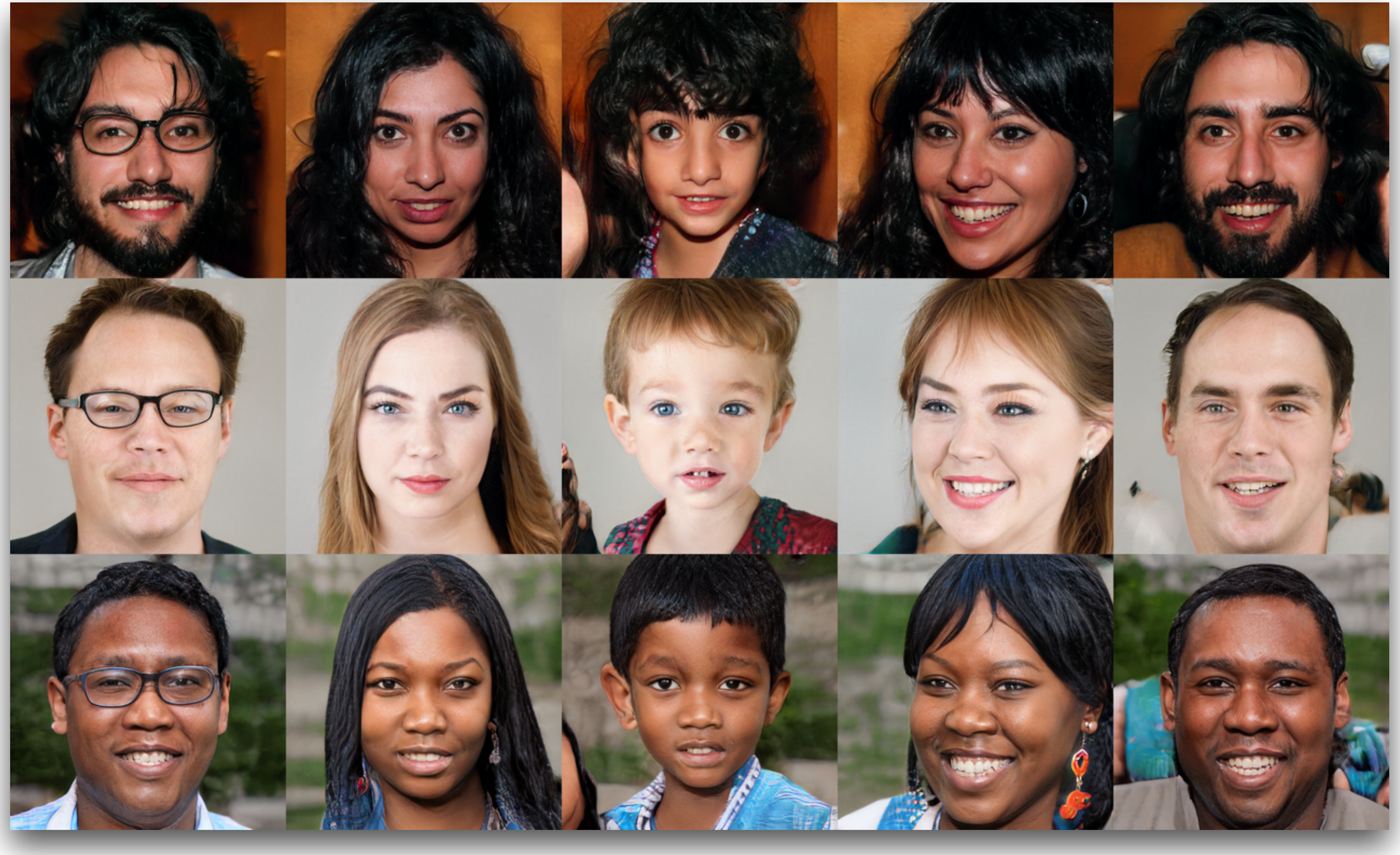
Figure 2: Visualization of samples from the model. Rightmost column shows the nearest training example of the neighboring sample, in order to demonstrate that the model has not memorized the training set. Samples are fair random draws, not cherry-picked. Unlike most other visualizations of deep generative models, these images show actual samples from the model distributions, not conditional means given samples of hidden units. Moreover, these samples are uncorrelated because the sampling process does not depend on Markov chain mixing. a) MNIST b) TFD c) CIFAR-10 (fully connected model) d) CIFAR-10 (convolutional discriminator and “deconvolutional” generator)

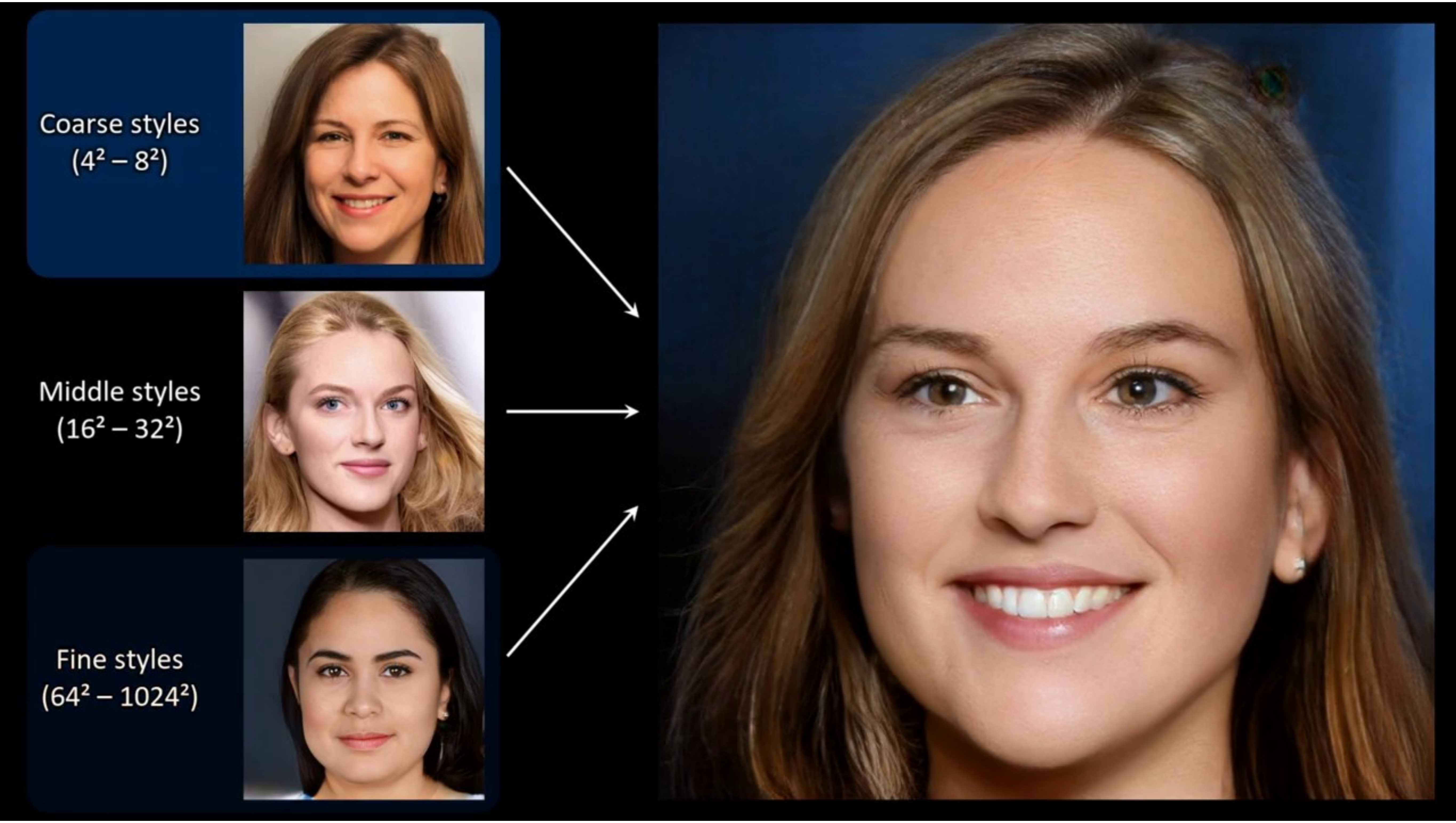
Generation of Images using Generative Adversarial Networks (GANs)

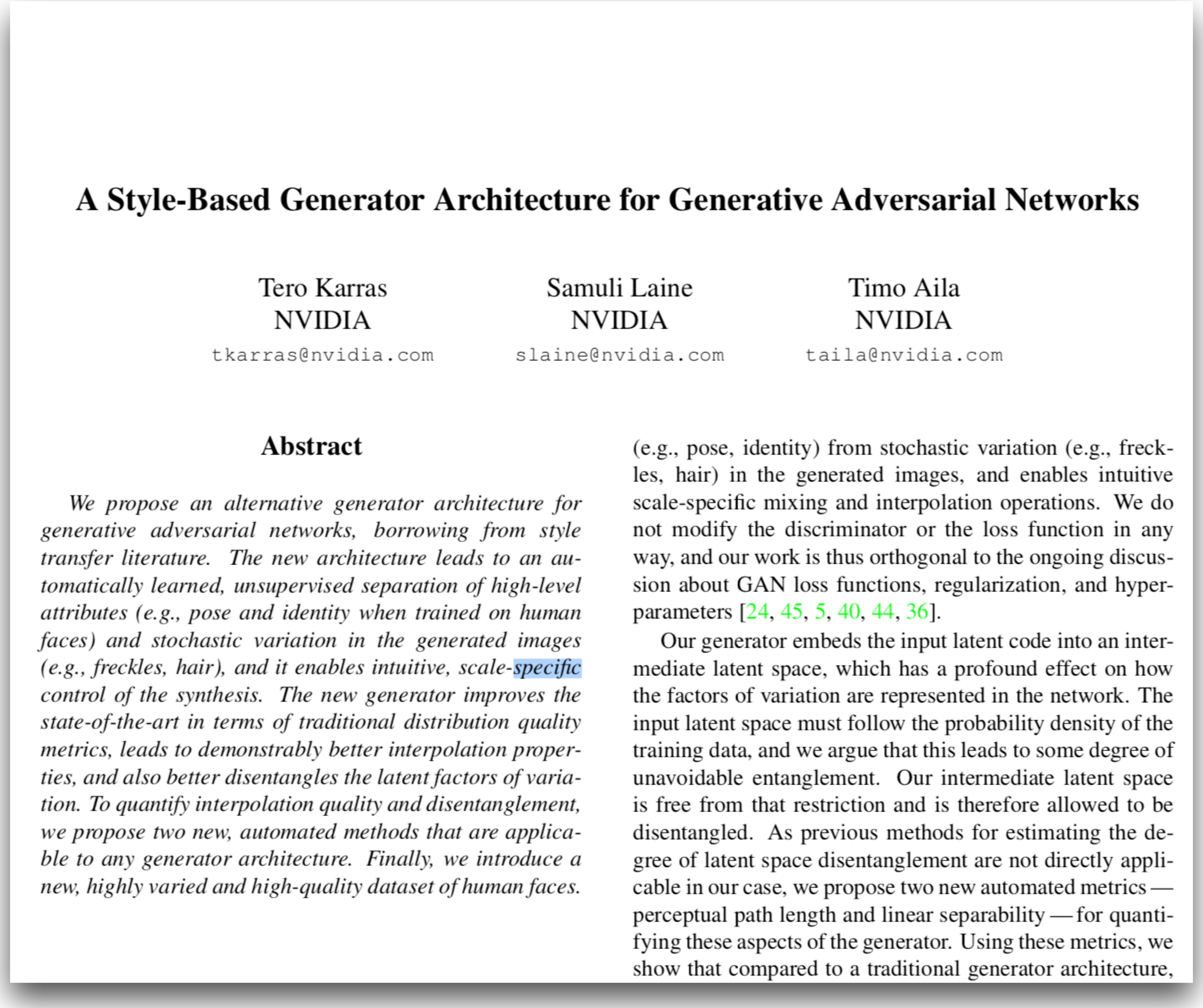


Source: David Foster. Generative Deep Learning. O’Reilly. 2019.

StyleGAN




Coarse styles
$(4^2 – 8^2)$
Middle styles
$(16^2 – 32^2)$
Fine styles
$(64^2 – 1024^2)$



A Style-Based Generator Architecture for Generative Adversarial Networks

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Abstract

We propose an alternative generator architecture for generative adversarial networks, borrowing from style transfer literature. The new architecture leads to an automatically learned, unsupervised separation of high-level attributes (e.g., pose and identity when trained on human faces) and stochastic variation in the generated images (e.g., freckles, hair), and it enables intuitive, scale-specific control of the synthesis. The new generator improves the state-of-the-art in terms of traditional distribution quality metrics, leads to demonstrably better interpolation properties, and also better disentangles the latent factors of variation. To quantify interpolation quality and disentanglement, we propose two new, automated methods that are applicable to any generator architecture. Finally, we introduce a new, highly varied and high-quality dataset of human faces.

(e.g., pose, identity) from stochastic variation (e.g., freckles, hair) in the generated images, and enables intuitive scale-specific mixing and interpolation operations. We do not modify the discriminator or the loss function in any way, and our work is thus orthogonal to the ongoing discussion about GAN loss functions, regularization, and hyper-parameters [24, 45, 5, 40, 44, 36].

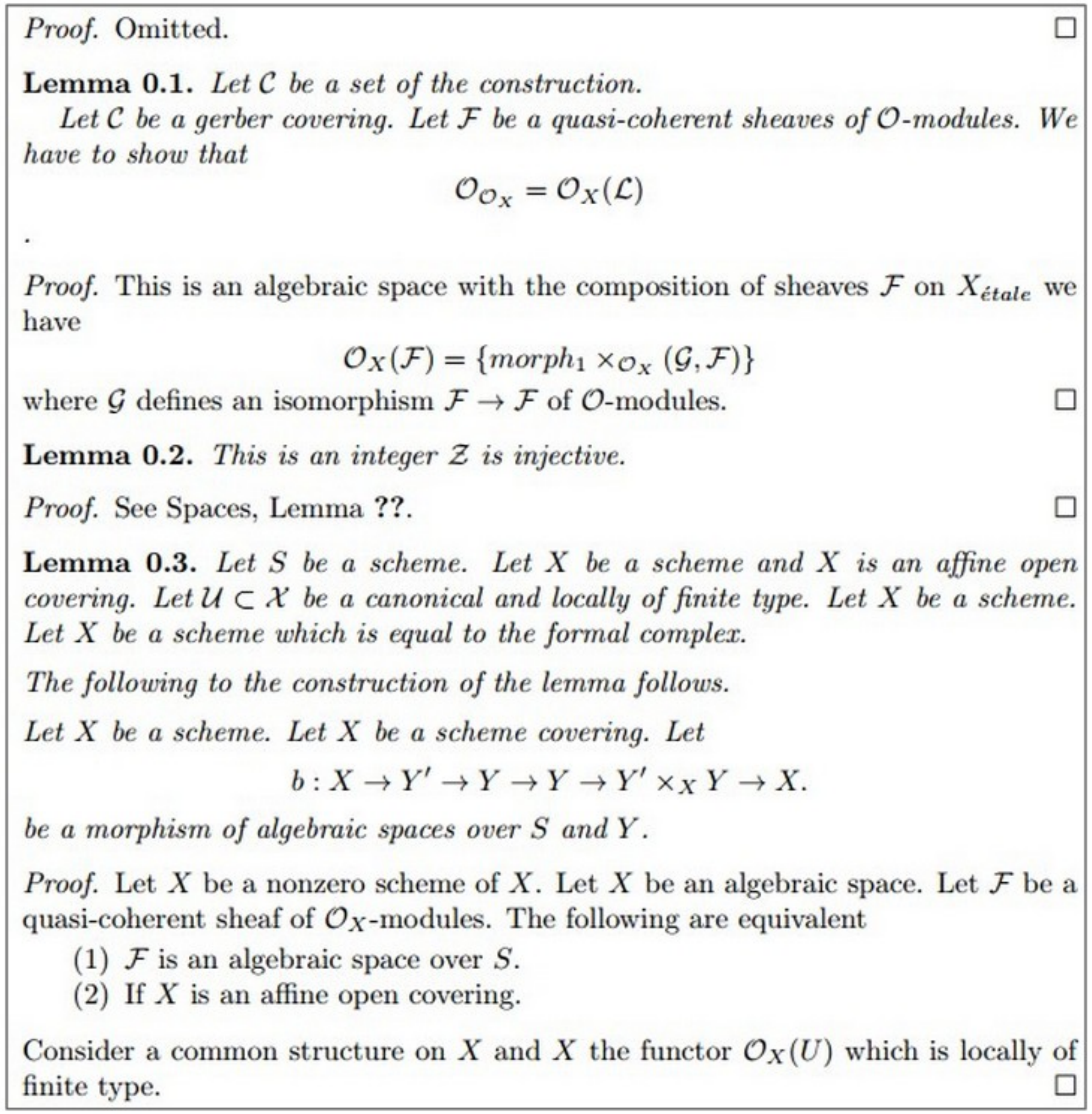
Our generator embeds the input latent code into an intermediate latent space, which has a profound effect on how the factors of variation are represented in the network. The input latent space must follow the probability density of the training data, and we argue that this leads to some degree of unavoidable entanglement. Our intermediate latent space is free from that restriction and is therefore allowed to be disentangled. As previous methods for estimating the degree of latent space disentanglement are not directly applicable in our case, we propose two new automated metrics — perceptual path length and linear separability — for quantifying these aspects of the generator. Using these metrics, we show that compared to a traditional generator architecture,

Text Generation

```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it
```

Source: Andrej Karpathy. The Unreasonable Effectiveness of Recurrent Neural Networks.
http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Text Generation



Proof. Omitted. □

Lemma 0.1. *Let $\mathcal{C}$ be a set of the construction.*

Let $\mathcal{C}$ be a gerber covering. Let $\mathcal{F}$ be a quasi-coherent sheaves of $\mathcal{O}$-modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

.

Proof. This is an algebraic space with the composition of sheaves $\mathcal{F}$ on $X_{\acute{e}tale}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where $\mathcal{G}$ defines an isomorphism $\mathcal{F} \to \mathcal{F}$ of $\mathcal{O}$-modules. □

Lemma 0.2. *This is an integer $\mathcal{Z}$ is injective.*

Proof. See Spaces, Lemma **??**. □

Lemma 0.3. *Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.*

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

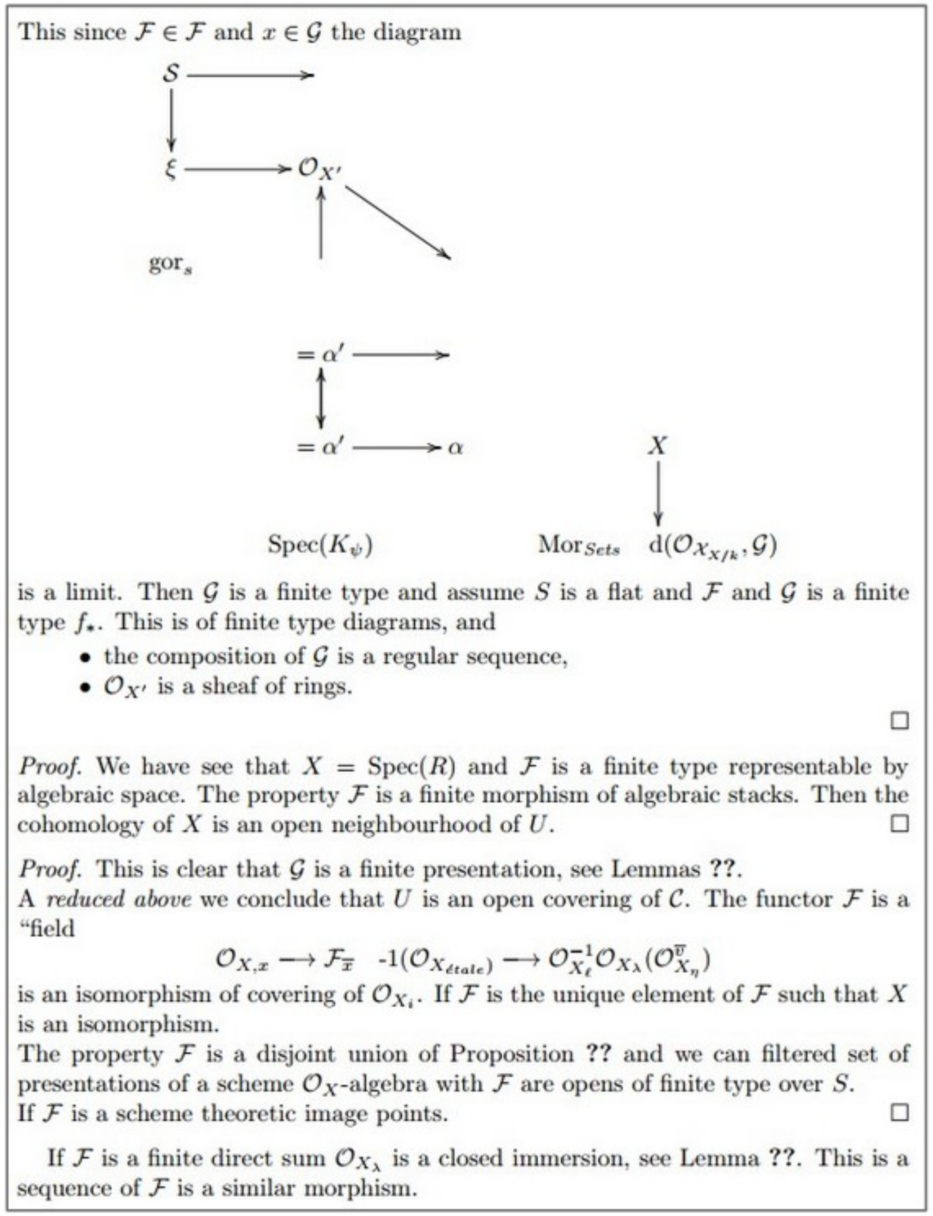
$$b : X \to Y' \to Y \to Y \to Y' \times_X Y \to X.$$

be a morphism of algebraic spaces over S and Y.

Proof. Let X be a nonzero scheme of X. Let X be an algebraic space. Let $\mathcal{F}$ be a quasi-coherent sheaf of $\mathcal{O}_X$-modules. The following are equivalent

(1) $\mathcal{F}$ is an algebraic space over S.
(2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. □



This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

$$\begin{tikzcd}
\mathcal{S} \arrow[r] \arrow[d] & {} & & & \\
\xi \arrow[r] & \mathcal{O}_{X'} \arrow[dr] & & & \\
\mathrm{gor}_s & {} \arrow[u] & {} & & \\
& {=\alpha'} \arrow[r] \arrow[d, leftrightarrow] & {} & & \\
& {=\alpha'} \arrow[r] & \alpha & & X \arrow[d] \\
& \mathrm{Spec}(K_\psi) & & \mathrm{Mor}_{Sets} & \mathrm{d}(\mathcal{O}_{\mathcal{X}_{X/k}}, \mathcal{G})
\end{tikzcd}$$

is a limit. Then $\mathcal{G}$ is a finite type and assume S is a flat and $\mathcal{F}$ and $\mathcal{G}$ is a finite type f_*. This is of finite type diagrams, and

- the composition of $\mathcal{G}$ is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

□

Proof. We have see that $X = \mathrm{Spec}(R)$ and $\mathcal{F}$ is a finite type representable by algebraic space. The property $\mathcal{F}$ is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U. □

Proof. This is clear that $\mathcal{G}$ is a finite presentation, see Lemmas **??**.
A *reduced above* we conclude that U is an open covering of $\mathcal{C}$. The functor $\mathcal{F}$ is a "field

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} \ \text{-1}(\mathcal{O}_{X_{\acute{e}tale}}) \longrightarrow \mathcal{O}_{X_\ell}^{-1}\mathcal{O}_{X_\lambda}(\mathcal{O}_{X_\eta}^{\overline{v}})$$

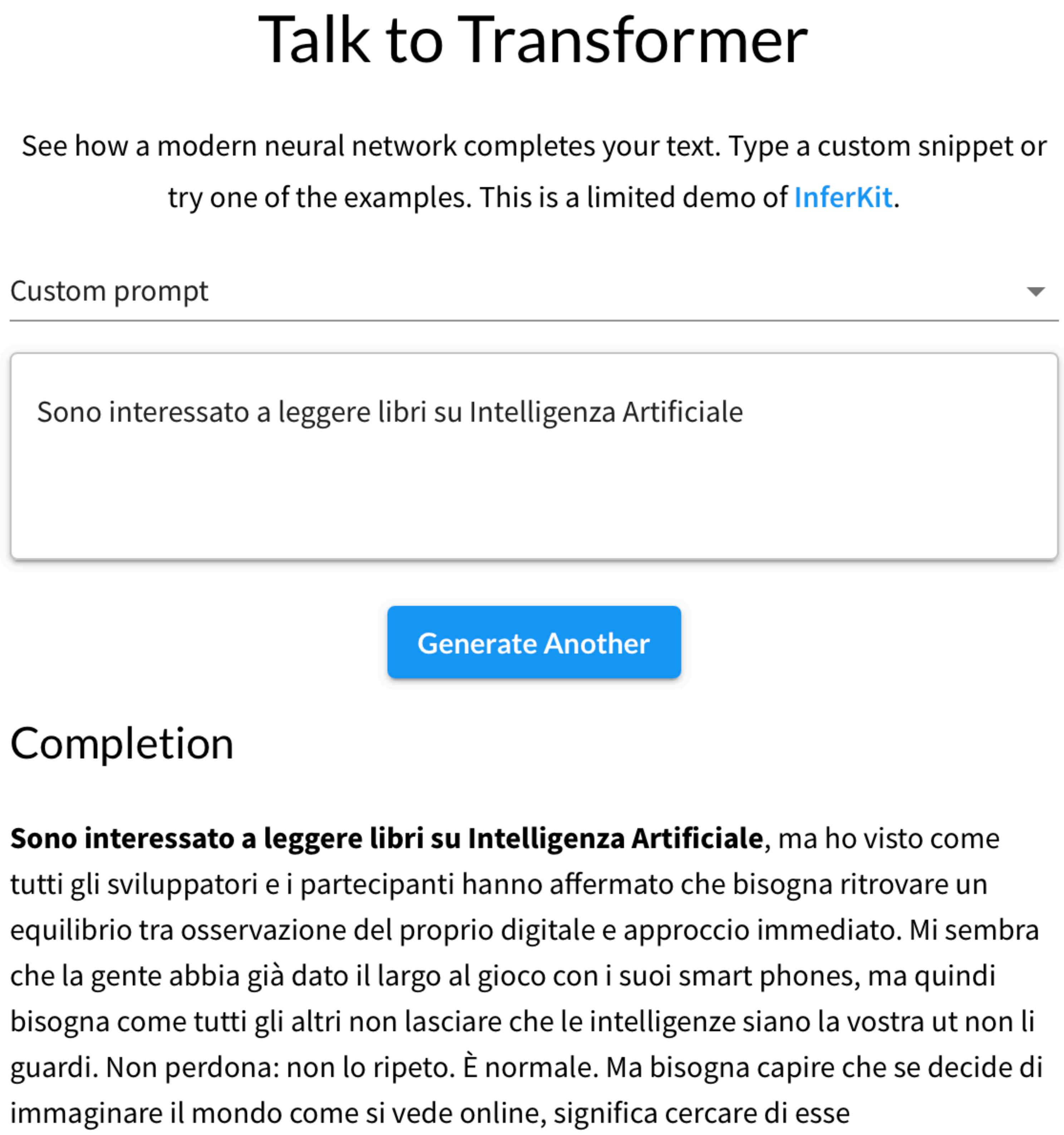
is an isomorphism of covering of $\mathcal{O}_{X_i}$. If $\mathcal{F}$ is the unique element of $\mathcal{F}$ such that X is an isomorphism.
The property $\mathcal{F}$ is a disjoint union of Proposition **??** and we can filtered set of presentations of a scheme $\mathcal{O}_X$-algebra with $\mathcal{F}$ are opens of finite type over S.
If $\mathcal{F}$ is a scheme theoretic image points. □

If $\mathcal{F}$ is a finite direct sum $\mathcal{O}_{X_\lambda}$ is a closed immersion, see Lemma **??**. This is a sequence of $\mathcal{F}$ is a similar morphism.

Source: Andrej Karpathy. The Unreasonable Effectiveness of Recurrent Neural Networks.
http://karpathy.github.io/2015/05/21/rnn-effectiveness/

GPT-3

- GPT-3 (Generative Pre-Trained Transformer 3 (GPT-3) is a language model that uses deep learning to produce human-like text.
- Created by OpenAI.
- GPT-3 model is based on 175 billion parameters.



Talk to Transformer

See how a modern neural network completes your text. Type a custom snippet or try one of the examples. This is a limited demo of InferKit.

Sono interessato a leggere libri su Intelligenza Artificiale

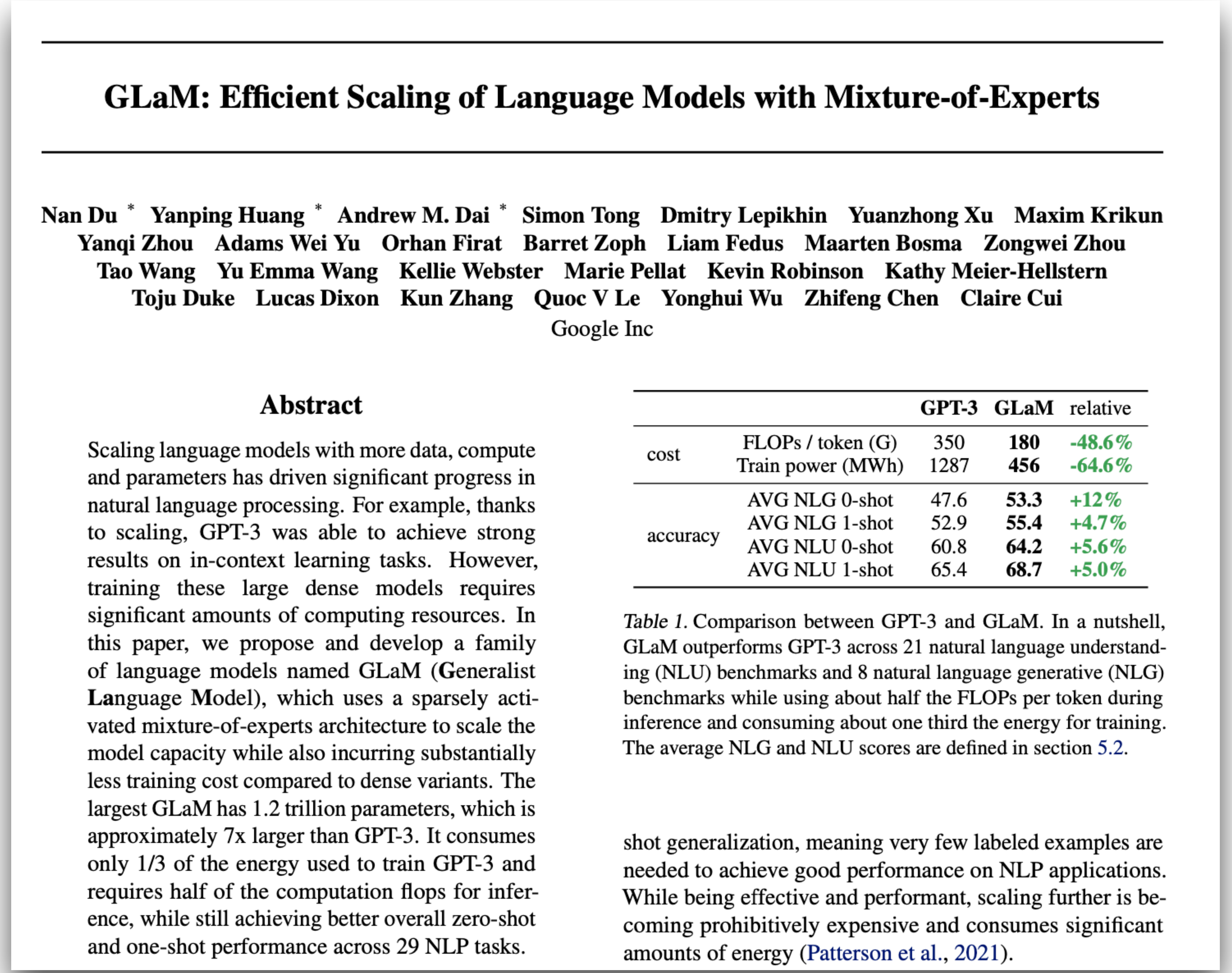
Completion

Sono interessato a leggere libri su Intelligenza Artificiale, ma ho visto come tutti gli sviluppatori e i partecipanti hanno affermato che bisogna ritrovare un equilibrio tra osservazione del proprio digitale e approccio immediato. Mi sembra che la gente abbia già dato il largo al gioco con i suoi smart phones, ma quindi bisogna come tutti gli altri non lasciare che le intelligenze siano la vostra ut non li guardi. Non perdona: non lo ripeto. È normale. Ma bisogna capire che se decide di immaginare il mondo come si vede online, significa cercare di esse

GLaM

- GLaM is a trillion-weight model based on a “mixture of experts” model:
  - Each expert is specialised on specify type of inputs.
  - The full version of GLaM has 1.2T parameters across 56 experts, but it activates only a subnetwork of 97B (%) parameters per token during prediction.
  - Experts are essentially partially activated (through a so-called gating network).
- Focus on energy efficiency.

GLaM



GLaM: Efficient Scaling of Language Models with Mixture-of-Experts

Nan Du * Yanping Huang * Andrew M. Dai * Simon Tong Dmitry Lepikhin Yuanzhong Xu Maxim Krikun Yanqi Zhou Adams Wei Yu Orhan Firat Barret Zoph Liam Fedus Maarten Bosma Zongwei Zhou Tao Wang Yu Emma Wang Kellie Webster Marie Pellat Kevin Robinson Kathy Meier-Hellstern Toju Duke Lucas Dixon Kun Zhang Quoc V Le Yonghui Wu Zhifeng Chen Claire Cui
Google Inc

Abstract

Scaling language models with more data, compute and parameters has driven significant progress in natural language processing. For example, thanks to scaling, GPT-3 was able to achieve strong results on in-context learning tasks. However, training these large dense models requires significant amounts of computing resources. In this paper, we propose and develop a family of language models named GLaM (**G**eneralist **La**nguage **M**odel), which uses a sparsely activated mixture-of-experts architecture to scale the model capacity while also incurring substantially less training cost compared to dense variants. The largest GLaM has 1.2 trillion parameters, which is approximately 7x larger than GPT-3. It consumes only 1/3 of the energy used to train GPT-3 and requires half of the computation flops for inference, while still achieving better overall zero-shot and one-shot performance across 29 NLP tasks.

		GPT-3	GLaM	relative
cost	FLOPs / token (G)	350	**180**	-48.6%
	Train power (MWh)	1287	**456**	-64.6%
accuracy	AVG NLG 0-shot	47.6	**53.3**	+12%
	AVG NLG 1-shot	52.9	**55.4**	+4.7%
	AVG NLU 0-shot	60.8	**64.2**	+5.6%
	AVG NLU 1-shot	65.4	**68.7**	+5.0%

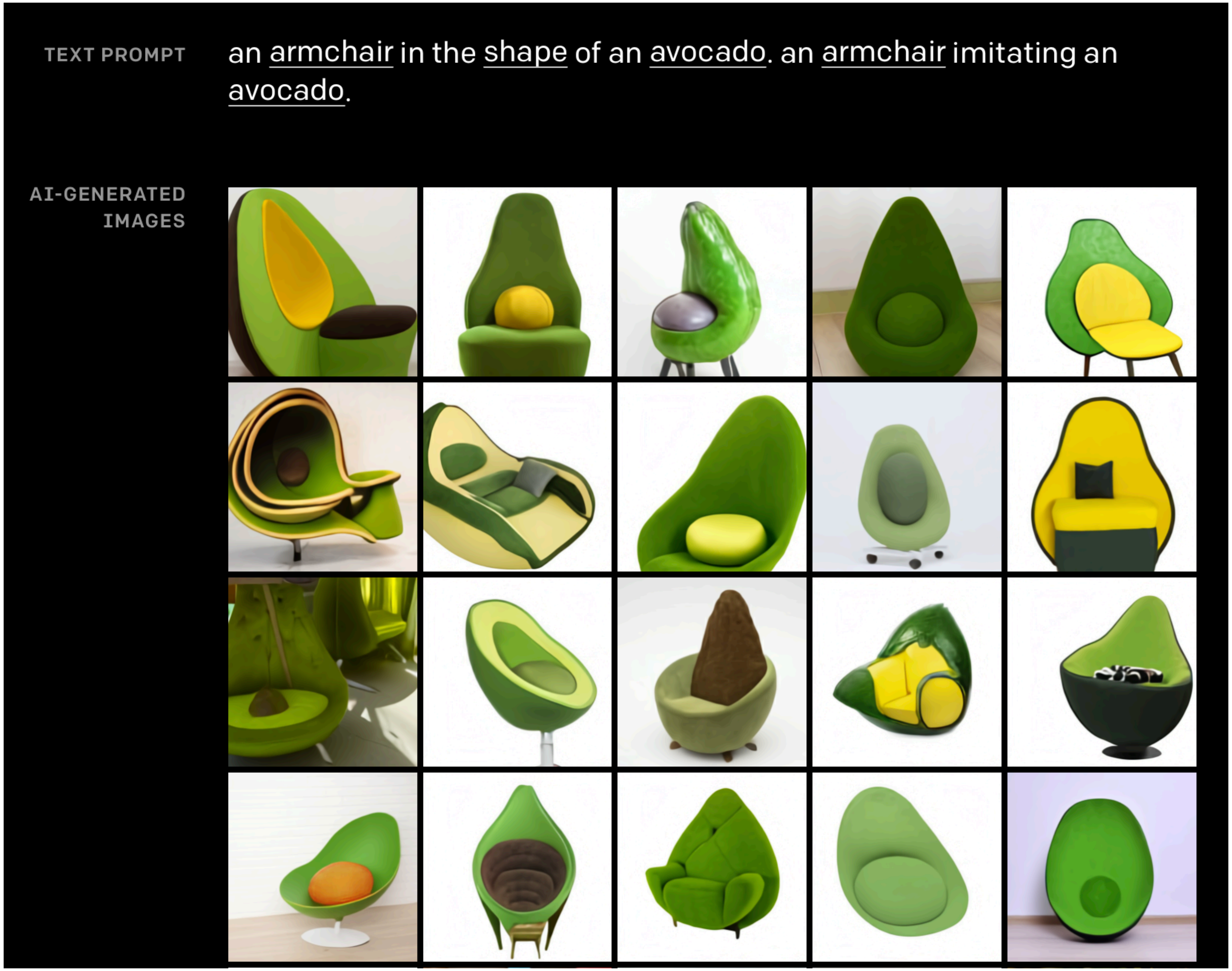
Table 1. Comparison between GPT-3 and GLaM. In a nutshell, GLaM outperforms GPT-3 across 21 natural language understanding (NLU) benchmarks and 8 natural language generative (NLG) benchmarks while using about half the FLOPs per token during inference and consuming about one third the energy for training. The average NLG and NLU scores are defined in section 5.2.

shot generalization, meaning very few labeled examples are needed to achieve good performance on NLP applications. While being effective and performant, scaling further is becoming prohibitively expensive and consumes significant amounts of energy (Patterson et al., 2021).

DALL·E

- Introduced in January 2021.
- DALL E is a 12-billion parameter version of GPT-3 trained to generate images from text descriptions using a dataset of text-image pairs.
- Different capabilities including:
    - Creation of anthropomorphised versions of animals and objects;
    - Linking unrelated concepts in novel ways;
    - Text rendering;
    - Transformation of existing images;
    - …

DALL·E

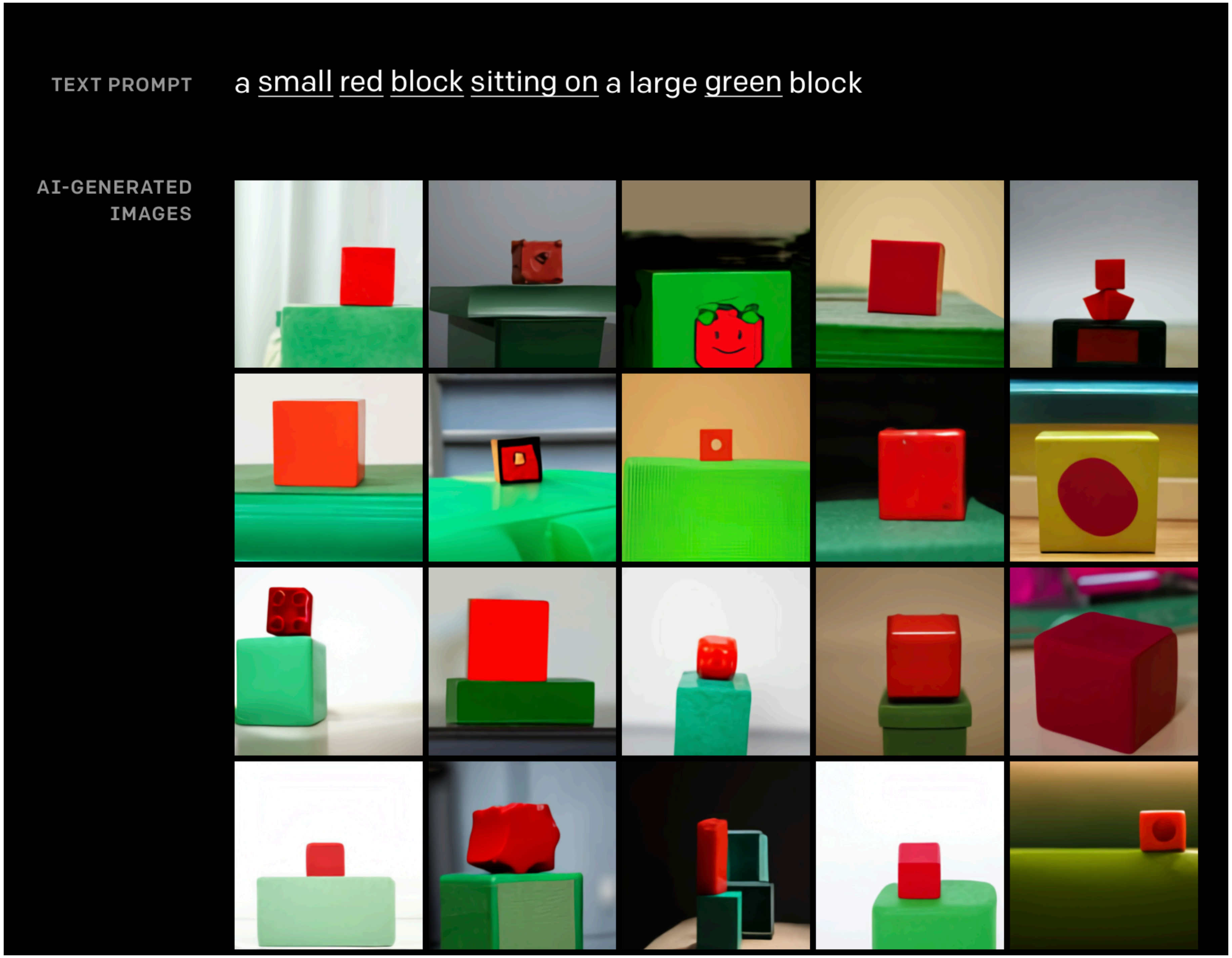


TEXT PROMPT

an armchair in the shape of an avocado. an armchair imitating an avocado.

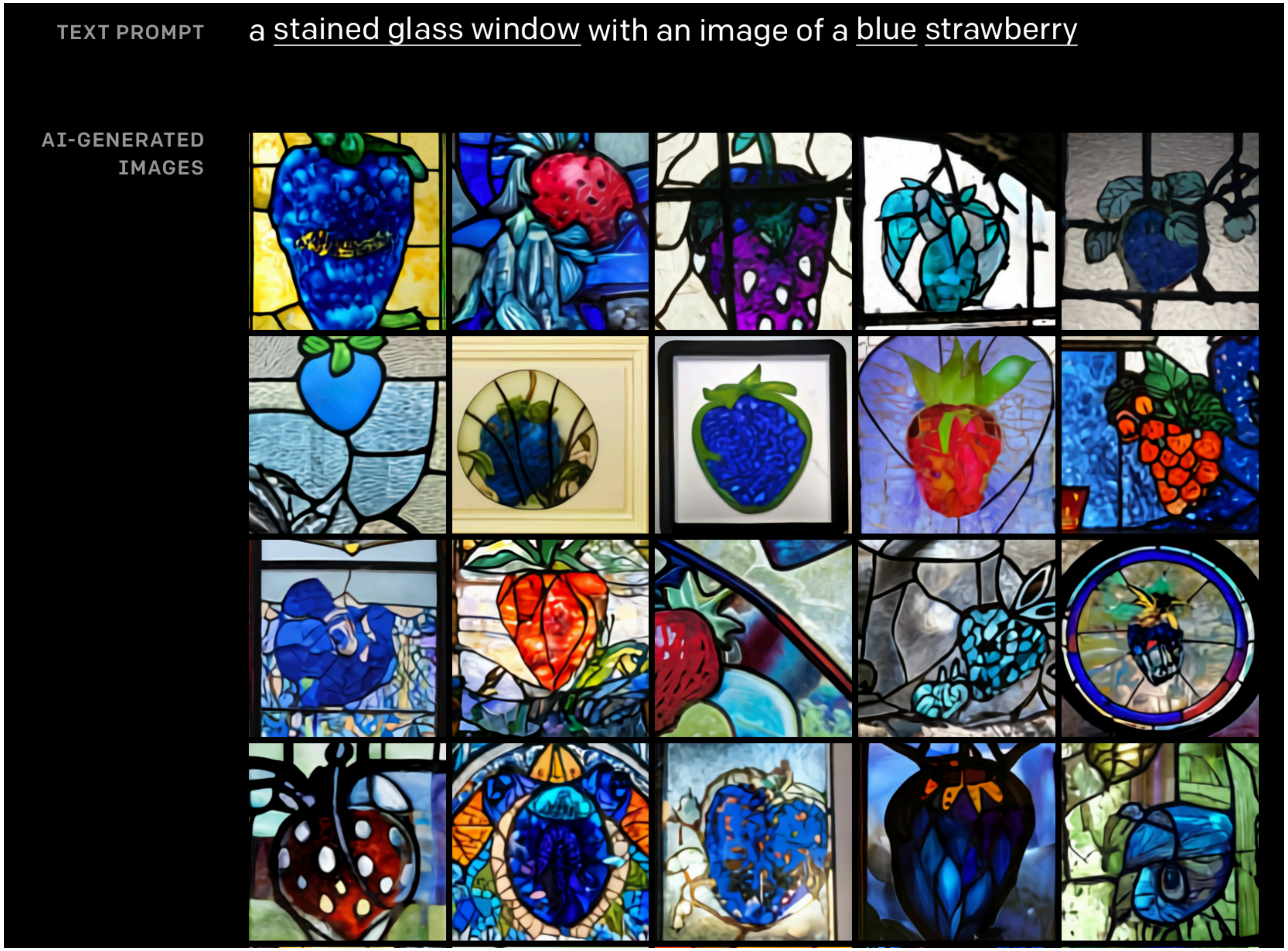
AI-GENERATED IMAGES

DALL·E



a small red block sitting on a large green block

DALL·E

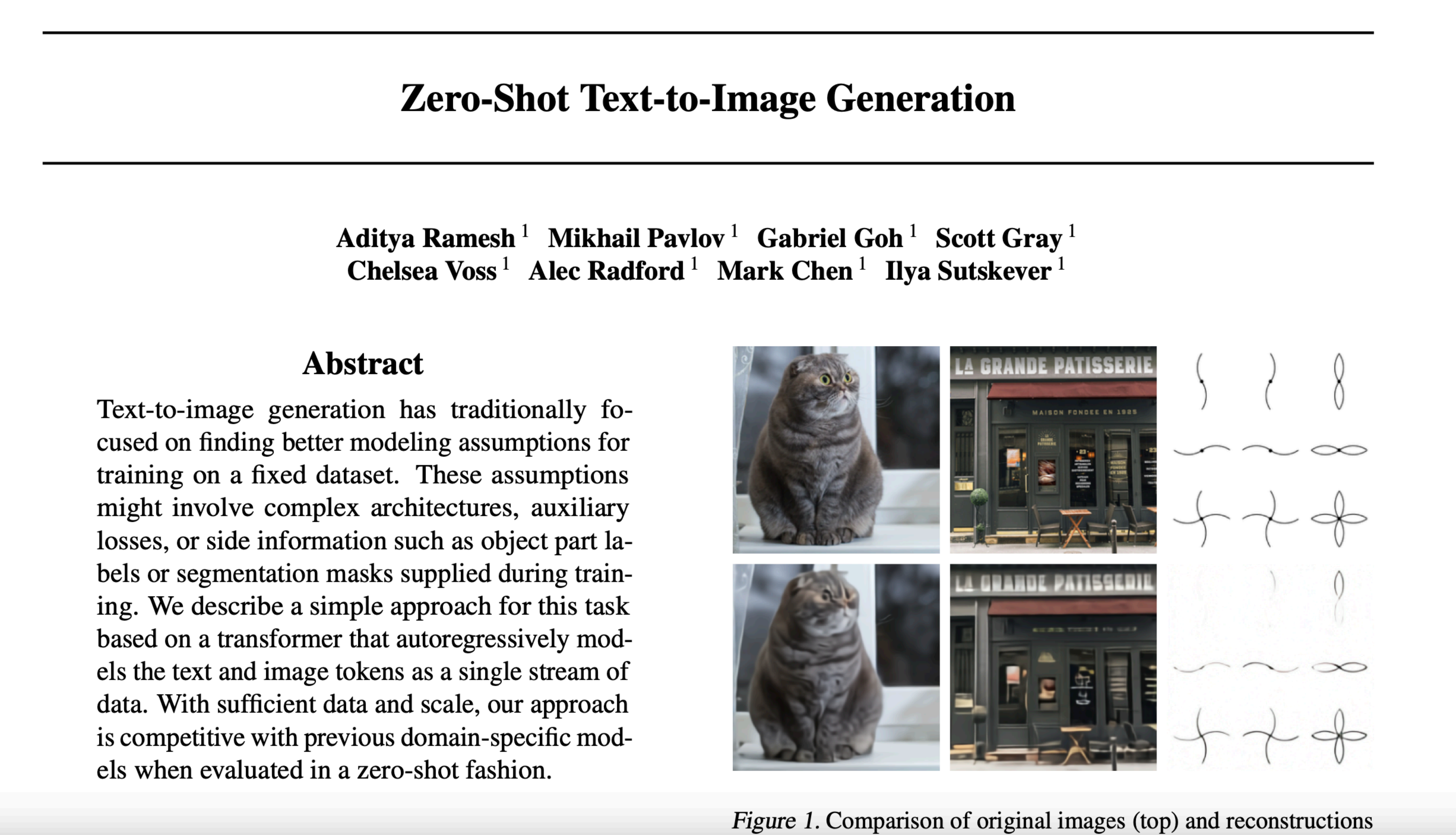


TEXT PROMPT

a stained glass window with an image of a blue strawberry

AI-GENERATED IMAGES

DALL·E



Zero-Shot Text-to-Image Generation

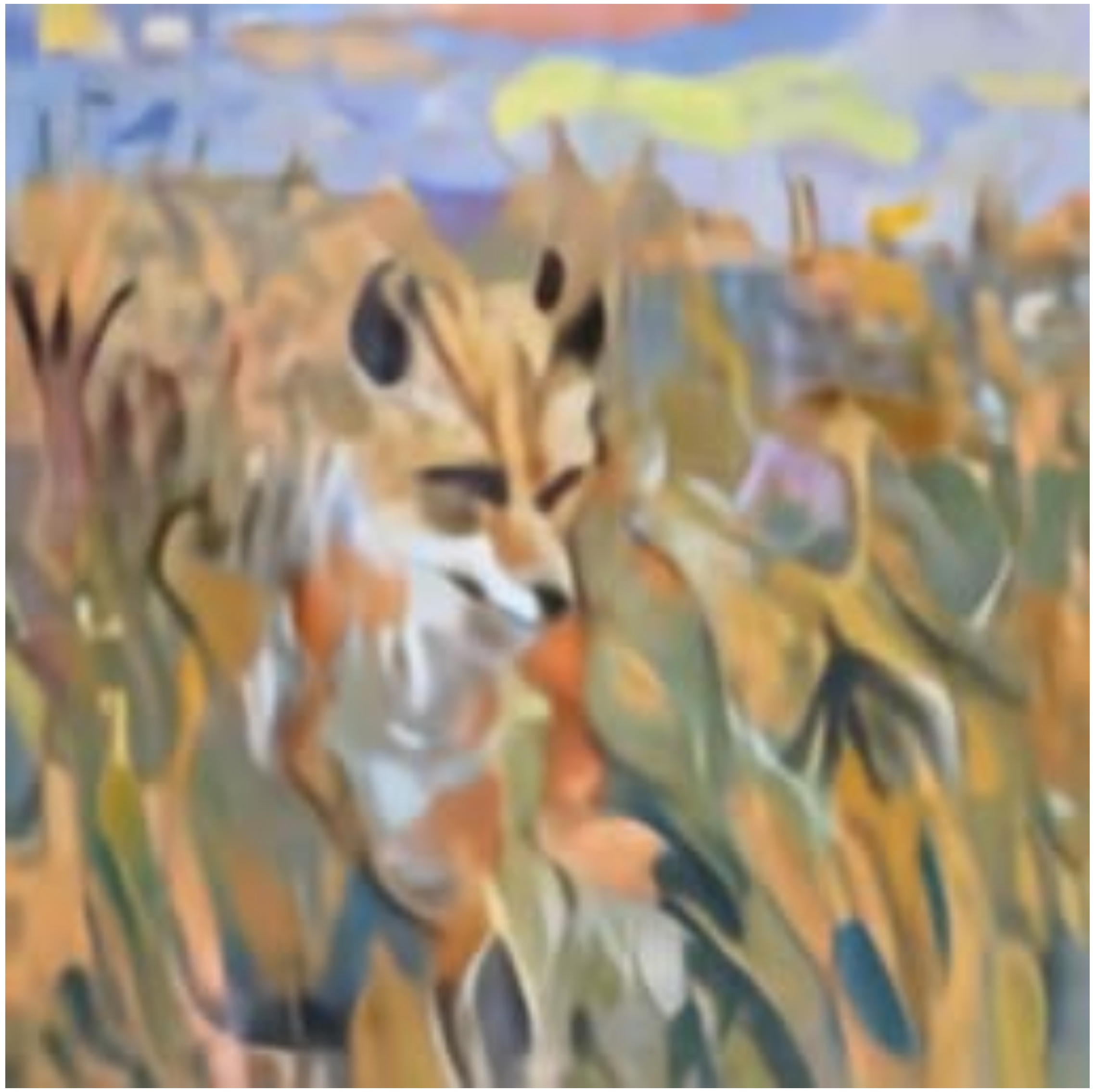
Aditya Ramesh [1] Mikhail Pavlov [1] Gabriel Goh [1] Scott Gray [1]
Chelsea Voss [1] Alec Radford [1] Mark Chen [1] Ilya Sutskever [1]

Abstract

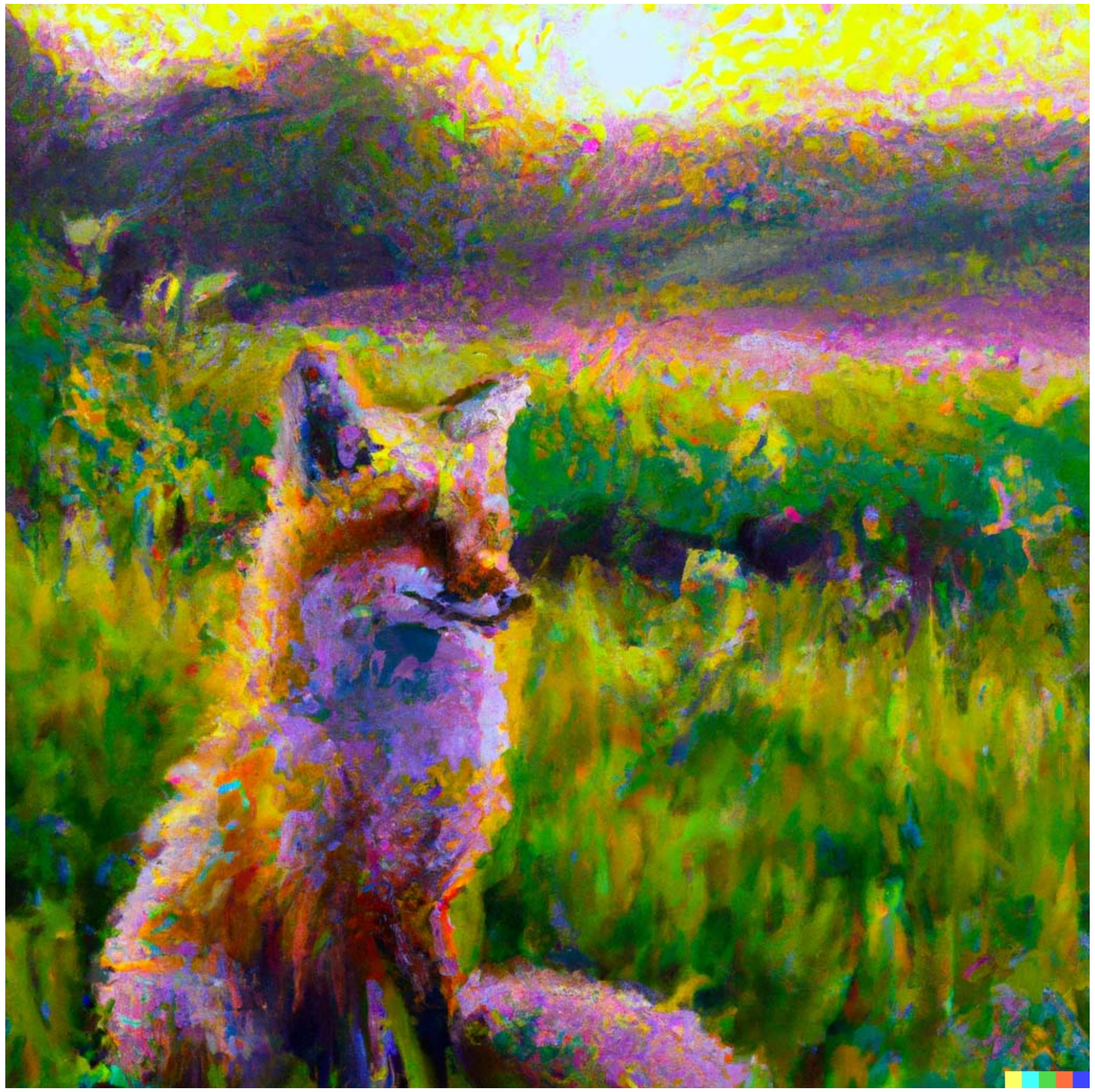
Text-to-image generation has traditionally focused on finding better modeling assumptions for training on a fixed dataset. These assumptions might involve complex architectures, auxiliary losses, or side information such as object part labels or segmentation masks supplied during training. We describe a simple approach for this task based on a transformer that autoregressively models the text and image tokens as a single stream of data. With sufficient data and scale, our approach is competitive with previous domain-specific models when evaluated in a zero-shot fashion.

Figure 1. Comparison of original images (top) and reconstructions

DALL·E 2



DALL·E 1



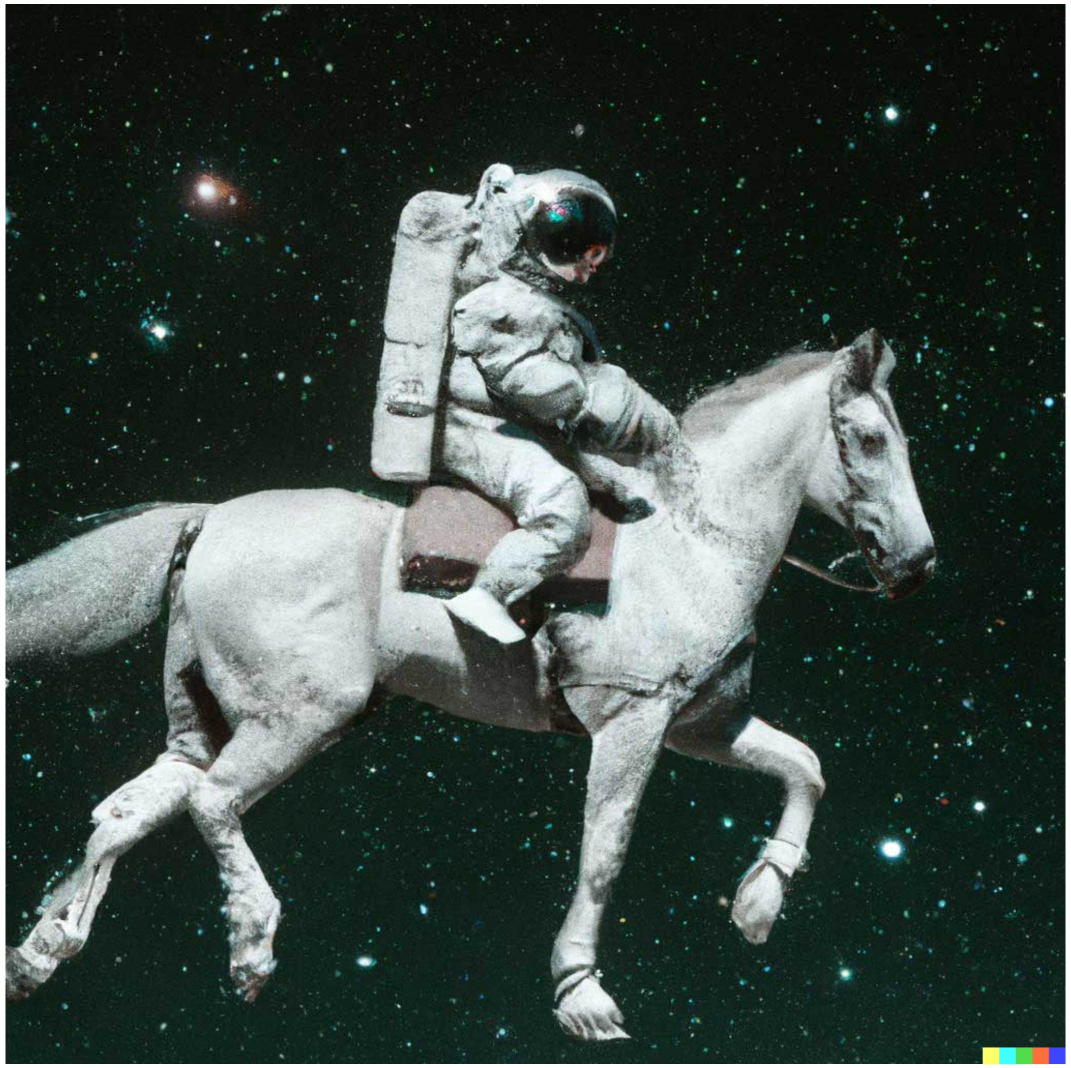
DALL·E 2

“a painting of a fox sitting in a field at sunrise in the style of Claude Monet”

DALL·E 2

- Launched in April 2022 - Dall·E is able to create “original, realistic images and art from a text description.”
- It is able to combine concept attributes and styles with visible improvements with respect to the previous version of the system.
- It can be used for photorealistic editing and creation of variations with high resolution.
- It learns the relationships between the images and the text used to describe them, including abstract ones.

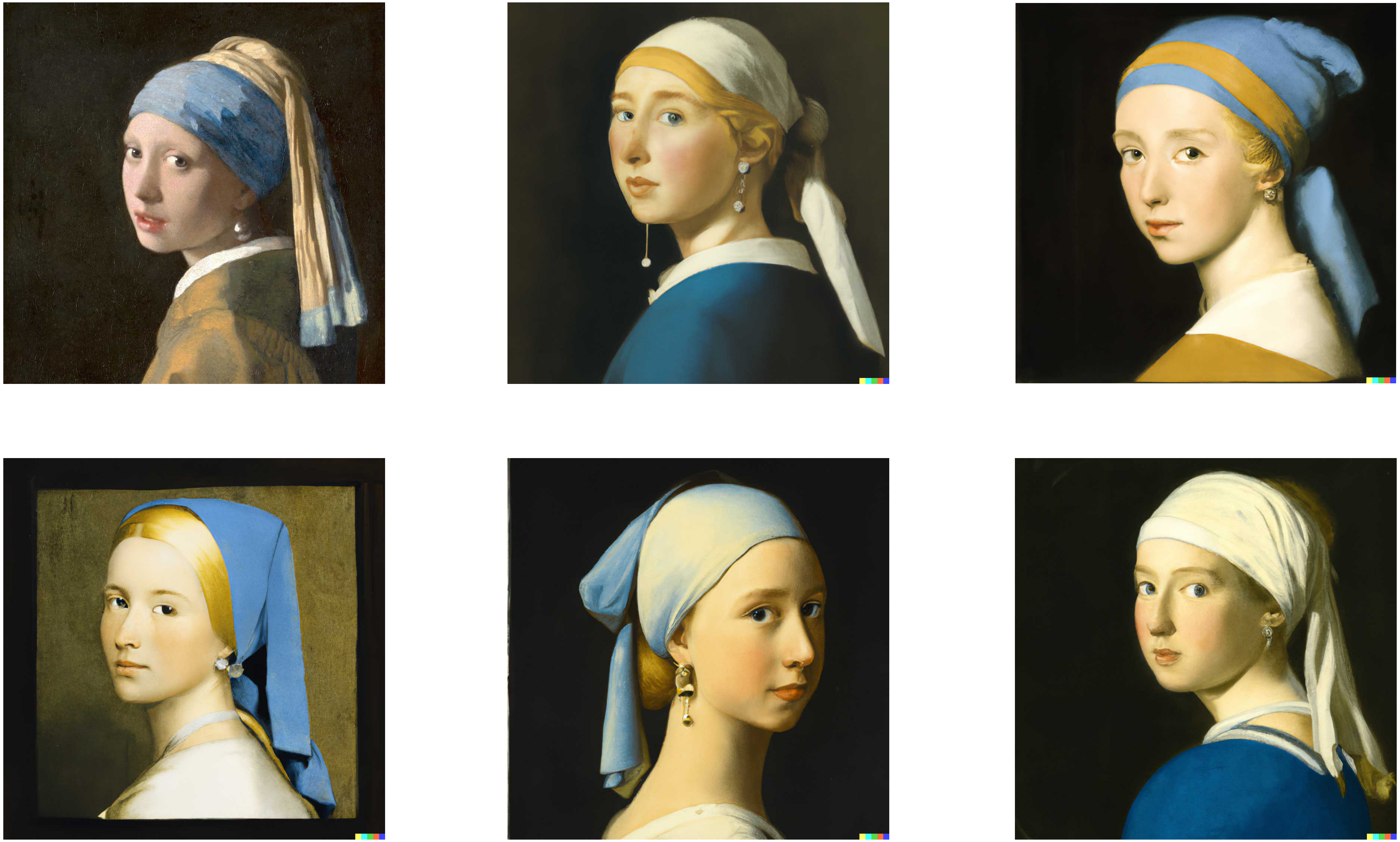
DALL·E 2



"an astronaut riding a horse lounging in a tropical resort in space in a photorealistic style”

DALL·E 2

DALL·E 2

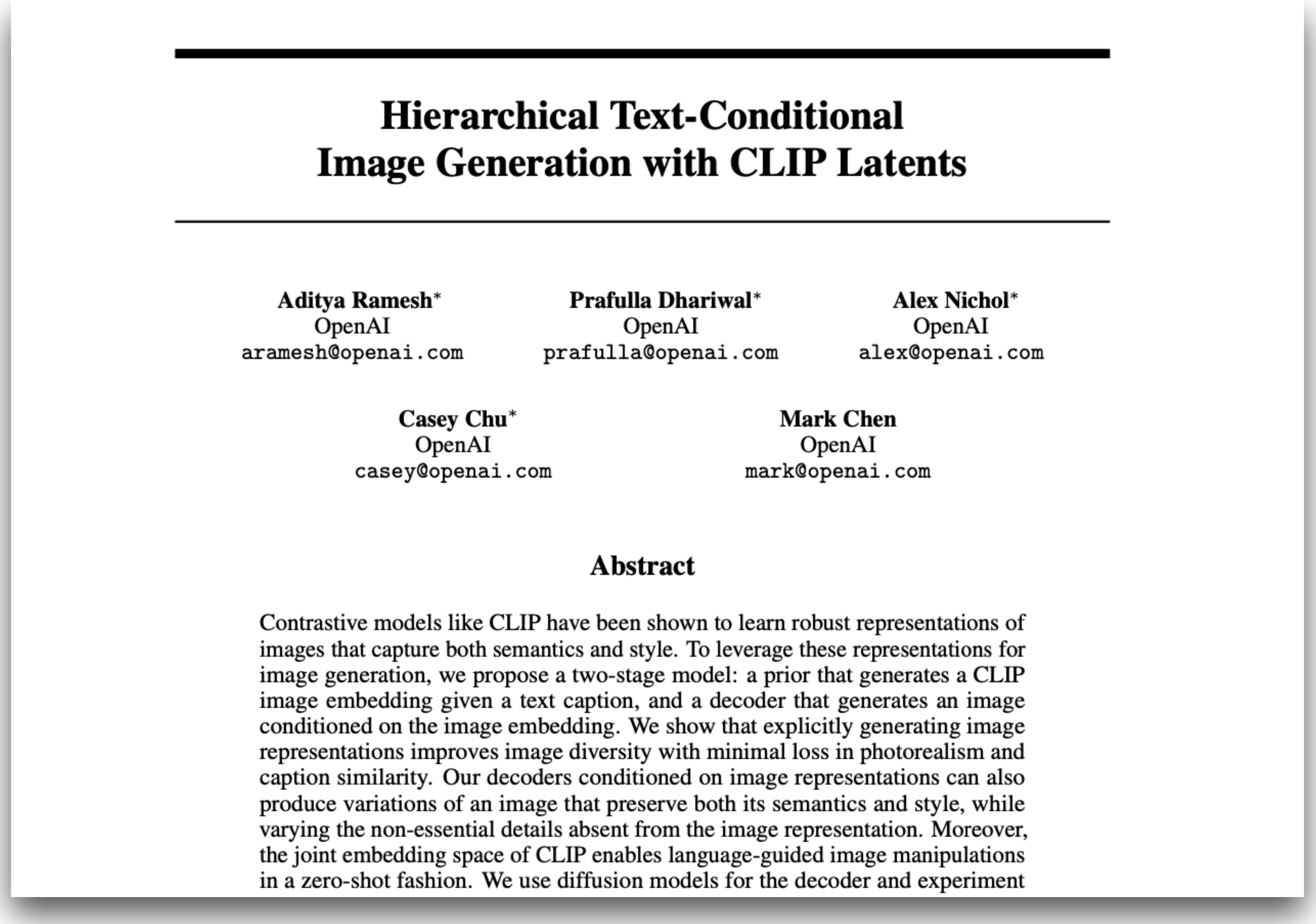


Variations of Vermeer's "Girl with a Pearl Earring"

DALL·E 2

- https://vimeo.com/692375454

DALL·E 2



Hierarchical Text-Conditional Image Generation with CLIP Latents

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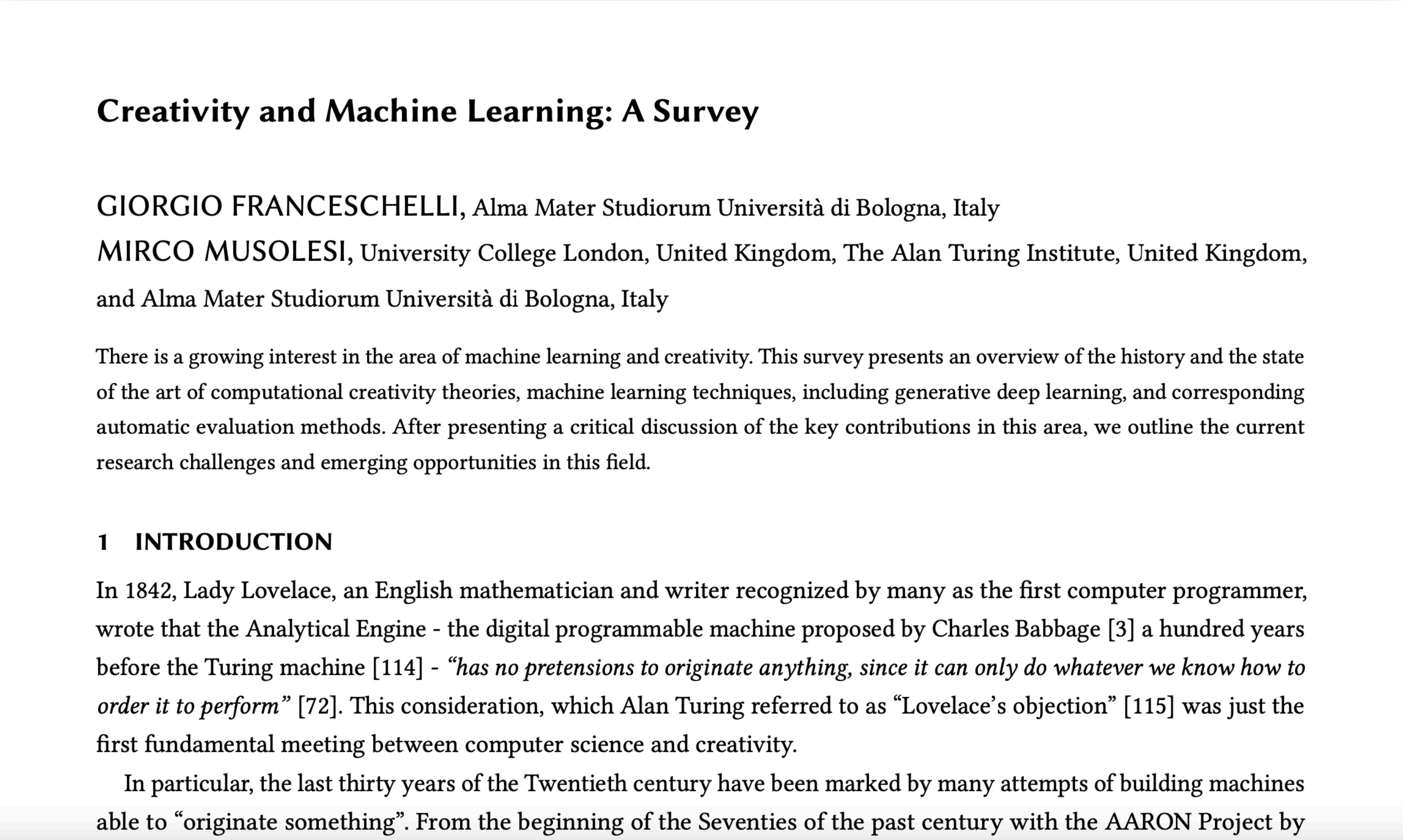
Abstract

Contrastive models like CLIP have been shown to learn robust representations of images that capture both semantics and style. To leverage these representations for image generation, we propose a two-stage model: a prior that generates a CLIP image embedding given a text caption, and a decoder that generates an image conditioned on the image embedding. We show that explicitly generating image representations improves image diversity with minimal loss in photorealism and caption similarity. Our decoders conditioned on image representations can also produce variations of an image that preserve both its semantics and style, while varying the non-essential details absent from the image representation. Moreover, the joint embedding space of CLIP enables language-guided image manipulations in a zero-shot fashion. We use diffusion models for the decoder and experiment



Creativity and Machine Learning: A Survey

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MIRCO MUSOLESI, University College London, United Kingdom, The Alan Turing Institute, United Kingdom, and Alma Mater Studiorum Università di Bologna, Italy

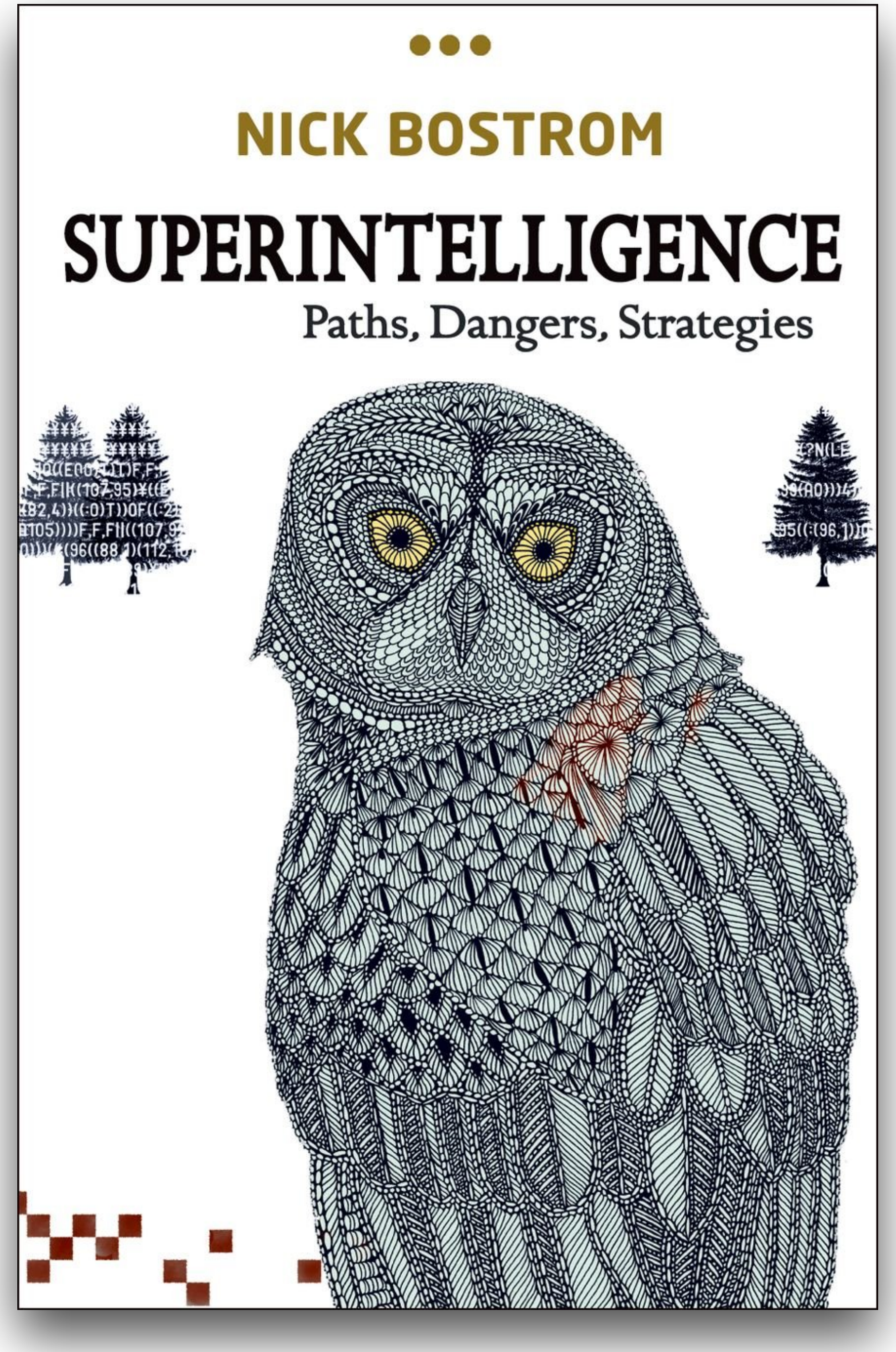
There is a growing interest in the area of machine learning and creativity. This survey presents an overview of the history and the state of the art of computational creativity theories, machine learning techniques, including generative deep learning, and corresponding automatic evaluation methods. After presenting a critical discussion of the key contributions in this area, we outline the current research challenges and emerging opportunities in this field.

1 INTRODUCTION

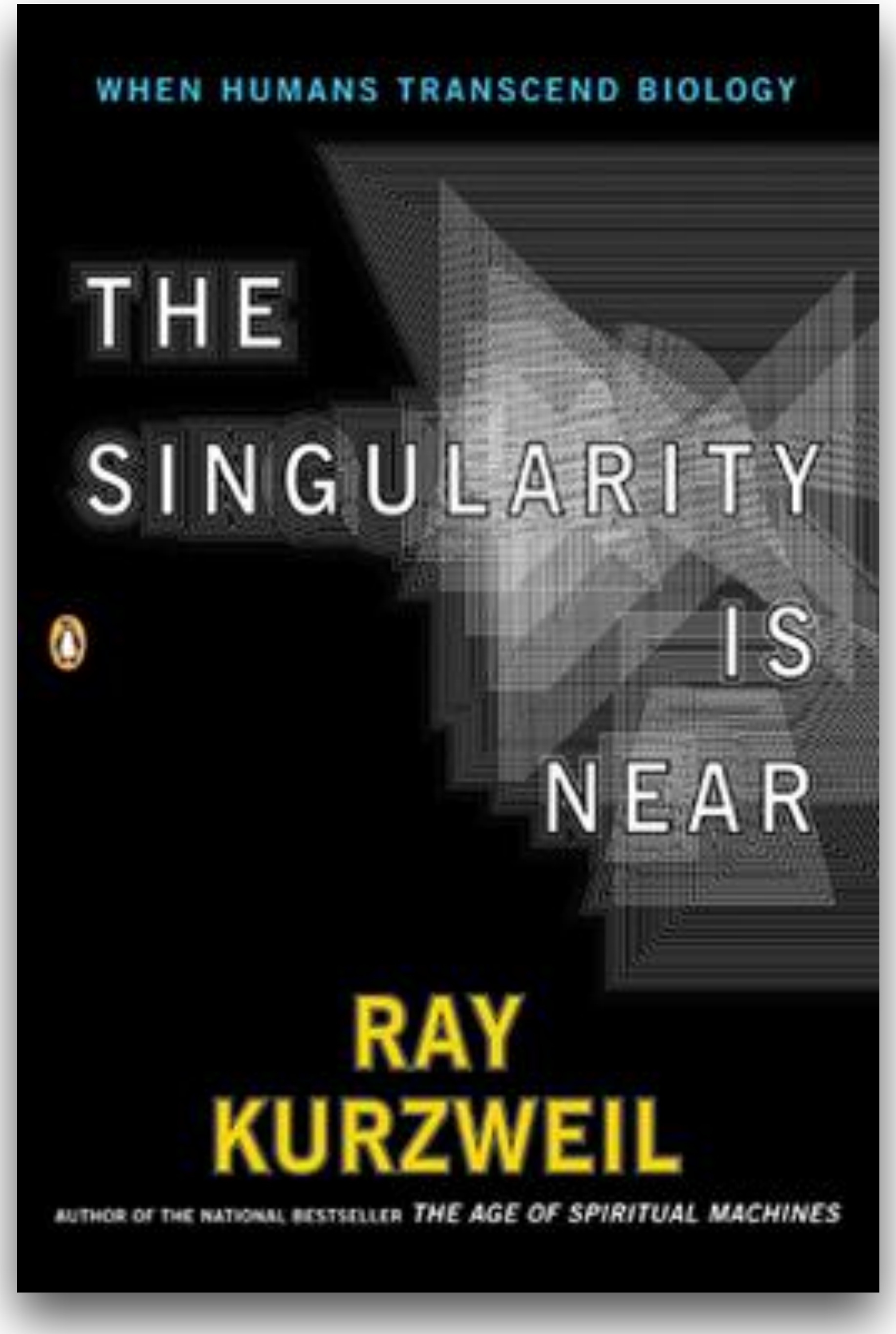
In 1842, Lady Lovelace, an English mathematician and writer recognized by many as the first computer programmer, wrote that the Analytical Engine - the digital programmable machine proposed by Charles Babbage [3] a hundred years before the Turing machine [114] - *"has no pretensions to originate anything, since it can only do whatever we know how to order it to perform"* [72]. This consideration, which Alan Turing referred to as "Lovelace's objection" [115] was just the first fundamental meeting between computer science and creativity.

In particular, the last thirty years of the Twentieth century have been marked by many attempts of building machines able to "originate something". From the beginning of the Seventies of the past century with the AARON Project by

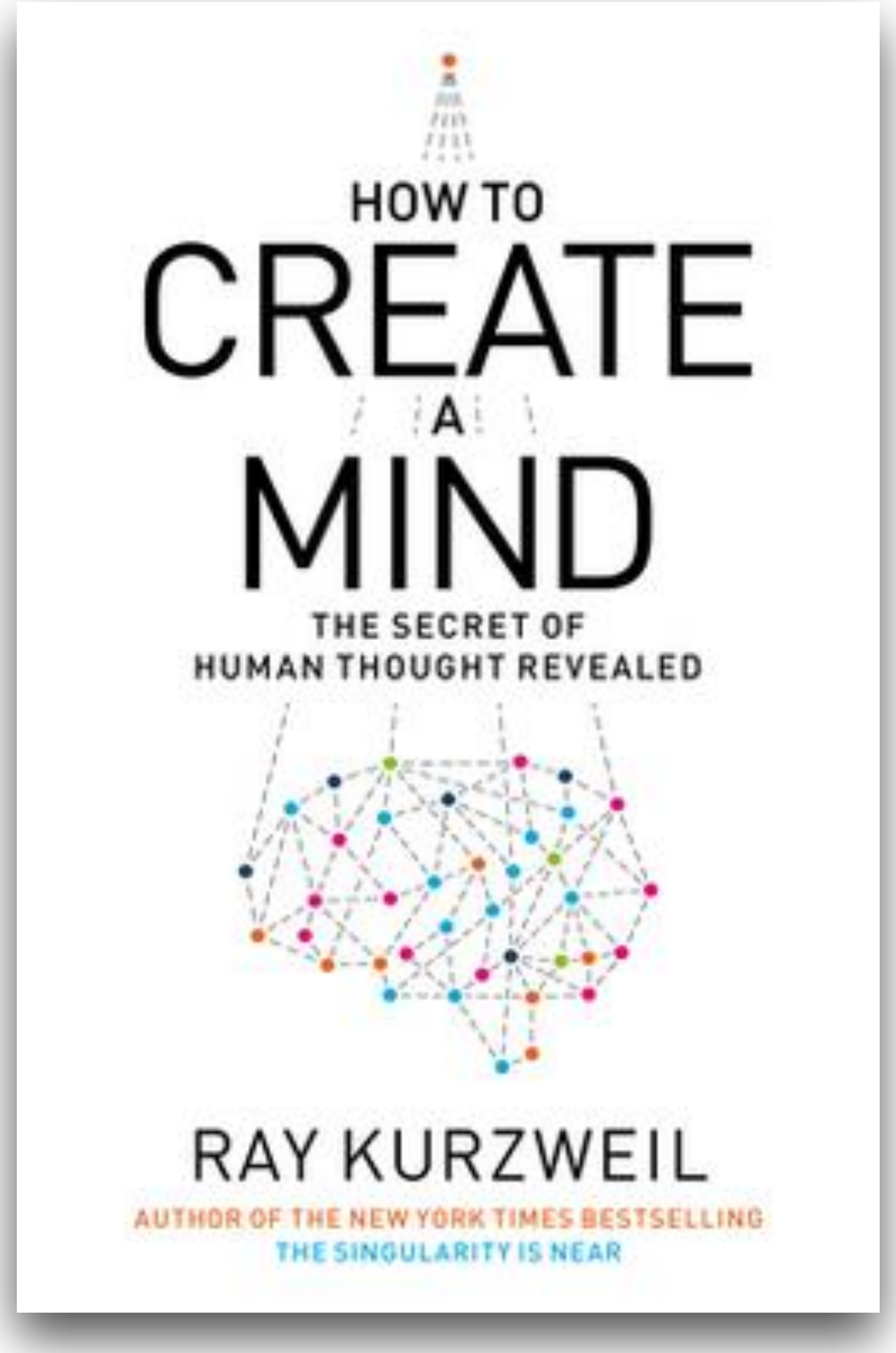
Superintelligence



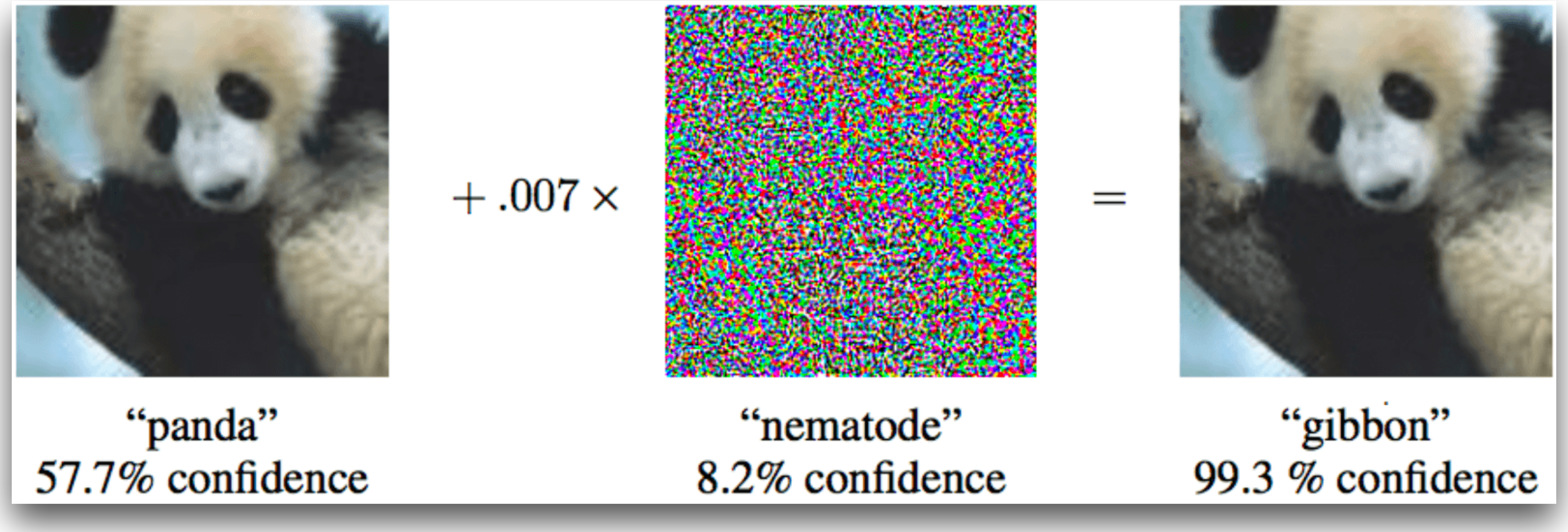
The Singularity is Near

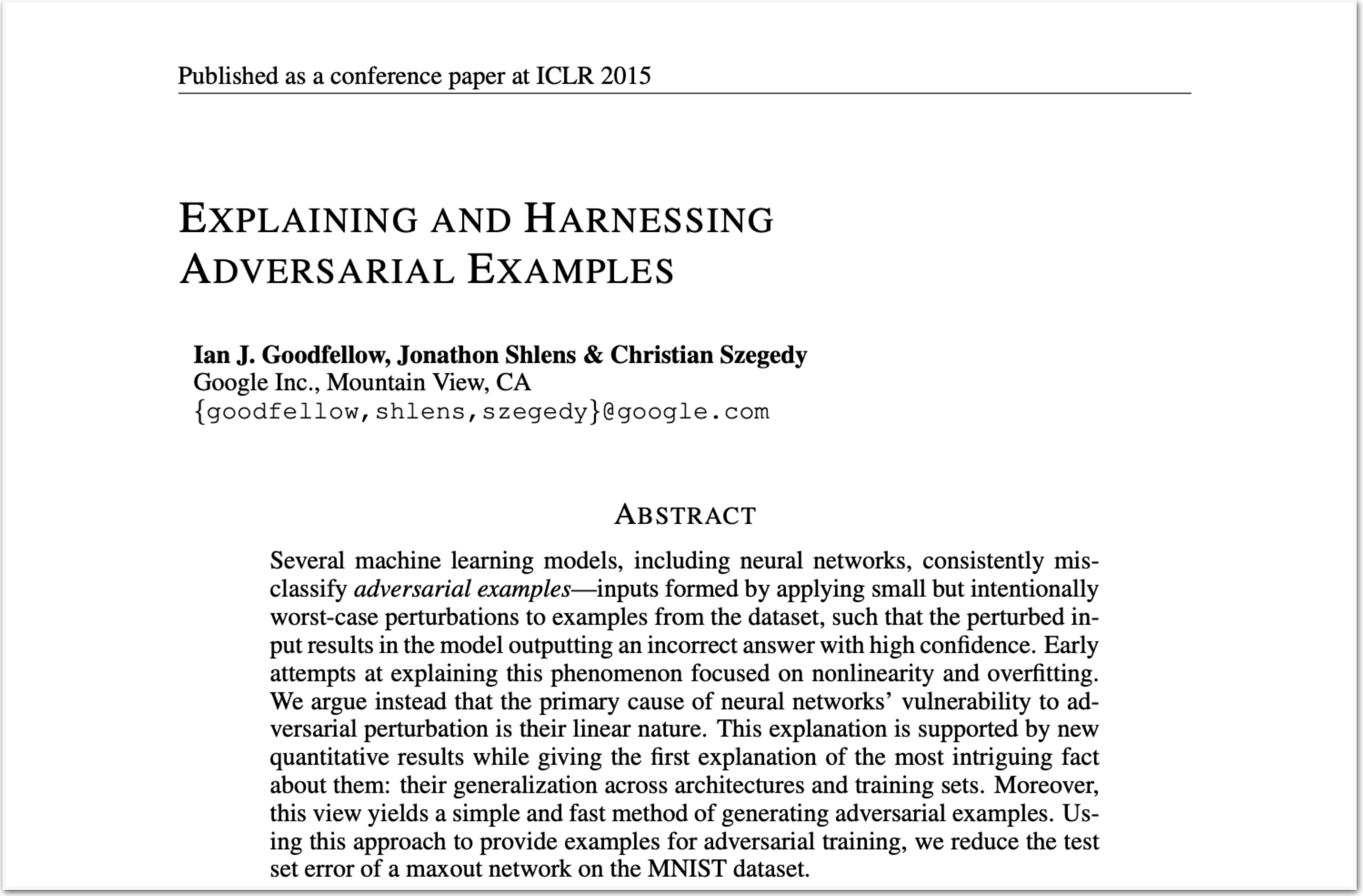

WHEN HUMANS TRANSCEND BIOLOGY
THE SINGULARITY IS NEAR
RAY KURZWEIL
AUTHOR OF THE NATIONAL BESTSELLER THE AGE OF SPIRITUAL MACHINES

How to Create a Mind



The Singularity is Near… Or Maybe Not





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Explaining and Harnessing Adversarial Examples

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Abstract

Several machine learning models, including neural networks, consistently misclassify *adversarial examples*—inputs formed by applying small but intentionally worst-case perturbations to examples from the dataset, such that the perturbed input results in the model outputting an incorrect answer with high confidence. Early attempts at explaining this phenomenon focused on nonlinearity and overfitting. We argue instead that the primary cause of neural networks' vulnerability to adversarial perturbation is their linear nature. This explanation is supported by new quantitative results while giving the first explanation of the most intriguing fact about them: their generalization across architectures and training sets. Moreover, this view yields a simple and fast method of generating adversarial examples. Using this approach to provide examples for adversarial training, we reduce the test set error of a maxout network on the MNIST dataset.

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