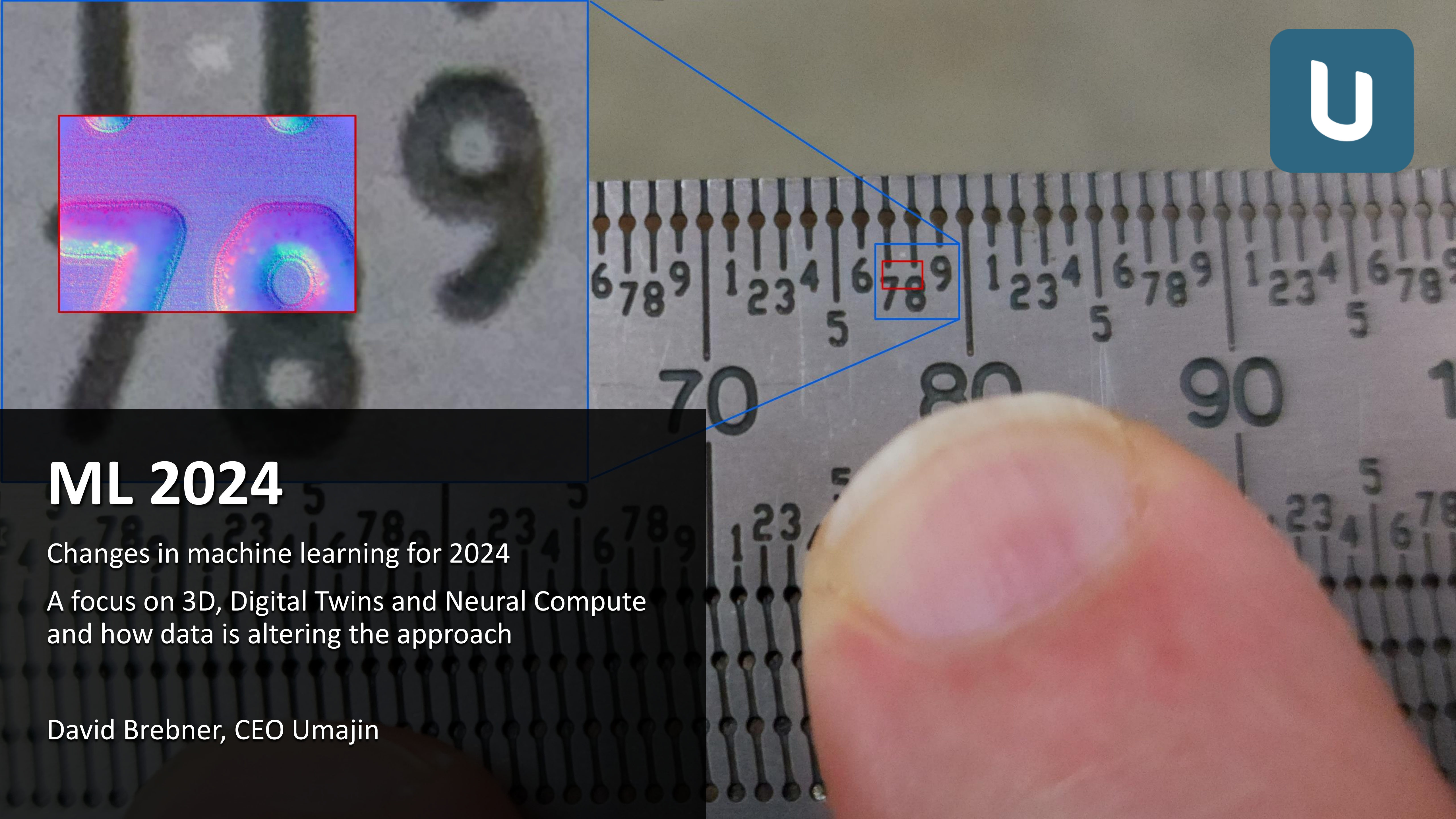


ML 2024

Changes in machine learning for 2024

A focus on 3D, Digital Twins and Neural Compute and how data is altering the approach

David Brebner, CEO Umajin

Industrial customers

- Frontline Applications
- Embedded Applications
- Cloud Applications

The Umajin Platform

umajin

- Powers Applications
- Supports Customisation
- Supports Integration

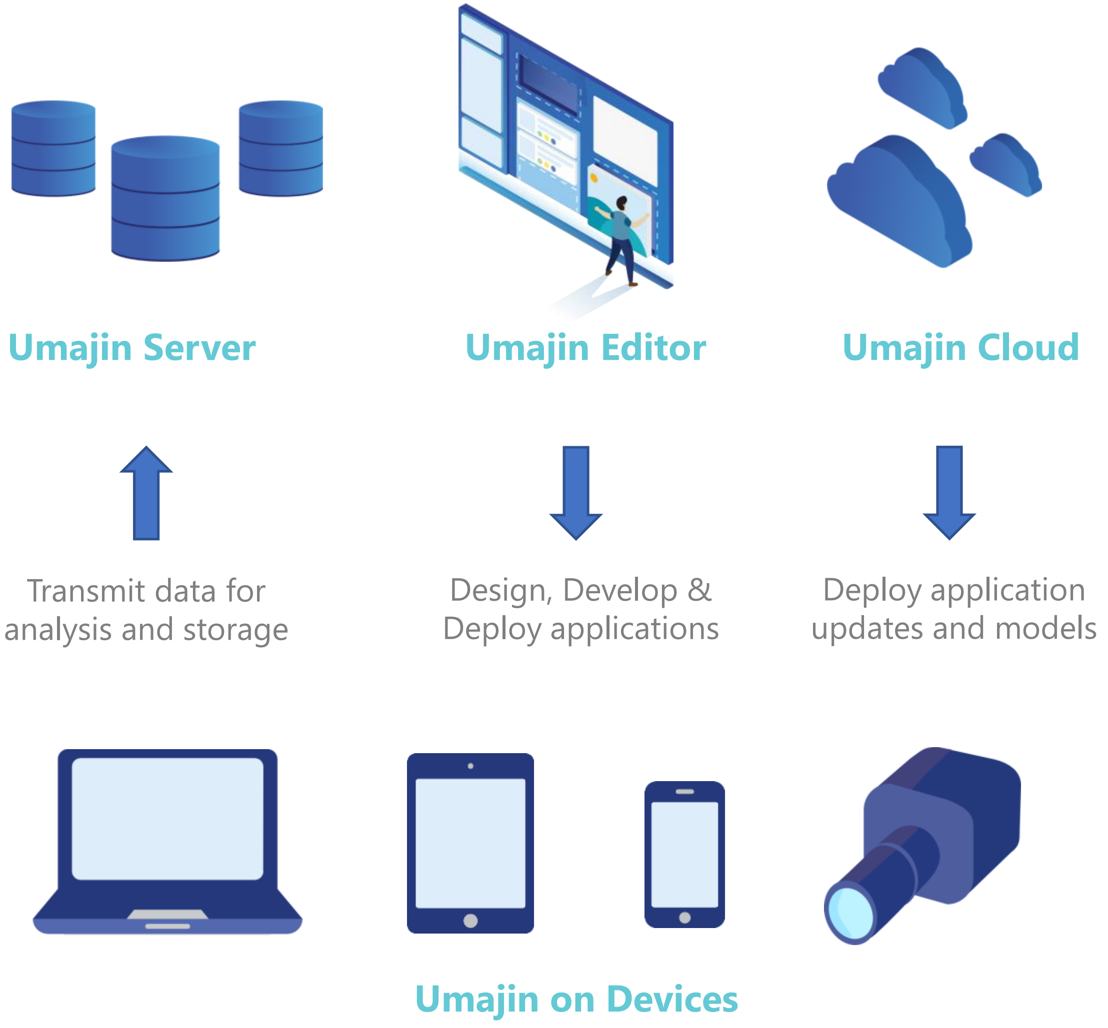
Enterprise devices

Enterprise systems

Umajin: Platform for Machine Vision & AI

All parts of the Umajin Platform contribute to delivering a flexible pipeline which allow new innovations in AI to be quickly applied in applications using your valuable datasets

- Umajin Server is a turnkey database and API layer making it easy to build applications and to collect raw data securely, to store, clean, classify and label data, to queue up training models based on your data using the latest machine learning approaches and finally distribute them using Umajin Cloud
- Umajin Editor and the Umajin Native Runtime on devices (computers, smartphones and embedded devices) allows high performance applications using cameras, lighting, CPU, GPU and TPU to be updated and distributed to the edge
- Umajin Cloud is a content management system that manages versions of assets. The content can be distributed from global content distribution networks right through to point to point encrypted connections

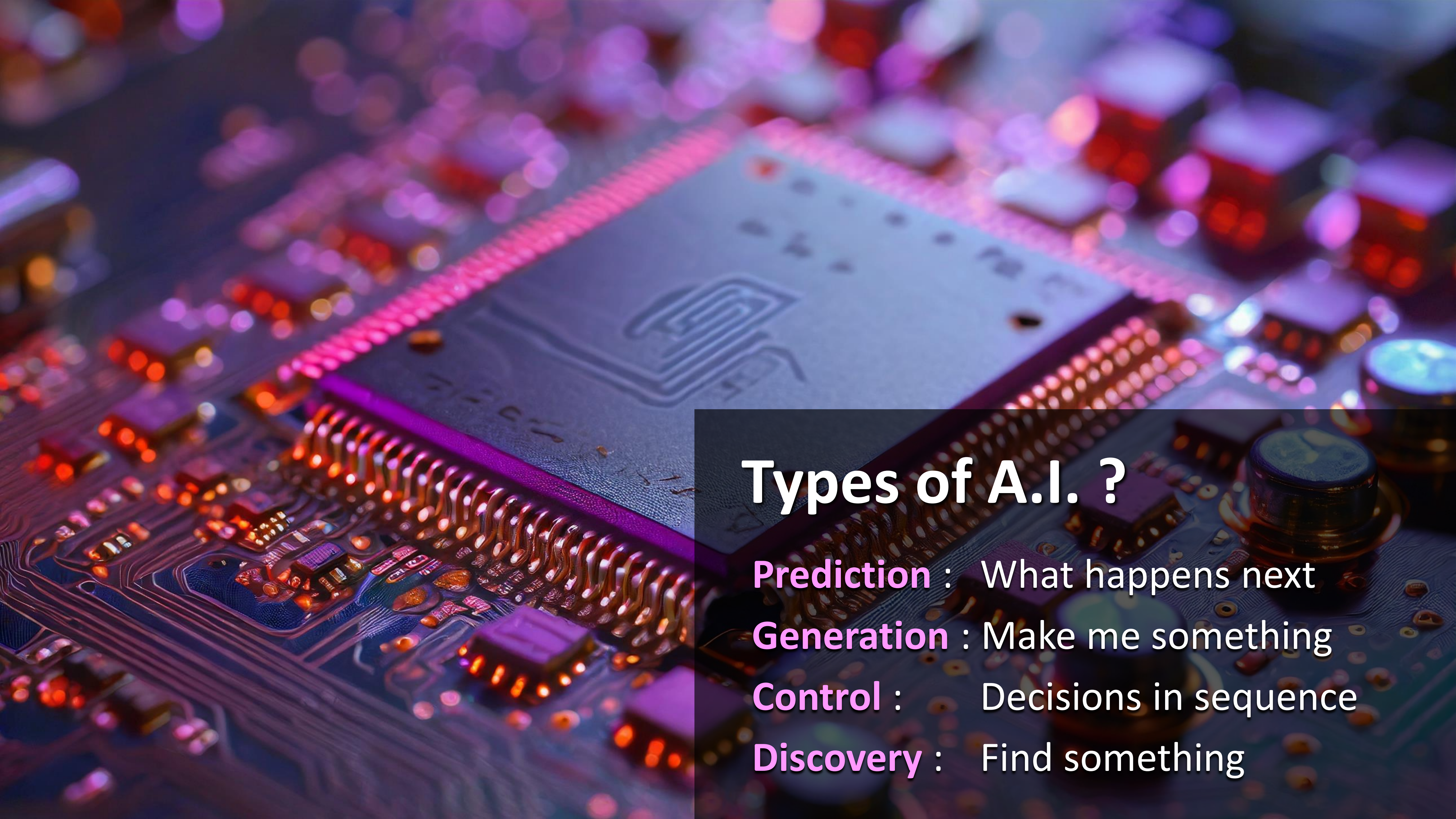


Data

Big Tech companies can't get enough data in the wild to crunch and compress

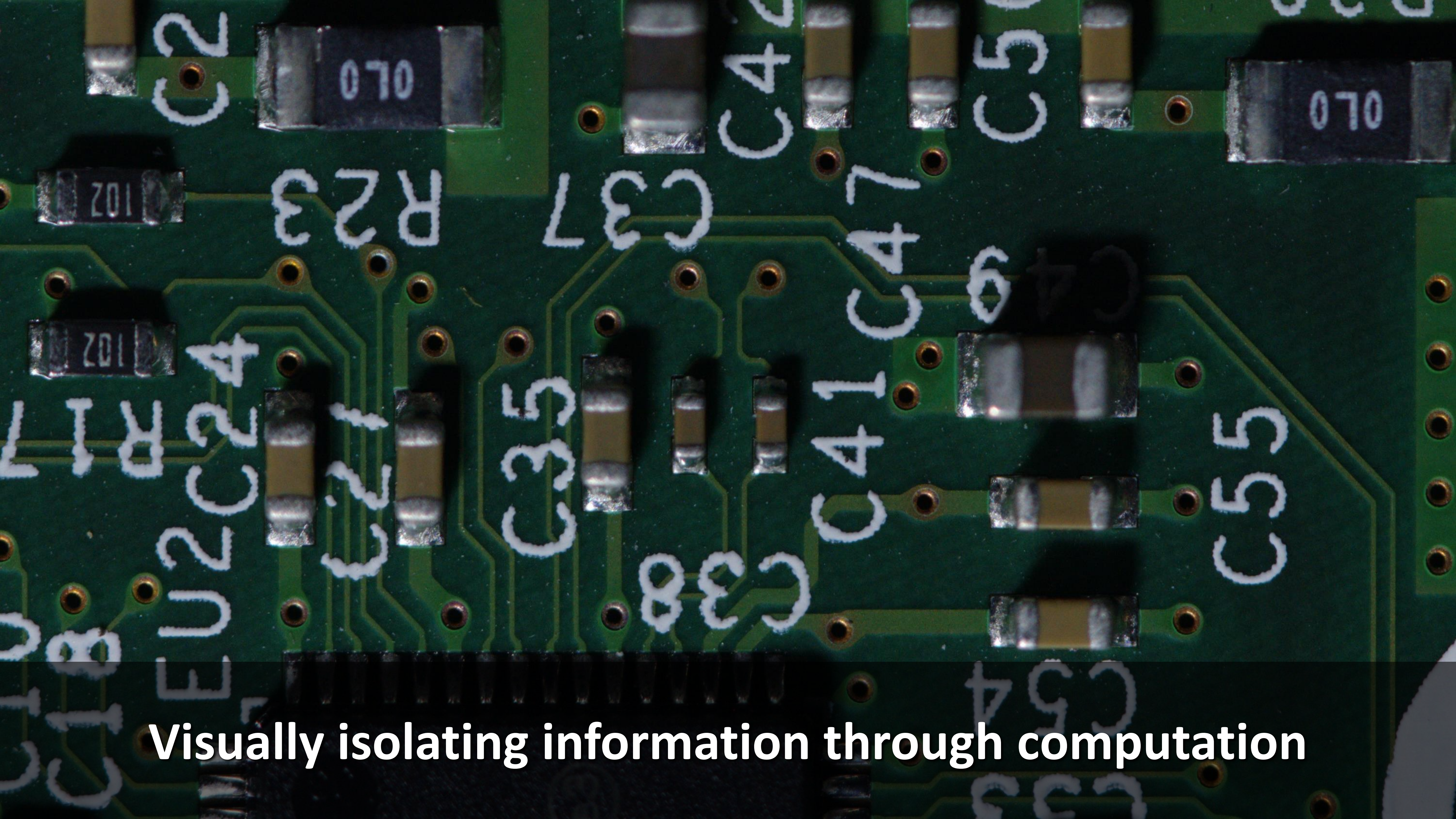
GPT4.X is trained on over 13 Trillion words

Constructed data like Microsoft Phi 2 outperforms wild data

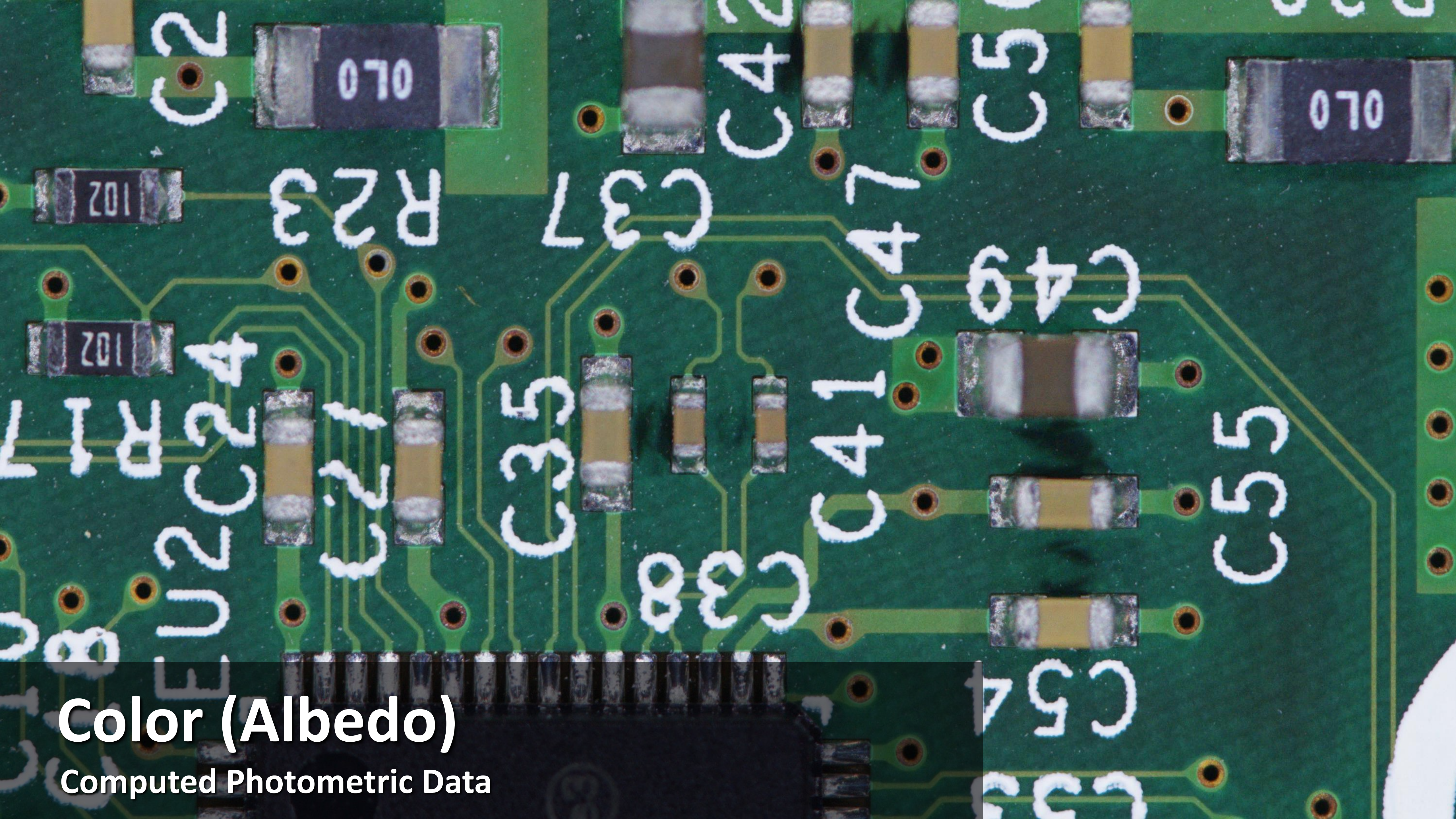


Types of A.I. ?

- **Prediction** : What happens next
- **Generation** : Make me something
- **Control** : Decisions in sequence
- **Discovery** : Find something

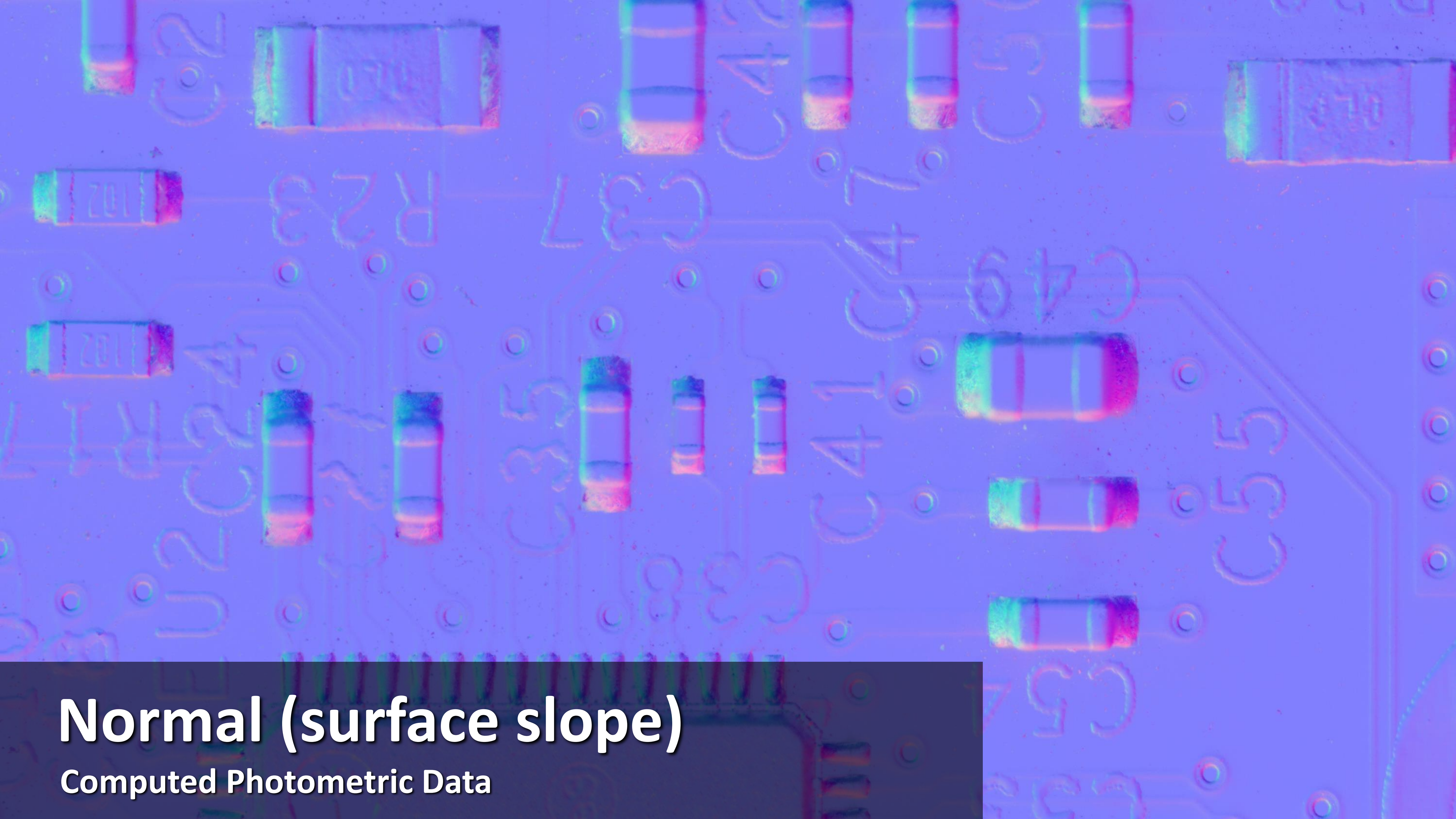


Visually isolating information through computation



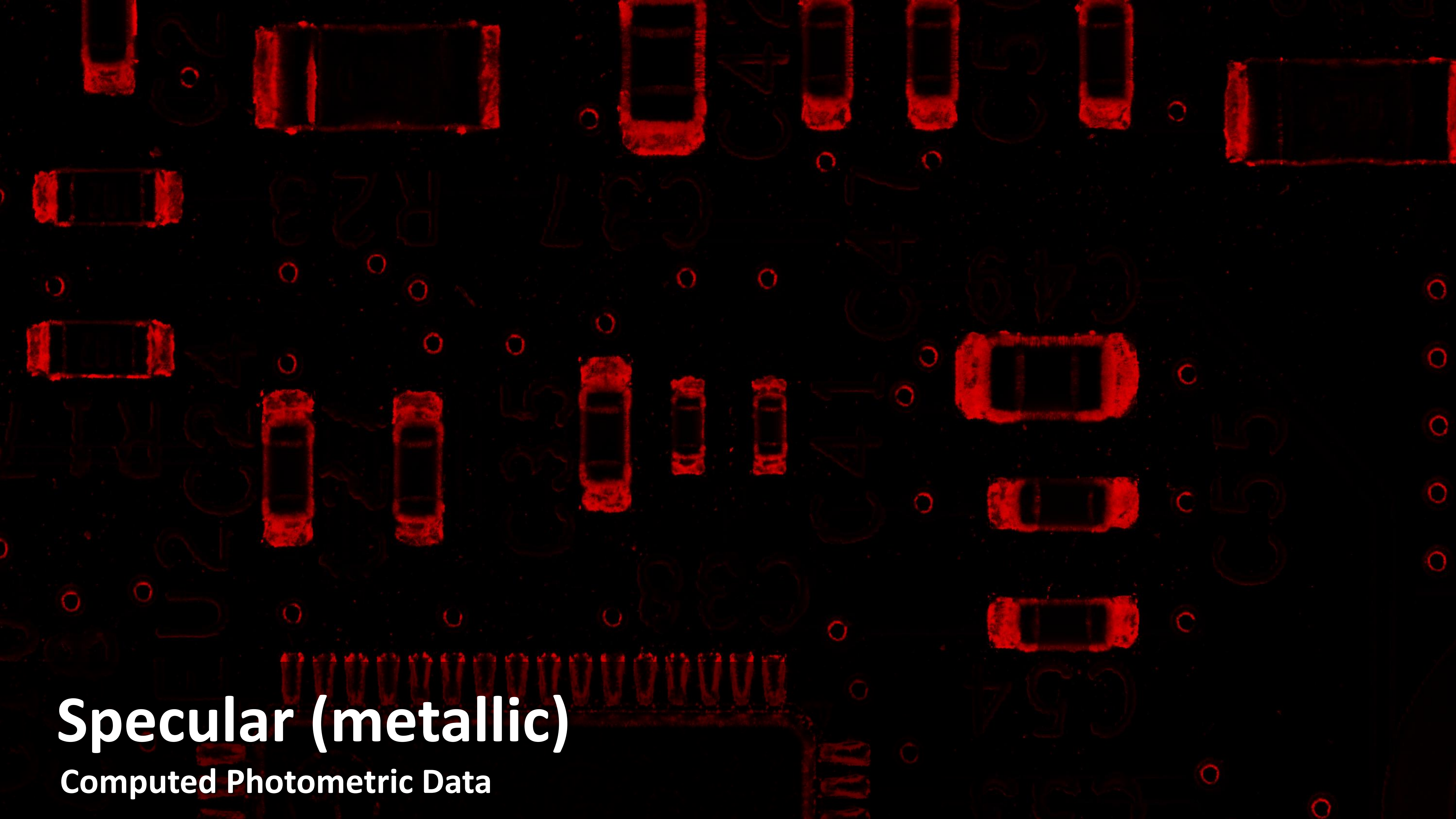
Color (Albedo)

Computed Photometric Data



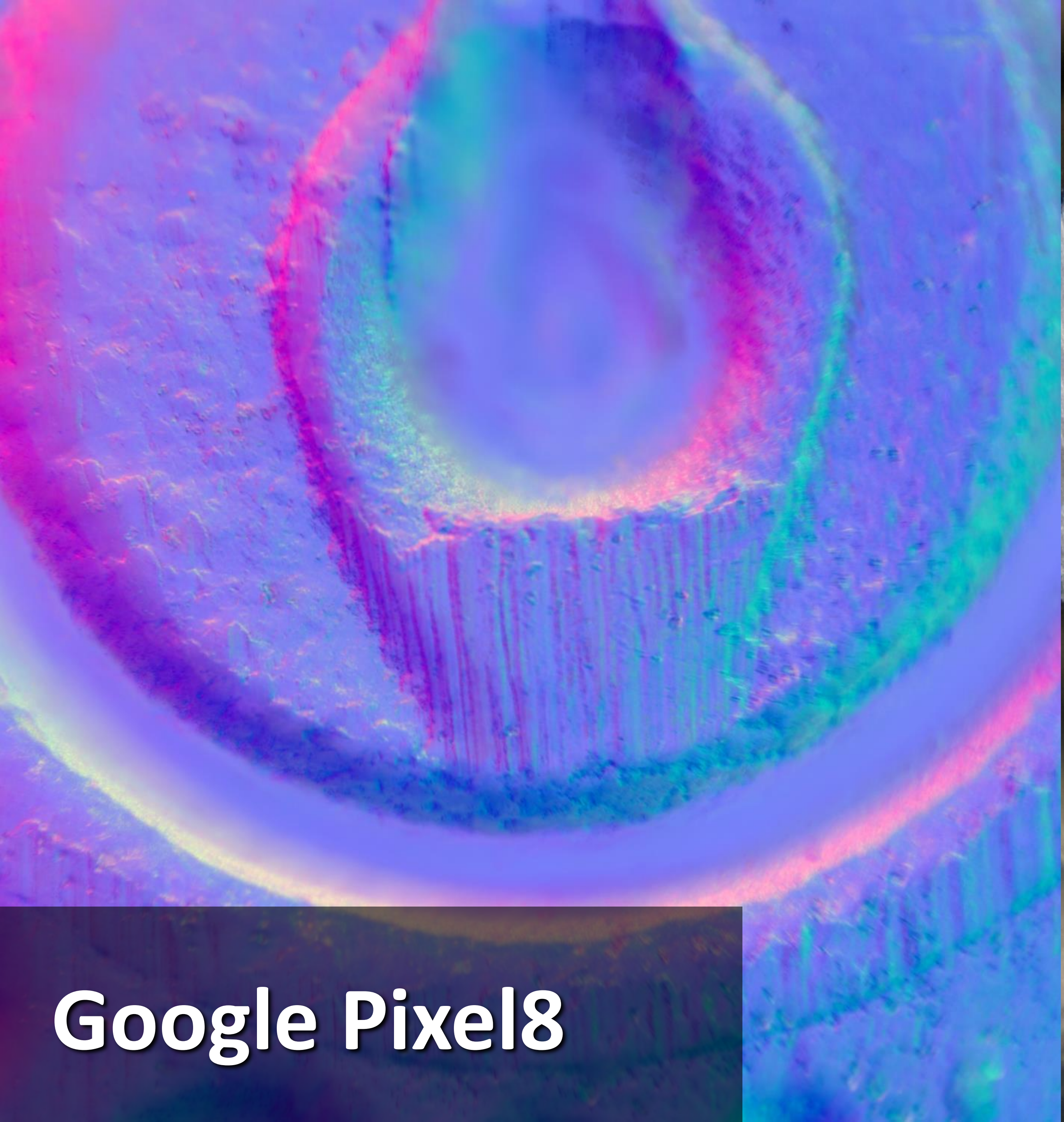
Normal (surface slope)

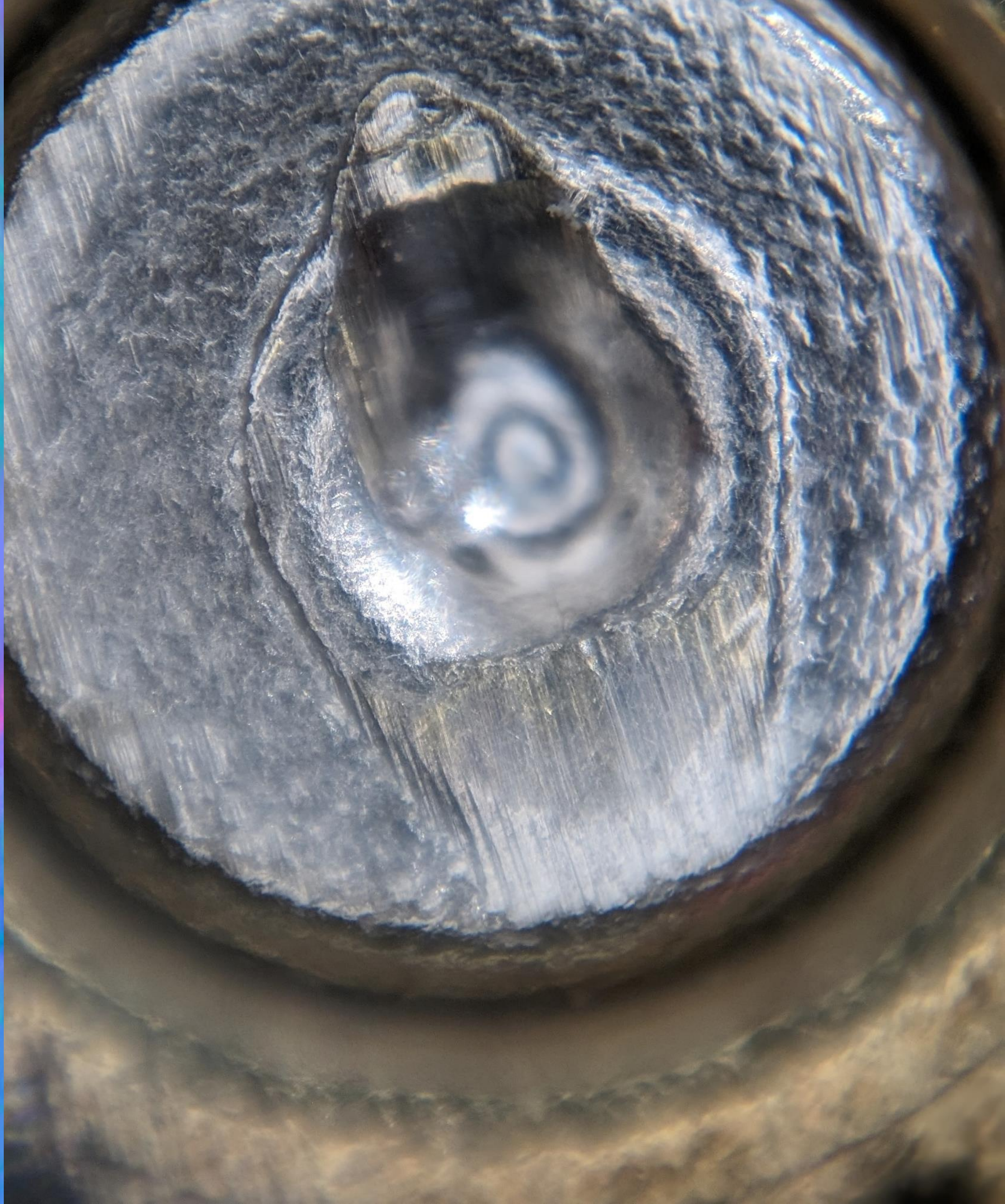
Computed Photometric Data

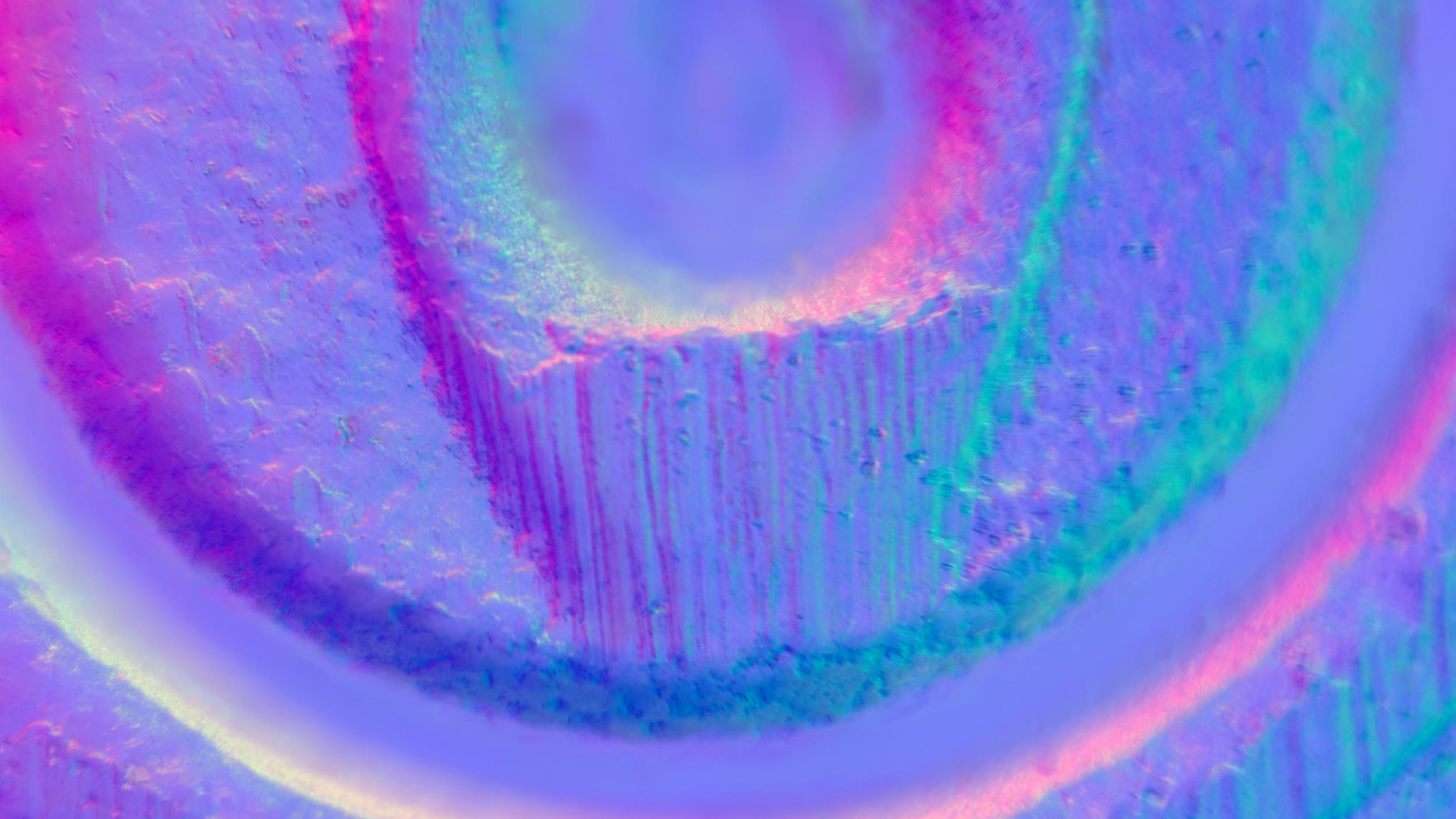


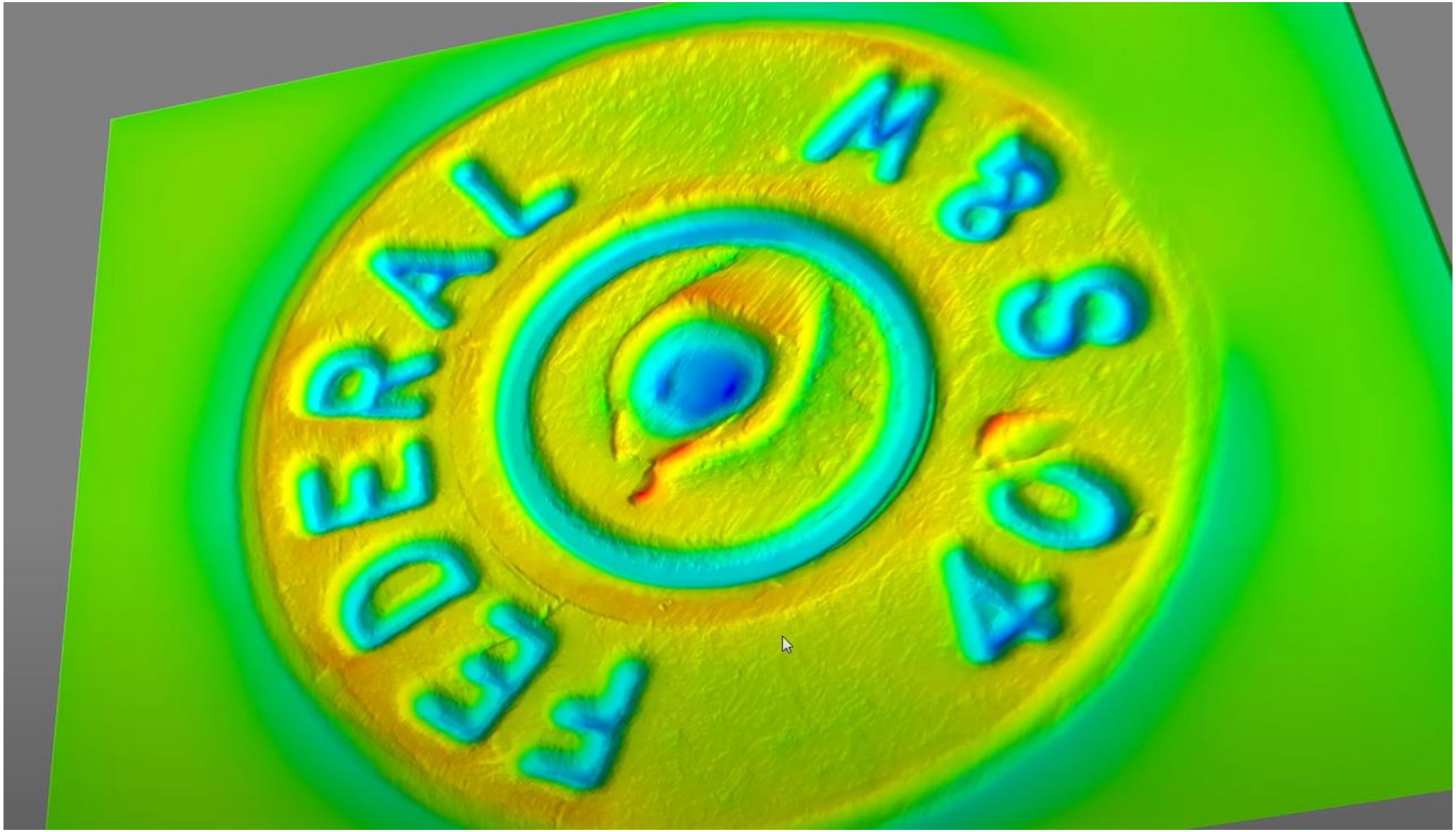
Specular (metallic)

Computed Photometric Data

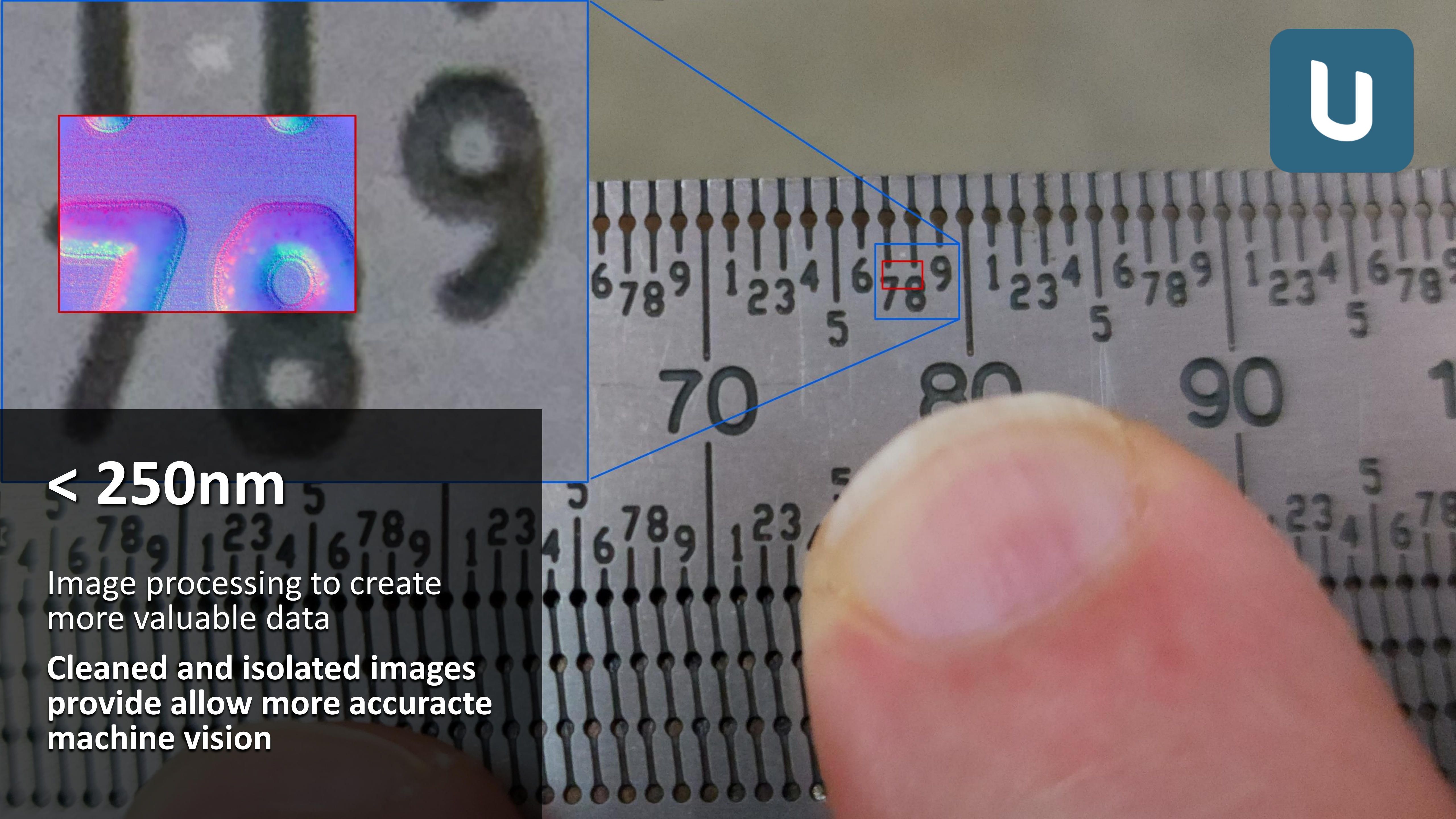

Google Pixel8

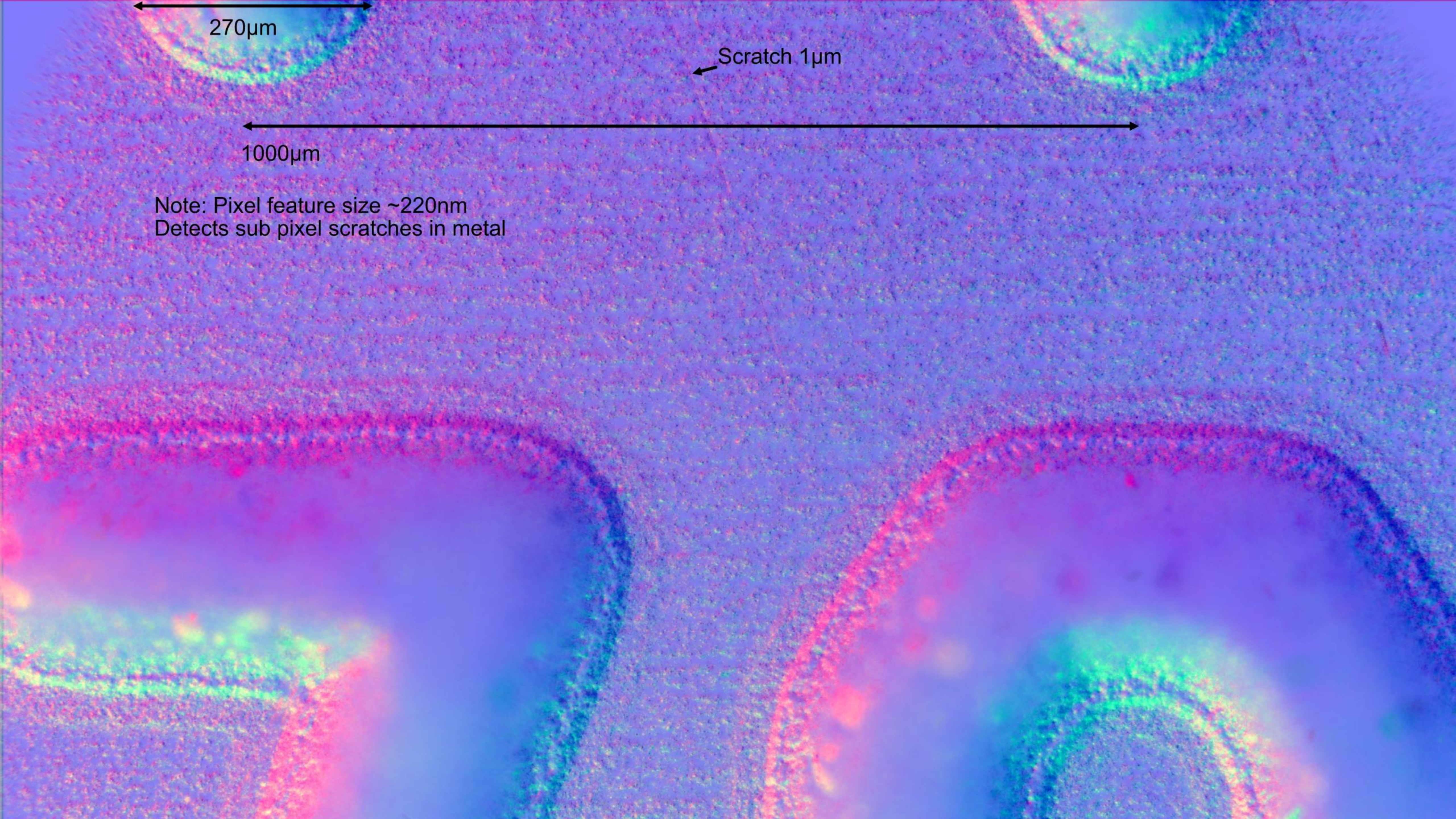


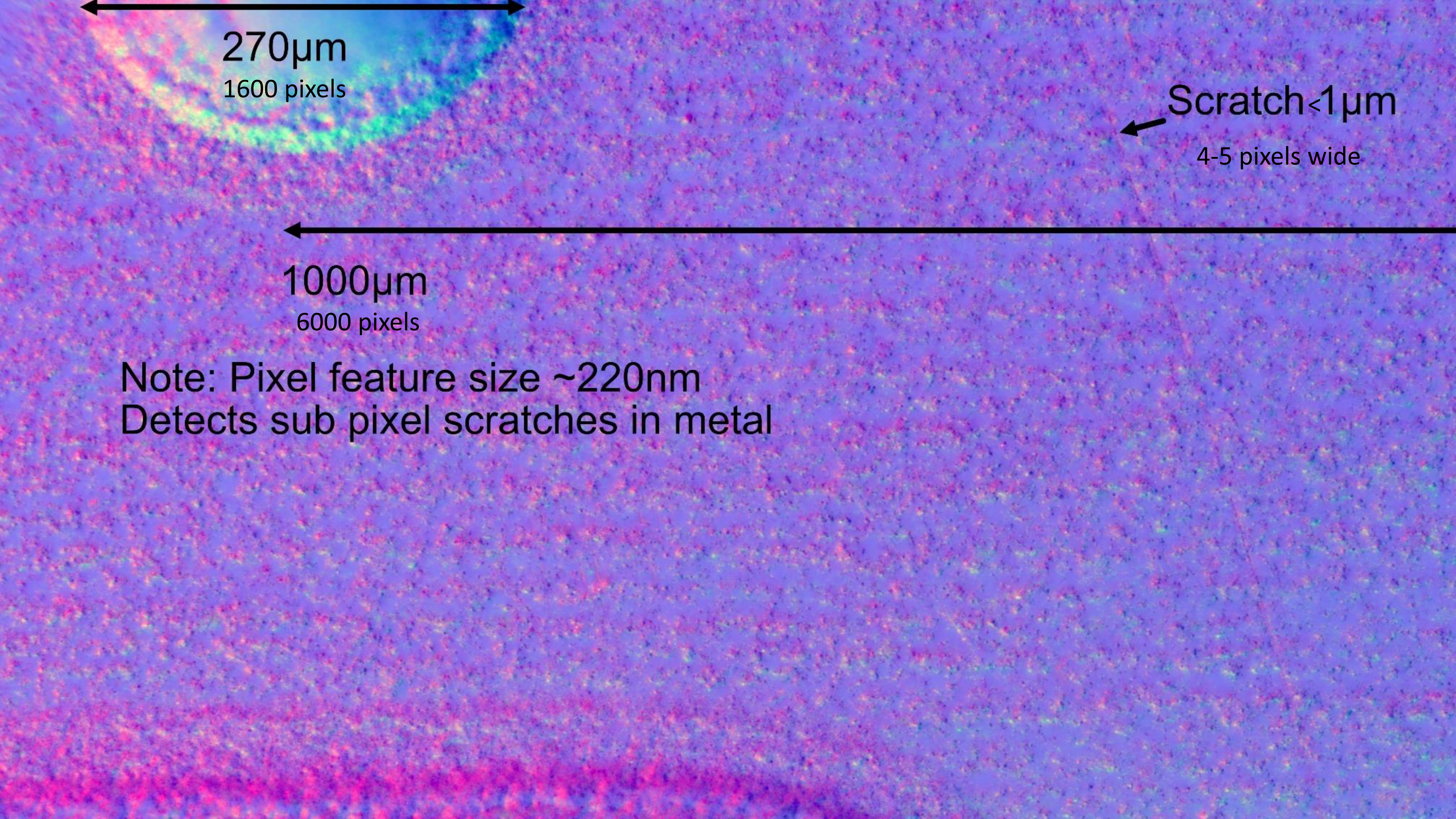




https://www.youtube.com/watch?v=KtSW03Dw8ek


< 250nm
Image processing to create more valuable data
Cleaned and isolated images provide allow more accuracte machine vision

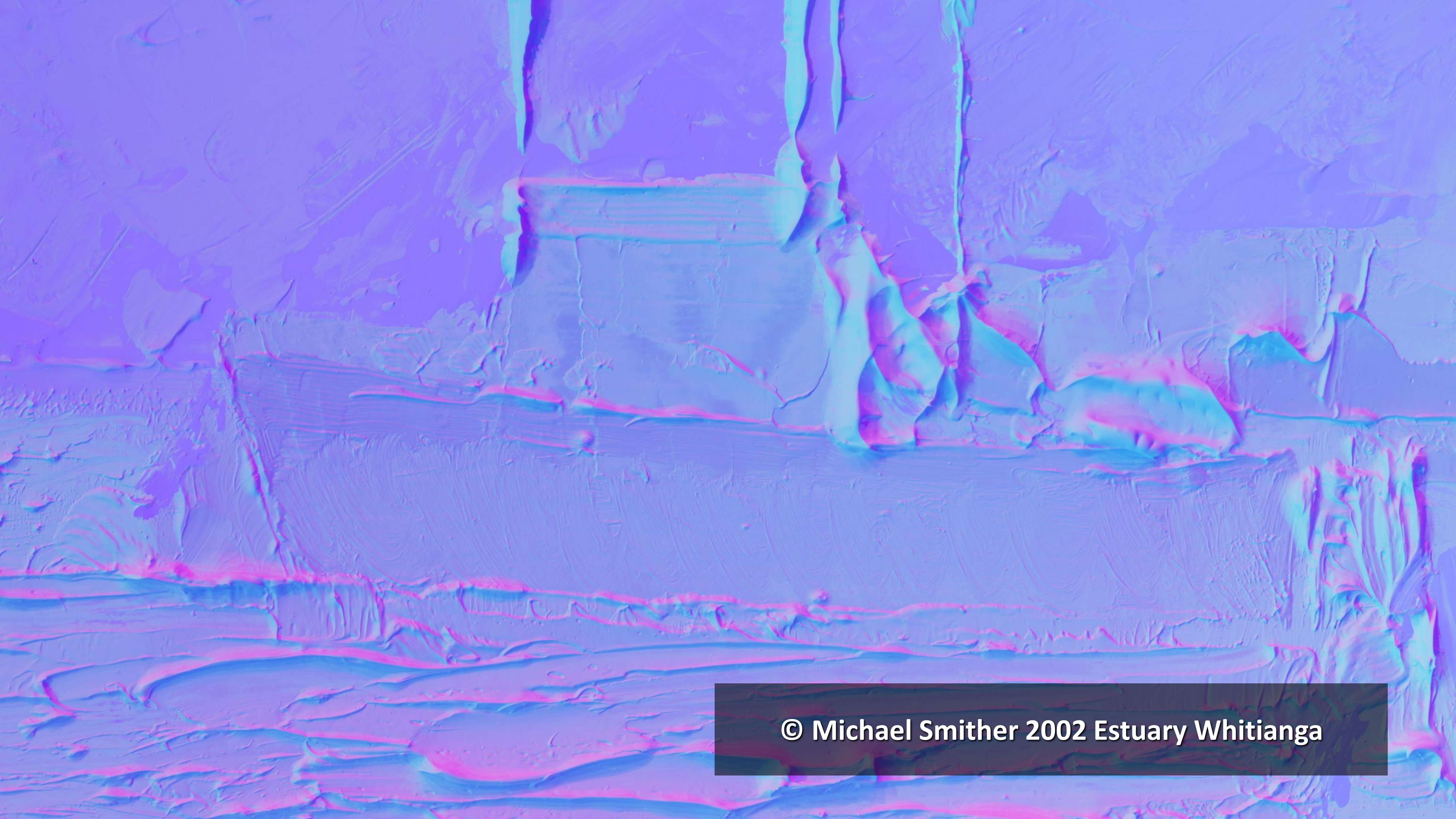

270μm
Scratch 1μm
1000μm
Note: Pixel feature size ~220nm
Detects sub pixel scratches in metal

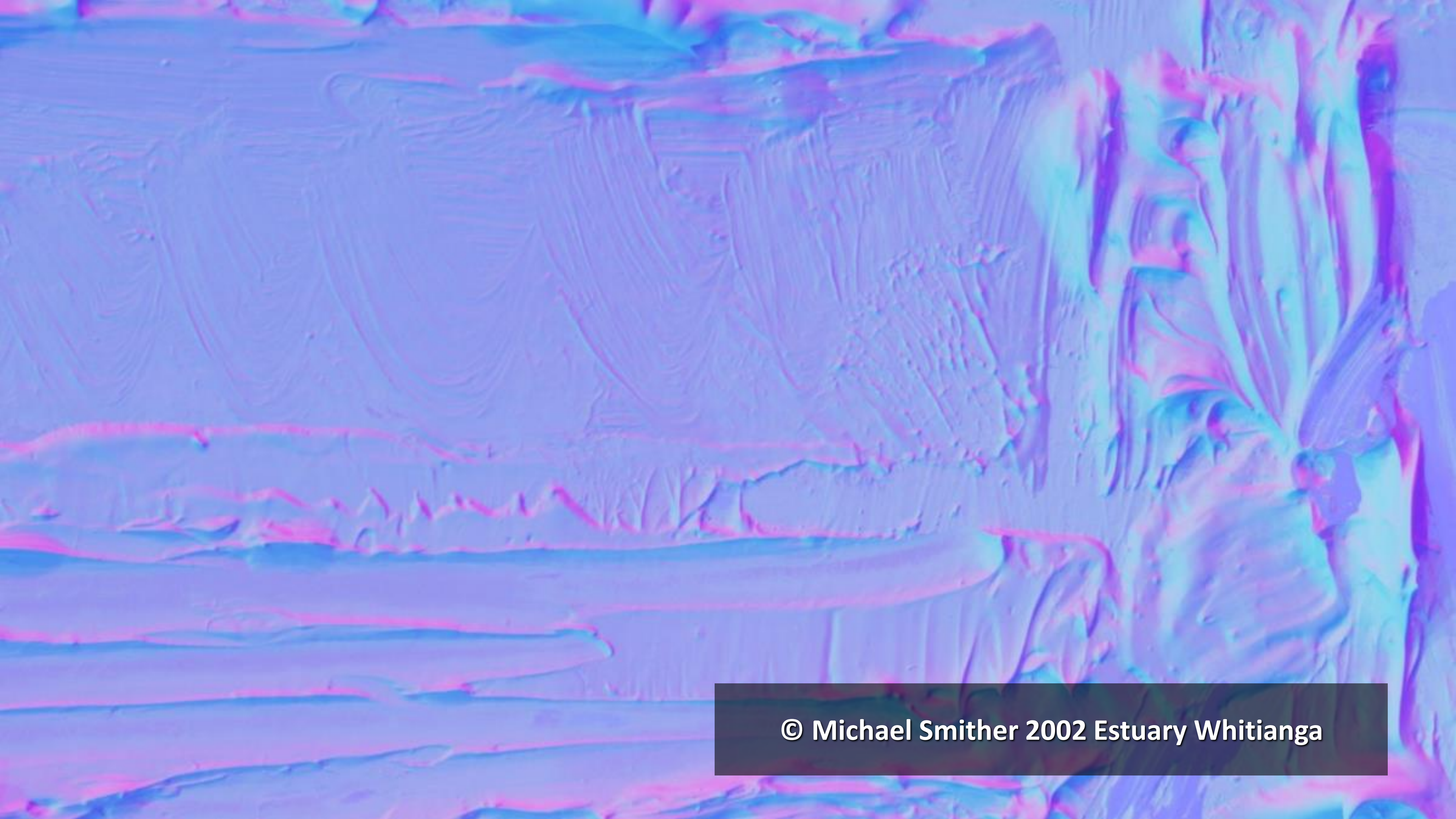

270µm
1600 pixels
Scratch<1µm
4-5 pixels wide
1000µm
6000 pixels
Note: Pixel feature size ~220nm
Detects sub pixel scratches in metal

NZ heritage in 3D

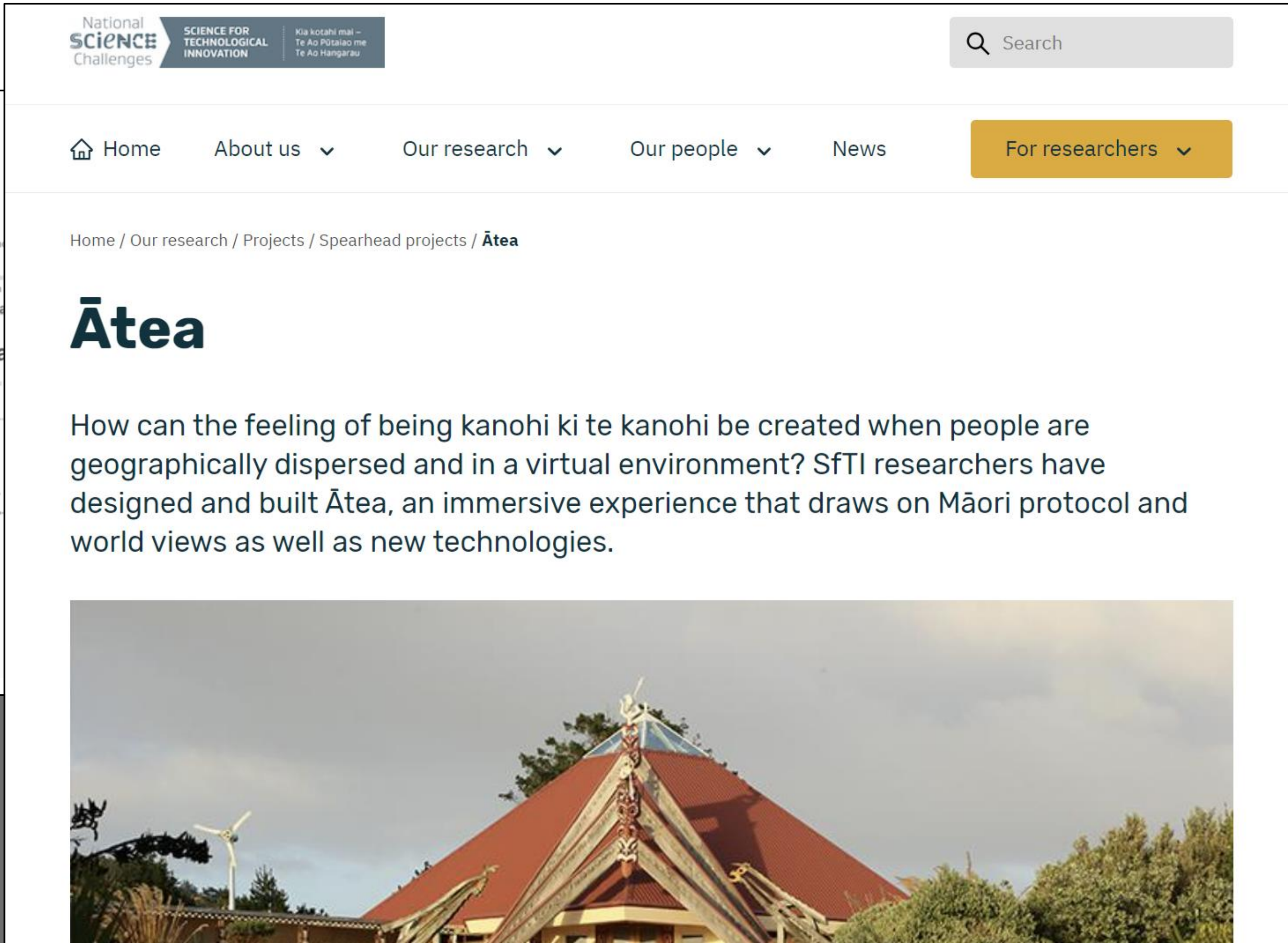
- Carvings
- Weaving
- Kete
- Cloaks
- Paintings

© Michael Smither 2002 Estuary Whitianga




© Michael Smither 2002 Estuary Whitianga

- https://blogs.nvidia.com/blog/te-hiku-media-maori-speech-ai/
- https://kaituhi.nz/
- https://www.sftichallenge.govt.nz/our-research/projects/spearhead/atea/



New Zealand Data

SYCL >>> CUDA or SPIR-V

Live Demo

Denser Data

3D Gaussian Splatting for Real-Time Radiance Field Rendering

SIGGRAPH 2023

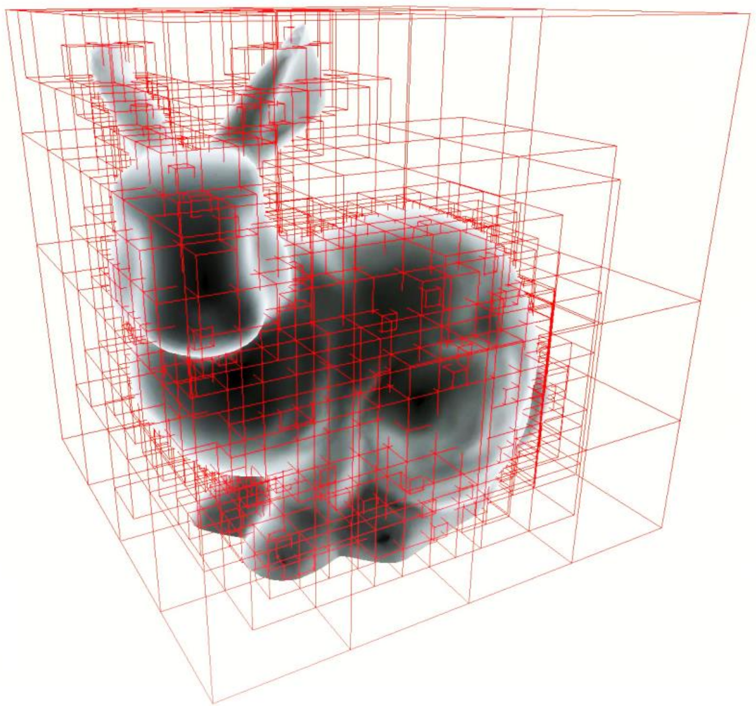
(ACM Transactions on Graphics)

Bernhard Kerbl[*1,2] Georgios Kopanas[*1,2] Thomas Leimkühler[3] George Drettakis[1,2]

[*] Denotes equal contribution

[1]Inria [2]Université Côte d'Azur [3]MPI Informatik

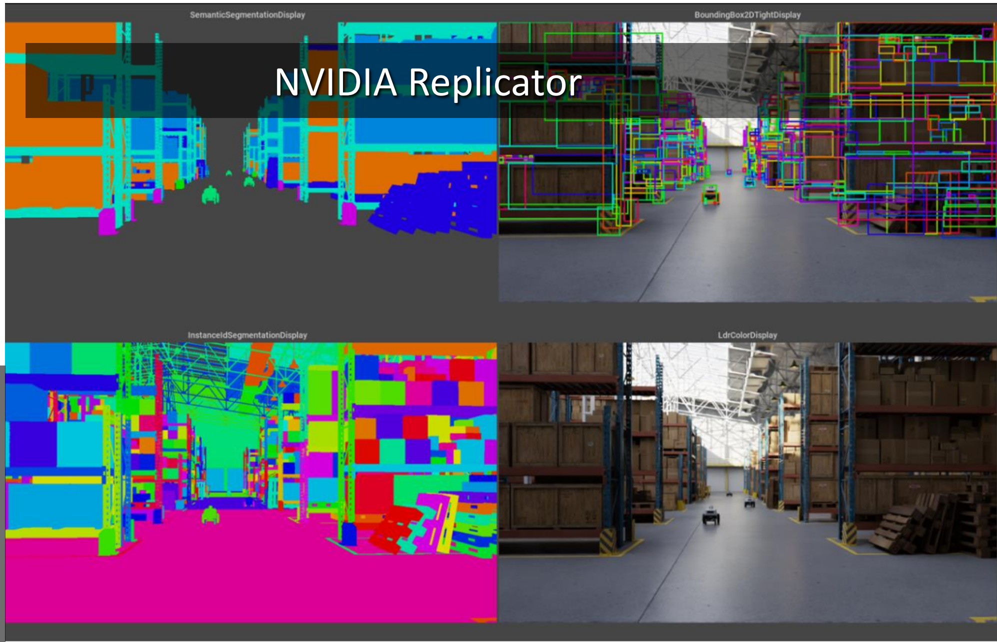
1 Inria 2 UNIVERSITÉ CÔTE D'AZUR 3 max planck institut informatik



Sparse Elliptical Points

Use a machine learning process to establish a best set of 3D ellipses which describe the scene photographically and volumetrically

https://www.youtube.com/watch?v=pFRC-HlcJ00



Synthetic Data & Ownership

Phi 1 & 2 (Microsoft)

Textbooks Are All You Need

Suriya Gunasekar Yi Zhang Jyoti Aneja Caio César Teodoro Mendes
Allie Del Giorno Sivakanth Gopi Mojan Javaheripi Piero Kauffmann
Gustavo de Rosa Olli Saarikivi Adil Salim Shital Shah Harkirat Singh Behl
Xin Wang Sébastien Bubeck Ronen Eldan Adam Tauman Kalai Yin Tat Lee
Yuanzhi Li

Microsoft Research

Abstract

We introduce **phi-1**, a new large language model for code, with significantly smaller size than competing models: **phi-1** is a Transformer-based model with 1.3B parameters, trained for 4 days on 8 A100s, using a selection of "textbook quality" data from the web (6B tokens) and synthetically generated textbooks and exercises with GPT-3.5 (1B tokens). Despite this small scale, **phi-1** attains **pass@1** accuracy 50.6% on HumanEval and 55.5% on MBPP. It also displays surprising emergent properties compared to **phi-1-base**, our model *before* our finetuning stage on a dataset of coding exercises, and **phi-1-small**, a smaller model with 350M parameters trained with the same pipeline as **phi-1** that still achieves 45% on HumanEval.

Better Data

Microsoft Phi 2
The surprising power of small language models

With only 2.7 billion parameters, Phi-2 surpasses the performance of Mistral and Llama-2 models at 7B, 13B and 70B parameter models on multi-step reasoning tasks, i.e., coding and math. Phi-2 outperforms Google Gemini Nano 2.

Insight: The massive increase in the size of language models to hundreds of billions of parameters has unlocked emergent capabilities – but the ceiling has quickly been reached as there is simply not enough good human generated data.

Verification

arXiv:2305.20050v1 [cs.LG] 31 May 2023

Let's Verify Step by Step

Hunter Lightman* **Vineet Kosaraju*** **Yura Burda*** **Harri Edwards**
Bowen Baker **Teddy Lee** **Jan Leike** **John Schulman** **Ilya Sutskever**
Karl Cobbe*

OpenAI

Abstract

In recent years, large language models have greatly improved in their ability to perform complex multi-step reasoning. However, even state-of-the-art models still regularly produce logical mistakes. To train more reliable models, we can turn either to outcome supervision, which provides feedback for a final result, or process supervision, which provides feedback for each intermediate reasoning step. Given the importance of training reliable models, and given the high cost of human feedback, it is important to carefully compare the both methods. Recent work has already begun this comparison, but many questions still remain. We conduct our own investigation, finding that process supervision significantly outperforms outcome supervision ... the ... problems from a representative subset of the MATH test set. Additionally, we show that active learning significantly improves the efficacy of process supervision. To support related research, we also release PRM800K, the

Data for Verification

[LG] 2 Jan 2024

Self-Play Fine-Tuning Converts Weak Language Models to Strong Language Models

Zixiang Chen*† Yihe Deng*‡ Huizhuo Yuan*§ Kaixuan Ji¶ Quanquan Gu‖

Abstract

Harnessing the power of human-annotated data through Supervised Fine-Tuning (SFT) is pivotal for advancing Large Language Models (LLMs). In this paper, we delve into the prospect of growing a strong LLM out of a weak one without the need for acquiring additional human-annotated data. We propose a new fine-tuning method called Self-Play fIne-tuNing (SPIN), which starts from a supervised fine-tuned model. At the heart of SPIN lies a self-play mechanism, where the LLM refines its capability by playing against instances of itself. More specifically, the

Scaling Scaling Laws with Board Games

Andy L. Jones

London, United Kingdom
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021

Abstract—**The largest experiments in machine learning now require resources far beyond the budget of all but a few institutions. Fortunately, it has recently been shown that the results of these huge experiments can often be extrapolated from the results of a sequence of far smaller, cheaper experiments. In this work, we show that not only can the extrapolation be done based on the size of the model, but on the size of the problem as**

frontiers discovered at large board sizes. More, the error in the prediction drops exponentially as more small board sizes are added to the fit.

Finally, while pursuing our main results we discovered an independently-interesting result: that for each extra order of magnitude of train-time compute, we can reduce test- ... performance

... on GitHub[1].

... ws in model ... vas the work

DeepMind

2023-8-22

ug 2023

Reinforced Self-Training (*ReST*) for Language Modeling

Caglar Gulcehre*†,1, Tom Le Paine*†,1, Srivatsan Srinivasan*†,1, Ksenia Konyushkova†,1, Lotte Weerts†,1
Abhishek Sharma†,1, Aditya Siddhant†,1, Alex Ahern1, Miaosen Wang1, Chenjie Gu1,
Wolfgang Macherey2, Arnaud Doucet1, Orhan Firat†,1, Nando de Freitas1

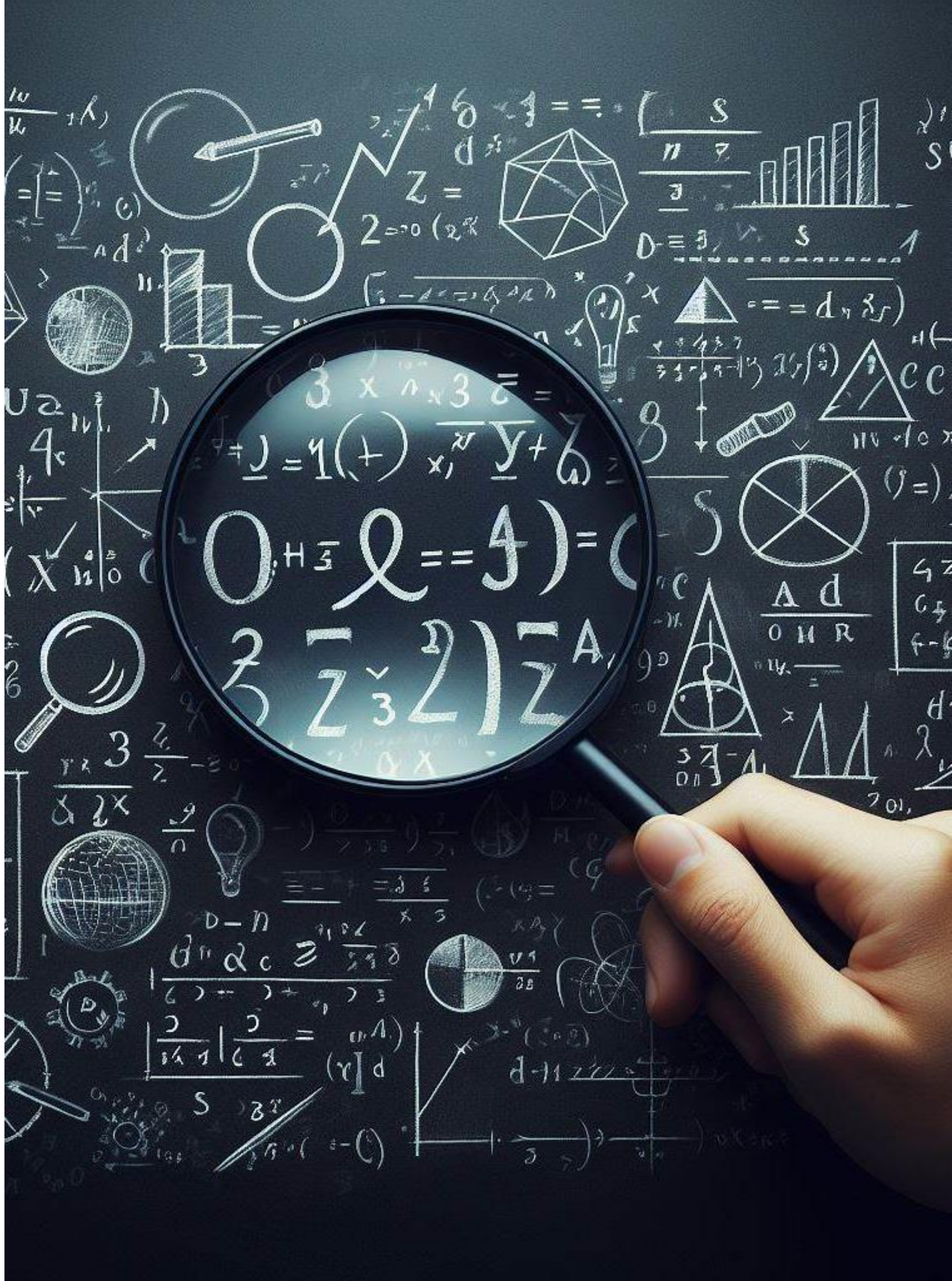
*Contributed equally, †Core contributors
1Google DeepMind, 2Google Research

Reinforcement learning from human feedback (RLHF) can improve the quality of large language model's (LLM) outputs by aligning them with human preferences. We propose a simple algorithm for aligning LLMs with human preferences inspired by growing batch reinforcement learning (RL), which we call *Reinforced Self-Training* (*ReST*). Given an initial LLM policy, *ReST* produces a dataset by generating samples from the policy, which are then used to improve the LLM policy using offline RL algorithms.

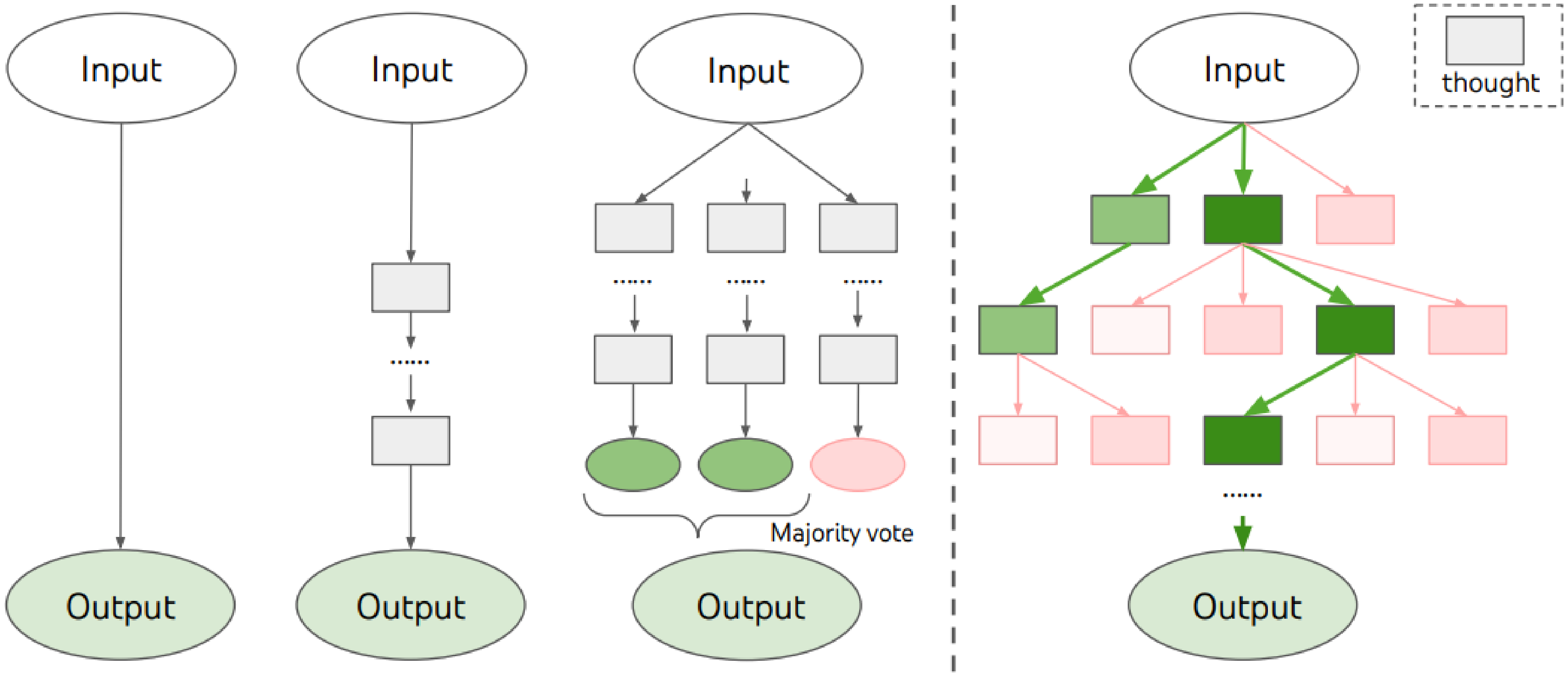
Verification

P vs NP asymmetry

It’s easier to **verify** a solution than to **find** one



Verification



(a) Input-Output Prompting (IO)
(c) Chain of Thought Prompting (CoT)
(c) Self Consistency with CoT (CoT-SC)
(d) Tree of Thoughts (ToT)

Tree of though explores the search space and can solve multi step reasoning problems incredibly well but it is prohibitively expensive because of all the extra computation – reducing each computation for each node of the tree by 100x is an exponential improvement.

Expert Block Expansion

Domain specific post-pretraining. This allows specialisation in you chosen domain like programming, mathematics, biomedical, or finance

LLaMA Pro: Progressive LLaMA with Block Expansion

Chengyue Wu[1,2] Yukang Gan[2] Yixiao Ge[2*]
Zeyu Lu[3] Jiahao Wang[1] Ye Feng[4] Ping Luo[1] Ying Shan[2]

[1]The University of Hong Kong [2]ARC Lab, Tencent PCG
[3]Shanghai Jiao Tong University [4]Beijing Language and Culture University

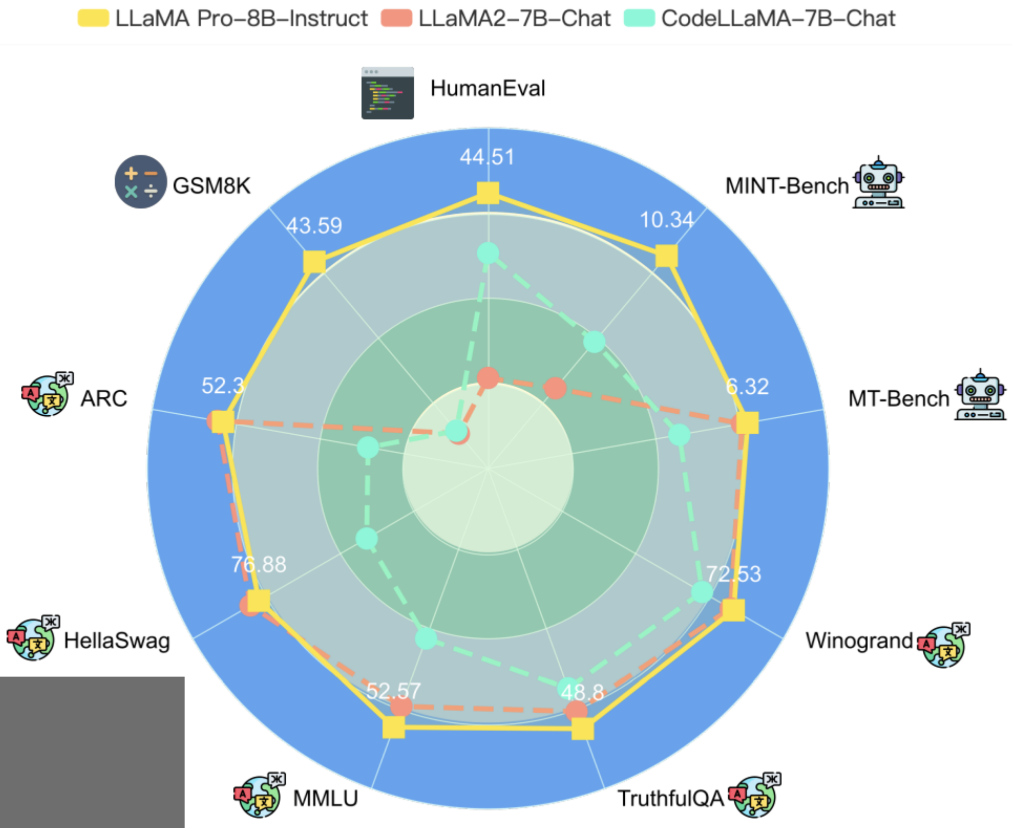


Figure 1: LLaMA Pro - Instruct delivers state-of-the-art performance across a wide variety of tasks, ranging from general language to specific domains, superior to existing models from the LLaMA series.

Expert Data

Mixtral of Experts

Albert Q. Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, Gianna Lengyel, Guillaume Bour, Guillaume Lample, Lélio Renard Lavaud, Lucile Saulnier, Marie-Anne Lachaux, Pierre Stock, Sandeep Subramanian, Sophia Yang, Szymon Antoniak, Teven Le Scao, Théophile Gervet, Thibaut Lavril, Thomas Wang, Timothée Lacroix, William El Sayed

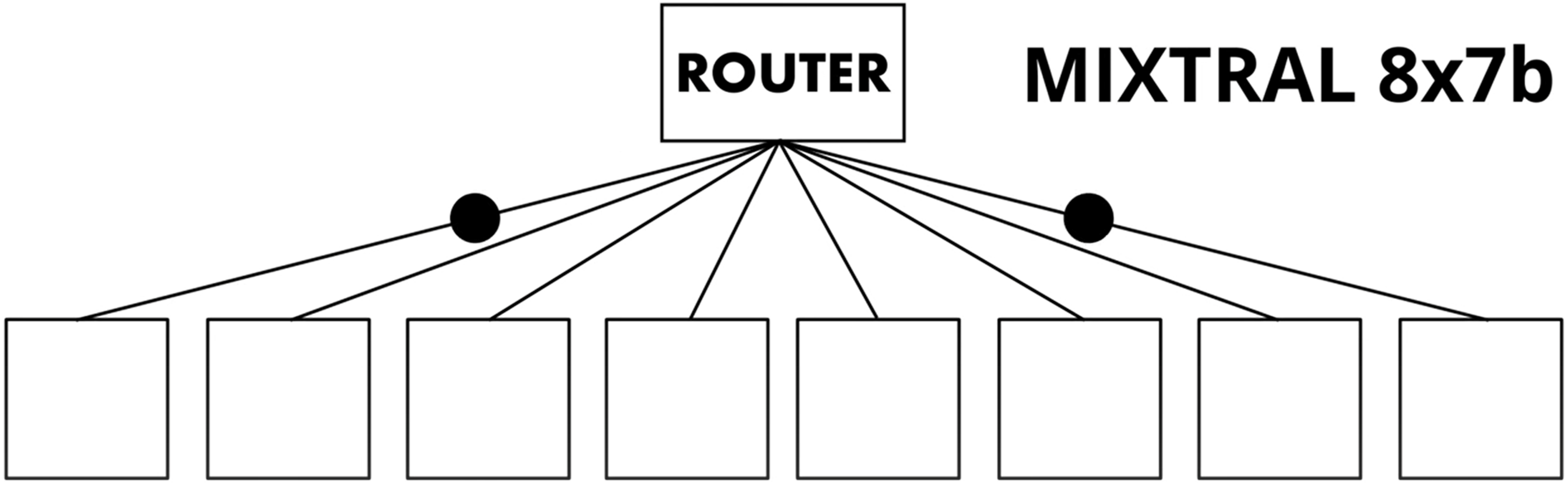
Expert Data

Abstract

We introduce Mixtral 8x7B, a Sparse Mixture of Experts (SMoE) language model. Mixtral has the same architecture as Mistral 7B, with the difference that each layer is composed of 8 feedforward blocks (i.e. experts). For every token, at each layer, a router network selects two experts to process the current state and combine their outputs. Even though each token only sees two experts,

Expert Mixture of Models

- Mixtrail 8x7b
- Mistral 7b parameter model with shared core model and fine tuned layers for 8 expert models



Preference for Data

Direct Preference Optimization: Your Language Model is Secretly a Reward Model

Rafael Rafailov[*†] **Archit Sharma**[*†] **Eric Mitchell**[*†]

Stefano Ermon[†‡] **Christopher D. Manning**[†] **Chelsea Finn**[†]

[†]Stanford University [‡]CZ Biohub
{rafailov,architsh,eric.mitchell}@cs.stanford.edu

Abstract

While large-scale unsupervised language models (LMs) learn broad world knowledge and some reasoning skills, achieving precise control of their behavior is difficult due to the completely unsupervised nature of their training. Existing methods for gaining such steerability collect human labels of the relative quality of model generations and fine-tune the unsupervised LM to align with these preferences, often with reinforcement learning from human feedback (RLHF). However, RLHF is a complex and often unstable procedure, first fitting a reward model that reflects the human preferences, and then fine-tuning the large unsupervised LM using reinforcement learning to maximize this estimated reward without drifting too far from the original model. In this paper we introduce a new parameterization [illegible] the corresponding optimal [illegible] LHF problem with only a simple classification loss. The resulting algorithm, which we call *Direct Preference Optimization* (DPO), is stable, performant, and computationally lightweight,

arXiv:2401.10020v1 [cs.CL] 18 Jan 2024

Self-Rewarding Language Models

Weizhe Yuan[1,2] Richard Yuanzhe Pang[1,2] Kyunghyun Cho[2]

Sainbayar Sukhbaatar[1] **Jing Xu**[1] **Jason Weston**[1,2]

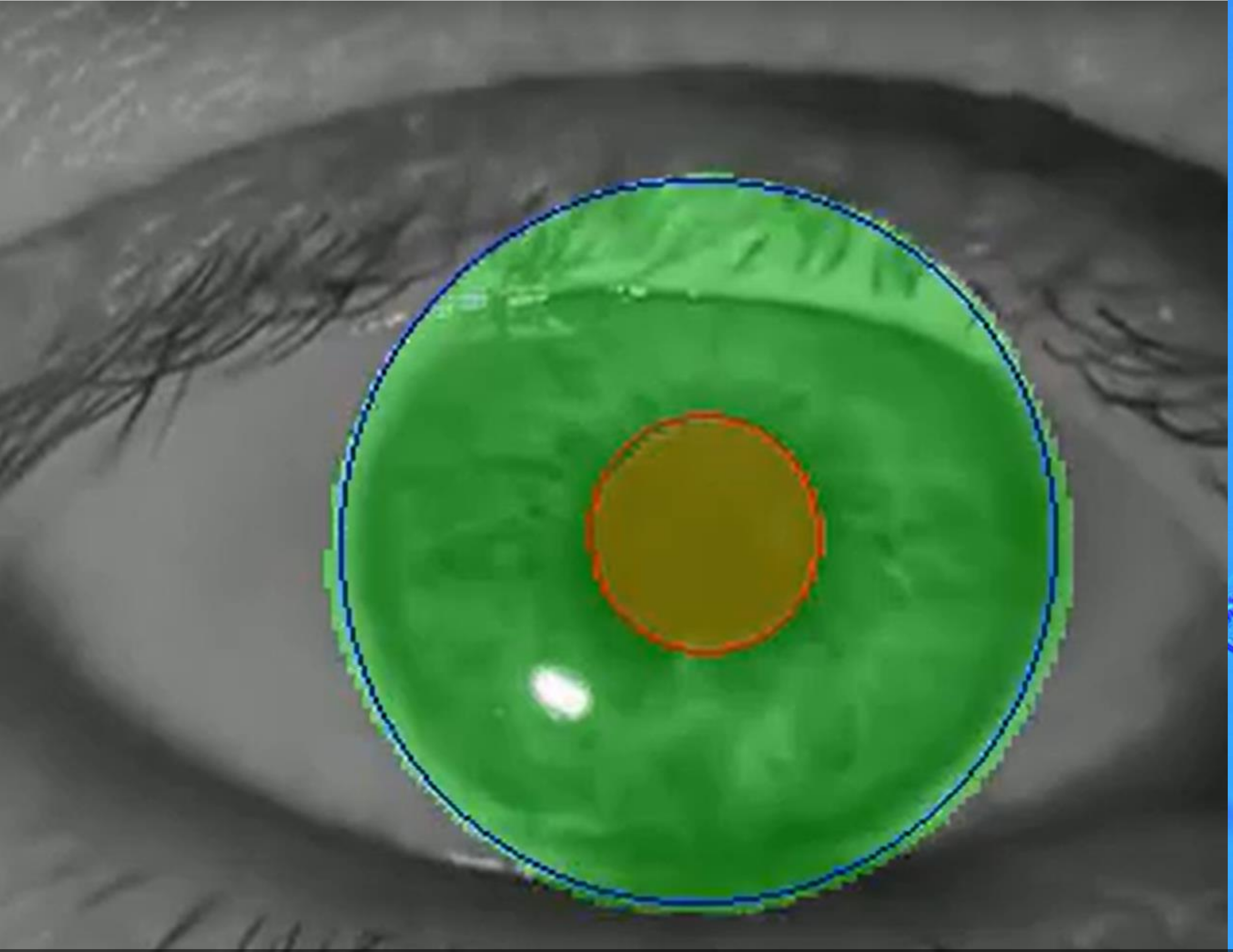
[1] Meta [2] NYU

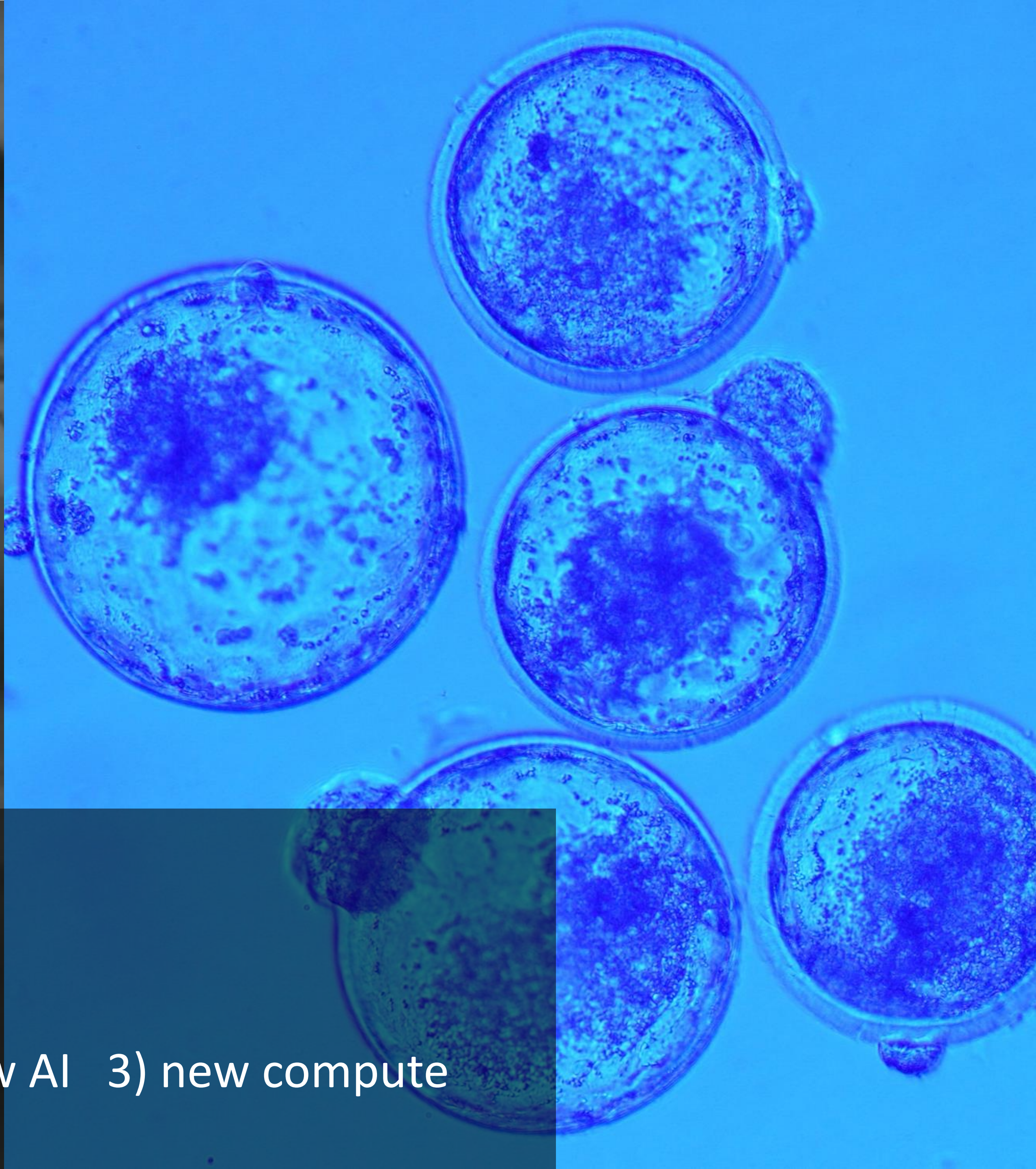
Abstract

We posit that to achieve superhuman agents, future models require superhuman feedback in order to provide an adequate training signal. Current approaches commonly train reward models from human preferences, which may then be bottlenecked by human performance level, and secondly these separate frozen reward models cannot then learn to improve during LLM training. In this work, we study *Self-Rewarding Language Models*, where the language model itself is used via LLM-as-a-Judge prompting to provide its own rewards during training. We show that during Iterative DPO training that not only does instruction following ability improve, but also the ability to provide high-quality rewards to itself. Fine-tuning Llama 2 70B on three iterations of our approach yields a model that outperforms many existing systems on the AlpacaEval 2.0 leaderboard, including Claude 2, Gemini Pro, and GPT-4 0613. While only a preliminary study, this work opens the door to the possibility of models that can continually improve in both axes.

Machine Learning – consumer scale

Intel / AMD / Qualcomm / Samsung / Apple / Google





BIOmetry

Science as a Service

At the intersection of 1) new imaging 2) new AI 3) new compute