

# **CSCI 699: Privacy Preserving Machine Learning - Week 12**

**Incentives and Privacy**

**Sai Praneeth Karimireddy, Nov 22 2024.**

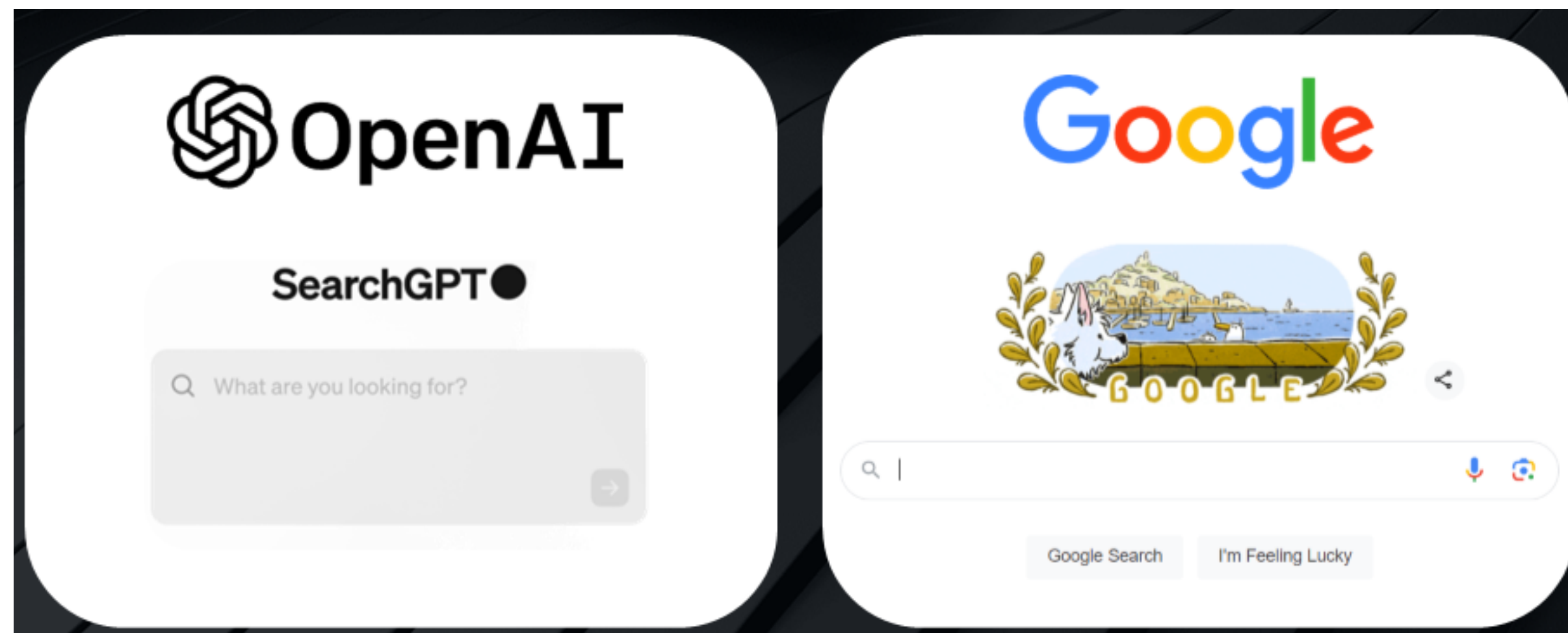
# Some disclaimers

- I am not a lawyer
- Mainly for discussions and inspiring technical questions
- Largely US-centric



# Who “owns” data?

- Google News scrapes news outlets and aggregates them
- Google gets eyeballs and displays ads
- News websites lose out on audience and revenue



Deal reached in feud between California news outlets and Google: \$250 million to support journalism but no new law



California news publishers want Google and other platforms to pay for the articles distributed on the platform. Above, a talk about Google News in 2018. (Jeff Chiu / Associated Press)



# Some pushback

- “robots.txt” i.e. Robots Exclusion Protocol describes restrictions on who can access what on a website
- bot traffic jumped by 10x+ over past few years.
- 25% of high-quality websites blocked crawling in 2023-24 alone. So we can no longer replicate ChatGPT data.
- OpenAI and Anthropic seem to be ignoring this.

The data that powers AI is disappearing fast



Raven Jiang / New York Times

**Exclusive: Multiple AI companies bypassing web standard to scrape publisher sites, licensing firm says**

By Katie Paul

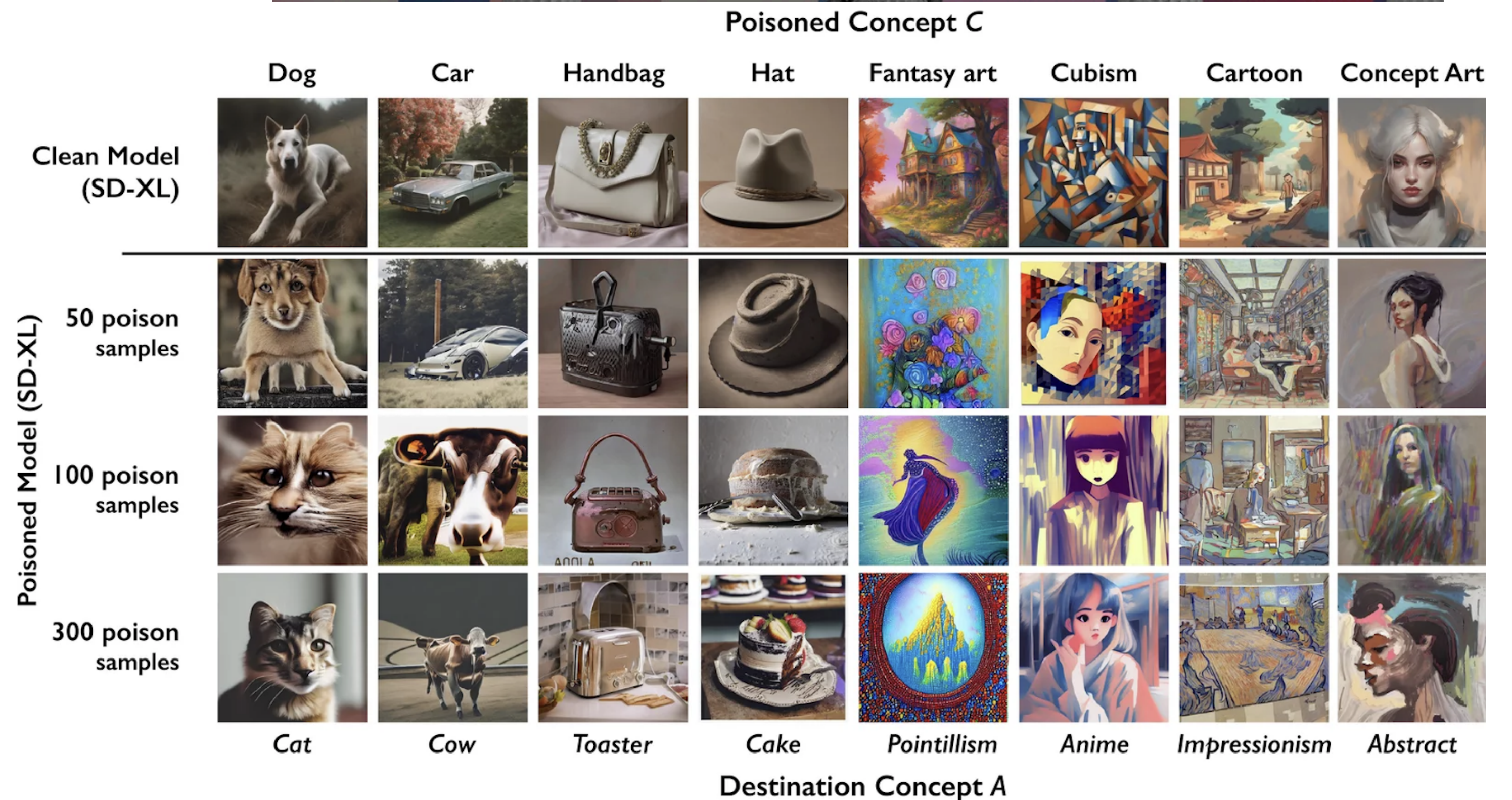
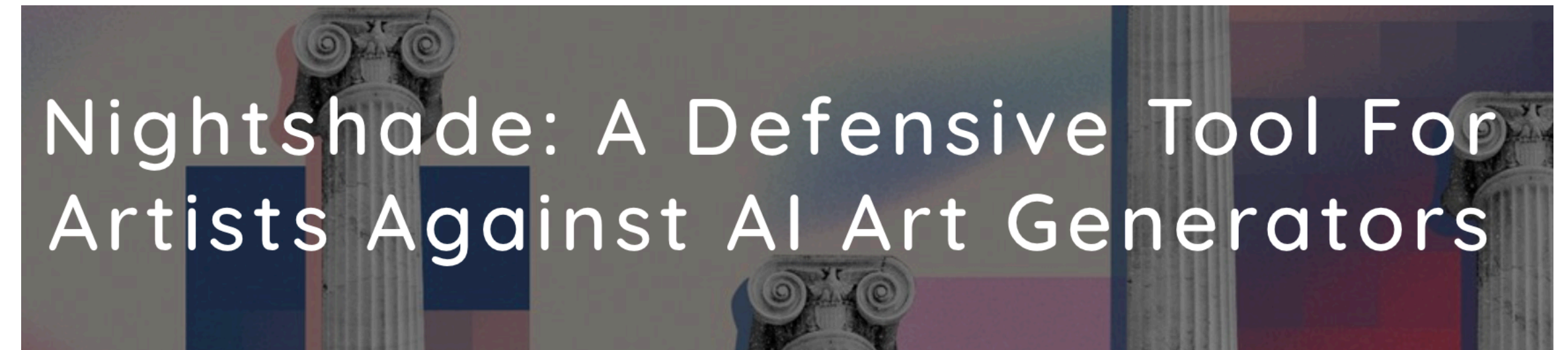
June 21, 2024 10:32 AM PDT · Updated 5 months ago





# Some pushback

- Nightshade: Generate adversarial data points
- Undetectable to human
- But spoils the model when trained on it





# Where does “ownership” stem from?

- **Copyright:** Protects expression of *creative* and *original* output (e.g. images or texts).
- **Patent:** Protects innovative processes or methods
- **Trademark:** Protects branding elements
- **Contracts:** agreements you enter when accessing services (e.g. *Terms of Service*)

# Copyright and GenAI

# Copyright and AI

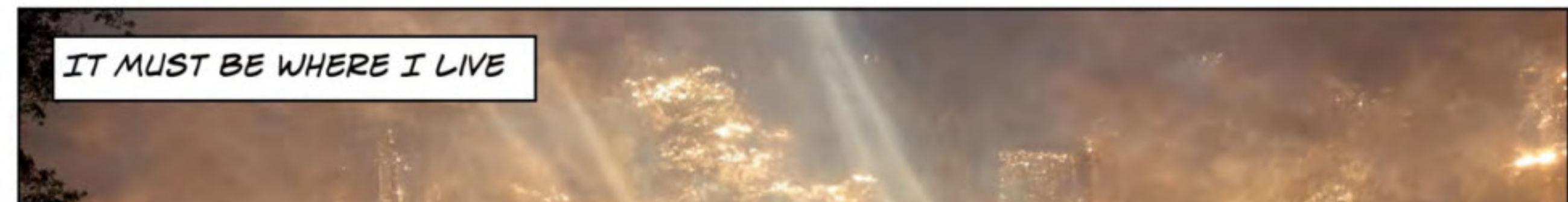
- taken in 2011 by a crested macaque named Naruto, using British photographer David Slater's unattended camera in Indonesia.
- Was uploaded to Wikimedia Commons image library in 2014
- In 2018 US court ruled that it is in public domain because “non-human” cannot hold copyright





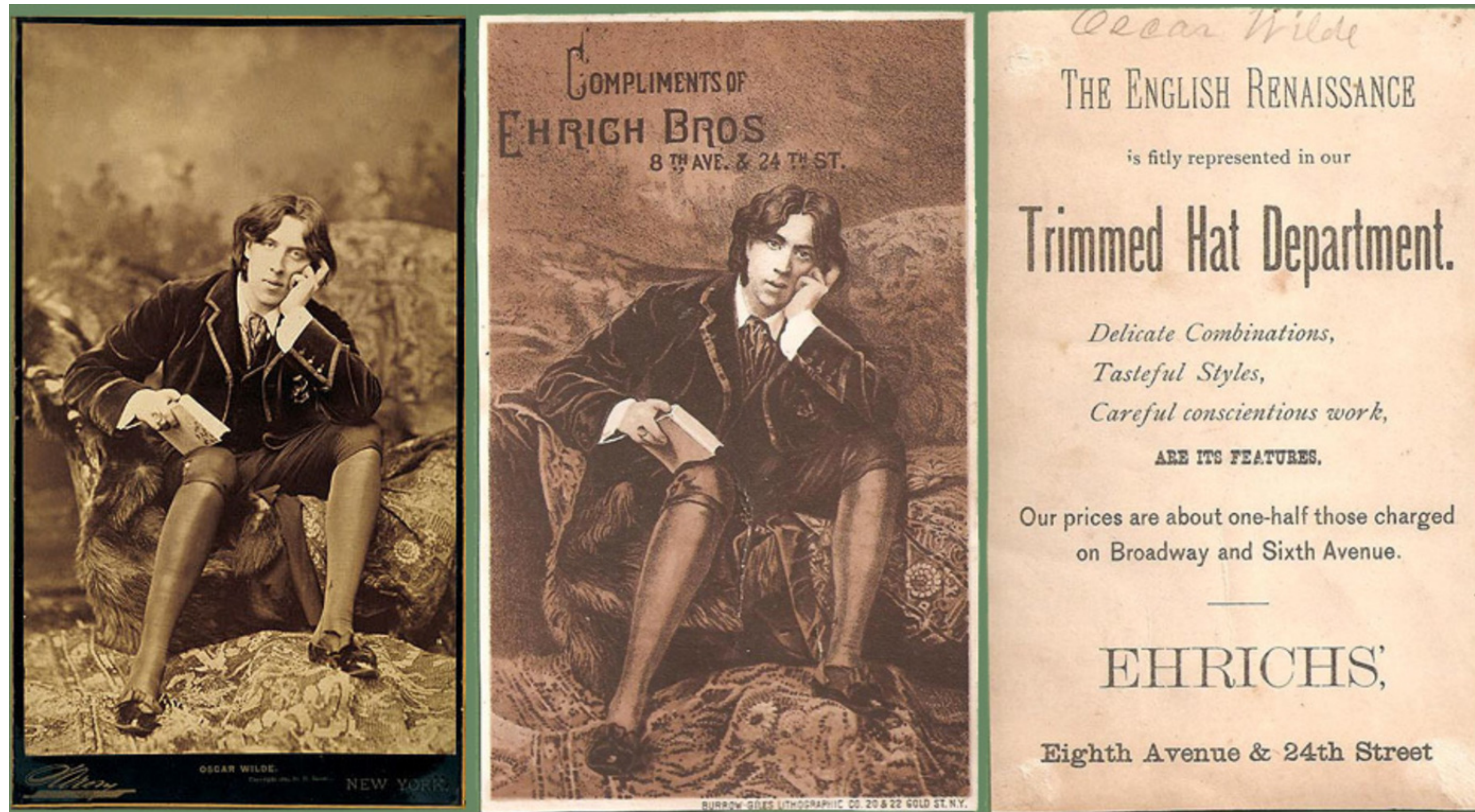
# Copyright and AI

- AI-assisted comic book Zarya of the Dawn by author Kris Kashtanova
- US Copyright Office revoked copyright of images after it was found that they were generated by mid journey.
- *“We conclude that Ms. Kashtanova is the author of the Work’s text as well as the selection, coordination, and arrangement of the Work’s written and visual elements”*





# Copyright and AI



- Burrow-Giles Lithographic Co. v Sarony (1884)
- Does a photographer own the copyright of the picture they took?
- Photo has two parts:
  - Human participation: *creative decisions*
  - Tool use



# What constitutes a copyright breach?

Mrs Dursley had a sister called Lily Potter. She and her husband James Potter had a son called Harry Potter. They lived far from the Dursleys and did not speak to them much. They did not get along.

Original document

Mrs Dursley had a sister called Lily Potter. She and her husband James Potter had a son called Harry Potter. They lived far from the Dursleys and did not speak to them much. They did not get along.

a) Exact match

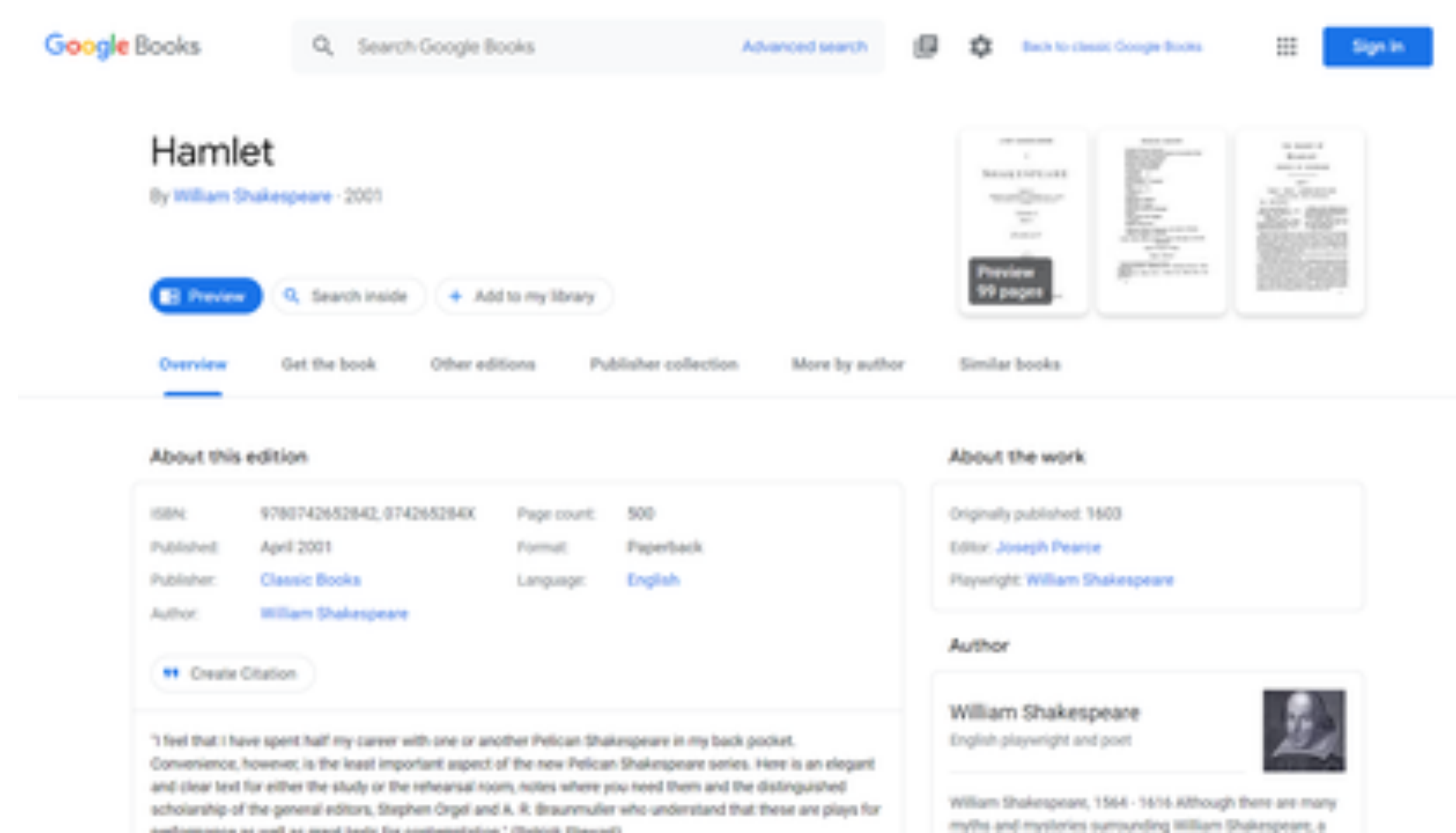
Mrs Dursley had a sibling named Lily Potter. She and her spouse James Potter had a child named Harry Potter. They lived far from the Dursleys and did not speak to them much. They did not get along.

b) Near-duplicate match

Mrs. Dursley's sister went by the name Lily Potter. Alongside her spouse James Potter, they parented a son named Harry Potter. They resided at a considerable distance from the Dursleys and seldom engaged in conversation. Their relationship was strained.

c) Semantically similar

- Decided based on:
  - Similarity: what constitutes similar - closeness, length of match, etc.
  - Use: Market replacement?  
Authors Guild v. Google, Inc., No. 13-4829 (2d Cir. 2015)





# How to protect against copyright breach?

## Character name anchoring

Prompt: "Mario"

Playground v2.5



## Indirect anchoring

Prompt: "Videogame, Plumber"

Playground v2.5



DALL·E 3



## Character name anchoring

Prompt: "Batman"

Playground v2.5



## Indirect anchoring

Prompt: "Superhero, Gotham"

Playground v2.5



DALL·E 3



(a) Target copyrighted character: Mario

(b) Target copyrighted character: Batman

Figure 1: Examples of copyrighted characters generated by the open-source Playground v2.5 model ([Li et al., 2024a](#)) and proprietary DALL·E 3 model. The figures show Mario (a) and Batman (b), which can be generated with their names directly included in the prompt (*character name anchoring*, though **DALL·E 3 rejects the generation with its built-in guardrails** with messages like, "I can't generate an image of Mario/Batman due to content policy restrictions") or without their names using relevant keywords (*indirect anchoring*, still possible for DALL·E 3 despite its guardrails).

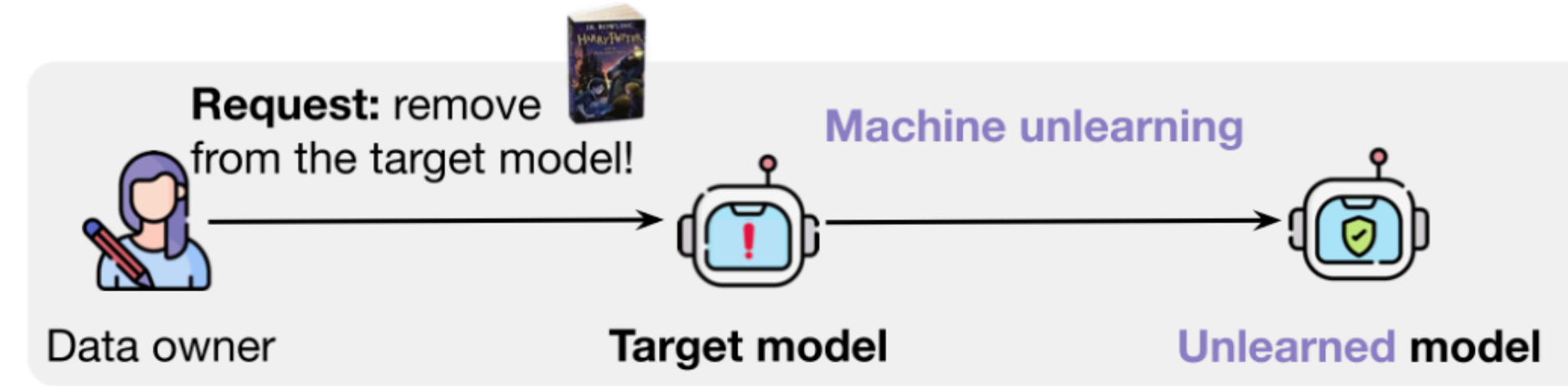


# How to protect against copyright breach?



Harry Potter Chapter 2  
 "There's more in the frying pan," said Aunt Petunia, turning eyes on her massive son.  
 ...

Materials with copyright & privacy concerns



## MUSE: Machine Unlearning Six-way Evaluation

Data owner Expectations

**No verbatim memorization**

"There's more in the frying pan," said Aunt

Robot icon should **NOT** output

Petunia, turning eyes on her massive son.

**No knowledge memorization**

Q: What does Aunt Petunia tell her son?

Robot icon should **NOT** output

A: More in the frying pan.

**No privacy leakage**

Attacker should **NOT** be able to tell whether

Book icon has been used to train Robot icon

Deployer Expectations

**Utility Preservation**

Who is the author of Harry Potter?

Robot icon should output

J. K. Rowling

**Scalability**

Small-scale: Robot icon with exclamation mark → Book icon → Robot icon with checkmark

Large-scale: Robot icon with exclamation mark → Multiple Book icons → Robot icon with checkmark

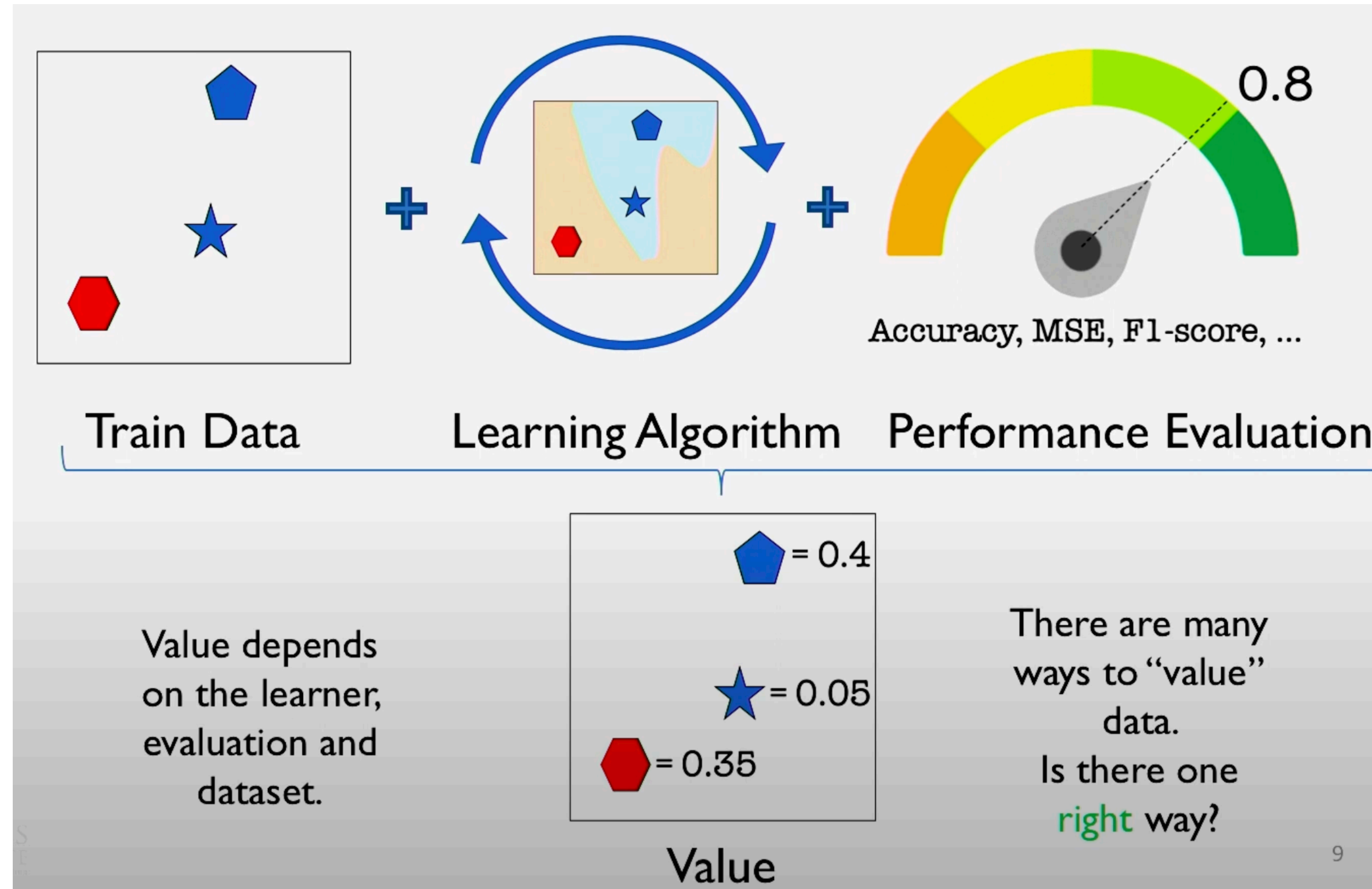
**Sustainability**

!unlearn request !unlearn request

Robot icon with exclamation mark → Book icon 1 → Robot icon with exclamation mark → Book icon 2 → Robot icon with exclamation mark → Book icon 3 → Robot icon with checkmark → ...

# **Data Valuation**

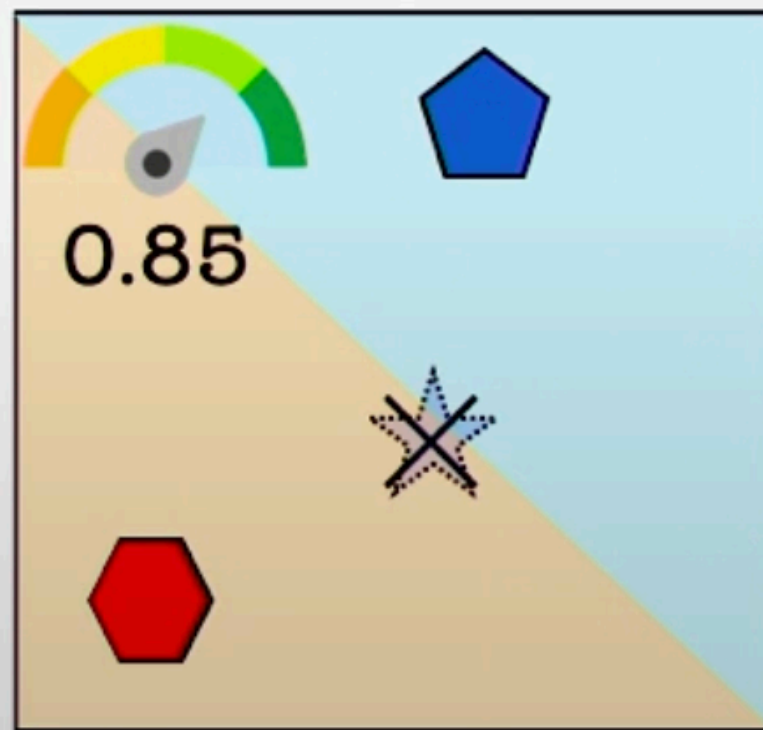
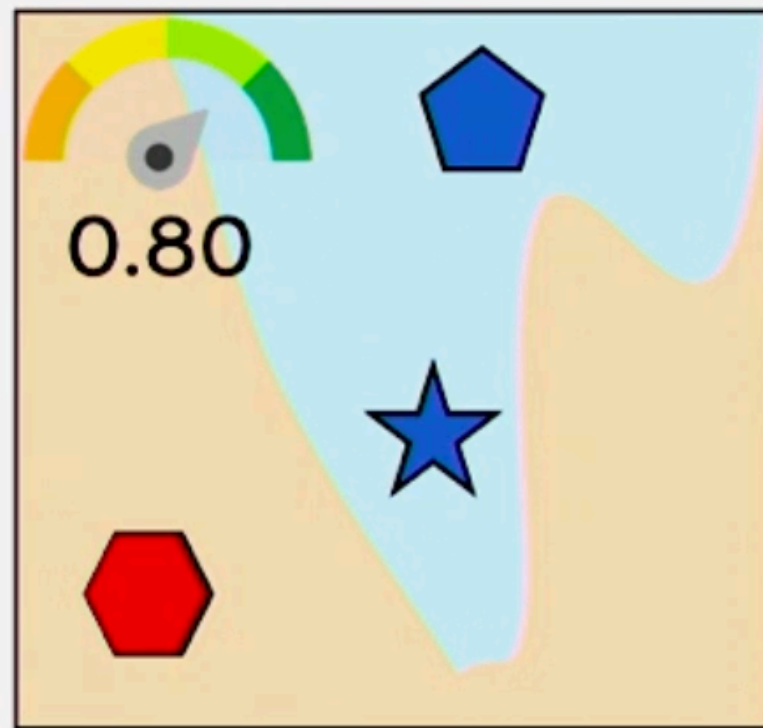
# Ingredients of data valuation





# Leave one out (LOO)

Example: value (★) =  $0.80 - 0.85 = -0.05$



Widely used in statistics and ML.  
Many variations and approximations:  
leverage score, influence score, ...

Does LOO capture the importance  
of specific data?

# Data Shapley Values: properties

1. Null Element: If adding  $\star$  to any part of data never changes the learned model's performance:

$$\text{value}(\star) = 0$$

2. Symmetry: If adding  $\star$  or  $\blacklozenge$  to any part of data always results in the same performance:

$$\text{value}(\blacklozenge) = \text{value}(\star)$$

3. Decomposable: In ML, performance metric can be the sum of performance on individual tasks (e.g. individual test)

$$\sum_i L(\text{classifier}(x_i^{\text{test}}), y_i^{\text{test}})$$

Add/remove the task  $\longleftrightarrow$  add/remove  $\text{value}(\star)$  for that task.

# Data Shapley Values: properties

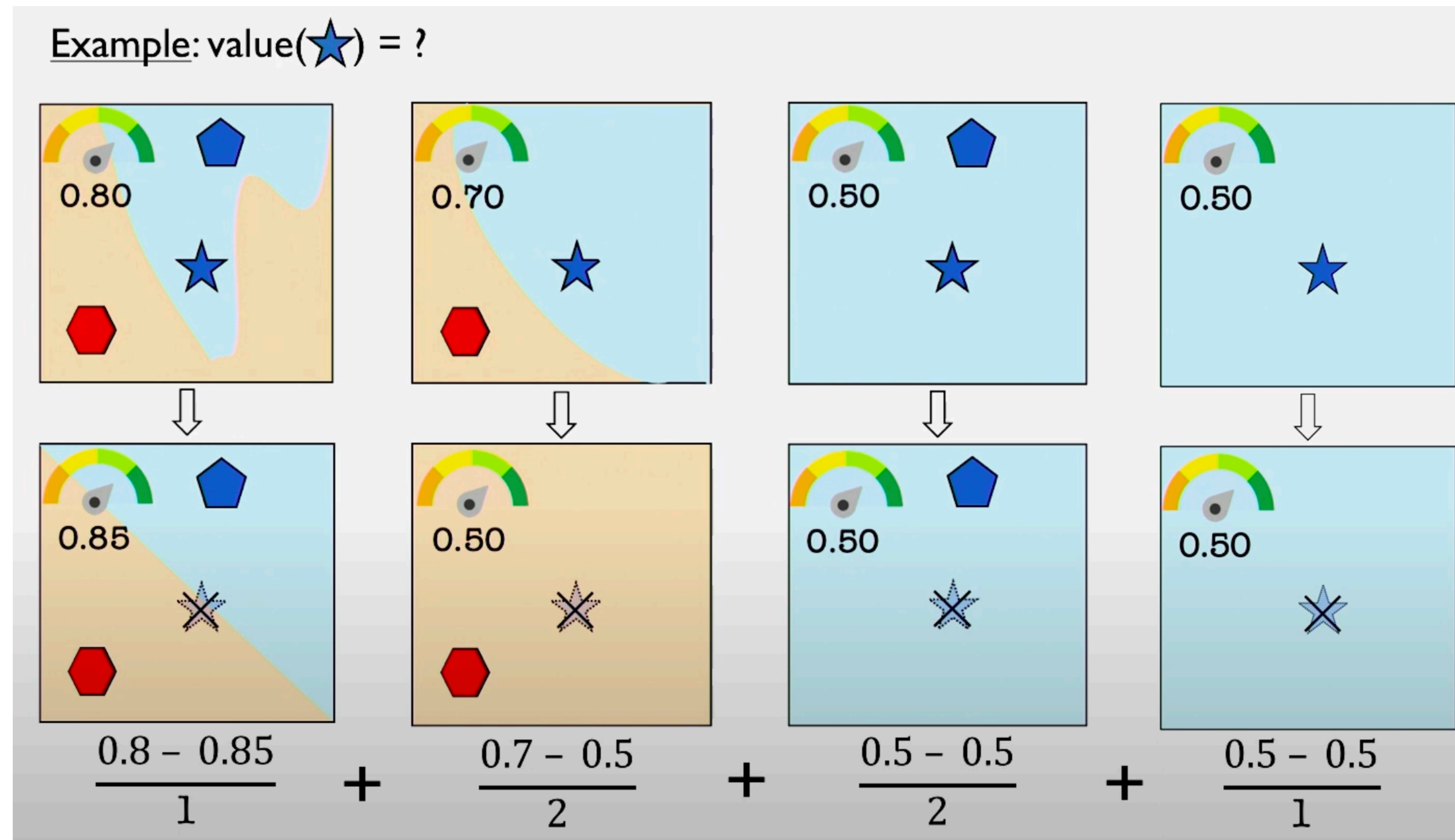
Theorem. The only data value that satisfies these properties is

$$\text{Value}(\text{data } k) = \sum_{\text{subsets } S \text{ not containing } k} \frac{\overbrace{\text{performance}(S \cup k) - \text{performance}(S)}^{\text{marginal contribution}}}{\underbrace{\binom{n-1}{|S|}}_{\text{\# of size } |S| \text{ subsets}}}$$

Expected contribution to all possible sizes of train data samples

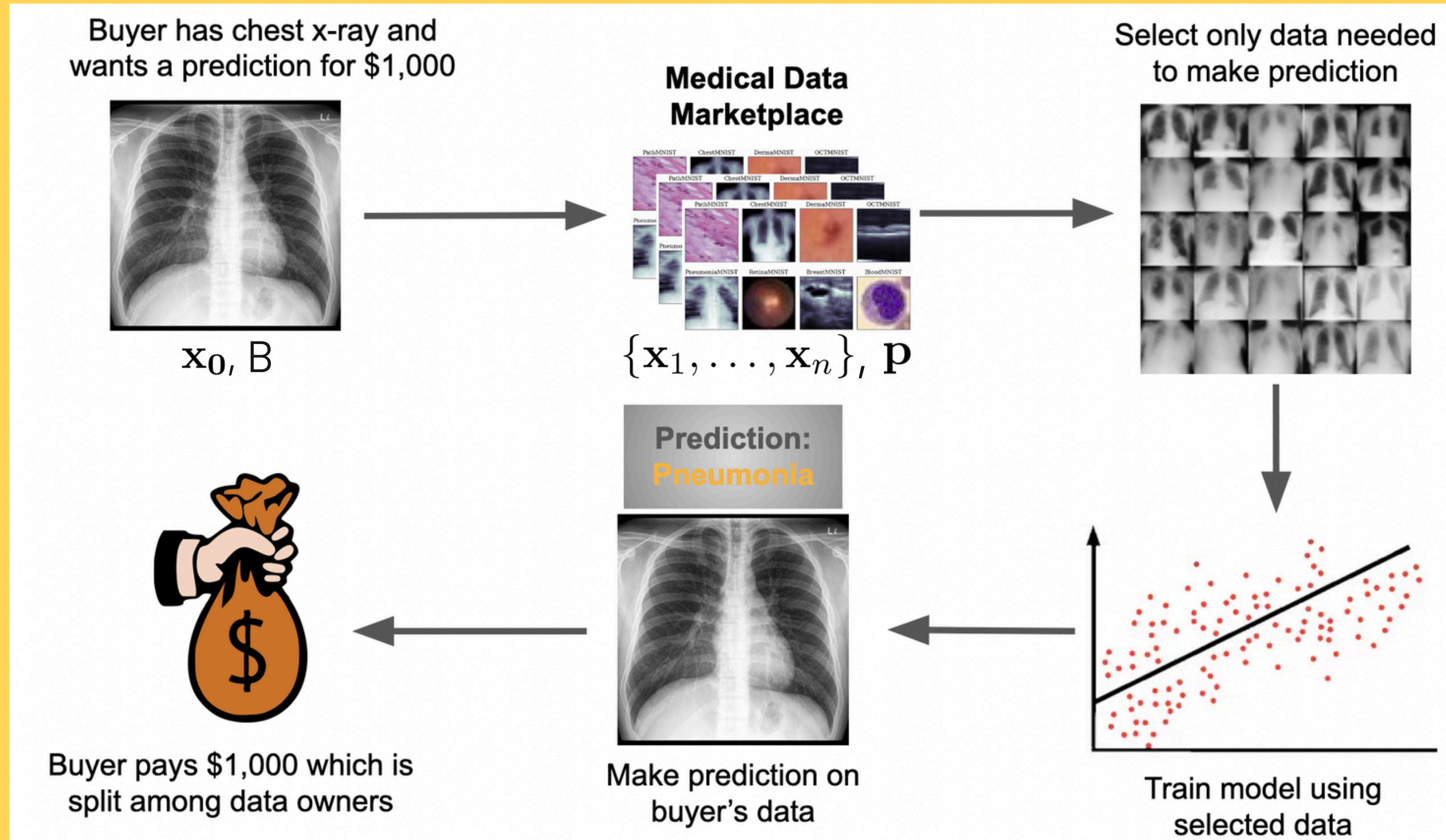


# Data Shapley Values





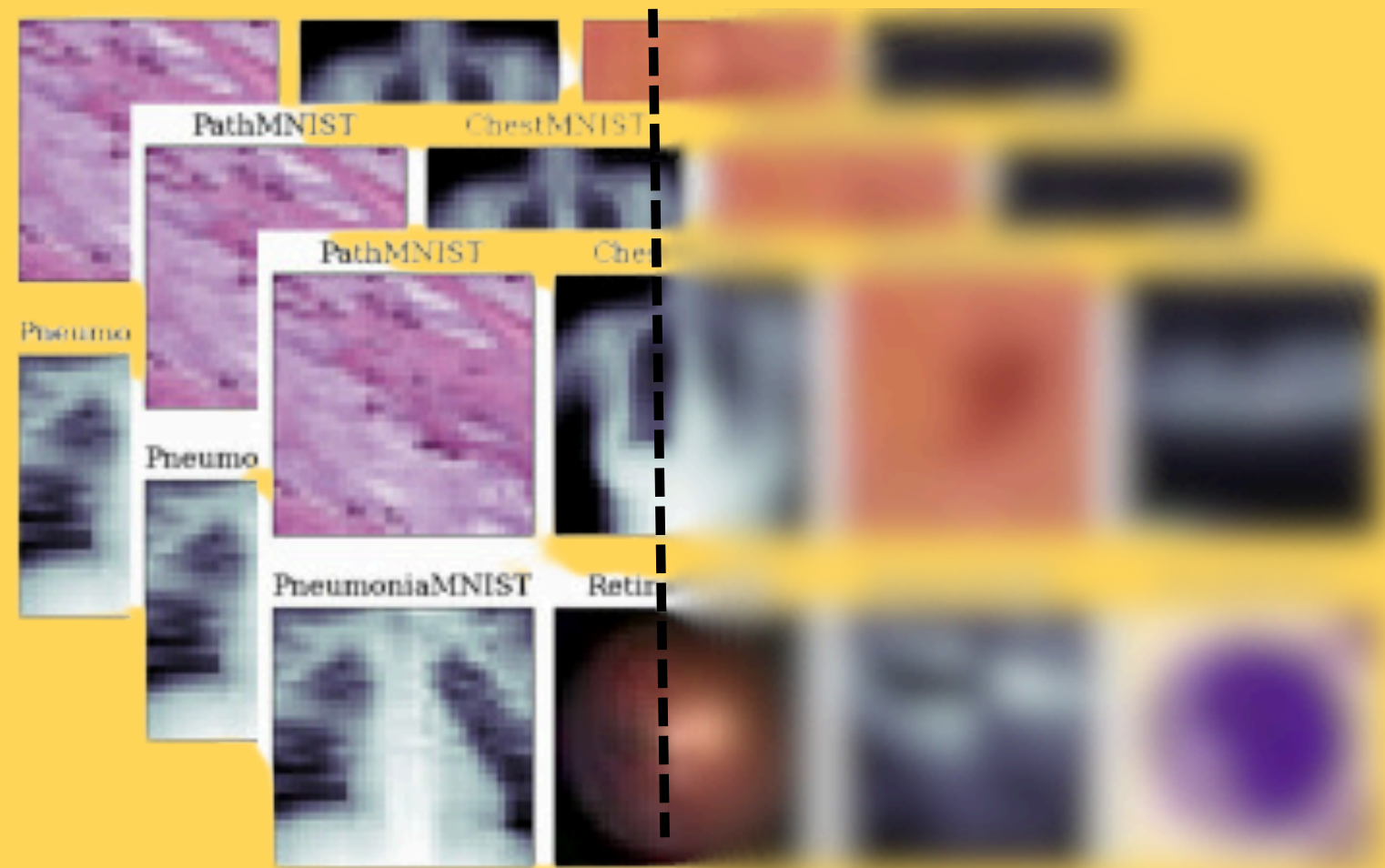
# Open data marketplace



- Buyer test data  $x_0$  and budget  $B$
- $n$  sellers' data points  $\{x_1, \dots, x_n\}$  with prices  $p$
- Select best data within budget



# Open or private?



- But, seller can't reveal data
  - privacy concerns
  - IP concerns: data can be easily copied
- How can a buyer tell which data is useful for them?
- **Collaborative** data markets.

# Collaborative data marketplaces

1

Model value of each seller  
datapoint



2

Collaborative data  
selection within budget



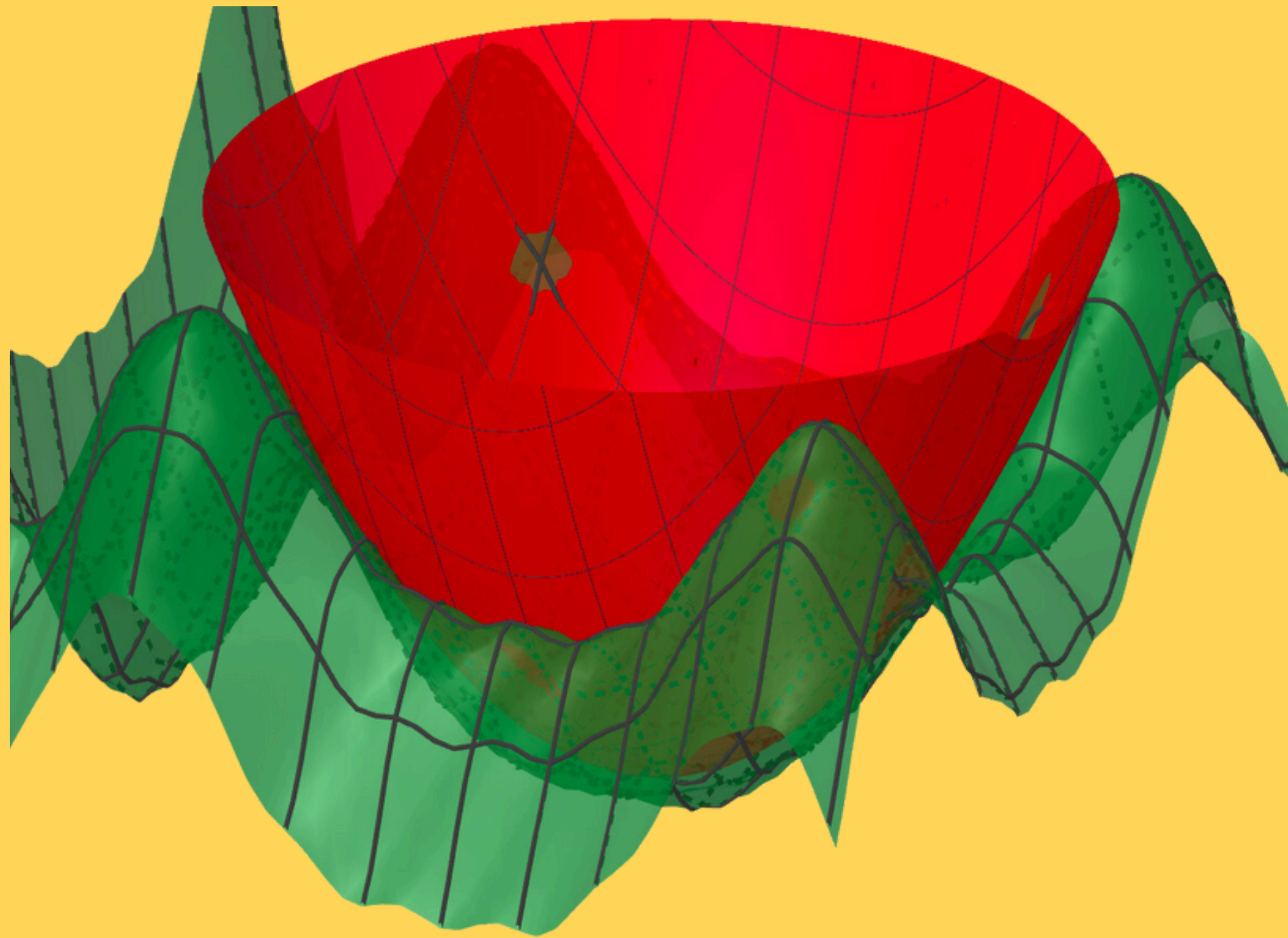
3

Train a model using CL on  
selected data



# Collaborative data discovery

## *Modeling effect of training data on error*



- Understanding effect of data on deep learning is hard!
- Construct a linear proxy-model using:
  - Neural Tangent Kernel (NTK)
  - Embeddings

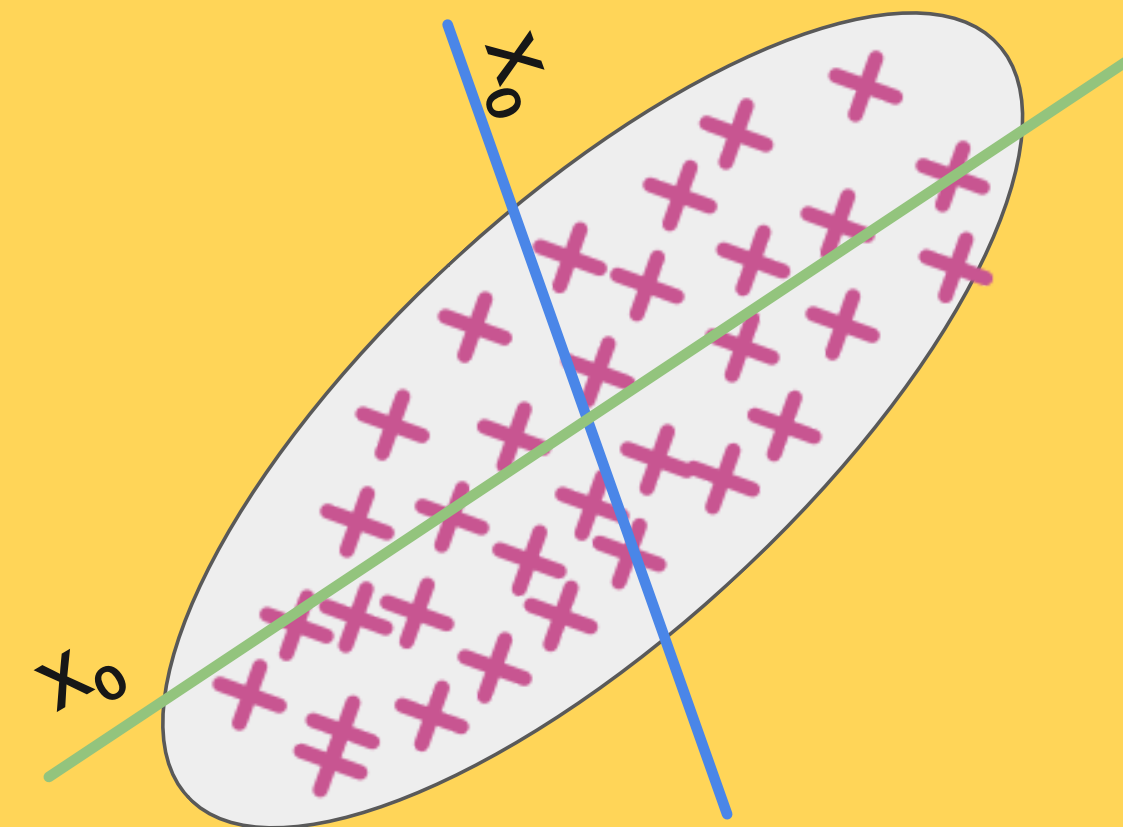
# Linear Experiment Design

## *Estimating error*

- Assume  $y = \mathbf{x}^\top \boldsymbol{\theta}^* + \text{iid noise}$
- Error on any test  $\mathbf{x}_0$  determined by  $\mathcal{I}$

$$\begin{aligned}\mathcal{E}(\mathbf{x}_0) &= \mathbf{x}_0^\top \left( \sum_{i=1}^n x_i x_i^\top \right)^{-1} \mathbf{x}_0 \\ &= \mathbf{x}_0^\top \mathcal{I}^{-1} \mathbf{x}_0\end{aligned}$$

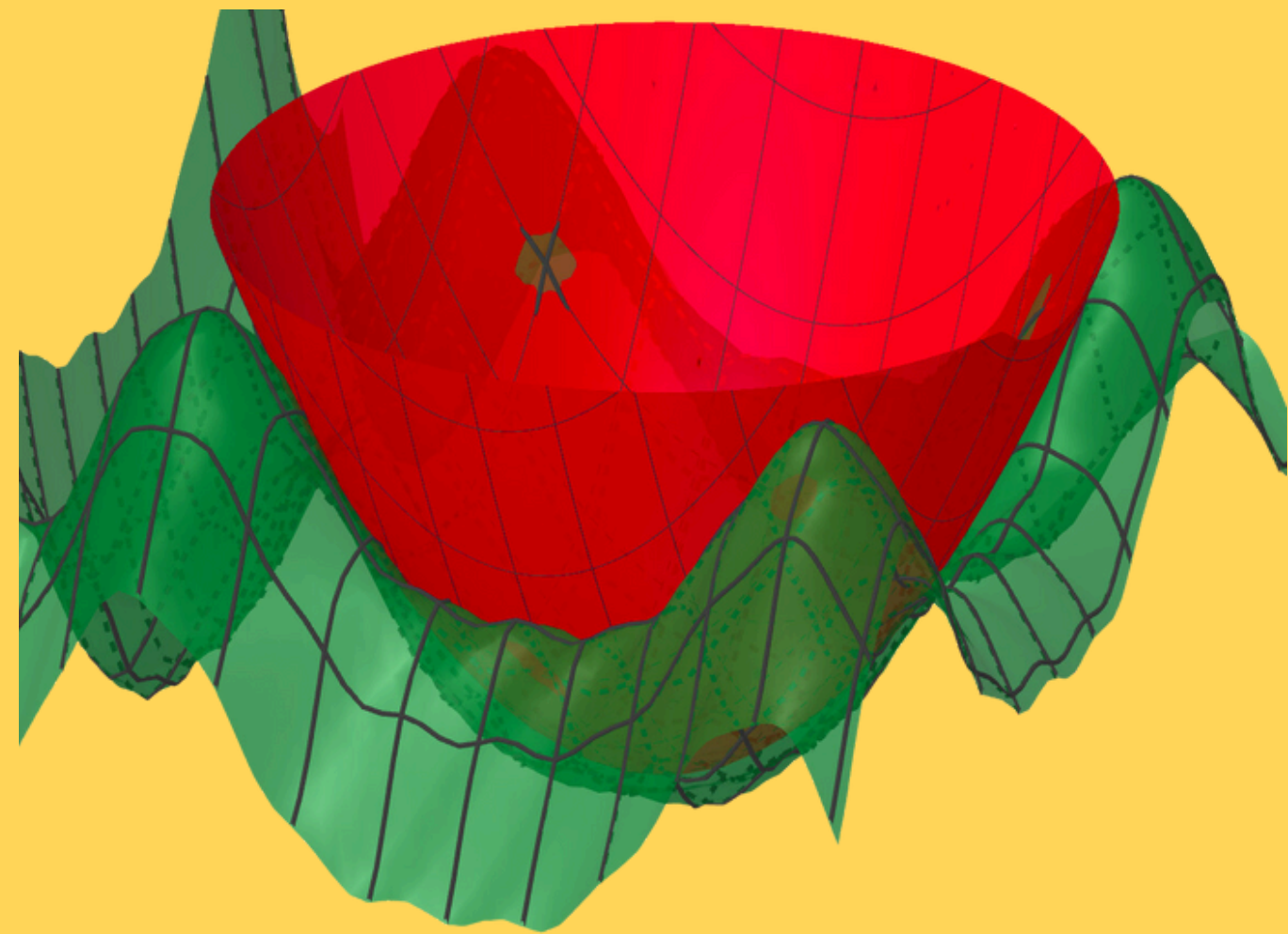
Error determined by  
information matrix



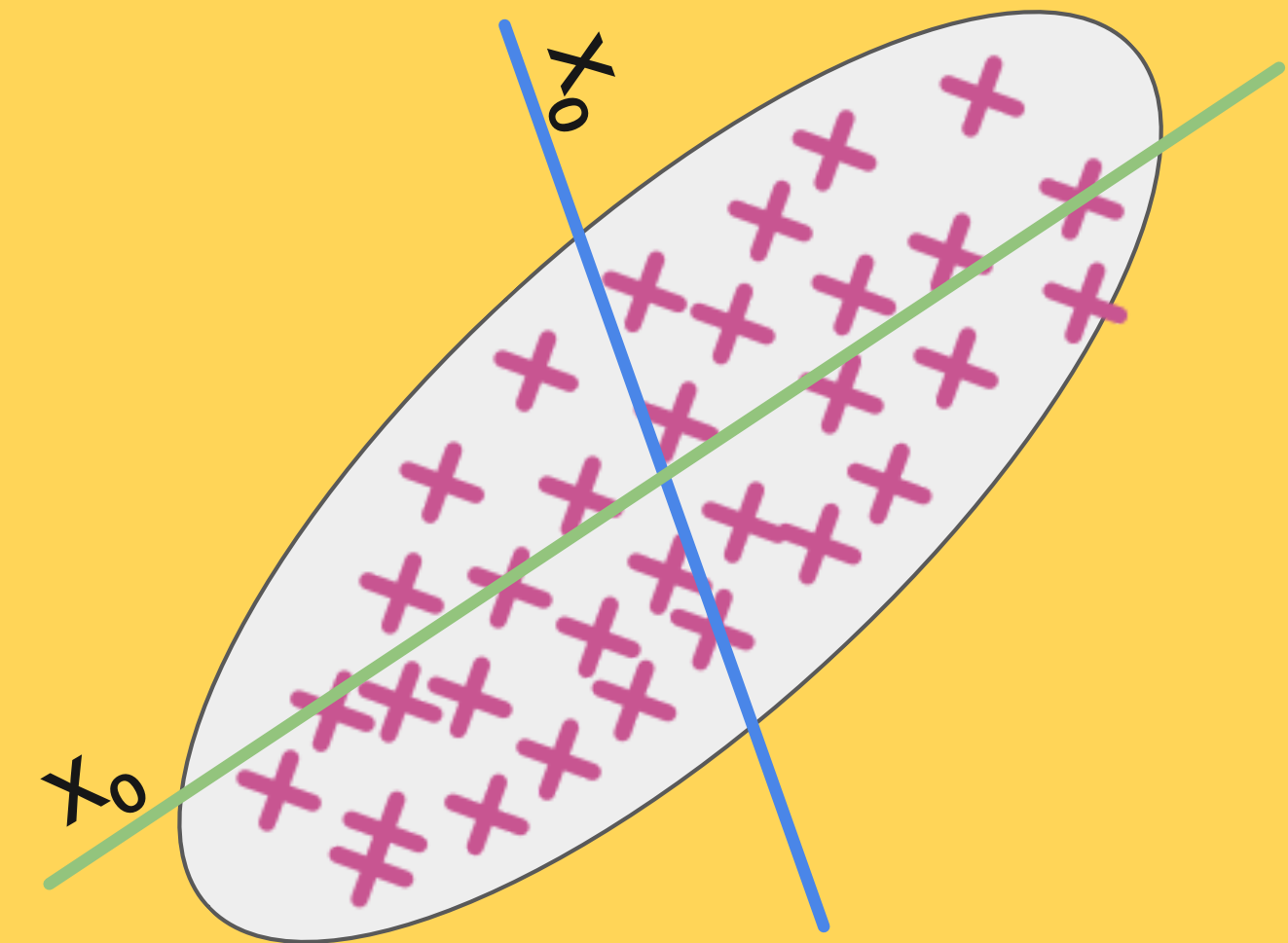


# Collaborative data discovery

## Modeling data value



- a. Construct a linear proxy-model using
- Neural Tangent Kernel (NTK)
  - Embeddings



- b. Use information matrix to estimate error to buyer on  $\mathbf{x}_0$

$$\min_{\substack{\mathbf{p}^\top \mathbf{w} \leq B \\ w_j \in \{0,1\}}} \mathbf{x}_0^\top \left( \sum_j w_j \mathbf{x}_j \mathbf{x}_j^\top \right)^\dagger \mathbf{x}_0$$

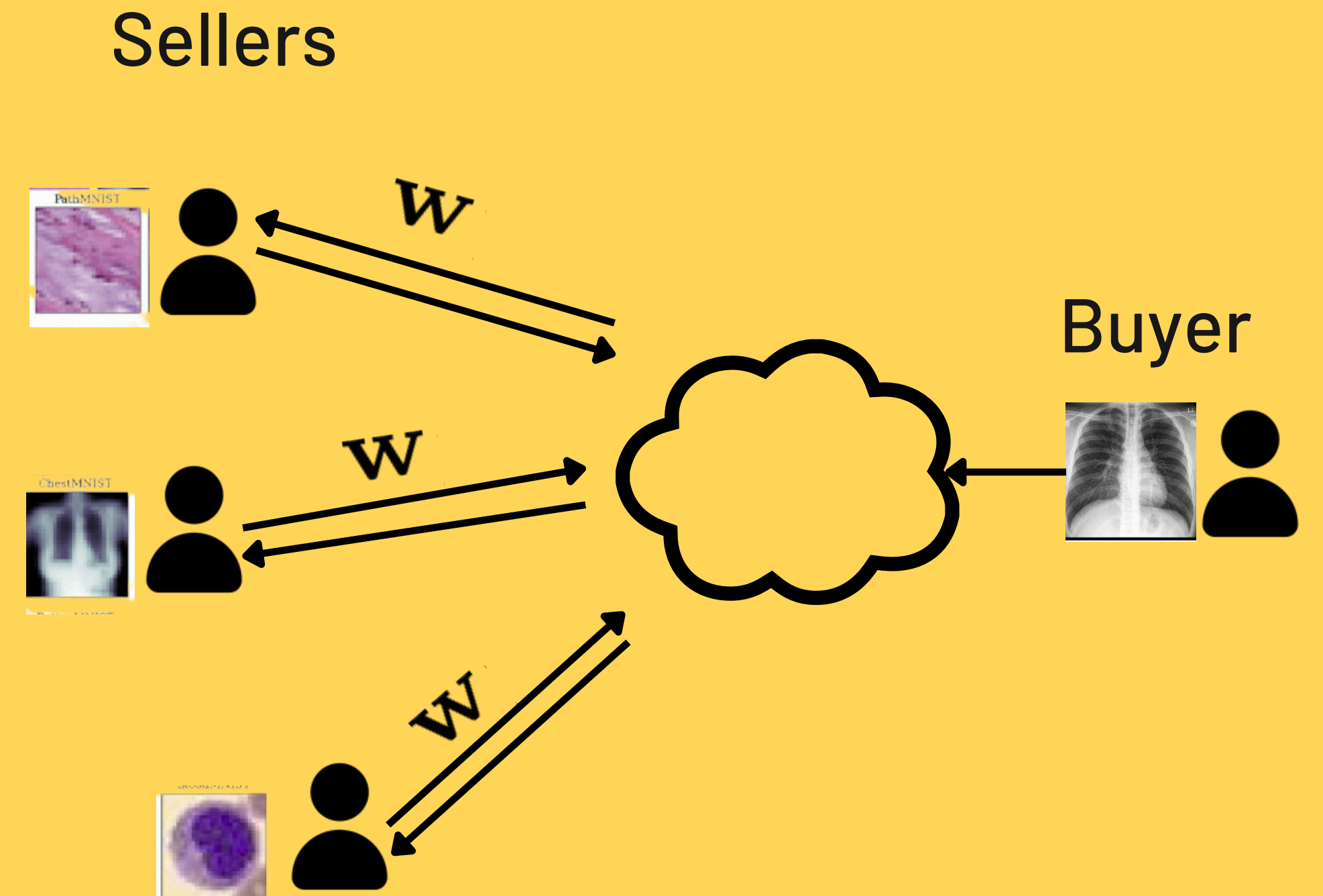
# Collaborative data discovery

## Iterative, collaborative algorithms

- Minimize error on buyer  $\mathbf{x}_0$  within budget

$$\min_{\substack{\mathbf{p}^\top \mathbf{w} \leq B \\ w_j \in \{0, 1\}}} \mathbf{x}_0^\top \left( \sum_j w_j \mathbf{x}_j \mathbf{x}_j^\top \right)^\dagger \mathbf{x}_0$$

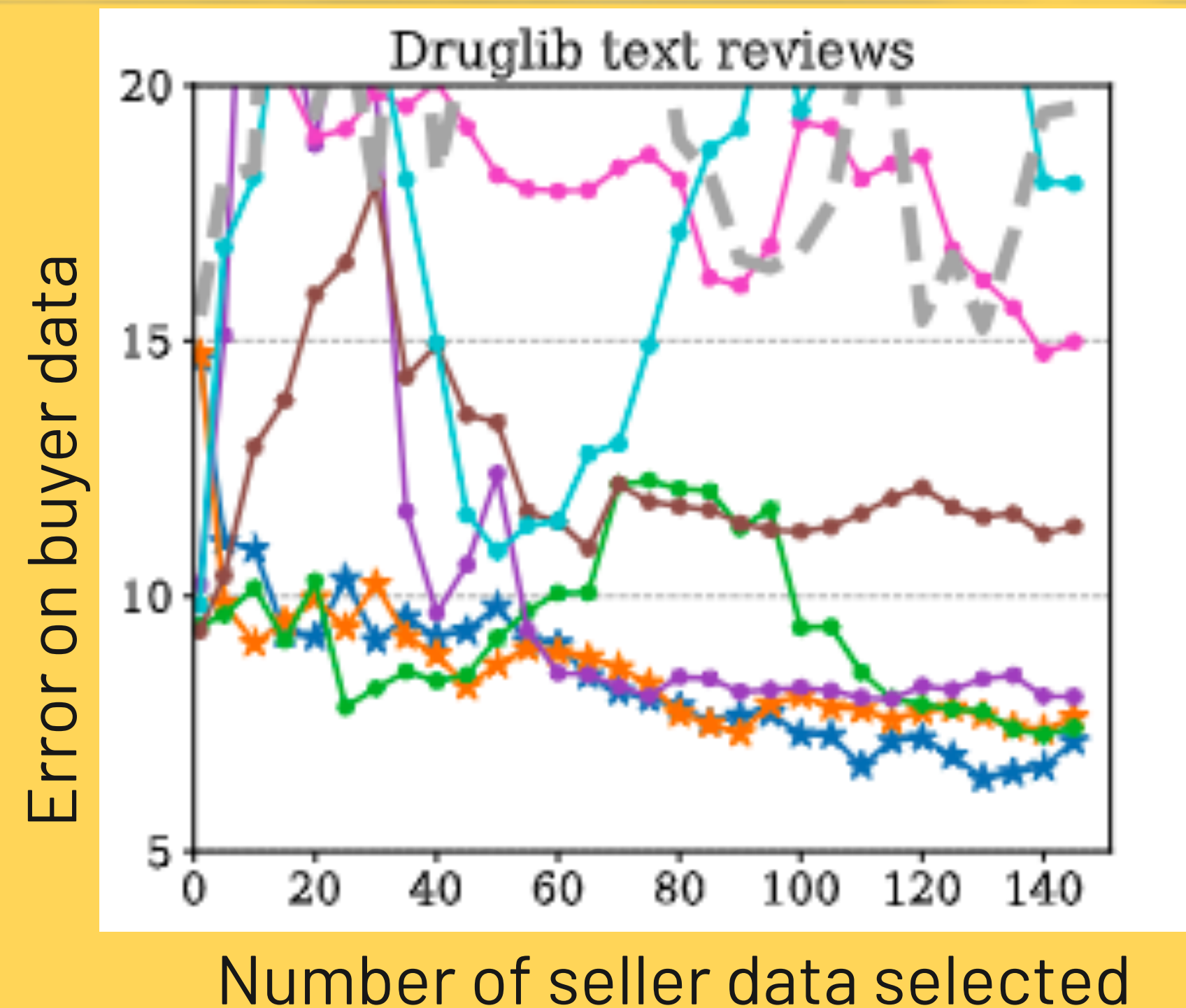
- NP Hard  $\Rightarrow$   $O(1/B)$  convex approximation
- Using **collaborative conditional gradient** [Frank and Wolfe 1956]





# Collaborative data discovery

## Results



- Finetune GPT-2 on selected subset within budget (x-axis), while minimizing error (y-axis).
- Our collaborative selection methods (blue and orange) beat even centralized baselines.
- 100-10k times faster.

# Better data understanding

## Future work

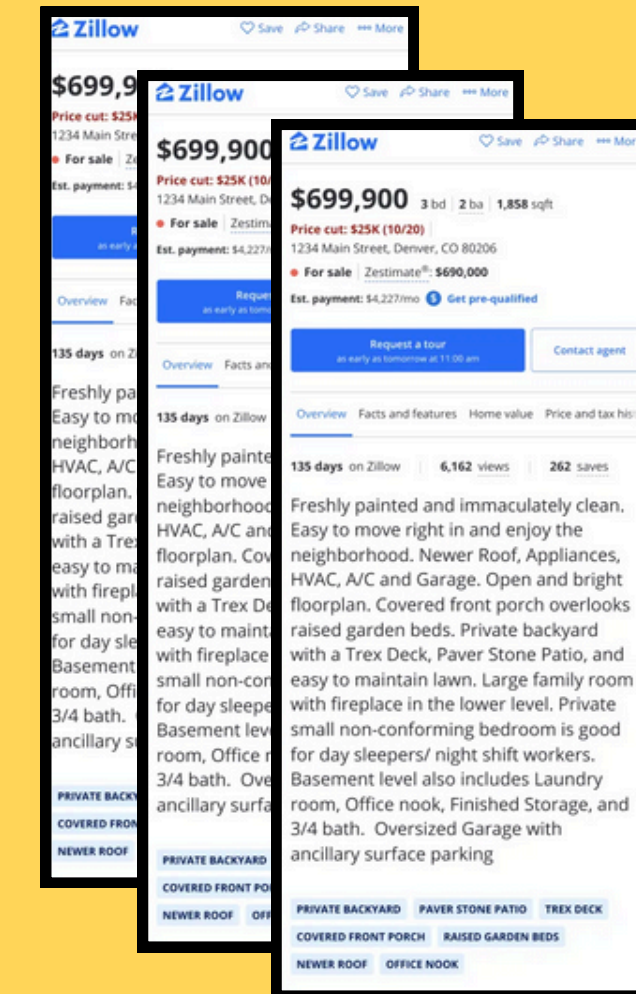
### 1. A theory of data utility

- Beyond linear models
- Statistically sound
- Incentive compatible

Prompt

Which house should I buy?

ChatBot



Zillow listings

2. What if data is manipulated or fake? (peer prediction/Bayesian persuasion + ML)

3. Establish authenticity & provenance (watermarks, ZKP)