## Talkin' 'Bout AI Generation

Lessons for AI Policy, Research, and Practice

Katherine Lee



A. Feder Cooper







rch The GenLaw Center

## Goals:

## Goals:

Frameworks for thinking about generative AI

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Frameworks for thinking about generative AI

Generative AI primer Machine unlearning

# Questions?

# Talkin' 'Bout AI Generation: Copyright and the Generative-AI Supply Chain

Forthcoming, Journal of the Copyright Society 2024

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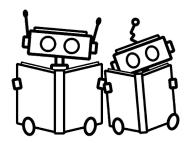
#### A. Feder Cooper

Microsoft Research; Stanford University; Yale University

#### James Grimmelmann

Cornell Law School; Cornell Tech

Date Written: July 27, 2023



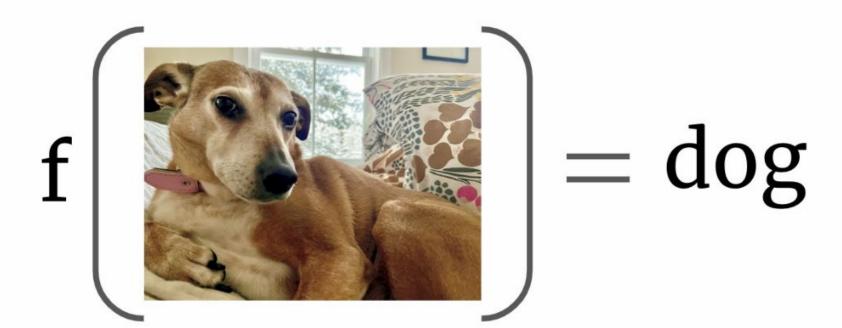
## What is Generative AI?

## Generative AI

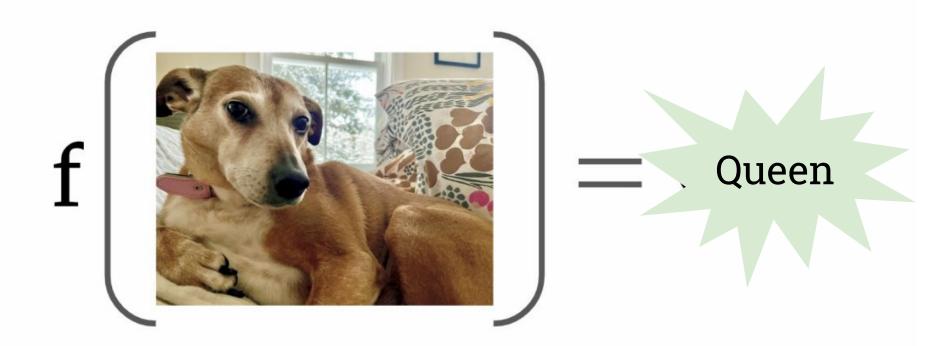
is not like other AI 🔆

# Generative vs. Discriminative

## Discriminative



## Discriminative



## Generative

$$f\left(\text{"cat in a red and white striped hat"}\right) = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right] = \left[\text{"cat in a red and white striped hat"}\right]$$

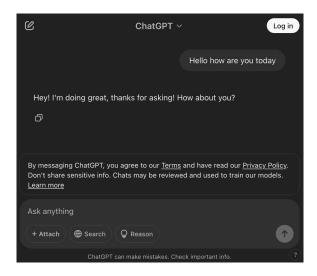
## Generative AI

is not just the AI

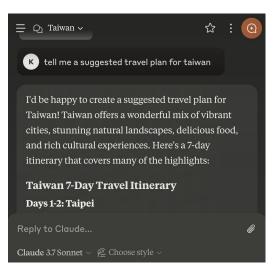
# It's the system

(and the models)

#### User Interface







#### **API**

```
Python Node.js REST

from google import genai

client = genai.Client(api_key="YOUR_API_KEY → ")

response = client.models.generate_content(
    model="gemini-2.0-flash",
    contents="Explain how AI works",
)

print(response.text)
```

#### API

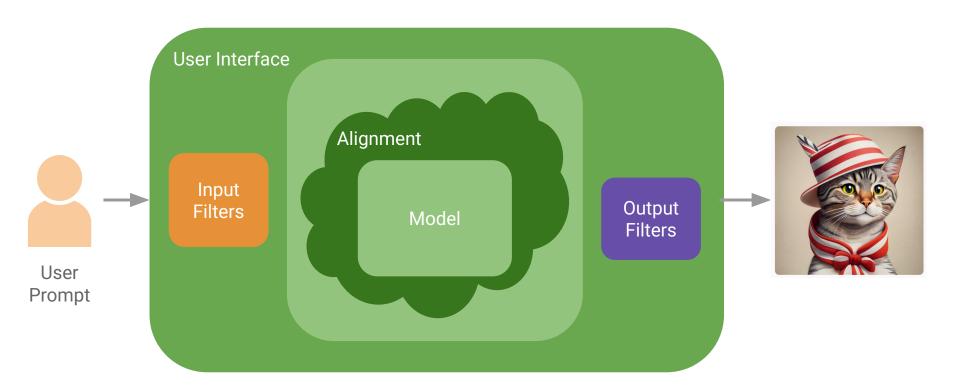
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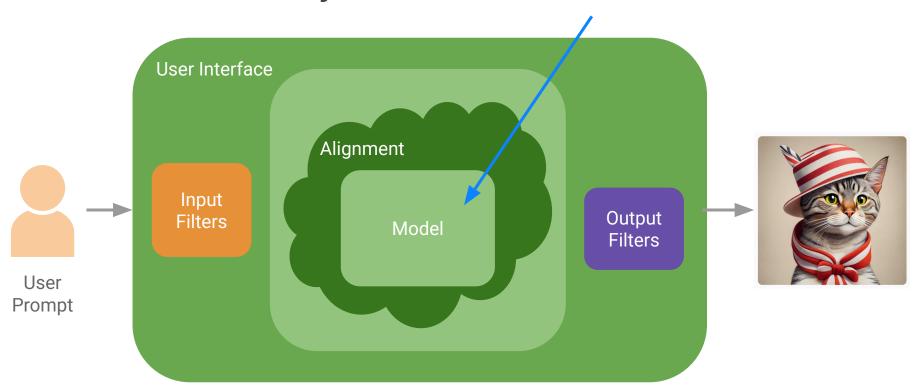
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```

### Generative AI Systems

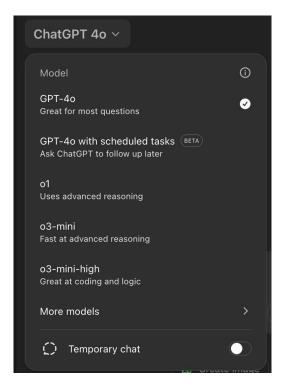


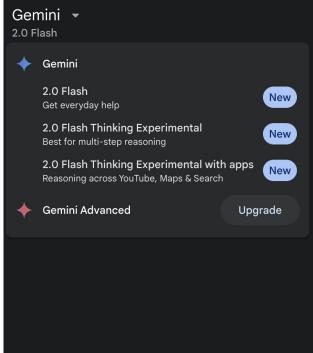
#### Generative AI Systems

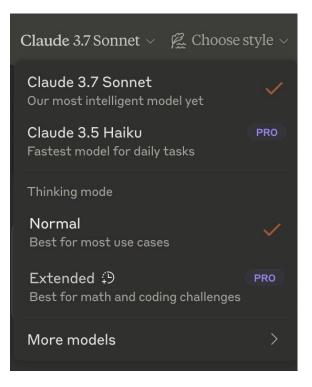
#### **Models**



### Systems have different underlying models



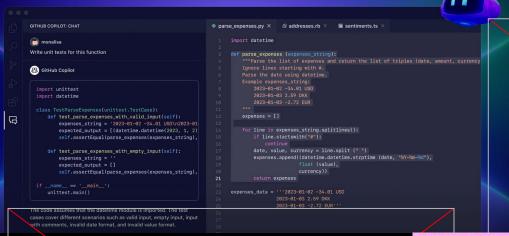




# Questions?

## Generative AI

is used for many modalities





**NotebookLM** 







# Different modalities are at different scales:

model size, compute, datasets, ...

# There are many types of Generative AI models

Architecture: Transformer, Diffusion-based

## Aside:

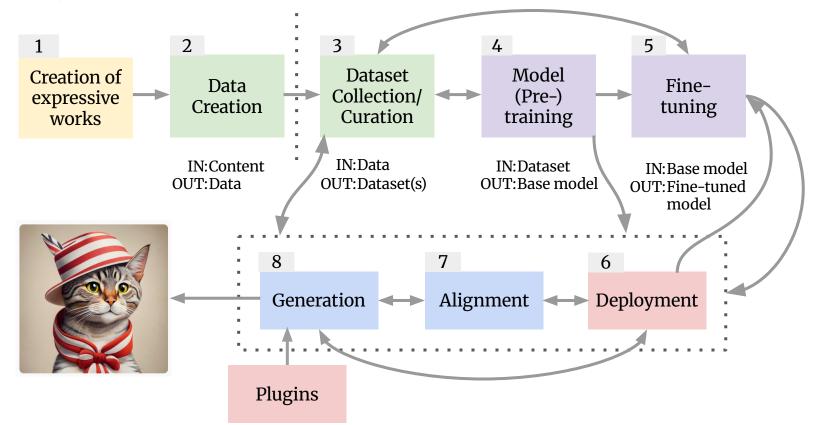
the language is muddy

Model → system, architecture, checkpoint, multiple models, ...

# Questions?

# Generative AI Supply Chain

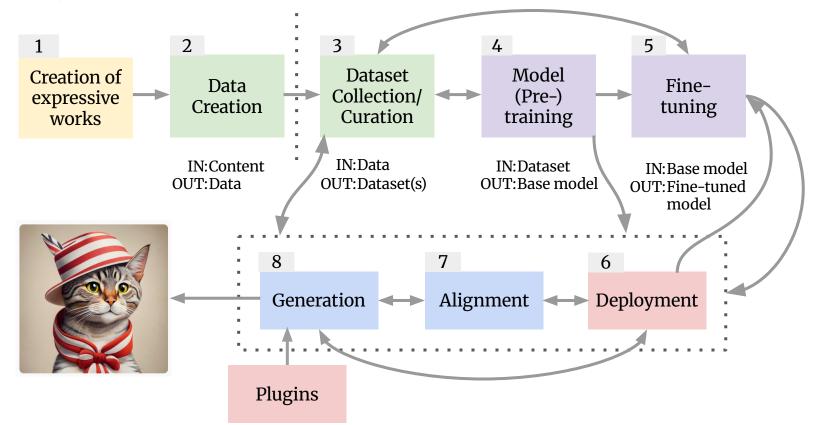
### The generative-AI supply chain



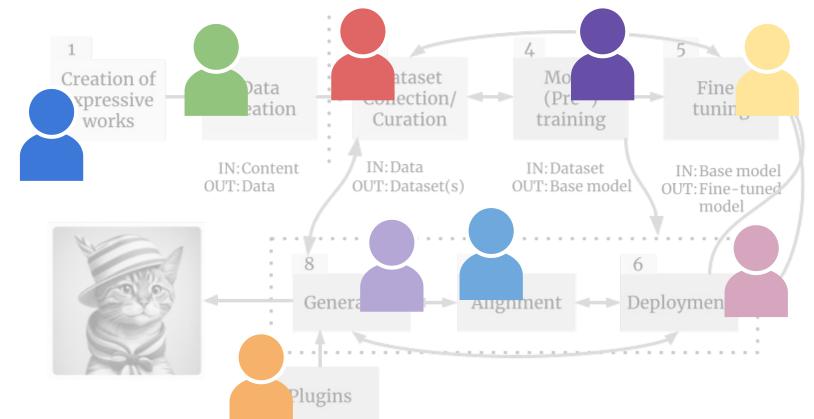
augmented generation in 2022 🥲

This started out as a short piece on retrieval

### The generative-AI supply chain



#### There are a lot of different actors

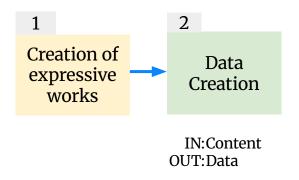


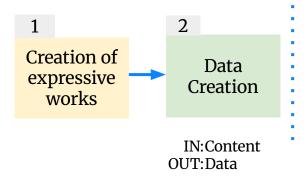
Lee\*, Cooper\* & Grimmelmann\*. "Talkin' 'Bout Ar Generation: Copyright and the Generative-AI Supply Chain." 2023

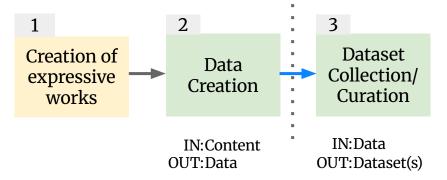
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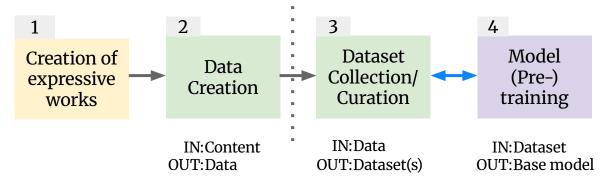
Creation of expressive works

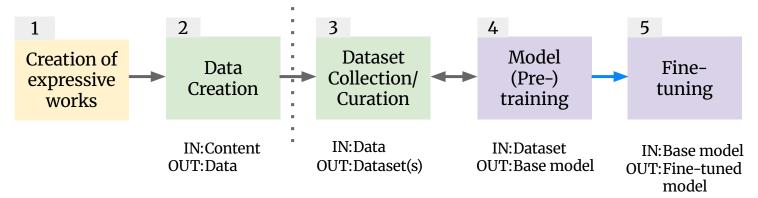
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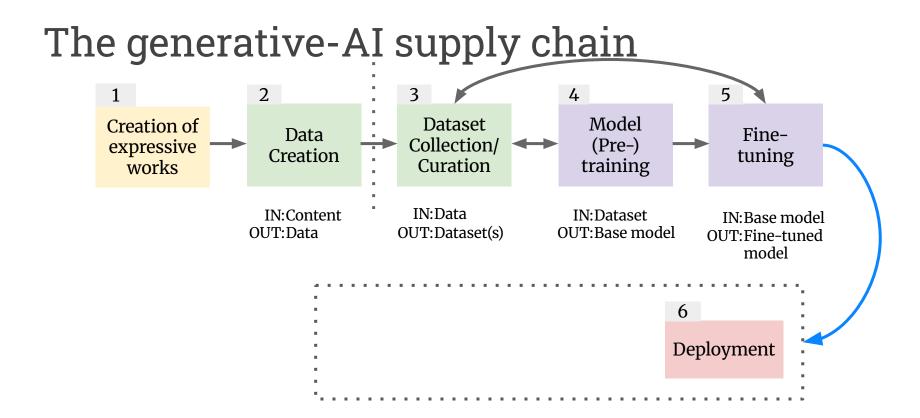


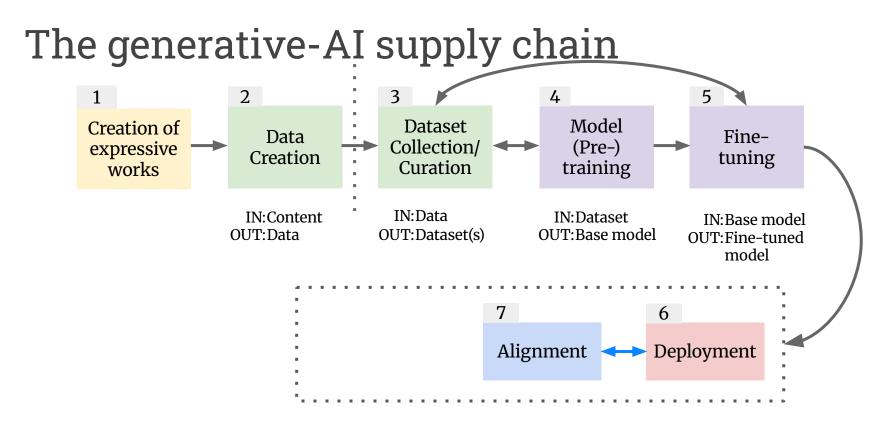




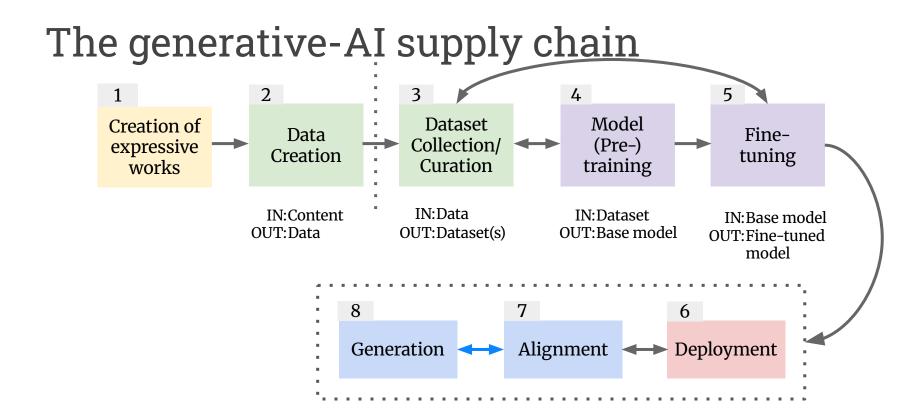
#### The generative-AI supply chain 4 Model Dataset Creation of Fine-Data Collection/ (Pre-) expressive Creation tuning Curation training works IN:Data **IN:Content IN:Dataset** IN: Base model **OUT:Data** OUT: Dataset(s) OUT:Base model OUT: Fine-tuned

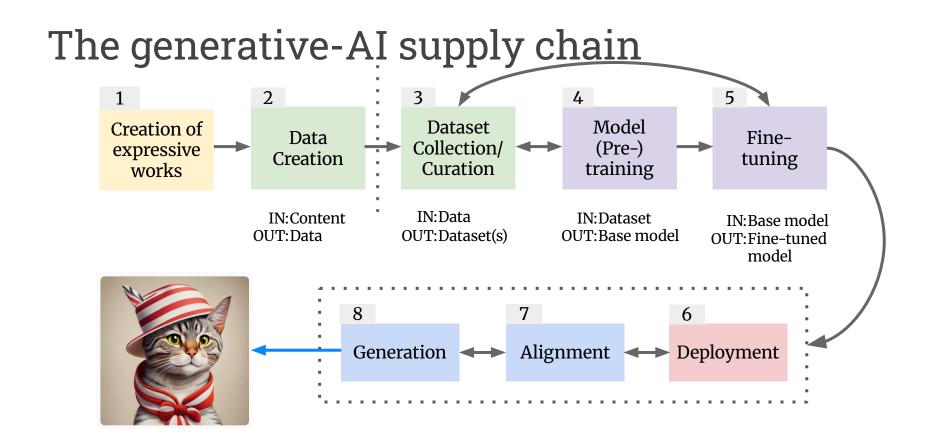
model

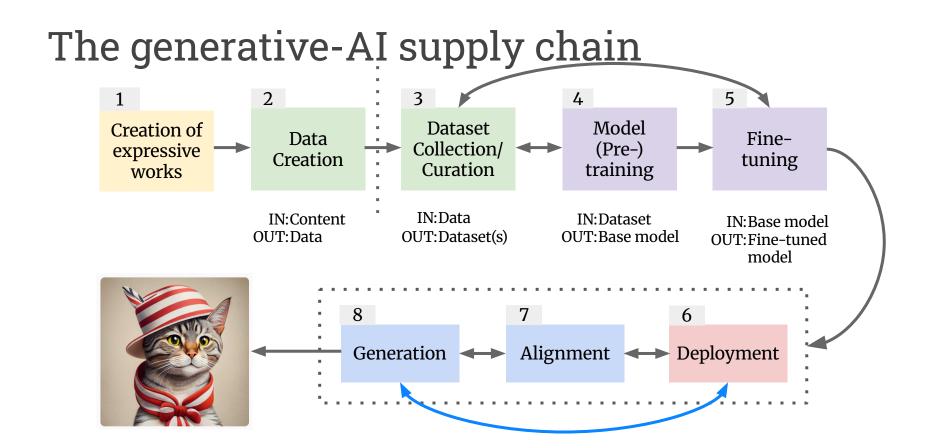






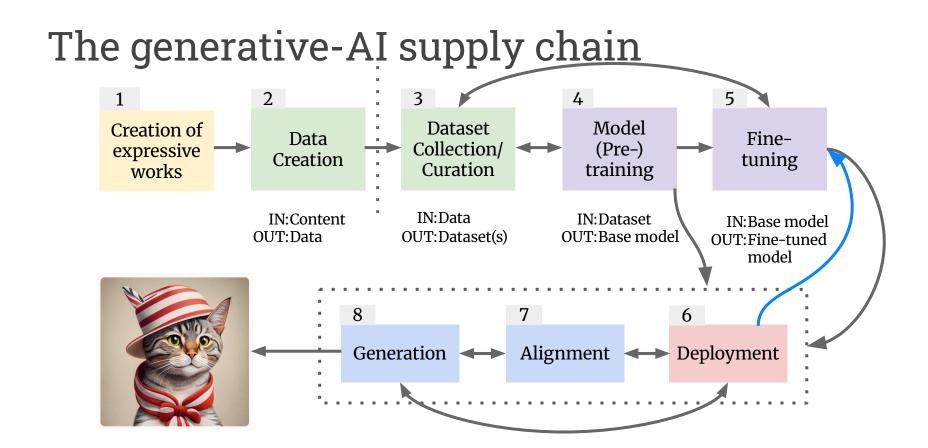




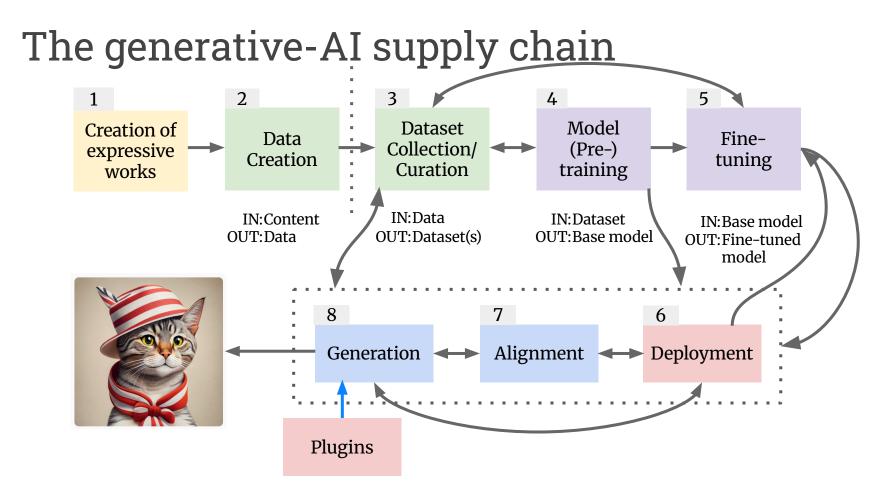


## Questions?

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The generative-AI supply chain Model Dataset Creation of Fine-Data Collection/ (Pre-) expressive tuning Creation Curation works training IN:Data **IN:Content IN:Dataset** IN:Base model **OUT:Data** OUT:Dataset(s) **OUT:Base model OUT:Fine-tuned** model 6 Generation Alignment Deployment



## Systems and terms will change,

"Post-training"

"Reasoning models" (e.g., O3, DeepSeek)

"Agents"

## the framework will continue to be useful

## Questions?

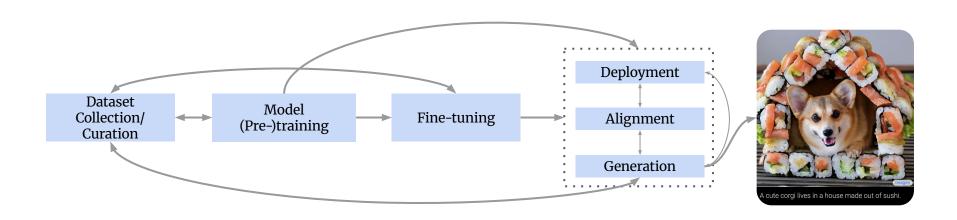
## Privacy:

A case study

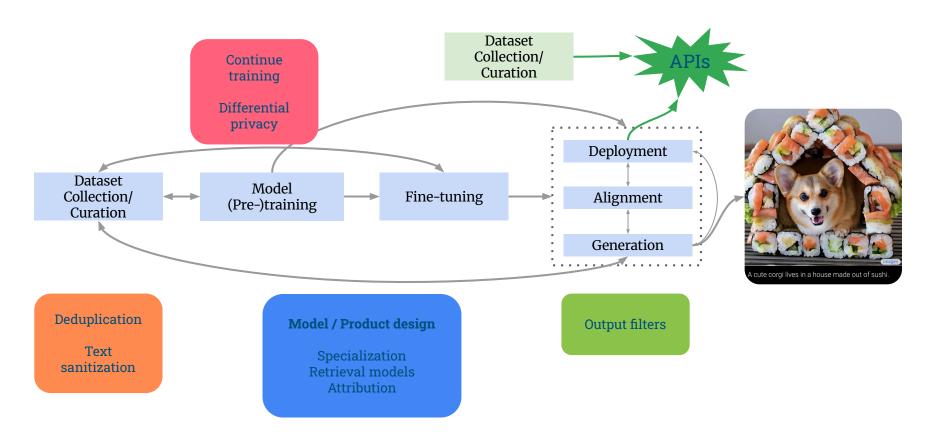
## Privacy:

Generation contains private information

### Mitigations are all across the supply chain



### Mitigations are all across the supply chain



### Lessons

- Different actions can be taken by different actors at different stages of the generative-AI supply chain
- 2. Concerns typically cannot be localized to a single link
- 3. Design choices matter
- 4. Analogies can be misleading

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## Questions?

## **Machine Unlearning**

4. Analogies can be misleading

E.g., Machine-learning models are **not** like databases

## Machine Unlearning Doesn't Do What You Think

4. Analogies can be misleading

E.g., Machine-learning models are **not** like databases

## Language models are leaky





Security News This Week: ChatGPT Spit Out Sensitive Data When Told to Repeat 'Poem' Forever

Plus: A major ransomware crackdown, the arrest of Ukraine's cybersecurity chief, and a hack-for-hire entrepreneur charged with attempted murder.



WHEN YOU TRAIN PREDICTIVE MODELS ON INPUT FROM YOUR USERS, IT CAN LEAK INFORMATION IN UNEXPECTED WAYS.



### Al is emitting secrets #45

Answered by nat dtjm asked this question in Report Bugs

```
dtjm 2 days ago
I tried to get it to tell me secrets and it did:
      package main
                                                                                                             from :=
       func main() {
                                                                                                          "SG. f7d2-"
                                                                                                             from :=
          apiKey :=
                                                                                                             host := "https://ep.senagrid.com"
                                                                                                             request := sendgrid.GetRequest(apiKey, "/v3/mail/send", host)
                                                                                                             request.Method = "POST"
                                                                                                             request.Body = []byte(` {
```

# If a model learned knowledge, capabilities, etc. ...

If a model **learned** knowledge, capabilities, etc. ...

Can we selectively unlearn undesirable information?

#### Machine Unlearning Doesn't Do What You Think: Lessons for Generative AI Policy, Research, and Practice

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#### Machine Unlearning Doesn't Do What You Think: Lessons for Generative AI Policy, Research, and Practice



Law

Policy

STS

ΑI

#### Machine Unlearning Doesn't Do What You Think: Lessons for Generative AI Policy, Research, and Practice



Academics

**Civil Society** 

Industry

## Preview of key points

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Generated outputs may be innocuous or have significant legitimate uses, but could be pressed into service for adversarial or malicious downstream uses

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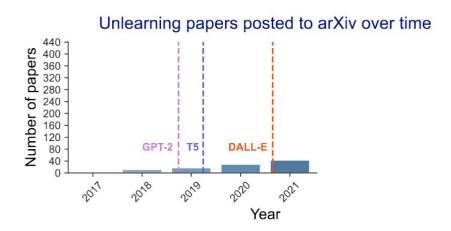
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### Original motivations from law & policy

**2016-2022** GDPR, Article 17 "right to be forgotten" (in **supervised** settings)



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latent information: data that are **not** explicitly presented to the model during training; derived from patterns learned during training

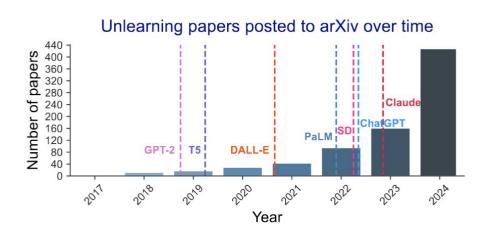
Machine unlearning is a subarea of machine learning that develops methods for the targeted removal\* of the effect of training data from the trained model.

\*Machine-learning models are <u>not</u> like databases

### Evolving motivations from law & policy

**2016-2022** GDPR, Article 17 "right to be forgotten" (in **supervised** settings)

2022- Mitigating unwanted data + capabilities for GenAI



### Evolving motivations from law & policy

Beyond **removal** of the influence of training data on a trained **model's parameters**...

Can unlearning also address possible undesirable **model outputs** when the model is **put to use**?

#### An **expanded**, **loose definition** of machine unlearning

**Machine unlearning** is now a sub-area of machine learning that both develops methods for

- (1) the **targeted removal** of the effect of training data **from the trained model** and
- (2) the targeted suppression of content in a generative-AI model's outputs

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Extending the personal data deletion example...

**Removal** of the influence of an individual's personal data from the model's parameters

+

**Suppression** of model outputs that reflect that individual's personal data at generation time

### Extending the personal data deletion example...

These are very different goals!

**Removal** of the influence of an individual's personal data from the model's parameters

+

**Suppression** of model outputs that reflect that individual's personal data at generation time

### Methods to address targets

Removal

**Suppression** 

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**Suppression** 

Applies to **observed information** 

Data is **removed** from the training dataset *before* training\*

\*(or this is approximated)

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#### **Suppression**

Modify the GenAI **model** (e.g., change the weights)

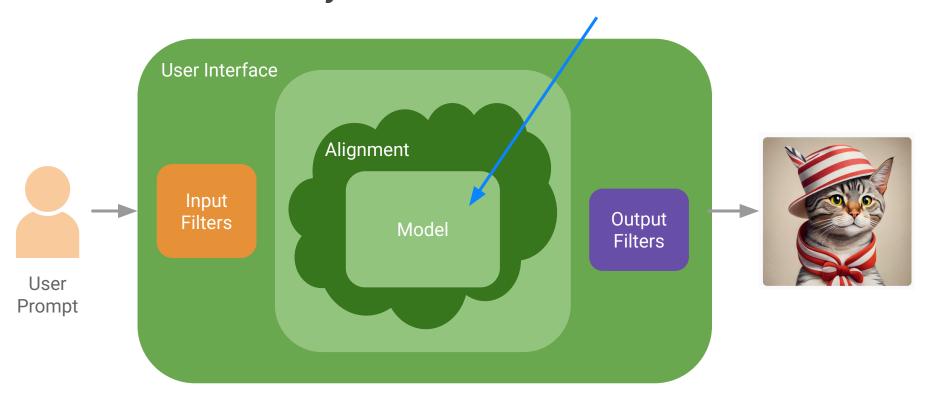
or

Modify the GenAI **system** (e.g., output filters)

<sup>\*(</sup>or this is approximated)

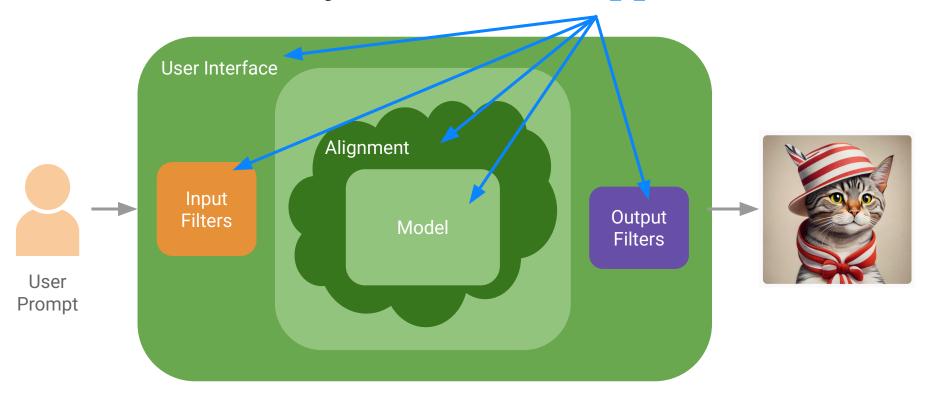
### Generative AI Systems

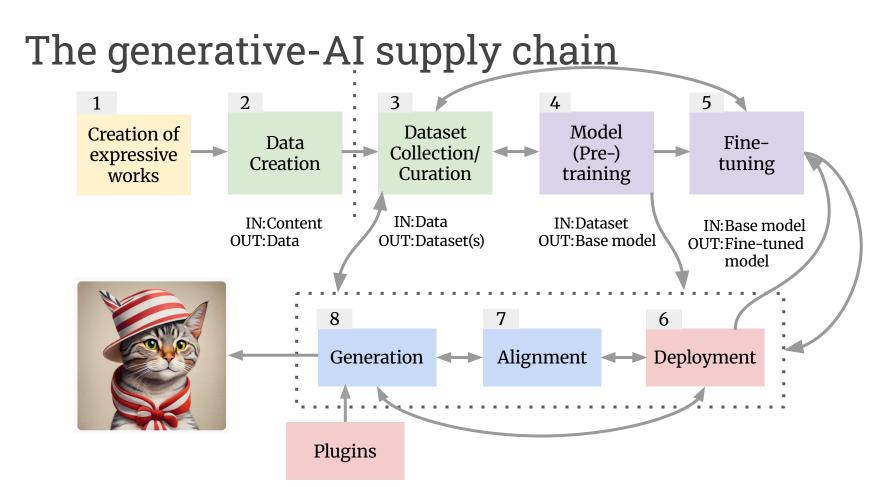
### Removal



### Generative AI Systems

### **Suppression**





#### Mismatches between removal and suppression

**Mismatch 1** Output suppression is not a replacement for removal of observed information.

**Mismatch 2** Removal of observed information does not guarantee meaningful output suppression.

Mismatch 3 Models are not equivalent to their outputs.

**Mismatch 4** Models are not equivalent to how their outputs are put to use.

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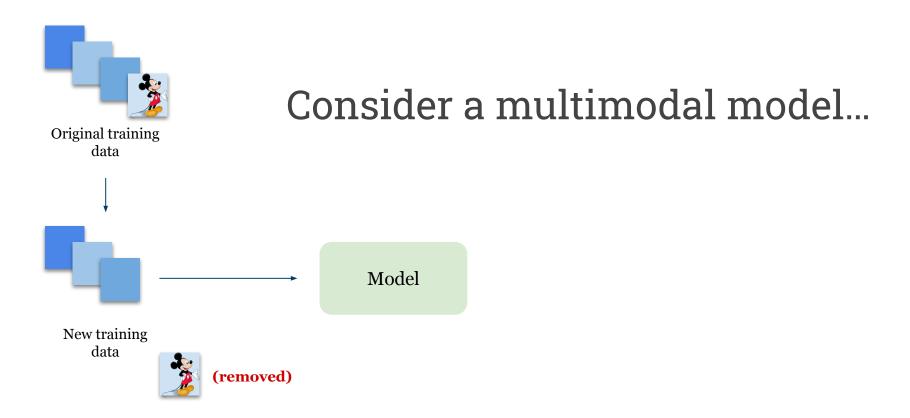
### Mismatches between removal and suppression

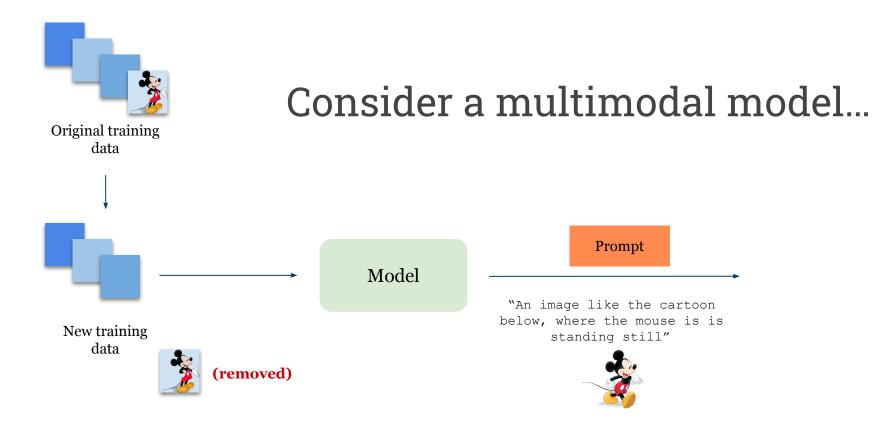
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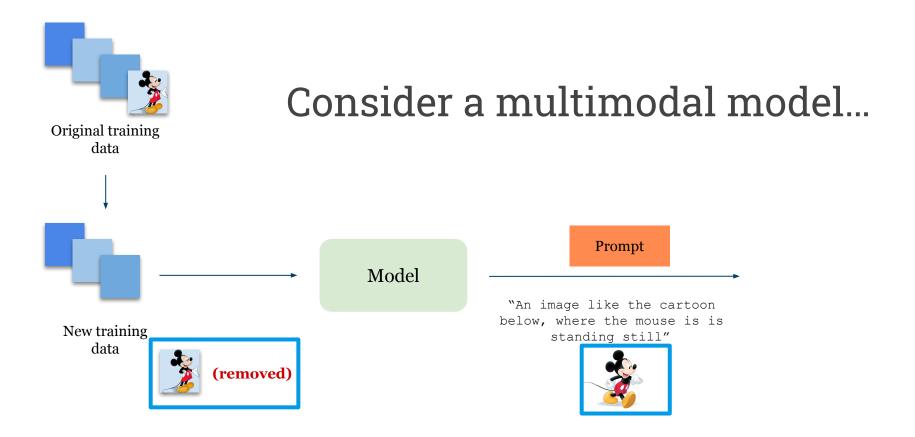
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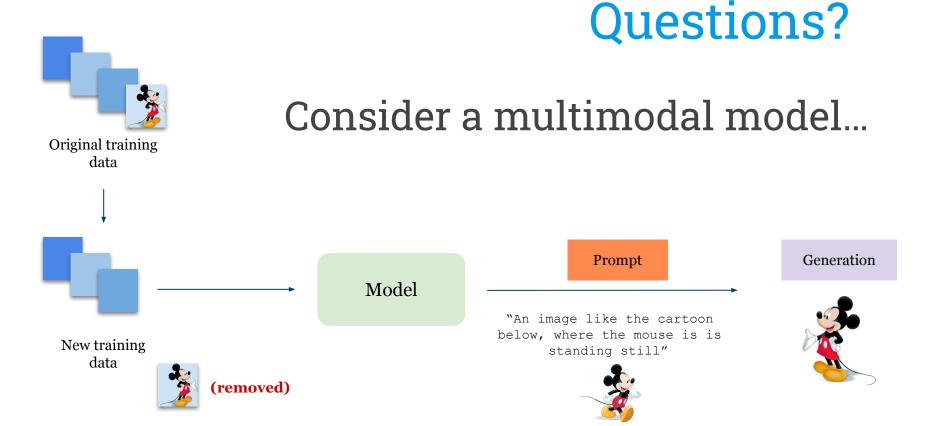
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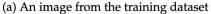
# These mismatches manifest differently in different contexts

### We look at

- U.S. Copyright
- Privacy
- Safety

#### U.S. Copyright







(b) A generation for the prompt Mickey Mouse

Figure 1: CommonCanvas is a research tool and text-to-image model [33], trained only using images with Creative Commons licenses. We can think of this model as a "gold standard" baseline that does not contain in-copyright images of "Mickey Mouse:" the only examples in the training data that reflect the higher-order concept of "Mickey Mouse" are from personal photographs, e.g., (a) (redacted for privacy). Even without in-copyright training examples of "Mickey Mouse," the model can generate outputs that resemble "Mickey Mouse," e.g., (b).

#### Privacy

#### **Data deletion requests**

Consider a deletion request to remove images of a particular data subject from the training data used to produce an image generation model.

#### Privacy

#### **Data deletion requests**

Consider a deletion request to remove images of a particular data subject from the training data used to produce an image generation model.

#### Should the set to remove include...

- images that only feature the data subject?
- family photos where other data subjects are also present?
- photos where the data subject is in the background?

### Safety

#### Unclear boundaries for target removal

Topics like synthetic biology and molecular generation are broad and under-specified.

#### Safety

#### Unclear boundaries for target removal

Topics like synthetic biology and molecular generation are broad and under-specified.

#### Should the set to remove include...

- A specific set of scientific papers?
- Graduate-level chemistry?
- High school chemistry?

#### Removal

#### Necessary?

Yes	No
e.g., CSAM, NCII, other	e.g., personal data that can
strictly forbidden observed	be processed in certain
information	jurisdictions but not others

#### Sufficient?

Maybe	No
judges, policymakers will need to make case- or domain-based decisions about what is reasonable	e.g., synthetic CSAM, NCII deepfakes (producible from latent information + user prompts)

★ suppression necessary, see right side

#### **Suppression**

#### Necessary?

Yes	No
e.g., synthetic CSAM, NCII	e.g., cases where the main
deepfakes, outputs that	issue is consent over use of
resemble in-copyright	personal data for training (for
"Spiderman" or real personal	which possible model
data (producible from latent	outputs might not be
information + user prompts)	relevant)

#### Sufficient?

Maybe	No
judges, policymakers will need to make case- or domain-based decisions about what is reasonable	e.g., unsafe downstream uses of otherwise innocuous or legitimate outputs

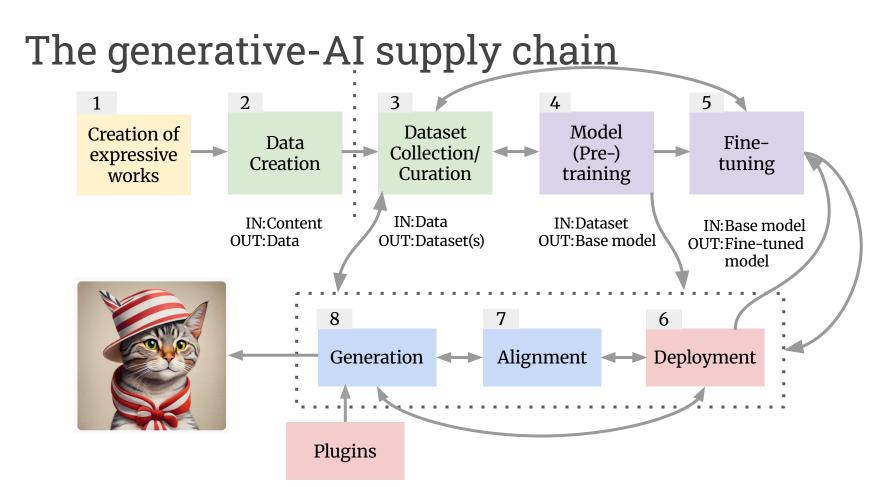
Figure 3: Following from the prior sections, four simple questions help clarify the usefulness of unlearning methods for removal and suppression to address policy aims for Generative AI. We consider if information removal of observed information is necessary and sufficient (left), and similarly if output suppression is necessary and sufficient (right). We provide examples of potential law and policy areas that could exhibit different answers to these questions. There are cases where removal may be necessary, but it is likely that removal is on its own insufficient. To moderate or constrain model outputs, suppression is likely always necessary, but suppression methods will also likely always be imperfect to catch all undesirable outputs.

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- Setting reasonable goals and expectations for unlearning
- There are no general-purpose solutions to constrain generative technologies

## Zooming out

The field moves extremely fast terms change (not quite as) fast

# Zooming out

System vs. model

Many actors & ways to act

Data (observed information) vs. inferred (latent information)

Removal vs. Suppression

### Please ask us questions!

**Katherine Lee\***, **A. Feder Cooper\*** & James Grimmelmann\*. "Talkin' 'Bout AI Generation: Copyright and the Generative-AI Supply Chain." 2023 (Forthcoming, *Journal of the Copyright Society*)

**A. Feder Cooper**\*, ... & **Katherine Lee**. "Machine Unlearning Doesn't Do What You Think: Lessons for Generative AI Policy, Research, and Practice." 2024.

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Milad Nasr\*, Nicholas Carlini\*, Jonathan Hayase, Matthew Jagielski, **A. Feder Cooper**, ... & **Katherine Lee**. "Scalable Extraction from (Production) Language Models." 2023.

Aaron Gokaslan, **A. Feder Cooper** et al. "CommonCanvas: Open Diffusion Models Trained on Creative Commons Images." *CVPR* 2024.

#### Please ask Cooper about memorization and copyright!

The Files are in the Computer: On Copyright, Memorization, and Generative AI

<u>Cornell Legal Studies Research Paper Forthcoming</u> <u>Chicago-Kent Law Review, Forthcoming</u>

75 Pages • Posted: 22 Jul 2024

#### A. Feder Cooper

Microsoft Research; Stanford University; Yale University

#### James Grimmelmann

Cornell Law School; Cornell Tech

Date Written: April 22, 2024

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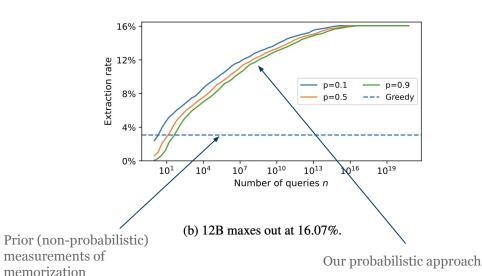
Microsoft Research; Stanford University; Yale University

#### James Grimmelmann

Cornell Law School; Cornell Tech

Date Written: April 22, 2024

Measuring memorization in language models via probabilistic extraction Forthcoming, NAACL 2025



#### Talk outline

- What is generative AI
  - Why is it different from other forms of AI
    - Svstem vs model
      - Model as data structure vs. software
      - Different forms of AT
      - Generative AI has databases in it
    - Modalities
    - Transformer, diffusion
    - Scale
- Who are the players and what is the game
- A note about the field
  - o Things are changing rapidly, terms change
- Good stuff and bad stuff (we need to talk about the stakes)
  - Cool capabilities
  - But...not such great stuff too (hallucination; emitting secrets)
- Transition
  - o Goals vs. objectives
    - Aside on metaphors
      - Note about databases
      - Data vs. patterns (observed information, vs. latent information)
- Unlearning →