## Al for Scientists: Perception, Reasoning, & Discovery

Jennifer J. Sun

6/5/2025

# A Bernese mountain dog giving a talk at the AI for animal science conference at ETH Zurich.



# A Bernese mountain dog giving a talk at the AI for animal science conference at ETH Zurich.

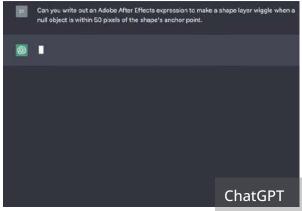




# A Bernese mountain dog giving a talk at the AI for animal science conference at ETH Zurich.



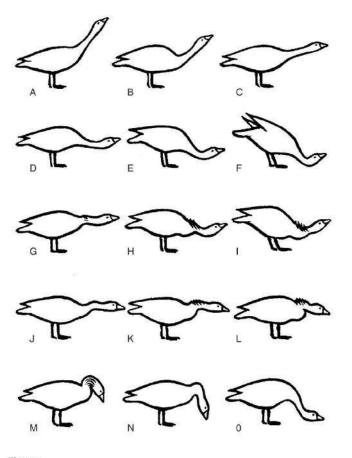




Insight

Raw Data

#### Insight



Konrad Lorenz, On Aggression ~1963, p.97

Figure 4

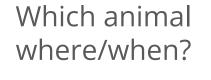


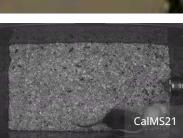




Cornell Dairy

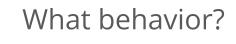






How many animals?







Are they healthy?

How does X affect Y?

Why does X affect Y?

Raw Data

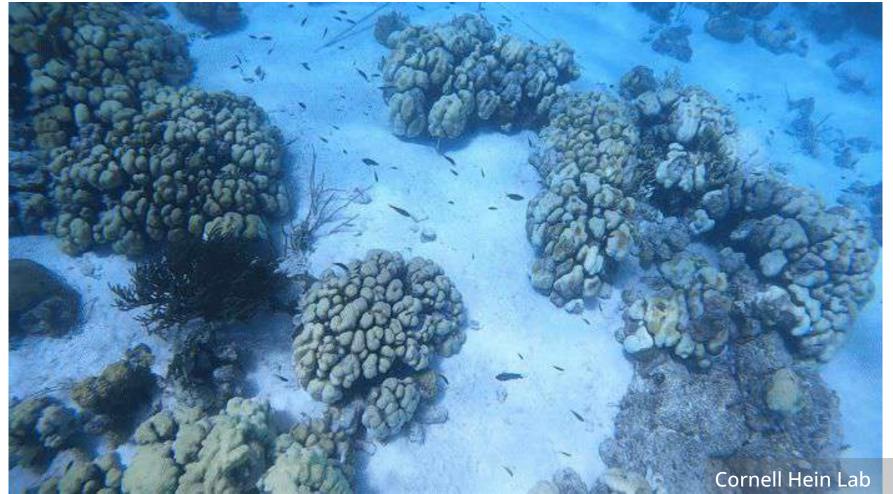
Insight

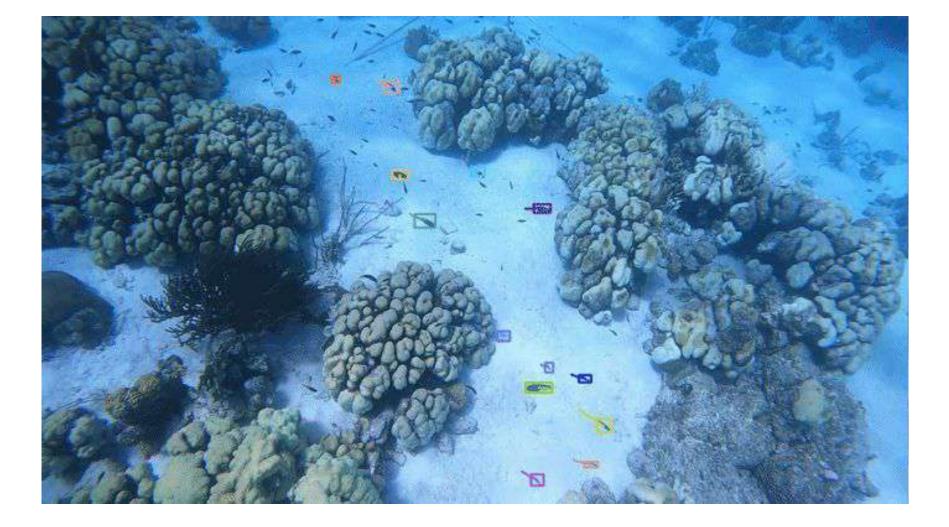
How to best use Al to extract

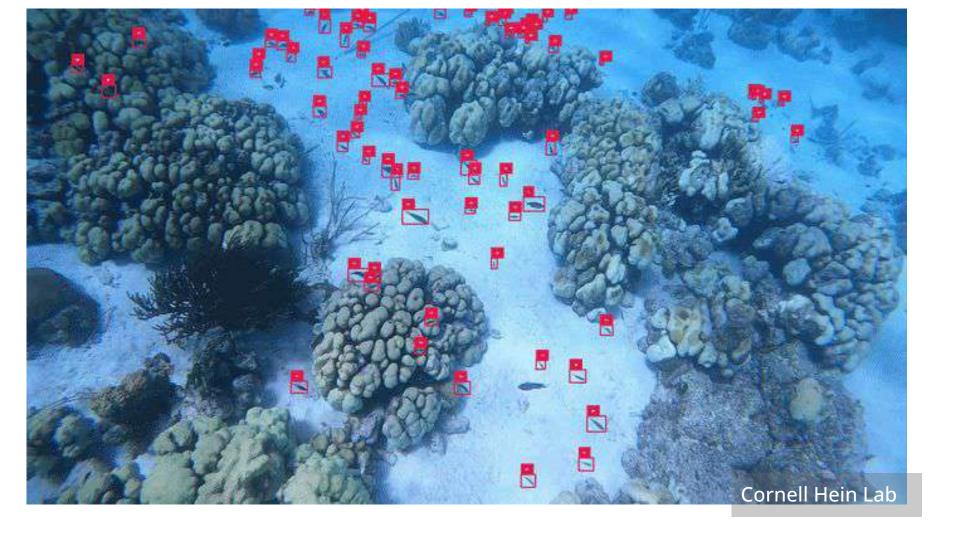
insight from raw data?

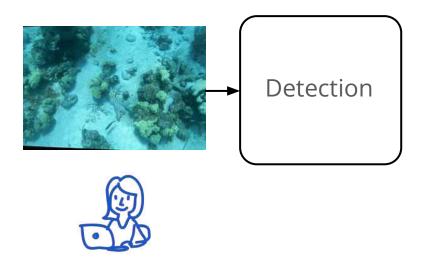


Can Al automatically track these fish?



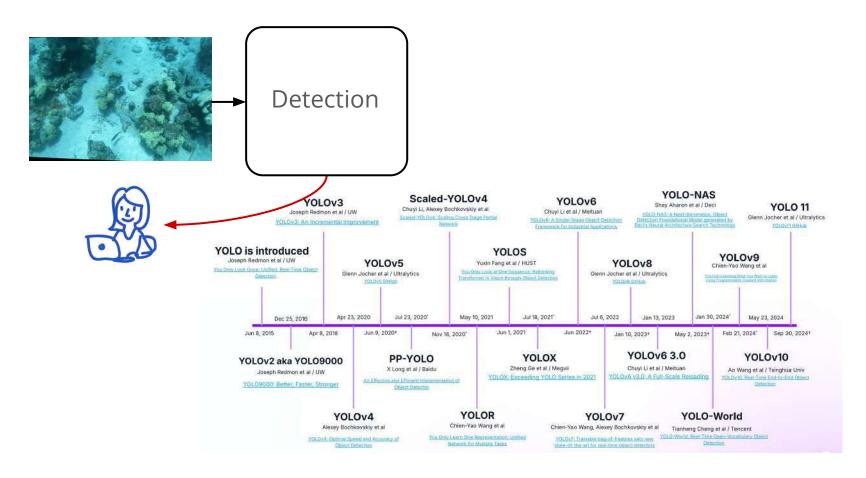




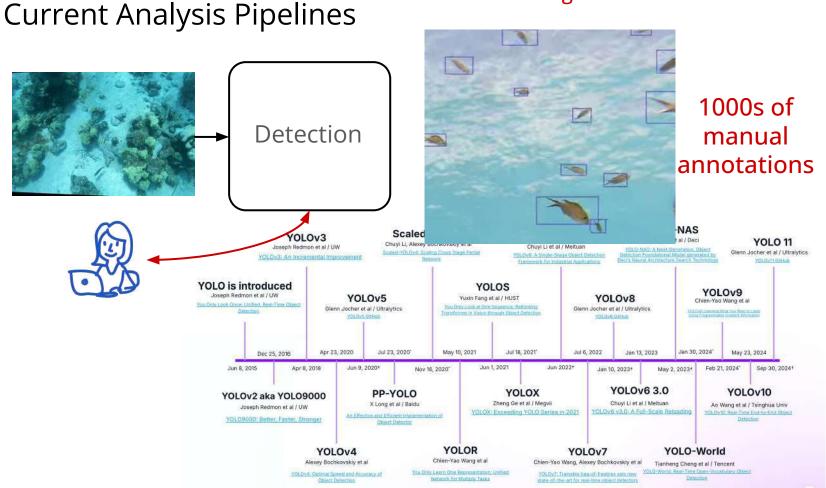


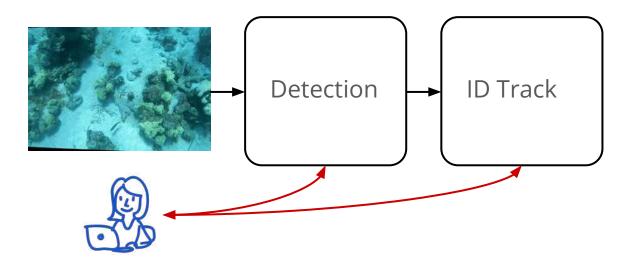


Abby Grassick

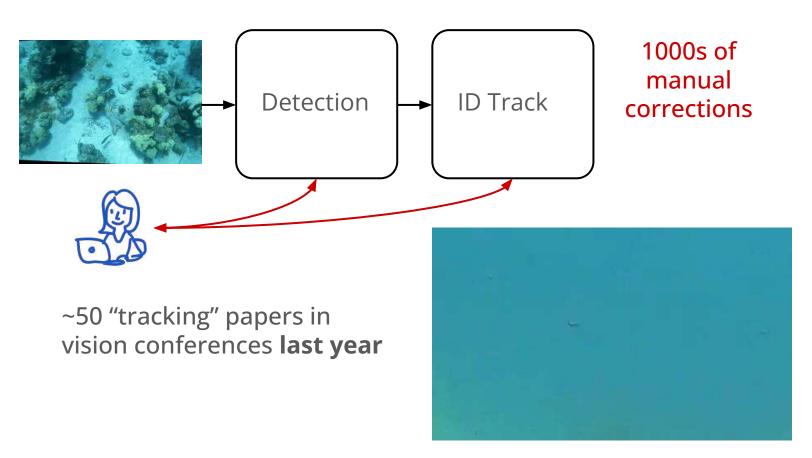


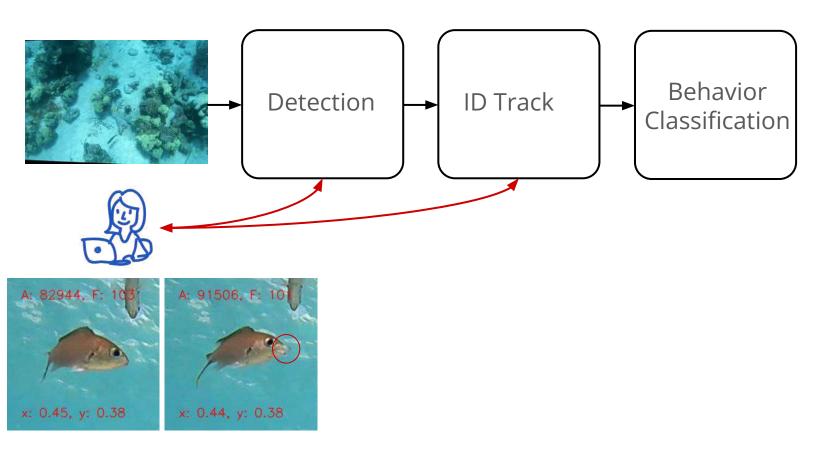
#### Challenge 1: Annotation bottleneck



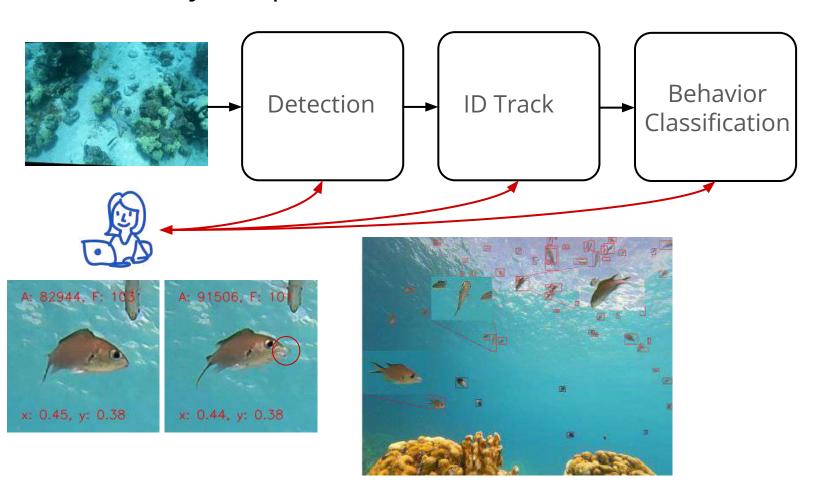


~50 "tracking" papers in vision conferences **last year** 

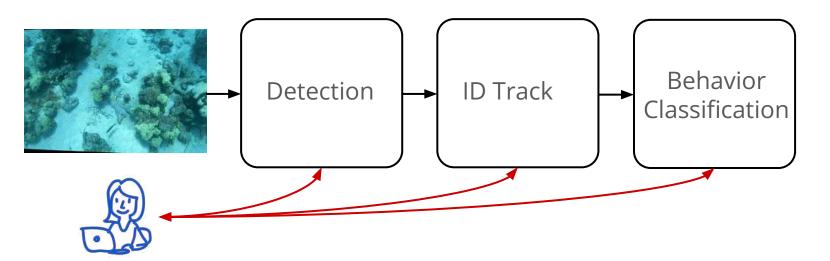




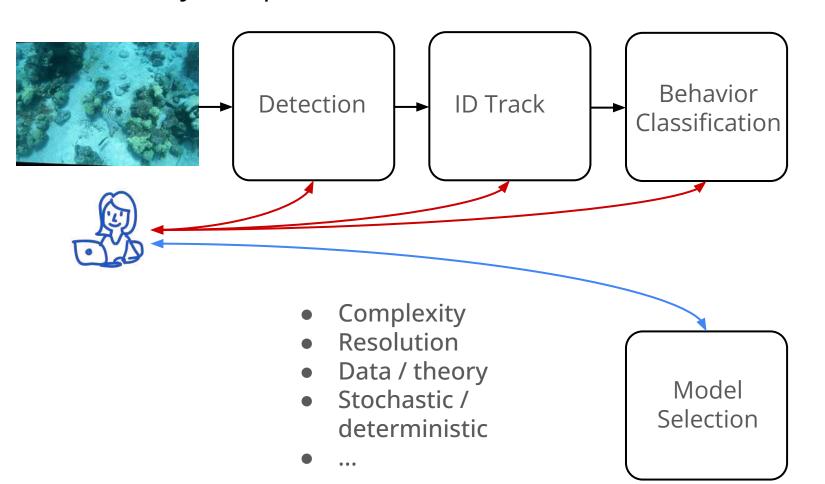
#### Challenge 1: Annotation bottleneck Challenge 2: Vast model space w/ feedback



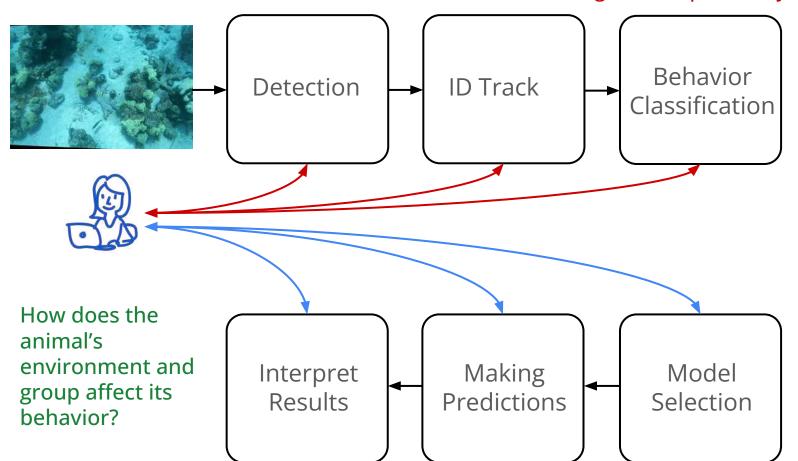
#### Challenge 1: Annotation bottleneck Challenge 2: Vast model space w/ feedback



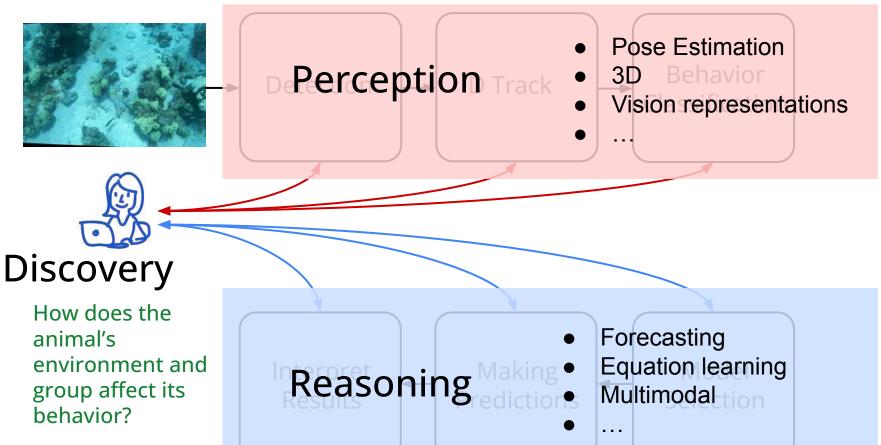
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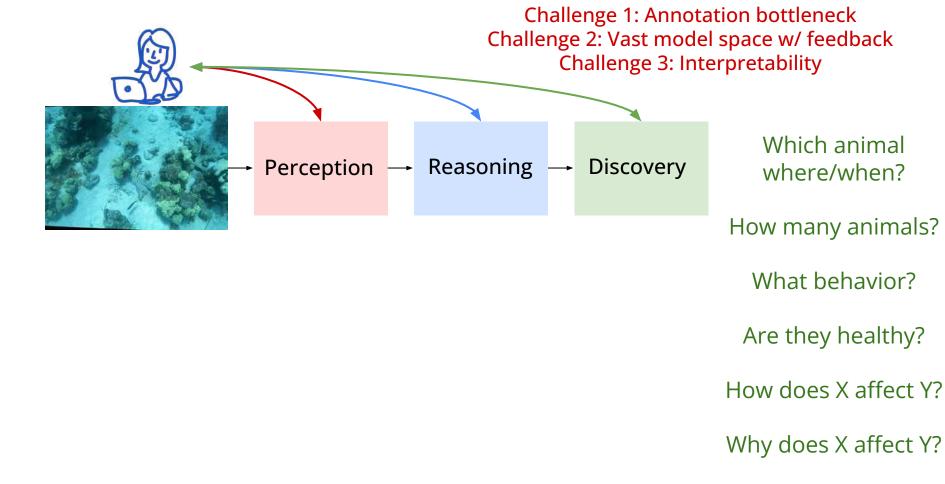


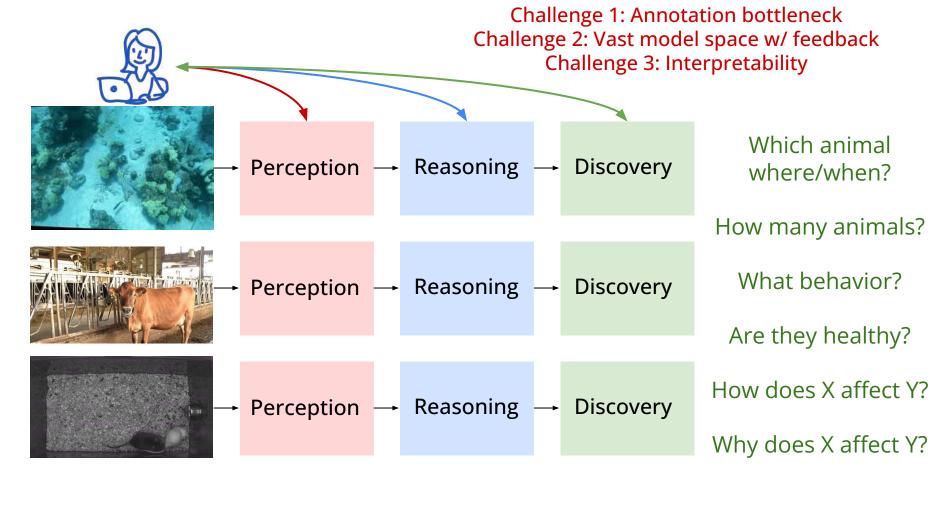
Challenge 1: Annotation bottleneck Challenge 2: Vast model space w/ feedback Challenge 3: Interpretability



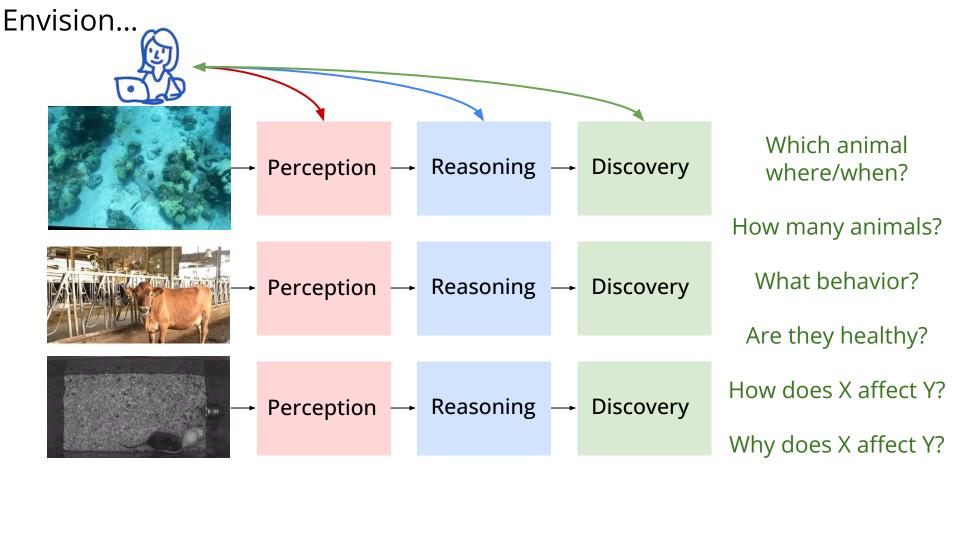
Challenge 1: Annotation bottleneck Challenge 2: Vast model space w/ feedback Challenge 3: Interpretability

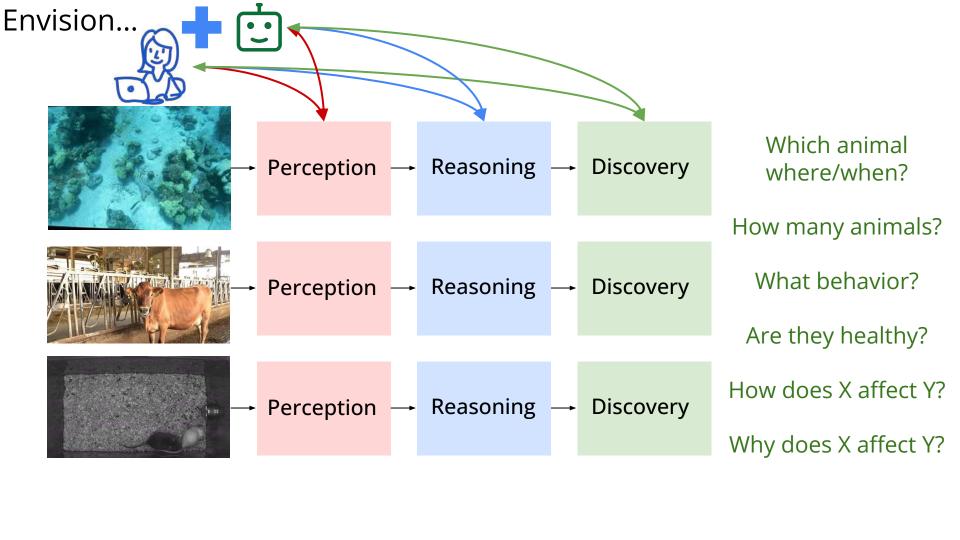


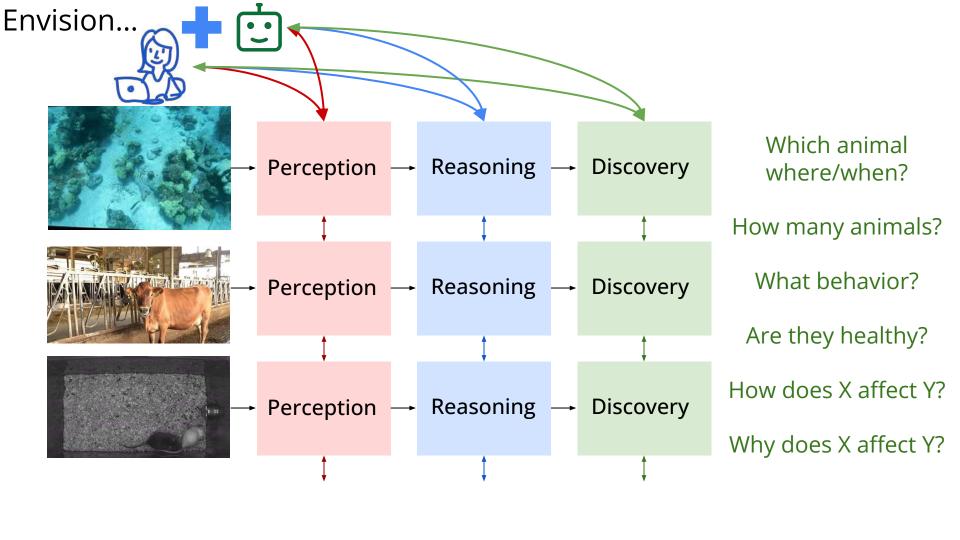




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## Our Approach









Efficient & impactful collaborations between scientists & AI systems

Which animal where/when?

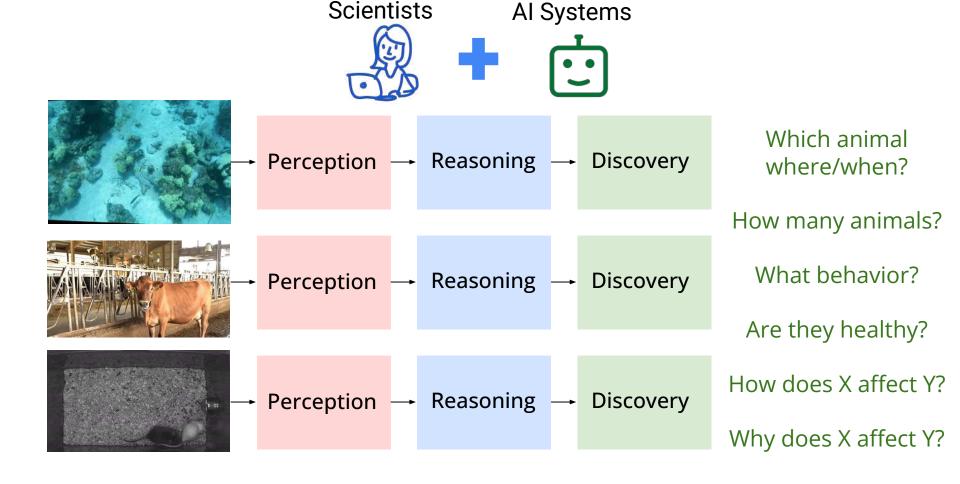
How many animals?

What behavior?

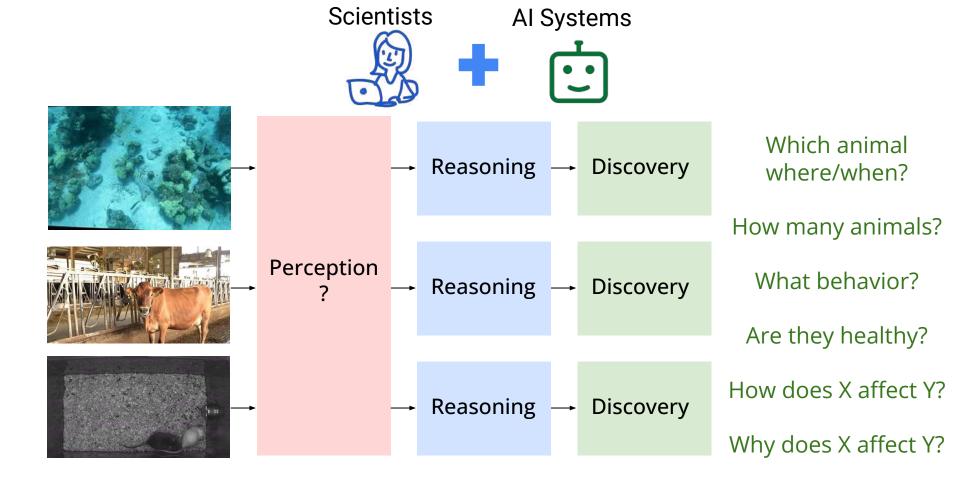
Are they healthy?

How does X affect Y?

Why does X affect Y?



. .

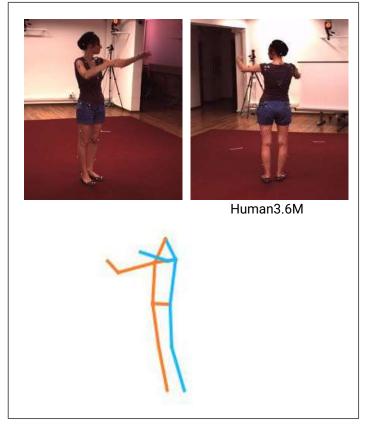


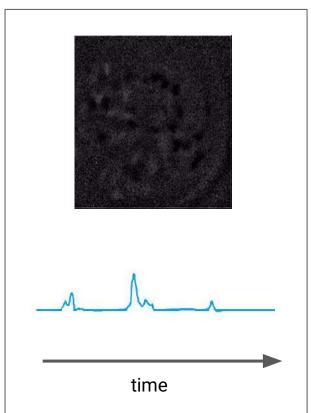
. .

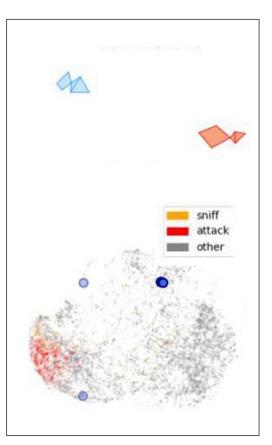
## Perception

 Why is it important to extract symbolically interpretable representations?

## Data has meaningful structure



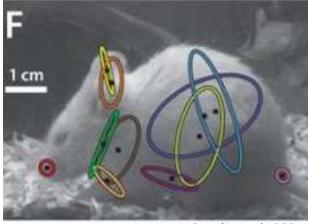




## Challenges of extracting structure

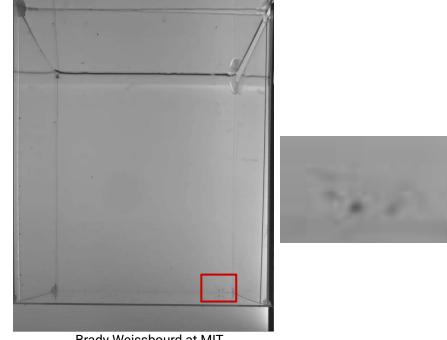


**Annotation Cost** 



Segalin et al., 2021

**Ambiguity & Variability** 



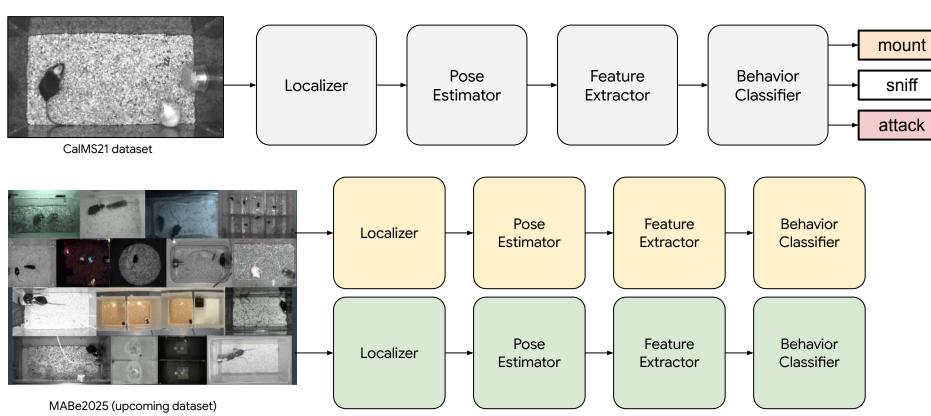
Brady Weissbourd at MIT

Low SNR

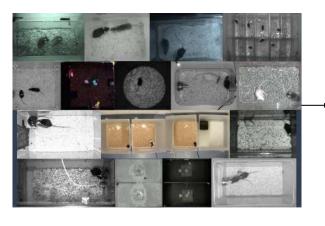
## Perception

- Why is it important to extract symbolically interpretable representations?
- Can we have a general-purpose foundation model for learning representations?

## Task-Specific Approach

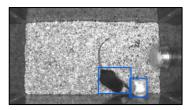


### Foundation Model Approach



Foundation Model System





Localization

<sniff>

<walk>

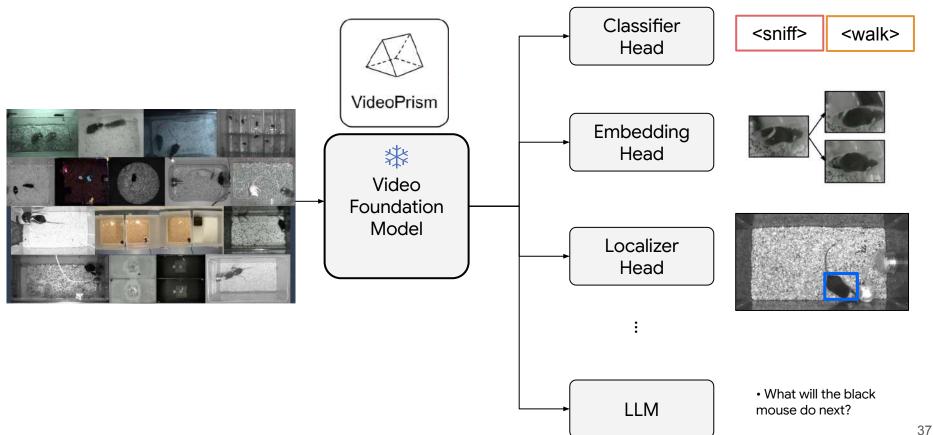
Classification

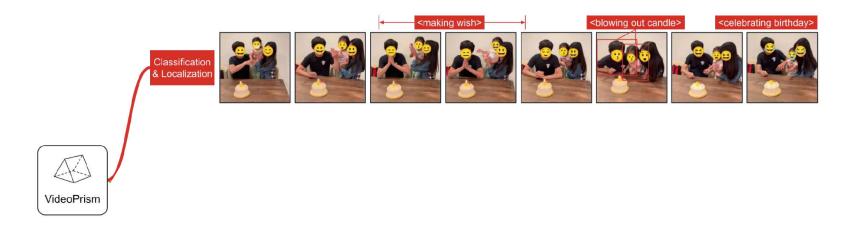
- What is the black mouse's sensory environment?
- What will the black mouse do next?

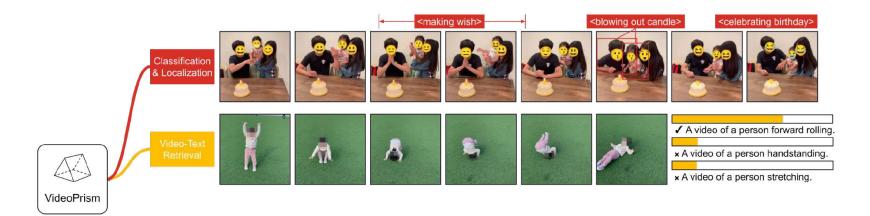
....

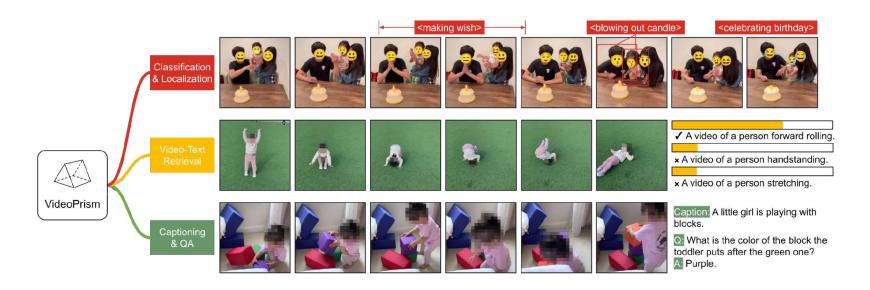
Scientific Video Analysis

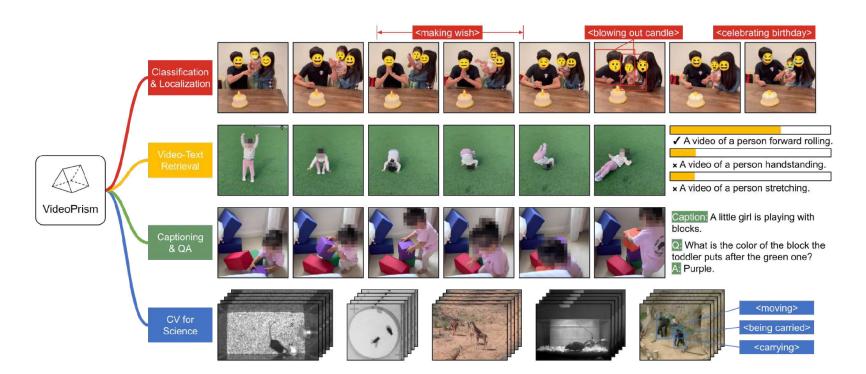
# Foundation Model Approach

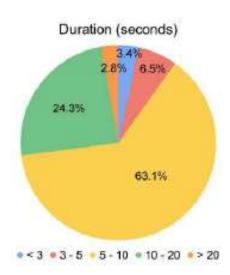


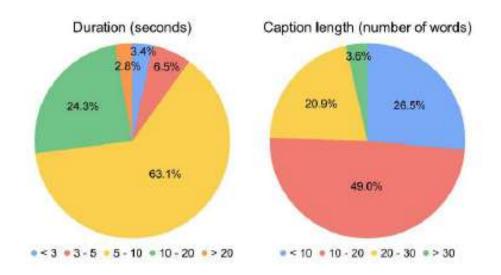


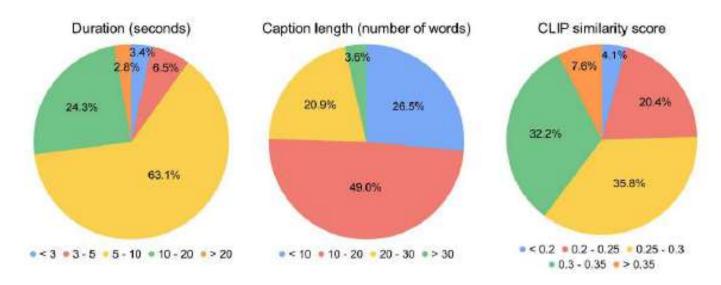






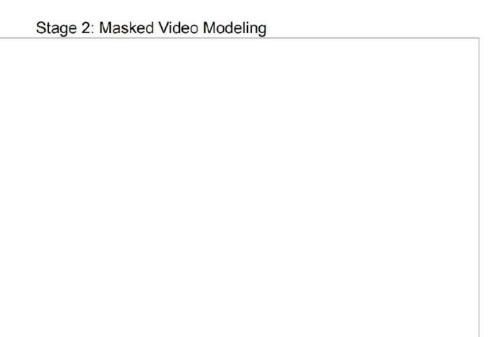




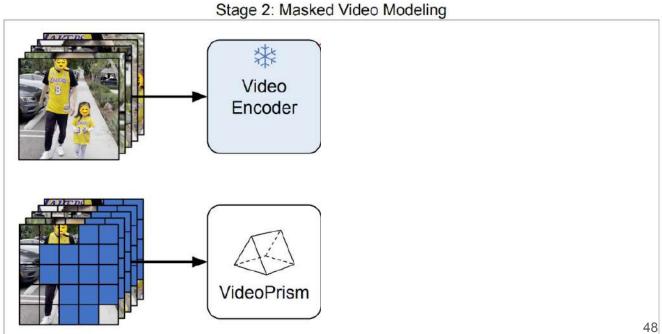


3

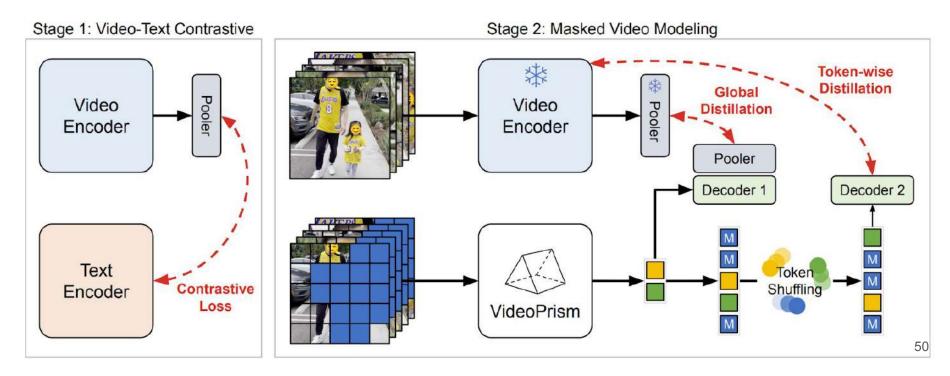
Stage 1: Video-Text Contrastive Video Encoder Text Contrastive Encoder Loss



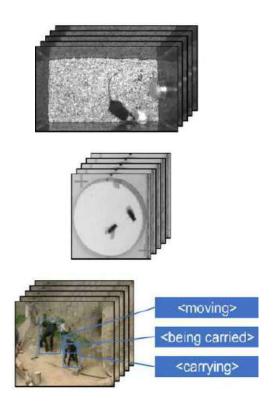
Stage 1: Video-Text Contrastive Video Encoder Text Contrastive Encoder Loss

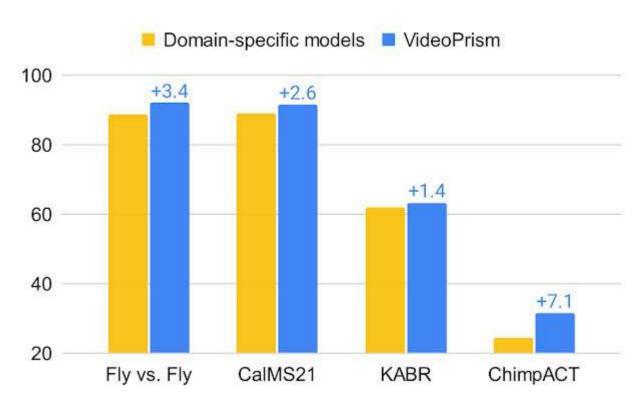


Stage 1: Video-Text Contrastive Stage 2: Masked Video Modeling Token-wise Distillation Video Video Encoder Encoder Decoder 2 Text Token Contrastive Shuffling Encoder Loss VideoPrism



# VideoPrism for science









Gundavarapu























Jennifer Sun







Yue Zhao

Rachel Hornung

Florian Schroff

Ming-Hsuan David Ross Yang















Huisheng Wang

Hartwig Adam

Mikhail Sirotenko

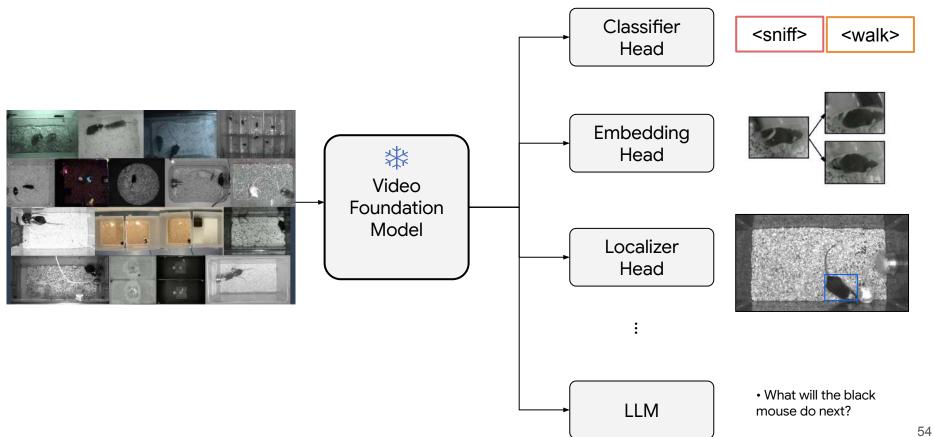
Ting Liu

**Boqing Gong** David Hendon

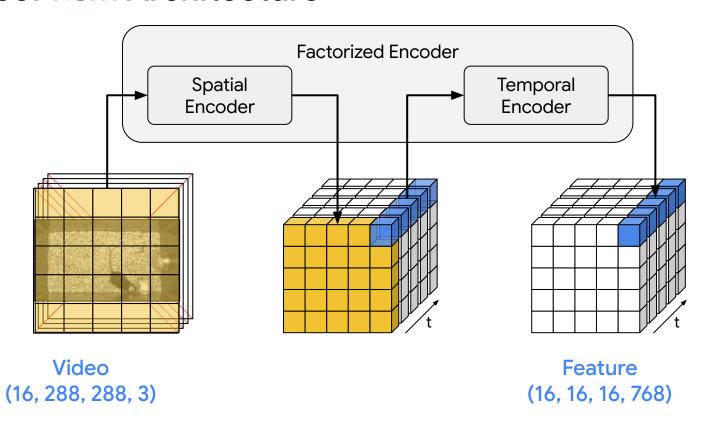
# Perception

- Why is it important to extract symbolically interpretable representations?
- Can we have a general-purpose foundation model for learning representations?
- Can they extract symbols from domain-specific data?

# Foundation Model Approach

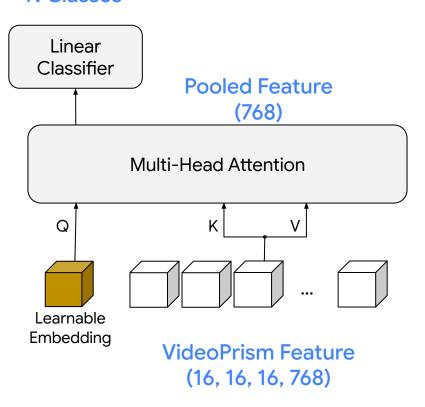


# VideoPrism Architecture

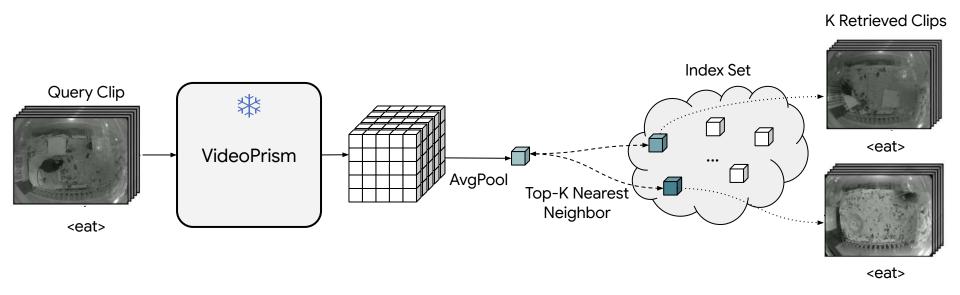


# Classification

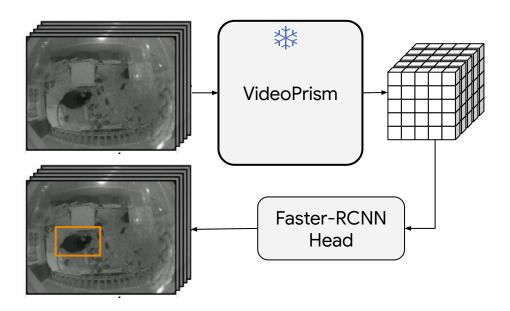
#### **N Classes**



# Retrieval



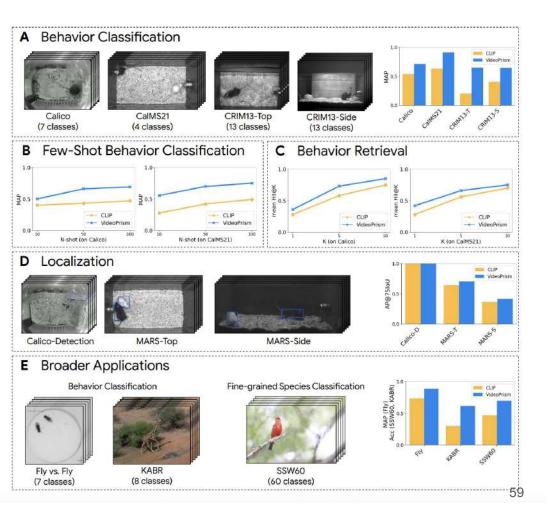
# Localization

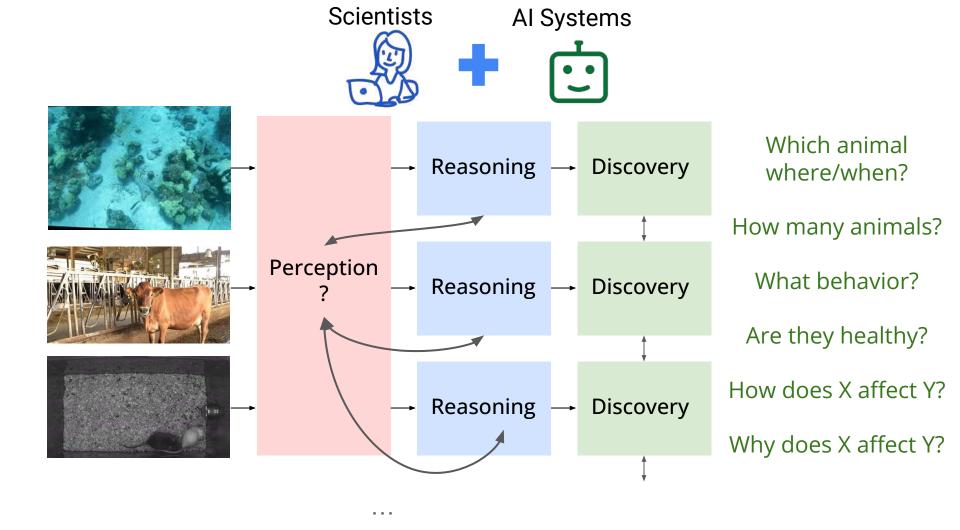


#### Video Foundation Models for Animal Behavior Analysis

Jennifer J. Sun\*, Hao Zhou, Long Zhao, Liangzhe Yuan, Bryan Seybold, David Hendon, Florian Schroff, David A. Ross Hartwig Adam, Bo Hu<sup>†</sup>, Ting Liu<sup>†\*</sup>

<sup>1</sup>Google.



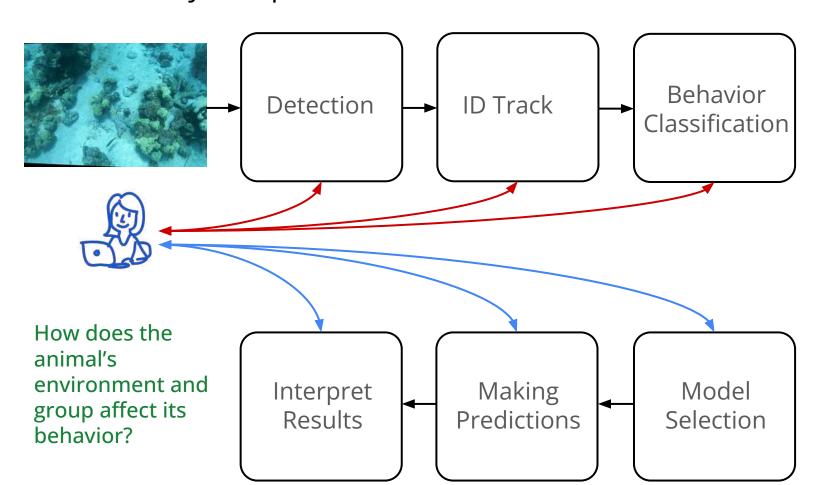


# **Perception** & Reasoning

Why is it so hard to build effective scientific workflows?

# **Current Analysis Pipelines**

#### Vast model space w/ feedback









YOLOv9 DETR

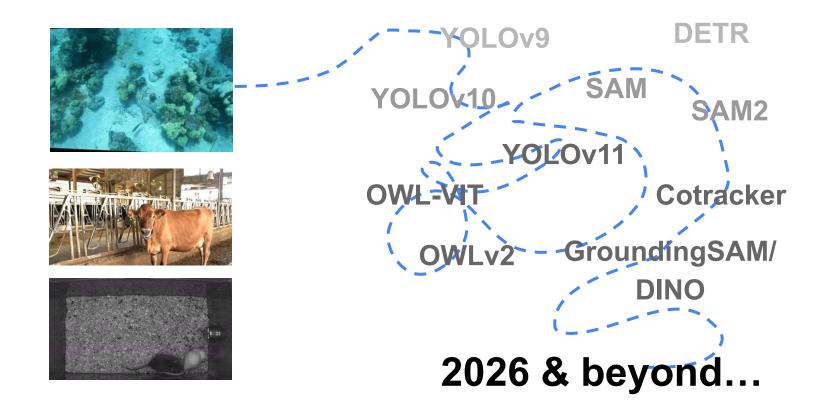
YOLOv10 SAM SAM2

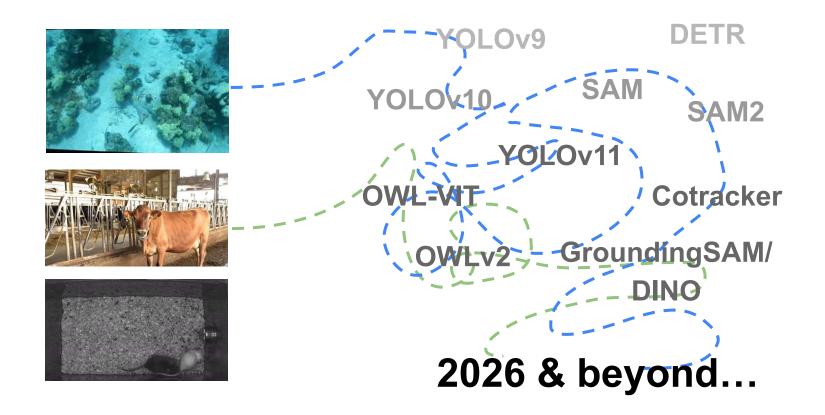
YOLOv11

OWL-VIT Cotracker

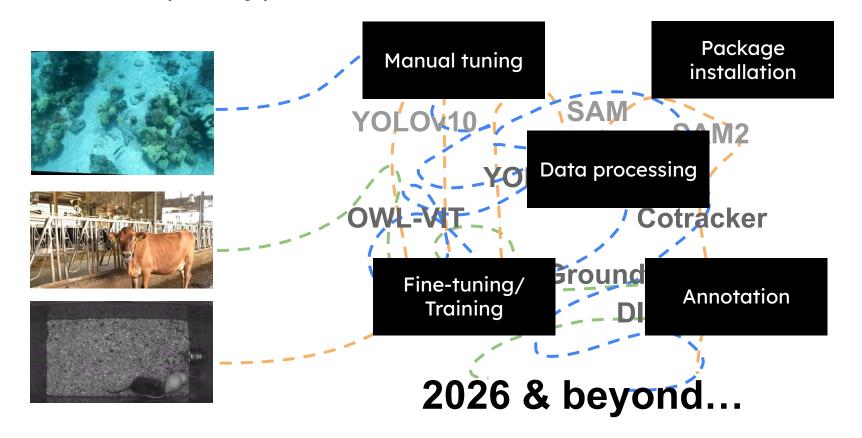
OWLv2 GroundingSAM/

2026 & beyond...





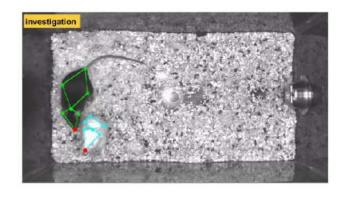




# **Perception** & Reasoning

- Why is it so hard to build effective scientific workflows?
- Instead of manual effort, can we have an AI agent discover an optimal workflow for us?

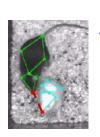
# Program Synthesis



IF (distance between noses) < A AND
 (facing angle) < B</pre>

THEN investigation | F (acceleration of mouse 1) > C

ELSE investigation | F (distance from nose 1 to centroid 2) < D





Features defined by experts (or language models)

# Superoptimization in Program Synthesis

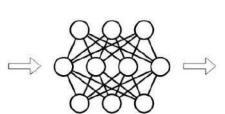
Find "better" programs (e.g. better = faster)

#### Human code

#### Synthesized code

```
#include <iostream>
using namespace std;

int main() {
   int n;
   cin >> n;
   int sum = 0;
   for (int i = 1; i <= n; i++) {
      sum += i;
   }
   cout << sum << endl;
   return 0;
}</pre>
```



```
#include <iostream>
using namespace std;
int main() {
   int n;
   cin >> n;
   cout << n*(n+1)/2 << endl;
   return 0;
}</pre>
```

# Can we superoptimize scientific analysis workflows?

Find "better" programs

(e.g. better = more accurate for analysis)

Human code

Synthesized of

Synthesized code

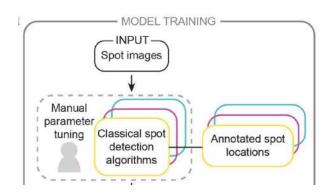
# Can we superoptimize scientific analysis workflows?

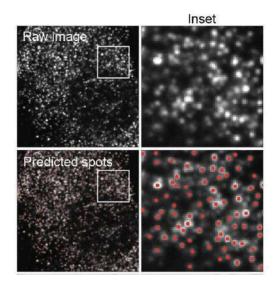
# Find "better" programs (e.g. better = more accurate for analysis)

Accurate single-molecule spot detection for image-based spatial

transcriptomics with weakly supervised deep learning

Emily Laubscher<sup>1</sup>, Xuefei (Julie) Wang<sup>2</sup>, Nitzan Razin<sup>2</sup>, Tom Dougherty<sup>2</sup>, Rosalind J. Xu<sup>3,4,5</sup>, Lincoln Ombelets<sup>1</sup>, Edward Pao<sup>2</sup>, William Graf<sup>2</sup>, Jeffrey R. Moffitt<sup>3,4,6</sup>, Yisong Yue<sup>7</sup>, and David Van Valen<sup>2</sup>





# Can we superoptimize scientific analysis workflows?

# Find "better" programs (e.g. better = more accurate for analysis)

#### Human code

```
def min max normalize clipping (image):
    image_processed = []
    for img in images.raw:
        img = np.clip(img,
    a_min=np.percentile(img, 0.01),
    a_max=np.percentile(img, 99.9))
        min_val = np.min(img)
        max_val = np.max(img)
        normal_image = (img - min_val) /
    (max val - min val)
        image processed.append(normal_image)
    return np.array(image_processed)
```

# ig

Expert function F1 Score: 0.841 Time: Weeks/Months

#### Synthesized code

```
def blurred laplacian of gaussian (images):
  processed images list = []
   for img array in images:
       img = np.copy(img array)
       img float32 = cv.normalize(img, None, 0, 1,
cv.NORM MINMAX).astype(np.float32)
       bilateral = cv.bilateralFilter(img float32, d=5,
sigmaColor=0.09, sigmaSpace=9)
       gauss = cv.GaussianBlur(bilateral, (3,3), 0)
       lap = cv.Laplacian(gauss, cv.CV 32F, ksize=3)
       abs lap = np.abs(lap)
       lap norm = cv.normalize(abs lap, None, 0, 1,
cv.NORM MINMAX).astype(np.float32)
       if img array.ndim == 3 and img array.shape[2] == 1:
           lap norm = lap norm[:, :, np.newaxis]
      processed images list.append(lap norm)
  return np.array(processed images list, dtype=np.float32)
```



Agent function F1 Score: 0.902 Time: 10 hours

# Can we superoptimize scientific analysis workflows?

Find "better" programs
(e.g. better = more accurate for analysis)

#### Human code

```
def min max normalize clipping (image):
    image_processed = []
    for img in images.raw:
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    a_max=np.percentile(img, 99.9))
        min_val = np.min(img)
        max_val = np.max(img)
        normal_image = (img - min_val) /
    (max val - min val)
        image processed.append(normal_image)
    return np.array(image_processed)
```



Expert function F1 Score: 0.841 Time: Weeks/Months Synthesized code





Agent function F1 Score: 0.902 Time: 10 hours

# Agentic Superoptimization of Scientific Analysis Workflows







Julie Wang

Jonathan Chen

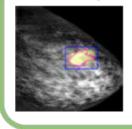
Yisong Yue

Scientific Analysis Workflow



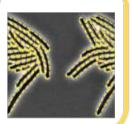
Experiment Design Pilot Data Collection Exploratory Analysis Large-Scale Data Collection Production-Level Analysis

**Medical Segmentation** 

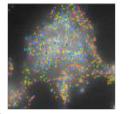


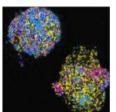


Cell Segmentation

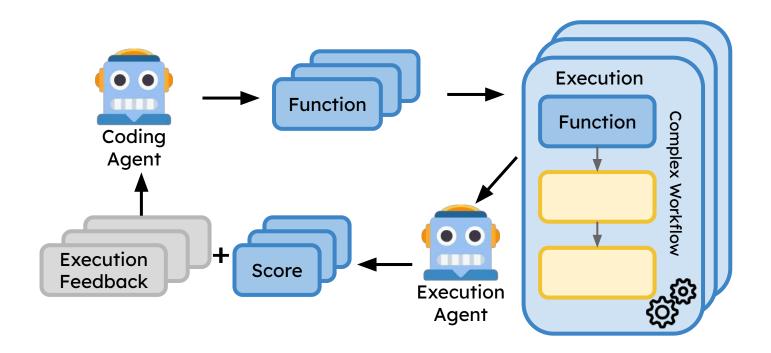


Single-molecule detection

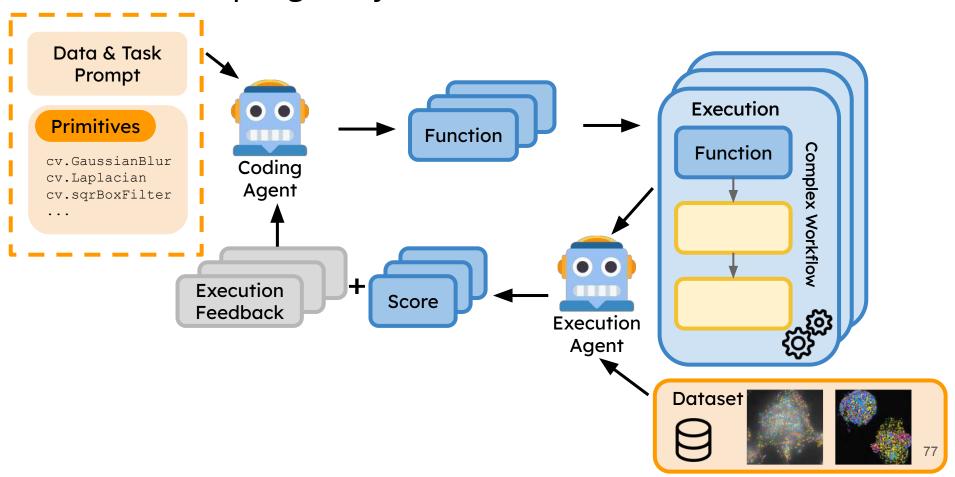




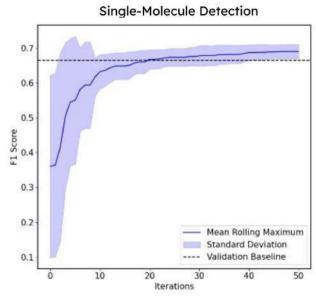
## Proof-of-concept Agent System

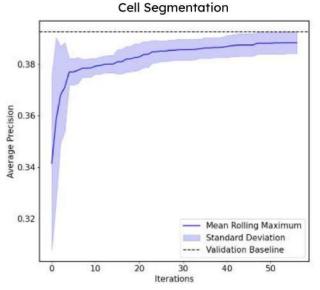


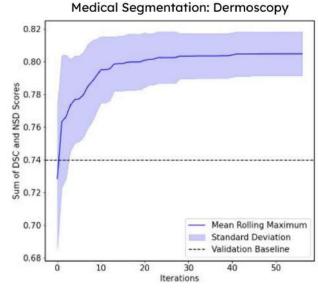
## Proof-of-concept Agent System



# Agentic Superoptimization Results







#### DeepCell Spots



#### Cellpose

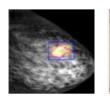






#### MedSAM

This is the official repository for MedSAM: Segment Anything in Medical Images.



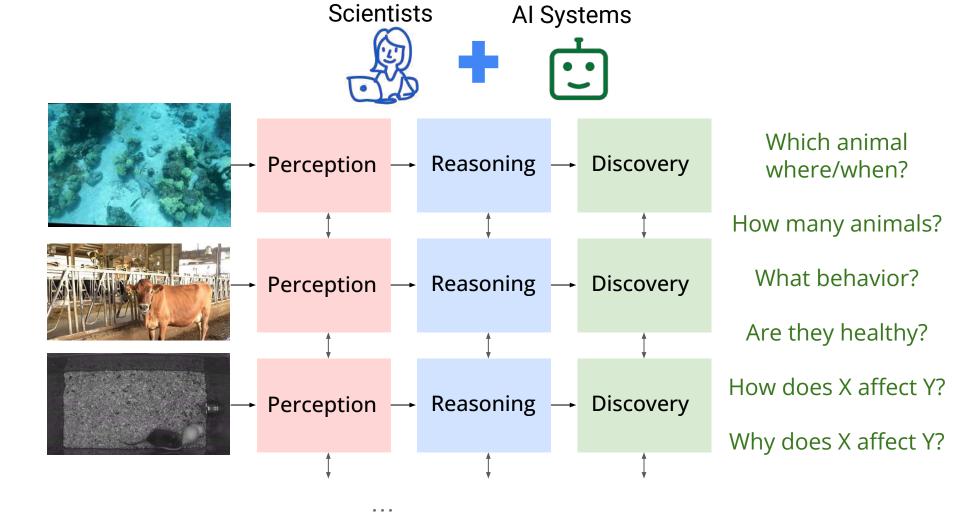




# **Perception** & Reasoning

- Why is it so hard to build effective scientific workflows?
- Instead of manual effort, can we have an AI agent discover an optimal workflow for us?
- Can we accelerate the discovery process?

Discovery

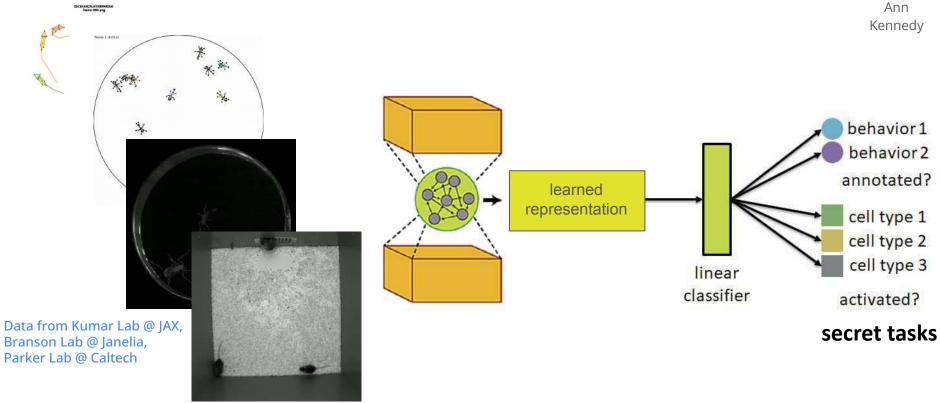


## Call to Action

Representative datasets & benchmarks

# Benchmarking Animal Behavior (in the lab)



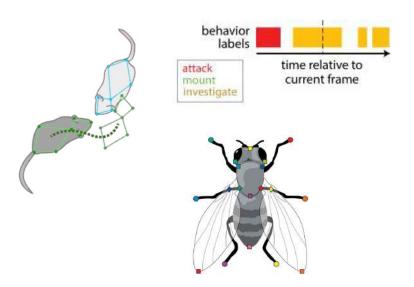


### Call to Action

- Representative datasets & benchmarks
- Quantifying discovery

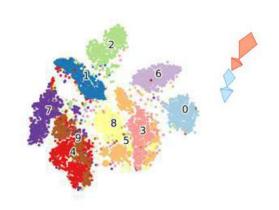
# **Accuracy Problem**

Given a way to measure success, I want to get the number as high as possible



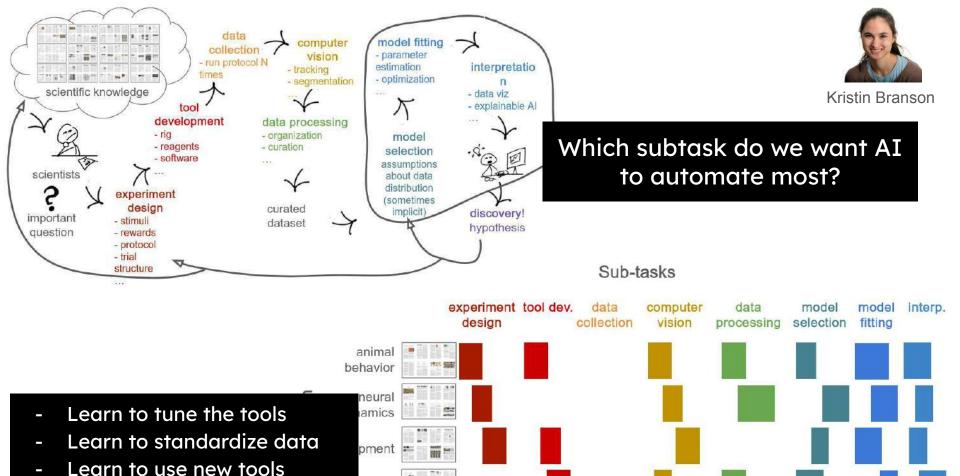
# **Discovery Problem**

I want the model to lead to new & true insights (typically hard to measure)



### Call to Action

- Representative datasets & benchmarks
- Quantifying discovery
- Collaborations across fields



biology

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