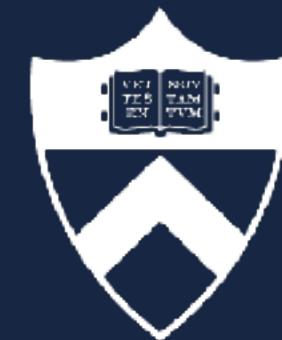
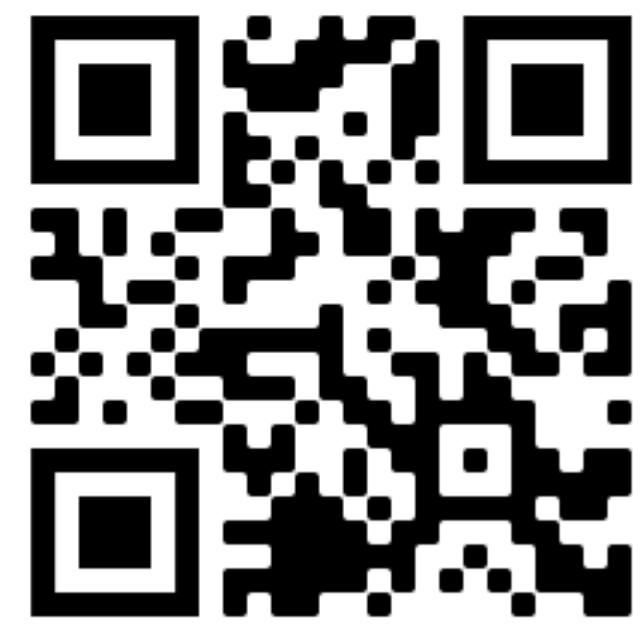


Directions in Interpretability

Ruth Fong

CVPR 2022, Human-Centered AI Tutorial

June 20, 2022



PRINCETON
UNIVERSITY

What is interpretability?

Research focused on explaining **complex AI systems** in a **human-interpretable** way.

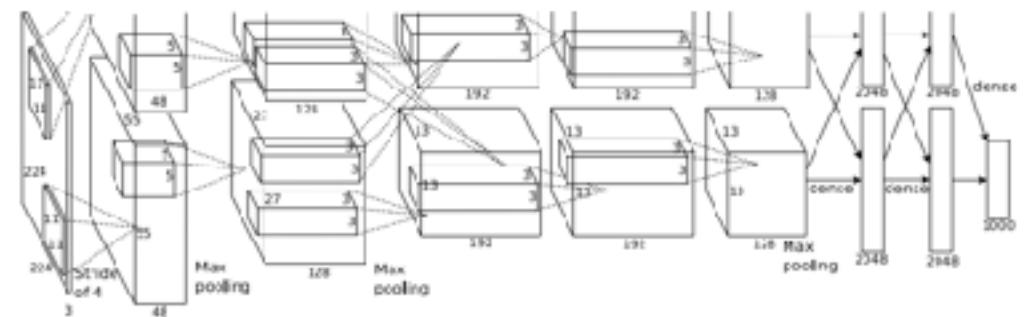
Why interpretability?

-  Science
-  Trust
-  Learning

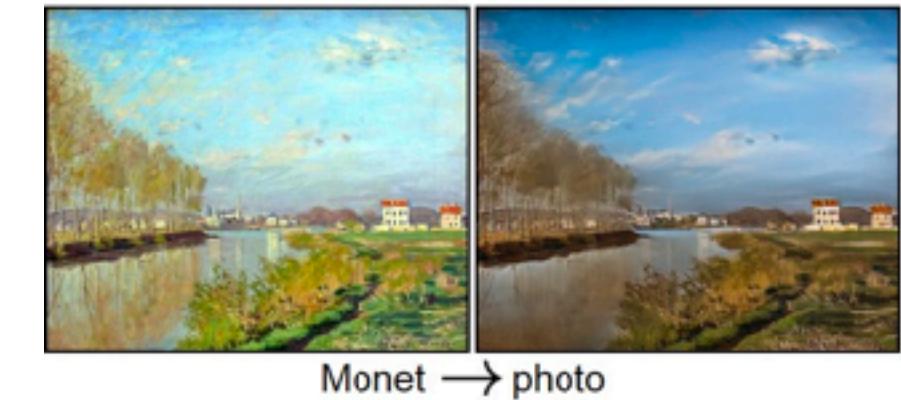
An incomplete retrospective: the first decade of deep learning



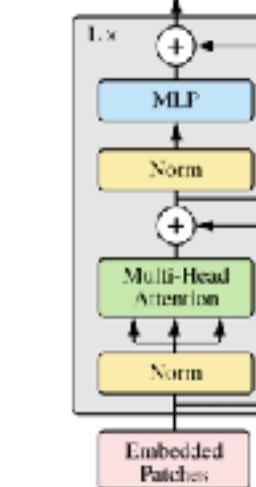
2012



CNNs (2012-2016)
AlexNet, VGG16,
GoogLeNet, ResNet50



GANs (2014-2018)
GAN, ProGAN, CycleGAN

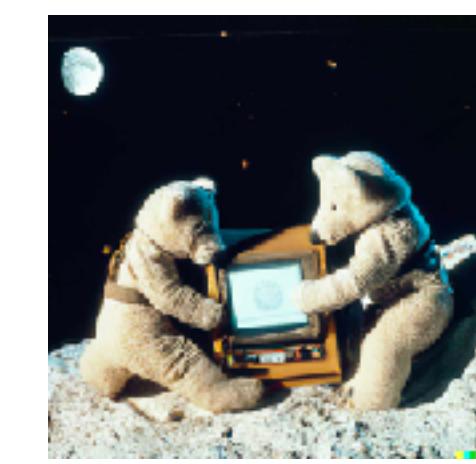


Transformers (2017-now)
Transformer, BERT, ViT

2022



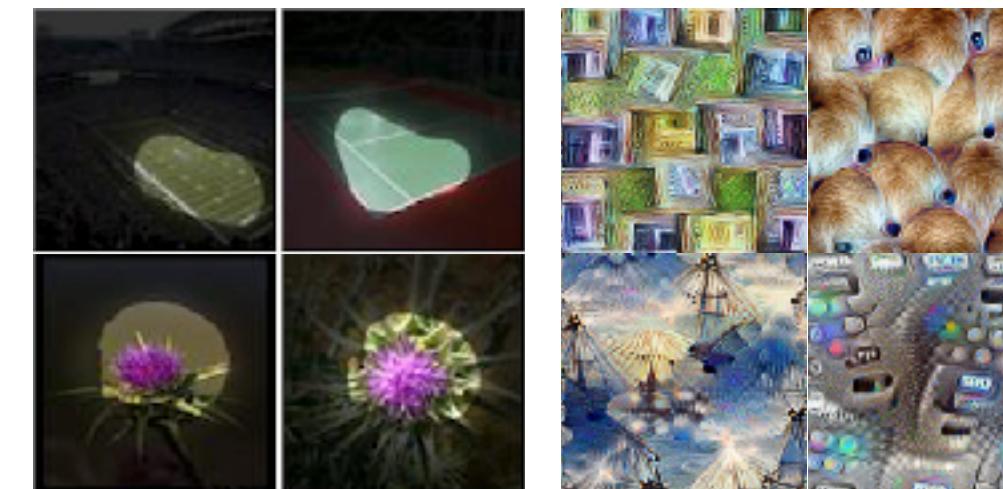
Self-supervised learning (2016-now)
Colorization, MOCO, SWaV



Diffusion models (2020-now)
DDPM, DALL-E 2, Imagen

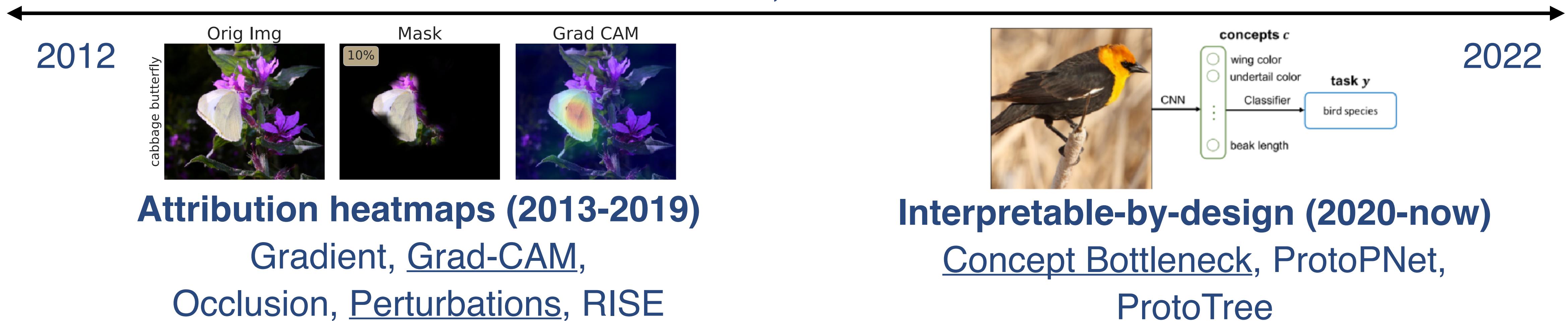
[Krizhevsky et al., NeurIPS 2012; Zhu* & Park* et al., ICCV 2017; Zhang et al., ECCV 2016;
Dosovitskiy* et al., ICLR 2021; Ramesh et al., arXiv 2022]

An incomplete retrospective: the first decade of interpretability



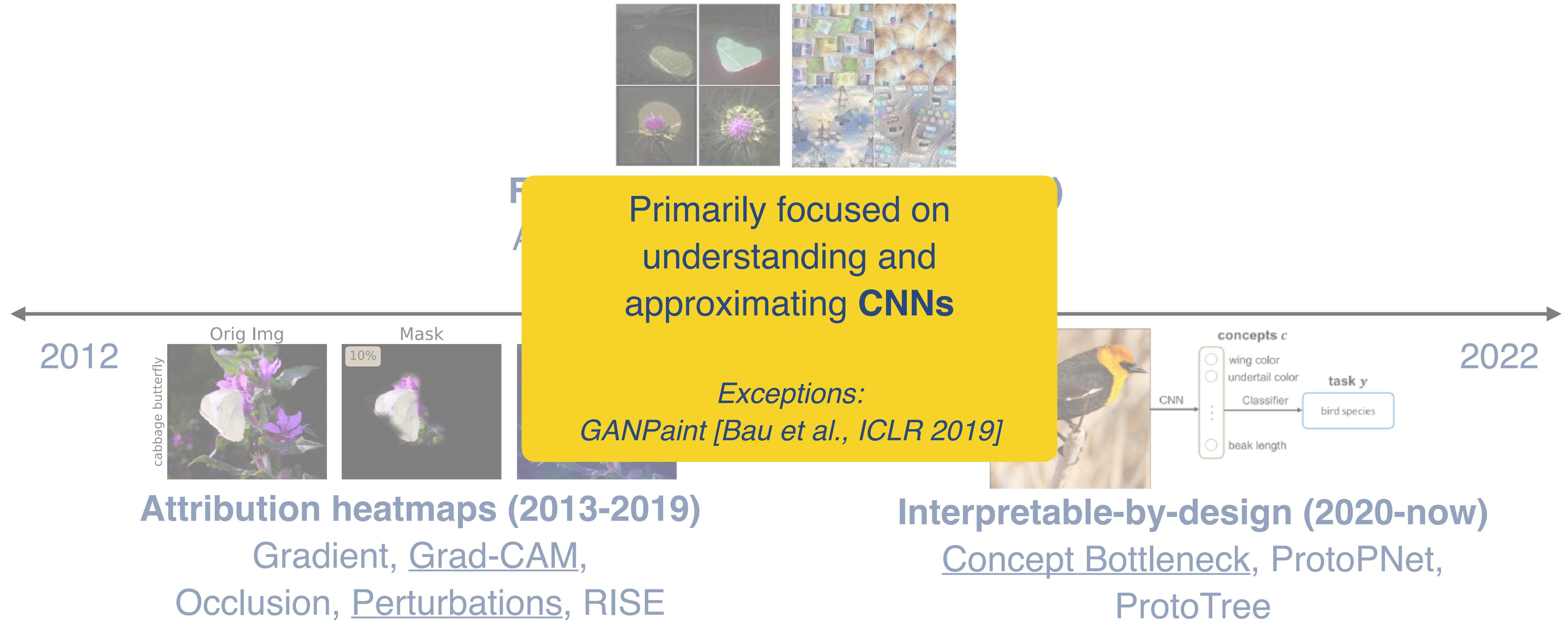
Feature visualization (2013-2018)

Activation Max., Feature Inversion, Net Dissect, Feature Vis.



[Selvaraju et al., ICCV 2017; Fong* & Patrick* et al., ICCV 2019; 5
7; Olah et al., Distill 2017; Koh*, Nguyen*, Tang* et al., ICML 2020]

An incomplete retrospective: the first decade of interpretability



[Selvaraju et al., ICCV 2017; Fong* & Patrick* et al., ICCV 2019;⁶
Bau* & Zhou* et al., CVPR 2017; Olah et al., Distill 2017; Koh*, Nguyen*, Tang* et al., ICML 2020]

Directions for the next decade of interpretability

1. Develop interpretability methods for **diverse domains**
 - Beyond CNN classifiers: self-supervised learning, generative models, etc.
2. Center **humans** throughout the development process
 - In design, co-develop methods with real-world stakeholders.
 - In evaluation, measure human interpretability and utility of methods.
 - In deployment, package interpretability tools for the wider community.

Roadmap

1. Automated evaluation of interpretability → **human-centered** evaluation

Sunnie S. Y. Kim, Nicole Meister, Vikram V. Ramaswamy, Ruth Fong, Olga Russakovsky, arXiv 2021.
HIVE: Evaluating the Human Interpretability of Visual Explanations.

2. Explanations via **labelled attributes** → explanations via **labelled attributes and unlabelled features**

Vikram V. Ramaswamy, Sunnie S. Y. Kim, Nicole Meister, Ruth Fong, Olga Russakovsky, arXiv 2022.
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4. **Static** visualizations → **interactive** visualizations

Ruth Fong, Alexander Mordvintsev, Andrea Vedaldi, Chris Olah, VISxAI 2021.
Interactive Similarity Overlays.

Roadmap



Sunnie S. Y.

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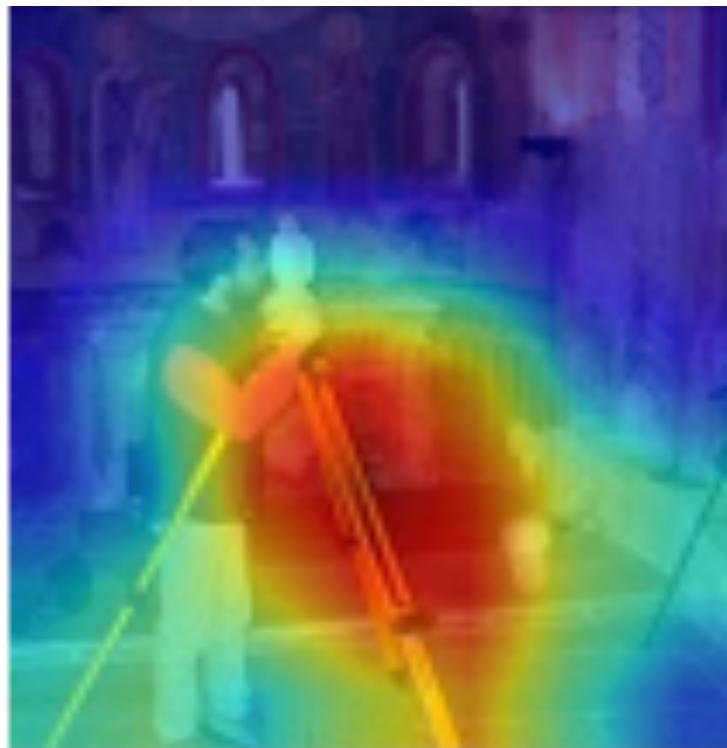
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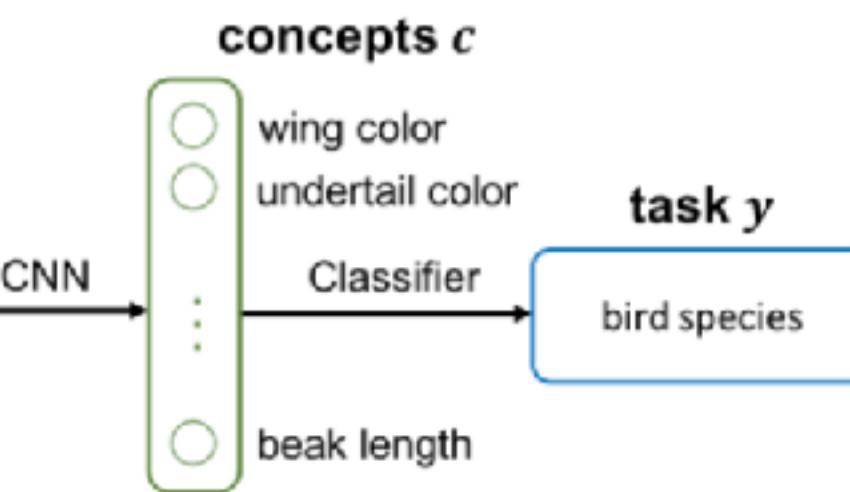
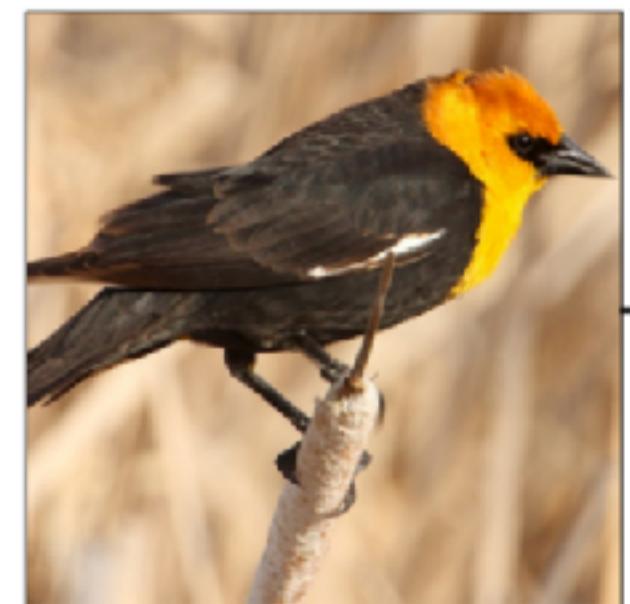
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Interactive Similarity Overlays.

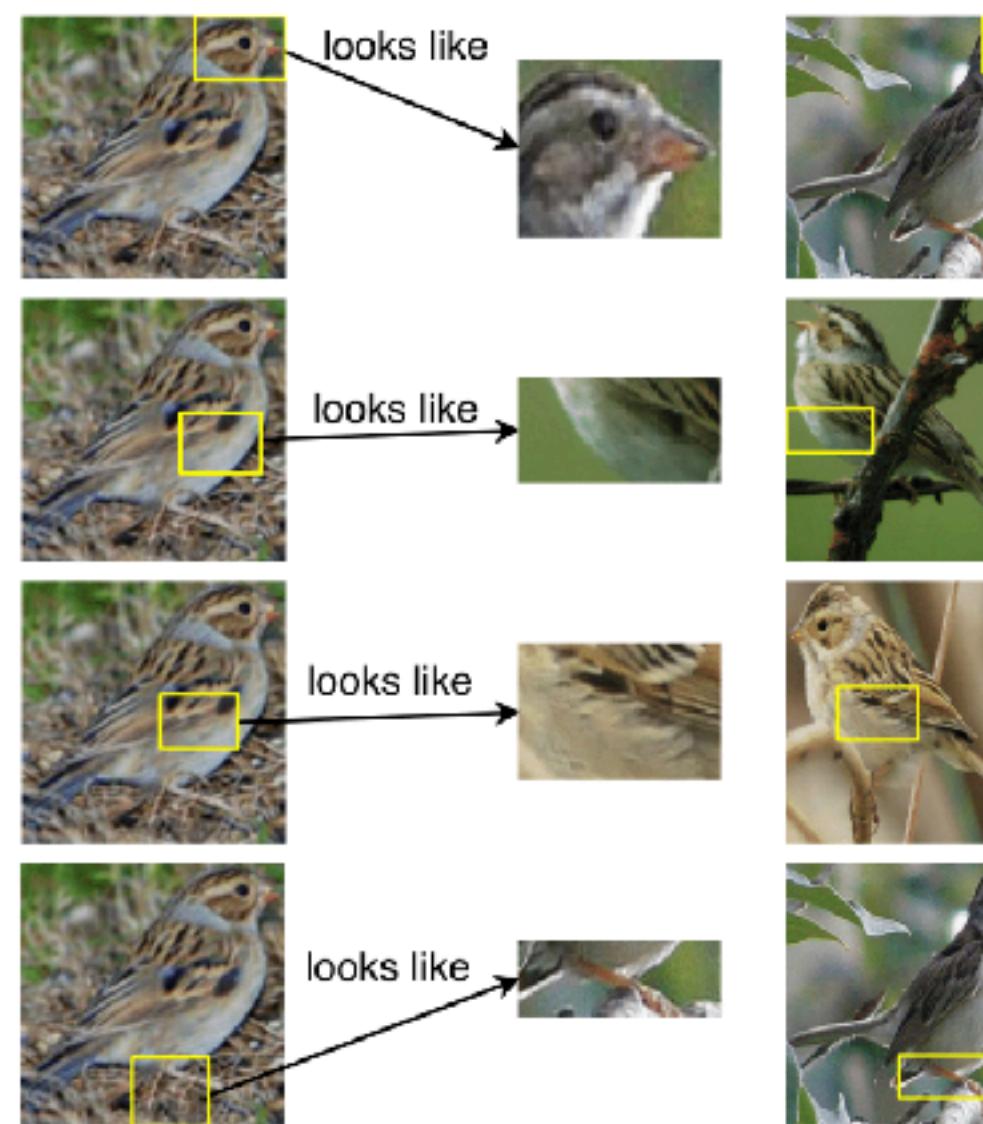
Explanation form factors: Why did the model predict Y?



Heatmap explanations
(e.g. Grad-CAM)

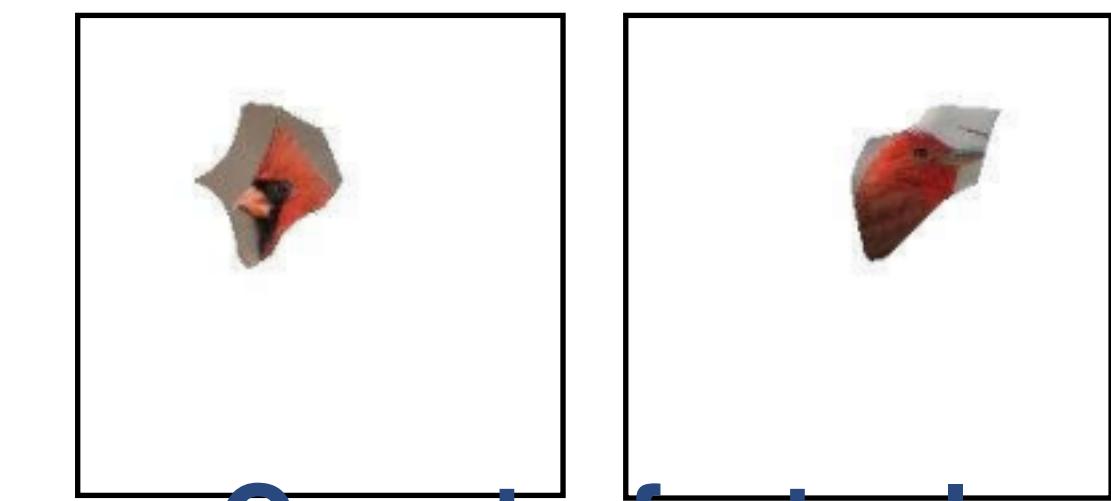


Concept-based explanations
(e.g. Concept Bottleneck)



Prototype explanations
(e.g. ProtoPNet)

Why Cardinal (L) and not
Summer Tanager (R)?



Counterfactual
explanations
(e.g. SCOUT)

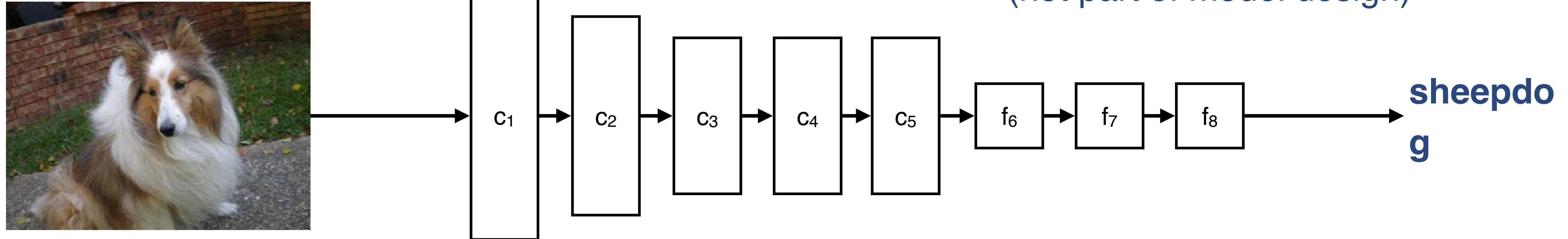
[Selvaraju et al., ICCV 2017; Koh*, Nguyen*, Tang* et al., ICML 2020;
Chen* & Li* et al., NeurIPS 2019; Wang & Vasconcelos, CVPR 2020]¹⁰

Post-hoc explanations

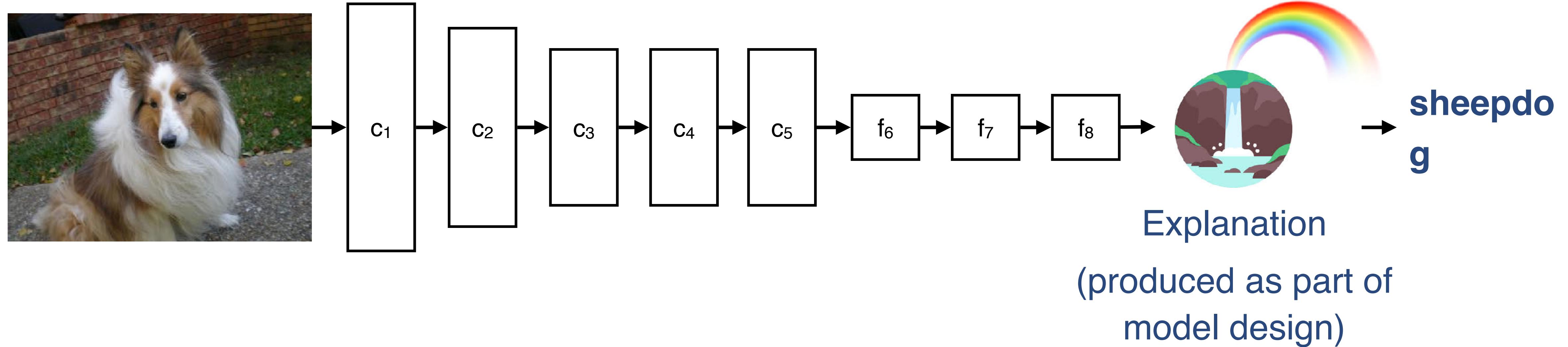


Explanation

(not part of model design)



Interpretable-by-design models



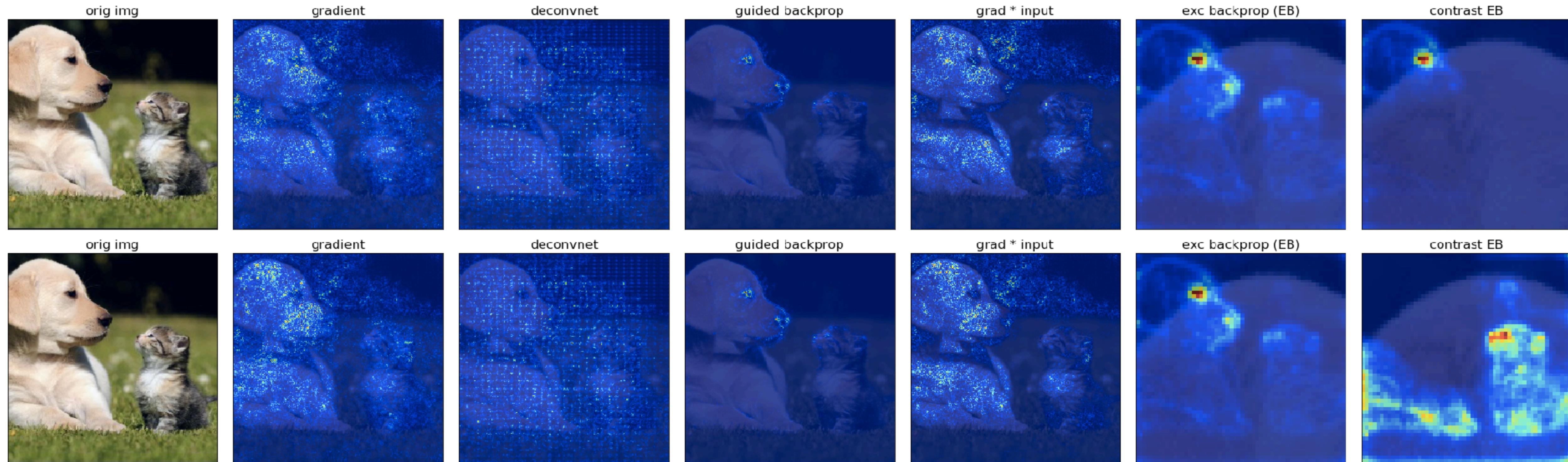
Current metrics focus on heatmap evaluation

- Weak localization performance [Zhang et al., ECCV 2016]
- Perturbation analysis
 - Deletion game [Samek et al., TNNLS 2017]
 - Retrain classifiers with removed features [Hooker et al., NeurIPS 2019]
- **Sensitivity to...**
 - **output neuron [Rebuffi*, Fong*, Ji* et al., CVPR 2020]**
 - **model parameters [Adebayo et al., NeurIPS 2018]**
- ...



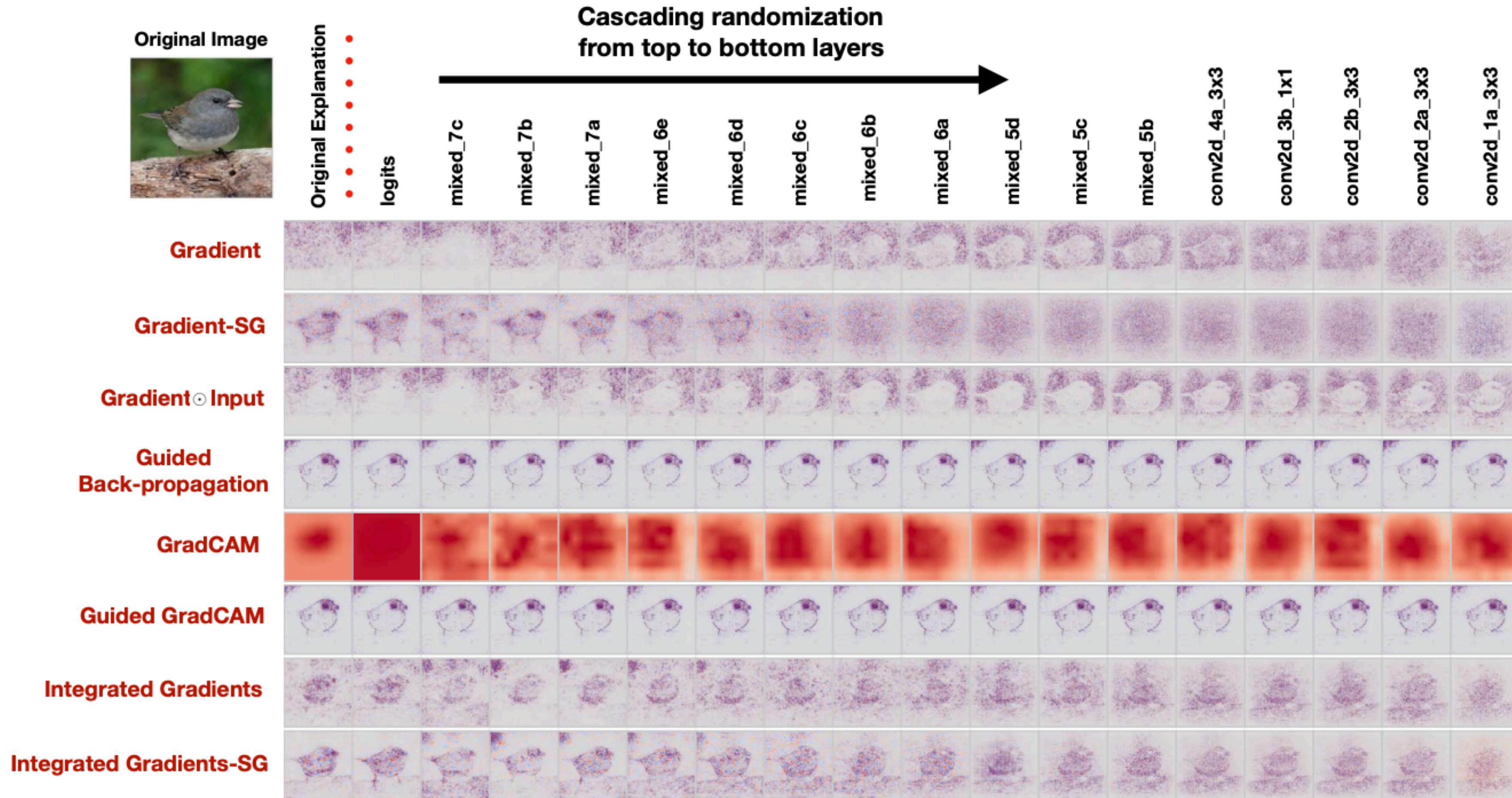
Automatic

Selectivity to output class



[Mahendran & Vedaldi, ECCV 2016; Rebuffi et al., CVPR 2020] ¹⁴

Sensitivity to model parameters (a.k.a. sanity checks)



Current metrics focus on heatmap evaluation

- Sheng & Huang, HCOMP 2020
Guess the incorrectly predicted label
- Nguyen et al., NeurIPS 2021
Is this prediction correct?
- Colin* & Fel* et al., arXiv 2021
What did the model predict (choose one of two)?



Human

Is this prediction correct?

AI's top-1 predicted label: **lorikeet**



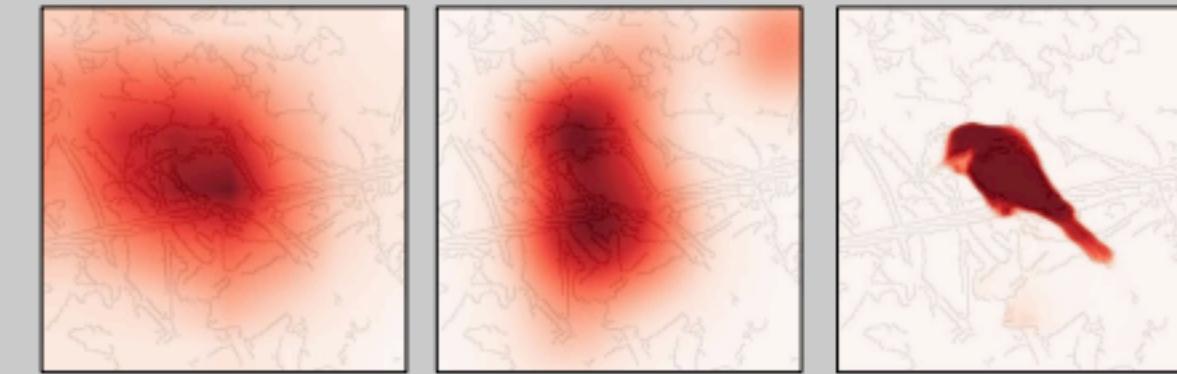
input

A confidence **20%**

B heatmaps

GradCAM EP SOD

C 3 nearest neighbors in **lorikeet**



lorikeet ?



Yes

vs

No

user

groundtruth label: "bee eater"

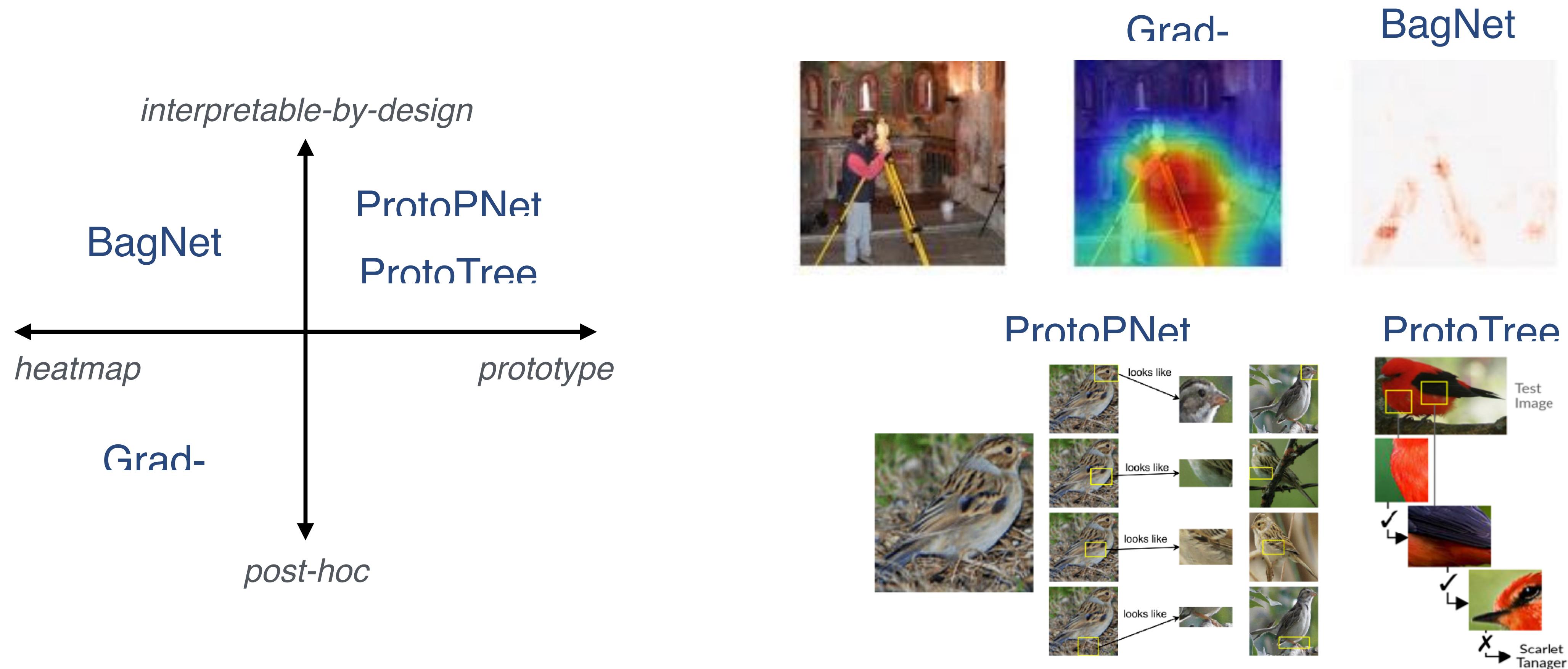
HIVE: Evaluating the Human Interpretability of Visual

1. Within method → **Cross-method comparison**
2. Automated evaluation → **Human-centered evaluation**
3. Intuition-based reasoning → **Falsifiable hypothesis testing**

Our contributions

- Novel human study design for evaluating 4 diverse interpretability methods
 - **First human study** for interpretable-by-design and prototype methods
 - Quantify the utility of explanations in distinguishing between **correct and incorrect predictions**
 - Quantify how users would trade off between **interpretability and accuracy**
 - **Open-source** HIVE studies to encourage reproducible research

1. Cross-method comparison



[Selvaraji et al., ICCV 2017; Brendel & Bethge, ICLR 2019;
Chen* & Li* et al., NeurIPS 2019, Nauta et al., CVPR 2021]

2. Human-centered evaluation

Agreement task

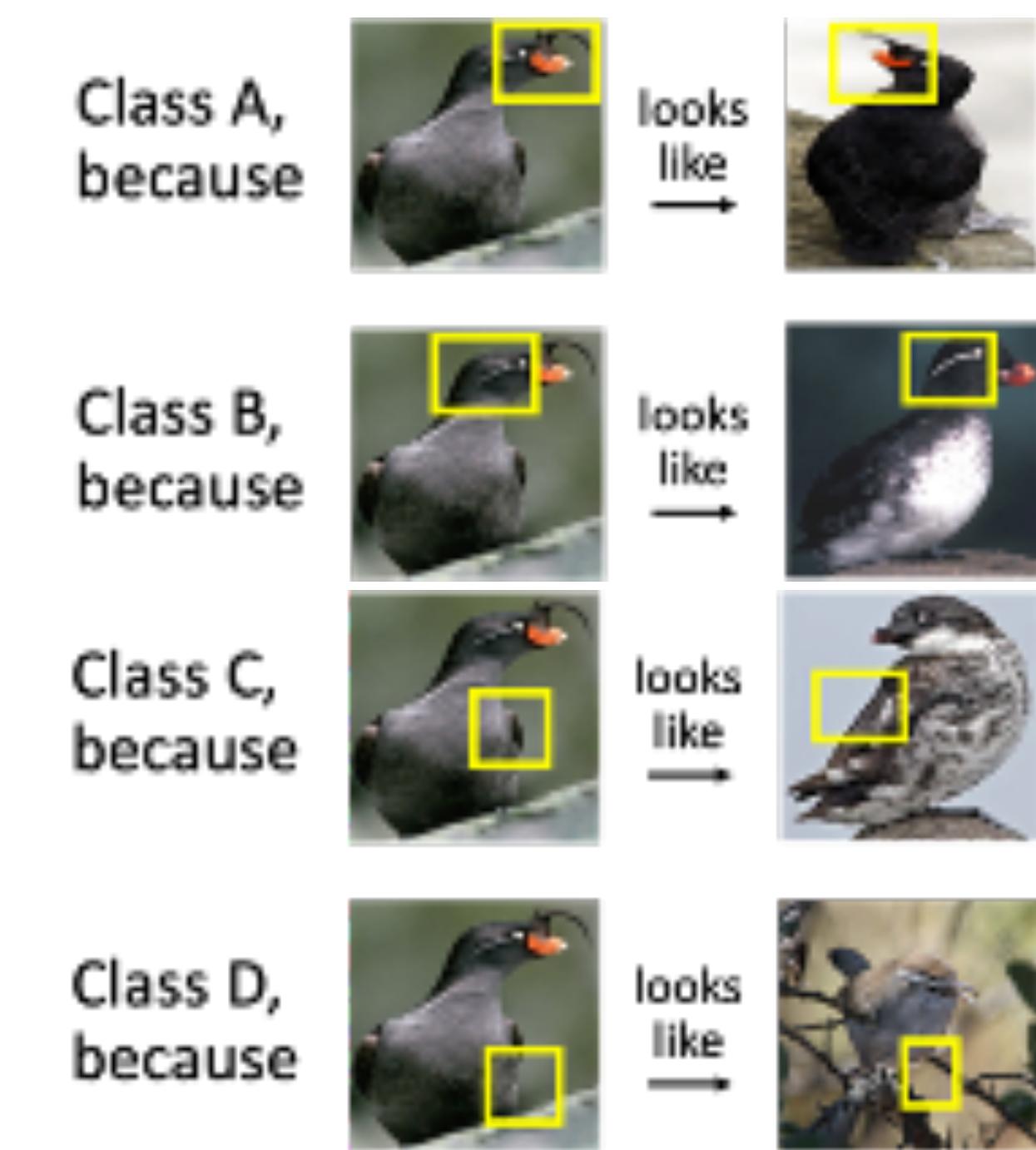
How confident are you in the model's prediction?



Experimental set-up: AMT studies with N=50 participants each

Distinction task

Which class do you think is correct?



2. Human-centered evaluation

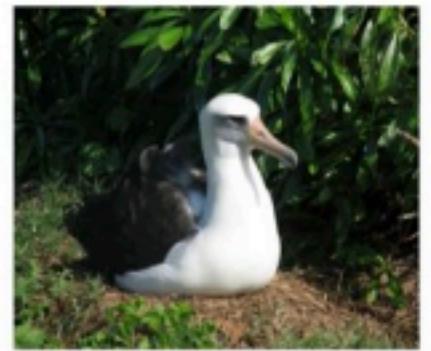
Agreement task

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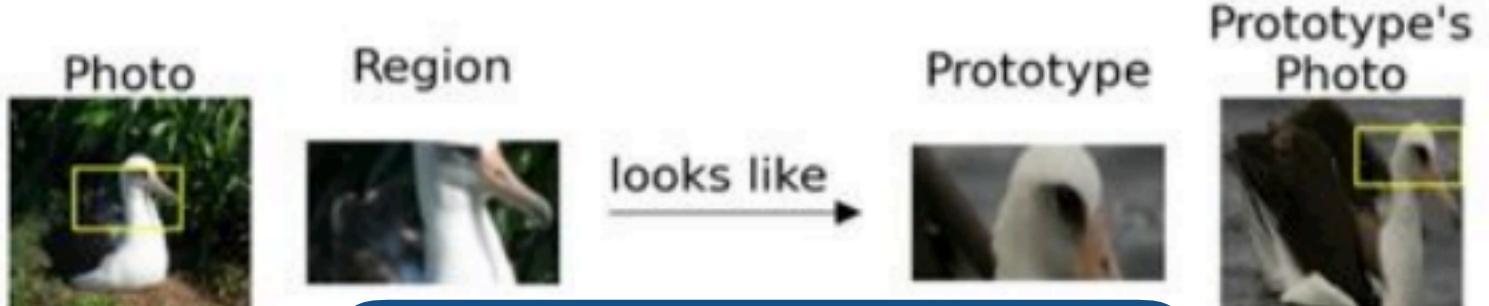
Finding #1: Prototype similarities often do not align with human notions of similarity.

Task: Rate the similarity of each row's prototype-region pair on a scale of 1-4.

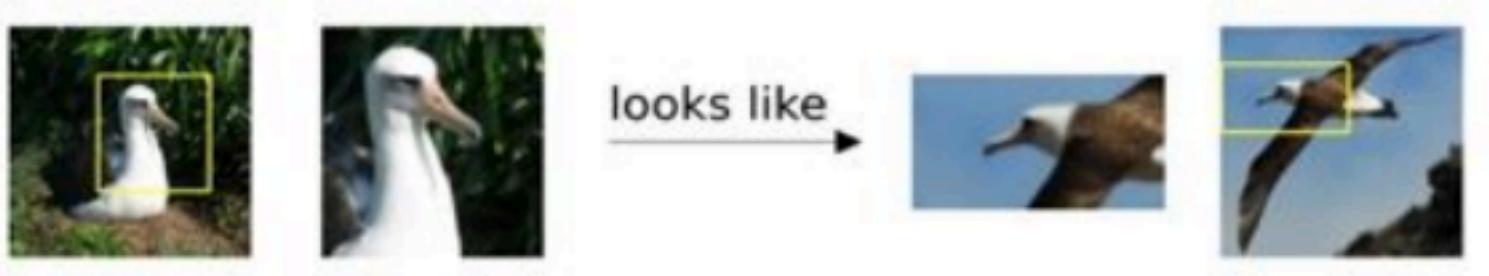
(1: Not Similar, 2: Somewhat Not Similar, 3: Somewhat Similar, 4: Similar)



Shown below is the model's explanation for its prediction (all prototypes and their source photos are from Species 2).



1 2 3 4



1 2 3 4

Q. What do you think about the model's prediction?

- Fairly confident that prediction is *correct*
- Somewhat confident that prediction is *correct*
- Somewhat confident that prediction is incorrect
- Fairly confident that prediction is incorrect

2. Human-centered evaluation

Agreement task

How confident are you in the model's prediction?

Finding #1: Prototype similarities often do not align with human notions of similarity.

Finding #2: Agreement task reveals confirmation bias.

Task: Rate the similarity of each row's prototype-region pair on a scale of 1-4.

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Shown below is the model's explanation for its prediction (all prototypes and their source photos are from Species 2).



○1 ○2 ○3 ○4



○1 ○2 ○3 ○4

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- Fairly confident that prediction is correct
- Somewhat confident that prediction is correct
- Somewhat confident that prediction is incorrect
- Fairly confident that prediction is incorrect

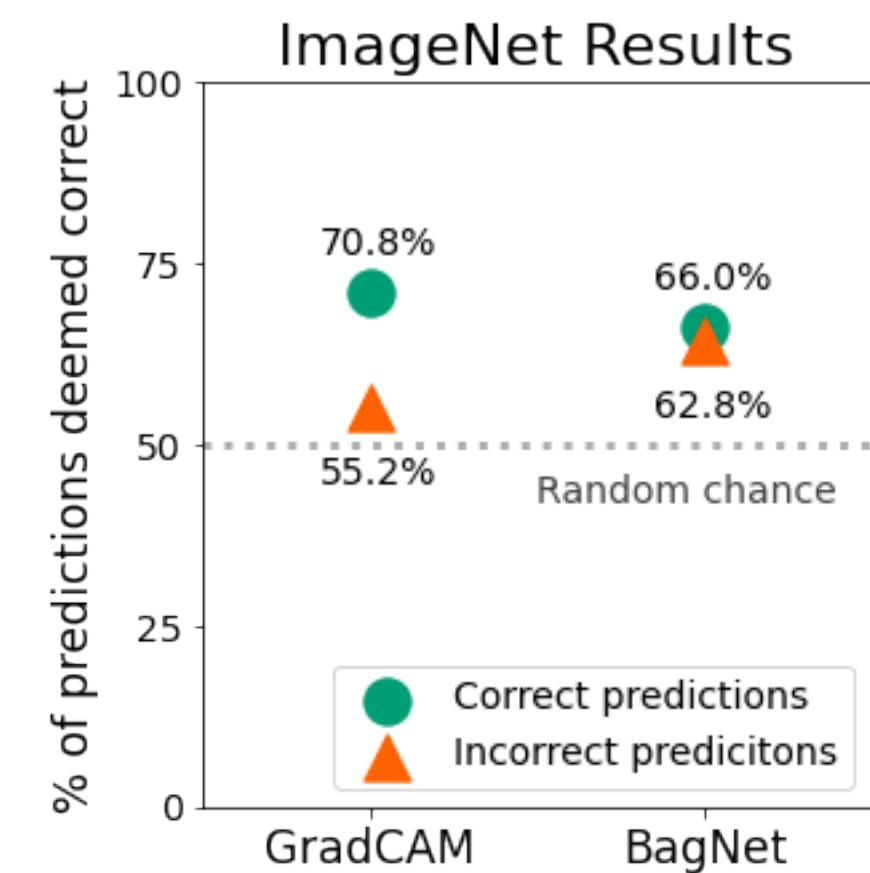
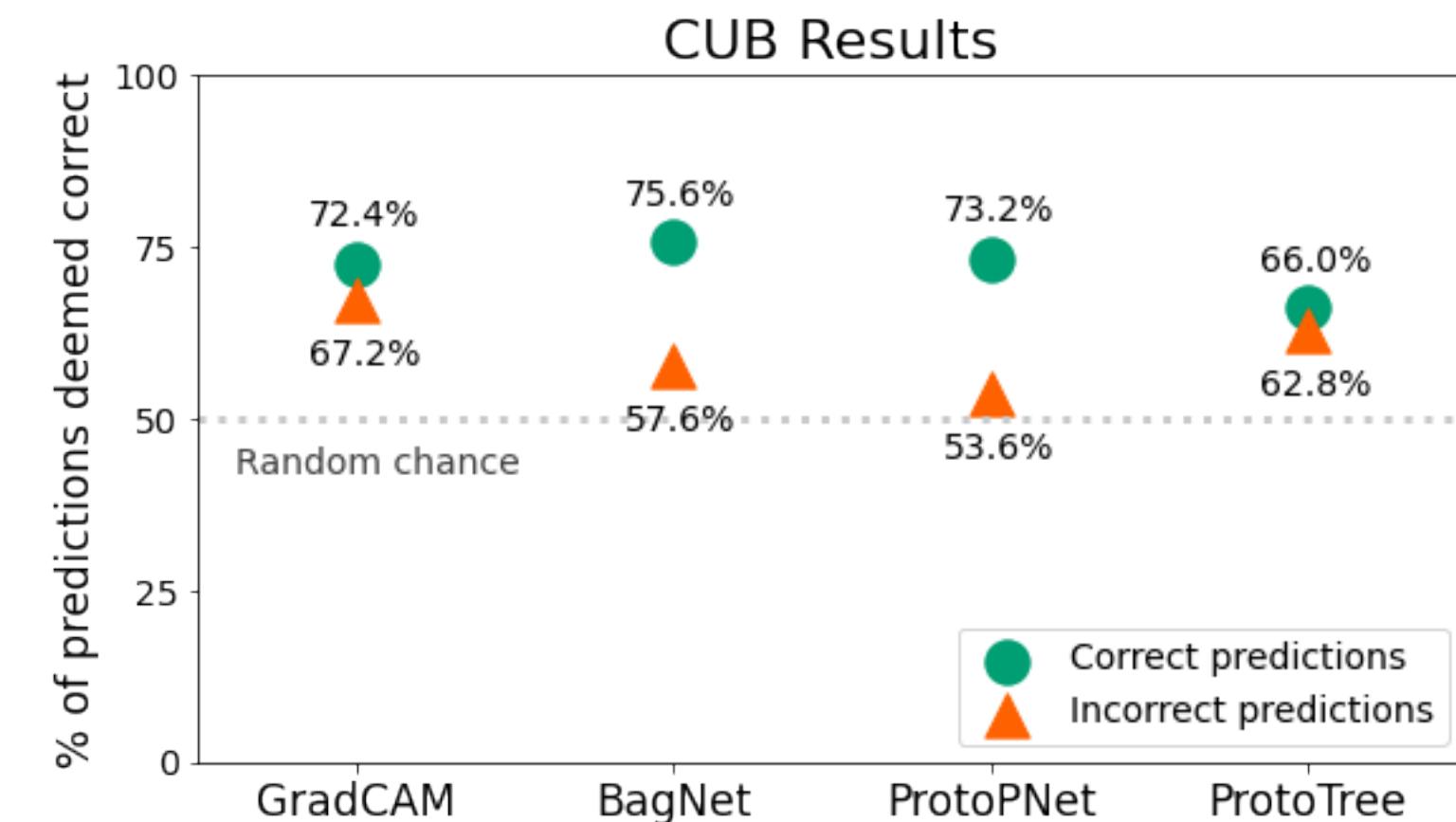
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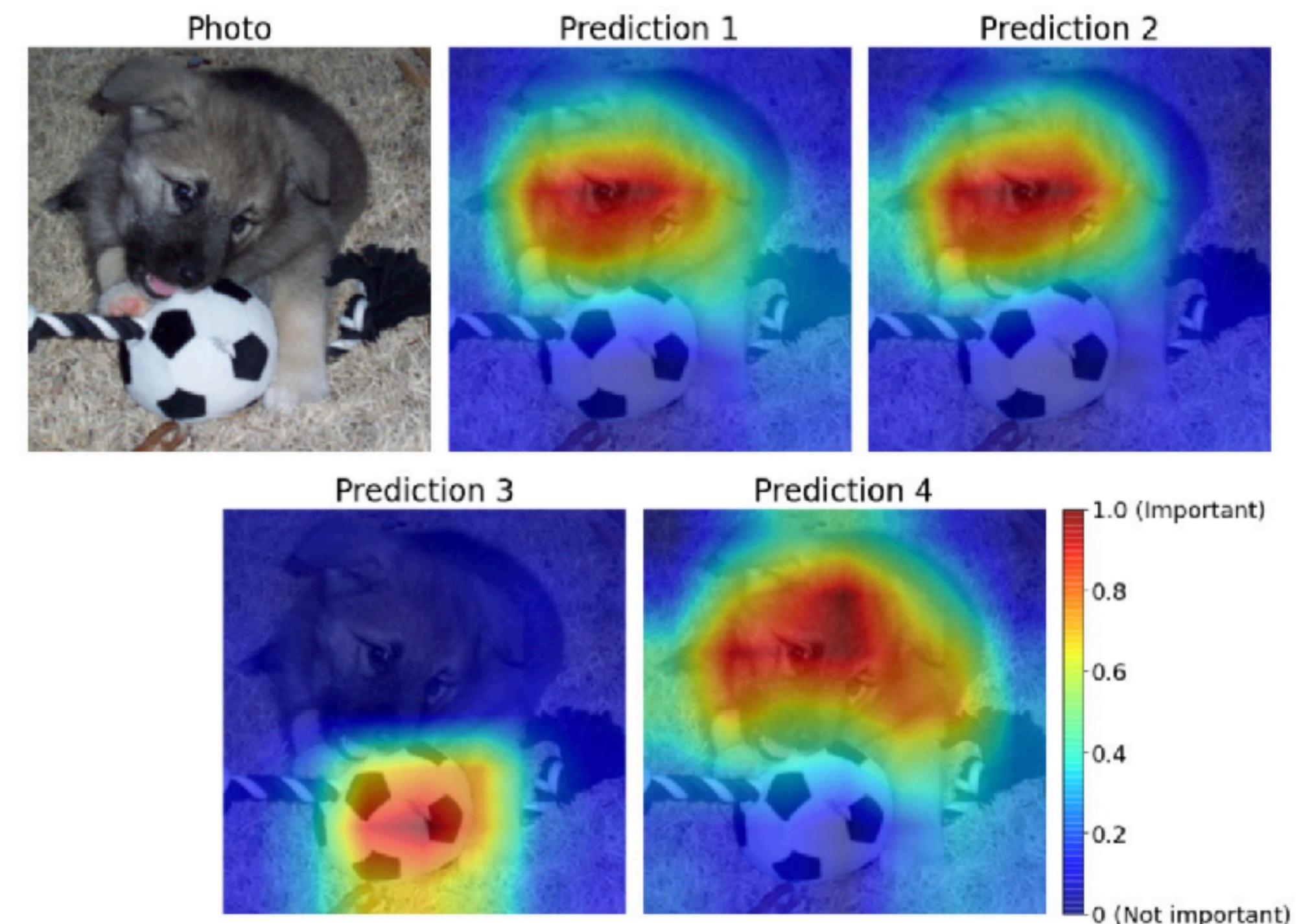
- Fairly confident that prediction is correct
- Somewhat confident that prediction is correct
- Somewhat confident that prediction is incorrect
- Fairly confident that prediction is incorrect

2. Human-centered evaluation

Distinction task

Which class do you think is correct?

Finding #3: Participants struggle to identify the **correct class**, esp. for incorrect



Q. Which class do you think is correct?

- 1 2 3 4

Q. How confident are you in your answer?

- Not confident at all
- Slightly confident
- Somewhat confident
- Fairly confident
- Completely confident

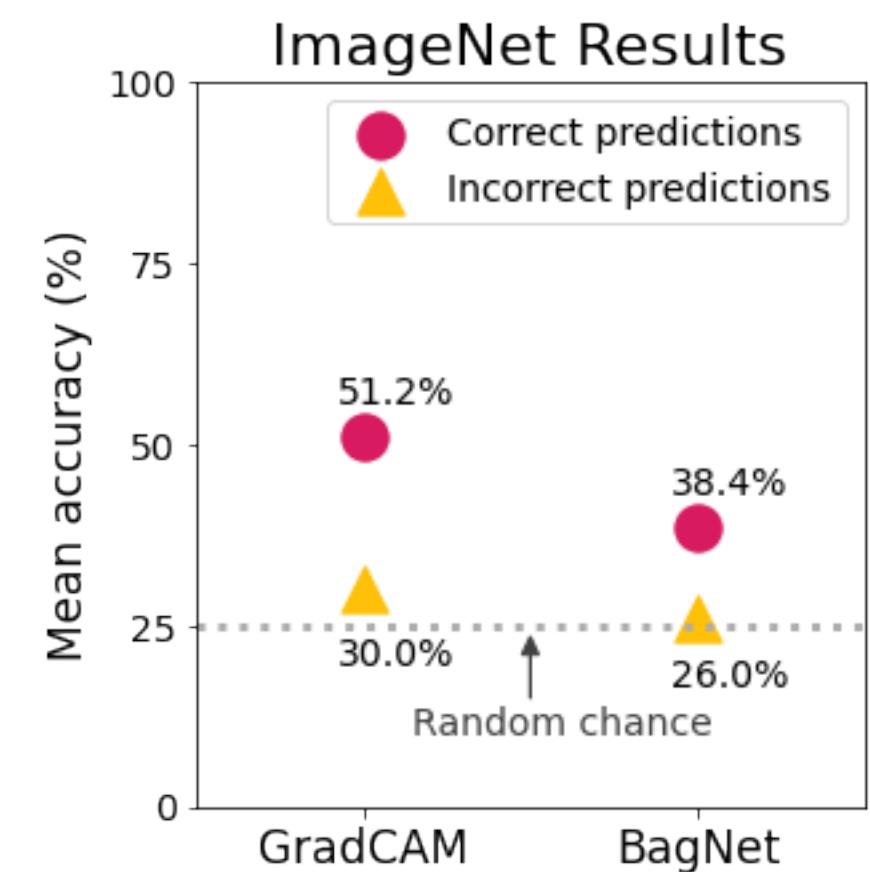
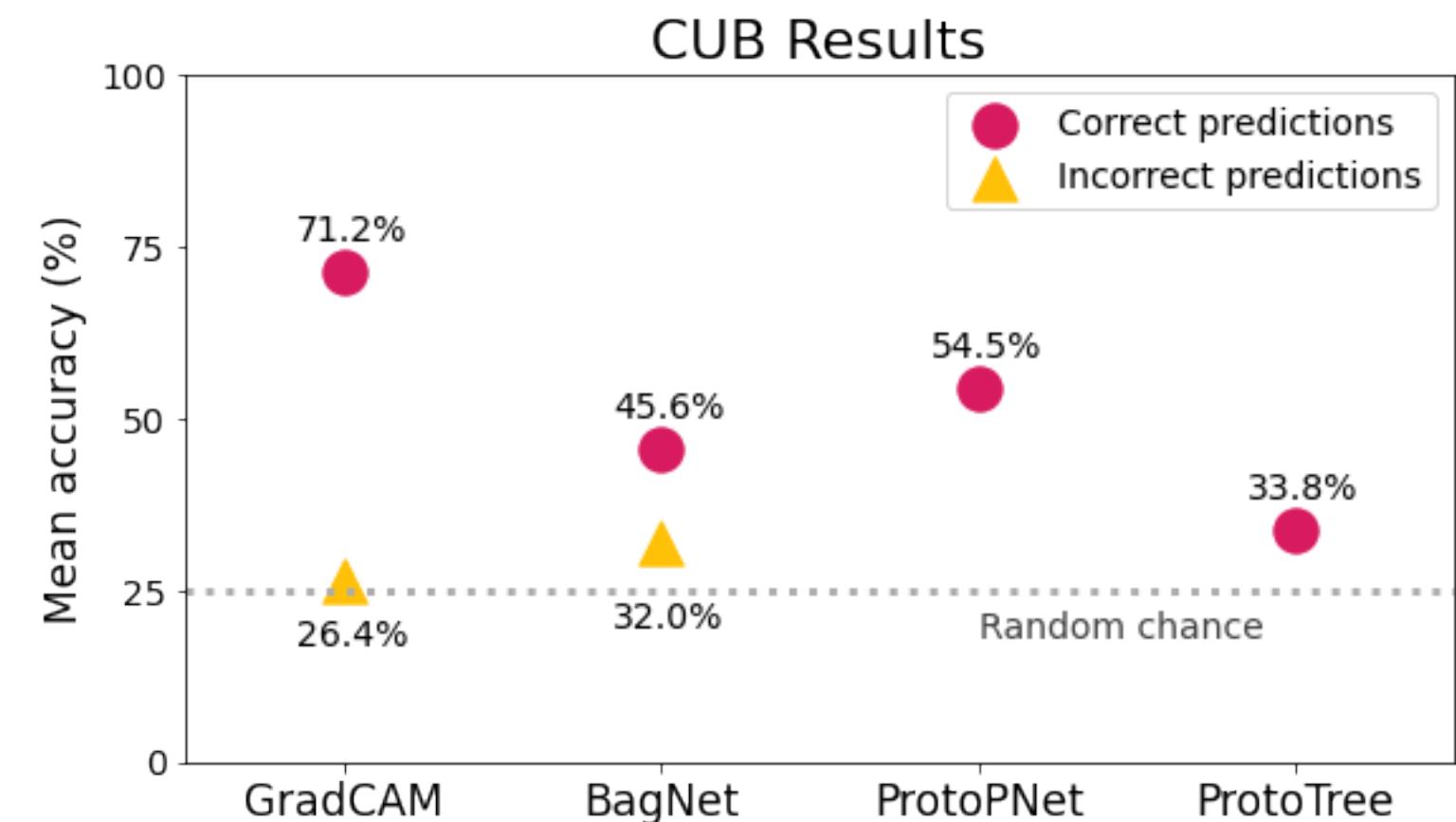
2. Human-centered evaluation

Distinction task

Which class do you think is correct?

Finding #3: Participants struggle to identify the **correct class**, esp. for incorrect

Goal: Interpretability should help humans identify and explain model errors.



Q. Which class do you think is correct?

- 1 2 3 4

Q. How confident are you in your answer?

- Not confident at all
- Slightly confident
- Somewhat confident
- Fairly confident
- Completely confident

3. Falsifiable hypothesis testing

Finding #1: Prototype similarities often **do not align** with human notions of similarity.

Finding #2: Agreement task reveals **confirmation bias**.

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3. Falsifiable hypothesis testing

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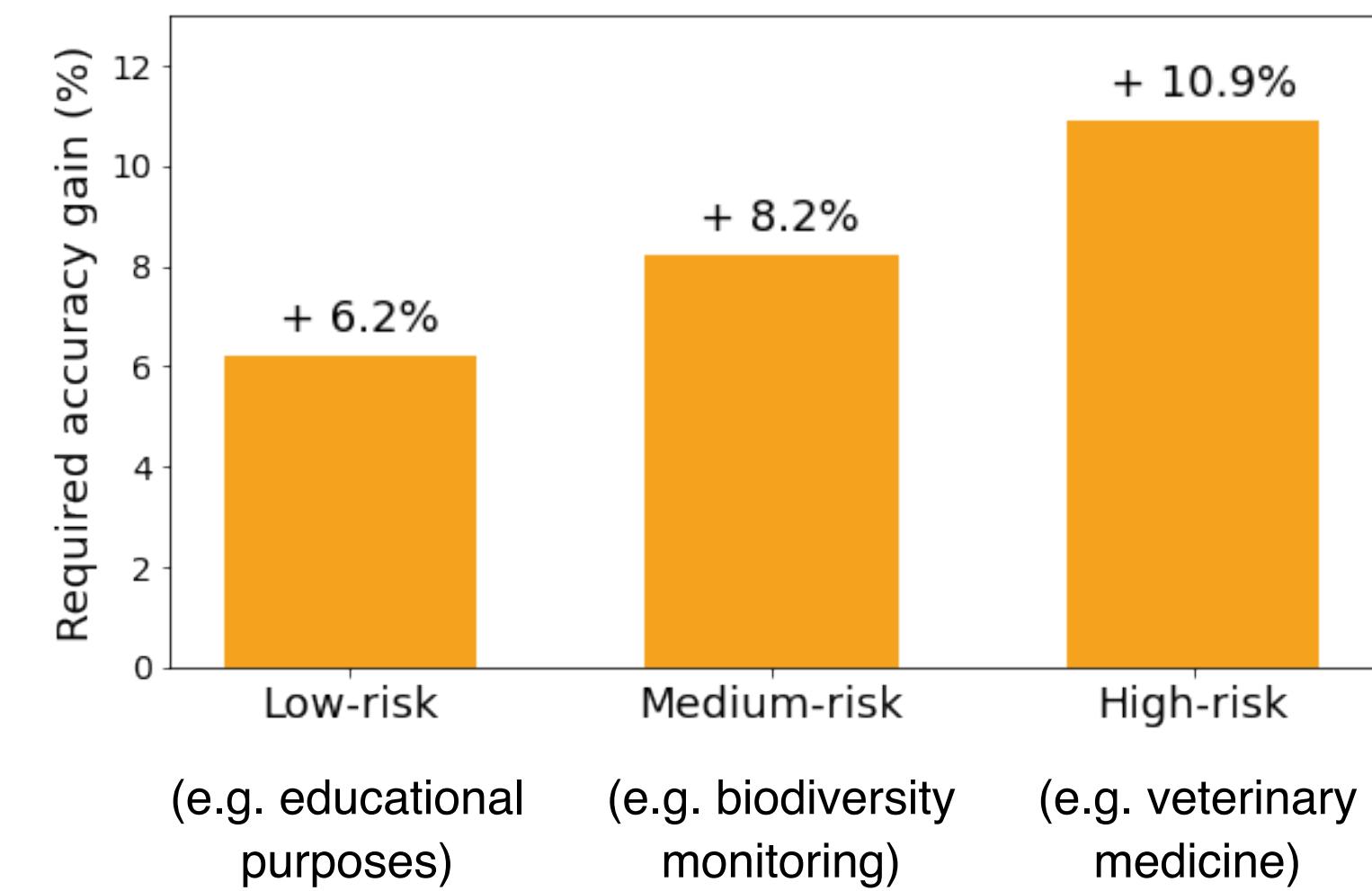
Finding #2: Agreement task reveals **confirmation bias**.

Finding #3: Participants struggle to identify the **correct class**, esp. for incorrect

Finding #4: Participants prefer interpretability over accuracy, esp. in high-

Interpretability-accuracy tradeoff

Q: What is the minimum accuracy of a baseline model that would convince you to use it over a model with explanations?



Challenges for human evaluation

- Skill cost: web development skills
- Financial cost: budget for AMT experiments
- Time cost: human study design and iteration (e.g. task feasibility, IRB approval, quality control)

Takeaway: As a research community, invest in and reward human evaluation studies (like dataset development).

Roadmap



Vikram V.

1. Automated evaluation of interpretability → **human-centered** evaluation

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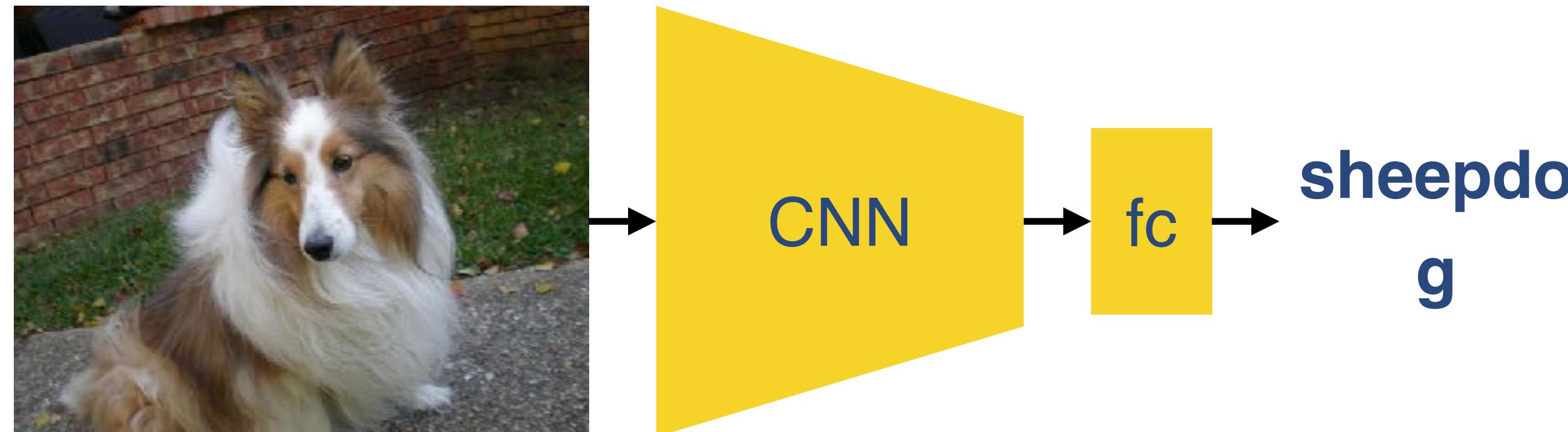
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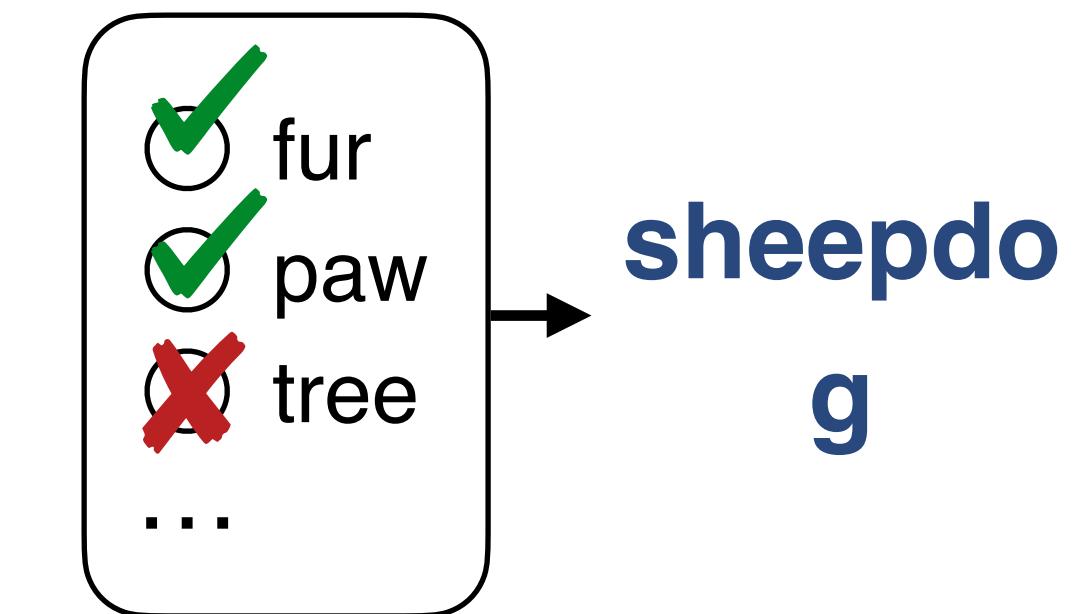
Ruth Fong, Alexander Mordvintsev, Andrea Vedaldi, Chris Olah, VISxAI 2021.
Interactive Similarity Overlays.

Concept-based explanations

Why did the model predict **sheepdog**?

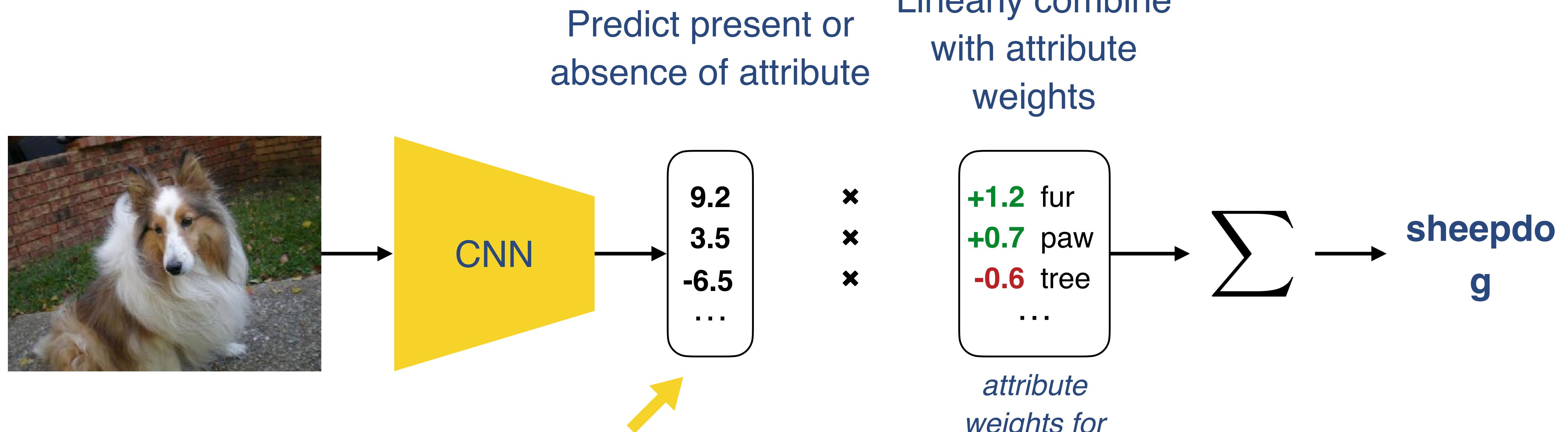


Concept-based explanation



Pro: Labelled concepts are interpretable to humans

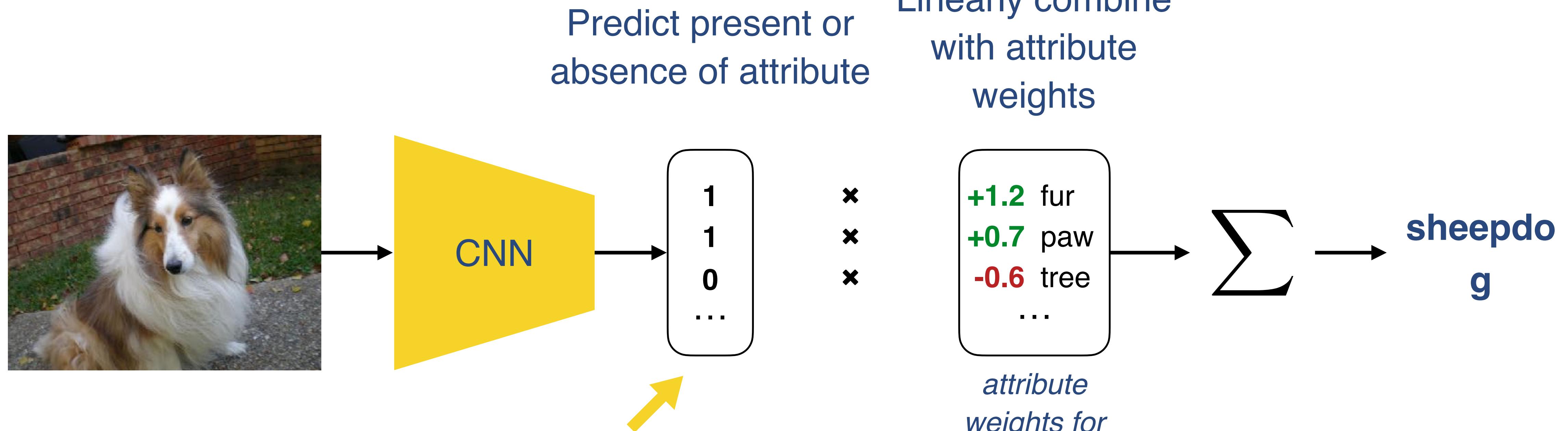
Concept Bottleneck: Linear Combination of Labelled Attributes



Con: Problems with predicting fractional values

- hard to interpret
- can encode hidden information

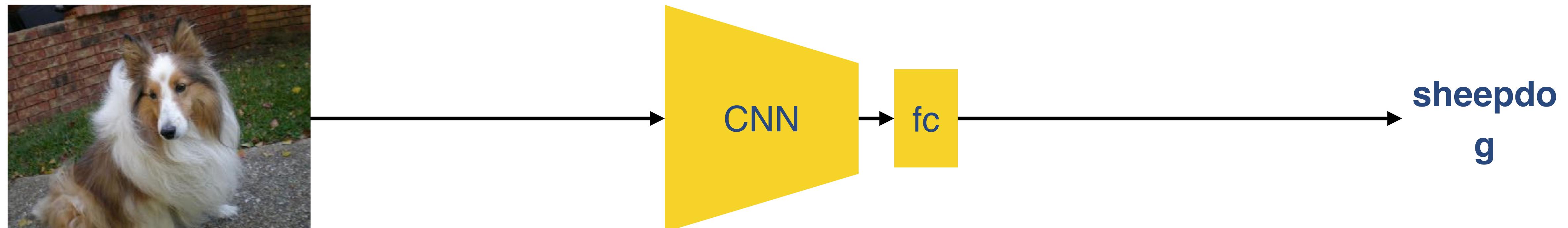
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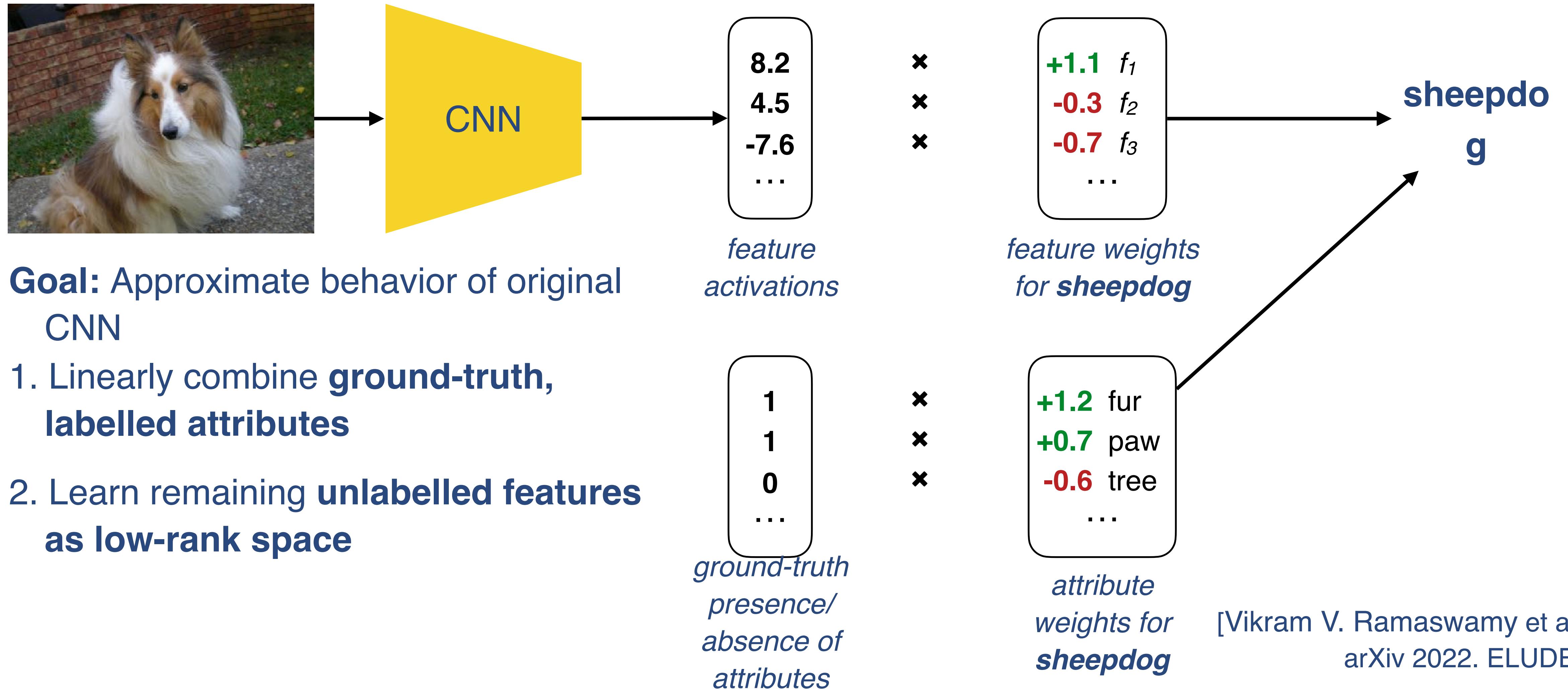
- hard to interpret
- can encode hidden information

ELUDE: Explanation via a Labelled and Unlabelled



Goal: Approximate behavior of original
CNN

ELUDE: Decomposition of labelled and unlabelled features



Attributes only: % of model explained via labelled attributes

Task	% Explained
2-way scene classification (indoor vs. outdoor)	95.7
16-way scene classification (home/hotel, workplace, etc.)	46.2
365-way scene classification (airfield, bowling alley, etc.)	28.8

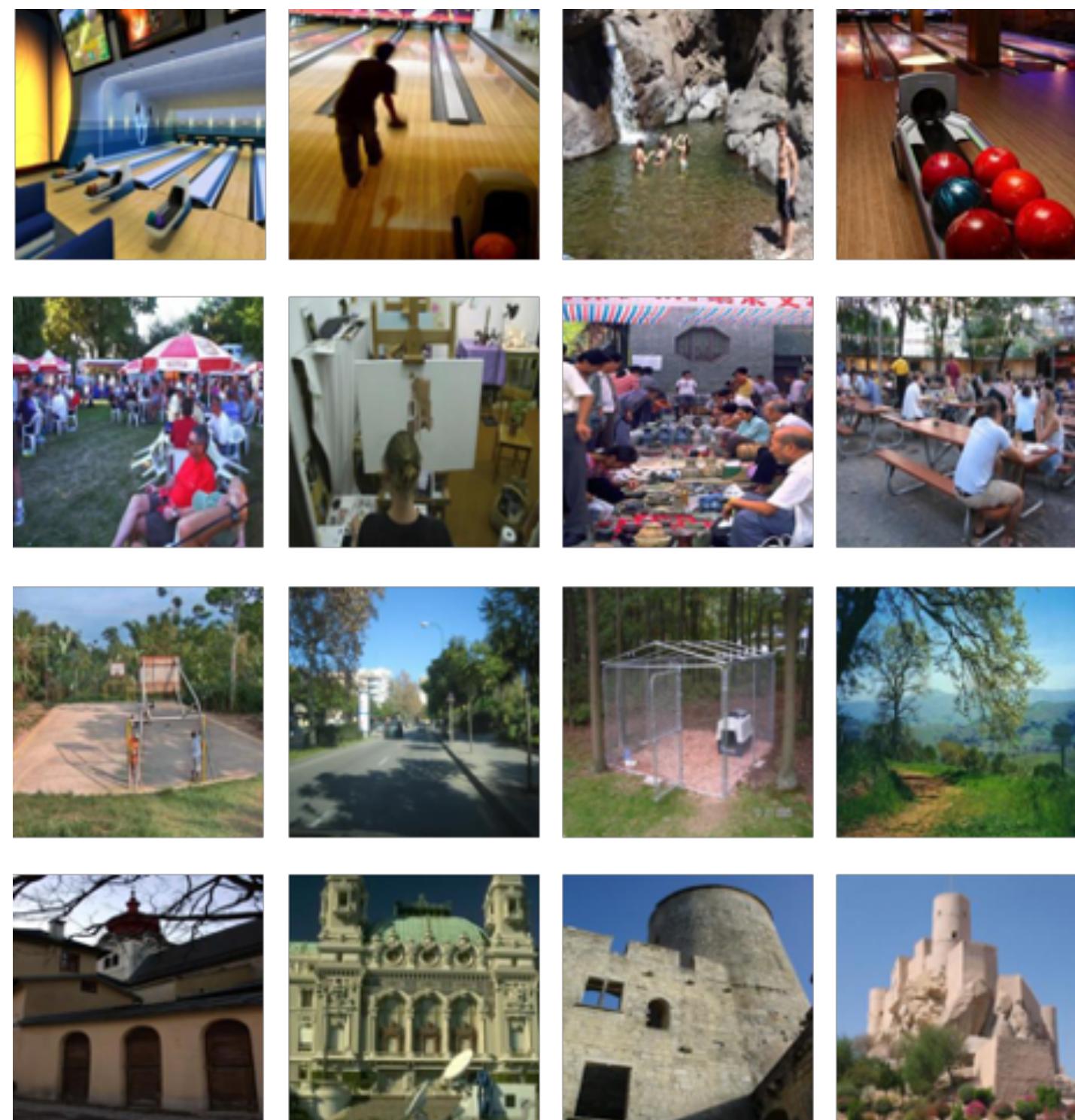
Without fractional values encoding hidden information,
attribute-only approaches are limited.

Attributes only: % of model explained via labelled attributes

Scene group	TPR
home/hotel	99.0
comm-buildings/towns	93.5
water/ice/snow	60.6
forest/field/jungle	40.2
workplace	14.2
shopping-dining	12.4
cultural/historical	6.5
cabins/gardens/farms	4.7
outdoor-transport	3.2
indoor-transport	0.0
indoor-sports/leisure	0.0
indoor-cultural	0.0
mountains/desert/sky	0.0
outdoor-manmade	0.0
outdoor-fields/parks	0.0
industrial-construction	0.0

Without fractional values encoding hidden information,
attribute-only approaches are limited.

Features + attributes: Unlabelled features correspond to



bowling alleys?

people eating?

outdoor sports fields?

castle-like buildings?

Scene group	TPR
home/hotel	99.0
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water/ice/snow	60.6
forest/field/jungle	40.2
workplace	14.2
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indoor-cultural	0.0
mountains/desert/sky	0.0
outdoor-manmade	0.0
outdoor-fields/parks	0.0
industrial-construction	0.0

attributes only

Challenges for concept-based methods

- Attributes-only approaches are incomplete
- Develop more methods to explain the “remainder”
 - Interpretable Basis Decomposition (IBD) [Zhou et al., ECCV 2018]
 - Automatic Concept-based Explanations (ACE) [Ghorbani et al., NeurIPS 2019]
 - ConceptSHAP [Yeh et al., NeurIPS 2020]
- Ensure that concept-based explanations are truly human-interpretable

Takeaway: Be realistic about the benefits and limitations of an interpretability method and work towards addressing the limitations.



Roadmap

Iro Laina

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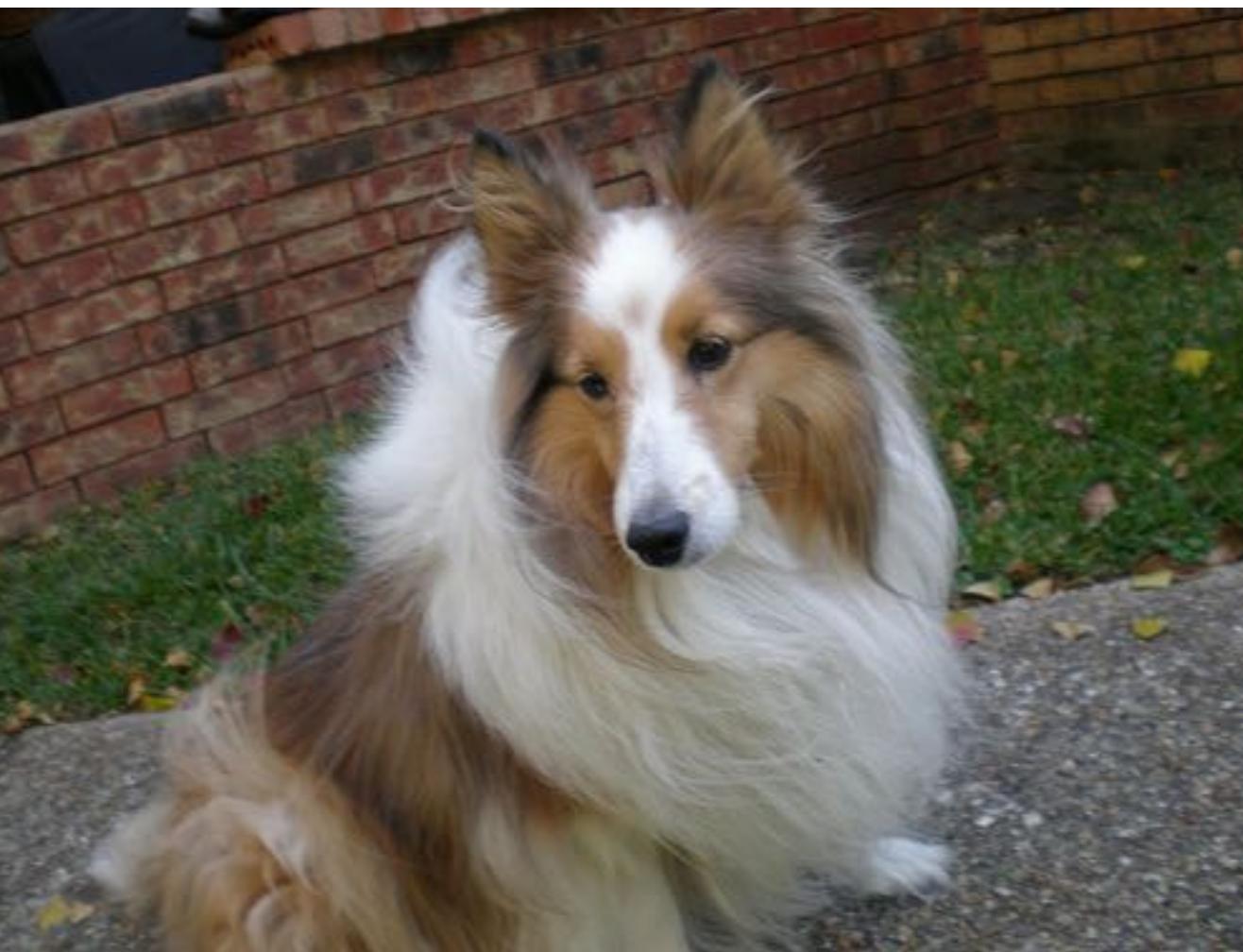
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Interactive Similarity Overlays.

Supervised Learning

(



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sheepdog

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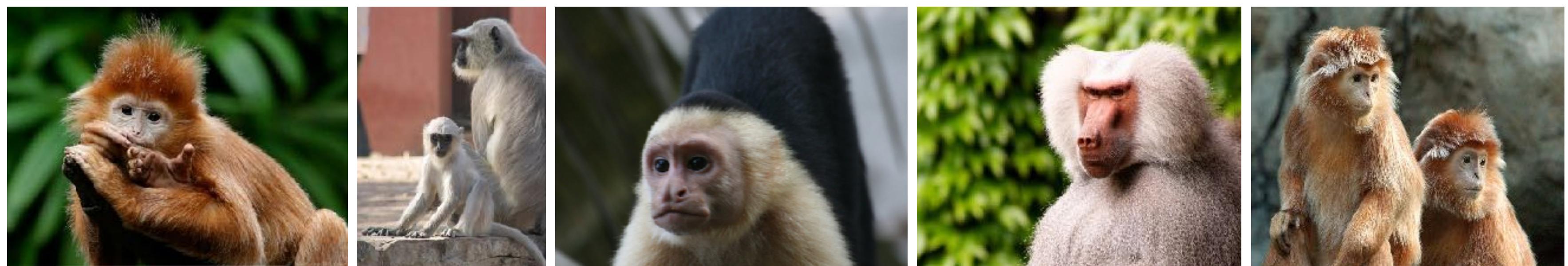
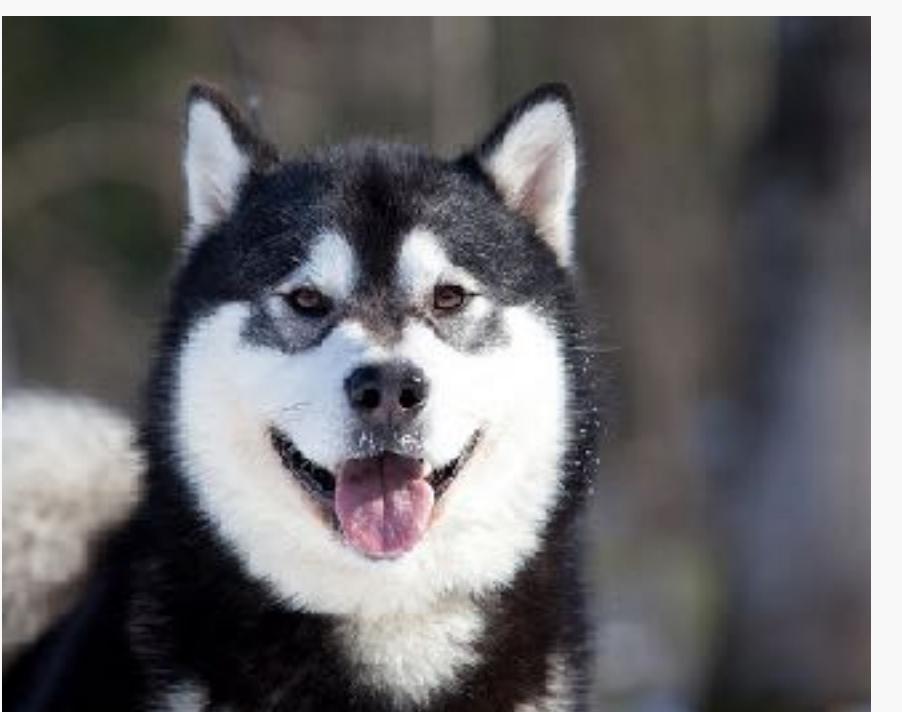
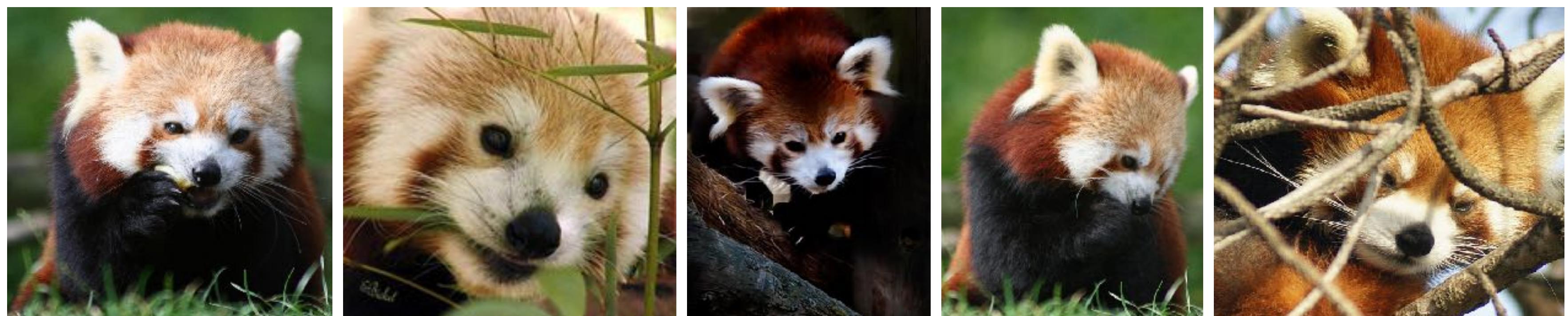
Self-Supervised Learning



X

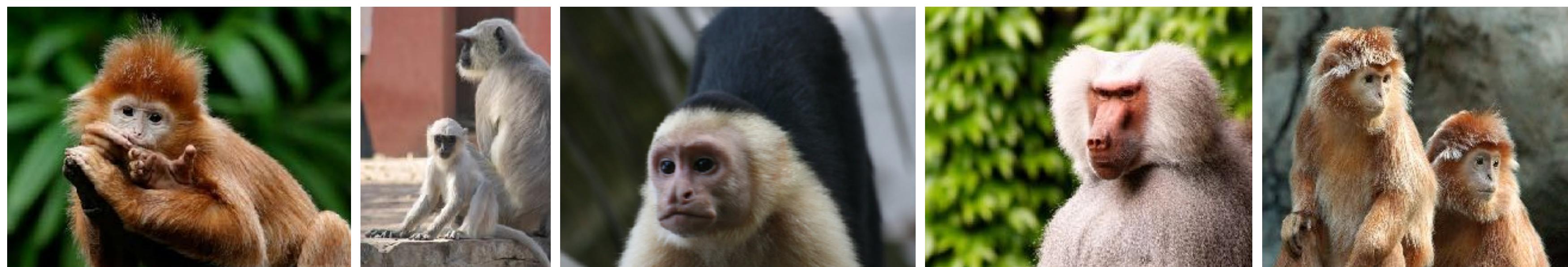
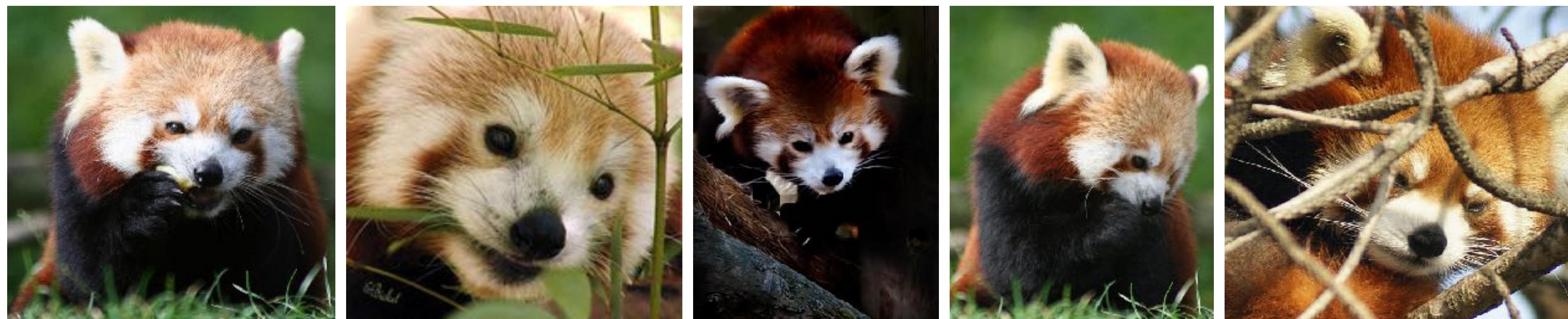
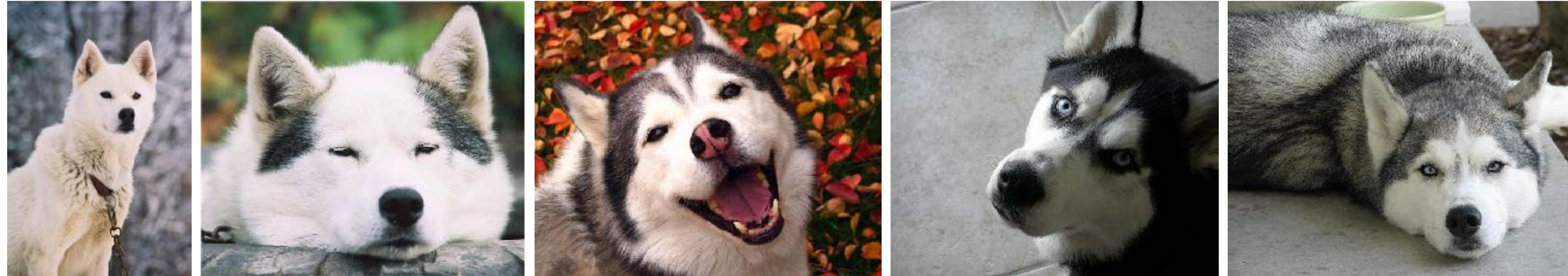
Visual Concept

Query

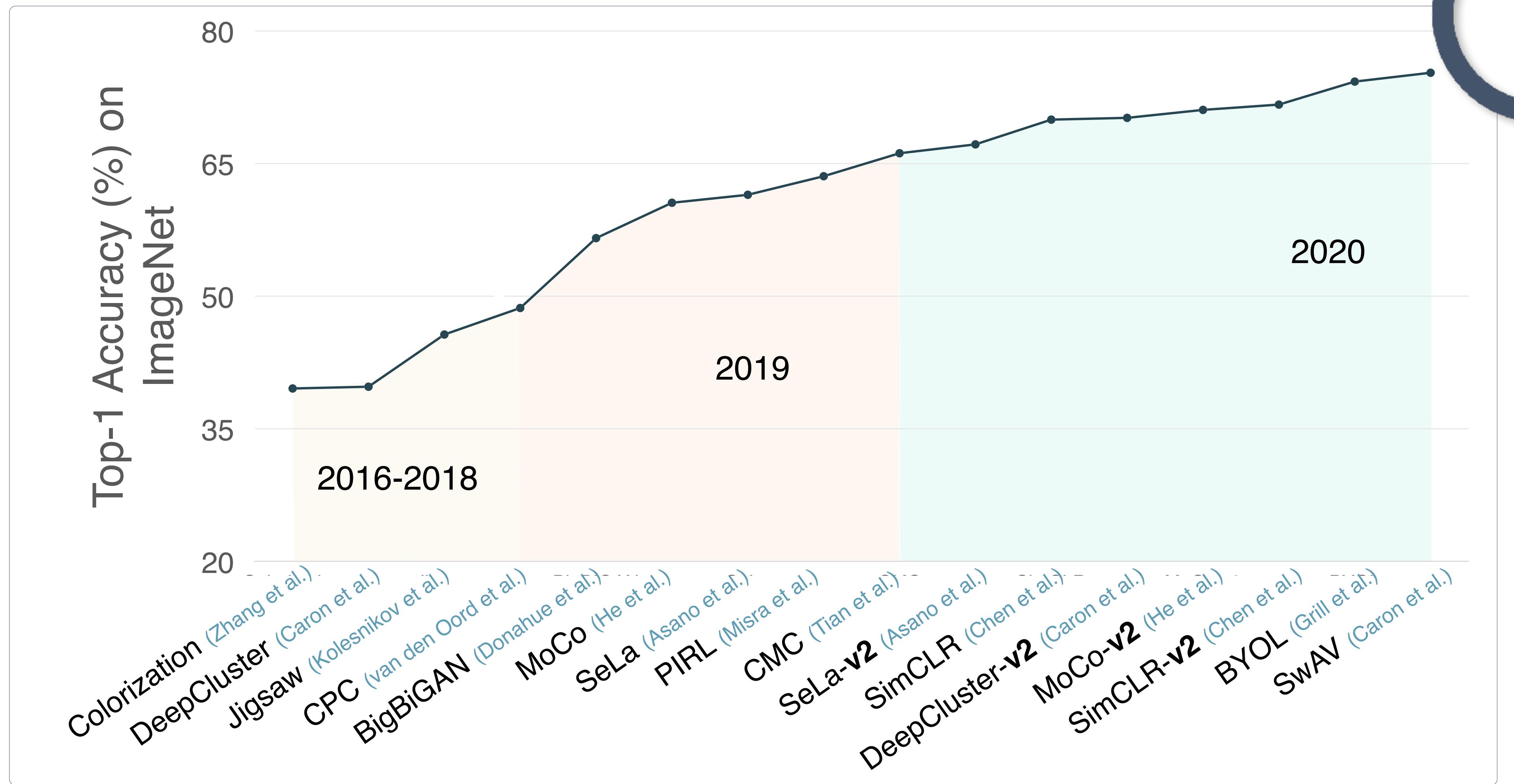


Visual Concept

Query

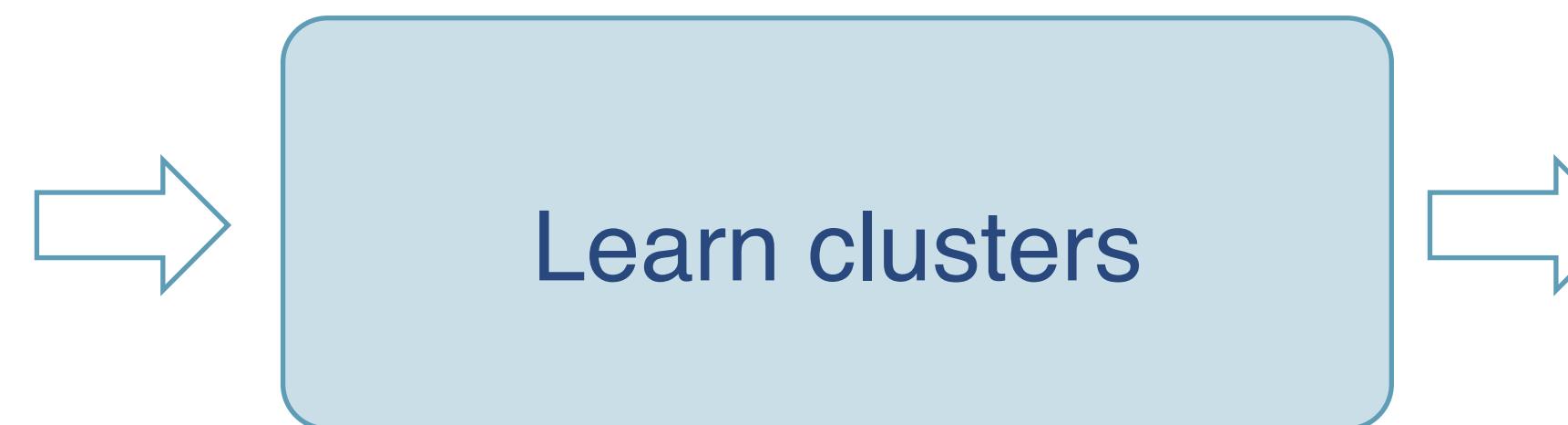


Self-Supervised Learning

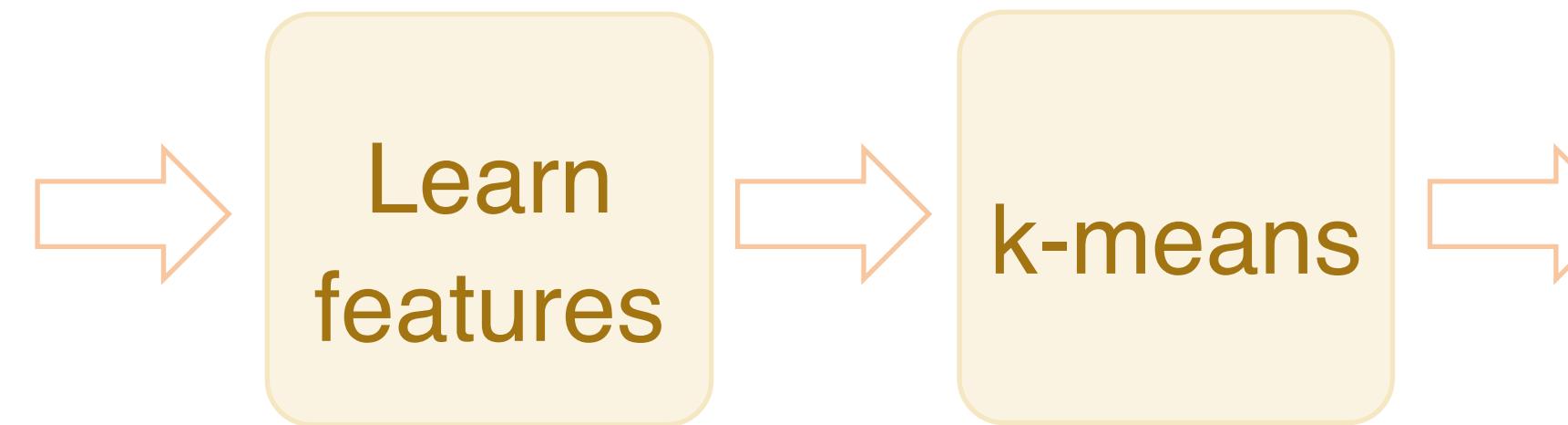
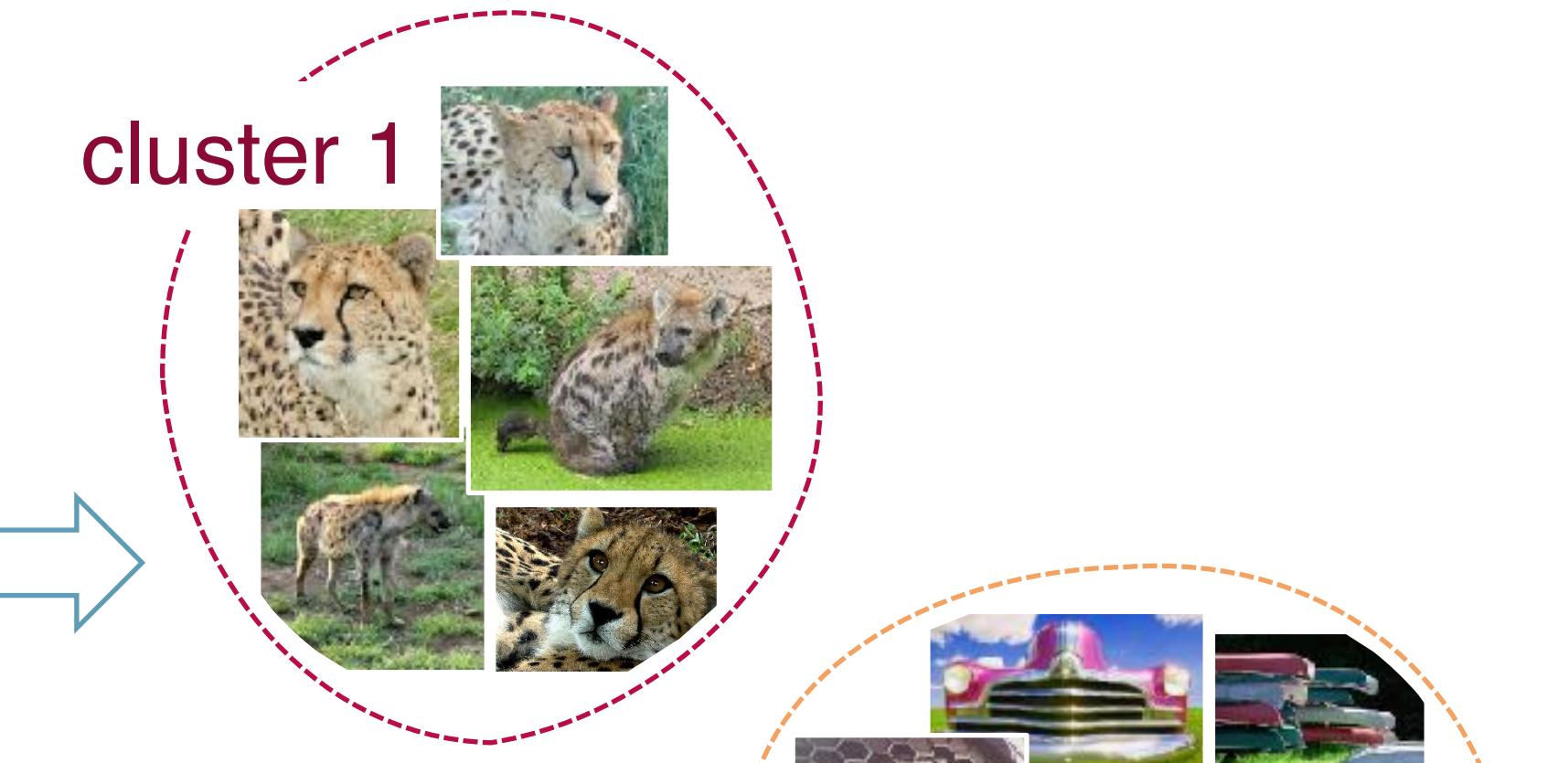


Self-Supervised Learning

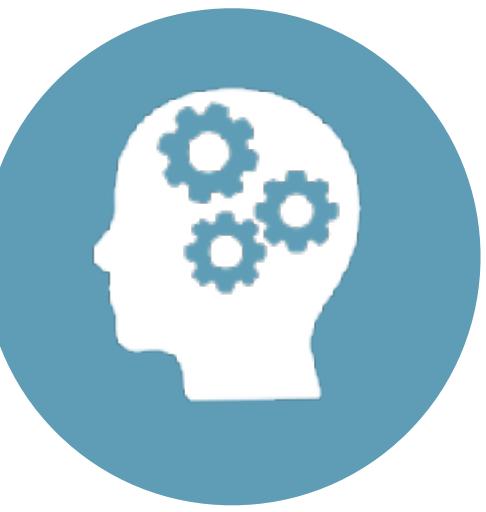
Unlabelled data



(e.g. DeepCluster, SeLa, SwaV)



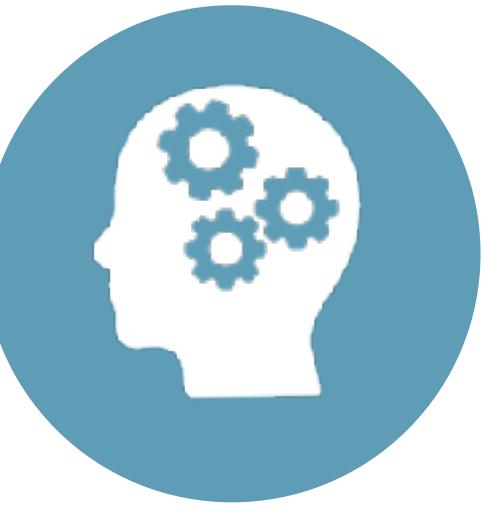
(e.g. SimCLR, MoCo, ...)



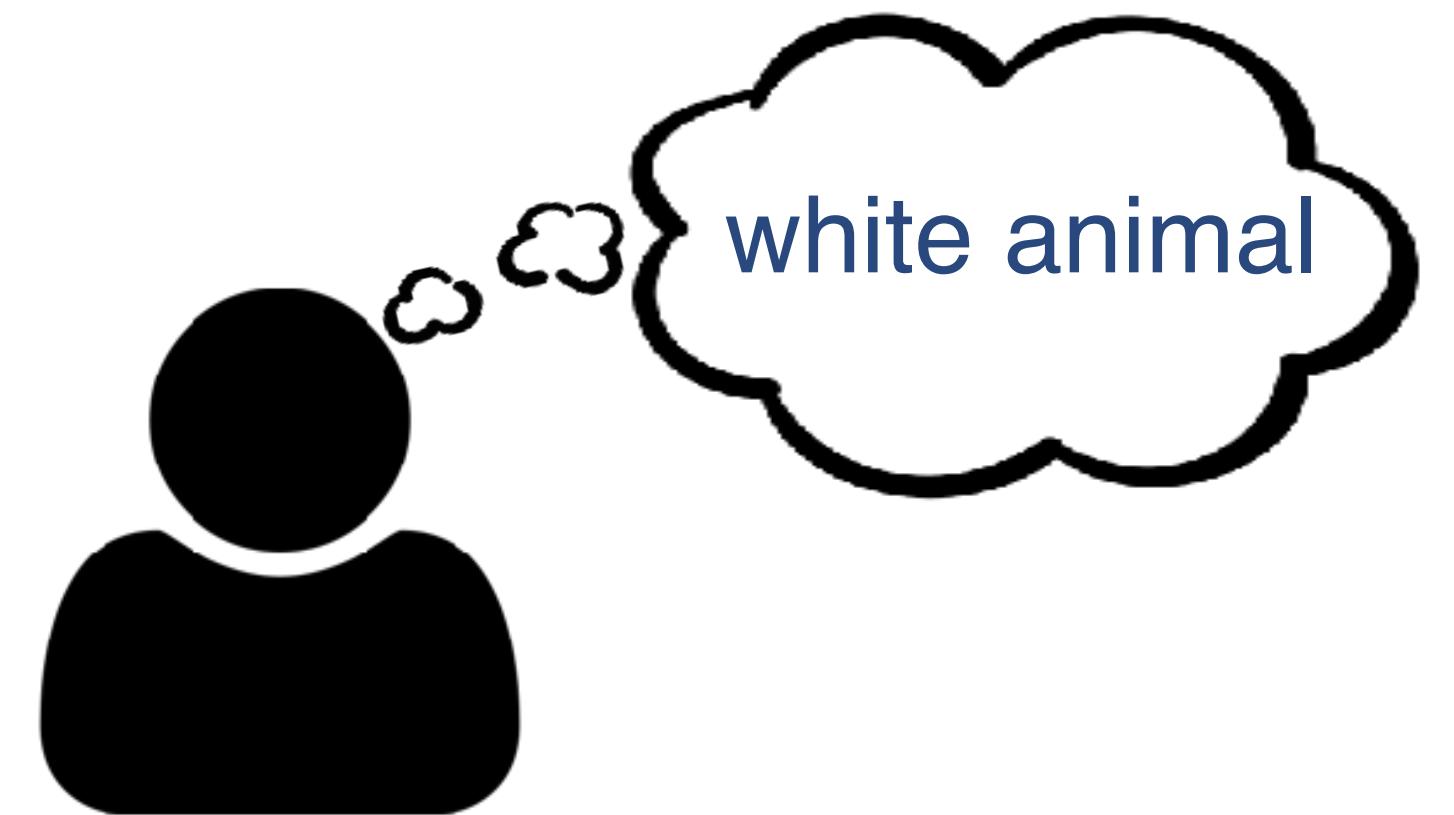
Learnability



[Iro Laina, et al., NeurIPS 2020. Quantifying Learnability and Describability.] [47](#)



Learnability



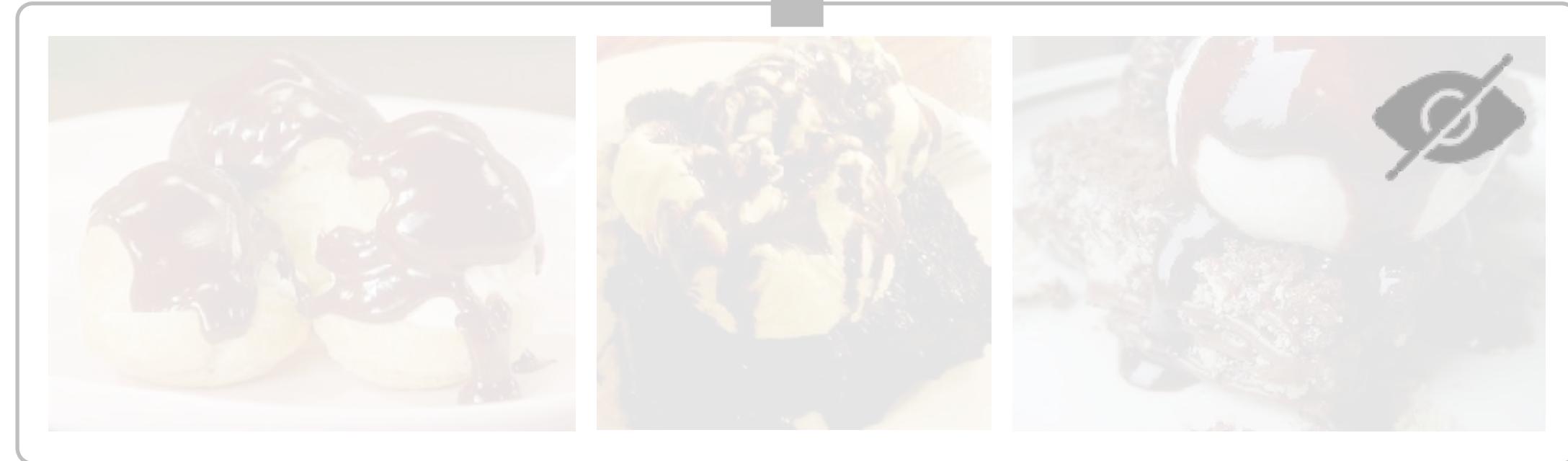
[Iro Laina, et al., NeurIPS 2020. Quantifying Learnability and Describability.] ⁴⁸



Describability

“

dessert with



(A)



(B)





Describability

“ dessert with



Manual

(A)



(B)





Describability

“

dessert with



Manual

OR



Automatic

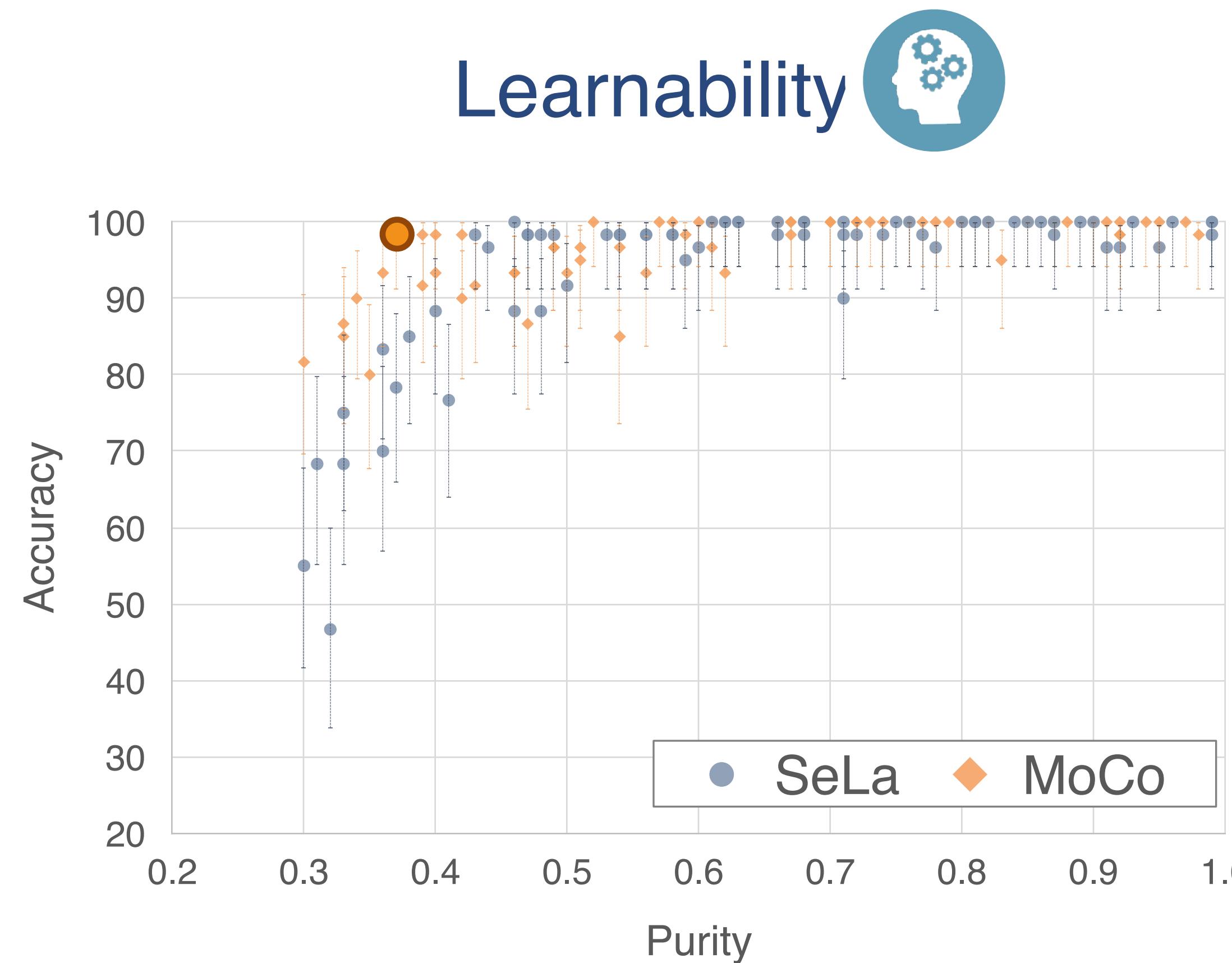
(A)



(B)



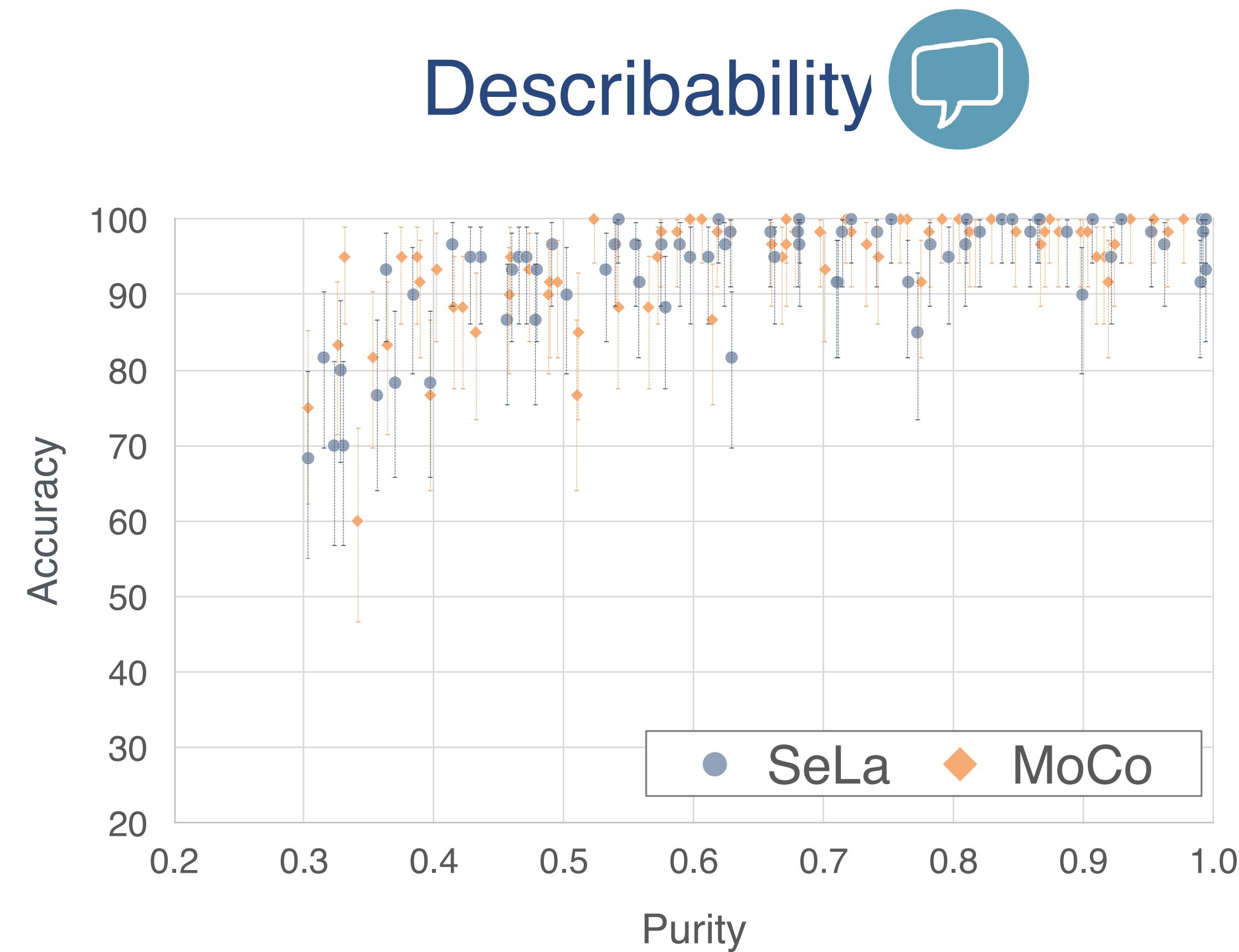
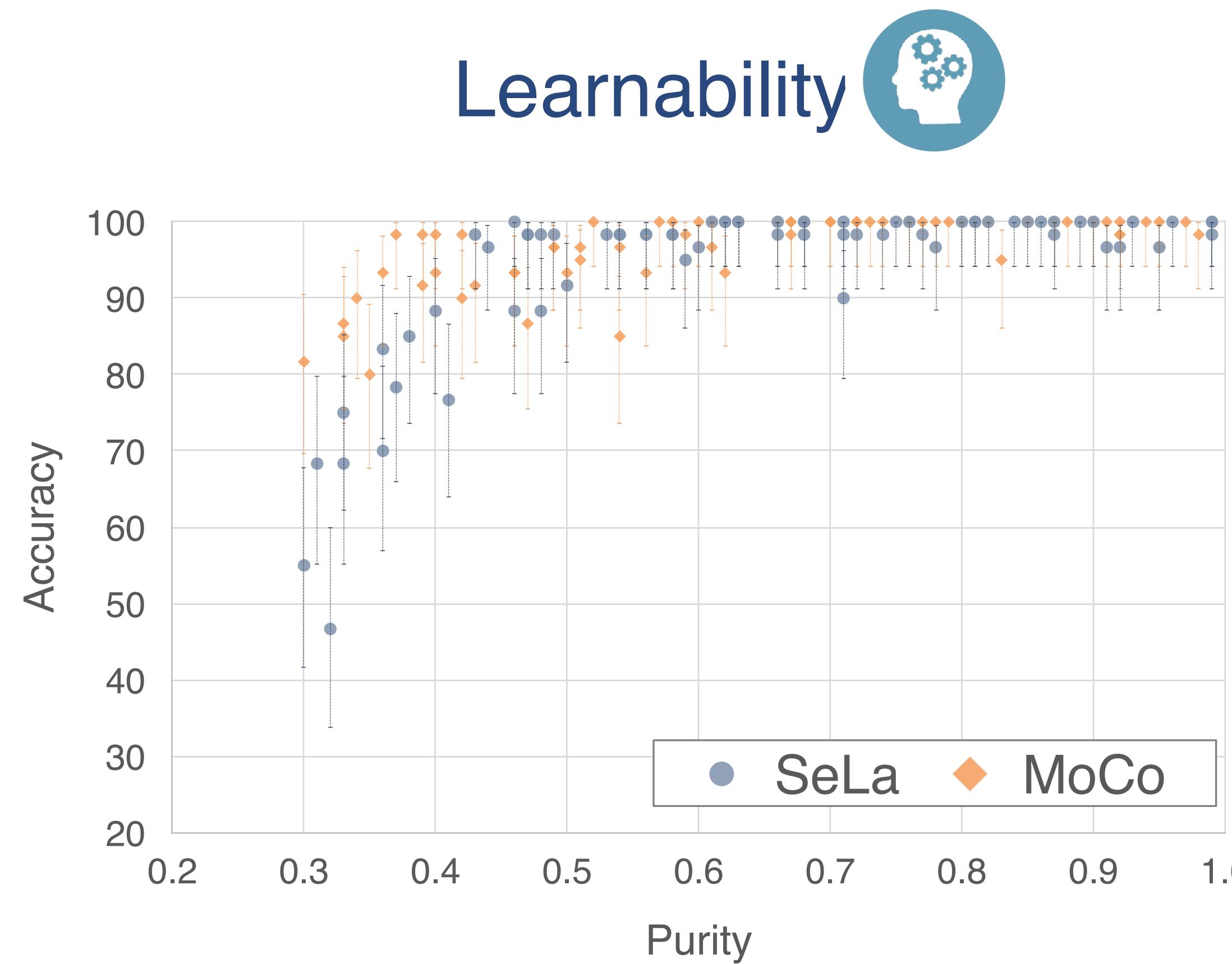
Evaluation



ImageNet cluster purity:
how correlated is a cluster's
contents to a single ImageNet
label?

*purity = 1 → cluster only contains
images from a single ImageNet label*

Evaluation



[Iro Laina, et al., NeurIPS 2020. Quantifying Learnability and Describability.]
[Asano et al., ICLR 2020; He et al., CVPR 2020]

Findings

SeLa: cluster 393 (0.668)
a newborn baby Irving on a



ImageNet cluster purity

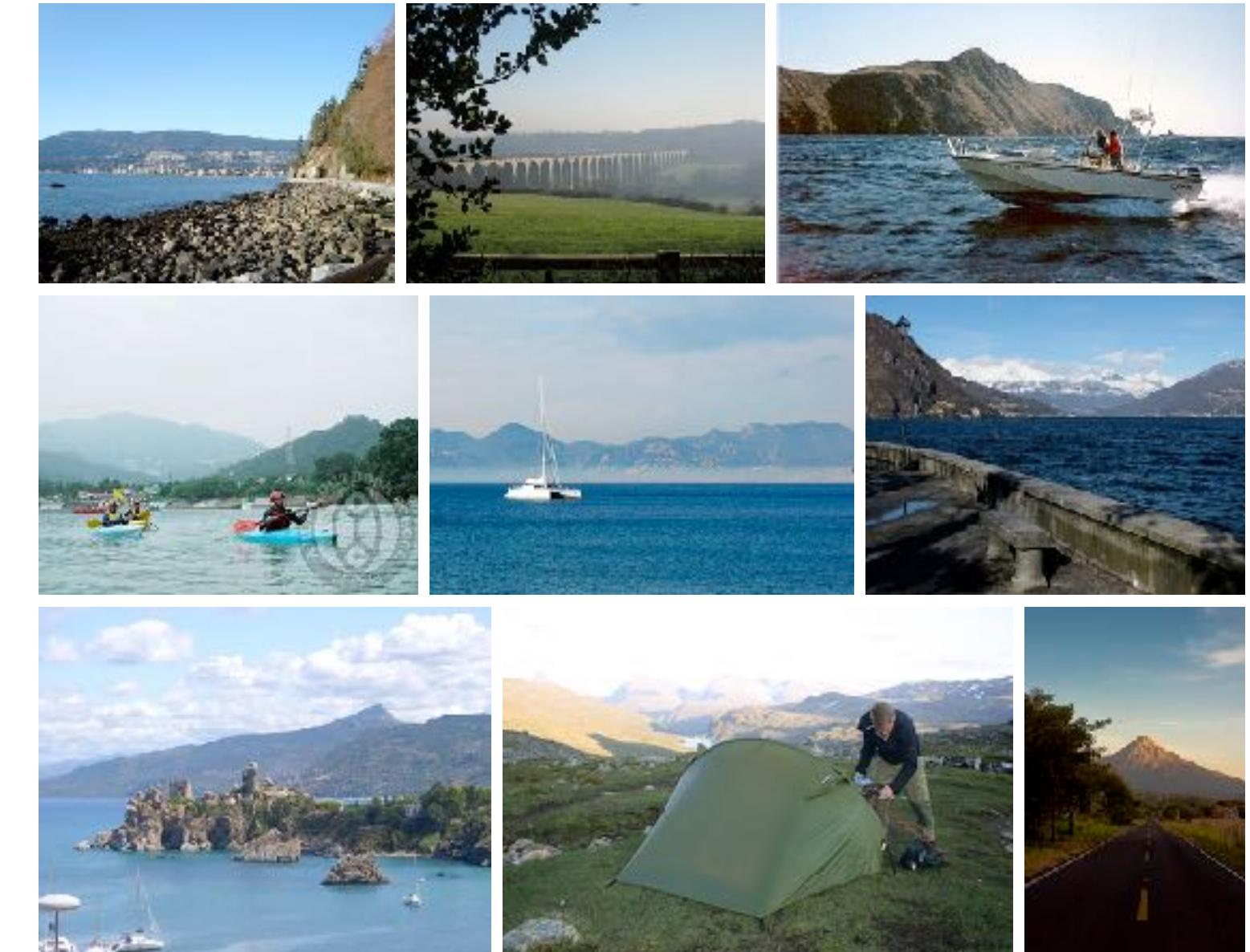


SeLa: cluster 332 (0.542)



Follow up: Laina et al., ICLR 2022.
Measuring the Interpretability of
Unsupervised Representations via

MoCo: cluster 2335 (0.459)
view of the mountains from the



98.3%



100.0%



93.3%



95.0%

[Iro Laina, et al., NeurIPS 2020. Quantifying Learnability and Describability.]
[Asano et al., ICLR 2020; He et al., CVPR 2020]

Challenges for novel frontiers in deep learning

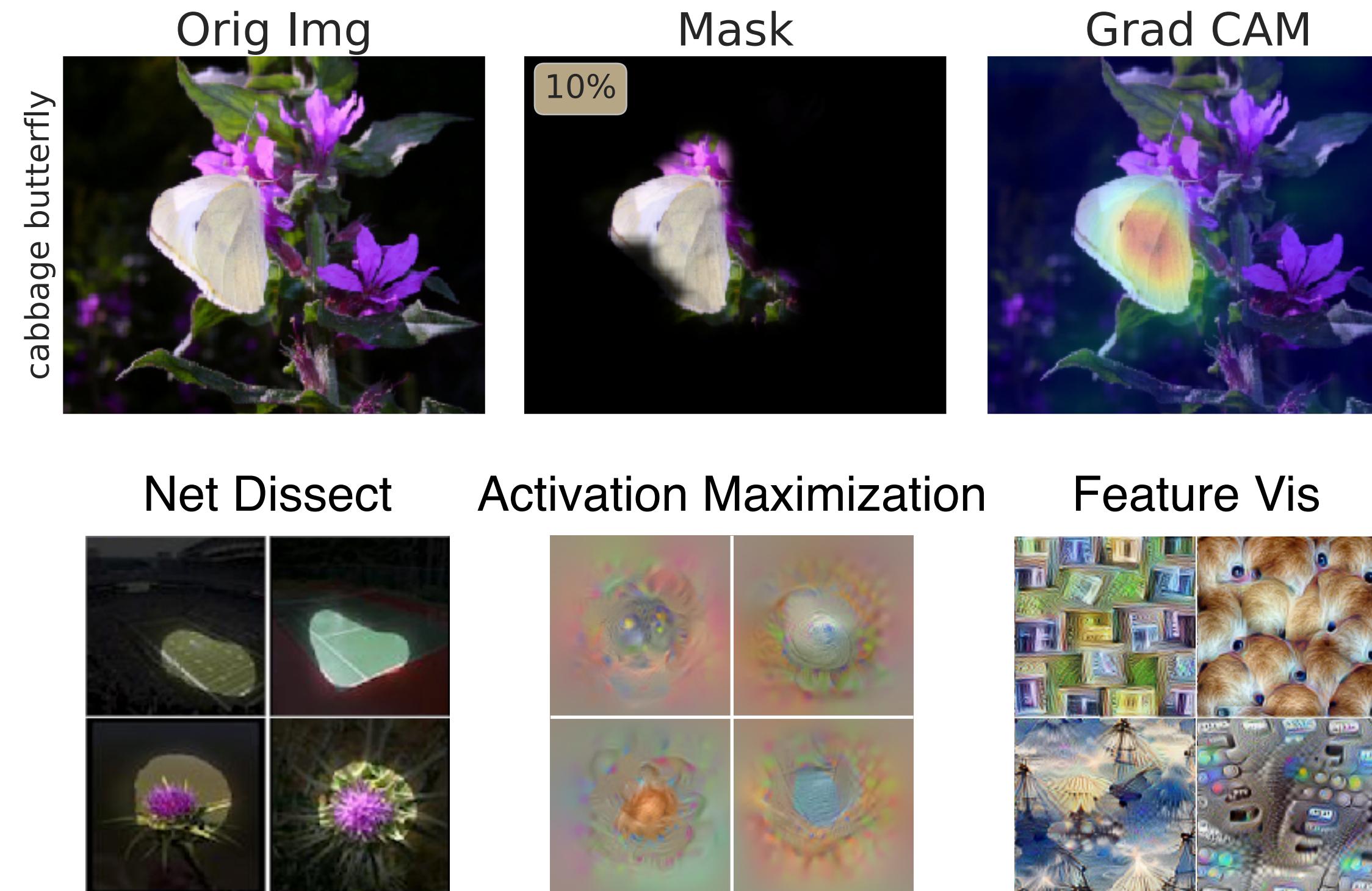
- Need to contextualize interpretability to the novel frontiers
- Lack of access to standardized implementations

Takeaway: Collaboration and buy-in from novel research areas is crucial for interpretability in those frontiers.

Roadmap

1. **Automated evaluation of interpretability → human-centered evaluation**
Sunnie S. Y. Kim, Nicole Meister, Vikram V. Ramaswamy, Ruth Fong, Olga Russakovsky, arXiv 2021.
HIVE: Evaluating the Human Interpretability of Visual Explanations.
2. **Explanations via labelled attributes → explanations via labelled attributes and unlabelled features**
Vikram V. Ramaswamy, Sunnie S. Y. Kim, Nicole Meister, Ruth Fong, Olga Russakovsky, arXiv 2022.
ELUDE: Generating Interpretable Explanations via a Decomposition into Labelled and Unlabelled Features.
3. **Interpretability of supervised models → interpretability of self-supervised models**
Iro Laina, Ruth Fong, Andrea Vedaldi, NeurIPS 2020.
Quantifying Learnability and Describability of Visual Concepts Emerging in Representation Learning.
4. **Static visualizations → interactive visualizations**
Ruth Fong, Alexander Mordvintsev, Andrea Vedaldi, Chris Olah, VISxAI 2021.
Interactive Similarity Overlays.

Interpretability Tools

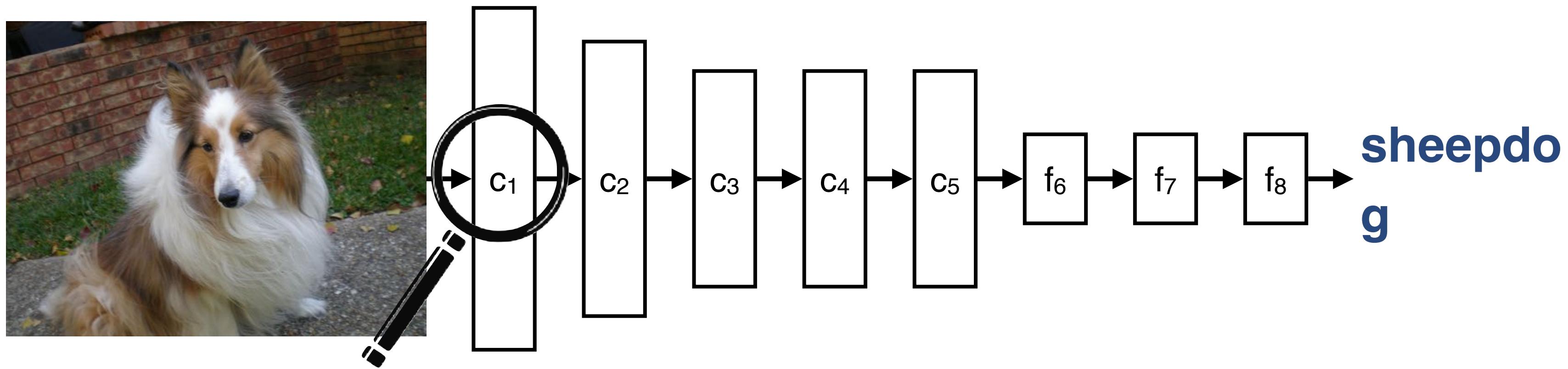


Current tools render **static images**.

Future tools should be **interactive!**

[Fong et al., ICCV 2019; Selvaraju et al., ICCV 2017; Bau et al., CVPR 2017;
Mahendran & Vedaldi, IJCV 2016; Olah et al., Distill 2018; Fong et al., VISxAI 2021]

Interpretability: Interactive. Exploratory. Easy-to-use



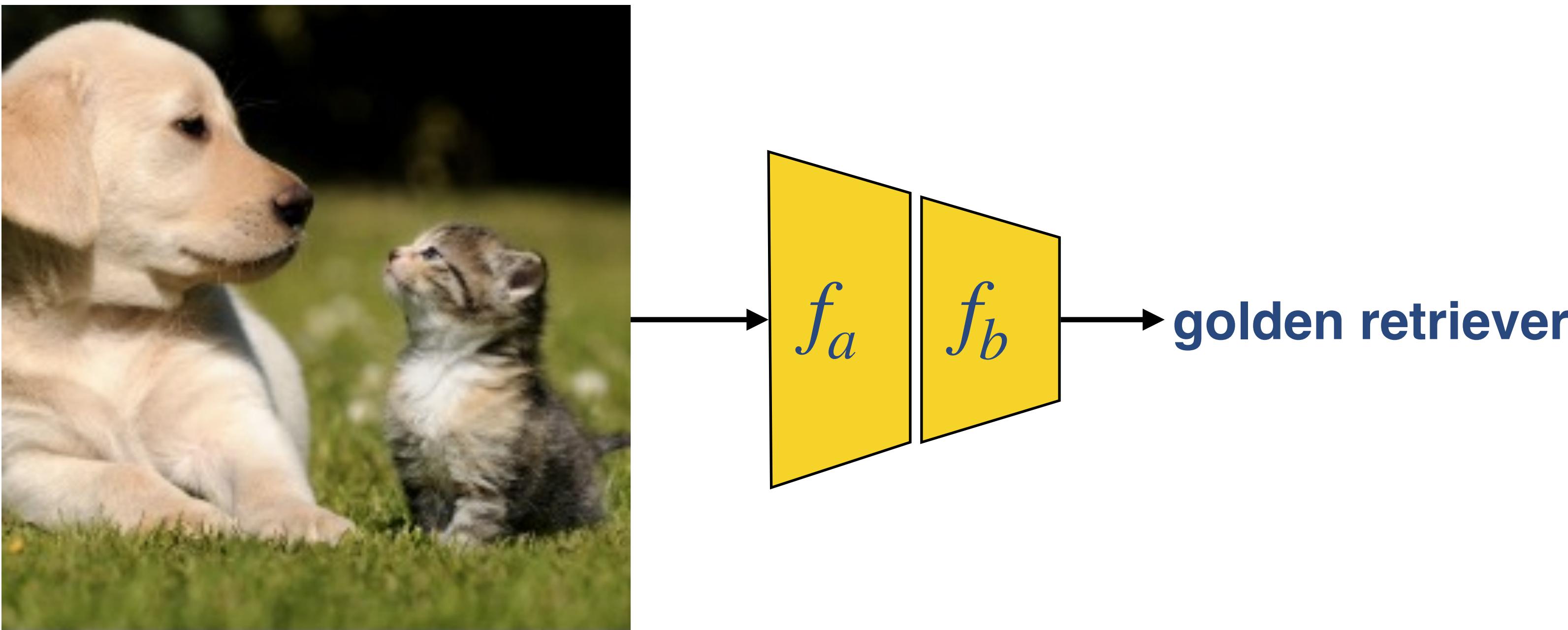
How can we **easily explore** hypotheses about the model?

Interactive Similarity Overlays

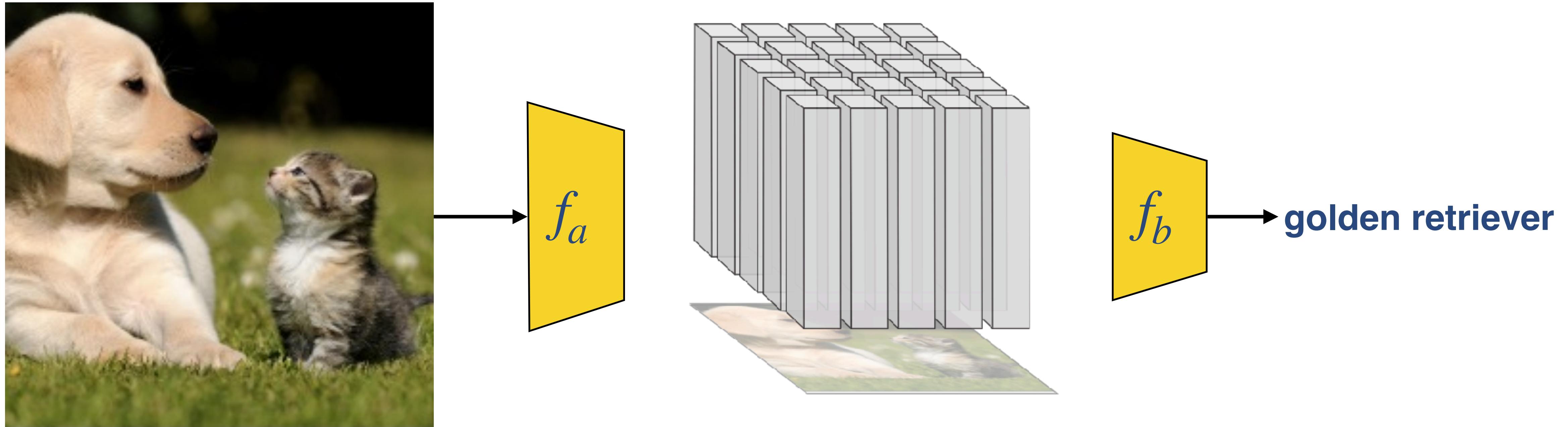


Ruth Fong, Alexander Mordvintsev, Andrea Vedaldi, Chris Olah, VISxAI 2021.
Interactive Similarity Overlays. 59

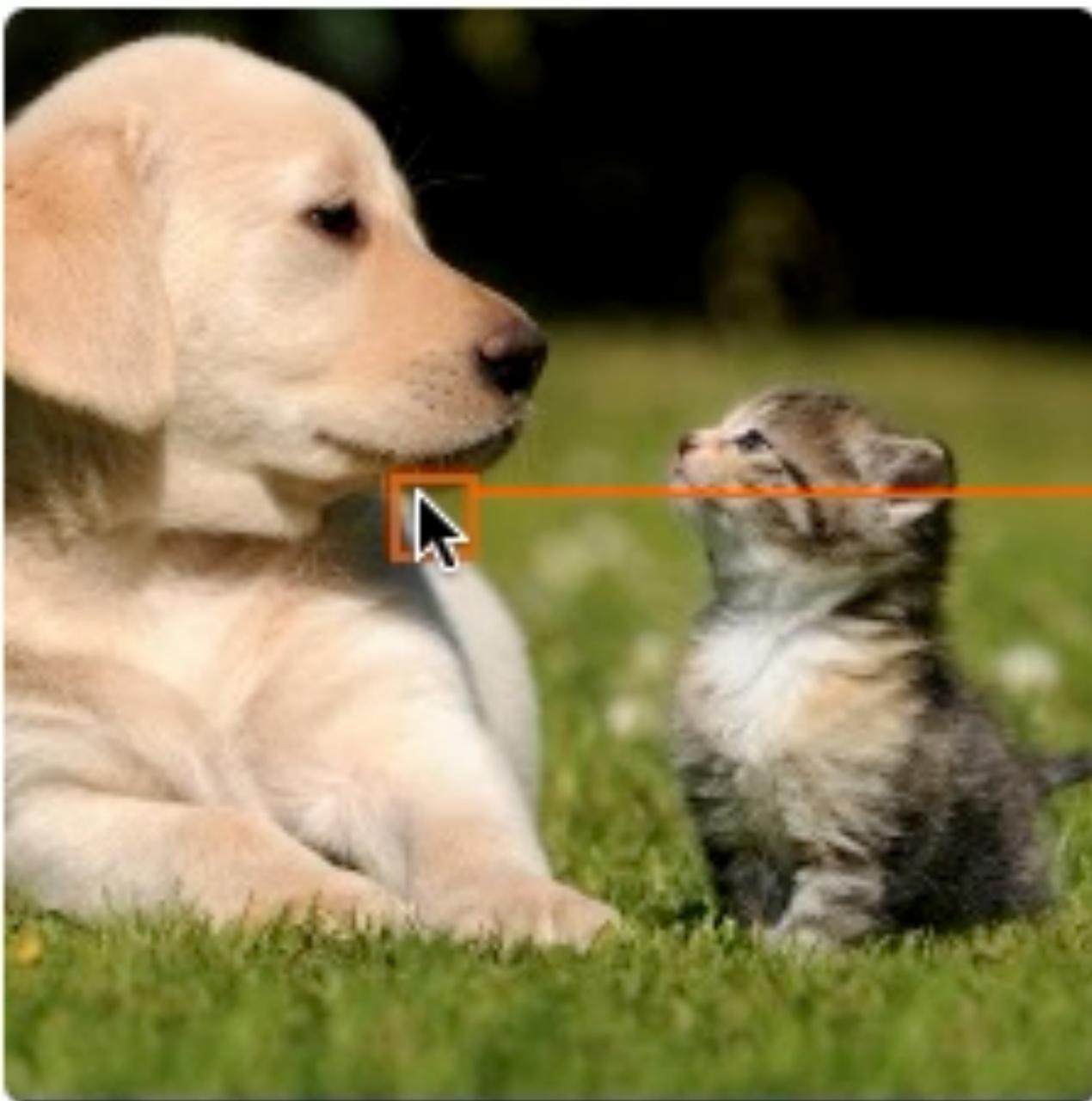
Spatial Activations



Spatial Activations

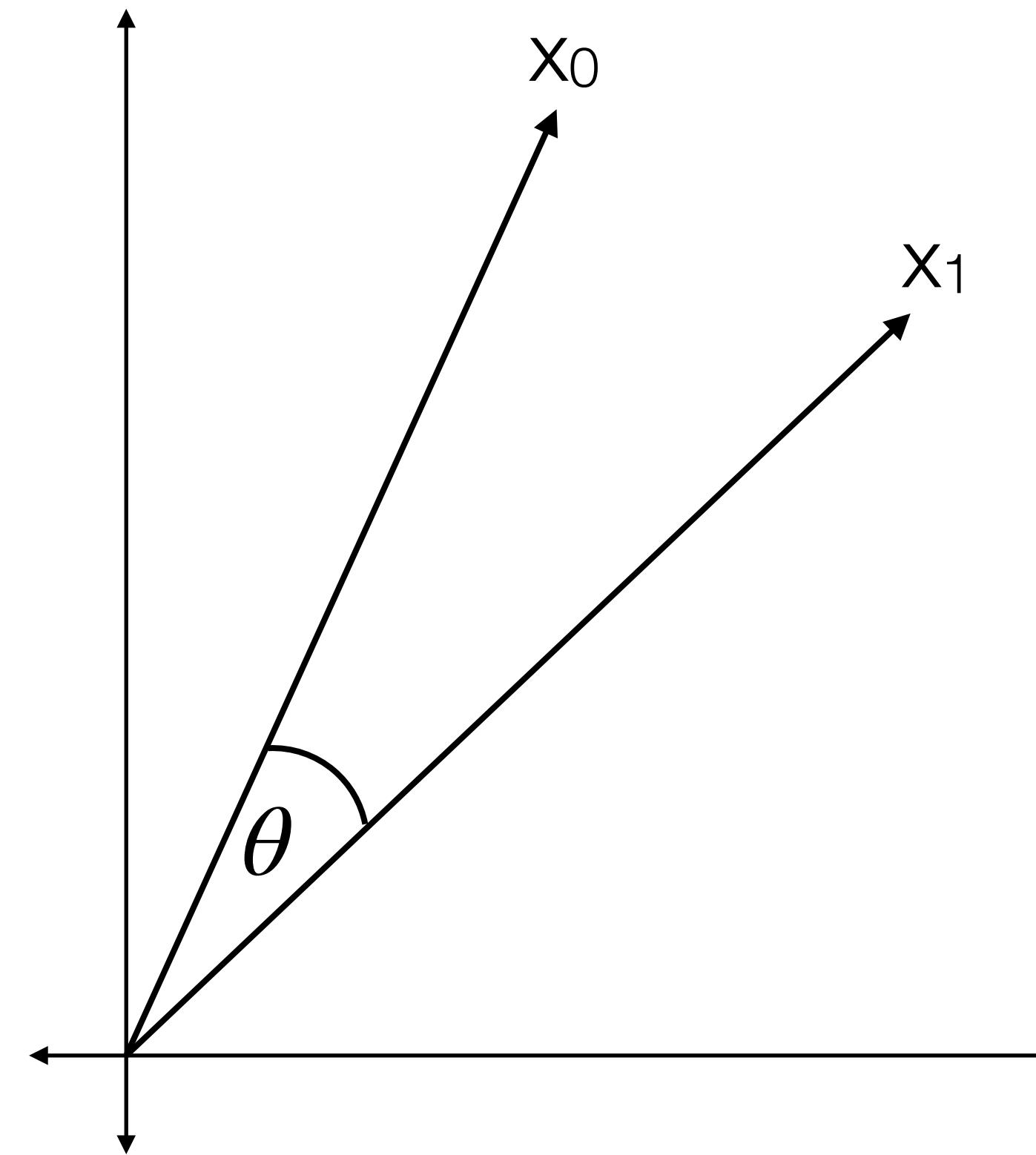
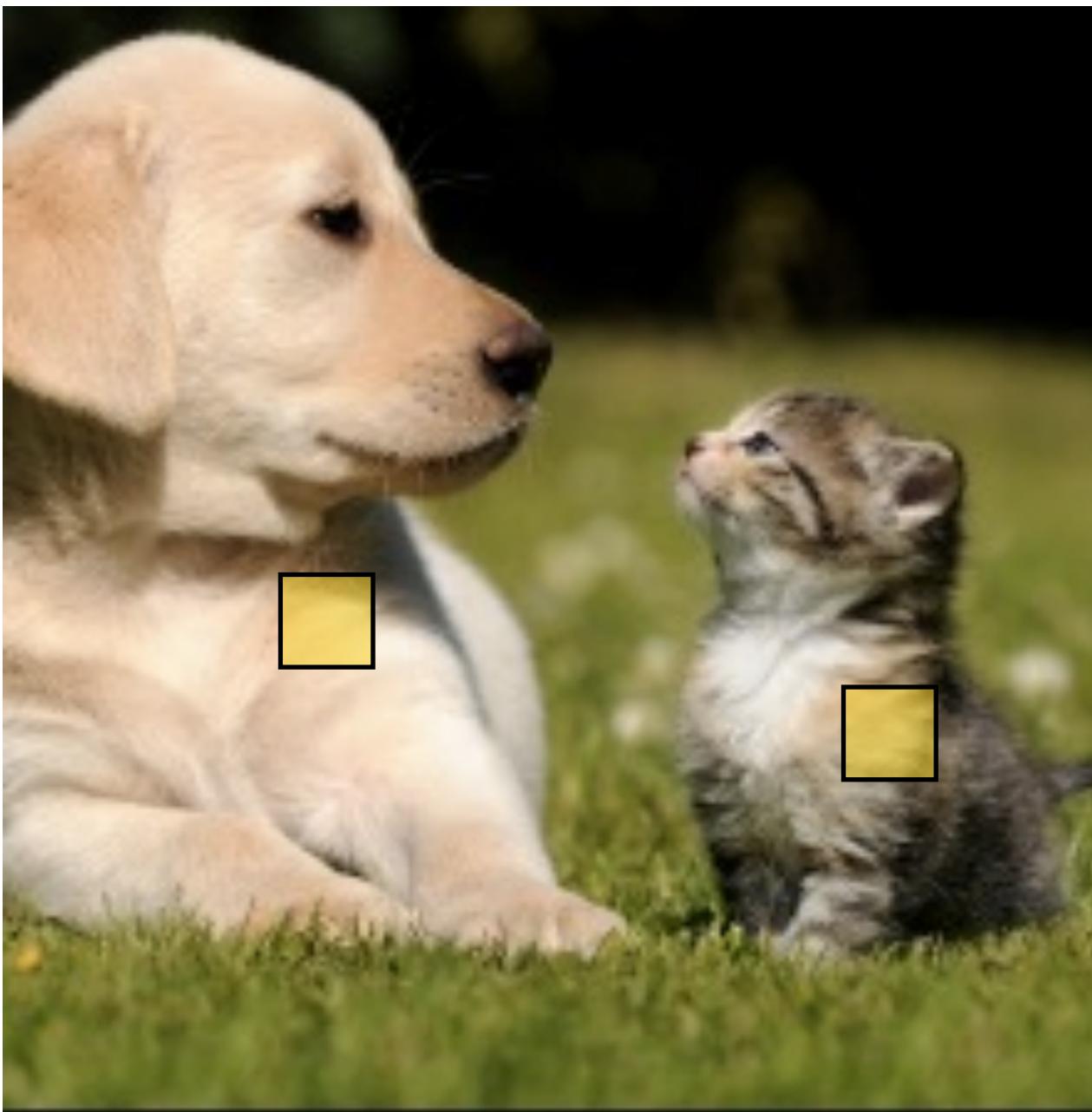


Interactive Similarity Overlays



$a_{6,5} = [17.7, 0, 103.4, 6.81, 0, 0, 0, 0, 32.0, 0, 0, 0, \dots]$

Interactive Similarity Overlays

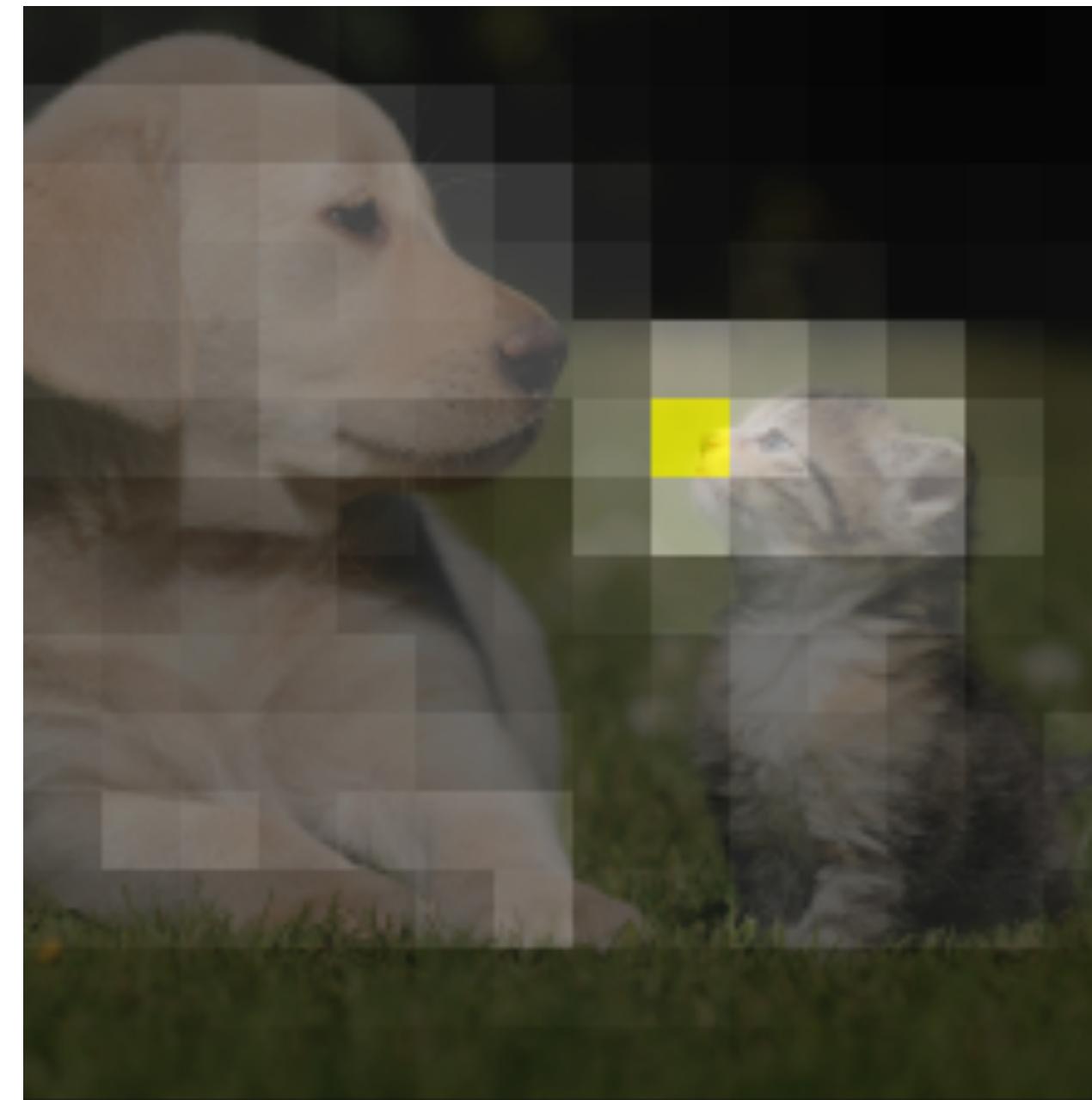


[Fong et al., VISxAI 2021. Interactive Similarity Overlays.] 63



Demo: Interactive Similarity Overlays

bit.ly/interactive_overlay

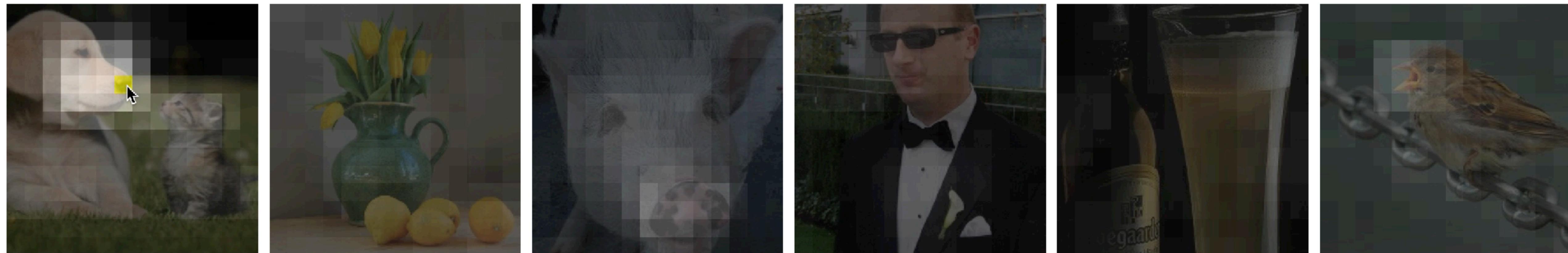


Interactive visualizations empower practitioners to easily explore model behavior.

[Fong et al., VISxAI 2021. Interactive Similarity Overlays.] ⁶⁴

Interactive Similarity Overlays

An interactive tool for understanding what neural networks consider similar and different.

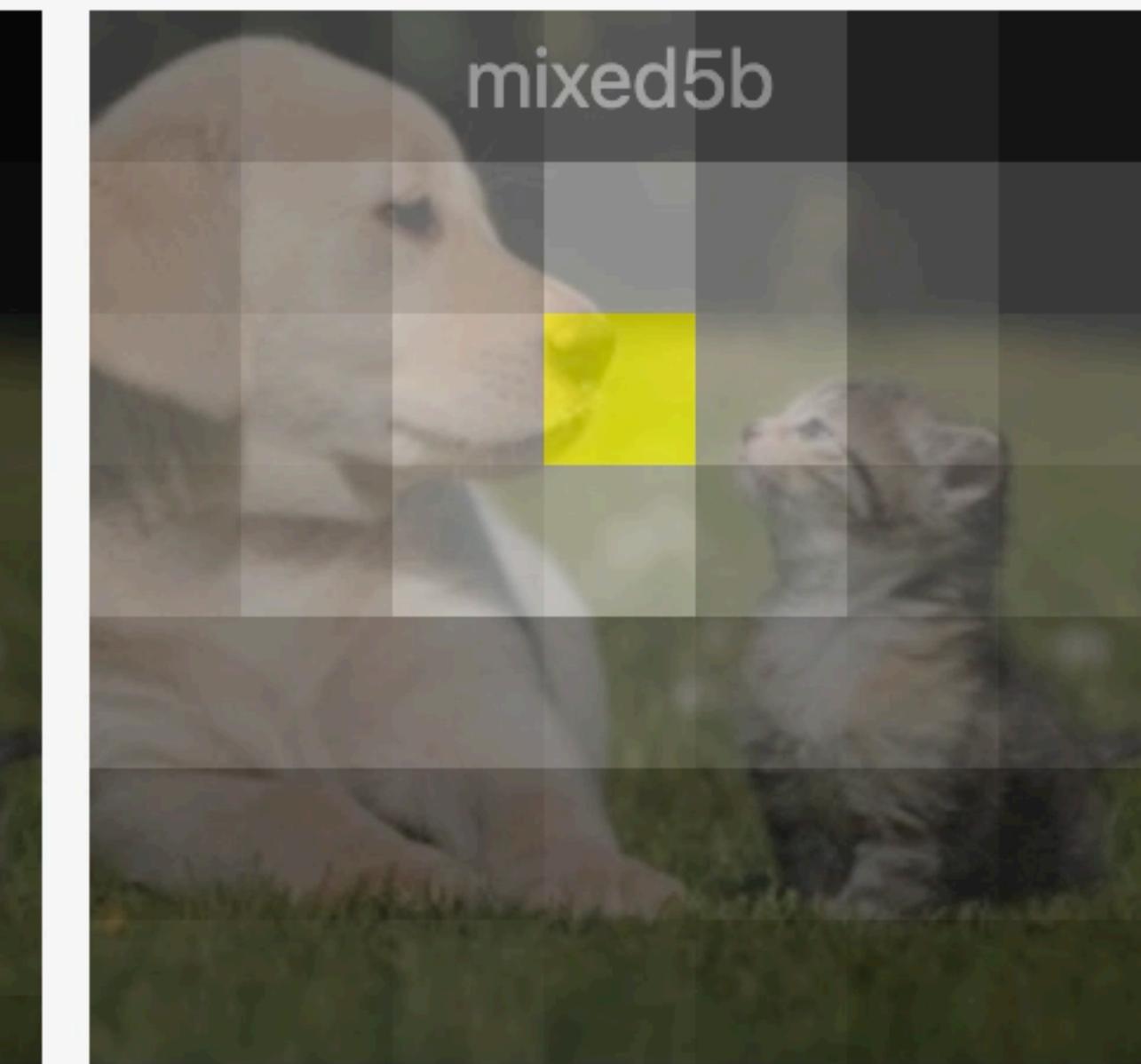
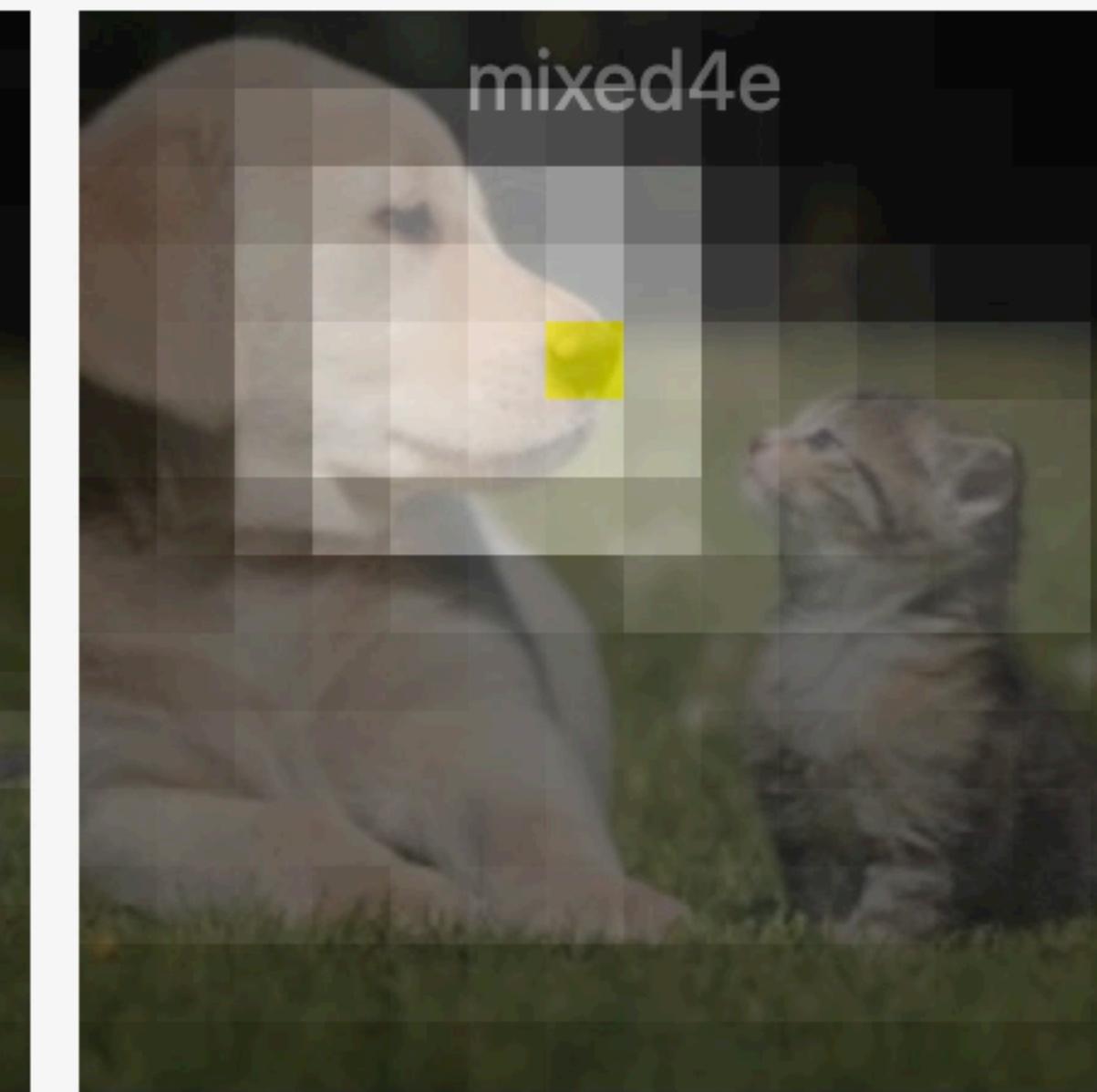
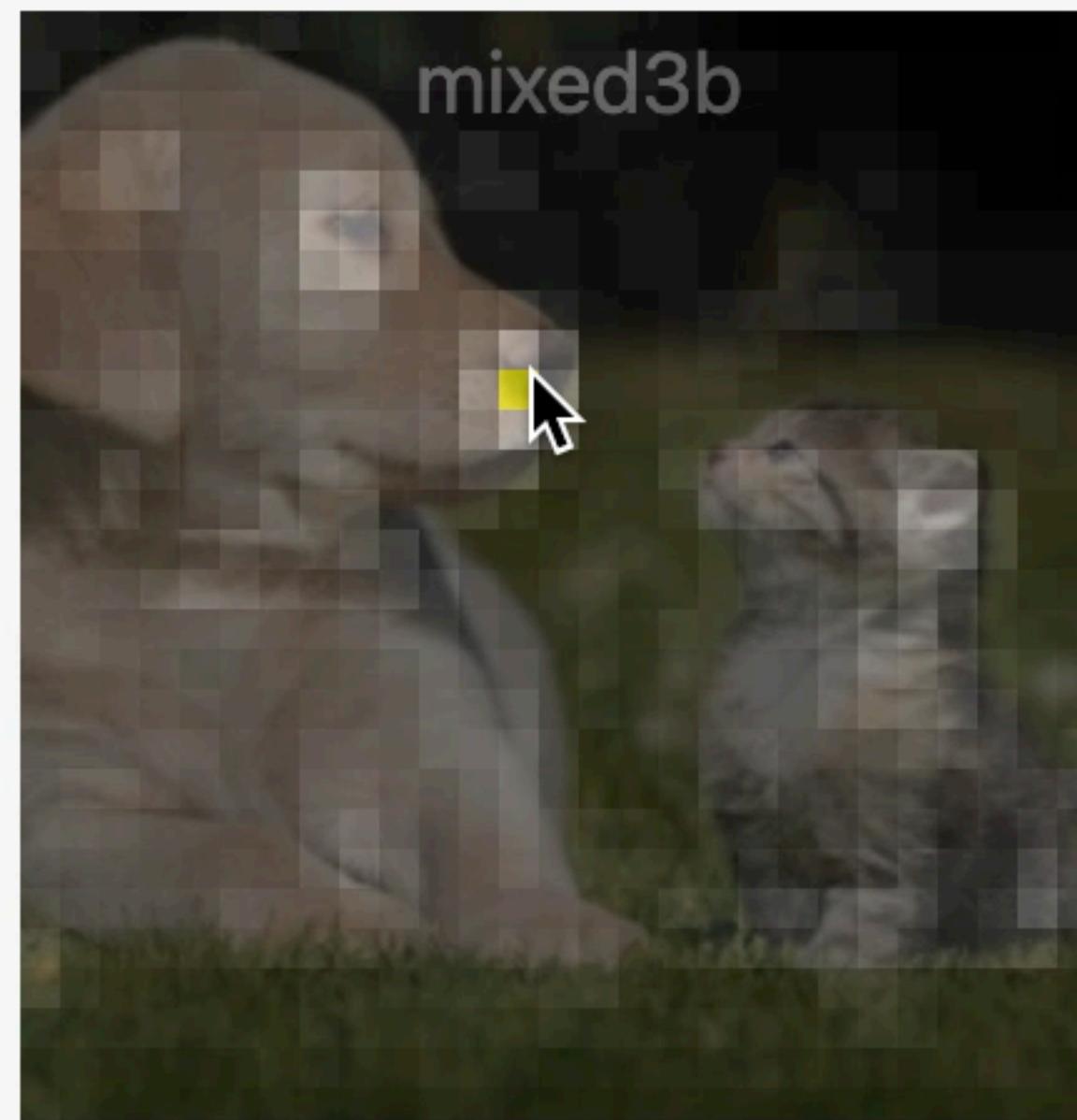


Hover over different parts of the above images. This interactive visualization shows how similar (or different) a neural network considers different image patches to the current image patch (highlighted in yellow). Try hovering over animal features (e.g., noses, eyes, faces) and background regions.

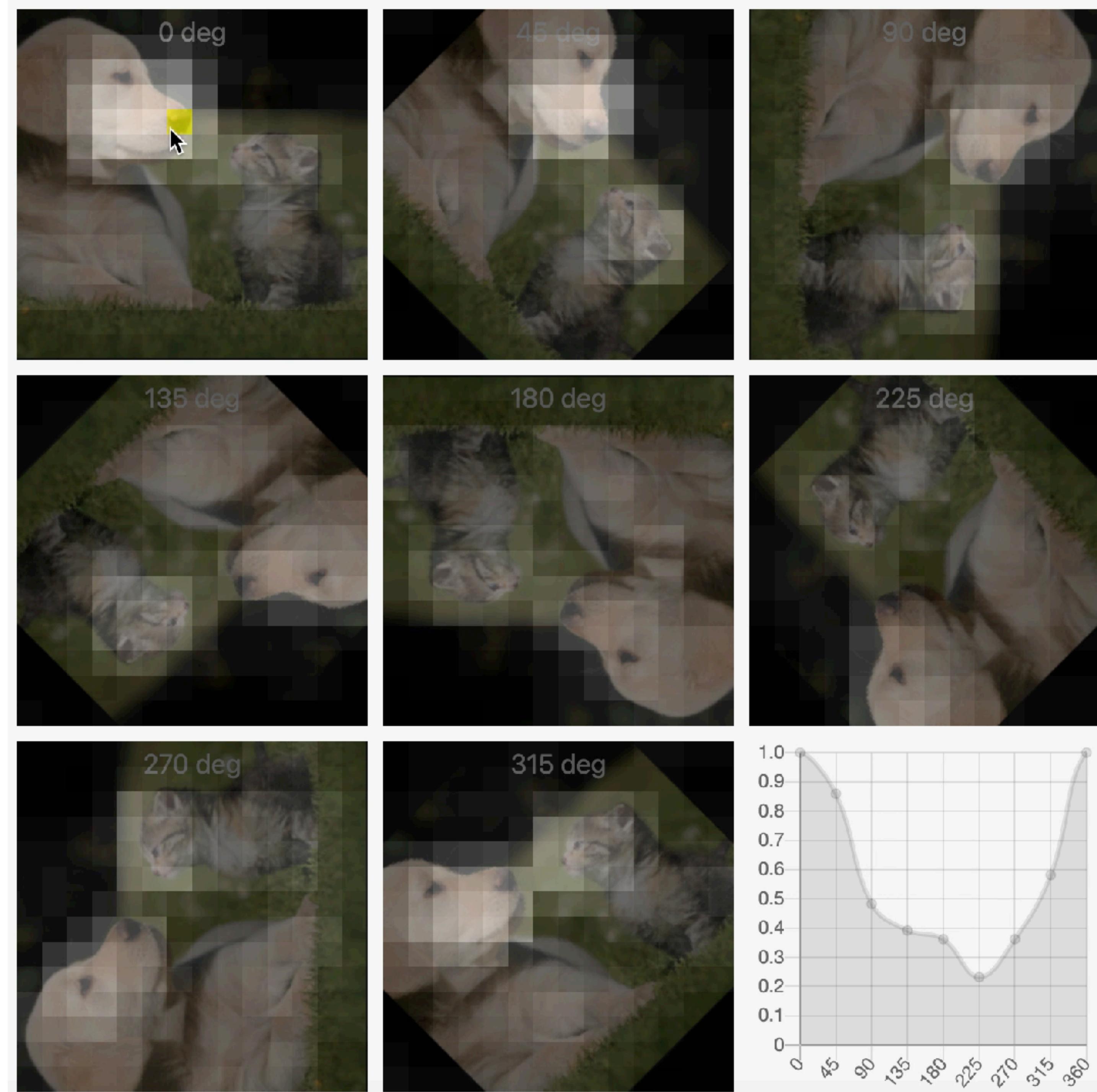
This article is best viewed in Google Chrome.

REPRODUCE IN A
 NOTEBOOK

Layers with different spatial resolutions.



The location of the highlighted image patch (in yellow) has been synchronized across images, such that the overlays show similarity scores with respect to each image's highlighted patch (i.e., no similarity scores were computed between images). Consider exploring edges in mixed3b layers and semantic features (e.g., objects and object parts, like noses and eyes) in mixed4e and mixed5b layers.





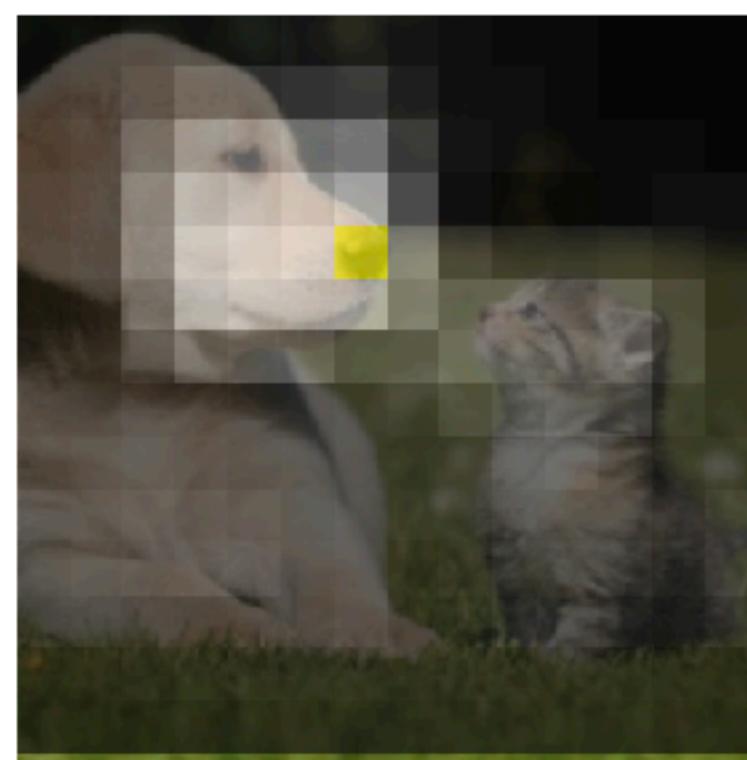
+ Code + Text Copy to Drive

```
[ ] # Get images
img_urls = [
    "https://raw.githubusercontent.com/ruthcfong/interactive_overlay/master/images/dog_cat.jpeg",
    "https://raw.githubusercontent.com/ruthcfong/interactive_overlay/master/images/flowers.jpeg",
    "https://raw.githubusercontent.com/ruthcfong/interactive_overlay/master/images/pig.jpeg",
    "https://raw.githubusercontent.com/ruthcfong/interactive_overlay/master/images/bowtie_guy.jpeg",
    "https://raw.githubusercontent.com/ruthcfong/interactive_overlay/master/images/beer.jpeg",
    "https://raw.githubusercontent.com/ruthcfong/interactive_overlay/master/images/chain.jpeg"
]
imgs = [load(url) for url in img_urls]
```

```
model = models.InceptionV1()
model.load_graphdef()
```

```
[ ] acts = get_acts(model, imgs[0], "mixed4d")
grid = np.hstack(np.hstack(cossim_grid(acts, acts)))
colored_grid = add_color_index(grid, acts.shape[0])
```

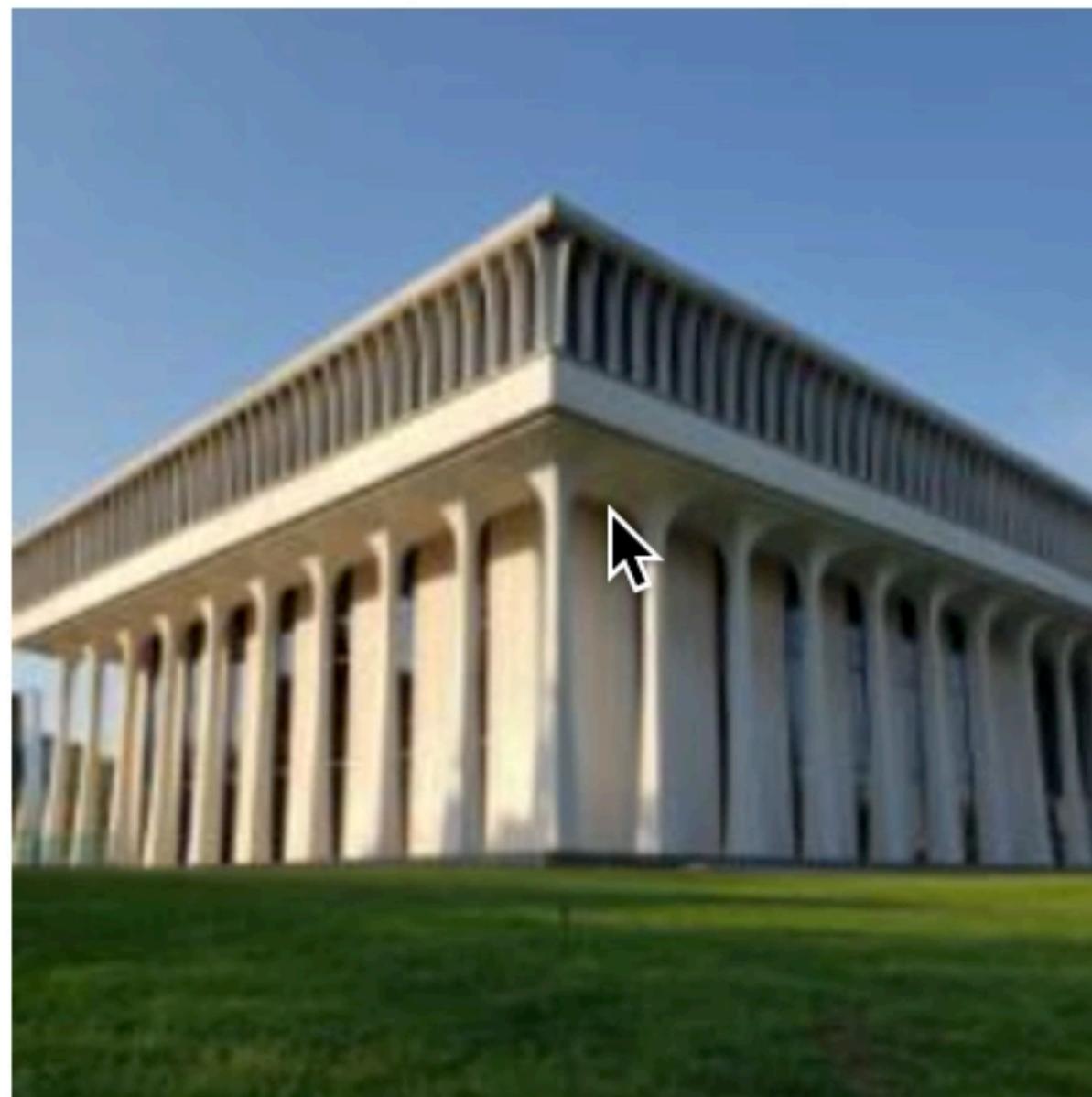
```
lucid_svelte.CossimOverlay({
    "image_url": _image_url(imgs[0]),
    "masks_url": _image_url(colored_grid),
    "size": 224,
    "N": acts.shape[0],
})
```



Preview: Interactive Visual Feature Search



bit.ly/interactive_search Devon Ulrich



Devon Ulrich and Ruth Fong, in prep 2022.
Interactive Visual Feature Search. ⁶⁹
Acknowledgement: David Bau

Challenges for interactive visualizations

- Skills cost: web development skills
 -  HuggingFace Spaces, Gradio, Streamlit
 - Potential misuse: Intuition-based insights should be validated via quantitative experiments
 - Poor incentives: software tooling for research is often not rewarded
 - Inadequate publishing structures: Sparse publishing venues for interactive articles and/or visualizations
 -  Distill journal hiatus
 -  CVPR demo track
 - Lack of cross-talk: HCI and AI communities are developing interpretability tools fairly independently
- Takeaway:** Relevant research communities should collectively invest in and reward software tooling for research, particularly interactive tools.

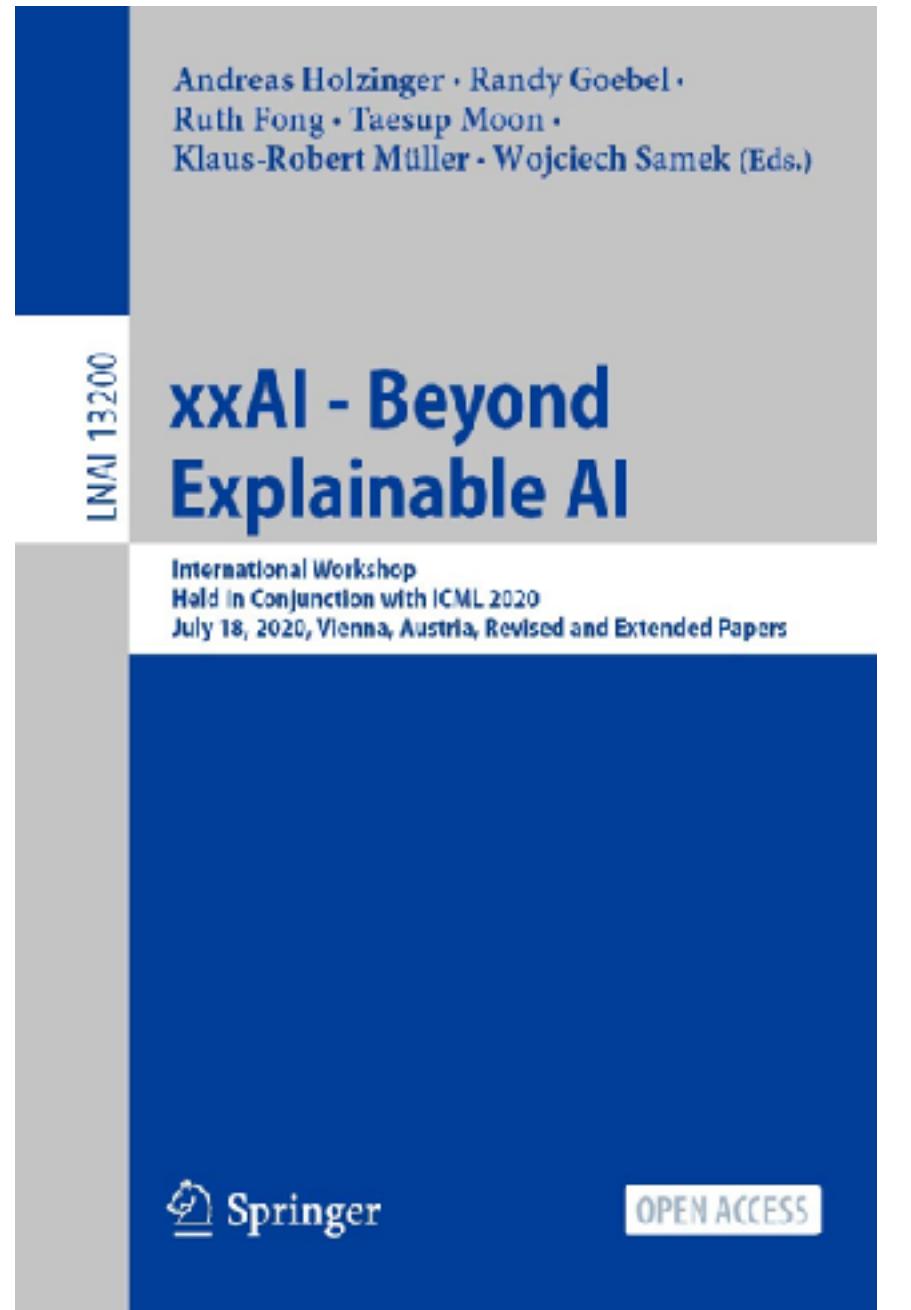
Takeaways from challenges in interpretability

- **Human studies:** As a research community, invest in and reward human evaluation studies (like dataset development).
- **(Concept-based) interpretability:** Be realistic about the benefits and limitations of an interpretability method and work towards addressing the limitations.
- **New frontiers:** Collaboration and buy-in from novel research areas is crucial for interpretability in those frontiers.
- **Interactive visualizations:** Relevant research communities should collectively invest in and reward software tooling for research, particularly interactive tools.

Directions for the next decade of interpretability

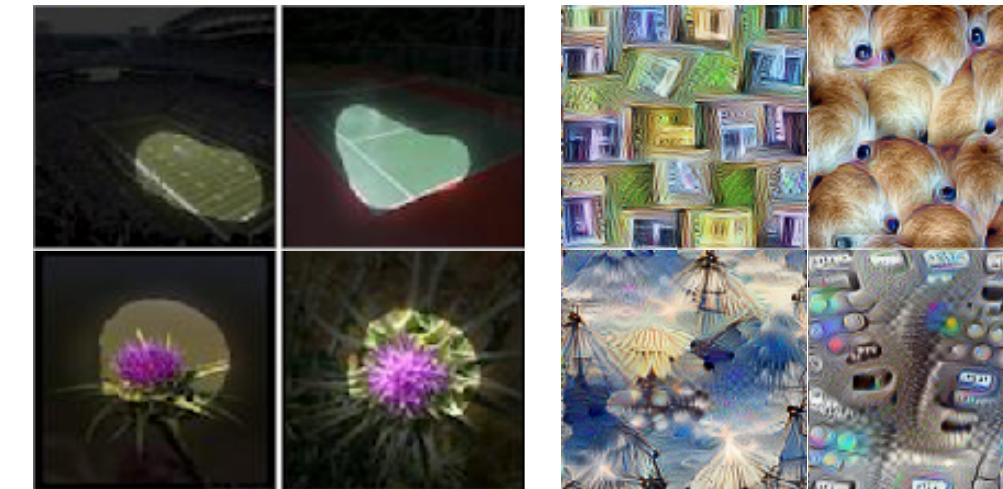
1. Develop interpretability methods for **diverse domains**
 - Beyond CNN classifiers: self-supervised learning, generative models, etc.

2. Center **humans** throughout the development process
 - In design, co-develop methods with real-world stakeholders.
 - In evaluation, measure human interpretability and utility of methods.
 - In deployment, package interpretability tools for the wider community.



[ICML 2020 workshop on XXAI](#)

An incomplete retrospective: the first decade of interpretability



Primarily focused on
understanding and

Feature visualization (2013-2018)
Activation Max., Feature Inversion,
Net Dissect, Feature Vis.



Attribution heatmaps (2013-2019)
Gradient, Grad-CAM,
Occlusion, Perturbations, RISE

Interpretable-by-design (2020-now)
Concept Bottleneck, ProtoPNet,
ProtoTree

[Selvaraju et al., ICCV 2017; Fong* & Patrick* et al., ICCV 2019; ⁷³
Bau* & Zhou* et al., CVPR 2017; Olah et al., Distill 2017; Koh*, Nguyen*, Tang* et al., ICML 2020]

Into the future: the next decade of interpretability

???





Iro Laina



Devon Ulrich



Nicole Meister



Sunnie S. Y.



Vikram V.



Andrea Vedaldi



Chris Olah



Alex



Olga

bit.ly/vai-lg-postdoc



We're hiring

Talk acknowledgements: Brian Zhang, Sunnie S. Y. Kim, Vikram V. Ramaswamy, Olga Russakovsky

Thank You