# Directions in Interpretability

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CVPR 2022, Human-Centered AI Tutorial

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Slides and links available at ruthfong.com

# What is interpretability?

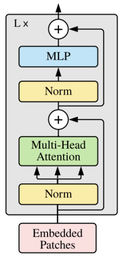
Research focused on explaining **complex AI systems** in a **human-interpretable** way.

# Why interpretability?

- 🔬 Science
- 🤝 Trust
- 🤖 Learning

# An incomplete retrospective: the first decade of deep learning

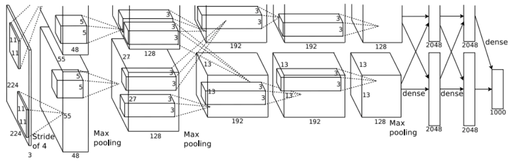

**GANs (2014-2018)**
GAN, ProGAN, CycleGAN




**Transformers (2017-now)**
Transformer, BERT, ViT

IMAGENET

2012 — 2022



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

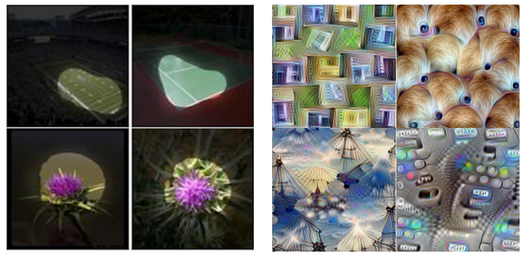
**Self-supervised learning (2016-now)**
Colorization, MOCO, SWaV

**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]

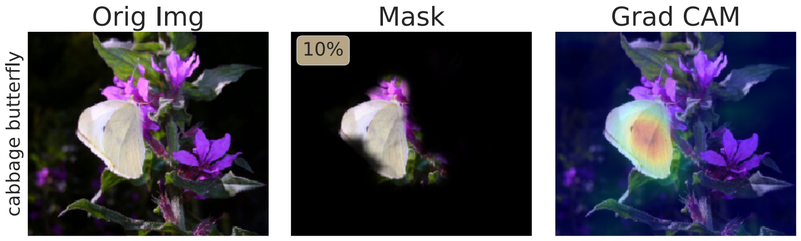
# An incomplete retrospective: the first decade of interpretability



**Feature visualization (2013-2018)**

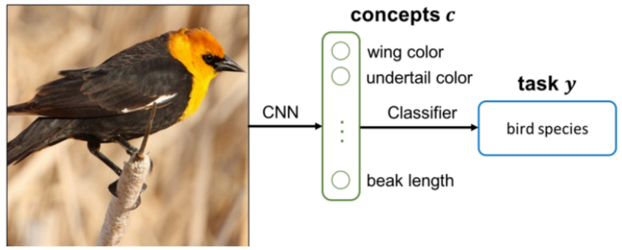
Activation Max., Feature Inversion,
Net Dissect, Feature Vis.

2012 — 2022




**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;
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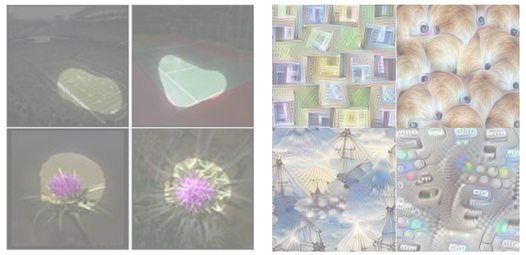


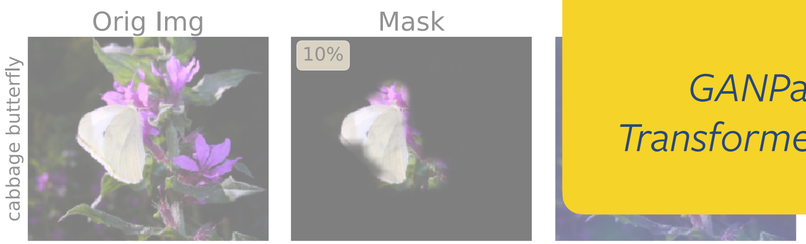


Primarily focused on understanding and approximating **CNNs**

*Exceptions:*
*GANPaint [Bau et al., ICLR 2019]*
*Transformer Circuits [Elhage et al., 2021]*

2012

2022

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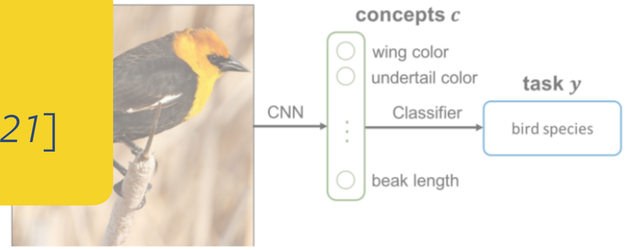


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# Directions for the next decade of interpretability

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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3. Interpretability of **supervised** models → interpretability of **self-supervised** models
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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. Kim

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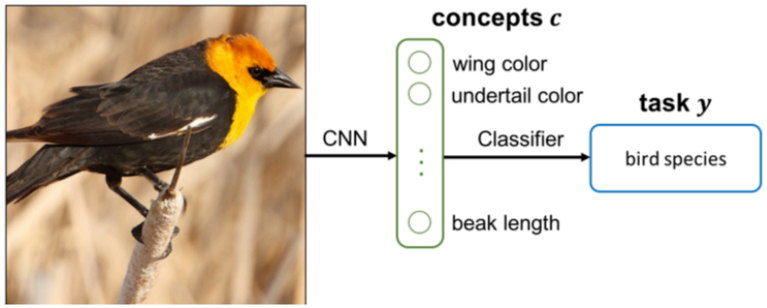
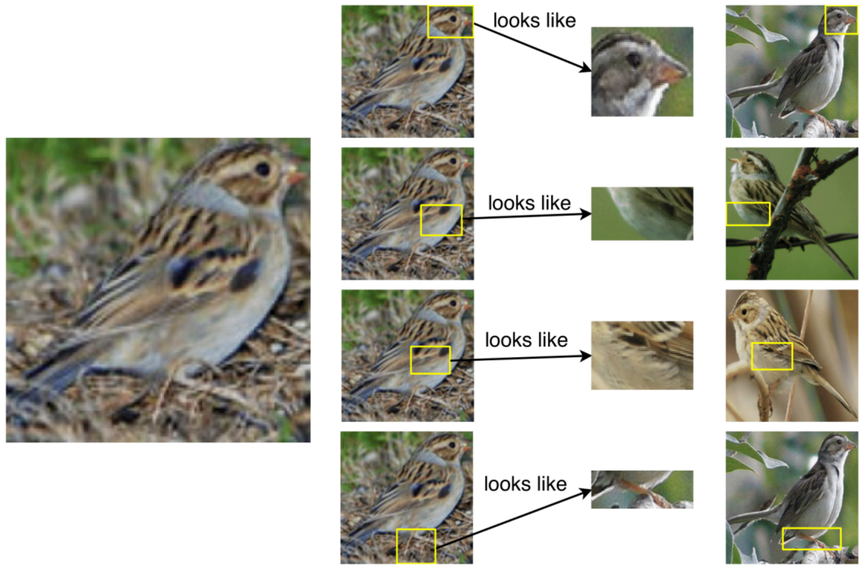
# Explanation form factors: Why did the model predict Y?

**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)?

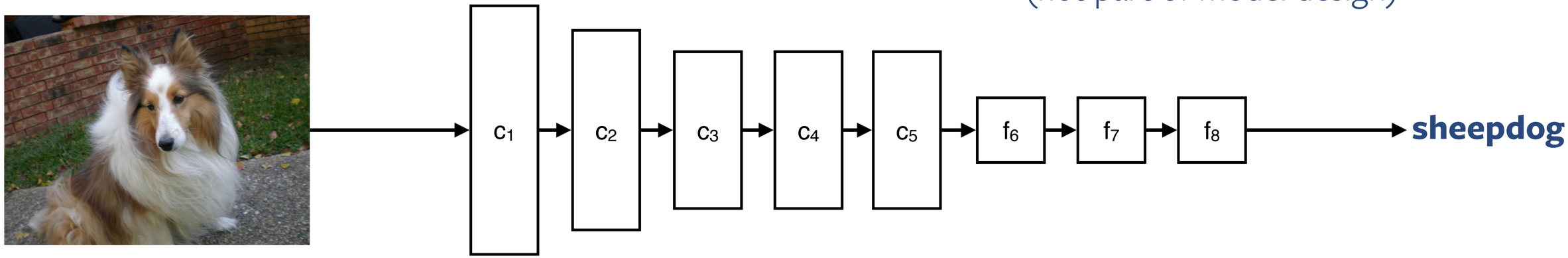
**Counterfactual** explanations
(e.g. SCOUT)

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

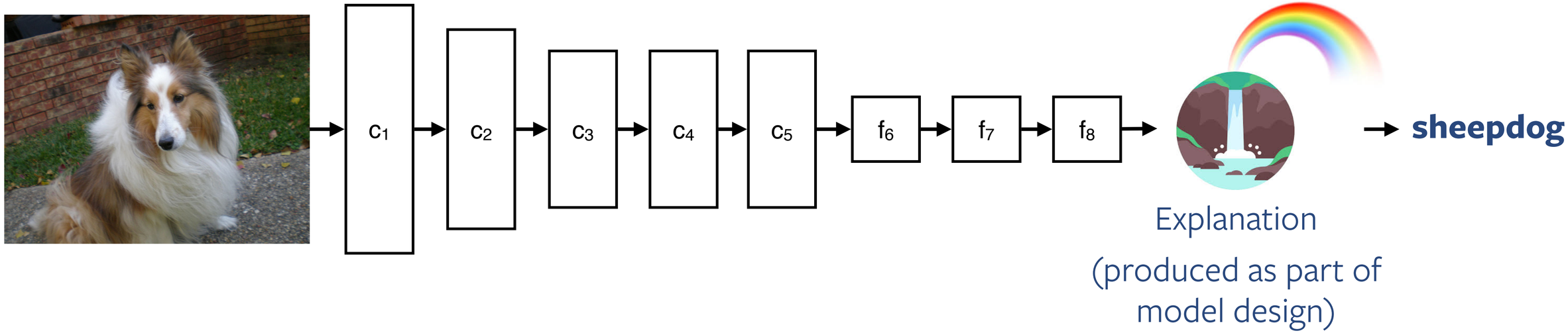
# Post-hoc explanations

Explanation

(not part of model design)

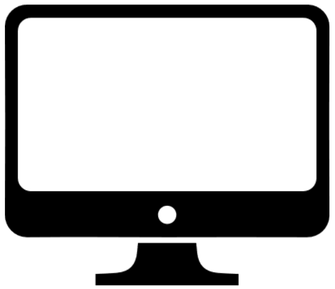


# Interpretable-by-design models



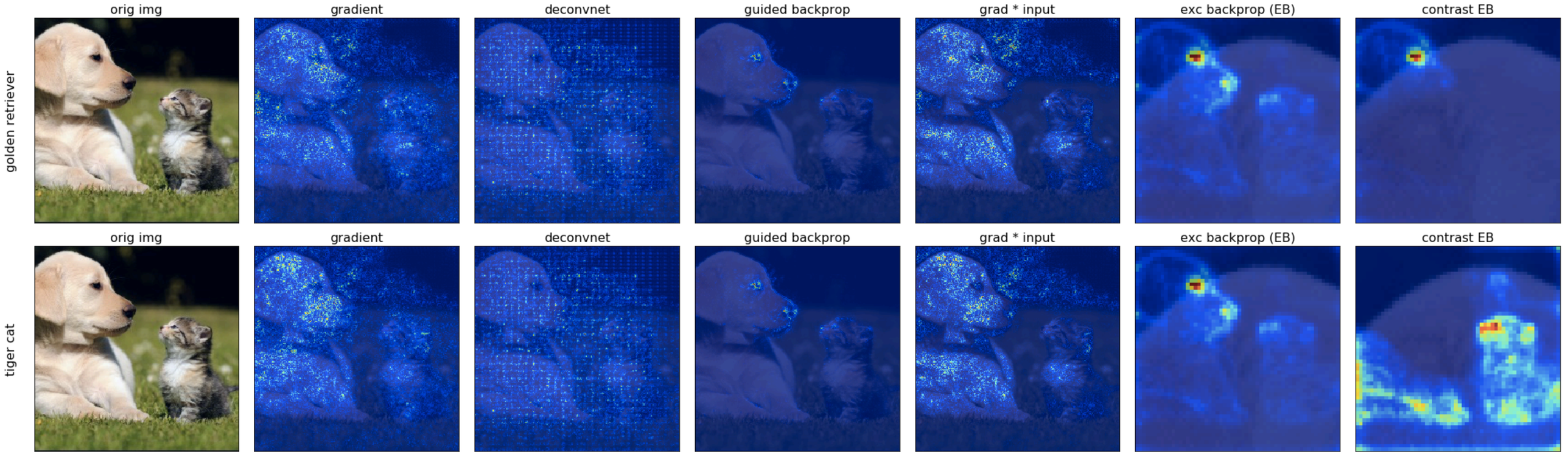
# Current metrics focus on heatmap evaluation

- 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]**
- …



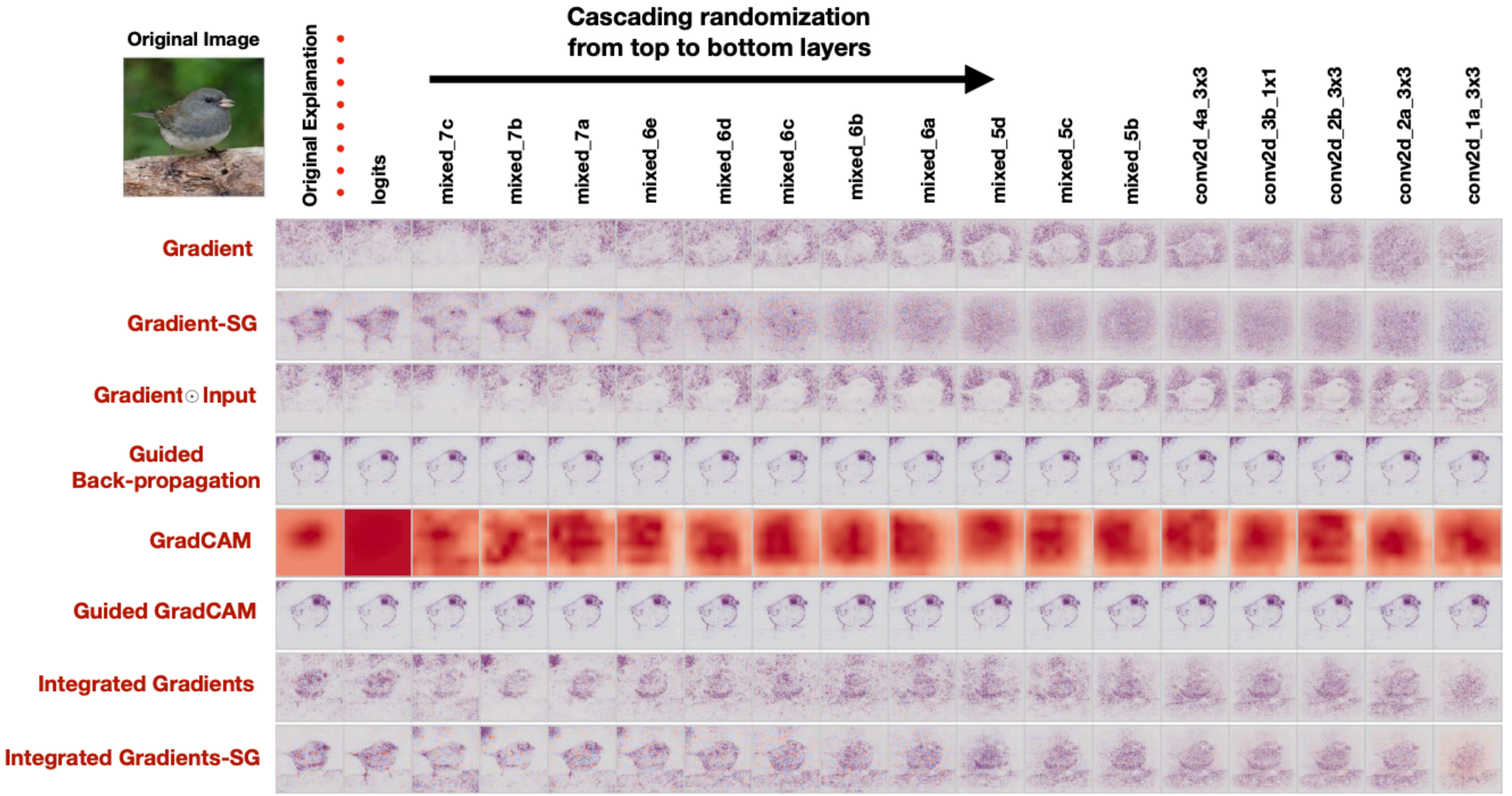
Automatic

# Selectivity to output class




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

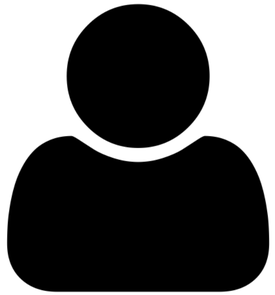
# Sensitivity to model parameters (a.k.a. sanity checks)




[Adebayo et al., NeurIPS 2018]

# 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

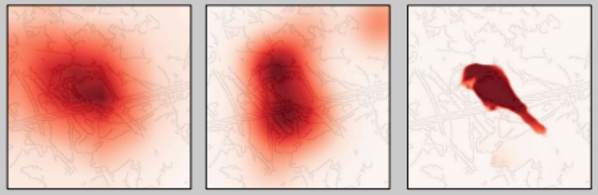
# Is this prediction correct?

input

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

A confidence **20%**

B heatmaps



GradCAM EP SOD

C 3 nearest neighbors in **lorikeet**

**lorikeet ?**

**Yes**

vs

**No**

user

groundtruth label: "bee eater"

[Nguyen et al., NeurIPS 2021]

# HIVE: Evaluating the Human Interpretability of Visual Explanations

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

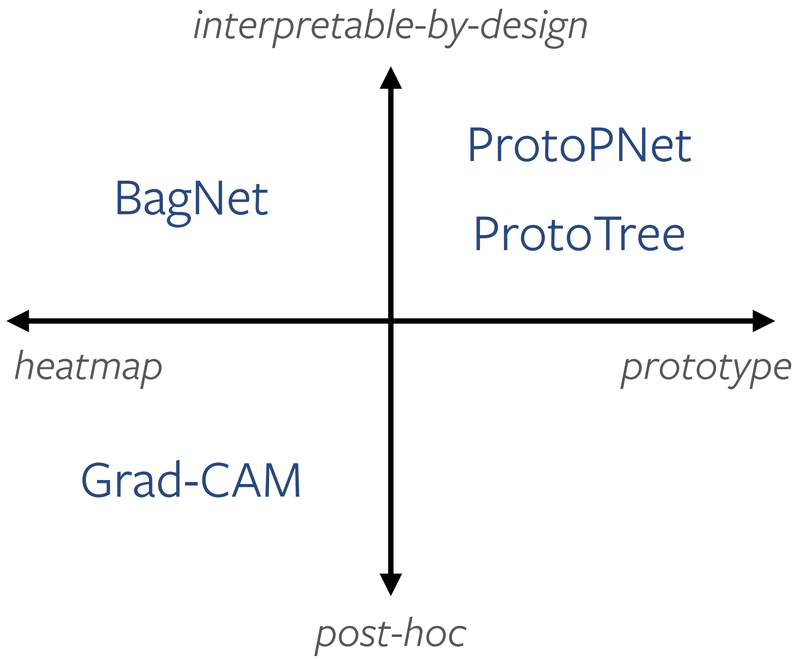
Sunnie S. Y. Kim, Nicole Meister, Vikram V. Ramaswamy, Ruth Fong, Olga Russakovsky, arXiv 2021.
HIVE: Evaluating the Human Interpretability of Visual Explanations.

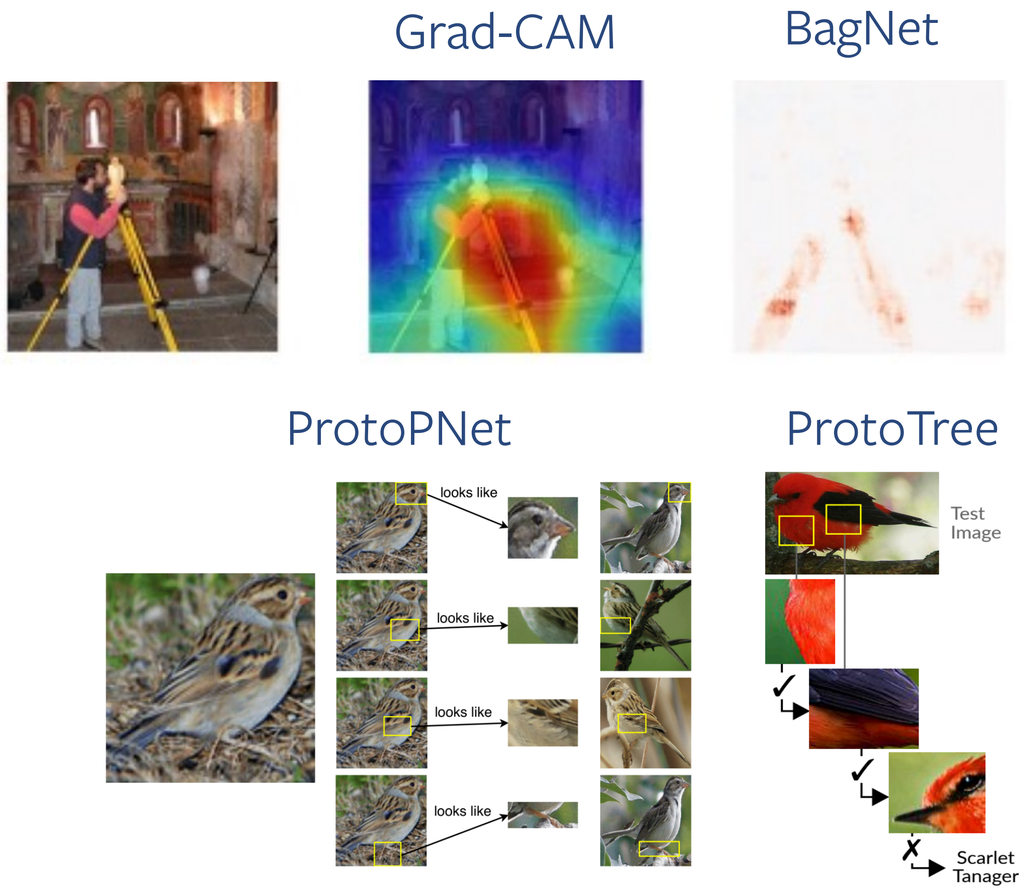
# Our contributions

- 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

[Sunnie S. Y. Kim et al., arXiv 2021. HIVE.]

# 1. Cross-method comparison




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

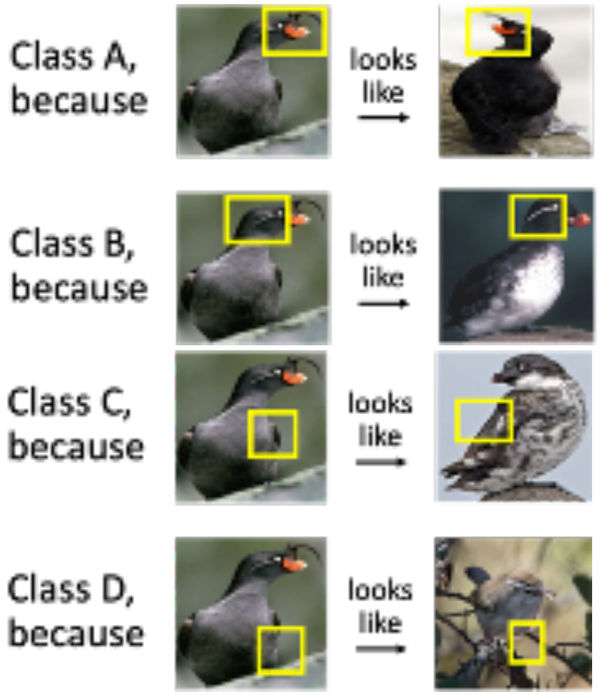
# 2. Human-centered evaluation

**Agreement task**

How confident are you in the model's prediction?


**Distinction task**

Which class do you think is correct?




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

[Sunnie S. Y. Kim et al., arXiv 2021. HIVE.; Chen* & Li* et al., NeurIPS 2019]

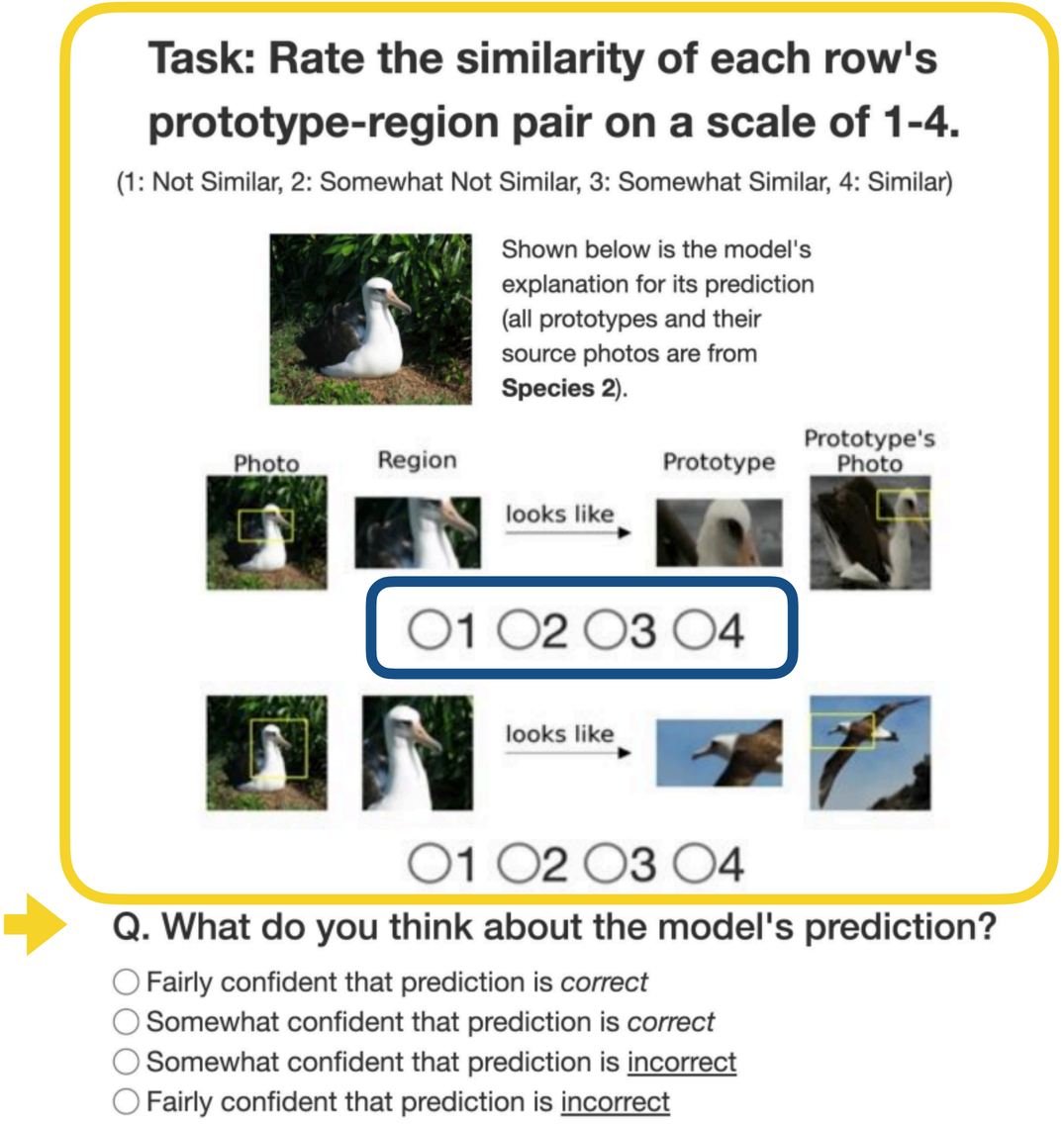
# 2. Human-centered evaluation

**Agreement task**

How confident are you in the model's prediction?

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

ProtoPNet and ProtoTree only

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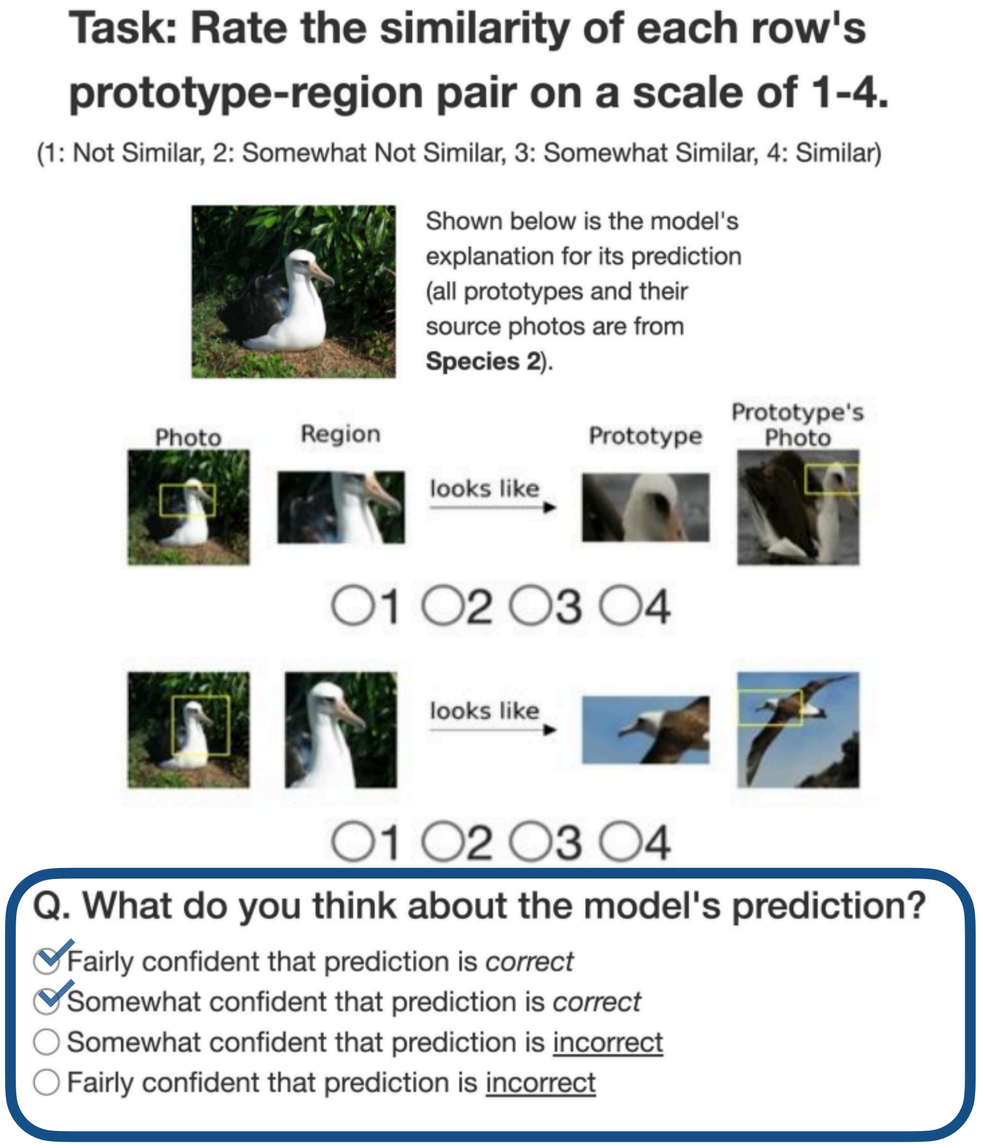
# 2. Human-centered evaluation

**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**.

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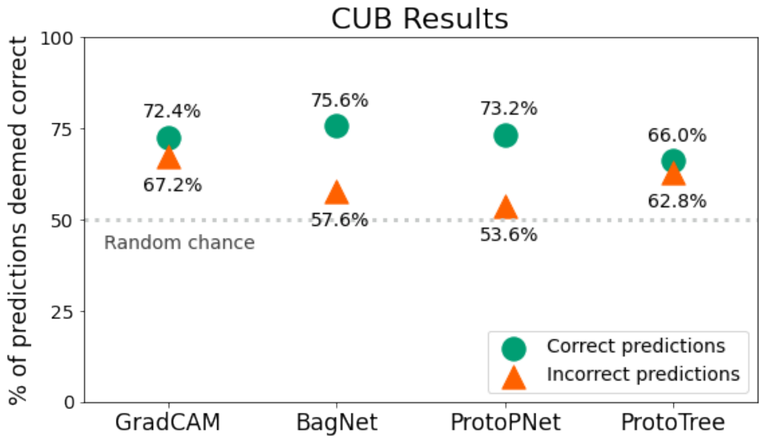
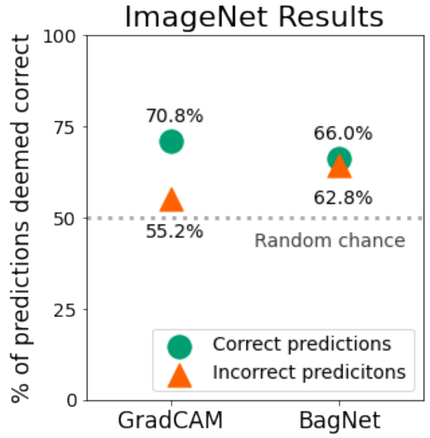



**Q. What do you think about the model's prediction?**

- [x] Fairly confident that prediction is *correct*
- [x] Somewhat confident that prediction is *correct*
- [ ] Somewhat confident that prediction is incorrect
- [ ] Fairly confident that prediction is incorrect

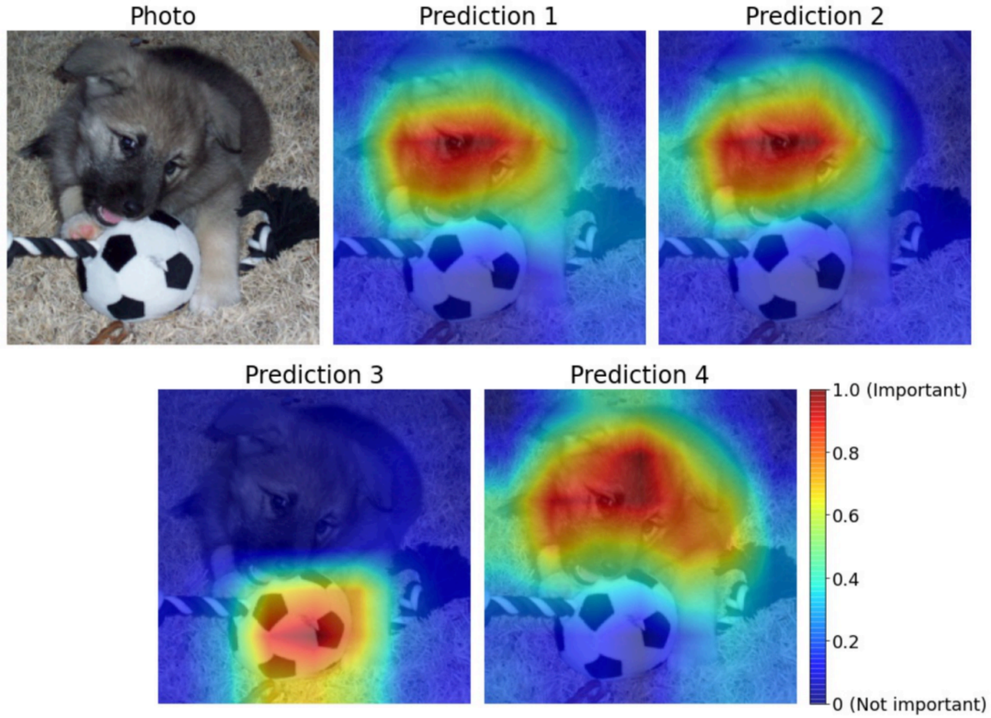
[Sunnie S. Y. Kim et al., arXiv 2021. HIVE.]

# 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 predictions.




**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

[Sunnie S. Y. Kim et al., arXiv 2021. HIVE.; Selvaraju et al., ICCV 2017]

# 2. Human-centered evaluation

**Distinction task**

Which class do you think is correct?

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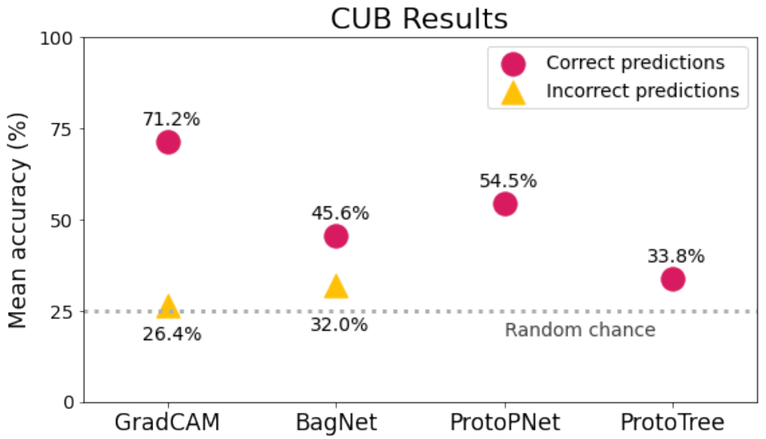
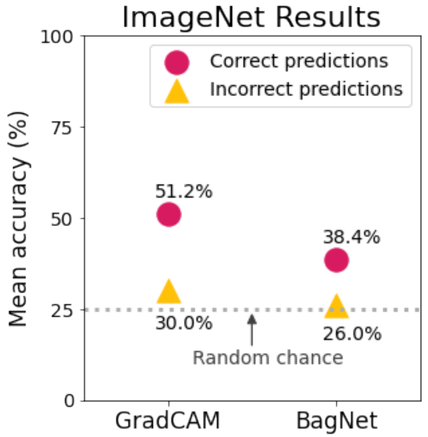
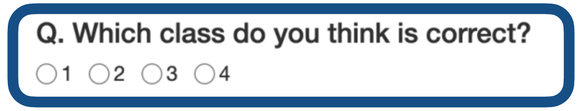
**Goal:** Interpretability should help humans identify and explain model errors.





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# 3. Falsifiable hypothesis testing

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

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[Sunnie S. Y. Kim et al., arXiv 2021. HIVE.]

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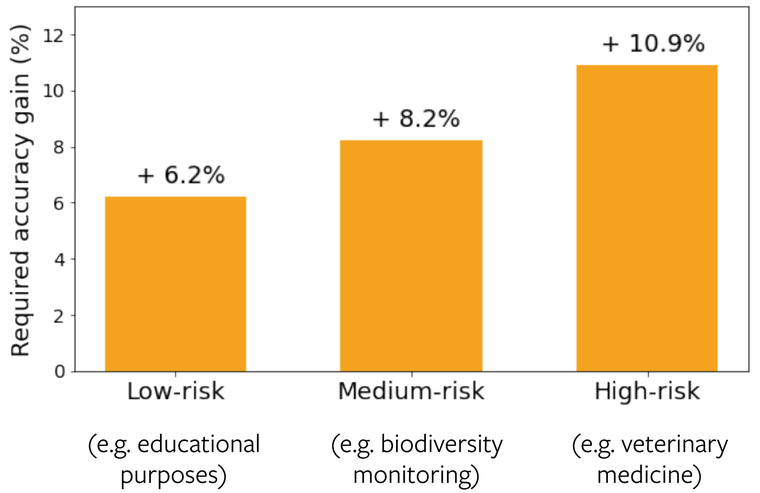
**Finding #2:** Agreement task reveals **confirmation bias**.

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

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

## 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?




[Sunnie S. Y. Kim et al., arXiv 2021. HIVE.]

# 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. Ramaswamy

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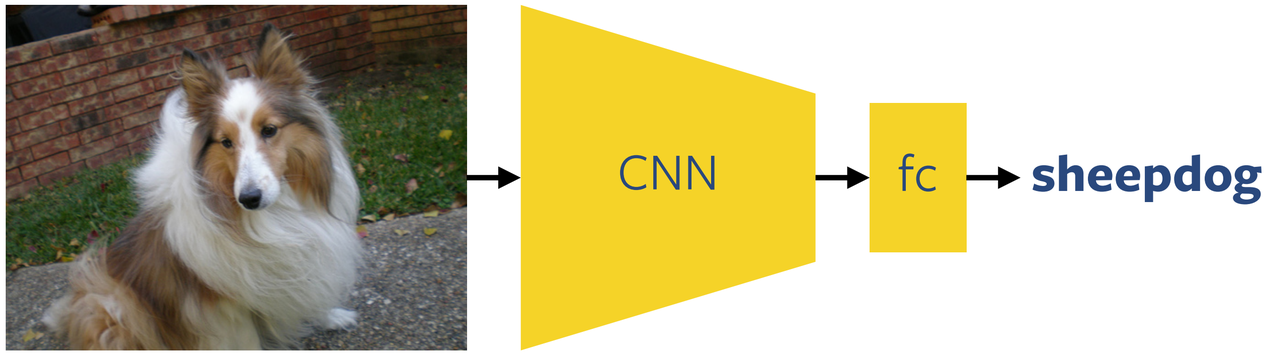
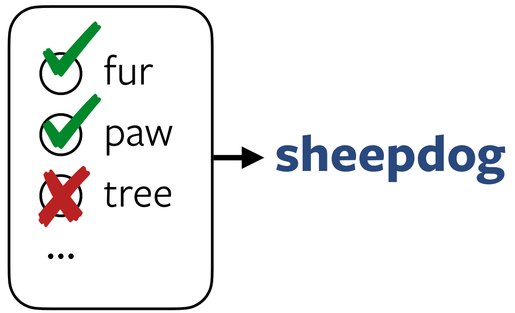
# Concept-based explanations

Why did the model predict **sheepdog**?

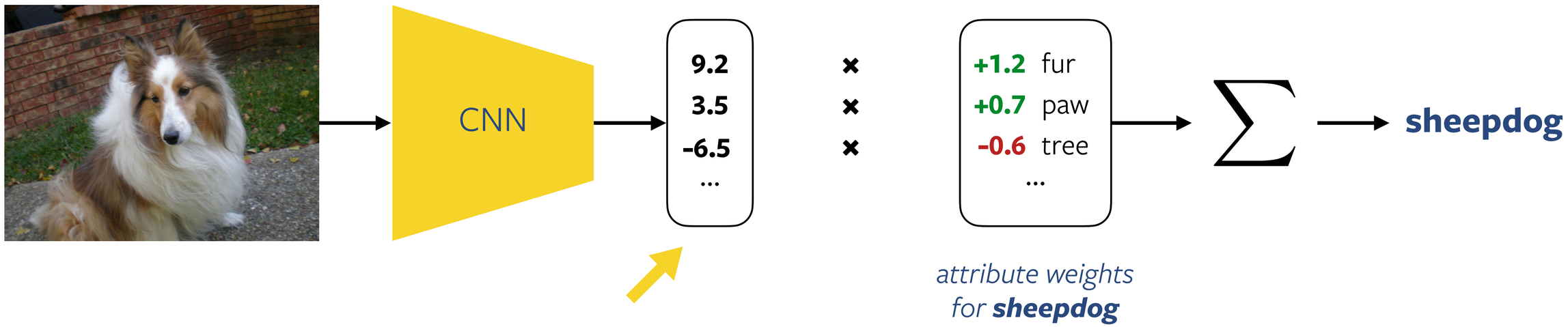



Concept-based explanation




**Pro:** Labelled concepts are interpretable to humans

# Concept Bottleneck: Linear Combination of Labelled Attributes

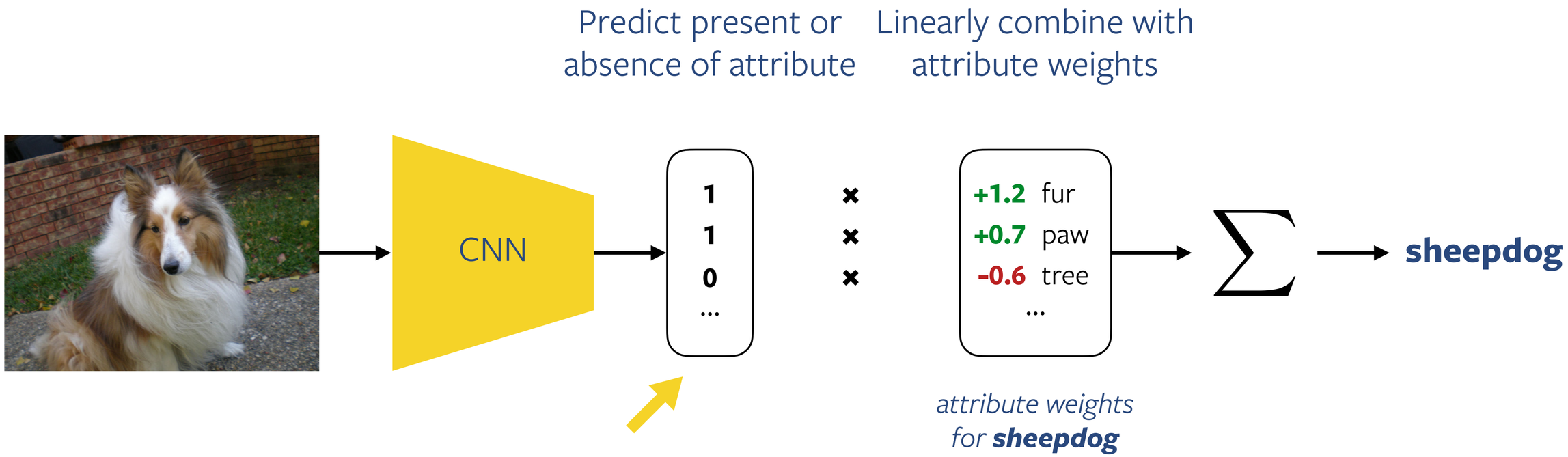



**Con:** Problems with predicting fractional values

- hard to interpret
- can encode hidden information

[Koh*, Nguyen*, Tang* et al., ICML 2020]

# Concept Bottleneck: Linear Combination of Labelled Attributes

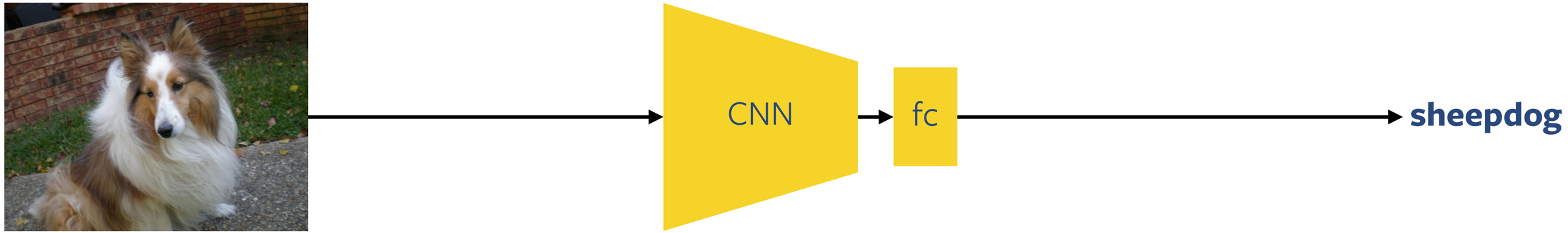



**Con:** Problems with predicting fractional values

- hard to interpret
- can encode hidden information

[Koh*, Nguyen*, Tang* et al., ICML 2020]

# ELUDE: **E**xplanation via a **L**abelled and **U**nlabelled **DE**composition of features




**Goal:** Approximate behavior of original CNN

[Vikram V. Ramaswamy et al., arXiv 2022. ELUDE.]

# ELUDE: Decomposition of labelled and unlabelled features

CNN

8.2
4.5
-7.6
...

*feature activations*

×
×
×

+1.1 $f_1$
-0.3 $f_2$
-0.7 $f_3$
...

*feature weights for **sheepdog***

**sheepdog**

**Goal:** Approximate behavior of original CNN

1. Linearly combine **ground-truth, labelled attributes**

2. Learn remaining **unlabelled features as low-rank space**

1
1
0
...

*ground-truth presence/absence of attributes*

×
×
×

+1.2 fur
+0.7 paw
-0.6 tree
...

*attribute weights for **sheepdog***

[Vikram V. Ramaswamy et al., arXiv 2022. ELUDE.]

# **Attributes only:** % of model explained via labelled attributes decreases as task complexity increases

| 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.

[Vikram V. Ramaswamy et al., arXiv 2022. ELUDE.]

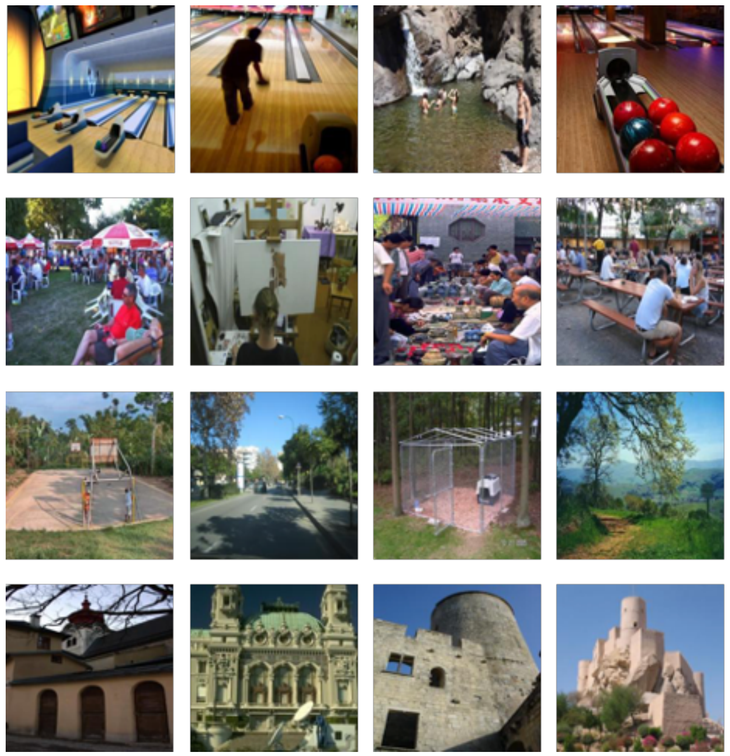
# **Attributes only:** % of model explained via labelled attributes decreases as task complexity increases

| 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.

[Vikram V. Ramaswamy et al., arXiv 2022. ELUDE.]

# **Features + attributes:** Unlabelled features correspond to human-interpretable concepts



bowling alleys?

people eating?

outdoor sports fields?

castle-like buildings?

| Scene group | TPR |
|---|---|
| home/hotel | 99.0 |
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| outdoor-fields/parks | 0.0 |
| industrial-construction | 0.0 |

attributes only

[Vikram V. Ramaswamy et al., arXiv 2022. ELUDE.]

# 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

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**
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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.

# Supervised Learning

(  , sheepdog )

**x** **y**

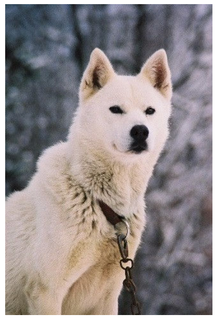
# Self-Supervised Learning

$\mathbf{x}$

# Visual Concept

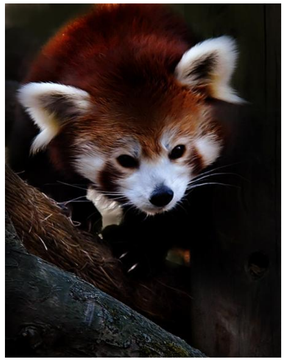
# Query

# Visual Concept

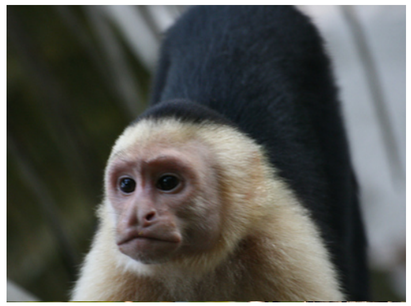








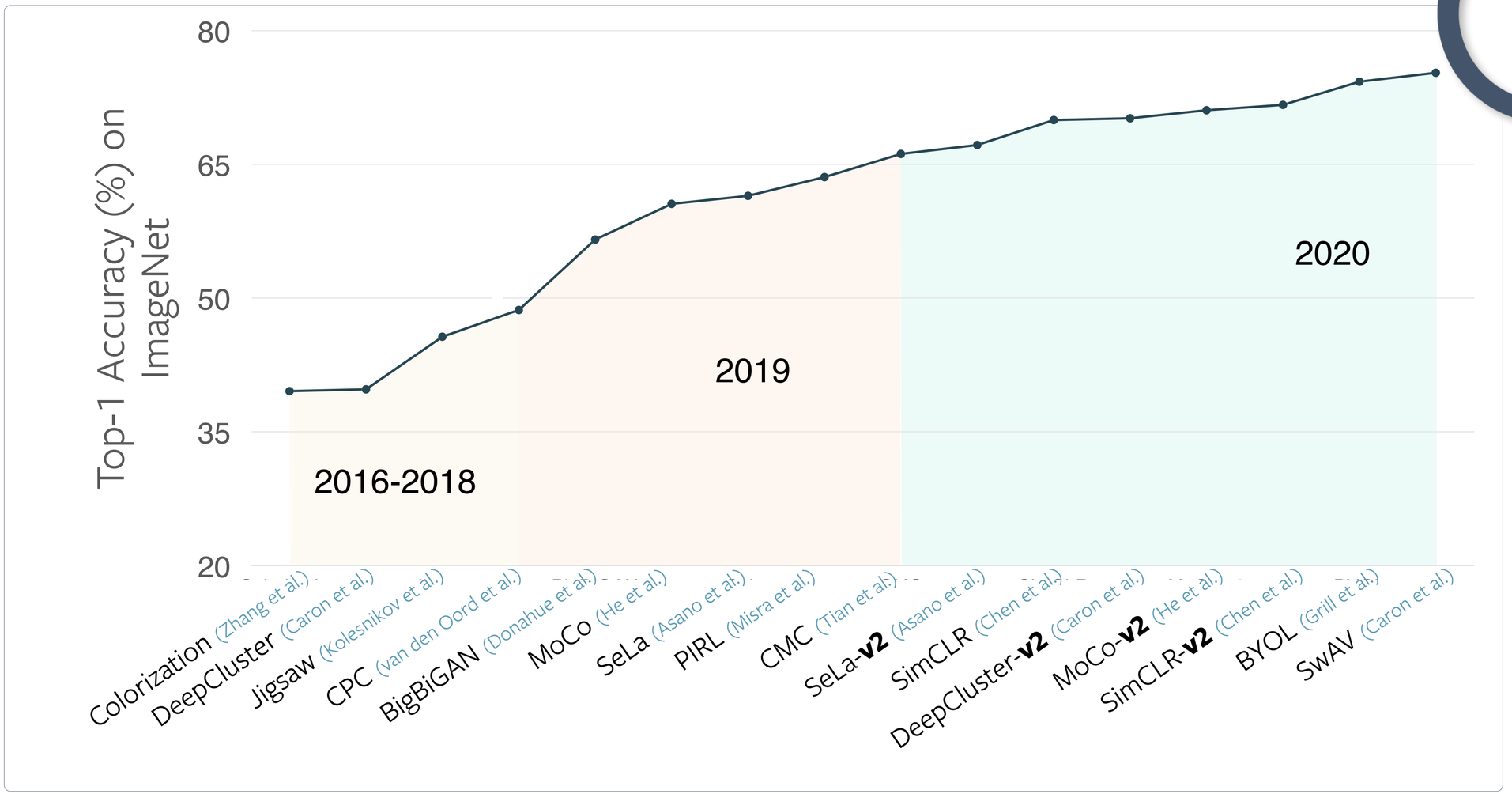




## Query



# Self-Supervised Learning

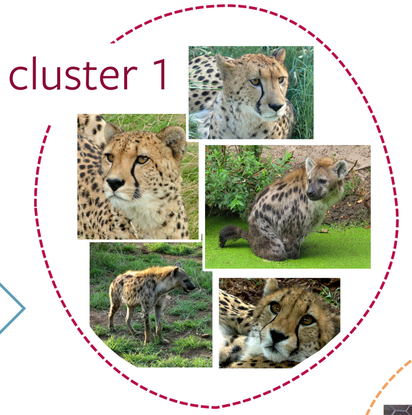


# Self-Supervised Learning

Unlabelled data

Learn clusters

(e.g. DeepCluster, SeLa, SwaV)





Learn features

k-means

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

# Learnability


(A)

(B)

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

# Learnability


(A)


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

# Describability

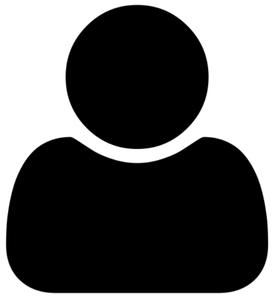
dessert with chocolate sauce

(A)

(B)

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

# Describability

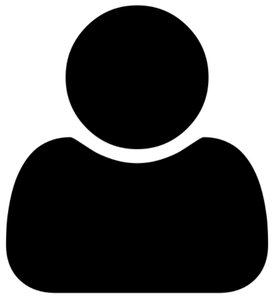
Manual

(A)

(B)

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

# Describability

Manual

**OR**

Automatic

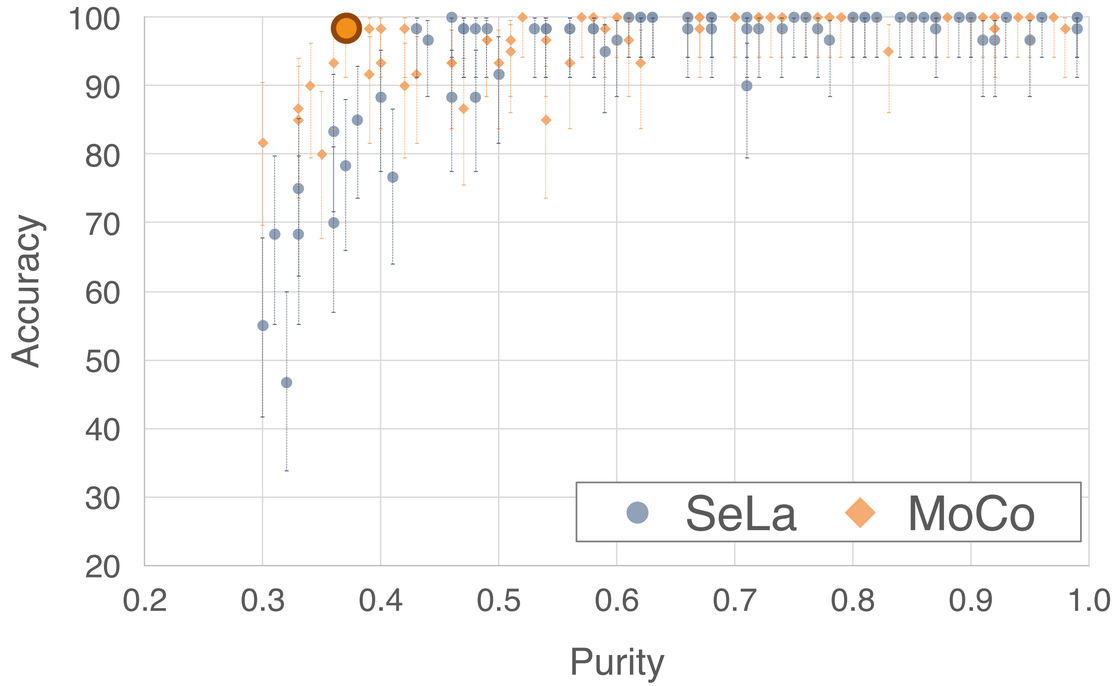
(A)

(B)

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

# Evaluation

## Learnability



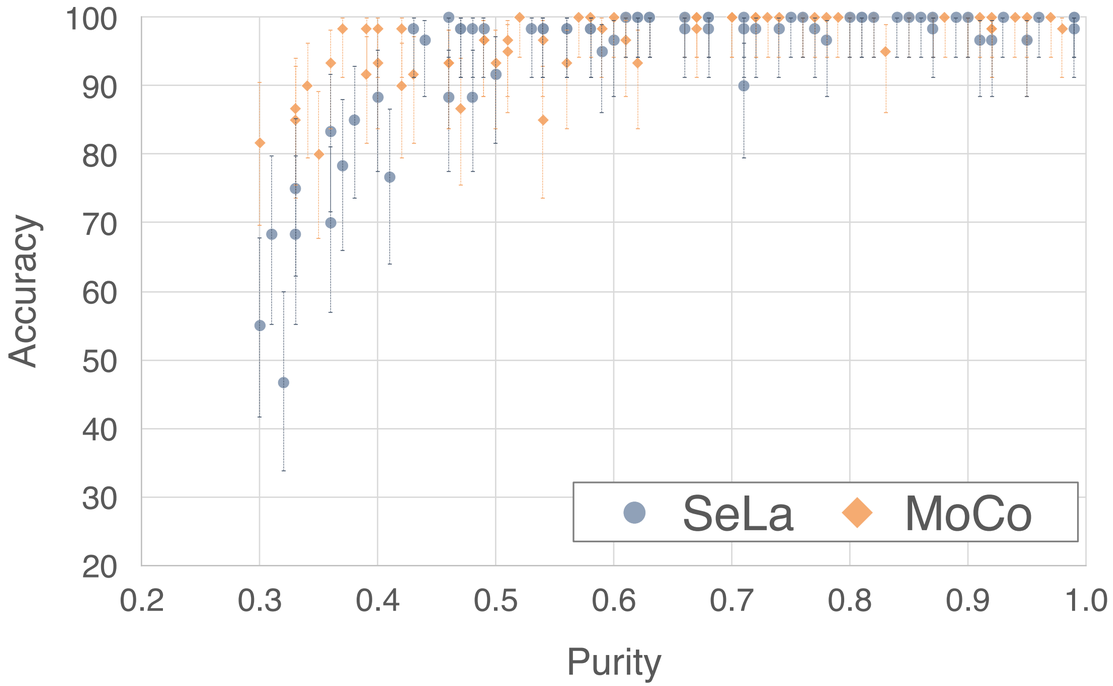

**ImageNet cluster purity:**
how correlated is a cluster's contents to a single ImageNet label?

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

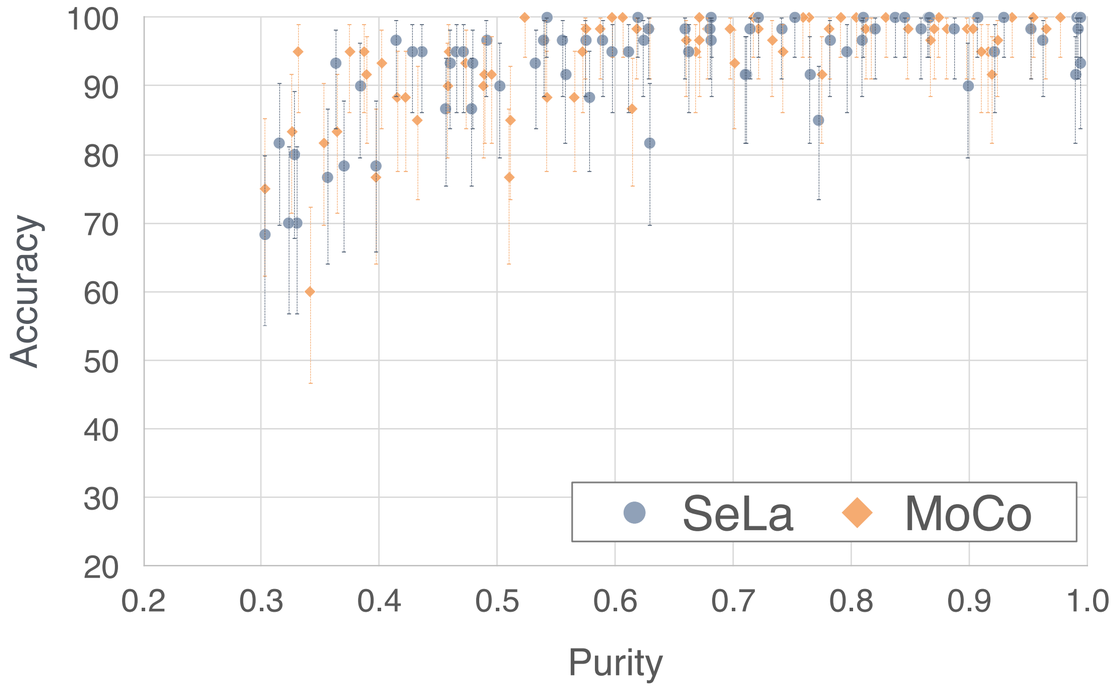
[Iro Laina, et al., NeurIPS 2020. Quantifying Learnability and Describability.]
[Asano et al., ICLR 2020; He et al., CVPR 2020]

# Evaluation

## Learnability




## Describability




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

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

# Findings

ImageNet cluster purity

**SeLa: cluster 393 (0.668)**
a newborn baby lying on a bed

**SeLa: cluster 332 (0.542)**
a snake on a hand

98.3% 100.0%

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

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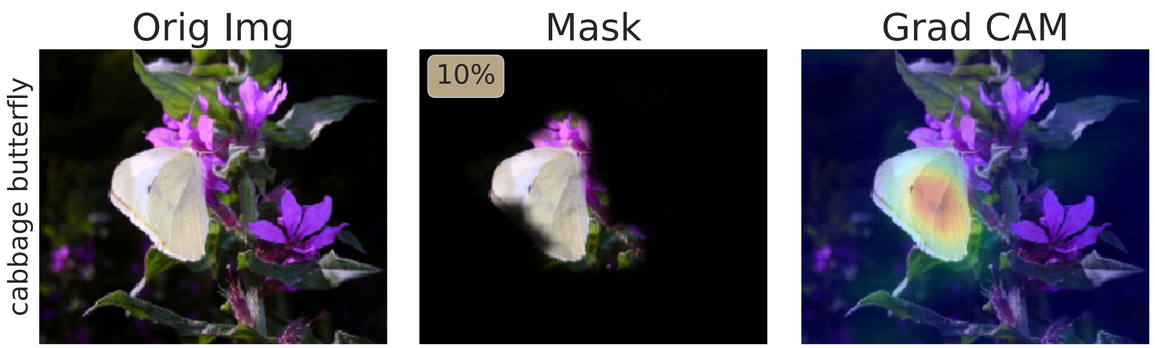
   Ruth Fong, Alexander Mordvintsev, Andrea Vedaldi, Chris Olah, VISxAI 2021.
   Interactive Similarity Overlays.

# Interpretability Tools



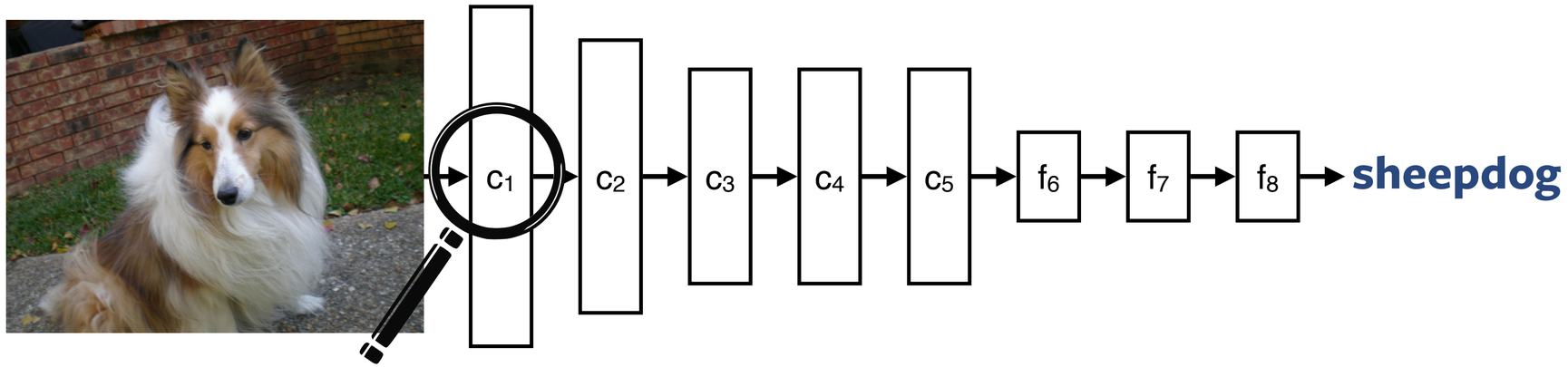


Current tools render **static images**.

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



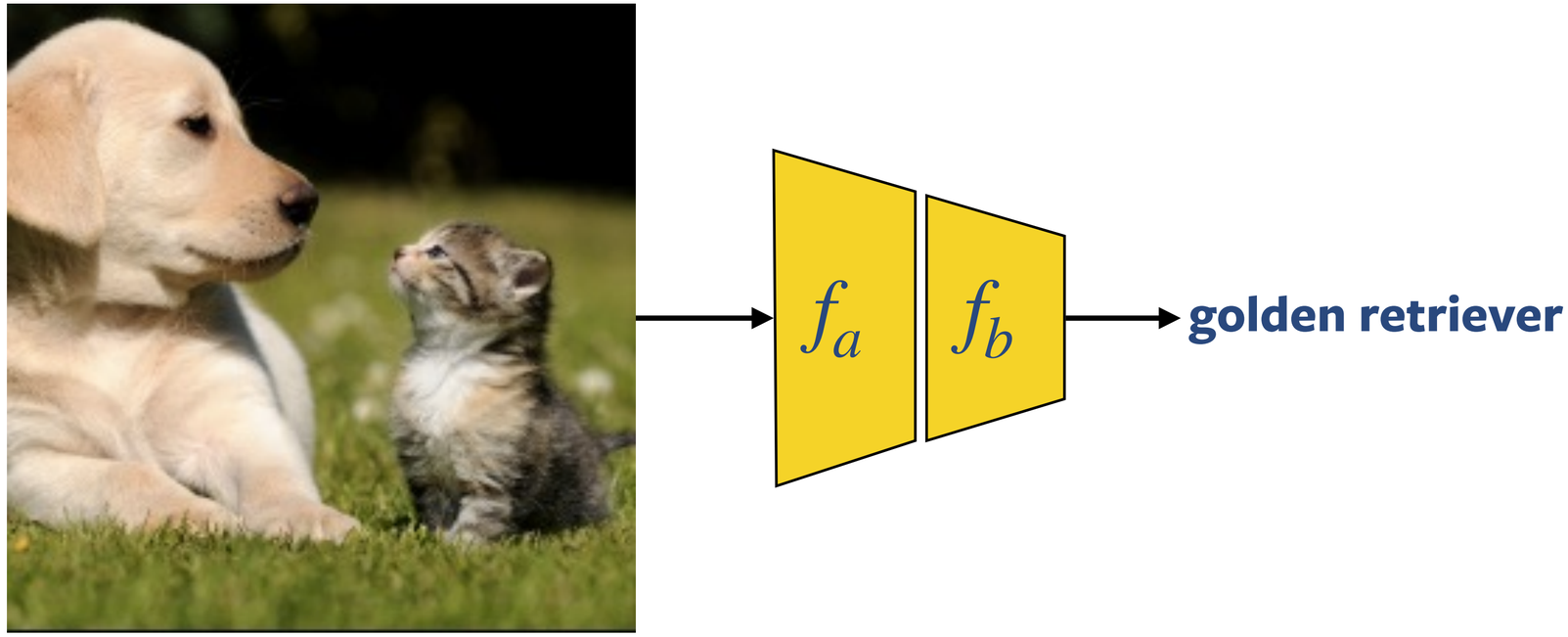

How can we **easily explore** hypotheses about the model?

Acknowledgement: Chris Olah

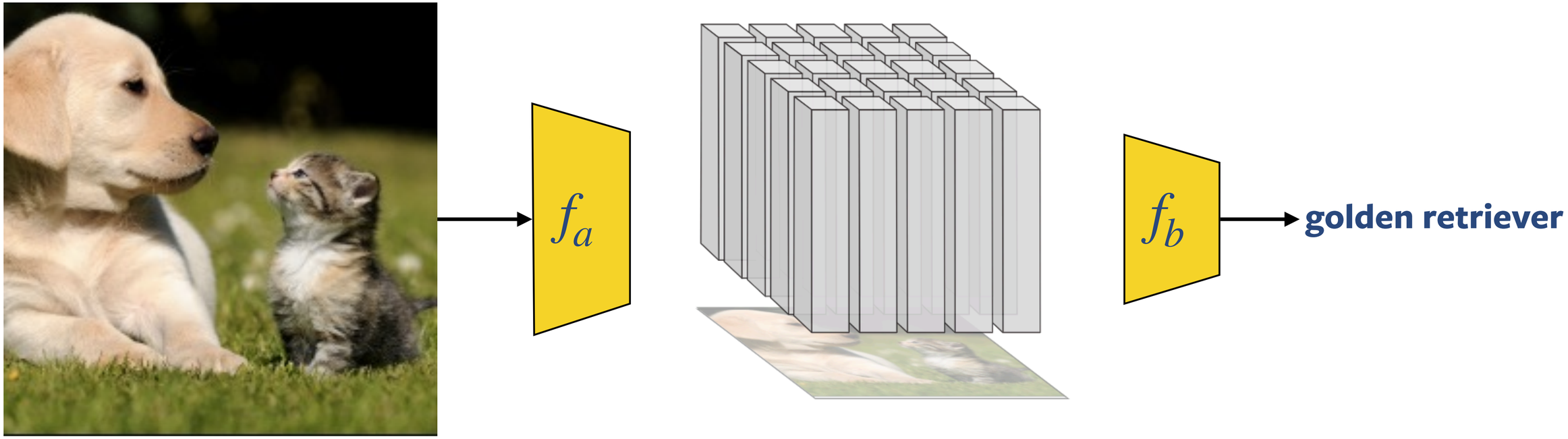
# Interactive Similarity Overlays

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

# Spatial Activations



# Spatial Activations



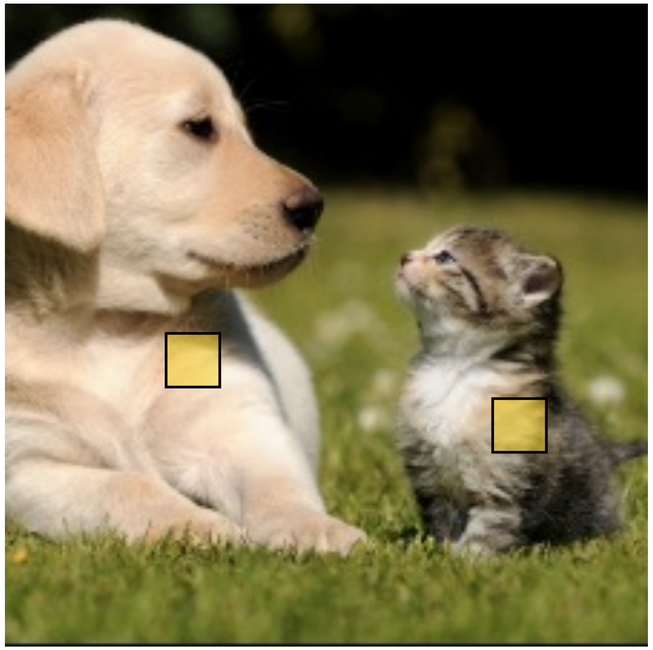

[Olah et al., Distill 2018]

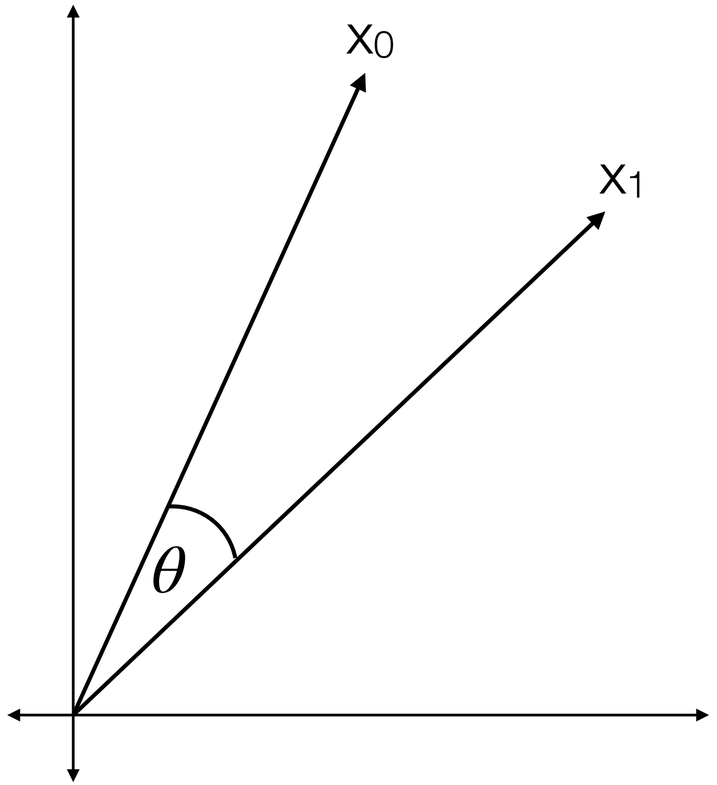
# Interactive Similarity Overlays

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

[Olah et al., Distill 2018]

# Interactive Similarity Overlays

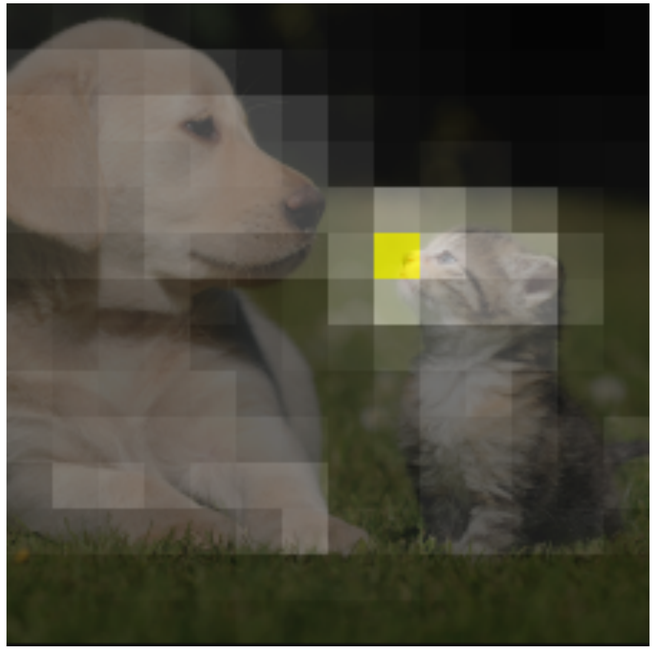





[Fong et al., VISxAI 2021. Interactive Similarity Overlays.]

# Live 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.]

# Preview: Interactive Visual Feature Search

bit.ly/interactive_search

Devon Ulrich

Devon Ulrich and Ruth Fong, in prep 2022.
Interactive Visual Feature Search.

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.

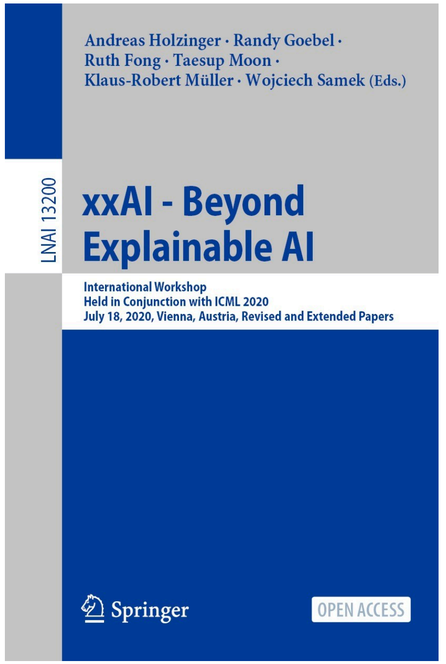
# Takeaways from challenges in interpretability

- **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

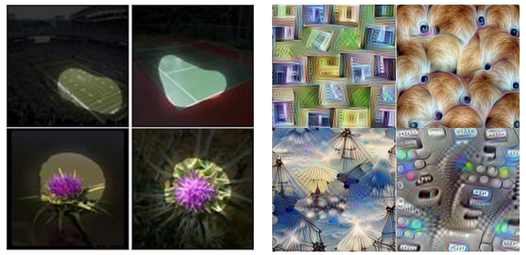
1. Develop interpretability methods for **diverse domains**
   - Beyond CNN classifiers: self-supervised learning, generative models, etc.

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

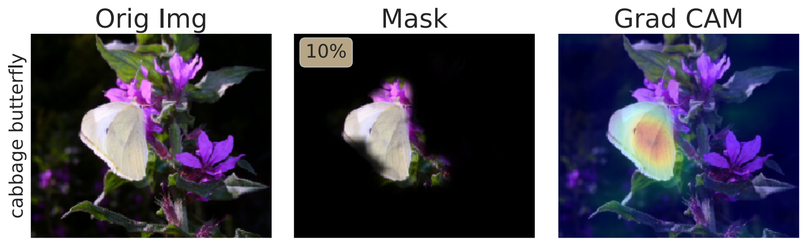


**Feature visualization (2013-2018)**

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

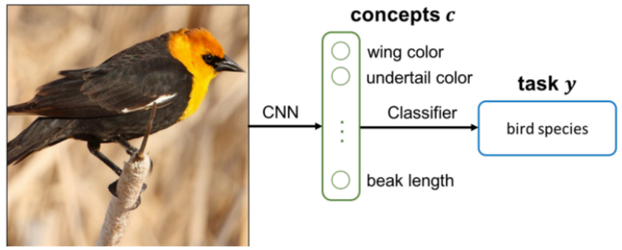
Primarily focused on understanding and approximating **CNNs**

2012 ⟶ 2022




**Attribution heatmaps (2013-2019)**

Gradient, Grad-CAM,
Occlusion, Perturbations, RISE




**Interpretable-by-design (2020-now)**

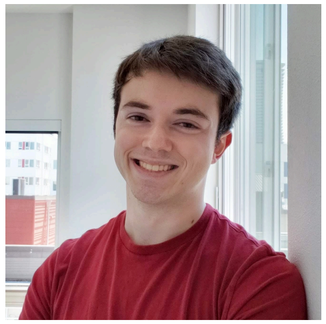
Concept Bottleneck, ProtoPNet,
ProtoTree

[Selvaraju et al., ICCV 2017; Fong* & Patrick* et al., ICCV 2019; 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

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Andrea Vedaldi

Chris Olah

Alex Mordvintsev

Olga Russakovsky

bit.ly/vai-lg-postdoc

We're hiring postdocs!

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

# Thank You