Adversarial Examples and Human-ML Alignment

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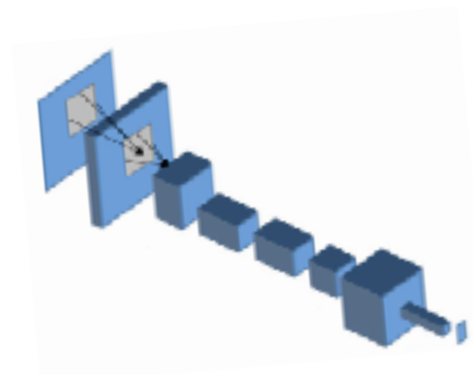
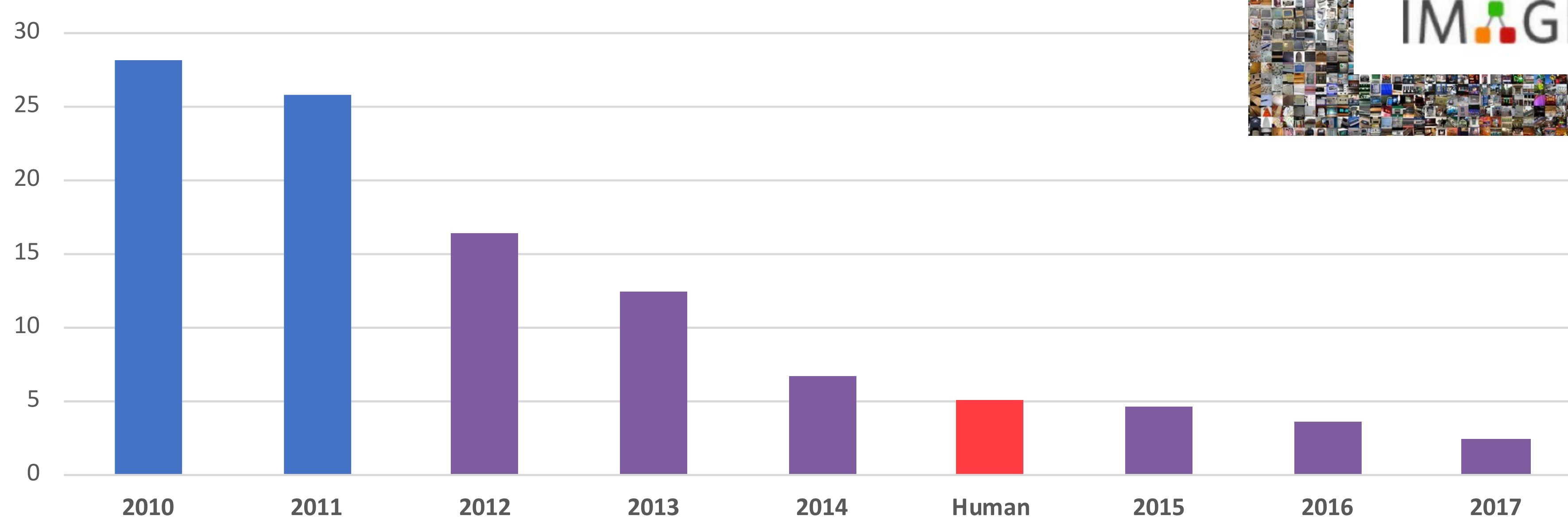
Deep Networks: Towards Human Vision

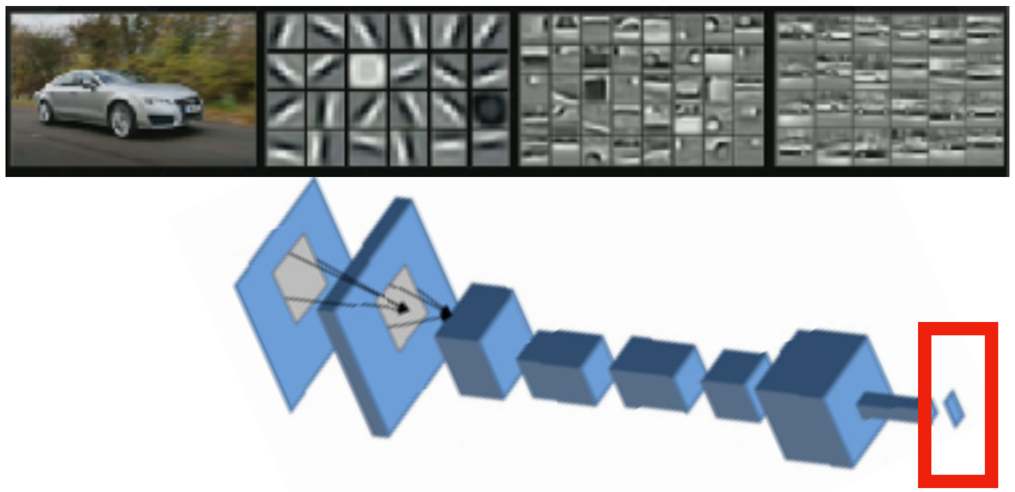


Pig: 91%
Dog: 3%
Cat: 2%
...

ILSVRC top-5 Error on ImageNet



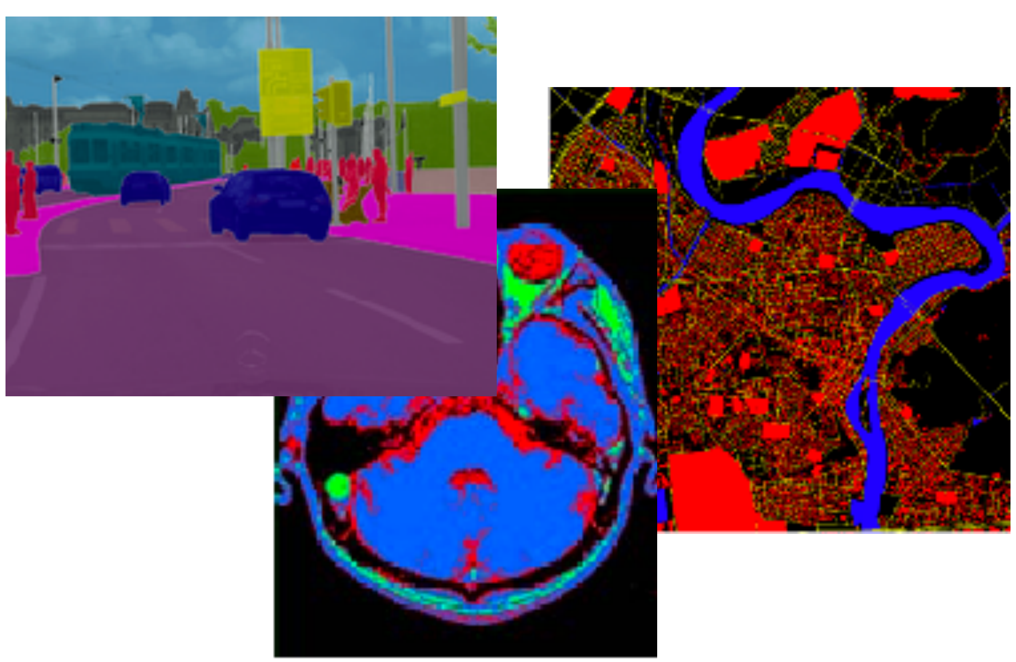
Deep Networks: Towards Human Vision



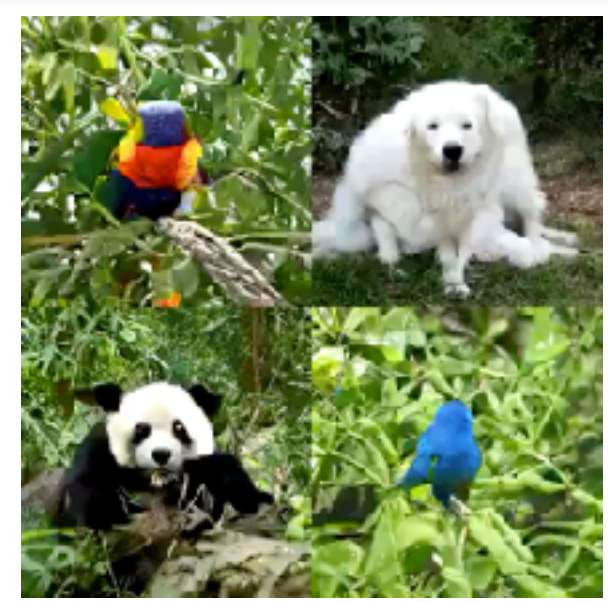
[NVIDIA GTC, 2019]

→ **"Meaningful"** data representations

Cross-task generalization



Generative models



[Brock et al 2018] + [Isola 2018]

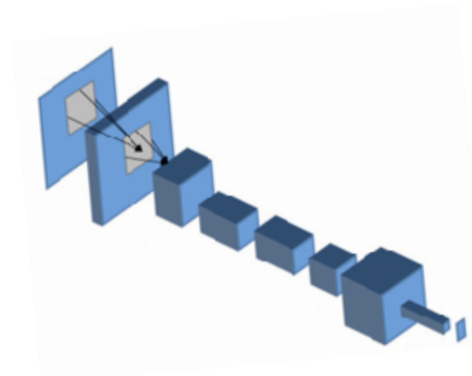
So: Are we on the right path?

(Is all we need “just” scaling up?)

Message for today: Models **deviate** from human perception in **unexpected** ways

→ It is all about features

Deep Networks: Towards Human Vision?

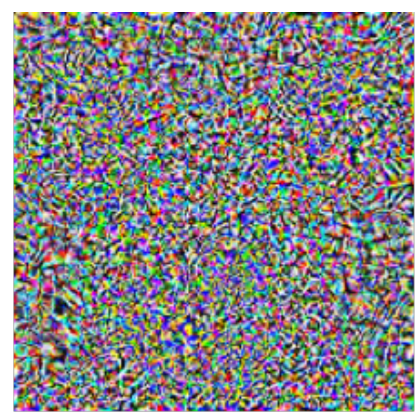


Pig: 91%
Dog: 3%
Cat: 2%
...

But…

Pig (91%)

+ 0.005x



Perturbation

=

Airplane (99%)

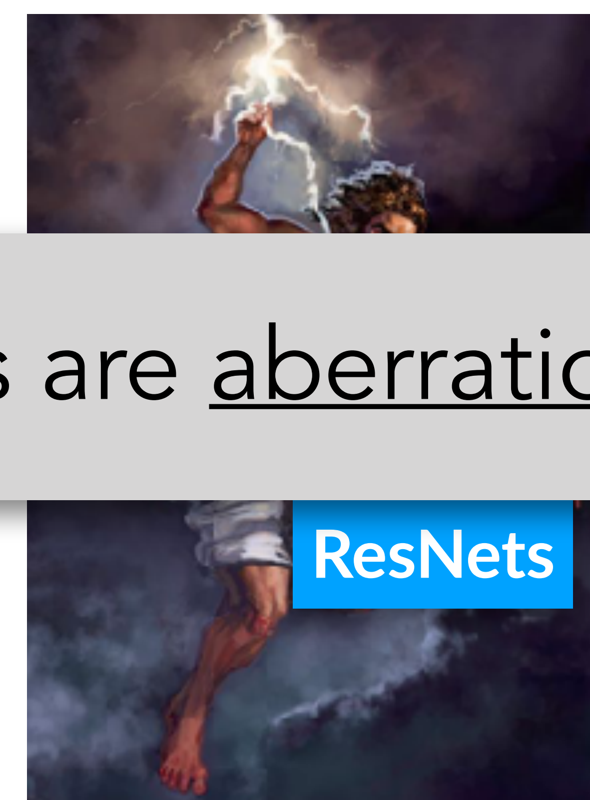
Adversarial Examples: Imperceptible changes fool models

[Szegedy et al 2013] [Biggio et al 2013]

Deep Networks: Towards Human Vision?

$$d \to \infty$$

Why do adv. examples exist?

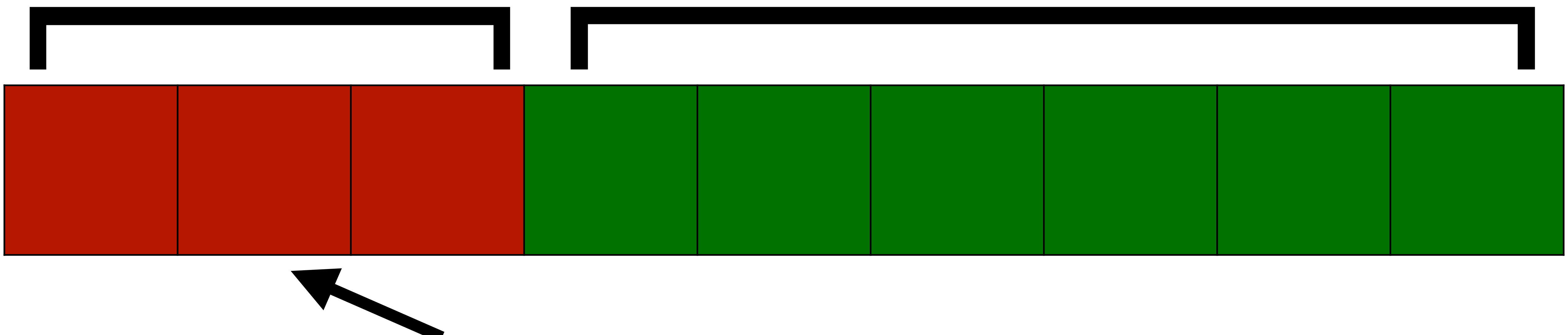


Unifying theme: Adversarial examples are <u>aberrations</u>

A Natural View on Adversarial Examples

"Useless" directions model is unreasonably **sensitive** to

Useful features that actually help in good classification

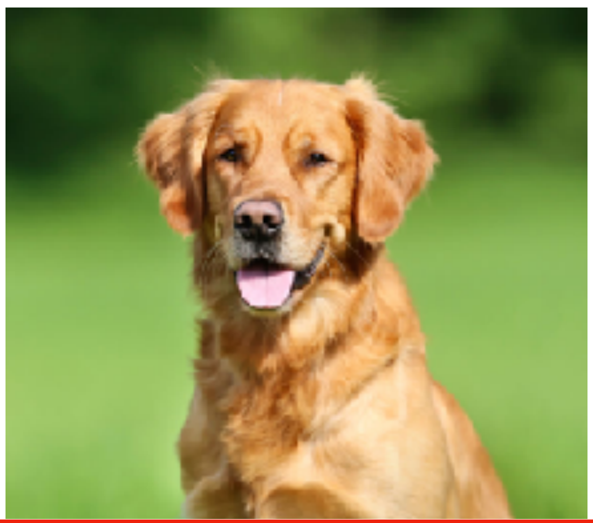


Adversary only changes these features to create an adversarial example

Underlying belief:
"Better" models would avoid this sensitivity

But: Is this view justified?

Why Are Adv. Perturbations Bad?



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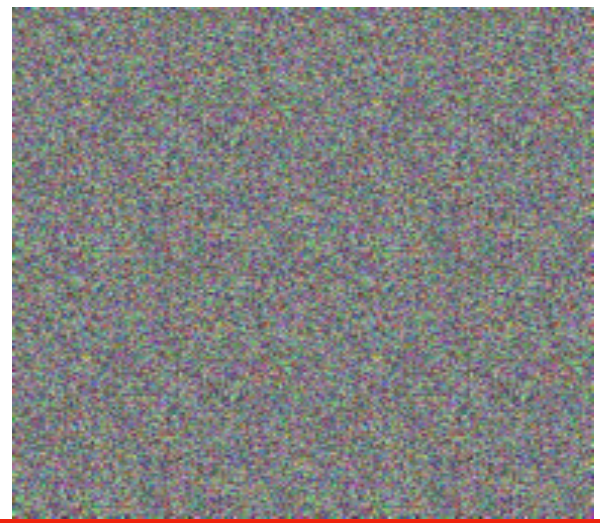

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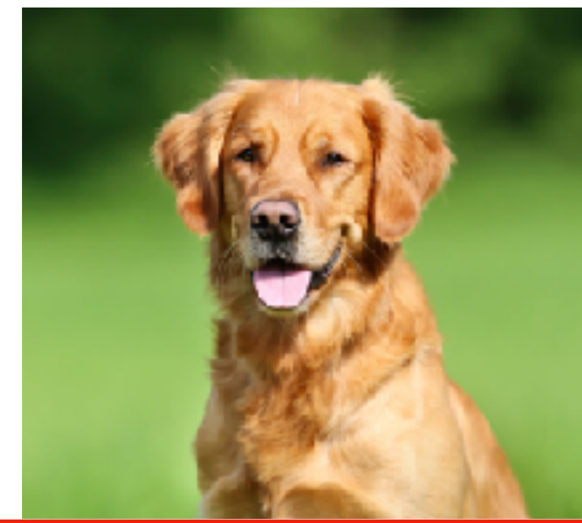
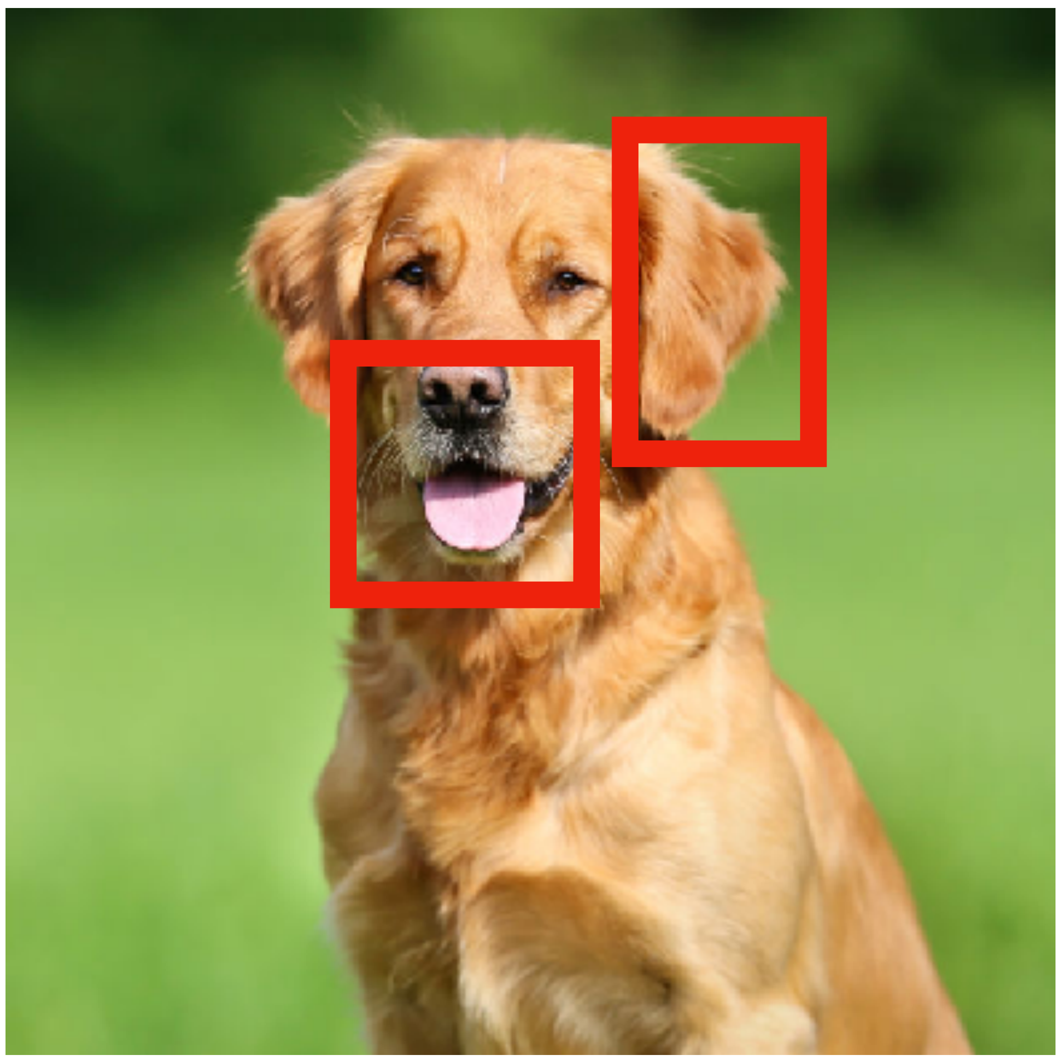


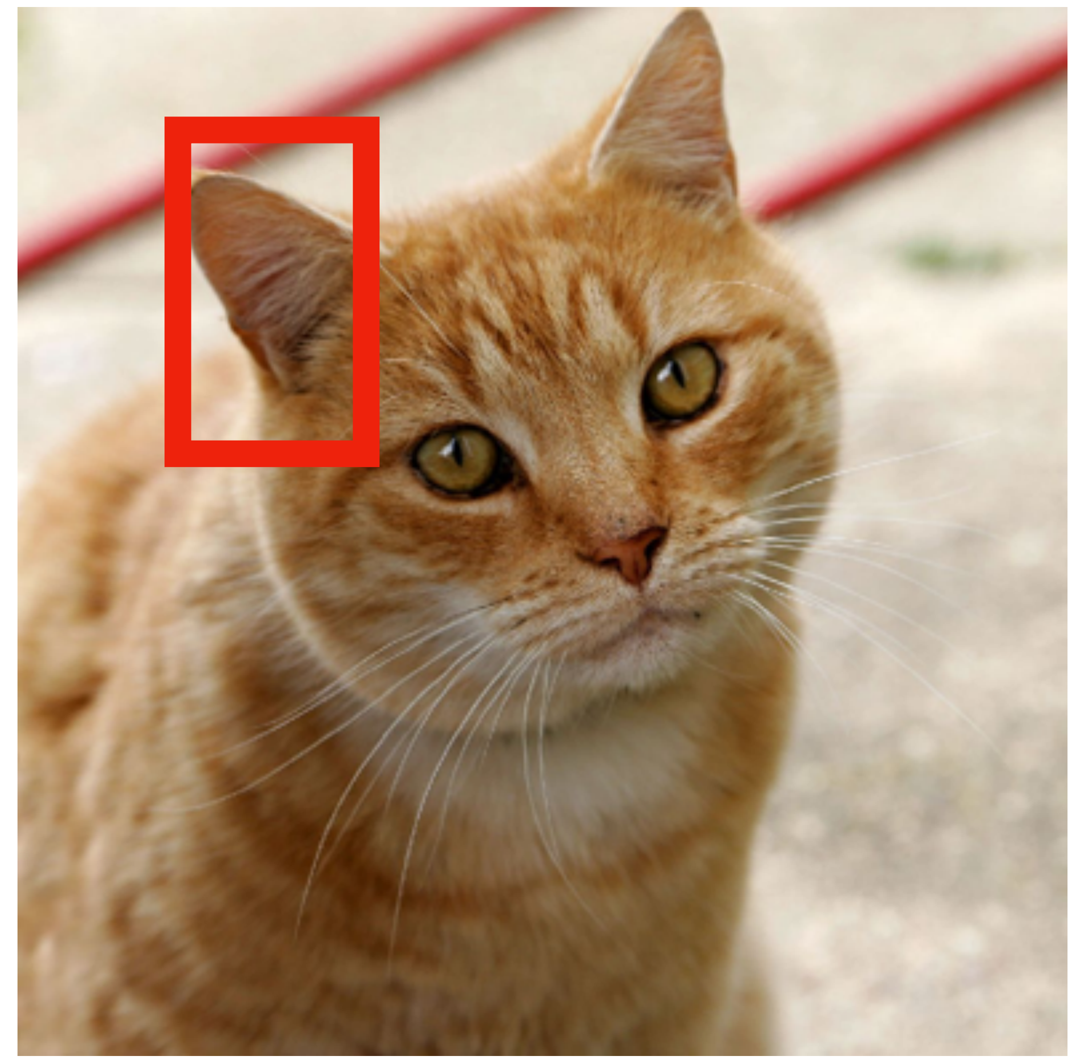
dog	**meaningless perturbation**	**cat**

But: This is only a “human” perspective

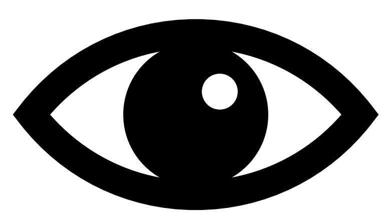
Human Perspective



dog



cat



ML Perspective

dog

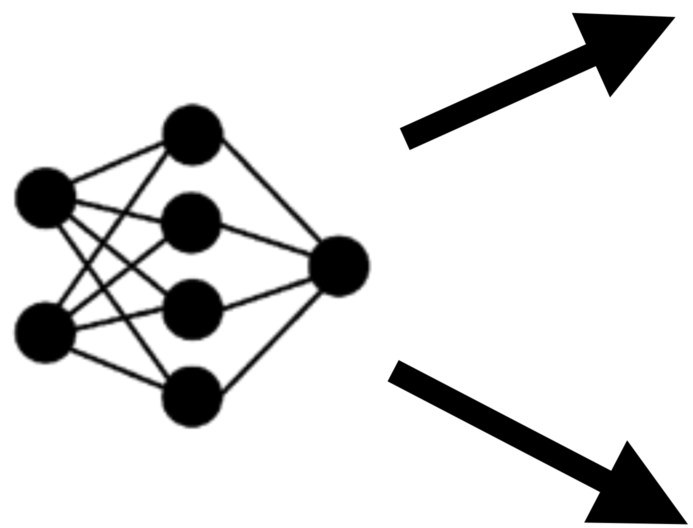


Image is meaningless

Classes are meaningless

Only goal:

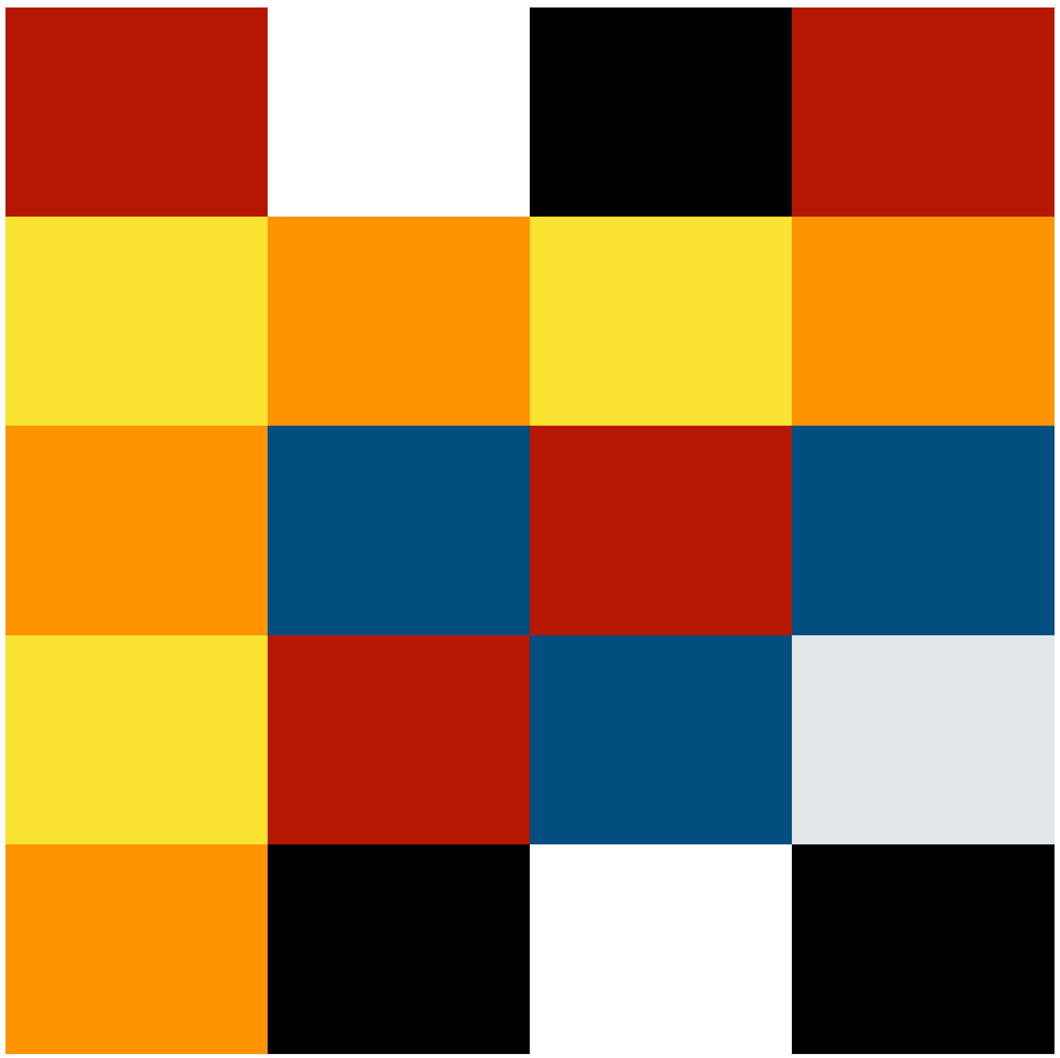
Max (test) accuracy

ML Perspective

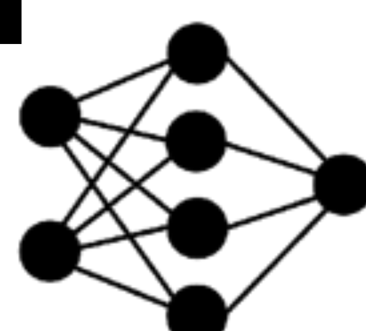
dog

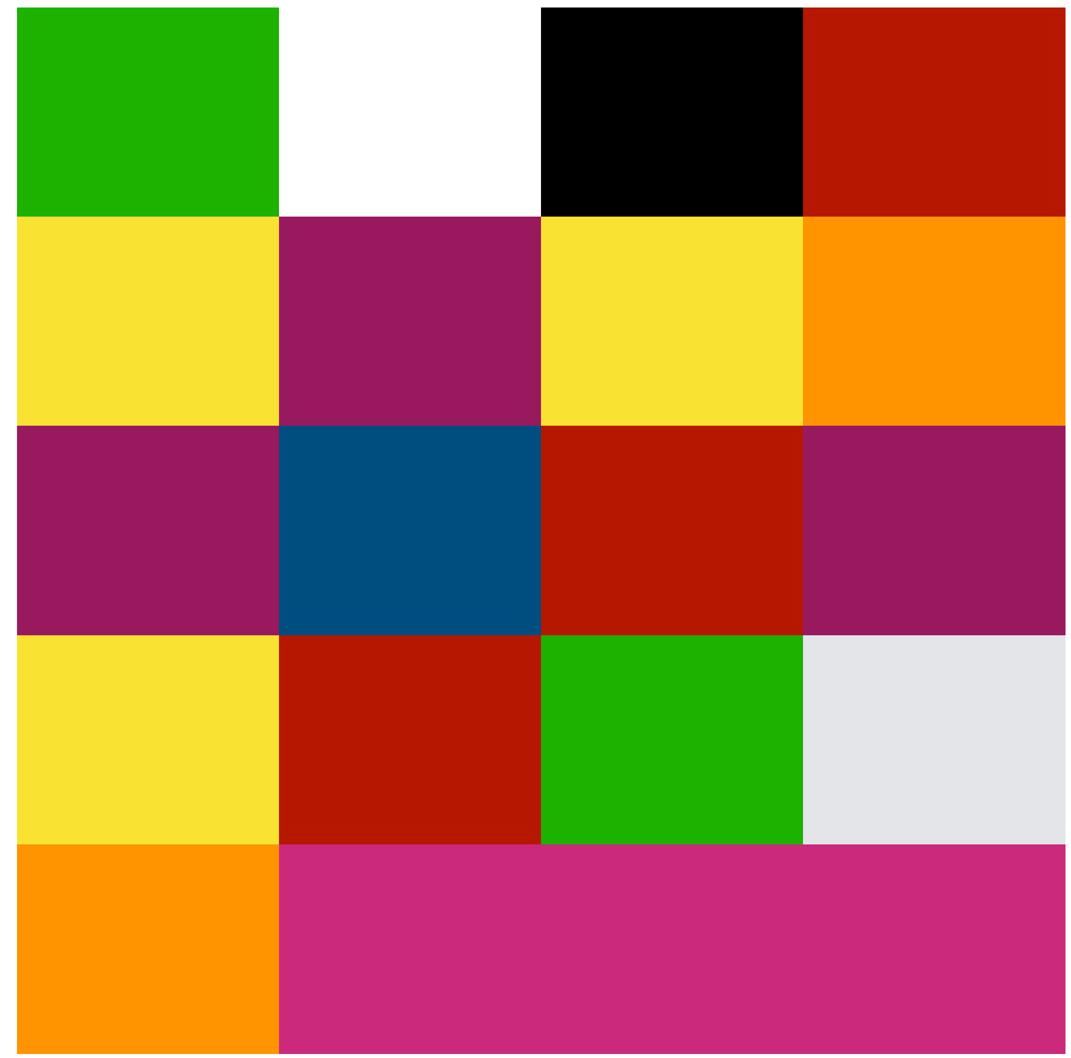
cat

ML Perspective



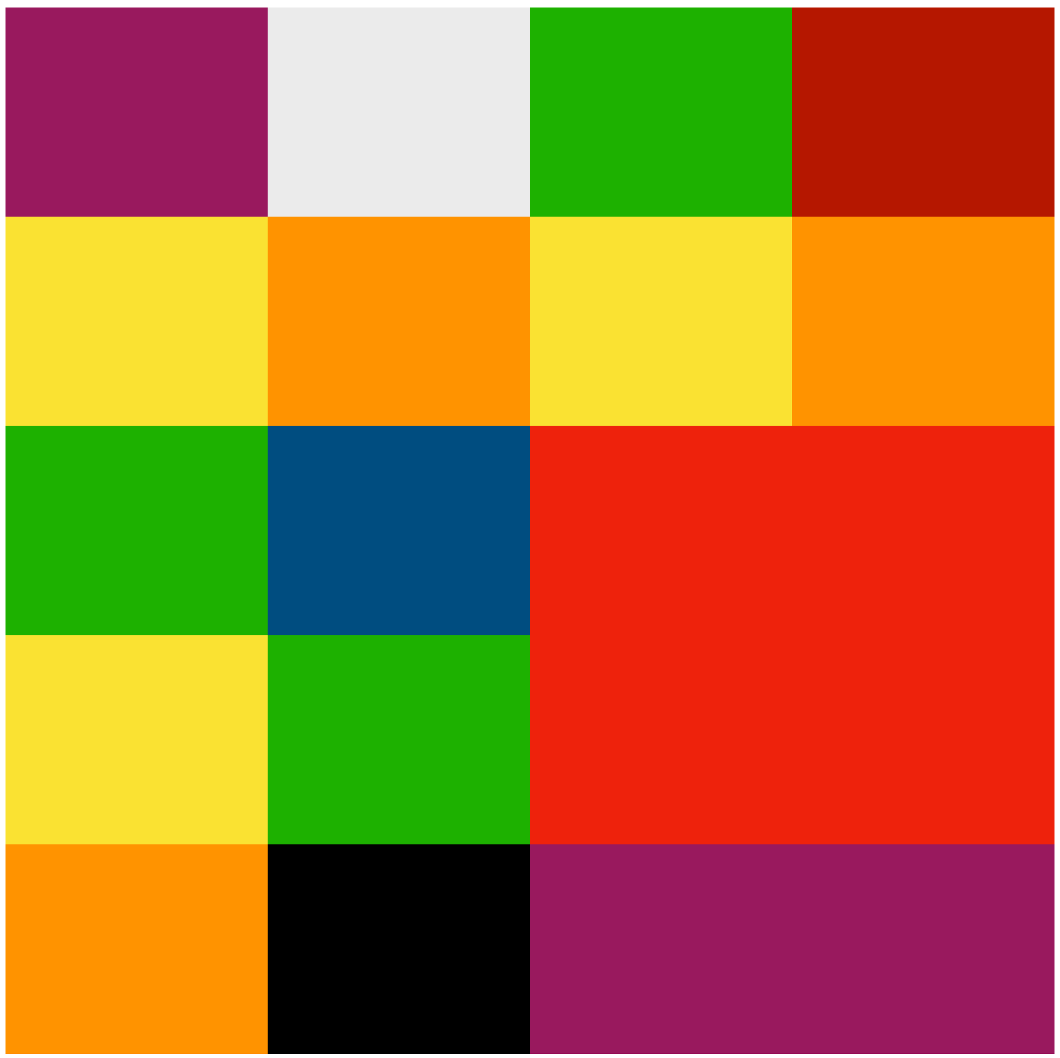
tap



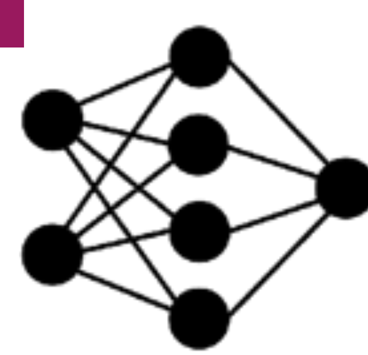


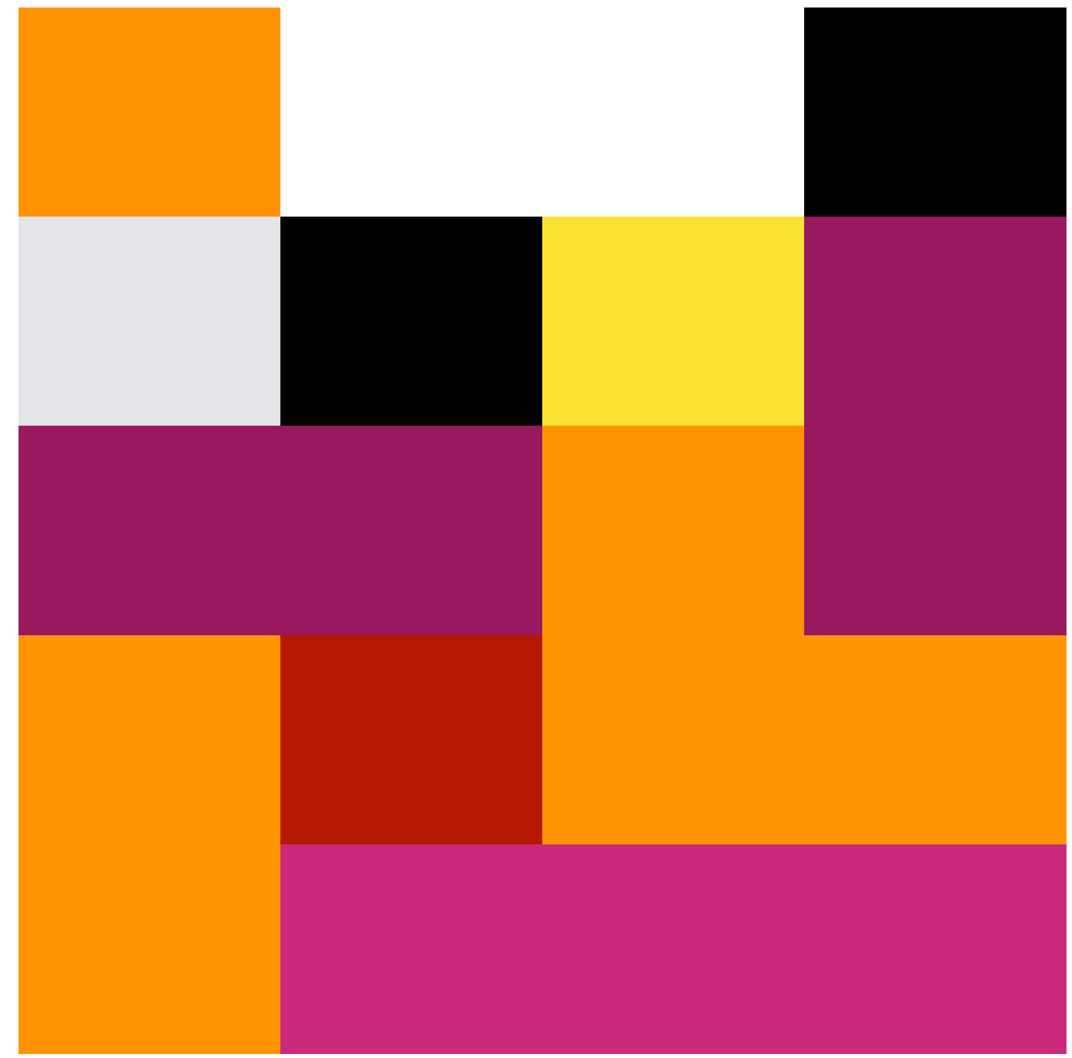
toc

ML Perspective



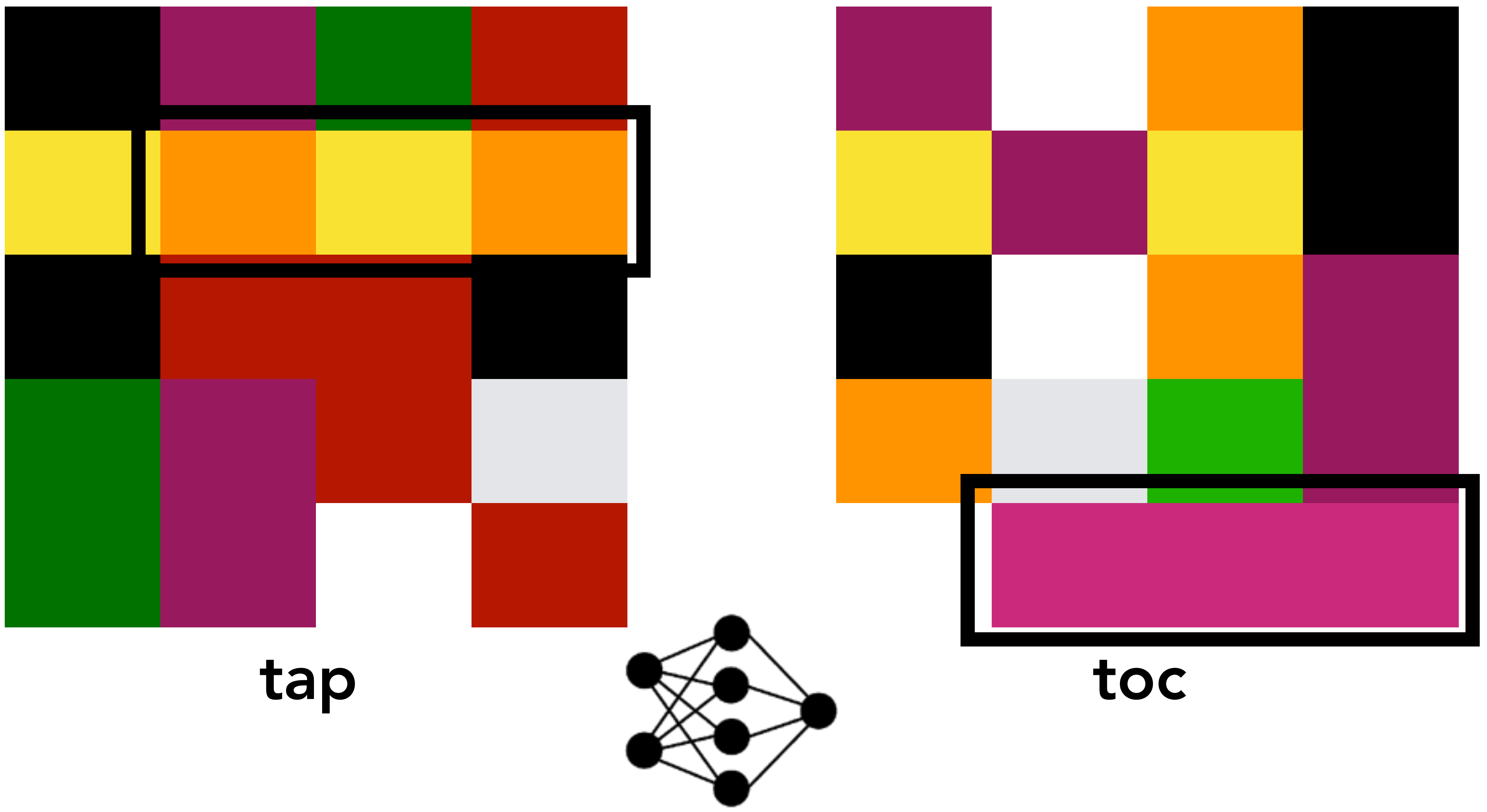
tap



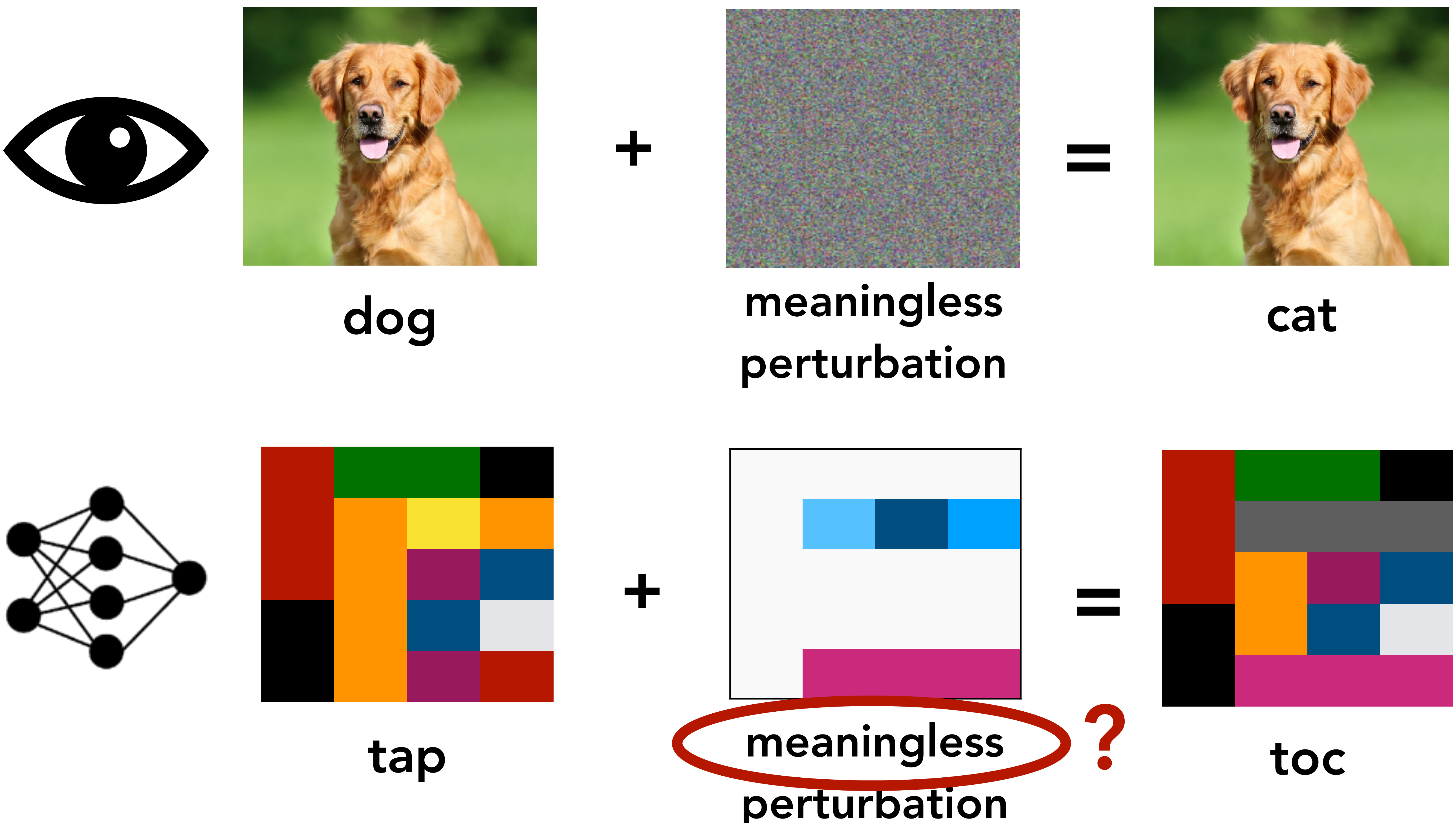


toc

ML Perspective



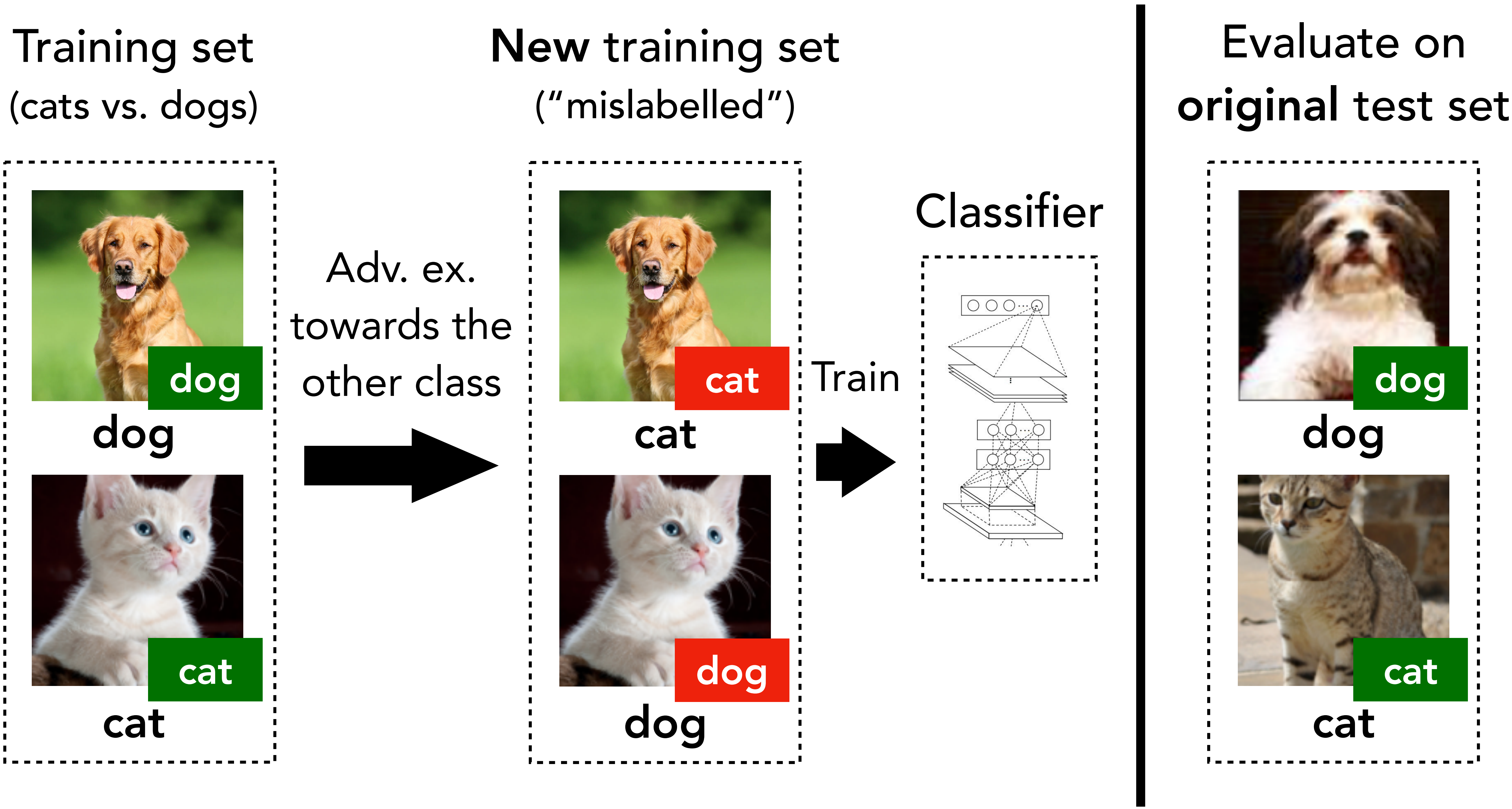
ML Perspective



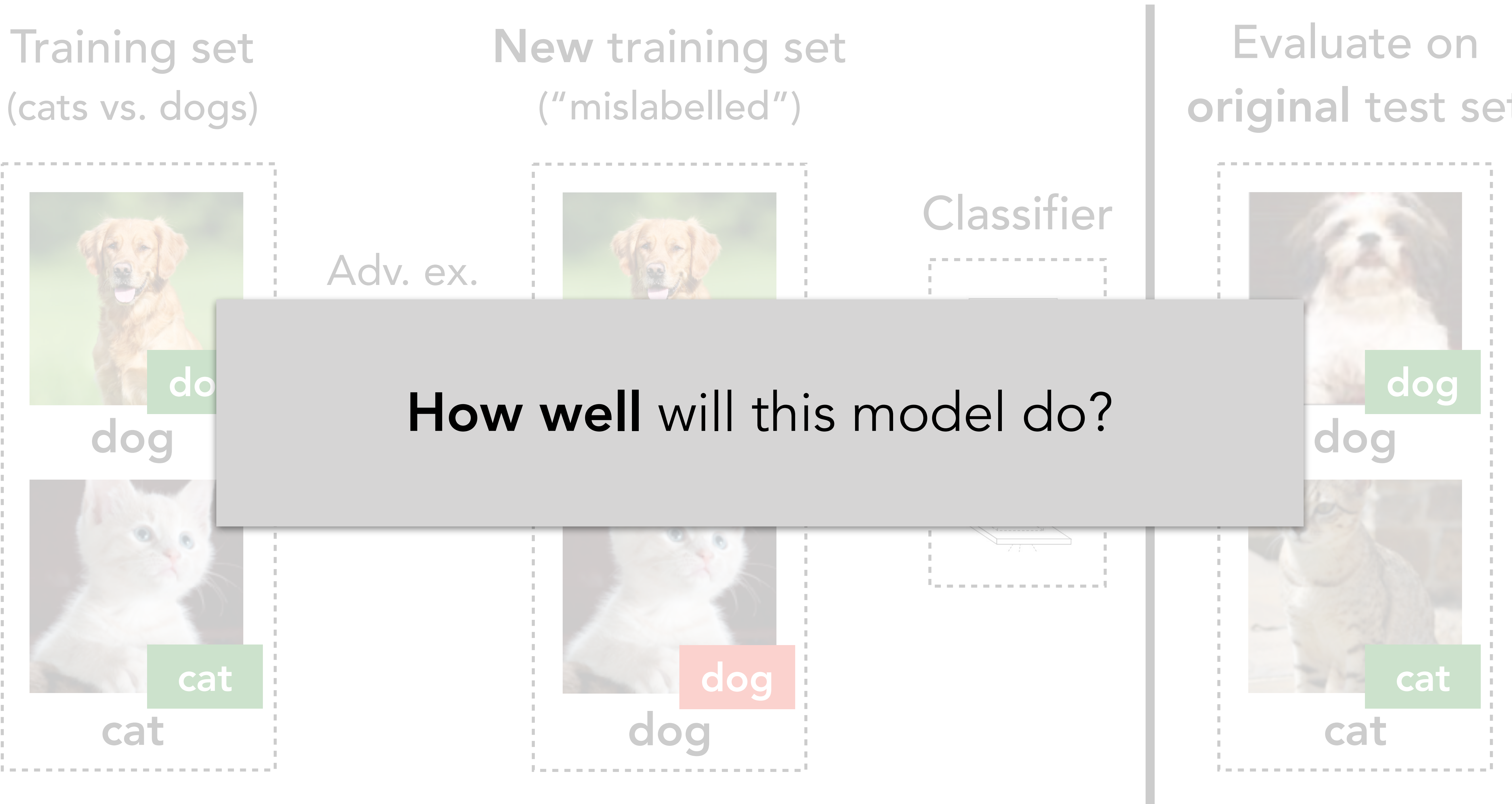
Are adversarial perturbations indeed meaningless?

[Ilyas Santurkar Tsipras Engstrom Tran M ‘19]

Simple experiment

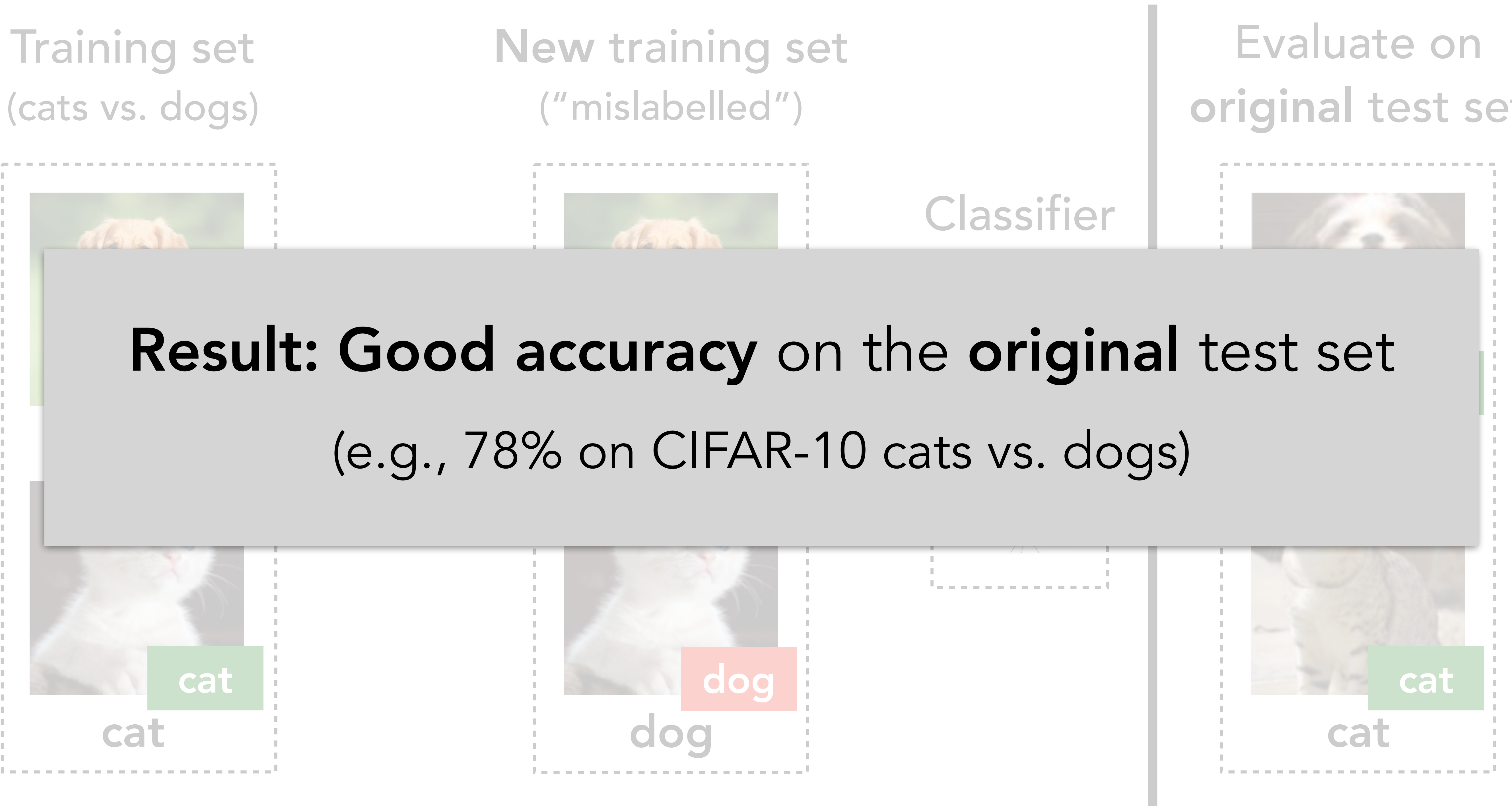


Simple experiment



How well will this model do?

Simple experiment



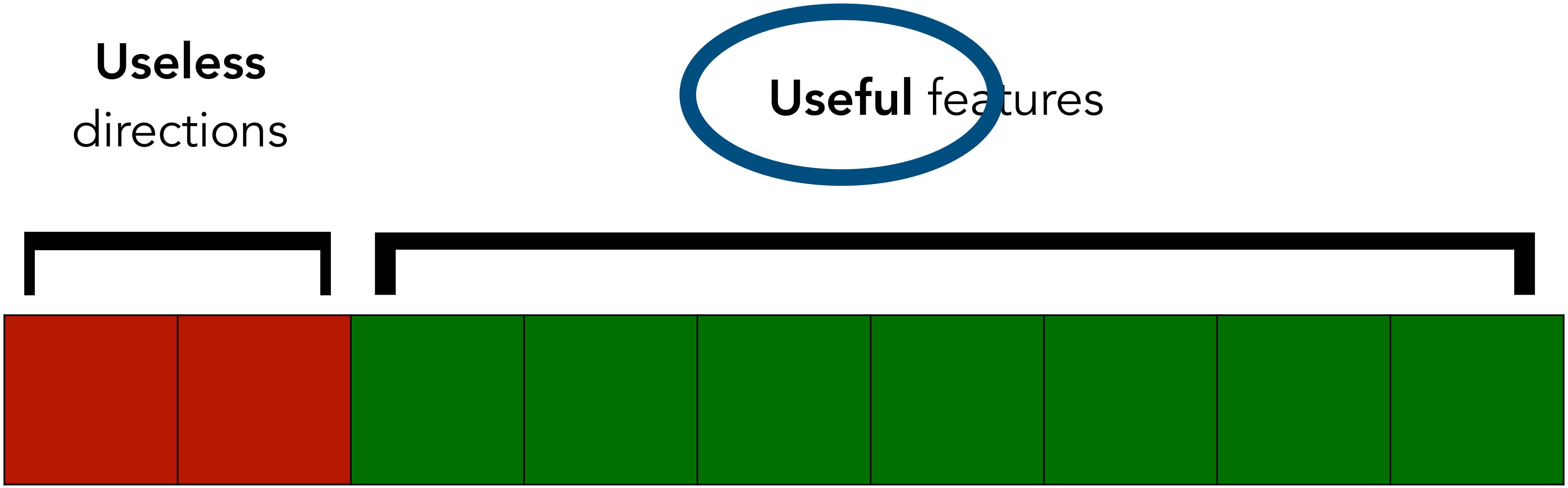
Result: Good accuracy on the **original** test set

(e.g., 78% on CIFAR-10 cats vs. dogs)

What’s going on?

What if adversarial perturbations are **not** aberrations but **features**?

The Robust Features Model

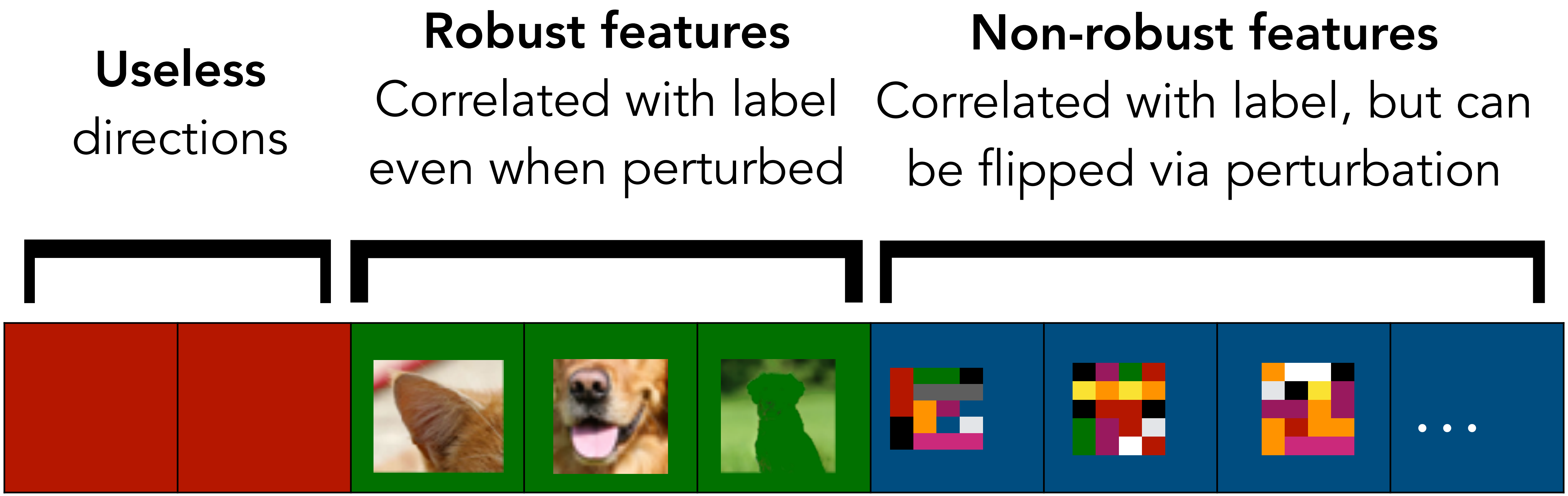


The Robust Features Model

Useless
directions

Robust features
Correlated with label
even when perturbed

The Robust Features Model



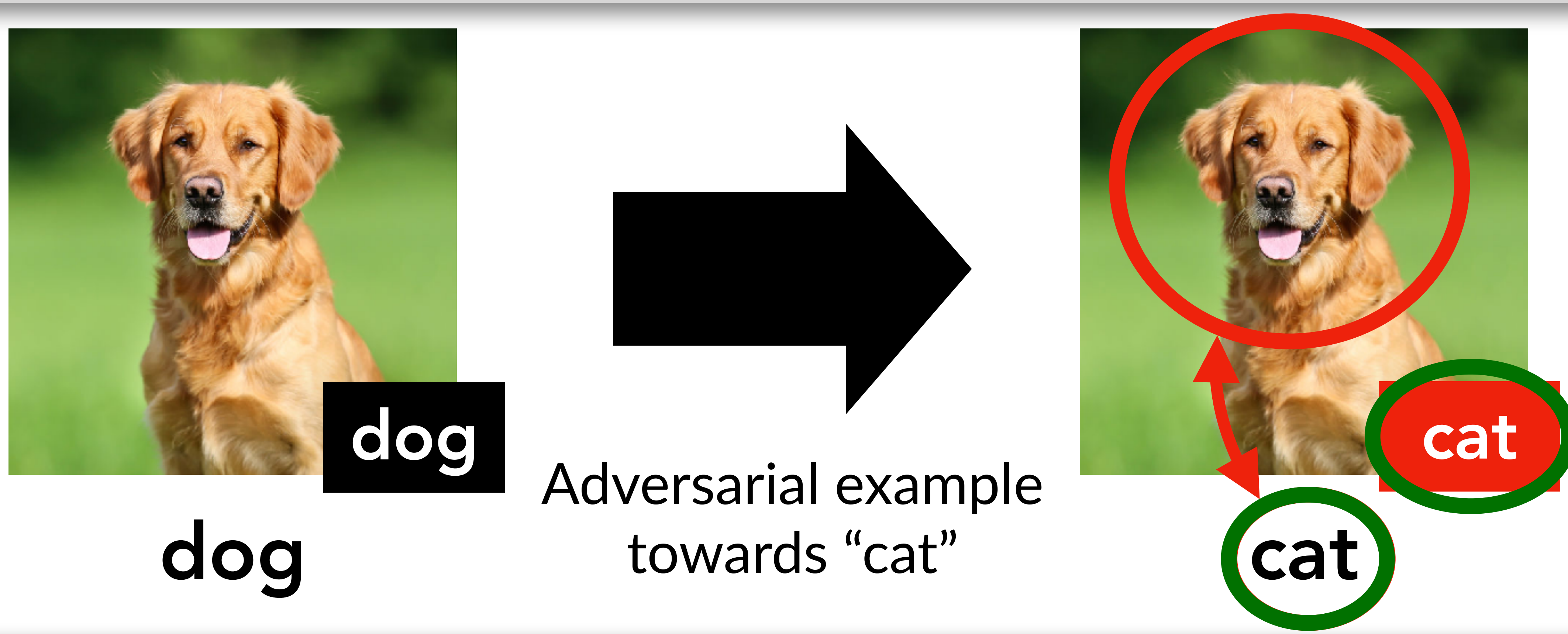
When maximizing (test) accuracy: All useful features are good

And: Non-robust features are often great!

That's why our models pick on them
(and **become vulnerable to adversarial perturbations**)

The Simple Experiment: A Second Look

All robust features are **misleading**



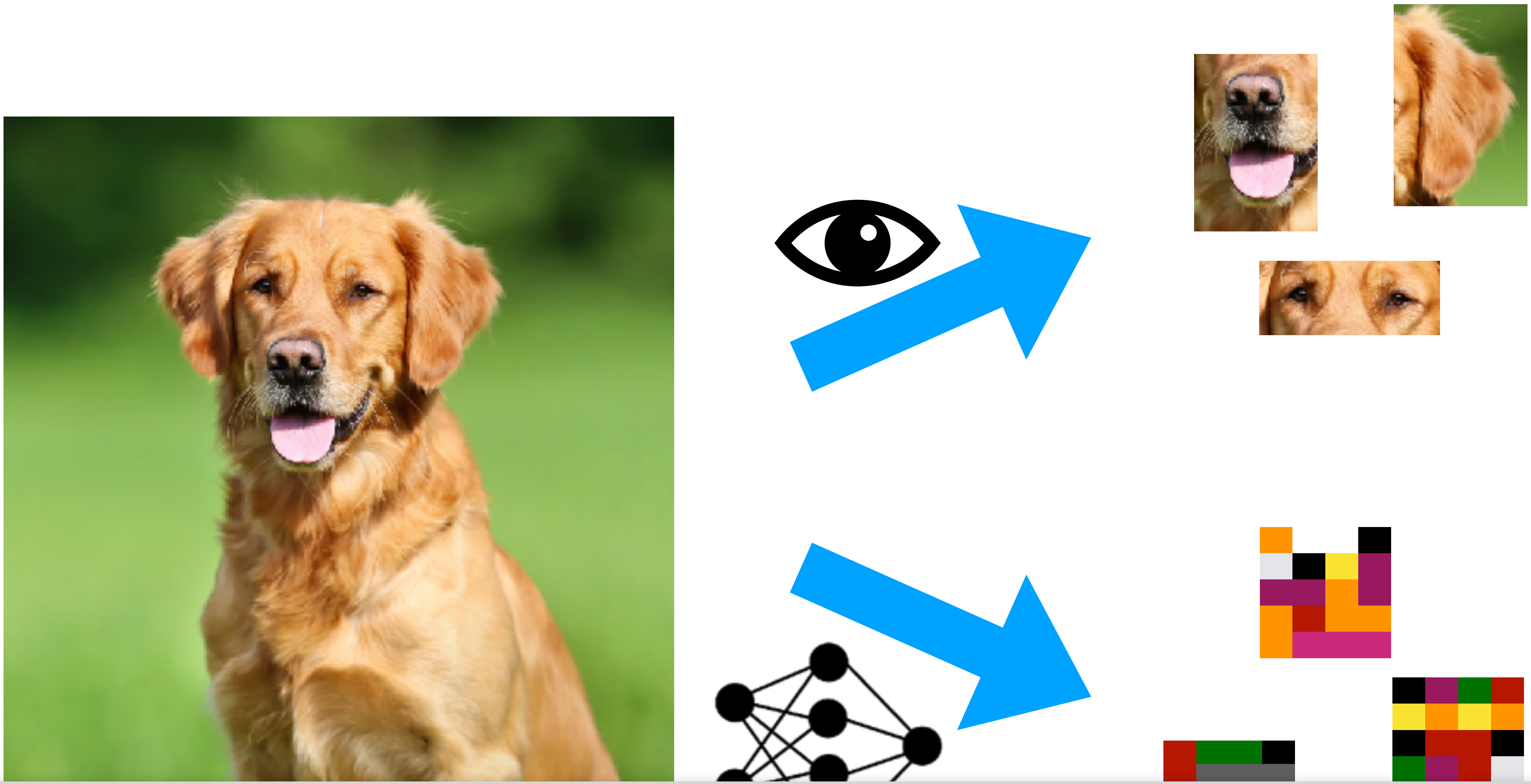
But: Non-robust features suffice for good generalization

What now?

A (new) perspective on adversarial robustness

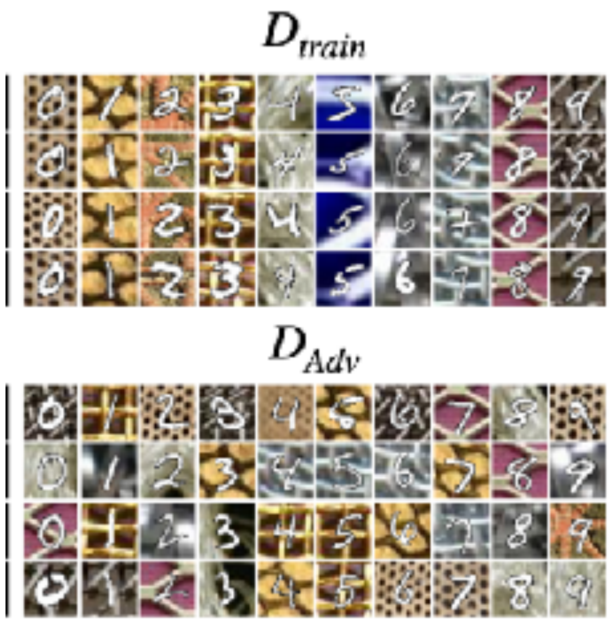
But also: Provides insight into how our models learn

Human vs ML Model Priors



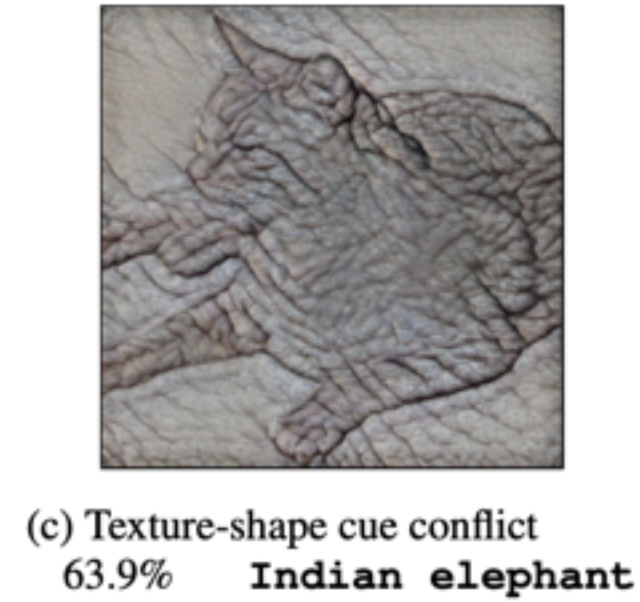
These are **equally valid** classification methods
→ No reason for our models to favor the “human” one

In fact, models…



…can be invariant to task-relevant features [Jacobsen et al 2019]

…depend unintuitively on linear directions [Jetley et al 2018]



…depend too much on texture [Geirhos et al 2019]

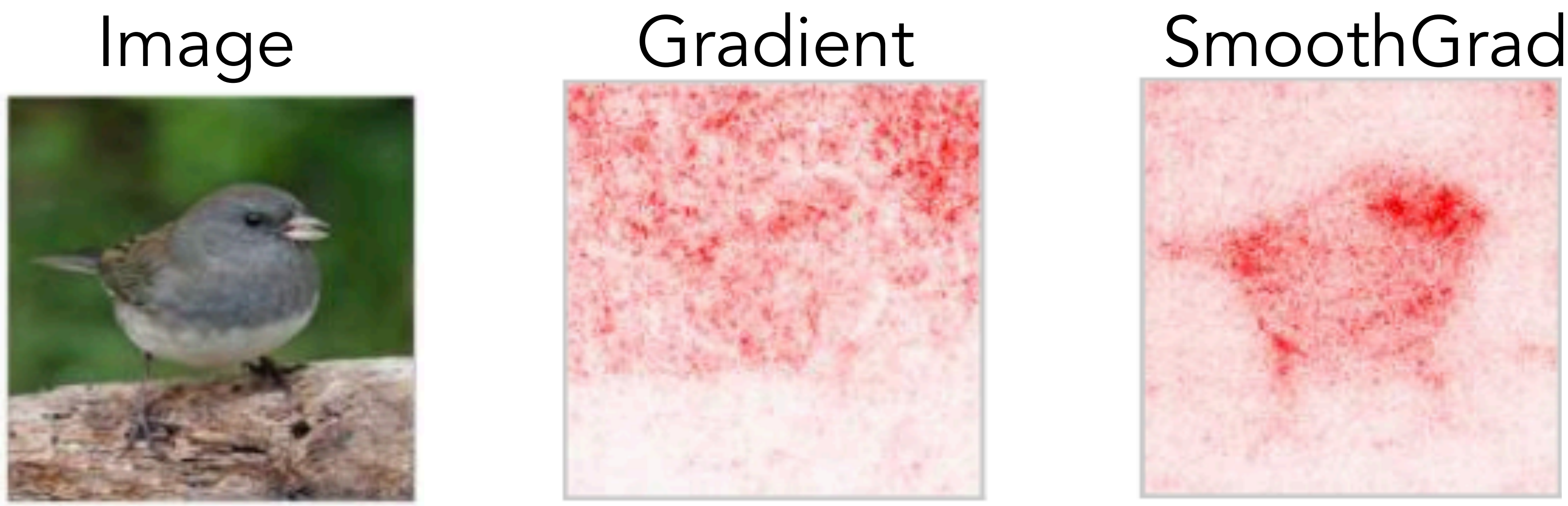
Adversarial examples are largely a **human** phenomenon

These are **equally valid** classification methods
→ No reason for our models to favor the "human" one

Consequence: Interpretability

Models that use non-robust features **cannot be human interpretable**

For instance: Input Saliency Maps



No hope for interpretability without intervention **at training time**

Post-hoc interpretations may mask features models depend on

Consequence: Training Modifications

To get **robust models** we need to explicitly train them to ignore non-robust features

Standard Training: $\min_{\theta} \mathbb{E}_{(x,y)\sim D}[\ell(\theta; x, y)]$

Robust Training: $\min_{\theta} \mathbb{E}_{(x,y)\sim D}[\max_{\delta\in\Delta} \ell(\theta; x+\delta, y)]$

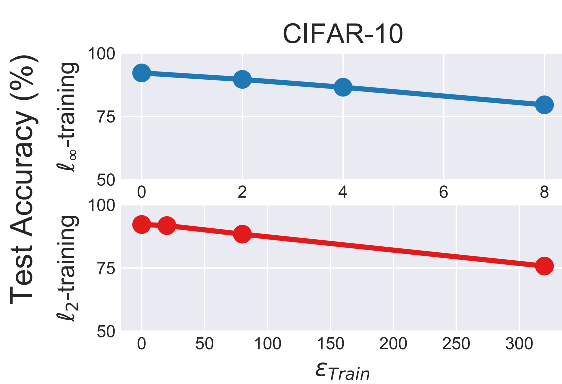
Desired invariance

Enforces **additional restrictions (priors)** on what features models can use to make predictions

Consequence: Robustness Tradeoffs

Robust models can only leverage **robust** features

(Even though non-robust features **do** help with accuracy)

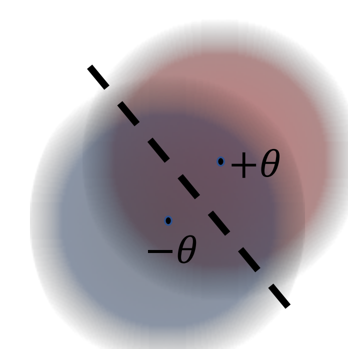


→ May get a **lower standard accuracy**

(vide **[Tsipras Santurkar Engstrom Turner M '18]**)

→ Need **more data** to get a given (robust) accuracy

(vide **[Schmidt Santurkar Tsipras Talwar M '18]**)

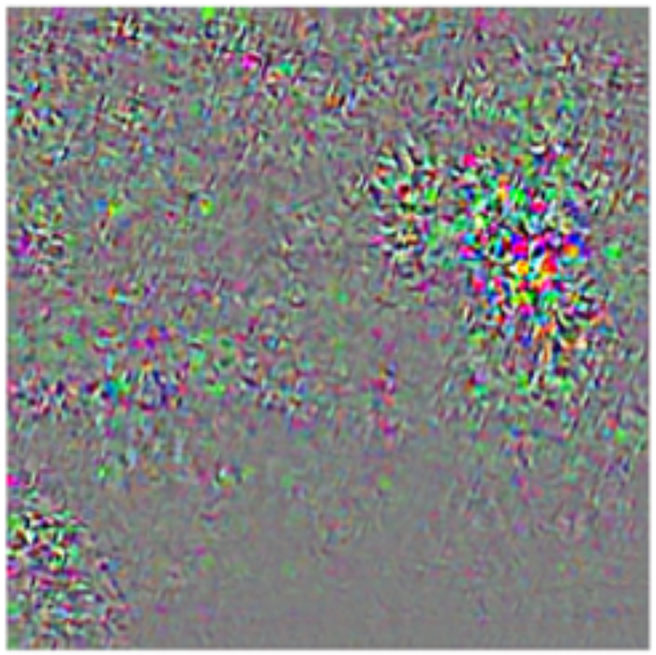


What if we force models to rely solely on robust features?

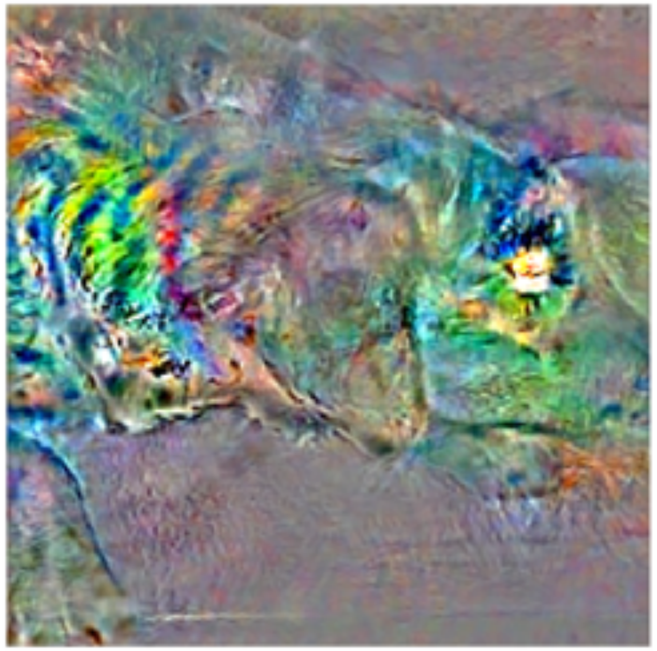
[Tsipras Santurkar Engstrom Turner M '18]
[Engstrom Ilyas Santurkar Tsipras Tran M '19]
[Santurkar Tsipras Tran Ilyas Engstrom M '19]

Robustness → Perception Alignment

Prediction: dog



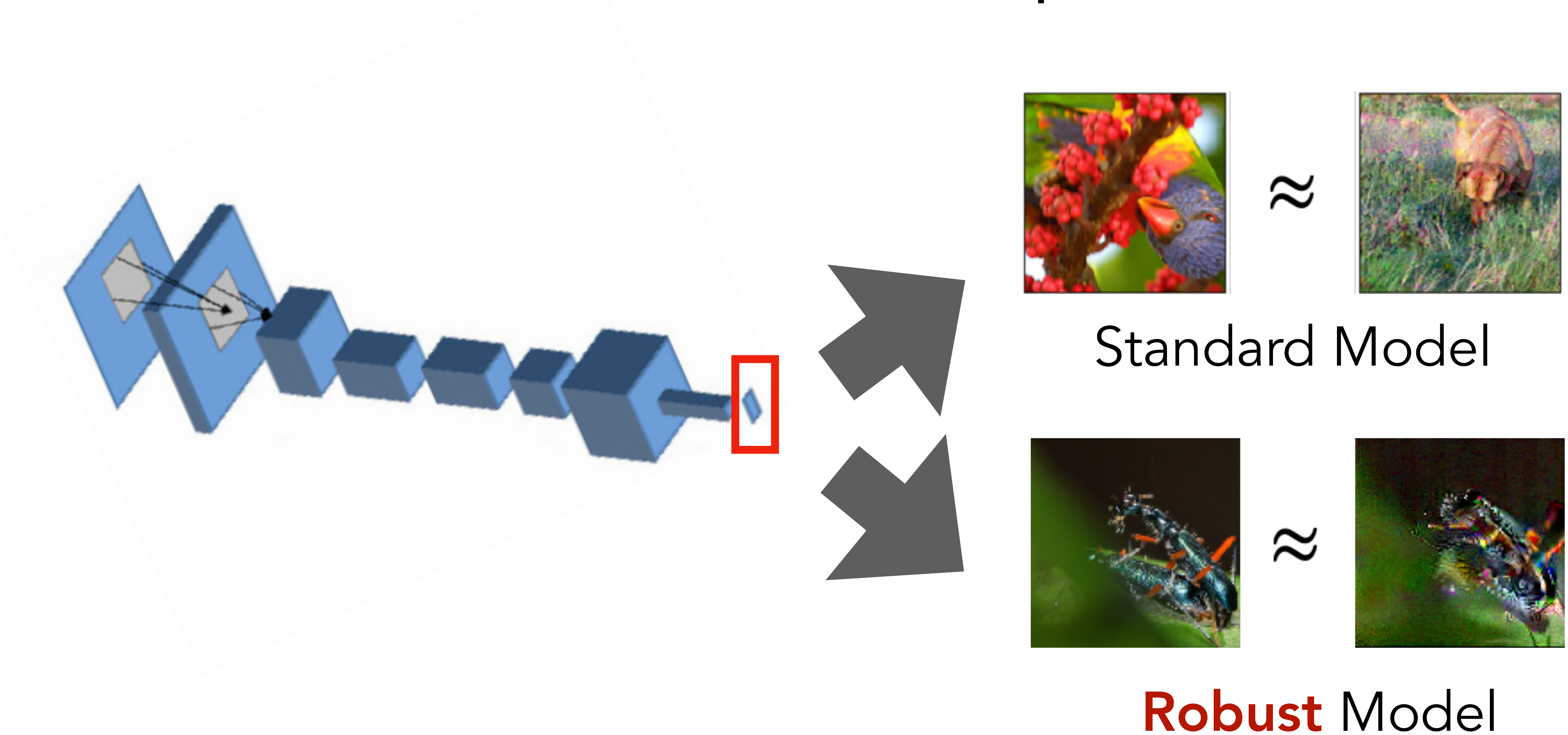
Pixel influence "heatmap" (standard)



Pixel influence "heatmap" (robust)

Models become more (human) perception aligned

Robustness → Better Representations

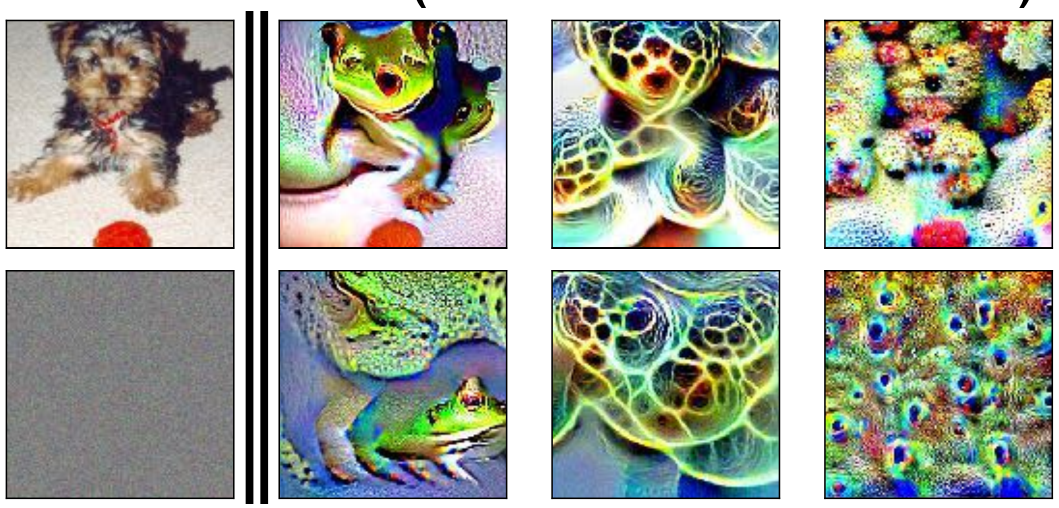


Robust representation distance tends
to **align better** with perceptual distance

Robustness → Better Representations

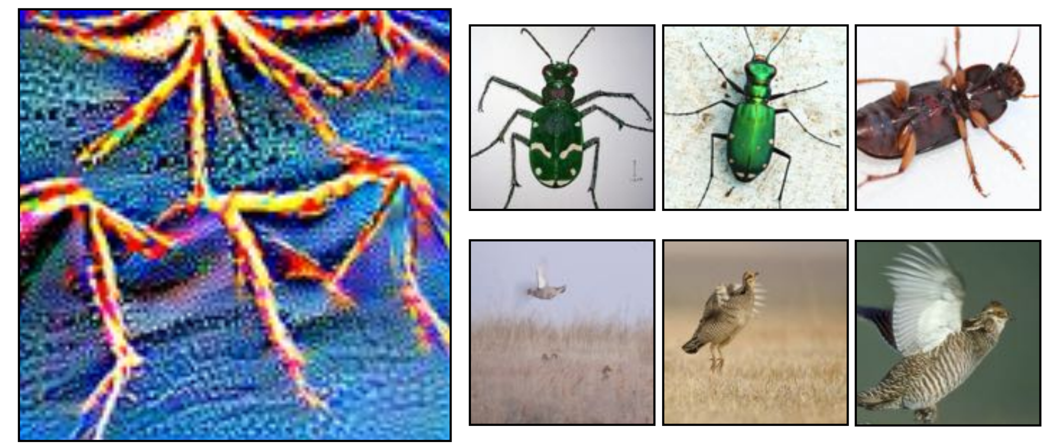
Direct feature visualization

Seed | Max(different coordinates)



(insect legs)

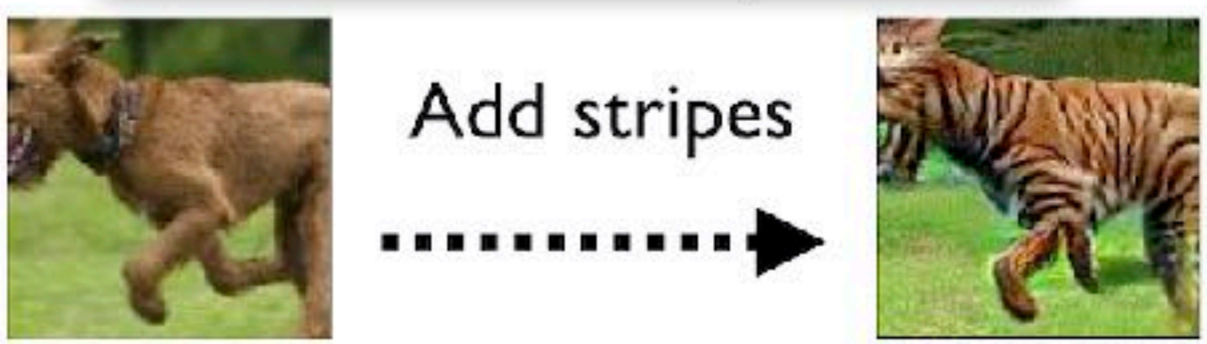
Most activated



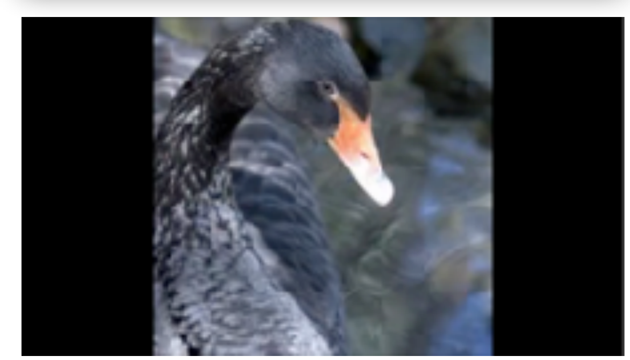
Maximized from noise

Least activated

Feature manipulation



Interpolation



Robust representations **transfer better** across tasks

[Salman Ilyas Engstrom Kapoor M '20]

Robustness → CV Applications

Generation

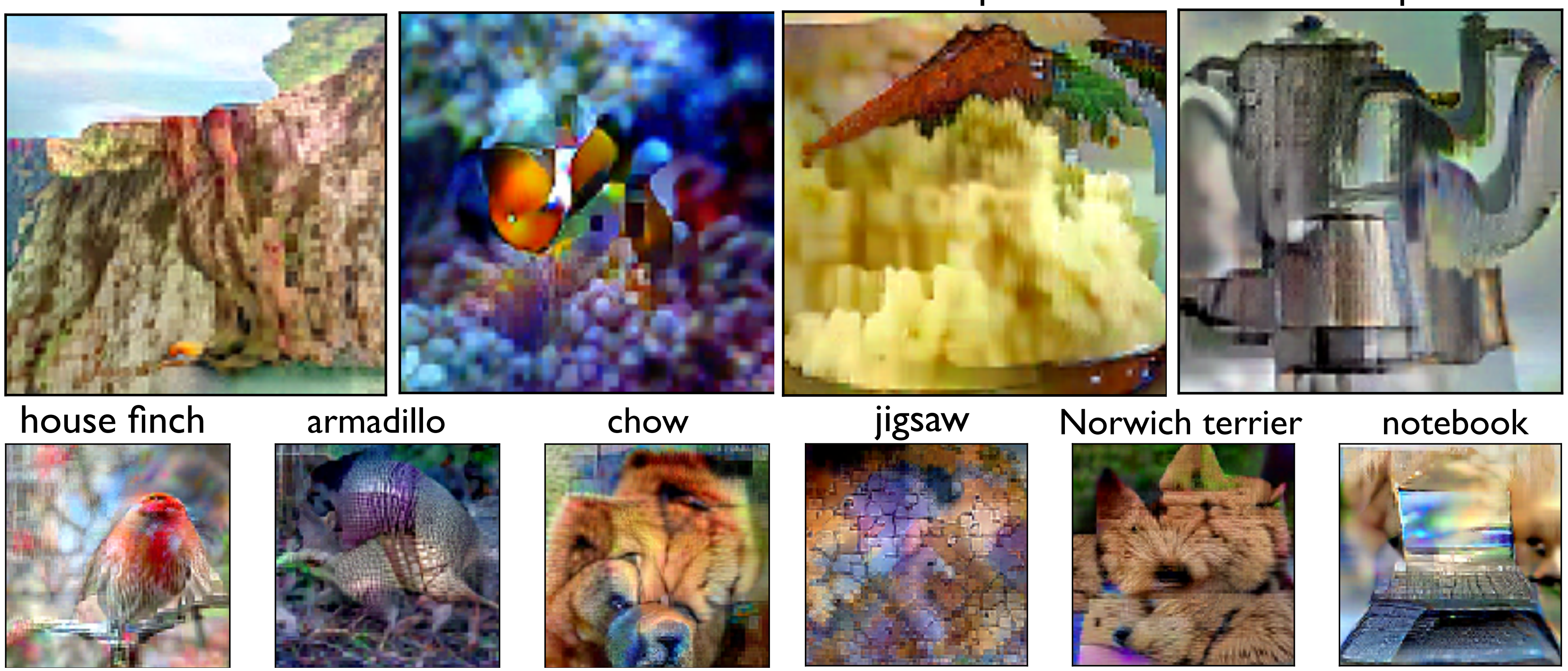
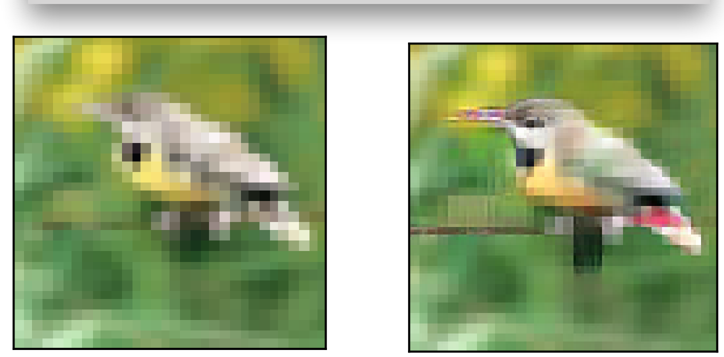


Image Translation

Superresolution



Inpainting

More Broadly

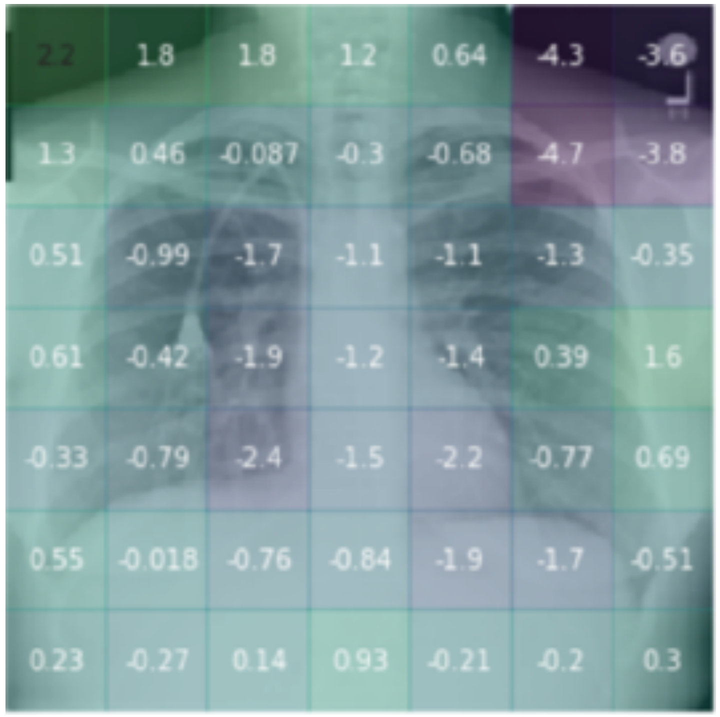
It is also about **choosing** what features our models should use

Problem: Correlations can be weird

Dogs

Cats

Problem: Correlations can be weird



"…if an image had a ruler in it, the algorithm was more likely to call a tumor malignant…"

[Esteva et al. 2017]

"CNNs were able to detect where an x-ray was acquired […] and calibrate predictions accordingly."

[Zech et al. 2018]

"Predictive" patterns can be misleading

"Counterfactual" Analysis with Robust Models

label: "insect"; prediction: "dog"

Robustness = Framework for controlling what correlations to extract

Takeaways

Adversarial examples arise from
non-robust features in the data

→ These features **do** help in generalization (a lot!) and that's why our models like to rely on them

→ Interpretability needs to be addressed **at training time**

Robustness induces more "human-aligned" representations

→ Enable a broad range of vision applications (in a simple way)

→ Support findings (simple) counterfactuals

But: It is really about **how (and what) our models learn**

→ What is the "right" notion of generalization?

→ What features do we want our models to use?

→ How much do we value human alignment/interpretability?

Adversarial robustness =
Framework for feature engineering

How can/should robust ML view inform/learn from neuroscience?

Questions?

(See the materials on the website)

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