Targeted perturbations reveal brain-like local coding axes in robustified, but not standard, ANN-based brain models

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Vision
Computation
Cognition
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Artificial neural networks as models of the brain

What do we want from a model of the brain?

- ***Precise, quantitative predictions*** *of neural data under novel conditions*

- *Implementation of* ***similar information-processing*** *strategies to the brain*

Artificial neural networks as models of the brain

What do we want from a model of the brain?

- ***Precise, quantitative predictions*** *of neural data under novel conditions*

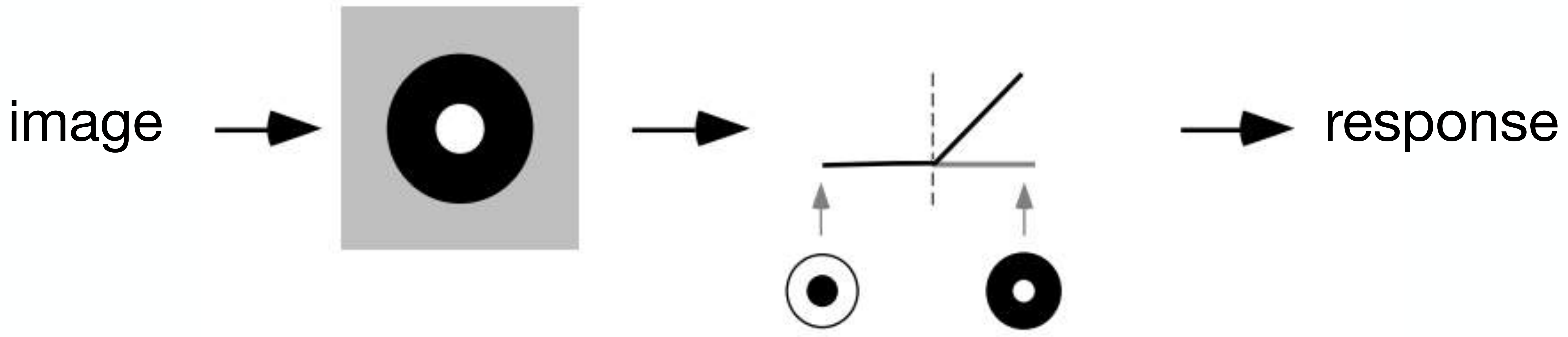
    "Encoding model" — input arbitrary sensory stimuli and predict exact brain responses

- *Implementation of* ***similar information-processing*** *strategies to the brain*

    Models with stable **brain-like** internal representations

How do we build predictive models?

- Early work used handcrafted features to predict brain responses
    - Image is convolved with feature and passed through a nonlinearity



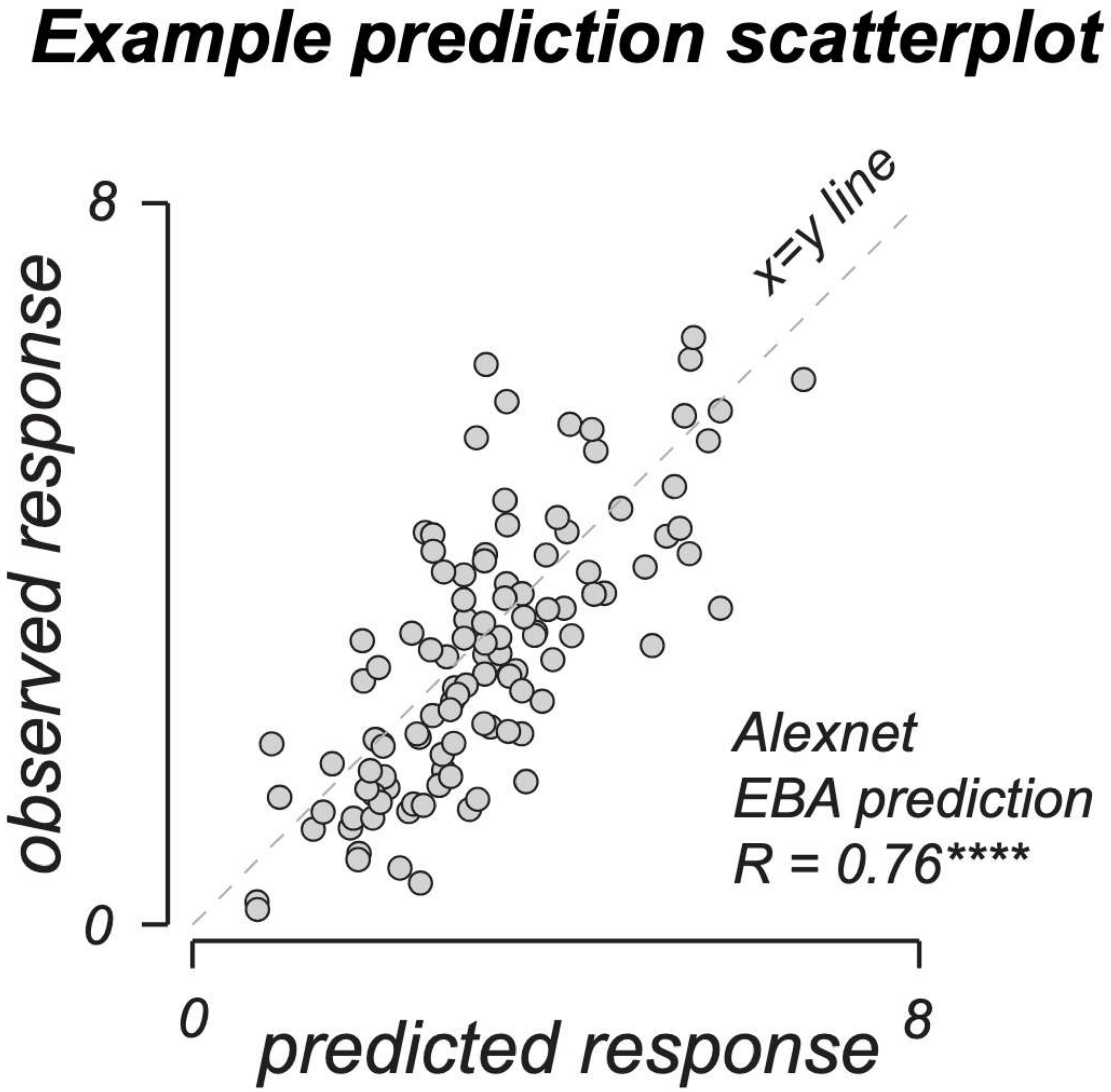
- Outputs are directly compared with neural firing rates (high correlation implies neuron is selective to this feature)

Artificial Neural Networks (ANNs) as models of the brain

- In more recent years, ANNs have emerged as leading models of the brain

- Features *learned by* ANNs are the most predictive

- We now have unprecedented predictive precision!

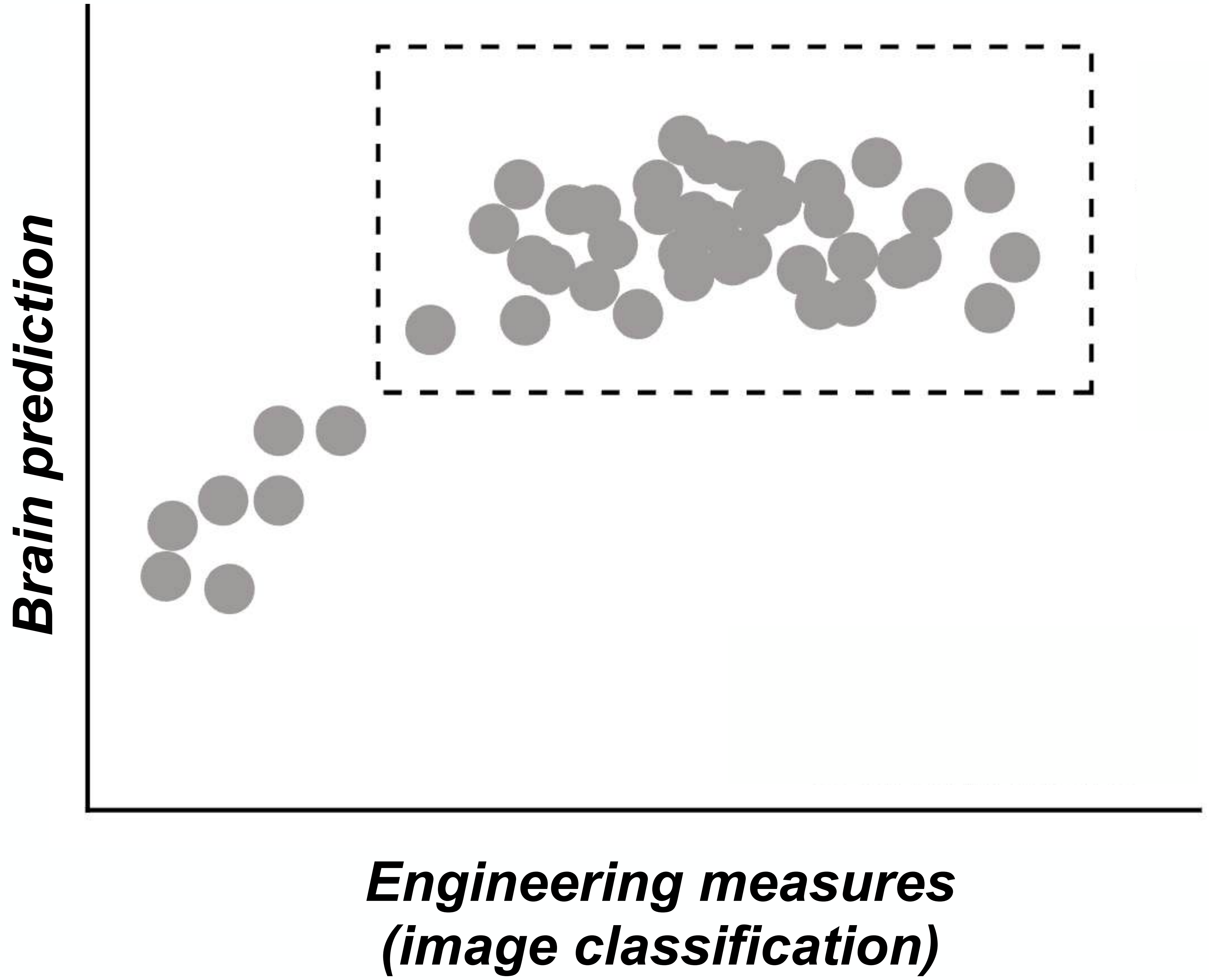


Artificial Neural Networks (ANNs) as models of the brain

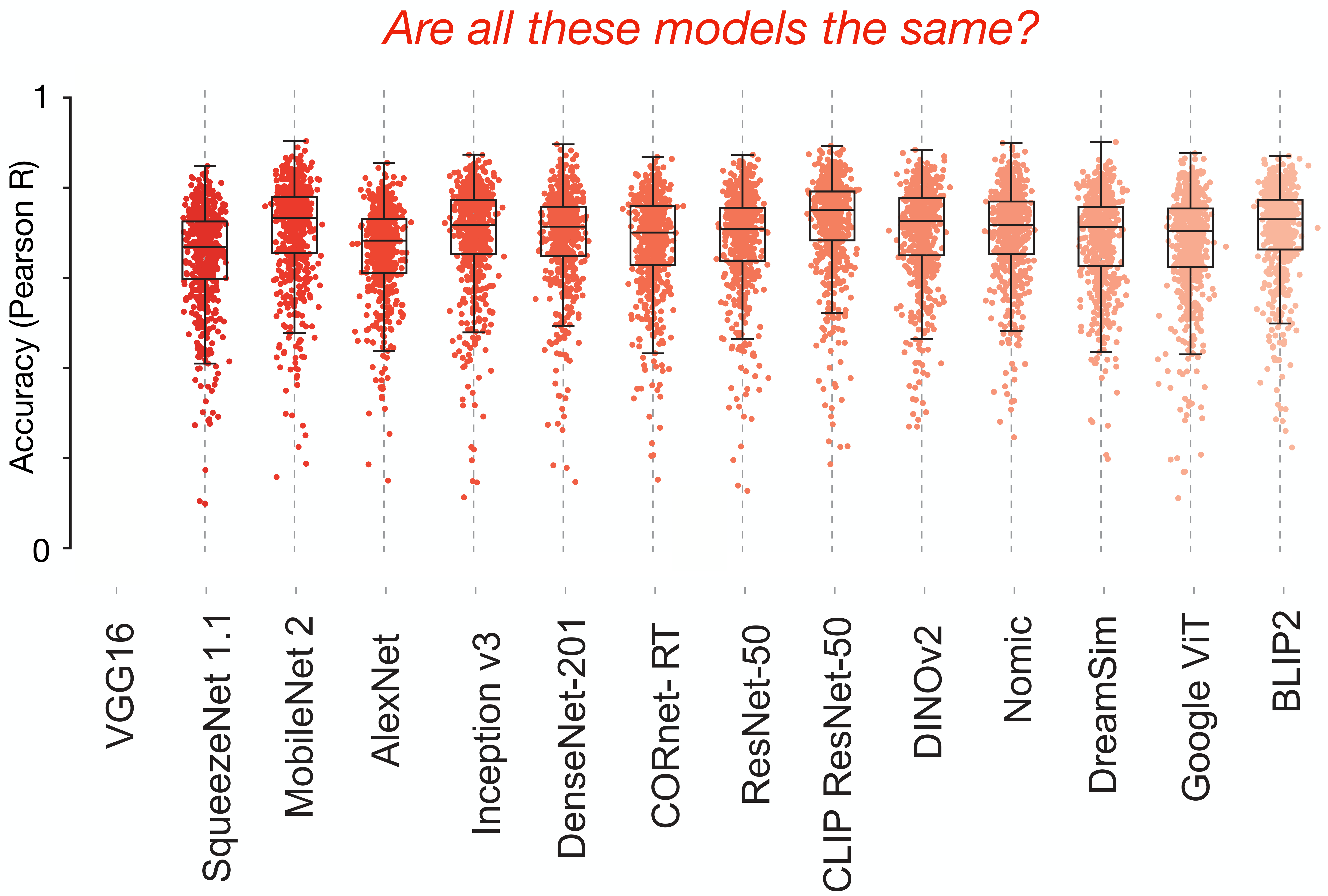
- As ANNs have become better on **engineering measures,** they typically have improved on **brain prediction**

This relationship has *plateaued!*

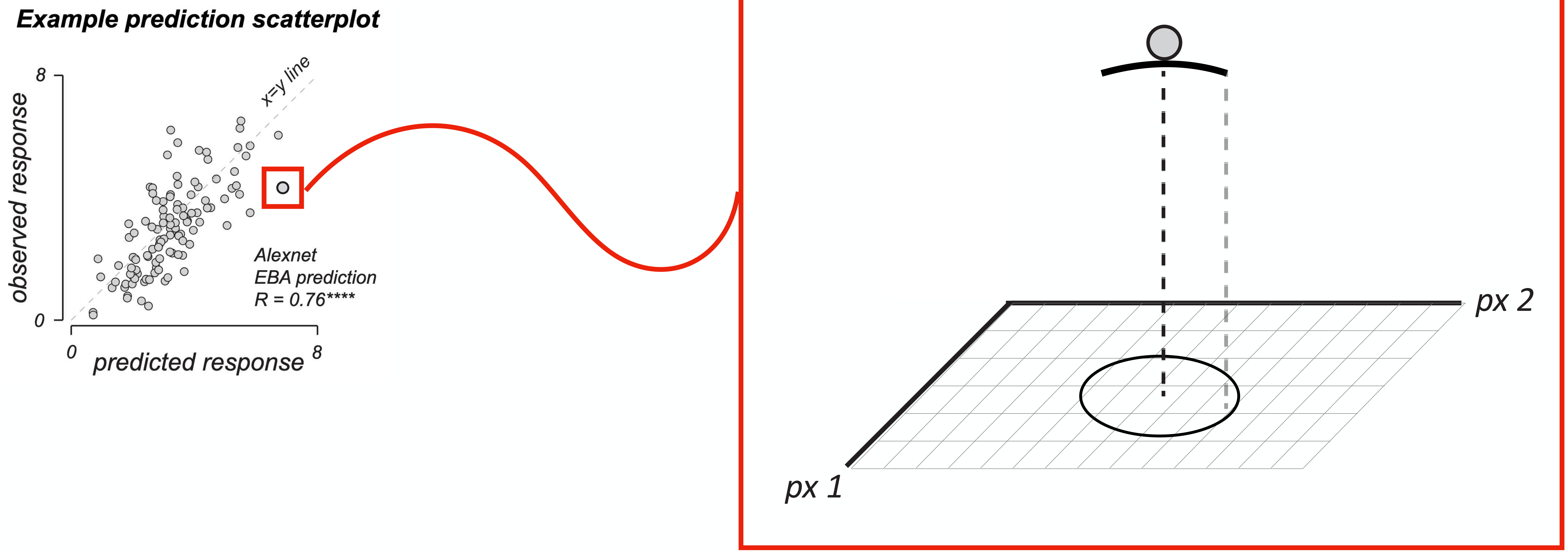
Do we need to move beyond prediction scores?



Artificial neural networks as models of the brain

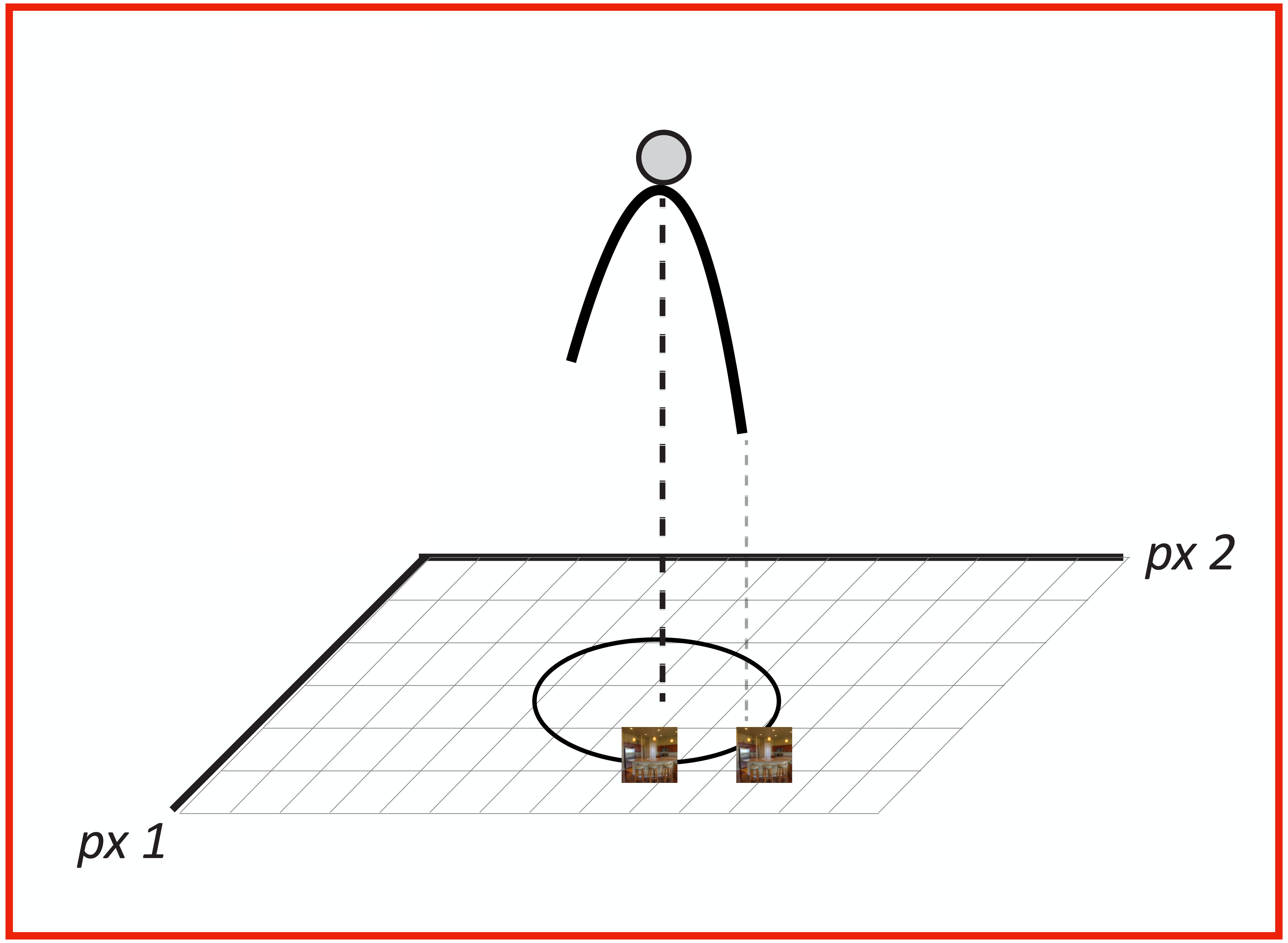


We should expect responses to be **stable** to small changes in the image



Can you tell the difference
between these two images?

If models have **failure modes,** this makes it a bad model!



Predictivity is an important metric, but a **predictive+stable** model is better than an **unstable+predictive** one

- How stable are model predictions?

- Do models share the same failure modes?

- Can we use stability to find better models of the brain?

- Can we use stable+predictive models to generate hypotheses about the brain?

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Small perturbations

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Bigger perturbations

- How stable are model predictions?

- Do models share the same failure modes?

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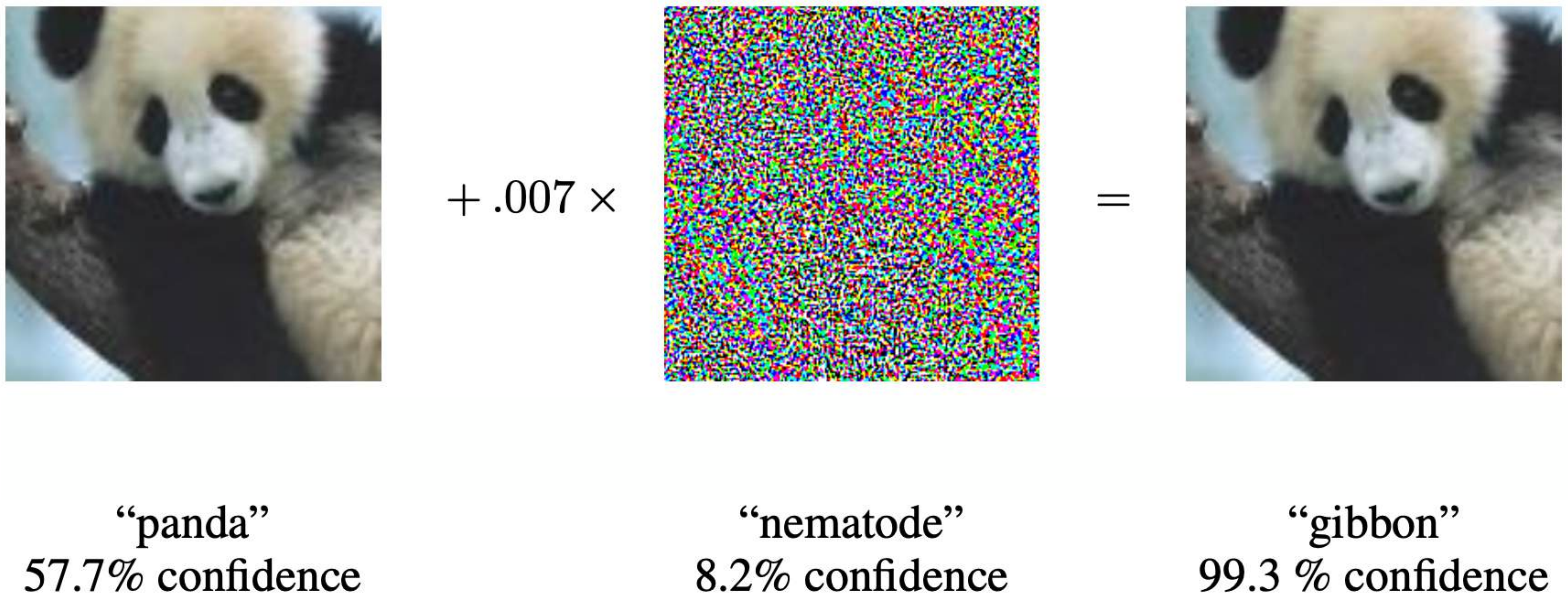
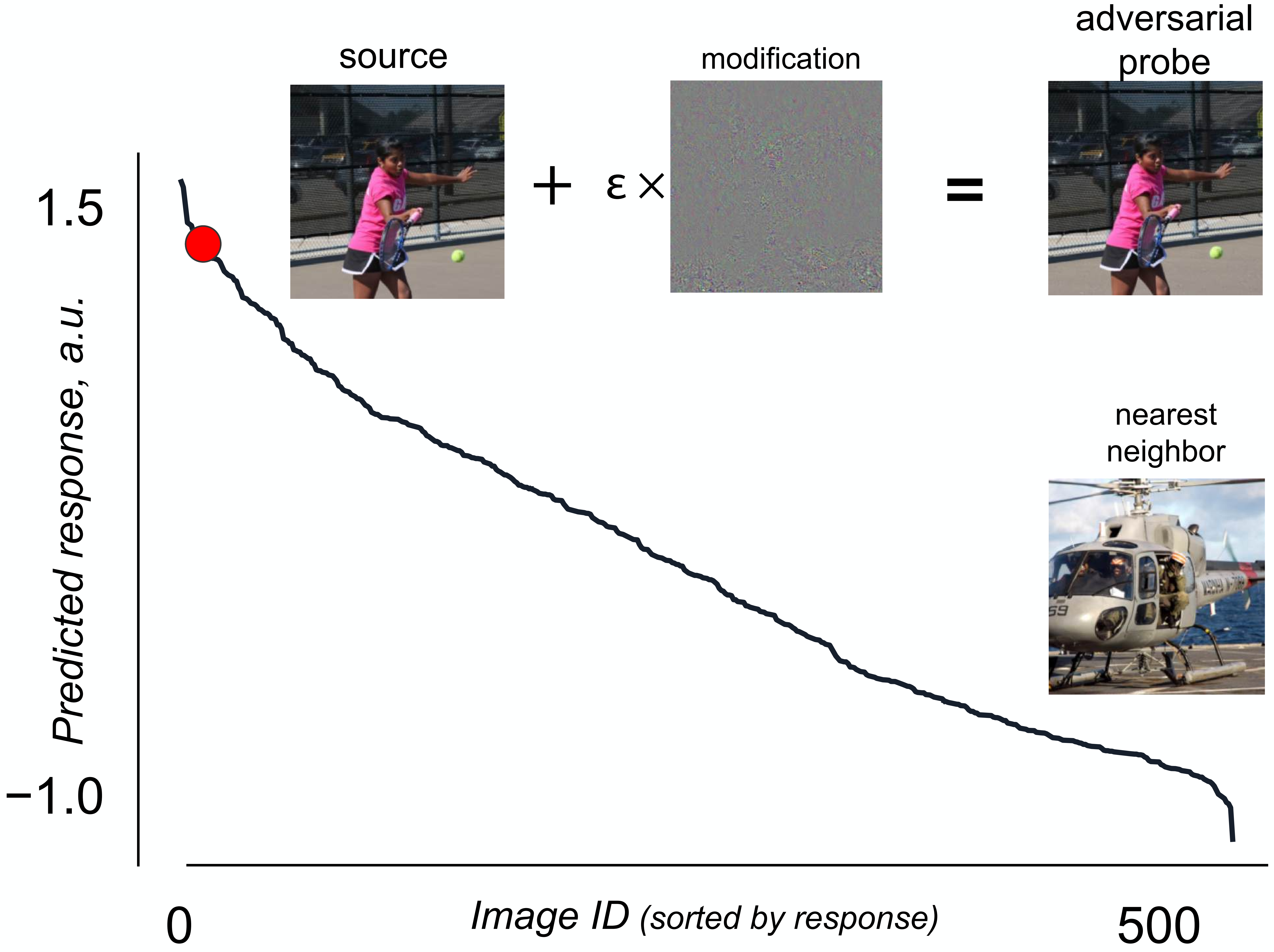
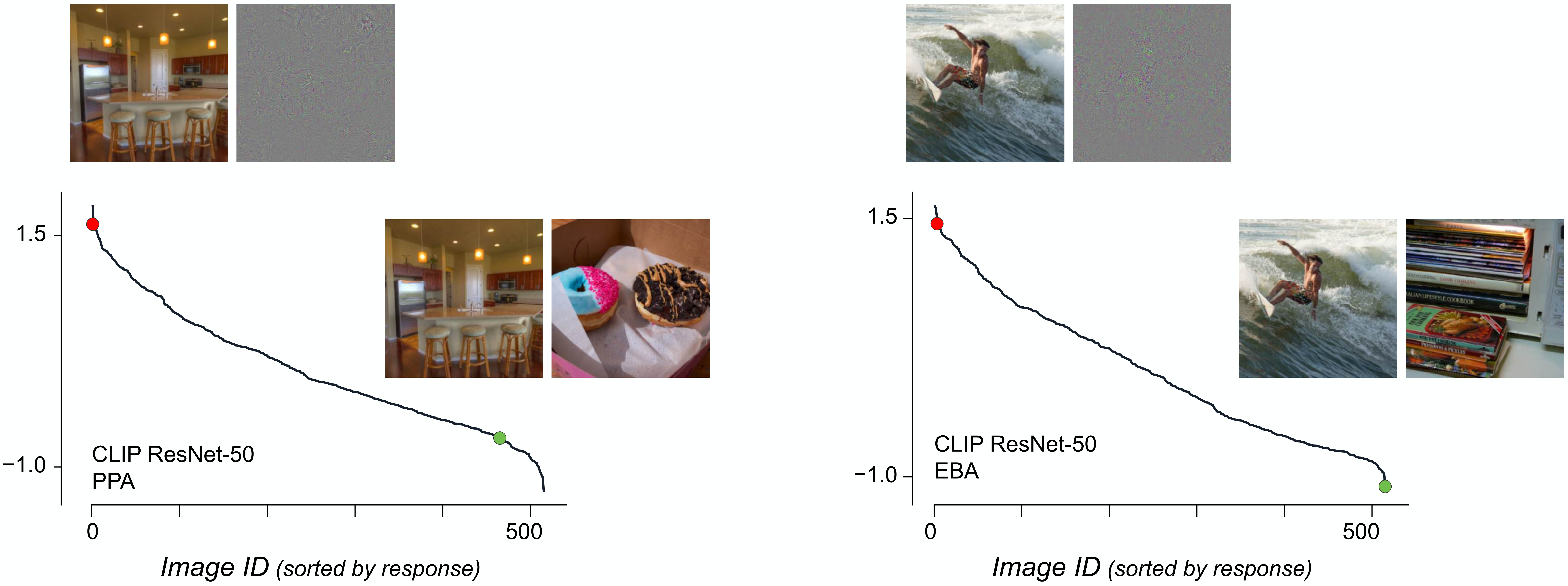
How do we find the worst-case change to an image?

- Machine learning work: ***adversarial attacks***
    - Formalizes “worst-case” perturbation under a certain pixel budget



Are brain models sensitive to small-scale noise?



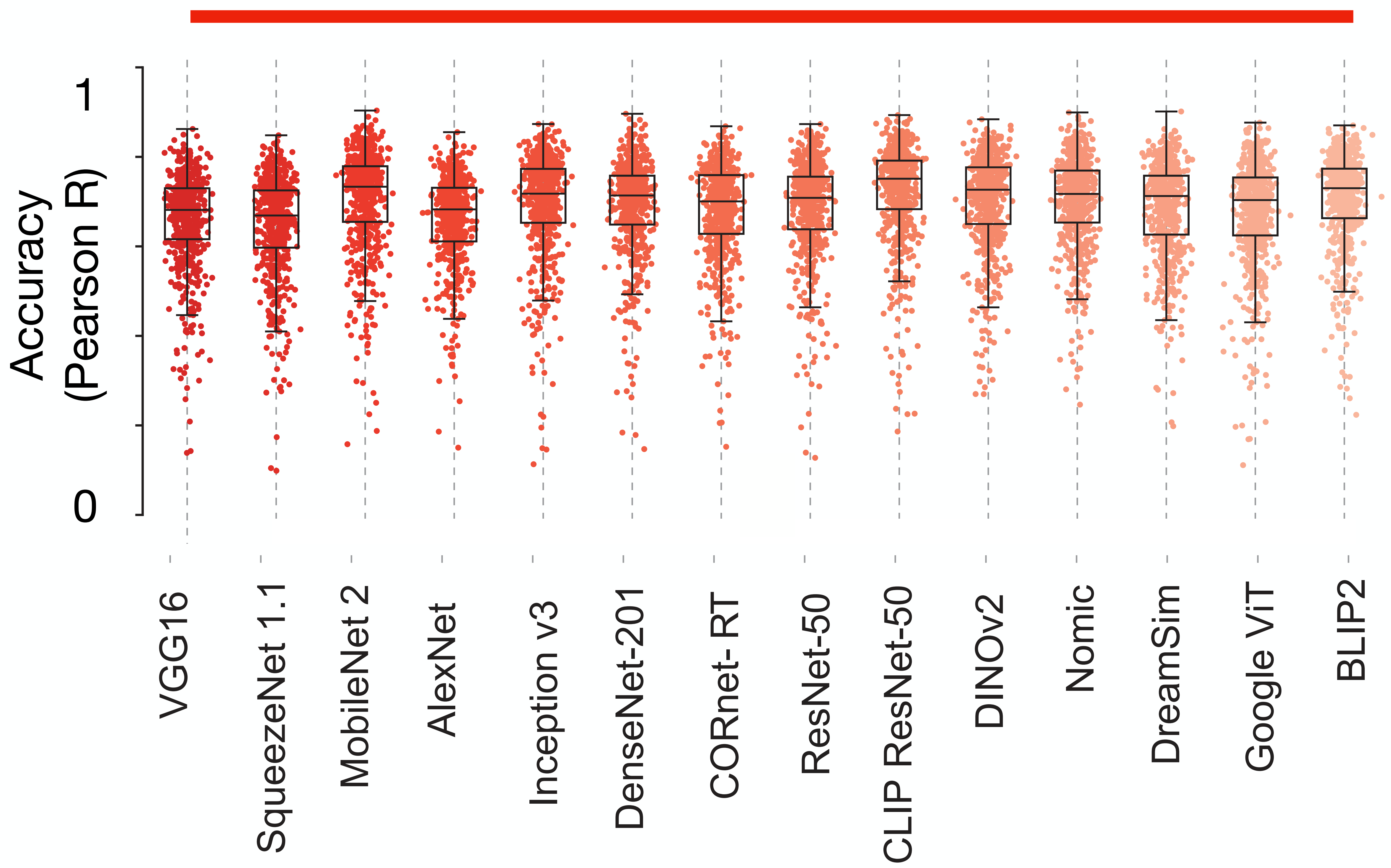

1.5
−1.0
CLIP ResNet-50
PPA
0
500
Image ID (sorted by response)
1.5
−1.0
CLIP ResNet-50
EBA
0
500
Image ID (sorted by response)

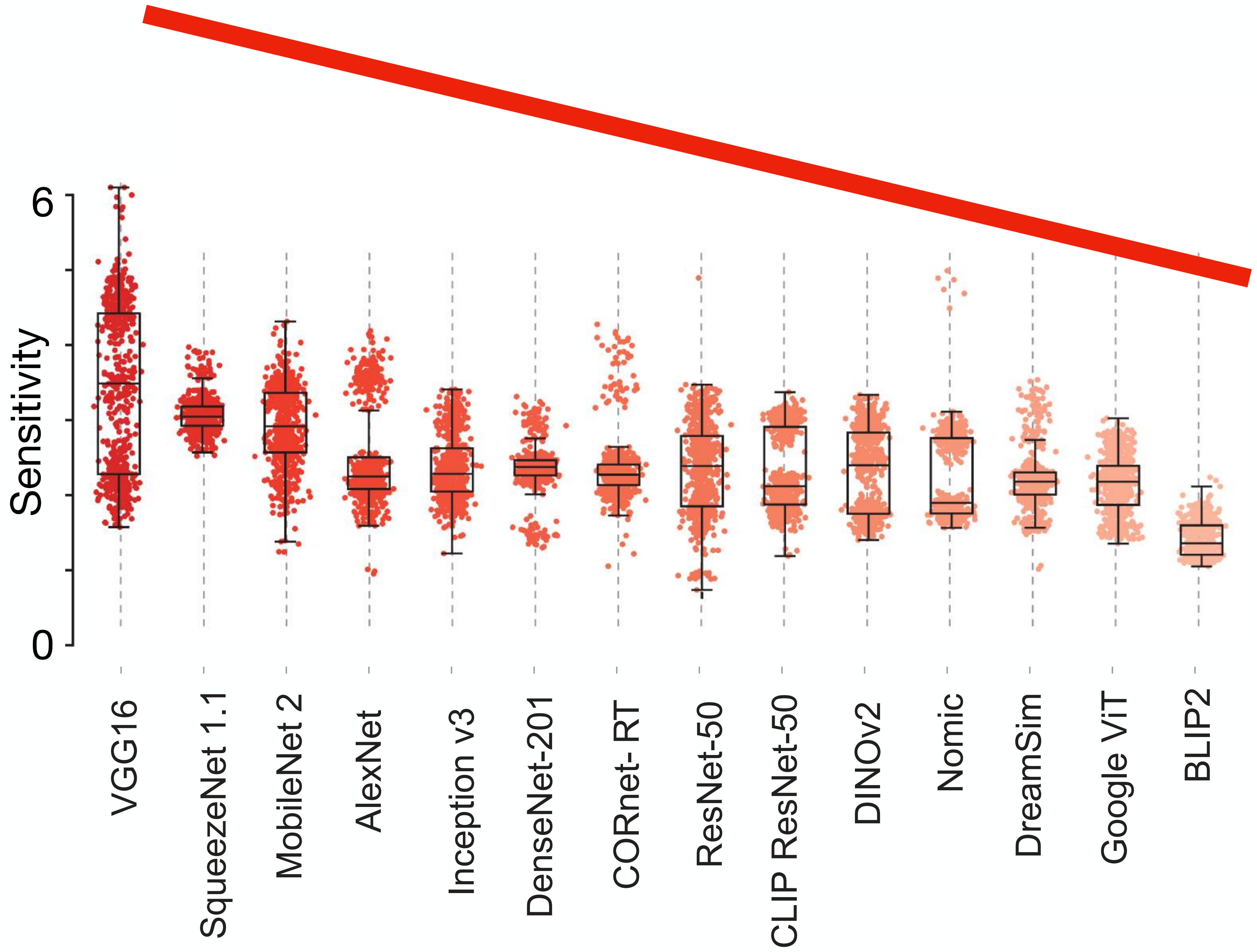
- We perform this experiment on **category-selective** regions (EBA, FFA, PPA)

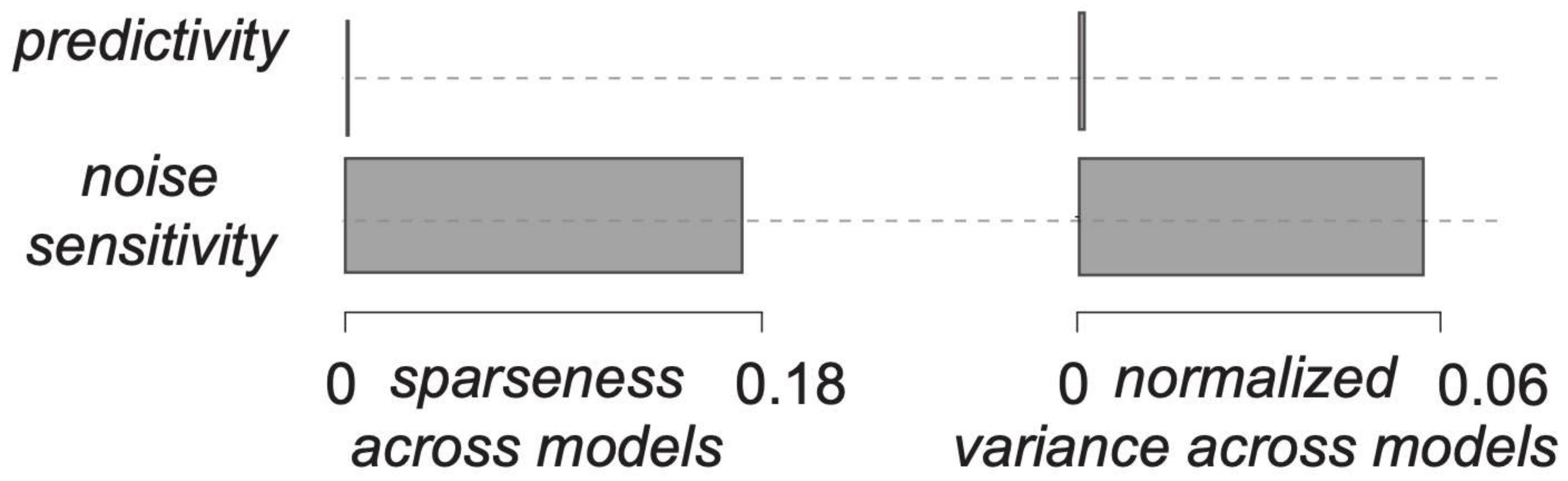
- Natural Scenes Dataset (NSD) for all analyses (515 shared stimuli, eight subjects)

- The readout of 14 pre-trained neural networks is is fit via linear regression to predict brain responses

Does adversarial sensitivity discriminate between equally well-predicting brain models?

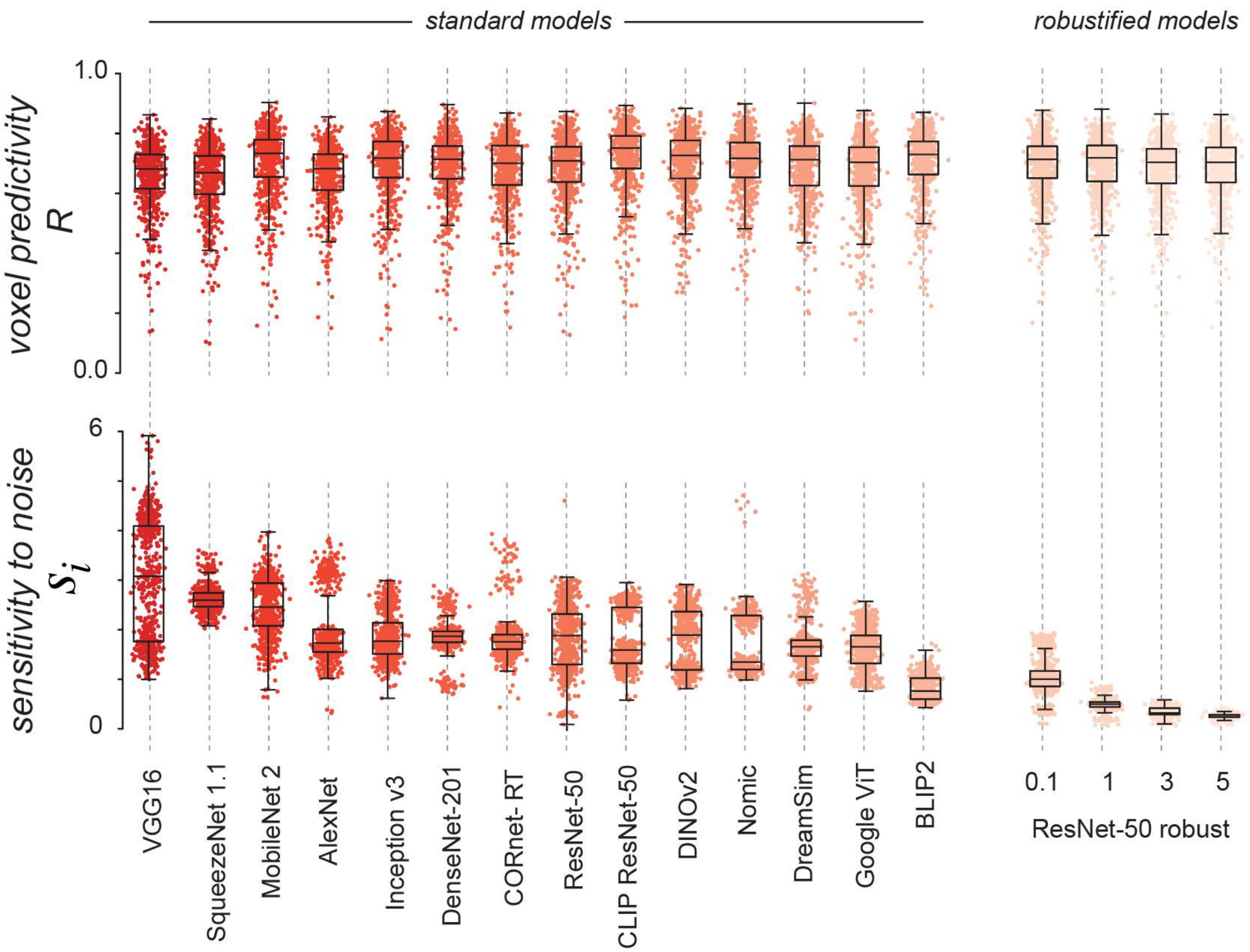






How do we find predictive models with ***low sensitivity***?

- *Robustified neural networks*
    - Models trained using an *adversarial loss* function
    - Trained to correctly classify adversarial images during training
    - Do *robustified ResNet-50* models solve our problem?



standard models
robustified models
voxel predictivity R
1.0
0.0
sensitivity to noise s_i
6
0
VGG16
SqueezeNet 1.1
MobileNet 2
AlexNet
Inception v3
DenseNet-201
CORnet- RT
ResNet-50
CLIP ResNet-50
DINOv2
Nomic
DreamSim
Google ViT
BLIP2
0.1
1
3
5
ResNet-50 robust

- How sensitive are brain models to adversarial attacks?

  Models are **very** sensitive to adversarial attacks

- Do models share the same failure modes?

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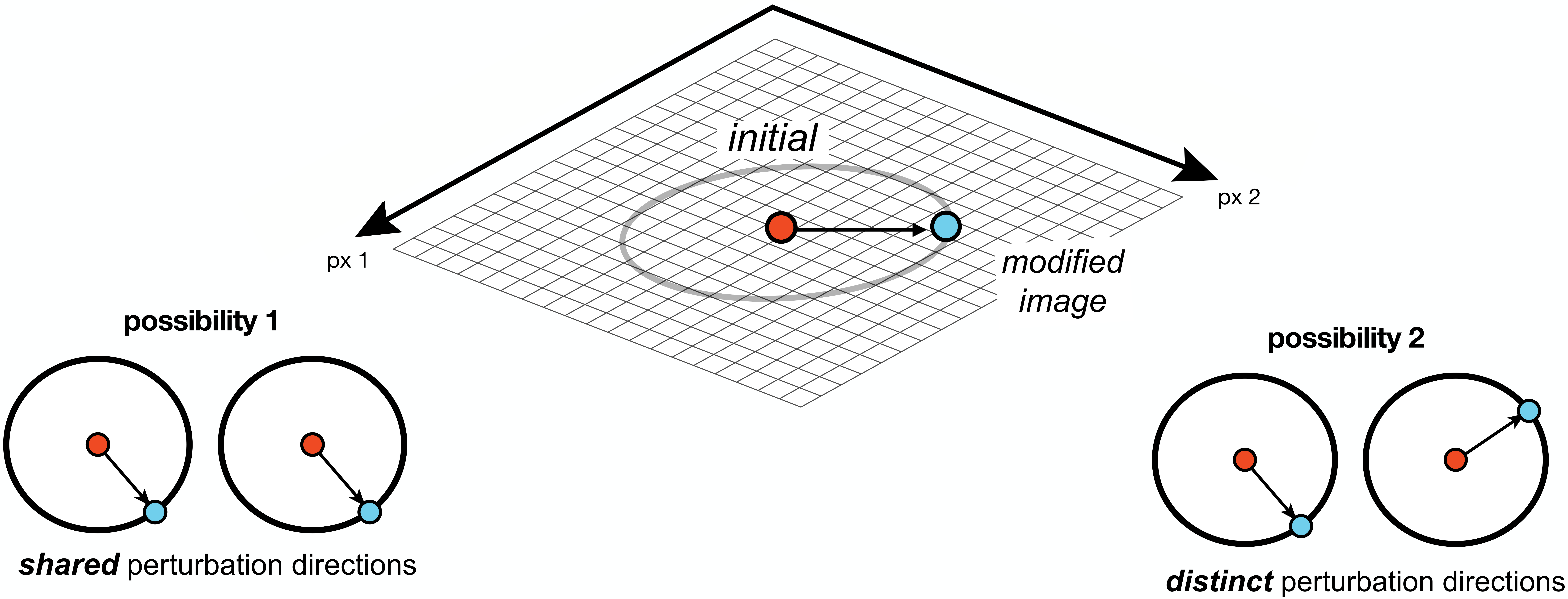
Do models share the same failure modes?



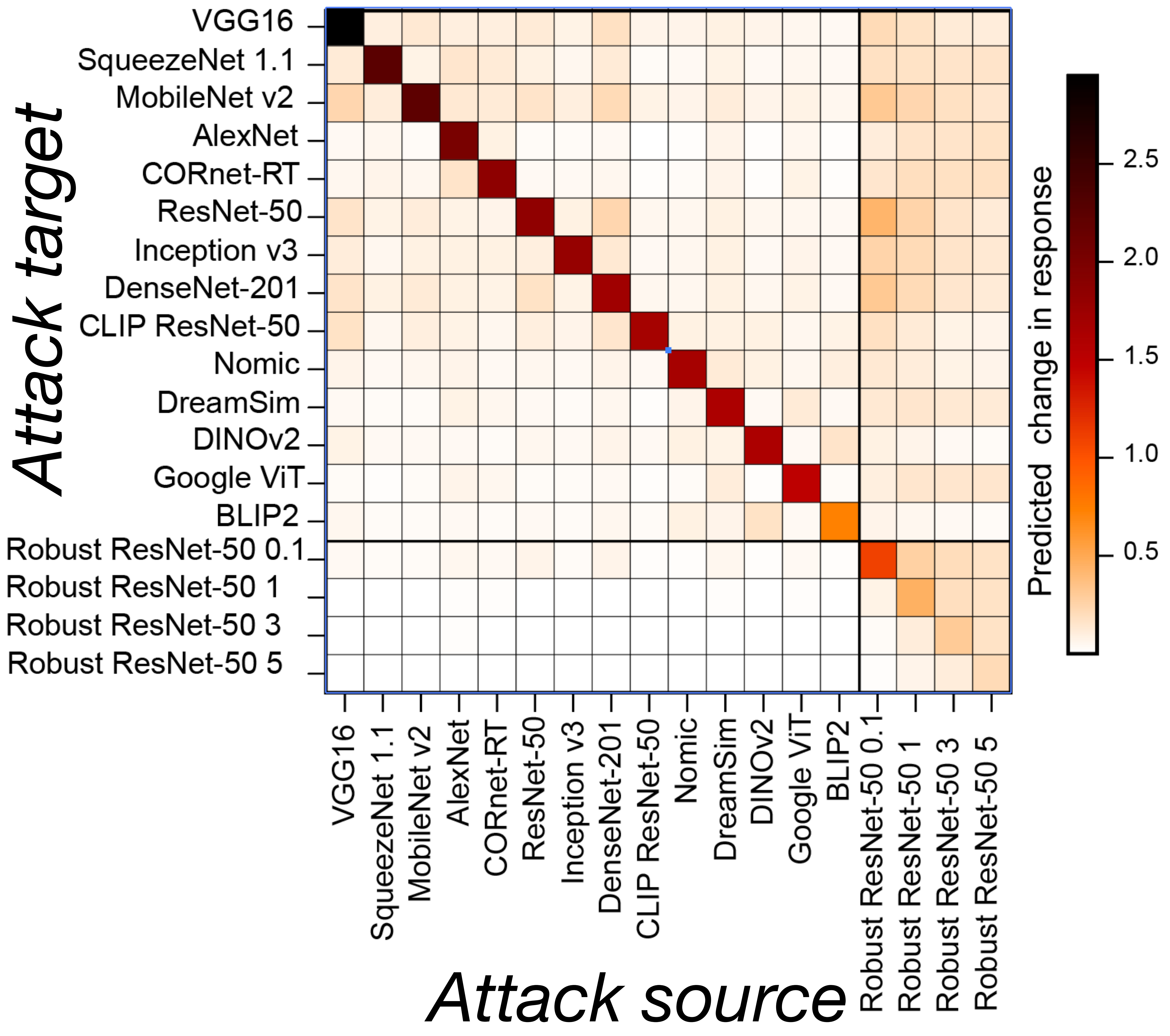
Do models share the same failure modes?

- If a model is sensitive to an **adversarial direction**, will other models also be sensitive to this direction?

- Darker colors represent **more transfer**

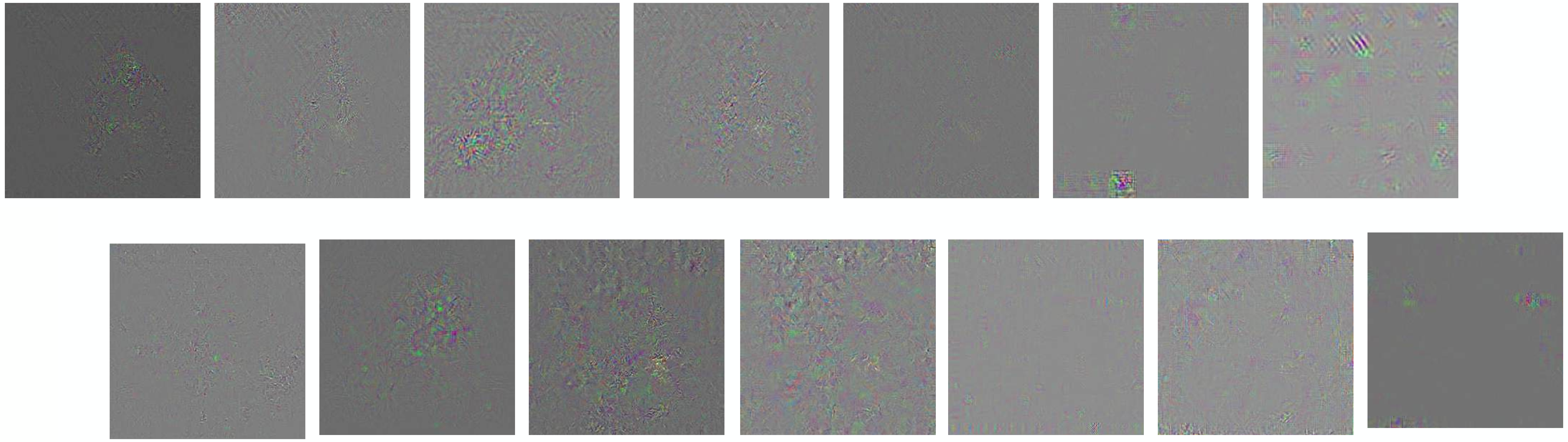
- Overall **limited transfer** between models

- Robust models tend to **transfer** a bit more



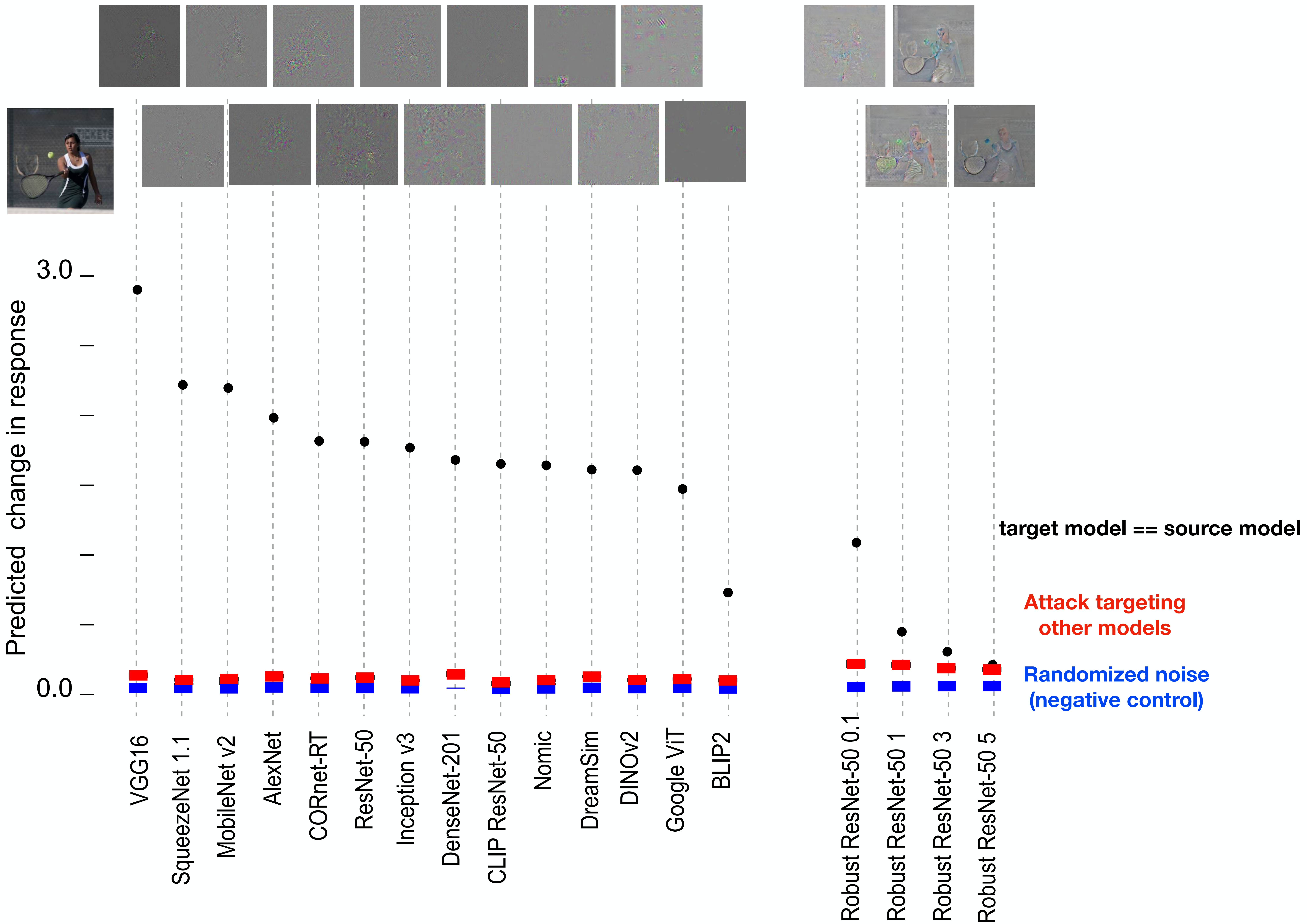
- Another way of thinking about this…
    - Consider this image
      And the associated noise patterns

Standard models



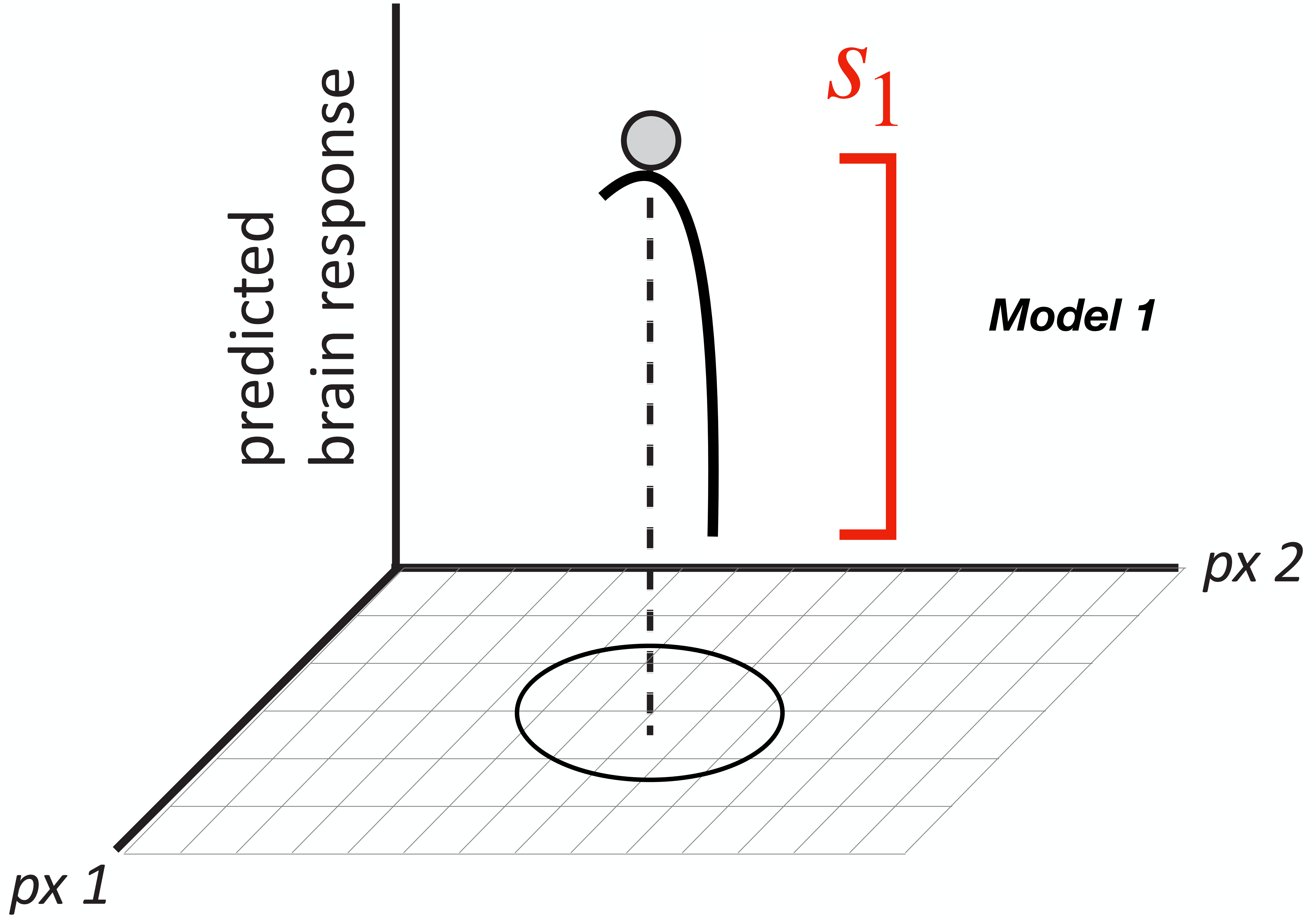
Robust models

Which of these sensitive directions **transfer** to other models?



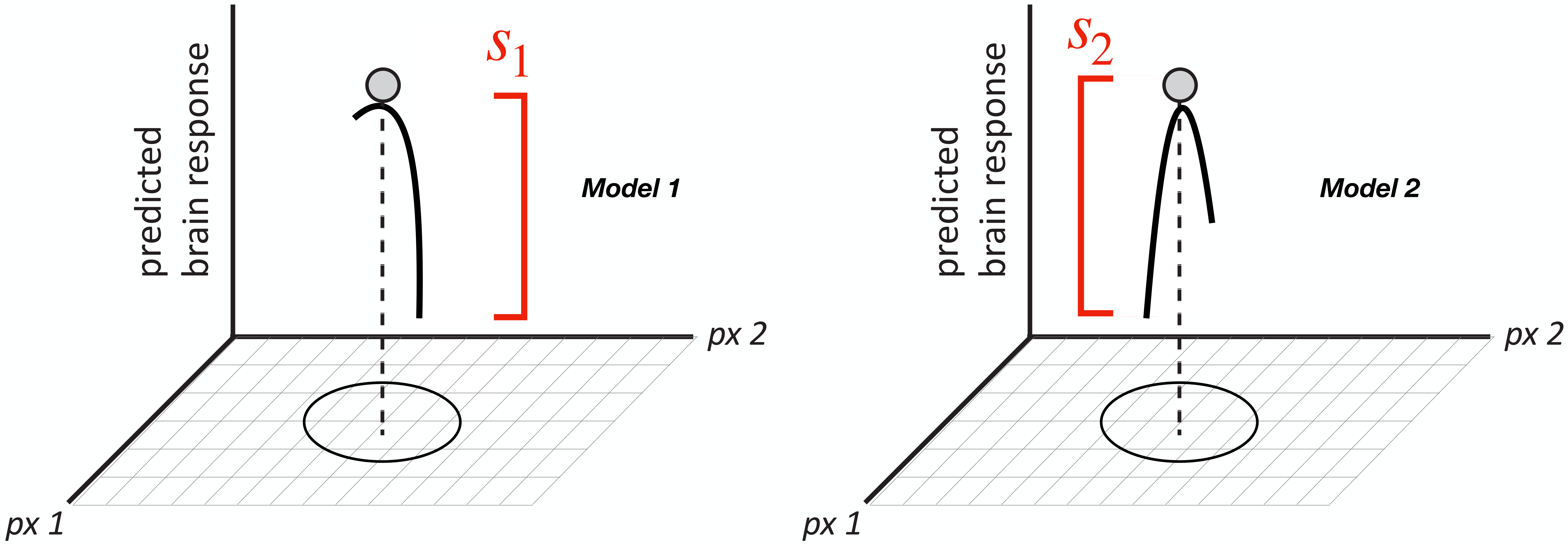
Predicted change in response
3.0
0.0
VGG16
SqueezeNet 1.1
MobileNet v2
AlexNet
CORnet-RT
ResNet-50
Inception v3
DenseNet-201
CLIP ResNet-50
Nomic
DreamSim
DINOv2
Google ViT
BLIP2
Robust ResNet-50 0.1
Robust ResNet-50 1
Robust ResNet-50 3
Robust ResNet-50 5
target model == source model
Attack targeting other models
Randomized noise (negative control)

So far…



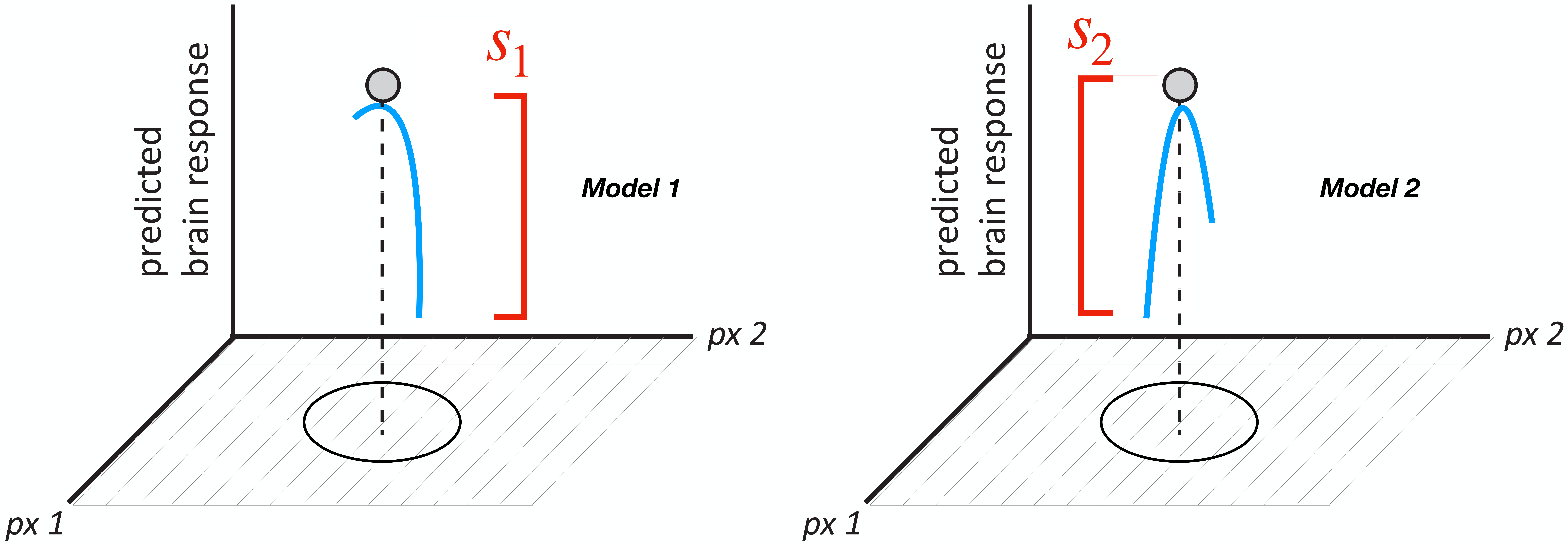
We've estimated the **adversarial sensitivity (s)** of each model

So far…



We've estimated the **adversarial sensitivity (s)** of each model

$$s = r(x) - r(x+\delta), \quad \delta = \underset{\|\delta\| \leq \epsilon}{\arg\max} \left[|r(x) - r(x+\delta)| \right]$$

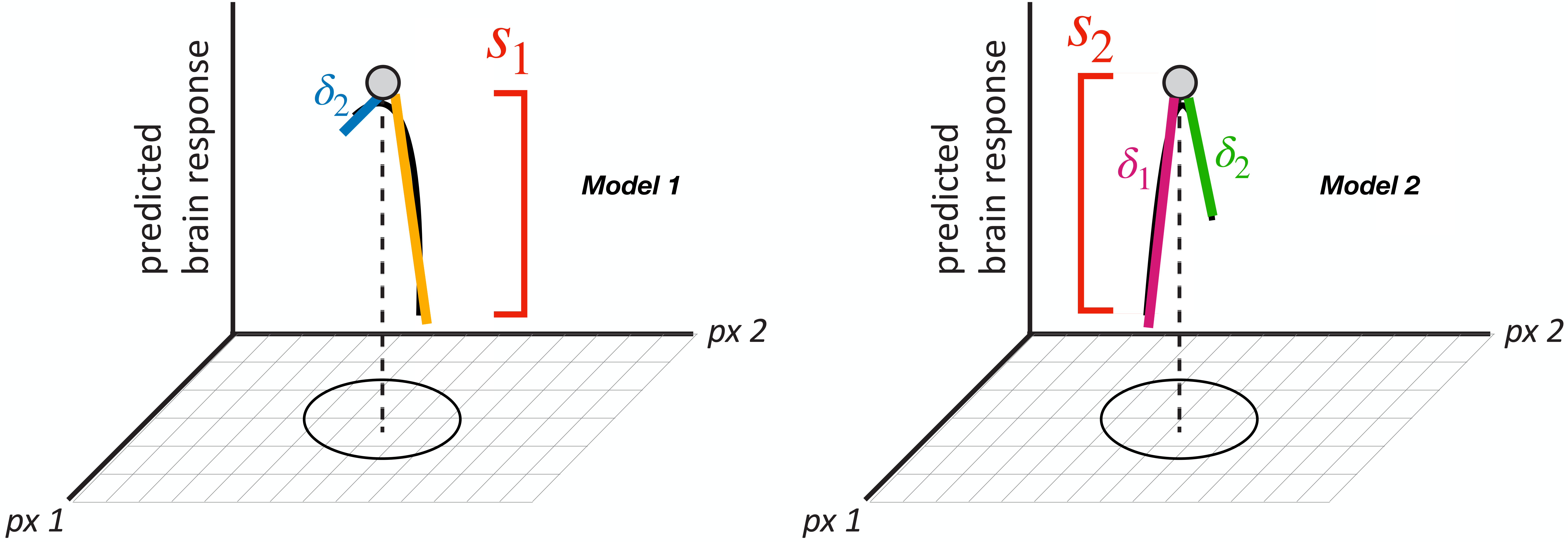


We've estimated the **adversarial sensitivity (s)** of each model

Two models with the same ***sensitivity*** might have different ***representational geometries***

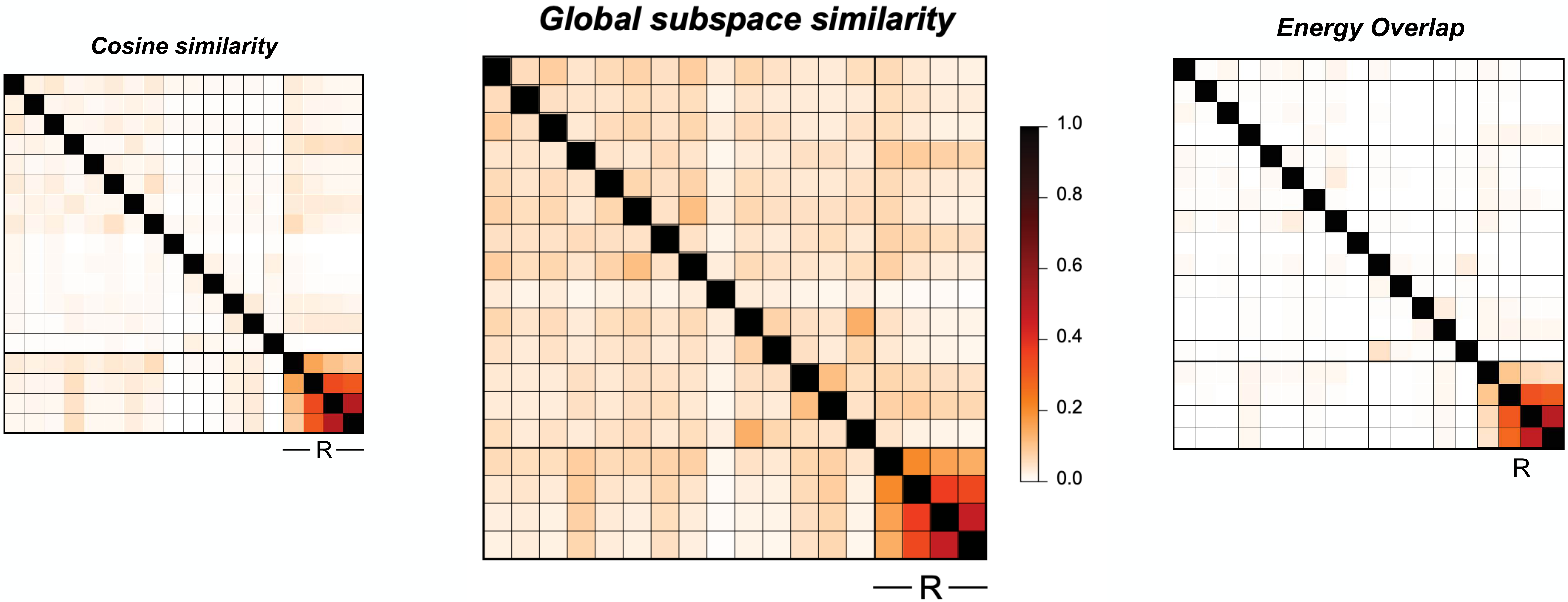
How do we characterize differences in geometry?

By looking at the *principle directions*



Stack the directions in a matrix,
forming a **perturbation subspace**

How similar are perturbation subspaces across models?



We wish to maximize the distance between $r(x)$ and $r(x+\delta)$

$$r(x) = r(x)$$

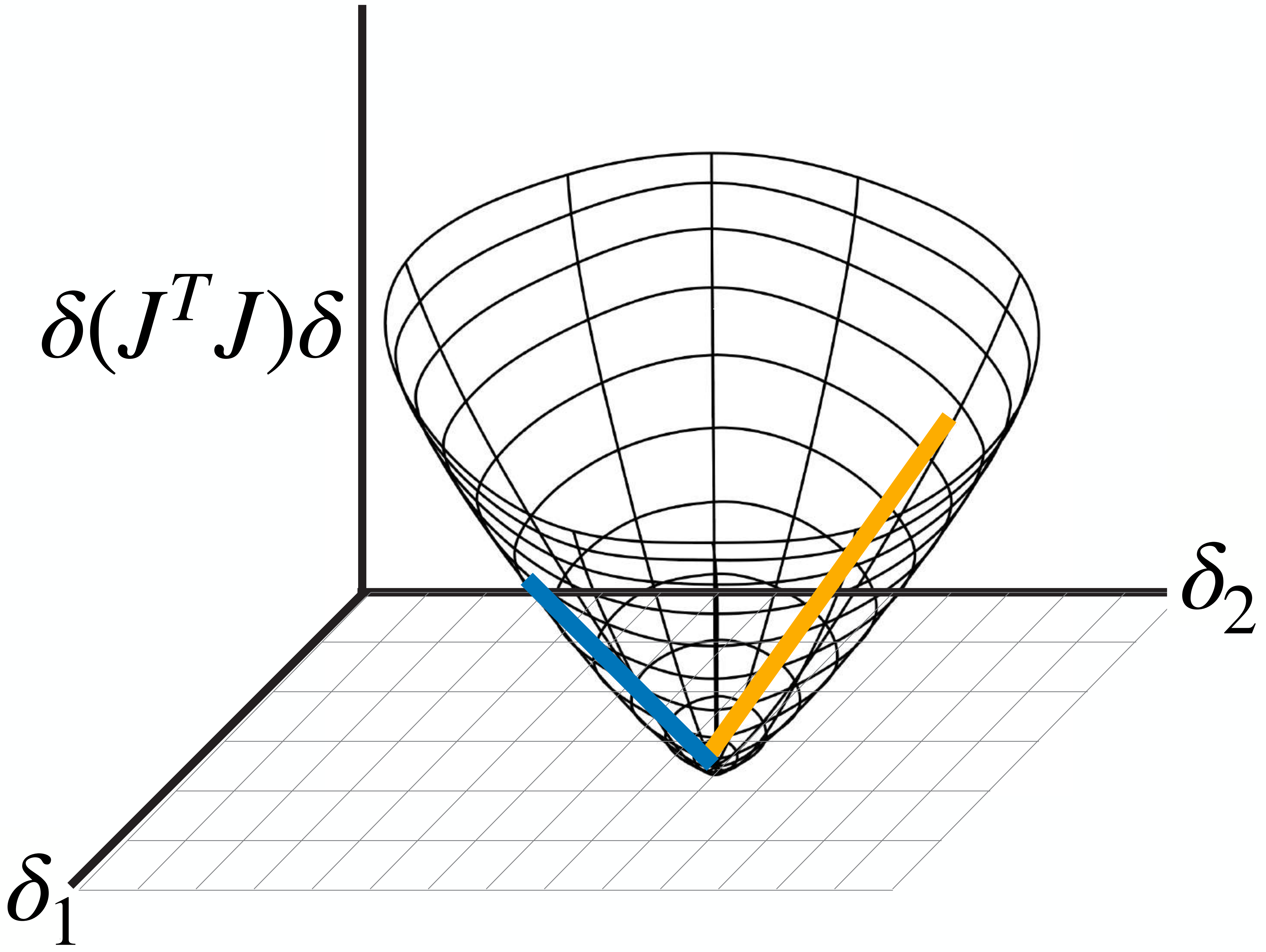
$$r(x+\delta) = r(x) + J\delta + \cancel{\frac{1}{2}\delta^T H(x+\theta\delta)\delta}$$

(first-order)
Taylor expansion

$$\Delta r \equiv r(x) - r(x+\delta) \approx J\delta$$

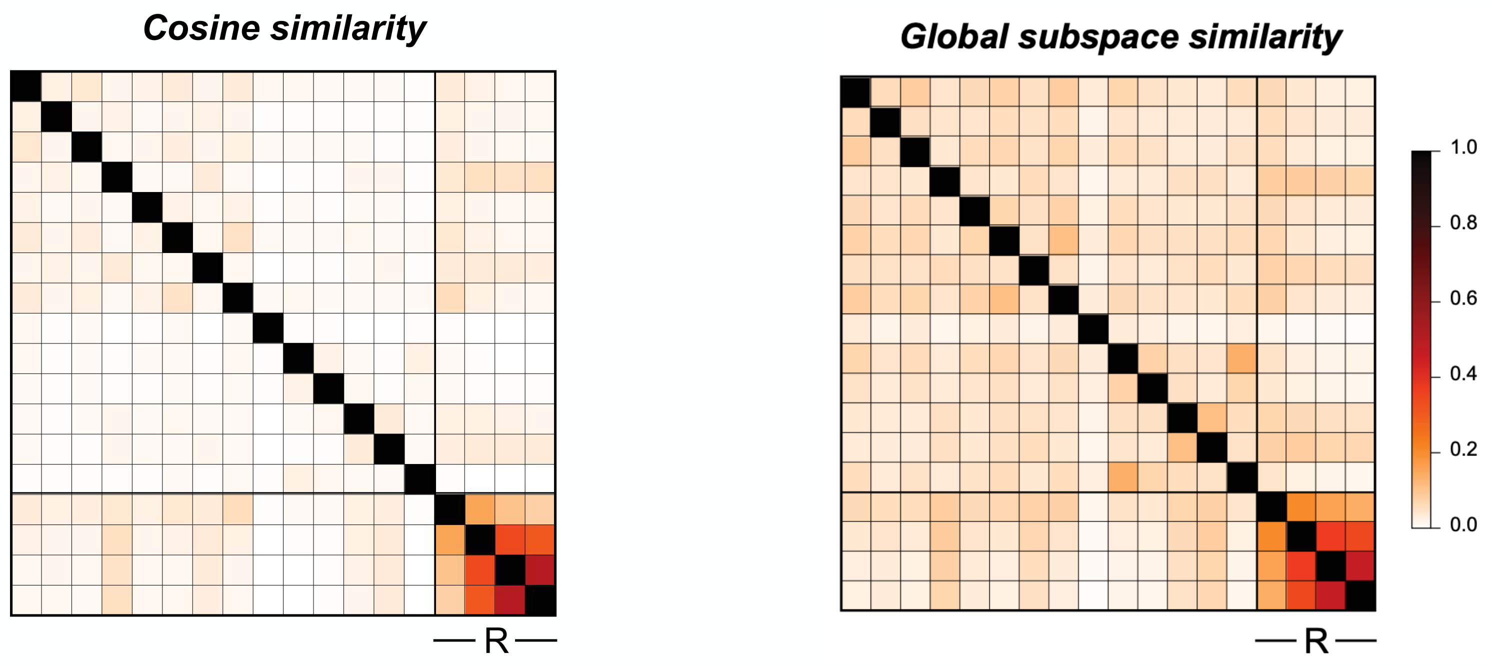
$$||\Delta r||_2^2 = \delta^T (J^T J)\delta$$

We want to find directions δ which **maximize** $\delta(J^T J)\delta$
(the eigenvectors!)

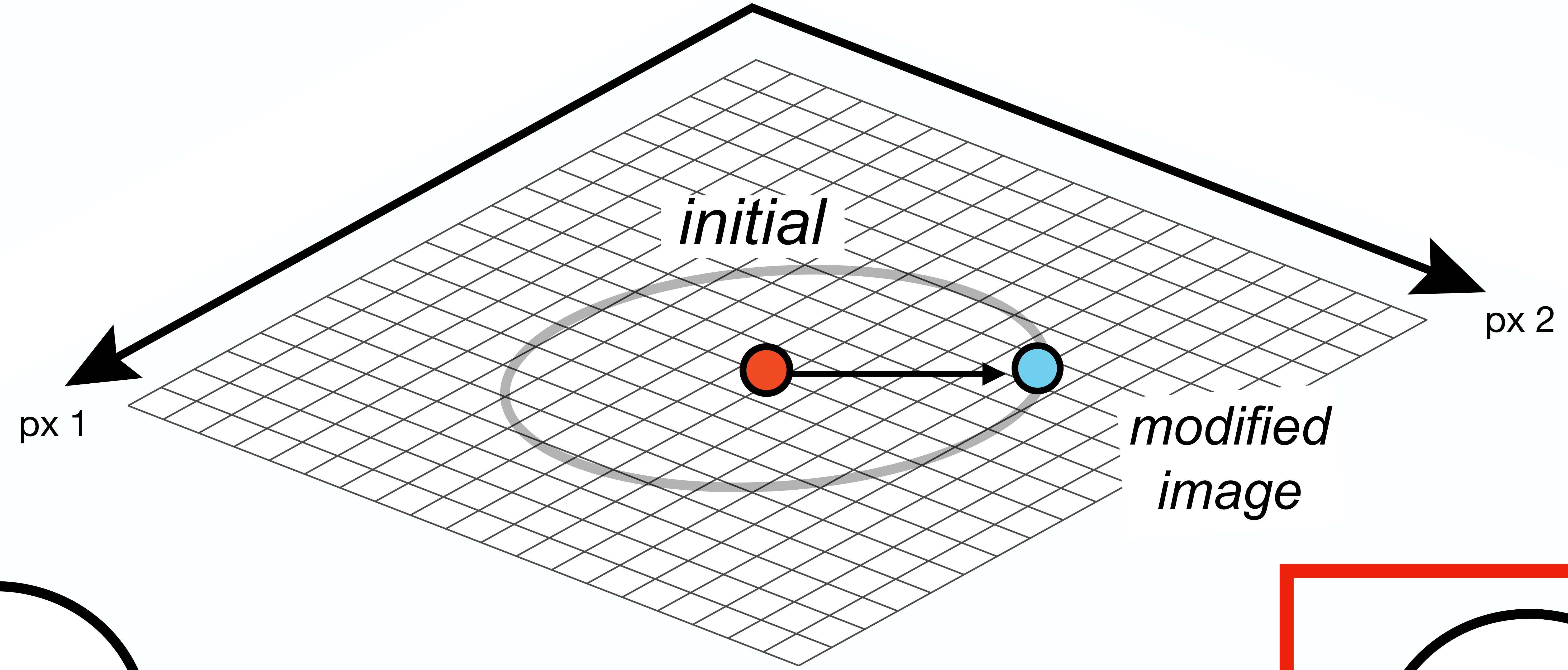


Top-k eigenvectors stacked in perturbation matrices P_i, P_j

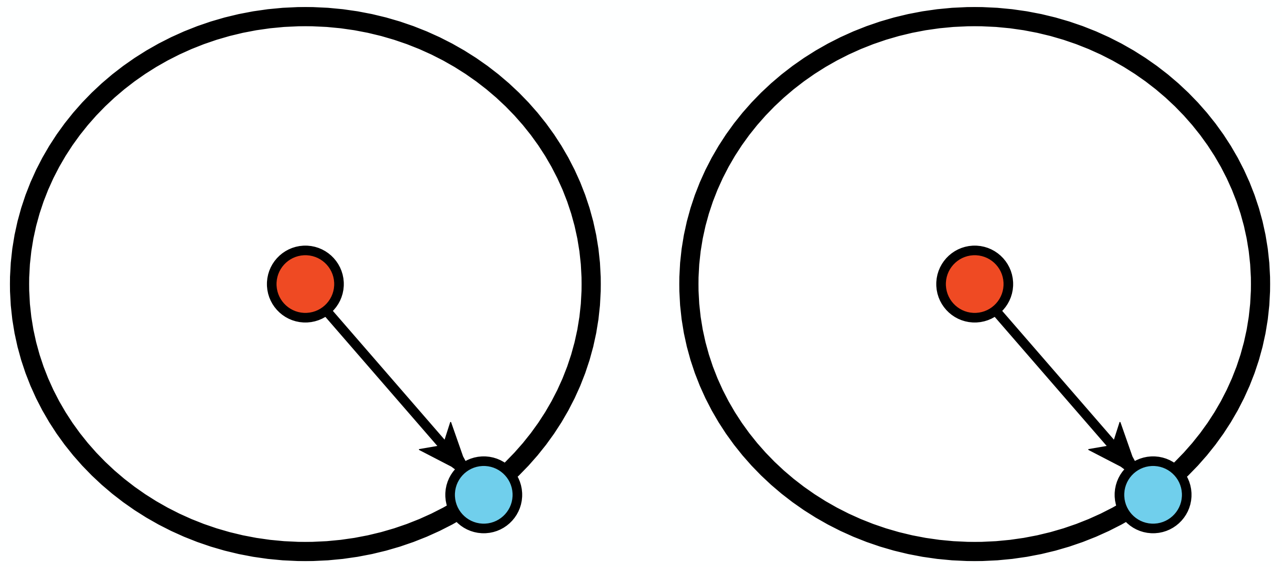
Similarity measurement $Sim(P_i, P_j)$



Do models share the same failure modes?

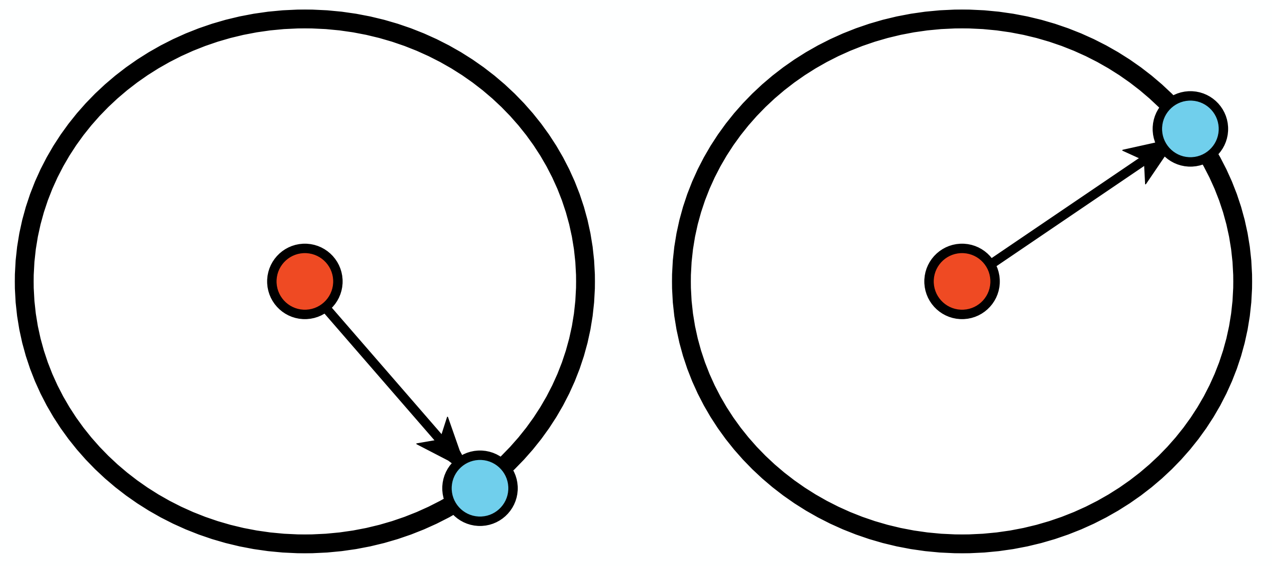


possibility 1



shared perturbation directions

possibility 2



distinct perturbation directions

- How sensitive are brain models to adversarial attacks?

  Models are **very** sensitive to adversarial attacks

- Do models share the same failure modes?

  Standard models generally have **distinct** failure modes; robust models have **shared** directions

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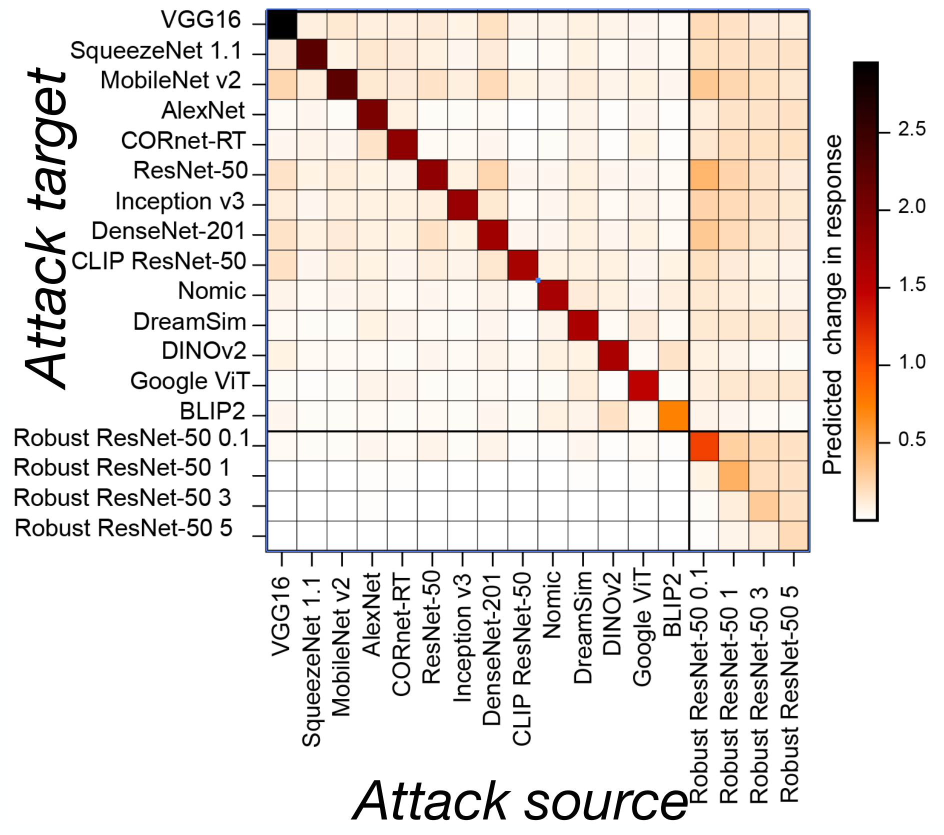
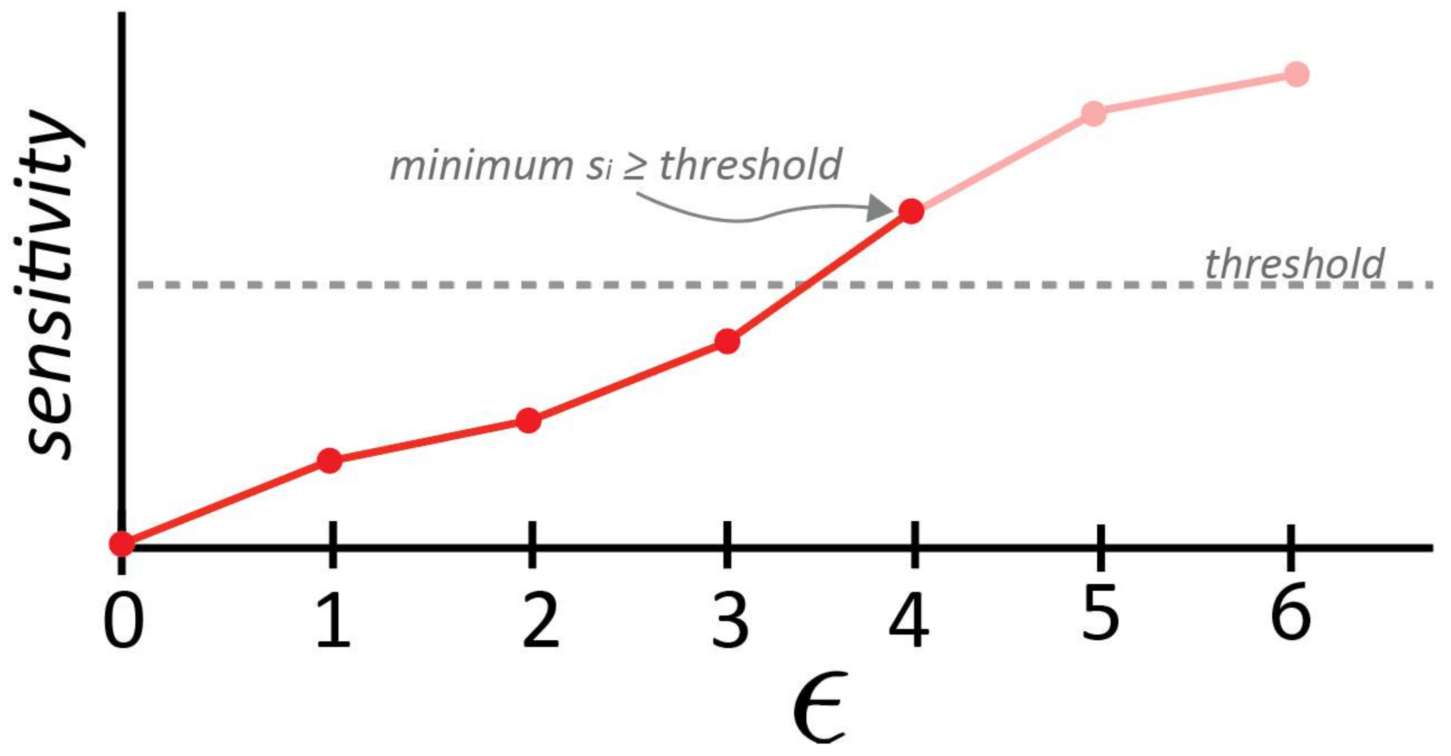
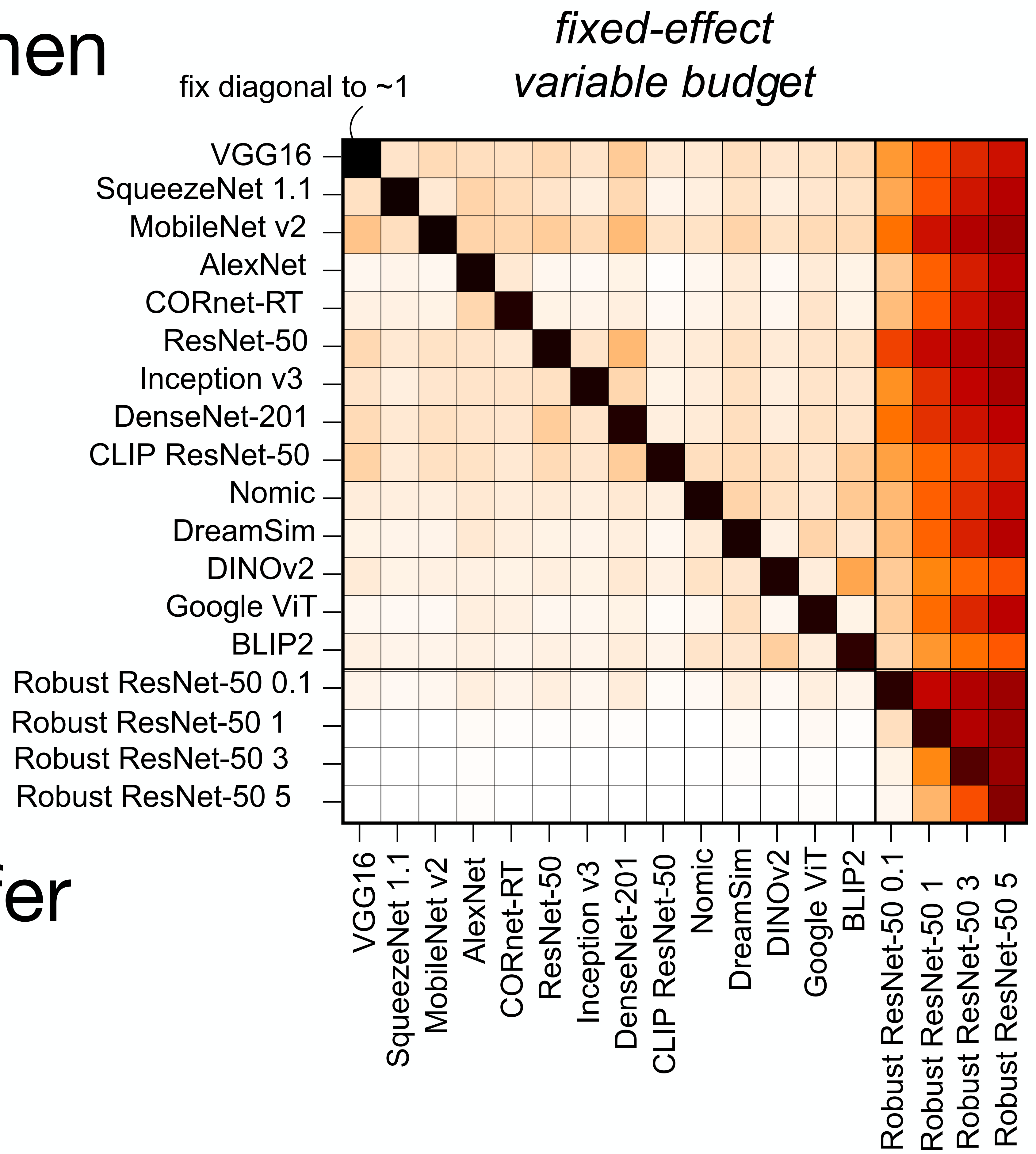
- Earlier, we fixed the **perturbation size** and evaluated how well attacks transferred between models



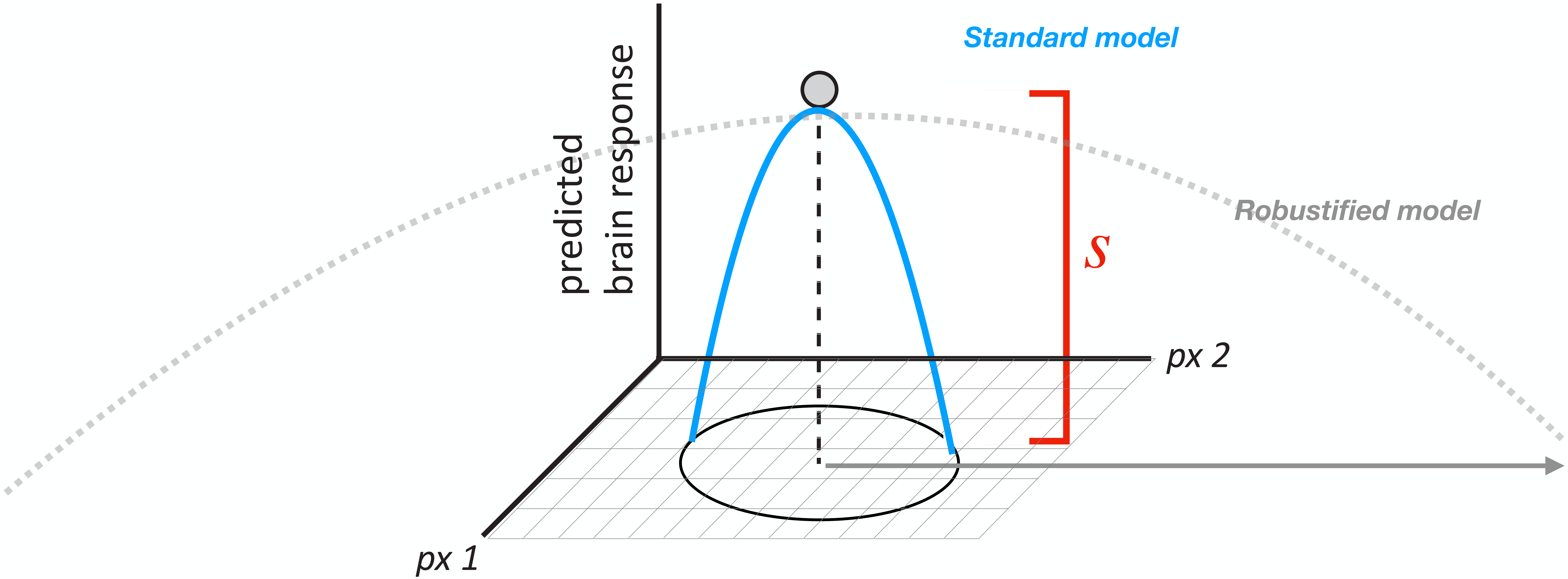
- What if we fix the **transfer effect first,** and then evaluate how well attacks transfer between models?





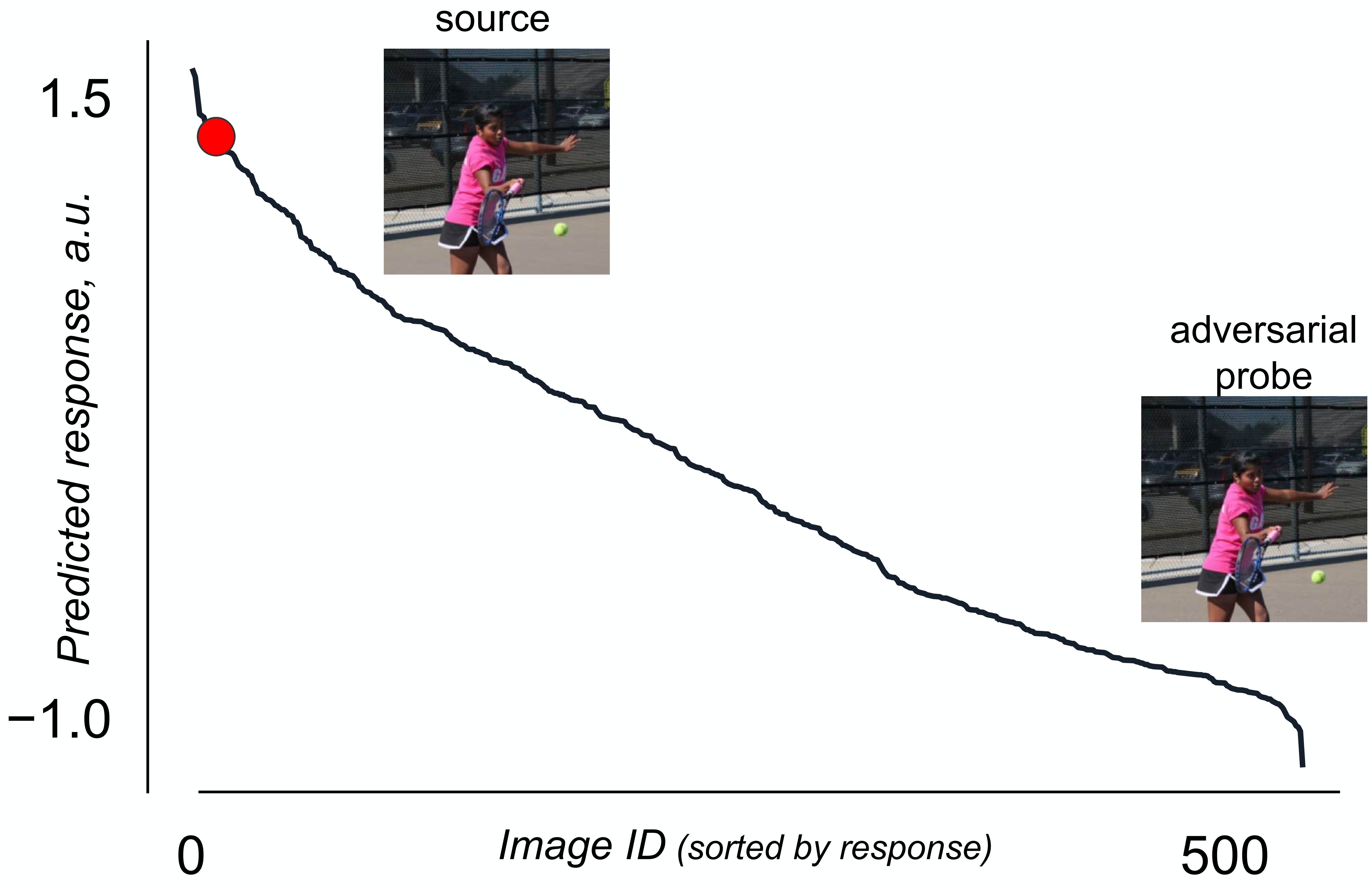
- Perturbations from robust models now transfer to all models! Possibly the **brain-like coding axis?**

Another way to think about this…



To achieve the same sensitivity, we need a much larger perturbation

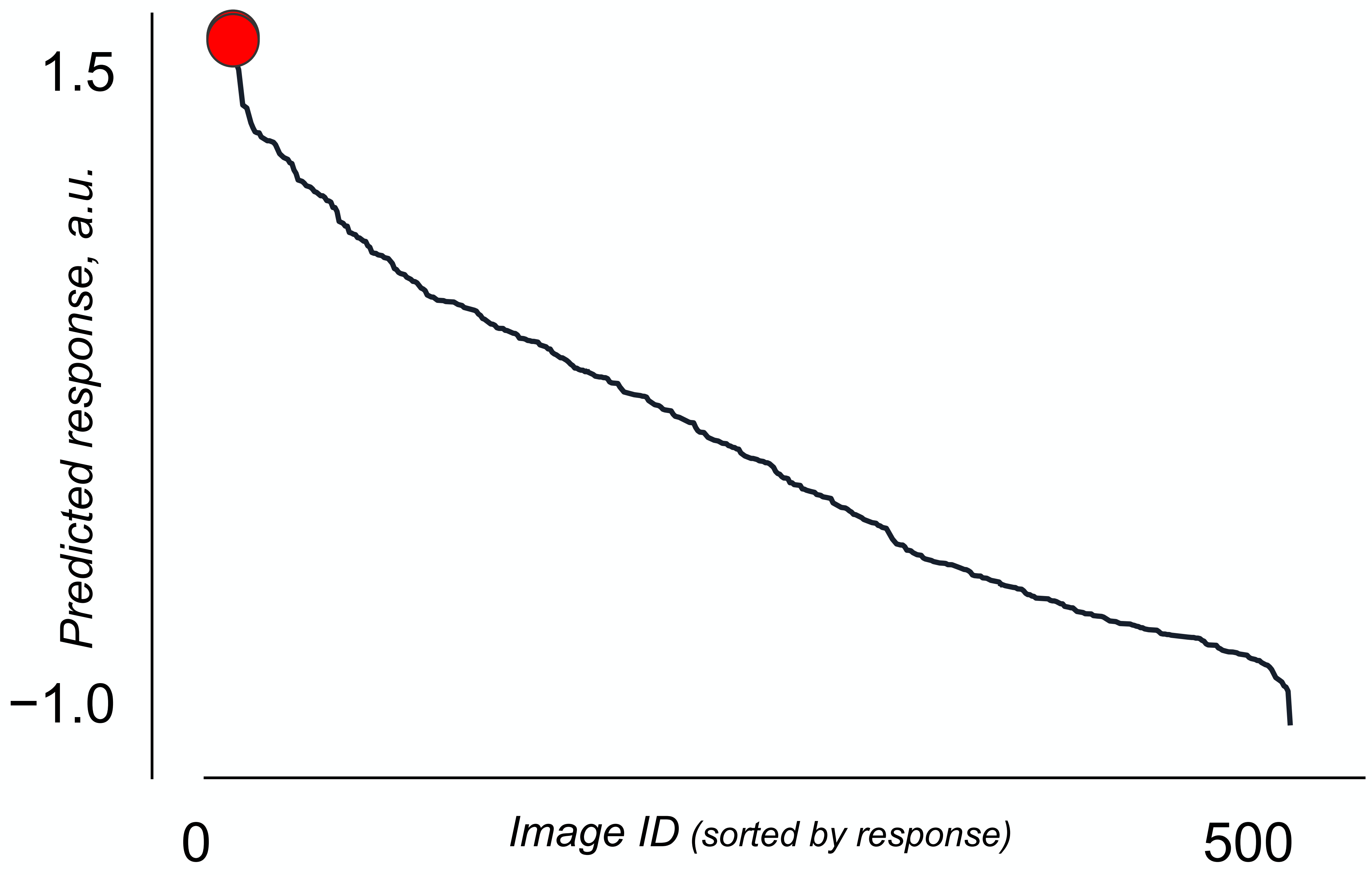
- Earlier, we saw how **imperceptible** noise patterns can drastically alter standard model predictions



Since *robustified* models need a larger perturbation size, what does the adversarial probe look like?

Consider an image with a **face** in it with a high **predicted FFA response**

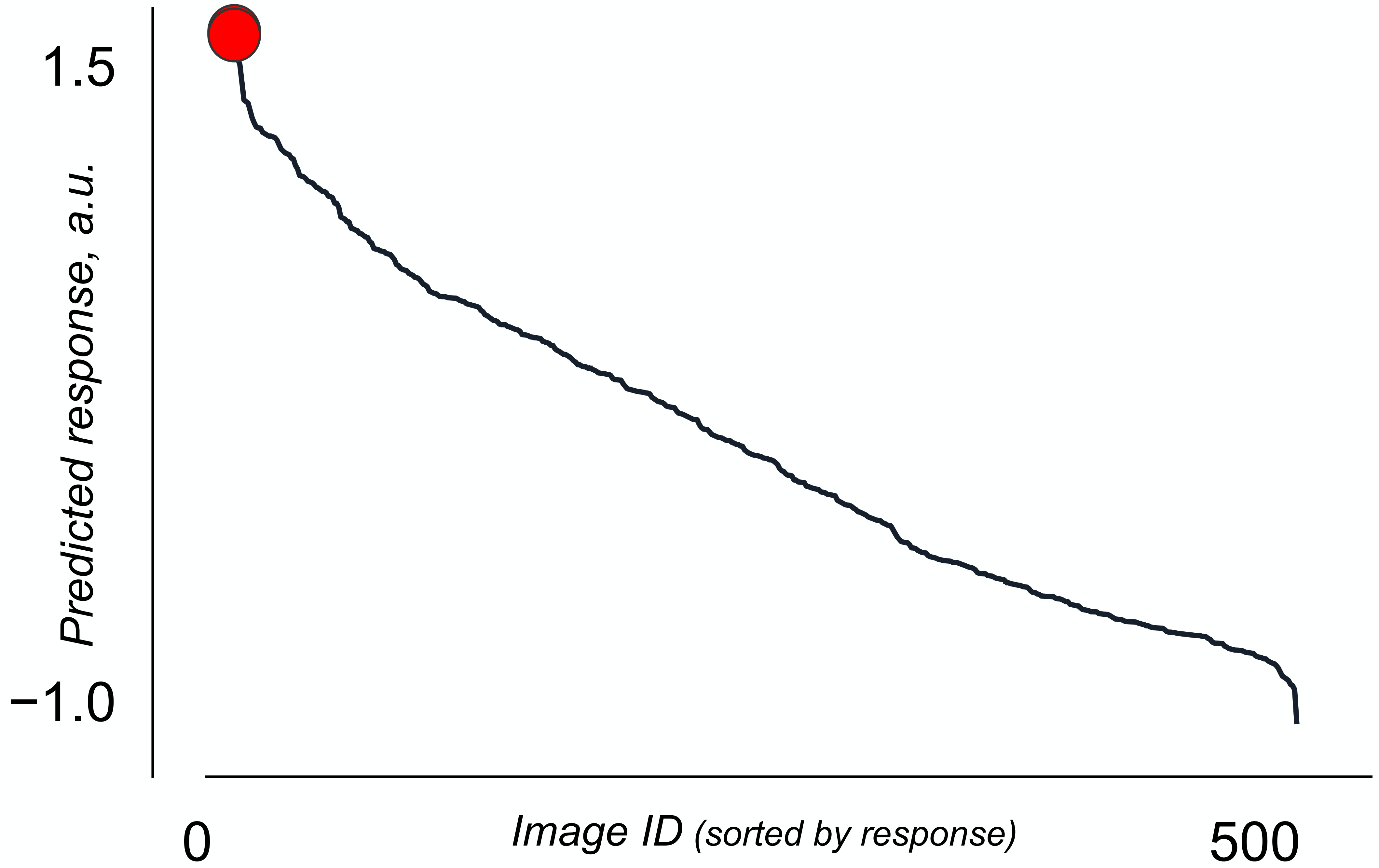
Let's use a **robustified** model to find a perturbation **which minimizes the predicted FFA response**



(video)

Another example…

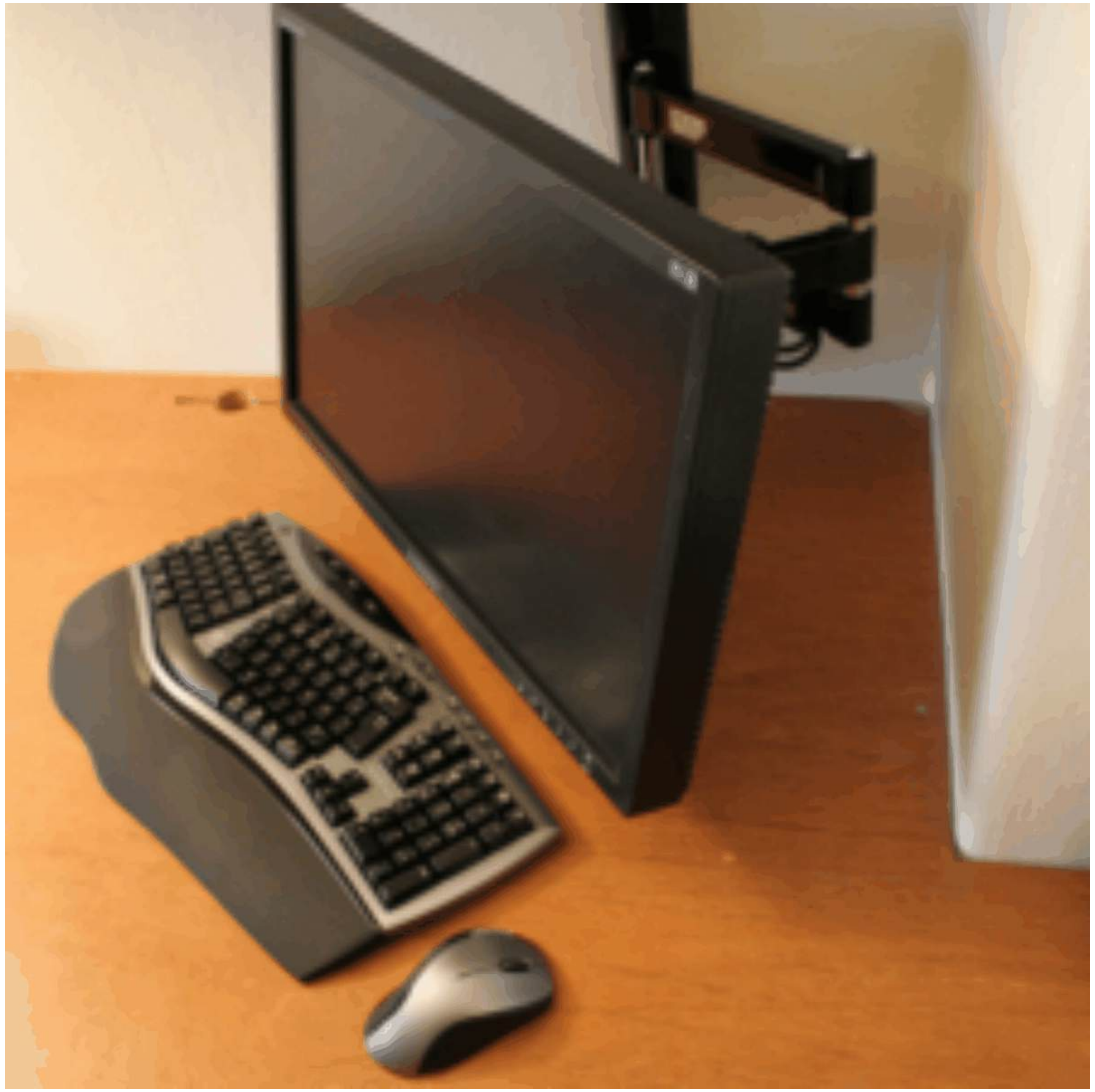
Let’s use a **robustified** model to find a perturbation **which minimizes the predicted FFA response**



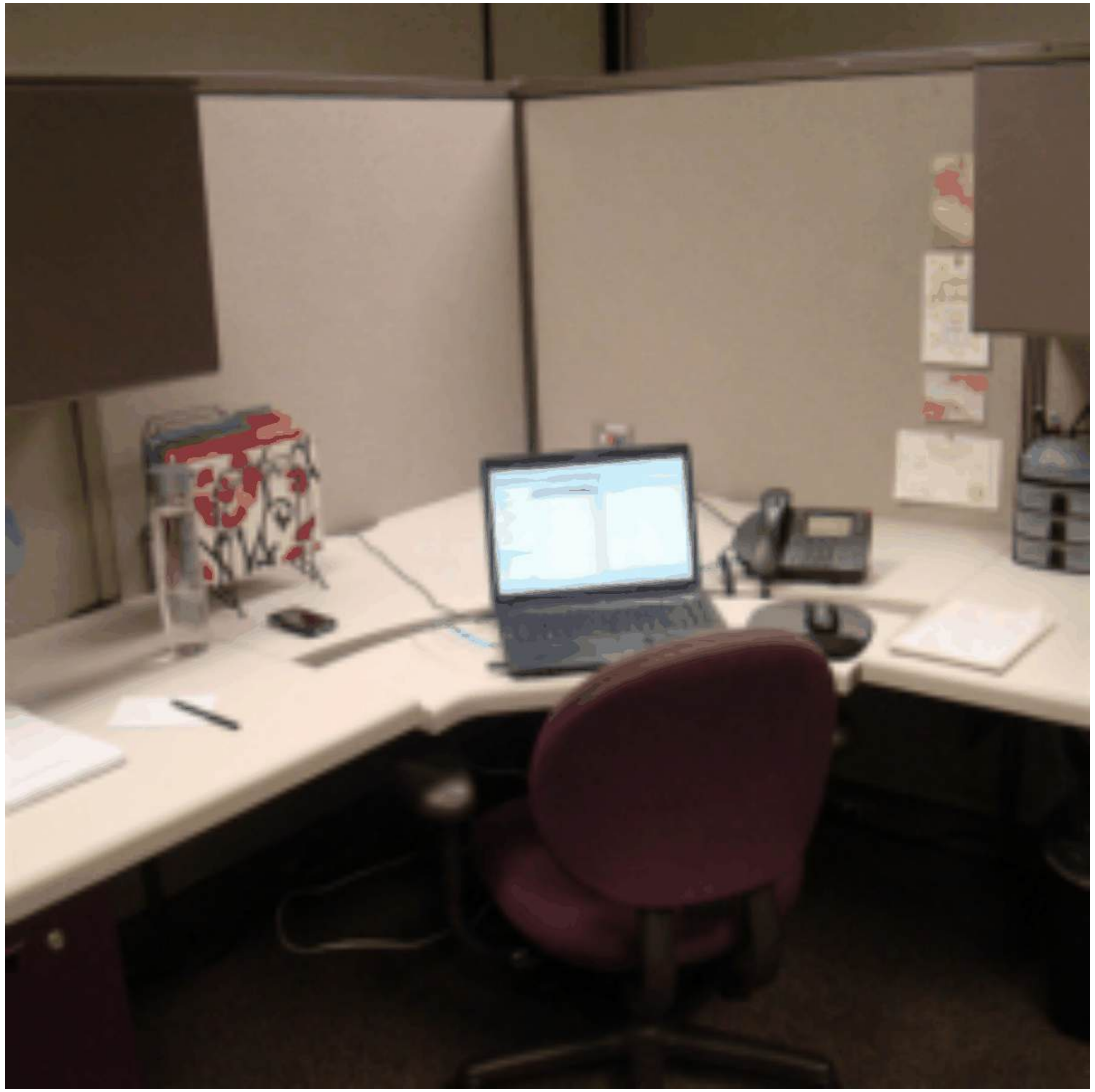
(video)

A challenging example… maximize **EBA**?

(video)



(video)

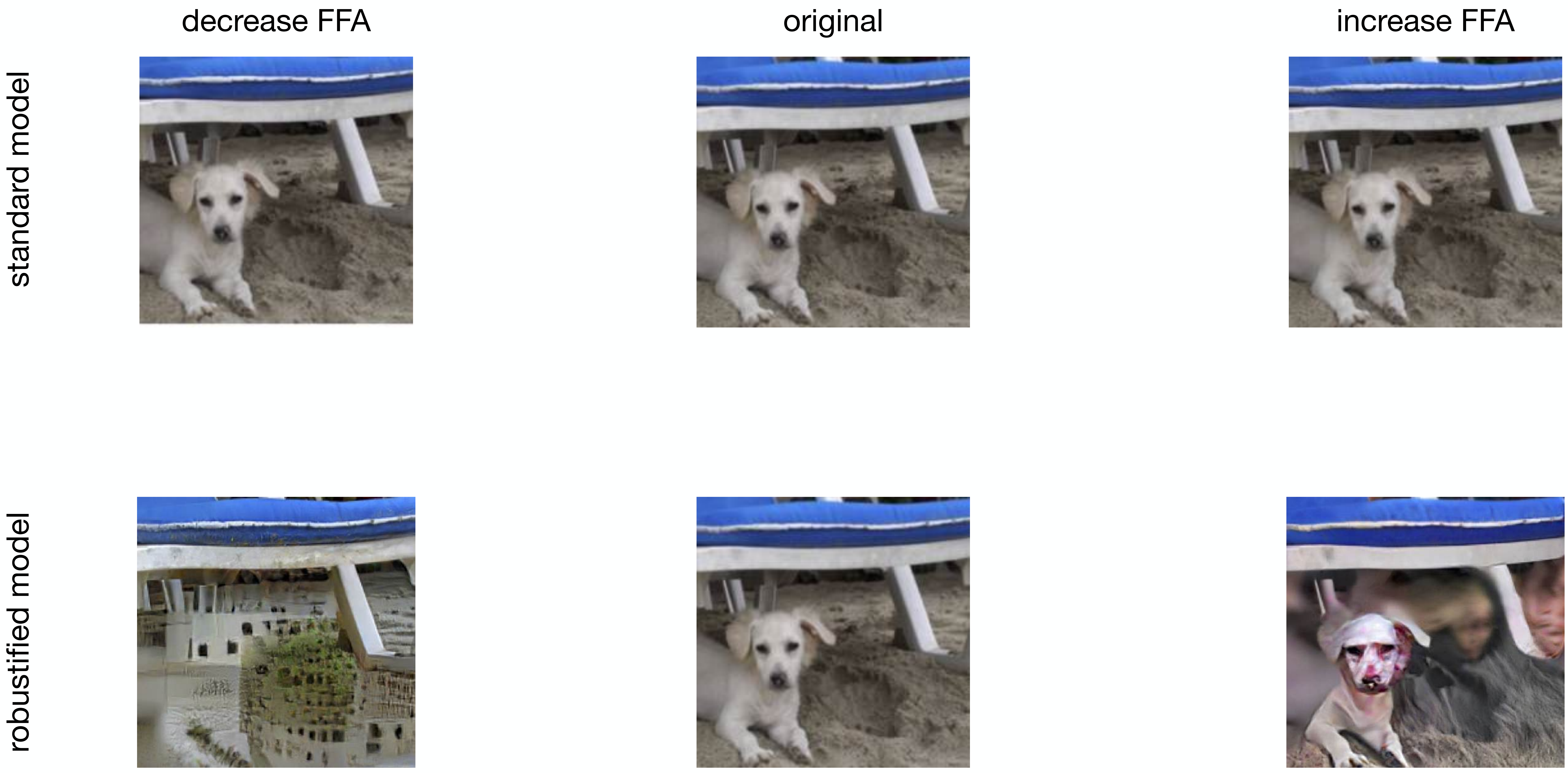


minimize EBA

(video)

maximize PPA

(video)


decrease FFA
original
increase FFA
standard model
robustified model

- How sensitive are brain models to adversarial attacks?

  Models are **very** sensitive to adversarial attacks

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- Can we use stability to find better models of the brain?

  Yes! Robustified models have *interpretable, semantically meaningful* features, whereas standard models are **unstable** and **brittle**

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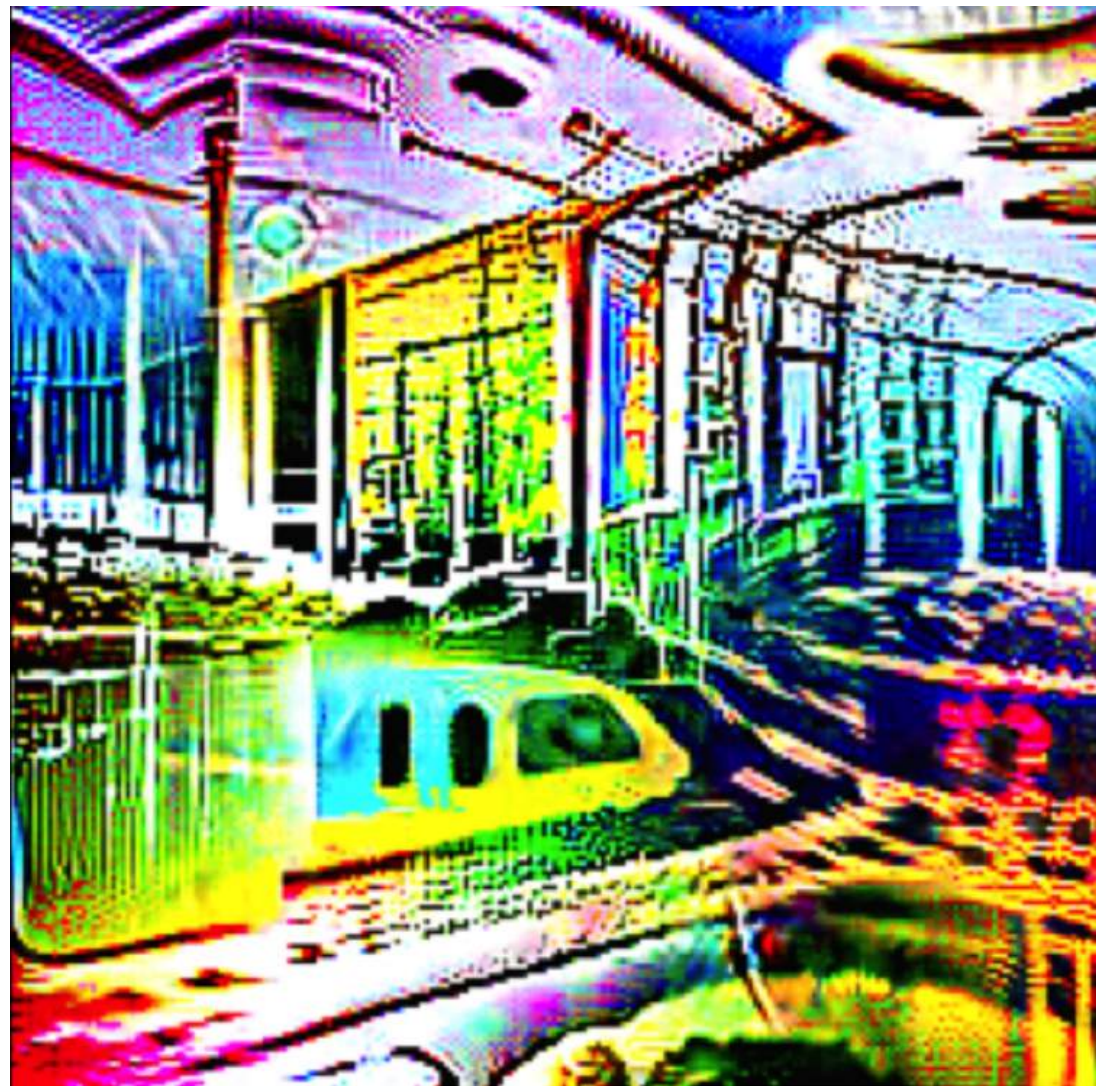
Hypothesis generation with robust encoding models

- In an unconstrained problem, we can continue maximizing the predicted response of a region to obtain a maximally exciting image

FFA

This may reveal the features encoded by a certain brain region

PPA



Many methods for identifying to what features a brain region is selective

BrainACTIV: Identifying visuo-semantic properties driving cortical selectivity using diffusion-based image manipulation

Diego García Cerdas[1,*], Christina Sartzetaki[1], Magnus Petersen[2], Gemma Roig[2], Pascal Mettes[1] and Iris Groen[1]

[1]Informa
[2]Departm
Corresp

Computational models of category-selective brain regions enable high-throughput tests of selectivity

N. Apurva Ratan Murty[1,2,3,5], Pouya Bashivan[4],
Nancy Kanwisher[1,2,3]

Energy Guided Diffusion for Generating Neurally Exciting Images

Brain Diffusion for Visual Exploration: Cortical Discovery using Large Scale Generative Models

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mized image synthesis for discovery

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Which method is most accurate in driving brain responses?
And under what constraints?

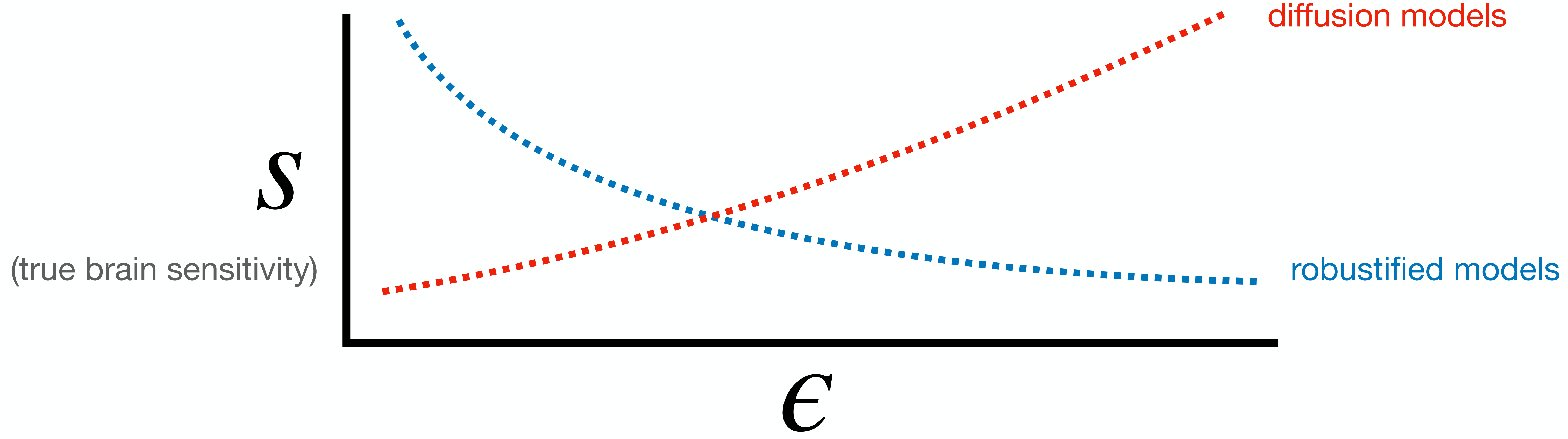
- Many of these methods use *priors* from generative models to guide the sampling

- This may be better for generating *realistic* images (high-norm perturbations), but worse for controlling neural responses to low-norm perturbations:

$$\delta = \arg\max_{||\delta|| \leq \epsilon} \left[|r(x) - r(x+\delta)| \right]$$

- Can we compare all these methods? We need *experimental tests* to validate these methods

An example hypothesis:



We don't know yet!

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Acknowledgements

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Haider Al Tahan
Junxia Wang
Mainak Deb
Nikolas McNeal

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TARGETED PERTURBATIONS REVEAL BRAIN-LIKE LOCAL CODING AXES IN ROBUSTIFIED, BUT NOT STANDARD, ANN-BASED BRAIN MODELS

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arXiv preprint (2025)

Small-scale adversarial perturbations expose differences between predictive encoding models of human fMRI responses

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NeurIPS workshop (UniReps) 2024