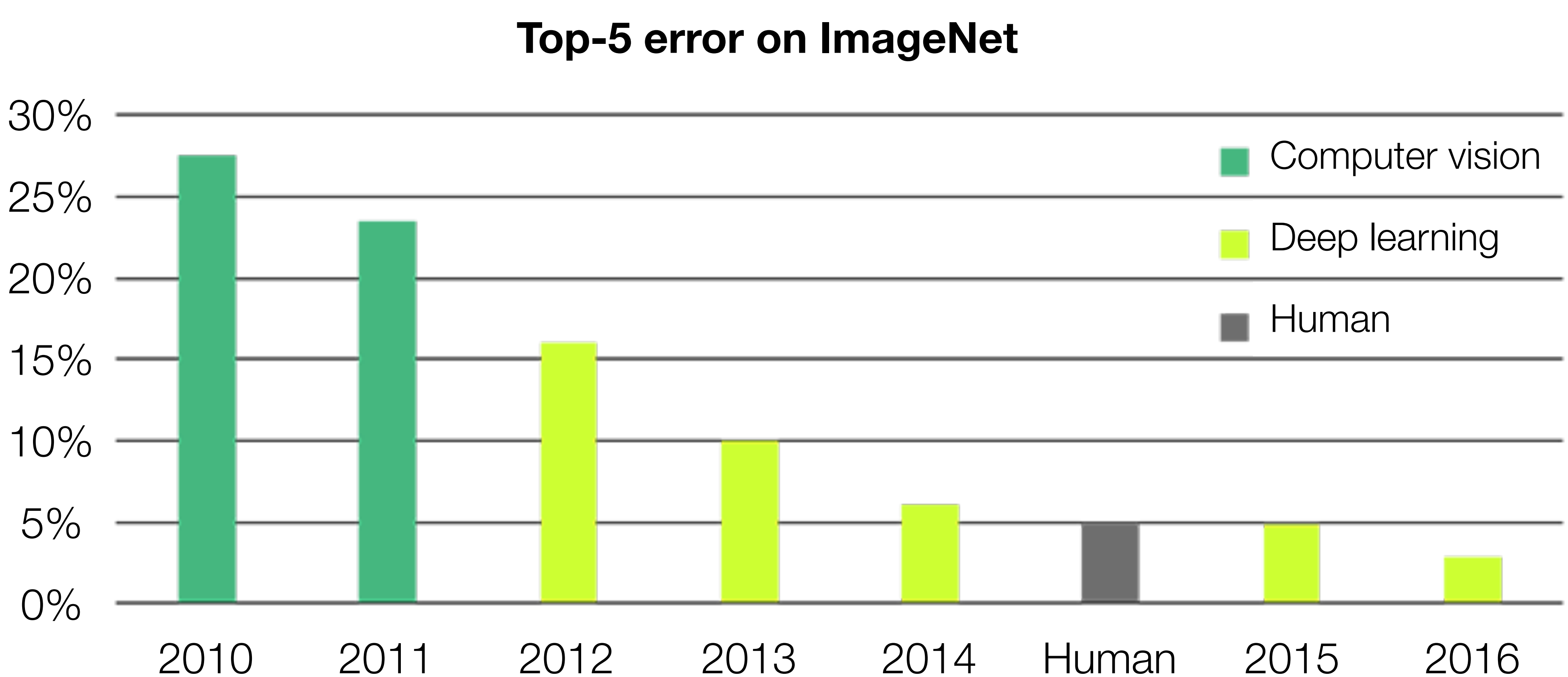
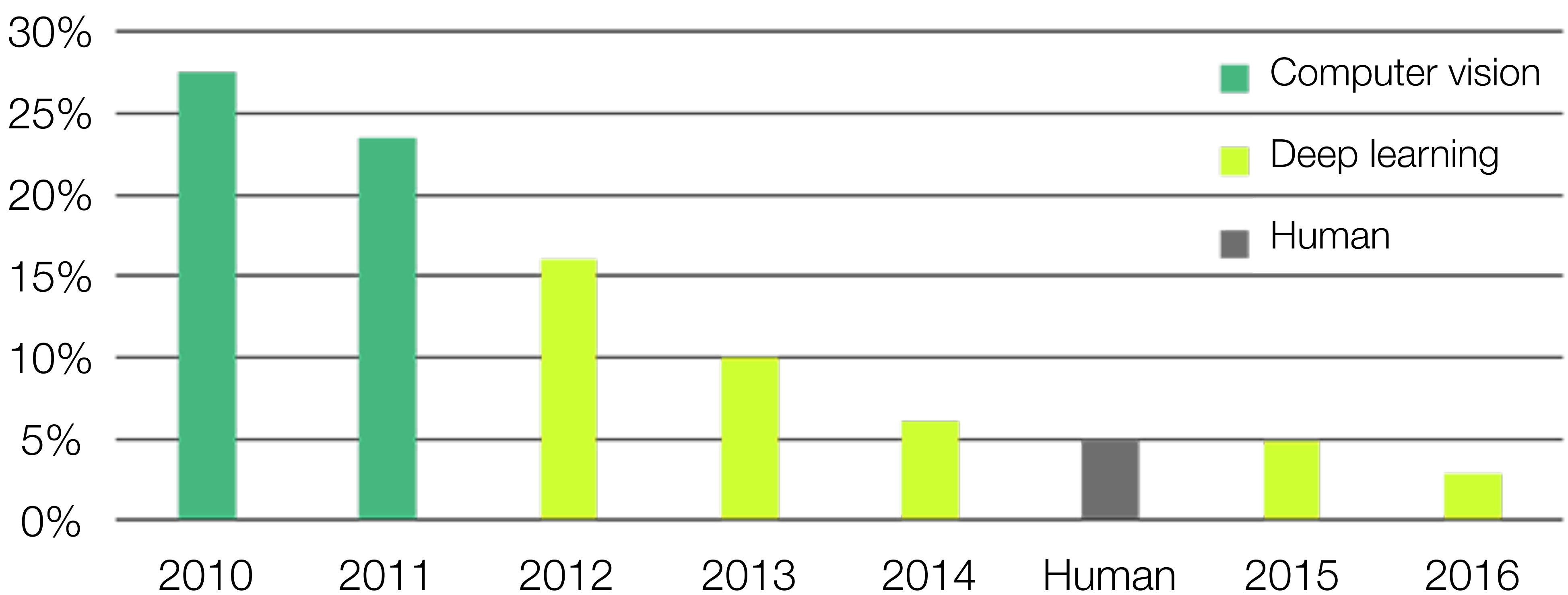
Understanding Black-box Predictions with Influence Functions

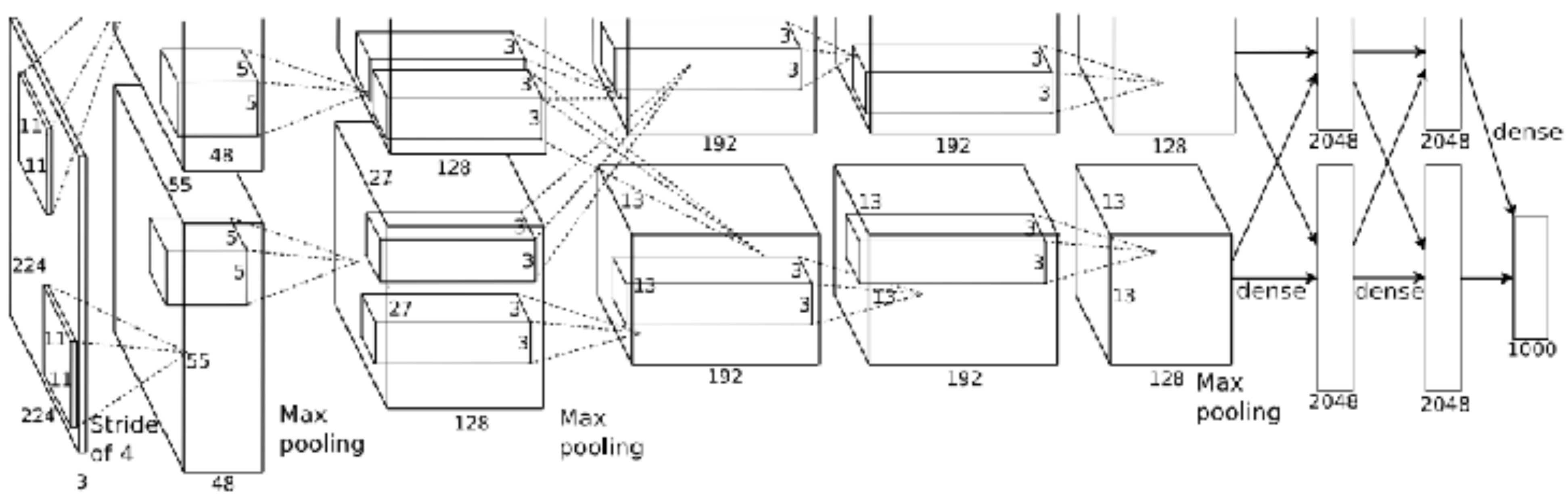
Pang Wei Koh
Percy Liang



[1] Defense Systems Information Analysis Center

Top-5 error on ImageNet





[1] Defense Systems Information Analysis Center
[2] Krizhevsky, Sutskever, and Hinton, 2012

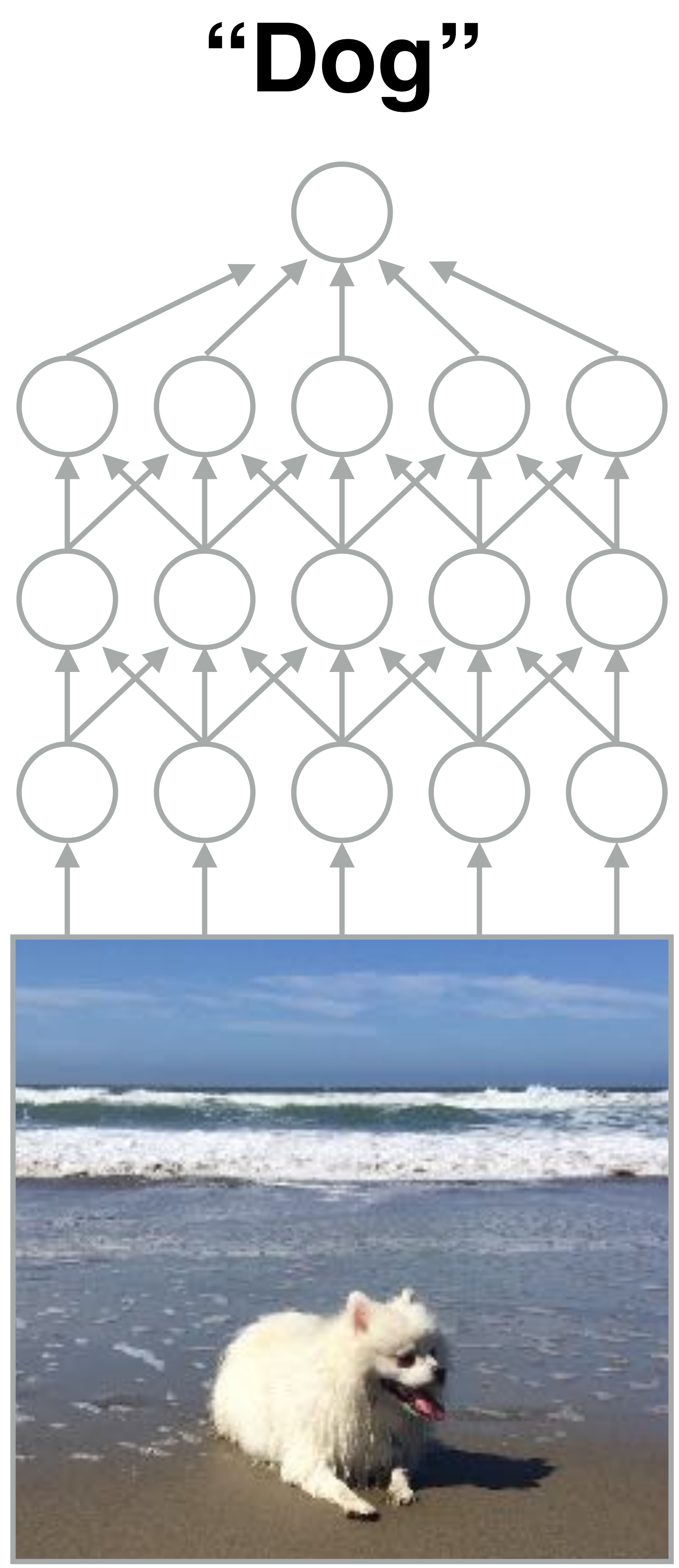
Given a high-accuracy,
black-box model,
and a prediction from it,
can we answer…

Why did the model make this prediction?

Why did the model make this prediction?

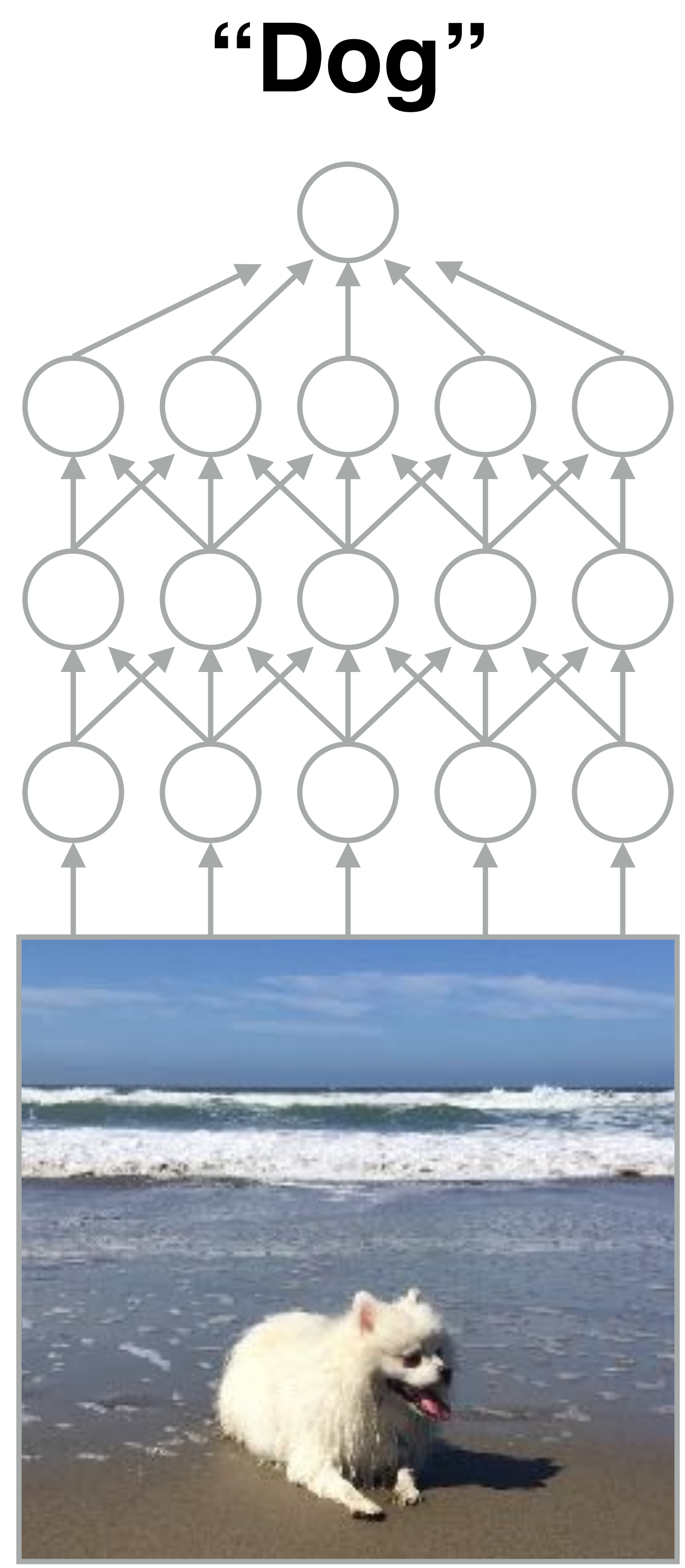
- Make better decisions [1]
- Improve the model [2]
- Discover new science [3]
- Provide end-users explanations [4]

[1] Lakkaraju, Bach, and Leskovec, 2016
[2] Amershi et al., 2015
[3] Shrikumar, Greenside, and Kundaje, 2017
[4] Goodman & Flaxman, 2016


"Dog"

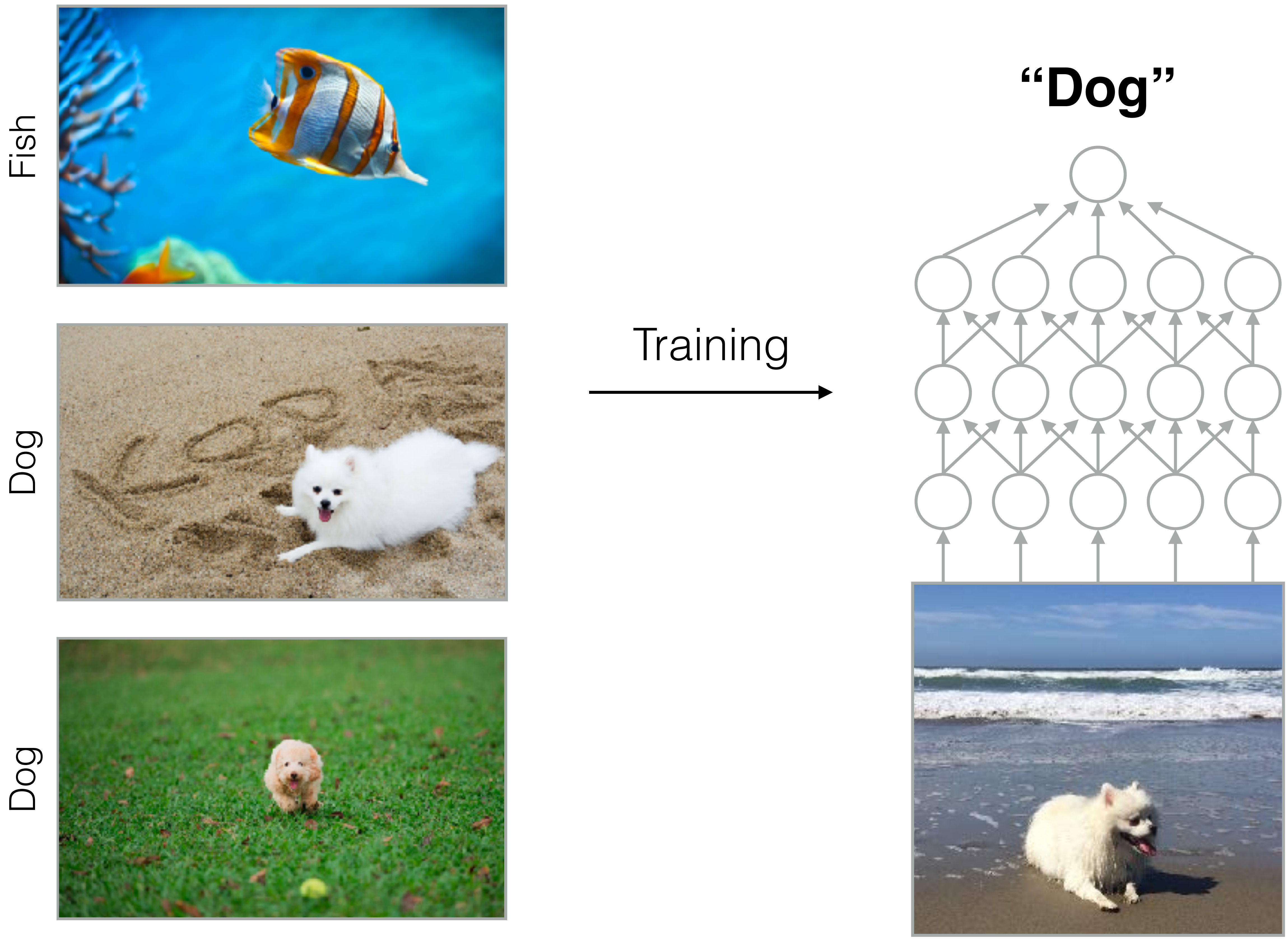
What inputs maximally activate these neurons? [1]

Can we represent this model with a simpler one? [2-3, 9]



Which part of the input was most responsible for this prediction? [4-9]

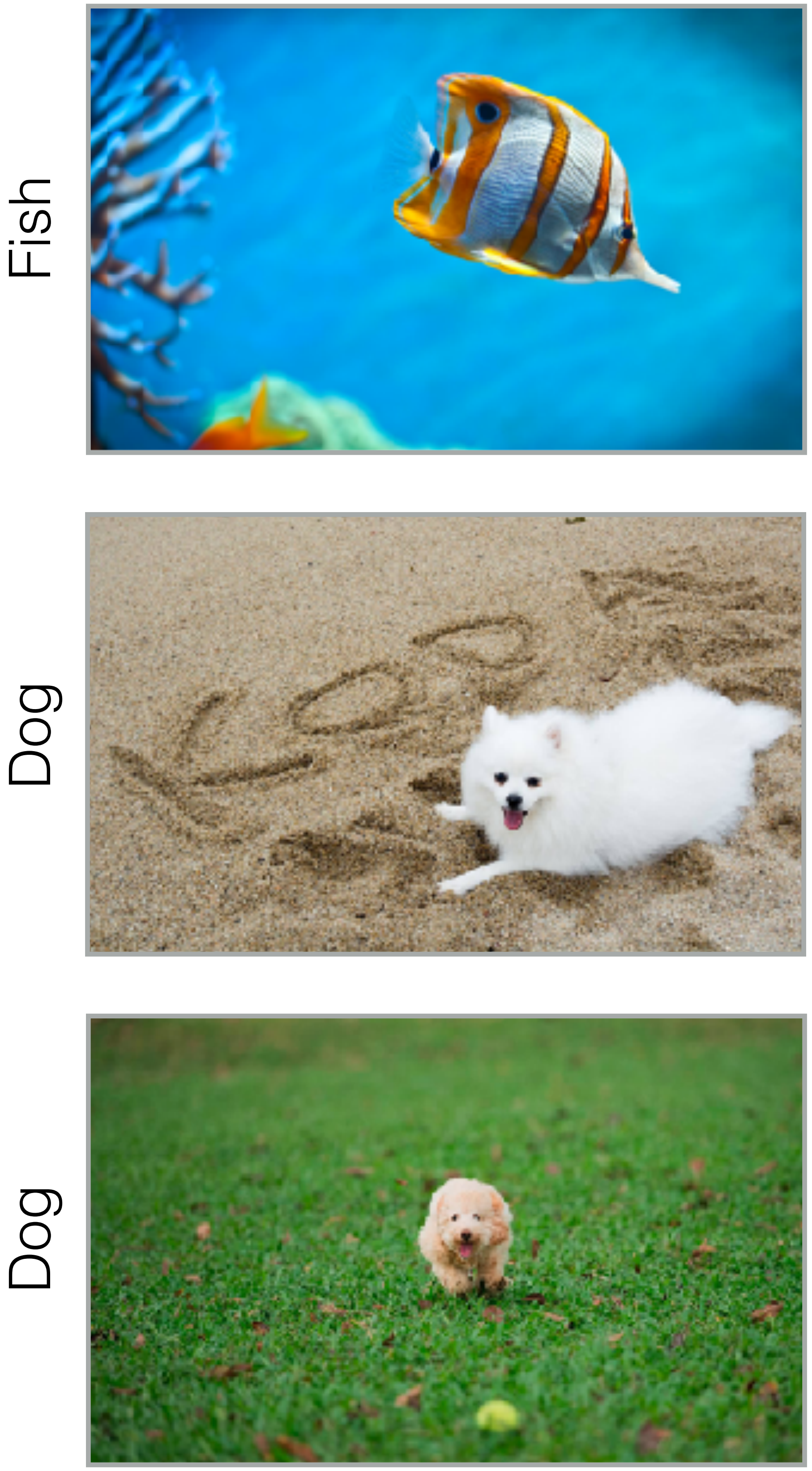
[1] Girshick et al., 2014
[2] Zeiler and Fergus, 2013
[3] Ribeiro, Singh, and Guestrin, 2016
[4] Bastani, Kim, and Bastani, 2017
[5] Simonyan, Vedaldi, and Zisserman, 2013
[6] Li, Monroe, and Jurafsky, 2016
[7] Shrikumar, Greenside, and Kundaje, 2017
[8] Sundararajan, Taly, and Yan, 2017
[9] Leino et al., 2018



Training data

Why did the model make this prediction?

Which training points were most responsible for this prediction?

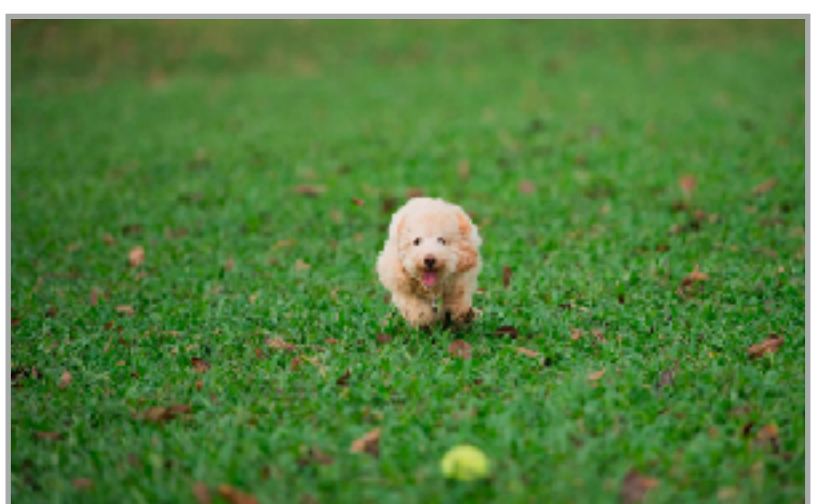


Training data $z_1, z_2, \ldots, z_n$

Fish

Dog

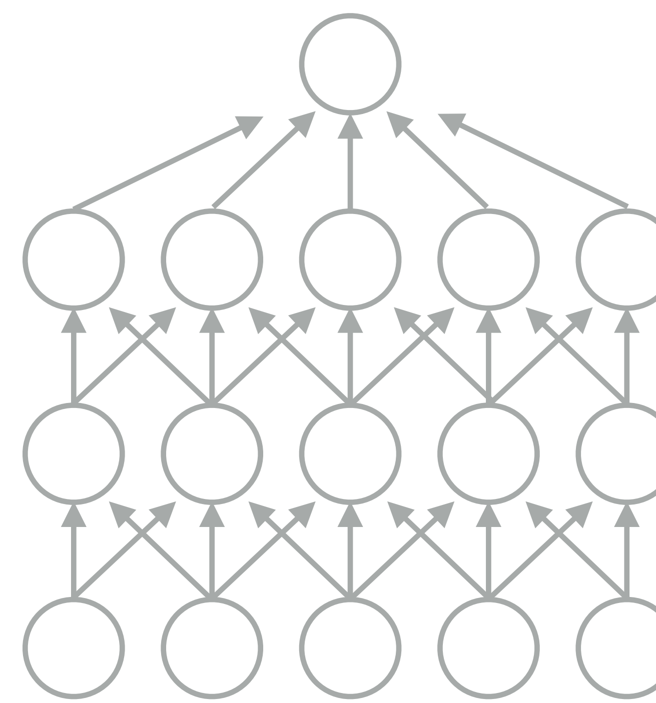
Dog



Training data $z_1, z_2, \ldots, z_n$

Pick $\hat{\theta}$ to minimize $\frac{1}{n}\sum_{i=1}^{n} L(z_i, \theta)$

“Dog”



$\hat{\theta}$

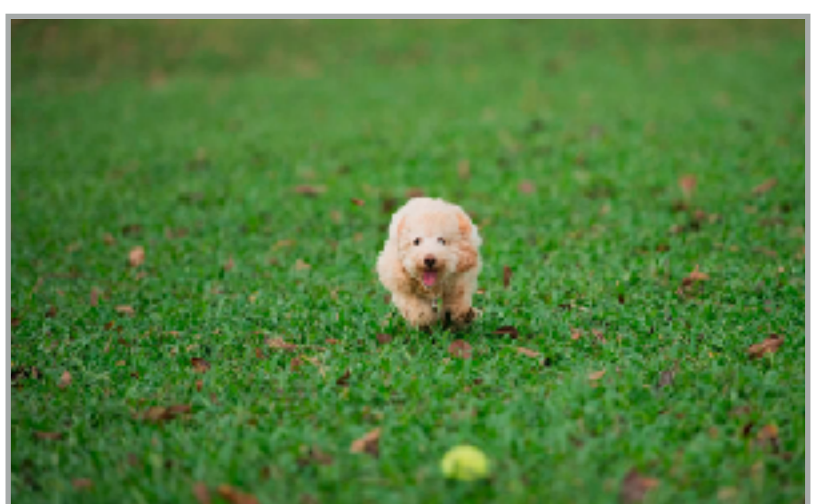
Pick $\hat{\theta}$ to minimize $\frac{1}{n}\sum_{i=1}^{n} L(z_i, \theta)$

Fish

Dog

z_{train}

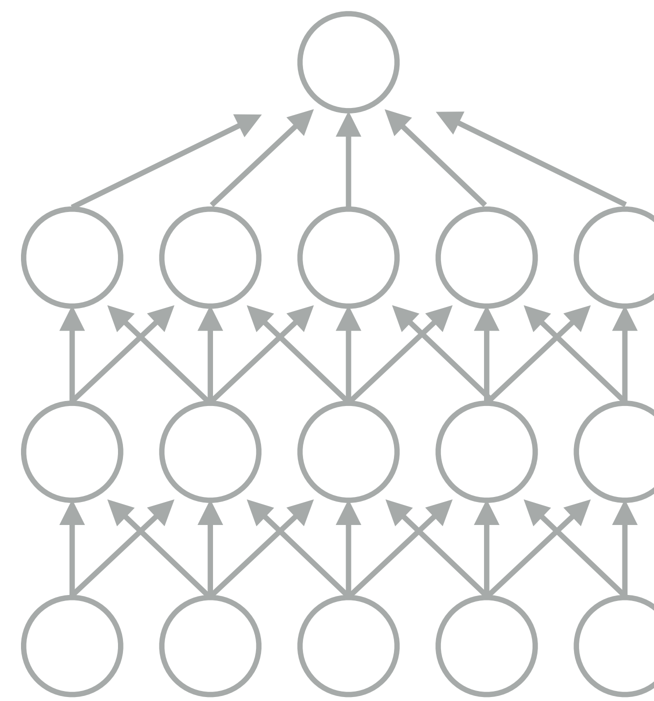
Dog



Training data $z_1, z_2, \ldots, z_n$

$\longrightarrow$

"Dog"



$\hat{\theta}$

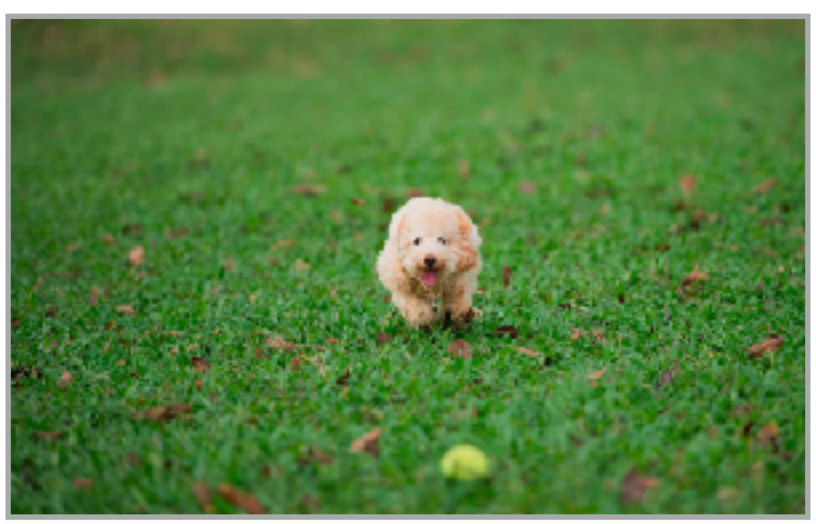
Pick $\hat{\theta}$ to minimize $\frac{1}{n}\sum_{i=1}^{n} L(z_i, \theta)$

Fish

Dog

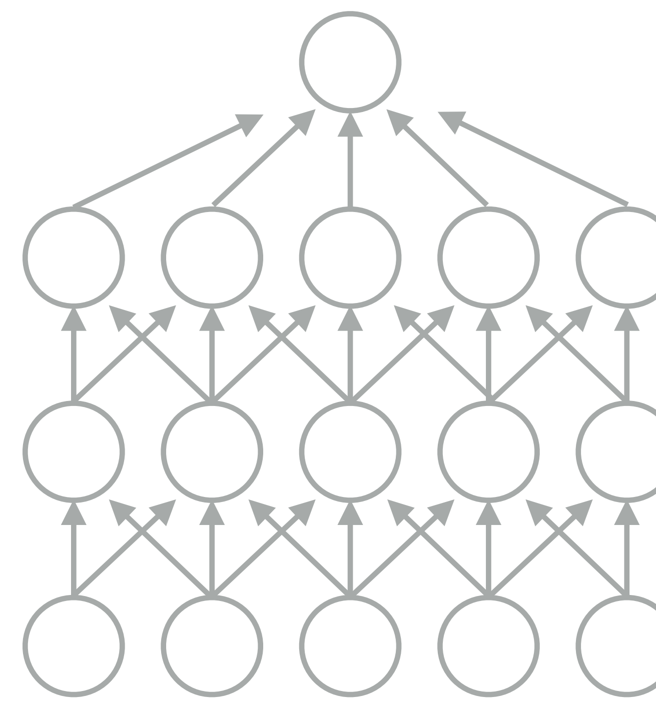
z_{train}

Dog



Training data $z_1, z_2, \ldots, z_n$

“Dog”



$\hat{\theta}$

Pick $\hat{\theta}$ to minimize $\frac{1}{n}\sum_{i=1}^{n} L(z_i, \theta)$

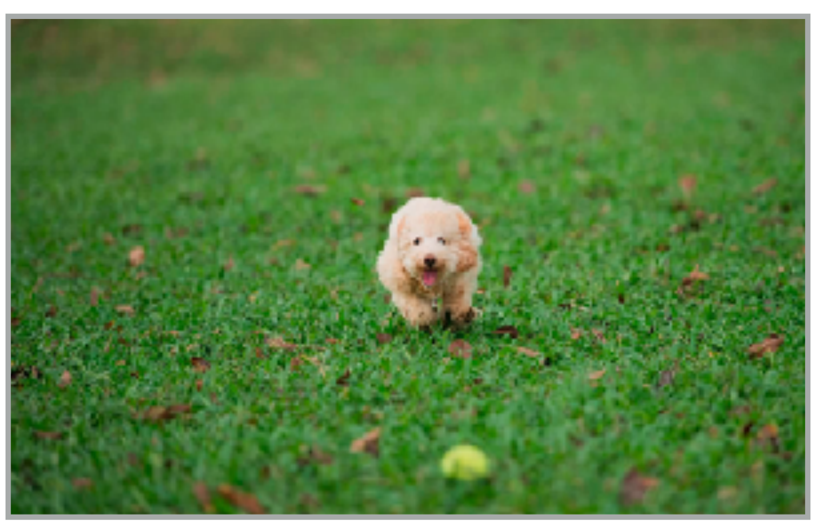
Pick $\hat{\theta}_{\epsilon, z_{\text{train}}}$ to minimize
$\frac{1}{n}\sum_{i=1}^{n} L(z_i, \theta) + \epsilon L(z_{\text{train}}, \theta)$

Fish

Dog

z_{train}

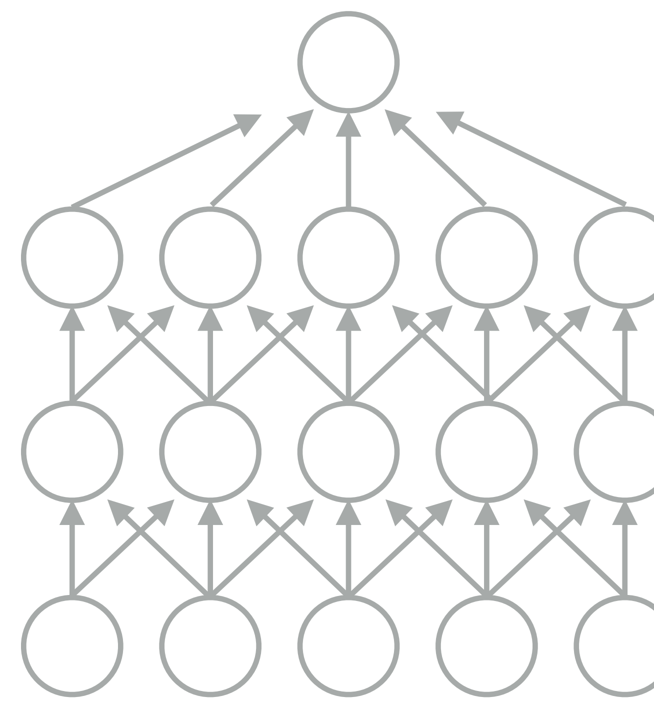
Dog



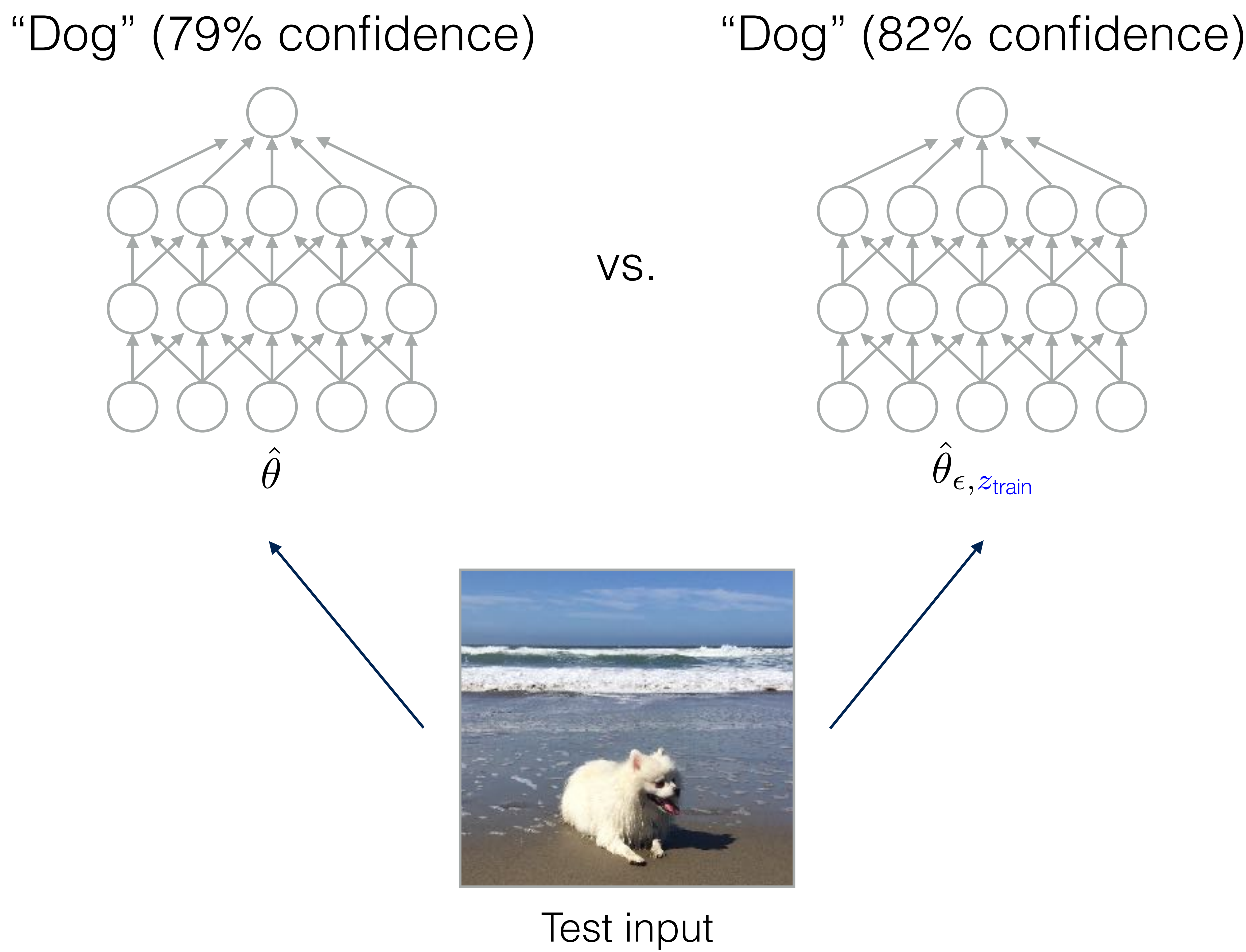
Training data $z_1, z_2, \ldots, z_n$

$\longrightarrow$

"Dog"

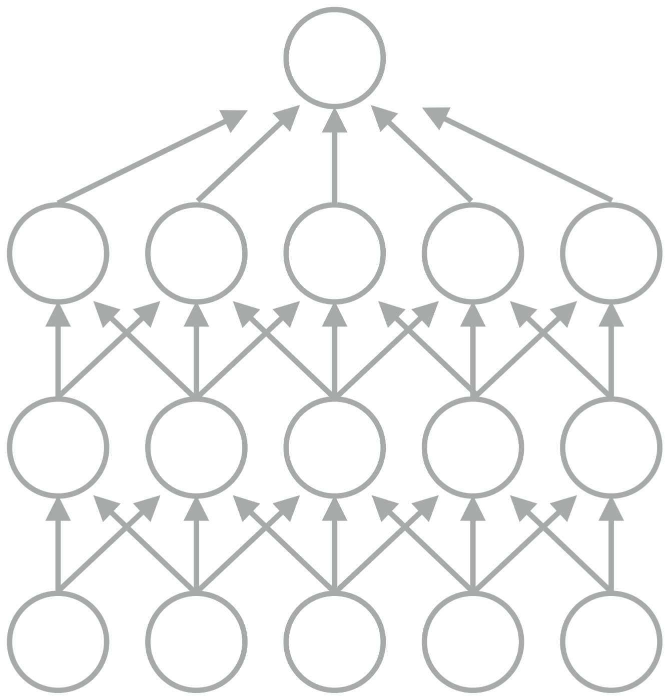


$\hat{\theta}_{\epsilon, z_{\text{train}}}$



"Dog" (79% confidence)
"Dog" (82% confidence)
$\hat{\theta}$
vs.
$\hat{\theta}_{\epsilon, z_{\text{train}}}$
Test input

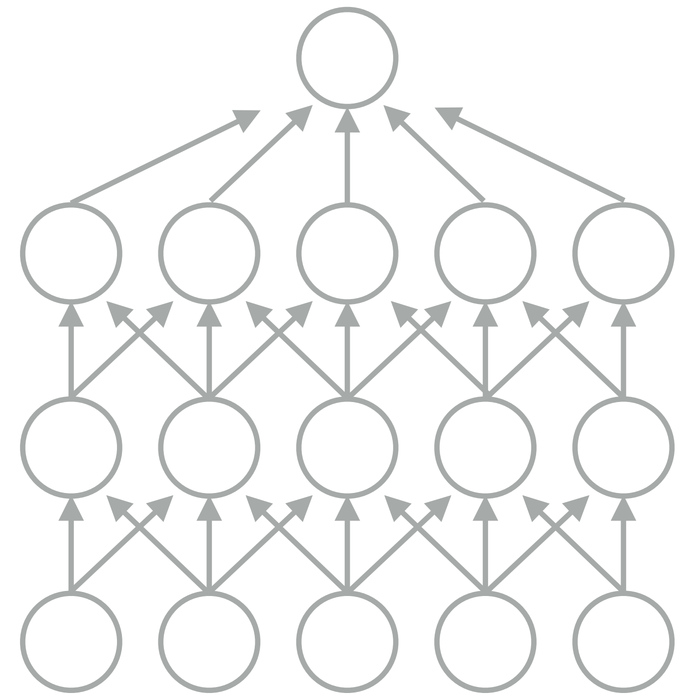
“Dog” (79% confidence)



$\hat{\theta}$

vs.

“Dog” (82% confidence)



$\hat{\theta}_{\epsilon, z_{\text{train}}}$

What is $L(z_{\text{test}}, \hat{\theta}_{\epsilon, z_{\text{train}}}) - L(z_{\text{test}}, \hat{\theta})$?

Why did the model make this prediction?

Which training points were most responsible for this prediction?

How would the prediction change if we upweighted each training point?

Motivation

> Influence functions

Applications

Conclusion

Influence functions

- Introduced in the 1970s in the field of robust statistics
  (e.g., Jaeckel, 1972; Cook, 1977; Cook and Weisberg, 1982)

Influence functions

- Introduced in the 1970s in the field of robust statistics
  (e.g., Jaeckel, 1972; Cook, 1977; Cook and Weisberg, 1982)

- Consider an estimator T that acts on a distribution F

- How much does T change if we perturb F?

Influence functions

- Goal: Measure change in $L(z_{\text{test}}, \hat{\theta}_{\epsilon, z_{\text{train}}})$ as we increase ϵ.

Influence functions

- Goal: Measure change in $L(z_{\text{test}}, \hat{\theta}_{\epsilon, z_{\text{train}}})$ as we increase ϵ.
- $\hat{\theta}_{\epsilon, z_{\text{train}}} \stackrel{\text{def}}{=} \arg\min_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^{n} L(z_i, \theta) + \epsilon L(z_{\text{train}}, \theta)$.

Influence functions

- Goal: Measure change in $L(z_{\text{test}}, \hat{\theta}_{\epsilon, z_{\text{train}}})$ as we increase ϵ.
- $\hat{\theta}_{\epsilon, z_{\text{train}}} \stackrel{\text{def}}{=} \arg\min_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^{n} L(z_i, \theta) + \epsilon L(z_{\text{train}}, \theta)$.
- Under smoothness assumptions,

$$\mathcal{I}_{\text{up,loss}}(z_{\text{train}}, z_{\text{test}}) \stackrel{\text{def}}{=} \left.\frac{dL(z_{\text{test}}, \hat{\theta}_{\epsilon, z_{\text{train}}})}{d\epsilon}\right|_{\epsilon=0}$$

Influence functions

- Goal: Measure change in $L(z_{\text{test}}, \hat{\theta}_{\epsilon, z_{\text{train}}})$ as we increase ϵ.
- $\hat{\theta}_{\epsilon, z_{\text{train}}} \stackrel{\text{def}}{=} \arg\min_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^{n} L(z_i, \theta) + \epsilon L(z_{\text{train}}, \theta)$.
- Under smoothness assumptions,

$$\begin{aligned}\mathcal{I}_{\text{up,loss}}(z_{\text{train}}, z_{\text{test}}) &\stackrel{\text{def}}{=} \left.\frac{dL(z_{\text{test}}, \hat{\theta}_{\epsilon, z_{\text{train}}})}{d\epsilon}\right|_{\epsilon=0} \\ &= -\nabla_\theta L(z_{\text{test}}, \hat{\theta})^\top H_{\hat{\theta}}^{-1} \nabla_\theta L(z_{\text{train}}, \hat{\theta}),\end{aligned}$$

- where $H_{\hat{\theta}} \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^{n} \nabla_\theta^2 L(z_i, \hat{\theta})$.

RBF SVM (raw pixels)

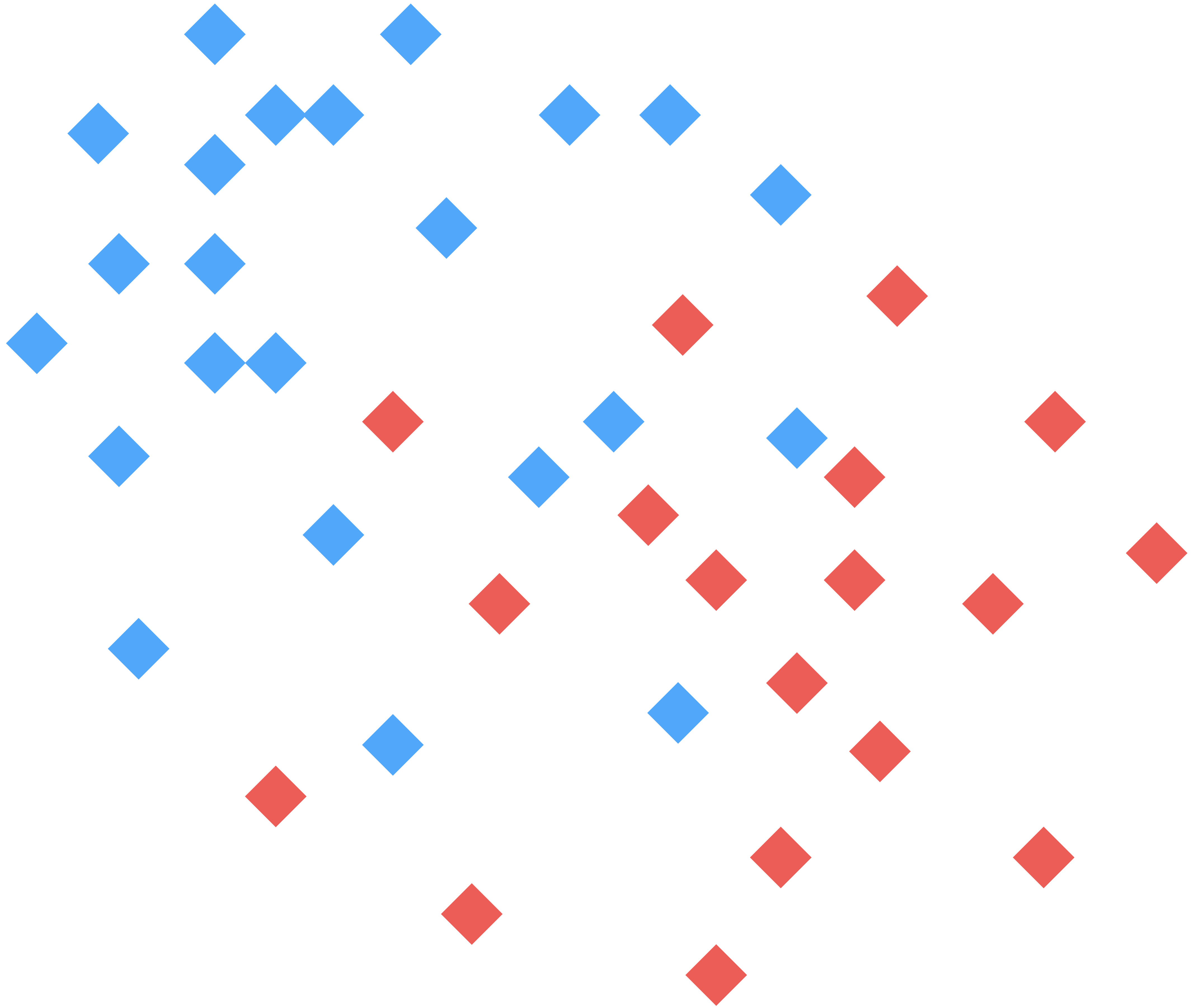
Logistic regression (Inception features)

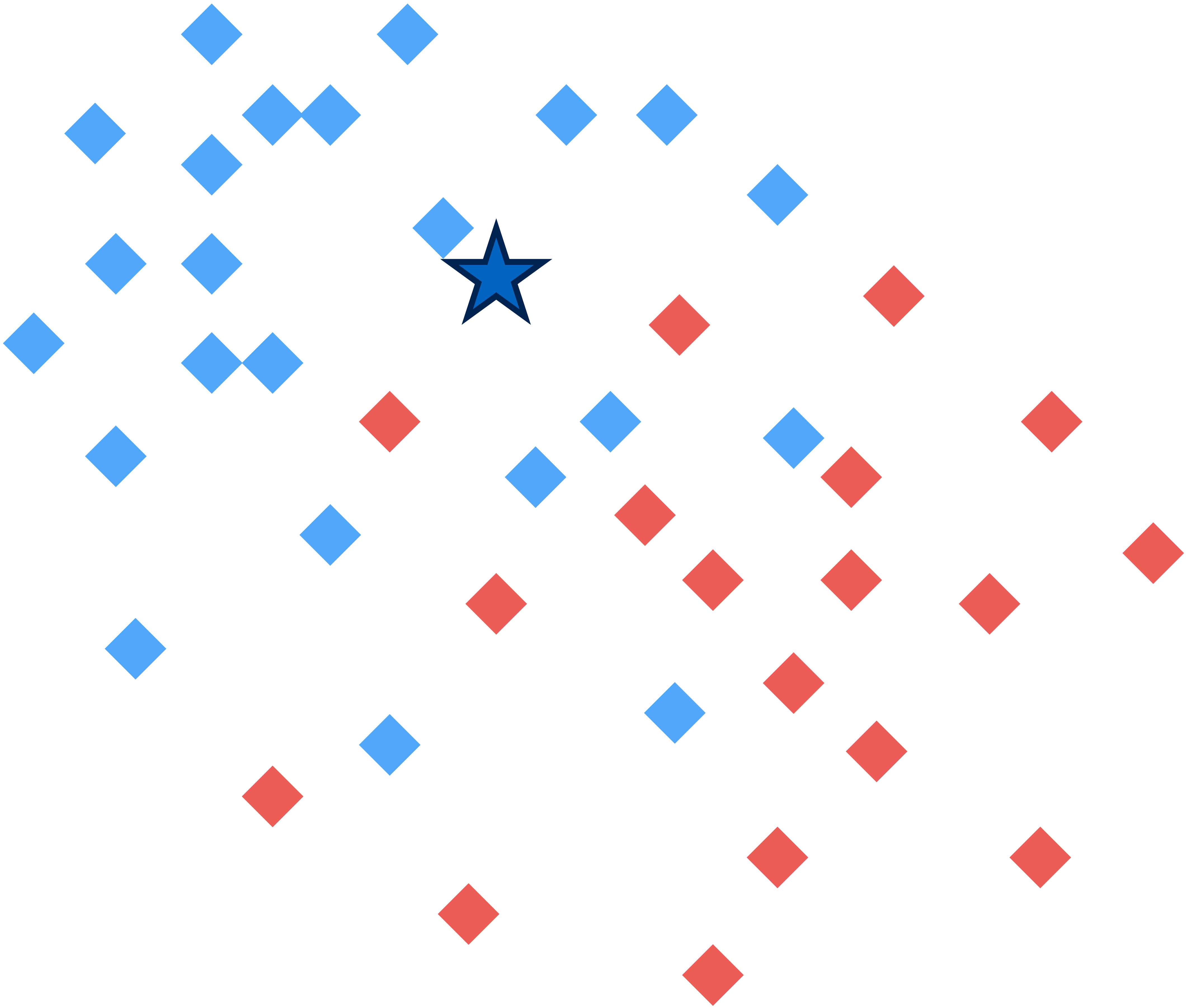
Test image

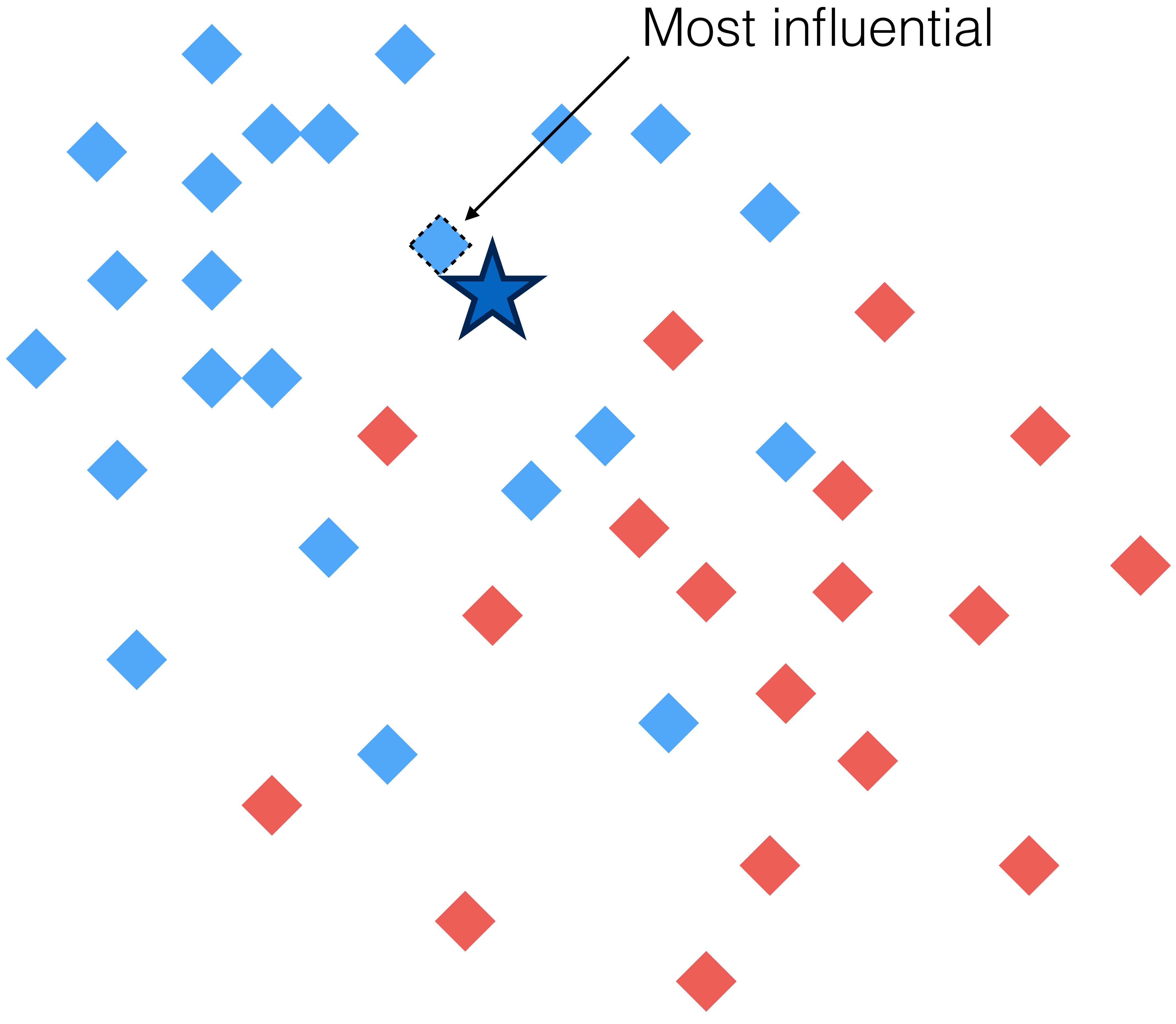
Test image

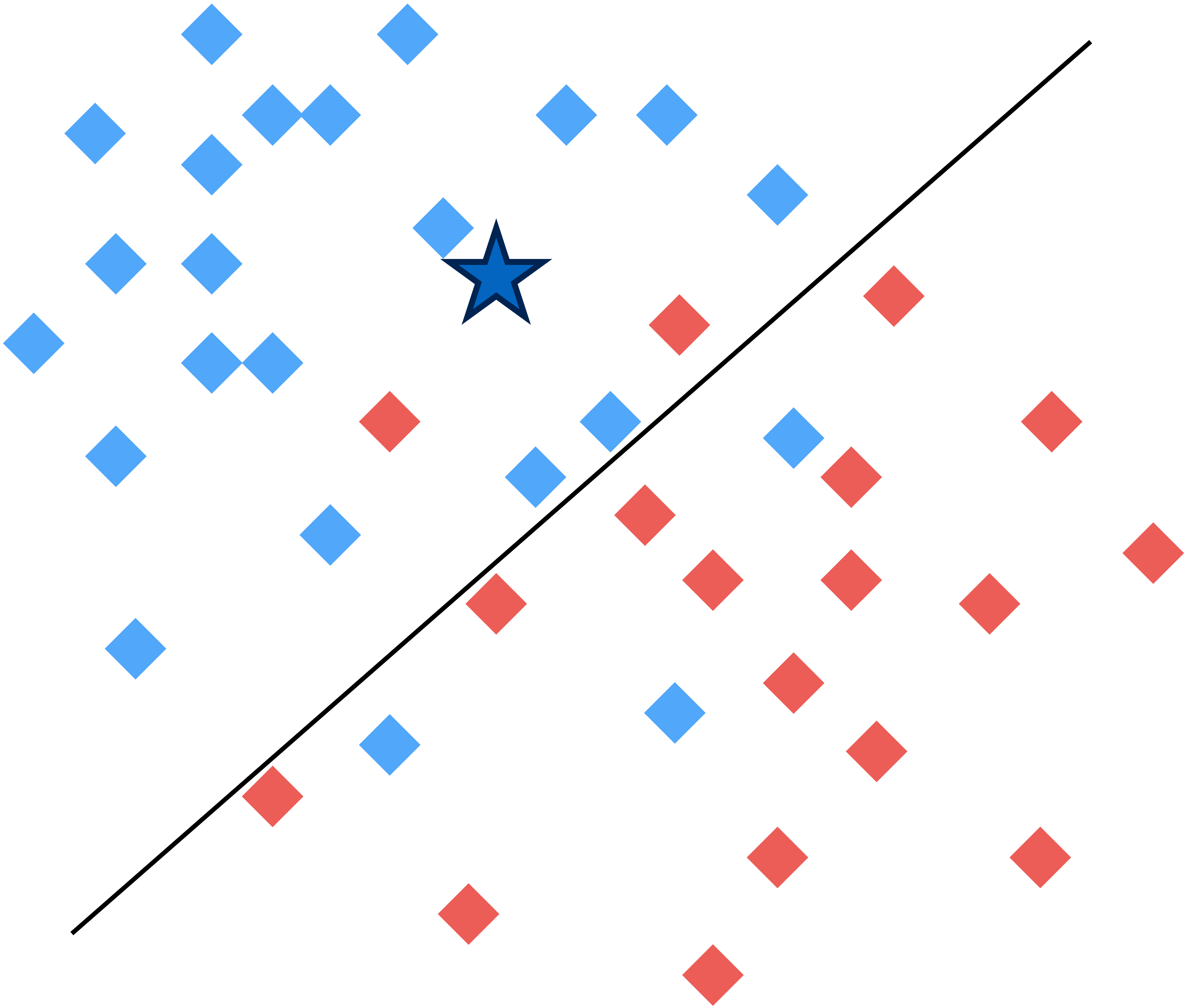
RBF SVM (raw pixels)

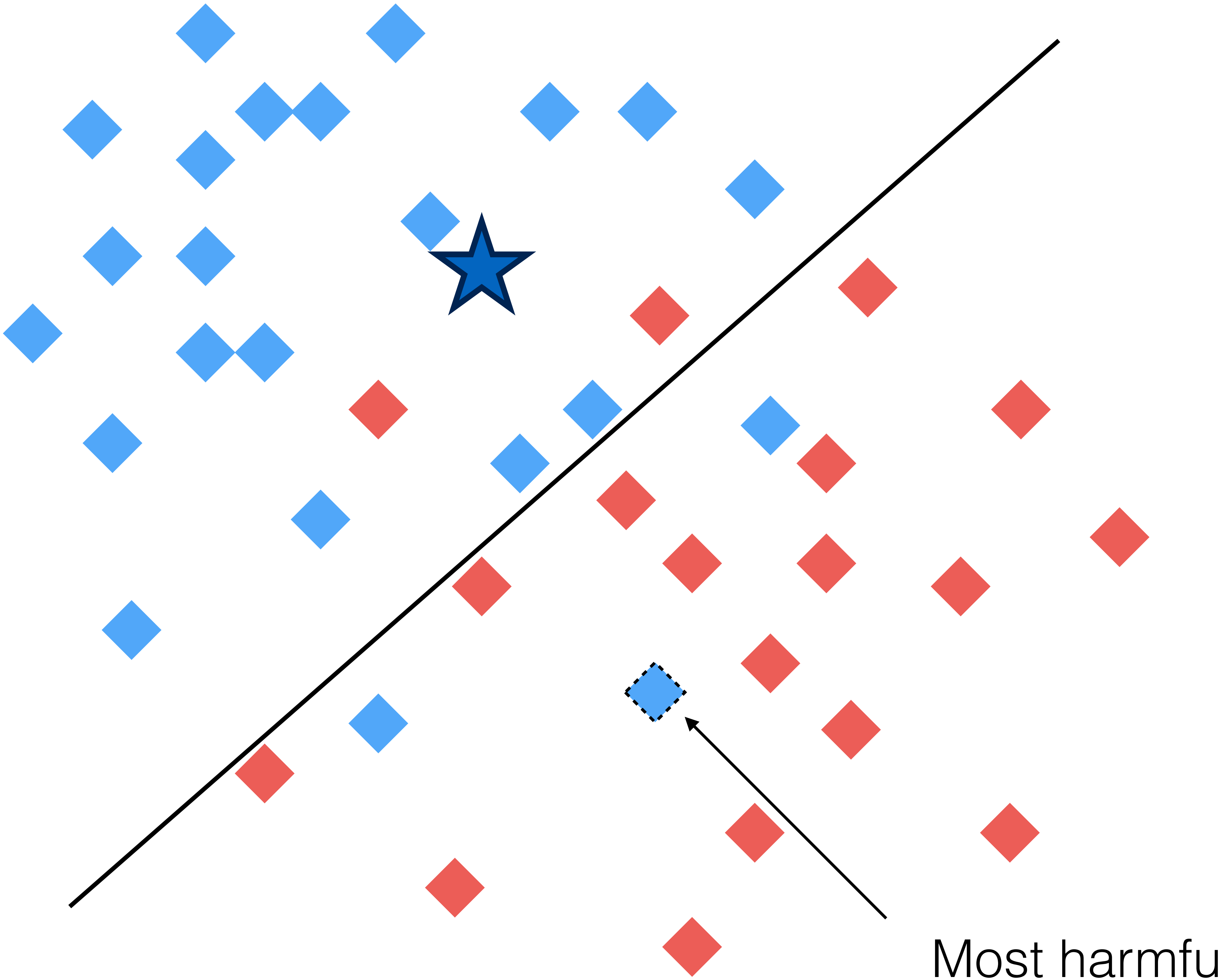
Logistic regression (Inception features)

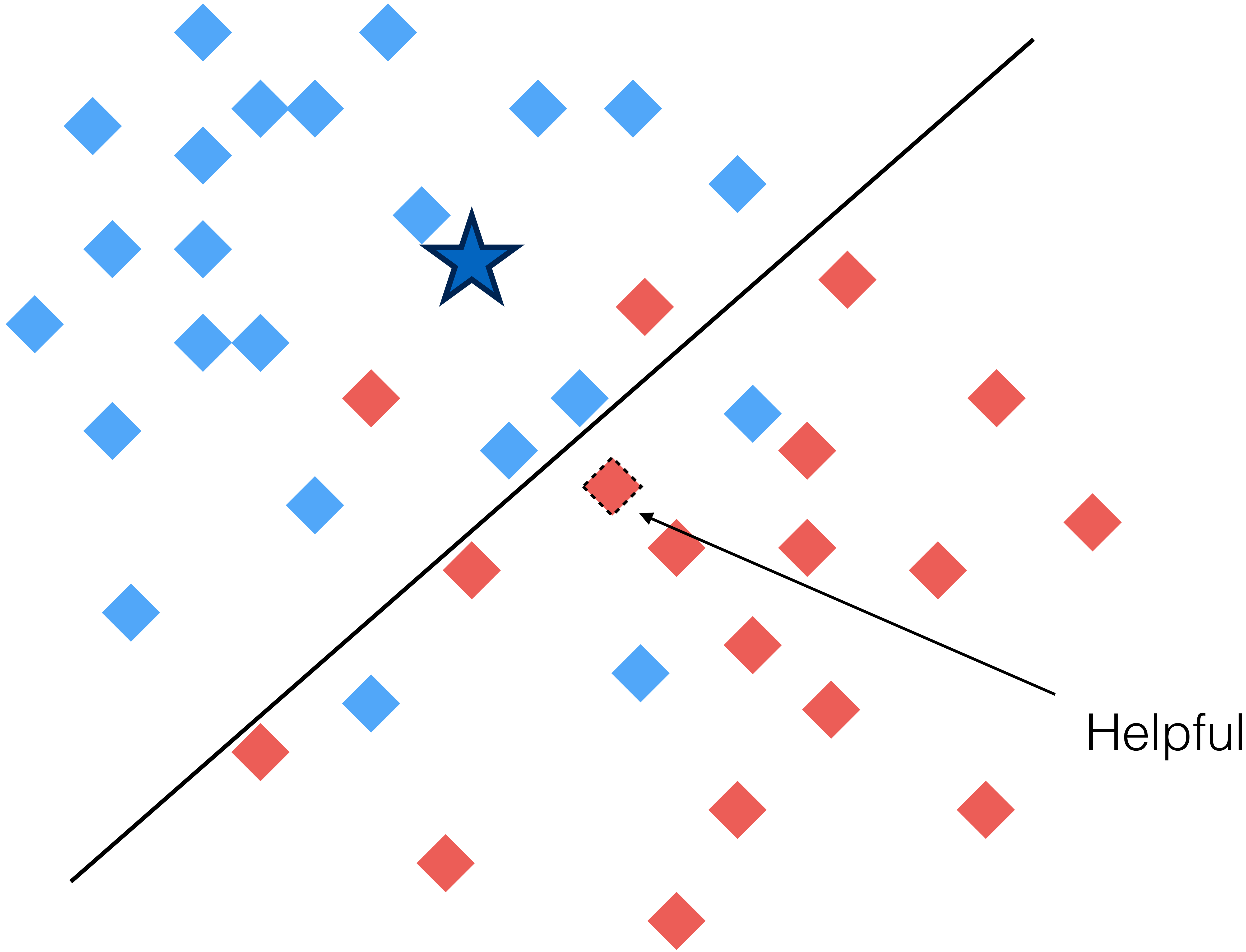





Most influential

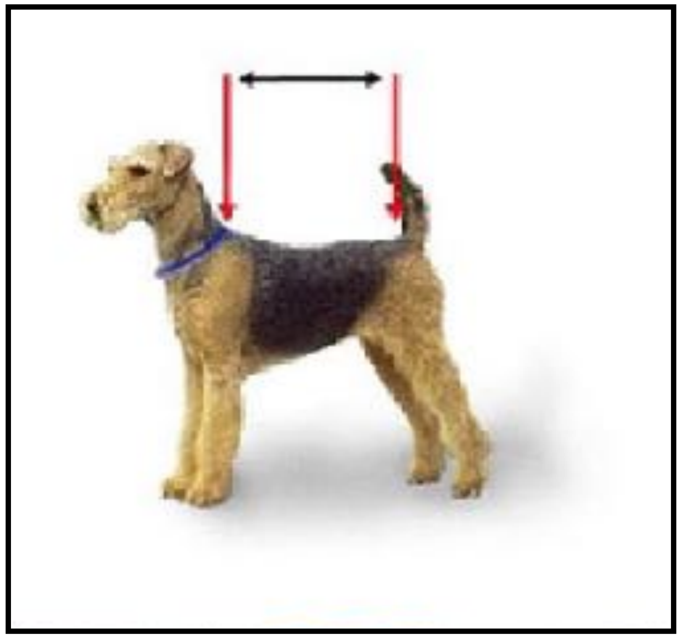



Most harmful


Helpful

Test image

Helpful dog



Potential issues

*More details in paper

Potential issues

1. Computational inefficiency

Potential issues

1. Computational inefficiency

$$\begin{bmatrix} \ddots & & \\ & \mathbf{H} & \\ & & \ddots \end{bmatrix}^{-1}$$

Slow

[1] Pearlmutter, 1994
[2] Martens, 2010
[3] Agarwal, Bullins, Hazan, 2016

Potential issues

1. Computational inefficiency

$$\begin{bmatrix} \ddots & & \\ & \mathbf{H} & \\ & & \ddots \end{bmatrix} \begin{bmatrix} \\ \mathbf{v} \\ \\ \end{bmatrix}$$

Fast [1]

$$\begin{bmatrix} \ddots & & \\ & \mathbf{H} & \\ & & \ddots \end{bmatrix}^{\mathbf{-1}}$$

Slow

[1] Pearlmutter, 1994
[2] Martens, 2010
[3] Agarwal, Bullins, Hazan, 2016

Potential issues

1. Computational inefficiency

$$\begin{bmatrix} \ddots & & \\ & \mathbf{H} & \\ & & \ddots \end{bmatrix} \begin{bmatrix} \\ \mathbf{v} \\ \\ \end{bmatrix} \xrightarrow[\text{[2, 3]}]{\text{approx}} \begin{bmatrix} \ddots & & \\ & \mathbf{H} & \\ & & \ddots \end{bmatrix}^{\mathbf{-1}} \begin{bmatrix} \\ \mathbf{v} \\ \\ \end{bmatrix}$$

Fast [1]

[1] Pearlmutter, 1994
[2] Martens, 2010
[3] Agarwal, Bullins, Hazan, 2016

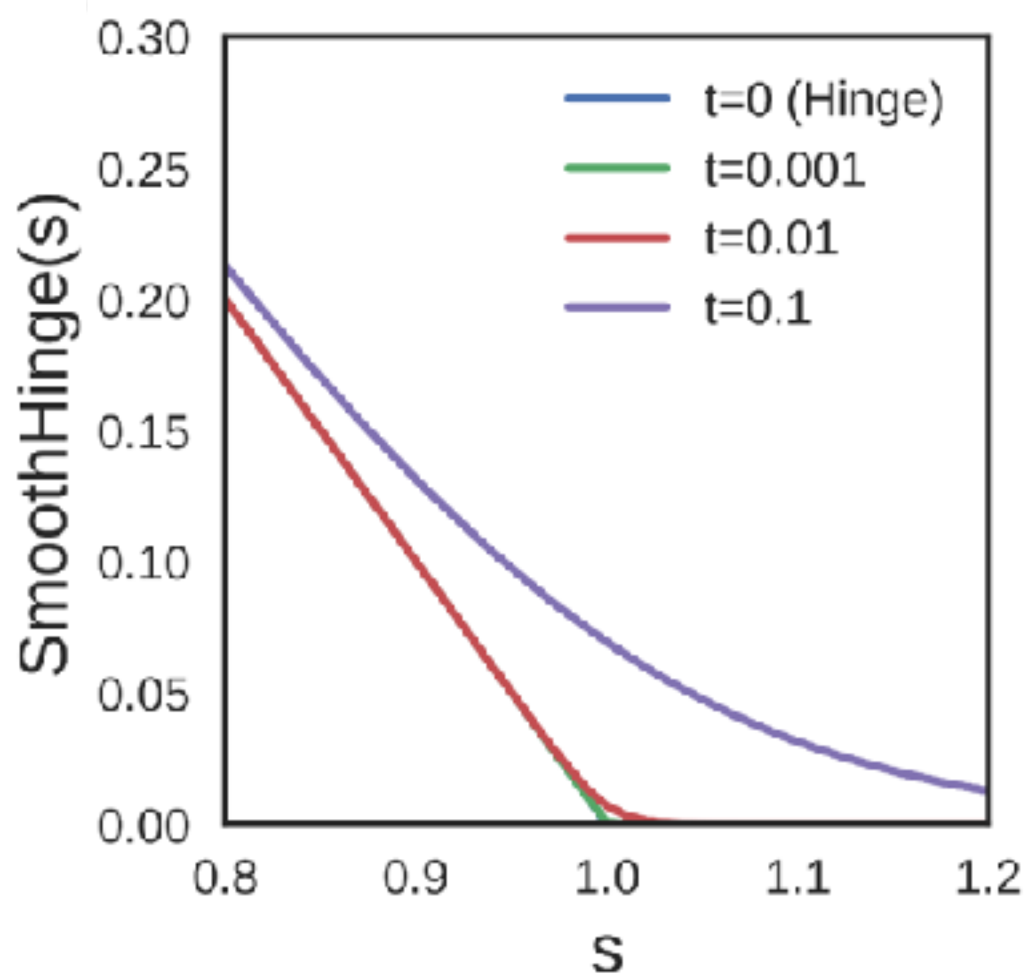
Potential issues

1. Computational inefficiency
2. Non-smooth losses

Potential issues

1. Computational inefficiency

2. Non-smooth losses



Potential issues

1. Computational inefficiency

2. Non-smooth losses

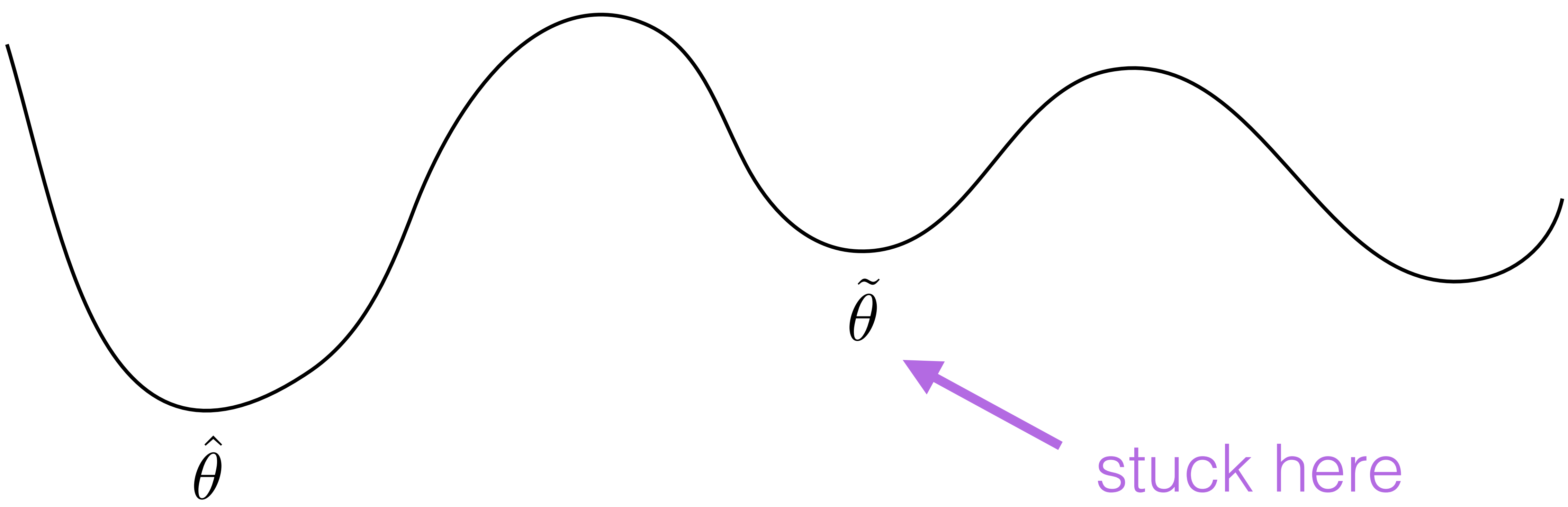
3. Difficulty in finding the global minimizer

Potential issues

1. Computational inefficiency

2. Non-smooth losses

3. Difficulty in finding the global minimizer

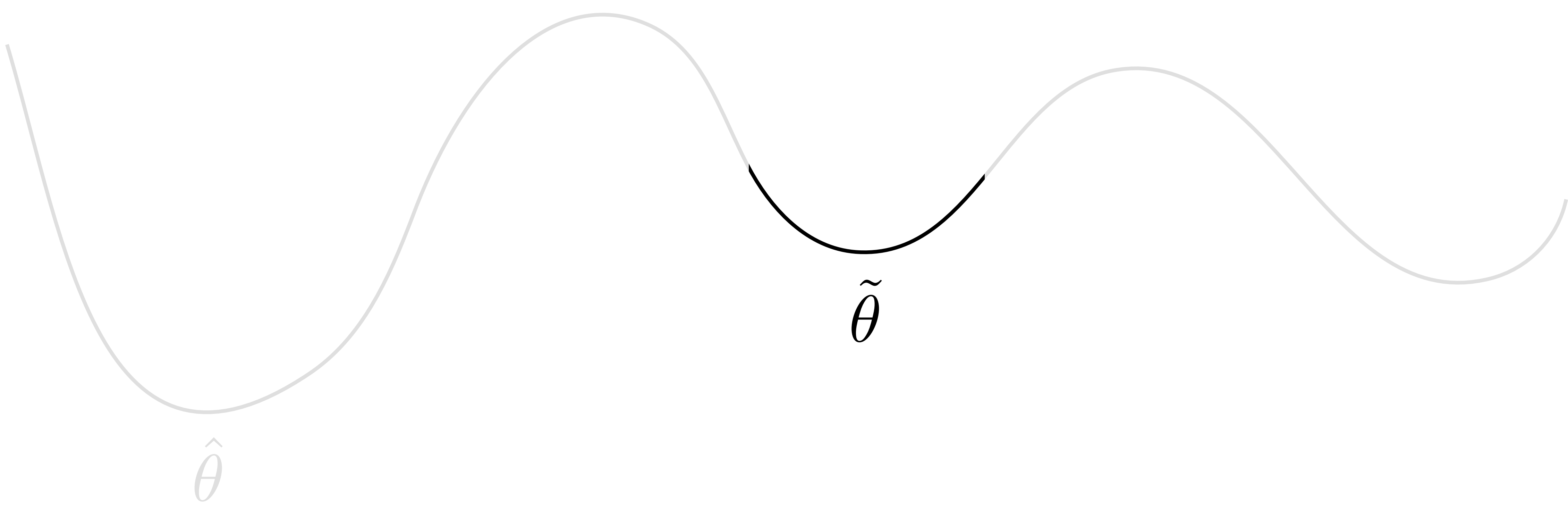


Potential issues

1. Computational inefficiency

2. Non-smooth losses

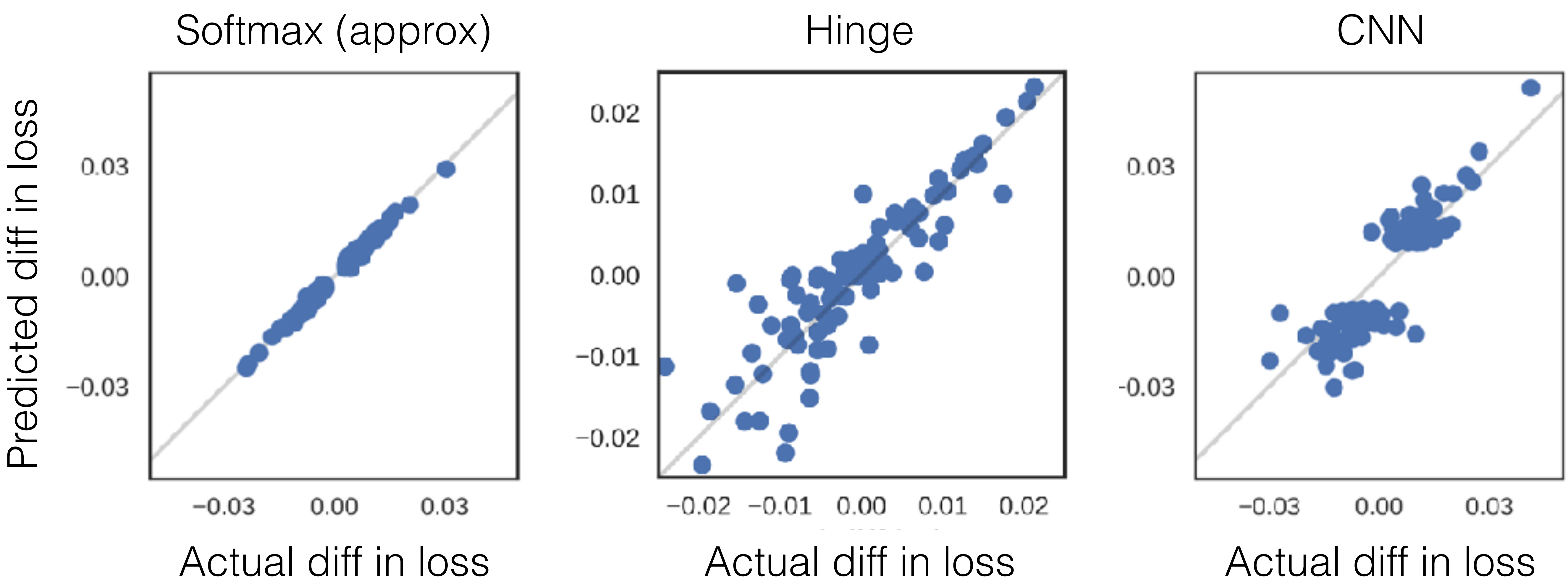
3. Difficulty in finding the global minimizer



Potential issues

For a fixed z_{test} and for each z_{train}, compared:

1. Actual change in $L(z_{\text{test}})$ after removing z_{train}
2. Predicted change in $L(z_{\text{test}})$ after removing z_{train}


Softmax (approx)
Hinge
CNN
Predicted diff in loss
Actual diff in loss
Actual diff in loss
Actual diff in loss
0.03
0.00
−0.03
0.02
0.01
0.00
−0.01
−0.02
−0.03
0.00
0.03
−0.02
−0.01
0.00
0.01
0.02
-0.03

Motivation

Influence functions

> Applications

Conclusion

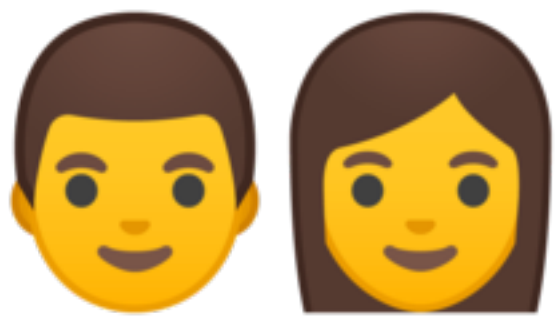
Application 1

Debugging model errors

Debugging model errors

- If a model makes a mistake, can we find out why?
- Case study: hospital re-admission (logistic regression, 20K patients, 127 features)

Debugging model errors

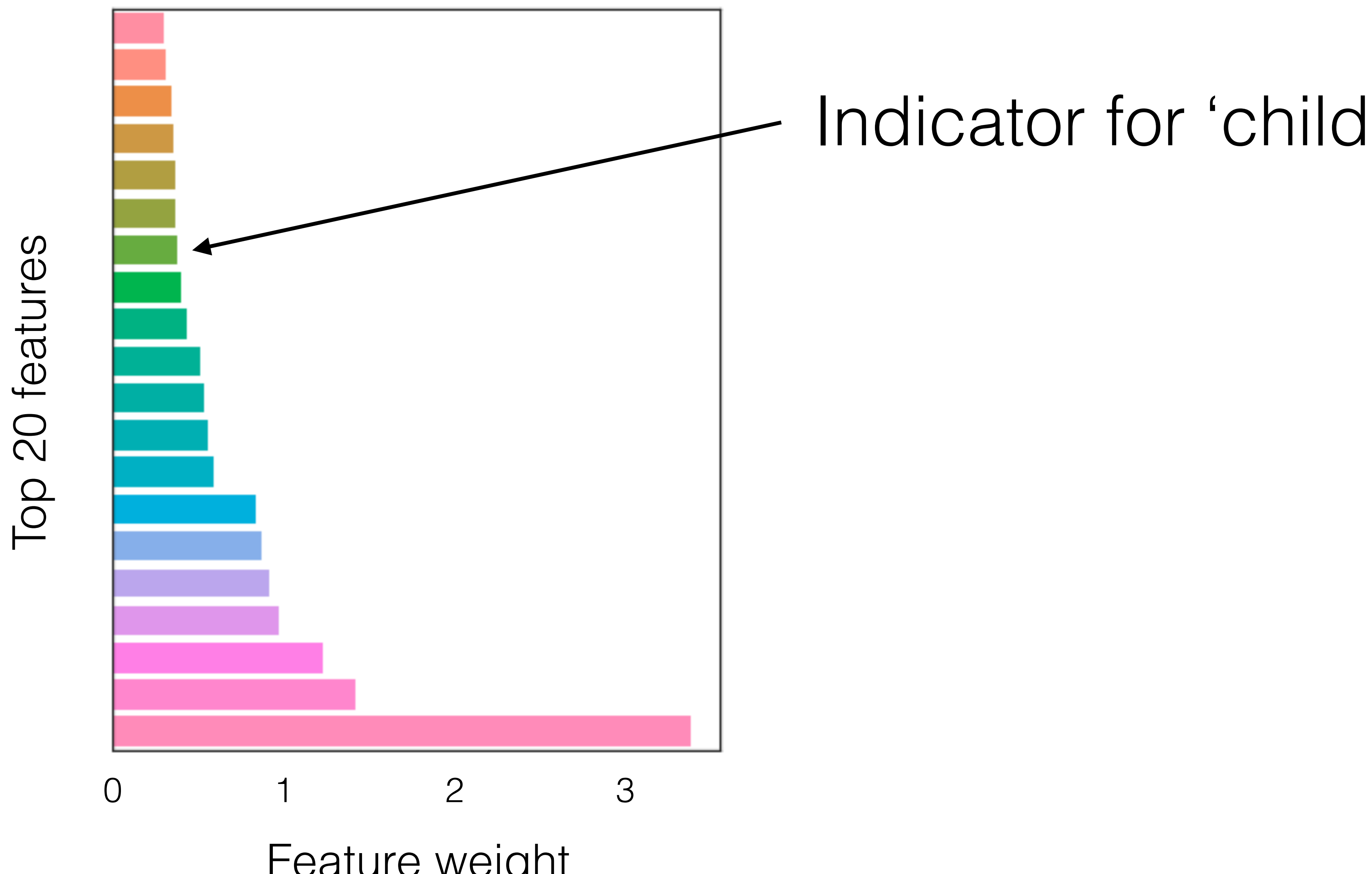
		Original		Modified
Healthy + re-admitted adults		~20k	same →	~20k
Healthy children		21	-20 →	1
Re-admitted children		3	same →	3

Debugging model errors

True test label: Healthy
Model predicts: Re-admitted

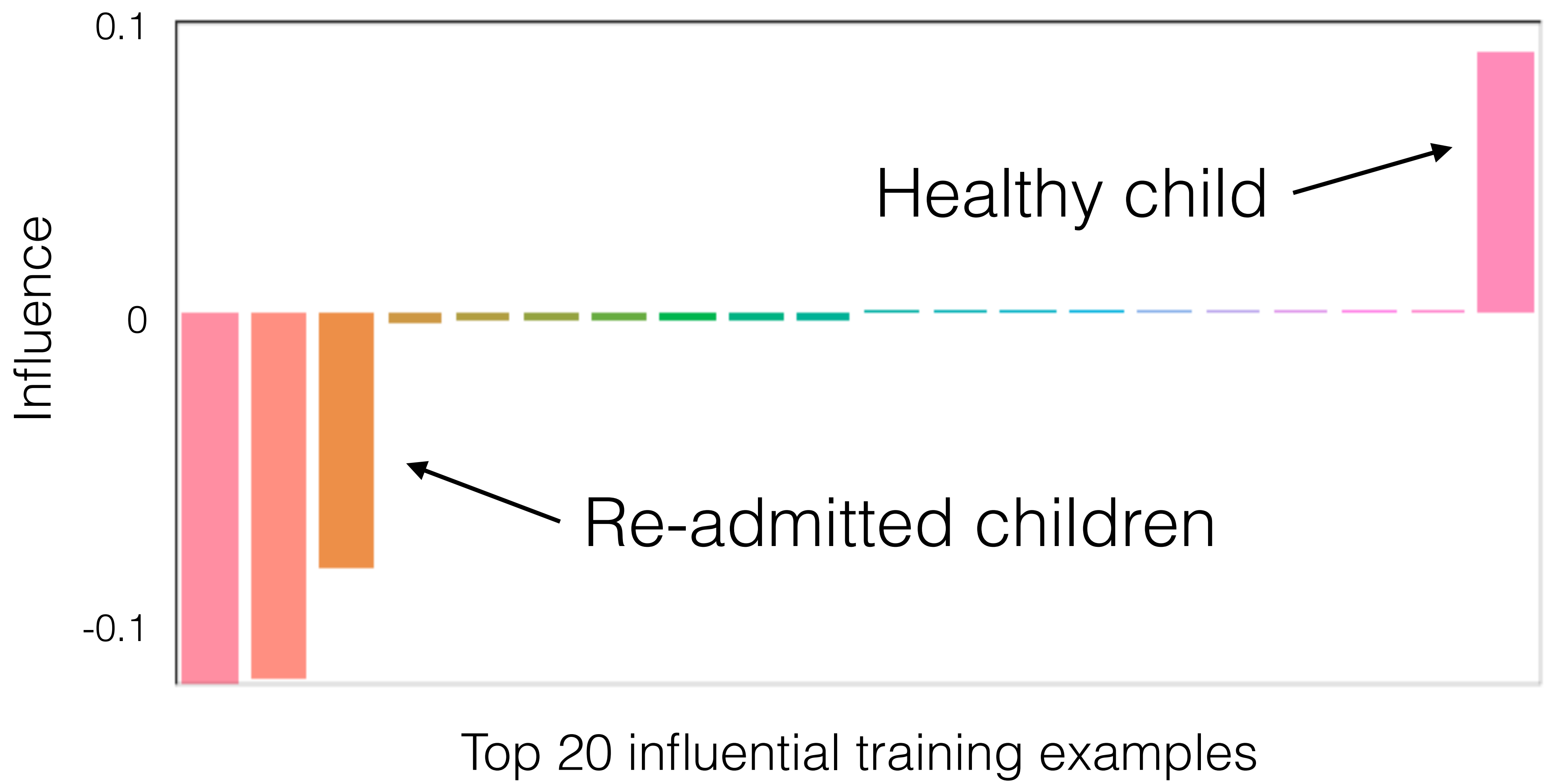
Debugging model errors

True test label: Healthy
Model predicts: Re-admitted



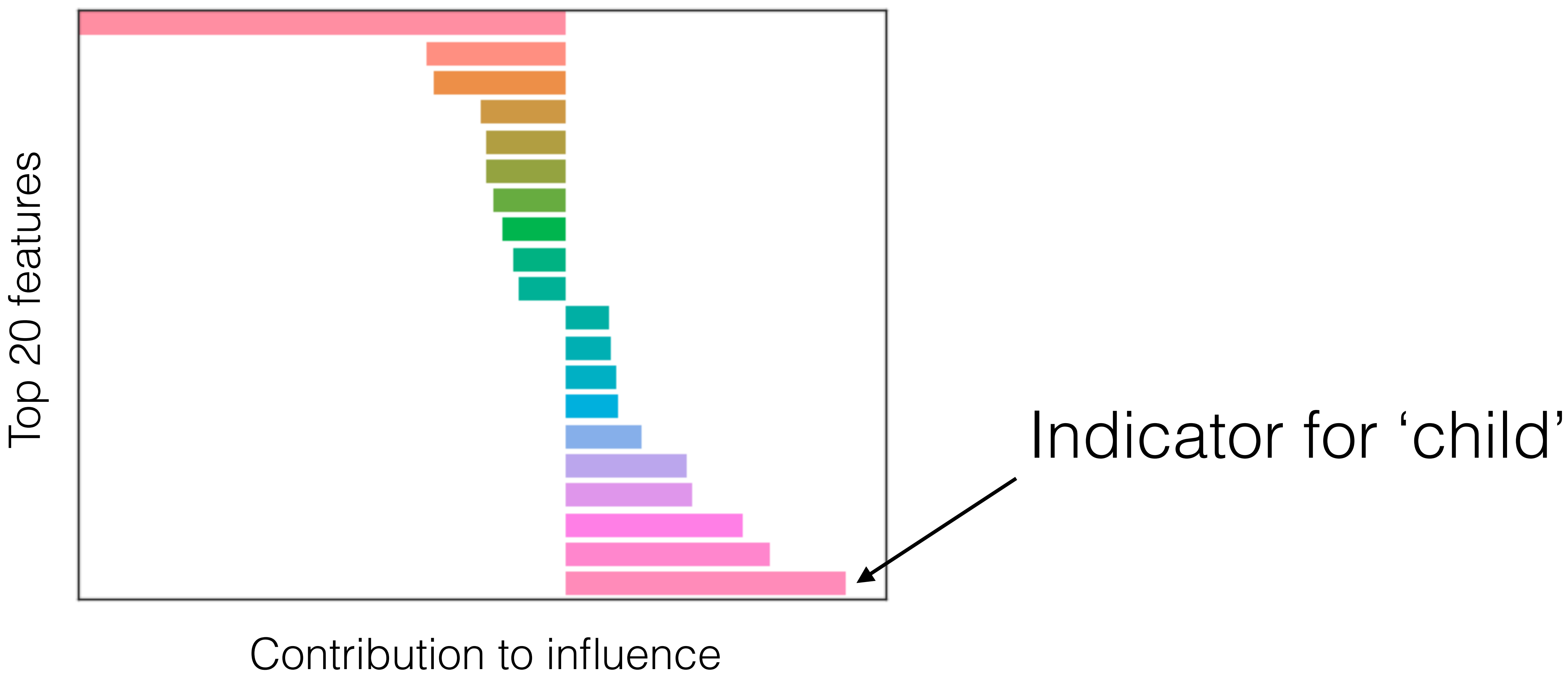
Debugging model errors

True test label: Healthy
Model predicts: Re-admitted



Debugging model errors

True test label: Healthy
Model predicts: Re-admitted



Application 2

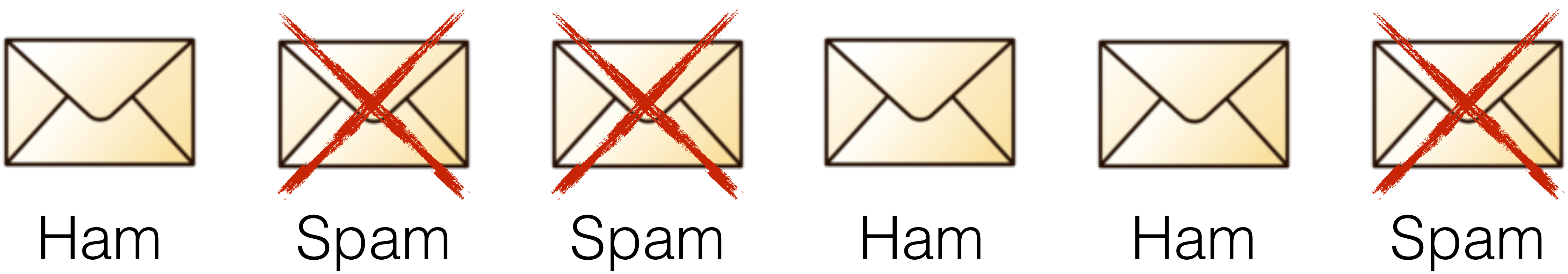
Fixing training data

Fixing training data

- Setup: training labels are noisy, and we have a small budget to manually inspect them
- Can we prioritize which labels to try to fix?

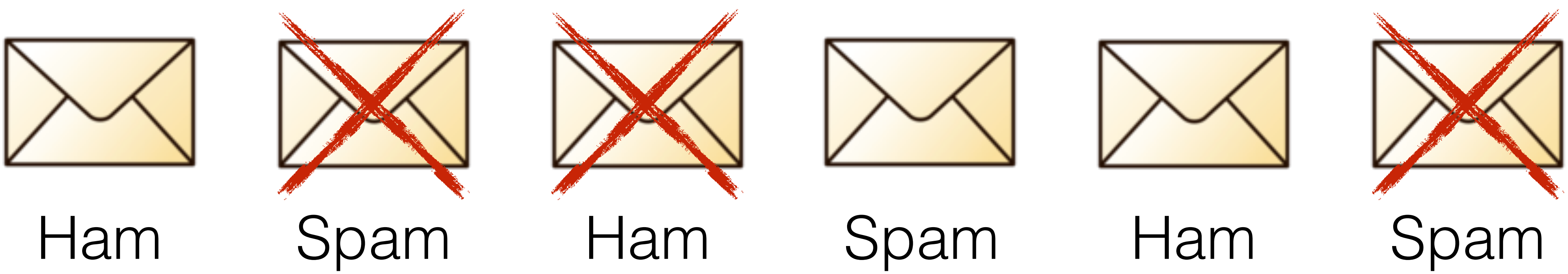
Fixing training data

- Setup: training labels are noisy, and we have a small budget to manually inspect them
- Can we prioritize which labels to try to fix?



Fixing training data

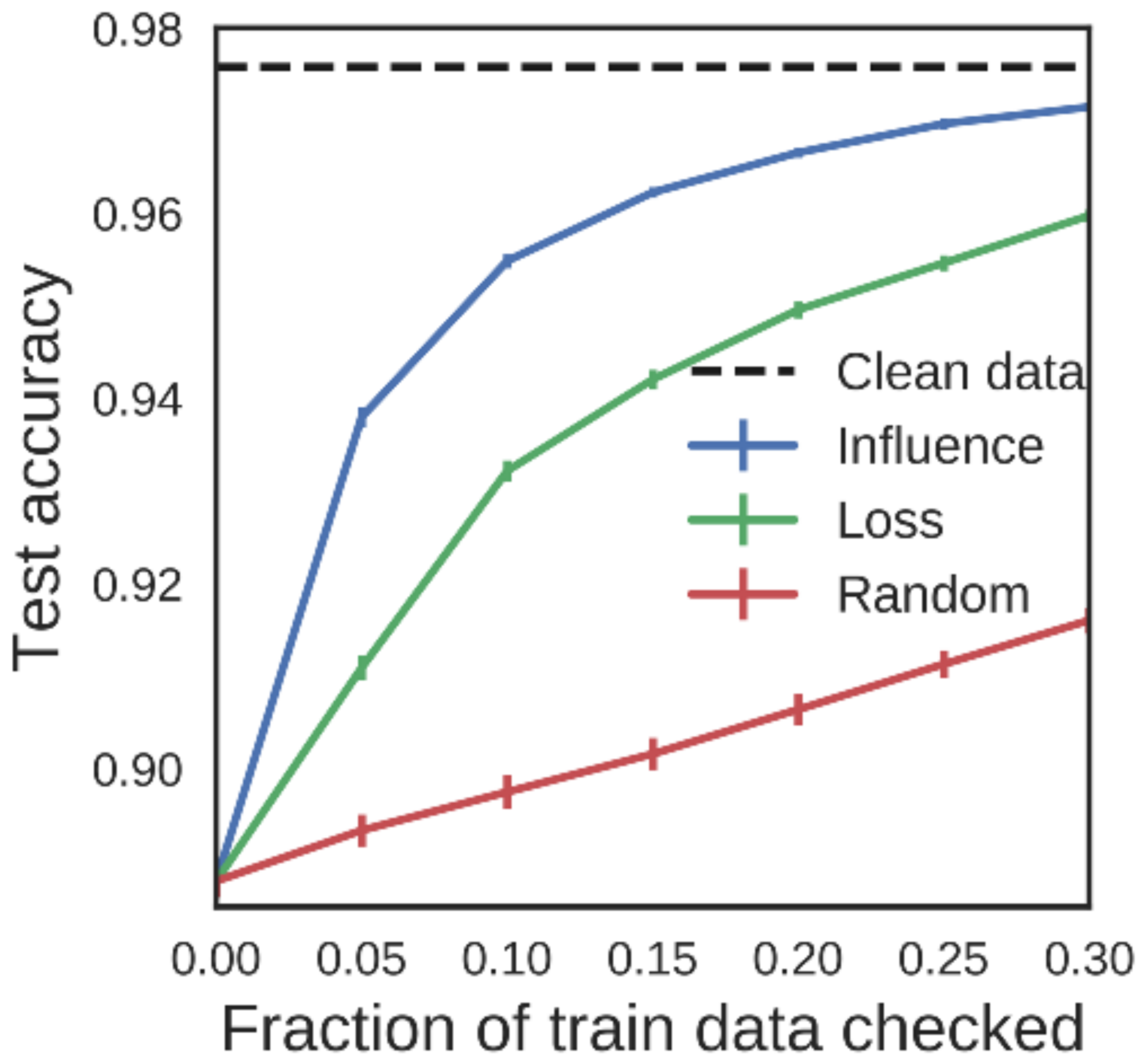
- Setup: training labels are noisy, and we have a small budget to manually inspect them
- Can we prioritize which labels to try to fix?



Fixing training data

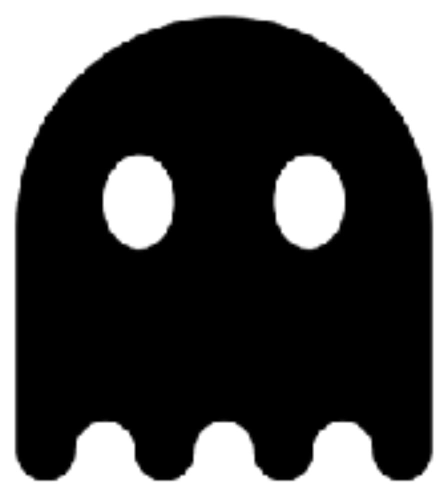
- Key idea: if a training point is not influential, don't waste effort checking it

Fixing training data

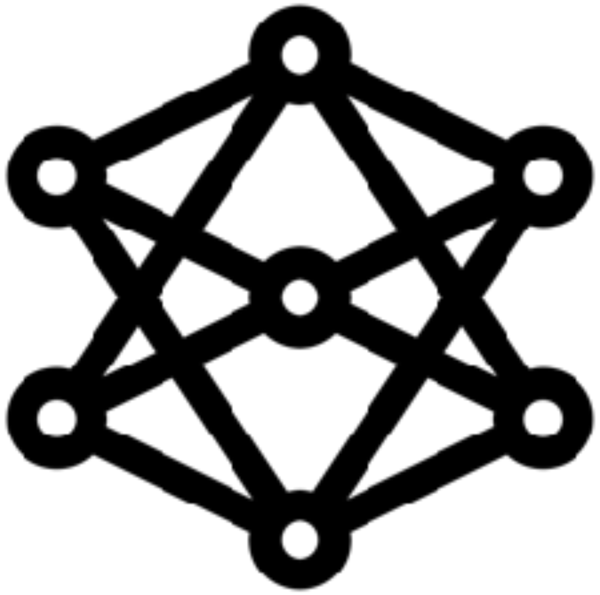


Application 3

Adversarial training examples

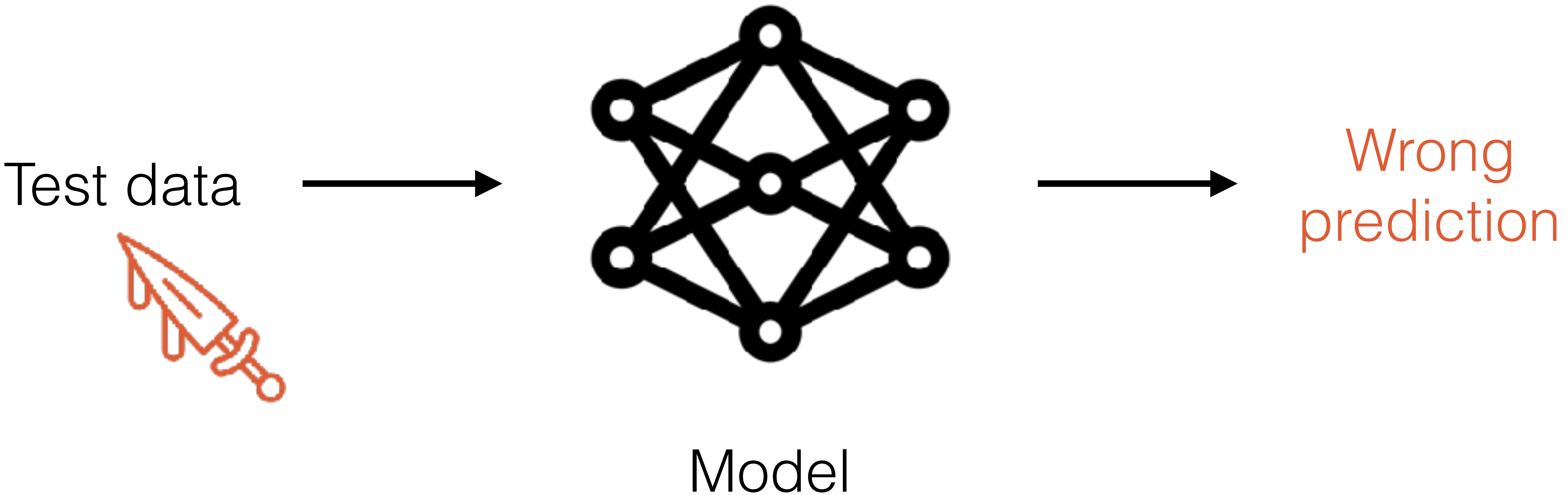


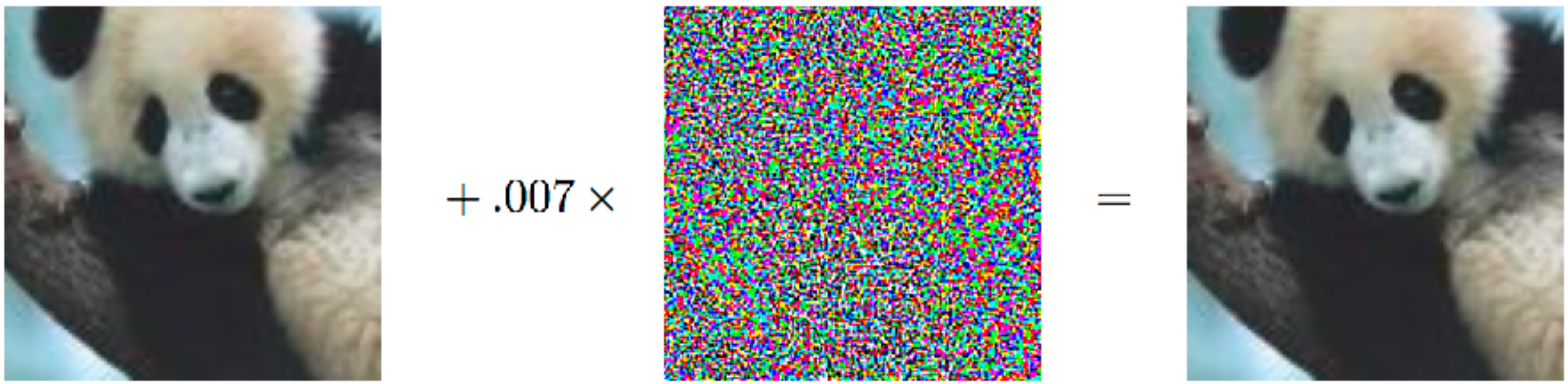
Test data



Model

Correct
prediction


Test data
Model
Wrong
prediction

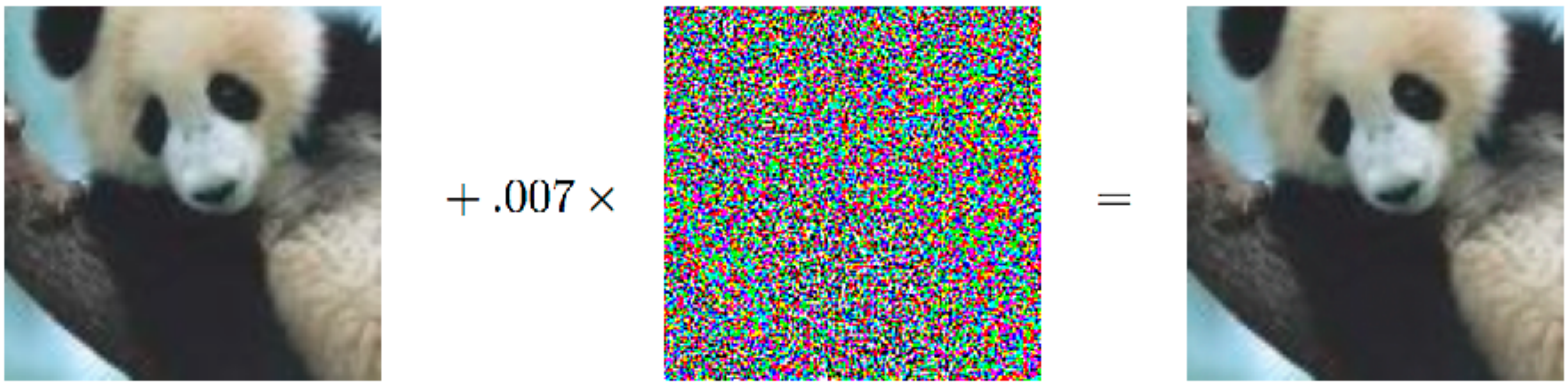


"panda"
57.7% confidence

"gibbon"
99.3% confidence

Image from Goodfellow, Shlens, Szegedy, 2015
Original demonstration from Szegedy et al., 2013

Adversarial test examples



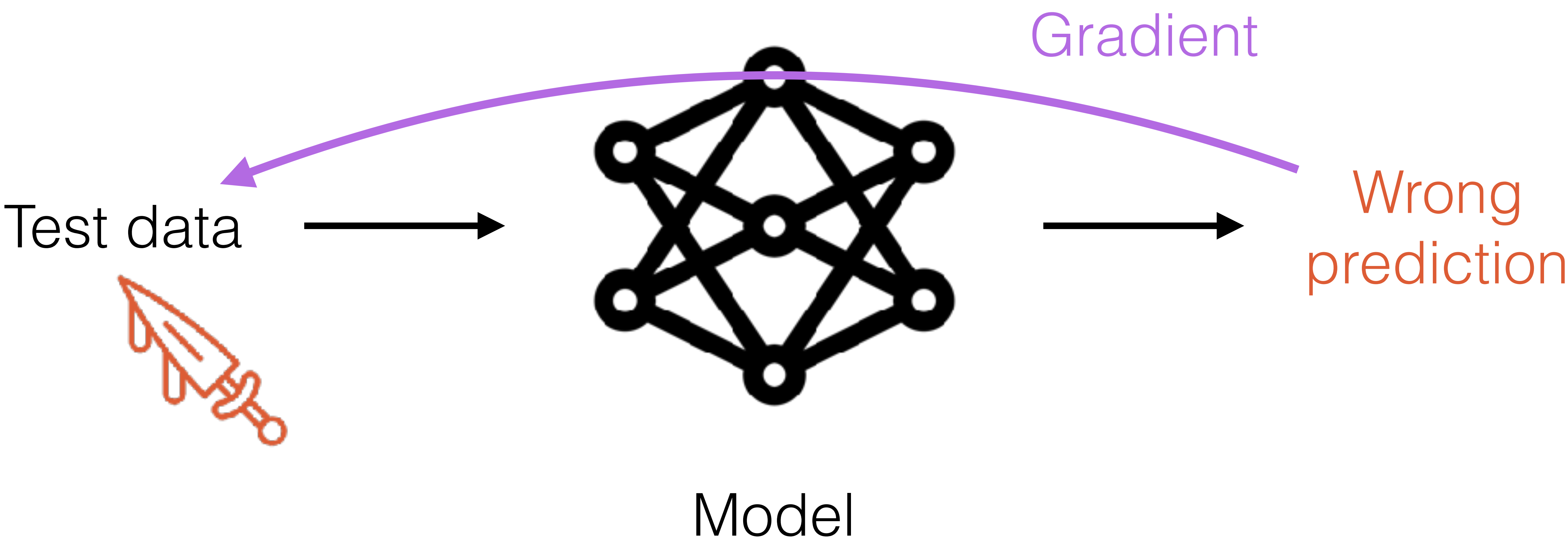
“panda”
57.7% confidence

“gibbon”
99.3% confidence

Image from Goodfellow, Shlens, Szegedy, 2015
Original demonstration from Szegedy et al., 2013

Adversarial test examples

Follow the gradient of the test loss w.r.t. test features (to increase loss) [1]

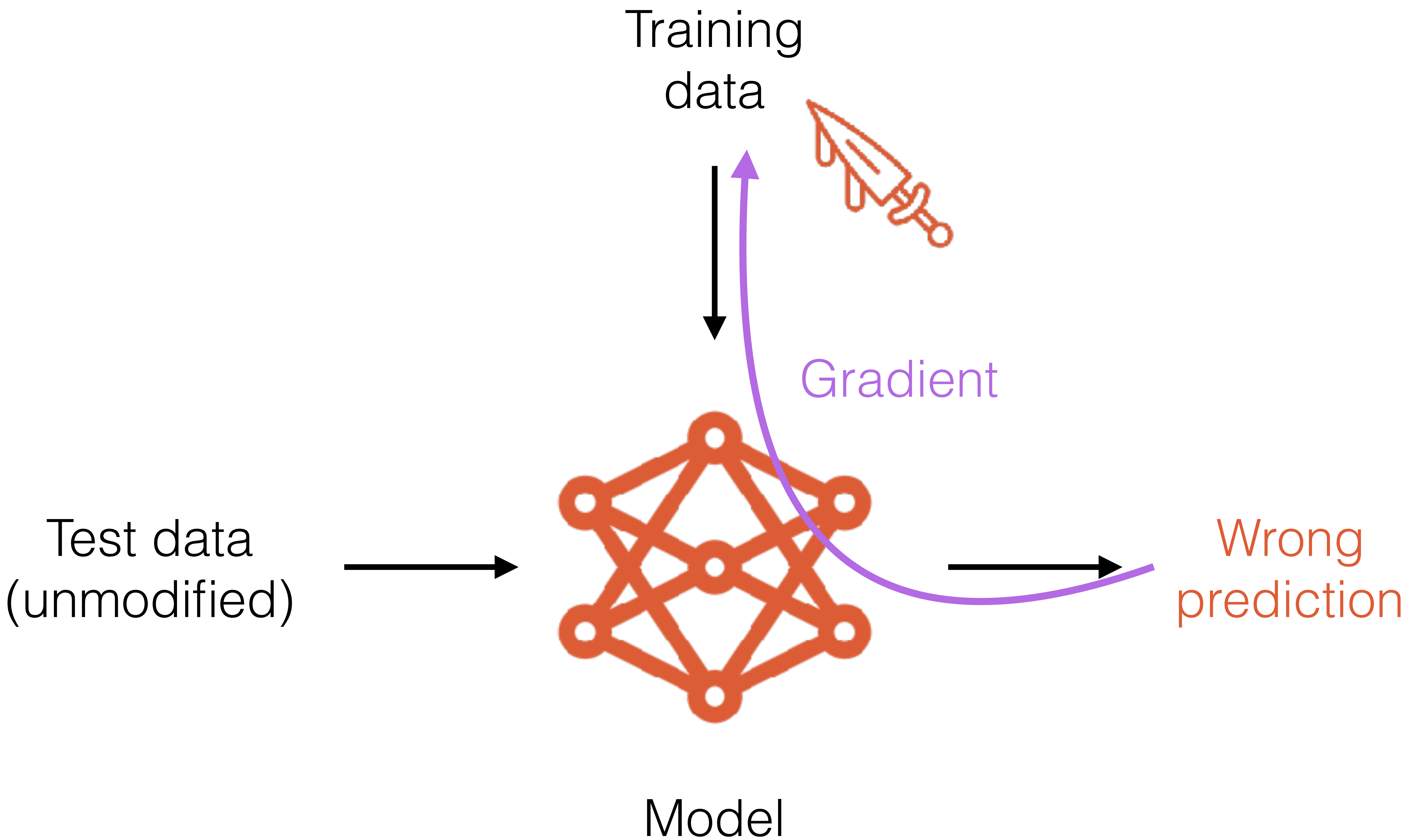


[1] Goodfellow, Shlens, Szegedy, 2015

We have adversarial test examples.
Can we create adversarial **training** examples?

Adversarial training examples

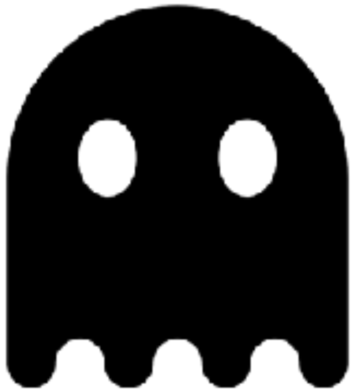
Follow the gradient of the test loss w.r.t. train features


Training data
Gradient
Test data (unmodified)
Wrong prediction
Model

Adversarial training examples

Follow the gradient of the test loss w.r.t. train features

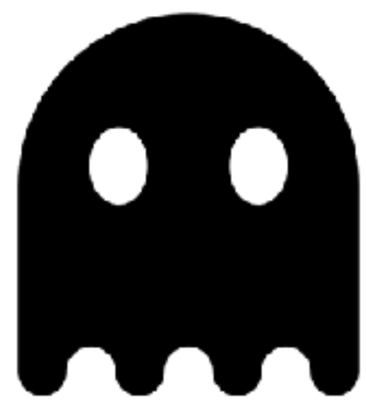
Influence functions help us calculate this gradient



Adversarial training examples

Follow the gradient of the test loss w.r.t. train features

Influence functions help us calculate this gradient

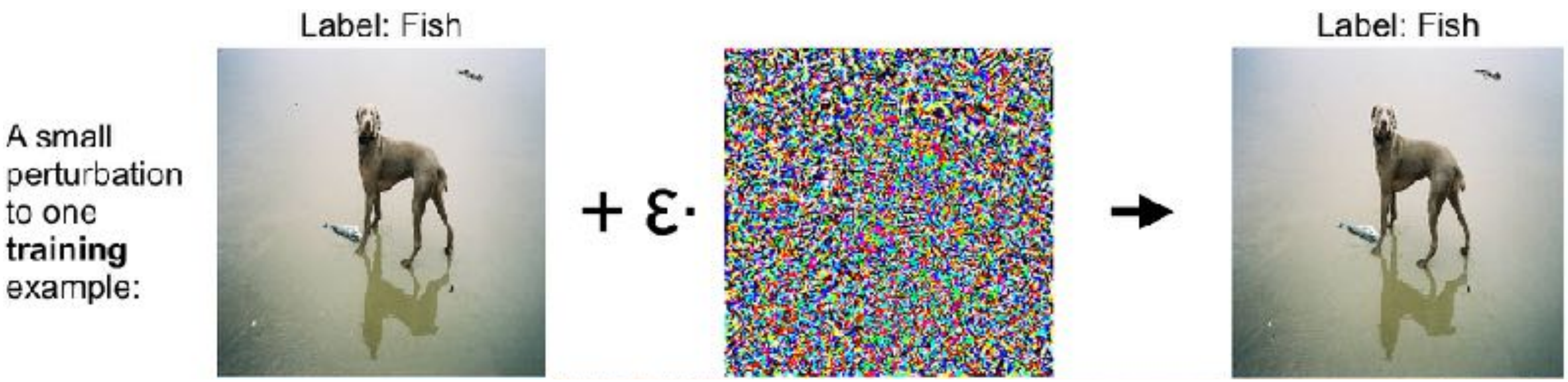


*Mathematically equivalent to gradient-based attacks explored by Biggio *et al.* (2012), Mei & Zhu (2015), and others

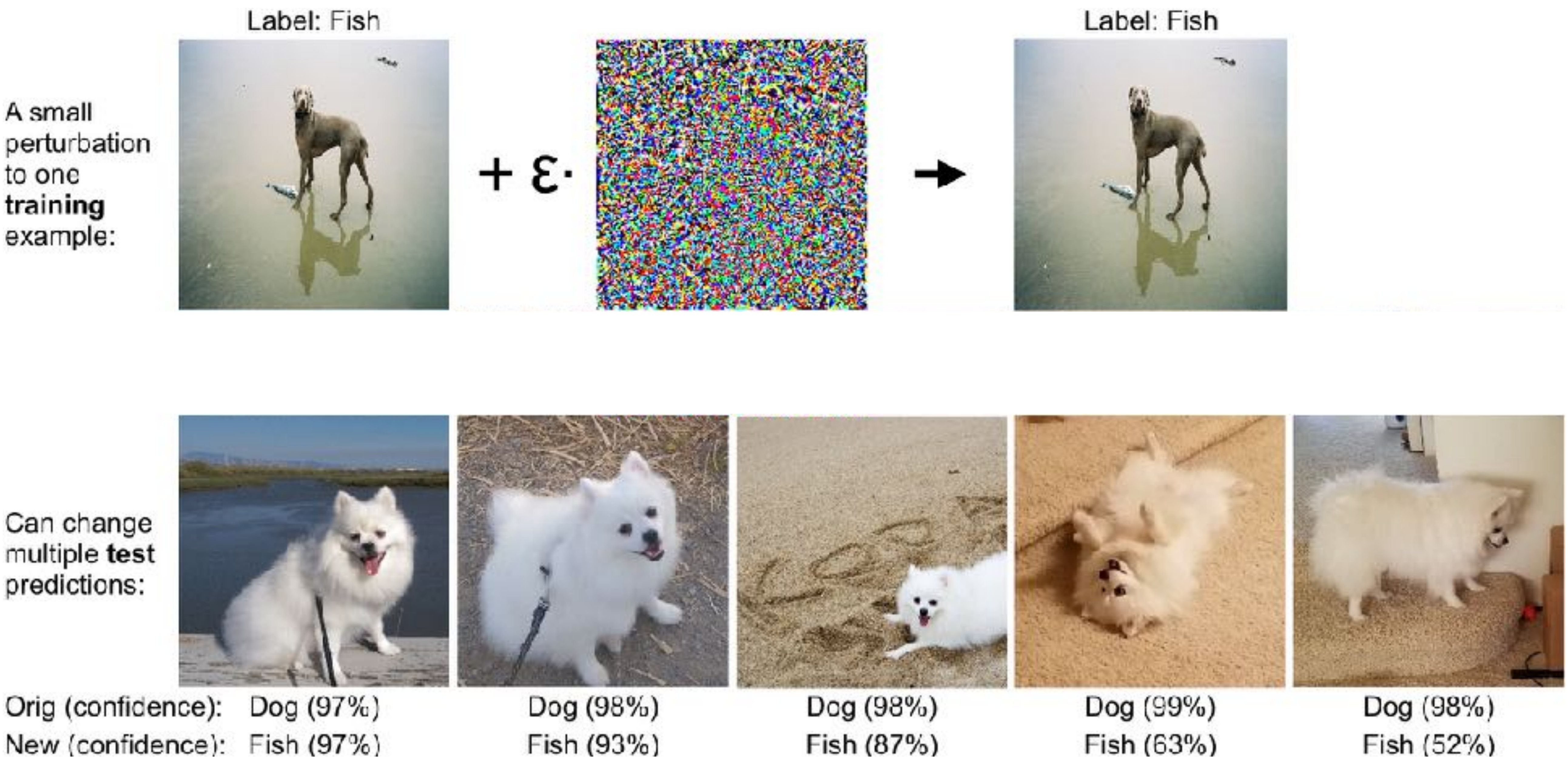
Adversarial training examples

- Setup: dog vs. fish classification, logistic regression on top of Inception features

Adversarial training examples



Adversarial training examples



Three observations

1. Ambiguous examples are good attack vectors

Label: fish

Three observations

1. Ambiguous examples are good attack vectors

Label: fish

Three observations

1. Ambiguous examples are good attack vectors

2. Small change in pixels but large change in feature space

Three observations

1. Ambiguous examples are good attack vectors

2. Small change in pixels but large change in feature space

3. Attack makes model overfit to specific test examples ($n \sim d$)

Three observations

1. Ambiguous examples are good attack vectors

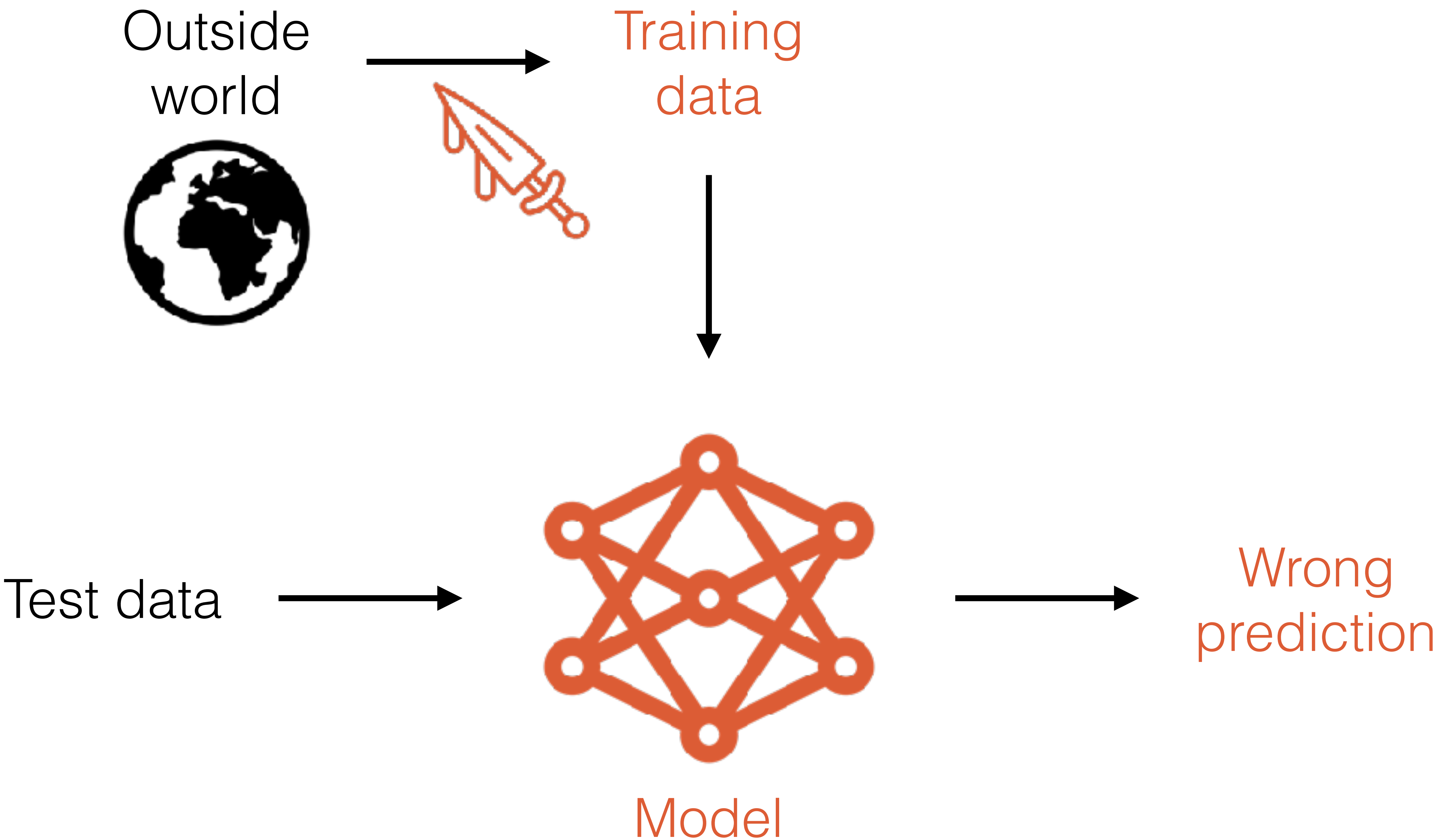
2. Small change in pixels but large change in feature space

3. Attack makes model overfit to specific test examples (n ~ d)

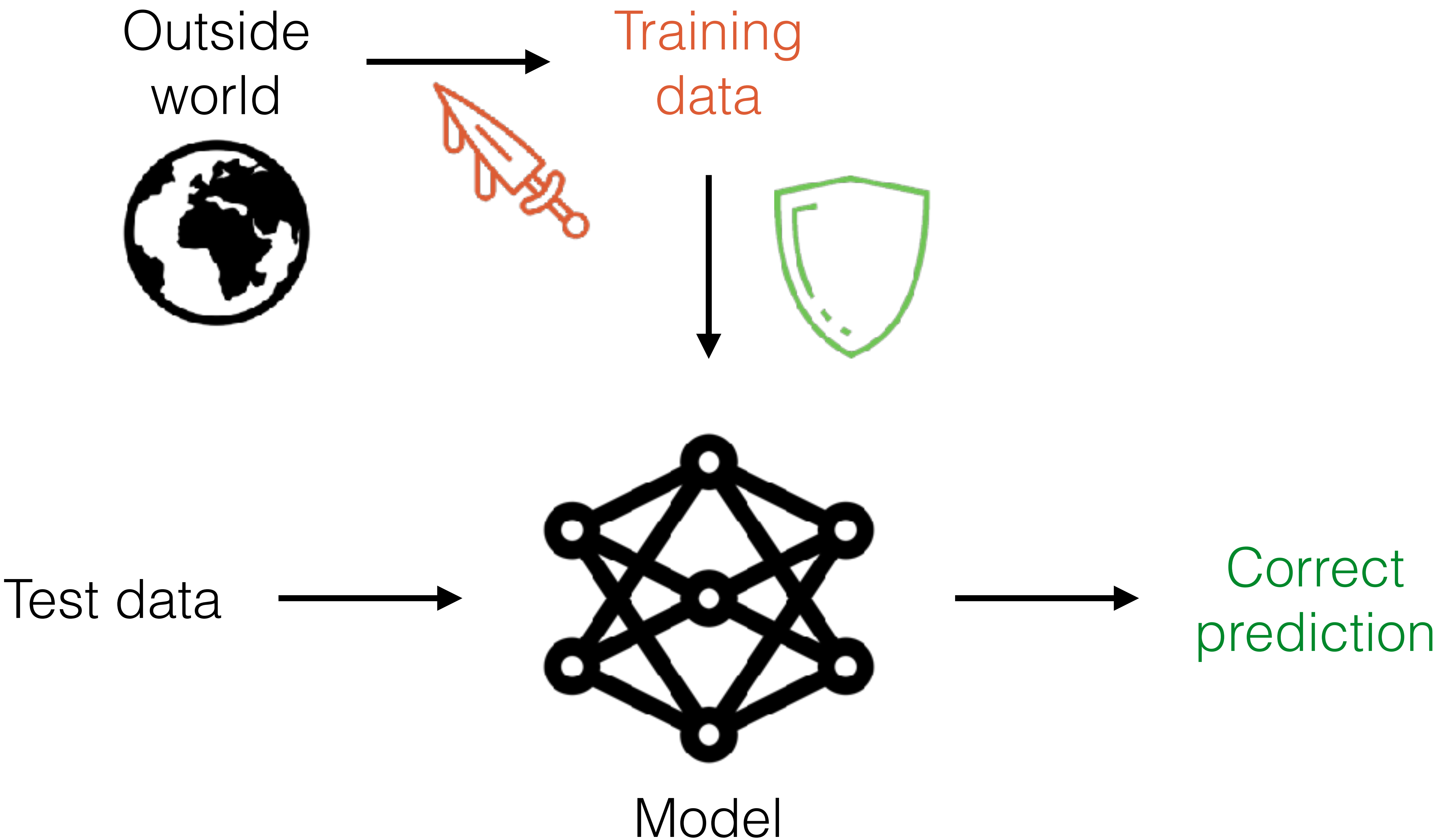
Certified Defenses for Data Poisoning Attacks, *NIPS,* 2017

Jacob Steinhardt

Percy Liang



[1] Barreno, Nelson, Joseph, and Tygar, 2010.
[2] Biggio, Nelson, and Laskov, 2012.



[1] Barreno, Nelson, Joseph, and Tygar, 2010.
[2] Biggio, Nelson, and Laskov, 2012.

Biggio et al., Poisoning attacks against support vector machines, 2012

Xiao et al., Is feature selection secure against training data poisoning?, 2015

Mei and Zhu, Using machine teaching to identify optimal training-set attacks on machine learners, 2015

Mozaffari-Kermani et al., Systematic poisoning attacks on and defenses for machine learning in healthcare, 2015

Burkard and Lagesse, Analysis of causative attacks against SVMs learning from data streams, 2017

…

Cretu et al., Casting out demons: Sanitizing training data for anomaly sensors, 2008

Rubinstein et al,. Antidote: Understanding and defending against poisoning of anomaly detectors, 2009

Laishram and Phoha, Curie: A method for protecting SVM classifier from poisoning attack, 2016

Chen, He, and Hsu, Chen, He, and Hsu, Data sanitization against adversarial label contamination based on data complexity, 2017

…

vs.

Given a defense and a dataset,
can we bound the damage that any attacker can do?

Motivation

Influence functions

Applications

> Conclusion

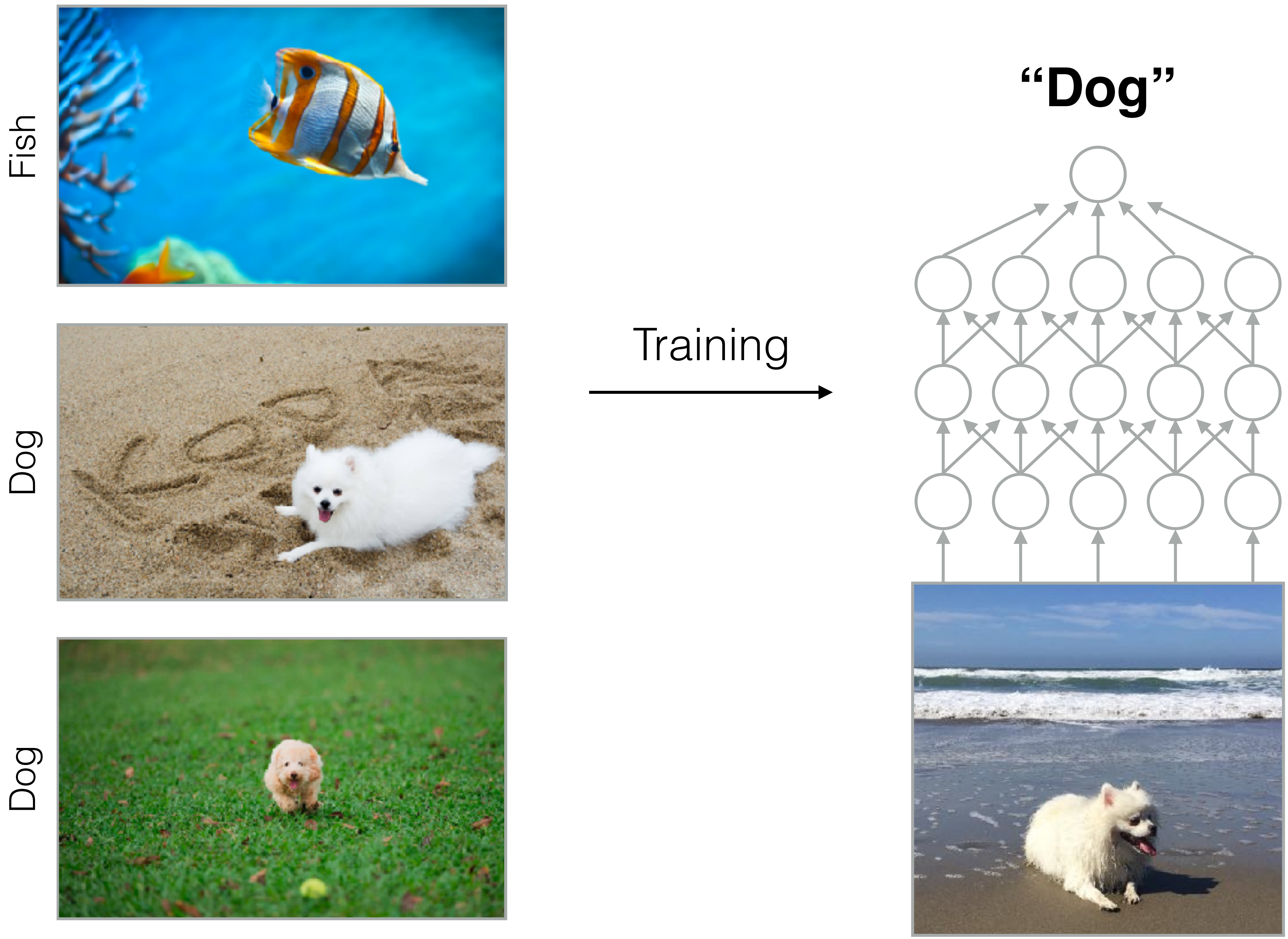
Why did the model make this prediction?

↓

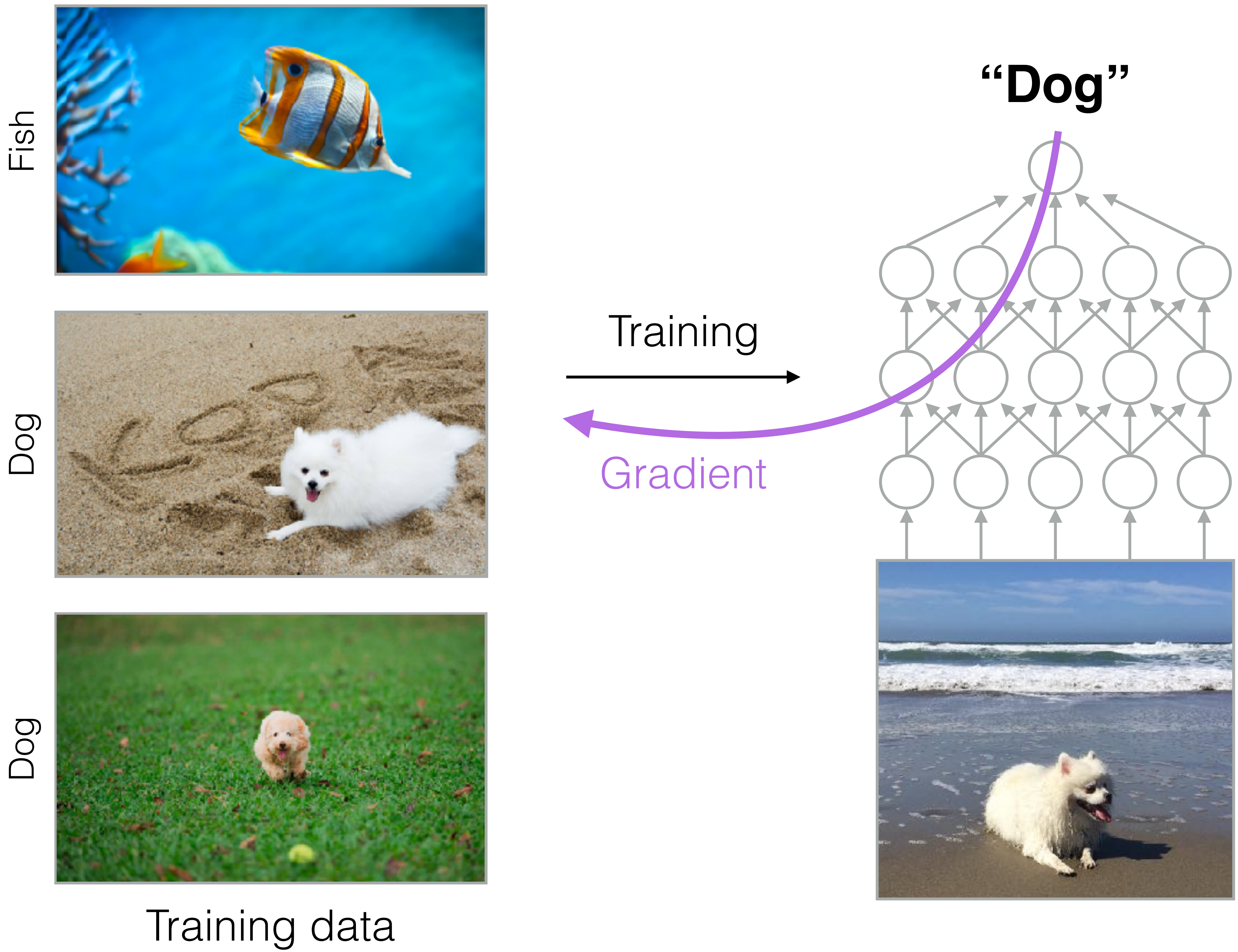
Which training points were most responsible for this prediction?

↓

How would the prediction change if we upweighted each training point?



Training data


Fish
Dog
Dog
Training data
Training
Gradient
"Dog"

Future work

- Real-world problems: hospitals (interpretability, uncertainty)
- Real-world models: scale [1], non-convexity, SGD
- Studying global perturbations
- Connections to reliability and privacy [2]
- Influence as part of the objective [3]

[1] Wojnowicz *et al.*, 2016
[2] Wang, 2017
[3] Ross, Hughes, Doshi-Velez, 2017

Thank you

Github: https://bit.ly/gt-influence
CodaLab: https://bit.ly/cl-influence
Paper: https://arxiv.org/abs/1703.04730

pangwei@cs.stanford.edu


Percy Liang


Koda

future of life INSTITUTE

This presentation uses images from the Noun Project:

Question by Valeriy | Box by Rockicon | Magnifying Glass by il Capitano | services by IconsGhost | Ghost by Bakunetsu Kaito
Neural Network by Knut M. Synstad | Poisoned Dagger by Ben Davis | world by Aleksandr Vector | Shield by Nikita Kozin