IS 6733: Deep Learning on Cloud Platforms

Explainable Machine Learning

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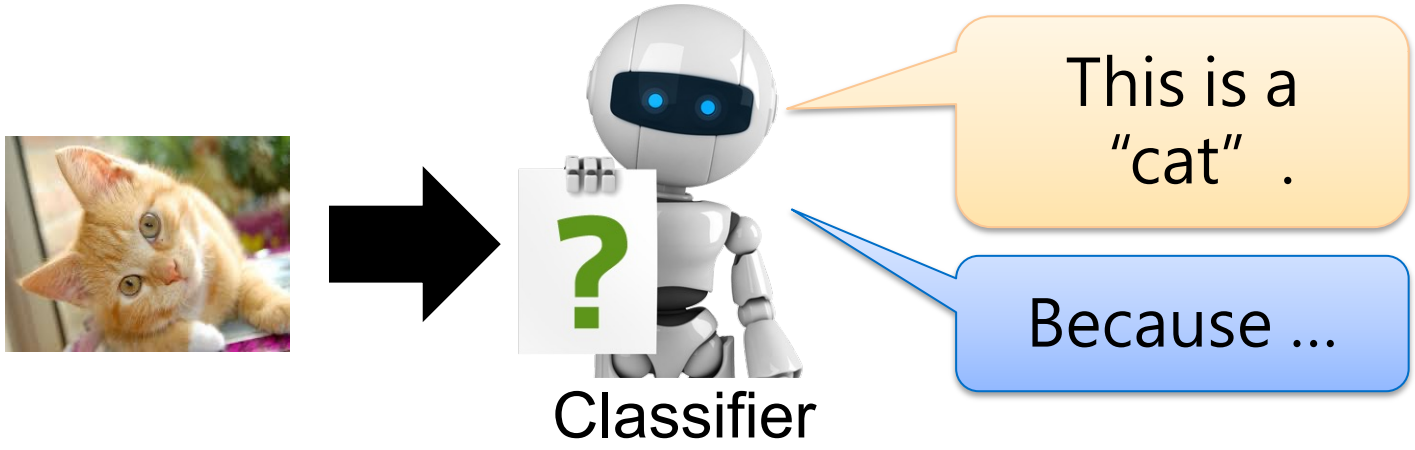
Explainable/Interpretable ML



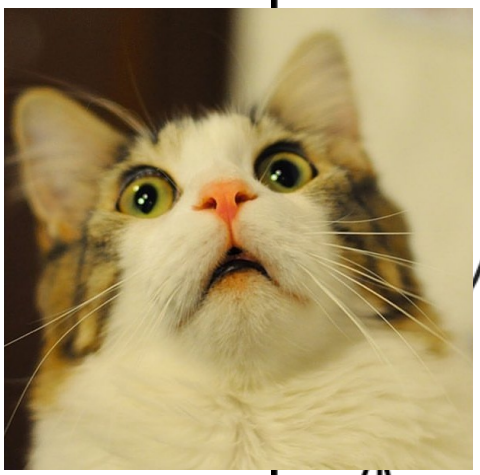
Local Explanation

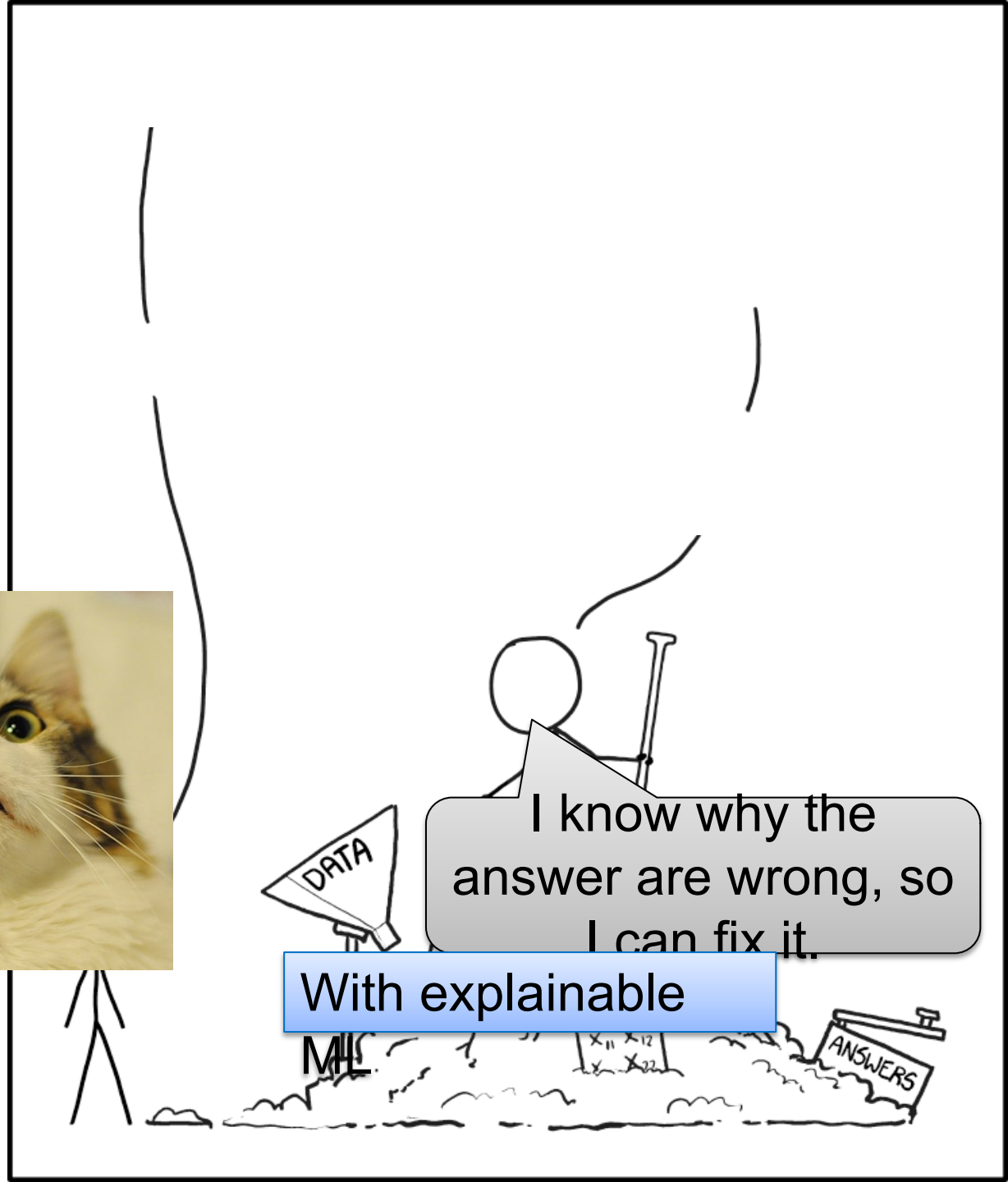
Why do you think *this image* is a cat?

Global Explanation

What do you think a “cat” looks like?

We can improve ML model based on explanation.





https://www.explainxkcd.com/wiki/index.php/1838:_Machine_Learning

Myth of Explainable ML

- **Goal of ML Explanation ≠ you completely know how the ML model work**
  - Human brain is also a Black Box!
  - People don't trust network because it is Black Box, but you trust the decision of human!
- **Goal of ML Explanation is (my point of view)**

Make people (your customers, your boss, yourself) comfortable.

Personalized explanation in the future

Interpretable v.s. Powerful

- **Some models are intrinsically interpretable.**
  - For example, linear model (from weights, you know the importance of features)
  - But ……. not very powerful.
- **Deep network is difficult to interpretable.**
  - Deep network is a black box.

Because deep network is a black box, we don't use it.

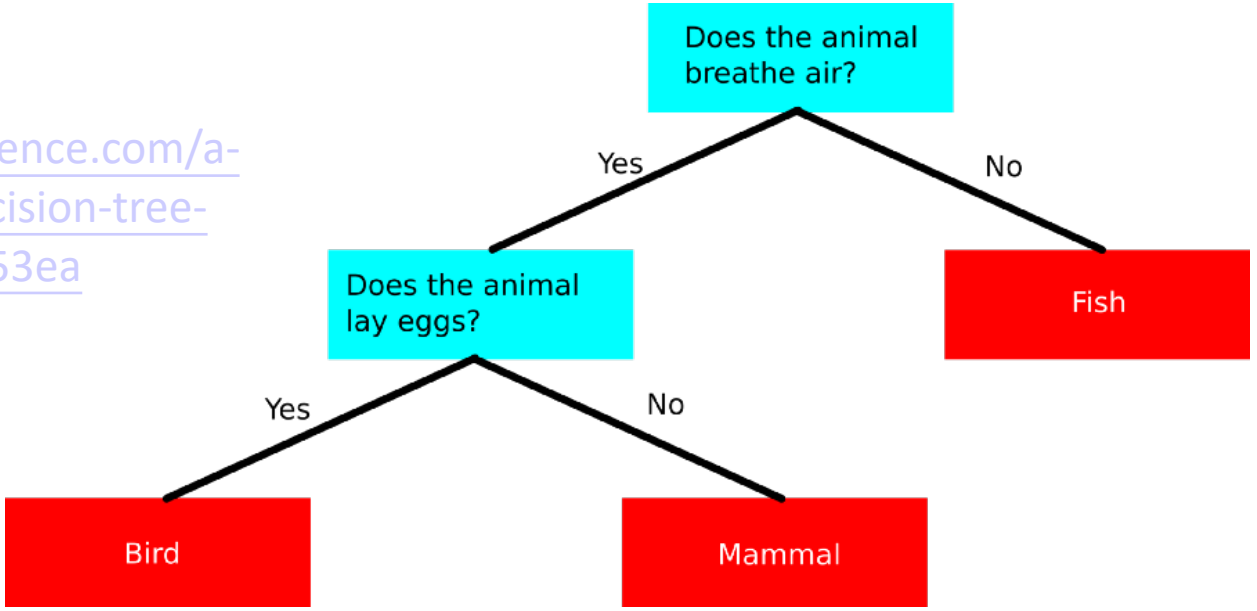
  - But it is more powerful than linear model …

Let's make deep network interpretable.

Interpretable v.s. Powerful

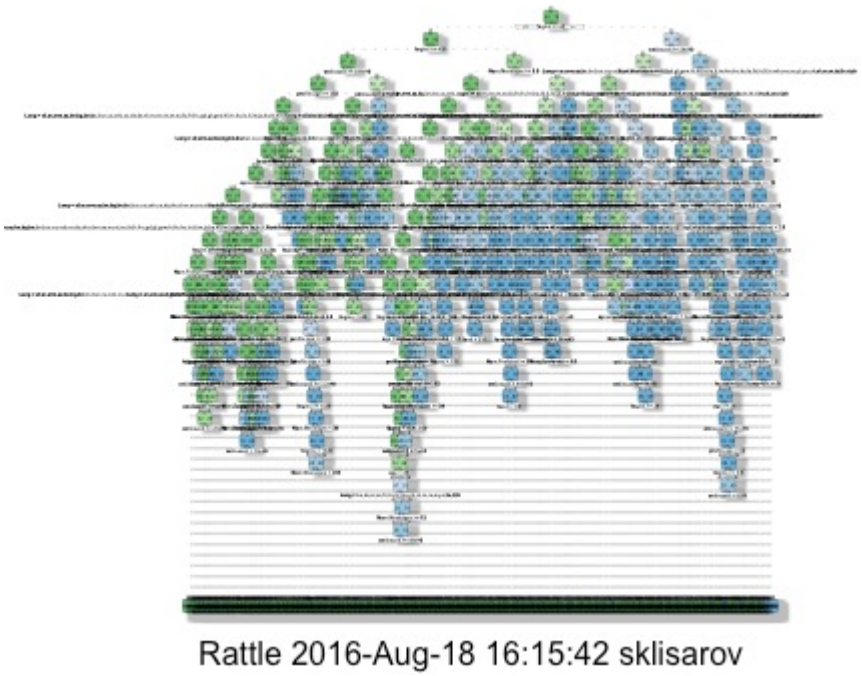
- **Are there some models interpretable and powerful at the same time?**
- **How about decision tree?**

Source of image: https://towardsdatascience.com/a-beginners-guide-to-decision-tree-classification-6d3209353ea



Interpretable v.s. Powerful

- A tree can still be terrible!
- We use a forest!



https://stats.stackexchange.com/questions/230581/decision-tree-too-large-to-interpret

Local Explanation: Explain the Decision

Questions: Why do you think this image is a cat?

Source of image: www.oreilly.com/learning/introduction-to-local-interpretable-model-agnostic-explar

Basic Idea

Image: pixel, segment, etc.
Text: a word

Object x → Components: $\{x_1, \cdots, x_n, \cdots, x_N\}$

We want to know the importance of each components for making the decision.

Idea: Removing or modifying the values of the components, observing the change of decision.

Large decision change → Important component

The size of the gray box can be crucial ……

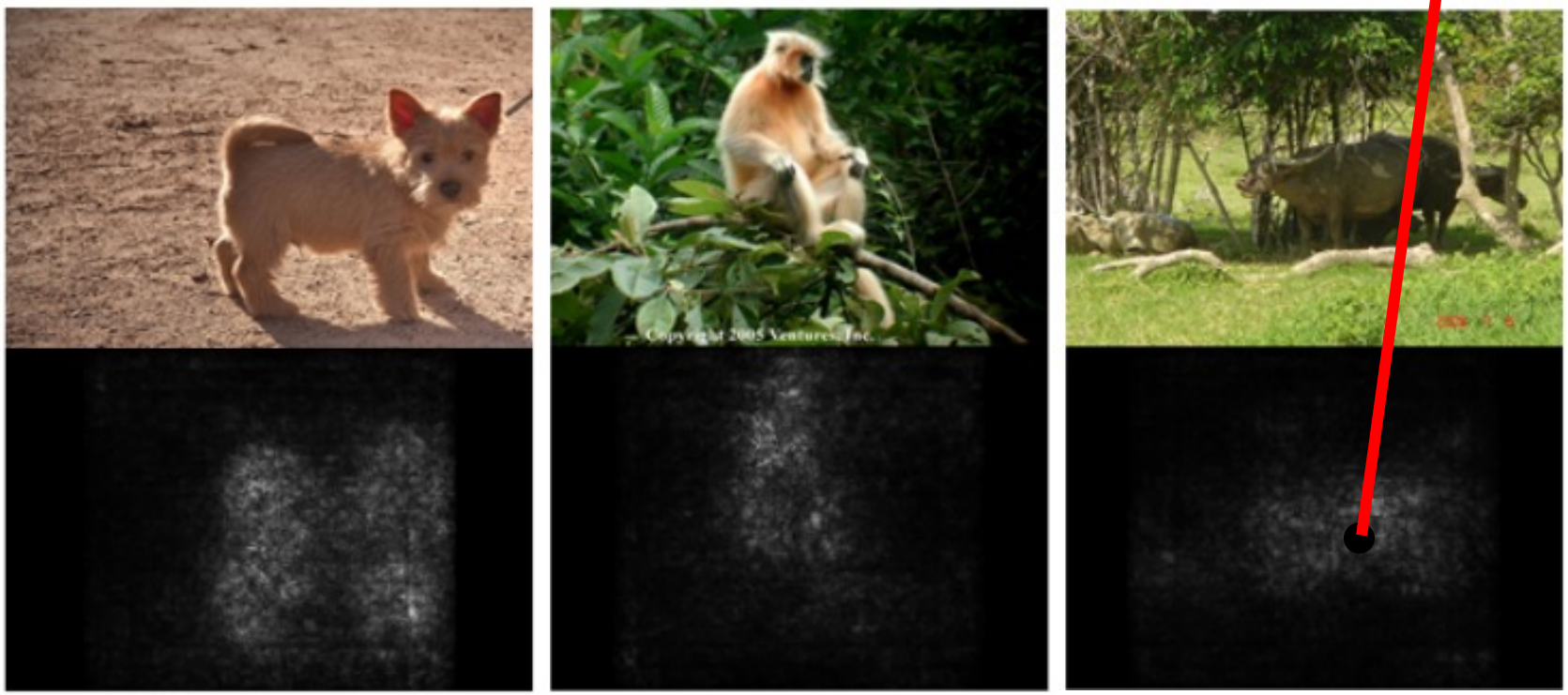
Reference: Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014* (pp. 818-833)

$\{x_1, \cdots, x_n, \cdots, x_N\} \rightarrow \{x_1, \cdots, x_n + \Delta x, \cdots, x_N\}$

$y_k \rightarrow y_k + \Delta y$

y_k: the prob of the predicted class of the model

$$\left|\frac{\Delta y}{\Delta x}\right| \rightarrow \left|\frac{\partial y_k}{\partial x_n}\right|$$



Saliency Map

Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR, 2014

Case Study: Pokémon v.s. Digimon

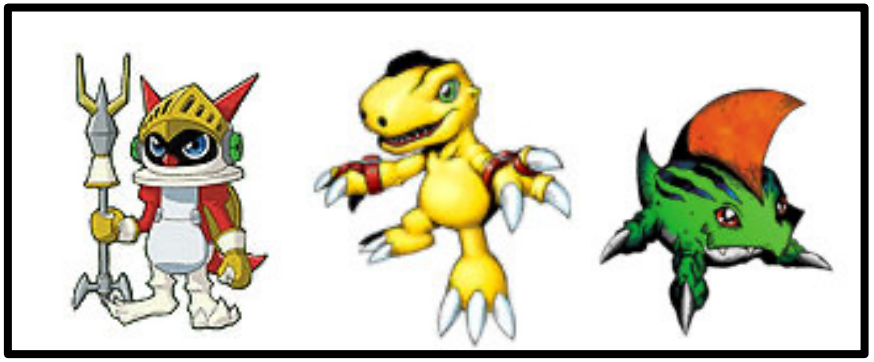
https://medium.com/@tyreeostevenson/teaching-a-computer-to-classify-anime-8c77bc89b

Task

Pokémon images:
https://www.Kaggle.com/kvpratama/pokemon-images-dataset/data

Digimon images:
https://github.com/DeathReaper0965/Digimon-Generator-GAN

Pokémon



Digimon

Testing Images:

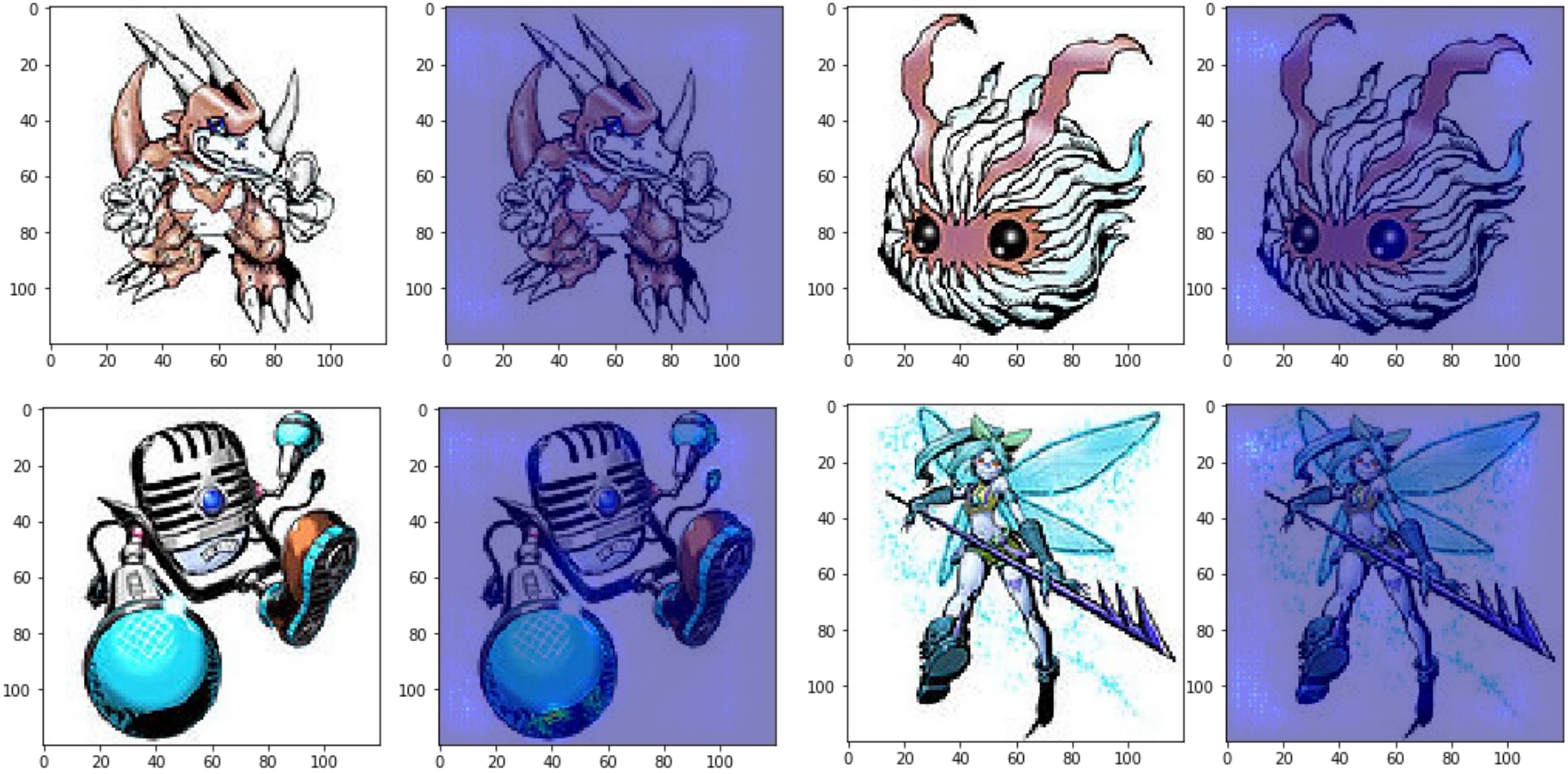
Experimental Results

```
model = Sequential()
model.add(Conv2D(32, (3, 3), padding='same', input_shape=(120,120,3)))
model.add(Activation('relu'))
model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(256, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(256, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dense(1024))
model.add(Activation('relu'))
model.add(Dense(2))
model.add(Activation('softmax'))
```

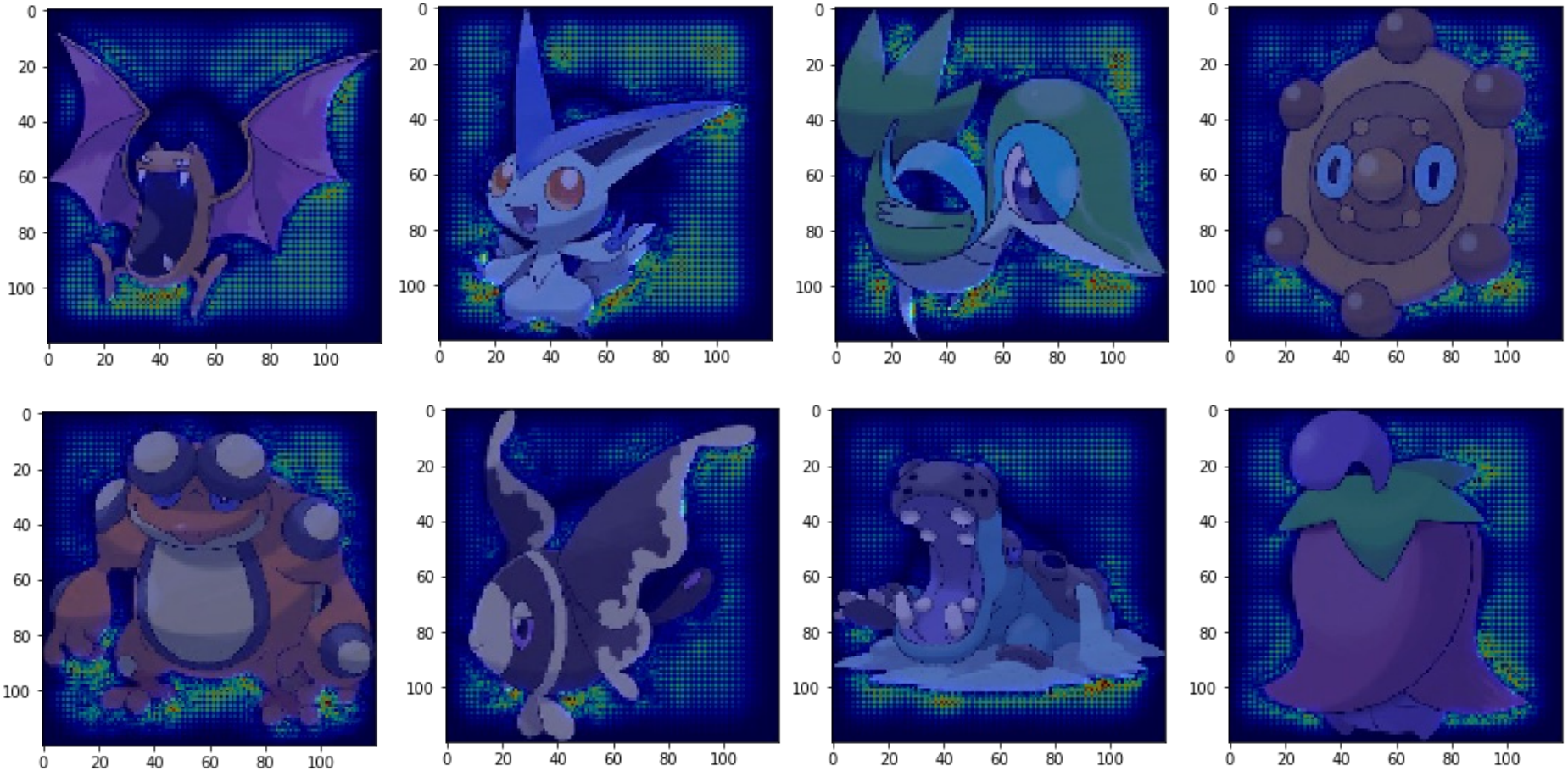
Training Accuracy: 98.9%

Testing Accuracy: 98.4%

Saliency Map



Saliency Map



What Happened?

- **All the images of Pokémon are PNG, while most images of Digimon are JPEG.**

PNG has a transparent background

After read in, it has a black background!

Machine discriminate Pokémon and Digimon based on Background color.

➡ This shows that explainable ML is very critic

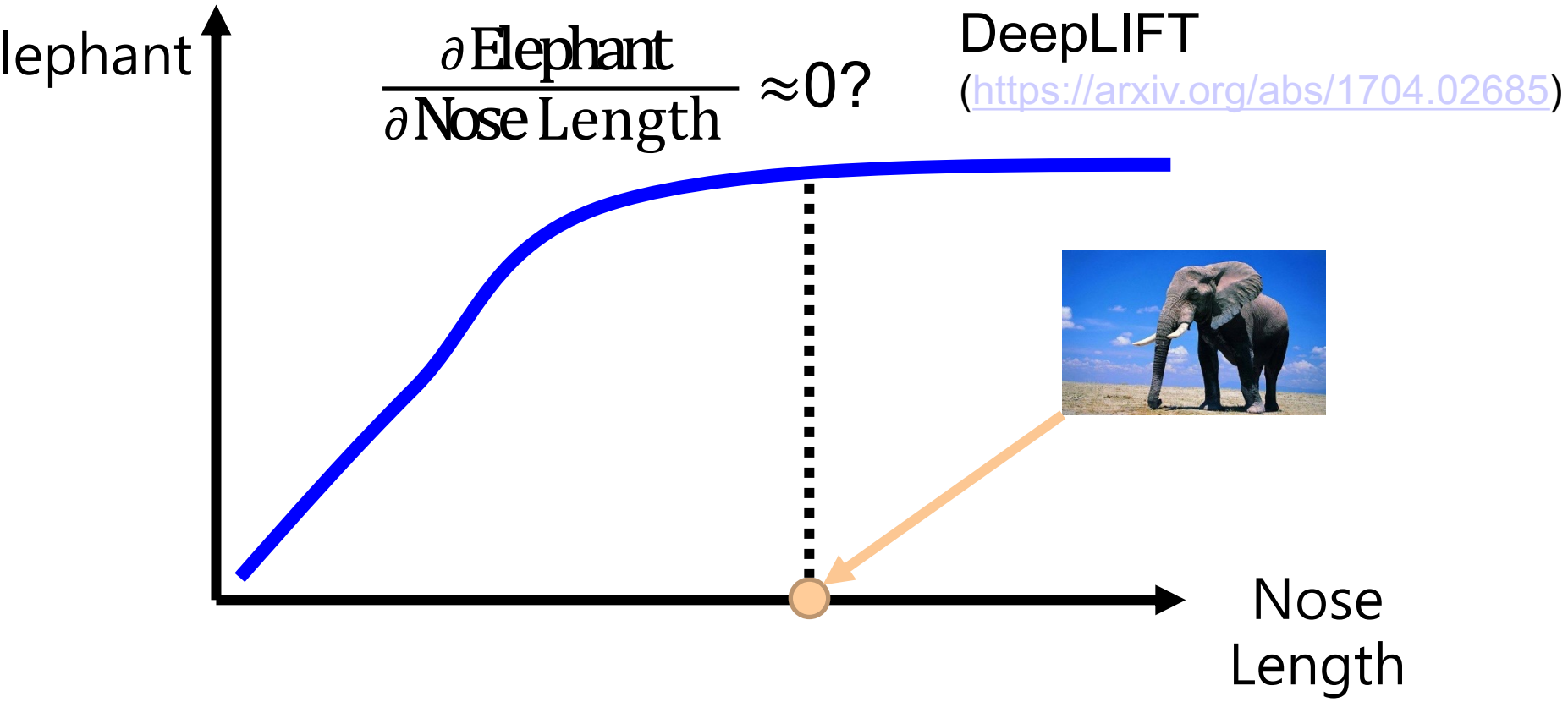
Limitation of Gradient based Approaches

- **Gradient Saturation**

To deal with this problem:

Integrated gradient
(https://arxiv.org/abs/1611.02639)

DeepLIFT
(https://arxiv.org/abs/1704.02685)

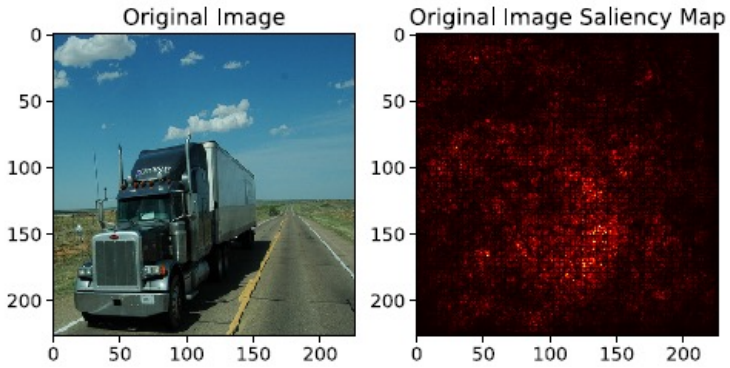


Attack Interpretation?!

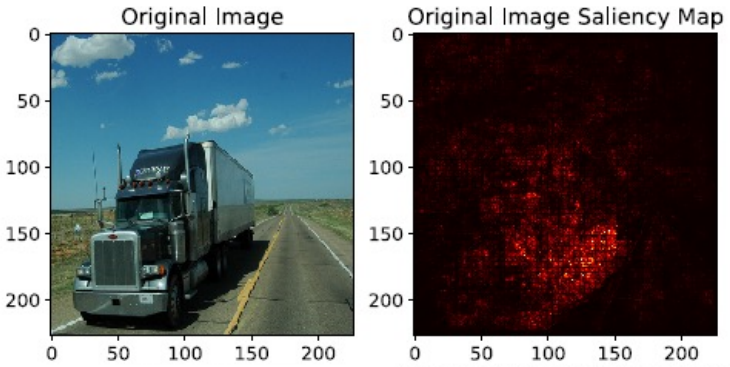
https://arxiv.org/abs/1710.10547

- **It is also possible to attack interpretation…**

Vanilla Gradient



Deep LIFT



The noise is small, and do not change the classification results.

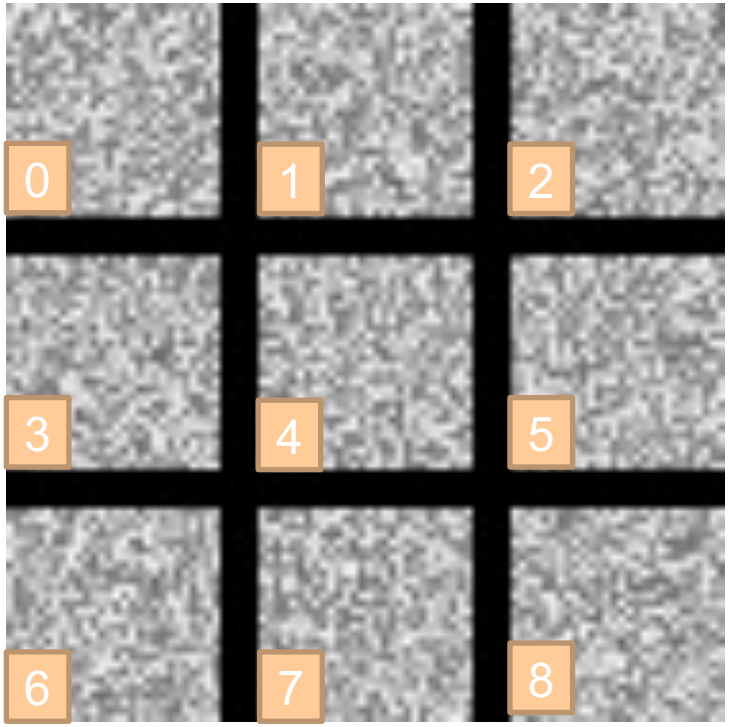
Global Explanation:
Explain the whole Model

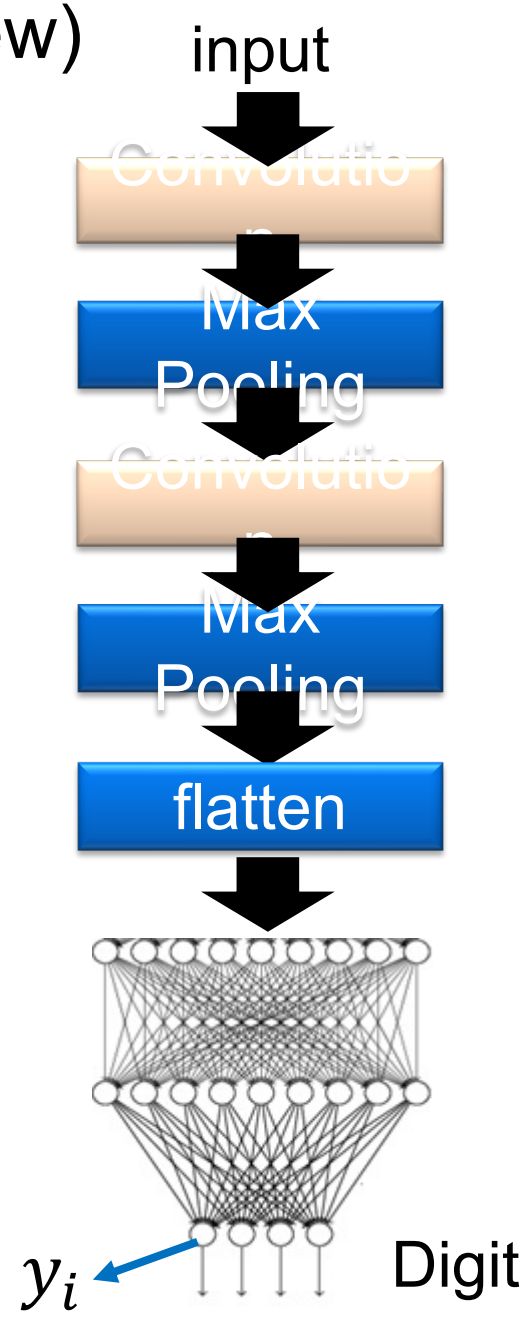
Question: What do you think a “cat” looks like?

Activation Minimization (review)

$$x^* = arg\max_x y_i$$

Can we see digits?





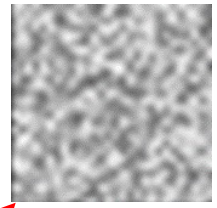
Deep Neural Networks are Easily Fooled

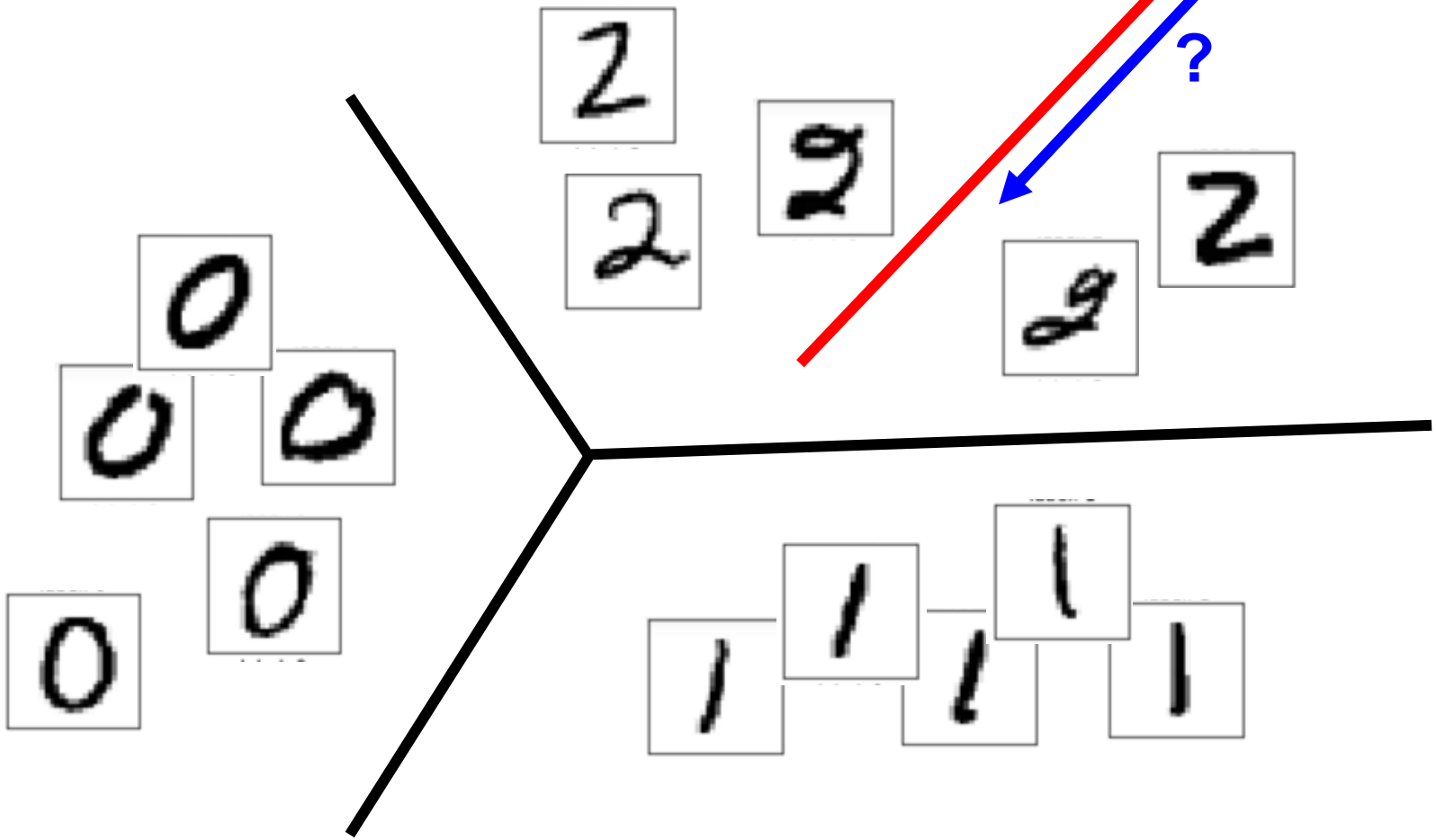
https://www.youtube.com/watch?v=M2IebCN9Ht4

Activation Maximization

- **Possible reason**

$$x^* = arg\max_x y_i$$

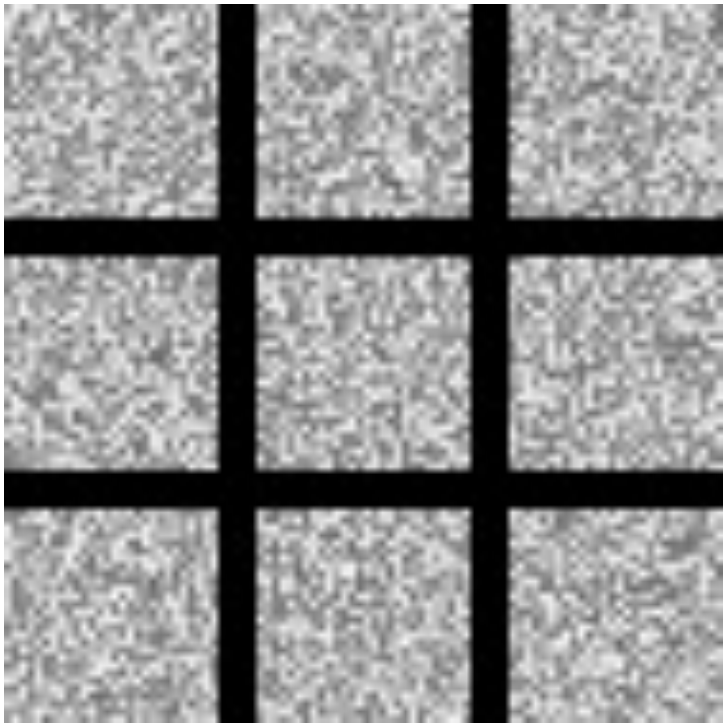




Activation Minimization (review)

Find the image that maximizes class probability

$$x^* = arg\max_x y_i$$

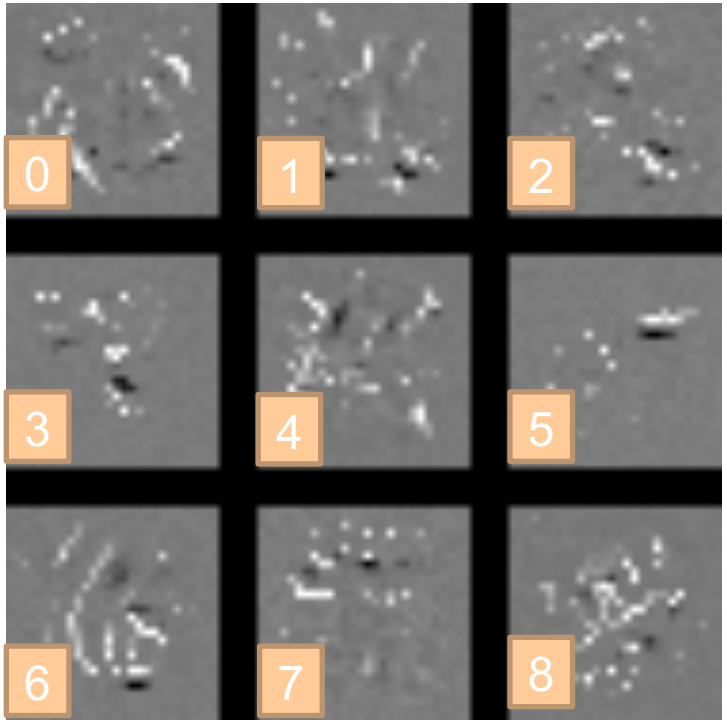


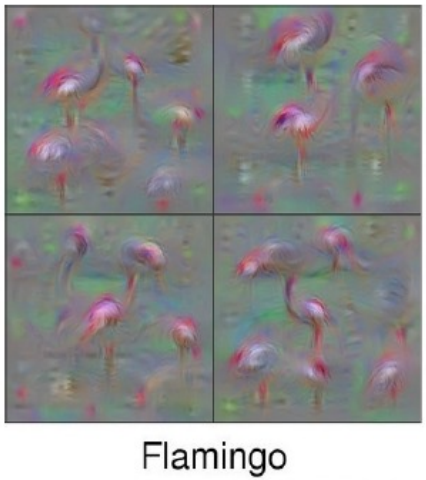
The image also looks like a digit.

$$x^* = arg\max_x y_i + R(x)$$

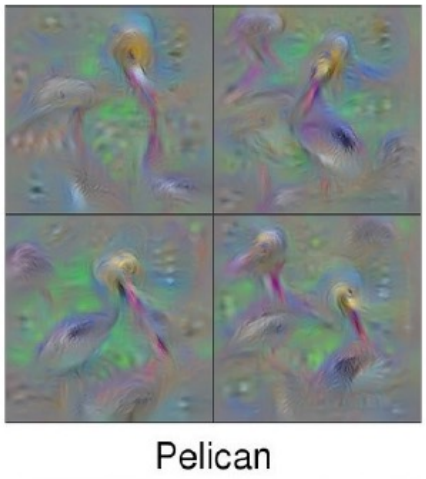
$$R(x) = -\sum_{i,j} |x_{ij}|$$

How likely x is a digit

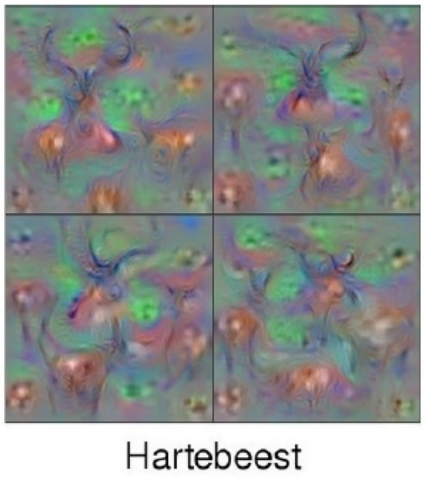




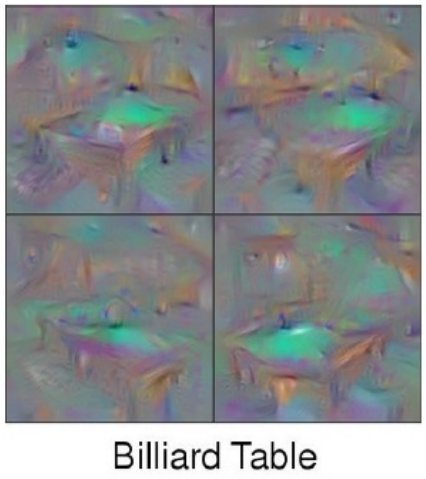
Flamingo



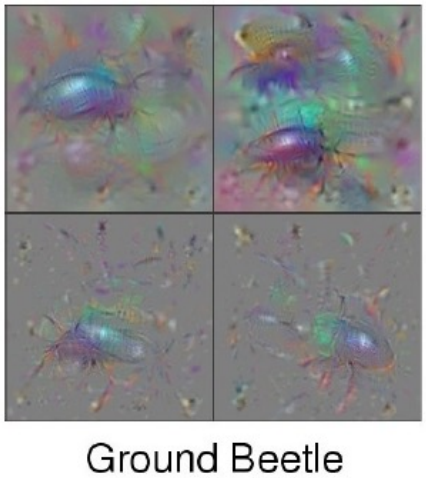
Pelican



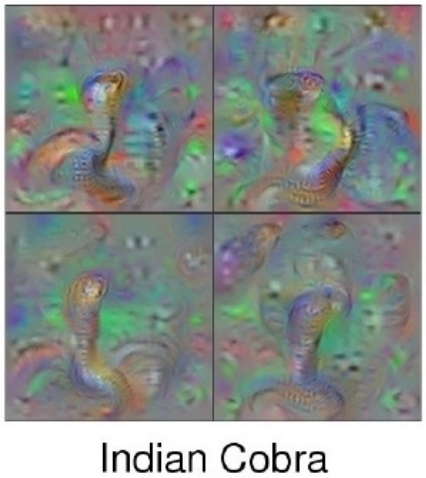
Hartebeest



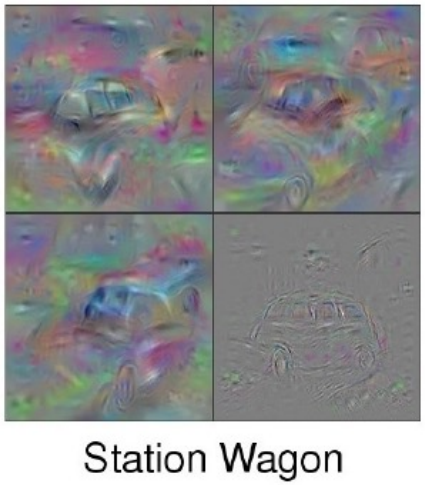
Billiard Table



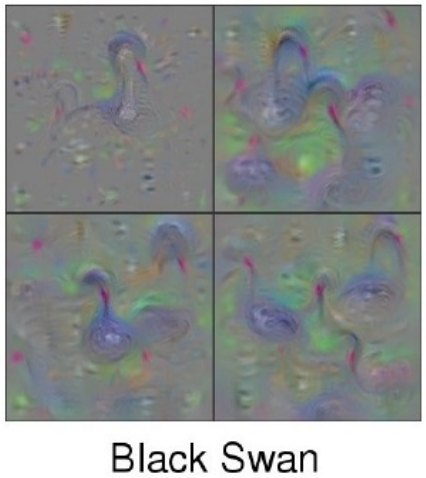
Ground Beetle



Indian Cobra



Station Wagon



Black Swan

With several regularization terms, and hyperparameter tuning …..

https://arxiv.org/abs/1506.06579

Constraint from Generator

(Simplified Version)

- **Training a generator** (by GAN, VAE, etc.)

Training Examples

low-dim vector z → Image Generator G → Image x

$x = G(z)$

$$x^* = arg\max_x y_i \Rightarrow z^* = arg\max_z y_i$$

Show image: $x^* = G(z^*)$

z → Image Generator → Image x → Image Classifier → y

redshank ant monastery

volcano

https://arxiv.org/abs/1612.00005

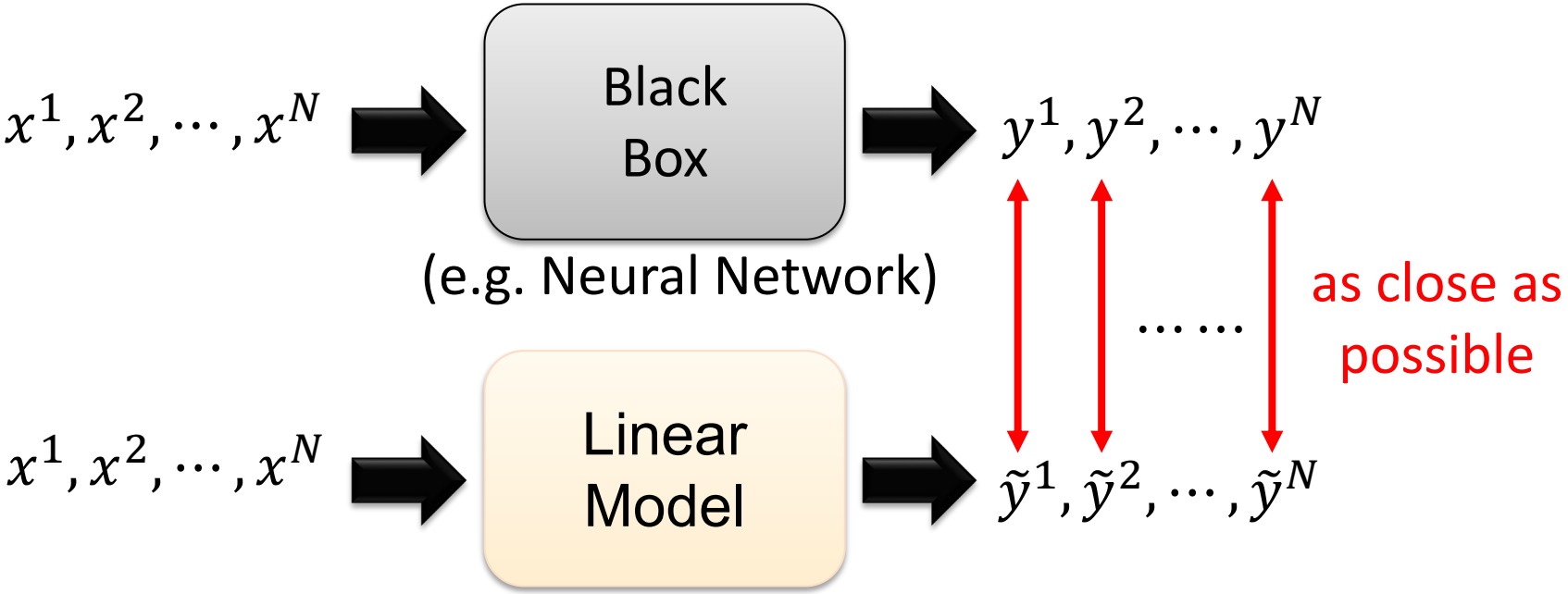
Using A Model to Explain Another

Some models are easier to Interpret.

Using interpretable model to mimic uninterpretable models.

Using a model to explain another

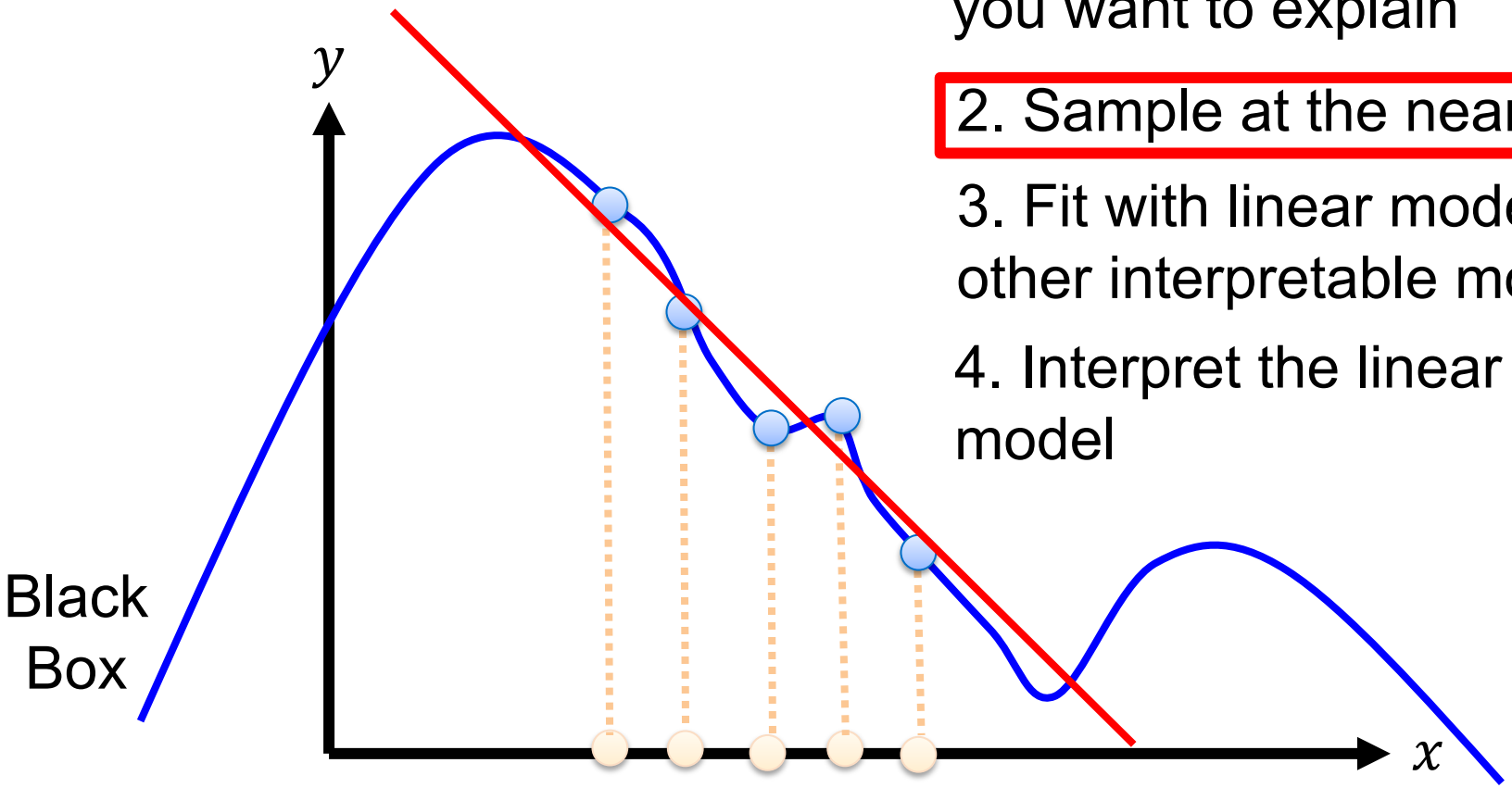
- **Using an interpretable model to mimic the behavior of an uninterpretable model.**



Problem: Linear model cannot mimic neural network …

However, it can mimic a local region.

Local Interpretable Model-Agnostic Explanations (LIME)



1. Given a data point you want to explain
2. Sample at the nearby
3. Fit with linear model (or other interpretable models)
4. Interpret the linear model

Local Interpretable Model-Agnostic Explanations (LIME)

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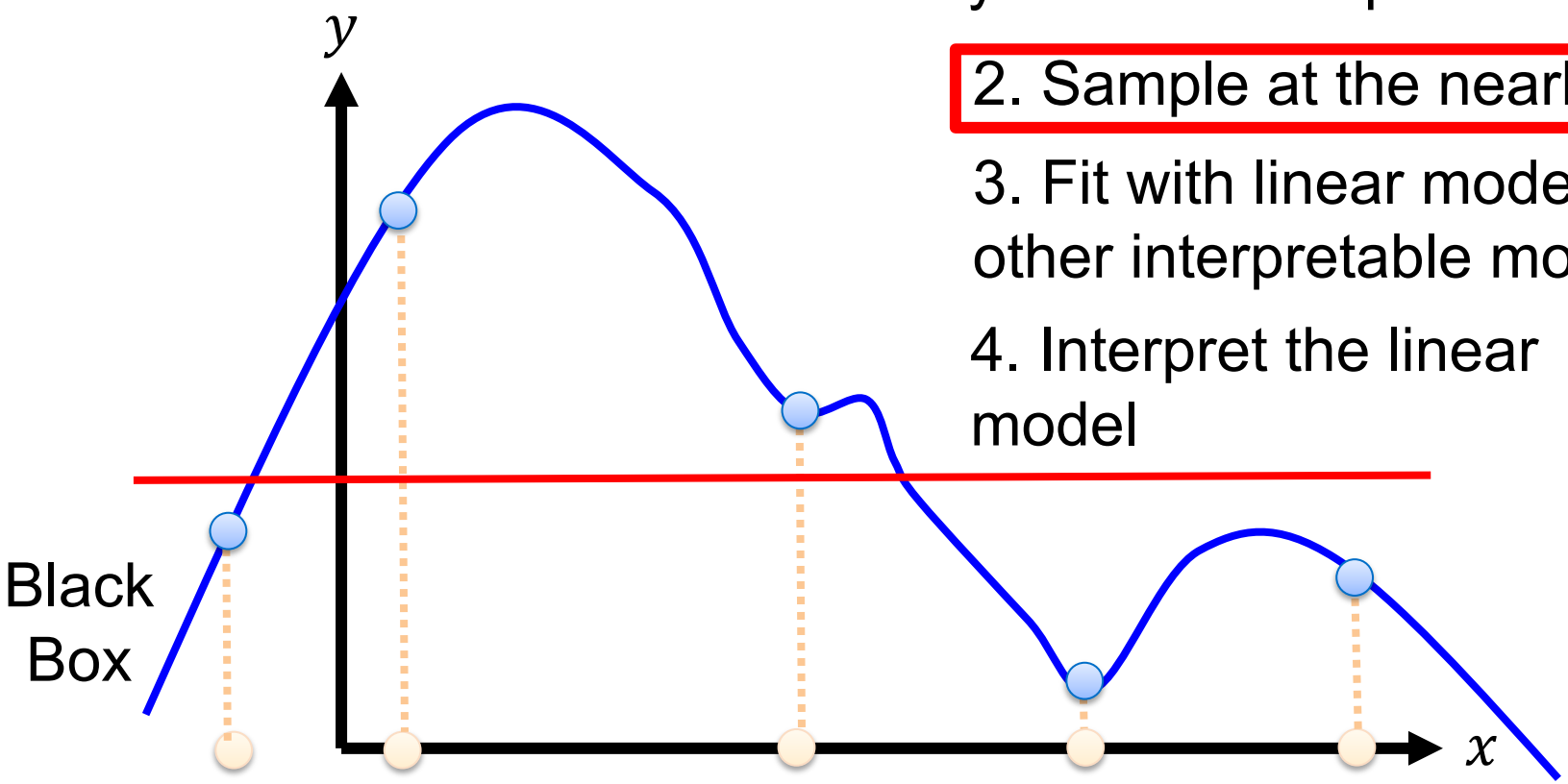
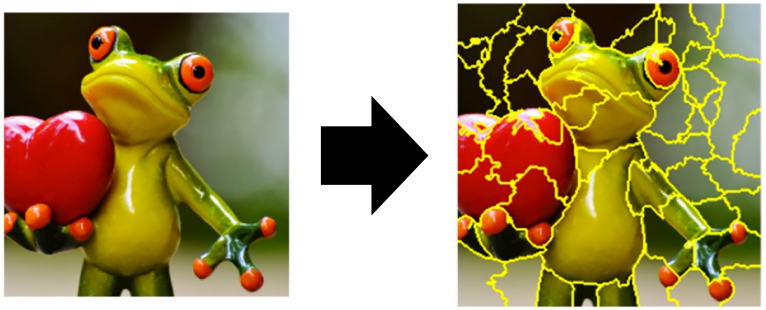
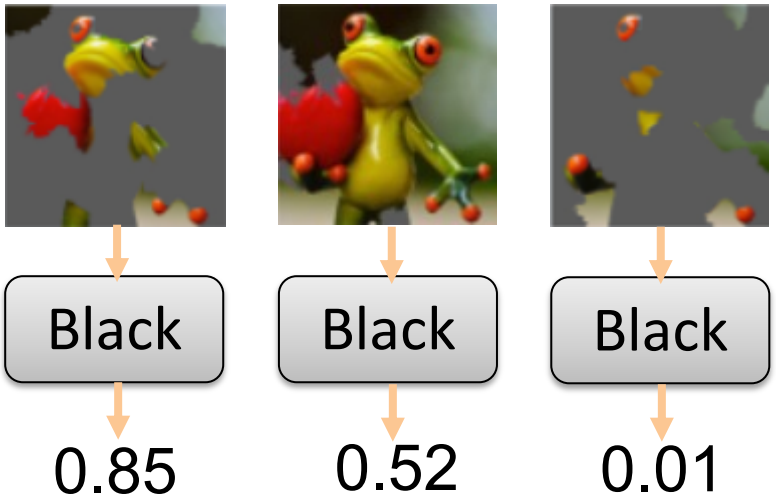


LIME – Image



- **1. Given a data point you want to explain**
- **2. Sample at the nearby**
  - Each image is represented as a set of superpixels (segments).



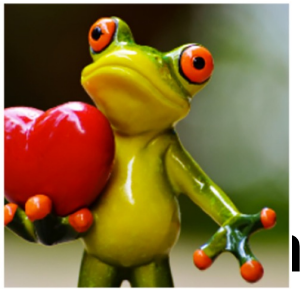
Randomly delete some segments.

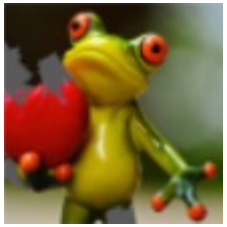
Compute the probability of “frog” by black box

Ref: https://medium.com/@kstseng/lime-local-interpretable-model-agnostic-explanation-%E6%8A%80%E8%A1%93%E4%BB%8B%E7%B4%B9-a67b6c34c3f8

LIME – Image

- 3. Fit with linear (or interpr[illegible]odel





Extrac t

Extrac t

Extrac t

Linear

Linear

Linear

0.85

0.52

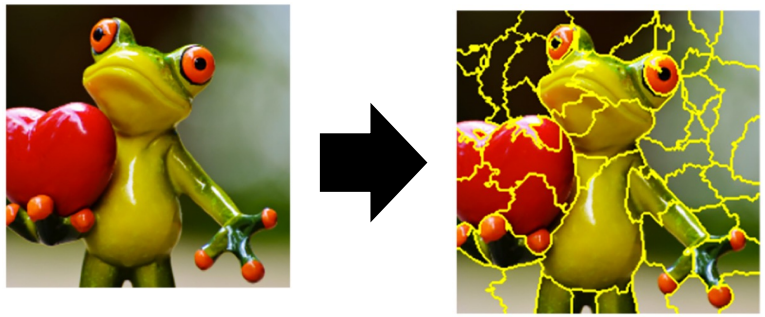
0.01

$x_1 \cdots\cdots x_m \cdots\cdots x_M$

$$x_m = \begin{cases} 0 & \text{Segment m is deleted.} \\ 1 & \text{Segment m exists.} \end{cases}$$

M is the number of segments.

LIME – Image



- **4. Interpret the model you learned**

$$y = w_1 x_1 + \cdots + w_m x_m + \cdots + w_M x_M$$

$$x_m = \begin{cases} 0 & \text{Segment m is deleted.} \\ 1 & \text{Segment m exists.} \end{cases}$$

M is the number of segments.

If $w_m \approx 0$ ➡ segment m is not related to “frog”

If w_m is positive
➡ segment m indicates the image is “frog”

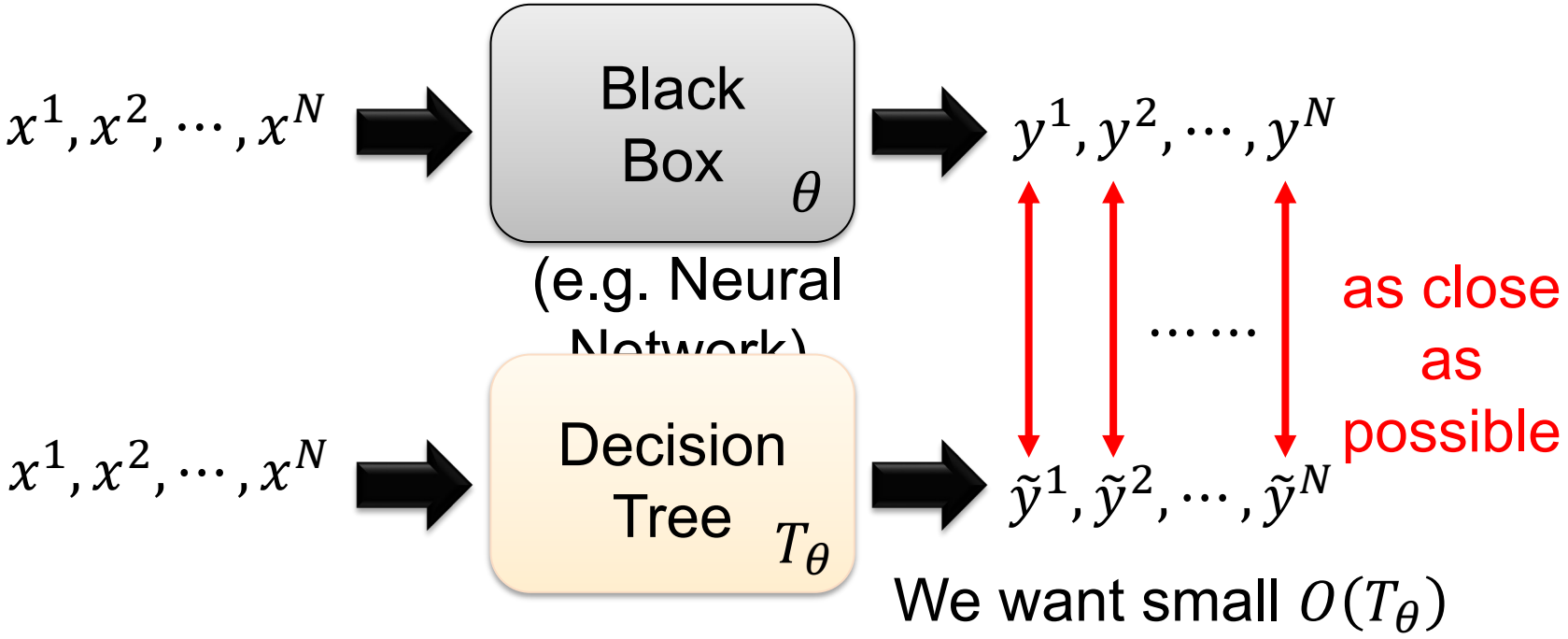
If w_m is negative
➡ segment m indicates the image is not “frog”

Decision Tree

$O(T_\theta)$: how complex T_θ is

e.g. average depth of T_θ

- **Using an interpretable model to mimic the behavior of an uninterpretable model.**



Problem: We don't want the tree to be too large.

Decision Tree – Tree regularization

https://arxiv.org/pdf/1711.06178.pdf

- **Train a network that is easy to be interpreted by decision tree.**

T_θ : tree mimicking network with parameters θ

$O(T_\theta)$: how complex T_θ is

$$\theta^* = arg\min_\theta L(\theta) + \lambda O(T_\theta)$$

Original loss function for training network

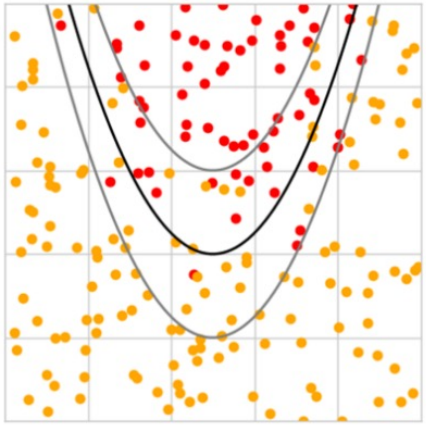
Preference for network parameters

➡ Tree Regularization

Is the objective function with tree regularization differentiable? No! Check the reference for solution.

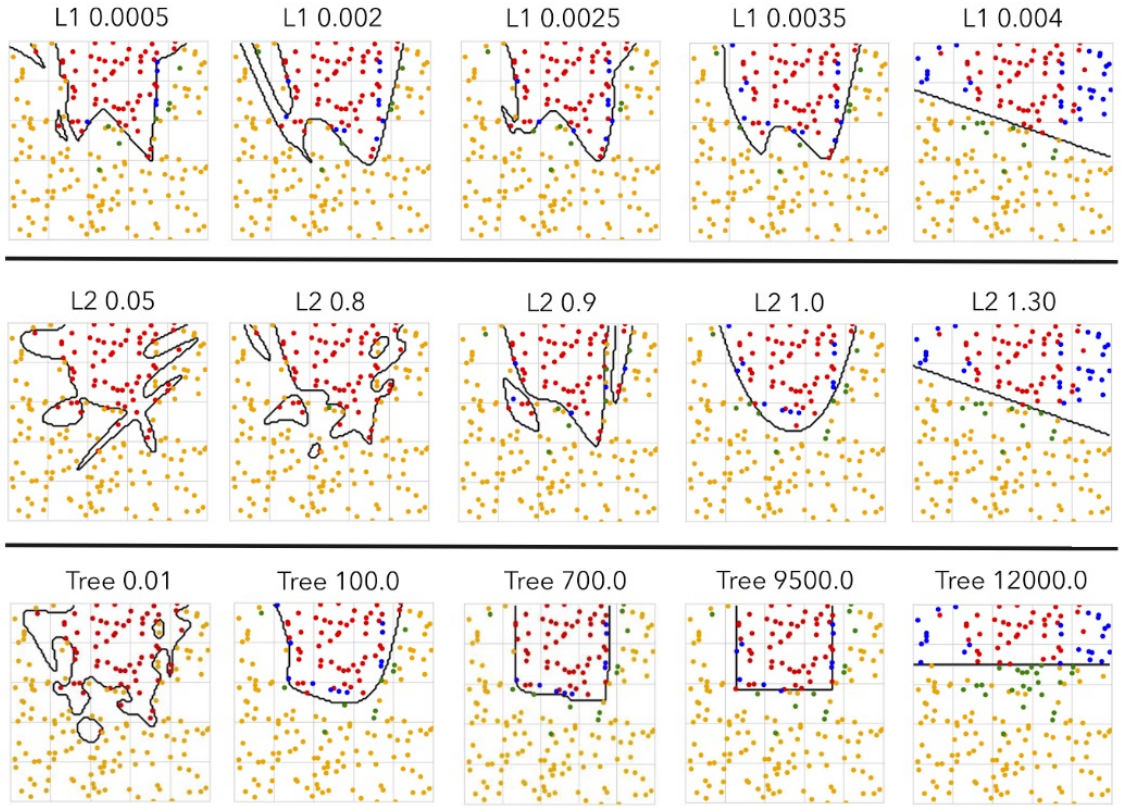
Decision Tree – Experimental Results

Dataset

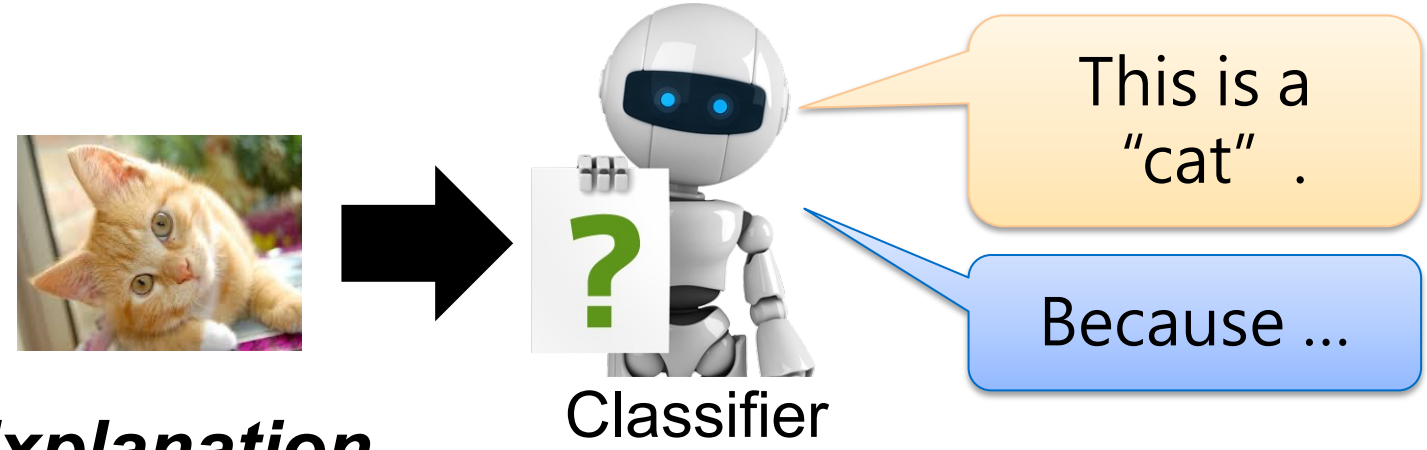


Red: Positive

Yellow: Negative



Concluding Remarks



Local Explanation

Why do you think *this image* is a cat?

Global Explanation

What do you think a "cat" look like?

Using an interpretable model to explain an uninterpretable model