Interpretable Deep Learning

2019.2.20

Beomsu Kim

KAIST Mathematical Science / Computer Science Double Major

SI Analytics Research Intern

Part 1 – Introduction to Interpretability

What is Interpretability?

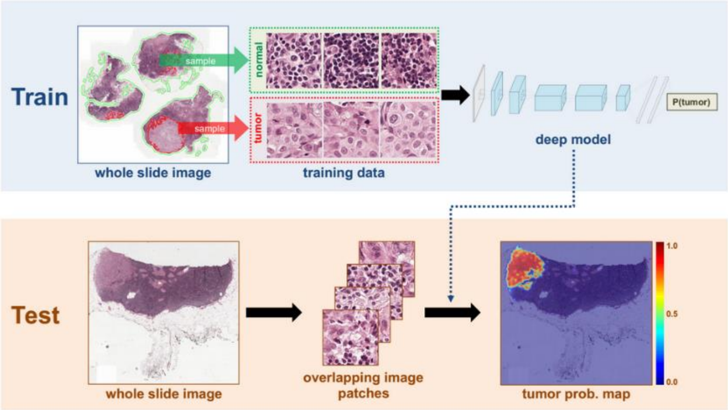
AlphaGo vs. Lee Sedol

ImageNet Challenge

IMAGENET

Self-driving Cars

Disease Diagnosis



Neural Machine Translation

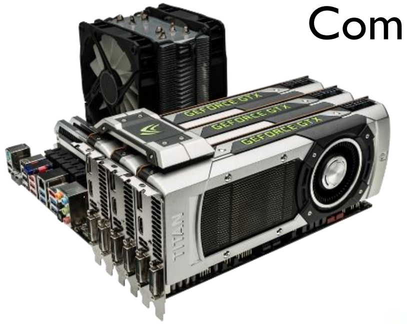
Google Translate

& More to Come!

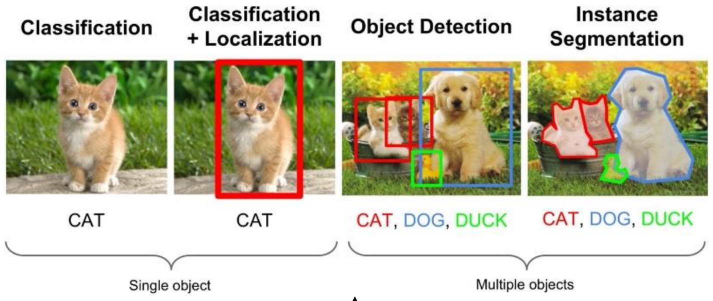
What is Interpretability?

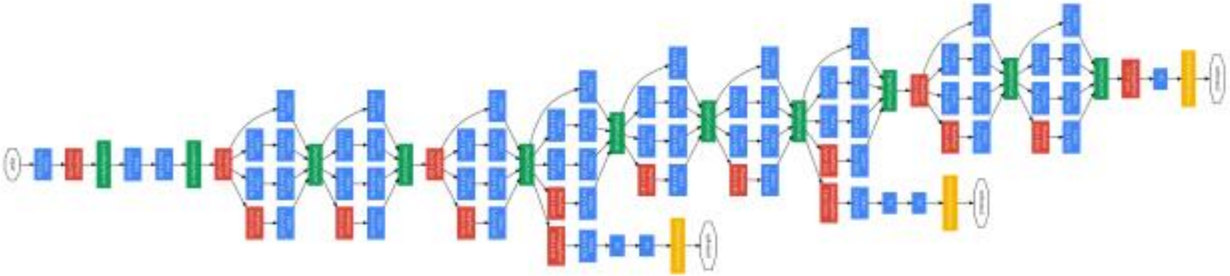
Large Dataset

Computing Power

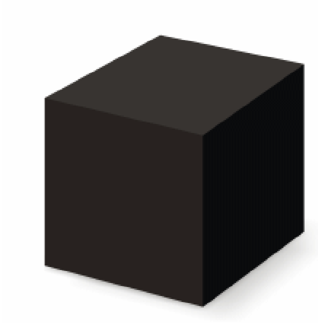


Task Solving





Deep Neural Networks

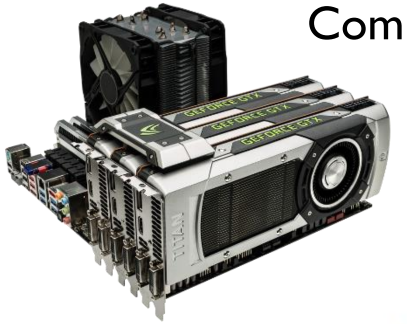


Implicit Information

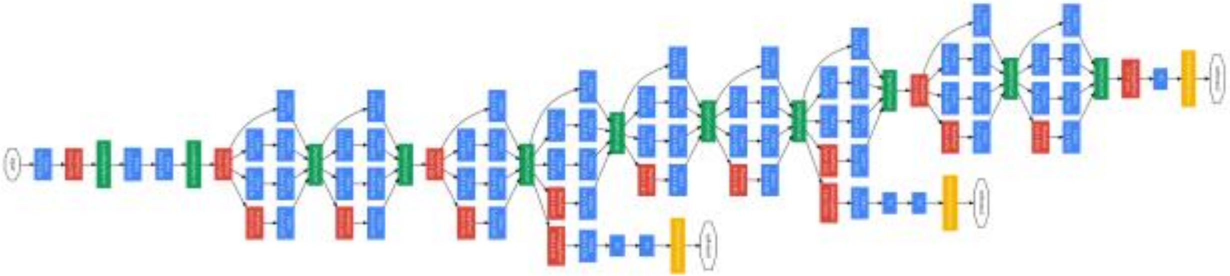
What is Interpretability?

Large Dataset

Computing Power



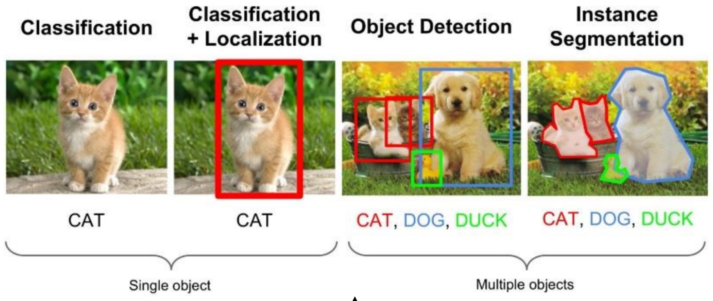
Deep Neural Networks

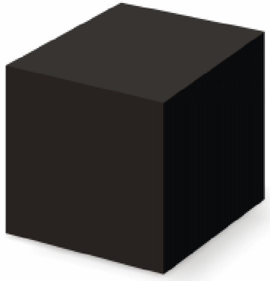


Interpretable Information

Conversion

Task Solving





Implicit Information

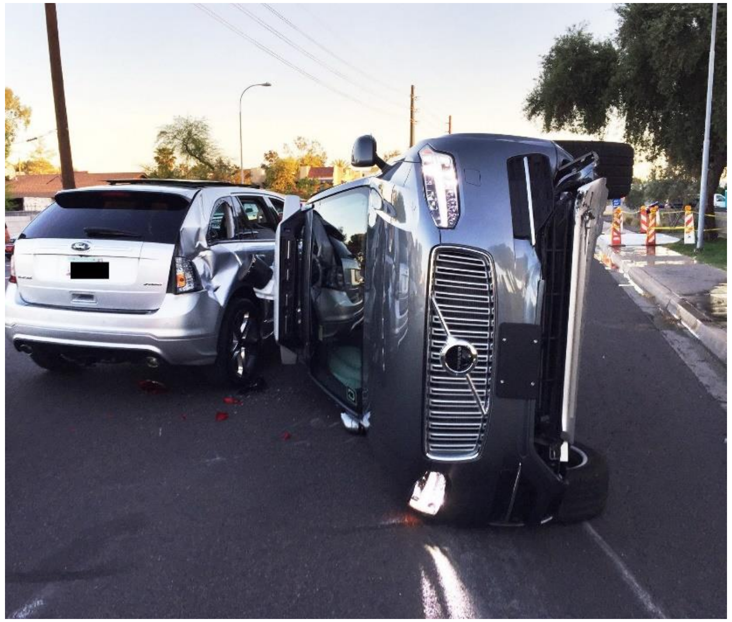
…So What?

Why Interpretability?

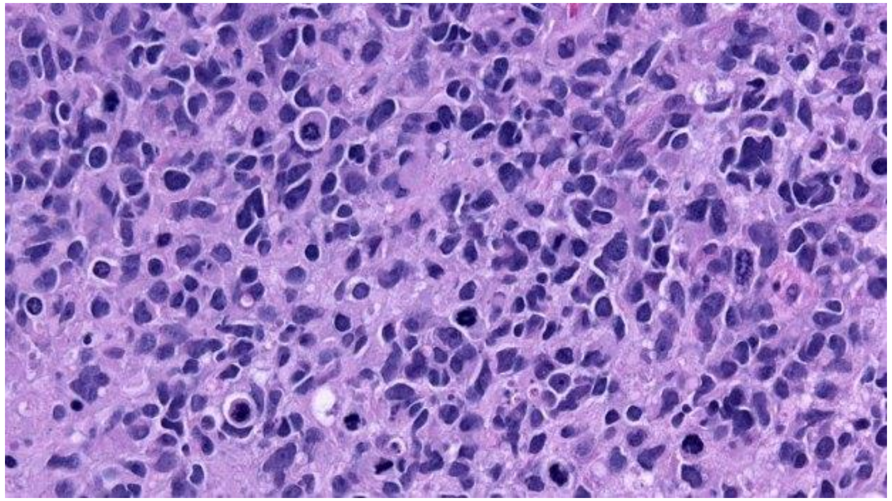
1. Verify that model works as expected

Wrong decisions can be costly and dangerous

Self-driving Uber kills Arizona woman in first fatal crash involving pedestrian

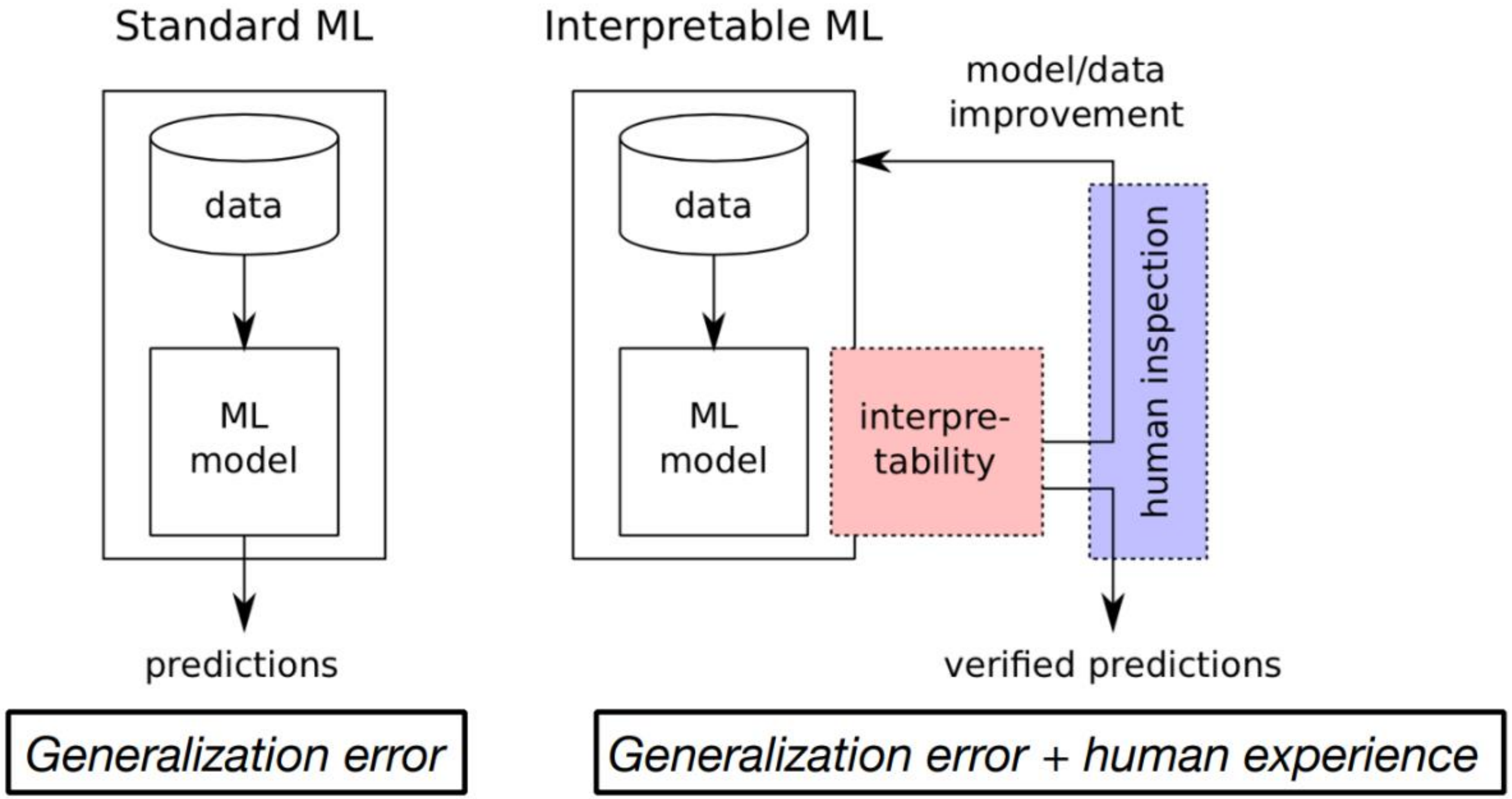


Disease Misclassification



Why Interpretability?

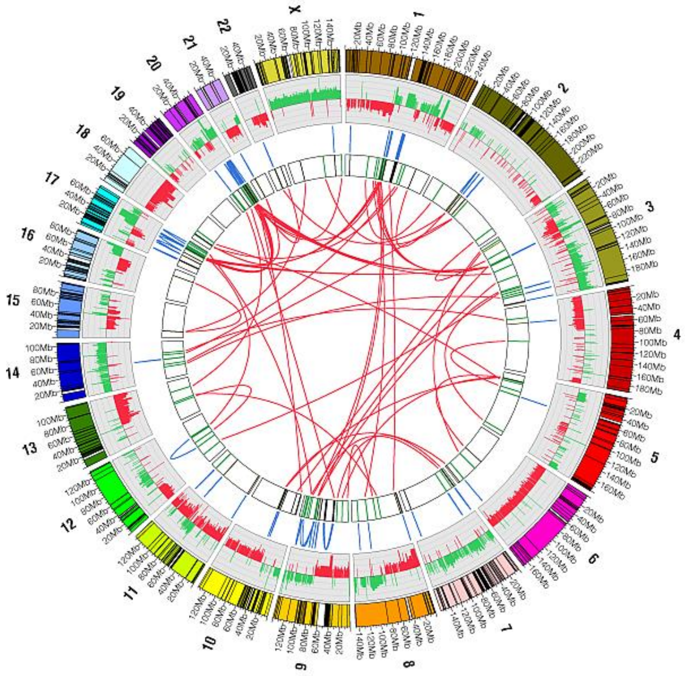
2. Improve / Debug classifier



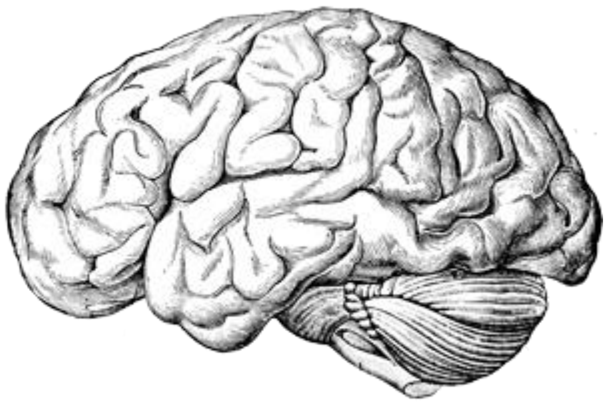
Why Interpretability?

3. Make new discoveries

Learn about the physical / biological / chemical mechanisms



Learn about the human brain



Why Interpretability?

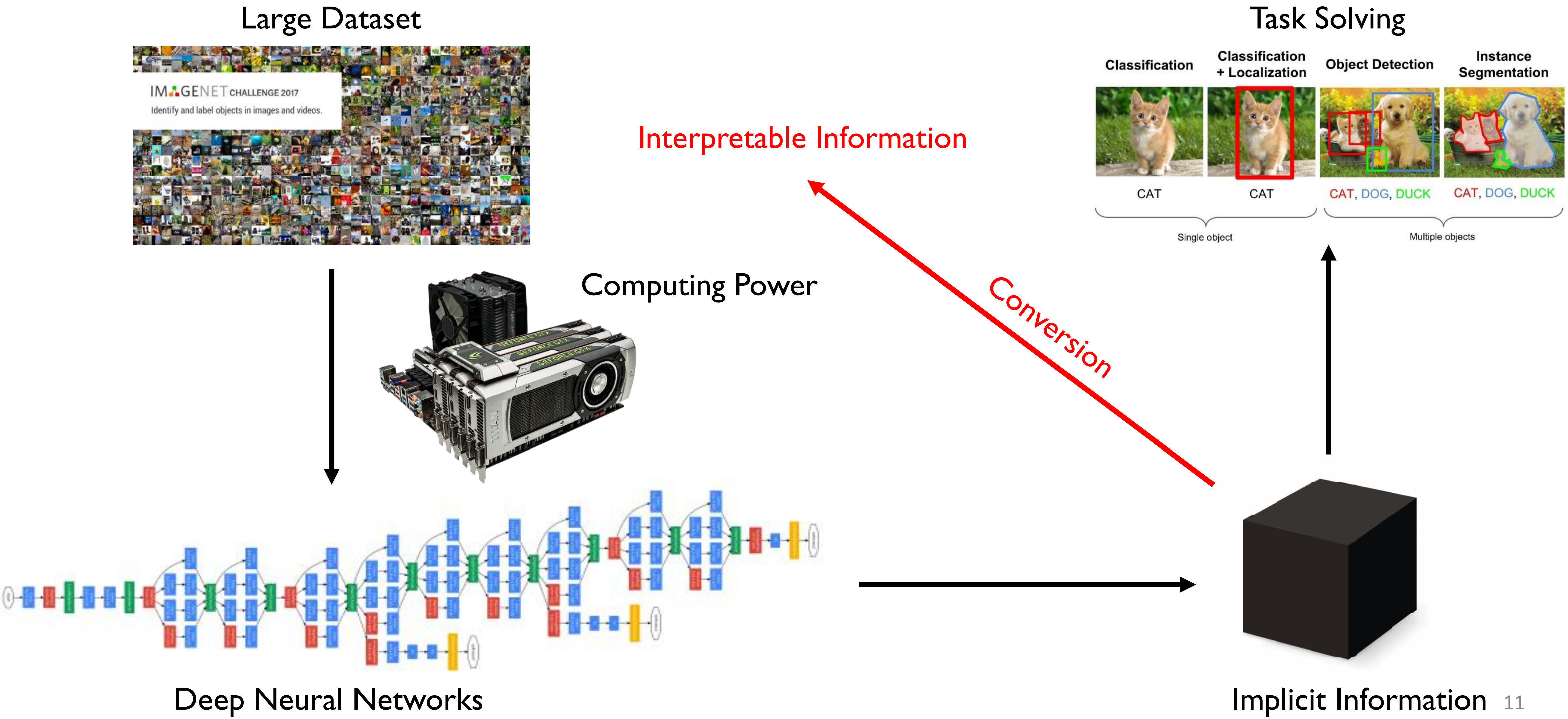
4. Right to explanation

“Right to be given an explanation for an output of the algorithm”

Ex.

- US Equal Credit Opportunity Act
- The European Union General Data Protection Regulation
- France Digital Republic Act

Back to Interpretability!

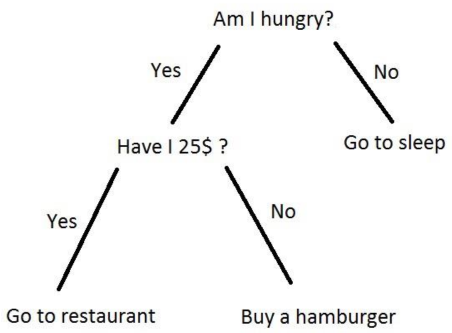


Types of Interpretability in ML

Ante-hoc Interpretability

Choose an interpretable model and train it.

Ex.



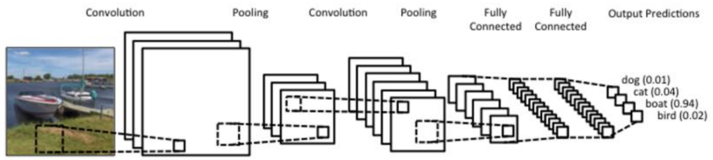
Decision Tree

Problem. Is the model expressive enough to predict the data?

Post-hoc Interpretability

Choose a complex model and develop a special technique to interpret it.

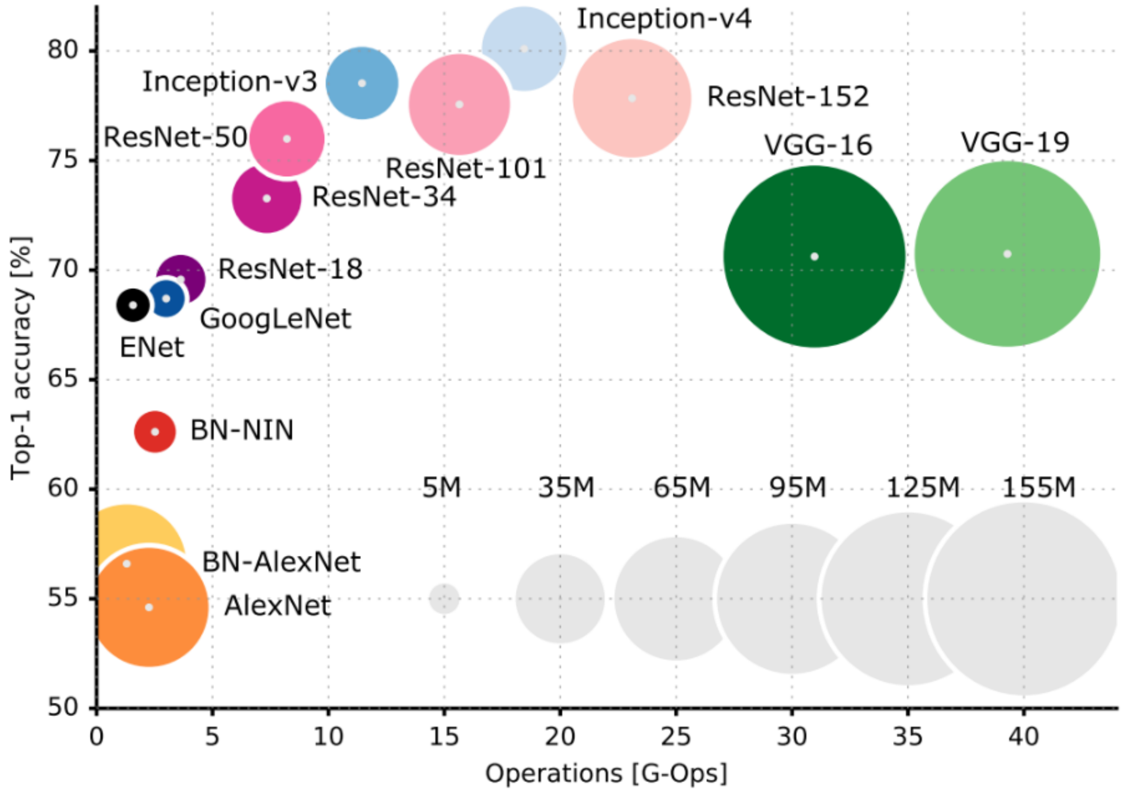
Ex.



Deep Neural Networks

Problem. How to interpret millions of parameters?

Types of Interpretability in ML



At least 5 million parameters!
(오백만)

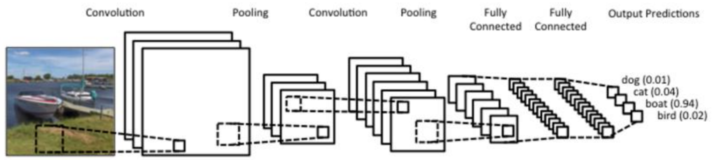
“An Analysis of Deep Neural Models for Practical Applications”, https://arxiv.org/pdf/1605.07678.pdf

Types of Interpretability in ML

Post-hoc Interpretability

Choose a complex model and develop a special technique to interpret it.

Ex.



Deep Neural Networks

Problem. How to interpret millions of parameters?

Types of Post-hoc Interpretability

Post-hoc interpretability techniques
can be classified by degree of "locality"

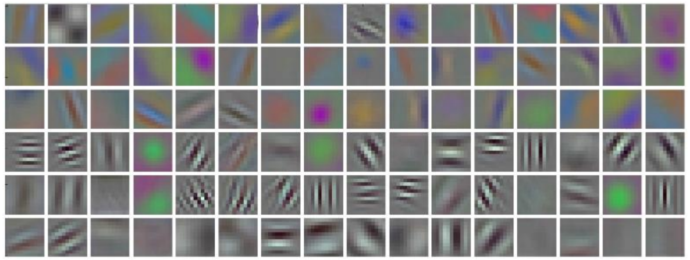
Model **Input**

Types of Post-hoc Interpretability

Post-hoc interpretability techniques
can be classified by degree of "locality"

Model **Input**

What representations have
the DNN learned?

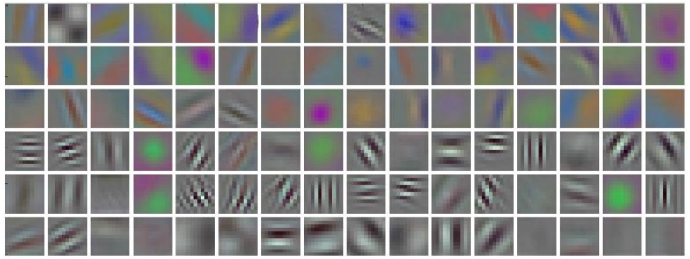


Types of Post-hoc Interpretability

Post-hoc interpretability techniques
can be classified by degree of "locality"

Model **Input**

What representations have the DNN learned?



What pattern / image maximally activates a particular neuron?

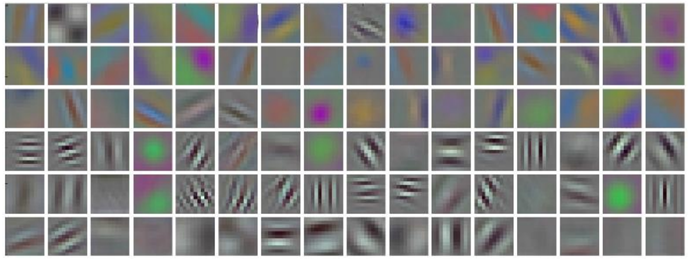
dumbbell

Types of Post-hoc Interpretability

Post-hoc interpretability techniques
can be classified by degree of "locality"

Model ⟷ **Input**

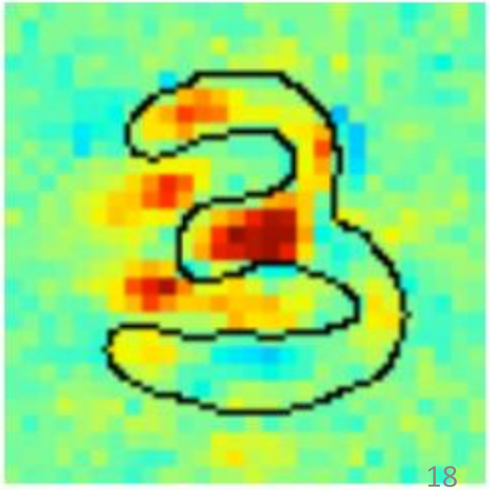
What representations have the DNN learned?



What pattern / image maximally activates a particular neuron?

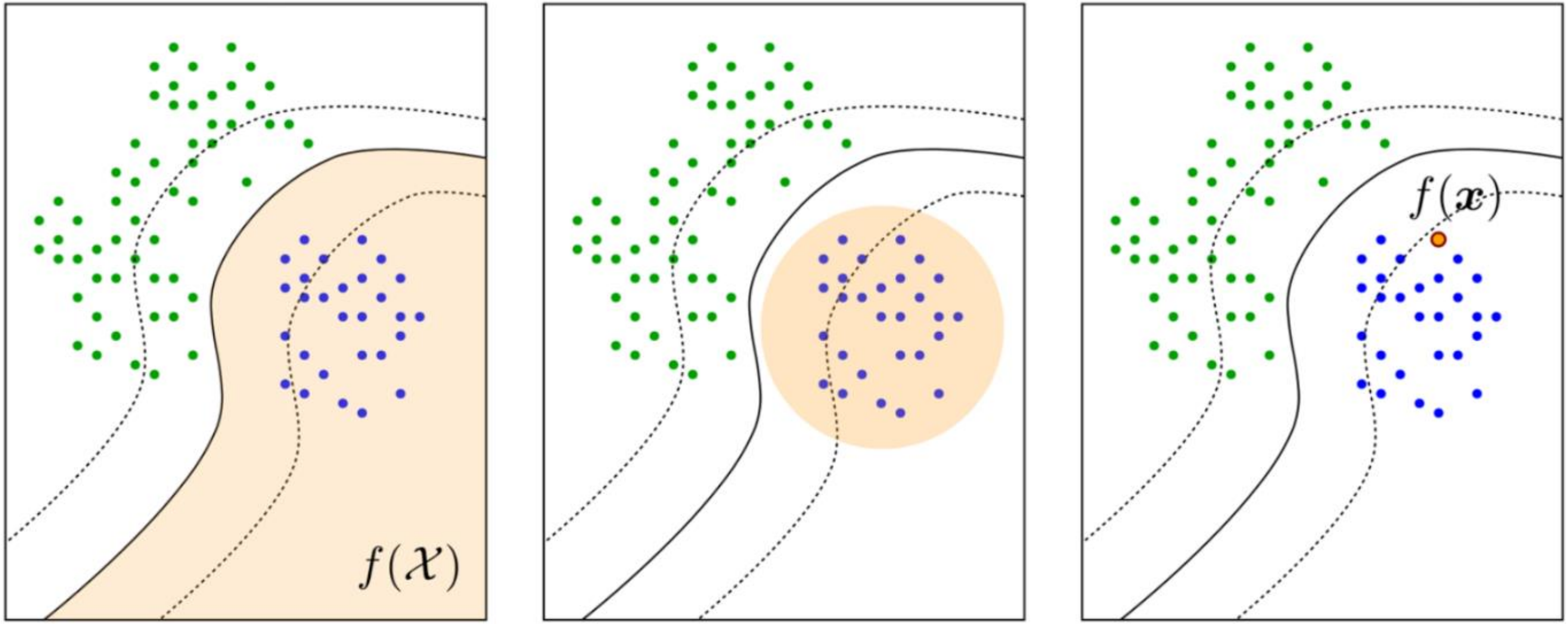
dumbbell

Explain why input x has been classified as $f(x)$.



Types of Post-hoc Interpretability

Model ⟷ **Input**



Part 1 Summary

1. What is interpretability in Deep Learning?

- Converting implicit information in DNN to (human) interpretable information

2. Why do we need interpretability in Deep Learning?

- Verify model works as intended
- Debug classifier
- Make discoveries
- Right to explanation

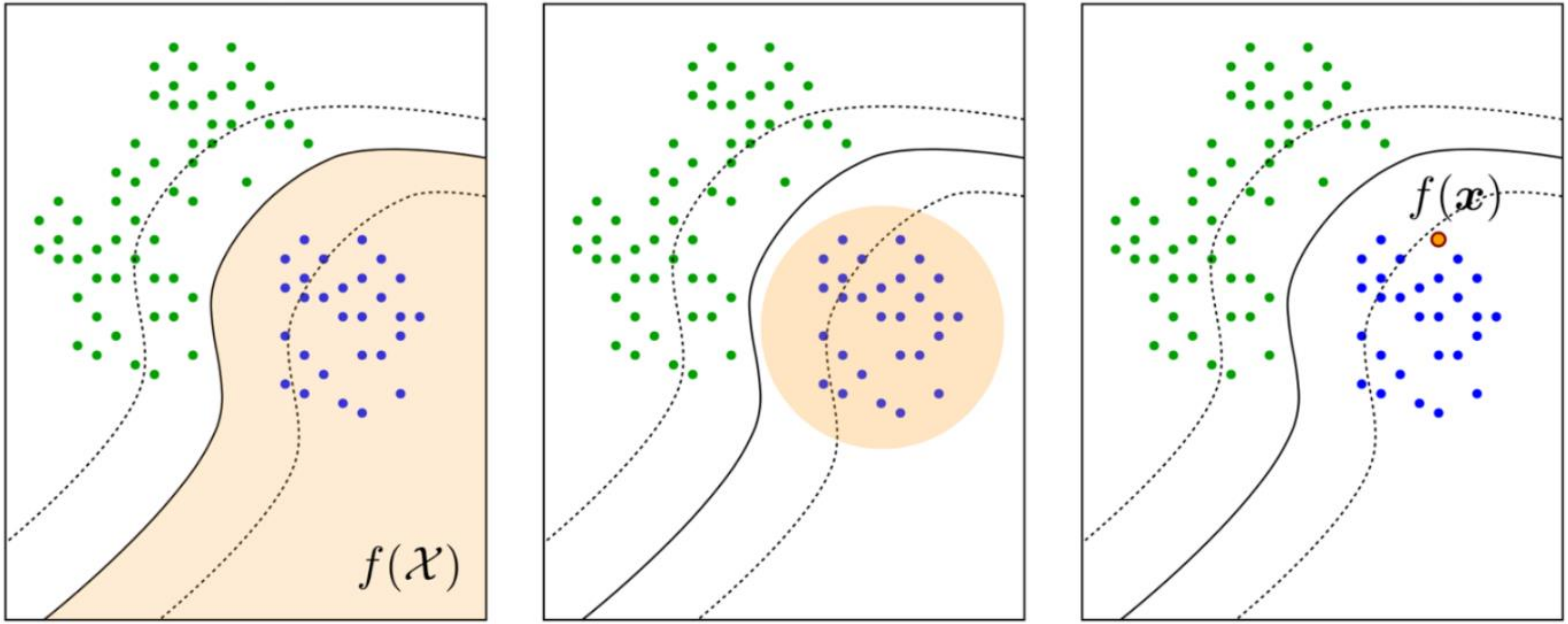
3. Types of Interpretability in ML

- Ante-hoc Interpretability: choose an interpretable model and train it
- Post-hoc Interpretability: choose a complex model and develop a special technique to interpret it
- Post-hoc interpretability techniques can be classified by degree of "locality"

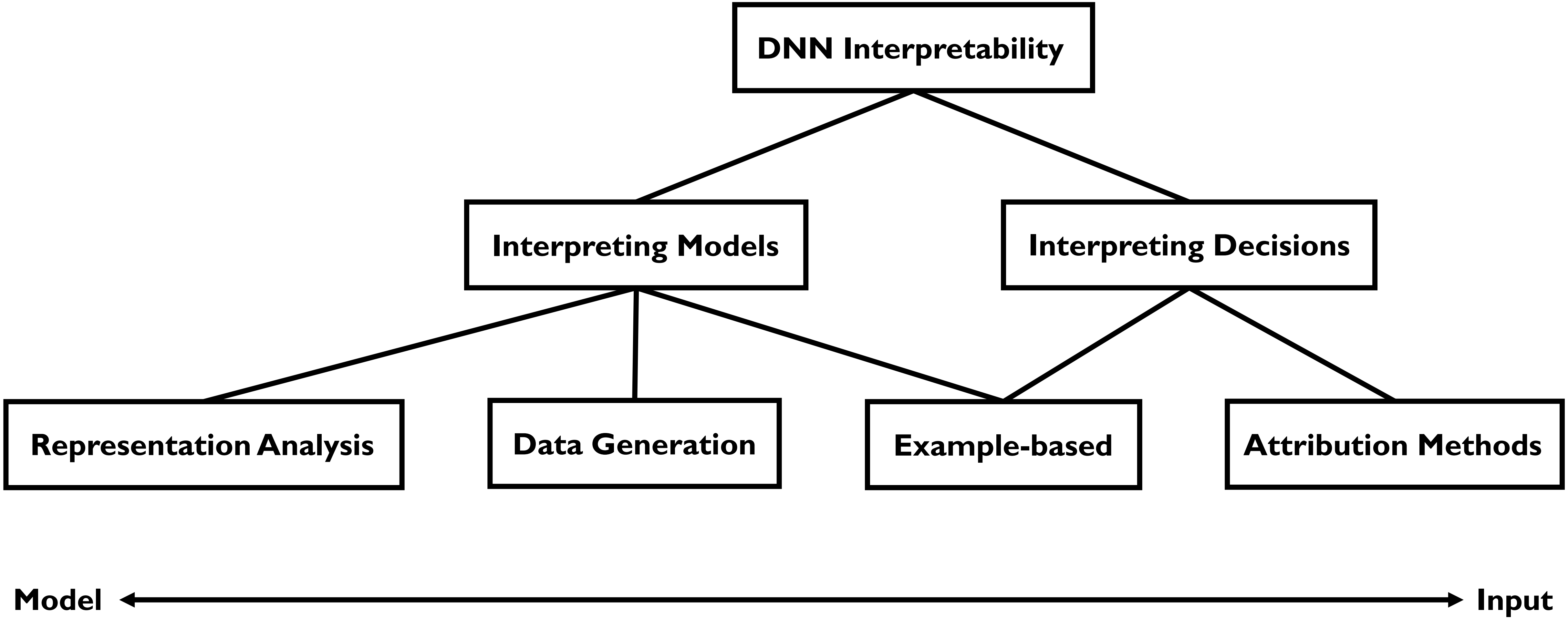
Part 2 – Interpreting Deep Neural Networks

Types of Post-hoc Interpretability

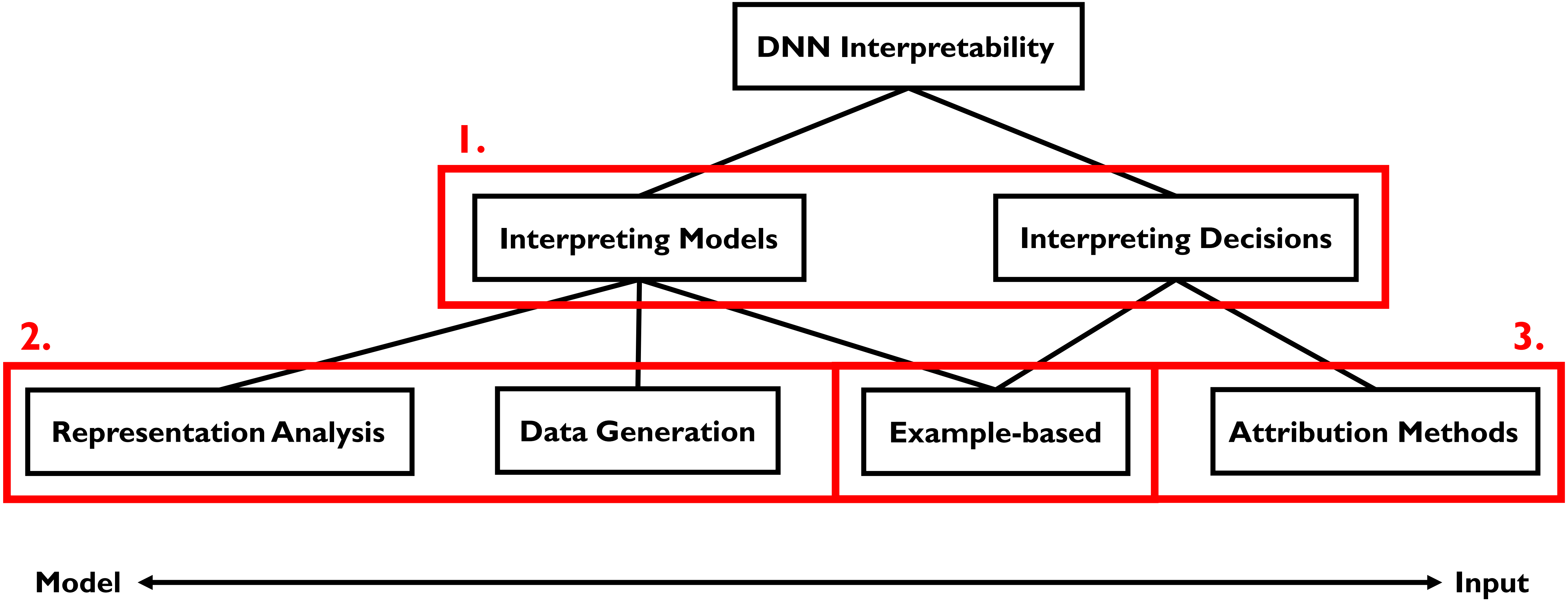
Model **Input**



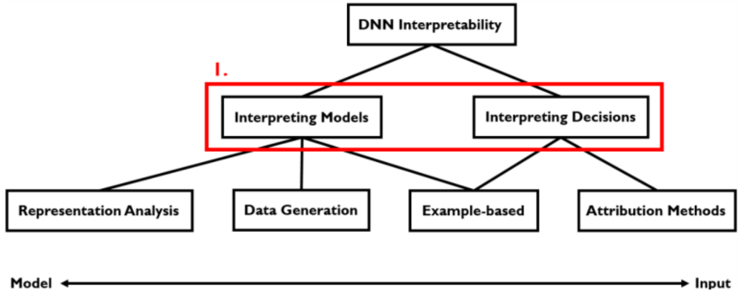
Types of DNN Interpretability



Types of DNN Interpretability



Types of DNN Interpretability



Interpreting Models
(Macroscopic)

- "Summarize" DNN with a simpler model (e.g. decision tree)
- Find prototypical example of a category
- Find pattern maximizing activation of a neuron

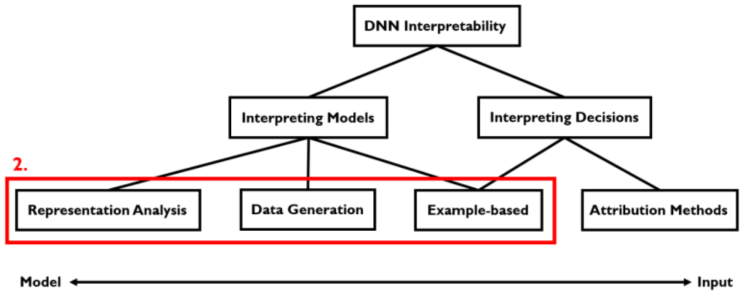
Better understand internal representations

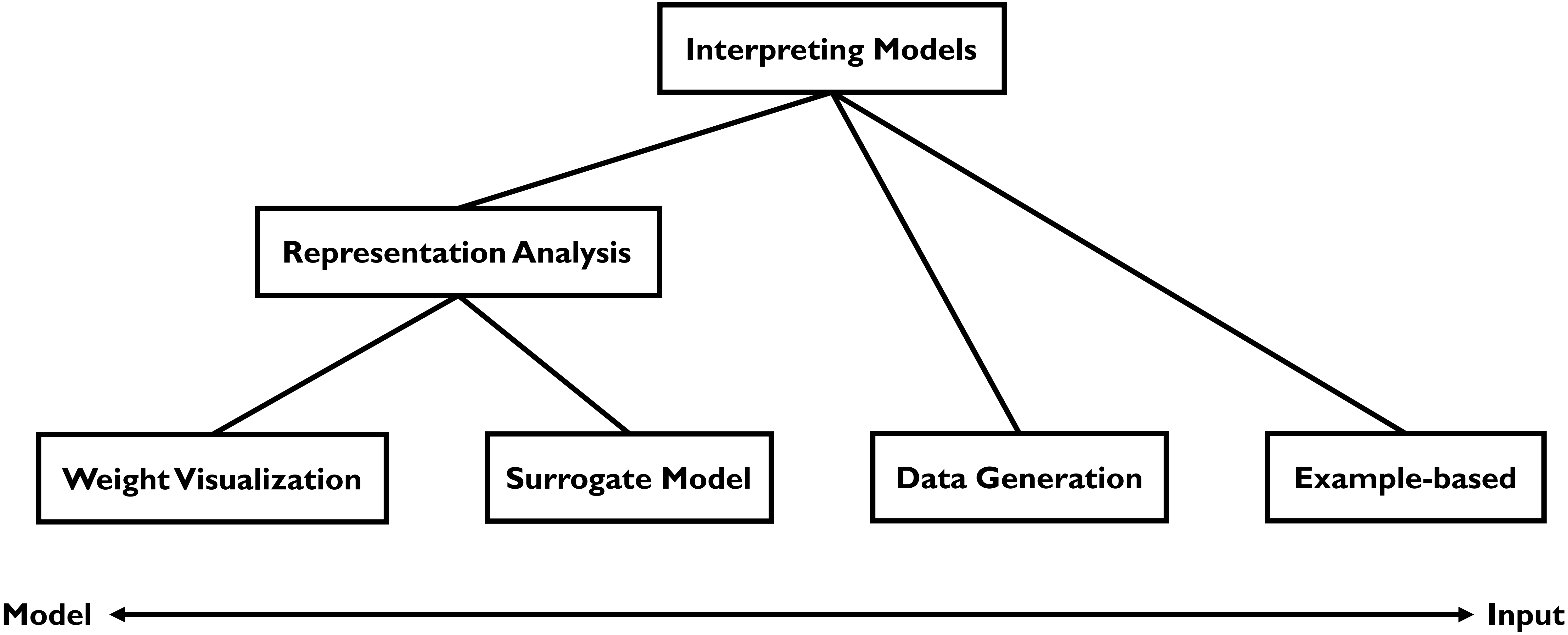
Interpreting Decisions
(Microscopic)

- Why did DNN make this decision
- Verify that model behaves as expected
- Find evidence for decision

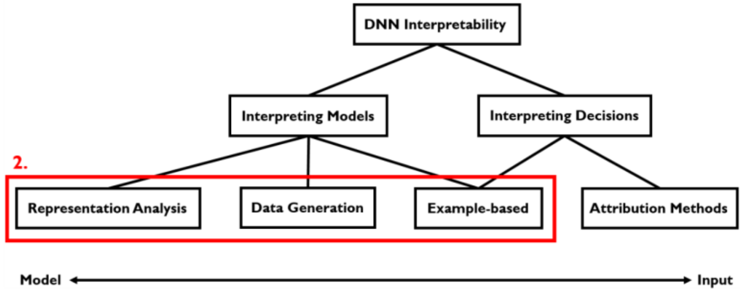
Important for practical applications

Types of DNN Interpretability



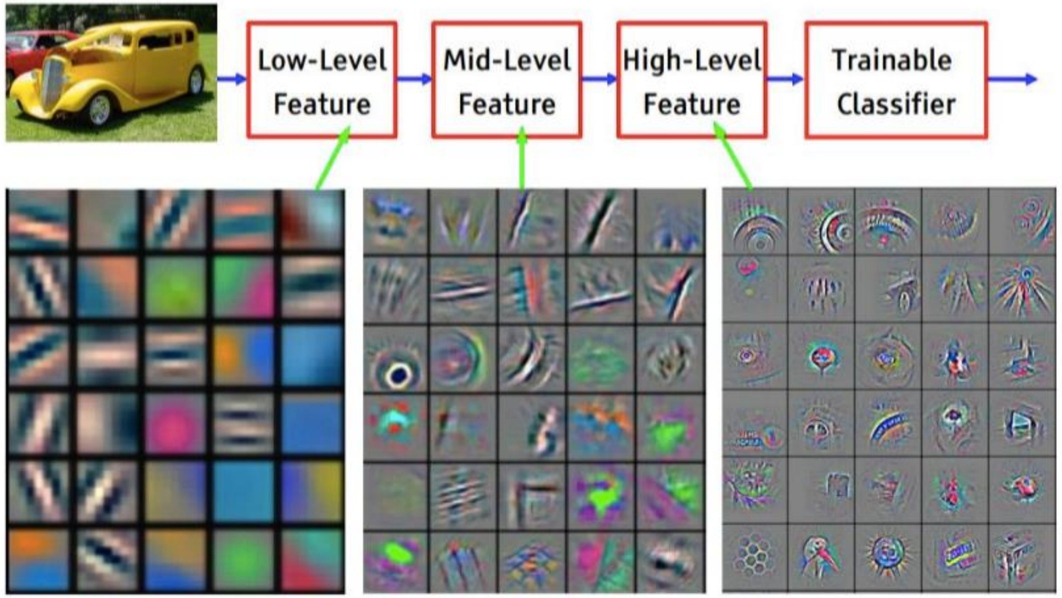


Types of DNN Interpretability



Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

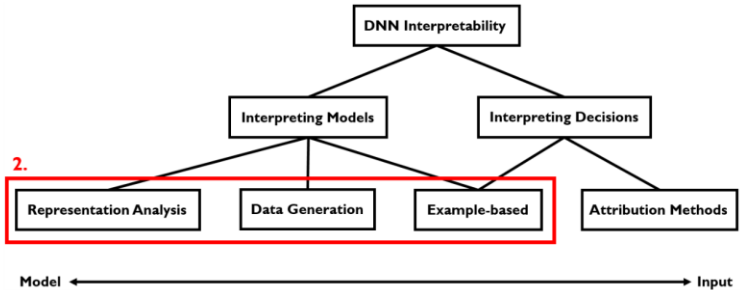
- Filter visualization in Convolutional Neural Networks
- Can understand what kind of features CNN has learned
- Still too many filters!



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

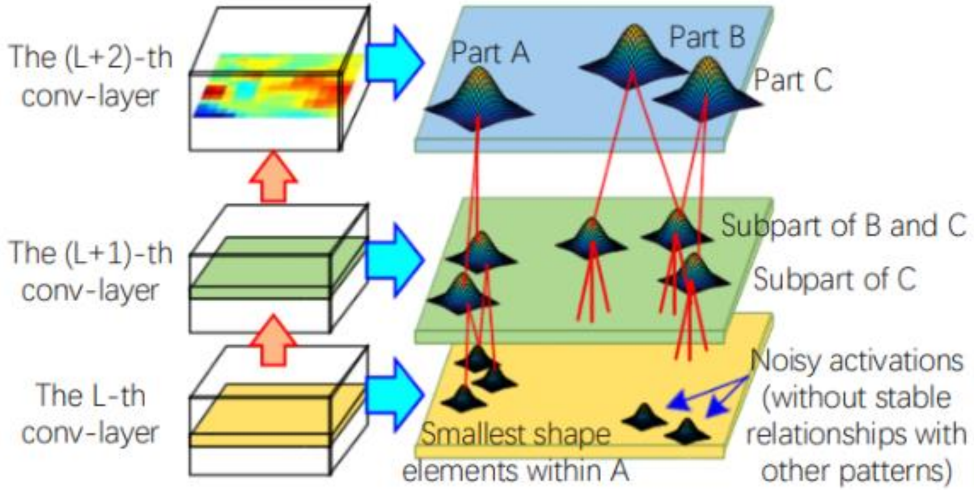
"Deep Inside Convolutional Networks: Visualizing Image Classification Models and Saliency Maps", https://arxiv.org/pdf/1312.6034.pdf

Types of DNN Interpretability



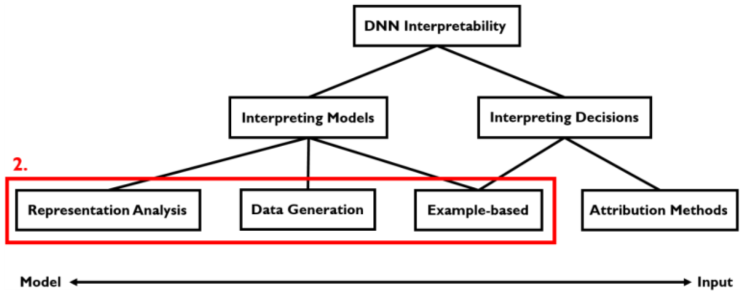
Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

- "Summarize" DNN with a simpler model
- E.g. Decision trees, graphs or linear models



"Explaining CNN Knowledge via an Explanatory Graph", https://arxiv.org/pdf/1605.07678.pdf

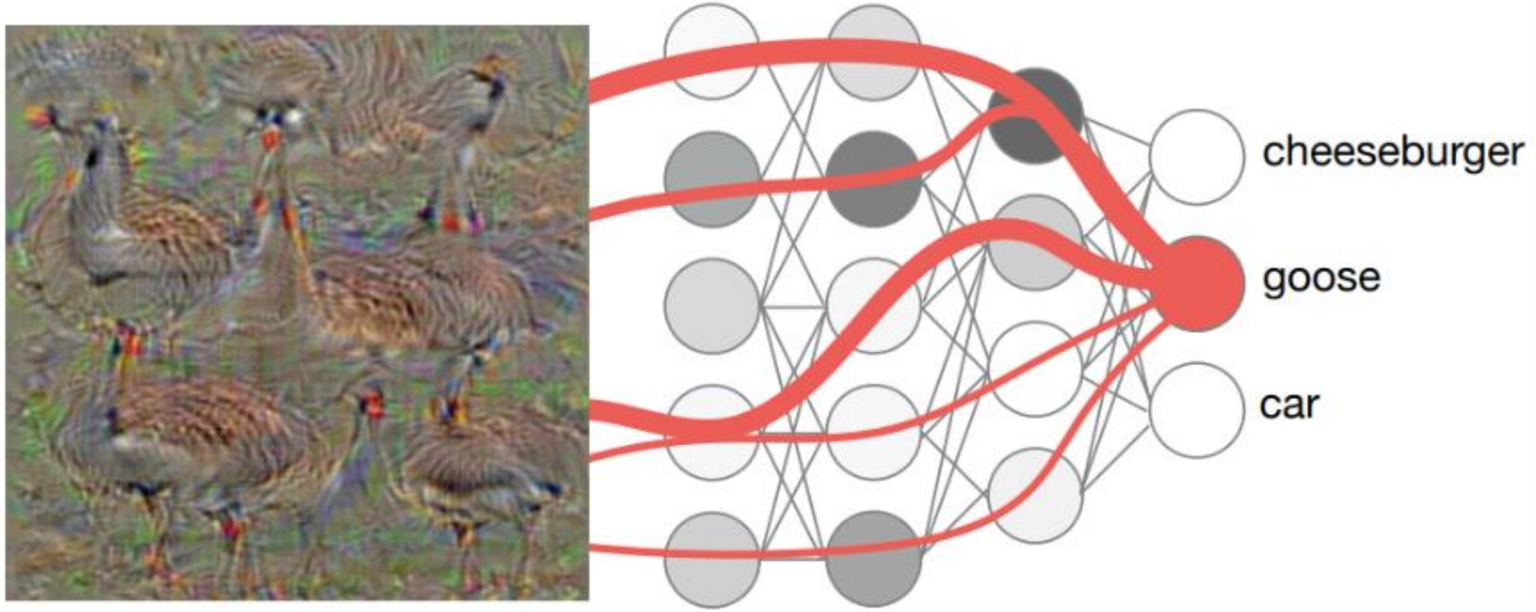
Types of DNN Interpretability



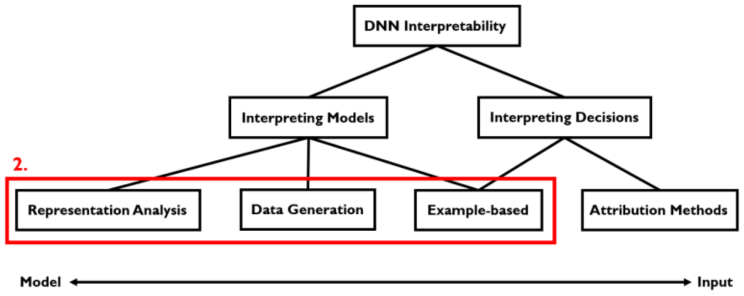
Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

Activation Maximization

- Find pattern maximizing activation of a neuron



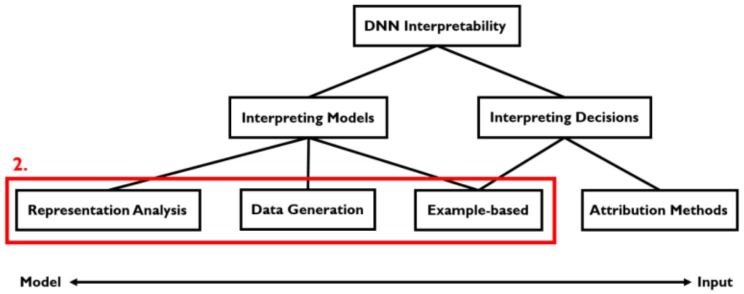
Types of DNN Interpretability



Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

$$\max_{x \in \mathcal{X}} p_\theta(\omega_c \,|\, x) + \lambda \Omega(x)$$

Types of DNN Interpretability



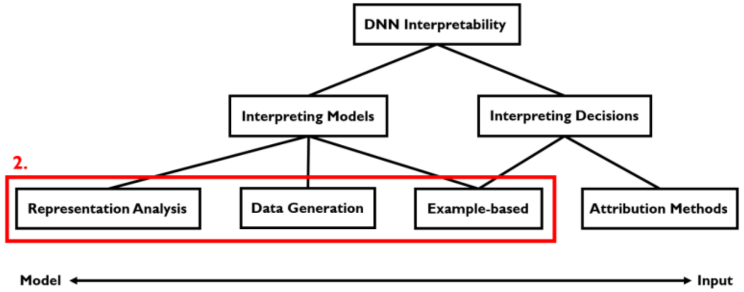
Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

$$\max_{x \in \mathcal{X}} \boxed{p_\theta(\omega_c \mid x)} + \boxed{\lambda \Omega(x)}$$

Class Probability

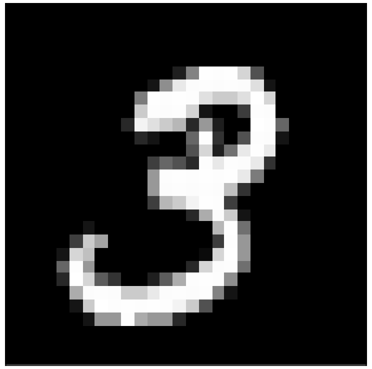
Regularization Term

Types of DNN Interpretability



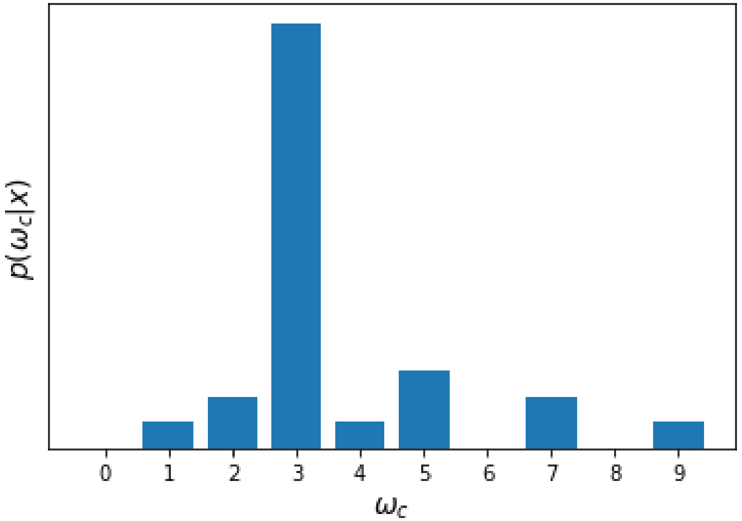
Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

x

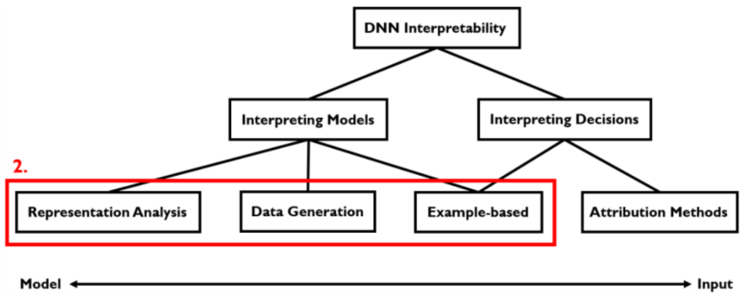


DNN

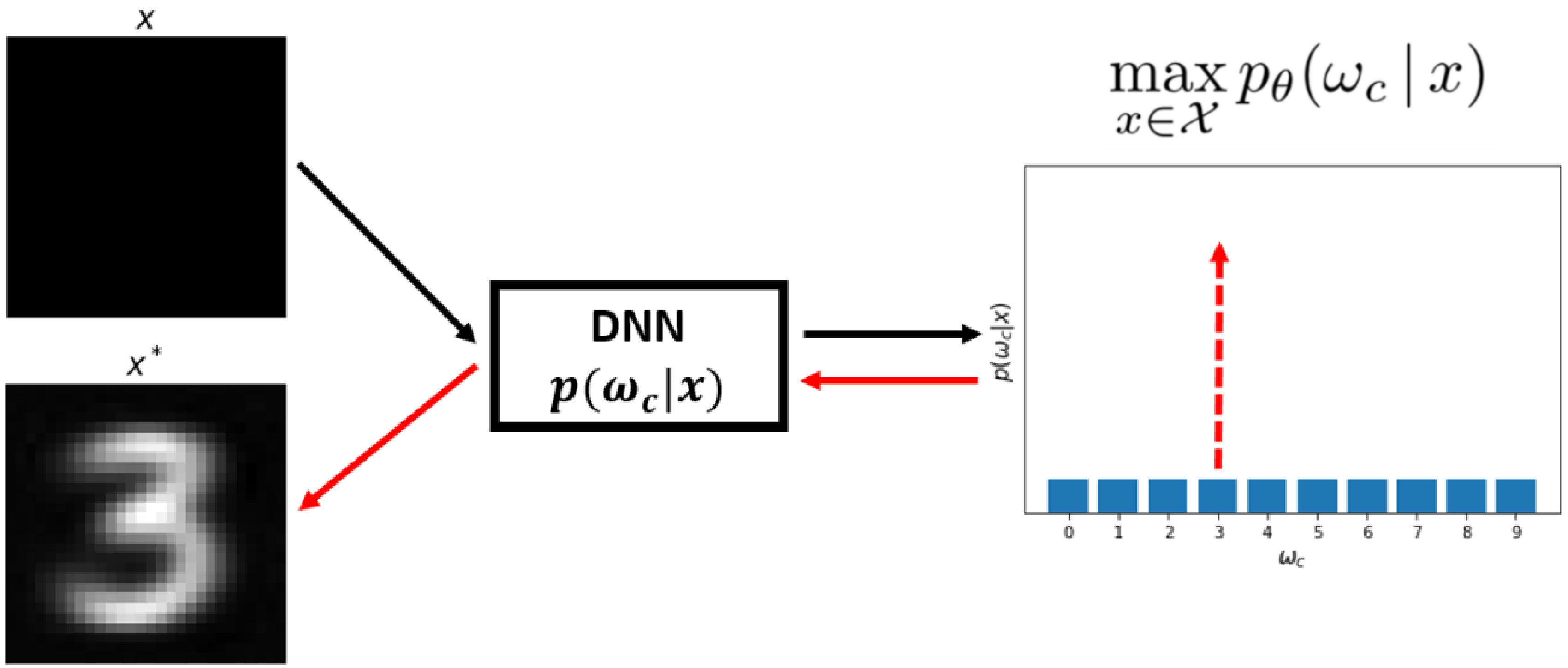
$p(\omega_c|x)$



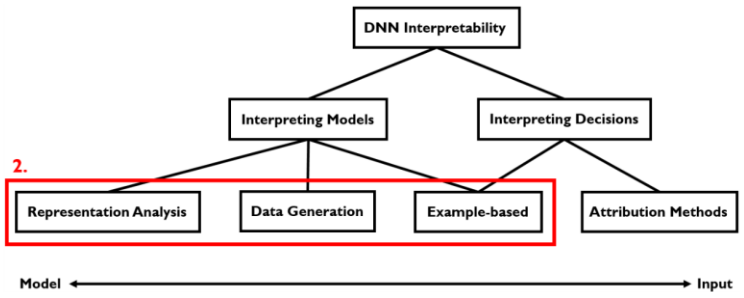
Types of DNN Interpretability



Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**



Types of DNN Interpretability

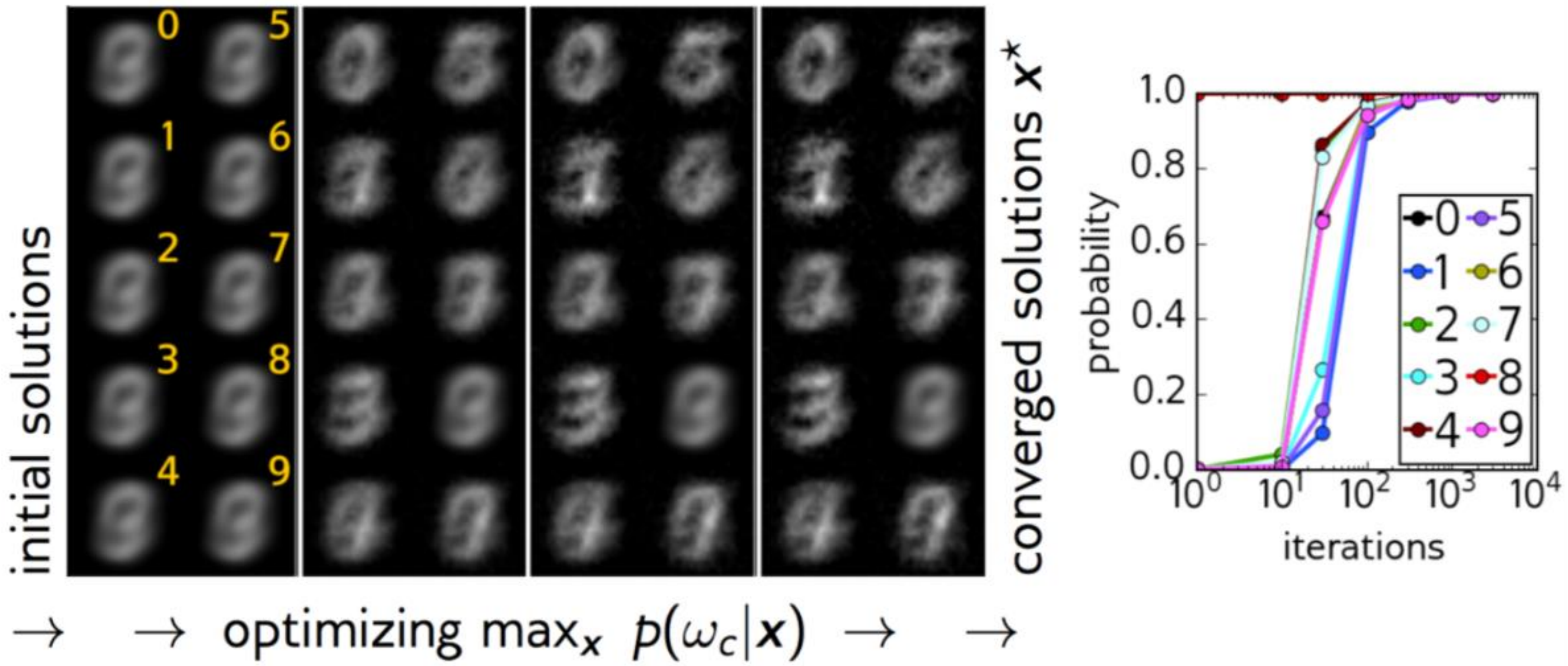


Weight Visualization

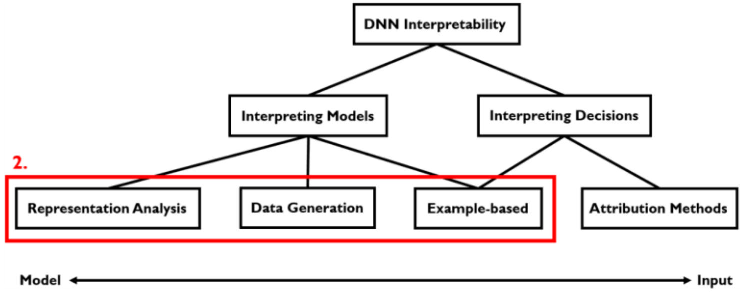
Surrogate Model

Data Generation

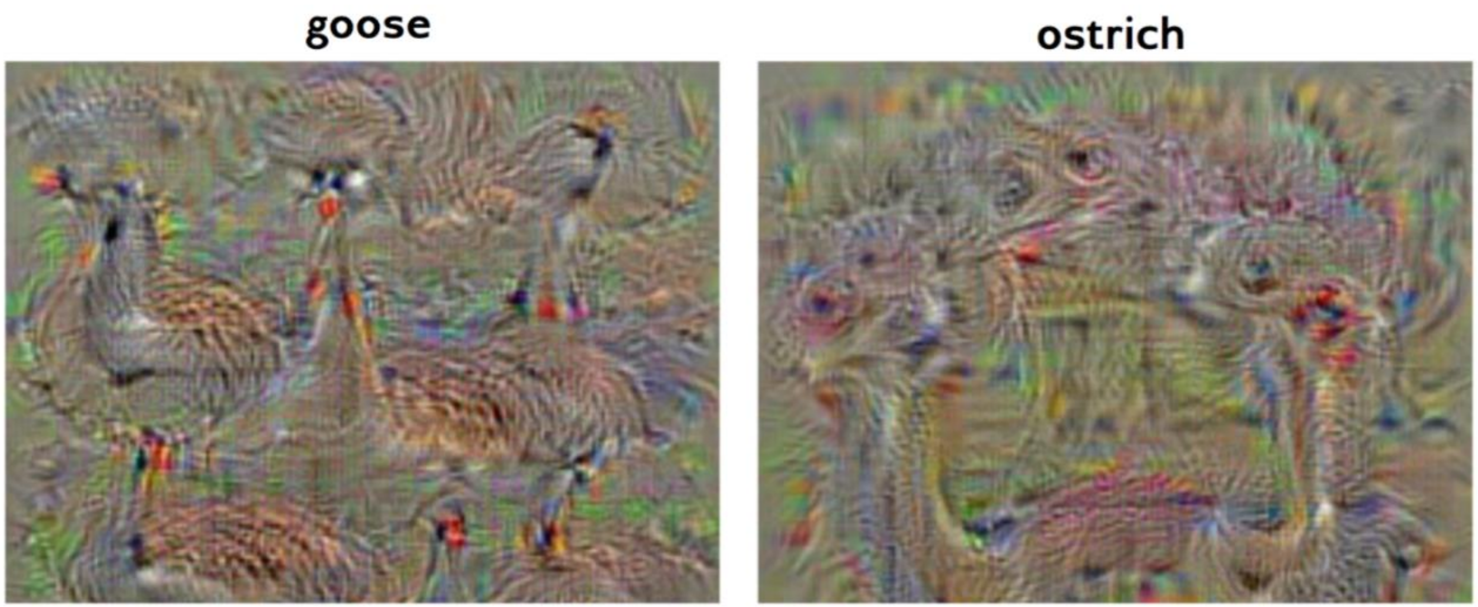
Example-based



Types of DNN Interpretability



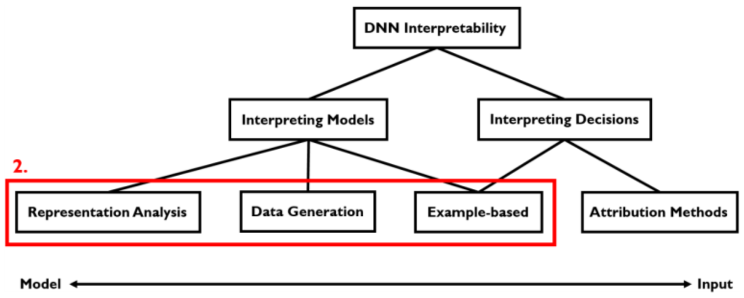
Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**



Images from **Simonyan et al. 2013** "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps"

"Deep Inside Convolutional Networks: Visualizing Image Classification Models and Saliency Maps", https://arxiv.org/pdf/1312.6034.pdf

Types of DNN Interpretability



Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

Advantages

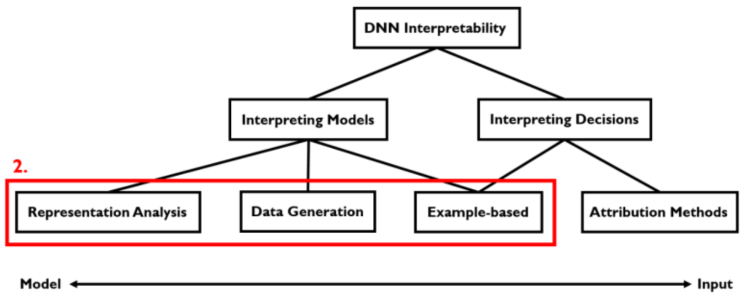
- AM builds typical patterns for given classes (e.g. beaks, legs)
- Unrelated background objects are not present in the image

Disadvantages

- Does not resemble class-related patterns
- Lowers the quality of the interpretation for given classes

Redefine optimization problem!

Types of DNN Interpretability



Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

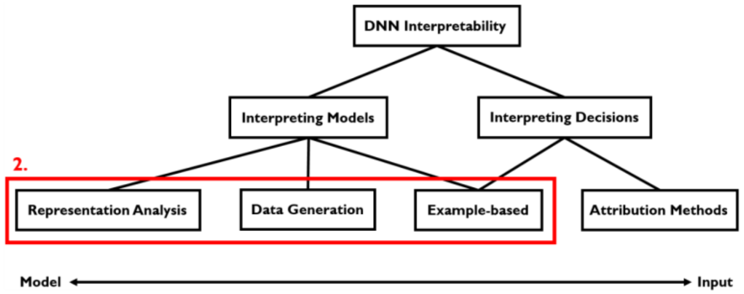
- Does not resemble class-related patterns
- Lowers the quality of the interpretation for given classes

Redefine optimization problem!

Force the generated data x^* to match the data more closely

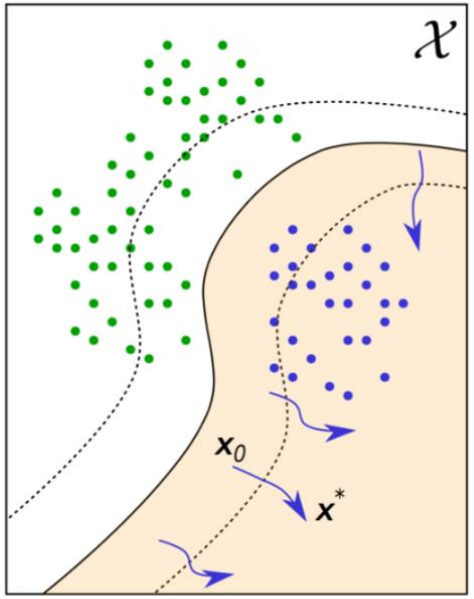
Find the input pattern that maximizes class probability → Find the most likely input pattern for a given class

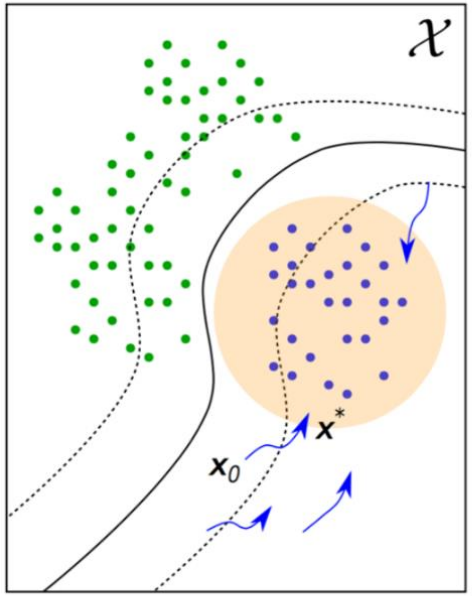
Types of DNN Interpretability



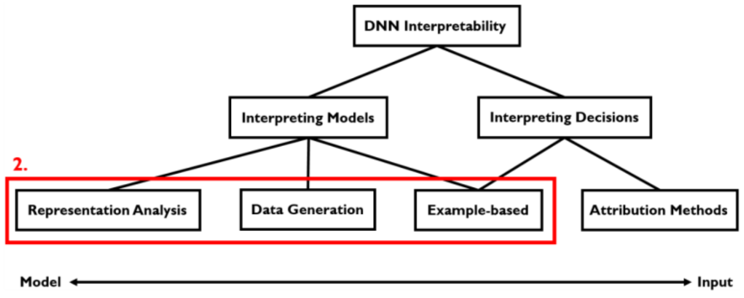
Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

Find the input pattern that maximizes class probability → Find the most likely input pattern for a given class



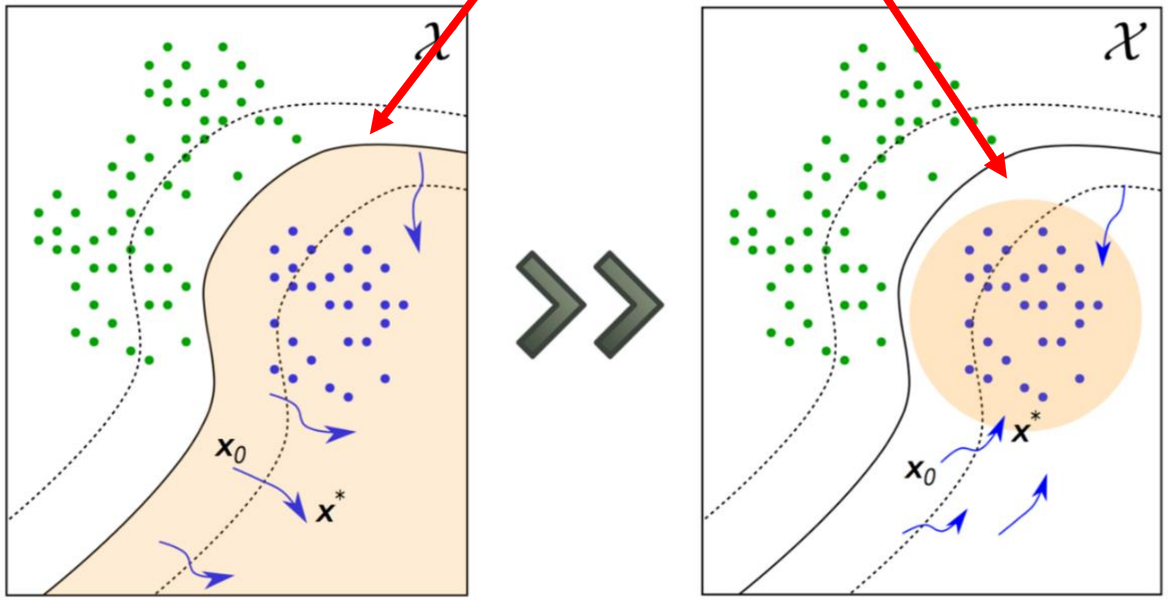


Types of DNN Interpretability

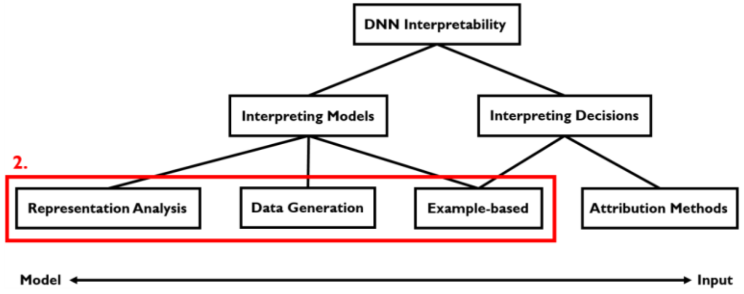


Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

$$\max_{x \in \mathcal{X}} \boxed{p_\theta(\omega_c \mid x)} + \boxed{\lambda \Omega(x)}$$



Types of DNN Interpretability



Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

Find the input pattern that maximizes class probability → Find the most likely input pattern for a given class

Activation Maximization with Expert

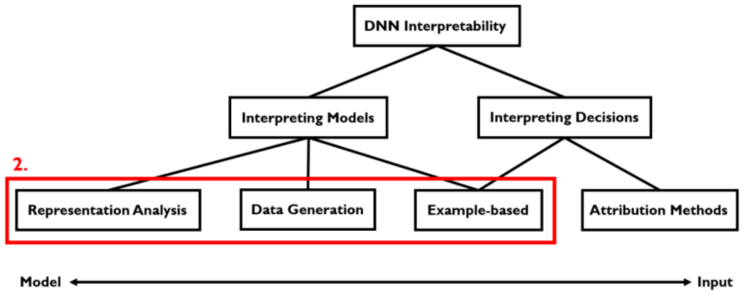
$$p(\boldsymbol{x}|\omega_c) \propto \underbrace{\boxed{p(\omega_c|\boldsymbol{x})}}_{\text{original}} \cdot p(\boldsymbol{x})$$

Activation Maximization in Code Space

$$\max_{\boldsymbol{z}\in\mathcal{Z}} p(\omega_c|\underbrace{g(\boldsymbol{z})}_{\boldsymbol{x}}) + \lambda\|\boldsymbol{z}\|^2 \qquad \boldsymbol{x}^\star = g(\boldsymbol{z}^\star)$$

These two techniques require an unsupervised model of the data, either a density model $p(\boldsymbol{x})$ or a generator $g(\boldsymbol{z})$

Types of DNN Interpretability

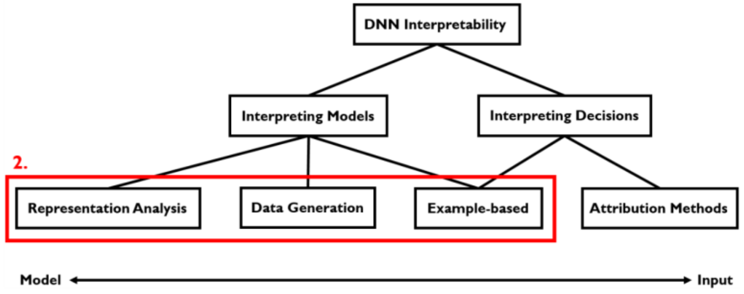


Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

simple AM (initialized to mean) | simple AM (init. to class means) | AM-density (init. to class means) | AM-gen (init. to class means)

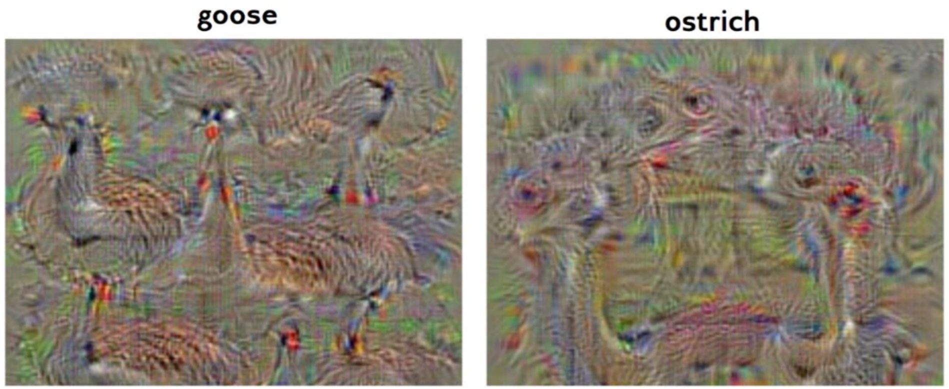
Observation: Connecting to the data leads to sharper visualizations.

Types of DNN Interpretability



Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

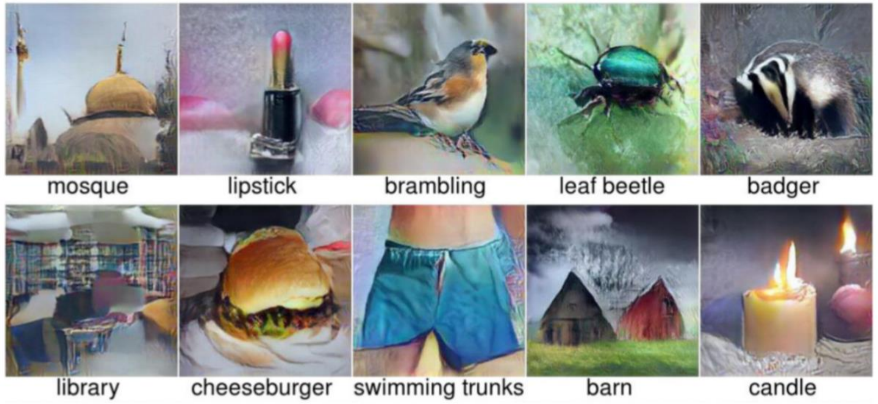
Activation Maximization



Images from **Simonyan et al. 2013** "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps"

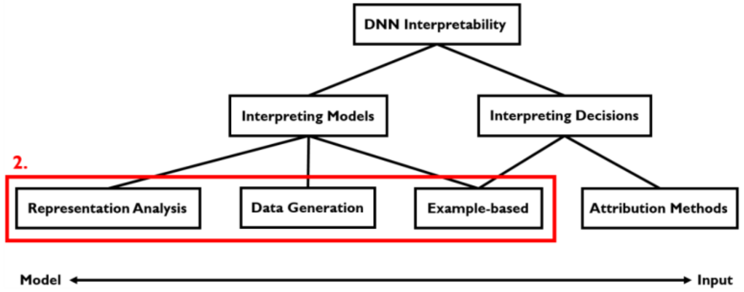
Activation Maximization in Code Space

Images from **Nguyen et al. 2016.** "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks"



Observation: Connecting to the data leads to sharper visualizations.

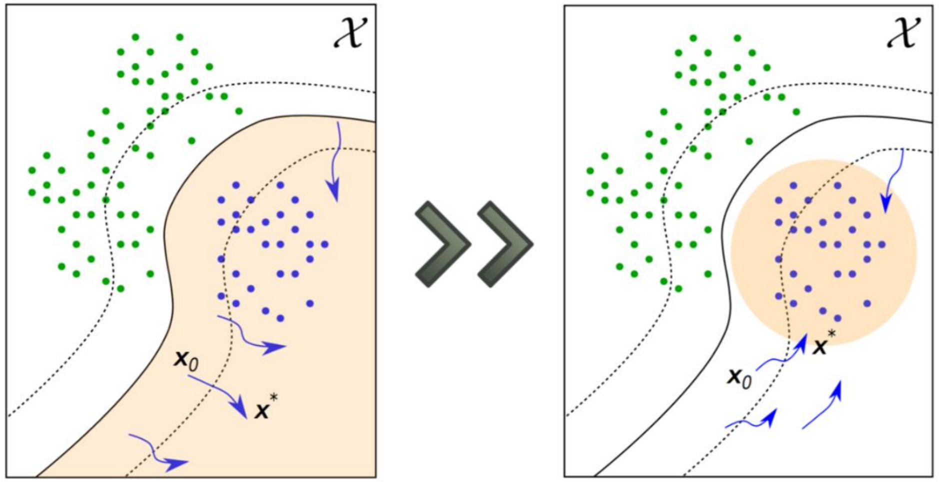
Types of DNN Interpretability



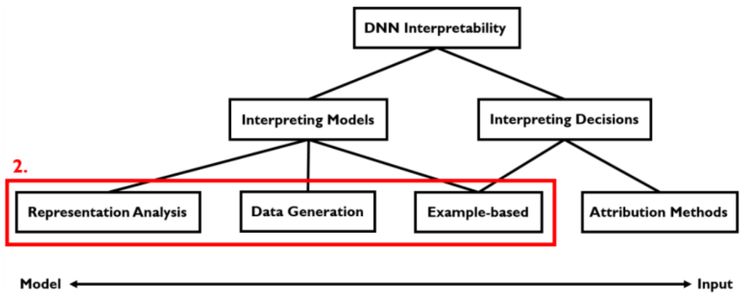
Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

Summary

- DNNs can be interpreted by finding input patterns that maximize a certain output quantity.
- Connecting to the data improves the interpretability of the visualization.

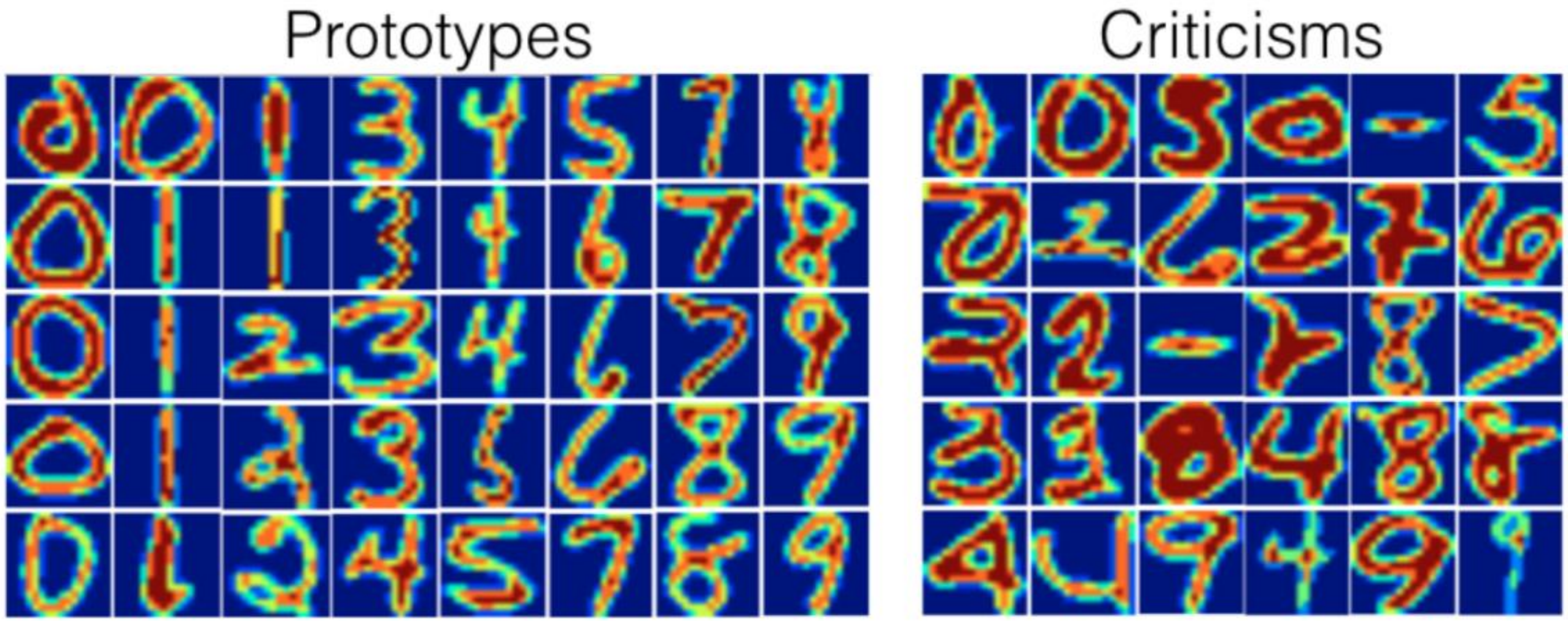


Types of DNN Interpretability



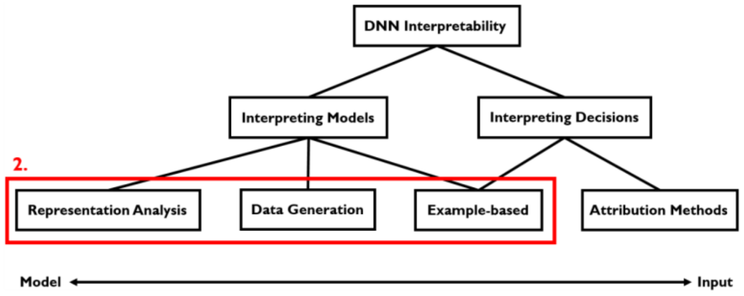
Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

- Find image instances that represent / do not represent the image class



"Examples are not Enough, Learn to Criticize! Criticism for Interpretability", https://people.csail.mit.edu/beenkim/papers/KIM2016NIPS_MMD.pdf

Types of DNN Interpretability



Weight Visualization | **Surrogate Model** | **Data Generation** | **Example-based**

- Find image instances that represent / do not represent the image class

“Examples are not Enough, Learn to Criticize! Criticism for Interpretability”, https://people.csail.mit.edu/beenkim/papers/KIM2016NIPS_MMD.pdf

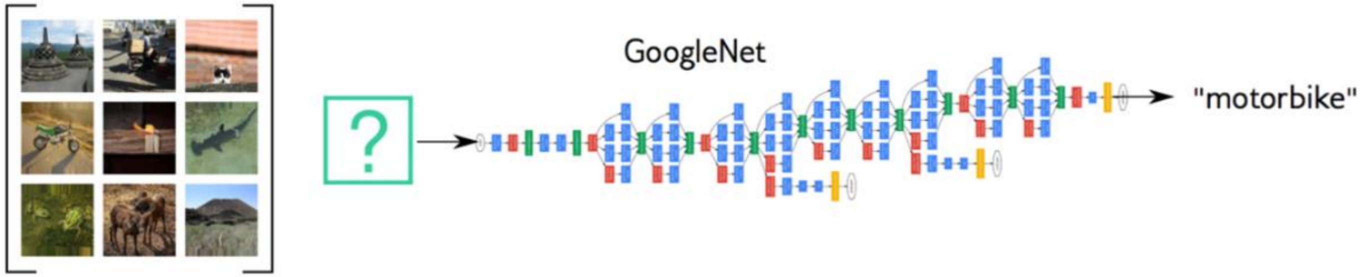
Limitation of Model Interpretations

Question: What would be the best image to interpret the class "motorcycle"?

- Summarizing a concept or a category like "motorcycle" into a single image is difficult.
- A good interpretation would grow as large as the diversity of the concept to interpret.

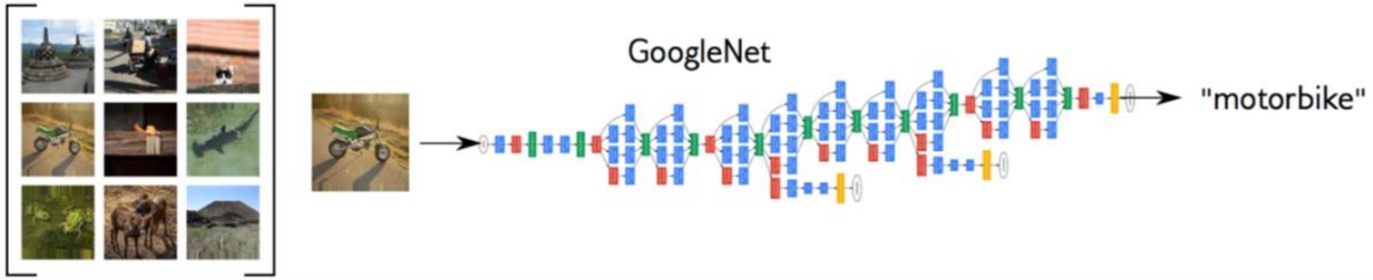
Limitation of Model Interpretations

Finding a prototype:



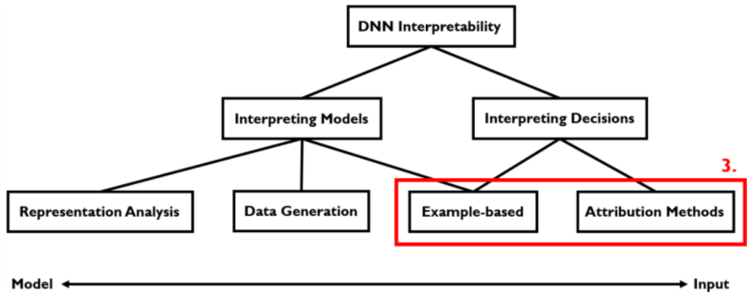
Question: How does a "motorbike" typically look like?

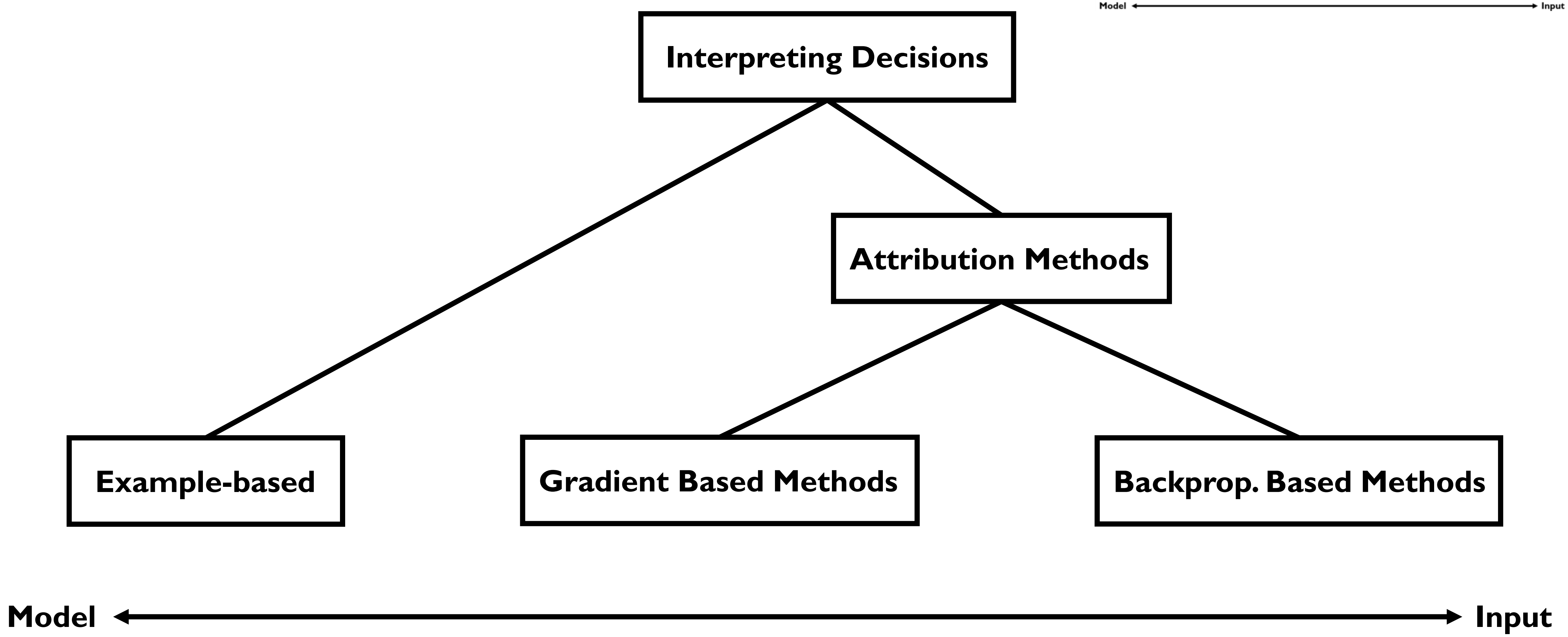
Decision explanation:



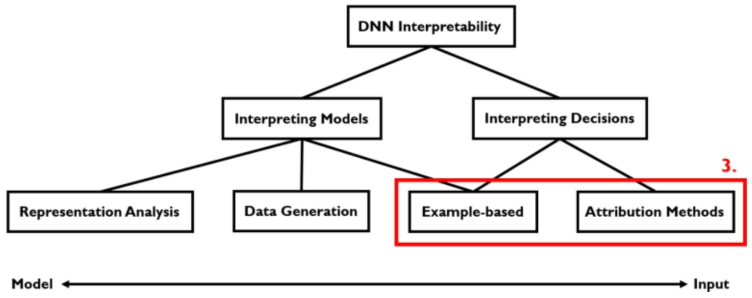
Question: Why is this example classified as a motorbike?

Types of DNN Interpretability





Types of DNN Interpretability

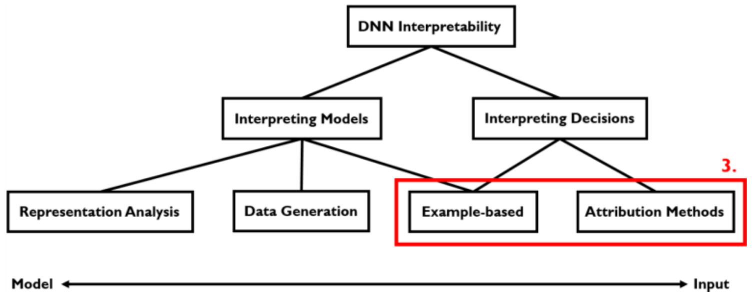


Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

- Which training instance influenced the decision most?
- Still does not specifically highlight which features were important.

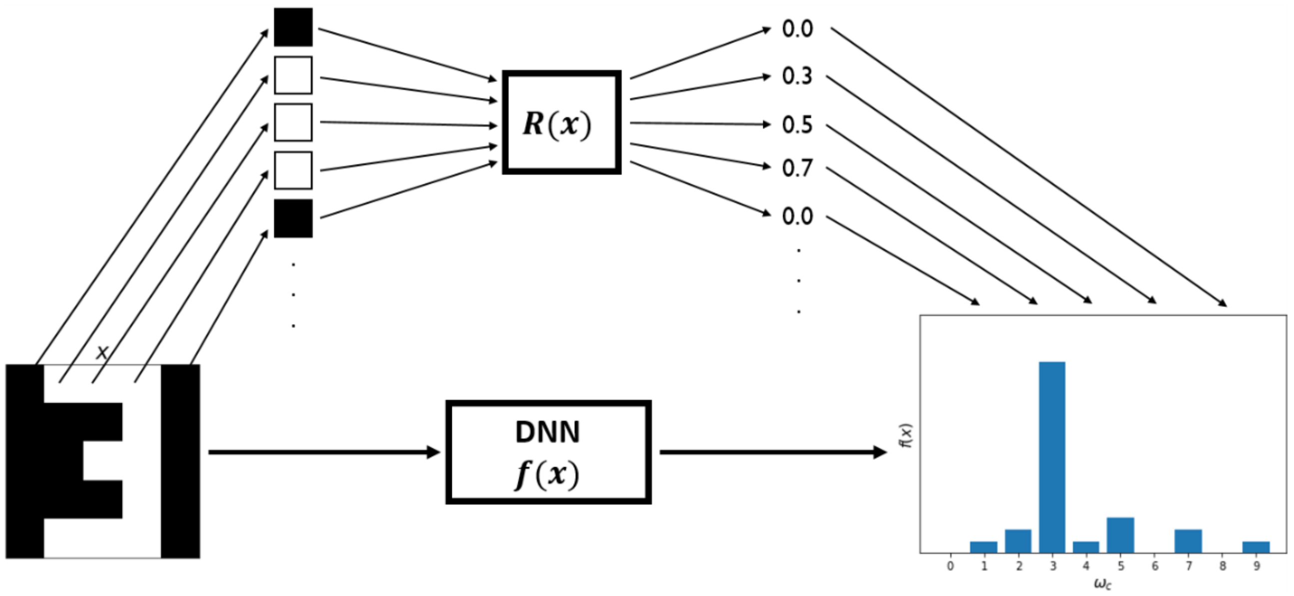
"Understanding Black-box Predictions via Influence Functions", https://arxiv.org/pdf/1703.04730.pdf
"Interpretation of Neural Networks is Fragile", https://arxiv.org/pdf/1710.10547.pdf

Types of DNN Interpretability

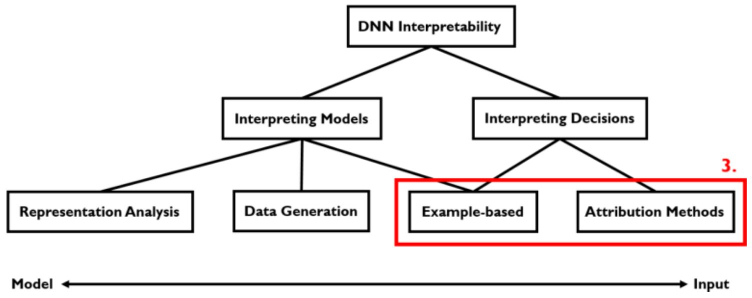


Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Given an image $\boldsymbol{x} \in \mathbb{R}^n$ and a decision $f(\boldsymbol{x})$,
assign to each pixel $\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n$ attribution values $R_1(\boldsymbol{x}), R_2(\boldsymbol{x}), \dots, R_n(\boldsymbol{x})$.

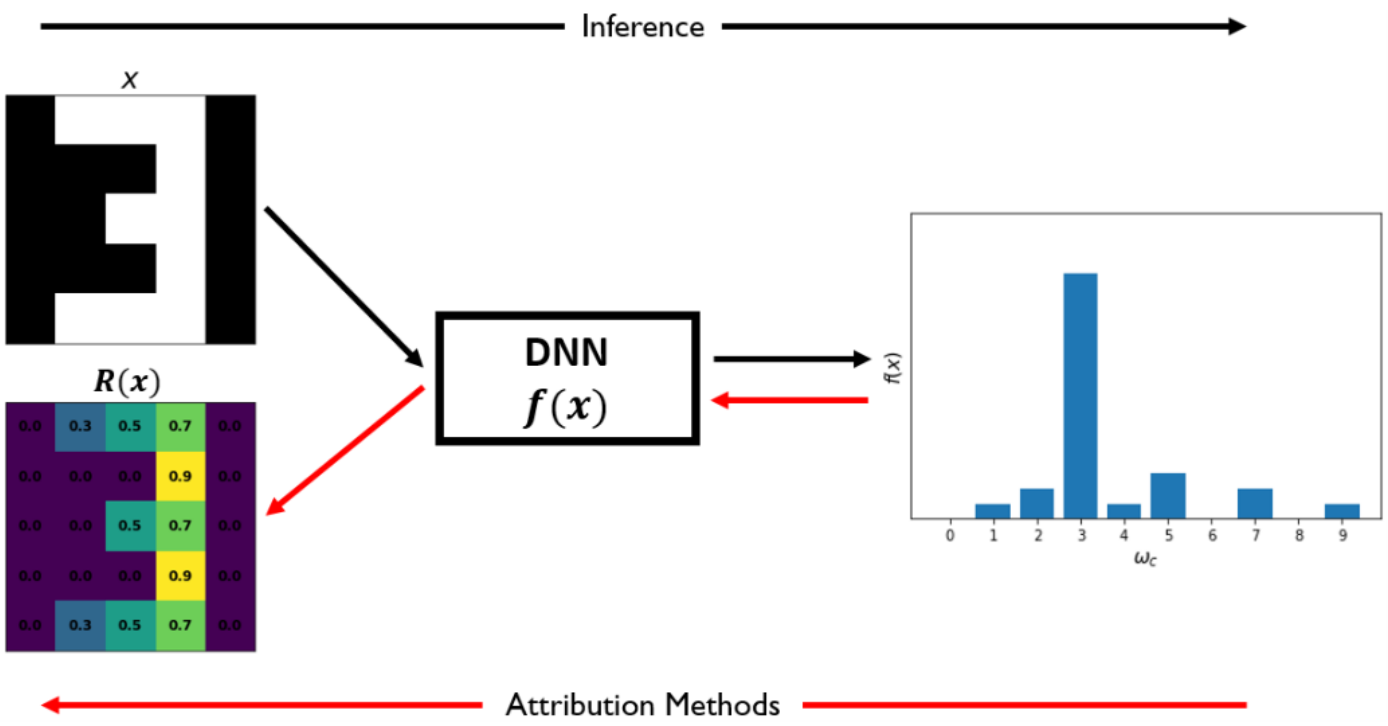


Types of DNN Interpretability

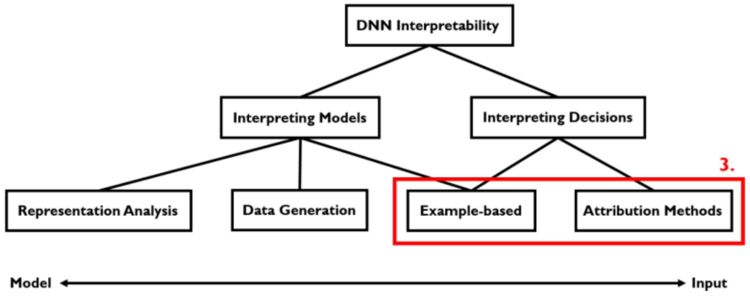


Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Usually visualized as heatmaps

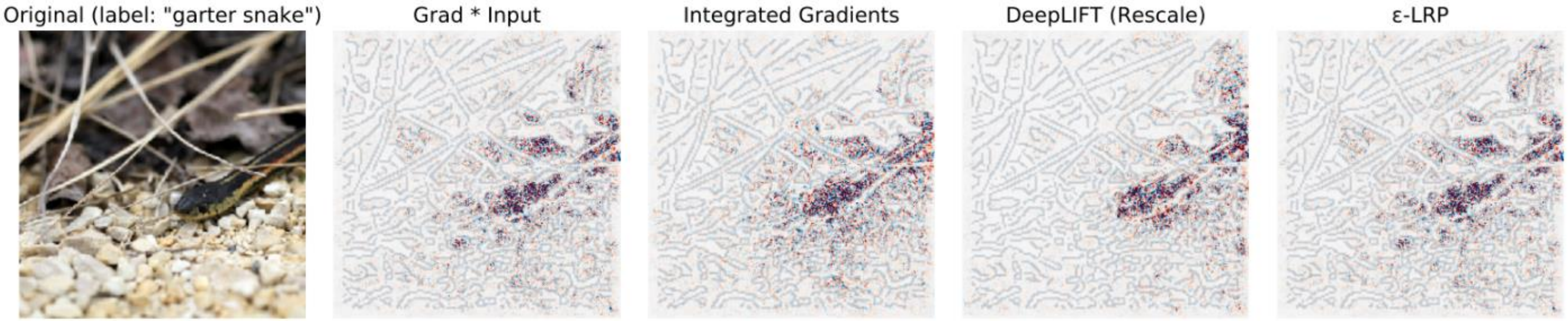


Types of DNN Interpretability



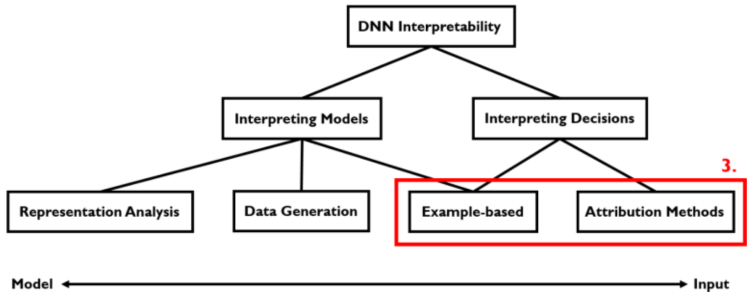
Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Usually visualized as heatmaps



"Towards better understanding of gradient-based attribution methods for Deep Neural Networks", https://arxiv.org/pdf/1711.06104.pdf

Types of DNN Interpretability



Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

The Baseline Attribution Method Saliency Map

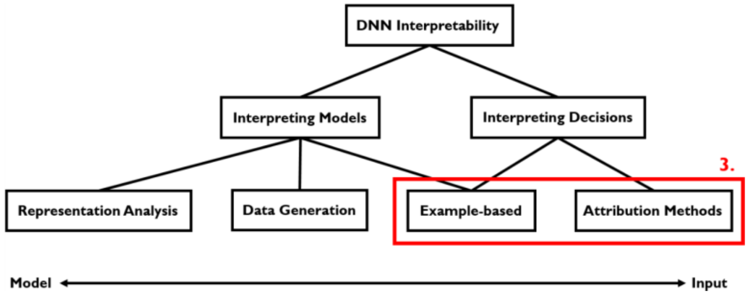
- Gradient of the decision $f(\boldsymbol{x})$ with respect to the input image $\boldsymbol{x}$:

$$Saliency(\boldsymbol{x}) \coloneqq \nabla_{\boldsymbol{x}} f(\boldsymbol{x}) = \frac{\partial f(\boldsymbol{x})}{\partial \boldsymbol{x}}$$

- Can be calculated through backpropagation.

"Deep Inside Convolutional Networks: Visualizing Image Classification Models and Saliency Maps", https://arxiv.org/pdf/1312.6034.pdf

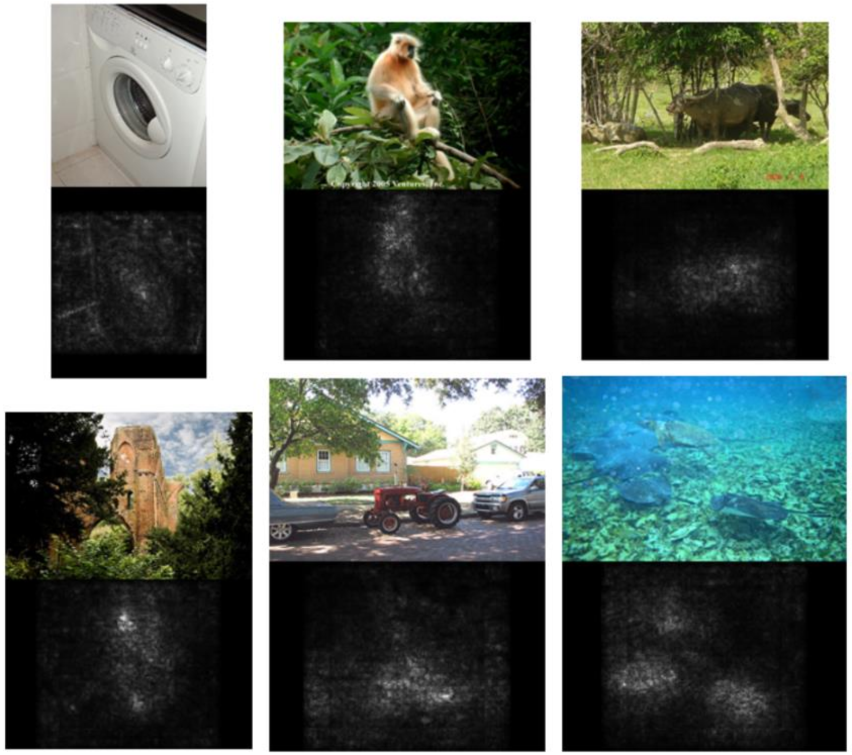
Types of DNN Interpretability



Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

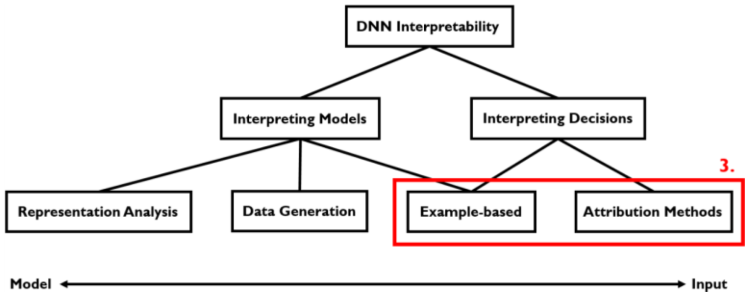
The Baseline Attribution Method Saliency Map

- Saliency maps are very noisy!
- Only roughly correlated with the object(s) of interest.



"Deep Inside Convolutional Networks: Visualizing Image Classification Models and Saliency Maps", https://arxiv.org/pdf/1312.6034.pdf

Types of DNN Interpretability

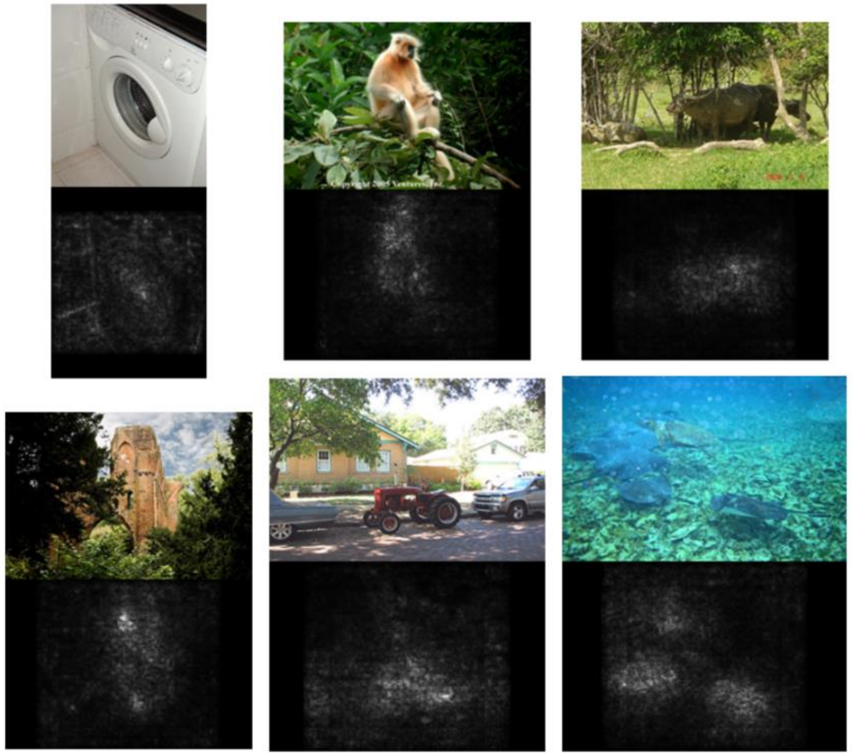


Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

The Baseline Attribution Method Saliency Map

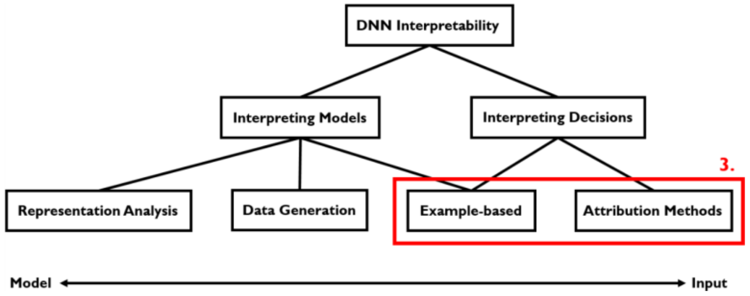
- Saliency maps are very noisy!
- Only roughly correlated with the object(s) of interest.

Question: How to improve saliency maps?



"Deep Inside Convolutional Networks: Visualizing Image Classification Models and Saliency Maps", https://arxiv.org/pdf/1312.6034.pdf

Types of DNN Interpretability



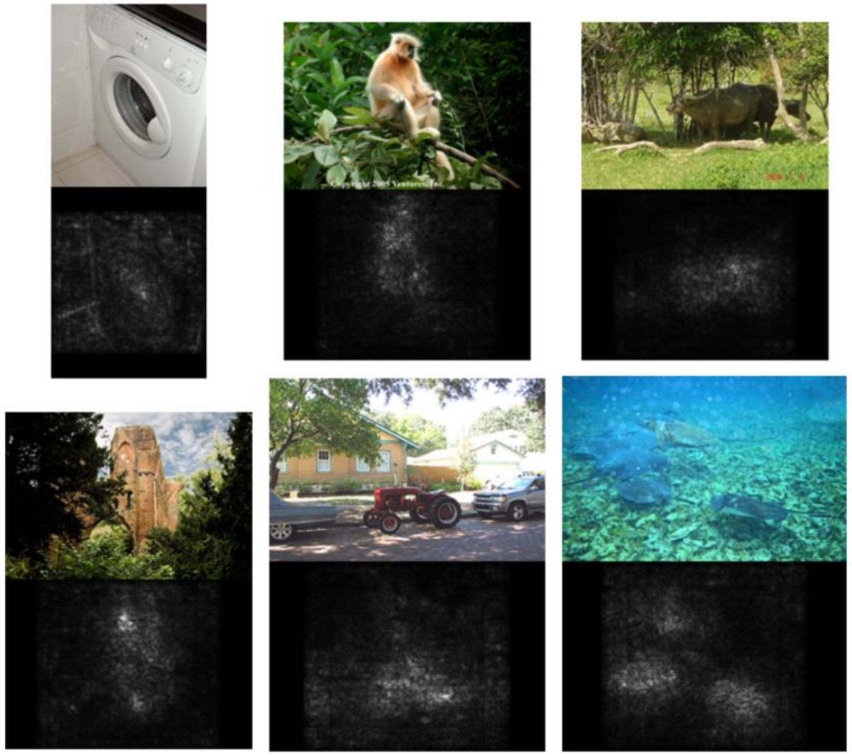
Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

The Baseline Attribution Method Saliency Map

- Saliency maps are very noisy!
- Only roughly correlated with the object(s) of interest.

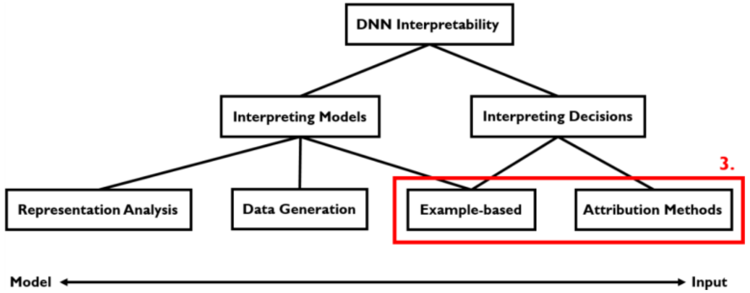
Question: How to improve saliency maps?

Question: Why are saliency maps noisy?



“Deep Inside Convolutional Networks: Visualizing Image Classification Models and Saliency Maps”, https://arxiv.org/pdf/1312.6034.pdf

Types of DNN Interpretability

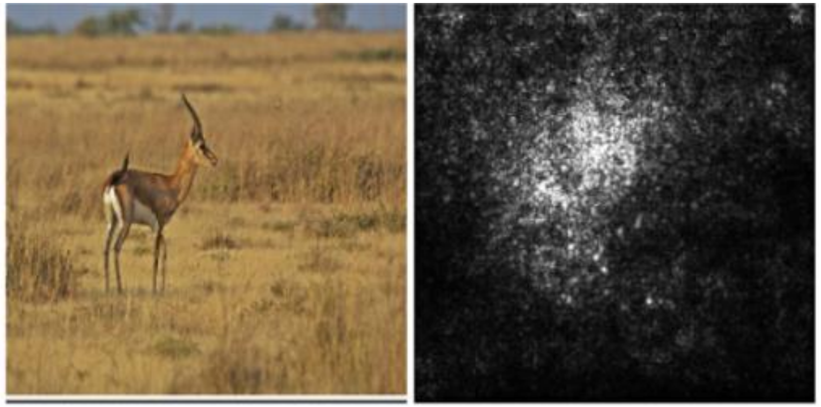


Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Question: Why are saliency maps noisy?

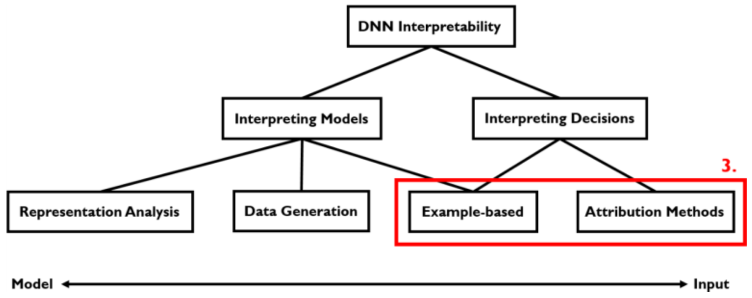
Hypothesis 1 – Saliency maps are truthful

- Certain pixels scattered randomly across the image are central to how the network is making a decision.
- Noise is important!



"SmoothGrad: removing noisy by adding noise", https://arxiv.org/pdf/1706.03825.pdf

Types of DNN Interpretability



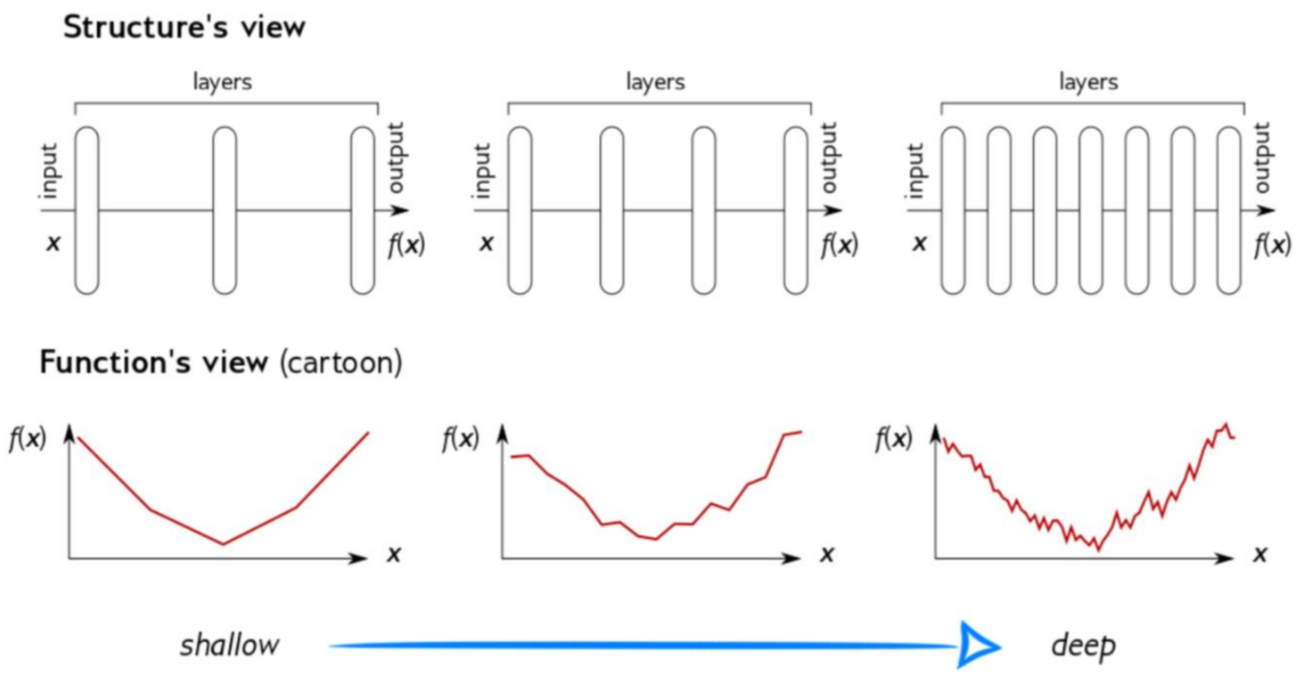
Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Question: Why are saliency maps noisy?

Hypothesis 2 – Gradients are discontinuous

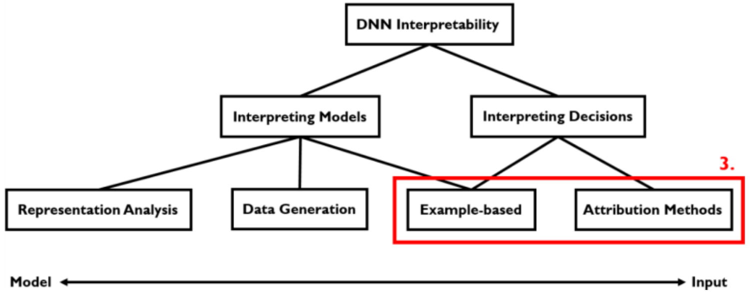
- DNN uses piecewise-linear functions (ReLU activation, max-pooling, etc.).

- Sudden jumps in the importance score over infinitesimal changes in the input.



"SmoothGrad: removing noisy by adding noise", https://arxiv.org/pdf/1706.03825.pdf

Types of DNN Interpretability



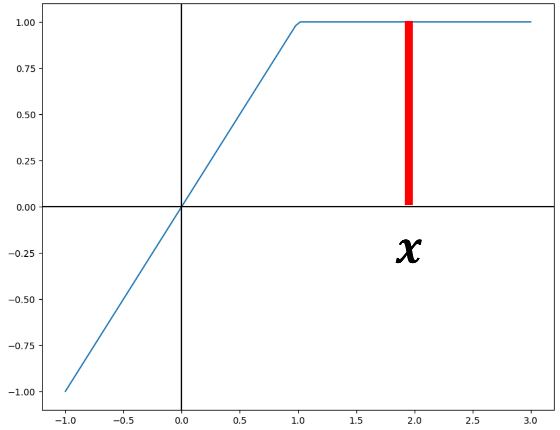
Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Question: Why are saliency maps noisy?

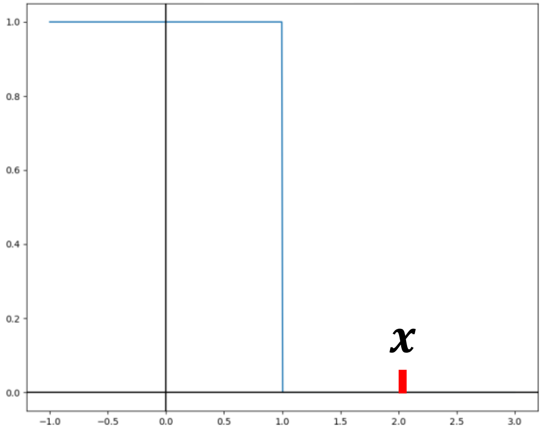
Hypothesis 3 – $f(x)$ saturates

- A feature may have a strong effect globally, but with a small derivative locally.

$f(x)$

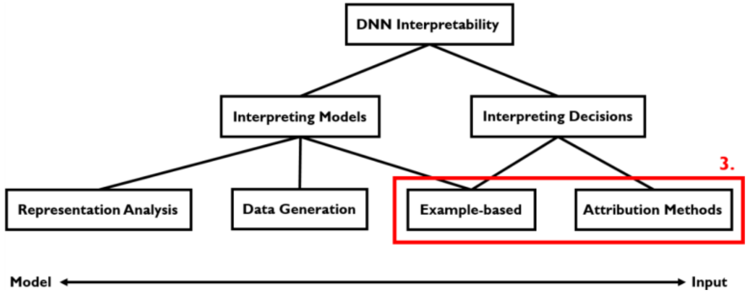


$f'(x)$



"Axiomatic Attribution for Deep Networks", https://arxiv.org/pdf/1703.01365.pdf

Types of DNN Interpretability



Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Question: How to improve saliency maps?

$$Saliency(\boldsymbol{x}) := \nabla_{\boldsymbol{x}} f(\boldsymbol{x}) = \frac{\partial f(\boldsymbol{x})}{\partial \boldsymbol{x}}$$

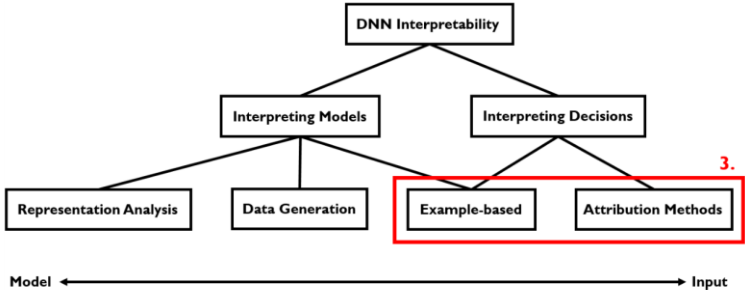
Gradient-based Methods

- Perturb the input $\boldsymbol{x}$ to $\boldsymbol{x}^*$ and use $\nabla_{\boldsymbol{x}^*} f(\boldsymbol{x}^*)$.
- Some methods take the average over the perturbation set $\{\boldsymbol{x}_1^*, \boldsymbol{x}_2^*, \ldots, \boldsymbol{x}_n^*\}$.

Backprop-based Methods

- Modify the backpropagation algorithm.

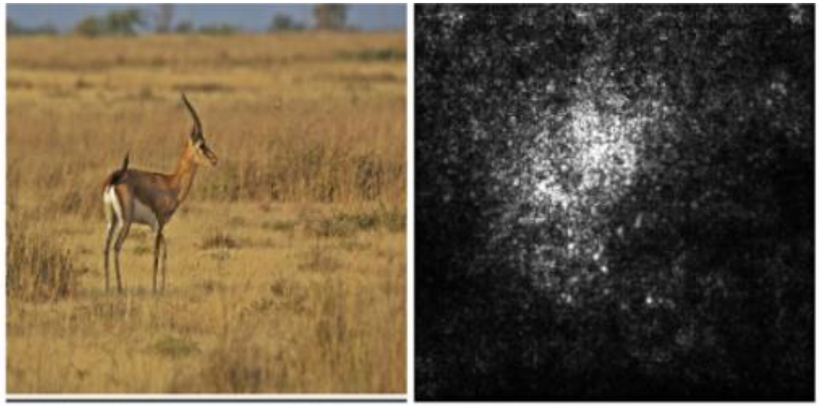
Types of DNN Interpretability



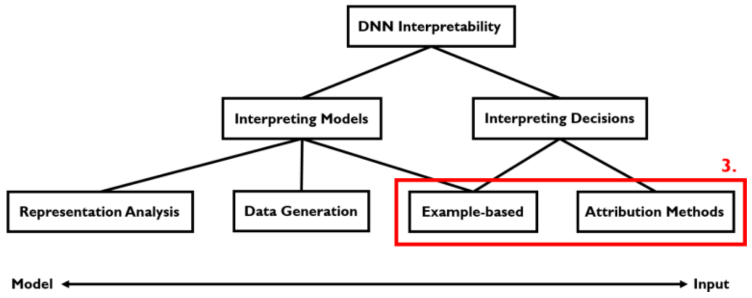
Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Summary

- Attribution method assigns "attribution score" to each input pixel.
- Baseline attribution method Saliency Map is noisy.
- Hypothesis 1: Saliency maps are truthful.
- Hypothesis 2: Gradients are discontinuous.
- Hypothesis 3: $f(x)$ saturates.
- Two solution approaches: Gradient based method and Backprop. based method.



Types of DNN Interpretability

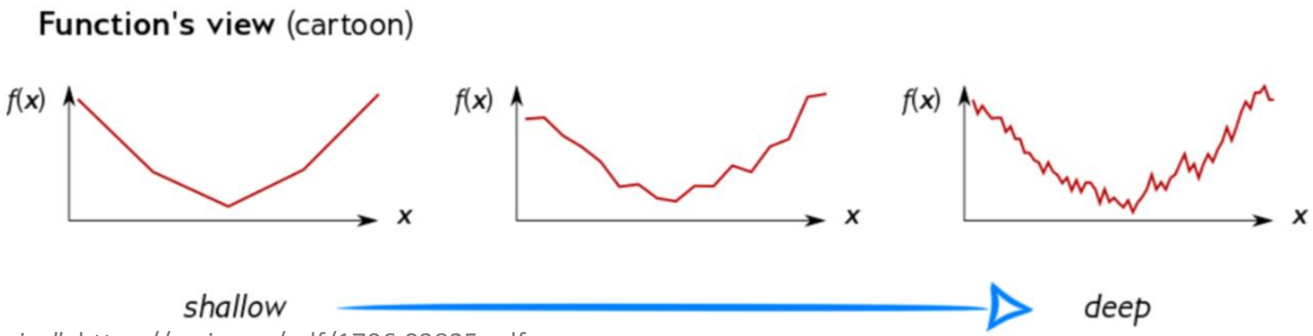


Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

1. SmoothGrad *Hypothesis 2 – Gradients are discontinuous*

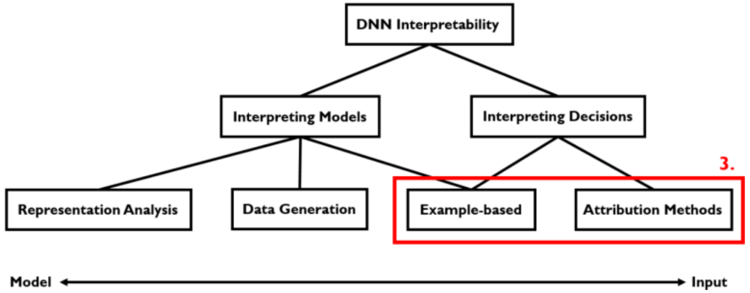
$$SmoothGrad(\boldsymbol{x}) := \frac{1}{n}\sum_{1}^{n}\frac{\partial f(\boldsymbol{x}^*)}{\partial \boldsymbol{x}^*}, \quad \boldsymbol{x}^* = \boldsymbol{x} + \mathcal{N}(0, \sigma^2)$$

Gaussian smoothing



"SmoothGrad: removing noisy by adding noise", https://arxiv.org/pdf/1706.03825.pdf

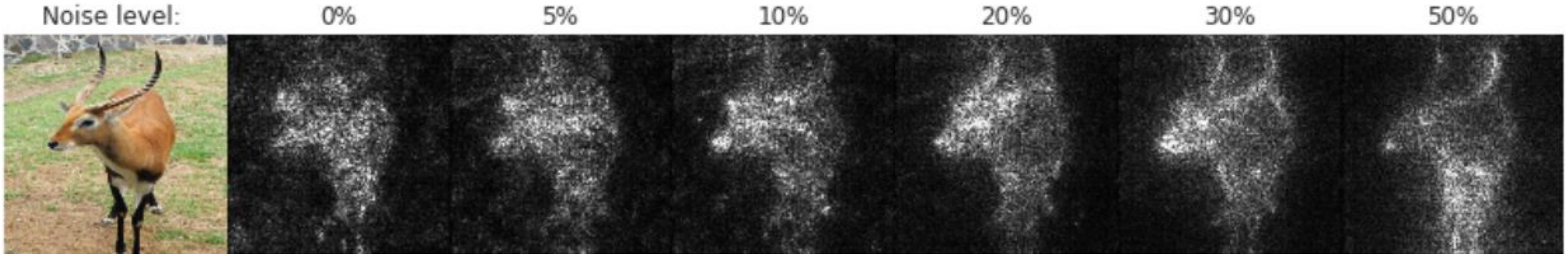
Types of DNN Interpretability



Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

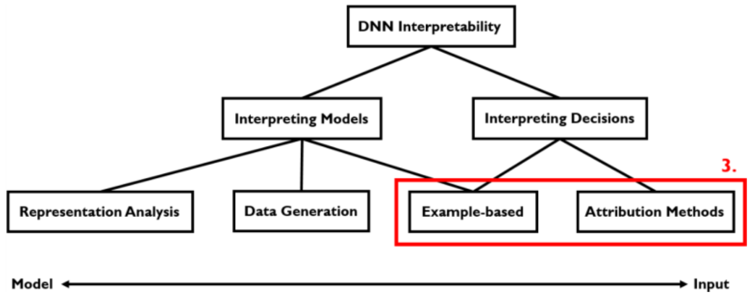
1. SmoothGrad *Hypothesis 2 – Gradients are discontinuous*

$$SmoothGrad(\boldsymbol{x}) \coloneqq \frac{1}{n}\sum_{1}^{n}\frac{\partial f(\boldsymbol{x}^*)}{\partial \boldsymbol{x}^*}, \quad \boldsymbol{x}^* = \boldsymbol{x} + \mathcal{N}(0,\sigma^2)$$



“SmoothGrad: removing noisy by adding noise”, https://arxiv.org/pdf/1706.03825.pdf

Types of DNN Interpretability

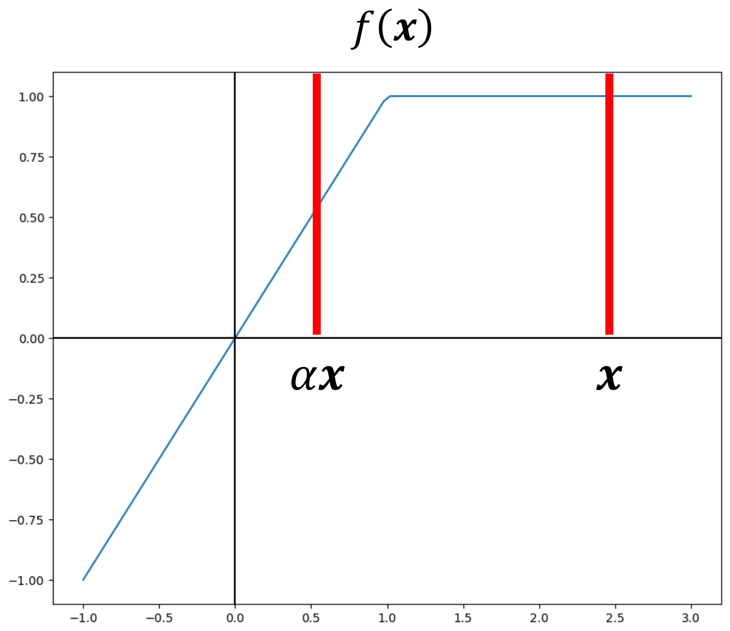


Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

2. Interior Gradient *Hypothesis 3 – $f(\boldsymbol{x})$ saturates*

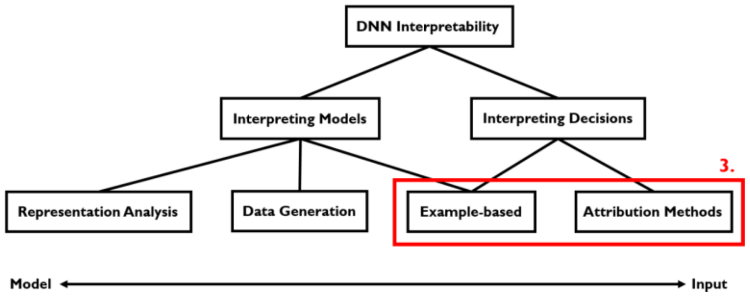
$$IntGrad(\boldsymbol{x}) := \frac{\partial f(\boldsymbol{x}^*)}{\partial \boldsymbol{x}^*}, \quad \boldsymbol{x}^* = \alpha \boldsymbol{x}, \quad 0 < \alpha \leq 1$$

- Appropriate α will trigger informative activation functions



"Gradients of Counterfactuals", https://arxiv.org/pdf/1611.02639.pdf

Types of DNN Interpretability



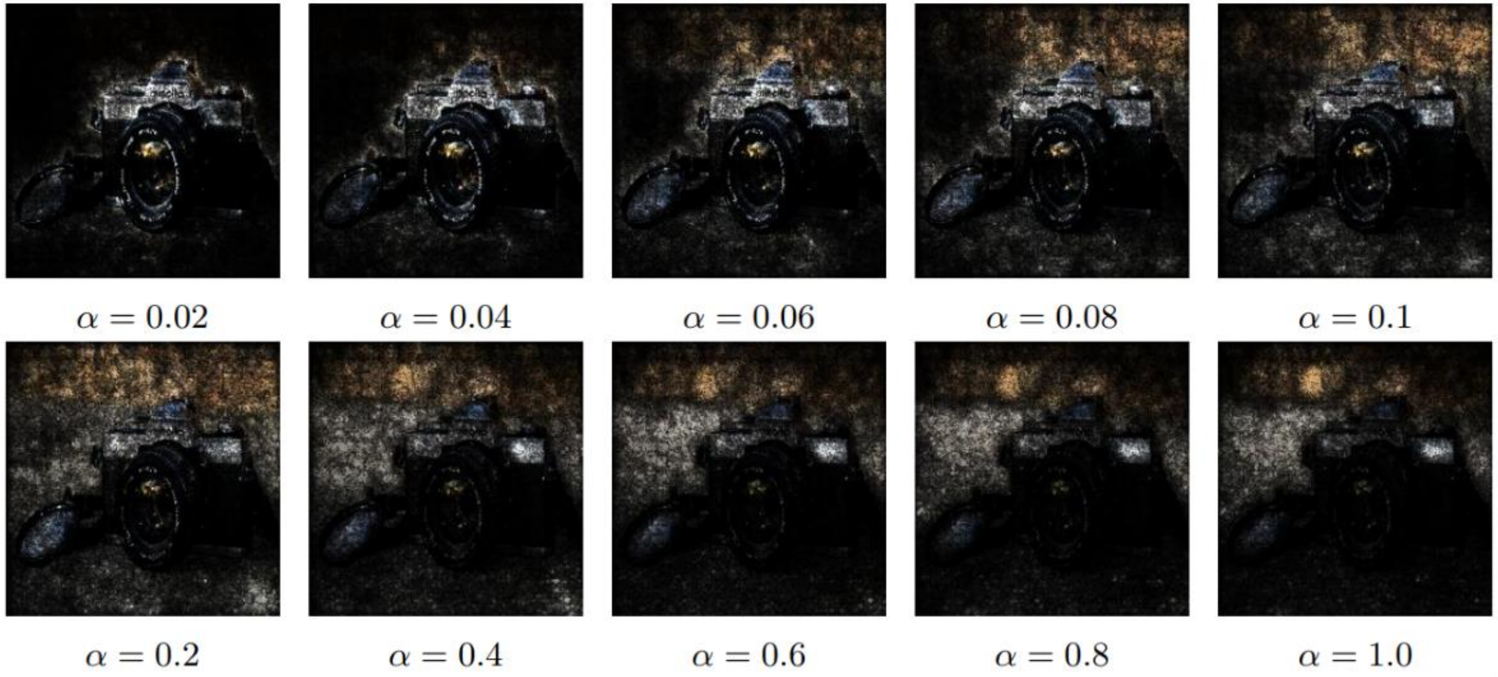
Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

2. Interior Gradient

$$IntGrad(\boldsymbol{x}) := \frac{\partial f(\boldsymbol{x}^*)}{\partial \boldsymbol{x}^*},$$

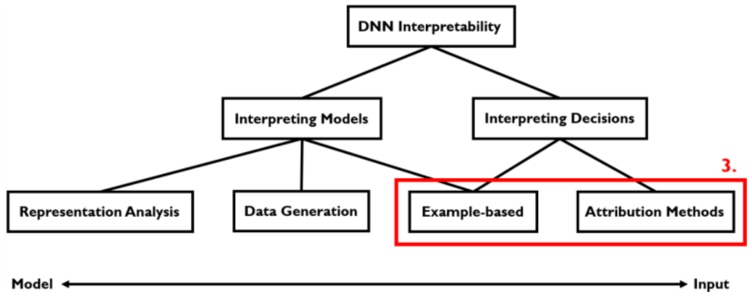
$$\boldsymbol{x}^* = \alpha \boldsymbol{x},$$

$$0 < \alpha \leq 1$$



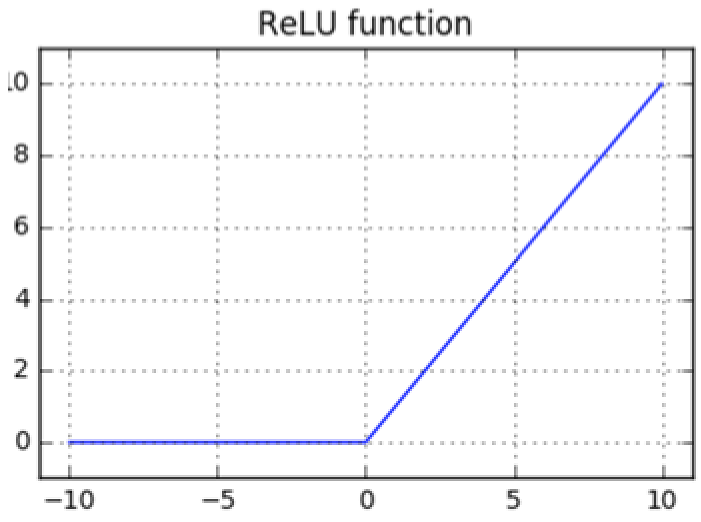
"Gradients of Counterfactuals", https://arxiv.org/pdf/1611.02639.pdf

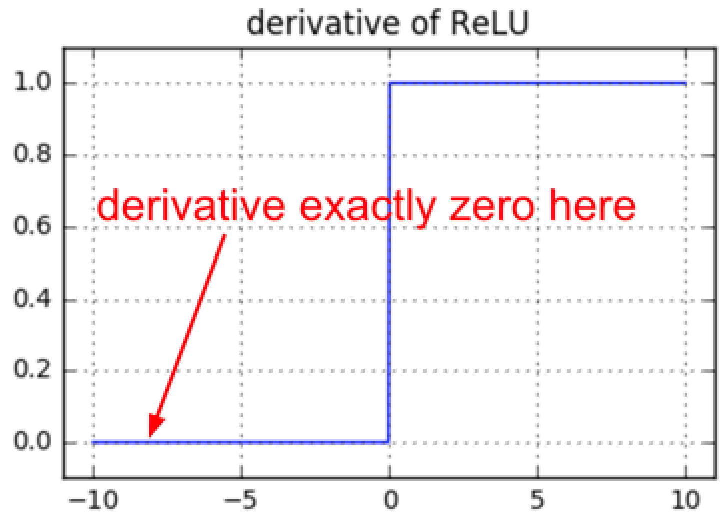
Types of DNN Interpretability



Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Review: Backpropagation at ReLU



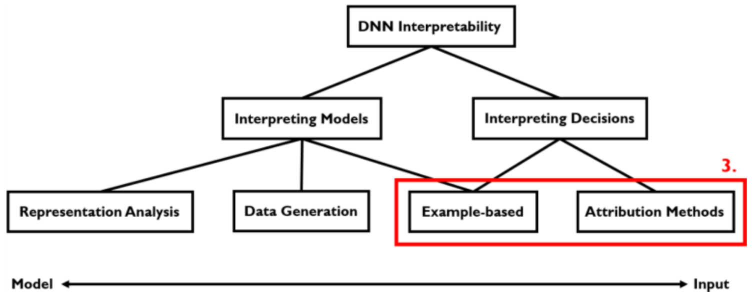


$$ReLU(z) = \max(0, z)$$

$$ReLU'^{(z)} = (z > 0)$$

“Striving for Simplicity: The All Convolutional Net”, https://arxiv.org/pdf/1412.6806.pdf

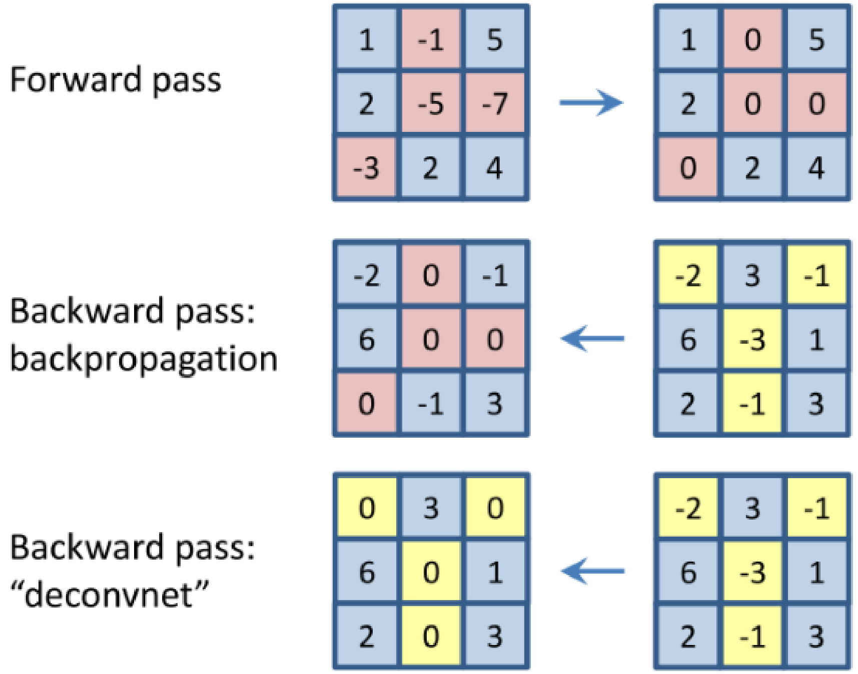
Types of DNN Interpretability



Example-based | Attribution Methods | Gradient Based | **Backprop. Based**

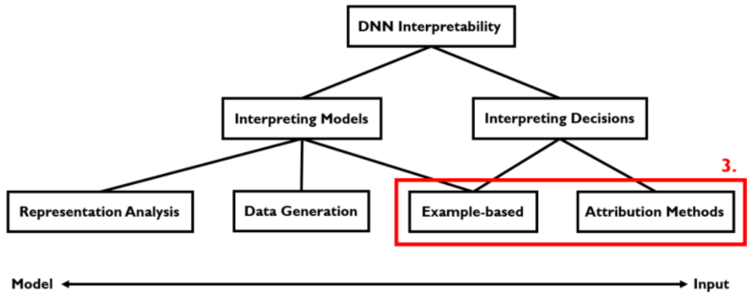
1. Deconvnet

- Maps feature pattern to input space (image reconstruction)
- To obtain valid feature reconstruction, pass the reconstructed signal through ReLUs
- Removing noise by removing negative gradient



"Visualizing and Understanding Convolutional Networks", https://arxiv.org/pdf/1311.2901.pdf

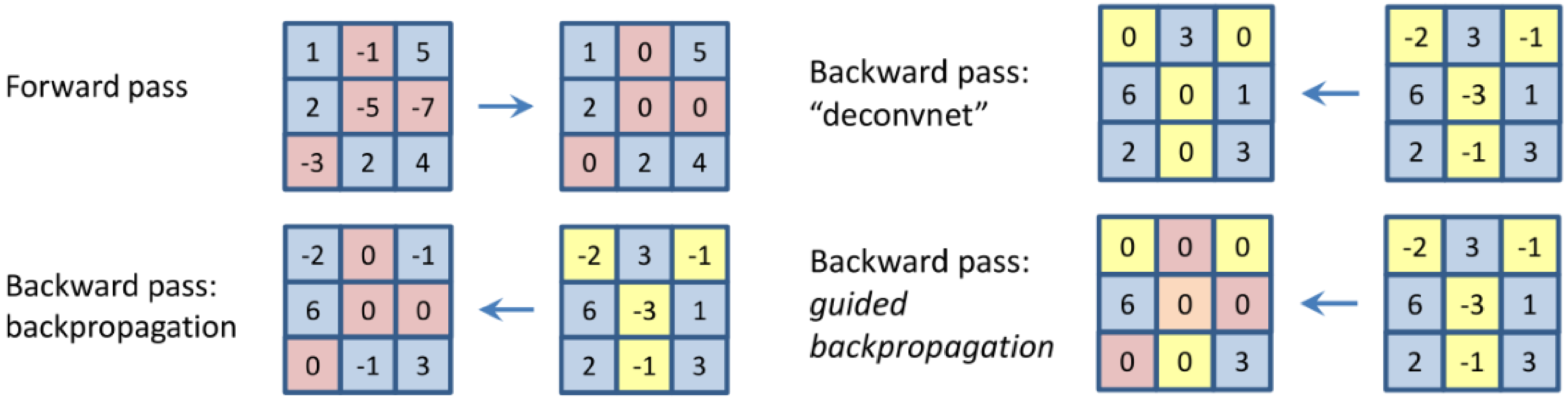
Types of DNN Interpretability



Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

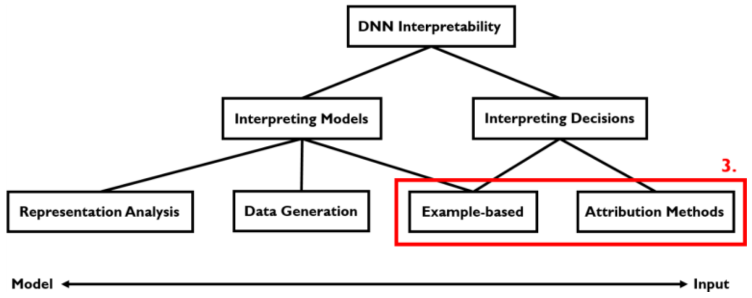
2. Guided Backpropagation

- Combine Deconvnet with Backpropagation
- Removing negative gradient + consider forward activations

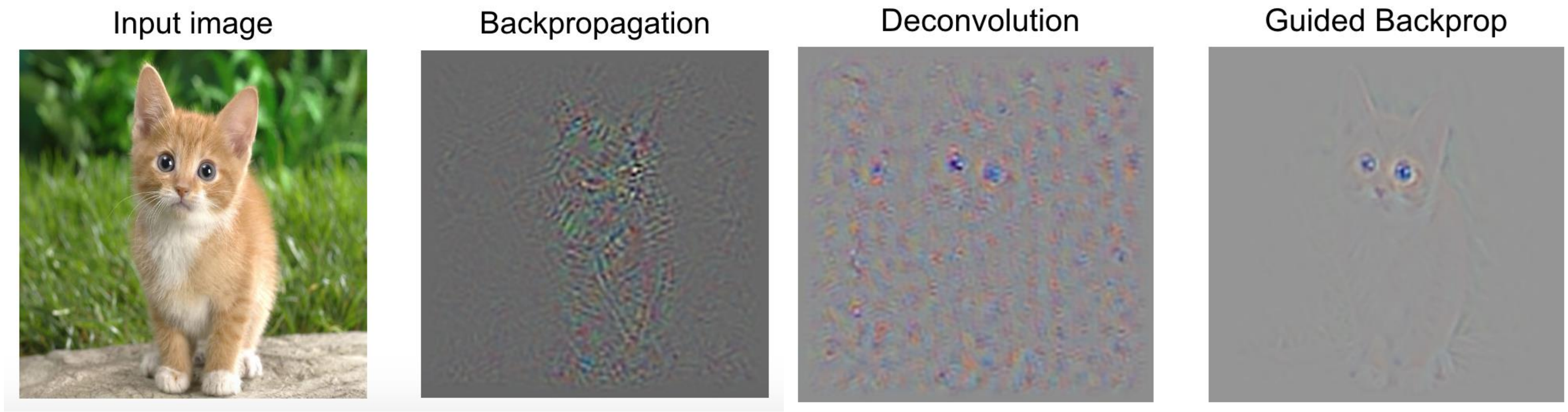


"Striving for Simplicity: The All Convolutional Net", https://arxiv.org/pdf/1412.6806.pdf

Types of DNN Interpretability

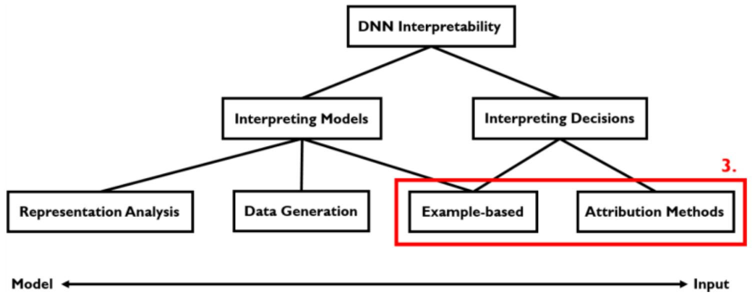


Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**



Observation: Removing more gradient leads to sharper visualizations

Types of DNN Interpretability



Example-based | **Attribution Methods** | **Gradient Based** | **Backprop. Based**

Other Attribution Methods

- Gradient * Input – https://arxiv.org/pdf/1704.02685.pdf
- Integrated Gradient – https://arxiv.org/pdf/1703.01365.pdf
- Layer-wise Relevance Propagation – https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0130140
- Deep Taylor Decomposition – https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0130140
- DeepLIFT – https://arxiv.org/pdf/1704.02685.pdf
- PatternNet and PatternAttribution – https://arxiv.org/pdf/1705.05598.pdf

Part 2 Summary

1. Interpreting Models vs. Interpreting Decisions

- Interpreting models: macroscopic view, better understand internal representations
- Interpreting decision: microscopic view, important for practical applications

2. Interpreting Models

- Weight visualization
- Surrogate model
- Activation maximization
- Example-based

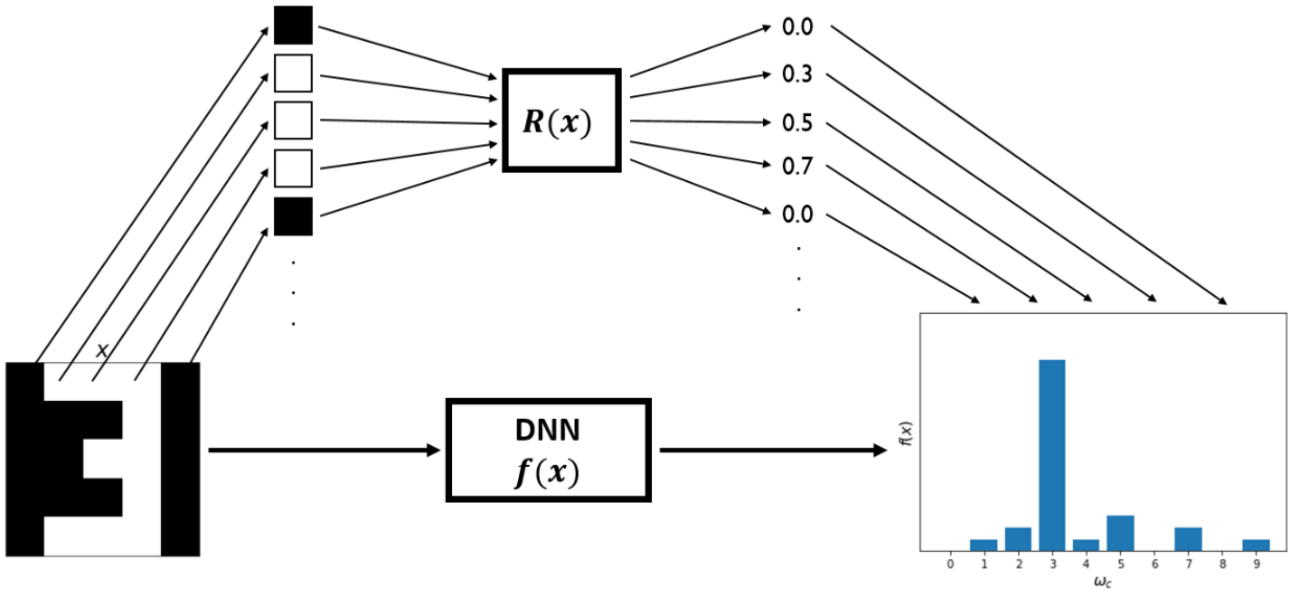
3. Interpreting Decisions

- Example-based
- Attribution Methods: why are gradients noisy?
- Gradient based Attribution Methods: SmoothGrad, Interior Gradient
- Backprop. based Attribution Methods: Deconvolution, Guided Backpropagation

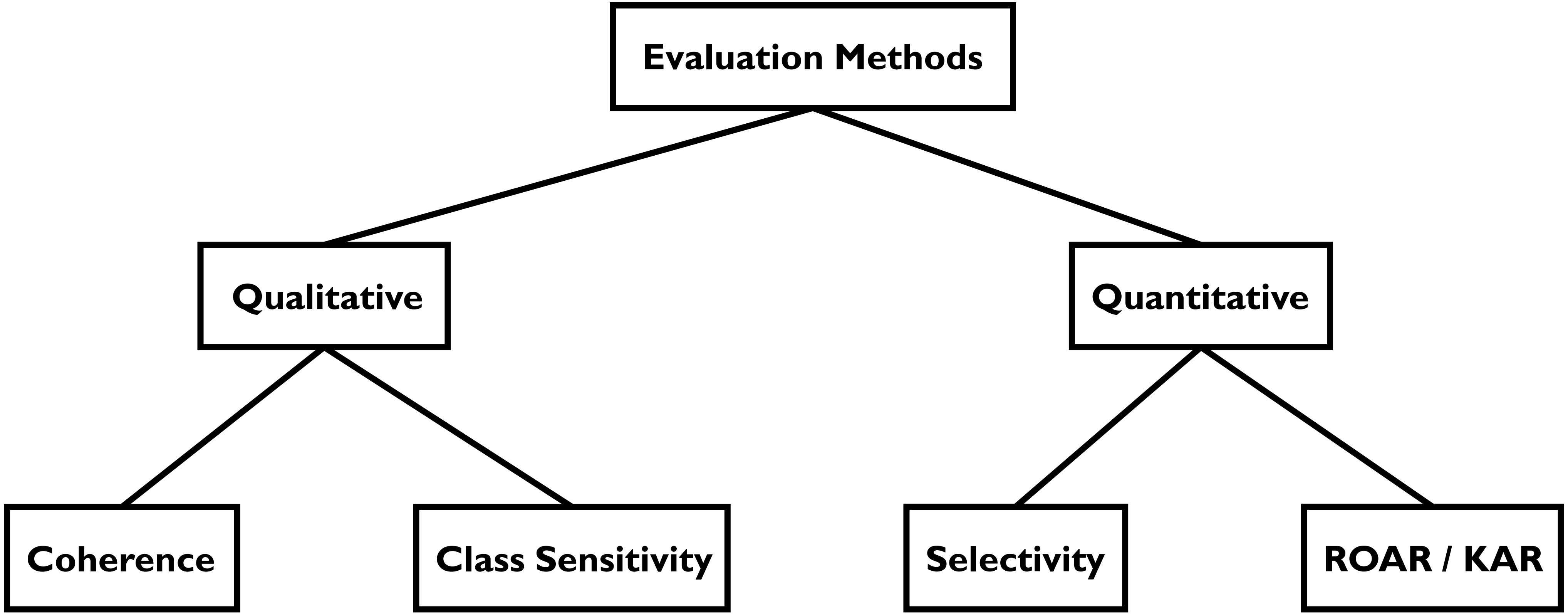
Part 3 – Evaluating Attribution Methods

Attribution Method Review

Given an image $\boldsymbol{x} \in \mathbb{R}^n$ and a decision $f(\boldsymbol{x})$,
assign to each pixel $\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n$ attribution values $R_1(\boldsymbol{x}), R_2(\boldsymbol{x}), \dots, R_n(\boldsymbol{x})$.



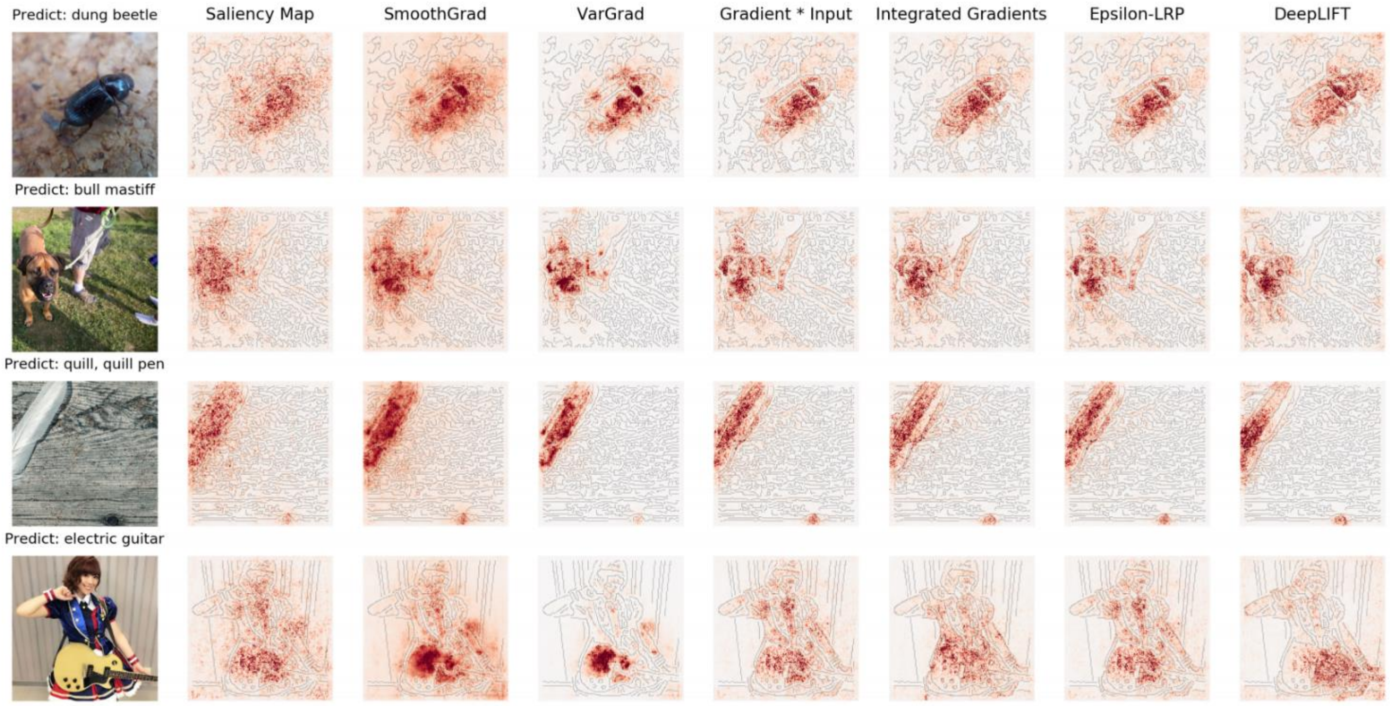
Evaluating Attribution Methods



Evaluating Attribution Methods

Coherence | **Class Sensitivity** | **Selectivity** | **ROAR / KAR**

- Attributions should fall on discriminative features (e.g. the object of interest)

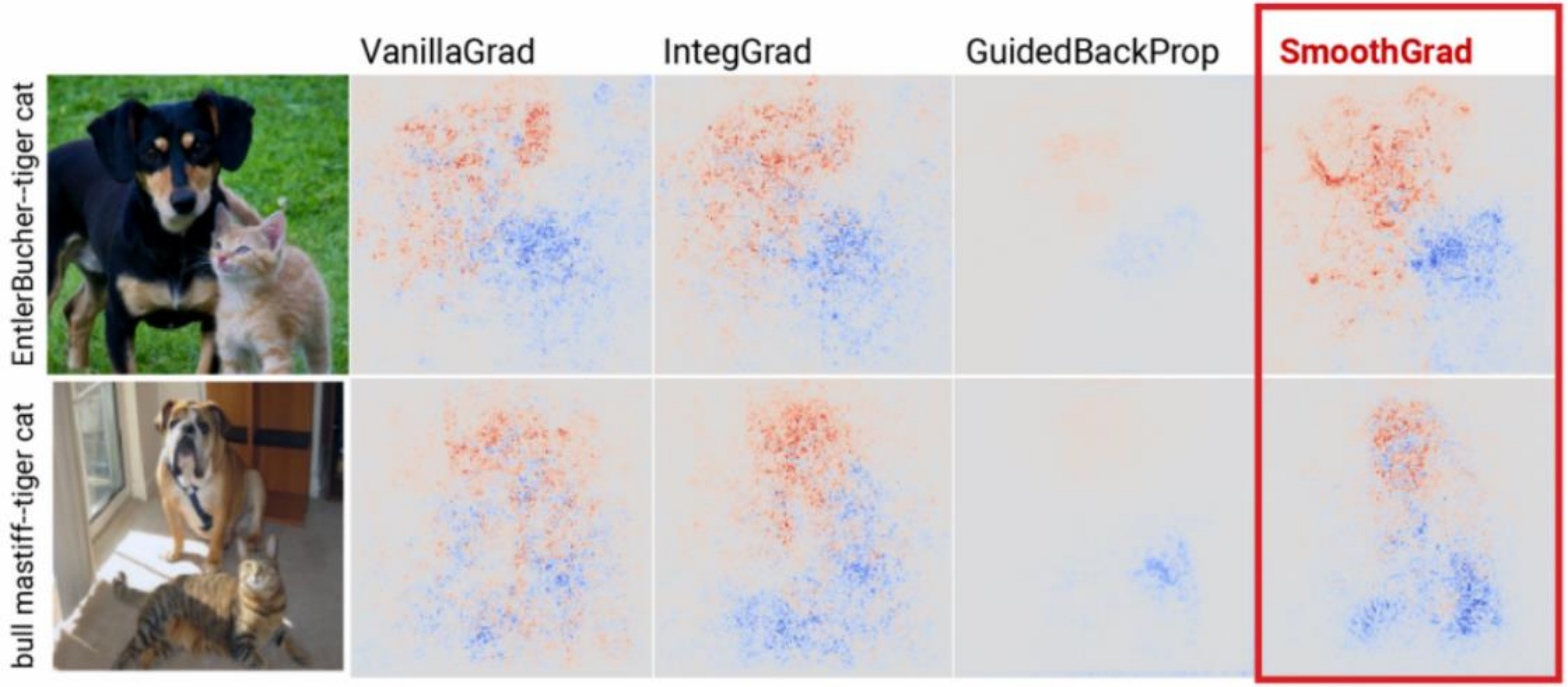


“Noise-adding Methods of Saliency Maps as Series of Higher Order Partial Derivative”, https://arxiv.org/pdf/1806.03000.pdf

Evaluating Attribution Methods

Coherence | **Class Sensitivity** | **Selectivity** | **ROAR / KAR**

- Attributions should be sensitive to class labels



"SmoothGrad: removing noisy by adding noise", https://arxiv.org/pdf/1706.03825.pdf

Evaluating Attribution Methods

Coherence | **Class Sensitivity** | **Selectivity** | **ROAR / KAR**

- Removing feature with high attribution should cause large decrease in class probability

Algorithm

Sort pixel attribution values $R_i(\boldsymbol{x})$

Iterate:

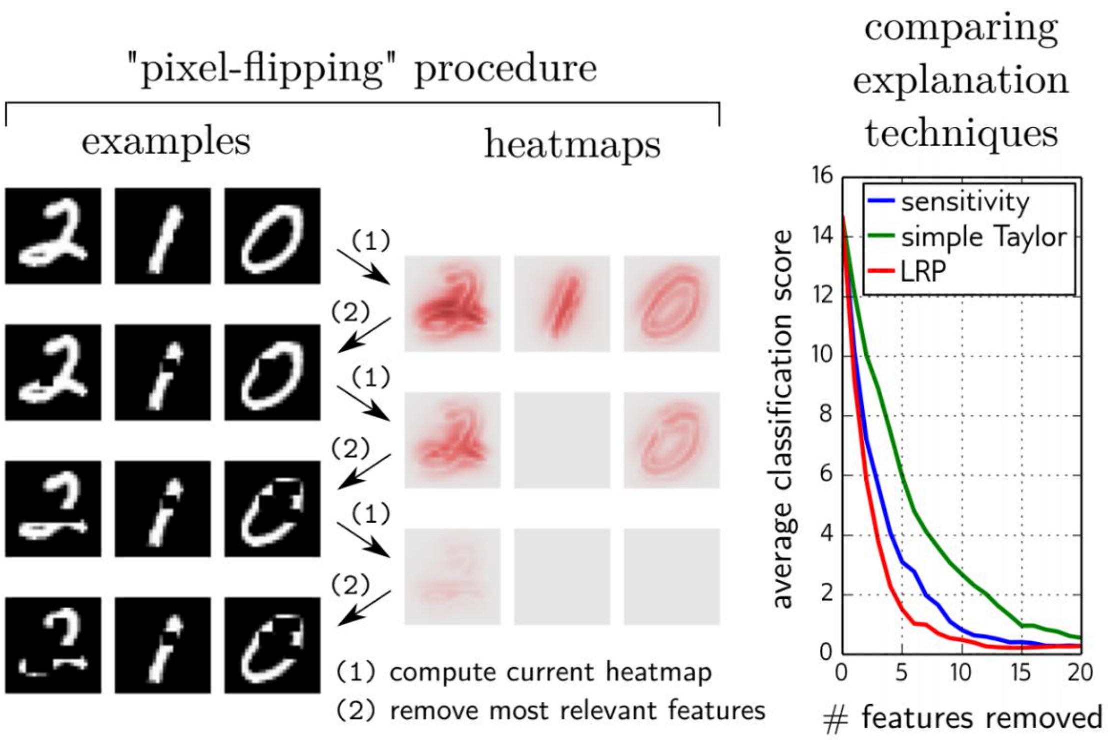
  Remove pixels

  Evaluate $f(\boldsymbol{x})$

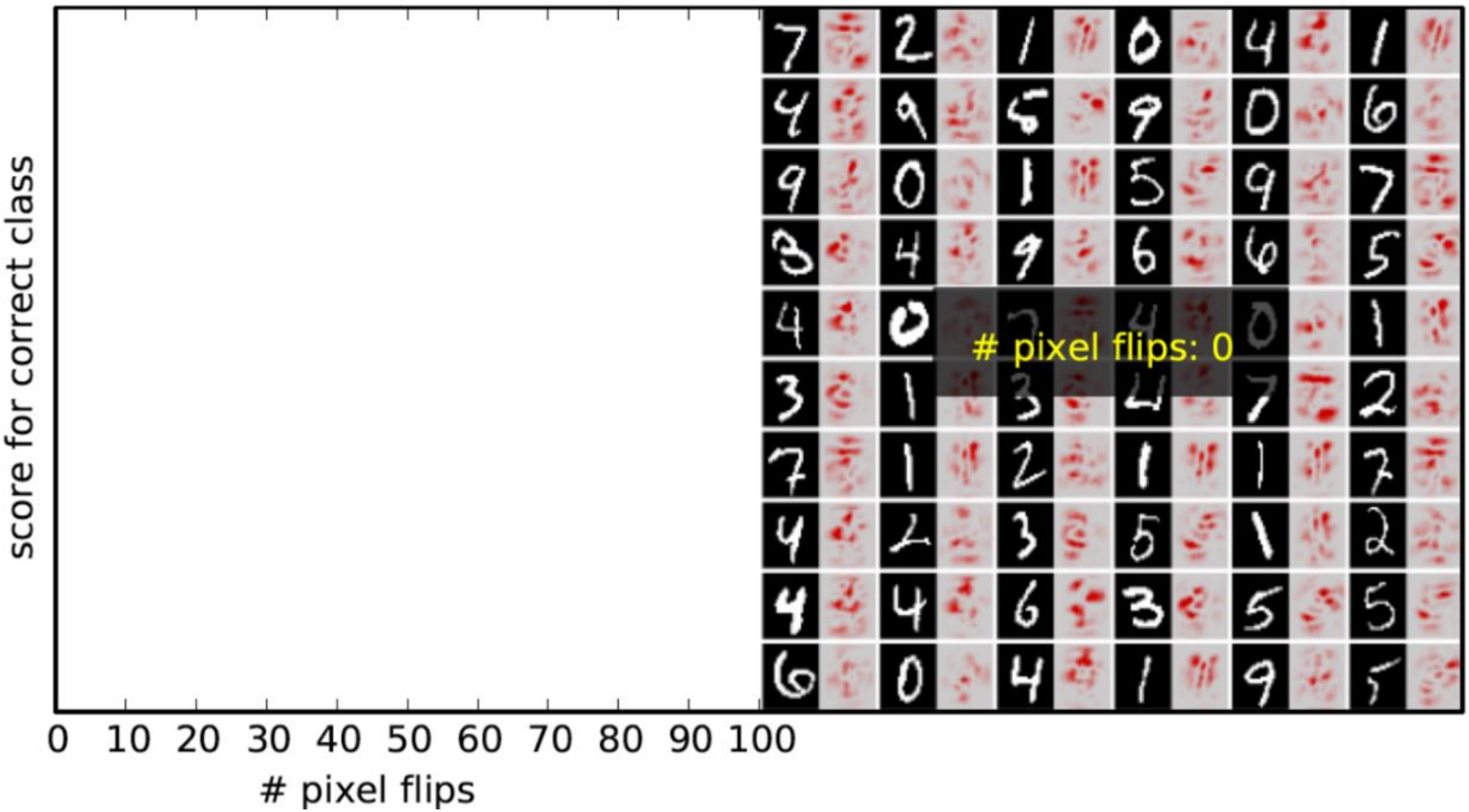
Measure decrease of $f(\boldsymbol{x})$

Evaluating Attribution Methods

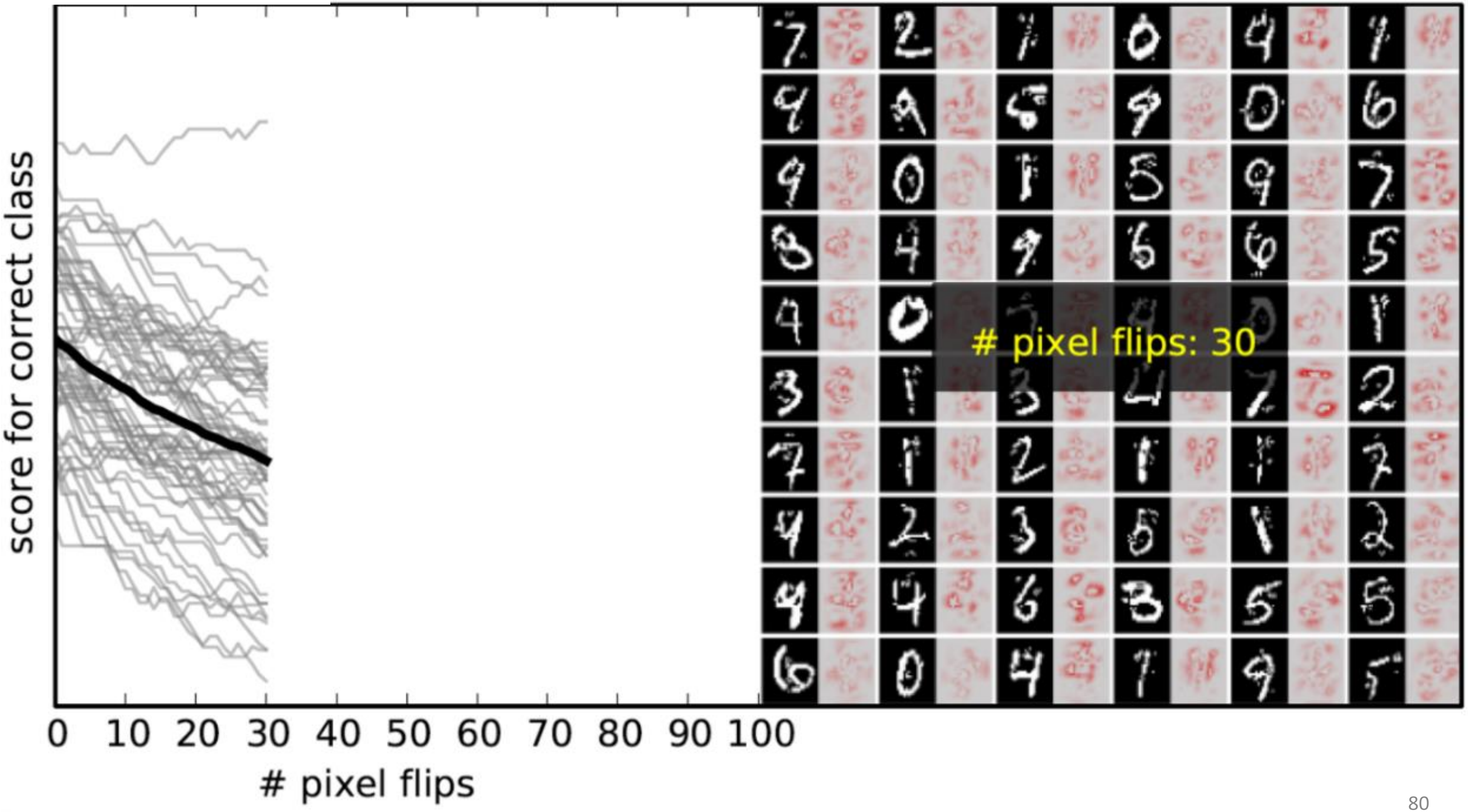
Coherence | **Class Sensitivity** | **Selectivity** | **ROAR / KAR**



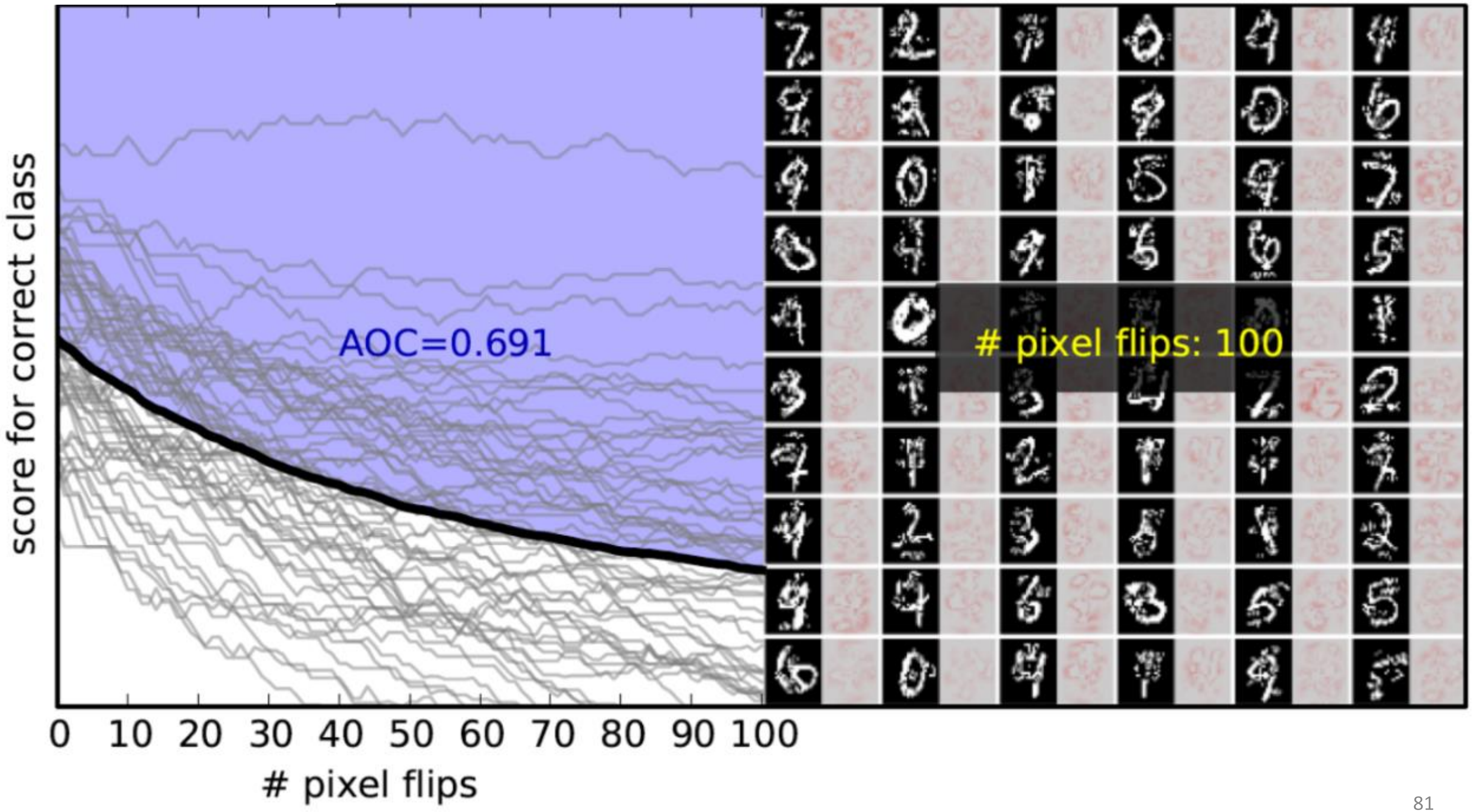
Selectivity on Saliency Map



Selectivity on Saliency Map



Selectivity on Saliency Map



Evaluating Attribution Methods

Coherence | **Class Sensitivity** | **Selectivity** | **ROAR / KAR**

- Sensitivity may not be accurate
- Class probability may decrease because the DNN has never seen such image

Remove and Retrain (ROAR) / **Keep and Retrain** (KAR)

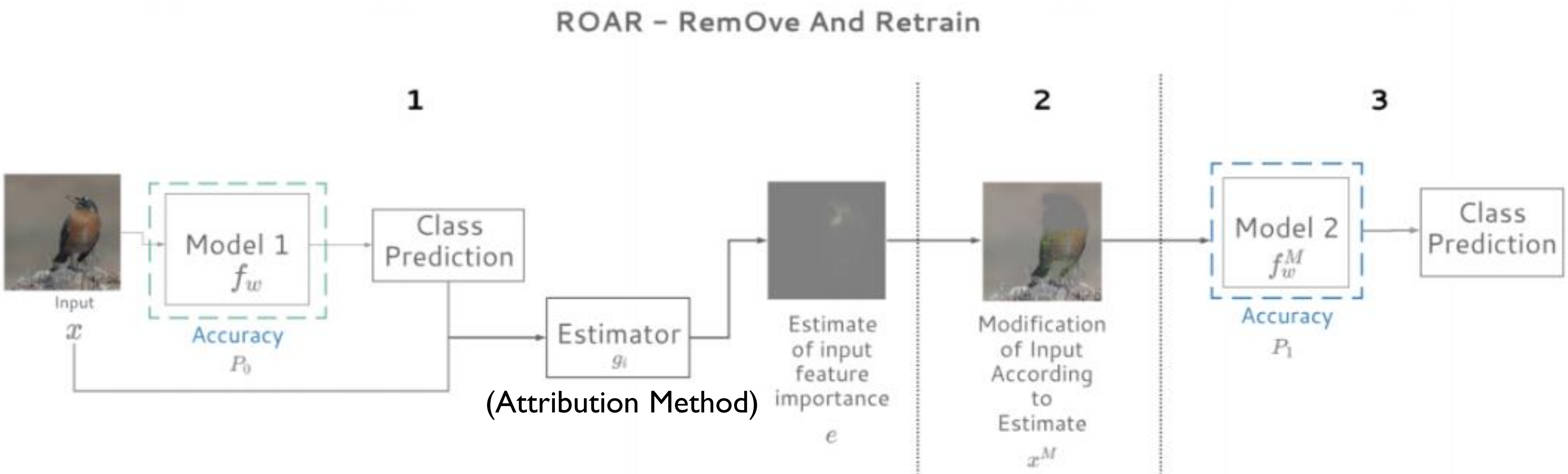
Measure how the performance of the classifier changes as features are removed based on the attribution method

- ROAR: replace $N\%$ of pixels estimated to be *most* important
- KAR: replace $N\%$ of pixels estimated to be *least* important
- Retrain DNN and measure change in test accuracy

"Evaluating Feature Importance Estimates", https://arxiv.org/pdf/1806.10758.pdf

Evaluating Attribution Methods

Coherence | **Class Sensitivity** | **Selectivity** | **ROAR / KAR**

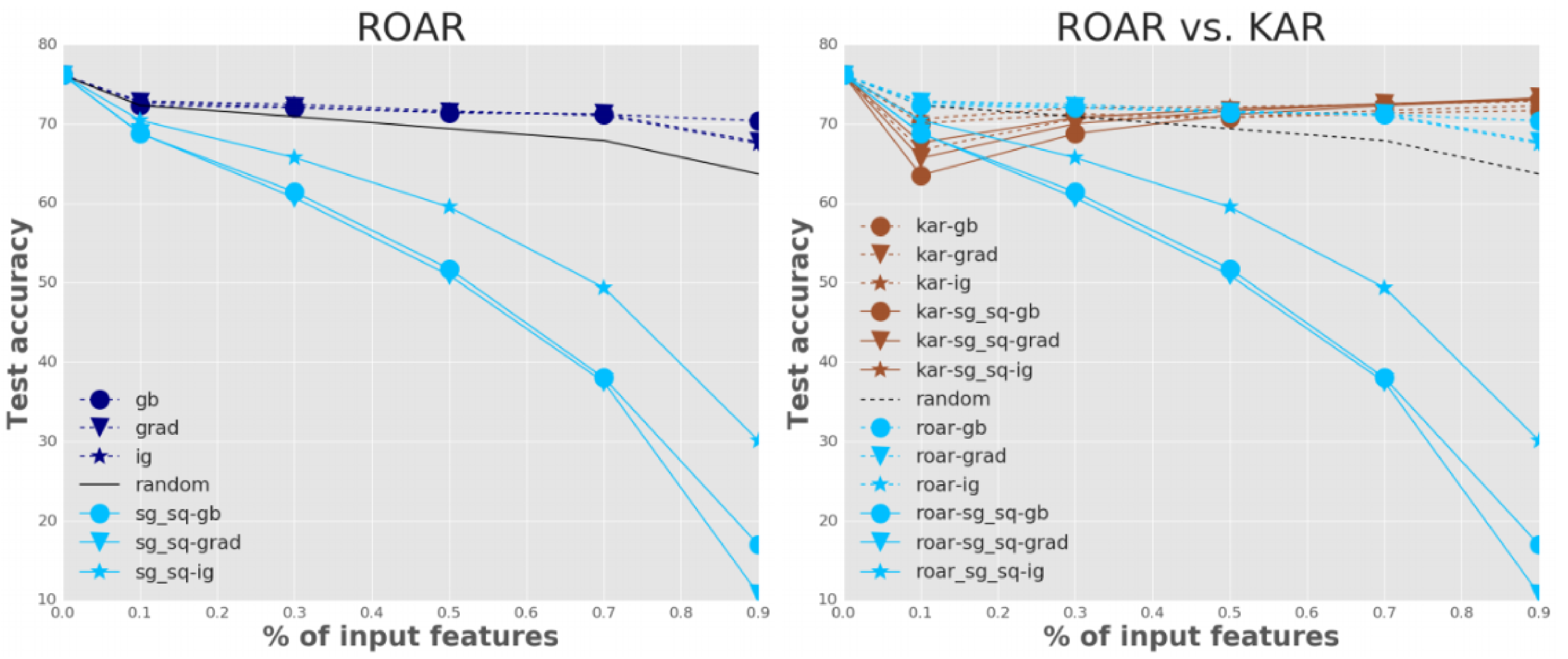


(Attribution Method)

“Evaluating Feature Importance Estimates”, https://arxiv.org/pdf/1806.10758.pdf

Evaluating Attribution Methods

Coherence | **Class Sensitivity** | **Selectivity** | **ROAR / KAR**



"Evaluating Feature Importance Estimates", https://arxiv.org/pdf/1806.10758.pdf

Part 3 Summary

1. Qualitative: Coherence

- Attributions should highlight discriminative features / objects of interest

2. Qualitative: Class Sensitivity

- Attributions should be sensitive to class labels

3. Quantitative: Sensitivity

- Removing feature with high attribution should cause large decrease in class probability

4. Quantitative: ROAR & KAR

- Problem: class probability may decrease because the DNN has never seen such image
- Solution: remove pixels, retrain and measure drop in accuracy

Summary

1. Introduction to Interpretability

- Interpretability is converting implicit information in DNN to (human) interpretable information
- Ante-hoc Interpretability vs. Post-hoc Interpretability
- Post-hoc interpretability techniques can be classified by degree of "locality"

2. Interpreting Deep Neural Networks

- Interpreting Models vs. Interpreting Decisions
- Interpreting Models: weight visualization, surrogate model, activation maximization, example-based
- Interpreting Decisions: example-based, attribution methods

3. Evaluating Attribution Methods

- Qualitative Evaluation Methods: coherence, class sensitivity
- Quantitative Evaluation Methods: Sensitivity, ROAR & KAR

Additional References

http://www.heatmapping.org/slides/2017_GCPR.pdf

https://www.kth.se/social/files/58fdbdfdf276546e343765e3/Lecture8.pdf

https://ramprs.github.io/2017/01/21/Grad-CAM-Making-Off-the-Shelf-Deep-Models-Transparent-through-Visual-Explanations.html

"Methods for Interpreting and Understanding Deep Neural Networks", https://arxiv.org/pdf/1706.07979.pdf