Explaining CNNs: Recent Methods

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Recall: Explaining using Vanilla Gradients[1]

- Forward pass the data $\mathbf{x}$, to get $y = f(\mathbf{x})$, where y is DNN's output corresponding to a given class.

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Original image *(left)*; Vanilla Gradients Attribution map *(right)*

Is this enough to explain a Deep Neural Network?

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Is this enough to explain a Deep Neural Network?
Not always!

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Saturation Problem!

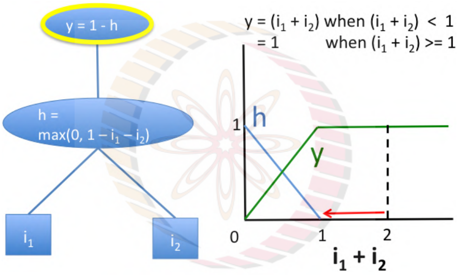

Illustration of saturation problem

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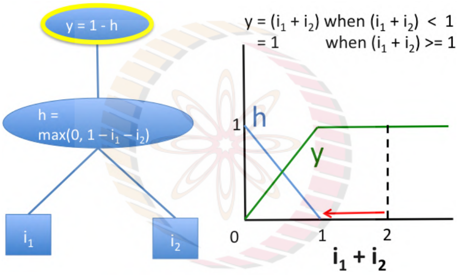

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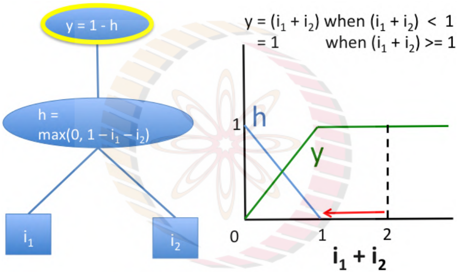

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- Gradient of h w.r.t both i_1 and i_2 is zero when $i_1 + i_2 > 1$ (causing both gradients and Guided Backprop to be zero)
- Gradient of y w.r.t. h is negative (causing Guided Backprop and deconvolutional networks to assign zero importance)

Deep Lift[2]

- **Idea**: Instead of gradients, measure difference in output from some 'reference' output (Δt) in terms of difference of input from some 'reference' input (Δx_i).

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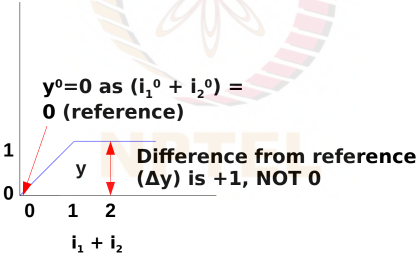

DeepLift overcomes saturation problem

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- $r_i^{(l)} = \sum_j \frac{z_{ji} - \overline{z_{ji}}}{\sum_{i'}(z_{ji'} - \overline{z_{ji'}})} r_j^{(l+1)}$

IG: Integrated Gradients[3]

Image of Fireboat *(left)*, Vanilla Gradients *(right)*

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- IG overcomes problem of saturating gradients by cumulating gradients at different pixel intensities, α's.

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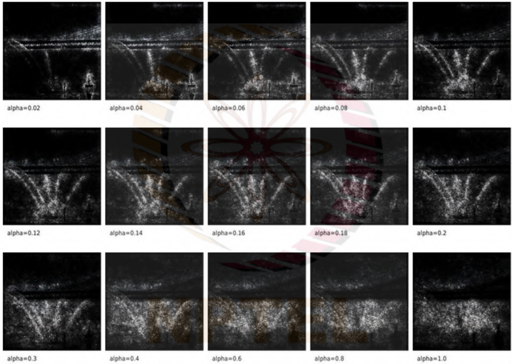

Gradients at increasing α values from top-left to bottom-right

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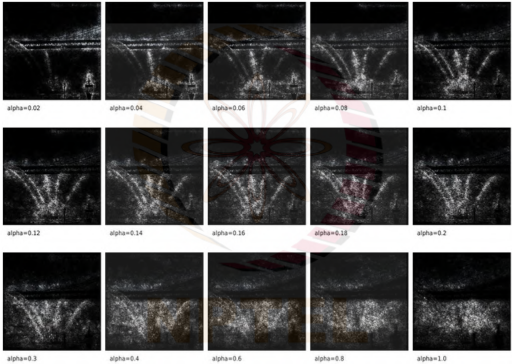

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- Region of importance is changing with increasing α. To get a more realistic picture of what is going on, cumulate these gradients using **path integral**

IG: Integrated Gradients

- **Integrated gradient** along i^{th} dimension for input x and baseline x' given by:

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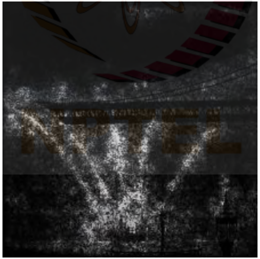

IG attribution map

SmoothGrad[4]

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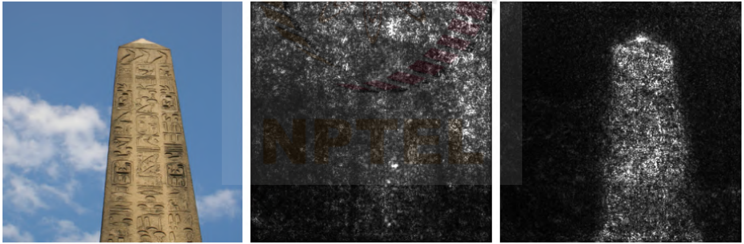

Original Image *(left)*, Vanilla Gradients *(center)*, SmoothGrad *(right)*

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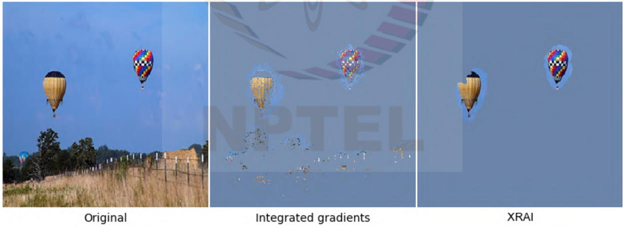

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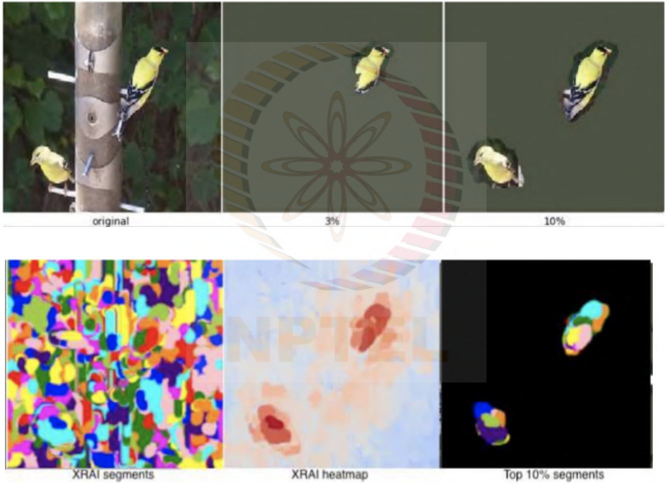

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LIME: Local Interpretable Model-agnostic Explanations[7]

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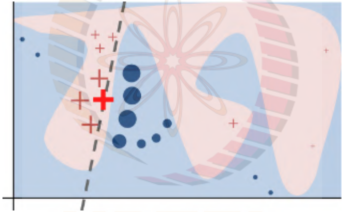

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- *Blue/Pink background:* black box model's decision function f

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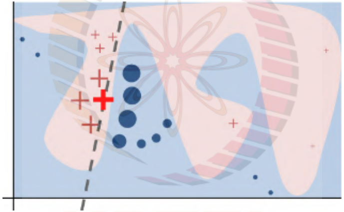

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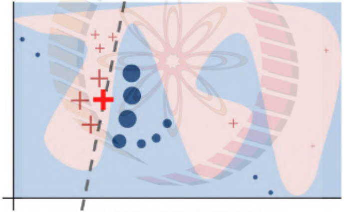

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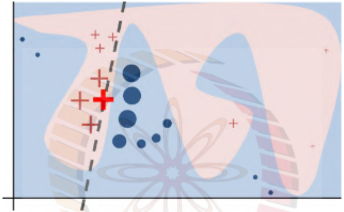

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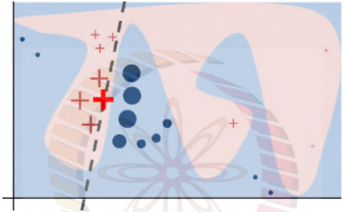

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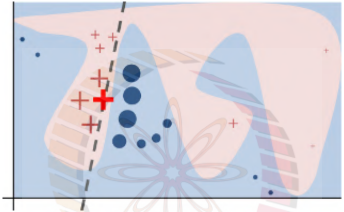

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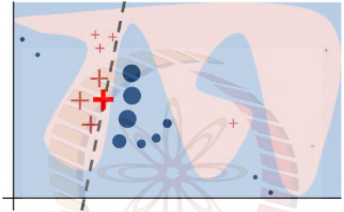

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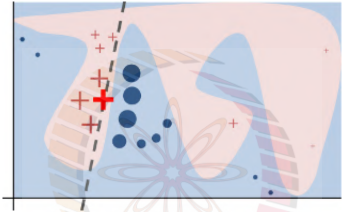

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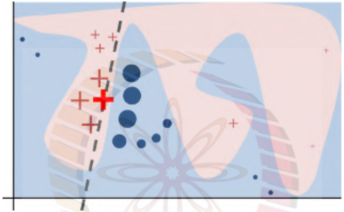

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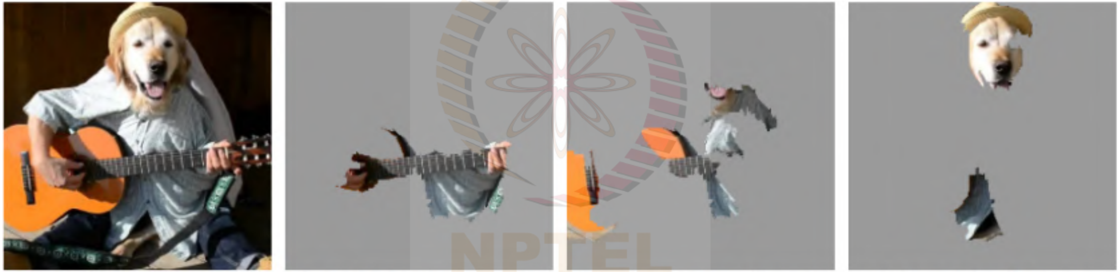

(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

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  - For images, $\Omega(g) = \mathbb{1}[||w_g||_0 > K]$ where K is limit on number of super-pixels
- **LIME explanation** obtained as a trade-off:

$$\varepsilon(x) = \arg\min_g \mathcal{L}(f, g, \pi_x) + \Omega(g)$$

SHAP[8]

- Inspired from Shapley values in game theory
- let N: Total number of features; v: Value function that assigns a real number to any coalition $S \subseteq N$; and $\phi_v(i)$: Attribution score for feature i

[8]Lundberg et al, A Unified Approach to Interpreting Model Predictions; NeurIPS 2017

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- **Attribution score:** Marginal contribution that player (in our case, feature) i makes upon joining the team, averaged over all orders in which team can be formed

$$\phi_v(i) = \sum_{S \subseteq \{1,2,\ldots,N\} \setminus \{i\}} \frac{1}{N!} |S|!(N - |S| - 1)! \underbrace{(v(S \cup i) - v(S))}_{\text{Value of adding player } i \text{ to a coalition}}$$

[8]Lundberg et al, A Unified Approach to Interpreting Model Predictions; NeurIPS 2017

SHAP[8]

- Inspired from Shapley values in game theory
- let N: Total number of features; v: Value function that assigns a real number to any coalition $S \subseteq N$; and $\phi_v(i)$: Attribution score for feature i
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- With $f(x)$ as model prediction, we marginalize over out-of-coalition features $x_{\bar{S}}$ where $\bar{S} = \{1, 2, \ldots, N\} \setminus S$ to get:

$$v(S) = \mathbb{E}_{p(x'|x_S)}[f(x_S \cup x'_{\bar{S}})]$$

- SHAP assumes features to be independent $\implies v(S) = \mathbb{E}_{p(x')}[f(x_S \cup x'_{\bar{S}})]$

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[9] Melis et al, Towards Robust Interpretability with Self-Explaining Neural Networks, NeurIPS 2018

[10] Petsiuk et al, RISE: Randomized Input Sampling for Explanation of Black-box Models, BMVC 2018

How to Evaluate Explanations?

- IoU of thresholded salient region with ground truth bounding box (if available)

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$$F = \langle \rho(R, \Delta) \rangle_{p(\mathbf{x})}$$

where R_i is relevance of pixel i and $\Delta_i = f(\mathbf{x}) - f(\mathbf{x}_i)$ where $\mathbf{x}_i$ is image obtained after perturbing pixel i

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  Similarly, **Insertion Metric** inserts pixels sequentially, least relevant first; higher AUC better

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  1. Get saliency map for each image in training data

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[12] Adebayo et al, Sanity Checks for Saliency Maps, NeurIPS 2018
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Summary

- Both DeepLIFT and Integrated Gradients overcome saturating gradients problem; although DeepLIFT is usually faster, it violates Implementation Invariance axiom[14] (one of the axioms for homework reading!) due to use of discrete gradients
- Smooth Integrated Gradients may be preferred over Integrated Gradients when sparsity is desired
- For better interpretability in terms of visual coherence, XRAI is good choice whose mask is composed of relevant segments rather than pixels
- LIME is model-agnostic and can be used for image, text as well as tabular data but is slow and appears inconsistent between runs
- SHAP has strong game-theoretic background but needs approximations for real world experiments

[14] Sundararajan et al, Axiomatic Attribution for Deep Networks, ICML 2017

Homework

Reading

- Go through list of axioms of attribution in Sundararajan et al, Axiomatic Attribution for Deep Networks, ICML 2017 and for each axiom try to identify the attribution algorithms that satisfy that
- Go through proposed sanity checks and experimental findings in Adebayo et al, Sanity Checks for Saliency Maps, NeurIPS 2018

Programming

- Play with Captum: A popular library for model interpretation by Facebook Open Source
- Try visualizing your models through the lens of OpenAI Microscope

Extra Resources

- Molnar, Interpretable machine learning: A Guide for Making Black Box Models Explainable, 2019: https://christophm.github.io/interpretable-ml-book/.
- For a collection of tutorials and software packages, please refer: https://github.com/jphall663/awesome-machine-learning-interpretability

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