Inherent Trade-offs with the Local Explanations Paradigm.

Julius Adebayo
MIT
Simons Workshop on Emerging Challenges in Deep Learning
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“Explanations”

- **Interpret** means “to explain or to present in understandable terms” to “a human” [Doshi-Velez & Kim, 2017].
“Explanations”

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- “Explanations [can] sort themselves into several distinct types corresponding to patterns of causation, content domains, and explanatory stances, all of which have cognitive consequences” [Keil, 2011].
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- “Explanations [can] sort themselves into several distinct types corresponding to patterns of causation, content domains, and explanatory stances, all of which have cognitive consequences” [Keil, 2011].

- An ‘artifact’, derived from a ‘model’, with the goal to provide ‘insights’ into the ‘factors’ most ‘relevant’ to the ‘model’ for an end-user.
Inspired by the ‘Fairness’ version from mrtz.
Some Motivation

[Challenges for Transparency, Weller 2017, & Doshi-Velez & Kim, 2017 ]

• Developer/Researcher: Model Debugging.

• Safety concerns.

• Ethical concerns.

• Trust: Satiate ‘societal’ need for reasoning to trust an automated system learned from data.
Goals: Model Debugging

- **Model Debugging**: reveal spurious correlations or the kinds of inputs that a model is most likely to have undesirable performance.

(a) Husky classified as wolf  
(b) Explanation

[Ribeiro+ 2016]
Systematic Subgroup Errors

[Morales+ 2019]

Gender Classification

Predictions
Systematic Subgroup Errors

[Morales+ 2019]

- Reveal subsets (non-intuitive) of the data for which the model has bad performance. This can be due to data labeling errors or others.
Promise of Explanations

- **Model Debugging**: reveal spurious correlations or the kinds of inputs that a model is most likely to have undesirable performance.
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## ‘Interpretability’ vs ‘Explainability’

**Interpretability: Constrained Model Class.**

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Probability</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>IF IrregularShape AND Age ≥ 60</td>
<td>85.22%</td>
<td>230</td>
</tr>
<tr>
<td>ELSE IF SpiculatedMargin AND Age ≥ 45</td>
<td>78.13%</td>
<td>64</td>
</tr>
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</tr>
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<td>63.40%</td>
<td>153</td>
</tr>
<tr>
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<td>39.68%</td>
<td>63</td>
</tr>
<tr>
<td>ELSE IF RoundShape AND Age ≥ 60</td>
<td>26.09%</td>
<td>46</td>
</tr>
<tr>
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<td>10.38%</td>
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Table 1: Falling rule list for mammographic mass dataset.
‘Interpretability’ vs ‘Explainability’

Interpretability: Constrained Model Class.

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Post-Hoc Explainability.

[Wang+ 2015]

[Ribeiro+ 2015]
Focus

• This talk will focus exclusively on post-hoc explanations.

• Post-hoc explanations ‘purport’ to provide flexibility for the model developer/designer.
This talk will focus exclusively on post-hoc explanations.

Post-hoc explanations ‘purport’ to provide flexibility for the model developer/designer.

Perhaps a questionable thing to do!

Please Stop Explaining Black Box Models for High-Stakes Decisions

Cynthia Rudin
Duke University
cynthia@cs.duke.edu
Saliency/Attribution Maps

$S : \mathbb{R}^d \rightarrow \mathbb{R}^C$

d = input dimension
C = number of output classes
Saliency/Attribution Maps

\[ E_{grad}(x) = \frac{\partial S_i}{\partial x} \]

\[ E : \mathbb{R}^d \rightarrow \mathbb{R}^d \]

[SVZ’13]
‘Examples’/‘Prototypes’

Test Point → Predictions

Training Points

[ Koh & Liang 2017, Yeh, 2018, …]
“Local Explanations”

- **Local Explanations**: focus on the behavior of the model around a single point.

- Why is this desirable?
Key Takeaways

• Difficult to assess quality and model fidelity of local explanations.

• Conjecture: local explanations seem to require significant privacy tradeoffs.
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Gradient/Sensitivity Map

Gradient

\[ E_{grad}(x) = \frac{\partial S_i}{\partial x} \]

Predictions

[SVZ'13]

\[ E : \mathbb{R}^d \rightarrow \mathbb{R}^d \]
Gradient/Sensitivity Map

$E_{grad}(x) = \frac{\partial S_i}{\partial x}$

$E : \mathbb{R}^d \rightarrow \mathbb{R}^d$

[SVZ’13]

```
self.gradients_node = tf.gradients(y, x)[0]
```

[Google Pair Saliency Codebase]
SmoothGrad

\[ E_{sg}(x) = \frac{1}{N} \sum_{i=1}^{N} E(x + g_i), \]

\[ E : \mathbb{R}^d \rightarrow \mathbb{R}^d \]

[STKVV’17]
Integrated Gradients

\[ E_{IG}(x) = (x - \bar{x}) \times \int_0^1 \frac{\partial S(\bar{x} + \alpha(x - \bar{x}))}{\partial x} d\alpha \]

\[ E : \mathbb{R}^d \rightarrow \mathbb{R}^d \]

[STY'17]
Several More

Explanation

Predictions

Corn

|  |  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|
| LIME | SHAP | Gradient | SmoothGrad | DeConvNet | Guided BackProp | PatternNet | Pattern Attribution |
| Deep Taylor | Grad-Input | Integrated Gradients | LRP-Z | LRP-EPS | LRP-PA | LRP-PB | Edge Detector |
Other Learned Kinds

Explanation

[FV’17]

Predictions

Corn
Non-Image Settings

Using attribution to decode binding mechanism in neural network models for chemistry

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\textsuperscript{a}Google Research, Mountain View, CA 94043; \textsuperscript{b}Institute of Computational Science, Università della Svizzera Italiana, CH-6900 Lugano, Switzerland; \textsuperscript{c}School of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02138; and \textsuperscript{d}Department of Chemistry, Cambridge University, Cambridge CB2 1EW, United Kingdom

Edited by Michael L. Klein, Institute of Computational Molecular Science, Temple University, Philadelphia, PA, and approved April 29, 2019 (received for review December 4, 2018)

![](image)

Fig. 1. An example of per-atom model attributions visualized for a molecule. Each atom is colored on a scale from red to blue in proportion to its attribution score, with red being the most positive and blue being the most negative.
Challenge 1: Assessment

- Input Perturbation.

- Localization error in an object localization task.

- Question: can we design simple tests to ‘sanity check’ the model fidelity attribution maps?

[Montavon+ 2017]
Sanity Checks for Saliency Maps

Joint work with

[Images of contributors]
Conjecture: If a model captures higher level class concepts, then saliency maps should change as the model is being randomized.

Sanity Check 1: Model Randomization

- **Gradient**
- **Gradient-SG**
- **Gradient × Input**
- **Guided Back-propagation**
- **GradCAM**
- **Guided GradCAM**
- **Integrated Gradients**
- **Integrated Gradients-SG**
**Sanity Check 1: Model Randomization**

**Conjecture:** If a model captures higher level class concepts, then saliency maps should change as the model is being randomized.
**Sanity Check: Model Randomization**

**Conjecture:** If a model captures higher level class concepts, then saliency maps should change as the model is being randomized.
Medical Setting

Skeletal Radiograph

Guided Backpropagation

Age
Nie et. al. theoretically analyze gradient, guided backpropagation (GBP), and deconvnet (DCN) on 1-hidden layer random CNN [Nie+ICML 2018].

In the limit (conv filters), gradient returns iid Gaussian noise, while GBP and DCN (w/pooling layer) seek to reconstruct the input.

<table>
<thead>
<tr>
<th></th>
<th>Original Image</th>
<th>Gradient</th>
<th>SmoothGrad</th>
<th>Guided BackProp</th>
<th>Guided GradCAM</th>
<th>Integrated Gradients</th>
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<th>Edge Detector</th>
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<tr>
<td>Junco Bird</td>
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- Gupta et. al. fix this with competition for gradients (CGI).

[Figure from Gupta et. al. 2019.]
Sanity Checks Useful?

- Sanity Checks are useful for ruling out methods, not selecting them.

- Some other recent work that aim to assess:
  - Hooker et. al. propose to remove and retrain.
  - Adel et. al. propose FSM which ‘quantifies’ information content of a map.
  - Yang et. al. introduce a benchmark (w/ground truth and other metrics to assess how well a map captures model behavior.

- Interactions with end-users [Collaris et. al.]
Attacks

- Mean-shift attack by Kindermans & Hooker et. al.

\[ E_{IG}(x) = (x - \bar{x}) \times \int_0^1 \frac{\partial S(\bar{x} + \alpha(x - \bar{x}))}{\partial x} d\alpha \]
Model Debugging Upshot

[Morales+ 2019]

- Reveal subsets (non-intuitive) of the data for which the model has bad performance. This can be due to data labeling errors or others.

- Difficulty might not be in finding these subgroup in data and not interpreting them.
Key Takeaways

• Difficult to assess quality and model fidelity of local explanations.

• Conjecture: local explanations seem to require significant privacy tradeoffs.
Motivation

Predictive Model

Input

Age

Explanation

Problematic!
Motivation

Fundamental Law of Information Recovery

“Overly accurate answers to too many questions will destroy privacy in a spectacular way.”

Dwork & Roth 2014.
Model Recovery

- **Tramer et. al. 2017** recover models through prediction APIs.

- **Milli et. al. 2019** should that one can recover models, (even misspecified ones) with access to local examples.

**Theorem 1** (informal). *Assuming the rows of the weight matrix $A$ are linearly independent, our algorithm recovers a functionally equivalent model from $O(h \log h)$ input gradient queries and function evaluations with high probability.*

- **Membership Inference Attacks** [Shokri et. al. 2019].
Privacy ‘Harms’: Examples & Prototypes

- Membership inference attacks are easier for these, and dataset reconstruction is easier with diverse point selection.

[ Koh & Liang 2017, Yeh, 2018, …]
Shokri et. al. also show membership inference attack possible with model learned on the norms of the local explanations.
Can Differential Privacy (DP) Help?

• One is revealing information about exactly the inputs we would like to protect.

**Definition 1.** A randomized mechanism $\mathcal{M}: \mathcal{D} \rightarrow \mathcal{R}$ with domain $\mathcal{D}$ and range $\mathcal{R}$ satisfies $(\varepsilon, \delta)$-differential privacy if for any two adjacent inputs $d, d' \in \mathcal{D}$ and for any subset of outputs $S \subseteq \mathcal{R}$ it holds that

$$\Pr[\mathcal{M}(d) \in S] \leq e^\varepsilon \Pr[\mathcal{M}(d') \in S] + \delta.$$
Abadi et. al. (2016) introduced a differentially private version of SGD as well as a moments accountant procedure to track the privacy budget.

**Algorithm 1** Differentially private SGD (Outline)

**Input:** Examples \( \{x_1, \ldots, x_N\} \), loss function \( \mathcal{L}(\theta) = \frac{1}{N} \sum_i \mathcal{L}(\theta, x_i) \). Parameters: learning rate \( \eta_t \), noise scale \( \sigma \), group size \( L \), gradient norm bound \( C \).

**Initialize** \( \theta_0 \) randomly

**for** \( t \in [T] \) **do**

Take a random sample \( L_t \) with sampling probability \( L/N \)

**Compute gradient**

For each \( i \in L_t \), compute \( \mathbf{g}_t(x_i) \leftarrow \nabla_{\theta_i} \mathcal{L}(\theta_t, x_i) \)

**Clip gradient**

\( \bar{\mathbf{g}}_t(x_i) \leftarrow \mathbf{g}_t(x_i) / \max(1, \|\mathbf{g}_t(x_i)\|_2/C) \)

**Add noise**

\( \tilde{\mathbf{g}}_t \leftarrow \frac{1}{L} \left( \sum_i \bar{\mathbf{g}}_t(x_i) + \mathcal{N}(0, \sigma^2 C^2 I) \right) \)

**Descent**

\( \theta_{t+1} \leftarrow \theta_t - \eta_t \tilde{\mathbf{g}}_t \)

**Output** \( \theta_T \) and compute the overall privacy cost \( (\varepsilon, \delta) \) using a privacy accounting method.
Local Explanations & DP?

- Can DP-trained models help alleviate these concerns?
Conclusions

• Difficult to assess quality and model fidelity of local explanations.

• Conjecture: local explanations seem to require significant privacy tradeoffs.

• Perhaps global explanations can help, since it fits the theme of differential privacy?