# Fooling Partial Dependence via Data Poisoning



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tinyurl.com/ECML22

# Outline

1. Adversary in explainable machine learning – Why should I care?
2. Fooling PD via Data Poisoning – What and how?
3. Experimental results
4. Discussion & future work

tinyurl.com/ECML22

# Explainable machine learning: from credit scoring to precision diagnostics in bio-medicine

The Washington Post
Democracy Dies in Darkness

This article was published more than **3 years ago**

**BUSINESS**

2019

## Apple Card algorithm sparks gender bias allegations against Goldman Sachs

Entrepreneur David Heinemeier Hansson says his credit limit was 20 times that of his wife, even th
higher credit score

By Taylor Telford
November 11, 2019 at 10:44 a.m. EST

nature machine intelligence

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2021

nature › nature machine intelligence › analyses › article

Analysis | Open Access | Published: 15 March 2021

## Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans

Michael Roberts, Derek Driggs, Matthew Thorpe, Julian Gilbey, Michael Yeung, Stephan Ursprung, Angelica I. Aviles-Rivero, Christian Etmann, Cathal McCague, Lucian Beer, Jonathan R. Weir-McCall, Zhongzhao Teng, Effrossyni Gkrania-Klotsas, AIX-COVNET, James H. F. Rudd, Evis Sala & Carola-Bibiane Schönlieb

*Nature Machine Intelligence* **3**, 199–217 (2021) | Cite this article

**74k** Accesses | **237** Citations | **1159** Altmetric | Metrics

*Many articles have been published in 2020 describing new machine learning-based models for [detection and prognostication of COVID-19], but it is unclear which are of potential clinical utility. [...] Our review finds that none of the models identified are of potential clinical use due to methodological flaws and/or underlying biases.*

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# We explain black-box machine learning for...

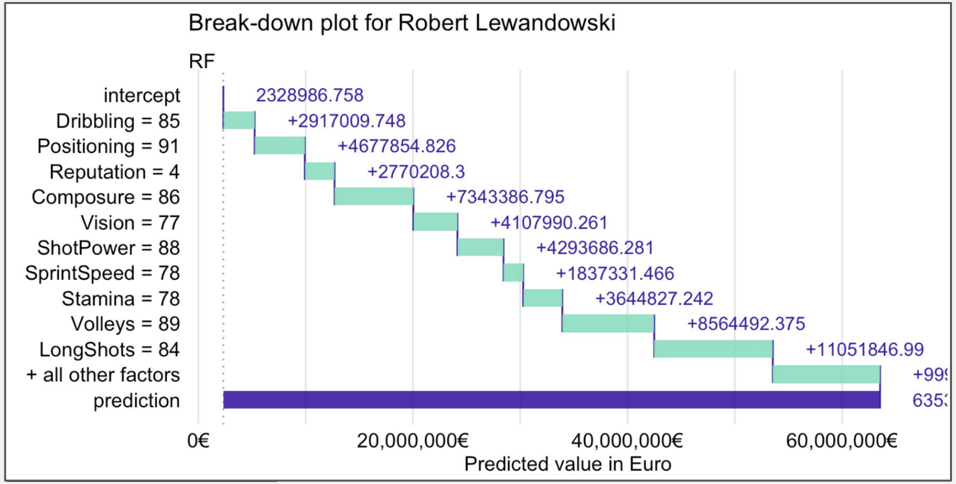
W. Samek (Monday, 4th XKDD Workshop @ECML PKDD 2022)

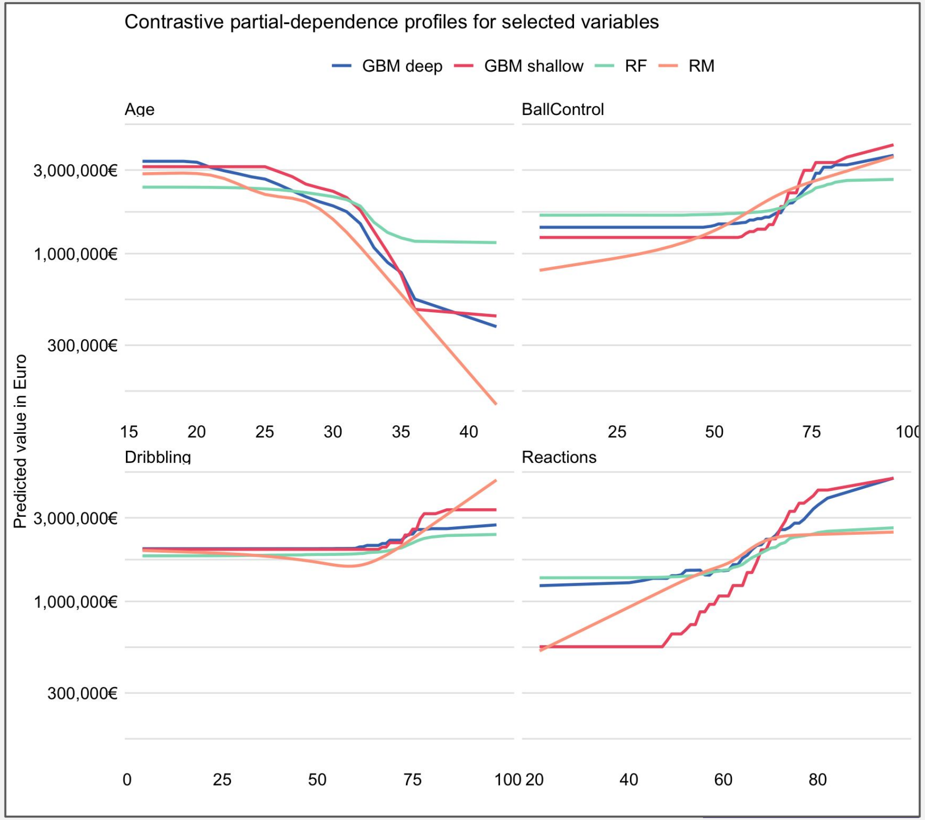
**(1)** Validation & debugging

**(2)** Scientific insights

**(3)** Model improvement

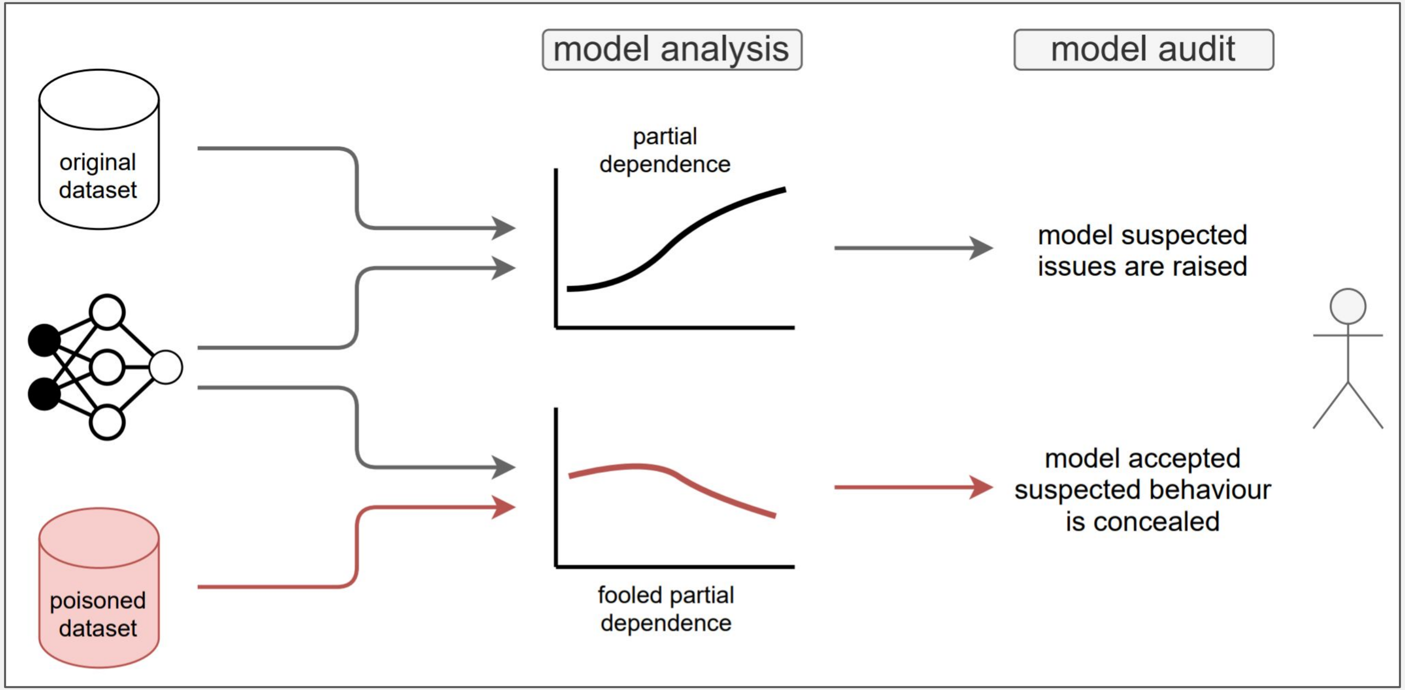
ema.drwhy.ai



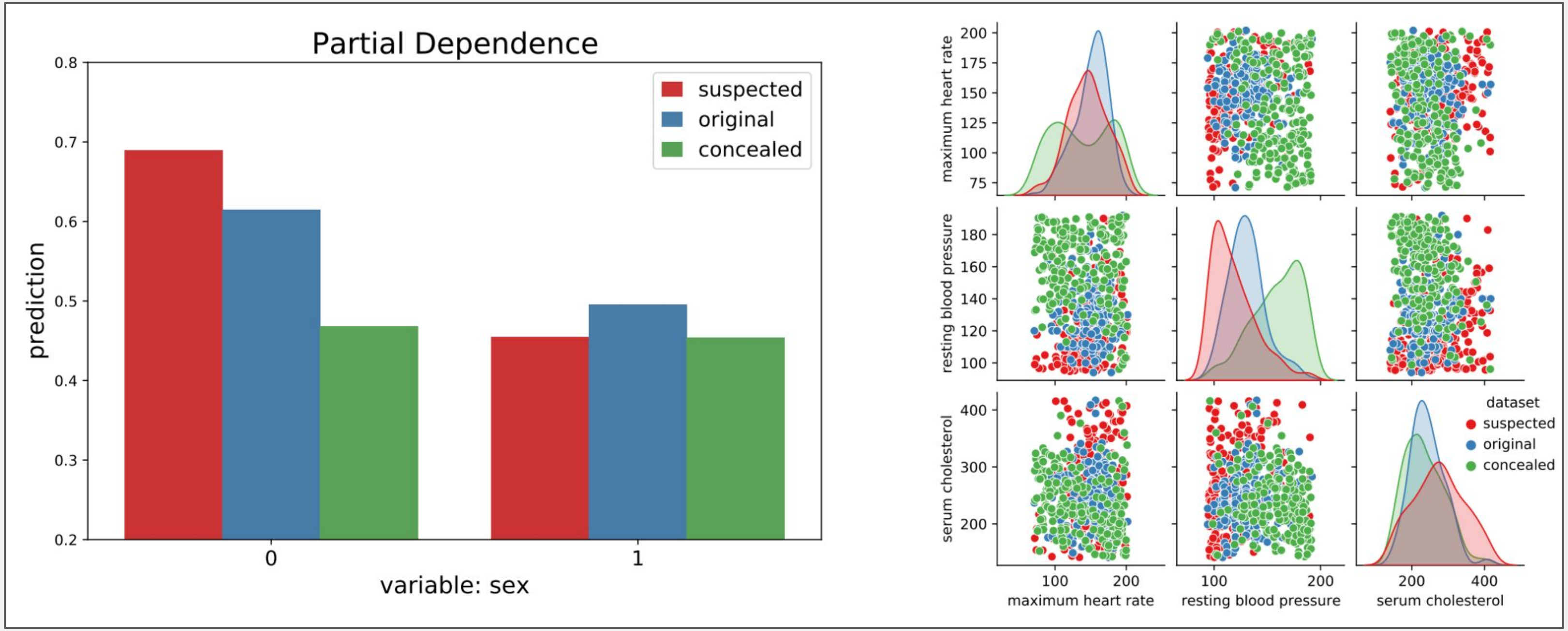



# Attacking model-agnostic explanations, e.g. PDP

**Why?**



# Motivational example (Heart disease classification)




We explain the same model – it is unchanged!

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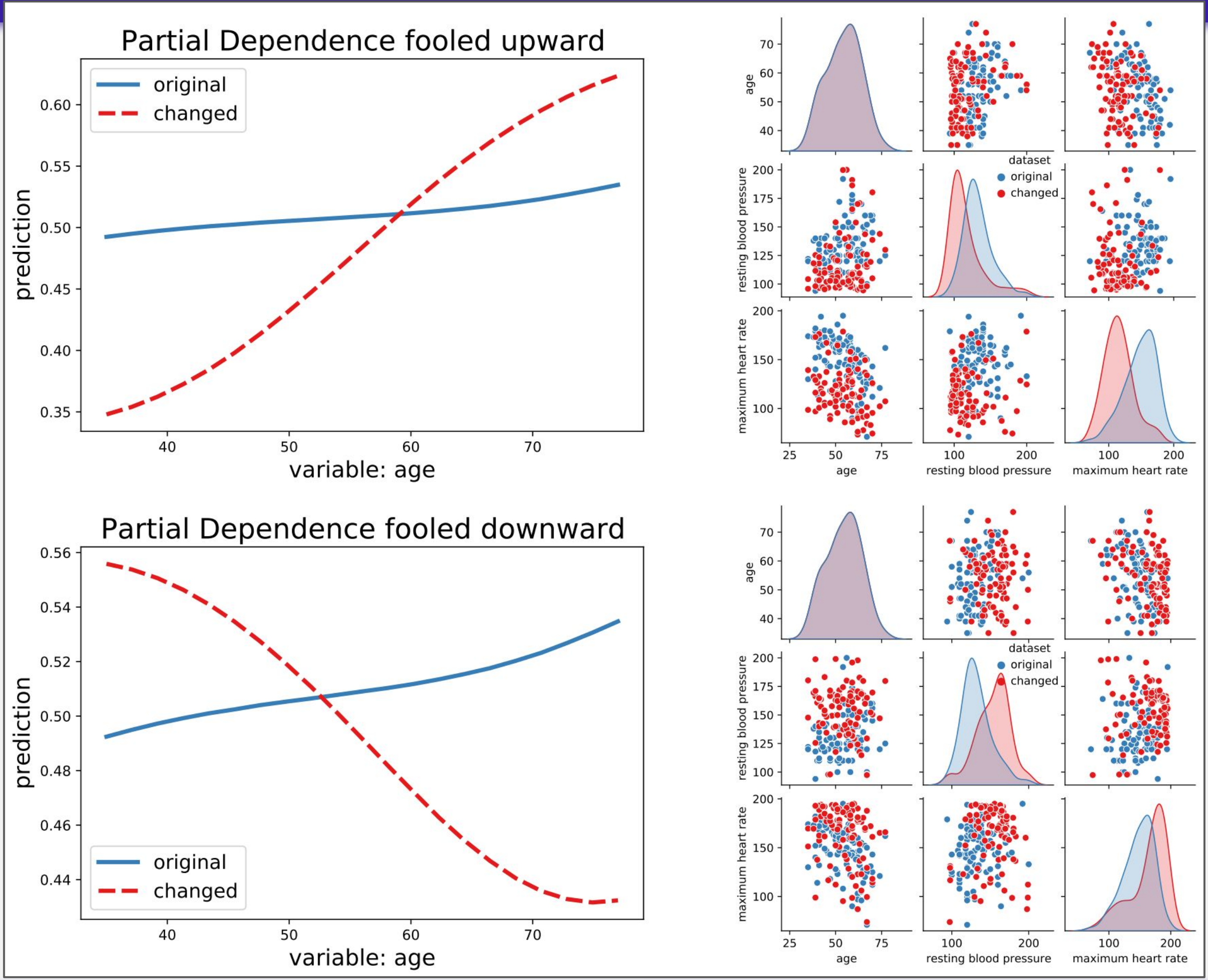
*Faking explanations to confirm a hypothesis?*




*Can we trust explanations?*

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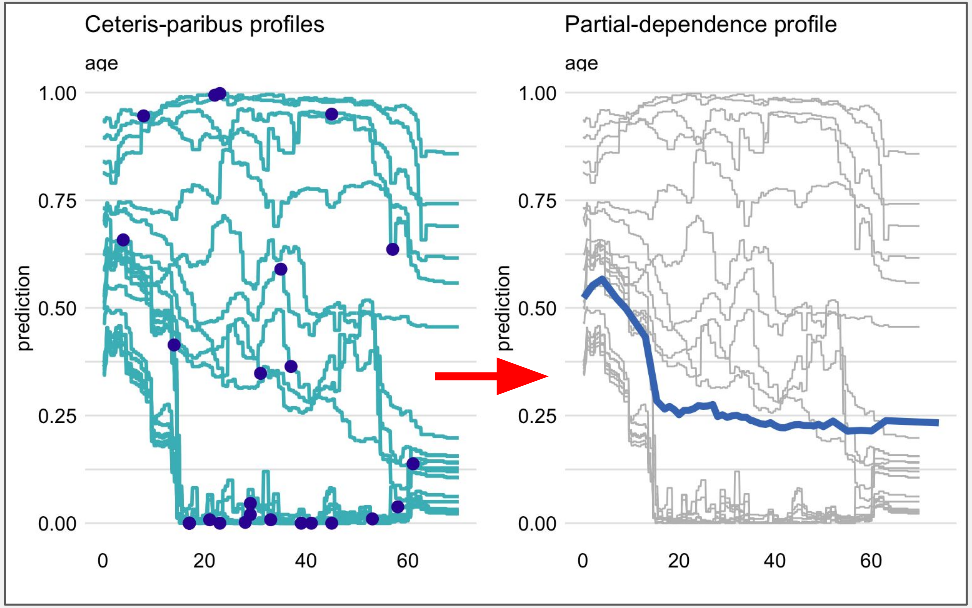
# Partial Dependence (plot, profile, PDP)

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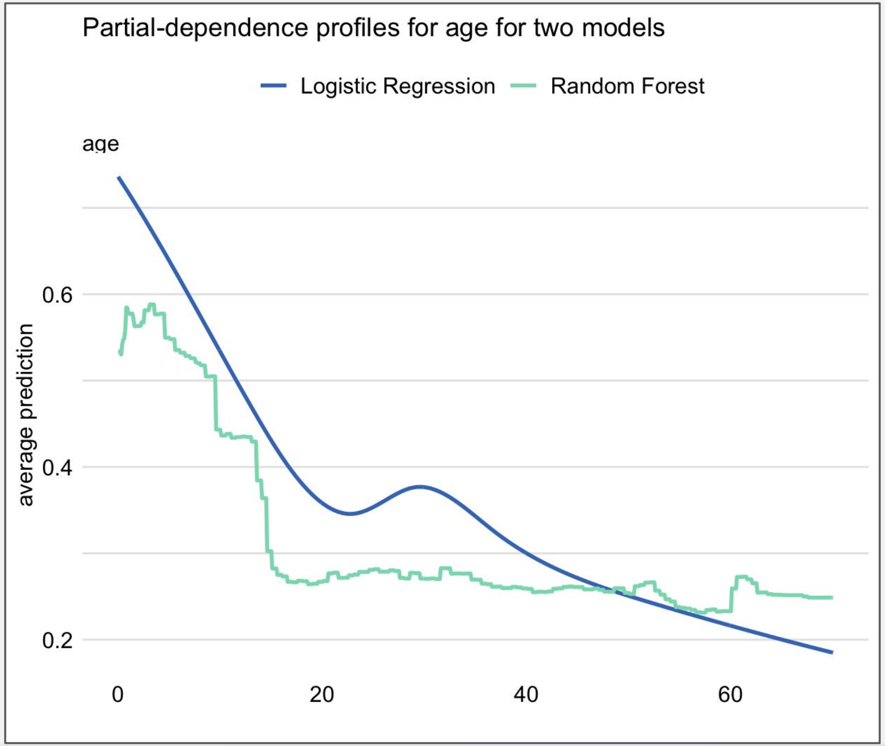

# Data Poisoning (1/2)

We want to **optimize the distance** between the original and changed explanation by **iteratively changing** the dataset. We propose:

**(1)** A flexible model-agnostic **genetic-based algorithm**, which does not assume any structure about the model or explanation. (Wright, 1991)

**(2)** An efficient **gradient-based algorithm**, which is specific to differentiable models, e.g. neural networks. **Analytical derivation + automatic differentiation.**

# Data Poisoning (2/2)

We want to **optimize the distance** between the original and changed explanation by **iteratively changing** the dataset. Possible strategies:

**(1) Targeted attack** changes the dataset to achieve the closest explanation result to the predefined desired function **T**.

**(2) Robustness check** aims for the most distant model explanation from the original one.

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# Experiments (1/2)



**Table 1.** Attack loss values of the robustness checks for Partial Dependence of various machine learning models (**top**), and complexity levels of tree-ensembles (**bottom**). Each value corresponds to the scaled distance between the original explanation and the changed one. We perform the fooling 6 times and report the mean $\pm$ sd. We observe that the explanations' vulnerability increases with GBM complexity.

| Task \ Model | LM | RF | GBM | DT | KNN | NN | SVM |
|---|---|---|---|---|---|---|---|
| `friedman` | $0_{\pm 0}$ | $152_{\pm 76}$ | $127_{\pm 71}$ | $332_{\pm 172}$ | $164_{\pm 61}$ | $269_{\pm 189}$ | $576_{\pm 580}$ |
| `heart` | $2_{\pm 3}$ | $20_{\pm 5}$ | $77_{\pm 28}$ | $798_{\pm 192}$ | $133_{\pm 21}$ | $501_{\pm 52}$ | $451_{\pm 25}$ |

| Task | Model \ Trees | 10 | 20 | 40 | 80 | 160 | 320 |
|---|---|---|---|---|---|---|---|
| `friedman` | GBM | $57_{\pm 12}$ | $114_{\pm 20}$ | $157_{\pm 37}$ | $176_{\pm 20}$ | $189_{\pm 8}$ | $210_{\pm 9}$ |
| | RF | $233_{\pm 22}$ | $219_{\pm 25}$ | $219_{\pm 9}$ | $201_{\pm 23}$ | $216_{\pm 13}$ | $209_{\pm 15}$ |
| `heart` | GBM | $1_{\pm 0}$ | $3_{\pm 1}$ | $29_{\pm 4}$ | $70_{\pm 24}$ | $152_{\pm 56}$ | $321_{\pm 95}$ |
| | RF | $62_{\pm 7}$ | $55_{\pm 3}$ | $29_{\pm 9}$ | $21_{\pm 6}$ | $14_{\pm 5}$ | $13_{\pm 2}$ |

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# Experiments (2/2)



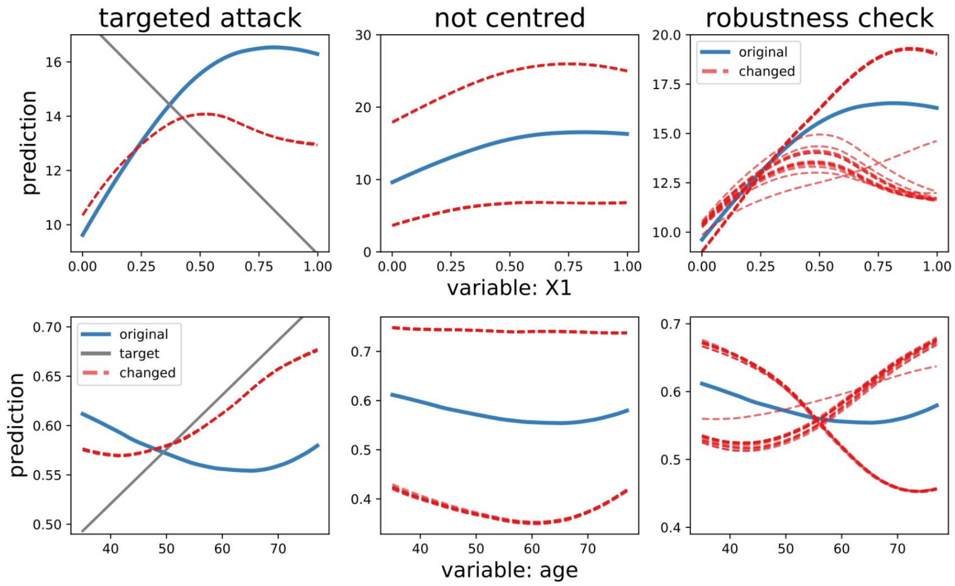


**Fig. 3.** Fooling Partial Dependence of a 3×32 neural network fitted to the `friedman` (**top** row) and `heart` (**bottom** row) datasets. We performed multiple randomly initiated gradient-based fooling algorithms on the explanations of variables $X_1$ and `age`

# Main contributions

**(1)** We highlight that Partial Dependence can be **manipulated** with adversarial data perturbations.

**(2)** We introduce a novel concept of using a **genetic algorithm** for attacking explanations of **any black-box**. We propose a gradient algorithm for neural networks.

**(3)** Experiments on various models and their sizes shows the **hidden debt of model complexity** related to explainable machine learning.

# Remarks

- **Claim:** Partial Dependence can be fooled, but not necessarily always
- **Assumption:** an auditor has no access to the original (unknown) data
- **Takeaway:** interpret model explanation in the context of data distribution

# Future? work

- Sanity checks for other explanations:
  - PDP **->** **A**ccumulated **L**ocal **E**ffects (Apley & Zhu, J. R. Stat. Soc. 2020)
  - SHAP (Lundberg & Lee, NeurIPS 2017) **->** (Baniecki & Biecek, AAAI 2022)
- Remove the **assumption** and analyze the **detectability** of data poisoning by measuring the distance between data distributions.

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# Details? Algorithms, benchmarks, and related work!

**Paper ID** 176

**Poster:**

- **When?** Tomorrow, 18:30 (Thursday)
- **Where?** A1, Robust & Adv. ML (1)

**Paper:** arXiv:2105.12837

**Contact:** hbaniecki.com

## Call for postdocs ;-)

www.mi2.ai

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