Why you shouldn’t trust me:
A survey on Adversarial Model Interpretation Manipulations.

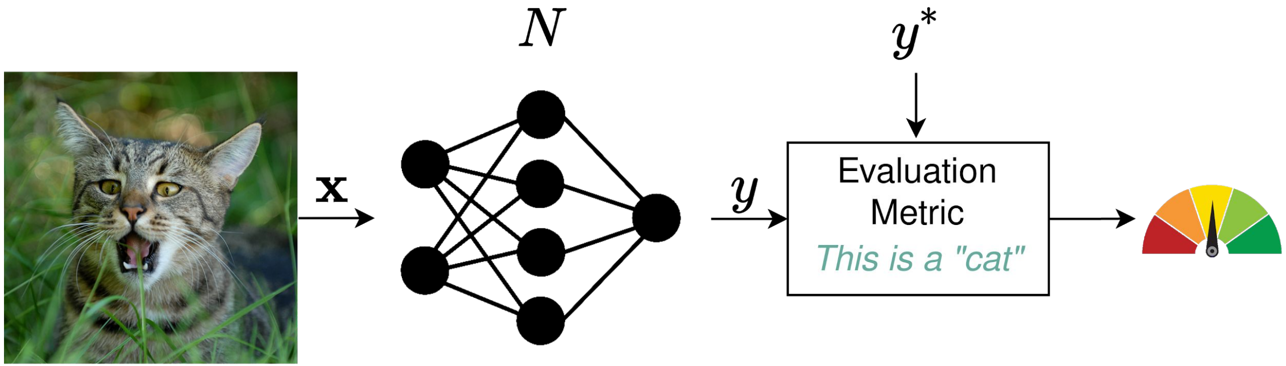
Verena Heusser

Seminar Explainable Machine Learning

Motivation

Motivation: Omnipresent ML

- Machine learning algorithms are moving out of the lab into the real world
- Performance comes at the cost of complexity



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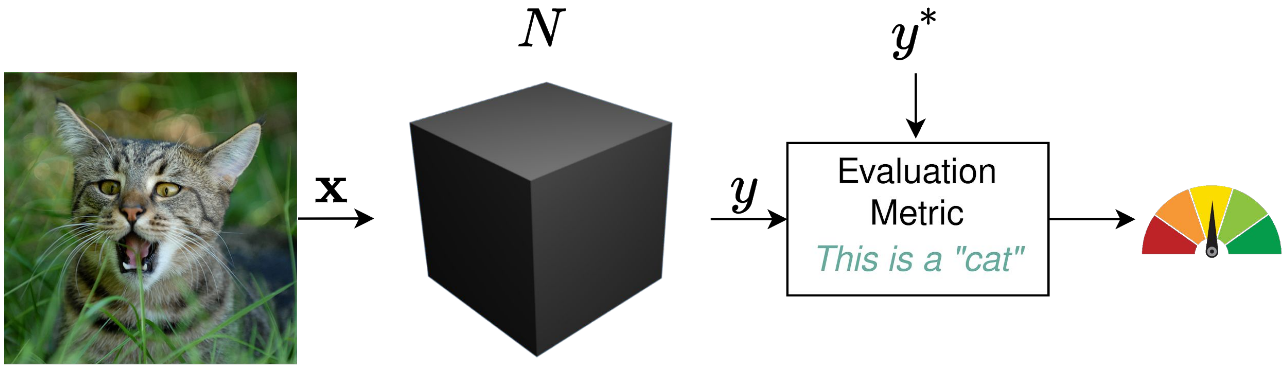

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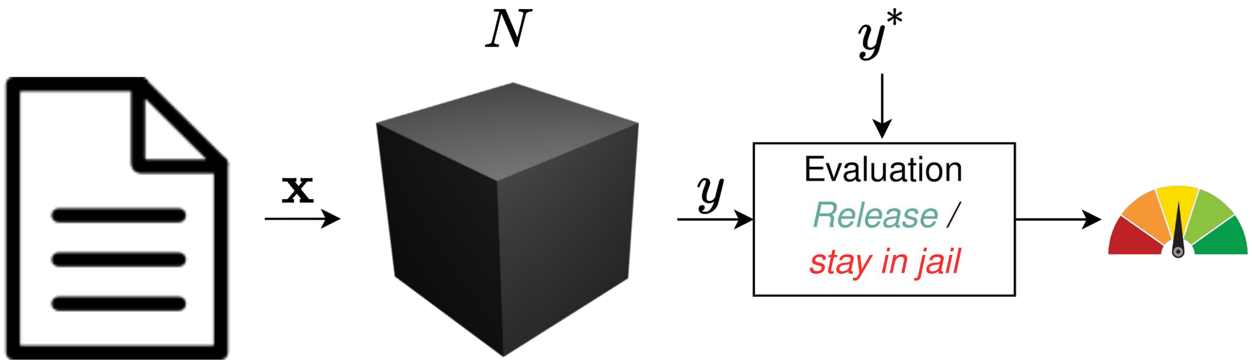

Motivation: Interpretable ML

- so far: *what* is the most likely label → accuracy
- now also: *why* does the model chose this label and
  which features are important for the decision

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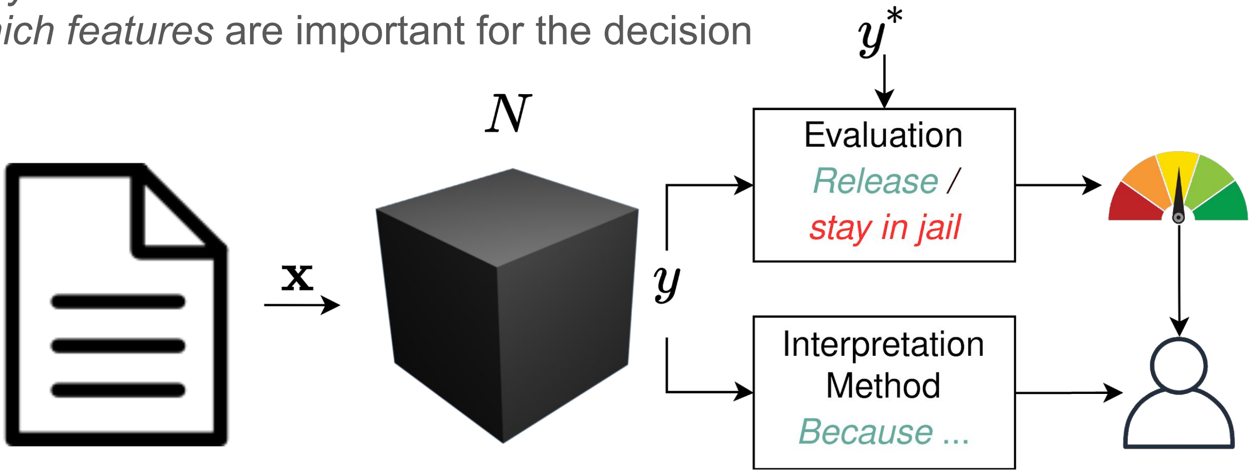

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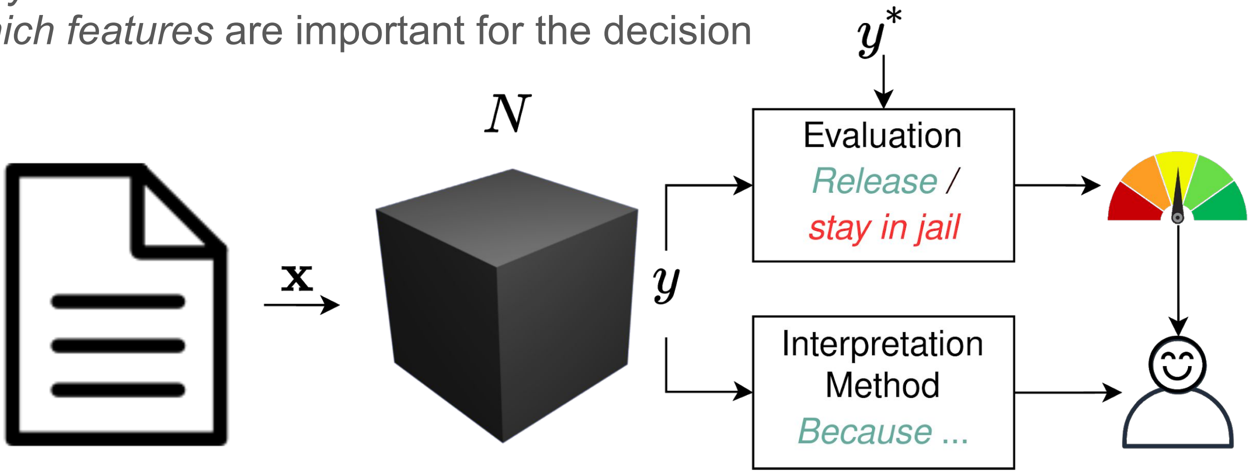
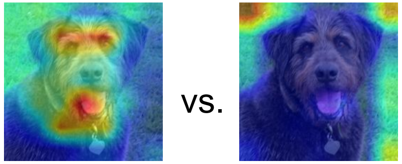


- →Reliability, robustness, fairness, trust



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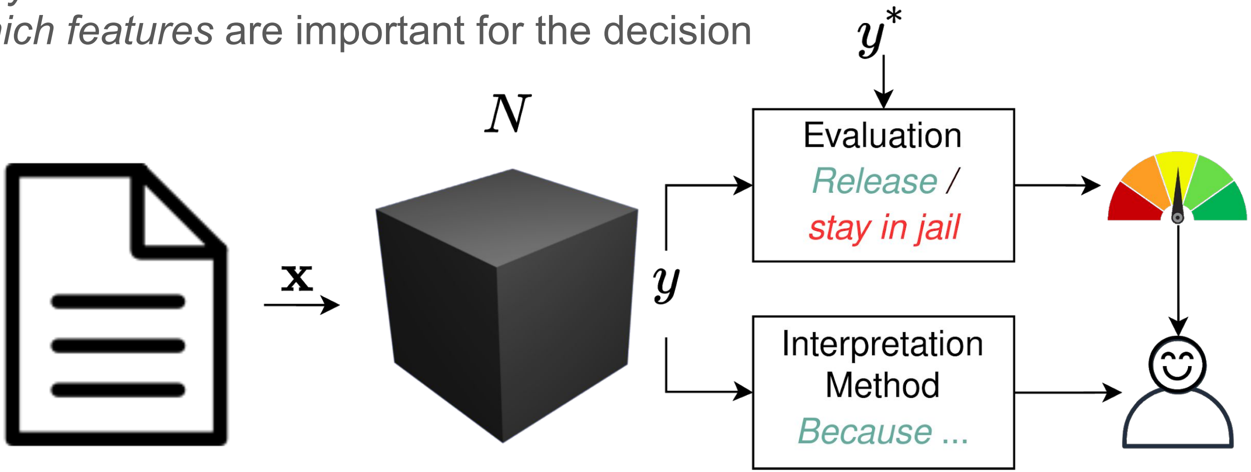

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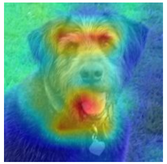
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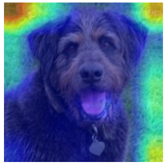

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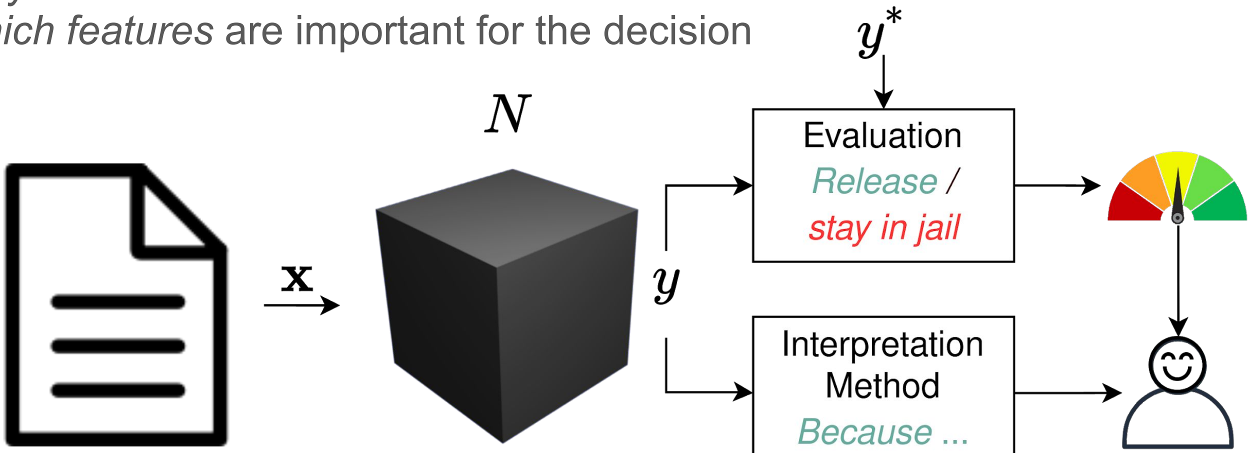

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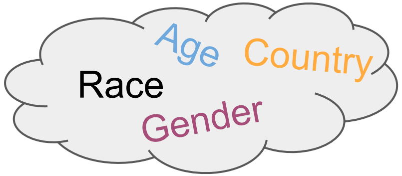

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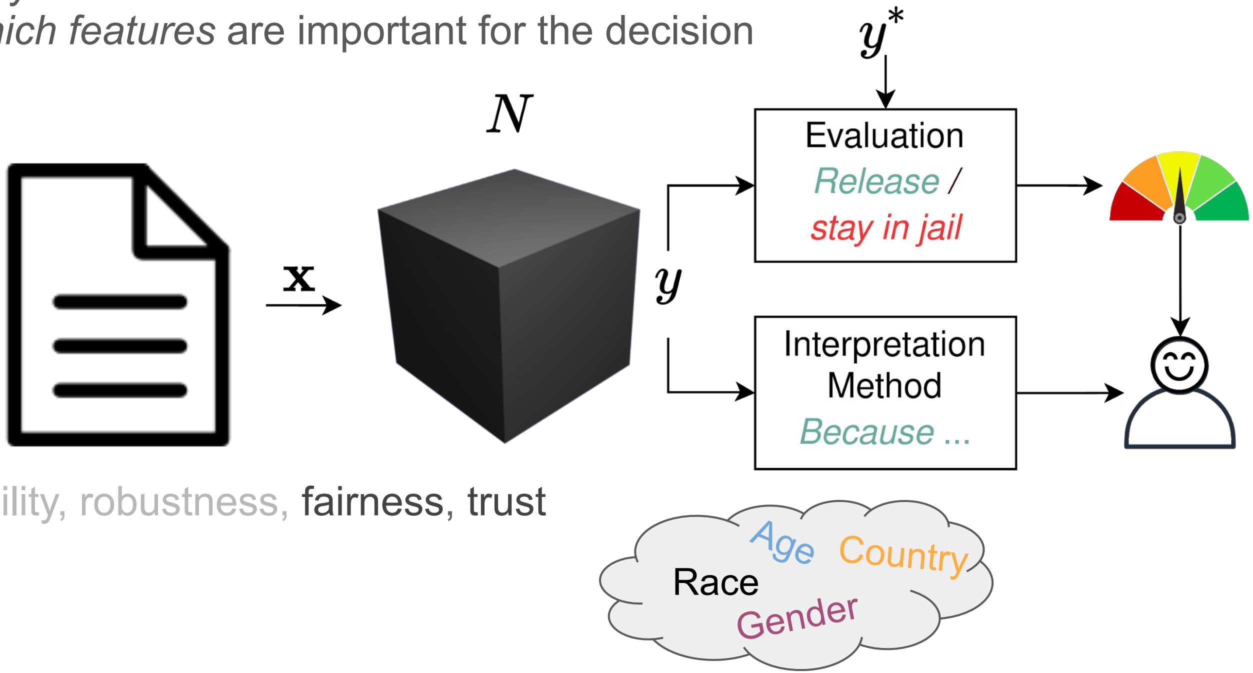

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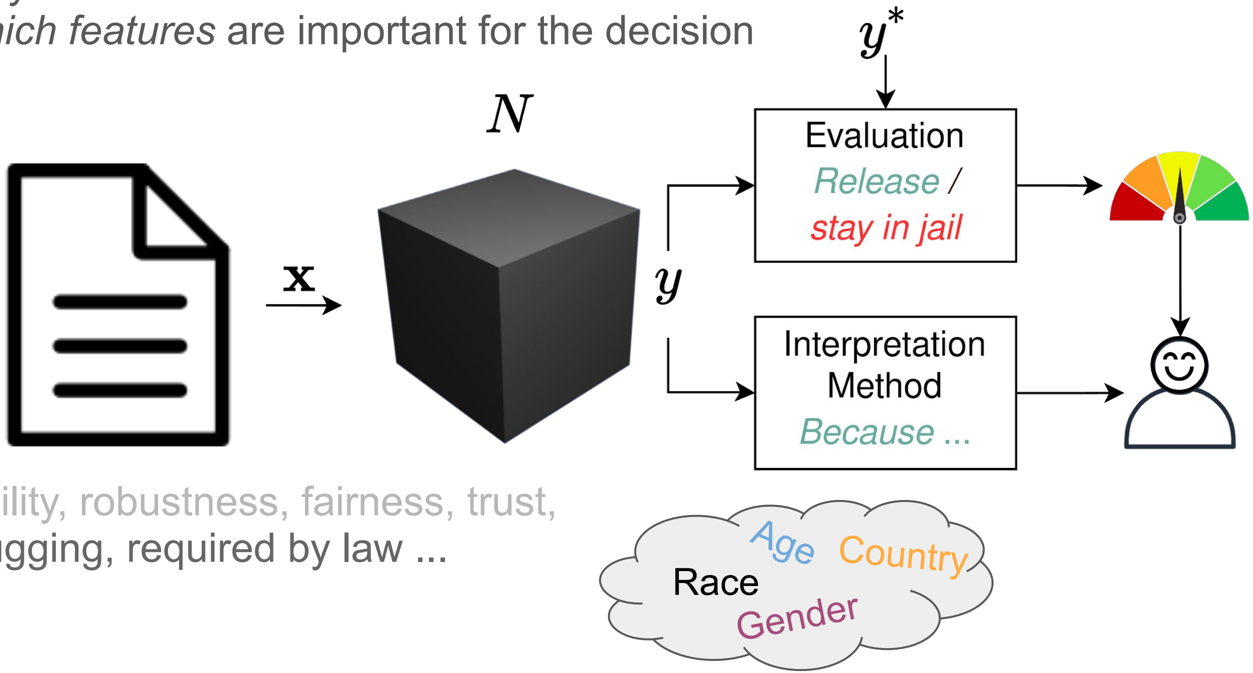


- →Reliability, robustness, fairness, trust,
  + debugging, required by law ...

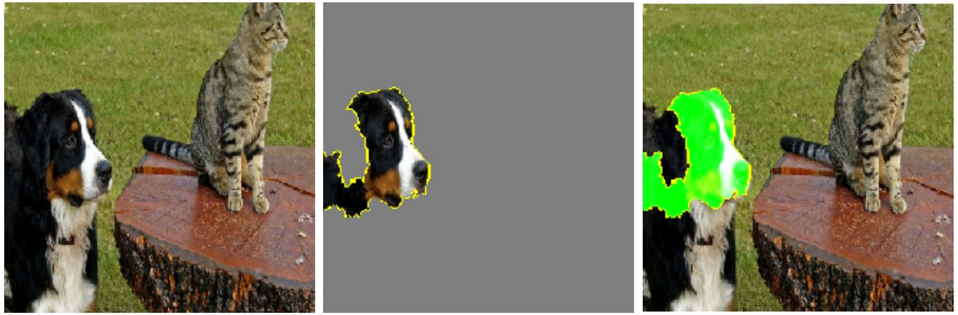
Motivation: Interpretable ML

- Local vs. global
  - Local: Explain the decision
    → Why is this image a cat?
  - Global: explain the whole model
    → What does a cat look like?

- White box vs. black box
  - White box: use the model itself to compute interpretations
  - Black box: use an interpretable model to mimic an uninterpretable model

(a) Original. (b) Map.

LRP [Bach et al., 2015]



(a) Original (b) Mask. (c) Saliency Map.

LIME [Ribeiro et al., 2016]

Motivation: Interpretable ML

- Problem solved? → Not quite …

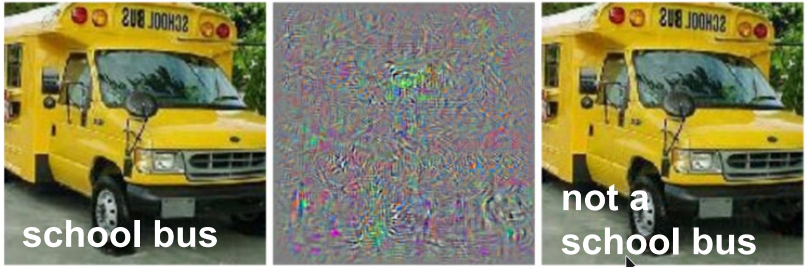
- Interpretation methods are already used in many domains for model validation

- However
  - Humans do not benefit from interpretation methods
    - they cannot build better models [Hase et al., 2020]
    - improve their performance [Hase et al., 2020]
    - and are not better at detecting false model decisions [Poursabzi-Sangdeh et al., 2018]

  - Methodological difficulties: it is unclear
    - how to evaluate
    - how to compare different interpreters

Motivation: Adversarial ML

- Adversarial model fooling
  - attacks on the **model**
  - altered input [Szegedy et al., 2013]
    → model makes false predictions

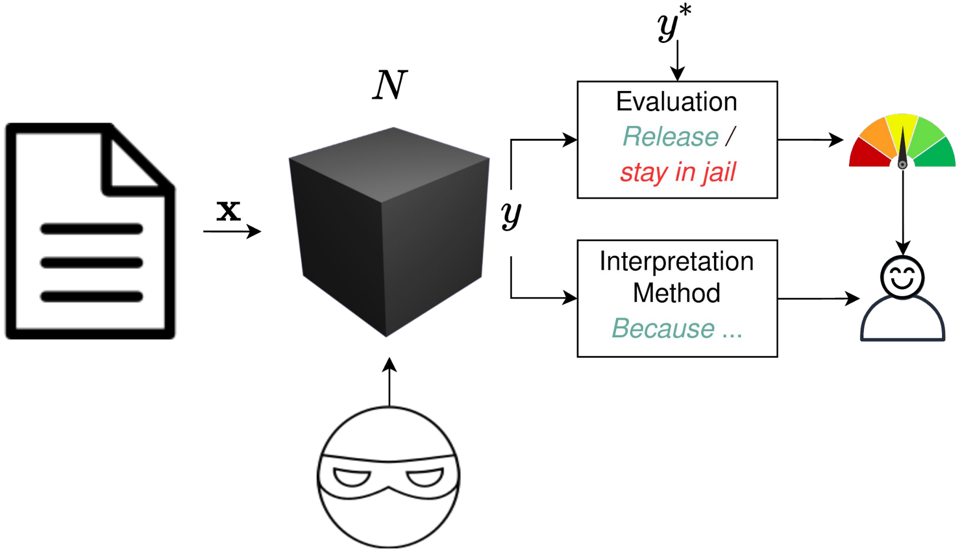


correctly labeled image | image difference | incorrectly labeled image

Motivation: Adversarial ML

- Adversarial model fooling
  - attacks on the **model**
  - altered input [Szegedy et al., 2013]
    → model makes false predictions

- **Adversarial interpreter fooling**
  - attacks on the **interpreter**
  - → interpreter makes false interpretations



Motivation: Adversarial ML

- Adversarial Interpreter Fooling

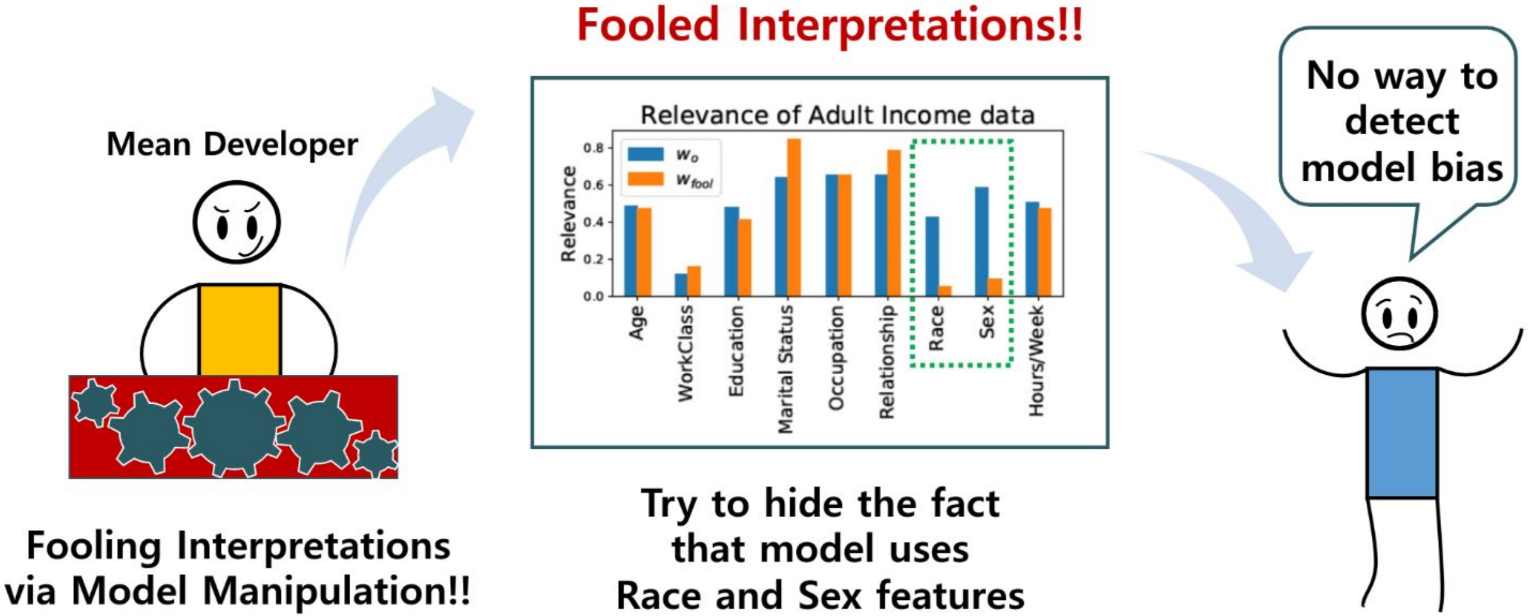
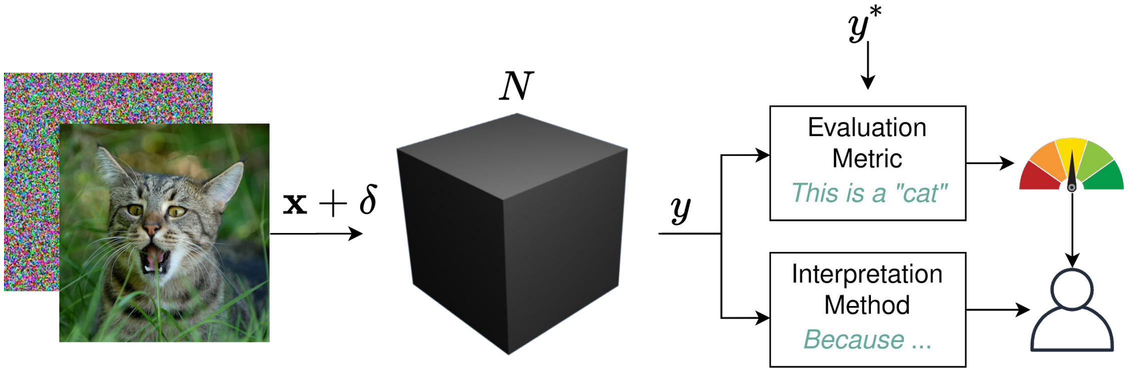


Image from: https://github.com/rmrisforbidden/Fooling_Neural_Network-Interpretations/blob/master/Materials/PPT.pdf
[Heo et al., 2019]

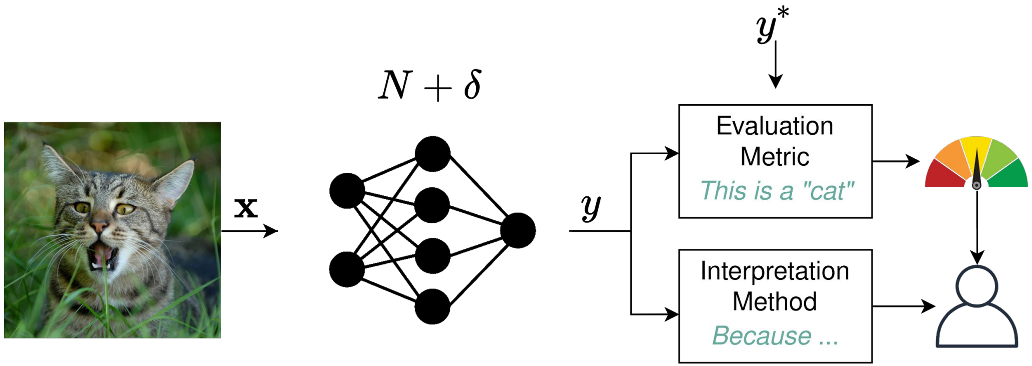
Manipulation Methods

Manipulation Types

- **Input** Level Manipulations
  - [Subramanya et al., 2019]
  - [Dombrowski et al., 2019]
  - [Ghorbani et al., 2019]



- **Model** Level Manipulations
  - [Heo et al., 2019]
  - [Dimanov et al., 2020]
  - [Slack et al., 2020]

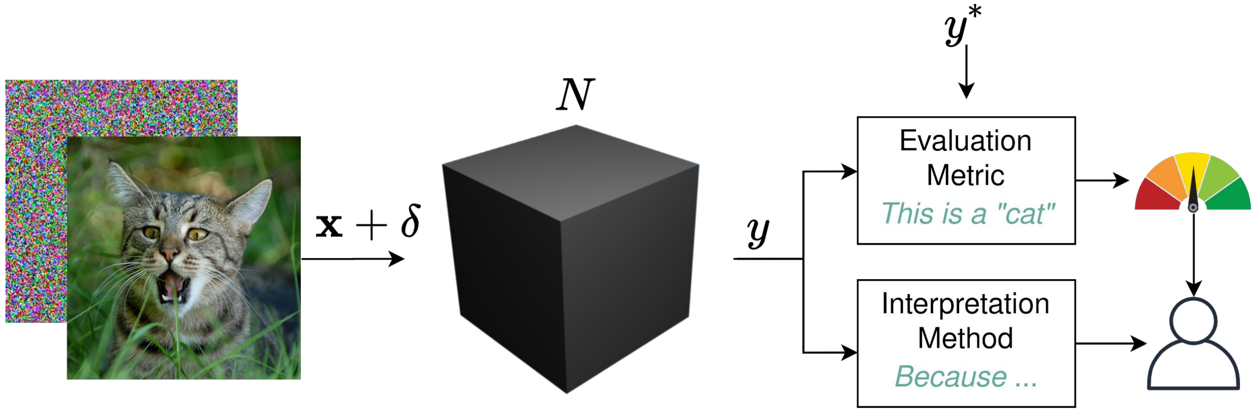


Evaluation Criteria: Is the fooling successful?

- Fooling successful if [Dimanov et al., 2020]
  - (Model prediction similarity)
  - Interpretation dissimilarity
- Other criteria
  - Effectiveness: no computational overhead
  - Transferability: manipulation does not only affect one type of interpretation
- Evaluation → which is the best interpreter?
  - Qualitative Evaluation: Inspection and random sampling
  - Quantitative Evaluation → similarity scores

Interpreter Manipulation Examples

Input Level



$$\mathbf{x} + \delta$$

Explanations can be manipulated and geometry is to blame

Ann-Kathrin Dombrowski[1], Maximilian Alber[5], Christopher J. Anders[1], Marcel Ackermann[2], Klaus-Robert Müller[1,3,4], Pan Kessel[1]

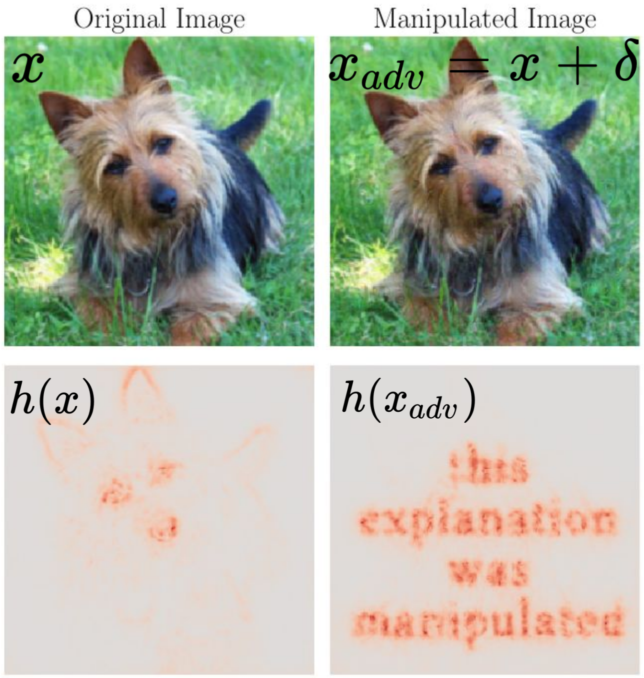
Explanations can be manipulated and geometry is to blame [Dombrowski et al., 2019]

$$\mathbf{x} + \delta$$

- **manipulate an image** with a hardly perceptible perturbation such that the explanation map matches an arbitrary target map

$$\mathcal{L} = \left\| h(x_{adv}) - h^t \right\|^2 + \gamma \left\| g(x_{adv}) - g(x) \right\|^2$$

- Practical implication:
    - adversary can imperceptibly change the input to a model
      → arbitrary + drastic manipulation of the interpreter



Further Studies

$$\mathbf{x} + \delta$$

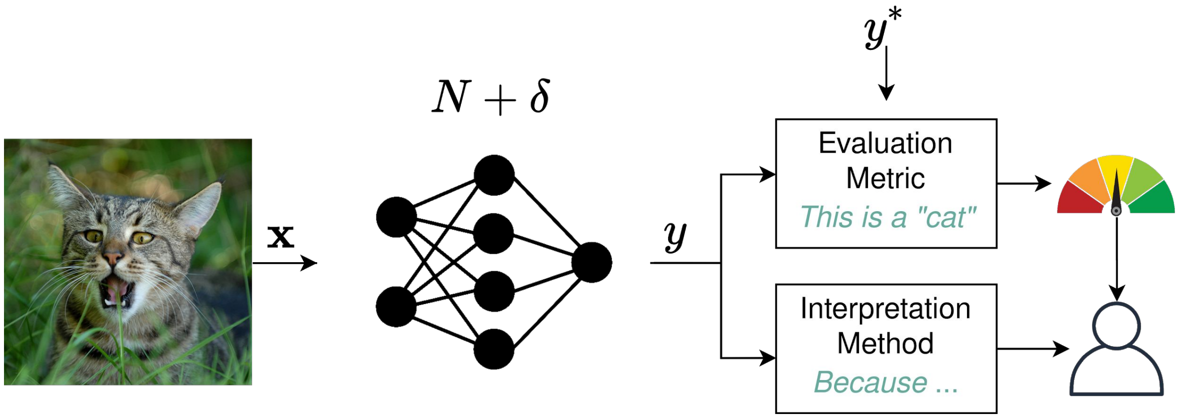
- Learned adversarial patches can cause both model and interpreter to fail [Subramanya et al., 2019]

(a) Original. Pred: 'French bulldog'. **(b)** Original with Patch. **(c)** Fooled Map, fooled model. Pred: 'Soccer ball'.

- Interpreters are susceptible even to infinitesimal perturbations [Ghorbani et al., 2019]

Interpreter Manipulation Examples

Model Level



$$N + \delta$$

Fooling Neural Network Interpretations via Adversarial Model Manipulation

Juyeon Heo[1,*], **Sunghwan Joo**[1,*] **and Taesup Moon**[1,2]
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Fooling Network Interpretations via Adversarial Model Manipulation [Heo et al., 2019]

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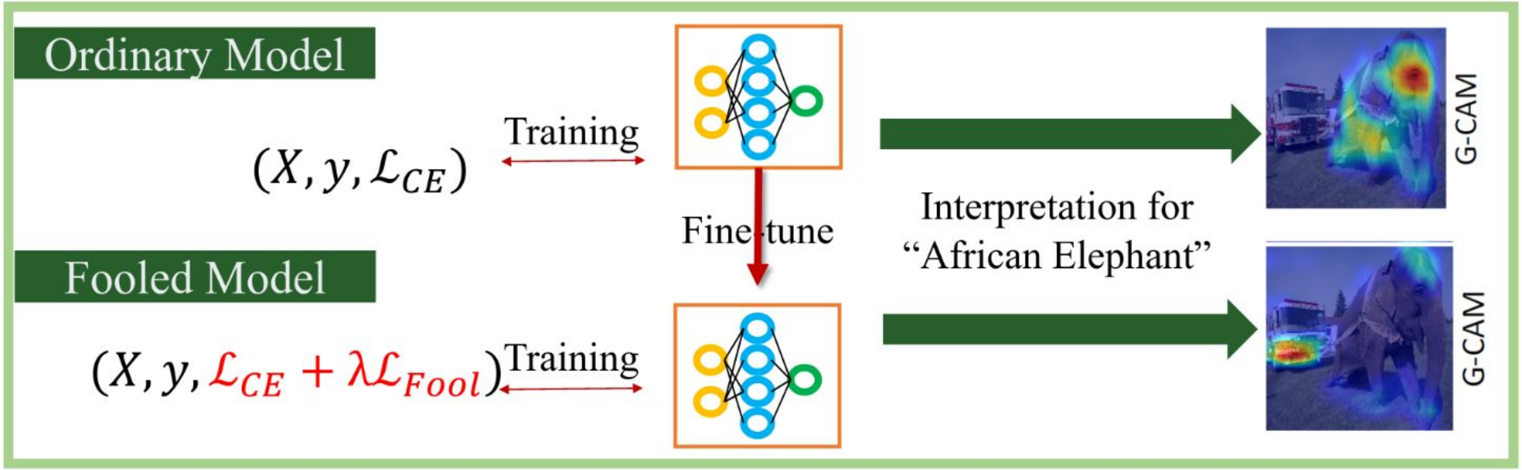

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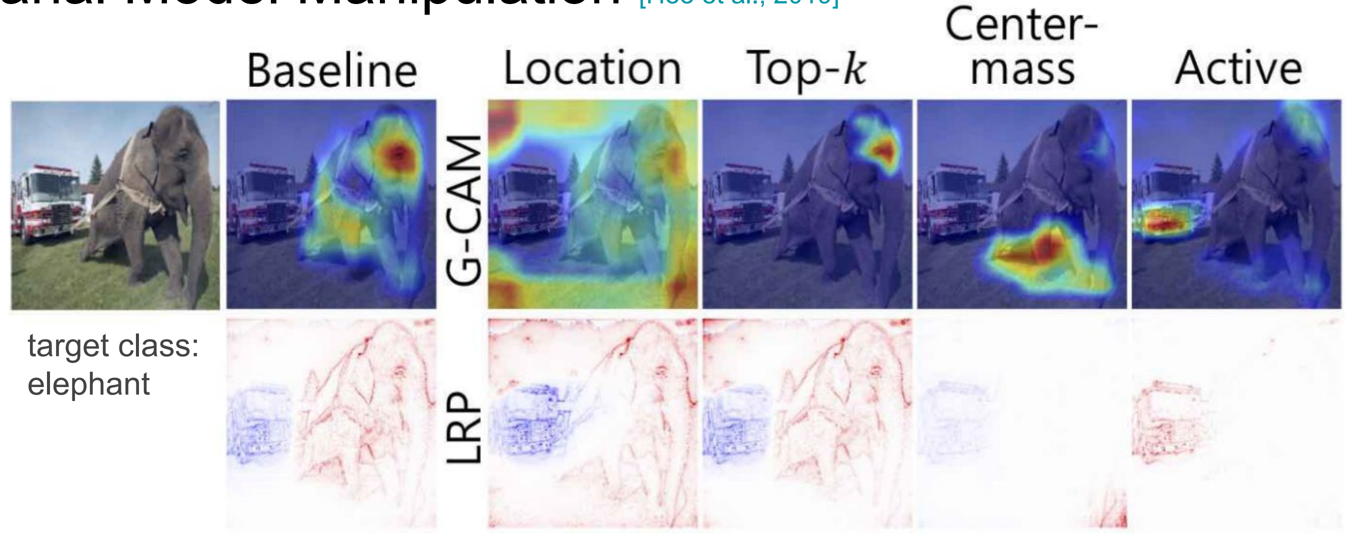


target class: elephant

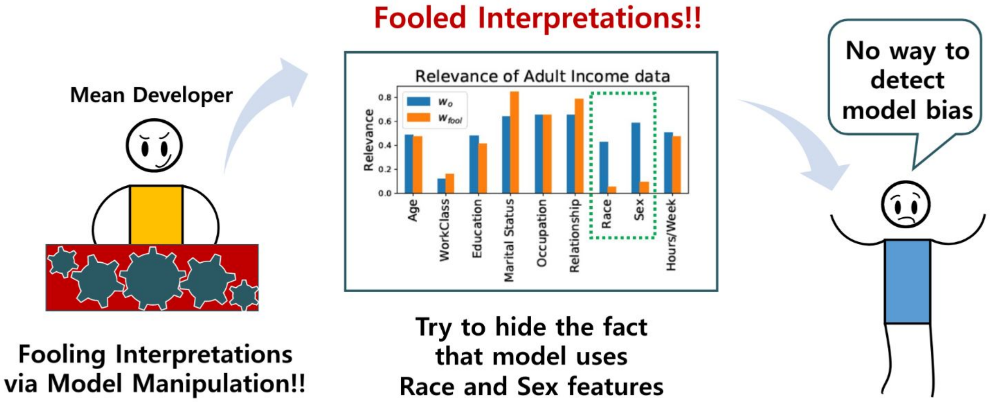
(b) Examples of different kinds of foolings

Fooling Network Interpretations via Adversarial Model Manipulation [Heo et al., 2019]

$$N + \delta$$

- Results:
  - generalization to unseen test samples
  - different types of interpreters are fooled
  - while the model performance stays approx. the same
  - → the model is robust but the interpreter is not

- Practical implication:
  - No way to detect the model inherent bias
  - Interpreters can be systematically manipulated to contain unfair biases



Further Studies

$$N + \delta$$

- Interpreters fail to decide if a model is fair [Dimanov et al., 2020]
  - create adversarial models that focus on sensitive features
  - → model interpreters fail to incorporate fairness and fail to detect model biases

→ use real-world datasets

⇒ Core motivational concern of Interpretable ML

Conclusion

Summary

→ Adversarial setting for fooling model interpreters

- Interpretation methods can be tricked by applying input and model perturbations

  - interpreters can be fooled with simple input perturbations $\mathbf{x} + \delta$

  - Biases can be encoded into the model
  - and there might be no way to uncover the hidden biases $N + \delta$

Conclusion

$$\mathbf{x} + \delta$$

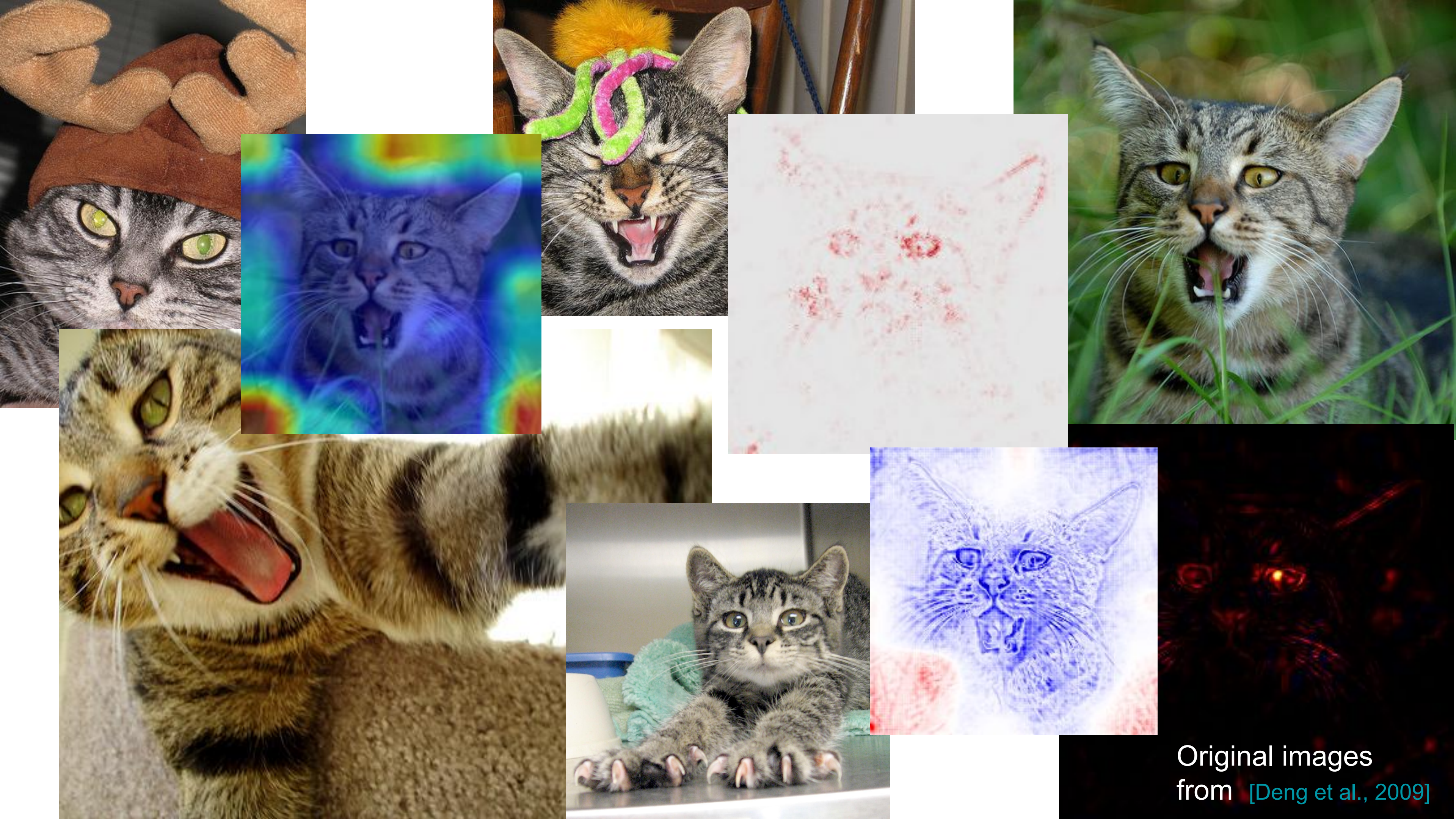
- Models and interpreters can be misled in a large and systematic manner

- However, this does not mean that interpreters are useless

⇒ **Caution** when using interpretation techniques

⇒ Future work:

  - Benchmarking
  - Robustness
  - Theoretical understanding
  - Extension to other task domains



Original images from [Deng et al., 2009]

Study Summaries

Study	Data + Task	Interpreters	Method	Results
[Dombrowski et al., 2019] Explanations can be manipulated and geometry is to blame	Images + Image Classification	LRP, Guided BP, Gradients, Integrated Gradients	generate x +δ by optimizing loss function using SGD $\mathbf{x} + \delta$	→ SmoothGrad ~ β-smoothing altered interpretations
[Subramanya et al., 2019] Fooling Network Interpretation in Image Classification	Images + Image Classification	GradCAM	generate patch z+δ by optimizing loss function $\mathbf{x} + \delta$	model + interpreter fooled
[Ghorbani et al., 2019] Interpretation of Neural Networks Is Fragile	Images + Image Classification	Integrated Gradients, DeepLift, SimpleGrad	generate samples by different schema $\mathbf{x} + \delta$	most difficult to create adv. examples for Integrated Gradients
[Heo et al., 2019] Fooling Neural Network Interpretations via Adversarial Model Manipulation	Images + Image Classification	LRP, GradCam, SimpleGrad	alter model by adapting the fine-tuning loss $N + \delta$	all interpreters are fooled, but least effect on SmoothGrad
[Dimanov et al., 2020] You Shouldn't Trust Me: Learning Models Which Conceal Unfairness From Multiple Explanation Methods	Tabular data + Classification	SHAP, LIME, IG, Gradients, etc.	alter model by adapting the fine-tuning loss to have low target feature attribution $N + \delta$	interpreters do not reveal unfairness
[Slack et al., 2019] Fooling LIME and SHAP: Adversarial Attacks on Post hoc Explanation Methods	Tabular data + Classification	LIME, SHAP	alter the original model by classifying arbitrarily on non-perturbed samples $N + \delta$	LIME is slightly more robust

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