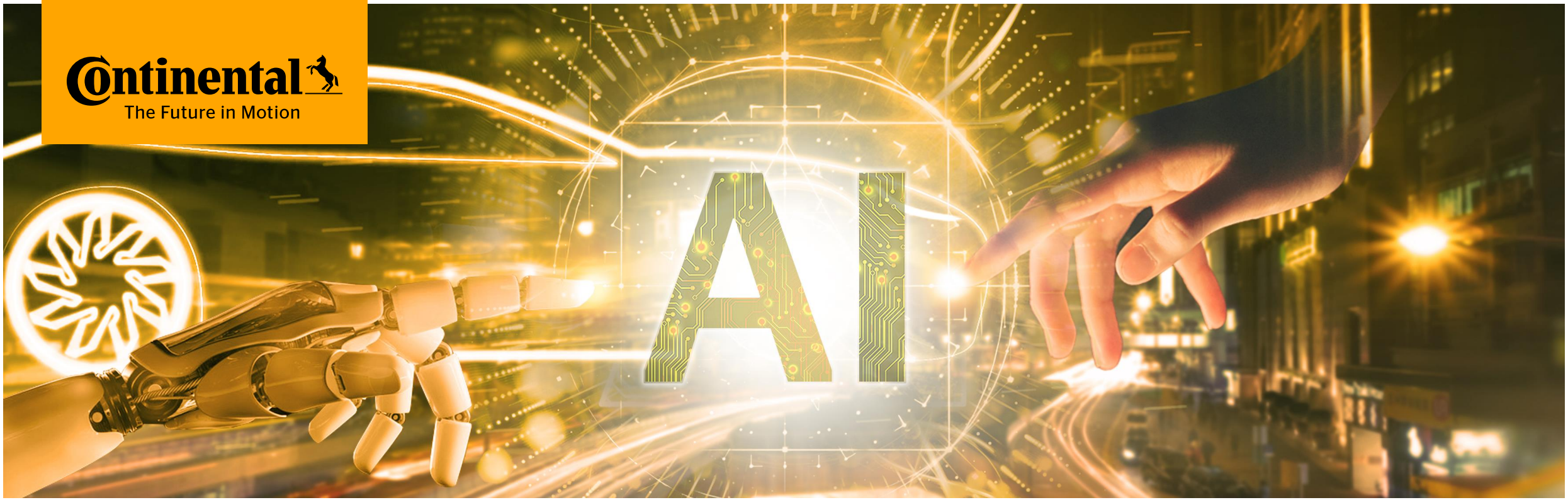

Diversity and Applications of Explainable Artificial Intelligence Methods

Gesina Schwalbe

www.continental.com

Agenda

1	What is Explainability?	3
2	Applications	5
3	A Method Taxonomy	8
4	Methods for Explaining ML Models	10

Agenda

1	**What is Explainability?**	**3**
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What Is Explainability?

Explainable decision system = There exists a

- **mechanism** providing an **explanation** (= explanator)
- to a **human** (= explainee)
- that allows them to **understand**
- one of (= explanandum)
  - the **model** resp. parts thereof,
  - evidence for a **model output**, or
  - the **context** of the system's reasoning.

XAI = lots of cognitive science!

Understanding = successful update of mental model; can be

- mechanistical = how it works, or
- functional = what is its purpose

Levels of **transparency** of a model (= mechanistic understanding):

- simulatable (= understandable as a whole)
- decomposable (into simulatable parts)
- algorithmically transparent (= mathematical understanding)

cf. (Schwalbe & Finzel 2022)

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Use-cases

- **Compliance** with law and standards (e.g. GDPR); assessment e.g. wrt. safety, security, fairness, privacy

- Developer and expert users:
  - **Debugging** (robustness, trustworthiness)
  - **Knowledge retrieval**, transferability
  - **Assess compliance** with behavioral requirements

- Users:
  - (appropriate!) **Trust**, informed consent
  - Easily **getting familiar** with system
  - **Recourse** (e.g. in ranking systems)

Exemplary Application Fields

Wherever automated decisions influence human well-being!

E.g.

- Automated driving
- Medical assistant systems
- Ranking systems (social, credits, …)
- Military decision systems
- Recommendation systems
- Data science
- HMI in Production
- …

Agenda

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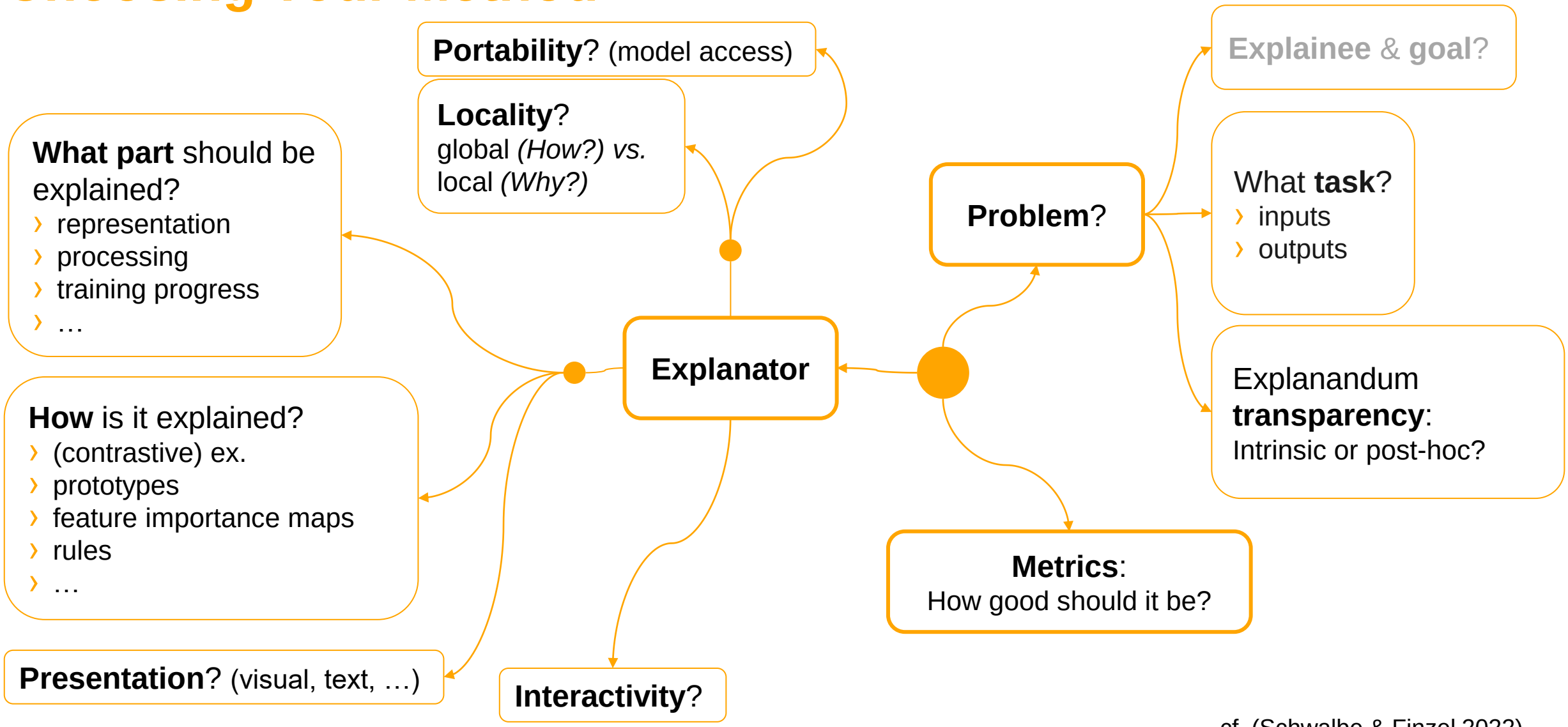
Choosing Your Method



cf. (Schwalbe & Finzel 2022)

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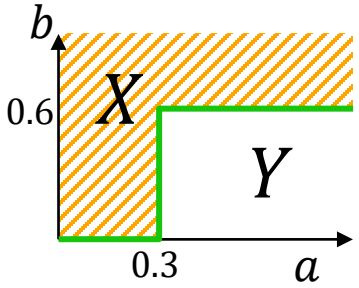
Inherently Interpretable Models

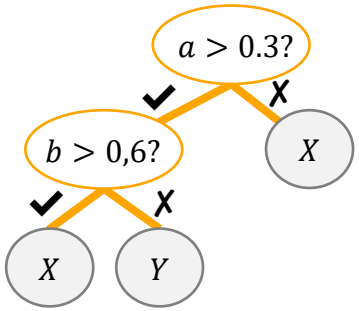
› Decision **Rules**

```
face(F) :- contains(F, A), isa(A, nose), contains(F, B), isa(B, mouth),
           top_of(A, B), contains(F, C), top_of(C, A).
```

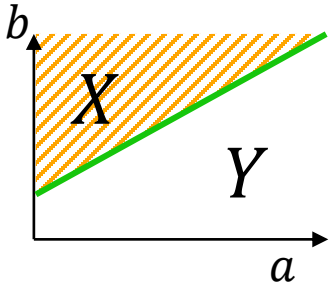
cf. (Rabold et al. 2020)

› Decision **Trees**





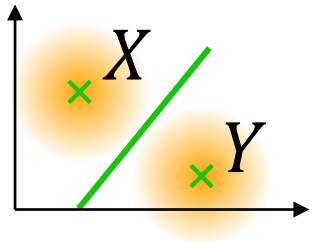
› **Linear** Models,
Generalized **Additive** Models



Linear: $f(x) = \alpha a + \beta b$

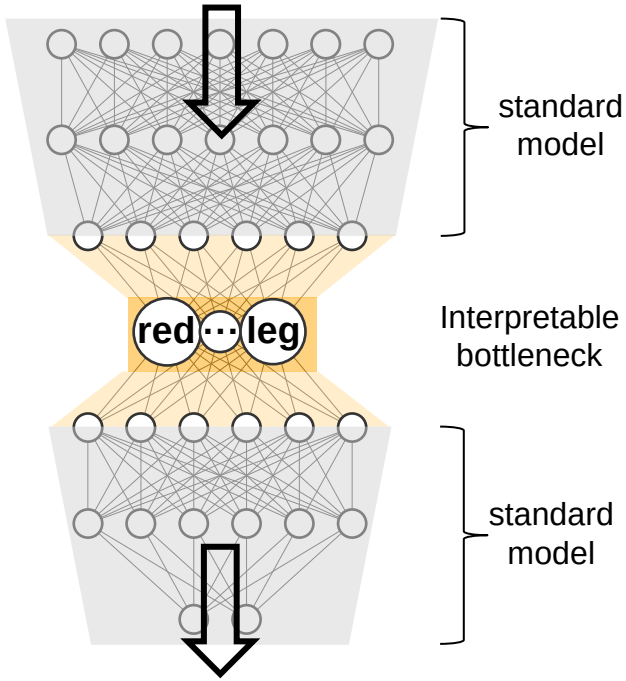
GAM: $f(x) = g^{-1}(f_a(a) + f_b(b))$

› **Clustering**

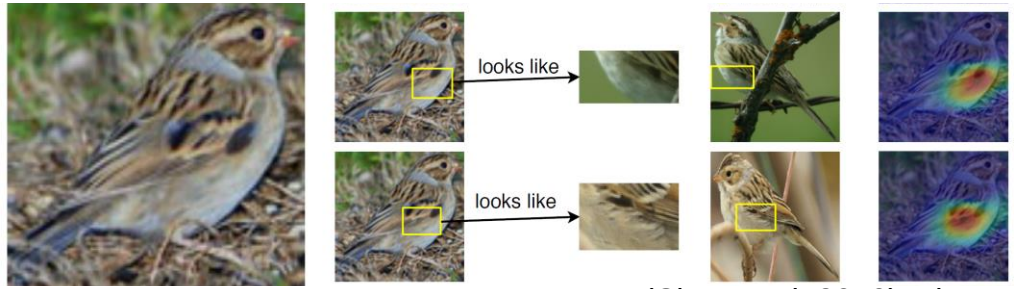


Blended and Self-explaining Models

Concept Bottlenecks (Losch et al. 2020), (Koh et al. 2020)
Disentangled Representations



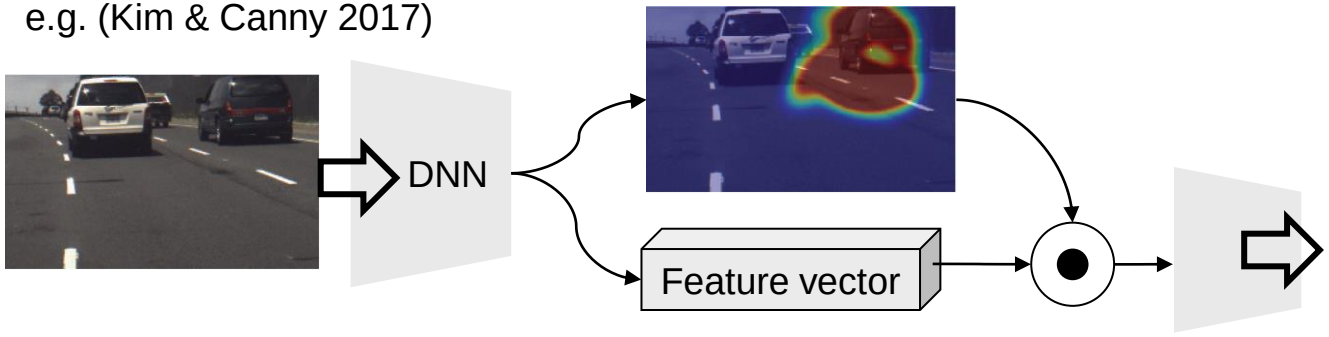
ProtoPNet (Chen et al. 2019)



(Chen et al. 2019), Fig. 1

Attention models
e.g. (Kim & Canny 2017)

(filtered) Attention



(Kim & Canny 2017, Fig. 5)

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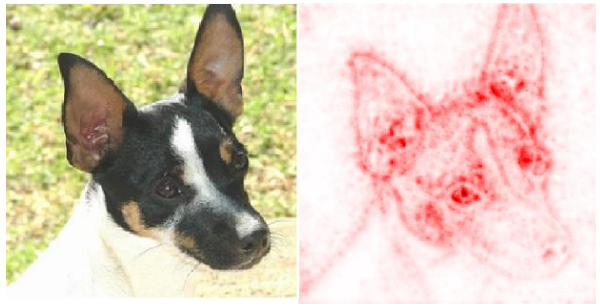
Feature Saliency

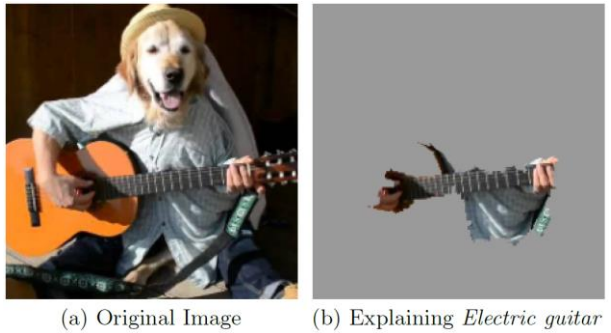
› What **input features** were (how) **important** to the **output**?

Works for features like …



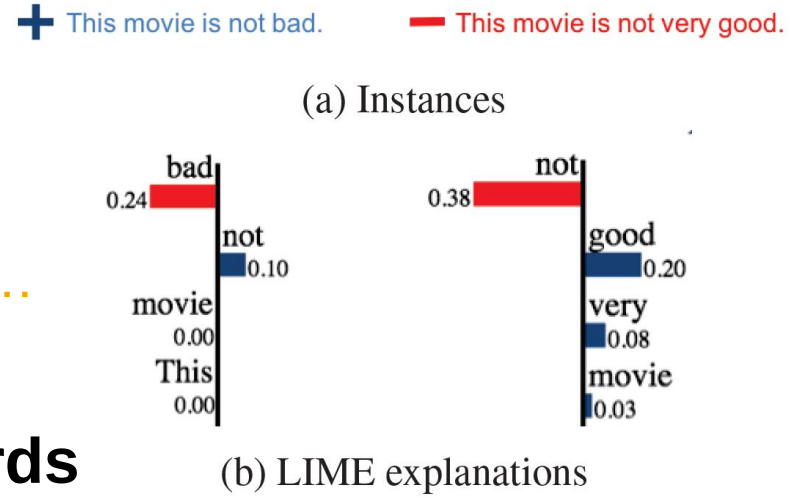
Pixels

(Kindermans et al. 2018), Fig. 6



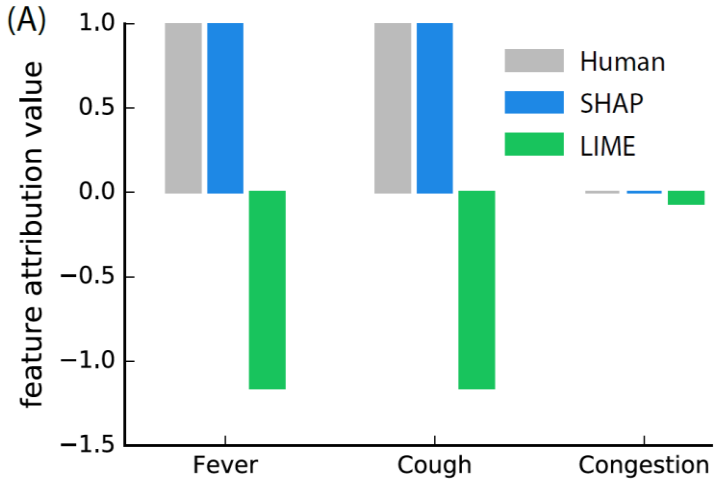
Super-pixels

(Ribeiro et al. 2016), Fig. 4



Words

(Ribeiro et al. 2018), Fig. 1



Tabular Features

(Lundberg & Lee 2017), Fig. 4

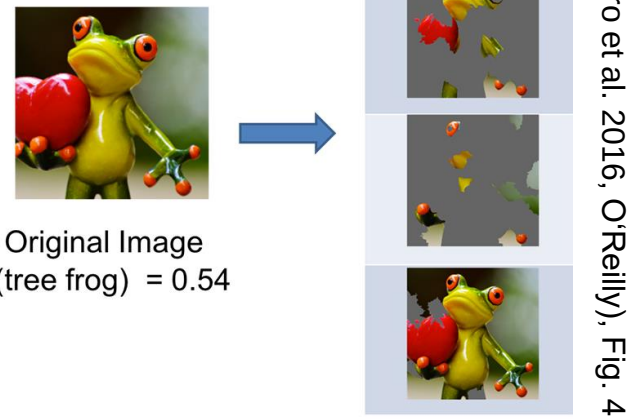
Feature Saliency: Types

› **Activation map**-based (Attention)

(cf. attention models)

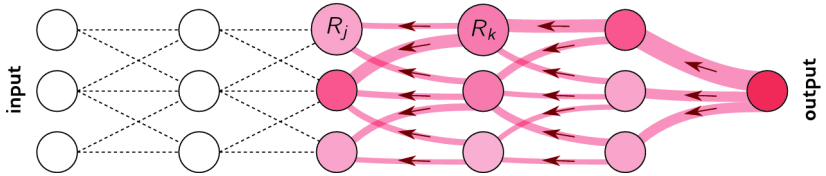
(Kim & Canny 2017, Fig. 5)

› **Perturbation**-based

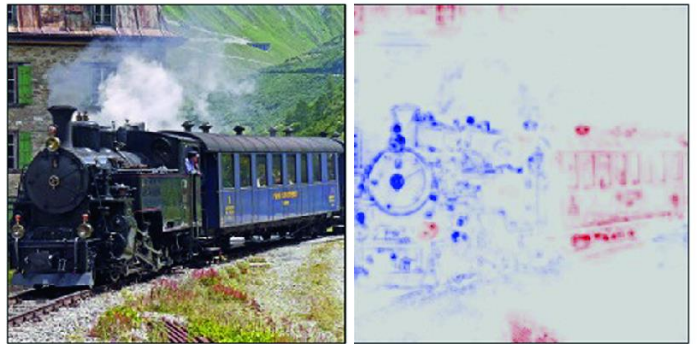


(Ribeiro et al. 2016, O'Reilly), Fig. 4

› **Backpropagation-** or **Gradient**-based



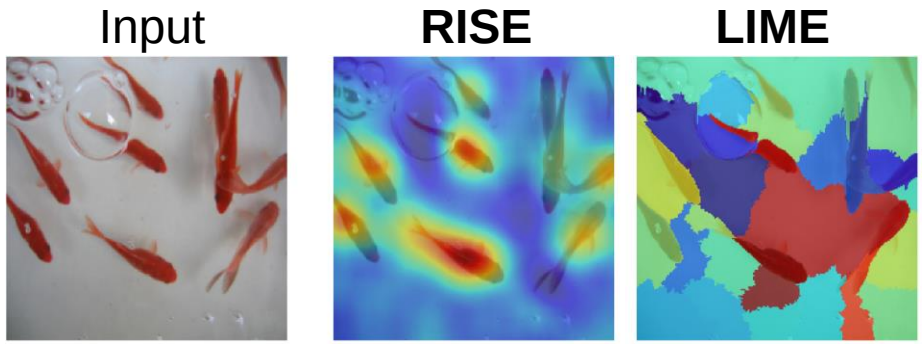
(Montavon et al. 2019), Fig. 10.2



(Montavon et al. 2019), Fig. 10.5

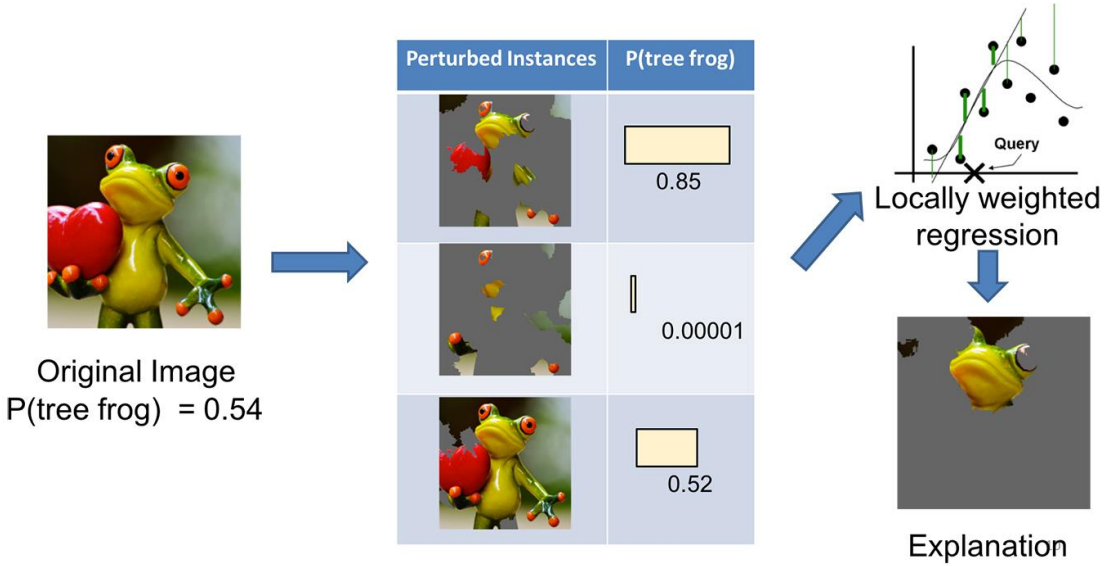
Feature Saliency: Perturbation-based

- *Idea:* “Remove” features and observe effect
- Often **model-agnostic**
- **Several inferences** needed
- *Differences:*
  - Definition of **features** & feature **removal**, *e.g.*

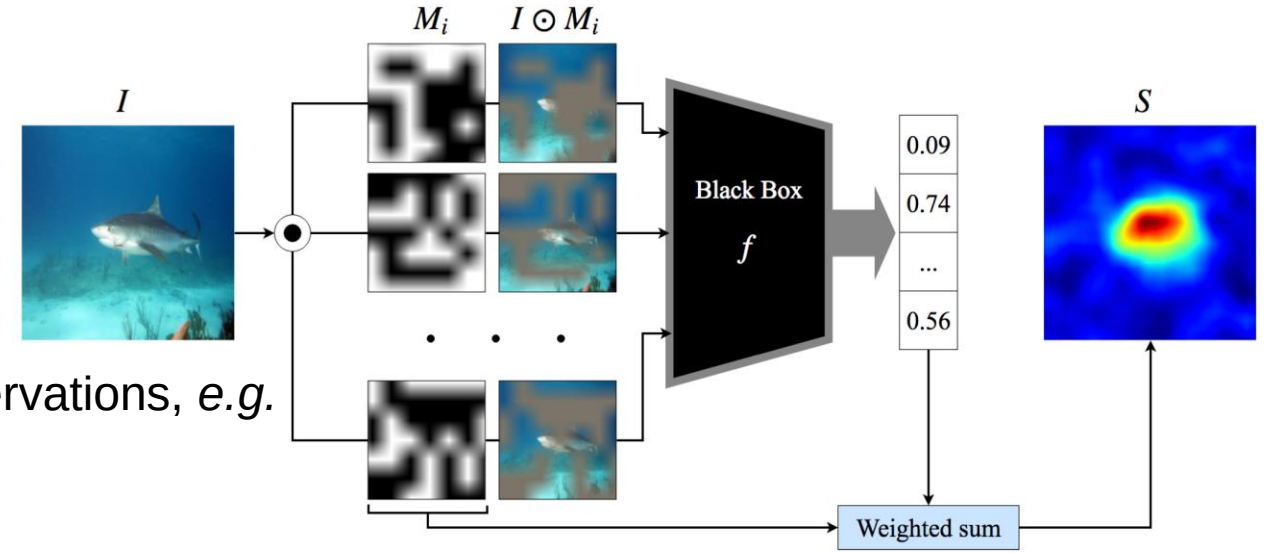


(Petsiuk et al. 2018), Fig. 2

  - **Calculation** of feature importance from observations, *e.g.* linear regression in LIME (Ribeiro et al. 2016) vs. gaming theory in SHAP (Lundberg & Lee 2017)



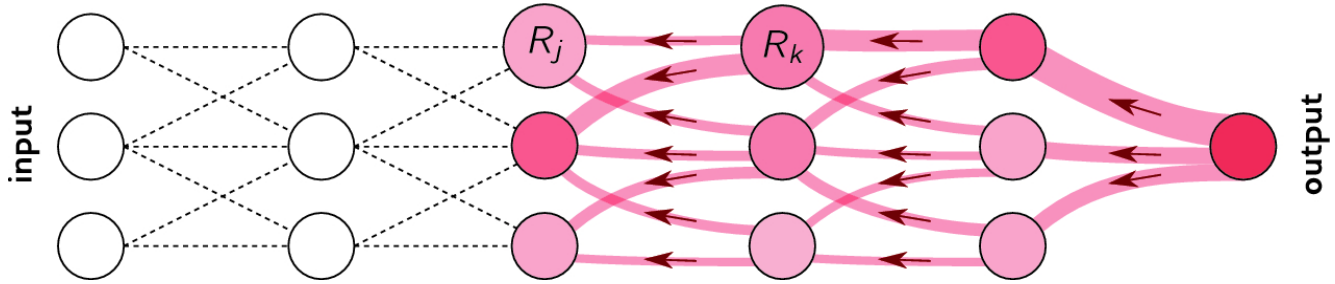
LIME
(Ribeiro et al. 2016, O'Reilly), Fig. 4



RISE
(Petsiuk et al. 2018), Fig. 3

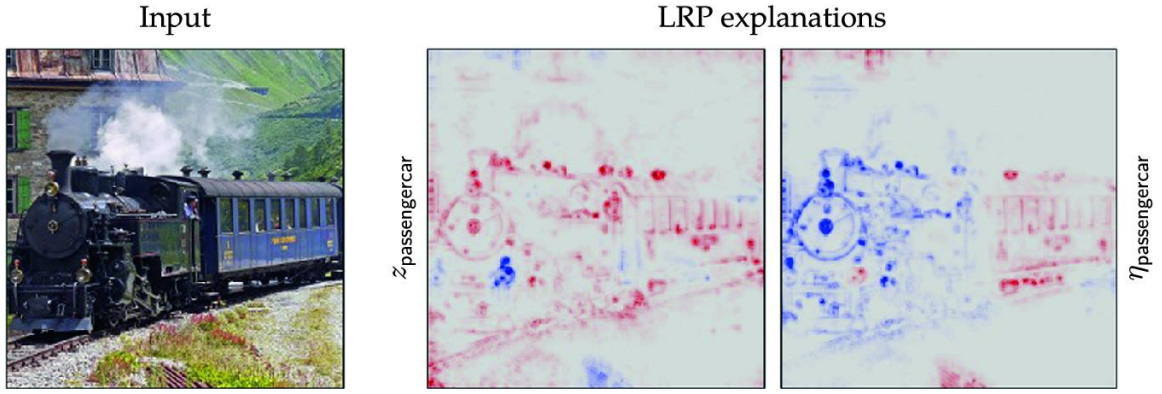
Feature Saliency: Backpropagation-based

- *Idea:*
  - **Trace back influence** (=*Relevance*) of activations from output to input
  - Total relevance within a layer l stays constant:
    $f(x) = \cdots = \sum_i R_i^{(l-1)} = \sum_i R_i^l$
- One additional **backwards-pass**
- Requires **access to model** internals
- Backpropagation functions **must be chosen carefully** wrt. layer type and question



(Montavon et al. 2019), Fig. 10.2

- Special case applicable to general differentiable models: Use gradients!



(Montavon et al. 2019), Fig. 10.5

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Latent Space Analysis: Feature Visualization

› *What does a network unit/part (e.g. neuron, channel) encode?* Use e.g.

Examples
activating unit strongly

DeepDream Prototypes
= starting image optimized to activate unit strongly

Baseball—or stripes? *mixed4a, Unit 6*

Animal faces—or snouts? *mixed4a, Unit 240*

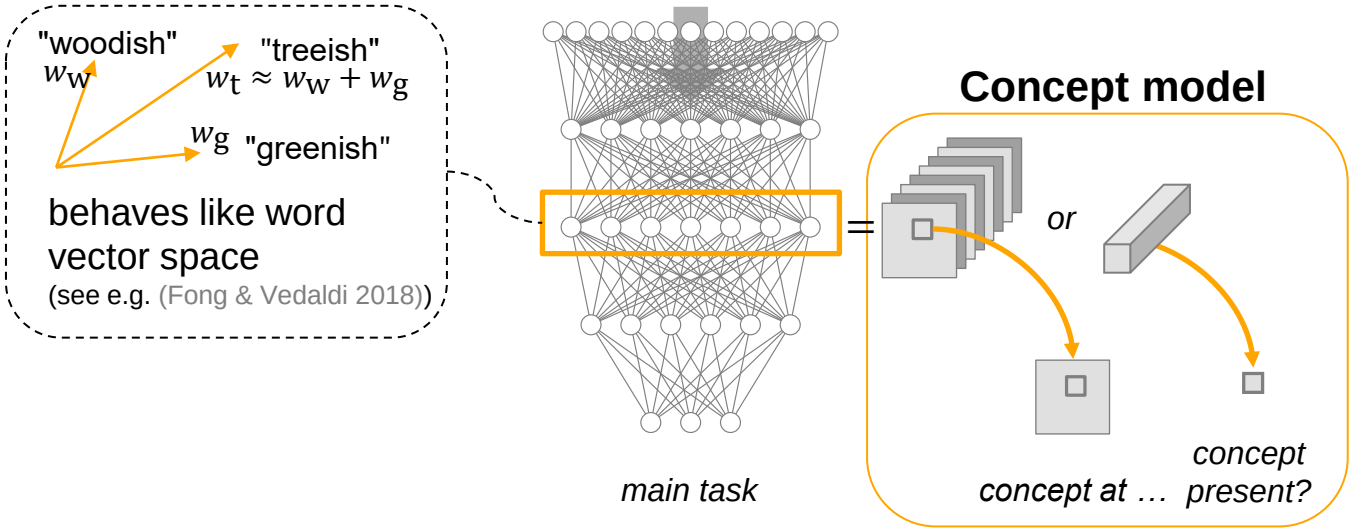
Clouds—or fluffiness? *mixed4a, Unit 453*

Buildings—or sky? *mixed4a, Unit 492*

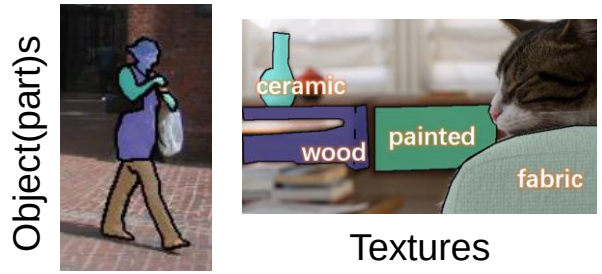
(Olah et al. 2017), Fig. 5

Latent Space Analysis: Concept Embedding Analysis

- *Goal: Associate semantic concept w/ latent space vector / subspace*
- *Idea:* Vector as parameters of simple predictor for concept (*concept model*)

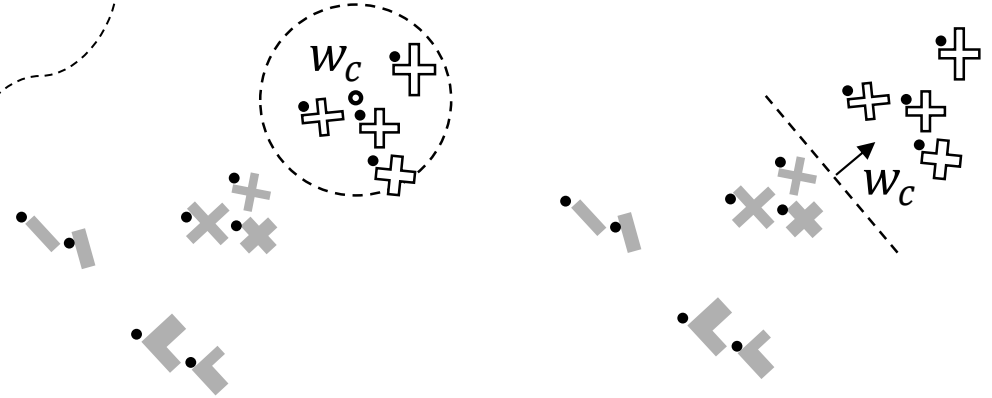


Some concept types



(Xiao et al. 2018), p. 6, Fig. 3

Main types of concept models:



Clustering & matrix factorization
e.g. ACE (Ghorbani et al. 2019), NCAV (Zhang et al. 2021)

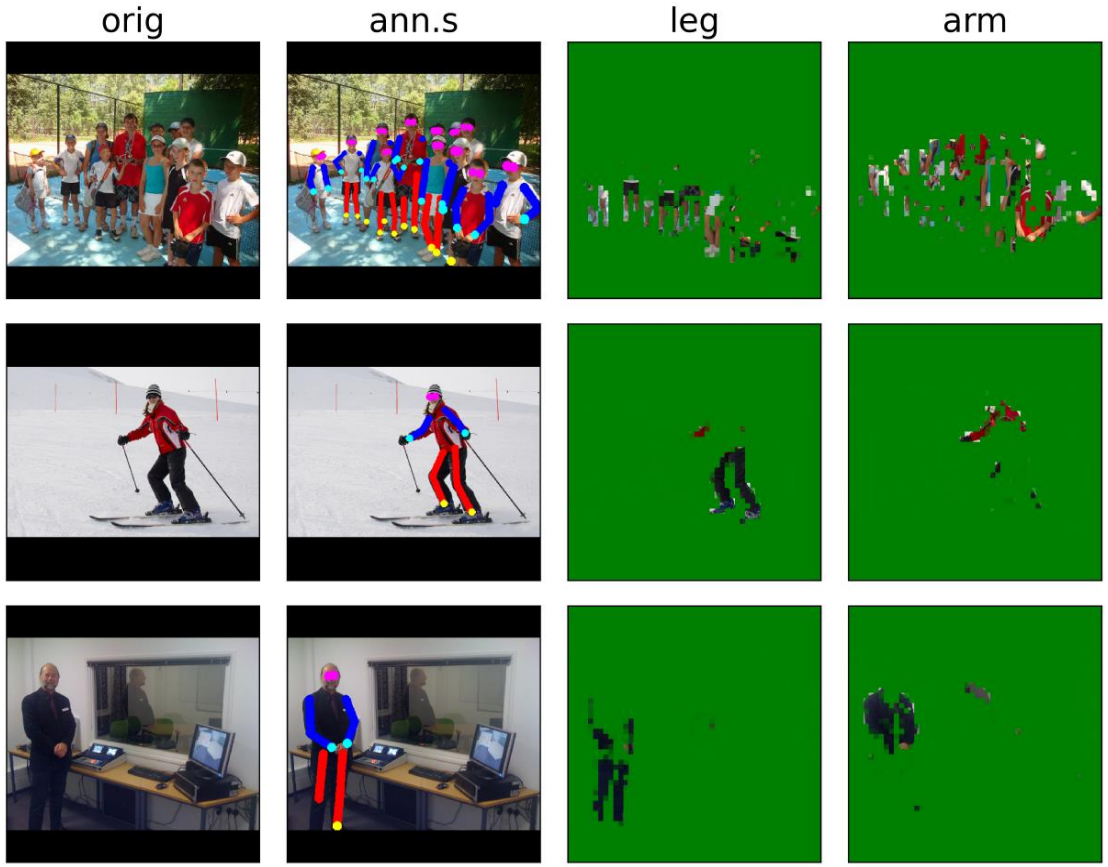
Linear
$f_c = \cdot \circ w_c + t_c$
e.g. TCAV (Kim et al. 2018), Net2Vec (Fong & Vedaldi 2018)

cf. (Schwalbe 2022), Fig. 3

Latent Space Analysis: Concept Embedding Analysis

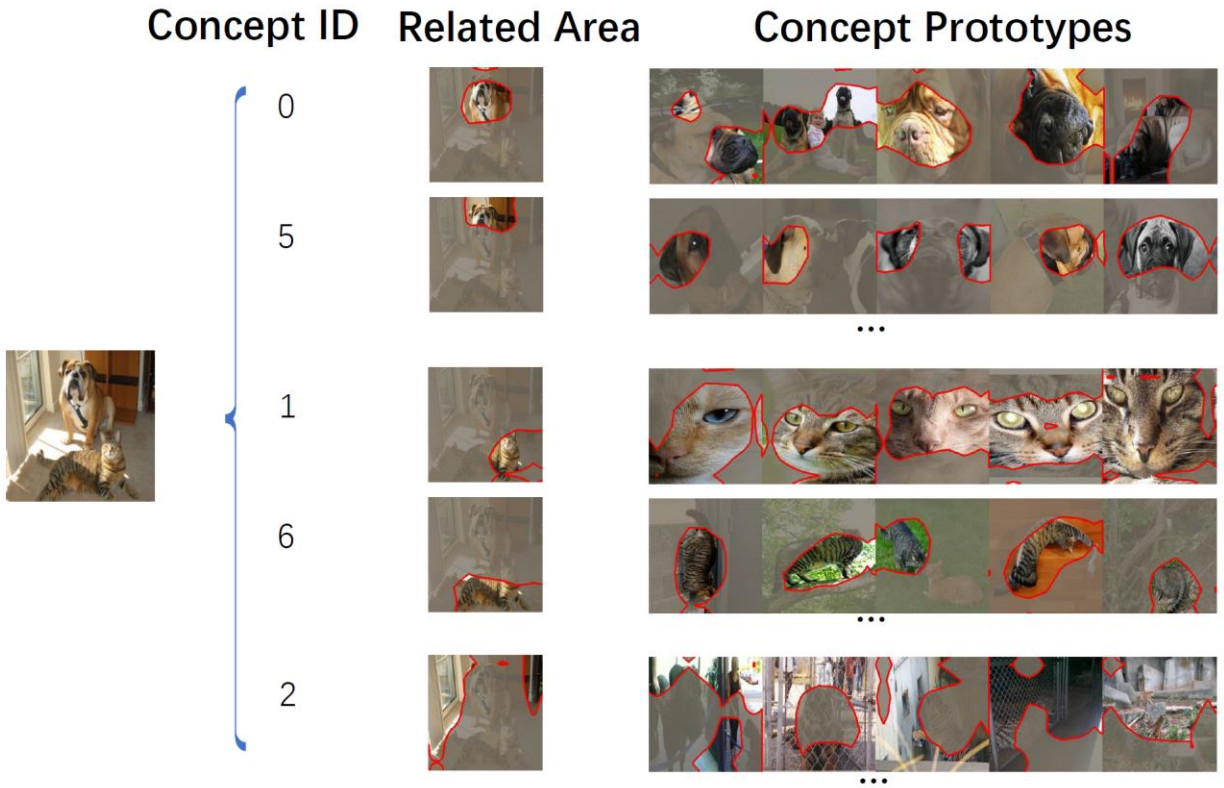
Examples

› **Supervised** using simplified Net2Vec on object detection DNN:



(Schwalbe 2021), Fig. 5

› **Unsupervised** using NCAV on classification DNN:



(Zhang et al. 2021), Fig. 1

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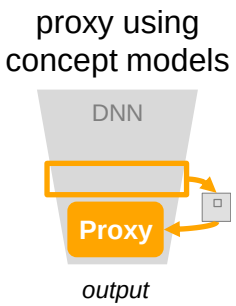
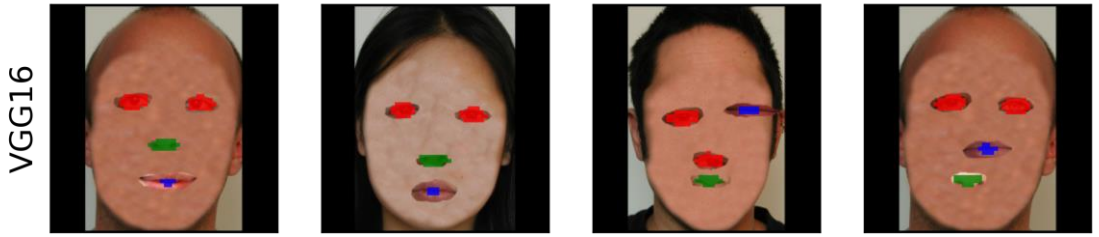
Explainable Surrogates

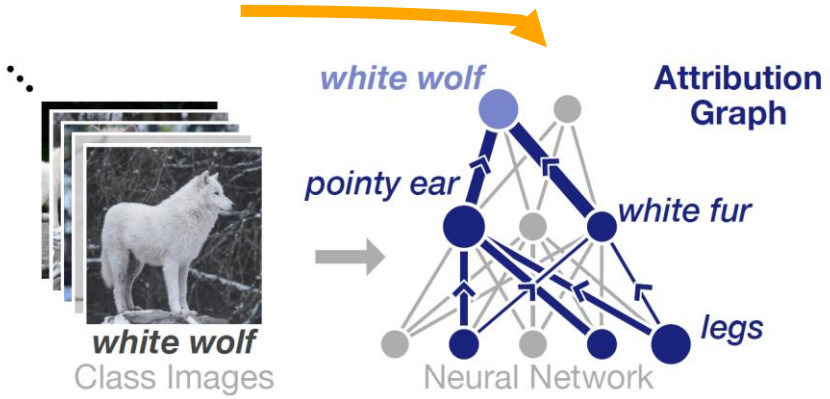
- *Idea:* Approximate DNN (parts) by interpretable model
- Example surrogate types:
  - (Locally) **linear**, *e.g.* LIME (Ribeiro et al. 2016)
  - Local or global **decision tree or rules**, *e.g.* **CA ILP** (Rabold et al. 2020) *(local)*
  - Dependency / flow **graphs**, *e.g.* **SUMMIT** (Hohman et al. 2020)



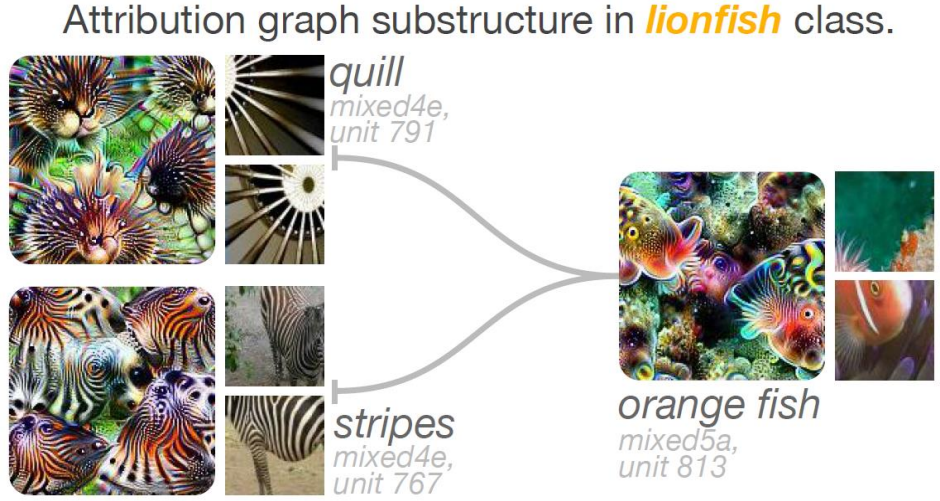


(Rabold et al. 2020), Fig. 4

```
face(F) :- contains(F, A), isa(A, nose), contains(F, B), isa(B, mouth),
           top_of(A, B), contains(F, C), top_of(C, A).
```



(Hohman et al. 2020), Fig. 2



(Hohman et al. 2020), Fig. 7

What Makes “Good” Explanations?

Recommendations:

On local explanations (=*“Why this decision?”*) (Miller 2019):

- Use **contrastive** explanations (=“Why this action *instead of another*?”)
- **Causal links** > probabilities
- **Explainee background** matters!
- **Context** matters for explanation selection! (Why is the explanation needed?)

On global explanations (=“How does it work?”):
Use interpretable models where possible! (Rudin 2019)

Metric examples:

- Functional level:
  - Faithfulness
  - Coverage
  - Accuracy
  - Scalability
  - …
- User level:
  - Comprehensibility
  - Improvement of human-AI system
  - …

Tradeoffs necessary
(no one-fits-all method)

Conclusion

- Explanation here means “*help a human understand an aspect of a model*”
  → *intrinsically cognitive!*

- Field of XAI:
  - very **diverse**
  - **needed** for many applications

- The **why**, **who**, **what**, and **how** matter!
- **Tradeoffs** require careful choice of method(s)

- More research needed!

Thanks for listening! Questions?

Contact: Gesina.Schwalbe@continental-corporation.com

Some further reading by us:

Schwalbe, Gesina, and Bettina Finzel. 2021. “A Comprehensive Taxonomy for Explainable Artificial Intelligence: A Systematic Survey of Surveys on Methods and Concepts.” https://arxiv.org/abs/2105.07190.

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