

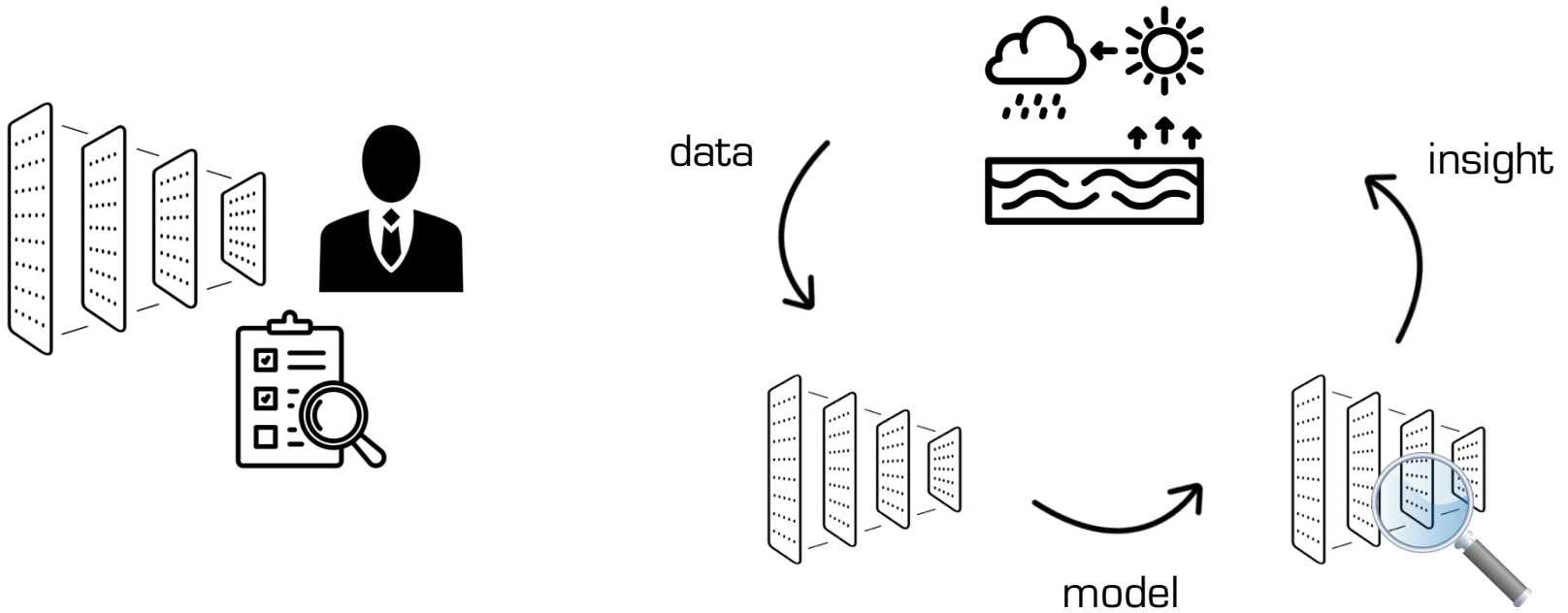
# Uncovering Input-Target Associations with Explainable AI

Grégoire Montavon

22 October 2025



# Two Distinct Uses of XAI



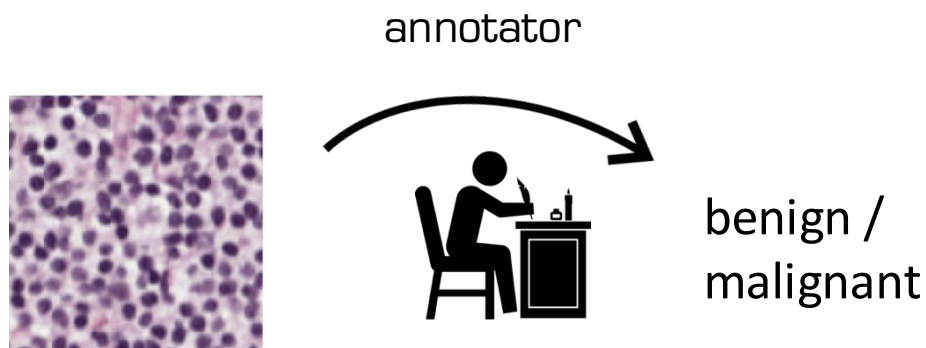
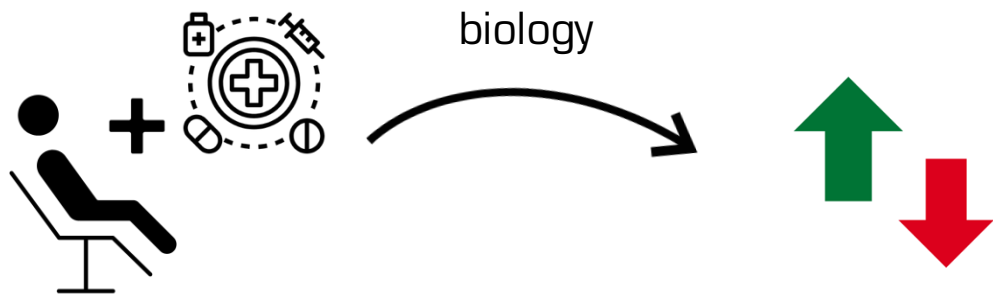
## 1. XAI for ML Auditing

- Object of interest is the ML model. XAI is the tool.

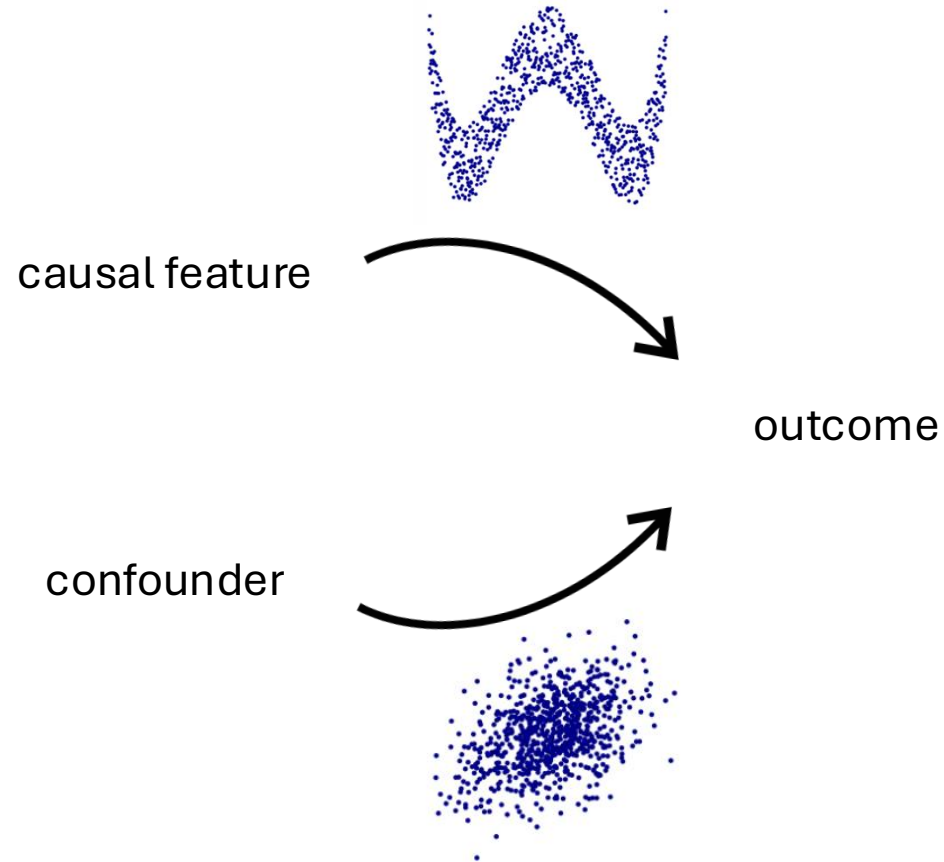
## 2. Understanding

- Object of interest is the natural system or process. ML/XAI are the tools.

# Examples of Systems of Interest



# Hypothesis on Causal Features

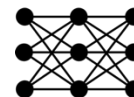


# Empirical Evidence

annotation  
→ horse



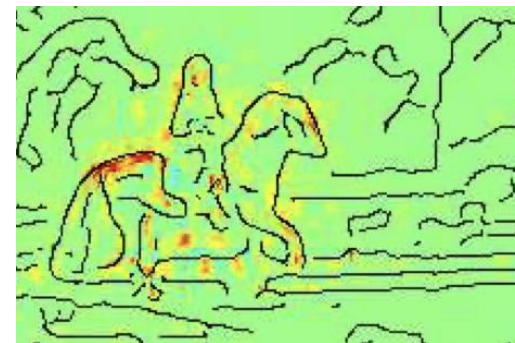
pre-2012



post-2012



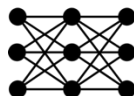
- limited data
- simple models
- weak correlates
- less generality



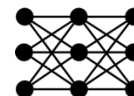
- big data
- complex models
- strong correlates
- more generality

# Empirical Evidence

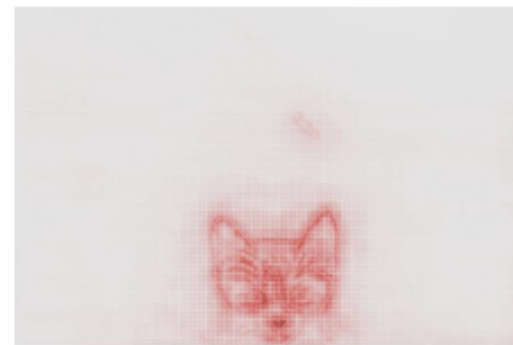
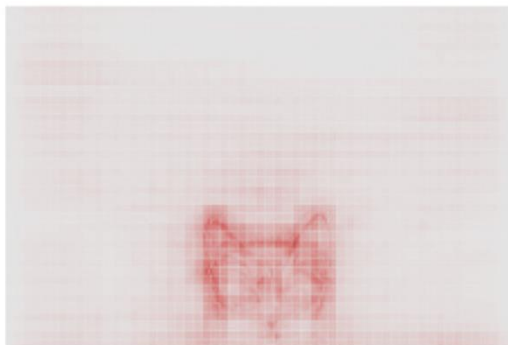
annotation  
→ cat



2012



2014

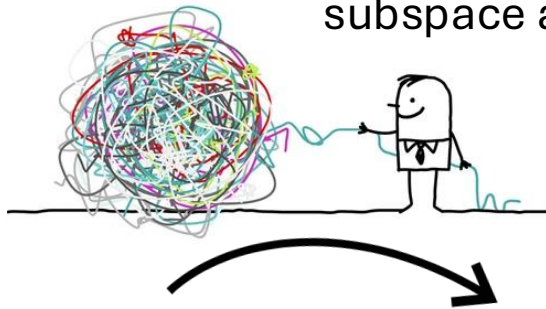


- limited data
- simple models
- weak correlates
- less generality

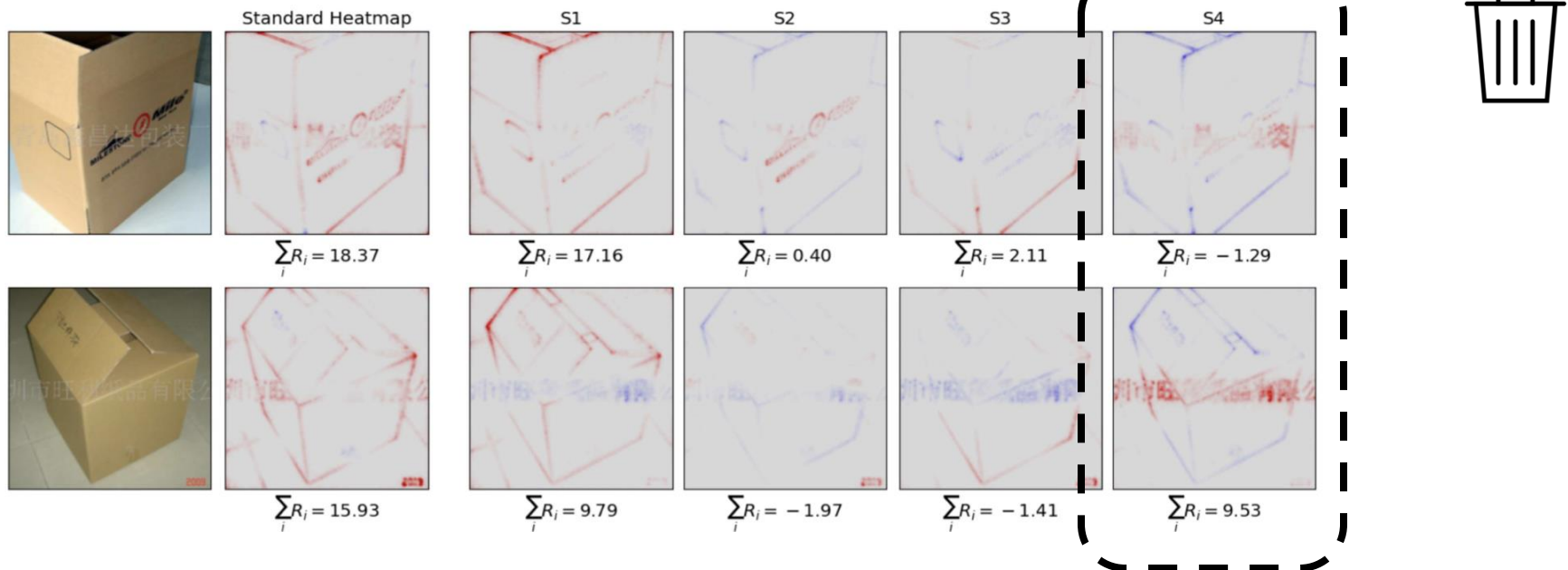
- big data
- complex models
- strong correlates
- more generality

# Deconfounding Methods

disentangled relevant  
subspace analysis (DRSA)

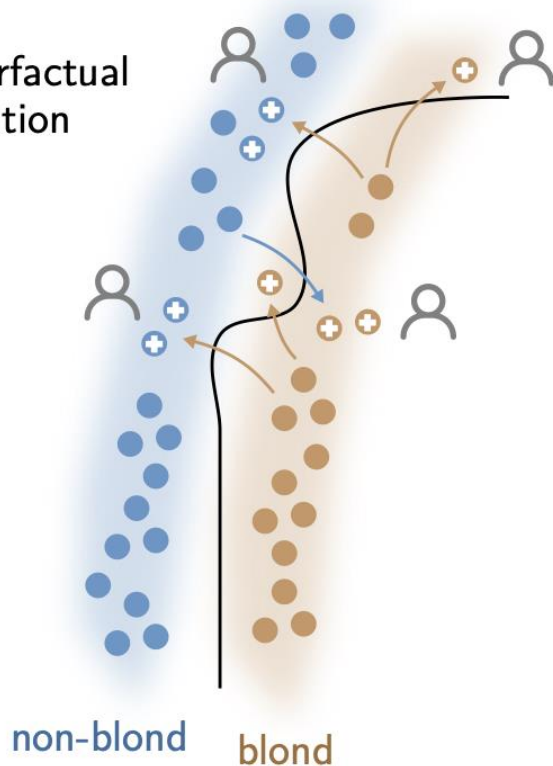


human  
inspection +  
pruning

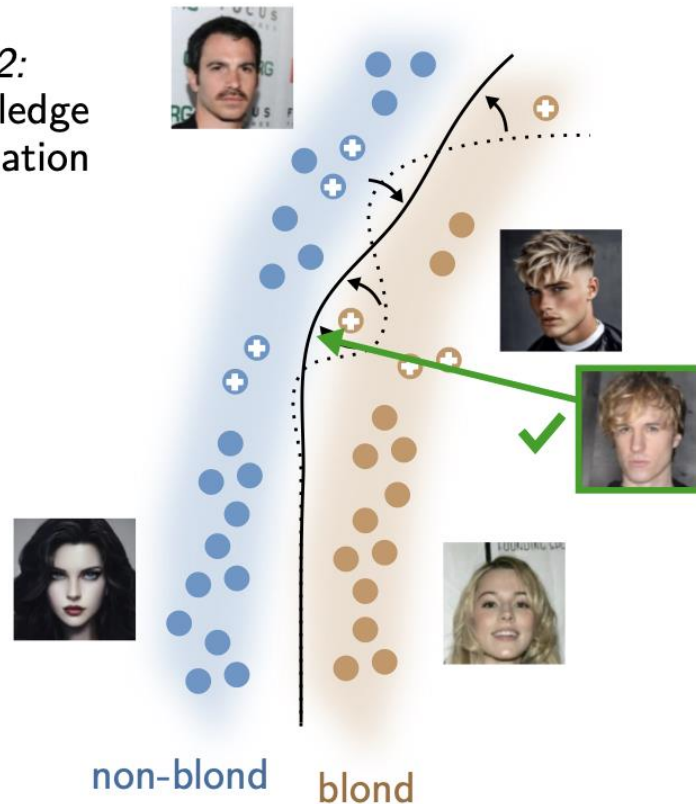


# Deconfounding Methods

step 1:  
counterfactual  
exploration



step 2:  
knowledge  
distillation





# Trends in AI for Medicine



- Large datasets publicly available.
- State-of-the-art ML architectures (e.g. transformers, Mamba, etc.) being applied.
- Methods to detect/remove confounders being developed.



uk  
**biobank**

TCGA 

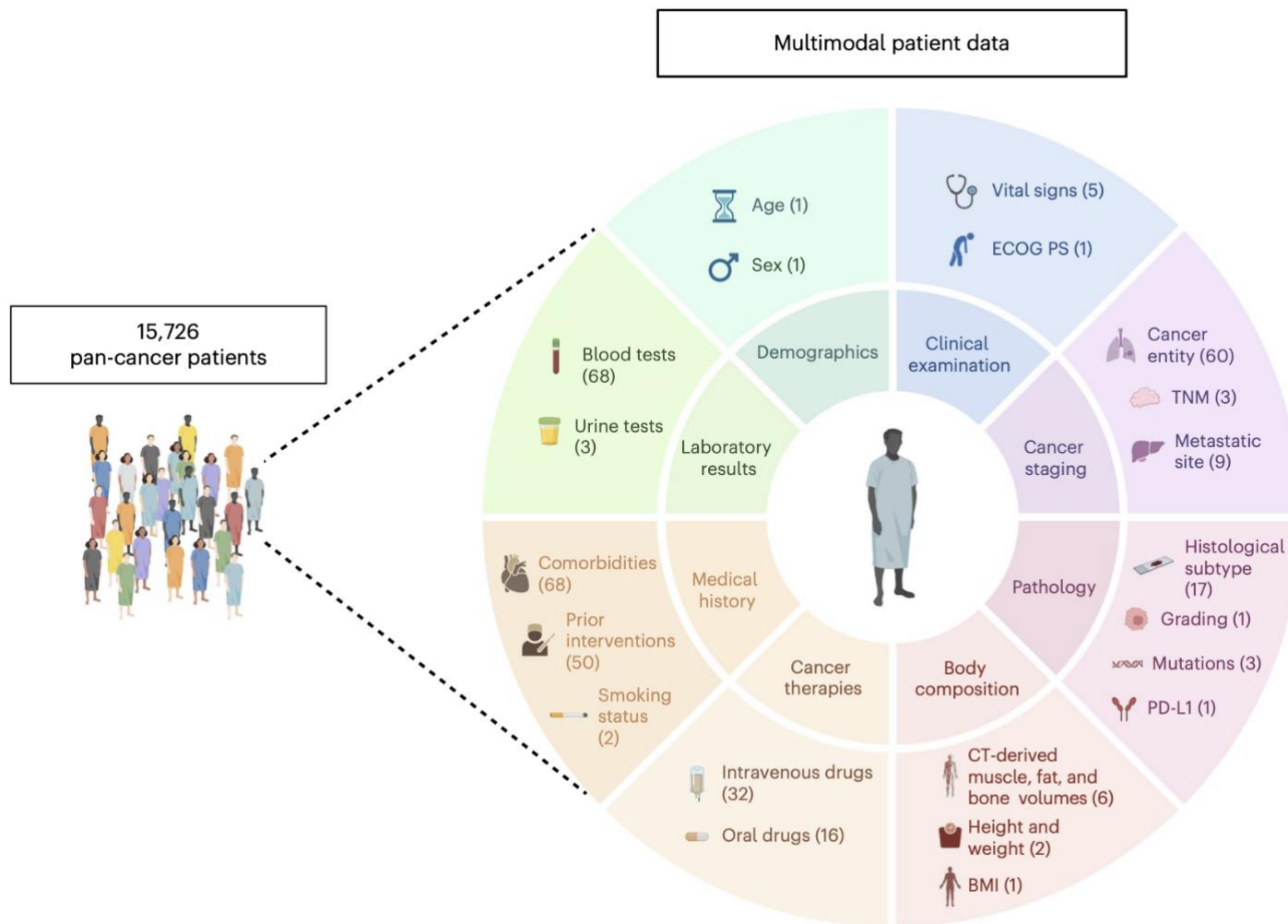
 **Meditron**



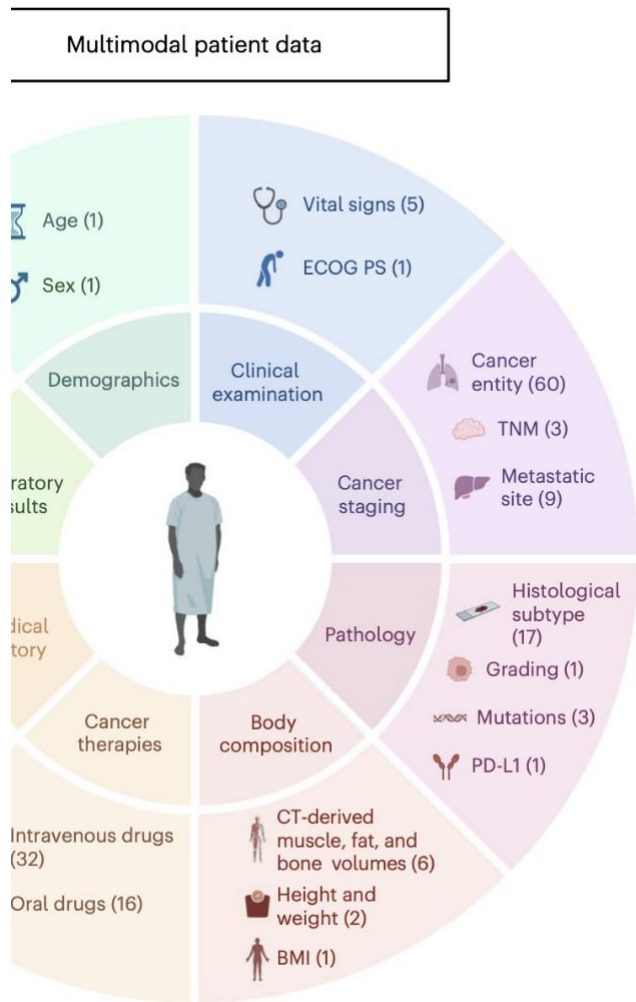
Med-PaLM

 OpenAI  
**CLIP**  
CONNECTING TEXT AND IMAGES

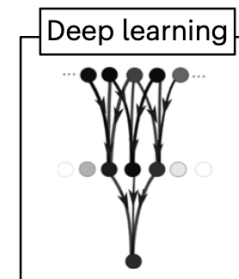
# Pan-Cancer XAI Analysis



# Pan-Cancer XAI Analysis

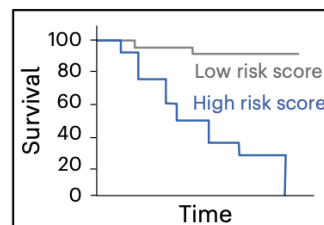


Step 1  
Risk prediction

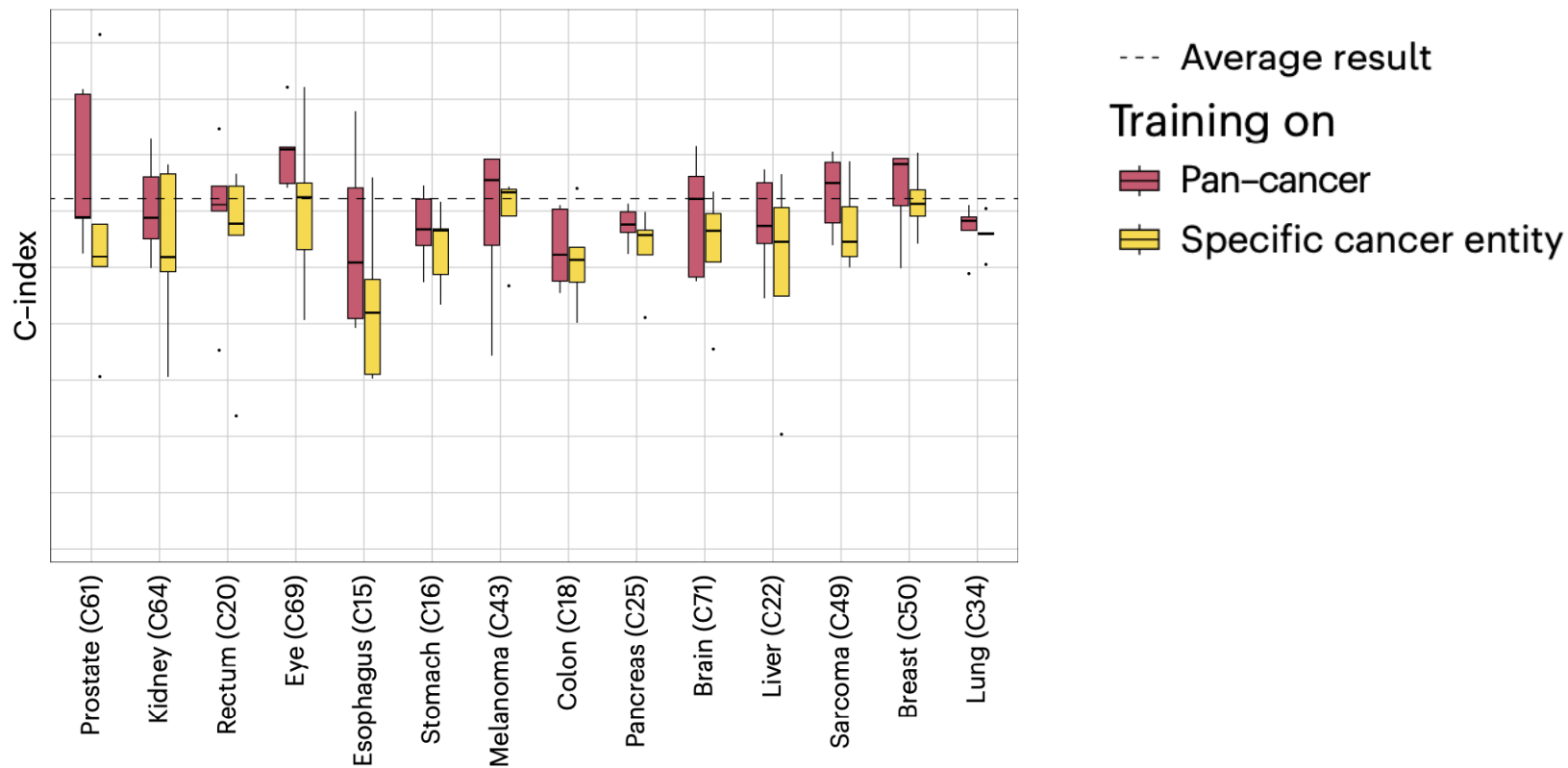


Patient risk

Cohort level analysis

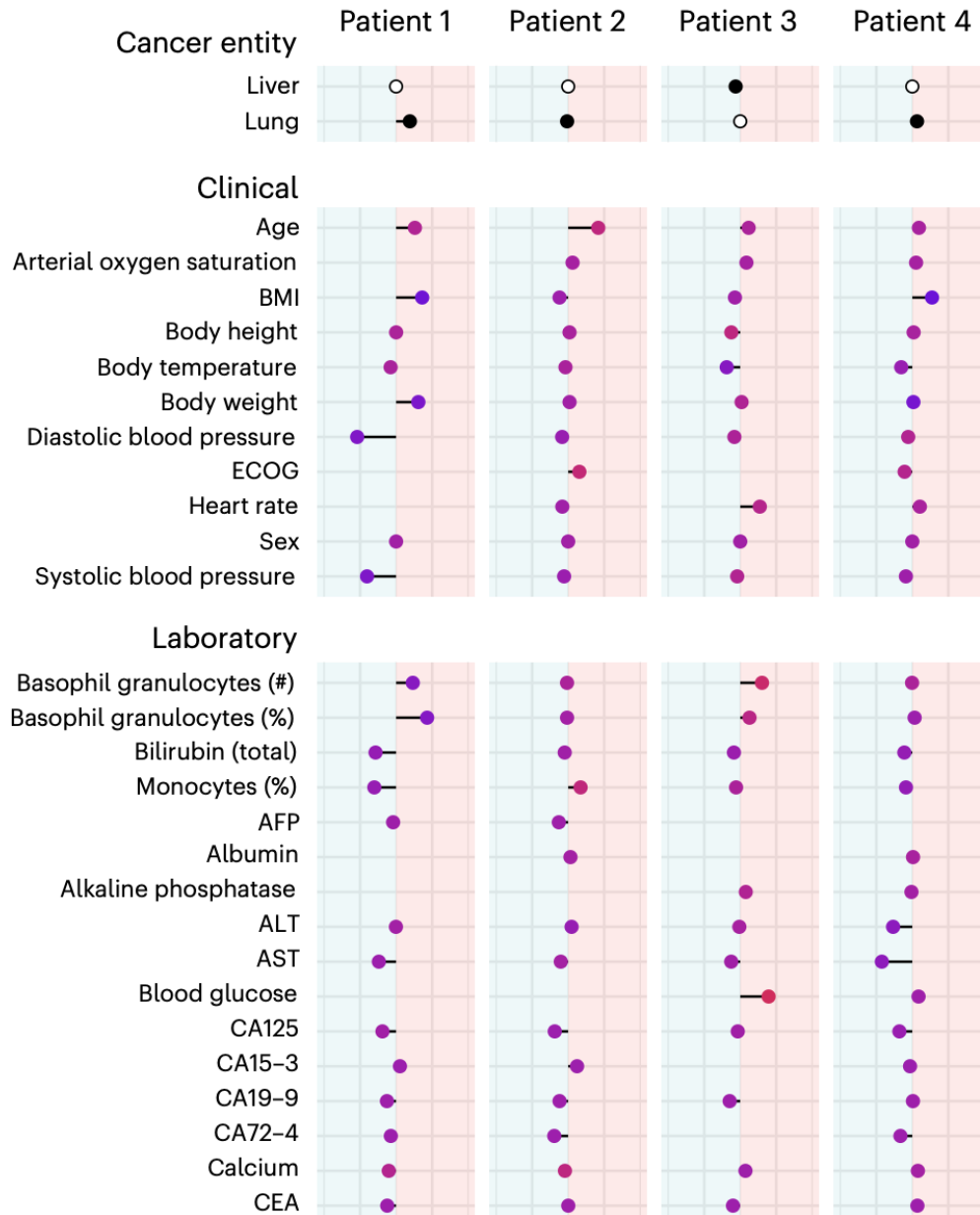


# Pan-Cancer XAI Analysis

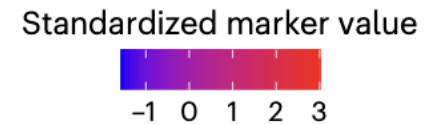


Pan-cancer increases data and benefits from statistical regularities across cancers.

# Pan-Cancer XAI Analysis



Better prognosis ↔ Worse prognosis



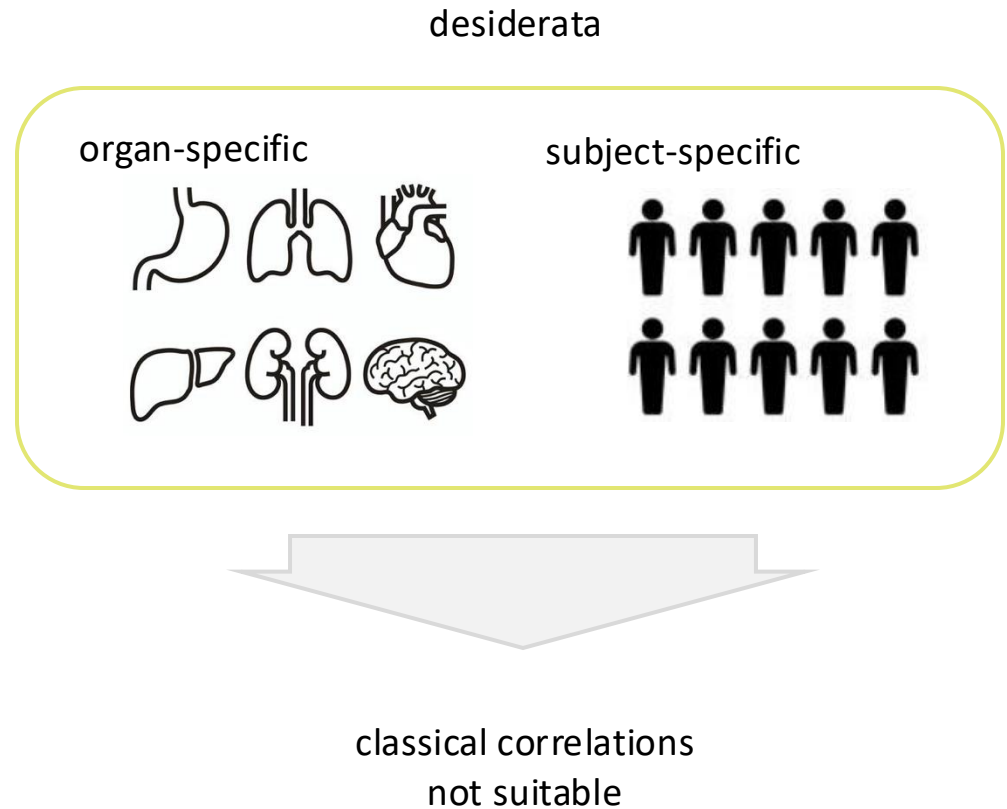
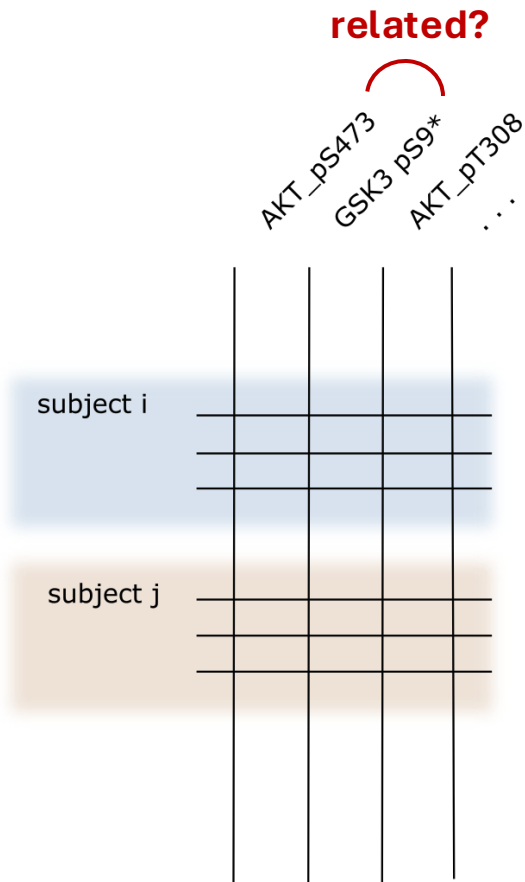
## Deconfounding through

- High accuracy (large datasets + nonlinear model)
- Early stopping + input dropout

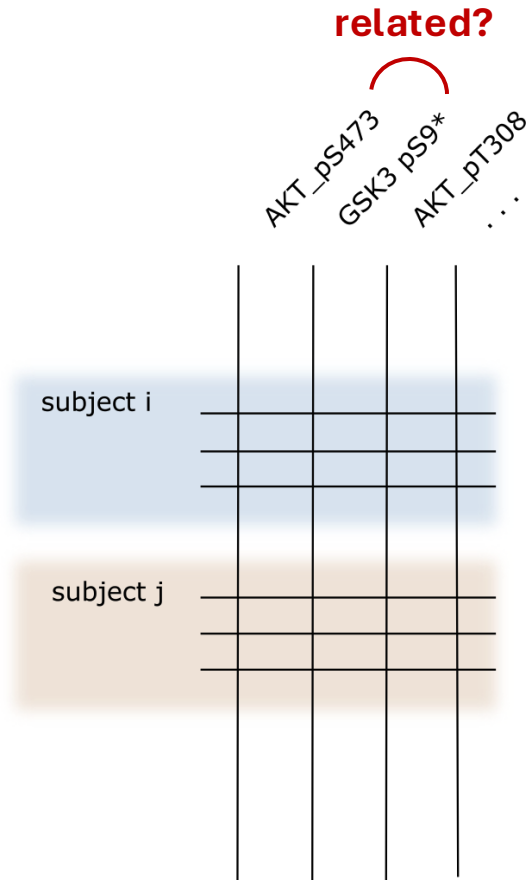
# Inferring Regulatory Networks

Part II

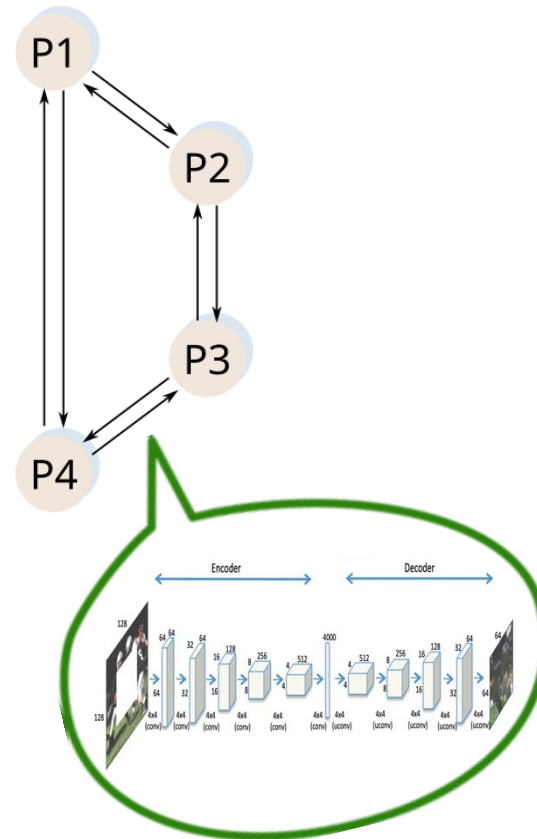
# Inferring Regulatory Networks



# Inferring Regulatory Networks



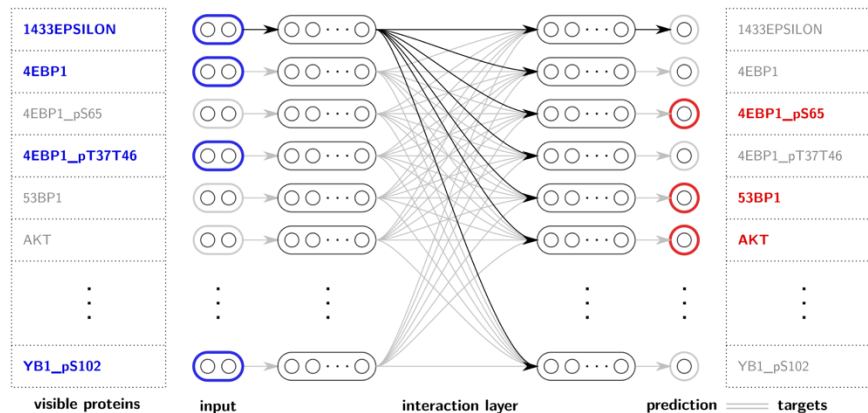
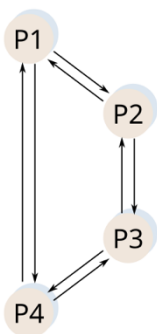
## Unsupervised learning approach



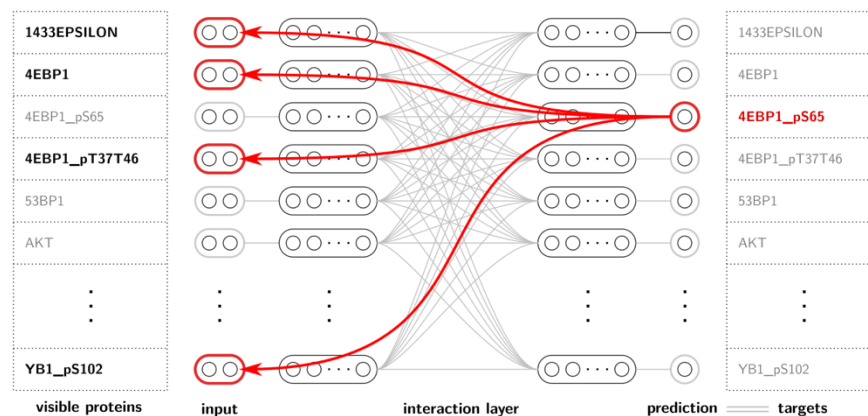
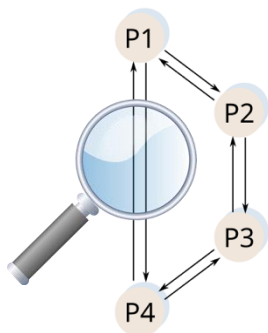


# Unsupervised ML/XAI Approach

## Step 1: Unsupervised learning



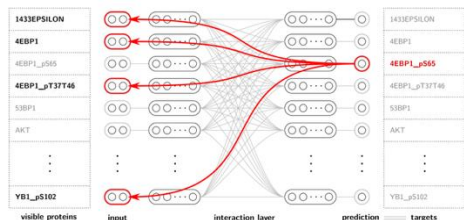
## Step 2: Explainable AI



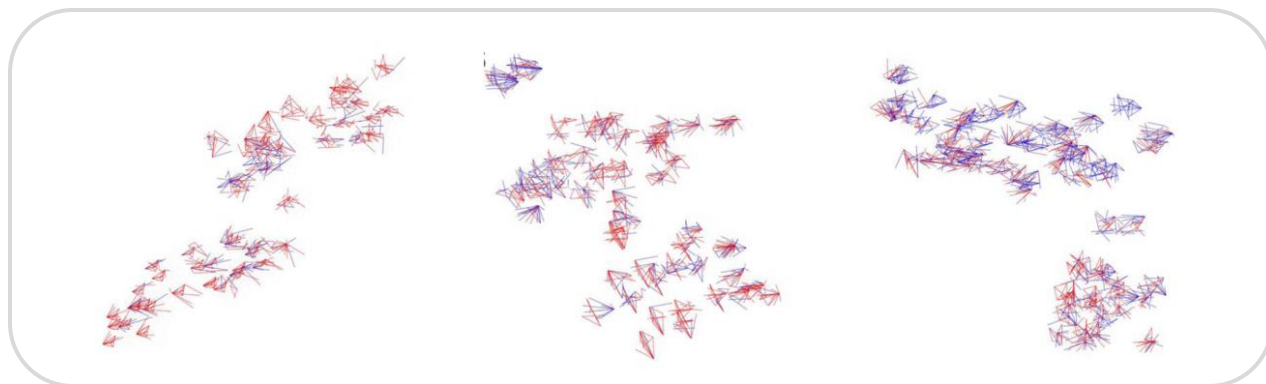
**LRP** (layer-wise relevance propagation)

# Inferring Regulatory Networks

## our approach



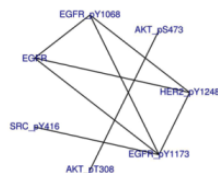
## cluster aggregation



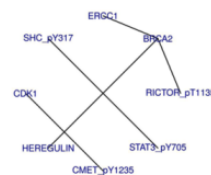
## full aggregation



### Cluster 4 (mostly GBM)



### Cluster 6 (THCA)



### Cluster 7 (THCA)

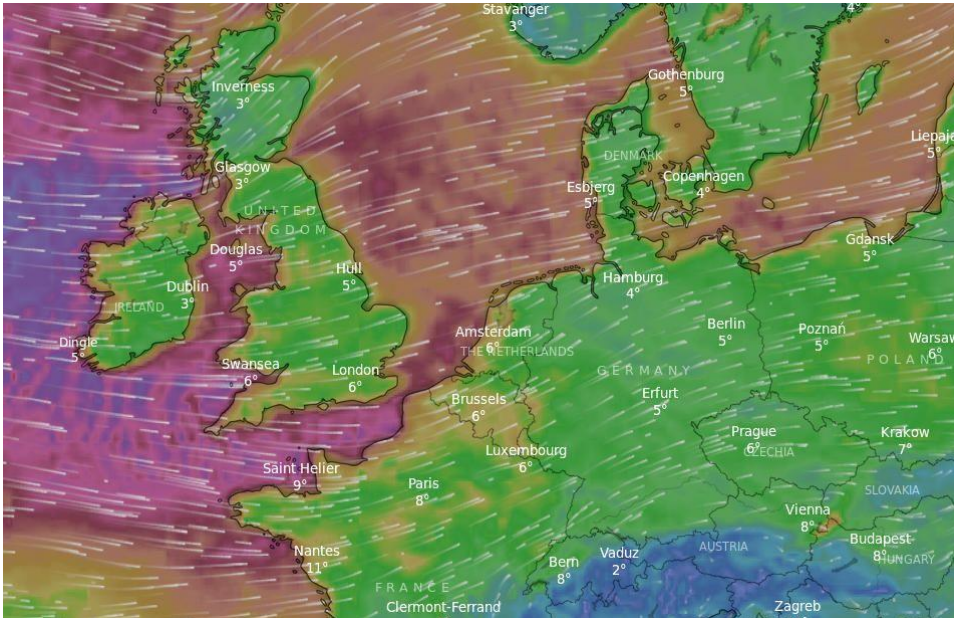


- Among the 100 strongest median interactions (out of 10,731) uncovered by our ML/XAI approach, 56 interactions were described in the Reactome database.
- In comparison, GENIE3, one of the state-of-the-art methods for network prediction, captured 42 Reactome interactions with its highest 100 predictions.

# Input-Uncertainty Associations

Part III

# Storm Sabine



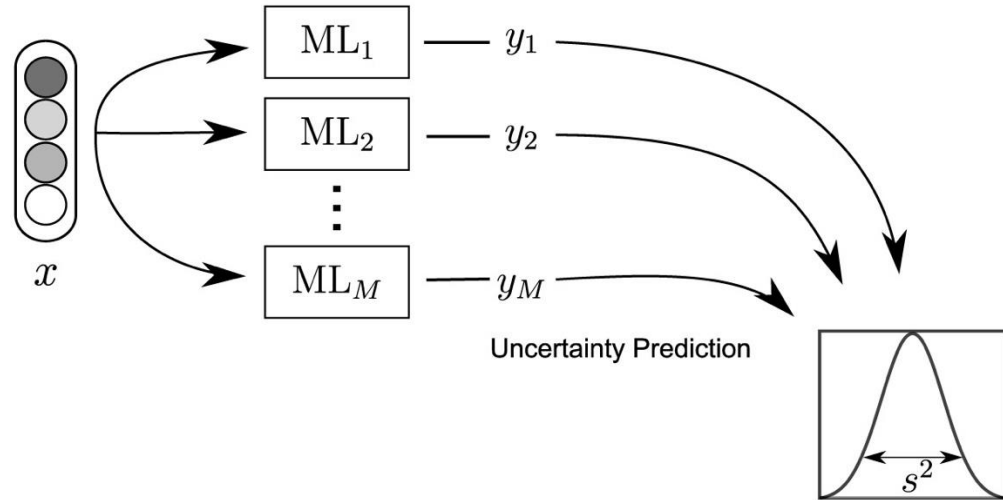
Storm Sabine  
9-11 Feb 2020

- High volatility in electricity prices observed.
- What are the factors that drive price volatility?
- How can we model volatility?

# Volatility as Uncertainty

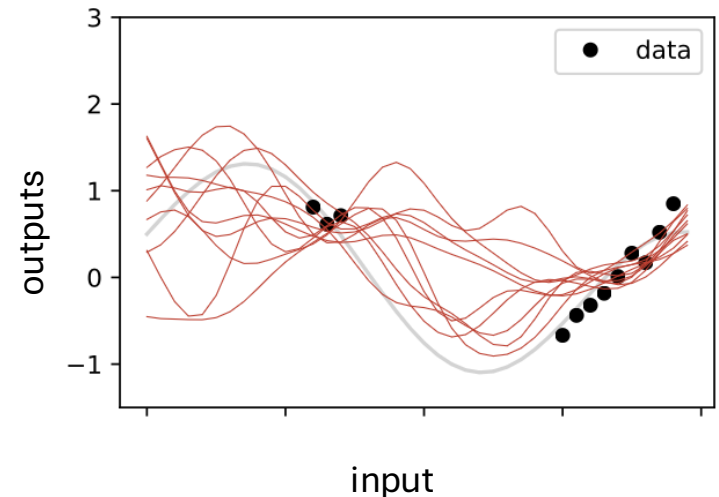
Ensemble-based ML model

$$x \mapsto \text{Var}\{y_1, \dots, y_M\}$$



## Advantages:

- ✓ Positive-constrained
- ✓ Prior encoded that uncertainty should increase in unknown situations.



Explanations of sums

$$\mathcal{E}\left\{\sum_m \alpha_m y_m\right\} = \sum_i \alpha_m \mathcal{E}\{y_m\}$$

Application to uncertainty

$$\mathcal{E}\{s^2\} = \mathcal{E}\left\{\sum_m \sum_{m'} b_{mm'} y_m y_{m'}\right\} = \sum_i \sum_j b_{mm'} \mathcal{E}\{y_m y_{m'}\}$$



can be attributed  
to pairs of  
features

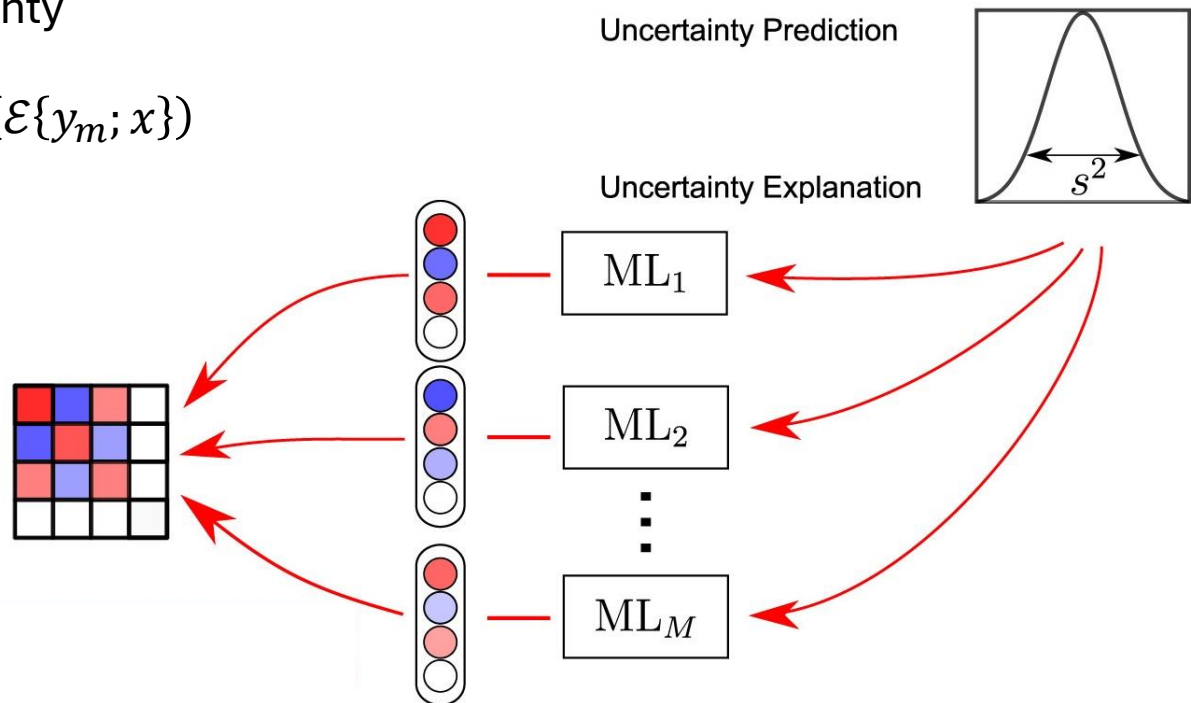
# Explaining Uncertainty

Explanation of products

$$\mathcal{E}\{y_m y_{m'}; x x^\top\} = \mathcal{E}\{y_m; x\} \otimes \mathcal{E}\{y_{m'}; x\}$$

Application to uncertainty

$$\mathcal{E}\{s^2; x x^\top\} = \text{Cov}_m(\mathcal{E}\{y_m; x\})$$



# Evaluating Explanation Fidelity

$$\mathcal{E}\{s^2\} = \text{Var}_m(\mathcal{E}\{y_m(x)\})$$

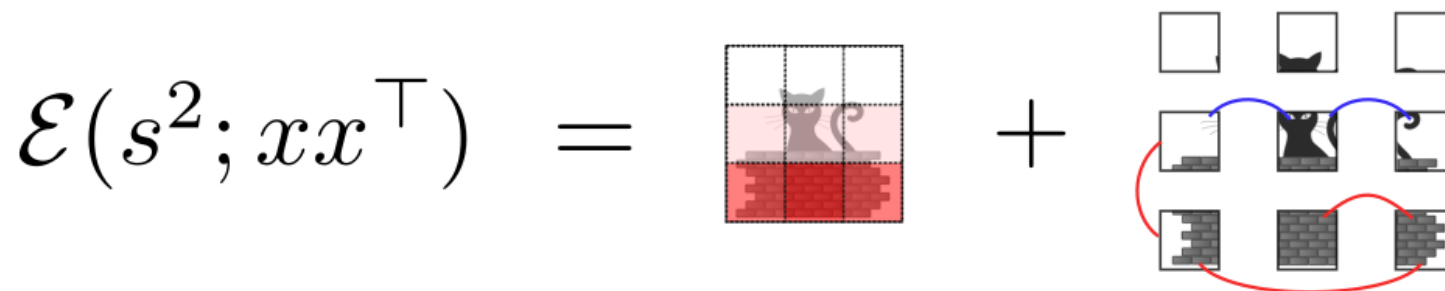
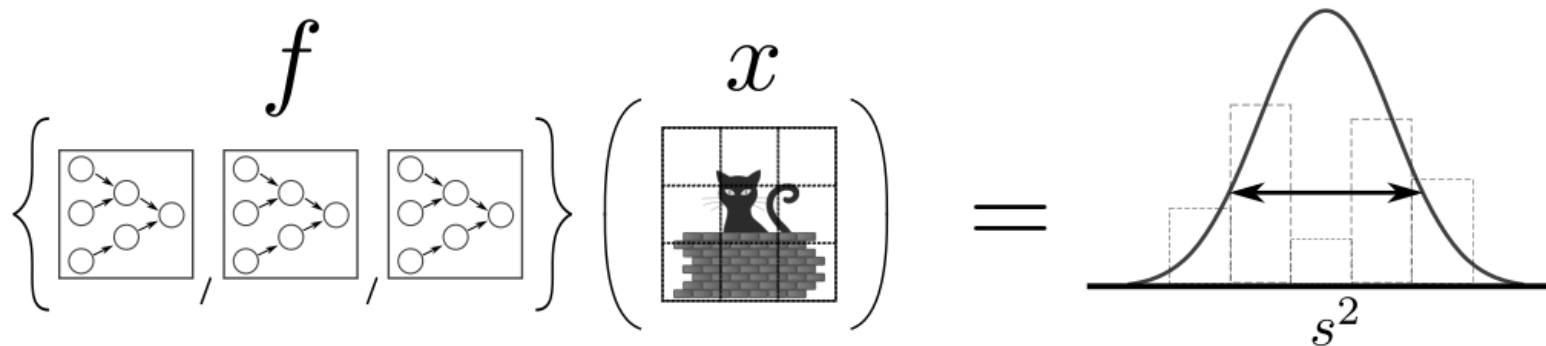
$$\mathcal{E}\{s^2\} = \text{Cov}_m(\mathcal{E}\{y_m(x)\})$$

Dataset ( $d$ )	Model	CovLRP		LRP	GI	IG	SVS
		diag	marg				
Bias Correction (21)	DeepEns	<b>0.352</b>	0.444	<u>0.411</u>	0.559	0.546	0.513
California Housing (8)	DeepEns	<b>0.344</b>	<u>0.370</u>	0.415	0.430	0.394	0.391
EPEX-FR (96)	DeepEns	<b>0.044</b>	<u>0.052</u>	0.106	0.113	0.099	0.062
kin8nm (8)	DeepEns	0.391	0.388	0.462	0.427	0.405	<u>0.386</u>
Seoul Bike Sharing (98)	DeepEns	<b>0.268</b>	0.294	<u>0.293</u>	0.350	0.338	0.329
Wine Quality (11)	DeepEns	<u>0.482</u>	<b>0.471</b>	0.526	0.517	0.500	0.495
YearPredictionMSD (90)	DeepEns	<b>0.155</b>	<u>0.173</u>	0.184	0.264	0.273	0.195
Bias Correction	MCDropout	<b>0.514</b>	<u>0.517</u>	0.568	0.651	0.530	0.672
California Housing	MCDropout	<b>0.674</b>	<u>0.691</u>	0.728	0.812	0.703	0.787
EPEX-FR	MCDropout	<b>0.085</b>	<u>0.091</u>	0.137	0.146	0.119	0.125
kin8nm	MCDropout	<b>0.483</b>	<u>0.486</u>	0.568	0.586	0.498	0.593
Seoul Bike Sharing	MCDropout	<b>0.520</b>	0.590	<u>0.555</u>	0.640	0.568	0.676
Wine Quality	MCDropout	<u>0.661</u>	<b>0.657</b>	0.713	0.729	0.662	0.767
YearPredictionMSD	MCDropout	<b>0.215</b>	0.258	<u>0.253</u>	0.391	0.273	0.403
YearPredictionMSD	DeepEns-5	<b>0.128</b>	<u>0.148</u>	0.155	0.197	0.212	0.153
YearPredictionMSD	DeepEns-10	<b>0.155</b>	<u>0.173</u>	0.184	0.264	0.273	0.195
YearPredictionMSD	DeepEns-20	<b>0.162</b>	<u>0.183</u>	0.247	0.250	0.267	0.218
YearPredictionMSD	DeepEns-40	<u>0.180</u>	<b>0.179</b>	0.235	0.267	0.277	0.213
EPEX-FR	ConvNet	<b>0.085</b>	0.101	0.210	0.159	0.108	<u>0.087</u>
Seoul Bike Sharing	ConvNet	<b>0.231</b>	0.308	0.422	0.331	<u>0.306</u>	0.321

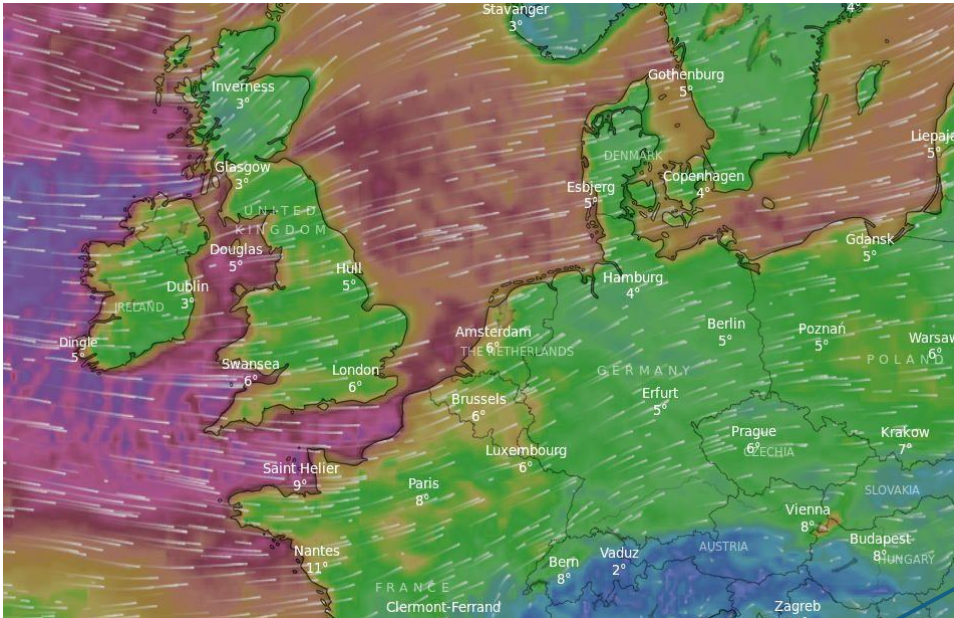
Dropping interaction terms improves explanation robustness.



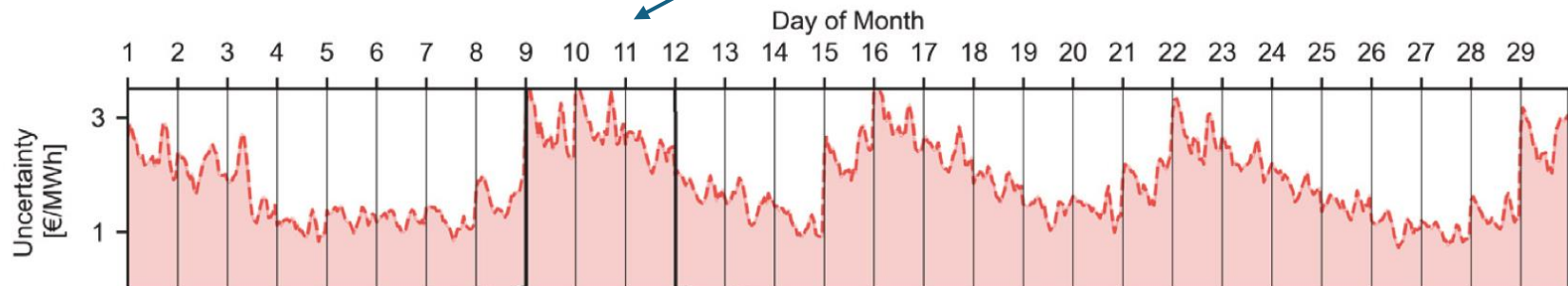
# Explaining Uncertainty: Recap



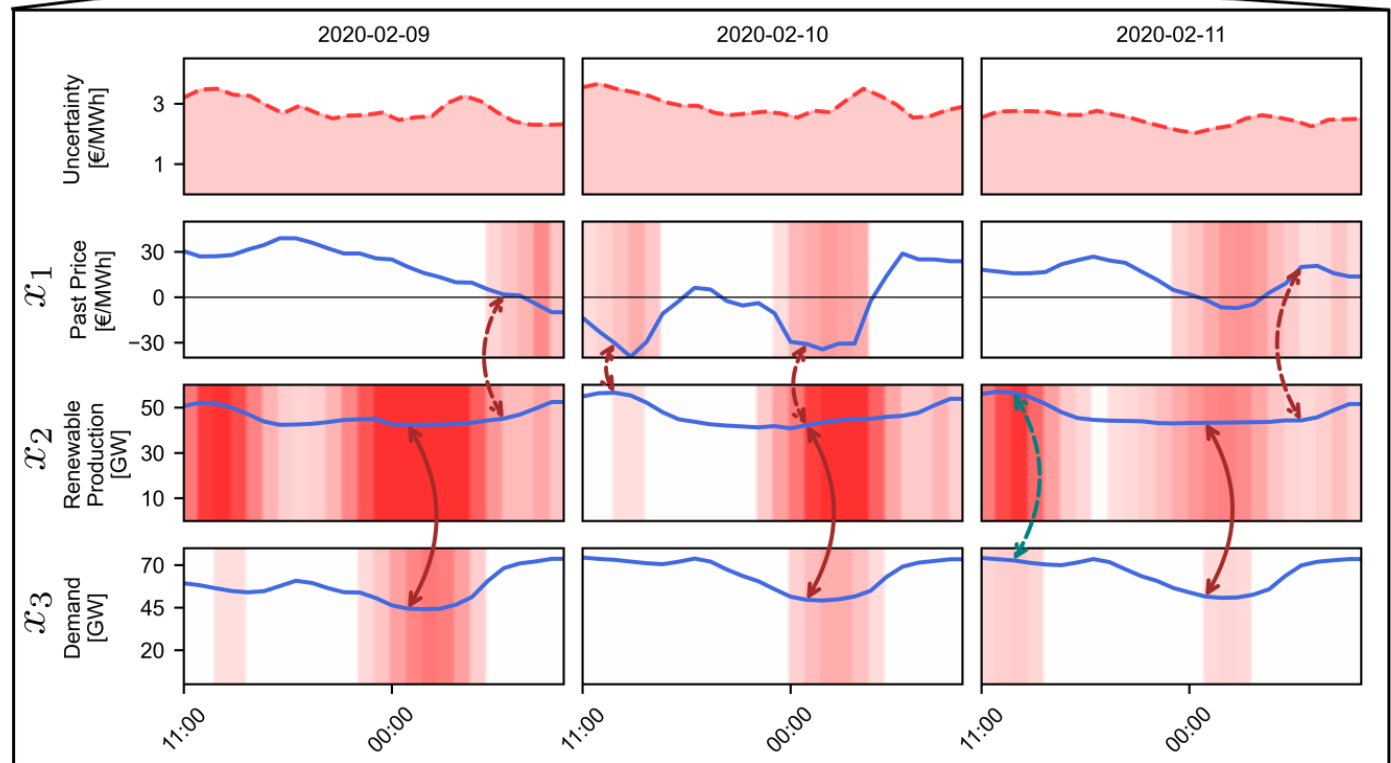
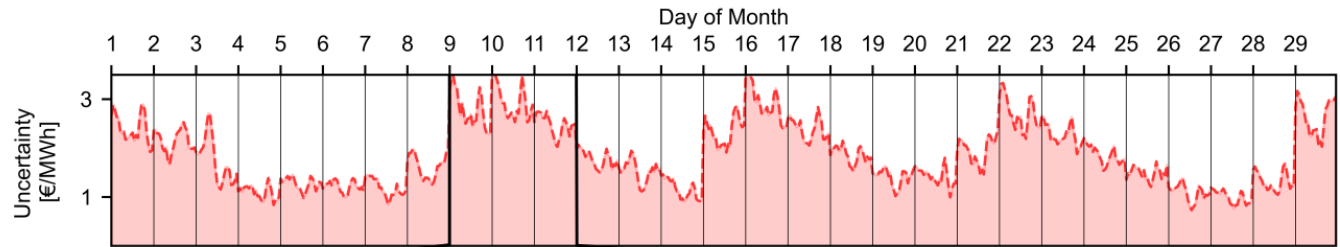
# Storm Sabine



Storm Sabine  
9-11 Feb 2020

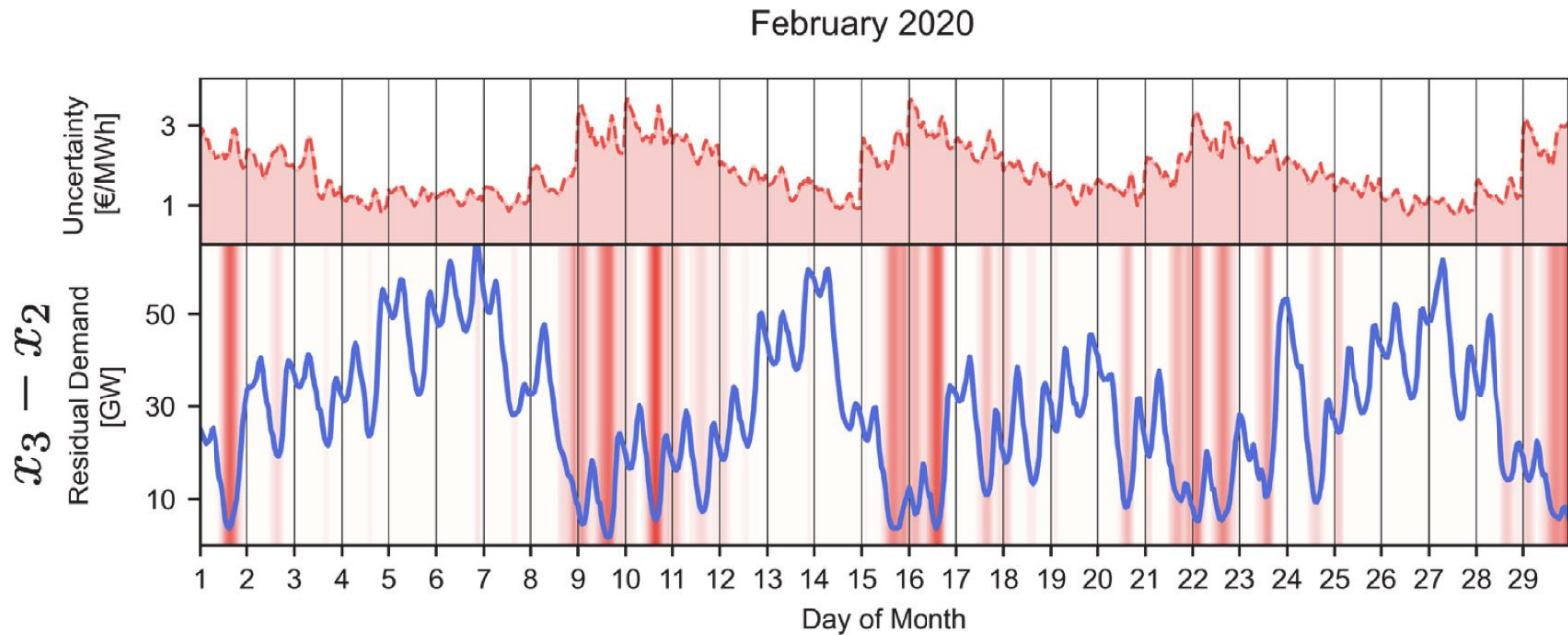


# Storm Sabine



$x_3 - x_2$   
is the  
“residual  
demand”

# Storm Sabine



- low residual demand is a clear driver of price uncertainty.
- price uncertainty might further increase due to the growing share of renewables.

# Summary

- With a lot of data, powerful ML models, and with the additional help of deconfounding techniques, many confounding effects can be avoided.
- Recent deep neural networks provide evidence for increased focus on causal features, making observational studies increasingly attractive.
- XAI can adapt to a wide range of ML models and tasks beyond classification (e.g. explaining uncertainty predictions).

# Thanks



- P Chormai, J Herrmann, KR Müller, G Montavon. Disentangled explanations of neural network predictions by finding relevant subspaces. [IEEE Transactions on Pattern Analysis and Machine Intelligence 46 \(11\), 7283-7299, 2024](#)
- S Bender, O Delzer, J Herrmann, HA Marxfeld, KR Müller, G Montavon. Mitigating Clever Hans Strategies in Image Classifiers through Generating Counterexamples. [arXiv:2510.17524, 2025](#)
- J Keyl, P Keyl, G Montavon, R Hosch, A Brehmer, L Mochmann, ... Decoding pan-cancer treatment outcomes using multimodal real-world data and explainable artificial intelligence. [Nature Cancer 6 \(2\), 307-322, 2025](#)
- P Keyl, M Bockmayr, D Heim, G Dernbach, G Montavon, KR Müller, F Klauschen. Patient-level proteomic network prediction by explainable artificial intelligence [NPJ Precision Oncology 6\(1\):35, 2022](#)
- P Keyl, P Bischoff, G Dernbach, M Bockmayr, R Fritz, D Horst, N Blüthgen, G Montavon, KR Müller, F Klauschen. Single-cell gene regulatory network prediction by explainable AI [Nucleic Acids Research, gkac1212, 2023](#)
- F Bley, S Lapuschkin, W Samek, G Montavon. Explaining predictive uncertainty by exposing second-order effects. [Pattern Recognition 160, 111171, 2024](#)