CENTER FOR SCALABLE DATA ANALYTICS
AND ARTIFICIAL INTELLIGENCE

Explainable Machine Learning

Robert Haase

Funded by

Bundesministerium für Bildung und Forschung

SACHSEN

Diese Maßnahme wird gefördert durch die Bundesregierung aufgrund eines Beschlusses des Deutschen Bundestages. Diese Maßnahme wird mitfinanziert durch Steuermittel auf der Grundlage des von den Abgeordneten des Sächsischen Landtags beschlossenen Haushaltes.

ScaDS.AI DRESDEN LEIPZIG

CENTER FOR SCALABLE DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE

Short Detour: Random Forest Classifiers

Robert Haase

Funded by

Bundesministerium für Bildung und Forschung

SACHSEN

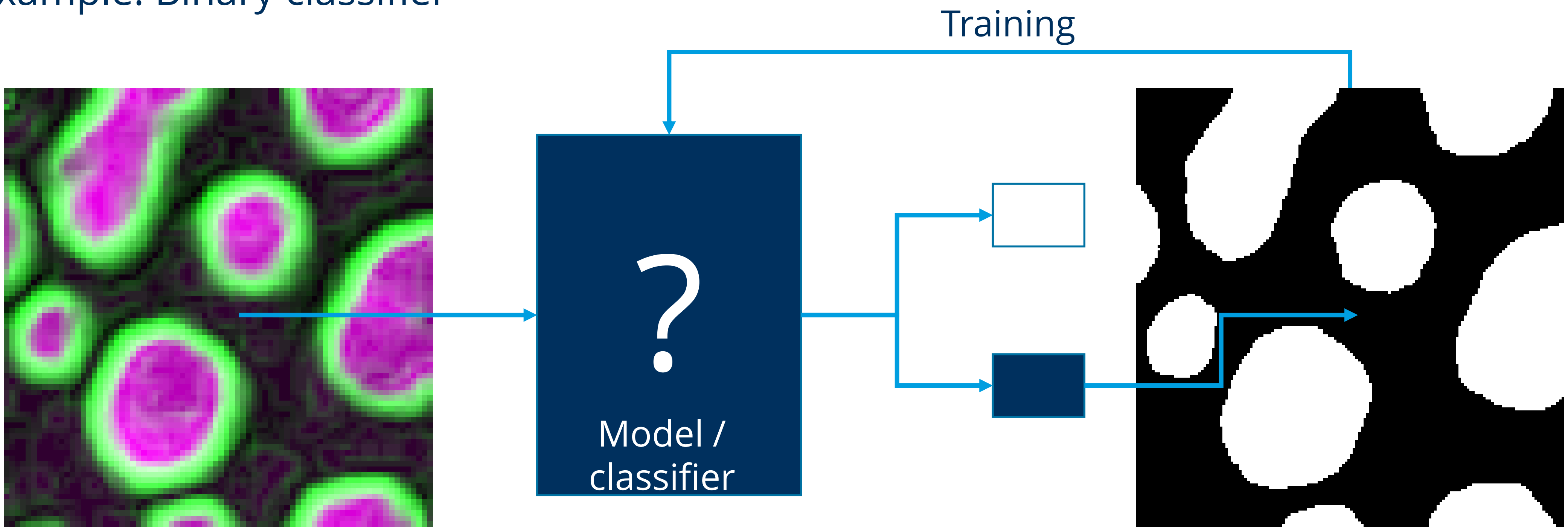
Diese Maßnahme wird gefördert durch die Bundesregierung aufgrund eines Beschlusses des Deutschen Bundestages. Diese Maßnahme wird mitfinanziert durch Steuermittel auf der Grundlage des von den Abgeordneten des Sächsischen Landtags beschlossenen Haushaltes.

Machine learning for image segmentation

Supervised machine learning: We give the computer some ground truth to learn from

The computer derives a *model* or a *classifier* which can judge if a pixel should be foreground (white) or background (black)

Example: Binary classifier



Raw image

Binary image

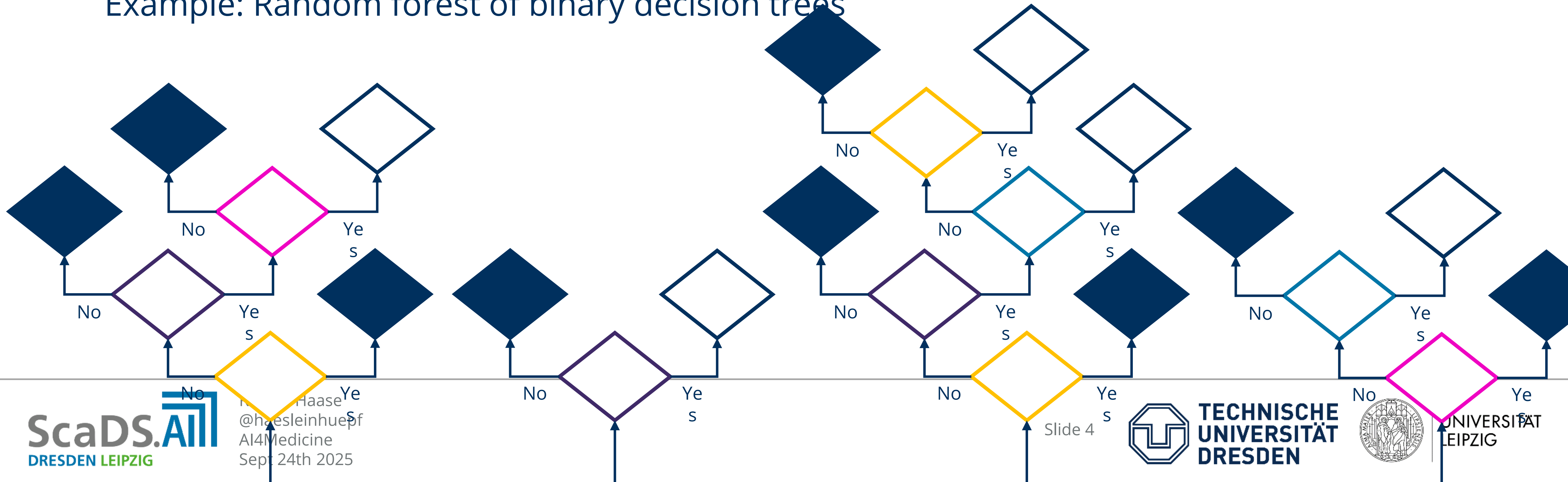
Random forest based image segmentation

Decision trees are classifiers, they decide if a pixel should be white or black

Random decision trees are randomly initialized, afterwards evaluated and selected

Random forests consist of many random decision trees

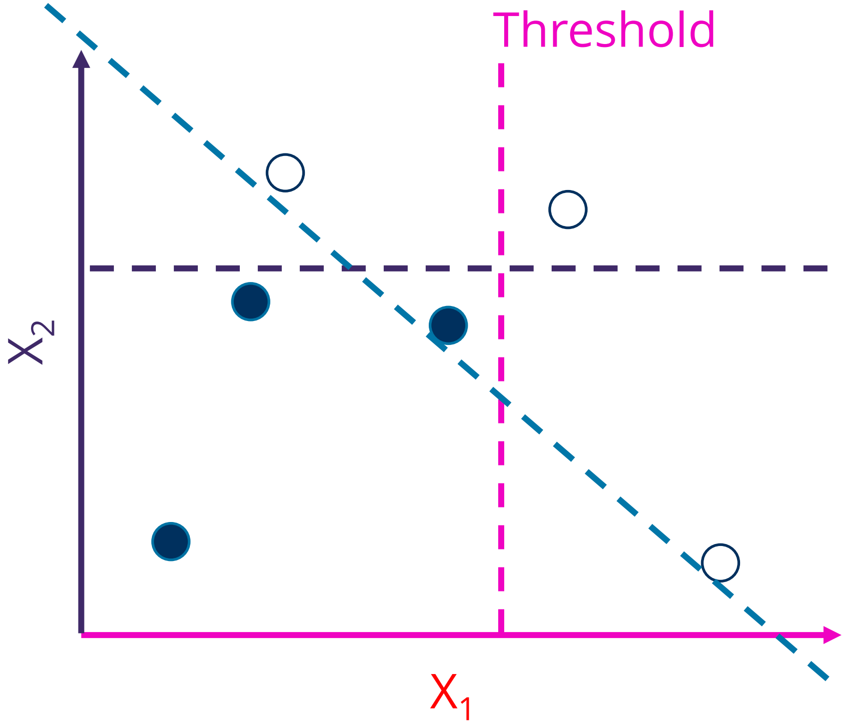
Example: Random forest of binary decision trees

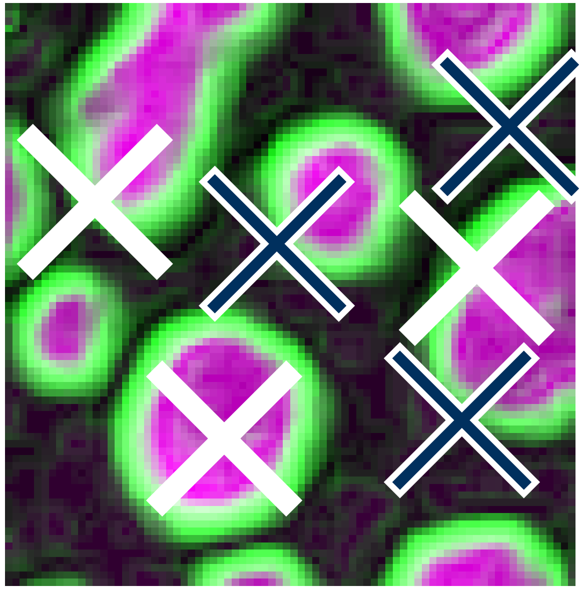


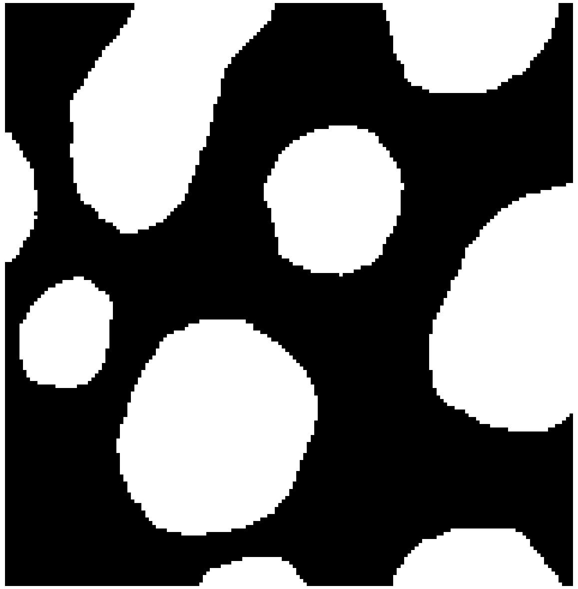
Deriving random decision trees

For efficient processing, we randomly *sample* our data set

- Individual pixels, their intensity and their classification



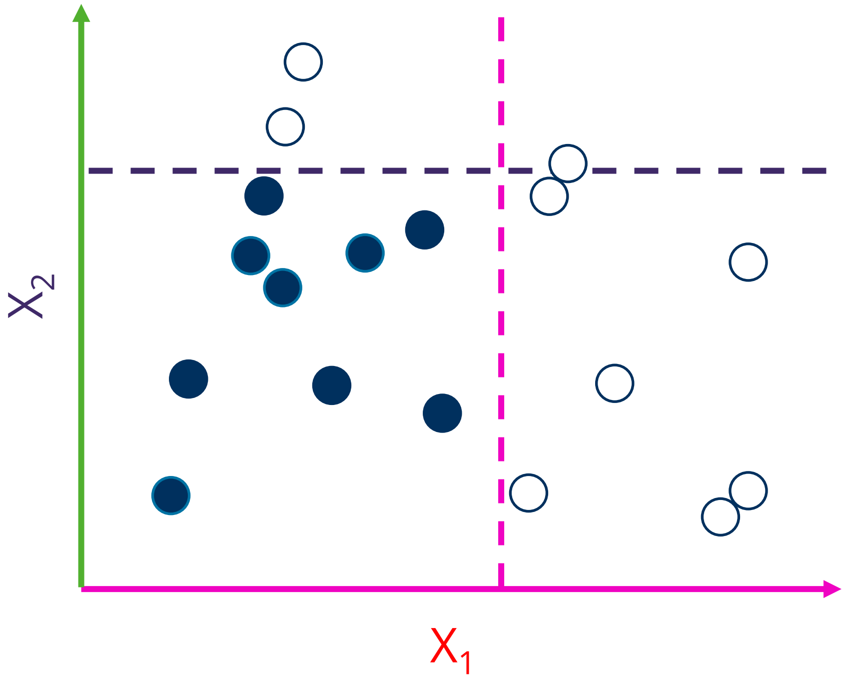


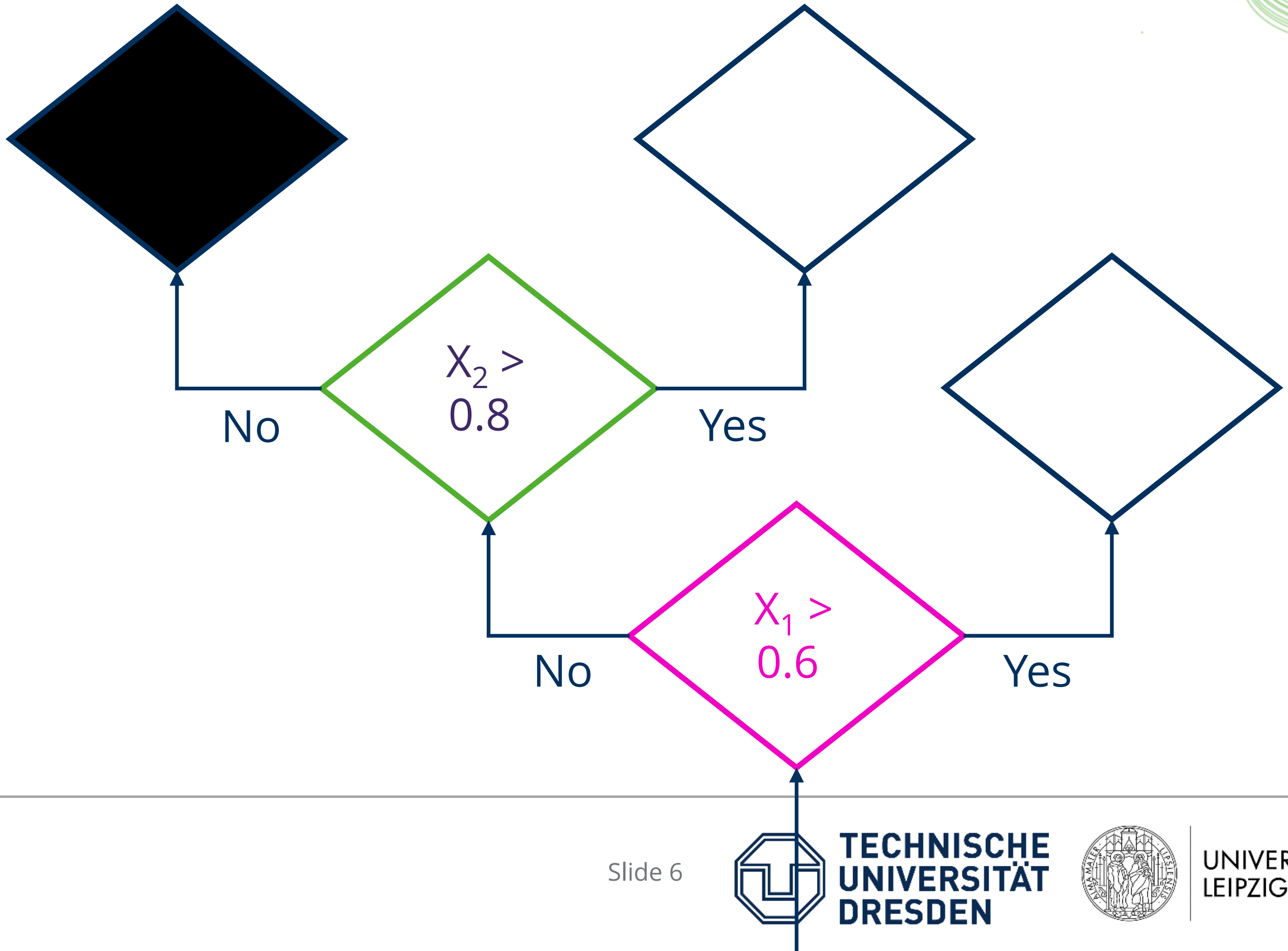


Note: You cannot use a single threshold to make the decision correctly

Deriving random decision trees

Decision trees combine several thresholds on several parameters

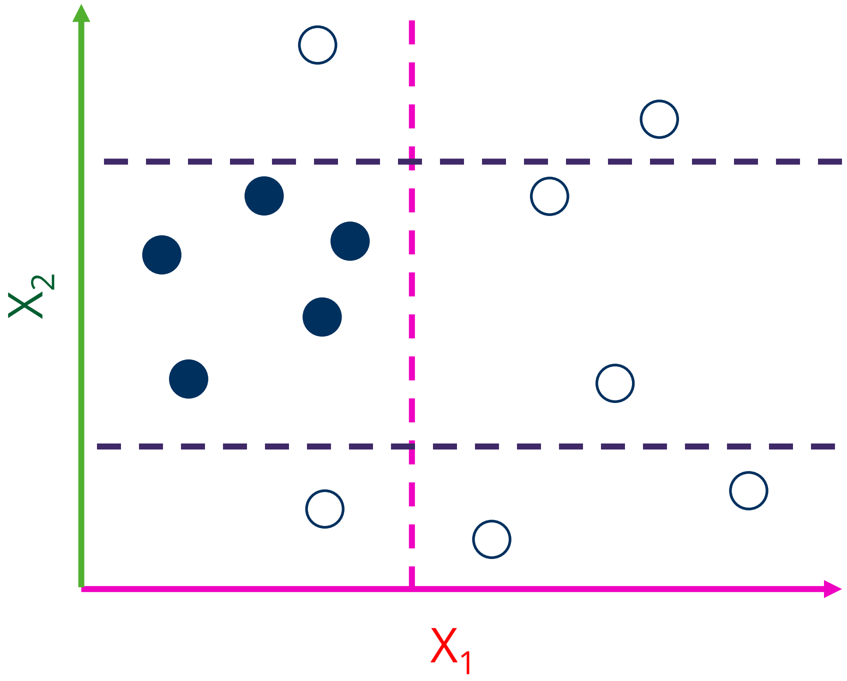


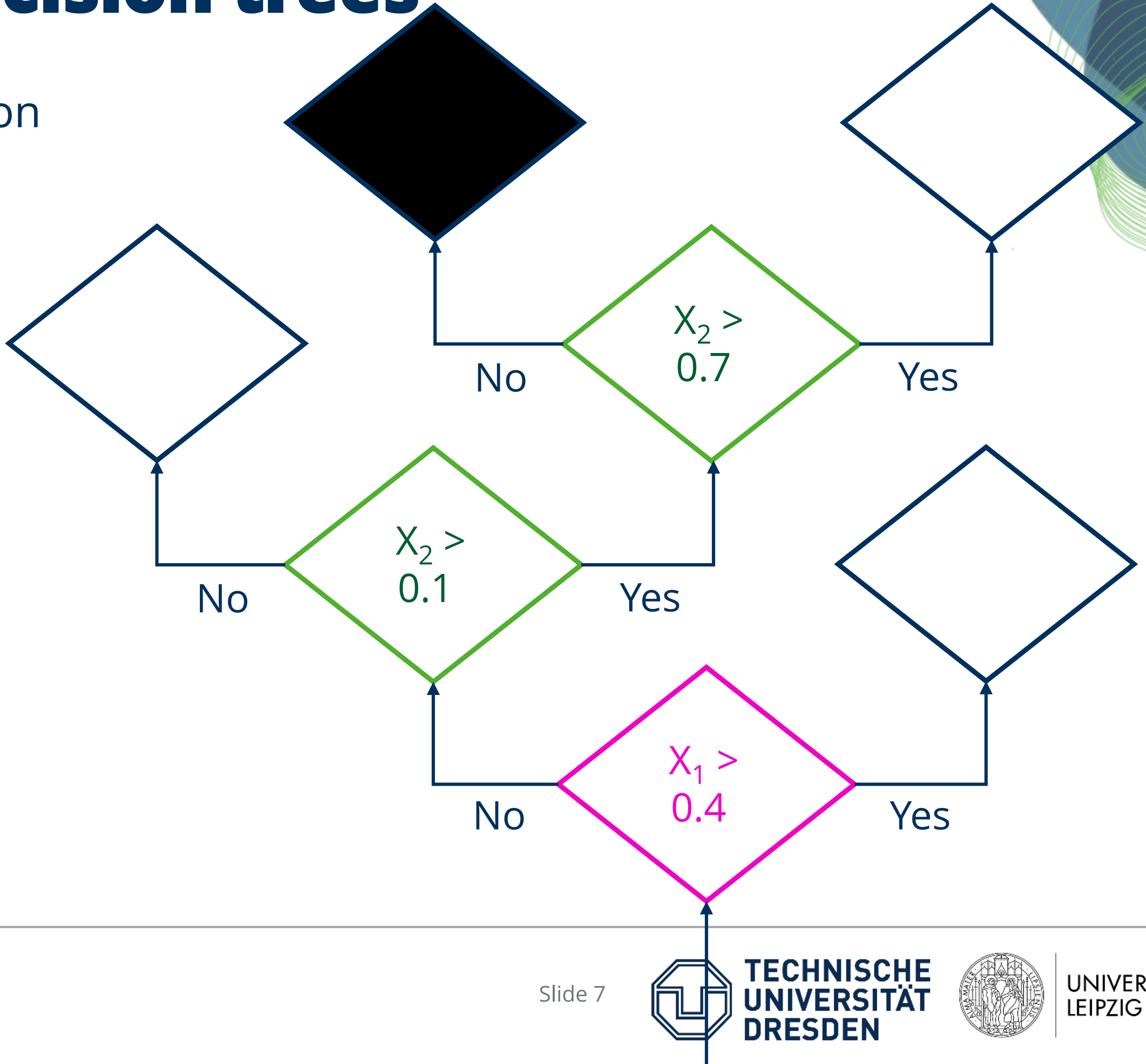


Robert Haase
@haesleinhuepf
AI4Medicine
Sept 24th 2025

Deriving random decision trees

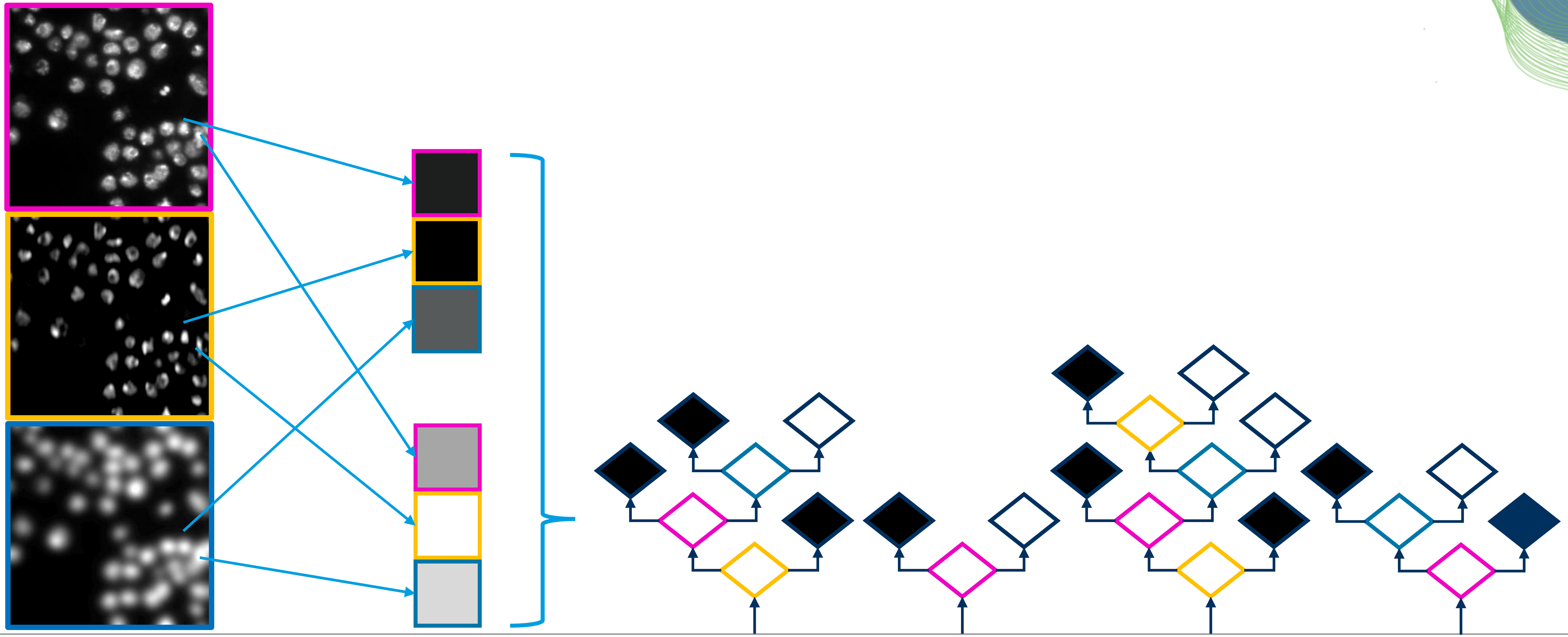
Depending on sampling, the decision trees are different





Random Forest Pixel Classifiers

By training many decision trees, errors are equilibrated

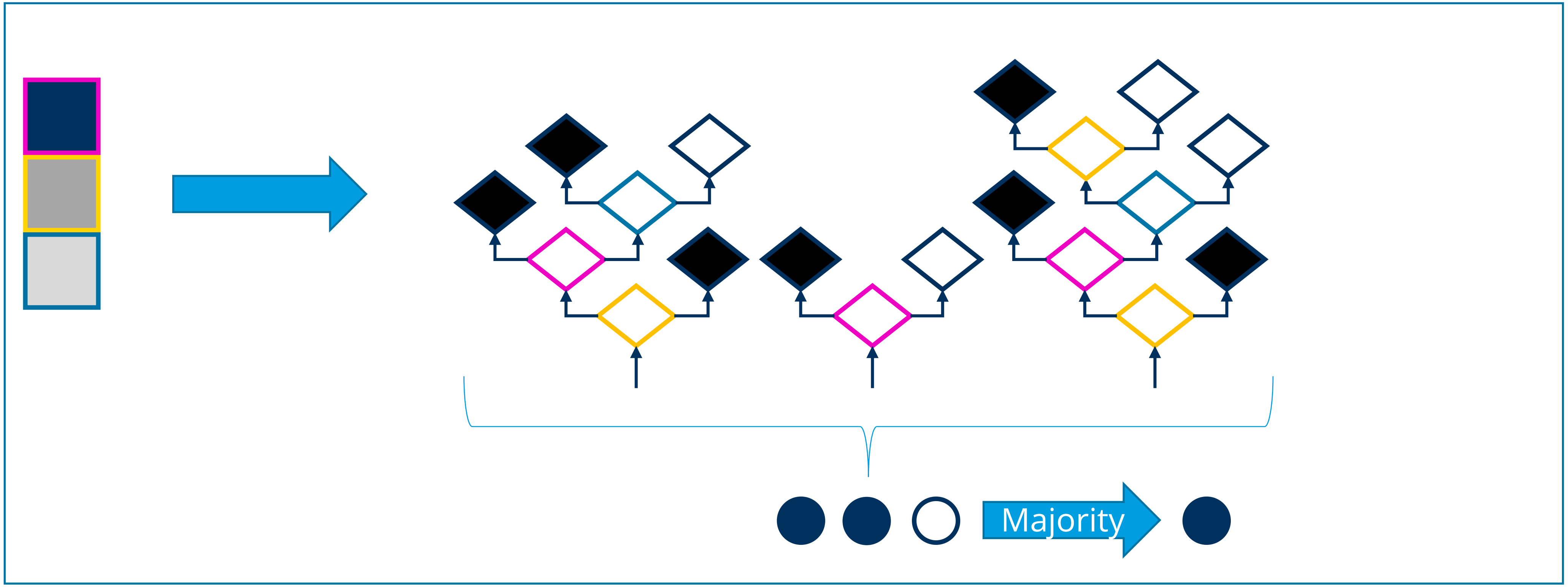


Sampling

Random Forest Pixel Classifiers

Combination of individual tree decisions by voting or max / mean

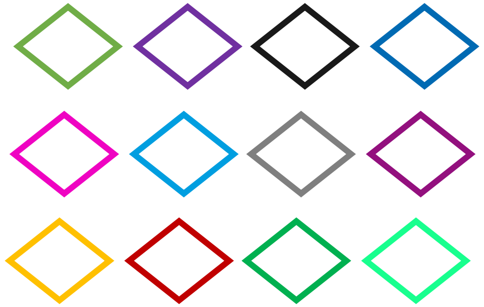
Prediction



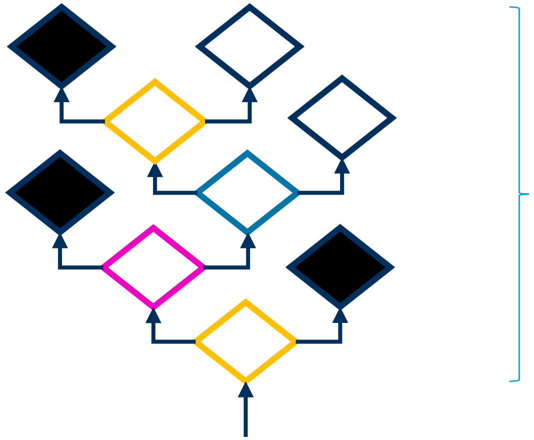
Random Forest Pixel Classifiers

Typical numbers for pixel classifiers in microscopy image analysis

Available features:

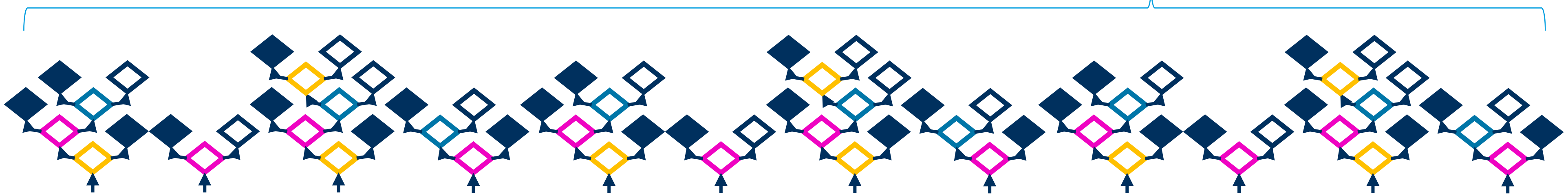


- Gaussian blur image
- DoG image
- LoG image
- Hessian
- ….



Depth <= 4

Number of trees > 100



Explainable Artificial Intelligence (XAI)

- “Es gibt derzeit noch keine allgemein akzeptierte Definition von XAI.”

Wikipedia [1]

Relevant Aspects:

- Explainability vs. Interpretability of AI-algorithms
- We seek to enable humans to
  - predict results of AI Systems,
  - trust AI-Systems and
  - using AI-Systems effectively.

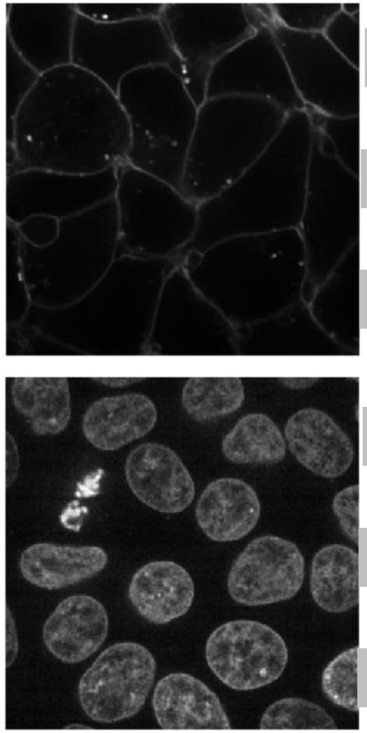
[1] https://de.wikipedia.org/wiki/Explainable_Artificial_Intelligence

Explanation of Random Forest Classifiers

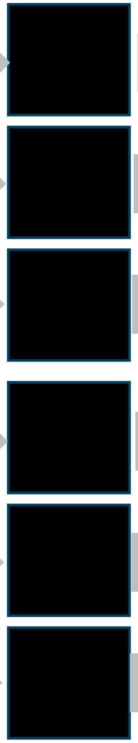
... by reading code

... is quite useless

Input images



Feature images



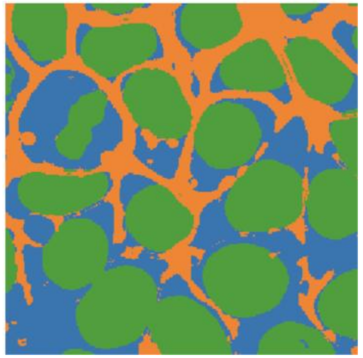
Decision trees (OpenCL)

```
if(i3<6093.5){
 if(i1<3335.03
  s0+=0.994917
  s1+=0.001270
  s2+=0.003811
 } else {
  s1+=1.0;
 }
} else {
 if(i4<8042.86
  s0+=0.818181
  s1+=0.181818
 } else {
  s0+=0.000885
  s1+=0.001180
  s2+=0.997933
 }
}
```

```
if(i3<6615.0){
 if(i1<3277.4873
  s0+=0.98595146
  s1+=0.00127713
  s2+=0.01277139
 } else {
  s1+=1.0;
 }
} else {
 if(i1<3244.2104
  s0+=0.00118835
  s2+=0.99881164
 } else {
  s1+=1.0;
 }
}
```

```
if(i0<2118.0){
 if(i4<8134.84912109375){
  s0+=1.0;
 } else {
  s0+=0.0012077294685990338;
  s2+=0.998792270531401;
 }
} else {
 if(i1<3335.035888671875){
  s0+=0.8279569892473119;
  s1+=0.005376344086021506;
  s2+=0.16666666666666666;
 } else {
  s1+=1.0;
 }
}
```

Classification result images



https://github.com/haesleinhuepf/apoc/blob/main/demo/mutlichannel_images.ipynb

Explainability

A logically consistent line of argumentation that depicts a situation or an algorithm with complete transparency.

Intrinsically explainable AI-algorithms

- Example: Linear Regression

$$f(x_1, x_2) = w_1 x_1 + w_2 x_2$$

If w_1 is much bigger than w_2, the result depends much more on x_1 compared to x_2.

Model explainable

Results predictable

Explainability

A logically consistent line of argumentation that depicts a situation or an algorithm with complete transparency.

Intrinsically explainable AI-algorithms

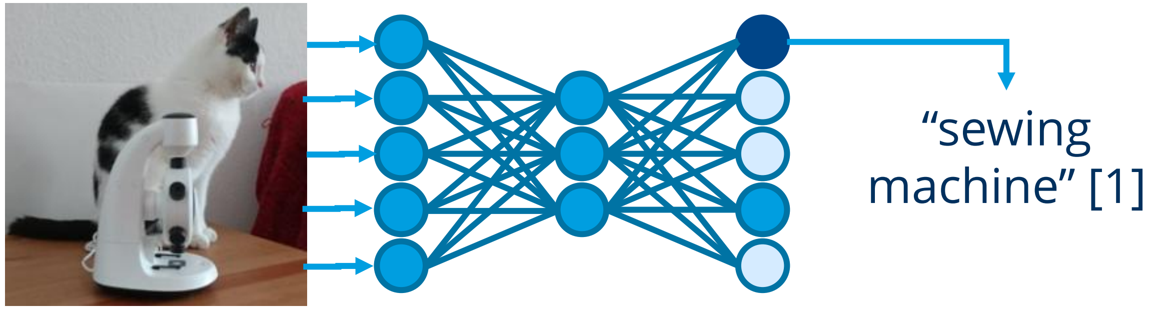
- Example: Linear Regression

$$f(x_1, x_2) = w_1 x_1 + w_2 x_2$$

If w_1 is much bigger than w_2, the result depends much more on x_1 compared to x_2.

Black-Box AI-algorithms

- Example: Deep Neural Networks (DNN)



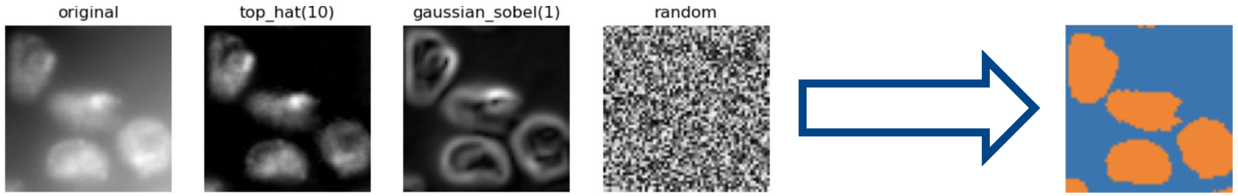
Not easily explainable and predictable

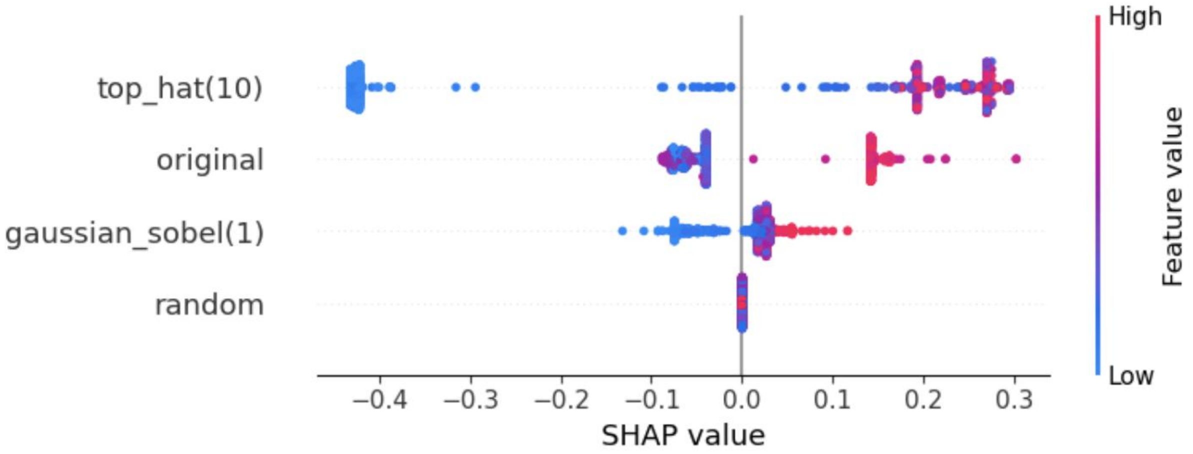
Interpretability

Visualization of intermediate results and their influence on results

Model-agnostic methods

Example: Shapley's Additive exPlanations (SHAP)



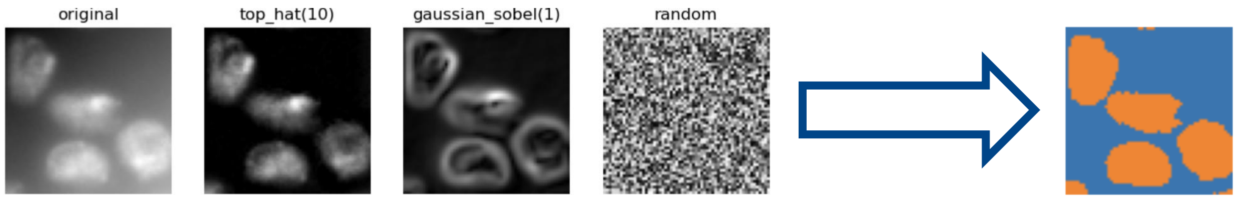


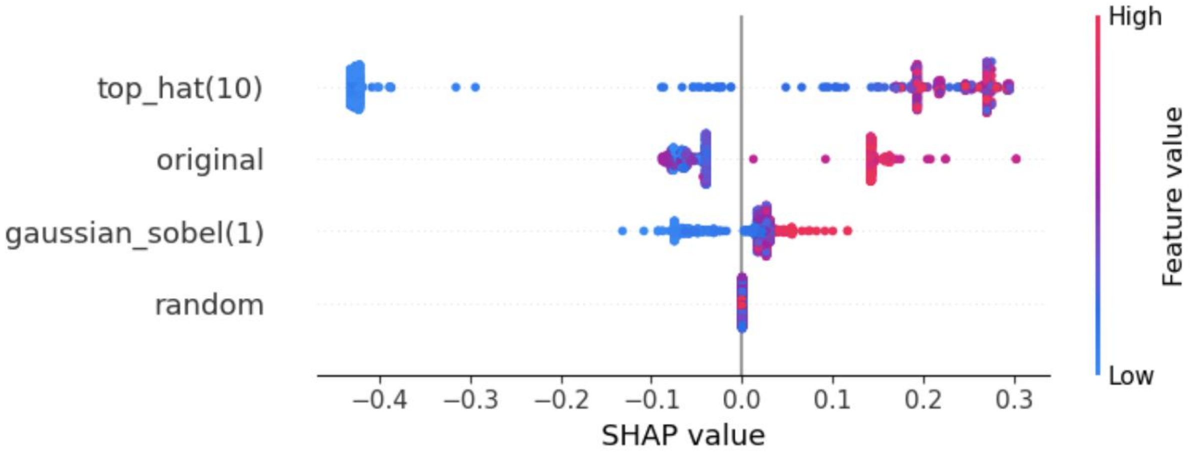
Interpretability

Visualization of intermediate results and their influence on results

Model-agnostic methods

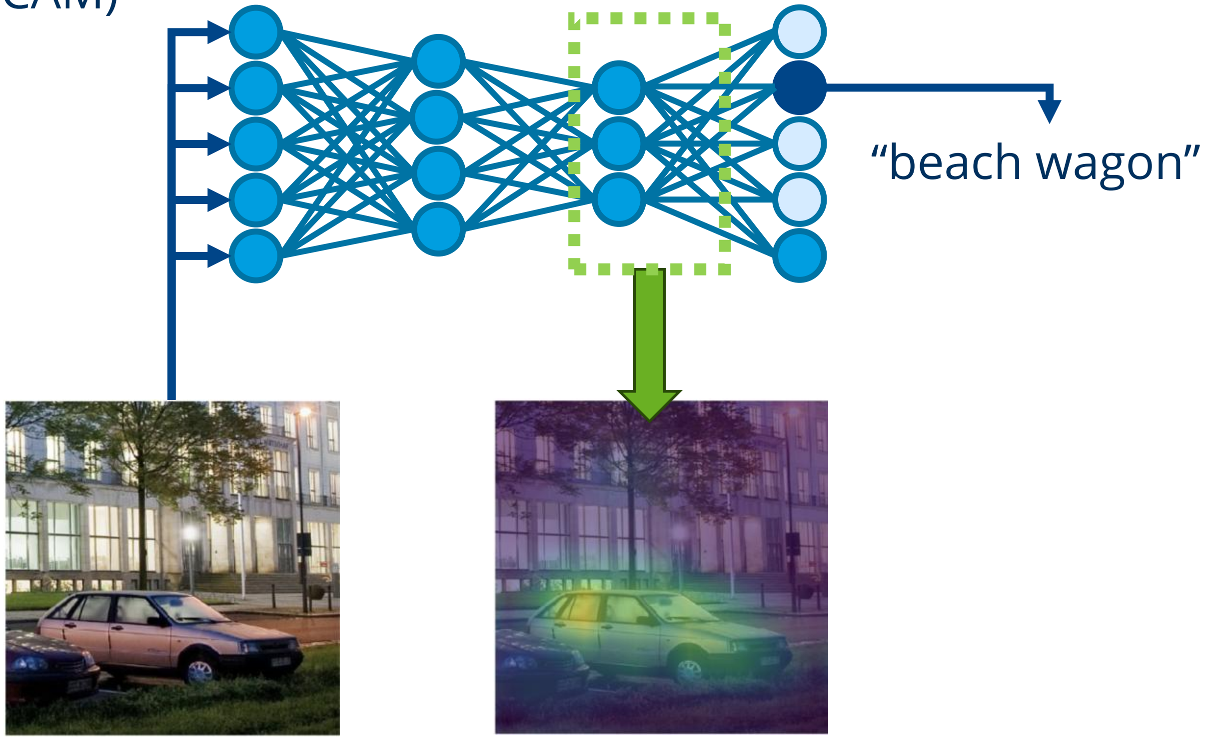
Example: Shapley's Additive exPlanations (SHAP)





Model-specific methods

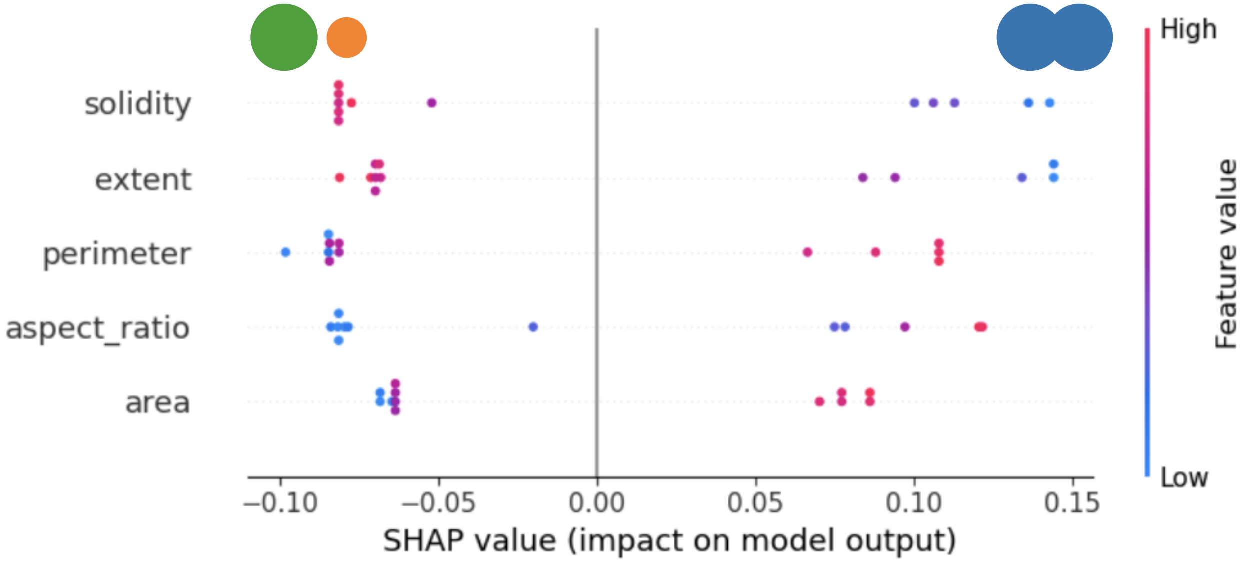
Example: Gradient Class Activation Maps (Grad-CAM)

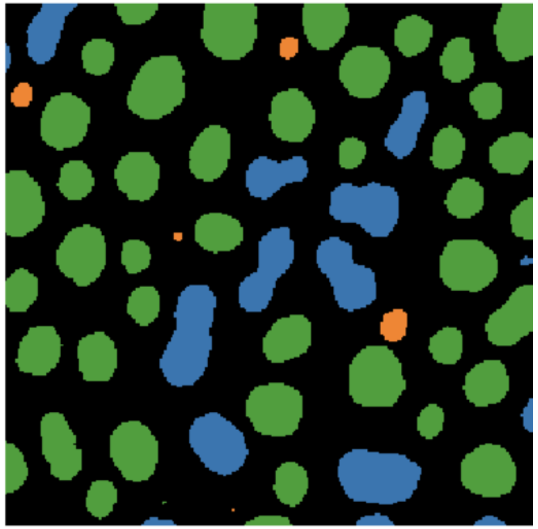


Explainable AI

Depending on the target group [for the explanation], the influence of data is more important than how AI algorithms work.

- Many computer scientists want to explain and understand AI methods.
- Biologists use AI as a method to explain biological processes.
- Example: "What parameters distinguish round objects from elongated ones?"





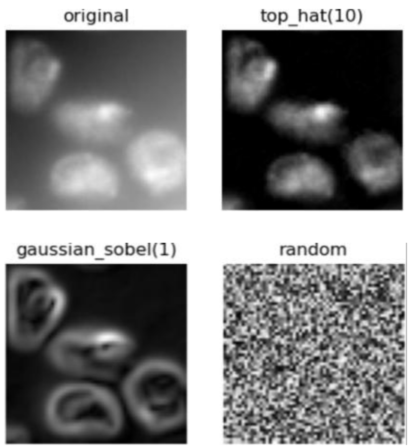
Recap: Feature selection

- Which measurement / parameter / feature is related to the effect I'm investigating?
- Example goals:

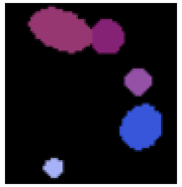
- Amplitude
- Energy
- Duration
- …

- Noise
- Tourists jumping on a sensor
- Earthquake approaching

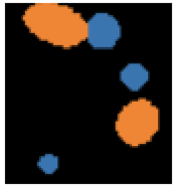
Signal classification



Pixel classification



- Area
- Perimeter
- Aspect ratio
- …



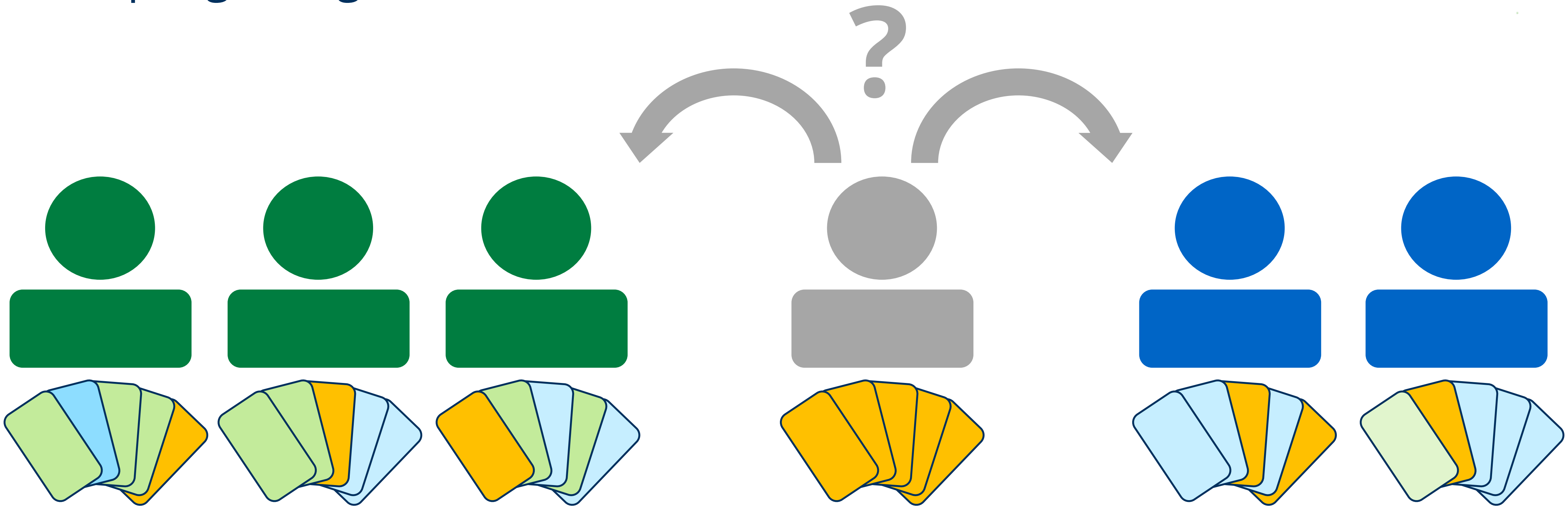
- Round
- Elongated

Object classification

Collaborative game theory

If players collaborate, how is the impact on a team if another player joins?

Example game goal: maximize cards of the same colour.

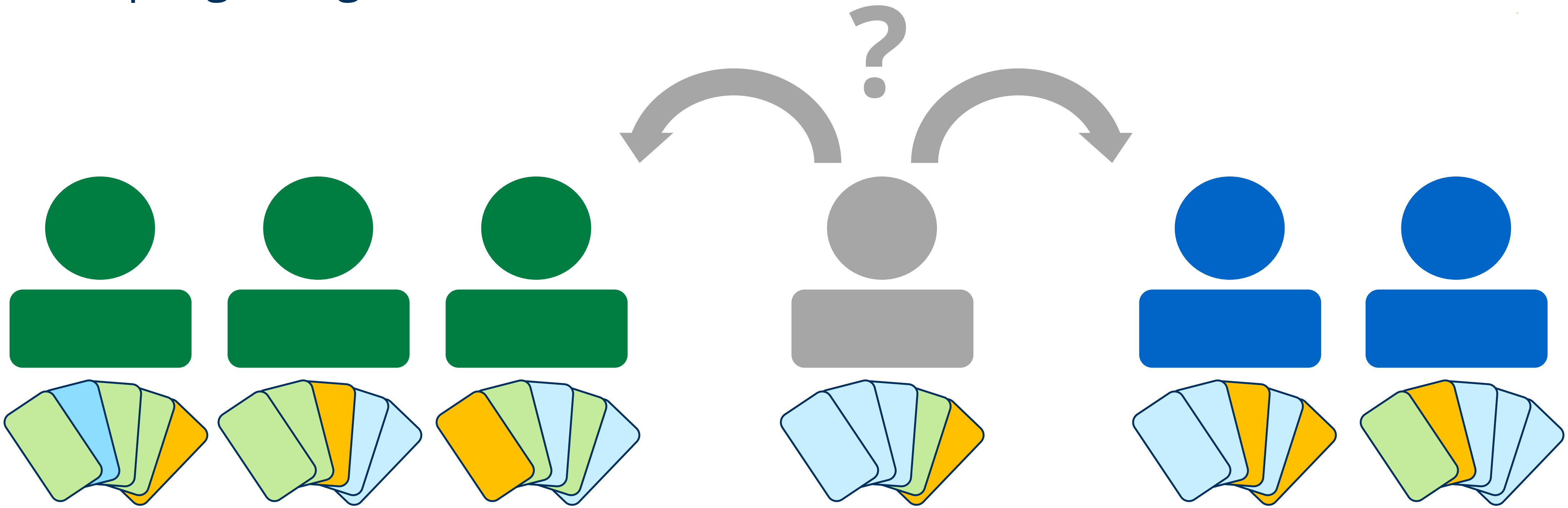


Value for both teams: 0

Collaborative game theory

If players collaborate, how is the impact on a team if another player joins?

Example game goal: maximize cards of the same colour.



Value for team green: 0.1
Value for team blue: 0.3

SHAP

Analogously, this can be done with data points instead of features.

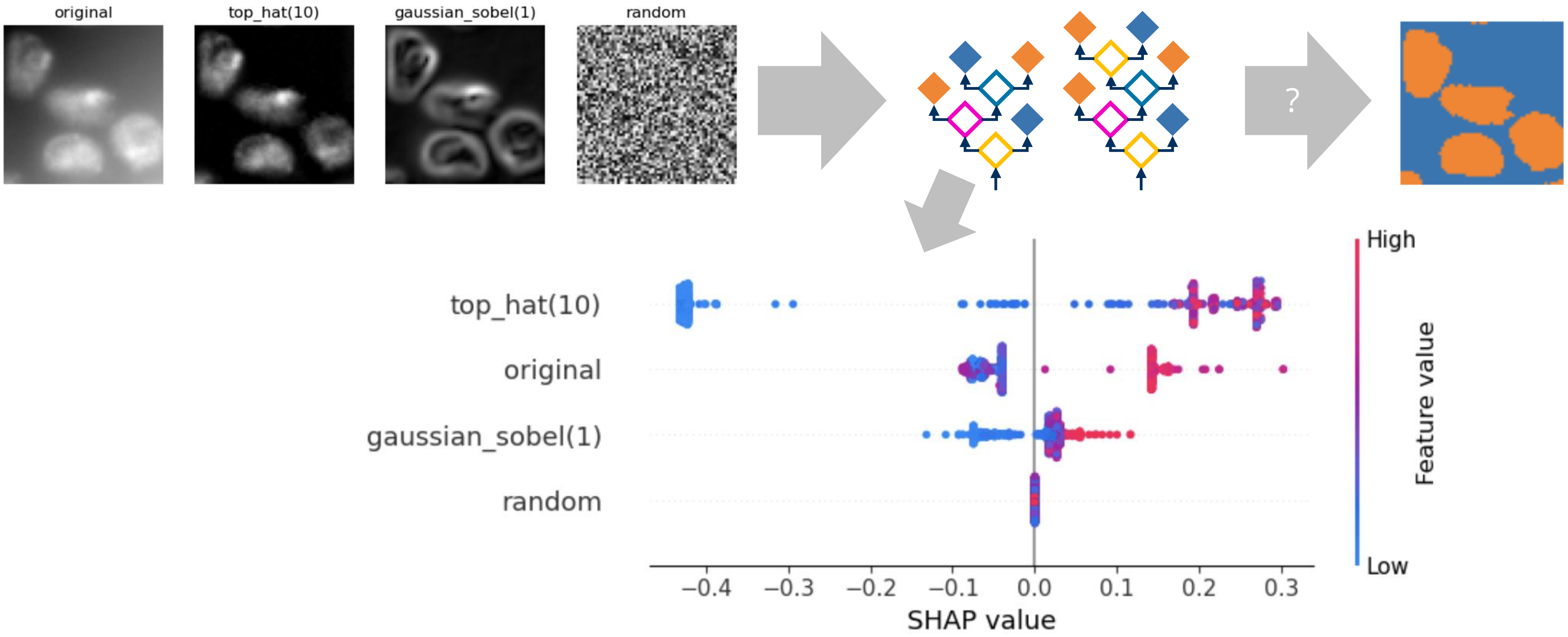
SHapley's Additive exPlanations

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f_x(S \cup \{i\}) - f_x(S)]$$

	SHAP value of feature i	Sum over all Subsets of Features not including i	Weight related to number of used features in relation all players	Quality of classifier using feature i	Quality of classifier *not* using feature i
Game theory	SHAP value of player i	Sum over all Subsets of Players not including i	Weight related to number of players in a coalition in relation to undecided players and all players	Chance to win game of coalition without player i	Chance to win game of coalition *including* player i

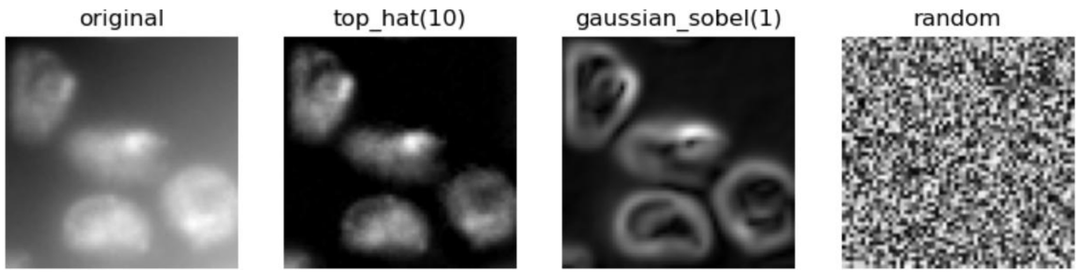
SHAP

Allows interpreting [pixel] classification results

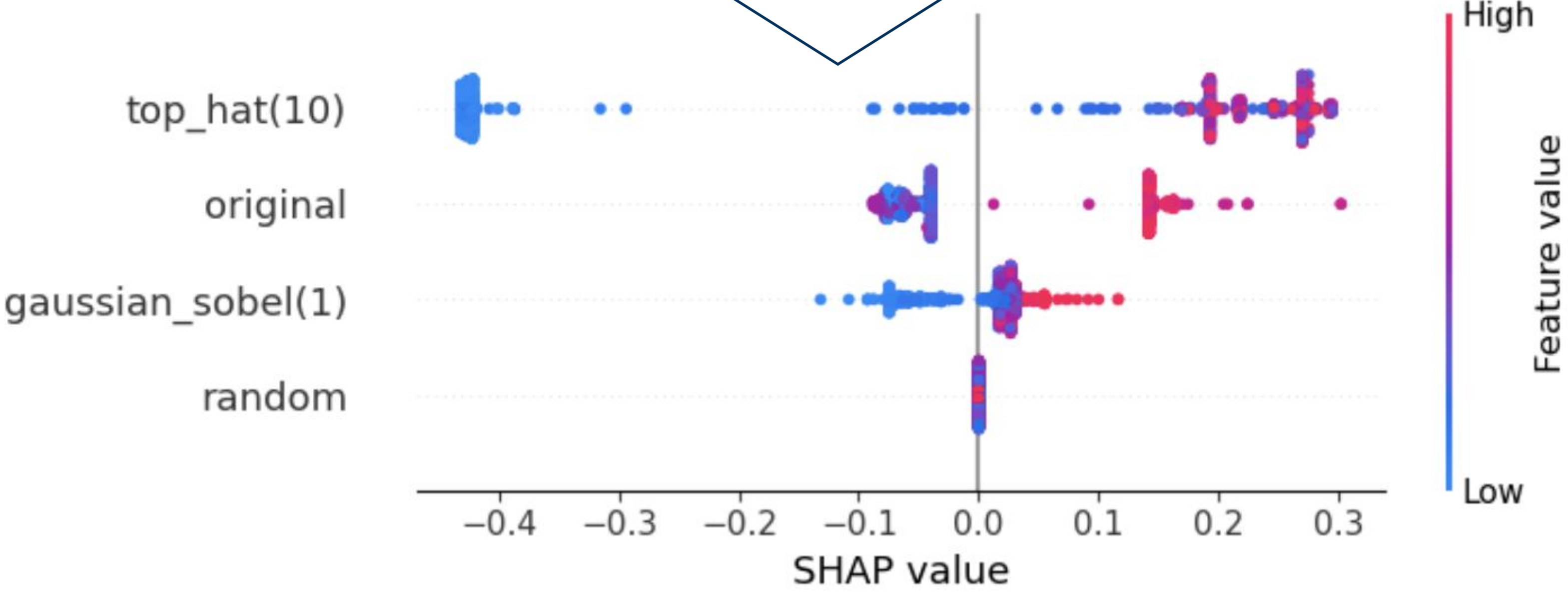


SHAP

Allows interpreting [pixel] classificatio

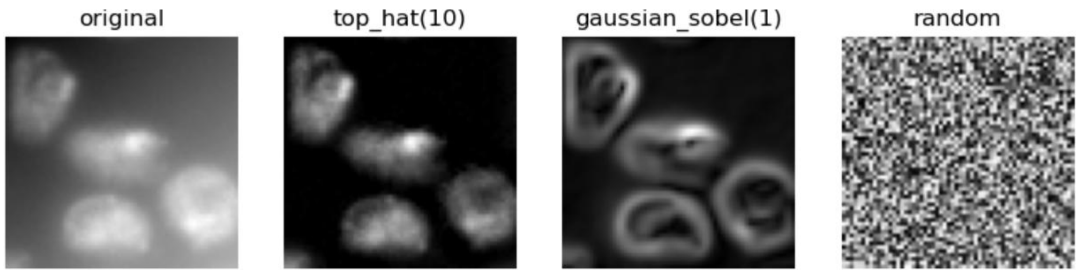


> “If intensity in the top-hat image is high, the classifier tends to select the positive class (orange).”

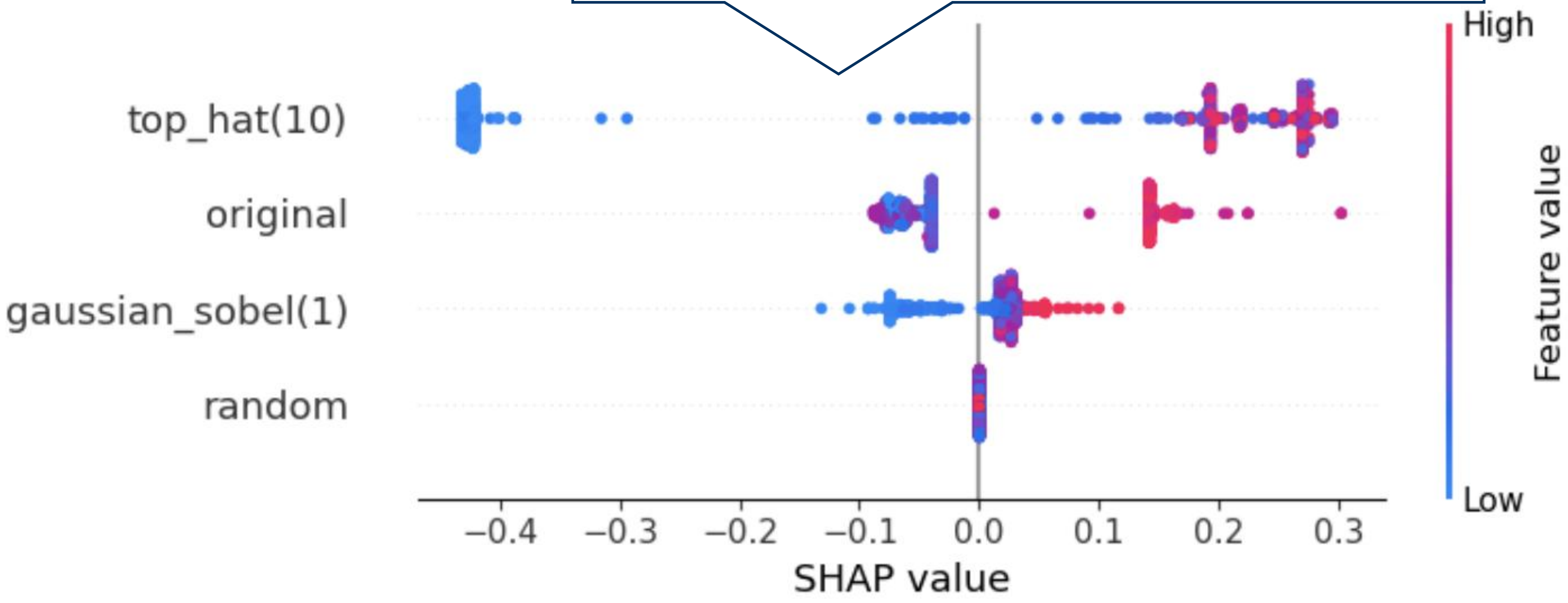


SHAP

Allows interpreting [pixel] classificatio



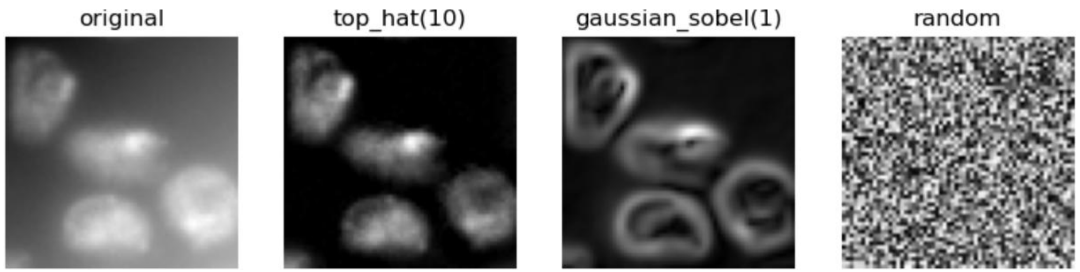
“If intensity in the top-hat image is low, the classifier needs to take other features into account.”

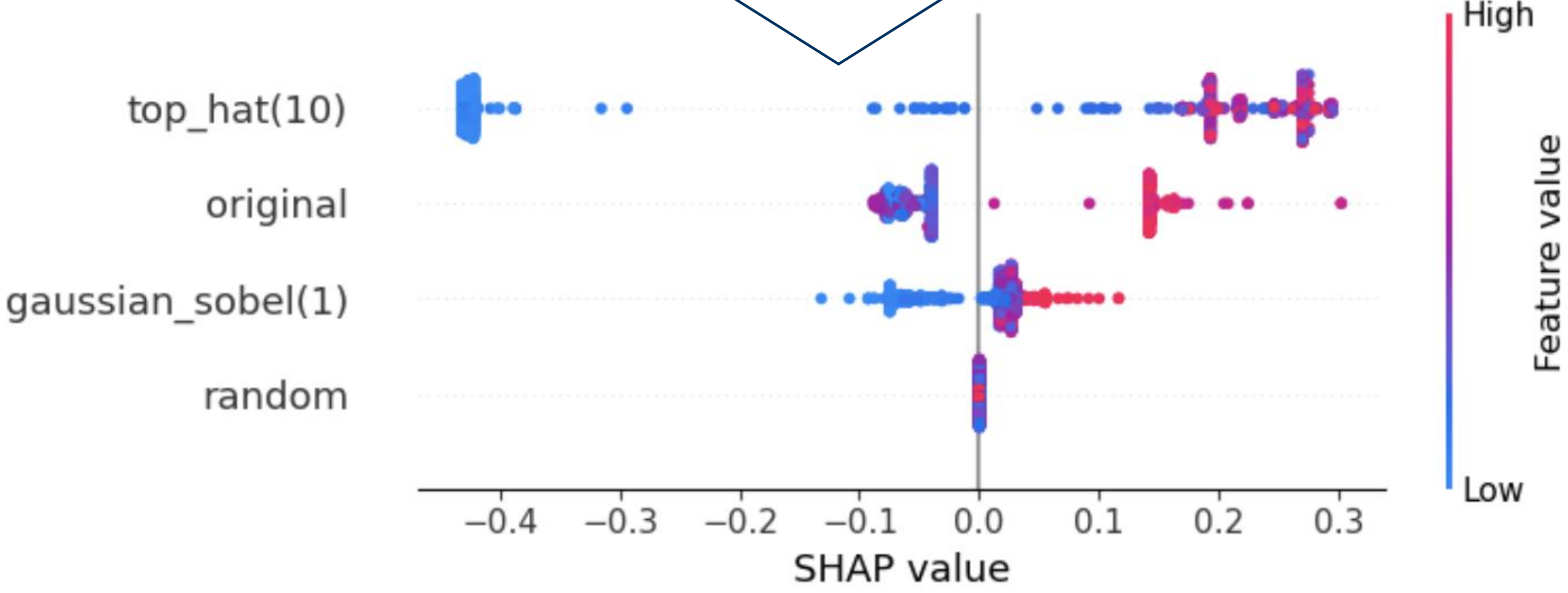


SHAP

Allows interpreting [pixel] classificatio

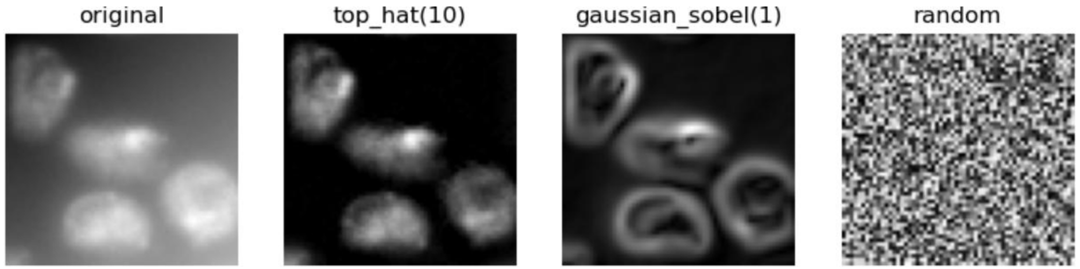
“The random feature has no value for classification.”

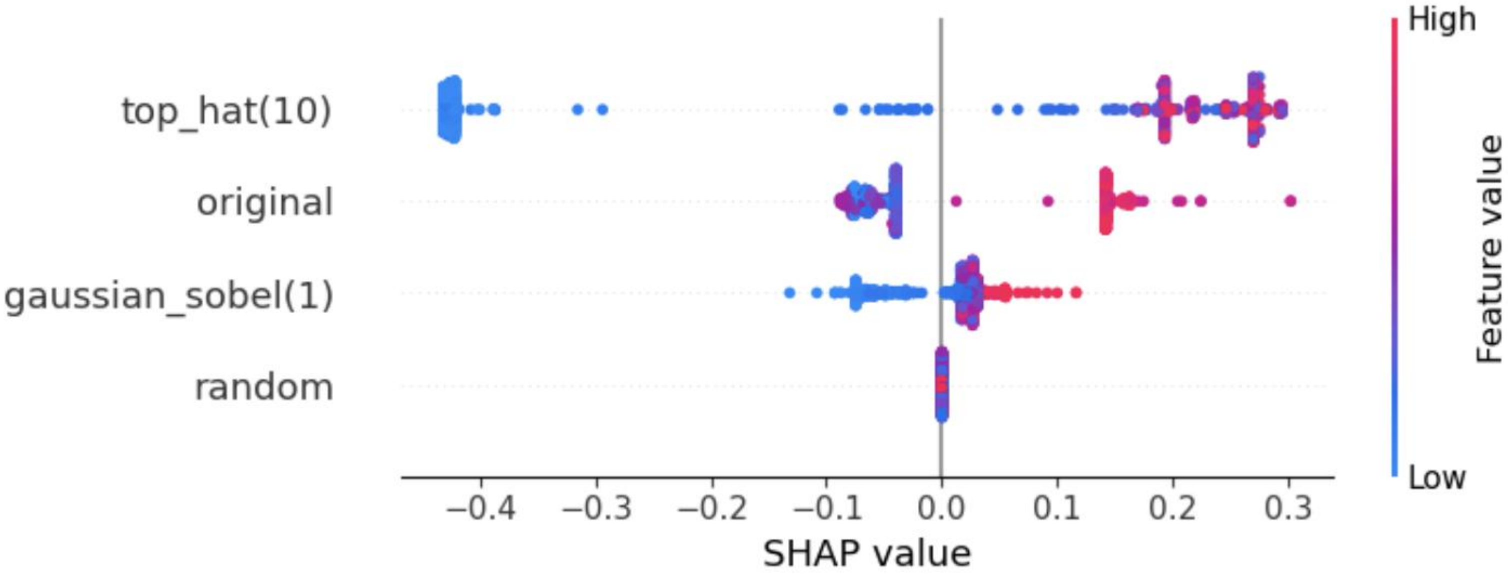




Pitfall: Correlation

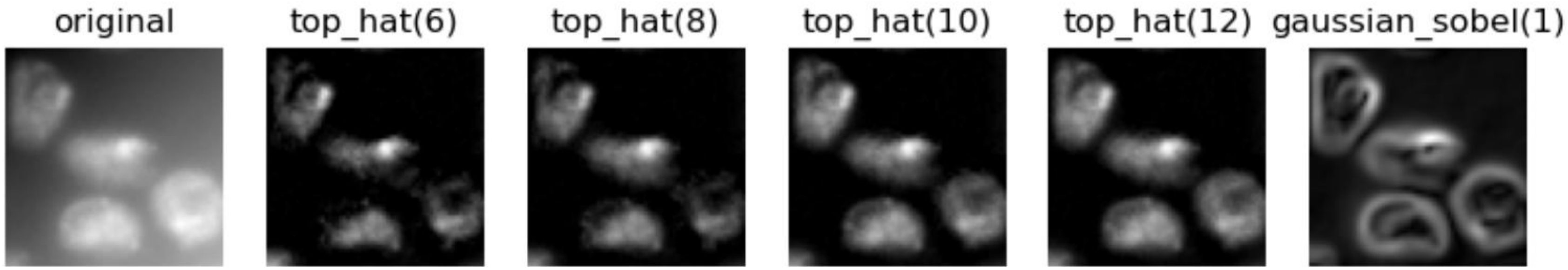
Correlated features may harm interpretability

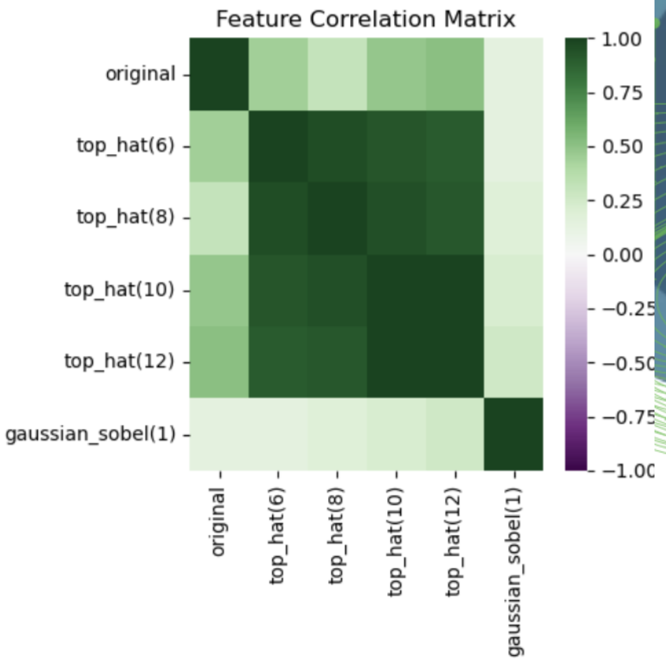


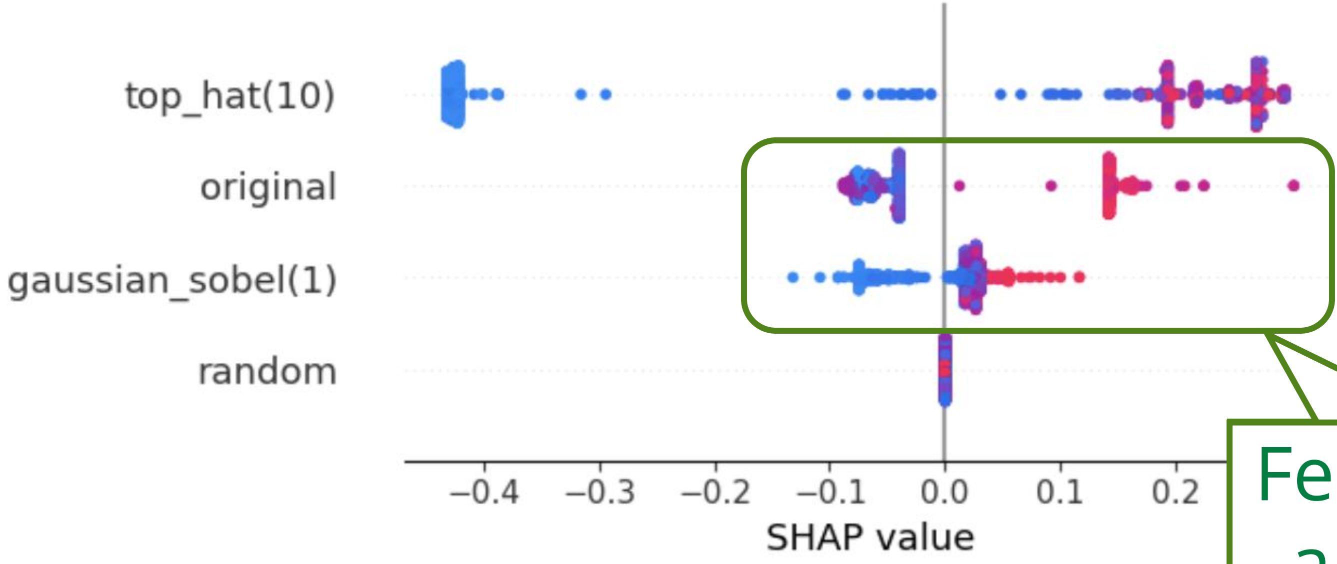


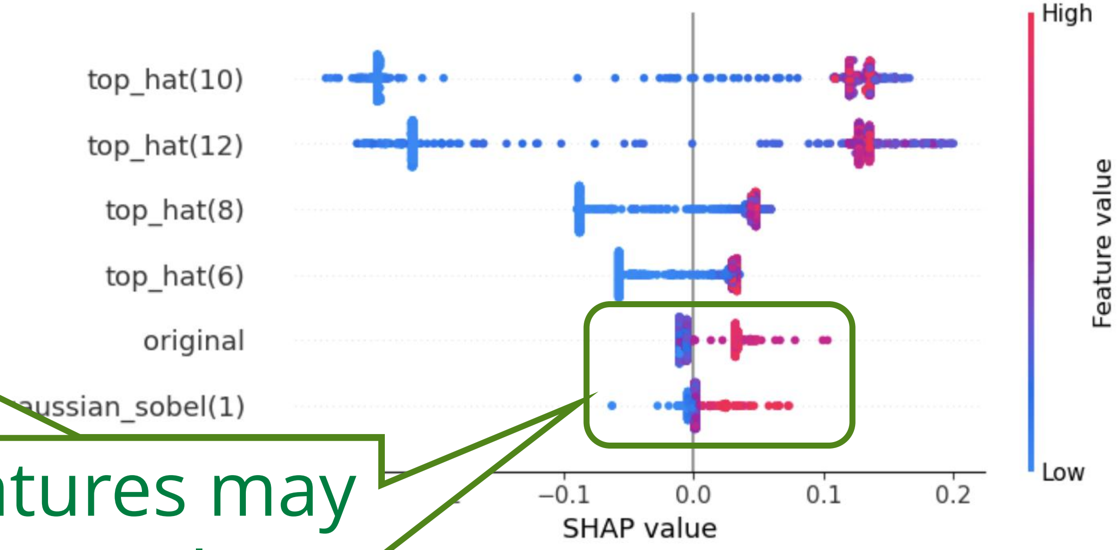
Pitfall: Correlation

Correlated features may harm interpretability



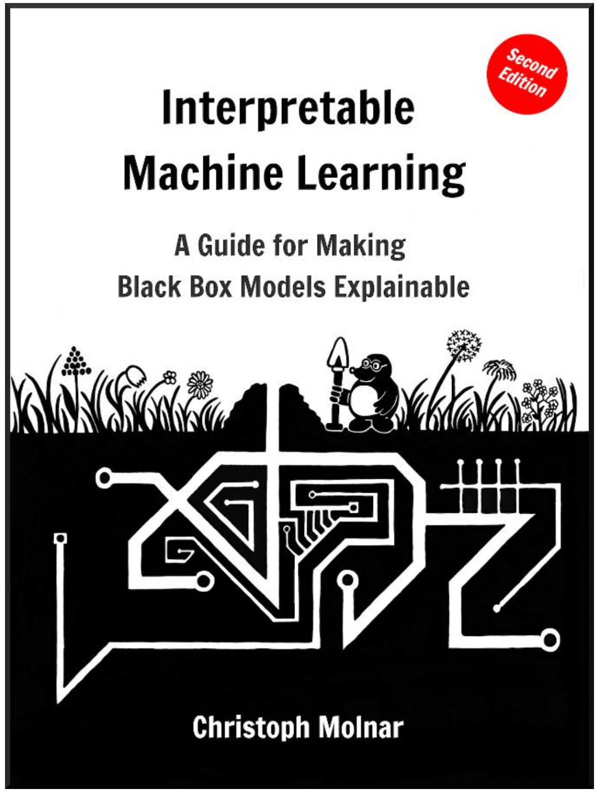




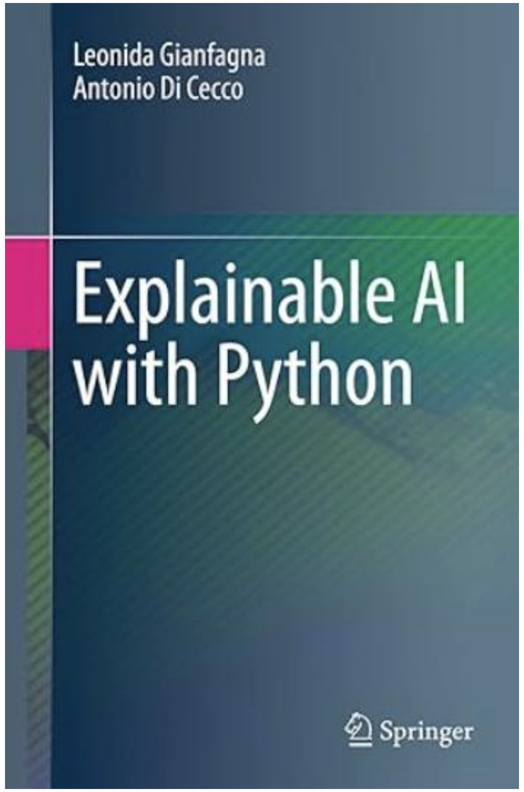


Features may appear less valuable.

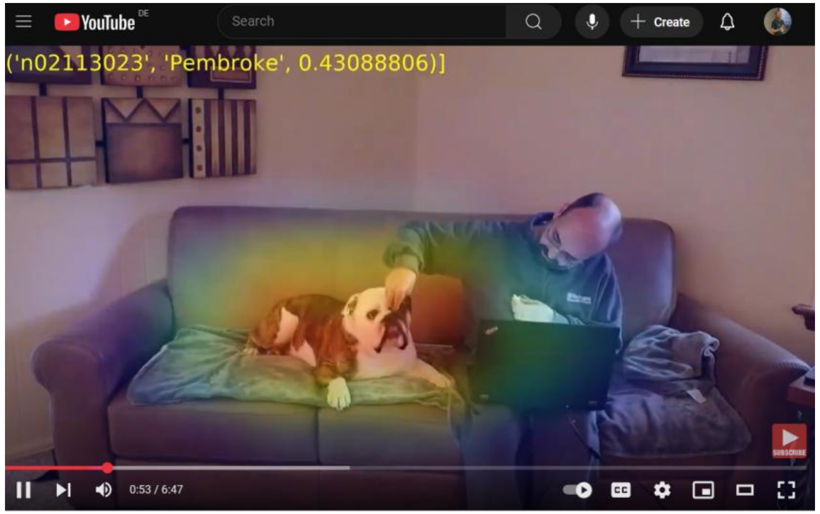
Read more...



https://christophm.github.io/interpretable-ml-book/



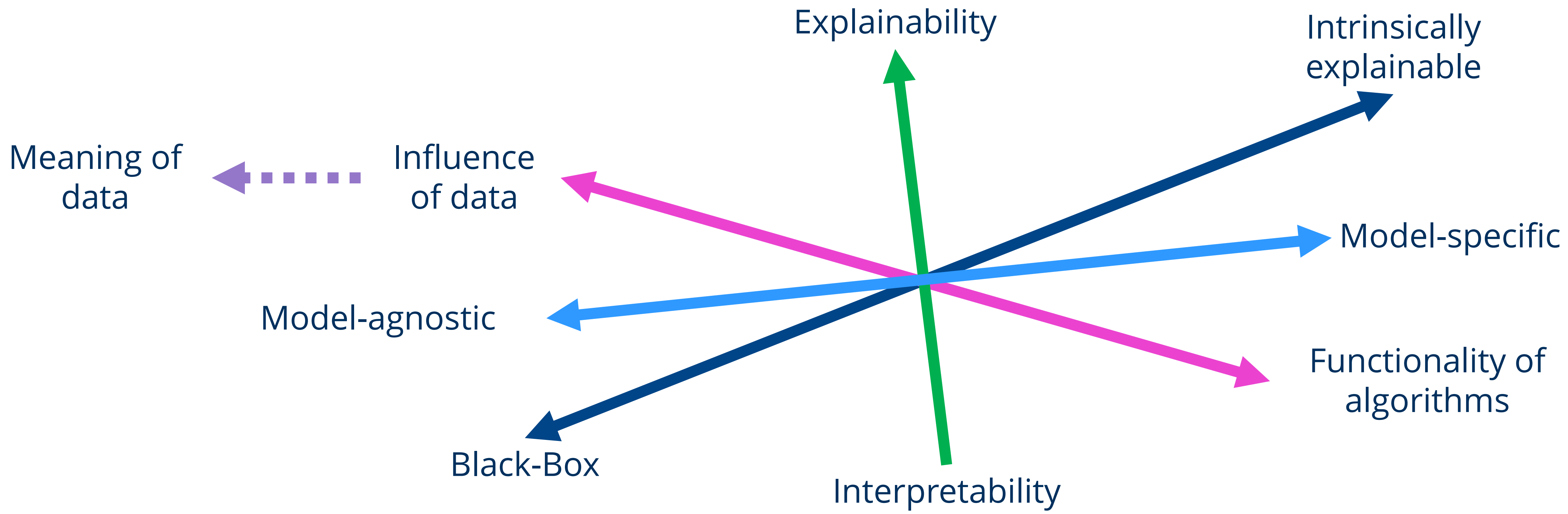
https://www.amazon.de/dp/3030686396



https://www.youtube.com/watch?v=dw63QH_b3Jo

Summary: Explainable AI

Methods of XAI can be classified on different scales



CENTER FOR SCALABLE DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE

Exercises

Robert Haase

Funded by

Bundesministerium für Bildung und Forschung

SACHSEN

Diese Maßnahme wird gefördert durch die Bundesregierung aufgrund eines Beschlusses des Deutschen Bundestages. Diese Maßnahme wird mitfinanziert durch Steuermittel auf der Grundlage des von den Abgeordneten des Sächsischen Landtags beschlossenen Haushaltes.

SHAP Analysis in Python

Use the opportunity and explain SHAP plots like this one!