

# Machine Learning Explainability

Some applications in medical settings

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Pei Liu

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Department of Computer Science @UESTC

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# Introduction

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## What is it

Models you built can explain how the event of interest is affected.

- VIP (What variables most affect it?)
- PDP (How do the variables affect it?)
- CASE STUDIES (For an individual?)

If I were in a *linear world*, then how does it become?

$$\hat{Y} = \text{Prob}(\text{The fruit is an apple}) = 0.4 \cdot \text{Color} + \dots + 0.2 \cdot \text{Shape} + 0.1 \cdot \text{Size}$$

## Why should we do it

But actually, we are building a complex model via Machine Learning methods.

In the realm of supervised learning, there are

- Decision Tree
- Neural Network
- And others

Especially in the medical settings, it is crucial to understand how the factors affect the survival of patients.

Let us focus on the prognostic predictive model that is derived from  
**West China Hospital!**

Just Explore it!

## Details of the model

More details in the IDFS model:

- X variables: Age, Education, ..., Tumor Size. (No. 19)
- Y variables: Follow-up time and status of relapse. (No. 2)
- Predictions: Hazard Ratio (a real number indicating risk of relapse).
- Algorithm: Cox Proportional Hazard model based on XGBoost.

Since it is indeed a Black Box, how can we interpret it just like a linear model?

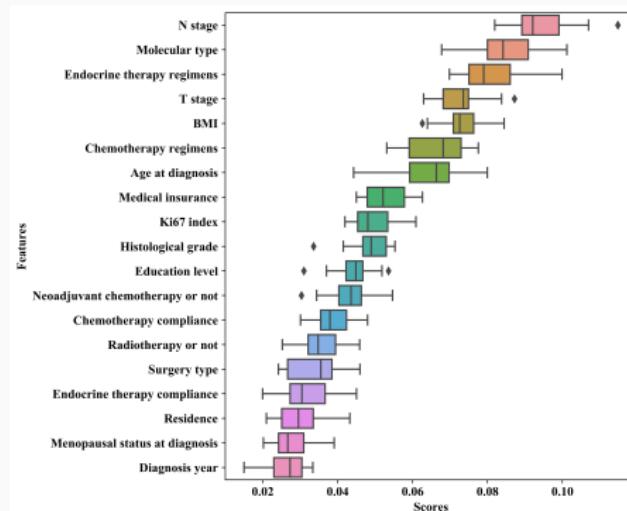
## Variable Importance

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# What variables most affect the relapse?

Recommended methods are as follows:

- Built-in functions
- Permutation Importance
- Other tricks?



**Figure 1:** Variable Importance of the IDFS Model

**How do the variables affect the  
relapse?**

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# Partial Dependency Plots

The method we discuss here is **Partial Dependency Plots**.

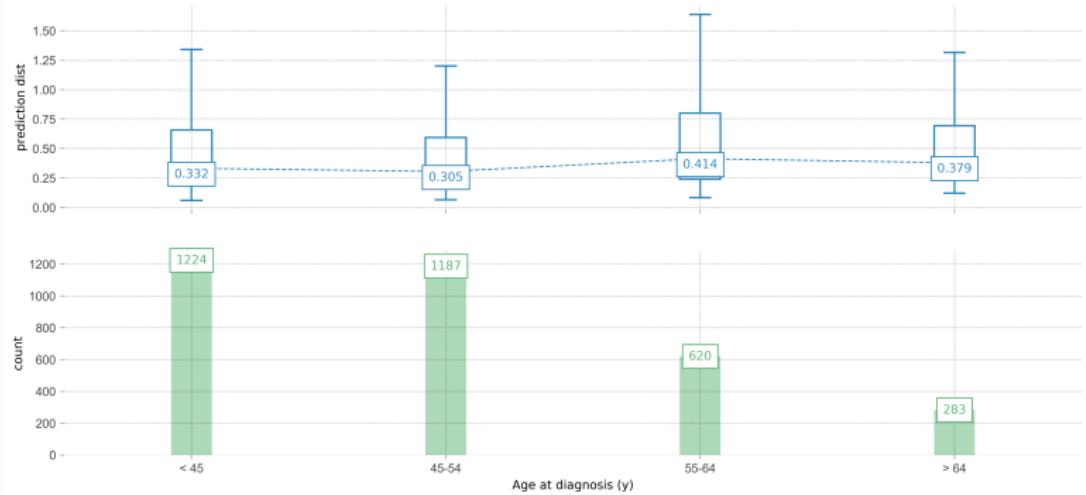
*This method takes a row of the dataset and repeatedly changes a value for one feature.*

*It is done multiple times with different rows and then aggregated in order to find out how the feature is influencing the target on a wide range.*

In order to investigate the effect of a feature, now we exploit it to our IDFS model!

# Partial Dependency Plots for A Feature

Actual predictions plot for Age at diagnosis (y)  
Distribution of actual prediction through different feature values.

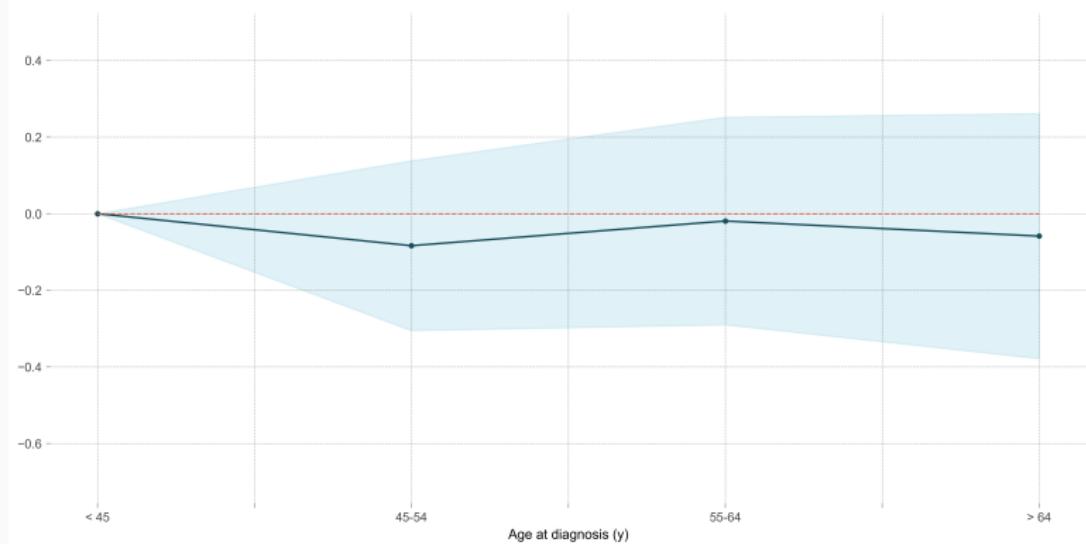


**Figure 2:** The Actual Prediction Distribution

# Partial Dependency Plots for A Feature

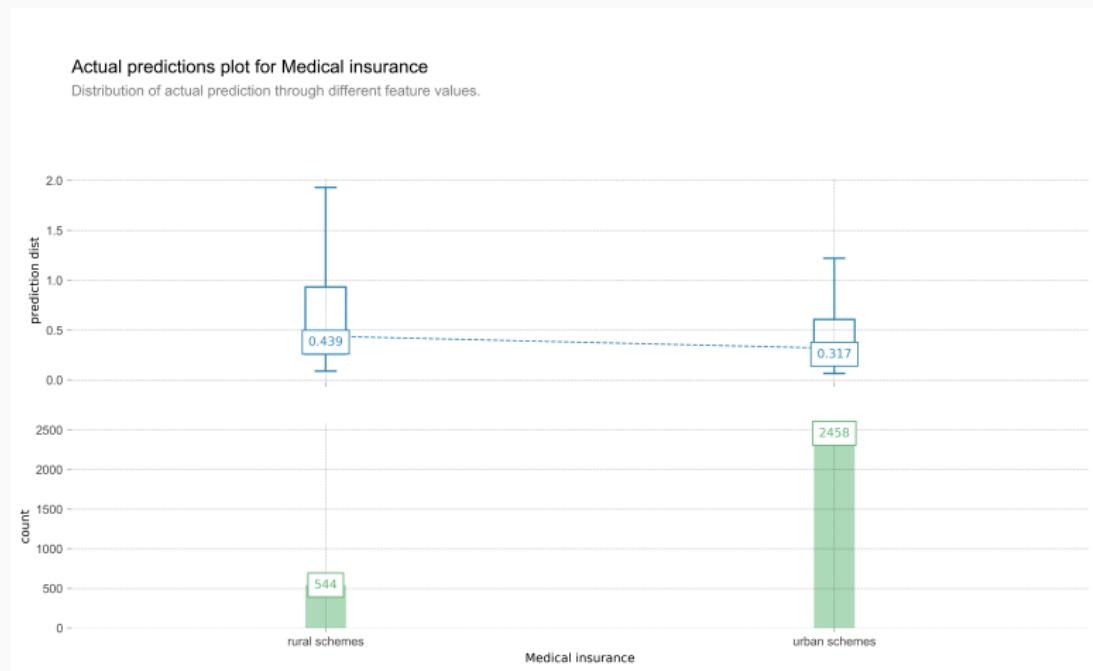
PDP for feature "Age at diagnosis (y)"

Number of unique grid points: 4



**Figure 3:** PDP.

# Partial Dependency Plots for A Feature

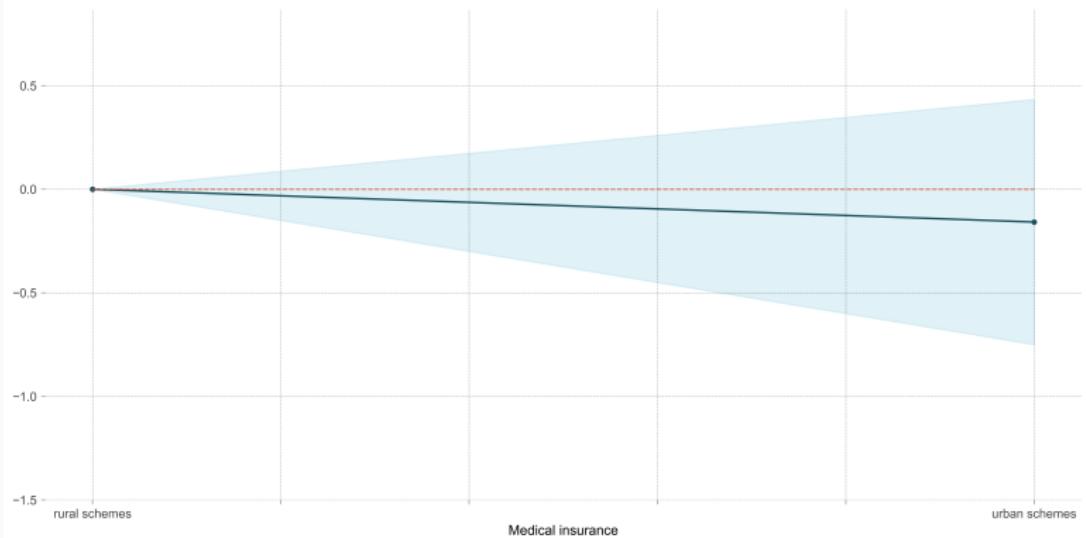


**Figure 4:** The Actual Prediction Distribution

# Partial Dependency Plots for A Feature

PDP for feature "Medical insurance"

Number of unique grid points: 2

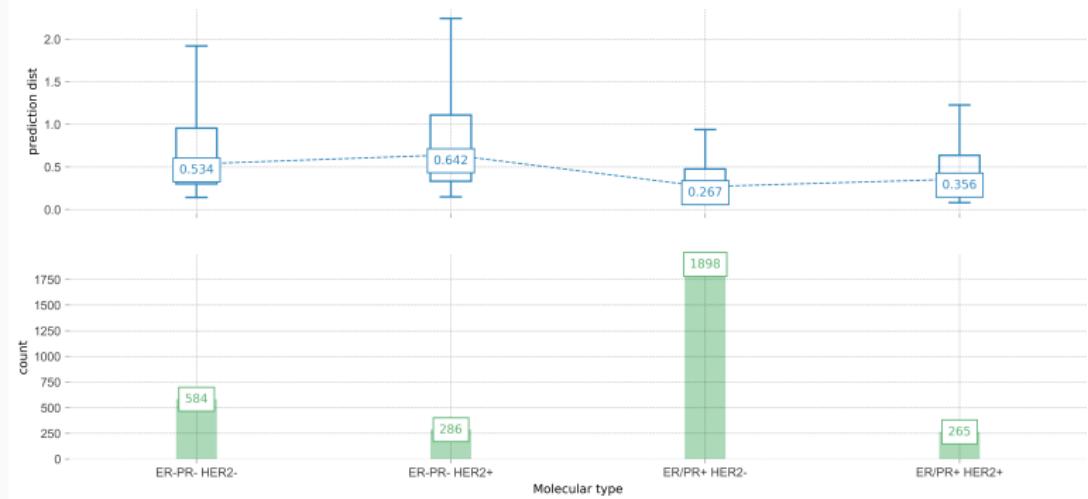


**Figure 5:** PDP.

# Partial Dependency Plots for A Feature

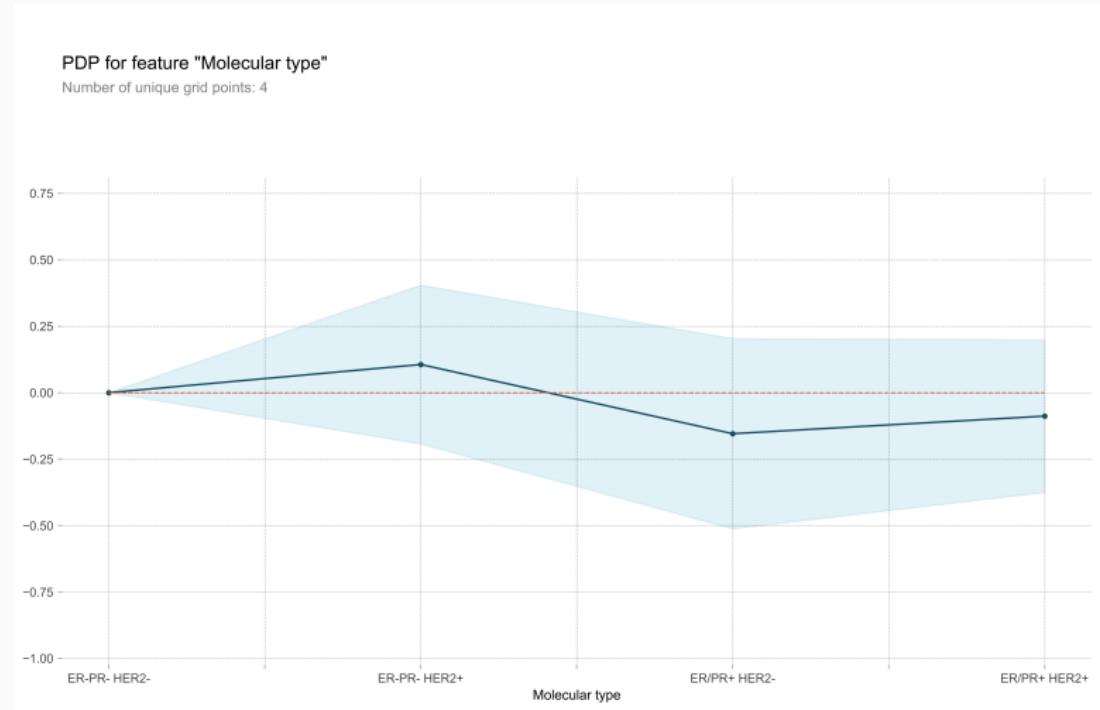
## Actual predictions plot for Molecular type

Distribution of actual prediction through different feature values.



**Figure 6:** The Actual Prediction Distribution

# Partial Dependency Plots for A Feature

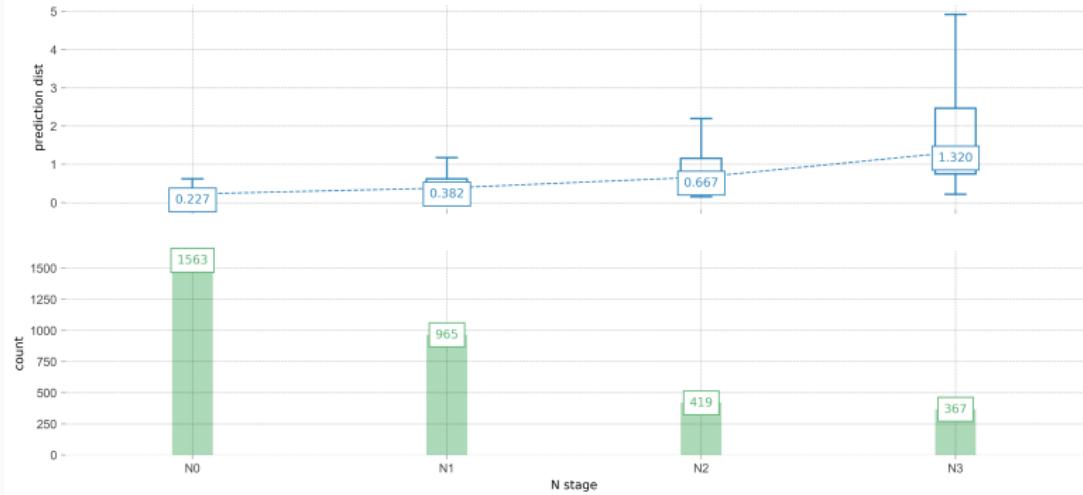


**Figure 7:** PDP.

# Partial Dependency Plots for A Feature

## Actual predictions plot for N stage

Distribution of actual prediction through different feature values.

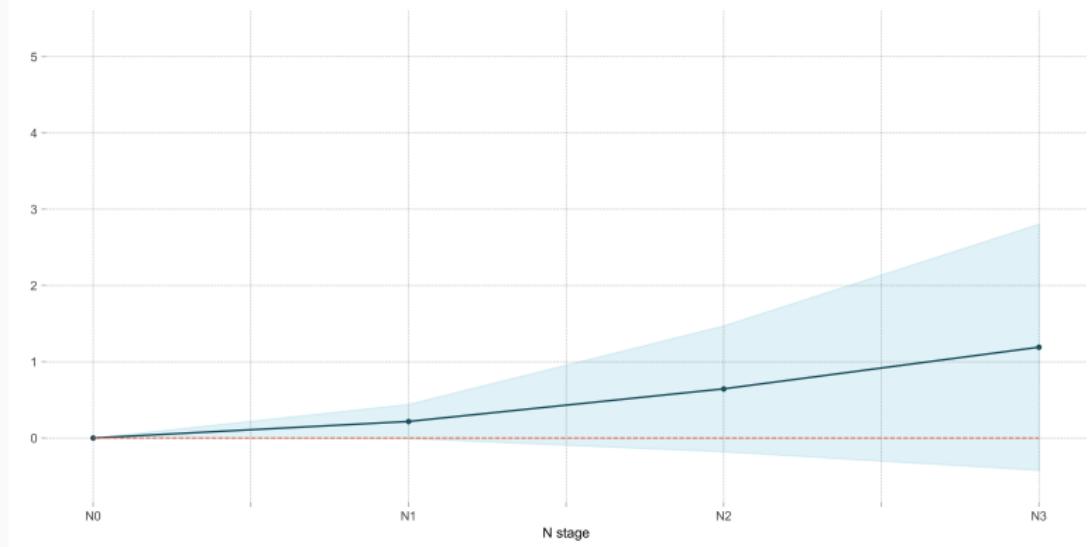


**Figure 8:** The Actual Prediction Distribution

# Partial Dependency Plots for A Feature

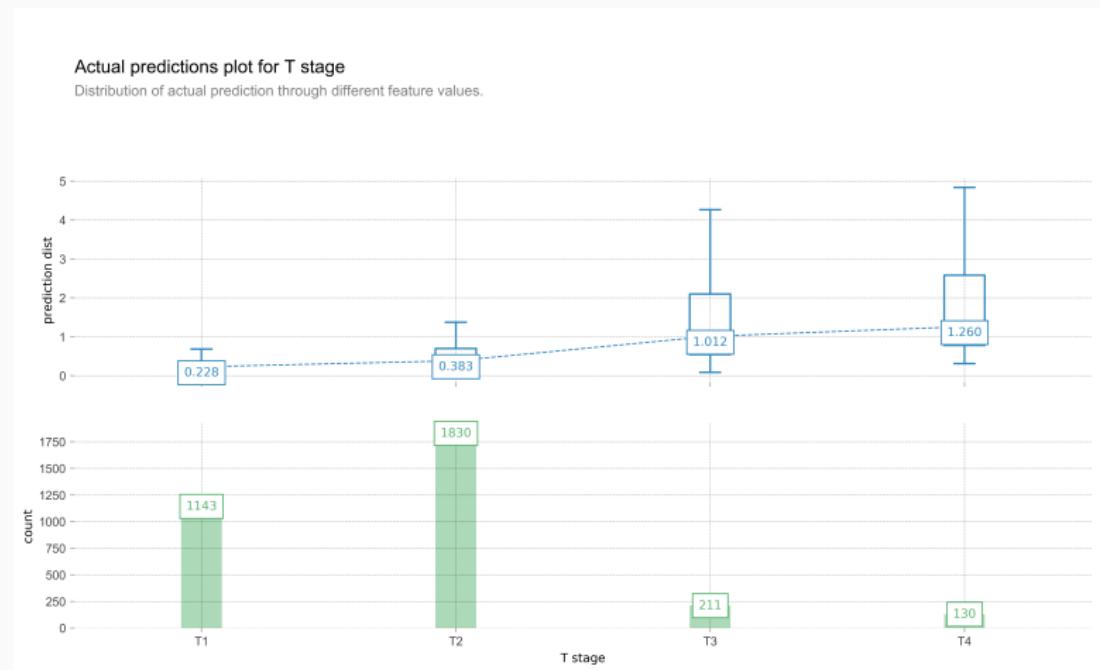
PDP for feature "N stage"

Number of unique grid points: 4



**Figure 9:** PDP.

# Partial Dependency Plots for A Feature

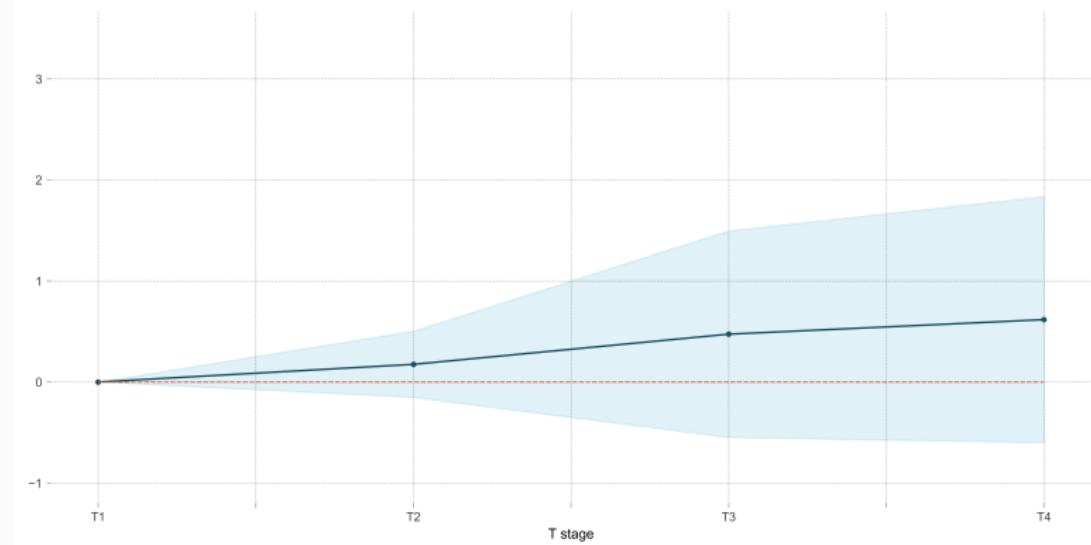


**Figure 10:** The Actual Prediction Distribution

# Partial Dependency Plots for A Feature

PDP for feature "T stage"

Number of unique grid points: 4

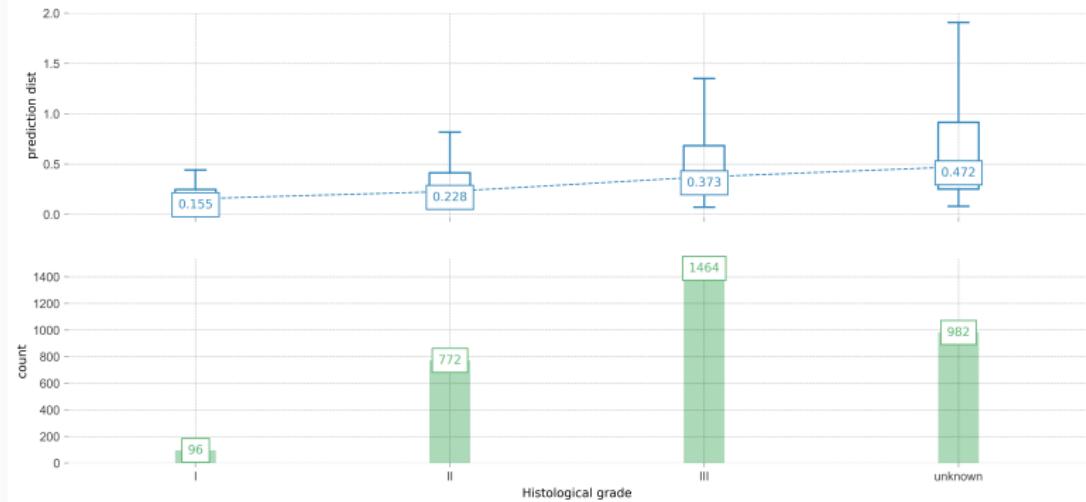


**Figure 11:** PDP.

# Partial Dependency Plots for A Feature

## Actual predictions plot for Histological grade

Distribution of actual prediction through different feature values.

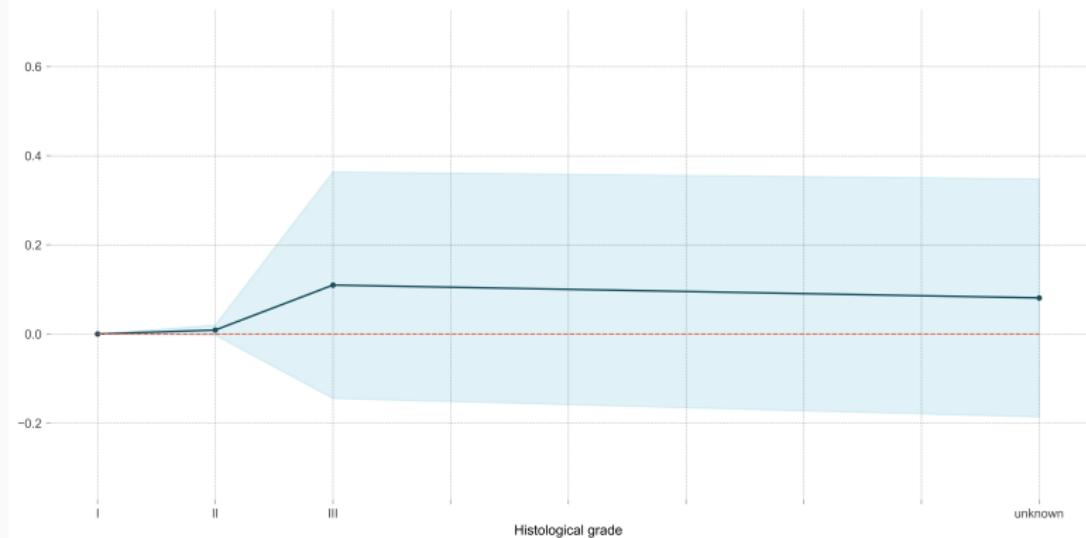


**Figure 12:** The Actual Prediction Distribution

# Partial Dependency Plots for A Feature

PDP for feature "Histological grade"

Number of unique grid points: 4



**Figure 13:** PDP.

## Disadvantages of Partial Dependency Plots

- Maximum number of features: up to 2 features.
- Feature distribution: you might overinterpret regions with almost no data.
- Assumption of independence: feature correlations (ridiculous combination of height and weights).
- Heterogeneous effects might be hidden: PD plots only show the average marginal effects.

## Case Studies

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## How did the variables affect the relapse of a specific patient?

The SHAP values are used to show the effects of the features of a single patient.

Here, the method also takes one feature and compares the value to a baseline value for that feature without changing the other features. That is done for all features.

Need more thinking for the principle!

# How did the variables affect the relapse of a specific patient?

An example for showing parameters of a specific patient influencing the risk of hazard ratio.



**Figure 14:** Case Studies

**Questions?**

# References

## References:

- Good Books: <https://christophm.github.io/interpretable-ml-book/agnostic.html>
- Inspired by the tutorial:  
<https://pan.baidu.com/s/1hF6tVG3JvzML00R4ozZkYQ>
- Permutation importance:  
<https://doi.org/10.1093/bioinformatics/btq134>
- PDPBOX library: <https://github.com/SauceCat/PDPbox>
- BEAMER template for presentation:  
<https://github.com/matze/mtheme>