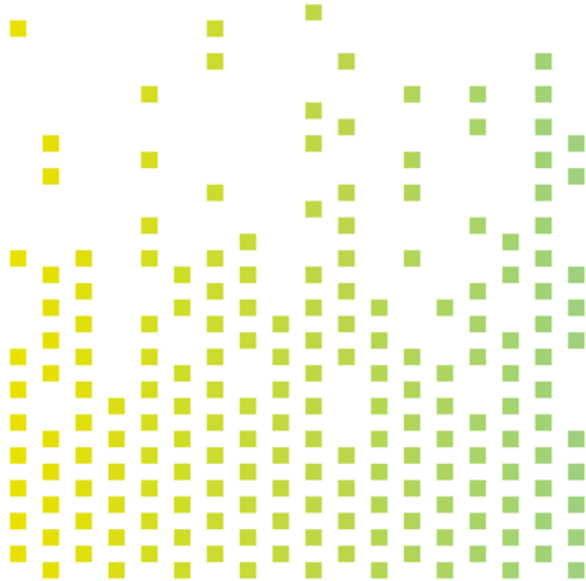


Black is the new White

using eXplainable Artificial Intelligence in
Business



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Data Juice Lab.

Biznes oparty na danych
data

Agenda

1. DO I NEED XAI?

2. DO I NEED BLACK-BOXES?

3. HOW CAN I USE XAI IN BUSINESS?



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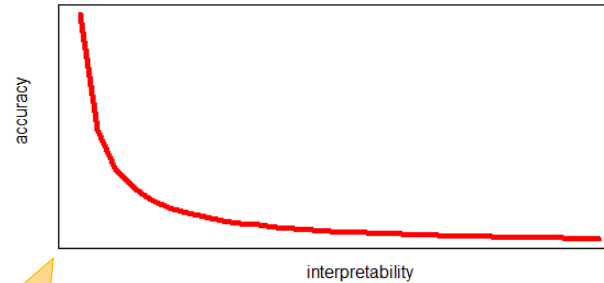
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1. DO I NEED XAI? (1/4)

Hype cycle



ML is easy!



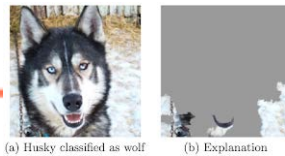
I know how it works 😊



AI?
Seriously?



Is it so?!

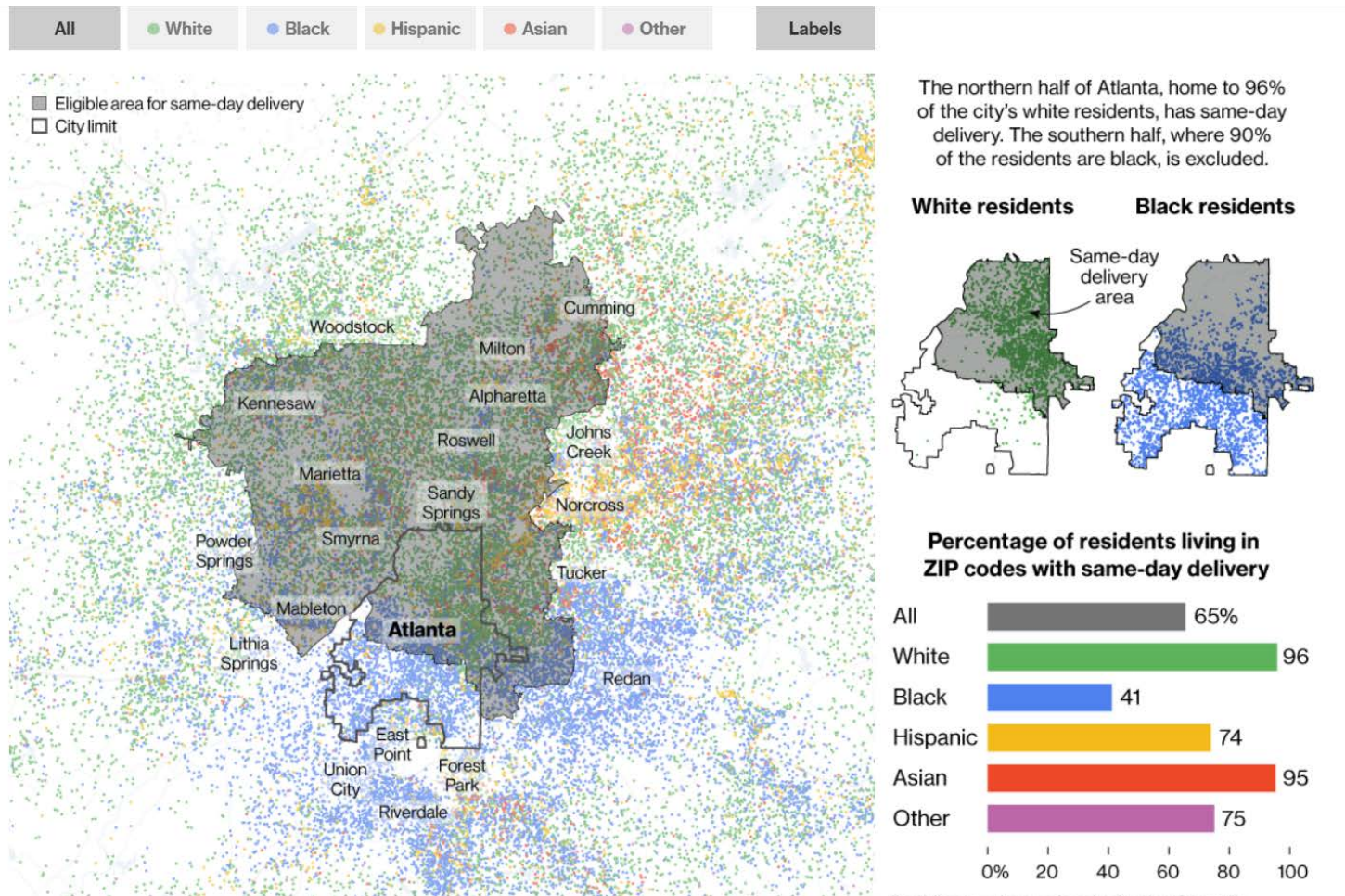


<https://github.com/ModelOriented/DrWhy/blob/master/README.md>

1. DO I NEED XAI? (2/4)

ML failures (1/2)

- In 2016 Amazon built a ML model that support same-day-delivery process
- Unintentionally model discriminate ethnic groups



<https://www.bloomberg.com/graphics/2016-amazon-same-day/>

1. DO I NEED XAI? (3/4)

ML failures (2/2)

THE VERGE

TECH ▾

SCIENCE ▾

CULTURE ▾

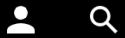
CARS ▾

REVIEWS ▾

LONGFORM

VIDEO

MORE ▾



TECH \ AMAZON \ ARTIFICIAL INTELLIGENCE \

Amazon reportedly scraps internal AI recruiting tool that was biased against women

21

The secret program penalized applications that contained the word “women’s”

By James Vincent | @jjvincent | Oct 10, 2018, 7:09am EDT

In effect, Amazon’s system taught itself that male candidates were preferable. It penalized resumes that included the word “women’s,” as in “women’s chess club captain.” And it downgraded graduates of two all-women’s colleges, according to people familiar with the matter. They did not specify the names of the schools.

<https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G>



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1. DO I NEED XAI? (4/4)

Can we trust the model?

Business

- Reason for a business decision
- Importance of a features
- What-if analyses
- Avoiding non-ethical decisions
- Fraud detection



Regulations

- GDPR - European Parliament (2018)
 - Trustworthy AI;
 - ethics, discrimination
- Right to know (2019) GDPR
- Know your model ('00)



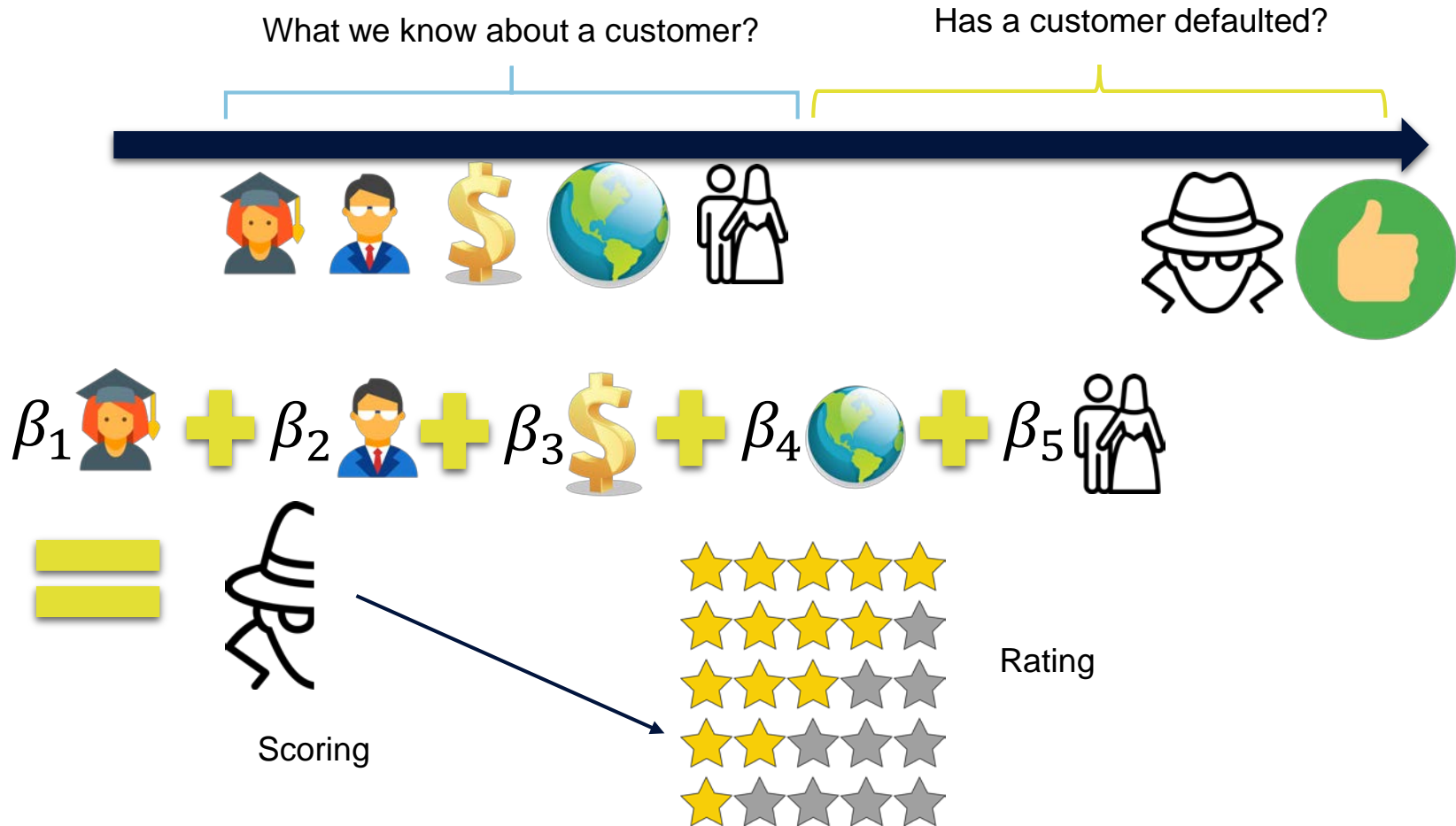
Confidence

- Intuition of results
- Stability of results
- Confidence of results



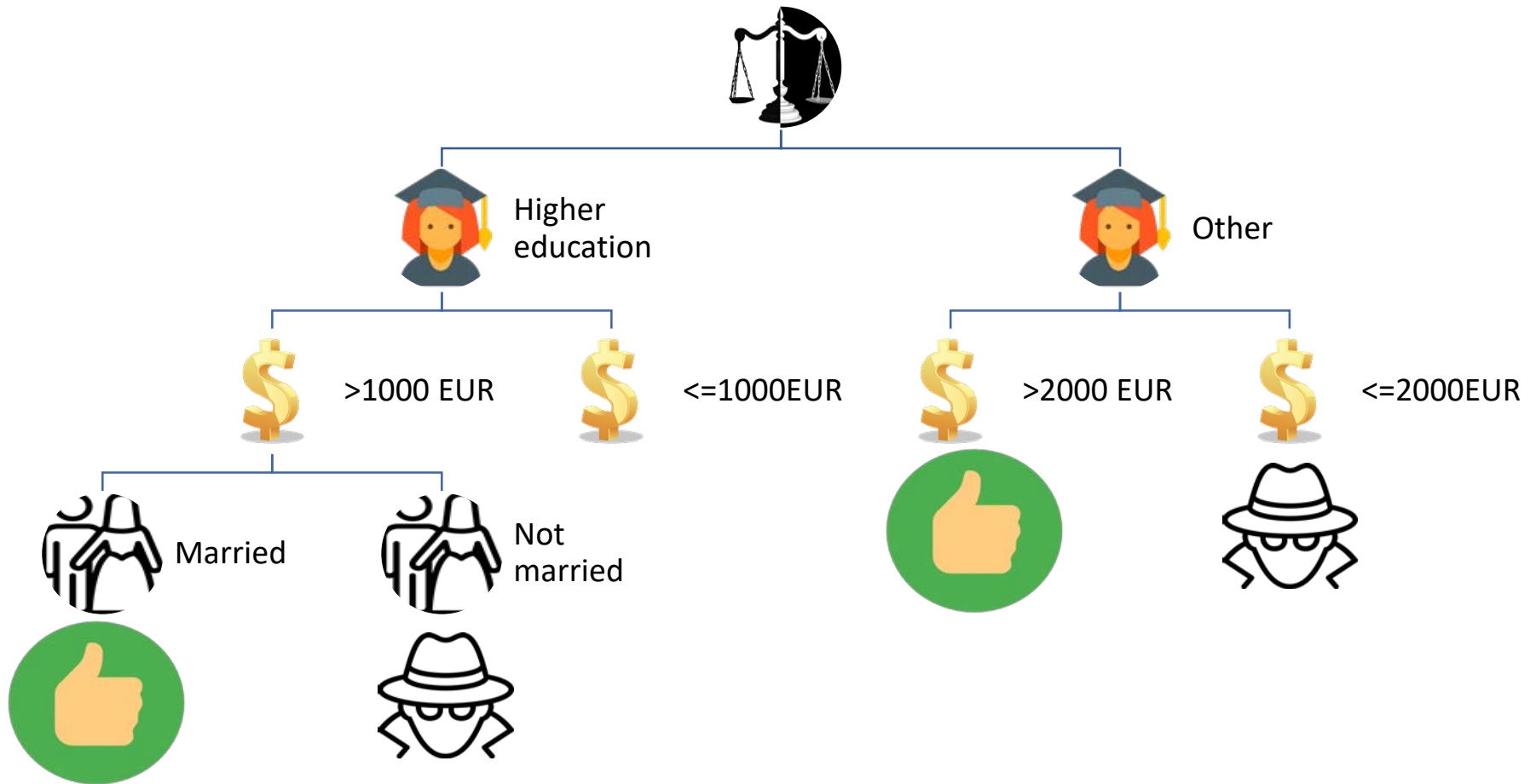
2. DO I NEED BLACK-BOXES? (1/7)

Logistic Regression



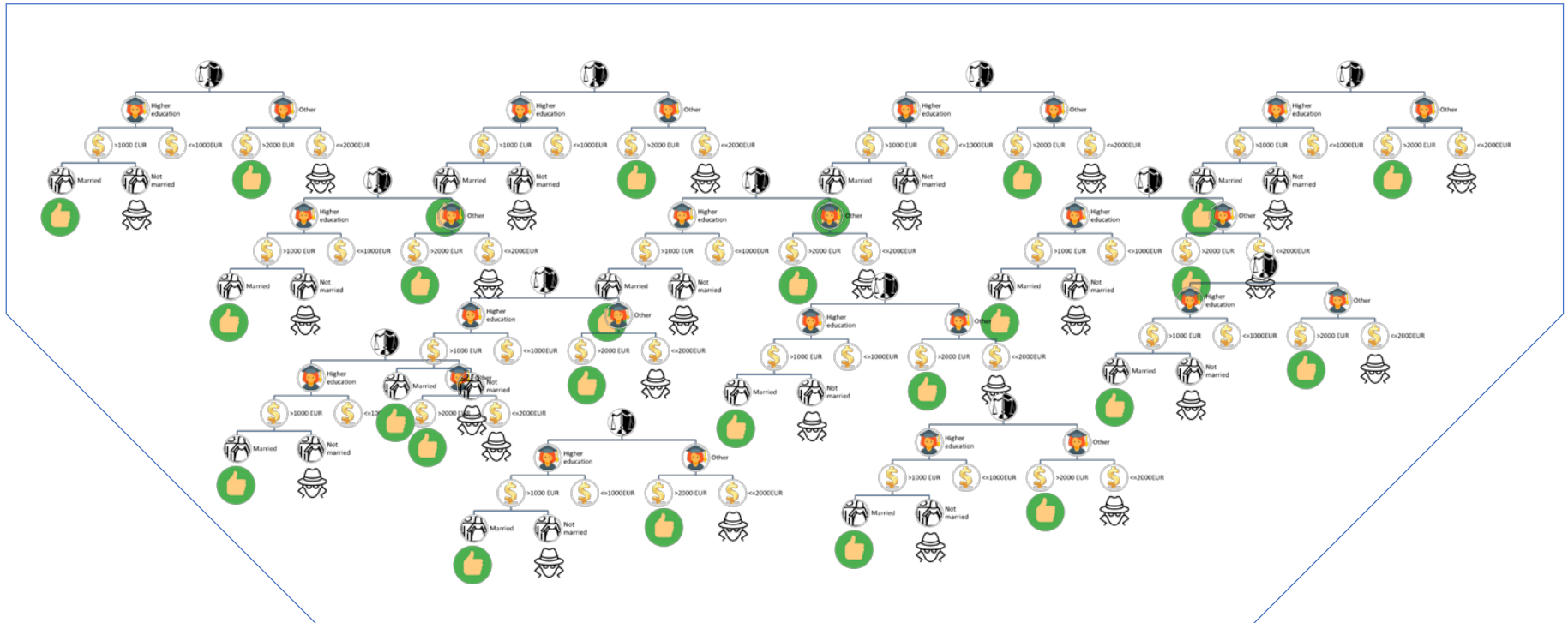
2. DO I NEED BLACK-BOXES? (2/7)

Decision Tree



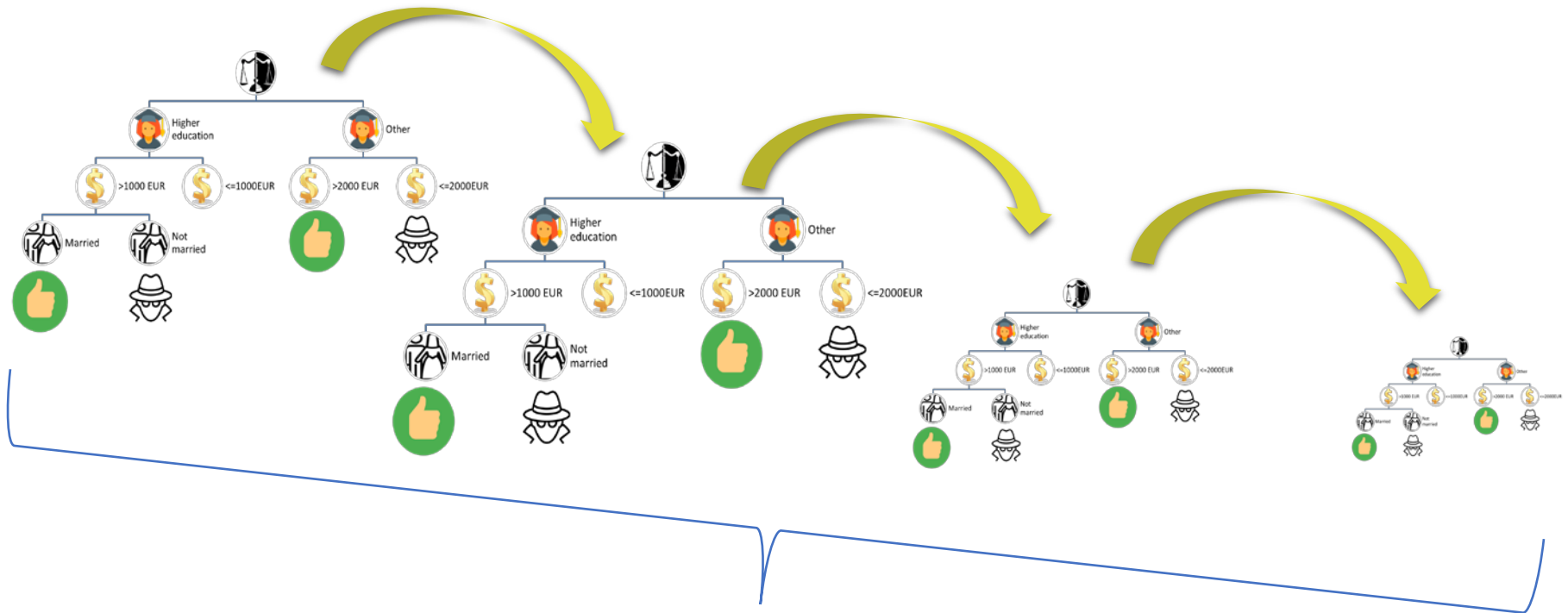
2. DO I NEED BLACK-BOXES? (3/7)

Random Forest



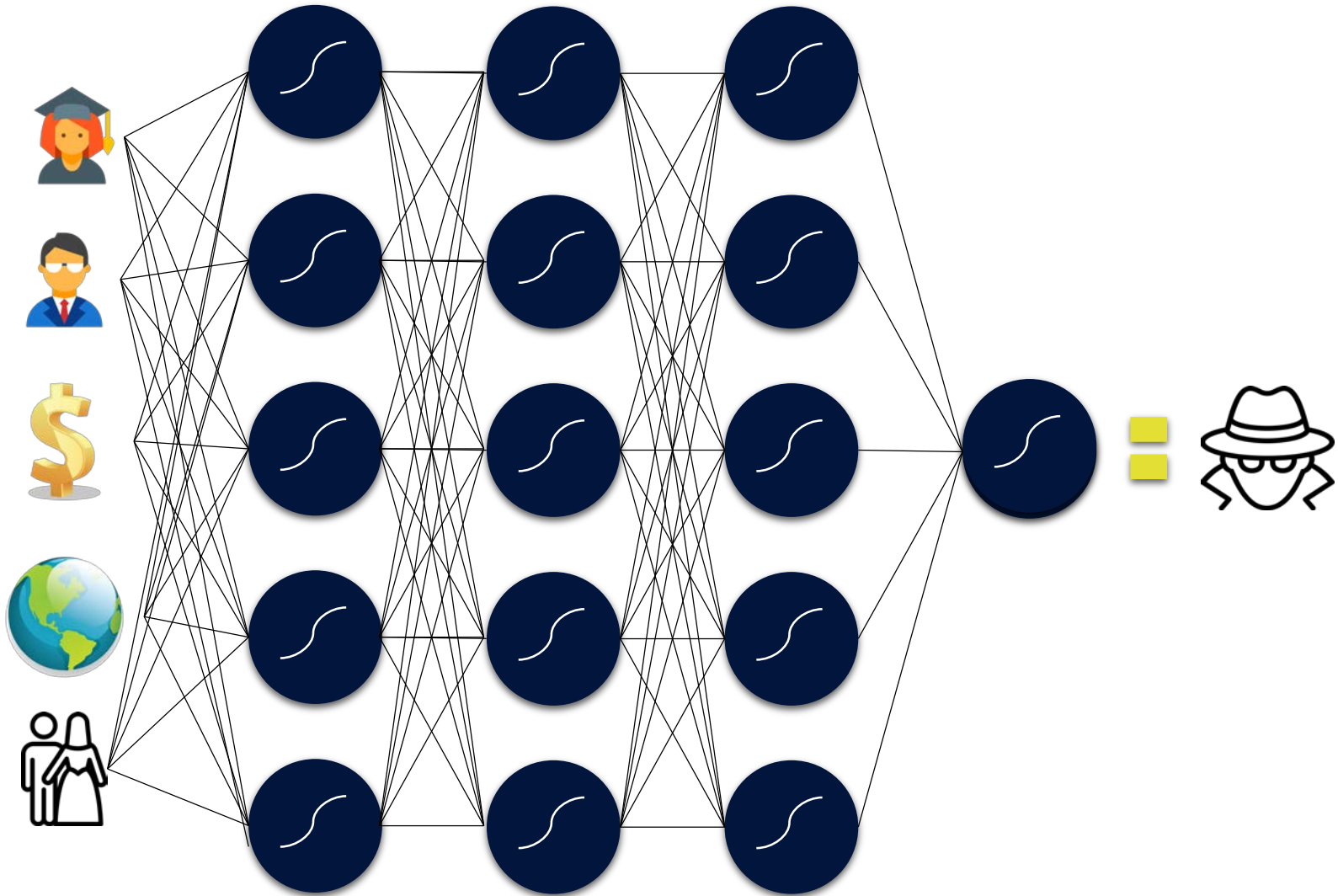
2. DO I NEED BLACK-BOXES? (4/7)

Boosted trees



2. DO I NEED BLACK-BOXES? (5/7)

Neural Network



2. DO I NEED BLACK-BOXES? (6/7)

White (Glass) Box

vs

Black Box

Pros

Cons

Interpretability

Stability

Transparency

Best Practices

Preparation time

Nonlinearities

Nothing new

Pros

Cons

Preparation time

Nonlinearities

Brand new!

Transparency

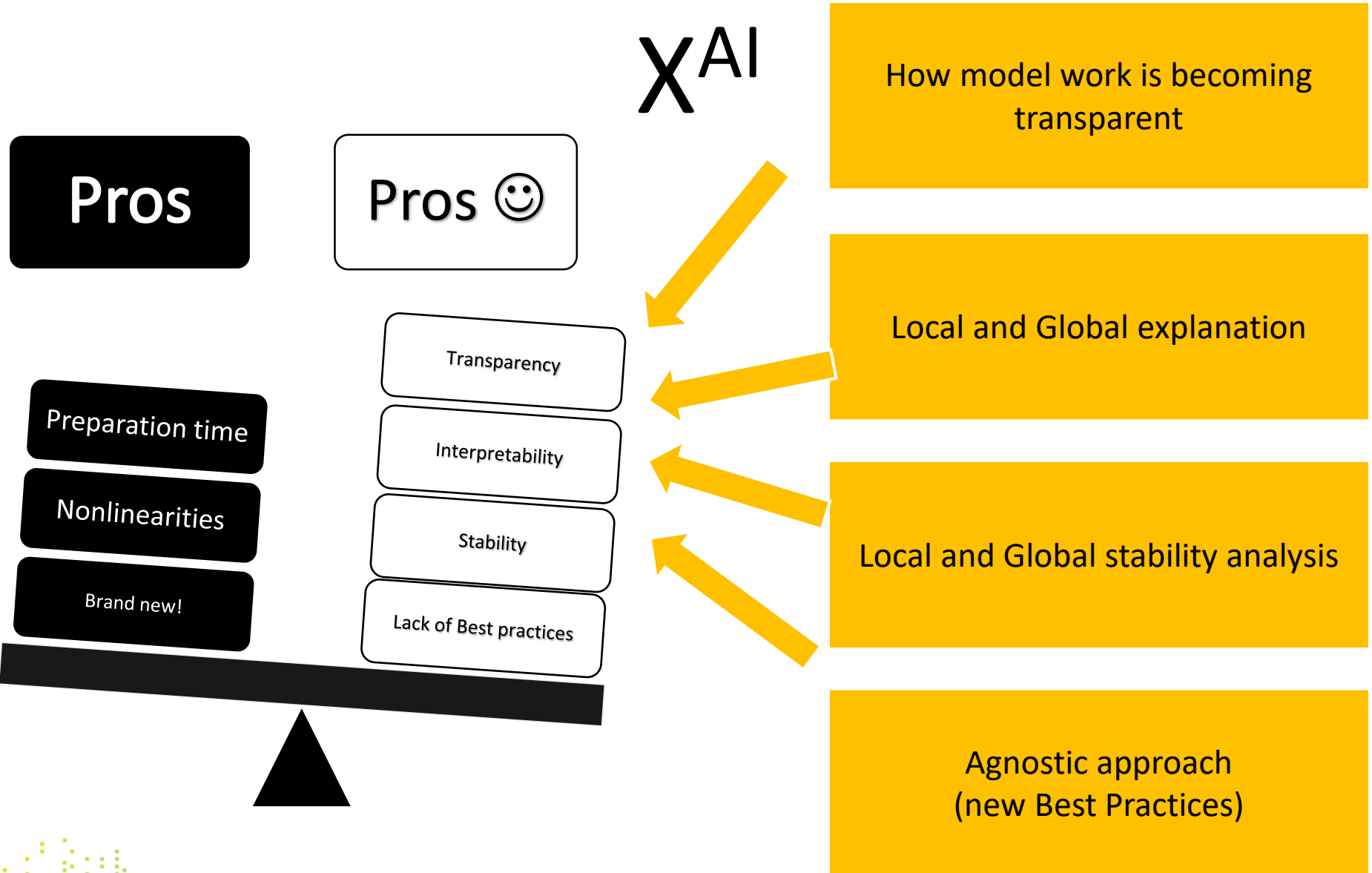
Interpretability

Stability

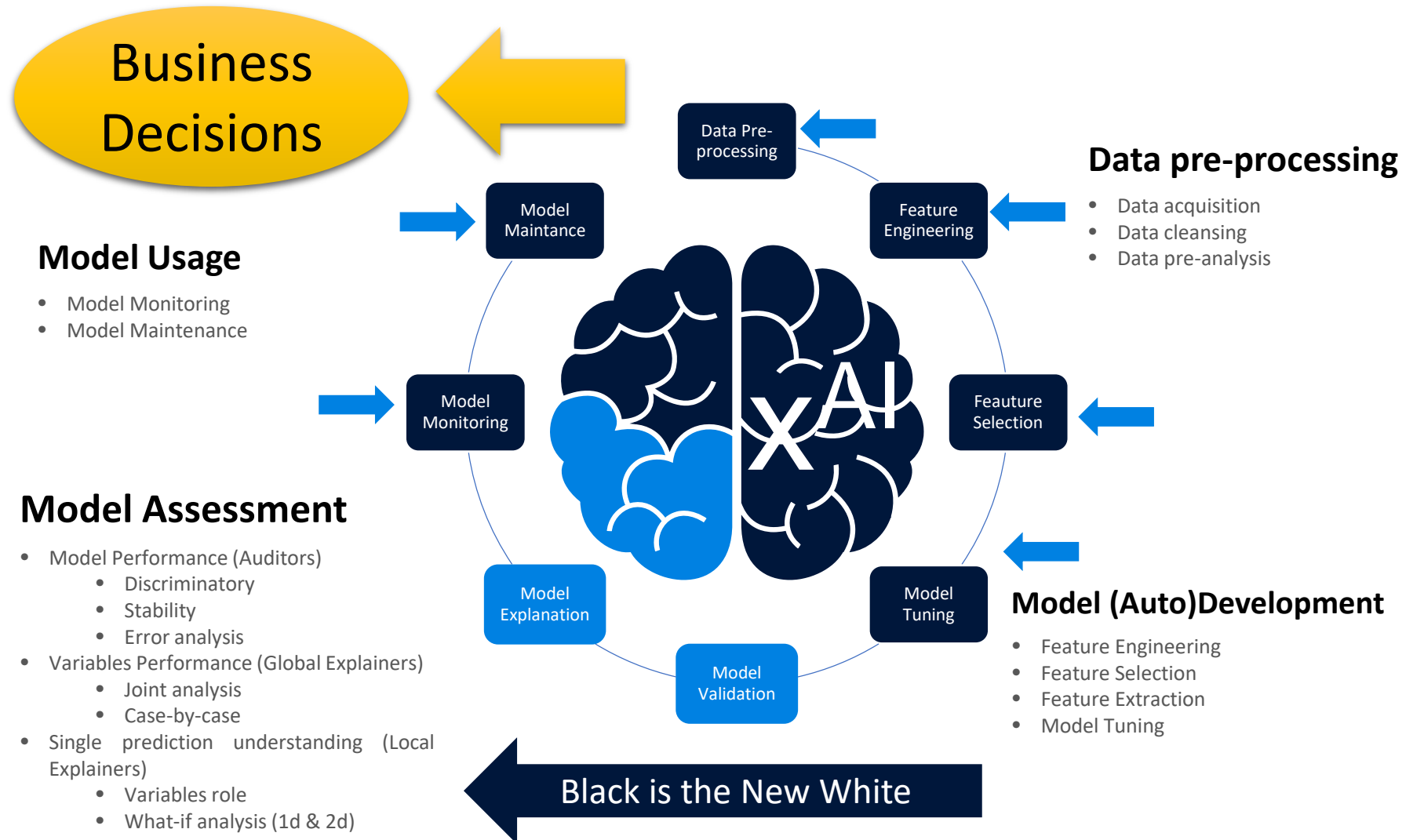
Lack of Best Practices

?

2. DO I NEED BLACK-BOXES? (7/7)



3. HOW CAN I USE XAI IN BUSINESS? (1/16)

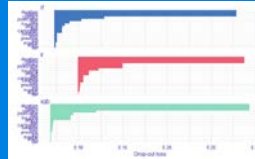


3. HOW CAN I USE XAI IN BUSINESS? (2/16)

Global and Local Explanation

Model performance

1. Variable Importance



Variable Importance

1. Confirmation wrt intuition
2. Reduction of complexity
3. Aspects identification

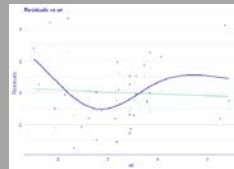
2. Variable effects



Model residuals

1. Identification of subpopulations where model is performing poorly
2. Non-random residuals patterns

3. Model residuals



Variables effects

1. Confirmation wrt intuition
2. Feature engineering
3. Getting knowledge about phenomenon
4. Model selection

3. HOW CAN I USE XAI IN BUSINESS? (3/16)

Dalex explainer

Black-box models may have very different structures. *explain()* creates a unified representation of a model, which can be further processed by various explainers.

Key parameters:

- model – the model that we want to explain
- data – data that we want to use to explain the model
- y – target variable
- predict_function – function that based on model and dataset provide predictions
- residual_function - function that based on model, dataset and target provide residuals
- label – name of an explainer



<https://github.com/ModelOriented/DALEX>

https://pbiecek.github.io/PM_VEE/



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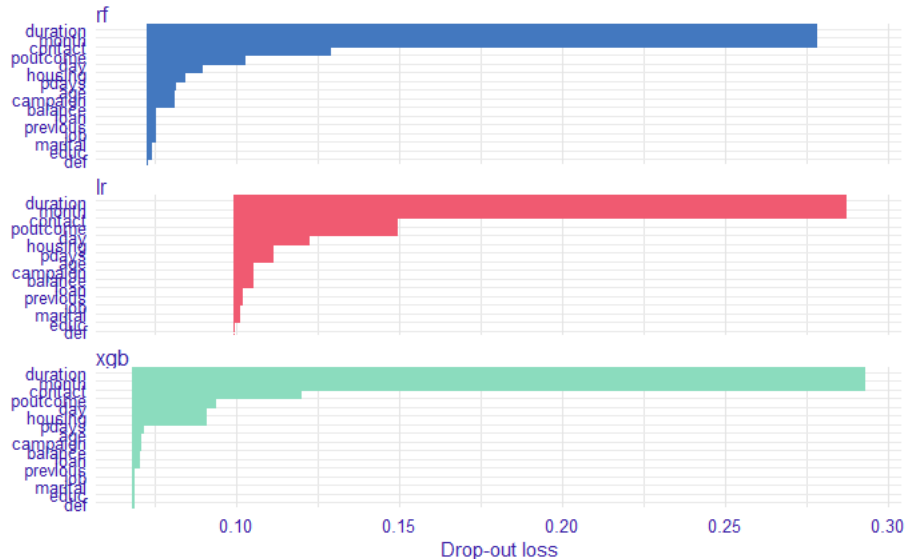
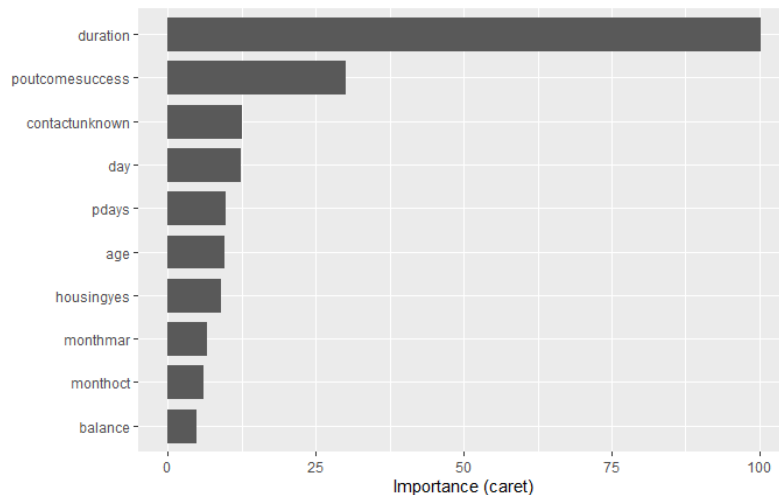
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3. HOW CAN I USE XAI IN BUSINESS? (4/16)

Feature importance

- A group of methods that help to assess the role of the variables in the model.
- Model specific (Caret) and model agnostic methods (Ingredients)

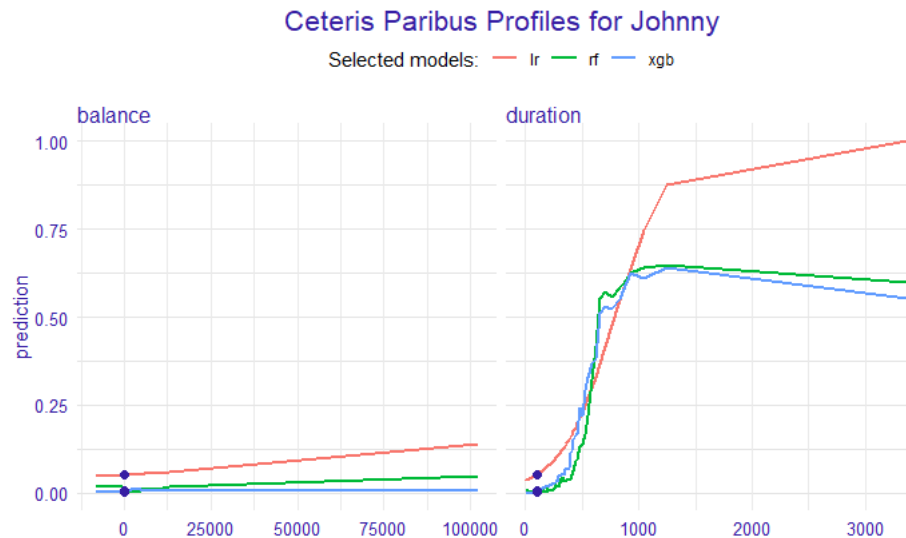


3. HOW CAN I USE XAI IN BUSINESS? (5/16)

Ceteris Paribus Plot



- In essence, a CP profile shows a conditional expectation of the dependent variable (response) for the particular explanatory variable.
- For a given observations all variables except one are kept, the one is changing and prediction of depvar is calculated



Pros:

1. Uniform and easy to understand concept
2. Many profiles in a single plot.
3. Easy to compare

Cons:

1. Collinearity of indepvars
2. Factors with many levels



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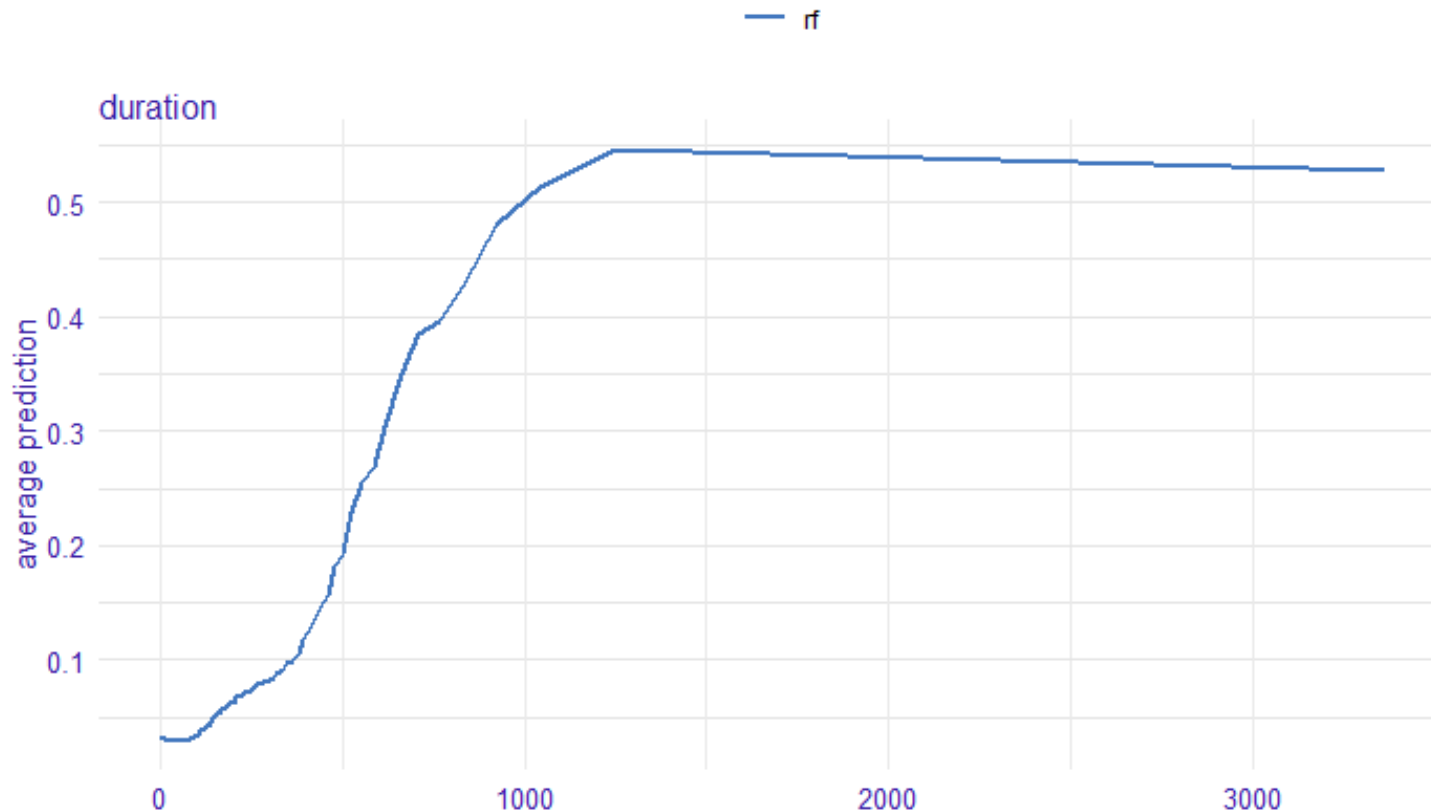
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3. HOW CAN I USE XAI IN BUSINESS? (6/16)

Partial Dependence Profiles



Feature effect analysis – average over CP for different instances



Pros:

- easy to interpret and understand.

Cons:

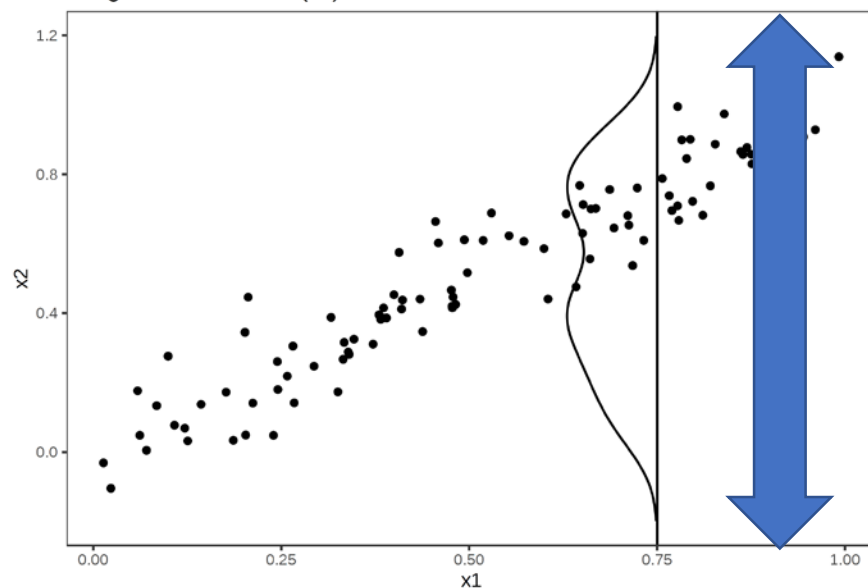
- Independency between indepvars
- Calculation over non-existed observations

3. HOW CAN I USE XAI IN BUSINESS? (7/16)

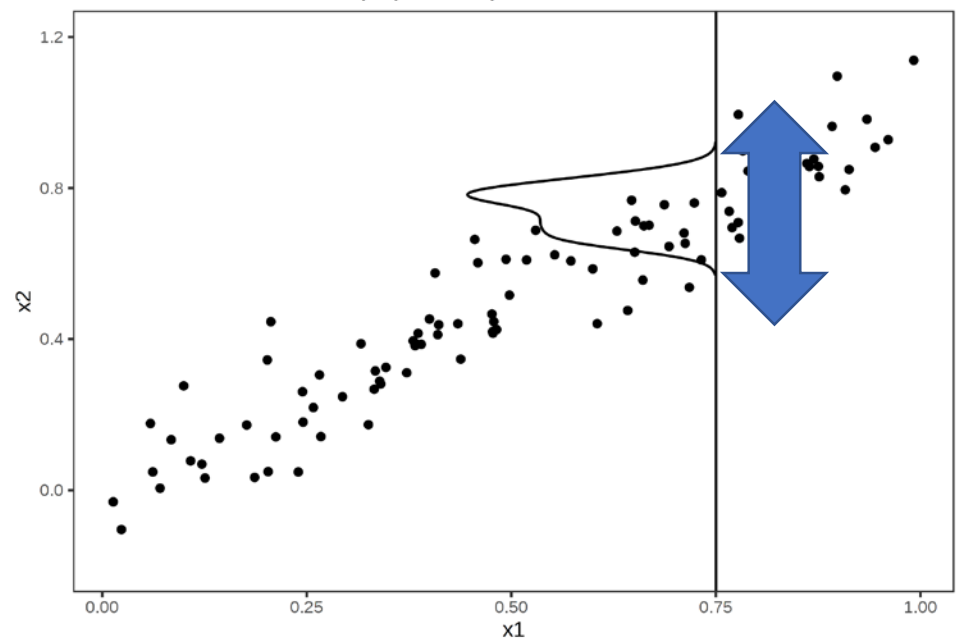
Conditional Dependency Profiles

- Instead of marginal distribution over X_2 a conditional distribution of X_2 is used
- Pros: Include information about correlated indepvar,
- Cons: report spurious relations via correlation (correlated vars effect)

Marginal distribution $P(x_2)$



Conditional distribution $P(x_2|x_1=0.75)$

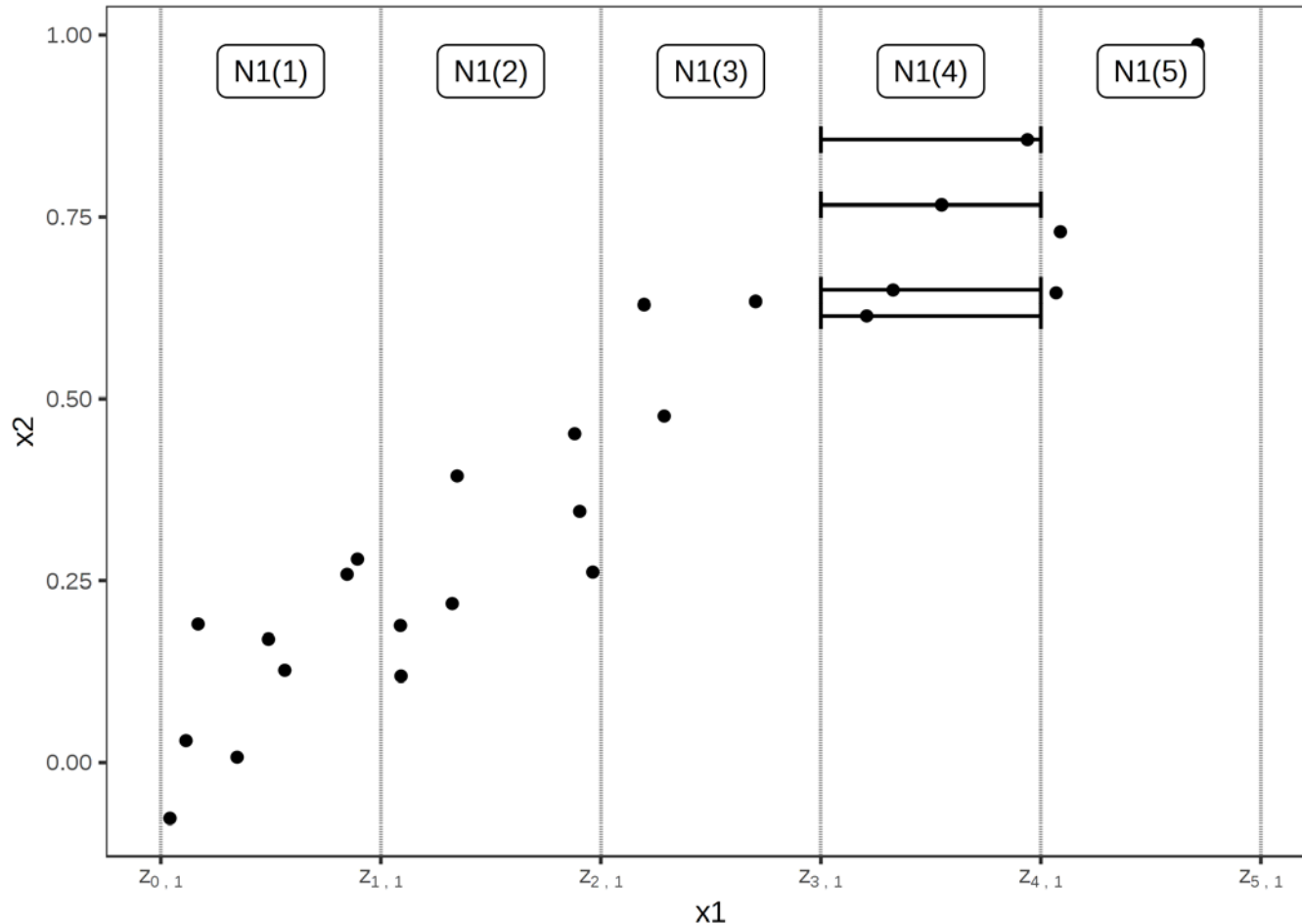


<https://christophm.github.io/interpretable-ml-book/>

3. HOW CAN I USE XAI IN BUSINESS? (8/16)

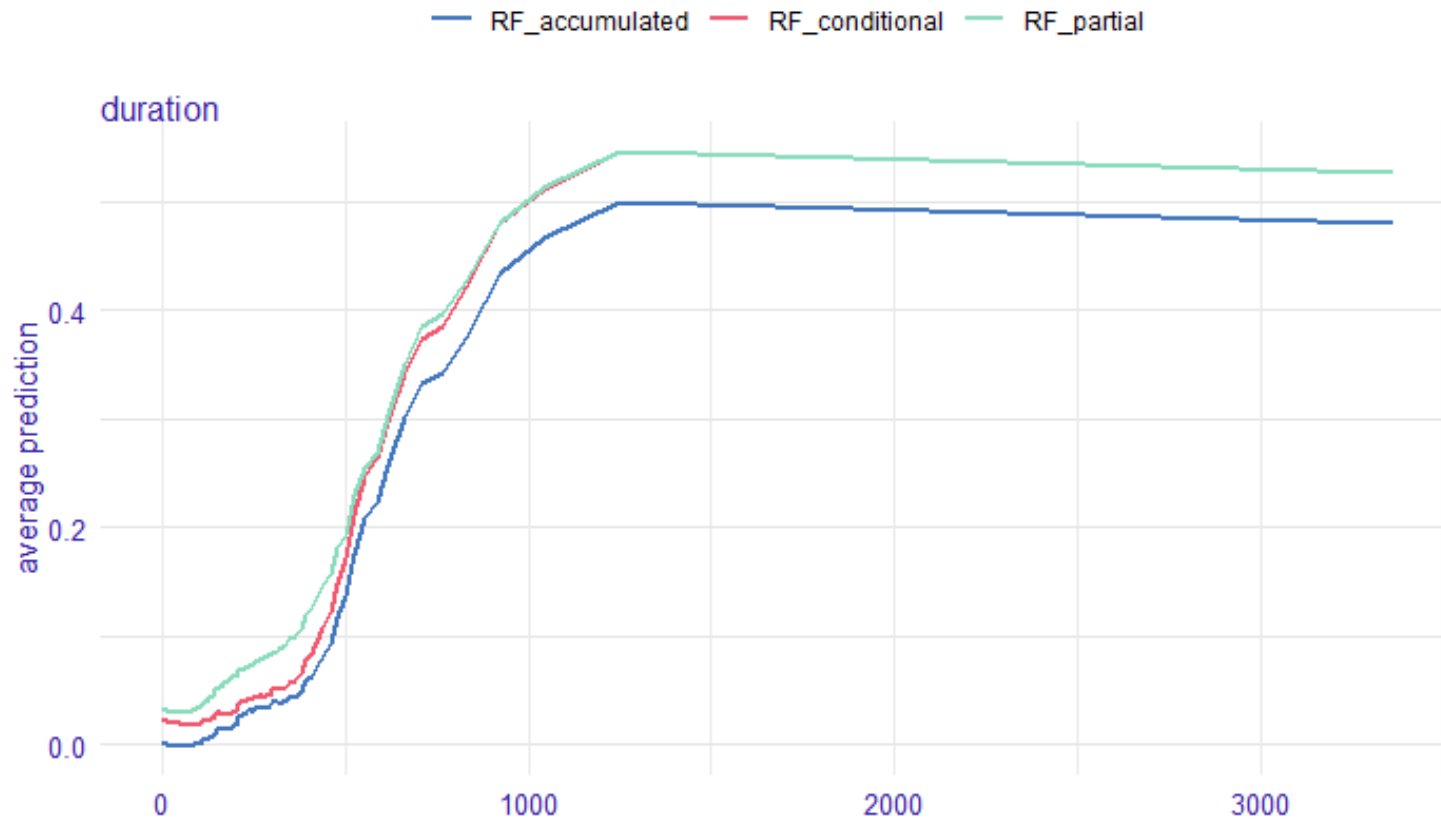
Accumulated local Effect Profile

- Based on the conditional distribution of the features – differences in predictions instead of averages



3. HOW CAN I USE XAI IN BUSINESS? (9/16)

PDP, CDP and ALE plots



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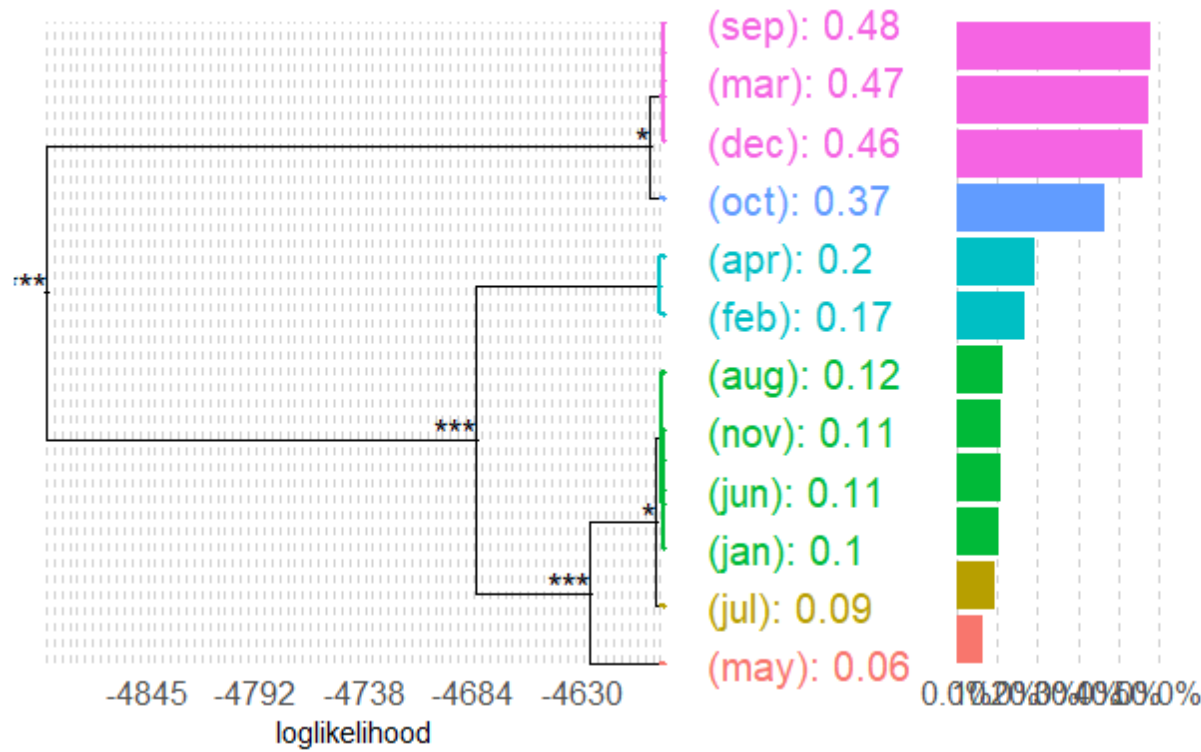
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3. HOW CAN I USE XAI IN BUSINESS? (10/16)

PDP for Factors and factorMerger

- Tool merging groups of categorical data into group of similar response based on LRT (likelihood ratio test)

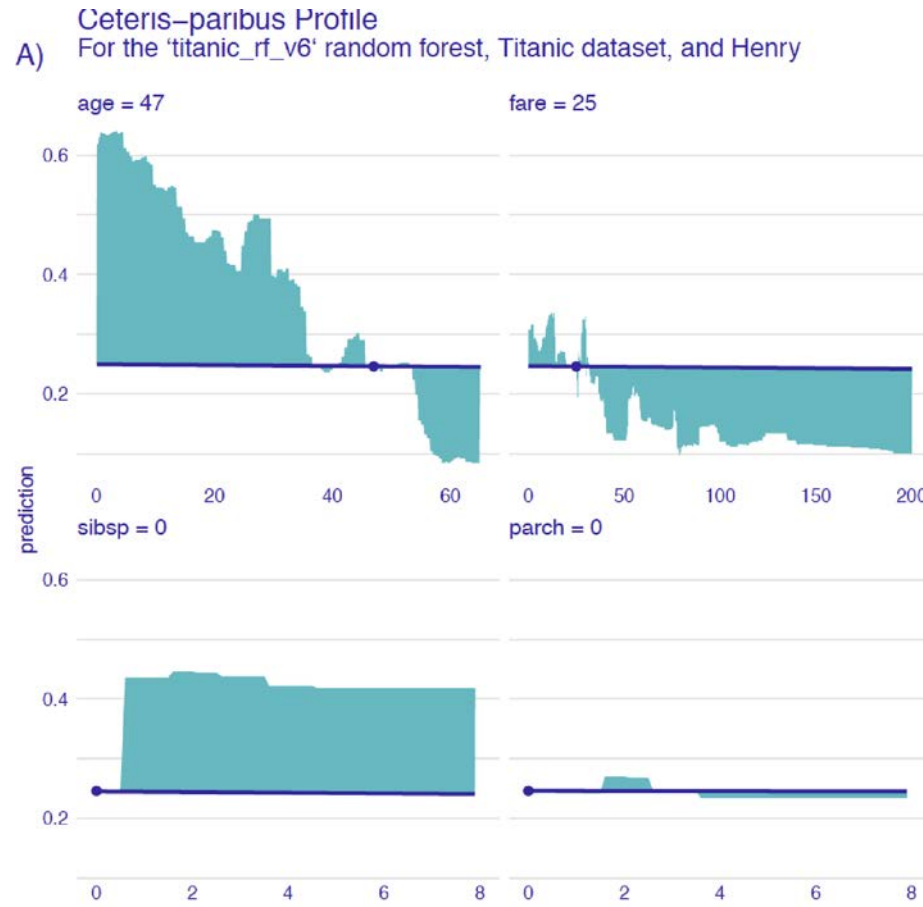
Factor Merger Tree



3. HOW CAN I USE XAI IN BUSINESS? (11/16)

Oscillations

- Idea: the larger influence of indepvar on prediction, the larger fluctuations along CP profile.



Pros:

- easy to interpret and understand.
- easily extendable to two or more variables.

Cons:

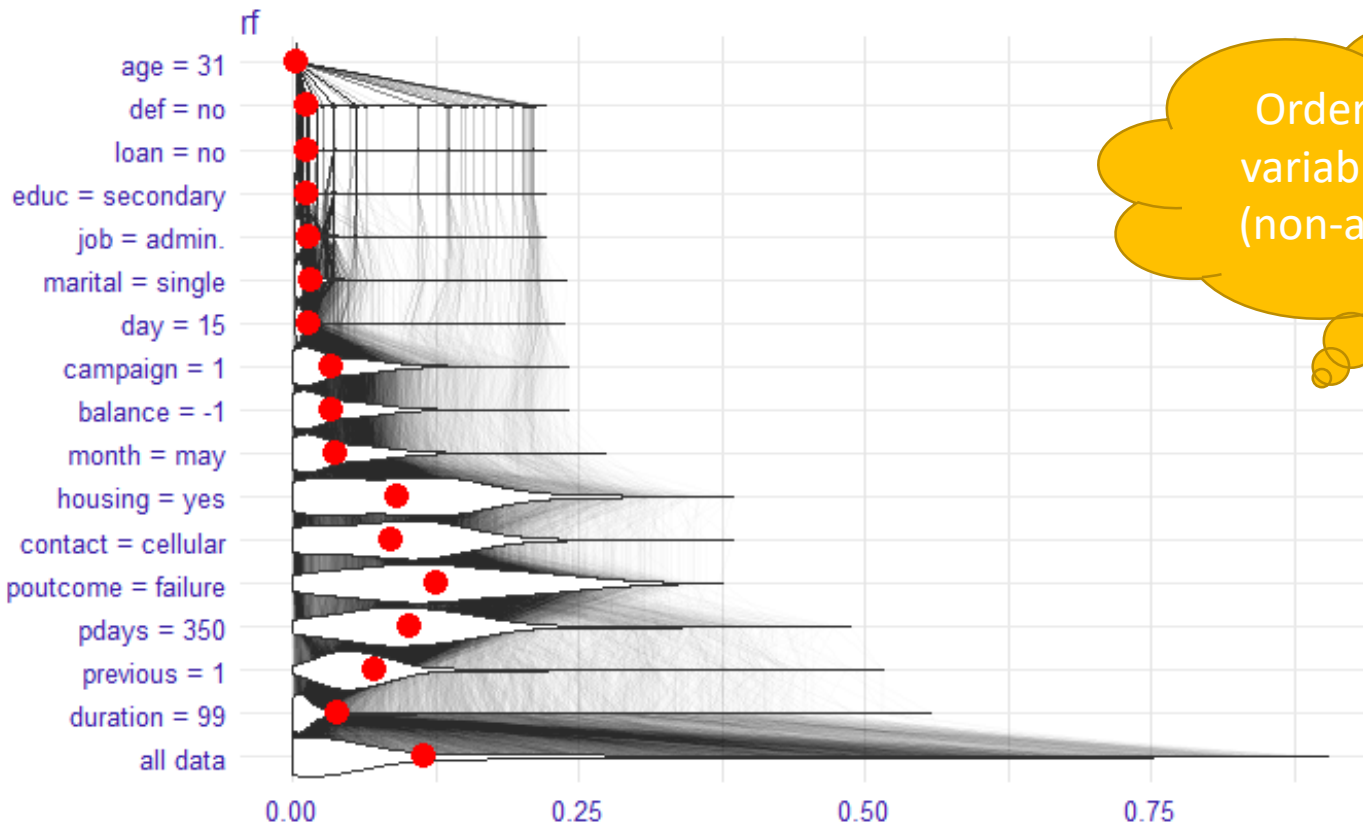
- Not working well if collinearity (based on CP)
- do not sum up to the instance prediction

3. HOW CAN I USE XAI IN BUSINESS? (12/16)

Break Down



- Idea: Decomposition of a prediction to baseline (average for a model) prediction and contribution of all variables separately



Ordering dependent variable contributions (non-additive models)

Avg. response for a model given duration = 99



Avg. response for a model



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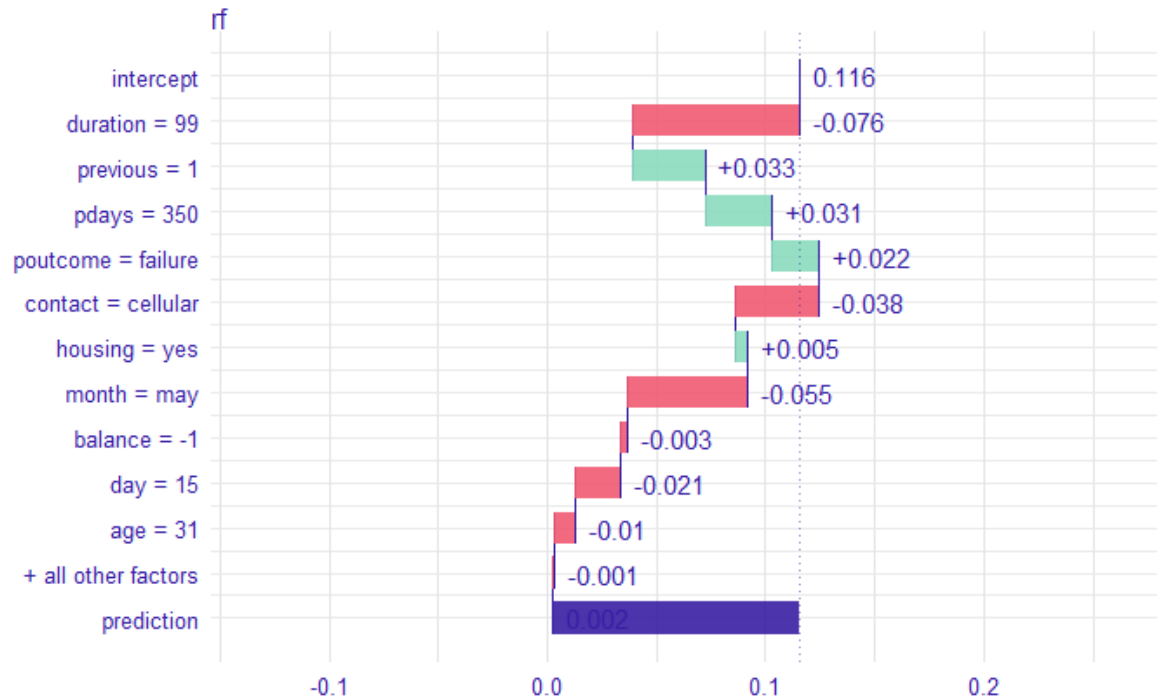
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3. HOW CAN I USE XAI IN BUSINESS? (13/16)

Break Down – ordering dependency

Solutions:

- Ordering wrt local variable importance (BreakDown)
- Interaction identification (iBreakDown)
- Average from all paths (Shapley values)



Pros

- easy to understand
- compact
- model agnostic
- complexity of Break Down Algorithm is linear in respect to the number of variables.

Cons

- selection of the ordering based on scores is subjective.
- different orderings may lead to different contributions.
- for non-additive model showing only additive contributions may be misleading.



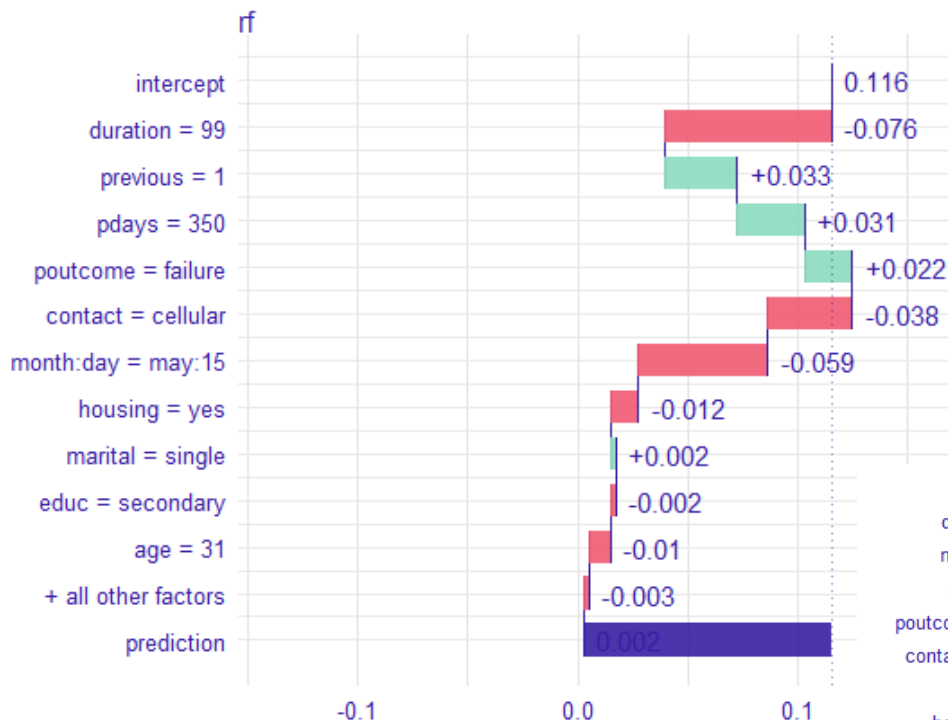
3. HOW CAN I USE XAI IN BUSINESS? (14/16)

iBreakDown and Shapley values



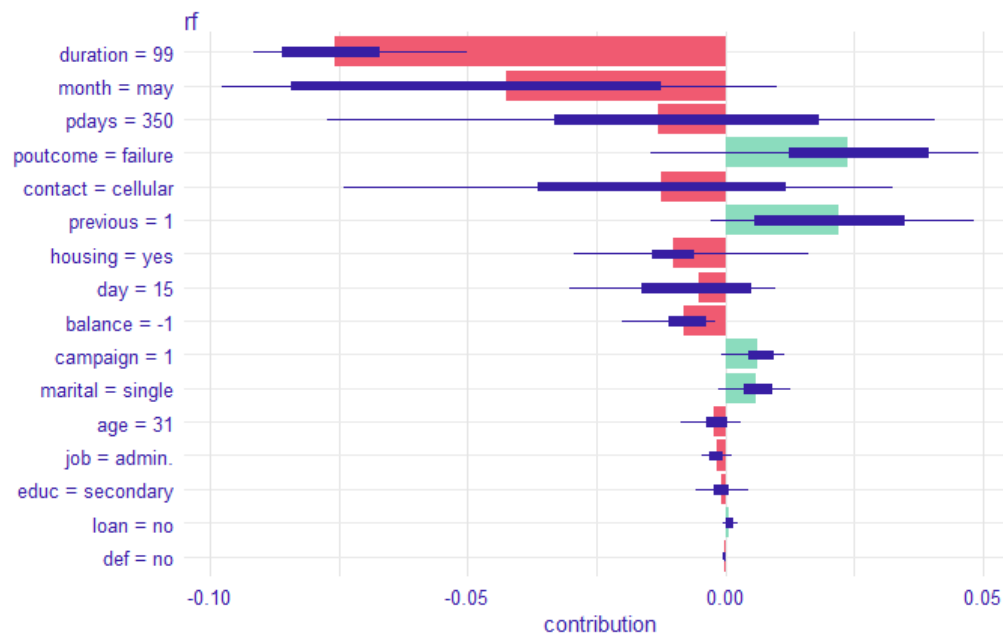
IDEA

$$Cont(x, y) \neq Cont(x) + Cont(y)$$



<https://arxiv.org/abs/1903.11420>

Averaging over all (large number of) paths



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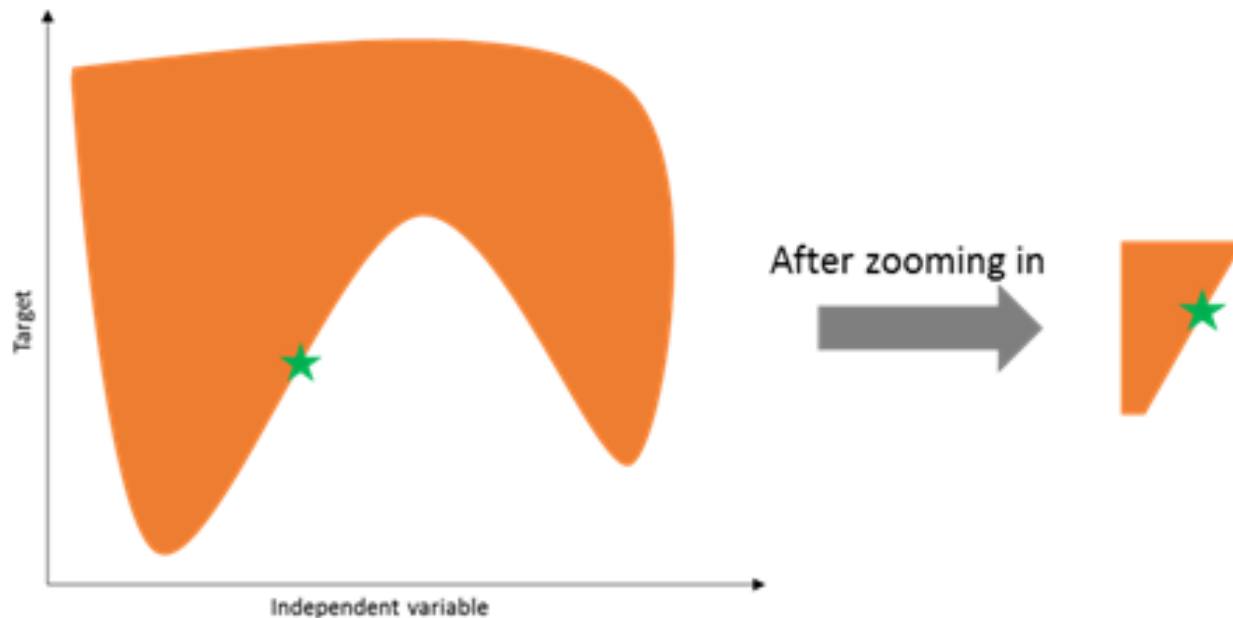
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3. HOW CAN I USE XAI IN BUSINESS? (15/16)

LIME

Local Interpretable Model-Agnostic Explanations. The key idea behind this method is to locally approximate a black-box model by a sparse local glass-box surrogate model, which is easier to interpret.



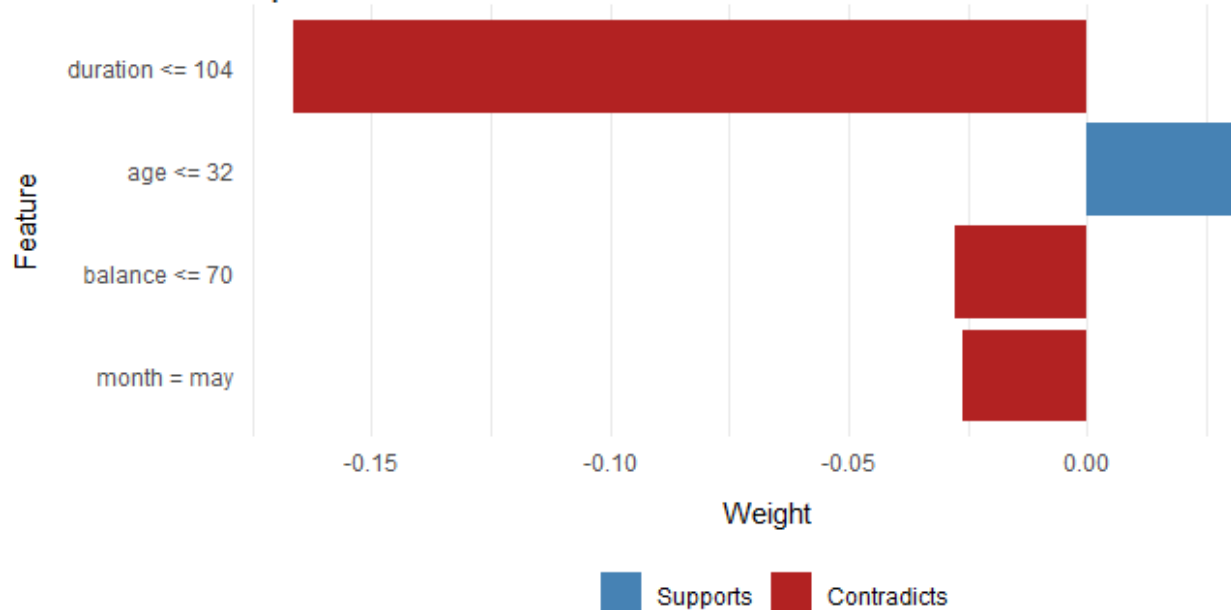
<https://towardsdatascience.com/lime-explaining-predictions-of-machine-learning-models-1-2-1802d56addf9>

3. HOW CAN I USE XAI IN BUSINESS? (16/16)

LIME



Case: 38507
Label: Success
Probability: 0.0025
Explanation Fit: 0.24



Pros

- Easy intuition
- Sparse explanations
- Can be applied to high dimensional models.

Cons

- For continuous variables and tabular data it is not that easy to find interpretable representations.
- Explaining Phenomen by BB, and BB by WB.



https://github.com/pbiecek/xai_resources/blob/master/README.md#tools