Gradient Boosted Utility Models

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Gradient Boosted Utility Models

1. Introduction
2. Methodology
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1. Introduction

Interpretable ML model

- Attempts to make machine learning models interpretable, but **with little success.**

- We propose a machine learning model that is **fully interpretable** based on **gradient boosting decision trees** (GBDT), and inspired by **random utility** models (RUM)

- We are able to derive **non-linear utility** functions

Introductory example – RUM

3 alternatives

Driving	PT	Walking
TT_d $Cost_d$	TT_{PT} $Cost_{PT}$	TT_w

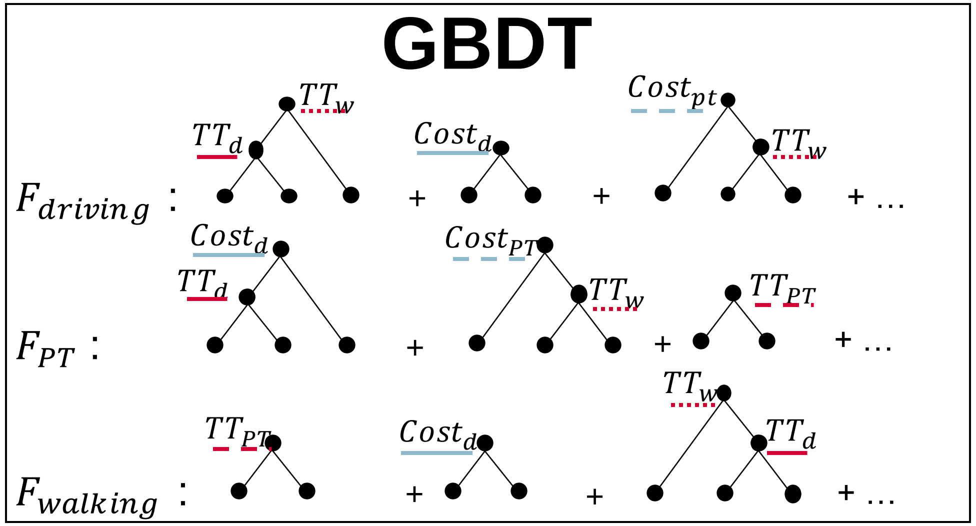
RUM (MNL)

$$V_{driving} = ASC_d + \beta_d TT_d + \beta_d Cost_d$$
$$V_{PT} = ASC_{PT} + \beta_{PT} TT_{PT} + \beta_{PT} Cost_{PT}$$
$$V_{walking} = ASC_w + \beta_w TT_w$$

Introductory example – GBDT

3 alternatives

Driving	PT	Walking
TT_d $Cost_d$	TT_{PT} $Cost_{PT}$	TT_w

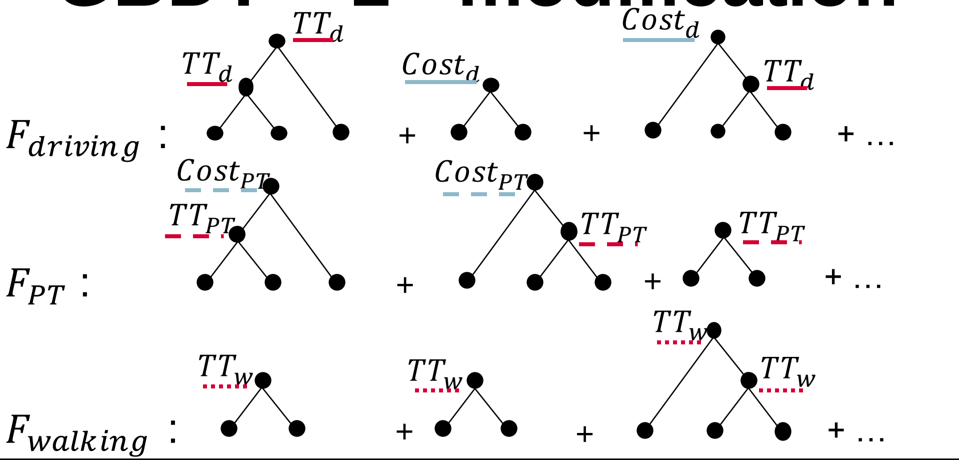


Introductory example – 1st modification

3 alternatives

Driving	PT	Walking
TT_d $Cost_d$	TT_{PT} $Cost_{PT}$	TT_w

GBDT – 1st modification



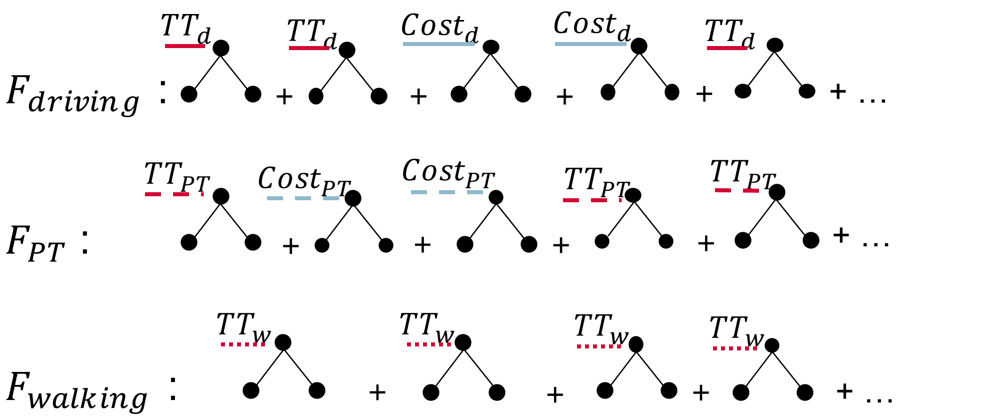
1. Choosing which features compose an ensemble

Introductory example – 2nd modification

3 alternatives

Driving	PT	Walking
TT_d $Cost_d$	TT_{PT} $Cost_{PT}$	TT_w

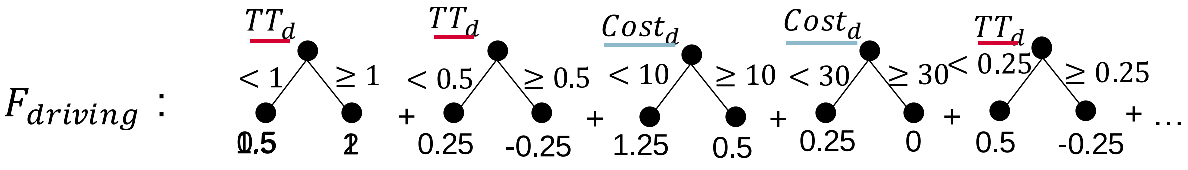
GBDT – 2nd modification



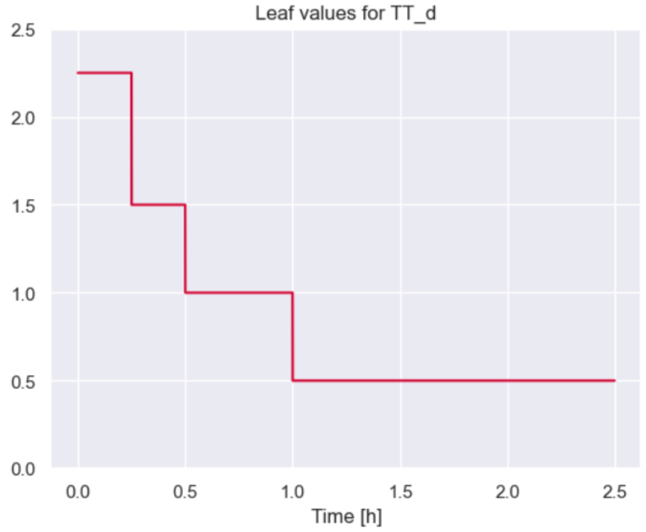
1. Choosing which features compose an ensemble
2. Restricting feature interaction

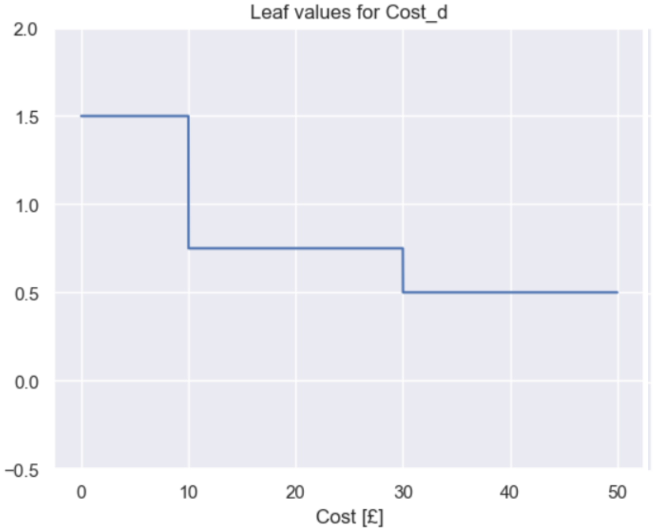
Introductory example – 3rd modification

GBDT – 3rd modification



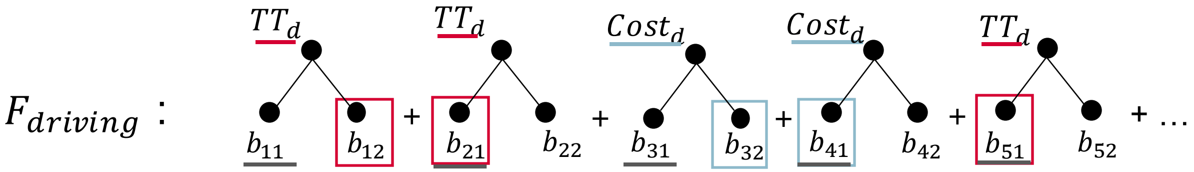
1. Choosing which features compose an ensemble
2. Restricting feature interaction
3. Monotonic constraint





Introductory example – Utility function

RUMBooster



$$V'_{driving} = (b_{12} + b_{21} + b_{51} + \cdots) \ +(b_{32} + b_{41} + \cdots)$$

$$V_{driving} \ = ASC_d \ + \beta_d TT_d \quad + \beta_d Cost_d$$

Motivations

- GBDT have great **predictive power**

  LightGBM and XGBoost are **state-of-the art** libraries and **powerful** tools

- Lack **behaviour interpretability** and exhibit **poor extrapolation** properties (Martin-Baos et al. 2023)

- We propose **gradient boosted utility models** (RUMBooster) were we aim to combine the predictive power of GBDT with RUM interpretability

RUMBoost

1. **Utility** specification: only chosen features can contribute to an alternative utility function

2. **Feature** interaction constraint: only specified features can interact with each other

3. **Monotonic** constraint: left and right leaf values can only be increasing or decreasing for a feature

RUMBooster

Interpretable model where **non-linear utilities** can be derived

2. Methodology

RUM to RUMBoost

- We can estimate **any MNL model** with gradient boosting
- We follow the **same** utility specification
- **Bounds** on Beta parameters are interpreted as **monotonic constraints**
- Since there is no feature interaction in RUMBoost, very **few risk of overfitting**

3. Results

LIVE DEMO

MNL model and dataset

- Used MNL model from Martin-Baos et al. (2023)

  The model has **76 parameters,** and its performance is compared with several ML models

- The model is trained on the **LPMC** dataset (Hillel et al. 2018)

  4 alternatives: walking, cycling, PT and driving, and over 80000 observations

Model specification

- **Ensembles** of RUMBooster are based on the **LightGBM** library

- **No interaction** between features

- Monotonic constraints:

Table 1: Monotonic constraints on features

Negative	Positive
Travel time, cost	Car ownership*, driving license*

For car utility only

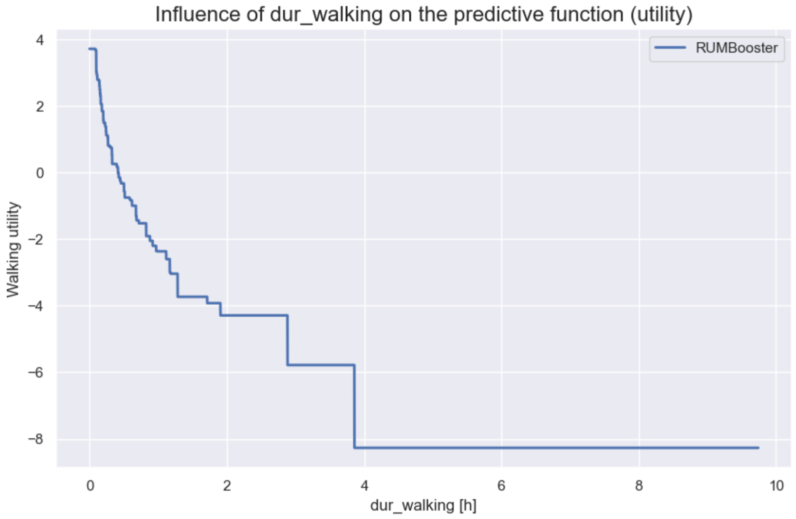
Negative cross-entropy

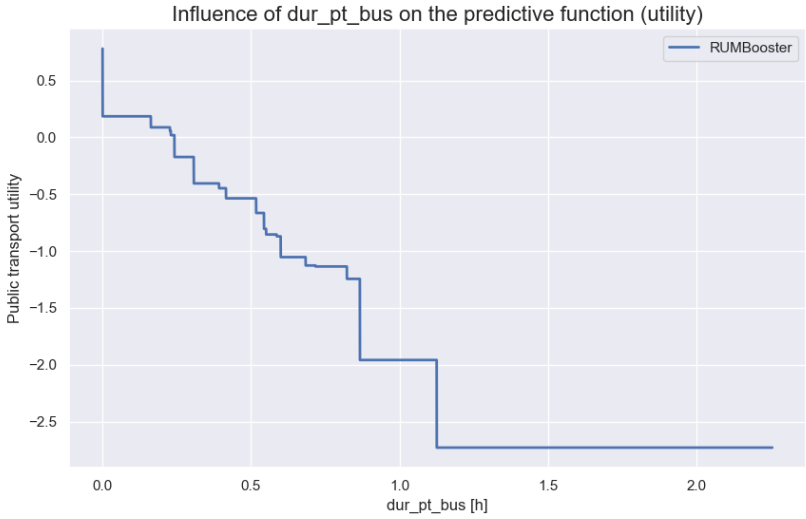
Table 2: Benchmark of classification on LTDS dataset (negative cross-entropy)

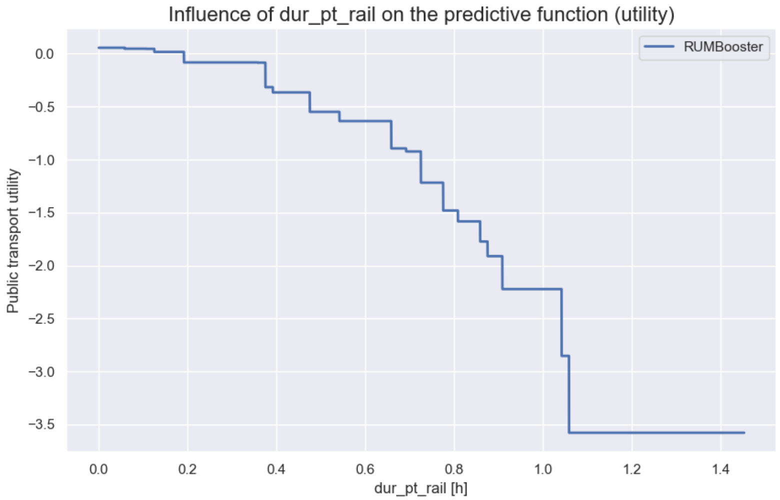
	MNL	NN	DNN	RF	SVM	XGBoost	RUMBooster
Martin-Baos et al. (2023)	0.7164	0.6728	0.6702	0.6900	0.6755	0.6568	0.6791

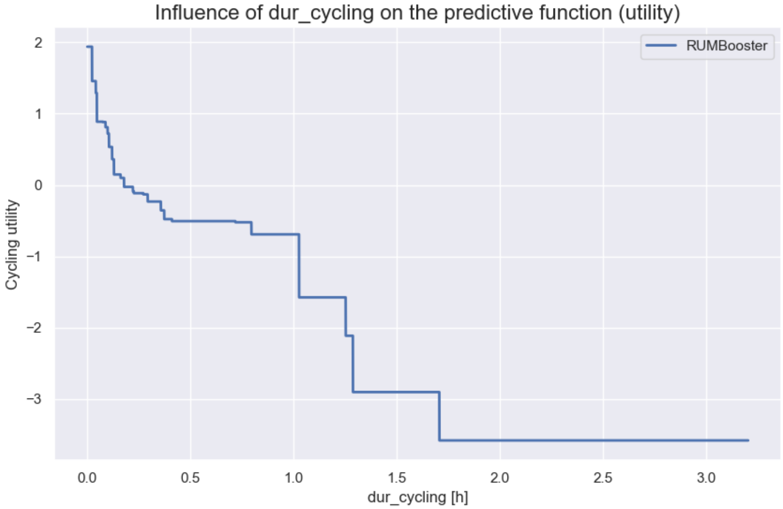
Learning rate = 0.1

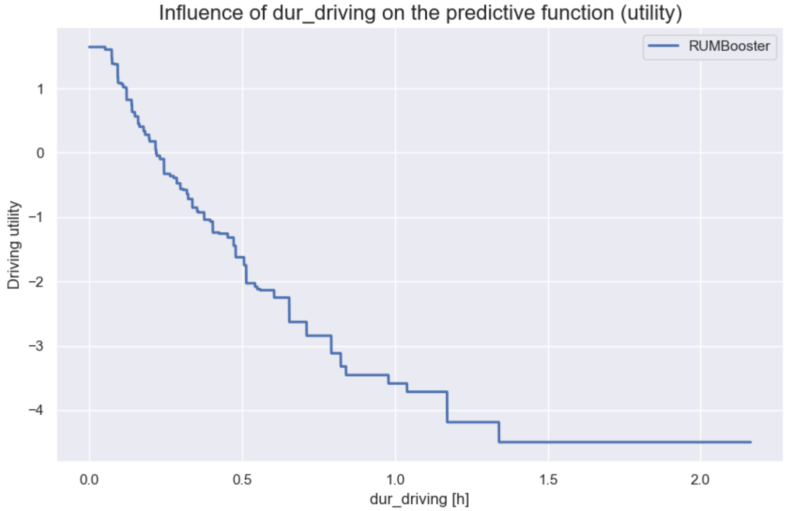
Impact of travel time



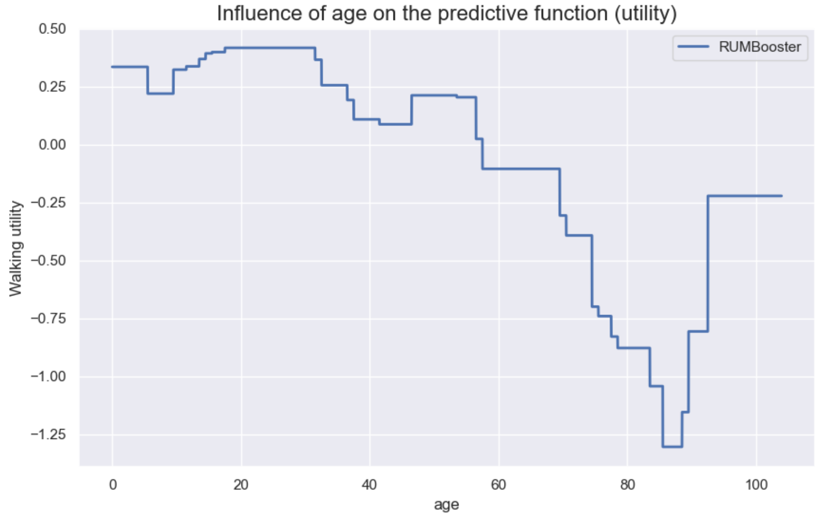


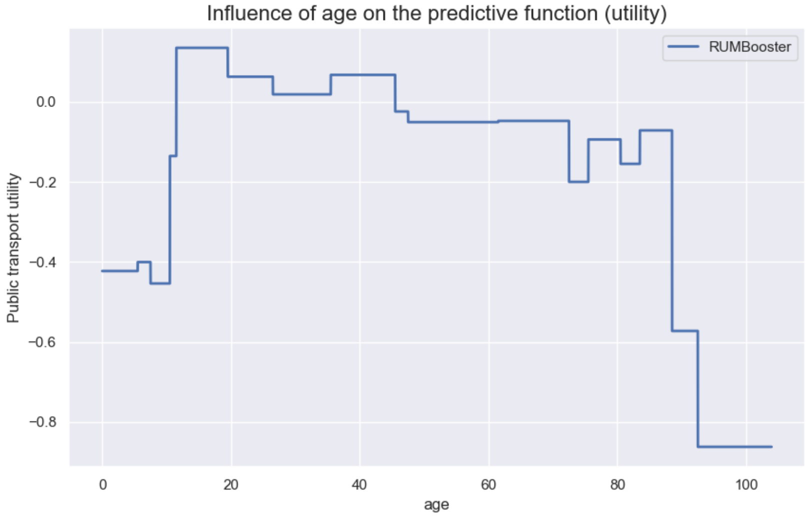


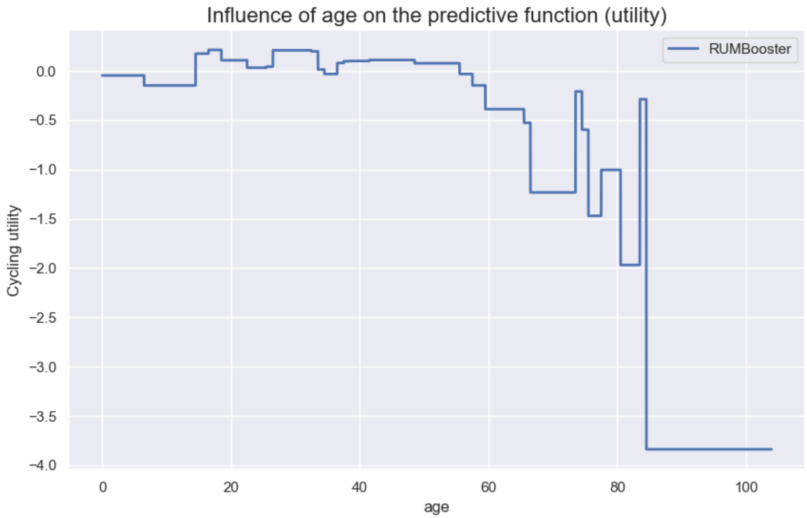


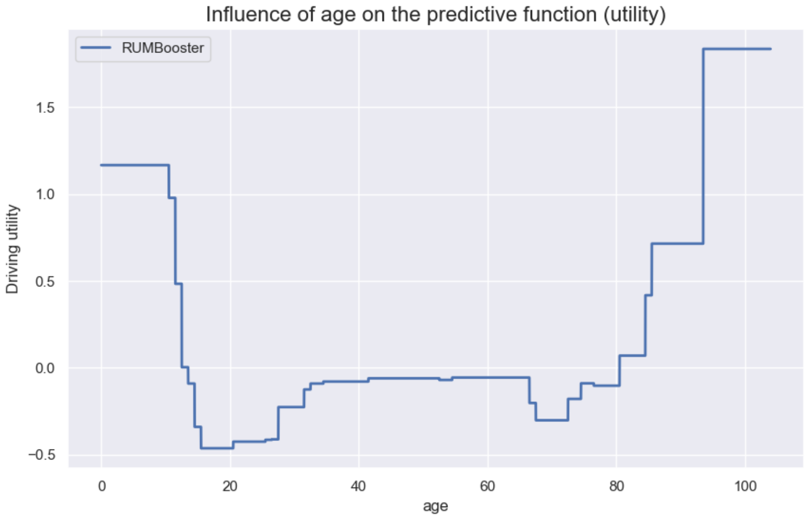


Impact of age









4. Further work

Further work

- Intersecting continuous and categorical variables as **latent variables** to keep nonlinear utility interpretability but increase predictive power

- **Generalise** RUMBooster to MEV models

- Apply the methodology on **different** datasets

Thank you!

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