TaDA workshop - VLDB 2024

Fast and accurate regional effect plots for automated tabular data analysis

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Program

1. Introduction
   - Problem Statement
   - Proposed Pipeline
   - Regional RHALE - our contribution

2. Regional RHALE - advantages
   - It is fast
   - It treats well correlated features

3. Effector - Python package

Program

Problem Statement

Tabular data

X				Y
hour	work-ing	temp	...	rents
8.3	0	27	...	169
16.32	1	14.7	...	234
...	...	...	...	...

Data Understanding Pipeline

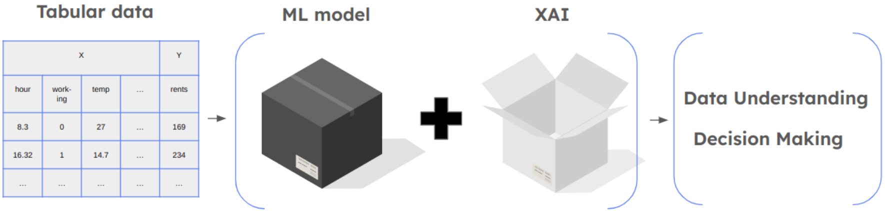
Data Understanding

Decision Making

I will try to convince you for 4 things!

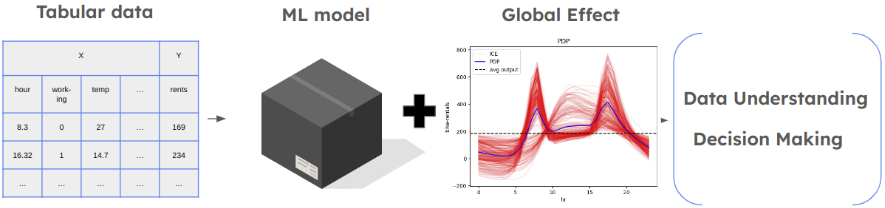
Program

Discussion point 1



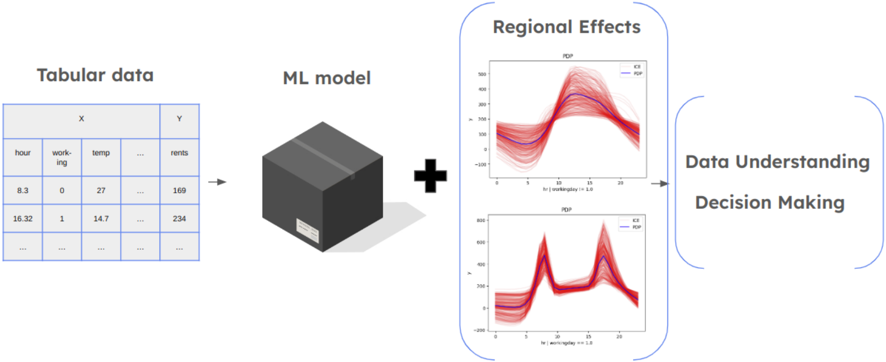
Black box ML model + XAI = a good pipeline!

Discussion point 2



Black box ML model + Global effect methods = a good pipeline!

Discussion point 3



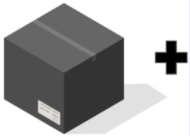
Black box ML model + Regional effect methods = a better pipeline!

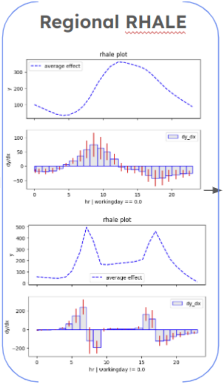
Discussion point 4

Tabular data

X				Y
hour	work-ing	temp	...	rents
8.3	0	27	...	169
16.32	1	14.7	...	234
...	...	...	...	...

Differentiable ML model





Data Understanding

Decision Making

Black box ML model + Regional RHALE = an even better pipeline!

Bike-sharing dataset

- hourly count of bike-rentals (2011, 2012)
- Design-matrix X:
  - year, month, day, hour
  - working day vs. non-working day
  - temperature
  - humidity
  - windspeed
- Target variable Y:
  - bike-rentals per hour
    - $Y_\mu = 189.5$
    - $Y_\sigma = 181.4$
- Decision Making: decide a discount policy
- Data Understanding: confirm/reject some ideas about bike rentals

Proposed pipeline: Fit and Explain

- decide a discount policy
  - which hour of the day to apply the discount
  - how the feature $x_{\texttt{hour}}$ relates to $y_{\texttt{bike\_rentals}}$
- Step 1: Fit a black-box ML model
  - Could be any ML model
  - a Neural Network achieves $\texttt{RMSE} \approx 45.35$ counts $(0.25 Y_\sigma)$
- Step 2: Use feature effect
  - Global effect: $x_{\texttt{hour}}$ vs $y_{\texttt{bike\_rentals}}$ globally
  - Regional effect: $x_{\texttt{hour}}$ vs $y_{\texttt{bike\_rentals}}$ regionally

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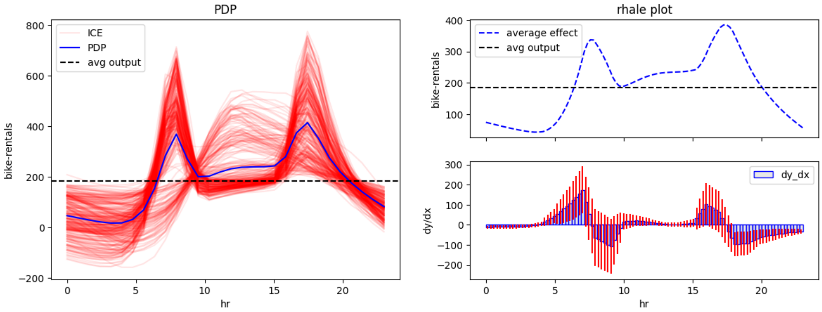
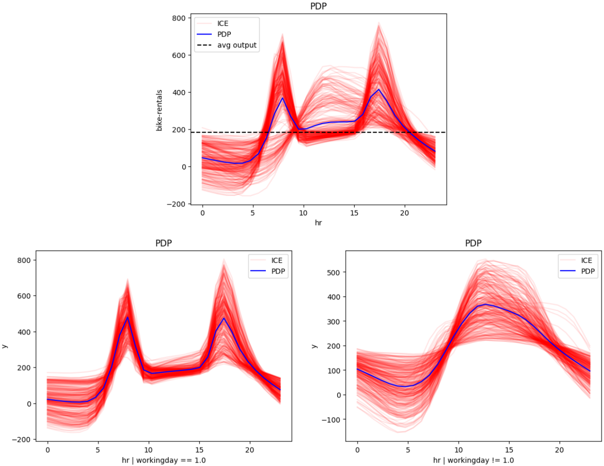
Let's see!

Global Effect: PDP and RHALE



RHALE paper (Gkolemis et al., 2023b): ALE + heterogeneity

Regional Effect: Regional-PDP



REPID Paper (Herbinger, Bischl, and Casalicchio, 2022)

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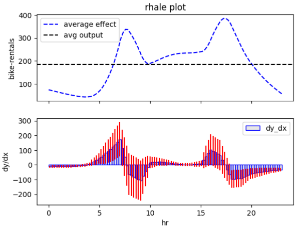
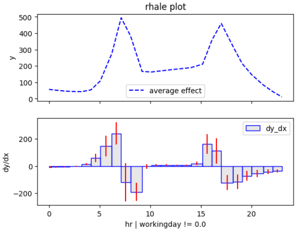
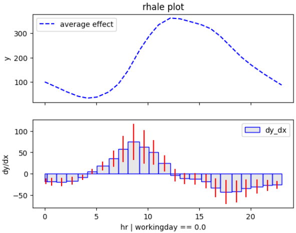
Regional Effect: Regional-RHALE







Regional RHALE - our proposal!

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Thank You!

- If you find this package useful, we would appreciate your feedback and a star on GitHub
- https://arxiv.org/abs/2404.02629
- https://github.com/givasile/effector
- https://xai-effector.github.io/

References I

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Gkolemis, Vasilis et al. (2023a). "Regionally Additive Models: Explainable-by-design models minimizing feature interactions". In: *arXiv preprint arXiv:2309.12215.*

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References III

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