XAI3

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GitHub: https://github.com/rus1904/Practica_ud5/tree/main

1   Intoduction

This analysis explores the interpretability of Random Forest models using Partial Dependence Plots (PDPs). This approach allows us to visualize the marginal influence of individual or combined variables on the predictions of complex models, without the need to inspect their internal structure.

Two case studies are addressed. The first focuses on a bike rental dataset, where we analyze how weather conditions and the passage of time affect rental demand. The second case examines house price prediction in the Seattle area, evaluating the influence of structural features such as the number of bedrooms, bathrooms, and living area. In both scenarios, Random Forest models are trained on relevant subsets of the data, and one-dimensional and two dimensional PDPs are generated to provide deeper insight into nonlinear relationships and variable interactions.

2   One dimensional Partial Dependence Plot

To analyze the influence of key variables on the predicted bike rentals (cnt), we trained a Random Forest model using the features temp, hum, windspeed, and instant (which represents the number of days since 2011). We then used Partial Dependence Plots (PDPs) to visualize the marginal effect of each feature on the model's predictions.
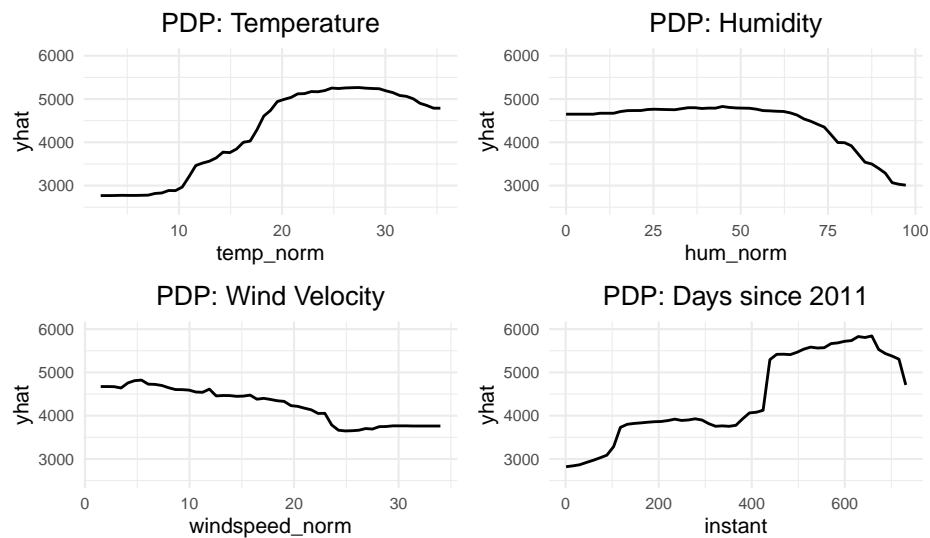
- **Temperature (`temp`)**
  Temperature shows a strong positive influence on bike rentals up to a value of approximately 27. As temperature rises, the number of predicted rentals increases significantly, peaking near that value. Beyond this point, the effect plateaus or slightly declines, suggesting that extreme heat may reduce bike usage.

- **Humidity (`hum`)**
  Humidity has a negative impact on bike rentals. When humidity is low to moderate, predicted rentals are stable and relatively high. However, as humidity approaches 100, the predicted bike count drops sharply. This implies that people are less likely to rent bikes under very humid conditions.

- **Wind speed (`windspeed`)**
  Wind speed also shows a decreasing relationship with bike usage. The PDP reveals that higher wind speeds slightly reduce the number of predicted rentals, although the effect is less dramatic compared to temperature or humidity.

- **Days since 2011 (`instant`)**
  This variable captures a clear upward trend. The PDP shows that over time, the number of predicted rentals increased significantly, especially after day 400 (roughly March 2012). This reflects the growing popularity and adoption of the bike rental service over the two-year period. This increase may be due to factors not observed in the dataset, such as an increase in the number of bicycles, stations, service improvements, growing rental popularity, and so on...

To sumarise, the temperature and time progression are the strongest drivers of bike rental demand, while humidity and wind speed act as deterrents under unfavorable weather conditions. The PDPs provide a model-agnostic explanation of how each feature affects predictions, offering interpretability regardless of the internal structure of the Random Forest.

3 Bidimensional Partial Dependency Plot.

In this section, we examine the joint effect of temperature (temp) and humidity (hum) on the predicted number of bike rentals (cnt) using a 2D Partial Dependence Plot.

To avoid performance issues due to dataset size, we selected a random sample of 500 rows from the day.csv dataset. A new Random Forest model was trained using only temp and hum as predictors. We then computed the partial dependence surface using a grid of resolution 20, and visualized the predictions using geom_tile() with a continuous color scale (viridis).

The following heatmap shows the predicted bike count (represented by color intensity) for combinations of temperature (x-axis) and humidity (y-axis):
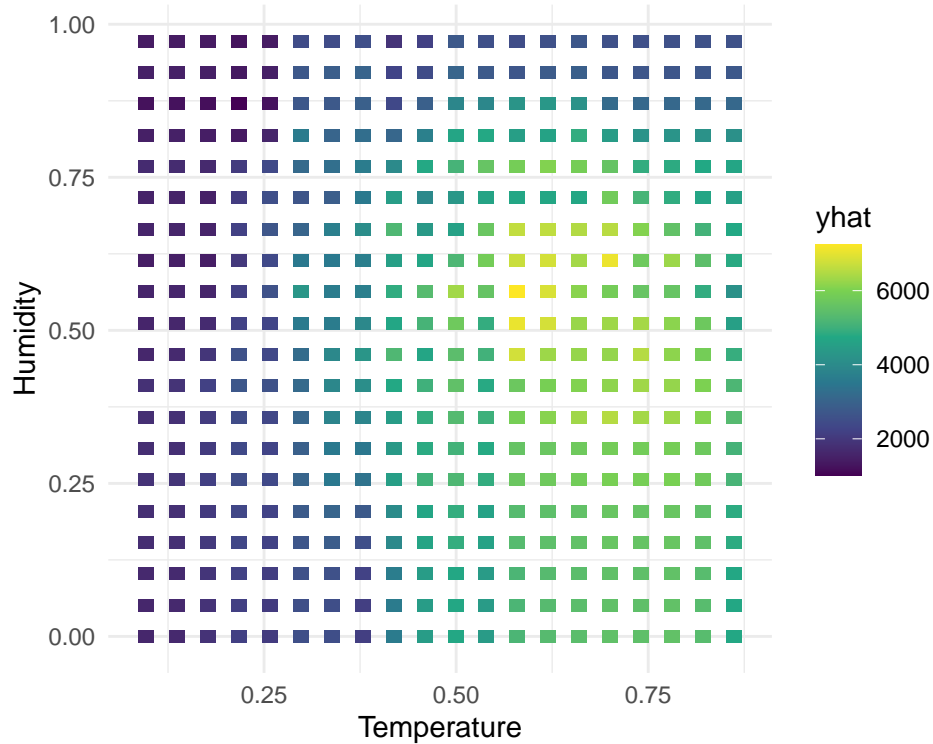
From the heatmap, we can clearly see that bike rental demand increases with temperature and decreases with humidity. The highest predicted values are observed in regions with medium to high temperatures (20.5°C to 31°C) and low to medium humidity (below 60%), which represent the most comfortable conditions for cycling.

In contrast, areas with high humidity, regardless of temperature, tend to produce lower rental predictions. This supports the idea that very humid days discourage biking even if temperatures are favorable. This 2D PDP effectively captures interaction effects between the two variables, which cannot be seen in the 1D plots. It confirms that ideal weather conditions (warm and dry) strongly favor bike usage.

4 PDP to explain the price of a house.

To analyze how specific features influence house prices, we used the kc_house_data.csv dataset. Due to its large size, we extracted a random sample of 1,000 rows and trained a Random Forest model to predict price using the variables bedrooms, bathrooms, sqft_living, sqft_lot, floors, and yr_built. Then, we visualized the partial dependence of four key variables: bedrooms, bathrooms, sqft_living, and floors.

PDP: Bedrooms

PDP: Bathrooms

PDP: Habitable m2

PDP: Number of floor
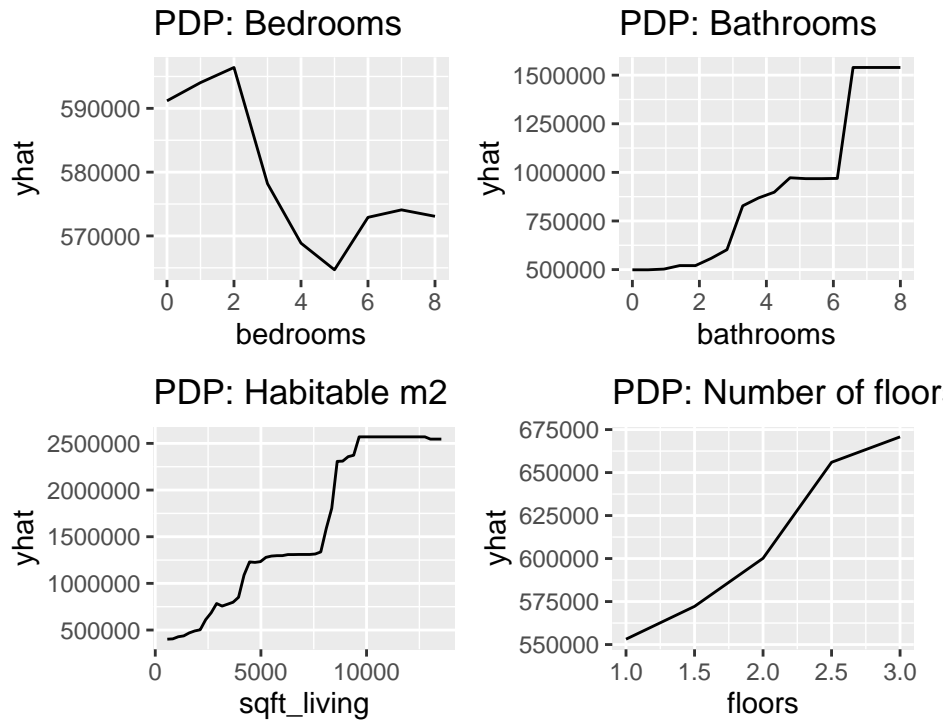
It's interesting to examine the PDPs with a fixed y-axis and explore the possible relationships among the variables using the correlation matrix.

PDP: Bedrooms

PDP: Bathrooms

PDP: Habitable m2

PDP: Number of floor

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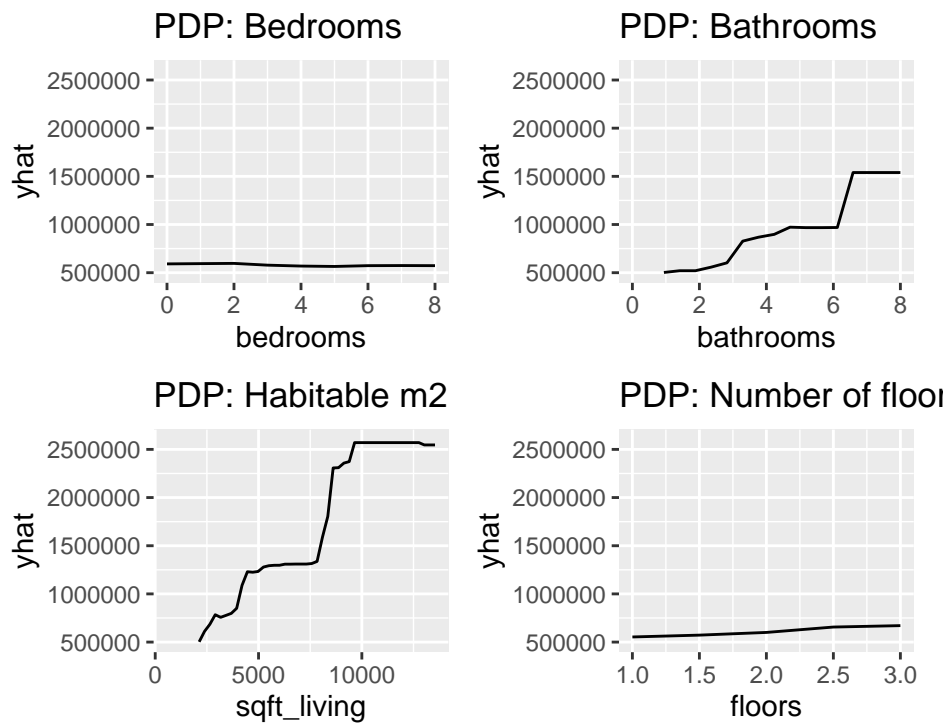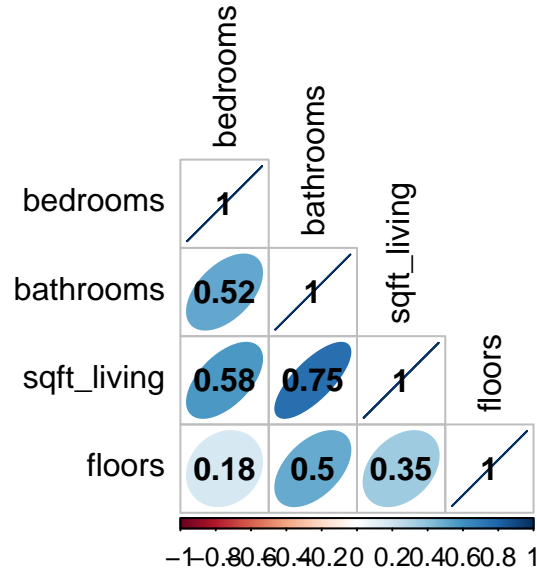
- **Bedrooms (`bedrooms`)**
  The number of bedrooms shows a weak, non-linear influence on predicted price. There is a moderate correlation between bedrooms and living area (sqft_living) (0.58), and between bedrooms and bathrooms (0.52), so the partial effect of this variable may be driven by these other correlated features.

- **Bathrooms (`bathrooms`)**
  Bathrooms have a strong, positive impact on price and a moderately strong correlation with living area (sqft_living) (0.75). Beyond three bathrooms, predicted prices rise rapidly, with a notable jump around six to seven bathrooms—likely indicating luxury homes. This effect may also reflect correlations with other variables, such as larger homes having more bedrooms and greater square footage.

- **Living area (`sqft_living`)**
  This variable exhibits the most pronounced effect. Predicted prices increase steadily with more habitable square footage, especially beyond 4,000 sqft. Larger properties consistently command higher valuations, underscoring the economic premium on spacious interiors.

- **Floors (`floors`)**
  The number of floors shows a clear upward trend: homes with more levels—particularly three-story houses—are predicted to have higher prices. This may be due to architectural prestige, better views, or simply increased usable area.

5 Conclusions

Partial Dependence Plot (PDP) analysis has proven to be a valuable tool for interpreting the behavior of complex machine learning models such as Random Forests:

- In the bike rental case, the most influential variables were temperature and the number of days since the start of the service, both showing a positive effect on demand. In contrast, high levels of humidity and wind speed had a discouraging impact. The two-dimensional PDP confirmed that ideal conditions for bike usage occur under warm temperatures and low humidity.

- In the housing price case, living area and the number of bathrooms were the most positively impactful factors. While features like the number of bedrooms and floors also influenced price predictions, their effects were more variable or moderate.

These results illustrate how PDPs can break down the contribution of each feature, making the model more interpretable and aiding informed decision-making in both urban planning and real estate contexts. This technique thus stands out as a practical explanatory tool for predictive models in applied data science.