XAI: Model-agnostic methods

Exercise 5: Partial Dependency Plots (PDP)

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1 Introduction

This report applies model-agnostic interpretation techniques using Partial Dependence Plots (PDPs) to understand how specific features affect predictions in machine learning models. The goal is to visualize and interpret the relationships learned by a random forest in two regression tasks: predicting bike rentals and house prices.

2 Exercise 1. One dimensional Partial Dependence Plot

In this section, we apply one-dimensional Partial Dependence Plots (PDPs) to interpret a random forest model trained to predict the number of bike rentals (cnt). The aim is to analyze how individual features—days since 2011, temperature, humidity, and wind speed—influence the model's predictions. This helps us understand the marginal effect of each variable while averaging out the impact of the others.

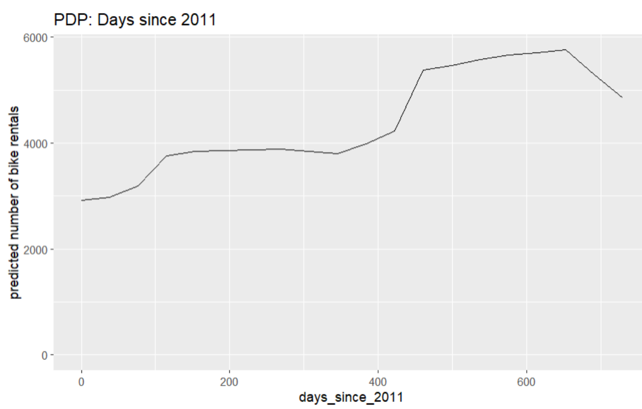

Figure 1: Partial Dependence Plot showing the effect of the number of days since 2011 on predicted bike rentals

The partial dependence plot for days since 2011 shows a general increase in predicted bike rentals over time, with a notable rise around day 450, followed by a slight decline after day 650. This suggests a seasonal or long-term trend in rental demand.

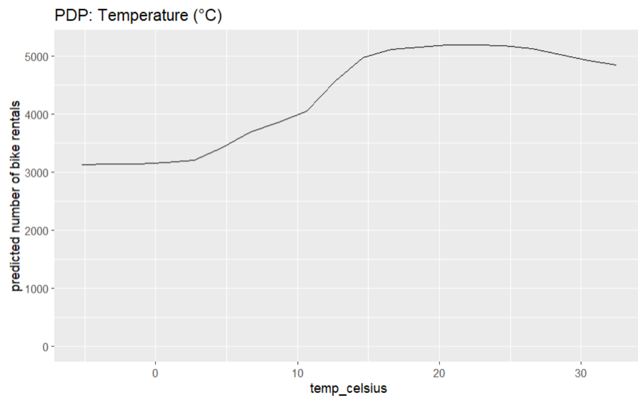

Figure 2: Partial Dependence Plot showing the effect of temperature (in °C) on predicted bike rentals.

For temperature, the relationship is clearly positive: as temperature increases up to around 20–25°C, the predicted number of rentals rises significantly. After that point, the effect plateaus or slightly decreases, possibly due to discomfort at high temperatures.

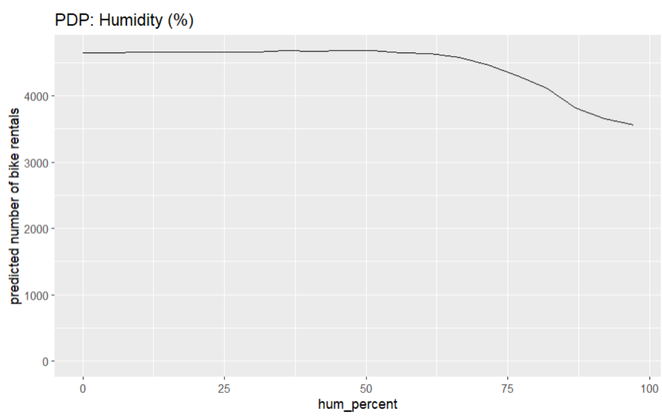

Figure 3: Partial Dependence Plot showing the effect of humidity on predicted bike rentals.

Humidity shows a negative relationship: higher humidity levels correspond to fewer bike rentals. The effect becomes more noticeable above 60%, where predicted rentals start to drop more sharply.

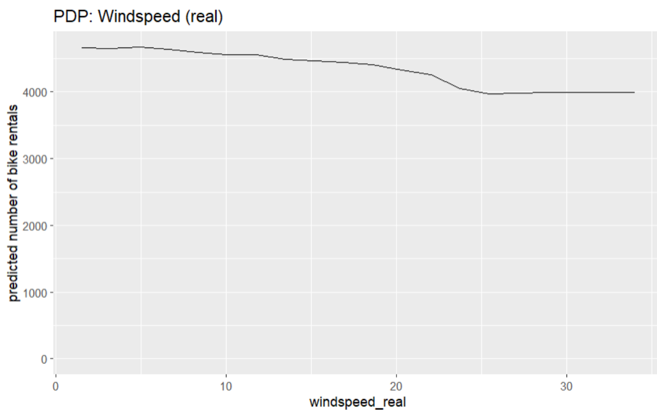

Figure 4: Partial Dependence Plot showing the effect of wind speed on predicted bike rentals.

Similarly, wind speed has a slightly negative effect on predicted bike rentals. As wind speed increases, the model predicts fewer rentals, which is consistent with the idea that strong wind discourages cycling.

3 Exercise 2. Bidimensional Partial Dependency Plot

In this section, we explore the joint effect of temperature and humidity on bike rental predictions using a two-dimensional Partial Dependence Plot (PDP).The PDP helps visualize how the interaction between both features influences the model's output.

The 2D PDP below reveals a clear interaction pattern:

Higher temperatures (15–25°C) are associated with the highest predicted number of bike rentals, especially when humidity is low to moderate (below 60%).

At lower temperatures and high humidity levels, the model predicts significantly fewer rentals.

The brightest region (yellow) indicates optimal conditions for bike rentals: warm and dry weather.

Conversely, the darkest region (blue) shows that cold and humid conditions lead to the lowest predictions.

These results confirm that both warm and dry conditions encourage bike usage, while poor weather (cold and humid) discourages it.

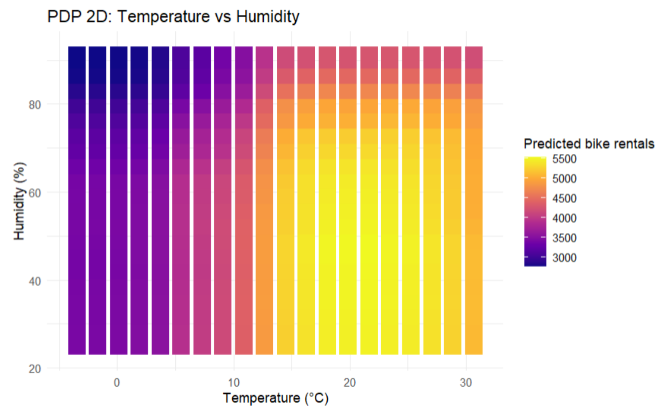

Figure 5: Two-dimensional Partial Dependence Plot showing the combined effect of temperature (°C) and humidity (%) on predicted bike rentals.

4 Exercise 3. PDP to explain the price of a house

In this section, we apply one-dimensional Partial Dependence Plots to interpret a random forest model trained on the kc_house_data.csv dataset. The model predicts house prices based on features such as bedrooms, bathrooms, sqft_living, and floors. The goal is to understand how each of these variables individually influences the model's predicted price.

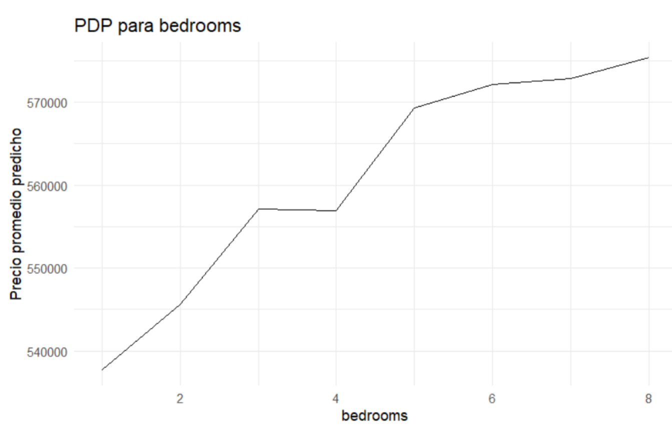

Figure 6: Partial Dependence Plot showing the effect of the number of bedrooms on predicted house price.

The PDP shows a slight increase in predicted price as the number of bedrooms increases. However, the effect is not very strong, suggesting that while more bedrooms may contribute to higher prices, their impact is limited compared to other variables.

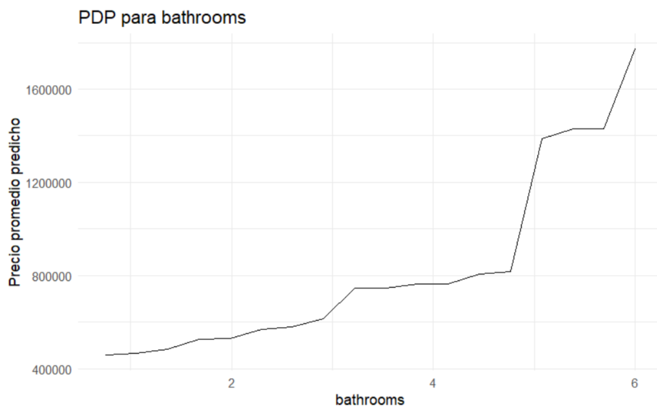

Figure 7: Partial Dependence Plot showing the effect of the number of bathrooms on predicted house price.

The number of bathrooms has a clearer positive effect. Properties with more than 3.5 bathrooms show a sharp increase in predicted price, indicating that bathrooms are a stronger indicator of property value.

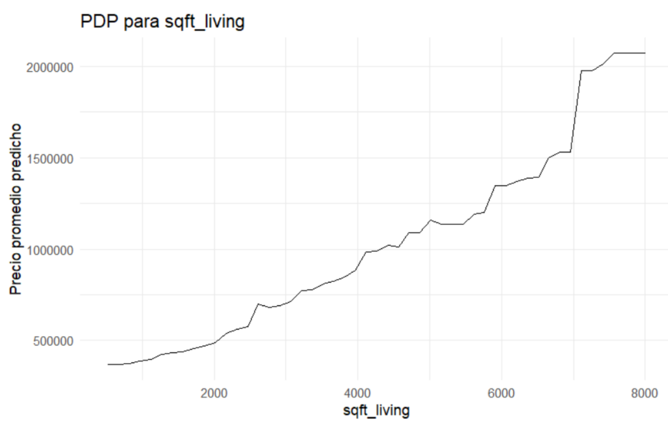

Figure 8: Partial Dependence Plot showing the effect of living area (in square feet) on predicted house price.

This feature has the strongest positive correlation with predicted price. As living space increases, the predicted price rises steadily and sharply, reflecting the importance of house size in property valuation.

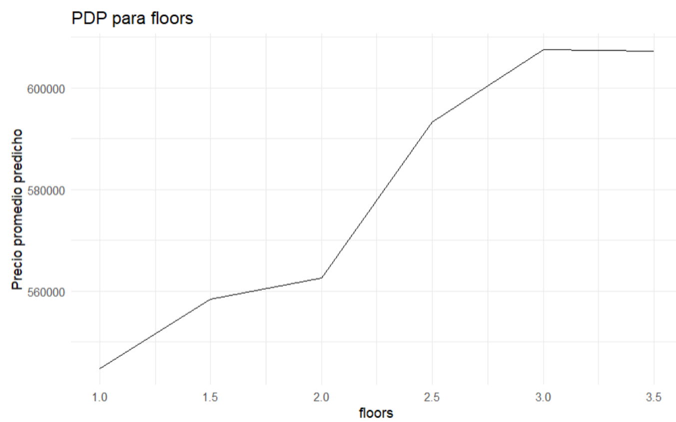

Figure 9: Partial Dependence Plot showing the effect of the number of floors on predicted house price

The number of floors shows a moderate effect. Prices tend to increase with more floors, especially from 1 to 3, after which the effect plateaus. This suggests that houses with multiple floors are generally valued higher, but the marginal gain diminishes.

5 Conclusions

Partial Dependence Plots (PDPs) proved useful for interpreting the behavior of complex machine learning models such as random forests. In the bike rental task, the model revealed that temperature had a strong positive effect, while humidity and wind speed negatively impacted rental predictions. In the house price prediction task, living space (sqft_living) was the most influential factor, followed by the number of bathrooms. The number of bedrooms and floors also contributed, but with a more moderate effect.

These insights help validate the model's logic and improve our understanding of which features most influence predictions in each context..