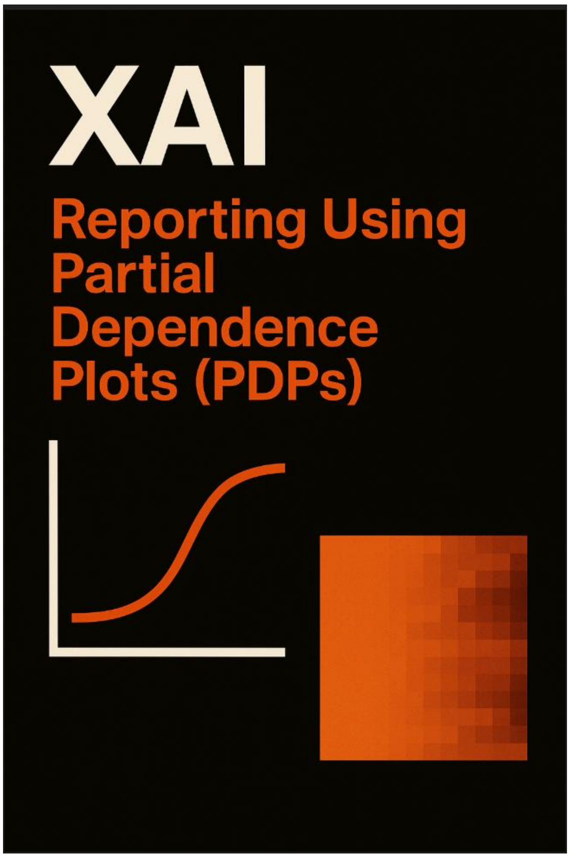

TASK XAI III

Model-agnostic Methods

BRIEF DESCRIPTION:

This report presents an analysis using Partial Dependency Plots (PDPs), a model-agnostic technique, to interpret how individual features influence the predictions of a machine learning model.

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1. Summary

In this report, we explore model-agnostic interpretation techniques using Partial Dependence Plots (PDPs). PDPs help us understand the impact of individual input features on a model's predictions by marginalizing over the other variables. We applied these methods to two regression problems:

1. Predicting daily bike rentals using weather and calendar features.
2. Predicting house prices using property-related features.

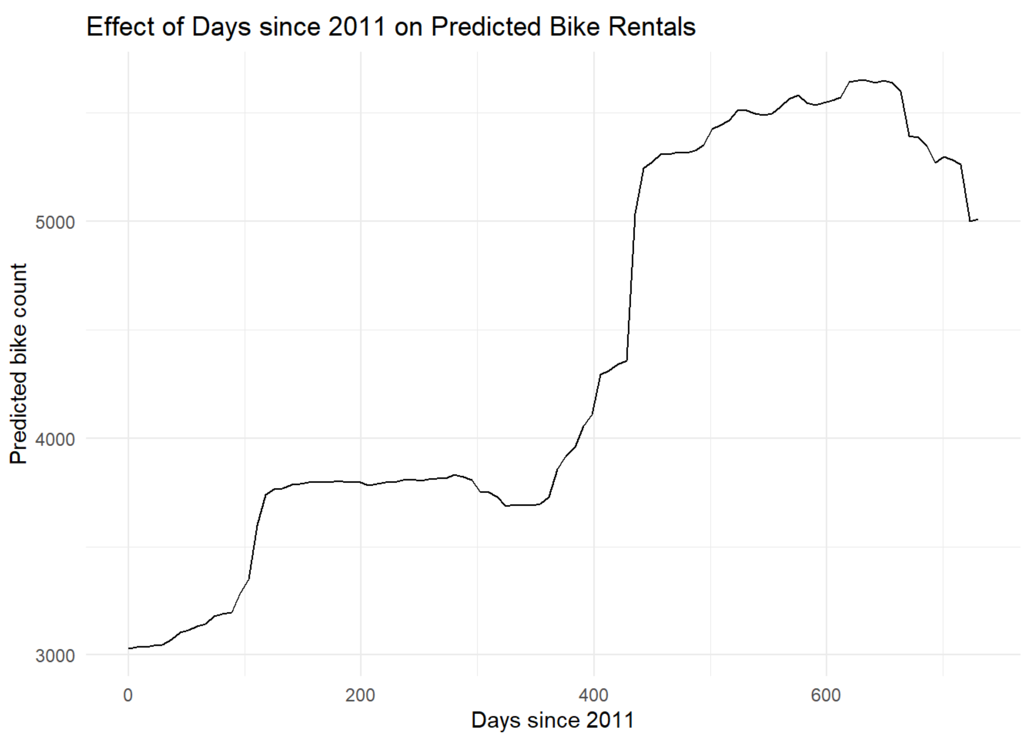
All models were trained using random forests, and visualizations were created to interpret what the model learned from the data.

2. One-dimensional Partial Dependence Plot for Bike Rentals

2.1 Analysis of Feature Influence on Predicted Bike Counts

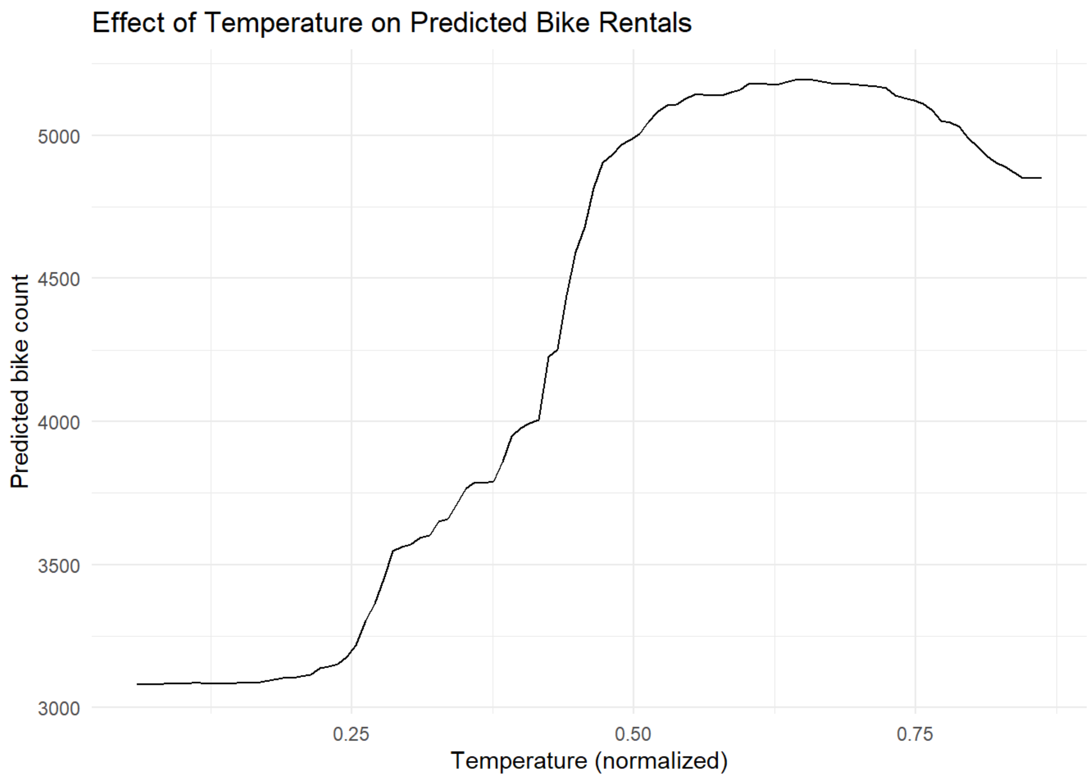
- **Days Since 2011**

The PDP for days since 2011 shows a clear upward trend, indicating that bike rentals have generally increased over time. This suggests a growing popularity of the bike rental service since its inception. The curve is not completely linear, it shows periods of faster growth and then levels off, which might correspond to seasonal trends or specific events that affected bike rental patterns. This temporal trend is valuable for understanding long-term business growth and planning.



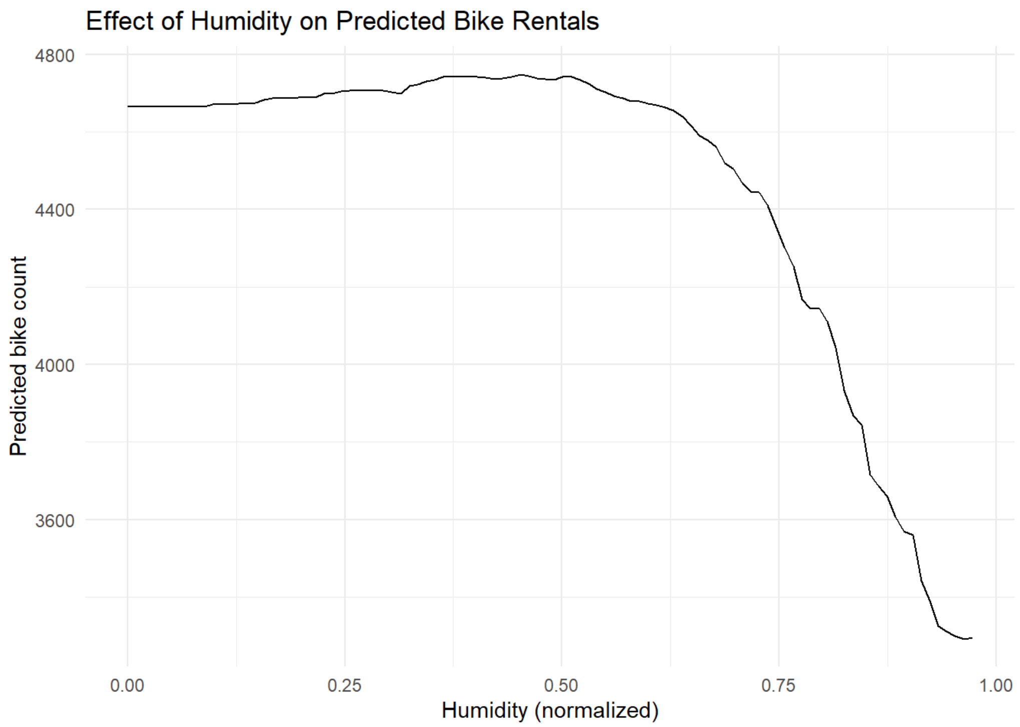
- **Temperature**

Temperature shows one of the strongest effects on bike rentals with a distinctly non-linear relationship. At lower temperatures, there are few rentals, but as temperature increases, the number of rentals rises dramatically until it reaches an optimal range (approximately 0.6-0.8 on the normalized scale). Beyond this optimal range, extremely high temperatures appear to slightly decrease bike rentals, suggesting that very hot weather discourages cycling. This insight confirms the intuitive understanding that people prefer cycling in warm but not excessively hot conditions.



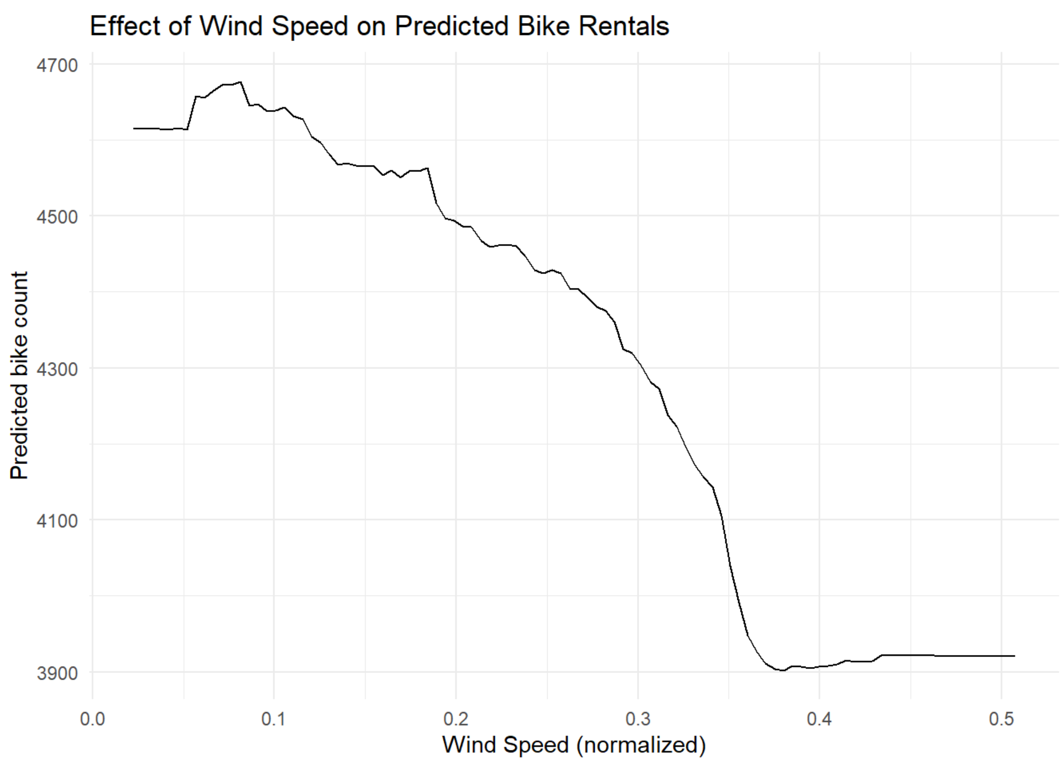
- **Humidity**

The humidity PDP reveals a negative correlation with bike rentals. As humidity increases, predicted bike counts steadily decrease. This decline is particularly pronounced at high humidity levels (above 0.7 on the normalized scale), where we see a sharp drop in predicted rentals. This indicates that cyclists strongly prefer dry conditions, and high humidity strongly discourages bike usage. This information could be valuable for operational planning, suggesting reduced bike availability needs during humid days.



- **Wind Speed**

Wind speed shows a negative correlation with bike rentals, but its impact is less significant compared to temperature or humidity. Higher wind speeds consistently predict lower bike rental counts. This makes intuitive sense as strong winds make cycling more physically demanding and potentially less safe. The model has correctly captured this relationship, confirming that wind speed is an important but not dominant factor in bike rental decisions.



3. Bidimensional Partial Dependency Plot

3.1 Interpretation of Humidity and Temperature Interaction

The 2D Partial Dependency Plot reveals a complex interaction between humidity and temperature in predicting bike rentals. Different key observations can be made:

1. **Optimal Conditions**: The highest predicted bike counts (shown in bright yellow/white areas) occur at moderate to high temperatures (0.6-0.8) combined with low humidity (0.2-0.4). This represents the ideal weather conditions for cycling.

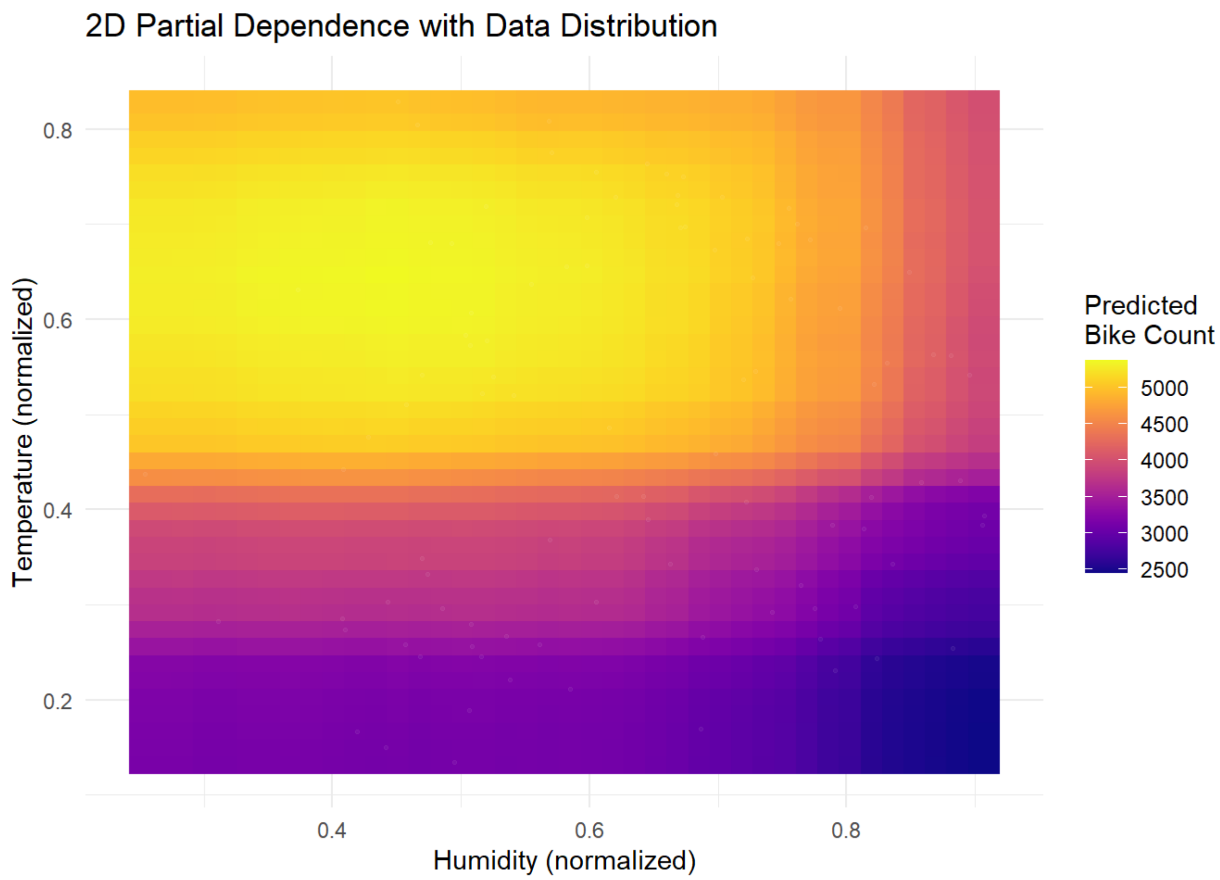
2. **Compensatory Effects**: While both high humidity and low temperature individually reduce bike rentals, the 2D plot shows that high temperature can partially compensate for high humidity. For example, even at higher humidity levels, moderately high temperatures still maintain reasonable rental predictions.

3. **Worst Conditions**: The lowest predicted bike counts (dark purple areas) occur when both unfavourable conditions coincide: low temperature and high humidity. Together, these two factors seem to make the situation worse than either one alone.

4. **Non-linear Boundaries**: The transitions between different prediction levels are not straight lines, confirming that the interaction between these variables is non-linear and would be difficult to capture with simpler models.

5. **Plateau Effect at High Temperature:** When the temperature gets very high (above 0.75), bike rentals stop increasing. In fact, they seem to level off or even drop a bit, no matter the humidity. This probably means it’s just too hot for people to feel comfortable riding bikes, so there's a limit to how much hot weather actually helps.

This bidimensional analysis provides valuable insights beyond what individual PDPs could reveal, showing how these weather factors interact to influence cycling behaviour. For operational planning, this suggests that forecasting models should consider these interactions rather than treating weather variables independently.



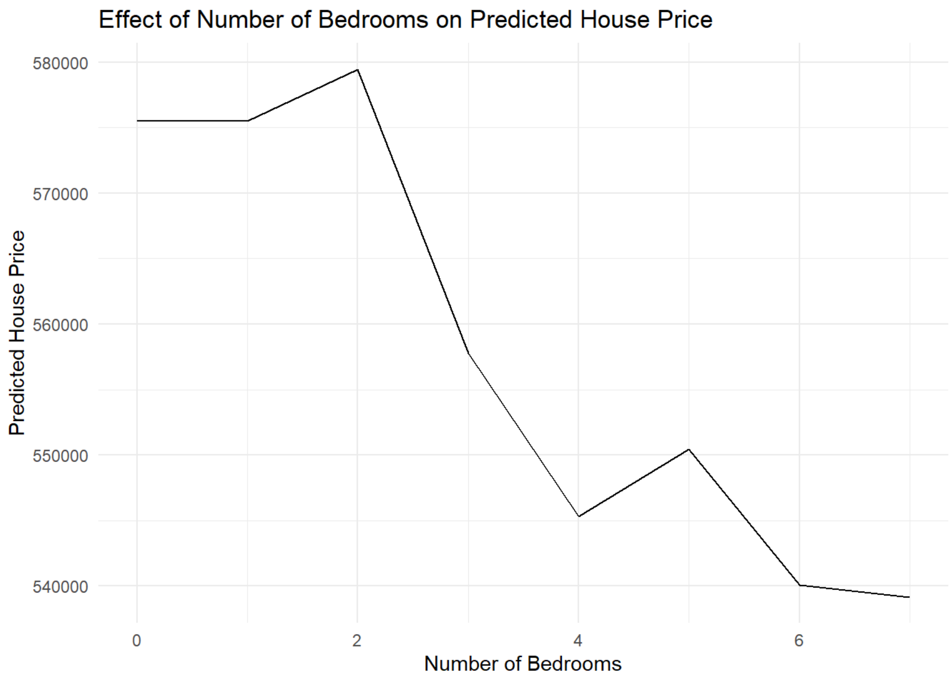
4. PDP to Explain House Prices

4.1 Analysis of Feature Influence on Predicted House Prices

- **Bedrooms**

The PDP for the number of bedrooms reveals a somewhat unexpected trend. While you might assume that more bedrooms would lead to higher prices, the model shows the opposite beyond a certain point. Prices slightly increase up to around 2 bedrooms, but after 3 or more, the predicted price starts to drop.

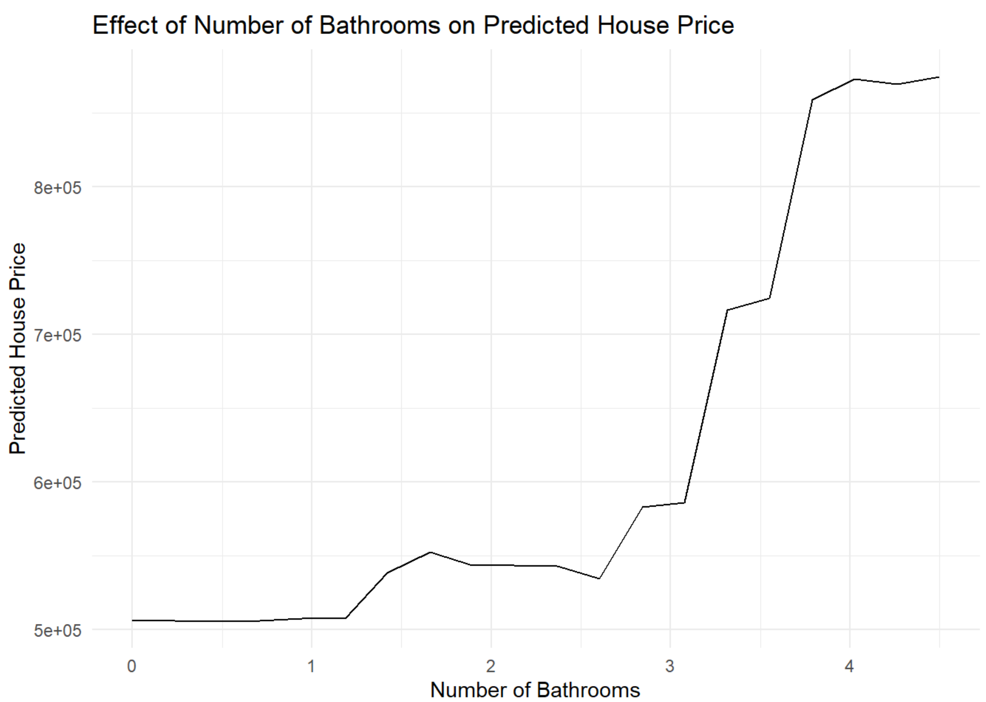
This could mean that simply having more bedrooms doesn't necessarily make a house more valuable, especially if the overall size or quality doesn't scale with them. In some cases, houses with many bedrooms might be older, less modern, or located in areas where large homes are less in demand. It's also possible that some of these homes are split into multiple small rooms, which could lower their appeal and, in turn, their predicted price.



- **Bathrooms**

The PDP for the number of bathrooms shows a clear and steady increase in predicted house price, especially between 2 and 4 bathrooms. This makes sense because extra bathrooms add convenience and are generally seen as a valuable upgrade.

After 4 bathrooms, the curve starts to flatten out, suggesting that adding more beyond that point doesn't boost the price much further. In other words, there's a limit to how much value additional bathrooms can add. Compared to bedrooms, the relationship here is much stronger and more consistent, reinforcing the idea that bathrooms play a more decisive role in how a home is valued.

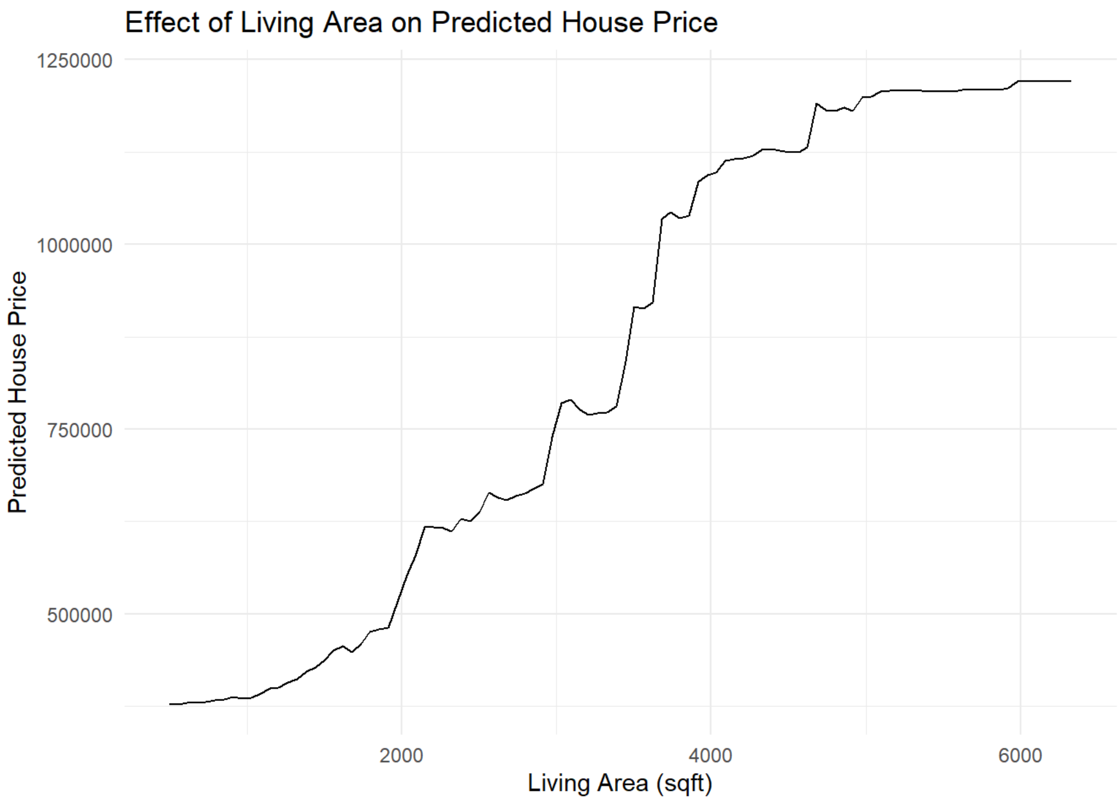


- **Living Area (sqft_living)**

The PDP for living area shows the clearest and strongest positive relationship with house price out of all the features analyzed. As the square footage increases, so does the predicted price.

What stands out is that this effect holds even at the higher end of the scale. Unlike other features that show diminishing returns (bedrooms or bathrooms) larger living areas continue to boost the estimated value of the home. This suggests that overall spaciousness is consistently perceived as a premium quality by the model, potentially reflecting market preferences for comfort, flexibility, or future expansion.

In short, living area emerges as the single most influential factor in the model and highlights how buyers may prioritize square footage over other individual features when assessing a home's value.

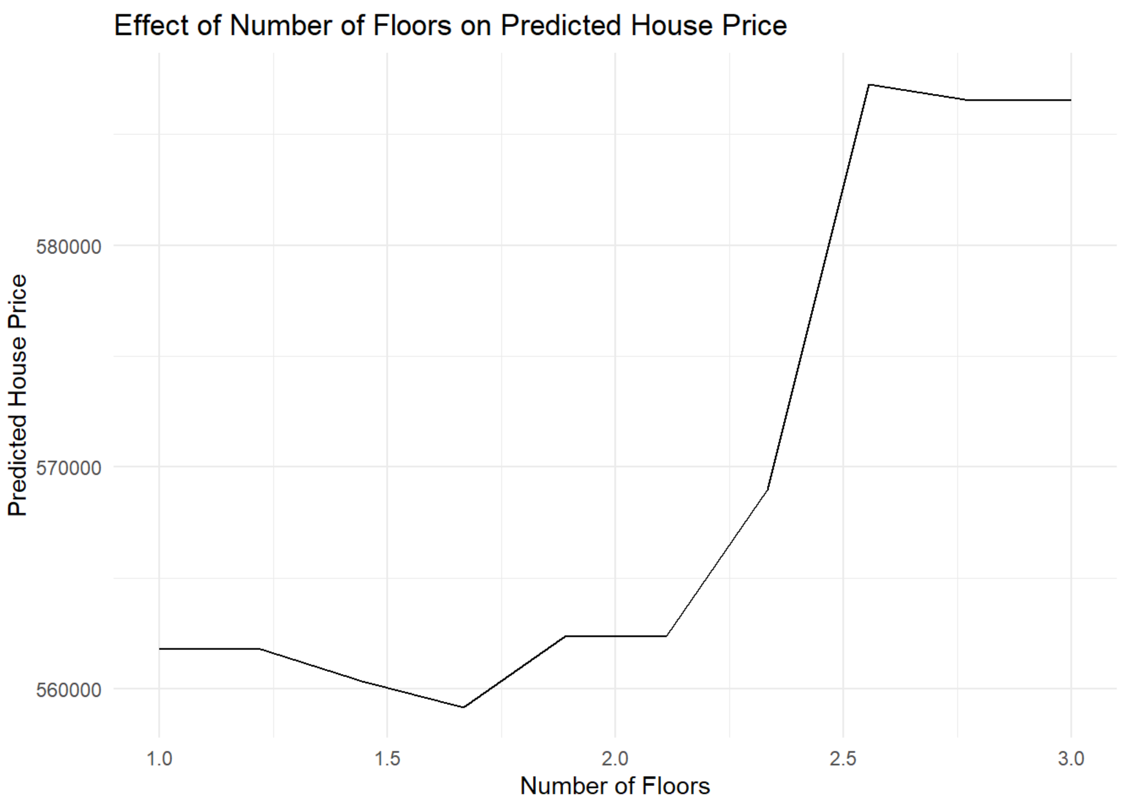


- **Floors**

The PDP for the number of floors shows a more complex relationship with house price. In general, houses with more than one floor tend to have slightly higher predicted prices than 1 floor homes, although the increase is not very strong until reaching 3 floors, where a more noticeable rise appears.

Homes with two floors seem to represent the most balanced option, combining space and practicality. The slight dip before the 3-floor mark may indicate that houses with many levels are less common or less attractive in certain areas, possibly due to factors like accessibility or higher maintenance needs.

Overall, the number of floors does have an effect on predicted price, but it is weaker and less consistent compared to more influential variables like living area or number of bathrooms.



5. Overall House Price Model Insights

The PDP analysis shows that square footage (living area) is the most influential predictor of house prices in this dataset, with the strongest and most consistent effect. Bathrooms also display a clear positive correlation with price, while bedrooms and floors reveal more complex, non-linear patterns. These insights can be useful for real estate professionals, developers, or homeowners planning renovations. For example, adding a bathroom or increasing the overall living area is likely to generate a higher return than simply increasing the number of bedrooms.

6. Conclusions

Partial Dependency Plots have proven to be an effective tool for interpreting complex machine learning models in these different domains. They reveal important non-linear relationships and interactions between features that would be difficult to detect with simpler analysis methods. These insights can inform business decisions, operational planning, and strategic investments by providing a clearer understanding of how individual factors influence outcomes.

The analysis demonstrates that Random Forest models, while powerful predictors, create "black box" systems that require interpretability techniques like PDPs to extract actionable insights. By understanding these feature relationships, we can make more informed decisions and potentially design better features or models in the future.