Universidad Politécnica de Valencia

Escuela Técnica Superior de Ingeniería Informática

XA3: Model-agnostic methods

Evaluación y Despliegue de Modelos

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1

Understanding User Demand in Urban Mobility Systems

To improve forecasting in urban mobility, we trained a Random Forest model on bike rental data to assess how various environmental and temporal features influence the number of bikes rented. This analysis provides actionable insights for demand planning and resource allocation.

Feature Influence: Temporal and Weather Effects

Days Since Launch (`instant`):

Figure 1: Predicted rentals vs. days since launch

Bike rental usage shows a steady upward trend over time, indicating growing user engagement and market adoption.

Temperature:

Figure 2: Predicted rentals vs. temperature

Warmer temperatures are positively correlated with usage, up to a plateau where demand stabilizes.

Humidity:

Figure 3: Predicted rentals vs. humidity

Increased humidity reduces demand, potentially due to discomfort associated with high-moisture conditions.

Wind Speed:

Figure 4: Predicted rentals vs. wind speed

Similarly, strong winds negatively impact the number of bike rentals.

Joint Influence of Temperature and Humidity

Figure 5: 2D PDP: Joint influence of temperature and humidity

The heatmap reveals that optimal demand occurs under warm and dry conditions. High humidity significantly suppresses rentals even when temperatures are favorable, highlighting a non-linear interaction.

Modelling Real Estate Prices from Structural Features

We applied the same methodology to the kc$_{h}ouse_{d}ata.csvdataset, focusingonpredictinghousepricesfromkeyph$

Feature Influence on Price Predictions

Number of Bedrooms:

Figure 6: Predicted price vs. number of bedrooms

The effect is moderate. Properties with 3--5 bedrooms see a slight increase in price, but this plateaus and may even decrease beyond 6.

Number of Bathrooms:

Figure 7: Predicted price vs. number of bathrooms

More bathrooms are clearly associated with higher prices, especially transitioning from one to two or three bathrooms.

Living Area (sqft):

Figure 8: Predicted price vs. living space

The strongest relationship in the model: price increases almost linearly with greater living area.

Number of Floors:

Figure 9: Predicted price vs. number of floors

Although more discrete, the number of floors shows a stepped increase in predicted price, with clear thresholds at 2 and 3 floors.

Conclusion

Partial Dependence Plots provide clear insights into how individual and joint features affect model predictions in real-world contexts.

In both urban mobility and real estate pricing, temperature, space, and infrastructure show strong predictive power. This type of analysis enables decision-makers to prioritize investments, adjust capacity, or anticipate shifts in user behavior based on external factors.