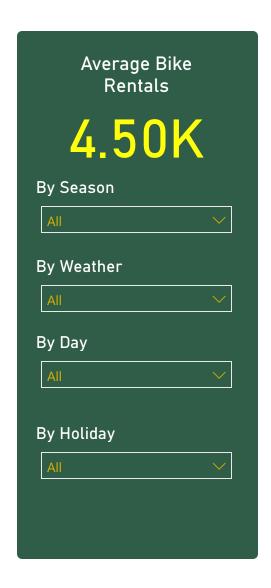
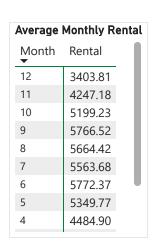
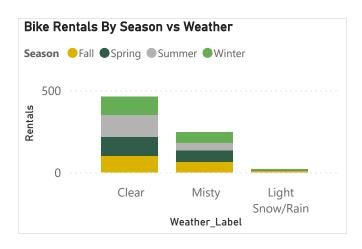
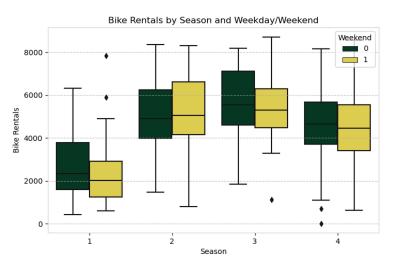
Data Exploration Bike Sharing Rental Data Exploration



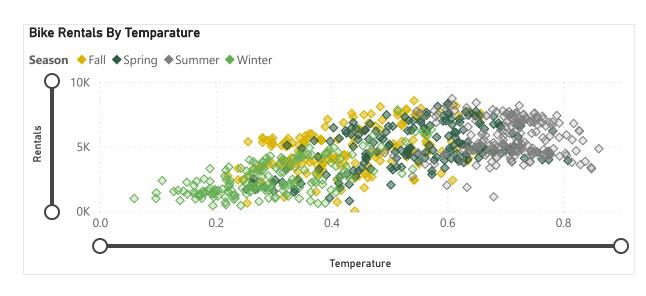






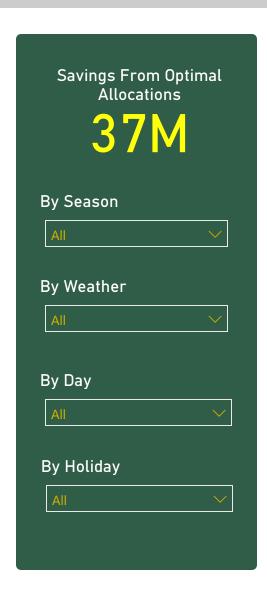
Data Insights

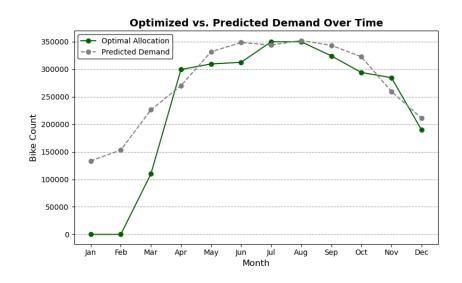
- Temperature strongly influences rentals; warmer weather increases demand.
- Weekend rentals consistently exceed weekday usage, particularly in warmer seasons.
- Clear weather significantly boosts rentals; adverse conditions sharply reduce demand.
- Temperature, humidity, and wind speed distributions are balanced, indicating good data quality.
- Temperature is most correlated with rentals, highlighting its predictive significance..



Prescriptive Dashboard

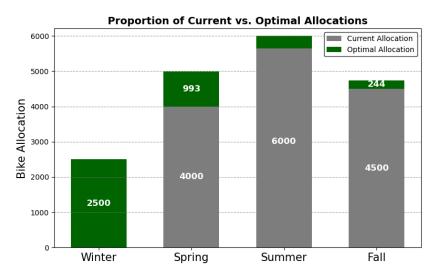
Optimal Bike Allocation: Optimizing Cost Savings & Smart Demand Planning

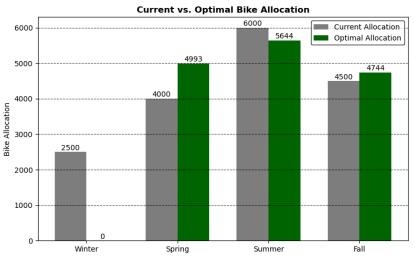




Actionable Recommendations

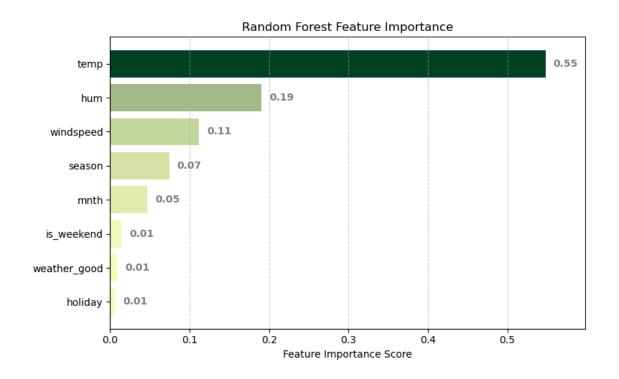
- Increase bike allocation in Spring & Summer to meet high demand.
- Reduce Winter allocation to minimize excess inventory costs.
- Adjust forecasting for Jan-March to better match rising demand.
- Use real-time rental data to refine allocation strategies dynamically.
- Explore seasonal promotions to boost bike usage in low-demand months.
- Monitor actual vs. optimized performance to continuously improve allocation.

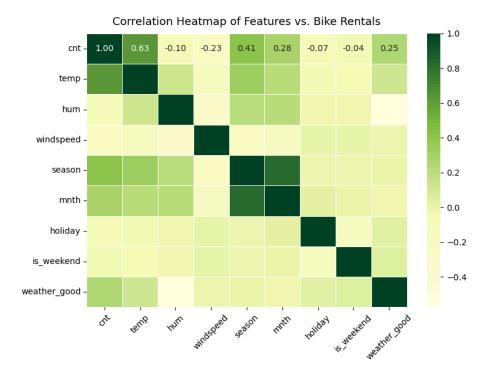




Feature Importance Analysis

for Regression Modelling





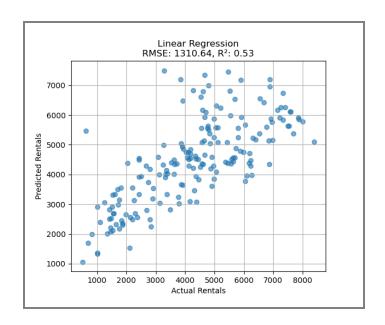
Random Forest Feature Importance

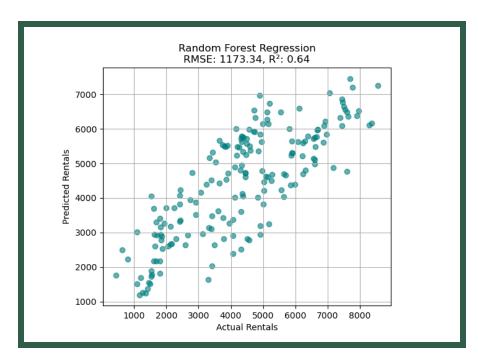
This chart displays the feature importance scores assigned by the Random Forest model. Higher scores indicate greater influence on predicting bike rental counts . Temperature clearly stands out as the most impactful feature, followed by humidity and wind speed. Features like holiday, is_weekend, and weather_good contribute less to the prediction, but may still add contextual value. This justifies the selection and weighting of features in our regression model.

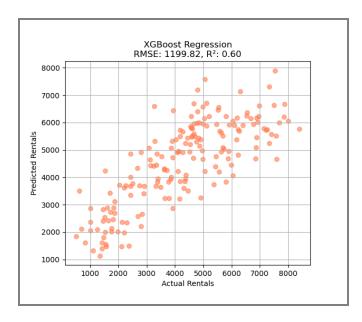
Correlation Heatmap of Features vs. Bike Rentals

The heatmap illustrates the strength and direction of linear relationships between features and bike rentals. Temperature shows the strongest positive correlation (0.63), reinforcing its predictive importance. Humidity and wind speed show weaker correlations, while seasonal and temporal features (month, season) also show meaningful associations. While correlation does not equal causation, it supports feature relevance and complements the model-driven importance scores.

Regression Model Comparison Actual vs Predicted Bike Rentals







Linear Regression

Linear Regression had the lowest performance (R² = 0.53), likely due to its inability to capture nonlinear patterns.

Random Forest Regression

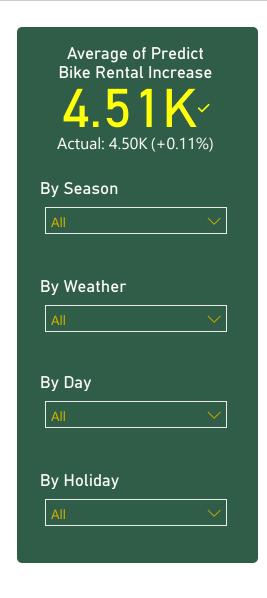
Random Forest achieved the highest predictive accuracy ($R^2 = 0.64$, RMSE = 1173), showing a strong fit between predicted and actual rentals.

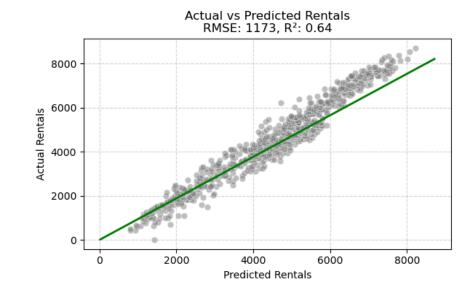
Conclusion: Random Forest was selected as the final model due to its balance of predictive strength, interpretability, and robustness across seasonal variations.

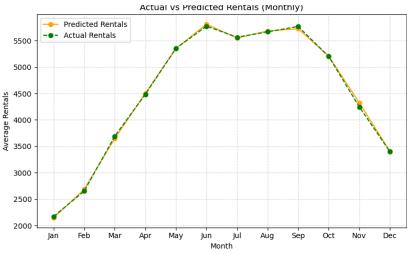
XGBoost

XGBoost performed slightly lower ($R^2 = 0.60$), still producing a reliable prediction curve.

Predictive Analysis Using Random Forest Regression Model







Insights

The Random Forest predictive model demonstrates good predictive accuracy. Rentals follow strong seasonal trends, peaking in summer. Actual and predicted counts are highly correlated, though improvements could be made for highdemand days. Consider refining model features or hyperparameters for further accuracy.

The Random Forest predictive model reliably tracks actual rentals closely monthto-month, indicating the model captures seasonality effectively. Slight variations suggest opportunities to improve predictions for peak months.

Summer clearly shows the highest predicted bike rentals, suggesting high demand. Strategic resource allocation during summer months could significantly enhance revenue.

