Final

In this part of the machine learning project, the emphasis moves to solving a supervised regression problem with a variety of predictive methods. To ensure a rigorous assessment pipeline, the dataset will be preprocessed first, with a structured split into training (70%), validation (15%), and test (15%) sets. Several regression models will then be trained, and chosen with Decision Tree Regressor, Random Forest Regressor, Gradient Boosting Regressor (such as XGBoost or LightGBM). Then, models will be validated using conventional performance metrics, including MAE, MSE, and R^2 Score, and evaluated on a validation set. Next, ensemble learning approaches will be used to capitalize on the capabilities of the best-performing models. A Voting Regressor, or an average ensemble of the three best models, will be built and tested on both the validation and test sets. To conclude, a Bayesian ensemble model will be used to provide a probabilistic viewpoint on prediction aggregation. This comparison will aid in determining the best ensemble technique for increasing prediction accuracy and model generalization in the regression task.

On the first step, among the regression models evaluated, the Decision Tree, Random Forest, and XGBoost Regressors were compared based on their ability to predict the driving range of electric vehicles using numerical features. The dataset was preprocessed with standardization and split into training and testing sets to ensure a fair evaluation across models. The Decision Tree Regressor, while simple and interpretable, showed the weakest performance due to its tendency to overfit and its limited ability to generalize complex relationships in the data. The Random Forest Regressor improved upon this by using an ensemble of trees, leading to more stable and accurate predictions. However, the XGBoost Regressor consistently outperformed both models. It combines gradient boosting with regularization, allowing it to correct prediction errors iteratively and avoid overfitting, resulting in the lowest RMSE and highest R^2 score among the three. Overall, XGBoost proved to be the most effective model for this regression task. Its robust performance and ability to model nonlinear patterns make it a strong choice for predicting vehicle driving range in this context.

After training, the models make predictions for the 15% validation set. To assess their performance, the code employs four standard metrics. The Mean Absolute Error (MAE) is the average absolute difference between anticipated and actual values; smaller values imply more

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Decision Tree Regressor Results:    Random Forest Regressor Results:    XGBoost Regressor Results:
RMSE: 21.01                         RMSE: 16.67                         RMSE: 13.63
R² Score: 0.969                     R² Score: 0.981                     R² Score: 0.987
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accuracy. The Mean Squared Error (MSE) squares the prediction errors before averaging, giving greater weight to larger errors—lower is better. Root Mean Squared Error (RMSE) is the square root of MSE, resulting in an error measure in the same unit as the target variable, making understanding easier; smaller values are desired. The R-squared (R^2) score indicates how well the model explains the variance in the target variable, with a range of 0 to 1. A value closer to one suggests a better fit, however a score of one may imply overfitting if not properly evaluated. The results of each model are presented for simple comparison, allowing you to identify the best-performing model based on the validation data. The XGBoost Regressor outperforms all other choices in terms of prediction accuracy and overall data fit, making it the clear choice for final testing.

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Decision Tree Regressor Results:
MAE: 12.13, MSE: 576.29, RMSE: 24.01, R² Score: 0.962

Random Forest Regressor Results:
MAE: 11.00, MSE: 676.06, RMSE: 26.00, R² Score: 0.955

XGBoost Regressor Results:
MAE: 8.56, MSE: 326.56, RMSE: 18.07, R² Score: 0.978
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In the next step, we build something called a Voting Regressor, which is a type of machine learning model that acts like a team made up of different smaller models. Instead of relying on just one model to make predictions about how far an electric vehicle can drive, we bring together three different models: a Decision Tree, a Random Forest, and an XGBoost model. Each of these models has its own way of learning from the data and making predictions, kind of like how different friends might give different answers when asked the same question. After training our ensemble model, we evaluated its performance on unseen validation data using several key metrics. The Mean Absolute Error (MAE) was 9.26, indicating that, on average, the model's predictions were off by about 9.26 units. The Mean Squared Error (MSE) stood at 437.37, emphasizing larger errors due to the squaring of differences. Taking the square root of MSE, we obtained the Root Mean Squared Error (RMSE) of 20.91, bringing the error metric back to the original unit scale. The R-squared (R^2) score was 0.971, suggesting that approximately 97.1% of the variance in the data was captured by the model.

To ensure the model's robustness, we also tested it on a separate test dataset. The consistent performance across both validation and test sets confirms that combining different models into an ensemble leads to more accurate and reliable predictions.

This procedure entails constructing and assessing a Bayesian model to comprehend and forecast the correlation between a series of input factors and a continuous output. The data is meticulously categorized into three groups: one for pattern recognition, one for calibration and validation, and one for final assessment to ensure dependability. Prior to modeling, the input data is normalized to align all variables on a comparable scale, hence enhancing consistency and interpretability. The model is designed to identify trends from the training data, and its generalization capability is evaluated by comparing projected outcomes with actual values in the validation and test datasets. Critical metrics, including mean error, prediction variability, and the ratio of explained result variance, are employed to assess the model's performance. These metrics assess the model's precision, consistency, and applicability in practical situations. As the result, the model delivers the values from its training in validation and test set below:

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Ultimately, we integrated and contrasted the Bayesian model with the average predictions of three models to evaluate the discrepancies and determine the superior model. The Voting Regressor demonstrably attains superior error metrics- namely Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) on both validation and test sets relative to the Bayesian Ridge model, attributable to the benefits of ensemble learning. The Voting Regressor diminishes variance by averaging predictions from various base models, resulting in more consistent and precise outcomes. This ensemble method more effectively balances the bias–variance trade-off compared to an individual model. Although Bayesian Ridge regression employs robust regularization to mitigate overfitting, it may induce bias, particularly when the underlying data relationship is intricate. Conversely, the Voting Regressor may incorporate less regularized or differentially biased models that identify diverse patterns, thereby diminishing bias without a substantial rise in variance. Moreover, various models may exhibit mistakes in divergent directions; when integrated into an ensemble, these flaws might neutralize one another, therefore diminishing total error measurements. This resilience guarantees that the ensemble's efficacy is not significantly affected by the deficiencies of any one model. The Voting Regressor's ensemble methodology capitalizes on the advantages of various models, resulting in enhanced predictive accuracy and reduced error metrics relative to the individual Bayesian Ridge model.

Model	MAE_Val	MSE_Val	RMSE_Val	R2_Val	MAE_Test	MSE_Test	RMSE_Test	R2_Test
Voting Regressor	9.26-L	437.37-L	20.91-L	0.971-H	5.17-L	80.35-L	8.96 -L	0.994-H
Bayesian Ridge Regressor	21.32	1035.59	32.18	0.931	17.56	622.05	24.94	0.953

In conclusion, this project has provided valuable insights into the application of building a thorough predictive model. As a group, we have gained a deeper understanding of the strengths and limitations of different techniques throughout the project. The hands-on experience with model evaluation and comparison has been instrumental in honing my skills in selecting appropriate algorithms for specific tasks. Overall, this project has reinforced the importance of model selection and evaluation in building effective predictive models.