RankLab

Ranking Dynamics in Multi-Criteria Decision Analysis

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Abstract

Multi-Criteria Decision Analysis (MCDA) has become integral to organizations that must evaluate numerous, often interdependent factors when ranking or prioritizing key elements such as suppliers. Traditional approaches provide basic ordinal regression, yet frequently overlook the nuance of multiple, time-varying criteria. Our study addresses this need by refining and deploying a dynamic risk ranking system using an ensemble of machine learning techniques.

Objective

The primary objective was to deploy a risk-ranking system into a production environment. This required accurate predictive modeling, transparent interpretation of factor importance, and creating a user-friendly web application for real-time rank forecasting. Ultimately, this would allow stakeholders to proactively manage supplier risks and optimize decision-making processes.

This research applies MCDA to evaluate and predict changes in Boeing's supplier rankings over time. Using anonymized data, we analyze patterns in rank fluctuations across performance criteria, which could include a multitude of factors such as cost efficiency, compliance levels, location-related risks, etc.

Data Summary

- 31,933 observations across 1,223 unique entities, each characterized by 17 ordinal decision-making factors.
- All 17 ordinal features were prioritized by predictive influence.
- Risk rankings ranged from 1 (highest risk) to 265 (lowest risk), with observations collected at irregular intervals.
- Risk rankings were a weighted score of three Boeing proprietary algorithms.
- Standardized irregular timestamps using data from May 2021 to October 2022 for consistent modeling.
- Feature engineering included calculating average previous rank, average change in previous rank, and days since last update.

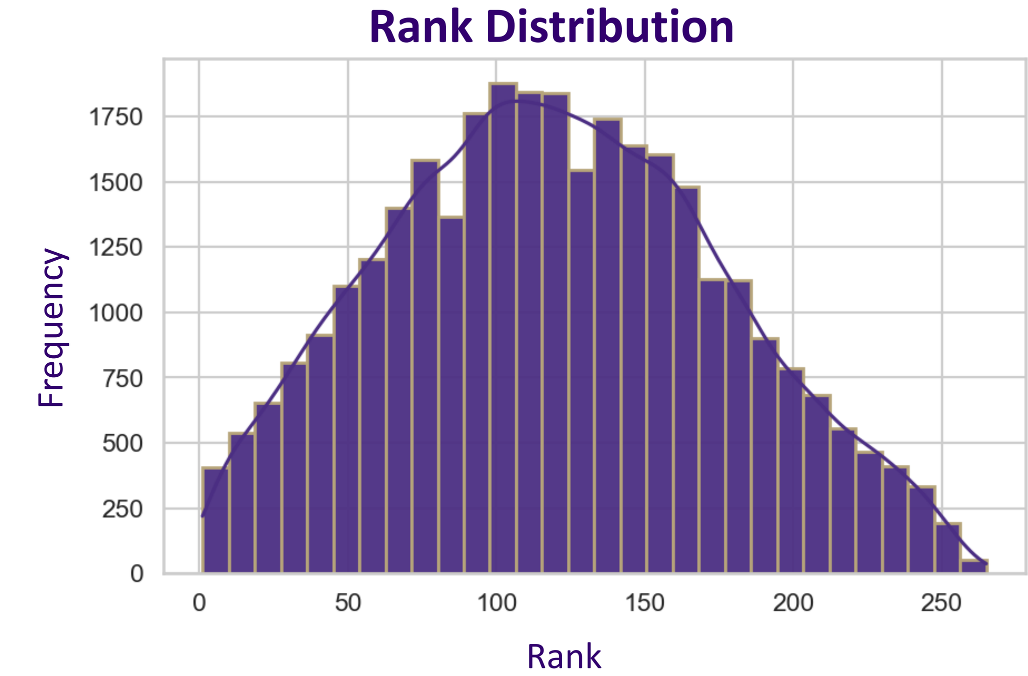
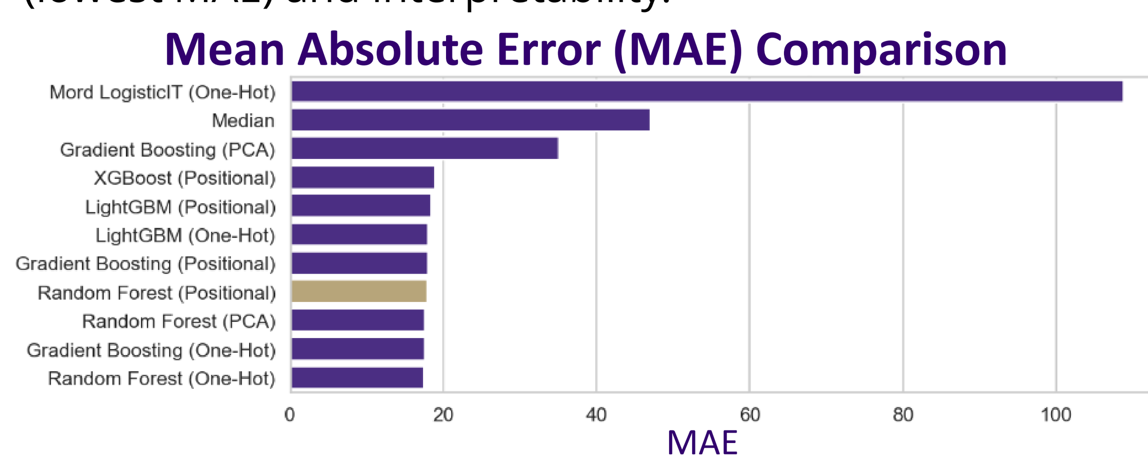


Figure 1. Distribution of Supplier Ranks Across the Full Dataset *(N=31,933). Illustrates a symmetric distribution of risk scores (1 = highest risk, 265 = lowest risk).*

Methodology and Results

Initially, we used the median rank to establish a baseline Mean Absolute Error (MAE) and then employed a Multivariate Ordinal Regression model (MORD). MORD struggled to account for complex factor interactions effectively. Consequently, we moved towards a more advanced modeling approach involving ensemble methods, specifically Random Forest, XGBoost, and LightGBM.

Each model was trained and hyperparameters were optimized, maximizing prediction accuracy. Positional Random Forest emerged as the best-performing model, consistently demonstrating superior predictive accuracy (lowest MAE) and interpretability.



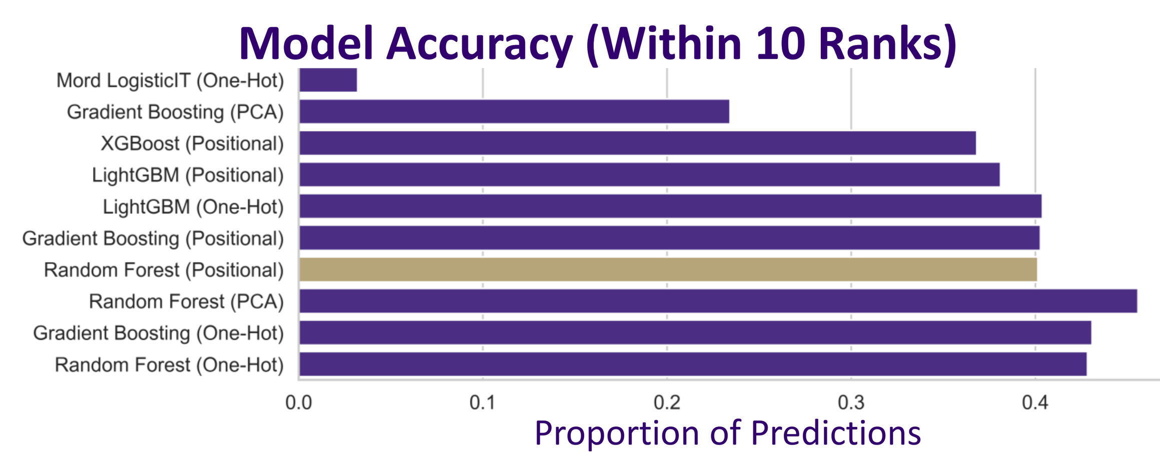


Figure 2. Comparison of model performance using MAE (top) and prediction accuracy within 10 ranks (bottom). *Ensemble methods such as XGBoost and Random Forest with positional encoding significantly outperformed the baseline median and MORD.*

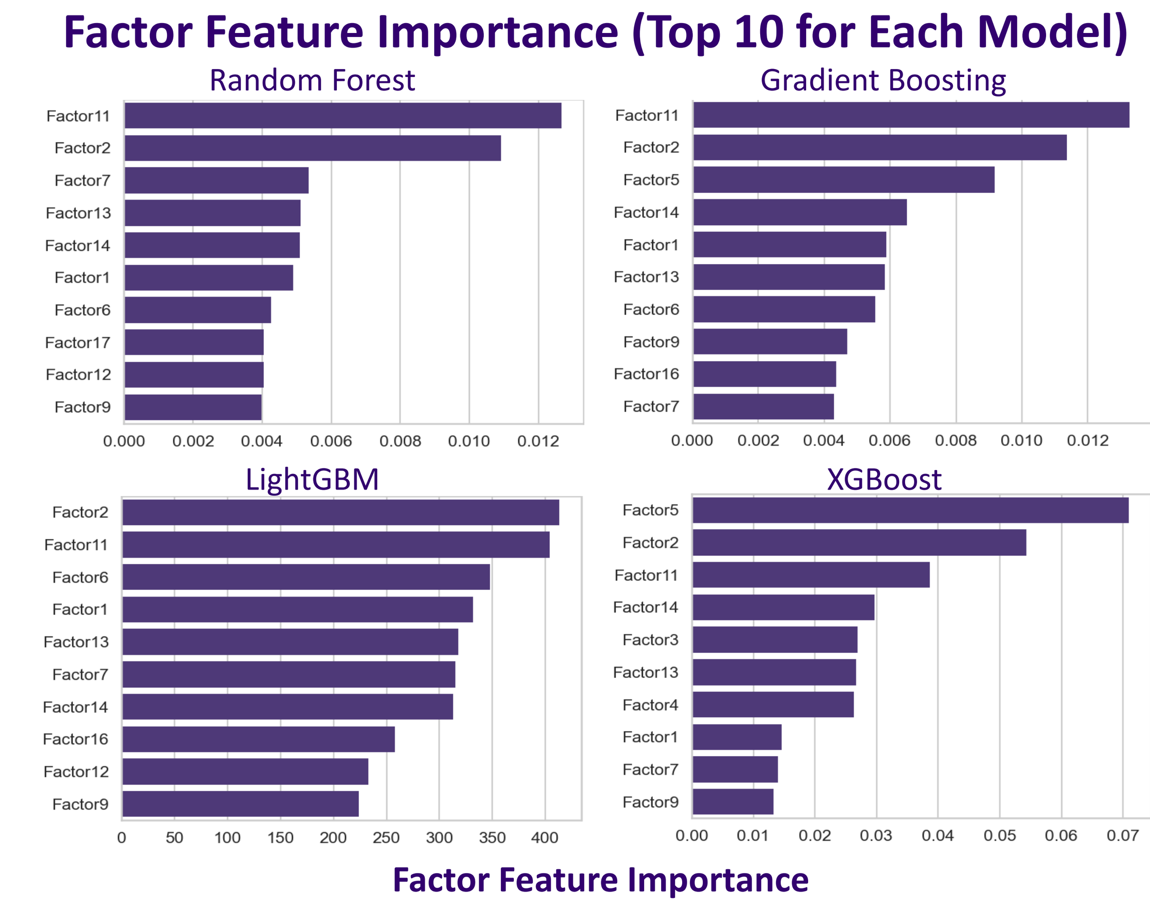


Figure 3. Factor Feature Importance Across Ensemble Methods *(Random Forest, Gradient Boosting, LightGBM, and XGBoost). Identified key variables influencing supplier rankings, such as Factor 2, Factor 11, and Factor 14.*

Our architecture consists of three distinct layers: the data storage layer, compute layer, and front-end. In the data storage layer, Amazon S3 stores raw supplier data while SQLite handles the structured data. These feed into the compute layer where Amazon EC2 instances, configured with Gunicorn and Docker, provide the infrastructure for our SKlearn modeling. The models generate prediction results that flow to the front-end layer, where a Dash interactive dashboard visualizes insights for Boeing end users.

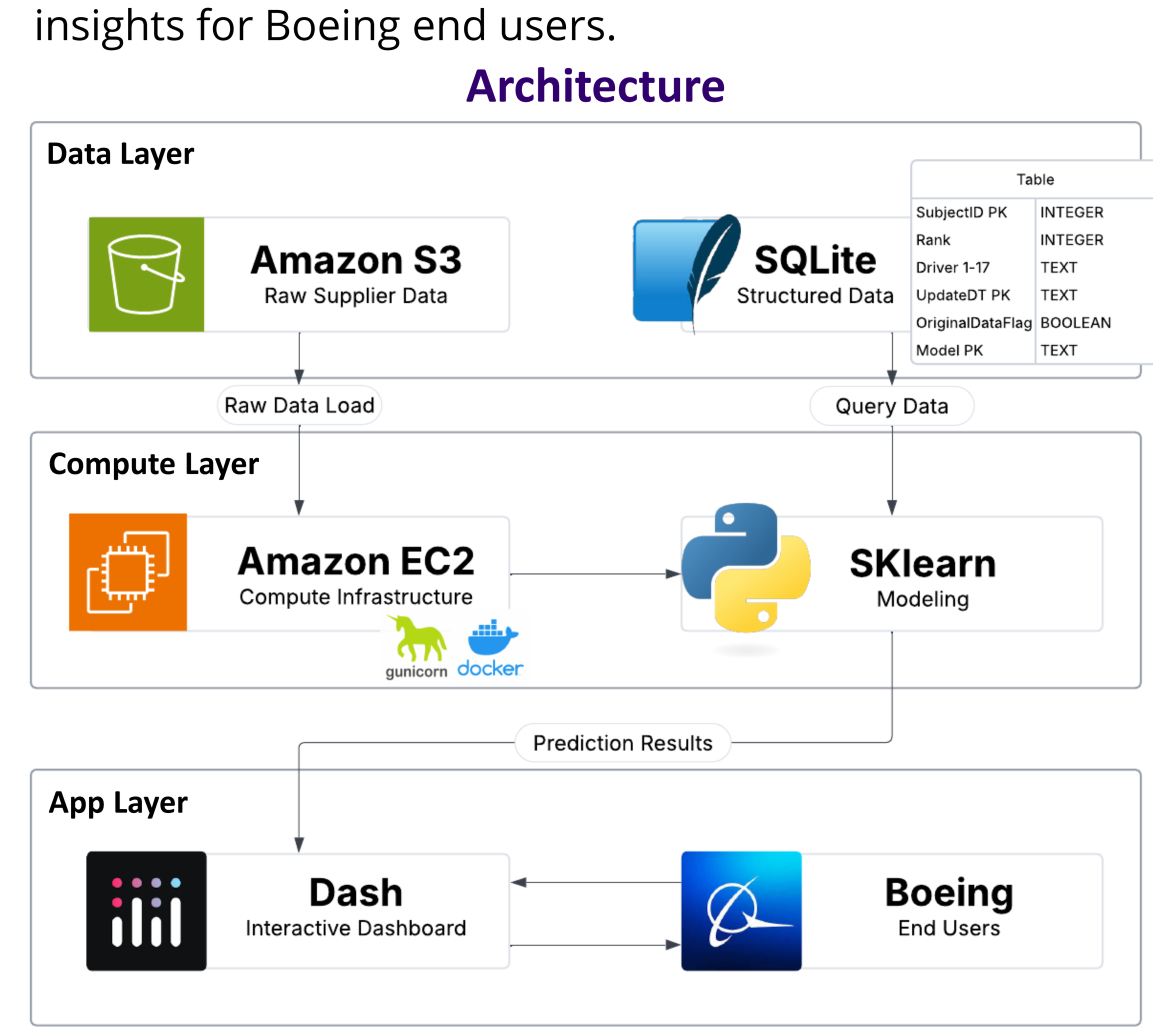


Figure 4. RankLab AWS Cloud Architecture and Data Pipeline. *The RankLab platform operates using Amazon S3, Amazon EC2, SQLite, SKlearn, and Dash.*

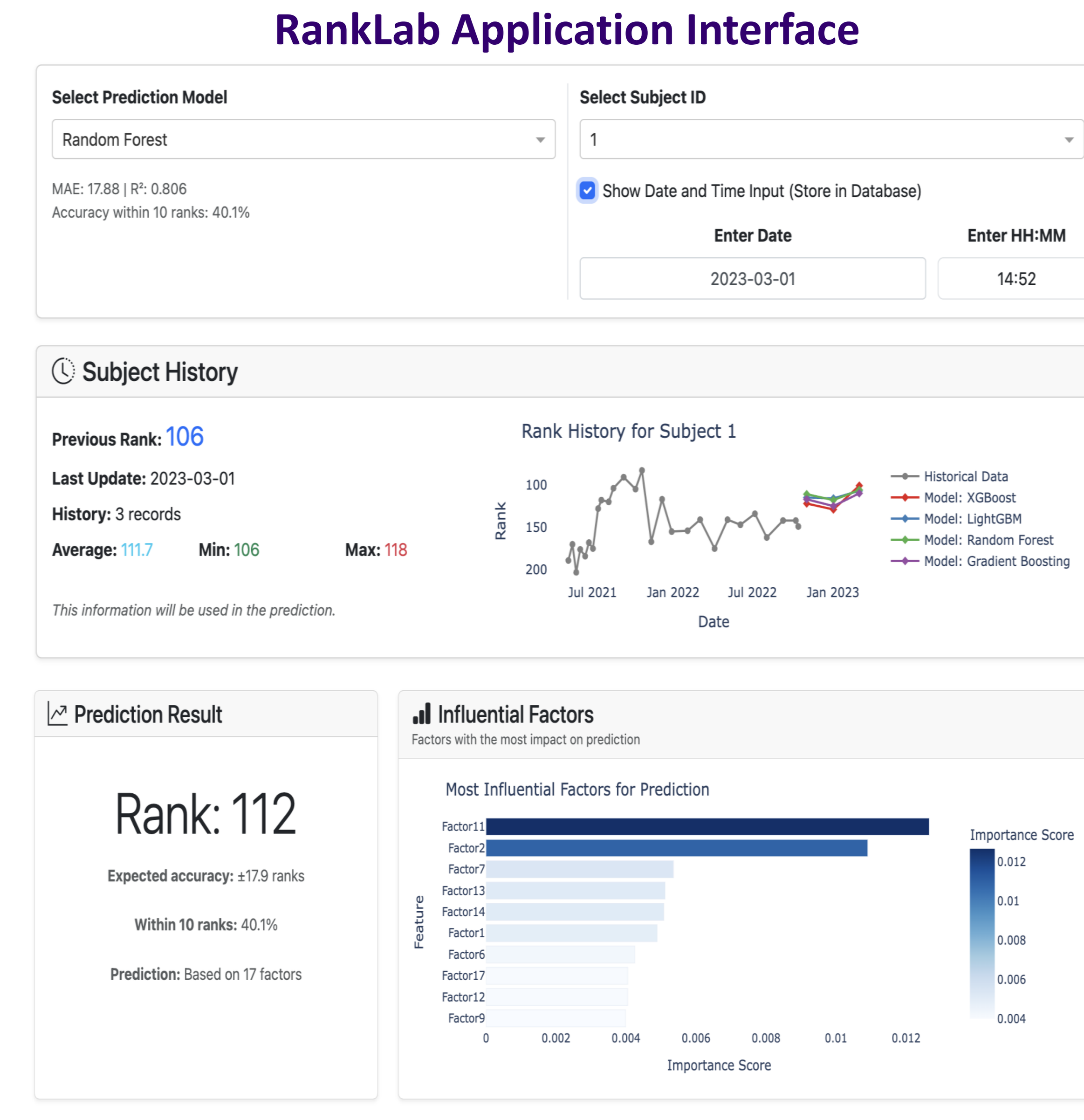


Figure 5. Model Forecasting for SubjectID 1*. The top panel displays a time series plot of rank, with forecasted trends color-coded by model selection. The bottom panel shows the prediction for the selected factors and datetime, along with accuracy metrics and feature importances.*

Our web application incorporates multi-model tracking, providing concurrent visualization of multiple prediction models (LightGBM, XGBoost, Gradient Boosting, and Random Forest) against historical data, enabling direct performance comparisons. Additionally, a summary dashboard offers a consolidated view displaying key performance indicators across suppliers, highlighting rank changes and summary statistics.

Conclusion

Our research demonstrates that tree-based ensemble methods outperform the baseline approaches (median rank and MORD) in ranking prediction accuracy. Positional Random Forest emerged as the superior model for supplier performance forecasting.

This work taught us valuable lessons about handling time-variant ranking problems, particularly when dealing with multiple competing criteria that change over time.

The RankLab application allows stakeholders to interact with the selected models and dynamically input data. In this way, stakeholders can anticipate performance trends rather than merely react to historical data.