Audience Q&A – Predicting Seoul Bike Rental Demand Based on Weather and Temporal Factors

1. What is needed to transition from pilot to full implementation?

The next steps include automating real-time data intake (for weather and rentals), finalizing a user interface like a dashboard, and collaborating with operations teams to integrate predictions into dispatch workflows.

2. How does the model handle unexpected weather shifts?

Currently, models are trained on historical patterns. To handle real-time weather changes, the system would benefit from integrating a live weather API and frequently retraining its models to adapt to new conditions.

3. Would geospatial data improve prediction accuracy?

Absolutely. Adding station-level or neighborhood-specific data would allow for hyper-local forecasts, making it easier to optimize bike distribution in targeted areas.

4. How does holiday demand differ from weekends?

Holiday usage is typically lower than weekends, likely due to reduced commuting. The model reflects this dip, helping to avoid oversupply during non-working holidays.

5. Can these forecasts integrate with mobile apps?

Yes, predictions can be incorporated into rider or admin-facing apps to provide availability alerts, route suggestions, or operational insights.

6. What insights can temperature bands provide to operators?

By grouping temperatures into bands (e.g., Very Cold, Cold, Mild, Warm, Hot), operators can easily anticipate low or high ridership and adjust inventory proactively — for example, reducing deployments during extreme heat.

7. Could prediction errors affect user experience?

Yes, underestimating demand could result in bike shortages, while overestimating might leave bikes sitting unused. Regular retraining and error monitoring are crucial for maintaining a reliable system.

8. How frequently should the model be retrained?

Weekly retraining is ideal, especially during seasonal shifts or weather anomalies. This keeps the model responsive to evolving patterns.

9. Are the models explainable enough for non-technical users?

Yes, decision tree models, such as Random Forest, can be easily visualized and interpreted. Summary dashboards can show which features (like time or weather) are driving predictions.

10. How can this project be expanded to real-time use?

To go real-time, the model would need to run on a cloud platform with scheduled weather pulls and hourly rental updates. Outputs could then feed into live dashboards for on-the-fly decision-making.

11. What would be required to scale this citywide?

Citywide scaling would involve adding geolocation data, mapping rental stations, and potentially clustering demand zones. With that, the same model logic could be applied to multiple locations simultaneously.