Bar Inventory Analysis & Forecasting – Project Summary

1. What is the core business problem and why does it matter?

The core business problem is inventory optimization for a bar. Specifically, the goal is to forecast future consumption of different liquor items and recommend optimal inventory levels such as par levels and reorder points.

This is critical for:
- Avoiding stockouts, which lead to customer dissatisfaction and lost revenue.
- Avoiding overstocking, which ties up capital and increases the risk of spoilage (especially for perishable mixers or seasonal items).
- Data-driven procurement, enabling better negotiation with suppliers and logistics planning.

Effective forecasting ensures a smooth bar operation, enhances customer experience, and improves overall profitability.

2. What assumptions did you make? Why?

- Historical consumption reflects future demand: Assumed because seasonality and trends are captured in historical usage patterns.

- Data quality is reliable after cleaning: Cleaning steps like handling mixed datetime formats and dropping invalid entries ensure modeling accuracy.

- Lead time and safety stock are static or inferred: For reorder point calculations, standard formulas are used assuming fixed lead time.

- Each item behaves independently: No correlation between consumption patterns of different SKUs is assumed for simplicity.

These assumptions simplify the modeling process while remaining realistic for a first-phase deployment.

3. What model did you use and why did you choose it? Why not others?

Several models were explored:

- Moving Averages: Useful for understanding trends, but not sufficient for prediction due to lag.

- ARIMA: Applied for items with stable seasonality and stationarity after differencing. It models autocorrelation well.

- Prophet (Facebook): Selected for its strength in handling seasonality, holidays, and missing data. It requires minimal tuning and works well with business time series.

Why these models?
- Both ARIMA and Prophet were chosen for their interpretability, forecasting accuracy, and flexibility with time series data.
- Models like LSTM or XGBoost were not used to avoid overfitting or unnecessary complexity given the dataset size.

4. How does your system perform? What would you improve?

The models provided reasonable short-term forecasts, especially when seasonality was visible.

Inventory simulations identified ideal par levels and reorder points, supporting procurement decisions.

Possible improvements:
- Incorporate sales and event data (e.g., holidays, promotions) to better capture spikes in demand.

- Introduce dynamic safety stock levels based on demand volatility.

- Use multi-variate forecasting or ensemble models for higher accuracy.

5. How would this solution work in a real hotel?

1. Daily/Weekly Consumption Data would be logged via POS systems.

2. The model would generate automated consumption forecasts.

3. The system would then suggest:
   - Par level: Minimum stock level to maintain.
   - Reorder Point: When to order next, based on lead time.

4. Inventory manager gets alerts if actual stock drops below reorder point.

This would ensure smooth service, reduce waste, and allow better supplier planning.

Optional: What would break at scale? What would you track in production?

Challenges at scale:

- Data volume from multiple outlets might slow down computation.

- Inconsistent naming of items could create data integrity issues.

- Holiday/event-driven spikes may not be captured unless explicitly modeled.

What to track:

- Forecast vs actual consumption error (e.g., MAE, RMSE).

- Stockout events and associated lost revenue.

- Inventory turnover ratio and holding costs.

- Feedback loop for model retraining every X weeks.