Red Bull Case Study

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Rainer Widmann, 02/19/2026

Agenda

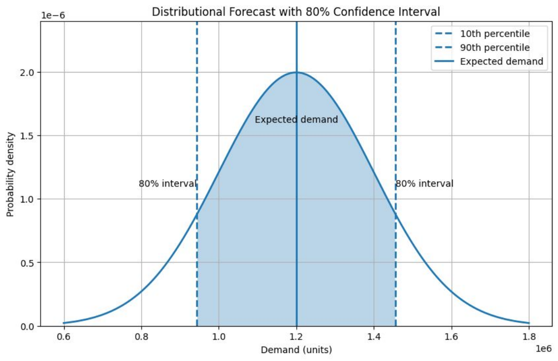
- Why Distributional Demand Forecasts are Useful
- Exploratory Analysis of Demand
- Forecasting Future Demand
- Notes on Forecasting Background
- Moose Hunting

Why Distributional Forecasts are Useful

- Demand uncertainty
  - Demand varies substantially over time, often due to factors that are unforeseeable
- Limitation of traditional point forecasts
  - Traditional forecasting produces a point forecast (single expected value)
  - Point forecasts do not quantify the risk of higher or lower demand realizations
- Inventory implications
  - Underestimating demand → stockouts and lost sales
  - Overestimating demand → excess inventory and higher holding costs

Why Distributional Forecasts are Useful

- Distributional forecasts
    - Forecasts provide a distribution of possible demand outcomes, not just a single value
    - **Confidence intervals** define the range in which demand is likely to fall
    - Example: an 80% confidence interval contains actual demand in approximately 80% of cases



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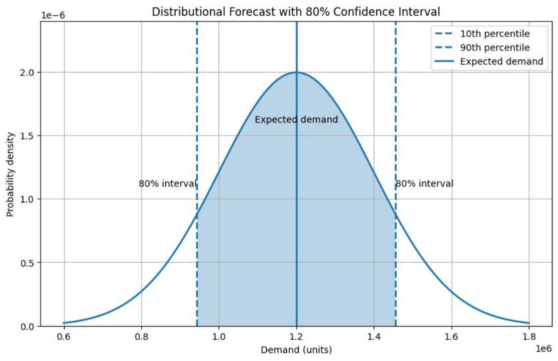
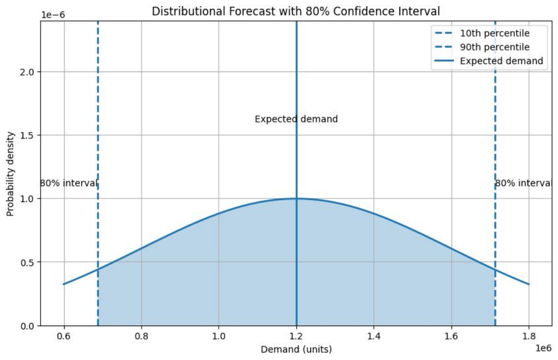
  - Wider intervals indicate higher uncertainty, narrower intervals indicate more predictable demand





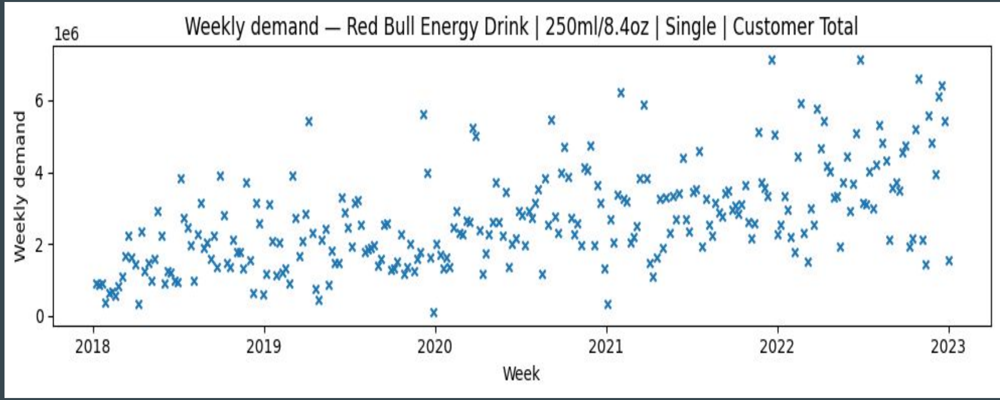
Why Distributional Forecasts are Useful

- Inventory decisions involve a trade-off between two costs
  - Overstock → holding costs
  - Understock → lost sales
- Distributional forecasts quantify the cost of inventory decisions
  - The demand distribution allows computing the total costs across all possible demand realizations
  - This enables selecting the inventory level that minimizes expected total cost
- Optimal inventory policy
  - Each service level corresponds to a quantile in the demand distribution
  - Example: stocking at the 80th percentile ensures demand is covered in ~80% of periods

Exploratory Analysis of Demand

- **Demand dataset:**
  - **Measured in units sold (number of SKUs)**
  - **7 SKUs** differing by
    - **Flavor** (Energy Drink, Blue Edition, Watermelon,.) and
    - **Size** (250ml, 355 ml, 4-Packs)
  - **3 Customer** (Groups)
    - A, B and C
  - **Time coverage**
    - Daily demand data from Jan 2018 until Dec 2022
    - No demand observation on weekends (Saturday, Sunday)
  - **Data Completeness**
    - Some product–customer combinations lack observations during certain periods
    - Negative values present, interpretation unclear

Exploratory Analysis of Demand



- Demand shows large spikes and sudden drops
- Extreme outlier occur

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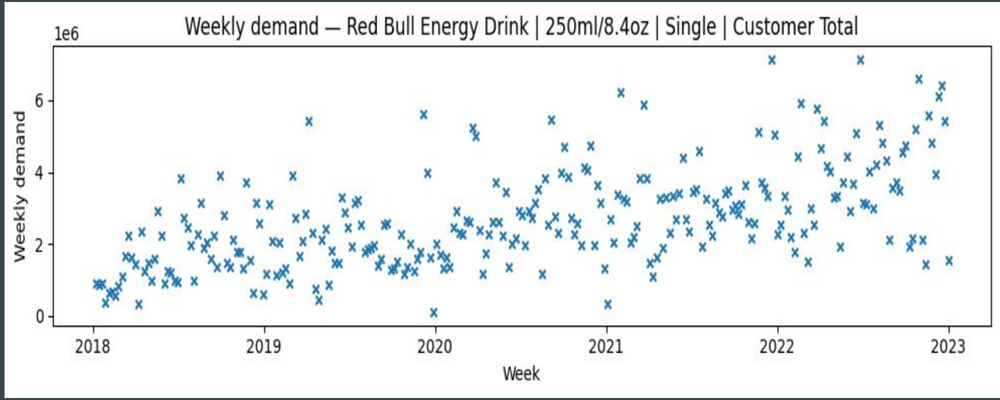

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- No visually apparent seasonality

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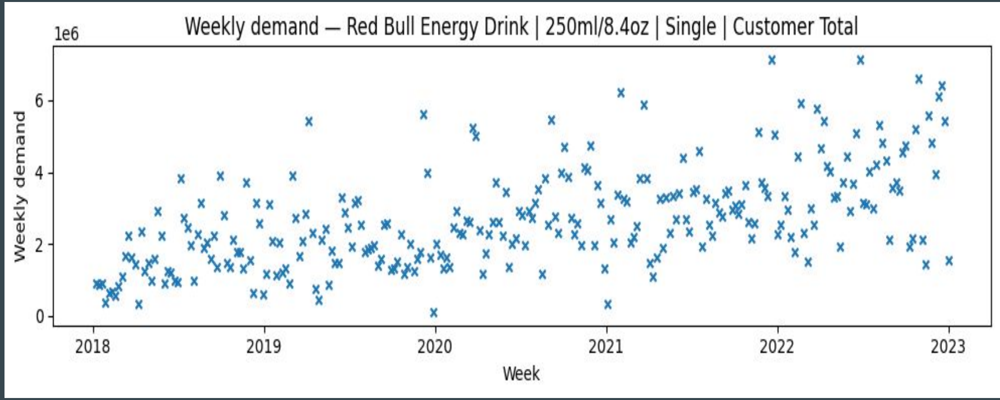

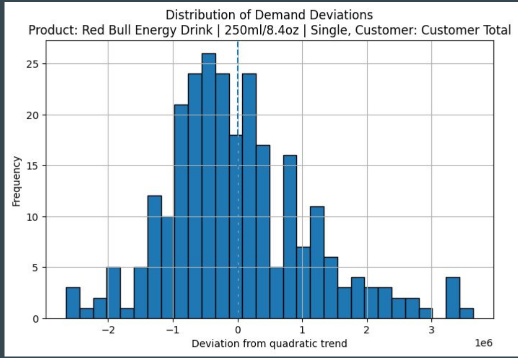

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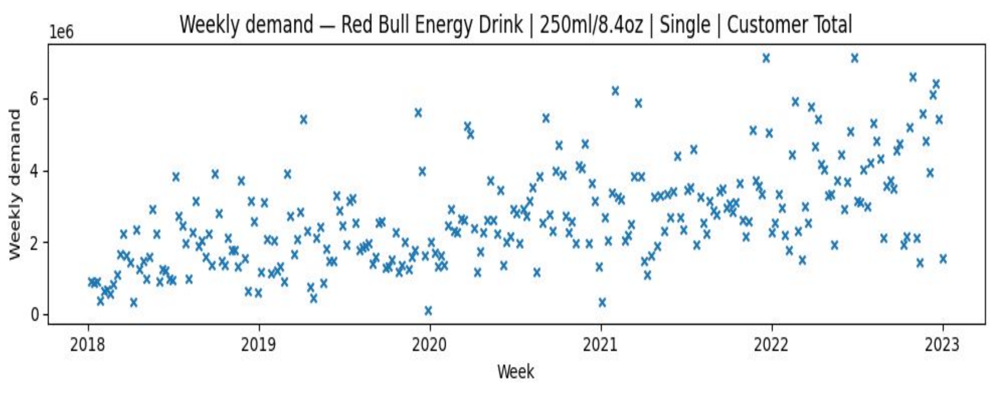

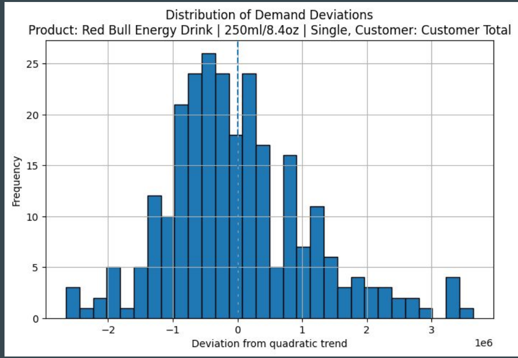

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Demand appears highly volatile and unpredictable

Exploratory Analysis of Demand

- Key data considerations:
  - **Demand availability and truncation:**
    - Are there periods where products were unavailable, resulting in censored demand?
    - Can stock availability data be incorporated to estimate latent demand?
  - Promotion and external demand drivers:
    - Do we have data on past promotions or marketing activities explaining demand spikes?
    - Can future promotion plans be incorporated to improve forecast accuracy?
  - Data quality and reporting rules
    - What do negative demand values represent (e.g., returns, corrections)?
    - Do missing values represent true zero demand or missing observations?
    - What is the exact definition of Customer Groups A, B and C?
    - What explains the observed large outliers and extreme short-term variability?

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Reliable forecast requires data clarifications and additional external data

Forecasting Future Demand

- Forecast structure
  - Weekly demand distributions forecasted separately for each product
  - Customer groups A, B, and C aggregated to reflect inventory constraints
  - Missing values treated as zero demand
  - Focus on 5 products with complete historical coverage

Forecasting Future Demand

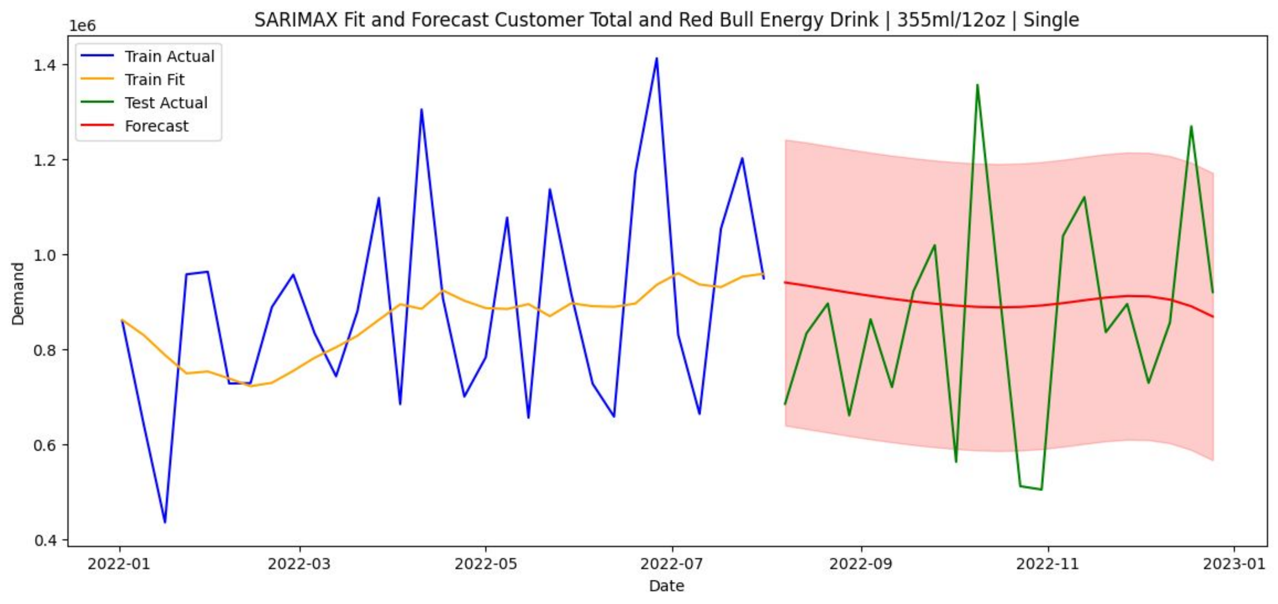
- Forecast structure
  - Weekly demand distributions forecasted separately for each product
  - Customer groups A, B, and C aggregated to reflect inventory constraints
  - Missing values treated as zero demand
  - Focus on 5 products with complete historical coverage
- Training and validation framework
  - Models trained on Jan 2018 – Jul 2022
  - Performance evaluated using rolling backtests with 12-week forecast horizon
  - Models selected based on accuracy of 80% prediction interval coverage
- Out-of-sample evaluation
  - Final model re-estimated and evaluated on Aug 2022 – Dec 2022 test set
  - Ensures reliable performance on unseen future demand

Forecasting Future Demand

- Model specification
  - Parametric Dynamic Regression Model, estimated separately for each product
  - Models weekly demand as a function of
    - Polynomial time trend (long-term demand evolution)
    - Weekly seasonality
    - Payday effect (exogenous demand driver)
  - Random shocks modeled using parametric error distribution
- Hyperparameters:
  - ARIMA structure for serial correlation in errors
    - autoregressive order (p), differencing (d), moving average (q)
  - Error distribution: Gaussian
  - Polynomial trend order (k)
  - Seasonal Fourier order (l)
  - Hyperparameters selected via rolling backtests optimizing 80% prediction interval coverage
    - 12-weeks forecast horizon at origin dates: 6/30/2021,12/31/2021, 4/30/2022

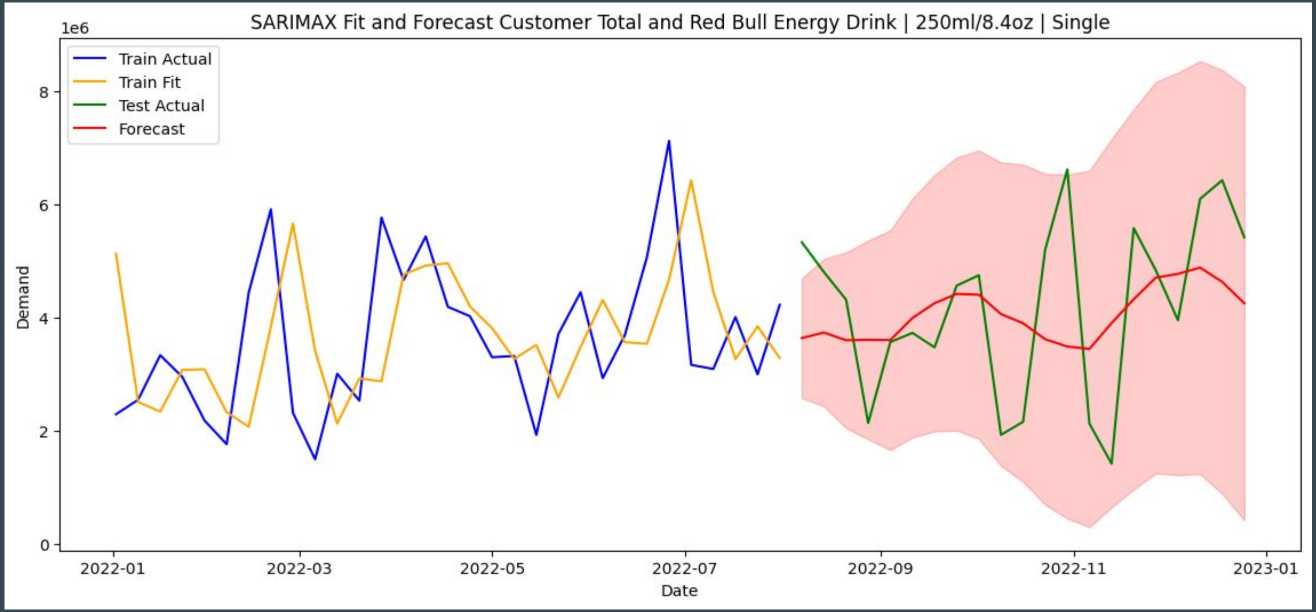
Forecasting Future Demand

- Red Bull Energy Drink | 355 ml/12oz | Single
  - Forecast origin: 7/31/2022, Forecast horizon: 8/1/2022-12/31/2022 (20 weeks)
  - 80% prediction interval coverage: 15/20 weeks (=75%)



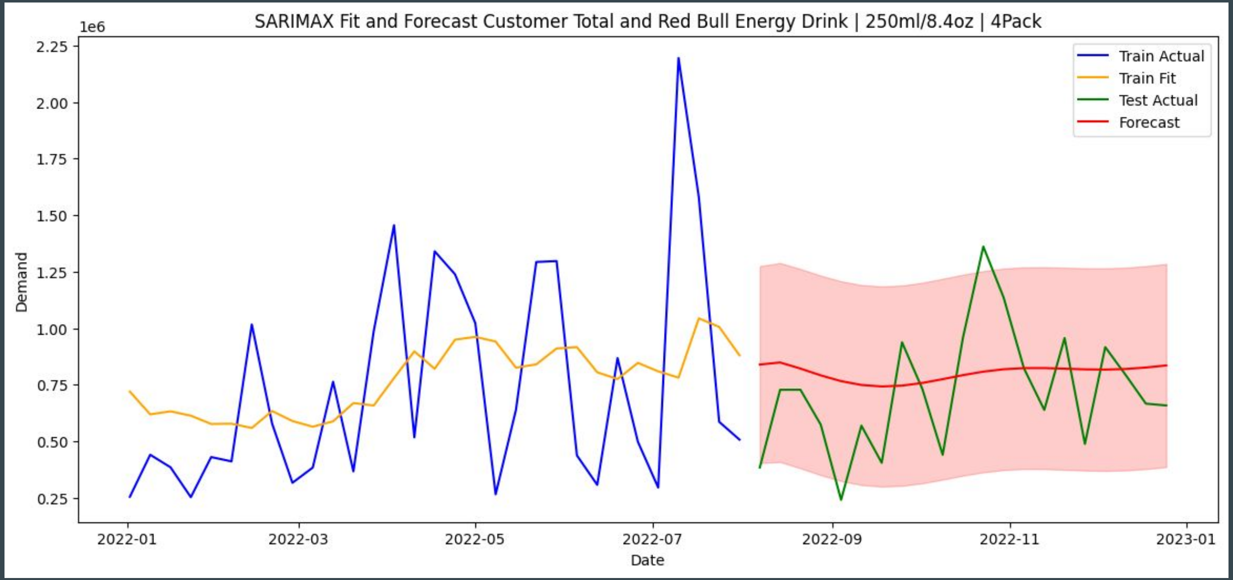
Forecasting Future Demand

- Red Bull Energy Drink | 250 ml/12oz | Single
  - Forecast origin: 7/31/2022, Forecast horizon: 8/1/2022-12/31/2022 (20 weeks)
  - 80% prediction interval coverage: 18/20 weeks (=90%)



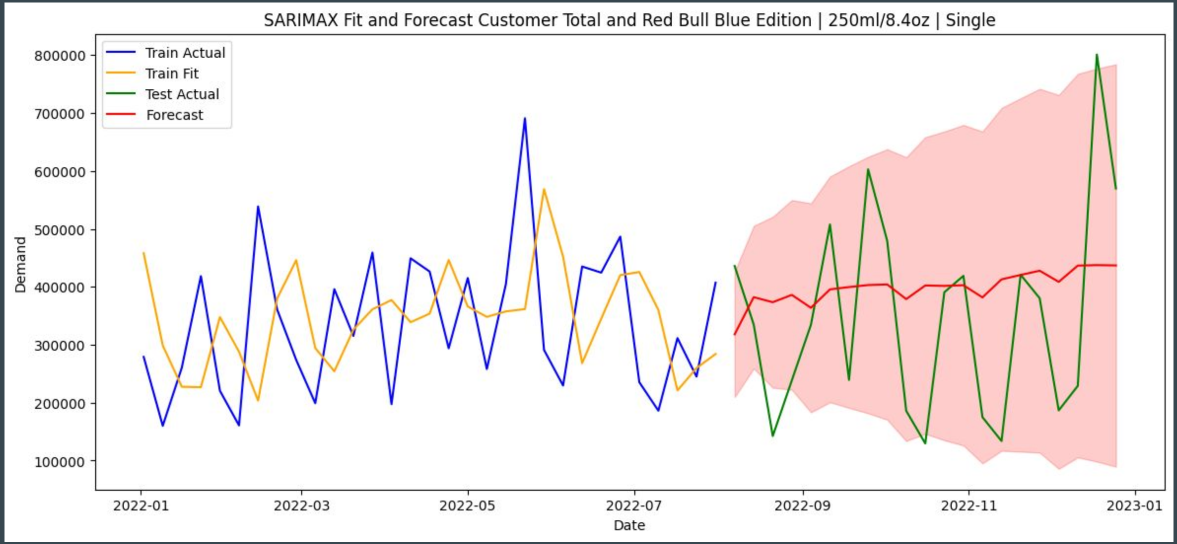
Forecasting Future Demand

- Red Bull Energy Drink | 250 ml/12oz | 4Pack
  - Forecast origin: 7/31/2022, Forecast horizon: 8/1/2022-12/31/2022 (20 weeks)
  - 80% prediction interval coverage: 17/20 weeks (=85%)



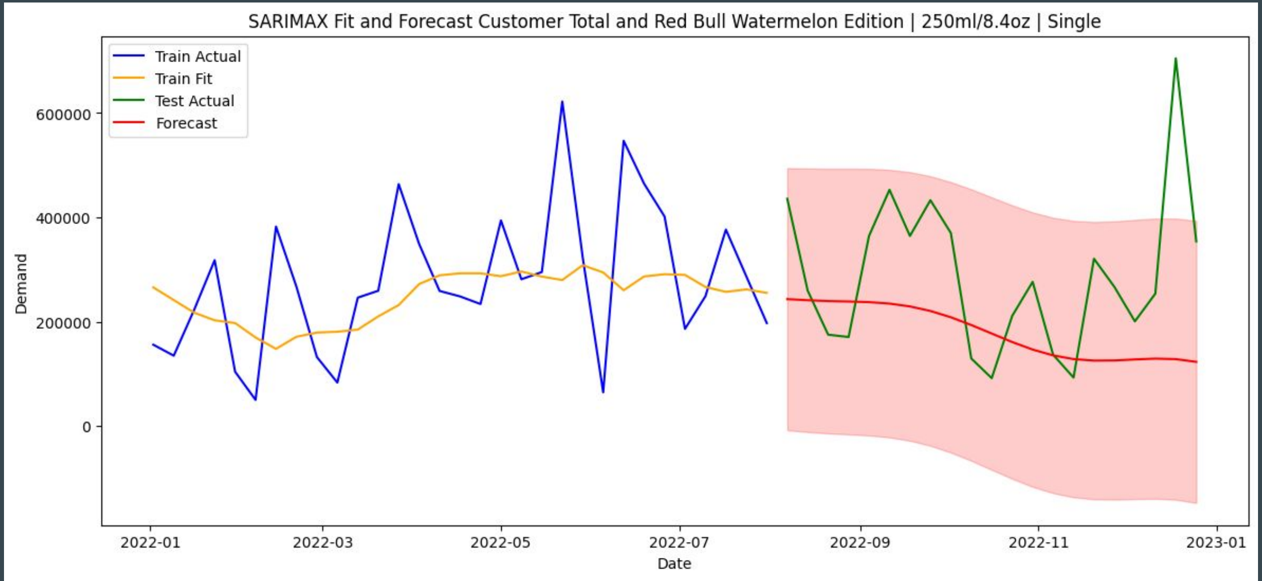
Forecasting Future Demand

- Red Bull Blue Edition | 250 ml/12oz | 4Pack
  - Forecast origin: 7/31/2022, Forecast horizon: 8/1/2022-12/31/2022 (20 weeks)
  - 80% prediction interval coverage: 17/20 weeks (=85%)



Forecasting Future Demand

- Red Bull Watermelon Edition | 250 ml/12oz | 4Pack
  - Forecast origin: 7/31/2022, Forecast horizon: 8/1/2022-12/31/2022 (20 weeks)
  - 80% prediction interval coverage: 19/20 weeks (=95%)



Forecasting Theory

- Demand is a stochastic process driven by systematic factors and randomness:
    - Demand$_t$ = f(Trend, Seasonality, External Factors, Past Demand, Random Shock$_t$)
        - Function captures systematic components of demand and
        - Irreducible randomness (the shock)
    - Estimate this relationship based on (past) data
        - Provided it is stable over time (“stationary”)
- Distributional forecast at time t
    - Forecast the distribution of demand for period t+n, given observed demand and systematic components up to time t, and the distribution of the (future) random shocks
    - Two sources of randomness:
        - random shocks (and their propagation over time)
        - uncertainty in the estimated relationship with systemic factors
- Model validation is essential
    - Misspecification of the functional form or error structure can lead to incorrect forecast distributions, so models must be validated using out-of-sample performance

Forecasting Theory

- Hierarchical Forecasting
  - Demand forecasts may be conducted at a disaggregated level (e.g. customers A, B and C separately) or at the aggregate (e.g. customers A, B and C summed)
  - The demands of the disaggregated components, and their forecasts, are generally jointly dependent
  - Forecasting the aggregate benefits from a diversification effect, reducing uncertainty (unless the components are perfectly correlated)
  - Conversely, forecasting at the disaggregated level allows better modeling of heterogeneity in systematic demand drivers (e.g., trends, seasonality, external effects)
  - The right granular level for forecasting is determined by operational factors, at the level where replenishment is slow or inflexible
    - e.g. if a warehouse is replenished weekly, which in turn replenishes locations daily, the relevant level for the forecast is the warehouse-level

Moose hunting

```python
def p_m(h,m):
    if m>=12:
        return 1
    if h>=m:
        return 0
    p=1/6*( p_m(h,m+1)+
            p_m(h,m+2)+
            p_m(h,m+3)+
            p_m(h,m+4)+
            p_m(h+5,m)+
            p_m(h+6,m)
          )
    return p
```

✓ 0.0s Python

```python
p_m(1,7)
```

✓ 0.0s Python

```
0.6127829218106995
```

Conceptual approach:

- start from all states (h,m) where the hunter or the moose has won (m>=12, h>=m), p_m=1 or p_m=0
- Compute the win probability for the states (10,11), (9,11),(8,11), (7,11) where p_m is known for all possible subsequent states
- Recursively compute p_m for all states where the possible subsequent states have a known p_m (e.g. (10,10) can be computed once (10,11) is etc.)