

# Red Bull Case Study

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Rainer Widmann, 02/14/2026

# Agenda

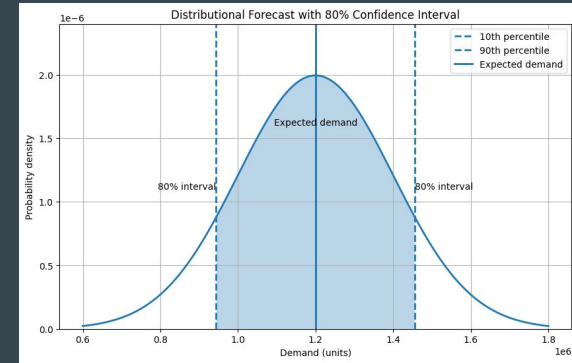
- Why Distributional Demand Forecasts are Useful
- Exploratory Analysis of Demand
- Forecasting Future Demand
- Notes on Forecasting Background
- Moose Hunting

# Why Distributional Forecasts are Useful

- Demand uncertainty
  - Demand varies substantially due to customer behavior and unforeseeable external factors
  - Actual demand often deviates significantly from forecasted levels
- 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

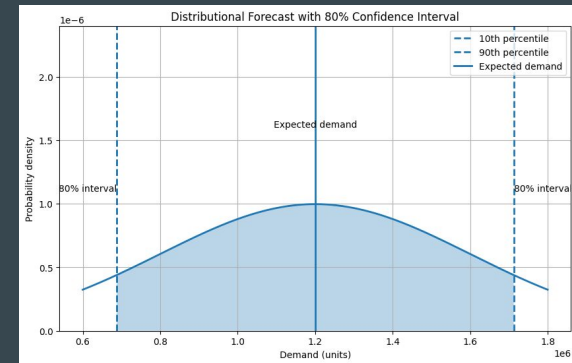
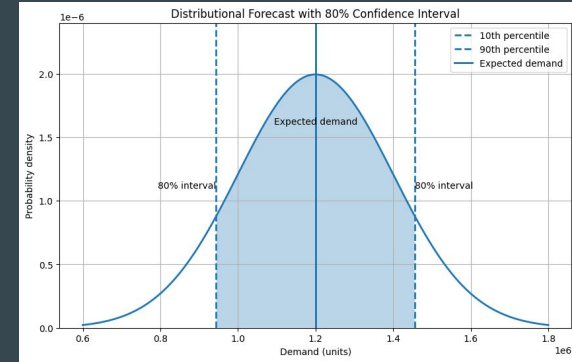
# Why Distributional Forecasts are Useful

- 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



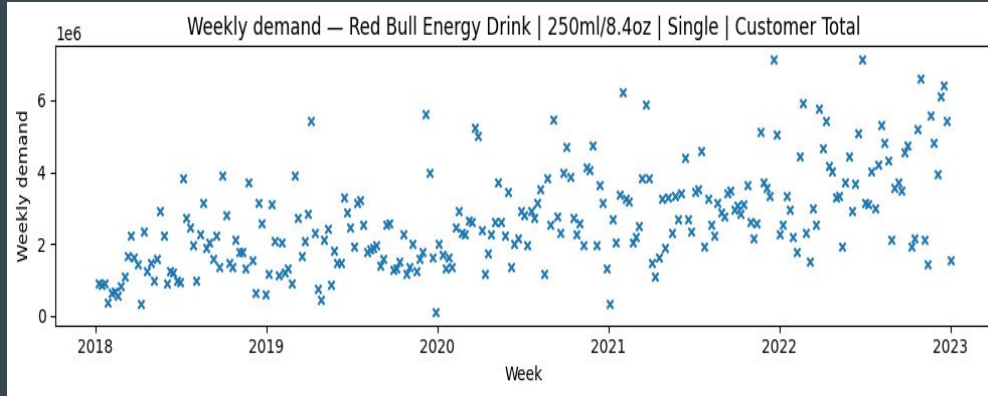
# Why Distributional Forecasts are Useful

- 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

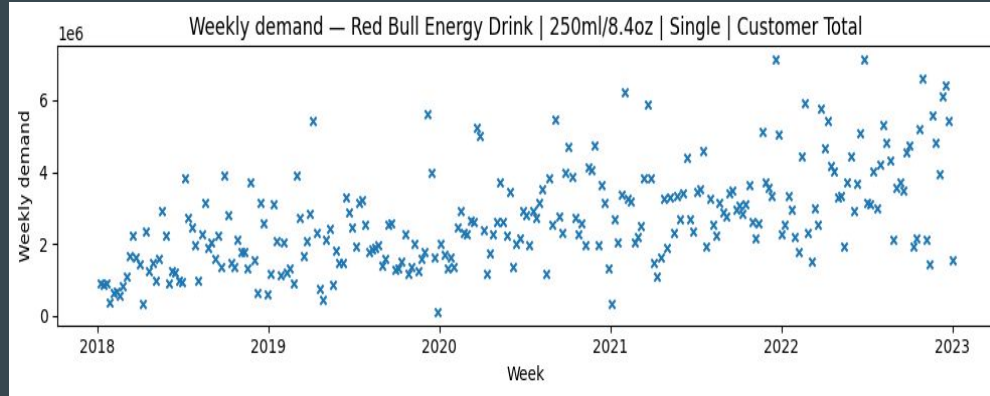
# Exploratory Analysis of Demand



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

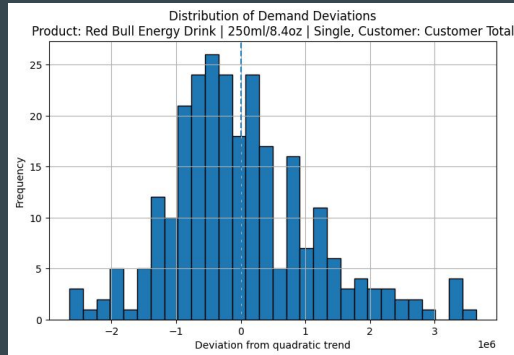
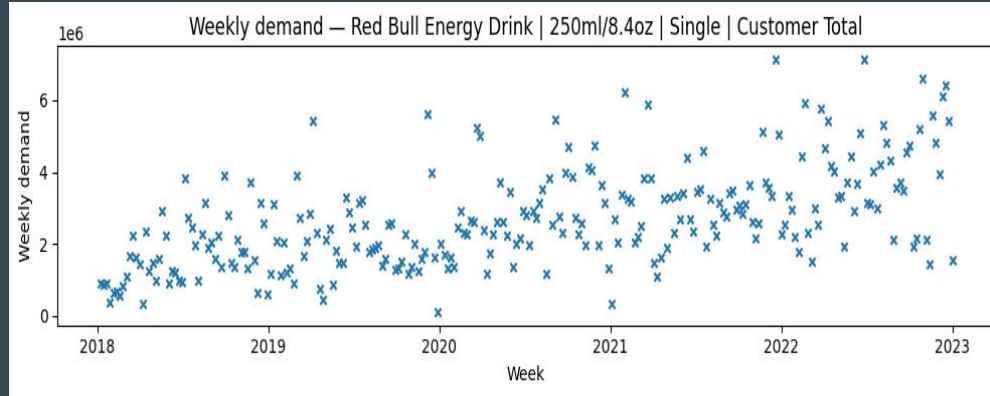


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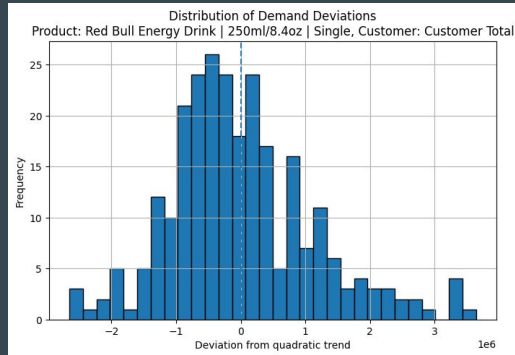
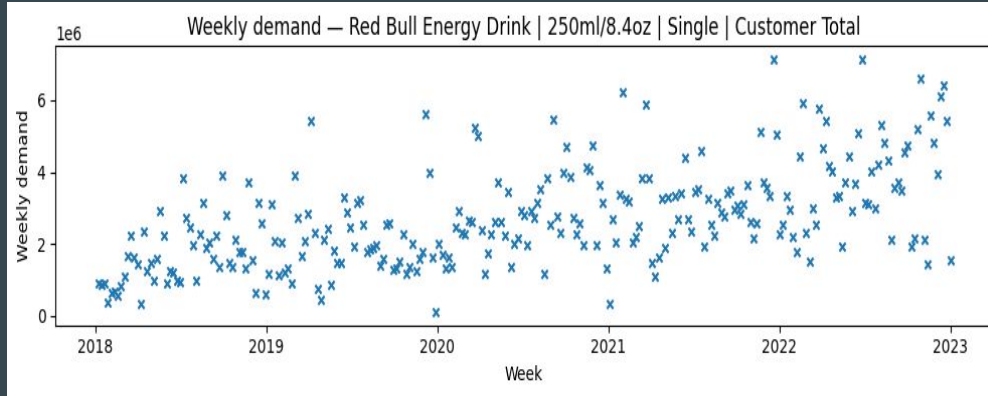
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- No visually apparent seasonality

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**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 distinguish zero demand from zero availability?
  - 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 4 products with complete historical coverage

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  - 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 4 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

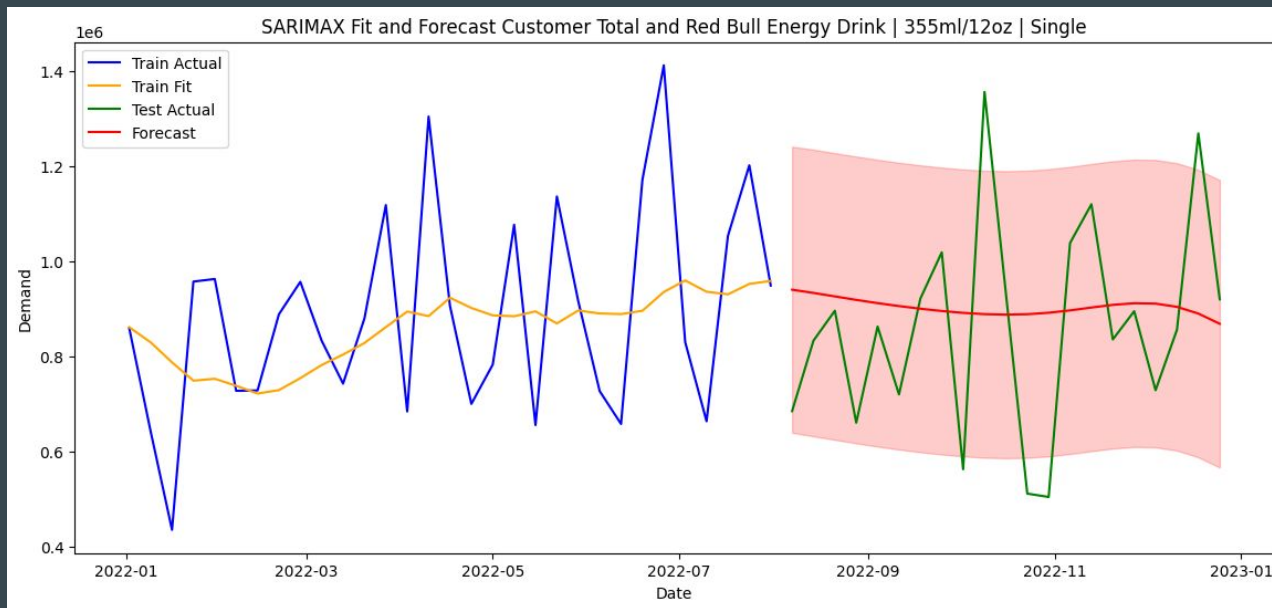
# Forecasting Future Demand

- 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)
  - Residual variability modeled using parametric error distribution
- Hyperparameters:
  - ARIMA structure for serial correlation in errors
    - autoregressive order (p), differencing (d), moving average (q)
  - Error distribution: Gaussian, Gamma
  - 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



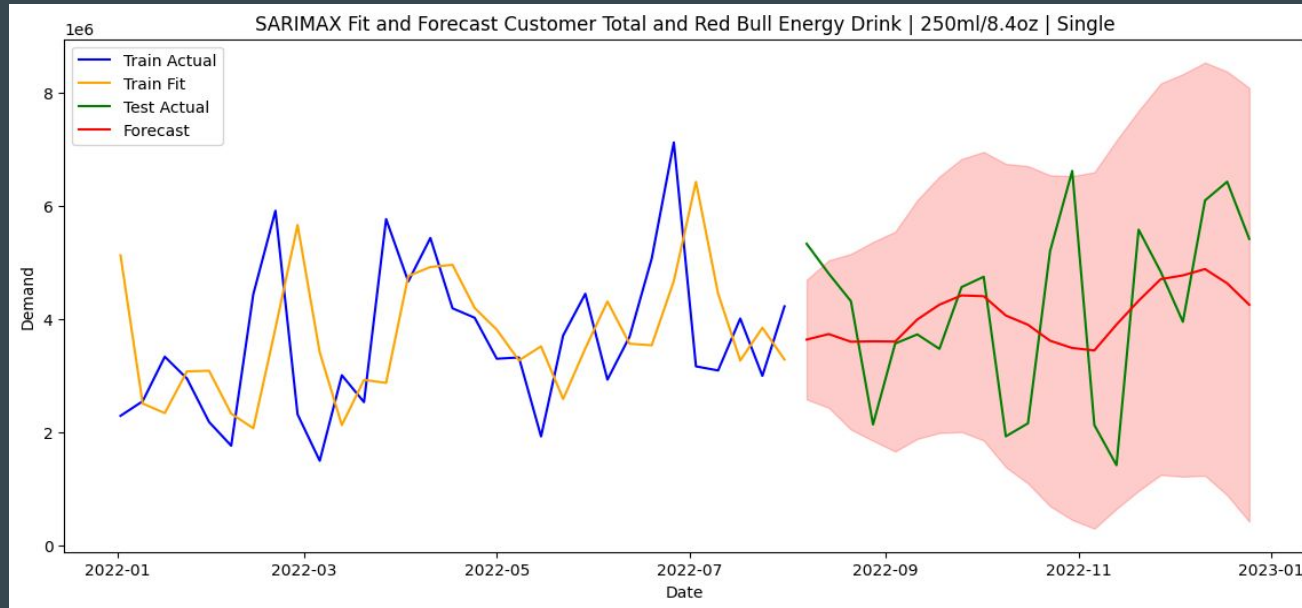
# Forecasting Future Demand

- 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%)



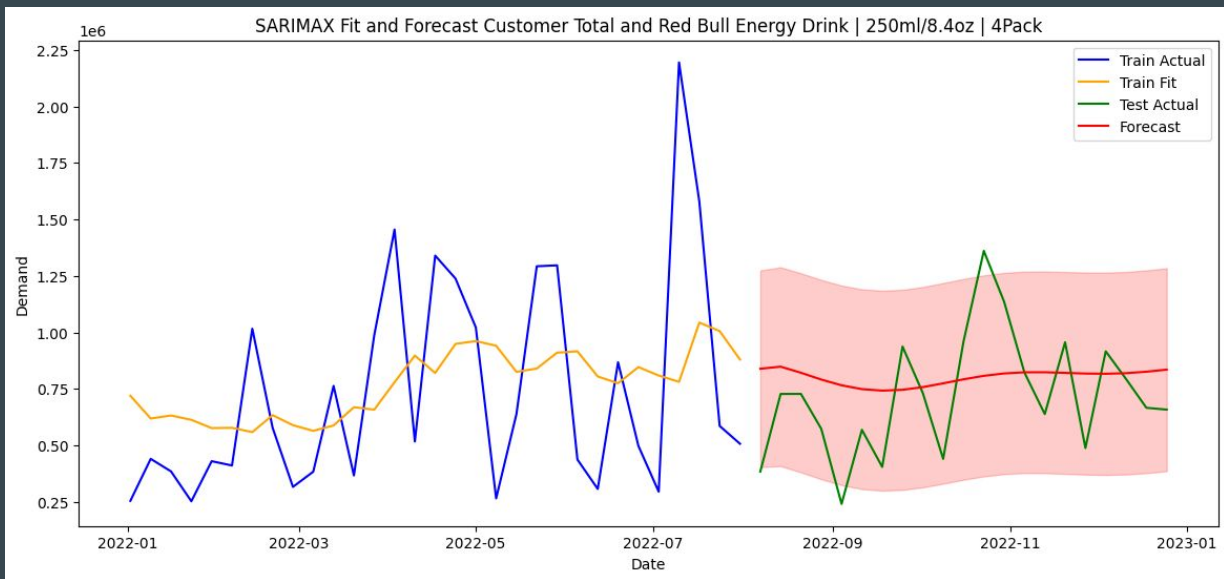
# Forecasting Future Demand

- 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%)



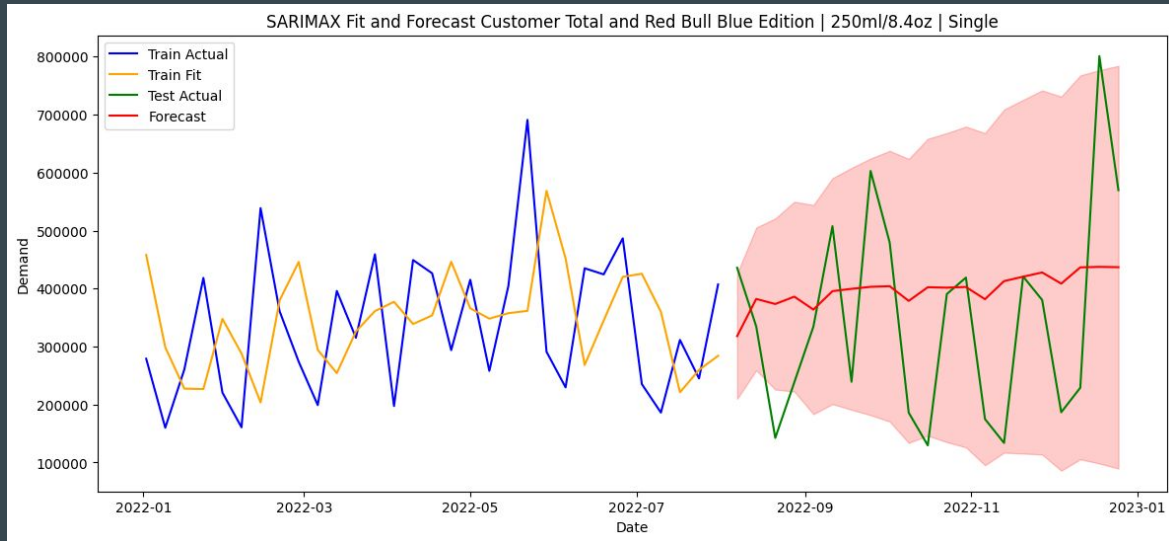
# Forecasting Future Demand

- 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%)



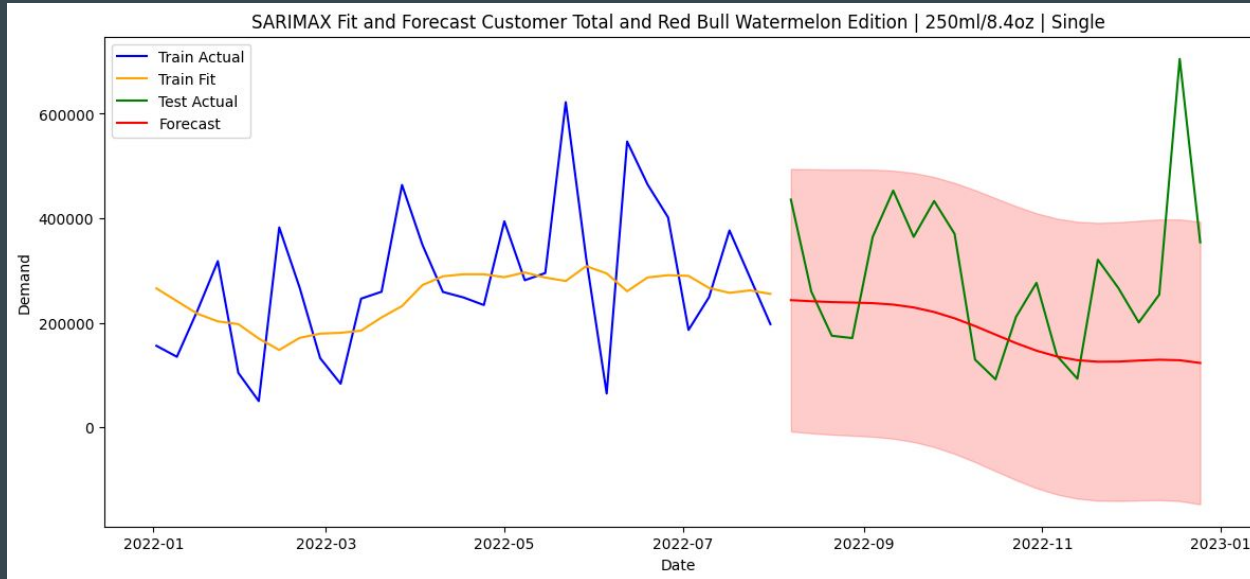
# Forecasting Future Demand

- 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%)



# Moose hunting

```
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

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 ( $m \geq 12$ ,  $h \geq m$ ),  $p_m = 1$  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.)