

Red Bull Case Study

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Rainer Widmann, 02/14/2026

Agenda

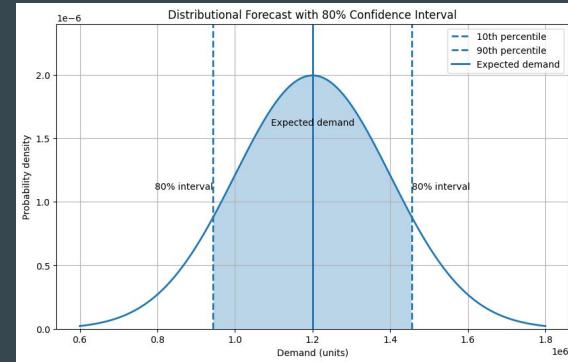
- Why Distributional Demand Forecasts are Useful
- Exploratory Analysis of Demand
- Forecasting Future Demand
- Notes on Forecasting Background
- Moose Hunting

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

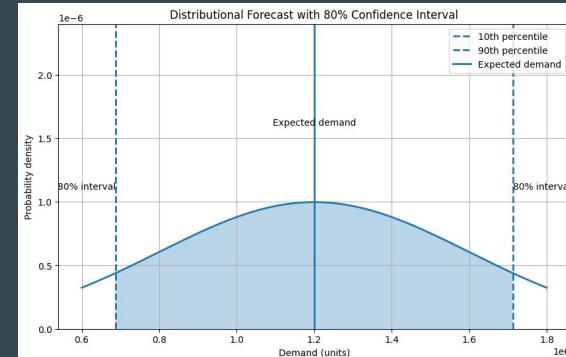
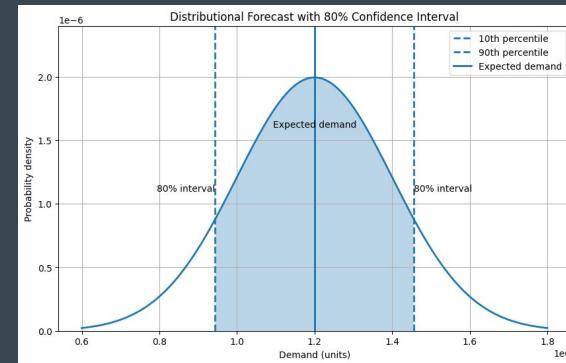
Why Distributional Forecasts are Useful

- 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



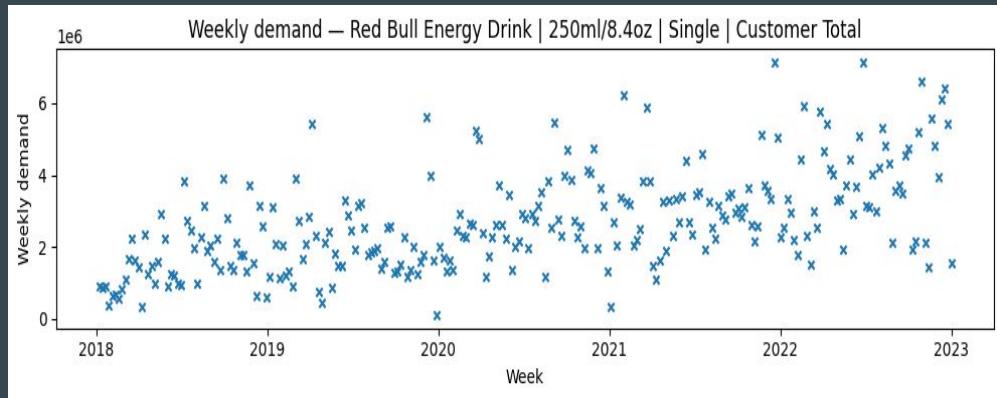
Why Distributional Forecasts are Useful

- 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

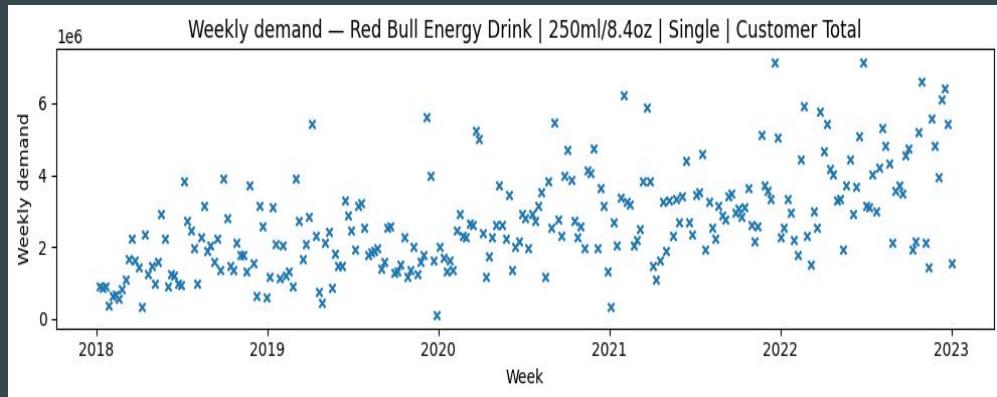
- **Demand dataset:**
 - **Measured in units sold (number of SKUs)**
 - **7 SKUs** differing by
 - **Flavor** (Energy Drink, Blue Edition, Watermelon,.) and
 - **Size** (250ml, 355 ml, 4-Packs)
 - **3 Customer** (Groups)
 - A, B and C
 - **Time coverage**
 - Daily demand data from Jan 2018 until Dec 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



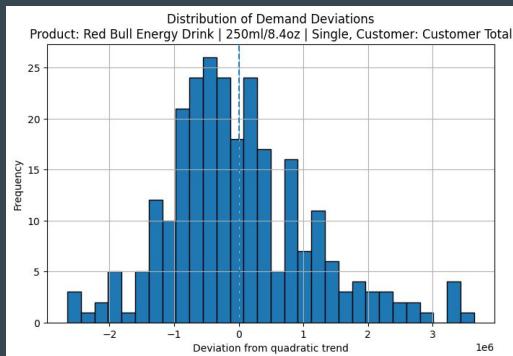
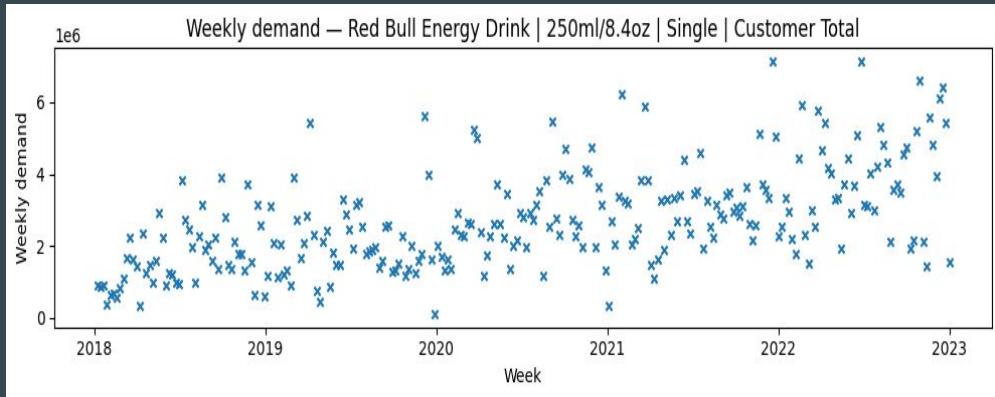
- Demand shows large spikes and sudden drops
- Extreme outlier occur

Exploratory Analysis of Demand



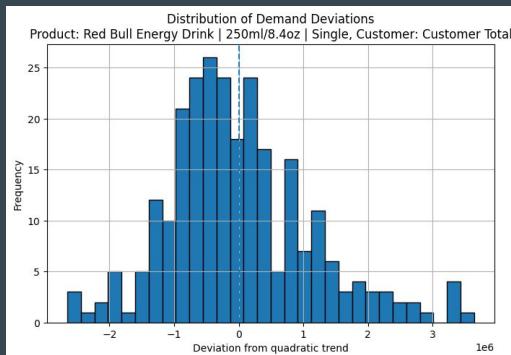
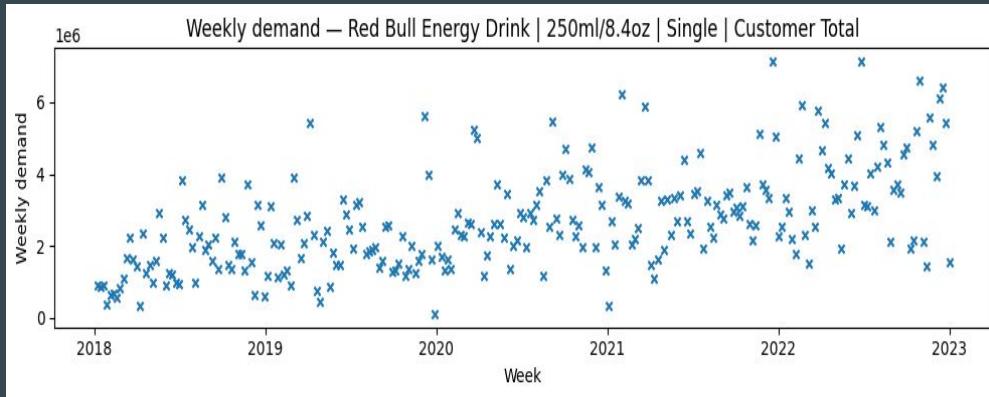
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- Substantial variation, even across consecutive days and weeks
- No visually apparent seasonality

Exploratory Analysis of Demand



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- High variability persists after removing trends

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

Forecasting Future Demand

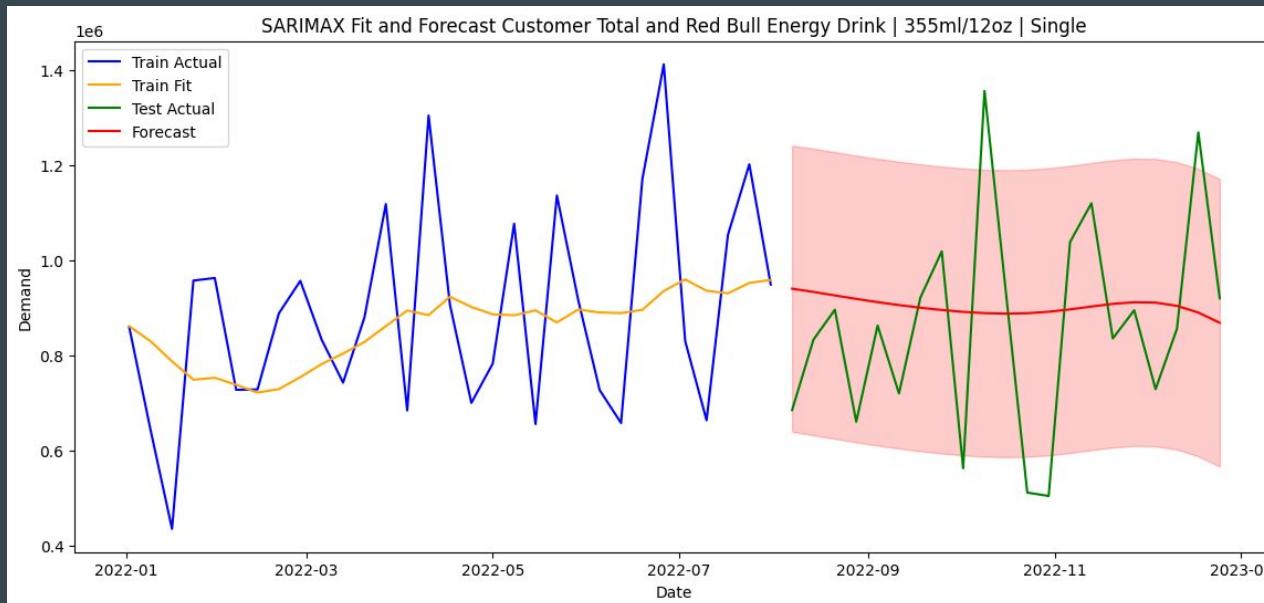
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 - Weekly demand distributions forecasted separately for each product
 - Customer groups A, B, and C aggregated to reflect inventory constraints
 - Missing values treated as zero demand
 - Focus on 4 products with complete historical coverage
- Training 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

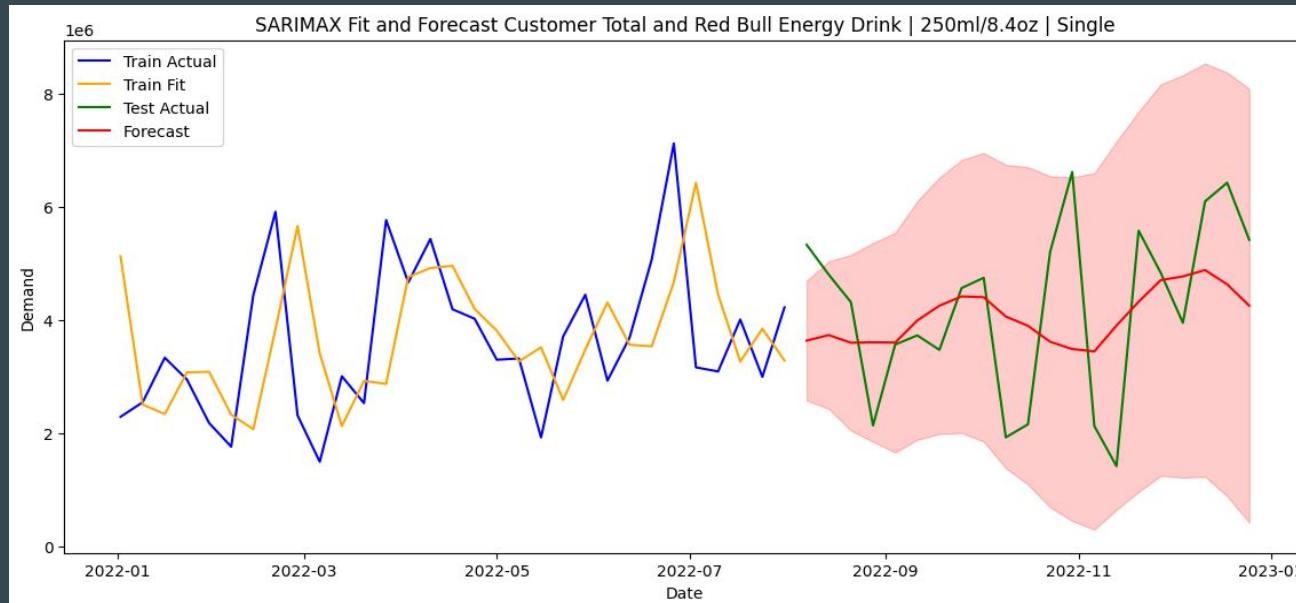
Forecasting Future Demand

- 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%)



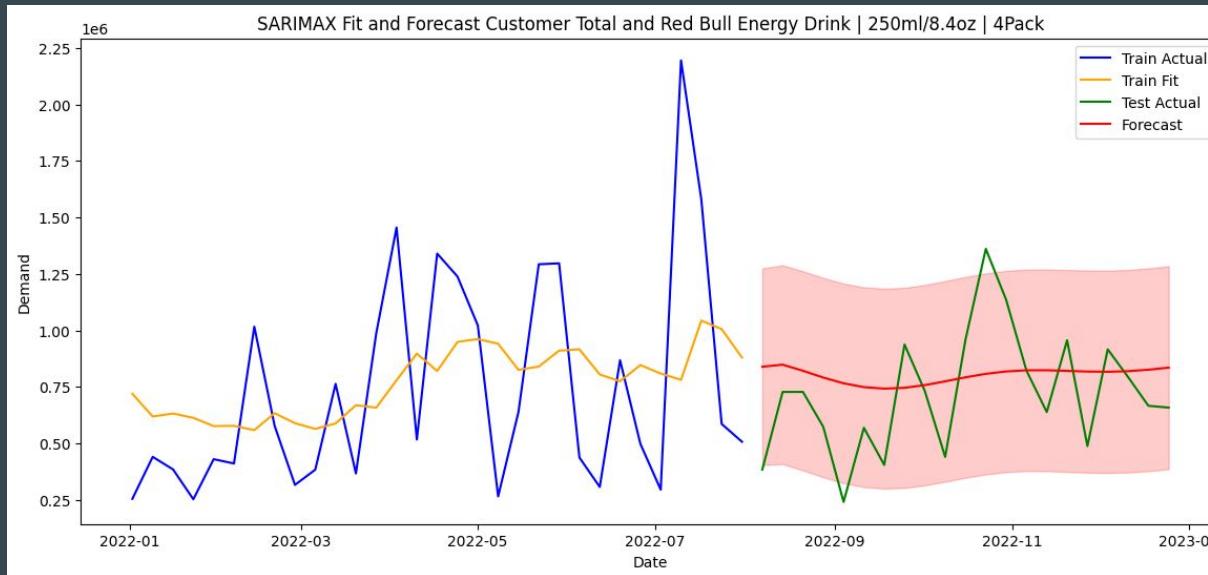
Forecasting Future Demand

- 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%)



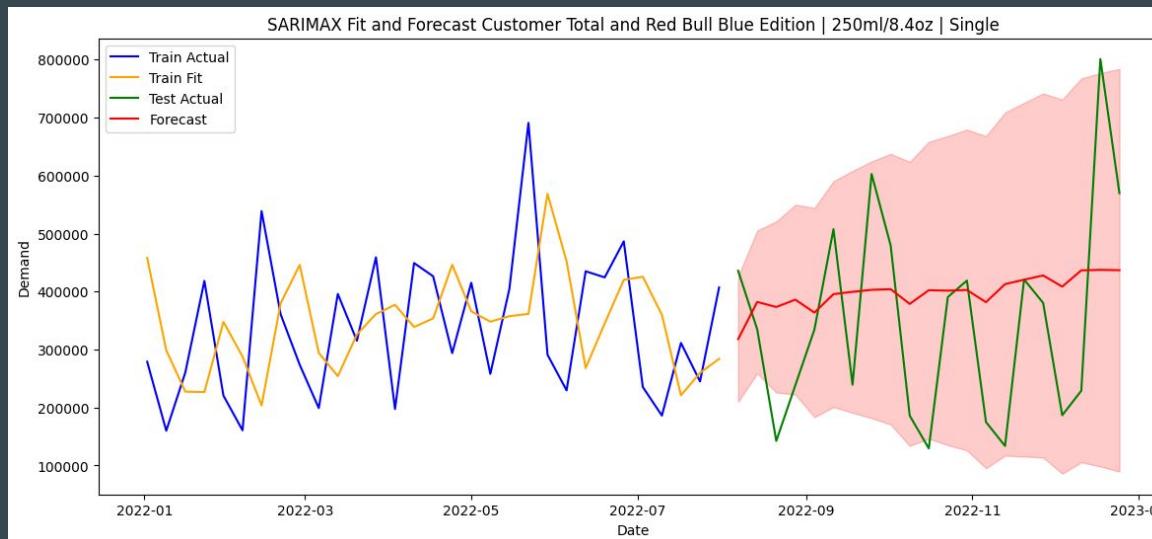
Forecasting Future Demand

- 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%)



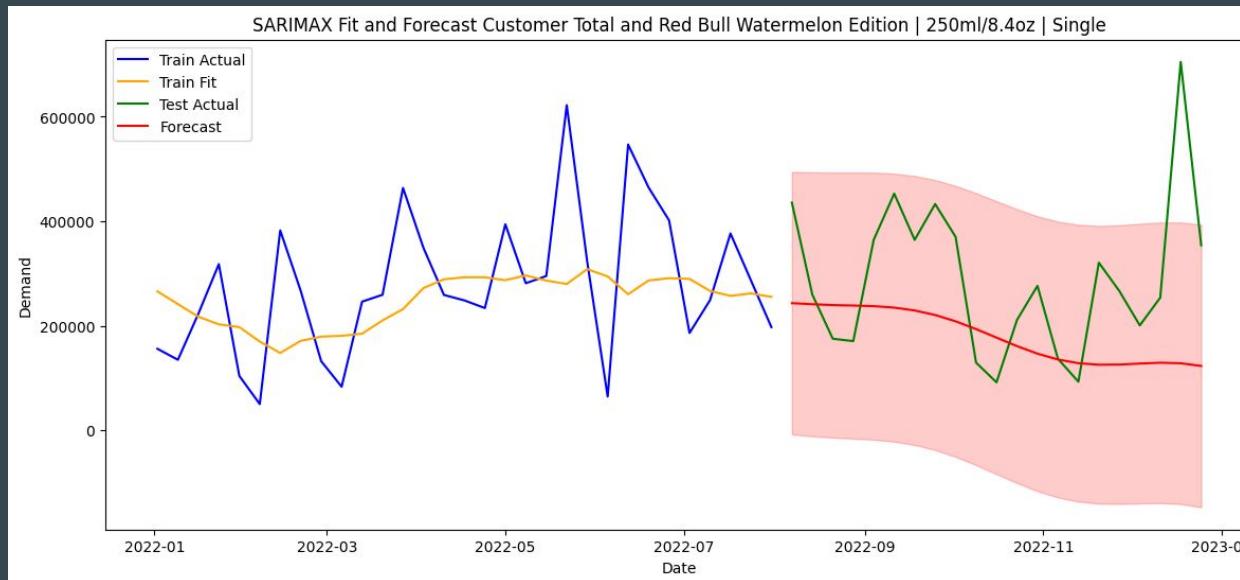
Forecasting Future Demand

- 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

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

✓ 0.0s

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.)