Anaplan

Driving a new age of connected planning

Statistical Forecasting Methods

Overview of all Methods from Anaplan Statistical Forecast Model

Predictive Analytics

30 Forecast Methods

Including:

- Simple Linear Regression
- Simple Exponential Smoothing
- Multiplicative Decomposition
- Holt-Winters
- Croston’s Intermittent Demand

Forecasting Methods Summary

Curve Fit

Capture historical trends and project future trends, cyclical or seasonality factors are not factored in.

- ✓ Trend analysis
- ✓ Long term planning

Smoothing

Useful in extrapolating values of given non-seasonal and trending data.

- ✓ Stable forecast for slow moving, trend & non-seasonal demand
- ✓ Short term and long term planning

Seasonal Smoothing

Break down forecast components of baseline, trend and seasonality.

- ✓ Good forecasts for items with both trend and seasonality
- ✓ Short to medium range forecasting

Basic & Intermittent

Simple techniques useful for specific circumstances or comparing effectiveness of other methods.

- ✓ Non-stationary, end-of-life, highly recurring demand, essential demand products types
- ✓ Short to medium range forecasting

Forecasting Methods List

Curve Fit

Linear Regression
Logarithmic Regression
Exponential Regression
Power Regression

Smoothing

Moving Average
Double Moving Average
Single Exponential Smoothing
Double Exponential Smoothing
Triple Exponential Smoothing
Holt’s Linear Trend

Seasonal Smoothing

Additive Decomposition
Multiplicative Decomposition
Multiplicative Decomposition Logarithmic
Multiplicative Decomposition Exponential
Multiplicative Decomposition Power
Winter’s Additive
Winter’s Multiplicative

Basic & Intermittent

Croston’s Method
Zero Method
Naïve Method
Prior Year
Manual Input
Calculated % Over Prior Year
Linear Approximation
Cumulative
Marketing End-of-Life
New Item Forecast
Driver Based
Gompertz Method
Custom

Curve Fit Methods

Curve Fit techniques capture historical trends and project future trends. Cyclical or seasonality factors are not factored into these methods.

- Curve fit models are
  - Most appropriate for trend analysis
  - Good for long term planning

Linear Regression

Method Overview

Simple (only one covariate/predictor variable) linear regression is used to develop an equation by which we can predict or estimate a dependent variable given an independent variable. It is used to perform trend analysis on a given time-series data set.

***Y_i is the dependent variable, *a* is the *y* intercept, *b* is the gradient or slope of the line, X_i is independent variable and is a random term associated with each observation.

Quick Facts

Advantage:
Useful in identifying overall trend patterns

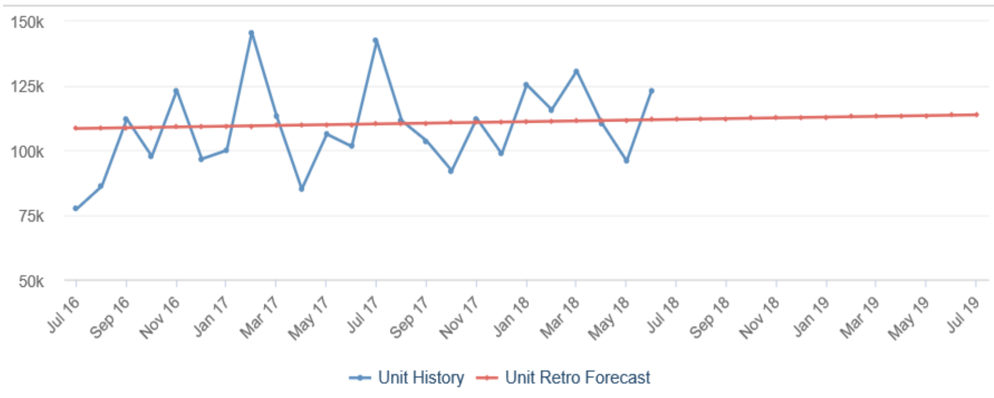
Disadvantage:
Does not identify seasonal or cyclical patterns.

Treats: Trend

Formula

$$Y_i = a + bX_i + \varepsilon_i$$

Output



Logarithmic Regression

Method Overview

This curve helps in modeling trend having non-linear behavior. It is useful in modeling trend following a logarithmic function.

Logarithmic regression is used to model situations where growth or decay accelerates rapidly at first and then slows over time.

Note that
all input values, x, must be non-negative.
when b > 0, the model is increasing.
when b < 0, the model is decreasing.

Quick Facts

Advantage:
Useful in identifying overall trend patterns

Disadvantage:
Does not identify seasonal or cyclical patterns.

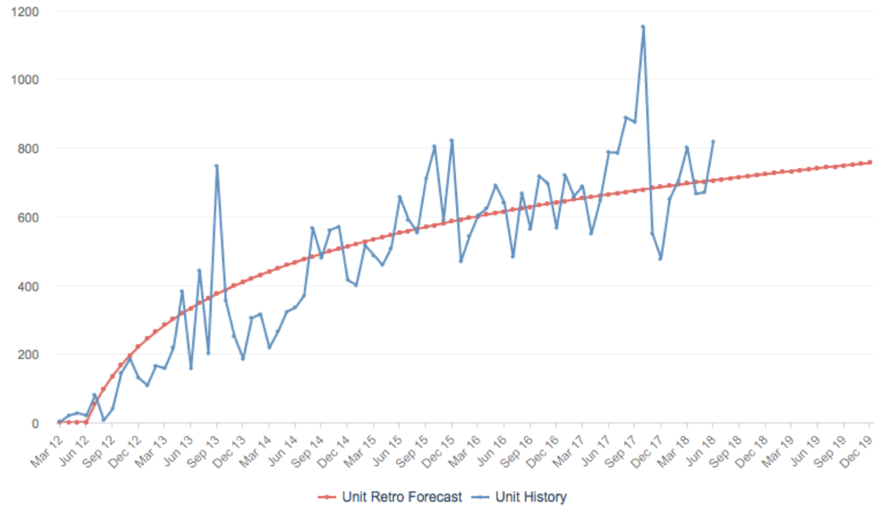
Treats: Trend

Min number of periods: 2

Formula

$$Y_i = a + b \ln X_i + \varepsilon_i$$

Output



Detailed formula: http://mathworld.wolfram.com/LeastSquaresFittingLogarithmic.html

Exponential Regression

Method Overview

Exponential Curve method belongs to a family of Least Squares models. It is useful in modeling a trend having a geometric growth.

Exponential regression is used to model situations in which growth begins slowly and then accelerates rapidly without bound, or where decay begins rapidly and then slows down to get closer and closer to zero.

- b must be non-negative.
- When b > 1, we have an exponential growth model.
- When 0 < b < 1, we have an exponential decay model.

Quick Facts

Advantage:
Useful in identifying overall trend patterns

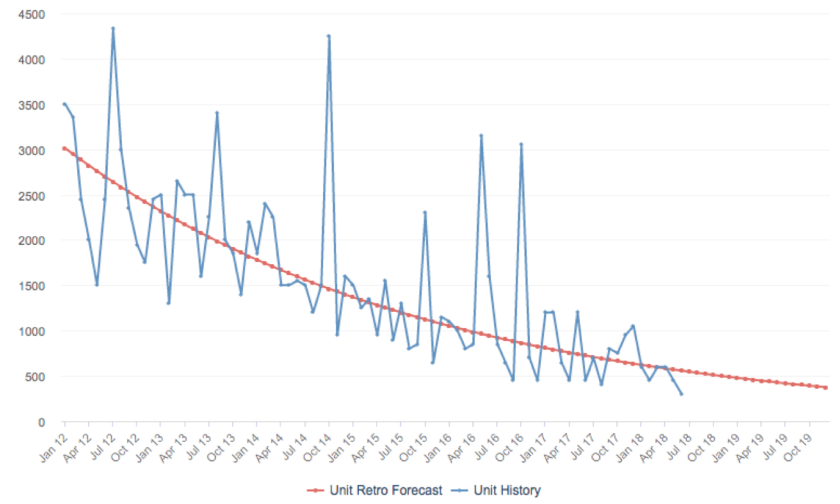
Disadvantage:
Does not identify seasonal or cyclical patterns. Demand should be greater than zero.

Treats: Trend

Formula

$$Y_i = ae^{bX_i} + \varepsilon_i$$

Output



Detailed formula: http://mathworld.wolfram.com/LeastSquaresFittingExponential.html

Power Regression

Method Overview

This curve helps in modeling trend having non-linear behavior. It is useful in modeling trend following a power function.

Power Regression is one in which the response variable is proportional to the explanatory variable raised to a power.

The values of both x and y must be greater than zero. (This is because the method for determining the values of a and b in the regression equation is a least-squares fit on the values for ln x and ln y.

Quick Facts

Advantage:
Useful in identifying overall trend patterns

Disadvantage:
Does not identify seasonal or cyclical patterns

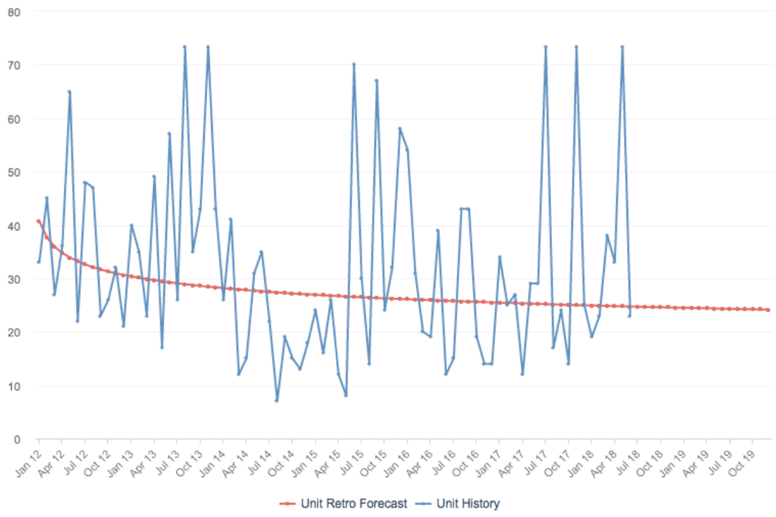
Treats: Trend

Min number of periods: 2

Formula

$$Y_i = aX_i^{\,b} + \varepsilon_i$$

Output



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Detailed formula: http://mathworld.wolfram.com/LeastSquaresFittingPowerLaw.html

Smoothing Methods

Smoothing techniques, such as averaging or exponential smoothing, are useful in extrapolating values of given non-seasonal and trending data. The basic assumption of averaging and smoothing models is that the time-series is “locally stationary”. In other words, wide fluctuations in past demand are given less significance than more recent, presumably more stable history. The moving average is often called a “smoothed” version of the original series, since short-term averaging has the effect of smoothing out the bumps in the original series. Exponential Smoothing assigns *exponentially decreasing weights* to older historical periods.

- Smoothing models
    - Provide stable forecasts for slow moving, trend and non-seasonal demand patterns
    - Are good for short term and long term planning

Moving Average

Method Overview

Moving Average (MA) is a popular method for averaging the results of recent sales history to determine a projection for the short term.

The smoothed statistic is the mean of the last T observations. This method is useful in smoothing noisy data. The selection of number of periods to consider to average can be done in two ways:

1. Assign a fixed N (number of historic periods).
2. Have system select optimized N (obtained by minimizing the forecast error)

Quick Facts

Advantage:
This method works better for short range forecasts of mature products.

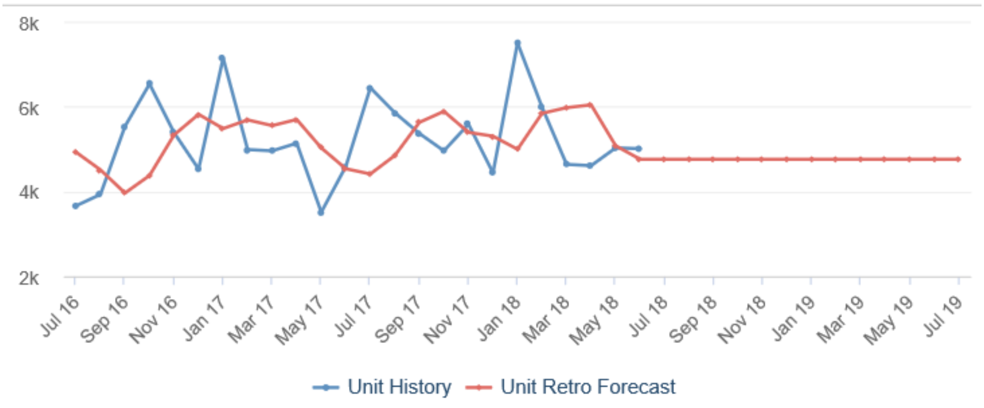
Disadvantage:
Lags behind trends, seasonal patterns

Treats: Level

Formula

$$F_{t+1} = \sum_{i=n-T}^{n} \frac{X_i}{T}$$

Output



*See appendix for detailed formula

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Double Moving Average

Method Overview

A variation of Moving Average that's devised to handle the linear trend process.

The process calculates a second moving average from the original moving average using the same value for N (number of historical periods to average). As soon as both the Single and Double Moving Averages are available, Slope and Intercept are computed and then used for forecasting future periods.

This method is useful for trending and noisy data.

Quick Facts

Advantage:
Smooths larger random variations and is less influenced by outliers

Disadvantage:
Does not identify seasonality

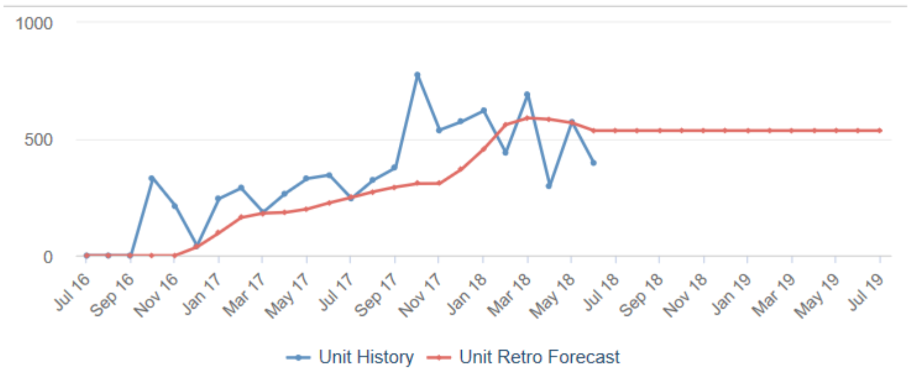
Treats: Level

Min number of periods: 2

Formula

$$F_{t+1} = L + T(m)$$

Output



*See appendix for detailed formula

Single Exponential Smoothing

Method Overview

SES is a weighted Moving Average Technique. It smoothens the data by using a feedback process where the previous forecast is used to arrive at the current forecast. The parameter α is used to specify the weight of the historical periods. Determination of parameter α plays a major roll. Typically, α should lie in the range of 0.01 to 0.3 (practical limit of α 0-1). The value of α can be either fixed (user specified) or optimized by the system (minimized RMSE error).

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level Pattern

Disadvantage:
Can't identify Seasonal, Trend Pattern

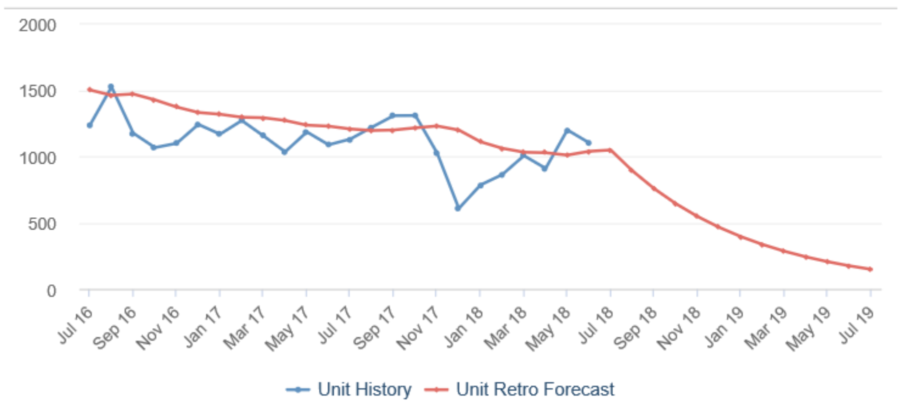
Treats: Level

Min number of periods: 2

Formula

$$F_{t+1} = \propto Y_t + (1- \propto)\, F_t$$

Output



*See appendix for detailed formula

Double Exponential Smoothing

Method Overview

Double Exponential Smoothing, also known as Brown's Linear, handles data where trend as well as mean vary slowly over time. A higher-order smoothing model is used to track trend. DES can also be treated as SES applied on the time-series twice

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level, Trend Pattern

Disadvantage:
Can't identify Seasonal Pattern

Treats: Level, Trend

Min number of periods: 2

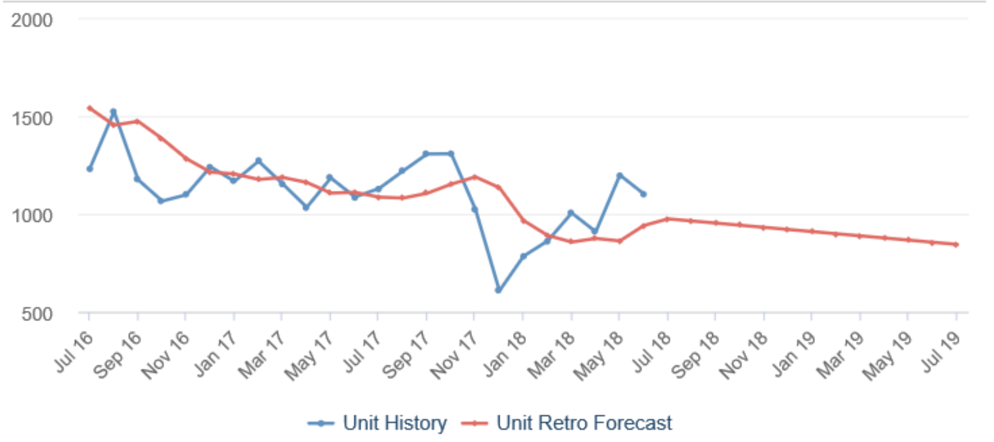
Formula

$$S'_t = \propto Y_t + (1\text{-} \propto)\, S'_{t-1}$$

$$S''_t = \propto S'_t + (1\text{-}\propto)\, S''_{t-1}$$

$$\ddot{Y}_t = a_t + (m)\, b_t\ ,\ \ddot{Y}_t \text{ is the forecast}$$

Output



*See appendix for detailed formula

Triple Exponential Smoothing

Method Overview

The Brown's Quadratic or TES is helpful in smoothing time-series having a quadratic (ex: Parabola) nature. The model can track mean and trend of quadratic nature. TES can also be treated as SES applied on the time-series three times.

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level, Trend Pattern

Disadvantage:
Can't identify Seasonal Pattern

Treats: Level, Trend

Min number of periods: 2

Formula

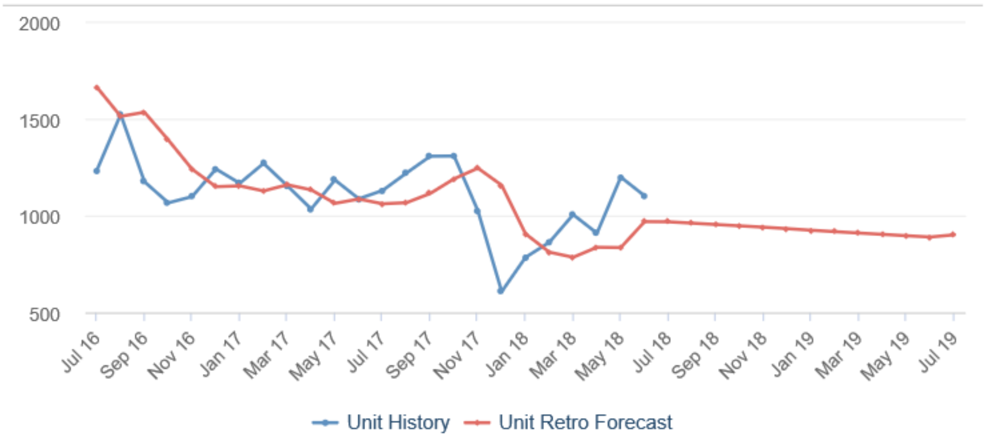
$$S'_t = \propto Y_t + (1\text{-} \propto)\, S'_{t-1}$$

$$S''_t = \propto S'_t + (1\text{-} \propto)\, S''_{t-1}$$

$$S'''_t = \propto S''_t + (1\text{-} \propto)\, S'''_{t-1}$$

$$\hat{Y}_t = a_t + b_t(\mathrm{m}) + \frac{1}{2} c_t(\mathrm{m})\,,\ \hat{Y}_t \text{ is the forecast}$$

Output



**See appendix for detailed formula*

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Holt’s Linear Trend

Method Overview

Extension of Single Exponential Smoothing. This method smooths the time series twice to arrive at the level and trend components.

It contains two smoothing constraints:

- α is the level smoothing constant
- β is the trend smoothing constant

This technique is best suited for data with moving mean and linear trend. The smoothing constants α and β can be either fixed or system optimized by minimizing the RMSE.

Quick Facts

Advantage:
Smooths larger random variations and is less influenced by outliers

Disadvantage:
Does not identify seasonality

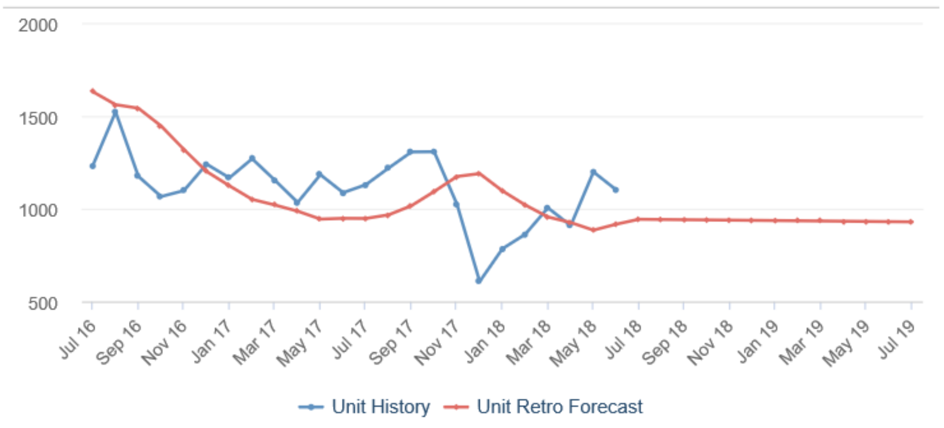
Treats: Level, Trend

Min number of periods: 2

Formula

$$A_t = \alpha y_t + (1-\alpha)(A_{t-1} + T_{t-1})$$
$$T_t = \beta(A_t - A_{t-1}) + (1-\beta)T_{t-1}$$
$$F_{t+m} = A_t + T_t m$$

Output



*See appendix for detailed formula

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Seasonal Smoothing Methods

Seasonal Techniques, such as Winters and decomposition, break down forecast components of baseline, trend and seasonality. Seasonal patterns may be additive or multiplicative. Cyclic patterns (non-annual) can be isolated in data sets of five years or greater.

❖Seasonal Smoothing models

- ❑ Provide useful forecasts for items containing elements of both trend and seasonality
- ❑ are good for short to medium range forecasting

Additive Decomposition

Method Overview

The Decomposition method separates the time-series into trend, cyclic, seasonality, and error components. The Additive model identifies seasonality in data that follows arithmetic progression. The process of decomposition is as follows:

- The time-series is de-trended by the process of centered moving average, after which the trend line is calculated.
- Using the actual and de-trended data, the seasonality and error factor are computed.
- Finally, the trend line + seasonality and error factor provide the future forecast.

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level, Trend and Seasonality Pattern

Disadvantage:

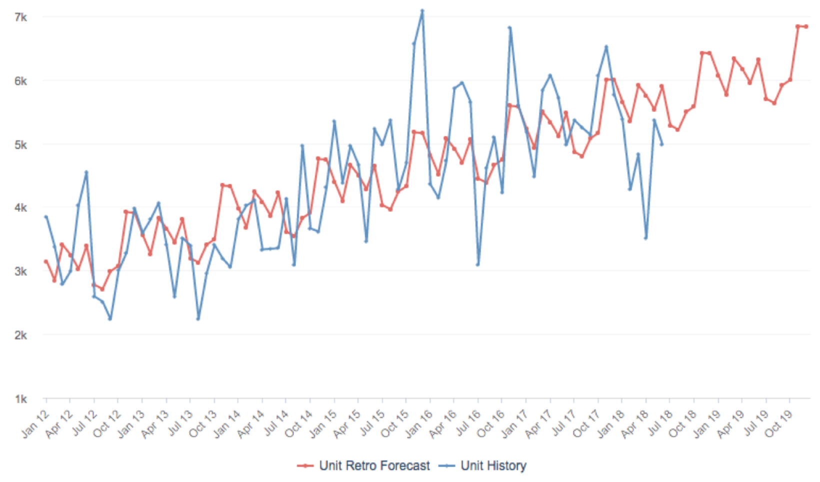
Treats: Level, Trend, Seasonality

Min number of periods: 24

Formula

$$F_t = T_t + C + SA_t + \varepsilon$$

Output



*See appendix for detailed formula

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Multiplicative Decomposition

Method Overview

Decomposition Method separates the time-series into trend, cyclic, seasonality and error components. The Multiplicative Model identifies seasonality in data which follows geometric progression. The process of decomposition is as follows. The time-series is de-trended by the process of centered moving average, then the trend line is calculated. Using the actual and de-trended data, the seasonality and error factor are computed. Finally, the trend line * seasonality and error factor provide the future forecast.

When 2+ years of historical data with clear seasonality are provided, this method is often times identified as the best fit forecast method.

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level, Trend and Seasonality Pattern

Disadvantage:

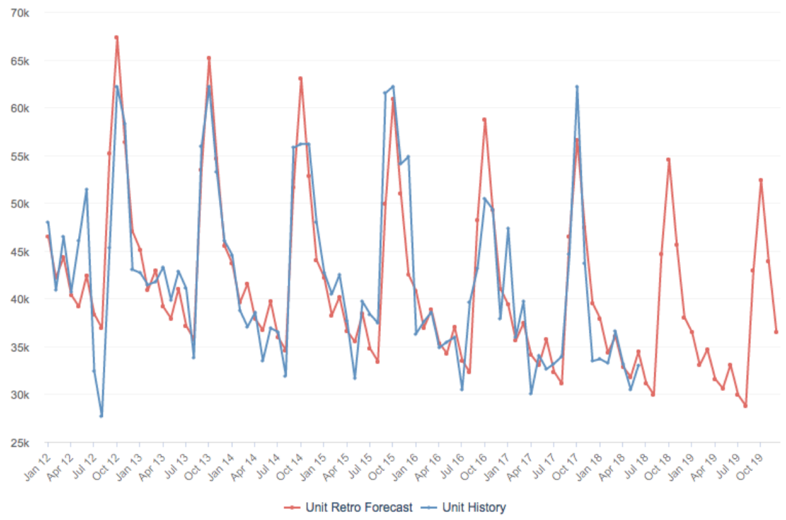
Treats: Level, Trend, Seasonality

Min. number of periods: 24

Formula

$$F_t = T_t * C * SA_t * \varepsilon$$

Output



*See appendix for detailed formula

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Multi Decomp Logarithmic

Method Overview

This method is a variation of the Multiplicative Decomposition method. It takes the Logarithmic Regression forecast and applies the Multiplicative Decomp Adjusted Seasonal index. First the Logarithmic Regression forecast is calculated using de-seasonalized history and then multiplied by the adjusted seasonal index to reapply seasonality.

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level, Trend and Seasonality Pattern

Disadvantage:

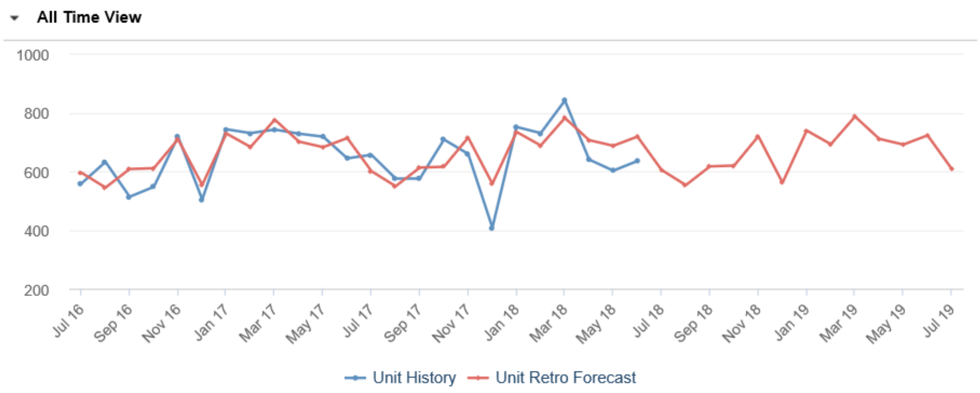
Treats: Level, Trend, Seasonality

Min. number of periods: 24

Formula

$$Y_i = (a + b\ln X_i + \varepsilon_i) \times MD\ Adjusted\ Seasonal\ Index$$

Output



*See appendix for detailed formula breakdown

Multi Decomp Exponential

Method Overview

This method is a variation of the Multiplicative Decomposition method. It takes the Exponential Regression forecast and applies the Multiplicative Decomp Adjusted Seasonal index. First the Exponential Regression forecast is calculated using de-seasonalized history and then multiplied by the adjusted seasonal index to reapply seasonality.

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level, Trend and Seasonality Pattern

Disadvantage:

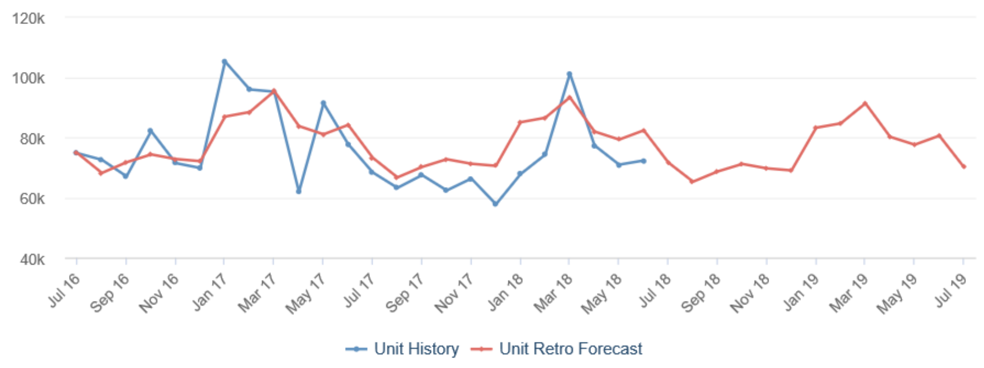
Treats: Level, Trend, Seasonality

Min. number of periods: 24

Formula

$$Y_i = (ae^{bX_i} + \varepsilon_i)\times MD\ Adjusted\ Seasonal\ Index$$

Output



*See appendix for detailed formula breakdown

Multi Decomp Power

Method Overview

This method is a variation of the Multiplicative Decomposition method. It takes the Power Regression forecast and applies the Multiplicative Decomp Adjusted Seasonal index. First the Power Regression forecast is calculated using de-seasonalized history and then multiplied by the adjusted seasonal index to reapply seasonality.

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level, Trend and Seasonality Pattern

Disadvantage:

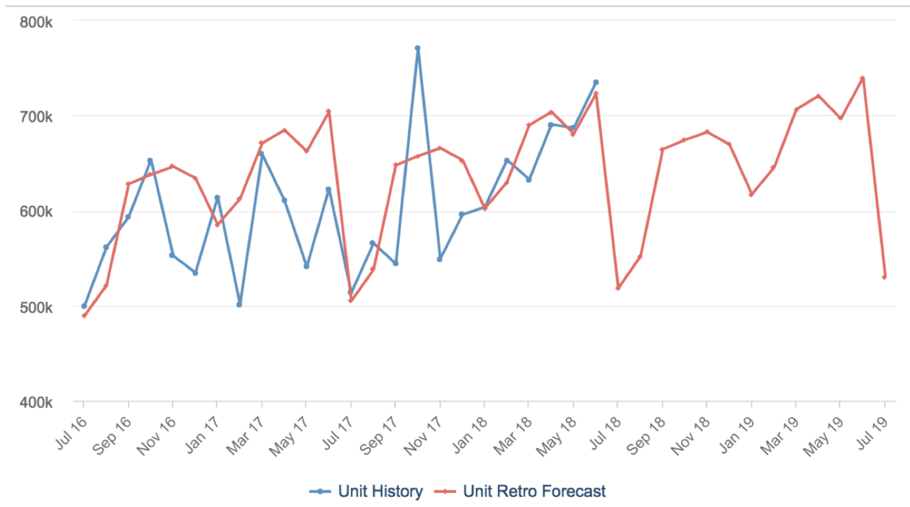
Treats: Level, Trend, Seasonality

Min. number of periods: 24

Formula

$$Y_i = (aX_i^{\,b} + \varepsilon_i) \times MD\ Adjusted\ Seasonal\ Index$$

Output



*See appendix for detailed formula breakdown

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Winter's Additive

Method Overview

This model leverages level, trend, and seasonality factors. Identifies seasonality pattern that is arithmetic in nature. Level, trend, and seasonality are smoothed based on three smoothing constants: α, β, γ.

These parameters can be fixed or system-selected, based on minimization of the error metric MAPE.

Quick Facts

Advantage:
Identifies seasonal trends.

Disadvantage:

Treats: Level, Trend, Seasonality

Min number of periods: 24

Formula

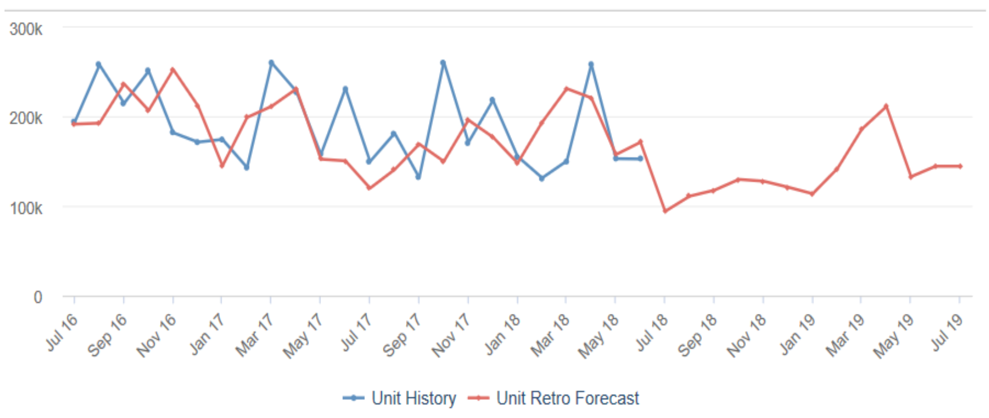
$$L_t = \alpha\left(\frac{S_t}{SA_{t-c}}\right) + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

$$SA_t = \gamma(S_t - L_t) + (1-\gamma)(SA_{t-c})$$

$$F_{t+m} = L_t + mT_t + SA_{t-c+m}$$

Output



*See appendix for detailed formula

Winter's Multiplicative

Method Overview

The Holt-Winters exponential smoothing method leverages level, trend and seasonality factors. The Winters Multiplicative model identifies seasonality pattern which is geometric in nature. Level, trend and seasonality are smoothed based on three smoothing constants α, β, γ. These three parameters can be either fixed or system selected based upon minimization of error metric MAPE.

Quick Facts

Advantage:
Very useful in Identifying Time-Series overall Level, Trend and Seasonality Pattern

Disadvantage:

Treats: Level, Trend, Seasonality

Min number of periods: 24

Formula

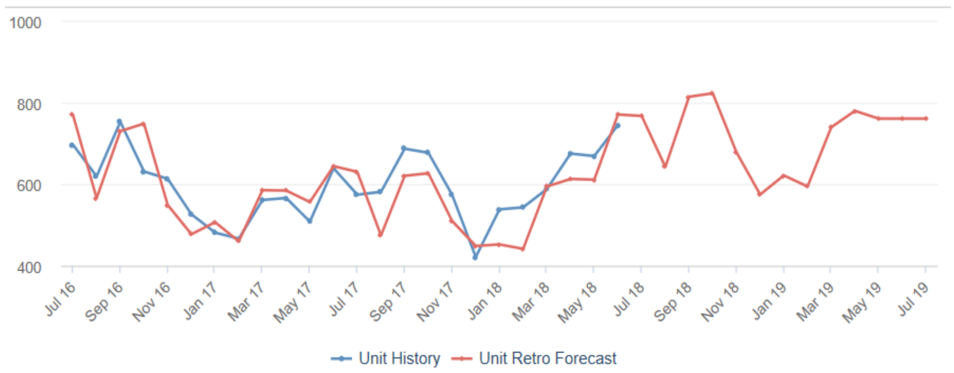
$$L_t = \alpha\left(\frac{S_t}{SA_{t-c}}\right) + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

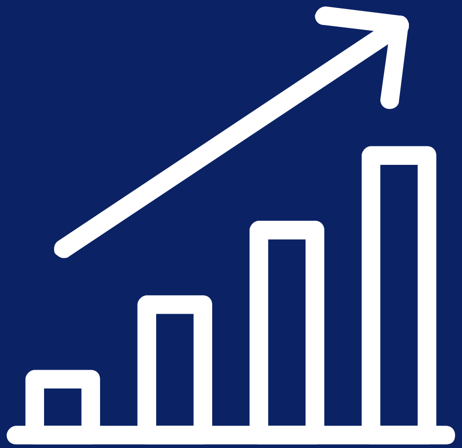
$$SA_t = \gamma\left(\frac{S_t}{L_t}\right) + (1-\gamma)(SA_{t-c})$$

$$F_{t+m} = (L_t * mT_t)SA_{t-c+m}$$

Output



*See appendix for detailed formula



Basic & Intermittent Methods

Basic Methods comprise simple techniques that are useful for specific circumstances or as a means to compare effectiveness of other methods.

❖Basic Methods

- ❑ Are useful for non-stationary, end-of-life, highly recurring demand, essential demand products types
- ❑ Are best for short to medium range forecasting

Intermittent Demand is characterized by periods of inactivity (zero demand) as well as periods of activity. The challenge is to forecast both inactive period pattern and quantities for active periods.

❖Intermittent Demand Models

- ❑ Are best suited for time series with sporadic demand history and multiple periods of inactivity
- ❑ Are best for short to medium range forecasting

Croston’s Method

Method Overview

Intermittent Demand

- Characterized by periods of inactivity (zero demand) as well as periods of activity.
- Best suited for time series with sporadic demand history and multiple periods of inactivity
- Best for short to medium range forecasting

A method where the given time series is separated into demand quantity and inter-arrival time between non-zero demand occurrences. The non-zero and zero patterns are forecasted separately using smoothing techniques. The final forecast is achieved by combining the two forecasts.

Intermittent demand patterns present a unique challenge. Forecasting using regular smoothing techniques fails as they are unable to trace the irregular demand occurrence. To treat this demand pattern, Croston proposed a technique where the given time series is separated into demand quantity and inter-arrival time between non-zero demand occurrences. The non-zero and zero patterns are forecast separately using smoothing techniques. The final forecast is achieved by combining the two forecasts.

Quick Facts

Advantage:
Highly regarded method for intermittent demand forecasting

Disadvantage:
Cannot treat trend, seasonality

Treats: Trend

Min number of periods: 1

Formula

$$If\ z_t = 0\ then$$

$$z'_t = z'_{t-1}$$

$$p'_t = p'_{t-1}$$

$$Otherwise$$

$$z'_t = az_t + (1-\alpha)z'_{t-1}$$

$$pz'_t = ap_t + (1-\alpha)z'_{t-1}\ where\ 0<\alpha$$

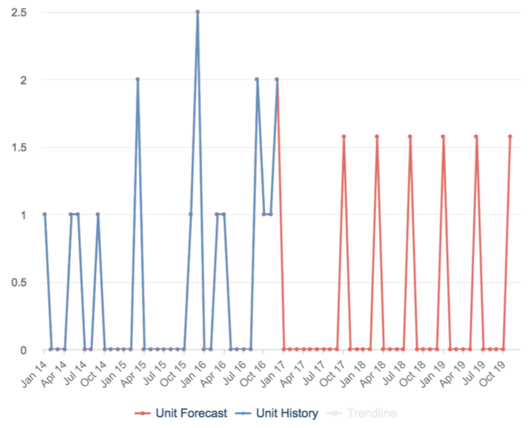
$$And\ finally\ by\ combining\ these\ forecasts$$

$$Y'_t = \frac{z'_t}{p'_t}$$

Formula Key:

Y'_t- average demand per period
z_t- Actual demand at period t
z'_t- Actual demand at period t
P– Demand size forecast for next period
P_t- Forecast of demand interval
α – Smoothing constant

Output



Zero Method

Method Overview

Forecasts Zero values into future periods regardless of past period values. Useful in projecting End of Life (EOL) products.

Quick Facts

Advantage:
EOL Products

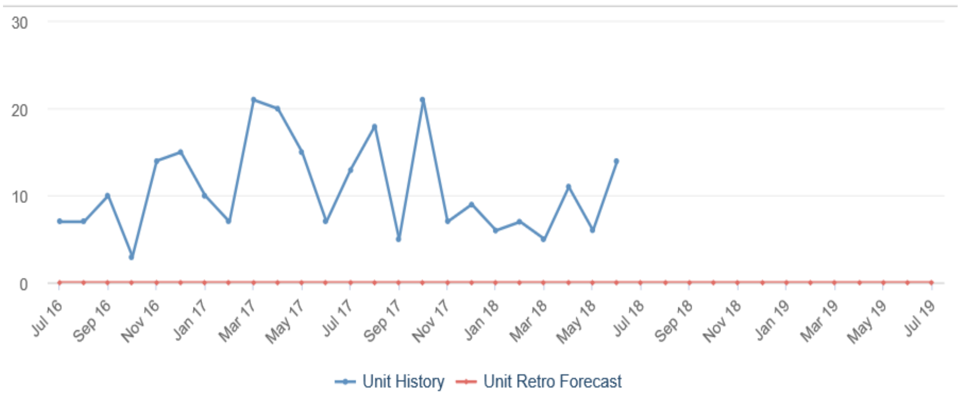
Disadvantage:
Cannot treat level, trend, seasonality

Min number of periods: 0

Formula

$$F_t = 0$$

Output



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Naïve Method

Method Overview

Forecasts most recent period value into the future regardless of past period values. Can be used to forecast essential products (such as in CPG markets).

Quick Facts

Advantage:
Essential products

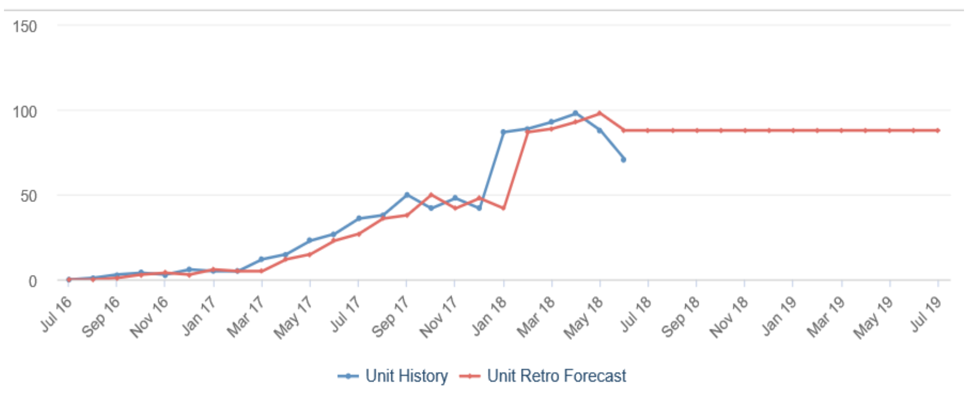
Disadvantage:
Cannot treat level, trend, seasonality

Min number of periods: 1

Formula

$$F_t = A_{t-1}$$

Output



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Prior Year

Method Overview

Forecasts by repeating the past values from previous corresponding annual periods. Useful in forecasting products with high demand recurrence year-over-year.

Quick Facts

Advantage:
High demand recurrence products

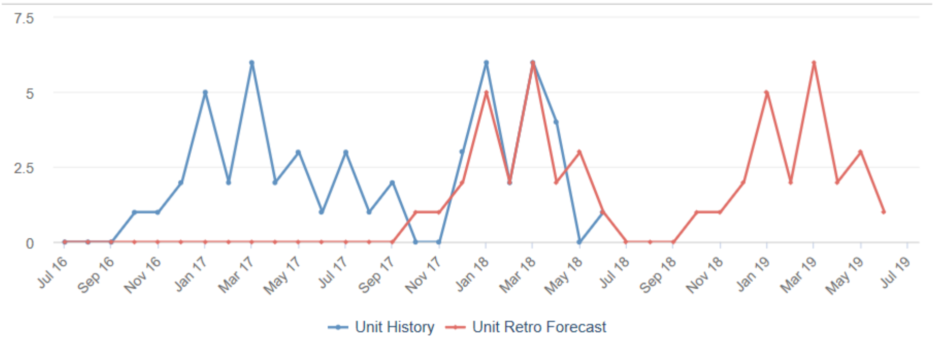
Disadvantage:
Gives no consideration to past data other than that of prior year

Min number of periods: 12 mo

Formula

$$F_t = A_{t-12}$$

Output



Manual Input

Method Overview

Forecasts for specific periods are entered manually by the user, based on external factors (e.g. promotions, builds, new product introductions, etc.)

Quick Facts

Advantage:
Useful for cases of new products and promotions

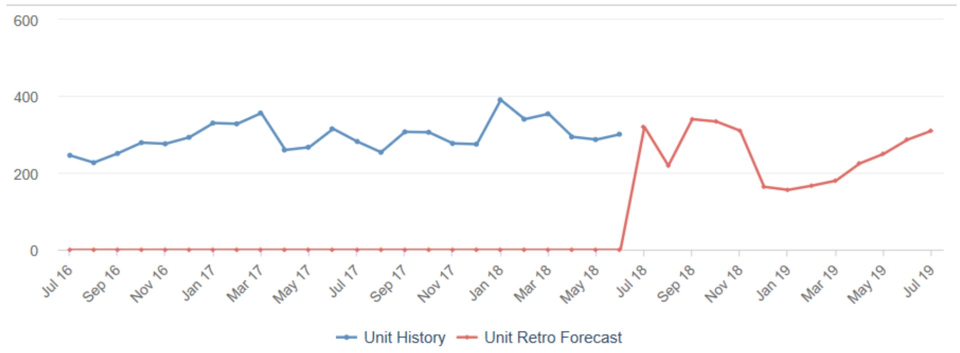
Disadvantage:
There is no statistical forecasting applied

Min number of periods:

Formula

$$F_t = [\ ]$$

Output



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Calculated % Over Prior Year

Method Overview

The Calculated Percent Over Last Year formula multiplies sales data from the previous year by a factor that is calculated by the system, and then it projects that result for the next year.

Quick Facts

Advantage:
Projects the effect of recent growth to next year, while preserving seasonal pattern from history

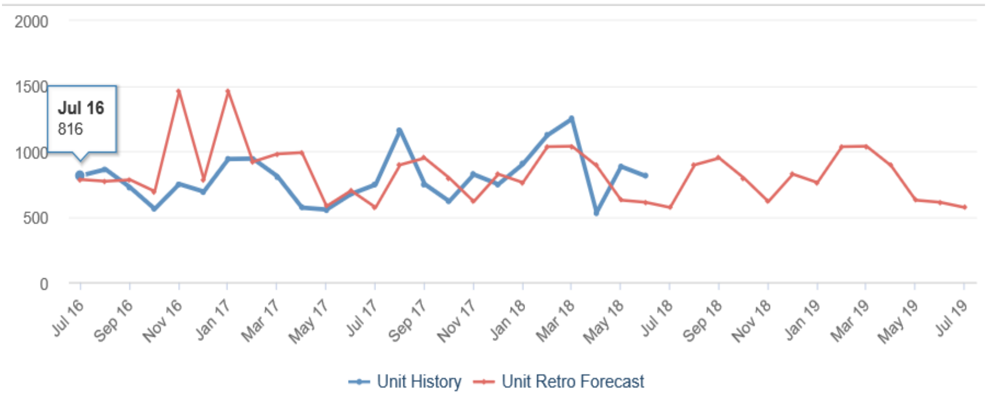
Disadvantage:

Min number of periods: 12 mo

Formula

$$(1 + \%\, Year\ Over\ Year\ Growth) * Prior\ Year\ Forecast$$

Output



Anaplan

Linear Approximation

Method Overview

This method uses the Linear Approximation formula to compute a trend from the number of periods of sales order history and to project this trend to the forecast. The trend should be recalculated monthly to detect changes in trend.

Linear Approximation calculates a trend that is based upon two sales history data points. Those two points define a straight trend line that is projected into the future. Use this method with caution because long range forecasts are leveraged by small changes in just two data points.

Quick Facts

Advantage:
Useful for new products and products with no consistent positive and negative trends.

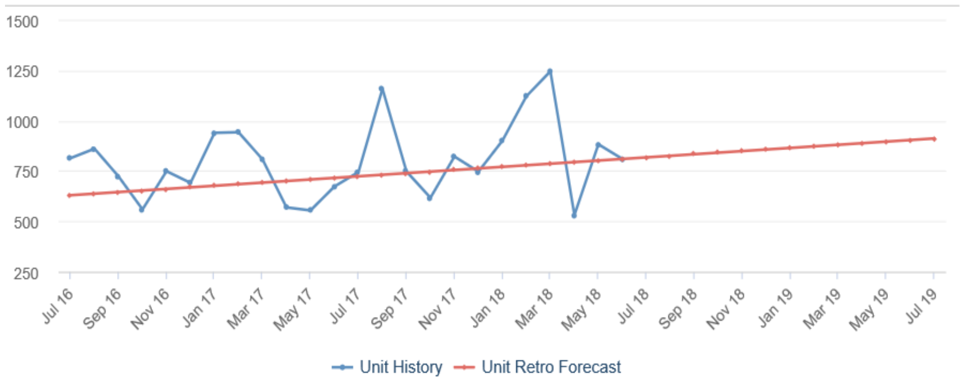
Disadvantage:

Min number of periods:

Formula

$$F_t = X_0 + X_i \frac{X_n - X_0}{n-1}$$

Output



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Cumulative

Method Overview

This method takes the running sum of demand to date and divides it by the number of periods.

Quick Facts

Advantage:

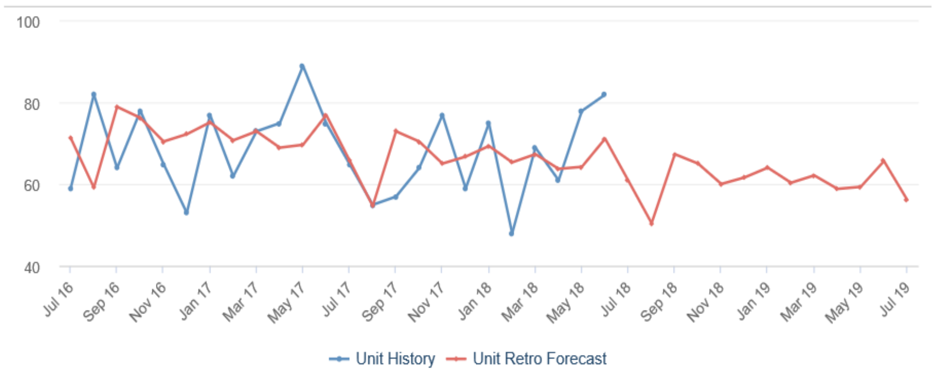
Disadvantage: Does not cinsider variations in history

Min number of periods:

Formula

$$F_{t+1} = \frac{\sum_{i=1}^{t} X_i}{t}$$

Output



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Marketing End-of-Life

Method Overview

Forecasts the phase-out timeline for specific products nearing the end of their life. This model contains end-of-life modeling functionality that allows the user to enter the phase out start and end dates. The EOL graph then displays the forecasted demand for that item, decreasing to zero over the indicated date range.

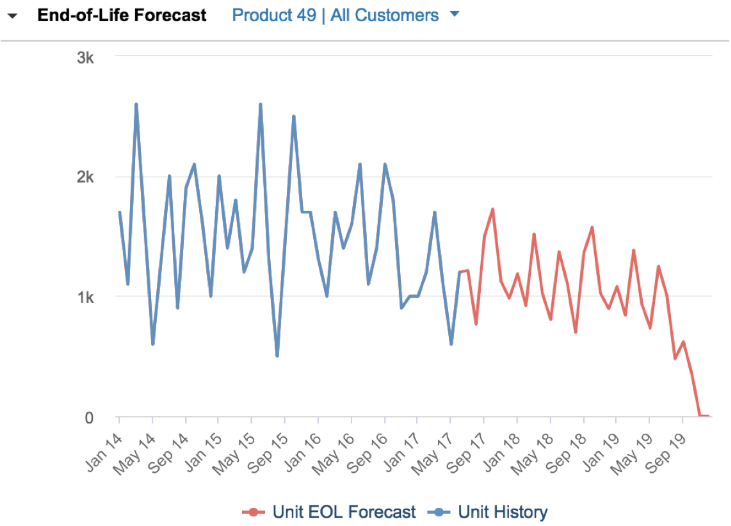
Quick Facts

Advantage:
Useful for products nearing EOL

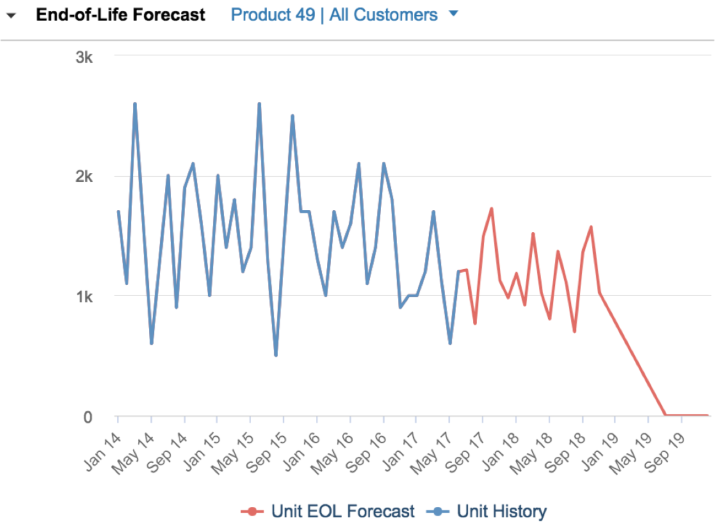
Disadvantage:

Output

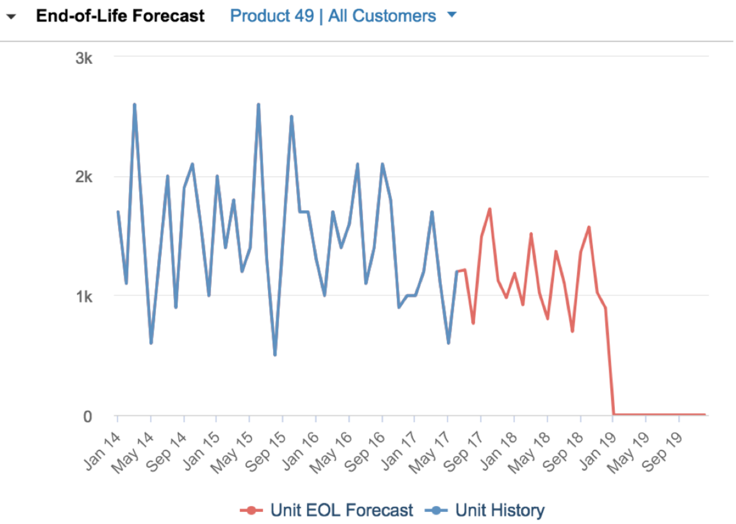
Depletion Method: Forecast Driven



Straight Line



Scrap



New Item Forecast

Method Overview

This method is useful in forecasting new products. This method can be set up to use the forecast for a similar product with the cannibalization percentage set, from the launch date of the product.
If the product is replacing the similar product then it can be marked as the successor.

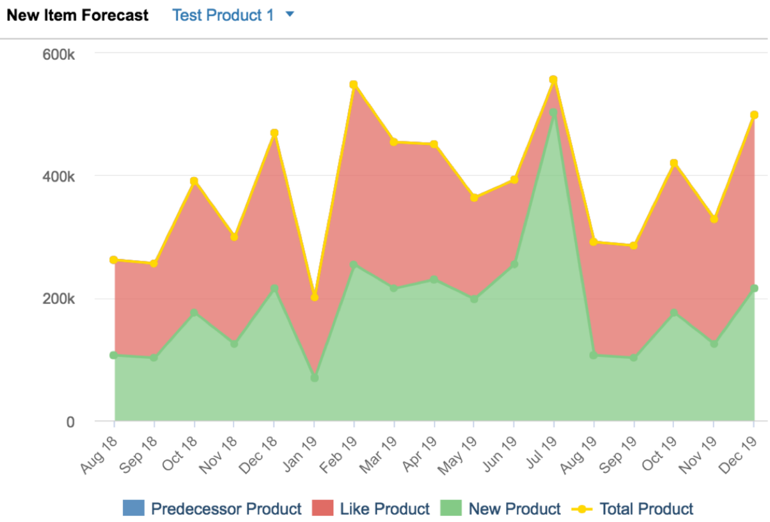
Quick Facts

Advantage:
Specific to new product introductions

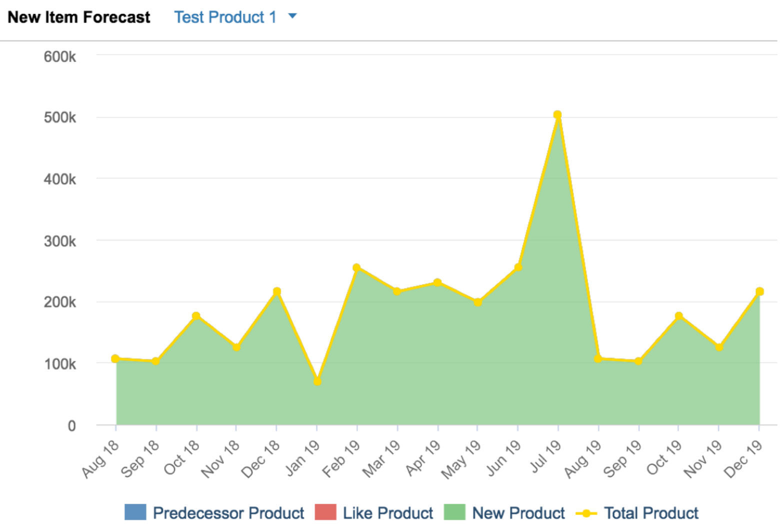
Disadvantage:

Output

New product with cannibalization of similar product set at 40%



New product as the successor of the similar product



New product drivers to calculate forecast

NPI Drivers Test Product 1

Annual Unit Sales	2,699,331
Current Similar Product	4PC x 24BX truffles |
Seasonality Basis	Product Specific
Estimated Selling Price	$ 60
Estimated Cost	$ 55

Driver-Based Method

Method Overview

The driver-based forecast method allow you to bring your own regression-based forecasts into Anaplan. Build out a linear or causal trend, or an exponential, logarithmic, power, or Gompertz curve and layer product seasonality onto it.

Quick Facts

Advantage: Specify & benchmark external forecasts in Anaplan

Disadvantage: Must provide external regression factors

Min number of periods: 0

Formulas

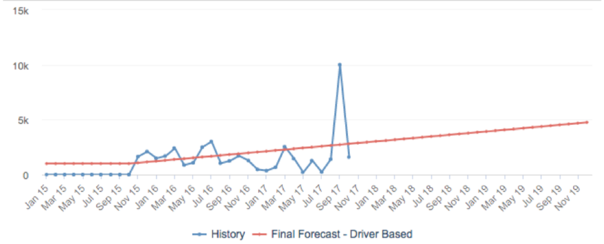
- Linear: $Y_i = ax + b + \varepsilon_i$
- Exponential Regression: $Y_i = ae^{bX_i} + \varepsilon_i$
- Logarithmic: $Y_i = a + b \ln X_i + \varepsilon_i$
- Power Regression: $Y_i = aX_i^{\,b} + \varepsilon_i$
- Gompertz: $Y_i = ab^{q^x} + \varepsilon_i$

(■ = User provides coefficients & constants)

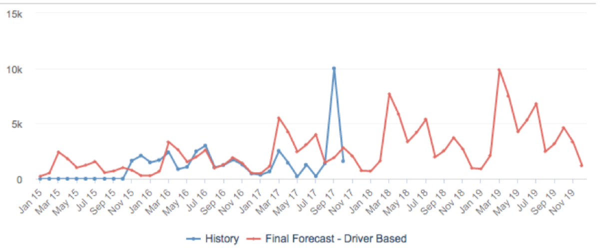
Output

Linear Example:

$Y_i = 75x + 1000$



Linear with Seasonality Applied:



Driver-Based Method: Gompertz

Method Overview

The Gompertz method is a driver-based method that generates an S-curve suitable for product lifecycle modeling.

The coefficient ***a*** represents the forecasted end state, while ***b*** and ***c*** determine the speed and steepness of the curve. The curve itself can be adjusted forward in time using the time offset t_0.

Quick Facts

Advantage: Specify & benchmark external forecasts in Anaplan

Disadvantage: Must provide coefficients

Min number of periods: 0

Formulas

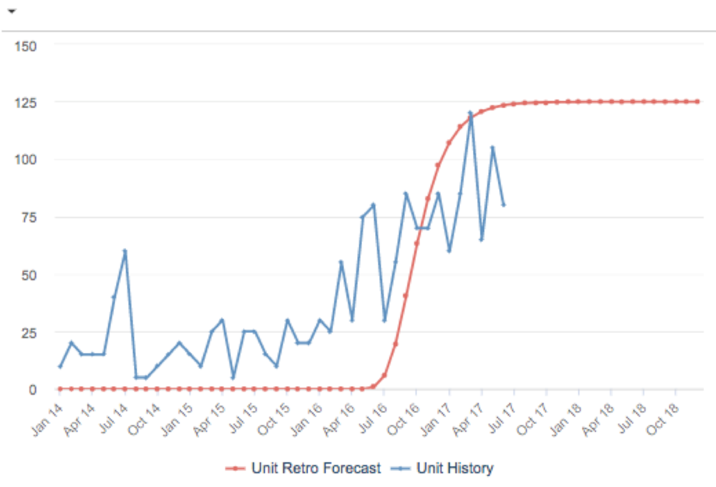
Gompertz: $Y_i = ae^{-be^{-c(t+t_0)}} + \varepsilon_i$

e is Euler's Number
a is the end state maturity forecasted value
b: displacement along x-axis
c: growth rate (y scaling)
t_0: Number of periods added to time t

(■ = User provides coefficients & constants)

Output

$a = 125$
$b = 0.25$
$c = 0.5$
$t_{offset} = 18$



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Driver-Based: Causal Method

Method Overview

The Causal Method builds a deterministic forecast from multiple causal factors. To replicate your multivariate forecast, specify up to three linear relationships and observations with corresponding historical observations and forecasted trends.

Quick Facts

Advantage: Bring your own multivariate forecasts

Disadvantage: Current implementation limited to linear relationships and does not perform regression

Min number of periods: 0

Formula

Formula Selected y = (a1x1+b1) + (a2x2 + b2) + (a3x3 + b3)

1. Linear Regression Table:

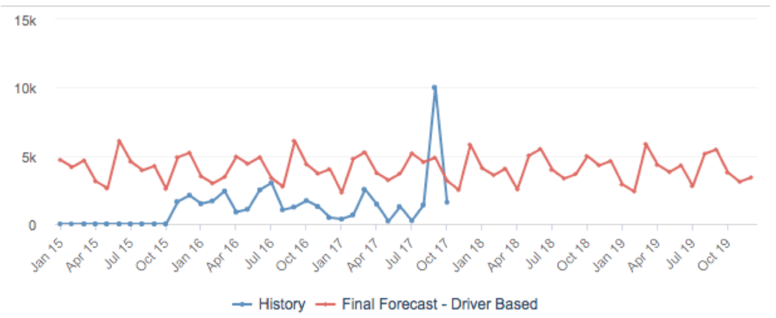
	Coefficient a	Intercept b
x1	40	400
x2	600	750
x3	50	500

2. Observation/Trend Table

	x1	x2	x3
Jan 19	1	2	0
Feb 19	3	1	0
Mar 19	5	5	20
Apr 19	7	4	0
May 19	9	3	0
Jun 19	11	2	20

Output

Causal Equation y = (40(x1) + 400)) + (600(x2) + 750)) + (400)) + (50(x3) + 500)



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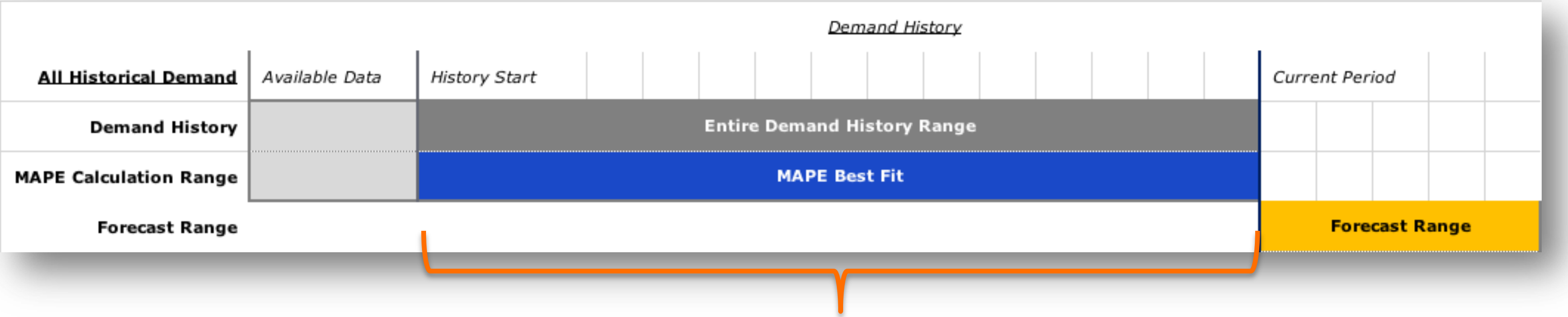
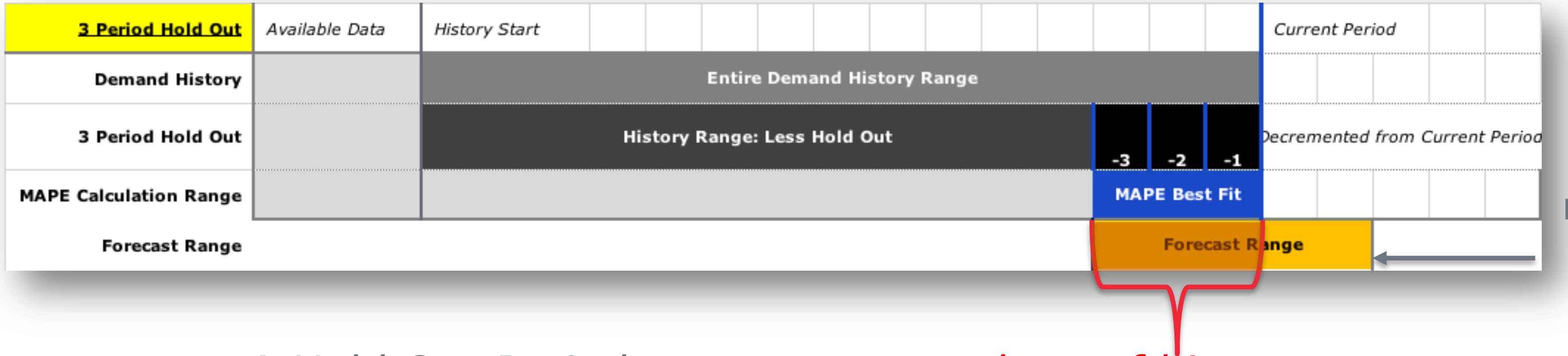
Appendix

Hold Out Periods

A *Hold Out* period compares how well forecasts methods predict recent history



Standard ranking uses the entire history interval to determine back best fit



History and Forecast now overlap in the Hold Out range

A Hold Out Period uses a recent subset of history

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Entire Range

Forecast Method List Item 3

Additive Decomposition

	All Periods
MAPE prep	6.174
history count	36

MAPE Best Fit

Forecast Accuracy & Validation

Calculations Item 3

Forecast Settings

History Type	Actual
Forecasting Method Best Fit	Multi Decomp Power
Forecasting Method Override	
Override Best Fit Forecast?	

Forecast Settings

<<< HOLD OUT SETTINGS >>>	
Hold Out Periods	6
Apply Hold Out?	

Algorithm Forecast Accuracy Item 3

	Additive Decomposition	Multi Decomp Power	Multi Decomp Logarithmic	Multi Decomp Exponential	Multiplicative Decomposition	Power Regression	Naive Method	Logarithmic Regression	Winter's Additive	Prior Year	Winter's Multiplicative
MAPE	17.1%	17.0%	17.8%	17.4%	18.1%	34.0%	38.0%	36.2%	30.0%	42.5%	33.1
RMSE	6.4	6.9	7.0	6.7	6.8	11.9	13.1	11.6	11.8	16.5	12
MAD	5.1	5.4	5.5	5.4	5.6	9.8	11.1	9.7	9.9	13.9	10

6 Period Hold Out

MAPE Best Fit

Forecast Method List Item 3

Additive Decomposition

	All Periods
MAPE prep	0.7744
history count	6

Forecast Accuracy & Validation

Calculations Item 3

Forecast Settings

History Type	Actual
Forecasting Method Best Fit	Additive Decomposition
Forecasting Method Override	
Override Best Fit Forecast?	

Forecast Settings

<<< HOLD OUT SETTINGS >>>	
Hold Out Periods	6
Apply Hold Out?	

Algorithm Forecast Accuracy Item 3

	Additive Decomposition	Multi Decomp Power	Multi Decomp Logarithmic	Multi Decomp Exponential	Multiplicative Decomposition	Power Regression	Naive Method	Logarithmic Regression	Winter's Additive	Prior Year	Winter's Multiplicative
MAPE	12.9%	15.1%	15.6%	16.5%	17.0%	24.2%	24.8%	25.1%	26.2%	26.9%	26.9%
RMSE	40.4	36.4	37.2	40.5	41.5	34.2	37.0	36.7	44.2	34.9	44.4
MAD	39.2	34.2	35.0	38.2	39.1	34.2	37.0	36.7	43.0	33.5	41.7