Operations & Business Process Management

Prof. Apurva Jain

MSIS 503

1. Identify Flow
2. Automate Workflow
   2.1 Characteristics for automation
   2.2 Value and Waste
   2.3 RPA

Session 3

3. Forecast Demand
   3.1 Time Series
   3.2 Trend and Seasonality
   3.3 Forecasting Software

Next

Quiz 1 is due

4. Balance Capacity

..

Where are we…(flow of the class)

What is the flow?: Flow-units, Resources, Activities,

What are the symptoms?: Cost, Time, Quality

Activities

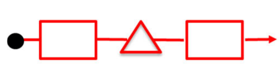
Which tasks to automate?
Which activities add value?
- scorecard
- value/waste

Flow-units

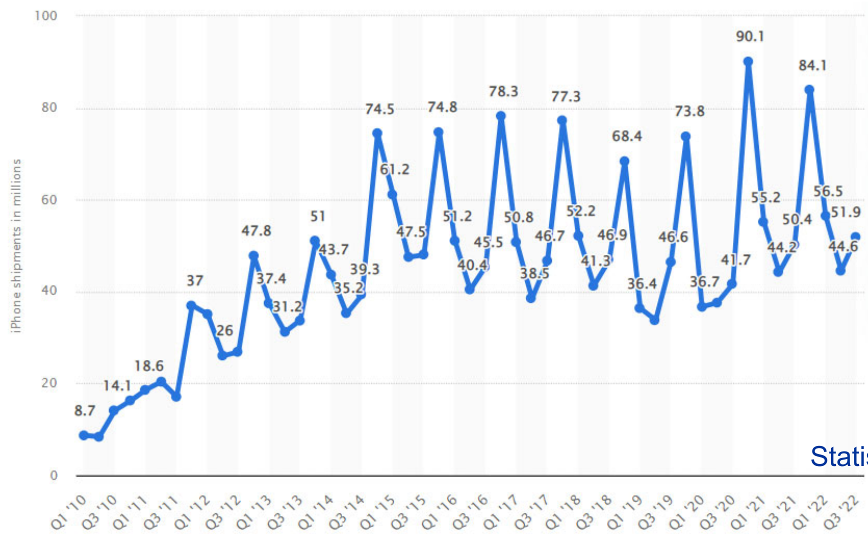
How many flow-units?
How to manage a variety of units?

Resources

What type of resources?
How many resources?



How do we estimate future demand?: Forecasting



Statista 2023

What is your best guess for Q4'22?

How did you make your estimate?

Use Time-series method to project the historical pattern. Then use Causal methods to adjust the time-series forecast for the outside factors. Finally, use Judgment methods to incorporate shocks.

How did the pandemic influence Apple supply chain?

The Washington Post
Democracy Dies in Darkness

TECHNOLOGY

Apple's iPhone sales fell as the coronavirus struck

Apple is a bellwether for consumer spending, and it's extremely dependent on Chinese manufacturing

https://www.theguardian.com › technology › apr › appl...

Apple sales rise to $90bn amid Covid buying surge

Apr 28, 2021 — Its sales in China doubled year-on-year. Mac computer sales were a third higher than predicted and iPhone sales came in **around $48bn** – roughly ...

MONEYWATCH ›

Apple faces "major shortages" of iPhone 14, analyst says

MONEY WATCH

BY ALAIN SHERTER

NOVEMBER 25, 2022 / 12:50 PM / MONEYWATCH

Apple faces up to $8 billion revenue hit due to Covid-19 lockdowns in China

As Shanghai entered the second month of lockdown and more cities in China face pandemic restrictions, demand for Apple products in the country might slow further, reports Nikkei Asia

Topics
China | Apple | Lockdown

IANS | San Francisco
Last Updated at April 30, 2022 14:08 IST

6

Reporting from Q4 '22

CNBC.com
.. Apple's iPhone business ..came up short versus analyst expectations. Apple's September quarter had 8 days of iPhone 14 sales, and analysts are closely looking for details about if Apple customers are trading up for more expensive models or if the new devices are poised to sustain higher sales through Apple's fiscal 2023.

Cook indicated… that the company's high-end phones, the iPhone 14 Pro, were supply constrained.

applemagazine.com
The reason for the decreased shipping totals was not demand but rather production problems in China, caused by the COVID-19 breakout at the Zhengzhou factory that produces the vast majority of the Pro series volumes.

Counterpoint Research's Jeff Fieldhack said about Apple's performance: its share of iPhone shipments could have been even higher if not for the production issues at the Zhengzhou factory. As a result, some Pro series volumes were pushed to January."

Global shipments of smartphones decreased by 18% year over year in the fourth quarter of 2022 to reach 304 million units, which was the lowest number for a holiday quarter since 2013. Shipments fell to 1.2 billion units for the entire year, which was also the lowest level since 2013.

Forecasting Methods: Three methods for three contexts

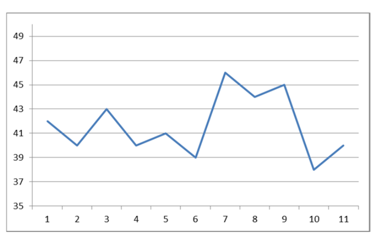
1. Historical sales data is available, and the forecast is made by considering its pattern over time: Time Series Methods.

2. Historical sales data is available, and forecast is made by considering its relationship with set of outside variables : Causal Methods.

3. Historical sales data is not available, and forecast is made by surveying opinions: Qualitative or Judgment Methods.

Time Series: A Simple Demand Model

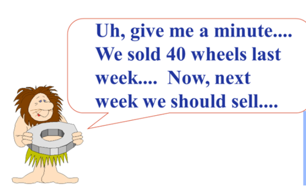
Period	Sales Data
1	42
2	40
3	43
4	40
5	41
6	39
7	46
8	44
9	45
10	38
11	40



Let us assume a demand model:
Demand = Level + Random
"Level" is an unknown value.
We need a forecasting method to estimate a value for "Level" and then use this estimate to make a forecast.

Naïve method estimates "Level" as equal to the latest period's actual observed sales. For example: At the end of period 6, the Naive forecast for period 7 is 39.

Can we do better?



Moving Average Method

Demand Model:
Demand = Level + Random

Period	Demand	
1	42	3-period moving average
2	40	forecast for period 6, made
3	43	at the end of period 5
4	40	= (43 + 40 + 41) / 3 = 41.33
5	41	= 41

Moving Average Method

Demand Model:
Demand = Level + Random

Period	Demand	
1	42	If actual sales in period 6 =39
2	40	3-period moving average
3	43	forecast for period 7, made
4	40	at the end of period 6
5	41	=
6	39	

Moving Average Method

Demand Model:
Demand = Level + Random

Period	Demand
1	42
2	40
3	43
4	40
5	41
6	39

If actual sales in period 6 =39
3-period moving average
forecast for period 7, made
at the end of period 6
= (40 + 41 + 39) / 3= 40

Simple Exponential Smoothing Method

Demand Model:
Demand = Level + Random

Period:	1	2	3	4	5	6	7
Actual:	D_1	D_2	D_3	D_4	D_5	D_6	D_7
Forecast:	F_{0+1}	F_{1+1}	F_{2+1}	F_{3+1}	F_{4+1}	F_{5+1}	F_{6+1}

*(1-α)
+
* α

Exponential Smoothing with smoothing parameter α:

Estimate of Level for next period, "new level" =

α * actual for this period +

(1- **α**) * estimate of level for this period "old level"

Where 0< α<1

Because Demand Model is Demand = Level + Random,
The forecast is simply equal to the estimate of "Level."

Simple Exponential Smoothing Method

Demand in next period =
Estimate of level at the end of this period + Error

Exponential Smoothing Updating parameters: α (between 0 and 1)

New estimate of Level at the end of this period =
α* (actual demand observation in this period)
+ (1 – α) (forecast for this period made in the previous period)
= Estimate of level at the end of the previous period
+ α* (actual demand – forecast in this period)
= Estimate of level at the end of the previous period
+ α* (error in this period)

This is so because forecast for this period made in the previous period =
Estimate of level at the end of the previous period

Use training data to search for α that minimize error measures like MAD or MSE.

Exponential Smoothing Method

Exponential Smoothing forecast using parameter α (alpha; 0< α<1)
= α * actual observed data + (1- α) * forecast

Period	Demand
1	42
2	40
3	43
4	40
5	41

Suppose an “initial” forecast for period 5 was given as 40. Actual observed data in period 5 is 41. Exponential smoothing forecast with parameter α=0.2 for period 6, made at the end of period 5

= 0.2*41 + (1-0.2)*40

= 40.2 = 40

Exponential Smoothing Method

Exponential Smoothing forecast using parameter α (alpha; 0< α<1)
= α * actual observed data + (1- α) * forecast

Period	Demand
1	42
2	40
3	43
4	40
5	41
6	39

From previous slide, forecast for period 6 =40. Actual observed data in period 6 is 39. Exponential smoothing forecast with parameter α=0.2 for period 7, made at the end of period 6

=

Exponential Smoothing Method

Exponential Smoothing forecast using parameter α (alpha; 0< α<1)
= α * actual observed data + (1- α) * forecast

Period	Demand
1	42
2	40
3	43
4	40
5	41
6	39

From previous slide, forecast for period 6 =40. Actual observed data in period 6 is 39. Exponential smoothing forecast with parameter α=0.2 for period 7, made at the end of period 6

= 0.2*39 + (1-0.2)*40

= 39.8 = 40

Moving Average & Exponential Smoothing

Period	Data
1	42
2	40
3	43
4	40
5	41
6	39
7	46
8	44
9	45
10	38
11	40

Demand Model: Level + random
We recognize the existence of random component
but focus only on estimating the systematic
(that is, non-random) component.

4-period moving average forecast MA(4) for period 11, made at the end of period 10=

4-period moving average forecast MA(4) for period 12, made at the end of period 11=

Given that forecast for period 11 was 35, what is the exponential smoothing forecast with alpha=0.2, ES(0.2) for period 12, made at the end of period 11=

What is ES(0.2) forecast for period 15, made at the End of period 11?

What is the ES(0.2) forecast for period 12 at the end of period 11?

39	36
25	40

Moving Average & Exponential Smoothing

Period	Data
1	42
2	40
3	43
4	40
5	41
6	39
7	46
8	44
9	45
10	38
11	40

Demand Model: Level + random
We recognize the existence of random component
but focus only on estimating the systematic
(that is, non-random) component.

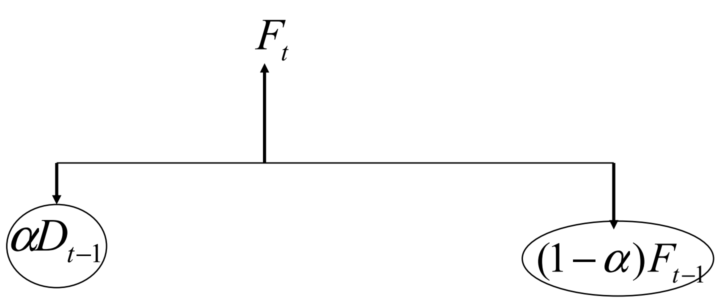
4-period moving average forecast MA(4) for period 11, made at the end of period 10=
(46+44+45+38)/4 = 43.25 = 43

4-period moving average forecast MA(4) for period 12, made at the end of period 11=
(44+45+38+40)/4 = 41.75 = 42

Given that forecast for period 11 was 35, what is the exponential smoothing forecast with alpha=0.2, ES(0.2) for period 12, made at the end of period 11=
=0.2*40 + (1-0.2)*35 = 36

Exponential Smoothing Parameter α

Idea--The most recent observations might have the highest predictive value along with the most recent forecast. Let us balance them:

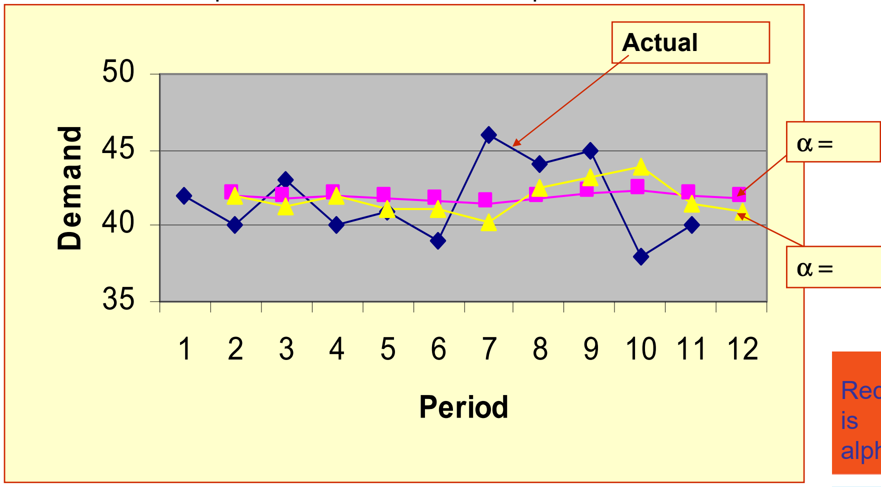


Exponential Smoothing with smoothing parameter α:
Forecast for next period =
α * actual for this period + (1- α) * forecast for this period
0< α<1

The role of smoothing parameter alpha is to determine the balance:
Weight on new data: alpha
Weight on forecast (based on previous data): (1-alpha)

Exponential Smoothing Parameter α

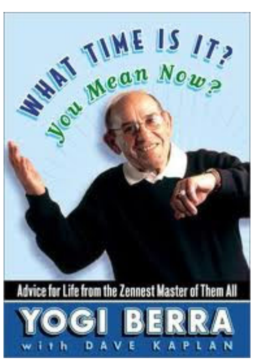
Which line is alpha=0.1? The other one is alpha=0.4



Red line is alpha=0.1

Yellow line is alpha=0.1

Any Questions / Comments / Sharing-of-Examples?



It's tough to make predictions, especially about the future. : Yogi Berra

Measuring Forecast Performance

Calculation of Error:

- Error Et or deviation = Forecast – Observed Value
- Absolute Error = Et = without the +/- sign
- MAD = Mean Absolute Deviation
- MSE = Mean Squared Error
- MAPE = Mean Absolute Percentage Error

Smaller MAD
MSE Better Forecasting method
MAPE

We seek forecasting method parameters (such as Alpha) that minimize error performance (such as MAD).

Error ranges are also used to develop estimates of the Random term in the demand model (such as standard deviation).

Dynamic Update & Forecast Errors

Most widely used time-series forecasting method is based on Exponential Smoothing: Exponential Smoothing forecast using parameter α (alpha; 0< α<1) = α * actual observed data + (1- α) * forecast

	Time	ES Forecast		Absolute
	Series	alpha=0.15	Error	Error
January	52	Initial forecast 55		
February	50			
March	57			
April	50			
May			Avg->	
				MAD

Evaluation of Forecasts:

- Error Et or deviation = Forecast – Observed Value
- Absolute Error = Et = without the +/- sign
- MAD = Mean Absolute Deviation (Average of the absolute error column)

Dynamic Update & Forecast Errors

Most widely used time-series forecasting method is based on Exponential Smoothing: Exponential Smoothing forecast using parameter α (alpha; 0< α<1) = α * actual observed data + (1- α) * forecast

	Time Series	ES Forecast alpha=0.15	ES Forecast alpha=0.15	Error	Absolute Error
January	52	Initial forecast 55	55	3	3
February	50	0.15*52+(1-0.15)*55=	55	5	5
March	57	0.15*50+(1-0.15)*55=	54	-3	3
April	50	0.15*57+(1-0.15)*54=	54	4	4
May		0.15*50+(1-0.15)*54=	53	Avg->	**3.75**
					MAD

Evaluation of Forecasts:

- Error Et or deviation = Forecast – Observed Value
- Absolute Error = Et = without the +/- sign
- MAD = Mean Absolute Deviation (Average of absolute error column)

Continued: We can change the alpha value and see How does it change error metrics like MAD and MSE

	Time Series	ES Forecast alpha= 0.45	Error	Absolute Error
January	52	55	3	3
February	50	54	4	4
March	57	52	-5	5
April	50	54	4	4
May		52	Avg->	**4**
				MAD

Practice: Exponential Smoothing & Errors

Use α=0.2

Month	Demand	Forecast	Error	Absolute |Error|	Error^2
April	105	-			
May	100	105	105-100=5	5	5*5=25
June	80	0.2*100+0.8*105= 104			
July	110				
August	115				
September	105				
October	110				
November	125				
December	120				

Average of the Absolute error column gives MAD.
Average of the Error^2 column gives MSE.

Practice: Exponential Smoothing & Errors

Use α=0.2

Month	Demand	Forecast	Error	Absolute |Error|	Error^2
April	105	-			
May	100	105	105-100=5	5	5*5=25
June	80	0.2*100+0.8*105= 104	24	24	576
July	110	99	-11	11	121
August	115	101	-14	14	196
September	105	104	-1	1	1
October	110	104	-6	6	36
November	125	105	-20	20	400
December	120	109	-11	11	121

Average of the Absolute error column gives MAD = (5+..+11)/8 = 11.5.
Average of the Error^2 column gives MSE = (25+…+121)/8=184.5

Practice: Should we use α=0.3?

		Alpha=				
		0.3				
Month	Demand	Forecast	Error	Abs Error	Error^2	
April	105					
May	100	105	5	5	25	
June	80	104	24	24	576	
July	110	97	-13	13	169	
August	115	101	-14	14	196	
Septembe	105	105	0	0	0	
October	110	105	-5	5	25	
Novembei	125	107	-18	18	324	
December	120	112	-8	8	64	
			MAD->	10.875	172.375	<-MSE

Operations & Business Process Management

Prof. Apurva Jain
MSIS 503

1. Identify Flow
2. Automate Workflow
   2.1 Characteristics for automation
   2.2 Value and Waste
   2.3 RPA

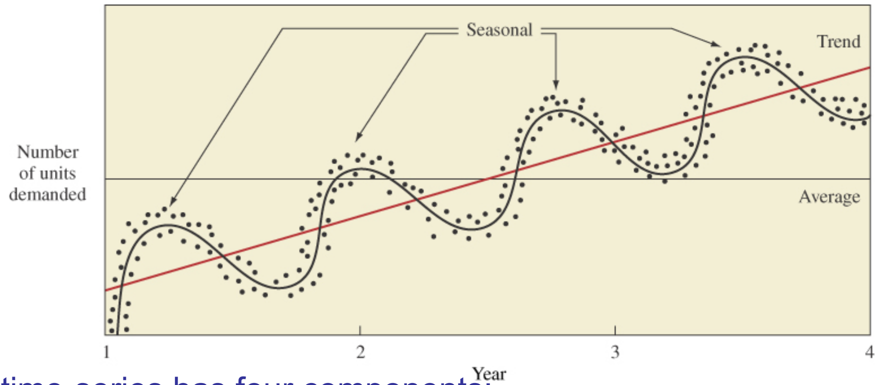
Session 3
3. Forecast Demand
   3.1 Time Series
      Moving Avg. Exp. Smoothing
      Errors: MAD, MSE
   3.2 Trend and Seasonality

   3.3 Forecasting Software

Next
Quiz 1 is due

4. Balance Capacity
..

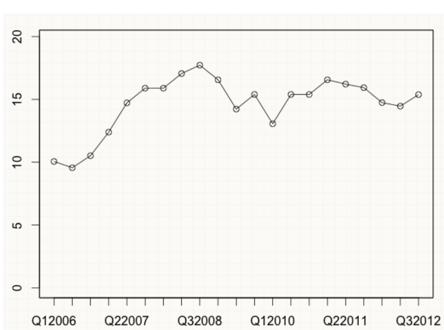
Demand Model Components

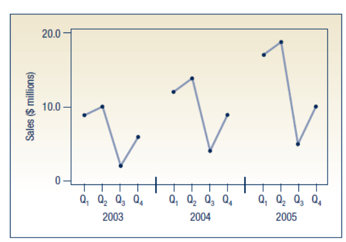


A time-series has four components:
Level, Trend, Seasonality & Random.

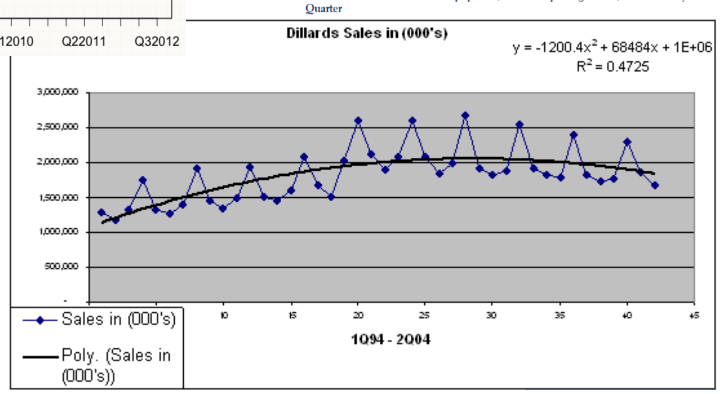
A demand model defines various components of a time-series and proposes a way to put them together.

Time Series Examples



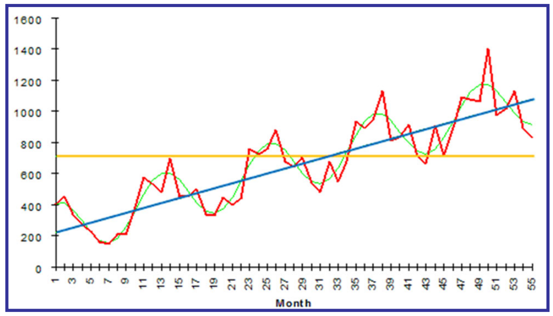


Sales of Baseball and Softball Equipment, Hercher Sporting Goods, 2003–2005 by Quarter



Identify demand components

Demand Model with Trend & Seasonality



Define components:
Level is height, Trend is step-size, Seasonal factors are multipliers
Demand model = (Level + look-ahead t*Trend) * Seasonal factor for the right season

Estimate component values:
Initialize values of Level, Trend, Seasonal Factors
With each new real data observation, *update* Level, Trend, Seasonal Factors,

Forecast:
At any point in time, use the latest Level, Trend, Seasonal Factors in the demand model

ETS Models

Triple Exponential Smoothing (Holt-Winters' seasonal Method)

Demand Model for t Periods Ahead=
{(Level + t * Trend) * Seasonal Factor for t Period Ahead} + Error

Exponential Smoothing Updating parameters: α, β, γ (all between 0 and 1)

New estimate of Level = α* (New Observation/ Corresponding Seasonal Factor)
+ (1 – α) (Old Level + Old Trend)

New estimate of Trend = β* (New Level – Old Level) + (1-β) * Old Trend

New estimate of Seasonal Factor for the corresponding season
= γ * (New Observation / New Level)
+ (1- γ) * Old Seasonal Factor for Corresponding Season

Use training data to search for α, β, γ that minimize error measures like MAD or MSE.

The model presented above is for the case of additive errors, additive trend, and multiplicative seasonality. Many other variations are possible. A good software system will automatically select the best variation.

ARIMA Models

SARIMAX (Seasonal Auto-Regressive Integrated Moving Average with eXternal variables)

Forecasting models hypothesize a relationship between predictor variables Y (future demand values) and explanatory variables like previous demand values, previous errors, and external variables. ARIMA models work with *differenced* versions of time series in order to achieve the stationarity required by the model. Parameter *d* captures the degree of differencing.

SARIMAX Model:
Predicted values of differenced Y = a constant
+ weighted sum of p latest values of differenced Y
+ weighted sum of q latest values of errors
+ weighted sum of some values of differenced Y from the previous corresponding season
+ weighted sum of some values of errors from the previous corresponding season
+ weighted sum of some external variables.
These weights or coefficients can be estimated by using a Python package.

Different combinations of parameters p,d,q (additional parameters are used for seasonal models) lead to different models; a good software will recommend the best set of parameter values.

Examples

SARIMAX Result for Glossy stickers - US region

Low AIC value

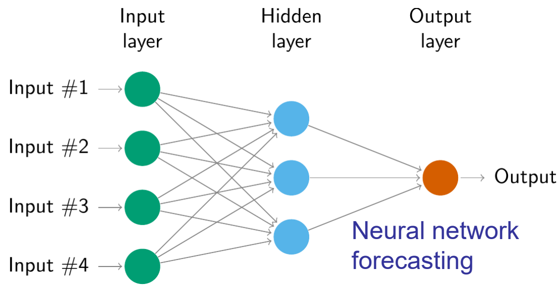
Impact of discount on sales

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                      Log_Sold_Units   No. Observations:                  184
Model:             SARIMAX(0, 1, 1)x(1, 0, [], 52)   Log Likelihood                  97.789
Date:                             Sat, 18 May 2024   AIC                           -187.578
Time:                                     23:33:16   BIC                           -176.077
Sample:                                          0   HQIC                          -182.905
                                             - 184
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Discount       4.2120      0.504      8.352      0.000       3.224       5.200
ma.L1         -0.6061      0.082     -7.363      0.000      -0.767      -0.445
ar.S.L52       0.4415      0.050      8.917      0.000       0.344       0.539
sigma2         0.0131      0.001      9.150      0.000       0.010       0.016
===================================================================================
Ljung-Box (L1) (Q):                   0.25   Jarque-Bera (JB):                 9.80
Prob(Q):                              0.62   Prob(JB):                         0.01
Heteroskedasticity (H):               0.76   Skew:                            -0.49
Prob(H) (two-sided):                  0.38   Kurtosis:                         3.91
===================================================================================
```

FOSTER SCHOOL OF BUSINESS

Machine Learning Models

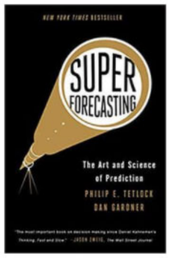
Useful when
- Errors are correlated
- Multiple seasonal cycles are present
- Very large amount of data
- Unclear which external variables are important
- Relationships are non-linear



Neural network forecasting

Examples of factors that are hard to estimate. Can machine learning help?

Can we rely on experts' Judgment?



Who are the **Superforecasters?**

Good Judgment's global network of Superforecasters has its roots in research funded by the US intelligence community. Reports that Superforecasters were 30% more accurate than intelligence analysts with access to classified information rocked the conventional wisdom.

https://goodjudgment.com/

Vote

Speaking of forecasting,
When did Bill Gates
make this prediction:
"Two years from now,
the problem of SPAM
will be solved." ?

2002	2004
2010	2008

Operations & Business Process Management

Prof. Apurva Jain
MSIS 503

1. Identify Flow
2. Automate Workflow
   2.1 Characteristics for automation
   2.2 Value and Waste
   2.3 RPA

Session 3
3. Forecast Demand
   3.1 Time Series
      Moving Avg. Exp. Smoothing
      Errors: MAD, MSE
   3.2 Trend and Seasonality
      Demand model
      Triple ES, Advanced methods
   3.3 Forecasting Software

Next
Quiz 1 is due

4. Balance Capacity
..

September 30, 2022 in Forecasting Software Survey

Survey: Forecasting Software Trends in a Challenging World

By Oliver Schaer, Ivan Svetunkov, Alisa Yusupova, Robert Fildes

- Practice-driven Trends
- Algorithm-driven Trends
- Process-driven Trends
- IT-driven Trends

Algopine Demand Planning Solution	FC365 Pharmaceutical Forecasting Platform	Prophecy
Analytica	Forecast Pro	Quantics Forecast
Autobox	gretl	RATS
Complete Advanced Time-Series	iData	RoadMap GPS
Enterprise Dynamics	Intuendi Demand Planning	SAS Forecast Server
ERS - Enterprise Resource Simulator	iqast desktop & iqast server & iqast control tower	SAS Visual Forecasting
EViews	Netstock IBP	SigmaXL
		Stella
		Tangent Information Modeller
		The Finished Goods Series (FGS)

https://www.informs.org/ORMS-Today/OR-MS-Today-Software-Surveys/Forecasting-Software-Survey

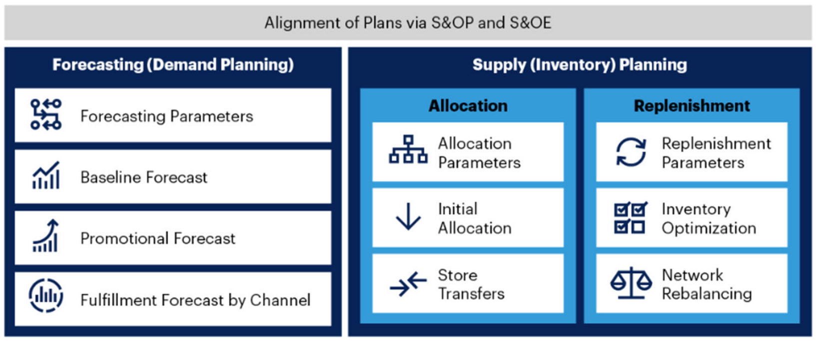
Go to Gartner Home

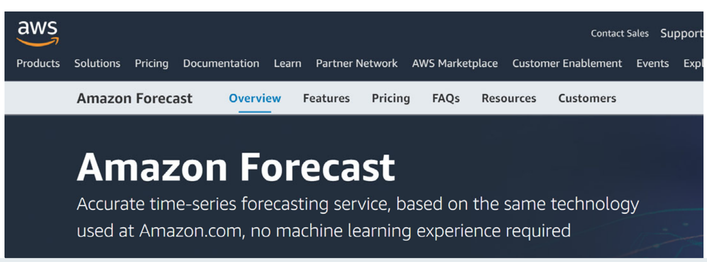
Market Guide for Retail Forecasting, Allocation and Replenishment Solutions

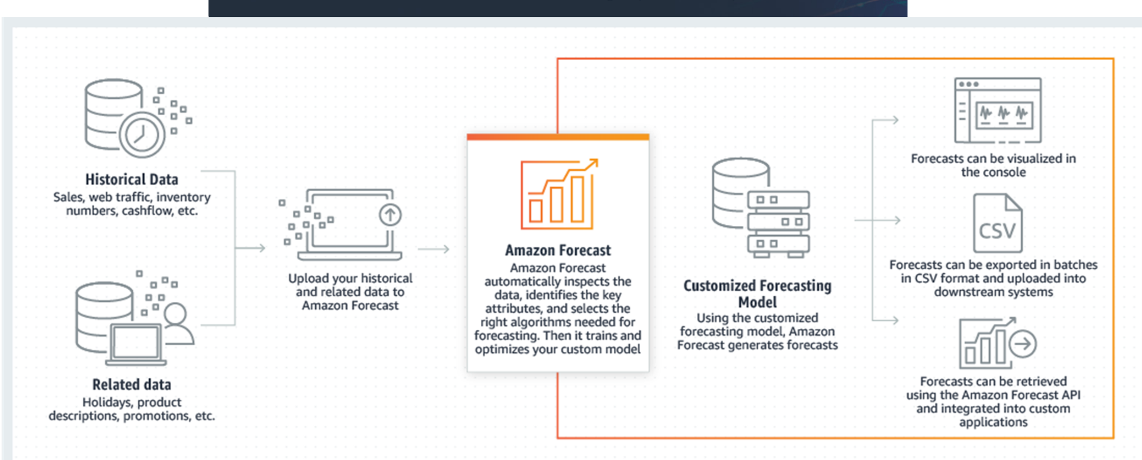
24 April 2024 - ID G00777432 - 19 min read

By Caleb Thomson, Gerhard Grimm, **and 1 more**

Forecasting, Allocation and Replenishment Application Model

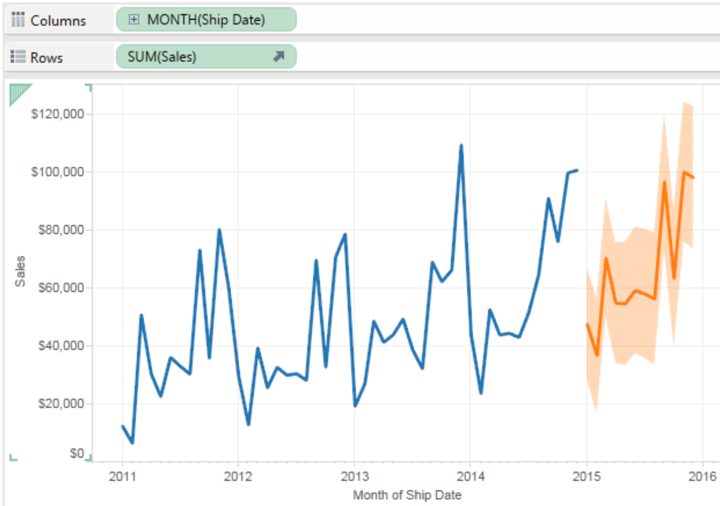






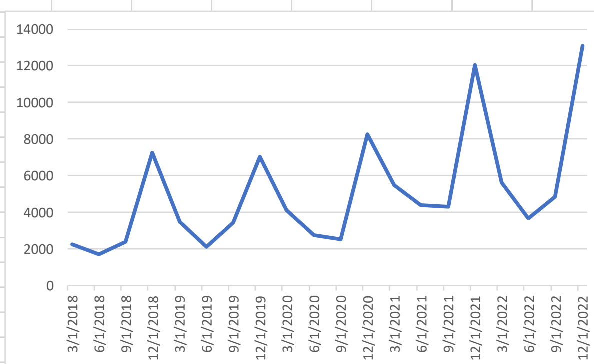
tableau

Forecasting



Data

Period	Demand
3/31/2018	2250
6/30/2018	1737
9/30/2018	2412
12/31/2018	7269
3/31/2019	3514
6/30/2019	2143
9/30/2019	3459
12/31/2019	7056
3/31/2020	4120
6/30/2020	2766
9/30/2020	2556
12/31/2020	8253
3/31/2021	5491
6/30/2021	4382
9/30/2021	4315
12/31/2021	12035
3/31/2022	5648
6/30/2022	3696
9/30/2022	4843
12/31/2022	13097



Implementation: Forecasting Plan

1. Specify the time-series data to gather: time-period and item unit. Plan how to deal with outliers, missing data and any other data-cleaning issues.

2. Specify the time-series method to be used and if any software is needed. How will we search for parameters? What error measure is appropriate? Estimation of variability.

3. Make a list of outside-the-time-series factors that can have an influence on forecast. Gather data to quantify these factors. Use regression or judgment to estimate adjustments to the time-series forecast.

4. Run it through the organizational forecasting process. Gather judgment forecasts from other departments like sales. Should other internal/external opinions be collected? Develop a process to combine these forecasts and track errors.

Combining the Methods

Start with time series methods:
Extrapolate the pattern to make a forecast

Brainstorm any outside-the-data influences:
Adjust the forecast to account for other factors

Run it through the organizational forecasting process:
gut-check based on internal/external opinions

Implementation Issues & Examples:

What should be the period-length?

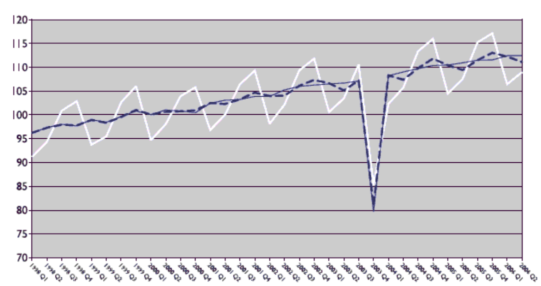
What should be the unit of forecasting?

How far in future should we forecast?

Implementation Issues & Examples:

What does the time-series actually represent?

Clean-up the data.



Improvement Ideas

- Make sure that a data-driven forecast is part of a regular planning process
- Focus on a few items, aggregate time-series data across items and time
- Use simple software first; complex algorithms are not necessarily better
- Adjust for prices and any other known external factors like demographic or competitive changes
- Automate the forecasting system
- Track and report Errors regularly to improve forecasting methods
- Combine with other forecasts (sales, product group); gain consensus
- Once the above is done, explore more sophisticated methods for items that have large errors

Key points and takeaways

- Time-series forecasting is the most common and useful method in many contexts.
- Moving Average and Exponential Smoothing formulas and calculations. Dynamic forecasting using Exponential Smoothing.
- Error computations: MAD and MSE
- Triple ES method uses parameters to learn from history to estimate level, trend, and seasonal factors.
- Easily available software tools like Tableau allow for easy implementation of forecasting methods.

Operations & Business Process Management

Prof. Apurva Jain
MSIS 503

Forecasting is a universal problem. In most cases, projecting historical patterns is a great and easy way to start.

Tracking errors closely shows us how to improve the demand forecasting model.

1. Identify Flow
2. Automate Workflow
    2.1 Characteristics for automation
    2.2 Value and Waste
    2.3 RPA

Session 3
3. Forecast Demand
    3.1 Time Series
        Moving Avg. Exp. Smoothing
        Errors: MAD, MSE
    3.2 Trend and Seasonality
        Demand model
        Triple ES, Advanced methods
    3.3 Forecasting Software
        Tableau
        Implementation examples

Next
Quiz 1 is due

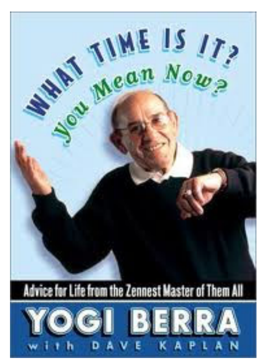
4. Balance Capacity
..

A Moment of Reflection

For most business demand forecasting applications, we can take the approach suggested here: start with time-series, adjust for outside-the-data causes, use judgment.

But there are many business and non-business applications where we may need to go beyond the above approach:
A completely new product
Length of govt. shutdown
Very long-term forecasts (797?)
Traffic in Seattle squeeze
Big projects completion dates (Big Bertha)
Brexit? Climate change?

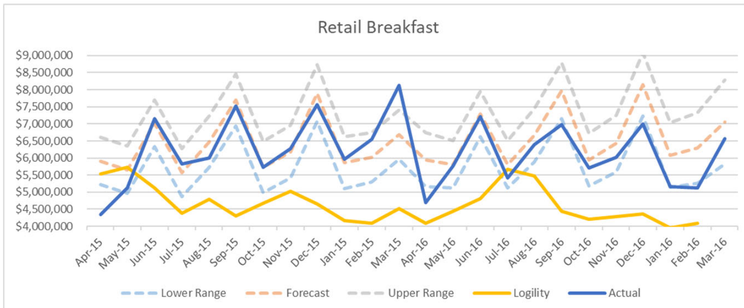
Please share ideas about how we may make these forecasts or share a problem that you find interesting.



It's tough to make predictions, especially about the future. : Yogi Berra

Examples from recent projects

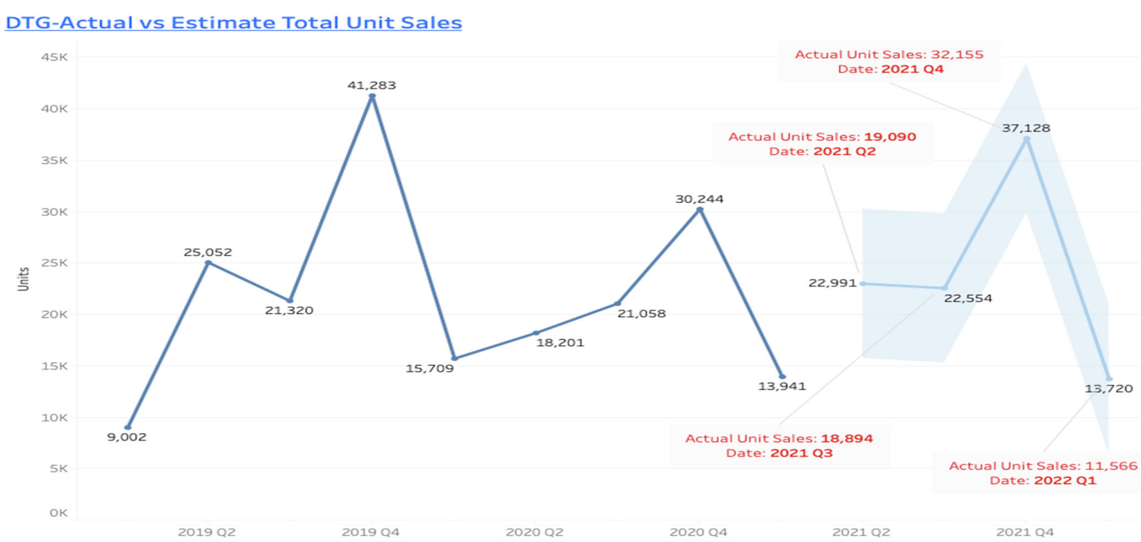
Control Forecast – Fiscal Year 20xx-yy



FOSTER SCHOOL OF BUSINESS
UNIVERSITY OF WASHINGTON

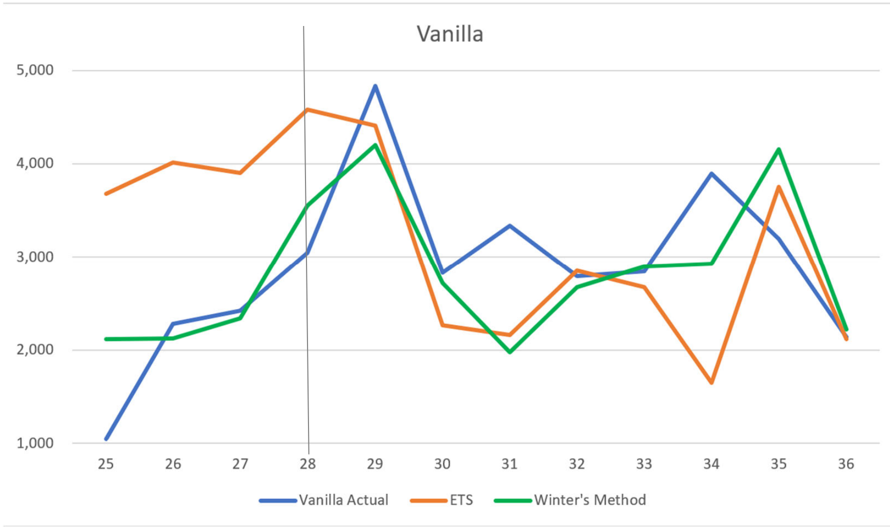
Examples

Actual vs Estimated: Forecast Analysis



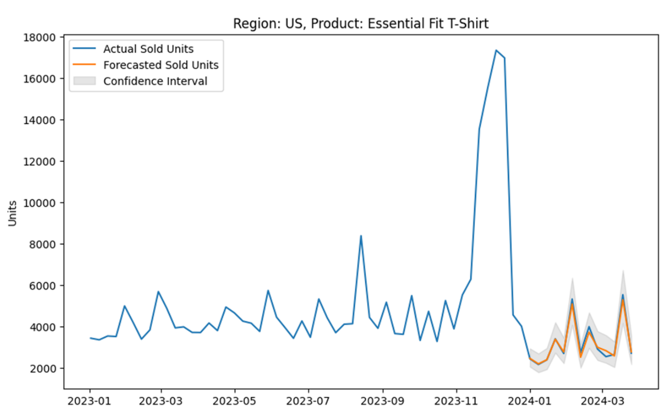
Introduction › *Data Cleaning* › *Sales Analysis* › ***Forecasting Method*** › *Conclusion*

Examples
Statistical Model Comparisons



Examples

Example - Low Difference



Week	Actual	Forecast	Difference	% of Diff
2024-01-01	2438	2460.91	22.91	0.94%
2024-01-08	2167	2196.10	29.10	1.34%
2024-01-15	2391	2395.22	4.22	0.18%
2024-01-22	3405	3388.13	16.86	0.50%
2024-01-29	2698	2771.92	73.92	2.74%
2024-02-05	5329	5091.13	237.86	4.46%
2024-02-12	2739	2517.31	221.68	8.09%
2024-02-19	3994	3726.85	267.14	6.69%
2024-02-26	2913	2997.20	84.20	2.89%
2024-03-04	2546	2833.55	287.55	11.29%
2024-03-11	2651	2582.31	68.68	2.59%
2024-03-18	5539	5293.67	245.32	4.43%
2024-03-25	2714	2779.85	65.85	2.43%
Mean absolute percentage error (MAPE)				**3.74%**

FOSTER SCHOOL OF BUSINESS