A Mariner White Paper

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Assessment of Retail Out-of-Stock Conditions Using Statistical Inference

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Abstract

In this example, we propose how to detect out of stock (OOS) conditions by applying a probabilistic approach using point of sale (POS) data to infer zero inventory-on-shelf, rather than infer inventory-on-shelf from traditional enterprise resource planning (ERP)/POS deterministic calculations.

The Retail Dilemma

19th Century Britain was famous for retailing. According to Adam Smith[8],

> *"To found a great (British) empire for the sole purpose of rising up a people of customers, may at first sight, appear fit only for a nation of shopkeepers."*

20th Century Britain's Heathrow Airport pioneered commercial Electronic Data Interchange (EDI)[2]. Tradacoms was a frontrunner in electronic data interchange for retailers[5]. Article Numbering Association, now GS1 UK, introduced barcodes and the first Electronic Point of Sale systems in the US shortly after.

21st Century GS1 UK, as part of a global organization, creates XML standards for EDI in 2002. In 2003, it creates a global electronic product code standard followed by an RFID standard and a global data synchronization network a year later.

200 plus years of retailing, 40 years of barcodes, 40 years of EDI, 11 years of RFID, decades of experience with Vendor Managed inventory (VMI) and Direct Store Delivery (DSD) fulfillment models and we still have a chronic out-of-stock (OOS) problem. It is a problem for large and small, as according to Bloomberg's news service, even Walmart suffers from OOS.[3]

OOS persists because all that technology and expertise still can't prevent inventory from being:

- Damaged
- Miscounted
- Out of date
- Not in Location
- Stolen

Process improvements and technology advances will continue to reduce the inaccuracy, but while the inaccuracies persist, why not use a probabilistic approach to replenishment planning instead of pretending the inventory numbers are always correct?

A Look at the Data

The data from the retailer's POS system is given in the following manner:

Store Number	*Item Number*	*Date*	*Number of Units Sold*
123	889900	1/1/2016	1
123	889900	1/2/2016	3
123	889900	1/3/2016	0
123	889900	1/4/2016	0
123	889900	1/5/2016	2
123	889900	1/6/2016	4
123	889900	1/7/2016	2
123	889900	1/8/2016	0
123	889900	1/9/2016	0
123	889900	1/10/2016	0
123	889900	1/11/2016	5
123	889900	1/12/2016	3

Notice the dates with zero sales (the 3rd,4th,8th,9th, and 10th). The next step is to understand the reason behind the lack of sales. Did store 123 not sell any of item 889900 because it was out of stock (a problem that can be remedied by sending more product to the store, or moving it from back stock onto shelves) or because no customers wanted that item on those particular days (a "desire" problem unrelated to the distribution of items to stores.)?

Conjecturing Out of Stock vs. Lack of Customer Demand

For this product manufacturer and distributor, they make many products. Each product, though, may have a very different selling behavior. Some flagship products are big sellers while others are more specialized and therefore less popular. For the flagship products, sales may be good. If a store fails to sell any one day, it is less likely that there was a lack of customer demand and more likely that it was truly out of stock. The opposite is also true for the less popular products. If a store does not sell any for a few days, that may be completely normal. So, seeing zeros in the POS data for *Number of Units Sold* is far less likely to be resulting from an out of stock situation.

We assess the distribution of consecutive "no-sales" days to make a confident selection of days where it is most likely that a day with zero sales is out of the norm and the product is probably out of stock.

Multiple Methodologies

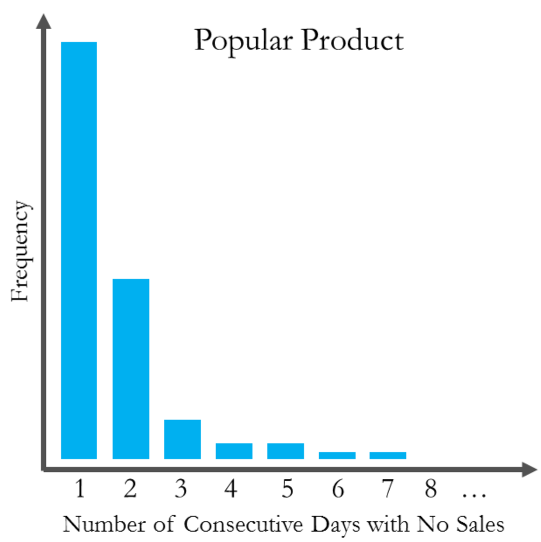
Various methods can be used to separate the different no-sales situations as described previously. Each method varies in its complexity and applicability to each scenario.

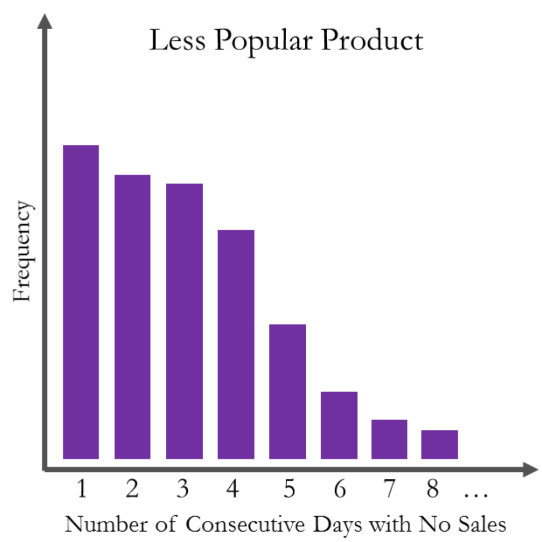
For example, Bayesian inference can be used, according to Li Chen of Cornell University, to provide a probabilistic "inventory belief".[1] In this method, the likelihood of having a particular level of inventory stock available is computed based on each stores' stock replenishment patterns and selling patterns. This yields a computed probability (belief) that the on hand stock of a particular item is 0 (true out-of-stock situation) or not. This method, since it uses actual on hand stock information, can be highly accurate, but also requires access to such information.

Another approach uses what is known as a Survival Model.[7] This method is generally used in population modeling or genetics to determine when or if a given population will die out or a particular genetic mutation will become the norm for the group. As you can see, this draws an easy parallel to product sales. In this situation, the individual populations are the quantities of products in each store. The condition of "dying out" is when a product becomes out of stock. However, setting up this analysis can be complex and only works in certain scenarios where the data is in the correct format.

Drawing the Line using a Probabilistic Distribution Approach

In order to quantify the selling behavior of each product, we chose to look at the distribution of the number of consecutive days the product goes without selling in a particular store. This determines what is "normal" behavior for a product. As stated previously, flagship/popular products may only go a day or so without selling whereas less popular items sell more infrequently. In the example figures below, note that popular products have a higher concentration of shorter consecutive periods with no sales and less popular products often have a more spread out pattern in their distribution.





From looking at the distributions, we now must determine a cutoff point between calling a day with no sales as a customer demand issue versus a stock issue. We draw the line by using percentiles. Calculating a percentile, say 99th percentile or 95th percentile, will give a dividing line between scenarios. Anything above the line is a presumed out of stock situation. Anything below the line is a customer demand issue. A percentile effectively returns the top n% of consecutive days with no sales; the extreme, out of the norm cases. The top percent have a higher likelihood of actually being out of stock.

Note about Percentile Selection:

There is no "correct" percentile to use. For more popular products with dense concentrations in shorter no-sale periods, a lower percentile may be better than higher percentiles. For products with highly infrequent selling patterns or highly variable behavior, a higher percentile may be necessary to weed out all of the no-sales due to lack of interest, which may be normal for less popular products.

Higher percentiles are much more selective since they select a smaller top percentage of days.

Percentiles, at multiple levels, are calculated for each product in each individual store. This captures the selling behavior at the store level rather than assuming a product has the same selling behavior across all retail stores.

This method, in contrast to the methods mentioned earlier, is very simple to implement since it is utilizing a single percentile calculation on the number of days a product goes without a sale. As mentioned earlier, much of the complexity of the other methods is due to the data requirements (on hand stock information, data format, etc.).

Calculation of Missed Sales

Once all the cutoff lines (percentiles) are known, the next step is treat days with no sales as holes in the dataset. Then, fill them in using the known, surrounding sales information. Imputing the values is done by looking at what happened before and after the no-sale period. In other words, how were sales before and after the no-sales period occurred?

Again, Multiple Methodologies

As with separating out of stock days with lack of customer interest days, there are a large number of options to try when attempting to predict what should have sold during the days where a product is out of stock.

Forecasting using a time series algorithm such as ARIMA or an exponential smoothing model is a popular approach to predicting values.[6] These methods take historical data and then predict into the future. They can even take into account seasonality changes and trends in the sales of each product. However, they are most often used to predict future data. So, it would be common to use this approach to predicting the stock market. Example: Take the last 2 years of stock data for a given company and predict the next month. This does not quite fit our problem since we are predicting values inside a data set. In our data, we may only have a few days or weeks of solid sales, but need to only predict a few days of presumed out of stocks for a given product. These forecasting methods are generally easy to implement, but require lots of historical data to make a good prediction.

Regression is also a good contender in the prediction game. Regression takes multiple input variables and then generates weights for how much each variable affects the dependent variable (the thing you are trying to predict). However, we do not really have any variables to use to predict an outcome. Regression might be a good approach for predicting how much a house will cost if it has 3 bedrooms, 2.5 bathrooms, and a large yard in the suburbs. In our case, we only have date and the number of units sold. We can't count store number or product as variables because we need to use these to build separate models for each. So, this isn't a good choice either.

Our Direct Approach: Inward Imputation

Imputation is the process by which we fill in holes in a dataset. This can be done in a multitude of ways by making assumptions about what should be in the missing spots. In some scenarios, we use averages or medians. In other circumstances, we remove data points altogether or fill in the values by looking a similar data points and assuming the missing values should be somewhere near those known cases.

Using this methodology for imputation, but applying it to the "zeros" in the POS data, we can fill in the days with no sales with probable values. However, as stated before, not every day with no sales for a given product cannot be treated as if there was no product on the shelf. Therefore, we use the use the cutoff points as described previously to determine which "zeros" are the days in question.

We calculate the weighted arithmetic mean for sales before and after the no-sale period. By using the weighted arithmetic mean, longer selling periods have greater influence on the prediction than shorter ones. Once means are computed, the mean is filled in for the value only on the days where the no-sale day number is greater than the percentile cutoff. Note that days with lack of interest (where the no-sale day is less than the percentile cutoff) are being left out intentionally. See the figure below.

Before After Before After

Group	A				B						C	
Date	1/1	1/2	1/3	1/4	1/5	1/6	1/7	1/8	1/9	1/10	1/11	1/12
Units	1	3	0	0	2	4	2	0	0	0	5	3
Out of Stock Day			1	2				1	2	3		
99th Percentile: 3 Days			×	×				×	×	✓		
95th Percentile: 2 Days			×	✓				×	✓	✓		

✓	Presumed Out of Stock Issue
×	Presumed Customer Demand Issue

$$\left[\frac{2}{5}\cdot\left(\frac{1+3}{2}\right)\right]+\left[\frac{3}{5}\cdot\left(\frac{2+4+2}{3}\right)\right]\approx 2$$

Weighted Average From Groups A & B

$$\left[\frac{3}{5}\cdot\left(\frac{2+4+2}{3}\right)\right]+\left[\frac{2}{5}\cdot\left(\frac{5+3}{2}\right)\right]\approx 3$$

Weighted Average From Groups B & C

Group	A				B						C	
Date	1/1	1/2	1/3	1/4	1/5	1/6	1/7	1/8	1/9	1/10	1/11	1/12
Units	1	3	0	0	2	4	2	0	0	0	5	3
99th Percentile Prediction			0	0				0	0	**3**		
95th Percentile Prediction			0	**2**				0	**3**	**3**		

After filling in these values, we can sum the numbers to give us a grand total of missed sales. Connecting back to financial information, we can then assess the financial impact those missed sales have on revenue and gross margin, which ultimately affect the bottom line.

Item Number	*Total Missing Units*	*Item Price*	*Item Gross Margin*	*Missed Revenue*	*Missed Gross Margin*
889900	286	$1.49	$0.74	$426.14	$211.64
889901	154	$5.99	$2.36	$922.46	$363.44
889902	302	$2.99	$1.12	$902.98	$338.24
889903	98	$3.49	$1.80	$342.02	$176.40
889904	169	$0.99	$0.34	$167.31	$57.46

In the figure above, a total amount of missed revenue and gross margin can be calculated from each items' pricing and gross margin figures. Dollarizing these missed sales is the best way to quickly determine where the best opportunity for improvement is at the individual product level, store level, or overall.

Research conducted by Gruen and Corsten in *A comprehensive guide to retail out-of-stock reduction in the fast-moving consumer goods industry* gives additional methodology into further assigning a true dollar value to missed sales.[4] Aside from simply taking the gross margin calculation performed earlier at face value, this study reports that a distributor must also take into account the total sales volume of the stores in comparison to each other. Combine this with the shopping behaviors, supply chain costs of getting the products to each store, and labor costs of stocking the shelves, the relationship between out-of-stock missed sales and revenue opportunity is not as simple. That is, a larger, busier store may feel the impact of fixing an out of stock issue differently than a smaller, calmer store. Luckily, the analysis is done at the individual item level in each store, so the information gained from the analysis can be personalized for use in diverse store environments. This avoids the "one size fits all" methodology of treating all products the same in all stores.

Another interesting notion from this study is that in order to reduce lost sales revenue, it may take focusing on the top products in the lowest performing stores. Conversely, it may take focusing on the worse performing products in the best stores to win back the lost sales revenue.

> "An examination of SKU sales frequency shows that only a small portion of items make the big difference. This has implications for identification, ordering, and shelf space allocation." – Gruen & Corsten, 2007

Conclusion

By repurposing the methodology of imputing missing values to filling in no-sale days, we can make a confident assessment of out of stock situations. This, in turn, reveals more information to the manufacturer about the efficacy of product distribution in retail stores. This can help answer questions like, "Are we sending the correct quantities of products to the stores?" or "Is there something that is not selling well enough to constitute it taking up shelf space for our other, better selling products?" Better predictions lead to more accurate supply chain decisions and better product placements on retail shelves, therefore positively affecting the bottom line by having the right products in the right place at the right time for your customers.

References and Related Studies

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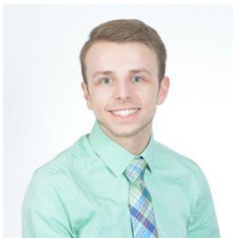

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Colby is a Data Scientist at Mariner. Using a background in mathematics and statistics, he puts the Azure Machine Learning system to work along with R to gain insight from data. Outside of work, Colby is a pianist, Netflix junkie, bioinformatics researcher and Ph.D. student at the University of North Carolina at Charlotte.

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