When traditional algorithms fail as trendlines are taken over by outliers
Using demand sensing algorithms to fine tune demand projection estimates in COVID times

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Traditional perspective of Demand Sensing

Demand sensing, as it has developed over last few years, has been used as a tool for assisting demand planners in making demand projections more useful to the businesses. It has been seen as a decentralized demand data sensing for real-time, fine-grained break-down of projected demand into small time and space units.

To put this in simple business language, if projected demand for the next 3 months for Brand X in geography P is 100, 120 and 110 respectively, demand sensing algorithms could be developed which would break this down by week or even day of week for each sub category. This aids in steering a business in ordering, production and logistics functions over short term. This is depicted in figure 1 below.

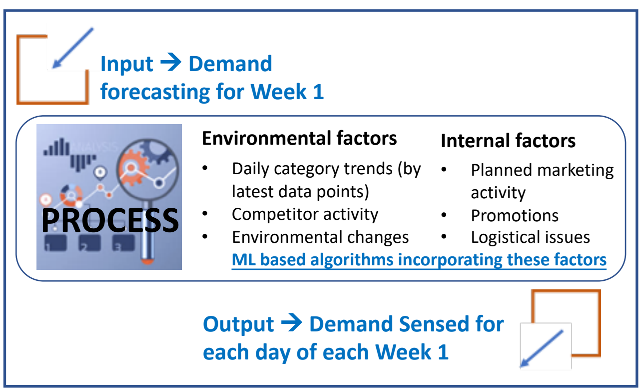

Figure 1 :- Visual representation of Demand Sensing

Demand Sensing takes demand projection as an input variable and as outcome, it gives breakdown of projection into finer grains of time and space, and in the process, it also enhances the accuracy of the projection. It provides short terms demand forecast with an accuracy which goes beyond core trend and seasonality that might have been assessed from the past data analysis.

In other words, if 3rd Saturday of October last year was a low day, and if a festival falls on that day in this year, it will not be a slow day. In reality, this becomes far too complicated , given thousands of such factors and hundreds of SKUs. This is therefore all built into regression based, ML powered algorithms which perpetually enhance their accuracy over time.

The COVID 19 scenario

The months of February, March, April and May 2020 have become outliers in the sales value / volume time series for almost all businesses. This may vary as per your region and the country but for some companies, business has come to a total stand still while for few others it is significantly down, though some have maintained and some have even grown in this period.

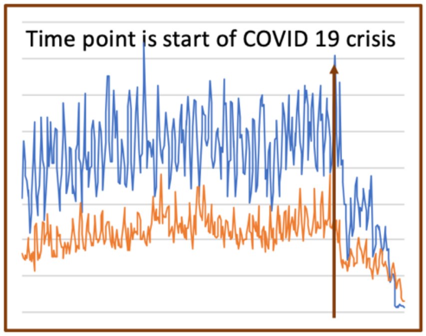

Figure 2:- Daily Sales data and impact of COVID

To make the point explicit, given herewith is a real life situation from a company operating in travel retail space. The chart indicates fluctuations on daily sales trends on two SBUs of the business. These overall sales could be broken down by brands, SKUs, outlets etc. Daily sales fluctuate a lot in retail as can be seen in the image (Fig 2) below. COVID crisis hit in the middle of March and sales dropped sharply and in a matter of days came to zero. This would now stay at zero till airport & travel opens up again.

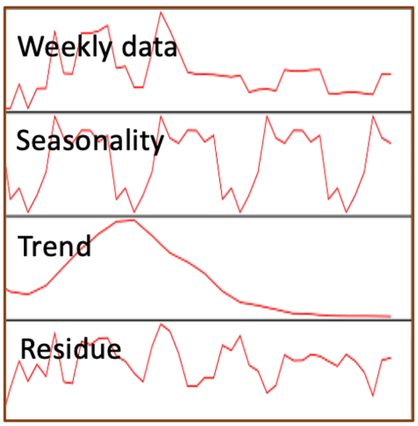

Figure 3 : Decomposition of Sales Data using time series algorithm

The business in the past used traditional time series decomposition mechanisms to break weekly sales into core trend and seasonality and project weekly demand with an error band to account for residual variance impact as depicted above (Fig 3). When the business is projecting sales in the long terms, i.e., after a year or so, it could consider these few months as outliers so that they don't impact the long term trends. That may also be possible only if the life is completely back to normal in a few months.

But what now? in the near future?

How can this business project demand for next 10 to 15 weeks as the time series models are now totally non applicable. There is an urgent need for newer advanced algorithms, which can help demand planners in this new world. This brings to relevance a re-look into the nascent art of demand sensing.

A look at consumers' perspective to the entire COVID situation.

Primarily it was lockdown which brought the industry down to its knees. First the retail stores were closed, then production units closed down affecting the total supply chains. Currently, even as lockdowns are being eased out, the customers are indoors and are worried about the pandemic.

We initiated a study in amongst general urban adult audience in India to track consumer sentiment over time. This would be a long term continued study. The key objective of this is to track consumer sentiment over time and project it to further in future once the data trends stabilize. This is an online in-depth survey covering various emotions which the respondents are feeling at a point of time. Respondents are being selected by paid campaigns across various digital marketing platforms with a demographic & geographic filter restricting to adults in key urban centers.

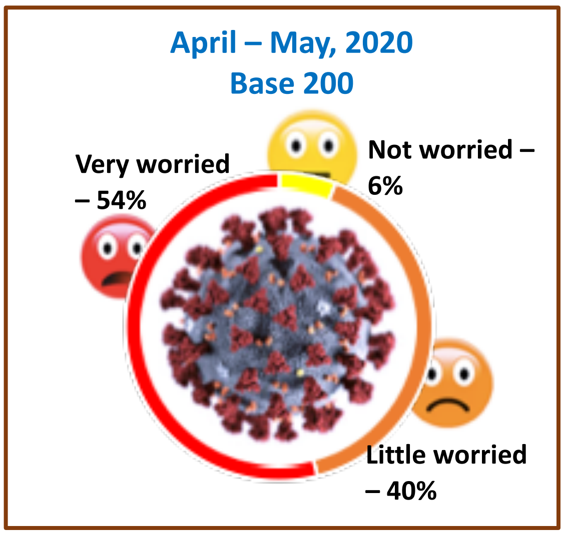

Figure 4 : How worried the general audiences in COVID situation ?

The results of the first phase on April & May which corresponds to shutdown and stay at home directives at most cities in India. More than half, (~ 54%) of respondents (splintering down may yield differences in different segments) are very worried about the situation out of the comfort of their homes. While 40% of the audience are only a little worried and 6% are not worried.

This comprehensive consumer sentiment analysis is required to understand a) what the consumer is going through, b) what products and services will the consumer come back into the market ? and c) when would he come back for which specific products and services?

Some other key findings from this study are as given herewith and indicate that daily life of the consumer is quite disturbed and they are also very worried about the situation.

1) COVID crisis has **very** negatively impacted earnings of 43%
2) It has negatively affected life of 30%
3) Hope and NOT fear are the key emotion people are living with
4) ~40% are buying essential commodities more than before

Need to build Sentiment Analytics into Demand Sensing

The Demand Sensing models would begin with two basic inputs. These would be

- Environmental factors (e.g., when will markets / stores / malls / airports etc. open up, what alternates consumers will have for your product / services)
- Internal business factors (e.g., planned marketing or promotion activities)

Environmental factors

- Daily category trends (by latest data points)
- Competitor activity
- Environmental changes

Internal factors

- Planned marketing activity
- Promotions
- Logistical issues

Figure 5 : Demand Sensing model pre COVID

Now consider the undeniable fact that consumer sentiment is the main factor behind demand depression in the current scenario, sentiment analytics becomes the third pillar in the Demand Sensing construct we have seen earlier. Therefore, in the current scenario, given below is how demand sensing constructs have to be modelled.

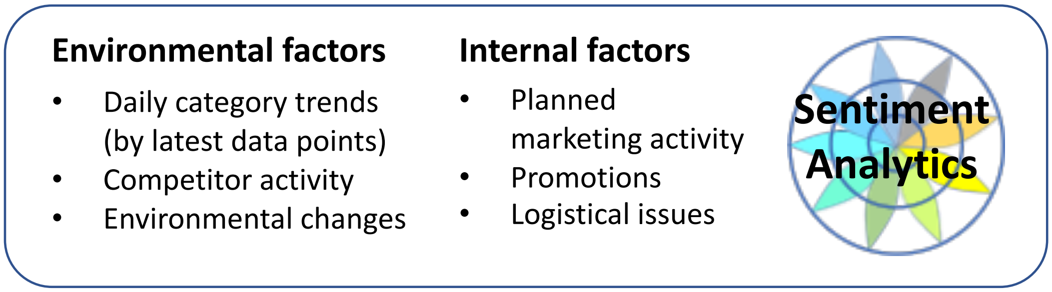

Figure 6 : Demand Sensing model post COVID

Sentiment Analytics for Demand Sensing algorithms

There are 3 pillars of sentiment analytics on which demand sensing will rest in the post COVID scenario – relating to the consumer per se, relating to the category and specific brand related sentiments.

These pillars of sentiment analytics are inter-connected and also often impact each other. This paper details how each of these impact demand for categories and or brands. Therefore, it is critical to understand them better. We are looking at 2 aspects of sentiment analytics in this paper

1) How do these factors impact demand for product / category / brand ?

2) How to measure / assess them to build them into Demand sensing modelling ?

The Core of Sentiment Analytics today is about understanding customer's world view and his/her product categories view. The three parts of the Sentiment which needs to be measured are as shown below .

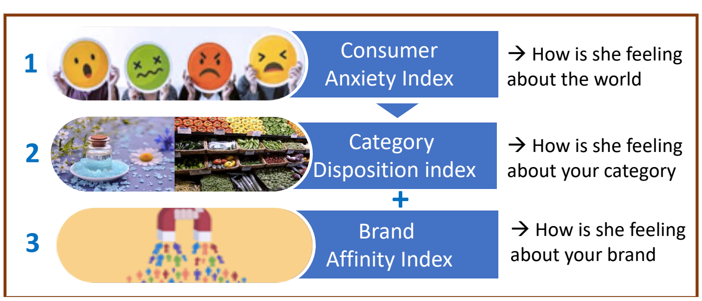

Figure 7 : Three components of Sentiment for Demand Sensing

a) Consumer Anxiety Index

The proportion of consumers who are very worried are less likely to step out for what they consider less critical. Therefore, we need to assess anxiety quotient for the target audience and track the proportion of very worried, somewhat worried and not worried. Once the trends stabilize this can be projected to longer term to predict Anxiety index for the audience a few months or weeks down the line. The impact of anxiety on consumer behavior, however, is not a standalone variable but interacts with category criticality. The behavior with respect to a category considered critical may not get affected despite extreme anxiety and on the other hand behavior with respect to a category considered non critical would get severely affected at a moderate anxiety level.

b) Category Disposition Index

Category disposition index is a mean of 2 distinct uncorrelated aspects :

1. Criticality Index – how essential does one consider a specific category to be. This simply means that categories considered more essential are less affected by consumer anxiety.

2. Risk assessment with product / service. This captures the associated risk with the product or service. For instance, going to a movie hall has high risk perception while going to golf course has much lower risk.

These two aspects are uncorrelated and have a simple additive relationship, therefore for a category Disposition index is assessed as mean of the two measures.

An anxious consumer is likely to avoid air travel for pleasure while have no second thoughts about buying regular groceries. Therefore, it is of utmost importance to build co-interactions of consumer anxiety and category disposition into Demand Sensing models.

c) Brand Affinity Index

In the times of COVID, consumer's relationship with brands may have taken a shift. This could be assumed to be of no importance if we are sure that there has been no reason for consumer brand relationship shift and, in those cases, the index is assumed to be 1.

However, some brands could see a significant shift on this for reasons like a patriotic fervor to support domestic corporations or avoidance of certain corporations due to their origins or may have repositioned themselves because of their contribution to consumer, society, country, or humanity in these troubled times. In such instances, the relationship index could range from 0 to 2 where 1 stands for status quo. This is then built into the demand estimates for the brand in the post COVID scenario.

How to measure Sentiment Analytics

The consumer anxiety index as well as category disposition index is being measured on a continuous basis on the online survey being done by us and referred in figure 4 above. This is generic and covers certain categories of interest. A similar survey could be instituted for specific categories and data collected by using online marketing channels or through SMS based campaigns on clients' existing databases.

Revisiting the problem case of travel retail client in post COVID scenario

We have considered the case of a company operating in travel retail space. The overall sales dropped sharply when COVID crisis hit and in a matter of days came to zero and stayed at zero for a few weeks. We need to use Demand Sensing modelling to assess its total likely demand when the market place opens. This has been assessed below using the revised Demand Sensing Model for 7 days after the market place reopens.

INPUTS TO THE MODEL

1) Estimated customer inflow – e.g. 60% of usual capacity. Data can be collected from the number of operating flights
2) Consumer Anxiety – e.g. 55%. Data can be collected from the online survey with a relevant geographic reach
3) Category Disposition Index – e.g. 30%. Data can be collected from the online survey with a relevant geographic reach
4) Brand Affinity Index – e.g. 1. Qualitatively assessed. Unless there is a strong reason, this would be 1
5) Base values – taken from projections done on historical data from pre COVID times for this time period

Demand estimate outcomes from the model are continuously assessed against the actual sales values which emerge over time. The model will use ML algorithms to continuously evolve and enhance accuracy of daily projections.

Conclusions

This model can be used for all types of retail stores, spanning across products and services, travel and tourism, and FMCG products. The model is currently being used for short term projection into near future time spans. However, once we have established clear trends of consumer sentiments over time, it will also be used for long term projections.

Brief Note on Authors

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Shubhra Misra has worked as a data scientist for the last 25 years. She is an expert in the field of market research and structured & unstructured data analytics. She has worked with corporates like Biocon, Pfizer, Eveready, Mylan, Abott etc. on multiple projects using primary, secondary research and advanced big data analytics . Shubhra Misra is an MBA from IIM Lucknow, India.

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Rishi Sanwal, has been a management consultant in Supply Chain & Operations area since 2001. He has worked at Accenture and IBM Business Consulting, advising large multinational and Indian firms like PepsiCo, Unilever, Heinz, Maruti, Bajaj Auto, L&T and many others in improving their supply chain performances. He now teaches at ISB Hyderabad, IIM Lucknow, IIM Kashipur and IRMA, as a visiting faculty in Executive and regular MBA programs. His areas of interest are Forecasting, Optimization, Supply Chain Analytics and Project Management. Rishi is a graduate from IIT Bombay, India & MBA from IIM Ahmedabad, India