Statistical study of Product Obsolescence Detection Techniques

Manasvi Gurnaney

Abstract— Obsolescence indicates the lifespan for which a product under study will be viable to sustain a particular market condition. This viability depends on the product features, the timing of product launch, the cost of the product and other secondary parameters. Researchers from various fields have proposed algorithms and techniques which utilize the product's parameters in order to predict and justify the product's obsolescence in the given market conditions. This study is based on statistically evaluating the product obsolescence detection methods and concluding as to which methods can be used for a particular application. This study also suggests some future research work which can be done on these algorithms in order to enhance the quality of obsolescence detection.

Keywords: Obsolescence, lifespan, market, product, application

1. INTRODUCTION

Obsolescence is a very crucial term when it comes to manufacturing, distribution and usage of any product. Day to day products usually do not face the risk of obsolescence, due to the fact that they are default daily drivers for most of the public, and changing a daily habit is usually very difficult. For example, if someone has a habit of using a colgate toothpaste, then even though there might be 100s of other brands in the market, but the common consumer will not take a risk while buying it. But, this is not the case with many other products like mobiles, electric and fuel operated automobiles, laptops, brick manufacturers and other non-day-to-day selling commodities. For such commodities accurate obsolescence forecasting is of the utmost importance in order to determine the unit economics of the product under test.

Obsolescence of a product is basically dependent on the following few crucial parameters,

- Product features
- Time of launching in the market
- Pricing of the product
- Social impact
- Other secondary parameters

The features of the product generally define the market value of it. A feature rich and high quality product will always be in better demand than it's counterpart. Features also define the usability of the product, as even the most feature packed product might not be useful if the target customer does not need all those features together. Thus, proper feature packaging is required in order to reduce the risk of a product being obsolete.

While product features are a very big deciding factor in determining product obsolescence, the timing of launch for a product is a much higher important factor for a product to be viable in the market. In general, about 60% of success rate of the product solely depends on when the product was launched. Take for example Orkut, it had most of the features that Facebook initially had, but it was launched way too early, and thus was not able to catch up with the growth that Facebook had, and thus became obsolete. This example might not be fair in every sense, but it is just to give a general idea about how product launch timing works. A perfect timing moderate quality product will have better sustainability then a mistimed superior quality one.

Pricing is another important feature of product launch. And as customers feel that high quality demands high costs, some good quality products are not purchased by customers due to very low costs, while some high cost but moderate to low quality products are in demand. Pricing also includes the price of advertising these products, but it can be and should be controlled for any product in picture. Nowadays, due to the impact of e-commerce platforms, the pricing is usually very competitive, and there are more than a handful of pricing models available for the product developers for reference.

Social impact of a product is a very trending issue these days. People go out and spend a lot on iPhones, Audis and luxury pens these days, due to their social impact. Facebook posts and WhatsApp statuses have modified the way people purchase certain products, and thus have affected the obsolescence of products in general. For example, if a friend of yours has bought a headphone of a particular brand, but due to some reason, that particular piece of electronics was faulty, and that friends posts a piece on Facebook stating that the product is not good, and even though the product is good in general, but due to that single piece of information, most of that person's friends will not purchase the product. Thus the product might become obsolete well before expected or anticipated by the manufacturer.

While these primary factors affect the obsolescence of the product, there are many secondary factors like type of advertising, appearance of product package, overall feel of the product in hand, the kind of distributers of the product & others which can change the product obsolescence cycle. There is no general rule which can make a product successful, but if a product is good on all the primary factors, then the probability of success of the product becomes significantly higher. Evaluation of this probability accurately based on some primary and secondary factors is what researchers in the field of obsolescence detection are trying to achieve. The next section will describe some of these research methods and statistically analyze them in order to conclude on the most effective obsolescence detection methods for a given application.

Revised Version Manuscript Received on March 08, 2019.

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2. LITERATURE REVIEW

In this section, we will be reviewing multiple techniques for obsolescence prediction as proposed by various researchers. The most accurate prediction of obsolescence is done in [1], where the researchers claim to have obtained 98% accuracy and they predict the obsolescence dates with the help of few months of data available about similar products. These researchers have used the scenario of smartphones in order to demonstrate their new algorithm which is based on machine learning and predictive modelling, they have labelled the algorithms as obsolescence risk forecasting using machine learning or ORML and life cycle forecasting using machine learning or LRML. Both algorithms are unique in their working, and can be used to effectively forecast the obsolescence of a product under test. Both ORML and LRML use a hybrid of support vector machines (SVMs), Random forest and neural networks in order to achieve the claim.

Table 1 shows the summary for model preferences for ORML.

Training Model	Random Forest	Neural Network	SVM
Average Accuracy(%)	98.3	91.1	91.6
Average MSE (%)	0.36	5.21	0.60

Another unique research is showcased in [2], where the researchers have worked on technology and part obsolescence, which basically means to detect the obsolescence of individual components of a full product. This is useful to product designers who want long lasting support in the parts which they use in their own products. In their research, they have reviewed Short-term and ordinal scale–based forecasting, Data mining–based long-term forecasting, Product life-cycle curve forecasting, Procurement life modeling, where they have evaluated that Procurement life modeling is the best method to evaluate the obsolescence of parts under test, and gives more than 90% confidence accuracy when it comes to prediction of obsolescence.

Machine learning is the pioneering technology behind forecasting obsolescence for any product. In [3], the researchers have used machine learning for predicting obsolescence of a product by checking out the obsolescence level of each of the individual parts used to produce the particular product, and claim to have obtained a 98.3% accuracy in doing so. They have also used ORML in order to achieve the feat, and tested their machine learning algorithm on cell phone datasets. Their research works on available and discontinued cell phone data available from various sources, and predict the obsolescence of the particular cell phone with good level of depth about the product configuration features.

Time series datasets play a major role in defining the accuracy of any obsolescence detection algorithm. In [4], the researchers have used a method which combines a time series alignment of a part family for capturing important patterns, time series modelling for forecasting life cycle curves and Box-Cox transformation for improving forecasting accuracy of obsolescence detection. Their experiments revolve around the flash memory product, and are able to achieve around 95% accuracy in prediction of obsolescence for the given product. They also compare their model with a the method of a researcher named Sandborn, and infer that Sandborn's method has 2 limitations, which are the requirement of gaussian distribution in data and requirement of evolutionary parametric drives, both of which might not be available for general datasets, and thus conclude that their method is superior than Sandborn's prediction method.

When talking about memories, the Dynamic Random Access Memory or DRAM, is one of the fastest option available these days. In [5], the researchers have shown that a single product like DRAM can have more than 6 deciding factors when predicting obsolescence for the same.

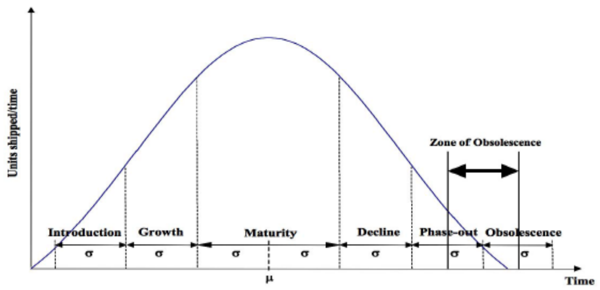

Figure 1: Product Life Cycle Curve for a device group where μ and σ represent curve fitting parameters

They have not included any method for obsolescence detection, but have opened the eyes of many researchers in terms of the depth and level of parameters which are needed for detection of obsolescence in such a simple product like DRAM, and that researchers need to work harder to get larger and broader datasets when it comes to detection of obsolescence for more complex products built up of higher order materials. Figure 1 shows Life Cycle Forecast using Guassian trend curve.

Avionics is a field of study where engineering concept of electronics are applied to aviation. In [6], the researchers have used obsolescence and life cycle prediction for avionics. The study claims to have achieved 70% to 80% accuracy in predicting the future of avionic products in the US military, based on the data obtained from more than 10 years of research across 100,000 parts of the avionic data space. In the paper, researchers have used linear classifiers and machine learning in order to predict the obsolescence accurately along such a wide variety of product part dataset.

Random forest based obsolescence detection algorithms are very commonly seen due to the fact that these algorithms take into consideration a wide variety of feature combinations (known as trees), and group them into an ensemble of classifiers (known a forests) in order to predict the obsolescence of a given product. In [7], the researchers have used random forests in order to predict obsolescence with a high accuracy of 85% in the cell phone dataset. Many researchers use the cell phone datasets due to it's availability and continuous updates in the dataset by the manufacturers and reviewers.

Published By:
Blue Eyes Intelligence Engineering
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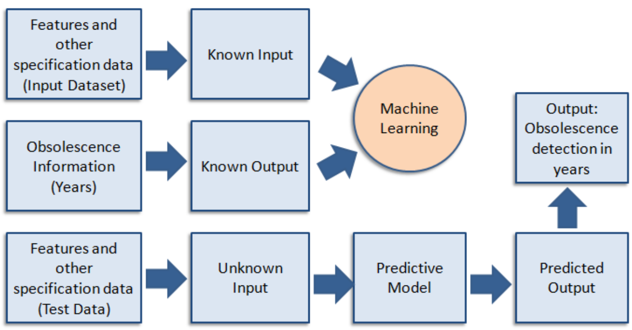
Evaluating obsolescence without expert data is very difficult because of the validity of the research. In [8], the researchers have claimed to be using demand data for various parts of a product in order to predict the obsolescence of the product itself. Their research has produced a method which can be used by companies for any product, where the product has enough data for enough number of parts, and this data can be cascaded to produce a obsolescence detection engine. This engine can have accuracies ranging from 50% to 90% depending on the data sources and the number of parts in the product.

3. PROPOSED WORK



Using machine learning algorithm the machine would be trained with input dataset consisting information about features of smart phones like brand, model, dimension, weight, display type, OS, CPU, RAM, primary camera, secondary camera, Bluetooth, USB, GPS, colours, announced date and obsolescence date. With the help of this model, the obsolescence of a smart phone in years would be predicted for any unknown input data sample.

4. RESULTS

The sample data is as follows:

Model	Dimension (mm)	Weight (g)	Display Type	OS	CPU	RAM	Primary Camera	Released Date	Obsolescence Date
Acer beTouch E140	104.5x55.8x12.8	95	TFT resistive touchscreen	Android 2.2	600 MHz	256 MB	3.15 MP	2010 December	January 2012
Apple iPhone	115 x 61 x 11.6	135	TFT capacitive touchscreen	iOS 3.1	412 MHz	4GB	2MP	2007 June	December 2009
Samsung E2232	109.2 x 46 x 14.9	79	TFT capacitive touchscreen	Android 2.3	1.0 GHz	512 MB	3.15 MP	2011 May	???

The obsolescence date for Samsung mobile will be predicted as the output of the model after getting trained using similar data

5. CONCLUSION

From the statistical review, we observe that most of the researchers have focussed on cell phone datasets for detection of obsolescence in the products. But, work is being carried out on other datasets as well. The current scenario suggests the use of machine learning algorithms like regression learning and Q-learning in order to predict obsolescence of products. The machine learning algorithms can produce accuracies upto 98% for prediction of obsolescence in products, but this accuracy is and will always be dataset dependent, because collection of proper time series data is a very necessary aspect of obsolescence detection algorithms. As a extension to the existing work, the researchers can use artificial intelligence techniques like deep nets and fuzzy deep nets in order to further enhance the performance of the obsolescence detection algorithms. Study on genetic algorithms, Elephant herd optimizations, and particle swarm optimization can be taken up as well.

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