A Bass Diffusion-Inspired Methodology to Predict Cumulative Device Activity to Improve Device Circularity Potential

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Understanding cumulative device activity over the lifetime of consumer electronic products is critical in two ways. First, it determines the extent to which a product maximizes utilization during its use, which is a critical consideration of circular products. Second, it allows for better estimations of the use phase carbon footprint, which is valuable in Life Cycle Assessment (LCA) of consumer electronics. This paper proposes a methodology for cold start forecasting of cumulative monthly device activity data over the lifetime of a product via a Bass diffusion inspired model.

Keywords: Bass diffusion, device activity, circularity, product reliability, optimization, consumer product

1. Introduction

A better understanding of the useful life of consumer electronics has two major benefits. First, optimizing the utilization of a product during its use phase is a pivotal pillar of improving the circularity potential of a circular product system design [1]. Secondly, inaccurate estimations of device lifetime can significantly skew the environmental impacts of a Life Cycle Assessment (LCA) for consumer electronics [2]. Most LCAs today make lifetime assumptions based on reliability lifetimes or warranty periods, and these assumptions may not reflect the true conditions in the field, nor do they take into account the actual utility the product is providing. Instead, we can use the useful life of a product to assess the true conditions of lifetime in the field as well as product utility. Useful life is governed not only by time spent in the field, but by actual customer engagement with the device, which can be captured via monitoring device activity. We can use a device activity metric, such as Monthly Active Devices (MAD) over time, in order to measure the useful life of a device [3]. During the product development cycle when a new generation of a product is launched, an estimation of the useful lifetime of a device is essential for informing the design decisions for the development of the next generation of the device to improve circularity potential. This paper proposes a methodology for cold start forecasting of MAD when only early lifetime device engagement is available.

2. MAD and Device Useful Lifetime

We define device useful life as:

$$L_{avg} = \frac{1}{12}\frac{\sum MAD_i}{Total\ Sales} \qquad (1)$$

Where L_{avg} is the average lifetime in years, MAD_i is the number of devices active in a given month over the lifetime of the product.

We have observed that the cumulative MAD profile of most consumer electronics over time follows an S-curve (Figure 1).

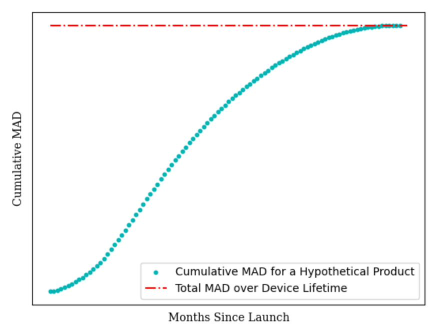

Figure 1 – Cumulative MAD for a hypothetical product

We can use the Bass Diffusion Model, [4] which was developed for technology adoption forecasting, to model the trend of cumulative MAD over time.

Proceedings of the 33rd European Safety and Reliability Conference
Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio

ISBN: 981-973-0000-00-0 :: doi: 10.3850/981-973-0000-00-0 esrel2023-paper

The Bass model is an S-curve and can be formulated as follows:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \tag{2}$$

In the original Bass model, $F(t)$ represents the cumulative adoption over time. p is the coefficient of innovation, which represents external influence or advertising effects and q is the coefficient of imitation and represents the internal adoption effects like word of mouth. Since, $F(t)$ is bounded between 0 and 1, we adjust equation (2) with a scaling factor:

$$f(t) = L\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \tag{3}$$

Where $f(t)$ would be the cumulative MAD at time t and L would be the total cumulative MAD over the lifetime of the device. Analogous to the original model p and q are parameters that define the shape of the function. We believe p represents the initial uptake effect while q corresponds to the retention effect of the utility provided.

3. Prediction

The challenge of predicting any S-curve is that early data may not be enough to find a unique solution to the curve-fitting problem needed to construct the whole MAD portfolio across the lifetime of the device. In order to alleviate this problem, we add a penalty function to the objective function to apply the knowledge we have from previous product generations to inform the optimization. Using the insights from historic MAD data, we formulate the following optimization problem:

$$\min:[y - (f(t) + E)]^2 \tag{4}$$

Where y is the observed MAD value and $f(t)$ corresponds to the Bass cumulative function and the added penalty term (E) ensures that the values of p^* and q^* stay within the accepted boundaries that make sense relative to the prior knowledge from the previous generations of the same product. We use the Powell's "dog-leg" [5] algorithm to solve the optimization problem formulated in Equation 4. Solving the optimization problem produces the results illustrated in Figure 2. In our case study, this method predicted the total cumulative MAD of a product within 10% of the actual data.

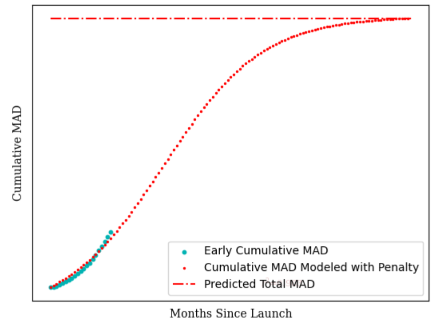

Figure 2 – Prediction of total cumulative MAD using a penalty function

4. Conclusions, limitations and future work

Early prediction of device activity over its lifetime is essential in informing the product development cycle to improve the circularity potential of future generations of a product. This study proposes a methodology for cold start forecasting of monthly active devices using the Bass model and a penalized nonlinear optimization approach. The current model has been tested on one device type in one case. Therefore, the future work will focus on collecting more data to validate the assumptions, robustness of the penalty function and to determine the amount of data needed for the model to perform well.

Acknowledgement

We thank our colleagues from Amazon Lab126 for offering their expertise and time for relevant discussion.

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