Disruptive Innovations: A Dedicated Forecasting Framework

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Abstract. This paper describes the design of a forecasting framework to predict disruptive innovations. First, the nature and characteristics of disruptive innovation are presented, as well as the conditions that enable such a phenomenon. Individual factors that feed into disruptive innovations are identified, as well as formulae to allocate quantifiable measurement to these factors. Suitable principles from two existing approaches to forecasting are adopted to put forward a new framework. This will consist of a four-step process that uses both mathematical models and the judgemental method. The findings are based on work that is part of a MSc dissertation [1].

Keywords: disruptive innovation . forecasting models . sales drivers modeling . social media . technology market

1 Introduction

The latter part of the last millennium has ushered in the era of the knowledge economy. In this new world, the three traditional resources of labor, land and capital were supplemented by a fourth resource, namely knowledge. With the focus on knowledge and learning at its core, it was inevitable that the pace of new developments, or innovations, accelerated.

Innovations can be changes that are introduced to improve the efficiency of the business or the quality of the products and services or, it can be a completely new idea that is targeted to a certain market or one that unintentionally enters a market. Irrespective of the size and area of the innovation, the effect can be limited or have a far reaching effect that will almost certainly disturb an existing balance in the market, a phenomenon referred to as disruptive innovation.

One way for businesses to foresee such oncoming threat and prepare to mitigate against it is by the use of forecasting models and tools. This paper presents such a model and reports on the findings of the work that is part of a MSc dissertation [1].

adfa, p. 1, 2011.

2 Disruptive Innovations

The term disruptive innovation was first coined in 1995 at Harvard Business School by Bower and Christensen [2] who investigated the phenomenon that may have a crucial impact on business and affects its ability to survive in the marketplace. They have defined innovations as two types; sustaining and disruptive. A sustaining innovation is the result of the quest for improvements in efficiencies or features of existing products and services and this can be evidenced by a healthy competition in the marketplace. A good example is the mobile phones industry where competition has led to higher quality cameras, longer battery life and a range of other improvements. A disruptive innovation on the other hand is one that will have far-reaching consequences and unexpectedly takes over an established market when the new innovation partially or completely replaces an old established one. Using the mobile phones example, the introduction of smart phones and tablets have created a new market with hundreds of businesses and disturbed the personal computers market.

A number of case studies revealed that some disruptive innovation manifests itself not through incremental enhancement of a product, but often as a product with lower performance or different attributes than the competing product. This often holds true for the technology sector. The initial understanding of the technology market was that existing firms and technologies are only displaced when a superior new firm or technology enters the market. However, Christensen and Bower have challenged this when they suggested that inferior products can also displace existing superior products. They called such innovations "disruptive" [2].

When a certain change creates appeal to a different market or the lower margin of the market, such products ultimately disrupt the market when main market customers eventually find the new product appealing and shift demand, leaving incumbents with great losses. This then may eventually lead to complete business failure [3,4]. Incumbent firms would typically dismiss the potential products that are not targeted at the main market and don't consider them a threat. The disruptive product then quickly gains higher market share and threatens the status quo [5].

3 Proposed Forecasting Framework

A literature review and an extensive study into forecasting systems have revealed that there are four different approaches to forecasting namely scenarios and simulation, extrapolation and trend analysis, judgmental methods, and models. It was necessary to determine which approach to use for this framework as a first step. The scenarios and simulation approach requires a lot of time and resources, and recent cases of disruption appeared relatively fast, indeed, faster than scenarios and simulations are able to predict and so it was disregarded. Using extrapolation and trend analysis for disruptive innovation forecasting was also disregarded as there is no clear trend in disruption; it often happens unexpectedly. The judgmental methods seemed to be the most commonly used and trusted for cases of high uncertainty. These methods depend on human judgment and extensive analysis of the status quo. However, issues of bias and inexperience of the forecasting team are problematic with this approach and it should be used with care. The last approach to forecasting is the use of mathematical models where a number of factors which are believed to affect the status of something are studied and combined in a mathematical equation to use as a forecasting tool. This approach seemed most feasible for forecasting disruptive innovations.

An analysis of the current forecasting models that exist today have revealed that none have been described as "persistent", and the best ones to date predict a product's emergence with +1 /-3 years accuracy [7] Additionally, most models do not employ more than one method of forecasting and are not open to public or voluntary participation. Further studies were done in order to understand better how to design a forecasting framework. Vanston [8] has advised that for any forecasting system to be reliable it should use at least two methods, especially in cases of high uncertainty. For this framework it is not advised to use more than two as speed is key, so the methods agreed on were judgmental and models. Further guidelines from the Committee on Forecasting Future Disruptive Technologies [6] were consulted to design a persistent and dedicated forecasting framework for disruptive technologies.

3.1 The Mathematical Model

Looking at disruption as the change in the market share of a product, it is necessary to first identify the factors that affect its sales. Literature review and historic data analysis concluded four such factors: competitive advantage, business status, marketing and lastly customer reactions. An equation was formulated for each of the four factors, producing four numerical values which are then used to produce a regression test. All data was scaled from 1 (lowest case) to 5 (highest case) on a Likert scale, thus permitting a symmetry preventing any variable from dominating the equation just by having a larger value [9]. The number 0 was not used as it may negatively affect the final results if multiplication was required.

a) Competitive Advantage

Competitive advantage is a term used to evaluate a certain product or service against those of competitors. It looks at either one of two aspects of competition; the price and the product itself. For this method, both aspects are used as they are considered equally important in affecting a product's sales. Price and product features will be given numerical categories and the simple average is taken of both for the final value. The scale for the price is defined as

1 = Overpriced	4 = Low Price
2 = High Price	5 = Valuable Price
3 = Expected Price	

For the product features, these are evaluated and categorized as follows

1 = Less features / value	4 = Some valuable features
2 = No new features / value	5 = Very valuable / innovative
3 = Almost as the competition	

The equation for competitive advantage is then defined as

$$\text{Competitive Advantage} = \frac{\text{Price+Value}}{2} \tag{1}$$

b) Business Status

Business status describes how well-established or well-known a business is at the time of introducing a new product. Finding a numeric value for business status is challenging as the business reputation may vary from country to country. To get a consistent measurement across countries, the net revenue is considered. First, the net revenue of all companies in that industry is listed from lowest to highest and then the company's ranking is considered accordingly. So for example if in an industry there are companies A, B, C, D, E and F, then the net revenues of these companies are found and ranked from lowest to highest such as:

1- Company B (lowest)
2- Company D
3- Company E
4- Company C
5- Company F
6- Company A (highest)

The measurement of company E equals 3/6 and that for company A equals 6/6, so company A has a higher business status. This equation will result in a number between 0 and 1. Thus the general equation for a business status would be:

$$\text{Business Status} = \frac{\text{Company rank}}{\text{Total number of companies in the market}} \tag{2}$$

c) Marketing

Research into the history of marketing and its effectiveness has shown that it is one of the most important factors of successful sales, especially when it is well designed to suit the target market. With the right message, audience, and reach, marketing can in fact change certain beliefs and even challenge social taboos to increase sales. This is illustrated with an example when Barnay's was able to make women smoke in the 1930s campaign "Torches of Freedom".

The challenge in using marketing as a factor for predicting is that the analysis is done only after the sales figures are available, and pending release of these figures as they are usually private company data. In other words, the measurement can only be done after the disruption has occurred, which is useless for forecasting. For that reason, a new approach had to be found.

The marketing factor was divided based on how it can affect sales, into three parts: cost, reach and effectiveness. Cost is the budget allocated to the marketing campaign, given that generally, the higher the cost of marketing campaign, the higher the expected sales. Reach is the number of media used in marketing, assuming that the more media channels are used, the more exposure and thus the more expected sales. And finally, effectiveness is the measurement of how well the message of marketing is conveyed to the target market, and this is to be evaluated by a marketing analyst. The three parts of marketing were again given a Likert scale from 1 to 5 and considered equally important. However, future data may reveal that a better relationship could be found. In addition, incorporating social media into the marketing model can provide better feedback and could be used to further adjust it. The currently suggested marketing scales are presented in Table 1.

Table 1. Likert scale for Cost, Effectiveness and Reach

Cost ($) [1]	**Value**
500,000 or less	1
500,000 – 5 Million	2
5 Million – 50 Million	3
50 Million – 300 Million	4
300 Million and above	5

Effectiveness	**Value**
Negative reactions (inappropriate for most people, ineffective, ill designed…)	1
Some negative reactions (inappropriate for certain markets/age groups/ religions/ gender… , ineffective, ill designed)	2
Neutral (other competitions, not very attractive, only if person knows the product)	3
Positive reactions (well thought of, attractive, considering culture)	4
Strong influence (correlated with politics, needs, emotions)	5

<table>
<tr><th>Reach</th><th>Value</th></tr>
<tr><td>Print advertising</td><td rowspan="6">For each of the methods of advertising used one point is added. So if print and broadcast and online are used, the value will be 3. The max number is 5</td></tr>
<tr><td>Outdoor advertising (street, booth)</td></tr>
<tr><td>Broadcast (television, radio)</td></tr>
<tr><td>Product Placement (in movies or shows)</td></tr>
<tr><td>Cellphone and Mobile</td></tr>
<tr><td>Online advertising</td></tr>
</table>

The equation for marketing would then be:

$$Marketing = \frac{Cost + Reach + Effectiveness}{3} \tag{3}$$

d) Reactions

The reactions factor gives a numerical value to how good or bad the customers' and reviewers' reactions were to learning about a product or buying and using it. People's reactions may differ based on their beliefs, needs, political agenda or the economy. But also it can differ because of reviews. The abundant availability of online reviews given by experts and users on almost anything sold has made it possible for potential

[1] The ranges are only a suggestion based on general knowledge of marketing but they are subject to revision according to the type of business, products or market

customers to be influenced on future sales by many different sources. Both the reactions of people and the reactions of reviewers must then be considered. In order to validate this relationship, a survey was done online where 52 random people from around the world were asked to read and watch videos about an upcoming product from Google called Google Glass. The product was still in its beta version and the company has tried to create the media hype around it before the selling date. After learning about the product the people were asked whether they would buy it or not. Based on their answer, a review was shown to them to contradict their wishes and they were asked again whether they changed their minds about buying it or not. The survey showed that 100% of them sought reviews before buying most technological products, 37% of those who said they would buy it changed their minds after reading a negative review and only 9% of those who said they wouldn't buy it changed their minds after reading a positive review. This seems to indicate that reviews are in fact an important part of purchases and that negative reviews may have a higher impact on sales than positive reviews. These findings are backed up by another study done on the effect of reviews on sales [10]. Given this, it was possible to determine the elements that go into the reactions equation:

1. Number of unique mentions of a product, those that are done by new authors every day.
2. The sentiment of the customers' mentions, which is the ratio of positive to negative mentions.
3. Customer engagement, this is the number of Facebook likes, Google +1 votes, subscriptions to YouTube channels, Twitter or Instagram followers and other social media channels that may be available.
4. Reviews sentiment which is the ratio of positive to negative reviews given on the product.

These numbers can be taken from automated engines that scan the web and present within certain dates the number of reactions and its sentiment. However, a research into this matter has showed that these engines tend to be less accurate than desirable [11]. Automated engines cannot always understand human language, including sarcasm and emotions. When it comes to languages other than English it becomes even less accurate. For example, the Arabic language includes 30 different dialects in addition to the classical Arabic language, making it difficult to analyze sentiment. A further level of complexity is added when Roman letters, rather than Arabic letters, are used to represent Arabic words on the Internet and using mobile phones. This means that it is not possible to depend on an engine to detect the sentiment. After consulting with experts in the area, it was decided that the sentiment ratio is to be found manually by picking up 500 random mentions of a product and split them into positive and negative.

To construct the final equation, the weighted average was selected as some factors have more impact on the sales than others. The weights were given based on the best knowledge of the researcher. The suggested weights were given as shown in Table 2.

Table 2. Weights given for reactions factor

Value (1-5)	Weight (out of 5)	Reason
Customers' Sentiment	1.0	This is the first indication of how positive is the reaction to a certain product and thus it was given a high weight
Unique Mentions Sentiment	1.5	This number indicates how many good mentions are made by new authors. It is more important than mentions sentiment as that can be purely repetitions of the unique mentions while this indicates further reach to more customers.
Customer Engagement	0.5	While this value is indicative of good or bad engagement it is not very accurate as many social media followers do not tend to follow because they like the brand or product but sometimes they are news agencies, competitors, even people who dislike the company but want to see their news. Thus it was given the less weight.
Reviews' Sentiment	2	From the survey conducted and from research it is found that reviews have a bigger impact on customer reaction thus it was given the highest weight

Therefore the final equation for reactions is:

$$Reactions = \frac{(Customer\ Sent \times 1.0) + (Unique\ Sentiment\ \times 1.5) + (Engagement\ \times 0.5) + (Reviews\ Sent\ \times 2)}{5} \quad (4)$$

e) The Model

With the four factors described above adopted, the forecasting model can be constructed. In order to create a regression test, one more definitions must be clarified, namely, how to calculate disruptiveness. Since disruptiveness is the actual disturbance in the market when a new product is introduced, the disruptiveness then can be defined as the percentage market share of the product. The forecasting question becomes: what is the expected market share the new product will have in the upcoming weeks or years? Since market share can be calculated based on unit sales or total revenues, the unit sales was considered for this model. This decision was made because revenues can have inaccurate results if a product was sold at a very high price and very few units were sold. Given that, disruptiveness is then calculated by:

$$Disruptiveness\ (market\ share) = \frac{Total\ Product\ Unit\ Sales}{Total\ Industry\ Unit\ Sales} \times 100\% \quad (5)$$

Using the equations (1) through (5) presented above, data was collected to establish the model. The aim was to collect at least five cases to fit into each one of four categories: successful disruptiveness by a small business, failed products by a small business, successful disruptiveness by established business and failed products by established businesses. Samples for testing included past and forecasting data. There was a challenge finding this data because marketing and sales information is not readily available. For market share figures, it was not clear whether this was based on revenue or sales. For the reactions factor, it is impossible to find at this late stage, also, social media was not widely used before 2005. With these limitations it was still possible to collect and estimate up to 12 cases and run the regression test on them.

Regression 1: All variables

Regression Statistics	
Multiple R	0.790903857
R Square	0.625528911
Adjusted R Square	0.411545431
Standard Error	0.146664302
Observations	12

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	0.251521995	0.062880499	2.923257966	0.102486431
Residual	7	0.150572921	0.021510417		
Total	11	0.402094917			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.312574217	0.242508952	-1.288918262	0.238384265	-0.886016767	0.260868333	-0.886016767	0.260868333
Competitive Advantage	0.048114447	0.080298738	0.599193075	0.567922018	-0.141761895	0.23799079	-0.141761895	0.23799079
Business Status	0.065004161	0.146062108	0.44504466	0.669723916	-0.280377843	0.410386165	-0.280377843	0.410386165
Marketing	0.068676254	0.054365597	1.26323002	0.246952737	-0.059877955	0.197230463	-0.059877955	0.197230463
Reactions	0.055205247	0.074268005	0.743324762	0.48148282	-0.120410679	0.230821174	-0.120410679	0.230821174

Fig. 1. Results of the regression test [1]

This regression has resulted in a Significance F of 0.1 but P-Values higher than 0.2 for all the four factors and a sum of errors of 0.07. Thus the model extracted will not be used for forecasting nor disregarded at this stage; it will only be used for demonstration. The model extracted is given as:

$$Expected\ Disruption = -0.31 + 0.048 \times Competitive\ Advantage + 0.065 \times Business\ Status + 0.068 \times Marketing + 0.055 \times Reactions \quad (6)$$

3.2 The Judgmental Method

In cases of high uncertainty such as disruptive innovations, there will be instances where human insight is required beyond the available data and numbers, therefore a judgmental process is required to further validate the findings of the mathematical model. After the model has been used and a result is found, five experts from each country where the product will be introduced will be consulted along with a survey to fill within 48 hours. The experts will have access to the data, but not the equations nor their results; this is in order to minimize the risk of bias or influence by presumed results. The criterion and conditions for choosing such experts and further details on the process are discussed further in the dissertation paper [1].

3.3 The Complete Framework Process

The complete forecasting process is shown in Figure 2. It is a merely four step process which starts with the data collection step. A selected team will collect the information needed from online resources with given guidelines [1]. The data is then used in the mathematical model to find a possible disruption percentage in step 2. Simultaneously, the experts' opinions are sought through the survey. The final step brings together the results to the head forecaster for a final validation and consolidation of the report. The complete forecasting process can take a period of two weeks and up to two months depending on the nature of the forecasting request. A long term forecast targets an upcoming product and is done typically on demand while a complete disruption forecast targets a new technology that may overtake the existing one and is done twice a year. Another version of the forecasting process, the short term forecast, discussed further in [1], is done in one day or two where two forecasters are requested to estimate the four factors and use the mathematical model to produce an executive forecast.

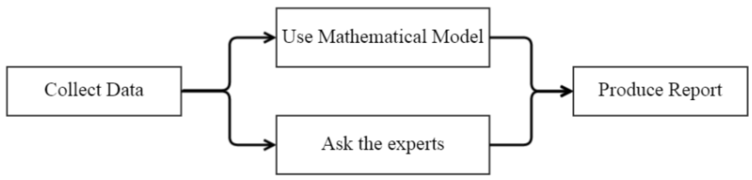

Fig. 2. The Forecasting Framework

4 Conclusion and Discussion

Disruptive innovations create a sudden unexpected disruption in the market causing losses to established businesses. The best way to avoid such losses is by being prepared and that is possible with forecasting. The paper has described work that was the result of a study of current forecasting methods and reported on principles, strengths and most importantly weaknesses of these methods. None was found to specifically forecast disruption. A new framework was suggested using two methods, mathematical models and the judgmental method. The metric that measures disruptiveness to sales in a market is based on four quantifiable factors. It is important to note that the Likert scales given in this paper are only a suggestion based on research of popular products. The forecaster using this model is advised to adjust the scales given for each variable of the equation according to the market/ product, while keeping the range between 1 and 5.

The mathematical model is likely to benefit from further validation using "future data" which will indicate whether an adjustment to the calculations provided are needed to improve the accuracy of the results. Such data however, may be challenging to find even in the future as there is no dedicated and trusted body to refer to, there are several resources and perhaps bias involved. This poses a limitation that requires further planning and studying. However, it is our position that the proposed framework covers most of the features the committee [6] has suggested as a persistent forecasting framework. Future work plans also include automation of parts of the process and a continuous refining of the model to achieve highest accuracy possible.

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