Exploring Expansion Opportunities with Optimizely

A case study of Optimizely (2014-2015)

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Abstract:

This research uncovers a model to understand how customer engagement impacts the likelihood of expansion of enterprise clients. The data was sourced from a case study done by Optimizely, a hyper growth SaaS company operating internationally. It proposes that upgrade is influenced by several key engagement factors: 1) number of goals, 2) multipage experiments, 3) number of users, 4) experiments, 5) AB experiments and 6) multi-variate experiments. The expansion decisions are modeled using a binary-logit model using data points from 161 enterprises that either upgraded or not. The model explains that customer engagement variables have a positive impact on cross-selling and up-selling opportunities. The results suggest that a larger-scale research should be conducted to develop a customer engagement score that can be standardised.

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Introduction

The newly erupted industry called SaaS has been a topic of conversation for the new digital era since its inception in 1999. Software as a Service (SaaS) is a software distribution model in which applications are hosted by a vendor or service provider and made available to customers over a network, typically the Internet (Software as a Service, 2006). SaaS companies provide their service and product for a subscription level to its clients and typically after 12 months, clients are allowed to cancel, renew, downgrade or upgrade their subscription. This research focuses on how enterprise clients upgrade or expand their subscriptions with their SaaS suppliers. "A product upgrade is a form of relationship expansion in which the customer purchases an expanded offering—a higher-price, augmented good or service (with higher service levels or additional features)—instead of repurchasing a low-price good or service (with lower service levels or fewer features) from the same supplier" (Bolton et. al. 2008). Previous research has developed predictive and normative models that are relevant to industries such as airlines banks, and theatres but little has been documented on the maturing industry of SaaS. As a researcher, I've had the opportunity to work with a hyper-growth SaaS company called Optimizely to provide relevant data to understand how expansion is being approached. The common wisdom in the technology industry is that "acquiring a customer costs 5 to 10 times more than retaining one" (eMarketer, 2002). Service organizations now recognize the value of current customers and seek to increase revenues and profits through targeted marketing expenditures. To do so, they need an in-depth understanding of the underlying sources of value derived from current customers and how to increase the revenue streams to enhance firm performance (Hogan, Lehmann, et al. 2002)

Retaining a customer is a top priority but once this has been met, the next step is expansion. Not only is there little research being conducted in the SaaS industry but also little has been shed on the expansion properties of online businesses. Therefore the research question goes as follows:

Is customer engagement a leading indicator to suggest expansion opportunities of enterprise accounts?

By creating a case study of Optimizely, the research will explore how customer engagement can be a predictive variable of future upgrade. The firm's decision to upgrade or not upgrade is represented by a binary logit model with dimensions captured through a principal component analysis (PCA). According to Skok (2012), customer engagement is a key driver of up-selling and cross-selling of clients which is the central theory of the research. Based on the findings, several customer engagement variables are found significant to uncovering upgrade opportunities. The study approaches B2B upgrading through an academic perspective and provides scientific rigor to how business is being conducted in Optimizely. The goal of creating a customer engagement score has implications not limited to Optimizely but across the entire SaaS industry. By developing a predictive model of expansion, SaaS companies can accurately use the tool to pinpoint key opportunities and take immediate action based on backed data. This method of delivering actionable insight will create more intelligent companies that optimise and match their services with the exact demand of their customers.

From an academic perspective, the study fills the void and goes into a more granular level on the implications of customer engagement on customer behavior of up-selling and cross-selling. Past research confirms that customers with higher satisfaction levels and better price perceptions have higher service usage levels (e.g., Bolton and Lemon 1999). In contrast, the effect of satisfaction and price fairness on customers' cross-buying is reported to be very modest (Verhoef, Franses, Hoekstra 2001). Research by Bolton et al. 2004 uncovered the relationship between the marketing instruments and customer behavior yet little research has been done on the relationship between the underlying user engagement and the customer behavior of upgrading. Additionally, relating the topic to the SaaS industry and creating a case study based on a company such as Optimizely has not been explored.

The first section reviews academic literature to provide context to the research. The next section focuses on the theoretical framework and the underlying concepts behind the research. The third section highlights the data specificities and the model specifications. Then the findings of the research are demonstrated. Finally, the implications and conclusion of the research is explored.

Literature Review

The SaaS industry is a relatively new domain with majority of best practices and laws created in the 21^{st} century thanks to the emergence of Salesforce in the year 1999. In the beginning of the 21^{st} century, Software as a Service was officially introduced and defined by the Software and Information Industry Association (Churakova and Mikhramova, 2010). It was a new concept and a new model of conducting business using the Internet. Since its inception, new technologies on the market have fully adopted the model to saturate the competitive landscape. Since August 2011, the marketing technology landscape has grown exponentially from over 100 to 1876 companies in just four years (Chiefmartec, 2015).

Understanding the SaaS business model equips the management team with critical forecast knowledge and allows them to take action to focus the business to maximise the return on investment of capital (Sukow and Grant, 2013). The SaaS model functions on a monthly subscription basis and requires the customer to continuously pay the subscribed amount for a minimum of 12 months to have a steady forecasting of revenue. Since the revenue is not yet incurred through the subscription model, forecasting of future revenue is so critical for the business to assess and take key decisions.

Financial viability for SaaS companies heavily relies on three key factors: acquiring customers, retaining customers, and monetizing customers. Using these three factors, Skok (2013) outlines four categories of metrics SaaS companies should track for their marketing strategy: funnel metrics, customer engagement and happiness, booking metrics, and unit economics (Magner et al 2014). Existing academic literature has focused on several metrics such as customer engagement in relation to certain KPIs such as retention and churn rate.

According to Skok (2011), customer engagement data is useful in three ways:

1. Identify customers that need help or that are ready to purchase
2. Identify customer that are about to churn
3. Identify customers that are appropriate for upsell or cross sell

Most of the industry and academic emphasis has been to identify and predict the first two aspects but little has been documented on the upsell and cross-sell power of customer engagement. One of the main reasons for the gap in knowledge is the fact that most companies have yet to realize the first two steps. Once SaaS companies have reached their potential through a high adoption rate along with a best in class retention rate then they can focus on expansion. Skok (2013) postulates that the two ways to achieve expansion revenue is through a pricing scheme that has a variable axis and the other way is through up-sell/cross-sell. With this in mind, the topic of the research is to shed light on the relationship between customer engagement on expansion i.e. upsell and cross-sell of clients.

In an ideal model, customer engagement can be measured by a customer engagement score that depends on the use of particular features of your SaaS that ensure a user is more or less engaged (Skok, 2013). Theoretically, the customer engagement score seems to be an objective predictor of expansion but it has still yet to be seen in application in the SaaS industry. The relation of the customer engagement to expansion ties very closely to the metrics that allows companies to forecast their future revenue. As it will be discussed below, the expansion rate counteracts the churn rate to produce the net expansion rate.

Many studies have ignored the contribution of other customer behaviors, such as service usage and cross- buying, to business performance (Blattberg, Getz, and Thomas 2001). Recent research confirms that customers with higher satisfaction levels and better price perceptions have higher service usage levels (Bolton and Lemon 1999). There is also some evidence that a loyalty program can stimulate service usage (Bolton, Kannan, and

Bramlett 2000). Yet there is little to be known about user engagement on customer behaviors such as cross-selling and up-selling of services.

A seminal study done by Bolton et al. 2004 discussed how customer behavior in the service industry is divided into three areas: the length, depth and breath of the customer-firm relationship (Verhoef 2001). Length or duration of a relationship corresponds to customer retention. Second, the depth is reflected in the frequency of usage over time. This behavior is reflected in customers' decisions to upgrade and purchase premium over time. Third, the breadth is reflected in cross-buying or "add-on" buying (Bolton et al. 2004). They introduced the framework of the customer asset management of services (CUSAMS) and "examined the effects of marketing instruments and relationship perceptions on three aspects of customer behavior" (Bolton et al. 2004). Refer to appendix 1 diagram 1 for the CUSAMS framework. They created an overview of the CUSAMS however an in-depth analysis on the customer behaviors of depth and breadth is missing. Their defined customer behavior in our context is the result of certain customer behaviors while using the service. This is where the study aims to contribute and understand how depth and breadth is influenced by customer behavior while interacting with the service.

Optimizely is a SaaS company and is currently at a rapid growth stage where the company-wide goal is to achieve positive net expansion. They are at the stage where they have met their churn and retention rate goals and are aggressively pursuing net expansion. According to VentureBeat (2014), Optimizely is the most highly adopted marketing technology in the enterprises arena[1]. This deems Optimizely to be the ideal SaaS company for an in-depth case study. Now with consideration of the previous literature, this research aims to create a case study of the customer engagement score through applying it in a SaaS company such as Optimizely.

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[1] https://venturebeat.com/2014/10/01/marketing-tech-50b-in-investment-but-top-tools-have-only-4-1-penetration/

Theoretical Framework

The characteristics of a valuable customer can be broken down into two components: their behavior and their Direct Natural Attributes (DNA). Their behavior represents how much they engage and benefit from our product. Their DNA refers to the static features of the company like size, website traffic, technologies etc. A valuable customer is one that is both highly engaged with the product and has the capacity to take full advantage of what it has to offer. Diagram 1 is a visual demonstration of the two components.

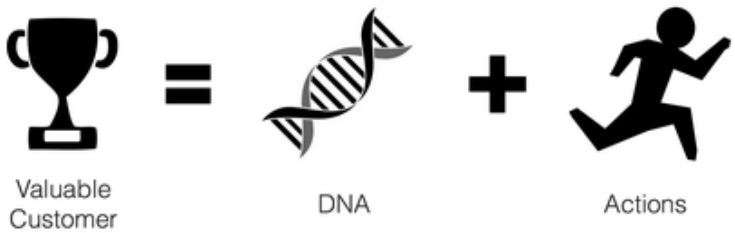

Diagram 1: Valuable Customer Equation (Optimizely, 2015)

In a previous report conducted for Optimizely, the results suggested that NPS, traffic utilisation and usage frequency were key variables in explaining the variance of the data sample. Refer to 1 diagram 2. Unlike these limited findings, this study has a more comprehensive and sharper focus on user behavior and product usage with relation to expansion opportunities. Since the data science team at Optimizely has already created a Customer DNA model to predict upsell opportunity, shedding light on product usage seemed to the logical next step.

There are 15 behavioral indicators incorporated in the analysis:

1. Experiments: The number of experiments created by the client.
2. Goals: The number of goals included in the experiments.
3. Users: The number of users of the account.
4. Web Projects: The number of projects created by the client.

5. Web Experiments: The number of web experiments created in the projects.
6. Web Experiments Running: The number of web experiments actively running.
7. iOS Projects: The number of iOS mobile projects created.
8. iOS Experiments: The number of iOS experiments in the projects.
9. Android Projects: The number of android mobile projects created.
10. Number of Multi-page Experiments
11. Number of Multi-variate Experiments
12. Number of Audiences: The number of audiences in the experiments.
13. Number of Dimensions: Dimension is each type of information collected by Optimizely.
14. Last 3 month utilisation: the percentage of traffic used divided by allocated traffic level
15. Last 3 month usage: the average traffic level in the last three months before expansion

Research Question:

What are some of the customer engagement factors that lead to the expansion of enterprise accounts?

The purpose of the study is to understand the relationship between these explanatory variables and the likelihood of predicting expansion potential. The hypothesis goes as follows:

H0: Product usage is not a leading indicator of expansion of enterprise accounts.

H1: Product usage is a leading indicator of expansion of enterprise accounts.

The predicted hypothesis is that behavioral inputs i.e. the factors that represent product engagement will be leading indicators of expansion of accounts. The intuition is that as the client increases the usage of the product, the chance of expansion rises since more value is created through engagement. Once that is established, another part of the paper will focus on the significance of each variable and its predictability power of expansion.

Net expansion is on the top agenda of the entire company thereby instilling more value to each client. Net expansion is defined as the difference between the MRR generated from expansion and the MRR that leaves through churn (Bauer, 2015). See diagram 2 to understand how MRR works. If an enterprise account expands, it demonstrates that the software provides significant return on investment excess of the initial fixed cost. One of the core metrics to evaluate the performance of SaaS companies is the retention rate. If retention rate is above 95% which Optimizely has achieved, net expansion becomes the core metric to improve. Essentially, the net expansion rate incorporates both expansion and churn rate. To give a simple example, if the annual churn rate is at 5% and the expansion rate is at 7% then the net expansion rate becomes 2% or a negative churn rate of 2%. Effectively, the expansion rate positively counteracts the churn rate.

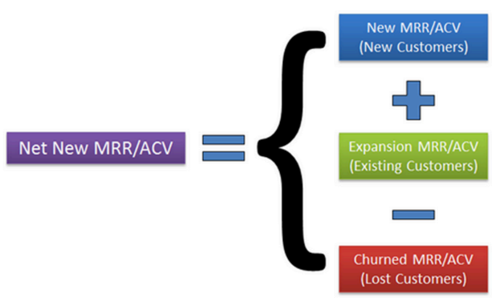

Diagram 2: Net New MRR Equation (Skok, 2013)

Diagram 3 shows that -2.5% churn rate is approximately three times larger in MRR than the 2.5% rate (Skok, 2012). By achieving -2.5% churn rate, almost double the MRR at 0% is yielded. The significant gap demonstrates how negative churn is so critical in the growth and financial stability of a SaaS company. As a SaaS company evolves, negative churn should be the main priority of top management. Now in relation to Optimizely, customer engagement will be analysed to determine if it has a positive impact on expansion. By understanding this relationship, Optimizely will be able to reach negative churn with an academic and data-driven approach.

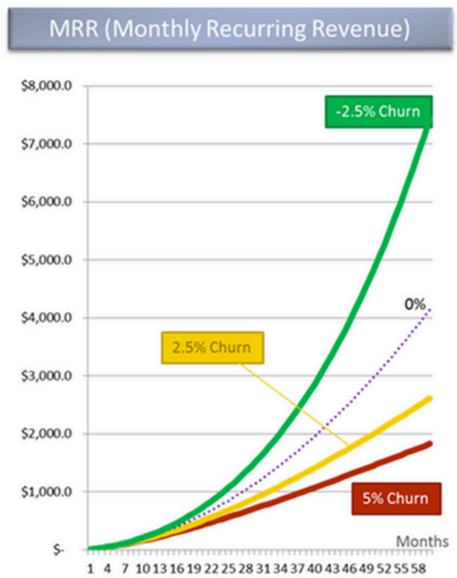

Diagram 3: Churn Graph (Skok, 2012)

Definitions:

A/B test: A method of testing different variations of the website to different visitors to measure which variation is the most effective at turning visitors into customers (Siroker and Koomen, 2013).

Multi-variate tests: a method of testing different variations of the web page in different combinations to determine which combination effectively boosts the conversion rate the highest.

Monthly Recurring Revenue (MRR): The monthly contracted, committed or predictable revenue stream. Assuming no churn, it is 1/12 of the ARR (Bauer, 2015).

Churn rate: The percentage of subscribers to a service that discontinue their subscription.

Retention rate: Difference between the customer at the end of the day and new customers on the day and divide that by customers at the beginning of the day.

Net Promoter Score (NPS): Based on the question: “how likely is it that you would recommend Optimizely to a friend or colleague?” It is a measurement to evaluate the performance of the company through the customer’s eyes. Customers respond on a 0-to-10 point rating scale (Bauer, 2015).

Data and Methodology

Data:

The primary data used for analysis was gathered by Optimizely’s data warehouse. With collaboration of the data science team, the specific characteristics of client behavior were extracted. The data warehouse contains all the user information including the 14 behavioral inputs and whether the accounts expanded or not. Majority of the behavioral factors are sourced from data warehouse via Totango, a customer success intelligence system. Totango is a platform that provides customizable and comprehensive data on customer health analytics. The customer engagement factors are logged through Totango and fed into the internal data warehouse. The customer engagement variables that are part of the analysis are: 1) results 2) last 3 month utilisation percentage 3) number of audiences 4) number of goals 5) number of experiments 6) number of users 7) number of web projects 8) number of ios projects 9) number of android projects 10) number of ios experiments 11) multipage experiments 12) number of multivariate experiments 13) number of audiences and 14) last three months usage. All the variables are captured three months prior to the close date of each expansion opportunity. The assumption is that the client activity three months prior to the close date is indicative of expansion. In total, there are 161 client data with 73% of the clients successfully expanded (117) and 27% of the clients who did not upgrade (44).

Methodology:

Using the data collected from the 14 explanatory variables, the eventual goal is to determine how much significance each variable contributes to the expansion of enterprise accounts. To uncover the relationship between the explanatory variables and expansion, binomial logistic regression otherwise known as the binomial logit model will be conducted. By design, it overcomes many of the restrictive assumptions of linear regression. For example, linearity, normality and equal variances are not assumed, nor is it assumed that the error term variance is normally distributed (Garson, 2009). The model predicts an observation falls into one of two categories based on one or more independent variables that can be either continuous or categorical. The two categories in this model will be whether the client expanded or failed to expand. Below is a model specification of the variables incorporated.

$$\pi_i = Pr(Y_i = 1 | X_i = x_i) = \frac{\exp(\beta_0 + \beta_1 x_i)}{1 + \exp(\beta_0 + \beta_1 x_i)}$$

$$\begin{aligned} \text{logit}(\pi_i) &= \log\left(\frac{\pi_i}{1 - \pi_i}\right) \\ &= \beta_0 + \beta_1 x_i \\ &= \beta_0 + \beta_1 x_{i1} + \ldots + \beta_k x_{ik} \end{aligned}$$

Diagram 4: Binary Logit Model Specification

Let Y be a binary response variable

$Y_i = 1$ if account was expanded

$Y_i = 0$ if account was not expanded

$X = (X_1, X_2, \ldots, X_k)$ are the independent variables i.e. customer usage factors

$B = (B_1, B_2, \ldots, B_k)$ are the respective coefficients of the explanatory variables

Firstly after gathering the data, a Pearson correlation matrix was conducted. This allows the elimination of variables with high correlation of each other. Then, principal component analysis (PCA) was performed. PCA minimises the sum of squared perpendicular distance to the axis of the principal component (Truxillo, 2003). It reduces the number of observed variables to a smaller number of principal components that accounts for most of the variance of the observed variables. Eigenvalues indicate the amount of a variance explained by each component and eigenvectors are the weights used to calculate component scores (Suhr, 2005). It reduces the correlated factors and explains the variance of the data as much as possible.

One of the main reasons why PCA is performed over exploratory factor analysis (EFA) is because EFA is related to latent constructs i.e. variables not measured directly. The data set from Optimizely about enterprise user behavior is in the form of interval and ratio measurements. The large sample size will permit stable estimates with over 100 observations per predictor variable.

Results

A Pearson correlation matrix was conducted on the 15 variables and based on that variable 7 (number of web experiments), variable 9 (number of AB experiments) and variable 13 (number of dimensions) were removed. They showed strong correlation greater than 0.9. Refer to appendix 1 table 1 for the full results. This left 12 variables to be included in the PCA analysis.

Based on the PCA analysis, the five dimensions greater than eigenvalue of 1 was retrieved. Diagram 5 shows the rotated component matrix containing the five key dimensions. Each dimension explains the variance of the data and captures a subset of the data. For example, dimension 1 captures the data of number of goals, multipage experiments, number of users, experiments, AB experiments and multi-variate experiments. Ideally, the matrix should contain the least amount of overlapping therefore the interpretation becomes easier.

	General Dimension 1	Experiments/Projects Dimension 2	Experiments/Last 3 month % Dimension 3	Mobile Dimension 4	Audience/MV Dimension 5
Number_goals	0.862				
Multipage experiments	0.839				
Number_users	0.778				
Experiments	0.741	0.363	0.386		
AB_experiments	0.657	0.402	0.429		
Last 3 month usage		0.874			
Num_ios_projects		0.866			
Num_web_projects		0.441			
Last 3 month utilisation %			0.841		
Num_android_projects				0.755	
ios_experiments				0.683	
Num_audiences					0.753
Mv_experiments	0.460				-0.470

Diagram 5: Rotated Component Matrix of Customer Engagement Dimensions

A logistic regression was performed to ascertain the effects of the dimensions on the likelihood of expansion. Based on diagram 6, the model explains 0.133 (Nagelkeke R Squared) of the variance in the expansion data and correctly classified 72.7% of the cases (refer to appendix 1 table 2). According to the regression output (diagram 7), dimension 1 is the only statistically significant variable at $p=0.035 < 0.05$. Based on that, it is safe to reject the null hypothesis and if we control for other variables, there is a positive relationship between dimension 1 and expansion. The significance to the model is the highest of the variables at 4.438 (Wald). General dimension 1 increases the likelihood of expansion by 0.915 units. The implication is that general dimension 1: *number of goals, multipage experiments, number of users, experiments, AB experiments and multi-variate experiments* are positively associated with predicting the expansion opportunities of accounts. Dimensions 2-5 had p-values greater than 0.05 signifying we could not reject the null hypothesis and the underlying variables contained in the dimensions do not contribute to expansion.

*Log(p/1-p) = 1.213 + 0.915*dimension1 + 0.611*dimension2 – 0.278*dimension3 + 0.228*dimension4 – 0.084*dimension5 + e*

Diagram 6: The Model Equation

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	173.294	0.092	0.133

Diagram 7: Nagelkerke R Squared

	B	S.E.	Wald	Df	Sig.	Exp(B)	Lower	Upper
General Dimension 1	0.915	0.434	4.438	1	0.035	2.497	1.066	5.849
Experiments/Projects Dimension 2	0.611	0.482	1.603	1	0.205	1.842	0.716	4.740
Experiments/Last 3 month % Dimension 3	- 0.278	0.196	2.021	1	0.155	0.757	0.516	1.111
Mobile Dimension 4	0.228	0.318	0.513	1	0.474	1.256	0.674	2.341
Audience/MV Dimension 5	- 0.084	0.210	0.161	1	0.688	0.919	0.609	1.387
Constant	1.213	0.226	28.886	1	0.000	3.364	95% C.I. for EXP(B)	

Diagram 8: Regression Output

Conclusion

Discussion:

There were a few unexpected results from the study. Firstly, we expected less overlaps between the variables in the PCA analysis. For instance, the variable experiments had overlap in dimension 1 through dimension 3. To have more robust results, there should have been less correlation between the variables in general. When performing the binary logistic regression, we expected more significant results from the dimensions. Only dimension 1 was significant out of the 5 and this limits the power of interpretation. The expectation was that variable *last three month utilisation %* would be significant considering the previous research results. In the future, more data on expansion would be necessary for the variables to become more significant.

Limitation:

One limitation to the dataset is that the data may not be consistently acquired in the same timeframe. The length of the contract for each account was also not incorporated as one of the variables. If a client has a longer length of contract, return on investment was likely achieved hence a stronger likelihood of expansion. It would be more ideal if more data points were available on expansion since out of the 161, only 44 did not expand. To have data more defined across both expansion and not expansion, an equal ratio of data points would be desired. There was an implicit assumption that there was heterogeneity across the firms and for further research, dividing the data into verticals would allow for more explanation in the variance of the data. Different industries have differing demand and the service of the solution should reflect that. Also, we conducted our study in only one industry context i.e. the SaaS industry. Other industries in the technology sector such as mobile applications could be enlightening.

The scope of the study is limited to purely the customer interaction with the product. To widen the scope, there's more research to be conducted on the interaction and influence of the account manager with the client. The next step is uncovering how account management plays in the role once the customer engagement score is fully implemented. To capture the interaction prior to the engagement, it would also be beneficial to research into the account executive's approach on selling to each client. Since there could be two scenarios where the account executive either oversold i.e. maximized the sell to diminish future up-sellable potential. Or the account executive could have moderately undersold which would give the client the bandwidth for future upgrade. There is an immense area across this study for further improvements and, it would be interesting in the future to refine this model to enhance the robustness of it.

Implication:

A predictive model to create a customer engagement score would be instrumental in propelling the company forward to the net expansion goal. Account managers across the company can make quick data-driven decisions based on the score and identify key expansion accounts. By understanding the customer engagement score throughout the whole client base, we can understand the threshold of a healthy and engaged account versus an account that is unhealthy. From a business metric perspective, this has implications across retention and expansion rate. Through the standardised score, we can immediately pinpoint unhealthy accounts that would contribute to reducing the retention rate unless serviced by the account managers. In that manner, retention rate can be further improved to achieve best in class. By identifying the high threshold of healthy accounts, account managers can target these accounts to provide even more value via up-selling and cross-selling. Overall, the customer engagement score has implications across both avenues thereby positively affecting the net expansion rate.

Concluding Remarks:

In summary, the research suggests that Optimizely needs to understand product usage of each client in order to predict future expansion opportunities. It is fair to say that customer engagement is positively associated to the expansion of enterprise accounts. Based on the logistic regression, the variables identified in dimension 1: *number of goals, multipage experiments, number of users, experiments, AB experiments and multi-variate experiments* are significant. Assigning significance for each variable is beyond this research and should be a point of improvement for further research. Decomposing the underlying variables is necessary to construct the customer engagement score however this was not feasible. The study was valuable in validating certain key variables relating to expansion but in order for it to make high impact across Optimizely and the SaaS industry, getting significant results for each variable and creating the customer engagement score is pre-requisite. Overall, the hypothesis in the research was accepted and customer engagement is a predictor of expansion however the stretch goal of the customer engagement score was not achieved. Further research should move beyond validation but towards a predictive model for expansion.

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Appendix:

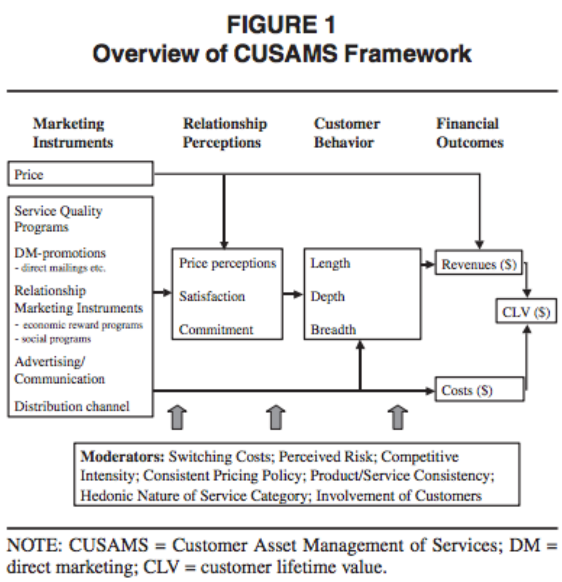
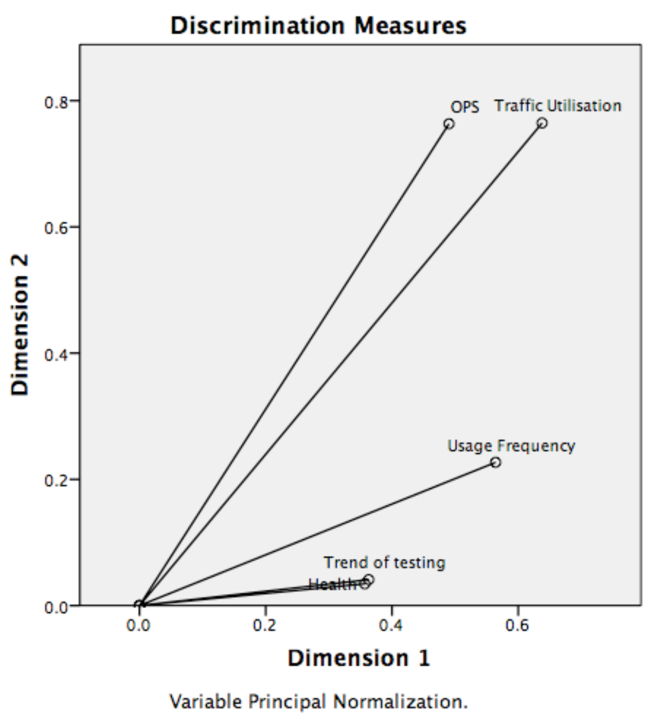


Diagram 1: CUSAMS framework



Correlation Matrix[a]

		V1	V2	V3	V4	V5	V6	V7	V9	V11	V12	V13	V15	V16	V17	V18
Correlation	V1	1.000	.041	.216	.041	-.044	-.034	-.068	-.007	.062	-.038	.037	1.000	-.066	-.003	.031
	V2	.041	1.000	.672	.610	.267	.348	.009	.024	.752	.314	.202	.041	.365	.194	.534
	V3	.216	.672	1.000	.436	.245	.201	-.030	.035	.488	.314	.126	.216	.371	.330	.441
	V4	.041	.610	.436	1.000	.197	.169	.184	.080	.635	.167	.154	.041	.144	.095	.531
	V5	-.044	.267	.245	.197	1.000	.243	-.060	-.017	.047	.114	.116	-.044	.164	.075	.199
	V6	-.034	.348	.201	.169	.243	1.000	-.013	.107	.100	.021	.090	-.034	.802	.313	.545
	V7	-.068	.009	-.030	.184	-.060	-.013	1.000	.181	-.036	-.043	-.023	-.068	.007	-.068	.125
	V9	-.007	.024	.035	.080	-.017	.107	.181	1.000	-.040	-.039	-.011	-.007	.001	-.050	.010
	V11	.062	.752	.488	.635	.047	.100	-.036	-.040	1.000	.231	.144	.062	.127	.114	.326
	V12	-.038	.314	.314	.167	.114	.021	-.043	-.039	.231	1.000	.040	-.038	.136	.051	.079
	V13	.037	.202	.126	.154	.116	.090	-.023	-.011	.144	.040	1.000	.037	.089	.022	.196
	V15	1.000	.041	.216	.041	-.044	-.034	-.068	-.007	.062	-.038	.037	1.000	-.066	-.003	.031
	V16	-.066	.365	.371	.144	.164	.802	.007	.001	.127	.136	.089	-.066	1.000	.458	.460
	V17	-.003	.194	.330	.095	.075	.313	-.068	-.050	.114	.051	.022	-.003	.458	1.000	.136
	V18	.031	.534	.441	.531	.199	.545	.125	.010	.326	.079	.196	.031	.460	.136	1.000

a. This matrix is not positive definite.

Diagram 2: Previous PCA report

Table 1: Correlation Matrix

Classification Table[a,b]

Observed			Predicted: Result .0	Predicted: Result 1.0	Predicted: Percentage Correct
Step 0	Result	.0	0	44	.0
		1.0	0	117	100.0
	Overall Percentage				72.7

a. Constant is included in the model.

b. The cut value is .500

Table 2: Classification Table