Ties as a Service

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Abstract

A predictive analysis of the marketing implications of the 'Software as a Service' (SaaS) model, which allows for the customer to be treated a series of recurring transactions instead of a single transaction. The analysis is based on 10,000 identitical and independently distributed samples, which were generated using a variation of the Monte Carlo method, which, due to basis on Geometric Brownion motion, is less erroneous than other traditional randomly-distributed simulations.

Introduction

Premise

This work creates a live Monte Carlo simulation of the Monthly Recurring Revenue (MRR) Model popularized by the Software as a Service model, using 'Ties as a Service' as an example business. All assumptions and interpretations herein are conjectured. Relevant references are linked.

Background

In this paper, we will attempt to analyze the features of the MRR model, as described by David Skok[1] in his analysis of SaaS businesses. Most of the functions designed here are based on his work.

SaaS is considered part of the nomenclature of the Cloud Computing industry. "Examples of SaaS include enterprise-level applications such as Salesforce, Netsuite ... Google Apps to personal applications such as GMail, TurboTax Online, Facebook, or Twitter".[2] It is essentially a system whereby a consumer subscribes to a particular software or service, instead of purchasing versions of it on a transactiational basis. This contractual format allows the purchasing consumer or firm to enjoy the features they need locally through apps while the majority of the computing, processing, design, and development of the software takes place offsite. In theory, this would allow a user to use intensive and specific software without depending on local processing power or technical background, but just internet access. One noteable example of this platform is Hootsuite:

In order to analyze the behavior of this family of functions, we will create a fictional business known as 'Ties as a Service', and use it as a basis to generate values using those functions in order to allow us to model the behavior of this example SaaS firm, and examine how they change over time with different input parameters.

[1] http://www.forentrepreneurs.com/saas-metrics-2/

[2] http://www.sciencedirect.com/science/article/pii/S0167923610002393

Company Overview

Ties as a Service

"Ties as a Service" is a fictional business that will be used to simulate the behavior of the 'Software as a Service' business model. It is similiar to the "Jerky as a Service" model by Noah Kagan[3], which was used as a basis to generate comparable numbers.

The business operates under the following assumptions:

1. For a monthly subscription of $30, the client recieves 2 ties every month.
2. The Average Revenue per Account (ARPA) is therefore $30 inititally.
3. The profit margin on every sale is 0.45%.
4. The initial customer base is assumed to be 60.
5. The initial Monthly Recurring Revenue (MRR) therefore is 1800.
6. The discount rate[4] is assumed to be 10%.
7. The initial advertising budget for this firm is assumed to be $200 monthly.

[3] http://www.appsumo.com/sumo-jerky/
[4] http://www.investopedia.com/terms/d/discountrate.asp

Methodology

The MRR model is affected by two key factors; Customer Churn/Growth and Revenue Churn/Growth. 'Churn' is the notion of loss over time; it is the factor by which a firm's customer base or MRR is eroded by customers leaving the firm or downgrading their subscription. Growth refers to the rate at which the firm acquires new customers and clients upgrade their service.

For the purposes of this example, our business has only 1 tier of service, so we cannot see the effects of customers upgrading or downgrading their subscription. In practice, this change is important, as losing 10 customers could mean losing 9 $100 accounts and 1 $1000 account, or losing 5 $100 accounts and 5 $1000 accounts, which have different effects on the MRR of a firm. However, for the purposes of this example, we will assume that all customers are equally valuable.

Let us assume that the Churn and Growth variables are randomly generated values that are distributed according to the following means and variations.

	Mean	SD
Churn	5 %	5 %
Growth	5 %	5 %

Table 1: Summary of Customer Variation

Using these values, it is possible for us to create randomly generated vectors, so we can then analyze how the following functions change over time.

Functions

Customers

The Customers $(C_1, C_2, \ldots, C_n)$ are the first key component of any MRR/SaaS business. It changes as a result of New Customers acquired over time $(NC_1, NC_2, \ldots, NC_n)$ and Churned Customers over time $(CC_1, CC_2, \ldots, CC_n)$. Therefore, it can be related to the Customer Churn, c_i and the Customer Growth factor, g_i in the following way:

$$C_{i+1} = C_i + NC_{i+1} - CC_{i+1}$$

$$C_{i+1} = C_i(1 + g_i - c_i)$$

MRR

The MRR $(MRR_1, MRR_2, \ldots, MRR_n)$ is the next natural measure. It changes as a function of customers and the monthly subscription rate (S_i), here \$1800:

$$MRR_i = C_i \cdot S_i$$

ARPA

The ARPA $(ARPA_1, ARPA_2, \ldots, ARPA_n)$ is a function of the MRR and Customers, and measures what the average revenue for each account acquired during the period is. It changes as a function of Customers (C_i) and the monthly subscription rate (S_i):

$$ARPA_{i+1} = \frac{(C_i \cdot ARPA_i) + ((NC_{i+1} - CC_{i+1}) \cdot S_{i+1}}{C_{i+1}}$$

LTV

The LTV $(LTV_1, LTV_2, \ldots, LTV_n)$ is the Lifetime Value of a Customer, and determines how much the 'lifetime' cash flow of a Customer acquired in any period i is. Here, the Customer lifetime can be calculated by realizing that the Churn factor c_i represents the monthly rate at which a specific monthly cohort exhausts itself. Therefore, $\frac{1}{c_i}$ is the amount of months it takes for a Cohort to exhaust itself, and similarly, the number of periods we need to discount this cashflow by the discount rate 10%.

For the sake of accuracy, we also apply the Profit Margin (PM_i), here 45% to the ARPA in order to account for profit exclusively:

$$LTV_i = \frac{ARPA_i \cdot PM_i \cdot \frac{1}{c_i}}{(1 + \frac{r}{c_i}))^{\frac{1}{c_i}}}$$

CAC

The CAC ($CAC_1, CAC_2, \ldots, CAC_n$) is the Cost to Acquire a Customer, and determines how much the cost to acquire each customer was in any period i is. It is a function of the Advertising Budget (AB_i), here \$200, and the number of Customers (C_i).

$$CAC_i = \frac{AB_i}{C_i}$$

CAC Recovery

The CAC Recovery ($CACr_1, CACr_2, \ldots, CACr_n$) is the Months taken to recover the CAC, and determines how long it takes to recover the cost to acquire each customer was in any period i is. It is a function of the Cost to Acquire a Customer (CAC_i), the monthly subscription rate (S_i), here \$30, and the Profit Margin (PM_i), here 45%:

$$CACr_i = \frac{CAC_i}{S_i \cdot PM_i}$$

LTV/CAC

The LTV/CAC ($\frac{LTV}{CAC}_1, \frac{LTV}{CAC}_2, \ldots, \frac{LTV}{CAC}_n$) is the ratio of the LTV to the CAC, and determines how much a customer is worth over his entire lifetime in terms of the cost taken to acquire him in any period i is. It is a function of the LTV (LTV_i), and the CAC (CAC_i):

$$\frac{LTV}{CAC} = \frac{LTV_i}{CAC_i}$$

Simulation

Generation

Therefore, using these functions, and a randomly generated expected Customer Churn and expected Customer Growth, it is possible to simulate a variety of "random walk" cases that allow us to simulate a variety of future scenarios using the Monte Carlo method. Table 2 and Table 3 are the vectors that result from running these functions on this simulation 4 times.

	Customers	Churned Customers	New Customers	Net Customer Change
January	60.00	3.48	1.64	-1.84
February	58.16	1.89	5.32	3.43
March	61.59	2.79	3.06	0.28
April	61.87	1.00	4.06	3.05
May	64.92	6.48	5.57	-0.91
June	64.01	3.14	2.80	-0.35
July	63.66	3.31	2.11	-1.20
August	62.46	5.99	4.89	-1.10
September	61.36	2.52	7.37	4.85
October	66.22	6.08	4.97	-1.11
November	65.11	6.62	4.79	-1.84
December	63.27	3.81	5.09	1.28

Table 2: Customer Projections

	Subscription	MRR	ARPA	LTV	CAC	Recover CAC	LTV/CAC
January	30.00	1800.00	30.00	235.70	50.55	4.75	4.79
February	30.00	1744.79	30.00	201.61	50.55	4.00	4.30
March	30.00	1847.68	30.00	244.27	50.55	4.03	5.30
April	30.00	1855.97	30.00	342.45	50.55	3.86	7.38
May	30.00	1947.60	30.00	177.62	50.55	3.57	3.70
June	30.00	1920.24	30.00	277.35	50.55	3.64	5.73
July	30.00	1909.87	30.00	205.09	50.55	3.67	4.46
August	30.00	1873.88	30.00	334.51	50.55	3.61	7.11
September	30.00	1840.90	30.00	213.13	50.55	3.40	4.60
October	30.00	1986.53	30.00	251.67	50.55	3.42	5.60
November	30.00	1953.29	30.00	234.71	50.55	3.44	5.25
December	30.00	1898.24	30.00	345.89	50.55	3.74	7.54

Table 3: MRR Projections

Visualization

However, the MRR model is most intuitively analyzed in terms of Cohorts. It is much easier to see how the erosion and expansion of each individual group of New Customers slowly decline over time. Table 4 and Table 5 are the Cohort tables that result from running this simulation 4 times.

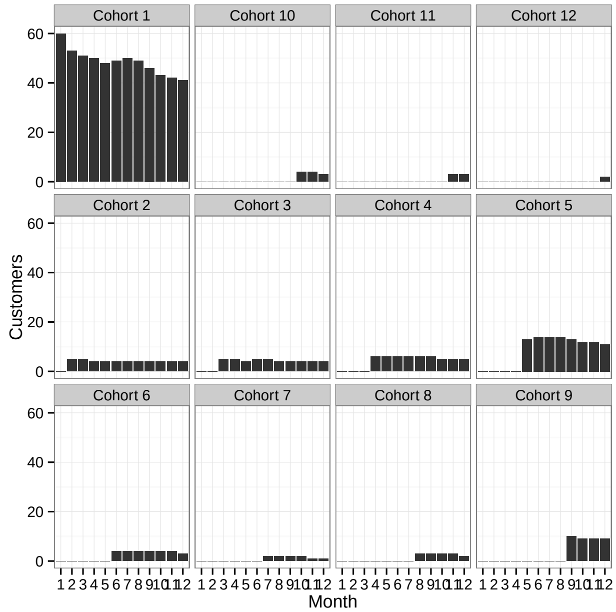
	January	February	March	April	May	June	July	August	September	October	November	December
1	60	53	51	50	48	49	50	49	46	43	42	41
2	0	5	5	4	4	4	4	4	4	4	4	4
3	0	0	5	5	4	5	5	4	4	4	4	4
4	0	0	0	6	6	6	6	6	6	5	5	5
5	0	0	0	0	13	14	14	14	13	12	12	11
6	0	0	0	0	0	4	4	4	4	4	4	3
7	0	0	0	0	0	0	2	2	2	2	1	1
8	0	0	0	0	0	0	0	3	3	3	3	2
9	0	0	0	0	0	0	0	0	10	9	9	9
10	0	0	0	0	0	0	0	0	0	4	4	3
11	0	0	0	0	0	0	0	0	0	0	3	3
12	0	0	0	0	0	0	0	0	0	0	0	2

Table 4: Customer Cohort Projections

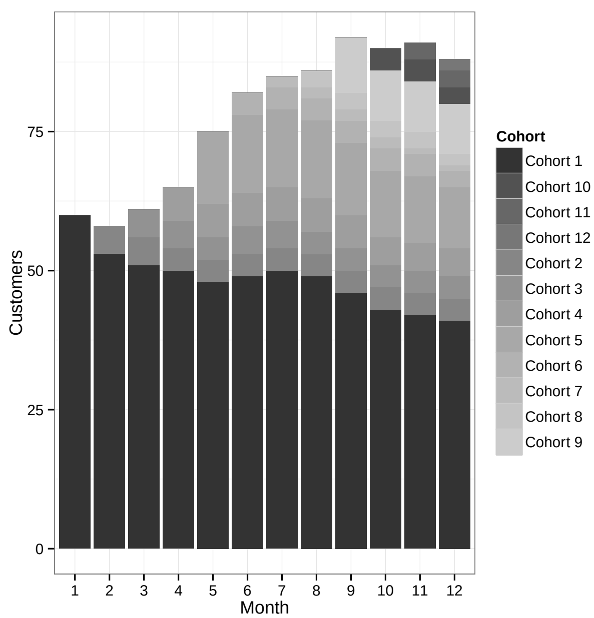
	January	February	March	April	May	June	July	August	September	October	November	December
1	1800.00	1603.53	1535.32	1506.90	1448.07	1474.46	1498.24	1461.17	1393.98	1277.10	1271.04	1220.70
2	0.00	142.78	136.71	134.18	128.94	131.29	133.41	130.11	124.12	113.72	113.18	108.69
3	0.00	0.00	141.27	138.66	133.24	135.67	137.86	134.45	128.27	117.51	116.95	112.32
4	0.00	0.00	0.00	180.92	173.85	177.02	179.88	175.43	167.36	153.33	152.60	146.55
5	0.00	0.00	0.00	0.00	404.25	411.61	418.25	407.90	389.14	356.52	354.82	340.77
6	0.00	0.00	0.00	0.00	0.00	124.49	126.49	123.36	117.69	107.82	107.31	103.06
7	0.00	0.00	0.00	0.00	0.00	0.00	52.94	51.63	49.25	45.12	44.91	43.13
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	87.56	83.53	76.53	76.17	73.15
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	301.34	276.08	274.76	263.88
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	106.67	106.16	101.96
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	84.91	81.54
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	48.00

Table 5: MRR Cohort Projections

The individual trends in the data become more obvious when we examine it visually.



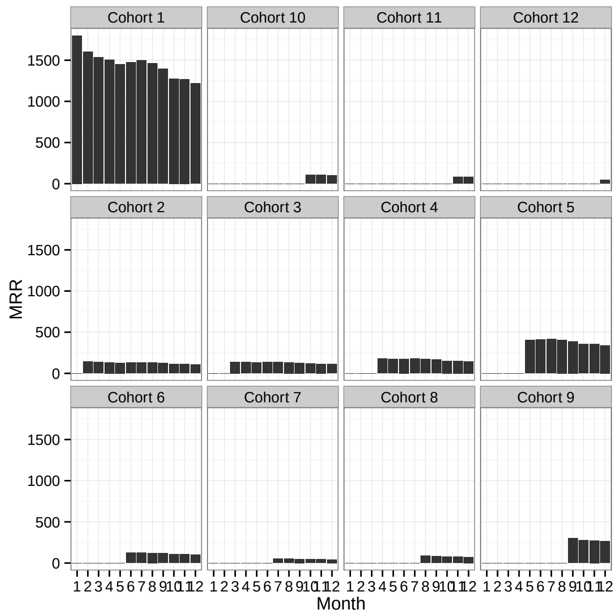
(a) Customer Cohorts over Time



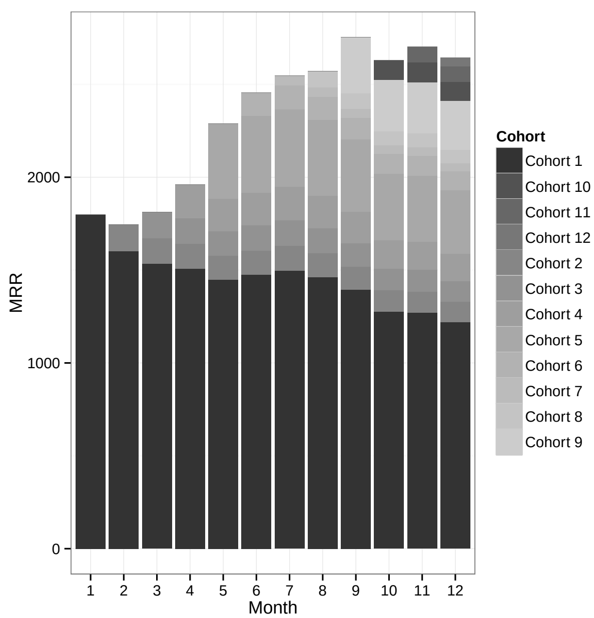
(b) Cumulative Customers over Time

In Figure 1a, we can see the growth and churn of each Customer Cohort over time. In Figure 1b we can also examine the Cumulative Customers, and see how the business is performing over time. As we can see, even though each indiviudal Cohort erodes over time as a result of the Churn factor, here roughly 0.05, the cumulative effect of acquiring new Customer Cohorts, at a rate of roughly 0.05 monthly counteracts this effect. Based on the strength of these factors, a typical SaaS business may grow or contract, and exhibit varying behavior over time.

In Figure 2a, we can see the growth and churn of each MRR Cohort over time. InFigure 2b we can examine the Cumulative MRR, and see how the business is performing over time. In this simple case, MRR is simply a function of Customer variation, not personal Growth or Churn, and is therefore primarily a reflection of Customer behavior.



(a) MRR Cohorts over Time



(b) Cumulative MRR over Time

Discussion

Revenue Churn & Growth

It is possible to design a model that takes into account how MRR variation into consideration, but such a model would require different 'tiers' of subscriptions for Customers to move inbetween. This would allow Customers to 'upgrade' and 'downgrade', which, coupled with the creation of New contracts for New Customers and Cancelations of contracts for Churned Customers, would cause significant fluctuation in the Monthly Recurring Revenue.

Therefore, it is possible to interpret Revenue churn and growth simply as a Tier weighted function of Churned Customers and New Customers[5]. In the general case, where j is the number of tiers of subscription:

$$rc_{i,j} = \frac{\sum_{n}^{j=1} S_{i,j} \cdot CC_{i,j}}{\sum_{n}^{j=1} S_{i,j} \cdot C_{i,j}} = \frac{\sum_{n}^{j=1} S_{i,j} C_{i,j}(c_i)}{\sum_{n}^{j=1} S_{i,j} C_{i,j}}$$

$$rc_{i,j} = \frac{\sum_{n}^{j=1} S_{i,j} \cdot NC_{i,j}}{\sum_{n}^{j=1} S_{i,j} \cdot C_{i,j}} = \frac{\sum_{n}^{j=1} S_{i,j} C_{i,j}(g_i)}{\sum_{n}^{j=1} S_{i,j} C_{i,j}}$$

Consider the following attempt to solve for $rc_{5,2}$, or the Revenue Churn on the 5th day for a 2-tier MRR/SaaS service:

for $i = 5$, $j = 2$

$$rc_{5,2} = \frac{(S_{5,1} \cdot CC_{5,1}) + (S_{5,2} \cdot CC_{5,2})}{S_{5,2} \cdot C_{5,2} + S_{5,2} \cdot C_{5,2}}$$

Thus, given the price of the different Subscription tiers $(S_i, 1, S_i, 2, \ldots, S_i, j)$ and the fluctuation of the Customers in those tiers $(C_i, 1, C_i, 2, \ldots, C_i, j)$, it is possible to examine the fluctuation in MRR over time. However, since TaaS has only 1 tier of subscription, such variation has not been included in this version of this paper.

As one can see, to do so would require an entire extra dimension of description, which while definitely possible, was impractical given the timeline for this paper. I intend to expend on such analysis in future; should there be interest in doing so.

Alternative Parameters

This document is capable of generating data, tables, figures, a CSV Dataset of values, and can be inputted with different paramaters to examine different scenarios. For an illustration of this feature, please examine the differences between the 'Good', 'Neutral', and 'Bad' versions of this document.

[5]http://chaotic-flow.com/what-is-mrr-churn-saas-metrics-faqs-part-2/

Conclusion

Thus, using these tools and methodologies, we have determined a way to use Random Walk theory and Monte Carlo-esque simulations to model this new Marketing theory. The MRR Subscription model has many differences from other traditional models, but its primary change is the fact that it's customers cannot be treated as a single transacation, but as a series of recurring transactions.

In that way, these Customer cohorts are similar to the idea of Asset cash flows, typically used in Financial modelling. By discounting an assets cash flow (Similar to how we treated a customer's LTV), it is possible to understand how much each individual customer is worth to us at a specific point in time, and take steps to improve and profit from that number.

The benefits of simulation are myriad. By accounting for natural 'variation'noise' and geometric brownion motion, our model is much more rigorous, and less erroneous the more sample 'random walks' we have. However, using this methodology to generate results is only a predictive exercise, and may not reflect the actual behavior of real market conditions.

The advantages of this method does mean that it is possible to simulate a variety of future cases given only a few input variables. During my original uploading of this paper, I uploaded 3 different versions, including a 'Good', 'Average' , and 'Bad' case analysis. All of these analyses were generated from a single file, which included all the code, plots, and PDF formatting, which can be repeated *ad infinitum* for every conceveiable case, and improved upon in the future. This 'living document' allows for real-time reproduceable research, and an all-inclusive method of report generation.

In the future, it is possible for this analysis to advance in scope. The inclusion of different subscription tiers, $(S_i, 1, S_i, 2 \ldots S_i, j)$ would significantly impact the relevence of the MRR model, and allow for much more rigorous analysis of MRR Variation. However, that would require splitting all analysis across the number of tiers, and would greatly impact the length of this project.

Opportunity

If this project receives significant attention, I am capable of proceeding with my analysis, and to perhaps even generate more auxiliary tools eg: R package, or an internet-accessable report generator for MRR evaluation.