Growth Accounting and Retention for Product Market Fit

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Abstract

In today's rapidly evolving business landscape, achieving product-market fit (PMF) is a critical milestone that often separates successful ventures from those that falter [1]. This paper delves into the intricacies of growth accounting and retention strategies, two fundamental pillars that underpin sustainable growth and long-term success to achieve PMF. In the ever-evolving business environment, PMF is characterized by the aligning of a product's value proposition with customer needs, driving demand and sustainable growth in the increasingly dynamic business environment [2]. This paper undertakes a deep exploration of growth accounting, a framework to be used to break down and understand the dynamics of growth, along with a retention analysis that ensures the customer's loyalty and value for a long period. Growth accounting is the basis of quantitative measures for business performance that cover things like DAU, WAU, MAU, and so on. The paper also discusses retention as the primary growth driver, thoroughly examining the methodologies for measuring retention, for example, cohort analysis, and focusing on the actionable strategies to improve the product's stickiness and customer satisfaction. By integrating these principles, businesses can optimize their resources, refine their strategies, and achieve a balance between scaling and main- taining customer engagement. This research outlines a clear path for startups and established organizations to measure growth effectively by aligning customer-centric approaches with robust metrics. Growth accounting and retention analysis are critical for understanding the trajectory of startups and established busi- nesses aiming for product-market fit (PMF). This paper provides a structured approach to these topics, integrating frameworks, and actionable insights. This study highlights how businesses can achieve sustainable growth and maintain competitive positioning by focusing on customer acquisition and retention. In this paper, we also discuss how to implement growth accounting and retention using modern distributed systems.

Keywords: Growth Accounting, Daily Active Users, Weekly Active Users, Monthly Active Users, Retention, Churn Analysis, Retained users, New users, Churned users, Resurrected users

INTRODUCTION

In the competitive and dynamic landscape of modern busi- ness, achieving product-market fit is a critical milestone that determines the success or failure of a product. PMF signifies the point where a product effectively satisfies a strong market demand, evidenced by high customer satisfaction, retention, and growth rates. Growth accounting and retention analysis are essential methodologies for navigating the journey toward PMF [3]. Growth accounting provides a structured framework to break down a company's growth into its fundamental components: new customer acquisition, retention of existing

customers. Retention emerges as a cornerstone of long-term success. While customer acquisition draws attention, retaining customers ensures the stability and scalability of a business.
High retention rates indicate strong alignment between a product's offerings and customer expectations, while poor retention often signals the need for strategic pivots or product improvements.
In next sections we delve into the details of growth ac- counting and retention frameworks, and about the details of implementation of these frameworks to enable businesses to identify and sustain PMF. Achieving product-market fit (PMF) is a pivotal milestone for any product or business. PMF occurs when a product satisfies a strong market demand, often measured through growth metrics and customer satisfaction. This paper delves into growth accounting, a framework to dissect growth into constituent parts, and retention strategies that underpin sustainable business growth.

Growth Accounting

A. Activeness

Growth Accounting for Daily Active Users, Weekly Active Users, Monthly Active Users involves analyzing the user engagement and growth trends of a product. Before we start building any datasets for growth accounting, first step is to define what activeness means for the product. Activeness definition will be defined once before starting data capture and is not changed throughout the life cycle of the datasets for calculating growth accounting. For any reason, if the activeness definition has to be changed, then all datasets needs to built from start with no historical data. If the definition is changed then metrics are not represented accurately which will cause confusion in evaluating growth of the product. For example, to calculate WAU (weekly active users), we need to look into all users that are active at least once in a week and if the definition of activeness is changed couple of days ago, then it causes uncertainity in the metric leading to misinterpretation of metrics and decision making. A user who satisfies the activity (ex: like, share, comment et. al.) of activeness definition is considered as active user.

B. Logging and Datasets

After activeness definition is locked and is agreed upon by all members of the team, next step is to work on implementing the logging to capture the data as per the activeness definition. In most cases, activity happens in the front-end or web based application. It requires logging implementation that captures the activity along with user related information to identify whether the same user is performing the activity multiple times in a given day. A user is consider to be active if the user has performed the activity at least once on a given day. User activity performed multiple times in a given day can be ignored for growth accounting metrics. For example, if we want to capture growth accounting metrics for likes then the first step is to capture from front-end if the user has liked. All likes should be logged from front-end and should be streamed using tools like Kakfa to back-end infra or any data warehouse that works for the organization. Logging framework can be implemented as a library which will be packaged into web tier application and logging framework when received data will be sent to Kafka distributed system which scales as the data size grow. Kafka consumers can be developed which reads data from Kafka queue, cleans and transforms the data if needed and creates datasets on the data warehouse. Transformations on these logging datasets include ensuring events are tied to unique users for accurate de-duplication.

C. Metrics and Definitions

Growth Accounting metrics are further break down into various components for better understanding of increase or decrease of DAU, WAU and MAU. Definitions of these breakdowns are

1. **New Users:** Users who are interacting with the product for the first time. Users might be performing some other activity on the platform already. A user is considered to be new user if the user has performed the action for the first time based on activeness definition for the use case. This metric represents new users to the product. Increase in this metric is always good to the product and the product should be able to bring back these users for growth.
2. **Returning Users:** Users who have interacted with the product in the past as per the activeness definition and returned during current period. For example, if the activeness definition is ”user has liked anything”, then for daily active users it is user who has liked yesterday and today, for weekly active users it is user who was weekly active (user has activity at least once in given week) yesterday and weekly active today. This represents users who likes the product and are interested in coming back. If this metric goes down, then it represents that users are not being retained.
3. **Churned Users:** Users who were active in previous period, but did not return back in current period as per the activeness definition. For example, if the activeness definition is ”user has liked anything”, then for daily active users it is user who has liked yesterday but did not have any activity today, for weekly active users it is user who was weekly active yesterday but not weekly active today. This metric represents users who are not liking the product and are not coming back after previous activity. This could be because of multiple reasons which can be analyzed by looking into various metrics.
4. **Resurrected Users:** Users who were not active in pre- vious period, but returned back in current period as per the activeness definition. For example, if the activeness definition is ”user has liked anything”, then for daily active users it is user who did not have any activity yesterday but did have like activity today, for weekly active users it is user who was not

TABLE I METRICS DEFINITIONS

Previous Period	**Current Period**	**State**
Active	Active (not new user)	Retained
Not Active	Active (Seen before)	Resurrected
Not Applicable	Active (First action date)	New
Active	Not Active	Churned
Not Active	Not Active	Stale

weekly active yesterday but is weekly active today. This metric represents users who are coming back after an inactivity.

Stale Users: Users who were not active in previous period, but returned back in current period as per the activeness definition. For example, if the activeness definition is ”user has liked anything”, then for daily active users it is user who did not have any activity yesterday but did have like activity today, for weekly active users it is user who was not weekly active yesterday but is weekly active today. This metric represents users who are not active anymore.

$$xAU_{daily|weekly} = NewUsers_{daily|weekly}$$
$$+ReturnUsers_{daily|weekly}$$
$$+ResurrectedUsers_{daily|weekly}$$

It is clear from the definition of above metrics that the computation of these metrics requires comparison of previous period's data with current period. In cases like batch pro- cessing in data warehouses, building current period dataset requires previous period dataset to be available. It takes lot of cost to build these datasets which can be optimized using few techniques. In next section, we discuss how to optimize building these datasets using bit based data structures.

D. Optimization

Batch pipelines in data warehouse often deal with huge amounts of data and running pipelines comparing previous period and current period increases the cost of pipeline run as it goes into future. In addition to this, we also need to save a list of dates when the users are active to determine whether the user is daily active or weekly active. Also, to compute new, retained, resurrected, churn and stale users it requires computation on the list saved. Operations on list takes lot of CPU and storing lists takes lot of storage as the data size increases. To address these, a new data structure based on bits can be used to save user activeness for past 63 days. Bigint data type is used to save the user history of activeness. As the limit of bigint data type is 64 bits and including the sign operator, bigint data type limit is $2^{63} - 1$. To compute whether the user is daily active, bigint saved in this data type is converted into bitwise and then very simply bitwise OR operations is applied with a bigint representing 2^0. This data type is called datelist. Dataset is built in a cumulative way, current period dataset always depends on previous period dataset. Current period dataset consists of all users data and the datelist representing the user activity for last 63 days based on activeness definition. A dimensional cube table can be built by using batch processing pipeline which computes all related metrics and save them to a dataset which will be of less size and doesn't contain any user information. As this dataset is small and doesn't contain user data, it can be saved with infinite retention and the queries will be faster as it is cube table. Most of the analysis at user level are usually done for past 30 days only. If the organization requires the data for analysis to be done beyond 63 days, string version of datelist can be saved which just takes the previous period datelist string and appends the 1 if the user is active in current period or appends 0 if the user is not active in current period. This data type grows as the number of days grows, and the bitwise OR operations cannot be performed on datelist string. Developers should build custom UDFs to parse the string and determine whether the user is daily active or weekly active N days ago.

$$xAU_{daily|weekly} = Datelist_{user}$$
$$||2^{daily|weekly} - 1$$
$$xNetGrowth = Lx_{new} + Lx_{resurrected} + Lx_{retained}$$

RETENTION

The concept of retention is a foundational principle in building consumer products. One of the best ways to prove if the product we are building provides value to the end user is by understanding retention [4]. Retention is a strong indicator to know if your product has good market fit. Without retention, users cannot really plan on growing the product. Retention for a product is defined as the percentage of people that are still active after a specific time period following their first action date. If the product is advertiser based then instead of number of people you would look at number of actors where an actor could be advertiser. Retention for a product is defined as the percentage of people that are still active after specific time period following their first action date.

$$R(Y) = V(Y)/V(0)$$

R(Y) is retention after Y days since first action, Y is days since first action, V(0) is volume of people who had the first action and V(Y) is volume of users active after Y days since first action. Retention is typically measured using a metric **xAU@Y**, where x is typically daily (D), weekly (W) or monthly (M). x is determined based on the product usage interval. A is active and activeness is based on the critical event defined. Y is days since first action. Y is age of the user in the product [6].

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CONCLUSION

Achieving product market fit is a critical milestone for any product aiming to establish sustainable presence in market. This paper explained concepts of growth accounting and retention analysis as key tools to evaluate and improve user engagement, ultimately leading to product market fit. This paper introduced a framework for breaking down user growth into new users, retained users, churned users, resurrected users, stale users. It also deep dived on how these concepts contribute to understanding overall growth dynamics. Further paper highlighted the importance of Daily Active Users, Weekly Active Users, Monthly Active Users for tracking engagement trends. Retention curves are identified as pivotal tools for diagnosing whether user derive sustained value for the product. Products with steeply declining retention curves were flagged as requiring intervention to address usability, value proposition, or market alignment. Growth accounting and retention metrics enable data-driven decision-making. Insights derived from these frameworks allow product teams to – focus on retaining high value users, improve on-boarding processes to reduce early stage churn, understand when and how churned users can be re-engaged. By quantifying growth and retention in a structured manner, the paper demonstrated that product teams could systematically identify the gaps between user needs and the product’s value proposition

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