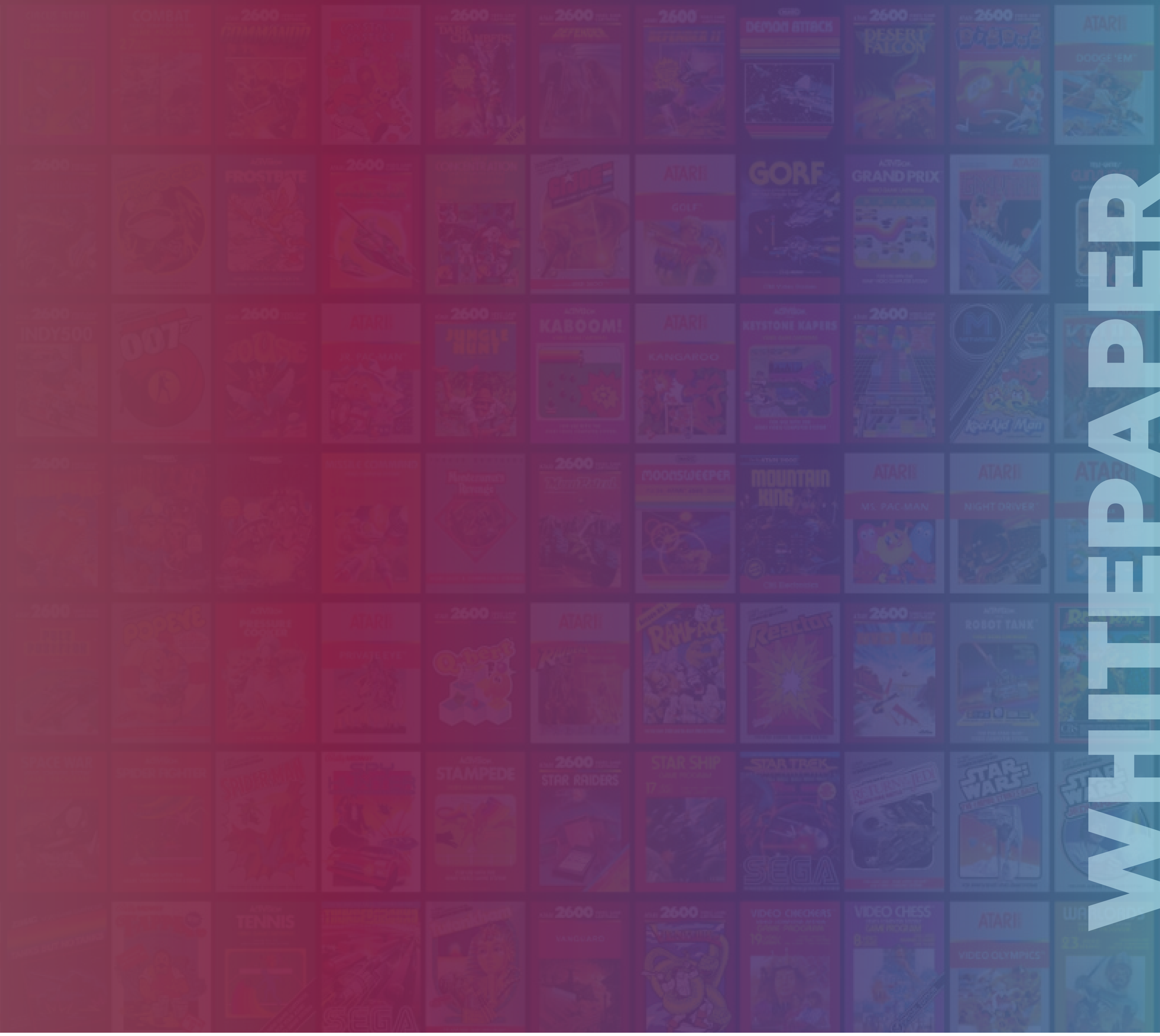

Structured & Data-driven Solution Framework to Identify Key Metrics to Predict Sales Before a Video Game Launch!

Deciphering the problem, challenges, and building solution framework to gather data; identify key metrics for predicting pre-launch video game sales.

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Introduction

Now more than ever, marketing and brand managers need to monitor a video game presence on the volatile and often unforgiving internet. Communicating a video game performance by weaving a narrative to key-stakeholders, be it the Directors or CEO's has become crucial at every gaming company. Thus, the marketing team and brand managers need to be alert that they are not merely tracking the signal in the noise but amplifying it when necessary. To execute this process successfully; it is crucial to forming a holistic solution framework as part of the long-term plans.

The Problem

Developing a game idea is complicated and muddled with unforeseeable challenges. The process of blending creativity with technical elements makes the process exciting and time-consuming. The sophistication of this process barely matters if it doesn't materialize to sales of the video game. To support this massive development and design process, gaming companies are cautious in picking teams by employing highly specialized professionals to tackle any challenges while ensuring their capability to provide instant solutions for the problems. These teams, through numerous iterations, will arrive at key-metrics in reports to analyze and improve gamers' experience but may fall short of knowing how the key metrics contribute to sales before a game released in the market. Thus, for gaming companies, identifying key metrics to predict sales before video game launches could pose several challenges.

Common challenges that gaming teams face while reporting key-metrics to predict sales:

1. There may be no alignment on the key-metrics due to different reporting methodologies and no consensus on an important metric as every metric is "important."
2. Different reporting structures within the organization sometimes lead to the performance of a week analyzed with a different lens providing no insights or direction to steer vital decisions.
3. When teams improve their reporting methods, there is a significant amount of time to educate executives on their process. The executives may not be willing to spend the amount of time required because they're unsure of the value of sales and might be worried about information overload.

The Solution

Formulating a structured data-driven solution framework based on imperative touchpoints mentioned below can help overcome challenges that various teams face while reporting key-metrics to predict sales before video game launch.

Collaborating data

Aggregating the data from different teams and identifying how it ties to sales and the contribution of each metric to sales.

Timely report tracking

Irrespective of tracking metrics periodically (daily or weekly), identifying the periods when to begin reporting and when to stop.

Sales-driven

Tying the contribution of key-metrics to sales and establishing a common language for the organization.

In this whitepaper, we have discussed how to help executives identify the statistically significant predictor of sales and move beyond, merely determining the important predictors to pointing to the weeks in which the variables stay significant. This way, we can help marketing executives to track the key-metrics and the windows in which they need to report.

Solution Framework to Identify Key Metrics:

1. Building a complete solution

It's crucial to proceed sequentially towards building the solution. Prior to that, we must develop an approach to identify key metrics.

Firstly, streamline the data collection process by combining all important metrics and create a dataset with the target variable being sales, which is a continuous independent variable. Secondly, initiate the statistical tests to understand the interaction between metrics and the weeks from game launch for a title along with the domain expertise required to create targets in the form of benchmarks. Machine learning should complement the expertise of domain knowledge holders but not to replace it.

Factors which may affect the sales of a product

Survey (Neilsen)	Web Mentions (Netbase)	Video Engagement (Tubular)	Ease & Volume of Search	Title Characterstics	Online Press Releases & Reach	Seasonality
First Choice	Net Sentiment	Total Views	Google Trends	Metacritic Score	Number of articles published	Competitors in the 3-month period
Game Rank	Total Impressions	Total Engagements	Google Index	User Review Score	Article Reach	Seasonality Effect
Unaided Awareness	Total Posts	Total Uploads	YouTube Index	No. of platforms the game was released on		
Def. Interest to Purchase	Total Replies			Whether it's a franchise		
Aided Awareness	Total Replies			Genre		
Pre-Order/Buy	Total Reposts					
Wait	Negative Sentiment					
Own	Positive Sentiment					
Def. Not Interested to Purchase						
Top 5 Rank						
Avg. Rank in Top 5						

2. Identifying important KPIs for post-launch sales

While creating the analytical dataset, many experts believe that unless there is a need for more granularity, a dataset with weekly metrics should suffice the need. This approach applies even when the need arises to either aggregate the dataset or to perform a deep-dive analysis.

Aggregating the metrics for each title by choosing a period uncovers the most consistent number of data points. Since the dependent variable, which is the post-launch sales of a title is a continuous variable, this problem can be framed as a classic regression problem. All the key performance indicators which can be predictors of this variable are classified as independent variables in the dataset.

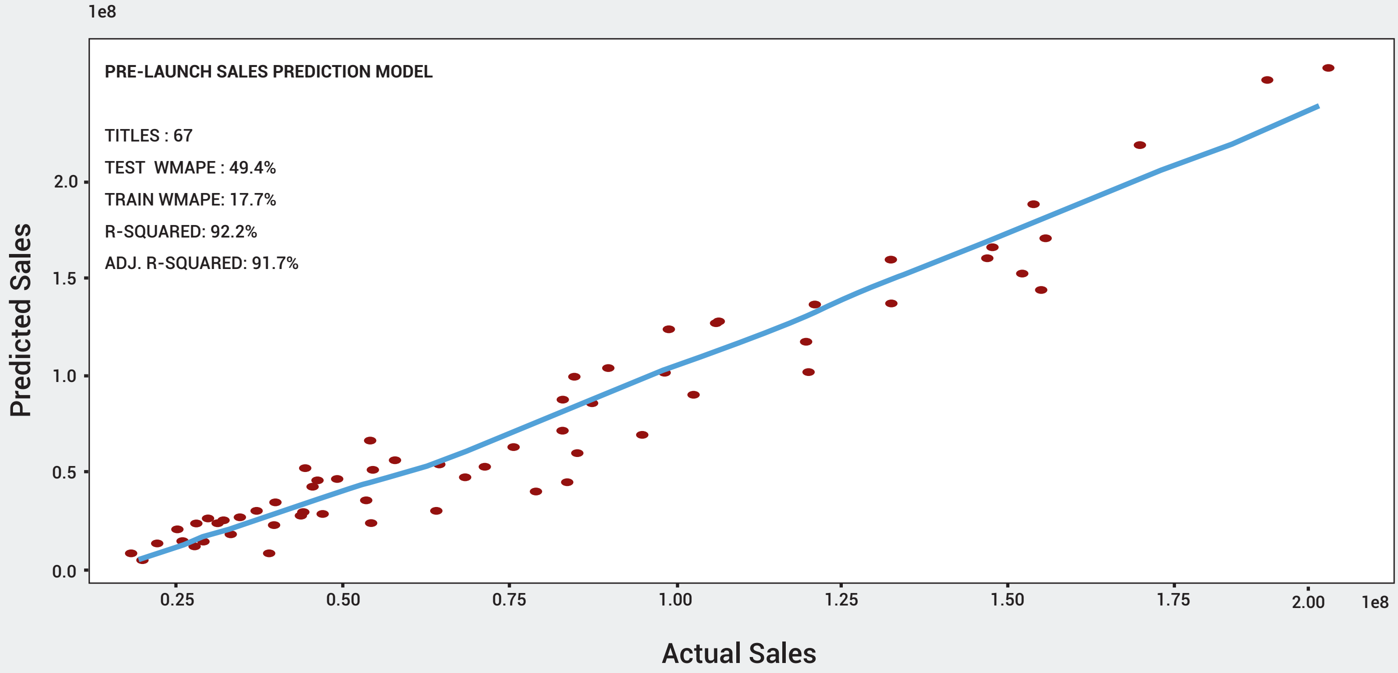
In a nutshell, each algorithm brings its own advantages and disadvantages. Thus, you should assess your requirement and team capability to choose the suitable one. However, below are few commonly used algorithms that many gaming companies prefer to use

1. **Multiple Linear Regression**
2. **Regression Trees**

A single evaluation metric could be less effective to evaluate model performance. You can choose a model that satisfies the below criteria to ensure implacable results.

1. **Training, test data error**
2. **Highest Adjusted R-squared**
3. **Root Mean Square Error**
4. **Weighted Mean Absolute Percentage Error**

Random Forest Regression vs Test Data



3. Validation windows for important KPIs

Using the rigor of a statistical framework to determine the validation periods in which Key Performance Indicators (KPI) show a statistically significant change over time, which in this case is weekly.

Simple Slopes Analysis to assess the validation periods for KPIs

The framework used to quantify and plot the interaction effect between variables is called simple-slopes analysis. The simple slopes analysis makes it easy to visually see how the interaction between two variables looks like – for example, the number of tweets posted with the weeks before the game's launch & helps us gauge the period in which we should be tracking a certain metric.

Every programming language has an implementation of the simple-slopes framework. Using the ***sim_slopes*** function from the interactions package in R to understand the weeks in which metrics were valid can be a viable option. To identify the intervals, you change the default option for the simple slopes function in R from ***johnson_neyman = FALSE to TRUE.***

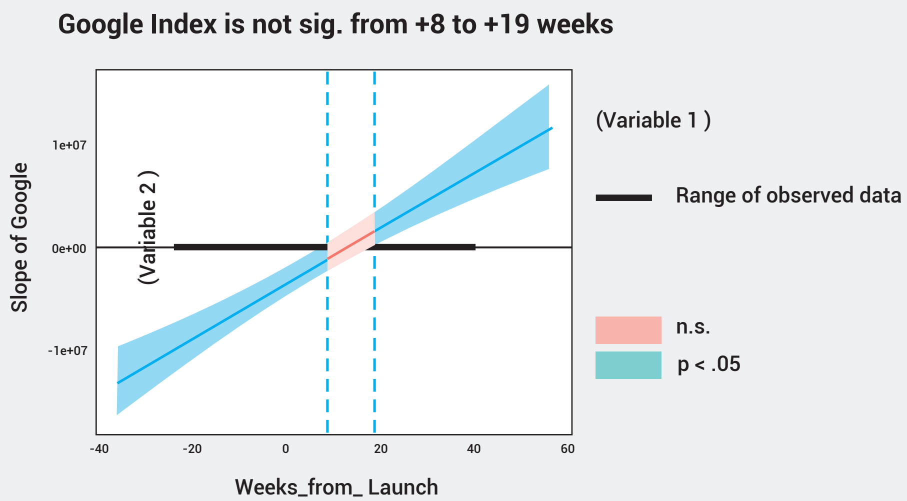
The ***johnson_neyman*** interval takes care of this process by providing all the values of the moderator function for which the metric might be valid.

With the interaction effect in place, the linear regression equation needs to be changed slightly:

Normal Linear Regression Equation: $\hat{y} = \hat{b}_0 + \hat{b}_1 x + \hat{b}_2 z$ **…. (1)**

Normal Linear Regression Equation with Interaction term: $\hat{y} = \hat{b}_0 + \hat{b}_1 x + \hat{b}_2 z + \hat{b}_3 xz$ **…. (2)**

For an instance assume $\hat{y}$ is the sales we're trying to predict using the KPIs in place, x is the 1st predictor, which we'll consider weeks from launch and z is the 2nd predictor, which for this example is the ease and volume of search variable, Google Index. To solve this equation and to capture the significant slope, we end up with a plot that reveals the number of weeks the Google Index is significant –



Thus, we establish the fact that Google Index can be tracked from the 40th week before a game's launch to the 8th week beyond which it doesn't change significantly for the next 11 weeks. This process can easily be replicated for the important KPIs to identify the periods of significant activity.

4. Creating benchmarks for setting targets

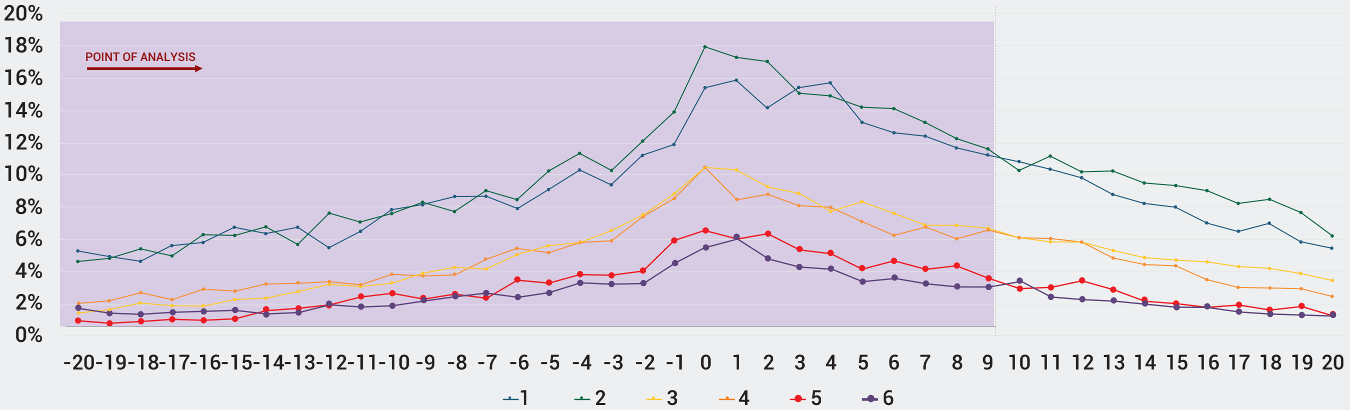
Before creating benchmarks, you would need to identify clusters of titles that have similar post-launch sales. While there are several ways to cluster, since the focus is on sales of the game, you can create clusters of titles with similar sales recorded. By creating groups of video game titles based on their sales, we could logically identify the titles which have generated higher revenue. For example, assume premium titles that earn $100M in their 1st 3-months post-launch have similar performance on the survey and social media to titles that earn $60M.

Using the dataset, which captures weekly performance, you can establish benchmarks by taking the average of the metric for each cluster separately leading up to a game's launch. The benchmark for a KPI in a cluster with higher sales should be different for a lower sales cluster. Using averages to create benchmarks is the easiest approach, which can be changed to a maximum of the metric for the week or minimum of the metric for the week depending on the context. You can also extend this concept by creating confidence intervals for each metric.

The below illustration represents the probable output:

Use Comparative benchmarks to track a title 20 weeks from release

UNAIDED AWARENESS: SAMPLE VIEW



5. Reporting significant percentage change week-over-week

Before overviewing the percentage value of week-over-week, let's understand how does a game's KPI shows a significant deviation week-over-week?

The inherent limitation of weekly/daily reporting is that we might accidentally highlight a metric's performance to be important when it isn't necessarily so. This is similar to reporting daily headlines and overestimating a general trend/-regular pattern. To overcome this problem, you need to dig deeper and highlight only those weeks in which there was a significant percentage change.

Within a cluster, for every individual title, note down the percentage change week-over-week. And later, calculate the standard error of percentage change for that particular week.

%Change = $(Metric_{Week2} - Metric_{Week1})/(Metric_{Week1})*100$

Standard Error (%Change) = $Mod(Metric_{Week2} / Metric_{Week1})*Sqrt\ (SE^2_{Week\ 2}/Metric^2_{Week\ 2} + SE^2_{Week\ 1}/Metric^2_{Week\ 1})*100$

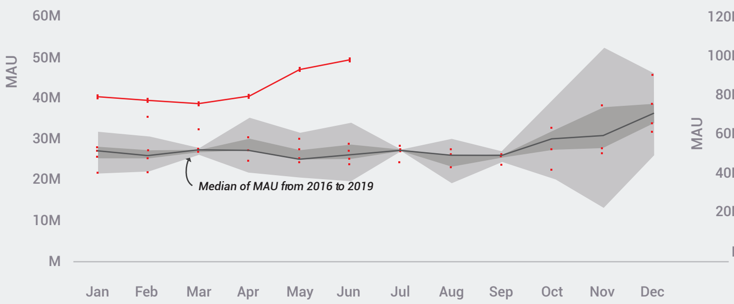
These calculations can now be used to create upper bounds and lower bounds

Lower bound (LB) = %Change – 1.65 * Standard Error (%Change)

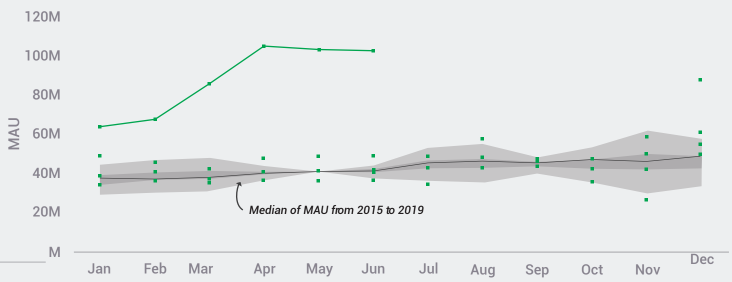
Upper bound (UB) = %Change + 1.65 * Standard Error (%Change)

Engagement was significantly up in 2Q20

Action-Adventure in 2020: +59% over Median MAU



Simulation in 2020: +124% over Median MAU



To determine whether the week-over-week percentage change was significant, use the following algorithm:

1. If either upper or lower bound is equal to zero, then the %change is not statistically significant
2. If both the upper and lower bound have the same sign, either positive or negative, then the percentage change is statistically significant
3. If the lower and upper bound has different signs (positive or negative), then the percentage change is not statistically significant

6. Analytical outcome

In the earlier stages, we already discussed how machine learning models can be used to extract important variables. Additionally, the role of simple slopes analysis is to identify the periods in which a variable is statistically significant. These methodologies help in creating weekly benchmarks for each cluster and set a target for every metric. Once the top metrics and benchmarks are created, the gaming company can focus on targeting only the key metrics and save time by not reporting metrics that don't tie directly to sales or show any statistical deviation.

Next, this solution can be deployed as a dashboard running on a web server, which through automation can be structured to report only the key-metrics, benchmarks, and highlight only those weeks with significant change. Once this is circulated within the organization, everyone will have access to the most important KPIs, and be in a better position to generate insights. This process of generating insights by narrowing down the metrics being reported brings clarity in deciding to set the targets for KPIs and be a top-performing title in the industry.

Projected impact of analytical outcome

1. Reducing the number of key-metrics to be tracked from 30+ to 8
2. Weekly targets enabled teams to measure the difference in the set goal v/s actual result
3. Empowers other teams to implement the solution as the framework to emulate the industry-agnostic approach

> **"The successful Analytical outcome is - running quarterly iterations of the developed solution and reducing the error to ensure constant improvement with the help of accurate forecasts and support the mission of the company to generating insights instead of just reporting numbers."**

Conclusion

Identify key metrics to predict sales before a video game launch could be a daunting challenge for many organizations given the preparations that must be made to plan, deploy, and ensure your approach is hassle-free and result oriented. Marketing managers in the video game industry are now working in a dynamic environment on social media with gaming communities exercising their power in inspiring massive successes or finding ways to overcome failure. The proposed solution framework in this whitepaper can be used to determine the most important variables throughout the process and be a forward-facing approach to solve and resolve business problems. Computing and reporting can never be a goal, but insights are.

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