1). ‘Sikka’ is a money earning app where you can earn cash rewards by completing simple offers daily that give you sikka coins, which you can withdraw to your bank account as real money. You can learn more about this app here Sikka.

Problem Statement:

Users come to this app through different marketing channels. They use the app to complete offers to earn money and we generate revenue in the process. Using the data furnished below, you need to: Calculate the lifetime value (LTV) of the users acquired through different marketing channels.

Ans: **Approach :- LTV** -> ARPU*PURCHASEAMOUNT*ESTIMATETIME(user last active days)

1) We have to calculate the total revenue generated from each user acquired through different marketing channels.
2) We have to calculate the average revenue per user (ARPU) for each marketing channel.
3) Estimate the customer lifetime for each marketing channel.
4) Then we calculate the lifetime value (LTV) of each user acquired through different marketing channels.

Total Revenue per user by each marketing channel→

join the user_signup_data, user_offer_completion_data, and rewards_details tables to calculate the total revenue generated by each user through different marketing channels. #then group the data by utm_source and user_id to calculate the total revenue for each user.

Code :-

with revenue_per_user as

(select utm_source, user_id, sum(total_revenue_in_paise) as total_revenue from

user_signup_data

Join user_offer_completion_data on user_signup_data.user_id=user_offer_completion_data.user_id

Join   rewards_details on

user_offer_completion_data.reward_id = rewards_details.reward_id

group by utm_source,user_id)

ARPU(Average Revenue per user)→ # Here we calculate the average revenue per user (ARPU) for each marketing channel by grouping the data by utm_source

Code: **,**ARPU as

(select utm_source ,avg(total_revenue) as avg_revenue_per_user from revenue_per_user

Group by utm_source)

customer lifetime for each marketing channel→

#estimate the average customer lifetime for each marketing channel by calculating the average number of days between the user account creation and last login.

Code: ,customer_lifetime as

(select utm_source , avg(datediff(day , last_login_at – created_at) as avg_customer_lifetime

From user_signup_data

Group by utm_source)

the lifetime value (LTV)→ connect table revenue_per_user and estimate lifetime

select utm_source, round((avg_revenue_per_user * avg_customer_lifetime)/ 100, 0)as ltv

from ARPU as A

join customer_lifetime as cl on A.utm_source = cl.utm_source

order by ltv desc;

Note:- We devide by 100 because it convert the revenue from paisa to rupees.

complete code: with revenue_per_user as

(select utm_source, user_id, sum(total_revenue_in_paise) as total_revenue from

user_signup_data

Join user_offer_completion_data on user_signup_data.user_id=user_offer_completion_data.user_id

Join rewards_details on

user_offer_completion_data.reward_id = rewards_details.reward_id

group by utm_source,user_id)

,ARPU as

(select utm_source ,avg(total_revenue) as avg_revenue_per_user from revenue_per_user

Group by utm_source)

,customer_lifetime as

(select utm_source , avg(datediff(day , last_login_at – created_at) as avg_customer_lifetime

```
From user_signup_data

Group by utm_source )

select utm_source, round((avg_revenue_per_user * avg_customer_lifetime )/ 100, 0)as ltv

from  ARPU as A

join customer_lifetime as cl on A.utm_source = cl.utm_source

order by ltv desc;
```

2. 'Sikka' is a type of Incent app. There is another similar incent app called 'Sikka Pro'. You need to find insights from the data for both these apps and tell which app is better of these two.

The data points you can consider to find the insights:

Offer Initiation by users

Offer Completion by users

Rewards earned by users

Revenue generated

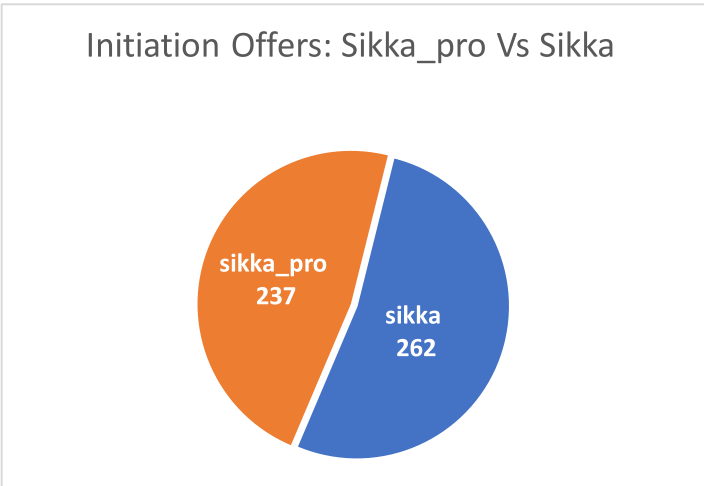
Ans : To find which app is better between 'Sikka' and 'Sikka Pro', we can analyze the data for the following data points:

(A).Offer initiation by users:

We can analyze the user offer data table to find the number of offers initiated by users for both apps. We can group the data by app_id and count the number of unique offer_ids initiated by users for each app. The app with a higher number of initiated offers can be considered more better.

1. We can connect the two table to get the app_id from the users_signup in user data table we use excel vlookup function then we make a matrix and create their pivot table and analyse data and create visualization for better understanding with pivot chart. Kindly check below reference for the same:

App_Name	Offer_initiation
sikka	262
sikka_pro	237



SQL query would be:

Select u2.app_id, count(distinct u1.offer_id) as initiated_offers

FROM user_offer_data as u1

Join users_signup_data as u2 on u1.user_id = u2.user_id

GROUP BY u1.app_id;

Based on the results of querie we can find which app has a higher number of offer initiations.

(B).Offer completion by users:

We can analyze the user offer completion data table to find the number of offers completed by users for both apps. We can group the data by app_id and count the number of unique reward_ids earned by users for each app. The app with a higher number of completed offers can be considered more better.

We can make the user_completion_offer_data table as pivot table and analyse our data and also create a visualization (chart) of data sets. Kindly check below reference for the same:

App Name	Completed Offers
sikka	27
sikka_pro	43

SQL query would be:

Select app_id , count(distinct reward_id) as completed_offers from user_offer_completion_data

Group by app_id;

Based on the results of the queries we can find which app has a higher number of completed offers.

(C). Rewards earned by users: We can analyze the rewards details table to find the total rewards earned by users for both apps. We can group the data by app_id and sum the total_payout_in_paise column for each app. The app with a higher total rewards earned can be considered better.

1. We can connect the two table to get the app_id from the users_offer_completion data table to Rewards table we use excel vlookup function then we make a matrix and create their pivot table and analyse data and create visualization for better understanding with pivot chart. Kindly check below reference for the same:

App Name	total_payout_in_paise
sikka	13966
sikka_pro	8154

SQL query would be:

Select u.app_id , sum(r.total_payout_in_paise) as total_rewards_earned

FROM rewards_details r

Join user_offer_completions_data as u on r.reward_id =u.reward_id

Group by u.app_id;

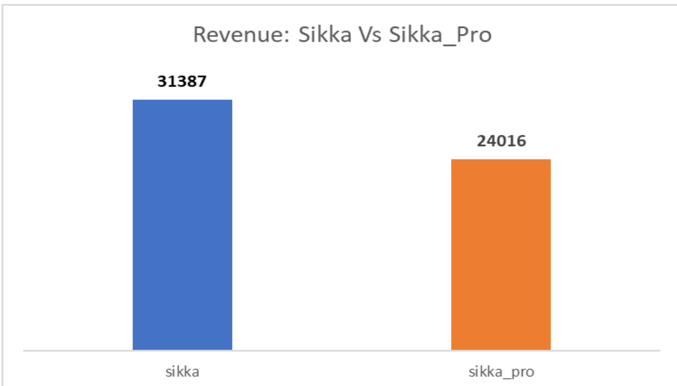
Based on the results of the queries, we can find which app has a higher total rewards earned.

(D).Revenue generated:

We can analyze the rewards details table to determine the total revenue generated by both apps. We can group the data by app_id and sum the total_revenue_in_paise column for each app. The app with a higher total revenue generated can be considered better.

1.We can connect the two table to get the app_id from the users_offer_completion data table to Rewards table we use excel vlookup function then we make a matrix and create their pivot table and analyse data and create visualization for better understanding with pivot chart. Kindly check below reference for the same:

App Name	total_revenue_in_paise
sikka	31387
sikka_pro	24016



SQL query would be:

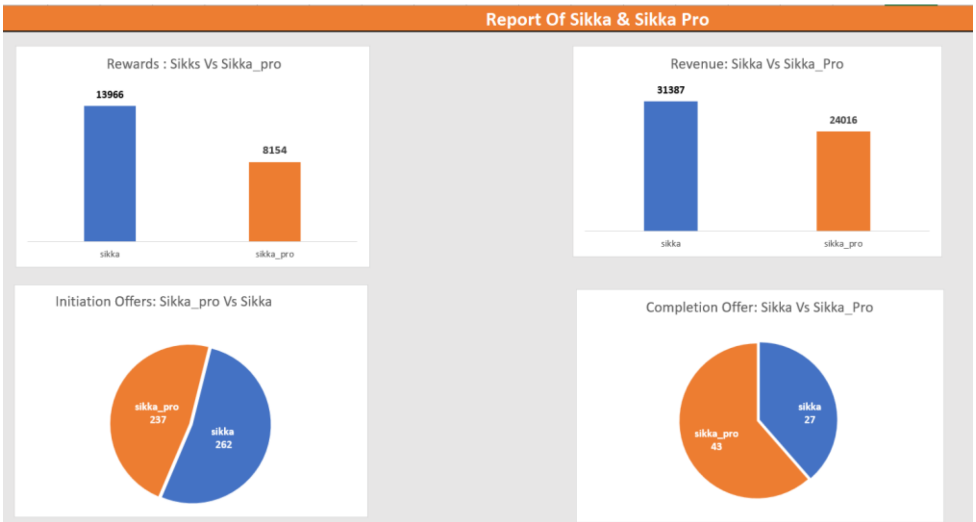
Select app_id , SUM(total_revenue_in_paise) AS total_revenue_generated, app_id

FROM rewards_details r

Join users_data_completions as u on r.reward_id =u.reward_id

Group by app_id;

DASHBOARD BY EXCEL:



Also I will upload these case study on github kindly check for the better Understanding.

GitHub Link:

3. **Here you are given the Install numbers, uninstall numbers, daily signups, number of daily activeusers and number of referrals made of the 'Sikka' app for the month of October 2022. Also, the Install numbers, uninstall numbers, daily signups, number of daily active users for the first 15 days of November is given.**

   You need to predict the number of referrals for these 15 days of November.

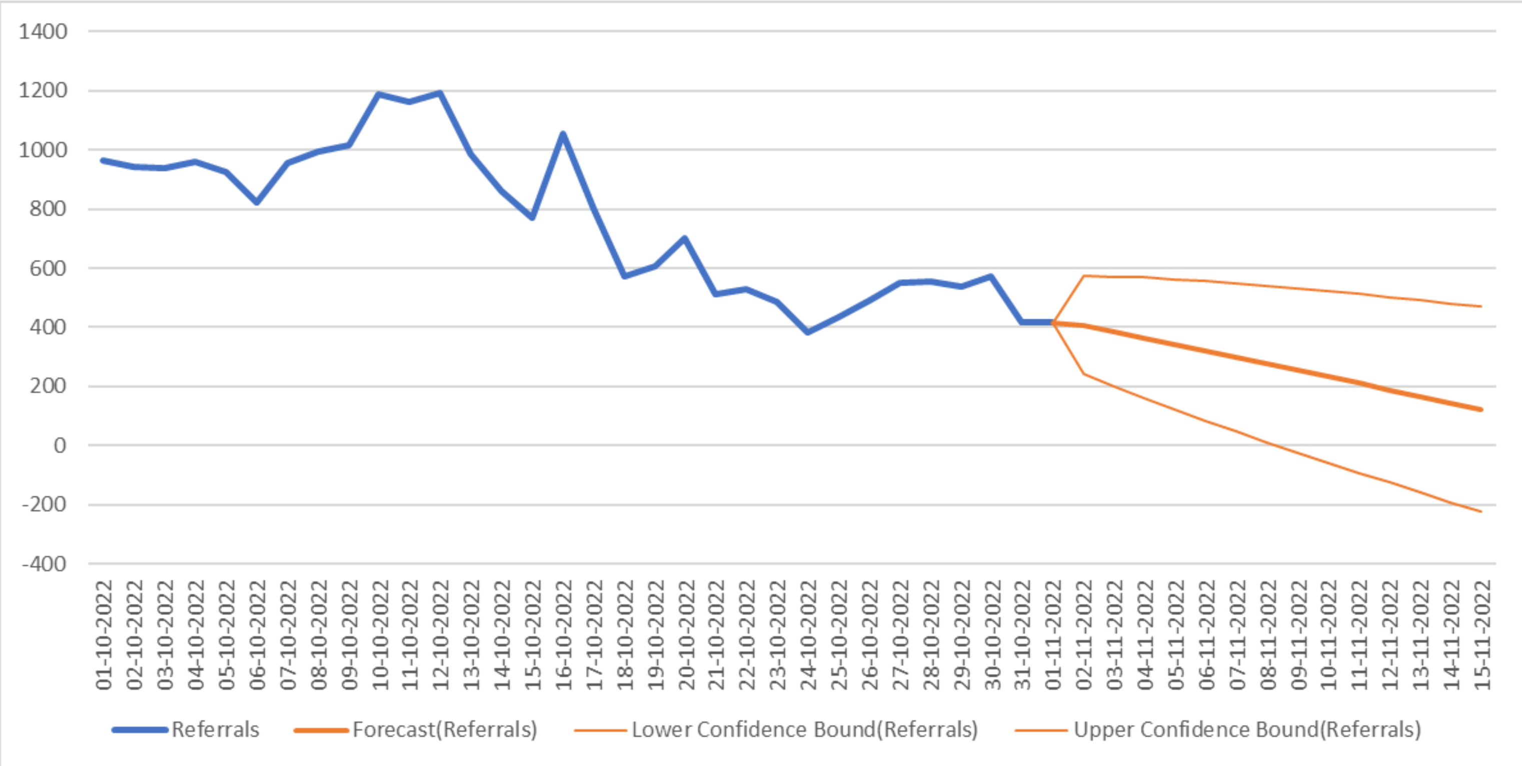
   Ans: To predict the number of referrals for the first 15 days of November, we can use the historical data from October 2022 to build a time series model and forecast the referrals for November.

   One approach could be to use a simple excel forecasting formula and then also we can make the chart. And also use the forecast sheet in Excel for the Result.

Referal Number with the help of Excel Forecast formula:

Date	DAU	Installs	Uninstalls	Signups	Referrals
01-10-2022	24071	6630	6994	3511	962
02-10-2022	23548	6366	6669	3387	941
03-10-2022	24572	6936	6899	3654	940
04-10-2022	24212	6561	6766	3532	960
05-10-2022	23247	6059	6402	3315	923
06-10-2022	24330	6230	6780	3288	822
07-10-2022	24213	6925	7073	3562	957
08-10-2022	25099	7826	7790	4110	994
09-10-2022	24099	8937	8149	4114	1016
10-10-2022	25156	8139	8215	4974	1186
11-10-2022	24497	7308	7532	4347	1161
12-10-2022	24152	8020	7867	4404	1193
13-10-2022	24094	7097	7081	4211	987
14-10-2022	21589	6729	7065	3494	860
15-10-2022	20829	5659	6519	2967	772
16-10-2022	22222	5861	6552	3096	1052
17-10-2022	20943	5860	6455	2828	801
18-10-2022	20180	6070	6611	2559	572
19-10-2022	19737	5267	6102	2278	606
20-10-2022	20148	5467	6125	2854	700
21-10-2022	17343	3845	4916	1726	512
22-10-2022	16270	3703	4727	1705	530
23-10-2022	15223	3397	4314	1545	484
24-10-2022	13482	3074	3904	1363	384
25-10-2022	14244	3714	4541	1658	435
26-10-2022	14659	3885	4564	1740	491
27-10-2022	14896	3707	4563	1905	551
28-10-2022	14473	3735	4381	1799	555
29-10-2022	13390	4072	4695	1872	536
30-10-2022	13370	3543	4343	1942	573
31-10-2022	13236	3313	4057	1562	419
01-11-2022	12816	3763	4149	1806	415.6
02-11-2022	12812	3087	3868	1550	383.5
03-11-2022	12042	3176	3815	1410	349.2
04-11-2022	12595	3172	3878	1629	314.1
05-11-2022	12361	3390	4021	1578	279.6
06-11-2022	13166	3441	4071	1656	242.3
07-11-2022	12565	3468	4011	1556	197.1
08-11-2022	12988	4468	4143	1808	159.4
09-11-2022	12992	4491	4638	2017	124.4
10-11-2022	13377	4261	4480	1997	91.8
11-11-2022	13826	4274	4512	2047	72.8
12-11-2022	13464	4660	4856	2066	56.7
13-11-2022	13415	4416	4749	2147	47.7
14-11-2022	13873	4097	4305	2065	30.3
15-11-2022	14459	4890	4593	2707	7.7

With Excel ForeCast Sheet :



Also I will upload these case study on github kindly check for the better Understanding.

GitHub Link:

4. A sample dataset with data for a few apps which uses ADX is given from the month of October.

You need to find out if there is any anomaly present in the data for any of the apps present in the sample dataset. The metrics you can look into are the requests, impressions, clicks,revenue, show-rate(impressions/responses), click-rate (clicks/impressions) or any other feature which you think will be helpful to gain more insight about any anomaly.

Ans : To find the anomalies in the data for any of the apps present in the sample dataset we can analyze various metrics such as requests, impressions, clicks, revenue, show-rate, and click-rate. Here are a few steps we can follow:

Requests: We can analyze the number of ad requests made by each app and look for any significant deviation from the expected values. If an app suddenly starts making a lot more or a lot fewer requests than usual, it could indicate an anomaly.

Impressions: We can also analyze the number of ad impressions generated by each app and look for any unusual patterns. If an app has a much lower or much higher impression count than other apps in the same category, it could indicate an anomaly.

Clicks: We can analyze the number of ad clicks generated by each app and look for any unusual patterns. If an app has a much lower or much higher click-through rate than other apps in the same category, it could indicate an anomaly.

Revenue: We can analyze the total revenue generated by each app and look for any unusual patterns. If an app suddenly generates a lot more or a lot less revenue than usual, it could indicate an anomaly.

Show-rate: We can calculate the show-rate for each app, which is the percentage of ad requests that resulted in an ad being displayed on the screen. If an app has a significantly different show-rate than other apps in the same category, it could indicate an anomaly.

Click-rate: We can calculate the click-rate for each app, which is the percentage of ad impressions that resulted in a click. If an app has a significantly different click-rate than other apps in the same category, it could indicate an anomaly.

In addition to these metrics, we can also look for correlations between different features and investigate any unusual patterns that emerge. We can use visualization techniques like scatterplots, histograms to help identify any anomalies or outliers in the data. Once we have identified an anomaly, we can investigate further to find the root cause and take appropriate actions to address the issue.