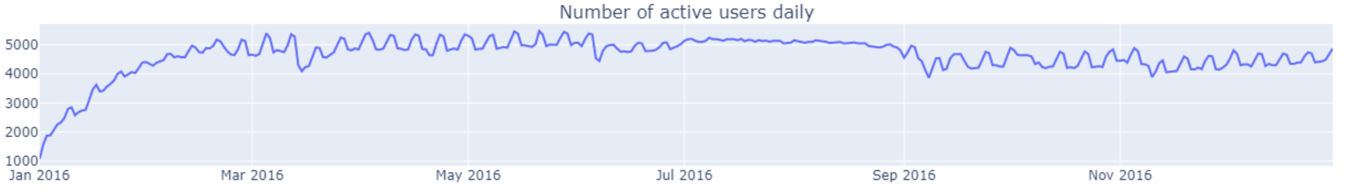
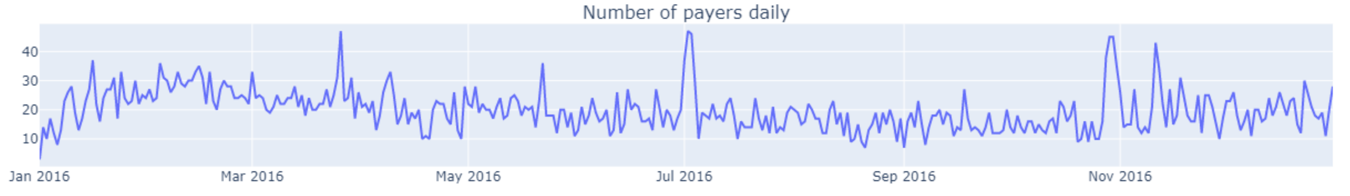
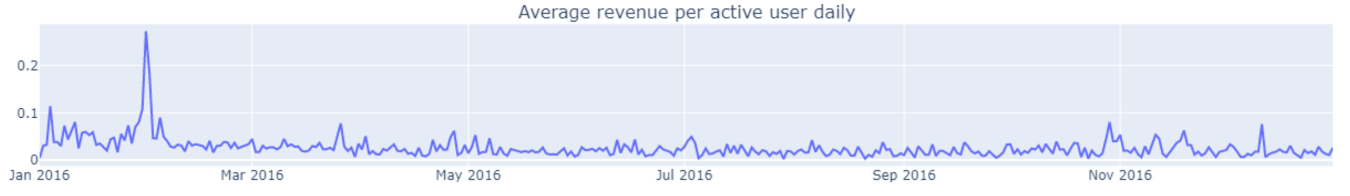
Supercell Data Scientist Challenge

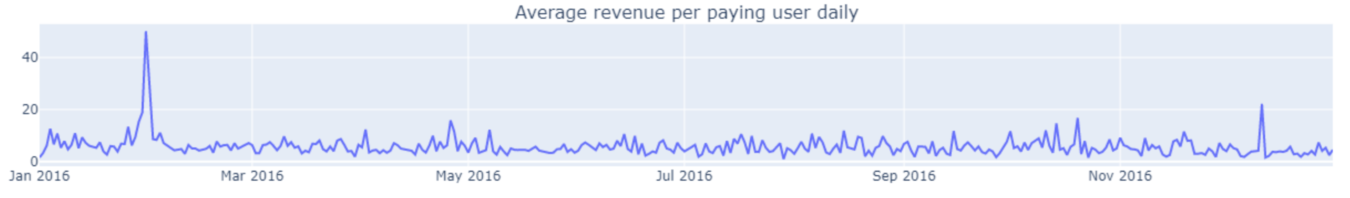
Revenue and Active Users

To research the state of hypothetical free-to-play mobile game in 2016 I have decided to start with such metrics as the number of active users (DAU), number of paying users, average revenue per active user (ARPU) and average revenue per paying user (ARPPU) daily. These metrics help to investigate the processes that generate total revenue.









The first plot shows that:

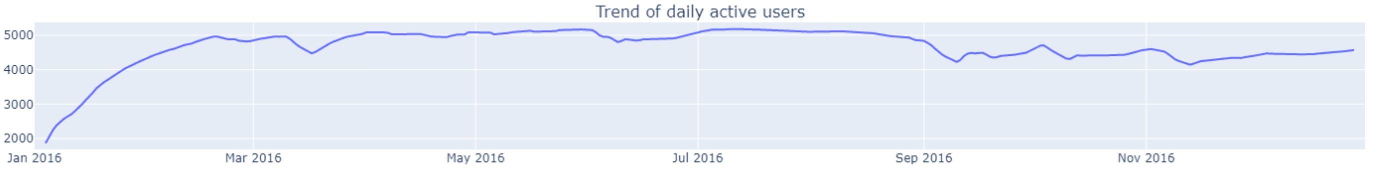
- there was an intense growth of daily active users during January and February and then this metric fluctuated between 3800 and 5500 users
- DAU had significant weekly seasonality throughout the year but in July and August it was smoother

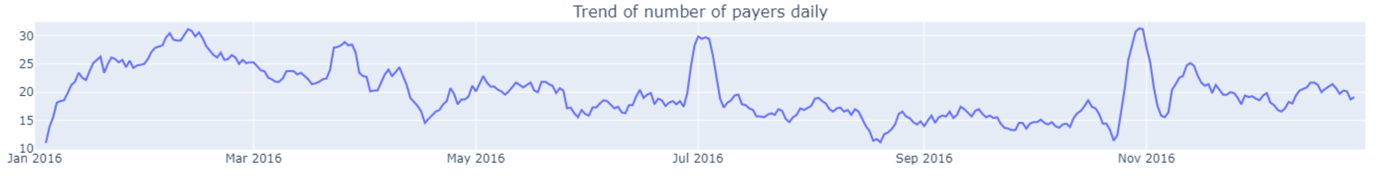
Number of paying users graph had another structure:

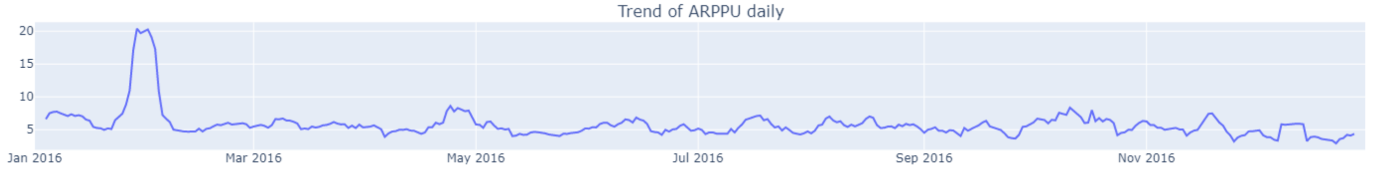
- it greatly peaked 3 times – on March 26, July 2, October 29 & October 30 (most likely because of holiday sales or special events)
- overall, it had decreasing trend from the end of February till the end of October
- more fluctuations were spotted in the last two month of the year

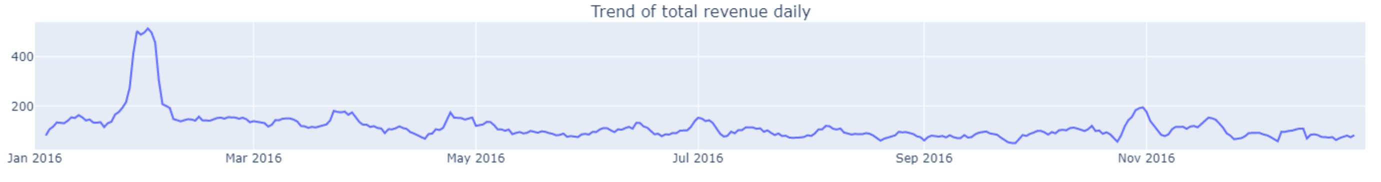
ARPU and ARPPU plots are quite similar as share of paying users is small (1% and less per day). They had one big peak on January 31 with the biggest average check and considering that number of payers didn't increase much on that day, that means there probably was some very attracting offer for players with total price above average.

Then I have used seasonal decomposition model which defined trend using moving averages and seasonality of the metrics including DAU, number of payers, ARPPU and total revenue.









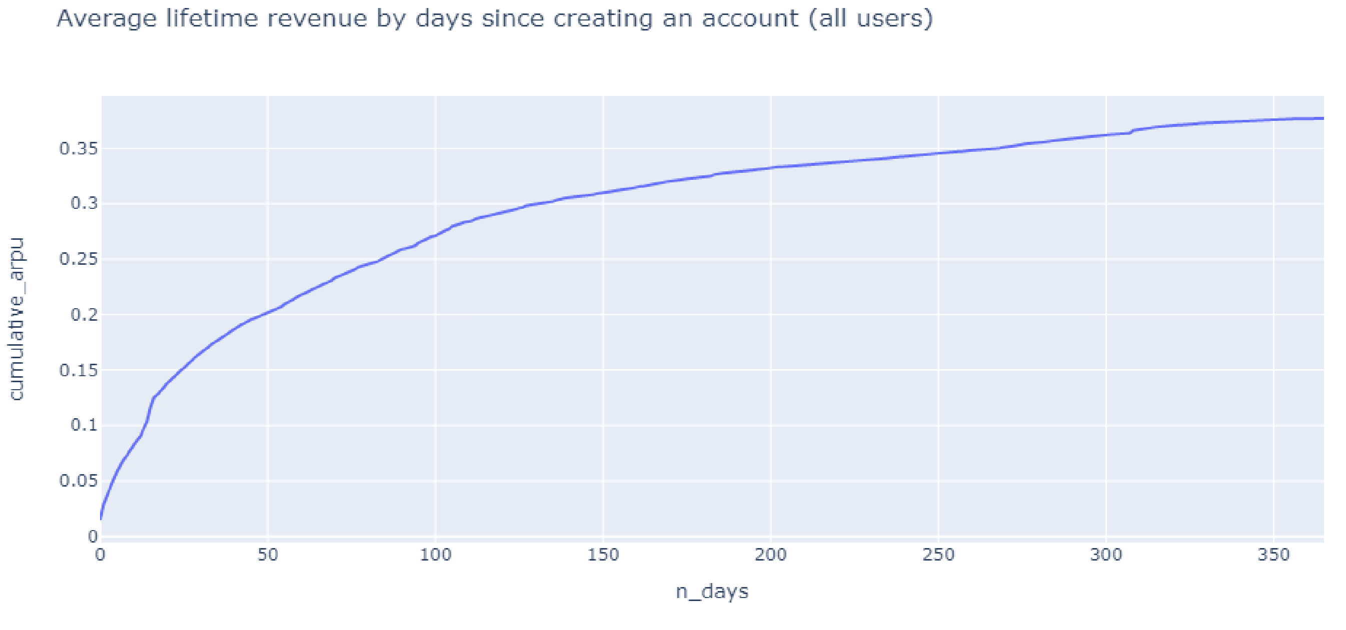
So, the decomposed trends reflect that:

- There was a plateau in daily active user number from April till September, then a slight decrease till November and by the end of the year it started to grow again.
- Also, in the last two months of 2016 daily number of payers was higher than in summer.
- However, average revenue per paying user slowly declined in November and December, therefore, total revenue also had decreasing trend by the end of the year.

Task 1. LTV

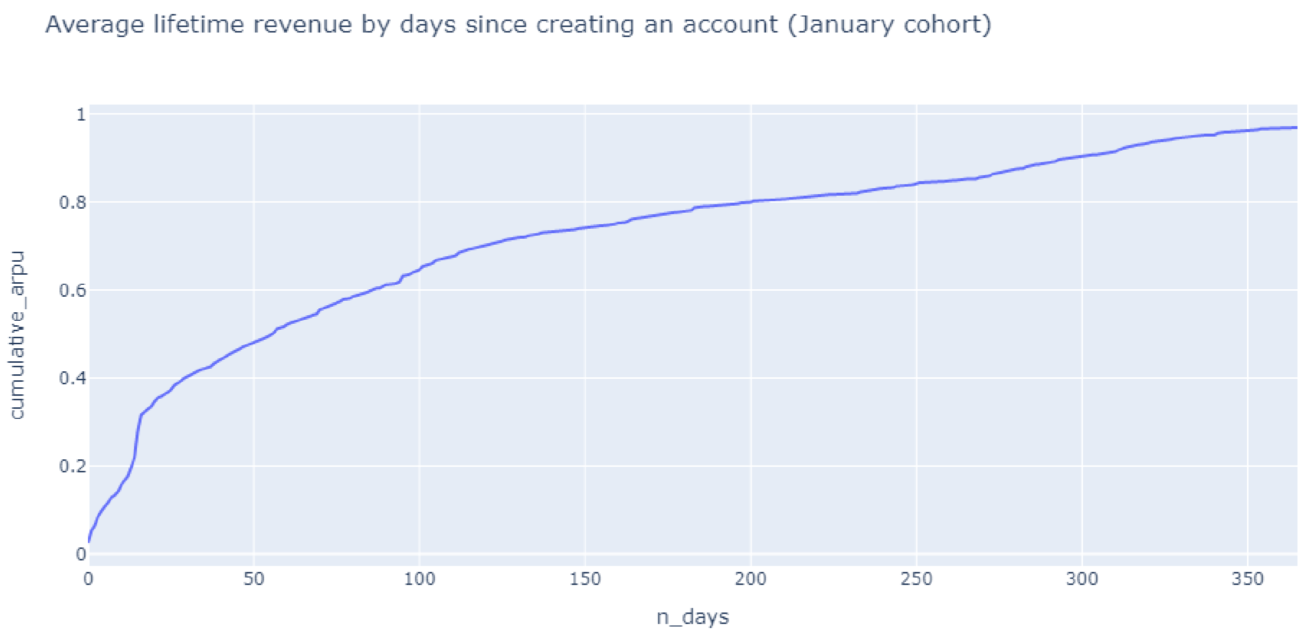
Lifetime value is the average amount of money received from one user during all his “life” in a game. It’s one of the most important financial metrics, that allows to optimize the costs for user acquisition campaigns, to plan revenue for a long-term period, to select the most financially attractive user segments and so on.

The LTV chart looks the same as the chart of cumulative ARPU, but it is calculated for cohorts. As I’m provided with data strictly restricted by a year, I can consider that all users have finite lifetime in the game and count their total cumulative ARPU by a number of days since registration.



Then the share of LTV generated during the first week considering all users - 18.38%. However, if a game is not closed at the end of a year, some users will play again the next year so their lifetime will be longer and revenue higher, therefore, they cannot be compared with already churned players.

That’s why it’s better to consider only one cohort of users who created their accounts in January as most of them have churned and most likely wouldn’t come back the next year. Then the share of LTV generated during the first week (by January cohort) is 13.19% . It differs from the previous estimation by 5 percentage points meaning that LTV of all users is significantly biased towards the first days since registration.

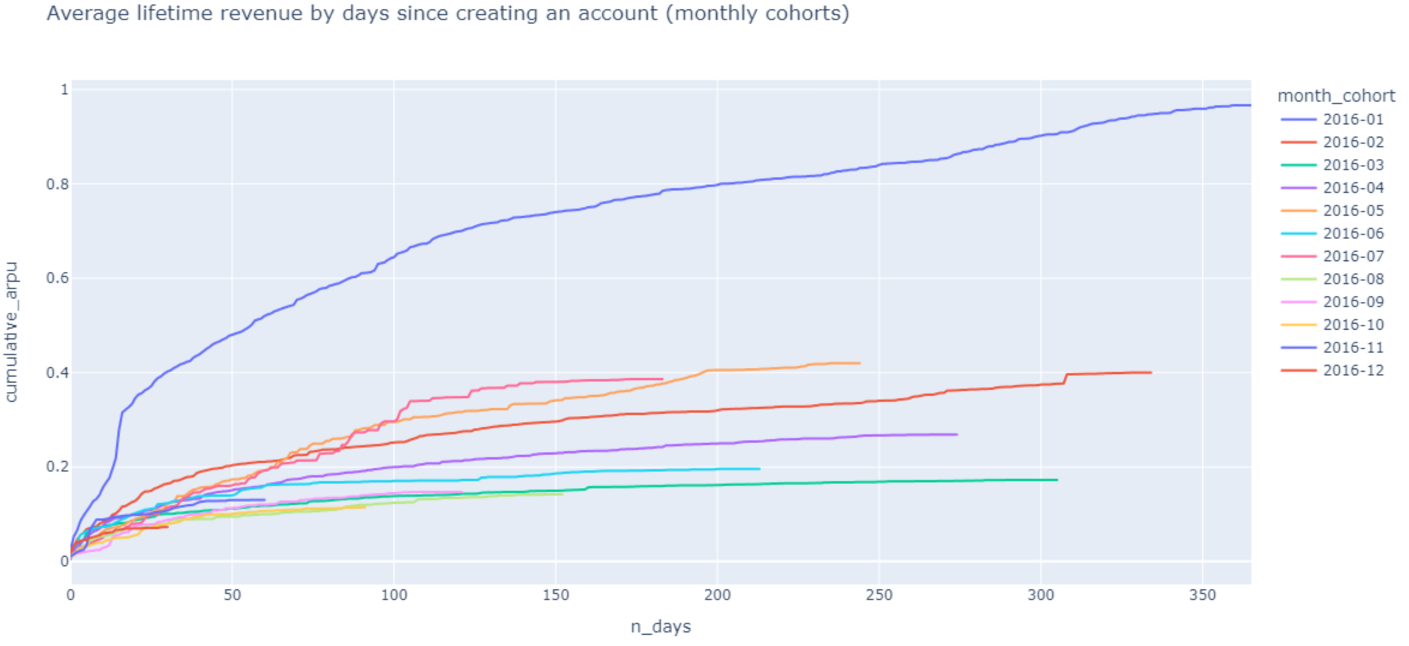


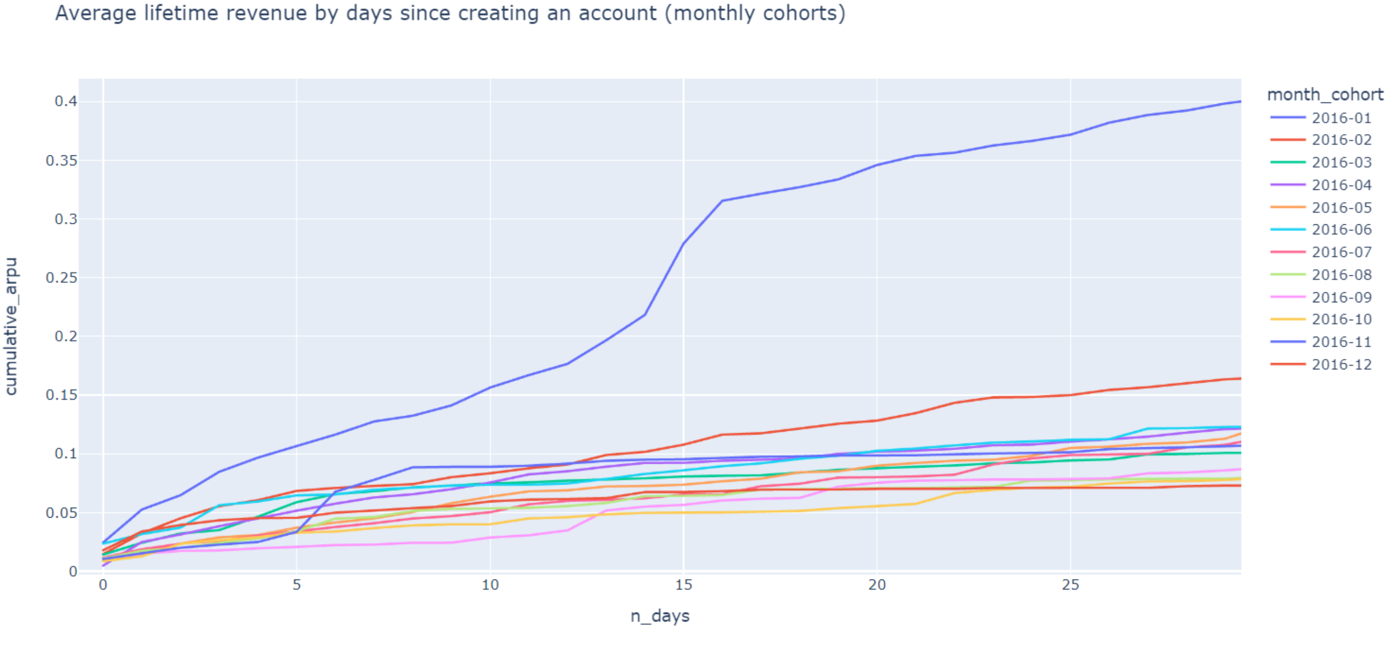
Besides, the LTV of cohorts by months definitely goes down from January to December based on the given data. If we compare cumulative revenue of cohorts by months, lower LTV doesn’t mean that players registered in December were less likely to pay, they just had less days to buy something in a game than players from January cohort and they could buy more later. Therefore, it’s not correct to compare such LTVs in total, the better way is to compare cumulative ARPU of different cohorts by days since registration.

Task 2. Conclusions

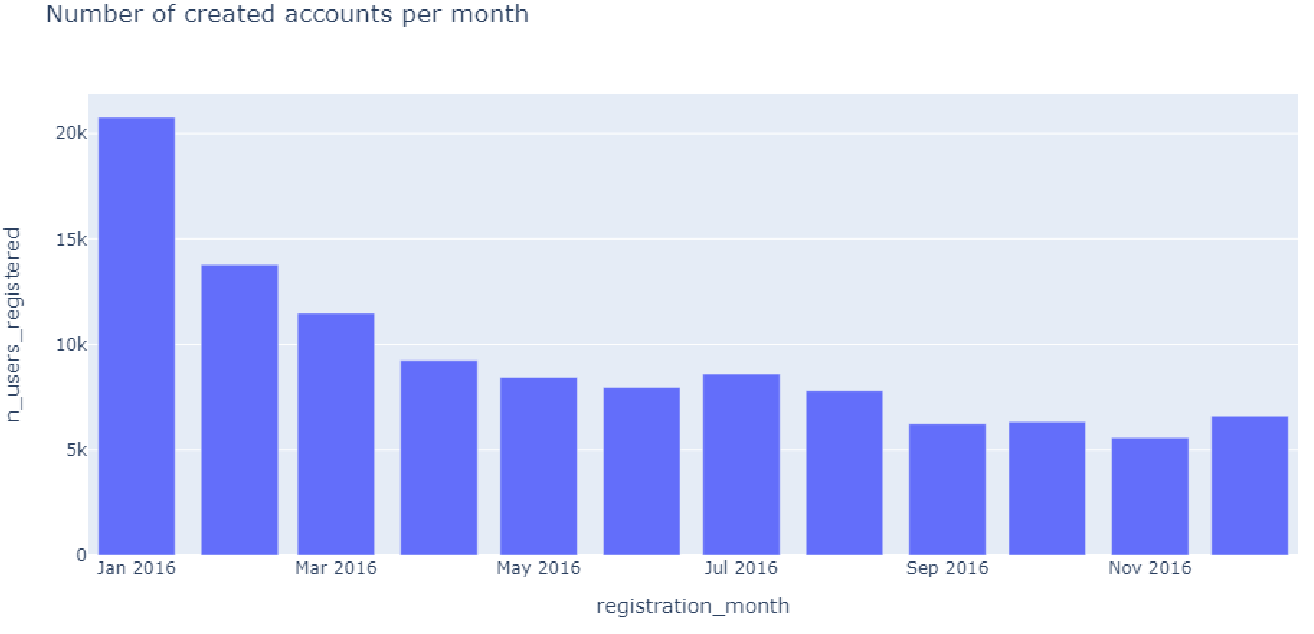
To sum up, the game had a good start in January and February gaining lots of active users and good payers. Later that year researched financial metrics didn't show constant positive trends (more like fluctuations within particular bounds). Moreover, the lifetime value of users was quite small – about $1 for January cohort and less than $0.5 for others.

To analyze further cohorts of players by months they registered in terms of their daily cumulative ARPU, I have created a graph on the given data. It allows to compare the growth dynamics of LTV between cohorts.





So, the most profitable players were from January cohort with the fastest increase of LTV, especially, on the 14th day. The second place held February cohort with more modest growth. The least ARPPU on day 7 had September cohort and on day 30 the December cohort. Besides, there were the least number of new accounts in September. It should be studied further with additional data what were the differences between January & February cohorts and others, perhaps, they were attracted with another traffic channel.



Furthermore, all the above metrics could be researched by groups of used devices, platforms, countries and app stores. With additional data it would be useful to investigate product metrics regarding traffic channels, in-game progress and so on.