WEEKLY COHORT ANALYSIS FOR 12 WEEKS

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This project refines Customer Lifetime Value (CLV) analysis by using cohort-based methods that track all website visitors, not just purchasers, over a 12-week engagement period. The results provide cumulative and forecasted ARPU insights, offering a more accurate and actionable view of long-term customer value and revenue potential.

* Use the turing_data_analytics.raw_events table for analysis.
* Assume the current week is 2021-01-24 (the last weekly cohort in the dataset).

* Marketing considers all users who visit the website, not just buyers. Adjust the analysis to include all visitors, not just purchasers.

  Customers do not tend to stay engaged for long. The manager wants a weekly cohort analysis for a 12-week period. Customers should not be expected to stay beyond 12 weeks.

  To address these issues, we will track users by their first event week (let's call it registration cohort from now on) and analyze their spending over 12 weeks.

  Calculate Cohort-Based CLV: Divide revenue from subsequent weeks by the number of users in the registration cohort, to get Average Revenue per User (ARPU) for each cohort.

* Another chart with weekly average revenue for each cohort expressed as a cumulative sum:

  Add each week's revenue to the previous week's revenue to create a **running total**.

  Ensure the cumulative calculations are based on the **first table's weekly averages** so the new cumulative cohort table accurately reflects these values.

* The initial chart tracks **how revenue grows over time** for users in a given cohort, monitoring spending over n weeks after registration. The **cumulative version** summarizes revenue growth over time, allowing for better forecasting and trend analysis. To summarise:
  - Each row should represent a cohort based on registration week, tracking their cumulative Average Revenue per User over time.
  - The **Cumulative Column Average** row shows the overall average revenue per cohort each week.
  - **Cumulative Growth %** (bottom row) indicates week-over-week revenue growth, which gradually slows down over time.

* Next, focus on the future and try to predict the missing data. In this case, missing data is the revenue we should expect from later acquired user cohorts. For example, for users who registered on 2021-01-24 week, we have only their first-week revenue, which is 0.19 USD per user. Hence, we are not sure what will happen in the next 12 weeks.

For this, we will simply use previously calculated Cumulative growth % and predict all 12 future weeks' values (ex., for this cohort, we can calculate expected revenue for week 1 as 0.19 USD x (1 + 23.29 %) = 0.24 USD, for week 2 as 0.24 USD x (1 + 12.26%) = 0.27 USD). Using average cumulative growth for each week, we can calculate that based on the 0.19 USD initial value, we can expect 0.35 USD as revenue on week 12. Provide a chart that calculates these numbers for all 12 future weeks.

You should calculate the average of cumulative revenue for the 12th week for all users who have been on your website. This not only provides a better estimate of CLV for all your users who have been on your website (including the ones who did not purchase anything), but it also allows you to see trends for weekly cohorts.

When writing insights from these 3 cohort analysis tables, focus on identifying key trends, such as revenue growth patterns, seasonal effects, and long-term customer value.

Dataset : 2020-11-01 - 2021-01-31
User_pseudo_Id are grouped by their first interaction week into cohorts. Then their average purchase revenue is calculated.
The dataset is too small to get significant insights

Average Revenue per User (ARPU)

	cohort_week	week_00	week_01	week_02	week_03	week_04	week_05	week_06	week_07	week_08	week_09	week_10	week_11	week_12
	2020-11-01	0,938	0,326	0,267	0,262	0,160	0,153	0,165	0,025	0,008	**0,014**	0,023	0,015	0,018
	2020-11-08	1,192	0,381	0,281	0,229	0,277	0,104	0,039	0,069		0,012	0,035	0,021	
	2020-11-15	1,382	0,297	0,219	0,228	0,167	0,026	0,029	**0,022**	0,021	0,006	0,004		
Black Friday	2020-11-22	1,647	0,236	0,225	0,119	0,037	0,013	**0,006**	0,011	0,035	0,004			
	2020-11-29	1,319	0,363	0,243	0,048	0,012	**0,022**	0,006	0,012	0,005				
	2020-12-06	1,203	0,329	0,081	0,034	**0,021**	0,027	0,024	0,002					
	2020-12-13	1,008	0,108	0,040	**0,030**	0,041	0,030	0,000						
Christmas	2020-12-20	0,369	0,054	**0,021**	0,023	0,018	0,008							
Christmas	2020-12-27	0,339	**0,051**	0,005	0,020	0,006								
Christmas	2021-01-03	**0,228**	0,064	0,027	0,005									
	2021-01-10	0,399	0,059	0,012										
New Years sale	2021-01-17	0,903	0,122											
	2021-01-24	0,192												
	Column average	0,855	0,199	0,129	0,100	0,082	0,048	0,039	0,024	0,017	**0,009**	0,021	0,018	0,018

* The biggest Average revenue per client is achieved in THe Black Friday week (2020-11-22 cohort). But this cohort does not show any better results in long term: it reaches the plateau phase in week_05 already. As the average plateau phase is reached in week_07.
* At the beginning of and during Christmas and New Year period - Average revenue drops to 0,334$ (from previuosly held 1,241$). This period cohort users do not spend much and reaches significant drop very fast - in two or three week time.
* I have maked diagonally the Christmas time weeks. It is significant that festive time gives bigger drop in revenue through all the cohorts. So our sales is sensitive to festive seasons. dataset is very small we can not derive very strong conclusions about this topic, but it looks like it is sensitive. I would recommend to look into the data of longer period - to compare other festive seasons, as well as the last and previuos years the same periods.
* As for the all 12 week period on all of our cohorts: the plateau phase is reached by the week_07 (0.024$) , and the biggest drop is achieved in week_09 (0.009$), which is followed by slight rise afterwards.
* What was done differently for the 2021-01-17 cohorts? It differs in its average revenue amount from the cohorts before and after. What marketing actions were taken? Is it The sale after New Year?
* What happened to 2020-11-08 cohorts week_08 data? Why is it missing?

CUMULATIVE Average Revenue

	cohort_week	week_00	week_01	week_02	week_03	week_04	week_05	week_06	week_07	week_08	week_09	week_10	week_11	week_12
	2020-11-01	0,938	1,264	1,532	1,793	1,953	2,106	2,272	2,297	2,305	2,318	2,341	2,356	2,375
	2020-11-08	1,192	1,573	1,854	2,084	2,360	2,465	2,504	2,574	2,574	2,586	2,621	2,642	
	2020-11-15	1,382	1,679	1,897	2,125	2,292	2,318	2,346	2,368	2,389	2,396	2,400		
Black Friday	2020-11-22	1,647	1,883	2,108	2,228	2,265	2,278	2,285	2,295	2,330	2,333			
	2020-11-29	1,319	1,683	1,926	1,974	1,987	2,009	2,015	2,027	2,032				
	2020-12-06	1,203	1,532	1,613	1,648	1,669	1,696	1,720	1,722					
	2020-12-13	1,008	1,116	1,156	1,186	1,227	1,257	1,258						
Christmas	2020-12-20	0,369	0,423	0,443	0,467	0,485	0,493							
Christmas	2020-12-27	0,339	0,390	0,394	0,415	0,421								
Christmas	2021-01-03	0,228	0,293	0,320	0,325									
	2021-01-10	0,399	0,458	0,470										
New Years sale	2021-01-17	0,903	1,025											
	2021-01-24	0,192												
	Cumulative column average	0,855	1,055	1,184	1,284	1,366	1,414	1,453	1,476	1,493	1,502	1,523	1,541	1,559
	Cumulative growth		23,29%	12,26%	8,44%	6,39%	3,51%	2,74%	1,62%	1,16%	0,60%	1,40%	1,16%	1,18%

* Cohorts till and including the Black Friday week generate bigger Cumulative value, as they begin with bigger initial moneatry value.

* Black Friday week (2020-11-22) is not the best in terms of Cumulative value, although it starts with the best starting figure.

* Christmas festive season cohorts show low Cumulative value.

* The lowest Cumulative growth is seen in the week_09

PREDICTIVE Average Revenue

	cohort_week	week_00	week_01	week_02	week_03	week_04	week_05	week_06	week_07	week_08	week_09	week_10	week_11	week_12
	2020-11-01													2,375
	2020-11-08												2,642	*2,673*
	2020-11-15											2,400	*2,428*	*2,457*
Black Friday	2020-11-22										2,333	*2,366*	*2,394*	*2,422*
	2020-11-29									2,032	*2,044*	*2,073*	*2,097*	*2,122*
	2020-12-06								1,722	*1,742*	*1,753*	*1,777*	*1,798*	*1,819*
	2020-12-13							1,258	*1,278*	*1,293*	*1,301*	*1,319*	*1,334*	*1,350*
Christmas	2020-12-20						0,493	*0,506*	*0,515*	*0,520*	*0,524*	*0,531*	*0,537*	*0,543*
Christmas	2020-12-27					0,421	*0,436*	*0,448*	*0,455*	*0,460*	*0,463*	*0,469*	*0,475*	*0,480*
Christmas	2021-01-03				0,325	*0,346*	*0,358*	*0,367*	*0,373*	*0,378*	*0,380*	*0,385*	*0,390*	*0,394*
	2021-01-10			0,470	*0,510*	*0,543*	*0,562*	*0,577*	*0,586*	*0,593*	*0,597*	*0,605*	*0,612*	*0,619*
New Years sale	2021-01-17		1,025	*1,151*	*1,248*	*1,328*	*1,374*	*1,412*	*1,435*	*1,452*	*1,460*	*1,481*	*1,498*	*1,516*
	2021-01-24	0,192	*0,237*	*0,266*	*0,288*	*0,307*	*0,318*	*0,326*	*0,332*	*0,335*	*0,337*	*0,342*	*0,346*	*0,350*
												AVERAGE LTV		1,471

* As we calculate our predictive revenue based on small historical dataset, our received prediction is not really reliable as it lacks proofing with the historical data.

* Customer Acquisition Cost CAC is 2$. From predicted table we weee the average Customer Lifetime Value CLV is equal to 1.471$. The CLV and CAC relationship is 0.7355. It is too low and the company does not do good job to acquire the right audience. THe right relationship to strive for is 3:1.

* When we divide our cohorts into 2 parts: till 2020-12-13 and from 2020-12-20 we get different average CLV: 2.174$ and 0.651$. We see big differences and the results would call for quite different actions. In the first situation company's effort would be considered quite plausible. The second situation is more than alarming.

More reasons and actions to make to improve the situation you can find below in the part CLV-CAC ratio explanations

SQL code used to get the required data:

```
WITH user_cohorts AS (
  SELECT
    user_pseudo_id,
    MIN (DATE_TRUNC(PARSE_DATE('%Y%m%d', event_date), WEEK)) AS cohort_week,
  FROM tc-da-1.turing_data_analytics.raw_events
  GROUP BY user_pseudo_id
   ),

revenue AS(
SELECT
user_pseudo_id,
DATE_TRUNC(PARSE_DATE('%Y%m%d', event_date), WEEK ) AS purchase_cohort_week,
purchase_revenue_in_usd AS revenue
  FROM tc-da-1.turing_data_analytics.raw_events
)

SELECT
  uc.cohort_week,
  Count(DISTINCT uc.user_pseudo_id) AS user_count,
  SUM ( CASE WHEN r.purchase_cohort_week = uc.cohort_week THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_00,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 1 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_01,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 2 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_02,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 3 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_03,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 4 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_04,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 5 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_05,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 6 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_06,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 7 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_07,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 8 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_08,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 9 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_09,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 10 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_10,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 11 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_11,
  SUM ( CASE WHEN r.purchase_cohort_week = DATE_ADD (uc.cohort_week, INTERVAL 12 WEEK ) THEN r.revenue END) / Count(DISTINCT uc.user_pseudo_id) AS week_12
FROM user_cohorts uc
JOIN  revenue r
ON uc.user_pseudo_id = r.user_pseudo_id
GROUP BY uc.cohort_week
ORDER BY uc.cohort_week
```

CLV - CAC ratio explanations

If the ratio is significantly lower (e.g., 1:1 or 2:1), it suggests that the cost of acquiring customers is too high relative to their lifetime value, which can lead to unsustainable growth.

Causes of a Low LTV to CAC Ratio

If you have a low LTV to CAC ratio — typically considered as anything below 3:1 — this signals that you're spending too much money to acquire customers relative to the revenue those customers generate over their lifetime. This imbalance can lead to cash flow issues and unsustainable growth, especially if you're a SaaS company or use a subscription-based pricing model.

Here are some possible causes of a low LTV to CAC ratio:

1. High Customer Acquisition Costs

When the cost of acquiring new customers is too high, you might end up with a low LTV to CAC ratio. This is often due to inefficient marketing spend, poorly targeted ads, or a lack of focus on the most profitable customer segments. For example, if you spend excessively on paid ads that target a broad audience, you will incur high acquisition costs but a low conversion rate.

2. High Customer Churn

If customers are leaving your business soon after signing up or making a purchase, you're experiencing a customer churn. This means you're currently unable to capture enough value from your customers to justify the acquisition costs.

3. Underpriced Products or Services

good example of this is a SaaS company with a freemium model that fails to convert enough users into paying customers, or charges too little for premium features.

4. Ineffective Onboarding or Product Experience

If your customers don't fully understand the value of your product or are frustrated during the onboarding process, they may churn early. And if they do, you won't be able to generate enough revenue to justify your CAC.

5. Poor Customer Support or Service

According to NICE's Digital-first Customer Experience Report, 95% of customers say that the quality of customer support impacts their brand loyalty. I think it's counterintuitive to spend a lot of money acquiring customers only to offer them subpar customer support when needed.

ow or unresponsive customer service can cause dissatisfaction and drive users to look for alternatives, even if they were initially satisfied with your produ

Tips on How to Improve Your LTV to CAC Ratio

If you have a low LTV to CAC ratio, here are some pro tips to help you improve it and use it to measure how sustainable your company is:

1. Monitor your LTV to CAC ratio regularly.

A healthy LTV to CAC ratio (typically between 3:1 and 5:1) indicates that your customers generate more revenue over time than the cost of acquiring them. Keep an eye on this metric over time to ensure that your customer base isn't only growing but also staying profitable. A lower or declining ratio can be a sign that your growth is unstable, and you need to make immediate adjustments to your business strategy.

For example, if you track your LTV to CAC ratio monthly and notice that it dropped from 3:1 to 2:1, you may decide to pause expensive ad campaigns and focus on retaining existing customers to restore balance.

2. Segment your customer base for deeper insights.

Different customer segments may have varying LTVs. By analyzing your ratio by segment, you can identify which customer groups are more profitable. This way, you can focus your marketing efforts on acquiring high-LTV customers to improve the ratio and ensure long-term sustainability.

A good example of this is the owner of an ecommerce business that finds that repeat customers aged between 25 and 35 have an LTV double that of younger buyers. So, they shift their marketing budget to target this segment more aggressively.

3. Optimize customer retention.

I learned that improving customer retention, which is your ability to keep your customers over time by encouraging repeat purchases or subscription renewals, can significantly boost your LTV. To do this, invest in post-purchase engagement, loyalty programs, and excellent customer service to lengthen customer lifecycles.

For example, you could introduce educational materials like tutorials or webinars to help your new customers understand the value of your product and reduce the likelihood of churn within the first three to six months.

4. Refine marketing spend to lower CAC.

Examine your customer acquisition costs and see if you're spending more than is necessary or investing in a channel that isn't yielding results. If you are, I suggest redirecting that portion of the budget toward channels that produce the most cost-effective conversions. This will reduce the CAC and improve the ratio.

Take a direct-to-consumer clothing brand, for example. The brand realizes that paid social ads are expensive and underperforming, so they shift to influencer partnerships, which cuts their CAC by 30% while bringing in their ideal customers.

5. Upsell and cross-sell to boost LTV.

You can increase the value customers bring over time by offering additional products or services. Upselling and cross-selling can drive up the average LTV without additional acquisition costs, which will improve the overall ratio and keep your business on a profitable trajectory.

For instance, if you own an online software company, you could introduce a premium add-on for existing users. If 25% of your customers upgrade, you would've raised the overall LTV without incurring customer acquisition costs.

6. Improve customer support.

As you invest money in acquiring customers, I recommend also investing in building a high-quality customer support team that is responsive and addresses customer issues quickly. For instance, you might add a chatbot to your website to handle customers' frequently asked questions and direct

You can also add live chat support or implement a dedicated account management team for higher-value customers to increase satisfaction and reduce churn.