



Pentathlon (Part 2): Testing for the best frequency

The department directors' meeting had not led to the outcome Anna Quintero expected. Neither the CMO nor the department directors were convinced by Quintero's survey data. She would need some direct evidence to test her hypothesis that limiting promotional e-mails could both improve customer satisfaction and benefit the bottom line. Quintero knew that the only way to provide such evidence was to run a randomized experiment that carefully tracked customer behavior and profits over time. When Quintero was hired as the director of digital marketing, she had insisted on having a small analytics team to undertake exactly this kind of task.

The experiment

Quintero knew that the department directors were focused on the incremental revenues that could be obtained by sending out more offers to e-mail recipients. Her primary concern, however, was that customers who received too many e-mails would choose to "unsubscribe." These customers would no longer receive any promotional e-mails, potentially lowering their profitability in the long run. To capture this short-run vs. long-run impact Quintero decided the experiment should last 8 weeks. She hoped this period would be long enough to observe customer behavior over time but short enough to argue that the existing policy should be kept in place until the experiment was completed.

The analytics team would test several different e-mail frequencies: 4 e-mails per week (which was close to the current "decentralized" average) and three more restrictive policies, namely 3, 2, or 1 e-mail(s) per week. In addition, François Cabret had insisted that a condition with 5 emails per week be added.

The team decided to randomly assign 10,000 customers to each condition (50,000 total). To make conditions as similar as possible, all customers in the test sample would receive e-mails featuring only one of the seven product departments during any given week of the experiment, irrespective of whether they received 1, 2, 3, 4, or 5 e-mails per week. In other words, test customers would receive different numbers of e-mails, but all from the same department in any given week.

The results

At the end of the 8-week experiment, Quintero received a spreadsheet with the following information from her team:

1 e-mail per week	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
Subscriber attrition for promotional e-mails	0.42%	0.46%	0.39%	0.49%	0.47%	0.52%	0.49%	0.51%
Average revenue from subscribed customer	\$0.29	\$0.31	\$0.30	\$0.32	\$0.29	\$0.26	\$0.27	\$0.28
Average revenue from unsubscribed customer	\$0.00	\$0.18	\$0.16	\$0.13	\$0.13	\$0.13	\$0.12	\$0.13
2 e-mails per week	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
Subscriber attrition for promotional e-mails	0.60%	0.70%	0.76%	0.73%	0.93%	0.64%	0.65%	0.60%
Average revenue from subscribed customer	\$0.35	\$0.30	\$0.35	\$0.39	\$0.31	\$0.33	\$0.35	\$0.34
Average revenue from unsubscribed customer	\$0.00	\$0.19	\$0.16	\$0.13	\$0.13	\$0.12	\$0.13	\$0.13
3 e-mails per week	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
Subscriber attrition for promotional e-mails	3.50%	2.90%	2.95%	2.80%	2.45%	2.20%	2.20%	2.20%
Average revenue from subscribed customer	\$0.37	\$0.31	\$0.36	\$0.40	\$0.33	\$0.35	\$0.37	\$0.36
Average revenue from unsubscribed customer	\$0.00	\$0.21	\$0.20	\$0.14	\$0.17	\$0.15	\$0.18	\$0.15
4 e-mails per week	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
Subscriber attrition for promotional e-mails	3.85%	5.25%	5.80%	4.13%	3.98%	3.10%	3.10%	3.10%
Average revenue from subscribed customer	\$0.36	\$0.34	\$0.30	\$0.38	\$0.39	\$0.34	\$0.36	\$0.37
Average revenue from unsubscribed customer	\$0.00	\$0.19	\$0.16	\$0.18	\$0.17	\$0.12	\$0.12	\$0.12
5 e-mails per week	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
Subscriber attrition for promotional e-mails	6.08%	6.00%	6.83%	6.45%	6.50%	6.08%	6.55%	5.93%
Average revenue from subscribed customer	\$0.36	\$0.33	\$0.30	\$0.38	\$0.37	\$0.39	\$0.37	\$0.37
Average revenue from unsubscribed customer	\$0.00	\$0.19	\$0.16	\$0.19	\$0.16	\$0.12	\$0.12	\$0.10

"Subscriber attrition for promotional e-mails" Reports the percentage of test customers subscribed to promotional emails at the beginning of the week that submitted a request to unsubscribe during the week

"Average revenue from subscribed customer" Reports the average weekly revenue for test customers who received promotional e-mails during that week

"Average revenue from unsubscribed customer" Reports the average weekly revenue for test customers who did **not** receive promotional e-mails during that week

In looking over the results Quintero noticed that unsubscribed customers still generated revenues for the company. Hence, while unsubscribed customers no longer received e-mails, they still bought from the company of their own accord. She also reminded herself that the "subscriber attrition" listed in the table referred to the percentage of customers subscribed to emails that decided to unsubscribe in a given week. This was not "churn" in a traditional sense – such churn was incorporated in the average revenue number: "Average revenue" as reported by her team was not per "active" customer but per customer that participated in the experiment and it accounted for the fact that some customers stopped buying altogether.

The spreadsheet summarized how customers reacted to different e-mail frequencies. To show which e-mail frequency would be most profitable for Pentathlon, Quintero still needed to calculate the CLV for customers in each of the five e-mail frequency conditions. This would require making a few assumptions about costs, discounting, and attrition.

1. The cost of goods sold was 60%.
2. Pentathlon used an annual discount rate of 10%.

3. Customers could submit a request to unsubscribe at any time. In line with EU regulations, all requests would be processed at the end of each week. Customers would continue to receive emails during the week in which they submitted the unsubscribe request.

Case questions

All necessary calculations should be done in a Python Jupyter notebook and submitted through GitLab.

1. Calculate the 8-week CLV for each of the five tested e-mail frequencies. (8 points)
2. Create a line graph of the **CLV** values for each plan change over the 8 week period. Your code should create a single plot with 5 lines (2 points)
3. What e-mail frequency should Pentathlon adopt based on the data in "pentathlon-2.xls"? Motivate your recommendation. (6 points)
4. What e-mail frequency would you recommend if you considered a longer time horizon? Why? Make your argument without formally extending the CLV calculation. (5 points)
5. Calculate the CLV for each of the plans after 104 weeks using the average subscriber churn and revenue numbers provided on GitLab ("pentathlon-2-avg.csv") (4 points)
6. Generate a line plot to compare the five CLV curves (2 points)
7. Are your results consistent with your answer to question 3? Why (or why not)? (2 points)

Note: Do not use any data from "pentathlon-2.xls" or any results that were based on "pentathlon-2.xls" to answer question 4. Only use the subscriber churn and revenue numbers from "pentathlon-II-avg.csv" and information from the case above.

8. Discuss at least two limitations of the experiment. How would you address these limitations? (5 points)

Hint: Recognize that while the unsubscribed customers no longer get e-mails from Pentathlon, they can still buy from the company by going to the website. Subscriber attrition in this case refers to the percentage of customers that switch status from subscribed to unsubscribed. Customers can also leave (i.e., no longer purchase) but this is already incorporated in the average revenue number. "Average revenue" is not per "active" customer but average revenue per customer who started as part of the experiment and it accounts for the fact that some may no longer buy products from Pentathlon at all.