

TripleTen: Analytics Challenge



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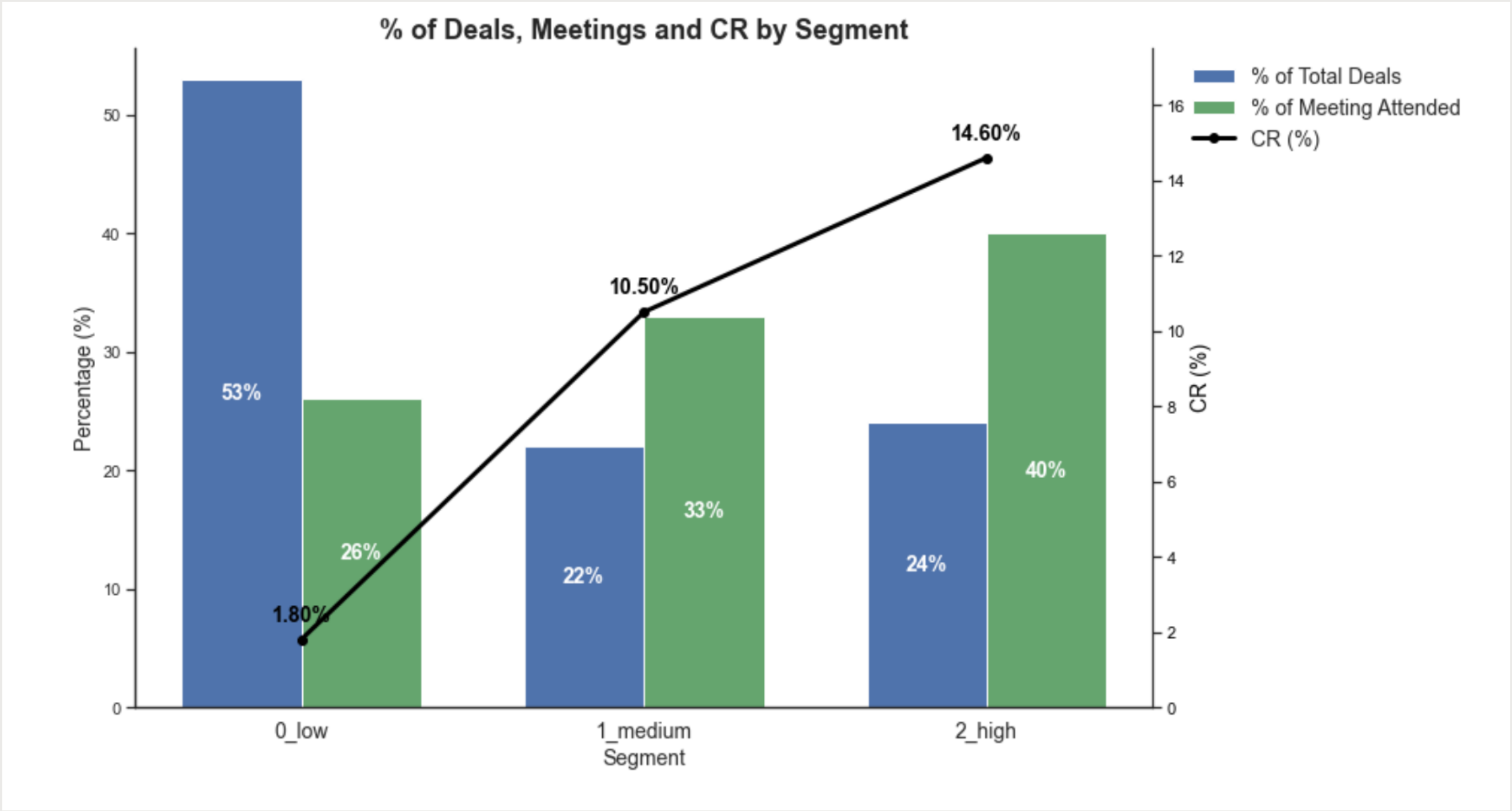
Scoring Model Evaluation

- Short Task Description:** You need to evaluate a lead scoring model for TripleTen.
- The scoring system is based on a questionnaire, which appears early in the acquisition funnel and allows the team to segment the audience into categories.
- Each answer for each question has its own weight (can be negative) and after completion weights are summarized (linearly), and results in a score in range of [-4,4].
 - In the table you can find scoring results (points), and a respective share of CRM deals (a deal is created after the scoring is completed and a person books a call with a salesperson), attended meeting with salespeople (MA, you can assume it is proportional to sales department capacity = how many calls they can reasonably conduct within the period), payments and overall CR(deal-payment). E.g. a group of leads, who scored 1 point in the survey, represents 15% of all our deals in September 2024, attended 26% of all meetings in the same cohort, and resulted in 38% of all cohort purchases (all purchases made in any month resulted from deals created in September 2024)
 - Is the model “good enough” for its current application? Describe a criteria for the growth team to stop/continue using the model.
 - Provide a ranked list of 3-4 hypothesis for how the growth team can boost acquisition of prospective students by utilizing this model in other ways

Score	% of Total Deals	% of Total Meeting Attended	% of Total Payment	Segment	CR(Deal-Payment)
-4	1%	0%	0%	low	1.8%
-3	4%	0%	0%		
-2	19%	1%	1%		
-1	29%	25%	13%		
0	22%	33%	33%	medium	10.5%
1	15%	26%	38%	high	14.6%
2	8%	12%	13%		
3	1%	2%	2%		
4	0%	0%	0%		

Scoring Model Evaluation

Distribution Deals, Meetings & CR with Segment Breakdown



Scoring Model Evaluation

Overview & Interpretation

Overview key model metrics from the table

1. Low segment (score ≤ -1): ~53% of deals but only 14% of payments \rightarrow very low conversion (1.8% CR).
2. Medium segment (score = 0): 22% of deals, 33% payments, CR = 10.5% \rightarrow better conversion.
3. High segment (score ≥ 1): 24% deals, 53% payments, CR = 14.6% \rightarrow best conversion.

Interpretation

1. The model clearly segments leads by quality:
 - Low segment has very low conversion rate.
 - Medium segment is better.
 - High segment is significantly better than low and medium.
2. The sales efforts seem to be distributed (meetings %), but high segment has disproportionately more payments despite fewer deals.
3. The conversion rate (CR) difference is the main success indicator here.

Scoring Model Evaluation

Define a simple criterion for the growth team

Criterion 1: Meeting Allocation Efficiency


The model is good enough if the High + Medium segments have:

-  At least 70% of Total Meetings
-  At least 70% of Total Payments

Why it matters:

This ensures that the sales team spends most of their time on leads that actually generate revenue, making the sales process more efficient and reducing wasted effort on low-potential leads.

Result:



- 73% of Meetings
- 86% of Payments
-  Pass

Scoring Model Evaluation

Define a simple criterion for the growth team

Criterion 2: Conversion Rate Separation


The model is good enough if:

-  High segment conversion rate is at least 5× the Low segment
-  Medium segment conversion rate is between Low and High

Why it matters:

This confirms the model meaningfully distinguishes between lead quality levels, so the scoring is predictive of actual buying behavior and can be trusted to guide sales prioritization.

Result:

- Low CR = 1.8%
- Medium CR = 10.5%
- High CR = 14.6% (~8× Low)
-  Pass


Conclusion:


The model meets both criteria and is good enough to continue using. It helps focus sales efforts and predicts lead quality well.


Scoring Model Evaluation

Question 2: What are the top 3 ranked hypothesis for how the growth team can boost acquisition of prospective students by utilizing this model in other ways

H1. Prioritize Sales Effort on High and Medium Segments to Maximize Conversion

 **Why:** High and Medium segments represent 63% of meetings but 86% of payments (40% + 33%), showing they convert much better than Low. Focusing sales effort here makes the best use of limited sales capacity.


 **Hypothesis:** If sales efforts (calls/meetings) are reallocated to focus more on leads in the High and Medium segments, overall conversion and revenue will increase without needing more sales resources.


 **Action:** Use the scoring model to automatically prioritize scheduling calls for leads in the High and Medium segments earlier and more frequently, before Low segment leads. **Note:** Once this segmentation-based prioritization shows consistent results, consider refining further by using the exact lead score within each segment to prioritize the highest-scoring leads first, for even better efficiency.


Scoring Model Evaluation

Question 2: What are the top 3 ranked hypothesis for how the growth team can boost acquisition of prospective students by utilizing this model in other ways

H2. Design Tailored Messaging or Nurturing for Low Segment Leads to Increase Their Quality

 **Why:** Low segment leads represent 53% of deals but only 14% of payments and have a very low conversion rate (1.8%).

 **Hypothesis:** If low-scoring leads receive targeted nurturing or educational content that helps qualify them better or encourages behaviors closer to Medium/High segments, their conversion rate will improve..


 **Action:** Create automated email campaigns or pre-sales content specifically tailored for low segment leads to engage and nurture them before they are passed to sales.


Scoring Model Evaluation

Question 2: What are the top 3 ranked hypothesis for how the growth team can boost acquisition of prospective students by utilizing this model in other ways

H3. Create Separate Sales Tracks or Offers Based on Segment

 **Why:** The conversion rate difference between segments is large (Low = 1.8%, Medium = 10.5%, High = 14.6%).

 **Hypothesis:** If sales and marketing messaging, offers, or pricing are customized by segment (e.g., higher-touch sales for High, self-service or trial offers for Low), overall funnel efficiency and conversion will improve..

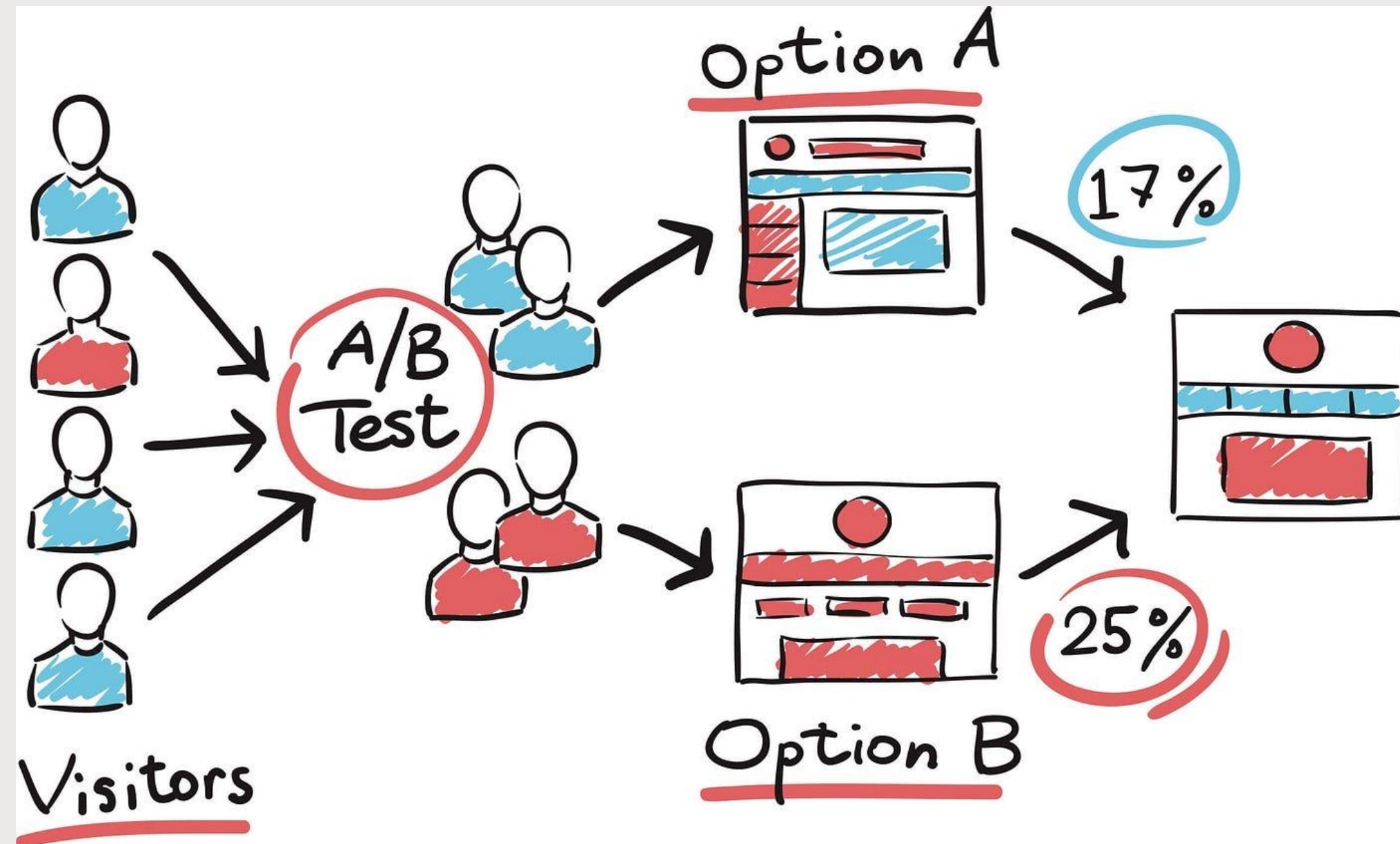
 **Action:** Experiment with segment-specific sales scripts, offers, or funnel flows to better match lead readiness and willingness to buy.

A/B test Evaluation

Short Task Description: Imagine that, together with the growth and marketing departments, you conducted an experiment with an expectation of revenue increase.

- Variant A: Payment screen without any promotional offers
- Variant B: Payment screen with the promotional offer "You might also like these"

Task is evaluate the results of the A/B test, formulate a conclusion, and provide recommendations for the growth department.



A/B test Evaluation

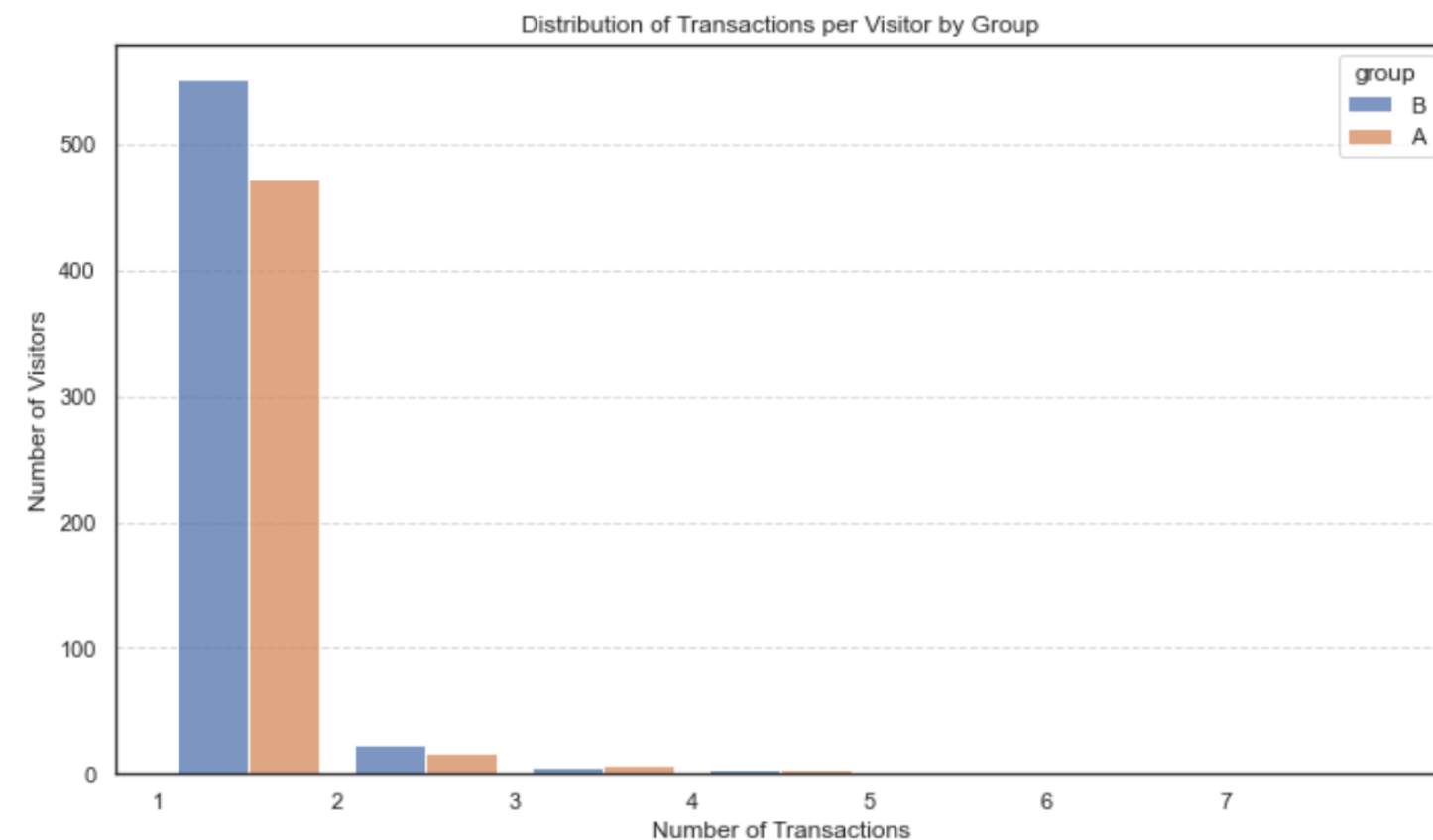
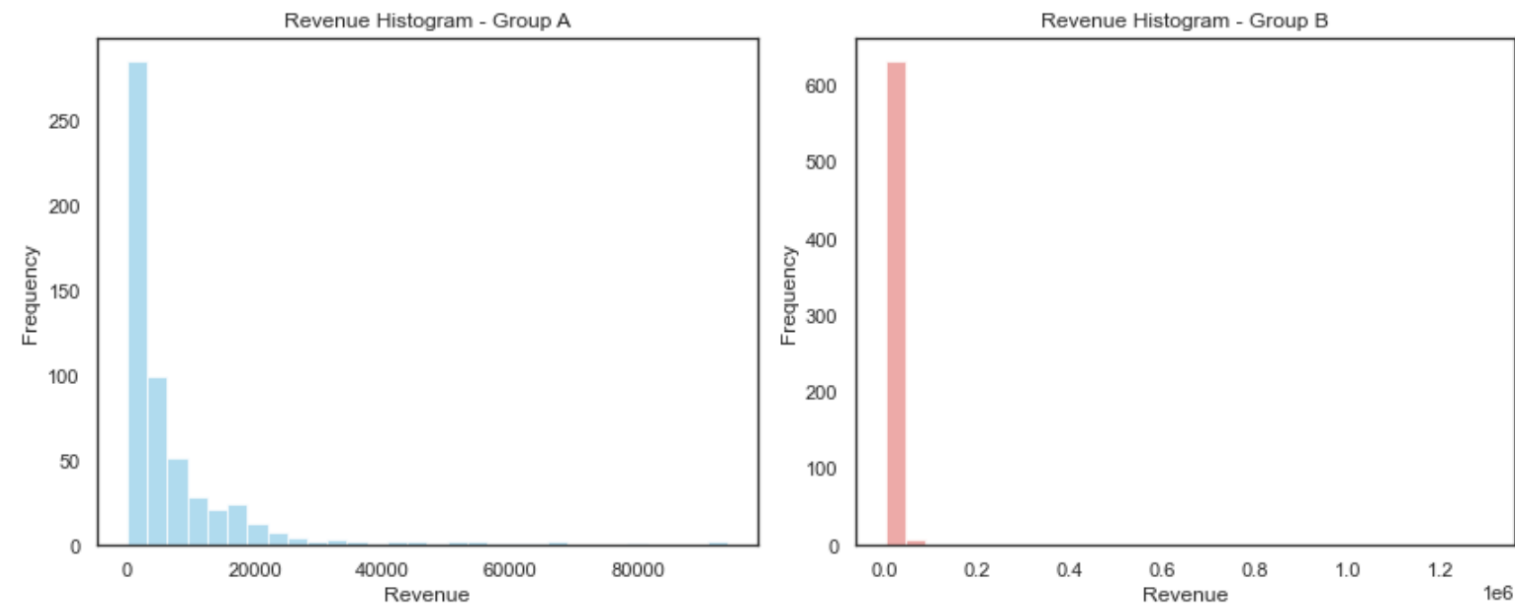
Exploratory Data Analysis

Found 2 issues:

- Intersection in groups
- Outliers

Fixed as:

- Removed users which are in both groups
- Calculated 95 & 99 percentiles, chosen 99 to filter outliers



A/B test Evaluation

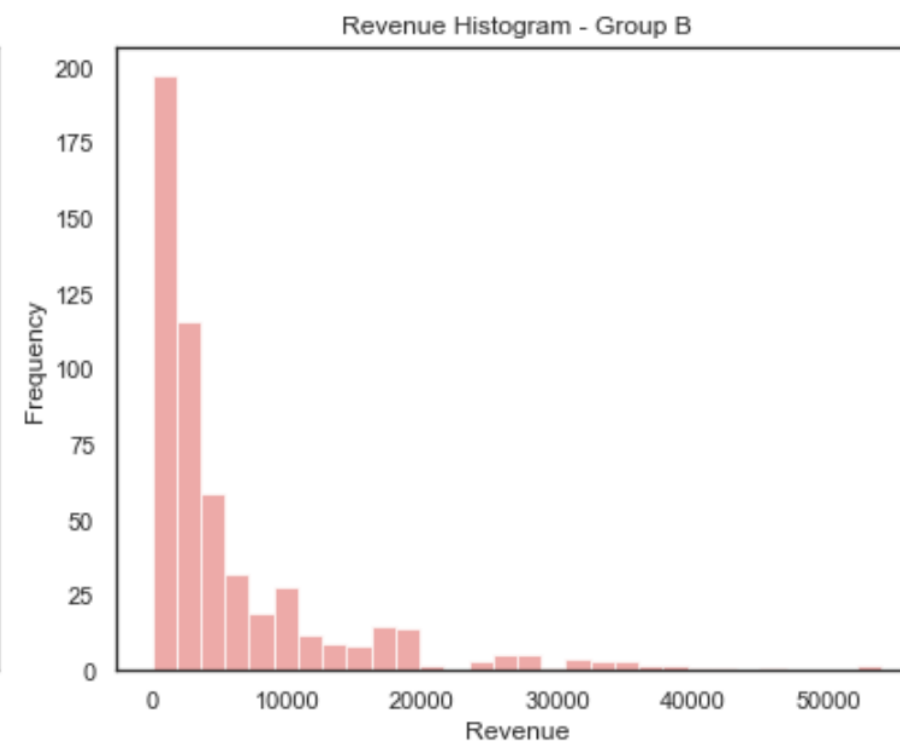
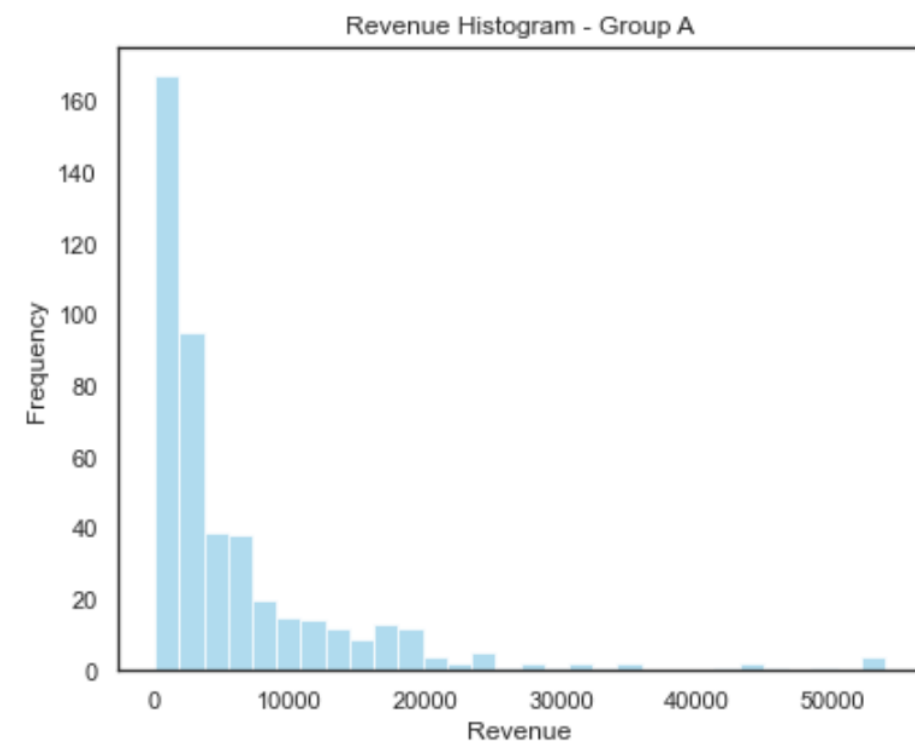
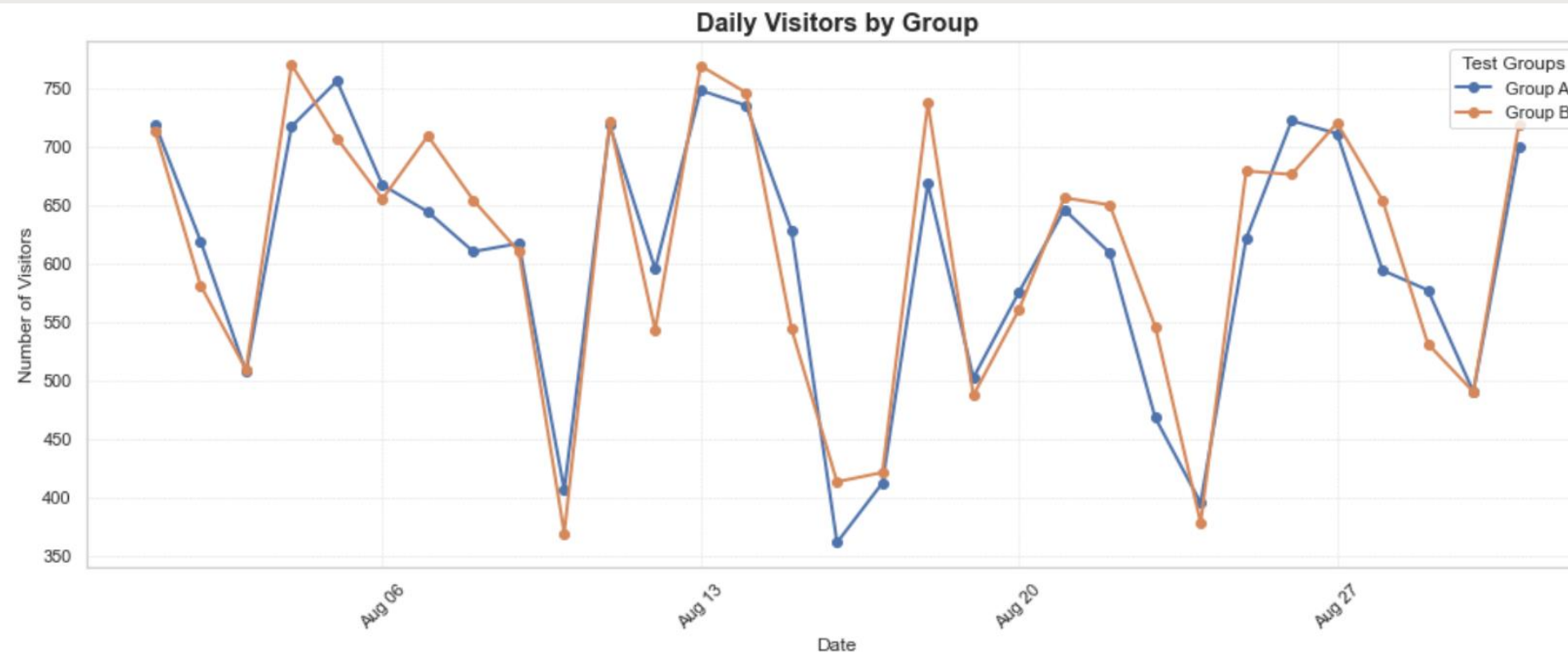
Exploratory Data Analysis

Found 2 issues:

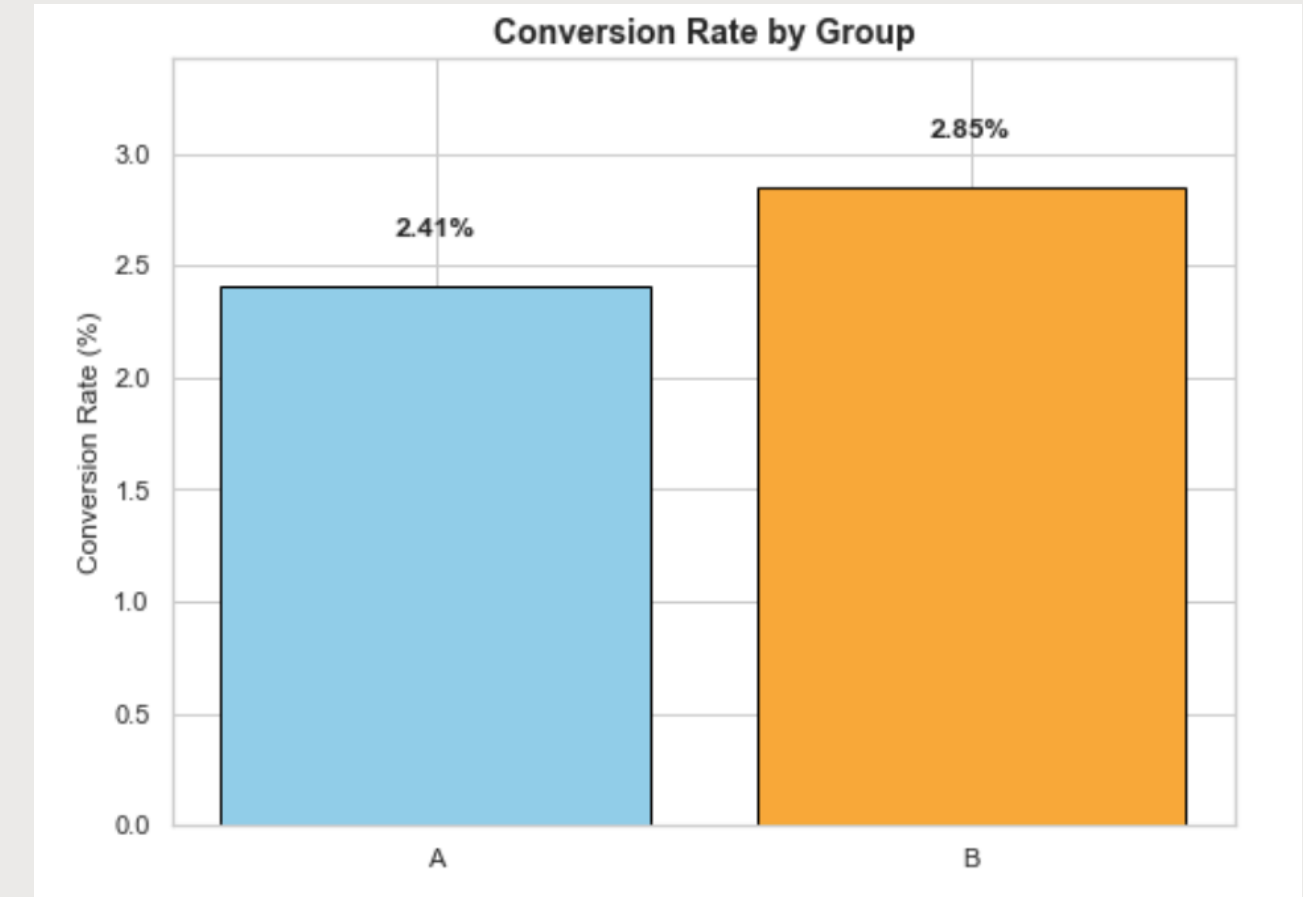
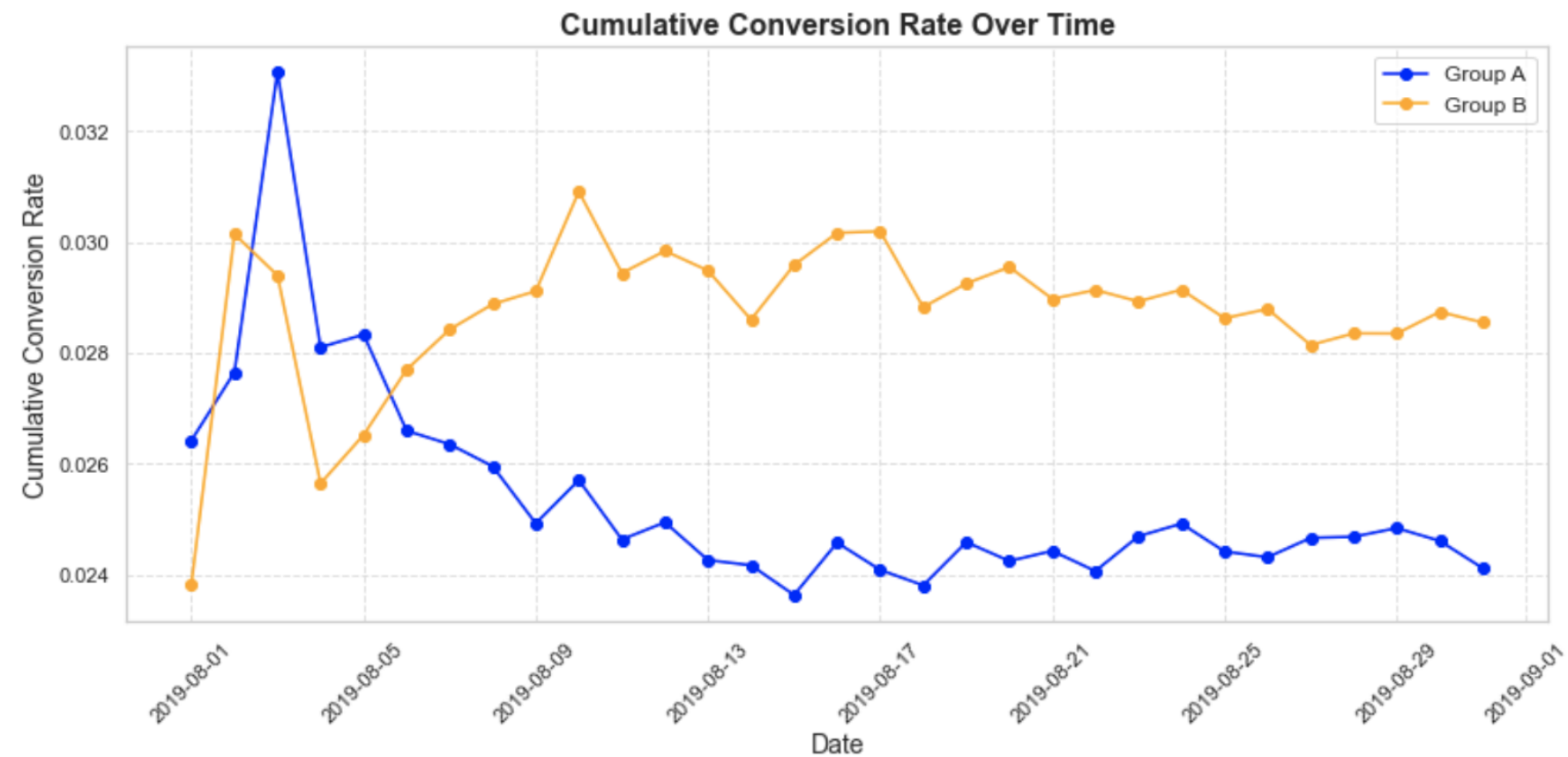
- Intersection in groups
- Outliers

Fixed as:

- Removed users which are in both groups
- Calculated 95 & 99 percentiles, chosen 99 to filter outliers



A/B test Evaluation



Conversion Rate

- Conversion rate A: 2.412%
- Conversion rate B: 2.855%

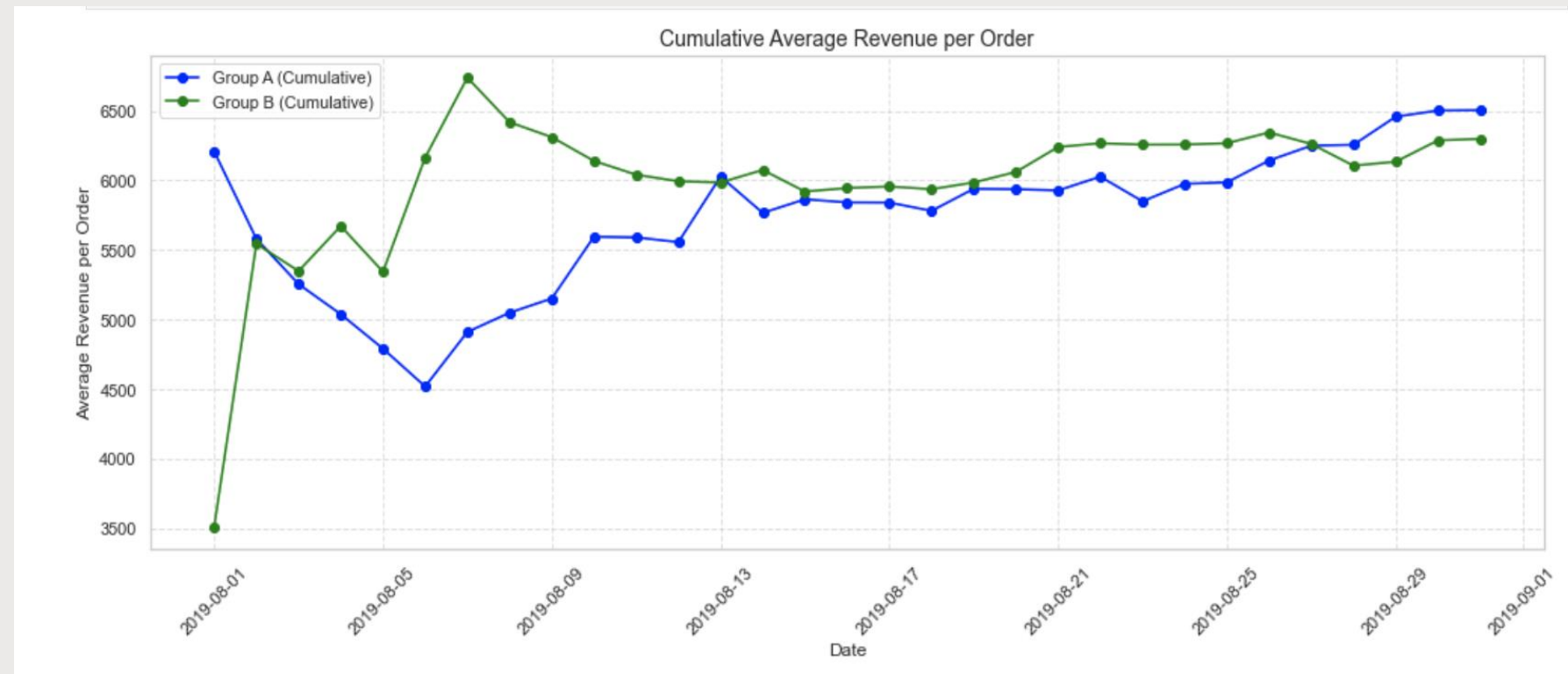
Conclusion:

The null hypothesis (no difference in conversion rates) is rejected.

There is a significant difference in conversion rates between the control and test groups.

Variant B performs significantly better.

A/B test Evaluation



Average Revenue per Order

- Average Order Value (AOV) for Group A: 6504.55
- Average Order Value (AOV) for Group B: 6298.83

Conclusion:

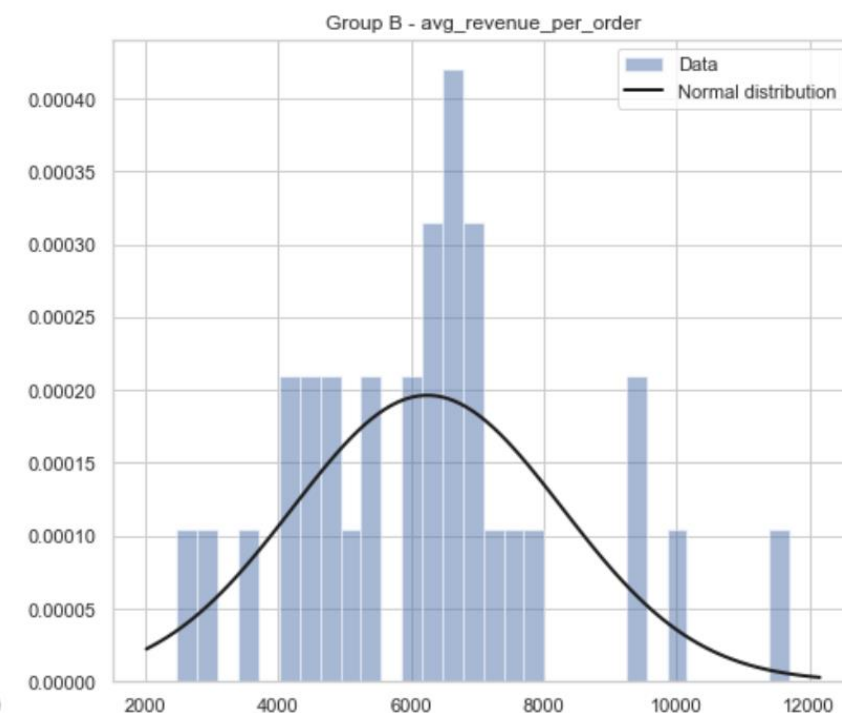
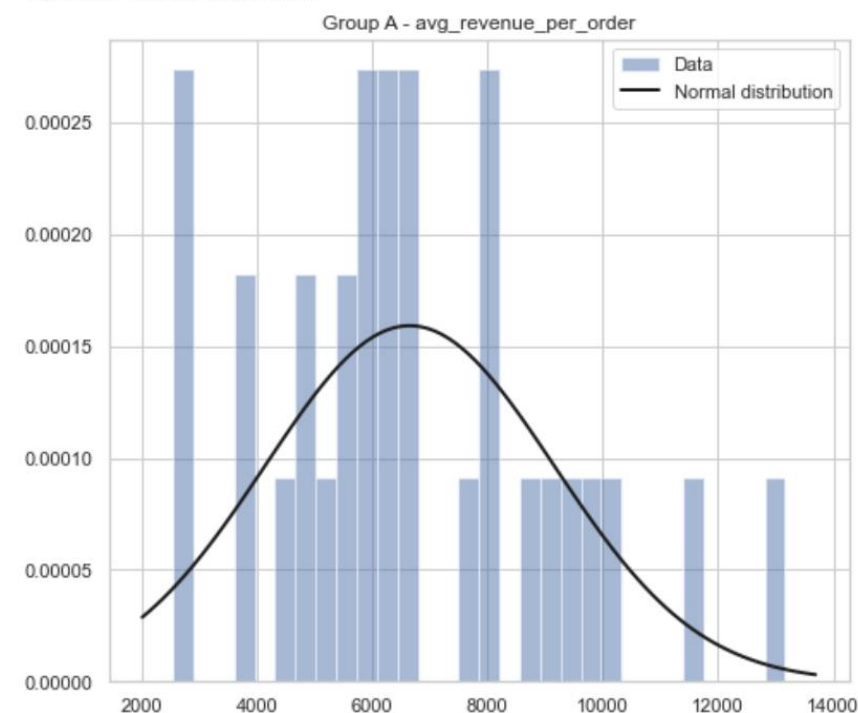
T-test statistic: 0.691

P-value: 0.4923

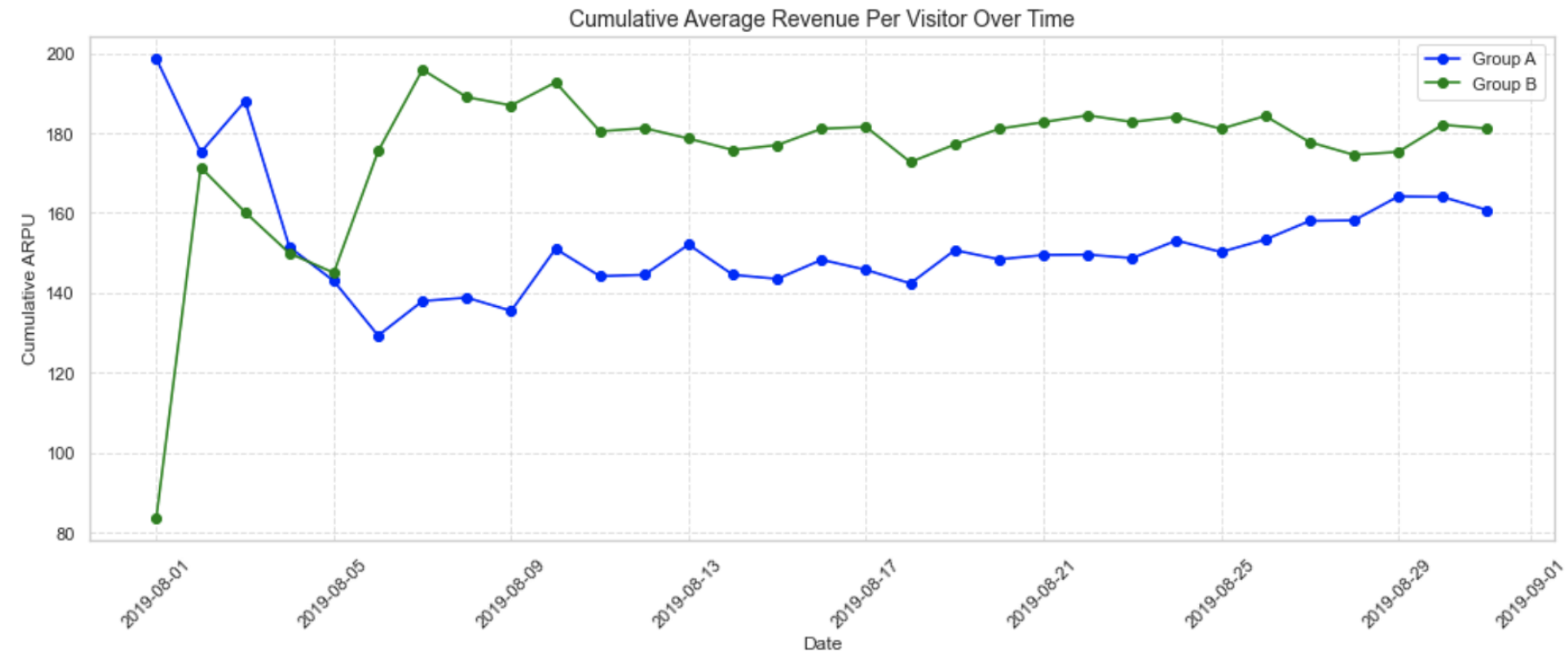
No statistically significant difference between groups (fail to reject H0)

Group A:
Normal distribution.

Group B:
Normal distribution.



A/B test Evaluation



ARPU

- ARPU for Group A: 160.74
- ARPU for Group B: 181.15

Conclusion:

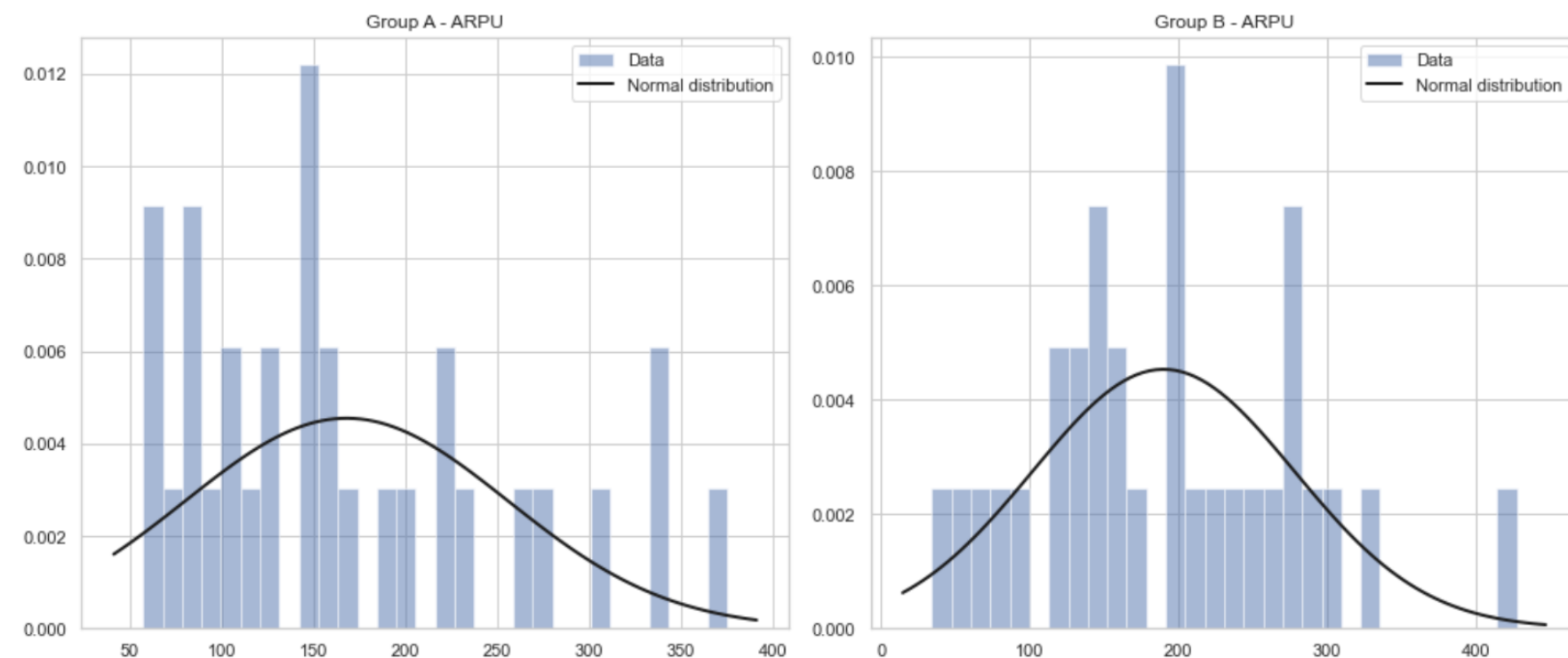
Mann-Whitney U statistic: 404.000

P-value: 0.2846

No statistically significant difference between groups (fail to reject H0)

Group A:
Not a normal distribution.

Group B:
Normal distribution.









A/B test Evaluation

Conclusion

- Variant B demonstrates a statistically significant improvement in conversion rate over Variant A.
- Although AOV is slightly lower in Variant B, the difference is not statistically significant.
- ARPU is higher in Variant B, indicating that the increase in conversions may be driving more total revenue per user, even though the difference is not statistically significant.
- Overall, Variant B improves user acquisition efficiency without sacrificing revenue quality.

Recommendations for Growth Team

-  Monitor AOV and ARPU post-rollout, especially since Variant B users place more orders but spend slightly less per order — focus on net revenue impact.
-  Adopt Variant B as the new default, given its proven impact on conversion rate and the trend toward higher ARPU.
-  Explore strategies to lift AOV in Variant B, such as:
 - Intelligent product bundling
 - Targeted promotions
 - Personalized upselling techniques
-  Consider running a follow-up experiment focused specifically on ARPU optimization — since Variant B shows potential, additional iterations may solidify revenue gains.
-  Communicate the success of Variant B to product and marketing stakeholders as a validated growth lever.
-  Take a close look at found error and investigate the root reasons



It is not the end
Let's discuss the project.

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