GLOBOX Project Report - Sebastian Gurgel - Aug 2, 2023

Table of Content - Globox Final Project

Summary

The new banner had a positive impact on the conversion rate but did not significantly affect the average amount spent per user. However, considering sample size limitations, and the lack of significant impact on revenue, it is not recommended to immediately launch the banner.

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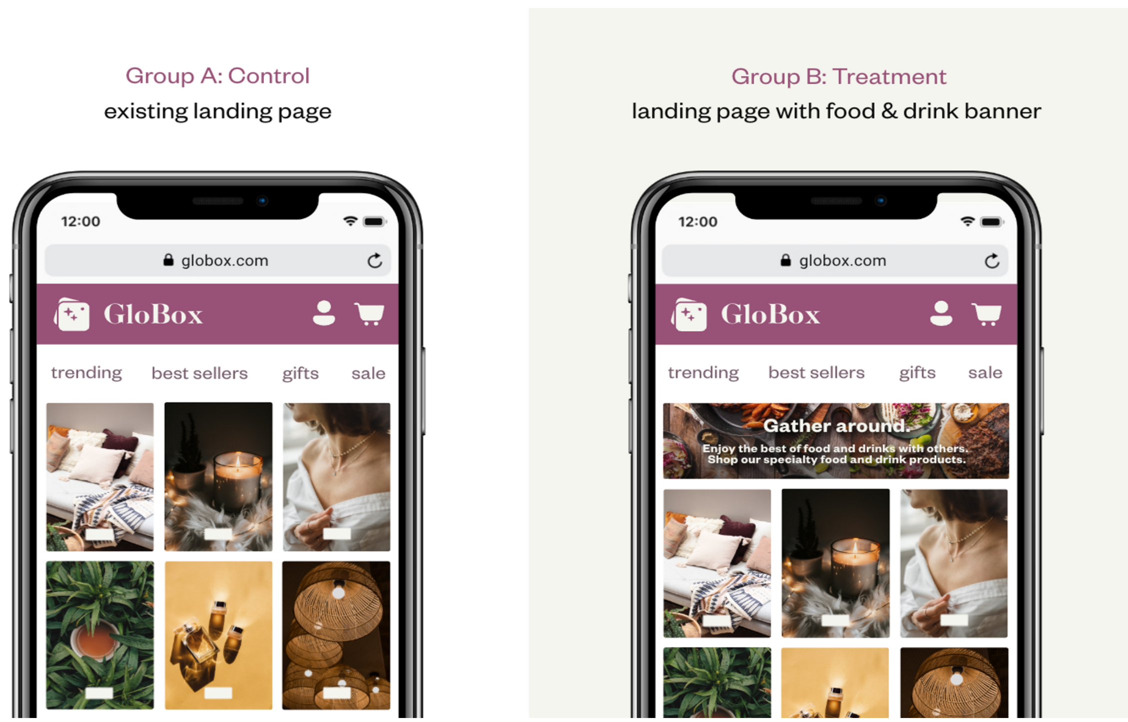
Context

GloBox, a company known for its boutique fashion items and high-end decor products, aims to expand awareness of their food and drink product category to attract new customers and boost revenue. To achieve this, the Growth team conducted an A/B test on the mobile website. The test group was shown a banner at the top of the website highlighting key products in the food and drink category, while the control group did not see the banner.



Setup A/B test

- The experiment is only being run on the mobile website.
- A user visits the GloBox main page and is randomly assigned to either the control or test group.
- The page loads the banner if the user is assigned to the test group, and does not load the banner if the user is assigned to the control group.
- The user subsequently may or may not purchase products from the website.
- It could be on the same day they join the experiment, or days later. If they do make one or more purchases, this is considered a "conversion".

Stakeholders

- Leila Al-Farsi, Alejandro Gonzalez, Mei Kim
- Growth Product & Engineering Team

Getting The Data

GloBox stores its data in a relational database, which was extracted with SQL queries to perform further Analysis and Visualisation with a CSV File. The A/B Test was held during a 13 day test period.

Success Metrics

The success metrics for our statistical analysis are mainly the Conversion Rate and the Average Amount Spent by user. For further Questions we also used the Day of Purchase by user.

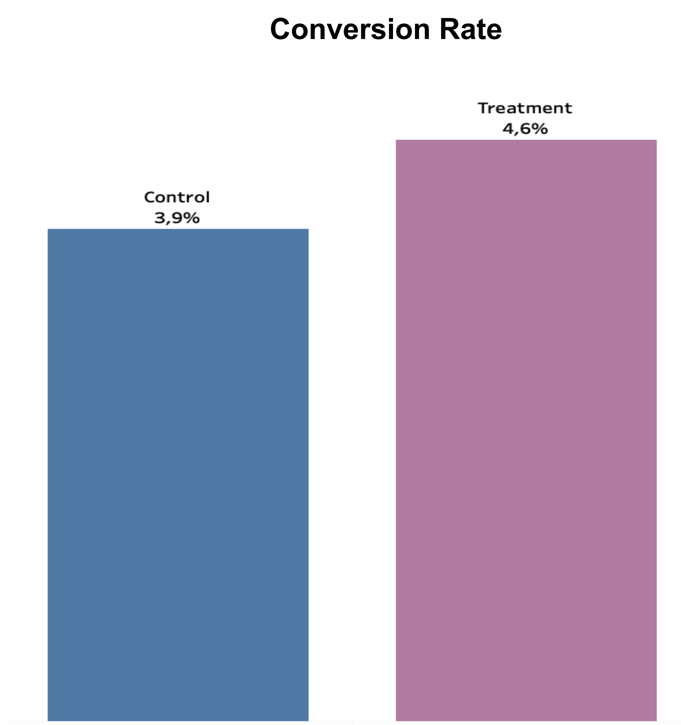
Data Preparation

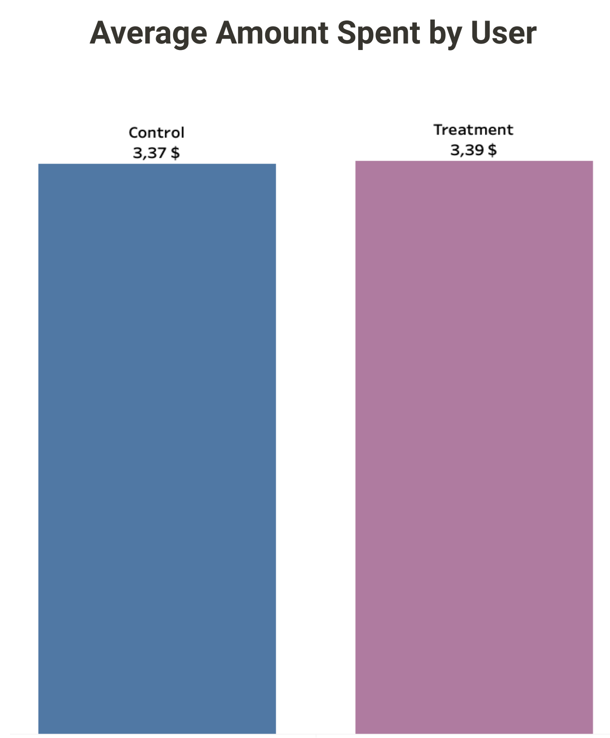
The Data was thoroughly checked for missing values and duplicates. The three tables containing the relevant columns had to be cleaned and joined together. I used the COALESCE() funcion to fill in NULL Values and to differentiate whether or not a User converted and how much a User spent in total. (See Appendix for SQL Code)

Descriptive Analysis

By using SQL queries to perform descriptive analysis, it was possible to gather relevant KPIs for this Study.

Total Users:	48,943
Control Group:	24,343
Treatment Group:	24,600
Control Conversion Rate:	3.92%
Treatment Conversion Rate:	4.63%
Control Average Amount Spent:	$3.37
Treatment Average Amount Spent:	$3.39


Conversion Rate
Treatment
4,6%
Control
3,9%


Average Amount Spent by User
Control
3,37 $
Treatment
3,39 $

Statistical Analysis

To ensure unbiased results, a hypothesis test was conducted to determine if there was a statistically significant difference in the conversion rate between the two groups. The null hypothesis assumed no difference in conversion rates, while the alternative hypothesis claimed a statistical significance between the groups. A two-sided Z-test was performed, resulting in a p-value of 0.0001, which is lower than the significance level of 0.05. Thus, the null hypothesis was rejected, indicating a significant difference in conversion rates between the groups.

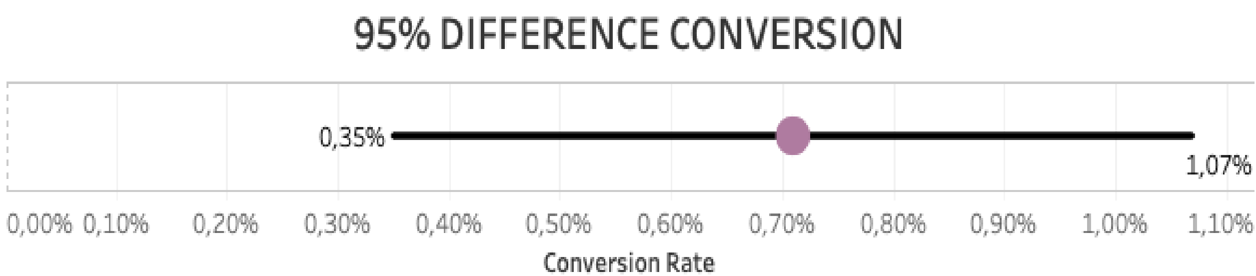
H0: There is no difference in the conversion rate between the two groups.

HA: There is a difference in the conversion rate between the two groups.

H0:Cr_A0=Cr_B **HA:Cr_A0 !=Cr_B**	
pooled_p	**0.042784**
standard error	**0.001830**
Z score	**-3.880786**
significance level	**0.05**
Critical value	**1.96**
P value	**0.0001**
H0_Result	**REJECT**

Based on the 95% confidence interval for the difference in the conversion rate between the treatment and control groups, which is approximately 0.0035 to 0.0107 , it can be concluded that there is a statistically significant difference in the conversion rates between the two groups. The confidence interval does not include zero, indicating a significant divergence in the conversion rates.

standard error	**0.001828159355**
critical value	**1.96**
margin of error	**0.003583192336**
lower bound	**0.0035**
Upper bound	**0.0107**



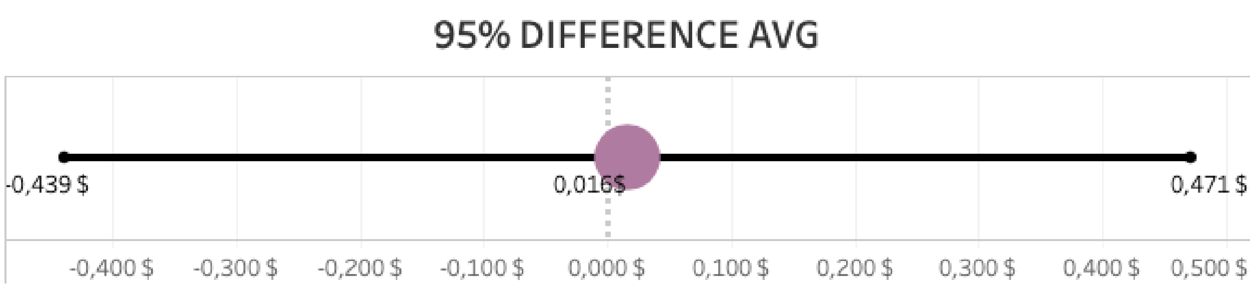
Additionally, a hypothesis test was conducted to examine the average amount spent per user between the control and treatment groups. The null hypothesis assumed no difference, while the alternative hypothesis sought to identify a statistical difference. Using the t-distribution with unequal variance, the T.TEST() function in Google Sheets was employed.

H0: spent_A = spent_B **HA: spent_A != spent_B**	
p_value cutoff	**0.05**
t_test	**0.944**
H0 Result	**FAIL TO REJECT**

The resulting p-value of 0.944 was higher than the cutoff value of 0.05, leading to the failure to reject the null hypothesis. Consequently, there was insufficient evidence to conclude a significant difference in the average amount spent per user between the two groups.

t-score	**-0.07042780472**
critical value	**1.960012504**
df	**48894.49765**
margin of error	**0.4549982947**
lower bound	**-0.4386491484**
upper bound	**0.4713474409**

With a 95% confidence level, the Confidence Interval for the true difference in the average amount spent per user between the treatment and control groups ranges from approximately -0.439 to 0.471 units. Notably, this interval includes zero, indicating a lack of statistical significance in terms of the average amount spent per user between the treatment and control groups. Thus, based on the available data, we do not have enough evidence to conclude that there is a statistically significant difference in the average amount spent per user between the two groups.



Power Analysis

To understand the necessary sample size in order to achieve our desired minimum detectable effect and statistical power, I used a Sample Size Calculator to estimate the right sample size in Terms of conversion rate and average spent. For that I used an MDE of 10% to make sure all connected costs with launching the banner are included.

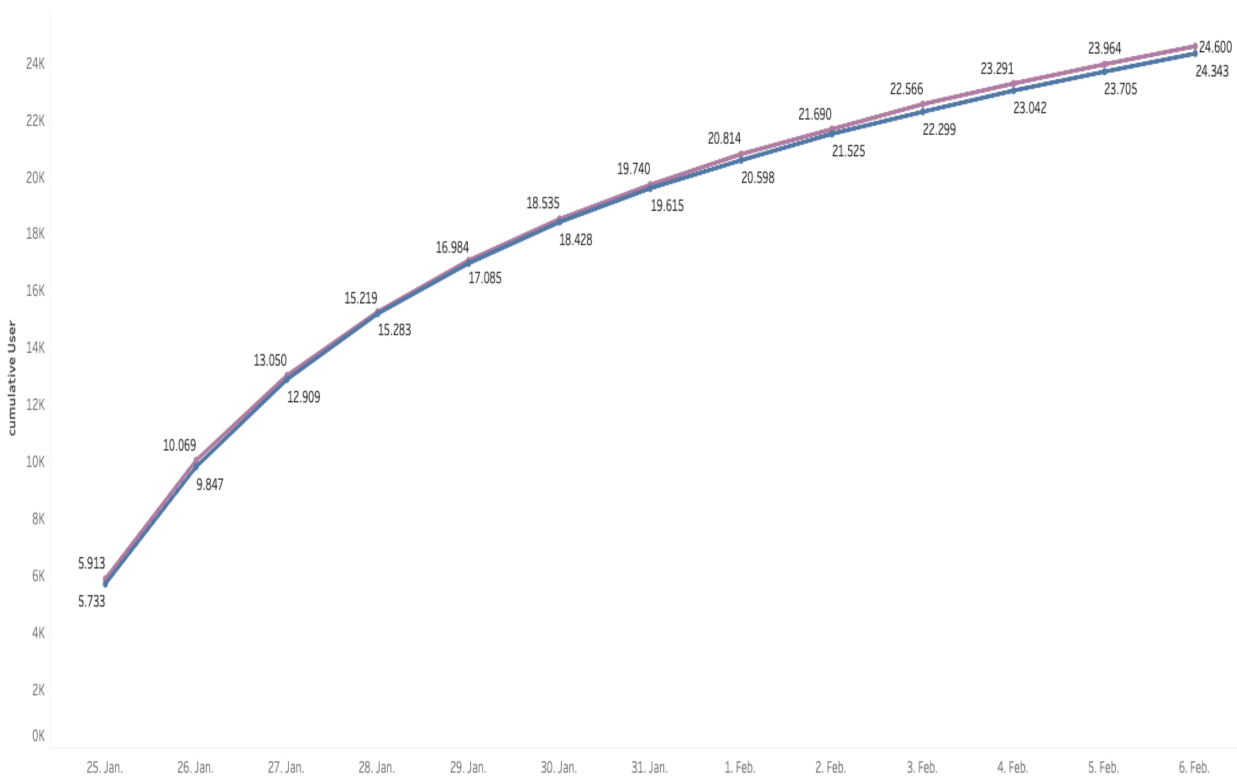
Baseline Conversion Rate	**3.92**
MDE	**10**
A/B Split Ratio	**0.5**
Significance (α)	**0.05**
Statistical Power (1 - β)	**0.8**
2 sided	
Sample Size needed:	**77000**
How Many Days more?	**7.45**

Mean Difference(MDE 10% of Mean A)	**0.337**
pooled Standard Deviation:	**25.93586523**
2 sided	
Sample Size needed	**185958**
How Many Days more?	**36**

To estimate the time required to reach a total sample size of approximately 77 000 users, considering a daily average accumulation of 3765 users, I performed a calculation based on the cumulative number of users. With a target sample size of

77000 and a daily accumulation of 3765 users, we can determine the number of days needed to achieve this goal.

Join Curve



Based on the given information, with a total of 48,943 customers and an accumulation rate of approximately 3765 customers per day, we can estimate the number of days required to reach a cumulative total of 77000 customers.

Number of days = (77000 - 48943) / 3765 , Number of days ≈ 7.45

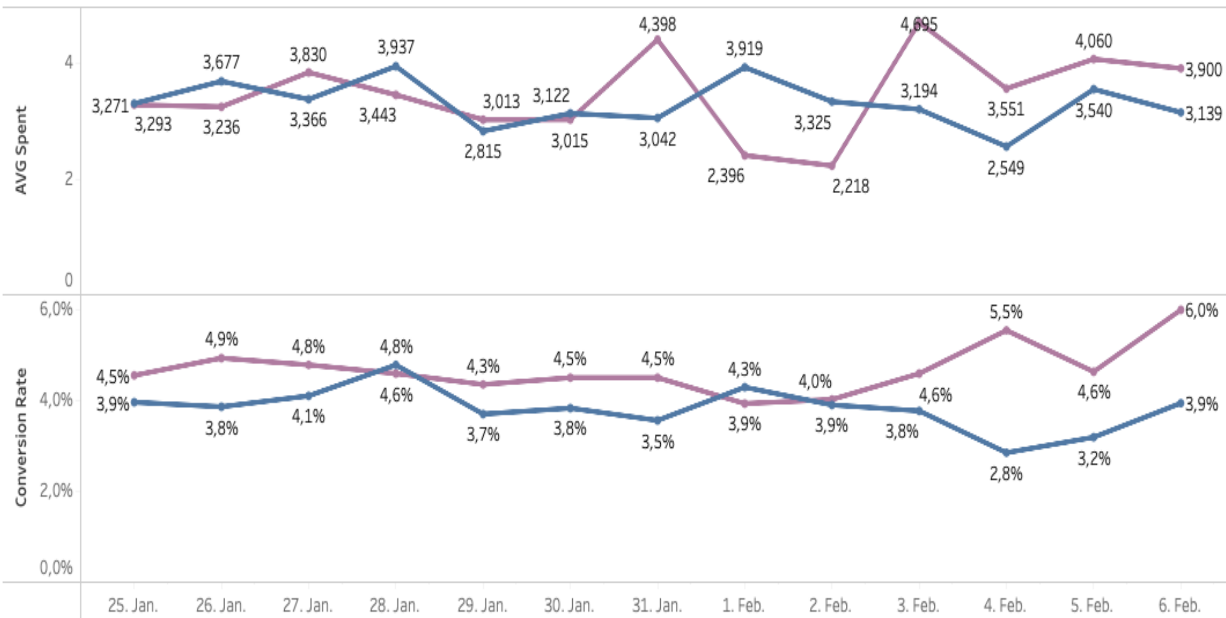
Due to the current rate of customer accumulation, it would take approximately 7 days more to reach a cumulative total of 77000 customers.

Using the same calculation on the AVG spent, it would take around 36 days to reach the desired sample size.

It's important to note that this estimation assumes a constant rate of customer accumulation and does not account for potential variations or external factors that could affect the actual time frame.

No Novelty Effect

Based on the data and observations, it appears that the banner implemented did not have a significantly different impact over time on the number of purchases or conversion rate per user in either group, indicating that there is no novelty effect.



Conclusion

Based on the statistical analysis, the new banner showed a positive impact on the conversion rate, with an increase of 0.7%. However, there was no significant effect observed on the average amount spent per user, raising some concerns about its potential impact on revenue.
Given the positive influence on the conversion rate, it is worth considering implementing the new banner. However, to make a more well-informed decision, it is recommended to conduct further A/B tests with different versions of the banner and a larger sample size. This will provide more reliable data to assess its long-term effectiveness and its actual influence on revenue.

Additionally, it is advisable to invest in improving the overall customer experience to encourage repeat visits and purchases, irrespective of the banner's impact. Enhancing personalization, implementing loyalty programs, streamlining the checkout process, and providing engaging content are some strategies that can foster a loyal customer base and potentially lead to increased revenue.

By combining the insights from A/B tests with improvements in the customer experience, the decision to launch the new banner or explore other approaches can be made with greater confidence, ultimately leading to better business outcomes.

APPENDIX

[Tableau Globox Final Project]

[Google Sheets Globox Final Project]

Globox Final project SQL Code used

1. **Can a user show up more than once in the `activity` table? Yes or no, and why?**

```
SELECT uid, COUNT(*) AS row_count
FROM activity
GROUP BY uid
HAVING COUNT(*) > 1;
```

Yes, a user can show up more than once in the activity table. This can happen if a user performs multiple purchases, resulting in multiple records in the activity table associated with that user.

2. **What type of join should we use to join the `users` table to the `activity` table?**

An INNER JOIN should be used to retrieve all the columns, where a purchase is made but if you wanna get all the data even if a purchase is not made then a LEFT JOIN would be appropriate.

3. **What SQL function can we use to fill in NULL values?**

```
SELECT gender, COALESCE(gender, 'O') AS new_gender
FROM users;
```

4. **What are the start and end dates of the experiment?**

```
SELECT MIN (dt), max (dt)
FROM activity
```

MIN: 2023-01-25/ MAX: 2023-02-06

5. **How many total users were in the experiment?**

```
SELECT COUNT(DISTINCT ID) AS total_user
FROM users
```

Total-users: 48943

6. **How many users were in the control and treatment groups?**

```
SELECT COUNT("group") AS user_in_A
FROM GROUPS
WHERE "group" = 'A'
```

user_in_A: 24343

```
SELECT COUNT("group") AS user_in_A
FROM GROUPS
WHERE "group" = 'B'
```

user_in_B: 24600

7. **What was the conversion rate of all users?**

```
WITH user_conversion AS
(
SELECT
g.uid,
g.group,
SUM(a.spent),
CASE WHEN a.uid IS NOT NULL THEN 1
ELSE 0 END AS converted

FROM groups g
LEFT JOIN activity a
ON g.uid = a.uid
GROUP BY
1,2,4
ORDER BY g.uid asc
)

SELECT
ROUND(AVG(converted) * 100.0, 2) AS conversion_rate
FROM user_conversion
```

User_conversion: 4.28%

8. **What is the user conversion rate for the control and treatment groups?**

```
WITH user_conversion AS
(
SELECT
g.uid,
g.group,
SUM(a.spent),
CASE WHEN a.uid IS NOT NULL THEN 1
ELSE 0 END AS converted

FROM groups g
LEFT JOIN activity a
ON g.uid = a.uid
GROUP BY
1,2,4
ORDER BY g.uid asc
)

SELECT "group",
ROUND(AVG(converted) * 100.0, 2) AS conversion_rate
FROM user_conversion
GROUP BY 1
ORDER BY 1
```

GROUP A: 3.92 %
GROUP B: 4.63 %

9. **What is the average amount spent per user for the control and treatment groups, including users who did not convert?**

```
WITH user_spending AS
(
```

```
SELECT u.id
AS user_id,
g.group AS test_group,
COALESCE(SUM(a.spent), 0) AS total_spent
FROM users u
LEFT JOIN groups g
ON u.id = g.uid
LEFT JOIN activity a
ON u.id = a.uid
GROUP BY u.id, g.group
)
SELECT
test_group,
ROUND(AVG(total_spent)::numeric, 2) AS average_spent
FROM user_spending
GROUP BY test_group
```

GROUP A: 3.37 $
GROUP B: 3.39 $

10. **Why does it matter to include users who did not convert when calculating the average amount spent per user?**

    Including users who did not convert when calculating the average amount spent per user is important because it provides a more comprehensive understanding of the spending behavior of all users, regardless of their conversion status.

Extract the analysis dataset

1. Write a SQL query that returns: the user ID, the user's country, the user's gender, the user's device type, the user's test group, whether or not they converted (spent > $0), and how much they spent in total ($0+).

```
SELECT
u.id,
u.country,
u.gender,
g."group" AS test_group,
g.device,
CASE WHEN a.spent > 0 THEN 1 ELSE 0 END AS converted,
COALESCE(SUM(a.spent), 0) AS total_spent
FROM users u
LEFT JOIN groups g
ON u.id = g.uid
LEFT JOIN activity a
ON u.id = a.uid
GROUP BY 1,2,3,4,5,6
ORDER BY u.id
```