A/B testing with rail image difference for cooking website

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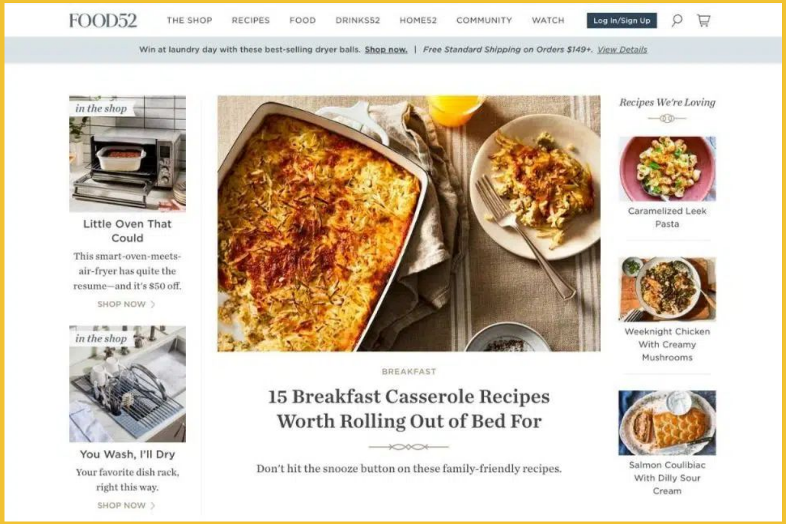
Scenario


FOOD52
THE SHOP
RECIPES
FOOD
DRINKS52
HOME52
COMMUNITY
WATCH
Log In/Sign Up
Win at laundry day with these best-selling dryer balls. Shop now. | Free Standard Shipping on Orders $149+. View Details
in the shop
Little Oven That Could
This smart-oven-meets-air-fryer has quite the resume—and it's $50 off.
SHOP NOW
in the shop
You Wash, I'll Dry
Your favorite dish rack, right this way.
SHOP NOW
BREAKFAST
15 Breakfast Casserole Recipes Worth Rolling Out of Bed For
Don't hit the snooze button on these family-friendly recipes.
Recipes We're Loving
Caramelized Leek Pasta
Weeknight Chicken With Creamy Mushrooms
Salmon Coulibiac With Dilly Sour Cream

A


PRODUCTS
GIFTS
COOKING CLASSES
BRANDS
SALE
DISCOVER
What are you looking for?
STAUB TOMATO COCOTTE, 3 QT.
66 Reviews | 7 Questions, 50 Answers
Sale $209.96 - $239.96
Sugg. $421.00 - $443.00
COLOR :
Availability
Select a color or size to add to your cart
ADD TO CART

B


PRODUCTS
GIFTS
COOKING CLASSES
BRANDS
SALE
DISCOVER
What are you looking for?
STAUB TOMATO COCOTTE, 3 QT.
66 Reviews | 7 Questions, 50 Answers
Sale $209.96 - $239.96
Sugg. $421.00 - $443.00
COLOR :
Availability
Select a color or size to add to your cart
ADD TO CART

Why we do A/B Testing?

A

B

- Perfect to check the impact of changes at first stage
- We don’t have clear metrics to target with this change yet
- Other options: Customer survey / Interview -> More times & money

A/B Test Design

Purpose: Improving the product page

Variable to test: rail image of product (vertical / horizontal)

Goal: Not specified

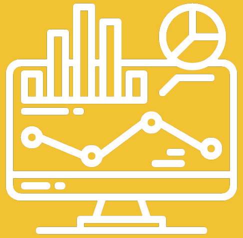
(Alternative) Hypothesis: Vertical rail image will increase the number of page views / clicks on media / time on page / GMV.

Steps of A/B test

Specify the goal & design

Randomly assign users

Log user actions and compute metrics



Test for differences

Make a conclusion

Checking the data

```
[ ] data
```

	Variant	Number of page views	GMV (in $)	Number of add to cart	Clicks on media	Time on Page (sec)	user_id
0	A	5	0.00	0	2	74	0
1	A	4	0.00	4	1	21	1
2	A	4	0.00	2	0	1	2
3	A	5	0.00	0	1	26	3
4	A	5	0.00	3	3	46	4
...	...	...	...	...	...	...	...
1995	B	3	0.00	1	0	1	1995
1996	B	3	0.00	1	2	31	1996
1997	B	3	0.00	2	0	3	1997
1998	B	4	87.08	2	1	11	1998
1999	B	7	0.00	5	6	35	1999

2000 rows × 7 columns

```
[ ] data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 7 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Variant                2000 non-null   object
 1   Number of page views   2000 non-null   int64
 2   GMV (in $)             2000 non-null   float64
 3   Number of add to cart  2000 non-null   int64
 4   Clicks on media        2000 non-null   int64
 5   Time on Page (sec)     2000 non-null   int64
 6   user_id                2000 non-null   int64
dtypes: float64(1), int64(5), object(1)
memory usage: 109.5+ KB
```

Sanity check

Sanity check

Checking the number of users in both group and see if sample ratio mismatch(SRM) is happened

[9]

```python
# Calculate the unique IDs per variant
data.groupby('Variant')['user_id'].nunique()

# Assign the unique counts to each variant
control_users = data[data['Variant']=='A']['user_id'].nunique()
exposed_users = data[data['Variant']=='B']['user_id'].nunique()
total_users = control_users + exposed_users

# Calculate allocation ratios per variant
control_perc = control_users / total_users
exposed_perc = exposed_users / total_users
print("Percentage of users in the control group: ", 100*round(control_perc,5), "%")
print("Percentage of users in the exposed group: ", 100*round(exposed_perc,5), "%")
```

```
Percentage of users in the control group:  50.0 %
Percentage of users in the exposed group:  50.0 %
```

[10]

```python
# Create lists of observed and expected counts per variant
observed = [control_users, exposed_users]
expected = [total_users/2, total_users/2]

# Import chisquare from scipy library
from scipy.stats import chisquare

# Run chisquare test on observed and expected lists
chi = chisquare(observed, f_exp=expected)

# Print test results and interpretation
print(chi)
if chi[1] > 0.01 :
  print("SRM may be present")
else:
  print("SRM likely not present")
```

```
Power_divergenceResult(statistic=0.0, pvalue=1.0)
SRM may be present
```

Sanity check: a basic test to quickly evaluate whether a claim or the result of a calculation can possibly be true (Wikipedia)

Basic assumption of A/B test: Random sampling, Independence, Normality

Finding the right metrics

```
data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 7 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Variant                2000 non-null   object
 1   Number of page views   2000 non-null   int64
 2   GMV (in $)             2000 non-null   float64
 3   Number of add to cart  2000 non-null   int64
 4   Clicks on media        2000 non-null   int64
 5   Time on Page (sec)     2000 non-null   int64
 6   user_id                2000 non-null   int64
dtypes: float64(1), int64(5), object(1)
memory usage: 109.5+ KB
```

Finding the right metrics

Primary metric

- Number of page views
- Number of add to cart
- Clicks on media
- Time on Page (sec)

Secondary metric

- GMV
- Conversion Rate

Ways to find difference:

- Basic statistical informations (count, median, mean, std, min and max)
- Two sample t-test & proportion z-test

Analyzing difference_ 1. Number of page views

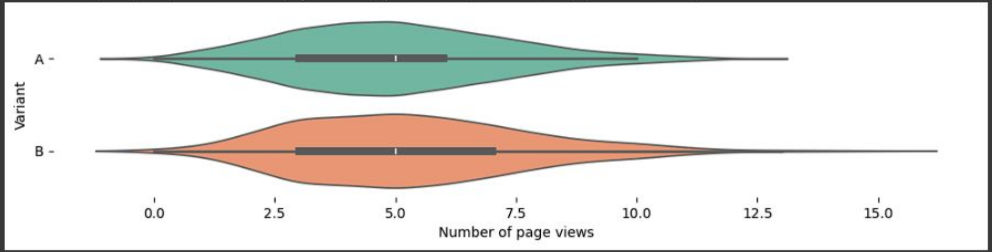
1. Number of pages views

```
# 1. Number of pages views

# Check the mean of Number of page views by group
data.groupby('Variant')['Number of page views'].agg(["count", "median", "mean", "std", "min", "max"])
```

Variant	count	median	mean	std	min	max
A	1000	5.0	4.985	2.236465	0	12
B	1000	5.0	5.317	2.417096	0	15

```
# Make violin plot
figsize = (12, 1.2 * len(data['Variant'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(data, x='Number of page views', y='Variant', inner='box', palette='Set2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<ipython-input-14-50d332ae4189>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(data, x='Number of page views', y='Variant', inner='box', palette='Set2')
```

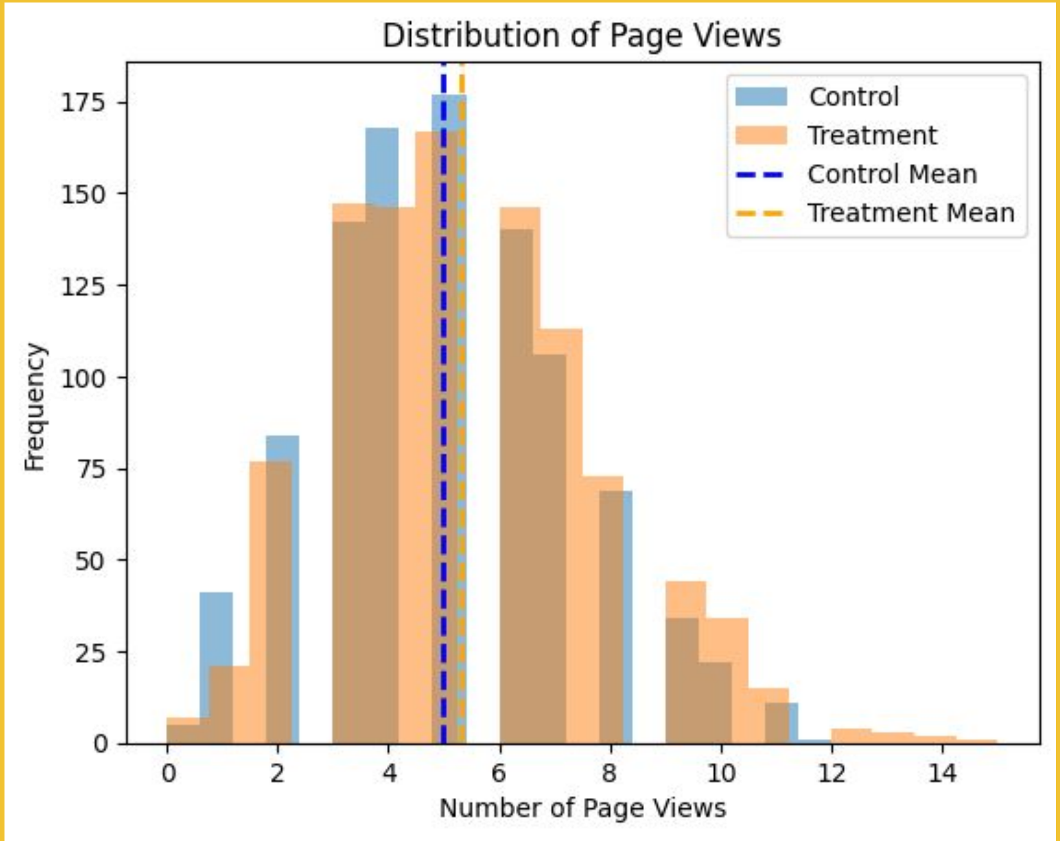


Analyzing difference_ 1. Number of page views

```
[ ] # Assuming 'Variant' column contains control and treatment groups
    control_group = data[data['Variant'] == 'A']
    treatment_group = data[data['Variant'] == 'B']

    # Calculate the mean of the number of page views for both groups
    mean_pv_control = control_group['Number of page views'].mean()
    mean_pv_treatment = treatment_group['Number of page views'].mean()

    # Calculate the difference in mean of the number of page views between treatment and control groups
    mean_pv_difference = mean_pv_treatment - mean_pv_control

    # Perform a two-sample t-test
    t_stat, p_value = ttest_ind(control_group['Number of page views'], treatment_group['Number of page views'], equal_var=False, nan_policy='omit')

    # Assume a significance level (e.g., 0.05)
    alpha = 0.05

    # Print results
    print(f"Mean of the number of page views (Control): {mean_pv_control}")
    print(f"Mean of the number of page views (Treatment): {mean_pv_treatment}")
    print(f"Difference in Mean of the number of page views: {mean_pv_difference}")
    print(f"T-statistic: {t_stat}")
    print(f"P-value: {p_value}")

    if p_value < alpha:
        print("Null hypothesis rejected. There is a statistically significant difference between groups.")
    else:
        print("Null hypothesis not rejected. There is no statistically significant difference between groups.")
```

```
Mean of the number of page views (Control): 4.985
Mean of the number of page views (Treatment): 5.317
Difference in Mean of the number of page views: 0.33199999999999985
T-statistic: -3.1881645133877003
P-value: 0.0014540761572158 42
Null hypothesis rejected. There is a statistically significant difference between groups.
```

Analyzing difference_ 1. Number of page views



Analyzing difference_ 2. Number of add to cart

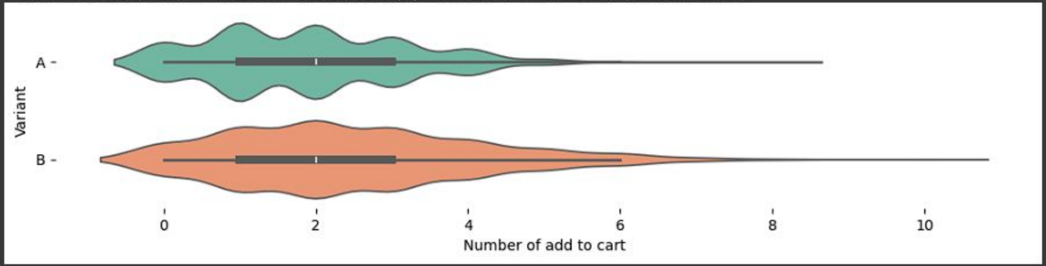
2. Number of add to cart

[15]
```
# 2. Number of add to cart

# Check the mean of Number of add to cart by group
data.groupby('Variant')['Number of add to cart'].agg(["count", "median", "mean", "std", "min", "max"])
```

Variant	count	median	mean	std	min	max
A	1000	2.0	1.884	1.297778	0	8
B	1000	2.0	2.469	1.660662	0	10

[16]
```
# Make violin plot
figsize = (12, 1.2 * len(data['Variant'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(data, x='Number of add to cart', y='Variant', inner='box', palette='Set2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<ipython-input-16-1a47fe30a362>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for th

  sns.violinplot(data, x='Number of add to cart', y='Variant', inner='box', palette='Set2')
```



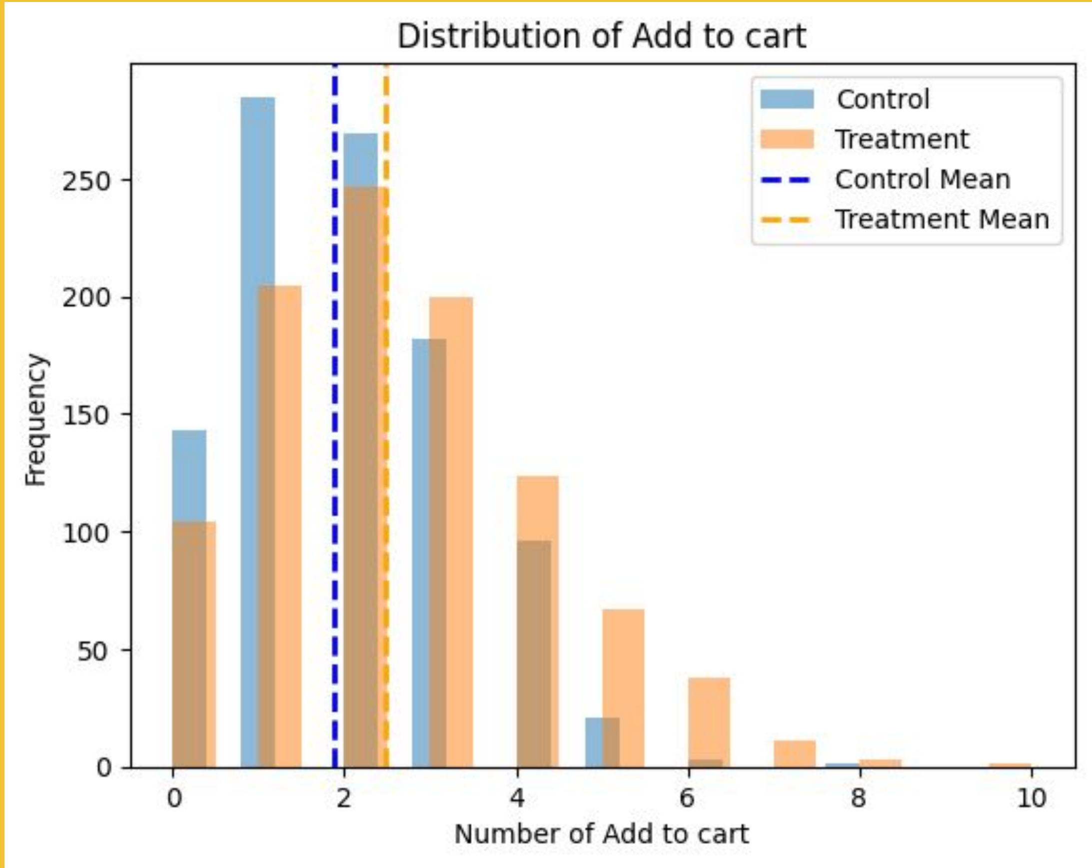
Analyzing difference_ 2. Number of add to cart

[17]

```python
# Assuming 'Variant' column contains control and treatment groups
control_group = data[data['Variant'] == 'A']
treatment_group = data[data['Variant'] == 'B']

# Calculate the mean of the number of add to cart for both groups
mean_ac_control = control_group['Number of add to cart'].mean()
mean_ac_treatment = treatment_group['Number of add to cart'].mean()

# Calculate the difference in mean of the number of add to cart between treatment and control groups
mean_ac_difference = mean_ac_treatment - mean_ac_control

# Perform a two-sample t-test
t_stat, p_value = ttest_ind(control_group['Number of add to cart'], treatment_group['Number of add to cart'], equal_var=False, nan_policy='omit')

# Assume a significance level (e.g., 0.05)
alpha = 0.05

# Print results
print(f"Mean of the number of add to cart (Control): {mean_ac_control}")
print(f"Mean of the number of add to cart (Treatment): {mean_ac_treatment}")
print(f"Difference in Mean of the number of add to cart: {mean_ac_difference}")
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

if p_value < alpha:
    print("Null hypothesis rejected. There is a statistically significant difference between groups.")
else:
    print("Null hypothesis not rejected. There is no statistically significant difference between groups.")
```

```
Mean of the number of add to cart (Control): 1.884
Mean of the number of add to cart (Treatment): 2.469
Difference in Mean of the number of add to cart: 0.585
T-statistic: -8.777389396187948
P-value: 3.668898697938531e-18
Null hypothesis rejected. There is a statistically significant difference between groups.
```

Analyzing difference_ 2. Number of add to cart



Analyzing difference_ 3. Clicks on media

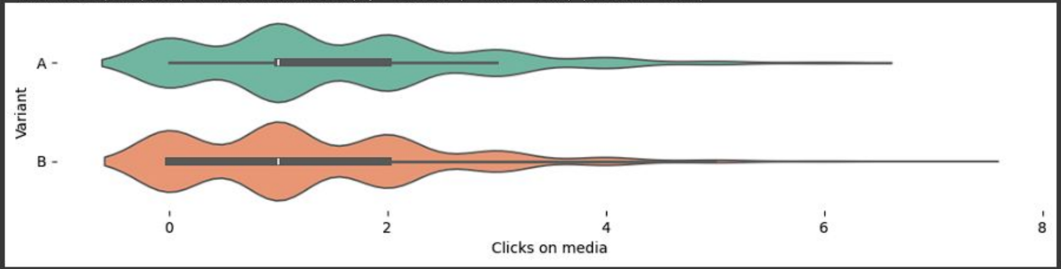
3. Clicks on media

```
[ ] # 3. Clicks on media

    # Check the mean of Clicks on media by group
    data.groupby('Variant')['Clicks on media'].agg(["count", "median", "mean", "std", "min", "max"])
```

Variant	count	median	mean	std	min	max
A	1000	1.0	1.495	1.230239	0	6
B	1000	1.0	1.324	1.180855	0	7

```
[ ] figsize = (12, 1.2 * len(data['Variant'].unique()))
    plt.figure(figsize=figsize)
    sns.violinplot(data, x='Clicks on media', y='Variant', inner='box', palette='Set2')
    sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<ipython-input-20-e71cfc79afbc>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for th

  sns.violinplot(data, x='Clicks on media', y='Variant', inner='box', palette='Set2')
```

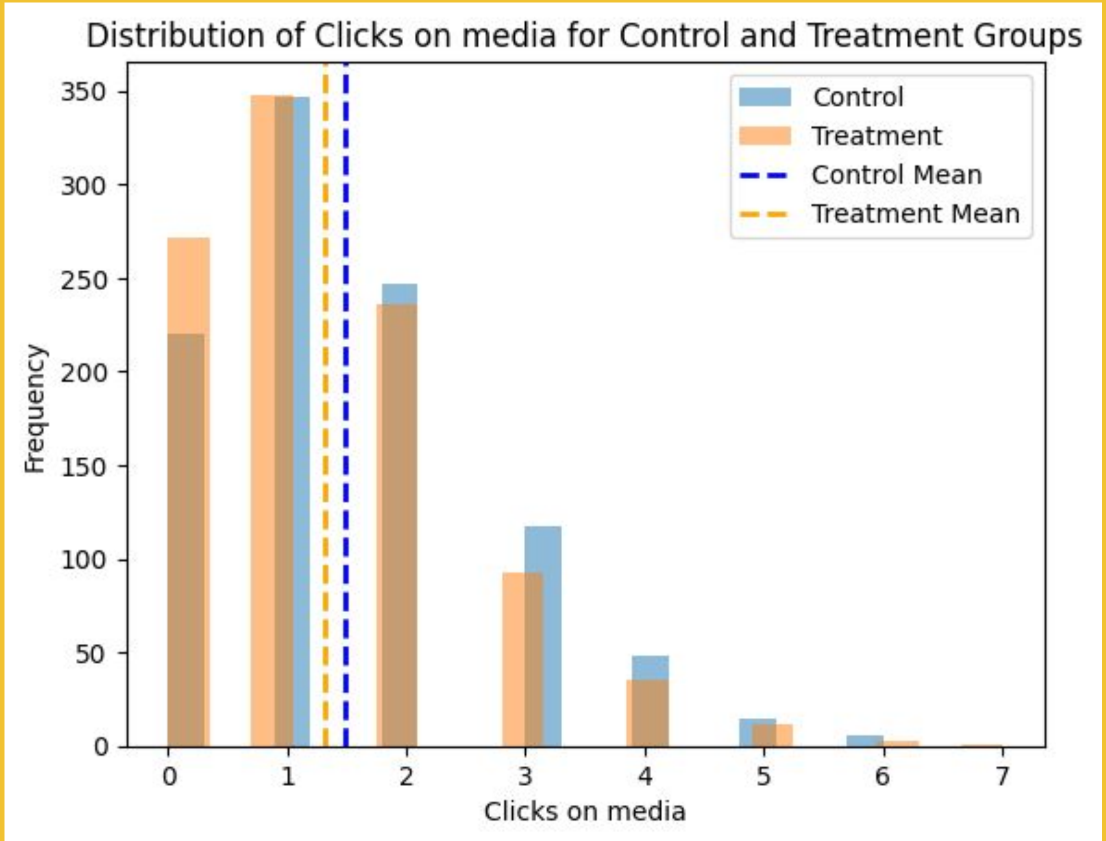


Analyzing difference_ 3. Clicks on media

```
# Assuming 'Variant' column contains control and treatment groups
control_group = data[data['Variant'] == 'A']
treatment_group = data[data['Variant'] == 'B']

# Calculate the mean of clicks on media for both groups
mean_clicks_control = control_group['Clicks on media'].mean()
mean_clicks_treatment = treatment_group['Clicks on media'].mean()

# Calculate the difference in mean of clicks on media between treatment and control groups
mean_clicks_difference = mean_clicks_treatment - mean_clicks_control

# Perform a two-sample t-test
t_stat, p_value = ttest_ind(control_group['Clicks on media'], treatment_group['Clicks on media'], equal_var=False, nan_policy='omit')

# Assume a significance level (e.g., 0.05)
alpha = 0.05

# Print results
print(f"Mean of clicks on media (Control): {mean_clicks_control}")
print(f"Mean of clicks on media (Treatment): {mean_clicks_treatment}")
print(f"Difference in Mean of clicks on media: {mean_clicks_difference}")
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

if p_value < alpha:
    print("Null hypothesis rejected. There is a statistically significant difference between groups.")
else:
    print("Null hypothesis not rejected. There is no statistically significant difference between groups.")
```

```
Mean of clicks on media (Control): 1.495
Mean of clicks on media (Treatment): 1.324
Difference in Mean of clicks on media: -0.17100000000000004
T-statistic: 3.1710702328903153
P-value: 0.0015418577159884 78
Null hypothesis rejected. There is a statistically significant difference between groups.
```

Analyzing difference_ 3. Clicks on media



Analyzing difference_ 4. Time on Page (sec)

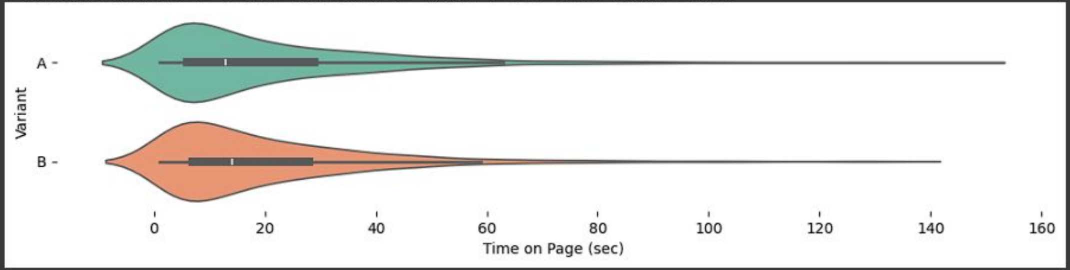
4. Time on Page (sec)

```
# 4. Time on Page (sec)

# Check the mean of the time on page by group
data.groupby('Variant')['Time on Page (sec)'].agg(["count", "median", "mean", "std", "min", "max"])
```

Variant	count	median	mean	std	min	max
A	1000	13.0	20.543	20.596076	1	143
B	1000	14.0	20.047	19.319784	1	132

```
figsize = (12, 1.2 * len(data['Variant'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(data, x='Time on Page (sec)', y='Variant', inner='box', palette='Set2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<ipython-input-24-2aa8e3db35e2>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(data, x='Time on Page (sec)', y='Variant', inner='box', palette='Set2')
```

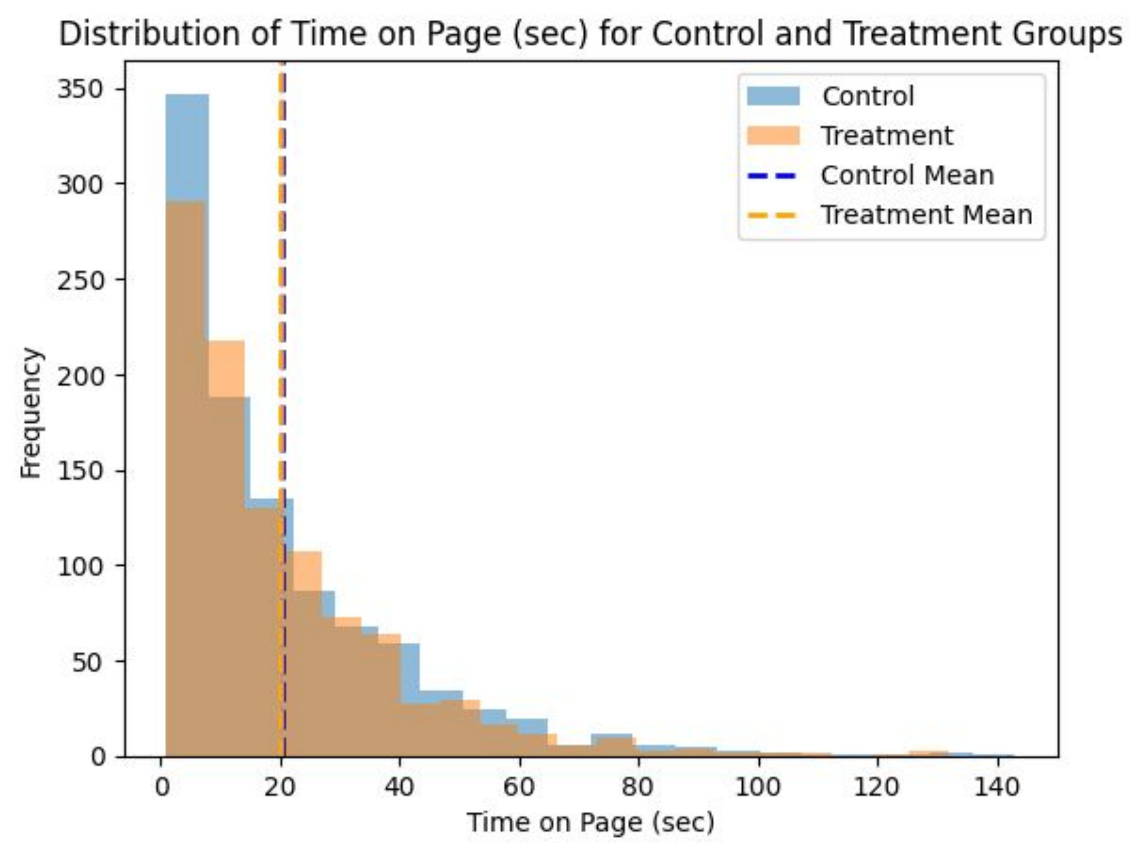


Analyzing difference_ 4. Time on Page (sec)

```python
# Assuming 'Variant' column contains control and treatment groups
control_group = data[data['Variant'] == 'A']
treatment_group = data[data['Variant'] == 'B']

# Calculate the mean of the time on page for both groups
mean_tp_control = control_group['Time on Page (sec)'].mean()
mean_tp_treatment = treatment_group['Time on Page (sec)'].mean()

# Calculate the difference in mean the time on page between treatment and control groups
mean_tp_difference = mean_tp_treatment - mean_tp_control

# Perform a two-sample t-test
t_stat, p_value = ttest_ind(control_group['Time on Page (sec)'], treatment_group['Time on Page (sec)'], equal_var=False, nan_policy='omit')

# Assume a significance level (e.g., 0.05)
alpha = 0.05

# Print results
print(f"Mean of the time on page (Control): {mean_tp_control}")
print(f"Mean of the time on page (Treatment): {mean_tp_treatment}")
print(f"Difference in Mean of the time on page: {mean_tp_difference}")
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

if p_value < alpha:
    print("Null hypothesis rejected. There is a statistically significant difference between groups.")
else:
    print("Null hypothesis not rejected. There is no statistically significant difference between groups.")
```

```
Mean of the time on page (Control): 20.543
Mean of the time on page (Treatment): 20.047
Difference in Mean of the time on page: -0.4959999999999866
T-statistic: 0.5554299489081426
P-value: 0.5786630478332149
Null hypothesis not rejected. There is no statistically significant difference between groups.
```

Analyzing difference_ 4. Time on Page (sec)



Analyzing difference_ 5. GMV (in $)

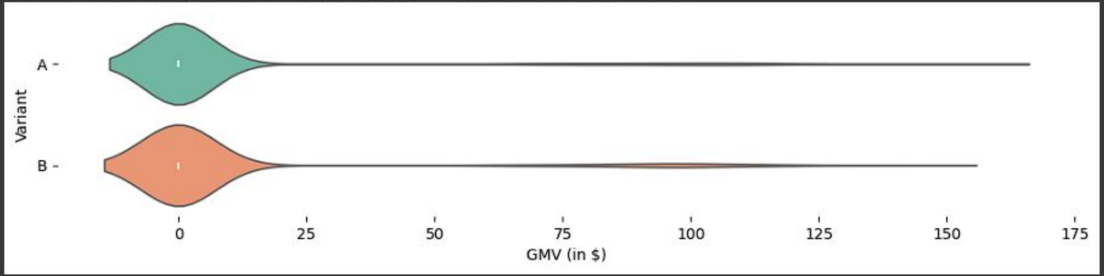
5. GMV (in $)

```
# 5. GMV (in $)

# Check the mean GMV on page by group
data.groupby('Variant')['GMV (in $)'].agg(["count", "median", "mean", "std", "min", "max"])
```

Variant	count	median	mean	std	min	max
A	1000	0.0	7.68999	26.794816	0.0	152.61
B	1000	0.0	9.28953	28.879687	0.0	141.27

```
figsize = (12, 1.2 * len(data['Variant'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(data, x='GMV (in $)', y='Variant', inner='box', palette='Set2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

```
<ipython-input-28-daf9c76b9a7b>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(data, x='GMV (in $)', y='Variant', inner='box', palette='Set2')
```

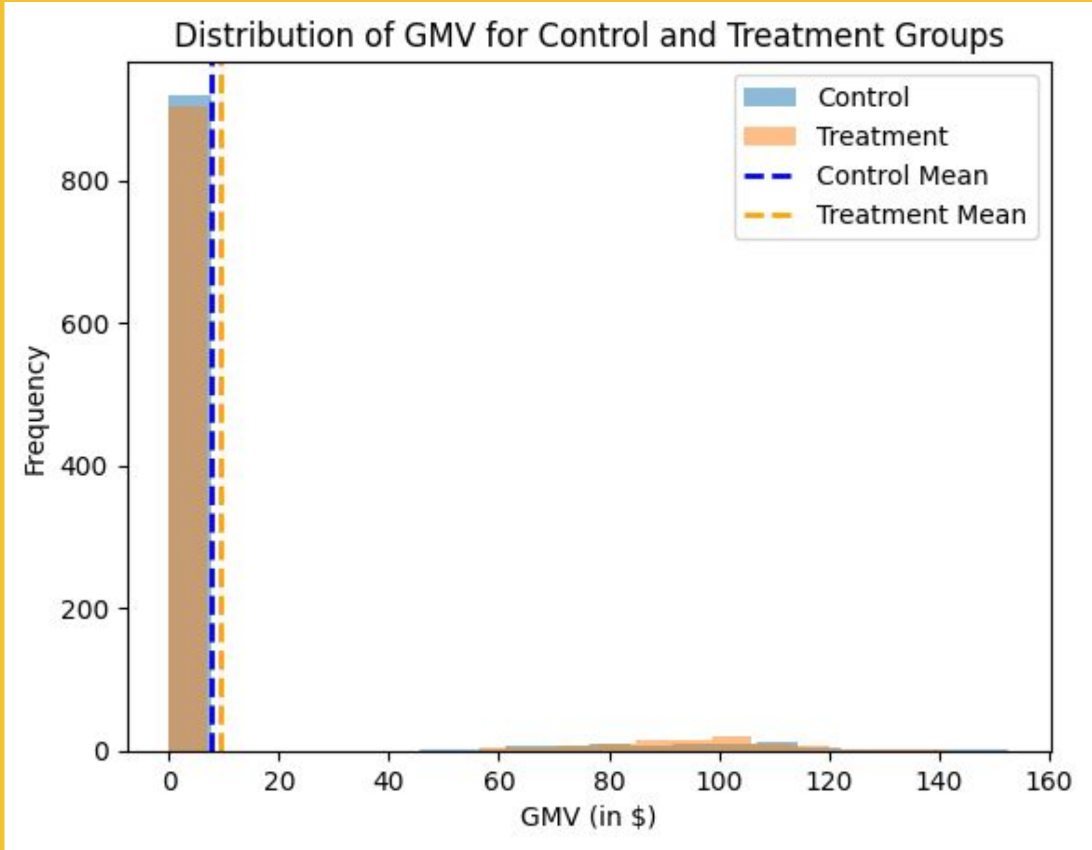


Analyzing difference_ 5. GMV (in $)

```python
# Assuming 'Variant' column contains control and treatment groups
control_group = data[data['Variant'] == 'A']
treatment_group = data[data['Variant'] == 'B']

# Calculate the mean GMV for both groups
mean_gmv_control = control_group['GMV (in $)'].mean()
mean_gmv_treatment = treatment_group['GMV (in $)'].mean()

# Calculate the difference in mean GMV between treatment and control groups
mean_gmv_difference = mean_gmv_treatment - mean_gmv_control

# Perform a two-sample t-test
t_stat, p_value = ttest_ind(control_group['GMV (in $)'], treatment_group['GMV (in $)'], equal_var=False, nan_policy='omit')

# Assume a significance level (e.g., 0.05)
alpha = 0.05

# Print results
print(f"Mean GMV (Control): {mean_gmv_control}")
print(f"Mean GMV (Treatment): {mean_gmv_treatment}")
print(f"Difference in Mean GMV: {mean_gmv_difference}")
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

if p_value < alpha:
    print("Null hypothesis rejected. There is a statistically significant difference between groups.")
else:
    print("Null hypothesis not rejected. There is no statistically significant difference between groups.")
```

```
Mean GMV (Control): 7.689989999999999
Mean GMV (Treatment): 9.28953
Difference in Mean GMV: 1.5995400000000002
T-statistic: -1.2839539769831623
P-value: 0.19930776178517312
Null hypothesis not rejected. There is no statistically significant difference between groups.
```

Analyzing difference_ 5. GMV (in $)



Analyzing difference_ 6. Conversion Rate

6. Conversion Rate

```python
# Assuming 'Variant' column contains control and treatment groups
control_group = data[data['Variant'] == 'A']
treatment_group = data[data['Variant'] == 'B']

# Define the conversion rate
def conversion_rate(data):
    return data['Number of add to cart'].sum() / data['Number of page views'].sum()

# Calculate the conversion rate for both groups
conversion_rate_control = conversion_rate(control_group)
conversion_rate_treatment = conversion_rate(treatment_group)

# Perform a two-sample t-test
t_stat, p_value = ttest_ind(control_group['Number of add to cart'], treatment_group['Number of add to cart'])

# Assume a significance level (e.g., 0.05)
alpha = 0.05

# Print results
print(f"Conversion Rate (Control): {conversion_rate_control}")
print(f"Conversion Rate (Treatment): {conversion_rate_treatment}")
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

if p_value < alpha:
    print("Null hypothesis rejected. There is a statistically significant difference between groups.")
else:
    print("Null hypothesis not rejected. There is no statistically significant difference between groups.")
```

```
Conversion Rate (Control): 0.3779338014042126
Conversion Rate (Treatment): 0.4643596012789167
T-statistic: -8.777389396187946
P-value: 3.517078745065221e-18
Null hypothesis rejected. There is a statistically significant difference between groups.
```

Analyzing difference_ 6. Conversion Rate

```
[ ] # Assuming 'Variant' column contains control and treatment groups
    control_group = data[data['Variant'] == 'A']
    treatment_group = data[data['Variant'] == 'B']

    # Define the conversion rate
    def conversion_rate(data):
        return data['GMV (in $)'].sum() / data['Number of page views'].sum()

    # Calculate the conversion rate for both groups
    conversion_rate_control = conversion_rate(control_group)
    conversion_rate_treatment = conversion_rate(treatment_group)

    # Perform a two-sample t-test
    t_stat, p_value = ttest_ind(control_group['GMV (in $)'], treatment_group['GMV (in $)'])

    # Assume a significance level (e.g., 0.05)
    alpha = 0.05

    # Print results
    print(f"Conversion Rate (Control): {conversion_rate_control}")
    print(f"Conversion Rate (Treatment): {conversion_rate_treatment}")
    print(f"T-statistic: {t_stat}")
    print(f"P-value: {p_value}")

    if p_value < alpha:
        print("Null hypothesis rejected. There is a statistically significant difference between groups.")
    else:
        print("Null hypothesis not rejected. There is no statistically significant difference between groups.")
```

```
Conversion Rate (Control): 1.5426258776328985
Conversion Rate (Treatment): 1.7471374835433513
T-statistic: -1.2839539769831623
P-value: 0.19930692918202245
Null hypothesis not rejected. There is no statistically significant difference between groups.
```

Conclusion

	Number of page views	Number of add to cart	Clicks on media	Time on Page	GMV	Conversion Rate	
						Add to cart / Page views	GMV / Page view
p-value	0.0015	< 0.0001	0.0015	0.5787	0.1993	< 0.0001	0.1993
Significant difference	Null hypothesis rejected	Null hypothesis rejected	Null hypothesis rejected	Null hypothesis is not rejected	Null hypothesis is not rejected	Null hypothesis rejected	Null hypothesis is not rejected

Conclusion

Full codes

https://github.com/zlal12/A-B-Testing_coming.soon/tree/main

Thank you for listening ❤️