

✓ A/B Testing

A/B Testing means analyzing two marketing strategies to choose the best marketing strategy that can convert more traffic into sales (or more traffic into your desired goal) effectively and efficiently.

In A/B testing, analyze the results of two marketing strategies to choose the best one for future marketing campaigns. For example, when I started an ad campaign on Instagram to promote my Instagram post for the very first time, my target audience was different from the target audience of my second ad campaign. After analyzing the results of both ad campaigns, I always preferred the audience of the second ad campaign as it gave better reach and followers than the first one.

That is what A/B testing means. Your goal can be to boost sales, followers, or traffic, but when we choose the best marketing strategy according to the results of our previous marketing campaigns, it is nothing but A/B testing.

```
import pandas as pd
import datetime
from datetime import date, timedelta
import plotly.graph_objects as go
import plotly.express as px
import plotly.io as pio
pio.templates.default = "plotly_white"
```

```
control_data = pd.read_csv('/content/control_group.csv', sep=';')
control_data.head(10)
```

	Campaign Name	Date	Spend [USD]	# of Impressions	Reach	# of Website Clicks	# of Searches	# of View Content	# of Add to Cart	# of Purchase
0	Control Campaign	1.08.2019	2280	82702.0	56930.0	7016.0	2290.0	2159.0	1819.0	618.0
1	Control Campaign	2.08.2019	1757	121040.0	102513.0	8110.0	2033.0	1841.0	1219.0	511.0
2	Control Campaign	3.08.2019	2343	131711.0	110862.0	6508.0	1737.0	1549.0	1134.0	372.0
3	Control Campaign	4.08.2019	1940	72878.0	61235.0	3065.0	1042.0	982.0	1183.0	340.0
4	Control Campaign	5.08.2019	1835	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5	Control Campaign	6.08.2019	3083	109076.0	87998.0	4028.0	1709.0	1249.0	784.0	764.0
6	Control Campaign	7.08.2019	2544	142123.0	127852.0	2640.0	1388.0	1106.0	1166.0	499.0
7	Control Campaign	8.08.2019	1900	90939.0	65217.0	7260.0	3047.0	2746.0	930.0	462.0
8	Control Campaign	9.08.2019	2813	121332.0	94896.0	6198.0	2487.0	2179.0	645.0	501.0
9	Control Campaign	10.08.2019	2149	117624.0	91257.0	2277.0	2475.0	1984.0	1629.0	734.0

Next steps: [Generate code with control_data](#) [View recommended plots](#)

Double-click (or enter) to edit

```
test_data = pd.read_csv(r'/content/test_group.csv', sep=';')
test_data.head(10)
```

	Campaign Name	Date	Spend [USD]	# of Impressions	Reach	# of Website Clicks	# of Searches	# of View Content	# of Add to Cart	# of Purchase
0	Test Campaign	1.08.2019	3008	39550	35820	3038	1946	1069	894	255
1	Test Campaign	2.08.2019	2542	100719	91236	4657	2359	1548	879	677
2	Test Campaign	3.08.2019	2365	70263	45198	7885	2572	2367	1268	578
3	Test Campaign	4.08.2019	2710	78451	25937	4216	2216	1437	566	340
4	Test Campaign	5.08.2019	2297	114295	95138	5863	2106	858	956	768
5	Test Campaign	6.08.2019	2458	42684	31489	7488	1854	1073	882	488
6	Test Campaign	7.08.2019	2838	53986	42148	4221	2733	2182	1301	890
7	Test Campaign	8.08.2019	2916	33669	20149	7184	2867	2194	1240	431
8	Test Campaign	9.08.2019	2652	45511	31598	8259	2899	2761	1200	845
9	Test Campaign	10.08.2019	2790	95054	79632	8125	2312	1804	424	275

Next steps:

[Generate code with test_data](#)[View recommended plots](#)

▼ Data Preparation :

The datasets have some errors in column names. Let's give new column names before moving to next step.

```
control_data.columns = ["Campaign Name", "Date", "Amount Spent",
                        "Number of Impressions", "Reach", "Website Clicks",
                        "Searches Received", "Content Viewed", "Added to Cart",
                        "Purchases"]
```

```
test_data.columns = ["Campaign Name", "Date", "Amount Spent",
                     "Number of Impressions", "Reach", "Website Clicks",
                     "Searches Received", "Content Viewed", "Added to Cart",
                     "Purchases"]
```

```
control_data.isnull().sum()
```

```
Campaign Name    0
Date             0
Amount Spent     0
Number of Impressions  1
Reach            1
Website Clicks   1
Searches Received 1
Content Viewed   1
Added to Cart    1
Purchases        1
dtype: int64
```

```
test_data.isnull().sum()
```

```
Campaign Name    0
Date             0
Amount Spent     0
Number of Impressions  0
Reach            0
Website Clicks   0
Searches Received 0
Content Viewed   0
Added to Cart    0
Purchases        0
dtype: int64
```

▼ Missing Values :

The dataset of the control campaign has missing values in a row. Let's fill in these missing values by the mean value of each column

```
control_data["Number of Impressions"].fillna(value=control_data["Number of Impressions"].mean(),
                                              inplace=True)
control_data["Reach"].fillna(value=control_data["Reach"].mean(),
                              inplace=True)
control_data["Website Clicks"].fillna(value=control_data["Website Clicks"].mean(),
                                       inplace=True)
control_data["Searches Received"].fillna(value=control_data["Searches Received"].mean(),
                                          inplace=True)
control_data["Content Viewed"].fillna(value=control_data["Content Viewed"].mean(),
                                       inplace=True)
control_data["Added to Cart"].fillna(value=control_data["Added to Cart"].mean(),
                                      inplace=True)
control_data["Purchases"].fillna(value=control_data["Purchases"].mean(),
                                  inplace=True)
```

✓ Merging DataSets :

Create a new dataset by merging both datasets

```
ab_data = control_data.merge(test_data,
                             how="outer").sort_values(["Date"])
ab_data = ab_data.reset_index(drop=True)
print(ab_data.head())
```

```

Campaign Name      Date  Amount Spent  Number of Impressions  Reach \
Campaign   1.08.2019      2280      82702.0  56930.0
Campaign   1.08.2019      3008      39550.0  35820.0
Campaign  10.08.2019      2790      95054.0  79632.0
Campaign  10.08.2019      2149     117624.0  91257.0
Campaign  11.08.2019      2420      83633.0  71286.0
```

```

Clicks  Searches Received  Content Viewed  Added to Cart  Purchases
7016.0      2290.0      2159.0      1819.0      618.0
3038.0      1946.0      1069.0      894.0      255.0
8125.0      2312.0      1804.0      424.0      275.0
2277.0      2475.0      1984.0      1629.0      734.0
3750.0      2893.0      2617.0      1075.0      668.0
```

```
put-17-7aaa495241ed>1: UserWarning: You are merging on int and float columns where the float values are not equal to their int repr
control_data.merge(test_data,
```

✓ Campaign Name :

Before moving forward, let's have a look if the dataset has an equal number of samples about both campaigns.

```
ab_data["Campaign Name"].value_counts()
```

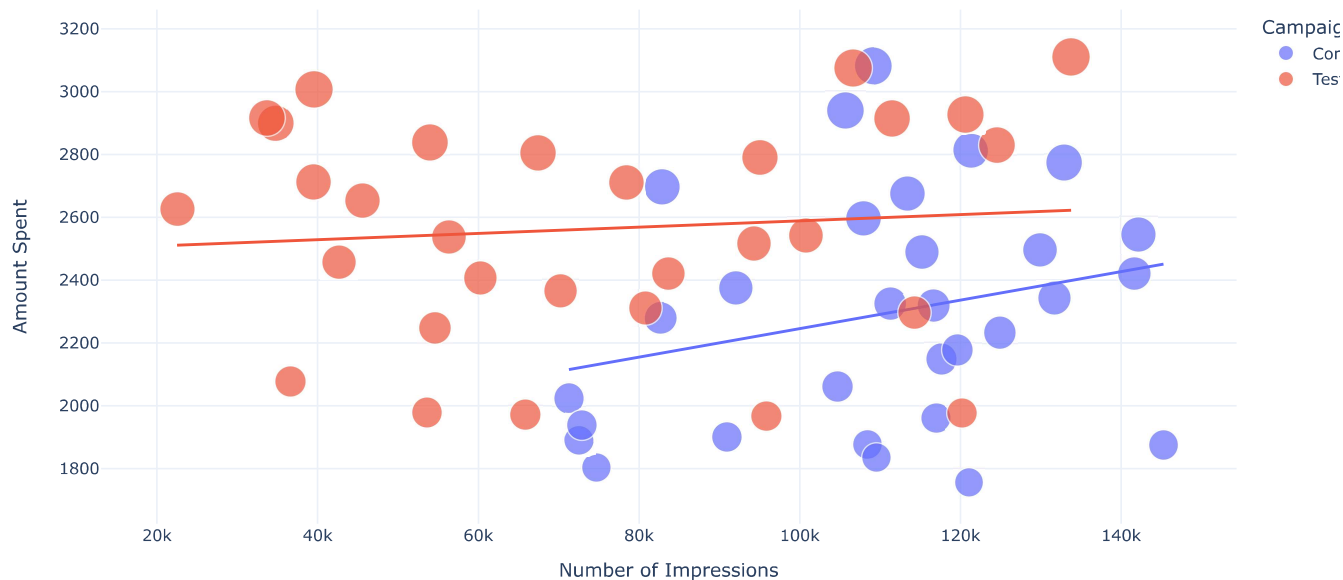
```

Campaign Name
Control Campaign    30
Test Campaign       30
Name: count, dtype: int64
```

✓ Best Marketing Strategy :

A/B Testing to Find the Best Marketing Strategy o get started with A/B testing, I will first analyze the relationship between the number of impressions we got from both campaigns and the amount spent on both campaigns.

```
figure = px.scatter(data_frame = ab_data,
                    x="Number of Impressions",
                    y="Amount Spent",
                    size="Amount Spent",
                    color= "Campaign Name",
                    trendline="ols")
figure.show()
```



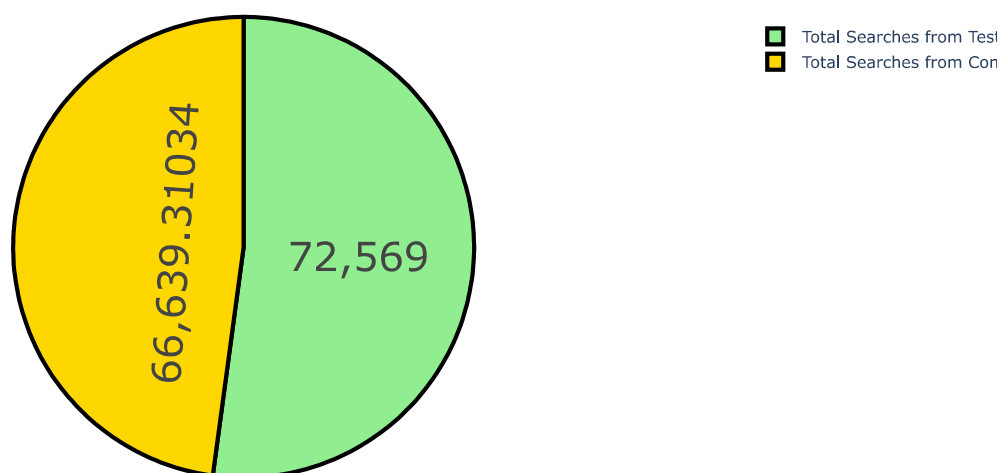
▼ Total Searches :

The control campaign resulted in more impressions according to the amount spent on both campaigns. Now let's have a look at the number of searches performed on the website from both campaigns.

```
label = ["Total Searches from Control Campaign",
        "Total Searches from Test Campaign"]
counts = [sum(control_data["Searches Received"]),
          sum(test_data["Searches Received"])]
colors = ['gold', 'lightgreen']
fig = go.Figure(data=[go.Pie(labels=label, values=counts)])
fig.update_layout(title_text='Control Vs Test: Searches')
fig.update_traces(hoverinfo='label+percent', textinfo='value',
                  textfont_size=30,
                  marker=dict(colors=colors,
                              line=dict(color='black', width=3)))
fig.show()
```



Control Vs Test: Searches



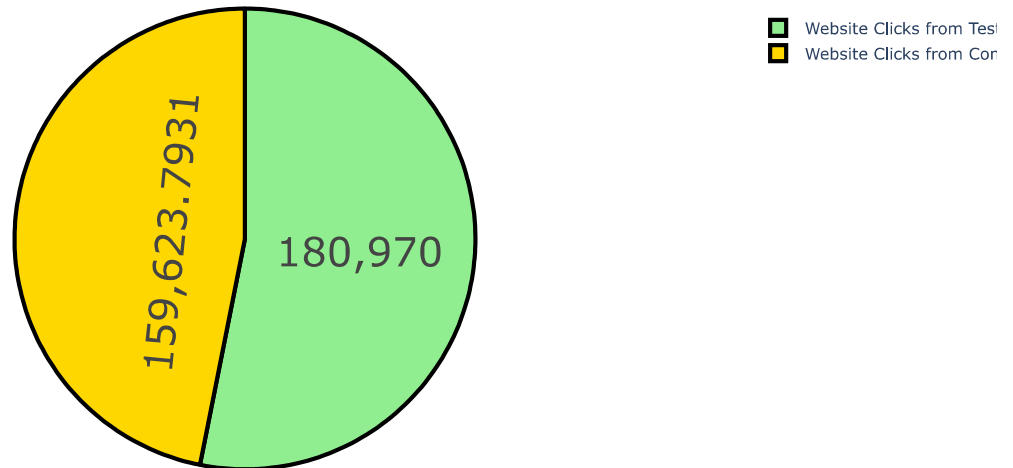
▼ Website Clicks :

The test campaign resulted in more searches on the website. Now let's have a look at the number of website clicks from both campaigns.

```
label = ["Website Clicks from Control Campaign",
        "Website Clicks from Test Campaign"]
counts = [sum(control_data["Website Clicks"]),
          sum(test_data["Website Clicks"])]
colors = ['gold', 'lightgreen']
fig = go.Figure(data=[go.Pie(labels=label, values=counts)])
fig.update_layout(title_text='Control Vs Test: Website Clicks')
fig.update_traces(hoverinfo='label+percent', textinfo='value',
                  textfont_size=30,
                  marker=dict(colors=colors,
                              line=dict(color='black', width=3)))
fig.show()
```



Control Vs Test: Website Clicks



Content Viewed :

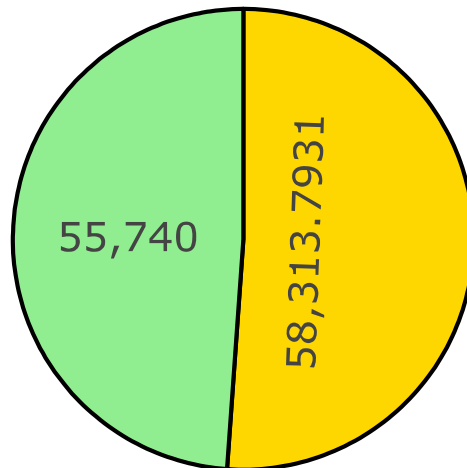
The test campaign wins in the number of website clicks. Now let's have a look at the amount of content viewed after reaching the website from both campaigns.

```
label = ["Content Viewed from Control Campaign",
        "Content Viewed from Test Campaign"]
counts = [sum(control_data["Content Viewed"]),
          sum(test_data["Content Viewed"])]
colors = ['gold', 'lightgreen']
fig = go.Figure(data=[go.Pie(labels=label, values=counts)])
fig.update_layout(title_text='Control Vs Test: Content Viewed')
fig.update_traces(hoverinfo='label+percent', textinfo='value',
                  textfont_size=30,
                  marker=dict(colors=colors,
                              line=dict(color='black', width=3)))
fig.show()
```



Control Vs Test: Content Viewed

■ Content Viewed from Cor
■ Content Viewed from Tes



The audience of the control campaign viewed more content than the test campaign. Although there is not much difference, as the website clicks of the control campaign were low, its engagement on the website is higher than the test campaign.

▼ Products Added to Cart :

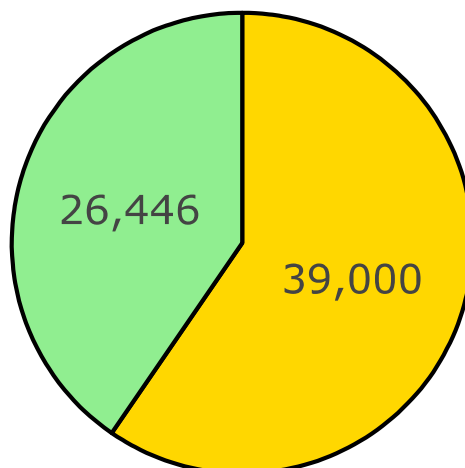
let's have a look at the number of products added to the cart from both campaigns.

```
label = ["Products Added to Cart from Control Campaign",  
        "Products Added to Cart from Test Campaign"]  
counts = [sum(control_data["Added to Cart"]),  
          sum(test_data["Added to Cart"])]  
colors = ['gold', 'lightgreen']  
fig = go.Figure(data=[go.Pie(labels=label, values=counts)])  
fig.update_layout(title_text='Control Vs Test: Added to Cart')  
fig.update_traces(hoverinfo='label+percent', textinfo='value',  
                  textfont_size=30,  
                  marker=dict(colors=colors,  
                              line=dict(color='black', width=3)))  
fig.show()
```



Control Vs Test: Added to Cart

■ Products Added to Cart from Cor
■ Products Added to Cart from Tes



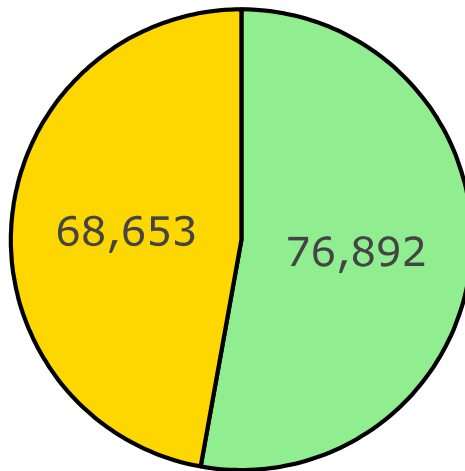
Amount Spent :

Let's have a look at the amount spent on both campaigns.

```
label = ["Amount Spent in Control Campaign",
        "Amount Spent in Test Campaign"]
counts = [sum(control_data["Amount Spent"]),
          sum(test_data["Amount Spent"])]
colors = ['gold', 'lightgreen']
fig = go.Figure(data=[go.Pie(labels=label, values=counts)])
fig.update_layout(title_text='Control Vs Test: Amount Spent')
fig.update_traces(hoverinfo='label+percent', textinfo='value',
                  textfont_size=30,
                  marker=dict(colors=colors,
                              line=dict(color='black', width=3)))
fig.show()
```



Control Vs Test: Amount Spent



The amount spent on the test campaign is higher than the control campaign. But as we can see that the control campaign resulted in more content views and more products in the cart, the control campaign is more efficient than the test campaign.

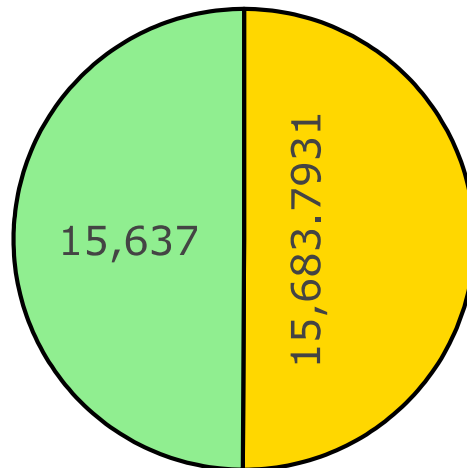
Purchases Made :

Let's have a look at the purchases made by both campaigns.

```
label = ["Purchases Made by Control Campaign",
        "Purchases Made by Test Campaign"]
counts = [sum(control_data["Purchases"]),
          sum(test_data["Purchases"])]
colors = ['gold', 'lightgreen']
fig = go.Figure(data=[go.Pie(labels=label, values=counts)])
fig.update_layout(title_text='Control Vs Test: Purchases')
fig.update_traces(hoverinfo='label+percent', textinfo='value',
                  textfont_size=30,
                  marker=dict(colors=colors,
                              line=dict(color='black', width=3)))
fig.show()
```



Control Vs Test: Purchases



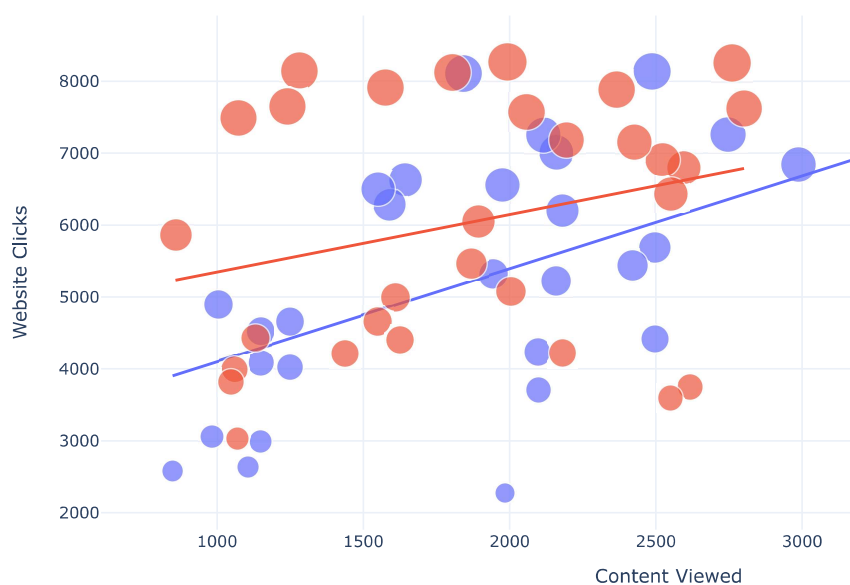
There's only a difference of around 1% in the purchases made from both ad campaigns. As the Control campaign resulted in more sales in less amount spent on marketing, the control campaign wins here!

Campaign Name :

Let's analyze some metrics to find which ad campaign converts more. I will first look at the relationship between the number of website clicks and content viewed from both campaigns.

```
figure = px.scatter(data_frame = ab_data,  
                    x="Content Viewed",  
                    y="Website Clicks",  
                    size="Website Clicks",  
                    color= "Campaign Name",  
                    trendline="ols")
```

```
figure.show()
```

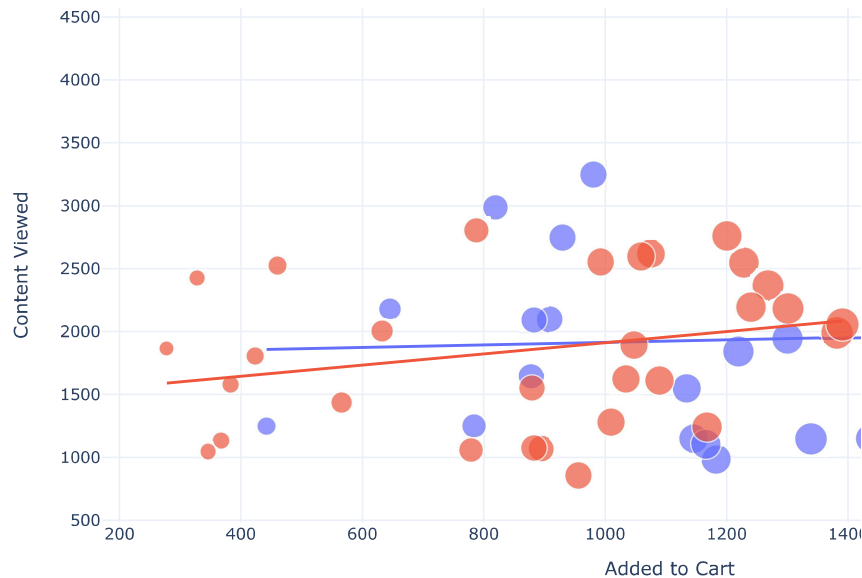


The website clicks are higher in the test campaign, but the engagement from website clicks is higher in the control campaign. So the control campaign wins!

Added to Cart :

```
figure = px.scatter(data_frame = ab_data,
                    x="Added to Cart",
                    y="Content Viewed",
                    size="Added to Cart",
                    color= "Campaign Name",
                    trendline="ols")
```

```
figure.show()
```



The control campaign wins!

Purchases:

Let's have a look at the relationship between the number of products added to the cart and the number of sales from both campaigns.

```
figure = px.scatter(data_frame = ab_data,
                    x="Purchases",
                    y="Added to Cart",
                    size="Purchases",
                    color= "Campaign Name",
                    trendline="ols")
```

```
figure.show()
```

