In [ ]:

Let’s import the necessary Python libraries and both the datasets to get started with the task of A/B testing

In [16]:
```
import pandas as pd
import datetime
from datetime import date, timedelta
import plotly as ply
import plotly.graph_objects as go
import plotly.express as px
import plotly.io as pio
pio.templates.default = "plotly_white"
```

Let’s have a look at both datasets:

In [17]:
```
control_data = pd.read_csv("control_group.csv", sep = ";")
test_data = pd.read_csv("test_group.csv", sep = ";")
```

Taking top 5 datasets from 2 datasets

In [18]:
```
print(control_data.head())
```

```
      Campaign Name       Date  Spend [USD]  # of Impressions     Reach  \
0  Control Campaign  1.08.2019         2280           82702.0   56930.0
1  Control Campaign  2.08.2019         1757          121040.0  102513.0
2  Control Campaign  3.08.2019         2343          131711.0  110862.0
3  Control Campaign  4.08.2019         1940           72878.0   61235.0
4  Control Campaign  5.08.2019         1835               NaN       NaN

   # of Website Clicks  # of Searches  # of View Content  # of Add to Cart  \
0               7016.0         2290.0             2159.0            1819.0
1               8110.0         2033.0             1841.0            1219.0
2               6508.0         1737.0             1549.0            1134.0
3               3065.0         1042.0              982.0            1183.0
4                  NaN            NaN                NaN               NaN

   # of Purchase
0         618.0
1         511.0
2         372.0
3         340.0
4           NaN
```

In [19]:
```
print(test_data.head())
```

```
   Campaign Name       Date  Spend [USD]  # of Impressions  Reach  \
0  Test Campaign  1.08.2019         3008             39550  35820
1  Test Campaign  2.08.2019         2542            100719  91236
2  Test Campaign  3.08.2019         2365             70263  45198
3  Test Campaign  4.08.2019         2710             78451  25937
4  Test Campaign  5.08.2019         2297            114295  95138

   # of Website Clicks  # of Searches  # of View Content  # of Add to Cart  \
0                 3038           1946              1069               894
1                 4657           2359              1548               879
2                 7885           2572              2367              1268
3                 4216           2216              1437               566
4                 5863           2106               858               956

   # of Purchase
0            255
1            677
2            578
3            340
4            768
```

DATA PREPARATION:

The datasets have some errors in column names. Let’s give new column names before moving forward

In [20]:
```
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"]
```

Checking 2 datasets that any of them having null values or not

In [21]:
```
print(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
```

In [22]:
```
print(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
```

Filling the missing values for 2 datasets filled by using mean values

In [31]:
```
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)
```

Converting the columns to integers

In [30]:
```
control_data["Number of Impressions"] = control_data["Number of Impressions"].astype(int)
test_data["Number of Impressions"] = test_data["Number of Impressions"].astype(int)
control_data["Reach"] = control_data["Reach"].astype(int)
test_data["Reach"] = test_data["Reach"].astype(int)
control_data["Website Clicks"] = control_data["Website Clicks"].astype(int)
test_data["Website Clicks"] = test_data["Website Clicks"].astype(int)
control_data["Searches Received"] = control_data["Searches Received"].astype(int)
test_data["Searches Received"] = test_data["Searches Received"].astype(int)
control_data["Content Viewed"] = control_data["Content Viewed"].astype(int)
test_data["Content Viewed"] = test_data["Content Viewed"].astype(int)
control_data["Added to Cart"] = control_data["Added to Cart"].astype(int)
test_data["Added to Cart"] = test_data["Added to Cart"].astype(int)
control_data["Purchases"] = control_data["Purchases"].astype(int)
test_data["Purchases"] = test_data["Purchases"].astype(int)
```

Now I will create a new dataset by merging both datasets:

In [33]:
```
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	\
0	Control Campaign	1.08.2019	2280	82702	56930	
1	Test Campaign	1.08.2019	3008	39550	35820	
2	Test Campaign	10.08.2019	2790	95054	79632	
3	Control Campaign	10.08.2019	2149	117624	91257	
4	Test Campaign	11.08.2019	2420	83633	71286	

	Website Clicks	Searches Received	Content Viewed	Added to Cart	Purchases
0	7016	2290	2159	1819	618
1	3038	1946	1069	894	255
2	8125	2312	1804	424	275
3	2277	2475	1984	1629	734
4	3750	2893	2617	1075	668

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

In [35]:
```
print(ab_data["Campaign Name"].value_counts())
```

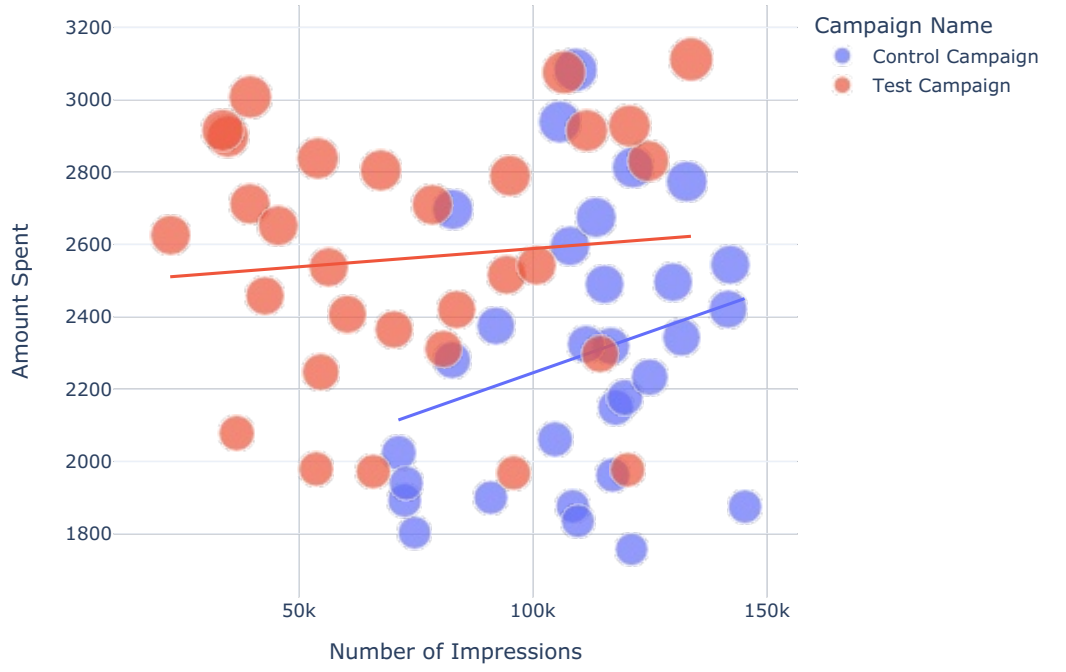
```
Campaign Name
Control Campaign    30
Test Campaign       30
Name: count, dtype: int64
```

The dataset has 30 samples for each campaign. Now let's start with A/B testing to find the best marketing strategy.

A/B Testing to Find the Best Marketing Strategy

To 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:

In [36]:
```
figure = px.scatter(data_frame=ab_data,
                    x="Number of Impressions",
                    y="Amount Spent",
                    size="Amount Spent",
                    color="Campaign Name",
                    trendline="ols")
figure.show()
```



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:

In [37]:
```
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()
```

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:

In [38]:
```
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()
```

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:

In [39]:
```
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()
```

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.s:

Now let’s have a look at the number of products added to the cart from both campaigns:

In [40]:
```
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()
```

Despite low website clicks more products were added to the cart from the control campaign. Now let’s have a look at the amount spent on both campaigns:

In [41]:
```
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()
```

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.

Now let’s have a look at the purchases made by both campaigns:

In [42]:
```
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()
```

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!

Now 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:

In [43]:
```
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!

Now I will analyze the relationship between the amount of content viewed and the number of products added to the cart from both campaigns:

In [44]:
```
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()
```

Again, the control campaign wins! Now 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:

In [45]:
```
figure = px.scatter(data_frame = ab_data,
                    x="Purchases",
                    y="Added to Cart",
                    size="Purchases",
                    color= "Campaign Name",
                    trendline="ols")
figure.show()
```

Although the control campaign resulted in more sales and more products in the cart, the conversation rate of the test campaign is higher.

CONCLUSION:

From the above A/B tests, we found that the control campaign resulted in more sales and engagement from the visitors. More products were viewed from the control campaign, resulting in more products in the cart and more sales. But the conversation rate of products in the cart is higher in the test campaign. The test campaign resulted in more sales according to the products viewed and added to the cart. And the control campaign results in more sales overall. So, the Test campaign can be used to market a specific product to a specific audience, and the Control campaign can be used to market multiple products to a wider audience.