Quora_DataChallenge

October 29, 2020

0.1 Improving User Engagement on Quora Mobile App

Suppose you are a Data Scientist on the Mobile team at Quora. The team has just introduced a new UI design to the Quora app. The goal of the new design is to increase user engagement (measured by minutes spent on site). The team ran an A/B test to evaluate the change. Using the data, help the team understand the impact of the UI change better.

Tables provided are as follows: 1. t1_user_active_min.csv 2. t2_user_variant.csv 3. t3_user_active_min_pre.csv 4. t4_user_attributes.csv

```
In [ ]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from datetime import datetime as dt
        from datetime import timedelta
        from IPython.core.interactiveshell import InteractiveShell
        InteractiveShell.ast_node_interactivity = "all"
        %matplotlib inline
        pd.set_option('float_format', '{:f}'.format)

        from scipy import stats
        from scipy.stats import ttest_ind_from_stats
        from statsmodels.stats.power import TTestIndPower
```

```
In [ ]: t1_usr_active_min = pd.read_csv("t1_user_active_min.csv")
        t2_usr_variant = pd.read_csv("t2_user_variant.csv")
        t3_usr_active_min_pre = pd.read_csv("t3_user_active_min_pre.csv")
        t4_usr_attributes = pd.read_csv("t4_user_attributes.csv")
```

```
In [ ]: print("t1_user_active_min")
        t1_usr_active_min.head(2)
        print("t2_user_variant")
        t2_usr_variant.head(2)
        print("t3_user_active_min_pre")
        t3_usr_active_min_pre.head(2)
        print("t4_user_attributes")
        t4_usr_attributes.head(2)
```

```
t1_user_active_min
```

```
Out[ ]:    uid          dt  active_mins
        0    0  2019-02-22     5.000000
        1    0  2019-03-11     5.000000
```

```
t2_user_variant
```

```
Out[ ]:    uid  variant_number          dt signup_date
        0    0                0  2019-02-06  2018-09-24
        1    1                0  2019-02-06  2016-11-07
```

```
t3_user_active_min_pre
```

```
Out[ ]:    uid          dt  active_mins
        0    0  2018-09-24     3.000000
        1    0  2018-11-08     4.000000
```

```
t4_user_attributes
```

```
Out[ ]:    uid gender   user_type
        0    0   male  non_reader
        1    1   male      reader
```

```
In [ ]: print("Pre Experiments date range:", t3_usr_active_min_pre.dt.min()," - ",t2_usr_varia
        print("Duration of Experiment:",t1_usr_active_min.dt.min()," - ", t1_usr_active_min.dt

        delta = dt.strptime(t1_usr_active_min.dt.max(),"%Y-%m-%d")-dt.strptime(t1_usr_active_m
        print("Experiment Duration(Days):",delta.days+1)
```

```
Pre Experiments date range: 2018-08-10  -  2019-02-06
Duration of Experiment: 2019-02-06  -  2019-07-05
Experiment Duration(Days): 150
```

0.1.1 Exploring User Distribtion for control & treatment group

```
In [ ]: t2_usr_variant['variant_number'].value_counts()
        print("Train - Test ratio: 80% - 20%")
```

```
Out[ ]: 0    40000
        1    10000
        Name: variant_number, dtype: int64
```

```
Train - Test ratio: 80% - 20%
```

```
In [ ]: ## Checking no. of unique users
        t2_usr_variant.uid.nunique()
        t1_usr_active_min.uid.nunique()
        t3_usr_active_min_pre.uid.nunique()
```

```
Out[ ]: 50000
```

```
Out[ ]: 46633
```

```
Out[ ]: 49697
```

0.1.2 Preparing a master table with user

Preparing now a master table with these following important user informations: User Daily Activity (uid, active_min), User Signup, User Variant Number, User characteristics (gender, user_types). Motive to prepare this dataset is to have table with complete user details and use this for hypothesis testing and further insights.

I have specifically done a left join of t2_usr_varient table with t1_usr_active_min so as to preserve the activity (or non-activity) of all the 50000 users who are are part of the control & treatment group.

```
In [ ]: usr_postexp_df = pd.merge(t2_usr_variant,t1_usr_active_min, on='uid', how='left')
        usr_postexp_df = pd.merge(usr_postexp_df,t4_usr_attributes, on='uid', how='left')
        usr_postexp_df.shape
        usr_postexp_df.uid.nunique()
        usr_postexp_df.head(2)
```

```
Out[ ]: (1069769, 8)
```

```
Out[ ]: 50000
```

```
Out[ ]:    uid  variant_number        dt_x  ... active_mins gender   user_type
        0    0               0  2019-02-06  ...    5.000000   male  non_reader
        1    0               0  2019-02-06  ...    5.000000   male  non_reader

        [2 rows x 8 columns]
```

```
In [ ]: usr_postexp_df.rename(columns={'dt_x':'experiement_dt','dt_y':'dt'}, inplace=True )
```

0.1.3 We know that the expriment was live for 150 days, so I am checking in the following codes if the user were active daily or not. My motive is to have an apple to apple comparison for same no of days, the mean active mins for control and treatment group

```
In [ ]: temp = usr_postexp_df.groupby(['uid','variant_number'], as_index=False).agg({'dt':'cou
        temp.rename(columns={'active_mins': 'tot_mins','dt': 'tot_days'},inplace=True)
        temp.head()
        temp.tot_days.unique()
        temp.groupby(['variant_number'], as_index=False).agg({'tot_days':'mean','tot_mins':'mea
```

Out[ ]:

	uid	variant_number	tot_days	tot_mins
0	0	0	13	43.000000
1	1	0	95	15205.000000
2	2	0	7	17.000000
3	3	0	24	77.000000
4	4	0	20	39.000000

Out[ ]:
```
array([ 13,  95,   7,  24,  20,  14,   0,   9,  31,   6,   2,  12,  18,
        89,  34,  10,  35,  33,  37,  81,  56,  17,  16,  21,  50,  30,
         5,  25,   1,  15,   8,  62,  11,  54,   3,   4,  55,  59,  27,
        40,  19,  58,  66,  64,  71,  29,  57,  41,  23, 103,  60,  80,
        76,  38,  32,  84,  92,  39,  70,  74,  51,  45,  77,  22,  63,
        75,  28,  72,  43,  53,  67,  26,  93,  88,  42,  36,  68,  91,
        83,  49,  48,  47,  86,  97,  99,  65,  69,  82,  44, 102,  61,
        98, 101,  46, 100,  85,  94,  78,  96,  52,  87,  79,  90,  73,
       106, 104, 107, 105, 108, 110, 109])
```

Out[ ]:

	variant_number	tot_days	tot_mins
0	0	22.173925	783.719625
1	1	17.944500	722.094000

0.1.4 Thus, from the above two aggregates function we see that no user (either 0/1 variant) was present for all single day of the experiment. Also the mean days control & treatment group users were active is 22 and 18 days respectively. Thus we now need to populate the above table for each day of the experiement and compare the means of the two groups

0.1.5 Also from the last table, we see that there is a difference between the average tot_mins spend by users in control and treatment groups, but we need to be check if there are many outliers (like15202.0) misrepresenting this number.

0.2 Outlier Treatment

From the `usr_postexp_df` df, only column 'active_mins' has outliers in it. Since a day has maximum 1440 mins, therefore I am removing all the entries with values greater than 1500 mins (taken a buffer of 60 mins more)

In [ ]:
```
usr_postexp_df.describe()
#plt.hist(usr_postexp_df.active_mins)
usr_postexp_df[usr_postexp_df.active_mins>=1500].shape
usr_postexp_df[usr_postexp_df.active_mins==99999].shape
```

Out[ ]:

	uid	variant_number	active_mins
count	1069769.000000	1069769.000000	1066402.000000
mean	24226.815362	0.168482	36.168091
std	14175.415856	0.374294	1270.483515
min	0.000000	0.000000	1.000000
25%	12023.000000	0.000000	2.000000
50%	23945.000000	0.000000	5.000000
75%	36186.000000	0.000000	17.000000
max	49999.000000	1.000000	99999.000000

```
Out[ ]: (172, 8)

Out[ ]: (172, 8)

In [ ]: usr_postexp_df.shape
        temp = usr_postexp_df['active_mins'] >=1500
        usr_postexp_df2 = usr_postexp_df[~temp]
        usr_postexp_df.shape[0]-usr_postexp_df2.shape[0]

Out[ ]: (1069769, 8)

Out[ ]: 172
```

Thus we have removed the outlier values: 172 entries with active_mins >=1500 mins

```
In [ ]: usr_postexp_df2.head()
        usr_postexp_df2.isna().sum()

Out[ ]:    uid  variant_number experiement_dt  ... active_mins gender   user_type
        0    0               0     2019-02-06  ...    5.000000   male  non_reader
        1    0               0     2019-02-06  ...    5.000000   male  non_reader
        2    0               0     2019-02-06  ...    3.000000   male  non_reader
        3    0               0     2019-02-06  ...    4.000000   male  non_reader
        4    0               0     2019-02-06  ...    9.000000   male  non_reader

        [5 rows x 8 columns]

Out[ ]: uid                0
        variant_number     0
        experiement_dt     0
        signup_date        0
        dt              3367
        active_mins     3367
        gender             0
        user_type          0
        dtype: int64
```

From the above NA value table, we see that there are around 3367 users for whom there is no activity even for a single day.

```
In [ ]: temp = usr_postexp_df2[usr_postexp_df2.active_mins.isna()]
        temp.shape
        temp.head()
        temp.uid.nunique()
        temp.groupby(['variant_number'],as_index=False).agg({'uid':'nunique'})

Out[ ]: (3367, 8)
```

```
Out[ ]:       uid  variant_number experiement_dt  ... active_mins  gender   user_type
        193     8                0     2019-02-06  ...         nan    male    new_user
        258    12                0     2019-02-06  ...         nan    male  non_reader
        797    35                0     2019-02-06  ...         nan    male    new_user
        1612   78                0     2019-02-06  ...         nan    male  non_reader
        1905   94                0     2019-02-06  ...         nan  female    new_user

        [5 rows x 8 columns]
```

```
Out[ ]: 3367
```

```
Out[ ]:    variant_number   uid
        0               0  2575
        1               1   792
```

0.2.1 Thus we see that a lot of users (3k+) from control group and also treatment groups have shown no activity during the experiment period.

0.2.2 Currently, I am removing these users since for these users the active_mins will be 0 for all days and since they were not active even for single day, so they didn't see the newly designed UI and hence have no role to play.

```
In [ ]: usr_postexp_dfnew = usr_postexp_df2[~usr_postexp_df2.active_mins.isna()]
        usr_postexp_dfnew.shape
        usr_postexp_dfnew.head()
```

```
Out[ ]: (1066230, 8)
```

```
Out[ ]:    uid  variant_number experiement_dt  ... active_mins gender   user_type
        0    0                0     2019-02-06  ...    5.000000   male  non_reader
        1    0                0     2019-02-06  ...    5.000000   male  non_reader
        2    0                0     2019-02-06  ...    3.000000   male  non_reader
        3    0                0     2019-02-06  ...    4.000000   male  non_reader
        4    0                0     2019-02-06  ...    9.000000   male  non_reader

        [5 rows x 8 columns]
```

Let's look at the variant number 0/1 wise the mean active_mins and it's std deviation.

```
In [ ]: usr_postexp_dfnew.groupby(['variant_number'],as_index=False).active_mins.agg({'mean','
```

```
Out[ ]:                      mean   median       std
        variant_number
        0              19.337660 5.000000 44.797631
        1              23.526294 7.000000 54.191356
```

Populating the above df for each user * 150 days of experiment. This will give us an apple-to-apply comparison, ie the daily acitve _min for each user for every single day when the experiment was live

```
In [ ]: daily_usr_act = usr_postexp_dfnew.pivot_table(index=['variant_number','uid','experiemer
                                                          'gender','user_type'],columns =
        daily_usr_act = daily_usr_act.melt(id_vars=['variant_number','uid','experiement_dt','s
                                                          'gender','user_type'], var_name=
        print("Before a& After reshaping the data at daily level:",usr_postexp_dfnew.shape, da
```

```
Before a& After reshaping the data at daily level: (1066230, 8) (6994950, 8)
```

0.2.3 Let's now see the impact of new UI on average active_mins for control and treatment group

```
In [ ]: daily_usr_act.groupby(['variant_number'],as_index=False).active_mins.agg({'mean','std'
```

Out[ ]:

variant_number	median	var	mean	std	count
0	0	366.763169	3.054808	19.151062	5613750
1	0	444.027311	3.056017	21.071956	1381200

```
In [ ]: mean_0 = daily_usr_act[daily_usr_act['variant_number']==0].active_mins.mean()
        mean_1 = daily_usr_act[daily_usr_act['variant_number']==1].active_mins.mean()

        std_0 = daily_usr_act[daily_usr_act['variant_number']==0].active_mins.std()
        std_1 = daily_usr_act[daily_usr_act['variant_number']==1].active_mins.std()

        nobs0 = daily_usr_act[daily_usr_act['variant_number']==0].active_mins.count()
        nobs1 = daily_usr_act[daily_usr_act['variant_number']==1].active_mins.count()
```

0.2.4 Performing t-test to understand if there was any impact of new UI on user's dUIaily engagement

Null Hypothesis Ho: New UI had no effect on daily user enagegment i.e. there is no difference in control and variant users' average active mins Alternate Hypothesis: New UI had an effect on daily user engagment, .e. there is a difference in control and variant users' average active mins

Here using the Welch t-test because both variane and sample sizes of two groups are different.

```
In [ ]: ttest_ind_from_stats(mean1=mean_1,std1=std_1,nobs1=nobs1,
                             mean2=mean_0,std2=std_0,nobs2=nobs0, equal_var=False)
```

```
Out[ ]: Ttest_indResult(statistic=0.06145955015857426, pvalue=0.9509932339796476)
```

The p-value from the above t-test is very high and thus we fail to reject the null-hypothesis. #### Preparing Confidence Interval

```
In [ ]: def calc_CI(mean_1,std_1,nobs1,mean_0,std_0,nobs0,CI_interval):
            se = np.sqrt((std_1 * std_1) / nobs1 + (std_0 * std_0) / nobs0)
            mean_diff = mean_1-mean_0
            qt = stats.norm.isf((1-CI_interval)/2)
            lower = mean_diff - qt*se
            upper = mean_diff + qt*se
            return (lower,upper)
```

```
In [ ]: CI = calc_CI(mean_1,std_1,nobs1,mean_0,std_0,nobs0,0.95)
        CI

Out[ ]: (-0.03733892403590165, 0.039756441143676366)
```

0.3 Pre and Post Experiment Data Analysis

You decide to dive deeper into the data, so you gather a table of active minutes by user from before the experiment began. You should now use table 3 (t3_user_active_min_pre.csv) along with tables 1 and 2 for this question.

Using the statistical method of your choice and the pre-experiment data, update your 95% confidence interval of the overall average treatment effect.

Please enter your confidence interval below, after rounding your answer to second place after the decimal.

```
In [ ]: print("Pre Experiments date range:", t3_usr_active_min_pre.dt.min()," - ",t2_usr_varia
        print("Duration of Experiment:",t1_usr_active_min.dt.min()," - ", t1_usr_active_min.dt

        delta = dt.strptime(t1_usr_active_min.dt.max(),"%Y-%m-%d")-dt.strptime(t1_usr_active_m
        predelta = dt.strptime(t3_usr_active_min_pre.dt.max(),"%Y-%m-%d")-dt.strptime(t3_usr_a
        print("Experiment Duration(Days):",delta.days+1)
        print("Pre Experiment Duration(Days):",predelta.days+1)

Pre Experiments date range: 2018-08-10  -  2019-02-06
Duration of Experiment: 2019-02-06  -  2019-07-05
Experiment Duration(Days): 150
Pre Experiment Duration(Days): 180
```

In the following lines of code, I reiterating steps & function used above to prepare data ready for t-test and CI calculation.

Steps taken:

- Preparing Master Table: pre-experiement 0/1 variant group's average activity mins
- Outlier removal
- Performing T-test for pre and post experiment data

```
In [ ]: usr_preexp_df = pd.merge(t2_usr_variant,t3_usr_active_min_pre,on="uid",how="left")
        preexp_usr_df = pd.merge(usr_preexp_df,t4_usr_attributes,on="uid",how="left")
        preexp_usr_df.shape
        preexp_usr_df.uid.nunique()
        preexp_usr_df.head(3)

Out[ ]: (1190396, 8)

Out[ ]: 50000
```

```
Out[ ]:    uid  variant_number        dt_x  ... active_mins gender   user_type
        0    0                0  2019-02-06  ...    3.000000   male  non_reader
        1    0                0  2019-02-06  ...    4.000000   male  non_reader
        2    0                0  2019-02-06  ...    3.000000   male  non_reader

        [3 rows x 8 columns]
```

```
In [ ]: preexp_usr_df.rename(columns={'dt_x':'experiement_dt','dt_y':'dt'}, inplace=True )
```

0.3.1 Outlier Treatment

```
In [ ]: preexp_usr_df.describe()
        #plt.hist(usr_postexp_df.active_mins)
        preexp_usr_df[preexp_usr_df.active_mins>=1500].shape
```

```
Out[ ]:                 uid  variant_number    active_mins
        count 1190396.000000  1190396.000000 1190093.000000
        mean    24206.442924        0.168585      32.203151
        std     14180.354303        0.374385    1181.530546
        min         0.000000        0.000000       1.000000
        25%     11975.000000        0.000000       2.000000
        50%     23933.000000        0.000000       4.000000
        75%     36197.250000        0.000000      14.000000
        max     49999.000000        1.000000   99999.000000
```

```
Out[ ]: (166, 8)
```

```
In [ ]: preexp_usr_df.shape
        temp = preexp_usr_df['active_mins'] >=1500
        preexp_usr_df2 = preexp_usr_df[~temp]
        preexp_usr_df.shape[0]-preexp_usr_df2.shape[0]
```

```
Out[ ]: (1190396, 8)
```

```
Out[ ]: 166
```

Thus we have removed the outlier values: 166 entries with active_mins >=1500 mins

```
In [ ]: preexp_usr_df2.head()
        preexp_usr_df2.isna().sum()
```

```
Out[ ]:    uid  variant_number experiement_dt  ... active_mins gender   user_type
        0    0                0     2019-02-06  ...    3.000000   male  non_reader
        1    0                0     2019-02-06  ...    4.000000   male  non_reader
        2    0                0     2019-02-06  ...    3.000000   male  non_reader
        3    0                0     2019-02-06  ...    6.000000   male  non_reader
        4    0                0     2019-02-06  ...    6.000000   male  non_reader

        [5 rows x 8 columns]
```

```
Out[ ]: uid                0
        variant_number     0
        experiement_dt     0
        signup_date        0
        dt                 303
        active_mins        303
        gender             0
        user_type          0
        dtype: int64
```

0.3.2 Here we see that around 303 users have no activity during the pre-experiment period. It would be interesting to see if they had any activity during the experiment days and if so, did they have signup enough days before the launch of experiment

```
In [ ]: temp = preexp_usr_df2[preexp_usr_df2.dt.isna()]
        check_ifactivity = pd.merge(usr_postexp_dfnew,temp, on = "uid",how="inner")
        check_ifactivity.shape
        check_ifactivity.uid.nunique()
        check_ifactivity.head()
```

```
Out[ ]: (642, 15)
```

```
Out[ ]: 155
```

```
Out[ ]:    uid  variant_number_x experiement_dt_x  ... active_mins_y gender_y  user_type_y
        0  148                 0       2019-02-06  ...           nan   female   non_reader
        1  148                 0       2019-02-06  ...           nan   female   non_reader
        2  148                 0       2019-02-06  ...           nan   female   non_reader
        3  148                 0       2019-02-06  ...           nan   female   non_reader
        4  148                 0       2019-02-06  ...           nan   female   non_reader

        [5 rows x 15 columns]
```

0.3.3 Out of the 303 non-active users duing pre-experiment phase, 155 had activity during the experiment. Let's now check if they had signed up enough days before the experiment or during the pre-experiment phase.

```
In [ ]: check_ifactivity.signup_date_x.min()
        check_ifactivity.signup_date_x.max()
        print("Duration of Experiment: 2019-02-06 - 2019-07-05")
```

```
Out[ ]: '2013-05-16'
```

```
Out[ ]: '2019-02-04'
```

```
Duration of Experiment: 2019-02-06 - 2019-07-05
```

0.3.4 Thus we see that pre-experiment phase contains user have signed up 2 days before the experiment began. Therefore for a fair comparison, we should only keep those users who had signedup 150 days before the experiment began. This will give us a fair monitoring period: 150 days before the experiment and 150 days after the experiment.

0.3.5 Experiment Begin Date: 2019-02-06

0.3.6 150 days before Experiment Start Date: 2018-09-09

Thus we will now eliminate all the users who have signup after the above date. Only for the filtered set of users, we will now perform pre-post expeirment

Since the experiment is for 150 days starting from 2019-02-06 whereas we have pre-experiment data for 180 days, for equal comparison we will only consider the last 150 days activity data for pre-experiment phase

```
In [ ]: print("Removing users signed up after 2018-09-09 from preexp df:")
        bef = preexp_usr_df2.shape[0]
        preexp_usr_df2.uid.nunique()
        preexp_usr_df2 = preexp_usr_df2[preexp_usr_df2.signup_date<='2018-09-09']
        aft = preexp_usr_df2.shape[0]
        print(bef-aft)
        preexp_usr_df2.uid.nunique()


        print("Removing users signed up after 2018-09-09 from postexp df:")
        bef = usr_postexp_dfnew.shape[0]
        usr_postexp_dfnew.uid.nunique()
        usr_postexp_final = usr_postexp_dfnew[usr_postexp_dfnew.signup_date<='2018-09-09']
        aft = usr_postexp_final.shape[0]
        print(bef-aft)
        usr_postexp_final.uid.nunique()

        print("Removing user activity older than 150 days before the start of experiment")
        preexp_usr_final = preexp_usr_df2[preexp_usr_df2.dt>='2018-09-09']
```

```
Removing users signed up after 2018-09-09 from preexp df:
```

```
Out[ ]: 50000
```

```
100947
```

```
Out[ ]: 36337
```

```
Removing users signed up after 2018-09-09 from postexp df:
```

```
Out[ ]: 46633
```

```
152041
```

Out[ ]: 35296

```
Removing user activity older than 150 days before the start of experiment
```

0.3.7 Thus, we see that we have eliminated around 13k+ users from pre-experiment dataframe who had signuped during our monitoring period. We have also done the same for our post experiment (or during experiment) dataframe. From the postexp df, we have removed around 11k around users.

0.3.8 This should now help us in comparing the pre & post experiment activity for our users better

0.3.9 Now, I am trying to have only those users in my t-test ready data who were present during both the pre-experiment and during experiment phase.

I had to debate a lot with myself about whether to include a)those user who were present in both pre & post experiment period or b)all those users who were present in either duration. After much thinking, I believe in first stage of analysis, I should focus on users present in both phases of experiment. Maybe in 2nd level of analysis, I can study those users who were present in pre-experiment period but not during experiment period and vice-versa.

I take this approach because since I have already filtered out users who had signed up 150 days before experiment, therefore there absolute absence in either the pre or during experiment phase is likely to be due to a cause unrelated to new UI design launched

In [ ]:
```
## Removing those users who had no activity registered during the pre-experiment phase
temp = preexp_usr_final[preexp_usr_final.dt.isna()]
temp = temp.drop_duplicates(subset=['uid'],keep='first')
preexp_usr_final.shape
preexp_usr_final = preexp_usr_final[~preexp_usr_final.uid.isin(temp.uid)]
preexp_usr_final.shape
```

Out[ ]: (923767, 8)

Out[ ]: (923767, 8)

In [ ]:
```
## Preparing user_ids
uids = preexp_usr_final.drop_duplicates(subset=['uid'],keep='first')
uids2 = usr_postexp_final.drop_duplicates(subset=['uid'],keep='first')
uids = pd.merge(uids,uids2, on='uid',how='inner')
uids.shape
print("Thus we see that we have 36k users for our study.")
```

Out[ ]: (35263, 15)

```
Thus we see that we have 36k users for our study.
```

0.3.10 Filtering out preexp and postexperiment data for above users only

```
In [ ]: lmtd_usr_postexp_df = usr_postexp_final[usr_postexp_final.uid.isin(uids.uid)]
        lmtd_preexp_usr_df = preexp_usr_final[preexp_usr_final.uid.isin(uids.uid)]
        print(lmtd_preexp_usr_df.shape,lmtd_usr_postexp_df.shape)
        lmtd_usr_postexp_df.head(2)
        lmtd_preexp_usr_df.head(2)
```

```
(916683, 8) (914047, 8)
```

```
Out[ ]:     uid  variant_number experiement_dt  ... active_mins gender  user_type
        13    1                0     2019-02-06  ...   79.000000   male     reader
        14    1                0     2019-02-06  ...  211.000000   male     reader

        [2 rows x 8 columns]
```

```
Out[ ]:     uid  variant_number experiement_dt  ... active_mins gender  user_type
        44    1                0     2019-02-06  ...  371.000000   male     reader
        45    1                0     2019-02-06  ...   70.000000   male     reader

        [2 rows x 8 columns]
```

Populating the above two df: preexp_usr_df2 & usr_postexp_dfnew2 for each user * 150 days of experiment. This will give us an apple-to-apply comparison, ie the daily acitve _min for each user for every single day when the experiment was live

```
In [ ]: daily_usr_act_prepost = lmtd_usr_postexp_df.pivot_table(index=['variant_number','uid',
                                                                'gender','user_type'],columns =
        daily_usr_act_prepost = daily_usr_act_prepost.melt(id_vars=['variant_number','uid','ex
                                                                'gender','user_type'], var_name=
        print("Post Exp Data: Before a& After reshaping the data at daily level:",lmtd_usr_pos
```

```
Post Exp Data: Before a& After reshaping the data at daily level: (914047, 8) (5289450, 8)
```

```
In [ ]: daily_usr_act_pre = lmtd_preexp_usr_df.pivot_table(index=['variant_number','uid','expe
                                                                'gender','user_type'],columns =
        daily_usr_act_pre = daily_usr_act_pre.melt(id_vars=['variant_number','uid','experiement
                                                                'gender','user_type'], var_name=
        print("Pre Exp Data:Before a& After reshaping the data at daily level:",lmtd_preexp_us
```

```
Pre Exp Data:Before a& After reshaping the data at daily level: (916683, 8) (5289450, 8)
```

```
In [ ]: #daily_usr_act.head()
        print("Before pre & post experiment analysis:")
        daily_usr_act.groupby(['variant_number'],as_index=False).active_mins.agg({'mean','std'
        print("After keeping users present in both phase + signup_dt<=2018-09-09 + dt>='2018-0
        daily_usr_act_prepost.groupby(['variant_number'],as_index=False).active_mins.agg({'mea
        print("Pre-experiment user activity for 0/1 variant number")
        daily_usr_act_pre.groupby(['variant_number'],as_index=False).active_mins.agg({'mean','
```

Before pre & post experiment analysis:

Out[ ]:

variant_number	median	var	mean	std	count
0	0	366.763169	3.054808	19.151062	5613750
1	0	444.027311	3.056017	21.071956	1381200

After keeping users present in both phase + signup_dt<=2018-09-09 + dt>='2018-09-09'

Out[ ]:

variant_number	median	var	mean	std	count
0	0	436.127385	3.597240	20.883663	4267500
1	0	527.369301	3.664980	22.964523	1021950

Pre-experiment user activity for 0/1 variant number

Out[ ]:

variant_number	median	var	mean	std	count
0	0	444.105545	3.567514	21.073812	4267500
1	0	185.709906	2.120730	13.627542	1021950

0.3.11 From the above grpah we see that compared with the pre-experiment activity, for the treatment group the average active_mins have improved significantly whereas for the control group, the average active_mins is similar. Let's see if this same result is validated from Welch test too!

```
In [ ]: mean_0_pp = daily_usr_act_prepost[daily_usr_act_prepost['variant_number']==0].active_mi
        mean_1_pp = daily_usr_act_prepost[daily_usr_act_prepost['variant_number']==1].active_mi

        std_0_pp = daily_usr_act_prepost[daily_usr_act_prepost['variant_number']==0].active_mi
        std_1_pp = daily_usr_act_prepost[daily_usr_act_prepost['variant_number']==1].active_mi

        nobs0_pp = daily_usr_act_prepost[daily_usr_act_prepost['variant_number']==0].active_mi
        nobs1_pp = daily_usr_act_prepost[daily_usr_act_prepost['variant_number']==1].active_mi
```

```
In [ ]: ttest_ind_from_stats(mean1=mean_1_pp,std1=std_1_pp,nobs1=nobs1_pp,
                             mean2=mean_0_pp,std2=std_0_pp,nobs2=nobs0_pp, equal_var=False)
```

```
Out[ ]: Ttest_indResult(statistic=2.7243687718351812, pvalue=0.0064425297082406855)
```

0.3.12 The p-value is now significant taking the alpha=0.05. We now have enough evidence to reject our null hypothesis. It seems that the new UI design has an impact over user enagagment.

0.3.13 Calculating Confidence Interval

```
In [ ]: CI = calc_CI(mean_1_pp,std_1_pp,nobs1_pp,mean_0_pp,std_0_pp,nobs0_pp,0.95)
        CI
```

```
Out[ ]: (0.01900648458041384, 0.11647323484016717)
```

```
In [ ]: daily_usr_act_prepost.head()
```

```
Out[ ]:    variant_number  uid experiement_dt  ...   user_type          dt active_mins
        0               0    1     2019-02-06  ...      reader  2019-02-06           0
        1               0    3     2019-02-06  ...  non_reader  2019-02-06           0
        2               0    4     2019-02-06  ...  non_reader  2019-02-06           0
        3               0    5     2019-02-06  ...  non_reader  2019-02-06           0
        4               0    6     2019-02-06  ...  non_reader  2019-02-06           0

        [5 rows x 8 columns]
```

0.3.14 Pre-Post Analysis with Covariates

Now we will be exploring the impact of new UI across two main covariates: gender and user_types. Here, we are interested to see if there had been significant change for any one group or not.

```
In [ ]: daily_usr_act_prepost.head()
        daily_usr_act_pre.head()
```

```
Out[ ]:    variant_number  uid experiement_dt  ...   user_type          dt active_mins
        0               0    1     2019-02-06  ...      reader  2019-02-06           0
        1               0    3     2019-02-06  ...  non_reader  2019-02-06           0
        2               0    4     2019-02-06  ...  non_reader  2019-02-06           0
        3               0    5     2019-02-06  ...  non_reader  2019-02-06           0
        4               0    6     2019-02-06  ...  non_reader  2019-02-06           0

        [5 rows x 8 columns]
```

```
Out[ ]:    variant_number  uid experiement_dt  ...   user_type          dt active_mins
        0               0    1     2019-02-06  ...      reader  2018-09-09         371
        1               0    3     2019-02-06  ...  non_reader  2018-09-09           0
        2               0    4     2019-02-06  ...  non_reader  2018-09-09           1
        3               0    5     2019-02-06  ...  non_reader  2018-09-09           0
        4               0    6     2019-02-06  ...  non_reader  2018-09-09           0

        [5 rows x 8 columns]
```

```
In [ ]: ## Merging both the pre & post dataset to have two main df with vairant number's activ
        temp1 = daily_usr_act_prepost[daily_usr_act_prepost.variant_number==1]
        temp2 = daily_usr_act_pre[daily_usr_act_pre.variant_number==1]
        daily_usr_1 = pd.concat([temp1,temp2],ignore_index=True)

        daily_usr_1.head(2)
        del temp1
        del temp2
```

```
check10 = daily_usr_act_prepost[daily_usr_act_prepost.variant_number==0]
check20 = daily_usr_act_pre[daily_usr_act_pre.variant_number==0]
daily_usr_0 = pd.concat([check10,check20],ignore_index=True)

del check10
del check20
```

Out[ ]:

	variant_number	uid	experiement_dt	...	user_type	dt	active_mins
0	1	40001	2019-02-06	...	non_reader	2019-02-06	0
1	1	40002	2019-02-06	...	non_reader	2019-02-06	0

[2 rows x 8 columns]

0.3.15 Checking if the distribution of users across gender and user_types is balanced or not!

In [ ]:
```
temp = pd.merge(t2_usr_variant,t4_usr_attributes,on="uid",how="left")
print(t2_usr_variant.shape[0], t4_usr_attributes.shape[0], temp.shape[0])
temp.groupby(['variant_number','gender'],as_index=False).agg({'uid':'count'})
```

```
50000 50000 50000
```

Out[ ]:

	variant_number	gender	uid
0	0	female	11607
1	0	male	22237
2	0	unknown	6156
3	1	female	2870
4	1	male	5520
5	1	unknown	1610

0.3.16 Thus we see that though the distribution of male-female users are same in both variant group the male users are more prominant than the female users

0.3.17 Gender-wise active_mins spent pre & post the new UI launch

In [ ]:
```
print("Before the Experiment:")
daily_usr_act_pre.groupby(['variant_number','gender'],as_index=False).active_mins.agg(

print("After the Experiment:")
daily_usr_act_prepost.groupby(['variant_number','gender'],as_index=False).active_mins.a
```

```
Before the Experiment:
```

Out[ ]:

		mean	median	std	count
variant_number	gender				
0	female	2.821831	0	18.242764	1176300
	male	4.106219	0	22.868391	2491800
	unknown	2.791405	0	18.215894	599400

```
        1              female  1.652412       0 10.456504   274650
                       male    2.369502       0 14.972533   597750
                       unknown 1.986459       0 13.097676   149550
```

After the Experiment:

Out[ ]:
```
                                 mean  median       std    count
        variant_number gender
        0              female  2.775077       0 17.458284  1176300
                       male    4.247247       0 23.219596  2491800
                       unknown 2.508522       0 16.165456   599400
        1              female  2.733810       0 17.665349   274650
                       male    4.202844       0 25.561195   597750
                       unknown 3.225242       0 20.400976   149550
```

In [ ]:
```
plt.figure(figsize=(18,8))
plt.subplot(2,1,1)
plt.title('Average time spent by gender - Variant Group',loc='left', fontsize=15)
data=daily_usr_1.groupby(['gender','dt'],as_index=False).active_mins.mean()
sns.lineplot(data=data,x='dt',y='active_mins',hue='gender')
plt.axvline(x = daily_usr_1.experiement_dt.max(), color = 'red')
plt.text(x = daily_usr_1.experiement_dt.max(),y=1,s ='experiment', fontsize =15)
plt.subplot(2,1,2)
plt.title('Average time spent by gender - Control Group',loc='left',fontsize=15)
data=daily_usr_0.groupby(['gender','dt'],as_index=False).active_mins.mean()
sns.lineplot(data=data,x='dt',y='active_mins',hue='gender')
plt.axvline(x = daily_usr_0.experiement_dt.max(), color = 'red')
plt.text(x = daily_usr_0.experiement_dt.max(),y=2,s ='experiment', fontsize =15)
plt.savefig("Time Series Analysis for Average time spent by gender")
```

Out[ ]: <Figure size 1296x576 with 0 Axes>

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4bab29f4e0>

Out[ ]: Text(0.0, 1.0, 'Average time spent by gender - Variant Group')

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4bab29f4e0>

Out[ ]: <matplotlib.lines.Line2D at 0x7f4baad395f8>

Out[ ]: Text(2019-02-06, 1, 'experiment')

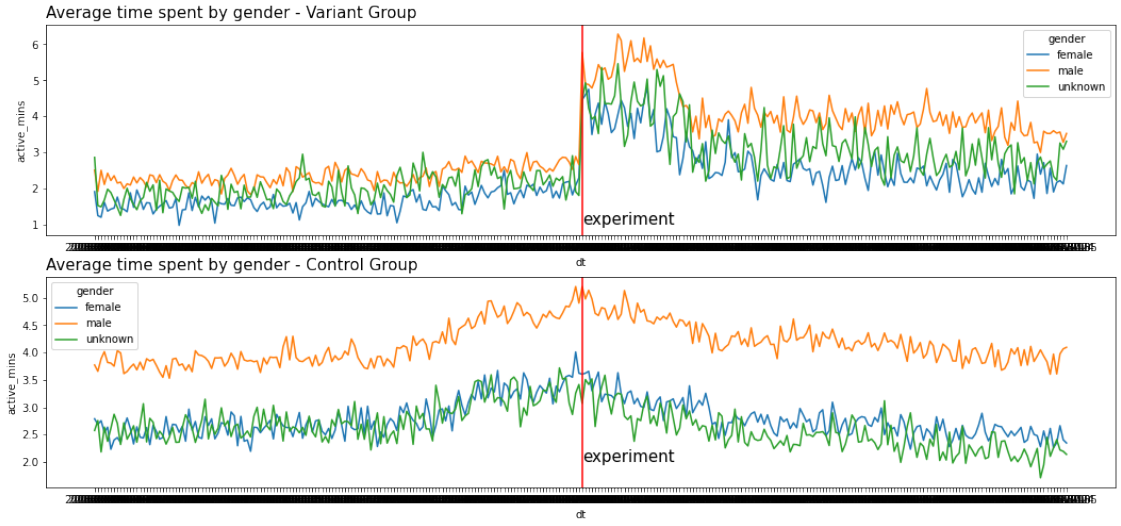
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4baa656eb8>

Out[ ]: Text(0.0, 1.0, 'Average time spent by gender - Control Group')

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4baa656eb8>

Out[ ]: <matplotlib.lines.Line2D at 0x7f4baa8e2828>

Out[ ]: Text(2019-02-06, 2, 'experiment')



Thus we see from above graph that for variant group=1 or Treatment group there is significant improvement in average acitve minutes. Also, comparing within the genders, we see male members have a higher activity in comparison their female counterparts. In control group there is not much change in acitivity.

1 Checking if the distribution of users across user_types is balanced or not!ű

In [ ]:
```
temp = pd.merge(t2_usr_variant,t4_usr_attributes,on="uid",how="left")
print(t2_usr_variant.shape[0], t4_usr_attributes.shape[0], temp.shape[0])
temp.groupby(['variant_number','user_type'],as_index=False).agg({'uid':'count'})
```

```
50000 50000 50000
```

Out[ ]:

	variant_number	user_type	uid
0	0	contributor	915
1	0	new_user	3653
2	0	non_reader	28699
3	0	reader	6733
4	1	contributor	129
5	1	new_user	1235
6	1	non_reader	7367
7	1	reader	1269

1.0.1 Thus we see that though the distribution of reader, non-reader & contributor users are same in both variant group there is a high proportion of non-reader users in the control & treatment groups. Given that the aim was to increase user engagement amongst all types of users, therefore the distribution should have been balanced. But having said so, I am also wondering if there was some critical changes introduced in new UI meant for converting non-reader users to other types. This information will be probably more useful.

In [ ]:
```
print("Before the Experiment:")
daily_usr_act_pre.groupby(['variant_number','user_type'],as_index=False).active_mins.ag

print("After the Experiment:")
daily_usr_act_prepost.groupby(['variant_number','user_type'],as_index=False).active_mi
```

```
Before the Experiment:
```

Out[ ]:

variant_number	user_type	mean	median	std	count
0	contributor	31.377330	0	78.160294	118350
	non_reader	0.679109	0	4.643202	3279300
	reader	10.672939	0	32.850768	869850
1	contributor	20.423425	0	59.951643	16350
	non_reader	0.632386	0	3.987967	838950
	reader	7.817684	0	25.093694	166650

```
After the Experiment:
```

Out[ ]:

variant_number	user_type	mean	median	std	count
0	contributor	30.591390	0	75.813302	118350
	non_reader	0.746917	0	5.362558	3279300
	reader	10.670074	0	32.702177	869850
1	contributor	31.027951	0	87.315865	16350
	non_reader	1.164220	0	8.378647	838950
	reader	13.569739	0	43.927194	166650

In [ ]:
```
plt.figure(figsize=(18,8))
plt.subplot(2,1,1)
plt.title('Average time spent by user_type - Variant Group',loc='left', fontsize=15)
data=daily_usr_1.groupby(['user_type','dt'],as_index=False).active_mins.mean()
sns.lineplot(data=data,x='dt',y='active_mins',hue='user_type')
#plt.xticks(np.arange(daily_usr_1.dt.min(),daily_usr_1.dt.max(),30))
plt.axvline(x = daily_usr_1.experiement_dt.max(), color = 'red')
plt.text(x = daily_usr_1.experiement_dt.max(),y=1,s ='experiment', fontsize =15)
plt.subplot(2,1,2)
plt.title('Average time spent by user_type - Control Group',loc='left',fontsize=15)
data=daily_usr_0.groupby(['user_type','dt'],as_index=False).active_mins.mean()
```

```
        sns.lineplot(data=data,x='dt',y='active_mins',hue='user_type')
        plt.axvline(x = daily_usr_0.experiement_dt.max(), color = 'red')
        plt.text(x = daily_usr_0.experiement_dt.max(),y=2,s ='experiment', fontsize =15)
        plt.savefig("Time Series Analysis for Average time spent by user_type")
```

```
Out[ ]: <Figure size 1296x576 with 0 Axes>
```

```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4bad5bf0f0>
```

```
Out[ ]: Text(0.0, 1.0, 'Average time spent by user_type - Variant Group')
```

```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4bad5bf0f0>
```

```
Out[ ]: <matplotlib.lines.Line2D at 0x7f4bab4bb6a0>
```

```
Out[ ]: Text(2019-02-06, 1, 'experiment')
```

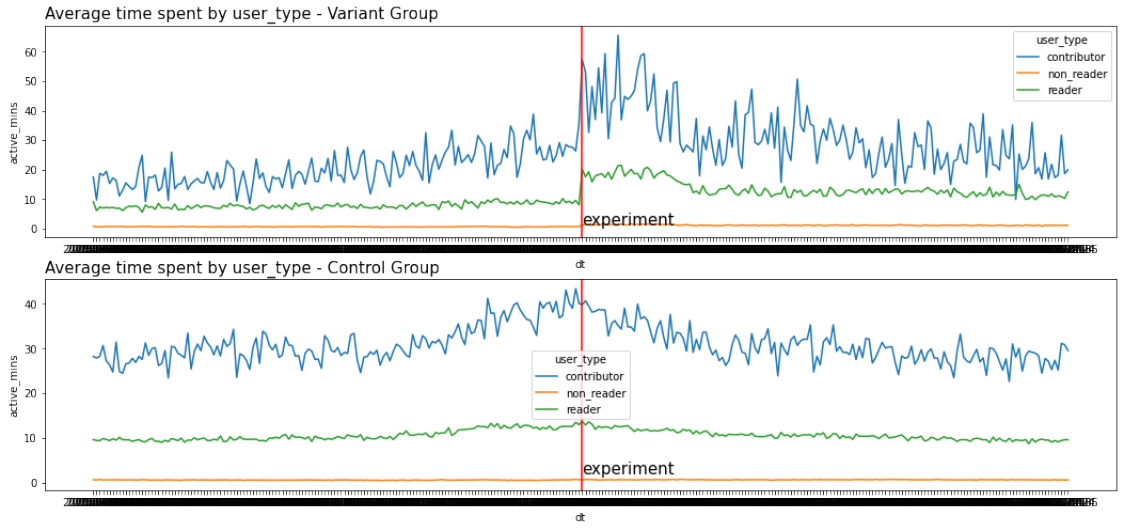
```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4baacff208>
```

```
Out[ ]: Text(0.0, 1.0, 'Average time spent by user_type - Control Group')
```

```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4baacff208>
```

```
Out[ ]: <matplotlib.lines.Line2D at 0x7f4bab33e3c8>
```

```
Out[ ]: Text(2019-02-06, 2, 'experiment')
```



1.1 Performing Co-variates test

1.1.1 Gender

```
In [ ]: gender = ['male','female','unknown']
        for user in gender:
            print(user)
            mean_0_pp = daily_usr_0[daily_usr_0['gender']==user].active_mins.mean()
            mean_1_pp = daily_usr_1[daily_usr_1['gender']==user].active_mins.mean()

            std_0_pp = daily_usr_0[daily_usr_0['gender']==user].active_mins.std()
            std_1_pp = daily_usr_1[daily_usr_1['gender']==user].active_mins.std()

            nobs0_pp = daily_usr_0[daily_usr_0['gender']==user].active_mins.count()
            nobs1_pp = daily_usr_1[daily_usr_1['gender']==user].active_mins.count()

            print('T-results for user type-',user)
            print(ttest_ind_from_stats(mean1=mean_1_pp,std1=std_1_pp,nobs1=nobs1_pp,
                            mean2=mean_0_pp,std2=std_0_pp,nobs2=nobs0_pp, equal_var=False))
```

```
male
T-results for user type- male
Ttest_indResult(statistic=-40.89238052193022, pvalue=0.0)
female
T-results for user type- female
Ttest_indResult(statistic=-26.555714805327135, pvalue=2.506335129311254e-155)
unknown
T-results for user type- unknown
Ttest_indResult(statistic=-1.2571698339802369, pvalue=0.2086927807651504)
```

1.1.2 User_Type

```
In [ ]: user_type = ['non_reader','contributor','reader']
        for user in user_type:
            print(user)

            mean_0_pp = daily_usr_0[daily_usr_0['user_type']==user].active_mins.mean()
            mean_1_pp = daily_usr_1[daily_usr_1['user_type']==user].active_mins.mean()

            std_0_pp = daily_usr_0[daily_usr_0['user_type']==user].active_mins.std()
            std_1_pp = daily_usr_1[daily_usr_1['user_type']==user].active_mins.std()

            nobs0_pp = daily_usr_0[daily_usr_0['user_type']==user].active_mins.count()
            nobs1_pp = daily_usr_1[daily_usr_1['user_type']==user].active_mins.count()

            print('T-results for user type-',user)
            print(ttest_ind_from_stats(mean1=mean_1_pp,std1=std_1_pp,nobs1=nobs1_pp,
                            mean2=mean_0_pp,std2=std_0_pp,nobs2=nobs0_pp, equal_var=False))
```

```
contributor
T-results for user type- contributor
Ttest_indResult(statistic=-11.834916226870043, pvalue=2.8930249870937706e-32)
reader
T-results for user type- reader
Ttest_indResult(statistic=0.3316864679767433, pvalue=0.7401261755642135)
non_reader
T-results for user type- non_reader
Ttest_indResult(statistic=34.09324557971776, pvalue=1.0829136072296474e-254)
```