Data Challenge 2: Yammer

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Problem

The number of weekly active users increased more than 100% between the beginning of May and the end of July, with only a few time periods showing even mild decreases. However, weekly active users decreased rougly 18% between the beginning and end of August, with the largest decrease occurring in the first week of August. What happened?

Hypotheses and Results

Hypothesis 1: Something happened in the account creation process that reduced conversion from pending to active.

Results: The rate of conversion from user creation to completing signup were similar in August as compared to May/June/July (52% vs. 50%), and the rate of attrition was similar at each step. The user activation funnel does not appear to be suffering from any new barriers to user activation.

Hypothesis 2: There is a drop in a particular type of user-driven engagement and, as a result, overall engagement has decreased.

Results: Even though overall user-driven engagements are down in August, the relative frequency of each type of engagement is remarkably consistent (less than 1% difference in each category), indicating that once users are on Yammer there is no signficant difference in their behavior.

Bottom line: I was unable to find any explanatory patterns for the decrease in customer engagement. With additional time, I would explore whether there are particular locations or companies where employee engagement is particularly sufferring and whether there has been a significant decrease in any particular types of Yammer-generated engagement events.

Takeaway: I should have invested in more EDA up front. I thought I was taking the right approach by starting with hypotheses, but I neglected to base the hypothesis on EDA and therefore wasted a significant amount of time. As a result, I was unable to reach a useful conclusion in the time given. My goal for this weekend is to increase my skills in EDA in Python so that I can explore datasets more quickly and efficiently.

Analysis

Hypothesis 1: Something happened in the account creation process that reduced conversion

from pending to active.

Approach: Split the dataset into before and after August 1, and use population pyramid to visualize the account creation/activation funnel with the goal of determining whether a problem occurred in August that is reducing the number of account activation and, if so, at what point in the process that problem occurred.

Method: Read in 'Events' yammer_events.csv dataset. Create a dummy variable that identifies whether an event occurred on or after August 1 (aug_event where 1 Yes, 0 No). *(Note that this does not identify cases where user authentification began in June or July but was completed in August, but should still include a reasonable approximation of the process since edge cases on either end are also included.)* Select only events that occur in the user authentication process (event_type == signup_flow). Visualize user authentication funnel (create_user, enter_email, enter_info, complete_signup) comparing before August to August using a population pyramid. If no bottleneck is visible, merge in user authentication date from 'Users' yammer_users.csv as new rows to check the number of activations (activated_at).

In [2]:
```
# Import likely packages
import pandas as pd
import matplotlib.pylab as plt
import numpy as np
%matplotlib inline
from sklearn.linear_model import LinearRegression
import seaborn as sns
```

In [3]:
```
# Read in 'Events' yammer_events.csv and look at data structure of first few rows
events = pd.read_csv('yammer_events.csv')
events.head()
```

Out[3]:

	user_id	occurred_at	event_type	event_name	location	device	user_type
0	10522.0	2014-05-02 11:02:39	engagement	login	Japan	dell inspiron notebook	3.0
1	10522.0	2014-05-02 11:02:53	engagement	home_page	Japan	dell inspiron notebook	3.0
2	10522.0	2014-05-02 11:03:28	engagement	like_message	Japan	dell inspiron notebook	3.0
3	10522.0	2014-05-02 11:04:09	engagement	view_inbox	Japan	dell inspiron notebook	3.0
4	10522.0	2014-05-02 11:03:16	engagement	search_run	Japan	dell inspiron notebook	3.0

In [4]:
```
events.shape
```

Out[4]:
```
(340832, 7)
```

In [5]:
```
# Create a dummy variable that identifies whether an event occurred
# on or after August 1 (aug_event where 1 Yes, 0 No).
events['in_august'] = 0
events['in_august'] = np.where((pd.to_datetime(pd.Series(events['occurred_at'])))
events.head()
```

Out[5]:

	user_id	occurred_at	event_type	event_name	location	device	user_type	in_august
0	10522.0	2014-05-02 11:02:39	engagement	login	Japan	dell inspiron notebook	3.0	0
1	10522.0	2014-05-02 11:02:53	engagement	home_page	Japan	dell inspiron notebook	3.0	0
2	10522.0	2014-05-02 11:03:28	engagement	like_message	Japan	dell inspiron notebook	3.0	0
3	10522.0	2014-05-02 11:04:09	engagement	view_inbox	Japan	dell inspiron notebook	3.0	0
4	10522.0	2014-05-02 11:03:16	engagement	search_run	Japan	dell inspiron notebook	3.0	0

In [6]:
```
events.tail()
```

Out[6]:

	user_id	occurred_at	event_type	event_name	location	device	user_type	in_august
340827	18815.0	2014-08-31 13:41:46	engagement	like_message	Ireland	dell inspiron notebook	2.0	1
340828	18815.0	2014-08-31 13:42:11	engagement	home_page	Ireland	dell inspiron notebook	2.0	1
340829	18815.0	2014-08-31 13:42:43	engagement	send_message	Ireland	dell inspiron notebook	2.0	1
340830	18815.0	2014-08-31 13:43:07	engagement	home_page	Ireland	dell inspiron notebook	2.0	1
340831	18815.0	2014-08-31 13:43:42	engagement	like_message	Ireland	dell inspiron notebook	2.0	1

In [7]:
```
events.shape
```

Out[7]:
```
(340832, 8)
```

In [8]:
```
# Select only events that occur in the user authentication process (event_type ==
auth_process = events[events.event_type == 'signup_flow']
auth_process.head()
```

Out[8]:

	user_id	occurred_at	event_type	event_name	location	device	user_type	in_august
391	11768.0	2014-05-01 08:01:36	signup_flow	create_user	France	macbook pro	NaN	0
392	11768.0	2014-05-01 08:02:06	signup_flow	enter_email	France	macbook pro	NaN	0
393	11768.0	2014-05-01 08:02:39	signup_flow	enter_info	France	macbook pro	NaN	0
394	11768.0	2014-05-01 08:03:12	signup_flow	complete_signup	France	macbook pro	3.0	0
401	11769.0	2014-05-01 02:37:43	signup_flow	create_user	United Kingdom	lenovo thinkpad	NaN	0

In [9]:
```
auth_process.tail()
```

Out[9]:

	user_id	occurred_at	event_type	event_name	location	device	user_type	in_august
51569	19063.0	2014-08-31 07:11:11	signup_flow	enter_email	Brazil	ipad mini	NaN	1
51570	19063.0	2014-08-31 07:11:40	signup_flow	enter_info	Brazil	ipad mini	NaN	1
51571	19063.0	2014-08-31 07:12:09	signup_flow	complete_signup	Brazil	ipad mini	3.0	1
51580	19064.0	2014-08-31 17:45:18	signup_flow	create_user	United States	iphone 5s	NaN	1
51581	19065.0	2014-08-31 19:29:19	signup_flow	create_user	Italy	lenovo thinkpad	NaN	1

In [10]:
```
auth_process.shape
```

Out[10]: (19257, 8)

In [11]:
```
funnel_data = auth_process.groupby(['in_august','event_name'], as_index=False).co
```

In [12]:
```
funnel_data
```

Out[12]:

	in_august	event_name	user_id	occurred_at	event_type	location	device	user_type
0	0	complete_signup	2649	2649	2649	2649	2649	2649
1	0	create_user	5308	5308	5308	5308	5308	0
2	0	enter_email	3211	3211	3211	3211	3211	0
3	0	enter_info	2793	2793	2793	2793	2793	0
4	1	complete_signup	1031	1031	1031	1031	1031	1031
5	1	create_user	1990	1990	1990	1990	1990	0
6	1	enter_email	1196	1196	1196	1196	1196	0
7	1	enter_info	1079	1079	1079	1079	1079	0

In [13]:
```
funnel_data = funnel_data.sort_values(['user_id'], ascending = False)
```

In [14]:
```
funnel_data
```

Out[14]:

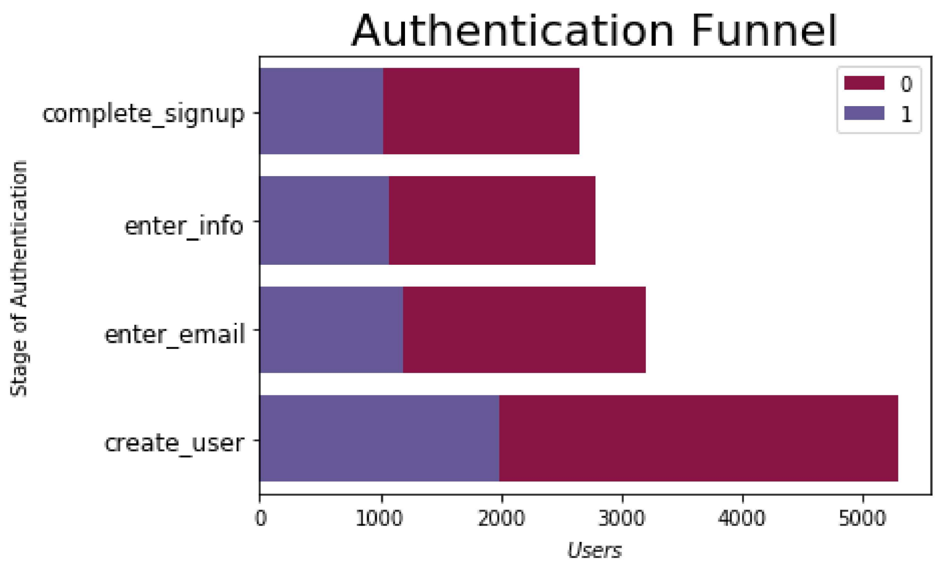
	in_august	event_name	user_id	occurred_at	event_type	location	device	user_type
1	0	create_user	5308	5308	5308	5308	5308	0
2	0	enter_email	3211	3211	3211	3211	3211	0
3	0	enter_info	2793	2793	2793	2793	2793	0
0	0	complete_signup	2649	2649	2649	2649	2649	2649
5	1	create_user	1990	1990	1990	1990	1990	0
6	1	enter_email	1196	1196	1196	1196	1196	0
7	1	enter_info	1079	1079	1079	1079	1079	0
4	1	complete_signup	1031	1031	1031	1031	1031	1031

In [66]:
```
# Visualize user authentication funnel: create_user, enter_email, enter_info, com
# Draw Plot
plt.figure(figsize=(13,10), dpi= 80)
group_col = 'in_august'
order_of_bars = funnel_data.event_name.unique()[::-1]
colors = [plt.cm.Spectral(i/float(len(funnel_data[group_col].unique())-1)) for i
```

```
<Figure size 1040x800 with 0 Axes>
```

In [67]:
```
for c, group in zip(colors, funnel_data[group_col].unique()):
    sns.barplot(x='user_id', y='event_name', data=funnel_data.loc[funnel_data[gro

# Decorations
plt.xlabel("$Users$")
plt.ylabel("Stage of Authentication")
plt.yticks(fontsize=12)
plt.title("Authentication Funnel", fontsize=22)
plt.legend()
plt.show()
```



The rate of conversion from user creation to completing signup were similar in August as compared to May/June/July (52% vs. 50%), and the rate of attrition was similar at each step, so the next step will be checking whether there was a significant dropoff in activation in August as compared to May/June/July.

Add activation into dataset

In [20]:
```
# Read in 'Events' yammer_events.csv and look at data structure of first few rows
users = pd.read_csv('yammer_users.csv')
users.head()
```

Out[20]:

	user_id	created_at	company_id	language	activated_at	state
0	0.0	2013-01-01 20:59:39	5737.0	english	2013-01-01 21:01:07	active
1	1.0	2013-01-01 13:07:46	28.0	english	NaN	pending
2	2.0	2013-01-01 10:59:05	51.0	english	NaN	pending
3	3.0	2013-01-01 18:40:36	2800.0	german	2013-01-01 18:42:02	active
4	4.0	2013-01-01 14:37:51	5110.0	indian	2013-01-01 14:39:05	active

In [25]:
```
# Create a dummy variable that identifies whether an event occurred on or after
# August 1 (aug_event where 1 Yes, 0 No)
users['in_august'] = 0
users['in_august'] = np.where((pd.to_datetime(pd.Series(users['activated_at']))
users.head()
```

Out[25]:

	user_id	created_at	company_id	language	activated_at	state	in_august
0	0.0	2013-01-01 20:59:39	5737.0	english	2013-01-01 21:01:07	active	0
1	1.0	2013-01-01 13:07:46	28.0	english	NaN	pending	0
2	2.0	2013-01-01 10:59:05	51.0	english	NaN	pending	0
3	3.0	2013-01-01 18:40:36	2800.0	german	2013-01-01 18:42:02	active	0
4	4.0	2013-01-01 14:37:51	5110.0	indian	2013-01-01 14:39:05	active	0

In [26]:
```
users.tail()
```

Out[26]:

	user_id	created_at	company_id	language	activated_at	state	in_august
19061	19061.0	2014-08-31 13:21:16	2156.0	chinese	2014-08-31 13:22:50	active	1
19062	19062.0	2014-08-31 19:21:23	7520.0	spanish	NaN	pending	0
19063	19063.0	2014-08-31 07:10:41	72.0	spanish	2014-08-31 07:12:09	active	1
19064	19064.0	2014-08-31 17:45:18	2.0	english	NaN	pending	0
19065	19065.0	2014-08-31 19:29:19	8352.0	italian	NaN	pending	0

In [27]:
```
# Create a dummy variable that identifies whether an event occurred before
# May 1 (before where 1 Yes, 0 No)
users['before'] = 0
users['before'] = np.where((pd.to_datetime(pd.Series(users['activated_at']))) < (
users.head()
```

Out[27]:

	user_id	created_at	company_id	language	activated_at	state	in_august	before
0	0.0	2013-01-01 20:59:39	5737.0	english	2013-01-01 21:01:07	active	0	1
1	1.0	2013-01-01 13:07:46	28.0	english	NaN	pending	0	0
2	2.0	2013-01-01 10:59:05	51.0	english	NaN	pending	0	0
3	3.0	2013-01-01 18:40:36	2800.0	german	2013-01-01 18:42:02	active	0	1
4	4.0	2013-01-01 14:37:51	5110.0	indian	2013-01-01 14:39:05	active	0	1

In [28]:
```
users.shape
```

Out[28]: (19066, 8)

In [35]:
```
# Drop users that activated before May 1
new_users = users[users.before == 0]
new_users.shape
```

Out[35]: (13365, 8)

In [36]:
```
# Select only active users
active_users = new_users[new_users.state == 'active']
active_users.head()
```

Out[36]:

	user_id	created_at	company_id	language	activated_at	state	in_august	before
11768	11768.0	2014-05-01 08:01:36	8099.0	french	2014-05-01 08:03:12	active	0	0
11770	11770.0	2014-05-01 06:07:24	7847.0	japanese	2014-05-01 06:08:50	active	0	0
11775	11775.0	2014-05-01 16:36:49	5545.0	english	2014-05-01 16:38:06	active	0	0
11778	11778.0	2014-05-01 18:48:21	3059.0	english	2014-05-01 18:49:49	active	0	0
11779	11779.0	2014-05-01 18:23:21	10905.0	german	2014-05-01 18:24:54	active	0	0

In [37]:
```
active_users.tail()
```

Out[37]:

	user_id	created_at	company_id	language	activated_at	state	in_august	before
19056	19056.0	2014-08-31 16:35:29	1234.0	english	2014-08-31 16:36:56	active	1	0
19059	19059.0	2014-08-31 19:51:59	6817.0	indian	2014-08-31 19:53:43	active	1	0
19060	19060.0	2014-08-31 12:19:23	1439.0	japanese	2014-08-31 12:20:48	active	1	0
19061	19061.0	2014-08-31 13:21:16	2156.0	chinese	2014-08-31 13:22:50	active	1	0
19063	19063.0	2014-08-31 07:10:41	72.0	spanish	2014-08-31 07:12:09	active	1	0

In [38]:
```
active_users.shape
```

Out[38]:
```
(3680, 8)
```

In [43]:
```
# Drop unneeded columns
active_users.columns.values
```

Out[43]:
```
array(['user_id', 'created_at', 'company_id', 'language', 'activated_at',
       'state', 'in_august', 'before'], dtype=object)
```

In [48]:
```
mask = ['user_id','in_august']
filtered_active_users = active_users[mask]
```

In [49]:
```
filtered_active_users.head()
```

Out[49]:

	user_id	in_august
11768	11768.0	0
11770	11770.0	0
11775	11775.0	0
11778	11778.0	0
11779	11779.0	0

In [50]:
```
filtered_active_users.tail()
```

Out[50]:

	user_id	in_august
19056	19056.0	1
19059	19059.0	1
19060	19060.0	1
19061	19061.0	1
19063	19063.0	1

In [52]:
```
activate = filtered_active_users.groupby('in_august', as_index = False).count()
activate
```

Out[52]:

	in_august	user_id
0	0	2649
1	1	1031

In [57]:
```
# Create new variable event_name = activate_user
activate['event_name'] = 'activate_user'
activate
```

Out[57]:

	in_august	user_id	event_name
0	0	2649	activate_user
1	1	1031	activate_user

Apparently, complete_signup is equivalent to activation, so adding an activation level based on the activation date and time didn't add any additional information. There did not appear to be any significant difference in the user authentication funnel between August and May-June, so a problem in the user authentication process is unlikely to be the issue.

Note: I realized at this point that some additional EDA might have kept me from spending too much time going down this road; for example, a simple line graph representing the number of new users over time would have shown me that there were no significant decreases in account creation.

Hypothesis 2: There is a drop in a particular type of user-driven engagement and, as a result, overall engagement has decreased.

Approach: Split the dataset into before and after August 1 and compare the distribution of engagement activities in each time period.

Method: Read in 'Events' yammer_events.csv dataset. Create a dummy variable that identifies whether an event occurred on or after August 1 (aug_event where 1 Yes, 0 No). *(Note that this does* *not identify cases where user authentification began in June or July but was completed in August, but should still include a reasonable approximation of the process since edge cases on either end are also included.)* Select only engagement events (event_type == engagement). Compare the distribution of engagement activities (home_page, like_message, login, search_autocomplete, search_run, search_click_result_X, send_message, view_inbox) comparing before August to August.

In [59]:
```
# Read in 'Events' yammer_events.csv and look at data structure of first few rows
events = pd.read_csv('yammer_events.csv')
events.head()
```

Out[59]:

	user_id	occurred_at	event_type	event_name	location	device	user_type
0	10522.0	2014-05-02 11:02:39	engagement	login	Japan	dell inspiron notebook	3.0
1	10522.0	2014-05-02 11:02:53	engagement	home_page	Japan	dell inspiron notebook	3.0
2	10522.0	2014-05-02 11:03:28	engagement	like_message	Japan	dell inspiron notebook	3.0
3	10522.0	2014-05-02 11:04:09	engagement	view_inbox	Japan	dell inspiron notebook	3.0
4	10522.0	2014-05-02 11:03:16	engagement	search_run	Japan	dell inspiron notebook	3.0

In [61]:
```
# Create a dummy variable that identifies whether an event occurred on or after
# August 1 (aug_event where 1 Yes, 0 No)
# Note that this dataset does not include events that occurred before May 1 (othe
# So there is no need to filter out old events
events['in_august'] = 0
events['in_august'] = np.where((pd.to_datetime(pd.Series(events['occurred_at'])))
events.head()
```

Out[61]:

	user_id	occurred_at	event_type	event_name	location	device	user_type	in_august
0	10522.0	2014-05-02 11:02:39	engagement	login	Japan	dell inspiron notebook	3.0	0
1	10522.0	2014-05-02 11:02:53	engagement	home_page	Japan	dell inspiron notebook	3.0	0
2	10522.0	2014-05-02 11:03:28	engagement	like_message	Japan	dell inspiron notebook	3.0	0
3	10522.0	2014-05-02 11:04:09	engagement	view_inbox	Japan	dell inspiron notebook	3.0	0
4	10522.0	2014-05-02 11:03:16	engagement	search_run	Japan	dell inspiron notebook	3.0	0

In [62]:
```
events.tail()
```

Out[62]:

	user_id	occurred_at	event_type	event_name	location	device	user_type	in_august
340827	18815.0	2014-08-31 13:41:46	engagement	like_message	Ireland	dell inspiron notebook	2.0	1
340828	18815.0	2014-08-31 13:42:11	engagement	home_page	Ireland	dell inspiron notebook	2.0	1
340829	18815.0	2014-08-31 13:42:43	engagement	send_message	Ireland	dell inspiron notebook	2.0	1
340830	18815.0	2014-08-31 13:43:07	engagement	home_page	Ireland	dell inspiron notebook	2.0	1
340831	18815.0	2014-08-31 13:43:42	engagement	like_message	Ireland	dell inspiron notebook	2.0	1

In [63]:
```
# Select only events user engagement process (event_type == engagement).
engagement = events[events.event_type == 'engagement']
engagement.head()
```

Out[63]:

	user_id	occurred_at	event_type	event_name	location	device	user_type	in_august
0	10522.0	2014-05-02 11:02:39	engagement	login	Japan	dell inspiron notebook	3.0	0
1	10522.0	2014-05-02 11:02:53	engagement	home_page	Japan	dell inspiron notebook	3.0	0
2	10522.0	2014-05-02 11:03:28	engagement	like_message	Japan	dell inspiron notebook	3.0	0
3	10522.0	2014-05-02 11:04:09	engagement	view_inbox	Japan	dell inspiron notebook	3.0	0
4	10522.0	2014-05-02 11:03:16	engagement	search_run	Japan	dell inspiron notebook	3.0	0

In [71]:
```
# Group data to compare August vs other
engagement_data = engagement.groupby(['in_august','event_name'], as_index=False).
```

In [72]:
```
engagement_data
```

Out[72]:

	in_august	event_name	user_id	occurred_at	event_type	location	device	user_type
0	0	home_page	72462	72462	72462	72462	72462	72462
1	0	like_message	45916	45916	45916	45916	45916	45916
2	0	login	29339	29339	29339	29339	29339	29339
3	0	search_autocomplete	13351	13351	13351	13351	13351	13351
4	0	search_click_result_1	1139	1139	1139	1139	1139	1139
5	0	search_click_result_10	403	403	403	403	403	403
6	0	search_click_result_2	1203	1203	1203	1203	1203	1203
7	0	search_click_result_3	899	899	899	899	899	899
8	0	search_click_result_4	1007	1007	1007	1007	1007	1007
9	0	search_click_result_5	786	786	786	786	786	786
10	0	search_click_result_6	635	635	635	635	635	635
11	0	search_click_result_7	556	556	556	556	556	556
12	0	search_click_result_8	555	555	555	555	555	555
13	0	search_click_result_9	642	642	642	642	642	642
14	0	search_run	10183	10183	10183	10183	10183	10183
15	0	send_message	25781	25781	25781	25781	25781	25781
16	0	view_inbox	42925	42925	42925	42925	42925	42925
17	1	home_page	21603	21603	21603	21603	21603	21603
18	1	like_message	13332	13332	13332	13332	13332	13332
19	1	login	9271	9271	9271	9271	9271	9271
20	1	search_autocomplete	4469	4469	4469	4469	4469	4469
21	1	search_click_result_1	274	274	274	274	274	274
22	1	search_click_result_10	103	103	103	103	103	103
23	1	search_click_result_2	296	296	296	296	296	296
24	1	search_click_result_3	235	235	235	235	235	235
25	1	search_click_result_4	257	257	257	257	257	257
26	1	search_click_result_5	182	182	182	182	182	182
27	1	search_click_result_6	170	170	170	170	170	170
28	1	search_click_result_7	153	153	153	153	153	153
29	1	search_click_result_8	135	135	135	135	135	135
30	1	search_click_result_9	142	142	142	142	142	142
31	1	search_run	2836	2836	2836	2836	2836	2836
32	1	send_message	7324	7324	7324	7324	7324	7324
33	1	view_inbox	13011	13011	13011	13011	13011	13011

In [78]:

```
engagement_data = engagement_data.sort_values(['in_august', 'event_name'], ascend
```

```
In [79]: engagement_data
```

Out[79]:

	in_august	event_name	user_id	occurred_at	event_type	location	device	user_type
33	1	view_inbox	13011	13011	13011	13011	13011	13011
32	1	send_message	7324	7324	7324	7324	7324	7324
31	1	search_run	2836	2836	2836	2836	2836	2836
30	1	search_click_result_9	142	142	142	142	142	142
29	1	search_click_result_8	135	135	135	135	135	135
28	1	search_click_result_7	153	153	153	153	153	153
27	1	search_click_result_6	170	170	170	170	170	170
26	1	search_click_result_5	182	182	182	182	182	182
25	1	search_click_result_4	257	257	257	257	257	257
24	1	search_click_result_3	235	235	235	235	235	235
23	1	search_click_result_2	296	296	296	296	296	296
22	1	search_click_result_10	103	103	103	103	103	103
21	1	search_click_result_1	274	274	274	274	274	274
20	1	search_autocomplete	4469	4469	4469	4469	4469	4469
19	1	login	9271	9271	9271	9271	9271	9271
18	1	like_message	13332	13332	13332	13332	13332	13332
17	1	home_page	21603	21603	21603	21603	21603	21603
16	0	view_inbox	42925	42925	42925	42925	42925	42925
15	0	send_message	25781	25781	25781	25781	25781	25781
14	0	search_run	10183	10183	10183	10183	10183	10183
13	0	search_click_result_9	642	642	642	642	642	642
12	0	search_click_result_8	555	555	555	555	555	555
11	0	search_click_result_7	556	556	556	556	556	556
10	0	search_click_result_6	635	635	635	635	635	635
9	0	search_click_result_5	786	786	786	786	786	786
8	0	search_click_result_4	1007	1007	1007	1007	1007	1007
7	0	search_click_result_3	899	899	899	899	899	899
6	0	search_click_result_2	1203	1203	1203	1203	1203	1203
5	0	search_click_result_10	403	403	403	403	403	403
4	0	search_click_result_1	1139	1139	1139	1139	1139	1139
3	0	search_autocomplete	13351	13351	13351	13351	13351	13351
2	0	login	29339	29339	29339	29339	29339	29339
1	0	like_message	45916	45916	45916	45916	45916	45916
0	0	home_page	72462	72462	72462	72462	72462	72462

In [85]:
```python
# Group data to calculate total engagement in both groups
total_engagement = engagement.groupby(['in_august'], as_index=False).count()
total_engagement
```

Out[85]:

	in_august	user_id	occurred_at	event_type	event_name	location	device	user_type
0	0	247782	247782	247782	247782	247782	247782	247782
1	1	73793	73793	73793	73793	73793	73793	73793

Even though overall engagements are down in August, the relative frequency of each type of engagement is remarkably consistent (less than 1% difference in each category), indicating that once users are on Yammer there is no signficant difference in their behavior.

In [ ]:
```python

```