

Springboard SQL Assignment with Mode Analytics

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Case study: Best A/B Test

The problem and possible explanations:

This A/B test involves a website variation that results in a dramatically higher apparent engagement in messaging with the variation being tested versus the control group (1.4 times the frequency of the control, two-tailed t-statistic reported as 7.6245, $0.05 \leq p \leq .1$, $df=1$). The result is extraordinary, leading the company to wonder if there is an error involved. The new variation does not appear to lead to an increase in use, but the messaging rate is high from this group to a surprising degree for the number of users in comparison with the control.

A first hypothesis to explain these results would be that there is a bottleneck affecting users (since the summary statistics indicate the test variation has about half the number of users that the control does, and this is unexplained); are the users who surpass any technical hurdle in the process simply more avid and inclined to actively message?

A second hypothesis would be that perhaps some sort of glitch automatically sends out a message (in error? as an ad? etc.) by people who engaged with the variation. This seems much less likely, as it would require active development of such a thing and for no obvious reason.

A third hypothesis is that the test did not have users randomly allocated to each group. Obviously, the control group would not be influenced by a new condition, but the treatment group could work better for or be used more effectively by some users than for others. Since number of users is smaller, perhaps some devices, languages, or locations do not work well with it, and perhaps the devices or locations that do interact well with it are also ones that are easy to message with or consist of a subpopulation that is more inclined to send messages using this software. This is similar to the first hypothesis case but involves less of an effort component by users and passively selects more for a more communicative subpopulation.

The first hypothesis could be assessed by querying for message histories of users. Judging the second hypothesis would not be possible without more information, but it is a low-likelihood scenario. Querying for data on devices, locations, and languages could give insight into the third hypothesis. Of course, these hypotheses also depend on how one is viewing the available data; where it describes users as those to whom the version is shown, I am taking that to mean those who have logged in and seen it, because there is an imbalance between groups for what is described as "users", while the "total treatment group" numbers are even. This is not explained in the summary information. In any case, login history would matter.

A quick glance at users:

This query below shows that the actual allocation of users to control group was 1746 (as posted in the summary and versus 849 users described for the test condition), so my initial interpretation of what the “users” column meant was incorrect. It appears that the “users” data column refers to those samplings of users to whom the experiment was actually applied out of total populations of 2595 each, rather than those who accessed the site and “viewed” their group’s variant. Still unclear is why the users allocated to each are not balanced in number.

```
SELECT COUNT(occurred_at) AS count
FROM tutorial.yammer_experiments
WHERE experiment_group LIKE 'control_group'
```

Result is: count 1746

Since we know that "users" does not refer to what I had hypothesized in hypothesis one (something to do with users hitting a glitch when accessing content), the next thing to examine is whether there is a difference for each group in logging in and accessing content, before judging whether anything is odd about the rate of message sending. The following query tells us about the rate of login attempts and message sending between each group:

```
SELECT COUNT(CASE WHEN events.event_name = 'login' THEN 1 ELSE NULL END) AS login_count,
COUNT(CASE WHEN events.event_name = 'send_message' THEN 1 ELSE NULL END) AS sends_count,
experiments.experiment_group
FROM tutorial.yammer_events events
JOIN tutorial.yammer_experiments experiments
ON events.user_id = experiments.user_id
GROUP BY experiments.experiment_group
```

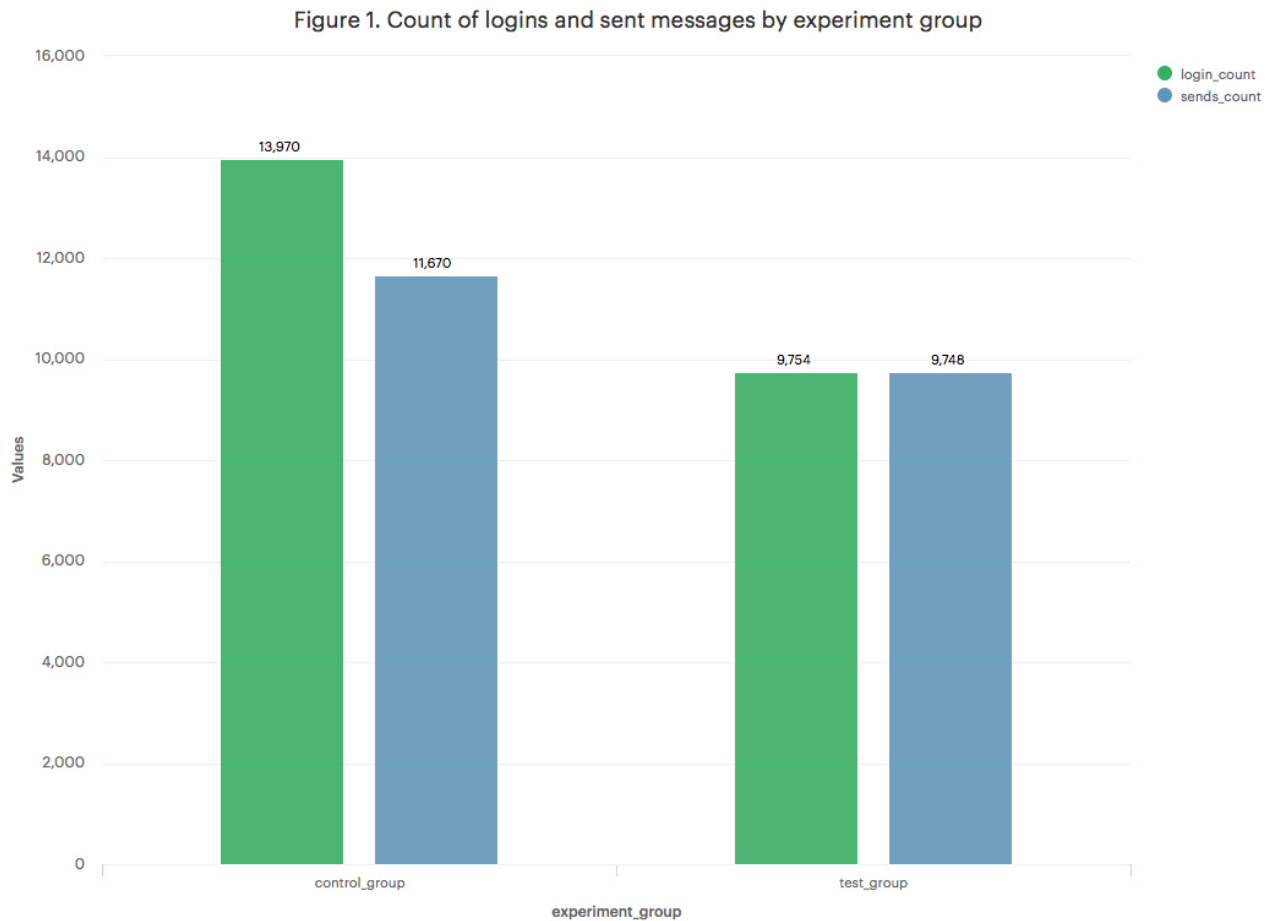
Results are:

control_group logins: 13970; messages sent: 11670

test_group logins: 9754; messages sent: 9748.

Login and message sending characteristics:

Logins and numbers of messages sent are roughly equal for the test group (but not exactly equal). The control group shows fewer messages sent than logins. Results for the test group make hypothesis two even less likely, because if a message was automatically sent from each (barring a few that failed to send), these results would also imply no one in the treatment sent an intentional message (which is possible if the service is not working, but there would likely be ample customer feedback in such a case). Hypothesis three, that there is a quality to the treatment group that makes it on the whole more likely to communicate than the control does, seems to be at play. This suggests a non-random group allocation. Figure 1 characterizes the results of this query.



A look at locations and device types:

The following query tells us how many locations and device types comprise each experimental group:

```
SELECT COUNT(DISTINCT events.location) AS locations,  
COUNT(DISTINCT events.device) AS devices,  
experiments.experiment_group  
FROM tutorial.yammer_events events  
JOIN tutorial.yammer_experiments experiments  
ON events.user_id = experiments.user_id  
GROUP BY experiments.experiment_group
```

Results are:

control_group locations: 47; device types: 26

test_group locations: 47; device types: 26.

Since these represent the totals possible for each of those categories, there is not a difference between the two groups in terms of which locations or devices are included in each. It would be possible for locations and devices to be distributed unevenly in each group, however.

The following query helps us assess if there is an obvious overrepresentation of any location in either group:

```
SELECT events.location,
       COUNT(*) AS count,
       experiments.experiment_group
FROM tutorial.yammer_events events
JOIN tutorial.yammer_experiments experiments
ON events.user_id = experiments.user_id
GROUP BY events.location, experiments.experiment_group
ORDER BY events.location, experiments.experiment_group
```

The pivot table shown below allows us to view the allocation of members from each country in each location. There are more individuals from many locations who are in the control group, but that is expected since that group has so many more members than the test group does. That would not explain a higher frequency of communication from members represented in the test condition, nor really does the small occurrence of some higher numbers in some locations that are in the test group. A multivariate or other analysis would really tell us if there is a connection between location and experiment group. However, just by eye it is clear that no particular locations stand out as being associated with the test condition in such a way as to explain the substantially higher frequency of messaging by people in that group.

location	experiment_group		Totals
	control_group	test_group	
Argentina	896	248	1144
Australia	2164	2427	4591
Austria	1268	734	2002
Belgium	1162	620	1782
Brazil	3235	4020	7255
Canada	4075	1858	5933
Chile	231	306	537
Colombia	296	578	874
Denmark	531	180	711

location	experiment_group		Totals
	control_group	test_group	
Egypt	1187	541	1728
Finland	821	462	1283
France	6648	4496	11144
Germany	6895	6597	13492
Greece	552	55	607
Hong Kong	290	553	843
India	4036	1814	5850
Indonesia	2026	1815	3841
Iran	1637	682	2319
Iraq	107	717	824
Ireland	150	381	531
Israel	425	720	1145
Italy	5305	1886	7191
Japan	9899	6403	16302
Korea	2631	2328	4959
Malaysia	952	679	1631
Mexico	3004	2686	5690
Netherlands	1797	652	2449
Nigeria	419	469	888
Norway	815	482	1297
Pakistan	351	61	412
Philippines	515	188	703
Poland	1121	1567	2688
Portugal	440	355	795
Russia	3315	3951	7266
Saudi Arabia	1270	1441	2711
Singapore	666	28	694
South Africa	869	230	1099

location	experiment_group		Totals
	control_group	test_group	
Spain	1999	1633	3632
Sweden	1942	930	2872
Switzerland	1491	718	2209
Taiwan	1033	1531	2564
Thailand	461	708	1169
Turkey	527	403	930
United Arab Emirates	834	842	1676
United Kingdom	5236	5091	10327
United States	32674	25021	57695
Venezuela	529	578	1107
Totals	118727	90665	20939

If location does not appear to generate artifact in messaging frequency in either experimental condition, the next question is whether device type does. The following query helps us figure this out:

```
SELECT events.device,
       COUNT(*) AS count,
       experiments.experiment_group
FROM tutorial.yammer_events events
JOIN tutorial.yammer_experiments experiments
ON events.user_id = experiments.user_id
GROUP BY events.device, experiments.experiment_group
ORDER BY events.device, experiments.experiment_group
```

As with location, device type does not clearly explain the higher messaging frequency shown by the test group, with users and device types presented in the pivot table below and organized by experiment group.

device	experiment_group		Totals
	control_group	test_group	
acer aspire desktop	1880	1413	3293
acer aspire notebook	3367	2335	5702

device	experiment_group		Totals
	control_group	test_group	
amazon fire phone	844	503	1347
asus chromebook	3459	2546	6005
dell inspiron desktop	4095	3081	7176
dell inspiron notebook	7525	6029	13554
hp pavilion desktop	3282	2387	5669
htc one	1747	995	2742
ipad air	2977	3144	6121
ipad mini	2143	1327	3470
iphone 4s	3509	2412	5921
iphone 5	8627	8128	16755
iphone 5s	5779	4053	9832
kindle fire	1492	1311	2803
lenovo thinkpad	13998	9104	23102
mac mini	1350	1624	2974
macbook air	10291	6395	16686
macbook pro	20647	16049	36696
nexus 5	6054	5310	11364
nexus 7	2532	1629	4161
nexus 10	1962	1594	3556
nokia lumia 635	2042	2043	4085
samsung galaxy tablet	488	569	1057
samsung galaxy note	788	1025	1813
samsung galaxy s4	6650	4806	11456
windows surface	1199	853	2052
Totals	118727	90665	20939

Language characteristics:

Location and device type do not explain the difference in messaging frequencies between control and treatment groups, but perhaps language does, especially if the test variation is available in one language or shows more fluency in one language, for instance. The following query should show this:

```
SELECT users.language,
       COUNT(*) AS count,
       experiments.experiment_group
FROM tutorial.yammer_users users
JOIN tutorial.yammer_experiments experiments
ON users.user_id = experiments.user_id
GROUP BY users.language, experiments.experiment_group
ORDER BY users.language, experiments.experiment_group
```

By the pivot table below, it can again be seen that there is a reasonable split between control and test groups for this condition. While it is impossible to judge from this the linguistic quality of the test variation in all languages, it is at least the case that all languages seem represented in a fair enough capacity for this experiment.

experiment_group			
language	control_group	test_group	Totals
arabic	62	31	93
chinese	55	33	88
english	907	439	1346
french	147	59	206
german	95	46	141
indian	56	22	78
italian	43	16	59
japanese	108	60	168
korean	29	15	44
portugese	41	23	64
russian	45	26	71
spanish	158	79	237
Totals	1746	849	2595

A glance at interaction types:

Next, we look at the frequencies of various interaction types between experimental groups and the software, using the following query:

```
SELECT events.event_name,
       COUNT(*) AS count,
       experiments.experiment_group
FROM tutorial.yammer_events events
JOIN tutorial.yammer_experiments experiments
ON events.user_id = experiments.user_id
GROUP BY events.event_name, experiments.experiment_group
ORDER BY events.event_name, experiments.experiment_group
```

As with prior examinations, there is not much difference between experimental groups according to numbers of interactions each group collectively has experienced with the software, as shown by the following pivot table. However, for some reason there is a more striking imbalance between the two groups for the first few rows – the test group shows fewer than one-fifth as many users have entries for the “complete_signup”, “create_user”, “enter_email”, and “enter_info” categories. Out of 1746 individuals in the control group, about 60% have these entries filled, while for the 849 users in the test group, only 24% do. It is not clear why this would have an impact, but it suggests we might look at more generic user-specific characteristics.

event_name	experiment_group		Totals
	control_group	test_group	
complete_signup	1055	203	1258
create_user	1055	203	1258
enter_email	1055	203	1258
enter_info	1055	203	1258
home_page	33553	26795	60348
like_message	20993	17097	38090
login	13970	9754	23724
search_autocomplete	6337	4338	10675
search_click_result_1	524	397	921
search_click_result_2	525	439	964
search_click_result_3	404	337	741
search_click_result_4	462	346	808
search_click_result_5	329	286	615
search_click_result_6	273	220	493

event_name	experiment_group		Totals
	control_group	test_group	
search_click_result_7	257	184	441
search_click_result_8	249	198	447
search_click_result_9	269	227	496
search_click_result_10	166	156	322
search_run	4666	3390	8056
send_message	11670	9748	21418
view_inbox	19860	15941	35801
Totals	118727	90665	209392

Account creation dates:

Among user characteristics from the users table, features that may relate to a user's history of interaction with the site include "created_at" date/time or "activated_at" date/time information. From the events table event types of "engagement" and "signup_flow" also exist and could be interesting, though it is not clear to what those terms refer or if they provide meaningful additional information beyond other characteristics to examine. Now, the following query will tell us about the history of creation of user accounts, allocated between control and test groups, in batches of time.

```
SELECT
  COUNT(CASE WHEN users.created_at BETWEEN '2013-01-01' AND '2013-04-01' THEN 1 ELSE NULL END) as
  first_batch,
  COUNT(CASE WHEN users.created_at BETWEEN '2013-04-02' AND '2013-08-01' THEN 1 ELSE NULL END) as
  second_batch,
  COUNT(CASE WHEN users.created_at BETWEEN '2013-08-02' AND '2013-12-31' THEN 1 ELSE NULL END) as
  third_batch,
  COUNT(CASE WHEN users.created_at BETWEEN '2014-01-01' AND '2014-04-01' THEN 1 ELSE NULL END) as
  fourth_batch,
  COUNT(CASE WHEN users.created_at BETWEEN '2014-04-02' AND '2014-07-01' THEN 1 ELSE NULL END) as
  fifth_batch,
  experiments.experiment_group
FROM tutorial.yammer_users users
JOIN tutorial.yammer_experiments experiments
ON users.user_id = experiments.user_id
GROUP BY experiments.experiment_group ORDER BY experiments.experiment_group
```

Batches of time in the below table refer to these: first batch, between '2013-01-01' and '2013-04-01'; second batch, between '2013-04-02' and '2013-08-01'; third batch, between '2013-08-

02' and '2013-12-31'; fourth batch, between '2014-01-01' and '2014-04-01'; and the fifth batch, between '2014-04-02' and '2014-07-01'. The results of this query into user account creation histories is interesting; the control and test groups are equally represented by users who have older accounts tracing back to early 2013. While both groups likely trace a growth in the overall numbers of users of the service over time, the control group shows an enormous number of users from the fifth batch of time, indicating a high representation of new user accounts filling well over half (65%) of the control group.

	control_group	test_group
first_batch	66	65
second_batch	95	108
third_batch	220	220
fourth_batch	224	163
fifth_batch	1134	288

A similar query for the “activated_at” entry for each batch in place of “created_at” produces identical results (not shown).

Conclusion:

The third hypothesis appears to be true; the allocation of users to control and test groups does not appear random, with a strong balance toward very new users within the control group. This very high prevalence of recently created accounts within the control group could explain the relatively lower frequency of messages sent by the group relative to the test group, as newer users may not be as familiar with or as dependent on the software for messaging purposes compared with users who have been around the software for a while.