

User Engagement Analysis @Showwcase

September 17, 2020

1 User Engagement Analysis

1.1 Introduction

According to mixpanel.com, **user engagement** measures whether users find value in a product/service. This can be measured by a variety/combination of activities. Highly engaged users are generally more profitable, *provided their activities are tied to valuable outcomes*.

User engagement is dependent on the company's business model. In Showwcase's case, key metrics for user engagement include positive actions such as *projects_added*, *likes_given*, *comments_given*, *session_projects_added*, *session_likes_given*, *session_comments_given*. Other metrics that help deepen the company's understanding of user engagement include actions that suggest lesser engagement. These include *bugs_occurred*, *bugs_in_session*, and the relationship between *inactive_duration* and *session_duration*. The following analyses will focus on these metrics.

My analyses also seeks to answer the following questions related to user engagement:

1. Projects are a unique feature that allow users to “showcase” their skills to the greater tech community. They also do well to increase a profile's visibility. **That being said, what proportion of users add at least one project to their profiles? Among those who add projects, how many do they add on average?**
2. It is useful to show activity trends over the course of the month. **Did the number of logins increase or decrease throughout October 2019?**
3. How many times a user logs onto Showwcase is a key metric for user engagement. We want to be seeing users logging on multiple times. **Thus, what proportion of users logged on more than once over the course of the week?**
4. The user experience is fundamental to maintaining user engagement. Smooth user experiences allow Showwcase to increase customer loyalty. **That being said, how many sessions experienced bugs, and in what proportion of sessions did bugs occur?**
5. Do any two variables affect one another? **Are any two metrics correlated with one another?**

These analyses will also use Python data analysis libraries, which are installed below.

```
[2]: # import libraries

import pandas as pd
import numpy as np
```

```
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns
```

We begin the analyses by exploring various properties of the data and cleaning the data as deemed fit.

```
[8]: # load the data into a pandas dataframe
sessions_df = pd.read_excel("showcase_sessions.xls")

# ensure the dataframe has loaded properly
sessions_df.head(10)
```

```
[8]:
```

	session_id	customer_id	login_date	projects_added	likes_given	\
0	624205	80746	2019-10-30	False	True	
1	624241	24520	2019-10-30	True	True	
2	111002	32047	2019-10-30	True	True	
3	545113	23404	2019-10-30	True	True	
4	750269	40235	2019-10-30	True	True	
5	744943	73245	2019-10-30	True	True	
6	922001	12407	2019-10-30	True	False	
7	823895	29375	2019-10-30	False	False	
8	490096	40572	2019-10-30	True	True	
9	919319	23404	2019-10-29	True	True	

	comment_given	inactive_status	bug_occured	session_projects_added	\
0	True	True	False		0
1	True	True	False		2
2	True	True	False		1
3	True	False	False		1
4	False	True	False		3
5	True	True	True		3
6	True	False	False		5
7	True	True	False		0
8	False	False	False		1
9	False	True	False		2

	session_likes_given	session_comments_given	inactive_duration	\
0	24.0	3	1146	
1	3.0	5	133	
2	5.0	5	1571	
3	10.0	21	0	
4	16.0	0	1405	
5	27.0	5	1746	
6	0.0	5	0	

7	0.0	5	2474
8	25.0	0	0
9	14.0	0	2031

	bugs_in_session	session_duration
0	0	1564
1	0	1766
2	0	2230
3	0	633
4	0	1679
5	4	1490
6	0	1329
7	0	1875
8	0	290
9	0	1957

```
[23]: # dimensions
print(sessions_df.shape)

# columns' datatypes
print(sessions_df.dtypes)
```

```
(300, 14)
session_id          int64
customer_id         int64
login_date          datetime64[ns]
projects_added      bool
likes_given         bool
comment_given       bool
inactive_status     bool
bug_occured         bool
session_projects_added int64
session_likes_given float64
session_comments_given int64
inactive_duration   int64
bugs_in_session     int64
session_duration    int64
dtype: object
```

```
[32]: # statistical properties of numeric variables
sessions_df.describe().apply(lambda s: s.apply(lambda x: format(x, 'f')))
```

```
[32]:
```

	session_id	customer_id	session_projects_added	session_likes_given	\
count	300.000000	300.000000	300.000000	299.000000	
mean	530643.296667	44956.766667	1.620000	10.458194	
std	280421.371240	26411.336491	1.334743	9.474839	
min	22885.000000	10246.000000	0.000000	0.000000	

25%	308358.000000	23571.250000	1.000000	0.000000
50%	553675.000000	38967.000000	2.000000	9.000000
75%	804120.250000	73245.000000	3.000000	19.000000
max	999480.000000	98653.000000	9.000000	27.000000

	session_comments_given	inactive_duration	bugs_in_session	\
count	300.000000	300.000000	300.000000	
mean	2.406667	732.933333	1.233333	
std	2.247545	838.143032	1.757608	
min	0.000000	0.000000	0.000000	
25%	0.750000	0.000000	0.000000	
50%	2.000000	313.500000	0.000000	
75%	4.000000	1524.750000	2.250000	
max	21.000000	2480.000000	5.000000	

	session_duration
count	300.000000
mean	1186.763333
std	688.632138
min	10.000000
25%	611.250000
50%	1152.000000
75%	1778.000000
max	2395.000000

There appears to be an outlier in the dataset. In one of the sessions, the inactive duration is greater than the session duration. Based on my understanding, the inactive duration is supposed to be less than or equal to the session_duration. Thus, the outlier will be removed and the dataframe will be checked for missing data.

All redundant columns, essentially the boolean columns for likes, comments, projects, bugs, and inactive status, will also be dropped because they can be explained by their numeric representations.

```
[40]: # dropping redundant columns
df_cleaned = sessions_df.drop(['projects_added', 'likes_given',
                               'comment_given', 'bug_occured',
                               'inactive_status'], axis = 1)
df_cleaned
```

```
[40]: session_id customer_id login_date session_projects_added \
0      624205      80746 2019-10-30      0
1      624241      24520 2019-10-30      2
2      111002      32047 2019-10-30      1
3      545113      23404 2019-10-30      1
4      750269      40235 2019-10-30      3
..      ...      ...      ...      ...
295     944212      40572 2019-10-01      3
296     558332      87323 2019-10-01      2
```

297	643880	51243	2019-10-01	2
298	844518	23083	2019-10-01	1
299	933954	38459	2019-10-01	1

	session_likes_given	session_comments_given	inactive_duration	\
0	24.0	3	1146	
1	3.0	5	133	
2	5.0	5	1571	
3	10.0	21	0	
4	16.0	0	1405	
..	
295	13.0	0	1174	
296	0.0	0	97	
297	0.0	0	906	
298	0.0	0	139	
299	0.0	0	0	

	bugs_in_session	session_duration
0	0	1564
1	0	1766
2	0	2230
3	0	633
4	0	1679
..
295	0	2255
296	0	1692
297	0	1990
298	0	1113
299	0	306

[300 rows x 9 columns]

```
[49]: # checking for missing values in the data
df_cleaned.isna()

# although it appears there are no missing data, drop rows which contain
↳ missing data
df_cleaned = df_cleaned.dropna(axis = 0, how = 'any')
df_cleaned
```

[49]:	session_id	customer_id	login_date	session_projects_added	\
0	624205	80746	2019-10-30	0	
1	624241	24520	2019-10-30	2	
2	111002	32047	2019-10-30	1	
3	545113	23404	2019-10-30	1	
4	750269	40235	2019-10-30	3	
..	

295	944212	40572	2019-10-01	3
296	558332	87323	2019-10-01	2
297	643880	51243	2019-10-01	2
298	844518	23083	2019-10-01	1
299	933954	38459	2019-10-01	1

	session_likes_given	session_comments_given	inactive_duration	\
0	24.0	3	1146	
1	3.0	5	133	
2	5.0	5	1571	
3	10.0	21	0	
4	16.0	0	1405	
..	
295	13.0	0	1174	
296	0.0	0	97	
297	0.0	0	906	
298	0.0	0	139	
299	0.0	0	0	

	bugs_in_session	session_duration
0	0	1564
1	0	1766
2	0	2230
3	0	633
4	0	1679
..
295	0	2255
296	0	1692
297	0	1990
298	0	1113
299	0	306

[299 rows x 9 columns]

One row contained missing data because we now have a 299 x 9 dataframe. This updated dataframe is stored in df_cleaned.

```
[50]: # how many unique values does each variable contain?
df_cleaned.nunique(axis = 0)
```

```
[50]: session_id          299
customer_id           48
login_date            30
session_projects_added  8
session_likes_given    28
session_comments_given  9
inactive_duration     169
```

```
bugs_in_session          6
session_duration         278
dtype: int64
```

Notable insight: 48 unique customers logged onto Showcase in October 2019.

```
[51]: df_cleaned.describe().apply(lambda s: s.apply(lambda x: format(x, 'f')))
```

```
[51]:
```

	session_id	customer_id	session_projects_added	session_likes_given \
count	299.000000	299.000000	299.000000	299.000000
mean	529534.652174	45028.849498	1.618729	10.458194
std	280232.153769	26426.038013	1.336799	9.474839
min	22885.000000	10246.000000	0.000000	0.000000
25%	307856.000000	23579.000000	1.000000	0.000000
50%	552796.000000	39475.000000	2.000000	9.000000
75%	802738.000000	73245.000000	3.000000	19.000000
max	999480.000000	98653.000000	9.000000	27.000000

	session_comments_given	inactive_duration	bugs_in_session \
count	299.000000	299.000000	299.000000
mean	2.408027	731.638796	1.237458
std	2.251190	839.247660	1.759100
min	0.000000	0.000000	0.000000
25%	0.500000	0.000000	0.000000
50%	2.000000	312.000000	0.000000
75%	4.000000	1525.500000	2.500000
max	21.000000	2480.000000	5.000000

	session_duration
count	299.000000
mean	1190.414716
std	686.871418
min	10.000000
25%	614.000000
50%	1152.000000
75%	1778.000000
max	2395.000000

1.2 Question 1

What proportion of users add at least one project to their profiles? Among those that have, how many do they add on average?

```
[108]: # creating a dataframe where 0 projects were added
no_projects_added = df_cleaned.query('session_projects_added == 0')

# counting the number of sessions where 0 projects were added
# 73
```

```
no_projects_added['session_id'].agg('count')

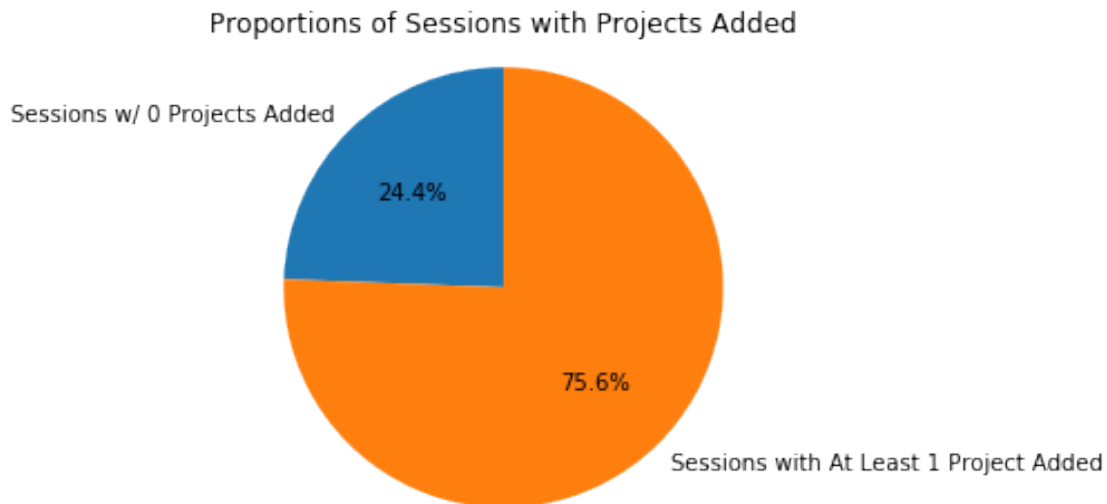
# average number of projects added per session
# 2.14 projects/session
df_cleaned.query('session_projects_added > 0')['session_projects_added'].
    ↪agg('mean')
```

[108]: 2.1415929203539825

```
[94]: # pie chart showing proportion of sessions where projects were added vs 0
    ↪projects

size = [100*73/299, 100*226/299]
labels = 'Sessions w/ 0 Projects Added', 'Sessions with At Least 1 Project_
    ↪Added'

fig1, ax1 = plt.subplots()
ax1.pie(size, labels=labels, autopct='%1.1f%%', startangle = 90)
ax1.axis('equal') # ensures pie is drawn as a circle
plt.title("Proportions of Sessions with Projects Added")
plt.show()
```



In 75.6% of sessions, users are adding at least 1 project to their profiles. This indicates that users are making use of the features relating to projects on Showcase. Of all users who added a project, on average 2.14 projects were added per user.

1.3 Question 2

We want to observe trends in user activity over the course of the month. Did the number of logins per day increase, decrease, or remain the same during October 2019?

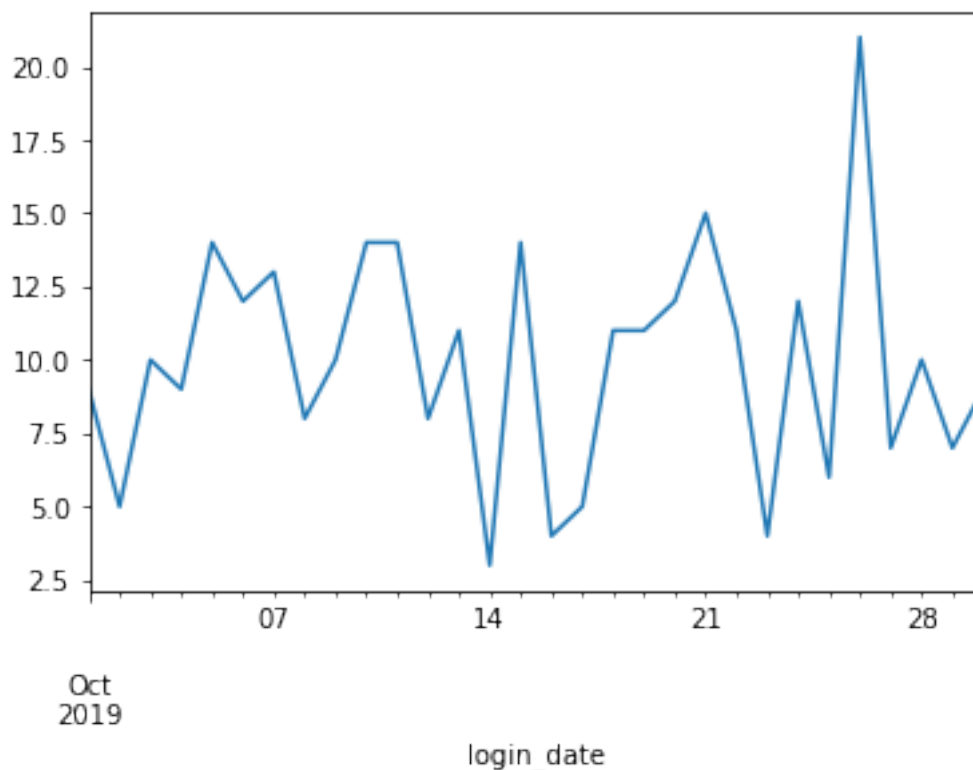
```
[85]: # line plot showing the number of logins per day for October 2019

# displays how many logins occurred each day
sessions_per_day = df_cleaned.groupby(df_cleaned.login_date).count()

# this line contains the login_dates and the number of logins per day
sessions_per_day['session_id']

sessions_per_day['session_id'].plot.line(x = 'login_date', y = 'login count')
```

```
[85]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8b6ba86d50>
```



Based on this simple pandas line plot, the number of logins fluctuates between days. However, the overall trend appears constant throughout October 2019.

1.4 Question 3

How many users logged onto Showwcase more than once in October 2019?

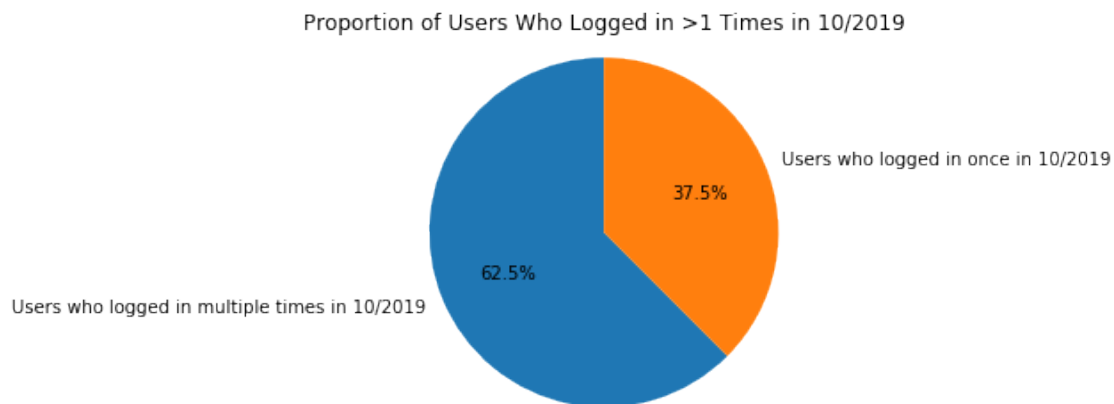
```
[93]: # group the dataframe by customer_id
logins_per_customer = df_cleaned.groupby(df_cleaned['customer_id']).count()
logins_per_customer

# the column we use after ...query(login_date > 1) doesn't matter because they
↳ all contain
# the same value, which is 30
# I am only doing this to extract a single value
multiple_login_users = logins_per_customer.query('login_date > 1')
↳ ['session_id'].count()
unique_users = df_cleaned['customer_id'].nunique()
single_login_users = unique_users - multiple_login_users
single_login_users
```

[93]: 18

```
[99]: # pie chart showing proportion of multiple login users vs those who logged in
↳ once
size = [100*multiple_login_users/unique_users, 100*single_login_users/
↳ unique_users]
labels = 'Users who logged in multiple times in 10/2019', 'Users who logged in
↳ once in 10/2019'

fig1, ax1 = plt.subplots()
ax1.pie(size, labels=labels, autopct='%1.1f%%', startangle = 90)
ax1.axis('equal') # ensures pie is drawn as a circle
plt.title("Proportion of Users Who Logged in >1 Times in 10/2019")
plt.show()
```



Of the 48 unique users who logged onto Showcase in October 2019, 5/8 of them logged in multiple times. This implies that the majority of users are repeat users of the product.

1.5 Question 4

How many sessions experienced bugs, and what proportion?

```
[101]: # number of sessions (299)
sessions = df_cleaned['session_id'].count()

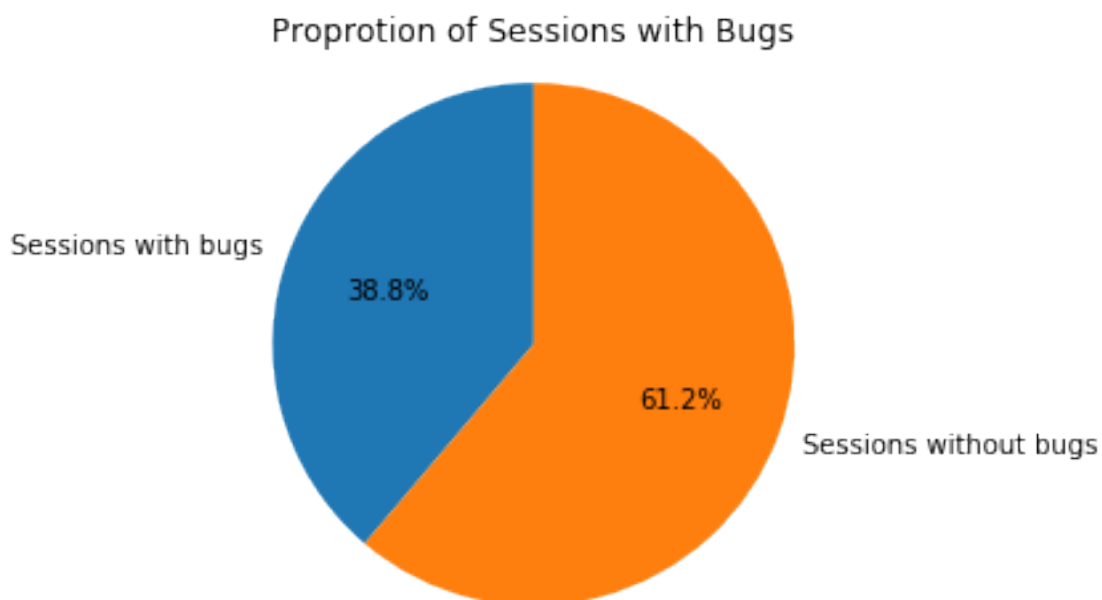
# number of buggy sessions (116)
buggy_sessions = df_cleaned.query('bugs_in_session > 0').count()
bug_sesh = buggy_sessions['bugs_in_session']

not_buggy = sessions - bug_sesh
not_buggy
```

[101]: 183

```
[102]: # pie chart for proportion of buggy sessions
size = [100*bug_sesh/sessions, 100*not_buggy/sessions]
labels = 'Sessions with bugs', 'Sessions without bugs'

fig1, ax1 = plt.subplots()
ax1.pie(size, labels=labels, autopct='%1.1f%%', startangle = 90)
ax1.axis('equal') # ensures pie is drawn as a circle
plt.title("Proportion of Sessions with Bugs")
plt.show()
```



The data shows that 38.8% of sessions in October 2019 experienced at least one bug, a relatively

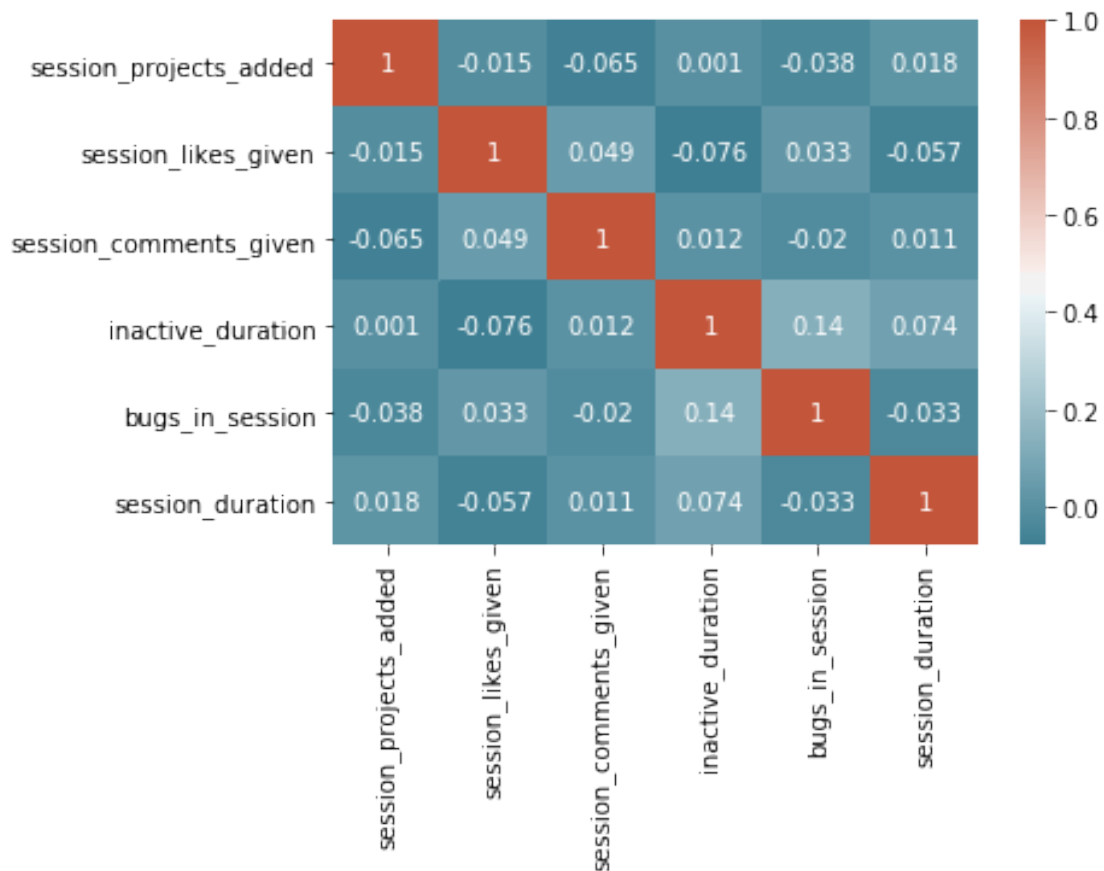
high figure. While it hasn't been shown that bugs directly affect user engagement in a negative manner, bugs affect the user's experience on Showwcase, which can be a determining factor for user engagement.

1.6 Question 5

Are any two metrics for user engagement positively/negatively correlated with one another?

```
[106]: # correlation matrix
# drop session_id, customer_id columns because they're not relevant here
corr_df = df_cleaned.drop(['session_id', 'customer_id'], axis = 1)
corr = corr_df.corr()
sns.heatmap(corr, xticklabels = corr.columns, yticklabels = corr.columns,
            annot=True, cmap=sns.diverging_palette(220, 20, as_cmap=True))
```

```
[106]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8b6c107690>
```



Correlation values range from -1 to 1, where -1 means two variables are strongly negatively correlated and 1 means they are strongly positively correlated. Based on my intuition of the variables, it could have been possible that variables such as *inactive_duration* and *session_duration* could have

been correlated in some way. The same goes for *bugs_in_session* and *inactive_duration* and *session_projects_added* and *session_duration*. Ultimately, no two variables are strongly correlated with one another, with the highest correlation value being 0.14 between *inactive_duration* and *bugs_in_session*.

1.7 Future Considerations

User engagement is loosely defined, and there were few definitive ways to gain a better understanding of it. These metrics are useful for understanding the way users interact with the platform. In the future, I think it would be useful to devise a way to score a user's engagement with the platform. For example, considering all metrics, we could assign a user an engagement score from 0-5, where 0 is not engaged and 5 is actively engaged. This overall user engagement score, as well as the engagement metrics already at our disposal, can provide the Product team greater insight when making important product/marketing decisions.

I also tried to access customer and session id's as little as possible because these identifiers are personal to the user. I tried my best to maintain integrity and data privacy.