Data challenge - Yammer

Background:

- Yammer is a social network for communicating with coworkers
- Individuals share documents, updates, and ideas by posting them in groups
- Companies must pay license fees if they want access to administrative controls, including integration with user management systems like ActiveDirectory.

Problem:

Drop (about 15%) in weekly engagement between beginning August and September. Figure out why.

Hypotheses

2 possibilities:

A) Internal reasons - something that can be fixed

- diagnose that drop in engagment comes from existing users or decrease in signups
- there was an overall outage in our platform = "catastrophic failures"
- only a specfic part is affected: specific device, specific part of platform, location

for both try to narrow down to device or company see what distinguishes usage that does go down from one that does not go down.

B) External reasons - things that cannot be fixed/need to be investigated further

- check per company usage pattern
- people go on Vacation in August - compare southern and northern hemisphere usage patterns

In [1]:
```
### Load in some useful packages

%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from scipy import stats
import qgrid
import seaborn as sns; sns.set() # this is another plotting program

pd.show_versions()
```

```
INSTALLED VERSIONS
------------------
commit: None
python: 3.7.1.final.0
python-bits: 64
OS: Darwin
OS-release: 18.2.0
machine: x86_64
processor: i386
byteorder: little
LC_ALL: None
LANG: en_US.UTF-8
LOCALE: en_US.UTF-8

pandas: 0.23.4
pytest: None
pip: 18.1
setuptools: 40.6.3
Cython: None
numpy: 1.15.4
scipy: 1.1.0
pyarrow: None
xarray: None
IPython: 7.2.0
sphinx: None
patsy: 0.5.1
dateutil: 2.7.5
pytz: 2018.9
blosc: None
bottleneck: None
tables: None
numexpr: None
feather: None
matplotlib: 3.0.2
openpyxl: None
xlrd: None
xlwt: None
xlsxwriter: None
lxml: None
bs4: None
html5lib: None
sqlalchemy: None
pymysql: None
psycopg2: None
jinja2: 2.10
s3fs: None
fastparquet: None
pandas_gbq: None
pandas_datareader: None
```

Part 1: Data reading in and preprocessing

In [2]:
```
## read in the data + get an idea how many samples I have

users = pd.read_csv('yammer_users.csv')
events = pd.read_csv('yammer_events.csv')
emails = pd.read_csv('yammer_emails.csv')
rollup_periods = pd.read_csv('dimension_rollup_periods.csv')

print(users.shape)
print(events.shape)
print(emails.shape)
print(rollup_periods.shape)
```

```
(19066, 6)
(340832, 7)
(90389, 4)
(56002, 6)
```

In [14]:
```
# analyze the Events table for usage by country
# first look at the table and if datatypes were read in correctly

print(events.dtypes)
print(emails.dtypes)
print(rollup_periods.dtypes)
print(users.dtypes)
```

```
user_id                float64
occurred_at     datetime64[ns]
event_type              object
event_name              object
location                object
device                  object
user_type              float64
dtype: object
user_id        float64
occurred_at     object
action          object
user_type      float64
dtype: object
period_id    float64
time_id       object
pst_start     object
pst_end       object
utc_start     object
utc_end       object
dtype: object
user_id         float64
created_at       object
company_id      float64
language         object
activated_at     object
state            object
dtype: object
```

In [16]:
```
# need to convert the occured_at column into a datatime
from datetime import datetime # this calls the datetime package

events['occurred_at'] = pd.to_datetime(events['occurred_at'])

rollup_periods['time_id'] = pd.to_datetime(rollup_periods['time_id'])
rollup_periods['pst_start'] = pd.to_datetime(rollup_periods['pst_start'
])
rollup_periods['pst_end'] = pd.to_datetime(rollup_periods['pst_end'])
rollup_periods['utc_start'] = pd.to_datetime(rollup_periods['utc_start'
])
rollup_periods['utc_end'] = pd.to_datetime(rollup_periods['utc_end'])


print(events.dtypes)
print(rollup_periods.dtypes)
```

```
user_id                float64
occurred_at     datetime64[ns]
event_type              object
event_name              object
location                object
device                  object
user_type              float64
dtype: object
period_id            float64
time_id       datetime64[ns]
pst_start     datetime64[ns]
pst_end       datetime64[ns]
utc_start     datetime64[ns]
utc_end       datetime64[ns]
dtype: object
```

In [161]:
```
users.head()
```

Out[161]:

	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 [162]:
```
users['created_at'] = pd.to_datetime(users['created_at'])
users['activated_at'] = pd.to_datetime(users['activated_at'])
users.dtypes
```

Out[162]:
```
user_id                float64
created_at      datetime64[ns]
company_id             float64
language                object
activated_at    datetime64[ns]
state                   object
dtype: object
```

In [266]:
```
emails['occurred_at'] = pd.to_datetime(emails['occurred_at'])
```

In [267]:
```
emails.dtypes
```

Out[267]:
```
user_id               float64
occurred_at    datetime64[ns]
action                 object
user_type             float64
dtype: object
```

In [6]:
```
events.location.unique()
```

Out[6]:
```
array(['Japan', 'Netherlands', 'Austria', 'Finland', 'United Kingdom',
       'India', 'United States', 'France', 'Iran', 'Germany', 'Australi
a',
       'Brazil', 'Thailand', 'Russia', 'Taiwan', 'Canada', 'Spain',
       'Israel', 'Colombia', 'Iraq', 'Indonesia', 'Greece', 'Norway',
       'United Arab Emirates', 'Korea', 'Venezuela', 'Belgium',
       'Saudi Arabia', 'Poland', 'Sweden', 'Denmark', 'Mexico', 'Ital
y',
       'Egypt', 'Nigeria', 'Pakistan', 'Portugal', 'Singapore',
       'South Africa', 'Hong Kong', 'Switzerland', 'Turkey', 'Chile',
       'Ireland', 'Argentina', 'Malaysia', 'Philippines'], dtype=objec
t)
```

In [7]:
```
events.head()
```

Out[7]:

	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 [10]:
```
# count total events/country

events['location'].value_counts()
```

Out[10]:
```
United States           94728
Japan                   26046
Germany                 23524
France                  17364
United Kingdom          16475
Russia                  12226
Italy                   11790
Brazil                  11240
India                    9620
Canada                   9126
Mexico                   9106
Australia                7494
Korea                    7180
Indonesia                6224
Spain                    5874
Netherlands              4494
Saudi Arabia             4104
Sweden                   3901
Poland                   3803
Switzerland              3760
Taiwan                   3600
Iran                     3122
Belgium                  2822
Malaysia                 2529
Austria                  2494
Turkey                   2432
United Arab Emirates     2343
South Africa             2324
Egypt                    2258
Denmark                  2191
Israel                   2130
Norway                   2020
Thailand                 2008
Colombia                 1945
Venezuela                1930
Finland                  1926
Argentina                1717
Nigeria                  1642
Hong Kong                1525
Singapore                1497
Iraq                     1400
Philippines              1373
Portugal                 1336
Chile                    1092
Ireland                  1073
Pakistan                 1035
Greece                    989
Name: location, dtype: int64
```

In [17]:
```
rollup_periods.head()
```

Out[17]:

	period_id	time_id	pst_start	pst_end	utc_start	utc_end
0	1.0	2013-01-01	2013-01-01	2013-01-02	2013-01-01 08:00:00	2013-01-02 08:00:00
1	1.0	2013-01-02	2013-01-02	2013-01-03	2013-01-02 08:00:00	2013-01-03 08:00:00
2	1.0	2013-01-03	2013-01-03	2013-01-04	2013-01-03 08:00:00	2013-01-04 08:00:00
3	1.0	2013-01-04	2013-01-04	2013-01-05	2013-01-04 08:00:00	2013-01-05 08:00:00
4	1.0	2013-01-05	2013-01-05	2013-01-06	2013-01-05 08:00:00	2013-01-06 08:00:00

In [18]:
```
# don't really know in which unit the time in events is  (utc vs pst) as
sumed utc since
# it's more standardized and the world doesn't care that much about pst
 and it's about
# time that Americans switched to the metric system


events['time_id'] = events['occurred_at'].apply(lambda time: rollup_peri
ods['time_id'][(rollup_periods['utc_start'] <= time) & (rollup_periods[
'utc_end'] > time)].values[0])
events.head()
```

Out[18]:

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

In [20]:
```
# the process before took a long time so better save the output as a .cs
v
events.to_csv('backup_events.csv')
```

In [21]:
```
events.dtypes
```

Out[21]:
```
user_id                 float64
occurred_at      datetime64[ns]
event_type               object
event_name               object
location                 object
device                   object
user_type               float64
time_id          datetime64[ns]
dtype: object
```

In [26]:
```
### curious what's in each column

print('event_type')
print(events['event_type'].value_counts())
print('event_name')
print(events['event_name'].value_counts())
print('device')
print(events['device'].value_counts())
```

```
event_type
engagement     321575
signup_flow     19257
Name: event_type, dtype: int64
event_name
home_page                  94065
like_message               59248
view_inbox                 55936
login                      38610
send_message               33105
search_autocomplete        17820
search_run                 13019
create_user                 7298
enter_email                 4407
enter_info                  3872
complete_signup             3680
search_click_result_2       1499
search_click_result_1       1413
search_click_result_4       1264
search_click_result_3       1134
search_click_result_5        968
search_click_result_6        805
search_click_result_9        784
search_click_result_7        709
search_click_result_8        690
search_click_result_10       506
Name: event_name, dtype: int64
device
macbook pro                59948
lenovo thinkpad            38679
macbook air                28104
iphone 5                   27134
dell inspiron notebook     20476
samsung galaxy s4          19594
nexus 5                    17249
iphone 5s                  16705
dell inspiron desktop      10569
iphone 4s                  10097
asus chromebook            10014
ipad air                    9994
acer aspire notebook        9372
hp pavilion desktop         9280
nexus 7                     6895
ipad mini                   5895
nokia lumia 635             5880
nexus 10                    5446
acer aspire desktop         5402
mac mini                    4622
htc one                     4485
kindle fire                 4280
windows surface             3673
samsung galaxy note         2821
amazon fire phone           2298
samsumg galaxy tablet       1920
Name: device, dtype: int64
```

In [28]:
```
#in which range do we have data
print(events['time_id'].min())
print(events['time_id'].max())
```

```
2014-04-30 00:00:00
2014-08-31 00:00:00
```

In [38]:
```
# sort the events dataframe, so that it's easier to plot

events = events.sort_values(by='time_id', ascending=True)
events.head()
```

Out[38]:

	user_id	occurred_at	event_type	event_name	location	device	us
145967	5830.0	2014-05-01 03:10:17	engagement	search_click_result_6	Philippines	macbook pro	3.0
261539	11276.0	2014-05-01 03:50:19	engagement	view_inbox	Indonesia	dell inspiron desktop	2.0
261538	11276.0	2014-05-01 03:49:43	engagement	home_page	Indonesia	dell inspiron desktop	2.0
261537	11276.0	2014-05-01 03:49:09	engagement	like_message	Indonesia	dell inspiron desktop	2.0
261536	11276.0	2014-05-01 03:48:38	engagement	send_message	Indonesia	dell inspiron desktop	2.0

In [41]:
```
events_over_time = events[events.event_type == 'engagement']
events_over_time = events_over_time['time_id'].value_counts()
events_over_time.head()
```

Out[41]:
```
2014-07-18    4293
2014-07-31    4215
2014-07-25    4135
2014-06-27    4028
2014-07-30    3974
Name: time_id, dtype: int64
```

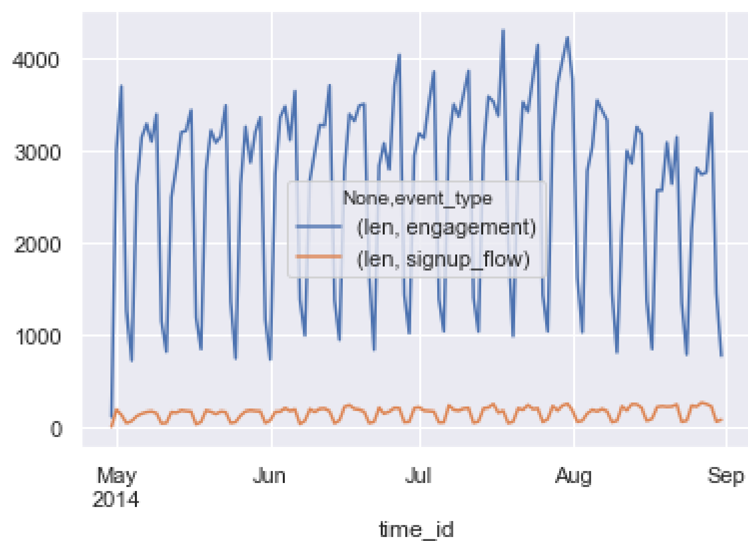
Part 2 - checking of hypotheses

A) Internal reasons - something that can be fixed

- diagnose that drop in engagment comes from existing users or decrease in signups

In [279]:
```
pd.pivot_table(events,index=["time_id"], values = 'device', columns=["event_type"],aggfunc=[len]).plot(legend=True)
```

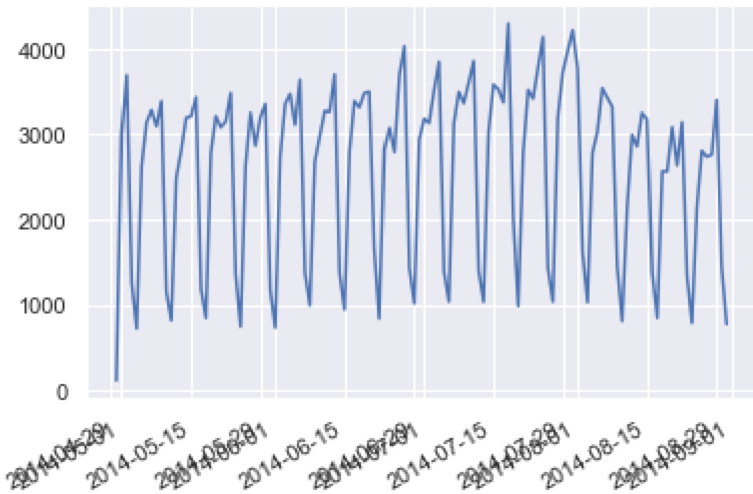
Out[279]: <matplotlib.axes._subplots.AxesSubplot at 0x1f3845ec88>



- there was an overall outage in our platform = "catastrophic failures"

In [42]:
```
# this is the total number of engagments per time period - dip makes sen
se
# this is probably because of weekends -
events_over_time.plot()
```

Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a25ebc978>
```



In [45]:
```
users_over_time = events[events.event_type == 'engagement']
users_over_time = users_over_time.groupby('time_id')['user_id'].nunique
()
users_over_time
```

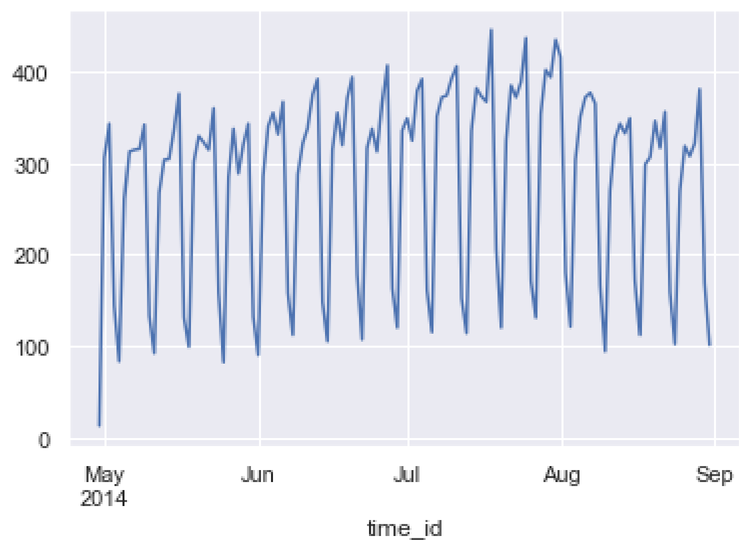
```
Out[45]: time_id
         2014-04-30     13
         2014-05-01    306
         2014-05-02    343
         2014-05-03    144
         2014-05-04     83
         2014-05-05    261
         2014-05-06    313
         2014-05-07    315
         2014-05-08    316
         2014-05-09    342
         2014-05-10    133
         2014-05-11     92
         2014-05-12    268
         2014-05-13    304
         2014-05-14    305
         2014-05-15    337
         2014-05-16    376
         2014-05-17    131
         2014-05-18     99
         2014-05-19    302
         2014-05-20    330
         2014-05-21    323
         2014-05-22    315
         2014-05-23    360
         2014-05-24    158
         2014-05-25     82
         2014-05-26    285
         2014-05-27    338
         2014-05-28    289
         2014-05-29    321
                      ...
         2014-08-02    180
         2014-08-03    121
         2014-08-04    304
         2014-08-05    351
         2014-08-06    372
         2014-08-07    377
         2014-08-08    365
         2014-08-09    166
         2014-08-10     94
         2014-08-11    270
         2014-08-12    327
         2014-08-13    343
         2014-08-14    333
         2014-08-15    349
         2014-08-16    172
         2014-08-17    112
         2014-08-18    299
         2014-08-19    307
         2014-08-20    346
         2014-08-21    317
         2014-08-22    356
         2014-08-23    159
         2014-08-24    102
         2014-08-25    270
         2014-08-26    319
```

```
2014-08-27    308
2014-08-28    322
2014-08-29    381
2014-08-30    169
2014-08-31    101
Name: user_id, Length: 124, dtype: int64
```

In [44]:
```
users_over_time.plot()
# this is unique users over time

# same dipping trend - so the fact that the pattern still seems normal b
ut reduced doesn't
# that there is general problems with the platform
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2bebbdd8>



Answer- daily usagepattern still looks the same as in August - no catastrophic failure

specifically there is a spike during the week and a dip on the weekend.

- only a specfic part is affected: specific device, specific part of platform, location

the following tables always plot a specific feature per montly usage. I compared July to August to identify if the dip happens in a specific case or is a general feature.

Event type of engagement

In [287]:
```
pd.pivot_table(events,index=["event_name"], values = 'device', columns=[
pd.Grouper(key='time_id', freq='M')],aggfunc=[len])
```

Out[287]:

	len				
time_id	2014-04-30	2014-05-31	2014-06-30	2014-07-31	2014-08-31
event_name					
complete_signup	2.0	777.0	877.0	1001.0	1023.0
create_user	5.0	1593.0	1735.0	1985.0	1980.0
enter_email	2.0	953.0	1071.0	1193.0	1188.0
enter_info	2.0	823.0	929.0	1047.0	1071.0
home_page	38.0	22667.0	23029.0	26796.0	21535.0
like_message	22.0	14738.0	14490.0	16706.0	13292.0
login	13.0	8976.0	9346.0	11032.0	9243.0
search_autocomplete	3.0	3988.0	4145.0	5225.0	4459.0
search_click_result_1	NaN	354.0	353.0	432.0	274.0
search_click_result_10	NaN	115.0	125.0	163.0	103.0
search_click_result_2	NaN	382.0	372.0	450.0	295.0
search_click_result_3	1.0	301.0	292.0	306.0	234.0
search_click_result_4	1.0	346.0	299.0	361.0	257.0
search_click_result_5	NaN	265.0	255.0	266.0	182.0
search_click_result_6	1.0	224.0	163.0	248.0	169.0
search_click_result_7	NaN	191.0	165.0	200.0	153.0
search_click_result_8	NaN	163.0	181.0	212.0	134.0
search_click_result_9	NaN	221.0	184.0	238.0	141.0
search_run	3.0	3209.0	3170.0	3817.0	2820.0
send_message	12.0	8220.0	8199.0	9371.0	7303.0
view_inbox	23.0	13234.0	13602.0	16107.0	12970.0

Emails

this is just looking at events within emails

In [292]:
```
pd.pivot_table(emails, index=["action"], values='user_id', columns=[pd.G
rouper(key='occurred_at', freq='M')],aggfunc=[len])
```

Out[292]:

	len			
occurred_at	**2014-05-31**	**2014-06-30**	**2014-07-31**	**2014-08-31**
action				
email_clickthrough	2023.0	2274.0	2721.0	1992.0
email_open	4212.0	4658.0	5611.0	5978.0
sent_reengagement_email	758.0	889.0	933.0	1073.0
sent_weekly_digest	11730.0	13155.0	15902.0	16480.0

this is just looking at events within emails after joining to the engagements from the table

In [293]:
```
pd.pivot_table(pd.merge(emails, events, on='user_id', how = 'left', sort
=False), values= 'device', index=["action"],columns=[pd.Grouper(key='tim
e_id', freq='M')],aggfunc=[len])
```

Out[293]:

	len				
time_id	**2014-04-30**	**2014-05-31**	**2014-06-30**	**2014-07-31**	**2014-08-31**
action					
email_clickthrough	177	170674	188163	214053	157831
email_open	391	375772	381418	419470	294044
sent_reengagement_email	15	25438	37237	48839	44397
sent_weekly_digest	1309	1071439	1030003	1096635	713362

Device used

In [282]:
```
pd.pivot_table(events,index=["device"], values= 'event_name',columns=[pd
.Grouper(key='time_id', freq='M')],aggfunc=[len])
```

Out[282]:

	len				
time_id	2014-04-30	2014-05-31	2014-06-30	2014-07-31	2014-08-31
device					
acer aspire desktop	12.0	1209.0	1177.0	1404.0	1600.0
acer aspire notebook	NaN	2028.0	2178.0	2563.0	2603.0
amazon fire phone	NaN	570.0	563.0	489.0	676.0
asus chromebook	NaN	2166.0	2511.0	2663.0	2674.0
dell inspiron desktop	13.0	2473.0	2927.0	2983.0	2173.0
dell inspiron notebook	NaN	4776.0	4861.0	5510.0	5329.0
hp pavilion desktop	NaN	1742.0	2573.0	2838.0	2127.0
htc one	NaN	1340.0	1093.0	1261.0	791.0
ipad air	NaN	2636.0	2491.0	2868.0	1999.0
ipad mini	NaN	1530.0	1358.0	1836.0	1171.0
iphone 4s	12.0	2448.0	2194.0	3298.0	2145.0
iphone 5	22.0	6411.0	6854.0	8150.0	5697.0
iphone 5s	6.0	4250.0	4115.0	4825.0	3509.0
kindle fire	NaN	1199.0	1147.0	1353.0	581.0
lenovo thinkpad	10.0	9234.0	8564.0	11391.0	9480.0
mac mini	NaN	1065.0	1067.0	1180.0	1310.0
macbook air	9.0	6477.0	6899.0	7912.0	6807.0
macbook pro	43.0	14778.0	13587.0	16116.0	15424.0
nexus 10	NaN	1293.0	1607.0	1434.0	1112.0
nexus 5	1.0	4829.0	4742.0	4464.0	3213.0
nexus 7	NaN	1437.0	1932.0	1976.0	1550.0
nokia lumia 635	NaN	1101.0	1718.0	1906.0	1155.0
samsumg galaxy tablet	NaN	371.0	499.0	633.0	417.0
samsung galaxy note	NaN	797.0	843.0	641.0	540.0
samsung galaxy s4	NaN	4805.0	4605.0	6178.0	4006.0
windows surface	NaN	775.0	877.0	1284.0	737.0

User type

In [285]:
```
pd.pivot_table(events,index=["user_type"], values='device', columns=[pd.
Grouper(key='time_id', freq='M')],aggfunc=[len])
```

Out[285]:

	len				
time_id	2014-04-30	2014-05-31	2014-06-30	2014-07-31	2014-08-31
user_type					
1.0	74	53557	52304	59402	45325
2.0	31	14230	14694	18302	15321
3.0	14	10584	12249	15227	13941

Location where engagment was recorded

In [283]:
```
pd.pivot_table(events,index=["location"], values= 'device', columns=[pd.
Grouper(key='time_id', freq='M')],aggfunc=[len])
```

Out[283]:

	len				
time_id	2014-04-30	2014-05-31	2014-06-30	2014-07-31	2014-08-31
location					
Argentina	NaN	227.0	512.0	332.0	646.0
Australia	20.0	1811.0	1934.0	1836.0	1893.0
Austria	NaN	382.0	577.0	927.0	608.0
Belgium	NaN	948.0	557.0	865.0	452.0
Brazil	NaN	2679.0	2751.0	3229.0	2581.0
Canada	9.0	2651.0	2222.0	2623.0	1621.0
Chile	NaN	134.0	167.0	485.0	306.0
Colombia	NaN	407.0	375.0	632.0	531.0
Denmark	NaN	289.0	332.0	655.0	915.0
Egypt	NaN	628.0	640.0	443.0	547.0
Finland	NaN	542.0	409.0	520.0	455.0
France	NaN	4022.0	4601.0	5314.0	3427.0
Germany	NaN	5440.0	5287.0	7316.0	5481.0
Greece	NaN	147.0	132.0	425.0	285.0
Hong Kong	6.0	440.0	363.0	351.0	365.0
India	9.0	2412.0	2153.0	3003.0	2043.0
Indonesia	13.0	1612.0	1581.0	1691.0	1327.0
Iran	NaN	695.0	875.0	783.0	769.0
Iraq	NaN	276.0	479.0	280.0	365.0
Ireland	NaN	252.0	238.0	229.0	354.0
Israel	NaN	460.0	568.0	545.0	557.0
Italy	NaN	2807.0	2397.0	3737.0	2849.0
Japan	21.0	5977.0	6537.0	7469.0	6042.0
Korea	NaN	1927.0	1716.0	2044.0	1493.0
Malaysia	NaN	657.0	490.0	702.0	680.0
Mexico	NaN	2532.0	2188.0	2560.0	1826.0
Netherlands	NaN	749.0	1039.0	1232.0	1474.0
Nigeria	NaN	511.0	269.0	454.0	408.0
Norway	NaN	658.0	527.0	532.0	303.0
Pakistan	NaN	240.0	185.0	286.0	324.0

	len				
time_id	**2014-04-30**	**2014-05-31**	**2014-06-30**	**2014-07-31**	**2014-08-31**
location					
Philippines	11.0	258.0	300.0	414.0	390.0
Poland	6.0	1149.0	925.0	817.0	906.0
Portugal	NaN	352.0	238.0	355.0	391.0
Russia	NaN	3747.0	2561.0	3130.0	2788.0
Saudi Arabia	NaN	931.0	1229.0	1138.0	806.0
Singapore	NaN	198.0	343.0	616.0	340.0
South Africa	NaN	306.0	519.0	775.0	724.0
Spain	NaN	1864.0	1703.0	1115.0	1192.0
Sweden	7.0	645.0	1252.0	1062.0	935.0
Switzerland	NaN	722.0	959.0	1368.0	711.0
Taiwan	NaN	906.0	905.0	967.0	822.0
Thailand	NaN	555.0	665.0	529.0	259.0
Turkey	NaN	366.0	493.0	777.0	796.0
United Arab Emirates	NaN	759.0	614.0	444.0	526.0
United Kingdom	2.0	4819.0	4050.0	4139.0	3465.0
United States	24.0	21177.0	23744.0	27327.0	22456.0
Venezuela	NaN	474.0	381.0	683.0	392.0

Language

In [284]:
```
pd.pivot_table(pd.merge(users, events, on='user_id', how = 'left', sort=
False),index=["language"],values='activated_at',columns=[pd.Grouper(key=
'time_id', freq='M')],aggfunc=[len])
```

Out[284]:

	len				
time_id	**2014-04-30**	**2014-05-31**	**2014-06-30**	**2014-07-31**	**2014-08-31**
language					
arabic	NaN	3173.0	3066.0	3230.0	2634.0
chinese	41.0	3592.0	3564.0	3517.0	2870.0
english	56.0	38619.0	41353.0	47973.0	39710.0
french	1.0	6813.0	6928.0	8870.0	6186.0
german	NaN	4968.0	4953.0	6796.0	5180.0
indian	9.0	2405.0	2307.0	2761.0	1954.0
italian	NaN	2151.0	1553.0	2248.0	1800.0
japanese	21.0	5550.0	6079.0	6955.0	5775.0
korean	NaN	1344.0	1256.0	1388.0	1012.0
portugese	NaN	2138.0	2019.0	2651.0	2185.0
russian	NaN	3089.0	2186.0	2613.0	2496.0
spanish	NaN	7898.0	7718.0	8154.0	7024.0

Conclusion:

- there is no specific platform that is mostly affected (both Mac/Windows Mobile and Desktop are affected)
- no specific pattern by language or location
- there is no specic pattern by user-type (whatever that means)
- the only thing that stood out that email sent and received was unchanded but fewer people clicked links in the emails - also something is going on in the engagement table when linkin that to the emails - would need some more time to figure this out...

B) External reasons - things that cannot be fixed/need to be investigated further

- check per company usage pattern -

if the pattern is specific for companies maybe they are changing their business practices which is decreasing our user engagement

In [197]:
```
pd.pivot_table(pd.merge(users, events, on='user_id', how = 'left', sort=
False), values = 'activated_at', index=["company_id"],columns=[pd.Groupe
r(key='time_id', freq='M')],aggfunc=[len])
```

Out[197]:

	len				
time_id	**2014-04-30**	**2014-05-31**	**2014-06-30**	**2014-07-31**	**2014-08-31**
company_id					
1.0	NaN	5751.0	4450.0	5584.0	4454.0
2.0	NaN	2530.0	2323.0	3584.0	1972.0
3.0	NaN	1386.0	1814.0	1470.0	1934.0
4.0	NaN	934.0	853.0	1306.0	993.0
5.0	NaN	284.0	903.0	1122.0	735.0
6.0	NaN	705.0	932.0	1300.0	523.0
7.0	NaN	341.0	424.0	892.0	393.0
8.0	NaN	563.0	566.0	765.0	974.0
9.0	NaN	516.0	550.0	695.0	328.0
10.0	NaN	302.0	504.0	482.0	419.0
11.0	NaN	401.0	238.0	455.0	450.0
12.0	NaN	586.0	657.0	273.0	105.0
13.0	NaN	250.0	535.0	590.0	443.0
14.0	NaN	347.0	340.0	374.0	319.0
15.0	NaN	120.0	126.0	435.0	120.0
16.0	NaN	227.0	232.0	180.0	170.0
17.0	NaN	177.0	251.0	304.0	162.0
18.0	NaN	292.0	304.0	253.0	126.0
19.0	NaN	103.0	72.0	97.0	236.0
20.0	NaN	141.0	285.0	326.0	252.0
21.0	NaN	105.0	176.0	97.0	41.0
22.0	NaN	35.0	13.0	130.0	116.0
23.0	NaN	345.0	49.0	244.0	254.0
24.0	NaN	155.0	35.0	349.0	34.0
25.0	NaN	306.0	179.0	187.0	188.0
26.0	NaN	123.0	293.0	89.0	275.0
27.0	NaN	99.0	8.0	147.0	47.0
28.0	NaN	346.0	181.0	306.0	190.0
29.0	NaN	150.0	168.0	182.0	181.0
30.0	NaN	49.0	49.0	65.0	34.0

	len				
time_id	**2014-04-30**	**2014-05-31**	**2014-06-30**	**2014-07-31**	**2014-08-31**
company_id					
...	...	...	...	...	...
13151.0	NaN	53.0	9.0	NaN	106.0
13152.0	NaN	NaN	NaN	2.0	NaN
13153.0	NaN	NaN	1.0	NaN	NaN
13154.0	NaN	NaN	NaN	NaN	8.0
13155.0	NaN	NaN	NaN	1.0	NaN
13157.0	NaN	NaN	1.0	NaN	NaN
13159.0	NaN	83.0	NaN	NaN	NaN
13160.0	NaN	NaN	21.0	NaN	NaN
13162.0	NaN	1.0	NaN	NaN	NaN
13165.0	NaN	72.0	135.0	85.0	38.0
13173.0	NaN	NaN	NaN	74.0	5.0
13174.0	NaN	NaN	NaN	NaN	1.0
13175.0	NaN	NaN	NaN	NaN	1.0
13176.0	NaN	NaN	3.0	NaN	NaN
13177.0	NaN	47.0	13.0	57.0	NaN
13178.0	NaN	23.0	NaN	NaN	NaN
13179.0	NaN	130.0	4.0	NaN	87.0
13180.0	NaN	NaN	NaN	NaN	1.0
13181.0	NaN	NaN	16.0	NaN	NaN
13183.0	NaN	NaN	19.0	NaN	NaN
13184.0	NaN	NaN	NaN	10.0	11.0
13185.0	NaN	NaN	NaN	NaN	109.0
13187.0	NaN	NaN	90.0	NaN	NaN
13188.0	NaN	36.0	NaN	96.0	59.0
13191.0	NaN	NaN	NaN	18.0	NaN
13192.0	NaN	NaN	NaN	40.0	NaN
13193.0	NaN	NaN	6.0	NaN	NaN
13194.0	NaN	NaN	NaN	1.0	NaN
13195.0	NaN	43.0	4.0	66.0	NaN

	len				
time_id	**2014-04-30**	**2014-05-31**	**2014-06-30**	**2014-07-31**	**2014-08-31**
company_id					
13197.0	NaN	29.0	NaN	NaN	NaN

6950 rows × 5 columns

In [149]:
```
## to get an idea how many users are there by company
users.groupby(['company_id']).count()
```

Out[149]:

	user_id	created_at	language	activated_at	state
company_id					
1.0	1036	1036	1036	510	1036
2.0	477	477	477	231	477
3.0	307	307	307	158	307
4.0	220	220	220	97	220
5.0	172	172	172	87	172
6.0	151	151	151	80	151
7.0	122	122	122	61	122
8.0	129	129	129	64	129
9.0	96	96	96	49	96
10.0	86	86	86	38	86
11.0	76	76	76	35	76
12.0	74	74	74	35	74
13.0	76	76	76	38	76
14.0	71	71	71	39	71
15.0	61	61	61	29	61
16.0	42	42	42	23	42
17.0	57	57	57	25	57
18.0	45	45	45	23	45
19.0	44	44	44	23	44
20.0	50	50	50	24	50
21.0	37	37	37	13	37
22.0	40	40	40	14	40
23.0	39	39	39	24	39
24.0	33	33	33	14	33
25.0	36	36	36	24	36
26.0	35	35	35	13	35
27.0	26	26	26	9	26
28.0	37	37	37	21	37
29.0	29	29	29	14	29
30.0	31	31	31	17	31
...	...	...	...	...	...

	user_id	created_at	language	activated_at	state
company_id					
13169.0	1	1	1	0	1
13170.0	1	1	1	0	1
13171.0	1	1	1	0	1
13172.0	1	1	1	0	1
13173.0	1	1	1	1	1
13174.0	1	1	1	0	1
13175.0	1	1	1	0	1
13176.0	1	1	1	0	1
13177.0	1	1	1	1	1
13178.0	1	1	1	1	1
13179.0	1	1	1	1	1
13180.0	1	1	1	0	1
13181.0	1	1	1	1	1
13182.0	1	1	1	0	1
13183.0	1	1	1	1	1
13184.0	1	1	1	1	1
13185.0	1	1	1	1	1
13186.0	1	1	1	0	1
13187.0	1	1	1	1	1
13188.0	1	1	1	1	1
13189.0	1	1	1	1	1
13190.0	1	1	1	1	1
13191.0	1	1	1	1	1
13192.0	1	1	1	1	1
13193.0	1	1	1	1	1
13194.0	1	1	1	0	1
13195.0	1	1	1	1	1
13196.0	1	1	1	1	1
13197.0	1	1	1	1	1
13198.0	1	1	1	0	1

13198 rows × 5 columns

Interesting pattern: there are definitly companies that more of a dip in engagment than others

compare company 3 to company 2 (about simliar size), also look at company 1 since it is the biggest one

company 2 = similar size but has dip in engagement company 3 = has no dip in engagment

In [187]:
```
# make new df with 2 companies

company1 = users.loc[users['company_id'] == 1.0]
company2 = users.loc[users['company_id'] == 2.0]
company3 = users.loc[users['company_id'] == 3.0]

company1.size
```

Out[187]: 6216

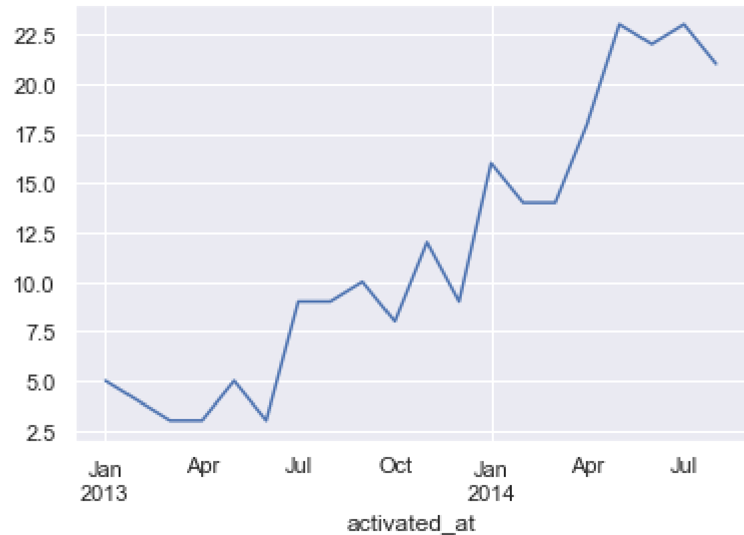
Plotting activated users over time for company 1, 2 and 3

In [215]:
```
company1.set_index('activated_at').resample('M')["state"].count().plot()
```

Out[215]: <matplotlib.axes._subplots.AxesSubplot at 0x238ce2fdd8>

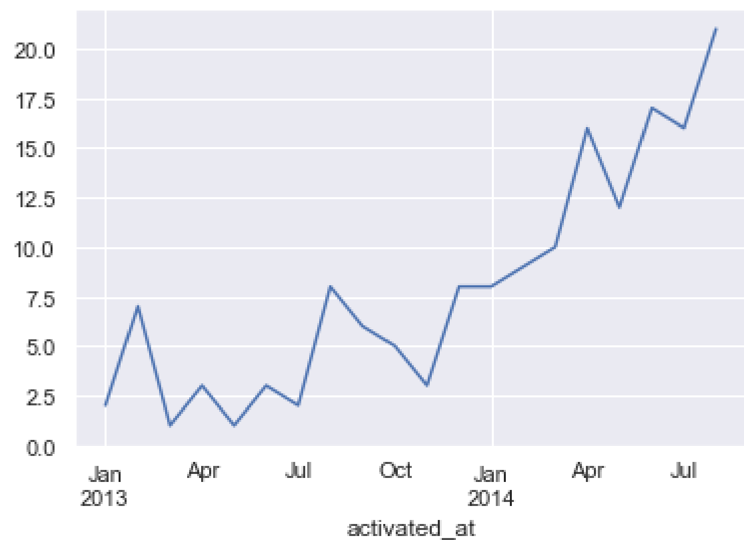
In [216]:
```
company2.set_index('activated_at').resample('M')["state"].count().plot()
```

Out[216]: <matplotlib.axes._subplots.AxesSubplot at 0x23540bee48>



In [217]:
```
company3.set_index('activated_at').resample('M')["state"].count().plot()
```

Out[217]: <matplotlib.axes._subplots.AxesSubplot at 0x231c50bdd8>

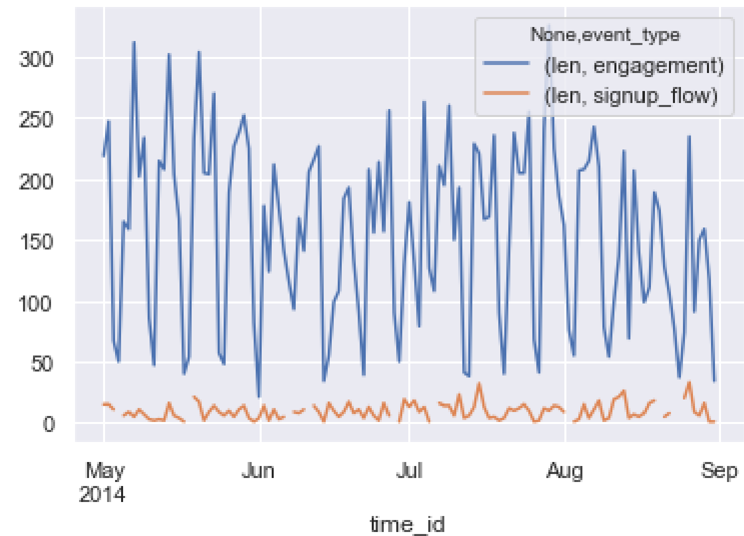


There seems to be a dip in activation also in August of 2013 for company 1, so maybe the dip in engagment is specific for some companies. Company2 and 3 had not that many users.

Looked also at daily use engagment patterns for company 1, 2 and 3 to see if there is a different pattern in cycling

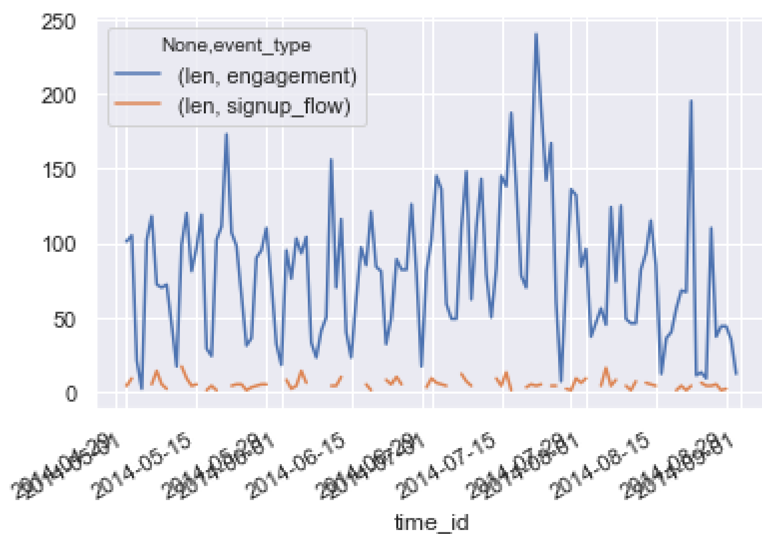
In [245]:
```
pd.pivot_table(pd.merge(company1, events, on='user_id', how = 'left', sort=False),values='activated_at', index=[pd.Grouper(key='time_id', freq='D')], columns=["event_type"],aggfunc=[len]).plot()
```

Out[245]: <matplotlib.axes._subplots.AxesSubplot at 0x22a3aeaf98>



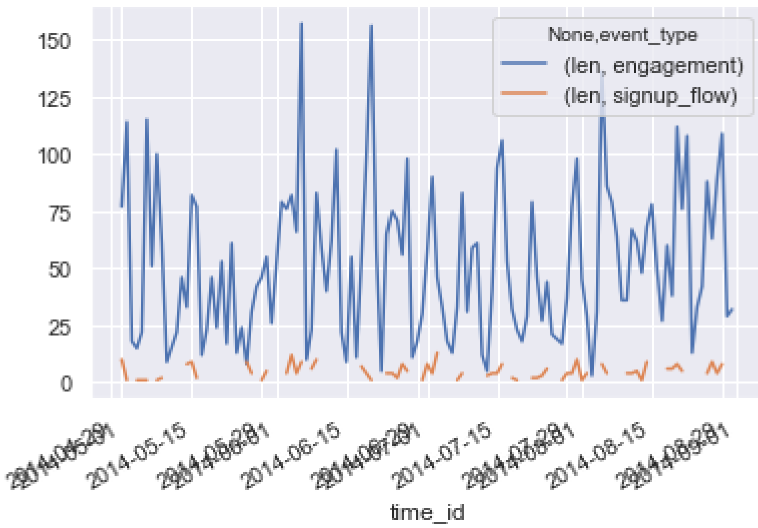
In [294]:
```
pd.pivot_table(pd.merge(company2, events, on='user_id', how = 'left', sort=False),values='activated_at', index=[pd.Grouper(key='time_id', freq='D')], columns=["event_type"],aggfunc=[len]).plot()
```

Out[294]: <matplotlib.axes._subplots.AxesSubplot at 0x1efceb2e48>



In [248]:
```
pd.pivot_table(pd.merge(company3, events, on='user_id', how = 'left', so
rt=False),values='activated_at', index=[pd.Grouper(key='time_id', freq=
'D')], columns=["event_type"],aggfunc=[len]).plot()
```

Out[248]: <matplotlib.axes._subplots.AxesSubplot at 0x21f8d97748>



cycling patterns for the companies didn't appear that much different. there might be some trend that company 1 and 2 might have been working up to some deadline in July (weekend usages increased) so maybe they are taking a break in August?

In [198]:
```
company1.head()
```

Out[198]:

	user_id	created_at	company_id	language	activated_at	state
9	9.0	2013-01-01 08:04:17	1.0	french	NaT	pending
47	47.0	2013-01-04 10:39:31	1.0	indian	2013-01-04 10:41:06	active
74	74.0	2013-01-08 21:11:48	1.0	english	NaT	pending
78	78.0	2013-01-08 12:58:44	1.0	english	2013-01-08 13:00:19	active
86	86.0	2013-01-09 13:24:02	1.0	indian	2013-01-09 13:25:27	active

- people go on Vacation in August - compare southern and northern hemisphere usage patterns -

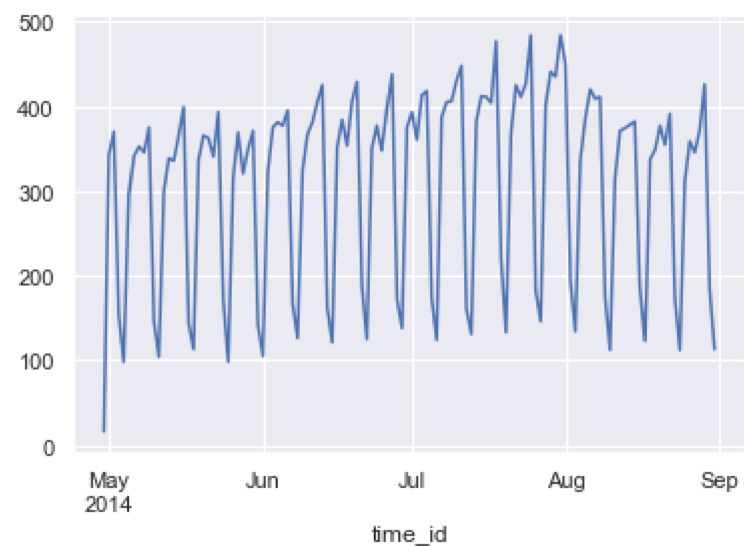
looked at the countries with a decent user base and then aggregated countries that don't have holidays in August. https://en.wikipedia.org/wiki/Summer_vacation (https://en.wikipedia.org/wiki/Summer_vacation)

In [56]:
```
events['location'].value_counts()
```

Out[56]:
```
United States           94728
Japan                   26046
Germany                 23524
France                  17364
United Kingdom          16475
Russia                  12226
Italy                   11790
Brazil                  11240
India                    9620
Canada                   9126
Mexico                   9106
Australia                7494
Korea                    7180
Indonesia                6224
Spain                    5874
Netherlands              4494
Saudi Arabia             4104
Sweden                   3901
Poland                   3803
Switzerland              3760
Taiwan                   3600
Iran                     3122
Belgium                  2822
Malaysia                 2529
Austria                  2494
Turkey                   2432
United Arab Emirates     2343
South Africa             2324
Egypt                    2258
Denmark                  2191
Israel                   2130
Norway                   2020
Thailand                 2008
Colombia                 1945
Venezuela                1930
Finland                  1926
Argentina                1717
Nigeria                  1642
Hong Kong                1525
Singapore                1497
Iraq                     1400
Philippines              1373
Portugal                 1336
Chile                    1092
Ireland                  1073
Pakistan                 1035
Greece                    989
Name: location, dtype: int64
```

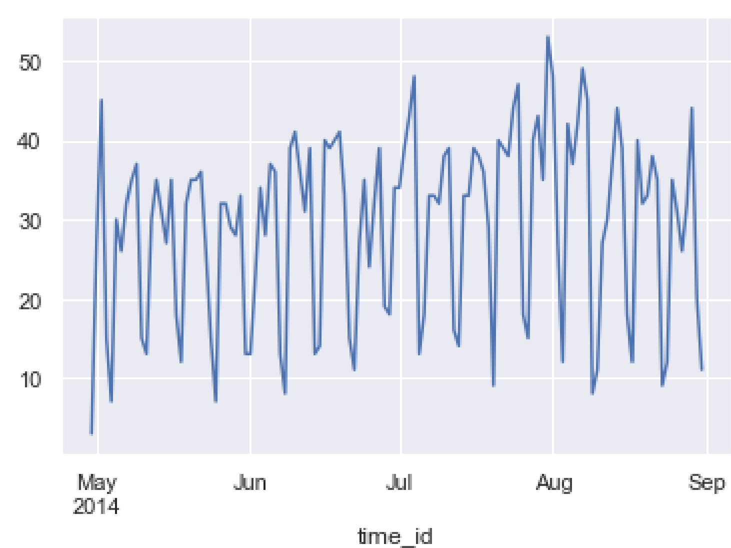
In [62]:
```
users_northern_HM = events[(events.location != 'India')|(events.location
!= 'Australia') | (events.location != 'Brazil') | (events.location != 'S
outh Africa') | (events.location != 'Chile' )]
users_northern_HM.groupby('time_id')['user_id'].nunique().plot()
```

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2caa4fd0>



In [61]:
```
users_southern_HM = events[(events.location == 'India')|(events.location
== 'Australia') | (events.location == 'Brazil') | (events.location == 'S
outh Africa') | (events.location == 'Chile' )]
users_southern_HM.groupby('time_id')['user_id'].nunique().plot()
```

Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2cc34748>



In [82]:
```
### look at engagement per month for southern hemisphere

users_southern_HM[users_southern_HM.event_type == 'engagement'].resample
('M').count()
```

Out[82]:

	user_id	occurred_at	event_type	event_name	location	device	user_type
time_id							
2014-04-30	29	29	29	29	29	29	29
2014-05-31	6957	6957	6957	6957	6957	6957	6957
2014-06-30	7149	7149	7149	7149	7149	7149	7149
2014-07-31	8833	8833	8833	8833	8833	8833	8833
2014-08-31	7008	7008	7008	7008	7008	7008	7008

there still is a dip in engagment in the "southern hemisphere" countries so elevated vacation in August that doesn't explain decreased engagemnt

Overall Conclusion:

- no catastrophic failure of platform
- no device specific, language specific, country specific outage
- mostly website affected and not email
- decrease is company specific - so companies need to be investigated further to see what the reason behind that is