Data Challenge 2

February 27, 2019

1 Data Challenge 2 - Yammer - Jeremy Ferlic - February 27, 2019

1.1 Problem Description

Yammer is a social network for communicating with coworkers. Individuals share documents, updates, and ideas by posting them in groups, it's like Slack. Yammer is free to use indefinitely, but companies must pay license fees if they want access to administrative controls, including integration with user management systems like ActiveDirectory.

On the morning of September 2, 2014, the head of the product team noticed something strange about the latest activity on the user engagement dashboards, as measured by the number of unique "engaged" users each week. An engaged user is one who has made a call to the Yammer servers corresponding to an "engagement" activity. The anomaly the product team head noticed was that up until August 1, there was a steady increase in the number of engaged users, but after August 1, there appears to be a decrease in this number. Our goal is to use the data available to investigate this scenario.

1.2 Data & Description

For this problem, data are available from four different databases: (1) a users table, (2) an events table, (3) an emails table, and (4) a date-rollup table. The first three items all contain a user_id, which can be used to link the information together. The users table contains descriptive information about the user's account. The events table is organized as one row per event, where an event is some action that a user of Yammer's platform has taken. The emails table contains information related to the sending of emails, and includes actions such as receiving the weekly digest email and clicking a link in an email. The rollup table is used to define time intervals of interest.

1.3 Assumptions

1.4 Package Imports

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        import sqlite3
        %matplotlib inline
```

1.5 Loading in Data

In [ ]:
```
# Read in various data frames
users = pd.read_csv("yammer_users.csv")
events = pd.read_csv("yammer_events.csv")
emails = pd.read_csv("yammer_emails.csv")
rollups = pd.read_csv("dimension_rollup_periods.csv")

# Convert to date-times
events['occurred_at'] =  pd.to_datetime(events['occurred_at'])
rollups['pst_start'] =  pd.to_datetime(rollups['pst_start'])
rollups['pst_end'] =  pd.to_datetime(rollups['pst_end'])

# The problem description only mentions the week-long periods with code 1007 as of int
rollups = rollups[rollups['period_id'] == 1007]
```

1.5.1 Creating events dataframe

In [3]:
```
# Use SQL commands to join the events to certain roll-ups
conn = sqlite3.connect(':memory:')

events.to_sql('events', conn, index=False)
rollups.to_sql('rollups', conn, index=False)
qry = '''
    SELECT
        *
    FROM events
    JOIN rollups
    ON events.occurred_at between rollups.pst_start and pst_end
    '''
df_events = pd.read_sql_query(qry, conn)
conn.close()
```

In [4]:
```
# Use SQL commands to join the events to user information
conn = sqlite3.connect(':memory:')

df_events.to_sql('df', conn, index=False)
users.to_sql('users', conn, index=False)
qry = '''
    SELECT
        *
    FROM df
    LEFT JOIN users USING(user_id)
    '''
df_events = pd.read_sql_query(qry, conn)
conn.close()
```

In [5]:
```
print(df_events.shape)
print(df_events.columns)
```

```
        print(df_events.head())
```

```
(2385824, 18)
Index(['user_id', 'occurred_at', 'event_type', 'event_name', 'location',
       'device', 'user_type', 'period_id', 'time_id', 'pst_start', 'pst_end',
       'utc_start', 'utc_end', 'created_at', 'company_id', 'language',
       'activated_at', 'state'],
      dtype='object')
   user_id          occurred_at  event_type event_name location  \
0  10522.0  2014-05-02 11:02:39  engagement      login    Japan
1  10522.0  2014-05-02 11:02:39  engagement      login    Japan
2  10522.0  2014-05-02 11:02:39  engagement      login    Japan
3  10522.0  2014-05-02 11:02:39  engagement      login    Japan
4  10522.0  2014-05-02 11:02:39  engagement      login    Japan

                  device  user_type  period_id              time_id  \
0  dell inspiron notebook        3.0     1007.0  2014-05-03 00:00:00
1  dell inspiron notebook        3.0     1007.0  2014-05-04 00:00:00
2  dell inspiron notebook        3.0     1007.0  2014-05-05 00:00:00
3  dell inspiron notebook        3.0     1007.0  2014-05-06 00:00:00
4  dell inspiron notebook        3.0     1007.0  2014-05-07 00:00:00

             pst_start              pst_end            utc_start  \
0  2014-04-26 00:00:00  2014-05-03 00:00:00  2014-04-26 07:00:00
1  2014-04-27 00:00:00  2014-05-04 00:00:00  2014-04-27 07:00:00
2  2014-04-28 00:00:00  2014-05-05 00:00:00  2014-04-28 07:00:00
3  2014-04-29 00:00:00  2014-05-06 00:00:00  2014-04-29 07:00:00
4  2014-04-30 00:00:00  2014-05-07 00:00:00  2014-04-30 07:00:00

               utc_end           created_at  company_id  language  \
0  2014-05-03 07:00:00  2014-04-04 16:48:03      1147.0  japanese
1  2014-05-04 07:00:00  2014-04-04 16:48:03      1147.0  japanese
2  2014-05-05 07:00:00  2014-04-04 16:48:03      1147.0  japanese
3  2014-05-06 07:00:00  2014-04-04 16:48:03      1147.0  japanese
4  2014-05-07 07:00:00  2014-04-04 16:48:03      1147.0  japanese

          activated_at   state
0  2014-04-04 16:49:36  active
1  2014-04-04 16:49:36  active
2  2014-04-04 16:49:36  active
3  2014-04-04 16:49:36  active
4  2014-04-04 16:49:36  active
```

1.5.2 Creating emails dataframe

In [6]:
```
# Use SQL commands to join the emails to certain roll-ups
conn = sqlite3.connect(':memory:')
```

```
emails.to_sql('emails', conn, index=False)
rollups.to_sql('rollups', conn, index=False)
qry = '''
    SELECT
        *
    FROM emails
    JOIN rollups
    ON emails.occurred_at between rollups.pst_start and pst_end
    '''
df_emails = pd.read_sql_query(qry, conn)
conn.close()
```

In [7]:
```
# Use SQL commands to join the emails to user information
conn = sqlite3.connect(':memory:')

df_emails.to_sql('df', conn, index=False)
users.to_sql('users', conn, index=False)
qry = '''
    SELECT
        *
    FROM df
    LEFT JOIN users USING(user_id)
    '''
df_emails = pd.read_sql_query(qry, conn)
conn.close()
```

In [8]:
```
print(df_emails.shape)
print(df_emails.columns)
print(df_emails.head())
```

```
(632723, 15)
Index(['user_id', 'occurred_at', 'action', 'user_type', 'period_id', 'time_id',
       'pst_start', 'pst_end', 'utc_start', 'utc_end', 'created_at',
       'company_id', 'language', 'activated_at', 'state'],
      dtype='object')
   user_id          occurred_at              action  user_type  period_id  \
0      0.0  2014-05-06 09:30:00  sent_weekly_digest        1.0     1007.0
1      0.0  2014-05-06 09:30:00  sent_weekly_digest        1.0     1007.0
2      0.0  2014-05-06 09:30:00  sent_weekly_digest        1.0     1007.0
3      0.0  2014-05-06 09:30:00  sent_weekly_digest        1.0     1007.0
4      0.0  2014-05-06 09:30:00  sent_weekly_digest        1.0     1007.0

               time_id            pst_start              pst_end  \
0  2014-05-07 00:00:00  2014-04-30 00:00:00  2014-05-07 00:00:00
1  2014-05-08 00:00:00  2014-05-01 00:00:00  2014-05-08 00:00:00
2  2014-05-09 00:00:00  2014-05-02 00:00:00  2014-05-09 00:00:00
3  2014-05-10 00:00:00  2014-05-03 00:00:00  2014-05-10 00:00:00
```

```
4  2014-05-11 00:00:00  2014-05-04 00:00:00  2014-05-11 00:00:00

             utc_start              utc_end           created_at  company_id  \
0  2014-04-30 07:00:00  2014-05-07 07:00:00  2013-01-01 20:59:39      5737.0
1  2014-05-01 07:00:00  2014-05-08 07:00:00  2013-01-01 20:59:39      5737.0
2  2014-05-02 07:00:00  2014-05-09 07:00:00  2013-01-01 20:59:39      5737.0
3  2014-05-03 07:00:00  2014-05-10 07:00:00  2013-01-01 20:59:39      5737.0
4  2014-05-04 07:00:00  2014-05-11 07:00:00  2013-01-01 20:59:39      5737.0

  language         activated_at   state
0  english  2013-01-01 21:01:07  active
1  english  2013-01-01 21:01:07  active
2  english  2013-01-01 21:01:07  active
3  english  2013-01-01 21:01:07  active
4  english  2013-01-01 21:01:07  active
```

1.6 Exploratory Analysis

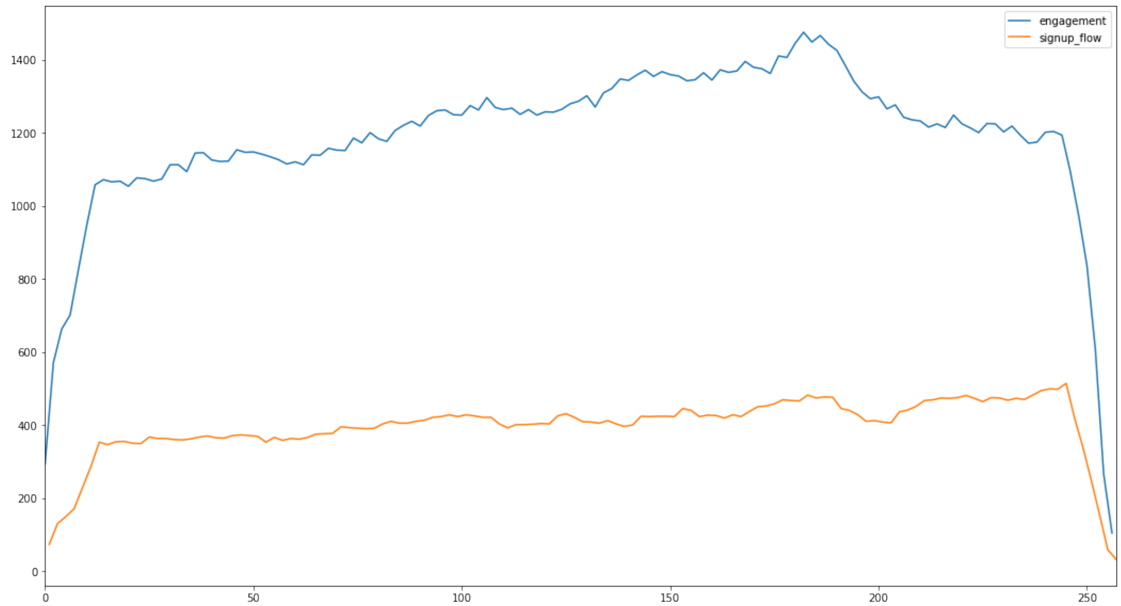
1.6.1 Event Data

In [35]:
```
# Use SQL commands to count distinct users for each time_id
conn = sqlite3.connect(':memory:')

df_events.to_sql('df', conn, index=False)
users.to_sql('users', conn, index=False)
qry = '''
    SELECT
        time_id, event_type, COUNT(DISTINCT df.user_id) AS activity
    FROM
        df
    GROUP BY time_id, event_type
    '''
df2 = pd.read_sql_query(qry, conn)
conn.close()
```

In [36]:
```
# Plot by event_type (engagement or signup)
fig, ax = plt.subplots(figsize=(18,6))
ax.legend(loc=1)
df2.groupby(['event_type'])['activity'].plot(ax=ax, legend=True, figsize=(18,10))
```

Out[36]:
```
event_type
engagement     AxesSubplot(0.125,0.125;0.775x0.755)
signup_flow    AxesSubplot(0.125,0.125;0.775x0.755)
Name: activity, dtype: object
```




```
In [43]: # When did we reach our max engagement
         df2.iloc[df2['activity'].idxmax()]
         peak = df2.iloc[df2['activity'].idxmax()]['time_id']
         print(peak)
```

```
2014-08-01 00:00:00
```

We are able to recreate the trend that the head of the department showed us. We see that our peak engagement time occurred on August 1 before the downward trend. We can see a similar trend in signup flow, but on to a much smaller extend; there is a dip in sign-ups, but not enough to be the driver in the trend we see in engagement.

1.6.2 Email Data

```
In [12]: print(df_emails.columns)
```

```
Index(['user_id', 'occurred_at', 'action', 'user_type', 'period_id', 'time_id',
       'pst_start', 'pst_end', 'utc_start', 'utc_end', 'created_at',
       'company_id', 'language', 'activated_at', 'state'],
      dtype='object')
```

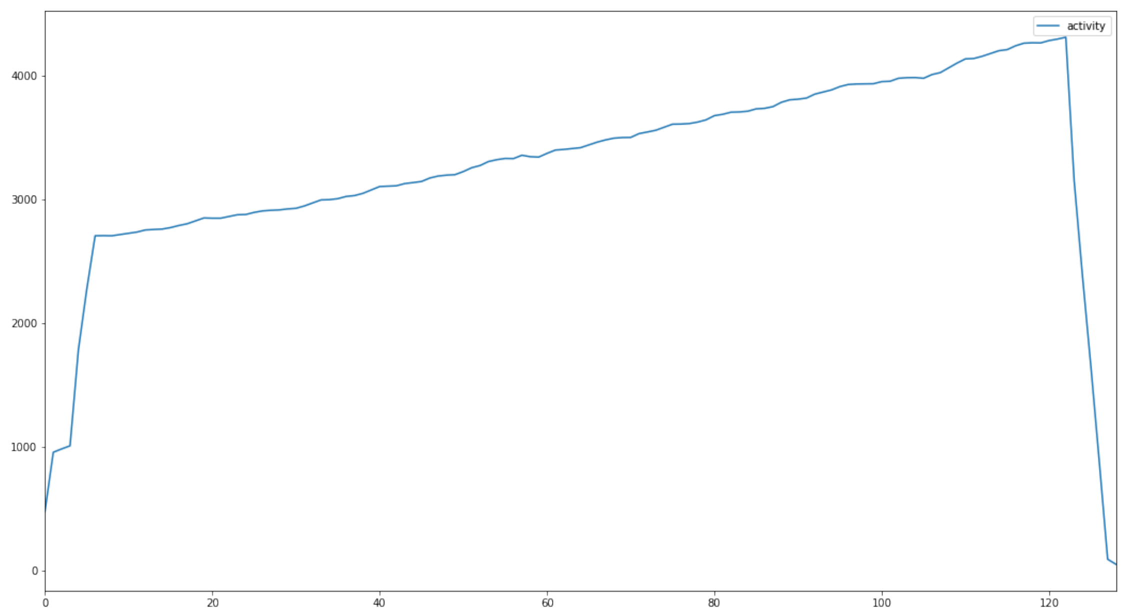
```
In [13]: # Use SQL commands to count unique number of users receiving emails
         conn = sqlite3.connect(':memory:')

         df_emails.to_sql('df', conn, index=False)
         users.to_sql('users', conn, index=False)
```

```
qry = '''
    SELECT
        time_id, COUNT(DISTINCT df.user_id) AS activity
    FROM
        df
    GROUP BY time_id
    '''
df2 = pd.read_sql_query(qry, conn)
conn.close()
```

In [14]:
```
# Plot
fig, ax = plt.subplots(figsize=(18,6))
ax.legend(loc=1)
df2['activity'].plot(ax=ax, legend=True, figsize=(18,10))
```

Out[14]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fccc6da6828>`



In [15]:
```
# When did we see our highest email engagement numbers
df2.iloc[df2['activity'].idxmax()]
```

Out[15]:
```
time_id     2014-09-01 00:00:00
activity                   4309
Name: 122, dtype: object
```

We don't see any such trend in total email activity. There may be a small dip around the same time as the engagement dip, but nothing visually significant. We can still dig down deeper to explore the email events.

1.7 Exploring the Event Data

1.7.1 By Event Name

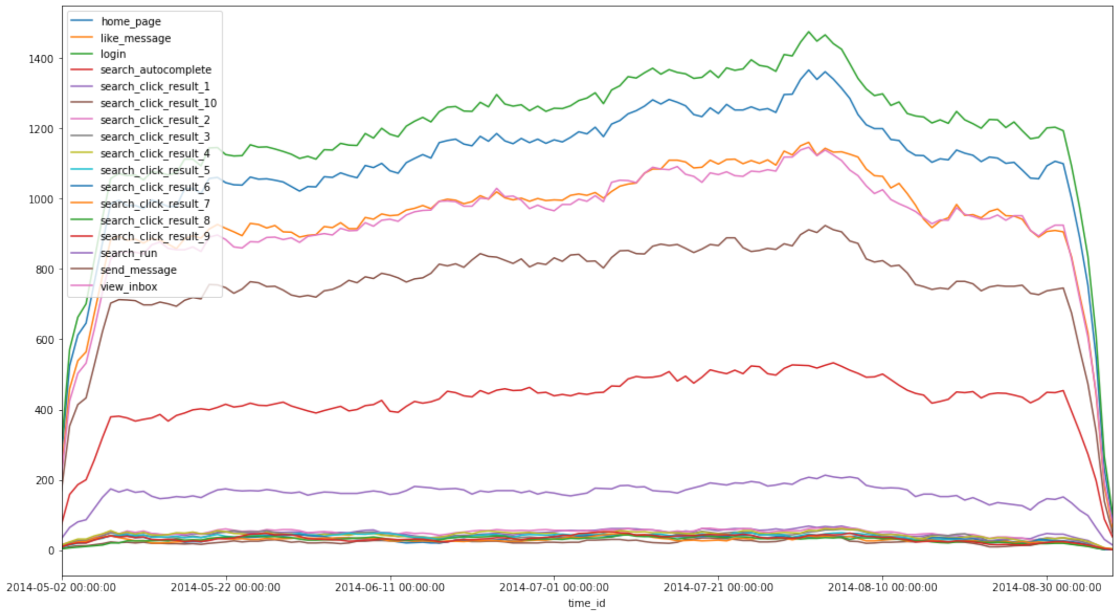
In [40]:
```
# Use SQL commands to join the events to certain roll-ups
conn = sqlite3.connect(':memory:')

df_events.to_sql('df', conn, index=False)
qry = '''
    SELECT
        time_id, event_type, event_name, COUNT(DISTINCT user_id) AS count
    FROM
        df
    WHERE
        event_type = 'engagement'
    GROUP BY time_id, event_type, event_name
    '''
df3 = pd.read_sql_query(qry, conn)
conn.close()
#print(df3)

fig, ax = plt.subplots(figsize=(18,6))
ax.legend(loc=1)

df3.set_index('time_id', inplace=True)
df3.groupby(['event_name'])['count'].plot(ax=ax, legend=True, figsize=(18,10))
#ax.axvline(x=peak)
```

Out[40]:
```
event_name
home_page                  AxesSubplot(0.125,0.125;0.775x0.755)
like_message               AxesSubplot(0.125,0.125;0.775x0.755)
login                      AxesSubplot(0.125,0.125;0.775x0.755)
search_autocomplete        AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_1      AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_10     AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_2      AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_3      AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_4      AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_5      AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_6      AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_7      AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_8      AxesSubplot(0.125,0.125;0.775x0.755)
search_click_result_9      AxesSubplot(0.125,0.125;0.775x0.755)
search_run                 AxesSubplot(0.125,0.125;0.775x0.755)
send_message               AxesSubplot(0.125,0.125;0.775x0.755)
view_inbox                 AxesSubplot(0.125,0.125;0.775x0.755)
Name: count, dtype: object
```



The dip in engagement seems to happen in the most frequent engagement types, those being logins, visits to the home page, like messages, and search auto-completes. This suggests that users are not visiting the Yammer page to begin with and means we can most likely rule out a catastrophic event where one of our search functions would have broken.

In [17]:
```
df_events.columns
```

Out[17]:
```
Index(['user_id', 'occurred_at', 'event_type', 'event_name', 'location',
       'device', 'user_type', 'period_id', 'time_id', 'pst_start', 'pst_end',
       'utc_start', 'utc_end', 'created_at', 'company_id', 'language',
       'activated_at', 'state'],
      dtype='object')
```

1.7.2 By User Language

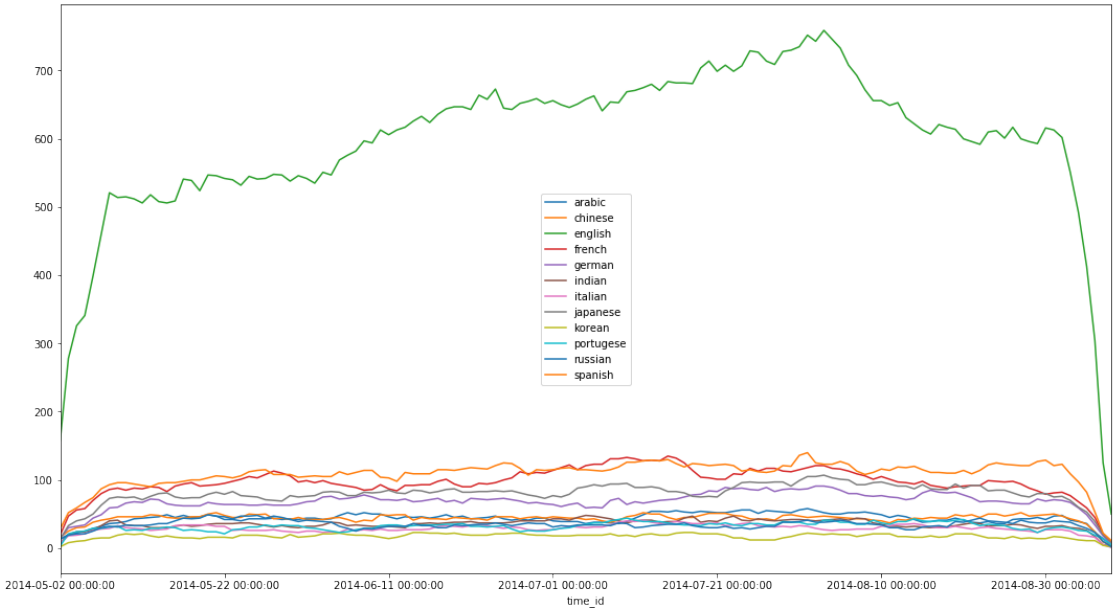
In [18]:
```
# Use SQL commands to join the events to certain roll-ups
conn = sqlite3.connect(':memory:')

df_events.to_sql('df', conn, index=False)
qry = '''
    SELECT
        time_id, language, COUNT(DISTINCT user_id) AS count
    FROM
        df
    WHERE
        event_type = 'engagement'
    GROUP BY time_id, language
    '''
```

```
df3 = pd.read_sql_query(qry, conn)
conn.close()
#print(df3)

df3.set_index('time_id', inplace=True)
df3.groupby('language')['count'].plot(legend=True, figsize=(18,10))
```

```
Out[18]: language
arabic       AxesSubplot(0.125,0.125;0.775x0.755)
chinese      AxesSubplot(0.125,0.125;0.775x0.755)
english      AxesSubplot(0.125,0.125;0.775x0.755)
french       AxesSubplot(0.125,0.125;0.775x0.755)
german       AxesSubplot(0.125,0.125;0.775x0.755)
indian       AxesSubplot(0.125,0.125;0.775x0.755)
italian      AxesSubplot(0.125,0.125;0.775x0.755)
japanese     AxesSubplot(0.125,0.125;0.775x0.755)
korean       AxesSubplot(0.125,0.125;0.775x0.755)
portugese    AxesSubplot(0.125,0.125;0.775x0.755)
russian      AxesSubplot(0.125,0.125;0.775x0.755)
spanish      AxesSubplot(0.125,0.125;0.775x0.755)
Name: count, dtype: object
```



In this plot, segmenting the users by language, we can see that a majority of our users are visiting the site in english, and they are also the major cause of our dip. None of the other languages appear to have a dip around the same time.

1.7.3 By User Location

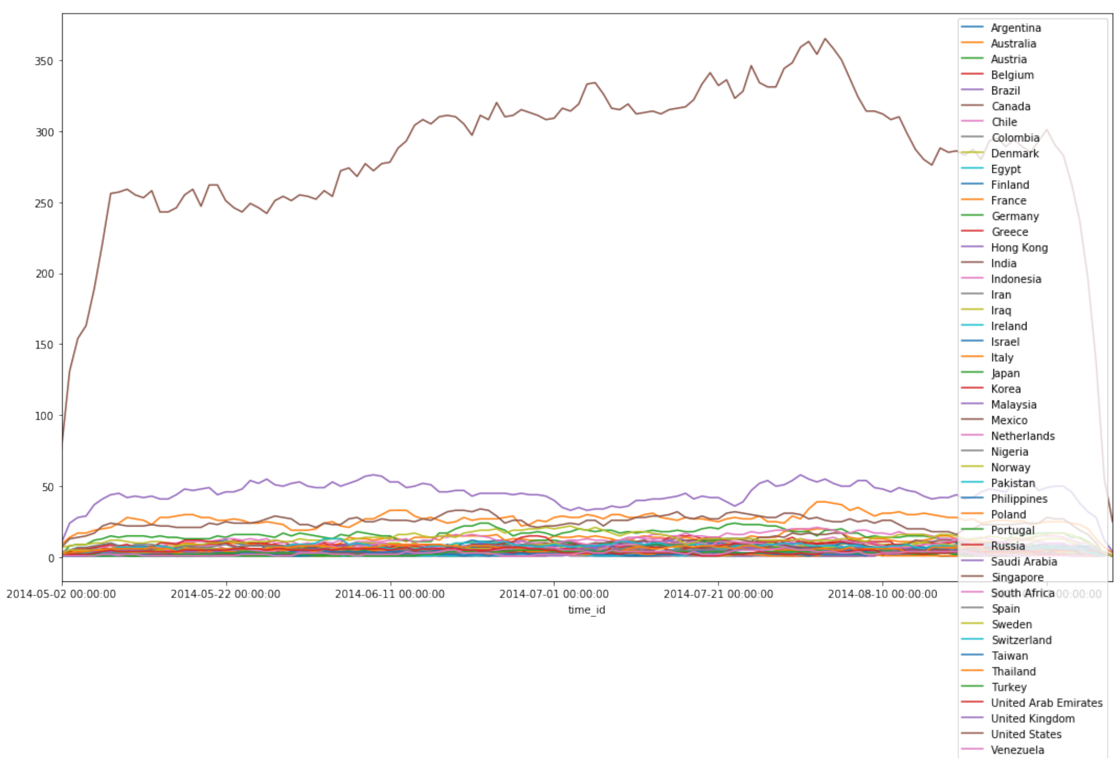
In [28]:
```
# Use SQL commands to join the events to certain roll-ups
conn = sqlite3.connect(':memory:')

df_events.to_sql('df', conn, index=False)
qry = '''
    SELECT
        time_id, location, COUNT(DISTINCT user_id) AS count
    FROM
        df
    WHERE
        event_type = 'engagement' AND language = 'english'
    GROUP BY time_id, location
    '''
df3 = pd.read_sql_query(qry, conn)
conn.close()
#print(df3)

df3.set_index('time_id', inplace=True)
df3.groupby('location')['count'].plot(legend=True, figsize=(18,10))
```

Out[28]:
```
location
Argentina                AxesSubplot(0.125,0.125;0.775x0.755)
Australia                AxesSubplot(0.125,0.125;0.775x0.755)
Austria                  AxesSubplot(0.125,0.125;0.775x0.755)
Belgium                  AxesSubplot(0.125,0.125;0.775x0.755)
Brazil                   AxesSubplot(0.125,0.125;0.775x0.755)
Canada                   AxesSubplot(0.125,0.125;0.775x0.755)
Chile                    AxesSubplot(0.125,0.125;0.775x0.755)
Colombia                 AxesSubplot(0.125,0.125;0.775x0.755)
Denmark                  AxesSubplot(0.125,0.125;0.775x0.755)
Egypt                    AxesSubplot(0.125,0.125;0.775x0.755)
Finland                  AxesSubplot(0.125,0.125;0.775x0.755)
France                   AxesSubplot(0.125,0.125;0.775x0.755)
Germany                  AxesSubplot(0.125,0.125;0.775x0.755)
Greece                   AxesSubplot(0.125,0.125;0.775x0.755)
Hong Kong                AxesSubplot(0.125,0.125;0.775x0.755)
India                    AxesSubplot(0.125,0.125;0.775x0.755)
Indonesia                AxesSubplot(0.125,0.125;0.775x0.755)
Iran                     AxesSubplot(0.125,0.125;0.775x0.755)
Iraq                     AxesSubplot(0.125,0.125;0.775x0.755)
Ireland                  AxesSubplot(0.125,0.125;0.775x0.755)
Israel                   AxesSubplot(0.125,0.125;0.775x0.755)
Italy                    AxesSubplot(0.125,0.125;0.775x0.755)
Japan                    AxesSubplot(0.125,0.125;0.775x0.755)
Korea                    AxesSubplot(0.125,0.125;0.775x0.755)
Malaysia                 AxesSubplot(0.125,0.125;0.775x0.755)
Mexico                   AxesSubplot(0.125,0.125;0.775x0.755)
```

```
Netherlands                AxesSubplot(0.125,0.125;0.775x0.755)
Nigeria                    AxesSubplot(0.125,0.125;0.775x0.755)
Norway                     AxesSubplot(0.125,0.125;0.775x0.755)
Pakistan                   AxesSubplot(0.125,0.125;0.775x0.755)
Philippines                AxesSubplot(0.125,0.125;0.775x0.755)
Poland                     AxesSubplot(0.125,0.125;0.775x0.755)
Portugal                   AxesSubplot(0.125,0.125;0.775x0.755)
Russia                     AxesSubplot(0.125,0.125;0.775x0.755)
Saudi Arabia               AxesSubplot(0.125,0.125;0.775x0.755)
Singapore                  AxesSubplot(0.125,0.125;0.775x0.755)
South Africa               AxesSubplot(0.125,0.125;0.775x0.755)
Spain                      AxesSubplot(0.125,0.125;0.775x0.755)
Sweden                     AxesSubplot(0.125,0.125;0.775x0.755)
Switzerland                AxesSubplot(0.125,0.125;0.775x0.755)
Taiwan                     AxesSubplot(0.125,0.125;0.775x0.755)
Thailand                   AxesSubplot(0.125,0.125;0.775x0.755)
Turkey                     AxesSubplot(0.125,0.125;0.775x0.755)
United Arab Emirates       AxesSubplot(0.125,0.125;0.775x0.755)
United Kingdom             AxesSubplot(0.125,0.125;0.775x0.755)
United States              AxesSubplot(0.125,0.125;0.775x0.755)
Venezuela                  AxesSubplot(0.125,0.125;0.775x0.755)
Name: count, dtype: object
```



Similarly, it would appear that the dip is being caused by users in the United States, who are by far our biggest customer location segment.

1.7.4 By User Device Type

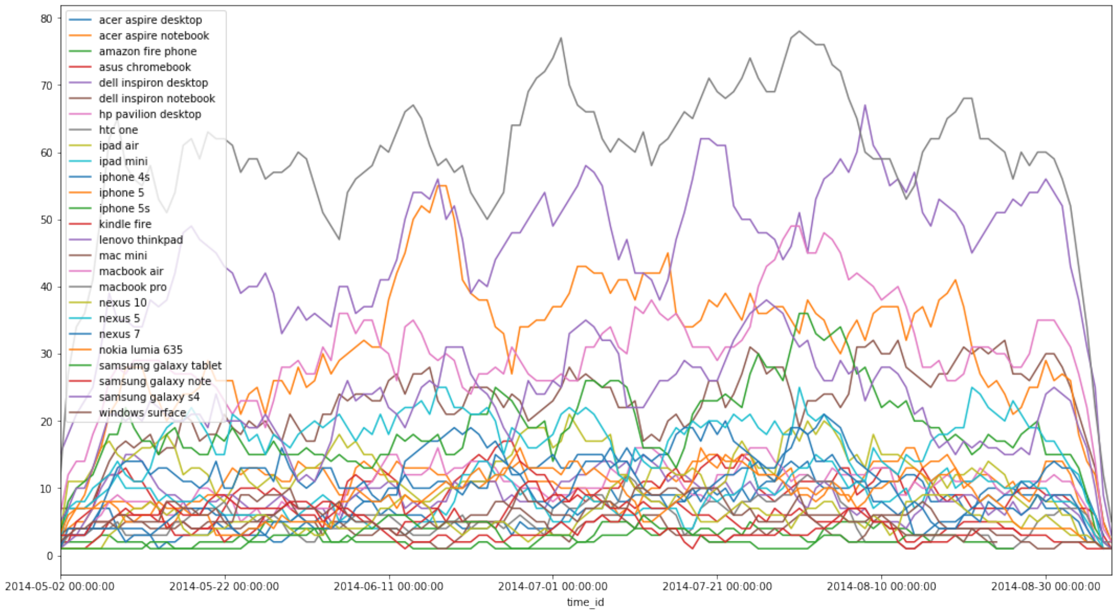
In [29]:
```
# Use SQL commands to join the events to certain roll-ups
conn = sqlite3.connect(':memory:')

df_events.to_sql('df', conn, index=False)
qry = '''
    SELECT
        time_id, device, COUNT(DISTINCT user_id) AS count
    FROM
        df
    WHERE
        event_type = 'engagement' AND language = 'english' AND location = 'United Sta
    GROUP BY time_id, device
    '''
df3 = pd.read_sql_query(qry, conn)
conn.close()
#print(df3)

df3.set_index('time_id', inplace=True)
df3.groupby('device')['count'].plot(legend=True, figsize=(18,10))
```

Out[29]:
```
device
acer aspire desktop       AxesSubplot(0.125,0.125;0.775x0.755)
acer aspire notebook      AxesSubplot(0.125,0.125;0.775x0.755)
amazon fire phone         AxesSubplot(0.125,0.125;0.775x0.755)
asus chromebook           AxesSubplot(0.125,0.125;0.775x0.755)
dell inspiron desktop     AxesSubplot(0.125,0.125;0.775x0.755)
dell inspiron notebook    AxesSubplot(0.125,0.125;0.775x0.755)
hp pavilion desktop       AxesSubplot(0.125,0.125;0.775x0.755)
htc one                   AxesSubplot(0.125,0.125;0.775x0.755)
ipad air                  AxesSubplot(0.125,0.125;0.775x0.755)
ipad mini                 AxesSubplot(0.125,0.125;0.775x0.755)
iphone 4s                 AxesSubplot(0.125,0.125;0.775x0.755)
iphone 5                  AxesSubplot(0.125,0.125;0.775x0.755)
iphone 5s                 AxesSubplot(0.125,0.125;0.775x0.755)
kindle fire               AxesSubplot(0.125,0.125;0.775x0.755)
lenovo thinkpad           AxesSubplot(0.125,0.125;0.775x0.755)
mac mini                  AxesSubplot(0.125,0.125;0.775x0.755)
macbook air               AxesSubplot(0.125,0.125;0.775x0.755)
macbook pro               AxesSubplot(0.125,0.125;0.775x0.755)
nexus 10                  AxesSubplot(0.125,0.125;0.775x0.755)
nexus 5                   AxesSubplot(0.125,0.125;0.775x0.755)
nexus 7                   AxesSubplot(0.125,0.125;0.775x0.755)
nokia lumia 635           AxesSubplot(0.125,0.125;0.775x0.755)
```

```
samsumg galaxy tablet     AxesSubplot(0.125,0.125;0.775x0.755)
samsumg galaxy note       AxesSubplot(0.125,0.125;0.775x0.755)
samsumg galaxy s4         AxesSubplot(0.125,0.125;0.775x0.755)
windows surface           AxesSubplot(0.125,0.125;0.775x0.755)
Name: count, dtype: object
```



In general, it would seem that the device information for users is too noisy to make any solid statement about. Some general observations include that the macbook pro users dip around the same time we see the global dip in engagement. Of course we can't really draw any causal conclusions from this data, such as a bug in the mac operating system is causing our low numbers because it may be that our system changed at that time and is no longer as compatible with macs, so our system numbers are actually the driver of the macbook pro effect.

1.7.5 By User Company

```
In [41]: # Use SQL commands to join the events to certain roll-ups
         conn = sqlite3.connect(':memory:')

         df_events.to_sql('df', conn, index=False)
         qry = '''
             SELECT
                 time_id, company_id, COUNT(DISTINCT user_id) AS count
             FROM
                 df
             WHERE
                 event_type = 'engagement' AND location = 'United States'
             GROUP BY time_id, company_id
             '''
```

```python
df3 = pd.read_sql_query(qry, conn)
conn.close()
#print(df3)

df3.to_csv("byCompany.csv")
df3.set_index('time_id', inplace=True)
df3.groupby('company_id')['count'].plot(legend=True, figsize=(18,10))
```

Out[41]:

```
company_id
1.0        AxesSubplot(0.125,0.125;0.775x0.755)
2.0        AxesSubplot(0.125,0.125;0.775x0.755)
3.0        AxesSubplot(0.125,0.125;0.775x0.755)
4.0        AxesSubplot(0.125,0.125;0.775x0.755)
5.0        AxesSubplot(0.125,0.125;0.775x0.755)
6.0        AxesSubplot(0.125,0.125;0.775x0.755)
7.0        AxesSubplot(0.125,0.125;0.775x0.755)
8.0        AxesSubplot(0.125,0.125;0.775x0.755)
9.0        AxesSubplot(0.125,0.125;0.775x0.755)
10.0       AxesSubplot(0.125,0.125;0.775x0.755)
11.0       AxesSubplot(0.125,0.125;0.775x0.755)
12.0       AxesSubplot(0.125,0.125;0.775x0.755)
13.0       AxesSubplot(0.125,0.125;0.775x0.755)
14.0       AxesSubplot(0.125,0.125;0.775x0.755)
15.0       AxesSubplot(0.125,0.125;0.775x0.755)
16.0       AxesSubplot(0.125,0.125;0.775x0.755)
17.0       AxesSubplot(0.125,0.125;0.775x0.755)
18.0       AxesSubplot(0.125,0.125;0.775x0.755)
19.0       AxesSubplot(0.125,0.125;0.775x0.755)
20.0       AxesSubplot(0.125,0.125;0.775x0.755)
21.0       AxesSubplot(0.125,0.125;0.775x0.755)
22.0       AxesSubplot(0.125,0.125;0.775x0.755)
23.0       AxesSubplot(0.125,0.125;0.775x0.755)
24.0       AxesSubplot(0.125,0.125;0.775x0.755)
25.0       AxesSubplot(0.125,0.125;0.775x0.755)
26.0       AxesSubplot(0.125,0.125;0.775x0.755)
27.0       AxesSubplot(0.125,0.125;0.775x0.755)
28.0       AxesSubplot(0.125,0.125;0.775x0.755)
29.0       AxesSubplot(0.125,0.125;0.775x0.755)
30.0       AxesSubplot(0.125,0.125;0.775x0.755)
                           ...
12933.0    AxesSubplot(0.125,0.125;0.775x0.755)
12943.0    AxesSubplot(0.125,0.125;0.775x0.755)
12957.0    AxesSubplot(0.125,0.125;0.775x0.755)
12959.0    AxesSubplot(0.125,0.125;0.775x0.755)
12981.0    AxesSubplot(0.125,0.125;0.775x0.755)
12982.0    AxesSubplot(0.125,0.125;0.775x0.755)
12989.0    AxesSubplot(0.125,0.125;0.775x0.755)
12993.0    AxesSubplot(0.125,0.125;0.775x0.755)
```