# Babak_Fard_Yammer

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# 1 Data Challeng 2 - Yammer

## 1.1 Overview

The product manager of the group wants to investigate a drop i user engagement in the last month.The timeseries diagram shows a constant trend from the second week of may until the start of Aug, then a sudden change in the trend sign. The initial observations include the following: * The change is very sudden. Therefore it more seems to be similar to a chatastrophic event that has suddenly caused the change. Such as a progressing break down in the servers that continuously has stopped service to growing number of customers * Another possibility might be related to the human groups or communities. For example an important business customer has decided to swith into another platform, e.g. Slack, and starting August the employees have started to switch into the other platform. Or it might be people from a community with a specific lenguage might have started to switch to a similar product which supports their language.

```
In [1]: %load_ext autoreload
        %autoreload 2

        %matplotlib inline
```

```
In [2]: import pandas as pd
        import datetime
        import numpy as np
        import scipy
        import seaborn as sns
        import matplotlib.pyplot as plt
        import pickle
```

```
In [49]: # Defining a parser for reading in the date fields in an appropriate format and type
         mydateparser = lambda x: pd.datetime.strptime(x, '%Y-%m-%d %H:%M:%S')

         # Reading all tables
         df_user = pd.read_csv('data_yammer/yammer_users.csv', parse_dates=["created_at"], date
         df_events = pd.read_csv('data_yammer/yammer_events.csv', parse_dates=["occurred_at"],
         df_emails = pd.read_csv('data_yammer/yammer_emails.csv', parse_dates=["occurred_at"],
         df_rollup = pd.read_csv('data_yammer/dimension_rollup_periods.csv', parse_dates=['time
                                date_parser=mydateparser)
```

```
In [50]: # Cleaning data
         # Based on the problem definition we are only looking into engagement type events
         df_events = df_events[df_events['event_type']=='engagement']
```

## 1.2 Exploratory Data Analysis

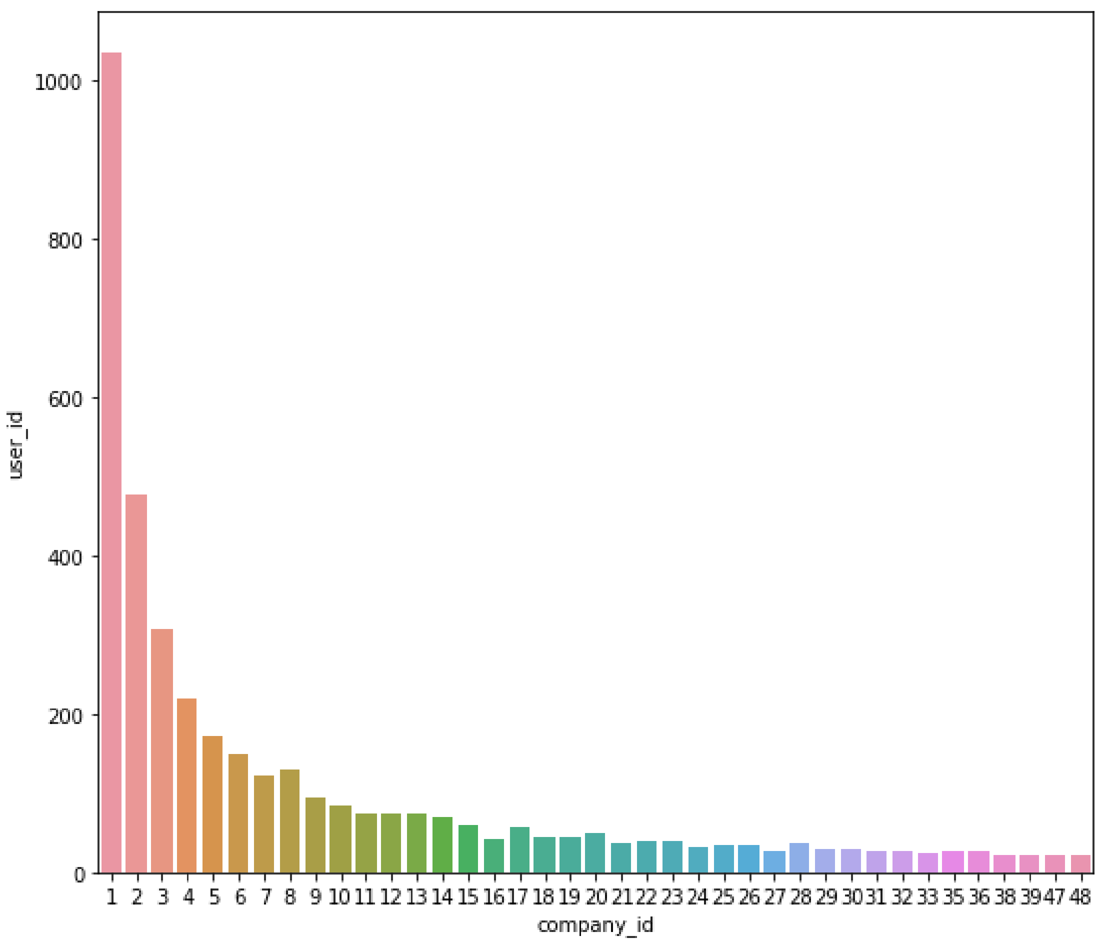
Looking into users data shows that 19066 users do not have activation dates

- Looking into the distribution of employees for different companies

```
In [51]: # counting the number of users in each company
         a = df_user.groupby('company_id').count()['user_id']
         a = a[a>20]     # there are a few thousand companies. let's keep the big plyers
         plt.figure(figsize=(9, 8))
         sns.barplot(a.index, a)

         #emp_lang = df_user.groupby('language').count()
         #plt.figure(figsize=(9, 8))
         #sns.barplot(emp_lang.index, emp_lang['user_id'])

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1f3ece80>
```



As seen in figure above, the distribution of the company sizes follows a power law distribution. If I want to draw any conclusion regarding the company wide changes in user behavior I will just look into the first 10 companies with the following number of users

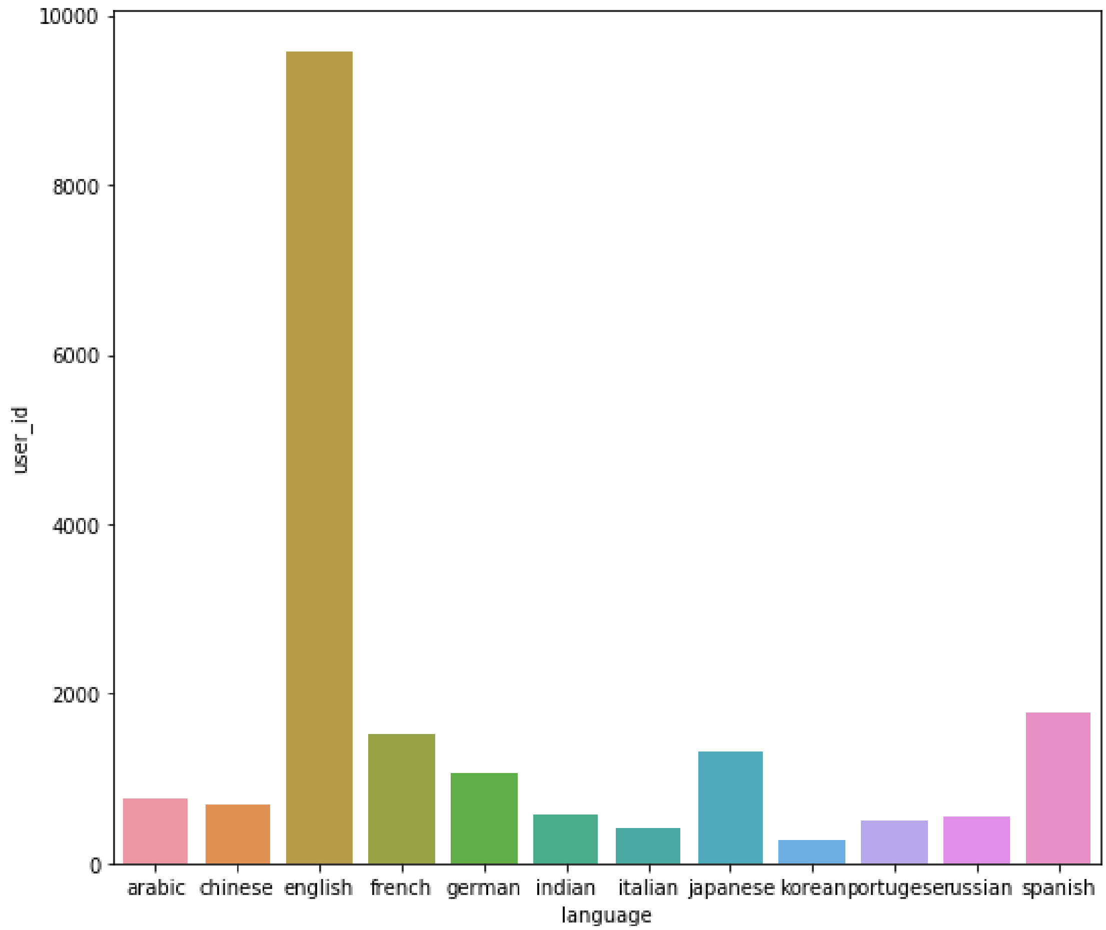
```
In [52]: a[:10]
```

```
Out[52]: company_id
         1     1036
         2      477
         3      307
         4      220
         5      172
         6      151
         7      122
         8      129
         9       96
         10      86
         Name: user_id, dtype: int64
```

What if users with some similar characteristics have started a change in their behavior? Let's take a look at how the languages of users are disperced.

```
In [53]: emp_lang = df_user.groupby('language').count()
         plt.figure(figsize=(9, 8))
         sns.barplot(emp_lang.index, emp_lang['user_id'])
```

```
Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x1a257bdb00>
```




English language speakers by far are the most number of users. Considering this we can probably add all others into one category named 'Non-english'. That can make calculations easier and better to undrestand

### 1.2.1 Looking into the timeseries of different features

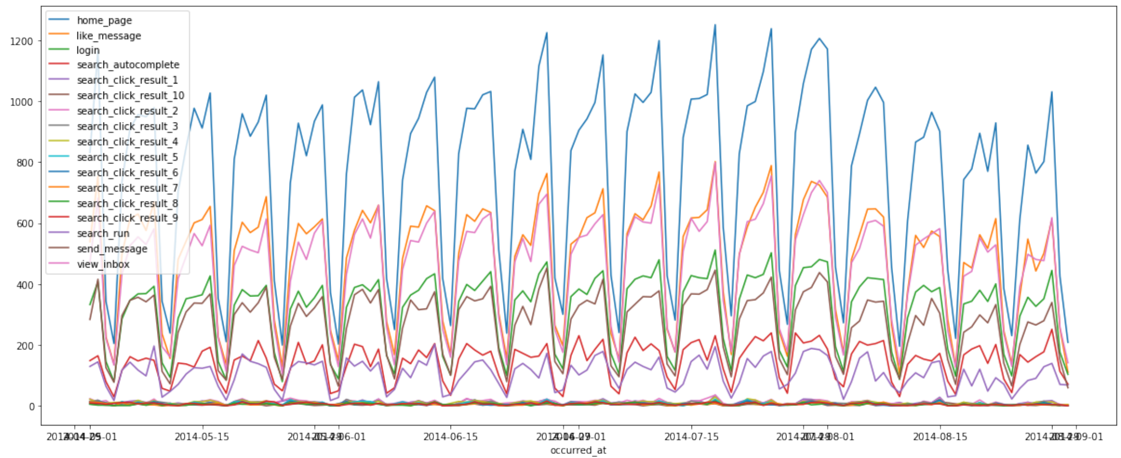
It will be very informative to look into the time series diagrams of different features and see if we can find any similarity in their behavior with the user activity diagram. In the follow I have plotted these timeseries for a few of features.

```
In [54]: # Joining tables to create timeseries for different features
         # df_user_events = df_user.join(df_events, on='user_id', how='right')
         df_user_events = pd.merge(df_user, df_events, on='user_id')
         df_user_events['occurred_at'] = df_user_events['occurred_at'].dt.date
         df_user_events.head(3)
```

```
In [55]: # I want to see different time series based on different parameters
         # Based on event name
         #ts_event_name = df_user_events.groupby(['event_name', 'occurred_at'])
```

```
        # reset_index() gives a column for counting, after groupby uses year and category
        ctdf = (df_user_events.reset_index().groupby(['occurred_at', 'event_name'], as_index=
                    .count()
                    # rename isn't strictly necessary here, it's just for readability
                    .rename(columns={'index':'ct'})
               )
```

```
In [56]: #from matplotlib import pyplot as plt
         fig, ax = plt.subplots(figsize=(20, 8))
         #plt.figure(figsize=(20,20))
         # key gives the group name (i.e. category), data gives the actual values
         for key, data in ctdf.groupby('event_name'):
             data.plot(x='occurred_at', y='ct', ax=ax, label=key)
```




A very clear similar trend, both in the direction and in the change point, can be seen in the first 5 event_names, which are "home_page",

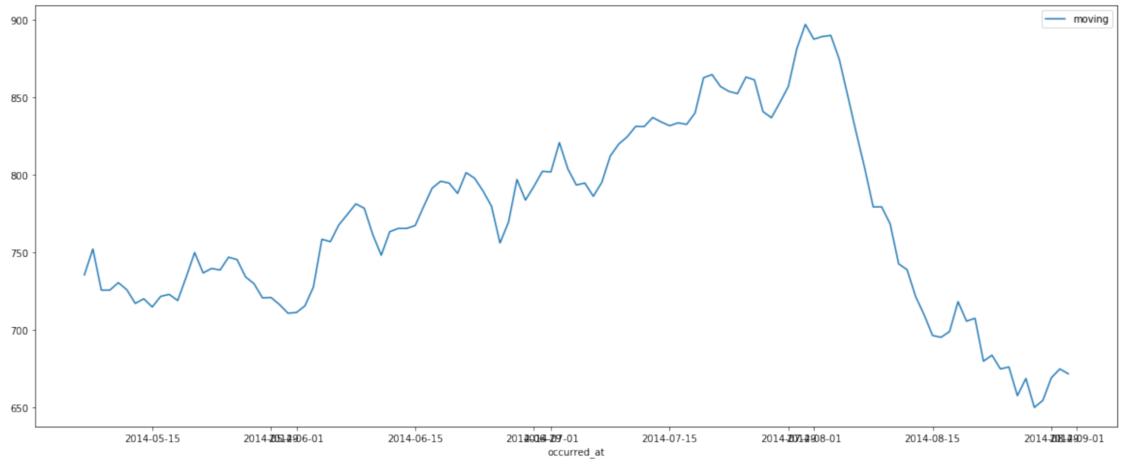
```
In [58]: # Creating the 7 day moving average for the most important event of 'home_page'
         sample = ctdf[ctdf['event_name']=='home_page']
         sample['moving'] = sample['ct'].rolling(7).mean()

         fig, ax = plt.subplots(figsize=(20, 8))
         #plt.figure(figsize=(20,20))
         # key gives the group name (i.e. category), data gives the actual values
         sample.plot(x='occurred_at', y='moving', ax=ax)
```

```
/anaconda3/envs/labx/lib/python3.6/site-packages/ipykernel_launcher.py:3: SettingWithCopyWarni
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  This is separate from the ipykernel package so we can avoid doing imports until
```

Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x1a226ed128>




The above diagram clearly shows that how the number of occurences for this specific, highest used event, has started an abrupt and fast decline. It is very similar to the user activity diagram time series.

### 1.3 Conclusion

The graphs, show that there is a correlation in the time series of some specific events and the diagram of question. One method can be adding all these high impact features into a set and perform a random forst or linear regression model to find out the reasons causing this problem