

## Relax Inc. Challenge

Problem statement: How can Relax Inc. increase its adopted user base by 30% over the next year.

### Methodology for data wrangling:

I explored the users data using ydata-profiling and I discovered that the last\_creation\_time series was missing more than 1/4 of the data, and invited\_by\_user\_id was missing nearly 1/2 of the data. I dropped the invited\_by\_user\_id series from my data frame and left the last\_creation\_time untouched.

### Feature engineering:

I created a target variable called “adopted” by assigning a 1 to each record that has logged into the product on three separate days in at least one seven-day period, and 0 otherwise using data from the takehome\_users csv. After merging with the engagement data, I compared the adopted user count to each account creation source type and I got the following results:

| Creation Source    | Adoption Percentage | Total Adopted User Count |
|--------------------|---------------------|--------------------------|
| GUEST_INVITE       | 23                  | 2163                     |
| ORG_INVITE         | 18                  | 4254                     |
| PERSONAL_PROJECTS  | 11                  | 2111                     |
| SIGNUP             | 20                  | 2087                     |
| SIGNUP_GOOGLE_AUTH | 22                  | 1385                     |

The highest adopted user conversion happens when a user is invited to an organization as a guest, and the lowest conversion happens when a user is invited to join another user’s personal workspace.

In addition, I thought the count of visits per user could be useful so I created another variable called ‘total\_visits’ using data from the takehome\_users csv. After observing average visit count by adoption status, the obvious result indicates that non adopted users have very few sign ins.

### Preprocessing and Modeling:

To prepare for modeling, I created dummy variables from the create\_source categorical variable, and I also extracted the year, month, day, and hour from the creation\_time and last\_session\_creation\_time variables. I used a Histogram-based Gradient Boosting Classification Tree model the results were very good supported by an accuracy score of 99.6%. After using permutation importance to rank the features, my engineered total\_visits variable ranked first with 30%.

### Recommendation for stakeholders:

To increase the adopted user base, I recommend an incentive for users to sign in more often. The user creation source for personal\_projects has the lowest adoption percentage and plenty of room for improvement considering the remaining four hover around 20% adoption.