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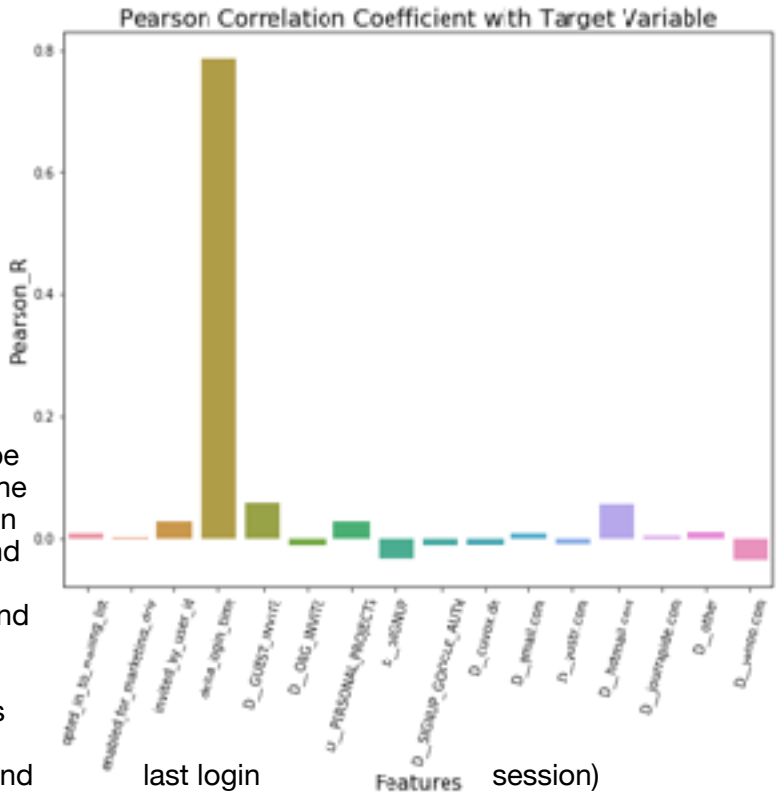
## Relax Challenge Results




For this take home challenge, I was presented with two tables, one with user information and another with user login timestamps, and was asked to determine the factors leading to becoming “adopted users.” These are defined as users who logged in three times in the span of a week, and was found to be 18.5% of all the users in the data given. Given the imbalanced dataset, I decided to look at pearson correlation coefficients between each feature and the target variable (adopted user or not).

Some features were given in the table, and included opted_in_to_mailing_list, enabled_for_marketing_drip, and invited_by_user_id. I created some new features using other columns given such as a delta_login_time (time difference between first and last login session) and dummy variables representing email domains and creation source of the user. I altered the invited_by_user_id variable to be a categorical binary variable of yes or no to deal with missing values and the meaningless quality of the id itself. Given the wealth of email domains used, I only looked at the top six email domains and used a seventh “other” category for the rest.

As seen in the figure, i found that the strongest predictive feature was the delta_login_time, implying that the longer a user is utilizing the service, the more likely they are to become an adoptive user, which makes intuitive sense. Other strong correlations are seen in the D_GUEST_INVITE and D_hotmail.com features, meaning there could be a relationship with those who join the service via an invitation, and those who use hotmail accounts for their emails. The first of those makes some sense to me, while the second is an interesting oddity that would warrant further study. The two strongest anti-correlations are seen with yahoo email account users, and those who signed up with the SIGNUP event. Though not shown on the figure, these correlations all have p values less than 0.05, and are thus statistically significant.

The pearson correlation coefficient method has a major weakness in that it looks at the effects of features individually on the target variable, but does not look into any combinatory effects of the variables together on the target. To do that more complex analysis, I would need to do some predictive modeling with machine learning algorithms. Different analyses can showcase different relationships, and so multiple methods would be good for use, such as logistic regression, random forest, and a neural network, to name a few. However, to undergo this type of modeling, I would need to look into any possible correlations between the features themselves to avoid overfitting, as well as balancing the dataset. Given that only 18.5% of users are adopted users, I would need to either oversample or undersample the data (or to try both) before using these algorithms.

Given the time constraints of the challenge (1-2 hours recommended), I leave this more complex analysis for future work.