Contributor Data Exploration at IndieGoGo

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1 Data Exploration

I explore a small sample of contribution data from IndieGoGo using minimal Python scripts in the iPython notebook environment.

The data file is placed in a Pandas DataFrame for the majority of the analysis. My first step is to take a quick look at the cateogories in each column of the data frame. There are many contributors, campaigns, and perk ids, of similar magnitude as the total number of records in the data set. These therefore are somewhat unsuitable for group analysis as there are only a handful of points in each subset. That said, there are four currencies, ninety-eight campaign countries and fifty contributor countries. These proved to be somewhat suitable for some group level statistics.

Globally, one can quickly find the mean and standard deviation using the "describe" method in Pandas. I note however that I restrict my global analysis to USD currency, so that transaction amounts can be combined sensibibly. For USD, the mean transaction amount is 78.78USD and the std is 243.24 USD. Looking at only USD records accounts for 88% of the data.

2 Claimed and Unclaimed Perks

Each record has an optional field reporting if a "perk" was claimed by the contributor. A non-NaN value means that the transaction amount exceeds some minimal perk amount, usually resulting in the contributor getting some benefit. To attempt to understand what effect, if any, claiming perks has on contributions, I plot a histogram of the number of transactions that fall into a transaction amount bin. The interesting thing I observe is that there are "favored values" which are usually "round numbers", i.e. 10, 50, 100 etc. (See attached html for images)

Presumably this clustering around nice numbers could come from either an incentive structure in the perk amounts, or some human behavior aspect to gravitate toward "nice numbers". I attempt to further investigate if the perk structure plays a role by plotting a histogram of the perk amounts. There is the same underlying favoring of roung numbers in the histogram of perk amounts, but this does not really tell us if they are driving the contribution distrubtion.

I plot another histogram, this time of contributions where a perk was not claimed (an unclaimed perk), hoping that the favoring of round numbers would not be as prevalent, but it is. Since the structure toward nice numbers appears with and without the presence of claimed perks, I am not able to say what effect perks incentivize users to spend in certain amounts.

I can look at the distrubtions of the two groups, claimed and unclaimed, and note differnces in the distrubtions. Both have similar means (78USD and 80USD) but different std (189USD and 335 USD), respectively. I next look at the difference in various quantiles(at the 25, 50 and 75 levels), and see that many more contributions occur at lower transaction amounts in the no claimed case.

	Claimed Perk	Unclaimed Perk
up to q 25%		
Total (USD)	21156	4826
Per Contribution	12.21	6.67

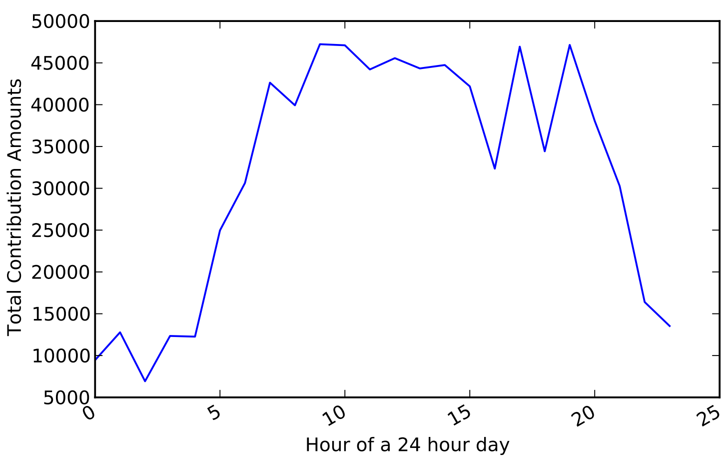
Percent Total	4.4%	2.2%
up to q 50%		
Total (USD)	59582	21328
Per Contribution	18.86	14.36
Percent Total	12.4%	9.9%
up to q 75%		
Total (USD)	137592	45312
Per Contribution	29.89	22.53
Percent Total	28.7%	21.1%

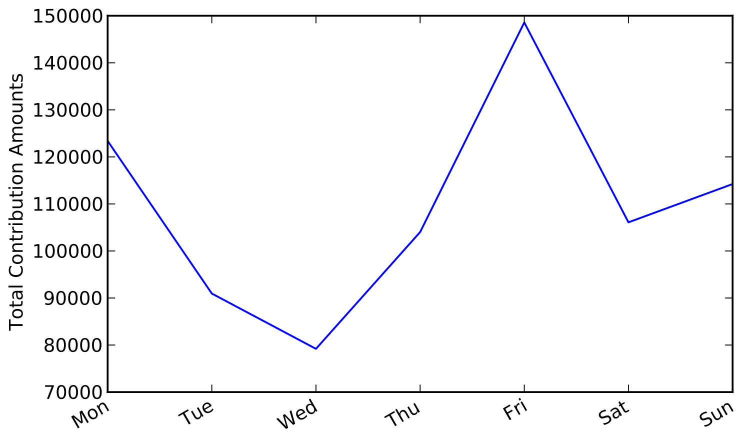
This is actionable. If one could convert or incentivize contributors to behave as in the claimed perk case, then more contributions would occur at the higher "per contribution" values that appear when perks are claimed. The total percent increase in contrubtions would look roughly as follows in the list below.

quantile	contribution increase	percent of all contribution increase
q=25%	4005.29 USD	0.58%
q=50%	6671.77 USD	0.96%
q=75%	14800.43 USD	2.13%

3 Peak Usage

We now turn to *when* contributions happen and look for patterns. Using the transaction time column, I can group together temporally conincident points and get an idea of trends across various time scales. I provide plots for the usage per day broken down by hour, the usage per week broken down by day. Additional plots for the whole set are provided in attached html file.





I conclude that most activity occurs between roughly 7AM and 6PM PST on an hourly basis. Additionaly, there is more activity on Fridays and to a lesser extent, over the weekend. Both of these conclusions make sense, given we are looking at USD contributions and those are mostly coming from continental US timezones.

4 Conclusions

Peak usage seems to be the clearest insight taken from the given dataset. In general, usage can help with add targeting and user retention efforts by better understanding when people use the site/service. Furthermore, usage can assist engineering efforts to assure that during peak usage, no infrastructure is taxed to the point of a failure in quality service.

Perk structure is interesting, but the causal relationships are unclear given the short analysis here. On an indvidual contributor level, I would think there would be very clear tendencies to try to reach perks on a regular basis. As there are minimal repeats of users in this dataset, no such analysis can be even considered. However, I think specific analysis on users and on the larger "genres" of campaigns they contribute to, would likely reveal some interesting patterns.