MANAGING THE CROWDS: THE EFFECT OF PRIZE GUARANTEES AND IN-PROCESS FEEDBACK ON PARTICIPATION IN CROWDSOURCING CONTESTS

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Appendix A

Study Site Description

Figure A1. Timeline of a Typical Contest
For each contest, the “Contest Title” column displays the title of the contest (masked out here for anonymity), a short description of the business (masked out), and an image of the business. The “Contest Holder” column shows the screen name (masked out) of the contest host. The “Ends” column shows the time left until the contest closes, the “Entries” column shows the total number of entries the contest has received so far, and the “Package” column shows the prize package, including the amount and whether the prize is guaranteed. Note: Contest # 3’s prize is guaranteed. “bronze” is a tag for the contest’s prize level. Higher prizes can be marked as silver, gold, and platinum.

**Figure A2. Screenshot of Page Displaying All Contests**

As of May 2016, the site we study has hosted more than 350,000 contests and paid more than $100 million to participants. At the time of our data collection in June 2011, 125,527 users were registered on the platform, and more than 6 million designs had been submitted. On this site, a typical contest goes through three stages (see Figure A1): before, during, and after the contest. As soon as a contest is launched, any visitor to the site can discover it by clicking the “browse projects” link on the front page. All projects at various stages are shown on this page (see Figure A2), including the title of the task, the name of the contest host, the time left, the number of entries received, and the prize amount. If a contest’s prize is guaranteed, the word “guaranteed” appears under the prize amount. A visitor can sort the contests by the last three columns (i.e., the time left on the contest, the number of entries received, and the prize amount).

By default, the contests are sorted such that those closing the soonest appear on the top. During a contest, all the existing entries are displayed in descending order of their ratings (see Figure A3). Underneath the design, the entry number (indicating the order in which it was submitted), the screen name of the contestant, and the rating it received (if any) are displayed.

**Figure A3. Screenshot of Three Entries Received and Rated in a Contest**
Appendix B

Robustness Test of Using the Cumulative Number of Entries by Period \( t-1 \) as the Control Variable for the Current Level of Participation

The results of replacing the control variable \( \log(\text{Contestants}_{i,t} - 1) \) with \( \log(\text{Entries}_{i,t} - 1) \) reported in Table B1. All the estimated coefficients are similar to those reported in Table 7 in their signs, magnitude, and statistical significance, except that the coefficient on \( \log(\text{NegativeReview}_{i,t} - 1) \times \text{Gua} \) has become statistically significant while it was not in the main model in Table 7, thus providing support for H7a (effect of negative reviews moderated).

### Table B1. Unconditional NB Model with FE as Dummies Predicting \( \text{NewEntries}_{i,t} \)

<table>
<thead>
<tr>
<th>DV = ( \text{NewEntries}_{i,t} )</th>
<th>Unconditional Negative Binomial with Dummy FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model (1)</td>
<td>Model (2)</td>
</tr>
<tr>
<td>( \log(\text{NegativeReview}_{i,t}) \times \text{Gua} )</td>
<td>0.07* (0.03)</td>
</tr>
<tr>
<td>( \log(\text{ReviewVolume}_{i,t}) \times \text{Gua} )</td>
<td>-0.13** (0.04)</td>
</tr>
<tr>
<td>( \log(\text{HighReview}_{i,t}) \times \text{Gua} )</td>
<td>0.10* (0.04)</td>
</tr>
<tr>
<td>( \log(\text{NegativeComments}_{i,t}) \times \text{Gua} )</td>
<td>-1.20 (0.76)</td>
</tr>
<tr>
<td>( \log(\text{CommentVolume}_{i,t}) \times \text{Gua} )</td>
<td>-0.29*** (0.08)</td>
</tr>
<tr>
<td>( \log(\text{HighComments}_{i,t}) \times \text{Gua} )</td>
<td>0.31* (0.14)</td>
</tr>
<tr>
<td>( \log(\text{Entries}_{i,t}) \times \text{Gua} )</td>
<td>0.18*** (0.04)</td>
</tr>
<tr>
<td>( \log(\text{NegativeReview}_{i,t}) )</td>
<td>-0.05*** (0.01)</td>
</tr>
<tr>
<td>( \log(\text{ReviewVolume}_{i,t}) )</td>
<td>0.21*** (0.02)</td>
</tr>
<tr>
<td>( \log(\text{HighReview}_{i,t}) )</td>
<td>-0.30*** (0.02)</td>
</tr>
<tr>
<td>( \log(\text{NegativeComments}_{i,t}) )</td>
<td>-0.94* (0.43)</td>
</tr>
<tr>
<td>( \log(\text{CommentVolume}_{i,t}) )</td>
<td>0.27*** (0.04)</td>
</tr>
<tr>
<td>( \log(\text{HighComments}_{i,t}) )</td>
<td>-0.20** (0.07)</td>
</tr>
<tr>
<td>( \log(\text{Entries}_{i,t}) )</td>
<td>-0.16*** (0.03)</td>
</tr>
<tr>
<td>( \log(\text{MedianSubm}_{i,t}) )</td>
<td>0.05 (0.04)</td>
</tr>
<tr>
<td>( \log(\text{NewContests}_{t}) )</td>
<td>0.02 (0.01)</td>
</tr>
</tbody>
</table>

| Contest-level fixed effects | Yes | Yes |
| Period and weekend dummies | Yes | Yes |
| Observations | 13,665 | 13,665 |
| Number of contests | 1,031 | 1,031 |
| Alpha | 0.68 | 0.67 |
| LL | -32,602.40 | -32,568.30 |
| AIC | 65,250.81 | 65,182.61 |
| BIC | 65,423.82 | 65,356.63 |

Bootstrapped standard errors are in parentheses. Alpha is the overdispersion parameter. “Gua” is short for Guarantee. ***p < 0.001, **p < 0.01, *p < 0.05.
Appendix C

Robustness Test of Dropping the Last Period

Figure C1. The Number of New Entries Submitted During Each Period

Figure C1 plots the mean number of new submissions by period. Because a spike was observed in the last period, a robustness check was conducted by dropping the last period in the panel. Our analyses show that dropping the last period does not change our results qualitatively. The estimated coefficients as reported in Table C1 are similar to those produced by the main model (in Table 7) in terms of their signs, magnitude, and statistical significance, except that the interaction effect $\log(\text{HighReview}_{i,t-1}) \times \text{Gua}$ has become marginally significant ($p = 0.06$).
**Table C1. Unconditional Negative Binomial Model with FE as Dummies Predicting the Number of New Entries During Period t in Contest i**

<table>
<thead>
<tr>
<th>DV = ( \text{NewEntries}_{i,t} )</th>
<th>Unconditional Negative Binomial with Dummy FE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model (1)</td>
</tr>
<tr>
<td>( \log(\text{NegativeReview}_{i,t-1}) \times \text{Gua} )</td>
<td>0.06</td>
</tr>
<tr>
<td>( \log(\text{ReviewVolume}_{i,t-1}) \times \text{Gua} )</td>
<td>-0.10*</td>
</tr>
<tr>
<td>( \log(\text{HighReview}_{i,t-1}) \times \text{Gua} )</td>
<td>0.09+</td>
</tr>
<tr>
<td>( \log(\text{NegativeComments}_{i,t-1}) \times \text{Gua} )</td>
<td>-1.53</td>
</tr>
<tr>
<td>( \log(\text{CommentVolume}_{i,t-1}) \times \text{Gua} )</td>
<td>-0.30**</td>
</tr>
<tr>
<td>( \log(\text{Entries}_{i,t-1}) \times \text{Gua} )</td>
<td>0.38*</td>
</tr>
<tr>
<td>( \log(\text{NegativeReview}_{i,t-1}) )</td>
<td>-0.05*</td>
</tr>
<tr>
<td>( \log(\text{ReviewVolume}_{i,t-1}) )</td>
<td>0.12***</td>
</tr>
<tr>
<td>( \log(\text{HighReview}_{i,t-1}) )</td>
<td>-0.20***</td>
</tr>
<tr>
<td>( \log(\text{NegativeComments}_{i,t-1}) )</td>
<td>-1.07**</td>
</tr>
<tr>
<td>( \log(\text{CommentVolume}_{i,t-1}) )</td>
<td>0.26***</td>
</tr>
<tr>
<td>( \log(\text{Entries}_{i,t-1}) )</td>
<td>0.09</td>
</tr>
<tr>
<td>( \log(\text{MedianSubm}_{i,t-1}) )</td>
<td>-0.12*</td>
</tr>
<tr>
<td>( \log(\text{NewContest}_{i,t}) )</td>
<td>0.04**</td>
</tr>
</tbody>
</table>

Contest-level fixed effects: Yes
Period and weekend dummies: Yes
Observations: 12,634
Number of contests: 1,031
Alpha: 0.68
LL: -28,355.70
AIC: 56,771.40
BIC: 56,994.73

Bootstrapped standard errors are in parentheses. Alpha is the over-dispersion parameter. “Gua” is short for Guarantee. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1
Appendix D

Propensity Score Matching Diagnosis

Figure D1 demonstrates that the distributions of propensity scores among contests with and without guarantees exhibit substantial overlap, indicating sufficient matching.

![Figure D1. Distribution of Propensity Scores Among Contests With and Without Prize Guarantees](image)

Appendix E

Instrument Variable Analyses

Descriptive statistics of the instrument variables are reported in Table E1 and the first stage regression results are reported in Table E2.

| Table E1. Descriptive Statistics of Instrumental Variables |
|-----------------|--------|-----------|--------|-------|-------|
| Variable        | N      | Mean      | Std. Dev. | Min   | Max   |
| SimNegativeReview$_{i,t-1}$ | 13,665 | 4.25      | 12.89     | 0     | 479.14 |
| SimReviewVolume$_{i,t-1}$     | 13,665 | 11.85     | 13.99     | 0     | 94.17  |
| SimHighReview$_{i,t-1}$       | 13,665 | 2.13      | 6.31      | 0     | 277.11 |
| SimNegativeComments$_{i,t-1}$ | 13,665 | 0.0001    | 0.002     | 0     | 0.07   |
| SimCommentVolume$_{i,t-1}$    | 13,665 | 0.58      | 0.82      | 0     | 3.43   |
| SimHighComments$_{i,t-1}$     | 13,665 | 0.11      | 0.34      | 0     | 2.2    |
Table E2. First Stage Regression Results

<table>
<thead>
<tr>
<th>DV</th>
<th>Log(NegReview_{i,t+1})</th>
<th>Log(ReviewVol_{i,t+1})</th>
<th>Log(HighReview_{i,t+1})</th>
<th>Log(NegComm_{i,t+1})</th>
<th>Log(CommVol_{i,t+1})</th>
<th>Log(HighComm_{i,t+1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(SimNegReview_{i,t})</td>
<td>0.35*** (0.02)</td>
<td>0.63*** (.01)</td>
<td>0.45*** (0.02)</td>
<td>0.00 (.00)</td>
<td>0.05** (0.02)</td>
<td>0.00 (.01)</td>
</tr>
<tr>
<td>Log(SimReviewVol_{i,t})</td>
<td>-0.06*** (0.01)</td>
<td>0.26*** (.00)</td>
<td>-0.04*** (0.01)</td>
<td>0.00* (.00)</td>
<td>-0.04*** (0.01)</td>
<td>0.00 (.00)</td>
</tr>
<tr>
<td>Log(SimHighReview_{i,t})</td>
<td>0.39*** (0.02)</td>
<td>0.15*** (.01)</td>
<td>0.31*** (0.02)</td>
<td>0.00 (.00)</td>
<td>0.10*** (0.02)</td>
<td>0.01* (.01)</td>
</tr>
<tr>
<td>Log(SimNegComm_{i,t})</td>
<td>-2.80 (2.48)</td>
<td>-2.10* (.87)</td>
<td>1.78 (2.45)</td>
<td>1.93*** (.10)</td>
<td>12.02*** (2.00)</td>
<td>-0.50 (.59)</td>
</tr>
<tr>
<td>Log(SimCommVol_{i,t})</td>
<td>-0.02* (0.01)</td>
<td>-0.03*** (.00)</td>
<td>0.13*** (0.01)</td>
<td>0.00* (.00)</td>
<td>0.34*** (0.01)</td>
<td>0.00 (.00)</td>
</tr>
<tr>
<td>Log(SimHighComm_{i,t})</td>
<td>-0.01 (0.03)</td>
<td>-0.02 (0.01)</td>
<td>0.21*** (0.03)</td>
<td>0.00 (.00)</td>
<td>1.81*** (0.03)</td>
<td>0.93*** (.01)</td>
</tr>
<tr>
<td>Log(Contestants_{i,t})</td>
<td>0.12*** (0.01)</td>
<td>0.11*** (.00)</td>
<td>-0.13*** (0.01)</td>
<td>0.00 (.00)</td>
<td>0.06*** (0.01)</td>
<td>-0.01 (.00)</td>
</tr>
<tr>
<td>Log(MedianSubm_{i,t+1})</td>
<td>-0.04*** (0.01)</td>
<td>0.03*** (.00)</td>
<td>0.06*** (0.01)</td>
<td>0.00 (.00)</td>
<td>0.06*** (0.01)</td>
<td>0.01*** (.00)</td>
</tr>
<tr>
<td>Log(NewContests_{i,t})</td>
<td>-0.01 (0.01)</td>
<td>-0.01* (.00)</td>
<td>-0.02** (0.01)</td>
<td>0.00 (.00)</td>
<td>-0.02** (0.01)</td>
<td>0.00 (.00)</td>
</tr>
</tbody>
</table>

Contest-level FE: Yes Yes Yes Yes Yes Yes
Period dummies: Yes Yes Yes Yes Yes Yes
Weekend dummies: Yes Yes Yes Yes Yes Yes
Number of contests: 1,031 1,031 1,031 1,031 1,031 1,031
R²: 0.49 0.96 0.55 0.07 0.58 0.65

Standard errors in parentheses. Due to space limitations, abbreviations are used, including “Neg” = Negative; “Comm” = Comment or Comments; “Vol” = Volume.
***p < 0.001, **p < 0.01, *p < 0.05

Appendix F

Robustness Test of Using Per-Period (i.e., Noncumulative) Independent Variables

We have added analyses by an alternative model in which the cumulative independent variables were replaced with per-period measures. In Table F1, we report results from an unconditional negative binomial model with fixed effects modeled as dummies. Overall, the results are qualitatively similar to our main results. All the main effects of in-process feedback have retained their signs, magnitude, and statistical significance except for the coefficient on Log(NewNegativeComments_{i,t+1}), which has retained the correct sign. The interaction effects have retained the expected signs but their statistical significance has changed. In particular, among the four moderating effects identified in the main model (Table 7), only the coefficient on Log(NewReviewVolume_{i,t+1}) \times \text{Gua} is still statistically significant. However, two other coefficients that were not statistically significant in the main model have become statistically significant: Log(NewNegativeReview_{i,t+1}) \times \text{Gua} and Log(NewNegativeComments_{i,t+1}) \times \text{Gua}. In summary, the results using per-period measures of independent variables are largely consistent with our main results.
### Table F1. Results of Robustness Tests Using Per-Period Independent Variables in an Unconditional Negative Binomial Model with FE as Dummies

<table>
<thead>
<tr>
<th>DV: NewEntries&lt;sub&gt;i,t&lt;/sub&gt;</th>
<th>Unconditional Negative Binomial with Dummy FE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model (1)</td>
</tr>
<tr>
<td><strong>Log(NewNegativeReview&lt;sub&gt;i,t&lt;/sub&gt;) × Gua</strong></td>
<td>0.09*** (0.03)</td>
</tr>
<tr>
<td><strong>Log(NewReviewVolume&lt;sub&gt;i,t&lt;/sub&gt;) × Gua</strong></td>
<td>-0.09*** (0.03)</td>
</tr>
<tr>
<td><strong>Log(NewHighReview&lt;sub&gt;i,t&lt;/sub&gt;) × Gua</strong></td>
<td>0.06 (0.05)</td>
</tr>
<tr>
<td><strong>Log(NewNegativeComments&lt;sub&gt;i,t&lt;/sub&gt;) × Gua</strong></td>
<td>29.00*** (1.72)</td>
</tr>
<tr>
<td><strong>Log(NewCommentVolume&lt;sub&gt;i,t&lt;/sub&gt;) × Gua</strong></td>
<td>-0.10 (0.12)</td>
</tr>
<tr>
<td><strong>Log(NewHighComments&lt;sub&gt;i,t&lt;/sub&gt;) × Gua</strong></td>
<td>0.22 (0.17)</td>
</tr>
<tr>
<td><strong>Log(Contestants&lt;sub&gt;i,t&lt;/sub&gt;) × Gua</strong></td>
<td>0.06* (0.03)</td>
</tr>
<tr>
<td><strong>Log(NewNegativeReview&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>-0.07*** (0.02)</td>
</tr>
<tr>
<td><strong>Log(NewReviewVolume&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>0.22*** (0.02)</td>
</tr>
<tr>
<td><strong>Log(NewHighReview&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>-0.16*** (0.02)</td>
</tr>
<tr>
<td><strong>Log(NewNegativeComments&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>-1.14 (0.85)</td>
</tr>
<tr>
<td><strong>Log(NewCommentVolume&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>0.33*** (0.05)</td>
</tr>
<tr>
<td><strong>Log(NewHighComments&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>-0.20* (0.10)</td>
</tr>
<tr>
<td><strong>Log(Contestants&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>0.10*** (0.03)</td>
</tr>
<tr>
<td><strong>Log(MedianSubm&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>-0.14*** (0.03)</td>
</tr>
<tr>
<td><strong>Log(NewContests&lt;sub&gt;i,t&lt;/sub&gt;)</strong></td>
<td>0.02** (0.01)</td>
</tr>
</tbody>
</table>

Contest-level fixed effects: Yes
Period and weekend dummies: Yes

Observations: 13,665
Number of contests: 1,031
Alpha: 0.66
LL: -32,545.46
AIC: 65,220.92
BIC: 65,709.89

Bootstrapped standard errors are in parentheses. Alpha is the over-dispersion parameter. "Gua" is short for Guarantee. ***p < 0.001, **p < 0.01, *p < 0.05

### Appendix G

**Robustness Test of Using Arellano-Bond Dynamic Panel-Data Estimator**

The results of Arellano-Bond dynamic panel-data estimator with a lagged DV are reported in Table G1. All the coefficients reported in the main model (Table 7) have retained their signs, magnitude, and statistical significance, except the coefficient on Log(NegativeComments<sub>i,t</sub>) which has the expected sign but has lost its statistical significance.
## Table G1. Results of Arellano-Bond Dynamic Panel-Data Estimator

<table>
<thead>
<tr>
<th>DV = Log(NewEntries_{it})</th>
<th>Arellano-Bond Dynamic Panel-Data Estimator</th>
<th>Model (1)</th>
<th>Model (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(NegativeReview_{it}) × Gua</td>
<td>0.12 (0.05)</td>
<td>0.12 (0.05)</td>
<td>0.12 (0.05)</td>
</tr>
<tr>
<td>Log(ReviewVolume_{it}) × Gua</td>
<td>-0.19* (0.04)</td>
<td>-0.19* (0.04)</td>
<td>-0.19* (0.04)</td>
</tr>
<tr>
<td>Log(HighReview_{it}) × Gua</td>
<td>0.08* (0.06)</td>
<td>0.08* (0.06)</td>
<td>0.08* (0.06)</td>
</tr>
<tr>
<td>Log(NegativeComments_{it}) × Gua</td>
<td>-3.20 (2.30)</td>
<td>-3.20 (2.30)</td>
<td>-3.20 (2.30)</td>
</tr>
<tr>
<td>Log(HighComments_{it}) × Gua</td>
<td>-0.15** (0.11)</td>
<td>-0.15** (0.11)</td>
<td>-0.15** (0.11)</td>
</tr>
<tr>
<td>Log(Contestants_{it}) × Gua</td>
<td>0.49* (0.20)</td>
<td>0.49* (0.20)</td>
<td>0.49* (0.20)</td>
</tr>
<tr>
<td>Log(NegativeReview_{t-1})</td>
<td>-0.22*** (0.03)</td>
<td>-0.26*** (0.03)</td>
<td>-0.26*** (0.03)</td>
</tr>
<tr>
<td>Log(ReviewVolume_{t-1})</td>
<td>0.17*** (0.02)</td>
<td>0.17*** (0.02)</td>
<td>0.17*** (0.02)</td>
</tr>
<tr>
<td>Log(HighReview_{t-1})</td>
<td>-0.50*** (0.03)</td>
<td>-0.50*** (0.03)</td>
<td>-0.50*** (0.03)</td>
</tr>
<tr>
<td>Log(NegativeComments_{t-1})</td>
<td>-3.81 (1.47)</td>
<td>-1.35 (0.58)</td>
<td>-1.35 (0.58)</td>
</tr>
<tr>
<td>Log(HighComments_{t-1})</td>
<td>-0.31* (0.10)</td>
<td>-0.62* (0.05)</td>
<td>-0.62* (0.05)</td>
</tr>
<tr>
<td>Log(Contestants_{t-1})</td>
<td>-0.21*** (0.03)</td>
<td>-0.22*** (0.03)</td>
<td>-0.22*** (0.03)</td>
</tr>
<tr>
<td>Log(MedianSubm_{it})</td>
<td>-0.01 (0.01)</td>
<td>-0.01 (0.01)</td>
<td>-0.01 (0.01)</td>
</tr>
<tr>
<td>Log(NewEntries_{t-1})</td>
<td>0.09*** (0.02)</td>
<td>0.09*** (0.02)</td>
<td>0.09*** (0.02)</td>
</tr>
</tbody>
</table>

Contest-level fixed effects

Yes
Yes

Period, day/night and weekend dummies

Yes
Yes

Observations

13,665
13,665

Number of contests

1,031
1,031

Wald $\chi^2$

3810.55(24)
3806.09(31)

Robust standard errors are in parentheses. “Gua” is short for Guarantee. For Wald $\chi^2$ tests, the degrees of freedom are reported in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05.

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## Appendix H

### Contestant-Level Analysis

We conducted individual-level analysis to verify our main results obtained at the contest level. In this contest-contestant-period dataset, each observation focuses on the outcome variable, $n_{ij,t}$, the number of submissions contestant $j$ submits to contest $i$ in period $t$. The dataset contains 1,031 contests and 5,545 contestants. An observation of contest $i$-contestant $j$-period $t$ is included in the dataset only if contestant $j$ has submitted at least an entry to contest $i$ before or during period $t$. In-process feedback variables are added into the model together with three sets of control variables, ContestantControls$_{ij,t}$, ContestantControls$_{t}$, and PeriodControls$_{i,t}$, as well as two fixed effects at the contest and contestant level respectively, $C_i$ and $C_j$.
\[
\log(n_{i,j,t}) = \alpha_0 + \alpha_1 \log(\text{NegativeReview}_{i,j,t-1}) + \alpha_2 \log(\text{ReviewVolume}_{i,t-1}) \\
+ \alpha_3 \log(\text{HighReview}_{i,j,t-1}) + \alpha_4 \log(\text{NegativeComment}_{i,t-1}) \\
+ \alpha_5 \log(\text{CommentReview}_{i,j,t-1}) + \alpha_6 \log(\text{HighComment}_{i,t-1}) \\
+ \alpha_7 \text{ContestControls}_{i,t-1} + \alpha_8 \text{ContestantControls}_{i,j,t-1} \\
+ \alpha_9 \text{PeriodControls}_{i,t} + \delta_i C_i + \delta_j C_j + \epsilon_{i,j,t}
\] 

(3)

The ContestControls_{i,t} is a vector of contest-period specific variables, which includes only Entries_{i,t-1} (cumulative number of entries contest \( i \) receives by period \( t-1 \)). ContestantControls_{i,j,t} includes three variables describing the cumulative reviews contestant \( j \) has received from contest \( i \) as of period \( t-1 \): SelfNegativeReview_{i,j,t-1}, SelfReviewVolume_{i,j,t-1}, and SelfHighReview_{i,j,t-1}. These three variables were introduced because prior research has shown that direct feedback received by participants to their own submissions have strong effects on their subsequent submissions (Jiang et al. 2016; Wooten and Ulrich 2016; Yang et al. 2013). The PeriodControl_{i,t} is a vector of contest-period specific variables, which includes Weekend, Period, and NewContest_{i,t}. To examine the interaction effects, we add

\[
\alpha_k = \alpha_{k0} + \alpha_{k1} \text{Guarantee}_i
\]

(4)

where \( k = \{1, 2, 3, 4, 5, 6, 7, 8\} \). That is, the first six independent variables in equation (3) are interacted with the variable Guarantee_{i}.

In Table H1, we report the results of contestant level analyses using two models: a linear model with both contest and contestant level fixed effects and an unconditional negative binomial model with contest-level fixed effects modeled as dummies. The results show that these two models yield results highly consistent in the sign and statistical significance of the coefficients. The results show that all our main results about in-process feedback are born out at the individual contestant level, except the main effect of negative comments (H3b), the effects of comment volume moderated (H5b) and high comments moderated (H7b).
Table H1. Results of Individual Contestant-Level Analyses

<table>
<thead>
<tr>
<th></th>
<th>DV = $\text{Log}(\text{NewEntries}_{i,t})$</th>
<th>DV = $\text{NewEntries}_{i,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Linear</td>
<td>Unconditional NB with FE as Dummies</td>
</tr>
<tr>
<td></td>
<td>Model (1)</td>
<td>Model (2)</td>
</tr>
<tr>
<td>$\text{Log}(\text{NegativeReview}_{i,t}) \times \text{Gua}$</td>
<td>0.00 (0.01)</td>
<td></td>
</tr>
<tr>
<td>$\text{Log}(\text{ReviewVolume}_{i,t}) \times \text{Gua}$</td>
<td>-0.06*** (0.01)</td>
<td>-0.13*** (0.03)</td>
</tr>
<tr>
<td>$\text{Log}(\text{HighReview}_{i,t}) \times \text{Gua}$</td>
<td>0.03 (0.01)</td>
<td>0.12*** (0.02)</td>
</tr>
<tr>
<td>$\text{Log}(\text{NegativeComments}_{i,t}) \times \text{Gua}$</td>
<td>0.27 (0.27)</td>
<td>0.14 (0.56)</td>
</tr>
<tr>
<td>$\text{Log}(\text{CommentVolume}_{i,t}) \times \text{Gua}$</td>
<td>-0.09 (0.07)</td>
<td>0.01 (0.11)</td>
</tr>
<tr>
<td>$\text{Log}(\text{HighComments}_{i,t}) \times \text{Gua}$</td>
<td>-0.03 (0.06)</td>
<td>-0.06 (0.10)</td>
</tr>
<tr>
<td>$\text{Log}(\text{NegativeReview}_{i,t})$</td>
<td>-0.02** (0.01)</td>
<td>-0.02* (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{ReviewVolume}_{i,t})$</td>
<td>0.12*** (0.01)</td>
<td>0.15*** (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{HighReview}_{i,t})$</td>
<td>-0.07*** (0.01)</td>
<td>-0.08*** (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{NegativeComments}_{i,t})$</td>
<td>-0.09 (0.09)</td>
<td>-0.35 (0.26)</td>
</tr>
<tr>
<td>$\text{Log}(\text{CommentVolume}_{i,t})$</td>
<td>0.13*** (0.03)</td>
<td>0.19*** (0.05)</td>
</tr>
<tr>
<td>$\text{Log}(\text{HighComments}_{i,t})$</td>
<td>-0.10*** (0.03)</td>
<td>-0.09 (0.05)</td>
</tr>
<tr>
<td>$\text{Log}(\text{SelfNegativeReview}_{i,t}) \times \text{Gua}$</td>
<td>0.01 (0.01)</td>
<td></td>
</tr>
<tr>
<td>$\text{Log}(\text{SelfReviewVolume}_{i,t}) \times \text{Gua}$</td>
<td>0.01 (0.01)</td>
<td>0.02* (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{SelfHighVolume}_{i,t}) \times \text{Gua}$</td>
<td>-0.03 (0.01)</td>
<td>-0.07*** (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{Entries}_{i,t}) \times \text{Gua}$</td>
<td>0.05*** (0.01)</td>
<td></td>
</tr>
<tr>
<td>$\text{Log}(\text{SelfNegativeReview}_{i,t})$</td>
<td>-0.02*** (0.00)</td>
<td>-0.02*** (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{SelfReviewVolume}_{i,t})$</td>
<td>0.02*** (0.00)</td>
<td>0.02*** (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{SelfHighVolume}_{i,t})$</td>
<td>0.09*** (0.01)</td>
<td>0.10*** (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{Entries}_{i,t})$</td>
<td>-0.47*** (0.01)</td>
<td>-0.49*** (0.01)</td>
</tr>
<tr>
<td>$\text{Log}(\text{NewContest}_{i})$</td>
<td>-0.01* (0.00)</td>
<td>-0.01* (0.00)</td>
</tr>
</tbody>
</table>

Individual-level fixed effects: Yes
Contest-level fixed effects: No
Period and weekend dummies: Yes
Observations: 132,575

Robust standard errors are in parentheses. Dataset contains 1,031 contests and 5,545 contestants. “Gua” is short for Guarantee. For Wald Chi² tests, the degrees of freedom are reported in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05.
Appendix I

Alternative DV: Number of New Contestants Entering Contest \( i \) in Period \( t \)

In our main results we focused on the number of new submissions as our dependent variable. An alternative measure of participation is the number of participants. It is important to test our model with this alternative dependent variable, for at least two reasons. First, it would potentially rule out an alternative hypothesis that in-process feedback led to more submissions simply because it encouraged more repeated submissions by the current participants (perhaps the direct receivers of the feedback), but not because it attracted more new participants. Second, the number of participants is of theoretical interest because in creative-design contests more participants might lead to more innovative ideas.

We retested our hypotheses by replacing the DV with \( Contestants_i \) (the total number of contestants) in the cross-sectional analysis and with \( NewContestants_{i,t} \) (the number of participants who made their first submissions to contest \( i \) during period \( t \)) in the panel analysis. \( Contestants_i \) has a mean of 18.25 and a standard deviation of 25.77 and \( NewContestants_{i,t} \) has a mean of 1.84 and a standard deviation of 4.30.

To test the effect of \( Guarantee \), we again report results from five estimates of treatment effects (i.e., PSM, NNM, RA, IPW, and IPWRA). Since the first stages (e.g., computing the propensity score or matching) were exactly the same as those used in the main model, their results as well as balance examinations are omitted. Treatment effects estimated across the five methods (Table I1) show that \( Guarantee \) had a positive effect on \( Contestants_i \). The ATETs were estimated to range from 12.24 to 14.45.

<table>
<thead>
<tr>
<th>Table I1. Treatment Effects of Guarantee on Total ( Contestants_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimated ATET</td>
</tr>
<tr>
<td>Propensity Score Matching (PSM)</td>
</tr>
<tr>
<td>Nearest Neighbor Matching (NNM)</td>
</tr>
<tr>
<td>Regression Adjustment (RA)</td>
</tr>
<tr>
<td>Inverse-Probability Weighting (IPW)</td>
</tr>
<tr>
<td>IPW Regression Adjustment (IPWRA)</td>
</tr>
</tbody>
</table>

Robust standard errors are in parentheses and for both PSM and NNM, robust Abadie-Imbens’ standard errors are reported. For both PSM and NNM, the matching ratio was 1:1. ***p < 0.001, **p < 0.01, *p < 0.05.

Results about the main effects of in-process feedback (reported in Table I2) are largely consistent with results from our main model, with a few losing statistical significance. While our main model has yielded support for all the main effects (H2a–H4b), with \( NewContestants_{i,t} \), H3a (effect of negative reviews), H3b (effect of negative comments), and H4b (effect of high comments), have lost support. For hypotheses regarding the interaction effects, the main model has yielded support for the following four hypotheses: H5a (effect of review volume moderated), H5b (effect of comment volume moderated), H7a (effect of high reviews moderated), and H7b (effect of high comments moderated). With this alternative DV (see AMEs reported in Table I3), all four coefficients have the correct signs, and H5a and H7a were supported (the coefficient supporting H7a was marginally significant).

Overall, the results predicting the number of new participants do not differ substantially with those predicting the number of new entries. The effect of \( Guarantee \) (H1) and the main effects of the review volume (H2a), comment volume (H2b), and high reviews (H4a) still hold. Two important interaction effects also hold, including the effect of review volume moderated (H5a) and the effect of high reviews moderated (H7a).

---

1The robust standard error for PSM was derived based on Abadie and Imbens (2016), accounting for the fact that the propensity score was estimated prior to matching. The robust standard error for NNM was computed based on methods derived by Abadie and Imbens (2006, 2011, 2016).
Table I2. Unconditional Negative Binomial Model with FE as Dummies, Predicting the Number of New Contestants Who Entered Contest $i$ During Period $t$

<table>
<thead>
<tr>
<th>DV = NewContestants$_{i,t}$</th>
<th>Unconditional Negative Binomial with Dummy FE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model (1)</td>
</tr>
<tr>
<td>Log(NegativeReview$_{i,t-1}$)</td>
<td>0.07* (0.03)</td>
</tr>
<tr>
<td>Log(ReviewVolume$_{i,t-1}$)</td>
<td>0.13** (0.05)</td>
</tr>
<tr>
<td>Log(HighReview$_{i,t-1}$)</td>
<td>-0.26* (0.11)</td>
</tr>
<tr>
<td>Log(NegativeComments$_{i,t-1}$)</td>
<td>0.23*** (0.05)</td>
</tr>
<tr>
<td>Log(ReviewVolume$_{i,t-1}$)</td>
<td>0.04* (0.02)</td>
</tr>
<tr>
<td>Log(HighReview$_{i,t-1}$)</td>
<td>-0.30*** (0.02)</td>
</tr>
<tr>
<td>Log(NegativeComments$_{i,t-1}$)</td>
<td>-0.44 (0.57)</td>
</tr>
<tr>
<td>Log(CommentVolume$_{i,t-1}$)</td>
<td>0.13** (0.05)</td>
</tr>
<tr>
<td>Log(HighComments$_{i,t-1}$)</td>
<td>-0.16 (0.08)</td>
</tr>
<tr>
<td>Log(Contestants$_{i,t-1}$)</td>
<td>-0.22*** (0.05)</td>
</tr>
<tr>
<td>Log(MedianSubmni$_{t-1}$)</td>
<td>0.02* (0.01)</td>
</tr>
</tbody>
</table>

Contest-level fixed effects | Yes | Yes |
Period and weekend dummies  | Yes | Yes |
Observations                 | 13,665 | 13,665 |
Number of contests           | 1,031 | 1,031 |
Alpha                        | 0.29 | 0.29 |
LL                           | -20,135.14 | -24,852.01 |
AIC                          | 40,332.29 | 40,216.32 |
BIC                          | 40,565.49 | 40,359.25 |

Bootstrapped standard errors are in parentheses. Alpha is the overdispersion parameter. “Gua” is for Guarantee. ***p < 0.001, **p < 0.01, *p < 0.05.

Table 20. Average Marginal Effects of In-Process Feedback on NewContestants$_{i,t}$

<table>
<thead>
<tr>
<th>Average Marginal Effects of Feedback on NewContestants$_{i,t}$</th>
<th>Guarantee = 1</th>
<th>Guarantee = 0</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(PositiveReview$_{i,t-1}$)</td>
<td>0.21 (0.14)</td>
<td>0.00 (0.06)</td>
<td>0.21 (0.14)</td>
</tr>
<tr>
<td>Log(ReviewVolume$_{i,t-1}$)</td>
<td>-0.07 (0.11)</td>
<td>0.26* (0.11)</td>
<td>-0.33* (0.17)</td>
</tr>
<tr>
<td>Log(HighReview$_{i,t-1}$)</td>
<td>-0.79*** (0.39)</td>
<td>-1.14* (0.50)</td>
<td>0.36+ (0.19)</td>
</tr>
<tr>
<td>Log(NegativeComments$_{i,t-1}$)</td>
<td>-2.00 (1.39)</td>
<td>-0.72 (18.96)</td>
<td>-1.28 (19.43)</td>
</tr>
<tr>
<td>Log(CommentVolume$_{i,t-1}$)</td>
<td>-0.11 (0.19)</td>
<td>0.64 (0.47)</td>
<td>-0.75 (0.56)</td>
</tr>
<tr>
<td>Log(HighComments$_{i,t-1}$)</td>
<td>-0.01 (0.20)</td>
<td>-0.98 (0.61)</td>
<td>0.97 (0.62)</td>
</tr>
</tbody>
</table>

Average marginal effects calculated as the mean marginal effects evaluated at the variables' values in the sample. Standard errors derived with the delta-method are reported in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05, +p < 0.10.
# coding: utf-8
import os
from datetime import datetime
import pandas as pd
import numpy as np
import csv
from operator import itemgetter

N_NEIGHBOR = 30

def compute_similarity_rated(contestid1, contestid2, day):
    contest1_exp = 0
    if (contestday_dict[contestid1]['contestsHeld'] > 0): contest1_exp = 1
    contest2_exp = 0
    if (contestday_dict[contestid2]['contestsHeld'] > 0): contest2_exp = 1

    gua_diff = (abs(contestday_dict[contestid1]['guaranteed'] - contestday_dict[contestid2]['guaranteed']))*100
    prize_diff = (abs(contestday_dict[contestid1]['prize'] - contestday_dict[contestid2]['prize']))/10
    weekend_diff = (abs(contestday_dict[contestid1][day]['weekend'] - contestday_dict[contestid2][day]['weekend']))*100
    daytime_diff = (abs(contestday_dict[contestid1][day]['contest_daytime'] - contestday_dict[contestid2][day]['contest_daytime']))*100
    contestsheld_diff = (abs(contest1_exp - contest2_exp))*100
    averagefb_diff = (abs(contestday_dict[contestid1]['averageFeedback'] - contestday_dict[contestid2]['averageFeedback']))

    simscore = gua_diff + prize_diff + weekend_diff + contestsheld_diff + averagefb_diff + daytime_diff
    return simscore

def compute_similarity_high(contestid1, contestid2, day):
    contest1_exp = 0
    if (contestday_dict[contestid1]['contestsHeld'] > 0): contest1_exp = 1
    contest2_exp = 0
    if (contestday_dict[contestid2]['contestsHeld'] > 0): contest2_exp = 1

    gua_diff = (abs(contestday_dict[contestid1]['guaranteed'] - contestday_dict[contestid2]['guaranteed']))*100
    prize_diff = (abs(contestday_dict[contestid1]['prize'] - contestday_dict[contestid2]['prize']))/10
    weekend_diff = (abs(contestday_dict[contestid1][day]['weekend'] - contestday_dict[contestid2][day]['weekend']))*100
    daytime_diff = (abs(contestday_dict[contestid1][day]['contest_daytime'] - contestday_dict[contestid2][day]['contest_daytime']))*100
    contestsheld_diff = (abs(contest1_exp - contest2_exp))*100
    averagefb_diff = (abs(contestday_dict[contestid1]['averageFeedback'] - contestday_dict[contestid2]['averageFeedback']))

    simscore = gua_diff + prize_diff + weekend_diff + daytime_diff + contestsheld_diff + averagefb_diff
    return simscore

def compute_similarity_elim(contestid1, contestid2, day):
    contest1_exp = 0
    if (contestday_dict[contestid1]['contestsHeld'] > 0): contest1_exp = 1
    contest2_exp = 0
if (contestday_dict[contestid2]['contestsHeld']>0): contest2_exp=1

gua_diff = (abs(contestday_dict[contestid1]['guaranteed'] - contestday_dict[contestid2]['guaranteed']))*100
prize_diff = (abs(contestday_dict[contestid1]['prize'] - contestday_dict[contestid2]['prize']))/10
weekend_diff = (abs(contestday_dict[contestid1][day]['weekend'] - contestday_dict[contestid2][day]['weekend']))*100
daytime_diff = (abs(contestday_dict[contestid1][day]['contest_daytime'] - contestday_dict[contestid2][day]['contest_daytime']))*100
contestsheld_diff = (abs(contest1_exp - contest2_exp))*100
averagefb_diff = (abs(contestday_dict[contestid1]['averageFeedback'] - contestday_dict[contestid2]['averageFeedback']))

simscore = gua_diff+prize_diff + weekend_diff + daytime_diff + contestsheld_diff+averagefb_diff
return simscore

def compute_similarity_comm(contestid1, contestid2, day):

contest1_exp = 0
if (contestday_dict[contestid1]['contestsHeld']>0): contest1_exp=1
contest2_exp = 0
if (contestday_dict[contestid2]['contestsHeld']>0): contest2_exp=1

gua_diff = (abs(contestday_dict[contestid1]['guaranteed'] - contestday_dict[contestid2]['guaranteed']))*100
prize_diff = (abs(contestday_dict[contestid1]['prize'] - contestday_dict[contestid2]['prize']))/10
weekend_diff = (abs(contestday_dict[contestid1][day]['weekend'] - contestday_dict[contestid2][day]['weekend']))*100
daytime_diff = (abs(contestday_dict[contestid1][day]['contest_daytime'] - contestday_dict[contestid2][day]['contest_daytime']))*100
contestsheld_diff = (abs(contest1_exp - contest2_exp))*100
averagefb_diff = (abs(contestday_dict[contestid1]['averageFeedback'] - contestday_dict[contestid2]['averageFeedback']))
comm_diff = (abs(contestday_dict[contestid1]['evercomm'] - contestday_dict[contestid2]['evercomm']))*100

simscore = gua_diff+prize_diff + weekend_diff + daytime_diff + contestsheld_diff+averagefb_diff+comm_diff
return simscore

def compute_similarity_negcomm(contestid1, contestid2, day):

contest1_exp = 0
if (contestday_dict[contestid1]['contestsHeld']>0): contest1_exp=1
contest2_exp = 0
if (contestday_dict[contestid2]['contestsHeld']>0): contest2_exp=1

gua_diff = (abs(contestday_dict[contestid1]['guaranteed'] - contestday_dict[contestid2]['guaranteed']))*100
prize_diff = (abs(contestday_dict[contestid1]['prize'] - contestday_dict[contestid2]['prize']))/10
weekend_diff = (abs(contestday_dict[contestid1][day]['weekend'] - contestday_dict[contestid2][day]['weekend']))*100
daytime_diff = (abs(contestday_dict[contestid1][day]['contest_daytime'] - contestday_dict[contestid2][day]['contest_daytime']))*100
contestsheld_diff = (abs(contest1_exp - contest2_exp))*100
averagefb_diff = (abs(contestday_dict[contestid1]['averageFeedback'] - contestday_dict[contestid2]['averageFeedback']))
comm_diff = (abs(contestday_dict[contestid1]['everncomm'] - contestday_dict[contestid2]['everncomm']))*100

simscore = gua_diff+prize_diff + weekend_diff + daytime_diff + contestsheld_diff+averagefb_diff+comm_diff
return simscore

def compute_similarity_highcomm(contestid1, contestid2, day):

contest1_exp = 0
if (contestday_dict[contestid1]['contestsHeld']>0): contest1_exp=1
contest2_exp = 0
if (contestday_dict[contestid2]['contestsHeld']>0): contest2_exp=1

gua_diff = (abs(contestday_dict[contestid1]['guaranteed'] - contestday_dict[contestid2]['guaranteed']))*100
prize_diff = \frac{\text{abs}(\text{contestday}_1['prize'] - \text{contestday}_2['prize'])}{10} \\
weekend_diff = \left(\frac{\text{abs}(\text{contestday}_1[\text{day}]['weekend'] - \text{contestday}_2[\text{day}]['weekend'])}{100}\right) \\
daytime_diff = \left(\frac{\text{abs}(\text{contestday}_1[\text{day}]['contest\_daytime'] - \text{contestday}_2[\text{day}]['contest\_daytime'])}{100}\right) \\
contestsheld_diff = \left(\frac{\text{abs}(\text{contest1}\_\text{exp} - \text{contest2}\_\text{exp})}{100}\right) \\
averagefb_diff = \left(\frac{\text{abs}(\text{contestday}_1['averageFeedback'] - \text{contestday}_2['averageFeedback'])}{100}\right) \\
comm_diff = \left(\frac{\text{abs}(\text{contestday}_1['everhcomm'] - \text{contestday}_2['everhcomm'])}{100}\right) \\
simscore = \text{gua} + \text{prize} + \text{weekend} + \text{daytime} + \text{contestsheld} + \text{averagefb} + \text{comm} \\
\text{return simscore}

def match\_two\_rows\_rated(contestid1, contestid2, day):
    simscore = -1
    row = \text{contestday}_1
    x = \text{contestday}_2
    if (\text{day} not in \text{contestday}_2): return -1
    if \left(\text{abs}(\text{row}['delay'] - x['delay']) == 0\right):
        \text{simscore} = \text{compute\_similarity\_rated}(\text{contestid1}, \text{contestid2}, \text{day})
    \text{return simscore}

def match\_two\_rows\_high(contestid1, contestid2, day):
    simscore = -1
    row = \text{contestday}_1
    x = \text{contestday}_2
    if (\text{day} not in \text{contestday}_2): return -1
    if \left(\text{contestday}_2[\text{day}]['cumRated2Ystd'] == 0\right): return -1
    if \left(\text{abs}(\text{row}['delay'] - x['delay']) == 0\right):
        \text{simscore} = \text{compute\_similarity\_high}(\text{contestid1}, \text{contestid2}, \text{day})
    \text{return simscore}

def match\_two\_rows\_elim(contestid1, contestid2, day):
    simscore = -1
    row = \text{contestday}_1
    x = \text{contestday}_2
    if (\text{day} not in \text{contestday}_2): return -1
    if \left(\text{contestday}_2[\text{day}]['cumRated2Ystd'] == 0\right): return -1
    if \left(\text{abs}(\text{row}['delay'] - x['delay']) == 0\right):
        \text{simscore} = \text{compute\_similarity\_elim}(\text{contestid1}, \text{contestid2}, \text{day})
    \text{return simscore}

def match\_two\_rows\_comm(contestid1, contestid2, day):
    simscore = -1
    row = \text{contestday}_1
    x = \text{contestday}_2
    if (\text{day} not in \text{contestday}_2): return -1
    if \left(\text{contestday}_2[\text{day}]['cumRated2Ystd'] == 0\right): return -1
    if \left(\text{abs}(\text{row}['delay'] - x['delay']) == 0\right):
        \text{simscore} = \text{compute\_similarity\_comm}(\text{contestid1}, \text{contestid2}, \text{day})
    \text{return simscore}
simscore = -1
row=contestday_dict[contestid1]
x=contestday_dict[contestid2]
if (day not in contestday_dict[contestid2]): return -1
if row['evercomm'] == x['evercomm']:
simscore = compute_similarity_comm(contestid1, contestid2, day)
return simscore

def match_two_rows_negcomm(contestid1, contestid2, day):
    simscore = -1
    row=contestday_dict[contestid1]
x=contestday_dict[contestid2]
    if (day not in contestday_dict[contestid2]): return -1
    if row['evercomm'] == x['evercomm']:
        simscore = compute_similarity_negcomm(contestid1, contestid2, day)
    return simscore

def match_two_rows_highcomm(contestid1, contestid2, day):
    simscore = -1
    row=contestday_dict[contestid1]
x=contestday_dict[contestid2]
    if (day not in contestday_dict[contestid2]): return -1
    if row['evercomm'] == x['evercomm']:
        simscore = compute_similarity_highcomm(contestid1, contestid2, day)
    return simscore

def find_sim_cases_rated(contestid, day):
    similarcases={'cumSimRatedYstd':0,'simcount':0}
cases_matched=[]
for key in contestday_dict:
    contestid1 = contestid
    contestid2 = key
    if contestid1 == contestid2: continue
    simscore = match_two_rows_rated(contestid1, contestid2, day)
if simscore >= 0:
    cumSimRatedYstd = contestday_dict[contestid2][day]['cumRated2Ystd']
    cases_matched.append([simscore, cumSimRatedYstd])

# Pick the N nearest neighbors
num_cases = min([N_NEIGHBOR, len(cases_matched_sorted)])
if num_cases > 0:
    index = num_cases
    total = 0
    while index > 0:
        index -= 1
        total += cases_matched_sorted[index][1]
    similarcases['cumSimRatedYstd'] = total/num_cases
    similarcases['simcount'] = len(cases_matched_sorted)
return similarcases

def find_sim_cases_high(contestid, day):
    similarcases = {'cumSimHighYstd_prop':0, 'simcount':0}
    cases_matched = []

    for key in contestday_dict:
        contestid1 = contestid
        contestid2 = key

        if contestid1 == contestid2: continue

        simscore = -1
        simscore = match_two_rows_high(contestid1, contestid2, day)

        if simscore >= 0:
            cumSimHighYstd_prop =
            contestday_dict[contestid2][day]['cumHigh2Ystd']/contestday_dict[contestid2][day]['cumRated2Ystd']
            cases_matched.append([simscore, cumSimHighYstd_prop])

    num_cases = min([N_NEIGHBOR, len(cases_matched_sorted)])
    if num_cases > 0:
        index = num_cases
        total = 0
        while index > 0:
            index -= 1
            total += cases_matched_sorted[index][1]
        similarcases['cumSimHighYstd_prop'] = total/num_cases
        similarcases['simcount'] = len(cases_matched_sorted)
    return similarcases
def find_sim_cases_elim(contestid, day):
    similarcases={'cumSimElimYstd_prop':0,'simcount':0}

    cases_matched = []
    for key in contestday_dict:
        contestid1 = contestid
        contestid2 = key

        if contestid1 == contestid2: continue

        simscore = match_two_rows_elim(contestid1, contestid2, day)

        if simscore >= 0:
            cumSimElimYstd_prop = contestday_dict[contestid2][day][\'cumElim2Ystd\']/contestday_dict[contestid2][day][\'cumRated2Ystd\']
            cases_matched.append([simscore, cumSimElimYstd_prop])

    # Pick the N nearest neighbors
    cases_matched_sorted = sorted(cases_matched, key=itemgetter(0))
    num_cases = min([N_NEIGHBOR, len(cases_matched_sorted)])
    if num_cases > 0:
        index = num_cases
        total = 0
        while index > 0:
            index -= 1
            total += cases_matched_sorted[index][1]

        similarcases[\'cumSimElimYstd_prop\'] = total/num_cases
        similarcases[\'simcount\'] = len(cases_matched_sorted)

    return similarcases

def find_sim_cases_comm(contestid, day):
    similarcases={'cumSimCommentsYstd':0,'simcount':0}

    cases_matched = []
    for key in contestday_dict:
        contestid1 = contestid
        contestid2 = key

        if contestid1 == contestid2: continue

        simscore = match_two_rows_comm(contestid1, contestid2, day)

        if simscore >= 0:
            cumSimCommentsYstd = contestday_dict[contestid2][day][\'cumHolderCommentsYstd\'
            cases_matched.append([simscore, cumSimCommYstd])

    # Pick the N nearest neighbors
    cases_matched_sorted = sorted(cases_matched, key=itemgetter(0))
    num_cases = min([N_NEIGHBOR, len(cases_matched_sorted)])
    if num_cases > 0:
        index = num_cases
        total = 0
        while index > 0:
            index -= 1
            total += cases_matched_sorted[index][1]

        similarcases[\'cumSimCommentsYstd\'] = total/num_cases
        similarcases[\'simcount\'] = len(cases_matched_sorted)

    return similarcases
cases_matched_sorted = sorted(cases_matched, key=itemgetter(0))

num_cases = min([N_NEIGHBOR, len(cases_matched_sorted)])
if num_cases > 0:
    index = num_cases
    total = 0
    while index > 0:
        index -= 1
        total += cases_matched_sorted[index][1]

similarcases['cumSimCommentsYstd'] = total/num_cases
similarcases['simcount'] = len(cases_matched_sorted)

return similarcases

def find_sim_cases_negcomm(contestid, day):
    similarcases = {'cumSimNegCommYstd': 0, 'simcount': 0}
    cases_matched = []

    for key in contestday_dict:
        contestid1 = contestid
        contestid2 = key

        if contestid1 == contestid2: continue

        simscore = match_two_rows_negcomm(contestid1, contestid2, day)

        if simscore >= 0:
            cumSimNegCommYstd = contestday_dict[contestid2][day]['cumNegCommYstd']
            cases_matched.append([simscore, cumSimNegCommYstd])

    # Pick the N nearest neighbors
    cases_matched_sorted = sorted(cases_matched, key=itemgetter(0))

    num_cases = min([N_NEIGHBOR, len(cases_matched_sorted)])
    if num_cases > 0:
        index = num_cases
        total = 0
        while index > 0:
            index -= 1
            total += cases_matched_sorted[index][1]

        similarcases['cumSimNegCommYstd'] = total/num_cases
        similarcases['simcount'] = len(cases_matched_sorted)

    return similarcases

def find_sim_cases_highcomm(contestid, day):
    similarcases = {'cumSimHighCommYstd': 0, 'simcount': 0}
    cases_matched = []
for key in contestday_dict:
    contestid1 = contestid
    contestid2 = key

    if contestid1 == contestid2: continue

    simscore = match_two_rows_highcomm(contestid1, contestid2, day)

    if simscore >= 0:
        cumSimHighCommYstd = contestday_dict[contestid2][day]['cumHighCommYstd']
        cases_matched.append([simscore, cumSimHighCommYstd])

    # Pick the N nearest neighbors
    cases_matched_sorted = sorted(cases_matched, key=itemgetter(0))

    num_cases = min([N_NEIGHBOR, len(cases_matched_sorted)])
    if num_cases > 0:
        index = num_cases
        total = 0
        while index > 0:
            index -= 1
            total += cases_matched_sorted[index][1]

        similarcases['cumSimHighCommYstd'] = total/num_cases
        similarcases['simcount']=len(cases_matched_sorted)

    return similarcases

def match_rated(row):
    contestid = row['contestID']
    day = row['day']

    similarcases={}

    row['cumSimRatedYstd'] = 0
    row['simcount'] = 0

    similarcases=find_sim_cases_rated(contestid, day)

    if similarcases['simcount'] > 0:
        row['cumSimRatedYstd'] = similarcases['cumSimRatedYstd']
        row['simcount'] = similarcases['simcount']
    return row

def match_high(row):
    contestid = row['contestID']
    day = row['day']

    similarcases={}

    row['cumSimHighYstd'] = 0

row['simcount'] = 0

similarcases=find_sim_cases_high(contestid, day)

if similarcases['simcount'] > 0:
    row['cumSimHighYstd'] = similarcases['cumSimHighYstd_prop'] * row['cumrated2ystd']
    row['simcount'] = similarcases['simcount']

return row

def match_elim(row):
    contestid = row['contestID']
    day = row['day']

    similarcases={}

    row['cumSimElimYstd'] = 0
    row['simcount'] = 0

    similarcases=find_sim_cases_elim(contestid, day)

    if similarcases['simcount'] > 0:
        row['cumSimElimYstd'] = similarcases['cumSimElimYstd_prop'] * row['cumrated2ystd']
        row['simcount'] = similarcases['simcount']

    return row

def match_comm(row):
    contestid = row['contestID']
    day = row['day']

    similarcases={}

    row['cumSimCommentsYstd'] = 0
    row['simcount'] = 0

    similarcases=find_sim_cases_comm(contestid, day)

    if similarcases['simcount'] > 0:
        row['cumSimCommentsYstd'] = similarcases['cumSimCommentsYstd']
        row['simcount'] = similarcases['simcount']

    return row

def match_negcomm(row):
    contestid = row['contestID']
    day = row['day']

    similarcases={}

    row['cumSimNegCommYstd'] = 0
    row['simcount'] = 0

if row['cumholdercommentsystd'] == 0:
    return row

similarcases=find_sim_cases_negcomm(contestid, day)

if similarcases['simcount'] > 0:
    row['cumSimNegCommYstd'] = similarcases['cumSimNegCommYstd']
    row['simcount'] = similarcases['simcount']

    return row

def match_highcomm(row):
    contestid = row['contestID']
    day = row['day']

    similarcases = {}

    row['cumSimHighCommYstd'] = 0
    row['simcount'] = 0

    if row['cumholdercommentsystd'] == 0:
        return row

    similarcases = find_sim_cases_highcomm(contestid, day)

    if similarcases['simcount'] > 0:
        row['cumSimHighCommYstd'] = similarcases['cumSimHighCommYstd']
        row['simcount'] = similarcases['simcount']

        return row

References